

DATA ANALYTICS 101

EXPLORATORY DATA ANALYSIS

Using



R

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Data Analytics 101 – Exploratory Data Analysis using R programming.

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Welcome

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Exploratory Data Analysis (EDA) is an approach to analyzing data sets to summarize their main characteristics, often using statistical graphics and other data visualization methods. EDA is primarily for seeing what the data can tell us beyond the formal modeling or hypothesis testing tasks.

The EDA approach can be broken down into the following steps:

Data Cleaning: This step includes handling missing data, removing outliers, and other data cleansing processes.

Univariate Analysis: Here, each field in the dataset is analyzed independently to better understand its distribution, outliers, and unique values. This could involve statistical plots for measuring central tendency like mean, median, mode, frequency distribution, quartiles, etc.

Bivariate Analysis: This step involves the analysis of two variables to determine the empirical relationship between them. It includes techniques such as scatter plots for continuous variables or crosstabs for categorical data.

Multivariate Analysis: This is an advanced step, involving analysis with more than two variables. It helps to understand the interactions between different fields in the dataset.

Data Visualization: This is the creation of plots such as histograms, box plots, scatter plots, etc., to identify patterns, relationships, or outliers within the dataset. This can be done using visualization tools or libraries.

Insight Generation: After visualizations and some statistical tests, analysts will generate insights that could lead to further questions, hypotheses, and model building.

The EDA process is an important precursor to more complex analyses because it allows for the researcher to confirm or invalidate some initial hypotheses and to formulate a more precise question or hypothesis that can lead to further statistical analysis and testing.

Our focus

- We ignore the Data Cleaning step, although we acknowledge it's practical relevance. We assume that we are working with a clean dataset.
- We emphasize Univariate and Bivariate Analysis of data and the corresponding Data Visualization.
- We cover some basic Multivariate Analysis.
- We emphasize Insight Generation.

We illustrate all of the above using the R programming language.

We further illustrate how to use R programming on a real-world dataset. Our dataset concerns the S&P500 stocks. This will demonstrate a practical aspect of using this book. We have many sample codes regarding this, using real-world data.. We will explore financial metrics such as the Return on Equity , Return on Assets, Return on Invested Capital of S&P500 shares.

1 Getting Started

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1.1 Overview of R programming

1. R is an **open-source** software environment and programming language designed for statistical computing, data analysis, and visualization. It was developed by Ross Ihaka and Robert Gentleman at the University of Auckland in New Zealand during the early 1990s.
2. R offers a **wide range of statistical techniques**, including linear and nonlinear modeling, classical statistical tests, and support for data manipulation, data import/export, and compatibility with various data formats.
3. R offers **free usage, distribution, and modification**, making it accessible to individuals with various budgets and resources who wish to learn and utilize it.
4. The **Comprehensive R Archive Network (CRAN)** serves as a valuable resource for the R programming language. It offers a vast collection of downloadable packages that expand the functionality of R, including tools for machine learning, data mining, and visualization.
5. R stands out as a prominent tool within the data analysis community, attracting a **large and active user base**. This community plays a vital role in the ongoing maintenance and development of R packages, ensuring a thriving ecosystem for continuous improvement.
6. One of R's strengths lies in its **powerful and flexible graphics system**, empowering users to create visually appealing and informative data visualizations for data exploration, analysis, and effective communication.
7. R facilitates the creation of **shareable and reproducible scripts**, promoting transparency and enabling seamless collaboration on data analysis projects. This feature enhances the ability to replicate and validate results, fostering trust and credibility in the analysis process.

8. R exhibits strong **compatibility with other programming languages** like Python and SQL, as well as with popular data storage and manipulation tools such as Hadoop and Spark. This compatibility allows for smooth integration and interoperability, enabling users to leverage the strengths of multiple tools and technologies for their data-centric tasks. [1]

1.2 Running R locally

R could be run locally or in the Cloud. We discuss running R locally. We discuss running it in the Cloud in the next sub-section.

1.2.1 Installing R locally

Before running R locally, we need to first install R locally. Here are general instructions to install R locally on your computer:\

1. Visit the official website of the R project at <https://www.r-project.org/>.
2. On the download page, select the appropriate version of R based on your operating system (Windows, Mac, or Linux).
3. After choosing your operating system, click on a mirror link to download R from a reliable source.
4. Once the download is finished, locate the downloaded file and double-click on it to initiate the installation process. Follow the provided instructions to complete the installation of R on your computer. [2]

1.2.2 Running R locally in an Integrated Development Environment (IDE)

An Integrated Development Environment (IDE) is a software application designed to assist in software development by providing a wide range of tools and features. These tools typically include a text editor, a compiler or interpreter, debugging tools, and various utilities that aid developers in writing, testing, and debugging their code.

When working with the R programming language on your local machine and looking to take advantage of IDE features, you have several options available:

1. **RStudio:** RStudio is a highly popular open-source IDE specifically tailored for R programming. It boasts a user-friendly interface, a code editor with features like syntax highlighting and code completion, as well as powerful debugging capabilities. RStudio also integrates seamlessly with version control systems and package management tools, making it an all-inclusive IDE for R development.

2. **Visual Studio Code (VS Code):** While primarily recognized as a versatile code editor, VS Code also offers excellent support for R programming through extensions. By installing the “R” extension from the Visual Studio Code marketplace, you can enhance your experience with R-specific functionality, such as syntax highlighting, code formatting, and debugging support.
3. **Jupyter Notebook:** Jupyter Notebook is an open-source web-based environment that supports multiple programming languages, including R. It provides an interactive interface where you can write and execute R code within individual cells. Jupyter Notebook is widely employed for data analysis and exploration tasks due to its ability to blend code, visualizations, and text explanations seamlessly.

These IDE options vary in their features and user interfaces, allowing you to choose the one that aligns best with your specific needs and preferences. It's important to note that while R can also be run through the command line or the built-in R console, utilizing an IDE can significantly boost your productivity and enhance your overall development experience. [3]

1.2.3 RStudio

RStudio is a highly popular integrated development environment (IDE) designed specifically for R programming. It offers a user-friendly interface and a comprehensive set of tools for data analysis, visualization, and modeling using R.

Some notable features of RStudio include:

1. Code editor: RStudio includes a code editor with advanced features such as syntax highlighting, code completion, and other functionalities that simplify the process of writing R code.
2. Data viewer: RStudio provides a convenient data viewer that allows users to examine and explore their data in a tabular format, facilitating data analysis.
3. Plots pane: The plots pane in RStudio displays graphical outputs generated by R code, making it easy for users to visualize their data and analyze results.
4. Console pane: RStudio includes a console pane that shows R code and its corresponding output. It enables users to execute R commands interactively, enhancing the coding experience.
5. Package management: RStudio offers tools for managing R packages, including installation, updating, and removal of packages. This simplifies the process of working with external libraries and extending the functionality of R.
6. Version control: RStudio seamlessly integrates with version control systems like Git, empowering users to efficiently manage and collaborate on their code projects.

7. Shiny applications: RStudio allows users to create interactive web applications using Shiny, a web development utility for R. This feature enables the creation of dynamic and user-friendly interfaces for R-based applications. [4]

To install RStudio on your computer, you can follow these simple steps:

1. Download RStudio: Visit the RStudio download page and choose the version of RStudio that matches your operating system.
2. Install RStudio: Once the RStudio installer is downloaded, run it and follow the instructions provided to complete the installation process on your computer.
3. Open RStudio: After the installation is finished, you can open RStudio by double-clicking the RStudio icon on your desktop or in the Applications folder.
4. Start an R session: In RStudio, click on the Console tab to initiate an R session. You can then enter R commands in the console and execute them by clicking the “Run” button or using the shortcut Ctrl+Enter (Windows) or Cmd+Enter (Mac). [5]

1.3 Running R in the Cloud

Running R in the cloud allows users to access R and RStudio from anywhere with an internet connection, eliminating the need to install R locally. Several cloud service providers, such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud Platform (GCP), offer virtual machines (VMs) with pre-installed R and RStudio.

Here are some key advantages and disadvantages of running R in the cloud:

Benefits:

1. Scalability: Cloud providers offer scalable computing resources that can be adjusted to meet specific workload requirements. This is particularly useful for data-intensive tasks that require significant computational power.
2. Accessibility and Collaboration: Cloud-based R allows users to access R and RStudio from any location with an internet connection, facilitating collaboration on projects and data sharing.
3. Cost-effectiveness: Cloud providers offer flexible pricing models that can be more cost-effective than running R on local hardware, especially for short-term or infrequent use cases.
4. Security: Cloud service providers implement various security features, such as firewalls and encryption, to protect data and applications from unauthorized access or attacks. [6]

Drawbacks:

1. Internet Dependency: Running R in the cloud relies on a stable internet connection, which may not be available at all times or in all locations. This can limit the ability to work on data analysis and modeling projects.
2. Learning Curve: Utilizing cloud computing platforms and tools requires familiarity, which can pose a learning curve for users new to cloud computing.
3. Data Privacy: Storing data in the cloud may raise concerns about data privacy, particularly for sensitive or confidential information. While cloud service providers offer security features, users must understand the risks and take appropriate measures to secure their data.
4. Cost Considerations: While cloud computing can be cost-effective in certain scenarios, it can also become expensive for long-term or high-volume use cases, especially if additional resources like data storage are required alongside computational capacity. [6]

1.3.1 Cloud Service Providers – Posit, AWS, Azure, GCP

Here is a comparison of four prominent cloud service providers: Posit, AWS, Azure, and GCP.

Posit:

- Posit is a relatively new cloud service provider that focuses on offering high-performance computing resources specifically for data-intensive applications.
- They provide bare-metal instances that ensure superior performance and flexibility.
- Posit is dedicated to data security and compliance, prioritizing the protection of user data.
- They offer customizable hardware configurations tailored to meet specific application requirements.

AWS:

- AWS is a well-established cloud service provider that offers a wide range of cloud computing services, including computing, storage, and database services.
- It boasts a large and active user community, providing abundant resources and support for users.
- AWS provides flexible pricing options, including pay-as-you-go and reserved instance pricing.

- They offer a comprehensive set of tools and services for managing and securing cloud-based applications.

Azure:

- Azure is another leading cloud service provider that offers various cloud computing services, including computing, storage, and networking.
- It tightly integrates with Microsoft's enterprise software and services, making it an attractive option for organizations using Microsoft technologies.
- Azure provides flexible pricing models, including pay-as-you-go, reserved instance, and spot instance pricing.
- They offer a wide array of tools and services for managing and securing cloud-based applications.

GCP:

- GCP is a cloud service provider that provides a comprehensive suite of cloud computing services, including computing, storage, and networking.
- It offers specialized tools and services for machine learning and artificial intelligence applications.
- GCP provides flexible pricing options, including pay-as-you-go and sustained use pricing.
- They offer a range of tools and services for managing and securing cloud-based applications. [7]

1.4 Getting Started – Inbuilt R functions

1.4.1 Mathematical Operations

R is a powerful programming language for performing mathematical operations and statistical calculations. Here are some common mathematical operations in R.

1. Arithmetic Operations: R can perform basic arithmetic operations such as addition (+), subtraction (-), multiplication (*), and division (/).

```
# Addition and Subtraction
5+9-3
```

[1] 11

```
# Multiplication and Division (5 + 3) * 7 / 2
```

2. Exponentiation and Logarithms: R can raise a number to a power using the `^` or `**` operator or take logarithms.

```
{r} # exponentiation 2^6 # Exponential of x=2 i.e. e^2 exp(2) # logarithms  
base 2 and base 10 log2(64) + log10(100)}
```

3. Other mathematical functions: R has many additional useful mathematical functions.

- We can find the absolute value, square roots, remainder on division.

```
{r} # absolute value of x=-5 abs(-9) # square root of x=70 sqrt(70) # remainder  
of the division of 11/3 11 %% 3}
```

- We can round numbers, find their floor, ceiling or up to a number of significant digits

```
{r} # Value of pi to 10 decimal places pi = 3.1415926536 # round(): This  
function rounds a number to the given number of decimal places # For example,  
round(pi, 3) returns 3.142 round(pi,3) # ceiling(): This function rounds  
a number up to the nearest integer. # For example, ceiling(pi) returns 4  
ceiling(pi) # floor(): This function rounds a number down to the nearest  
integer. # For example, floor(pi) returns 3. floor(pi) # signif(): This  
function rounds a number to a specified number of significant digits. # For  
example, signif(pi, 3) returns 3.14. signif(pi,3)}
```

4. Statistical calculations: R has many built-in functions for statistical calculations, such as mean, median, standard deviation, and correlation.

```
{r} x <- c(0, 1, 1, 2, 3, 5, 8) # create a vector of 7 Fibonacci numbers  
length(x) # count how many numbers do we have mean(x) # calculate the  
mean median(x) # calculate the median sd(x) # calculate the standard  
deviation y <- c(1, 2, 3, 4, 5, 6, 7) # create a new vector of positive  
integers cor(x,y) # calculate the correlation between x and y}
```

1.4.2 Assigning values to variables

1. A variable can be used to store a value. For example, the R code below will store the sales in a variable, say “sales”:

```
{r} # use the assignment operator <- sales <- 9 # alternately, use = sales =  
9}
```

2. It is possible to use `<-` or `=` for variable assignments.

3. R is case-sensitive. This means that `Sales` is different from `sales`

4. It is possible to perform some operations with it.

```
{r} # multiply sales by 2 2 * sales}
```

5. We can change the value stored in a variable

```
{r} # change the value sales <- 15 # display the revised sales sales}
```

6. The following R code creates two variables holding the sales and the price of a product and we can use them to compute the revenue.

```
{r} # sales sales <- 5 # price price <- 7 # Calculate the revenue revenue  
<- price*sales revenue}
```

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2 R Packages

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1. R packages are collections of code, data, and documentation that enhance the capabilities of R, a programming language and software environment used for statistical computing and graphics.
2. R packages are created by R users and developers and provide additional tools, functions, and datasets that serve various purposes, such as data analysis, visualization, and machine learning.
3. R packages can be obtained from various sources, including the Comprehensive R Archive Network (CRAN), Bioconductor, GitHub, and other online repositories.
4. To utilize R packages, they can be imported into R using the `library()` function, allowing access to the functions and data within them for use in R scripts and interactive sessions. [1]

2.1 Benefits of R Packages

There are numerous advantages to using R packages:

1. **Reusability:** R packages enable users to write code that is readily reusable across applications. Once a package has been created and published, others can install and use it, sparing them time and effort in coding.
2. **Collaboration:** Individuals or teams can develop packages collaboratively, enabling the sharing of code, data, and ideas. This promotes collaboration within the R community and the creation of new tools and techniques.
3. **Standardization:** Packages help standardize the code and methodology used for particular duties, making it simpler for users to comprehend and replicate the work of others. This decreases the possibility of errors and improves the dependability of results.
4. **Scalability:** Packages can manage large data sets and sophisticated analyses, enabling users to scale up their work to larger, more complex problems.
5. **Accessibility:** R packages are freely available and can be installed on a variety of operating systems, making them accessible to a broad spectrum of users. [1]

2.2 Comprehensive R Archive Network (CRAN)

1. The Comprehensive R Archive Network (CRAN) is a global network of servers dedicated to maintaining and distributing R packages. These packages consist of code, data, and documentation that enhance the functionality of R.
2. CRAN serves as a centralized and well-organized repository, simplifying the process for users to find, obtain, and install the required packages. With thousands of packages available, users can utilize the `install.packages()` function in R to download and install them.
3. CRAN categorizes packages into various groups such as graphics, statistics, and machine learning, facilitating easy discovery of relevant packages based on specific needs.
4. CRAN is maintained by the R Development Core Team and is accessible to anyone with an internet connection, ensuring broad availability and accessibility. [2]

2.3 Installing a R Package

1. The `install.packages()` function can be employed to install R packages.
2. For instance, to install the `ggplot2` package in R, you would execute the following code:

```
install.packages("ggplot2")
```

3. Executing the code provided will download and install the `ggplot2` package, along with any necessary dependencies, on your system.
4. It's important to remember that a package needs to be installed only once on your system. Once installed, you can easily import the package into your R session using the `library()` function.
5. For example, to import the `ggplot2` package in R, you can execute the following code:

```
library(ggplot2)
```

6. By executing the provided code, you will enable access to the functions and datasets of the `ggplot2` package for use within your R session.

2.3.1 Popular R Packages

There are several popular R packages useful for summarizing, transforming, manipulating and visualizing data. Here is a list of some commonly used packages along with a brief description of each:

1. **dplyr**: A grammar of data manipulation, providing a set of functions for easy and efficient data manipulation tasks like filtering, summarizing, and transforming data frames.
2. **tidyr**: Provides tools for tidying data, which involves reshaping data sets to facilitate analysis by ensuring each variable has its own column and each observation has its own row.
3. **plyr**: Offers a set of functions for splitting, applying a function, and combining results, allowing for efficient data manipulation and summarization.
4. **reshape2**: Provides functions for transforming data between different formats, such as converting data from wide to long format and vice versa.
5. **data.table**: A high-performance package for data manipulation, offering fast and memory-efficient tools for tasks like filtering, aggregating, and joining large data sets.
6. **lubridate**: Designed specifically for working with dates and times, it simplifies common tasks like parsing, manipulating, and formatting date-time data.
7. **stringr**: Offers a consistent and intuitive set of functions for working with strings, including pattern matching, string manipulation, and string extraction.
8. **magrittr**: Provides a simple and readable syntax for composing data manipulation and transformation operations, making code more readable and expressive.
9. **ggplot2**: A powerful and flexible package for creating beautiful and customizable data visualizations using a layered grammar of graphics approach.
10. **plotly**: Enables interactive and dynamic data visualizations, allowing users to create interactive plots, charts, and dashboards that can be explored and analyzed. [2]

2.4 Sample Plot

As an illustration, here is a sample code for a scatterplot created using the `ggplot2` package.

Figure 2.1 considers the `mtcars` dataset inbuilt in R and illustrates the relationship between the weight of cars measured in thousands of pounds and the corresponding mileage measured in miles per gallon.

```
library(ggplot2)
data(mtcars)

ggplot(mtcars, aes(wt, mpg)) +
  geom_point()
```



Figure 2.1: Scatterplot of Car Mileage with Car Weight

2.4.1 Getting help

To seek assistance with an R package, you can explore the following avenues:

1. Documentation: Most R packages come with comprehensive documentation that explains the package's functions, datasets, and provides usage examples. You can access the documentation by using the `help()` function or typing `?package_name` in the R console, where "package_name" is the name of the specific package you want to learn about.
2. Integrated help system: R has an integrated help system that offers documentation and demonstrations for functions and packages. In the R console, you can access the help system by typing `help(topic)` or `?topic`, where "topic" represents the name of the function or package you need assistance with.

3. Online Resources: Numerous online resources are available for obtaining help with R packages. Blogs, forums, and question-and-answer platforms like Stack Overflow offer valuable insights and solutions to specific problems. These platforms are particularly helpful for finding answers to specific questions and obtaining general guidance on package usage. [3]

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3 Data Structures

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The R programming language includes a number of data structures that are frequently employed in data analysis and statistical modeling. These are some of the most popular data structures in R:

1. **Vector**: A vector is a one-dimensional array that stores identical data types, such as numeric, character, or logical. The `c()` function can be used to create vectors, and indexing can be used to access individual vector elements.
2. **Factor**: A factor is a vector representing **categorical** data, with each distinct value or category represented as a level. Using indexing, individual levels of a factor can be accessed using the `factor()` function.
3. **Dataframe**: A data frame is a two-dimensional table-like structure similar to a spreadsheet, that can store various types of data in columns. The `data.frame()` function can be used to construct data frames, and individual elements can be accessed using row and column indexing.
4. **Matrix**: A matrix is a two-dimensional array of data with identical rows and columns. The `matrix()` function can be used to construct matrices, and individual elements can be accessed using row and column indexing.
5. **Array**: An array is a multidimensional data structure that can contain data of the same data type in user-specified dimensions. Arrays can be constructed using the `array()` function, and elements can be accessed using multiple indexing.
6. **List**: A list is an object that may comprise elements of various data types, including vectors, matrices, data frames, and even other lists. The `list()` function can be used to construct lists, while indexing can be used to access individual elements.

These data structures are helpful for storing and manipulating data in R, and they can be utilized in numerous applications, such as statistical analysis and data visualization. We will focus our attention on Vectors, Factors and Dataframes, since we believe that these are the three most useful data structures. [1]

3.1 Vectors

1. A vector is a fundamental data structure in R that can hold a sequence of values of the same data type, such as integers, numeric, character, or logical values.
2. A vector can be created using the `c()` function.
3. R supports two forms of vectors: atomic vectors and lists. Atomic vectors are limited to containing elements of a single data type, such as numeric or character. Lists, on the other hand, can contain elements of various data types and structures. [1]

3.1.1 Vectors in R

1. The following R code creates a numeric vector, a character vector and a logical vector respectively.

```
# Read data into vectors
names <- c("Ashok", "Bullu", "Charu", "Divya")
ages <- c(72, 49, 46, 42)
weights <- c(65, 62, 54, 51)
income <- c(-2, 8, 19, 60)
females <- c(FALSE, TRUE, TRUE, TRUE)
```

2. The `c()` function is employed to combine the four character elements into a single vector.
3. Commas separate the elements of the vector within the parentheses.
4. Individual elements of the vector can be accessed via indexing, which utilizes square brackets `[]`. For instance, `names[1]` returns `Ashok`, while `names[3]` returns `Charu`.
5. We can also perform operations such as categorizing and filtering on the entire vector. For instance, `sort(names)` returns a vector of sorted names, whereas `names[names!="Bullu"]` returns a vector of names excluding `Bullu`.

3.1.2 Vector Operations

Vectors can be used to perform the following vector operations:

1. **Accessing Elements:** We can use indexing with square brackets to access individual elements of a vector. To access the second element of the `names` vector, for instance, we can use:

```
names[2]
```



```
[1] "Bullu"
```

This returns Bullu, the second element of the `people` vector.

2. **Concatenation:** The `c()` function can be used to combine multiple vectors into a single vector. For instance, to combine the `names` and `ages` vectors into the “people” vector, we can use:

```
persons <- c(names, ages)
persons
```

```
[1] "Ashok" "Bullu" "Charu" "Divya" "72"    "49"    "46"    "42"
```

This generates an eight-element vector containing the names and ages of the four people.

3. **Subsetting:** We can use indexing with a logical condition to construct a new vector that contains a subset of elements from an existing vector. For instance, to construct a new vector named `female_names` containing only the female names, we can use:

```
female_names <- names[females == TRUE]
female_names
```

```
[1] "Bullu" "Charu" "Divya"
```

This generates a new vector comprising three elements containing the names of the three females Bullu, Charu, and Divya.

4. **Arithmetic Operations:** We can perform element-wise arithmetic operations on vectors.

```
# Addition
addition <- ages + weights
print(addition)
```

```
[1] 137 111 100 93
```

```
# Subtraction
subtraction <- ages - weights
```

```
print(subtraction)
```

```
[1] 7 -13 -8 -9
```

```
# Multiplication
multiplication <- ages * weights
print(multiplication)
```

```
[1] 4680 3038 2484 2142
```

```
# Division
division <- ages / weights
print(division)
```

```
[1] 1.1076923 0.7903226 0.8518519 0.8235294
```

```
# Exponentiation
exponentiation <- ages^2
print(exponentiation)
```

```
[1] 5184 2401 2116 1764
```

In the above code, we perform addition, subtraction, multiplication, division, and exponentiation on these vectors using the arithmetic operators `+`, `-`, `*`, `/`, and `^` respectively.

In addition to the common arithmetic operations (addition, subtraction, multiplication, division, and exponentiation), R also supports other arithmetic operations such as modulus, integer division, and absolute value. Let's demonstrate these operations

```
# Modulus
modulus <- ages %% income
print(modulus)
```

```
[1] 0 1 8 42
```

```
# Integer Division
integer_division <- ages %/% income
print(integer_division)
```

```
[1] -36    6    2    0
```

```
# Absolute Value
absolute_value <- abs(ages)
print(absolute_value)
```

```
[1] 72 49 46 42
```

Let's explore a few additional arithmetic operations:

```
# Floor Division
floor_division <- floor(ages / income)
print(floor_division)
```

```
[1] -36    6    2    0
```

```
# Ceiling Division
ceiling_division <- ceiling(ages / income)
print(ceiling_division)
```

```
[1] -36    7    3    1
```

```
# Logarithm
logarithm <- log(ages)
print(logarithm)
```

```
[1] 4.276666 3.891820 3.828641 3.737670
```

```
# Square Root
square_root <- sqrt(ages)
print(square_root)
```

```
[1] 8.485281 7.000000 6.782330 6.480741
```

```
# Sum
sum_total <- sum(ages)
print(sum_total)
```

```
[1] 209
```

`floor` calculates the largest integer not exceeding the quotient.

`ceiling` calculates the smallest integer not less than the quotient.

`log` calculates the natural logarithm of each element.

`sum` calculates the sum of all the elements.

5. **Logical Operations:** We can perform logical operations on vectors, which are also executed element-by-element.

```
# Equality comparison
age_equal_46 <- (ages == 46)
print(age_equal_46)
```

```
[1] FALSE FALSE TRUE FALSE
```

```
# Inequality comparison
weight_not_equal_54 <- (weights != 54)
print(weight_not_equal_54)
```

```
[1] TRUE TRUE FALSE TRUE
```

```
# Logical AND
female_and_income <- females & (income > 0)
```

```
print(female_and_income)
```

```
[1] FALSE TRUE TRUE TRUE
```

```
# Logical OR
age_or_weight_greater_50 <- (ages > 50) | (weights > 50)
print(age_or_weight_greater_50)
```

```
[1] TRUE TRUE TRUE TRUE
```

```
# Logical NOT
not_female <- !females
print(not_female)
```

```
[1] TRUE FALSE FALSE FALSE
```

In the above code, we perform the following logical operations:

Equality Comparison (==): It checks if the elements of the ages vector are equal to 46. The resulting vector, `age_equal_46`, contains TRUE for elements that are equal to 46 and FALSE otherwise.

Inequality Comparison (!=): It checks if the elements of the weights vector are not equal to 54. The resulting vector, `weight_not_equal_54`, contains TRUE for elements that are not equal to 54 and FALSE otherwise.

Logical AND (&): It performs a logical AND operation between the females vector and the condition (`income > 0`). The resulting vector, `female_and_income`, contains TRUE for elements that satisfy both conditions and FALSE otherwise.

Logical OR (|): It performs a logical OR operation between the conditions (`ages > 50`) and (`weights > 50`). The resulting vector, `age_or_weight_greater_50`, contains TRUE for elements that satisfy either condition or both.

Logical NOT (!): It negates the values in the females vector. The resulting vector, `not_female`, contains TRUE for elements that were originally FALSE and FALSE for elements that were originally TRUE.

```
# Greater than comparison
age_greater_50 <- ages > 50
print(age_greater_50)
```

```
[1] TRUE FALSE FALSE FALSE
```

```
# Less than or equal to comparison
weight_less_equal_54 <- weights <= 54
print(weight_less_equal_54)
```

```
[1] FALSE FALSE TRUE TRUE
```

```
# Element-wise AND
age_and_weight_greater_50 <- (ages > 50) & (weights > 50)
print(age_and_weight_greater_50)
```

```
[1] TRUE FALSE FALSE FALSE
```

```
# Element-wise OR
age_or_weight_less_equal_50 <- (ages > 50) | (weights <= 50)
print(age_or_weight_less_equal_50)
```

```
[1] TRUE FALSE FALSE FALSE
```

```
# Element-wise XOR
age_xor_weight_greater_50 <- xor(ages > 50, weights > 50)
print(age_xor_weight_greater_50)
```

```
[1] FALSE TRUE TRUE TRUE
```

```
# Any True
any_female <- any(females)
print(any_female)
```

```
[1] TRUE
```

```
# All True
all_female <- all(females)
print(all_female)
```

```
[1] FALSE
```

Greater than Comparison ($>$): It checks if each element of the ages vector is greater than 50. The resulting vector, `age_greater_50`, contains TRUE for elements that satisfy the condition and FALSE otherwise.

Less than or Equal to Comparison ($<=$): It checks if each element of the weights vector is less than or equal to 54. The resulting vector, `weight_less_equal_54`, contains TRUE for elements that satisfy the condition and FALSE otherwise.

Element-wise AND ($&$): It performs an element-wise logical AND operation between the conditions (`ages > 50`) and (`weights > 50`). The resulting vector, `age_and_weight_greater_50`, contains TRUE for elements that satisfy both conditions and FALSE otherwise.

Element-wise OR ($|$): It performs an element-wise logical OR operation between the conditions (`ages > 50`) and (`weights <= 50`). The resulting vector, `age_or_weight_less_equal_50`, contains TRUE for elements that satisfy either condition or both.

Element-wise XOR (`xor()`): It performs an element-wise exclusive OR operation between the conditions (`ages > 50`) and (`weights > 50`). The resulting vector, `age_xor_weight_greater_50`, contains TRUE for elements where exactly one condition is true and FALSE otherwise.

Any True (`any()`): It checks if at least one element in the females vector is TRUE. The result, `any_female`, is TRUE if there is at least one TRUE value in the vector and FALSE otherwise.

All True (`all()`): It checks if all elements in the females vector are TRUE. The result, `all_female`, is TRUE if all values in the vector are TRUE and FALSE otherwise.

```
# Negation
not_female <- !females
print(not_female)
```

```
[1] TRUE FALSE FALSE FALSE
```

```
# Any True
any_age_greater_50 <- any(ages > 50)
print(any_age_greater_50)
```

[1] TRUE

```
# All True
all_income_positive <- all(income > 0)
print(all_income_positive)
```

[1] FALSE

```
# Subset with Logical Vector
female_names <- names[females]
print(female_names)
```

[1] "Bullu" "Charu" "Divya"

```
# Combined Logical Operation
combined_condition <- (ages > 50 & weights <= 54) | (income > 0 & females)
print(combined_condition)
```

[1] FALSE TRUE TRUE TRUE

```
# Logical Function anyNA()
has_na <- anyNA(names)
print(has_na)
```

[1] FALSE

```
# Logical Function is.na()
is_na <- is.na(ages)
print(is_na)
```

[1] FALSE FALSE FALSE FALSE


```
# Finding unique values
unique(ages)
```

```
[1] 72 49 46 42
```

Negation (!): It negates the values in the females vector. The resulting vector, not_female, contains TRUE for elements that were originally FALSE and FALSE for elements that were originally TRUE.

Any True (any()): It checks if there is at least one TRUE value in the logical vector ages > 50. The result, any_age_greater_50, is TRUE if at least one element in ages is greater than 50 and FALSE otherwise.

All True (all()): It checks if all elements in the logical vector income > 0 are TRUE. The result, all_income_positive, is TRUE if all values in the income vector are greater than 0 and FALSE otherwise.

Subset with Logical Vector: It uses a logical vector females to subset the names vector. The resulting vector, female_names, contains only the names where the corresponding element in females is TRUE.

Combined Logical Operation: It combines multiple conditions using logical AND (&) and logical OR (|). The resulting vector, combined_condition, contains TRUE for elements that satisfy the combined condition and FALSE otherwise.

Logical Function anyNA(): It checks if there are any missing values (NA) in the names vector. The result, has_na, is TRUE if there is at least one NA value and FALSE otherwise.

Logical Function is.na(): It checks if each element of the ages vector is NA. The resulting vector, is_na, contains TRUE for elements that are NA and FALSE otherwise.

unique(): It finds the unique values in the ages vector

6. **Sorting:** We can sort a vector in ascending or descending order using the sort() function. For example, to sort the ages vector in descending order, we can use:

```
# Sort in ascending order
sorted_names <- sort(names)
print(sorted_names)
```

```
[1] "Ashok" "Bullu" "Charu" "Divya"
```

```
# Sort in descending order
sorted_names_desc <- sort(names, decreasing = TRUE)
print(sorted_names_desc)
```

```
[1] "Divya" "Charu" "Bullu" "Ashok"
```

In the above code, we demonstrate sorting the names vector in both ascending and descending order using the `sort()` function. By default, `sort()` sorts the vector in ascending order. To sort in descending order, we set the `decreasing` argument to `TRUE`.

3.1.3 Statistical Operations on Vectors

1. **Length:** The length represents the count of the number of elements in a vector.

```
length(ages)
```

```
[1] 4
```

2. **Maximum** and **Minimum:** The maximum and minimum values are the vector's greatest and smallest values, respectively.
3. **Range:** The range is a measure of the spread that represents the difference between the maximum and minimum values in a vector.

```
min(ages)
```

```
[1] 42
```

```
max(ages)
```

```
[1] 72
```

```
range(ages)
```

```
[1] 42 72
```

4. **Mean:** The mean is a central tendency measure that represents the average value of a vector's elements.
5. **Standard Deviation:** The standard deviation is a measure of dispersion that reflects the amount of variation in a vector's elements.

```
mean(ages)
```

```
[1] 52.25
```

```
sd(ages)
```

```
[1] 13.47529
```

6. **Median:** The median is a measure of central tendency that represents the middle value of a sorted vector.

```
median(ages)
```

```
[1] 47.5
```

7. **Quantiles:** The quantiles are a set of cut-off points that divide a sorted vector into equal-sized groups.

```
quantile(ages)
```

```
0%    25%    50%    75%   100%  
42.00 45.00 47.50 54.75 72.00
```

This will return a set of five values, representing the minimum, first quartile, median, third quartile, and maximum of the four ages.

8. Additional Functionality:

```
# Standard Error of the Mean  
se_ages <- sqrt(var(ages) / length(ages))  
print(se_ages)
```

```
[1] 6.737643
```

```
# Cumulative Sum
cumulative_sum_ages <- cumsum(ages)
print(cumulative_sum_ages)
```

```
[1] 72 121 167 209
```

```
# Correlation Coefficient
correlation_ages_females <- cor(ages, females)
print(correlation_ages_females)
```

```
[1] -0.9770974
```

Standard Error of the Mean: It calculates the standard error of the mean for the ages vector. The result is stored in `se_ages`.

Cumulative Sum: It calculates the cumulative sum of the elements in the ages vector. The cumulative sum is stored in `cumulative_sum_ages`.

Correlation Coefficient: It calculates the correlation coefficient between the ages and females vectors using the `cor()` function. T

Thus, we note that the R programming language provides a wide range of statistical operations that can be performed on vectors for data analysis and modeling. Vectors are clearly a potent and versatile data structure that can be utilized in a variety of ways.

3.1.4 Strings

Here are some common string operations that can be conducted using the provided vector examples.

1. **Substring:** The `substr()` function can be used to extract a substring from a character vector. To extract the first three characters of each name in the “names” vector, for instance, we can use:

```
substring_names <- substr(names, start = 2, stop = 4)
print(substring_names)
```

```
[1] "sho" "ull" "har" "ivy"
```

This returns a new character vector containing three letters of each name.

2. **Concatenation:** Using the `paste()` function, we can concatenate two or more character vectors into a singular vector. To create a new vector containing the names and ages of the individuals, for instance, we can use:

```
persons <- paste(names, ages)
print(persons)
```

```
[1] "Ashok 72" "Bullu 49" "Charu 46" "Divya 42"
```

```
full_names <- paste(names, "Kumar")
print(full_names)
```

```
[1] "Ashok Kumar" "Bullu Kumar" "Charu Kumar" "Divya Kumar"
```

This will generate a new eight-element character vector containing the name and age of each individual, separated by a space.

3. **Case Conversion:** The `toupper()` and `tolower()` functions can be used to convert the case of characters within a character vector. To convert the “names” vector to uppercase letters, for instance, we can use:

```
toupper(names)
```

```
[1] "ASHOK" "BULLU" "CHARU" "DIVYA"
```

This will generate a new character vector with all of the names converted to uppercase.

4. **Pattern Matching:** Using the `grep()` and `grepl()` functions, we can search for a pattern within the elements of a character vector. To find the names in the “names” vector that contain the letter “a”, for instance, we can use:

```
grep("a", names)
```

```
[1] 3 4
```

This returns a vector containing the indexes of the “names” vector elements that contain the letter “a.”

```
pattern_match <- grep("l", names, value = TRUE)
print(pattern_match)
```

```
[1] "Bullu"
```

```
# Length of Strings
name_lengths <- nchar(names)
print(name_lengths)
```

```
[1] 5 5 5 5
```

```
# %in% Operator
names_found <- names %in% c("Ashok", "Charu")
print(names_found)
```

```
[1] TRUE FALSE TRUE FALSE
```

```
# Logical Function ifelse()
age_category <- ifelse(ages > 50, "Old", "Young")
print(age_category)
```

```
[1] "Old" "Young" "Young" "Young"
```

`%in%` Operator: It checks if each element in the names vector is present in the specified set of names. The resulting vector, `names_found`, contains `TRUE` for elements that are found in the set and `FALSE` otherwise.

Logical Function `ifelse()`: It evaluates a logical condition and returns values based on the condition. In this example, we use `ifelse()` to assign the value “Old” to elements in the `age_category` vector where the corresponding element in `ages` is greater than 50, and “Young” otherwise.

3.2 References

[1] R Core Team. (2021). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. <https://www.R-project.org/>

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4 Reading Data

July 21, 2023

Dataframes and Tibbles are frequently employed data structures in R for storing and manipulating data. They facilitate the organization, exploration, and analysis of data.

4.1 Dataframes

1. A dataframe is a two-dimensional table-like data structure in R that stores data in rows and columns, with distinct data types for each column.
2. Similar to a spreadsheet or a SQL table, it is one of the most frequently employed data structures in R. Each column in a `data.frame` is a constant-length vector, and each row represents an observation or case.
3. Using the `data.frame()` function or by importing data from external sources such as CSV files, Excel spreadsheets, or databases, dataframe objects can be created in R.
4. dataframe objects have many useful built-in methods and functions for manipulating and summarizing data, including subsetting, merging, filtering, and aggregation. [1]

4.1.1 Creating a dataframe using raw data

5. The following code generates a `data.frame` named `df` containing three columns - `names`, `ages`, and `heights`, and four rows of data for each individual.

```
# Create input data as vectors
names <- c("Ashok", "Bullu", "Charu", "Divya")
ages <- c(72, 49, 46, 42)
heights <- c(170, 167, 160, 166)

# Combine input data into a data.frame
people <- data.frame(Name = names, Age = ages, Height = heights)

# Print the resulting dataframe
```



```
print(people)
```

	Name	Age	Height
1	Ashok	72	170
2	Bullu	49	167
3	Charu	46	160
4	Divya	42	166

4.2 Reading Inbuilt datasets in R

1. R contains a number of built-in datasets that can be accessed without downloading or integrating from external sources. Here are some of the most frequently used built-in datasets in R:

- **women:** This dataset includes the heights and weights of a sample of 15,000 women.
- **mtcars:** This dataset contains information on 32 distinct automobile models, including the number of cylinders, engine displacement, horsepower, and weight.
- **diamonds:** This dataset includes the prices and characteristics of approximately 54,000 diamonds, including carat weight, cut, color, and clarity.
- **iris:** This data set measures the sepal length, sepal width, petal length, and petal breadth of 150 iris flowers from three distinct species.

4.2.1 The women dataset

As an illustration, consider the **women** dataset inbuilt in R, which contains information about the heights and weights of women. It has just two variables:

1. **height:** Height of each woman in inches
2. **weight:** Weight of each woman in pounds
3. The **data()** function is used to import any inbuilt dataset into R. The **data(women)** command in R loads the **women** dataset

```
data(women)
```

4. The **str()** function gives the dimensions and data types and also previews the data.

```
str(women)
```

```
'data.frame':  15 obs. of  2 variables:
 $ height: num  58 59 60 61 62 63 64 65 66 67 ...
 $ weight: num  115 117 120 123 126 129 132 135 139 142 ...
```

5. The `summary()` function gives some summary statistics.

```
summary(women)
```

height	weight
Min. :58.0	Min. :115.0
1st Qu.:61.5	1st Qu.:124.5
Median :65.0	Median :135.0
Mean :65.0	Mean :136.7
3rd Qu.:68.5	3rd Qu.:148.0
Max. :72.0	Max. :164.0

4.2.2 The `mtcars` dataset

The `mtcars` dataset inbuilt in R comprises data on the fuel consumption and other characteristics of 32 different automobile models. Here is a concise description of the 11 `mtcars` data columns:

1. `mpg`: Miles per gallon (fuel efficiency)
2. `cyl`: Number of cylinders
3. `disp`: Displacement of the engine (in cubic inches)
4. `hp`: gross horsepower
5. `drat`: Back axle ratio wt: Weight (in thousands of pounds)
6. `wt`: Weight (in thousands of pounds)
7. `qsec`: 1/4 mile speed (in seconds)
8. `vs`: Type of engine (0 = V-shaped, 1 = straight)
9. `am`: Type of transmission (0 for automatic, 1 for manual)
10. `gear`: the number of forward gears
11. `carb`: the number of carburetors

```
data(mtcars)
str(mtcars)
```

```
'data.frame':  32 obs. of  11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : num   6  6  4  6  8  6  8  4  4  6 ...
 $ disp: num  160 160 108 258 360 ...
 $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
 $ drat: num   3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt  : num   2.62 2.88 2.32 3.21 3.44 ...
 $ qsec: num   16.5 17 18.6 19.4 17 ...
 $ vs  : num   0  0  1  1  0  1  0  1  1  1 ...
 $ am  : num   1  1  1  0  0  0  0  0  0  0 ...
 $ gear: num   4  4  4  3  3  3  3  4  4  4 ...
 $ carb: num   4  4  1  1  2  1  4  2  2  4 ...
```

4.3 Reading different file formats into a dataframe

1. We examine how to read data into a dataframe in R when the original data is stored in prominent file formats such as CSV, Excel, and Google Sheets.
2. Before learning how to accomplish this, it is necessary to comprehend how to configure the Working Directory in R.

4.3.1 Working Directory

1. The working directory is the location where R searches for and saves files by default.
2. By default, when we execute a script or import data into R, R will search the working directory for files.
3. Using R's `getwd()` function, we can examine our current working directory:

```
getwd()
```

```
[1] "/cloud/project"
```

4. We are running R in the Cloud and hence we are seeing that the working directory is specified as `/cloud/project/DataAnalyticsBook101`. If we are doing R programming on a local computer, and if our working directory is the Desktop, then we may see a different response such as `C:/Users/YourUserName/Desktop`.
5. Using R's `setwd()` function, we can change our current working directory. For example, the following code will set our working directory to the Desktop:

```
setwd("C:/Users/YourUserName/Desktop")
```

6. We should choose an easily-remembered and accessible working directory to store our R scripts and data files. Additionally, we should avoid using spaces, special characters, and non-ASCII characters in file paths, as these can cause file handling issues in R. [2]

4.3.2 Reading a CSV file into a dataframe

1. CSV is the abbreviation for “Comma-Separated Values.” A CSV file is a plain text file that stores structured tabular data.
2. Each entry in a CSV file represents a record, whereas each column represents a field. The elements in each record are separated by commas (hence the name Comma-Separated Values), semicolons, or tabs.
3. Before proceeding ahead, it is imperative that the file that we wish to read is located in the Working Directory.
4. Suppose we wish to import a CSV file named `mtcars.csv`, located in the Working Directory. We can use the `read.csv()` function, illustrated as follows.

```
df_csv <- read.csv("mtcars.csv")
```

4. In this example, the `read.csv()` function reads the `mtcars.csv` file into a data frame named `df_csv`.
5. If the file is not in the current working directory, the complete file path must be specified in the `read.csv()` function argument; otherwise, an error will occur.

4.3.3 Reading an Excel (xlsx) file into a dataframe

1. Suppose we wish to import a Microsoft Excel file named `mtcars.xlsx`, located in the Working Directory.
2. We can use the `read_excel` function in the R package `readxl`, illustrated as follows.

```
library(readxl)
df_xlsx <- read_excel("mtcars.xlsx")
```

4.3.4 Reading a Google Sheet into a dataframe

1. Google Sheets is a ubiquitous cloud-based spreadsheet application developed by Google. It is a web-based application that enables collaborative online creation and modification of spreadsheets.
2. We can import data from a Google Sheet into a R dataframe, as follows.
 - Consider a Google Sheet whose preferences have been set such that anyone can view it using its URL. If this is not done, then some authentication would become necessary.
 - Every Google Sheet is characterized by a unique Sheet ID, embedded within the URL. For example, consider a Google Sheet containing some financial data concerning S&P500 index shares.
 - Suppose the Sheet ID is: `11ahk9uWxBkDqrhNm7qYmiTwrlSC53N1zvXYfv7ttOCM`
 - We can use the function `gsheet2tbl` in package `gsheet` to read the Google Sheet into a dataframe, as demonstrated in the following code.

```
# Read S&P500 stock data present in a Google Sheet.
library(gsheet)

prefix <- "https://docs.google.com/spreadsheets/d/"
sheetID <- "11ahk9uWxBkDqrhNm7qYmiTwrlSC53N1zvXYfv7ttOCM"

# Form the URL to connect to
url500 <- paste(prefix, sheetID)

# Read the Google Sheet located at the URL into a dataframe called sp500
sp500 <- gsheet2tbl(url500)
```

No encoding supplied: defaulting to UTF-8.

- The first line imports the `gsheet` package required to access Google Sheets into R.
- The following three lines define URL variables for Google Sheets. The `prefix` variable contains the base URL for accessing Google Sheets, the `sheetID` variable contains the ID of the desired Google Sheet.
- The `paste()` function is used to combine the `prefix`, `sheetID` variables into a complete URL for accessing the Google Sheet.
- The `gsheet2tbl()` function from the `gsheet` package is then used to read the specified Google Sheet into a dataframe called `sp500`, which can then be analyzed further in R.

4.3.5 Joining or Merging two dataframes

- Suppose we have a second S&P 500 data located in a second Google Sheet and suppose that we would like to join or merge the data in this dataframe with the above dataframe `sp500`.
- The ID of this second sheet is: `1F5KvFATcehrdJuGjYVqppNYC9hEKSww9rXYHck2g60A`
- We can read the data present in this Google Sheet using the following code, similar to the one discussed above, using the following code.

```
# Read additional S&P500 data that is posted in a Google Sheet.
library(gsheet)

prefix <- "https://docs.google.com/spreadsheets/d/"
sheetID <- "1nm688a3GsPM5cadJIwu6zj336WBaduglY9TSTUaM9jk"

# Form the URL to connect to
url <- paste(prefix, sheetID)

# Read the Google Sheet located at the URL into a dataframe called gf
gf <- gsheet2tbl(url)
```

No encoding supplied: defaulting to UTF-8.

- We now have two dataframes named `sp500` and `gf` that we wish to merge or join.
- The two dataframes have a column named `Stock` in common, which will serve as the key, while doing the join.
- The following code illustrates how to merge two dataframes:

```
# merging dataframes
df <- merge(sp500, gf , id = "Stock")
```

- We now have a new dataframe named `df`, which contains the data got from merging the two dataframes `sp500` and `gf`.

4.4 Tibbles

1. A tibble is a contemporary and enhanced variant of a R data frame that is part of the tidyverse package collection.
2. Tibbles are created and manipulated using the dplyr package, which provides a suite of functions optimized for data manipulation.
3. The following characteristics distinguish a tibble from a conventional data frame:
4. Tibbles must always have unique, non-empty column names. Tibbles do not permit the creation or modification of columns using partial matching of column names. Tibbles improve the output of large datasets by displaying by default only a few rows and columns.
5. Tibbles have a more consistent behavior for subsetting, with the use of `[[` always returning a vector or NULL, and `[]` always returning a tibble.
6. Here is an example of using the `tibble()` function in dplyr to construct a tibble:

```
library(dplyr, warn.conflicts = FALSE)

# Create a tibble
my_tibble <- tibble(
  name = c("Alice", "Bob", "Charlie"),
  age = c(25, 30, 35),
  gender = c("F", "M", "M")
)

# Print the tibble
my_tibble
```

```
# A tibble: 3 x 3
  name      age gender
<chr>   <dbl> <chr>
1 Alice     25 F
```

```
2 Bob      30 M
3 Charlie  35 M
```

7. This will generate a tibble consisting of three columns (name, age, and gender) and three rows of data. Note that the column names are preserved and the tibble is printed in a compact and legible manner.

4.4.1 Converting a dataframe into a tibble

```
# Create a data frame
my_df <- data.frame(
  name = c("Alice", "Bob", "Charlie"),
  age = c(25, 30, 35),
  gender = c("F", "M", "M")
)

# Convert the data frame to a tibble
my_tibble <- as_tibble(my_df)

# Print the tibble
my_tibble
```

```
# A tibble: 3 x 3
  name      age gender
<chr>   <dbl> <chr>
1 Alice     25 F
2 Bob       30 M
3 Charlie   35 M
```

8. This assigns the tibble representation of the data frame `my_df` to the variable `my_tibble`.
9. Note that the resulting tibble has the same column names and data as the original data frame, but has the additional characteristics and behaviors of a tibble.

4.4.2 Converting a tibble into a dataframe

```
library(dplyr)

# Convert the tibble to a data frame
my_df <- as.data.frame(my_tibble)
```



```
# Print the data frame
my_df
```

	name	age	gender
1	Alice	25	F
2	Bob	30	M
3	Charlie	35	M

10. A tibble offers several advantages over a data frame in R:

- Large datasets can be printed with greater clarity and precision using Tibbles. By default, they only print the first few rows and columns, making it simpler to read and comprehend the data structure.
- Better subsetting behavior: With `[[` (always returning a vector or NULL) and `[]` (always returning a tibble), Tibbles have a more consistent subsetting behavior. This facilitates the subset and manipulation of data without unintended consequences.
- Consistent naming: Tibbles always have column names that are distinct and non-empty. This makes it simpler to refer to specific columns and prevents errors caused by duplicate or unnamed column names.
- More informative errors: Tibbles provides more informative error messages that make it simpler to diagnose and resolve data-related problems.
- Fewer surprises: Tibbles have more stringent constraints than data frames, resulting in fewer surprises and unexpected behavior when manipulating data.

4.5 References

[1]

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R Core Team. (2022, March 2). Data Frames. R Documentation. <https://www.rdocumentation.org/packages/base/versions/4.1.3/topics/data-frame>

[2]

OpenIntro. (2022). 1.3 RStudio and working directory. In *Introductory Statistics with Randomization and Simulation* (1st ed.). <https://www.openintro.org/book/isrs/>

R Core Team. (2021). `getwd()`: working directory; `setwd(dir)`: change working directory. In *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://stat.ethz.ch/R-manual/R-devel/library/base/html/getwd.html>

5 Exploring Dataframes

July 21, 2023

The `mtcars` dataset is a readily available set in R, originally sourced from the 1974 Motor Trend US magazine. It includes data related to fuel consumption and 10 other factors pertaining to car design and performance, recorded for 32 vehicles from the 1973-74 model years.

To load the `mtcars` dataset in R, use this command:

```
data(mtcars)
```

5.1 Reviewing a dataframe

`View()`: This function opens the dataset in a spreadsheet-style data viewer.

```
View(mtcars)
```

`head()`: This function prints the first six rows of the dataframe.

```
head(mtcars)
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225	105	2.76	3.460	20.22	1	0	3	1

`tail()`: This function prints the last six rows of the dataframe.

```
tail(mtcars)
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.7	0	1	5	2
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.9	1	1	5	2
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.5	0	1	5	4
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.5	0	1	5	6
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.6	0	1	5	8
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.6	1	1	4	2

`dim()`: This function retrieves the dimensions of a dataframe, i.e., the number of rows and columns.

`nrow()`: This function retrieves the number of rows in the dataframe.

`ncol()`: This function retrieves the number of columns in the dataframe.

```
dim(mtcars)
```

```
[1] 32 11
```

```
nrow(mtcars)
```

```
[1] 32
```

```
ncol(mtcars)
```

```
[1] 11
```

`names()`: This function retrieves the column names of a dataframe.

`colnames()`: This function also retrieves the column names of a dataframe.

```
names(mtcars)
```

```
[1] "mpg" "cyl" "disp" "hp" "drat" "wt" "qsec" "vs" "am" "gear"
[11] "carb"
```

```
colnames(mtcars)
```

```
[1] "mpg" "cyl" "disp" "hp" "drat" "wt" "qsec" "vs" "am" "gear"
[11] "carb"
```

5.2 Accessing data within a dataframe

\$: In R, the dollar sign \$ is a unique operator that lets us retrieve specific columns from a dataframe or elements from a list.

For instance, consider the dataframe mtcars. If we wish to fetch the data from the mpg (miles per gallon) column, we would use mtcars\$mpg. This action will yield a vector containing the data from the mpg column.

```
# Extract the mpg column in mtcars dataframe as a vector
mpg_vector <- mtcars$mpg

# Print the mpg vector
print(mpg_vector)
```

```
[1] 21.0 21.0 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 17.8 16.4 17.3 15.2 10.4
[16] 10.4 14.7 32.4 30.4 33.9 21.5 15.5 15.2 13.3 19.2 27.3 26.0 30.4 15.8 19.7
[31] 15.0 21.4
```

This operator offers a simple and readable shortcut for accessing data.

[: The usage of \$ is limited since it doesn't support character substitution for dynamic column access inside functions. In such cases, we resort to using double square brackets [[or single square brackets [.

As an example, if we have a character string stored in a variable var as var <- "mpg", using mtcars\$var will not return the mpg column. But if we use mtcars[[var]] or mtcars[, var], we will correctly get the mpg column.

```
# Let's say we have a variable var
var <- "mpg"

# Now we can access the mpg column in mtcars dataframe using [[
mpg_data1 <- mtcars[[var]]
print(mpg_data1)
```

```
[1] 21.0 21.0 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 17.8 16.4 17.3 15.2 10.4
[16] 10.4 14.7 32.4 30.4 33.9 21.5 15.5 15.2 13.3 19.2 27.3 26.0 30.4 15.8 19.7
[31] 15.0 21.4
```

```
# Alternatively, we can use [
mpg_data2 <- mtcars[, var]
print(mpg_data2)
```

```
[1] 21.0 21.0 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 17.8 16.4 17.3 15.2 10.4
[16] 10.4 14.7 32.4 30.4 33.9 21.5 15.5 15.2 13.3 19.2 27.3 26.0 30.4 15.8 19.7
[31] 15.0 21.4
```

5.3 Data Structures

str(): This function displays the internal structure of an R object.

```
str(mtcars)
```

```
'data.frame':  32 obs. of  11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : num   6  6  4  6  8  6  8  4  4  6 ...
 $ disp: num  160 160 108 258 360 ...
 $ hp  : num  110 110  93 110 175 105 245  62  95 123 ...
 $ drat: num   3.9  3.9  3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt  : num   2.62 2.88 2.32 3.21 3.44 ...
 $ qsec: num  16.5 17 18.6 19.4 17 ...
 $ vs  : num   0  0  1  1  0  1  0  1  1  1 ...
 $ am  : num   1  1  1  0  0  0  0  0  0  0 ...
 $ gear: num   4  4  4  3  3  3  3  4  4  4 ...
 $ carb: num   4  4  1  1  2  1  4  2  2  4 ...
```

class(): This function is used to determine the class or data type of an object. It returns a character vector specifying the class or classes of the object.

```
x <- c(1, 2, 3) # Create a numeric vector
class(x)        # Output: "numeric"
```

```
[1] "numeric"
```

```
y <- "Hello, My name is Sameer Mathur!" # Create a character vector
class(y)                                # Output: "character"
```

```
[1] "character"
```

`class(x)` returns “numeric” because `x` is a numeric vector. Similarly, `class(y)` returns “character” because `y` is a character vector.

```
z <- data.frame(a = 1:5, b = letters[1:5]) # Create a data frame
class(z) # Output: "data.frame"
```

```
[1] "data.frame"
```

`class(z)` returns “data.frame” because `z` is a data frame.

```
sapply(mtcars, class)
```

```
      mpg      cyl      disp      hp      drat      wt      qsec      vs
"numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric" "numeric"
      am      gear      carb
"numeric" "numeric" "numeric"
```

5.4 Factors

In R, factors are a specific data type used for representing categorical variables or data with discrete levels or categories. They are employed to store data that has a limited number of distinct values, such as “male” or “female,” “red,” “green,” or “blue,” or “low,” “medium,” or “high.”

Factors in R consist of both values and levels. The values represent the actual data, while the levels correspond to the distinct categories or levels within the factor. Factors are particularly useful for statistical analysis as they facilitate the representation and analysis of categorical data efficiently.

To change the data type of the `am`, `cyl`, `vs`, and `gear` variables in the `mtcars` dataset to factors, you can utilize the `factor()` function. Here’s an example demonstrating how to achieve this:

```
# Convert variables to factors
mtcars$am <- factor(mtcars$am)
mtcars$cyl <- factor(mtcars$cyl)
mtcars$vs <- factor(mtcars$vs)
mtcars$gear <- factor(mtcars$gear)
```

The code above applies the `factor()` function to each variable, thereby converting them to factors. By assigning the result back to the respective variables, we effectively change their data type to factors. This conversion retains the original values while establishing levels based on the distinct values present in each variable.

After executing this code, the `am`, `cyl`, `vs`, and `gear` variables in the `mtcars` dataset will be of the factor data type. And we can verify this by re-running the `str()` function

```
str(mtcars)
```

```
'data.frame':  32 obs. of  11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : Factor w/ 3 levels "4","6","8": 2 2 1 2 3 2 3 1 1 2 ...
 $ disp: num  160 160 108 258 360 ...
 $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
 $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
 $ qsec: num  16.5 17 18.6 19.4 17 ...
 $ vs  : Factor w/ 2 levels "0","1": 1 1 2 2 1 2 1 2 2 2 ...
 $ am  : Factor w/ 2 levels "0","1": 2 2 2 1 1 1 1 1 1 1 ...
 $ gear: Factor w/ 3 levels "3","4","5": 2 2 2 1 1 1 1 2 2 2 ...
 $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
```

When the `cyl` variable in the `mtcars` dataset is converted to a factor, the `levels()` function can be used to extract the distinct levels or categories of that factor. By executing `levels(mtcars$cyl)`, you will receive an output that reveals the levels present in the `cyl` variable.

For example, if the `cyl` variable has been transformed into a factor with levels “4”, “6”, and “8”, the result of `levels(mtcars$cyl)` will be a character vector displaying these three levels:

```
levels(mtcars$cyl)
```

```
[1] "4" "6" "8"
```

It is important to note that the order of the levels in the output corresponds to their appearance in the original data.

Utilizing the `levels()` function on factor variables in R allows you to examine the particular categories or levels present within a factor, aiding in understanding the data’s composition and facilitating operations that target specific levels if necessary.

To change the base level of a factor variable in R, you can use the `relevel()` function. This function allows you to reassign a new base level by rearranging the order of the levels in the factor variable.

Here's an example of how you can change the base level of a factor variable:

```
# Assuming 'cyl' is a factor variable with levels "4", "6", and "8"
mtcars$cyl <- relevel(mtcars$cyl, ref = "6")
```

In the code above, we apply the `relevel()` function to the `cyl` variable, specifying `ref = "6"` to set "6" as the new base level.

After executing this code, the levels of the `mtcars$cyl` factor variable will be reordered, with "6" becoming the new base level. The order of the levels will be "6", "4", and "8" instead of the original order.

Changing the base level can be particularly useful when conducting statistical modeling or interpreting the effects of categorical variables in regression models. By selecting a specific level as the base, we can compare the effects of the other levels relative to the chosen base level, facilitating more meaningful analysis and interpretation.

For convenience, we will change the base level back to "4".

```
# Assuming 'cyl' is a factor variable with levels "4", "6", and "8"
mtcars$cyl <- relevel(mtcars$cyl, ref = "4")
```

`droplevels()`: This function is helpful for removing unused factor levels. It removes levels from a factor variable that do not appear in the data, reducing unnecessary levels and ensuring that the factor only includes relevant levels.

```
# Assuming 'cyl' is a factor variable with levels "4", "6", and "8"
# Check the levels of 'cyl' before removing unused levels
levels(mtcars$cyl)
```

```
[1] "4" "6" "8"
```

```
# Remove unused levels from 'cyl'
mtcars$cyl <- droplevels(mtcars$cyl)

# Check the levels of 'cyl' after removing unused levels
levels(mtcars$cyl)
```

```
[1] "4" "6" "8"
```

We apply `droplevels()` to `mtcars$cyl` to remove any unused levels from the factor variable. This function removes factor levels that are not present in the data. In this case all three levels were present in the data and therefore nothing was removed.

`cut()`: The `cut()` function allows you to convert a continuous variable into a factor variable by dividing it into intervals or bins. This is useful when you want to group numeric data into categories or levels.

```
# Create a new factor variable 'mpg_category' by cutting 'mpg' into intervals
mtcars$mpg_category <- cut(mtcars$mpg,
                           breaks = c(0, 20, 30, Inf),
                           labels = c("Low", "Medium", "High"))

# Summarize the resulting 'mpg_category' variable
summary(mtcars$mpg_category)
```

Low	Medium	High
18	10	4

In the provided code, a new factor variable called `mpg_category` is generated based on the `mpg` (miles per gallon) variable from the `mtcars` dataset. This is achieved using the `cut()` function, which segments the `mpg` values into distinct intervals and assigns appropriate factor labels.

The `cut()` function takes several arguments:

`mtcars$mpg` represents the variable to be divided.

`breaks` specifies the cutoff points for interval creation. Here, we define three intervals: values up to 20, values between 20 and 30 (inclusive), and values greater than 30. The `breaks` argument is defined as `c(0, 20, 30, Inf)` to indicate these intervals.

`labels` assigns labels to the resulting factor levels. In this instance, the labels “Low”, “Medium”, and “High” are provided to correspond with the respective intervals.

Having demonstrated how to create the new column `mpg_category`, we will now drop this column from the dataframe.

```
# drop the column `mpg_category`
mtcars$mpg_category = NULL
```

5.5 Logical operations

Here are some logical operations functions in R.

`subset()`: This function returns a subset of a data frame according to condition(s).

```
# Find cars that have cyl = 4 and mpg < 28
subset(mtcars, cyl == 4 & mpg < 22)
```

		mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Toyota	Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1
Volvo	142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2

```
# Find cars that have wt > 5 or mpg < 15
subset(mtcars, wt > 5 | mpg < 15)
```

		mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Duster	360	14.3	8	360	245	3.21	3.570	15.84	0	0	3	4
Cadillac	Fleetwood	10.4	8	472	205	2.93	5.250	17.98	0	0	3	4
Lincoln	Continental	10.4	8	460	215	3.00	5.424	17.82	0	0	3	4
Chrysler	Imperial	14.7	8	440	230	3.23	5.345	17.42	0	0	3	4
Camaro	Z28	13.3	8	350	245	3.73	3.840	15.41	0	0	3	4

`which()`: This function returns the indexes of a vector's members that satisfy a condition.

```
# Find the indices of rows where mpg > 20
indices <- which(mtcars$mpg > 20)
indices
```

```
[1] 1 2 3 4 8 9 18 19 20 21 26 27 28 32
```

`ifelse()`: This function applies a logical condition to a vector and returns a new vector with values depending on whether the condition is TRUE or FALSE.

```
# Create a new column "high_mpg" based on mpg > 20
mtcars$high_mpg <- ifelse(mtcars$mpg > 20, "Yes", "No")
```

Dropping a column: We can drop a column by setting it to NULL.

```
# Drop the column "high_mpg"
mtcars$high_mpg <- NULL
```

all(): If every element in a vector satisfies a logical criterion, this function returns TRUE; otherwise, it returns FALSE.

```
# Check if all values in mpg column are greater than 20
all(mtcars$mpg > 20)
```

```
[1] FALSE
```

any(): If at least one element in a vector satisfies a logical criterion, this function returns TRUE; otherwise, it returns FALSE.

```
# Check if any of the values in the mpg column are greater than 20
any(mtcars$mpg > 20)
```

```
[1] TRUE
```

Subsetting based on a condition:

The logical expression `[]` and square bracket notation can be used to subset the mtcars dataset according to one or more conditions.

```
# Subset mtcars based on mpg > 20
mtcars_subset <- mtcars[mtcars$mpg > 20, ]
mtcars_subset
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1

Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2

sort(): This function arranges a vector in an increasing or decreasing sequence.

```
sort(mtcars$mpg) # increasing order
```

```
[1] 10.4 10.4 13.3 14.3 14.7 15.0 15.2 15.2 15.5 15.8 16.4 17.3 17.8 18.1 18.7
[16] 19.2 19.2 19.7 21.0 21.0 21.4 21.4 21.5 22.8 22.8 24.4 26.0 27.3 30.4 30.4
[31] 32.4 33.9
```

```
sort(mtcars$mpg, decreasing = TRUE) # decreasing order
```

```
[1] 33.9 32.4 30.4 30.4 27.3 26.0 24.4 22.8 22.8 21.5 21.4 21.4 21.0 21.0 19.7
[16] 19.2 19.2 18.7 18.1 17.8 17.3 16.4 15.8 15.5 15.2 15.2 15.0 14.7 14.3 13.3
[31] 10.4 10.4
```

order(): This function provides an arrangement which sorts its initial argument into ascending or descending order.

```
mtcars[order(mtcars$mpg), ] # ascending order
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0	3	4
Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0	3	4
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0	3	4
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0	3	2
Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0	3	2
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	4

Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	4
Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3	2
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2
Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1

```
mtcars[order(-mtcars$mpg), ] # descending order
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	4
Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3	2
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2

Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	4
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0	3	2
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0	3	2
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8
Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0	3	4
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0	3	4
Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0	3	4

5.6 Statistical functions

`mean()`: This function computes the arithmetic mean.

```
mean(mtcars$mpg)
```

```
[1] 20.09062
```

`median()`: This function computes the median.

```
median(mtcars$mpg)
```

```
[1] 19.2
```

`sd()`: This function computes the standard deviation.

```
sd(mtcars$mpg)
```

```
[1] 6.026948
```

`var()`: This function computes the variance.

```
var(mtcars$mpg)
```

```
[1] 36.3241
```

cor(): This function computes the correlation between variables.

```
cor(mtcars$mpg, mtcars$wt)
```

```
[1] -0.8676594
```

unique(): This function extracts the unique elements of a vector.

```
unique(mtcars$mpg)
```

```
[1] 21.0 22.8 21.4 18.7 18.1 14.3 24.4 19.2 17.8 16.4 17.3 15.2 10.4 14.7 32.4  
[16] 30.4 33.9 21.5 15.5 13.3 27.3 26.0 15.8 19.7 15.0
```

5.7 Summarizing a dataframe

summary(): This function is a convenient tool to generate basic descriptive statistics for your dataset. It provides a succinct snapshot of the distribution characteristics of your data.

```
summary(mtcars$mpg)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
10.40	15.43	19.20	20.09	22.80	33.90

When applied to a vector or a specific column in a dataframe, it generates the following:

Min: This represents the smallest recorded value in the mpg column.

1st Qu: This indicates the first quartile or the 25th percentile of the mpg column. It implies that 25% of all mpg values fall below this threshold.

Median: This value signifies the median or the middle value of the mpg column, also known as the 50th percentile. Half of the mpg values are less than this value.

Mean: This denotes the average value of the mpg column.

3rd Qu: This represents the third quartile or the 75th percentile of the mpg column. It shows that 75% of all mpg values are less than this value.

Max: This indicates the highest value observed in the mpg column.

When we use `summary(mtcars$mpg)`, it returns these six statistics for the mpg (miles per gallon) column in the mtcars dataset.

When used with an entire dataframe, it applies to each column individually and provides a quick overview of the data.

```
summary(mtcars$cyl)
```

```
 4  6  8
11  7 14
```

The output of `summary(mtcars$cyl)` displays the frequency distribution of the levels within the cyl factor variable. It shows the count or frequency of each level, which in this case are “4”, “6”, and “8”. The summary will provide a concise overview of the distribution of these levels within the dataset.

```
summary(mtcars)
```

mpg	cyl	disp	hp	drat
Min. :10.40	4:11	Min. : 71.1	Min. : 52.0	Min. :2.760
1st Qu.:15.43	6: 7	1st Qu.:120.8	1st Qu.: 96.5	1st Qu.:3.080
Median :19.20	8:14	Median :196.3	Median :123.0	Median :3.695
Mean :20.09		Mean :230.7	Mean :146.7	Mean :3.597
3rd Qu.:22.80		3rd Qu.:326.0	3rd Qu.:180.0	3rd Qu.:3.920
Max. :33.90		Max. :472.0	Max. :335.0	Max. :4.930

wt	qsec	vs	am	gear	carb
Min. :1.513	Min. :14.50	0:18	0:19	3:15	Min. :1.000
1st Qu.:2.581	1st Qu.:16.89	1:14	1:13	4:12	1st Qu.:2.000
Median :3.325	Median :17.71			5: 5	Median :2.000
Mean :3.217	Mean :17.85				Mean :2.812
3rd Qu.:3.610	3rd Qu.:18.90				3rd Qu.:4.000
Max. :5.424	Max. :22.90				Max. :8.000

5.8 Creating new functions in R

We illustrate how to create a custom function in R that computes the mean of any given numeric column in the mtcars dataframe:

```
# Function creation
compute_average <- function(df, column) {
  # Compute the average of the specified column
  average_val <- mean(df[[column]], na.rm = TRUE)

  # Return the computed average
  return(average_val)
}

# Utilize the created function
average_mpg <- compute_average(mtcars, "mpg")
print(average_mpg)
```

```
[1] 20.09062
```

```
average_hp <- compute_average(mtcars, "hp")
print(average_hp)
```

```
[1] 146.6875
```

In the above code, `compute_average` is a custom function which takes two arguments: a dataframe (`df`) and a column name (as a string) `column`. The function computes the mean of the specified column in the provided dataframe, with `na.rm = TRUE` ensuring that NA values (if any) are removed before the mean calculation.

After defining the function, we utilize it to calculate the average values of the “mpg” and “hp” columns in the mtcars dataframe. These computed averages are then printed.

This demonstrates a simple way to create a custom function in R.

Function to calculate average mileage for cars with a specific number of cylinders:

```
avg_mileage_by_cyl <- function(data, cyl) {
  mean(data$mpg[data$cyl == cyl])
}
```

```
# Usage
```

```
# Returns the average mileage of cars with 4 cylinders  
avg_mileage_by_cyl(mtcars, 4)
```

```
[1] 26.66364
```

```
# Returns the average mileage of cars with 6 cylinders  
avg_mileage_by_cyl(mtcars, 6)
```

```
[1] 19.74286
```

6 Case Study: Analyze S&P500 Data (1)

July 21, 2023

6.1 S&P 500.

The S&P 500, also called the Standard & Poor's 500, is a stock market index that tracks the performance of 500 major publicly traded companies listed on U.S. stock exchanges. It serves as a widely accepted benchmark for assessing the overall health and performance of the U.S. stock market.

S&P Dow Jones Indices, a division of S&P Global, is responsible for maintaining the index. The selection of companies included in the S&P 500 is determined by a committee, considering factors such as market capitalization, liquidity, and industry representation.

The S&P is a float-weighted index, meaning the market capitalizations of the companies in the index are adjusted by the number of shares available for public trading. <https://www.investopedia.com/terms/s/sp500.asp>

The performance of the S&P 500 is frequently used to gauge the broader stock market and is commonly referenced by investors, analysts, and financial media. It provides a snapshot of how large-cap U.S. stocks are faring and is considered a reliable indicator of overall market sentiment.

Typically, the S&P 500 index consists of 500 stocks. However, in reality, there are actually 503 stocks included. This discrepancy arises because three of the listed companies have multiple share classes, and each class is considered a separate stock that needs to be included in the index.

Among these 503 stocks, Apple, the technology giant, holds the top position with a market capitalization of \$2.35 billion. Following Apple, Microsoft and Amazon.com rank as the second and third largest stocks in the S&P 500, respectively. The next positions are held by Nvidia Corp, Tesla, Berkshire Hathaway, and two classes of shares from Google's parent company, Alphabet..

6.2 S&P 500 Data - Preliminary Analysis

We will analyze a real-world, recent dataset containing information about the S&P500 stocks. The dataset is located in a Google Sheet

The data is disorganized and challenging to understand. We will review the data and proceed in a step-by-step manner.

6.2.1 Read the S&P500 data from a Google Sheet into a tibble dataframe.

1. The complete URL is
`https://docs.google.com/spreadsheets/d/11ahk9uWxBkDqrhNm7qYmiTwrlSC53N1zvXYfv7ttOCM/`
2. The Google Sheet ID is: `11ahk9uWxBkDqrhNm7qYmiTwrlSC53N1zvXYfv7ttOCM`. We can use the function `gsheet2tbl` in package `gsheet` to read the Google Sheet into a tibble or dataframe, as demonstrated in the following code.

```
# Read S&P500 stock data present in a Google Sheet.
library(gsheet)
prefix <- "https://docs.google.com/spreadsheets/d/"
sheetID <- "11ahk9uWxBkDqrhNm7qYmiTwrlSC53N1zvXYfv7ttOCM"
url500 <- paste(prefix,sheetID) # Form the URL to connect to
sp500 <- gsheet2tbl(url500) # Read it into a tibble called sp500
```

No encoding supplied: defaulting to UTF-8.

6.3 Review the data

1. We want to understand the different data columns and their data structure. For this purpose, we run the `str()` function.

```
str(sp500)
```

```
Classes 'tbl_df', 'tbl' and 'data.frame':   503 obs. of  36 variables:
 $ Date           : chr  "7/21/2023" "7/21/2023" "7/21/2023" "7/21/2023" ...
 $ Ticker          : chr  "A" "AAL" "AAP" "AAPL" ...
 $ Description     : chr  "Agilent Technologies, Inc." "American Airl..."
 $ Sector          : chr  "Health Technology" "Transportation" "Retail..."
 $ Industry        : chr  "Medical Specialties" "Airlines" "Specialty..."
```

```

$ Market.Capitalization      : num  3.54e+10 1.18e+10 4.20e+09 3.00e+12 2.40e+1
$ Price                      : num  119.8 18.1 70.7 190.7 136 ...
$ X52.Week.Low              : num  113.3 11.7 63.6 124.2 131 ...
$ X52.Week.High             : num  160 19.1 212 194 168 194 116 78.3 328 524 .
$ Return.on.Equity..TTM.    : num  24.8 NA 14.6 146 51.1 389 16 14.8 30.7 33.7
$ Return.on.Assets..TTM.    : num  12.7 2.64 3.35 27.6 5.43 2.79 7.82 4.98 14.
$ Return.on.Invested.Capital..TTM. : num  16.51 5.44 6.17 57.18 9.9 ...
$ Gross.Margin..TTM.        : num  54.1 21.7 43.8 43.2 72.2 ...
$ Operating.Margin..TTM.    : num  23.78 7.3 5.63 29.16 41.07 ...
$ Net.Margin..TTM.          : num  19.19 3.39 3.61 24.49 13.3 ...
$ Price.to.Earnings.Ratio..TTM. : num  26.39 7.13 10.51 32.4 32.03 ...
$ Price.to.Book..FY.        : num  6.66 NA 1.56 60 13.95 ...
$ Enterprise.Value.EBITDA..TTM. : num  18.8 7.03 8.84 24.7 9.3 12.8 19.3 NA 17.5 3
$ EBITDA..TTM.              : num  1.97e+09 6.02e+09 9.21e+08 1.24e+11 3.18e+1
$ EPS.Diluted..TTM.         : num  4.54 2.54 6.72 5.89 4.25 ...
$ EBITDA..TTM.YoY.Growth.    : num  10.52 NA -16 -5.36 10.6 ...
$ EBITDA..Quarterly.YoY.Growth. : num  8.2 NA -39.01 -4.58 11.68 ...
$ EPS.Diluted..TTM.YoY.Growth. : num  9.17 NA -25.21 -4.33 -39.11 ...
$ EPS.Diluted..Quarterly.YoY.Growth. : num  11.69944 NA -68.36829 -0.00656 -94.89037 ..
$ Price.to.Free.Cash.Flow..TTM. : num  30.06 6.94 NA 31 10.27 ...
$ Free.Cash.Flow..TTM.YoY.Growth. : num  11.81 NA -100.23 -7.85 6.68 ...
$ Free.Cash.Flow..Quarterly.YoY.Growth. : num  55.7078 648.1481 -176.1352 -0.0312 -15.3392
$ Debt.to.Equity.Ratio..MRQ. : num  0.473 NA 1.582 1.763 4.678 ...
$ Current.Ratio..MRQ.       : num  2.37 0.718 1.244 0.94 0.96 ...
$ Quick.Ratio..MRQ.         : num  1.708 0.624 0.238 0.878 0.821 ...
$ Dividend.Yield.Forward    : num  0.752 NA 1.416 0.503 4.353 ...
$ Dividends.per.share..Annual.YoY.Growth. : num  8.25 NA 84.62 5.88 7.53 ...
$ Price.to.Sales..FY.       : num  5.246 0.243 0.385 7.895 4.166 ...
$ Revenue..TTM.YoY.Growth.   : num  7.8597 50.2948 1.4153 -0.2544 0.0282 ...
$ Revenue..Quarterly.YoY.Growth. : num  6.85 36.97 1.29 -2.51 -9.7 ...
$ Technical.Rating           : chr  "Sell" "Strong Buy" "Neutral" "Strong Buy"

```

2. The `str(sp500)` output provides valuable insights into the structure and data types of the columns in the `sp500` tibble. Let's delve into the details.
3. The output reveals that `sp500` is a tibble with dimensions $[503 \times 36]$. This means it consists of 503 rows, each representing a specific S&P500 stock, and 36 columns containing information about each stock.
4. Here is a preliminary breakdown of the information associated with each column:
 - The columns labeled `Date`, `Stock`, `Description`, `Sector`, and `Industry` are character columns. They respectively represent the date, stock ticker symbol, description, sector, and industry of each S&P500 stock.

- Columns such as `Market.Capitalization`, `Price`, `X52.Week.Low`, `X52.Week.High`, and other numeric columns contain diverse financial metrics and stock prices related to the S&P500 stocks.
 - The column labeled `Technical.Rating` is a character column that assigns a technical rating to each stock.
5. By examining the `str(sp500)` output, we gain a preliminary understanding of the data types and column names present in the `sp500` tibble, enabling us to grasp the structure of the dataset.

6.3.1 Rename Data Columns

1. The names of the data columns are lengthy and confusing.
2. We will rename the data columns to make it easier to work with the data, using the `rename_with()` function.

```
# Define a mapping of new column names
new_names <- c(
  "Date", "Stock", "StockName", "Sector", "Industry",
  "MarketCap", "Price", "Low52Wk", "High52Wk",
  "ROE", "ROA", "ROIC", "GrossMargin",
  "OperatingMargin", "NetMargin", "PE",
  "PB", "EVEBITDA", "EBITDA", "EPS",
  "EBITDA_YOY", "EBITDA_QYOY", "EPS_YOY",
  "EPS_QYOY", "PFCF", "FCF",
  "FCF_QYOY", "DebtToEquity", "CurrentRatio",
  "QuickRatio", "DividendYield",
  "DividendsPerShare_YOY", "PS",
  "Revenue_YOY", "Revenue_QYOY", "Rating"
)
# Rename the columns using the new_names vector
sp500 <- sp500 %>%
  rename_with(~ new_names, everything())
```

This code is designed to rename the columns of the `sp500` tibble using a predefined mapping of new column names. Let's go through the code step by step:

1. A vector named `new_names` is created, which contains the desired new names for each column in the `sp500` tibble. Each element in the `new_names` vector corresponds to a specific column in the `sp500` tibble and represents the desired new name for that column.

2. The `%>%` operator, often referred to as the pipe operator, is used to pass the `sp500` tibble to the subsequent operation in a more readable and concise manner.
3. The `rename_with()` function from the `dplyr` package is applied to the `sp500` tibble. This function allows us to rename columns based on a specified function or formula.
4. In this case, a formula `~ new_names` is used as the first argument of `rename_with()`. This formula indicates that the new names for the columns should be sourced from the `new_names` vector.
5. The second argument, `everything()`, specifies that the renaming should be applied to all columns in the `sp500` tibble.
6. Finally, the resulting tibble with the renamed columns is assigned back to the `sp500` variable, effectively updating the tibble with the new column names.
7. We could also use the following code to rename the columns.

```
# Rename the columns using the new_names vector
colnames(sp500) <- new_names
```

In essence, the code uses the `new_names` vector as a mapping to assign new column names to the `sp500` tibble, ensuring that each column is given the desired new name specified in `new_names`.

6.3.2 Review the data again after renaming columns

1. We review the column names again after renaming them, using the `colnames()` function can help.

```
colnames(sp500)
```

```
[1] "Date"           "Stock"           "StockName"
[4] "Sector"         "Industry"         "MarketCap"
[7] "Price"          "Low52Wk"         "High52Wk"
[10] "ROE"            "ROA"              "ROIC"
[13] "GrossMargin"    "OperatingMargin"  "NetMargin"
[16] "PE"             "PB"               "EVEBITDA"
[19] "EBITDA"         "EPS"              "EBITDA_YOY"
[22] "EBITDA_QYOY"    "EPS_YOY"          "EPS_QYOY"
[25] "PFCF"           "FCF"              "FCF_QYOY"
[28] "DebtToEquity"   "CurrentRatio"     "QuickRatio"
[31] "DividendYield"  "DividendsPerShare_YOY" "PS"
```


[34] "Revenue_YOY"

"Revenue_QYOY"

"Rating"

6.3.3 Understand the Data Columns

1. The complete data has 36 columns. Our goal is to gain a deeper understanding of what the data columns mean.
2. We reorganize the column names into eight tables, labeled Table 1a, 1b.. 1h.
 - a. The column names described in Table 1a. concern basic **Company Information** of each stock.

Table 1a: Data Columns giving basic Company Information	
ColumnName	Description
Date	Date (e.g. "7/15/2023")
Stock	Stock Ticker (e.g. AAL)
StockName	Name of the company (e.g "American Airlines Group, Inc.")
Sector	Sector the stock belongs to (e.g. "Transportation")
Industry	Industry the stock belongs to (e.g "Airlines")
MarketCap	Market capitalization of the company
Price	Recent Stock Price

- b. The column names described in Table 1b. are related to **Technical Analysis** of each stock, including the 52-Week High and Low prices.

Table 1b: Data Columns related to Pricing and Technical Analysis	
ColumnName	Description
Low52Wk	52-Week Low Price
High52Wk	52-Week High Price
Rating	Technical Rating

- c. The column names described in Table 1c. are related to the **Profitability** of each stock.

Table 1c: Data Columns related to Profitability	
ColumnName	Description
ROE	Return on Equity
ROA	Return on Assets
ROIC	Return on Invested Capital
GrossMargin	Gross Profit Margin

Table 1c: Data Columns related to Profitability	
ColumnName	Description
OperatingMargin	Operating Profit Margin
NetMargin	Net Profit Margin

The column names described in Table 1d are related to the **Earnings** of each stock.

Table 1d: Data Columns related to Earnings	
ColumnName	Description
PE	Price-to-Earnings Ratio
PB	Price-to-Book Ratio
EVEBITDA	Enterprise Value to EBITDA Ratio
EBITDA	EBITDA
EPS	Earnings per Share
EBITDA_YOY	EBITDA Year-over-Year Growth
EBITDA_QYOY	EBITDA Quarterly Year-over-Year Growth
EPS_YOY	EPS Year-over-Year Growth
EPS_QYOY	EPS Quarterly Year-over-Year Growth

The column names described in Table 1e are related to the **Free Cash Flow** of each stock.

Table 1e: Data Columns related to Free Cash Flow	
ColumnName	Description
PFCF	Price-to-Free Cash Flow
FCF	Free Cash Flow
FCF_QYOY	Free Cash Flow Quarterly Year-over-Year Growth

The column names described in Table 1f concern the **Liquidity** of each stock.

Table 1f: Data Columns related to Liquidity	
ColumnName	Description
DebtToEquity	Debt-to-Equity Ratio
CurrentRatio	Current Ratio
QuickRatio	Quick Ratio

The column names described in Table 1g are related to the **Revenue** of each stock.

Table 1g: Data Columns related to Revenue	
ColumnName	Description
PS	Price-to-Sales Ratio
Revenue_YOY	Revenue Year-over-Year Growth
Revenue_QYOY	Revenue Quarterly Year-over-Year Growth

The column names described in Table 1h are related to the **Dividends** of each stock.

Table 1h: Data Columns related to Dividends	
ColumnName	Description
DividendYield	Dividend Yield
DividendsPerShare_YOY	Annual Dividends per Share Year-over-Year Growth

6.3.4 Remove Rows containing no data or Null values

1. The following code checks if the “Stock” column in the sp500 dataframe contains any null or blank values. If there are null or blank values present, it removes the corresponding rows from the sp500 dataframe, resulting in a filtered dataframe without null or blank values in the “Stock” column.

```
# Check for blank or null values in the "Stock" column
hasNull <- any(sp500$Stock == "" | is.null(sp500$Stock))
if (hasNull) {
  # Remove rows with null or blank values from the dataframe tibble
  sp500 <- sp500[!(is.null(sp500$Stock) | sp500$Stock == ""), ]
}
```

Here’s an alternate code using `dplyr` to achieve the same result:

```
library(dplyr)
# Check for blank or null values in the "Stock" column
hasNull <- any(sp500 %>% pull(Stock) == "" | is.null(sp500 %>% pull(Stock)))
if (hasNull) {
  # Remove rows with null or blank values from the dataframe tibble
  sp500 <- sp500 %>% filter(!(is.null(Stock) | Stock == ""))
}
```

```
# View the filtered dataframe
nrow(sp500)
```

```
[1] 502
```

Thus, we have 502 stocks of the S&P500 in our dataset.

6.3.5 S&P500 Sector

The S&P500 shares are divided into multiple Sectors. Each stock belongs to a unique sector. Thus, it makes sense to model Sector as a `factor()` variable.

```
sp500$Sector <- as.factor(sp500$Sector)
```

It makes sense to convert Sector to a factor variable, since there are 19 distinct Sectors in the S&P500 and each stock belongs to a unique sector. We confirm that Sector is now modelled as a factor variable, by running the `str()` function.

```
str(sp500$Sector)
```

```
Factor w/ 19 levels "Commercial Services",...: 11 18 16 7 11 6 11 9 17 17 ...
```

Now that Sectors is a factor variable, we can use the `levels()` function to review the different levels it can take.

```
levels(sp500$Sector)
```

```
[1] "Commercial Services"    "Communications"        "Consumer Durables"
[4] "Consumer Non-Durables"  "Consumer Services"     "Distribution Services"
[7] "Electronic Technology"  "Energy Minerals"       "Finance"
[10] "Health Services"        "Health Technology"     "Industrial Services"
[13] "Non-Energy Minerals"    "Process Industries"    "Producer Manufacturing"
[16] "Retail Trade"           "Technology Services"   "Transportation"
[19] "Utilities"
```

The `table()` function allows us to count how many stocks are part of each sector.

```
table(sp500$Sector)
```

Commercial Services	Communications	Consumer Durables
13	3	12
Consumer Non-Durables	Consumer Services	Distribution Services
31	29	9
Electronic Technology	Energy Minerals	Finance
49	16	91
Health Services	Health Technology	Industrial Services
12	47	9
Non-Energy Minerals	Process Industries	Producer Manufacturing
7	24	31
Retail Trade	Technology Services	Transportation
23	50	15
Utilities		
31		

Thus, we can see how many stocks are part of each one of the 19 sectors.

We can sum them to confirm that they add up to 502.

```
sum(table(sp500$Sector))
```

```
[1] 502
```

This completes our review of the Sector variable.

6.3.6 Stock Ratings

In the data, the S&P500 shares have Technical Ratings such as {Buy, Sell, ..}. Since each Stock has a unique Technical Rating, it makes sense to model the data column Rating as a factor() variable.

```
sp500$Rating <- as.factor(sp500$Rating)
```

We confirm that Rating is now modelled as a factor variable, by running the str() function.

```
str(sp500$Rating)
```

Factor w/ 5 levels "Buy","Neutral",...: 3 4 2 4 2 1 2 4 4 1 ...

We can use the `levels()` function to review the different levels it can take.

```
levels(sp500$Rating)
```

```
[1] "Buy"          "Neutral"      "Sell"         "Strong Buy"   "Strong Sell"
```

The `table()` function allows us to count how many stocks have each Rating.

```
table(sp500$Rating)
```

Buy	Neutral	Sell	Strong Buy	Strong Sell
210	69	110	98	15

Thus, we can see how many stocks have ratings ranging from “Strong Sell” to “Strong Buy”. This completes our review of Technical Rating.

6.3.7 Summary

We believe this dataset of S&P500 shares is now ready for further analysis. We end this stage of our analysis in this chapter, by running the `str()` function to review the data columns.

```
str(sp500)
```

```
tibble [502 x 36] (S3: tbl_df/tbl/data.frame)
 $ Date           : chr [1:502] "7/21/2023" "7/21/2023" "7/21/2023" "7/21/2023" ...
 $ Stock          : chr [1:502] "A" "AAL" "AAP" "AAPL" ...
 $ StockName      : chr [1:502] "Agilent Technologies, Inc." "American Airlines Group,
 $ Sector         : Factor w/ 19 levels "Commercial Services",...: 11 18 16 7 11 6 11 9
 $ Industry       : chr [1:502] "Medical Specialties" "Airlines" "Specialty Stores" "T
 $ MarketCap      : num [1:502] 3.54e+10 1.18e+10 4.20e+09 3.00e+12 2.40e+11 ...
 $ Price          : num [1:502] 119.8 18.1 70.7 190.7 136 ...
 $ Low52Wk        : num [1:502] 113.3 11.7 63.6 124.2 131 ...
 $ High52Wk       : num [1:502] 160 19.1 212 194 168 194 116 78.3 328 524 ...
 $ ROE            : num [1:502] 24.8 NA 14.6 146 51.1 389 16 14.8 30.7 33.7 ...
 $ ROA            : num [1:502] 12.7 2.64 3.35 27.6 5.43 2.79 7.82 4.98 14.9 17.9 ...
```

\$ ROIC	: num [1:502]	16.51 5.44 6.17 57.18 9.9 ...
\$ GrossMargin	: num [1:502]	54.1 21.7 43.8 43.2 72.2 ...
\$ OperatingMargin	: num [1:502]	23.78 7.3 5.63 29.16 41.07 ...
\$ NetMargin	: num [1:502]	19.19 3.39 3.61 24.49 13.3 ...
\$ PE	: num [1:502]	26.39 7.13 10.51 32.4 32.03 ...
\$ PB	: num [1:502]	6.66 NA 1.56 60 13.95 ...
\$ EVEBITDA	: num [1:502]	18.8 7.03 8.84 24.7 9.3 12.8 19.3 NA 17.5 33.2 ...
\$ EBITDA	: num [1:502]	1.97e+09 6.02e+09 9.21e+08 1.24e+11 3.18e+10 ...
\$ EPS	: num [1:502]	4.54 2.54 6.72 5.89 4.25 ...
\$ EBITDA_YOY	: num [1:502]	10.52 NA -16 -5.36 10.6 ...
\$ EBITDA_QYOY	: num [1:502]	8.2 NA -39.01 -4.58 11.68 ...
\$ EPS_YOY	: num [1:502]	9.17 NA -25.21 -4.33 -39.11 ...
\$ EPS_QYOY	: num [1:502]	11.69944 NA -68.36829 -0.00656 -94.89037 ...
\$ PFCF	: num [1:502]	30.06 6.94 NA 31 10.27 ...
\$ FCF	: num [1:502]	11.81 NA -100.23 -7.85 6.68 ...
\$ FCF_QYOY	: num [1:502]	55.7078 648.1481 -176.1352 -0.0312 -15.3392 ...
\$ DebtToEquity	: num [1:502]	0.473 NA 1.582 1.763 4.678 ...
\$ CurrentRatio	: num [1:502]	2.37 0.718 1.244 0.94 0.96 ...
\$ QuickRatio	: num [1:502]	1.708 0.624 0.238 0.878 0.821 ...
\$ DividendYield	: num [1:502]	0.752 NA 1.416 0.503 4.353 ...
\$ DividendsPerShare_YOY	: num [1:502]	8.25 NA 84.62 5.88 7.53 ...
\$ PS	: num [1:502]	5.246 0.243 0.385 7.895 4.166 ...
\$ Revenue_YOY	: num [1:502]	7.8597 50.2948 1.4153 -0.2544 0.0282 ...
\$ Revenue_QYOY	: num [1:502]	6.85 36.97 1.29 -2.51 -9.7 ...
\$ Rating	: Factor w/ 5 levels "Buy","Neutral",...:	3 4 2 4 2 1 2 4 4 1 ...