



**American International University-Bangladesh (AIUB)**

**Department of Computer Science**

**Faculty of Science & Technology (FST)**

**FALL 23-24**

**Section: C**

**INTRODUCTION TO DATA SCIENCE**

**REPORT SUBMITTED BY**

SN	Student Name	Student ID
1	RIAZ SARKER	20-42362-1
2	MD. RAFID HASAN	20-42421-1

**SUBMITTED TO**

**TOHEDUL ISLAM**

Assistant Professor, Faculty, Department of Computer Science

## Description:

The heart\_attack\_data dataset is widely recognized for its information on patient. According to the provided information, the medical dataset classifies either heart attack or none. It is frequently employed as a benchmark in data analysis and machine learning tasks. This dataset offers valuable insights into the demographics and characteristics of the heart attack patient, as well as their heart condition. By studying this dataset, researchers and data scientists can explore various factors that potentially influenced heart Disease rates on patient, including Age, Sex, ChestPain Type, RestingBp, Cholesterol, FastingBS, RestingECG, MaxHr etc.

## Attributes:

Age: Age of the patient

Sex: Sex of the patient

ChestPain Type: There is four type of ChestPain Type of patient (Typical Angina, Atypical Angina, Non-Anginal Pain, Asymptomatic)

RestingBP: Resting blood pressure (in mm Hg) of Patient.

Cholesterol: Cholesterol in mg/dl fetched via BMI sensor

FastingBS: Fasting blood sugar > (120 mg/dl)

RestingECG: Resting Electrocardiographic results of Patient

MaxHR: Maximum heart rate achieved of Patient.

ExerciseAngina: Exercise induced angina on heart attack Patient.

Oldpeak: ST depression induced by exercise relative to rest.

ST\_Slope: The slope of the peak exercise ST segment

HeartDisease: Diagnosis of heart disease (angiographic disease status).

## Import Dataset:

```
heart_attack_data <- read.csv("D:/Dataset_MIdterm_Sectoin(C).csv",header=TRUE, sep=",")
```

```
View(heart_attack_data)
```

```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> heart_attack_data <- read.csv("D:/Dataset_MIDterm_Sectoin(C).csv",header=TRUE, sep=",")
> View(heart_attack_data)
> |
```

**Explanation:** Imports the heart\_attack\_data dataset from a designated file path, storing it in the variable "heart\_attack\_data". The dataset is read as a CSV file, with headers included and values separated by patient information. To facilitate exploration and analysis, executing "View(heart\_attack\_data)" opens a separate viewer window, displaying the imported dataset.

## DISPLAYING THE DATA\_SET (heart\_attack\_data):

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease
1	40	M	ATA	140	289	0	Normal	172	N	0.0	Up	0
2	49	F	NAP	160	180	0	Normal	156	N	1.0	Flat	1
3	37	M	ATA	130	283	0	ST	98	N	0.0	Up	0
4	NA	F	ASY	138	214	0	Normal	108	Y	1.5	Flat	1
5	54	M	NAP	-150	195	0	Normal	122	N	0.0	Up	0
6	39	M	NAP	120	339	0	Normal	170	N	0.0	Up	0
7	45	F	ATA	130	237	0	Normal	170		0.0	Up	0
8	54	M	ATA	110	208	0	Normal	142	N	0.0	Up	0
9	37		ASY	140	207	0	Normal	130	Y	1.5	Flat	1
10	48	F	ATA	120	284	0	Normal	120	N	0.0	Up	0
11	37	F	NAP	130	1000	0	Normal	142	N	0.0	Up	0
12	58	M	ATA	136	1005	0	ST	99	Y	2.0	Flat	1
13	39	M	ATA	120	204	0	Normal	145	N	0.0	Up	0
14	49	M	ASY	140	234	0	Normal	140	Y	1.0	Flat	1
15	42	M	NAP	115	211	0	ST	137	N	0.0	Up	0
16	54	M	ATA	120	273	0	Normal	150	N	1.5	Flat	0
17	38	M	ASY	110	196	0	Normal	166	N	0.0	Flat	1
18	43	F	ATA	120	201	0	Normal	165	N	0.0	Up	0
19	60	M	ASY	100	248	0	Normal	125	N	1.0	Flat	1
20	36	M	ATA	120	267	0	Normal	160	N	3.0	Flat	1

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease
21	43	M	TA	100	223	0	Normal	142	N	0.0	Up	0
22	44	M	ATA	120	184	0	Normal	142	N	1.0	Flat	0
23	49	F	ATA	124	201	0	Normal	164	N	0.0	Up	0
24	NA	M	ATA	150	288	0	Normal	150	Y	3.0	Flat	1
25	40	M	NAP	130	215	0	Normal	138	N	0.0	Up	0
26	36		NAP	130	209	0	Normal	178	N	0.0	Up	0
27	53	M	ASY	124	260	0	ST	112		3.0	Flat	0
28	52	M	ATA	120	284	0	Normal	118	N	0.0	Up	0
29	53	F	ATA	113	468	0	Normal	127	N	0.0	Up	0
30	51	M	ATA	125	188	0	Normal	145	N	0.0	Up	0
31	53	M	NAP	145	518	0	Normal	130	N	0.0	Flat	1
32	56	M	NAP	130	167	0	Normal	114	N	0.0	Up	0
33	NA	M	ASY	125	224	0	Normal	122	N	2.0	Flat	1
34	41	M	ASY	130	172	0	ST	130	N	2.0	Flat	1
35	43	F	ATA	150	186	0	Normal	154	N	0.0	Up	0
36	54	M	ATA	125	254	0	Normal	155	N	0.0	Up	0
37	65	M	ASY	140	306	1	Normal	87	Y	1.5	Flat	1
38	41	F	ATA	110	250	0	ST	142	N	0.0	Up	0
39	48	M	ATA	120	177	1	ST	148	N	0.0	Up	0
40	48		ASY	150	227	0	Normal	130	Y	1.0	Flat	0

Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease	
130	42	M	NAP	120	228	0	Normal	152	Y	1.5	Flat	0
131	54	M	NAP	145	292	0	Normal	130	N	0.0	Up	0
132	46	M	ASY	110	202	0	Normal	150	Y	0.0	Flat	1
133	56	M	ASY	170	388	0	ST	122	Y	2.0	Flat	1
134	56	M	ASY	150	230	0	ST	124	Y	1.5	Flat	1
135	61	F	ASY	130	294	0	ST	120	Y	1.0	Flat	0
136	54	M	NAP	115	265	0	Normal	175	N	0.0	Flat	1
137	43	F	ATA	120	215	0	ST	175	N	0.0	Up	0
138	39	M	ATA	120	241	0	ST	146	N	2.0	Up	0
139	54	M	ASY	140	166	0	Normal	118	Y	0.0	Flat	1
140	54	M	ASY	150	247	0	Normal	130	Y	2.0	Flat	1
141	52	M	ASY	160	331	0	Normal	94	Y	2.5	Flat	1
142	50	M	ASY	140	341	0	ST	125	Y	2.5	Flat	1
143	54	M	ASY	160	291	0	ST	158	Y	3.0	Flat	1
144	53	M	ASY	140	243	0	Normal	155	N	0.0	Up	0
145	54	F	ATA	120	279	0	Normal	150	N	1.0	Flat	1
146	39	M	ASY	110	273	0	Normal	132	N	0.0	Up	0
147	42	M	ATA	120	198	0	Normal	155	N	0.0	Up	0
148	43	F	ATA	120	249	0	ST	176	N	0.0	Up	0
149	50	M	ATA	120	168	0	Normal	160	N	0.0	Up	0
150	54	M	ASY	130	603	1	Normal	125	Y	1.0	Flat	1

## Visualizing the Dataset:

```
names(heart_attack_data)
```

```
str(heart_attack_data)
```

```
dim(heart_attack_data)
```

```
summary(heart_attack_data)
```

```
R 4.3.2 · D:/Data Science/
> names(heart_attack_data)
[1] "Age"      "Sex"      "ChestPainType" "RestingBP"  "Cholesterol"
[6] "FastingBS" "RestingECG" "MaxHR"        "ExerciseAngina" "Oldpeak"
[11] "ST_Slope"  "HeartDisease"
> str(heart_attack_data)
'data.frame': 150 obs. of 12 variables:
 $ Age      : int  40 49 37 NA 54 39 45 54 37 48 ...
 $ Sex      : chr   "M" "F" "M" "F" ...
 $ ChestPainType : chr   "ATA" "NAP" "ATA" "ASY" ...
 $ RestingBP   : int  140 160 130 138 -150 120 130 110 140 120 ...
 $ Cholesterol : int  289 180 283 214 195 339 237 208 207 284 ...
 $ FastingBS   : int   0 0 0 0 0 0 0 0 0 0 ...
 $ RestingECG   : chr   "Normal" "Normal" "ST" "Normal" ...
 $ MaxHR       : int  172 156 98 108 122 170 170 142 130 120 ...
 $ ExerciseAngina: chr   "N" "N" "N" "Y" ...
 $ Oldpeak     : num   0 1 0 1.5 0 0 0 0 1.5 0 ...
 $ ST_Slope    : chr   "Up" "Flat" "Up" "Flat" ...
 $ HeartDisease : int   0 1 0 1 0 0 0 0 1 0 ...
> dim(heart_attack_data)
[1] 150 12
```

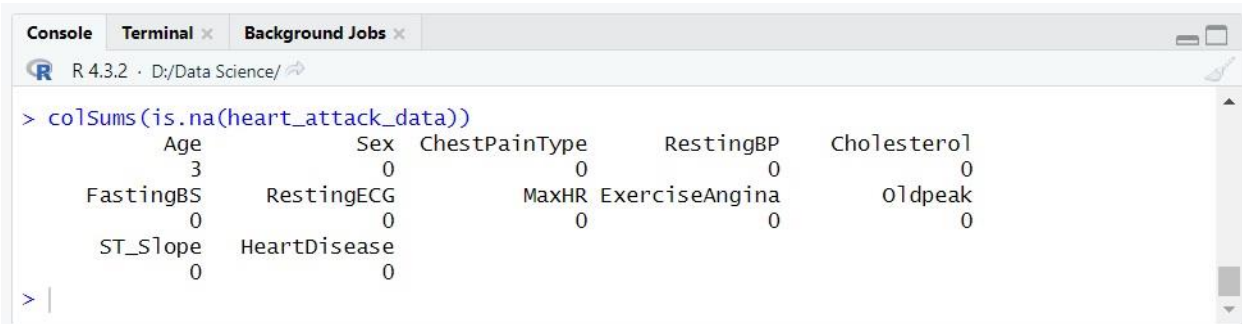
```
R 4.3.2 · D:/Data Science/
> summary(heart_attack_data)
      Age      Sex      ChestPainType      RestingBP
Min.   : 32.00  Length:150  Length:150  Min.   : -150.0
1st Qu.: 42.00  Class :character  Class :character  1st Qu.: 120.0
Median : 49.00  Mode  :character  Mode  :character  Median : 130.0
Mean   : 49.81
3rd Qu.: 54.00
Max.   :172.00
NA's   : 3
      Cholesterol      FastingBS      RestingECG      MaxHR
Min.   : 85.0  Min.   :0.00000  Length:150  Min.   : 82.0
1st Qu.: 205.2  1st Qu.:0.00000  Class :character  1st Qu.:124.0
Median : 239.0  Median :0.00000  Mode  :character  Median :140.0
Mean   : 258.3  Mean   :0.08667          Mean :140.1
3rd Qu.: 277.0  3rd Qu.:0.00000          3rd Qu.:155.8
Max.   :1005.0  Max.   :1.00000          Max.   :190.0

      ExerciseAngina      Oldpeak      ST_Slope      HeartDisease
Length:150  Min.   :0.0000  Length:150  Min.   :0.00
Class :character  1st Qu.:0.0000  Class :character  1st Qu.:0.00
Mode  :character  Median :0.0000  Mode  :character  Median :0.00
                  Mean   :0.5933          Mean   :0.38
                  3rd Qu.:1.0000          3rd Qu.:1.00
                  Max.   :4.0000          Max.   :1.00
```

**Explanation:** Visualizing the dataset involves exploring its variables and structure. The command "names(heart\_attack\_data)" retrieves the column names, providing an overview of the available data. "str(heart\_attack\_data)" displays the structure, data types, and summaries of the variables. Additionally, "dim(heart\_attack\_data)" reveals the dataset dimensions, giving insights into its size. Lastly, "summary(heart\_attack\_data)" provides statistical summaries, aiding in understanding the numerical aspects of the dataset. These visualization techniques contribute to comprehending the dataset and supporting data analysis and decision-making processes.

## Find Missing Values:

```
colSums(is.na(heart_attack_data))
```



```
R 4.3.2 · D:/Data Science/
> colSums(is.na(heart_attack_data))
      Age      Sex ChestPainType      RestingBP      Cholesterol
      3        0          0          0          0
FastingBS  RestingECG      MaxHR ExerciseAngina      Oldpeak
      0          0          0          0          0
ST_Slope  HeartDisease
      0          0
```

**Explanation:** Identifying missing values in the heart\_attack\_data dataset involves assessing the presence of null or missing data points. This process allows researchers to determine the extent of missingness across different variables. By analyzing the column-wise sums of missing values, insights can be gained into the distribution and quantity of missing data, aiding in subsequent data cleaning and imputation strategies.

## Remove Missing Values (Age):

```
missing_Age <- is.na(heart_attack_data$Age)
```

```
heart_attack_data_1 <- subset(heart_attack_data, !missing_Age)
```

```
colSums(is.na(heart_attack_data_1))
```

```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> missing_Age <- is.na(heart_attack_data$Age)
> heart_attack_data_1 <- subset(heart_attack_data, !missing_Age)
> colSums(is.na(heart_attack_data_1))
      Age      Sex ChestPainType      RestingBP      Cholesterol
      0       0         0         0         0
FastingBS      RestingECG      MaxHR ExerciseAngina      Oldpeak
      0       0         0         0         0
      ST_Slope      HeartDisease
      0       0
```

**Explanation:** To address missing values (Age) in the heart\_attack\_data dataset, a process of removal can be performed. By creating a logical variable, "missing\_Age," to identify the missing values, the dataset can be subsetted to exclude these cases. The resulting dataset, "heart\_attack\_data\_1," will no longer contain missing Age values. By subsequently checking for missing values using "colSums(is.na(heart\_attack\_data\_1))," researchers can confirm that the Age variable is now free of missing data.

## Find Empty Data:

```
colSums(heart_attack_data_1 == "")
```

```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> colSums(heart_attack_data_1 == '')
      Age      Sex ChestPainType      RestingBP      Cholesterol
      0       3         0         0         0
FastingBS      RestingECG      MaxHR ExerciseAngina      Oldpeak
      0       0         0         2         0
      ST_Slope      HeartDisease
      0       0
```

## Remove Empty Data (Sex):

```
heart_attack_data_2 <- heart_attack_data_1[!heart_attack_data_1$Sex == "", ]
```

```
colSums(heart_attack_data_2 == "")
```

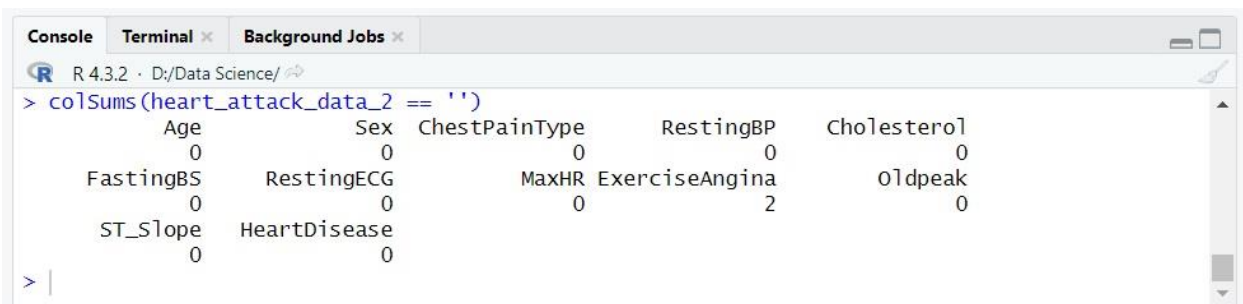
```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> colSums(heart_attack_data_2 == '')
      Age      Sex ChestPainType      RestingBP      Cholesterol
      0       0         0         0         0
FastingBS      RestingECG      MaxHR ExerciseAngina      Oldpeak
      0       0         0         2         0
      ST_Slope      HeartDisease
      0       0
```



**Explanation:** To remove empty or blank values from the heart\_attack\_data dataset, an assessment is conducted to determine the presence of empty data using column-wise calculations. After identifying the empty values, the dataset is filtered to exclude rows where specific variables have empty entries. By reevaluating the dataset, it can be confirmed that the empty data has been successfully removed.

## Again Find Empty Data:

```
colSums(heart_attack_data_2 == "")
```



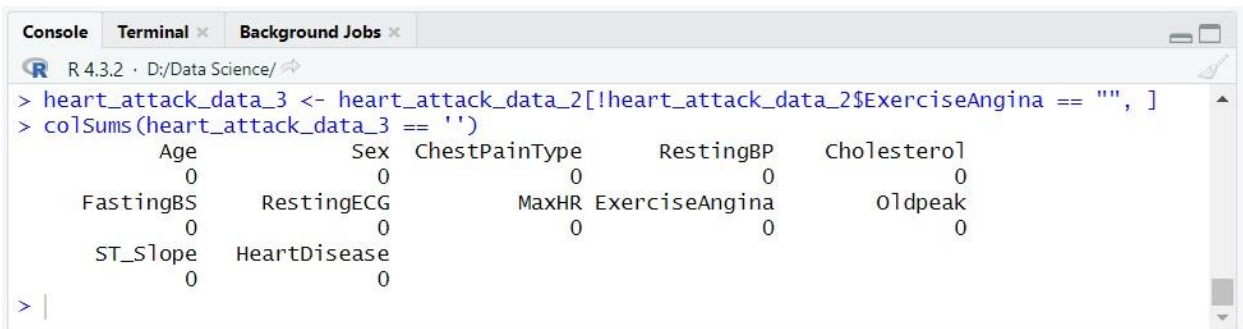
The screenshot shows an R console window with the following output for the command `colSums(heart_attack_data_2 == '')`:

Age	Sex	ChestPainType	RestingBP	Cholesterol
0	0	0	0	0
FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak
0	0	0	2	0
ST_Slope	HeartDisease			
0	0			

## Remove Empty Data (ExerciseAngina):

```
heart_attack_data_3 <- heart_attack_data_2[!heart_attack_data_2$ExerciseAngina == "", ]
```

```
colSums(heart_attack_data_3 == "")
```



The screenshot shows an R console window with the following output for the command `colSums(heart_attack_data_3 == '')`:

Age	Sex	ChestPainType	RestingBP	Cholesterol
0	0	0	0	0
FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak
0	0	0	0	0
ST_Slope	HeartDisease			
0	0			

**Explanation:** To remove empty or blank values from the heart\_attack\_data dataset, an assessment is conducted to determine the presence of empty data using column-wise calculations. After identifying the empty values, the dataset is filtered to exclude rows where specific variables have empty entries. By reevaluating the dataset, it can be confirmed that the empty data has been successfully removed.



## Find Outlier in Age attribute:

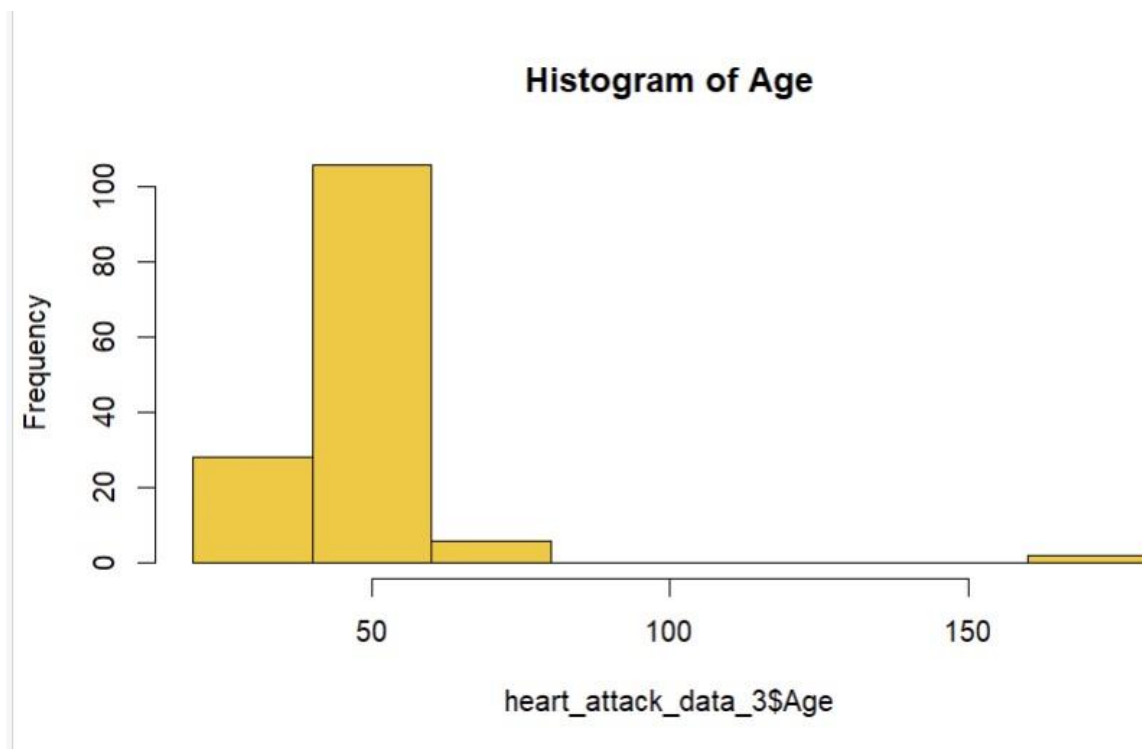
```
hist(heart_attack_data_3$Age, main = "Histogram of Age",col=c(7))
```

```
boxplot(heart_attack_data_3$Age, main = " Boxplot of Age" ,col=c(3))
```

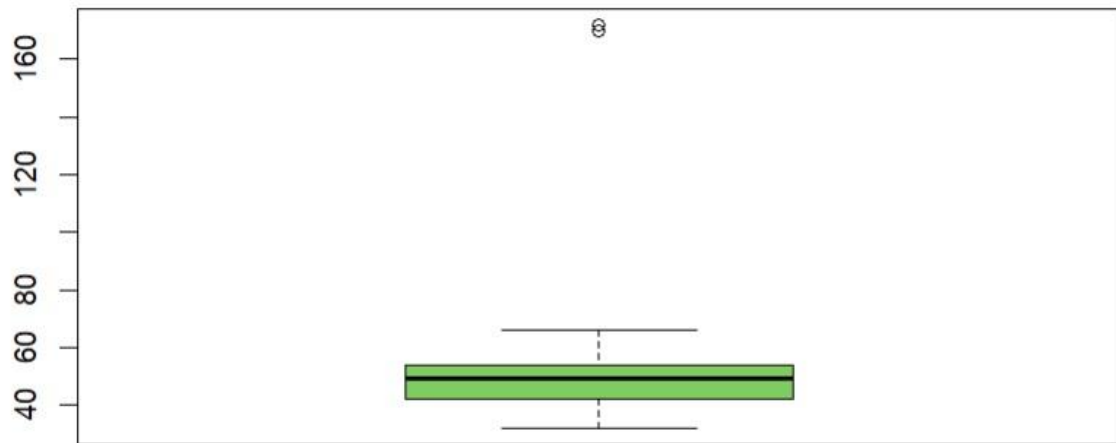
```
plot(heart_attack_data_3$Age, main = "Plot of Age" ,col=c(6))
```

```
barplot(heart_attack_data_3$Age, main = "Bar of Age" ,col=c(6))
```

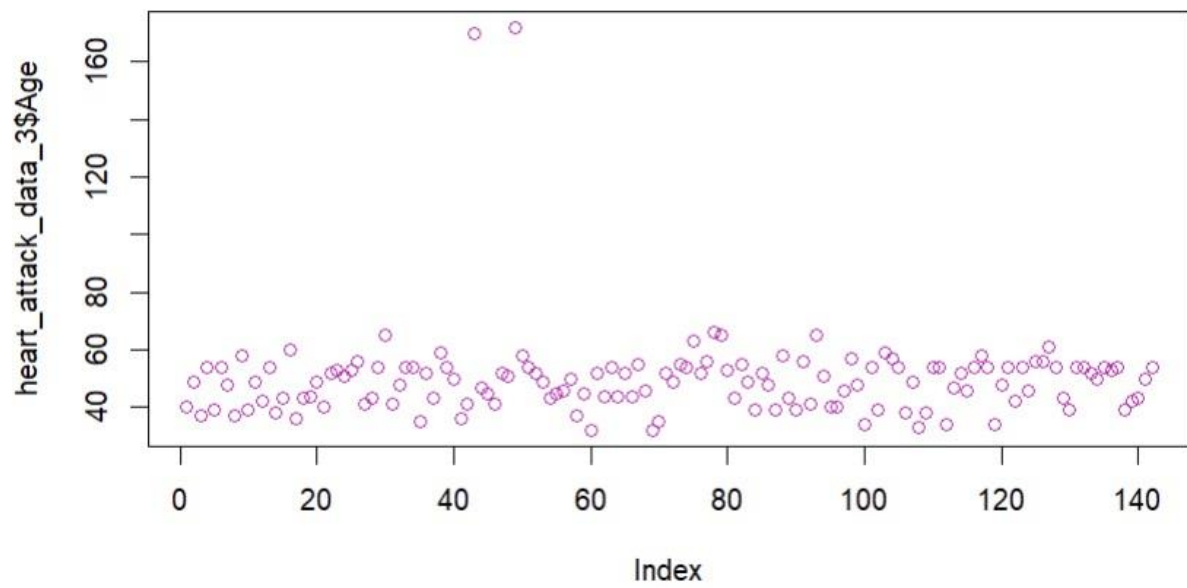
```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> hist(heart_attack_data_3$Age, main = "Histogram of Age",col=c(7))
> boxplot(heart_attack_data_3$Age, main = " Boxplot of Age" ,col=c(3))
> plot(heart_attack_data_3$Age, main = "Plot of Age" ,col=c(6))
```

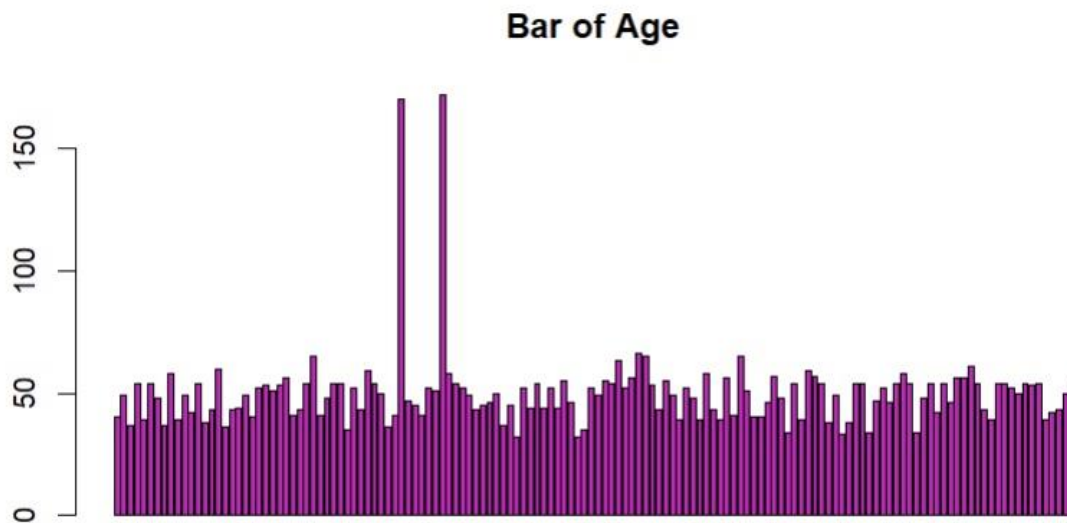


**Boxplot of Age**



**Plot of Age**





**Explanation:** To identify outliers in the Age attribute of the heart\_attack\_data dataset, various visualization techniques can be employed. A histogram provides an overview of the Age distribution, highlighting any unusual values. A box plot visually represents the range and distribution of Ages, making it easier to identify outliers. Scatter plots can also be utilized to examine individual data points and detect any extreme values that deviate significantly from the overall pattern. These visualization approaches help in identifying and understanding outliers within the Age attribute.

### **Remove Outliers in Age attribute:**

```
Age_Q1 <- quantile(heart_attack_data_3$Age, 0.25, na.rm = TRUE)
```

```
Age_Q3 <- quantile(heart_attack_data_3$Age, 0.75, na.rm = TRUE)
```

```
Age_IQR <- Age_Q3 - Age_Q1
```

```
lower_Age <- Age_Q1 - 1.5 * Age_IQR
```

```
upper_Age <- Age_Q3 + 1.5 * Age_IQR
```

```
Age_outliers <- heart_attack_data_3$Age < lower_Age | heart_attack_data_3$Age > upper_Age
```

```
heart_attack_data_4 <- heart_attack_data_3[!Age_outliers, ]
```

```
R 4.3.2 · D:/Data Science/
> Age_Q1 <- quantile(heart_attack_data_3$Age, 0.25, na.rm = TRUE)
> Age_Q3 <- quantile(heart_attack_data_3$Age, 0.75, na.rm = TRUE)
> Age_IQR <- Age_Q3 - Age_Q1
> lower_Age <- Age_Q1 - 1.5 * Age_IQR
> upper_Age <- Age_Q3 + 1.5 * Age_IQR
> Age_outliers <- heart_attack_data_3$Age < lower_Age | heart_attack_data_3$Age > upper_Age
> heart_attack_data_4 <- heart_attack_data_3[!Age_outliers, ]
```

## For Graph (Age):

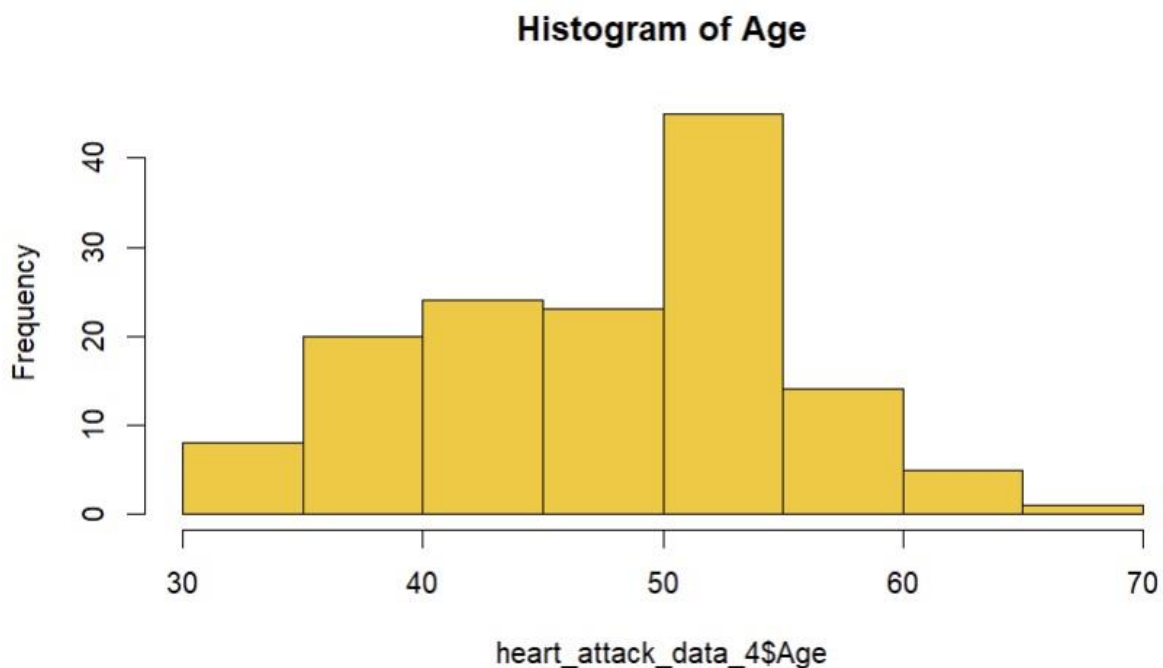
```
hist(heart_attack_data_4$Age, main = "Histogram of Age", col=c(7))
```

```
boxplot(heart_attack_data_4$Age, main = "Boxplot of Age", col=c(5))
```

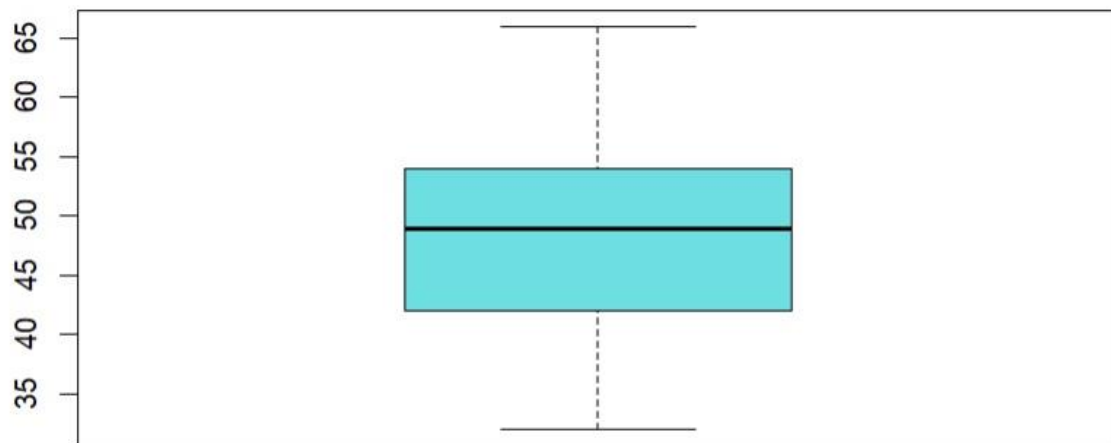
```
plot(heart_attack_data_4$Age, main = "Plot of Age", col=c(3))
```

```
barplot(heart_attack_data_4$Age, main = "bar of Age", col=c(6))
```

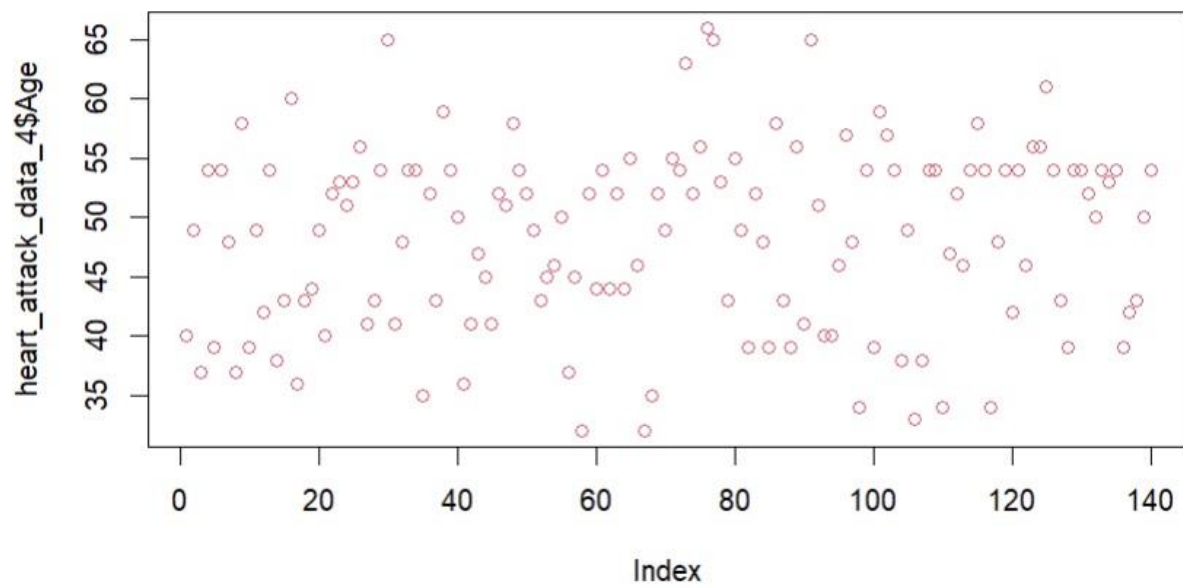
```
R 4.3.2 · D:/Data Science/
> hist(heart_attack_data_4$Age, main = "Histogram of Age", col=c(7))
> boxplot(heart_attack_data_4$Age, main = "Boxplot of Age", col=c(5))
> plot(heart_attack_data_4$Age, main = "Plot of Age", col=c(2))
>
```

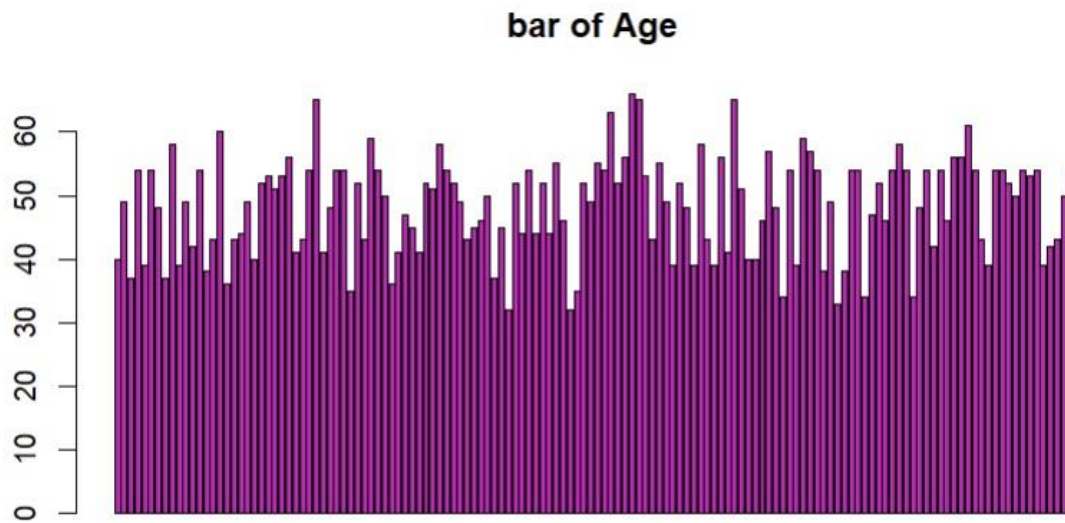


**Boxplot of Age**



**Plot of Age**





**Explanation:** To remove outliers in Age attribute from the heart\_attack\_data dataset using Tukey's fences method. The lower quartile (Q1) and upper quartile (Q3) are calculated, and the interquartile range (IQR) is determined. The lower and upper fences are established by subtracting and adding 1.5 times the IQR, respectively. Age values falling outside these fences are identified as outliers and filtered out, resulting in a new dataset, heart\_attack\_data\_4, without outliers in Age. The resulting Age distribution can be visualized using a Histogram, Boxplot, Plot and Barplot.

### Checking of Error Values:

```
attribute_names <- names(heart_attack_data_4)

for (attribute in attribute_names)
{
  unique_values <- unique(heart_attack_data_4[[attribute]])

  print(paste("Unique values in", attribute, ":"))

  print(unique_values)
}
```

```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> attribute_names <- names(heart_attack_data_4)
> for (attribute in attribute_names)
+ {
+   unique_values <- unique(heart_attack_data_4[[attribute]])
+   print(paste("Unique values in", attribute, ":"))
+   print(unique_values)
+ }
```

```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
[1] "Unique values in Age :"  
[1] 40 49 37 54 39 48 58 42 38 43 60 36 44 52 53 51 56 41 65 35 59 50 47 45 46 32 55 63  
[29] 66 57 34 33 61  
[1] "Unique values in Sex :"  
[1] "M" "F"  
[1] "Unique values in ChestPainType :"  
[1] "ATA" "NAP" "ASY" "TA"  
[1] "Unique values in RestingBP :"  
[1] 140 160 130 -150 120 110 136 115 100 124 113 125 145 150 112 132 118  
[18] 170 142 190 135 180 108  
[1] "Unique values in Cholesterol :"  
[1] 289 180 283 195 339 208 284 1000 1005 204 234 211 273 196 201 248  
[17] 267 223 184 215 468 188 518 167 172 186 254 306 250 177 230 294  
[33] 264 259 175 318 216 340 205 224 245 194 213 365 342 253 277 202  
[49] 260 297 225 246 412 265 182 218 268 163 529 100 206 238 139 263  
[65] 291 229 307 210 329 207 147 85 269 275 179 392 466 214 129 241  
[81] 255 276 282 338 160 156 272 240 393 161 228 292 388 166 247 331  
[97] 341 243 279 198 249 168 603  
[1] "Unique values in FastingBS :"  
[1] 0 1  
[1] "Unique values in RestingECG :"  
[1] "Normal" "ST"  
[1] "Unique values in MaxHR :"  
[1] 172 156 98 122 170 142 120 99 145 140 137 150 166 165 125 160 164 138 118 127 130  
[22] 114 154 155 87 148 100 168 184 134 96 174 175 144 82 135 115 128 116 94 112 110  
[43] 92 180 152 124 106 185 139 190 146 158 132 176  
[1] "Unique values in ExerciseAngina :"  
[1] "N" "Y"  
[1] "Unique values in Oldpeak :"  
[1] 0.0 1.0 2.0 1.5 3.0 4.0 0.5 2.5  
[1] "Unique values in ST_Slope :"  
[1] "Up" "Flat"  
[1] "Unique values in HeartDisease :"  
[1] 0 1  
>
```

**Explanation:** During the analysis of the heart\_attack\_data dataset, a rigorous assessment was performed to identify and rectify error values. This involved iterating through each attribute and extracting unique values to detect anomalies. Among the attributes examined, special attention was given to the "Sex" attribute, where valid values were sought after verifying data accuracy. By meticulously addressing the short form of Male and Female and confirming the validity of attribute values, the dataset's integrity was ensured, laying the foundation for reliable analysis and interpretations.



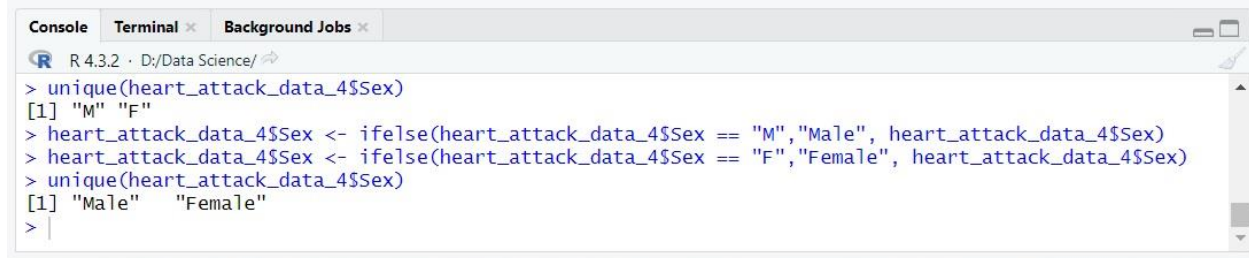
## Fixing the Value of Sex:

```
unique(heart_attack_data_4$Sex)
```

```
heart_attack_data_4$Sex <- ifelse(heart_attack_data_4$Sex == "M", "Male",  
heart_attack_data_4$Sex)
```

```
heart_attack_data_4$Sex <- ifelse(heart_attack_data_4$Sex == "F", "Female",  
heart_attack_data_4$Sex)
```

```
unique(heart_attack_data_4$Sex)
```



```
R 4.3.2 · D:/Data Science/
> unique(heart_attack_data_4$Sex)
[1] "M" "F"
> heart_attack_data_4$Sex <- ifelse(heart_attack_data_4$Sex == "M", "Male", heart_attack_data_4$Sex)
> heart_attack_data_4$Sex <- ifelse(heart_attack_data_4$Sex == "F", "Female", heart_attack_data_4$Sex)
> unique(heart_attack_data_4$Sex)
[1] "Male" "Female"
>
```

## Previous Data (Sex):

```
View(heart_attack_data_3)
```



```
R 4.3.2 · D:/Data Science/
> View(heart_attack_data_3)
>
```

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_S
1	40	M	ATA	140	289	0	Normal	172	N	0.0	U
2	49	F	NAP	160	180	0	Normal	156	N	1.0	FI
3	37	M	ATA	130	283	0	ST	98	N	0.0	U
5	54	M	NAP	150	195	0	Normal	122	N	0.0	U
6	39	M	NAP	120	339	0	Normal	170	N	0.0	U
8	54	M	ATA	110	208	0	Normal	142	N	0.0	U
10	48	F	ATA	120	284	0	Normal	120	N	0.0	U
11	37	F	NAP	130	1000	0	Normal	142	N	0.0	U
12	58	M	ATA	136	1005	0	ST	99	Y	2.0	FI
13	39	M	ATA	120	204	0	Normal	145	N	0.0	U
14	49	M	ASY	140	234	0	Normal	140	Y	1.0	FI
15	42	M	NAP	115	211	0	ST	137	N	0.0	U
16	54	M	ATA	120	273	0	Normal	150	N	1.5	FI
17	38	M	ASY	110	196	0	Normal	166	N	0.0	FI
18	43	F	ATA	120	201	0	Normal	165	N	0.0	U
19	60	M	ASY	100	248	0	Normal	125	N	1.0	FI
20	36	M	ATA	120	267	0	Normal	160	N	3.0	FI
21	43	M	TA	100	223	0	Normal	142	N	0.0	U
22	44	M	ATA	120	184	0	Normal	142	N	1.0	FI

## Updated Data (Sex):

View(heart\_attack\_data\_4)

```

Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> View(heart_attack_data_4)
>

```

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_S
1	40	Male	ATA	140	289	0	Normal	172	N	0.0	U
2	49	Female	NAP	160	180	0	Normal	156	N	1.0	FI
3	37	Male	ATA	130	283	0	ST	98	N	0.0	U
5	54	Male	NAP	-150	195	0	Normal	122	N	0.0	U
6	39	Male	NAP	120	339	0	Normal	170	N	0.0	U
8	54	Male	ATA	110	208	0	Normal	142	N	0.0	U
10	48	Female	ATA	120	284	0	Normal	120	N	0.0	U
11	37	Female	NAP	130	1000	0	Normal	142	N	0.0	U
12	58	Male	ATA	136	1005	0	ST	99	Y	2.0	FI
13	39	Male	ATA	120	204	0	Normal	145	N	0.0	U
14	49	Male	ASY	140	234	0	Normal	140	Y	1.0	FI
15	42	Male	NAP	115	211	0	ST	137	N	0.0	U
16	54	Male	ATA	120	273	0	Normal	150	N	1.5	FI
17	38	Male	ASY	110	196	0	Normal	166	N	0.0	FI
18	43	Female	ATA	120	201	0	Normal	165	N	0.0	U
19	60	Male	ASY	100	248	0	Normal	125	N	1.0	FI
20	36	Male	ATA	120	267	0	Normal	160	N	3.0	FI
21	43	Male	TA	100	223	0	Normal	142	N	0.0	U
22	44	Male	ATA	120	184	0	Normal	142	N	1.0	FI

**Explanation:** To correct or write the full form of values in the "Sex" attribute of the heart\_attack\_data dataset, the unique values in this attribute were examined. Subsequently, erroneous entries such as "M" were replaced with the correct label "Male" using conditional statements. Similarly, "F" were corrected to "Female". By fixing these incorrect values, the dataset's integrity was restored. A final examination of the unique values confirmed that the corrections were successfully implemented.

## Detect Noisy Value (Cholesterol):

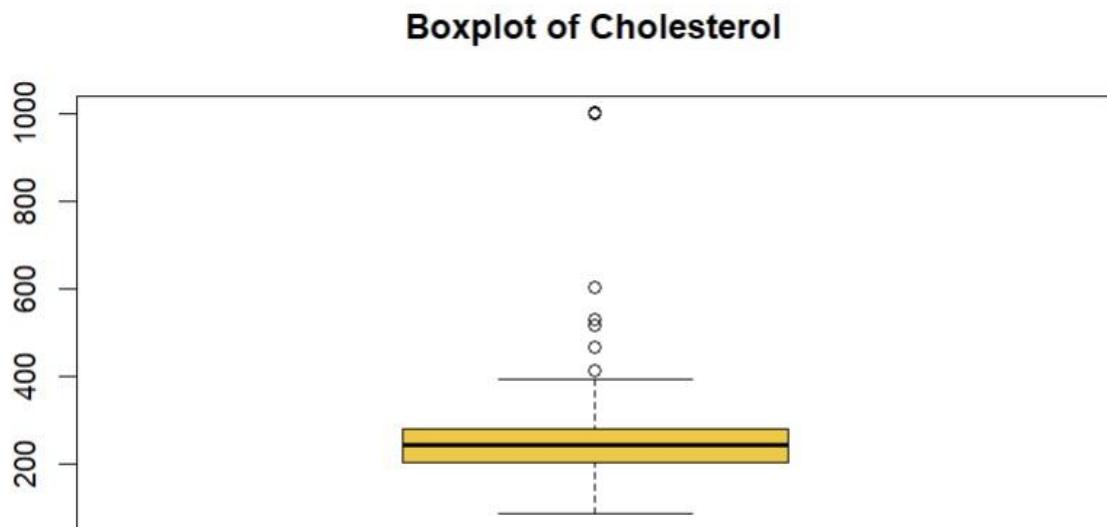
```
summary(heart_attack_data_4$Cholesterol)
```

```
boxplot(heart_attack_data_4$Cholesterol, main = "Boxplot of Cholesterol", col=c(7))
```

```

R 4.3.2 · D:/Data Science/
> summary(heart_attack_data_4$Cholesterol)
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  85.0  202.0   241.0  259.8  279.8 1005.0
> boxplot(heart_attack_data_4$Cholesterol, main = "Boxplot of Cholesterol", col=c(7))
>

```



### After resolve the noisy value (Cholesterol):

```
Cholesterol_Q1 <- quantile(heart_attack_data_4$Cholesterol, 0.25, na.rm = TRUE)
```

```
Cholesterol_Q3 <- quantile(heart_attack_data_4$Cholesterol, 0.75, na.rm = TRUE)
```

```
Cholesterol_IQR <- Cholesterol_Q3 - Cholesterol_Q1
```

```
lower_Cholesterol <- Cholesterol_Q1 - 1.5 * Cholesterol_IQR
```

```
upper_Cholesterol <- Cholesterol_Q3 + 1.5 * Cholesterol_IQR
```

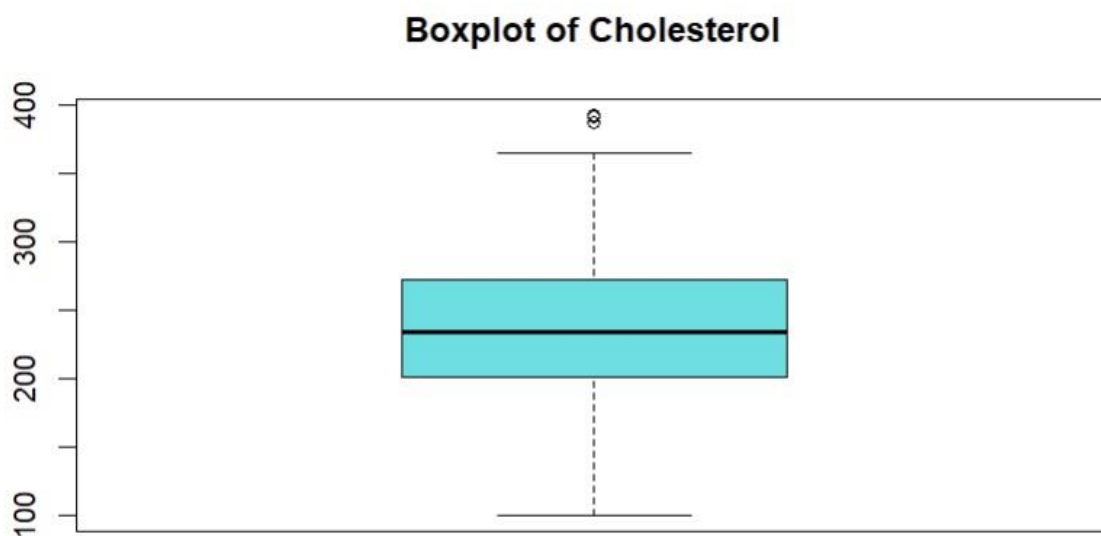
```
Cholesterol_noisyvalue <- heart_attack_data_4$Cholesterol < lower_Cholesterol |
```

```
heart_attack_data_4$Cholesterol > upper_Cholesterol
```

```
heart_attack_data_5 <- heart_attack_data_4[!Cholesterol_noisyvalue, ]
```

```
boxplot(heart_attack_data_5$Cholesterol, main = "Boxplot of Cholesterol", col=c(5))
```

```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> Cholesterol_Q1 <- quantile(heart_attack_data_4$Cholesterol, 0.25, na.rm = TRUE)
> Cholesterol_Q3 <- quantile(heart_attack_data_4$Cholesterol, 0.75, na.rm = TRUE)
> Cholesterol_IQR <- Cholesterol_Q3 - Cholesterol_Q1
> lower_Cholesterol <- Cholesterol_Q1 - 1.5 * Cholesterol_IQR
> upper_Cholesterol <- Cholesterol_Q3 + 1.5 * Cholesterol_IQR
> Cholesterol_noisyvalue <- heart_attack_data_4$Cholesterol < lower_Cholesterol | heart_attack_data_4$Cholesterol > upper_Cholesterol
> heart_attack_data_5 <- heart_attack_data_4[!Cholesterol_noisyvalue, ]
> boxplot(heart_attack_data_5$Cholesterol, main = "Boxplot of Cholesterol", col=c(5))
> |
```



**Explanation:** To identify noisy values in the "Cholesterol" attribute of the heart\_attack\_data dataset, the summary statistics of Cholesterol were examined. This provided insights into the distribution and range of values. Additionally, a box plot was created to visualize the distribution, enabling the detection of potential outliers or extreme values. By analyzing these statistical measures and visual representations, noisy values within the "Cholesterol" attribute could be detected for further investigation and data quality assurance.

## Remove Duplicate Data:

```
sum(duplicated(heart_attack_data_5))
```

```
heart_attack_data_6 <- heart_attack_data_5[!duplicated(heart_attack_data_5), ]
```

```
sum(duplicated(heart_attack_data_6))
```

```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> sum(duplicated(heart_attack_data_5))
[1] 0
> heart_attack_data_6 <- heart_attack_data_5[!duplicated(heart_attack_data_5), ]
> sum(duplicated(heart_attack_data_6))
[1] 0
> |
```

**Explanation:** To eliminate duplicate data from the heart\_attack\_data dataset, a process of removing identical observations based on all variables can be performed. This helps ensure that each row in the dataset is unique and prevents any redundant information from skewing the analysis or results. By eliminating duplicate data, researchers can work with a more accurate and reliable dataset for further exploration and analysis. But fortunately there is no Duplicate data on the heart\_attack\_data dataset.

## Conversion Data Type of Attributes:

```
heart_attack_data_6$RestingECG <-  
factor(heart_attack_data_6$RestingECG,levels=c('Normal','ST'),labels=c("NORMAL","ABNOR  
MALITY"))
```

```
heart_attack_data_6$Sex <-  
factor(heart_attack_data_6$Sex,levels=c('Male','Female'),labels=c("MALE","FEMALE"))
```

```
heart_attack_data_6$ExerciseAngina <-  
factor(heart_attack_data_6$ExerciseAngina,levels=c('Y','N'),labels=c("YES","NO"))
```

```
unique(heart_attack_data_5$ChestPainType)
```

```
heart_attack_data_6$ChestPainType <-  
factor(heart_attack_data_6$ChestPainType,levels=c('ATA','NAP','ASY','TA'),labels=c("ATYPICAL ANGINA","NON-ANGINAL PAIN","ASYMPTONIC",  
", "TYPICAL ANGINA"))
```

```
heart_attack_data_6$HeartDisease <-  
factor(heart_attack_data_6$HeartDisease,levels=c(1,0),labels=c("MORE CHANCE","LESS CHANCE"))
```

```
unique(heart_attack_data_5$ST_Slope)
```

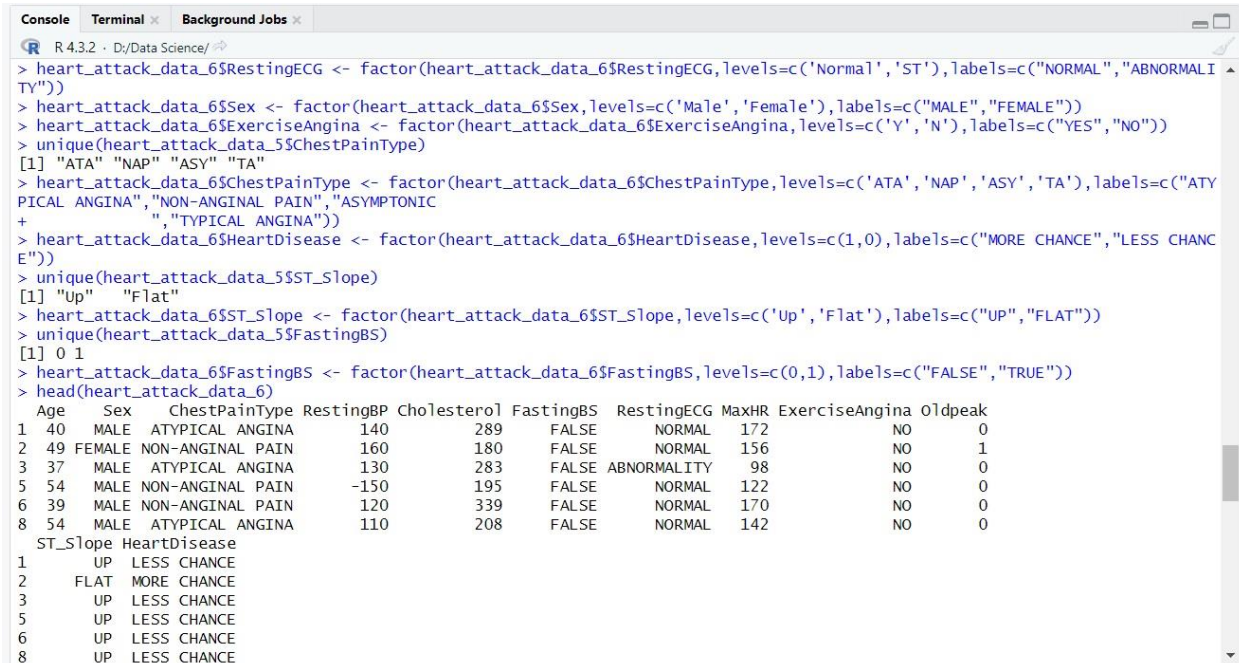
```
heart_attack_data_6$ST_Slope <-  
factor(heart_attack_data_6$ST_Slope,levels=c('Up','Flat'),labels=c("UP","FLAT"))
```

```
unique(heart_attack_data_5$FastingBS)
```

```
heart_attack_data_6$FastingBS <-
```

```
factor(heart_attack_data_6$FastingBS, levels=c(0,1), labels=c("FALSE", "TRUE"))
```

```
head(heart_attack_data_6)
```



```
R 4.3.2 · D:/Data Science/
> heart_attack_data_6$RestingECG <- factor(heart_attack_data_6$RestingECG, levels=c('Normal', 'ST'), labels=c("NORMAL", "ABNORMALITY"))
> heart_attack_data_6$Sex <- factor(heart_attack_data_6$Sex, levels=c('Male', 'Female'), labels=c("MALE", "FEMALE"))
> heart_attack_data_6$ExerciseAngina <- factor(heart_attack_data_6$ExerciseAngina, levels=c('Y', 'N'), labels=c("YES", "NO"))
> unique(heart_attack_data_5$ChestPainType)
[1] "ATA" "NAP" "ASY" "TA"
> heart_attack_data_6$ChestPainType <- factor(heart_attack_data_6$ChestPainType, levels=c('ATA', 'NAP', 'ASY', 'TA'), labels=c("ATYPICAL ANGINA", "NON-ANGINAL PAIN", "ASYMPTONIC", "TYPICAL ANGINA"))
> heart_attack_data_6$HeartDisease <- factor(heart_attack_data_6$HeartDisease, levels=c(1,0), labels=c("MORE CHANCE", "LESS CHANCE"))
> unique(heart_attack_data_5$ST_Slope)
[1] "Up" "Flat"
> heart_attack_data_6$ST_Slope <- factor(heart_attack_data_6$ST_Slope, levels=c('Up', 'Flat'), labels=c("UP", "FLAT"))
> unique(heart_attack_data_5$FastingBS)
[1] 0 1
> heart_attack_data_6$FastingBS <- factor(heart_attack_data_6$FastingBS, levels=c(0,1), labels=c("FALSE", "TRUE"))
> head(heart_attack_data_6)
  Age  Sex ChestPainType RestingBP Cholesterol FastingBS RestingECG MaxHR ExerciseAngina Oldpeak
1  40 MALE  ATYPICAL ANGINA      140         289     FALSE     NORMAL     172          NO          0
2  49 FEMALE NON-ANGINAL PAIN      160         180     FALSE     NORMAL     156          NO          1
3  37 MALE  ATYPICAL ANGINA      130         283     FALSE ABNORMALITY     98          NO          0
5  54 MALE NON-ANGINAL PAIN     -150         195     FALSE     NORMAL     122          NO          0
6  39 MALE NON-ANGINAL PAIN      120         339     FALSE     NORMAL     170          NO          0
8  54 MALE  ATYPICAL ANGINA      110         208     FALSE     NORMAL     142          NO          0
ST_Slope HeartDisease
1      UP  LESS CHANCE
2     FLAT  MORE CHANCE
3      UP  LESS CHANCE
5      UP  LESS CHANCE
6      UP  LESS CHANCE
8      UP  LESS CHANCE
```

**Explanation:** To ensure appropriate data representation, several attribute data types were converted in the heart\_attack\_data dataset. The "Sex" attribute was transformed into a factor variable with labels "MALE" and "FEMALE". The "ChestPainType" attribute was converted there full form after rounding. Similarly, the "RestingECG" attribute was changed to a factor variable with labels "NORMAL", "ABNORMALITY". The "ExerciseAngina" attribute was converted to a factor variable with labels "YES" and "NO". Lastly, the "HeartDisease" attribute was transformed into a factor variable with labels "HIGH CHANCE" and "LOW CHANCE". A preview of the updated dataset can be observed through the head of "heart\_attack\_data\_6".

## Remove Negative Values from Dataset:

```
heart_attack_data_7 <- heart_attack_data_6
```

```
heart_attack_data_7[heart_attack_data_6 < 0] <- NA
```



```
R 4.3.2 · D:/Data Science/
> heart_attack_data_7 <- heart_attack_data_6
> heart_attack_data_7[heart_attack_data_6 < 0] <- NA
```



Before:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG
1	40	MALE	ATYPICAL ANGINA	140	289	0	NORMAL
2	49	FEMALE	NON-ANGINAL PAIN	160	180	0	NORMAL
3	37	MALE	ATYPICAL ANGINA	130	283	0	STANDARD
5	54	MALE	NON-ANGINAL PAIN	-150	195	0	NORMAL
6	39	MALE	NON-ANGINAL PAIN	120	339	0	NORMAL
8	54	MALE	ATYPICAL ANGINA	110	208	0	NORMAL

After:

	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG
1	40	MALE	ATYPICAL ANGINA	140	289	0	NORMAL
2	49	FEMALE	NON-ANGINAL PAIN	160	180	0	NORMAL
3	37	MALE	ATYPICAL ANGINA	130	283	0	STANDARD
5	54	MALE	NON-ANGINAL PAIN	NA	195	0	NORMAL
6	39	MALE	NON-ANGINAL PAIN	120	339	0	NORMAL
8	54	MALE	ATYPICAL ANGINA	110	208	0	NORMAL
10	48	FEMALE	ATYPICAL ANGINA	120	284	0	NORMAL

```
colSums(is.na(heart_attack_data_7))
```

```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> colSums(is.na(heart_attack_data_7))
      Age      Sex ChestPainType RestingBP Cholesterol FastingBS RestingECG
      0       0         0         1         0           0           0
MaxHR ExerciseAngina      oldpeak      ST_Slope HeartDisease
      0         0         0         0         0           0
```

```
missing_RestingBP <- is.na(heart_attack_data_7$RestingBP)

heart_attack_data_8 <- subset(heart_attack_data_7, !missing_RestingBP)

colSums(is.na(heart_attack_data_8))
```

```
R 4.3.2 - D:/Data Science/
> missing_RestingBP <- is.na(heart_attack_data_7$RestingBP)
> heart_attack_data_8 <- subset(heart_attack_data_7, !missing_RestingBP)
> colSums(is.na(heart_attack_data_8))
```

Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG
0	0	0	0	0	0	0
MaxHR	ExerciseAngina	oldpeak	ST_Slope	HeartDisease		
0	0	0	0	0		

**Explanation:** To eliminate Negative data from the heart\_attack\_data dataset, a process of removing negative data based on all variables can be performed. This helps ensure that each row in the dataset is Positive values and prevents any redundant information from skewing the analysis or results. By eliminating Negative data, researchers can work with a more accurate and reliable dataset for further exploration and analysis.

## Univariate Data Exploration:

```
summary(heart_attack_data_8$Age)

summary(heart_attack_data_8$MaxHR)
```

```
R 4.3.2 - D:/Data Science/
> summary(heart_attack_data_8$Age)
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 32.00  42.25   49.00   48.31   54.00   66.00
> summary(heart_attack_data_8$MaxHR)
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  82.0  124.2   142.0   140.8   159.5   190.0
>
```

## For Age attribute:

```
mean(heart_attack_data_8$Age)

median(heart_attack_data_8$Age)

var(heart_attack_data_8$Age)

sd(heart_attack_data_8$Age)

install.packages("ggplot2")
```

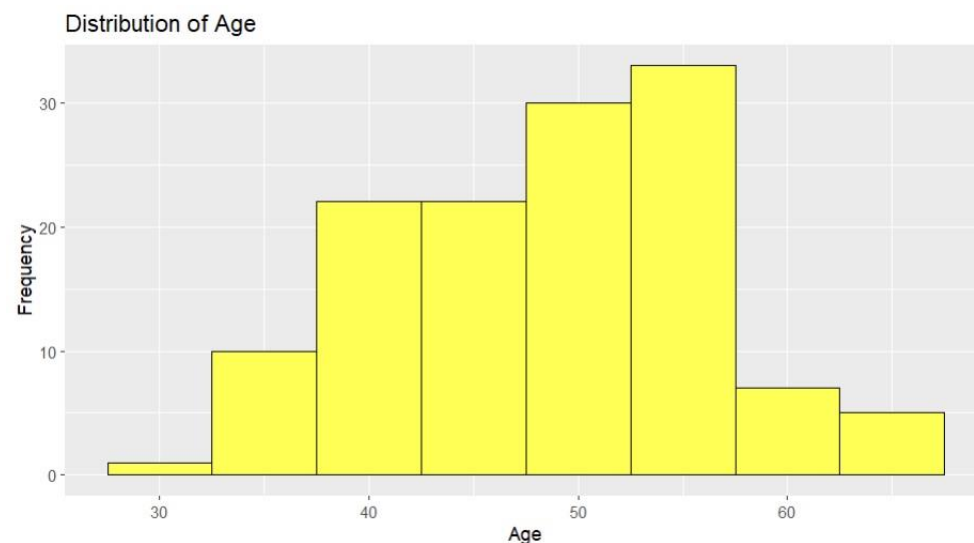
```
library(ggplot2)
```

```
ggplot(heart_attack_data_8, aes(x = Age)) +
```

```
geom_histogram(binwidth = 5, fill = "yellow", color = "black") +
```

```
labs(x = "Age", y = "Frequency", title = "Distribution of Age")
```

```
Console Terminal Background Jobs
R 4.3.2 · D:/Data Science/
> mean(heart_attack_data_8$Age)
[1] 48.30769
> median(heart_attack_data_8$Age)
[1] 49
> var(heart_attack_data_8$Age)
[1] 59.25343
> sd(heart_attack_data_8$Age)
[1] 7.697625
> library(ggplot2)
> ggplot(heart_attack_data_8, aes(x = Age)) +
+   geom_histogram(binwidth = 5, fill = "yellow", color = "black") +
+   labs(x = "Age", y = "Frequency", title = "Distribution of Age")
> |
```



## For MaxHR attribute:

```
mean(heart_attack_data_8$MaxHR)
```

```
median(heart_attack_data_8$MaxHR)
```

```
var(heart_attack_data_8$MaxHR)
```

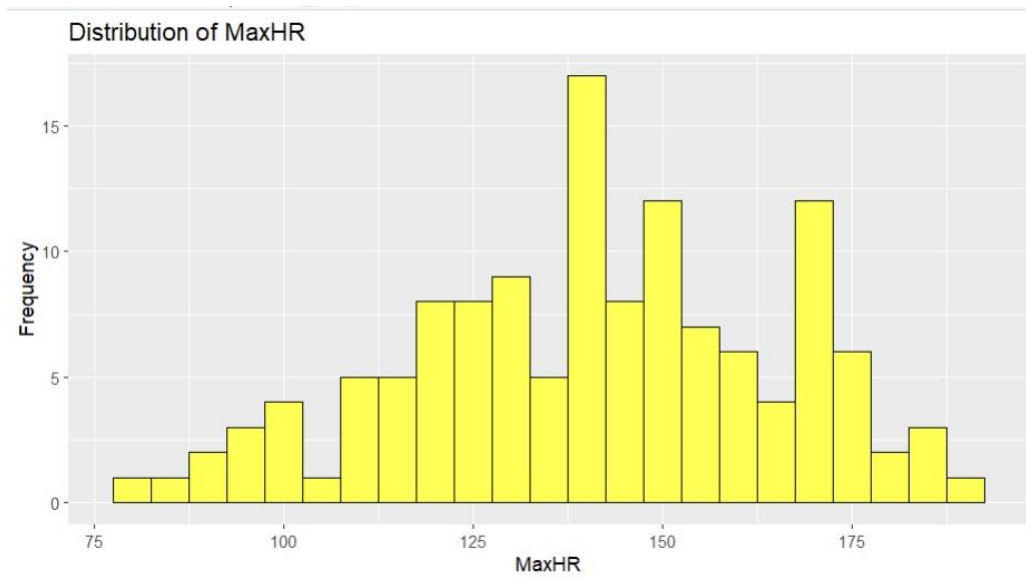
```
sd(heart_attack_data_8$MaxHR)
```

```
library(ggplot2)

ggplot(heart_attack_data_8, aes(x = MaxHR)) +

  geom_histogram(binwidth = 5, fill = "yellow", color = "black") +

  labs(x = "MaxHR", y = "Frequency", title = "Distribution of MaxHR")
```



**Explanation:** Univariate data exploration involves examining individual variables in the dataset. Measures such as the mean, median, variance, and standard deviation provide insights into the central tendency, spread, and variability of the data. The "ggplot2" library is commonly used for creating visualizations, such as histograms, to visualize the distribution of variables. Additionally, labeling the axes and adding titles using "labs()" further enhances the interpretability of the visualizations, enabling a comprehensive exploration of the dataset.

## Discussion and Conclusion:

The dataset that was given to us at the beginning of the study showed a significant level of disarray. It had a large number of outliers, missing values, and null values. A number of data preparation procedures were used to solve these problems and get the data ready for analysis. To learn more about each variable in the dataset, a univariate data exploration was also carried out on it.

# Unprepared Dataset-

DS Project Test.R* × heart_attack_data_8 × heart_attack_data ×												
Filter												
	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease
1	40	M	ATA	140	289	0	Normal	172	N	0.0	Up	0
2	49	F	NAP	160	180	0	Normal	156	N	1.0	Flat	1
3	37	M	ATA	130	283	0	ST	98	N	0.0	Up	0
4	NA	F	ASY	138	214	0	Normal	108	Y	1.5	Flat	1
5	54	M	NAP	150	195	0	Normal	122	N	0.0	Up	0
6	39	M	NAP	120	339	0	Normal	170	N	0.0	Up	0
7	45	F	ATA	130	237	0	Normal	170		0.0	Up	0
8	54	M	ATA	110	208	0	Normal	142	N	0.0	Up	0
9	37		ASY	140	207	0	Normal	130	Y	1.5	Flat	1
10	48	F	ATA	120	284	0	Normal	120	N	0.0	Up	0
11	37	F	NAP	130	1000	0	Normal	142	N	0.0	Up	0
12	58	M	ATA	136	1005	0	ST	99	Y	2.0	Flat	1
13	39	M	ATA	120	204	0	Normal	145	N	0.0	Up	0
14	49	M	ASY	140	234	0	Normal	140	Y	1.0	Flat	1
15	42	M	NAP	115	211	0	ST	137	N	0.0	Up	0
16	54	M	ATA	120	273	0	Normal	150	N	1.5	Flat	0
17	38	M	ASY	110	196	0	Normal	166	N	0.0	Flat	1
18	43	F	ATA	120	201	0	Normal	165	N	0.0	Up	0
19	60	M	ASY	100	248	0	Normal	125	N	1.0	Flat	1
20	36	M	ATA	120	267	0	Normal	160	N	3.0	Flat	1

Showing 1 to 20 of 150 entries, 12 total columns

DS Project Test.R* × heart_attack_data_8 × heart_attack_data ×												
Filter												
	Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease
131	54	M	NAP	145	292	0	Normal	130	N	0.0	Up	0
132	46	M	ASY	110	202	0	Normal	150	Y	0.0	Flat	1
133	56	M	ASY	170	388	0	ST	122	Y	2.0	Flat	1
134	56	M	ASY	150	230	0	ST	124	Y	1.5	Flat	1
135	61	F	ASY	130	294	0	ST	120	Y	1.0	Flat	0
136	54	M	NAP	115	265	0	Normal	175	N	0.0	Flat	1
137	43	F	ATA	120	215	0	ST	175	N	0.0	Up	0
138	39	M	ATA	120	241	0	ST	146	N	2.0	Up	0
139	54	M	ASY	140	166	0	Normal	118	Y	0.0	Flat	1
140	54	M	ASY	150	247	0	Normal	130	Y	2.0	Flat	1
141	52	M	ASY	160	331	0	Normal	94	Y	2.5	Flat	1
142	50	M	ASY	140	341	0	ST	125	Y	2.5	Flat	1
143	54	M	ASY	160	291	0	ST	158	Y	3.0	Flat	1
144	53	M	ASY	140	243	0	Normal	155	N	0.0	Up	0
145	54	F	ATA	120	279	0	Normal	150	N	1.0	Flat	1
146	39	M	ASY	110	273	0	Normal	132	N	0.0	Up	0
147	42	M	ATA	120	198	0	Normal	155	N	0.0	Up	0
148	43	F	ATA	120	249	0	ST	176	N	0.0	Up	0
149	50	M	ATA	120	168	0	Normal	160	N	0.0	Up	0
150	54	M	ASY	130	603	1	Normal	125	Y	1.0	Flat	1



## Prepared Dataset-

DS Project Test.R\* × heart\_attack\_data\_8 × heart\_attack\_data × heart\_attack\_data\_6 × heart\_attack\_data\_7 ×

Filter

<

Age	Sex	ChestPainType	RestingBP	Cholesterol	FastingBS	RestingECG	MaxHR	ExerciseAngina	Oldpeak	ST_Slope	HeartDisease	
118	54	FEMALE	ASYMPTONIC	130	338	TRUE	ABNORMALITY	130	YES	1.5	FLAT	MORE CHANCE
119	54	FEMALE	TYPICAL ANGINA	120	160	FALSE	ABNORMALITY	185	NO	0.0	UP	LESS CHANCE
120	34	MALE	TYPICAL ANGINA	140	156	FALSE	NORMAL	180	NO	0.0	FLAT	MORE CHANCE
121	47	FEMALE	NON-ANGINAL PAIN	135	248	TRUE	NORMAL	170	NO	0.0	FLAT	MORE CHANCE
122	52	FEMALE	NON-ANGINAL PAIN	125	272	FALSE	NORMAL	139	NO	0.0	UP	LESS CHANCE
123	46	MALE	ASYMPTONIC	110	240	FALSE	ABNORMALITY	140	NO	0.0	UP	LESS CHANCE
124	54	FEMALE	ATYPICAL ANGINA	180	393	FALSE	NORMAL	110	YES	1.0	FLAT	MORE CHANCE
125	58	MALE	ATYPICAL ANGINA	130	230	FALSE	NORMAL	150	NO	0.0	UP	LESS CHANCE
126	54	MALE	ATYPICAL ANGINA	120	246	FALSE	NORMAL	110	NO	0.0	UP	LESS CHANCE
127	34	FEMALE	ATYPICAL ANGINA	130	161	FALSE	NORMAL	190	NO	0.0	UP	LESS CHANCE
128	48	FEMALE	ASYMPTONIC	108	163	FALSE	NORMAL	175	NO	2.0	UP	LESS CHANCE
129	54	FEMALE	ATYPICAL ANGINA	120	230	TRUE	NORMAL	140	NO	0.0	UP	LESS CHANCE
130	42	MALE	NON-ANGINAL PAIN	120	228	FALSE	NORMAL	152	YES	1.5	FLAT	LESS CHANCE
131	54	MALE	NON-ANGINAL PAIN	145	292	FALSE	NORMAL	130	NO	0.0	UP	LESS CHANCE
132	46	MALE	ASYMPTONIC	110	202	FALSE	NORMAL	150	YES	0.0	FLAT	MORE CHANCE
133	56	MALE	ASYMPTONIC	170	388	FALSE	ABNORMALITY	122	YES	2.0	FLAT	MORE CHANCE
134	56	MALE	ASYMPTONIC	150	230	FALSE	ABNORMALITY	124	YES	1.5	FLAT	MORE CHANCE
135	61	FEMALE	ASYMPTONIC	130	294	FALSE	ABNORMALITY	120	YES	1.0	FLAT	LESS CHANCE
136	54	MALE	NON-ANGINAL PAIN	115	265	FALSE	NORMAL	175	NO	0.0	FLAT	MORE CHANCE
137	43	FEMALE	ATYPICAL ANGINA	120	215	FALSE	ABNORMALITY	175	NO	0.0	UP	LESS CHANCE
138	39	MALE	ATYPICAL ANGINA	120	241	FALSE	ABNORMALITY	146	NO	2.0	UP	LESS CHANCE
139	54	MALE	ASYMPTONIC	140	166	FALSE	NORMAL	118	YES	0.0	FLAT	MORE CHANCE
140	54	MALE	ASYMPTONIC	150	247	FALSE	NORMAL	130	YES	2.0	FLAT	MORE CHANCE

