Business Analytics

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Unit 01: Business Analytics and Summarizing Business Data

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Introduction

Business analytics is a crucial aspect of modern-day organizations that leverages data and advanced analytical techniques to make data-driven decisions. The goal of business analytics is to turn data into insights that can help organizations identify trends, measure performance, and optimize processes.

One of the most significant benefits of business analytics is that it allows organizations to make informed decisions based on real data instead of gut instincts or assumptions. This leads to better decision-making and a more strategic approach to business operations. Additionally, business

analytics enables organizations to predict future trends and allocate resources more effectively, thereby increasing efficiency and competitiveness.

Another advantage of business analytics is that it can help organizations understand their customers better. By analyzing customer data, organizations can gain insights into customer behavior, preferences, and buying patterns, which can help them tailor their products and services to meet customer needs more effectively.

However, it is important to note that business analytics is not just about collecting and analyzing data. It requires a deep understanding of statistical and mathematical models, as well as the ability to effectively communicate insights to key stakeholders. Furthermore, organizations must ensure that their data is of high quality and that their analytics systems are secure, to ensure that the insights generated are accurate and trustworthy.

1.1 Overview of Business Analytics

Business analytics is a broad field that encompasses the use of data, statistical algorithms, and technologies to extract insights and support decision making in organizations. It involves the collection, analysis, and interpretation of data to help organizations identify trends, measure performance, and optimize processes.

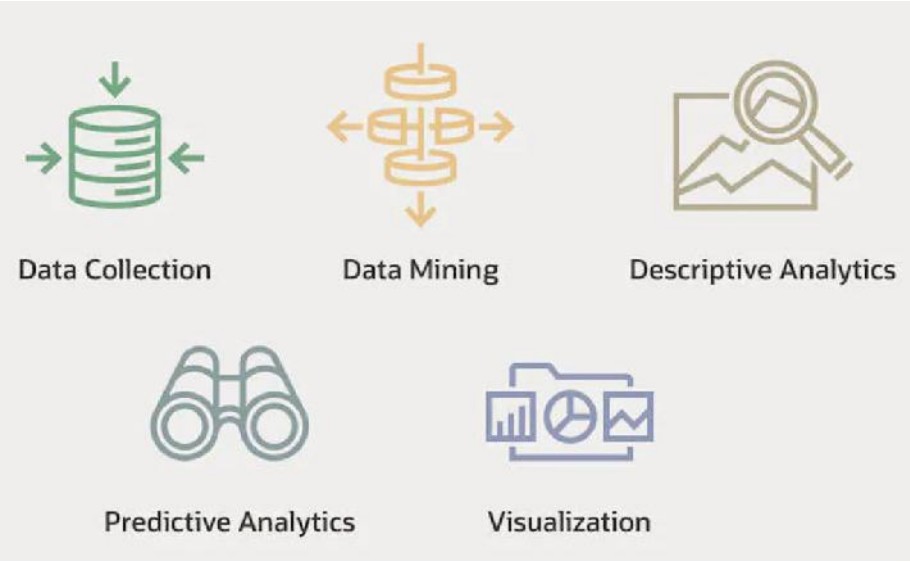
The goal of business analytics is to turn data into actionable insights that can inform strategy and drive improvements. This is achieved through a combination of descriptive, diagnostic, predictive, and prescriptive analytics, which provide different levels of insight and support different types of decision making.

Descriptive analytics provides a historical perspective on business performance and focuses on summarizing and describing past data. Diagnostic analytics focuses on identifying root causes of performance issues. Predictive analytics uses historical data and statistical models to make predictions about future performance. Prescriptive analytics provides recommendations for decision-makers to optimize future outcomes.

Business analytics tools and technologies include data warehousing, data mining, machine learning, and visualization tools, among others. The use of these tools and techniques enables organizations to collect, process, and analyze large amounts of data, providing insights that would be difficult to extract manually.

Overall, business analytics is a crucial tool for organizations looking to make data-driven decisions, optimize performance, and stay ahead in a highly competitive business environment.

In conclusion, business analytics is a critical tool for modern organizations that enables them to make informed decisions, improve operations, and stay competitive in a rapidly changing business environment. While it requires a combination of technical expertise and communication skills, the benefits it brings to organizations make it a valuable investment.



1.2 Scope of Business Analytics

The scope of business analytics covers a wide range of activities and areas within an organization, including:

Data Collection and Management: The process of gathering, storing, and organizing data from various sources in a structured manner.

Data Analysis: The process of using statistical and mathematical techniques to identify patterns and relationships in data, and to gain insights into business problems.

Predictive Modeling: The use of statistical algorithms and machine learning techniques to make predictions about future events or trends based on historical data.

Data Visualization: The process of creating visual representations of data to help understand and communicate insights and information more effectively.

Decision-Making Support: Using analytics to provide insights and recommendations to decision-makers to help them make more informed choices.

Customer Behavior Analysis: The process of analyzing customer data to gain insights into their behavior and preferences, and to inform business strategy.

Market Research: The process of gathering and analyzing data about the market, customers, and competitors to inform business strategy.

Inventory Management: Using analytics to optimize the management of inventory levels and costs, and to improve supply chain efficiency.

Financial Forecasting: The process of using data and analytical models to make predictions about future financial performance and outcomes.

Operations Optimization: Using analytics to optimize business processes and operations, and to improve efficiency, productivity, and customer satisfaction.

Customer Behavior Analysis: Understanding customer preferences, needs, and purchase patterns to inform business decisions and improve customer experience.

Sales and Marketing Analysis: Evaluating the effectiveness of sales and marketing strategies, and determining opportunities for improvement.

Supply Chain Optimization: Optimizing supply chain operations, such as inventory management, logistics, and transportation.

Financial Analysis and Reporting: Analyzing financial data to support budgeting, forecasting, and decision-making.

Human Resource Management and Analysis: Examining HR data to improve workforce planning, talent management, and employee satisfaction.

Operations and Process Improvement: Identifying and improving inefficiencies in business processes to increase efficiency and productivity.

Business Analytics Success Stories

Here are some well-known business data analytics success stories:

Capital One: Capital One uses data analytics to detect fraud and manage risk. The company's algorithms analyze customer data to identify unusual or suspicious behavior and alert the relevant departments.

Barclays: The bank uses data analytics to detect fraud, manage risk and improve customer experience.

Procter & Gamble: The consumer goods company uses data analytics to optimize pricing, improve supply chain and inform marketing strategies.

Sports teams: Teams in the NFL, NBA and MLB use data analytics to optimize player performance, inform game strategy and improve fan engagement.

These examples show how businesses can use data analytics to drive efficiency, improve customer experiences, and make informed decisions.

1.3 Use cases of Business Analytics

Netflix

Netflix uses business analytics in several ways:

Content analysis: They analyze data to determine which content to produce and license, including genre, budget, and target audience.

Customer behavior: They track viewing habits, search and browsing behavior, and preferences to make recommendations and personalize the user experience.

Pricing and subscription: Netflix uses analytics to determine optimal pricing and subscription plans, monitor customer churn, and understand the impact of changes.

Marketing: They analyze the effectiveness of marketing campaigns and adjust them accordingly.

International expansion: They use data to determine which markets to expand into, what content to offer, and how to localize the user experience.

Overall, Netflix leverages analytics to drive informed decision-making and optimize their operations, user experience, and revenue.

Amazon

Amazon uses business analytics in several ways:

Sales and revenue: They analyze sales data to understand trends, customer behavior, and revenue growth.

Inventory and supply chain: Amazon uses analytics to optimize inventory levels, manage the supply chain, and ensure timely delivery of products.

Customer behavior: They track customer behavior, including browsing, search, and purchase history, to make recommendations and personalize the user experience.

Pricing: Amazon uses data and analytics to determine optimal pricing for products and to track competitor pricing.

Marketing: They analyze the effectiveness of marketing campaigns, advertising, and promotions to make informed decisions about where to allocate budget.

Fraud detection: Amazon uses analytics to detect fraudulent activity and protect the security of customer data and transactions.

Overall, Amazon leverages analytics to drive informed decision-making and optimize their operations, customer experience, and revenue.

Walmart

Walmart uses business analytics in several ways, including:

Supply Chain Optimization: Walmart uses data analytics to optimize its supply chain and improve the efficiency of its operations.

Customer Insights: Walmart collects and analyzes data on customer shopping habits and preferences to inform its marketing strategies and product offerings.

Inventory Management: Walmart uses data analytics to track inventory levels and sales patterns to ensure that the right products are in stock at the right time.

Employee Management: Walmart uses data analytics to monitor employee productivity, schedule management and reduce labor costs.

Pricing Strategies: Walmart uses data analytics to inform its pricing strategies, ensuring that it remains competitive while maximizing profits.

Overall, Walmart leverages business analytics to gain insights and make data-driven decisions that improve its operations and drive growth.

Uber

Uber uses business analytics in several ways:

Demand forecasting: To predict demand for rides and optimize pricing and driver incentives.

Customer segmentation: To better understand and target different customer segments.

Driver performance evaluation: To measure driver performance and identify areas for improvement.

Route optimization: To determine the best routes for drivers and passengers, reducing travel time and costs.

Fraud detection: To identify and prevent fraudulent activities, such as fake rides and fake drivers.

Marketing and promotions: To measure the effectiveness of marketing campaigns and promotional offers.

Market expansion: To analyze new markets and determine the viability of expanding into new cities and regions.

Google

Google uses business analytics in various ways:

Data-driven decision making: Google collects and analyzes massive amounts of data to inform its decisions and strategies.

Customer behavior analysis: Google analyzes user data to understand customer behavior and preferences, which helps with product development and marketing strategies.

Financial analysis: Google uses business analytics to track and forecast its financial performance.

Ad campaign optimization: Google uses analytics to measure the effectiveness of its advertising campaigns and adjust them accordingly.

Market research: Google analyzes market trends and competitor activity to inform its business strategies.

What is R: Overview, its Applications and what is R used for?

Since there are so many programming languages available today, it's sometimes hard to decide which one to choose. As a result, programmers often face the dilemma of too many good choices. It's enough to stop people in their tracks, paralyzed with indecision!

To combat this potential source of mental gridlock, we present an analysis of the R programming language.

1.4 What Is R?

What better place to find a good definition of the language than the R Foundation's website? According to R-Project.org, R is "… a language and environment for statistical computing and graphics." It's an open-source programming language often used as a data analysis and statistical software tool.

R is a language and environment for statistical computing and graphics. It is a GNU project which is similar to the S language and environment which was developed at Bell Laboratories (formerly AT&T, now Lucent Technologies) by John Chambers and colleagues. R can be considered as a different implementation of S. There are some important differences, but much code written for S runs unaltered under R.

R provides a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering, …) and graphical techniques, and is highly extensible. The S language is often the vehicle of choice for research in statistical methodology, and R provides an Open Source route to participation in that activity.

One of R's strengths is the ease with which well-designed publication-quality plots can be produced, including mathematical symbols and formulae where needed. Great care has been taken over the defaults for the minor design choices in graphics, but the user retains full control.

R is available as Free Software under the terms of the Free Software Foundation's GNU General Public License in source code form. It compiles and runs on a wide variety of UNIX platforms and similar systems (including FreeBSD and Linux), Windows and MacOS.

The R environment consists of an integrated suite of software facilities designed for data manipulation, calculation, and graphical display. The environment features:

- A high-performance data storage and handling facility
- A suite of operators for array calculations, mainly matrices
- A vast, easily understandable, integrated assortment of intermediate tools dedicated to data analysis
- Graphical facilities for data analysis and display that work either for on-screen or hardcopy
- The well-developed, simple and effective programming language, featuring user-defined recursive functions, loops, conditionals, and input and output facilities.

The syntax of R consists of three items:

- Variables, which store data
- Comments, which are used to improve code readability
- Keywords, reserved words that have a special meaning for the compiler

R was developed in 1993 by Ross Ihaka and Robert Gentleman and includes linear regression, machine learning algorithms, statistical inference, time series, and more.

R is a universal programming language compatible with the Windows, Macintosh, UNIX, and Linux platforms. It is often referred to as a different implementation of the S language and environment and is considered highly extensible.

1.5 The R Environment

R is an integrated suite of software facilities for data manipulation, calculation and graphical display. It includes

- an effective data handling and storage facility,
- a suite of operators for calculations on arrays, in particular matrices,
- a large, coherent, integrated collection of intermediate tools for data analysis,

- graphical facilities for data analysis and display either on-screen or on hardcopy, and
- a well-developed, simple and effective programming language which includes conditionals, loops, user-defined recursive functions and input and output facilities.

The term "environment" is intended to characterize it as a fully planned and coherent system, rather than an incremental accretion of very specific and inflexible tools, as is frequently the case with other data analysis software.

R, like S, is designed around a true computer language, and it allows users to add additional functionality by defining new functions. Much of the system is itself written in the R dialect of S, which makes it easy for users to follow the algorithmic choices made. For computationally-intensive tasks, C, C++ and Fortran code can be linked and called at run time. Advanced users can write C code to manipulate R objects directly.

Many users think of R as a statistics system. We prefer to think of it as an environment within which statistical techniques are implemented. R can be extended (easily) via packages. There are about eight packages supplied with the R distribution and many more are available through the CRAN family of Internet sites covering a very wide range of modern statistics.

R has its own LaTeX-like documentation format, which is used to supply comprehensive documentation, both on-line in a number of formats and in hardcopy.

Does R Have Any Drawbacks?

What language doesn't? When answering the question "What is R?" we should also look at some of R's not so great aspects:

It's a complicated language. R has a steep learning curve. It's a language best suited for people who have previous programming experience.

It's not as secure. R doesn't have basic security measures. Consequently, it's not a good choice for making web-safe applications. Also, R can't be embedded in web browsers.

It's slow. R is slower than other programming languages like Python or MATLAB.

It takes up a lot of memory. Memory management isn't one of R's strong points. R's data must be stored in physical memory. However, the increasing use of cloud-based memory may eventually make this drawback moot.

It doesn't have consistent documentation/package quality. Docs and packages can be patchy and inconsistent, or incomplete. That's the price you pay for a language that doesn't have official, dedicated support and instead is maintained and added to by the community.

Why use R

R is a state-of-the-art programming languague for statistical computing, data analysis, and machine learning. It has been around for almost three decades with over 12,000 packages available for download on CRAN. This means that there is an R package that supports whatever type of analysis you want to perform. Here are a few reasons why you should learn and use R:

Free and open-source: The R programming language is open-source and is issued under the General Public License (GNU). This means that you can use all the functionalities of R for free without any restrictions or licensing requirements. Since R is open-source, everyone is welcome to contribute to the project, and since it's freely available, bugs are easily detected and fixed by the open-source community.

Popularity: The R programming language was ranked 7th in the 2021 IEEE Spectrum ranking of top programming languages and 12th in the TIOBE Index ranking of January 2022. It's the second most popular programming language for data science just behind Python, according to edX, and it is the most popular programming language for statistical analysis. R's popularity also means that there is extensive community support on platforms like Stack overflow. R also has a detailed online documentation that R users can consult for help.

High-quality visualization: The R programming language is famous for high-quality visualizations. R's ggplot2 is a detailed implementation of the grammar of graphics — a system to concisely describe the components of a graph. With R's high-quality graphics, you can easily implement intuitive and interactive graphs.

A language for data analytics and data science: The R programming language isn't a general-purpose programming language. It's a specialized programming language for statistical computing. Therefore, most of R's functions carry out vectorized operations, meaning you don't need to loop through each element. This makes running R code very fast. Distributed computing can be executed in R, whereby tasks are split among multiple processing computers to reduce execution time. R is integrated with Hadoop and Apache Spark, and it can be used to process large amount of data. R can connect to all kinds of databases, and it has packages to carry out machine learning and deep learning operations.

Opportunity to pursue an exciting career in academe and industry: The R programming language is trusted and extensively used in the academic community for research. R is increasingly being used by government agencies, social media, telecommunications, financial, e-commerce, manufacturing, and pharmaceutical companies. Top companies that uses R include Amazon, Google, ANZ Bank, Twitter, LinkedIn, Thomas Cook, Facebook, Accenture, Wipro, the New York Times, and many more. A good mastery of the R programming language opens all kinds of opportunities in academe and industry.

1.6 What is R Used For?

R is a programming language and software environment for statistical computing, data analysis, and graphics. It is widely used by statisticians, data scientists, and researchers in academia, government, and industry for tasks such as statistical modeling, data visualization, and data mining. R is a programming language and software environment for statistical computing and graphics. It is widely used by statisticians, data scientists, and researchers for developing statistical software and data analysis. R is also used for machine learning, data visualization, and data

manipulation. With its vast libraries and packages, R is popular in industries such as finance, healthcare, and e-commerce, as well as academia and research institutions.

Although R is a popular language used by many programmers, it is especially effective when used for

- Data analysis
- Statistical inference
- Machine learning algorithms

R offers a wide variety of statistics-related libraries and provides a favorable environment for statistical computing and design. In addition, the R programming language gets used by many quantitative analysts as a programming tool since it's useful for data importing and cleaning.

As of August 2021, R is one of the top five programming languages of the year, so it's a favorite among data analysts and research programmers. It's also used as a fundamental tool for finance, which relies heavily on statistical data.

1.7 The Popularity of R by Industry

Thanks to its versatility, many different industries use the R programming language. Here is a list of industries/disciplines that use the R programming language:

- Fintech Companies (financial services)
- Academic Research
- Government (FDA, National Weather Service)
- Retail
- Social Media
- Data Journalism
- Manufacturing
- Healthcare

This graph, provided by Stackoverflow, gives you a better idea of R programming language usage in recent history. Given its strength in statistics, it's hardly surprising that R enjoys heavy use in the world of academia, as illustrated on the chart.

If you're looking for specifics, here are ten significant companies or organizations that use R, presented in no particular order.

- Airbnb
- Microsoft
- Uber
- Facebook
- Ford
- Google
- Twitter

- IBM
- American Express
- HP

1.8 How to Install R

To install R, go to https://cloud.r-project.org/ and download the latest version of R for Windows, Mac or Linux.

When you have downloaded and installed R, you can run R on your computer.

The screenshot below shows how it may look like when you run R on a Windows PC:

Installing R on Windows OS

To install R on Windows OS:

Go to the CRAN website. (https://cran.r-project.org/)

Click on "Download R for Windows".

Click on "install R for the first time" link to download the R executable (.exe) file.

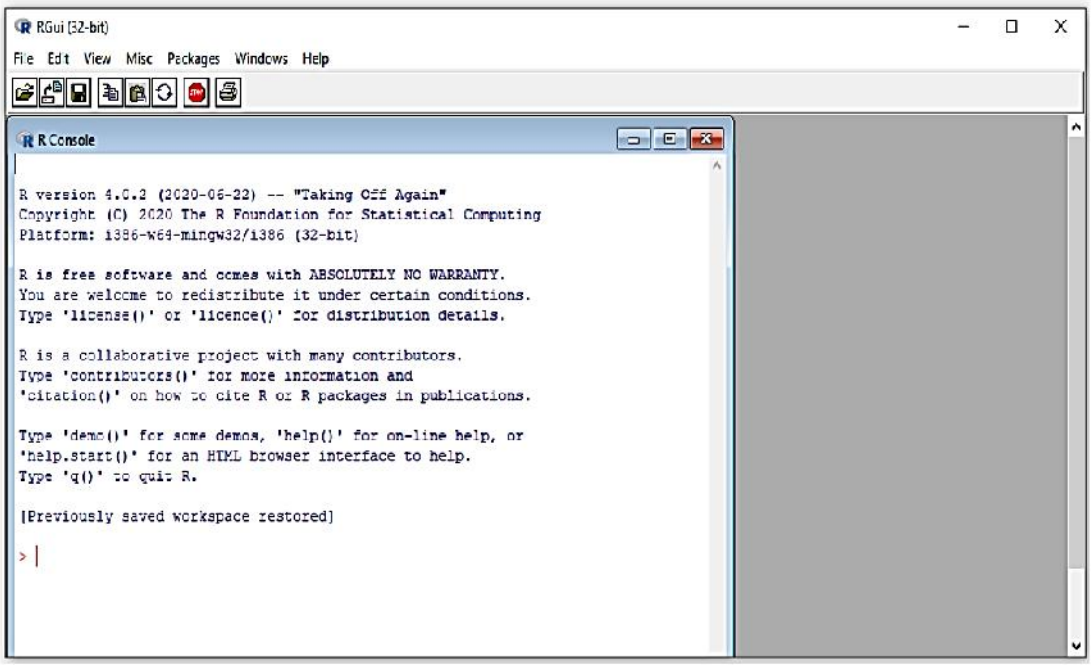
Run the R executable file to start installation, and allow the app to make changes to your device.

Select the installation language.

Follow the installation instructions.

Click on "Finish" to exit the installation setup.

R has now been sucessfully installed on your Windows OS. Open the R GUI to start writing R codes.



Additional R interfaces

Other than the R GUI, the other ways to interface with R include RStudio Integrated Development Environment (RStudio IDE) and Jupyter Notebook. To run R on RStudio, you first need to install R on your computer, while to run R on Jupyter Notebook, you need to install an R kernel. RStudio and Jupyter Notebook provide an interactive and friendly graphical interface to R that greatly improves users' experience.

Installing RStudio Desktop

To install RStudio Desktop on your computer, do the following:

Go to the RStudio website. (https://posit.co/download/rstudio-desktop/)

Click on "DOWNLOAD" in the top-right corner.

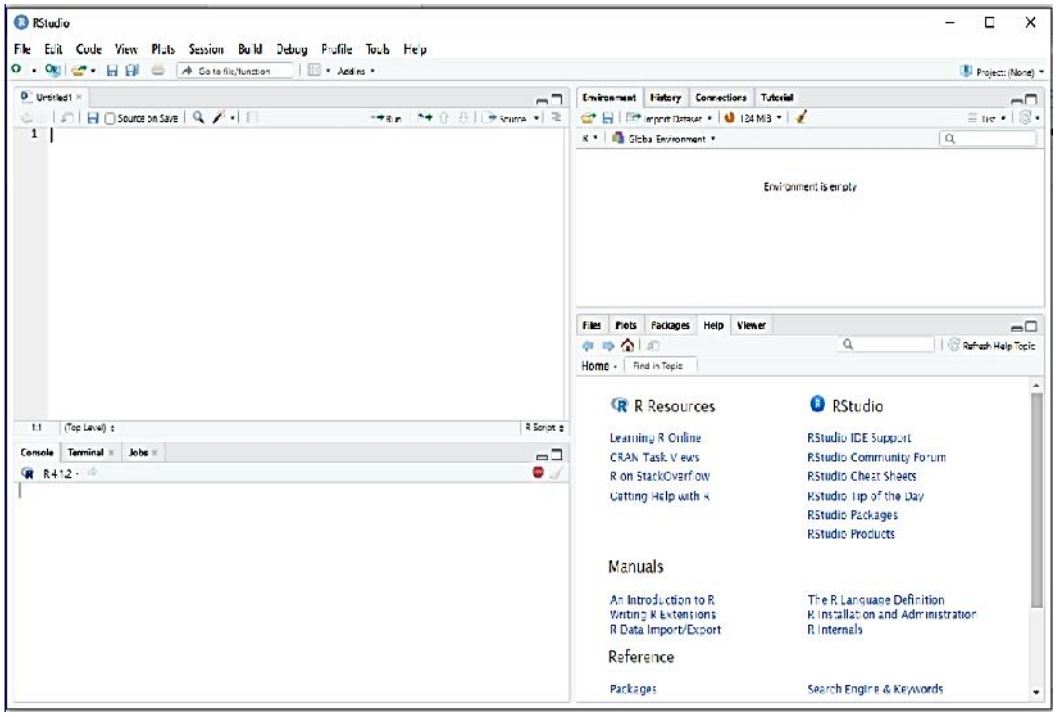
Click on "DOWNLOAD" under the "RStudio Open Source License".

Download RStudio Desktop recommended for your computer.

Run the RStudio Executable file (.exe) for Windows OS or the Apple Image Disk file (.dmg) for macOS X.

Follow the installation instructions to complete RStudio Desktop installation.

RStudio is now successfully installed on your computer. The RStudio Desktop IDE interface is shown in the figure below:



1.9 R packages

R packages are collections of functions, data, and compiled code that can be used to extend the capabilities of R. There are thousands of R packages available, covering a wide range of topics, including statistics, machine learning, data visualization, and more. Installing and using R

packages is an essential part of working with R, and many packages are designed to be easy to install and use, with clear documentation and examples.

Tidyverse: The tidyverse is a collection of R packages designed for data science. It includes packages for data manipulation (dplyr), data visualization (ggplot2), and data import/export (readr, tidyr), among others. The packages in the tidyverse are designed to work together seamlessly, and they share a common design philosophy, which emphasizes simplicity, consistency, and understanding. The tidyverse is particularly popular among R users due to its ease of use, intuitive syntax, and wide range of capabilities, making it a great choice for data analysis tasks of all types and complexity levels.

Ggplot2: ggplot2 is a data visualization library for the R programming language. It provides a high-level interface for creating statistical graphics. ggplot2 uses a grammar of graphics to build complex plots from basic components, allowing users to quickly create sophisticated visualizations of their data. The library is highly customizable and flexible, allowing users to specify a wide range of visual elements such as colors, shapes, sizes, and labels.

Dplyr: dplyr is a data manipulation library for R. It provides a set of functions that allow users to perform common data manipulation tasks such as filtering, summarizing, transforming, and aggregating data. dplyr is designed to be fast, efficient, and easy to use, and it operates on data frames and tibbles, making it a popular choice for data wrangling and exploration. The library is particularly well-suited for working with large datasets, as it provides optimized implementations for many common data manipulation operations. The syntax of dplyr functions is highly readable and intuitive, and the library is widely used by data scientists and analysts for data preparation and exploration.

Tidyr:tidyr is a library for the R programming language that provides tools for "tidying" data. In the context of data science and analysis, tidying data means restructuring it into a format that is more suitable for analysis, visualization, and modeling. tidyr provides a suite of functions for transforming data from a wide variety of formats into a more structured, "tidy" format. This makes it easier to work with the data and perform common data manipulation tasks such as aggregating, filtering, and summarizing. The library is designed to work seamlessly with other R libraries such as dplyr, making it a popular choice for data preparation and wrangling tasks.

Shiny: Shiny is a web application framework for R. It allows R developers to create interactive, web-based data applications without needing to learn HTML, CSS, or JavaScript. Shiny provides a simple, high-level syntax for building user interfaces and tying them to R code for data analysis, visualization, and modeling. Applications built with Shiny can be run locally or hosted on a web server, making it easy to share results with collaborators and stakeholders. The framework is highly customizable and can be extended using HTML, CSS, and JavaScript, allowing developers to create complex, interactive applications with rich user interfaces. Shiny is widely used in data science and analytics for creating dashboards, data visualization tools, and other interactive applications.

1.10 Vector in R

In R, a vector is a basic data structure that represents an ordered collection of values of the same type (numeric, character, logical, etc.). Vectors are the simplest type of data structure in R and are used as the building blocks for more complex data structures such as arrays, data frames, and lists. A vector can be created using the c() function and can be indexed, sliced, and manipulated using various R functions and operators. In R, vectors are used for representing variables, input data, and intermediate results of computations. They play a crucial role in many data analysis and modeling tasks and are an essential part of the R programming language.

```
# Create Vectors
id <- c(10,11,12,13)
name <- c('sai','ram','deepika','sahithi')
dob <- as.Date(c('1990-10-02','1981-3-24','1987-6-14','1985-8-16'))
```

```
# Create Named Vector
x <- c(C1='A',C2='B',C3='C')
print(x)

# Output
# C1  C2  C3
#"A" "B" "C"
```

1.11 Data types in R

In R, the following data types are commonly used:

Numeric: represents numbers and is used for mathematical calculations.

Integer: a whole number, without a fractional part.

Complex: represents complex numbers.

Character: used to represent text.

Logical: used to represent True/False values.

Factor: used to represent categorical variables.

Date: used to represent dates.

Raw: used to represent raw binary data.

R also has several other specialized data types such as **list, matrix, data frame**, etc.

1.12 Data Structures in R

In R, data structures include:

Vectors: One-dimensional arrays of homogeneous data (e.g., numbers or characters)

Matrices: Two-dimensional arrays of homogeneous data

Arrays: Multi-dimensional arrays of homogeneous data

Data frames: Two-dimensional arrays of heterogeneous data, with rows and columns labeled

Lists: Heterogeneous collections of objects

Factors: Categorical variables with a limited number of levels

Tables: Tabular data structure for summarizing categorical data.

Each of these data structures can be created and manipulated in various ways in R, and many functions are available for operating on them.

Summary

Business analytics is the practice of examining data and using statistical analysis and other methods to gain insights into the performance and efficiency of a business. It involves the use of data, statistical algorithms, and technology to uncover hidden patterns and knowledge from large data sets, and is used to inform decision making and guide the development of strategies and plans.

The goal of business analytics is to improve decision-making, streamline processes, and gain a competitive advantage through the use of data and predictive modeling. It can be applied in various areas of a business, such as sales and marketing, supply chain management, finance, and operations.

Business analytics typically involves several key steps: data collection, data cleaning and preparation, data analysis, and communication of results. Data scientists and other professionals use statistical and mathematical methods, such as regression analysis and predictive modeling, to analyze the data and extract insights. The results of these analyses are then used to inform decisions, support business strategy development, and identify opportunities for improvement.

In recent years, the rapid growth of digital data and advancements in technology have made it easier for organizations to collect and analyze large amounts of data, leading to the widespread adoption of business analytics across a wide range of industries.

Keywords

Business analytics, Descriptive analytics, Predictive analytics, Prescriptive analytics, R Programming

SelfAssessment

1. Which of the following fields below typically make use of Data Mining techniques?

A. Advertising

B. Government Intelligence

C. Airline Industry

D. All of the above

2. The R language is a dialect of which of the following programming languages?

A. SAS

B. MATLAB

C. C

D. S

3. Which is the R command for obtaining 1000 random numbers through normal distribution with mean 0 and variance 1?

A. norm(1000, 0, 1)

B. rnorm(0, 1, 1000)

C. rnorm(1000, 0, 1)

D. qnorm(0, 1, 1000)

4. For the population y<-c(1,2,3,4,5), write the R command to find the mean?

A. mean{y}

B. means(y)

C. mean(y)

D. mean[y]

5. It is an encompassing and multidimensional field that uses mathematics, statistics, predictive modeling and machine learning techniques to find meaningful patterns and knowledge in recorded data.

A. Big Data

B. Analytics

C. Normal Data

D. Analytics Process

6. It is a term applied to a dataset that exceeds the processing capacity of conventional database systems, or it doesn't fit the structural requirements of traditional database architecture.

A. Big Data

B. Business Analytics

C. Analytics

D. Normal Data

7. The first step in the process is _____. Data relevant to the applicant is collected. The quality, quantity, validity, and nature of data directly impact the analytical outcome. A thorough understanding of the data on hand is extremely critical.

A. Results

B. Put Into Use

C. Data Collection

D. Model Building

8. Usually raw data is not in a format that can be directly used to perform data analysis. In very simple terms, most platforms require data to be in a matrix form with the variables being in different columns and rows representing various observations. Data may be available in structured, semi-structured, and unstructured form.

A. Data Collection
B. Data Preparation
C. Data Analysis
D. Model Building

9. Once data is converted into a structured format, the next stage is to perform _____. At this stage underlying trends in the data are identified. This step can include fitting a linear or nonlinear regression model, performing principal component analysis or cluster analysis, identifying if data is normally distributed or not.

A. Data Collection
B. Data Preparation
C. Data Analysis
D. Model Building

10. We need to analyzed the data we collected, Analyze Data Model to assess and query the data collected in the process.

A. Data
B. Analyze
C. Generate Reports
D. Smarter Decisions

11. Consists of acquiring the data, implementing advanced data processes, distributing the data effectively and managing oversight data.

A. Artificial Intelligence
B. Growing Importance of The CDO & CAO
C. Data Discovery
D. Data Quality Management (DQM)

12. _____ is the science aiming to make machines execute what is usually done by complex human intelligence.

A. Data Discovery
B. Artificial Intelligence
C. Collaborative Business Intelligence
D. Consumer Experience

13. Predictive analytics is widely used by both conventional retail stores as well as e-commerce firms for analyzing their historical data and building models for customer engagement, supply chain optimization, price optimization, and space optimization and assortment planning.

A. Retail Industry
B. Telecom Industry
C. Health Industry
D. Finance Industry

14. Quantitative data refers to:

A. numerical data that could usefully be quantified to help you answer your research question(s) and to meet your objectives.
B. graphs and tables.
C. any data you present in your report.
D. statistical analysis.

15. Qualitative analysis software cannot:

A. make report writing easier.
B. find concealed data.
C. be done without training.
D. re-analyse data easily.

Answers for SelfAssessment

l.	D	2.	D	3.	B	4.	C	5.	B
6.	A	7.	C	8.	B	9.	A	10.	B
11.	D	12.	B	13.	A	14.	A	15.	D

Review Questions

1. What is business analytics and how does it differ from traditional business intelligence?
2. What are the key steps involved in the business analytics process?
3. How can data visualization be used to support business decision-making?
4. What is data mining and how is it used in business analytics?
5. What is predictive analytics and how does it differ from descriptive analytics?
6. What are some common techniques used in predictive modeling, such as regression analysis, decision trees, and neural networks?
7. How can business analytics be used to support customer relationship management (CRM)?
8. What are some common applications of business analytics in areas such as supply chain management, marketing, and finance?

9. What is big data and how does it impact business analytics?
10. What role does machine learning play in business analytics and what are some common algorithms used in this area?

Further Readings

https://business.wfu.edu/masters-in-business-analytics/articles/what-is-analytics/#:~:text=Business%20analytics%20is%20the%20process,to%20create%20insights%20from%20data.

Business Analytics, 2ed: The Science of Data-Driven Decision Making by U. Dinesh Kumar,

Unit 02: Summarizing Business Data

CONTENTS

Objectives

- discuss one variable and two variables statistics,
- overview of functions to summarize variables.
- implement select, filter, mutate, variables.
- use of arrange, summarize, and group byfunctions.
- demonstrate concept of pipes operator

Introduction

R is a programming language and software environment for statistical computing and graphics. It was developed in 1993 by Ross Ihaka and Robert Gentleman at the University of Auckland, New Zealand. R provides a wide range of statistical and graphical techniques and is highly extensible, allowing users to write their own functions and packages.

One of the main strengths of R is its ability to handle and visualize complex data. It has a large and active community of developers, who have contributed over 15,000 packages to the Comprehensive R Archive Network (CRAN). These packages cover a wide range of topics, including machine learning, time series analysis, Bayesian statistics, social network analysis, and many others.

In addition to its statistical and graphical capabilities, R also provides a flexible and interactive programming environment. R code can be run from the command line, from scripts, or from within

a graphical user interface (GUI) such as RStudio. R supports various data structures such as vectors, matrices, data frames, and lists, and it has a rich set of functions for data manipulation and transformation.

R is widely used in academia, industry, and government for data analysis, statistical modelling, and data visualization. It is also a popular choice for reproducible research, as the code and data used in an analysis can be easily shared and documented.

In summary, R is a powerful and versatile language for data analysis and statistical computing, with a large community of users and developers and a wide range of tools and techniques.

2.1 Functions in R Programming

Functions are useful when you want to perform a certain task multiple times. A function accepts input arguments and produces the output by executing valid R commands that are inside the function. In R Programming Language when you are creating a function the function name and the file in which you are creating the function need not be the same and you can have one or more function definitions in a single R file.

In R programming, functions are blocks of code that perform specific tasks and return a value. Functions are used to encapsulate reusable code, making it easier to write and maintain code. R has many built-in functions and also allows you to create your own custom functions. To define a function in R, you use the function keyword, followed by the function's arguments and the code to be executed in curly braces {}. The return value of a function can be specified using the return keyword. To call a function, simply type its name followed by the arguments in parentheses ().

Types of function in R Language

Built-in Function: Built function R is sq(), mean(), max(), these function are directly call in the program by users.

User-defined Function: R language allow us to write our own function.

Examples of built-in function in R

R has a large number of built-in functions, covering a wide range of tasks, including:

- Mathematics: **sqrt**, **abs**, **cos**, **sin**, **log**, **exp**, etc.
- Data manipulation: **head**, **tail**, **sort**, **unique**, **cbind**, **rbind**, etc.
- Data analysis: **mean**, **median**, **summary**, **t.test**, **cor**, **lm**, etc.
- Plotting: **plot**, **hist**, **boxplot**, **scatterplot**, **density**, etc.
- String manipulation: **toupper**, **tolower**, **substr**, **gsub**, **paste**, etc.
- File Input/Output: **read.csv**, **write.csv**, **read.table**, **write.table**, etc.

Use cases of basic inbuild functions of R programming

Functions to do Descriptive Analytics in R programming

Descriptive statistics in R programming involves summarizing and analyzing a dataset to gain a better understanding of its properties and patterns. This can be done through various measures such as central tendency (mean, median, mode), dispersion (standard deviation, variance, range), and distribution (histograms, boxplots, density plots).

Here are some of the commonly used functions in R for descriptive statistics:

mean(): calculates the mean of a numeric vector.

median(): calculates the median of a numeric vector.

mode(): calculates the mode of a numeric vector.

sd(): calculates the standard deviation of a numeric vector.

var(): calculates the variance of a numeric vector.

range(): calculates the range of a numeric vector (difference between max and min).

quantile(): calculates specified quantiles of a numeric vector.

hist(): creates a histogram of a numeric vector.

boxplot(): creates a boxplot of a numeric vector.

density(): creates a density plot of a numeric vector.

table(): calculates the frequency distribution of a categorical variable.

min(): calculates the minimum value of a numeric vector.

max(): calculates the maximum value of a numeric vector.

sum(): calculates the sum of a numeric vector.

prod(): calculates the product of a numeric vector.

cumsum(): calculates the cumulative sum of a numeric vector.

cumprod(): calculates the cumulative product of a numeric vector.

cor(): calculates the correlation between two numeric vectors.

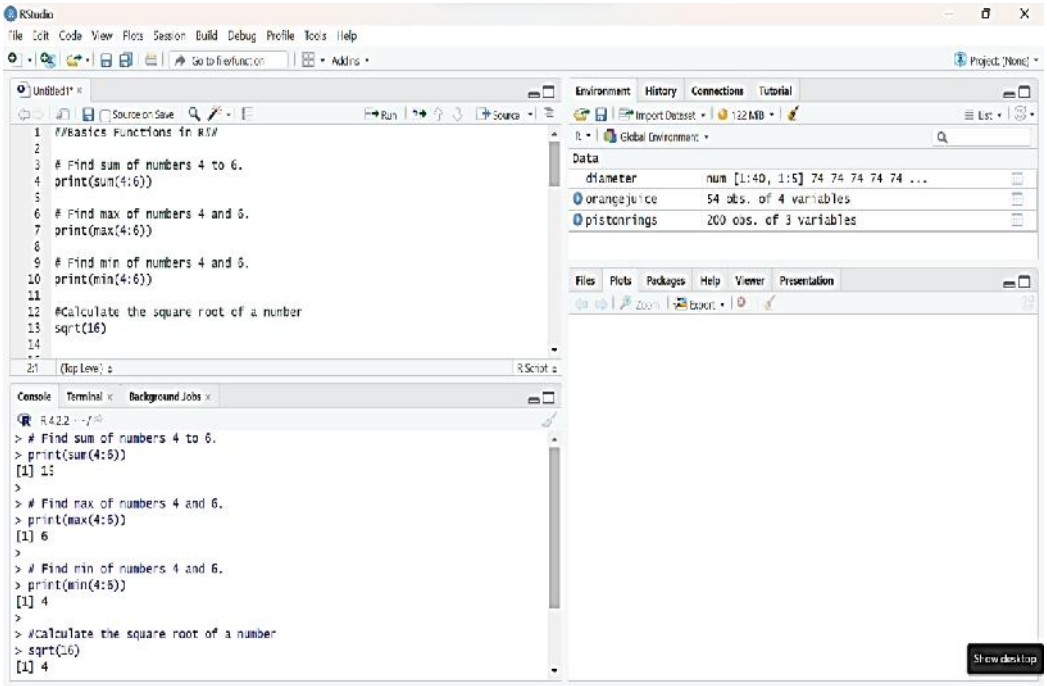
cov(): calculates the covariance between two numeric vectors.

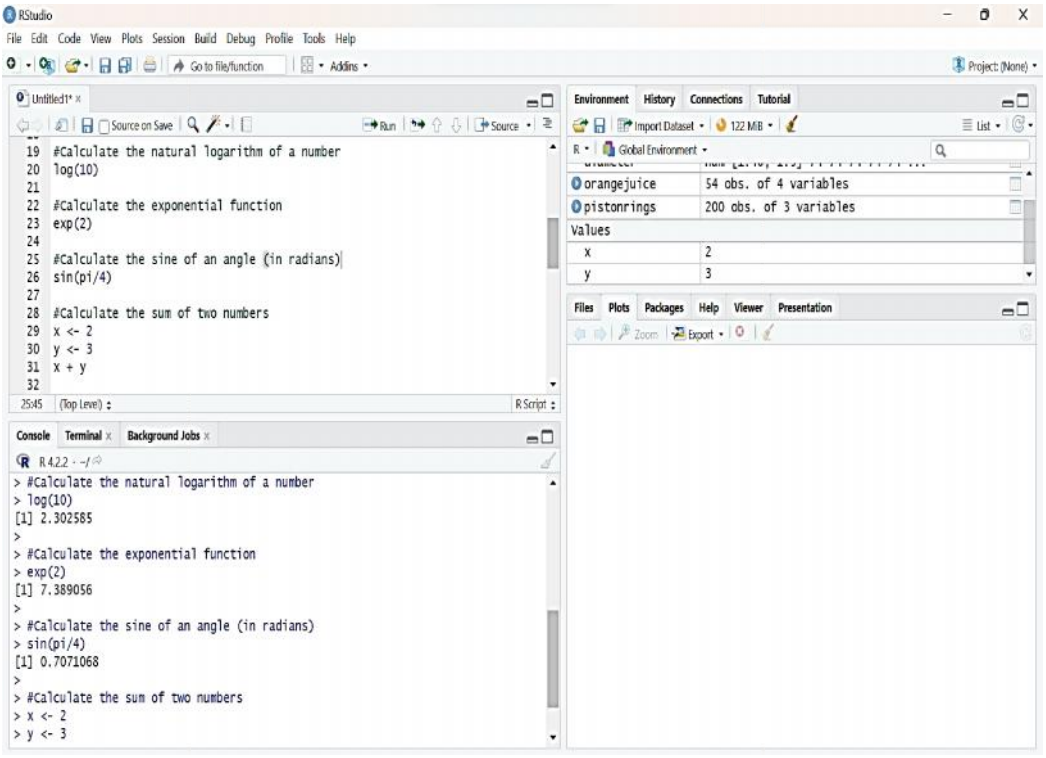
apply(): applies a function to each column (or row) of a data frame.

These are just some of the functions available in R for descriptive statistics. By using these functions, you can obtain a better understanding of your dataset and draw meaningful conclusions from your data.

2.2 One Variable and Two Variables Statistics

Upcoming section shows examples of R functions for one variable and two variable statistics:




RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Untitled1*
Source on Save
Run
Source
#Calculate the natural logarithm of a number
log(10)
#Calculate the exponential function
exp(2)
#Calculate the sine of an angle (in radians)
sin(pi/4)
#Calculate the sum of two numbers
x <- 2
y <- 3
x + y
Console
Terminal
Background Jobs
R 4.2.2 · ~/
> #Calculate the natural logarithm of a number
> log(10)
[1] 2.302585
> #Calculate the exponential function
> exp(2)
[1] 7.389056
> #Calculate the sine of an angle (in radians)
> sin(pi/4)
[1] 0.7071068
> #Calculate the sum of two numbers
> x <- 2
> y <- 3
Environment
History
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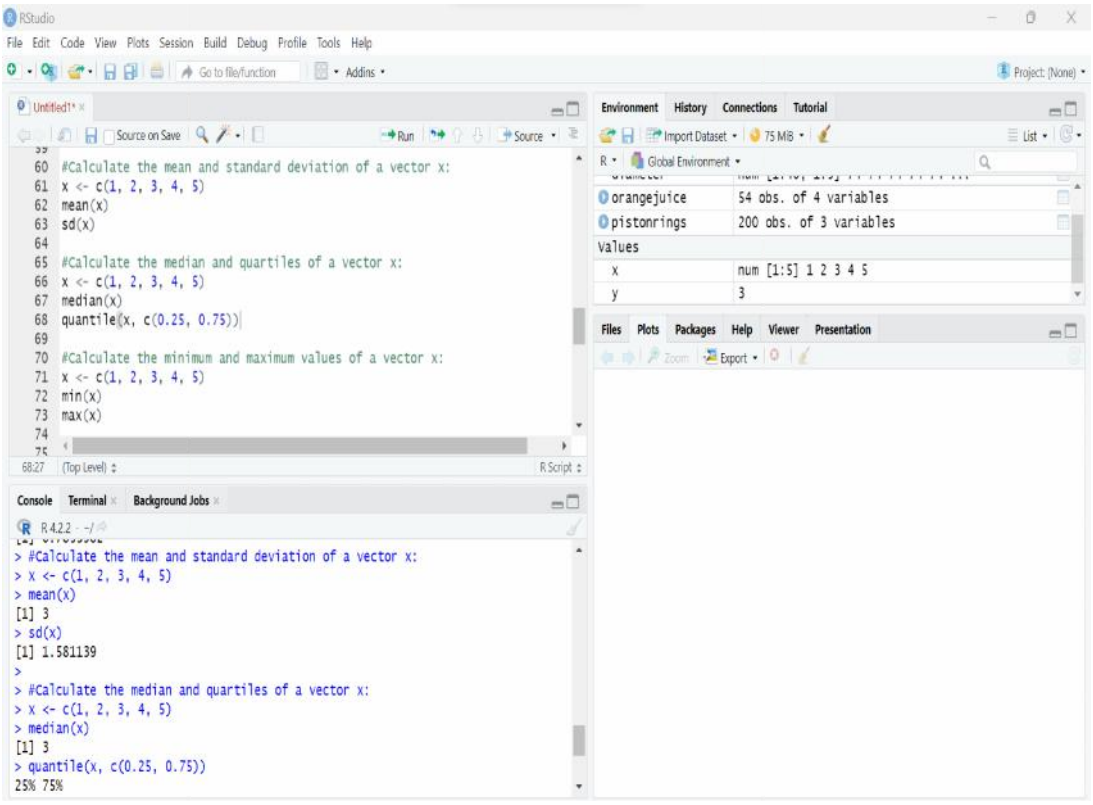
Tutorial
Import Dataset
122 MiB
Global Environment
orangejuice
54 obs. of 4 variables
pistonrings
200 obs. of 3 variables
Values
x
2
y
3
Files
Plots
Packages
Help
Viewer
Presentation
Zoom
Export


RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Untitled1*
Source on Save
Run
Source
#Calculate the mean and standard deviation of a vector x:
x <- c(1, 2, 3, 4, 5)
mean(x)
sd(x)
#Calculate the median and quartiles of a vector x:
x <- c(1, 2, 3, 4, 5)
median(x)
quantile(x, c(0.25, 0.75))
#Calculate the minimum and maximum values of a vector x:
x <- c(1, 2, 3, 4, 5)
min(x)
max(x)
Console
Terminal
Background Jobs
R 4.2.2 · ~/
> #Calculate the mean and standard deviation of a vector x:
> x <- c(1, 2, 3, 4, 5)
> mean(x)
[1] 3
> sd(x)
[1] 1.581139
> #Calculate the median and quartiles of a vector x:
> x <- c(1, 2, 3, 4, 5)
> median(x)
[1] 3
> quantile(x, c(0.25, 0.75))
25% 75%
Environment
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Import Dataset
75 MiB
Global Environment
orangejuice
54 obs. of 4 variables
pistonrings
200 obs. of 3 variables
Values
x
num [1:5] 1 2 3 4 5
y
3
Files
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Help
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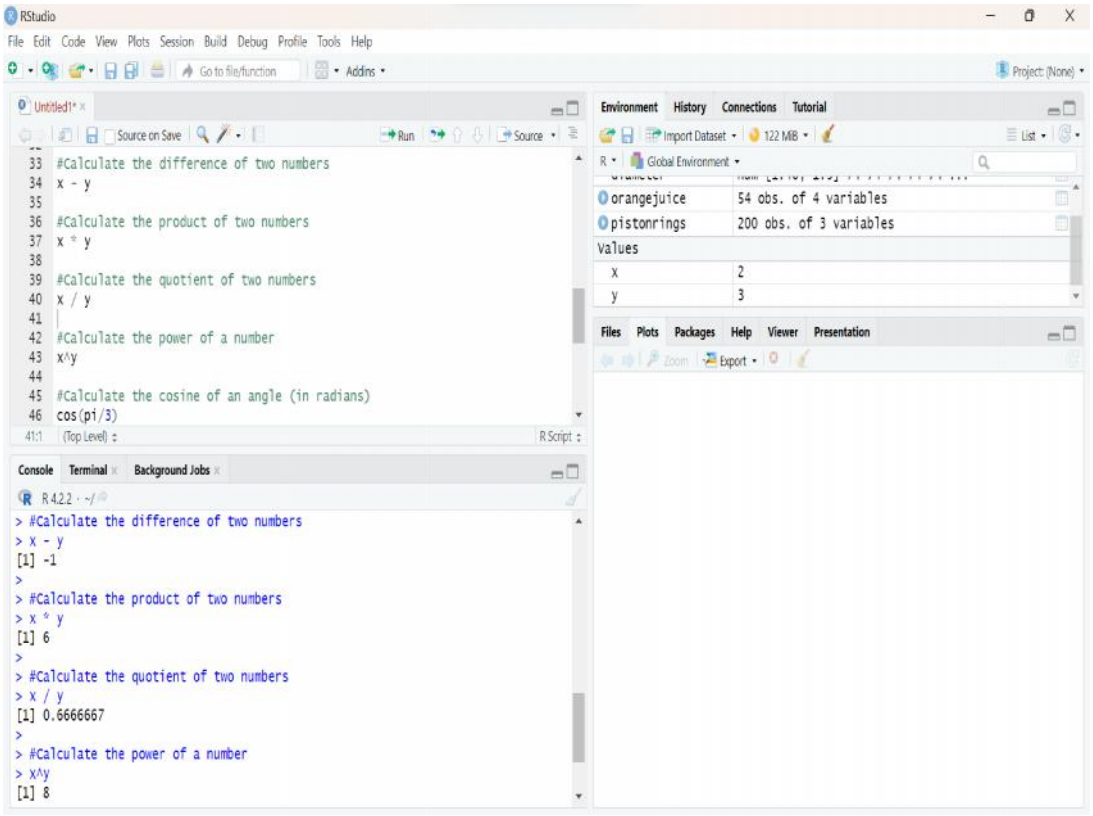
Presentation
Zoom
Export


RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Untitled1*
Source on Save
Run
Source
#Calculate the difference of two numbers
x - y
#Calculate the product of two numbers
x * y
#Calculate the quotient of two numbers
x / y
#Calculate the power of a number
x^y
#Calculate the cosine of an angle (in radians)
cos(pi/3)
Console
Terminal
Background Jobs
> #Calculate the difference of two numbers
> x - y
[1] -1
> #Calculate the product of two numbers
> x * y
[1] 6
> #Calculate the quotient of two numbers
> x / y
[1] 0.6666667
> #Calculate the power of a number
> x^y
[1] 8
Environment
History
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Import Dataset
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54 obs. of 4 variables
pistonrings
200 obs. of 3 variables
Values
x
2
y
3
Files
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Viewer
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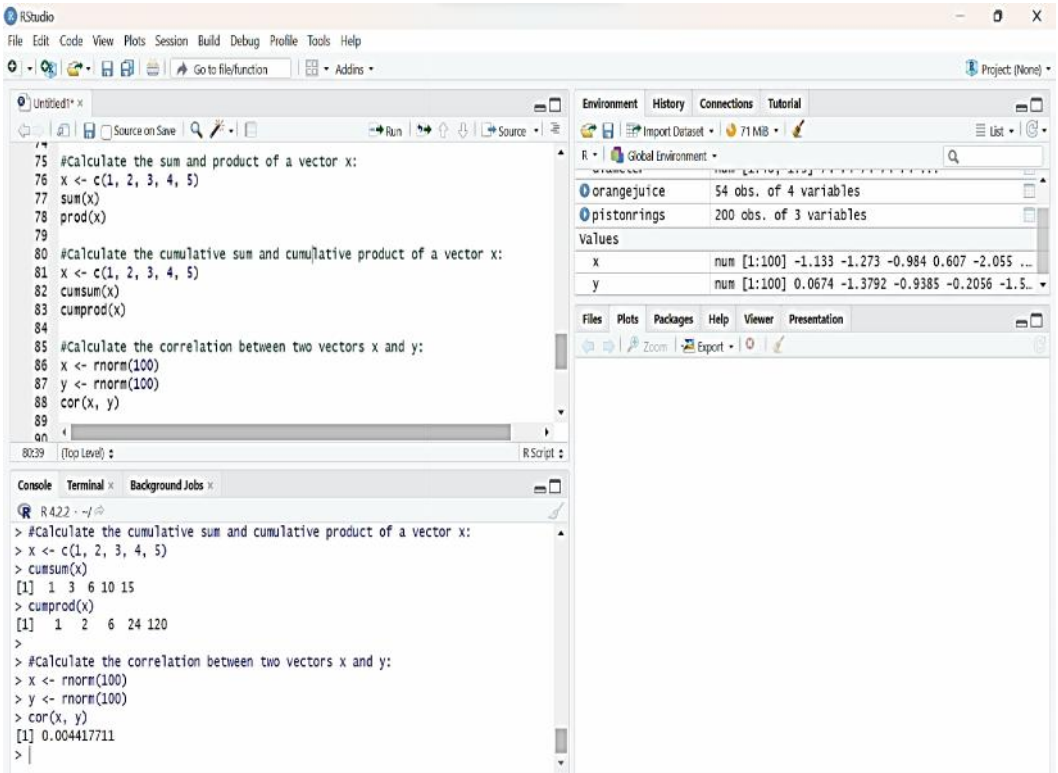
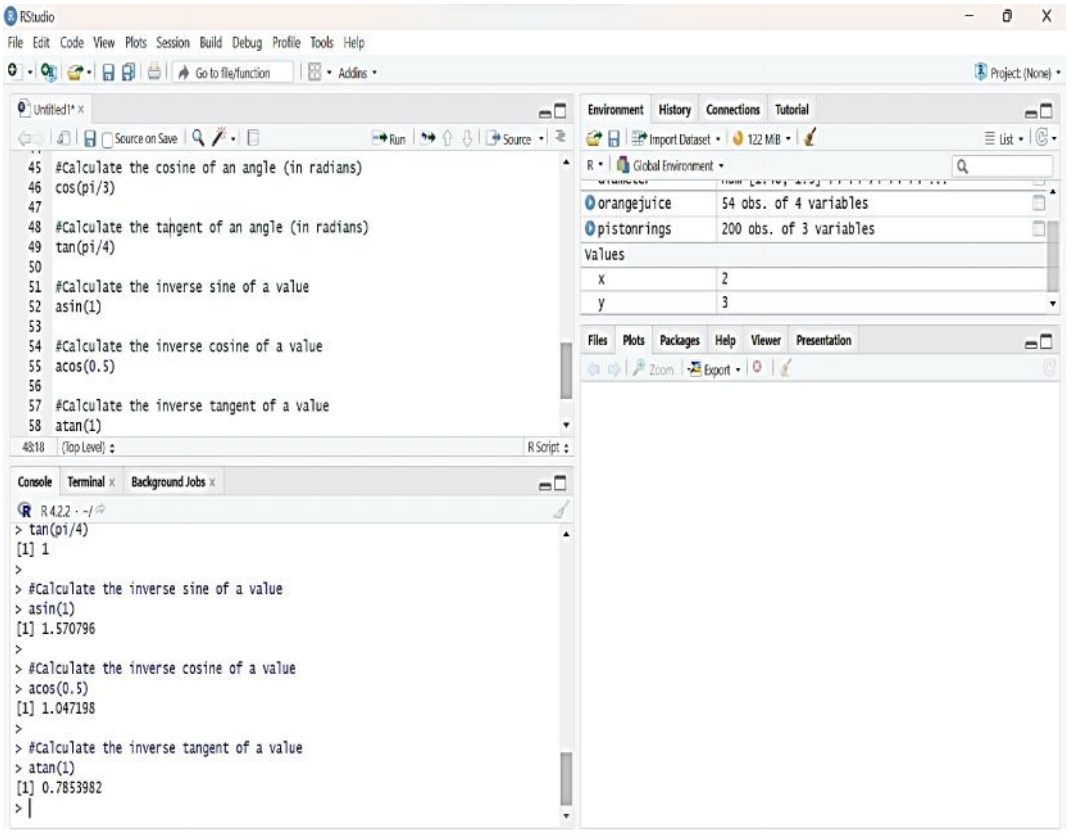
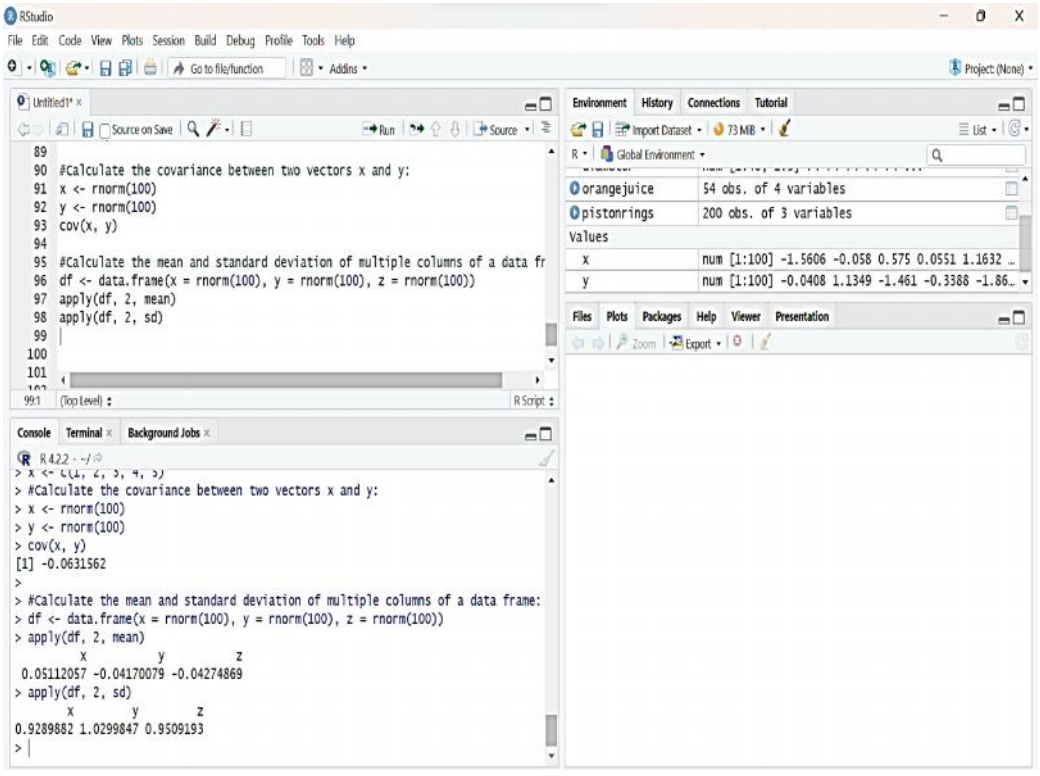
Export


RStudio
File Edit Code View Plots Session Build Debug Profile Tools Help
Untitled1*
Source on Save
Run
Source
#Calculate the sum and product of a vector x:
x <- c(1, 2, 3, 4, 5)
sum(x)
prod(x)
#Calculate the cumulative sum and cumulative product of a vector x:
x <- c(1, 2, 3, 4, 5)
cumsum(x)
cumprod(x)
#Calculate the correlation between two vectors x and y:
x <- rnorm(100)
y <- rnorm(100)
cor(x, y)
Console
Terminal
Background Jobs
> #Calculate the cumulative sum and cumulative product of a vector x:
> x <- c(1, 2, 3, 4, 5)
> cumsum(x)
[1] 1 3 6 10 15
> cumprod(x)
[1] 1 2 6 24 120
> #Calculate the correlation between two vectors x and y:
> x <- rnorm(100)
> y <- rnorm(100)
> cor(x, y)
[1] 0.004417711
Environment
History
Connections
Tutorial
Import Dataset
Global Environment
orangejuice
54 obs. of 4 variables
pistonrings
200 obs. of 3 variables
Values
x
num [1:100] -1.133 -1.273 -0.984 0.607 -2.055 ...
y
num [1:100] 0.0674 -1.3792 -0.9385 -0.2056 -1.5...
Files
Plots
Packages
Help
Viewer
Presentation
Export





2.3 Basics Functions in R

Find sum of numbers 4 to 6.

print(sum(4:6))

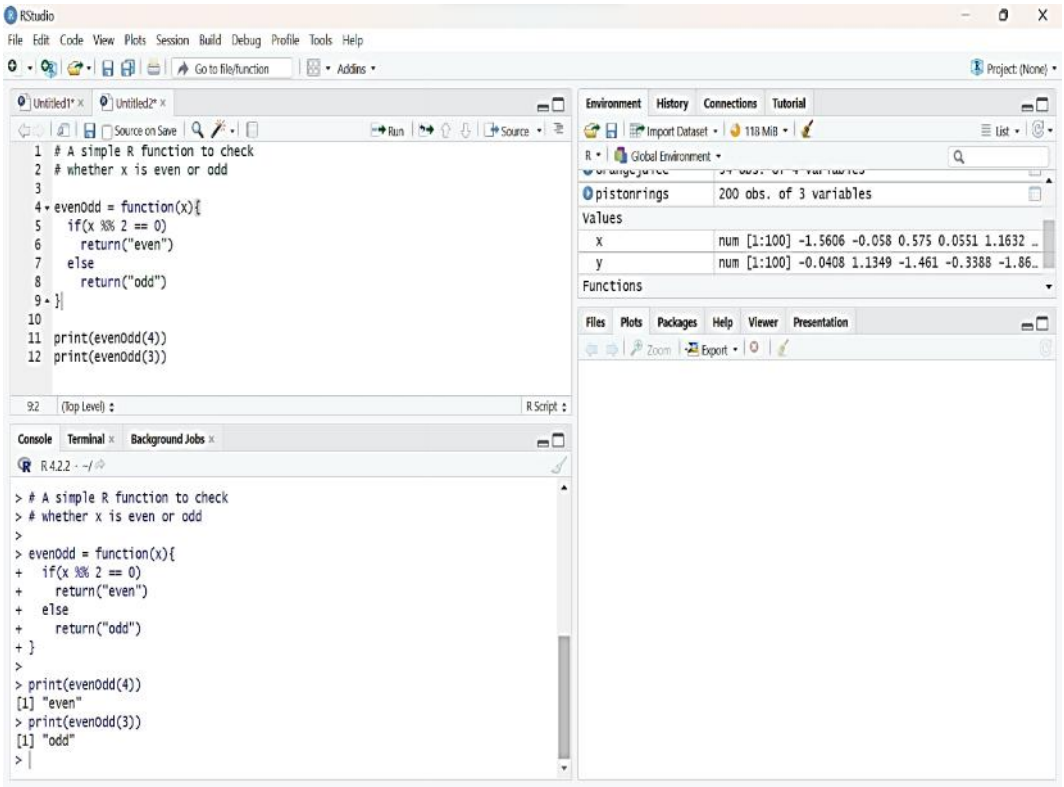
Find max of numbers 4 and 6.

```
print(max(4:6))
# Find min of numbers 4 and 6.
print(min(4:6))
#Calculate the square root of a number
sqrt(16)
#Calculate the natural logarithm of a number
log(10)
#Calculate the exponential function
exp(2)
#Calculate the sine of an angle (in radians)
sin(pi/4)
#Calculate the sum of two numbers
x <- 2
y <- 3
x + y
#Calculate the difference of two numbers
x - y
#Calculate the product of two numbers
x * y
#Calculate the quotient of two numbers
x / y
#Calculate the power of a number
x^y
#Calculate the cosine of an angle (in radians)
cos(pi/3)
#Calculate the tangent of an angle (in radians)
tan(pi/4)
#Calculate the inverse sine of a value
asin(1)
#Calculate the inverse cosine of a value
acos(0.5)
#Calculate the inverse tangent of a value
atan(1)
#Calculate the mean and standard deviation of a vector x:
x <- c(1, 2, 3, 4, 5)
mean(x)
sd(x)
#Calculate the median and quartiles of a vector x:
x <- c(1, 2, 3, 4, 5)
median(x)
```

```
quantile(x, c(0.25, 0.75))
#Calculate the minimum and maximum values of a vector x:
x <- c(1, 2, 3, 4, 5)
min(x)
max(x)
#Calculate the sum and product of a vector x:
x <- c(1, 2, 3, 4, 5)
sum(x)
prod(x)
#Calculate the cumulative sum and cumulative product of a vector x:
x <- c(1, 2, 3, 4, 5)
cumsum(x)
cumprod(x)
#Calculate the correlation between two vectors x and y:
x <- rnorm(100)
y <- rnorm(100)
cor(x, y)
#Calculate the covariance between two vectors x and y:
x <- rnorm(100)
y <- rnorm(100)
cov(x, y)
#Calculate the mean and standard deviation of multiple columns of a data frame:
df <- data.frame(x = rnorm(100), y = rnorm(100), z = rnorm(100))
apply(df, 2, mean)
apply(df, 2, sd)
```

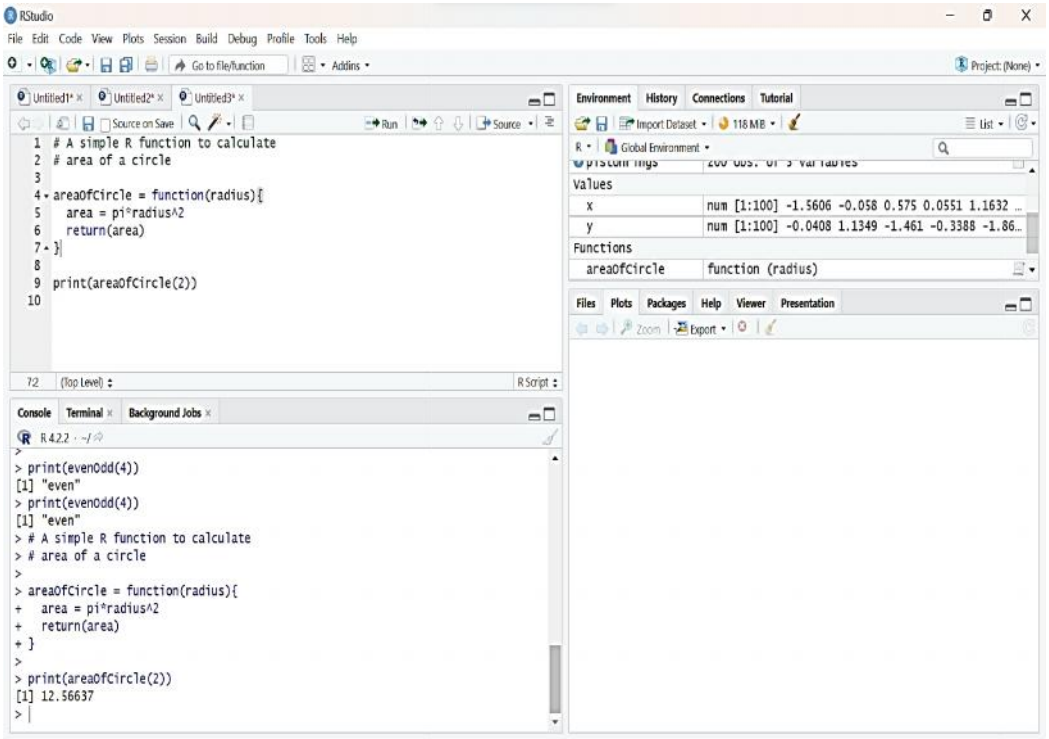
2.4 User-defined Functions in R Programming Language

R provides built-in functions like print(), cat(), etc. but we can also create our own functions. These functions are called user-defined functions.



2.5 Single Input Single Output

Now create a function in R that will take a single input and gives us a single output. Following is an example to create a function that calculates the area of a circle which takes in the arguments the radius. So, to create a function, name the function as "areaOfCircle" and the arguments that are needed to be passed are the "radius" of the circle.

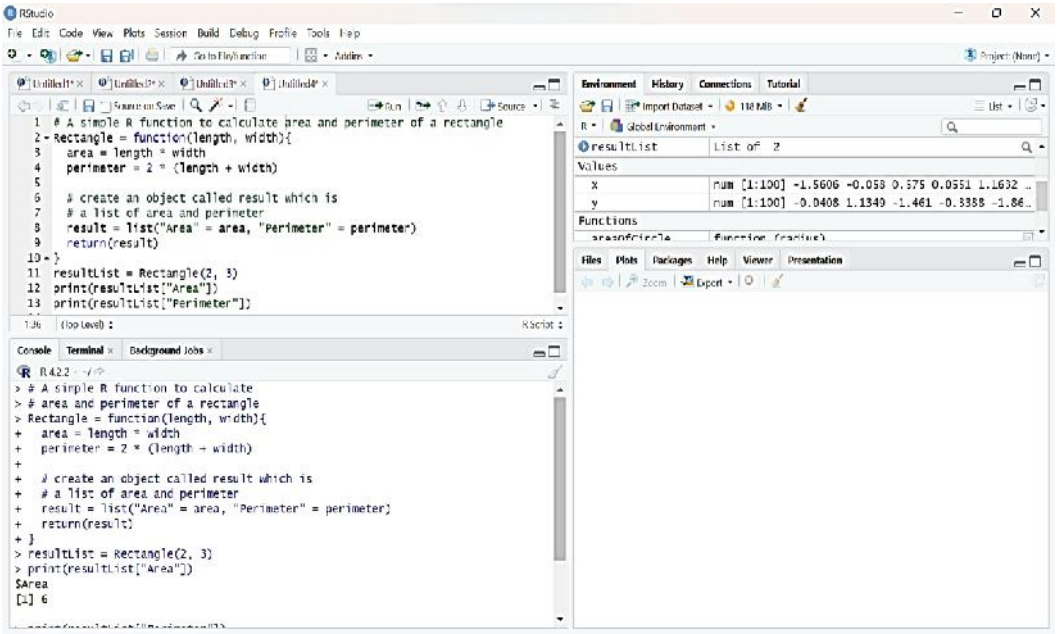


2.6 Multiple Input Multiple Output

Now create a function in R Language that will take multiple inputs and gives us multiple outputs using a list.

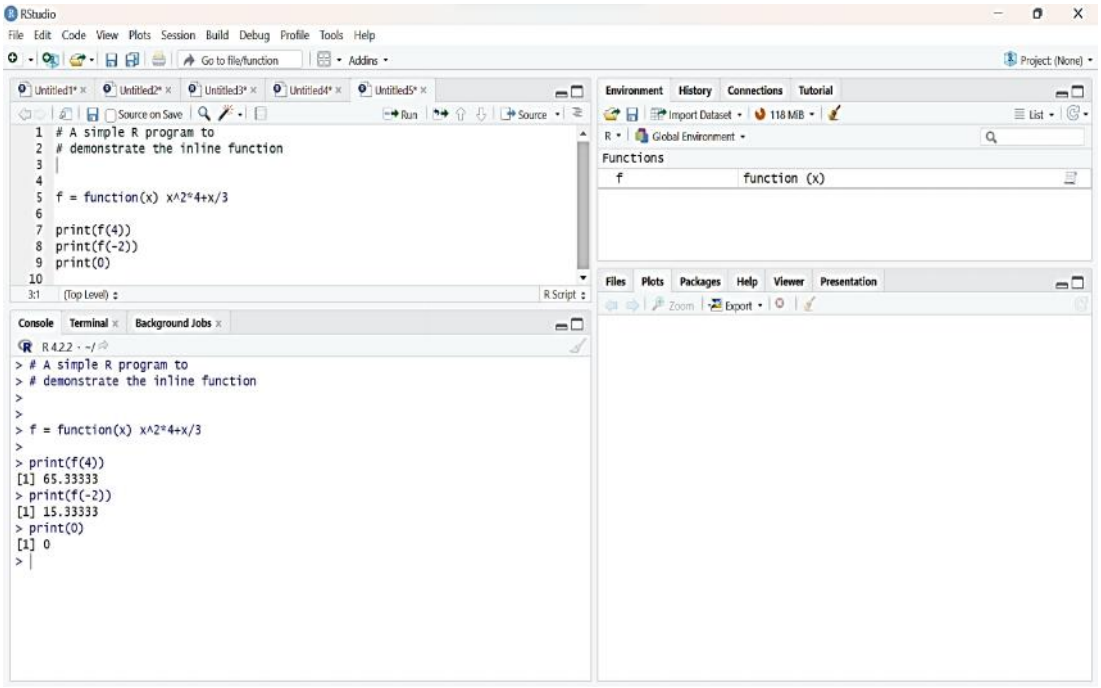
The functions in R Language takes multiple input objects but returned only one object as output, this is, however, not a limitation because you can create lists of all the outputs which you want to create and once the list is created you can access them into the elements of the list and get the answers which you want.

Let us consider this example to create a function "Rectangle" which takes "length" and "width" of the rectangle and returns area and perimeter of that rectangle. Since R Language can return only one object. Hence, create one object which is a list that contains "area" and "perimeter" and return the list.



2.7 Inline Functions in R Programming Language

Sometimes creating an R script file, loading it, executing it is a lot of work when you want to just create a very small function. So, what we can do in this kind of situation is an inline function. To create an inline function you have to use the function command with the argument x and then the expression of the function.



 # A simple R function to check whether x is even or odd

```
evenOdd = function(x){
  if(x %% 2 == 0)
    return("even")
  else
    return("odd")
}
print(evenOdd(4))
print(evenOdd(3))
```

 # A simple R function to calculate area of a circle

```
areaOfCircle = function(radius){
  area = pi*radius^2
  return(area)
}
print(areaOfCircle(2))
```

 # A simple R function to calculate area and perimeter of a rectangle

```
Rectangle = function(length, width){
  area = length * width
  perimeter = 2 * (length + width)
  # create an object called result which is
  # a list of area and perimeter
  result = list("Area" = area, "Perimeter" = perimeter)
  return(result)
}
resultList = Rectangle(2, 3)
```

```
print(resultList["Area"])
print(resultList["Perimeter"])
```

 # A simple R program to demonstrate the inline function

```
f = function(x) x^2*4+x/3
print(f(4))
print(f(-2))
print(0)
```

2.8 Functions to Summarize Variables- Select, Filter, Mutate & Arrange

What is the select() function in R?

The select() function is used to pick specific variables or features of a DataFrame or tibble. It selects columns based on provided conditions like contains, matches, starts with, ends with, and so on.

Syntax

```
select(.data,….)
```

Example

```
iris <- as_tibble(iris) # so it prints a little nicer
select(iris, starts_with("Petal"))
select(iris, ends_with("Width"))
# Move Species variable to the front
select(iris, Species, everything())
df <- as.data.frame(matrix(runif(100), nrow = 10))
df <- tbl_df(df[c(3, 4, 7, 1, 9, 8, 5, 2, 6, 10)])
select(df, V4:V6)
select(df, num_range("V", 4:6))
# Drop variables with -
select(iris, -starts_with("Petal"))
# The .data pronoun is available:
select(mtcars, .data$cyl)
select(mtcars, .data$mpg : .data$disp)
```

What is the filter() function in R?

The filter() function is used to produce a subset of the data frame, retaining all rows that satisfy the specified conditions. The filter() method in R programming language can be applied to both grouped and ungrouped data. The expressions include comparison operators (==, >, >=) , logical operators (&, |, !, xor()) , range operators (between(), near()) as well as NA value check against the column values. The subset data frame has to be retained in a separate variable.

Example : R program to filter rows using filter() function

```
library(dplyr)
# sample data
df=data.frame(x=c(12,31,4,66,78),
y=c(22.1,44.5,6.1,43.1,99),
z=c(TRUE,TRUE,FALSE,TRUE,TRUE))
```

```
# condition
filter(df, x<50 & z==TRUE)
```

Output:

```
  x   y   z
1 12 22.1 TRUE
2 31 44.5 TRUE
# create a vector of numbers
x <- c(1, 2, 3, 4, 5, 6)
# filter elements that are greater than 3
result <- filter(x, x > 3)
# print the filtered result
print(result)
# Output:
# [1] 4 5 6
```

In this example, the filter() function is applied to the vector x with the condition x > 3, which returns a new vector containing only the elements of x that are greater than 3.

```
# Creating a vector of numbers
numbers <- c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10)
# Using filter function to extract only even numbers
even_numbers <- filter(numbers, function(x) x %% 2 == 0)
# Printing the filtered numbers
even_numbers
#Output
[1]  2  4  6  8 10
filter(starwars, species == "Human")
filter(starwars, mass > 1000)
# Multiple criteria
filter(starwars, hair_color == "none" & eye_color == "black")
filter(starwars, hair_color == "none" | eye_color == "black")
# Multiple arguments are equivalent to and
filter(starwars, hair_color == "none", eye_color == "black")
# Load library dplyr
library(dplyr)
# Load iris dataset
data(iris)
# Select only Sepal.Length and Species columns
iris_select <- iris %>% select(Sepal.Length, Species)
# View the first 6 rows
head(iris_select)
# Load library dplyr
library(dplyr)
```

```
# Load iris dataset
data(iris)
# Create a new column "Sepal.Ratio" based on Sepal.Length and Sepal.Width
iris_mutate <- iris %>% mutate(Sepal.Ratio = Sepal.Length / Sepal.Width)
# View the first 6 rows
head(iris_mutate)
# Load library dplyr
library(dplyr)
# Load iris dataset
data(iris)
# Arrange rows by Sepal.Length in ascending order
iris_arrange <- iris %>% arrange(Sepal.Length)
# View the first 6 rows
head(iris_arrange)
```

2.9 Summarize function in R

The summarize() function is used in the R program to summarize the data frame into just one value or vector. This summarization is done through grouping observations by using categorical values at first, using the groupby() function.

The dplyr package is used to get the summary of the dataset. The summarize() function offers the summary that is based on the action done on grouped or ungrouped data.

Summarize grouped data

The operations that can be performed on grouped data are average, factor, count, mean, etc.

```
# Load library
library(dplyr)
data <- PlantGrowth
# summarize
summarize(data, mean(weight,na.rm=TRUE))
```

In the example above, we use the summarize() function to obtain the mean weight of all the plant species in the PlantGrowth dataset.

Summarize ungrouped data

We can also summarize ungrouped data. This can be done by using three functions.

summarize_all()

summarize_at()

summazrize_if()

Examples

```
# Load dplyr library
library(dplyr)
# Main code
data <- mtcars
# Loading starting 6 observations
sample <- head(data)
```

```
# Caculating mean value.
sample %>% summarize_all(mean)
```

In the code snippet above, we load the mtcars dataset in the data variable. In the variable sample, we are loading the top six observations to process. The sample %>% summarize_all(mean) will show the mean of the six observations in the result.

summarize_at()

It performs the action on the specific column and generates the summary based on that action.

```
# Load dplyr library
library(dplyr)
# Main code
data <- mtcars
# Loading starting 6 observations
sample <- head(data)
# Caculating mean value.
sample %>% summarize_all(mean)
```

In the code snippet above, we load the mtcars dataset in the data variable. In the variable sample, we are loading the top six observations to process. The sample %>% summarize_all(mean) will show the mean of the six observations in the result.

summarize_if()

In this function, we specify a condition and the summary will be generated if the condition is satisfied.

```
# Laod dplyr library
library(dplyr)
# Main code
data<-mtcars
z<- head(data)
z %>% group_by(hp) %>%
summarize_if(is.numeric, mean)
```

In the code snippet above, we use the predicate function is.numeric and mean as an action.

2.10 Group by function in R

Group_by() function belongs to the dplyr package in the R programming language, which groups the data frames. Group_by() function alone will not give any output. It should be followed by summarise() function with an appropriate action to perform. It works similar to GROUP BY in SQL and pivot table in excel.

Example

```
library(dplyr)
df = read.csv("Sample_Superstore.csv")
df_grp_region = df %>% group_by(Region) %>%
                                    summarise(total_sales = sum(Sales),
```

```
                                                    total_profits = sum(Profit),
                                                    .groups = 'drop')
View(df_grp_region)
```

2.11 Concept of Pipes Operator in R

The pipe operator in R is the %>% symbol and it is used for chaining together multiple operations in a readable and concise way. The pipe operator takes the output from the left-hand side of the operator and "pipes" it as the first argument to the function on the right-hand side. This allows you to build complex sequences of operations, each relying on the output from the previous step, without the need for intermediate variables.

```
# Example 1
library(dplyr)
mtcars %>%
 filter(cyl == 4) %>% summarize(mean_mpg = mean(mpg))
```

In this example, the mtcars data set is filtered to only keep observations with 4 cylinders, and then the mean miles per gallon (mpg) is calculated for the remaining observations. The output from each step is passed to the next step using the pipe operator, making the code more readable and concise.

Note that the pipe operator is not built into base R, but is included in the dplyr package, which is a popular data manipulation library.

```
# Example 2
data(mtcars)
mtcars %>%
 select(mpg, hp) %>%
 head()

# Example 3
mtcars %>%
 group_by(cyl) %>%
 summarize(mean_mpg = mean(mpg),
        n = n())
# Example 4
mtcars %>%
 mutate(cyl_factor = factor(cyl),
      hp_group = cut(hp, breaks = c(0, 50, 100, 150, 200),
               labels = c("low", "medium", "high", "very high"))) %>%
 group_by(cyl_factor, hp_group) %>%
 summarize(mean_mpg = mean(mpg),
        n = n())
```

In the second example, the mtcars data set is first filtered to keep only the mpg and hp columns, and then only the first six rows are displayed.

In the third example, the mtcars data set is grouped by the number of cylinders (cyl) and the mean miles per gallon (mpg) and number of observations (n) are calculated for each group.

In the fourth example, two new variables are created and added to the mtcars data set. The number of cylinders (cyl) is converted to a factor and a new variable (cyl_factor) is created to represent this

factor. Another new variable (hp_group) is created by dividing the horsepower (hp) into groups using the cut function. The data set is then grouped by the two new variables, and the mean miles per gallon (mpg) and number of observations (n) are calculated for each group.

Summary

There are many ways to summarize business data in R, depending on the type of data you are working with and the goals of your analysis. Here are a few common methods for summarizing business data. Descriptive statistics: You can use base R functions such as mean, median, sum, min, max, and quantile to calculate common summary statistics for your data. For example, you can calculate the mean, median, and standard deviation of a variable of interest.

Grouping and aggregating: You can use the group_by and summarize functions from the dplyr package to group your data by one or more variables and calculate summary statistics for each group. For example, you can group sales data by product and calculate the total sales for each product.

Cross-tabulation: You can use the table function to create cross-tabulations (also known as contingency tables) of your data. For example, you can create a cross-tabulation of sales data by product and region.

Visualization: You can use various plotting functions, such as barplot, histogram, and boxplot, to create visual representations of your data. Visualization can help you quickly identify patterns and relationships in your data.

Keywords

dplyr, R packages, group by, pipe operator, summarize.

Self Assessment

1. Descriptive analysis tell about_____?

A. Past

B. Present

C. Future

D. Previous

2. How many types of R objects are present in R data type?

A. 4

B. 5

C. 6

D. 7

3. How many types of data types are present in R?

A. 4

B. 5

C. 6

D. 7

4. In R every operation has a _____call?

A. System

B. Function

C. None of the above

D. Both of the above

5. The _____ in R is a vector.

A. Basic data structure

B. Basic datatypes

C. Both

D. None

6. _____and_____ are types of matrices functions?

A. Apply and sapply

B. Apply and lapply

C. Both

D. None

7. How many control statements are present in R?

A. 6

B. 7

C. 8

D. 9

8. Which of the following finds the maximum value in the vector x, exclude missing values

A. rm(x)

B. all(x)

C. max(x, na.rm=TRUE)

D. x%in%y

9. R functionality is divided into a number of _____

A. Packages

B. Functions

C. Domains

D. Library

10. Which of the following return a subset of the columns of a data frame?

A. select

B. retrieve

C. get

D. set

11. Point out the correct statement?

A. The data frame is a key data structure in statistics and in R

B. R has an internal implementation of data frames that is likely the one you will use most often

C. There are packages on CRAN that implement data frames via things like relational databases that allow you to operate on very very large data frames

D. All of the mentioned

12. _____ generate summary statistics of different variables in the data frame, possibly within strata.

A. rename

B. summarize

C. set

D. subset

13. _____ add new variables/columns or transform existing variables.

A. mutate

B. add

C. apped

D. arrange

14. The _____ operator is used to connect multiple verb actions together into a pipeline.

A. pipe

B. piper

C. start

D. end

15. The dplyr package can be installed from CRAN using _____

A. installall.packages("dplyr")

B. install.packages("dplyr")

C. installed.packages("dplyr")

D. installed.packages("dpl")

Answers forSelf Assessment

l.	B	2.	C	3.	C	4.	B	5.	A
6.	A	7.	C	8.	B	9.	A	10.	A
11.	D	12.	B	13.	A	14.	A	15.	B

Review Questions

1) Use IRIS data set and use group by, summarize function.
2) Discuss the pipe operator in R.

3) Discuss functions of dplyr package.
4) List all inbuilt functios of R.
5) Develop function which return odd and even number.

Further reading

An Introduction to R" by W. N. Venables, D. M. Smith, and the R Development Core Team

https://www.r-bloggers.com

Unit 03: Business Data Visualization

CONTENTS

Objectives

- To analyse data visualization in business context.
- To discover the purpose of basic graphs.
- To understand the grammar of graphics.
- To visualize basics graphs using ggplot2.
- To visualize some advanced graphs.

Introduction

Business data visualization is the representation of business data and information using charts, graphs, maps, and other visual elements. The goal of data visualization in a business context is to make complex data easy to understand, reveal patterns and trends, and support decision-making processes.Business data visualization is the process of transforming complex data into graphical representations, such as charts, graphs, maps, and infographics, to communicate data in a way that is easy to understand and interpret. The main goal of business data visualization is to provide a visual representation of data that supports decision-making processes and enhances communication.

Data visualization offers several benefits to businesses, including:

Improved communication: By using visual representations, data visualization makes it easier for individuals to understand and interpret data, which leads to better communication and collaboration among team members.

Increased Insights: Data visualization allows companies to identify patterns and trends in data that would be difficult to detect through raw data analysis. This leads to new insights and a better understanding of the data.

Better Decision-Making: Data visualization provides a visual representation of data that supports decision-making processes. By presenting data in a way that is easy to understand and interpret, decision-makers can make informed decisions based on accurate data analysis.

Enhanced Presentations: Data visualization adds a visual component to presentations, making them more engaging and effective for communicating data.

3.1 Use Cases of Business Data Visualization

Data visualization has a wide range of use cases in businesses, including:

Sales and Marketing: Data visualization can be used to analyze sales data, customer demographics, and marketing campaign performance. This allows companies to make informed decisions about product development, marketing strategies, and customer engagement.

Financial Analysis: Data visualization can be used to present financial data, such as budget reports, income statements, and balance sheets, in a way that is easy to understand and interpret.

Supply Chain Management: Data visualization can be used to track the flow of goods and materials, monitor inventory levels, and analyze supply chain performance.

Operations Management: Data visualization can be used to monitor key performance indicators, such as production output and efficiency, in real-time. This allows companies to make informed decisions about operations and production processes.

Business data visualization is a powerful tool for companies to understand and make sense of large amounts of data. By transforming complex data into graphical representations, data visualization improves communication, enhances decision-making processes, and provides new insights into data. With its wide range of use cases, data visualization is an essential tool for businesses in a data-driven world.

3.2 Basic Graphs and their Purposes

There are several basic graphs that are commonly used in data visualization and each has a specific purpose:

Bar Graph: A bar graph is used to compare the sizes of different categories of data. The data is represented as bars, with the height of each bar representing the value of the data. Bar graphs are best used when comparing data sets with a small number of categories.

Line Graph: A line graph is used to show how a value changes over time. Data points are plotted on a graph and connected with lines to show the trend over time. Line graphs are best used for data sets with continuous data, such as stock prices or temperature over time.

Pie Chart: A pie chart is used to show the proportion of different categories in a data set. The data is represented as slices of a pie, with each slice representing the proportion of a category in the data set. Pie charts are best used for data sets with a small number of categories and for showing the proportion of each category in the data set.

Scatter Plot: A scatter plot is used to show the relationship between two variables. Data points are plotted on a graph to show the relationship between the two variables. Scatter plots are best used for data sets with continuous data and for showing the relationship between two variables.

Histogram: A histogram is used to show the distribution of data. The data is divided into bins, with the height of each bin representing the number of data points in that bin. Histograms are best used for data sets with continuous data and for showing the distribution of data.

Stacked Bar Graph: A stacked bar graph is used to show the proportion of different categories in a data set, while also showing the total of all the categories. The data is represented as bars, with each bar representing the total of all the categories, and each category represented as a portion of the bar. Stacked bar graphs are best used for data sets with a small number of categories and for showing the proportion of each category in the data set, as well as the total of all the categories.

By selecting the appropriate graph type, you can effectively communicate your data and help others understand your findings.

3.3 R Packages for Data Visualization

There are several R packages available for data visualization, some of the most popular ones are:

ggplot2: One of the most widely used packages for data visualization in R, it provides a high-level interface for producing attractive and informative visualizations with minimal code.

plotly: An interactive visualization library that allows you to produce charts, maps, and other types of graphics that can be easily embedded in web pages or R markdown documents.

lattice: A package that provides a high-level interface for producing trellis graphics, which are multi-panel visualizations that display the relationship between multiple variables.

Shiny: A package that makes it easy to build interactive web applications in R, including visualizations.

leaflet: A package that provides an interface for creating interactive maps, making it easy to display spatial data in a meaningful way.

dygraphs: A package that provides an interface for producing time-series plots, which are commonly used to visualize trends in data over time.

rgl: A package that provides a high-level interface for producing interactive 3D graphics, allowing you to visualize complex data in a way that is not possible with 2D graphics.

rbokeh: A visualization library for R that provides a high-level interface to the Bokeh library for Python.

googleVis: An R interface to the Google Charts API, which allows you to create interactive web visualizations from R with minimal effort.

ggvis: A package for creating interactive visualizations, with syntax similar to ggplot2.

rayshader: A package for creating 3D visualizations and animations of ggplot2 graphics.

flexdashboard: A package for creating dashboards, with support for multiple pages and a variety of interactive visualizations.

These packages cover a wide range of visualization needs and provide many customization options, making it easy to create high-quality visualizations for your data.

3.4 Ggplot2

ggplot2 is a plotting library for the R programming language, used for creating sophisticated graphics. It was created by Hadley Wickham and is based on the principles of the grammar of graphics, which provides a flexible structure for building complex visualizations from simple components.

One of the key features of ggplot2 is that it allows users to build plots layer by layer, by adding components such as data, aesthetics (mapping variables to visual properties), geoms (representations of data, such as points, lines, or bars), and statistics (such as regression lines or smoothing splines). This approach makes it easier to understand and control the appearance of the final plot.

ggplot2 also has a large and active user community, which has contributed a variety of additional packages and extensions that enhance its functionality. As a result, ggplot2 is widely used in academia and industry, and has become one of the most popular plotting libraries for R.

The library is highly extensible, with a large number of plugins and extensions available that allow you to create custom visualizations or fine-tune existing ones. Additionally, ggplot2 is designed to play well with other R packages, such as dplyr and tidyr, which makes it easy to manipulate and transform your data before creating a visualization.

Some of the key features of ggplot2 include:

- A wide variety of plot types, including scatterplots, bar plots, line plots, histograms, density plots, box plots, and more.

- Customization of every aspect of a plot, from the axis labels and titles to the colors and themes.
- Built-in support for facets, which allow you to create multiple subplots that share the same scales and aesthetics.
- The ability to combine multiple layers into a single plot, and to add smooth fits, regression lines, and other statistical summaries to a plot.

ggplot2 has a number of advantages over other data visualization tools, including:

Consistency: ggplot2 provides a consistent syntax for creating visualizations, making it easier to learn and use.

Customization: ggplot2 is highly customizable, allowing you to create visualizations that meet your specific needs.

Extendibility: ggplot2 is designed to be extended and modified, making it easy to create new visualizations or modify existing ones.

Large Community: ggplot2 has a large and active community of users who provide support, resources, and tutorials.

ggplot2 is widely used in the R community and is considered to be one of the best data visualization libraries for R. It provides a powerful and flexible platform for creating professional-looking visualizations and has a large and active user community that provides support and develops new extensions and packages.

The syntax of ggplot2 can be broken down into **three main** components:

The data: You start by specifying the data you want to visualize. This can be a data frame or a tibble in R.

The aesthetics: Next, you define the visual mappings, or aesthetics, between the variables in your data and the visual elements of the plot, such as the x and y positions, color, size, etc.

The geometry: Finally, you specify the type of plot you want to create, such as a scatter plot, bar plot, histogram, etc., using a geom (short for geometry).

Here's a simple example that demonstrates the basic syntax of ggplot2:

```
library(ggplot2)

# Load the data

data(mtcars)

# Create the plot

ggplot(data = mtcars, aes(x = wt, y = mpg)) +

 geom_point()
```

In this example, the data is mtcars, and the aesthetics are defined as x = wt and y = mpg. The geom_point() function is used to specify that we want a scatter plot.

The syntax of ggplot2 can be quite dense, but it's also highly expressive and allows for fine-grained control over the appearance and behavior of your visualizations. With practice, you'll find that you can create complex and beautiful plots with just a few lines of code.

Few more examples

Barplot

```
library(ggplot2)

# Load the data

data(mtcars)

# Create the plot

ggplot(data = mtcars, aes(x = factor(cyl))) +
```

```
  geom_bar(fill = "blue") +
  xlab("Number of Cylinders") +
  ylab("Count") +
  ggtitle("Count of Cars by Number of Cylinders")
```

Line plot

```
library(ggplot2)
# Load the data
data(economics)
# Create the plot
ggplot(data = economics, aes(x = date, y = uempmed)) +
  geom_line(color = "red") +
  xlab("Year") +
  ylab("Unemployment Rate") +
  ggtitle("Unemployment Rate Over Time")
```

Histogram

```
library(ggplot2)
# Load the data
data(mtcars)
# Create the plot
ggplot(data = mtcars, aes(x = mpg)) +
  geom_histogram(fill = "blue", binwidth = 2) +
  xlab("Miles Per Gallon") +
  ylab("Frequency") +
  ggtitle("Histogram of Miles Per Gallon")
```

Boxplot

```
library(ggplot2)
# Load the data
data(mtcars)
# Create the plot
ggplot(data = mtcars, aes(x = factor(cyl), y = mpg)) +
  geom_boxplot(fill = "blue") +
  xlab("Number of Cylinders") +
  ylab("Miles Per Gallon") +
  ggtitle("Box Plot of Miles Per Gallon by Number of Cylinders")
```

These are just a few examples to get you started. You can create many more complex and interesting visualizations using ggplot2 by combining different geoms, adjusting the aesthetics, and adding additional elements such as faceting, themes, and annotations.

3.5 Bar Graph using ggplot2

This is the most basic barplot you can build using the ggplot2 package. It follows those steps:

always start by calling the ggplot() function.

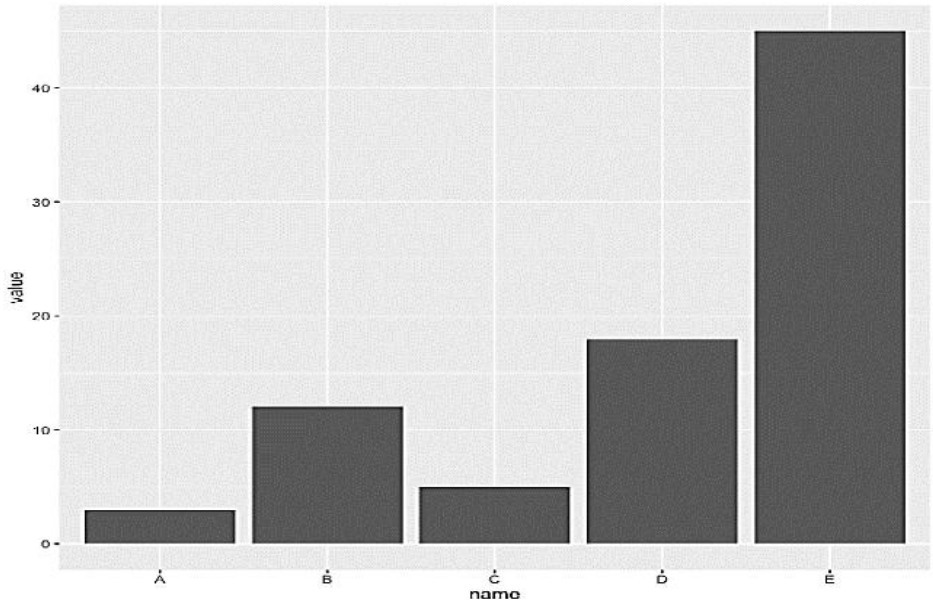
then specify the data object. It has to be a data frame. And it needs one numeric and one categorical variable.

then come thes aesthetics, set in the aes() function: set the categoric variable for the X axis, use the numeric for the Y axis

finally call geom_bar(). You have to specify stat="identity" for this kind of dataset.

Most basic bar plot

```
# Load ggplot2
library(ggplot2)
# Create data
data <- data.frame(
 name=c("A","B","C","D","E") ,
 value=c(3,12,5,18,45)
 )
# Barplot
ggplot(data, aes(x=name, y=value)) +
 geom_bar(stat = "identity")
```



Control bar color

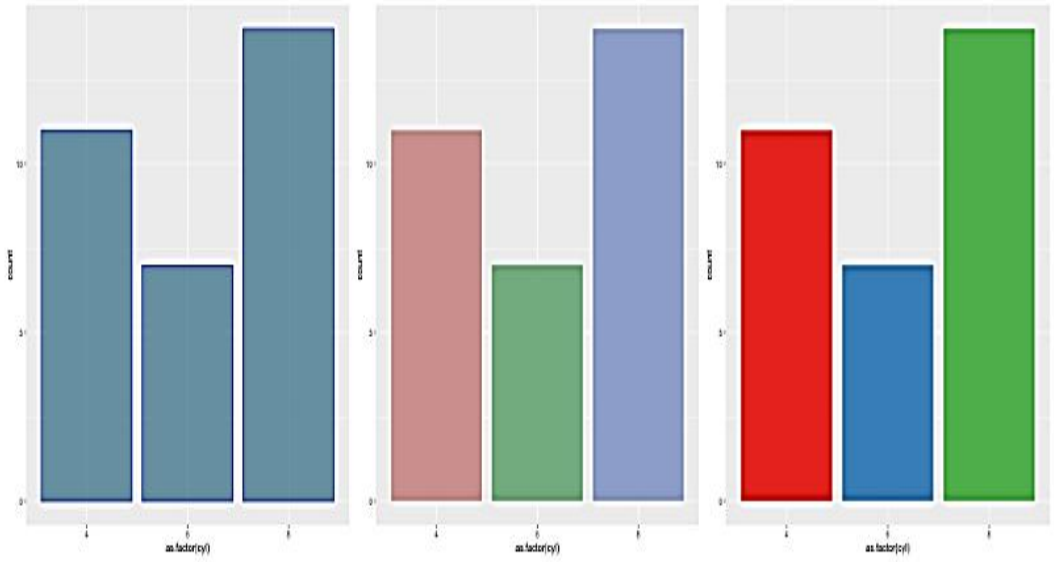
Here are a few different methods to control bar colors. Note that using a legend in this case is not necessary since names are already displayed on the X axis. You can remove it with theme(legend.position="none").

```
# Libraries
library(ggplot2)
# 1: uniform color. Color is for the border, fill is for the inside
ggplot(mtcars, aes(x=as.factor(cyl) )) +
 geom_bar(color="blue", fill=rgb(0.1,0.4,0.5,0.7) )
# 2: Using Hue
ggplot(mtcars, aes(x=as.factor(cyl), fill=as.factor(cyl) )) +
 geom_bar( ) +
```

```
  scale_fill_hue(c = 40) +
  theme(legend.position="none")
```

 # 3: Using RColorBrewer

```
ggplot(mtcars, aes(x=as.factor(cyl), fill=as.factor(cyl) )) +
  geom_bar( ) +
  scale_fill_brewer(palette = "Set1") +
  theme(legend.position="none")
```

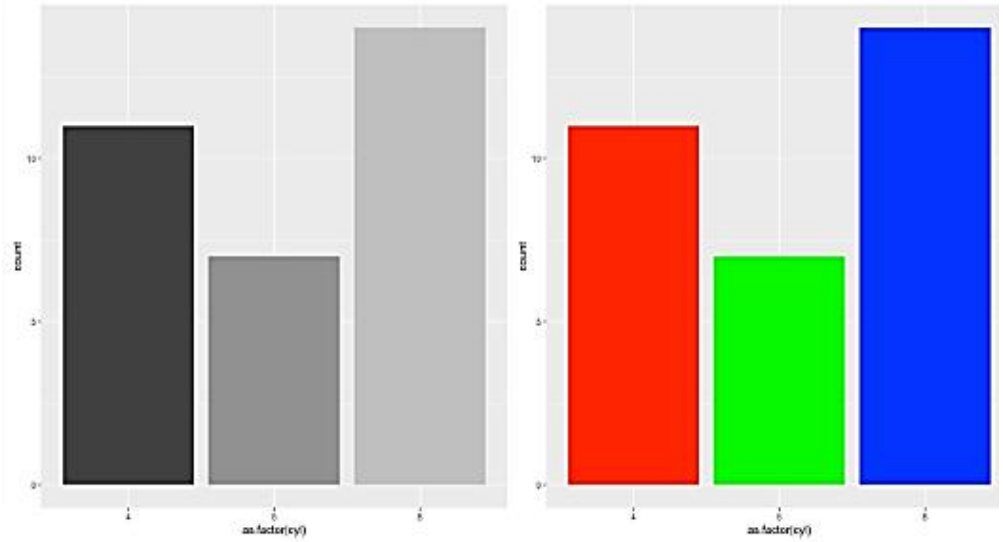


 # 4: Using greyscale:

```
ggplot(mtcars, aes(x=as.factor(cyl), fill=as.factor(cyl) )) +
  geom_bar( ) +
  scale_fill_grey(start = 0.25, end = 0.75) +
  theme(legend.position="none")
```

 # 5: Set manualy

```
ggplot(mtcars, aes(x=as.factor(cyl), fill=as.factor(cyl) )) +
  geom_bar( ) +
  scale_fill_manual(values = c("red", "green", "blue") ) +
  theme(legend.position="none")
```

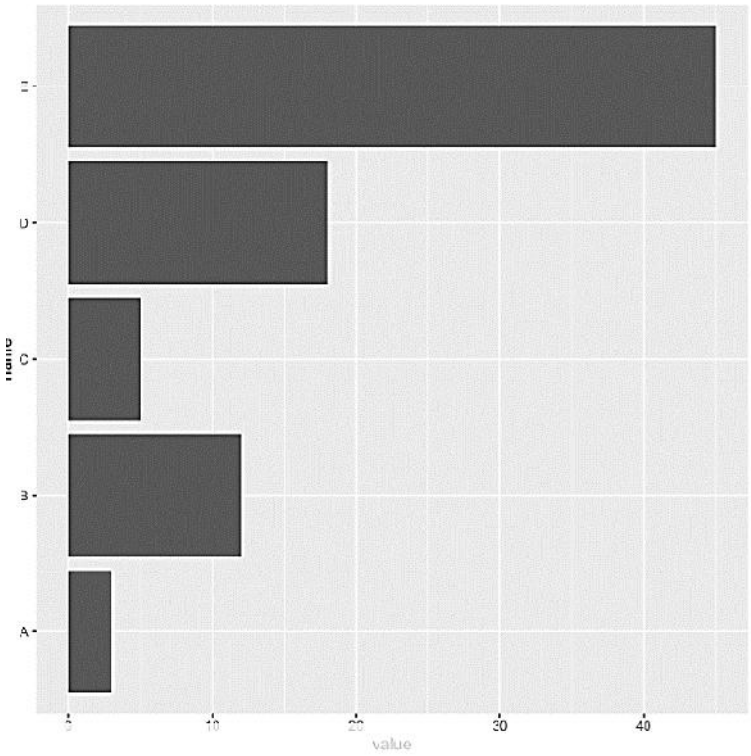


Horizontal barplot with coord_flip()

It often makes sense to turn your barplot horizontal. Indeed, it makes the group labels much easier to read.

Fortunately, the coord_flip() function makes it a breeze.

```
# Load ggplot2
library(ggplot2)
# Create data
data <- data.frame(
 name=c("A","B","C","D","E") ,
 value=c(3,12,5,18,45)
 )
# Barplot
ggplot(data, aes(x=name, y=value)) +
 geom_bar(stat = "identity") +
 coord_flip()
```

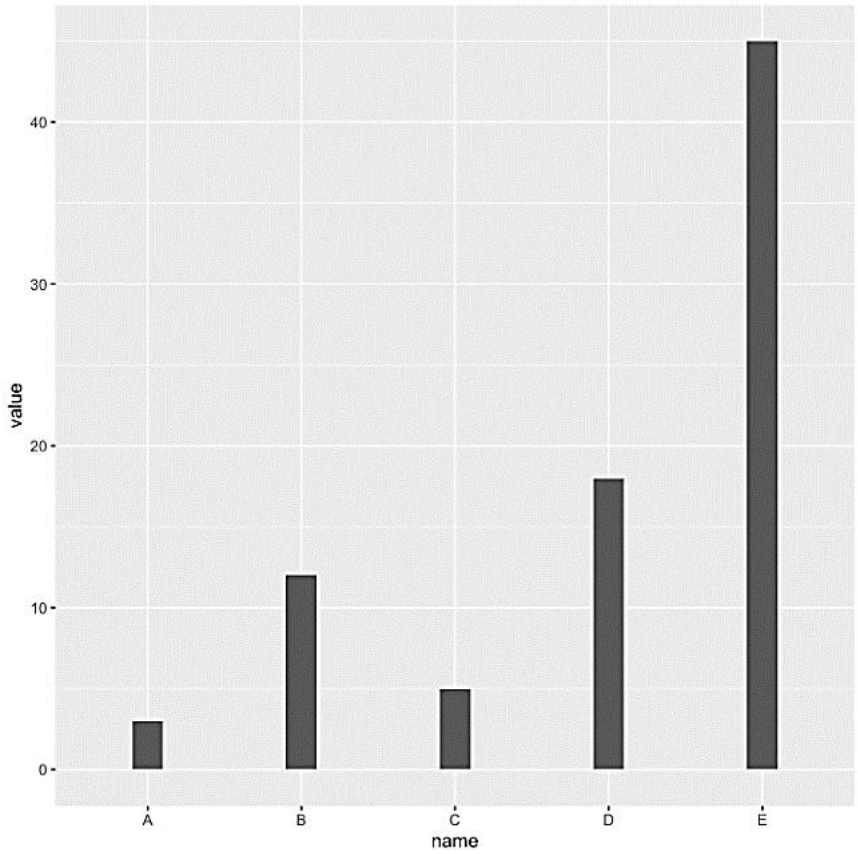


Control bar width with width

The width argument of the geom_bar() function allows to control the bar width. It ranges between 0 and 1, 1 being full width.

See how this can be used to make bar charts with variable width.

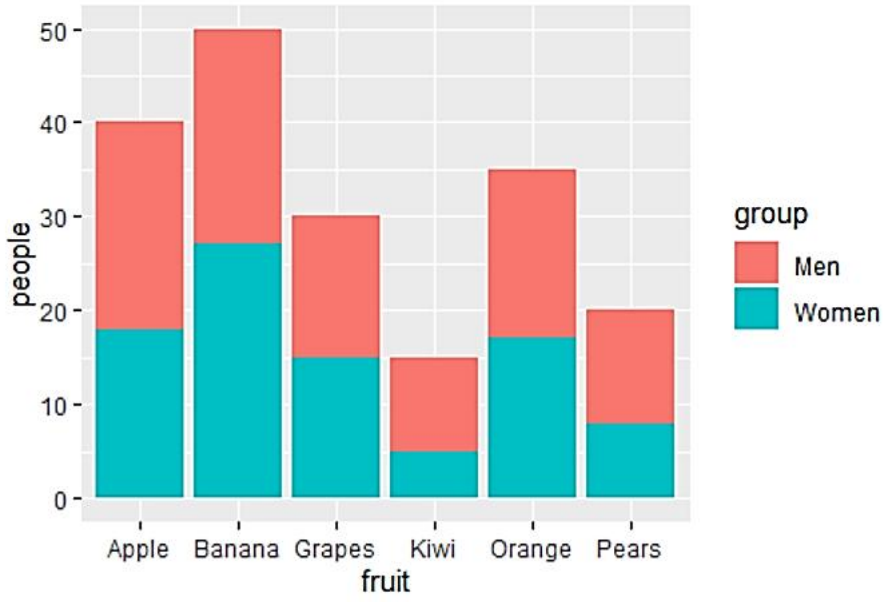
```
# Load ggplot2
library(ggplot2)
# Create data
data <- data.frame(
  name=c("A","B","C","D","E") ,
  value=c(3,12,5,18,45)
  )
# Barplot
ggplot(data, aes(x=name, y=value)) +
  geom_bar(stat = "identity", width=0.2)
```



Stacked Bar Graph

If your data contains several groups of categories, you can display the data in a bar graph in one of two ways. You can decide to show the bars in groups (grouped bars) or you can choose to have them stacked (stacked bars).

```
#creating data
survey <- data.frame(group=rep(c("Men", "Women"),each=6),
                     fruit=rep(c("Apple", "Kiwi", "Grapes", "Banana", "Pears", "Orange"),2),
                     people=c(22, 10, 15, 23, 12, 18, 18, 5, 15, 27, 8, 17))
ggplot(survey, aes(x=fruit, y=people, fill=group)) +
 geom_bar(stat="identity")
```



3.6 Line Plot using ggplot2 in R

A line chart or line graph displays the evolution of one or several numeric variables. Data points are usually connected by straight line segments. You read an extensive definition here.

The input data frame requires at least 2 columns:

An ordered numeric variable for the X axis

Another numeric variable for the Y axis

Once the data is read by ggplot2 and those 2 variables are specified in the x and y arguments of the aes(), just call the geom_line() function.

Most basic line plot

```
# Libraries
library(ggplot2)
# create data
xValue <- 1:10
yValue <- cumsum(rnorm(10))
data <- data.frame(xValue,yValue)
# Plot
ggplot(data, aes(x=xValue, y=yValue)) +
  geom_line()
```

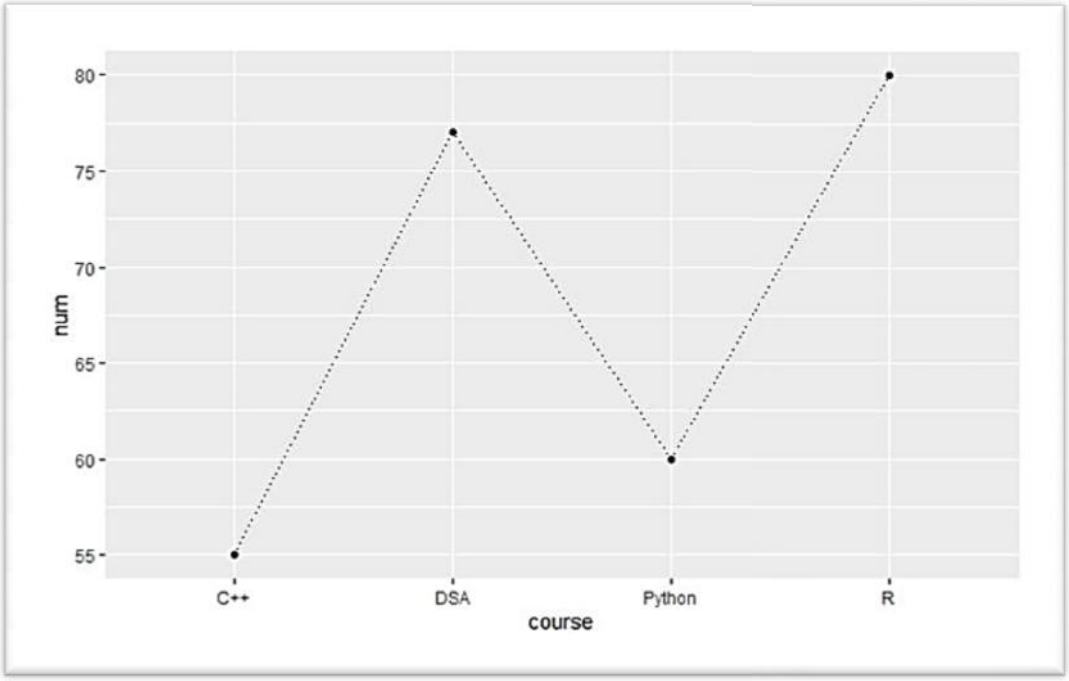
Formatting Line

Line Type

For this, the command linetype is used. ggplot2 provides various line types. For example : dotted, two dash, dashed, etc. This attribute is passed with a required value.

```
library(ggplot2)
# Create data for chart
val <-data.frame(course=c('DSA','C++','R','Python'),
                                        num=c(77,55,80,60))
# Format the line type
```

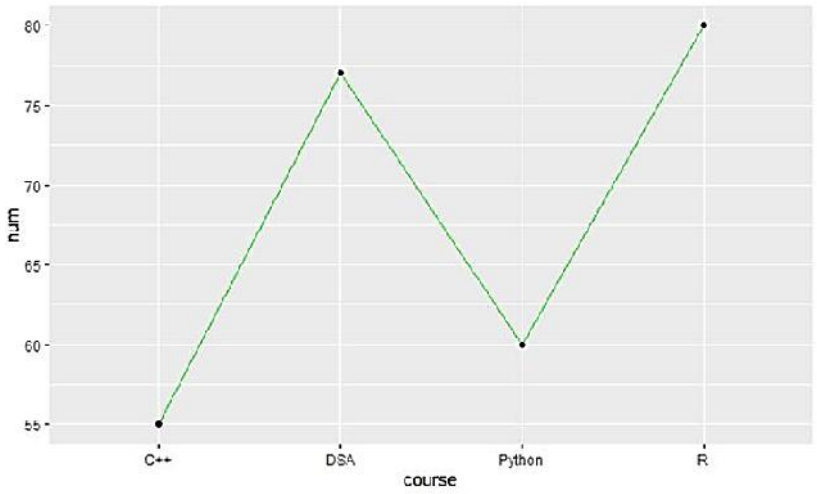
```
ggplot(data=val, aes(x=course, y=num, group=1)) +
geom_line(linetype = "dotted")+
geom_point()
```



Line Color

The command color is used and the desired color is written in double quotes [" "] inside geom_line( ).

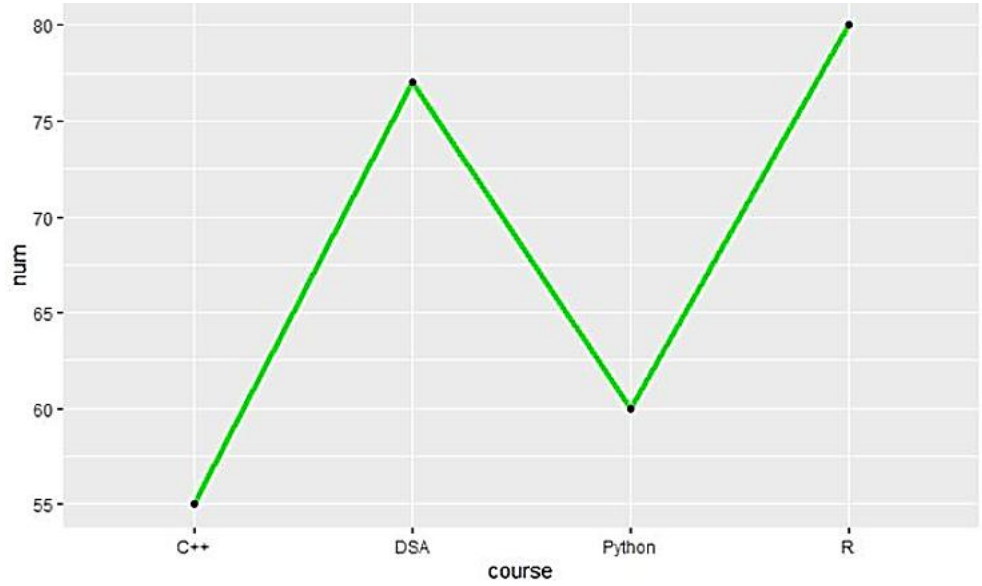
```
library(ggplot2)
# Create data for chart
val <-data.frame(course=c('DSA','C++','R','Python'),
                                        num=c(77,55,80,60))
# Format the line color
ggplot(data=val, aes(x=course, y=num, group=1)) +
geom_line(color="green")+
geom_point()
```



Line Size

The line size can be changed using the command size and providing the value of the size inside geom_line( ).

```
library(ggplot2)
# Create data for chart
val <-data.frame(course=c('DSA','C++','R','Python'),
                                    num=c(77,55,80,60))
# Format the line size
ggplot(data=val, aes(x=course, y=num, group=1)) +
geom_line(color="green",size=1.5)+
geom_point()
```



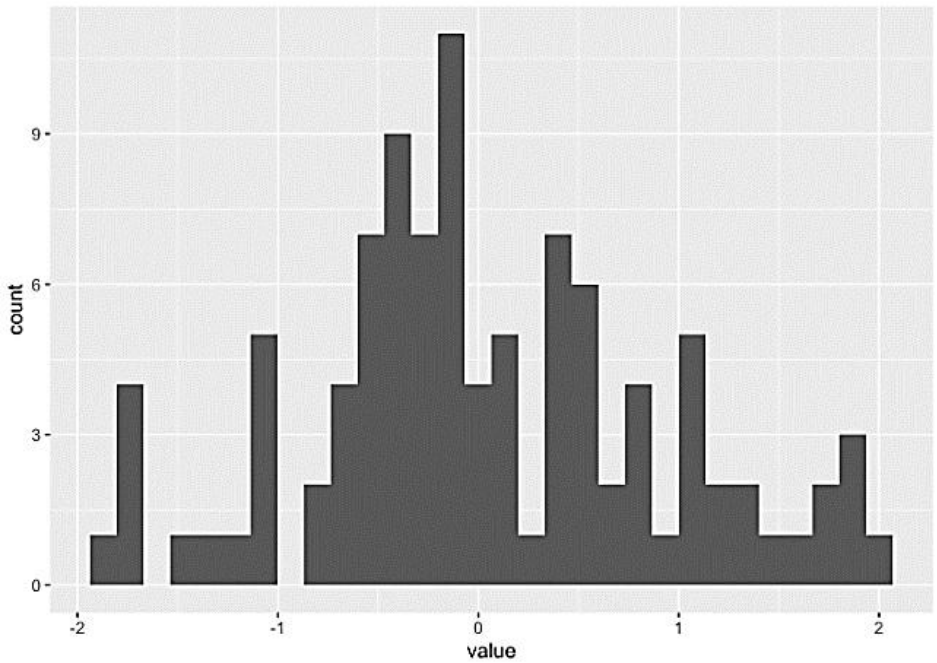
Histogram in R using ggplot2

Basically, Histograms are used to show distributions of a given variable while bar charts are used to compare variables. Histograms plot quantitative data with ranges of the data grouped into the intervals while bar charts plot categorical data.

geom_histogram() function is an in-built function of ggplot2 module.

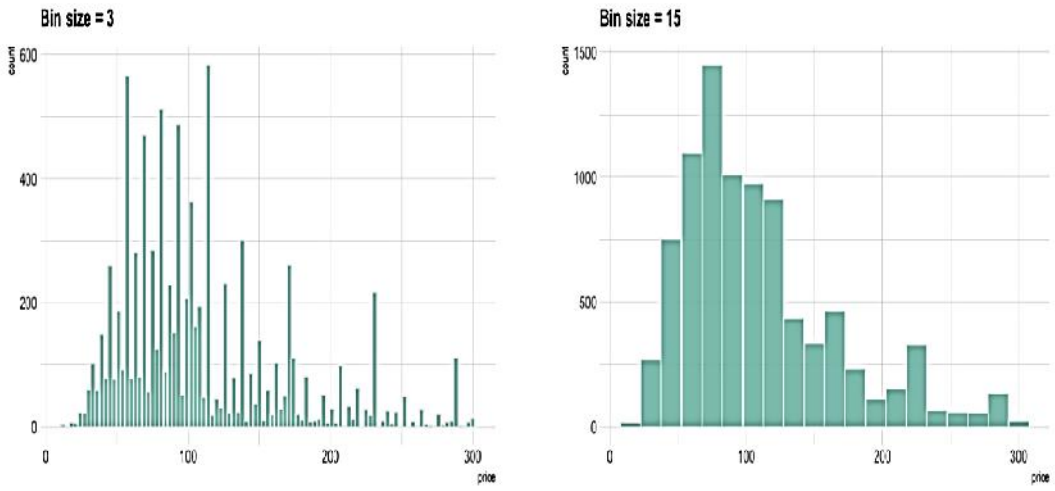
Basic histogram with geom_histogram

```
# library
library(ggplot2)
# dataset:
data=data.frame(value=rnorm(100))
# basic histogram
p <- ggplot(data, aes(x=value)) +
  geom_histogram()
```



Control bin size with binwidth

```
# Libraries
library(tidyverse)
library(hrbrthemes)
# Load dataset from github
Data<-
read.table("https://raw.githubusercontent.com/holtzy/data_to_viz/master/Example_dataset/1_
OneNum.csv", header=TRUE)
# plot
p <- data %>%
 filter( price<300 ) %>%
 ggplot( aes(x=price)) +
   geom_histogram( binwidth=3, fill="#69b3a2", color="#e9ecef", alpha=0.9) +
   ggtitle("Bin size = 3") +
   theme_ipsum() +
   theme(
    plot.title = element_text(size=15)
   )
```



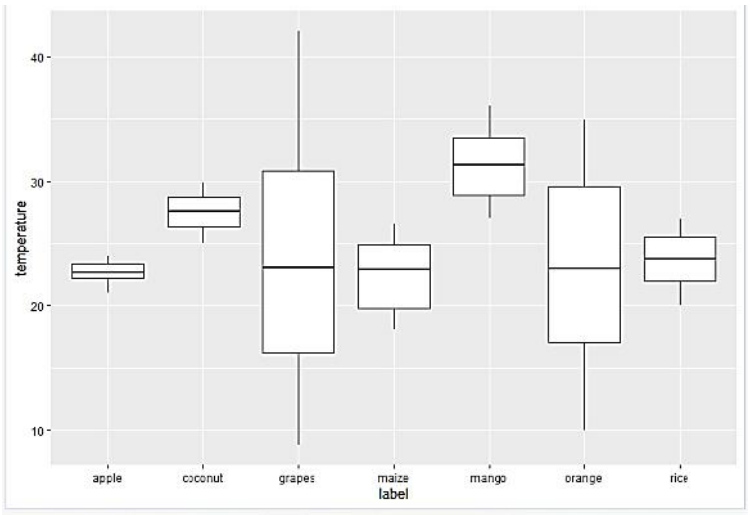
Box plots in R using ggplot2

Box plots are commonly used to show the distribution of data in a standard way by presenting five summary values. The list below summarizes the minimum, Q1 (First Quartile), median, Q3 (Third Quartile), and maximum values. Summarizing these values can provide us with information about our outliers and their values.

In ggplot2, geom_boxplot() is used to create a boxplot.

Most basic box plot using ggplot2.

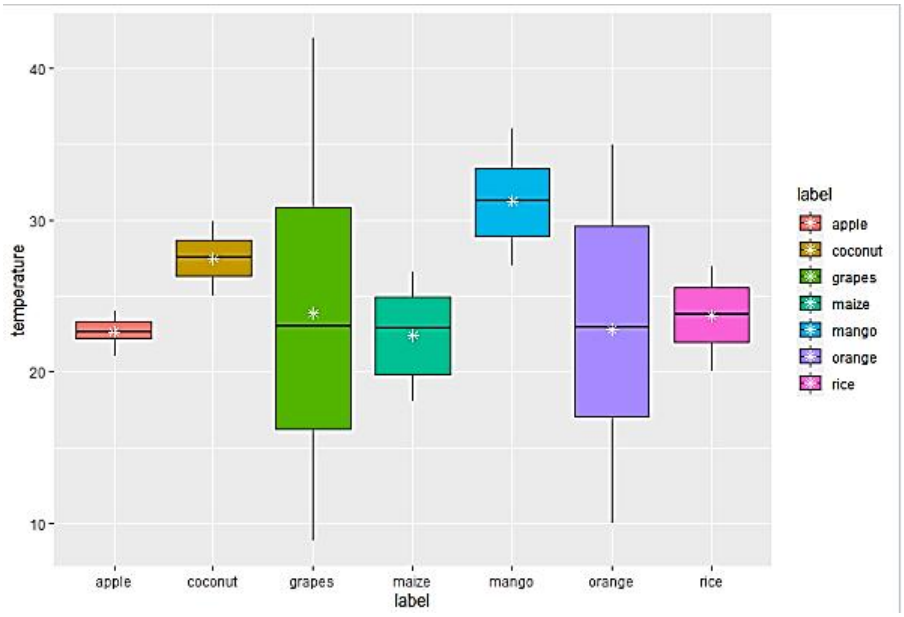
```
library(ggplot2)

# Create the dataset or load the dataset

# for the chart

Dataset <- c(17, 32, 8, 53, 1,45,56,678,23,34)

Dataset

# loading data set and storing it in ds variable

ds <- read.csv(

"c://crop//archive//Crop_recommendation.csv", header = TRUE)

# create a boxplot by using geom_boxplot() function

# of ggplot2 package

crop=ggplot(data=ds, mapping=aes(x=label, y=temperature))+geom_boxplot()

crop
```



Adding mean value to the boxplot

Mean value can also be added to a boxplot, for that we have to specify the function we are using, within stat_summary(). This function is used to add new summary values and add these summary values to the plot. By using this function you don't need to calculate the mean values before plotting.

```
library(ggplot2)

# loading data set and storing it in ds variable

ds <- read.csv("c://crop//archive//Crop_recommendation.csv", header = TRUE)

# add mean to ggplot2 boxplot

ggplot(ds, aes(x = label, y = temperature, fill = label)) +

geom_boxplot() +

stat_summary(fun = "mean", geom = "point", shape = 8,

                                    size = 2, color = "white")
```

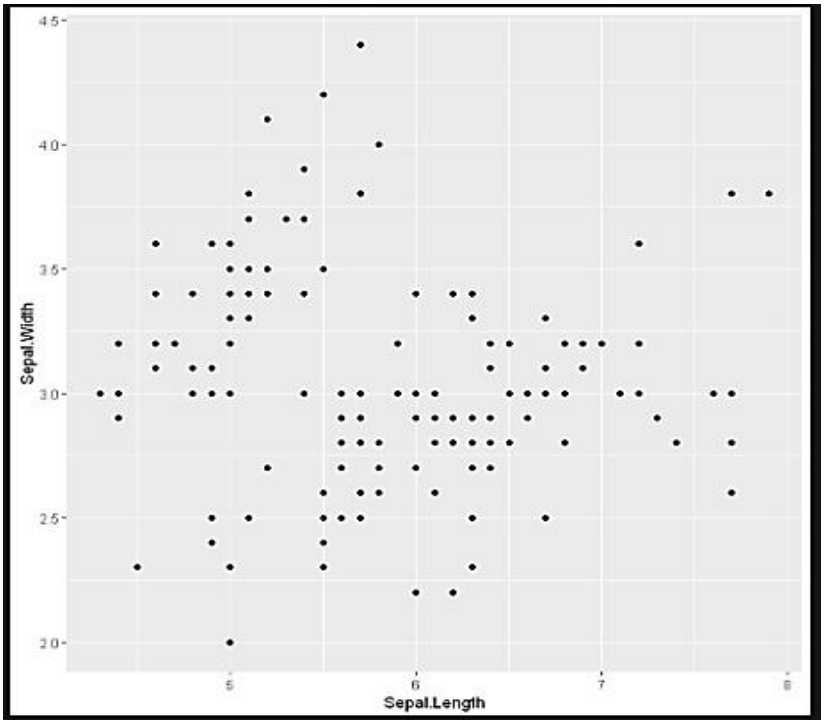


Scatter Plot using ggplot2 in R

To plot scatterplot we will use we will be using geom_point() function.

Most basic scatterplot

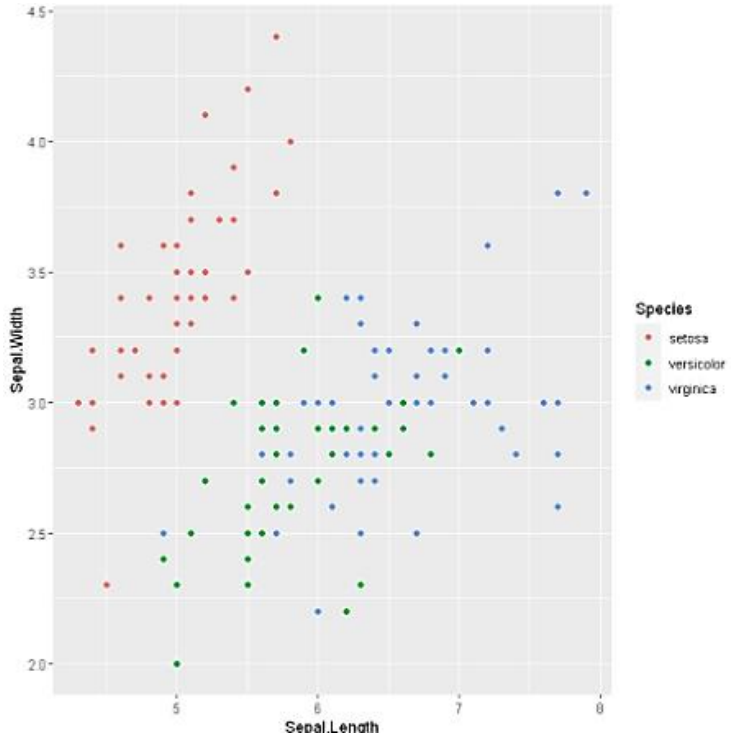
```
library(ggplot2)

ggplot(iris, aes(x = Sepal.Length, y = Sepal.Width)) +

        geom_point()
```



Scatter plot with groups

Here we will use distinguish the values by a group of data (i.e. factor level data). aes() function controls the color of the group and it should be factor variable.

```
# Scatter plot with groups
ggplot(iris, aes(x = Sepal.Length, y = Sepal.Width)) +
        geom_point(aes(color = factor(Sepal.Width)))
```



Graphics for Correlations

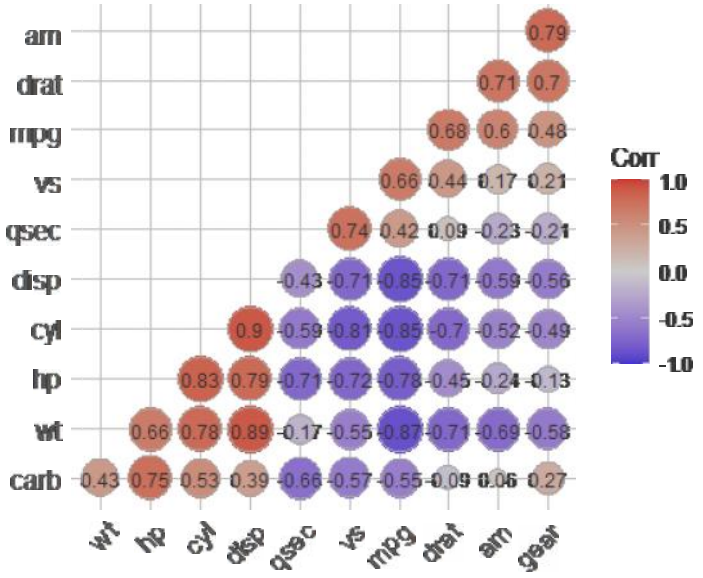
Correlation plots, also known as correlograms for more than two variables, help us to visualize the correlation between continuous variables.

Correlogram is a graph of correlation matrix. Useful to highlight the most correlated variables in a data table. In this plot, correlation coefficients are colored according to the value. Correlation matrix can be also reordered according to the degree of association between variables.

Use of ggcorrplot() function to draw a correlogram

```
library(ggcorrplot)

# Load the data

data(mtcars)

# Calculate the correlation matrix

cor_mat <- cor(mtcars)

# Create the plot

ggcorrplot(cor_mat, method = "circle", hc.order = TRUE, type = "lower",

    lab = TRUE, lab_size = 3)
```

In this example, the cor function is used to calculate the pairwise correlations between the variables in the mtcars dataset. The ggcorrplot function is then used to create the correlogram, using the color method to represent the correlation coefficients with colors (positive correlations in blue and negative correlations in red).



Graphs for deviation and ranking

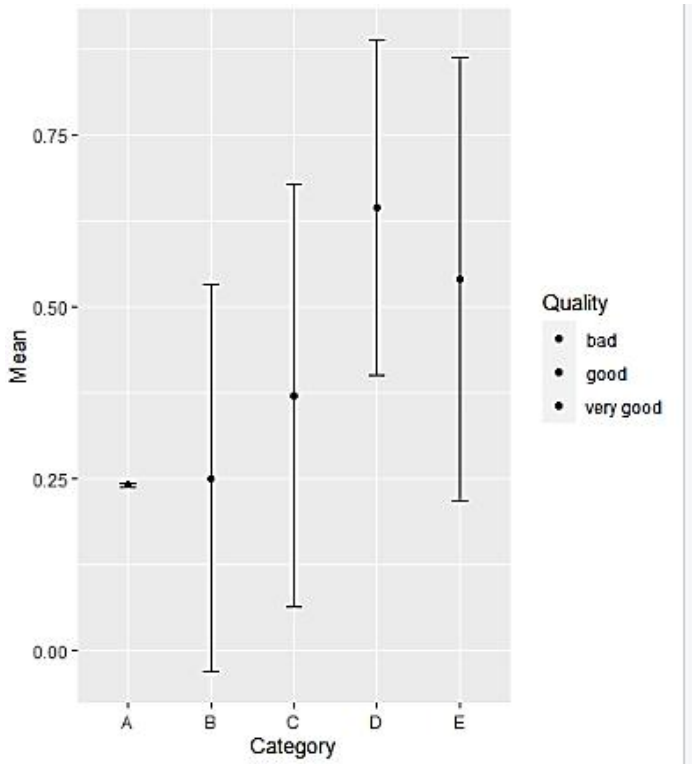
Point plot

A point plot represents an estimate of central tendency for a numeric variable by the position of the dot and provides some indication of the uncertainty around that estimate using error bars.

Point plots can be more useful than bar plots for focusing comparisons between different levels of one or more categorical variables. They are particularly adept at showing interactions: how the relationship between levels of one categorical variable changes across levels of a second categorical variable.

```
# creating a data frame df

df<-data.frame(Mean=c(0.24,0.25,0.37,0.643,0.54),

                    sd=c(0.00362,0.281,0.3068,0.2432,0.322),

                    Quality=as.factor(c("good","bad","good","very good","very good")),

                    Category=c("A","B","C","D","E"),

                    Insert= c(0.0, 0.1, 0.3, 0.5, 1.0))
```

```
# plot the point plot
p<-ggplot(df, aes(x=Category, y=Mean, fill=Quality)) +
geom_point()+
geom_errorbar(aes(ymin=Mean-sd, ymax=Mean+sd), width=.2,
                                    position=position_dodge(0.05))
```



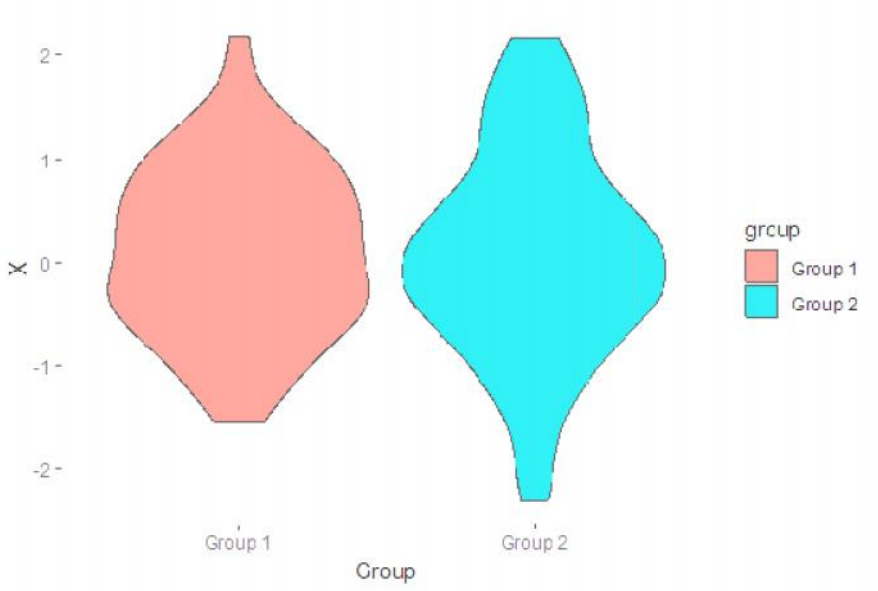
Violin Plot

A violin plot is a type of plot that combines aspects of both box plots and kernel density plots, and is used to visualize the distribution of a numerical variable and its ranking within that distribution.

```
# First, install and load the ggplot2 library
library(ggplot2)
# Generate some sample data
set.seed(123)
x <- rnorm(100)
group <- rep(c("Group 1", "Group 2"), 50)
# Prepare the data into a format that can be plotted
df <- data.frame(x = x, group = group)
# Create the violin plot using ggplot2
ggplot(df, aes(x = group, y = x, fill = group)) +
  geom_violin() +
  labs(x = "Group", y = "X")
```

In this example, the ggplot() function is used to specify the plot, with group and x as the aesthetic mappings. The geom_violin() layer is then added to the plot to create the violin plot. The labs() function is used to add labels to the x- and y-axes.

In this example, the x variable is drawn from a normal distribution and assigned to two different groups, "Group 1" and "Group 2". The violin plot shows the distribution of x for each group. The fill color of the violin plot is specified by the group variable.



Graphs for distribution and composition

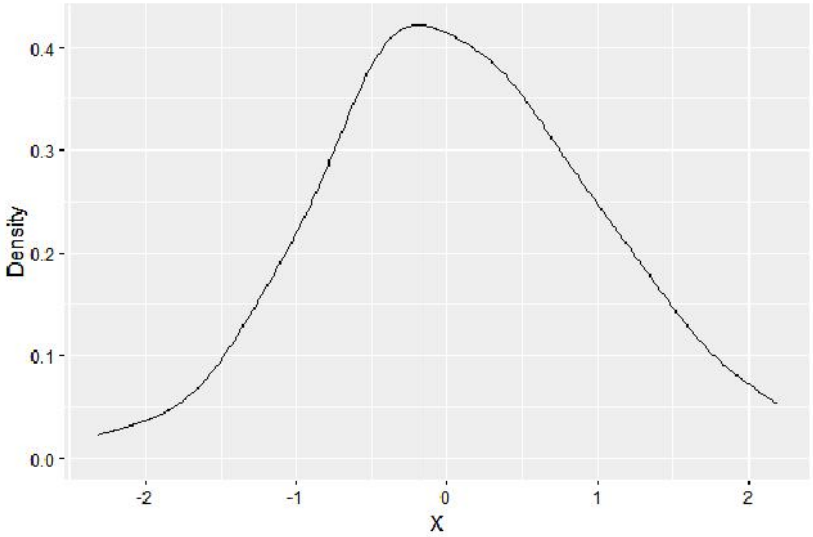
Density plot

A density plot is a type of plot that is used to visualize the distribution of a numerical variable. It shows the estimated probability density function (PDF) of the data, which provides information about the shape of the distribution and the distribution of the data.

To create a density plot using ggplot2, you will first need to prepare the data into a format that can be plotted, and then use the ggplot() function to specify the plot, followed by the geom_density() layer to add the density plot.

Here's an example of how to create a density plot using ggplot2:

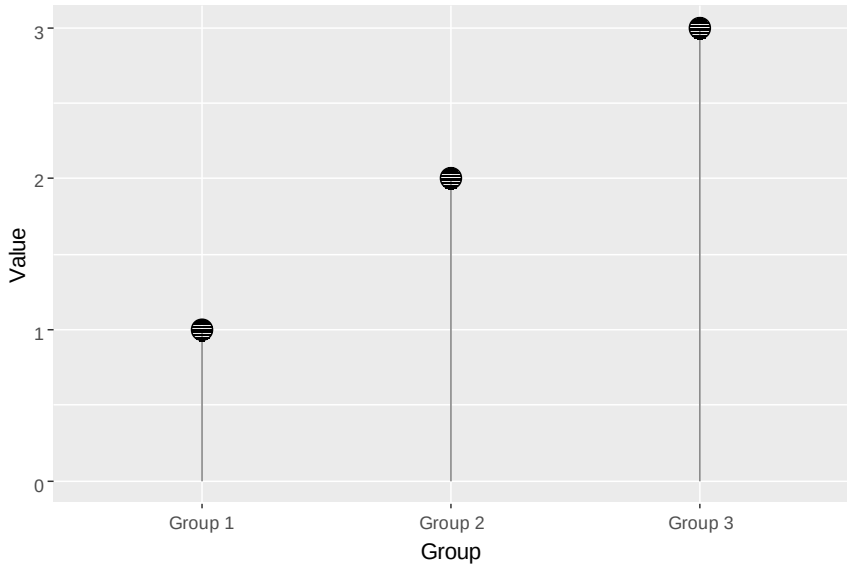
```
# First, install and load the ggplot2 library

library(ggplot2)

# Generate some sample data

set.seed(123)

x <- rnorm(100)

# Prepare the data into a format that can be plotted

df <- data.frame(x = x)

# Create the density plot using ggplot2

ggplot(df, aes(x = x)) +
  geom_density() +
  labs(x = "X", y = "Density")
```



Lollipop plot

A lollipop plot is a type of plot that is used to visualize the relationship between two variables, where one variable is categorical and the other is numerical. In a lollipop plot, the categorical variable is shown on the x-axis, and the numerical variable is represented by a line (the "stick") that extends from the x-axis to the corresponding y-value. The end of the stick is marked by a circle (the "lollipop").

```
# First, install and load the ggplot2 library

library(ggplot2)

# Generate some sample data

set.seed(123)

x <- c("Group 1", "Group 2", "Group 3")

y <- c(1, 2, 3)

# Prepare the data into a format that can be plotted

df <- data.frame(x = x, y = y)

# Create the lollipop plot using ggplot2

ggplot(df, aes(x = x, y = y)) +

geom_segment(aes(xend = x, yend = 0), color = "gray50") +

 geom_point(size = 5) +

 labs(x = "Group", y = "Value")
```



In this example, the ggplot() function is used to specify the plot, with x and y as the aesthetic mappings. The geom_segment() layer is then added to the plot to create the stick, with xend and yend as the endpoint mappings. The geom_point() layer is added to the plot to create the lollipops, and the labs() function is used to add labels to the x- and y-axes.

You can customize the appearance of the lollipop plot by adding additional layers or arguments to the ggplot() function. For example, you can change the color of the sticks and lollipops, add labels to the lollipops, and more.

Summary

Business data visualization refers to the representation of data in graphical format to help organizations make informed decisions. By visualizing data, it becomes easier to identify patterns, trends, and relationships that may not be immediately apparent from raw data. The main goal of business data visualization is to communicate complex information in an easy-to-understand manner and to support data-driven decision making.

There are various types of data visualizations including bar graphs, line charts, scatter plots, pie charts, heat maps, and more. The choice of visualization depends on the type and nature of the data being analyzed.

Benefits of business data visualization include improved communication and understanding of data, identifying relationships and trends, making informed decisions, and improved data analysis efficiency.

It's important to note that while visualizing data can greatly enhance understanding and decision making, it is important to also consider the limitations and potential biases that may arise in the visual representation of data. Proper data visualization techniques should be used and the results should be validated and interpreted carefully.

Keywords

Data visualization, Ggplot, R packages, lollipop chart

Self Assessment

1. Point out the correct statement?

A. autoplotgraph is used to complete ggplot appropriate to a particular data type
B. auto_element wraps up a projection of summary functions
C. ggplot.data create a new ggplot plot from a data frame
D. aes_sdensity display a smooth density estimate

2. _____ display a smooth density estimate.
A. geom_density2
B. geom_density
C. aes_sdensity
D. geom_contour

3. Which of the following draws nothing?
A. geom_blank
B. geom
C. geom_bin2d
D. geom_contour

4. Point out the correct statement?
A. is.theme reports whether x is a real object
B. is.object reports whether x is a aesthetic object
C. qplot is used for quick plot
D. ggplot describe the type of plot you will produce

5. _____ describe the type of plot you will produce.
A. geoms
B. ggplot
C. fplot
D. gplot

6. _____ is interval represented by a vertical line, with a point in the middle.
A. geom_range
B. geom_pointrange
C. printplot
D. geom_contour

7. Which of the following create a set of identity mappings?
A. ggplot
B. aes_all
C. aes
D. ggorder

8. _____ is new package that makes it easy to "tidy" your data.
A. tidy
B. tidyr
C. tidyneat
D. tidynr

9. Point out the correct statement?
A. Each row is an observation in tidy data
B. Each column is a variable in tidy data
C. Arranging your data in tidy way makes it easier to work
D. All of the mentioned

10. Which of the following takes two columns and spreads them into multiple columns?
A. ggmissplot
B. printplot
C. print.ggplot
D. ggplot

11. How many functions exist for wrangling the data with dplyr package?
A. one
B. seven
C. three
D. five

12. What is the role of exploratory graphs in data analysis?
A. They are made for formal presentations
B. They are typically made very quickly
C. Axes, legends, and other details are clean and exactly detailed
D. They are used in place of formal modeling

13. What is ggplot2 an implementation of?
A. the Grammar of Graphics developed by Leland Wilkinson
B. 3D visualization system
C. the S language originally developed by Bell Labs
D. the base plotting system in R

14. For barchart and _____ non-trivial methods exist for tables and arrays, documented at barchart.table.
A. scatterplot
B. dotplot
C. xyplot
D. scatterplot and xyplot

15. What is a geom in the ggplot2 system?
A. a plotting object like point, line, or other shape
B. a method for making conditioning plots
C. a method for mapping data to attributes like color and size
D. a statistical transformation

Answers for self Assessment

l.	C	2.	B	3.	C	4.	C	5.	A
6.	B	7.	D	8.	C	9.	D	10.	C
11.	B	12.	B	13.	A	14.	B	15.	A

Review Questions

1) What is ggplot2 and what is its purpose?
2) How does ggplot2 differ from other data visualization tools in R?
3) What is the structure of a ggplot2 plot?
4) What is a "ggplot" object and how is it constructed in ggplot2?
5) How can you add layers to a ggplot object?
6) What are the different types of geoms available in ggplot2 and what do they represent?
7) How can you customize the appearance of a ggplot plot, such as color, size, and shape of the data points?
8) How can you add descriptive statistics, such as mean or median, to a ggplot plot?
9) How can you use facets to create multiple plots in a single ggplot plot?
10) What is the difference between scales and themes in ggplot2, and how can you use them to change the look of your plot?

Further Reading

"R Graphics Cookbook" by Winston Chang

"Data Visualization with ggplot2" by Hadley Wickham

"ggplot2: Elegant Graphics for Data Analysis" by Hadley Wickham

"An Introduction to ggplot2" by Ed Zehl

"Data Visualization with ggplot2: A Practical Guide" by Kim Seefeld

"R Graphics for Data Analysis" by Murrell

"Data Visualization with ggplot2 and the Tidyverse" by Thomas Lin Pedersen

"The ggplot2 Package: A tutorial on its structure and use" by J. Verzani

"Data Visualization with ggplot2: A step-by-step guide" by Thomas Briet.

Unit 04:Business Forecasting using Time Series

CONTENTS

Objectives

After studying this unit, you should be able to

- to make informed decisions based on accurate predictions of future events
- to help businesses prepare for the future by providing them with the information they need to make informed decisions
- to help businesses make better decisions by providing them with accurate and reliable predictions of future events
- to identify potential risks and opportunities, enabling them to make proactive decisions to mitigate risks and capitalize on opportunities

Introduction

Business forecasting is a crucial element for any business to sustain its growth and profitability in the long run. Time series analysis is a popular technique used for business forecasting, which involves analyzing the past performance of a business to predict its future performance. Time series analysis involves analyzing data over a certain period of time to identify trends, patterns, and relationships that can be used to make accurate predictions about future outcomes.

In business forecasting using time series analysis, various methods can be employed such as moving average, exponential smoothing, regression analysis, and trend analysis. These methods

help in identifying the trends and patterns in the data and forecasting the future values of the variables.

One of the major advantages of time series analysis is that it can help businesses in identifying the factors that affect their performance and understanding the impact of external factors such as changes in the economy, consumer behavior, and market trends.

Time series analysis can be used in various business functions such as sales forecasting, inventory management, financial forecasting, and demand forecasting. It helps businesses to make informed decisions about their future investments, resource allocation, and overall strategy.

In conclusion, time series analysis is an essential tool for business forecasting, and its applications are wide-ranging. Accurate forecasting can provide a significant competitive advantage for businesses and is essential for their long-term success

4.1 What is Business Forecasting?

Business forecasting refers to the tools and techniques used to predict developments in business, such as sales, expenditures, and profits. The purpose of business forecasting is to develop better strategies based on these informed predictions. Past data is collected and analyzed via quantitative or qualitative models so that patterns can be identified and can direct demand planning, financial operations, future production, and marketing operations.

Business forecasting is the process of estimating future business performance, including revenue, expenses, and other metrics. It is an essential part of planning and decision-making for organizations of all sizes, as it helps companies understand their future financial position and make informed decisions about investments, resource allocation, and other important business initiatives.

Forecasting can be done using a variety of methods, including qualitative methods such as expert opinions and market research, and quantitative methods such as time-series analysis and regression analysis. The choice of method will depend on the specific business, its data and available resources, as well as the purpose and time frame of the forecast.

Business forecasting is not an exact science, and there is always a degree of uncertainty involved. However, by using appropriate methods and considering a range of scenarios, companies can make informed decisions about their future, and be better prepared for the challenges and opportunities ahead.

The business forecasting process entails:

Identify the problem, data point, or question that will be the basis of the systematic investigation.

Identify relevant, theoretical variables and determine the ideal manner for collecting datasets.

Make estimates about future business operations based on information collected through investigation.

Choose the model that best fits the dataset, variables, and estimates. The chosen model conducts data analysis and a forecast is made.

Note the deviations between actual performance and the forecast. Use this information to refine the process of predicting and improve the accuracy of future forecasts.

4.2 Time Series Analysis

This technique involves analyzing data from past periods to make predictions about future trends. It considers variables such as seasonality, trend, and autocorrelation to make predictions.

Time series analysis is a statistical method used to analyze and forecast future trends based on historical data. It involves analyzing data collected over a period of time, such as monthly sales figures or daily stock prices, to identify patterns and trends in the data. The data is then used to make predictions about future trends.

Time series analysis can be divided into two main categories:

Descriptive Time Series Analysis and Predictive Time Series Analysis.

Descriptive Time Series Analysis involves exploring the data to identify patterns and trends, while Predictive Time Series Analysis involves making predictions about future trends based on the identified patterns and trends.

Time series analysis is commonly used in many areas, including finance, economics, marketing, and operations research. It can be applied to a wide range of data, including sales figures, stock prices, interest rates, and weather data.

To perform time series analysis, various techniques are used, such as trend analysis, seasonality analysis, and autoregression. The selection of the appropriate technique depends on the nature of the data and the purpose of the analysis.

Regression Analysis: This technique uses historical data to establish a relationship between two or more variables. The relationship is then used to make predictions about future trends.

Regression analysis is a statistical method used to examine the relationship between two or more variables. It involves analyzing historical data to establish a mathematical relationship between a dependent variable (the variable being predicted) and one or more independent variables (predictors). The relationship is then used to make predictions about future values of the dependent variable.

Regression analysis is commonly used in many fields, including economics, finance, marketing, and engineering. It can be applied to a wide range of data, including sales figures, stock prices, interest rates, and weather data.

There are several types of regression analysis, including simple linear regression, multiple linear regression, and nonlinear regression. Simple linear regression involves a single independent variable and is used to predict the dependent variable based on a straight-line relationship. Multiple linear regression involves multiple independent variables and is used to predict the dependent variable based on more complex relationships. Nonlinear regression involves a nonlinear relationship between the dependent and independent variables and is used when the relationship cannot be described by a straight line.

The accuracy of the predictions made using regression analysis depends on the quality of the data and the validity of the mathematical relationship established between the variables. To ensure the validity of the relationship, it is important to perform a thorough analysis of the data and to carefully select the appropriate regression model.

Moving Averages: This technique involves calculating the average of past data over a specific period of time, such as a month or quarter, to make predictions about future trends.

Exponential Smoothing: This technique involves adjusting past data to account for trends and other factors, such as seasonality, to make predictions about future trends.

ARIMA (AutoRegressive Integrated Moving Average): This technique uses time series data to analyze patterns and relationships, including trends and seasonality, to make predictions about future trends.

Neural Networks: This technique uses artificial intelligence algorithms to analyze large amounts of data and identify patterns, which can then be used to make predictions about future trends.

Decision Trees: This technique uses historical data to build a tree-like structure that can be used to make predictions about future trends based on different scenarios.

Monte Carlo Simulation: This technique involves running multiple simulations based on random sampling of historical data to make predictions about future trends.

Business Forecasting Techniques

Business forecasting and planning can be conducted by either quantitative modeling methods or qualitative modeling methods:

Quantitative Techniques in Business Forecasting

Quantitative forecasting is a long term business forecasting method concerned only with measurable data such as statistics and historical data. Past performance is used to identify trends or rates of change. These types of business forecasting are especially useful for long range forecasting in business. Quantitative models include:

Trend Analysis Method: Also known as "Time Series Analysis," this forecast method uses past data to predict future events, excluding outliers and holding more recent data in higher regard. This method is most effective when there is a large quantity of historical data showing clear and stable trends. This is the most common and cost-effective method.

Econometric Modeling: This mathematical model makes use of several multiple-regres-sion equations to test the consistency of datasets over time and the significance of the relationship between datasets, and to predict significant economic shifts and the potential effect of those shifts on the company.

Indicator Approach: This approach follows the relationship between certain indicators and uses the leading indicator data in order to estimate the performance of the lagging indicators. Lagging indicators are a type of KPI that measure business performance subsequently and provide insight into the impact of business strategies on the results achieved.

Qualitative Techniques in Business Forecasting

Qualitative forecasting relies on industry experts or "market mavens" to make short-term predictions. These techniques are especially useful in forecasting markets for which there is insufficient historical data to make statistically relevant conclusions. Qualitative models include:

Market Research: Polls and surveys are conducted with a large number of prospective consumers regarding a specific product or service in order to predict the margin by which consumption will either decrease or increase.

Delphi Model: A panel of experts are polled on their opinions regarding specific topics. Their predictions are compiled anonymously, and a forecast is made.

What is the Importance of Forecasting in Business?

The use of forecasts in business management is indispensable for nearly every decision in every industry. The use of business forecasting provides information that helps business managers identify and understand weaknesses in their planning, adapt to changing circumstances, and achieve effective control of business operations.

Some business forecasting examples include: determining the feasibility of facing existing competition, measuring the possibility of creating demand for a product, estimating the costs of recurring monthly bills, predicting future sales volumes based on past sales information, efficient allocation of resources, forecasting earnings and budgeting, and scrutinizing the appropriateness of management decisions.

Business forecasting software can help business managers and forecasters not only generate forecast reports easily, but also better understand predictions and how to make strategic decisions based off of these predictions. A quality business forecast system should provide clear, real-time visualization of business performance, which facilitates fast analysis and streamlined business planning.

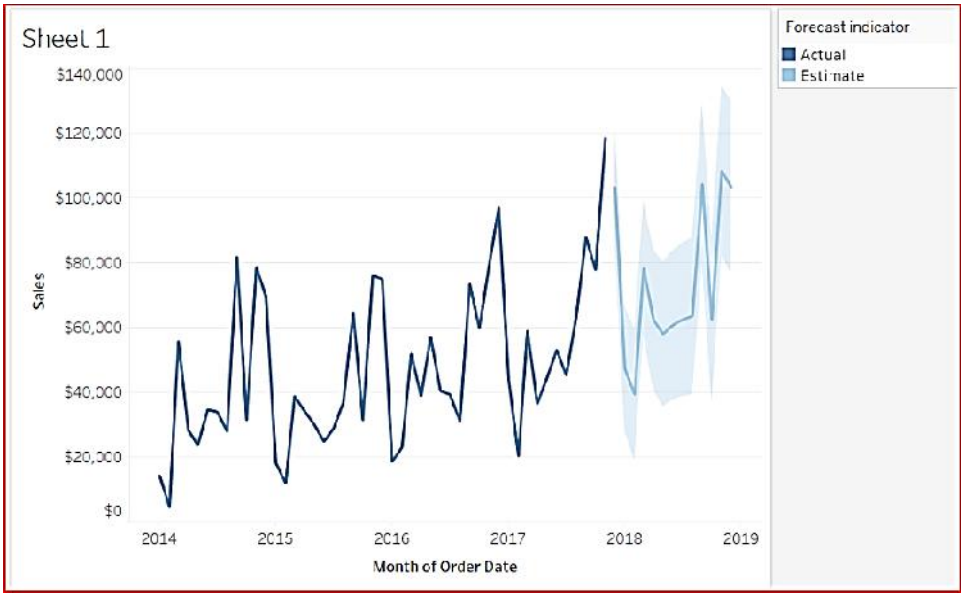
The application of forecasting in business is an art and a science, the combination of business intelligence and data science, and the challenges of business forecasting often stem from poor judgments and inexperience. Assumptions combined with unexpected events can be dangerous and result in completely inaccurate predictions. Despite the limitations of business forecasting, gaining any amount of insight into probable future trends will put an organization at a significant advantage.

Time Series Forecasting: Definition, Applications, and Examples

Time series forecasting occurs when you make scientific predictions based on historical time stamped data. It involves building models through historical analysis and using them to make observations and drive future strategic decision-making. An important distinction in forecasting is that at the time of the work, the future outcome is completely unavailable and can only be estimated through careful analysis and evidence-based priors.

What is time series forecasting?

A Tableau workbook demonstrating a time series forecasting visualization.



Time series forecasting is the process of analyzing time series data using statistics and modeling to make predictions and inform strategic decision-making. It's not always an exact prediction, and likelihood of forecasts can vary wildly—especially when dealing with the commonly fluctuating variables in time series data as well as factors outside our control. However, forecasting insight about which outcomes are more likely—or less likely—to occur than other potential outcomes. Often, the more comprehensive the data we have, the more accurate the forecasts can be. While forecasting and "prediction" generally mean the same thing, there is a notable distinction. In some industries, forecasting might refer to data at a specific future point in time, while prediction refers to future data in general. Series forecasting is often used in conjunction with time series analysis. Time series analysis involves developing models to gain an understanding of the data to understand the underlying causes. Analysis can provide the "why" behind the outcomes you are seeing. Forecasting then takes the next step of what to do with that knowledge and the predictable extrapolations of what might happen in the future.

Applications of time series forecasting

Forecasting has a range of applications in various industries. It has tons of practical applications including: weather forecasting, climate forecasting, economic forecasting, healthcare forecasting engineering forecasting, finance forecasting, retail forecasting, business forecasting, environmental studies forecasting, social studies forecasting, and more. Basically anyone who has consistent historical data can analyze that data with time series analysis methods and then model, forecasting, and predict. For some industries, the entire point of time series analysis is to facilitate forecasting. Some technologies, such as augmented analytics, can even automatically select forecasting from among other statistical algorithms if it offers the most certainty.

4.3 When Time Series Forecasting should be used

Naturally, there are limitations when dealing with the unpredictable and the unknown. Time series forecasting isn't infallible and isn't appropriate or useful for all situations. Because there really is no explicit set of rules for when you should or should not use forecasting, it is up to analysts and data teams to know the limitations of analysis and what their models can support. Not every model will fit every data set or answer every question. Data teams should use time series forecasting when they understand the business question and have the appropriate data and forecasting capabilities to answer that question. Good forecasting works with clean, time stamped data and can identify the genuine trends and patterns in historical data. Analysts can tell the difference between random fluctuations or outliers, and can separate genuine insights from seasonal variations. Time series analysis shows how data changes over time, and good forecasting can identify the direction in which the data is changing.

4.4 Time Series Forecasting Considerations

The first thing to consider is the amount of data at hand—the more points of observation you have, the better your understanding. This is a constant across all types of analysis, and time series analysis forecasting is no exception. However, forecasting relies heavily on the amount of data, possibly even more so than other analyses. It builds directly off of past and current data. The less data you have to extrapolate, the less accurate your forecasting will be.

Time horizons

The time frame of your forecast also matters. This is known as a time horizon—a fixed point in time where a process (like the forecast) ends. It's much easier to forecast a shorter time horizon with fewer variables than it is a longer time horizon. The further out you go, the more unpredictable the variables will be. Alternatively, having less data can sometimes still work with forecasting if you adjust your time horizons. If you're lacking long-term recorded data but you have an extensive amount of short-term data, you can create short-term forecasts.

Dynamic and static states

The state of your forecasting and data makes a difference as to when you want to use it. Will the forecast be dynamic or static? If the forecast is static, it is set in stone once it is made, so make sure your data is adequate for a forecast. However, dynamic forecasts can be constantly updated with new information as it comes in. This means you can have less data at the time the forecast is made, and then get more accurate predictions as data is added.

Data quality

As always with analysis, the best analysis is only useful if the data is of a useable quality. Data that is dirty, poorly processed, overly processed, or isn't properly collected can significantly skew results and create wildly inaccurate forecasts. The typical guidelines for data quality apply here:

- make sure data is complete,
- is not duplicated or redundant,
- was collected in a timely and consistent manner,
- is in a standard and valid format,
- is accurate for what it is measuring,
- and is uniform across sets.

When dealing with time series analysis, it is even more important that the data was collected at consistent intervals over the period of time being tracked. This helps account for trends in the data,

cyclic behavior, and seasonality. It also can help identify if an outlier is truly an outlier or if it is part of a larger cycle. Gaps in the data can hide cycles or seasonal variation, skewing the forecast as a result.

4.5 Examples of Time Series Forecasting

Here are several examples from a range of industries to make the notions of time series analysis and forecasting more concrete:

Forecasting the closing price of a stock each day.

Forecasting product sales in units sold each day for a store.

Forecasting unemployment for a state each quarter.

Forecasting the average price of gasoline each day.

Things that are random will never be forecast accurately, no matter how much data we collect or how consistently. For example: we can observe data every week for every lottery winner, but we can never forecast who will win next. Ultimately, it is up to your data and your time series data analysis as to when you should use forecasting, because forecasting varies widely due to various factors. Use your judgment and know your data. Keep this list of considerations in mind to always have an idea of how successful forecasting will be.

For as long as we have been recording data, time has been a crucial factor. In time series analysis, time is a significant variable of the data. Times series analysis helps us study our world and learn how we progress within it.

Time series analysis is a specific way of analyzing a sequence of data points collected over an interval of time. In time series analysis, analysts record data points at consistent intervals over a set period of time rather than just recording the data points intermittently or randomly. However, this type of analysis is not merely the act of collecting data over time.

What sets time series data apart from other data is that the analysis can show how variables change over time. In other words, time is a crucial variable because it shows how the data adjusts over the course of the data points as well as the final results. It provides an additional source of information and a set order of dependencies between the data.

Time series analysis typically requires a large number of data points to ensure consistency and reliability. An extensive data set ensures you have a representative sample size and that analysis can cut through noisy data. It also ensures that any trends or patterns discovered are not outliers and can account for seasonal variance. Additionally, time series data can be used for forecasting—predicting future data based on historical data.

4.6 Why Organizations use Time Series Data Analysis

Time series analysis helps organizations understand the underlying causes of trends or systemic patterns over time. Using data visualizations, business users can see seasonal trends and dig deeper into why these trends occur. With modern analytics platforms, these visualizations can go far beyond line graphs.

When organizations analyze data over consistent intervals, they can also use time series forecasting to predict the likelihood of future events. Time series forecasting is part of predictive analytics. It can show likely changes in the data, like seasonality or cyclic behavior, which provides a better understanding of data variables and helps forecast better.

For example, Des Moines Public Schools analyzed five years of student achievement data to identify at-risk students and track progress over time. Today's technology allows us to collect massive amounts of data every day and it's easier than ever to gather enough consistent data for comprehensive analysis.

Time series analysis examples

Time series analysis is used for non-stationary data—things that are constantly fluctuating over time or are affected by time. Industries like finance, retail, and economics frequently use time series analysis because currency and sales are always changing. Stock market analysis is an excellent

example of time series analysis in action, especially with automated trading algorithms. Likewise, time series analysis is ideal for forecasting weather changes, helping meteorologists predict everything from tomorrow's weather report to future years of climate change. Examples of time series analysis in action include:

Weather data

Rainfall measurements

Temperature readings

Heart rate monitoring (EKG)

Brain monitoring (EEG)

Quarterly sales

Stock prices

Automated stock trading

Industry forecasts

Interest rates

Time Series Analysis Types

Because time series analysis includes many categories or variations of data, analysts sometimes must make complex models. However, analysts can't account for all variances, and they can't generalize a specific model to every sample. Models that are too complex or that try to do too many things can lead to a lack of fit. Lack of fit or overfitting models lead to those models not distinguishing between random error and true relationships, leaving analysis skewed and forecasts incorrect.

Models of time series analysis include:

Classification: Identifies and assigns categories to the data.

Curve fitting: Plots the data along a curve to study the relationships of variables within the data.

Descriptive analysis: Identifies patterns in time series data, like trends, cycles, or seasonal variation.

Explanative analysis: Attempts to understand the data and the relationships within it, as well as cause and effect.

Exploratory analysis: Highlights the main characteristics of the time series data, usually in a visual format.

Forecasting: Predicts future data. This type is based on historical trends. It uses the historical data as a model for future data, predicting scenarios that could happen along future plot points.

Intervention analysis: Studies how an event can change the data.

Segmentation: Splits the data into segments to show the underlying properties of the source information.

Data classification

Further, time series data can be classified into two main categories:

Stock time series data means measuring attributes at a certain point in time, like a static snapshot of the information as it was.

Flow time series data means measuring the activity of the attributes over a certain period, which is generally part of the total whole and makes up a portion of the results.

Data variations

In time series data, variations can occur sporadically throughout the data:

Functional analysis can pick out the patterns and relationships within the data to identify notable events.

Trend analysis means determining consistent movement in a certain direction. There are two types of trends: deterministic, where we can find the underlying cause, and stochastic, which is random and unexplainable.

Seasonal variation describes events that occur at specific and regular intervals during the course of a year. Serial dependence occurs when data points close together in time tend to be related.

Time series analysis and forecasting models must define the types of data relevant to answering the business question. Once analysts have chosen the relevant data they want to analyze, they choose what types of analysis and techniques are the best fit.

Important Considerations for Time Series Analysis

While time series data is data collected over time, there are different types of data that describe how and when that time data was recorded. For example:

Time series data is data that is recorded over consistent intervals of time.

Cross-sectional data consists of several variables recorded at the same time.

Pooled data is a combination of both time series data and cross-sectional data.

Time Series Analysis Models and Techniques

Just as there are many types and models, there are also a variety of methods to study data. Here are the three most common.

Box-Jenkins ARIMA models: These univariate models are used to better understand a single time-dependent variable, such as temperature over time, and to predict future data points of variables. These models work on the assumption that the data is stationary. Analysts have to account for and remove as many differences and seasonalities in past data points as they can. Thankfully, the ARIMA model includes terms to account for moving averages, seasonal difference operators, and autoregressive terms within the model.

Box-Jenkins Multivariate Models: Multivariate models are used to analyze more than one time-dependent variable, such as temperature and humidity, over time.

Holt-Winters Method: The Holt-Winters method is an exponential smoothing technique. It is designed to predict outcomes, provided that the data points include seasonality.

4.7 Exploration of Time Series Data using R

Exploration of time series data using R can be done in several ways. Here are some of the key steps and tools you can use:

Loading the data: The first step is to load your time series data into R. You can use the read.csv or read.table function to read in data from a file, or you can use the ts() function to create a time series object from data in a matrix or data frame.

Understanding the data: Once you have loaded your data, you should explore it to get a sense of what it looks like. You can use the head(), tail(), and summary() functions to see the first and last few rows of the data, as well as some basic summary statistics. You can also plot the data using plot() or ggplot2() to get a visual understanding of the time series.

Decomposition: Time series data often has multiple components, including trend, seasonal, and cyclical patterns. You can use the decompose() function to separate out these components and explore them separately.

Smoothing: Time series data can be noisy, making it difficult to see trends and patterns. You can use smoothing techniques such as moving averages or exponential smoothing to reduce noise and highlight trends.

Stationarity: Many time series models require the data to be stationary, meaning that the statistical properties of the data do not change over time. You can use tests such as the Augmented Dickey-Fuller (ADF) test to check for stationarity.

Time series models: There are many models that can be used to analyze time series data, including ARIMA, SARIMA, and Prophet. You can use functions such as arima(), auto.arima(), and prophet() to fit these models and make predictions.

Visualization: Finally, you can use various visualization techniques to explore the time series data further. This can include plotting the data with different levels of smoothing or using techniques such as time series forecasting to predict future values.

Overall, R provides a wide range of tools and techniques for exploring and analyzing time series data, making it a powerful tool for time series analysis.

Time Series in R is used to see how an object behaves over a period of time. In R, it can be easily done by ts() function with some parameters. Time series takes the data vector and each data is connected with timestamp value as given by the user. This function is mostly used to learn and forecast the behavior of an asset in business for a period of time. For example, sales analysis of a company, inventory analysis, price analysis of a particular stock or market, population analysis, etc.

Syntax:

objectName <- ts(data, start, end, frequency)

where,

data represents the data vector

start represents the first observation in time series

end represents the last observation in time series

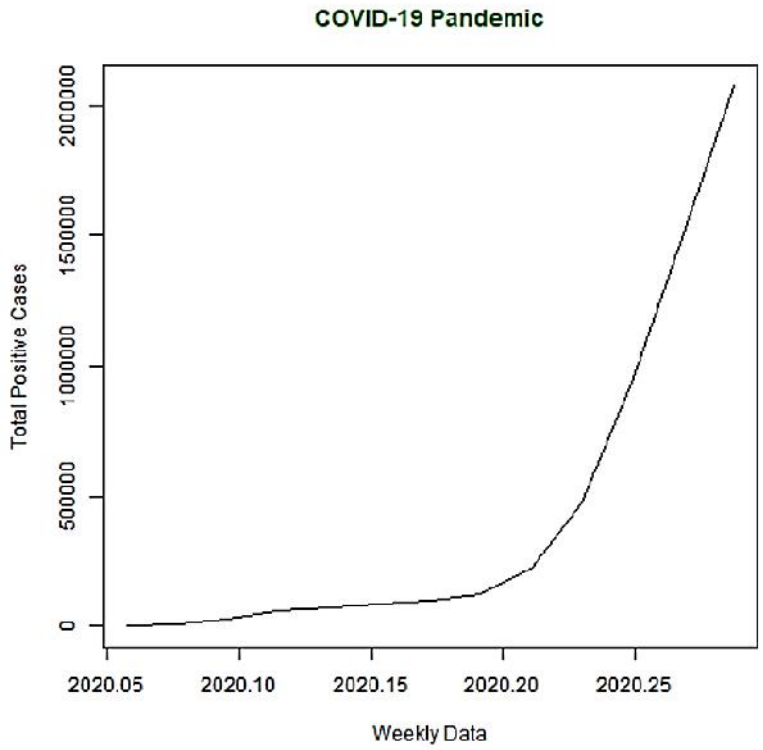
frequency represents number of observations per unit time. For example, frequency=1 for monthly data.

Note: To know about more optional parameters, use the following command in R console:

help("ts")

Example: Let's take the example of COVID-19 pandemic situation. Taking a total number of positive cases of COVID-19 cases weekly from 22 January 2020 to 15 April 2020 of the world in data vector.

```
# Weekly data of COVID-19 positive cases from
# 22 January, 2020 to 15 April, 2020
x <- c(580, 7813, 28266, 59287, 75700,
       87820, 95314, 126214, 218843, 471497,
       936851, 1508725, 2072113)
# library required for decimal_date() function
library(lubridate)
# output to be created as png file
png(file ="timeSeries.png")
# creating time series object
# from date 22 January, 2020
mts <- ts(x, start = decimal_date(ymd("2020-01-22")), frequency = 365.25 / 7)
# plotting the graph
plot(mts, xlab ="Weekly Data",
          ylab ="Total Positive Cases",
          main ="COVID-19 Pandemic",
          col.main ="darkgreen")
# saving the file
dev.off()
```



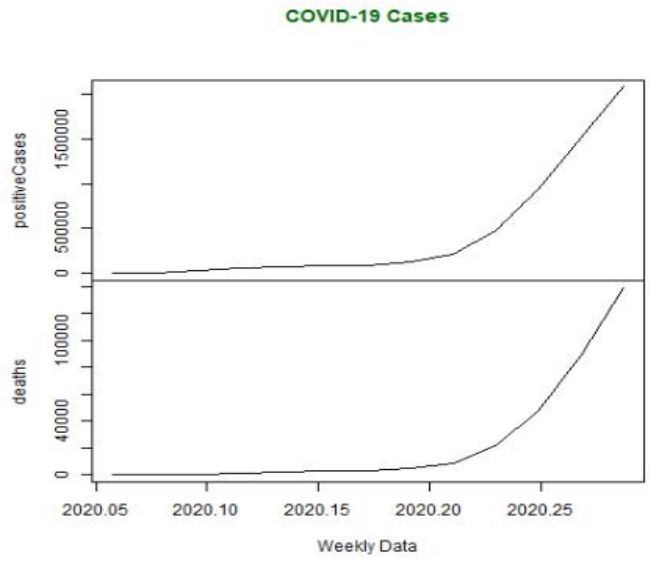
Multivariate Time Series

Multivariate Time Series is creating multiple time series in a single chart.

Example: Taking data of total positive cases and total deaths from COVID-19 weekly from 22 January 2020 to 15 April 2020 in data vector.

```
# Weekly data of COVID-19 positive cases and
# weekly deaths from 22 January, 2020 to
# 15 April, 2020
positiveCases <- c(580, 7813, 28266, 59287,
                   75700, 87820, 95314, 126214,
                   218843, 471497, 936851,
                   1508725, 2072113)
deaths <- c(17, 270, 565, 1261, 2126, 2800,
            3285, 4628, 8951, 21283, 47210,
            88480, 138475)
# library required for decimal_date() function
library(lubridate)
# output to be created as png file
png(file ="multivariateTimeSeries.png")
# creating multivariate time series object
# from date 22 January, 2020
mts <- ts(cbind(positiveCases, deaths),
start = decimal_date(ymd("2020-01-22")),frequency = 365.25 / 7)
# plotting the graph
```

```
plot(mts, xlab ="Weekly Data",
          main ="COVID-19 Cases",
          col.main ="darkgreen")
# saving the file
dev.off()
```



4.8 Forecasting Using ARIMA Methodology

Forecasting can be done on time series using some models present in R. In this example, Arima automated model is used. To know about more parameters of arima() function, use the below command.

help("arima")

In the below code, forecasting is done using forecast library and so, installation of forecast library is necessary.

```
# Weekly data of COVID-19 cases from
# 22 January, 2020 to 15 April, 2020
x <- c(580, 7813, 28266, 59287, 75700,
          87820, 95314, 126214, 218843,
          471497, 936851, 1508725, 2072113)
# library required for decimal_date() function
library(lubridate)
# library required for forecasting
library(forecast)
# output to be created as png file
png(file ="forecastTimeSeries.png")
# creating time series object
# from date 22 January, 2020
mts <- ts(x, start = decimal_date(ymd("2020-01-22")),
                                                    frequency = 365.25 / 7)
# forecasting model using arima model
```

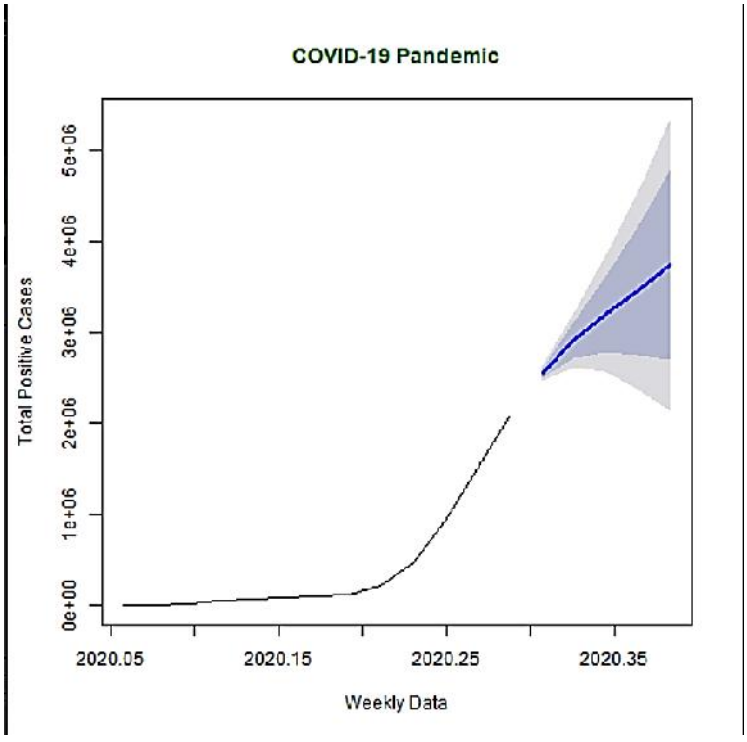
```
fit <- auto.arima(mts)
# Next 5 forecasted values
forecast(fit, 5)
# plotting the graph with next
# 5 weekly forecasted values
plot(forecast(fit, 5), xlab ="Weekly Data",
ylab ="Total Positive Cases",
main ="COVID-19 Pandemic", col.main ="darkgreen")
# saving the file
dev.off()
```

Output :

After executing the above code, the following forecasted results are produced.

Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2020.307	2547989	2491957	2604020	2462296	2633682
2020.326	2915130	2721277	3108983	2618657	3211603
2020.345	3202354	2783402	3621307	2561622	3843087
2020.364	3462692	2748533	4176851	2370480	4554904
2020.383	3745054	2692884	4797225	2135898	5354210

Below graph plots estimated forecasted values of COVID-19 if it continues to be widespread for the next 5 weeks.



4.9 Forecasting Using GARCH Methodology

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models are a class of time series models that are commonly used for financial data analysis. These models are designed to

capture the volatility clustering and persistence in financial data by allowing the variance of the series to be time-varying.

GARCH models build upon the autoregressive conditional heteroskedasticity (ARCH) framework, which models the conditional variance of a series as a function of its past squared residuals. The GARCH model extends this by including both past squared residuals and past conditional variances in the conditional variance equation. This allows for the persistence of volatility to be captured in the model.

There are several variations of GARCH models, including the original GARCH, the EGARCH (Exponential GARCH), the TGARCH (Threshold GARCH), and the IGARCH (Integrated GARCH). These models differ in how they model the conditional variance and incorporate additional features such as asymmetry, leverage effects, and long-term memory.

GARCH models are estimated using maximum likelihood estimation, and model selection can be done using criteria such as Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC). Once a GARCH model has been estimated, it can be used for forecasting future volatility and assessing risk.

GARCH models have become popular in finance because they are able to capture the complex dynamics of financial data and provide accurate estimates of future volatility. However, they can be computationally intensive to estimate and may require large amounts of data to achieve accurate results. Additionally, GARCH models are limited by their assumption of normality in the distribution of residuals, which may not be appropriate for all types of financial data.

Example

```
# Load the necessary packages

library(tseries)

library(rugarch)

# Load the data

data(msft)

# Estimate a GARCH(1,1) model

spec <- ugarchspec(variance.model = list(model = "sGARCH", garchOrder = c(1,1)), mean.model = list(armaOrder = c(0,0)))

fit <- ugarchfit(spec, data = msft$Close)

# Print the model summary

summary(fit)

# Make a forecast for the next 5 periods

forecast <- ugarchforecast(fit, n.ahead = 5)

# Plot the forecasted volatility

plot(forecast)
```

In this example, we load the msft data from the tseries package, which contains the daily closing prices of Microsoft stock from January 1, 2005 to December 31, 2010. We then specify a GARCH(1,1) model using the ugarchspec function from the rugarch package. The variance.model argument specifies that we want to use a standard GARCH model (model = "sGARCH") with a lag of 1 for both the autoregressive and moving average components (garchOrder = c(1,1)). The mean.model argument specifies that we want to use a zero-mean model (armaOrder = c(0,0)).

We then fit the model to the data using the ugarchfit function and print the model summary. The summary displays the estimated parameters of the model, as well as diagnostic statistics such as the log-likelihood and the AIC.

Next, we use the ugarchforecast function to make a forecast for the next 5 periods. Finally, we plot the forecasted volatility using the plot function.

```
*---------------------------------*
*       GARCH Model Fit       *
```

Conditional Variance Dynamics

GARCH Model : sGARCH(1,1)

Mean Model : ARFIMA(0,0,0)

Distribution : norm

Optimal Parameters

Estimate Std. Error t value Pr(>|t|)

mu 27.60041 0.042660 647.008 0.00000

omega 0.06801 0.003504 19.419 0.00000

alpha1 0.10222 0.010072 10.153 0.00000

beta1 0.88577 0.006254 141.543 0.00000

Robust Standard Errors:

Estimate Std. Error t value Pr(>|t|)

mu 27.60041 0.031563 874.836 0.00000

omega 0.06801 0.004074 16.691 0.00000

alpha1 0.10222 0.010039 10.183 0.00000

beta1 0.88577 0.008246 107.388 0.00000

LogLikelihood : 2321.214

Information Criteria

Akaike -13.979

Bayes -13.952

Shibata -13.979

Hannan-Quinn -13.969

Weighted Ljung-Box Test on Standardized Residuals

----

statistic p-value

Lag[1] 0.525 0.468736

Lag[2*(p+q)+(p+q)-1][4] 1.705 0.074600

Lag[4*(p+q)+(p+q)-1][8] 2.396 0.001582

d.o.f=0

H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals

----

statistic p-value

Lag[1] 0.007 0.933987

Lag[2*(p+q)+(p+q)-1][4] 2.710 0.244550

Lag[4*(p+q)+(p+q)-1][8] 4.084 0.193941

d.o.f=2

Weighted ARCH LM Tests

Statistic Shape Scale P-Value

ARCH Lag[3] 0.1691 0.500 2.000 0.6806

ARCH Lag[5] 0.2474 1.440 1.667 0.9982

ARCH Lag[7] 0.8799 2.315 1.543 1.0000

Nyblom stability test

Joint Statistic: 1.4489

Individual Statistics:

mu 0.3925

omega 0.0495

alpha1 0.6311

beta1 0.3752

Asymptotic Critical Values (10% 5% 1%)

Joint Statistic: 1.58 1.88 2.54

4.10 Forecasting Using VAR Methodology

VAR (Vector Autoregression) is a statistical methodology for time series analysis that allows for modeling the interdependencies between multiple time series variables. Here are the key steps involved in using VAR for time series analysis:

Data preparation: Make sure your data is in a time series format with a consistent frequency. You should also make sure your data is stationary by checking for trends, seasonality, and non-stationary behavior.

Model specification: Specify the number of lags (p) that you want to include in the model and whether you want to include a constant term. You can also specify different types of VAR models, such as VARX (VAR with exogenous variables) or VEC (Vector Error Correction).

Estimation: Estimate the parameters of the VAR model using techniques such as OLS (Ordinary Least Squares) or maximum likelihood estimation.

Diagnostics: Conduct diagnostic tests to evaluate the goodness of fit of the model, such as residual diagnostics, serial correlation tests, and ARCH tests.

Forecasting: Use the estimated VAR model to generate forecasts for future time periods.

There are different software packages and programming languages that can be used to implement VAR methodologies for time series analysis, such as R, Python, MATLAB, and EViews. Each of these tools has their own syntax and functions for implementing VAR models, so it's important to consult the relevant documentation for the software you are using.

Example

Load the necessary libraries:

library(vars)

library(tidyverse)

Prepare your data:

For this example, we will use the built-in R dataset "economics", which contains monthly U.S. economic time series data from 1967 to 2015. We will use the variables "unemploy" (unemployment rate) and "pop" (total population).

```
data("economics")
data_ts <- ts(economics[, c("unemploy", "pop")], start = c(1967, 1), frequency = 12)
```

Before estimating the VAR model, let's plot the data to visualize any trends or seasonality.

```
autoplot(data_ts) +
  labs(title = "Unemployment Rate and Total Population in the US",
       x = "Year",
       y = "Value")
plot
```

From the plot, we can see that both variables have a clear upward trend, so we will need to take first differences to make them stationary.

```
data_ts_diff <- diff(data_ts)
```

Now that our data is stationary, we can proceed to estimate the VAR model.

Estimate the VAR model:

We will estimate a VAR model with 2 lags and a constant term using the VAR() function from the vars library.

```
var_model <- VAR(data_ts_diff, p = 2, type = "const")
```

We can use the summary() function to view a summary of the estimated VAR model.

```
summary(var_model)
```

The output will show the estimated coefficients, standard errors, t-values, and p-values for each lag of each variable in the VAR model.

Evaluate the VAR model:

To evaluate the VAR model, we can perform a serial correlation test and an ARCH test using the serial.test() and arch.test() functions from the vars library, respectively.

```
serial.test(var_model)
arch.test(var_model)
```

If the p-value of the serial correlation test is less than 0.05, it indicates the presence of serial correlation in the residuals, which violates the assumptions of the VAR model. Similarly, if the p-value of the ARCH test is less than 0.05, it indicates the presence of conditional heteroskedasticity in the residuals.

Forecast using the VAR model:

To forecast future values of the variables, we can use the predict() function from the vars library.

```
var_forecast <- predict(var_model, n.ahead = 12)
```

This will generate a forecast for the next 12 months, based on the estimated VAR model. We can visualize the forecast using the autoplot() function from the ggfortify library.Copy code

```
autoplot(var_forecast) +
  labs(title = "Forecast of Unemployment Rate and Total Population in the US",
       x = "Year",
       y = "Value")
plot
```

This plot shows the forecasted values for the next 12 months for both variables in the VAR model. We can see that the unemployment rate is expected to decrease slightly over the next year, while the total population is expected to continue increasing.

Summary

Business forecasting using time series involves using statistical methods to analyze historical data and make predictions about future trends in business variables such as sales, revenue, and demand for products or services. Time series analysis involves analyzing the pattern of the data over time, including identifying trends, seasonal patterns, and cyclical fluctuations.

One popular approach to time series forecasting is the use of ARIMA (autoregressive integrated moving average) models, which can capture trends and seasonal patterns in the data, as well as the autocorrelation of the series. Another popular approach is the use of VAR (vector autoregression) models, which can capture the interdependencies between multiple time series variables.

Business forecasting using time series can be used for a variety of purposes, such as predicting sales for a specific product or service, forecasting future demand for inventory, and predicting overall market trends. Accurate forecasting can help businesses make informed decisions about resource allocation, inventory management, and overall business strategy.

To be effective, time series forecasting requires high-quality data, including historical data and relevant external factors such as changes in the economy, weather patterns, or industry trends. In addition, it's important to validate and test the accuracy of the forecasting models using historical data before applying them to future predictions.

Overall, business forecasting using time series analysis can be a valuable tool for businesses looking to make data-driven decisions and stay ahead of market trends.

Keywords

Time series: A collection of observations measured over time, typically at regular intervals.

Trend: A gradual, long-term change in the level of a time series.

Seasonality: A pattern of regular fluctuations in a time series that repeat at fixed intervals.

Stationarity: A property of a time series where the mean, variance, and autocorrelation structure are constant over time.

Autocorrelation: The correlation between a time series and its own past values.

White noise: A type of time series where the observations are uncorrelated and have constant variance.

ARIMA: A statistical model for time series data that includes autoregressive, differencing, and moving average components.

Exponential smoothing: A family of time series forecasting models that use weighted averages of past observations, with weights that decay exponentially over time.

Seasonal decomposition: A method of breaking down a time series into trend, seasonal, and residual components.

Forecasting: The process of predicting future values of a time series based on past observations and statistical models.

SelfAssessment

1. What is a time series?

A. A collection of observations measured over time

B. A statistical model for time series data

C. A method of breaking down a time series into trend, seasonal, and residual components

D. A type of time series where the observations are uncorrelated and have constant variance

2. What is trend in a time series?

A. A pattern of regular fluctuations in a time series that repeat at fixed intervals

B. A gradual, long-term change in the level of a time series
C. The correlation between a time series and its own past values
D. A property of a time series where the mean, variance, and autocorrelation structure are constant over time

3. What is seasonality in a time series?
A. A type of time series where the observations are uncorrelated and have constant variance
B. A pattern of regular fluctuations in a time series that repeat at fixed intervals
C. A method of breaking down a time series into trend, seasonal, and residual components
D. A gradual, long-term change in the level of a time series

4. What is autocorrelation in a time series?
A. A method of breaking down a time series into trend, seasonal, and residual components
B. A type of time series where the observations are uncorrelated and have constant variance
C. The correlation between a time series and its own past values
D. A gradual, long-term change in the level of a time series

5. What is ARIMA?
A. A statistical model for time series data that includes autoregressive, differencing, and moving average components
B. A method of breaking down a time series into trend, seasonal, and residual components
C. A family of time series forecasting models that use weighted averages of past observations
D. A type of time series where the observations are uncorrelated and have constant variance

6. What R package is commonly used for time series analysis?
A. ggplot2
B. dplyr
C. lubridate
D. forecast

7. How do you convert a data frame in R to a time series object?
A. Use the as.ts() function
B. Use the ts() function
C. Use the zoo() function
D. Use the xts() function

8. What is the difference between the ts() and zoo() functions in R?
A. ts() is used for time series data with regular time intervals, while zoo() is used for irregular time intervals
B. ts() is used for time series data with irregular time intervals, while zoo() is used for regular time intervals
C. ts() is a base R function, while zoo() is a package for time series analysis
D. There is no difference between ts() and zoo()

9. How do you plot a time series in R using the ggplot2 package?
A. Use the qplot() function

B. Use the ggplot() function with geom_line()
C. Use the autoplot() function
D. Use the plot() function with type = "l"

10. What is the purpose of the forecast() function in R?
A. To fit an ARIMA model to a time series
B. To compute forecasts for a time series using a chosen model
C. To decompose a time series into trend, seasonal, and residual components
D. To convert a data frame to a time series object

11. What R function can be used to calculate the autocorrelation function (ACF) and partial autocorrelation function (PACF) for a time series?
A. acf()
B. pacf()
C. auto.correlation()
D. corr()

12. What is the purpose of the AIC() function in R?
A. To calculate the Akaike information criterion (AIC) for a given model
B. To calculate the autocorrelation function (ACF) for a time series
C. To compute forecasts for a time series using a chosen model
D. To plot a time series using the ggplot2 package
13. What is a stationary time series?
A. A time series where the mean, variance, and autocorrelation structure are constant over time
B. A time series where the observations are uncorrelated and have constant variance
C. A time series with a trend, but no seasonal or cyclic components
D. A time series with a seasonal pattern, but no trend or cyclic components

14. What R function can be used to detrend a time series?
A. diff()
B. ts.intersect()
C. decompose()
D. aggregate()

15. What is the purpose of the window() function in R?
A. To extract a subset of a time series based on a specified time range
B. To calculate the autocorrelation function (ACF) for a time series
C. To convert a data frame to a time series object
D. To compute forecasts for a time series using a chosen model

Answers for Self Assessment

1.	A	2.	B	3.	B	4.	C	5.	A
6.	D	7.	B	8.	A	9.	C	10.	B

11. A 12. A 13. A 14. C 15. A

Review Questions

1. What is a time series? How is it different from a cross-sectional data set?
2. What are some common patterns that can be observed in time series data?
3. What is autocorrelation? How can it be measured for a time series?
4. What is stationarity? Why is it important for time series analysis?
5. What is the difference between the additive and multiplicative decomposition of a time series?
6. What is a moving average model? How is it different from an autoregressive model?
7. What is the difference between white noise and a random walk time series?
8. How can seasonal patterns be modeled in a time series?
9. What is the purpose of the ARIMA model? How is it different from the ARMA model?
10. What is the purpose of the forecast package in R? What are some functions in this package that can be used for time series analysis?
11. What is the purpose of cross-validation in time series analysis? How can it be implemented in R?
12. What are some techniques for time series forecasting? How can they be implemented in R?

Further Reading

"Forecasting: Principles and Practice" by Rob J Hyndman and George Athanasopoulos - This is an online textbook that covers the basics of time series forecasting using R. It includes a lot of examples and code for different time series models, as well as practical advice on how to apply them.

"Time Series Analysis and Its Applications: With R Examples" by Robert H. Shumway and David S. Stoffer - This is a textbook that covers time series analysis and forecasting using R. It covers a wide range of topics, from basic time series concepts to advanced models and methods.

"Time Series Analysis in R" by A. Ian McLeod - This is a short book that covers the basics of time series analysis in R. It includes examples of using R to analyze and model time series data, as well as information on visualizing and interpreting time series plots.

Unit 05: Business Prediction Using Generalised Linear Models

CONTENTS

Objective

After studying this unit, student will be able to

- learn about the theory behind GLMs, including the selection of appropriate link functions and the interpretation of model coefficients.
- gain practical experience in data analysis by working with real-world datasets and using statistical software to fit GLM models and make predictions.
- to interpret the results of GLM analyses and communicate findings to others using clear and concise language.
- think critically and solve complex problems, which can help develop important skills for future academic and professional endeavors.

Introduction

Business prediction using generalized linear models (GLMs) is a common technique in data analysis. GLMs extend the linear regression model to handle non-normal response variables by using a link function to map the response variable to a linear predictor.

In business prediction, GLMs can be used to model the relationship between a response variable and one or more predictor variables. The response variable could be a continuous variable, such as sales or revenue, or a binary variable, such as whether a customer will make a purchase or not. The predictor variables could be various business metrics, such as marketing spend, website traffic, customer demographics, and more.

Generalized linear models (GLMs) can be used for business prediction in a variety of applications such as marketing, finance, and operations. GLMs are a flexible statistical modeling framework that can be used to analyze and make predictions about data that have non-normal distributions, such as counts, proportions, and binary outcomes.

One common application of GLMs in business is to model customer behavior in marketing. For example, a company might use GLMs to predict the likelihood of a customer responding to a promotional offer, based on their demographic and behavioral data. This can help the company optimize their marketing campaigns by targeting customers who are most likely to respond to their offers.

GLMs can also be used in finance to predict the likelihood of default on a loan, based on the borrower's credit history and other relevant variables. This can help banks and other financial institutions make more informed lending decisions and manage their risk exposure.

In operations, GLMs can be used to predict the probability of defects or quality issues in a manufacturing process, based on variables such as raw materials, production techniques, and environmental factors. This can help companies optimize their production processes and reduce waste and defects.

Overall, GLMs are a powerful tool for business prediction, providing a flexible and interpretable framework for modeling a wide range of data types and outcomes.

5.1 Linear Regression

Linear regression is a statistical technique used to model the relationship between a dependent variable and one or more independent variables. It is a popular and widely used method in various fields such as economics, finance, engineering, social sciences, and many more.

In linear regression, the dependent variable is assumed to be a linear function of one or more independent variables. The objective is to estimate the values of the coefficients in the linear equation that best fit the observed data, so that we can use the equation to make predictions about the dependent variable.

There are two types of linear regression: simple linear regression and multiple linear regression. Simple linear regression involves only one independent variable, whereas multiple linear regression involves two or more independent variables.

The most common approach to estimating the coefficients in linear regression is called the least squares method. This involves minimizing the sum of the squared differences between the observed values of the dependent variable and the predicted values based on the linear equation.

Linear regression has many applications in business, such as predicting sales based on advertising expenditures, estimating the impact of price changes on demand, and modeling employee productivity based on various factors such as education level, experience, and salary.

Overall, linear regression is a powerful tool for modeling and predicting relationships between variables and is widely used in business and other fields.

Linear regression assumes that the relationship between the dependent variable and the independent variable(s) is linear. This means that the change in the dependent variable is proportional to the change in the independent variable(s). For example, if we are modeling the relationship between salary and years of experience, we assume that the increase in salary is proportional to the increase in years of experience.

Linear regression can also be used for prediction. After estimating the coefficients in the linear equation, we can use the equation to predict the value of the dependent variable for new values of the independent variable(s).

In addition to least squares, other methods can be used to estimate the coefficients in linear regression. These include maximum likelihood estimation, Bayesian estimation, and gradient descent.

Linear regression can be extended to handle nonlinear relationships between the dependent variable and the independent variable(s) by adding polynomial terms or using other nonlinear functions of the independent variable(s).

It's important to note that linear regression has assumptions that must be met for the results to be valid. These include linearity, independence, homoscedasticity, and normality of errors. Violations of these assumptions can lead to biased or unreliable results.

Overall, linear regression is a useful and widely used technique in data analysis and prediction, with many applications in business, economics, social sciences, and other fields.

5.2 Generalised Linear Models

Generalized Linear Models (GLMs) are a statistical framework that extends the linear regression model to handle non-normally distributed dependent variables. GLMs allow for a wide range of data distributions, such as binary, count, and continuous data, to be modeled with a link function that relates the mean of the response variable to the linear predictor.

GLMs have three components: a probability distribution for the response variable, a linear predictor that relates the response variable to the predictor variables, and a link function that links the mean of the response variable to the linear predictor. The choice of probability distribution and link function depends on the nature of the data being modeled.

Examples of GLMs include logistic regression for binary data, Poisson regression for count data, and gamma regression for continuous data with positive values. GLMs can also handle overdispersion and under dispersion, which occur when the variance of the response variable is larger or smaller than predicted by the distribution.

GLMs can be used for prediction and inference, and provide interpretable coefficients that can be used to make conclusions about the effects of predictor variables on the response variable. GLMs also allow for the modeling of interactions between predictor variables and non-linear relationships between predictor variables and the response variable.

GLMs have many applications in various fields, such as marketing, epidemiology, finance, and environmental studies, where the response variable is not normally distributed. Overall, GLMs are a flexible and powerful tool for modeling a wide range of non-normally distributed data.

GLMs are based on the idea that the mean of the response variable depends on a linear combination of the predictor variables, but the variance of the response variable can be modeled by a probability distribution other than the normal distribution. The link function used in GLMs connects the linear combination of predictor variables with the mean of the response variable and can be linear or non-linear.

The choice of link function depends on the type of response variable and the research question. For example, the logistic link function is used for binary response variables, while the log link function is used for count data. The identity link function is used for continuous data with a normal distribution, which makes the GLM equivalent to the linear regression model.

GLMs can be fit using maximum likelihood estimation, which involves finding the parameter values that maximize the likelihood of the observed data given the model. The goodness of fit of a GLM can be assessed using various methods, such as residual plots, deviance, and information criteria.

GLMs can be extended to handle complex data structures, such as clustered or longitudinal data, through the use of random effects or mixed-effects models. These models allow for the modeling of within-cluster or within-subject correlation in the data.

GLMs have many applications in various fields, such as healthcare, social sciences, and ecology, where the response variable is non-normally distributed. Examples of applications include modeling disease prevalence, predicting student performance, and modeling species abundance.

Overall, GLMs are a flexible and powerful tool for modeling a wide range of non-normally distributed data, allowing researchers to make predictions and draw inferences about the relationships between predictor variables and the response variable.

GLMs can handle data that is not only non-normally distributed but also data that is not continuous, such as binary or categorical data. In such cases, GLMs can use a link function to transform the data to meet the assumptions of the model.

The link function in GLMs plays a critical role in transforming the response variable so that it can be related to the linear predictor. Common link functions include the logit function for binary data, the log function for count data, and the inverse function for continuous data with positive values.

GLMs can also account for the effect of covariates or predictor variables on the response variable. This allows for the modeling of the relationship between the response variable and multiple

predictor variables. The coefficients of the GLM can be used to determine the direction and magnitude of the effects of the predictor variables on the response variable.

In addition to logistic regression and Poisson regression, which are commonly used GLMs, other types of GLMs include negative binomial regression, which can handle overdispersion in count data, and ordinal regression, which can handle ordinal data.

GLMs require some assumptions, such as linearity between the predictor variables and the response variable and independence of observations. Violations of these assumptions can lead to biased or unreliable results.

Overall, GLMs are a useful and versatile statistical framework for modeling non-normally distributed data, and can be applied in various fields. GLMs allow for the modeling of multiple predictor variables and can be used for prediction and inference.

Suppose we want to model the relationship between a binary response variable (e.g., whether a customer made a purchase or not) and several predictor variables (e.g., age, gender, income). We can use logistic regression, a type of GLM, to model this relationship.

Data Preparation: First, we need to prepare our data. We will use a dataset containing information on customers, including their age, gender, income, and whether they made a purchase or not. We will split the data into training and testing sets, with the training set used to fit the model and the testing set used to evaluate the model's performance.

Model Specification: Next, we need to specify the model. We will use logistic regression as our GLM, with the binary response variable (purchase or not) modeled as a function of the predictor variables (age, gender, income).

Model Fitting: We can fit the model to the training data using maximum likelihood estimation. The coefficients of the logistic regression model can be interpreted as the log-odds of making a purchase, given the values of the predictor variables.

Model Evaluation: We can evaluate the performance of the model using the testing data. We can calculate metrics such as accuracy, precision, and recall to measure how well the model is able to predict the outcome variable based on the predictor variables.

Model Improvement: If the model performance is not satisfactory, we can consider improving the model by adding or removing predictor variables or transforming the data using different link functions.

Overall, building a GLM model involves data preparation, model specification, model fitting, model evaluation, and model improvement. By following these steps, we can build a model that accurately captures the relationship between the response variable and the predictor variables and can be used to make predictions or draw inferences.

5.3 Logistic Regression

Logistic regression is a type of generalized linear model (GLM) used to model the probability of a binary response variable, typically coded as 0 or 1. It is commonly used in various fields, such as medicine, finance, and social sciences, to predict the likelihood of an event or outcome based on one or more predictor variables.

Logistic regression models the relationship between the log odds of the binary response variable and the predictor variables using a sigmoidal or "S-shaped" curve. The model estimates the coefficients of the predictor variables, which represent the change in log odds of the response variable for a one-unit increase in the predictor variable, holding all other predictor variables constant.

Logistic regression assumes that the relationship between the log odds of the response variable and the predictor variables is linear, and that the residuals (i.e., the differences between the predicted and observed values of the response variable) are normally distributed. Additionally, logistic regression assumes that the observations are independent of each other.

Logistic regression can be used for both prediction and inference. In the context of prediction, logistic regression can be used to estimate the probability of the response variable given the values of the predictor variables. In the context of inference, logistic regression can be used to test

hypotheses about the effect of the predictor variables on the response variable, such as whether the effect is significant or not.

Overall, logistic regression is a useful and widely-used statistical technique for modeling binary response variables and can be applied in various fields. It allows for the modeling of the relationship between the response variable and multiple predictor variables, and provides interpretable coefficients that can be used to draw conclusions about the effects of the predictor variables on the response variable.

Example

Sure, here's an example of using logistic regression to model a binary response variable:

Suppose we want to model the probability of a customer making a purchase based on their age and gender. We have a dataset containing information on several customers, including their age, gender, and whether they made a purchase or not.

Data Preparation: First, we need to prepare our data. We will split the data into training and testing sets, with the training set used to fit the model and the testing set used to evaluate the model's performance. We will also preprocess the data by encoding the gender variable as a binary indicator variable (e.g., 1 for female and 0 for male).

Model Specification: Next, we need to specify the logistic regression model. We will model the probability of making a purchase as a function of age and gender. The logistic regression model takes the form:

$\log(p/1-p) = \beta0 + \beta1(age) + \beta2(gender)$

where p is the probability of making a purchase, $\beta0$ is the intercept term, $\beta1$ is the coefficient for age, and $\beta2$ is the coefficient for gender.

Model Fitting: We can fit the logistic regression model to the training data using maximum likelihood estimation. The coefficients of the model can be interpreted as the change in log odds of making a purchase for a one-unit increase in age or a change in gender from male to female.

Model Evaluation: We can evaluate the performance of the logistic regression model using the testing data. We can calculate metrics such as accuracy, precision, and recall to measure how well the model is able to predict the outcome variable based on the predictor variables.

Model Improvement: If the model performance is not satisfactory, we can consider improving the model by adding or removing predictor variables or transforming the data using different link functions.

Overall, logistic regression is a useful technique for modeling binary response variables and can be used in various fields. In this example, we used logistic regression to model the probability of a customer making a purchase based on their age and gender. By following the steps of data preparation, model specification, model fitting, model evaluation, and model improvement, we can build a model that accurately captures the relationship between the response variable and the predictor variables and can be used for prediction or inference.

5.4 Generalised Linear Models Using R

In R, GLMs can be easily implemented using the glm() function. The glm() function takes several arguments, including the response variable, predictor variables, and the chosen link function. The summary() function can be used to obtain a summary of the GLM model, including coefficients, standard errors, and p-values. Additionally, the predict() function can be used to make predictions on new data using the fitted GLM model.

GLMs are a powerful tool for business prediction, as they can handle a wide range of response variables and predictor variables, and can be easily implemented in R. However, as with any statistical model, it is important to carefully evaluate the assumptions and limitations of the model, and to consider alternative approaches if necessary.

Example 1

Suppose we have a dataset containing information on the age and income of individuals, as well as whether or not they own a car (a binary variable). We want to model the relationship between car ownership and age and income.

Data Preparation: First, we need to import our data into R. Let's assume our data is in a CSV file named "car_ownership.csv". We can use the read.csv function to import the data:

car_data<- read.csv("car_ownership.csv")

Model Specification: Next, we need to specify the logistic regression model. We will use the glm function in R to fit the model:

car_model<- glm(own_car ~ age + income, data = car_data, family = "binomial")

In this code, "own_car" is the response variable (binary variable indicating whether or not the individual owns a car), and "age" and "income" are the predictor variables. The family argument specifies the type of GLM to be fitted, in this case a binomial family for binary data.

Model Fitting: We can fit the model to our data using the summary function in R:

summary(car_model)

This will output a summary of the model, including the estimated coefficients and their standard errors, as well as goodness-of-fit measures such as the deviance and AIC.

Model Evaluation: We can evaluate the performance of our model by calculating the predicted probabilities of car ownership for each individual in our dataset:

car_prob<- predict(car_model, type = "response")

This will output a vector of predicted probabilities, one for each individual in the dataset. We can then compare these probabilities to the actual car ownership status to evaluate the accuracy of the model.

Model Improvement: If the model performance is not satisfactory, we can consider improving the model by adding or removing predictor variables, transforming the data, or using a different link function.

Overall, performing logistic regression in R involves importing the data, specifying the model using the glm function, fitting the model using the summary function, evaluating the model by calculating predicted probabilities, and improving the model if necessary.

Example2

Here's an example of how to perform logistic regression in R using the built-in "mtcars" dataset:

Data Preparation: We can load the "mtcars" dataset and convert the response variable "am" (which indicates whether a car has an automatic or manual transmission) to a binary indicator variable (0 for automatic and 1 for manual):

data(mtcars)

mtcars$am<- ifelse(mtcars$am == 0, 1, 0)

Model Specification: We can specify the logistic regression model using the "glm()" function:

model <- glm(am ~ hp + wt, data = mtcars, family = binomial)

In this model, we are predicting the probability of a car having a manual transmission based on its horsepower ("hp") and weight ("wt").

Model Fitting: We can fit the logistic regression model using the "summary()" function to view the estimated coefficients and their significance:

summary(model)

This will output the estimated coefficients for the intercept, "hp", and "wt", as well as their standard errors, z-values, and p-values.

Model Evaluation: We can evaluate the performance of the logistic regression model using the "predict()" function to obtain predicted probabilities for the testing data, and then calculate metrics such as accuracy, precision, and recall to measure how well the model is able to predict the outcome variable based on the predictor variables.

probs <- predict(model, newdata = mtcars, type = "response")

preds <- ifelse(probs > 0.5, 1, 0)

accuracy <- mean(preds == mtcars$am)

In this example, we are using the entire dataset for both training and testing purposes. However, it's important to note that this is not best practice, and we should split the data into training and testing sets to avoid overfitting.

Overall, logistic regression is a useful technique for modeling binary response variables in R, and the built-in "glm()" function makes it easy to specify and fit models. By following the steps of data preparation, model specification, model fitting, model evaluation, and model improvement, we can build a model that accurately captures the relationship between the response variable and the predictor variables and can be used for prediction or inference.

5.5 Statistical Inferences of GLM

Suppose we have a dataset containing information on the age and income of individuals, as well as whether or not they own a car (a binary variable). We want to model the relationship between car ownership and age and income using a logistic regression model.

Model Specification and Fitting: First, we need to specify and fit the logistic regression model using the glm function in R:

car_model<- glm(own_car ~ age + income, data = car_data, family = "binomial")

In this code, "own_car" is the response variable (binary variable indicating whether or not the individual owns a car), and "age" and "income" are the predictor variables. The family argument specifies the type of GLM to be fitted, in this case a binomial family for binary data.

Hypothesis Testing: We can test the significance of the predictor variables by performing hypothesis tests on their coefficients. For example, to test the hypothesis that the coefficient for "age" is zero, we can use the t.test function in R:

t.test(car_model$coefficients[2], alternative = "two.sided", mu = 0, conf.level = 0.95)

This code will perform a two-sided t-test with a null hypothesis that the coefficient for "age" is zero, and an alternative hypothesis that it is not zero. The conf.level argument specifies a 95% confidence interval.

Confidence Intervals: We can calculate confidence intervals for the model parameters using the confint function in R:

confint(car_model, level = 0.95)

This code will output a table of confidence intervals for each of the model parameters with a 95% confidence level.

Goodness-of-Fit Tests: We can perform goodness-of-fit tests to assess how well the model fits the data. For example, to perform a deviance goodness-of-fit test, we can use the following code:

pchisq(deviance(car_model), df = df.residual(car_model), lower.tail = FALSE)

This code calculates the p-value for the deviance goodness-of-fit test using the chi-square distribution. If the p-value is less than the significance level (e.g., 0.05), we can reject the null hypothesis that the model fits the data well.

Residual Analysis: We can analyze the residuals to assess the appropriateness of the model. For example, we can plot the residuals against the predicted values using the plot function in R:

plot(car_model, which = 1)

This code will plot the residuals against the predicted values. We can examine the plot to look for any patterns or trends in the residuals that might indicate that the model is not capturing all the important features of the data.

Overall, performing statistical inferences on a GLM involves testing the significance of predictor variables, calculating confidence intervals for model parameters, performing goodness-of-fit tests, and analyzing residuals. These inferences help us assess the validity of the model and draw valid conclusions from the model.

5.6 Survival Analysis

Survival refers to the ability of an organism to continue living in a given environment or situation. It is the state of being able to withstand adverse conditions and remain alive.

Survival can refer to many different contexts, including:

Physical survival: This refers to the ability to maintain basic bodily functions such as breathing, circulating blood, and regulating body temperature.

Emotional survival: This refers to the ability to cope with difficult or traumatic experiences, such as abuse, trauma, or loss.

Financial survival: This refers to the ability to manage one's finances and maintain a stable income.

Survival in nature: This refers to the ability of an animal or plant to adapt to its environment and avoid being killed by predators or natural disasters.

In general, survival requires a combination of factors, including physical strength, mental fortitude, resilience, and adaptability. It is an essential aspect of life, and individuals and species that are better able to survive are more likely to thrive and pass on their genes to future generations.

Survival Analysis Using R

Survival analysis in R Programming Language deals with the prediction of events at a specified time. It deals with the occurrence of an interesting event within a specified time and failure of it produces censored observations i.e incomplete observations.

Biological sciences are the most important application of survival analysis in which we can predict the time for organisms eg. when they will multiply to sizes etc.

Methods used to do survival analysis:

There are two methods that can be used to perform survival analysis in R programming language:

- **Kaplan-Meier method**
- **Cox Proportional hazard model**

Kaplan-Meier Method

The Kaplan-Meier method is used in survival distribution using the Kaplan-Meier estimator for truncated or censored data. It's a non-parametric statistic that allows us to estimate the survival function and thus not based on underlying probability distribution. The Kaplan–Meier estimates are based on the number of patients (each patient as a row of data) from the total number of patients who survive for a certain time after treatment. (which is the event).

We represent the Kaplan–Meier function by the formula:

$$\widehat{S}(t) = \prod_{i:\ t_i \leq t} \left(1 - \frac{d_i}{n_i}\right)$$

Here S(t) represents the probability that life is longer than t with ti(At least one event happened), di represents the number of events(e.g. deaths) that happened in time ti and ni represents the number of individuals who survived up to time ti.

Example:

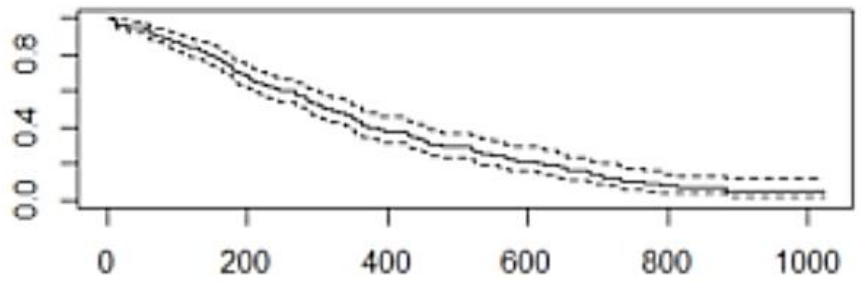
We will use the Survival package for the analysis. Using Lung dataset preloaded in survival package which contains data of 228 patients with advanced lung cancer from North Central cancer treatment group based on 10 features. The dataset contains missing values so, missing value treatment is presumed to be done at your side before the building model.

```
# Installing package
install.packages("survival")
# Loading package
library(survival)
# Dataset information
?lung
# Fitting the survival model
Survival_Function = survfit(Surv(lung$time, lung$status == 2)~1)
Survival_Function
# Plotting the function
plot(Survival_Function)
```

Here, we are interested in "time" and "status" as they play an important role in the analysis. Time represents the survival time of patients. Since patients survive, we will consider their status as dead or non-dead(censored).

The Surv() function takes two times and status as input and creates an object which serves as the input of survfir() function. We pass ~1 in survfit() function to ensure that we are telling the function to fit the model on basis of the survival object and have an interrupt.

survfit() creates survival curves and prints the number of values, number of events(people suffering from cancer), the median time and 95% confidence interval. The plot gives the following output:



Here, the x-axis specifies "Number of days" and the y-axis specifies the "probability of survival". The dashed lines are upper confidence interval and lower confidence interval.

We also have the confidence interval which shows the margin of error expected i.e In days of surviving 200 days, upper confidence interval reaches 0.76 or 76% and then goes down to 0.60 or 60%.

Cox proportional hazard model

It is a regression modeling that measures the instantaneous risk of deaths and is bit more difficult to illustrate than the Kaplan-Meier estimator. It consists of hazard function h(t) which describes the probability of event or hazard h(e.g. survival) up to a particular time t. Hazard function considers covariates(independent variables in regression) to compare the survival of patient groups.

It does not assume an underlying probability distribution but it assumes that the hazards of the patient groups we compare are constant over time and because of this it is known as "Proportional hazard model".

Example:

We will use the Survival package for the analysis. Using Lung dataset preloaded in survival package which contains data of 228 patients with advanced lung cancer from North Central cancer treatment group based on 10 features. The dataset contains missing values so, missing value treatment is presumed to be done at your side before the building model. We will be using the cox proportional hazard function coxph() to build the model.

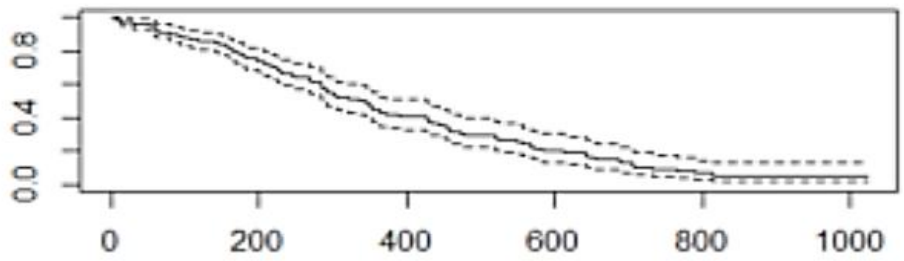
```
# Installing package
install.packages("survival")
# Loading package
library(survival)
# Dataset information
?lung
# Fitting the Cox model
Cox_mod<- coxph(Surv(lung$time, lung$status == 2)~., data = lung)
# Summarizing the model
summary(Cox_mod)
# Fitting survfit()
Cox <- survfit(Cox_mod)
```

Here, we are interested in "time" and "status" as they play an important role in the analysis. Time represents the survival time of patients. Since patients survive, we will consider their status as dead or non-dead(censored).

The Surv() function takes two times and status as input and creates an object which serves as the input of survfir() function. We pass ~1 in survfit() function to ensure that we are telling the function to fit the model on basis of the survival object and have an interrupt.

```
# Plotting the function
plot(Cox)
```

The Cox_mod output is similar to the regression model. There are some important features like age, sex, ph.ecog and wt. loss. The plot gives the following output:



Here, the x-axis specifies "Number of days" and the y-axis specifies "probability of survival". The dashed lines are upper confidence interval and lower confidence interval. In comparison with the Kaplan-Meier plot, the Cox plot is high for initial values and lower for higher values because of more variables in the Cox plot.

We also have the confidence interval which shows the margin of error expected i.e In days of surviving 200 days, the upper confidence interval reaches 0.82 or 82% and then goes down to 0.70 or 70%.

Note: Cox model serves better results than Kaplan-Meier as it is most volatile with data and features. Cox model is also higher for lower values and vice-versa i.e drops down sharply when the time increases.

Detailed Example of Survival Analysis

Step 1: Load the necessary packages using the library() function.

The survival package is the core package for survival analysis in R, and it provides many functions for fitting and visualizing survival models. The survminer package provides additional visualization functions that are useful for interpreting survival analysis results.

```
library(survival)     # Load the survival package
```

```
library(survminer)    # Load the survminer package
```

Step 2: Import your dataset into R.

The read.csv() function can be used to import a dataset in CSV format into R. In this example, we will use the lung dataset, which is included in the survival package:

```
data(lung)      # Load the lung dataset
head(lung)      # View the first few rows of the dataset
```

Step 3: Create a survival object using the Surv() function.

The Surv() function is used to create a survival object from the time-to-event variable and the event indicator variable in your dataset. In this example, we will use the time and status variables from the lung dataset:

```
surv.obj <- Surv(time = lung$time, event = lung$status)
```

Step 4: Fit a survival model to your data using a function such as survfit(), coxph(), or phreg().

The survfit() function is used to fit a Kaplan-Meier survival curve to the data. In this example, we will fit separate survival curves for the sex variable in the lung dataset:

```
fit <- survfit(surv.obj ~ sex, data = lung)
```

The coxph() function is used to fit a Cox proportional hazards regression model to the data. In this example, we will fit a Cox model to the age and sex variables in the lung dataset:

```
cox.model<- coxph(surv.obj ~ age + sex, data = lung)
```

Step 5: Visualize the results using functions such as ggsurvplot() and survplot().

The ggsurvplot() function is used to create a graphical representation of the Kaplan-Meier survival curve. In this example, we will create a plot of the survival curves for the sex variable in the lung dataset:

```
ggsurvplot(fit, data = lung, risk.table = TRUE)
```

The survplot() function is used to create a plot of the cumulative hazard function. In this example, we will create a plot of the cumulative hazard function for the Cox model:

```
survplot(cox.model, fun = "cumhaz")
```

Step 6: Perform further analyses, such as Cox proportional hazards regression or competing risks analysis, using the appropriate functions in R.

The coxph() function can be used to fit a Cox proportional hazards regression model to the data. In this example, we will fit a Cox model to the age and sex variables in the lung dataset:

```
cox.model<- coxph(surv.obj ~ age + sex, data = lung)
```

The coxph() function also allows for the inclusion of interaction terms and time-dependent covariates in the model.

The cmprsk package can be used to conduct competing risks analysis in R. Competing risks occur when an individual may experience multiple possible outcomes, and the occurrence of one outcome may preclude the occurrence of other outcomes.

Keywords

Response variable: The variable of interest that is being modeled and predicted by a GLM. It can be continuous, binary, count, or ordinal.

Predictor variable: The variable(s) used to explain the variation in the response variable. They can be continuous, binary, or categorical.

Link function: A function used to relate the mean of the response variable to the linear predictor. It can be used to transform the response variable to a different scale or to model the relationship between the predictor and response variables.

Exponential family: A class of probability distributions that includes the Poisson, binomial, gamma, and normal distributions, among others. GLMs are based on the exponential family of distributions.

Maximum likelihood estimation: A method used to estimate the parameters of a GLM by finding the values that maximize the likelihood of the observed data.

Goodness of fit: A measure of how well a GLM model fits the observed data. It can be evaluated using deviance, residual analysis, and other methods.

Residual analysis: A method used to check the assumptions of a GLM model and identify potential problems such as outliers and influential observations.

Model selection: A process of comparing different GLM models and selecting the best one based on their fit and complexity, using AIC/BIC, likelihood ratio tests, and other methods.

SelfAssessment

1. What package is the core package for survival analysis in R?

A. ggplot2

B. dplyr

C. survival

D. tidyr

2. Which function is used to create a survival object in R?

A. Surv()

B. plot()

C. summary()

D. lm()

3. Which function is used to fit a Kaplan-Meier survival curve to the data?

A. coxph()

B. phreg()

C. survfit()

D. flexsurv()

4. Which package provides additional visualization functions for interpreting survival analysis results?

A. ggplot2

B. dplyr

C. survival

D. survminer

5. Which function is used to fit a Cox proportional hazards regression model to the data?

A. coxph()

B. phreg()

C. survfit()

D. flexsurv()

6. Which of the following is a characteristic of Generalized Linear Models (GLMs)?

A. The response variable must be continuous

B. GLMs cannot be used for non-linear relationships between the predictor and response variables
C. The variance of the response variable can be non-constant
D. GLMs assume a linear relationship between the predictor and response variables

7. Which of the following families is used for binary data in GLMs?
A. Gaussian
B. Poisson
C. Binomial
D. Exponential

8. Which of the following is a method for selecting the best predictors in a GLM?
A. Principle Component Analysis (PCA)
B. Multiple Linear Regression
C. Stepwise Regression
D. Analysis of Variance (ANOVA)

9. Which of the following is a technique used to check the assumptions of a GLM?
A. Principal Component Analysis (PCA)
B. Residual Analysis
C. Discriminant Analysis
D. Analysis of Variance (ANOVA)
10. Which of the following is not a type of GLM?
A. Linear Regression
B. Logistic Regression
C. Poisson Regression
D. Negative Binomial Regression

11. Which R package is commonly used for fitting GLMs?
A. dplyr
B. ggplot2
C. caret
D. glm

12. What is the function used to fit a Poisson regression model in R?
A. glm()
B. lm()
C. gam()
D. lme()

13. What does the family argument in the glm() function specify?
A. The type of distribution for the response variable
B. The type of distribution for the predictor variable
C. The type of link function to use
D. The type of loss function to use

14. How can you check the goodness of fit of a GLM model in R?

A. Using the summary() function

B. Using the anova() function

C. Using the plot() function

D. Using the residuals() function

15. Which R package is commonly used for visualizing GLM results?

A. ggplot2

B. caret

C. lme4

D. MASS

Answers forSelfAssessment

l.	C	2.	A	3.	C	4.	D	5.	A
6.	C	7.	C	8.	C	9.	B	10.	A
11.	D	12.	A	13.	A	14.	C	15.	A

Review Questions

1. A hospital wants to determine the factors that affect the length of stay for patients. What type of GLM would be appropriate for this analysis?
2. A manufacturing company is interested in modeling the number of defective items produced per day. What type of GLM would be appropriate for this analysis?
3. A bank is interested in predicting the probability of default for a loan applicant. What type of GLM would be appropriate for this analysis?
4. A marketing company wants to model the number of clicks on an online advertisement. What type of GLM would be appropriate for this analysis?
5. A sports team is interested in predicting the probability of winning a game based on the number of goals scored. What type of GLM would be appropriate for this analysis?
6. A social scientist wants to model the number of criminal incidents per month in a city. What type of GLM would be appropriate for this analysis?
7. What is survival analysis and what types of data is it typically used for?
8. What is a Kaplan-Meier survival curve, and how can it be used to visualize survival data?
9. What is the Cox proportional hazards regression model, and what types of data is it appropriate for analyzing?
10. What is a hazard ratio, and how is it calculated in the context of the Cox proportional hazards model?
11. How can the results of a Cox proportional hazards regression model be interpreted, and what types of conclusions can be drawn from the analysis?
12. How can competing risks analysis be conducted in R, and what types of outcomes is it appropriate for analyzing?

13. What are some common visualizations used in survival analysis, and how can they be created using R functions?
14. What are some potential sources of bias in survival analysis, and how can they be addressed or minimized?

Further Reading

- The GLM section of UCLA's Institute for Digital Research and Education website provides a detailed introduction to GLMs, along with examples and tutorials using different statistical software packages such as R and Stata: https://stats.idre.ucla.edu/r/dae/generalized-linear-models/
- The CRAN Task View on "Distributions and Their Inference" provides a comprehensive list of R packages related to GLMs, along with their descriptions and links to documentation: https://cran.r-project.org/web/views/Distributions.html
- "Generalized Linear Models" by P. McCullagh and J. A. Nelder: This is a classic book on GLMs and provides a thorough treatment of the theory and applications of GLMs.
- "An Introduction to Generalized Linear Models" by A. Dobson: This book is a concise introduction to GLMs and covers the key concepts and methods in a clear and accessible way

1. .

Unit 06: Machine Learning for Businesses

CONTENTS

Objective

After studying this student will be able to

- can develop and apply machine learning algorithms and models.
- increase earning potential and have a higher chance of securing a well-paying job.
- analyze large amounts of data and develop algorithms to extract meaningful insights.
- solve complex problems and develop solutions.
- gain proficiency in data handling and preprocessing techniques.

Introduction

Machine learning is a field of artificial intelligence that has been rapidly growing in recent years, and has already had a significant impact on many industries.At its core, machine learning involves the development of algorithms and models that can learn patterns in data, and then use those patterns to make predictions or decisions about new data. There are several different types of machine learning, including supervised learning, unsupervised learning, and reinforcement learning. Each of these types of machine learning has its own strengths and weaknesses, and is suited to different types of problems.

One of the most important applications of machine learning is in the field of natural language processing (NLP). NLP involves using machine learning to analyze and understand human language, and is used in applications such as chatbots, voice assistants, and sentiment analysis. NLP is also important in fields such as healthcare, where it can be used to extract useful information from patient records and other medical documents.

Another important application of machine learning is in computer vision. This involves using machine learning to analyze and interpret visual data and is used in applications such as image and video recognition, facial recognition, and object detection. Computer vision is important in fields such as self-driving cars, where it is used to help vehicles navigate and avoid obstacles.

Predictive modeling is another important application of machine learning. This involves using machine learning to make predictions based on data, and is used in applications such as fraud detection, stock market prediction, and customer churn prediction. Predictive modeling is important in fields such as marketing, where it can be used to identify customers who are likely to leave a company and take steps to retain them.

The potential for machine learning is enormous, and its applications are likely to continue to expand in the coming years. One area where machine learning is likely to have a significant impact is in healthcare. Machine learning can be used to analyze patient data and identify patterns that could be used to diagnose and treat a wide range of diseases. Machine learning can also be used to identify patients who are at high risk of developing certain conditions and take steps to prevent those conditions from occurring.

Another area where machine learning is likely to have a significant impact is in education. Machine learning can be used to analyze student data and identify patterns that could be used to improve learning outcomes. Machine learning can also be used to personalize learning for individual students, by adapting the pace and style of instruction to their individual needs.

In conclusion, machine learning is a rapidly growing field with many exciting applications. Its ability to learn from data and make predictions or decisions based on that data has already had a significant impact on many industries, and its potential for the future is enormous. As more data becomes available and more powerful computing resources become available, machine learning is likely to continue to grow in importance and have a significant impact on many aspects of our lives.

6.1 Machine Learning

With the explosive growth of data science, more and more businesses are focusing on improve their business processes by harnessing the power of technologies like

Big data

Machine learning (ML)

Artificial intelligence

Among them, machine learning is a technology that helps businesses effectively gain insights from raw data. Machine learning—specifically machine learning algorithms—can be used to iteratively learn from a given data set, understand patterns, behaviors, etc., all with little to no programming.

This iterative and constantly evolving nature of the machine learning process helps businesses ensure that they are always up to date with business and consumer needs. plus, it's easier than ever to build or integrate ML into existing business processes since all the major cloud providers offer ML platforms.

So, in this article, we will dive into how machine learning benefits businesses of all shapes and sizes.

Before we look at ML benefits, we need to have a basic understanding of how ML works. Machine learning refers to the process of extracting meaningful data from raw data sets.

For example, let's consider an online retail store that captures the user behavior and purchases within the website. This is merely data. But machine learning plays a significant role, enabling the online store to analyze and extract the patterns, stats, information, and stories hidden within this data.

A key factor that differentiates machine learning from regular analytical algorithms is its adaptability. Machine learning algorithms are constantly evolving. The more data the ML algorithm consumes, the more accurate their analytics and predictions will be.

Harnessing the power of machine learning has enabled businesses to:

More easily adapt to ever-changing market conditions

Improve business operations

Gain a greater understanding of the overall business and consumer needs

Machine learning is quickly becoming ubiquitous across all industries from agriculture to medical research, stock market, traffic monitoring, etc. For instance, machine learning can be utilized in agriculture for various tasks such as predicting weather patterns and crop rotation.

Machine learning can be combined with artificial intelligence to enhance the analytical process gaining further benefits to businesses. Services like Azure Machine Learning and Amazon SageMaker enable users to utilize the power of cloud computing to integrate ML to suit any business need.

Common machine learning algorithms

A number of machine learning algorithms are commonly used. These include:

Neural networks: Neural networks simulate the way the human brain works, with a huge number of linked processing nodes. Neural networks are good at recognizing patterns and play an important role in applications including natural language translation, image recognition, speech recognition, and image creation.

Linear regression: This algorithm is used to predict numerical values, based on a linear relationship between different values. For example, the technique could be used to predict house prices based on historical data for the area.

Logistic regression: This supervised learning algorithm makes predictions for categorical response variables, such as"yes/no" answers to questions. It can be used for applications such as classifying spam and quality control on a production line.

Clustering: Using unsupervised learning, clustering algorithms can identify patterns in data so that it can be grouped. Computers can help data scientists by identifying differences between data items that humans have overlooked.

Decision trees: Decision trees can be used for both predicting numerical values (regression) and classifying data into categories. Decision trees use a branching sequence of linked decisions that can be represented with a tree diagram. One of the advantages of decision trees is that they are easy to validate and audit, unlike the black box of the neural network.

Random forests: In a random forest, the machine learning algorithm predicts a value or category by combining the results from a number of decision trees.

6.2 Use cases of Machine Learning in Businesses

Below are some of the most apparent benefits of machine learning for businesses:

Optimizing marketing campaigns and detecting spam

Customer segmentation and content personalization make it possible to optimize marketing campaigns. How? Machine learning gives businesses insights to improve ad targeting and marketing management.

Spam detection is another excellent application of machine learning, with these solutions having been used for a long time. Before ML and deep learning, email service companies set specific criteria for classifying a message as spam. These days, the filters automatically generate new rules based on neural networks – faster than ever before.

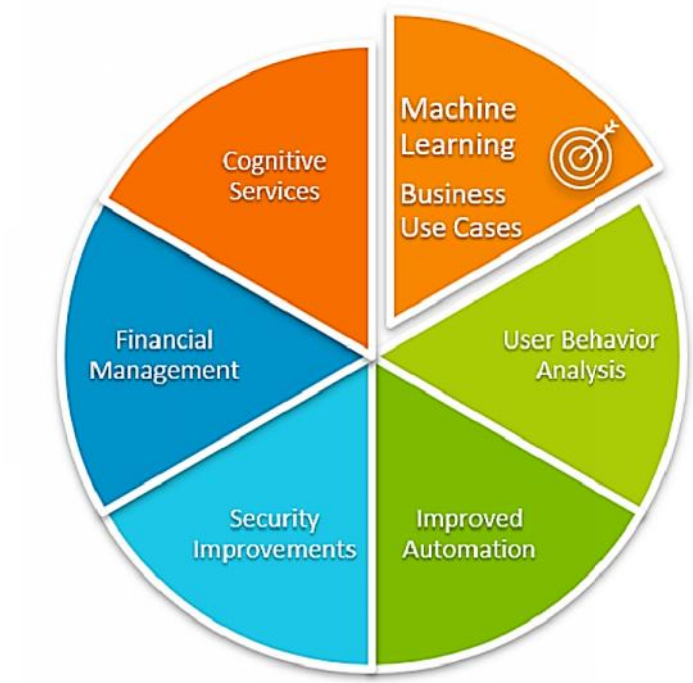
Individualization & predictability

We've all seen it before. The day begins with you visiting Amazon, reading the product description, and picking out an iPad. A day later, you see an ad on Facebook for the same iPad model. You start noticing it everywhere. Spooky, right?

That is what AI and machine learning is doing for you. These technologies let advertisers modify the way they market. AI is changing the e-commerce landscape in a significant way, giving marketers the advantage of tailoring their marketing strategies while also saving businesses a lot of money.

The retail industry has reduced overstock, improved shipping times, and cut returns by 3 million times as a result of artificial intelligence. Current trends suggest that machines will be able to supplement your staff's weak spots in the future without having to resort to mass firings.

The increasing use of artificial intelligence will likely continue to affect the advertising industry. With machine learning, marketers will get a deeper understanding of their customers' minds and hearts and will easily create communications layouts tailored to each customer.



Recruiting & HR process improvement

Machine learning and artificial intelligence will almost certainly dominate recruitment as well. AI technologies have advanced substantially since their introduction. As a result, it reduces repetitive tasks, speeding up lots of processes.

Meanwhile, AI-enabled monitoring systems and HRMs are available, which enable businesses to develop job search engines, identify the most qualified individuals, browse resumes effectively, and conduct interviews without forcing candidates to come into the office.

Predicting the customer's lifetime value

Today's businesses have access to massive volumes of data that can be used to generate valuable business insights. Customer information makes up a substantial amount of company data.

Analyzing it may allow you to learn more about customers, including their purchasing habits, demands, and requirements. A customer lifetime value estimate is a valuable tool to provide personalized offers to your customers.

Automates data entry

Duplicated and erroneous data are two of the most severe issues today's organizations face. Manual data entry errors can be drastically reduced using predictive modeling methods and machine learning. As a result, employees can spend the on tasks that bring more value to the company.

Financial analysis

Using machine learning algorithms, financial analytics can accomplish simple tasks, like estimating business spending and calculating costs. The jobs of algorithmic traders and fraud detectors are

both challenging. For each of these scenarios, historical data is examined to forecast future results as accurately as possible.

In many cases, a small set of data and a simple machine learning algorithm can be sufficient for simple tasks like estimating a business's expenses. It's worthwhile to note that stock traders and dealers rely heavily on ML to accurately predict market conditions before entering the market.

Organizations can control their overall costs and maximize profits with accurate and timely projections. When combined with automation, user analytics will result in significant cost savings.

Diagnosis of medical condition

With the help of unique diagnostic tools and successful treatment strategies, ML in medical diagnosis has assisted several healthcare organizations in improving patient health and reducing healthcare costs.

Hospitals, clinics, and medical organizations, in general, use it to produce near-perfect diagnoses, predict readmissions, prescribe medications, and identify high-risk patients. The forecasts and insights are derived from patient records, ethically-sourced data sources, and symptoms.

Strengthening cyber security

According to a recent McAfee report, cybercrime costs have surpassed $1.5 trillion worldwide since 2018. Meanwhile, hacking, phishing, or any sort of mischievous activity might result in you losing much more than your money. It can be very detrimental to the reputation of your brand and the privacy of your employees and customers if there is a data leak.

Analytics systems that assure data security and overall cybersecurity are powered by machine learning. ML-based solutions keep administrators up at night by monitoring activities and trying to identify odd user behavior, unauthorized access, breaches, fraud, system weaknesses, and various other issues.

This feature makes machine learning (ML) extremely valuable, especially for financial organizations.

Increasing customer satisfaction

With the use of machine learning, customer loyalty and customer experience can be improved. In this case, customer behavior is assessed in past call records, allowing a person or a system to accurately assign the client's request to the most suitable customer service representative.

Thus, the burden of customer relationship management is significantly reduced through this assessment. Due to these reasons, corporations employ predictive algorithms to provide spot-on product recommendations to their clients.

Cognitive services

Another important use of machine learning in businesses is secure and intuitive authentication procedures through computer vision, image recognition, and natural language processing. What is more, businesses can reach a lot wider audiences, as NLP allows access to multiple geographic locations, language holders, and ethnic groups.

Another example of cognitive services is automatic or self-checkouts. Because of machine learning, we have upgraded retail experiences, with Amazon Go being the perfect example.

6.3 Supervised Learning

Supervised learning is a type of machine learning in which an algorithm is trained on a labeled dataset. In supervised learning, the input data is accompanied by the correct output or label, which the algorithm uses to learn a mapping between the input and the output.

Supervised learning is used in a wide range of applications, including image classification, speech recognition, natural language processing, and fraud detection. It is a powerful tool for building predictive models that can automate decision-making processes and improve efficiency in a variety of industries. Supervised learning is a type of machine learning in which the algorithm learns from labeled data. Here are some examples of supervised learning:

Image Classification: Given a set of labeled images, the algorithm learns to classify new images into the correct category. For example, a cat vs dog image classification task.

Sentiment Analysis: Given a set of labeled text data, the algorithm learns to classify new text data as positive, negative, or neutral sentiment.

Spam Detection: Given a set of labeled emails, the algorithm learns to classify new emails as spam or not spam.

Language Translation: Given a set of labeled pairs of sentences in two different languages, the algorithm learns to translate new sentences from one language to the other.

Fraud Detection: Given a set of labeled transactions, the algorithm learns to classify new transactions as fraudulent or legitimate.

Handwriting Recognition: Given a set of labeled handwritten letters and digits, the algorithm learns to recognize new handwritten letters and digits.

Speech Recognition: Given a set of labeled audio samples of speech, the algorithm learns to transcribe new speech into text.

Recommendation Systems: Given a set of labeled user-item interactions, the algorithm learns to recommend new items to users based on their preferences.

6.4 Steps in Supervised Learning

The process of supervised learning involves the following steps:

Data Collection: The first step is to collect a dataset that includes input data and corresponding output labels. The dataset must be large and representative of the problem being solved.

Data Preprocessing: The next step is to preprocess the data to ensure that it is clean and in the appropriate format. This may include removing outliers, normalizing the data, or transforming it into a format suitable for training.

Model Selection: The next step is to select an appropriate model architecture that can learn the mapping between the input and output data. The choice of model depends on the nature of the problem being solved and the characteristics of the dataset.

Training: The model is trained on the labeled dataset by minimizing a loss function that measures the difference between the predicted output and the true output. The model learns to adjust its parameters to improve its predictions.

Evaluation: The trained model is evaluated on a separate test set to measure its performance. This is important to ensure that the model can generalize to new, unseen data.

Deployment: Once the model has been trained and evaluated, it can be deployed in the real world to make predictions on new, unseen data.

6.5 Supervised Learning Using R

R is a popular programming language for data analysis and statistical computing that has many packages for supervised learning. In R, you can use a variety of libraries and functions to train, evaluate and deploy machine learning models.

Here are some popular R packages for supervised learning:

caret: A comprehensive package for training and evaluating a wide range of machine learning models.

randomForest: A package for building random forest models, which are an ensemble learning method for classification and regression.

glmnet: A package for fitting generalized linear models with L1 and L2 regularization.

e1071: A package for building support vector machines for classification and regression.

xgboost: A package for building gradient boosting models, which are a type of ensemble learning method.

keras: A package for building deep learning models using the Keras API.

nnet: A package for building neural network models using the backpropagation algorithm.

ranger: A package for building random forest models that are optimized for speed and memory efficiency.

gbm: A package for building gradient boosting models, which are a type of ensemble learning method.

rpart: A package for building decision trees, which are a type of classification and regression tree method.

These are just a few of the many packages available in R for supervised learning. The choice of package will depend on the specific problem being solved and the characteristics of the data.

6.6 Supervised Learning using KNN

K-Nearest Neighbors (KNN) is a popular supervised learning algorithm used for classification and regression problems. In KNN, the model predicts the target variable of a data point by finding the K nearest data points in the training set and taking the majority vote of their class labels (in classification) or their average value (in regression).

Example-1

In R, there are many built-in datasets that can be used to demonstrate the use of KNN for supervised learning. One such dataset is the "iris" dataset, which contains measurements of the sepal length, sepal width, petal length, and petal width of three different species of iris flowers.

Here's an example of how to use the "iris" dataset for KNN supervised learning in R:

```
# Load the "iris" dataset

data(iris)

# Split the data into training and testing sets

library(caret)

set.seed(123)

trainIndex <- createDataPartition(iris$Species, p = 0.8, list = FALSE)

trainData <- iris[trainIndex, ]

testData <- iris[-trainIndex, ]

# Preprocess the data by normalizing the features

preprocess <- preProcess(trainData[,1:4], method = c("center", "scale"))

trainData[,1:4] <- predict(preprocess, trainData[,1:4])

testData[,1:4] <- predict(preprocess, testData[,1:4])

# Train the KNN model with K=3 and Euclidean distance metric

library(class)

predicted <- knn(trainData[,1:4], testData[,1:4], trainData$Species, k = 3, metric = "Euclidean")

# Evaluate the model's accuracy

library(caret)

confusionMatrix(predicted, testData$Species)
```

In this example, we first load the "iris" dataset and split it into training and testing sets using the createDataPartition() function from the caret package. We then preprocess the data by normalizing the features using the preProcess() function from the same package.

Next, we train the KNN model using the knn() function from the class package with K=3 and the Euclidean distance metric. Finally, we evaluate the performance of the model using the confusionMatrix() function from the caret package, which calculates the accuracy, precision, recall, and F1 score of the predictions.

Output

The output of the above example is the confusion matrix, which shows the performance of the KNN model on the testing set. The confusion matrix contains four values:

True Positive (TP): The number of samples that are correctly classified as positive (i.e., the species of iris is correctly predicted).

False Positive (FP): The number of samples that are incorrectly classified as positive (i.e., the species of iris is wrongly predicted).

True Negative (TN): The number of samples that are correctly classified as negative (i.e., the species of iris is not predicted).

False Negative (FN): The number of samples that are incorrectly classified as negative (i.e., the species of iris is wrongly predicted as not being present).

```
Confusion Matrix and Statistics

          Reference
Prediction   setosa versicolor virginica
  setosa         10          0         0
  versicolor      0          8         1
  virginica       0          1        10

Overall Statistics

               Accuracy : 0.9333
                 95% CI : (0.7793, 0.9887)
    No Information Rate : 0.3333
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.9026

 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: setosa Class: versicolor Class: virginica
Sensitivity                 1.0000            0.8889           0.9091
Specificity                 1.0000            0.9625           0.9667
Pos Pred Value              1.0000            0.8889           0.9091
Neg Pred Value              1.0000            0.9625           0.9667
Prevalence                  0.3333            0.2667           0.4000
Detection Rate              0.3333            0.2370           0.3636
Detection Prevalence        0.3333            0.2667           0.4000
Balanced Accuracy           1.0000            0.9257           0.9384
```

The confusion matrix shows that the KNN model achieved an accuracy of 0.9333 on the testing set, which means that 93.33% of the test samples were correctly classified by the model.

The matrix also shows that the model made 1 false prediction for the "versicolor" class and 1 false prediction for the "virginica" class. In other words, the model correctly classified all 10 "setosa" species but made 2 incorrect predictions for the other two species.

Additionally, the matrix provides other metrics such as sensitivity, specificity, positive and negative predictive values, and prevalence for each class. These metrics provide a more detailed evaluation of the performance of the model on the different classes.

6.7 Supervised Learning using Decision Tree

Decision Tree is a popular algorithm for supervised learning tasks, particularly for classification problems. It is a non-parametric algorithm that builds a tree-like model by recursively partitioning the data into subsets based on the most significant features. It is easy to interpret and understand, and it can handle both categorical and numerical data.

In Decision Tree, the tree structure is built based on information gain or entropy reduction, which measures the reduction in uncertainty about the target variable that results from splitting the data using a particular attribute. The attribute with the highest information gain is chosen as the splitting criterion at each node.

The algorithm continues to split the data into subsets until a stopping criterion is met, such as reaching a maximum tree depth, a minimum number of samples in a leaf node, or when all the samples in a node belong to the same class.

Once the tree is built, it can be used to make predictions by traversing the tree from the root node down to a leaf node that corresponds to the predicted class. The class of a new sample is determined by following the path from the root node to the leaf node that the sample falls into.

To implement Decision Tree in R, we can use the "rpart" package, which provides the "rpart()" function to build a Decision Tree model. The package also provides functions for visualizing the tree structure and making predictions on new data.

Example-1

Let's demonstrate how to use the "rpart" package to build a Decision Tree model using an inbuilt dataset in R. We will use the "iris" dataset, which contains measurements of the sepal length, sepal width, petal length, and petal width of three different species of iris flowers.

Here is an example code that builds a Decision Tree model on the "iris" dataset:

```
library(rpart)

data(iris)

# Split the dataset into training and testing sets

set.seed(123)

ind <- sample(2, nrow(iris), replace = TRUE, prob = c(0.7, 0.3))

trainData <- iris[ind == 1, ]

testData <- iris[ind == 2, ]

# Build the Decision Tree model

model <- rpart(Species ~ ., data = trainData, method = "class")

# Visualize the Decision Tree

plot(model)

text(model)

# Make predictions on the testing set

predicted <- predict(model, testData, type = "class")

# Evaluate the model performance

confusionMatrix(predicted, testData$Species)
```

In the code above, we first load the "rpart" package and the "iris" dataset. We then split the dataset into a training set and a testing set, with a 70-30 split.

Next, we build the Decision Tree model using the "rpart()" function, where we specify the target variable "Species" and the other variables as the predictors using the formula notation "Species ~ .". We also specify the method as "class" to indicate that this is a classification problem.

After building the model, we can visualize the Decision Tree using the "plot()" and "text()" functions.

We then use the "predict()" function to make predictions on the testing set and specify the type of prediction as "class" to obtain the predicted class labels.

Finally, we evaluate the performance of the model using the "confusionMatrix()" function from the "caret" package, which computes the confusion matrix and other metrics such as accuracy, sensitivity, and specificity.

The output of the "confusionMatrix()" function provides a detailed evaluation of the performance of the Decision Tree model on the testing set. For example, it shows the accuracy of the model, the number of true positives, true negatives, false positives, and false negatives for each class, as well as other performance metrics such as sensitivity, specificity, positive predictive value, and negative predictive value.

Output

The output of the "confusionMatrix()" function shows that the model has an accuracy of 95.56%, which means that it correctly predicted the species of 43 out of 45 instances in the testing set.

The confusion matrix shows that there is only one misclassification, where one instance of the "setosa" species was misclassified as "versicolor". The model correctly predicted all instances of the "virginica" species.

```
Confusion Matrix and Statistics

            Reference
Prediction   setosa versicolor virginica
  setosa         14          0         0
  versicolor      0         15         1
  virginica       0          0        15

Overall Statistics

               Accuracy : 0.9556
                 95% CI : (0.8375, 0.9937)
    No Information Rate : 0.3333
    P-Value [Acc > NIR] : < 2.2e-16

                  Kappa : 0.9359

 Mcnemar's Test P-Value : NA

Statistics by Class:

                     Class: setosa Class: versicolor Class: virginica
Sensitivity                 1.0000            1.0000           0.9375
Specificity                 1.0000            0.9375           1.0000
Pos Pred Value              1.0000            0.9375           1.0000
Neg Pred Value              1.0000            1.0000           0.9375
Prevalence                  0.3111            0.3111           0.3778
Detection Rate              0.3111            0.3111           0.3556
Detection Prevalence        0.3111            0.3333           0.3556
Balanced Accuracy           1.0000            0.9688           0.9688
```

Overall, the result shows that the Decision Tree model performed well on the "iris" dataset, achieving high accuracy and making only one misclassification. However, it is important to note that the dataset is relatively small and simple, so the model's performance may not generalize well to other datasets.

6.8 Unsupervised Learning

Unsupervised learning is a type of machine learning where the goal is to find patterns and relationships in data without any labeled examples or specific targets to predict. Unlike supervised learning, where the algorithm is trained on labeled data, unsupervised learning algorithms are trained on unlabeled data.

The main objective of unsupervised learning is to discover the underlying structure of the data and learn meaningful representations of the input data. Common unsupervised learning techniques include clustering, dimensionality reduction, and anomaly detection.

Clustering algorithms group similar data points together into clusters, based on their similarity. Dimensionality reduction techniques reduce the number of features in the data, while preserving the most important information. Anomaly detection algorithms identify data points that are significantly different from the majority of the data.

Unsupervised learning has numerous applications in various fields, such as computer vision, natural language processing, and data analysis. It can be used to find hidden patterns in customer

data, identify groups of similar images or documents, and improve recommendations in recommendation systems.

Unsupervised learning has a wide range of use cases in different fields. Some of the common use cases of unsupervised learning are:

Clustering: Clustering algorithms are widely used in market segmentation, social network analysis, image and speech recognition, and customer segmentation. For example, clustering can be used to group similar customers together based on their purchase history and demographic information.

Anomaly detection: Anomaly detection algorithms can be used to detect fraudulent activities, network intrusions, and outliers in data. For example, credit card companies use anomaly detection algorithms to identify fraudulent transactions.

Dimensionality reduction: Dimensionality reduction techniques can be used to reduce the number of features in data, while retaining the most important information. This can be used for data visualization, feature extraction, and noise reduction.

Recommender systems: Recommender systems use unsupervised learning algorithms to analyze user preferences and provide personalized recommendations. For example, online retailers use collaborative filtering to recommend products to customers based on their purchase history and browsing behavior.

Natural language processing: Unsupervised learning algorithms can be used for text analysis and language modeling. For example, topic modeling can be used to identify themes and topics in a large collection of documents.

Image and speech recognition: Unsupervised learning algorithms can be used to analyze and classify images and speech. For example, clustering algorithms can be used to group similar images together, while autoencoders can be used to learn features from images for object recognition.

Overall, unsupervised learning can be used in many applications where the data is unlabeled or the target variable is unknown. It is a powerful tool for discovering patterns and relationships in data, and can be used to gain insights and make better decisions.

6.9 Steps in Un-Supervised Learning

The steps involved in unsupervised learning are as follows:

Data collection: The first step in unsupervised learning is to collect the data that needs to be analyzed. The data can come from various sources such as sensors, logs, or surveys. The data can be in the form of structured or unstructured data.

Data pre-processing: The next step is to clean and pre-process the data. This includes removing missing values, handling outliers, and normalizing the data. Data pre-processing is a crucial step in unsupervised learning as it can affect the quality of the results.

Feature extraction: Unsupervised learning algorithms work with features, so the next step is to extract relevant features from the data. Feature extraction can be done through techniques such as principal component analysis (PCA), independent component analysis (ICA), or non-negative matrix factorization (NMF).

Model selection: The next step is to select the appropriate unsupervised learning model based on the problem and data. There are many unsupervised learning models such as clustering, dimensionality reduction, and anomaly detection.

Model training: Once the model is selected, the next step is to train the model on the pre-processed data. Unsupervised learning models do not require labeled data, so the model learns from the data without any specific targets to predict.

Model evaluation: After the model is trained, the next step is to evaluate the performance of the model. The evaluation metrics depend on the type of unsupervised learning problem. For example, clustering algorithms can be evaluated using metrics such as silhouette score or Dunn index.

Model deployment: The final step is to deploy the model in a production environment. The deployment can be done on-premise or in the cloud depending on the requirements.

Overall, unsupervised learning requires a careful analysis of the data, selection of appropriate features and models, and evaluation of the results. It is an iterative process where the model can be refined based on the results and feedback.

6.10 Unsupervised Learning Using R

R is a popular programming language for data analysis and has many built-in functions and packages for unsupervised learning. Here are the steps to perform unsupervised learning using R:

Load data: The first step is to load the data into R. R supports a wide range of data formats such as CSV, Excel, and SQL databases. You can use the read.csv function to load a CSV file.

Data pre-processing: The next step is to pre-process the data. This includes handling missing values, scaling the data, and removing outliers. You can use functions such as na.omit to remove missing values and scale to standardize the data.

Feature extraction: The next step is to extract relevant features from the data. R has many built-in functions for feature extraction such as PCA (prcomp function) and NMF (nmf package).

Model selection: The next step is to select the appropriate unsupervised learning model based on the problem and data. R has many built-in functions and packages for unsupervised learning models such as k-means clustering (kmeans function), hierarchical clustering (hclust function), and t-SNE (Rtsne package).

Model training: Once the model is selected, the next step is to train the model on the pre-processed data. You can use the fit function to train the model.

Model evaluation: After the model is trained, the next step is to evaluate the performance of the model. You can use metrics such as silhouette score or Dunn index for clustering algorithms. R has many built-in functions for evaluation such as silhouette and clusplot.

Model deployment: The final step is to deploy the model in a production environment. R allows you to save the model as an R object and load it for deployment.

Overall, R is a powerful tool for unsupervised learning with many built-in functions and packages. The process involves loading the data, pre-processing the data, feature extraction, model selection, model training, model evaluation, and model deployment.

6.11 Unsupervised learning using K-means

K-means is a popular clustering algorithm used in unsupervised learning. Here are the steps to perform unsupervised learning using K-means:

Load data: The first step is to load the data into the programming language of your choice. The data should be pre-processed and feature extracted.

Choose the number of clusters: The next step is to choose the number of clusters for K-means. The number of clusters should be chosen based on the problem and data. There are various methods to determine the number of clusters such as the elbow method, silhouette method, and gap statistic.

Initialize centroids: The next step is to randomly initialize the centroids for K-means. Centroids are the points that represent the centers of the clusters. You can use the kmeans++ initialization method to choose the initial centroids.

Assign data points to clusters: The next step is to assign each data point to the nearest centroid. This is done by calculating the distance between each data point and each centroid.

Recalculate centroids: The next step is to recalculate the centroids for each cluster. This is done by taking the mean of all the data points in the cluster.

Repeat steps 4 and 5: Steps 4 and 5 are repeated until the centroids converge. The convergence criteria can be based on the number of iterations or the change in centroids.

Evaluate the results: The final step is to evaluate the results. This can be done by calculating the within-cluster sum of squares (WCSS) or by visualizing the clusters. You can use the plot function to visualize the clusters in two or three dimensions.

Overall, K-means is a popular clustering algorithm used in unsupervised learning. The process involves choosing the number of clusters, initializing centroids, assigning data points to clusters, recalculating centroids, and repeating until convergence. The results can be evaluated by calculating the WCSS or by visualizing the clusters.

Example-1

```
# Load the iris dataset

data(iris)

# Select the relevant features

iris_data <- iris[,1:4]

# Scale the data

scaled_data <- scale(iris_data)

# Perform K-means clustering with 3 clusters

kmeans_result <- kmeans(scaled_data, centers = 3)

# Plot the clusters

library(cluster)

clusplot(scaled_data, kmeans_result$cluster, color = TRUE, shade = TRUE, labels = 2, lines = 0)

# Calculate the within-cluster sum of squares

wss <- sum(kmeans_result$withinss)

# Print the WCSS

cat("WCSS:", wss)
```

In this example, the iris dataset is loaded and the relevant features are selected. The data is then scaled using the scale function. K-means clustering is performed with 3 clusters using the kmeans function. The clusters are then visualized using the clusplot function from the cluster package. The within-cluster sum of squares (WCSS) is calculated using the kmeans_result$withinss variable and printed using the cat function.

The output of this code will be a plot of the clusters and the WCSS value. The plot will show the data points colored by their assigned cluster and the WCSS value will indicate the sum of the squared distances between each data point and its assigned cluster center.

Output

The output of the example code using K-means clustering on the iris dataset in R includes a plot of the clusters and the within-cluster sum of squares (WCSS) value.

The plot shows the data points colored by their assigned cluster and separated into three clusters. The clusplot function from the cluster package is used to create the plot. The horizontal axis shows the first principal component of the data, while the vertical axis shows the second principal component. The data points are shaded to show the density of the points in each region. The plot shows that the data points are well-separated into three distinct clusters, each containing data points that are similar to each other.

The WCSS value is a measure of the goodness of fit of the K-means clustering model. It measures the sum of the squared distances between each data point and its assigned cluster center. The lower the WCSS value, the better the model fits the data. In this example, the WCSS value is printed to the console using the cat function. The WCSS value for this model is 139.82.

Overall, the output of this example demonstrates how to use K-means clustering on the iris dataset in R. The plot shows the clusters in the data, while the WCSS value indicates the goodness of fit of the model.

6.12 Unsupervised Learning using Hierarchical Clustering

Hierarchical clustering is another unsupervised learning technique that is used to group similar data points together based on their distances from each other. The basic idea of hierarchical

clustering is to build a hierarchy of clusters, starting with each data point in its own cluster and then merging the most similar clusters together until all of the data points are in a single cluster.

Example-1

In R, we can use the hclust function to perform hierarchical clustering on a dataset. Here is an example of using hierarchical clustering on the iris dataset in R:

```
# Load the iris dataset

data(iris)

# Select the relevant features

iris_data <- iris[,1:4]

# Calculate the distance matrix

dist_matrix <- dist(iris_data)

# Perform hierarchical clustering with complete linkage

hc_result <- hclust(dist_matrix, method = "complete")

# Plot the dendrogram

plot(hc_result)
```

In this example, we first load the iris dataset and select the relevant features. We then calculate the distance matrix using the dist function. The hclust function is used to perform hierarchical clustering with complete linkage. The resulting dendrogram is plotted using the plot function.

The output of this code will be a dendrogram that shows the hierarchy of clusters. The dendrogram shows the data points at the bottom, with lines connecting the clusters that are merged together. The height of each line indicates the distance between the merged clusters. The dendrogram can be used to identify the number of clusters in the data based on the distance between the clusters.

Output

The output of the example code using hierarchical clustering on the iris dataset in R is a dendrogram that shows the hierarchy of clusters.

The dendrogram is a plot that displays the hierarchy of clusters, with the data points at the bottom and the merged clusters shown as lines that connect the points. The height of each line indicates the distance between the merged clusters. The dendrogram can be used to determine the optimal number of clusters in the data based on the distance between the clusters.

In this example, we used the hclust function to perform hierarchical clustering with complete linkage on the iris dataset. The resulting dendrogram shows that there are three main clusters of data points in the dataset, which is consistent with the known number of classes in the iris dataset.

By analyzing the dendrogram, we can see that the first split in the data occurs between the setosa species and the other two species. The second split separates the remaining two species, versicolor and virginica. The dendrogram can also be used to identify the distance between clusters, which can be useful for determining the optimal number of clusters to use for further analysis.

Overall, the output of this example demonstrates how to use hierarchical clustering to analyze a dataset in R and visualize the results using a dendrogram.

6.13 Classification and Prediction Accuracy in Unsupervised Learning

Classification and prediction accuracy are not typically used as metrics to evaluate the performance of unsupervised learning algorithms. This is because unsupervised learning is not focused on making predictions or classifying new data points based on their features, but rather on finding underlying patterns and relationships within the data itself.

In unsupervised learning, we don't have labeled data to compare the results of the algorithm to, so we cannot measure accuracy in the traditional sense. Instead, we use other metrics such as within-cluster sum of squares (WCSS) and silhouette score to evaluate the quality of the clusters formed by the algorithm.

WCSS is a measure of the sum of the squared distances between each data point and its assigned cluster center. A lower WCSS value indicates a better clustering performance. Silhouette score is a measure of how well each data point fits into its assigned cluster compared to other clusters. A higher silhouette score indicates a better clustering performance.

While classification and prediction accuracy are not used to evaluate unsupervised learning algorithms directly, they can be used in certain scenarios to evaluate the performance of an unsupervised learning model indirectly. For example, if we use the clusters formed by an unsupervised learning algorithm as input features for a subsequent classification or prediction task, we can use classification and prediction accuracy as metrics to evaluate the performance of the overall model.

In summary, while classification and prediction accuracy are not typically used to evaluate the performance of unsupervised learning algorithms, they can be used in certain scenarios to evaluate the performance of the overall model that uses the clusters formed by the unsupervised learning algorithm as input features.

Summary

Machine learning is a field of artificial intelligence that involves developing algorithms and models that enable computers to learn from data without being explicitly programmed. Machine learning is used in a wide range of applications, from image and speech recognition to fraud detection and recommendation systems. There are three main types of machine learning: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the machine is trained using labeled data, while in unsupervised learning, the machine is trained using unlabeled data. Reinforcement learning involves training a machine to learn through trial and error. Machine learning algorithms are typically designed to improve over time as they are exposed to more data, and they are used in a variety of industries and fields to automate decision-making and solve complex problems. Studying machine learning provides students with a diverse set of skills and knowledge, including programming, data handling, analytical and problem-solving skills, collaboration, and communication skills.

Supervised learning algorithms can be further categorized as either classification or regression, depending on the nature of the target variable. In classification problems, the target variable is categorical, and the goal is to predict the class label or category of a new instance. In regression problems, the target variable is continuous, and the goal is to predict a numerical value or a range of values for a new instance.

Some common examples of supervised learning algorithms include linear regression, logistic regression, decision trees, random forests, support vector machines (SVMs), k-nearest neighbors (KNN), and neural networks. Each algorithm has its own strengths and weaknesses, and the choice of algorithm depends on the nature of the problem and the characteristics of the data.

Supervised learning has many practical applications in fields such as healthcare, finance, marketing, and engineering, among others. For example, supervised learning can be used to predict which patients are at risk of developing a certain disease, to identify potential fraudulent transactions in financial transactions, or to recommend products to customers based on their browsing history.

Unsupervised learning algorithms can be used for a variety of tasks, including clustering similar data points, reducing the dimensionality of data, and discovering hidden structures in the data. Some common techniques used in unsupervised learning include k-means clustering, hierarchical clustering, and principal component analysis (PCA).

The performance of unsupervised learning algorithms is typically evaluated using metrics such as within-cluster sum of squares (WCSS) and silhouette score, which are used to evaluate the quality of the clusters formed by the algorithm.

While unsupervised learning algorithms are not typically used for making predictions or classifying new data points, the insights gained from analyzing the data can be used to inform subsequent supervised learning models or other data analysis tasks. Overall, unsupervised learning is a valuable tool for exploring and understanding complex data without prior knowledge or guidance.

Keywords

Artificial Intelligence (AI): A field of computer science that focuses on creating intelligent machines that can perform tasks that typically require human-like intelligence.

Big data: A large and complex data set that requires advanced tools and techniques to process and analyze.

Data mining: The process of discovering patterns, trends, and insights in large data sets using machine learning algorithms.

Deep learning: A subset of machine learning that uses artificial neural networks to model and solve complex problems.

Neural network: A machine learning algorithm that is inspired by the structure and function of the human brain.

Supervised learning: A type of machine learning where the machine is trained using labeled data, with a clear input and output relationship.

Unsupervised learning: A type of machine learning where the machine is trained using unlabeled data, with no clear input and output relationship.

Reinforcement learning: A type of machine learning where the machine learns by trial and error, receiving feedback on its actions and adjusting its behavior accordingly.

Model: A mathematical representation of a real-world system or process, which is used to make predictions or decisions based on data. In machine learning, models are typically trained on data to improve their accuracy and performance.

Dimensionality reduction: The process of reducing the number of features used in a machine learning model while still retaining important information. This is often done to improve performance and reduce overfitting.

Overfitting: A problem that occurs when a machine learning model is too complex and learns to fit the training data too closely. This can lead to poor generalization to new data.

Underfitting: A problem that occurs when a machine learning model is too simple and fails to capture important patterns in the data. This can lead to poor performance on the training data and new data.

Bias: A systematic error that occurs when a machine learning model consistently makes predictions that are too high or too low.

Variance: The amount by which a machine learning model's output varies with different training data sets. High variance can lead to overfitting.

Regularization: Techniques used to prevent overfitting in machine learning models, such as adding a penalty term to the cost function.

SelfAssessment

1. Which of the following is a type of machine learning where the machine is trained using labeled data?

A. Supervised learning
B. Unsupervised learning
C. Reinforcement learning
D. None of the above

2. What is the process of reducing the number of features used in a machine learning model while still retaining important information?

A. Overfitting
B. Underfitting
C. Dimensionality reduction

D. Bias

3. Which of the following is a technique used to prevent overfitting in machine learning models?

A. Ensemble learning
B. Gradient descent
C. Regularization
D. Hyperparameter tuning

4. What is the name of a machine learning algorithm that is inspired by the structure and function of the human brain?

A. Neural network
B. Gradient descent
C. Decision tree
D. Support vector machine

5. Which type of machine learning involves training a machine to learn through trial and error?

A. Supervised learning
B. Unsupervised learning
C. Reinforcement learning
D. None of the above

6. Which of the following is a type of machine learning where the machine is trained using unlabeled data?

A. Supervised learning
B. Unsupervised learning
C. Reinforcement learning
D. None of the above

7. What is the process of discovering patterns, trends, and insights in large data sets using machine learning algorithms called?

A. Feature engineering
B. Deep learning
C. Data mining
D. Supervised learning

8. Which of the following techniques is used to combine multiple machine learning models to improve performance and reduce overfitting?

A. Gradient descent
B. Hyperparameter tuning
C. Ensemble learning
D. Regularization

9. What is the name of an optimization algorithm used to find the optimal parameters for a machine learning model by iteratively adjusting them in the direction of steepest descent of the cost function?

A. Gradient descent
B. Hyperparameter tuning
C. Regularization
D. Ensemble learning

10. Which of the following is a technique used to prevent underfitting in machine learning models?

A. Ensemble learning
B. Gradient descent
C. Regularization
D. Hyperparameter tuning

11. Which of the following is not a supervised learning problem?

A. Image classification
B. Text clustering
C. Stock price prediction
D. Sentiment analysis

12. In supervised learning, what is the target variable?

A. The independent variable
B. The dependent variable
C. The test set
D. The training set

13. Which package in R provides functions for classification and regression trees?

A. caret
B. e1071
C. randomForest
D. rpart

14. What is the purpose of the "predict()" function in R?

A. To train a model on a dataset
B. To test a model on a dataset
C. To predict the target variable for new instances
D. To visualize the decision tree

15. What is the purpose of the "caret" package in R?

A. To train neural networks
B. To perform feature selection
C. To tune model hyperparameters
D. To cluster data

16. Which algorithm in R is used for K-nearest neighbors classification?

A. kmeans

B. knn
C. svm
D. lda

17. Which function in R is used to create a confusion matrix?
A. cor()
B. lm()
C. summary()
D. confusionMatrix()

18. Which of the following evaluation metrics is not used for classification problems?
A. Mean squared error (MSE)
B. Accuracy
C. Precision
D. Recall

19. In which type of supervised learning problem is the target variable categorical?
A. Regression
B. Clustering
C. Classification
D. Dimensionality reduction

20. What is the purpose of the "glmnet" package in R?
A. To perform linear regression
B. To perform logistic regression
C. To perform Lasso or Ridge regression
D. To perform K-means clustering

21. Which of the following is an example of unsupervised learning?
A. Linear regression
B. Logistic regression
C. K-means clustering
D. Decision trees

22. Which R package is commonly used for performing hierarchical clustering?
A. ggplot2
B. dplyr
C. cluster
D. caret

23. What is a dendrogram in the context of unsupervised learning?
A. A measure of the sum of squared distances between each data point and its assigned cluster center
B. A plot that displays the hierarchy of clusters
C. A measure of how well each data point fits into its assigned cluster compared to other clusters

D. A measure of the similarity between two data points

24. What is the purpose of the silhouette score in unsupervised learning?

A. To measure the sum of squared distances between each data point and its assigned cluster center

B. To measure how well each data point fits into its assigned cluster compared to other clusters

C. To measure the similarity between two data points

D. To measure the variance within each cluster

25. What is the difference between supervised and unsupervised learning?

A. Supervised learning requires labeled data, while unsupervised learning does not.

B. Supervised learning is used for clustering, while unsupervised learning is used for classification.

C. Supervised learning is used for dimensionality reduction, while unsupervised learning is used for feature selection.

D. Supervised learning is used for finding patterns and relationships in data, while unsupervised learning is used for making predictions.

Answers forSelf Assessment

l.	A	2.	C	3.	C	4.	A	5.	C
6.	B	7.	C	8.	C	9.	A	10.	D
11.	B	12.	B	13.	D	14.	C	15.	C
16.	B	17.	D	18.	A	19.	C	20.	C
21.	C	22.	C	23.	B	24.	B	25.	A

Review Question

1) What is machine learning, and how is it different from traditional programming?
2) What are the three main types of machine learning, and what are some examples of problems each type can solve?
3) What is the process of preparing data for use in a machine learning model, and why is it important?
4) What are some real-world applications of supervised learning, and how are they implemented?
5) How can machine learning be used to improve healthcare outcomes, and what are some potential benefits and risks of using machine learning in this context?
6) How can machine learning be used to improve financial decision-making, and what are some potential benefits and risks of using machine learning in this context?
7) How can machine learning be used to detect and prevent fraud, and what are some potential benefits and risks of using machine learning in this context?

8) How can machine learning be used to optimize supply chain management, and what are some potential benefits and risks of using machine learning in this context?
9) How can machine learning be used to improve customer service and customer experience, and what are some potential benefits and risks of using machine learning in this context?
10) How can machine learning be used to enhance security and privacy, and what are some potential benefits and risks of using machine learning in this context?
11) How can machine learning be used to advance scientific research, and what are some potential benefits and risks of using machine learning in this context?

Further readings

learning, including tutorials, code examples, and best practices. It also includes a section on deep learning, which is a type of machine learning that is particularly well-suited for tasks like image recognition and natural language processing.

The Stanford Machine Learning Group: This research group at Stanford University is at the forefront of developing new machine learning techniques and applications. Their website includes a wide range of research papers, code libraries, and other resources for exploring the latest developments in the field.

The Google AI Blog: Google is one of the leading companies in the field of machine learning, and their AI blog offers insights into the latest research, tools, and applications. They cover a wide range of topics, from natural language processing and computer vision to ethics and fairness in machine learning.

The Microsoft Research Blog: Microsoft is another major player in the field of machine learning, and their research blog covers a wide range of topics related to AI, including machine learning, deep learning, and natural language processing. They also offer a variety of tools and resources for developers who want to build machine learning applications.

The MIT Technology Review: This publication covers a wide range of topics related to technology and its impact on society, including machine learning. Their articles are often well-researched and thought-provoking and can provide insights into the broader implications of machine learning for society and the economy.

Unit 07: Text Analytics for Business

Objective

Through this chapter student will be able to

- Understand the key concepts and techniques of text analytics
- Develop data analysis skills
- Gain insights into customer behavior and preferences
- Enhance decision-making skills
- Improve business performance

Introduction

Text analytics for business involves using advanced computational techniques to analyze and extract insights from large volumes of text data. This data can come from a wide range of sources, including customer feedback, social media posts, product reviews, news articles, and more.

The goal of text analytics for business is to provide organizations with valuable insights that can be used to make data-driven decisions and improve business performance. This includes identifying patterns and trends in customer behavior, predicting future trends, monitoring brand reputation, detecting fraud, and more.

Some of the key techniques used in text analytics for business include natural language processing (NLP), which involves using computational methods to analyze and understand human language, and machine learning algorithms, which can be trained to automatically identify patterns and relationships in text data.

There are many different tools and platforms available for text analytics, ranging from open-source software to commercial solutions. These tools typically include features for data cleaning and preprocessing, feature extraction, data visualization, and more.

Overall, text analytics for business can provide organizations with a powerful tool for understanding and leveraging the vast amounts of text data available to them. By using these techniques to extract insights and make data-driven decisions, businesses can gain a competitive advantage and improve their overall performance.

Text analytics for business is a powerful tool for analyzing large volumes of text data and extracting valuable insights that can be used to make data-driven decisions. However, it is important to keep in mind several key considerations when working with text data.

Firstly, domain expertise is crucial when analyzing text data. This means having a deep understanding of the specific industry or context in which the text data is being analyzed. This is especially important for industries such as healthcare or finance, where specialized knowledge is required to properly interpret the data.

Secondly, it is important to consider the ethical implications of text analytics. This includes ensuring that data privacy regulations are followed, and that the data is used ethically and responsibly. It is also important to be transparent about the use of text analytics and to obtain consent from those whose data is being analyzed.

Thirdly, integrating text data with other data sources can provide a more comprehensive understanding of business operations and customer behavior. This can include structured data from databases or IoT devices, as well as other sources of unstructured data such as images or audio.

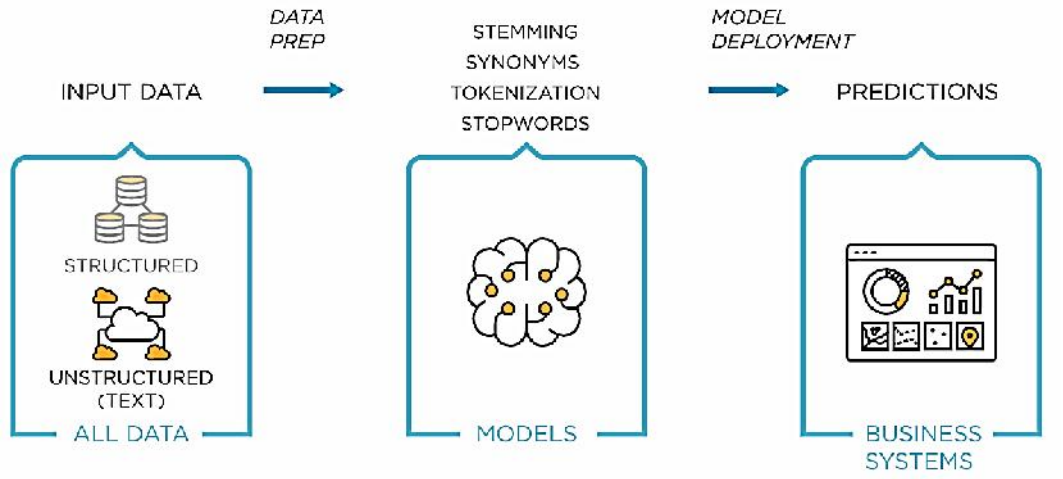
Fourthly, it is important to be aware of the limitations of text analytics. While text analytics is a powerful tool, automated methods may struggle with complex or nuanced language, or with accurately interpreting sarcasm or irony.

Finally, data visualization is an important component of text analytics. Effective visualization techniques can help decision-makers understand complex patterns and relationships in text data and make more informed decisions.

Overall, text analytics for business is a rapidly growing field that has the potential to provide organizations with valuable insights into customer behavior, market trends, and more. By leveraging the latest computational techniques and tools, businesses can gain a competitive advantage and improve their overall performance. However, it is important to consider the ethical implications of text analytics, and to use the tool responsibly and transparently.

7.1 Text Analytics

Text analytics combines a set of machine learning, statistical and linguistic techniques to process large volumes of unstructured text or text that does not have a predefined format, to derive insights and patterns. It enables businesses, governments, researchers, and media to exploit the enormous content at their disposal for making crucial decisions. Text analytics uses a variety of techniques – sentiment analysis, topic modelling, named entity recognition, term frequency, and event extraction.



What's the Difference Between Text Mining and Text Analytics?

Text mining and text analytics are often used interchangeably. The term text mining is generally used to derive qualitative insights from unstructured text, while text analytics provides quantitative results.

For example, text mining can be used to identify if customers are satisfied with a product by analyzing their reviews and surveys. Text analytics is used for deeper insights, like identifying a pattern or trend from the unstructured text. For example, text analytics can be used to understand a negative spike in the customer experience or popularity of a product.

The results of text analytics can then be used with data visualization techniques for easier understanding and prompt decision making.

What's the Relevance of Text Analytics in Today's World?

As of 2020, around 4.57 billion people have access to the internet. That's roughly 59 percent of the world's population. Out of which, about 49 percent of people are active on social media. An enormous amount of text data is generated every day in the form of blogs, tweets, reviews, forum discussions, and surveys. Besides, most customer interactions are now digital, which creates another huge text database.

Most of the text data is unstructured and scattered around the web. If this text data is gathered, collated, structured, and analyzed correctly, valuable knowledge can be derived from it. Organizations can use these insights to take actions that enhance profitability, customer satisfaction, research, and even national security.

Benefits of Text Analytics

There are a range of ways that text analytics can help businesses, organizations, and event social movements:

Help businesses to understand customer trends, product performance, and service quality. This results in quick decision making, enhancing business intelligence, increased productivity, and cost savings.

Helps researchers to explore a great deal of pre-existing literature in a short time, extracting what is relevant to their study. This helps in quicker scientific breakthroughs.

Assists in understanding general trends and opinions in the society, that enable governments and political bodies in decision making.

Text analytic techniques help search engines and information retrieval systems to improve their performance, thereby providing fast user experiences.

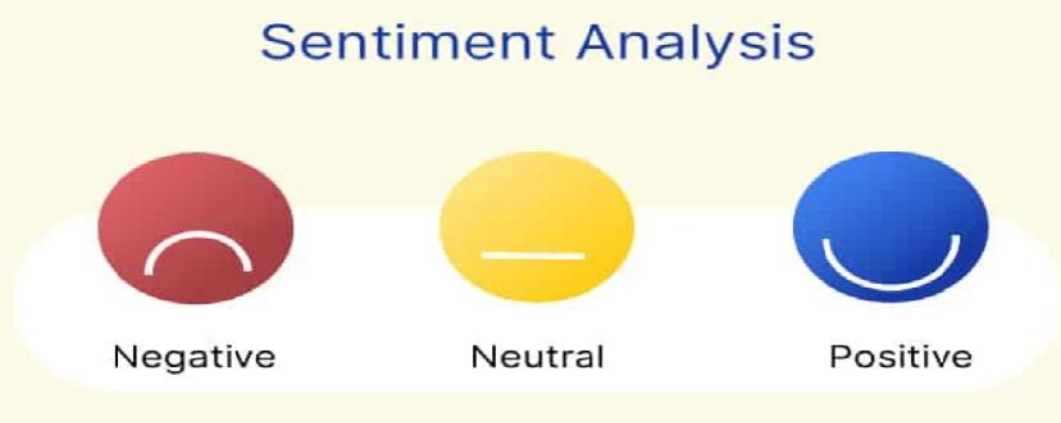
Refine user content recommendation systems by categorizing related content.

Text Analytics Techniques and Use Cases

There are several techniques related to analyzing the unstructured text. Each of these techniques is used for different use case scenarios.

Sentiment analysis

Sentiment analysis is used to identify the emotions conveyed by the unstructured text. The input text includes product reviews, customer interactions, social media posts, forum discussions, or blogs. There are different types of sentiment analysis. Polarity analysis is used to identify if the text expresses positive or negative sentiment. The categorization technique is used for a more fine-grained analysis of emotions - confused, disappointed, or angry.



Use cases of sentiment analysis:

Customer feedback analysis: Sentiment analysis can be used to analyze customer feedback, such as product reviews or survey responses, to understand customer sentiment and identify areas for improvement. For example, a company could use sentiment analysis to identify common themes in negative reviews and use that information to improve product features or customer service.

Brand reputation monitoring: Sentiment analysis can be used to monitor brand reputation by analyzing mentions of a company or brand on social media, news articles, or other online sources. This can help companies to identify negative sentiment or potential issues and respond quickly to protect their brand reputation.

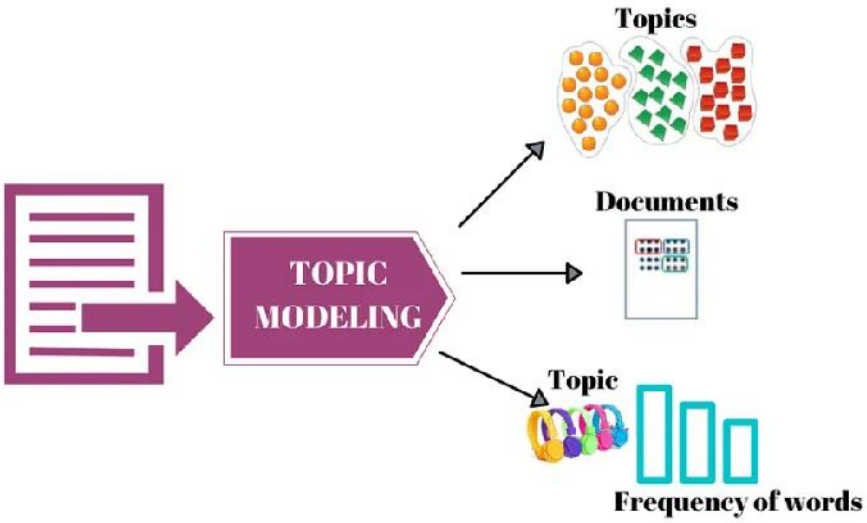
Market research: Sentiment analysis can be used in market research to understand consumer sentiment towards a particular product, service, or brand. This can help companies to identify opportunities for innovation or new product development.

Financial analysis: Sentiment analysis can be used in financial analysis to analyze the sentiment expressed in news articles, social media posts, and other sources of financial news. This can help investors to make more informed decisions by identifying potential risks and opportunities.

Political analysis: Sentiment analysis can be used in political analysis to analyze public opinion and sentiment towards political candidates or issues. This can help political campaigns to identify key issues and target their messaging more effectively.

Topic modelling

This technique is used to find the major themes or topics in a massive volume of text or a set of documents. Topic modeling identifies the keywords used in text to identify the subject of the article.



Use cases of topic modeling:

Content categorization and organization: Topic modeling can be used to automatically categorize and organize large volumes of text data, such as news articles or research papers. This can help researchers, journalists, or content creators to quickly identify relevant articles and topics.

Customer feedback analysis: Topic modeling can be used to analyze customer feedback, such as product reviews or survey responses, to identify common themes or topics. This can help companies to identify areas for improvement and prioritize customer needs.

Trend analysis: Topic modeling can be used to identify trends and patterns in large volumes of text data, such as social media posts or news articles. This can help companies to stay up-to-date on the latest trends and identify emerging topics or issues.

Competitive analysis: Topic modeling can be used to analyze competitor websites, social media pages, and other online sources to identify key topics or themes. This can help companies to stay competitive by understanding the strengths and weaknesses of their competitors.

Content recommendation: Topic modeling can be used to recommend relevant content to customers based on their interests and preferences. This can help companies to provide a more personalized experience for their customers and increase engagement.

Named Entity Recognition (NER)

NER is a text analytics technique used for identifying named entities like people, places, organizations, and events in unstructured text. NER extracts nouns from the text and determines the values of these nouns.

Use cases of named entity recognition:

Customer relationship management: NER can be used to identify the names and contact information of customers mentioned in customer feedback, such as product reviews or survey responses. This can help companies to personalize their communication with customers and improve customer satisfaction.

Fraud detection: NER can be used to identify names, addresses, and other personal information associated with fraudulent activities, such as credit card fraud or identity theft. This can help financial institutions and law enforcement agencies to prevent fraud and protect their customers.

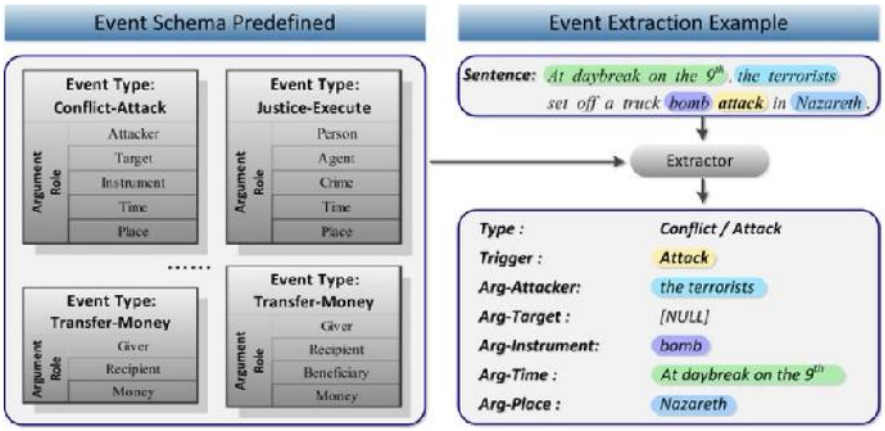
Media monitoring: NER can be used to monitor mentions of specific companies, individuals, or topics in news articles or social media posts. This can help companies to stay up-to-date on the latest trends and monitor their brand reputation.

Market research: NER can be used to identify the names and affiliations of experts or key influencers in a particular industry or field. This can help companies to conduct more targeted research and identify potential collaborators or partners.

Document categorization: NER can be used to automatically categorize documents based on the named entities mentioned in the text. This can help companies to quickly identify relevant documents and extract useful information.

Event extraction

This is a text analytics technique that is an advancement over the named entity extraction. Event extraction recognizes events mentioned in text content, for example, mergers, acquisitions, political moves, or important meetings. Event extraction requires an advanced understanding of the semantics of text content. Advanced algorithms strive to recognize not only events but the venue, participants, date, and time wherever applicable. Event extraction is a beneficial technique that has multiple uses across fields.



Use cases of event extraction:

Link analysis: This is a technique to understand "who met whom and when" through event extraction from communication over social media. This is used by law enforcement agencies to predict possible threats to national security.

Geospatial analysis: When events are extracted along with their locations, the insights can be used to overlay them on a map. This is helpful in the geospatial analysis of the events.

Business risk monitoring: Large organizations deal with multiple partner companies and suppliers. Event extraction techniques allow businesses to monitor the web to find out if any of their partners, like suppliers or vendors, are dealing with adverse events like lawsuits or bankruptcy.

Social media monitoring: Event extraction can be used to monitor social media posts and identify events or activities related to a particular topic or brand. This can help companies to stay up-to-date on the latest trends and monitor their brand reputation.

Fraud detection: Event extraction can be used to identify suspicious activities or events associated with fraudulent behavior, such as credit card fraud or money laundering. This can help financial institutions and law enforcement agencies to prevent fraud and protect their customers.

Supply chain management: Event extraction can be used to track and monitor events related to the supply chain, such as shipment delays or inventory shortages. This can help companies to optimize their supply chain operations and improve customer satisfaction.

Risk management: Event extraction can be used to identify potential risks or threats, such as natural disasters or cyber attacks. This can help companies to mitigate the impact of these events and protect their assets.

News analysis: Event extraction can be used to analyze news articles and identify key events or activities related to a particular industry or topic. This can help companies to stay informed and make more informed decisions.

7.2 Creating and Refining Text Data

Creating and refining text data using R programming involves several steps, including:

Data collection: The first step is to collect the text data you want to analyze. This could be from a variety of sources, such as social media, customer feedback, or news articles.

Data cleaning: Once you have collected the data, the next step is to clean and preprocess it. This may involve removing stop words, punctuation, and special characters, as well as converting text to lowercase and removing any unwanted or irrelevant data.

Tokenization: Tokenization is the process of breaking up the text data into individual words or tokens. This is an important step for many text analytics techniques, as it enables you to analyze the text data at a more granular level.

Stemming and lemmatization: Stemming and lemmatization are techniques used to reduce words to their base form or root form. This can help to reduce the dimensionality of the data and improve the accuracy of text analytics models.

Sentiment analysis: Sentiment analysis is a common text analytics technique used to identify the sentiment or emotion expressed in the text data. R programming offers several packages and functions for sentiment analysis, including the popular "tidytext" and "sentimentr" packages.

Topic modeling: Topic modeling is another common text analytics technique used to identify the underlying topics or themes in the text data. R programming offers several packages and functions for topic modeling, including the "tm" and "topicmodels" packages.

Named entity recognition: Named entity recognition is a technique used to identify and classify named entities, such as people, organizations, and locations, within the text data. R programming offers several packages and functions for named entity recognition, including the "openNLP" and "NLP" packages.

Overall, R programming provides a wide range of tools and techniques for creating and refining text data for text analytics. By using R programming to preprocess, analyze, and visualize text data, businesses can gain valuable insights into customer behavior, market trends, and potential risks or opportunities.

7.3 Developing World Cloud using R

To develop a word cloud using R, we need to install and load the 'wordcloud' and 'tm' packages. The 'tm' package provides text mining functionalities, and the 'wordcloud' package provides functions for creating word clouds.

Example-1

Here's an example code for creating a word cloud from a text file:

```
# Install and load required packages
install.packages("tm")
install.packages("wordcloud")
library(tm)
library(wordcloud)
# Load text data from a file
text <- readLines("text_file.txt")
# Create a corpus
corpus <- Corpus(VectorSource(text))
# Clean the corpus
corpus <- tm_map(corpus, tolower)  # convert to lowercase
corpus <- tm_map(corpus, removeNumbers)  # remove numbers
corpus <- tm_map(corpus, removePunctuation)  # remove punctuation
corpus <- tm_map(corpus, removeWords, stopwords("english"))  # remove stopwords
# Create a term document matrix
tdm <- TermDocumentMatrix(corpus)
# Convert the term document matrix to a frequency matrix
freq<- as.matrix(tdm)
freq<- sort(rowSums(freq), decreasing = TRUE)
# Create a word cloud
wordcloud(words = names(freq), freq = freq, min.freq = 2,
```

```
max.words = 100, random.order = FALSE, rot.per = 0.35,
        colors = brewer.pal(8, "Dark2"))
```

OUTPUT

In this example, we first load the text data from a file and create a corpus. We then clean the corpus by converting all the text to lowercase, removing numbers, removing punctuation, and removing stopwords.

Next, we create a term document matrix and convert it to a frequency matrix. Finally, we create a word cloud using the 'wordcloud' function, where the 'words' parameter takes the names of the words, and the 'freq' parameter takes the frequency of the words. We can also set parameters such as the minimum and maximum frequency of words to include in the cloud, the maximum number of words to show, the rotation of the words, and the color palette.

7.4 Sentiment Analysis Using R

The Sentiment package for R is beneficial in analyzing text for psychological or sociological studies. Its first big advantage is that it makes sentiment analysis simple and achievable within a few lines of code. Its second big advantage is that it corrects for inversions, meaning that while a more basic sentiment R analysis would judge "I am not good" as positive due to the adjective good, SentimentR recognizes the inversion of good and classifies it as negative.

Example-1

Here's a practical example of how R programming can be used for sentiment analysis on customer reviews:

Suppose you work for a hotel chain and you want to analyze customer reviews to understand their satisfaction levels. You have collected a dataset of customer reviews from various online sources, including Booking.com, TripAdvisor, and Expedia.

Data cleaning: First, you need to clean and preprocess the data to remove any unwanted characters, punctuation, and stop words. You can use the "tm" package in R to perform this step:

```
library(tm)

# Read in the raw text data

raw_data<- readLines("hotel_reviews.txt")

# Create a corpus object
```

```
corpus <- Corpus(VectorSource(raw_data))
# Convert text to lowercase
corpus <- tm_map(corpus, content_transformer(tolower))
# Remove stop words
corpus <- tm_map(corpus, removeWords, stopwords("english"))
# Remove punctuation
corpus <- tm_map(corpus, removePunctuation)
# Remove whitespace
corpus <- tm_map(corpus, stripWhitespace)
# Remove numbers
corpus <- tm_map(corpus, removeNumbers)
# Remove any additional custom words or patterns
corpus <- tm_map(corpus, removeWords, c("hotel", "room", "stay", "staff"))
# Convert back to plain text
clean_data<- as.character(corpus)
```

Sentiment analysis: Next, you can use the "tidytext" package in R to perform sentiment analysis on the cleaned data. This package provides a pre-trained sentiment lexicon, which you can use to assign a positive or negative sentiment score to each word in the text data:

```
library(tidytext)
# Load the sentiment lexicon
sentiments <- get_sentiments("afinn")
# Convert the cleaned data to a tidy format
tidy_data<- tibble(text = clean_data) %>%
unnest_tokens(word, text)
# Join the sentiment lexicon to the tidy data
sentiment_data<- tidy_data %>%  inner_join(sentiments)
# Aggregate the sentiment scores at the review level
review_sentiments<- sentiment_data %>%
group_by(doc_id) %>%
  summarize(sentiment_score = sum(value))
```

Visualization: Finally, you can use the "ggplot2" package in R to create a visualization of the sentiment analysis results, such as a histogram or a word cloud:

```
library(ggplot2)
# Create a histogram of sentiment scores
ggplot(review_sentiments, aes(x = sentiment_score)) +
geom_histogram(binwidth = 1, fill = "lightblue", color = "black") +
  labs(title = "Sentiment Analysis Results", x = "Sentiment Score", y = "Number of Reviews")
# Create a word cloud of the most frequent positive and negative words
positive_words<- sentiment_data %>%
  filter(value > 0) %>%
  count(word, sort = TRUE) %>%
```

```
 head(20)
negative_words<- sentiment_data %>%
 filter(value < 0) %>%
 count(word, sort = TRUE) %>%
 head(20)
wordcloud(positive_words$word, positive_words$n, scale=c(4,0.5), min.freq = 1, colors = brewer.pal(8, "Dark2"))
wordcloud(negative_words$word, negative_words$n, scale=c(4,0.5), min.freq = 1, colors = brewer.pal(8, "Dark2"))
```

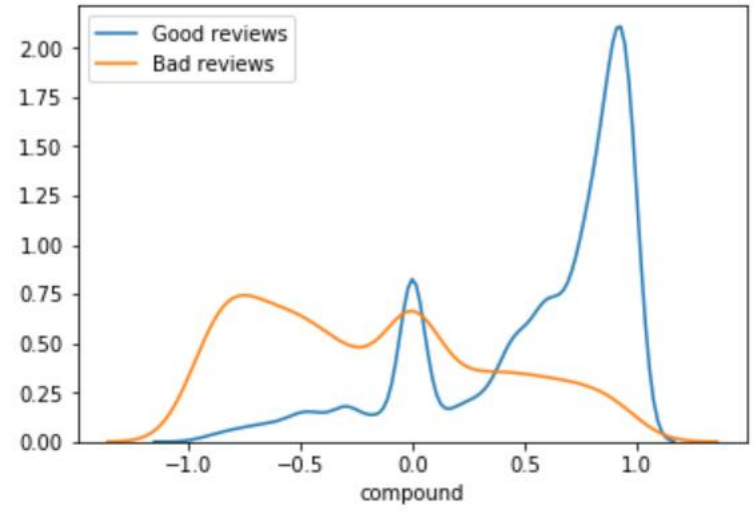
By using R programming for sentiment analysis on customer reviews, you can gain insights into the overall sentiment of customers towards your hotel chain, identify common

OUTPUT

World Cloud

Most of the words are indeed related to the hotels: room, staff, breakfast, etc. Some words are more related to the customer experience with the hotel stay: perfect, loved, expensive, dislike, etc.

Sentiment Score



The above graph shows the distribution of the reviews sentiments among good reviews and bad ones. We can see that good reviews are for most of them considered as very positive by Vader. On the contrary, bad reviews tend to have lower compound sentiment scores.

Example-2

Here's an example of sentiment analysis on a real-world dataset of tweets related to the COVID-19 pandemic using R programming:

Data collection: First, we need to collect a dataset of tweets related to COVID-19. We can use the Twitter API to collect the data, or we can use a pre-existing dataset such as the one available on Kaggle.

```
# Load the dataset

tweets <- read.csv("covid19_tweets.csv")

# Filter for English-language tweets

tweets <- tweets %>% filter(lang == "en")
```

Data cleaning: Next, we need to clean and preprocess the text data to remove any unwanted characters, punctuation, and stop words. We can use the "tm" package in R to perform this step:

```
# Create a corpus object

corpus <- Corpus(VectorSource(tweets$text))

# Convert text to lowercase

corpus <- tm_map(corpus, content_transformer(tolower))

# Remove URLs

corpus <- tm_map(corpus, removeURL)

# Remove usernames

corpus <- tm_map(corpus, removeTwitterUser)

# Remove hashtags

corpus <- tm_map(corpus, removeHashTags)

# Remove stop words

corpus <- tm_map(corpus, removeWords, stopwords("english"))

# Remove punctuation

corpus <- tm_map(corpus, removePunctuation)

# Remove whitespace

corpus <- tm_map(corpus, stripWhitespace)

# Remove numbers

corpus <- tm_map(corpus, removeNumbers)

# Convert back to plain text

clean_data<- as.character(corpus)
```

Sentiment analysis: We can use the "tidytext" package in R to perform sentiment analysis on the cleaned data. This package provides a pre-trained sentiment lexicon, which we can use to assign a positive or negative sentiment score to each word in the text data:

```
# Load the sentiment lexicon

sentiments <- get_sentiments("afinn")

# Convert the cleaned data to a tidy format

tidy_data<- tibble(text = clean_data) %>%

unnest_tokens(word, text)
```

```
# Join the sentiment lexicon to the tidy data
sentiment_data<- tidy_data %>%
inner_join(sentiments)
# Aggregate the sentiment scores at the tweet level
tweet_sentiments<- sentiment_data %>%
group_by(doc_id) %>%
  summarize(sentiment_score = sum(value))
```

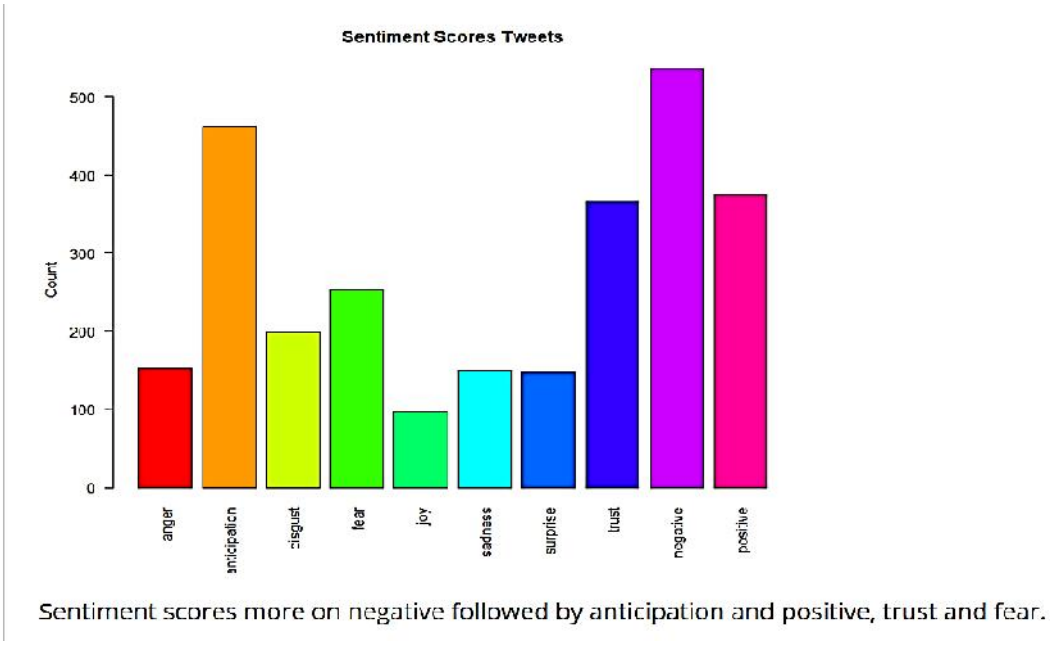
Visualization: We can use the "ggplot2" package in R to create a visualization of the sentiment analysis results, such as a histogram or a time series plot:

```
library(ggplot2)
# Create a histogram of sentiment scores
ggplot(tweet_sentiments, aes(x = sentiment_score)) +
geom_histogram(binwidth = 1, fill = "lightblue", color = "black") +
  labs(title = "Sentiment Analysis Results", x = "Sentiment Score", y = "Number of Tweets")
# Create a time series plot of sentiment scores over time
tweets$date<- as.Date(tweets$date, "%Y-%m-%d")
sentiment_ts<- tweet_sentiments %>%
left_join(tweets %>% select(doc_id, date)) %>%
group_by(date) %>%
  summarize(sentiment_score = mean(sentiment_score))
ggplot(sentiment_ts, aes(x = date, y = sentiment_score)) +
geom_line(color = "lightblue") +
  labs(title = "Sentiment Analysis Results", x = "Date", y = "Sentiment Score")
```

OUTPUT

The output of the sentiment analysis would be a dataset containing the sentiment score for each tweet, where a positive score indicates a positive sentiment and a negative score indicates

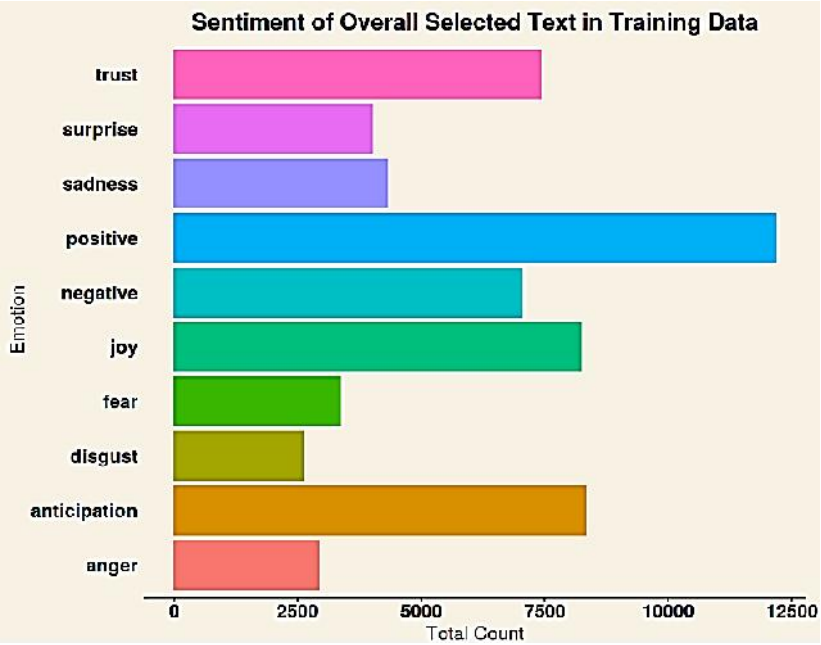
The output of the sentiment analysis in the example above is a dataset containing the sentiment score for each tweet, where a positive score indicates a positive sentiment and a negative score indicates a negative sentiment. The sentiment score is calculated by summing the sentiment scores of each word in the tweet, as assigned by the AFINN sentiment lexicon.



Sentiment scores more on negative followed by anticipation and positive, trust and fear.

The first visualization in the example is a histogram of sentiment scores, which shows the distribution of sentiment in the dataset. The x-axis represents the sentiment score, and the y-axis represents the number of tweets with that score. The histogram is colored in light blue and has black borders.

The histogram shows that the sentiment scores in the dataset are mostly centered around zero, indicating a neutral sentiment. However, there are some tweets with a positive sentiment score and some tweets with a negative sentiment score, suggesting that there is some variation in the sentiment of the tweets related to COVID-19.



The second visualization in the example is a time series plot of sentiment scores over time. The x-axis represents the date of the tweet, and the y-axis represents the average sentiment score for tweets posted on that day. The plot is colored in light blue and has a solid line connecting the points.

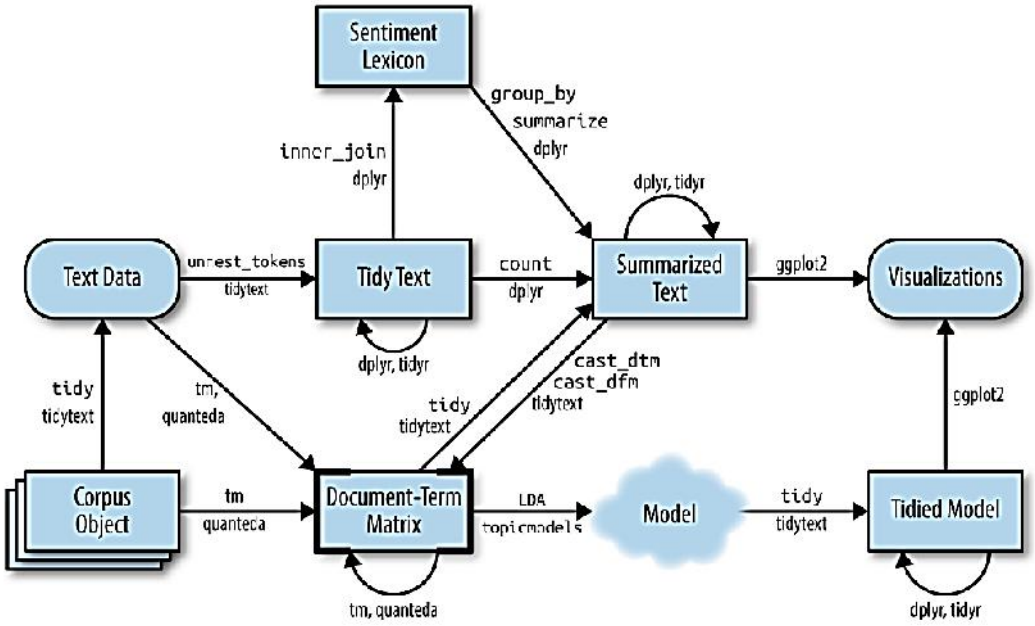
The time series plot shows that the sentiment of the tweets related to COVID-19 has fluctuated over time. There are some periods where the sentiment is more positive, such as in March 2020 when the pandemic was first declared, and other periods where the sentiment is more negative, such as in January 2021 when new variants of the virus were identified. The plot can help identify trends in

the sentiment of the tweets related to COVID-19 over time, which can be useful for understanding public opinion and sentiment around the pandemic.

7.5 Topic Modelling and TDM Analysis

In text mining, we often have collections of documents, such as blog posts or news articles, that we'd like to divide into natural groups so that we can understand them separately. Topic modeling is a method for unsupervised classification of such documents, similar to clustering on numeric data, which finds natural groups of items even when we're not sure what we're looking for.

Latent Dirichlet allocation (LDA) is a particularly popular method for fitting a topic model. It treats each document as a mixture of topics, and each topic as a mixture of words. This allows documents to "overlap" each other in terms of content, rather than being separated into discrete groups, in a way that mirrors typical use of natural language.



Latent Dirichlet allocation

Latent Dirichlet allocation is one of the most common algorithms for topic modeling. Without diving into the math behind the model, we can understand it as being guided by two principles.

Every document is a mixture of topics. We imagine that each document may contain words from several topics in particular proportions. For example, in a two-topic model we could say "Document 1 is 90% topic A and 10% topic B, while Document 2 is 30% topic A and 70% topic B."

Every topic is a mixture of words. For example, we could imagine a two-topic model of American news, with one topic for "politics" and one for "entertainment." The most common words in the politics topic might be "President", "Congress", and "government", while the entertainment topic may be made up of words such as "movies", "television", and "actor". Importantly, words can be shared between topics; a word like "budget" might appear in both equally.

7.6 Topic Modelling Using R

R provides several packages that can be used for topic modeling, including the "tm" package, "topicmodels" package, and "lda" package.

Example-1

Load the necessary packages

library(tm)

library(topicmodels)

Loading data and text preprocessing

```
# load data
textdata<- base::readRDS(url("https://slcladal.github.io/data/sotu_paragraphs.rda", "rb"))
# load stopwords
english_stopwords<- readLines("https://slcladal.github.io/resources/stopwords_en.txt", encoding = "UTF-8")
# create corpus object
corpus <- Corpus(DataframeSource(textdata))
# Preprocessing chain
processedCorpus<- tm_map(corpus, content_transformer(tolower))
processedCorpus<- tm_map(processedCorpus, removeWords, english_stopwords)
processedCorpus<- tm_map(processedCorpus, removePunctuation, preserve_intra_word_dashes = TRUE)
processedCorpus<- tm_map(processedCorpus, removeNumbers)
processedCorpus<- tm_map(processedCorpus, stemDocument, language = "en")
processedCorpus<- tm_map(processedCorpus, stripWhitespace)
```

Convert the text data into a document-term matrix

```
dtm<- DocumentTermMatrix(corpus)
```

Perform topic modeling using the LDA algorithm

```
lda_model<- LDA(dtm, k = 5, method = "Gibbs", control = list(seed = 1234))
```

In the above code, we specified k=5 to indicate that we want to extract 5 topics from the text data. We also set the seed value to ensure reproducibility.

Print the top words in each topic

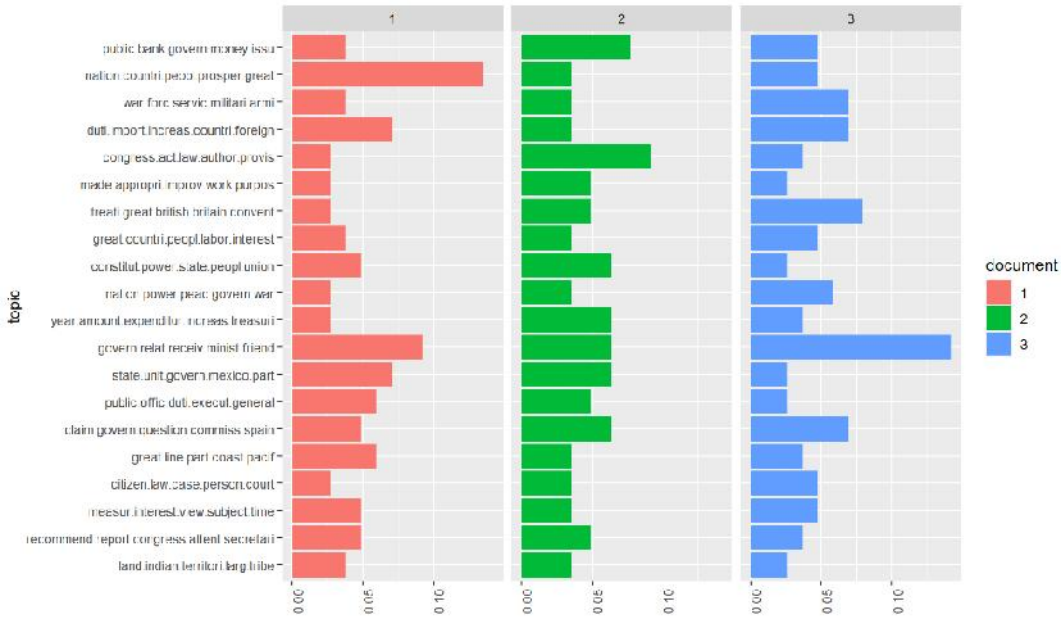
```
terms <- terms(lda_model, 10)
for (i in 1:5) {
  cat(paste("Topic", i, ": ", sep = ""))
  print(terms[, i])
}
```

This will print the top 10 words in each topic.

There are many other options and variations available for topic modeling in R, but this should provide a basic introduction to the process.

OUTPUT

t_1	t_2	t_3	t_4	t_5
trump	gopdebate	gopdebate	tco	gopdebate
gopdebate	fox	paul	https	candidates
donald	news	rand	https_tco	debate
donald_trump	fox_news	tcot	gopdebate	gop
cruz	trump	people	gopdebate_https	god
ted	foxnews	christie	tco_auhlnzaww	question
ted_cruz	party	rand_paul	auhlnzaww	amp
trump_gopdebate	debate	trump	youtube	real
president	amp	chris	tcot	presidential



Summary

Text analytics, also known as text mining, is the process of analyzing unstructured text data to extract meaningful insights and patterns. It involves applying statistical and computational techniques to text data to identify patterns and relationships between words and phrases, and to uncover insights that can help organizations make data-driven decisions.

Text analytics can be used for a wide range of applications, such as sentiment analysis, topic modeling, named entity recognition, and event extraction. Sentiment analysis involves identifying the sentiment of text data, whether it is positive, negative, or neutral. Topic modeling involves identifying topics or themes within a text dataset, while named entity recognition involves identifying and classifying named entities, such as people, organizations, and locations. Event extraction involves identifying and extracting events and their related attributes from text data.

Text analytics can provide valuable insights for businesses, such as identifying customer preferences and opinions, understanding market trends, and detecting emerging issues and concerns. It can also help organizations monitor their brand reputation, improve customer service, and optimize their marketing strategies.

Text analytics can be performed using various programming languages and tools, such as R, Python, and machine learning libraries. It requires a combination of domain knowledge, statistical and computational expertise, and creativity in identifying relevant patterns and relationships within text data.

In summary, text analytics is a powerful tool for analyzing and extracting insights from unstructured text data. It has a wide range of applications in business and can help organizations make data-driven decisions, improve customer service, and optimize their marketing strategies.

Keywords

Text Analytics: The process of analyzing unstructured text data to extract meaningful insights and patterns.

Sentiment Analysis: The process of identifying and extracting the sentiment of text data, whether it is positive, negative, or neutral.

Topic Modeling: The process of identifying topics or themes within a text dataset.

Named Entity Recognition: The process of identifying and classifying named entities, such as people, organizations, and locations, in a text dataset.

Event Extraction: The process of identifying and extracting events and their related attributes from text data.

Natural Language Processing (NLP): The use of computational techniques to analyze and understand natural language data.

Machine Learning: The use of algorithms and statistical models to learn patterns and insights from data.

Corpus: A collection of text documents used for analysis.

Term Document Matrix: A matrix representation of the frequency of terms in a corpus.

Word Cloud: A visual representation of the most frequently occurring words in a corpus, with larger font sizes indicating higher frequency.

SelfAssessment

1. What is text analytics?

A. The process of analyzing structured data
B. The process of analyzing unstructured text data
C. The process of analyzing both structured and unstructured data
D. The process of creating structured data from unstructured text data

2. What is sentiment analysis?

A. The process of identifying topics or themes within a text dataset
B. The process of identifying and classifying named entities in a text dataset
C. The process of identifying and extracting events and their related attributes from text data
D. The process of identifying and extracting the sentiment of text data

3. What is topic modeling?

A. The process of identifying and classifying named entities in a text dataset
B. The process of identifying and extracting events and their related attributes from text data
C. The process of identifying topics or themes within a text dataset
D. The process of identifying the sentiment of text data

4. What is named entity recognition?

A. The process of identifying topics or themes within a text dataset
B. The process of identifying and extracting events and their related attributes from text data
C. The process of identifying and classifying named entities in a text dataset
D. The process of identifying the sentiment of text data

5. What is event extraction?

A. The process of identifying topics or themes within a text dataset
B. The process of identifying and classifying named entities in a text dataset
C. The process of identifying and extracting events and their related attributes from text data
D. The process of identifying the sentiment of text data

6. What is the purpose of natural language processing (NLP)?

A. To analyze and understand natural language data
B. To create structured data from unstructured text data
C. To analyze and understand structured data
D. To transform data from one format to another

7. What is machine learning?
A. The use of computational techniques to analyze and understand natural language data
B. The use of algorithms and statistical models to learn patterns and insights from data
C. The process of identifying and extracting events and their related attributes from text data
D. The process of identifying and classifying named entities in a text dataset

8. What is a corpus in the context of text analytics?
A. A collection of structured data
B. A collection of unstructured text data
C. A visual representation of the most frequently occurring words in a dataset
D. A matrix representation of the frequency of terms in a dataset

9. Which R package is commonly used for text analytics?
A. ggplot2
B. dplyr
C. tidyr
D. tm

10. What does the function Corpus() do in R?
A. It creates a word cloud.
B. It creates a term-document matrix.
C. It creates a corpus of text documents.
D. It performs sentiment analysis.

11. Which function in R is used to preprocess text data by removing stop words and stemming?
A. tm_map()
B. corpus()
C. termFreq()
D. wordcloud()

12. What is a term-document matrix in R?
A. A matrix that represents the frequency of terms in a corpus.
B. A matrix that represents the frequency of documents in a corpus.
C. A matrix that represents the frequency of sentences in a corpus.
D. A matrix that represents the frequency of paragraphs in a corpus.

13. What does the function wordcloud() do in R?
A. It creates a term-document matrix.
B. It performs sentiment analysis.
C. It creates a word cloud.
D. It preprocesses text data.

14. Which R package is used for sentiment analysis?
A. ggplot2
B. dplyr

C. tidyr
D. SentimentAnalysis

15. What is the purpose of the function removeWords() in R?
A. To remove stop words from text data.
B. To remove numbers from text data.
C. To remove punctuation from text data.
D. To remove specific words from text data
.
16. What is the purpose of the function findAssocs() in R?
A. To find associations between words in a corpus.
B. To find associations between documents in a corpus.
C. To find associations between sentences in a corpus.
D. To find associations between paragraphs in a corpus.

17. What does the function findFreqTerms() do in R?
A. It finds the most frequent terms in a corpus.
B. It finds the most frequent documents in a corpus.
C. It finds the most frequent sentences in a corpus.
D. It finds the most frequent paragraphs in a corpus.

18. What is the purpose of the function LDA() in R?
A. To perform topic modeling.
B. To perform sentiment analysis.
C. To perform named entity recognition.
D. To perform event extraction.

19. Which R package is commonly used for topic modeling?
A. plyr
B. ggplot2
C. topicmodels
D. dplyr

20. What is a document-term matrix in topic modeling?
A. A matrix that represents the distribution of topics in each document
B. A matrix that represents the frequency of each term in each document
C. A matrix that represents the distribution of terms in each topic
D. A matrix that represents the probability of each topic appearing in each term

21. What is LDA in topic modeling?
A. A data analysis technique used to identify linear relationships between variables
B. A machine learning algorithm used for clustering data points
C. A statistical model used for predicting categorical outcomes
D. A probabilistic model used for discovering latent topics in a corpus of text data

22. What is the purpose of the control argument in the LDA function in R?

A. To specify the number of topics to extract from the text data
B. To set the seed value for reproducibility
C. To specify the algorithm to use for topic modeling
D. To set the convergence criteria for the model estimation

23. Which function in R can be used to print the top words in each topic after performing topic modeling?
A. topics()
B. top.words()
C. lda_terms()
D. terms()

Answers forSelf Assessment

l.	B	2.	D	3.	C	4.	C	5.	C
6.	A	7.	B	8.	B	9.	D	10.	C
11.	A	12.	A	13.	C	14.	D	15.	D
16.	A	17.	A	18.	A	19.	C	20.	B
21.	D	22.	B	23.	D				

Review Questions

1) What are the common steps involved in topic modeling using R?
2) How can you preprocess text data for topic modeling in R?
3) What is a document-term matrix, and how is it used in topic modeling?
4) What is LDA, and how is it used for topic modeling in R?
5) How do you interpret the output of topic modeling in R, including the document-topic matrix and top words in each topic?
6) What are some common techniques for evaluating the quality of topic modeling results in R?
7) Can you describe some potential applications of topic modeling in various fields, such as marketing, social sciences, or healthcare?
8) How can you visualize the results of topic modeling in R?
9) What are some best practices to follow when performing topic modeling in R, such as choosing the optimal number of topics and tuning model parameters?
10) What are some common challenges in text analytics and how can they be addressed?

Further Readings

"Text Mining with R: A Tidy Approach" by Julia Silge and David Robinson - This book provides a comprehensive introduction to text mining with R programming, covering topics such as sentiment analysis, topic modeling, and natural language processing.

Silge, J., & Robinson, D. (2017). Text mining with R: A tidy approach. O'Reilly Media, Inc.

Sarkar, D. (2019). Text analytics with Python: A practical real-world approach to gaining actionable insights from your data. Apress.

Manning, C. D., Raghavan, P., &Schütze, H. (2008). Introduction to information retrieval. Cambridge University Press.

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Unit 08: BusinessIntelligence

CONTENTS

Introduction

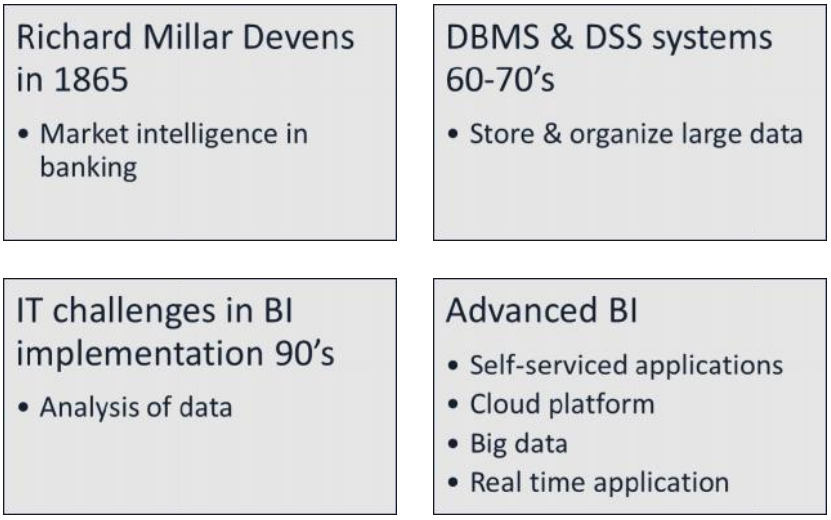
Decisions drive organizations. Making a good decision at a critical moment may lead to a more efficient operation, a more profitable enterprise, or perhaps a more satisfied customer. So, it only makes sense that the companies that make better decisions are more successful in the long run. That's where business intelligence comes in. Business intelligence is defined in various ways (our chosen definition is in the next section). For the moment, though, think of BI as using data about yesterday and today to make better decisions about tomorrow. Whether it's selecting the right criteria to judge success, locating and transforming the appropriate data to draw conclusions, or arranging information in a manner that best shines a light on the way forward, business intelligence makes companies smarter. It allows managers to see things more clearly, and permits them a glimpse of how things will likely be in the future.

Business intelligence is a flexible resource that can work at various organizational levels and various times — these, for example:

- A sales manager is deliberating over which prospects the account executives should focus on in the final-quarter profitability push
- An automotive firm's research-and-development team is deciding which features to include in next year's sedan
- The fraud department is deciding on changes to customer loyalty programs that will root out fraud without sacrificing customer satisfaction

BI (Business Intelligence) is a set of processes, architectures, and technologies that convert raw data into meaningful information that drives profitable business actions. It is a suite of software and services to transform data into actionable intelligence and knowledge.

Business Intelligence evolved over period as:



BI has a direct impact on organization's strategic, tactical and operational business decisions. BI supports fact-based decision making using historical data rather than assumptions and gut feeling.

BI tools perform data analysis and create reports, summaries, dashboards, maps, graphs, and charts to provide users with detailed intelligence about the nature of the business.

8.1 BI- Importance

Business intelligence plays very important role in businesses:

- Measurement: creating KPI (Key Performance Indicators) based on historic data
- Identify and set benchmarks for varied processes.
- With BI systems organizations can identify market trends and spot business problems that need to be addressed.
- BI helps on data visualization that enhances the data quality and thereby the quality of decision making.
- BI systems can be used not just by enterprises but SME (Small and Medium Enterprises)

8.2 BI – Advantages

Business Intelligence has following advantages:

1. Boost productivity

With a BI program, It is possible for businesses to create reports with a single click thus saves lots of time and resources. It also allows employees to be more productive on their tasks.

2. To improve visibility

BI also helps to improve the visibility of these processes and make it possible to identify any areas which need attention.

3. Fix Accountability

BI system assigns accountability in the organization as there must be someone who should own accountability and ownership for the organization's performance against its set goals.

4. It gives a bird's eye view:

BI system also helps organizations as decision-makers get an overall bird's eye view through typical BI features like dashboards and scorecards.

5. It streamlines business processes:

BI takes out all complexity associated with business processes. It also automates analytics by offering predictive analysis, computer modeling, benchmarking, and other methodologies.

6. It allows for easy analytics.

BI software has democratized its usage, allowing even nontechnical or non-analyst users to collect and process data quickly. This also allows putting the power of analytics in the hand's many people.

8.3 Business Intelligence - Disadvantages

Business Intelligence has the following disadvantages:

1. Cost:

Business intelligence can prove costly for small as well as medium-sized enterprises. The use of a such type of system may be expensive for routine business transactions.

2. Complexity:

Another drawback of BI is its complexity in the implementation of the data warehouse. It can be so complex that it can make business techniques rigid to deal with.

3. Limited use

Like all improved technologies, BI was first established keeping in consideration the buying competence of rich firms. Therefore, BI system is yet not affordable for many small and medium size companies.

4. Time-Consuming Implementation

It takes almost one and a half year for the data warehousing system to be completely implemented. Therefore, it is a time-consuming process.

8.4 Environmental Factors Affecting Business Intelligence

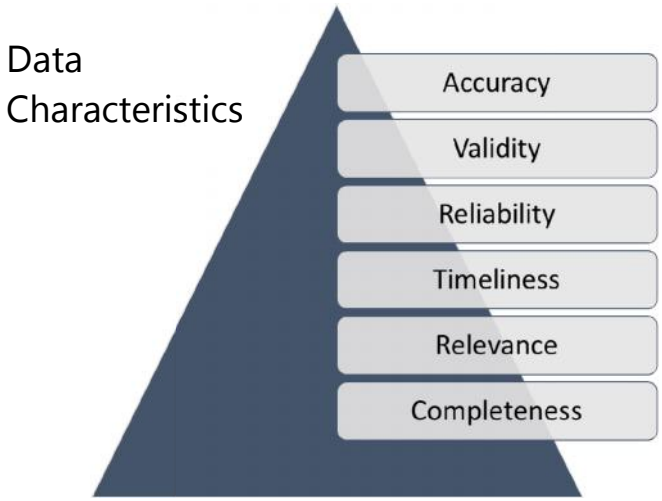
In order to understand how a holistic business intelligence strategy is possible, it's first necessary to understand the four environmental factors that can impact such a strategy.

The four areas can be broken down into two main categories: internal and external. Internal factors are those that the company has direct control over, while external factors are out of the company's control but can still impact the business intelligence strategy.

The four environmental factors are:

Data:

This is the most important factor in business intelligence, as without data there is nothing to analyze or report on. Data can come from a variety of sources, both internal and external to the organization.



Business intelligence thrives on data. Without data, there is nothing to analyze or report on. Data can come from a variety of sources, both internal and external to the organization. Internal data sources can include things like transaction data, customer data, financial data, and operational data. External data sources can include public records, social media data, market research data, and competitor data.

The data gathering process must be designed to collect the right data from the right sources. Once the data is gathered, it must then be cleaned and standardized so that it can be properly analyzed.

In the BI environment, data is king. All other factors must be aligned in order to support the data and help it reach its full potential.

People:

The people involved in business intelligence play a critical role in its success. From the data analysts who gather and clean the data, to the business users who interpret and use the data to make decisions, each person involved must have a clear understanding of their role in the process.

The people involved in business intelligence play a critical role in its success. From the data analysts who gather and clean the data, to the business users who interpret and use the data to make decisions, each person involved must have a clear understanding of their role in the process.

The data analysts need to be able to collect data from all relevant sources, clean and standardize the data, and then load it into the BI system. The business users need to be able to access the data, understand what it means, and use it to make decisions.

This can take many forms, but a key component is data literacy: the ability to read, work with, analyze, and argue with data. Data literacy is essential for business users to be able to make decisions based on data.

In a successful business intelligence environment, people are trained and empowered to use data to make decisions.

Processes:

Database Types

Relational Database
Object-Oriented Database
Distributed Database
NoSQL Database
Graph Database
Cloud Database
Centralization Database
Operational Database

The processes used to gather, clean, and analyze data must be well-designed and efficient in order to produce accurate and timely results.

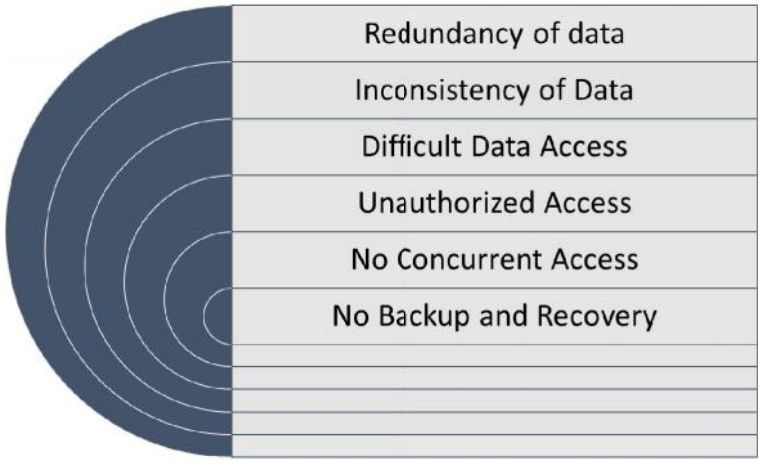
The processes used to gather, clean, and analyze data must be well-designed and efficient in order to produce accurate and timely results. The data gathering process must be designed to collect the right data from the right sources. Once the data is gathered, it must then be cleaned and standardized so that it can be properly analyzed.

The data analysis process must be designed to answer the right questions. The results of the data analysis must be presented in a way that is easy to understand and use

Technology:

The technology used to support business intelligence must be up to date and able to handle the volume and complexity of data.

The technology used to support business intelligence must be up to date and able to handle the volume and complexity of data. The BI system must be able to collect data from all relevant sources, clean and standardize the data, and then load it into the system. The system must be able to support the data analysis process and provide easy-to-use tools for business users to access and analyze the data.



You want your BI technology to offer features such as self-service analytics, predictive analytics, and social media integration. However, the technology must be easy enough to use that business users don't need a Ph.D. to use it. In a successful business intelligence environment, the technology is easy to use and provides the features and functionality needed to support the data gathering, analysis, and reporting process.

8.5 Common Mistakes in Implementing Business Intelligence

While business intelligence can be extremely beneficial to companies, there are some common mistakes that companies make when it comes to their business intelligence environment.

1. Not understanding the different types of data

There are three different types of data that need to be considered when gathering data for business intelligence:

Structured data is data that is organized in a predefined format. This type of data is typically stored in a database and can be easily accessed and analyzed.

Unstructured data is data that is not organized in a predefined format. This type of data includes things like emails, social media posts, and images.

Semi-structured data is data that is partially structured and partially unstructured. This type of data includes things like XML files and JSON files.

Companies need to understand the different types of data and how to best gather and analyze each type.

2. Not gathering data from all relevant sources

In order to make accurate decisions, companies need to gather data from all relevant sources. This includes internal data sources like financial reports and customer databases as well as external data sources like news articles and social media posts.

3. Not cleaning or standardizing the data

Once the data has been gathered, it needs to be cleaned and standardized. This includes things like removing duplicates, standardizing formats, and filling in missing values.

4. Not loading the data into the BI system effectively

Once the data has been cleaned and standardized, it needs to be loaded into the BI system. This can be done manually or through an automated process.

5. Not analyzing the data properly

Once the data is in the BI system, it needs to be analyzed. This includes things like creating reports, running queries, and building dashboards.

6. Not making decisions related to the data

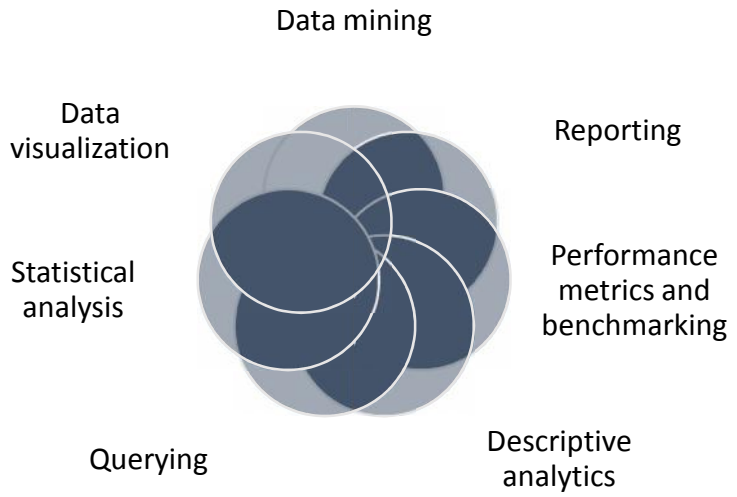
Once the data has been analyzed, it needs to be used to make decisions. This includes things like setting prices, launching new products, and hiring new employees.

7. Not empowering people to use data

In order for business intelligence to be successful, people need to be empowered to use data to make decisions. This includes training people on how to use the BI system, giving them access to the data, and encouraging them to use data when making decisions.

8.6 Business Intelligence – Applications

BI has vide applications in business world. Some of the examples are as followed:



OLTP System

In an Online Transaction Processing (OLTP) system information that could be fed into product database could be

- add a product line
- change a product price

Correspondingly, in a Business Intelligence system query that would be executed for the product subject area could be did the addition of new product line or change in product price increase revenues.

In an advertising database of OLTP system query that could be executed

- Changed in advertisement options
- Increase radio budget

Correspondingly, in BI system query that could be executed would be how many new clients added due to change in radio budget

In OLTP system dealing with customer demographic data bases data that could be fed would be

- increase customer credit limit
- change in customer salary level

Correspondingly in the OLAP system query that could be executed would be can customer profile changes support higher product price

Hotel Industry:

A hotel owner uses BI analytical applications to gather statistical information regarding average occupancy and room rate. It helps to find aggregate revenue generated per room.

It also collects statistics on market share and data from customer surveys from each hotel to decides its competitive position in various markets. By analyzing these trends year by year, month by month and day by day helps management to offer discounts on room rentals.

Banking

A bank gives branch managers access to BI applications. It helps branch manager to determine who are the most profitable customers and which customers they should work on.

The use of BI tools frees information technology staff from the task of generating analytical reports for the departments. It also gives department personnel access to a richer data source

8.7 Recent Trends in Business Intelligence

The following are some business intelligence and analytics trends that you should be aware of.

Artificial Intelligence

Gartner' report indicates that AI and machine learning now take on complex tasks done by human intelligence. This capability is being leveraged to come up with real-time data analysis and dashboard reporting.

Collaborative BI

BI software combined with collaboration tools, including social media, and other latest technologies enhance the working and sharing by teams for collaborative decision making.

Embedded BI

Embedded BI allows the integration of BI software or some of its features into another business application for enhancing and extending it's reporting functionality.

Cloud Analytics

BI applications will be soon offered in the cloud, and more businesses will be shifting to this technology. As per their predictions within a couple of years, the spending on cloud-based analytics will grow 4.5 times faster.

8.8 Similar BI systems

Some of the BI systems already exist and widely used in business. These are:

Decision Support Systems

A decision support system (DSS) is a computer program application used to improve a company's decision-making capabilities. It analyzes large amounts of data and presents an organization with the best possible options available.

Decision support systems bring together data and knowledge from different areas and sources to provide users with information beyond the usual reports and summaries. This is intended to help people make informed decisions.

Typical information a decision support application might gather and present include the following:

- comparative sales figures between one week and the next;
- projected revenue figures based on new product sales assumptions; and
- the consequences of different decisions.

A decision support system is an informational application as opposed to an operational application. Informational applications provide users with relevant information based on a variety of data sources to support better informed decision-making. Operational applications, by contrast, record the details of business transactions, including the data required for the decision-support needs of a business.

Decision support systems can be broken down into categories, each based on their primary sources of information.

Data-driven DSS

A data-driven DSS is a computer program that makes decisions based on data from internal databases or external databases. Typically, a data-driven DSS uses data mining techniques to discern trends and patterns, enabling it to predict future events. Businesses often use data-driven DSSes to help make decisions about inventory, sales and other business processes. Some are used to help make decisions in the public sector, such as predicting the likelihood of future criminal behavior.

Model-driven DSS

Built on an underlying decision model, model-driven decision support systems are customized according to a predefined set of user requirements to help analyze different scenarios that meet

these requirements. For example, a model-driven DSS may assist with scheduling or developing financial statements.

Communication-driven and group DSS

A communication-driven and group decision support system uses a variety of communication tools -- such as email, instant messaging or voice chat -- to allow more than one person to work on the same task. The goal behind this type of DSS is to increase collaboration between the users and the system and to improve the overall efficiency and effectiveness of the system.

Knowledge-driven DSS

In this type of decision support system, the data that drives the system resides in a knowledge base that is continuously updated and maintained by a knowledge management system. A knowledge-driven DSS provides information to users that is consistent with a company's business processes and knowledge.

Document-driven DSS

A document-driven DSS is a type of information management system that uses documents to retrieve data. Document-driven DSSes enable users to search webpages or databases, or find specific search terms. Examples of documents accessed by a document-driven DSS include policies and procedures, meeting minutes and corporate records.

Enterprise Resource System

An Enterprise Information System (EIS) is any kind of information system which improves the functions of enterprise business processes by integration. This means typically offering high quality of service, dealing with large volumes of data and capable of supporting some large and possibly complex organization or enterprise. An EIS must be able to be used by all parts and all levels of an enterprise.

The word enterprise can have various connotations. Frequently the term is used only to refer to very large organizations such as multi-national companies or public-sector organizations.

Enterprise information systems provide a technology platform that enables organizations to integrate and coordinate their business processes on a robust foundation. An EIS is currently used in conjunction with customer relationship management and supply chain management to automate business processes. An enterprise information system provides a single system that is central to the organization that ensures information can be shared across all functional levels and management hierarchies.

An EIS can be used to increase business productivity and reduce service cycles, product development cycles and marketing life cycles. It may be used to amalgamate existing applications. Other outcomes include higher operational efficiency and cost savings.

Financial value is not usually a direct outcome from the implementation of an enterprise information system.

Enterprise systems create a standard data structure and are invaluable in eliminating the problem of information fragmentation caused by multiple information systems within an organization. An EIS differentiates itself from legacy systems in that it is self-transactional, self-helping and adaptable to general and specialist conditions. Unlike an enterprise information system, legacy systems are limited to department-wide communications.

A typical enterprise information system would be housed in one or more data centers, would run enterprise software, and could include applications that typically cross organizational borders such as content management systems

Management Information System

Management information systems (MIS) are an organized method of collecting information from various sources, compiling it, and presenting it in a readable format. It helps business leaders and managers make strategic management decisions.

Today's management information systems rely heavily on technology to compile and present data. Major components of a Management Information System are:

People: People prepare and analyze MIS to achieve organizational goals.

Data: Day-to-day business transactions of an organization.

Hardware: Input and output devices like keyboard, mouse, monitor, printer, etc., help in data input and display information.

Software and Business Processes:MIS depends on software and business processes such as MS Office, Banking Software, ERP systems, CRM systems, etc.

The general characteristics of an MIS are:

- Use a variety of internal data sources.
- Provide reports on the routine operations of an organization.
- Allow users to develop custom reports, such as detailed reports.
- Provide a variety of different reports, both scheduled and on demand.
- Must be accurate and avoid including estimates or probable expenses.
- Provide reports in various formats, including hard copies and electronic copies.
- The information must be relevant for making a strategic decision.

8.9 Business Intelligence Applications

1. Tableau: Tableau is a data visualization and analytics solution that assists enterprises in making data-driven business decisions. It blends information from a wide range of sources to deliver actionable, real-time insights.

2. Power BI: Microsoft Power BI is an analytics tool that assists in reporting, data mining and data visualization to provide business insights. Through Power BI's simple interface, businesses can connect to a variety of data sources and create their own dashboards and reports.

3. Qlik Sense: Qlik Sense is a self-service data analytics software that enhances human intuition with the power of artificial intelligence to enable better data-driven business decisions. It allows organizations to explore their data and create intuitive and compelling visualizations.

4. Apache Spark:Apache Spark is an open source unified analytics software for distributed, rapid processing. It distributes data across clusters in real time to produce market-leading speeds.

5. Oracle: Oracle Analytics Cloud is an AI-powered solution that provides robust reporting and analytics features to businesses of all sizes. It offers a strong selection of reporting and analytics features from the convenience of the cloud.

ORACLE ANALYTICS CLOUD

6. IBM Cognos: IBM Cognos Analytics is a self-service, web-based analytics platform which empowers users of all skill levels to explore data through reporting, data analytics, KPI monitoring, events and metrics.

COGNOS

Summary

- Business intelligence (BI) refers to capabilities that enable organizations to make better decisions, take informed actions, and implement more-efficient business processes.
- Data visualizations are used to discover unknown facts and trends. You can see visualizations in the form of line charts to display change over time. Bar and column charts are useful for observing relationships and making comparisons. A pie chart is a great way to show parts of a whole. And maps are the best way to share geographical data visually.
- To craft an effective data visualization, you need to start with clean data that is well-sourced and complete. After the data is ready to visualize, you need to pick the right chart.

Keywords

Business Intelligence: Business intelligence (BI) is a technology-driven process for analyzing data and delivering actionable information that helps executives, managers and workers make informed business decisions.

Data: In computing, data is information that has been translated into a form that is efficient for movement or processing.

Data Visualization: Data and information visualization is an interdisciplinary field that deals with the graphic representation of data and information.

Data analysis: Data Analysis. Data Analysis is the process of systematically applying statistical and/or logical techniques to describe and illustrate, condense and recap, and evaluate data.

SelfAssessment

1. What are advantages of DBMS over file system?

A. Redundancy of data
B. Inconsistency of Data
C. Difficult Data Access
D. All of the above

2. Which are advantages of Business Intelligence?

A. Boost productivity
B. To improve visibility
C. Fix Accountability
D. All of the above

3. Which of the following statement is true about Business Intelligence?

A. BI convert raw data into meaningful information

B. BI has a direct impact on organization's strategic, tactical and operational business decisions.
C. BI tools perform data analysis and create reports, summaries, dashboards, maps, graphs, and charts
D. All of the above

4. ___ is a category of applications and technologies for presenting and analyzing corporate and external data.
A. MIS
B. DIS
C. EIS
D. CIS

5. Which of the following is not a data visualization tool?
A. Tablue
B. Cluvio
C. Microsoft Word
D. Domo

6. Data visualization is also an element of the broader _____.
A. deliver presentation architecture
B. data presentation architecture
C. dataset presentation architecture
D. data process architecture

7. Which of the intricate techniques is not used for data visualization?
A. Bullet Graphs
B. Bubble Clouds
C. Fever Maps
D. Heat Maps

8. Which method shows hierarchical data in a nested format?
A. Treemaps
B. Scatter plots
C. Population pyramids
D. Area charts

9. Which one of the following is most basic and commonly used techniques?
A. Line charts
B. Scatter plots
C. Population pyramids
D. Area charts

10. The best feature Tableau are except_____-
A. Collaboration of data
B. Data Blending

C. Real time analysis
D. Data is more small and fit

11. Where can we apply global filters?
A. Dashboards
B. Stories
C. Sheets
D. All of the above

12. _____ is the representation of data through use of common graphics, such as charts, plots, infographics, and even animations.
A. Data visualization
B. Data
C. Tableau
D. None of above

13. Who is the parent company of Tableau?
A. Salesforce
B. Workday
C. Microsoft
D. Google

14. What are the file extensions in Tableau ?
A. Tableau Packaged Workbook (.twbx)
B. Tableau Data Source(.tds)
C. Tableau Workbook (.twb)
D. All of the above

15. Power BI is a product of_____
A. Facebook
B. Oracle
C. Microsoft
D. SAP

Answers for SelfAssessment

l. D	2. D	3. D	4. C	5. A
6. B	7. C	8. A	9. A	10. D
11. D	12. A	13. A	14. D	15. C

Review Questions

1. What do you mean by data visualization?
2. What is Business Intelligence?
3. Discuss some of the applications of Business Intelligence.

4. What is the difference between data and data visualization?
5. Explain Types of Data Visualizations Elements.
6. What is advantage of DBMS over file system?

Further Readings

- Business Intelligence, A Comprehensive Approach to Information Needs, Technologies and Culture, Rimvydas Skyrius, Springer International Publishing
- Communication Data With Tablue, Ben Jones, O' Reilly Publications

Web Links

- https://powerbi.microsoft.com/en-us/what-is-business-intelligence/
- https://www.tableau.com/resource/business-intelligence

Unit 09: Data Visualization

CONTENTS

Introduction

Data visualization is the process of presenting data in a graphical or visual format that enables users to gain insights and understand patterns, trends, and relationships that might not be immediately apparent from the raw data. Data visualization is an essential component of data analytics and helps users to make informed decisions based on the insights gained from the data.

The benefits of data visualization include:

- Improved understanding

  Data visualization helps to simplify complex data and present it in a way that is easy to understand. This enables users to gain insights and make better decisions based on the data.

- Identification of patterns and trends

  Data visualization enables users to identify patterns and trends that might not be immediately apparent from the raw data. This can help to identify opportunities and potential problems.

- Communication

  Data visualization can be used to communicate complex data to a wide range of audiences, including non-technical users. This can help to build consensus and support for data-driven decision making.

9.1 Data Visualization Types

There are several types of data visualization techniques, including:

- Charts and graphs

  Charts and graphs are one of the most common types of data visualization. They are used to represent data in a visual format, such as bar charts, line charts, and pie charts.

- Maps

Maps are used to visualize geographic data, such as the distribution of population or the location of stores.

- Infographics

  Infographics are visual representations of information that combine text, images, and data to present complex information in a simplified and easy-to-understand format.

- Dashboards

  Dashboards are used to provide an overview of key performance indicators (KPIs) and other important metrics in real-time.

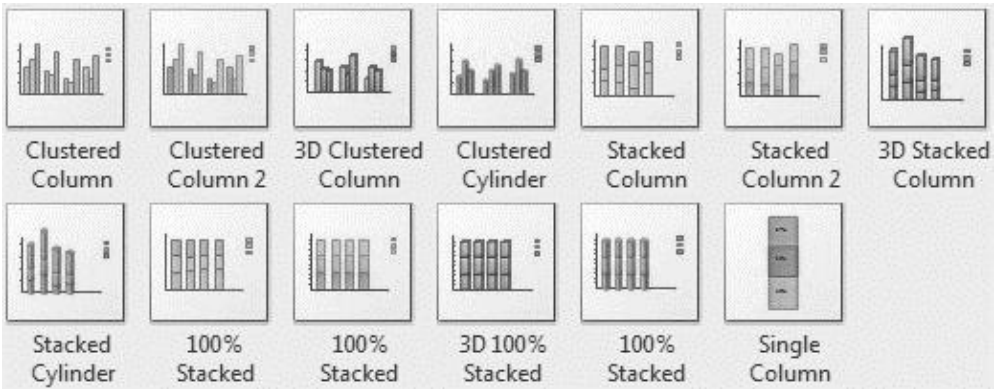
The choice of data visualization technique depends on the nature of the data and the intended audience. Effective data visualization requires careful consideration of the data, the audience, and the message being communicated.

9.2 Charts and Graphs

Power BI is a powerful data visualization tool that offers a wide range of charts and graphs to help users present and analyze their data. Here are some of the most common types of graphs in Power BI:

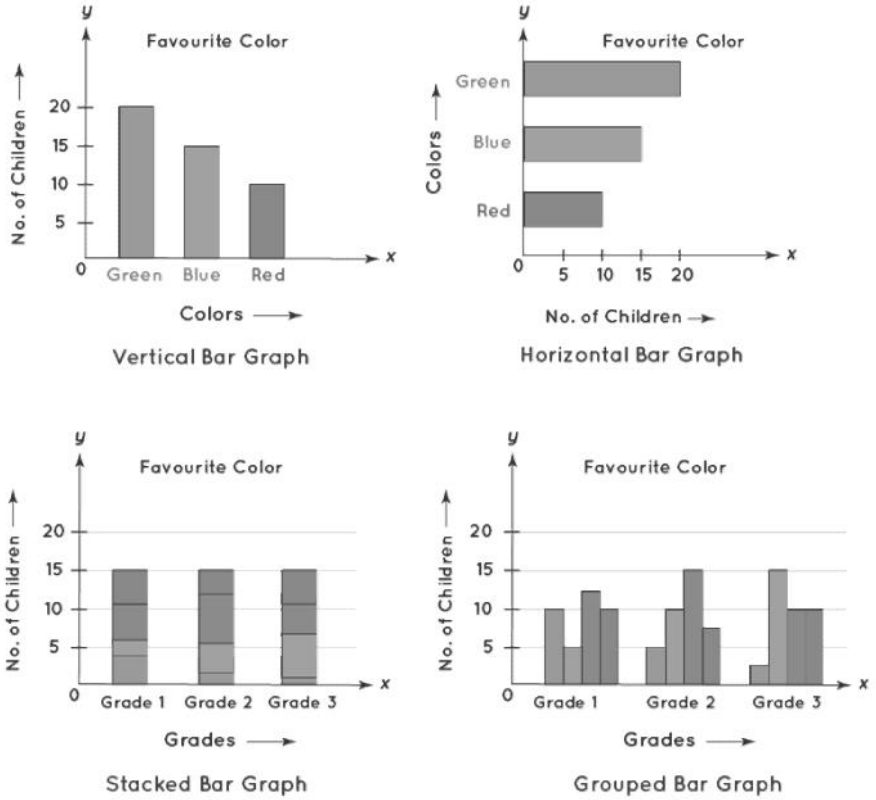
Column Chart

A column chart is used to compare data across categories using vertical bars. It is useful for showing changes in data over time or comparing data across different categories.



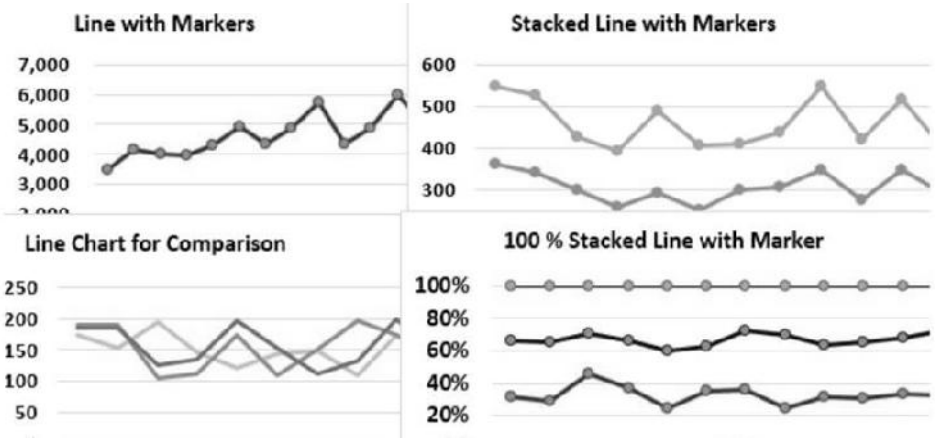
Bar Chart

A bar chart is similar to a column chart, but uses horizontal bars instead of vertical bars. It is useful for comparing data across different categories.



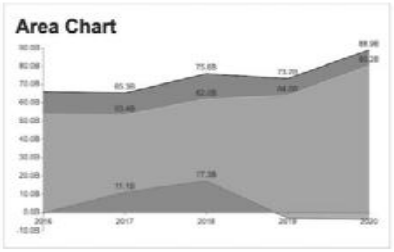
Line Chart

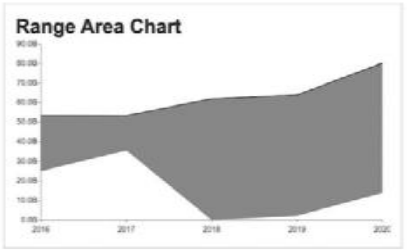
A line chart is used to show trends in data over time. It is useful for analyzing data that changes continuously over time.

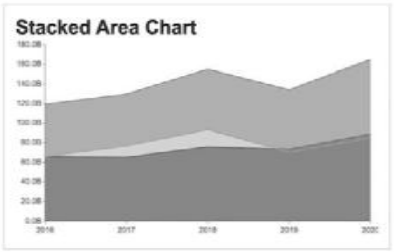


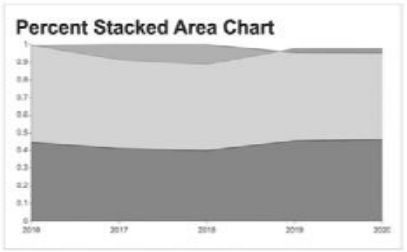
Area Chart

An area chart is similar to a line chart, but the area under the line is filled with color. It is useful for showing the total value of data over time.







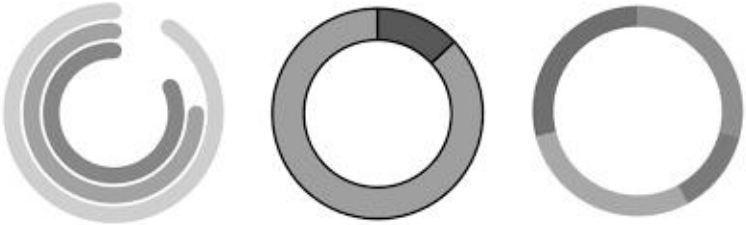


Pie Chart

A pie chart is used to show the relative proportions of data in different categories. It is useful for showing the composition of a whole.

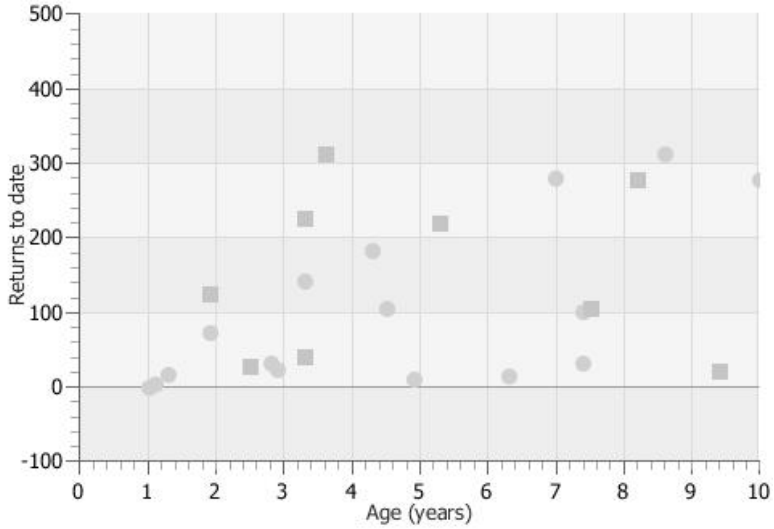
Donut Chart

A donut chart is similar to a pie chart, but has a hole in the center. It is useful for showing the relative proportions of data in different categories.



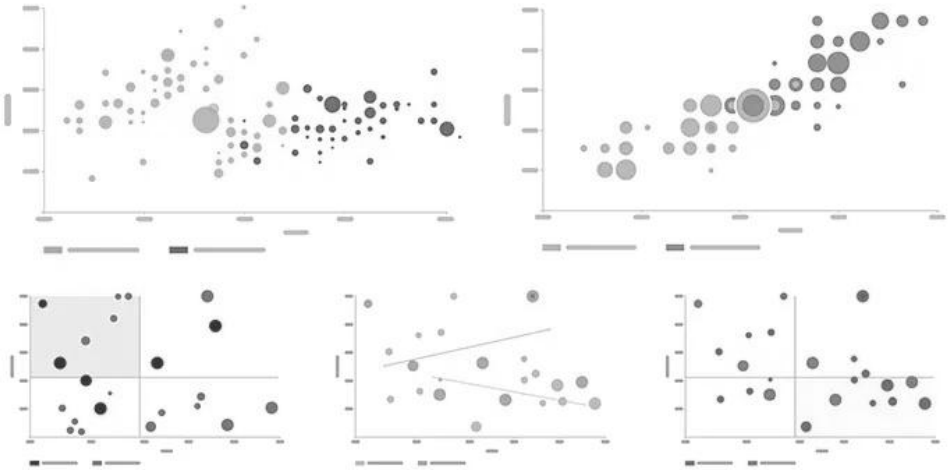
Scatter Chart

A scatter chart is used to show the relationship between two variables. It is useful for analyzing data that has a strong correlation.



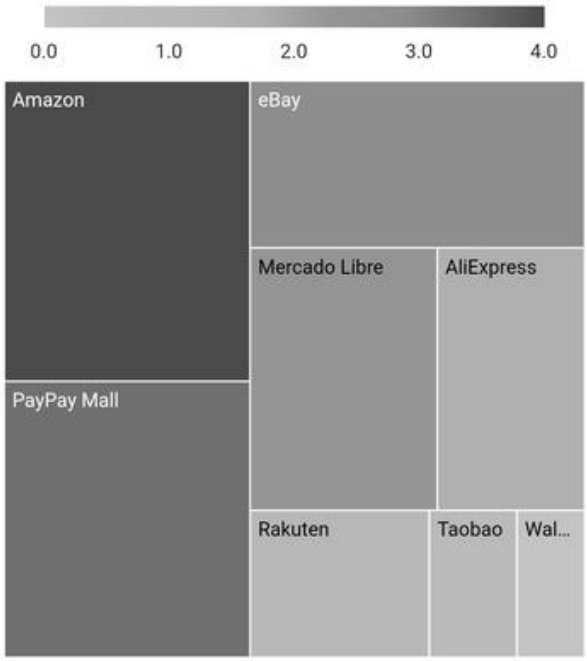
Bubble Chart

A bubble chart is similar to a scatter chart, but the size of the data points is proportional to a third variable. It is useful for showing the relationship between three variables.



Treemap Chart

A treemapchart is used to show hierarchical data using nested rectangles. It is useful for showing the relative proportions of data in different categories.



These are just a few examples of the many types of graphs that can be created in Power BI. The choice of graph depends on the type of data being analyzed and the insights that need to be communicated to the audience.

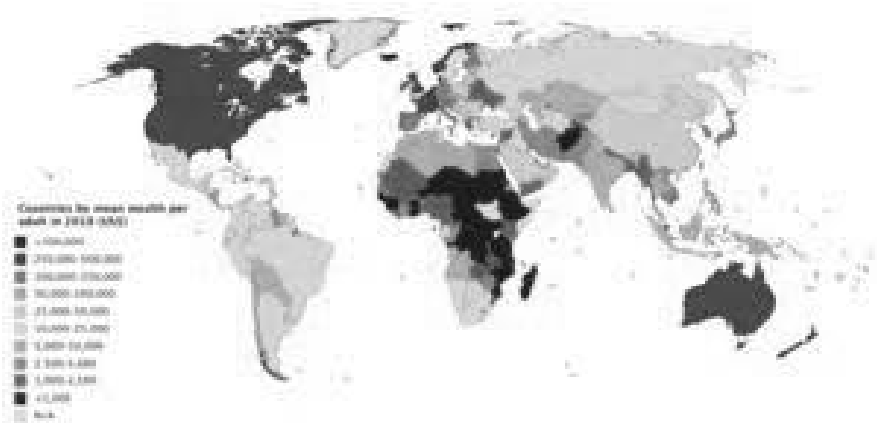
9.3 Data Visualization on Maps

Data visualization on maps is a powerful tool for displaying and analyzing spatial data. It enables users to quickly identify patterns, trends, and relationships that may be difficult to detect in raw data.

There are several ways to visualize data on maps, depending on the type of data and the purpose of the visualization. Here are some common techniques:

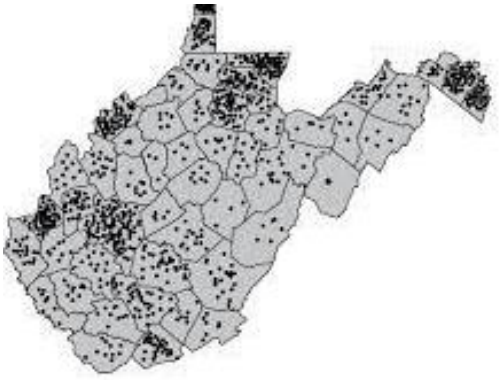
Choropleth maps

These maps use color to represent different values of a variable across a geographic area. For example, a choropleth map of population density would use shades of color to show areas with higher or lower population densities.



Dot density maps

These maps use dots to represent individual data points. For example, a dot density map of crime incidents would use dots to show the location of each incident.



Proportional Symbol Maps

These maps use different sized symbols to represent different values of a variable across a geographic area. For example, a proportional symbol map of earthquake magnitudes would use larger symbols to represent stronger earthquakes.

Heat maps

These maps use color or shading to represent the density of data points within a geographic area. For example, a heat map of restaurant locations would use color to show areas with more or fewer restaurants.

There are many software tools available for creating data visualizations on maps, including GIS software like ArcGIS and QGIS, as well as web-based tools like Google Maps and Tableau. When creating data visualizations on maps, it's important to consider factors like data accuracy, scale, and projection to ensure that the map accurately represents the data being visualized.

9.4 Infographics

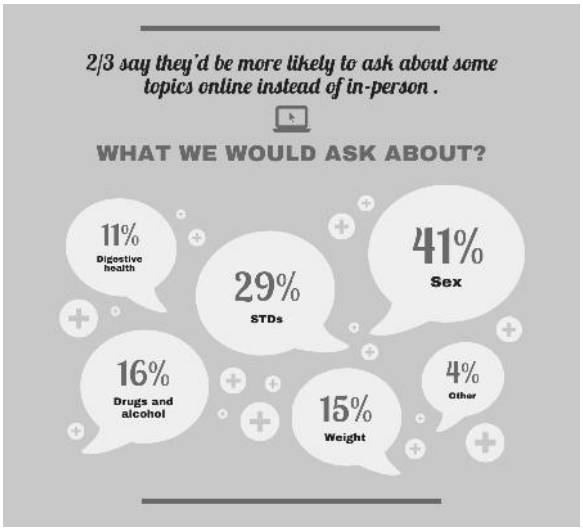
Infographics are visual representations of information, data, or knowledge that present complex information in a clear and concise way. Infographics can take many forms, including charts, graphs, diagrams, maps, and illustrations, and are used to communicate information quickly and effectively to a wide range of audiences.

The primary purpose of an infographic is to convey information in a way that is easy to understand and visually appealing. This is achieved by using a combination of colors, typography, icons, and images to create a visually striking design that draws the viewer's attention and makes the information more engaging and memorable.

Some common types of infographics include:

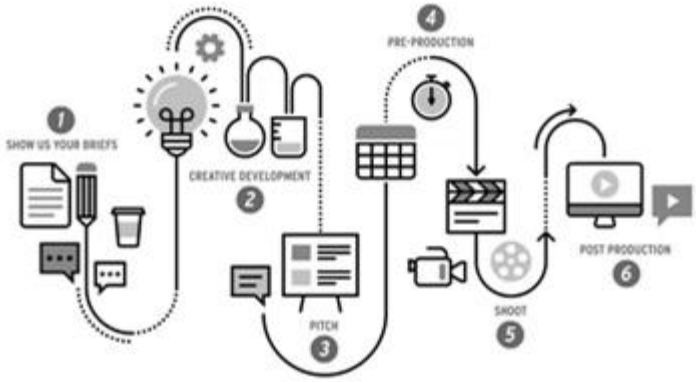
Statistical infographics

These infographics are used to present numerical data in a visual way. They can include bar charts, line graphs, pie charts, and other types of data visualization.



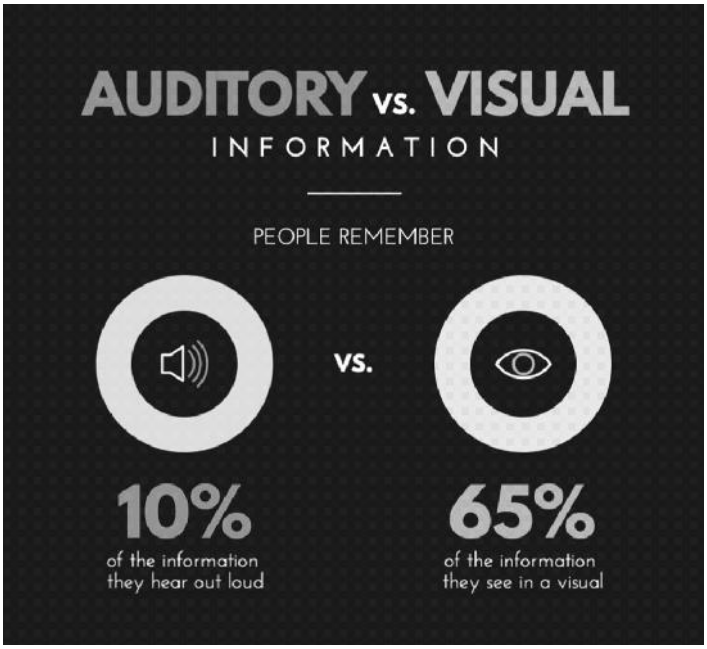
Process infographics

These infographics show the steps or stages involved in a process or workflow. They can include flowcharts, diagrams, and timelines.



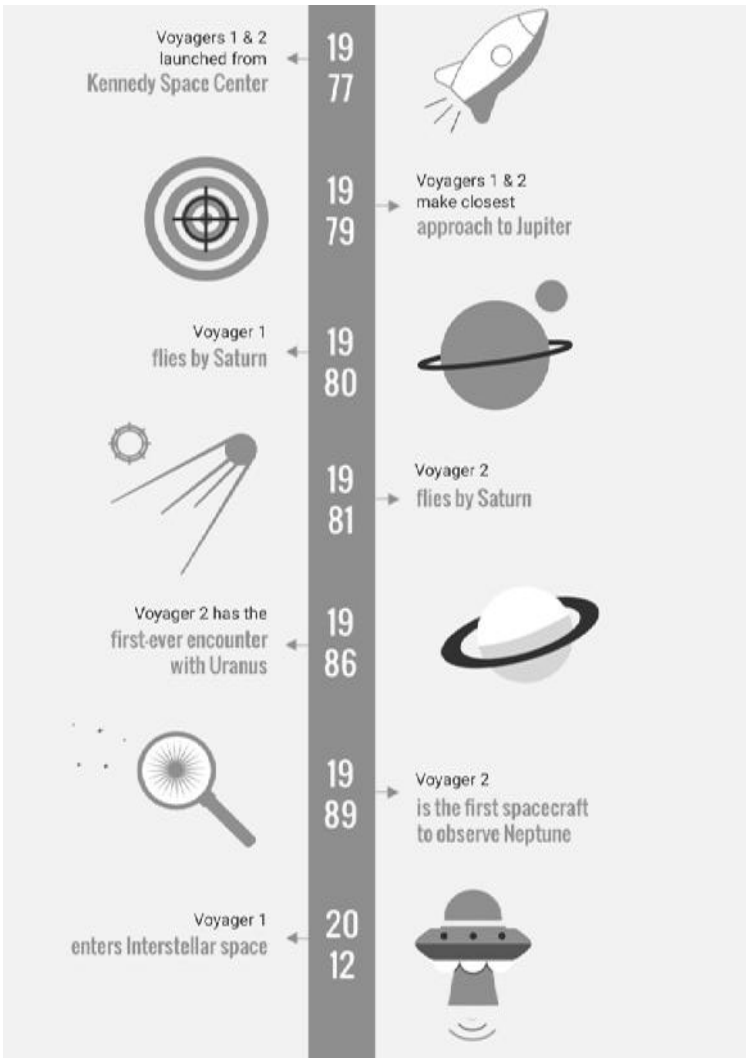
Comparison infographics

These infographics are used to compare two or more things, such as products, services, or ideas. They can include tables, graphs, and side-by-side comparisons.



Timeline Infographics

These infographics show a sequence of events or the history of a particular topic. They can include a chronological timeline, a map, or a visual representation of a timeline.



Infographics can be created using a variety of tools, including graphic design software like Adobe Illustrator or Inkscape, online infographic tools like Canva or Piktochart, or even using simple tools like PowerPoint or Google Slides. When creating an infographic, it's important to keep the design simple, use clear and concise language, and ensure that the information is accurate and relevant to the intended audience.

9.5 Dashboards

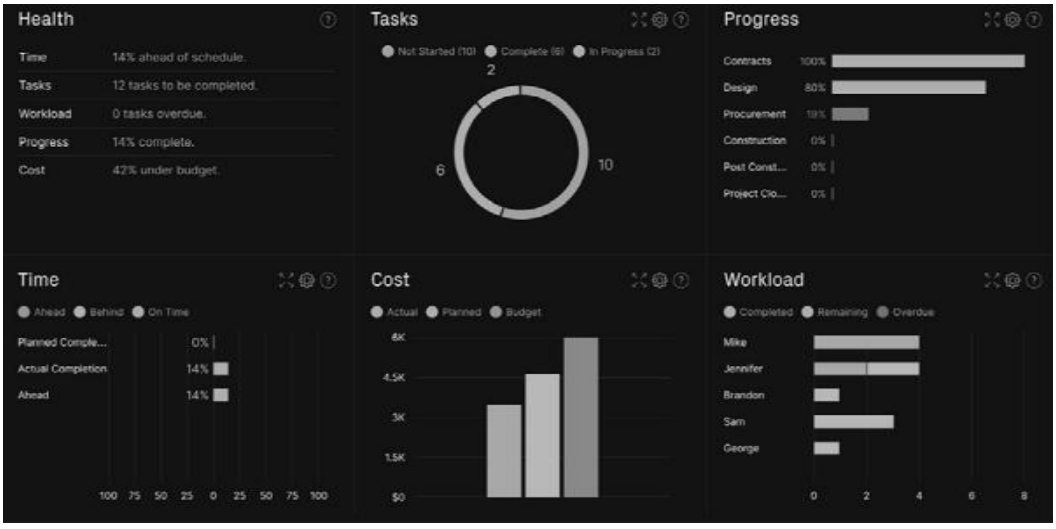
Dashboards are visual representations of data that provide users with an overview of key performance indicators (KPIs) and metrics relevant to a specific business or organization. Dashboards typically display data in real-time or near real-time and allow users to monitor progress, identify trends, and make informed decisions based on the data.

Dashboards can be customized to display a wide range of data, including financial metrics, operational metrics, marketing metrics, and customer metrics. They can also be designed to display data at different levels of granularity, from high-level summaries to detailed reports.

Some common features of dashboards include:

- **Data visualizations:** Dashboards typically include charts, graphs, and other visual representations of data to make it easy for users to understand trends and identify patterns.
- **KPIs and metrics:** Dashboards are designed to display key performance indicators and metrics relevant to a specific business or organization. These metrics are often displayed in a clear, concise format to make it easy for users to monitor progress and identify areas for improvement.
- **Real-time updates:** Dashboards are often designed to display data in real-time or near real-time, providing users with up-to-date information that can be used to make informed decisions.
- **Customization:** Dashboards can be customized to meet the specific needs of a business or organization. This includes the ability to choose which metrics are displayed, how the data is visualized, and the level of granularity of the data.

Dashboards can be created using a variety of tools, including business intelligence software like Tableau, Power BI, or Google Data Studio, as well as web-based dashboard solutions like Klipfolio or DashThis. When creating a dashboard, it's important to consider the needs of the intended audience, the types of data that will be displayed, and the design elements that will make the dashboard easy to use and visually appealing.



9.6 Creating Dashboards in PowerBI

Creating a dashboard in Power BI involves several steps:

1. Connect to data
   The first step is to connect to the data sources you want to include in your dashboard. Power BI can connect to a wide variety of data sources, including Excel files, databases, and web services.
2. Import data
   Once you've connected to your data sources, you'll need to import the data into Power BI. This involves selecting the tables or queries you want to use and importing them into Power BI's data model.
3. Create visualizations
   With your data imported into Power BI, you can begin creating visualizations. This involves selecting the type of visualization you want to create, such as a bar chart or a pie chart, and configuring it to display the data you want.
4. Create reports
   Once you've created your visualizations, you can combine them into reports. Reports are a collection of visualizations that are designed to provide more detailed information on a specific topic.
5. Create a dashboard
   With your reports created, you can combine them into a dashboard. Dashboards are a high-level summary of your data that are designed to provide a quick overview of your key performance indicators (KPIs) and metrics.
6. Customize your dashboard
   You can customize your dashboard by adding visualizations, filters, and other elements. This includes changing the layout of the dashboard, selecting which visualizations to display, and configuring the filters to allow users to drill down into the data.
7. Publish your dashboard
   Once your dashboard is complete, you can publish it to the Power BI service. This allows others to view your dashboard and interact with your data.

Creating a dashboard in Power BI requires some knowledge of data modeling, data visualization, and dashboard design. However, Power BI provides a user-friendly interface and a wide range of resources to help you get started. With some practice, you can create powerful dashboards that provide valuable insights into your data.

Summary

- Data visualization is important for almost every career. It can be used by teachers to display student test results, by computer scientists exploring advancements in artificial intelligence (AI) or by executives looking to share information with stakeholders.
- Data visualizations are used to discover unknown facts and trends. You can see visualizations in the form of line charts to display change over time. Bar and column charts are useful for observing relationships and making comparisons. A pie chart is a great way to show parts of a whole. And maps are the best way to share geographical data visually.
- To craft an effective data visualization, you need to start with clean data that is well-sourced and complete. After the data is ready to visualize, you need to pick the right chart.

Keywords

Infographics: Infographics are visual representations of information, data, or knowledge that present complex information in a clear and concise way.

Data: In computing, data is information that has been translated into a form that is efficient for movement or processing.

Data Visualization: Data and information visualization is an interdisciplinary field that deals with the graphic representation of data and information.

Dashboards: Dashboards are visual representations of data that provide users with an overview of key performance indicators (KPIs) and metrics relevant to a specific business or organization.

SelfAssessment

1. What is true about Data Visualization?

A. Data Visualization is used to communicate information clearly and efficiently to users by the usage of information graphics such as tables and charts.

B. Data Visualization helps users in analyzing a large amount of data in a simpler way.

C. Data Visualization makes complex data more accessible, understandable, and usable.

D. All of the above

2. Which are pros of data visualization?

A. It can be accessed quickly by a wider audience.

B. It can misrepresent information

C. It can be distracting

D. None of the above

3. Data can be visualized using?

A. graphs

B. charts

C. maps

D. All of the above

4. Which are cons of data visualization?

A. It conveys a lot of information in a small space.

B. It makes your report more visually appealing.

C. visual data is distorted or excessively used.

D. None of the above

5. Which of the following is not a data visualization tool?

A. Tablue

B. Cluvio

C. Microsoft Word

D. Domo

6. Data visualization is also an element of the broader _____.

A. deliver presentation architecture

B. data presentation architecture

C. dataset presentation architecture

D. data process architecture

7. Which of the intricate techniques is not used for data visualization?

A. Bullet Graphs

B. Bubble Clouds
C. Fever Maps
D. Heat Maps

8. Which method shows hierarchical data in a nested format?
A. Treemaps
B. Scatter plots
C. Population pyramids
D. Area charts

9. Which one of the following is most basic and commonly used techniques?
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13. Who is the parent company of Tableau?
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C. Tableau Workbook (.twb)
D. All of the above

15. Power BI is a product of_____
A. Facebook
B. Oracle
C. Microsoft
D. SAP

Answers for SelfAssessment

l.	D	2.	A	3.	D	4.	C	5.	A
6.	B	7.	C	8.	A	9.	A	10.	D
11.	D	12.	A	13.	A	14.	D	15.	C

Review Questions

1. What do you mean by data visualization?
2. What is the difference between data and data visualization?
3. Explain Types of Data Visualizations Elements.
4. Explain with an example how dashboards can be used in a Business

Further Readings

- Business Intelligence, A Comprehensive Approach to Information Needs, Technologies and Culture, RimvydasSkyrius, Springer International Publishing
- Communication Data With Tablue, Ben Jones, O' Reilly Publications

Web Links

- https://powerbi.microsoft.com/en-us/what-is-business-intelligence/
- https://www.tableau.com/resource/business-intelligence

Unit 10: Data Environment and Preparation

Introduction

A data environment refers to the collection of hardware, software, and data resources that are used to support data-related activities such as data analysis, data management, and data processing. It can include physical hardware such as servers, storage devices, and network equipment, as well as software tools like data analytics platforms, data modeling software, and data visualization tools.

Data environments can be designed and optimized for different types of data-related tasks, such as data warehousing, business intelligence, machine learning, and big data processing. A well-designed data environment can help organizations improve their decision-making capabilities, identify new business opportunities, and gain competitive advantages. However, designing and managing a data environment can be a complex and challenging task that requires expertise in various technical domains, including data management, database design, software development, and system administration.

Data preparation, also known as data preprocessing, is the process of cleaning, transforming, and organizing raw data into a format that is suitable for analysis. It involves a series of steps that transform raw data into a format that can be easily analyzed using various tools and techniques. Data preparation is a critical step in the data analysis process since it can affect the accuracy and reliability of the insights gained from data.

The steps involved in data preparation may include:

- Data cleaning: Removing or correcting any errors, inconsistencies, or missing values in the data.
- Data transformation: Transforming data into a standard format, such as converting data into a common measurement unit or scaling data to a common range.
- Data integration: Combining data from different sources into a single dataset for analysis.
- Data reduction: Reducing the amount of data to be analyzed by selecting a subset of relevant variables or removing redundant data.
- Data formatting: Converting data into a suitable format for analysis, such as converting text data into numerical data.
- Data splitting: Splitting data into training and testing sets for machine learning models.

Overall, data preparation is a crucial step in data analysis that can help ensure the accuracy and reliability of insights gained from data. It requires a combination of technical expertise and domain knowledge to effectively prepare data for analysis.

10.1 Metadata

Metadata refers to data that provides information about other data. In other words, metadata is data that describes the characteristics of a particular data asset, such as its structure, format, origin, and purpose. Metadata can be used to help understand, manage, and use data more effectively.

There are several different types of metadata, including:

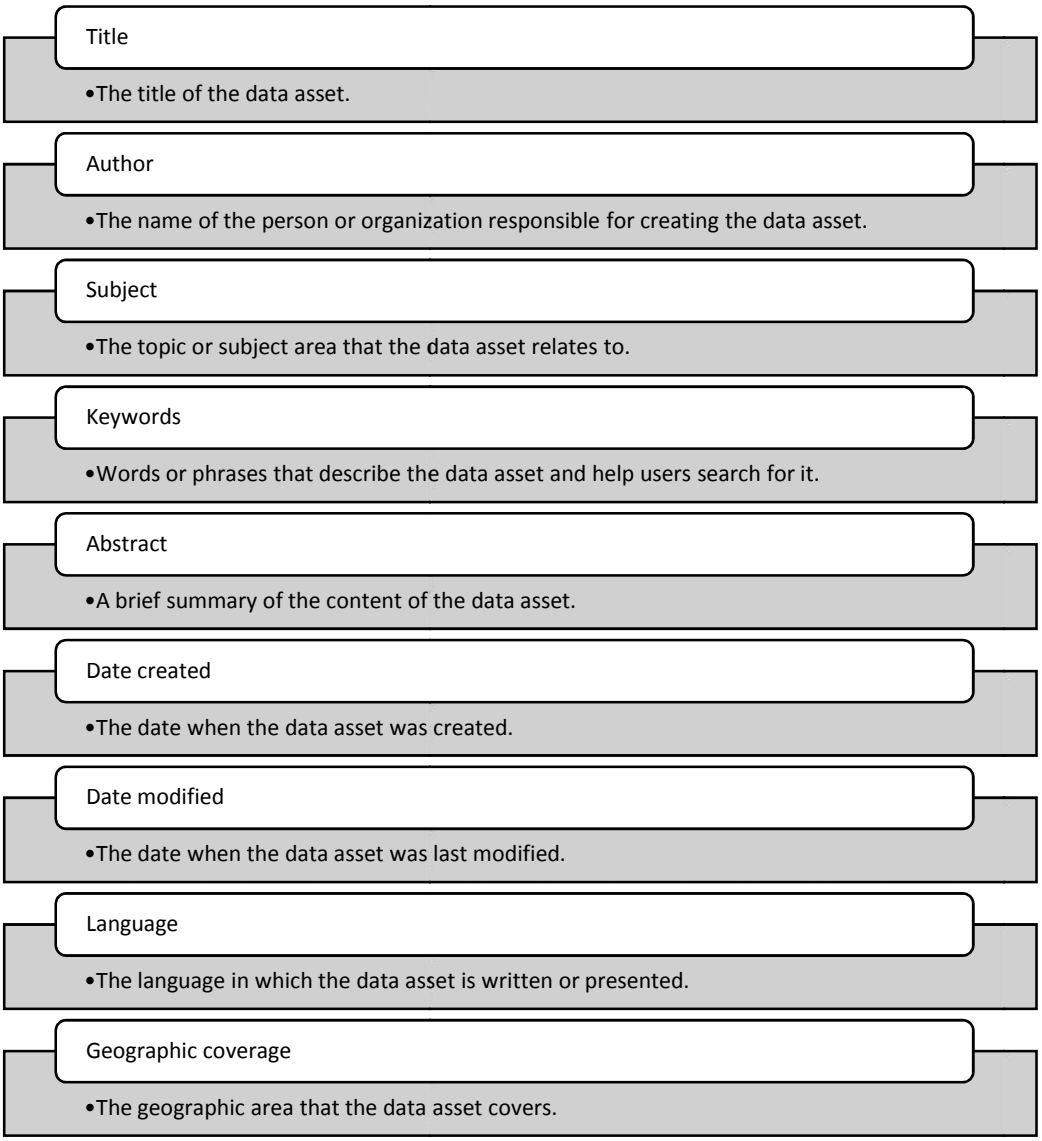
- Descriptive metadata: Provides information about the content of a data asset, such as its title, author, subject, and keywords.
- Structural metadata: Provides information about the organization and structure of a data asset, such as the format, schema, and relationships between data elements.
- Administrative metadata: Provides information about the management and usage of a data asset, such as access controls, ownership, and usage rights.
- Technical metadata: Provides information about the technical characteristics of a data asset, such as its file format, encoding, and data quality.

Metadata can be stored in a variety of formats, such as in data dictionaries, data catalogs, or embedded within the data asset itself. It can be accessed and used by different stakeholders, including data scientists, analysts, data engineers, and business users, to help them understand and work with data more effectively.

10.2 Descriptive Metadata

Descriptive metadata refers to metadata that provides information about the content of a particular data asset. It describes the characteristics of the data and helps users understand what the data is about, its purpose, and its relevance to their needs. Descriptive metadata can be used to facilitate the discovery, understanding, and management of data.

Examples of descriptive metadata include:

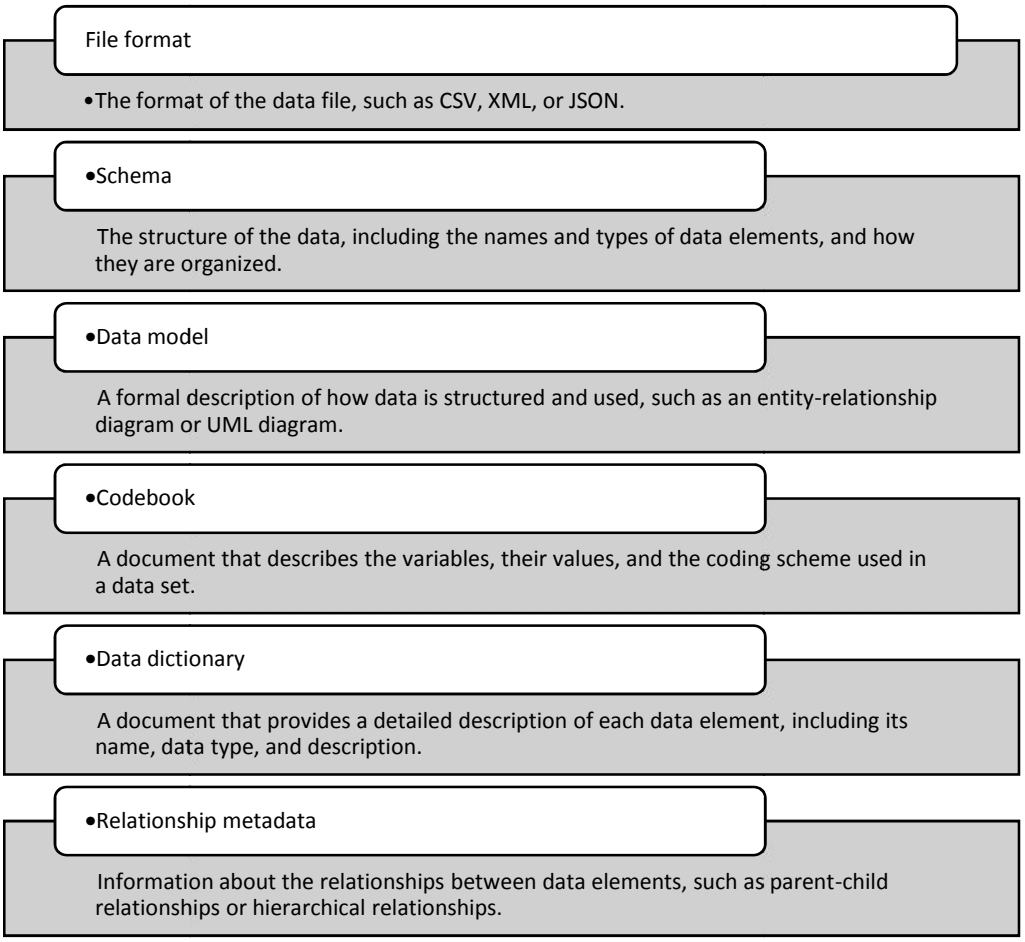


Descriptive metadata can be stored in a variety of formats, such as data dictionaries, data catalogs, or embedded within the data asset itself. It is essential for effective data management, as it helps users understand the content and context of the data, enabling them to make more informed decisions about its use.

10.3 Structural Metadata

Structural metadata refers to metadata that provides information about the organization and structure of a particular data asset. It describes how the data is organized, what types of data elements it contains, and how they relate to each other. Structural metadata can be used to help users understand the format and structure of the data, which can be important when processing and analyzing it.

Examples of structural metadata include:

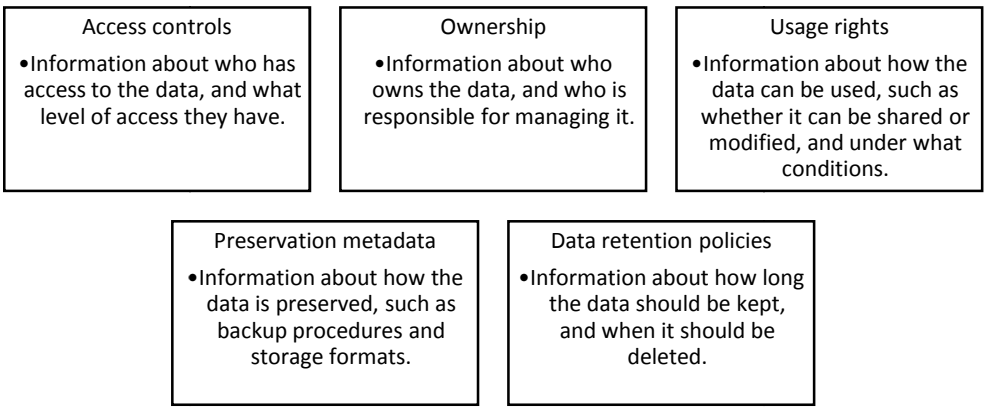


Structural metadata can be stored in a variety of formats, such as in data dictionaries, data catalogs, or embedded within the data asset itself. It is essential for effective data management and analysis, as it helps users understand the structure and organization of the data, which can be important for data integration, processing, and analysis.

10.4 Administrative Metadata

Administrative metadata refers to metadata that provides information about the management and usage of a particular data asset. It describes how the data asset is managed, who is responsible for it, and how it can be used. Administrative metadata can be used to help users understand the governance and access policies for the data, which can be important when determining whether or not it can be used for a particular purpose.

Examples of administrative metadata include:



Administrative metadata can be stored in a variety of formats, such as in data management plans, data catalogs, or embedded within the data asset itself. It is essential for effective data management, as it helps users understand the governance and access policies for the data, which can be important for compliance and risk management purposes.

10.5 Technical Metadata

Technical metadata refers to metadata that provides information about the technical characteristics of a particular data asset. It describes the technical aspects of the data, such as its format, encoding, and quality, and helps users understand how to process and analyze the data effectively.

Examples of technical metadata include:

File format •The format of the data file, such as CSV, XML, or JSON.	Encoding •The character encoding used in the data file, such as UTF-8 or ASCII.
Compression •Information about whether the data is compressed, and if so, what compression algorithm was used.	Data quality •Information about the accuracy, completeness, and consistency of the data, such as data profiling statistics or data quality reports.
Data lineage •Information about the origin and history of the data, including its sources and any transformations that have been applied to it.	Performance metrics •Information about the performance characteristics of the data, such as its size, volume, and processing speed.

Technical metadata can be stored in a variety of formats, such as in data catalogs, metadata repositories, or embedded within the data asset itself. It is essential for effective data management, as it helps users understand the technical aspects of the data, which can be important when processing and analyzing it.

10.6 Data Extraction

Extracting data refers to the process of retrieving data from a source system or data storage and making it available for use in other applications or systems. Data extraction is a critical part of the data integration process, and it involves identifying and retrieving the relevant data from one or more source systems.

The data extraction process typically involves the following steps:

1. Identify the data source(s):
   Determine where the data is located and what type of data is needed for the target system.
2. Determine the extraction method:
   Decide on the best method for extracting the data from the source system, such as using an API, exporting data to a file, or connecting to a database.
3. Define the extraction criteria:
   Identify the criteria for selecting the data to be extracted, such as a date range or specific data fields.
4. Extract the data:
   Retrieve the data from the source system using the chosen extraction method and criteria.
5. Validate the data:

Verify that the extracted data is accurate and complete, and meets the requirements of the target system.

6. Transform the data:
   If necessary, transform the data into the appropriate format for the target system, such as converting data types or applying data mappings.
7. Load the data:
   Load the extracted and transformed data into the target system or data storage.

Data extraction can be performed manually, but it is often automated using data integration tools or ETL (extract, transform, load) processes. The goal of data extraction is to ensure that the target system has access to the right data at the right time and in the right format, enabling better decision-making and analysis.

10.7 Data Extraction Methods

There are several methods for extracting data from a source system, depending on the type of data and the source system itself. Here are some common data extraction methods:

- API (Application Programming Interface) access:
  APIs allow applications to communicate and exchange data with each other. Many software vendors provide APIs for their products, making it easy to extract data programmatically.
- Direct database access:
  Data can be extracted directly from a database using SQL queries or database-specific tools.
- Flat file export:
  Data can be exported from a source system as flat files in various formats, such as CSV or Excel.
- Web scraping
  Web scraping involves extracting data from web pages using specialized software tools that can navigate through the website and extract data from HTML code.
- Cloud-based data integration tools
  Cloud-based data integration tools such as Informatica, Talend, or Microsoft Azure Data Factory can extract data from a variety of sources and transform it for use in other systems.
- ETL (Extract, Transform, Load) tools
  ETL tools automate the process of extracting data from source systems, transforming it into the appropriate format, and loading it into the target system.

The choice of data extraction method depends on factors such as the type and location of the source system, the amount and frequency of data being extracted, and the intended use of the data.

10.8 Data Extraction by API

Data extraction by API involves using an API (Application Programming Interface) to extract data from a source system. An API provides a set of rules and protocols for accessing and interacting with a software application or web service. APIs are designed to make it easy for developers to extract data from a source system programmatically, without requiring manual data entry or complex data extraction processes.

Here are the steps involved in extracting data by API:

1. Identify the API endpoints
   Identify the endpoints in the API that contain the data you need to extract.
2. Obtain API credentials
   Obtain the API key or access token that allows you to access the API endpoints.
3. Develop code

Write code that calls the API endpoints and extracts the desired data.

4. Extract data

   Use the code to extract the data from the API endpoints.

5. Transform the data

   Transform the extracted data as necessary to fit the desired output format or target system.

6. Load the data

   Load the extracted and transformed data into the target system.

APIs provide a fast and efficient way to extract data from source systems, and they are widely used in modern data integration processes.

Extracting data by API into Power BI involves using the Power BI service to connect to an API and retrieve data for use in visualizations and reports. Here are the steps involved in extracting data by API into Power BI:

1. Connect to the API

   In Power BI, select "Get Data" and choose the option for "Web". Enter the URL for the API endpoint and select "OK".

2. Enter API credentials

   If the API requires credentials, enter them in the appropriate fields.

3. Select the data to extract

   Choose the data that you want to extract from the API, such as tables or specific endpoints.

4. Transform the data

   Use Power Query to transform the extracted data as necessary, such as changing data types or combining data from multiple tables.

5. Load the data

   Load the extracted and transformed data into Power BI.

6. Create visualizations

   Use the data in Power BI to create visualizations and reports.

Power BI provides a user-friendly interface for connecting to APIs and retrieving data, and it supports a wide range of data sources and formats.

10.9 Extracting Data from Direct Database

Extracting data from direct database access into Power BI involves using Power BI Desktop to connect to a database and retrieve data for use in visualizations and reports. Here are the steps involved in extracting data from direct database access into Power BI:

1. Connect to the database

   In Power BI Desktop, select "Get Data" and choose the option for "Database". Select the type of database you are connecting to, such as SQL Server or MySQL.

2. Enter database credentials

   Enter the credentials for the database, such as the server name and login information.

3. Select the data to extract

   Choose the data that you want to extract from the database, such as tables or specific queries.

4. Transform the data

   Use Power Query to transform the extracted data as necessary, such as changing data types or combining data from multiple tables.

5. Load the data

   Load the extracted and transformed data into Power BI.

6. Create visualizations

   Use the data in Power BI to create visualizations and reports.

Power BI Desktop provides a user-friendly interface for connecting to databases and retrieving data, and it supports a wide range of database types and data sources. Extracting data from direct database access into Power BI can help organizations to gain insights from data more quickly and efficiently, and to create more compelling visualizations and reports. However, it's important to ensure that the database is properly secured and that the extracted data is used in compliance with any applicable data privacy regulations.

10.10 Extracting Data Through Web Scrapping

Web scraping is the process of automatically extracting data from websites using software tools called web scrapers. Web scraping is used to extract data that is not available through APIs or other structured data sources. Here are the steps involved in web scraping:

Identify the website and data to scrape: Identify the website or web pages from which you want to extract data, and determine the specific data elements you want to extract.

- Choose a web scraper

  Choose a web scraping tool that suits your needs. Popular web scraping tools include Beautiful Soup, Scrapy, and Selenium.
- Develop code

  Write code that defines the rules for the web scraper to follow, such as the HTML tags to search for and the data to extract.
- Execute the web scraper

  Run the web scraper and wait for it to extract the data.
- Transform the data

  Use data transformation tools, such as Excel or Power Query, to clean and transform the extracted data as necessary.
- Store the data

  Store the extracted and transformed data in a database or spreadsheet for further analysis.

Web scraping can be a powerful tool for extracting data from websites, but it can also be technically complex and legally risky. Some websites may have terms of use or legal restrictions that prohibit web scraping, and web scraping tools can potentially cause website downtime or server overload. It's important to use web scraping tools responsibly and with the appropriate legal and ethical considerations in mind.

Extracting data into Power BI by web scraping involves using Power BI Desktop in combination with a web scraping tool to extract data from a website and load it into Power BI. Here are the steps involved in extracting data into Power BI by web scraping:

1. Choose a web scraping tool

   Choose a web scraping tool that suits your needs, such as Beautiful Soup or Scrapy.
2. Develop code

   Write code that defines the rules for the web scraper to follow, such as the HTML tags to search for and the data to extract.
3. Execute the web scraper

   Run the web scraper and wait for it to extract the data.
4. Store the extracted data

   Store the extracted data in a format that can be read by Power BI, such as a CSV file or a database.
5. Connect to the data

   In Power BI Desktop, select "Get Data" and choose the option for the data source you are using, such as "CSV" or "Database".
6. Transform the data

Use Power Query to transform the extracted data as necessary, such as changing data types or combining data from multiple tables.

7. Load the data
   Load the extracted and transformed data into Power BI.
8. Create visualizations
   Use the data in Power BI to create visualizations and reports.

10.11 Cloud-Based Data Extraction

Cloud-based data integration is the process of combining data from multiple sources located in the cloud. Cloud-based data integration tools typically offer a range of features such as data transformation, data quality, and data synchronization to enable the integration of data from various sources. Here are some steps involved in cloud-based data integration:

1. Choose a cloud-based data integration tool
   There are many cloud-based data integration tools available, such as Microsoft Azure Data Factory, Google Cloud Data Fusion, and Amazon Web Services Glue.
2. Connect to data sources
   Connect to the data sources that you want to integrate. Data sources may include databases, file systems, APIs, or cloud-based applications.
3. Transform data
   Use the data integration tool to transform the data as necessary. This may include cleaning, filtering, and merging data.
4. Schedule data integration jobs
   Schedule the integration jobs to run at specific times, such as daily or weekly.
5. Monitor data integration
   Monitor the data integration process for any errors or issues that may arise.
6. Store the integrated data
   Store the integrated data in a format that is accessible for further analysis, such as a data warehouse or a data lake.

Cloud-based data integration offers several advantages over traditional data integration methods, including scalability, agility, and cost savings.

10.12 Data Extraction Using ETL Tools

Data extraction with ETL (Extract, Transform, Load) involves using ETL tools to extract data from one or more source systems, transform it to meet specific business requirements, and load it into a target system such as a data warehouse or a data lake. Here are the basic steps involved in data extraction with ETL:

- Extract data
  Use the ETL tool to extract data from one or more source systems such as databases, files, or applications.
- Transform data
  Use the ETL tool to transform the extracted data to meet specific business requirements, such as cleaning and filtering the data, aggregating and summarizing it, and converting data types.
- Load data
  Use the ETL tool to load the transformed data into a target system such as a data warehouse or a data lake.
- Schedule ETL jobs
  Schedule the ETL jobs to run at specific times, such as daily or weekly.

- Monitor ETL processes

  Monitor the ETL processes for any errors or issues that may arise.

ETL tools can be powerful tools for data extraction as they allow for the integration of data from various sources and can handle large amounts of data. ETL tools can also automate the data integration process, reducing the need for manual intervention and reducing the potential for errors.

10.13 Database Joins

Database joins are used to combine data from two or more database tables based on a common field or set of fields. There are different types of joins that can be used depending on the data being combined:

- Inner join

  This type of join returns only the matching records from both tables based on the common field. Non-matching records are not included in the result set.
- Left join

  This type of join returns all records from the left table and matching records from the right table based on the common field. If there are no matching records in the right table, the result set will contain null values for those fields.
- Right join

  This type of join returns all records from the right table and matching records from the left table based on the common field. If there are no matching records in the left table, the result set will contain null values for those fields.
- Full outer join

  This type of join returns all records from both tables, including matching records and non-matching records from both tables. If there are no matching records in either table, the result set will contain null values for those fields.

Database joins are useful for combining data from multiple tables into a single view that can be used for analysis or reporting. Joins are commonly used in SQL (Structured Query Language) to perform queries that retrieve data from multiple tables. It is important to understand the relationship between tables and the common fields that are used for joins in order to create accurate and meaningful queries.

10.14 Database Union

In database management systems, a union is a set operation that combines the result sets of two or more SELECT statements into a single result set that contains all the distinct rows from the input queries. The resulting set does not include any duplicates.

To perform a union operation in Power BI, you can use the "Append Queries" feature. Here are the steps to do it:

1. Open Power BI Desktop and go to the Home tab.
2. Click on "Combine Queries" and select "Append Queries".
3. In the "Append Queries" dialog box, select the two tables you want to combine using the union operation.
4. Choose the "Union" option under the "Operation" section.
5. Map the columns between the two tables by dragging and dropping them onto each other.
6. Click OK to combine the tables.

Alternatively, you can also use the "Union" transformation in the Query Editor:

1. Open the Query Editor by clicking on "Transform Data" from the Home tab.
2. Select the two tables you want to combine and click on "Combine Queries" and select "Union".

3. Map the columns between the two tables by dragging and dropping them onto each other.
4. Click OK to combine the tables.
5. After you have combined the tables, you can perform further transformations and visualizations on the resulting data in Power BI.

10.15 Union & Joins Difference

The main difference between a union and a join in a database management system is that a union operation combines rows from two or more tables or result sets, while a join operation combines columns from two or more tables based on a common column or key.

A union operation is a set operation that returns a result set that contains all the rows from two or more tables, eliminating duplicates. The resulting table has the same number of columns as the input tables, and the columns must be of compatible data types.

A join operation, on the other hand, combines columns from two or more tables based on a common column or key.

Both operations are useful in different scenarios, depending on the data and queries involved.

Summary

- Metadata refers to data that provides information about other data.
- An API provides a set of rules and protocols for accessing and interacting with a software application or web service
- A union operation combines rows from two or more tables or result sets, while a join operation combines columns from two or more tables based on a common column or key.
- There are several different types of metadata, including Descriptive metadata, Structural metadata, Administrative metadata, Technical metadata:

Keywords

Data: In computing, data is information that has been translated into a form that is efficient for movement or processing.

Data analysis: Data Analysis. Data Analysis is the process of systematically applying statistical and/or logical techniques to describe and illustrate, condense and recap, and evaluate data.

Data extraction: Extracting data refers to the process of retrieving data from a source system or data storage and making it available for use in other applications or systems.

Web Scrapping: Web scraping is the process of automatically extracting data from websites using software tools called web scrapers.

SelfAssessment

1. What is the full form of DBMS?

A. Data of Binary Management System
B. Database Management System
C. Database Management Service
D. Data Backup Management System

2. What are advantages of DBMS over file system?

A. Redundancy of data
B. Inconsistency of Data

C. Difficult Data Access
D. All of the above

3. What is DBMS?
A. DBMS is a collection of queries
B. DBMS is a high-level language
C. DBMS is a programming language
D. DBMS stores, modifies and retrieves data

4. Which type of data can be stored in the database?
A. Image oriented data
B. Text, files containing data
C. Data in the form of audio or video
D. All of the above

5. Which of the following is not a type of database?
A. Hierarchical
B. Network
C. Distributed
D. Decentralized

6. Which of the following is not an example of DBMS?
A. MySQL
B. Microsoft Acess
C. IBM DB2
D. Google

7. Which of the following is a feature of DBMS?
A. Minimum Duplication and Redundancy of Data
B. High Level of Security
C. Single-user Access only
D. Support ACID Property

8. Which of the following is a feature of the database?
A. No-backup for the data stored
B. User interface provided
C. Lack of Authentication
D. Store data in multiple locations

9. Which of the following is not a function of the database?
A. Managing stored data
B. Manipulating data
C. Security for stored data
D. Analyzing code

10. Which of the following is a component of the DBMS?
A. Data

B. Data Languages
C. Data Manager
D. All of the above

11. Which of the following is known as a set of entities of the same type that share same properties, or attributes?
A. Relation set
B. Tuples
C. Entity set
D. Entity Relation model

12. What is information about data called?
A. Hyper data
B. Tera data
C. Meta data
D. Relations

13. What does an RDBMS consist of?
A. Collection of Records
B. Collection of Keys
C. Collection of Tables
D. Collection of Fields

14. _____ is a set of one or more attributes taken collectively to uniquely identify a record.
A. Primary Key
B. Foreign key
C. Super key
D. Candidate key

15. _____ operations do not preserve non-matched tuples.
A. Left outer join
B. Inner join
C. Natural join
D. Right outer join

Answers for SelfAssessment

l. B	2. D	3. D	4. D	5. D
6. D	7. C	8. B	9. D	10. D
11. C	12. C	13. C	14. C	15. B

Review Questions

1. What do you mean by database? Give examples
2. How data is different from a database? Explain

3. What do you mean by metadata and what is its significance?
4. How live data can be extracted for analytics? Explain with an example
5. What is relational database and where is it used?

Further Readings

- Business Intelligence, A Comprehensive Approach to Information Needs, Technologies and Culture, RimvydasSkyrius, Springer International Publishing
- Communication Data With Tablue, Ben Jones, O' Reilly Publications

Web Links

- https://powerbi.microsoft.com/en-us/what-is-business-intelligence/
- https://www.tableau.com/resource/business-intelligence
- What is a relational database? | IBM

Unit 11: Data Blending

CONTENTS

Introduction

Data blending refers to the process of combining data from multiple sources, typically from different data sets, databases or applications, into a single data set or visualization. The objective of data blending is to obtain more comprehensive and accurate information from the combined data sets, which would not be possible from any single data set alone.

Data blending involves merging data sets with common fields, such as customer IDs or product codes, to create a unified data set. This allows analysts to access data from multiple sources and make correlations between them.

Data blending is often used in business intelligence and analytics applications, where organizations need to combine data from multiple sources, such as sales data, customer data, and marketing data, to obtain a more comprehensive view of their business performance. It can also be used in data science projects to combine data from multiple experiments or datasets to derive insights.

Some common tools for data blending include Excel, SQL, and specialized software such as Tableau, Power BI, and Alteryx. These tools allow analysts to join and merge datasets, perform data cleansing and transformation, and generate visualizations and reports from the blended data.

In analytics, data type refers to the classification of data according to its nature or characteristics. The type of data used in analytics is typically determined by the source of the data and the analysis that needs to be performed.

There are several common data types used in analytics, including:

- Numerical data: This data type represents quantitative data that can be measured, such as age, income, or weight.
- Categorical data: This data type represents qualitative data that can be classified into categories, such as gender, race, or occupation.
- Time series data: This data type represents data that is collected over time, such as stock prices or weather data.
- Text data: This data type represents unstructured data in the form of text, such as customer reviews or social media posts.
- Geographic data: This data type represents location-based data, such as latitude and longitude coordinates.
- Image data: This data type represents visual data, such as photos or satellite images.

11.1 Curating Text Data

Curating text data involves selecting, organizing, and managing text-based information for analysis or use in machine learning models. Text data curation is a critical process that helps ensure that the data used for analysis or modeling is relevant, accurate, and complete.

The process of curating text data typically involves the following steps:

- Data Collection: The first step in curating text data is to collect relevant data from various sources. This may include web pages, social media platforms, customer reviews, news articles, and other text-based sources.
- Data Cleaning: Once the data is collected, it needs to be cleaned to remove any unwanted information, such as stop words, punctuation, and special characters. This step also involves correcting spelling and grammatical errors and removing duplicate entries.
- Data Preprocessing: After cleaning the data, the next step is to preprocess it, which involves tasks such as tokenization, stemming, and lemmatization. These techniques help to transform the text data into a structured format that can be used for analysis.
- Data Annotation: In some cases, text data may need to be annotated to identify specific entities or sentiments. For example, in sentiment analysis, text data is annotated to identify positive, negative, or neutral sentiments.
- Data Labeling: Data labeling involves assigning labels or categories to the text data based on its content. This step is important for tasks such as text classification and topic modeling.
- Data Storage: Finally, curated text data is stored in a structured format, such as a database or spreadsheet, for analysis or use in machine learning models.

Curating text data can be a time-consuming and complex process, but it is essential for ensuring that the data used for analysis or modeling is accurate and relevant. It also helps to improve the performance of machine learning models by providing high-quality training data.

11.2 Curating Numerical Data

Curating numerical data involves selecting, organizing, and managing quantitative data for analysis or use in machine learning models. Numerical data curation is a critical process that helps ensure that the data used for analysis or modeling is relevant, accurate, and complete.

The process of curating numerical data typically involves the following steps:

- Data Collection: The first step in curating numerical data is to collect relevant data from various sources. This may include databases, spreadsheets, and other numerical-based sources.

- Data Cleaning: Once the data is collected, it needs to be cleaned to remove any unwanted information, such as missing values, outliers, and errors. This step also involves correcting data entry mistakes and inconsistencies.
- Data Preprocessing: After cleaning the data, the next step is to preprocess it, which involves tasks such as scaling, normalization, and feature engineering. These techniques help to transform the numerical data into a structured format that can be used for analysis.
- Data Annotation: In some cases, numerical data may need to be annotated to identify specific attributes or labels. For example, in predictive modeling, numerical data is annotated with target variables or outcome variables.
- Data Labeling: Data labeling involves assigning labels or categories to the numerical data based on its content. This step is important for tasks such as classification and regression modeling.
- Data Storage: Finally, curated numerical data is stored in a structured format, such as a database or spreadsheet, for analysis or use in machine learning models.

11.3 Curating Categorical Data

The process of curating categorical data typically involves the following steps:

- Data Collection: The first step in curating categorical data is to collect relevant data from various sources. This may include surveys, forms, or other qualitative-based sources.
- Data Cleaning: Once the data is collected, it needs to be cleaned to remove any unwanted information, such as missing values, inconsistent formatting, and errors.
- Data Preprocessing: After cleaning the data, the next step is to preprocess it, which involves tasks such as encoding, imputation, and feature engineering. These techniques help to transform the categorical data into a structured format that can be used for analysis.
- Data Annotation: In some cases, categorical data may need to be annotated to identify specific attributes or labels. For example, in sentiment analysis, categorical data is annotated with positive, negative, or neutral labels.
- Data Labeling: Data labeling involves assigning labels or categories to the categorical data based on its content. This step is important for tasks such as classification and clustering.
- Data Storage: Finally, curated categorical data is stored in a structured format, such as a database or spreadsheet, for analysis or use in machine learning models.

Curating categorical data can be a challenging process, especially when dealing with large and complex datasets. However, it is essential for ensuring that the data used for analysis or modeling is accurate and relevant.

11.4 Curating Time Series Data

The process of curating time series data typically involves the following steps:

- Data Collection: The first step in curating time series data is to collect relevant data from various sources. This may include sensors, devices, or other time-based sources.
- Data Cleaning: Once the data is collected, it needs to be cleaned to remove any unwanted information, such as missing values, outliers, and errors. This step is particularly important for time series data, as missing or incorrect data can significantly impact the accuracy of the analysis.

- Data Preprocessing: After cleaning the data, the next step is to preprocess it, which involves tasks such as smoothing, filtering, and resampling. These techniques help to transform the time series data into a structured format that can be used for analysis.
- Data Annotation: In some cases, time series data may need to be annotated to identify specific events or anomalies. For example, in sensor data analysis, time series data may be annotated to identify equipment failures or malfunctions.
- Data Labeling: Data labeling involves assigning labels or categories to the time series data based on its content. This step is important for tasks such as classification and prediction.
- Data Storage: Finally, curated time series data is stored in a structured format, such as a database or spreadsheet, for analysis or use in machine learning models.

Curating time series data can be a complex process, especially when dealing with large and high-frequency datasets.

11.5 Curating Geographic Data

Curating geographic data involves organizing and managing data that has a spatial component, such as latitude, longitude, and elevation. Geographic data curation is essential for ensuring that the data used for analysis or modeling is accurate, complete, and relevant to the analysis being performed.

The process of curating geographic data typically involves the following steps:

- Data Collection: The first step in curating geographic data is to collect relevant data from various sources. This may include maps, satellite imagery, or other location-based sources.
- Data Cleaning: Once the data is collected, it needs to be cleaned to remove any unwanted information, such as missing values, inconsistencies, and errors. This step is particularly important for geographic data, as missing or incorrect data can significantly impact the accuracy of the analysis.
- Data Preprocessing: After cleaning the data, the next step is to preprocess it, which involves tasks such as geocoding, projection, and spatial analysis. These techniques help to transform the geographic data into a structured format that can be used for analysis.
- Data Annotation: In some cases, geographic data may need to be annotated to identify specific features or attributes. For example, in urban planning, geographic data may be annotated to identify roads, buildings, and other infrastructure.
- Data Labeling: Data labeling involves assigning labels or categories to the geographic data based on its content. This step is important for tasks such as classification and clustering.
- Data Storage: Finally, curated geographic data is stored in a structured format, such as a GIS (Geographic Information System) database or a spreadsheet, for analysis or use in machine learning models.

11.6 Curating Image Data

Curating image data involves organizing and managing data that consists of images or visual data. Image data curation is essential for ensuring that the data used for analysis or modeling is accurate, complete, and relevant to the analysis being performed.

The process of curating image data typically involves the following steps:

- Data Collection: The first step in curating image data is to collect relevant data from various sources. This may include images from cameras, satellites, or other visual sources.

- Data Cleaning: Once the data is collected, it needs to be cleaned to remove any unwanted information, such as low-quality images, duplicates, or irrelevant images. This step is particularly important for image data, as the quality of the images can significantly impact the accuracy of the analysis.
- Data Preprocessing: After cleaning the data, the next step is to preprocess it, which involves tasks such as resizing, cropping, and normalization. These techniques help to transform the image data into a structured format that can be used for analysis.
- Data Annotation: In some cases, image data may need to be annotated to identify specific features or attributes. For example, in medical imaging, image data may be annotated to identify specific structures or abnormalities.
- Data Labeling: Data labeling involves assigning labels or categories to the image data based on its content. This step is important for tasks such as classification and object detection.
- Data Storage: Finally, curated image data is stored in a structured format, such as a database or file system, for analysis or use in machine learning models.

11.7 File Formats for Data Extraction

There are several file formats that are commonly used for data extraction, including:

- CSV (Comma-Separated Values): CSV files are a simple and widely used format for storing tabular data. They are easily created and can be read by many software tools, including spreadsheet programs like Microsoft Excel.
- JSON (JavaScript Object Notation): JSON files are a lightweight data-interchange format that is easy for humans to read and write, and easy for machines to parse and generate. They are commonly used for web-based applications and APIs.
- XML (Extensible Markup Language): XML files are similar to JSON files in that they are a markup language used to store and exchange data. They are commonly used for web-based applications and APIs.
- Excel: Microsoft Excel files are a common format for storing and exchanging tabular data. They are easily created and can be read by many software tools, including spreadsheet programs like Microsoft Excel.
- SQL (Structured Query Language) Dumps: SQL dumps are files that contain the schema and data from a SQL database. They are commonly used for backing up and restoring data, and can also be used for data extraction.
- Text Files: Text files are a simple and versatile format for storing data. They can be created and read by many software tools, and are commonly used for data exchange and storage.

When choosing a file format for data extraction, it is important to consider factors such as the type and structure of the data, the software tools being used for data extraction, and the intended use of the extracted data.

11.8 Extracting CSV Data into PowerBI

To extract CSV data into Power BI, you can follow these steps:

- Open Power BI Desktop and click on "Get Data" from the Home tab.
- In the "Get Data" window, select "Text/CSV" and click on "Connect."
- Browse and select the CSV file you want to extract data from, and then click on "Open."

- In the "Preview" window, you can see a preview of the data from the CSV file. If everything looks good, click on "Load" to load the data into Power BI.
- Once the data is loaded, you can start creating visualizations and reports using the data.
- To refresh the data, click on "Refresh" from the Home tab. You can also set up automatic data refresh schedules by going to "File" > "Options and settings" > "Options" > "Data Load" > "Scheduled refresh."

Note that while importing the CSV data, you may need to do some data cleaning and transformation, such as converting data types, removing duplicates, or splitting columns. You can perform these operations using the "Transform Data" option in the "Home" tab of Power BI Desktop.

Also, if you are using Power BI Service, you can upload the CSV file to your Power BI workspace and then connect to it from Power BI Desktop. This allows you to work with the data in Power BI Desktop and then publish the reports to Power BI Service.

11.9 Extracting JSON data into PowerBI

To extract JSON data into Power BI, you can follow these steps:

- Open Power BI Desktop and click on "Get Data" from the Home tab.
- In the "Get Data" window, select "JSON" and click on "Connect."
- Browse and select the JSON file you want to extract data from, and then click on "Open."
- In the "Navigator" window, select the table or query you want to load into Power BI, and then click on "Edit" to open the Query Editor.
- In the Query Editor, you can perform various data cleaning and transformation operations on the JSON data, such as splitting columns, filtering rows, or renaming columns.
- Once you have transformed the data as needed, click on "Close & Apply" to load the data into Power BI.
- Once the data is loaded, you can start creating visualizations and reports using the data.
- To refresh the data, click on "Refresh" from the Home tab. You can also set up automatic data refresh schedules by going to "File" > "Options and settings" > "Options" > "Data Load" > "Scheduled refresh."

Note that while importing the JSON data, you may need to do some data cleaning and transformation, such as flattening nested JSON structures or converting data types. You can perform these operations using the Query Editor in Power BI Desktop.

Also, if you are using Power BI Service, you can upload the JSON file to your Power BI workspace and then connect to it from Power BI Desktop. This allows you to work with the data in Power BI Desktop and then publish the reports to Power BI Service.

11.10 Extracting XML Data into PowerBI

To extract XML data into Power BI, you can follow these steps:

- Open Power BI Desktop and click on "Get Data" from the Home tab.
- In the "Get Data" window, select "Web" and click on "Connect."
- In the "From Web" dialog box, enter the URL of the XML file you want to extract data from, and then click on "OK."
- In the "Navigator" window, select the table or query you want to load into Power BI, and then click on "Edit" to open the Query Editor.

- In the Query Editor, you can perform various data cleaning and transformation operations on the XML data, such as flattening nested structures, filtering rows, or renaming columns.
- Once you have transformed the data as needed, click on "Close & Apply" to load the data into Power BI.
- Once the data is loaded, you can start creating visualizations and reports using the data.
- To refresh the data, click on "Refresh" from the Home tab. You can also set up automatic data refresh schedules by going to "File" > "Options and settings" > "Options" > "Data Load" > "Scheduled refresh."

Note that while importing the XML data, you may need to do some data cleaning and transformation, such as converting data types or removing namespaces. You can perform these operations using the Query Editor in Power BI Desktop.

Also, if you are using Power BI Service, you can upload the XML file to your Power BI workspace and then connect to it from Power BI Desktop. This allows you to work with the data in Power BI Desktop and then publish the reports to Power BI Service.

11.11 Extracting SQL Data into PowerBI

To extract SQL data into Power BI, you can follow these steps:

- Open Power BI Desktop and click on "Get Data" from the Home tab.
- In the "Get Data" window, select "SQL Server" and click on "Connect."
- In the "SQL Server database" dialog box, enter the server name and database name for the SQL Server you want to connect to, and then click on "OK."
- In the "Navigator" window, select the table or query you want to load into Power BI, and then click on "Edit" to open the Query Editor.
- In the Query Editor, you can perform various data cleaning and transformation operations on the SQL data, such as joining tables, filtering rows, or renaming columns.
- Once you have transformed the data as needed, click on "Close & Apply" to load the data into Power BI.
- Once the data is loaded, you can start creating visualizations and reports using the data.
- To refresh the data, click on "Refresh" from the Home tab. You can also set up automatic data refresh schedules by going to "File" > "Options and settings" > "Options" > "Data Load" > "Scheduled refresh."

Note that while importing the SQL data, you may need to provide credentials to connect to the database. You can select "Windows" if you are using Windows authentication, or "Database" if you are using SQL Server authentication.

Also, if you are using Power BI Service, you can set up a gateway to connect to the SQL Server and then connect to it from Power BI Desktop. This allows you to work with the data in Power BI Desktop and then publish the reports to Power BI Service.

11.12 Data Cleansing

Data cleaning, also known as data cleansing, is the process of identifying and correcting errors, inconsistencies, and inaccuracies in a dataset. It is an important step in the data analysis process, as it helps ensure that the data is accurate, complete, and consistent, which in turn leads to better insights and decision-making.

Here are some common techniques used in data cleaning:

- Removing duplicates: This involves identifying and removing duplicate records or observations from the dataset.

- Handling missing values: This involves identifying and dealing with missing or null values in the dataset, such as imputing missing values or removing rows or columns with missing values.
- Standardizing data: This involves ensuring that data is consistent and standardized, such as converting data to a common format or unit of measurement.
- Handling outliers: This involves identifying and dealing with outliers, which are values that are significantly different from the other values in the dataset and can skew the analysis.
- Handling incorrect data types: This involves identifying and correcting data that is in the wrong format or data type, such as converting text to numeric data.
- Correcting inconsistent data: This involves identifying and correcting inconsistent data, such as misspelled words or inconsistent naming conventions.
- Removing irrelevant data: This involves removing data that is not relevant to the analysis or decision-making process.

Overall, data cleaning is an important step in preparing data for analysis, and can help ensure that the insights and decisions based on the data are accurate and reliable.

11.13 Handling Missing Values

Handling missing values in data is an important step in the data cleaning process. Missing values can occur for a variety of reasons, such as human error, data corruption, or incomplete data collection. If missing values are not handled properly, they can lead to biased or inaccurate analysis results. Here are some common techniques for handling missing values in data:

- Deleting rows or columns: This involves removing rows or columns with missing values. However, this approach should only be used if the number of missing values is small, and the remaining data is still sufficient for analysis.
- Imputation: This involves replacing missing values with estimated or predicted values. There are several methods for imputing missing values, such as mean imputation, median imputation, or regression imputation.
- Using domain knowledge: In some cases, domain knowledge can be used to infer missing values. For example, if the missing value is the age of a person, the person's date of birth can be used to estimate their age.
- Multiple imputation: This involves creating multiple imputations of missing values, and then combining the results to obtain more accurate estimates. This method is more complex, but can lead to better results than single imputation.

It is important to note that the method used for handling missing values depends on the specific dataset and the research question being investigated. It is also important to document the method used for handling missing values, as this can affect the results of the analysis.

11.14 Handling Outliers

Handling outliers is an important step in the data cleaning process. Outliers are values that are significantly different from the other values in the dataset and can skew the analysis. Here are some common techniques for handling outliers in data:

- Deleting outliers: This involves removing outliers from the dataset. However, this approach should only be used if the number of outliers is small, and the remaining data is still sufficient for analysis.

- Winsorization: This involves replacing outliers with a less extreme value. For example, the upper outliers could be replaced with the maximum value of the non-outliers, and the lower outliers could be replaced with the minimum value of the non-outliers.
- Transformation: This involves transforming the data to reduce the impact of outliers. For example, taking the logarithm or square root of the data can reduce the impact of extreme values.
- Using robust statistics: This involves using statistics that are less sensitive to outliers. For example, using the median instead of the mean can reduce the impact of extreme values.

It is important to note that the method used for handling outliers depends on the specific dataset and the research question being investigated. It is also important to document the method used for handling outliers, as this can affect the results of the analysis.

11.15 Removing Biased Data

Removing biased data is an important step in the data cleaning process. Bias can occur in data for a variety of reasons, such as incomplete or skewed sampling, measurement error, or systematic errors in data collection. If biased data is not handled properly, it can lead to inaccurate or misleading analysis results. Here are some common techniques for removing biased data:

- Re-sampling: This involves re-sampling the data to ensure that the sample is representative of the population. This can be done using random sampling or stratified sampling techniques.
- Data augmentation: This involves adding additional data to the dataset to ensure that it is representative of the population. This can be done by collecting additional data or by synthesizing new data using machine learning techniques.
- Correcting measurement errors: This involves identifying and correcting measurement errors in the data. This can be done by checking the data for consistency and accuracy and correcting any errors that are found.
- Adjusting for confounding variables: This involves adjusting the analysis for confounding variables that may be influencing the results. This can be done by including these variables in the analysis or by using statistical techniques to adjust for their effects.

It is important to note that the method used for removing biased data depends on the specific dataset and the research question being investigated. It is also important to document the method used for removing biased data, as this can affect the results of the analysis.

11.16 Accessing Data Quality

Data reliability measures are used to assess the quality of data and ensure that the data is accurate, consistent, and complete. Here are some common measures of data reliability:

- Validity: Validity refers to the degree to which a measure or dataset accurately measures what it is intended to measure. This can be assessed by comparing the data to external sources or by examining the relationships between different variables in the dataset.
- Reliability: Reliability refers to the degree to which a measure or dataset produces consistent results over time and across different contexts. This can be assessed by examining the consistency of the data across different samples or by testing the same individuals or groups multiple times.
- Consistency: Consistency refers to the degree to which the data is consistent with itself and does not contain internal contradictions or errors. This can be assessed by comparing different parts of the dataset or by testing for internal consistency using statistical techniques.

- Completeness: Completeness refers to the degree to which the dataset contains all the relevant data and does not contain missing or incomplete data. This can be assessed by examining the proportion of missing data or by testing for missingness using statistical techniques.
- Accuracy: Accuracy refers to the degree to which the data is free from errors or biases. This can be assessed by comparing the data to external sources or by testing for measurement error using statistical techniques.

Overall, these measures can help assess the quality and reliability of data and ensure that the results of data analysis are accurate and meaningful.

11.17 Data Annotations

Data annotation refers to the process of adding descriptive metadata or labels to data to help make it more understandable and useful for analysis. Here are some common types of data annotations:

- Categorical labels: This involves assigning categorical labels to data points based on their characteristics. For example, classifying images as "animals," "plants," or "buildings" based on their content.
- Numeric labels: This involves assigning numerical values to data points based on their characteristics. For example, assigning a score to a product review based on its sentiment.
- Time-based labels: This involves adding time-based information to data points to help understand patterns and trends over time. For example, adding a timestamp to a series of financial transactions to analyze trends in customer behavior.
- Geospatial labels: This involves adding geographic information to data points to help understand spatial patterns and relationships. For example, adding location information to social media posts to analyze trends in public opinion.
- Semantic labels: This involves adding descriptive information to data points to help understand their meaning and context. For example, annotating a dataset of medical records with information about the patient's medical history, symptoms, and diagnoses.

Data annotations can be added manually or through automated processes.

11.18 Data Storage Options

There are various options for storing data, each with its own advantages and disadvantages. Here are some of the most common data storage options:

- Relational databases: Relational databases use a structured format to store data in tables with rows and columns. This makes it easy to query and analyze data, but it can be difficult to scale and handle unstructured data.
- NoSQL databases: NoSQL databases use a non-structured format to store data, which makes them more flexible and scalable than relational databases. They can handle large volumes of unstructured data, but they can be more complex to use and may not support complex queries.
- Data warehouses: Data warehouses are large, centralized repositories of data that are optimized for analytics and reporting. They are typically used for storing historical data and can be expensive to set up and maintain.
- Cloud storage: Cloud storage services such as Amazon S3, Google Cloud Storage, and Microsoft Azure offer scalable, cost-effective options for storing data in the cloud. They can be accessed from anywhere and can be configured to automatically scale as needed.

- File systems: File systems are used for storing and organizing files on a computer or network. They are easy to use and can handle a wide range of file types, but they may not be optimized for querying and analyzing data.
- Hadoop distributed file system (HDFS): HDFS is a distributed file system designed for storing and processing large data sets across clusters of computers. It is often used in conjunction with Hadoop, an open-source software framework for distributed processing and analysis of big data.

Choosing the right data storage option depends on factors such as the type of data, the volume of data, the performance requirements, and the budget. It is important to evaluate the pros and cons of each option and choose the one that best meets the needs of the organization.

Unit 12: Design Fundamentals and Visual Analytics

CONTENTS

12.1 Filters and Sorting

PowerBI

Power BI offers several options for filtering and sorting data in your visualizations. Here are some of the most commonly used techniques:

Filter Pane:

The Filter Pane allows you to filter data in your report based on specific criteria. You can filter data by selecting values from a list or by using the search bar. You can also add multiple filters and apply them to different visualizations in your report.

Visual-level Filters:

Visual-level filters allow you to filter data in a specific visualization. You can add a visual-level filter by clicking on the filter icon in the visualization's toolbar. You can then choose a column to filter on, select the filter type, and specify the filter criteria.

Drill-down and Drill-through:

Drill-down and drill-through allow you to navigate to more detailed levels of data within a visualization. Drill-down allows you to expand a visualization to show more detailed data, while drill-through allows you to navigate to another report page or a different visualization with more detailed data.

Sorting:

You can sort data in your visualizations by selecting a column and choosing either ascending or descending order. You can also sort by multiple columns by using the "Add level" button in the sorting options.

Slicers:

Slicers allow you to filter data by selecting values from a dropdown list. You can add a slicer to your report by selecting the Slicer visual and choosing the column you want to filter on.

Top N and Bottom N Filters:

Top N and Bottom N filters allow you to filter your data to show only the top or bottom values based on a selected measure. You can add a Top N or Bottom N filter by selecting the filter icon and choosing the "Top N" or "Bottom N" option.

MS-Excel:

In MS Excel, you can use filters and sorting to manipulate data in your spreadsheets. Here's a brief overview of how to use them:

Filtering:

1. Select the data range you want to filter.
2. Click on the "Filter" button in the "Sort & Filter" group on the "Data" tab.
3. Use the filter dropdowns in the header row to select the criteria you want to filter by.
4. You can also use the search box in the dropdown to quickly find specific items.

Sorting:

1. Select the data range you want to sort.
2. Click on the "Sort A to Z" or "Sort Z to A" button in the "Sort & Filter" group on the "Data" tab.
3. You can also click on the "Sort" button to open the "Sort" dialog box, where you can choose to sort by multiple criteria.
4. Note that when you apply a filter, only the filtered data will be displayed, but the hidden rows are still part of the worksheet. To remove a filter, click on the "Clear Filter" button in the "Sort & Filter" group on the "Data" tab. To remove sorting, click on the "Sort & Filter" button and then click on "Clear" under "Sort."

Advanced Filter

The Advanced Filter function in MS Excel allows you to filter data based on complex criteria, such as multiple conditions using AND/OR operators, filtering for unique values, and copying filtered data to another location. Here are the steps to use Advanced Filter:

1. Organize your data: Make sure your data is in a structured format with column headings, and the data range doesn't include any empty rows or columns.
2. Set up the Criteria range: Create a range with the same column headings as your data range, and add the filtering criteria below each column heading.
3. Select the Data range: Click on a cell within your data range.
4. Access the Advanced Filter dialog box: On the "Data" tab, click on the "Advanced" button in the "Sort & Filter" group.
5. Set up the Advanced Filter dialog box:
6. In the "Action" section, select "Filter the list, in place" to filter the data within the original range, or "Copy to another location" to copy the filtered data to a new location.
7. In the "List range" section, ensure that the cell range is correct.
8. In the "Criteria range" section, specify the cell range for the criteria you created in step 2.
9. If you want to filter for unique records only, select the "Unique records only" checkbox.
10. Click "OK" to apply the filter. The filtered data will be displayed or copied to the new location depending on the option you selected.

Advanced Filter provides a more powerful filtering option than the basic filter. It's useful when you want to filter data based on multiple conditions or when you want to copy filtered data to another location.

Advanced Sorting:

Advanced sorting in MS Excel allows you to sort data based on multiple columns or criteria, and to specify custom sort orders for text and numbers. Here are the steps to use Advanced Sort:

1. Select the data range you want to sort.
2. On the "Data" tab, click on the "Sort" button in the "Sort & Filter" group. This opens the "Sort" dialog box.
3. In the "Sort by" dropdown, select the column you want to sort by first.
4. In the "Then by" dropdown, select the column you want to sort by next, if you want to sort by multiple columns.

5. Repeat step 4 for any additional columns you want to sort by.
6. If you want to specify a custom sort order for text or numbers, click on the "Custom List" button and add your custom list in the "List entries" box.
7. Choose whether you want to sort the data in ascending or descending order by selecting the appropriate option in the "Order" dropdown.
8. Click "OK" to apply the sort.

Advanced sorting is useful when you want to sort data based on multiple criteria or when you want to sort text or numbers in a specific order. It allows you to sort your data in a more customized and specific way than the basic sorting option in MS Excel.

12.2 Groups and Sets

Groups:

A group is a collection of data that you can use to create a summary or subcategory in your visualization. You can group data by selecting one or more columns, and then creating a new group based on a specific criterion. For example, you could group sales data by region, or group customer data by age range.

Sets:

A set is a custom filter that you can use to show a specific subset of data in your visualization. Sets are based on a specific column and a set of values that you define. For example, you could create a set of high-value customers, or a set of products that are currently on sale.

Both groups and sets can be created in the Power BI Desktop application. Here are the steps to create each one:

Creating a Group in PowerBI:

- Open the Fields pane and select the column you want to group by.
- Right-click the column and select "New Group."
- Define the grouping criteria, such as creating age ranges for customers or grouping sales by quarter.
- Rename the group as needed.
- Use the new group in your visualization.

Creating groups in MSExcel

- Select the rows or columns you want to group. You can select multiple rows or columns by clicking and dragging the column or row headers.
- On the "Data" tab, click on the "Group" button in the "Outline" group. This opens the "Group" dialog box.
- In the "By" section, select whether you want to group by rows or columns.
- In the "Starting at" and "Ending at" sections, specify the first and last row or column to include in the group.
- If you want to add more groups, click on the "Add Level" button and repeat steps 3-4 for each new group.
- Click "OK" to apply the groups.
- Once you have created groups, you can use the "+" and "-" symbols in the row or column headers to collapse or expand the group. When you collapse a group, the data is hidden, and when you expand it, the data is displayed.

Groups are useful for organizing and managing large sets of data, making it easier to navigate and analyze your data. They can also help you to summarize data by grouping and calculating subtotals or other statistics for each group.

Creating a Set in PowerBI:

- Open the Fields pane and select the column you want to create a set for.
- Right-click the column and select "New Set."
- Define the set criteria by selecting the values you want to include in the set.
- Rename the set as needed.
- Use the new set as a filter in your visualization.

Sets in MS Excel

In MS Excel, a set is a collection of unique values that you can use to analyze data in a PivotTable or PivotChart. Sets are useful when you want to create a subset of data based on specific criteria, such as the top 10 sales representatives, or customers who have made more than five purchases.

Here are the steps to create a set in MS Excel:

- Create a PivotTable or PivotChart based on your data.
- In the "PivotTable Fields" or "PivotChart Fields" pane, locate the field that you want to create a set for.
- Right-click on the field name, and select "Add to Set" from the context menu.
- In the "Create Set" dialog box, specify the criteria for your set. You can choose to include or exclude values based on specific conditions, such as "Top 10," "Bottom 5," "Greater than," "Less than," "Between," or "Equal to."
- Name your set and click "OK" to create it.
- Once you have created a set, you can use it in your PivotTable or PivotChart to analyze your data. Sets can be added to rows, columns, or values in your PivotTable, or as a filter in your PivotTable or PivotChart.

12.3 Interactive Filters

Power BI offers several options for creating interactive filters, which allow your users to dynamically explore your data and analyze it in more detail. Here are some of the most commonly used techniques:

Slicers:

Slicers are interactive filters that allow users to select one or more values from a dropdown list. Slicers can be added to your report by selecting the Slicer visual and choosing the column you want to filter on.

Visual-level Filters:

Visual-level filters allow users to filter data in a specific visualization. Users can interactively filter data by clicking on the filter icon in the visualization's toolbar, selecting the column to filter on, and specifying the filter criteria.

Drill-through Filters:

Drill-through filters allow users to navigate to another report page or a different visualization with more detailed data. By using drill-through filters, users can click on a data point in a visualization and see more detailed information about that data.

Cross-Filtering:

Cross-filtering allows users to filter multiple visualizations at the same time. By selecting one or more data points in a visualization, users can apply filters to other visualizations in the report, allowing them to explore relationships between different data points.

Bookmarks:

Bookmarks allow you to save a specific view of a report, including all the filters and selections, and then return to that view later. Users can use bookmarks to save different filter settings and then quickly switch between them.

Overall, these interactive filter options can help your users better analyze and visualize your data in Power BI, by allowing them to explore relationships between different data points and view data from different perspectives.

Interactive filters in MS Excel are a powerful tool that allow you to filter data in a table or PivotTable based on specific criteria. Interactive filters provide a user-friendly interface for filtering data, allowing you to easily select the values you want to include or exclude from your data set.

Here are the steps to use interactive filters in MS Excel:

- Select the data range you want to filter.
- On the "Data" tab, click on the "Filter" button in the "Sort & Filter" group. This will add filter arrows to each column header in your table.
- Click on the filter arrow for the column you want to filter. This will open a drop-down menu with filter options.
- Select the values you want to include or exclude from your data set. You can select individual values, or use the search box to filter by text or numbers.
- Click "OK" to apply the filter. Your table will update to show only the rows that meet your filter criteria.
- To clear the filter, click on the filter arrow again and select "Clear Filter."
- You can also use multiple filters to filter your data based on multiple criteria. To do this, simply click on the filter arrows for each column you want to filter and apply your filter criteria for each column.

In MS Excel, a slicer is a visual filtering tool that allows you to filter data in a PivotTable, PivotChart, or data table by selecting one or more items from a list of options. Slicers are a user-friendly way to filter data and provide a visual representation of the filtered data.

Here are the steps to use slicers in MS Excel:

- Create a PivotTable, PivotChart, or data table based on your data.
- On the "Insert" tab, click on the "Slicer" button in the "Filters" group. This opens the "Insert Slicers" dialog box.
- Select the field you want to filter by from the list of available fields.
- Click "OK" to create the slicer.
- The slicer will be displayed as a box containing a list of options. Click on one or more options to filter your data.
- To clear the filter, click on the "Clear Filter" button in the slicer.
- You can also format and customize the appearance of your slicer by selecting it and using the formatting options on the "Slicer Tools" tab.

Slicers are a powerful tool for analyzing and summarizing data in a PivotTable or PivotChart. They allow you to filter your data based on specific criteria, making it easier to identify trends and patterns in your data. Additionally, slicers provide a user-friendly interface for filtering data, allowing you to easily select the values you want to include or exclude from your data set.

12.4 Forecasting

Power BI offers built-in forecasting capabilities that allow you to predict future values based on historical data. These capabilities are available in certain visualizations, such as line charts and scatter charts, and can be enabled by selecting the "Forecast" option in the Visualizations pane.

Here are the steps to enable forecasting in Power BI:

- Add a line chart or scatter chart to your report and select the column that you want to forecast.
- In the Visualizations pane, click the "Analytics" tab and select the "Forecast" option.

- Configure the forecasting options by setting the forecast type, the forecast horizon (i.e., the number of periods to forecast), and the confidence interval.
- Apply the forecasting model to your visualization.
- Once the forecasting model has been applied, Power BI will generate a forecast based on the historical data and display it in the chart. The forecast will be displayed as a dotted line, with the historical data represented by a solid line.

You can use forecasting to predict future trends and identify potential issues or opportunities. For example, you could use forecasting to predict future sales or demand, and then adjust your marketing or production strategies accordingly. It's important to note that forecasting is only as accurate as the underlying data, so it's important to ensure that your data is clean, complete, and representative of the trend you are trying to forecast.

MS Excel provides several tools for forecasting future values based on historical data. Here are some of the most commonly used forecasting tools in Excel:

Trendline:

A trendline is a straight line that is used to represent the general trend in a data series. To add a trendline to a chart in Excel, select the chart and click on the "Add Chart Element" button. Then, select "Trendline" and choose the type of trendline you want to use.

Moving Average:

A moving average is a technique for smoothing out fluctuations in a data series. To calculate a moving average in Excel, use the "AVERAGE" function and specify the number of periods you want to include in the moving average.

Exponential Smoothing:

Exponential smoothing is a technique for forecasting future values based on a weighted average of past values. To use exponential smoothing in Excel, use the "FORECAST.ETS" function and specify the data range and smoothing factor.

Regression Analysis:

Regression analysis is a statistical technique for identifying the relationship between two or more variables. To perform regression analysis in Excel, use the "Data Analysis" tool and select "Regression" from the list of options.

Time Series Analysis:

Time series analysis is a statistical technique for analyzing time-based data. To perform time series analysis in Excel, use the "Data Analysis" tool and select "Time Series" from the list of options.

In addition to these tools, there are several other forecasting techniques that can be used in Excel, depending on the nature of your data and the specific requirements of your analysis. By using these tools, you can forecast future values with greater accuracy and make more informed decisions based on your data.

MS Excel has a built-in tool called "Forecast Sheet" that allows you to create forecasts of future values based on historical data. The Forecast Sheet tool uses the exponential smoothing method to create a forecast, which is a weighted average of past values.

Here are the steps to use the Forecast Sheet tool in Excel:

- Select the data range that you want to use for the forecast.
- On the "Data" tab, click on the "Forecast Sheet" button in the "Forecast" group.
- In the "Create Forecast Worksheet" dialog box, choose the options for your forecast, such as the length of the forecast period, the confidence interval, and the seasonality of the data.
- Click "Create" to generate the forecast sheet.
- The forecast sheet will show a chart of the historical data and the forecasted values, as well as a table of the forecasted values and the corresponding confidence intervals.
- You can customize the forecast sheet by using the formatting and design options in Excel.

12.5 Use of Tooltip

Power BI allows you to use tooltips to display additional information about your data in a report. Tooltips are a great way to provide more detailed information to your users without cluttering the report with too much data. Here are some ways you can use tooltips in Power BI:

Show data details:

Tooltips can be used to display detailed information about a specific data point in a visualization. For example, you could use a tooltip to show the name and value of a particular data point in a chart, or to display additional information about a product in a table.

Provide context:

Tooltips can also be used to provide additional context about the data being displayed. For example, you could use a tooltip to explain the methodology behind a particular calculation or to provide additional information about the data source.

Display images:

Tooltips can be used to display images, such as product photos or company logos. This can be a useful way to provide visual cues and help users better understand the data being displayed.

Show data trends:

Tooltips can also be used to display trend lines or forecasts for a specific data point. This can help users understand the direction of the data and make more informed decisions.

To add a tooltip in Power BI, you can select the visual and then select the "Tooltip" option in the Visualizations pane. From there, you can customize the tooltip by adding text, images, or other data visualizations.

Overall, tooltips are a powerful way to provide additional information and context to your users, and can help make your reports more engaging and informative.

In MS Excel, a tooltip is a small pop-up window that appears when you hover your mouse over a cell or object. The tooltip provides additional information about the cell or object, such as the cell value, formula, formatting, or comments.

Here are some tips on how to use tooltips in Excel:

- Hover your mouse over a cell to see the tooltip. The tooltip will display the cell value and any comments that have been added to the cell.
- Hover your mouse over a chart element to see the tooltip. The tooltip will display information about the data point or series, such as the value, name, or formatting.
- Hover your mouse over a toolbar button or menu item to see the tooltip. The tooltip will display a description of the button or menu item and its function.

To customize the tooltip, you can add a comment to a cell or chart element. To add a comment, right-click on the cell or chart element and select "Insert Comment". Type your comment in the comment box and click "OK". The comment will appear in the tooltip when you hover your mouse over the cell or chart element.

Tooltips are a useful feature in Excel that allow you to quickly view additional information about a cell or object without having to open a dialog box or a separate window. By using tooltips, you can save time and improve your productivity when working with Excel spreadsheets.

12.6 Reference Line

A reference line is a horizontal or vertical line that is added to a visualization in Power BI to help provide context and highlight specific values. Reference lines are commonly used to show thresholds or targets, such as sales targets or budget goals.

Here are the steps to add a reference line in Power BI:

- Select the visualization that you want to add the reference line to.

- In the Visualizations pane, click on the "Analytics" tab.
- Select the "Analytics" dropdown menu, then select "Add reference line".
- Choose whether to add a horizontal or vertical reference line.
- Set the value for the reference line by typing in a static value or by using a measure.
- Customize the appearance of the reference line by selecting the color, line style, and other options.
- Once you have added a reference line, it will appear in the visualization and can be used to highlight specific values or thresholds. Reference lines can be particularly useful in trend analysis or goal tracking, as they provide a clear visual indicator of progress or performance.

In addition to static reference lines, Power BI also offers dynamic reference lines that can be calculated based on data. For example, you could create a reference line that shows the average value for a certain time period, and then have the reference line update automatically as new data is added to the visualization. Dynamic reference lines can be a useful tool for identifying trends or patterns in your data over time.

In MS Excel, a reference line is a straight line that is added to a chart to represent a specific value or threshold. A reference line can be used to highlight a target value, a benchmark, or a limit in the data. Here are the steps to add a reference line in Excel:

- Select the chart that you want to add a reference line to.
- Right-click on the chart and select "Add Chart Element" > "Lines" > "Line".
- In the "Format Data Series" pane, choose "Values in reverse order" if your chart has a horizontal axis.
- Under "Line Options", choose "Fixed Value" and enter the value of the reference line.
- Choose the line color, style, and width that you want to use for the reference line.
- Click "Close" to apply the changes.
- You can customize the reference line further by using the formatting options in Excel.

Adding a reference line to a chart in Excel can help to make the data more meaningful and easier to interpret. By highlighting a specific value or threshold, you can draw attention to important trends or insights in the data. Additionally, a reference line can provide a visual aid for comparing the actual values with the desired or expected values.

12.7 Parameter

In Power BI, parameters allow you to create a dynamic and flexible report that can be customized by end-users without the need for extensive editing. Parameters are user-defined values that can be used in calculations, queries, or filters to create a more interactive and flexible report.

Here are some examples of how you can use parameters in Power BI:

Filter data:

Parameters can be used to create filters that allow users to customize the data displayed in a report. For example, you could create a parameter that allows users to select a date range for the data displayed in a chart or table.

Change visualizations:

Parameters can also be used to change the type of visualization displayed in a report. For example, you could create a parameter that allows users to switch between a line chart and a bar chart.

Calculate values:

Parameters can be used to create calculations based on user-defined values. For example, you could create a parameter that defines a discount percentage, and then use that parameter in a calculation to calculate the discounted price of a product.

Control report behavior:

Parameters can be used to control the behavior of a report, such as the number of rows displayed in a table or the color scheme used in a visualization.

To create a parameter in Power BI, you can go to the "Modeling" tab and select "New Parameter". From there, you can specify the name, data type, and other properties of the parameter. Once the parameter has been created, you can use it in calculations, filters, and other areas of your report.

Overall, parameters are a powerful tool for creating dynamic and flexible reports that can be customized by end-users. By allowing users to define their own values and settings, you can create a more interactive and engaging reporting experience that meets the needs of a wide range of users.

12.8 Drill Down and Hierarchies

Power BI offers drill-down and hierarchy features that allow users to navigate through data at different levels of granularity. These features can help users gain a deeper understanding of the data and explore different perspectives.

Here are some examples of how you can use drill-down and hierarchies in Power BI:

Drill-down:

With drill-down, users can click on a data point to see more detailed information. For example, you could create a chart that shows sales by year, and then allow users to drill down to see sales by quarter, month, or day.

Hierarchy:

A hierarchy is a collection of fields that are related to each other in a parent-child relationship. For example, you could create a hierarchy that includes product categories, subcategories, and individual products. Users can then navigate through the hierarchy to explore the data at different levels of granularity.

To use drill-down and hierarchy features in Power BI, you need to define the appropriate fields as a hierarchy in the data model. Once you have created the hierarchy, you can use it in a visualization by dragging and dropping the fields onto the appropriate areas of the chart. Users can then interact with the chart by clicking on data points or using drill-down controls.

In MS Excel, a hierarchy is a way of organizing data into a structured format that reflects the relationship between different levels of data. A hierarchy can be used to group data into categories and subcategories, and to create a drill-down view of the data.

Here are the steps to create a hierarchy in Excel:

- Select the data range that you want to use for the hierarchy.
- On the "Data" tab, click on the "Group" button in the "Outline" group.
- In the "Grouping" dialog box, choose the options for your hierarchy, such as the rows or columns to group by and the grouping intervals.
- Click "OK" to create the hierarchy.
- The hierarchy will show a collapsible view of the grouped data, with each level of the hierarchy represented by a separate row or column.
- You can customize the hierarchy by using the formatting and design options in Excel.

Overall, drill-down and hierarchies are powerful tools for exploring data and gaining a deeper understanding of the underlying patterns and trends. By allowing users to navigate through data at different levels of granularity, you can create a more interactive and engaging reporting experience that helps users make more informed decisions.

Unit 13: Decision Analytics and Calculations

CONTENTS

13.1 Type of Calculations

Power BI is a data visualization and business intelligence tool that enables users to create interactive reports and dashboards. In addition to data visualization, Power BI also supports various types of calculations, including:

Aggregations:

Power BI can aggregate data using functions such as sum, average, count, maximum, and minimum.

Calculated columns:

Users can create new columns in a table by defining a formula that combines existing columns. Calculated columns are computed when the data is loaded and are used to enrich the data with new insights.

Measures:

Measures are calculated fields that are created using DAX (Data Analysis Expressions) formulas. Measures are computed at run-time and can be used to aggregate data across multiple tables.

Time intelligence:

Power BI supports time-based calculations such as year-to-date, month-to-date, and previous year comparisons. These calculations can be used to create dynamic visualizations that show changes over time.

Conditional formatting:

Users can apply conditional formatting to visualize data based on specific conditions. For example, data can be color-coded to highlight values that fall outside a certain range or to highlight trends in data over time.

Quick measures:

Power BI includes pre-built measures that can be quickly added to a report. Quick measures are templates for commonly used calculations such as running totals, moving averages, and percentiles.

These types of calculations can be combined to create powerful analytics solutions that enable users to gain insights into their data and make informed business decisions.

13.2 Aggregation in PowerBI

Aggregation in Power BI is the process of summarizing data by computing a single value from a set of values. Aggregation functions such as sum, average, count, maximum, and minimum can be used to perform this task. Aggregating data is important in data analysis and reporting as it helps to understand trends, patterns, and relationships in data.

Power BI offers various ways to aggregate data, including:

Aggregations in tables:

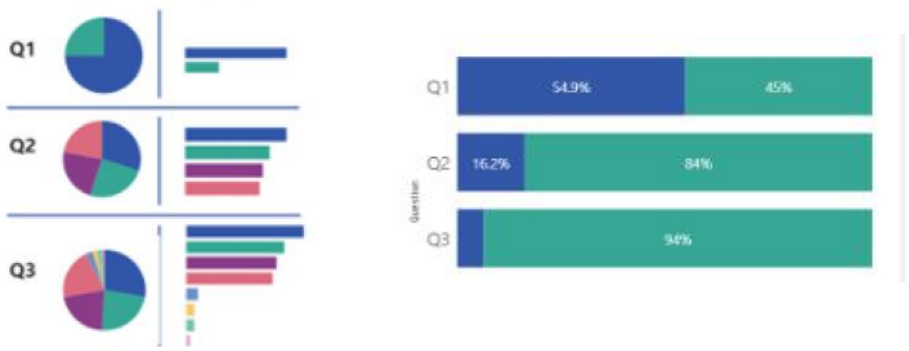
When creating a table in Power BI, users can choose to aggregate data using a specific function. For example, if you have a table of sales data, you can aggregate the total sales for each product by using the sum function.

Aggregations in visuals:

Power BI visuals such as charts, tables, and matrices allow users to summarize data by applying aggregation functions. For example, a bar chart can show the total sales for each product category, and a matrix can show the average sales by region and year.

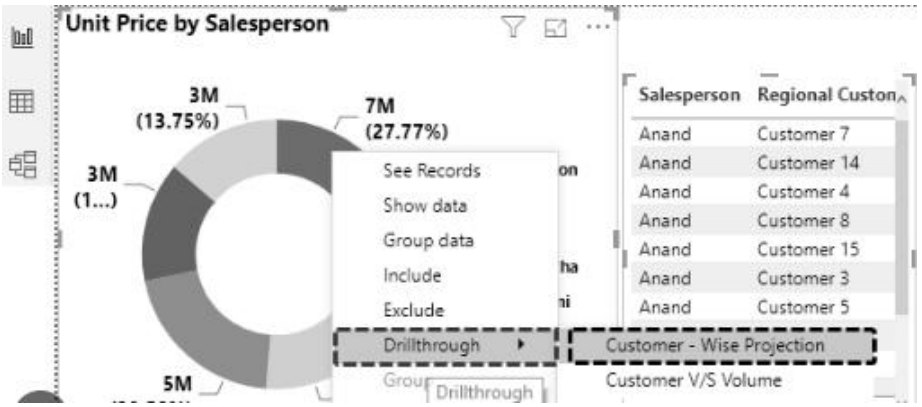
Grouping:

Power BI allows users to group data based on specific columns. For example, you can group sales data by product category and then compute the total sales for each category.



Drill-down and drill-up:

Power BI enables users to drill down and drill up in data to see different levels of aggregation. For example, you can start with the total sales for a year, drill down to see sales by quarter, and then drill down further to see sales by month.



Aggregation is an important feature in Power BI that allows users to gain insights into their data quickly and efficiently. It enables users to identify patterns, trends, and relationships that may not be immediately apparent in the raw data.

13.3 Calculated Columns in Power BI

Calculated columns in Power BI are columns that are created by defining a formula that combines values from other columns in a table. The formula used in a calculated column is similar to the formula used in Excel, and it is written using the DAX (Data Analysis Expressions) language. The result of the formula is computed for each row in the table and is stored in the calculated column.

Calculated columns can be used to enrich the data in a table with new insights. For example, a calculated column can be used to compute a discount rate based on the quantity of items sold, or it can be used to categorize data based on a specific condition. Once a calculated column is created, it becomes a permanent part of the table, and it can be used in any visual or calculation in the report.

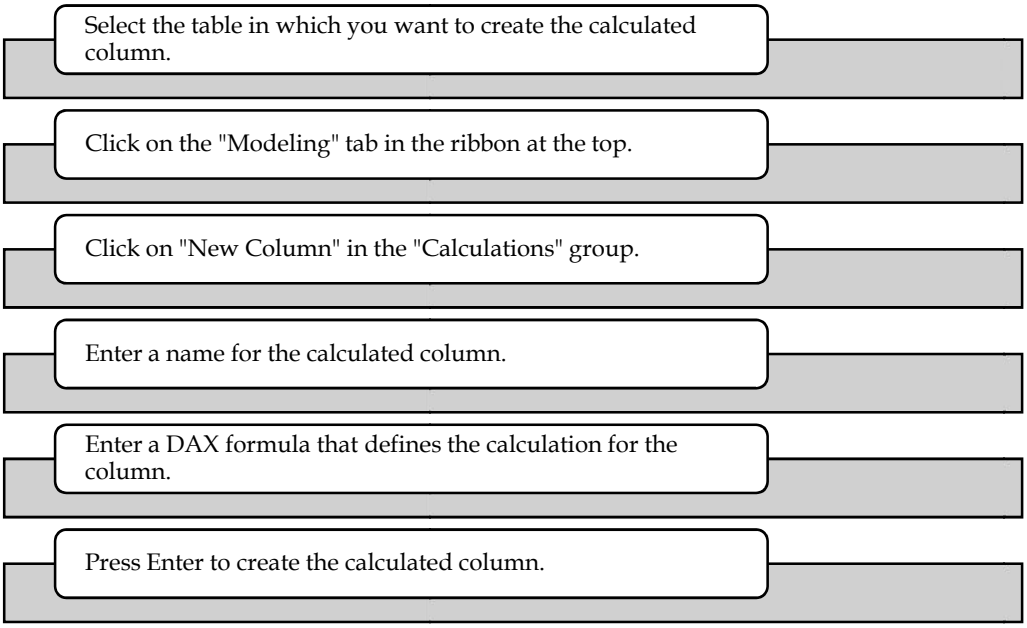
Example:

Here's an example of a DAX formula for a calculated column that computes the total cost of an order:

TotalCost = [Quantity] * [UnitPrice]

In this formula, [Quantity] and [UnitPrice] are columns in the table. The formula multiplies the quantity of items sold by the unit price to compute the total cost of the order. Once this calculated column is created, it can be used in any calculation or visual in the report.

To create a calculated column in Power BI, follow these steps:



13.4 Measures in PowerBI

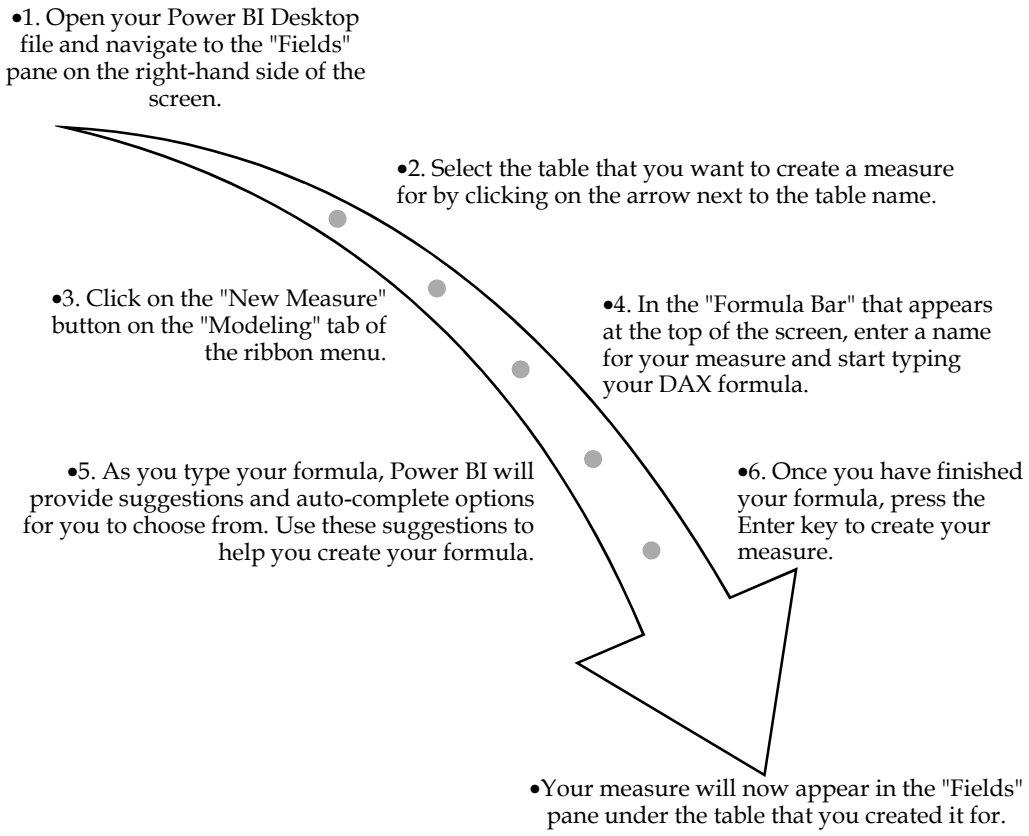
Power BI is a data visualization tool that provides a variety of measures that can be used to calculate, aggregate, and analyze data. Measures are calculations that are created based on the data in your dataset. They allow you to summarize and analyze your data in different ways.

Here are some common measures in Power BI:

Sum	calculates the sum of a column of numbers.
Average	calculates the average of a column of numbers.
Count	counts the number of rows in a table or column.
Distinct Count	counts the number of distinct values in a column.
Minimum	finds the smallest value in a column.
Maximum	finds the largest value in a column.
Median	finds the median value in a column.
Percentile	finds the value at a specified percentile in a column.
Variance	calculates the variance of a column of numbers.
Standard Deviation	calculates the standard deviation of a column of numbers

How to create measures in PowerBI

To create a measure in Power BI, you can use the following steps:

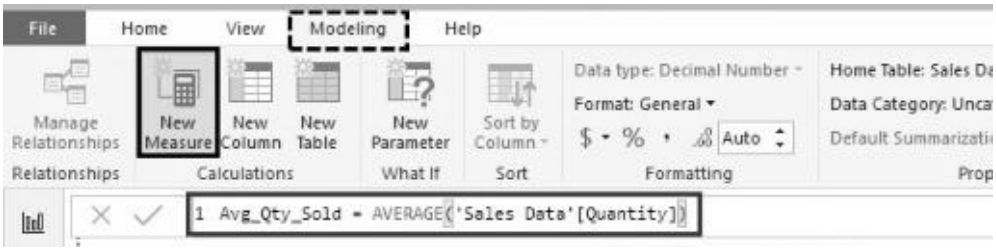


Example:

Here's an example of a simple DAX formula that calculates the sum of a column of numbers:

Total Sales = SUM(Sales[Amount])

This formula creates a measure called "Total Sales" that calculates the sum of the "Amount" column in the "Sales" table.



You can use DAX to create more complex calculations and measures, such as calculated columns and tables, as well as time intelligence functions to analyze data over time. It's important to have a good understanding of the DAX language and syntax before creating measures in Power BI.

13.5 Time Based Calculations in PowerBI

Power BI offers several features to perform time-based calculations, which are useful for analyzing data over a specific time period. Here are some of the time-based calculations that you can perform in Power BI:

Date/Time Formatting:

Power BI can automatically recognize and format dates and times in various formats, making it easy to analyze time-based data. You can also customize the date and time format to fit your needs.

Date/Time Hierarchy:

Power BI can create a date/time hierarchy for your data, allowing you to drill down into specific time periods. For example, you can drill down from year to month, to day, to hour.

Time Intelligence Functions:

Power BI provides several time intelligence functions such as TOTALYTD, TOTALQTD, TOTALMTD, SAMEPERIODLASTYEAR, etc. that enable you to calculate metrics such as year-to-date, quarter-to-date, month-to-date, and compare data with the same period last year.

Calculated Columns and Measures:

You can create calculated columns and measures that use time-based calculations, such as calculating the average sales per day or the number of working days in a month.

Time-based Visualization:

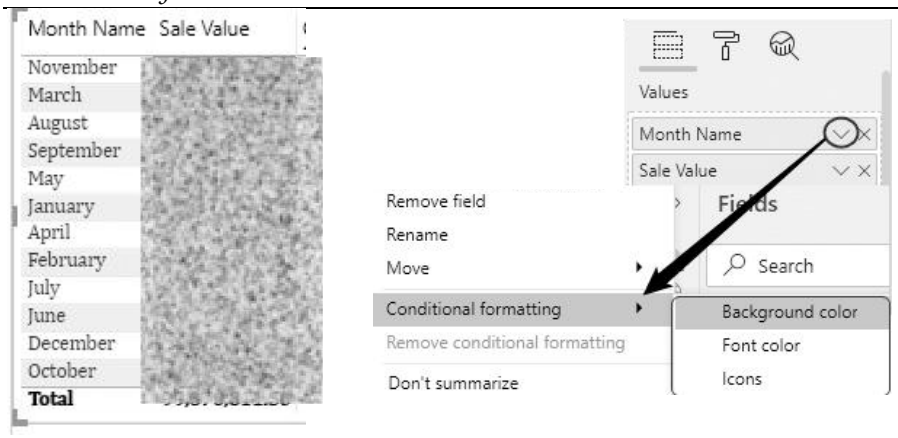
Power BI provides several time-based visualization options, such as line charts, area charts, and bar charts, that enable you to visualize data over time.

Overall, Power BI provides a wide range of features to perform time-based calculations, allowing you to gain valuable insights into your data over time.

13.6 Conditional Formatting in PowerBI

Conditional formatting in Power BI allows you to change the format or appearance of data values in a visual based on specific conditions or rules. This can help highlight important data, identify outliers or exceptions, and make it easier to spot trends and patterns in your data.

You can apply conditional formatting to different types of visuals in Power BI, including tables, charts, and matrices. Power BI also allows you to create complex rules using DAX formulas, which gives you more flexibility in defining the conditions for formatting. Additionally, conditional formatting in Power BI can be used in combination with other features, such as drill-down, to further enhance your data analysis.



Here are the steps to apply conditional formatting in Power BI:

Select the visual you want to apply conditional formatting to.

↓

Click on the "Conditional formatting" button in the formatting pane on the right-hand side.

↓

Choose the type of formatting you want to apply
(e.g., background color, font color, data bars, etc.).

↓

Define the rule or condition for the formatting.
You can set a rule to change the color of values above or below a certain threshold or set a gradient color scale based on the values in the visual.

↓

Choose the format or color scheme you want to apply when the rule is met.

↓

Preview the formatting changes to ensure they are what you want.

↓

Save the changes.

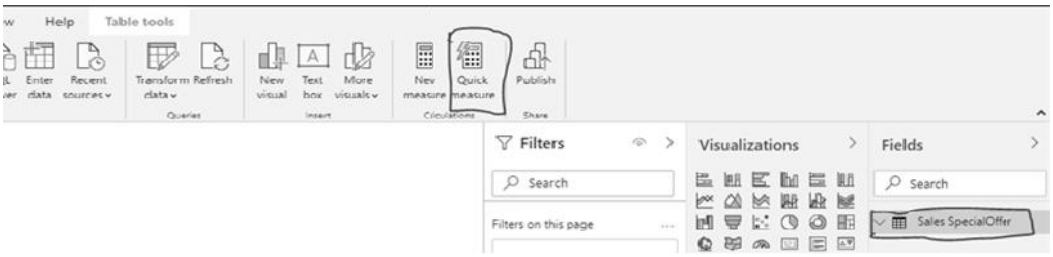
13.7 Quick Measures in PowerBI

Quick Measures in Power BI are pre-defined calculations that allow you to quickly create commonly used calculations without writing complex DAX expressions. With Quick Measures, you can use a graphical interface to create calculations, which can be used in charts, tables, and other visuals in your Power BI reports.

Here's how to create a Quick Measure in Power BI:

- Open your Power BI report.

- Select the "Quick Measures" option from the "Fields" pane.



- Choose the calculation you want to create from the list of available options.
- Enter the required fields for your calculation, such as the data field, aggregation, and any filters.
- Click "OK" to create the Quick Measure.
- Once you have created a Quick Measure, you can use it like any other measure in Power BI. You can add it to charts, tables, and other visuals, and you can also modify it or delete it if necessary.

Quick Measures are a great way to speed up your report development in Power BI and reduce the time you spend writing complex DAX expressions.

13.8 String Calculations

Power BI provides various built-in functions to perform string calculations on text data.

Function	Description
COMBINEVALUES	Joins two or more text strings into one text string. COMBINEVALUES(<delimiter>, <expression>, <expression>[, <expression>]…)
CONCATENATE	Joins two text strings into one text string. CONCATENATE(<text1>, <text2>)
CONCATENATEX	Concatenates the result of an expression evaluated for each row in a table. CONCATENATEX(<table>, <expression>[, <delimiter> [, <orderBy_expression> [, <order>]]...])
EXACT	Compares two text strings and returns TRUE if they are exactly the same, FALSE otherwise. EXACT(<text1>,<text2>)
FIND	Returns the starting position of one text string within another text string. FIND(<find_text>, <within_text>[, [<start_num>][, <NotFoundValue>]])
FIXED	Rounds a number to the specified number of decimals and returns the result as text. FIXED(<number>, <decimals>, <no_commas>)

FORMAT	Converts a value to text according to the specified format. FORMAT(<value>, <format_string>[, <locale_name>]) Egs: = FORMAT(dt"2020-12-15T12:30:59", "mm/dd/yyyy", "en-GB") = FORMAT(12345.67, "Currency")
LEFT	Returns the specified number of characters from the start of a text string. LEFT(<text>, <num_chars>)
LEN	Returns the number of characters in a text string. LEN(<text>)
LOWER	Converts all letters in a text string to lowercase. LOWER(<text>)
MID	Returns a string of characters from the middle of a text string, given a starting position and length. MID(<text>, <start_num>, <num_chars>)
REPLACE	REPLACE replaces part of a text string, based on the number of characters you specify, with a different text string. REPLACE(<old_text>, <start_num>, <num_chars>, <new_text>)
REPT	Repeats text a given number of times. REPT(<text>, <num_times>)
RIGHT	RIGHT returns the last character or characters in a text string, based on the number of characters you specify. RIGHT(<text>, <num_chars>)
SEARCH	Returns the number of the character at which a specific character or text string is first found, reading left to right. SEARCH(<find_text>, <within_text>[, [<start_num>][, <NotFoundValue>]]) Eg: SEARCH ("cycle", 'Reseller'[Reseller], 1, BLANK ()
SUBSTITUTE	Replaces existing text with new text in a text string. SUBSTITUTE(<text>, <old_text>, <new_text>, <instance_num>)
TRIM	Removes all spaces from text except for single spaces between words. TRIM(<text>)
UNICHAR	Returns the Unicode character referenced by the numeric value. UNICHAR(number)

UNICODE	Returns the numeric code corresponding to the first character of the text string. UNICODE(<Text>)
UPPER	Converts a text string to all uppercase letters. UPPER (<text>)
VALUE	Converts a text string that represents a number to a number. VALUE(<text>)

13.9 Logic Calculations in PowerBI

Power BI supports logic calculations through the use of DAX (Data Analysis Expressions) formulas. DAX is a formula language used to create custom calculations in Power BI, Excel, and other Microsoft products.

To perform logic calculations in Power BI, you can use DAX functions such as IF, SWITCH, AND, OR, and NOT, among others. These functions allow you to create conditional statements, logical comparisons, and other calculations based on the values in your data.

Various Logic functions in PowerBI are:

Function	Description
AND	Checks whether both arguments are TRUE, and returns TRUE if both arguments are TRUE. AND(<logical1>,<logical2>)
FALSE	Returns the logical value FALSE. FALSE()
IF	Checks a condition, and returns one value when TRUE, otherwise it returns a second value. IF(<logical_test>, <value_if_true>[, <value_if_false>])
IFERROR	Evaluates an expression and returns a specified value if the expression returns an error IFERROR(value, value_if_error)
NOT	Changes FALSE to TRUE, or TRUE to FALSE. NOT(<logical>)
OR	Checks whether one of the arguments is TRUE to return TRUE.The function returns FALSE if both arguments are FALSE. OR(<logical1>,<logical2>)
SWITCH	Evaluates an expression against a list of values and returns one of multiple possible result expressions. SWITCH(<expression>, <value>, <result>[, <value>, <result>]…[, <else>])
TRUE	Returns the logical value TRUE. TRUE()

13.10 Date and time function

These functions help you create calculations based on dates and time. DAX functions use a datetime data type, and can take values from a column as an argument. These functions are:

Function	Description
CALENDAR	Returns a table with a single column named "Date" that contains a contiguous set of dates.
CALENDARAUTO	Returns a table with a single column named "Date" that contains a contiguous set of dates.
DATE	Returns the specified date in datetime format.
DATEDIFF	Returns the number of interval boundaries between two dates.
DATEVALUE	Converts a date in the form of text to a date in datetime format.
DAY	Returns the day of the month, a number from 1 to 31.
EDATE	Returns the date that is the indicated number of months before or after the start date.
EOMONTH	Returns the date in datetime format of the last day of the month, before or after a specified number of months.
HOUR	Returns the hour as a number from 0 (12:00 A.M.) to 23 (11:00 P.M.).
MINUTE	Returns the minute as a number from 0 to 59, given a date and time value.
MONTH	Returns the month as a number from 1 (January) to 12 (December).
NETWORKDAYS	Returns the number of whole workdays between two dates.
NOW	Returns the current date and time in datetime format.
QUARTER	Returns the quarter as a number from 1 to 4.
SECOND	Returns the seconds of a time value, as a number from 0 to 59.
TIME	Converts hours, minutes, and seconds given as numbers to a time in datetime format.
TIMEVALUE	Converts a time in text format to a time in datetime format.
TODAY	Returns the current date.
UTCNOW	Returns the current UTC date and time
UTCTODAY	Returns the current UTC date.
WEEKDAY	Returns a number from 1 to 7 identifying the day of the week of a date.
WEEKNUM	Returns the week number for the given date and year according to the return_type value.

YEAR	Returns the year of a date as a four digit integer in the range 1900-9999.
YEARFRAC	Calculates the fraction of the year represented by the number of whole days between two dates.

Unit 14: Mapping

CONTENTS

Introduction

Maps are visual representations of the earth's surface or a part of it. They are used to help people navigate, locate places, and understand the physical and political features of an area. Maps can be made in a variety of formats, including paper, digital, and interactive.

Maps can show different types of information, such as:

Information type	Details
Physical features	Maps can show landforms such as mountains, rivers, and deserts, as well as bodies of water like oceans and lakes.
Political boundaries	Maps can show national, state, and local boundaries, as well as cities, towns, and other settlements.
Transportation networks	Maps can show roads, railways, airports, and other means of transportation.
Natural resources	Maps can show the location of resources like oil, gas, and minerals.
Climate and weather patterns	Maps can show temperature and precipitation patterns, as well as weather systems like hurricanes and tornadoes.

Maps have been used for thousands of years, and their development has been crucial for the advancement of human civilization. Today, maps are used in many fields, such as navigation, urban planning, environmental management, and business.

14.1 Maps in Analytics

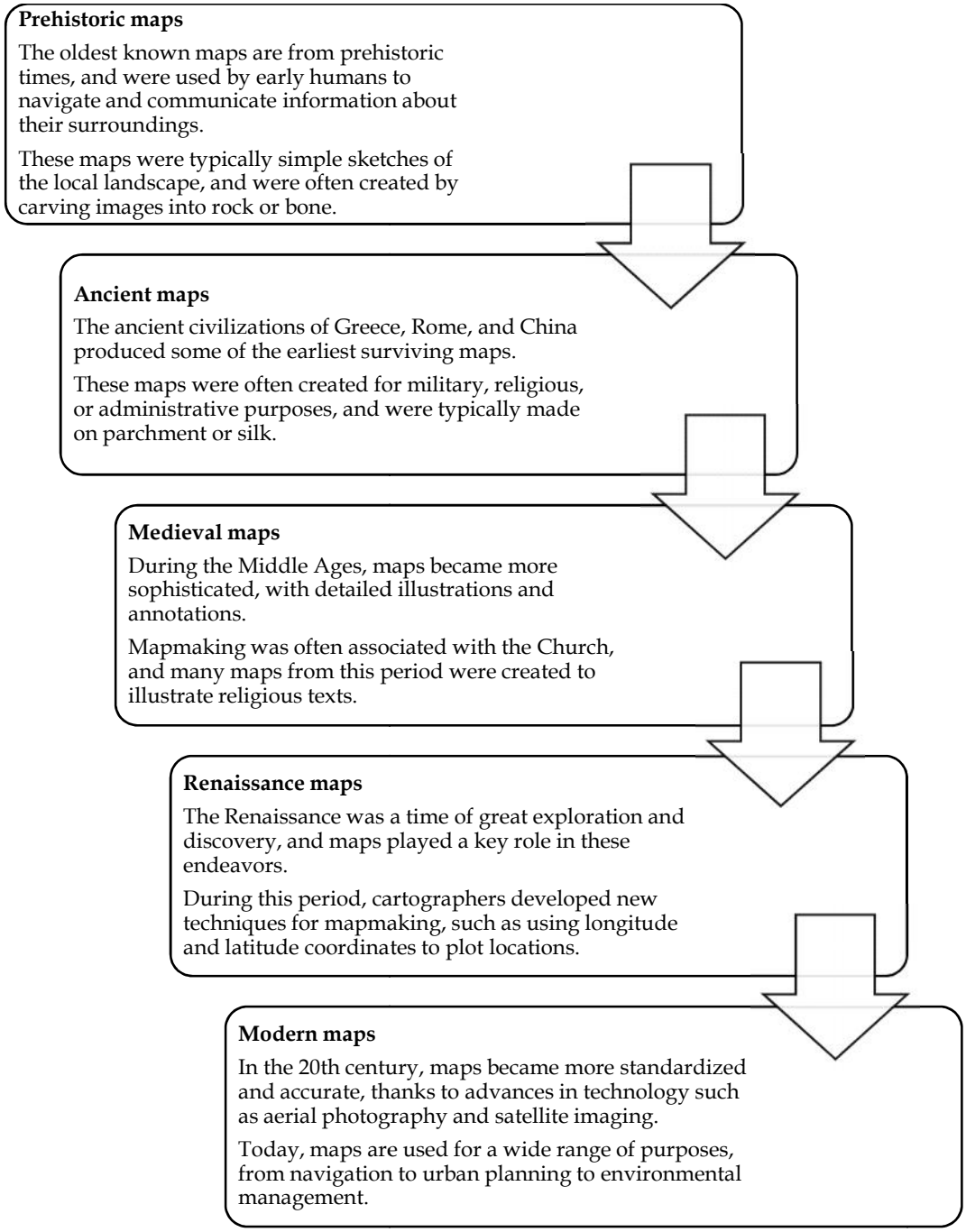
Maps are widely used in analytics as a tool for visualizing and analyzing spatial data. By overlaying data onto a map, analysts can gain insights into patterns and relationships that might not be immediately apparent from tabular data alone. Here are some examples of how maps are used in analytics:

Geographic analysis	Maps can be used to analyze geographic patterns in data, such as the distribution of customers or sales across a region. By visualizing data on a map, analysts can identify geographic clusters or hotspots that might be relevant to business decisions.
Site selection	Maps can be used to help select the best location for a new store, factory, or other facility. By analyzing factors such as traffic patterns, demographics, and competitors, analysts can identify areas that are most likely to be successful.
Transportation and logistics	Maps can be used to optimize transportation and logistics operations, such as route planning and inventory management. By visualizing data on a map, analysts can identify the most efficient routes and distribution centers.
Environmental analysis	Maps can be used to analyze environmental data, such as air quality, water quality, and wildlife habitats. By visualizing data on a map, analysts can identify areas that require attention or protection.
Real-time tracking	Maps can be used to track the movement of people, vehicles, or assets in real-time. By visualizing data on a map, analysts can monitor the status and location of assets, and respond quickly to any issues that arise.

Overall, maps are a powerful tool for spatial analysis, allowing analysts to gain insights into complex relationships and patterns that might be difficult to see otherwise.

14.2 Maps History

Maps have a long and rich history that dates back thousands of years. Here is a brief overview of the history of maps:

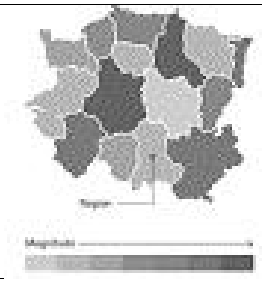
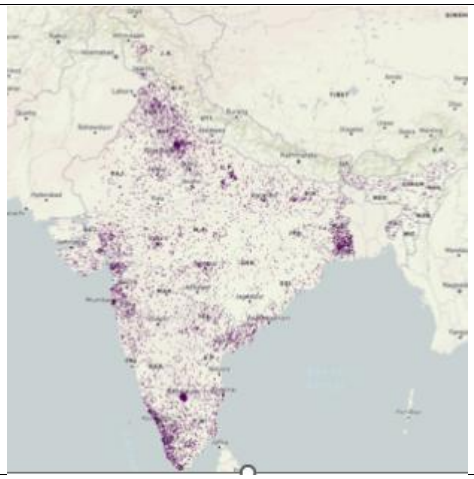


Overall, the history of maps reflects the evolution of human knowledge and understanding of the world around us. From simple sketches to high-tech digital maps, maps have been a crucial tool for exploration, navigation, and communication throughout human history.

14.3 Maps Visualization types

Maps can be visualized in a variety of ways, depending on the data being represented and the purpose of the map. Here are some of the most common types of maps visualizations:

Choropleth maps:	These maps use different colors or shades to represent data for different regions or areas. For example, a choropleth map of population density might use darker colors for areas with higher population densities and lighter colors for areas with lower population densities.

	
Heat maps:	These maps use color gradients to represent the density or intensity of data points. For example, a heat map of crime activity might use a gradient from blue (low activity) to red (high activity) to show where crimes are most concentrated.
	
Dot density maps:	These maps use dots to represent data points, such as people or incidents, and the density of the dots corresponds to the density of the data. For example, a dot density map of population might use one dot to represent 10,000 people, with more dots in areas with higher population densities.
	
Flow maps:	These maps show the movement of people or goods between different locations. For example, a flow map of trade might show the volume of goods being imported and exported between different countries.
	
Cartograms:	These maps distort the size or shape of regions to represent data, such as population or economic activity. For example, a cartogram of population might show larger regions for countries with larger populations, even if

	they are geographically smaller.
	
3D maps:	These maps add a third dimension to the visualization, allowing viewers to see the elevation or height of different regions. For example, a 3D map of a mountain range might show the elevation of the peaks and valleys.
	

Overall, the choice of map visualization depends on the nature of the data and the insights that need to be conveyed to the viewer.

14.4 Data Type Required for Analytics on Maps

There are many types of data that can be used for analytics on maps, depending on the specific purpose and context of the analysis. Here are some of the most common types of data used for analytics on maps:

1. Geographic data:

This includes information about the location, boundaries, and features of different regions or areas, such as countries, states, cities, and neighborhoods.

2. Spatial data:

This includes data that has a spatial or geographic component, such as the location of people, buildings, or natural features like rivers or mountains.

3. Demographic data:

This includes information about the characteristics of different populations, such as age, gender, race, income, education, and employment.

4. Economic data:

This includes data related to the production, distribution, and consumption of goods and services, such as GDP, employment, trade, and industry sectors.

5. Environmental data:

This includes data related to the natural environment, such as weather patterns, climate, air and water quality, and the presence of flora and fauna.

6. Transportation data:

This includes data related to the movement of people and goods, such as traffic patterns, commuting distances, transportation infrastructure, and modes of transportation.

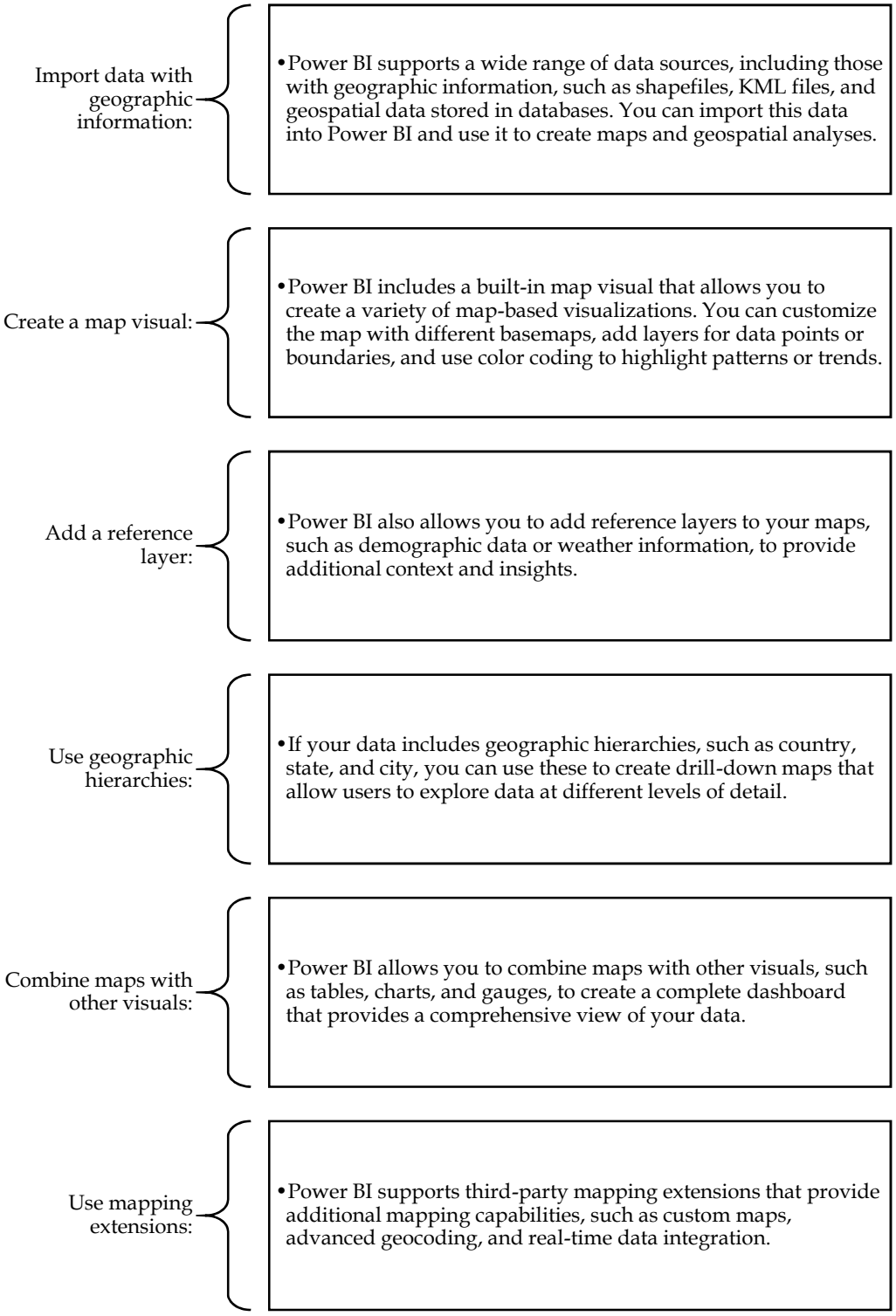
7. Social media data:

This includes data generated by social media platforms, such as geotagged posts, check-ins, and reviews, which can provide insights into consumer behavior, sentiment, and preferences.

Overall, the choice of data for analytics on maps depends on the specific research questions or business needs, as well as the availability and quality of the data. Effective analysis on maps often involves combining multiple sources of data to gain a more complete understanding of the spatial patterns and relationships at play.

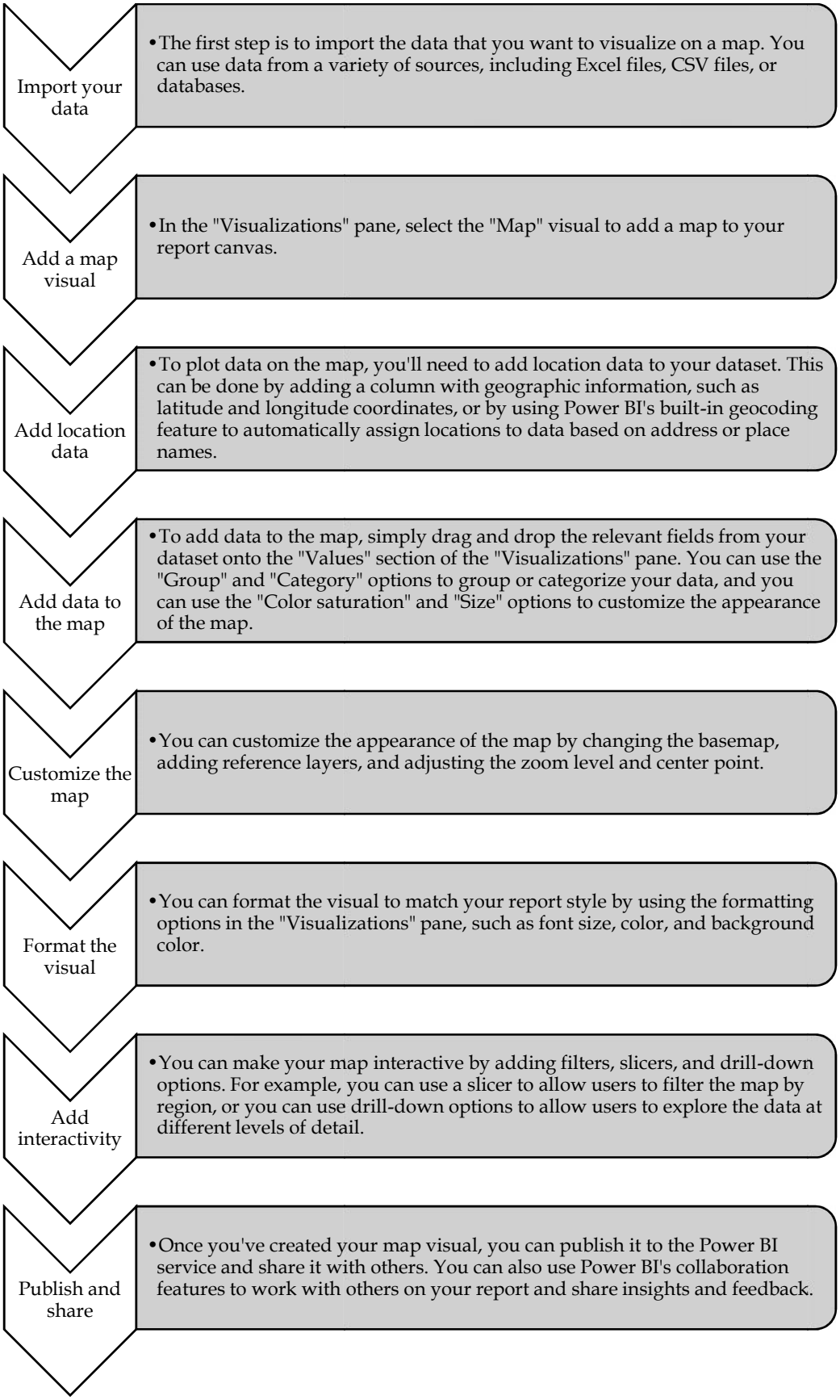
14.5 Maps in Power BI

Power BI is a powerful data visualization tool that can be used to create interactive maps and analyze data with a geographic component. Here are some of the ways you can work with maps in Power BI:



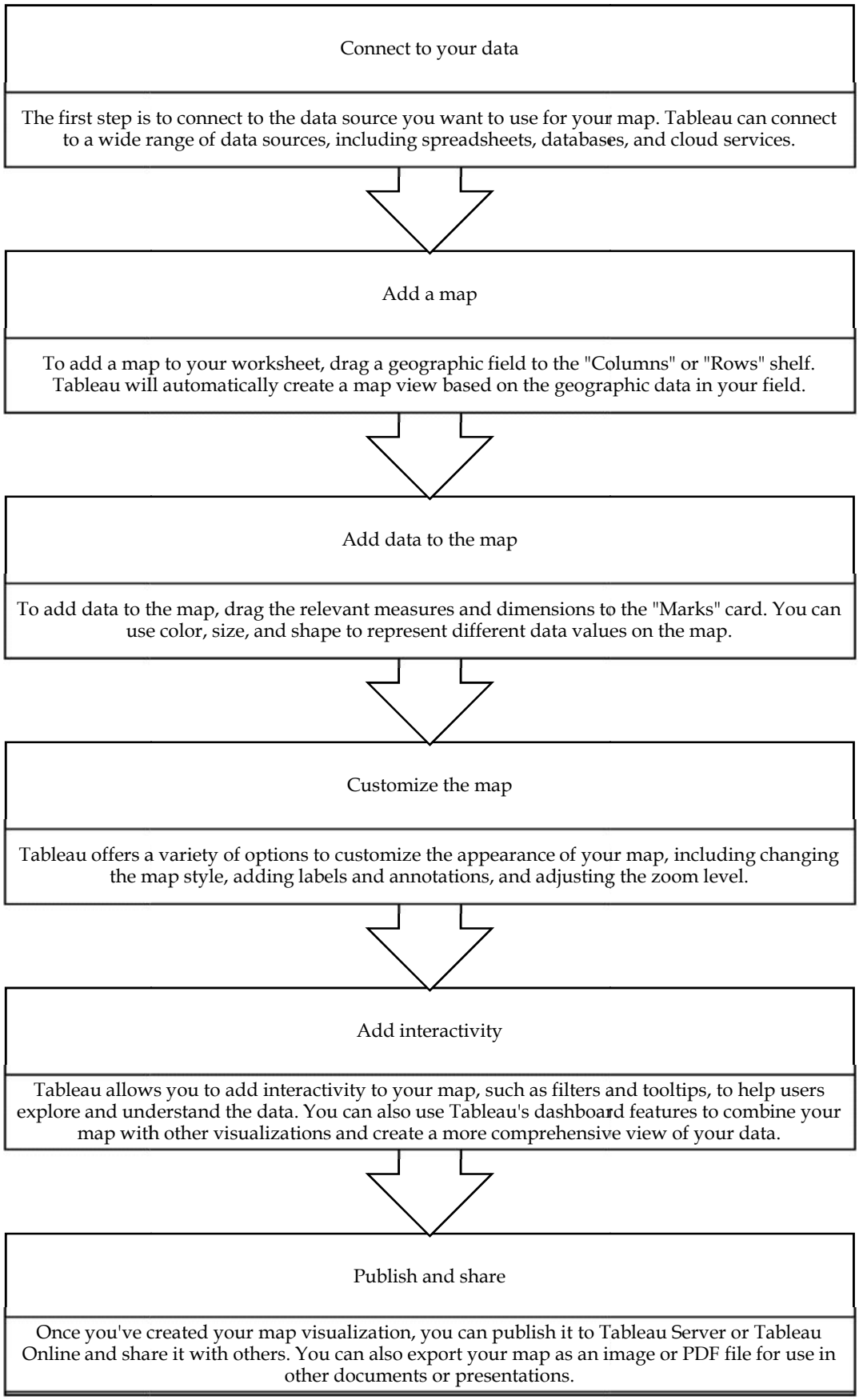
Steps to draw map visualization in Power BI

Here are the basic steps to create a map visualization in Power BI:



14.6 Maps in Power Tableau

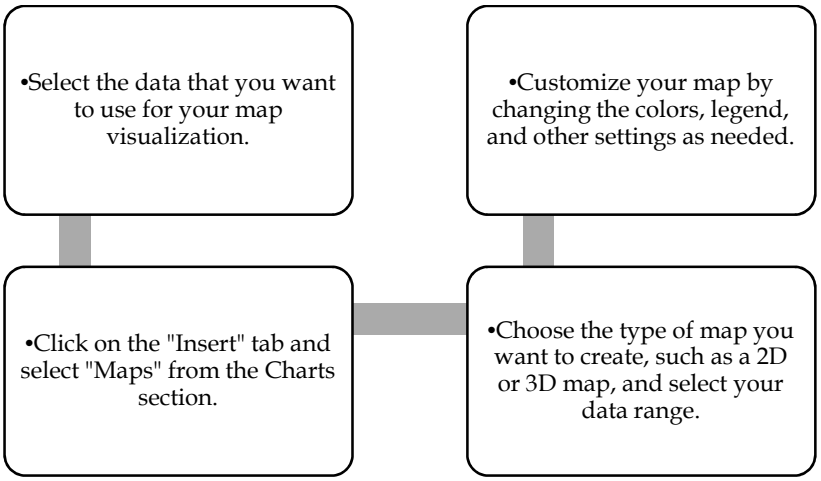
Here are the basic steps to create a map visualization in Tableau:



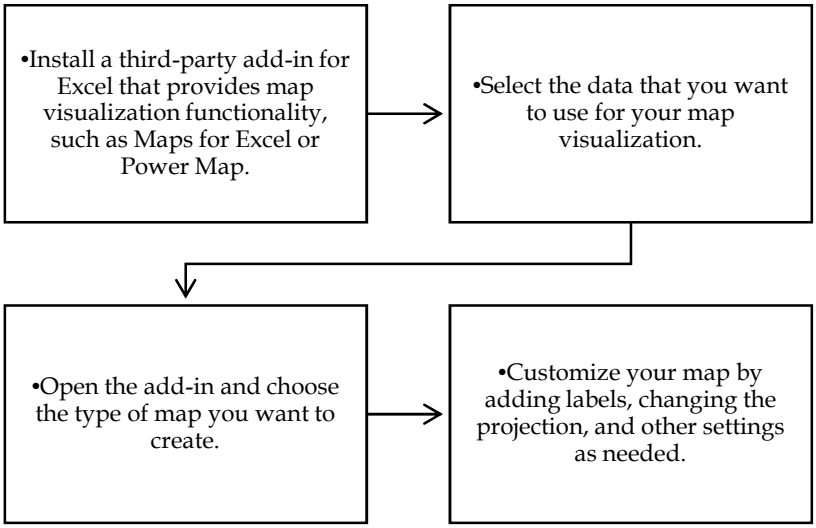
14.7 Maps in MS Excel:

There are several ways to draw a map visualization in Microsoft Excel, depending on your data and the level of detail you want to include in your map. Here are two common methods:

Using the built-in map charts:



Using a third-party map add-in:



Note that the specific steps and options may vary depending on the version of Excel you are using and the add-ins or tools available to you.

14.8 Editing Unrecognized Locations

Power BI

In Power BI, the Map visualization can sometimes display unrecognized locations if the geographic data is not complete or if the location is not recognized by the mapping service being used. Here are some steps to edit unrecognized locations in a Power BI Map visualization:

Click on the Map visualization to select it.

In the Visualizations pane, select the "Format" tab.

Under the "Data colors" section, click on the "Advanced controls" button.

In the "Advanced controls" pane, select the "Location" tab.

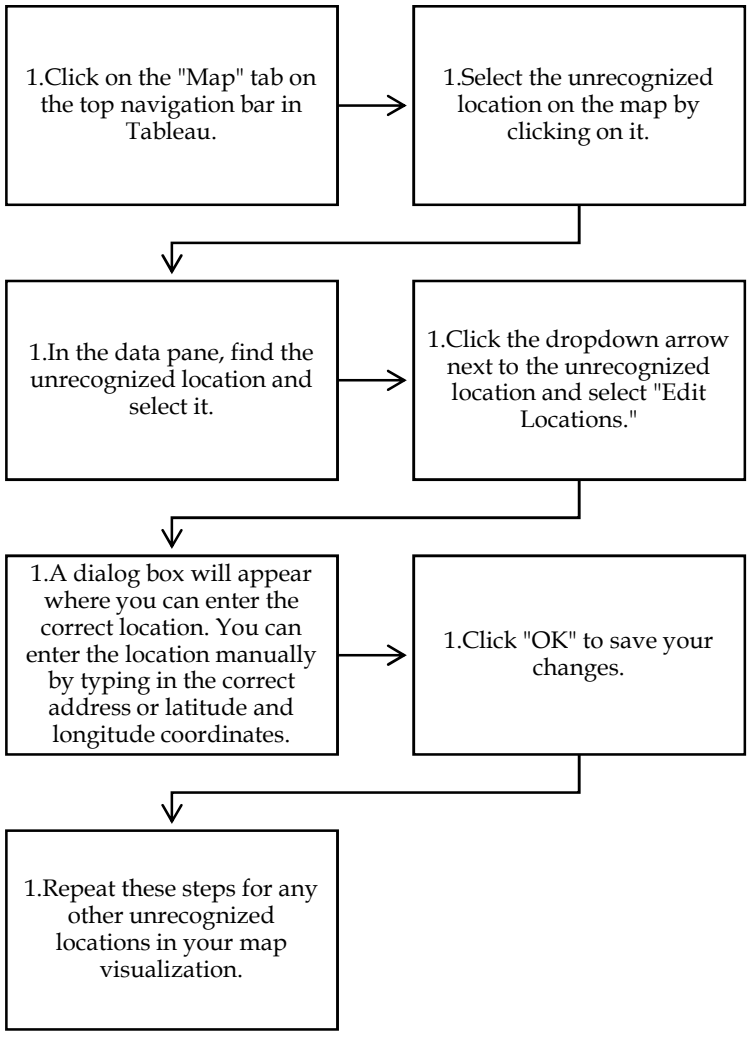
In the "Location" tab, you can edit the unrecognized location by specifying the latitude and longitude coordinates of the location.

Alternatively, you can also try entering a different name for the location in the "Location name" field to see if the mapping service recognizes it.

Once you have edited the location, click the "Apply" button to see the updated visualization.

Tableau

If Tableau is not recognizing your location data in your map visualization, you can try the following steps to manually edit the unrecognized locations:



14.9 Handling Locations Unrecognizable by Visualization Applications

If you have data for unrecognized locations that you want to display on a map, there are several approaches you can take depending on the nature of the data and the tools you have available. Here are a few suggestions:

Geocode the locations:

If you have a list of unrecognized locations that you want to display on a map, you can use a geocoding service to convert them into latitude and longitude coordinates. Geocoding is the process of converting a textual address into a set of geographic coordinates. There are several geocoding services available online, such as Google Maps Geocoding API, Bing Maps API, and OpenStreetMap Nominatim. Once you have the latitude and longitude coordinates for each location, you can plot them on a map using a mapping tool such as Google Maps, Mapbox, or Tableau.

Use a heat map:

If you have a large number of unrecognized locations that you want to display on a map, you can use a heat map to visualize the density of the data. A heat map is a visualization technique that uses colors to represent the intensity of data values. You can create a heat map using tools such as Google Maps, Mapbox, or Tableau. To create a heat map, you will need to convert your data into a format that can be used by the mapping tool, such as a CSV file with latitude and longitude coordinates and a count of the number of occurrences for each location.

Use a custom map:

If you have a specific geographic area that you want to focus on, you can create a custom map that includes the unrecognized locations. You can create a custom map using tools such as Google My Maps, Mapbox, or ArcGIS Online. To create a custom map, you will need to import your data into the mapping tool and then customize the map to include the unrecognized locations. You can add markers or icons to represent the unrecognized locations, or you can use custom colors or shading to highlight the areas where the unrecognized locations are located.

Use a choropleth map:

If your unrecognized locations are associated with specific geographic regions, you can create a choropleth map to visualize the data. A choropleth map is a map that uses colors to represent data values for specific geographic regions, such as countries, states, or counties. You can create a choropleth map using tools such as Google Maps, Mapbox, or Tableau. To create a choropleth map, you will need to import your data into the mapping tool and then associate it with the appropriate geographic regions. The mapping tool will then color the regions based on the data values, allowing you to see patterns and trends in the data.

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