Introduction to R

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1 R Basics

1.1 Using R as a Calculator

At its simplest, you can use R as a basic calculator.

```
#You can perform addition...
3 + 5 # Displays 8
```

```
## [1] 8
```

```r
#...subtraction...
10 - 7 # Displays 3
```

```
## [1] 3
```

```r
#...multiplication...
4 * 2 # Displays 8
```

```
## [1] 8
```

```r
#...and division.
10 / 5 # Displays 2
```

```
## [1] 2
```

1.2 Object Assignment

R allows us to assign values to objects (which can be thought of as variables). To assign a value to an object in R, we use the "<-" symbol.

```r
# Example of object assignment:
x <- 10  # Assigning the value 10 to the object 'x'.
print(x)  # Printing the value of 'x'. This will output 10.
```

```
## [1] 10
```

1.3 Data Types in R

In R, we have several types of data. These include:

1. Numeric: Any number with or without decimal points.
2. Integer: Whole numbers without decimal points.
3. Complex: Complex numbers, comprising a real and imaginary part.
4. Character: Text or string data.
5. Logical: Boolean values - TRUE or FALSE.

Let's assign each of these types to a variable:

```r
# Creating a numeric variable
numeric_var <- 5.3
print(numeric_var)  # This will output 5.3.
```

```
## [1] 5.3
```

```r
# Creating an integer variable
integer_var <- 4L
print(integer_var)  # This will output 4.
```

```
## [1] 4
```

```r
# Creating a complex variable
complex_var <- 3 + 2i
print(complex_var)  # This will output 3+2i.
```

```
## [1] 3+2i
```

```r
# Creating a character variable
character_var <- "Hello, World!"
print(character_var)  # This will output "Hello, World!".
```

```
## [1] "Hello, World!"
```

```r
# Creating a logical variable
logical_var <- TRUE
print(logical_var)   # This will output TRUE.
```

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

1.4 Vectors/List in R

One of the key data structures in R is a vector. Vectors are one-dimensional arrays that can store numeric, character or logical data elements.

```r
# Here's an example of a numeric vector:
numeric_vector <- c(1, 2, 3)
print(numeric_vector)  # This will output "1 2 3".
```

```
## [1] 1 2 3
```

```r
# Here's an example of a character vector:
character_vector <- c("Welcome", "to", "R!")
print(character_vector)  # This will output "Welcome to R!".
```

```
## [1] "Welcome" "to"      "R!"
```

```r
# Here's an example of a logical vector
logical_vector <- c(TRUE, FALSE, TRUE, FALSE)
print(logical_vector)  # This will output "TRUE FALSE TRUE FALSE".
```

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

1.5 Boolean in R

R has logical operators to perform operations involving booleans (TRUE and FALSE).

```r
# Here's an example of using boolean values in R:
x <- 5
y <- 10

# Check if x is less than y
result <- x < y  # This will return TRUE since 5 is indeed less than 10.

print(result)
```

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

2 Handling Dataframes: An Introductory Example.

This detailed guide instructs about fundamental R operations through a realistic example — a classroom scenario. It will cover creating data frames, alteration of data frames, plotting, working with categorical data (factors), and handling missing data in R.

Let's imagine we are teachers gathering students' data such as name, age, scores in recent tests, and gender.

2.1 Building Data Frames

Data frames in R function similar to tables in a database or Excel spreadsheet, with rows and columns that store data.

```
# Constructing a data frame named 'studentdata'.
# Our data includes "Name", "Age", "Gender", and "Score" of each student.

studentdata <- data.frame(
    Name = c("John", "Alice", "Bob", "Emily", "Jack", "Sandy"),
    Age = c(23, 35, 45, 22, 33, 29),
    Gender = c("Male", "Female", "Male", "Non-binary", "Male", "Female"),
    Score = c(89, 92, 76, 88, 75, 95)
)

print(studentdata)
```

```
##    Name Age     Gender Score
## 1  John  23       Male    89
## 2 Alice  35     Female    92
## 3   Bob  45       Male    76
## 4 Emily  22 Non-binary    88
## 5  Jack  33       Male    75
## 6 Sandy  29     Female    95
```

2.2 Modifying Data Frames

Adding and removing columns to a data frame are routine tasks - requirement changes might need adding new variables or erasing irrelevant ones.

```
# Adding a new column
# A new column "Passed" is added indicating if each student passed or not (a
score above 80 is deemed a pass)

studentdata$Passed <- studentdata$Score > 80

# Removing a column
# Now, we opt to remove the 'Score' column as it's not required after we
```

```
ascertain who's passed.

studentdata$Score <- NULL

print(studentdata)
```

```
##    Name Age     Gender Passed
## 1  John  23       Male   TRUE
## 2 Alice  35     Female   TRUE
## 3   Bob  45       Male  FALSE
## 4 Emily  22 Non-binary   TRUE
## 5  Jack  33       Male  FALSE
## 6 Sandy  29     Female   TRUE
```

Accessing parts of a data frame is similar to picking specific cells or a range in a spreadsheet, let's see how:

```
# Accessing a specific element - 'Name' of the first student.
print(studentdata[1, "Name"])
```

```
## [1] "John"
```

```
# Accessing an entire column - 'Age' of all students
print(studentdata$Age)
```

```
## [1] 23 35 45 22 33 29
```

2.3 Factors

Factors handle categorical data in R - understanding this is essential to handle and analyze categorical variables.

```
# We've already stored the gender of each student in the 'Gender' column.
# Let's convert that into factor.
studentdata$Gender <- factor(studentdata$Gender)

# Checking levels in Gender
print(levels(studentdata$Gender))
```

```
## [1] "Female"     "Male"       "Non-binary"
```

2.4 Handling Missing Data

Real-world datasets often contain missing values. Handling missing data can involve techniques such as detection, deletion, and imputation.

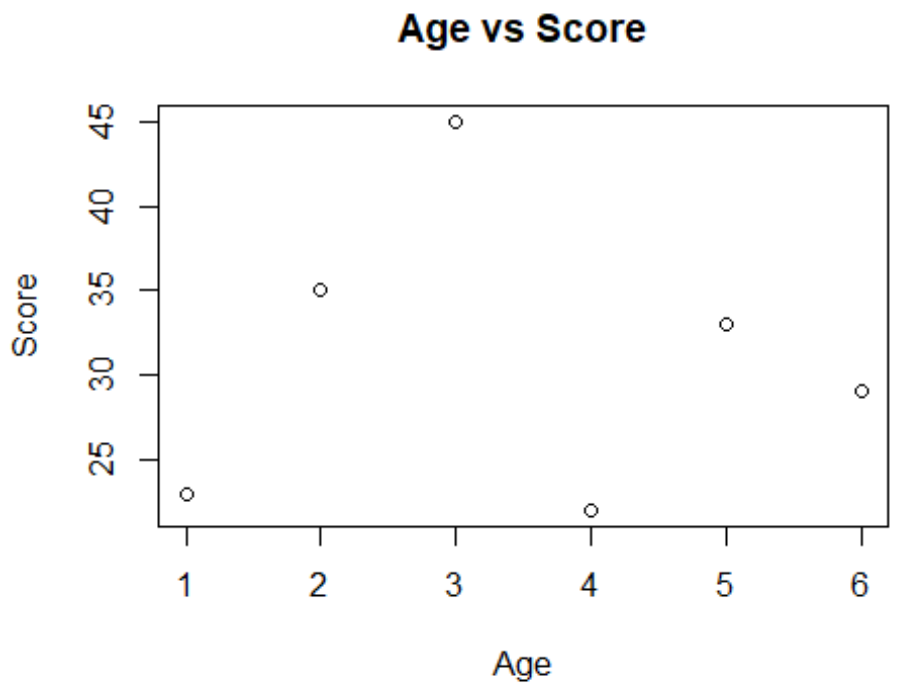
```
# Let's presume a scenario where student Age data has missing values.
# 'NA' denotes missing value in R.
AgeData <- c(23, 35, NA, 22, NA, 29)

# Identifying missing values with 'is.na'
print(is.na(AgeData))
```

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

# Replacing missing values via a specific value, let's replace 'NA' with
median age of students.
Age_median <- median(AgeData, na.rm = TRUE)
AgeData[is.na(AgeData)] <- Age_median

print(AgeData)

## [1] 23 35 26 22 26 29
```

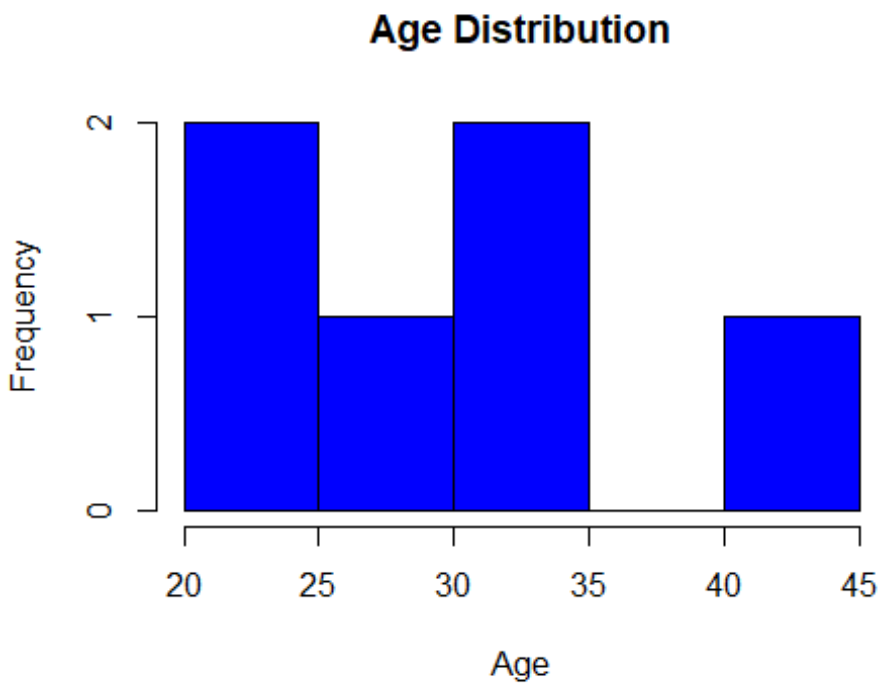
2.5 Plotting Data

Visualization broadens the understanding of data by highlighting patterns and distributions in a visually intuitive manner.

```
# A scatter plot between Age and Score of students.
plot(studentdata$Age, studentdata$Score, main = "Age vs Score", xlab = "Age",
ylab = "Score")
```




```
# A histogram represents 'Age' distribution among the students.
hist(studentdata$Age, main = "Age Distribution", xlab = "Age", col = "blue")
```



3 USArrests Dataset

Let's now use this knowledge to explore the USArrests dataset. Please note that to use the USArrests dataset, it requires the 'datasets' package to be installed and loaded. The USArrests dataset contains statistics about violent crimes in US states.

Variables Included: - Murder: Murder arrests (per 100,000) - Assault: Assault arrests (per 100,000) - UrbanPop: Percent urban population - Rape: Rape arrests (per 100,000)

```
# Install 'datasets'
install.packages('datasets') # You just need to install packages once. Then
you can comment this line with '#'

## Warning: package 'datasets' is in use and will not be installed

# Loading the USArrests data
data(USArrests)

# Printing the first few entries of the USArrests dataset
print(head(USArrests))

##            Murder Assault UrbanPop Rape
## Alabama      13.2     236       58 21.2
## Alaska       10.0     263       48 44.5
## Arizona       8.1     294       80 31.0
## Arkansas      8.8     190       50 19.5
```

```
## California    9.0     276       91 40.6
## Colorado      7.9     204       78 38.7
```

3.1 Subsetting in R

Let's first look at the structure of the USArrests dataset:

```
# The function str() provides a neat, human-readable summary of a complex R
data structure
str(USArrests)

## 'data.frame':    50 obs. of  4 variables:
##  $ Murder  : num  13.2 10 8.1 8.8 9 7.9 3.3 5.9 15.4 17.4 ...
##  $ Assault : int  236 263 294 190 276 204 110 238 335 211 ...
##  $ UrbanPop: int  58 48 80 50 91 78 77 72 80 60 ...
##  $ Rape    : num  21.2 44.5 31 19.5 40.6 38.7 11.1 15.8 31.9 25.8 ...
```

This output provides us crucial information about our dataset, such as there are 50 observations (rows) and 4 variables (columns).

Subsetting in R is a way to extract parts of your data from larger data structures based on certain conditions, generally done using the square bracket notation [row, col]. The concept works on principles of rows and columns, similar to how we understand data in a spreadsheet. Here, 'row' and 'col' represent the indices of the rows and columns respectively.

For instance, if we have a dataset 'USArrests', we can extract data from the second row and third column by specifying the indices as USArrests[2, 3]. In more realistic scenarios, you will want to subset data based on certain conditions, which is where logical subsetting is useful.

The condition needs to generate a list of boolean (TRUE/FALSE) values of equal length to the number of rows in the data structure. This list tells R which rows to keep (for TRUE) and which to exclude (for FALSE).

We can create these logical conditions manually or use a logical statement. For example, we might want to subset rows of the dataset where the 'Murder' rate is above 5. We can create a logical condition 'logical_condition <- USArrests[,"Murder"] > 5', which returns a list of TRUE or FALSE values for each row, depending on whether that row's 'Murder' rate is higher than 5. Subsequently, we subset the dataframe using this logical_condition: 'high_murder_rate <- USArrests[logical_condition ,]'.

This entire process can be concisely written in one line as 'high_murder_rate <- USArrests[USArrests,"Murder"] > 5,]'.

3.1.1 Basic Subsetting

Subsetting is accomplished primarily through the use of square brackets [].

```
# To select the 'Murder' column from the USArrests dataset, we can use
murder_data <- USArrests[c("Murder")]
```

```r
# This line of code gives us the 'Murder' rate for the different states.
Let's print the first few values.
print(head(murder_data))
```

```
##            Murder
## Alabama      13.2
## Alaska       10.0
## Arizona       8.1
## Arkansas      8.8
## California    9.0
## Colorado      7.9
```

3.1.2 Quick Access Subsetting

If we only need a single entry from our dataset. For instance, let's say we want to know the Assault rate of the tenth state in the dataset. We can subset this as follows:

```r
# Assault rate for the 10th state
tenth_state_assault <- USArrests[10, "Assault"]

# Printing the Assault rate of the 10th state
print(tenth_state_assault)
```

```
## [1] 211
```

3.1.3 Condition-Based Subsetting

Quite often, we want to subset our data based on certain conditions. To achieve this, we can use logical conditions inside our square brackets.

```r
# Suppose we want only the entries of states that have a murder rate more
than 5 per 100,000. We can achieve this by applying a condition on the
'Murder' column.

# First, start by creating a vector with the logical condition.
logical_condition <- USArrests[,"Murder"] > 5
```

This vector has the same number of rows than our dataset, and has the value TRUE whenever $Murder > 5$, and FALSE otherwise.

Then, we can select the rows of the dataset by subsetting on the logical values of this vector as follows:

```r
# Apply the desired subsetting
high_murder_rate <- USArrests[logical_condition,]

# Printing the first few rows of the states with high murder rate data.
print(head(high_murder_rate))
```

```
##            Murder Assault UrbanPop Rape
## Alabama      13.2     236       58 21.2
```

```
## Alaska       10.0     263       48 44.5
## Arizona       8.1     294       80 31.0
## Arkansas      8.8     190       50 19.5
## California    9.0     276       91 40.6
## Colorado      7.9     204       78 38.7
```

We can do the two steps, in one compact line of code in which we obtain 'high_murder_rate':

```
# Suppose we want only the entries of states that have a murder rate more
than 5 per 100,000. We can achieve this by applying a condition on the
'Murder' column.
high_murder_rate <- USArrests[USArrests[,"Murder"] > 5,]

# Printing the first few rows of the states with high murder rate data.
print(head(high_murder_rate))
```

```
##            Murder Assault UrbanPop Rape
## Alabama      13.2     236       58 21.2
## Alaska       10.0     263       48 44.5
## Arizona       8.1     294       80 31.0
## Arkansas      8.8     190       50 19.5
## California    9.0     276       91 40.6
## Colorado      7.9     204       78 38.7
```

This gives us a dataset that only includes states that have a murder rate exceeding our specified threshold.

3.1.4 Complex Subsetting

When dealing with diverse datasets like USArrests, we often require subsets based on multiple conditions. R allows for complex subsetting using & (and) or | (or) operators.

```
# Suppose we want data of states that not only have a high murder rate, but
also have an Assault rate more than 150.

high_murder_and_assault <- USArrests[USArrests[,"Murder"] > 5 &
USArrests[,"Assault"] > 150,]

# Let's print this data:
print(high_murder_and_assault) # States matching the criteria
```

```
##               Murder Assault UrbanPop Rape
## Alabama         13.2     236       58 21.2
## Alaska          10.0     263       48 44.5
## Arizona          8.1     294       80 31.0
## Arkansas         8.8     190       50 19.5
## California       9.0     276       91 40.6
## Colorado         7.9     204       78 38.7
## Delaware         5.9     238       72 15.8
## Florida         15.4     335       80 31.9
```

```
## Georgia          17.4     211       60 25.8
## Illinois         10.4     249       83 24.0
## Louisiana        15.4     249       66 22.2
## Maryland         11.3     300       67 27.8
## Michigan         12.1     255       74 35.1
## Mississippi      16.1     259       44 17.1
## Missouri          9.0     178       70 28.2
## Nevada           12.2     252       81 46.0
## New Jersey        7.4     159       89 18.8
## New Mexico       11.4     285       70 32.1
## New York         11.1     254       86 26.1
## North Carolina   13.0     337       45 16.1
## Oklahoma          6.6     151       68 20.0
## South Carolina   14.4     279       48 22.5
## Tennessee        13.2     188       59 26.9
## Texas            12.7     201       80 25.5
## Virginia          8.5     156       63 20.7
## Wyoming           6.8     161       60 15.6
```

We successfully derived a subset of data that matches our criteria.

3.2 Changing the name of rows

The following command show the rownames of the dataset. There are different ways that you can name them, but often datasets will have numeric values are row names

```
# Print Row Names
rownames(USArrests)
```

```
##  [1] "Alabama"        "Alaska"         "Arizona"        "Arkansas"
##  [5] "California"     "Colorado"       "Connecticut"    "Delaware"
##  [9] "Florida"        "Georgia"        "Hawaii"         "Idaho"
## [13] "Illinois"       "Indiana"        "Iowa"           "Kansas"
## [17] "Kentucky"       "Louisiana"      "Maine"          "Maryland"
## [21] "Massachusetts"  "Michigan"       "Minnesota"      "Mississippi"
## [25] "Missouri"       "Montana"        "Nebraska"       "Nevada"
## [29] "New Hampshire"  "New Jersey"     "New Mexico"     "New York"
## [33] "North Carolina" "North Dakota"   "Ohio"           "Oklahoma"
## [37] "Oregon"         "Pennsylvania"   "Rhode Island"   "South Carolina"
## [41] "South Dakota"   "Tennessee"      "Texas"          "Utah"
## [45] "Vermont"        "Virginia"       "Washington"     "West Virginia"
## [49] "Wisconsin"      "Wyoming"
```

For our purposes, it is useful to have the rownames in a variable inside the dataset. We can create a new variable to do this using the following syntax:

```
# Print Row Names
USArrests$State <- rownames(USArrests)

# Get the first values of the variable
head(USArrests$State)
```

```
## [1] "Alabama"    "Alaska"     "Arizona"    "Arkansas"   "California"
## [6] "Colorado"
```

In R, the $ sign is a special operator used for accessing and manipulating columns within a data frame or list. When working with data frames, $ allows you to reference a specific column by its name and is commonly used to extract or assign values to that column. For example, in the command `USArrests$State <- rownames(USArrests)`, the $ sign is used to create a new column named `State` in the `USArrests` data frame and assign the row names of the data frame to this column.

3.2.1 How $ Sign Works in Data Frames

When you use the $ sign with a data frame, it follows the syntax:

```
# Code to create a new variable
data_frame$column_name <- "(some valid expression)"
```

- Accessing Values: If the column already exists, this syntax allows you to access the values in that column. For instance, USArrests$Murder would give you the values of the Murder column in the USArrests data frame.
- Creating or Modifying a Column: If the column doesn't exist, using the $ sign with an assignment (<-) will create a new column with that name and fill it with the values on the right-hand side of the assignment. In the example USArrests$State <- rownames(USArrests), a new column State is created, and the row names of USArrests are stored in it. Conditions for Data Frame to Accept New Values

For a data frame to accept new values in a column using the $ operator, a few conditions must be met:

- Matching Row Count: The number of values you assign to the new column must match the number of rows in the data frame. For example, if USArrests has 50 rows, the vector or list assigned to USArrests$State must also contain 50 elements. Otherwise, R will throw an error or recycle the values, which may lead to unexpected results.
- Column Name Validity: The name you provide after the $ sign must be a valid R identifier. This means it should start with a letter and can only contain letters, numbers, periods, or underscores. If you try to create a column name that doesn't follow these rules, R will either give an error or automatically adjust the name (e.g., replacing spaces with periods).
- No Conflicts with Existing Columns: If the column name already exists in the data frame, the new values will overwrite the existing values in that column. It's important to be cautious when doing this to avoid unintentionally losing data

4 Data Manipulation in R

R provides a comprehensive set of tools for manipulating, transforming, and summarizing data. In this section of the tutorial we will create a new column in the USArrests dataset,

which will be a unified crime score. This score will be a single measure that combines the 'Murder', 'Assault', and 'Rape' variables. Following this, we will create a histogram of the crime scores and will summarize this score.

4.1 Creating a Unified Crime Score

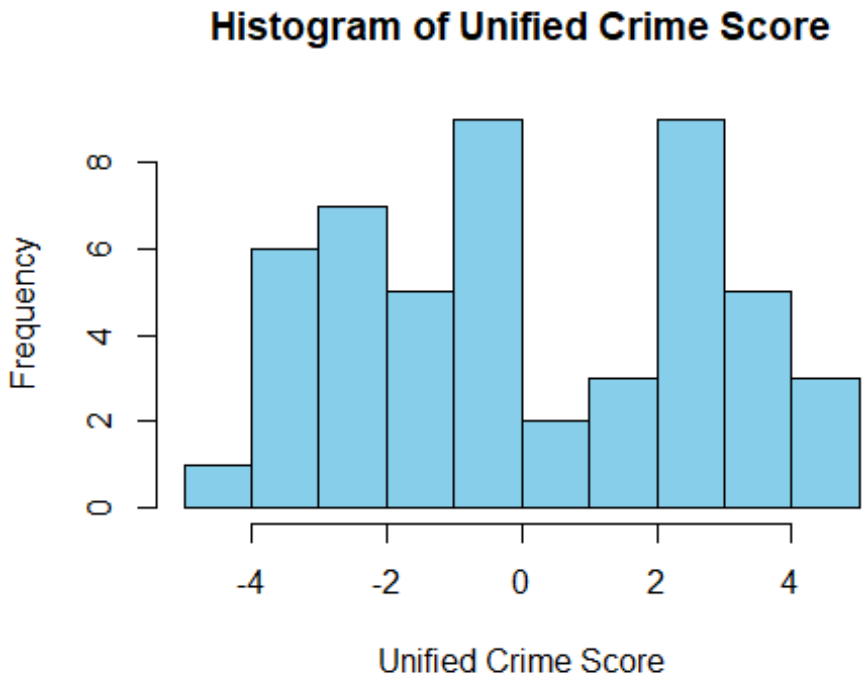
First, we need to create a new column that combines the 'Murder', 'Assault', and 'Rape' columns. One simple way to do this is to add up the three columns. However, to ensure that each type of crime gets an equal weight in the combined score, we first need to scale the data. We will do this by subtracting the mean of each column and dividing by the standard deviation. This process, also known as standardizing or z-score normalization, gives each column a mean of 0 and a standard deviation of 1.

```
# Adding packages
library(dplyr) # the dplyr package gives us access to the mutate(), mean()
and sd() functions which will be handy.

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

# We standardize the 'Murder', 'Assault', and 'Rape' columns
USArrests <- USArrests %>%
  mutate(
    Murder = (Murder - mean(Murder)) / sd(Murder),
    Assault = (Assault - mean(Assault)) / sd(Assault),
    Rape = (Rape - mean(Rape)) / sd(Rape)
  )

# We create a new column named 'crime_score' that is the sum of the
standardizes 'Murder', 'Assault' and 'Rape' columns
USArrests <- USArrests %>%
  mutate(
    crime_score = Murder + Assault + Rape
  )
```

4.2 Creating a Histogram of the Crime Score

Now that we have a unified crime score for each state, we can create a histogram to visualize the distribution of crime scores across all states.

```
# Generate a histogram of the unified crime score
hist(USArrests$crime_score, main="Histogram of Unified Crime Score",
xlab="Unified Crime Score", col="skyblue")
```



4.3 Getting Summary Statistics for the Crime Score

Finally, we will generate some summary statistics for the crime score.

```
# Compute summary statistics of the unified crime score
summary_stats <- summary(USArrests$crime_score)
print(summary_stats)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -4.6009 -2.1666 -0.5656  0.0000  2.4669  4.8574
```

The summary() function provides us with the minimum, maximum, mean, and quartile values for the crime score.

Now we have examined the USArrests dataset using various statistical methods including data subsetting, renaming variables, scaling data, creating histograms and getting summary statistics.