

# From Data to Diagnosis: Predicting Diabetes

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## 1. INTRODUCTION

Dataset : Diabetes Patients Data

Source : <https://www.kaggle.com/datasets/akshaydattatraykhare/diabetes-dataset?resource=download>

This report discusses the problem of using different medical measurements to predict diabetes in Pima Indian women. The patients in the dataset are female Pima Indians, who are at least 21 years old and are known to have one of the highest rates of Type 2 diabetes globally.

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### Context

Type 2 diabetes is a chronic condition characterized by high blood sugar levels due to the body's inability to use insulin effectively. More than 50% of people in the Pima Indian population have been diagnosed with this condition, making them significantly at risk. The increasing number of cases of diabetes has been correlated to environmental factors, changes in lifestyle, and hereditary factors. Understanding and predicting diabetes within this population can help in early diagnosis and effective management of the disease.

### Importance and Relevance

1. Diabetes causes serious health issues, such as hypertension and kidney failure, in which, both of them are common among Pima Indians.
2. In order to manage and lower the risk of diabetes, early detection may help in the implementation of changes in lifestyle and prevention strategies.

### **Intended Audience**

1. Researchers who are interested in understanding the factors that may cause to diabetes in Pima Indian women.
2. Anyone interested in the wider effects of diabetes and the health issues the Pima Indian population is facing.

### **Goals**

1. What factors that cause diabetes?
2. What variables can be the indicators of diabetes?
3. Why should we be aware of diabetes and what insight can we gain?

### **Methods**

1. Exploratory Data Analysis (EDA): Statistic summary (location, spread, shape), Data visualization (identify outliers and find relationship between variables)
2. Statistical Analytic: Shapiro-Wilk test (data normality) and Pearson Correlation (linear relationship)

### **Assumptions and Limitations**

- Assumptions: Based on the variables in this dataset, there are two major factors that affect diabetes, lifestyle (BMI, SkinThickness) and heredity (DiabetesPedigreeFunction).
- Limitations: This analysis is limited to the variables provided in the dataset, while there are external factors that may also affect diabetes. Thus, the analytical conclusion might not apply to other populations.

### **Conclusion**

Prediction based on the analysis we conducted is important because diabetes can lead to many damages in the body, such as hypertension, which has the potential to damage blood circulation throughout the body. When we predict and identify people at risk of diabetes, healthcare professionals can step in with early preventive method to reduce the chances of issues for example high blood pressure and heart problems that come with diabetes. This analysis can significantly improve the overall health outcomes and quality of life for individuals affected by diabetes.

## **2. DATA DESCRIPTION**

### **a) PROBLEM IDENTIFICATION**

The data used for this analysis is originally from the National Institute of Diabetes and Digestive and Kidney Diseases and is made available on Kaggle by Mehmet Akturk. The objective of the dataset is to diagnostically predict whether or not a patient has diabetes, based on some measurement that is included in the dataset as well. All patients in the dataset are females Pima Indian heritage with at least 21 years old.

**Who is Pima Indians female?** Pima Indians (of Arizona, USA) have one of the highest recorded prevalence rates (total number of cases of a disease in a given statistical population at a given time, divided by the number of individuals in that population) of Type 2 diabetes in the world. Studies have shown that more than 50% of the adult population has Type 2 diabetes.

#### **What is Type 2 diabetes?**

Type 2 diabetes is a chronic condition can be recognized by high blood sugar levels due to the body's inability to use insulin effectively, often paired with insufficient insulin production. Insulin is a hormone produced by pancreas that helps glucose enter cells to be used for energy. In type 2 diabetes, the body's cells become resistant to insulin's effects, and the pancreas cannot produce enough insulin to overcome this resistance. And this can lead the pancreas to produce less insulin.

There are several factors that took part of these problem, such as:

#### **1. Genetic factors**

- The studies show that having a first-degree relative with diabetes (Diabetes Pedigree Function), will significantly increase a person's risk to develop diabetes as well.

#### **2. Environment and lifestyle changes**

- Pima Indians depending their life food supply by traditional agricultural, but due to the environmental change (weather), it is more possible to get food from the retail stores, rather than planting food themselves.
- So we can say, they move on to more modern lifestyle food, mostly processed foods that have high rates of sugar, compared with the food they gain from agricultural.
- The modernization also affect the amount of physical activity of the Pima Indians. They tend to be more 'lazy' because they rely on retail food stores, rather than growing their food by hand.
- The physical activity may contribute as an important factor in weight control (prevent obesity) and therefore, the prevention of diabetes.

#### **Side affect of diabetes on Pima Indias?**

1. **Hyperglycemia** : The cause of diabetes is because the body either does not produce enough insulin (Type 1 diabetes) or cannot effectively use the insulin it produces (Type 2 diabetes), leading to elevated blood glucose levels.
2. **Hypertension** : People with diabetes are more likely to have high blood pressure (hypertension) due to insulin resistance (in which the studies have found similar issue in Pima Indians), inflammation, and vascular damage caused by high blood glucose levels.

**In conclusion**, historical data suggest that diabetes was rare among the Pima before the adoption of modern lifestyles and diets. This is bad because the Arizona Pimas have an extraordinarily high rate of kidney disease in a result of diabetes, while kidney failure is a leading cause of death.

Source : <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4418458/>

## **b) DESCRIPTION**

Explanation of attributes (variables):

- **Pregnancies**: To express the Number of pregnancies
- **Glucose**: Plasma glucose concentration a 2 hours in an oral glucose tolerance test (OGTT) (mg/dL)
- **BloodPressure**: To express the Blood pressure measurement, Diastolic blood pressure (mm Hg)
- **SkinThickness**: To express the thickness of the skin, Triceps skin fold thickness (mm)
- **Insulin**: To express the Insulin level in blood, 2-Hour serum insulin ( $\mu$ U/ml)
- **BMI**: To express the Body mass index ( $\text{weight in kg}/(\text{height in m})^2$ )
- **DiabetesPedigreeFunction**: To express the Diabetes percentage
- **Age**: To express the age
- **Outcome**: To express the final result 1 is Yes and 0 is No

### **EXPLANATION**

What is **Oral Glucose Tolerance Test (OGTT)**?

The OGTT is a diagnostic tool that measures how well the body processes glucose, in which can help to identify insulin resistance and diabetes. Insulin resistance is a condition where the body's cells become less responsive to insulin, often leading to elevated blood sugar levels. Insulin is crucial for regulating blood glucose levels by making it easier for cells to absorb glucose and use it as energy.

Distributions of 2-hours **blood glucose levels** in OGTT:

- Normal: Less than 140 mg/dL (7.8 mmol/L)
- Prediabetes: 140 to 199 mg/dL (7.8 to 11.0 mmol/L)
- Diabetes: 200 mg/dL (11.1 mmol/L) or higher

Distributions of diastolic **blood pressure**:

- Normal: Less than 80 mm Hg
- Elevated: Less than 80 mm Hg q - Hypertension Stage 1: 80-89 mm Hg
- Hypertension Stage 2: 90 mm Hg or higher
- Hypertensive Crisis: Higher than 120 mm Hg (requires immediate medical attention)

**SkinThickness** for female adults:

People with higher skin fold thickness indicates higher body fat which is a major risk factor of Type 2 diabetes due to obesity & insulin resistance that can lead to higher glucose level. - Low: < 10mm

- Average: 10-25mm
- High: > 25mm

#### Insulin:

Insulin concentration in the blood measured two hours after consuming the glucose drink in OGTT (16 to 166 U/mL).

**BMI** can indicate whether a female has obesity or not: - Underweight: less than 18.5 kg/m<sup>2</sup>

- Normal: between 18.5 and 24.9 kg/m<sup>2</sup>
- Overweight: between 25.0 and 29.9 kg/m<sup>2</sup>
- Obesity: 30.0 kg/m<sup>2</sup> and above

#### DiabetesPedigreeFunction:

percentage of risk of developing diabetes based on family history.

### 3. DATA PREPROCESSING

```
source("explorationFunction.R") # BasicSummary function
library(corrplot) # correlation plot
library(ggplot2) # bar plot, scatter plot
library(dplyr)
library(plotly)
tinytex::install_tinytex()
```

```
# import CSV file
data <- read.csv("C:/Users/acer/Downloads/diabetes.csv")
df <- data.frame(data)
head(df)
```

```
## Pregnancies Glucose BloodPressure SkinThickness Insulin BMI
## 1          6      148           72           35         0 33.6
## 2          1       85           66           29         0 26.6
## 3          8      183           64            0         0 23.3
## 4          1       89           66           23        94 28.1
## 5          0      137           40           35       168 43.1
## 6          5      116           74            0         0 25.6
## DiabetesPedigreeFunction Age Outcome
## 1          0.627    50         1
## 2          0.351    31         0
## 3          0.672    32         1
## 4          0.167    21         0
## 5          2.288    33         1
## 6          0.201    30         0
```

How many records do we have? How many variables?

a. str function

```
str(df)
```

```
## 'data.frame':    768 obs. of  9 variables:
## $ Pregnancies      : int  6 1 8 1 0 5 3 10 2 8 ...
## $ Glucose          : int  148 85 183 89 137 116 78 115 197 125 ...
## $ BloodPressure    : int  72 66 64 66 40 74 50 0 70 96 ...
## $ SkinThickness    : int  35 29 0 23 35 0 32 0 45 0 ...
## $ Insulin          : int  0 0 0 94 168 0 88 0 543 0 ...
## $ BMI              : num  33.6 26.6 23.3 28.1 43.1 25.6 31 35.3 30.5 0 ...
## $ DiabetesPedigreeFunction: num  0.627 0.351 0.672 0.167 2.288 ...
## $ Age              : int  50 31 32 21 33 30 26 29 53 54 ...
## $ Outcome          : int  1 0 1 0 1 0 1 0 1 1 ...
```

#### EXPLANATION

1. the first line shows that 'data' is a data frame, with 768 observations (rows), and 9 variables (attributes/columns).
2. the second, third, fourth, fifth, sixth, ninth, and tenth line tells us that they are integer variable (whole numbers).
3. the seventh and eighth line tells us that they are num variables (both integer and floating-point number).
4. although the variable 'outcome' get identified as int variable, it classified as categorical variable because 1 = yes, 0 = no.

#### b. summary function

```
summary(df)
```

```
##   Pregnancies      Glucose    BloodPressure    SkinThickness
##   Min.   : 0.000   Min.    : 0.0   Min.    : 0.00   Min.    : 0.00
##   1st Qu.: 1.000   1st Qu.: 99.0   1st Qu.: 62.00   1st Qu.: 0.00
##   Median : 3.000   Median :117.0   Median : 72.00   Median :23.00
##   Mean   : 3.845   Mean    :120.9   Mean    : 69.11   Mean    :20.54
##   3rd Qu.: 6.000   3rd Qu.:140.2   3rd Qu.: 80.00   3rd Qu.:32.00
##   Max.   :17.000   Max.    :199.0   Max.    :122.00   Max.    :99.00
##   Insulin        BMI      DiabetesPedigreeFunction      Age
##   Min.   : 0.0   Min.    : 0.00   Min.    :0.0780   Min.    :21.00
##   1st Qu.: 0.0   1st Qu.:27.30   1st Qu.:0.2437   1st Qu.:24.00
##   Median : 30.5   Median :32.00   Median :0.3725   Median :29.00
##   Mean   : 79.8   Mean    :31.99   Mean    :0.4719   Mean    :33.24
##   3rd Qu.:127.2   3rd Qu.:36.60   3rd Qu.:0.6262   3rd Qu.:41.00
##   Max.   :846.0   Max.    :67.10   Max.    :2.4200   Max.    :81.00
##   Outcome
##   Min.   :0.000
##   1st Qu.:0.000
##   Median :0.000
##   Mean   :0.349
##   3rd Qu.:1.000
##   Max.   :1.000
```

#### EXPLANATION

For all of the numeric variables, it shows the Tukey's five-number result (sample minimum, lower quartile, sample median, upper quartile, sample maximum) and the mean value of each variable.

## What type is each variable (numeric, categorical, logical)?

Categorical (logical):

- Outcome : Represents final result, where 1 indicates “Yes” and 0 indicates “No” for diabetes

Numerical:

- Pregnancies : Represents number of pregnancies
- Glucose : Represents glucose level in blood
- BloodPressure : Represents blood pressure measurement
- SkinThickness : Represents thickness of the skin
- Insulin : Represents insulin level in blood
- BMI : Represents body mass index
- DiabetesPedigreeFunction : Represents diabetes percentage (genetic probability of diabetes based on family history)
- Age : Represents age

## How many unique values does each variable have?

```
sapply(df, function(x) length(unique(x)))
```

##	Pregnancies	Glucose	BloodPressure
##	17	136	47
##	SkinThickness	Insulin	BMI
##	51	186	248
##	DiabetesPedigreeFunction	Age	Outcome
##	517	52	2

### EXPLANATION

Pregnancies: 17 unique values ranging from 0 to 17.

Glucose: 135 unique values ranging from 0 to 199.

BloodPressure: 47 unique values ranging from 0 to 122.

SkinThickness: 52 unique values ranging from 0 to 99.

Insulin: 186 unique values ranging from 0 to 846.

BMI: 248 unique values ranging from 0 to 67.1.

DiabetesPedigreeFunction: 517 unique values ranging from 0.078 to 2.42.

Age: 52 unique values ranging from 21 to 81.

Outcome: 2 unique values, either 0 or 1, indicating the absence or presence of diabetes, respectively.

## Is there duplicated data?

```
sum(duplicated(df))
```

```
## [1] 0
```

## What value occurs most frequently, and how often does it occur?

```
BasicSummary(df)
```

```
##           variable      type levels topLevel topCount topFrac missFreq
## 1      Pregnancies integer     17         1      135  0.176         0
## 2         Glucose integer    136        99       17  0.022         0
## 3   BloodPressure integer     47        70       57  0.074         0
## 4   SkinThickness integer     51         0      227  0.296         0
## 5         Insulin integer    186         0      374  0.487         0
## 6             BMI numeric    248        32       13  0.017         0
## 7 DiabetesPedigreeFunction numeric 517    0.254        6  0.008         0
## 8             Age integer     52        22       72  0.094         0
## 9         Outcome integer      2         0      500  0.651         0
##   missFrac
## 1         0
## 2         0
## 3         0
## 4         0
## 5         0
## 6         0
## 7         0
## 8         0
## 9         0
```

#### EXPLANATION

Or we can see from the BasicSummary from 'topLevel' and 'topCount' column.

- Pregnancies : 1
- Glucose : 99
- BloodPressure : 70 - SkinThickness : 0
- Insulin : 0
- BMI : 32
- DiabetesPedigreeFunction : 0.254
- Age : 22
- Outcome : 0

Are there missing observations? If so, how frequently does this occur?

```
missing_value <- sapply(df, function(x) sum(is.na(x)))
missing_value
```

```
##           Pregnancies           Glucose           BloodPressure
##                0                0                0
##           SkinThickness           Insulin                BMI
##                0                0                0
## DiabetesPedigreeFunction           Age           Outcome
##                0                0                0
```

If we observe the dataset manually, we may found it weird there are so many 0 value. So in this dataset the missing value is not represent by N/A or NULL but with 0.

```
sum(df$Pregnancies == 0)
```

```
## [1] 111
```

```
sum(df$Glucose == 0)
```

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

```
sum(df$BloodPressure == 0)
```

```
## [1] 35
```

```
sum(df$SkinThickness == 0)
```

```
## [1] 227
```

```
sum(df$Insulin == 0)
```

```
## [1] 374
```

```
sum(df$BMI == 0)
```

```
## [1] 11
```

```
sum(df$DiabetesPedigreeFunction == 0)
```

```
## [1] 0
```

```
sum(df$Age == 0)
```

```
## [1] 0
```

```
sum(df$Outcome == 0)
```

```
## [1] 500
```

The possibility of variable Pregnancies, DiabetesPedigreeFunction, and Outcome to have 0 as their value is understandable, because in fact not all of them have pregnant. There's possibility they have 0 percentage of having diabetes. Outcome is categorical variable that act as the final result whether a person has diabetes or not (1 yes, 0 no).

```
## Replace missing values with mean/median for numerical variable
median_SkinThickness <- median(df$SkinThickness)
median_Insulin <- median(df$Insulin)
mean_Glucose <- mean(df$Glucose)
mean_BloodPressure <- mean(df$BloodPressure)
mean_BMI <- mean(df$BMI)
```



```
df$Glucose[df$Glucose==0] <- mean_Glucose
df$BloodPressure[df$BloodPressure==0] <- mean_BloodPressure
df$SkinThickness[df$SkinThickness==0] <- median_SkinThickness
df$Insulin[df$Insulin==0] <- median_Insulin
df$BMI[df$BMI==0] <- mean_BMI
```

```
sum(df$Glucose==0)
```

```
## [1] 0
```

```
sum(df$BloodPressure==0)
```

```
## [1] 0
```

```
sum(df$SkinThickness==0)
```

```
## [1] 0
```

```
sum(df$Insulin==0)
```

```
## [1] 0
```

```
sum(df$BMI==0)
```

```
## [1] 0
```

So the preprocessing of the dataset: replacing rows that have 0 in Glucose/BloodPressure/SkinThickness/Insulin/BMI with the median or mean of the variables itself.

## 4. DATA EXPLORATION

### a) EXAMINE DESCRIPTIVE STATISTIC

#### Location (Central Tendency)

```
# numerical (mean/median/variance)
# average value for each variable, representing the central tendency or location
mean_Pregnancies = mean(df$Pregnancies)
mean_Glucose = mean(df$Glucose)
mean_BloodPressure = mean(df$BloodPressure)
mean_SkinThickness = mean(df$SkinThickness)
mean_Insulin = mean(df$Insulin)
mean_BMI = mean(df$BMI)
mean_DiabetesPedigreeFunction = mean(df$DiabetesPedigreeFunction)
mean_Age = mean(df$Age)

mean_Pregnancies
```

```
## [1] 3.845052
```

```
mean_Glucose
```

```
## [1] 121.6816
```

```
mean_BloodPressure
```

```
## [1] 72.25481
```

```
mean_SkinThickness
```

```
## [1] 27.33464
```

```
mean_Insulin
```

```
## [1] 94.65234
```

```
mean_BMI
```

```
## [1] 32.45081
```

```
mean_DiabetesPedigreeFunction
```

```
## [1] 0.4718763
```

```
mean_Age
```

```
## [1] 33.24089
```

#### *EXPLANATION*

1. The mean frequencies of pregnancy occur is 3.85.
2. The average of Glucose (Plasma glucose concentration) level of (121.68 mg/dL) on Oral glucose tolerance tests (OGTT) shows that it was categorized as normal glucose level (Normal: Less than 140 mg/dL).
3. The average of diastolic blood pressure (72.25 mm Hg) shows that it was indeed normal (Normal: Less than 80 mm Hg).
4. The average of skinThickness (27.33mm) show that it was consider as High, in which can indicates higher body fat (obesity), but there might be other factor that can affect this (SkinThickness alone may not necessarily mean obesity).
5. The average of insulin concentration in the blood measured two hours after consuming the glucose drink in OGTT (94.65 U/mL) can be considered as low (normal 100-150) and may indicate the insulin resistance (problems of handling glucose).
6. The average BMI of (32.45 kg/m<sup>2</sup>) shows that there are general obesity trend within the samples (obesity : 30.0 kg/m<sup>2</sup> and above), and this can lead to higher risk for diabetes.
7. The average of diabetesPedigree-Function (0.47 or 47%) shows that there are significant heredity predisposition towards diabetes, in which may be a major factor in predicting the diabetes outcome considering heredity plays a huge part in diabetes.
8. The mean frequencies of age is around 33.

```
# categorical
outcome_counts <- table(df$Outcome)
labels_outcome <- c("No Diabetes", "Has Diabetes")

outcome_pie <- plot_ly(labels = labels_outcome,
                      values = as.numeric(outcome_counts),
                      type = 'pie',
                      textinfo = 'label+percent') %>%
  layout(title = "Diabetes Distribution")

outcome_pie
```

There are 34.9% of adult female participants sample in Pima Indians of Arizona that has diabetes.

## Spread

```
# numerical(IQR/range)
# Function to calculate Q1, Q3, and IQR
calculate_quartiles <- function(x) {
  q1 <- quantile(x, 0.25, na.rm = TRUE)
  q3 <- quantile(x, 0.75, na.rm = TRUE)
  iqr <- IQR(x, na.rm = TRUE)
  return(c(Q1 = q1, Q3 = q3, IQR = iqr))
}

quartile_stats <- sapply(df, calculate_quartiles)
quartile_stats <- t(quartile_stats)
print(quartile_stats)
```

##	Q1.25%	Q3.75%	IQR
## Pregnancies	1.00000	6.00000	5.0000
## Glucose	99.75000	140.25000	40.5000
## BloodPressure	64.00000	80.00000	16.0000
## SkinThickness	23.00000	32.00000	9.0000
## Insulin	30.50000	127.25000	96.7500
## BMI	27.50000	36.60000	9.1000
## DiabetesPedigreeFunction	0.24375	0.62625	0.3825
## Age	24.00000	41.00000	17.0000
## Outcome	0.00000	1.00000	1.0000

### EXPLANATION

1. With a Q1 of 1, a Q3 of 6, and an IQR of 5, the number of pregnancies shows that 50% of the data lies between 1 and 6 pregnancies.
2. The glucose levels have a Q1 of 99.75, a Q3 of 140.25, and an IQR of 40.5. Altho the data also shows that 50% of the participant's blood glucose levels in the OGTT remain considered as normal, the spread (IQR) indicates that there is medium variability in blood glucose levels among individuals.
3. The diastolic blood pressure measurements, which have a Q1 of 64, a Q3 of 80, and an IQR of 16, shows that although individual variations may exist in the data, 50% of the participant's blood pressure still considered as normal.
4. Skin thickness values show a narrow distribution in the data, with a range from a Q1 of 23 to a Q3 of 32 with an IQR of 9. However, 50% of participants have a skin thickness level that can be considered high,

showing higher levels of body fat.

5. Insulin levels have a Q1 of 30.5, a Q3 of 127.25, and an IQR of 96.75, showing there are significant variability that might be caused by outliers.
6. The body mass index has a Q1 of 27.5, a Q3 of 36.6, and an IQR of 9.1, indicating there are variability of body mass indices. However, 50% of participants are considered as Overweight and Obesed.
7. The Diabetes Pedigree Function has a Q1 of 0.24375, a Q3 of 0.62625, and an IQR of 0.3825, showing there are medium variability in the percentage of risk of developing diabetes.
8. The age distribution shows a Q1 of 24, a Q3 of 41, and an IQR of 17, showing that there is a wide age range among individuals.
9. The outcome variable, which is categorical of (0 = non-diabetical) and (1 = diabetical), has a Q1 of 0, a Q3 of 1, and an IQR of 1.

## Shape

```
# graphical (histogram)

create_histogram <- function(data, variable_name){
  plot <- plot_ly(
    data = data,
    x = ~get(variable_name),
    type = 'histogram',
    textinfo = "text") %>%
    layout(
      title = paste("Histogram of", variable_name),
      xaxis = list(title = variable_name),
      yaxis = list(title = "Frequency")
    )
  return(plot)
}

histograms <- lapply(names(df), function(var) create_histogram(df, var))
for(plot in histograms){
  print(plot)
}
```

## EXPLANATION

From the histogram above we can conclude that:

- Pregnancies : right (positive) skewed
- Glucose : almost normally distributed but right (positive) skewed
- BloodPressure : normally distributed
- SkinThickness : right (positive) skewed
- Insulin : right (positive) skewed
- BMI : right (positive) skewed
- DiabetesPedigreeFunction : right (positive) skewed
- Age : right (positive) skewed
- Outcome : right (positive) skewed

```
# Function to calculate skewness
calculate_skewness <- function(x){
  n <- length(x)
  mean_x <- mean(x, na.rm = TRUE)
  sd_x <- sd(x, na.rm = TRUE)
```

```

    skewness <- sum((x - mean_x)^3, na.rm = TRUE) / (n * sd_x^3)
    return(skewness)
}

# Function to calculate kurtosis
calculate_kurtosis <- function(x){
  n <- length(x)
  mean_x <- mean(x, na.rm = TRUE)
  sd_x <- sd(x, na.rm = TRUE)
  kurtosis <- sum((x - mean_x)^4, na.rm = TRUE) / (n * sd_x^4) - 3
  return(kurtosis)
}

skewness_results <- sapply(df, function(x) if (is.numeric(x)) calculate_skewness(x) else NA)
kurtosis_results <- sapply(df, function(x) if (is.numeric(x)) calculate_kurtosis(x) else NA)

results <- data.frame(
  Skewness = skewness_results,
  Kurtosis = kurtosis_results
)

print(results)

```

##	Skewness	Kurtosis
## Pregnancies	0.8981549	0.1421840
## Glucose	0.5311437	-0.2720579
## BloodPressure	0.1723748	1.0538400
## SkinThickness	1.2182837	4.6585559
## Insulin	2.6826696	9.6369965
## BMI	0.5987572	0.8973587
## DiabetesPedigreeFunction	1.9124179	5.5285389
## Age	1.1251880	0.6217269
## Outcome	0.6325383	-1.6019762

#### EXPLANATION Pregnancies

- Skewness: 0.898 (positively skewed or it means right tailed distribution)

- Kurtosis: 0.142 (normal distribution)

#### Glucose

- Skewness: 0.531 (positively skewed or right tailed distribution)

- Kurtosis: -0.272 (slightly lighter tails or lesser outlier)

#### BloodPressure

- Skewness: 0.172 (symmetric)

- Kurtosis: 1.054 (slightly heavier tails or more outlier)

#### SkinThickness

- Skewness: 1.218 (positively skewed or right tailed distribution)

- Kurtosis: 4.659 (significantly heavy tails or more outlier)

#### Insulin

- Skewness: 2.683 (positively skewed or right tailed distribution)

- Kurtosis: 9.637 (very heavy tails or there so many outlier)

#### BMI

- Skewness: 0.599 (positively skewed or right tailed distribution)

- Kurtosis: 0.897 (slightly heavier tails or more outlier)

#### DiabetesPedigreeFunction

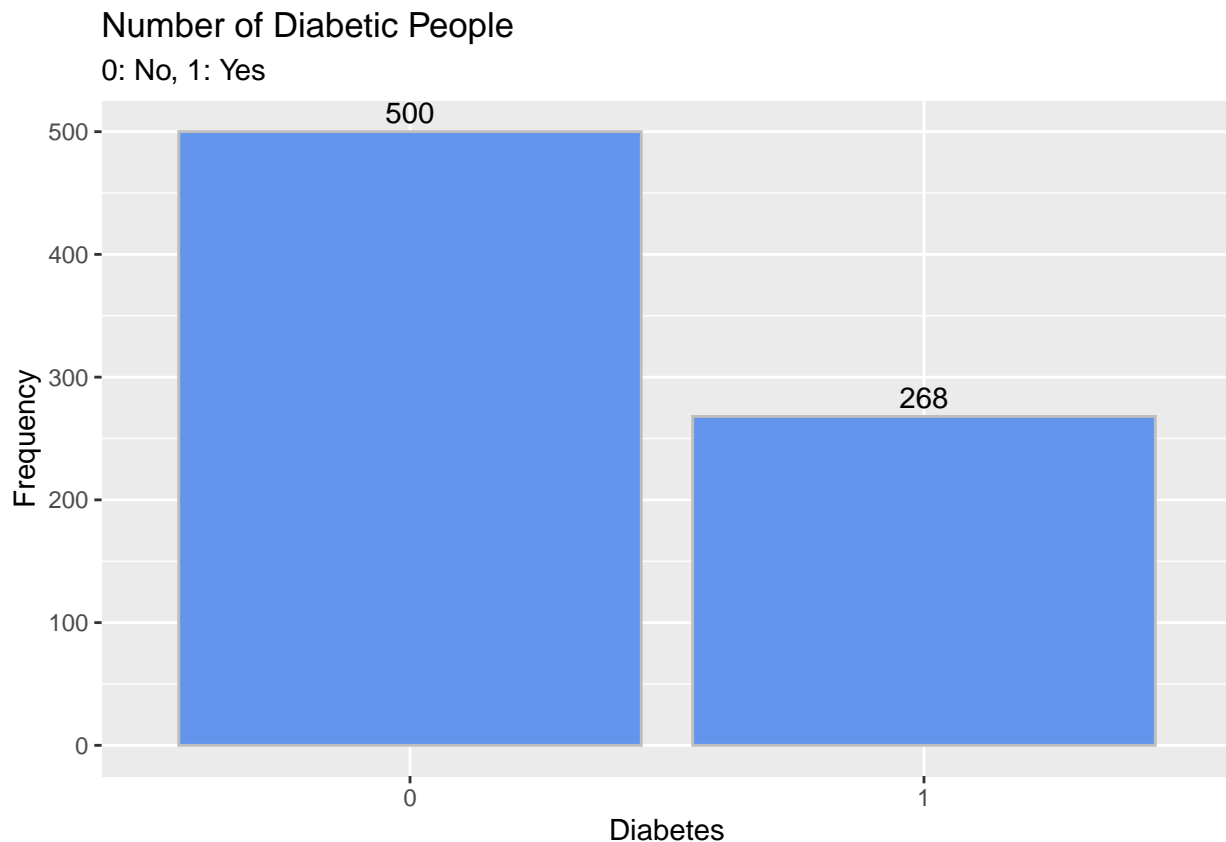
- Skewness: 1.912 (positively skewed or right tailed outlier)
  - Kurtosis: 5.529 (significantly heavy tails or more outlier)
- Age
- Skewness: 1.125 (positively skewed or right tailed distribution)
  - Kurtosis: 0.622 (slightly heavier tails or more outlier)
- Outcome
- Skewness: 0.633 (positively skewed or right tailed distribution)
  - Kurtosis: -1.602 (significantly lighter tails or lesser outlier)

## b) FREQUENCY DISTRIBUTION

### Number of Diabetic People

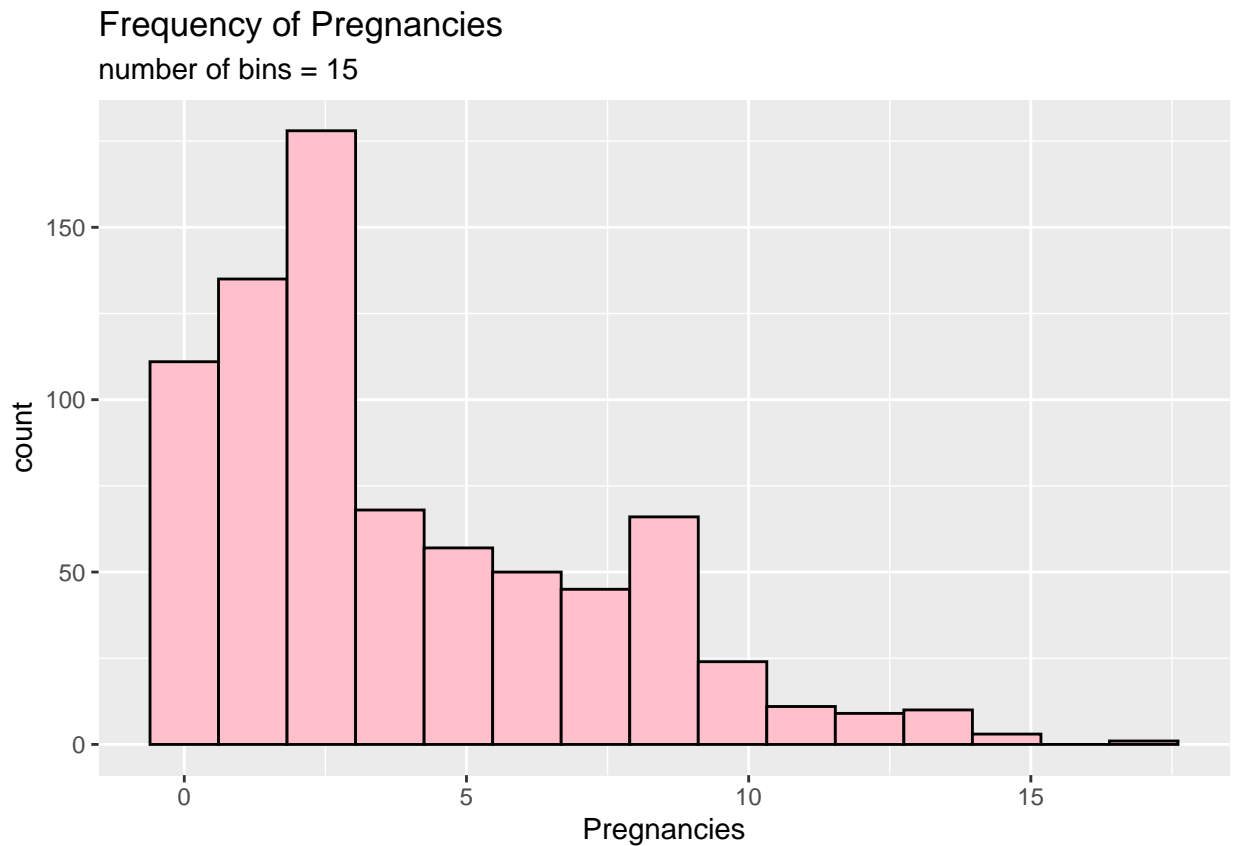
```
plotdata <- df %>%
  count(Outcome)

ggplot(plotdata,
  aes(x = reorder(Outcome, -n), y = n)) +
  geom_bar(stat="identity", fill = "cornflowerblue", color="gray") + geom_text(aes(label = n), vjust=-0.5) +
  labs(x = "Diabetes",
    y = "Frequency",
    title = "Number of Diabetic People",
    subtitle = "0: No, 1: Yes")
```



#### Frequency of Pregnancies

```
ggplot(df, aes(x = Pregnancies)) +
  geom_histogram(fill = "pink",
                 color = "black",
                 bins = 15) +
  labs(title="Frequency of Pregnancies",
        subtitle = "number of bins = 15",
        x = "Pregnancies")
```

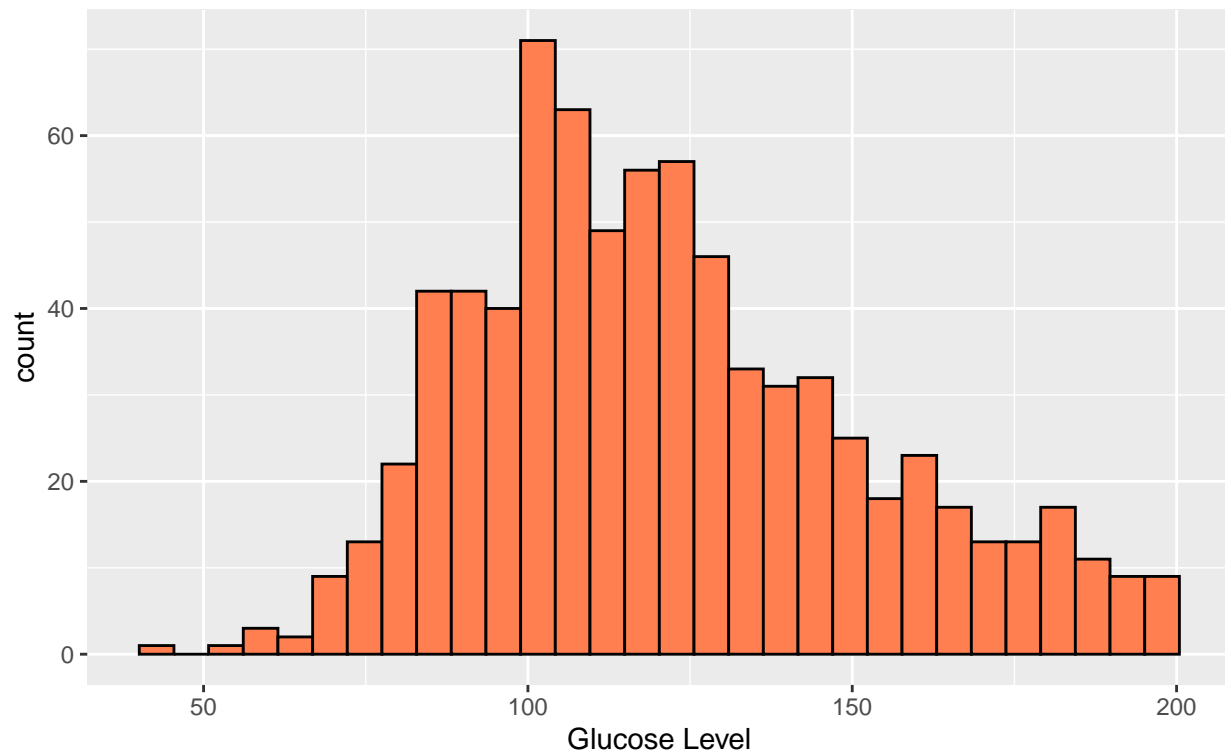


### Glucose level

```
ggplot(df, aes(x = Glucose)) +
  geom_histogram(fill = "coral",
                 color = "black",
                 bins = 30) +
  labs(title="Patient by Glucose Level",
        subtitle = "number of bins = 30",
        x = "Glucose Level")
```

## Patient by Glucose Level

number of bins = 30



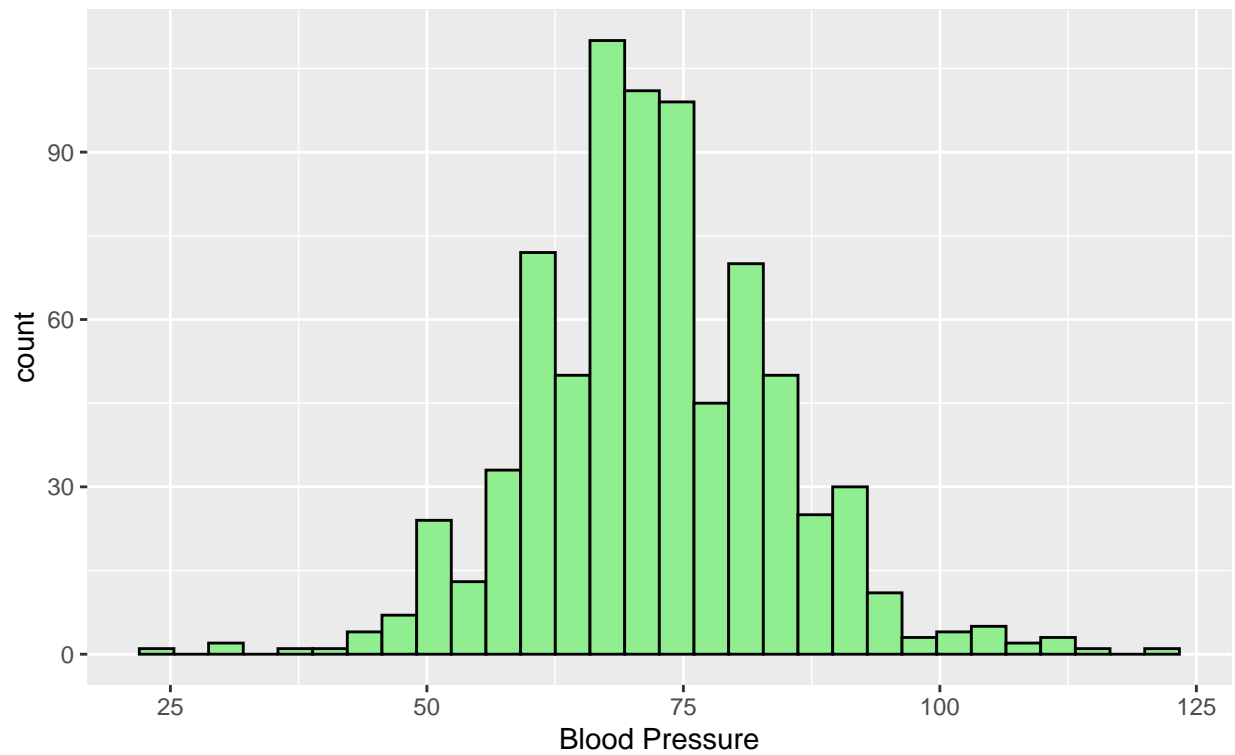
### Blood Pressure level

```
ggplot(df, aes(x = BloodPressure)) +  
  geom_histogram(fill = "lightgreen",  
                 color = "black",  
                 bins = 30) +  
  labs(title="Patient by Blood Pressure Level",  
        subtitle = "number of bins = 30",  
        x = "Blood Pressure")
```



## Patient by Blood Pressure Level

number of bins = 30

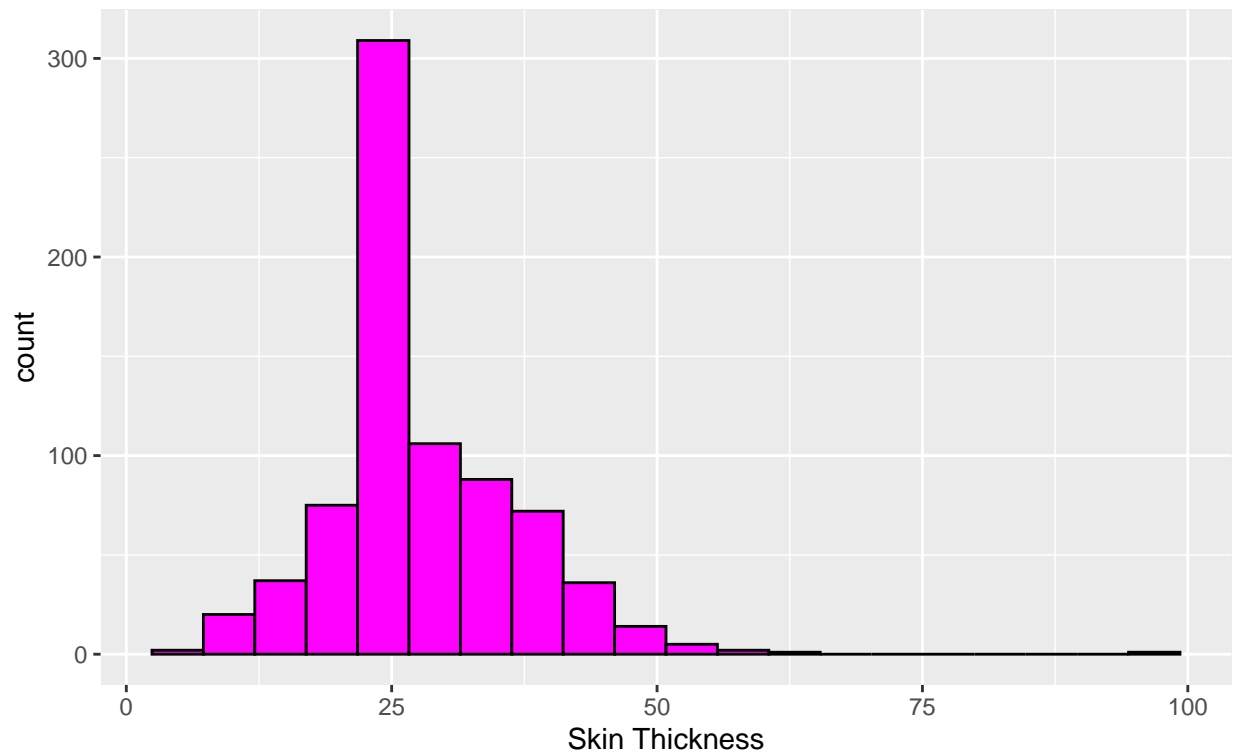


### Participant by Skin Thickness

```
ggplot(df, aes(x = SkinThickness)) +  
  geom_histogram(fill = "magenta",  
                 color = "black",  
                 bins = 20) +  
  labs(title="Patient by Skin Thickness",  
        subtitle = "number of bins = 20",  
        x = "Skin Thickness")
```

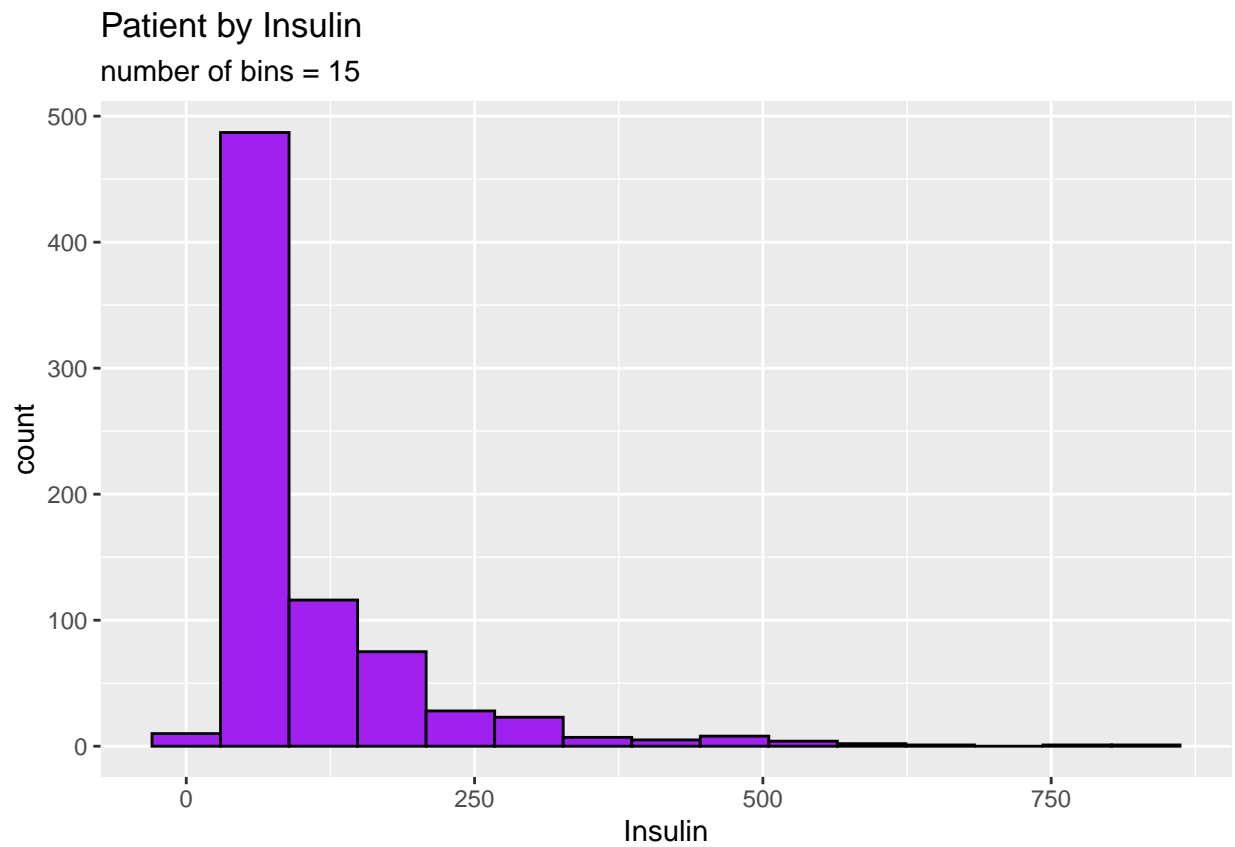
## Patient by Skin Thickness

number of bins = 20



### Participant by Insulin

```
ggplot(df, aes(x = Insulin)) +  
  geom_histogram(fill = "purple",  
                 color = "black",  
                 bins = 15) +  
  labs(title="Patient by Insulin",  
        subtitle = "number of bins = 15",  
        x = "Insulin")
```

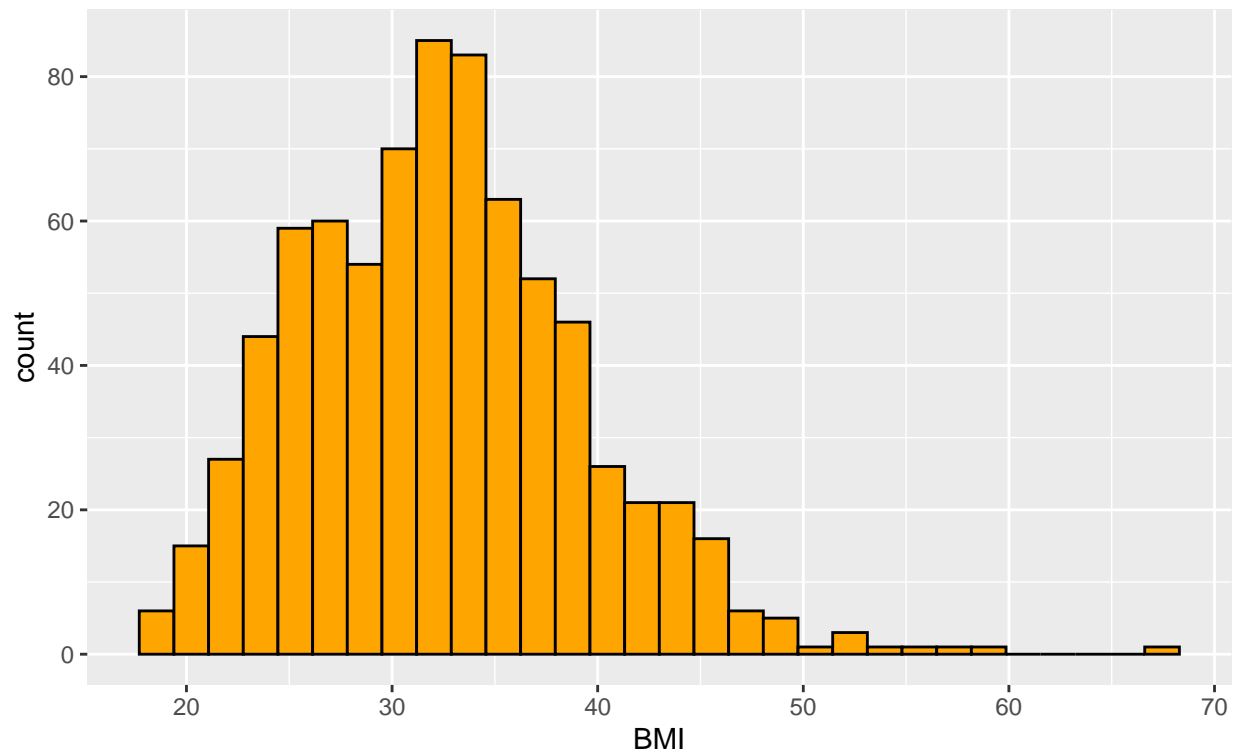


#### Participant by BMI

```
ggplot(df, aes(x = BMI)) +  
  geom_histogram(fill = "orange",  
                 color = "black",  
                 bins = 30) +  
  labs(title="Patient by BMI",  
        subtitle = "number of bins = 30",  
        x = "BMI")
```

## Patient by BMI

number of bins = 30

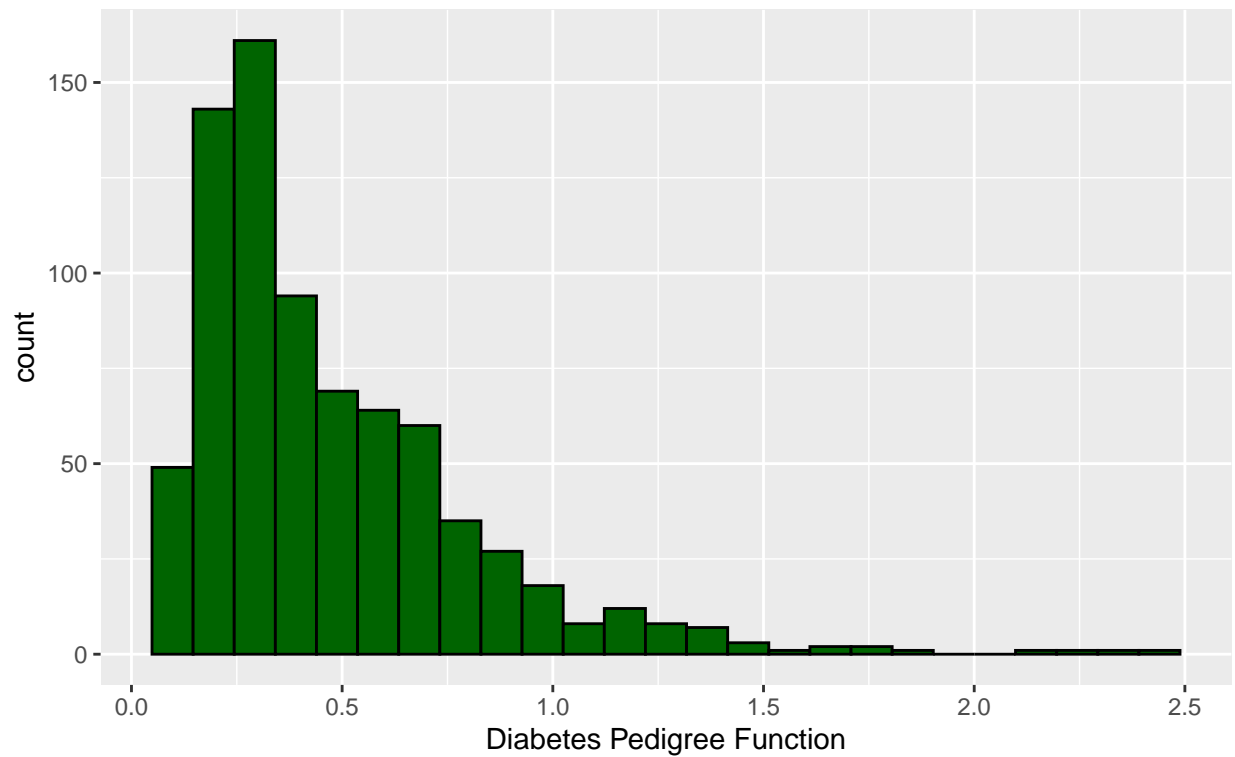


#### Diabetes Pedigree Function

```
ggplot(df, aes(x = DiabetesPedigreeFunction)) +  
  geom_histogram(fill = "darkgreen",  
                 color = "black",  
                 bins = 25) +  
  labs(title="Patient by Diabetes Pedigree Function",  
        subtitle = "number of bins = 25",  
        x = "Diabetes Pedigree Function")
```

## Patient by Diabetes Pedigree Function

number of bins = 25

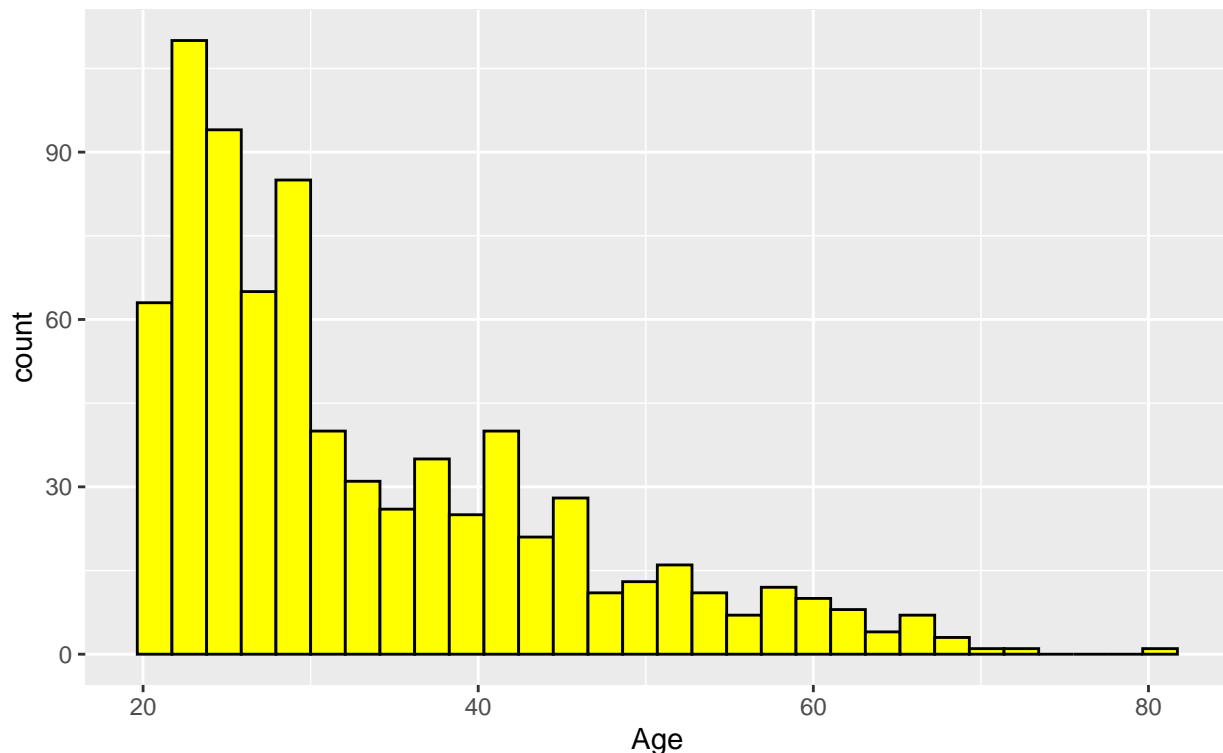


#### Participant by Age

```
ggplot(df, aes(x = Age)) +  
  geom_histogram(fill = "yellow",  
                 color = "black",  
                 bins = 30) +  
  labs(title="Patient by Age",  
        subtitle = "number of bins = 30",  
        x = "Age")
```

## Patient by Age

number of bins = 30



## c) DATA VISUALIZATION

What is the indicator of Diabetes?

Glucose vs Outcome

```
plot_ly(data = df, x = ~Outcome, y = ~Glucose, type = "box", boxmean = TRUE,
        marker = list(color = 'red'),
        line = list(color = 'red'),
        fillcolor = 'rgba(255,0,0,0.5)') %>%
  layout(title = "Glucose Levels vs Outcome",
        xaxis = list(title = "Outcome"),
        yaxis = list(title = "Glucose Level"))
```

As mentioned before, the dataset contains the result of Oral Glucose Tolerance Test (OGTT), in which is used to observe the body's reaction in processing glucose, which can help to identify insulin resistance and diabetes.

Here in the plot, we can see median glucose level is significantly higher for individuals with diabetes (Outcome = 1) compared to those without diabetes (Outcome = 0).

- Median glucose level without diabetes = 107.5
- Median glucose level with diabetes = 140
- Mean glucose level without diabetes = 110.7
- Mean glucose level with diabetes = 142.2

By looking the outliers between each group, we can see that the diabetic group glucose levels are closer to a

normal distribution, while the non-diabetic group glucose level are right-skewed. The diabetical group has fewer outliers showing that they have more consistency in their range of glucose level.

The IQR is higher for individuals with diabetes, indicating there is more variability in glucose levels within the diabetic group (IQR = 119 ~ 167), while the non-diabetic group has more narrow variation (IQR = 93 ~ 125).

In conclusion, the box plot clearly shows that the result of OGTT for individuals with diabetes, tend to keep their glucose levels high even after 2 hours, showing there are insulin incapability of regulate glucose concentration in blood, this condition is also known as Insulin Resistance.

### Insulin vs Outcome

```
plot_ly(data = df, x = ~Outcome, y = ~Insulin, type = "box", boxmean = TRUE,
        marker = list(color = 'red'),
        line = list(color = 'red'),
        fillcolor = 'rgba(255,0,0,0.5)') %>%
  layout(title = "Insulin Levels vs Outcome",
        xaxis = list(title = "Outcome"),
        yaxis = list(title = "Insulin Level"))
```

Here in the plot, we can see median glucose level is higher for individuals without diabetes (Outcome = 0) compared to those with diabetes (Outcome = 1).

- Median glucose level without diabetes = 39
- Median glucose level with diabetes = 30.5
- Mean glucose level without diabetes = 83.188
- Mean glucose level with diabetes = 116.041

By looking the outliers between each group, we can see that both the diabetic and non-diabetical group insulin levels have many extreme values, showing that there are individuals with or without diabetes that tend to have a high insulin level posttest.

The IQR is higher for individuals with diabetes, indicating there is more variability in insulin levels within the diabetic group (IQR = 30.5 ~ 167.5), while the non-diabetic group has more narrow variation (IQR = 30.5 ~ 105).

In conclusion, the box plot shows that the result of OGTT for people with diabetes, the insulin levels remains high or show a delayed response, indicating the failed body's attempt to manage the high blood glucose levels. That makes insulin can't really get the job done breaking down glucose.

### How does lifestyle affect Diabetes?

#### SkinThickness vs BMI vs Outcome

```
plot_ly(
  data = df,
  x = ~SkinThickness,
  y = ~BMI,
  type = "scatter",
  mode = "markers",
  color = ~Outcome,
  colors = c('Non Diabetes' = 'yellow', 'Diabetes' = 'red')
) %>%
  layout(
    title = "Skin Thickness vs BMI",
    xaxis = list(title = "Skin Thickness"),
```

```

yaxis = list(title = "BMI"),
legend = list(title = list(text = 'Outcome'))
)

```

On the plot we can see there a positive linear relationship between BMI and SkinThickness. Having a thicker skin fold indicates a higher body fat, people that have higher BMI will also have a high skinfold thickness.

In the plot we can also see that individuals that in fact have a higher BMI and higher levels of SkinThickness are more likely to suffers from diabetes, due to obesity.

```

df.temp <- df
df.temp$BMI[df$BMI<18.5] <- "Underweight"
df.temp$BMI[df$BMI>=18.5 & df$BMI<=24.9] <- "Normal"
df.temp$BMI[df$BMI>=25.0 & df$BMI<=29.9] <- "Overweight"
df.temp$BMI[df$BMI>=30.0] <- "Obesity"
df.temp

```

##	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI
## 1	6	148.0000	72.00000	35	30.5	Obesity
## 2	1	85.0000	66.00000	29	30.5	Overweight
## 3	8	183.0000	64.00000	23	30.5	Normal
## 4	1	89.0000	66.00000	23	94.0	Overweight
## 5	0	137.0000	40.00000	35	168.0	Obesity
## 6	5	116.0000	74.00000	23	30.5	Overweight
## 7	3	78.0000	50.00000	32	88.0	Obesity
## 8	10	115.0000	69.10547	23	30.5	Obesity
## 9	2	197.0000	70.00000	45	543.0	Obesity
## 10	8	125.0000	96.00000	23	30.5	Obesity
## 11	4	110.0000	92.00000	23	30.5	Obesity
## 12	10	168.0000	74.00000	23	30.5	Obesity
## 13	10	139.0000	80.00000	23	30.5	Overweight
## 14	1	189.0000	60.00000	23	846.0	Obesity
## 15	5	166.0000	72.00000	19	175.0	Overweight
## 16	7	100.0000	69.10547	23	30.5	Obesity
## 17	0	118.0000	84.00000	47	230.0	Obesity
## 18	7	107.0000	74.00000	23	30.5	Overweight
## 19	1	103.0000	30.00000	38	83.0	Obesity
## 20	1	115.0000	70.00000	30	96.0	Obesity
## 21	3	126.0000	88.00000	41	235.0	Obesity
## 22	8	99.0000	84.00000	23	30.5	Obesity
## 23	7	196.0000	90.00000	23	30.5	Obesity
## 24	9	119.0000	80.00000	35	30.5	Overweight
## 25	11	143.0000	94.00000	33	146.0	Obesity
## 26	10	125.0000	70.00000	26	115.0	Obesity
## 27	7	147.0000	76.00000	23	30.5	Obesity
## 28	1	97.0000	66.00000	15	140.0	Normal
## 29	13	145.0000	82.00000	19	110.0	Normal
## 30	5	117.0000	92.00000	23	30.5	Obesity
## 31	5	109.0000	75.00000	26	30.5	Obesity
## 32	3	158.0000	76.00000	36	245.0	Obesity
## 33	3	88.0000	58.00000	11	54.0	Normal
## 34	6	92.0000	92.00000	23	30.5	Normal
## 35	10	122.0000	78.00000	31	30.5	Overweight



## 36	4	103.0000	60.00000	33	192.0	Normal
## 37	11	138.0000	76.00000	23	30.5	Obesity
## 38	9	102.0000	76.00000	37	30.5	Obesity
## 39	2	90.0000	68.00000	42	30.5	Obesity
## 40	4	111.0000	72.00000	47	207.0	Obesity
## 41	3	180.0000	64.00000	25	70.0	Obesity
## 42	7	133.0000	84.00000	23	30.5	Obesity
## 43	7	106.0000	92.00000	18	30.5	Normal
## 44	9	171.0000	110.00000	24	240.0	Obesity
## 45	7	159.0000	64.00000	23	30.5	Overweight
## 46	0	180.0000	66.00000	39	30.5	Obesity
## 47	1	146.0000	56.00000	23	30.5	Overweight
## 48	2	71.0000	70.00000	27	30.5	Overweight
## 49	7	103.0000	66.00000	32	30.5	Obesity
## 50	7	105.0000	69.10547	23	30.5	Obesity
## 51	1	103.0000	80.00000	11	82.0	Normal
## 52	1	101.0000	50.00000	15	36.0	Normal
## 53	5	88.0000	66.00000	21	23.0	Normal
## 54	8	176.0000	90.00000	34	300.0	Obesity
## 55	7	150.0000	66.00000	42	342.0	Obesity
## 56	1	73.0000	50.00000	10	30.5	Normal
## 57	7	187.0000	68.00000	39	304.0	Obesity
## 58	0	100.0000	88.00000	60	110.0	Obesity
## 59	0	146.0000	82.00000	23	30.5	Obesity
## 60	0	105.0000	64.00000	41	142.0	Obesity
## 61	2	84.0000	69.10547	23	30.5	Obesity
## 62	8	133.0000	72.00000	23	30.5	Obesity
## 63	5	44.0000	62.00000	23	30.5	Overweight
## 64	2	141.0000	58.00000	34	128.0	Overweight
## 65	7	114.0000	66.00000	23	30.5	Obesity
## 66	5	99.0000	74.00000	27	30.5	Overweight
## 67	0	109.0000	88.00000	30	30.5	Obesity
## 68	2	109.0000	92.00000	23	30.5	Obesity
## 69	1	95.0000	66.00000	13	38.0	Normal
## 70	4	146.0000	85.00000	27	100.0	Overweight
## 71	2	100.0000	66.00000	20	90.0	Obesity
## 72	5	139.0000	64.00000	35	140.0	Overweight
## 73	13	126.0000	90.00000	23	30.5	Obesity
## 74	4	129.0000	86.00000	20	270.0	Obesity
## 75	1	79.0000	75.00000	30	30.5	Obesity
## 76	1	120.8945	48.00000	20	30.5	Normal
## 77	7	62.0000	78.00000	23	30.5	Obesity
## 78	5	95.0000	72.00000	33	30.5	Obesity
## 79	0	131.0000	69.10547	23	30.5	Obesity
## 80	2	112.0000	66.00000	22	30.5	Overweight
## 81	3	113.0000	44.00000	13	30.5	Normal
## 82	2	74.0000	69.10547	23	30.5	Obesity
## 83	7	83.0000	78.00000	26	71.0	Overweight
## 84	0	101.0000	65.00000	28	30.5	Normal
## 85	5	137.0000	108.00000	23	30.5	Obesity
## 86	2	110.0000	74.00000	29	125.0	Obesity
## 87	13	106.0000	72.00000	54	30.5	Obesity
## 88	2	100.0000	68.00000	25	71.0	Obesity
## 89	15	136.0000	70.00000	32	110.0	Obesity

## 90	1	107.0000	68.00000	19	30.5	Overweight
## 91	1	80.0000	55.00000	23	30.5	Normal
## 92	4	123.0000	80.00000	15	176.0	Obesity
## 93	7	81.0000	78.00000	40	48.0	Obesity
## 94	4	134.0000	72.00000	23	30.5	Normal
## 95	2	142.0000	82.00000	18	64.0	Normal
## 96	6	144.0000	72.00000	27	228.0	Obesity
## 97	2	92.0000	62.00000	28	30.5	Obesity
## 98	1	71.0000	48.00000	18	76.0	Normal
## 99	6	93.0000	50.00000	30	64.0	Overweight
## 100	1	122.0000	90.00000	51	220.0	Obesity
## 101	1	163.0000	72.00000	23	30.5	Obesity
## 102	1	151.0000	60.00000	23	30.5	Overweight
## 103	0	125.0000	96.00000	23	30.5	Normal
## 104	1	81.0000	72.00000	18	40.0	Overweight
## 105	2	85.0000	65.00000	23	30.5	Obesity
## 106	1	126.0000	56.00000	29	152.0	Overweight
## 107	1	96.0000	122.00000	23	30.5	Normal
## 108	4	144.0000	58.00000	28	140.0	Overweight
## 109	3	83.0000	58.00000	31	18.0	Obesity
## 110	0	95.0000	85.00000	25	36.0	Obesity
## 111	3	171.0000	72.00000	33	135.0	Obesity
## 112	8	155.0000	62.00000	26	495.0	Obesity
## 113	1	89.0000	76.00000	34	37.0	Obesity
## 114	4	76.0000	62.00000	23	30.5	Obesity
## 115	7	160.0000	54.00000	32	175.0	Obesity
## 116	4	146.0000	92.00000	23	30.5	Obesity
## 117	5	124.0000	74.00000	23	30.5	Obesity
## 118	5	78.0000	48.00000	23	30.5	Obesity
## 119	4	97.0000	60.00000	23	30.5	Overweight
## 120	4	99.0000	76.00000	15	51.0	Normal
## 121	0	162.0000	76.00000	56	100.0	Obesity
## 122	6	111.0000	64.00000	39	30.5	Obesity
## 123	2	107.0000	74.00000	30	100.0	Obesity
## 124	5	132.0000	80.00000	23	30.5	Overweight
## 125	0	113.0000	76.00000	23	30.5	Obesity
## 126	1	88.0000	30.00000	42	99.0	Obesity
## 127	3	120.0000	70.00000	30	135.0	Obesity
## 128	1	118.0000	58.00000	36	94.0	Obesity
## 129	1	117.0000	88.00000	24	145.0	Obesity
## 130	0	105.0000	84.00000	23	30.5	Overweight
## 131	4	173.0000	70.00000	14	168.0	Overweight
## 132	9	122.0000	56.00000	23	30.5	Obesity
## 133	3	170.0000	64.00000	37	225.0	Obesity
## 134	8	84.0000	74.00000	31	30.5	Obesity
## 135	2	96.0000	68.00000	13	49.0	Normal
## 136	2	125.0000	60.00000	20	140.0	Obesity
## 137	0	100.0000	70.00000	26	50.0	Obesity
## 138	0	93.0000	60.00000	25	92.0	Overweight
## 139	0	129.0000	80.00000	23	30.5	Obesity
## 140	5	105.0000	72.00000	29	325.0	Obesity
## 141	3	128.0000	78.00000	23	30.5	Normal
## 142	5	106.0000	82.00000	30	30.5	Obesity
## 143	2	108.0000	52.00000	26	63.0	Obesity

## 144	10	108.0000	66.00000	23	30.5	Obesity
## 145	4	154.0000	62.00000	31	284.0	Obesity
## 146	0	102.0000	75.00000	23	30.5	Obesity
## 147	9	57.0000	80.00000	37	30.5	Obesity
## 148	2	106.0000	64.00000	35	119.0	Obesity
## 149	5	147.0000	78.00000	23	30.5	Obesity
## 150	2	90.0000	70.00000	17	30.5	Overweight
## 151	1	136.0000	74.00000	50	204.0	Obesity
## 152	4	114.0000	65.00000	23	30.5	Normal
## 153	9	156.0000	86.00000	28	155.0	Obesity
## 154	1	153.0000	82.00000	42	485.0	Obesity
## 155	8	188.0000	78.00000	23	30.5	Obesity
## 156	7	152.0000	88.00000	44	30.5	Obesity
## 157	2	99.0000	52.00000	15	94.0	Normal
## 158	1	109.0000	56.00000	21	135.0	Overweight
## 159	2	88.0000	74.00000	19	53.0	Overweight
## 160	17	163.0000	72.00000	41	114.0	Obesity
## 161	4	151.0000	90.00000	38	30.5	Overweight
## 162	7	102.0000	74.00000	40	105.0	Obesity
## 163	0	114.0000	80.00000	34	285.0	Obesity
## 164	2	100.0000	64.00000	23	30.5	Overweight
## 165	0	131.0000	88.00000	23	30.5	Obesity
## 166	6	104.0000	74.00000	18	156.0	Overweight
## 167	3	148.0000	66.00000	25	30.5	Obesity
## 168	4	120.0000	68.00000	23	30.5	Overweight
## 169	4	110.0000	66.00000	23	30.5	Obesity
## 170	3	111.0000	90.00000	12	78.0	Overweight
## 171	6	102.0000	82.00000	23	30.5	Obesity
## 172	6	134.0000	70.00000	23	130.0	Obesity
## 173	2	87.0000	69.10547	23	30.5	Overweight
## 174	1	79.0000	60.00000	42	48.0	Obesity
## 175	2	75.0000	64.00000	24	55.0	Overweight
## 176	8	179.0000	72.00000	42	130.0	Obesity
## 177	6	85.0000	78.00000	23	30.5	Obesity
## 178	0	129.0000	110.00000	46	130.0	Obesity
## 179	5	143.0000	78.00000	23	30.5	Obesity
## 180	5	130.0000	82.00000	23	30.5	Obesity
## 181	6	87.0000	80.00000	23	30.5	Normal
## 182	0	119.0000	64.00000	18	92.0	Obesity
## 183	1	120.8945	74.00000	20	23.0	Overweight
## 184	5	73.0000	60.00000	23	30.5	Overweight
## 185	4	141.0000	74.00000	23	30.5	Overweight
## 186	7	194.0000	68.00000	28	30.5	Obesity
## 187	8	181.0000	68.00000	36	495.0	Obesity
## 188	1	128.0000	98.00000	41	58.0	Obesity
## 189	8	109.0000	76.00000	39	114.0	Overweight
## 190	5	139.0000	80.00000	35	160.0	Obesity
## 191	3	111.0000	62.00000	23	30.5	Normal
## 192	9	123.0000	70.00000	44	94.0	Obesity
## 193	7	159.0000	66.00000	23	30.5	Obesity
## 194	11	135.0000	69.10547	23	30.5	Obesity
## 195	8	85.0000	55.00000	20	30.5	Normal
## 196	5	158.0000	84.00000	41	210.0	Obesity
## 197	1	105.0000	58.00000	23	30.5	Normal

## 198	3	107.0000	62.00000	13	48.0	Normal
## 199	4	109.0000	64.00000	44	99.0	Obesity
## 200	4	148.0000	60.00000	27	318.0	Obesity
## 201	0	113.0000	80.00000	16	30.5	Obesity
## 202	1	138.0000	82.00000	23	30.5	Obesity
## 203	0	108.0000	68.00000	20	30.5	Overweight
## 204	2	99.0000	70.00000	16	44.0	Normal
## 205	6	103.0000	72.00000	32	190.0	Obesity
## 206	5	111.0000	72.00000	28	30.5	Normal
## 207	8	196.0000	76.00000	29	280.0	Obesity
## 208	5	162.0000	104.00000	23	30.5	Obesity
## 209	1	96.0000	64.00000	27	87.0	Obesity
## 210	7	184.0000	84.00000	33	30.5	Obesity
## 211	2	81.0000	60.00000	22	30.5	Overweight
## 212	0	147.0000	85.00000	54	30.5	Obesity
## 213	7	179.0000	95.00000	31	30.5	Obesity
## 214	0	140.0000	65.00000	26	130.0	Obesity
## 215	9	112.0000	82.00000	32	175.0	Obesity
## 216	12	151.0000	70.00000	40	271.0	Obesity
## 217	5	109.0000	62.00000	41	129.0	Obesity
## 218	6	125.0000	68.00000	30	120.0	Obesity
## 219	5	85.0000	74.00000	22	30.5	Overweight
## 220	5	112.0000	66.00000	23	30.5	Obesity
## 221	0	177.0000	60.00000	29	478.0	Obesity
## 222	2	158.0000	90.00000	23	30.5	Obesity
## 223	7	119.0000	69.10547	23	30.5	Overweight
## 224	7	142.0000	60.00000	33	190.0	Overweight
## 225	1	100.0000	66.00000	15	56.0	Normal
## 226	1	87.0000	78.00000	27	32.0	Obesity
## 227	0	101.0000	76.00000	23	30.5	Obesity
## 228	3	162.0000	52.00000	38	30.5	Obesity
## 229	4	197.0000	70.00000	39	744.0	Obesity
## 230	0	117.0000	80.00000	31	53.0	Obesity
## 231	4	142.0000	86.00000	23	30.5	Obesity
## 232	6	134.0000	80.00000	37	370.0	Obesity
## 233	1	79.0000	80.00000	25	37.0	Overweight
## 234	4	122.0000	68.00000	23	30.5	Obesity
## 235	3	74.0000	68.00000	28	45.0	Overweight
## 236	4	171.0000	72.00000	23	30.5	Obesity
## 237	7	181.0000	84.00000	21	192.0	Obesity
## 238	0	179.0000	90.00000	27	30.5	Obesity
## 239	9	164.0000	84.00000	21	30.5	Obesity
## 240	0	104.0000	76.00000	23	30.5	Underweight
## 241	1	91.0000	64.00000	24	30.5	Overweight
## 242	4	91.0000	70.00000	32	88.0	Obesity
## 243	3	139.0000	54.00000	23	30.5	Overweight
## 244	6	119.0000	50.00000	22	176.0	Overweight
## 245	2	146.0000	76.00000	35	194.0	Obesity
## 246	9	184.0000	85.00000	15	30.5	Obesity
## 247	10	122.0000	68.00000	23	30.5	Obesity
## 248	0	165.0000	90.00000	33	680.0	Obesity
## 249	9	124.0000	70.00000	33	402.0	Obesity
## 250	1	111.0000	86.00000	19	30.5	Obesity
## 251	9	106.0000	52.00000	23	30.5	Obesity

## 252	2	129.0000	84.00000	23	30.5	Overweight
## 253	2	90.0000	80.00000	14	55.0	Normal
## 254	0	86.0000	68.00000	32	30.5	Obesity
## 255	12	92.0000	62.00000	7	258.0	Overweight
## 256	1	113.0000	64.00000	35	30.5	Obesity
## 257	3	111.0000	56.00000	39	30.5	Obesity
## 258	2	114.0000	68.00000	22	30.5	Overweight
## 259	1	193.0000	50.00000	16	375.0	Overweight
## 260	11	155.0000	76.00000	28	150.0	Obesity
## 261	3	191.0000	68.00000	15	130.0	Obesity
## 262	3	141.0000	69.10547	23	30.5	Obesity
## 263	4	95.0000	70.00000	32	30.5	Obesity
## 264	3	142.0000	80.00000	15	30.5	Obesity
## 265	4	123.0000	62.00000	23	30.5	Obesity
## 266	5	96.0000	74.00000	18	67.0	Obesity
## 267	0	138.0000	69.10547	23	30.5	Obesity
## 268	2	128.0000	64.00000	42	30.5	Obesity
## 269	0	102.0000	52.00000	23	30.5	Overweight
## 270	2	146.0000	69.10547	23	30.5	Overweight
## 271	10	101.0000	86.00000	37	30.5	Obesity
## 272	2	108.0000	62.00000	32	56.0	Overweight
## 273	3	122.0000	78.00000	23	30.5	Normal
## 274	1	71.0000	78.00000	50	45.0	Obesity
## 275	13	106.0000	70.00000	23	30.5	Obesity
## 276	2	100.0000	70.00000	52	57.0	Obesity
## 277	7	106.0000	60.00000	24	30.5	Overweight
## 278	0	104.0000	64.00000	23	116.0	Overweight
## 279	5	114.0000	74.00000	23	30.5	Normal
## 280	2	108.0000	62.00000	10	278.0	Overweight
## 281	0	146.0000	70.00000	23	30.5	Obesity
## 282	10	129.0000	76.00000	28	122.0	Obesity
## 283	7	133.0000	88.00000	15	155.0	Obesity
## 284	7	161.0000	86.00000	23	30.5	Obesity
## 285	2	108.0000	80.00000	23	30.5	Overweight
## 286	7	136.0000	74.00000	26	135.0	Overweight
## 287	5	155.0000	84.00000	44	545.0	Obesity
## 288	1	119.0000	86.00000	39	220.0	Obesity
## 289	4	96.0000	56.00000	17	49.0	Normal
## 290	5	108.0000	72.00000	43	75.0	Obesity
## 291	0	78.0000	88.00000	29	40.0	Obesity
## 292	0	107.0000	62.00000	30	74.0	Obesity
## 293	2	128.0000	78.00000	37	182.0	Obesity
## 294	1	128.0000	48.00000	45	194.0	Obesity
## 295	0	161.0000	50.00000	23	30.5	Normal
## 296	6	151.0000	62.00000	31	120.0	Obesity
## 297	2	146.0000	70.00000	38	360.0	Overweight
## 298	0	126.0000	84.00000	29	215.0	Obesity
## 299	14	100.0000	78.00000	25	184.0	Obesity
## 300	8	112.0000	72.00000	23	30.5	Normal
## 301	0	167.0000	69.10547	23	30.5	Obesity
## 302	2	144.0000	58.00000	33	135.0	Obesity
## 303	5	77.0000	82.00000	41	42.0	Obesity
## 304	5	115.0000	98.00000	23	30.5	Obesity
## 305	3	150.0000	76.00000	23	30.5	Normal

## 306	2	120.0000	76.00000	37	105.0	Obesity
## 307	10	161.0000	68.00000	23	132.0	Overweight
## 308	0	137.0000	68.00000	14	148.0	Normal
## 309	0	128.0000	68.00000	19	180.0	Obesity
## 310	2	124.0000	68.00000	28	205.0	Obesity
## 311	6	80.0000	66.00000	30	30.5	Overweight
## 312	0	106.0000	70.00000	37	148.0	Obesity
## 313	2	155.0000	74.00000	17	96.0	Overweight
## 314	3	113.0000	50.00000	10	85.0	Overweight
## 315	7	109.0000	80.00000	31	30.5	Obesity
## 316	2	112.0000	68.00000	22	94.0	Obesity
## 317	3	99.0000	80.00000	11	64.0	Normal
## 318	3	182.0000	74.00000	23	30.5	Obesity
## 319	3	115.0000	66.00000	39	140.0	Obesity
## 320	6	194.0000	78.00000	23	30.5	Normal
## 321	4	129.0000	60.00000	12	231.0	Overweight
## 322	3	112.0000	74.00000	30	30.5	Obesity
## 323	0	124.0000	70.00000	20	30.5	Overweight
## 324	13	152.0000	90.00000	33	29.0	Overweight
## 325	2	112.0000	75.00000	32	30.5	Obesity
## 326	1	157.0000	72.00000	21	168.0	Overweight
## 327	1	122.0000	64.00000	32	156.0	Obesity
## 328	10	179.0000	70.00000	23	30.5	Obesity
## 329	2	102.0000	86.00000	36	120.0	Obesity
## 330	6	105.0000	70.00000	32	68.0	Obesity
## 331	8	118.0000	72.00000	19	30.5	Normal
## 332	2	87.0000	58.00000	16	52.0	Obesity
## 333	1	180.0000	69.10547	23	30.5	Obesity
## 334	12	106.0000	80.00000	23	30.5	Normal
## 335	1	95.0000	60.00000	18	58.0	Normal
## 336	0	165.0000	76.00000	43	255.0	Obesity
## 337	0	117.0000	69.10547	23	30.5	Obesity
## 338	5	115.0000	76.00000	23	30.5	Obesity
## 339	9	152.0000	78.00000	34	171.0	Obesity
## 340	7	178.0000	84.00000	23	30.5	Obesity
## 341	1	130.0000	70.00000	13	105.0	Overweight
## 342	1	95.0000	74.00000	21	73.0	Overweight
## 343	1	120.8945	68.00000	35	30.5	Obesity
## 344	5	122.0000	86.00000	23	30.5	Obesity
## 345	8	95.0000	72.00000	23	30.5	Obesity
## 346	8	126.0000	88.00000	36	108.0	Obesity
## 347	1	139.0000	46.00000	19	83.0	Overweight
## 348	3	116.0000	69.10547	23	30.5	Normal
## 349	3	99.0000	62.00000	19	74.0	Normal
## 350	5	120.8945	80.00000	32	30.5	Obesity
## 351	4	92.0000	80.00000	23	30.5	Obesity
## 352	4	137.0000	84.00000	23	30.5	Obesity
## 353	3	61.0000	82.00000	28	30.5	Obesity
## 354	1	90.0000	62.00000	12	43.0	Overweight
## 355	3	90.0000	78.00000	23	30.5	Obesity
## 356	9	165.0000	88.00000	23	30.5	Obesity
## 357	1	125.0000	50.00000	40	167.0	Obesity
## 358	13	129.0000	69.10547	30	30.5	Obesity
## 359	12	88.0000	74.00000	40	54.0	Obesity

## 360	1	196.0000	76.00000	36	249.0	Obesity
## 361	5	189.0000	64.00000	33	325.0	Obesity
## 362	5	158.0000	70.00000	23	30.5	Overweight
## 363	5	103.0000	108.00000	37	30.5	Obesity
## 364	4	146.0000	78.00000	23	30.5	Obesity
## 365	4	147.0000	74.00000	25	293.0	Obesity
## 366	5	99.0000	54.00000	28	83.0	Obesity
## 367	6	124.0000	72.00000	23	30.5	Overweight
## 368	0	101.0000	64.00000	17	30.5	Normal
## 369	3	81.0000	86.00000	16	66.0	Overweight
## 370	1	133.0000	102.00000	28	140.0	Obesity
## 371	3	173.0000	82.00000	48	465.0	Obesity
## 372	0	118.0000	64.00000	23	89.0	Obesity
## 373	0	84.0000	64.00000	22	66.0	Obesity
## 374	2	105.0000	58.00000	40	94.0	Obesity
## 375	2	122.0000	52.00000	43	158.0	Obesity
## 376	12	140.0000	82.00000	43	325.0	Obesity
## 377	0	98.0000	82.00000	15	84.0	Overweight
## 378	1	87.0000	60.00000	37	75.0	Obesity
## 379	4	156.0000	75.00000	23	30.5	Obesity
## 380	0	93.0000	100.00000	39	72.0	Obesity
## 381	1	107.0000	72.00000	30	82.0	Obesity
## 382	0	105.0000	68.00000	22	30.5	Normal
## 383	1	109.0000	60.00000	8	182.0	Overweight
## 384	1	90.0000	62.00000	18	59.0	Overweight
## 385	1	125.0000	70.00000	24	110.0	Normal
## 386	1	119.0000	54.00000	13	50.0	Normal
## 387	5	116.0000	74.00000	29	30.5	Obesity
## 388	8	105.0000	100.00000	36	30.5	Obesity
## 389	5	144.0000	82.00000	26	285.0	Obesity
## 390	3	100.0000	68.00000	23	81.0	Obesity
## 391	1	100.0000	66.00000	29	196.0	Obesity
## 392	5	166.0000	76.00000	23	30.5	Obesity
## 393	1	131.0000	64.00000	14	415.0	Normal
## 394	4	116.0000	72.00000	12	87.0	Normal
## 395	4	158.0000	78.00000	23	30.5	Obesity
## 396	2	127.0000	58.00000	24	275.0	Overweight
## 397	3	96.0000	56.00000	34	115.0	Normal
## 398	0	131.0000	66.00000	40	30.5	Obesity
## 399	3	82.0000	70.00000	23	30.5	Normal
## 400	3	193.0000	70.00000	31	30.5	Obesity
## 401	4	95.0000	64.00000	23	30.5	Obesity
## 402	6	137.0000	61.00000	23	30.5	Normal
## 403	5	136.0000	84.00000	41	88.0	Obesity
## 404	9	72.0000	78.00000	25	30.5	Obesity
## 405	5	168.0000	64.00000	23	30.5	Obesity
## 406	2	123.0000	48.00000	32	165.0	Obesity
## 407	4	115.0000	72.00000	23	30.5	Overweight
## 408	0	101.0000	62.00000	23	30.5	Normal
## 409	8	197.0000	74.00000	23	30.5	Overweight
## 410	1	172.0000	68.00000	49	579.0	Obesity
## 411	6	102.0000	90.00000	39	30.5	Obesity
## 412	1	112.0000	72.00000	30	176.0	Obesity
## 413	1	143.0000	84.00000	23	310.0	Obesity

## 414	1	143.0000	74.00000	22	61.0	Overweight
## 415	0	138.0000	60.00000	35	167.0	Obesity
## 416	3	173.0000	84.00000	33	474.0	Obesity
## 417	1	97.0000	68.00000	21	30.5	Overweight
## 418	4	144.0000	82.00000	32	30.5	Obesity
## 419	1	83.0000	68.00000	23	30.5	Underweight
## 420	3	129.0000	64.00000	29	115.0	Overweight
## 421	1	119.0000	88.00000	41	170.0	Obesity
## 422	2	94.0000	68.00000	18	76.0	Overweight
## 423	0	102.0000	64.00000	46	78.0	Obesity
## 424	2	115.0000	64.00000	22	30.5	Obesity
## 425	8	151.0000	78.00000	32	210.0	Obesity
## 426	4	184.0000	78.00000	39	277.0	Obesity
## 427	0	94.0000	69.10547	23	30.5	Obesity
## 428	1	181.0000	64.00000	30	180.0	Obesity
## 429	0	135.0000	94.00000	46	145.0	Obesity
## 430	1	95.0000	82.00000	25	180.0	Obesity
## 431	2	99.0000	69.10547	23	30.5	Normal
## 432	3	89.0000	74.00000	16	85.0	Obesity
## 433	1	80.0000	74.00000	11	60.0	Obesity
## 434	2	139.0000	75.00000	23	30.5	Overweight
## 435	1	90.0000	68.00000	8	30.5	Normal
## 436	0	141.0000	69.10547	23	30.5	Obesity
## 437	12	140.0000	85.00000	33	30.5	Obesity
## 438	5	147.0000	75.00000	23	30.5	Overweight
## 439	1	97.0000	70.00000	15	30.5	Underweight
## 440	6	107.0000	88.00000	23	30.5	Obesity
## 441	0	189.0000	104.00000	25	30.5	Obesity
## 442	2	83.0000	66.00000	23	50.0	Obesity
## 443	4	117.0000	64.00000	27	120.0	Obesity
## 444	8	108.0000	70.00000	23	30.5	Obesity
## 445	4	117.0000	62.00000	12	30.5	Overweight
## 446	0	180.0000	78.00000	63	14.0	Obesity
## 447	1	100.0000	72.00000	12	70.0	Overweight
## 448	0	95.0000	80.00000	45	92.0	Obesity
## 449	0	104.0000	64.00000	37	64.0	Obesity
## 450	0	120.0000	74.00000	18	63.0	Obesity
## 451	1	82.0000	64.00000	13	95.0	Normal
## 452	2	134.0000	70.00000	23	30.5	Overweight
## 453	0	91.0000	68.00000	32	210.0	Obesity
## 454	2	119.0000	69.10547	23	30.5	Normal
## 455	2	100.0000	54.00000	28	105.0	Obesity
## 456	14	175.0000	62.00000	30	30.5	Obesity
## 457	1	135.0000	54.00000	23	30.5	Overweight
## 458	5	86.0000	68.00000	28	71.0	Obesity
## 459	10	148.0000	84.00000	48	237.0	Obesity
## 460	9	134.0000	74.00000	33	60.0	Overweight
## 461	9	120.0000	72.00000	22	56.0	Normal
## 462	1	71.0000	62.00000	23	30.5	Normal
## 463	8	74.0000	70.00000	40	49.0	Obesity
## 464	5	88.0000	78.00000	30	30.5	Overweight
## 465	10	115.0000	98.00000	23	30.5	Normal
## 466	0	124.0000	56.00000	13	105.0	Normal
## 467	0	74.0000	52.00000	10	36.0	Overweight



## 468	0	97.0000	64.00000	36	100.0	Obesity
## 469	8	120.0000	69.10547	23	30.5	Obesity
## 470	6	154.0000	78.00000	41	140.0	Obesity
## 471	1	144.0000	82.00000	40	30.5	Obesity
## 472	0	137.0000	70.00000	38	30.5	Obesity
## 473	0	119.0000	66.00000	27	30.5	Obesity
## 474	7	136.0000	90.00000	23	30.5	Overweight
## 475	4	114.0000	64.00000	23	30.5	Overweight
## 476	0	137.0000	84.00000	27	30.5	Overweight
## 477	2	105.0000	80.00000	45	191.0	Obesity
## 478	7	114.0000	76.00000	17	110.0	Normal
## 479	8	126.0000	74.00000	38	75.0	Overweight
## 480	4	132.0000	86.00000	31	30.5	Overweight
## 481	3	158.0000	70.00000	30	328.0	Obesity
## 482	0	123.0000	88.00000	37	30.5	Obesity
## 483	4	85.0000	58.00000	22	49.0	Overweight
## 484	0	84.0000	82.00000	31	125.0	Obesity
## 485	0	145.0000	69.10547	23	30.5	Obesity
## 486	0	135.0000	68.00000	42	250.0	Obesity
## 487	1	139.0000	62.00000	41	480.0	Obesity
## 488	0	173.0000	78.00000	32	265.0	Obesity
## 489	4	99.0000	72.00000	17	30.5	Overweight
## 490	8	194.0000	80.00000	23	30.5	Overweight
## 491	2	83.0000	65.00000	28	66.0	Obesity
## 492	2	89.0000	90.00000	30	30.5	Obesity
## 493	4	99.0000	68.00000	38	30.5	Obesity
## 494	4	125.0000	70.00000	18	122.0	Overweight
## 495	3	80.0000	69.10547	23	30.5	Obesity
## 496	6	166.0000	74.00000	23	30.5	Overweight
## 497	5	110.0000	68.00000	23	30.5	Overweight
## 498	2	81.0000	72.00000	15	76.0	Obesity
## 499	7	195.0000	70.00000	33	145.0	Overweight
## 500	6	154.0000	74.00000	32	193.0	Overweight
## 501	2	117.0000	90.00000	19	71.0	Overweight
## 502	3	84.0000	72.00000	32	30.5	Obesity
## 503	6	120.8945	68.00000	41	30.5	Obesity
## 504	7	94.0000	64.00000	25	79.0	Obesity
## 505	3	96.0000	78.00000	39	30.5	Obesity
## 506	10	75.0000	82.00000	23	30.5	Obesity
## 507	0	180.0000	90.00000	26	90.0	Obesity
## 508	1	130.0000	60.00000	23	170.0	Overweight
## 509	2	84.0000	50.00000	23	76.0	Obesity
## 510	8	120.0000	78.00000	23	30.5	Overweight
## 511	12	84.0000	72.00000	31	30.5	Overweight
## 512	0	139.0000	62.00000	17	210.0	Normal
## 513	9	91.0000	68.00000	23	30.5	Normal
## 514	2	91.0000	62.00000	23	30.5	Overweight
## 515	3	99.0000	54.00000	19	86.0	Overweight
## 516	3	163.0000	70.00000	18	105.0	Obesity
## 517	9	145.0000	88.00000	34	165.0	Obesity
## 518	7	125.0000	86.00000	23	30.5	Obesity
## 519	13	76.0000	60.00000	23	30.5	Obesity
## 520	6	129.0000	90.00000	7	326.0	Normal
## 521	2	68.0000	70.00000	32	66.0	Overweight

## 522	3	124.0000	80.00000	33	130.0	Obesity
## 523	6	114.0000	69.10547	23	30.5	Obesity
## 524	9	130.0000	70.00000	23	30.5	Obesity
## 525	3	125.0000	58.00000	23	30.5	Obesity
## 526	3	87.0000	60.00000	18	30.5	Normal
## 527	1	97.0000	64.00000	19	82.0	Underweight
## 528	3	116.0000	74.00000	15	105.0	Overweight
## 529	0	117.0000	66.00000	31	188.0	Obesity
## 530	0	111.0000	65.00000	23	30.5	Normal
## 531	2	122.0000	60.00000	18	106.0	Overweight
## 532	0	107.0000	76.00000	23	30.5	Obesity
## 533	1	86.0000	66.00000	52	65.0	Obesity
## 534	6	91.0000	69.10547	23	30.5	Overweight
## 535	1	77.0000	56.00000	30	56.0	Obesity
## 536	4	132.0000	69.10547	23	30.5	Obesity
## 537	0	105.0000	90.00000	23	30.5	Overweight
## 538	0	57.0000	60.00000	23	30.5	Normal
## 539	0	127.0000	80.00000	37	210.0	Obesity
## 540	3	129.0000	92.00000	49	155.0	Obesity
## 541	8	100.0000	74.00000	40	215.0	Obesity
## 542	3	128.0000	72.00000	25	190.0	Obesity
## 543	10	90.0000	85.00000	32	30.5	Obesity
## 544	4	84.0000	90.00000	23	56.0	Obesity
## 545	1	88.0000	78.00000	29	76.0	Obesity
## 546	8	186.0000	90.00000	35	225.0	Obesity
## 547	5	187.0000	76.00000	27	207.0	Obesity
## 548	4	131.0000	68.00000	21	166.0	Obesity
## 549	1	164.0000	82.00000	43	67.0	Obesity
## 550	4	189.0000	110.00000	31	30.5	Overweight
## 551	1	116.0000	70.00000	28	30.5	Overweight
## 552	3	84.0000	68.00000	30	106.0	Obesity
## 553	6	114.0000	88.00000	23	30.5	Overweight
## 554	1	88.0000	62.00000	24	44.0	Overweight
## 555	1	84.0000	64.00000	23	115.0	Obesity
## 556	7	124.0000	70.00000	33	215.0	Overweight
## 557	1	97.0000	70.00000	40	30.5	Obesity
## 558	8	110.0000	76.00000	23	30.5	Overweight
## 559	11	103.0000	68.00000	40	30.5	Obesity
## 560	11	85.0000	74.00000	23	30.5	Obesity
## 561	6	125.0000	76.00000	23	30.5	Obesity
## 562	0	198.0000	66.00000	32	274.0	Obesity
## 563	1	87.0000	68.00000	34	77.0	Obesity
## 564	6	99.0000	60.00000	19	54.0	Overweight
## 565	0	91.0000	80.00000	23	30.5	Obesity
## 566	2	95.0000	54.00000	14	88.0	Overweight
## 567	1	99.0000	72.00000	30	18.0	Obesity
## 568	6	92.0000	62.00000	32	126.0	Obesity
## 569	4	154.0000	72.00000	29	126.0	Obesity
## 570	0	121.0000	66.00000	30	165.0	Obesity
## 571	3	78.0000	70.00000	23	30.5	Obesity
## 572	2	130.0000	96.00000	23	30.5	Normal
## 573	3	111.0000	58.00000	31	44.0	Overweight
## 574	2	98.0000	60.00000	17	120.0	Obesity
## 575	1	143.0000	86.00000	30	330.0	Obesity

## 576	1	119.0000	44.00000	47	63.0	Obesity
## 577	6	108.0000	44.00000	20	130.0	Normal
## 578	2	118.0000	80.00000	23	30.5	Obesity
## 579	10	133.0000	68.00000	23	30.5	Overweight
## 580	2	197.0000	70.00000	99	30.5	Obesity
## 581	0	151.0000	90.00000	46	30.5	Obesity
## 582	6	109.0000	60.00000	27	30.5	Overweight
## 583	12	121.0000	78.00000	17	30.5	Overweight
## 584	8	100.0000	76.00000	23	30.5	Obesity
## 585	8	124.0000	76.00000	24	600.0	Overweight
## 586	1	93.0000	56.00000	11	30.5	Normal
## 587	8	143.0000	66.00000	23	30.5	Obesity
## 588	6	103.0000	66.00000	23	30.5	Normal
## 589	3	176.0000	86.00000	27	156.0	Obesity
## 590	0	73.0000	69.10547	23	30.5	Normal
## 591	11	111.0000	84.00000	40	30.5	Obesity
## 592	2	112.0000	78.00000	50	140.0	Obesity
## 593	3	132.0000	80.00000	23	30.5	Obesity
## 594	2	82.0000	52.00000	22	115.0	Overweight
## 595	6	123.0000	72.00000	45	230.0	Obesity
## 596	0	188.0000	82.00000	14	185.0	Obesity
## 597	0	67.0000	76.00000	23	30.5	Obesity
## 598	1	89.0000	24.00000	19	25.0	Overweight
## 599	1	173.0000	74.00000	23	30.5	Obesity
## 600	1	109.0000	38.00000	18	120.0	Normal
## 601	1	108.0000	88.00000	19	30.5	Overweight
## 602	6	96.0000	69.10547	23	30.5	Normal
## 603	1	124.0000	74.00000	36	30.5	Overweight
## 604	7	150.0000	78.00000	29	126.0	Obesity
## 605	4	183.0000	69.10547	23	30.5	Overweight
## 606	1	124.0000	60.00000	32	30.5	Obesity
## 607	1	181.0000	78.00000	42	293.0	Obesity
## 608	1	92.0000	62.00000	25	41.0	Normal
## 609	0	152.0000	82.00000	39	272.0	Obesity
## 610	1	111.0000	62.00000	13	182.0	Normal
## 611	3	106.0000	54.00000	21	158.0	Obesity
## 612	3	174.0000	58.00000	22	194.0	Obesity
## 613	7	168.0000	88.00000	42	321.0	Obesity
## 614	6	105.0000	80.00000	28	30.5	Obesity
## 615	11	138.0000	74.00000	26	144.0	Obesity
## 616	3	106.0000	72.00000	23	30.5	Overweight
## 617	6	117.0000	96.00000	23	30.5	Overweight
## 618	2	68.0000	62.00000	13	15.0	Normal
## 619	9	112.0000	82.00000	24	30.5	Overweight
## 620	0	119.0000	69.10547	23	30.5	Obesity
## 621	2	112.0000	86.00000	42	160.0	Obesity
## 622	2	92.0000	76.00000	20	30.5	Normal
## 623	6	183.0000	94.00000	23	30.5	Obesity
## 624	0	94.0000	70.00000	27	115.0	Obesity
## 625	2	108.0000	64.00000	23	30.5	Obesity
## 626	4	90.0000	88.00000	47	54.0	Obesity
## 627	0	125.0000	68.00000	23	30.5	Normal
## 628	0	132.0000	78.00000	23	30.5	Obesity
## 629	5	128.0000	80.00000	23	30.5	Obesity

## 630	4	94.0000	65.00000	22	30.5	Normal
## 631	7	114.0000	64.00000	23	30.5	Overweight
## 632	0	102.0000	78.00000	40	90.0	Obesity
## 633	2	111.0000	60.00000	23	30.5	Overweight
## 634	1	128.0000	82.00000	17	183.0	Overweight
## 635	10	92.0000	62.00000	23	30.5	Overweight
## 636	13	104.0000	72.00000	23	30.5	Obesity
## 637	5	104.0000	74.00000	23	30.5	Overweight
## 638	2	94.0000	76.00000	18	66.0	Obesity
## 639	7	97.0000	76.00000	32	91.0	Obesity
## 640	1	100.0000	74.00000	12	46.0	Normal
## 641	0	102.0000	86.00000	17	105.0	Overweight
## 642	4	128.0000	70.00000	23	30.5	Obesity
## 643	6	147.0000	80.00000	23	30.5	Overweight
## 644	4	90.0000	69.10547	23	30.5	Overweight
## 645	3	103.0000	72.00000	30	152.0	Overweight
## 646	2	157.0000	74.00000	35	440.0	Obesity
## 647	1	167.0000	74.00000	17	144.0	Normal
## 648	0	179.0000	50.00000	36	159.0	Obesity
## 649	11	136.0000	84.00000	35	130.0	Overweight
## 650	0	107.0000	60.00000	25	30.5	Overweight
## 651	1	91.0000	54.00000	25	100.0	Overweight
## 652	1	117.0000	60.00000	23	106.0	Obesity
## 653	5	123.0000	74.00000	40	77.0	Obesity
## 654	2	120.0000	54.00000	23	30.5	Overweight
## 655	1	106.0000	70.00000	28	135.0	Obesity
## 656	2	155.0000	52.00000	27	540.0	Obesity
## 657	2	101.0000	58.00000	35	90.0	Normal
## 658	1	120.0000	80.00000	48	200.0	Obesity
## 659	11	127.0000	106.00000	23	30.5	Obesity
## 660	3	80.0000	82.00000	31	70.0	Obesity
## 661	10	162.0000	84.00000	23	30.5	Overweight
## 662	1	199.0000	76.00000	43	30.5	Obesity
## 663	8	167.0000	106.00000	46	231.0	Obesity
## 664	9	145.0000	80.00000	46	130.0	Obesity
## 665	6	115.0000	60.00000	39	30.5	Obesity
## 666	1	112.0000	80.00000	45	132.0	Obesity
## 667	4	145.0000	82.00000	18	30.5	Obesity
## 668	10	111.0000	70.00000	27	30.5	Overweight
## 669	6	98.0000	58.00000	33	190.0	Obesity
## 670	9	154.0000	78.00000	30	100.0	Obesity
## 671	6	165.0000	68.00000	26	168.0	Obesity
## 672	1	99.0000	58.00000	10	30.5	Overweight
## 673	10	68.0000	106.00000	23	49.0	Obesity
## 674	3	123.0000	100.00000	35	240.0	Obesity
## 675	8	91.0000	82.00000	23	30.5	Obesity
## 676	6	195.0000	70.00000	23	30.5	Obesity
## 677	9	156.0000	86.00000	23	30.5	Normal
## 678	0	93.0000	60.00000	23	30.5	Obesity
## 679	3	121.0000	52.00000	23	30.5	Obesity
## 680	2	101.0000	58.00000	17	265.0	Normal
## 681	2	56.0000	56.00000	28	45.0	Normal
## 682	0	162.0000	76.00000	36	30.5	Obesity
## 683	0	95.0000	64.00000	39	105.0	Obesity

## 684	4	125.0000	80.00000	23	30.5	Obesity
## 685	5	136.0000	82.00000	23	30.5	Obesity
## 686	2	129.0000	74.00000	26	205.0	Obesity
## 687	3	130.0000	64.00000	23	30.5	Normal
## 688	1	107.0000	50.00000	19	30.5	Overweight
## 689	1	140.0000	74.00000	26	180.0	Normal
## 690	1	144.0000	82.00000	46	180.0	Obesity
## 691	8	107.0000	80.00000	23	30.5	Normal
## 692	13	158.0000	114.00000	23	30.5	Obesity
## 693	2	121.0000	70.00000	32	95.0	Obesity
## 694	7	129.0000	68.00000	49	125.0	Obesity
## 695	2	90.0000	60.00000	23	30.5	Normal
## 696	7	142.0000	90.00000	24	480.0	Obesity
## 697	3	169.0000	74.00000	19	125.0	Overweight
## 698	0	99.0000	69.10547	23	30.5	Overweight
## 699	4	127.0000	88.00000	11	155.0	Obesity
## 700	4	118.0000	70.00000	23	30.5	Obesity
## 701	2	122.0000	76.00000	27	200.0	Obesity
## 702	6	125.0000	78.00000	31	30.5	Overweight
## 703	1	168.0000	88.00000	29	30.5	Obesity
## 704	2	129.0000	69.10547	23	30.5	Obesity
## 705	4	110.0000	76.00000	20	100.0	Overweight
## 706	6	80.0000	80.00000	36	30.5	Obesity
## 707	10	115.0000	69.10547	23	30.5	Obesity
## 708	2	127.0000	46.00000	21	335.0	Obesity
## 709	9	164.0000	78.00000	23	30.5	Obesity
## 710	2	93.0000	64.00000	32	160.0	Obesity
## 711	3	158.0000	64.00000	13	387.0	Obesity
## 712	5	126.0000	78.00000	27	22.0	Overweight
## 713	10	129.0000	62.00000	36	30.5	Obesity
## 714	0	134.0000	58.00000	20	291.0	Overweight
## 715	3	102.0000	74.00000	23	30.5	Overweight
## 716	7	187.0000	50.00000	33	392.0	Obesity
## 717	3	173.0000	78.00000	39	185.0	Obesity
## 718	10	94.0000	72.00000	18	30.5	Normal
## 719	1	108.0000	60.00000	46	178.0	Obesity
## 720	5	97.0000	76.00000	27	30.5	Obesity
## 721	4	83.0000	86.00000	19	30.5	Overweight
## 722	1	114.0000	66.00000	36	200.0	Obesity
## 723	1	149.0000	68.00000	29	127.0	Overweight
## 724	5	117.0000	86.00000	30	105.0	Obesity
## 725	1	111.0000	94.00000	23	30.5	Obesity
## 726	4	112.0000	78.00000	40	30.5	Obesity
## 727	1	116.0000	78.00000	29	180.0	Obesity
## 728	0	141.0000	84.00000	26	30.5	Obesity
## 729	2	175.0000	88.00000	23	30.5	Normal
## 730	2	92.0000	52.00000	23	30.5	Obesity
## 731	3	130.0000	78.00000	23	79.0	Overweight
## 732	8	120.0000	86.00000	23	30.5	Overweight
## 733	2	174.0000	88.00000	37	120.0	Obesity
## 734	2	106.0000	56.00000	27	165.0	Overweight
## 735	2	105.0000	75.00000	23	30.5	Normal
## 736	4	95.0000	60.00000	32	30.5	Obesity
## 737	0	126.0000	86.00000	27	120.0	Overweight

## 738	8	65.0000	72.00000	23	30.5	Obesity
## 739	2	99.0000	60.00000	17	160.0	Obesity
## 740	1	102.0000	74.00000	23	30.5	Obesity
## 741	11	120.0000	80.00000	37	150.0	Obesity
## 742	3	102.0000	44.00000	20	94.0	Obesity
## 743	1	109.0000	58.00000	18	116.0	Overweight
## 744	9	140.0000	94.00000	23	30.5	Obesity
## 745	13	153.0000	88.00000	37	140.0	Obesity
## 746	12	100.0000	84.00000	33	105.0	Obesity
## 747	1	147.0000	94.00000	41	30.5	Obesity
## 748	1	81.0000	74.00000	41	57.0	Obesity
## 749	3	187.0000	70.00000	22	200.0	Obesity
## 750	6	162.0000	62.00000	23	30.5	Normal
## 751	4	136.0000	70.00000	23	30.5	Obesity
## 752	1	121.0000	78.00000	39	74.0	Obesity
## 753	3	108.0000	62.00000	24	30.5	Overweight
## 754	0	181.0000	88.00000	44	510.0	Obesity
## 755	8	154.0000	78.00000	32	30.5	Obesity
## 756	1	128.0000	88.00000	39	110.0	Obesity
## 757	7	137.0000	90.00000	41	30.5	Obesity
## 758	0	123.0000	72.00000	23	30.5	Obesity
## 759	1	106.0000	76.00000	23	30.5	Obesity
## 760	6	190.0000	92.00000	23	30.5	Obesity
## 761	2	88.0000	58.00000	26	16.0	Overweight
## 762	9	170.0000	74.00000	31	30.5	Obesity
## 763	9	89.0000	62.00000	23	30.5	Normal
## 764	10	101.0000	76.00000	48	180.0	Obesity
## 765	2	122.0000	70.00000	27	30.5	Obesity
## 766	5	121.0000	72.00000	23	112.0	Overweight
## 767	1	126.0000	60.00000	23	30.5	Obesity
## 768	1	93.0000	70.00000	31	30.5	Obesity

##	DiabetesPedigreeFunction	Age	Outcome
## 1	0.627	50	1
## 2	0.351	31	0
## 3	0.672	32	1
## 4	0.167	21	0
## 5	2.288	33	1
## 6	0.201	30	0
## 7	0.248	26	1
## 8	0.134	29	0
## 9	0.158	53	1
## 10	0.232	54	1
## 11	0.191	30	0
## 12	0.537	34	1
## 13	1.441	57	0
## 14	0.398	59	1
## 15	0.587	51	1
## 16	0.484	32	1
## 17	0.551	31	1
## 18	0.254	31	1
## 19	0.183	33	0
## 20	0.529	32	1
## 21	0.704	27	0
## 22	0.388	50	0

## 23	0.451	41	1
## 24	0.263	29	1
## 25	0.254	51	1
## 26	0.205	41	1
## 27	0.257	43	1
## 28	0.487	22	0
## 29	0.245	57	0
## 30	0.337	38	0
## 31	0.546	60	0
## 32	0.851	28	1
## 33	0.267	22	0
## 34	0.188	28	0
## 35	0.512	45	0
## 36	0.966	33	0
## 37	0.420	35	0
## 38	0.665	46	1
## 39	0.503	27	1
## 40	1.390	56	1
## 41	0.271	26	0
## 42	0.696	37	0
## 43	0.235	48	0
## 44	0.721	54	1
## 45	0.294	40	0
## 46	1.893	25	1
## 47	0.564	29	0
## 48	0.586	22	0
## 49	0.344	31	1
## 50	0.305	24	0
## 51	0.491	22	0
## 52	0.526	26	0
## 53	0.342	30	0
## 54	0.467	58	1
## 55	0.718	42	0
## 56	0.248	21	0
## 57	0.254	41	1
## 58	0.962	31	0
## 59	1.781	44	0
## 60	0.173	22	0
## 61	0.304	21	0
## 62	0.270	39	1
## 63	0.587	36	0
## 64	0.699	24	0
## 65	0.258	42	1
## 66	0.203	32	0
## 67	0.855	38	1
## 68	0.845	54	0
## 69	0.334	25	0
## 70	0.189	27	0
## 71	0.867	28	1
## 72	0.411	26	0
## 73	0.583	42	1
## 74	0.231	23	0
## 75	0.396	22	0
## 76	0.140	22	0

## 77	0.391	41	0
## 78	0.370	27	0
## 79	0.270	26	1
## 80	0.307	24	0
## 81	0.140	22	0
## 82	0.102	22	0
## 83	0.767	36	0
## 84	0.237	22	0
## 85	0.227	37	1
## 86	0.698	27	0
## 87	0.178	45	0
## 88	0.324	26	0
## 89	0.153	43	1
## 90	0.165	24	0
## 91	0.258	21	0
## 92	0.443	34	0
## 93	0.261	42	0
## 94	0.277	60	1
## 95	0.761	21	0
## 96	0.255	40	0
## 97	0.130	24	0
## 98	0.323	22	0
## 99	0.356	23	0
## 100	0.325	31	1
## 101	1.222	33	1
## 102	0.179	22	0
## 103	0.262	21	0
## 104	0.283	24	0
## 105	0.930	27	0
## 106	0.801	21	0
## 107	0.207	27	0
## 108	0.287	37	0
## 109	0.336	25	0
## 110	0.247	24	1
## 111	0.199	24	1
## 112	0.543	46	1
## 113	0.192	23	0
## 114	0.391	25	0
## 115	0.588	39	1
## 116	0.539	61	1
## 117	0.220	38	1
## 118	0.654	25	0
## 119	0.443	22	0
## 120	0.223	21	0
## 121	0.759	25	1
## 122	0.260	24	0
## 123	0.404	23	0
## 124	0.186	69	0
## 125	0.278	23	1
## 126	0.496	26	1
## 127	0.452	30	0
## 128	0.261	23	0
## 129	0.403	40	1
## 130	0.741	62	1



## 131	0.361	33	1
## 132	1.114	33	1
## 133	0.356	30	1
## 134	0.457	39	0
## 135	0.647	26	0
## 136	0.088	31	0
## 137	0.597	21	0
## 138	0.532	22	0
## 139	0.703	29	0
## 140	0.159	28	0
## 141	0.268	55	0
## 142	0.286	38	0
## 143	0.318	22	0
## 144	0.272	42	1
## 145	0.237	23	0
## 146	0.572	21	0
## 147	0.096	41	0
## 148	1.400	34	0
## 149	0.218	65	0
## 150	0.085	22	0
## 151	0.399	24	0
## 152	0.432	37	0
## 153	1.189	42	1
## 154	0.687	23	0
## 155	0.137	43	1
## 156	0.337	36	1
## 157	0.637	21	0
## 158	0.833	23	0
## 159	0.229	22	0
## 160	0.817	47	1
## 161	0.294	36	0
## 162	0.204	45	0
## 163	0.167	27	0
## 164	0.368	21	0
## 165	0.743	32	1
## 166	0.722	41	1
## 167	0.256	22	0
## 168	0.709	34	0
## 169	0.471	29	0
## 170	0.495	29	0
## 171	0.180	36	1
## 172	0.542	29	1
## 173	0.773	25	0
## 174	0.678	23	0
## 175	0.370	33	0
## 176	0.719	36	1
## 177	0.382	42	0
## 178	0.319	26	1
## 179	0.190	47	0
## 180	0.956	37	1
## 181	0.084	32	0
## 182	0.725	23	0
## 183	0.299	21	0
## 184	0.268	27	0

## 185	0.244	40	0
## 186	0.745	41	1
## 187	0.615	60	1
## 188	1.321	33	1
## 189	0.640	31	1
## 190	0.361	25	1
## 191	0.142	21	0
## 192	0.374	40	0
## 193	0.383	36	1
## 194	0.578	40	1
## 195	0.136	42	0
## 196	0.395	29	1
## 197	0.187	21	0
## 198	0.678	23	1
## 199	0.905	26	1
## 200	0.150	29	1
## 201	0.874	21	0
## 202	0.236	28	0
## 203	0.787	32	0
## 204	0.235	27	0
## 205	0.324	55	0
## 206	0.407	27	0
## 207	0.605	57	1
## 208	0.151	52	1
## 209	0.289	21	0
## 210	0.355	41	1
## 211	0.290	25	0
## 212	0.375	24	0
## 213	0.164	60	0
## 214	0.431	24	1
## 215	0.260	36	1
## 216	0.742	38	1
## 217	0.514	25	1
## 218	0.464	32	0
## 219	1.224	32	1
## 220	0.261	41	1
## 221	1.072	21	1
## 222	0.805	66	1
## 223	0.209	37	0
## 224	0.687	61	0
## 225	0.666	26	0
## 226	0.101	22	0
## 227	0.198	26	0
## 228	0.652	24	1
## 229	2.329	31	0
## 230	0.089	24	0
## 231	0.645	22	1
## 232	0.238	46	1
## 233	0.583	22	0
## 234	0.394	29	0
## 235	0.293	23	0
## 236	0.479	26	1
## 237	0.586	51	1
## 238	0.686	23	1

## 239	0.831	32	1
## 240	0.582	27	0
## 241	0.192	21	0
## 242	0.446	22	0
## 243	0.402	22	1
## 244	1.318	33	1
## 245	0.329	29	0
## 246	1.213	49	1
## 247	0.258	41	0
## 248	0.427	23	0
## 249	0.282	34	0
## 250	0.143	23	0
## 251	0.380	42	0
## 252	0.284	27	0
## 253	0.249	24	0
## 254	0.238	25	0
## 255	0.926	44	1
## 256	0.543	21	1
## 257	0.557	30	0
## 258	0.092	25	0
## 259	0.655	24	0
## 260	1.353	51	1
## 261	0.299	34	0
## 262	0.761	27	1
## 263	0.612	24	0
## 264	0.200	63	0
## 265	0.226	35	1
## 266	0.997	43	0
## 267	0.933	25	1
## 268	1.101	24	0
## 269	0.078	21	0
## 270	0.240	28	1
## 271	1.136	38	1
## 272	0.128	21	0
## 273	0.254	40	0
## 274	0.422	21	0
## 275	0.251	52	0
## 276	0.677	25	0
## 277	0.296	29	1
## 278	0.454	23	0
## 279	0.744	57	0
## 280	0.881	22	0
## 281	0.334	28	1
## 282	0.280	39	0
## 283	0.262	37	0
## 284	0.165	47	1
## 285	0.259	52	1
## 286	0.647	51	0
## 287	0.619	34	0
## 288	0.808	29	1
## 289	0.340	26	0
## 290	0.263	33	0
## 291	0.434	21	0
## 292	0.757	25	1

## 293	1.224	31	1
## 294	0.613	24	1
## 295	0.254	65	0
## 296	0.692	28	0
## 297	0.337	29	1
## 298	0.520	24	0
## 299	0.412	46	1
## 300	0.840	58	0
## 301	0.839	30	1
## 302	0.422	25	1
## 303	0.156	35	0
## 304	0.209	28	1
## 305	0.207	37	0
## 306	0.215	29	0
## 307	0.326	47	1
## 308	0.143	21	0
## 309	1.391	25	1
## 310	0.875	30	1
## 311	0.313	41	0
## 312	0.605	22	0
## 313	0.433	27	1
## 314	0.626	25	0
## 315	1.127	43	1
## 316	0.315	26	0
## 317	0.284	30	0
## 318	0.345	29	1
## 319	0.150	28	0
## 320	0.129	59	1
## 321	0.527	31	0
## 322	0.197	25	1
## 323	0.254	36	1
## 324	0.731	43	1
## 325	0.148	21	0
## 326	0.123	24	0
## 327	0.692	30	1
## 328	0.200	37	0
## 329	0.127	23	1
## 330	0.122	37	0
## 331	1.476	46	0
## 332	0.166	25	0
## 333	0.282	41	1
## 334	0.137	44	0
## 335	0.260	22	0
## 336	0.259	26	0
## 337	0.932	44	0
## 338	0.343	44	1
## 339	0.893	33	1
## 340	0.331	41	1
## 341	0.472	22	0
## 342	0.673	36	0
## 343	0.389	22	0
## 344	0.290	33	0
## 345	0.485	57	0
## 346	0.349	49	0

## 347	0.654	22	0
## 348	0.187	23	0
## 349	0.279	26	0
## 350	0.346	37	1
## 351	0.237	29	0
## 352	0.252	30	0
## 353	0.243	46	0
## 354	0.580	24	0
## 355	0.559	21	0
## 356	0.302	49	1
## 357	0.962	28	1
## 358	0.569	44	1
## 359	0.378	48	0
## 360	0.875	29	1
## 361	0.583	29	1
## 362	0.207	63	0
## 363	0.305	65	0
## 364	0.520	67	1
## 365	0.385	30	0
## 366	0.499	30	0
## 367	0.368	29	1
## 368	0.252	21	0
## 369	0.306	22	0
## 370	0.234	45	1
## 371	2.137	25	1
## 372	1.731	21	0
## 373	0.545	21	0
## 374	0.225	25	0
## 375	0.816	28	0
## 376	0.528	58	1
## 377	0.299	22	0
## 378	0.509	22	0
## 379	0.238	32	1
## 380	1.021	35	0
## 381	0.821	24	0
## 382	0.236	22	0
## 383	0.947	21	0
## 384	1.268	25	0
## 385	0.221	25	0
## 386	0.205	24	0
## 387	0.660	35	1
## 388	0.239	45	1
## 389	0.452	58	1
## 390	0.949	28	0
## 391	0.444	42	0
## 392	0.340	27	1
## 393	0.389	21	0
## 394	0.463	37	0
## 395	0.803	31	1
## 396	1.600	25	0
## 397	0.944	39	0
## 398	0.196	22	1
## 399	0.389	25	0
## 400	0.241	25	1

## 401	0.161	31	1
## 402	0.151	55	0
## 403	0.286	35	1
## 404	0.280	38	0
## 405	0.135	41	1
## 406	0.520	26	0
## 407	0.376	46	1
## 408	0.336	25	0
## 409	1.191	39	1
## 410	0.702	28	1
## 411	0.674	28	0
## 412	0.528	25	0
## 413	1.076	22	0
## 414	0.256	21	0
## 415	0.534	21	1
## 416	0.258	22	1
## 417	1.095	22	0
## 418	0.554	37	1
## 419	0.624	27	0
## 420	0.219	28	1
## 421	0.507	26	0
## 422	0.561	21	0
## 423	0.496	21	0
## 424	0.421	21	0
## 425	0.516	36	1
## 426	0.264	31	1
## 427	0.256	25	0
## 428	0.328	38	1
## 429	0.284	26	0
## 430	0.233	43	1
## 431	0.108	23	0
## 432	0.551	38	0
## 433	0.527	22	0
## 434	0.167	29	0
## 435	1.138	36	0
## 436	0.205	29	1
## 437	0.244	41	0
## 438	0.434	28	0
## 439	0.147	21	0
## 440	0.727	31	0
## 441	0.435	41	1
## 442	0.497	22	0
## 443	0.230	24	0
## 444	0.955	33	1
## 445	0.380	30	1
## 446	2.420	25	1
## 447	0.658	28	0
## 448	0.330	26	0
## 449	0.510	22	1
## 450	0.285	26	0
## 451	0.415	23	0
## 452	0.542	23	1
## 453	0.381	25	0
## 454	0.832	72	0

## 455	0.498	24	0
## 456	0.212	38	1
## 457	0.687	62	0
## 458	0.364	24	0
## 459	1.001	51	1
## 460	0.460	81	0
## 461	0.733	48	0
## 462	0.416	26	0
## 463	0.705	39	0
## 464	0.258	37	0
## 465	1.022	34	0
## 466	0.452	21	0
## 467	0.269	22	0
## 468	0.600	25	0
## 469	0.183	38	1
## 470	0.571	27	0
## 471	0.607	28	0
## 472	0.170	22	0
## 473	0.259	22	0
## 474	0.210	50	0
## 475	0.126	24	0
## 476	0.231	59	0
## 477	0.711	29	1
## 478	0.466	31	0
## 479	0.162	39	0
## 480	0.419	63	0
## 481	0.344	35	1
## 482	0.197	29	0
## 483	0.306	28	0
## 484	0.233	23	0
## 485	0.630	31	1
## 486	0.365	24	1
## 487	0.536	21	0
## 488	1.159	58	0
## 489	0.294	28	0
## 490	0.551	67	0
## 491	0.629	24	0
## 492	0.292	42	0
## 493	0.145	33	0
## 494	1.144	45	1
## 495	0.174	22	0
## 496	0.304	66	0
## 497	0.292	30	0
## 498	0.547	25	0
## 499	0.163	55	1
## 500	0.839	39	0
## 501	0.313	21	0
## 502	0.267	28	0
## 503	0.727	41	1
## 504	0.738	41	0
## 505	0.238	40	0
## 506	0.263	38	0
## 507	0.314	35	1
## 508	0.692	21	0

## 509	0.968	21	0
## 510	0.409	64	0
## 511	0.297	46	1
## 512	0.207	21	0
## 513	0.200	58	0
## 514	0.525	22	0
## 515	0.154	24	0
## 516	0.268	28	1
## 517	0.771	53	1
## 518	0.304	51	0
## 519	0.180	41	0
## 520	0.582	60	0
## 521	0.187	25	0
## 522	0.305	26	0
## 523	0.189	26	0
## 524	0.652	45	1
## 525	0.151	24	0
## 526	0.444	21	0
## 527	0.299	21	0
## 528	0.107	24	0
## 529	0.493	22	0
## 530	0.660	31	0
## 531	0.717	22	0
## 532	0.686	24	0
## 533	0.917	29	0
## 534	0.501	31	0
## 535	1.251	24	0
## 536	0.302	23	1
## 537	0.197	46	0
## 538	0.735	67	0
## 539	0.804	23	0
## 540	0.968	32	1
## 541	0.661	43	1
## 542	0.549	27	1
## 543	0.825	56	1
## 544	0.159	25	0
## 545	0.365	29	0
## 546	0.423	37	1
## 547	1.034	53	1
## 548	0.160	28	0
## 549	0.341	50	0
## 550	0.680	37	0
## 551	0.204	21	0
## 552	0.591	25	0
## 553	0.247	66	0
## 554	0.422	23	0
## 555	0.471	28	0
## 556	0.161	37	0
## 557	0.218	30	0
## 558	0.237	58	0
## 559	0.126	42	0
## 560	0.300	35	0
## 561	0.121	54	1
## 562	0.502	28	1



## 563	0.401	24	0
## 564	0.497	32	0
## 565	0.601	27	0
## 566	0.748	22	0
## 567	0.412	21	0
## 568	0.085	46	0
## 569	0.338	37	0
## 570	0.203	33	1
## 571	0.270	39	0
## 572	0.268	21	0
## 573	0.430	22	0
## 574	0.198	22	0
## 575	0.892	23	0
## 576	0.280	25	0
## 577	0.813	35	0
## 578	0.693	21	1
## 579	0.245	36	0
## 580	0.575	62	1
## 581	0.371	21	1
## 582	0.206	27	0
## 583	0.259	62	0
## 584	0.190	42	0
## 585	0.687	52	1
## 586	0.417	22	0
## 587	0.129	41	1
## 588	0.249	29	0
## 589	1.154	52	1
## 590	0.342	25	0
## 591	0.925	45	1
## 592	0.175	24	0
## 593	0.402	44	1
## 594	1.699	25	0
## 595	0.733	34	0
## 596	0.682	22	1
## 597	0.194	46	0
## 598	0.559	21	0
## 599	0.088	38	1
## 600	0.407	26	0
## 601	0.400	24	0
## 602	0.190	28	0
## 603	0.100	30	0
## 604	0.692	54	1
## 605	0.212	36	1
## 606	0.514	21	0
## 607	1.258	22	1
## 608	0.482	25	0
## 609	0.270	27	0
## 610	0.138	23	0
## 611	0.292	24	0
## 612	0.593	36	1
## 613	0.787	40	1
## 614	0.878	26	0
## 615	0.557	50	1
## 616	0.207	27	0

## 617	0.157	30	0
## 618	0.257	23	0
## 619	1.282	50	1
## 620	0.141	24	1
## 621	0.246	28	0
## 622	1.698	28	0
## 623	1.461	45	0
## 624	0.347	21	0
## 625	0.158	21	0
## 626	0.362	29	0
## 627	0.206	21	0
## 628	0.393	21	0
## 629	0.144	45	0
## 630	0.148	21	0
## 631	0.732	34	1
## 632	0.238	24	0
## 633	0.343	23	0
## 634	0.115	22	0
## 635	0.167	31	0
## 636	0.465	38	1
## 637	0.153	48	0
## 638	0.649	23	0
## 639	0.871	32	1
## 640	0.149	28	0
## 641	0.695	27	0
## 642	0.303	24	0
## 643	0.178	50	1
## 644	0.610	31	0
## 645	0.730	27	0
## 646	0.134	30	0
## 647	0.447	33	1
## 648	0.455	22	1
## 649	0.260	42	1
## 650	0.133	23	0
## 651	0.234	23	0
## 652	0.466	27	0
## 653	0.269	28	0
## 654	0.455	27	0
## 655	0.142	22	0
## 656	0.240	25	1
## 657	0.155	22	0
## 658	1.162	41	0
## 659	0.190	51	0
## 660	1.292	27	1
## 661	0.182	54	0
## 662	1.394	22	1
## 663	0.165	43	1
## 664	0.637	40	1
## 665	0.245	40	1
## 666	0.217	24	0
## 667	0.235	70	1
## 668	0.141	40	1
## 669	0.430	43	0
## 670	0.164	45	0

## 671	0.631	49	0
## 672	0.551	21	0
## 673	0.285	47	0
## 674	0.880	22	0
## 675	0.587	68	0
## 676	0.328	31	1
## 677	0.230	53	1
## 678	0.263	25	0
## 679	0.127	25	1
## 680	0.614	23	0
## 681	0.332	22	0
## 682	0.364	26	1
## 683	0.366	22	0
## 684	0.536	27	1
## 685	0.640	69	0
## 686	0.591	25	0
## 687	0.314	22	0
## 688	0.181	29	0
## 689	0.828	23	0
## 690	0.335	46	1
## 691	0.856	34	0
## 692	0.257	44	1
## 693	0.886	23	0
## 694	0.439	43	1
## 695	0.191	25	0
## 696	0.128	43	1
## 697	0.268	31	1
## 698	0.253	22	0
## 699	0.598	28	0
## 700	0.904	26	0
## 701	0.483	26	0
## 702	0.565	49	1
## 703	0.905	52	1
## 704	0.304	41	0
## 705	0.118	27	0
## 706	0.177	28	0
## 707	0.261	30	1
## 708	0.176	22	0
## 709	0.148	45	1
## 710	0.674	23	1
## 711	0.295	24	0
## 712	0.439	40	0
## 713	0.441	38	1
## 714	0.352	21	0
## 715	0.121	32	0
## 716	0.826	34	1
## 717	0.970	31	1
## 718	0.595	56	0
## 719	0.415	24	0
## 720	0.378	52	1
## 721	0.317	34	0
## 722	0.289	21	0
## 723	0.349	42	1
## 724	0.251	42	0

## 725	0.265	45	0
## 726	0.236	38	0
## 727	0.496	25	0
## 728	0.433	22	0
## 729	0.326	22	0
## 730	0.141	22	0
## 731	0.323	34	1
## 732	0.259	22	1
## 733	0.646	24	1
## 734	0.426	22	0
## 735	0.560	53	0
## 736	0.284	28	0
## 737	0.515	21	0
## 738	0.600	42	0
## 739	0.453	21	0
## 740	0.293	42	1
## 741	0.785	48	1
## 742	0.400	26	0
## 743	0.219	22	0
## 744	0.734	45	1
## 745	1.174	39	0
## 746	0.488	46	0
## 747	0.358	27	1
## 748	1.096	32	0
## 749	0.408	36	1
## 750	0.178	50	1
## 751	1.182	22	1
## 752	0.261	28	0
## 753	0.223	25	0
## 754	0.222	26	1
## 755	0.443	45	1
## 756	1.057	37	1
## 757	0.391	39	0
## 758	0.258	52	1
## 759	0.197	26	0
## 760	0.278	66	1
## 761	0.766	22	0
## 762	0.403	43	1
## 763	0.142	33	0
## 764	0.171	63	0
## 765	0.340	27	0
## 766	0.245	30	0
## 767	0.349	47	1
## 768	0.315	23	0

First, we categorized the BMI category into Underweight, Normal, Overweight, and Obesity.

**\*\* Obesity vs Outcome\*\***

```
counts <- as.data.frame(with(df.temp, table(BMI, Outcome)))
colnames(counts) <- c("BMI", "Outcome", "Freq")

counts <- counts %>%
  group_by(BMI) %>%
```

```

mutate(prop = Freq / sum(Freq))

outcome_colors <- c("1" = 'salmon', "0" = 'lightyellow')

plot_ly(
  data = counts,
  x = ~BMI,
  y = ~prop,
  color = ~Outcome,
  colors = outcome_colors,
  type = "bar"
) %>%
  layout(
    title = "Proportion of Outcomes by BMI Category",
    barmode = "stack",
    xaxis = list(title = "BMI", categoryorder = "array", categoryarray = c("Underweight", "Normal", "Overweight")),
    yaxis = list(title = "Frequency"),
    legend = list(title = list(text = "Outcome", font = list(size = 15, color = "black")))
  )

```

The graph shows that there is no Underweight individual that has diabetes, only 6.9% individuals with Normal BMI that have diabetes, 22.3% Overweight individuals in fact have diabetes, and lastly, 45.8% individuals that have obesity also suffer from diabetes.

Here we can conclude that individuals that classified as Overweight and Obese have significantly higher risk of having diabetes compared to those with a Normal BMI or who are Underweight. So it is crucial to maintain a healthy BMI to reduce the risk of diabetes.

### Age vs Outcome

```

age_counts <- as.data.frame(with(df, table(Age, Outcome)))
colnames(age_counts) <- c("Age", "Outcome", "Freq")

age_counts <- age_counts %>%
  group_by(Age) %>%
  mutate(prop = Freq / sum(Freq))

outcome_colors <- c('0' = '#FFDD0', '1' = 'lightblue')

# Plot the stacked bar chart with Plotly
plot_ly(
  data = age_counts,
  x = ~Age,
  y = ~prop,
  color = ~Outcome,
  colors = outcome_colors,
  type = "bar"
) %>%
  layout(
    barmode = "stack",
    xaxis = list(title = "Age"),
    yaxis = list(title = "Frequency")
  )

```

There is higher proportion of outcome 0 (non-diabetical) in younger individuals between ages 20 to 35, with

gradual decrease in frequencies in between. Between the age of 36 to 54, the outcome 1 (diabetical) start to become dominant where it is more common than outcome 0. From age 55 and above the green bars (diabetical) is continue to dominate.

This suggest that non-diabetical is more relevant to younger people, while diabetes issue becomes increasingly common as people starting to age, dominating in the older age groups.

## How heredity affect diabetes?

### DiabetesPedigreeFunction vs Outcome

```
pedigree_counts <- as.data.frame(with(df, table(DiabetesPedigreeFunction, Outcome)))
colnames(pedigree_counts) <- c("DiabetesPedigreeFunction", "Outcome", "Freq")

pedigree_counts <- pedigree_counts %>%
  group_by(DiabetesPedigreeFunction) %>%
  mutate(propp = Freq / sum(Freq))

# Plotting the scatter plot
plot_ly(
  data = pedigree_counts,
  x = ~DiabetesPedigreeFunction,
  y = ~propp,
  type = "bar",
  #mode = "lines+markers",
  jitter = 0.1,
  color = ~Outcome,
  colors = c('0' = 'lightyellow', '1' = 'red')
) %>%
layout(
  title = "Proportion of Outcomes by Diabetes Pedigree Function",
  xaxis = list(title = "Diabetes Pedigree Function"),
  yaxis = list(title = "Frequency")
)
```

From the graph we can see, at lower values of DiabetesPedigreeFunction, there are more yellow bars, showing there is a higher proportion of non-diabetical individuals. But as the DiabetesPedigreeFunction value increase the proportion of diabetic individuals (red bars) is also increasing.

We can conclude that DiabetesPedigreeFunction is in fact affect the Outcome of diabetes, with a positive linear relationship.

## Why DiabetesS is a problem?

```
count_data <- df %>%
  group_by(BloodPressure, Outcome) %>%
  summarise(Count = n()) %>%
  ungroup()

count_data_0 <- count_data %>% filter(Outcome == 0)
count_data_1 <- count_data %>% filter(Outcome == 1)
```

```

fig <- plot_ly()

fig <- fig %>% add_trace(
  x = ~count_data_0$BloodPressure,
  y = ~count_data_0$Count,
  type = "scatter",
  mode = "lines",
  name = "No Diabetes",
  line = list(color = 'darkred') # Darker shade of red
)

fig <- fig %>% add_trace(
  x = ~count_data_1$BloodPressure,
  y = ~count_data_1$Count,
  type = "scatter",
  mode = "lines+markers",
  name = "Has Diabetes",
  line = list(color = 'red')
)

fig <- fig %>% layout(
  title = "Distributions Blood Pressure by Outcome",
  xaxis = list(title = "Blood Pressure"),
  yaxis = list(title = "Count"),
  legend = list(title = list(text = 'Outcome'))
)

fig

```

From the graph, we can see that both groups have a quite similar range of blood pressure values, with non-diabetical's bloodPressure range from 24 to 122 mm hg, and diabetical's bloodPressure range from 30 to 144 mm hg. This shows that there is possible increase of blood pressure in individuals with diabetes and it is crucial for people with diabetes to continue monitoring their blood pressure to prevent further complications.

## d) DATA ANOMALIES/OUTLIERS

### ThreeSigma, Hampel, Boxplot Rule

```

# nMiss for missing value, nOut for outlier
# lowLim upLim, lower and upper outlier detection limits

find_outliers_summary <- function(x){
  outliers <- FindOutliers(x)
  return(outliers$summary)
}

summary_list <- lapply(df, find_outliers_summary)
summary_list

## $Pregnancies

```

```

##          method    n nMiss nOut    lowLim    upLim minNom maxNom
## 1  ThreeSigma 768      0   4 -6.263682 13.95379      0    13
## 2    Hampel 768      0  23 -5.895600 11.89560      0    11
## 3 BoxplotRule 768      0   4 -1.500000 13.50000      0    13
##
## $Glucose
##          method    n nMiss nOut    lowLim    upLim minNom maxNom
## 1  ThreeSigma 768      0   0 30.37356 212.9897     44    199
## 2    Hampel 768      0   0 28.04400 205.9560     44    199
## 3 BoxplotRule 768      0  36 79.50000 201.0000     80    199
##
## $BloodPressure
##          method    n nMiss nOut    lowLim    upLim minNom maxNom
## 1  ThreeSigma 768      0   8 35.90701 108.6026     38    108
## 2    Hampel 768      0  10 36.41760 107.5824     38    106
## 3 BoxplotRule 768      0  63 56.00000 104.0000     56    104
##
## $SkinThickness
##          method    n nMiss nOut    lowLim    upLim minNom maxNom
## 1  ThreeSigma 768      0   4 -0.3524075 55.02168      7     54
## 2    Hampel 768      0  31 0.7610000 45.23900      7     45
## 3 BoxplotRule 768      0 124 18.5000000 45.50000     19     45
##
## $Insulin
##          method    n nMiss nOut    lowLim    upLim minNom maxNom
## 1  ThreeSigma 768      0  19 -221.99045 411.29514     14    402
## 2    Hampel 768      0 316  -5.44435  67.94435     14     67
## 3 BoxplotRule 768      0  49 -17.87500 272.37500     14    272
##
## $BMI
##          method    n nMiss nOut    lowLim    upLim minNom maxNom
## 1  ThreeSigma 768      0   5 11.82468 53.07693    18.2    52.9
## 2    Hampel 768      0   8 11.98490 52.01510    18.2    50.0
## 3 BoxplotRule 768      0  58 22.95000 50.25000    23.0    50.0
##
## $DiabetesPedigreeFunction
##          method    n nMiss nOut    lowLim    upLim minNom maxNom
## 1  ThreeSigma 768      0  11 -0.5221095 1.465862  0.078  1.461
## 2    Hampel 768      0  40 -0.3725065 1.117506  0.078  1.114
## 3 BoxplotRule 768      0  29 0.0525000 1.200000  0.078  1.191
##
## $Age
##          method    n nMiss nOut    lowLim    upLim minNom maxNom
## 1  ThreeSigma 768      0   5 -2.039809 68.52158     21     68
## 2    Hampel 768      0  27 -2.134600 60.13460     21     60
## 3 BoxplotRule 768      0   9 15.500000 66.50000     21     66
##
## $Outcome
##          method    n nMiss nOut    lowLim    upLim minNom maxNom
## 1  ThreeSigma 768      0   0 -1.081896 1.779812      0      1
## 2    Hampel 768      0 268 0.000000 0.000000      0      0
## 3 BoxplotRule 768      0   0 -0.500000 2.500000      0      1

```

Number of outliers using ThreeSigma method:



- Pregnancies : 4
- Glucose : 0
- BloodPressure : 8
- SkinThickness : 4
- Insulin : 19
- BMI : 5
- DiabetesPedigreeFunction : 11
- Age : 5 - Outcome : 0

Number of outliers using Hampel method:

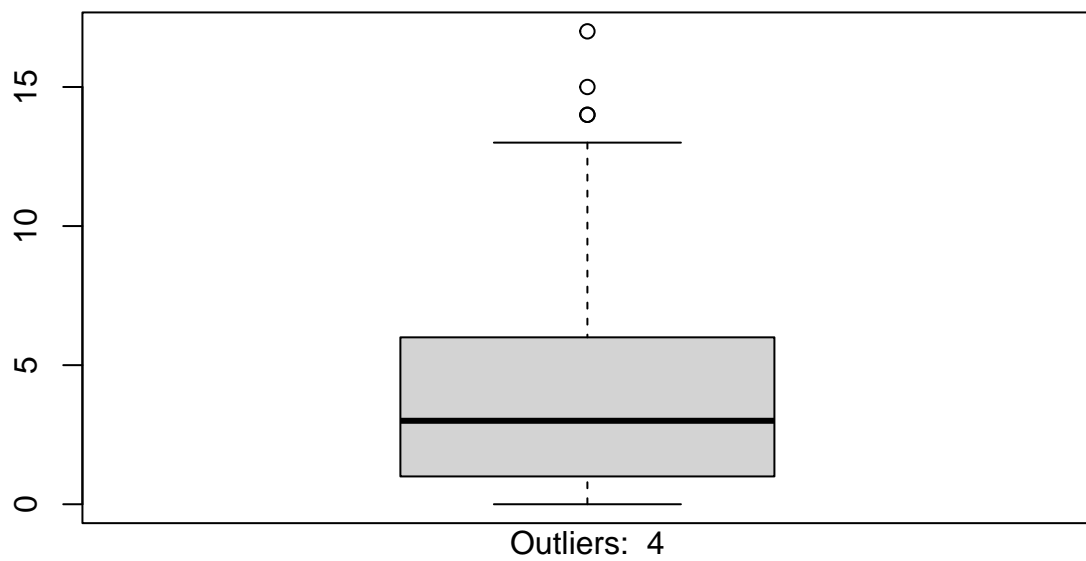
- Pregnancies : 23
- Glucose : 0
- BloodPressure : 10
- SkinThickness : 31
- Insulin : 316
- BMI : 8
- DiabetesPedigreeFunction : 40
- Age : 27
- Outcome : 268

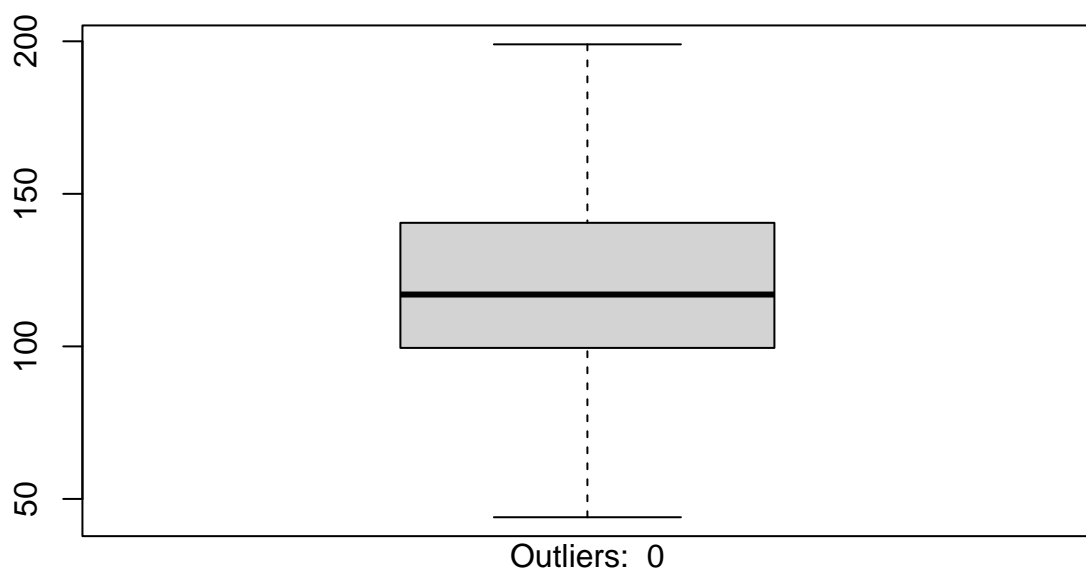
Number of outliers using BoxplotRule method:

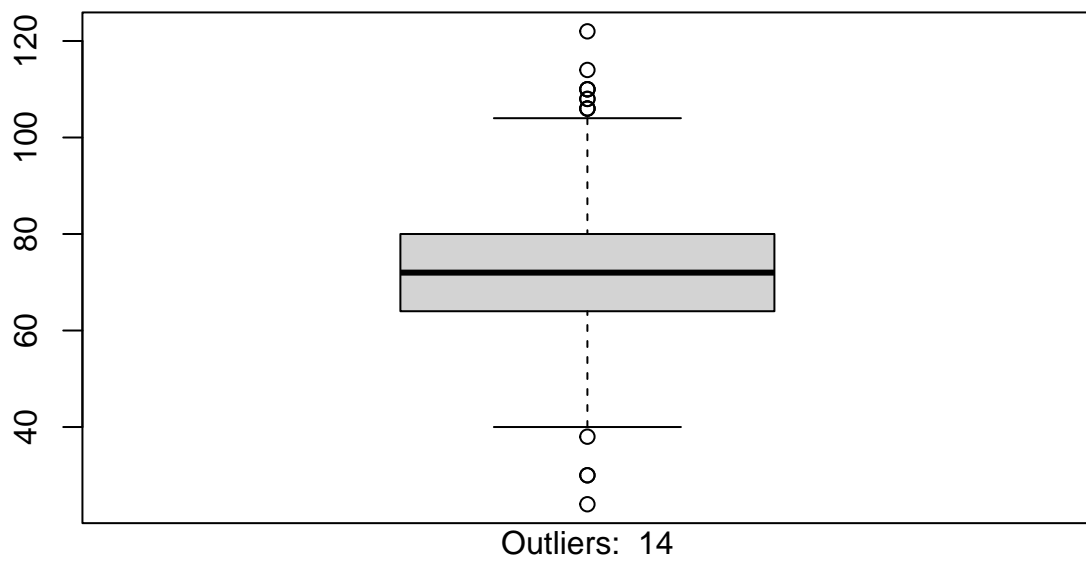
- Pregnancies : 4
- Glucose : 36
- BloodPressure : 63
- SkinThickness : 124
- Insulin : 49
- BMI : 58
- DiabetesPedigreeFunction : 29
- Age : 9 - Outcome : 0

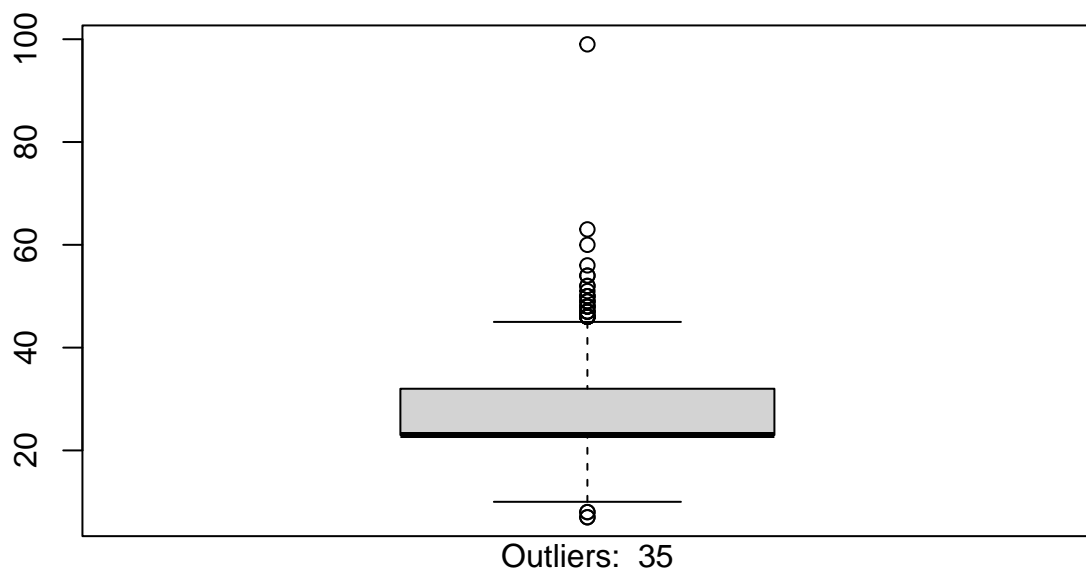
**using boxplot**

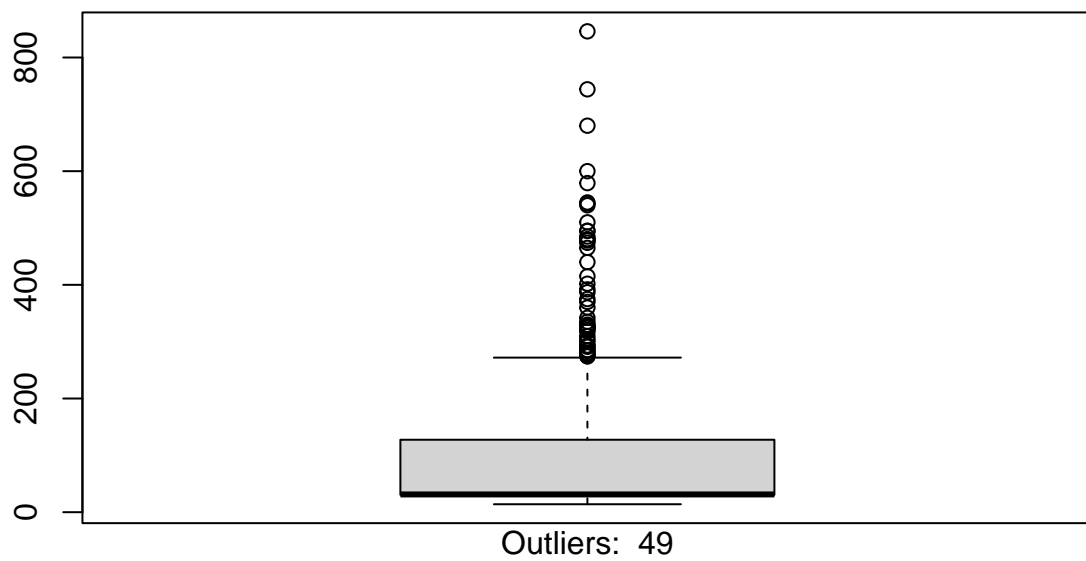
```
count_outliers <- function(x) {  
  bp <- boxplot(x, plot = FALSE)  
  out <- length(bp$out)  
  boxplot(x)  
  mtext(paste("Outliers: ", out), side = 1)  
}  
  
sapply(df, count_outliers)
```

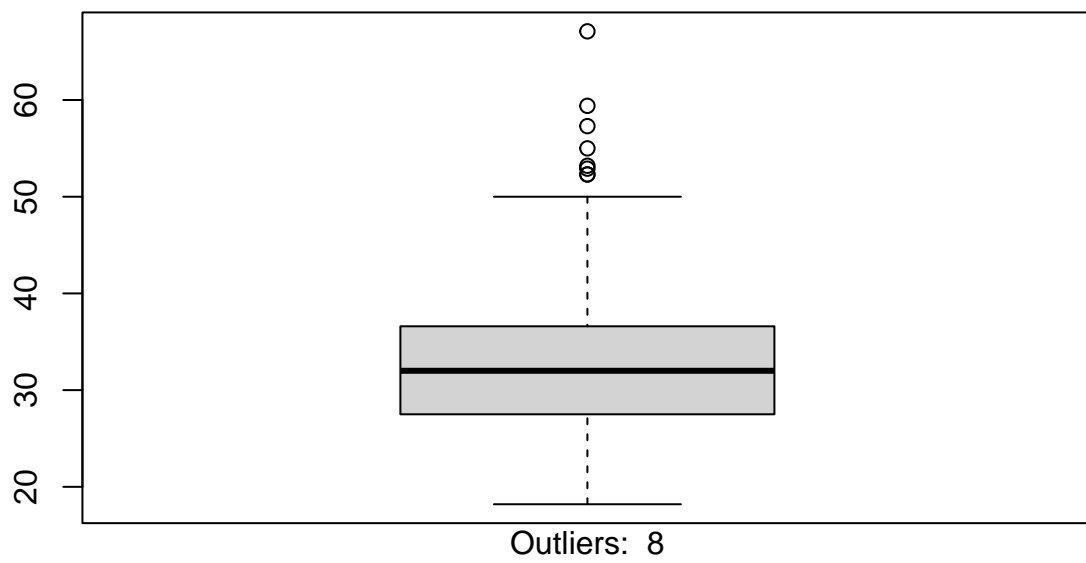


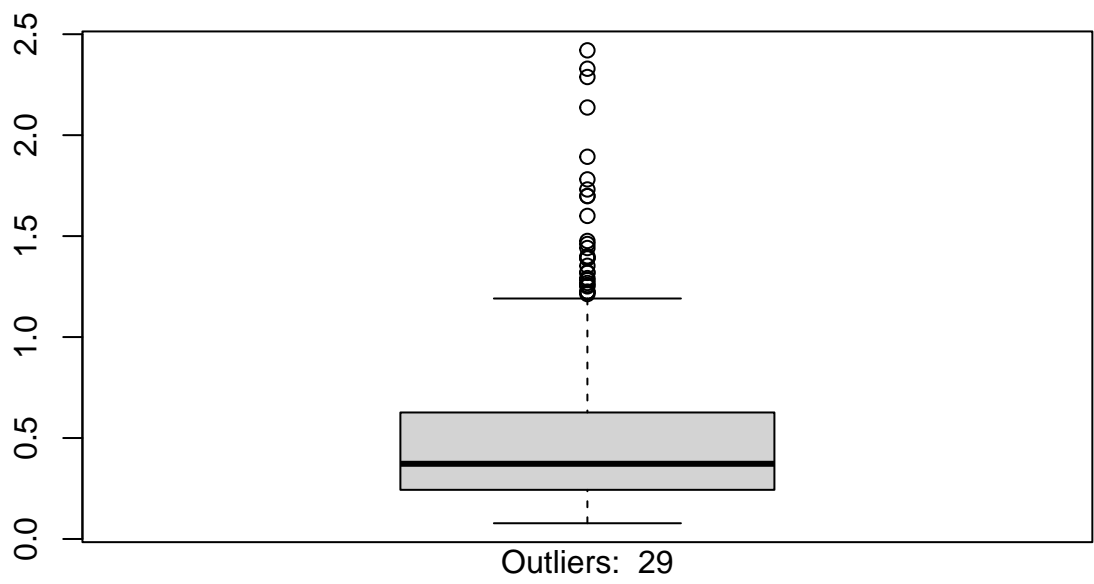




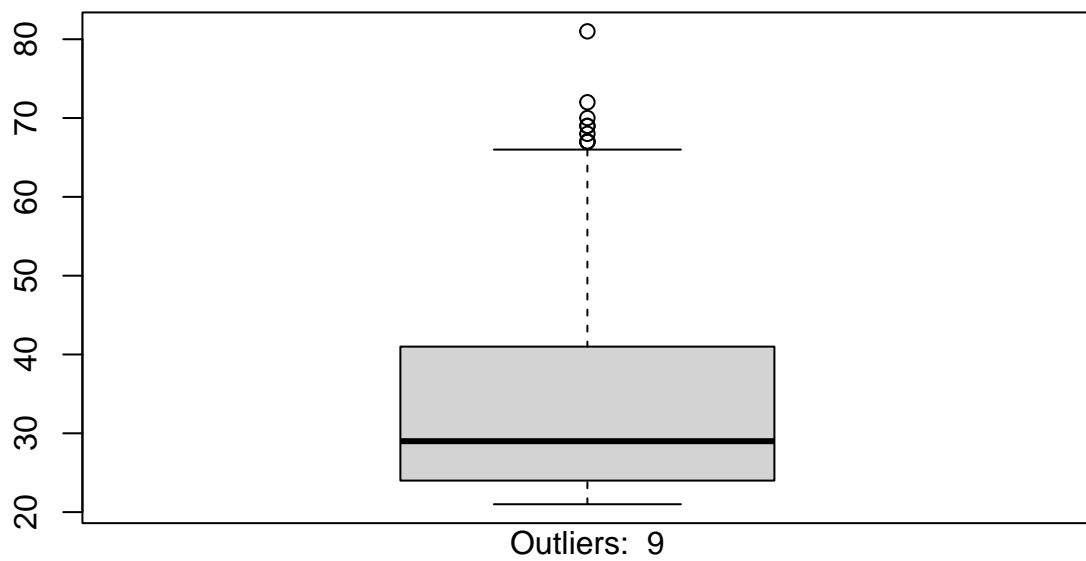














```
## $Pregnancies
## NULL
##
## $Glucose
## NULL
##
## $BloodPressure
## NULL
##
## $SkinThickness
## NULL
##
## $Insulin
## NULL
##
## $BMI
## NULL
##
## $DiabetesPedigreeFunction
## NULL
##
## $Age
## NULL
##
## $Outcome
## NULL
```

The numbers of outlier using boxplot:

- Pregnancies : 4
- Glucose : 0
- BloodPressure : 14
- SkinThickness : 35
- Insulin : 49
- BMI : 8
- DiabetesPedigreeFunction : 29
- Age : 9 - Outcome : 0

### Using formula

```
count_outliers2 <- function(x) {  
  q1 <- quantile(x, p = 0.25)  
  q3 <- quantile(x, p = 0.75)  
  iqr <- IQR(x)  
  # determine outliers  
  outliers <- ifelse(x < q1 - 1.5 * iqr | x > q3 + 1.5 * iqr, TRUE, FALSE)  
  # sum of outliers  
  num_outliers <- sum(outliers)  
  
  return(num_outliers)  
}  
  
num_outliers <- sapply(df, count_outliers2)  
print(num_outliers)
```

##	Pregnancies	Glucose	BloodPressure
##	4	0	14
##	SkinThickness	Insulin	BMI
##	35	49	8
##	DiabetesPedigreeFunction	Age	Outcome
##	29	9	0

## 5. STATISTICAL ANALYSIS

### a) Checking Precondition

shapiro-wilk test

```
shapiro.test(df$Glucose)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: df$Glucose  
## W = 0.96986, p-value = 1.733e-11
```

```
shapiro.test(df$BloodPressure)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: df$BloodPressure  
## W = 0.98782, p-value = 5.255e-06
```

```
shapiro.test(df$SkinThickness)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: df$SkinThickness  
## W = 0.91367, p-value < 2.2e-16
```

```
shapiro.test(df$Insulin)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: df$Insulin  
## W = 0.66564, p-value < 2.2e-16
```

```
shapiro.test(df$BMI)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: df$BMI  
## W = 0.9794, p-value = 6.247e-09
```

```
shapiro.test(df$DiabetesPedigreeFunction)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: df$DiabetesPedigreeFunction  
## W = 0.83652, p-value < 2.2e-16
```

```
shapiro.test(df$Outcome)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: df$Outcome  
## W = 0.60251, p-value < 2.2e-16
```

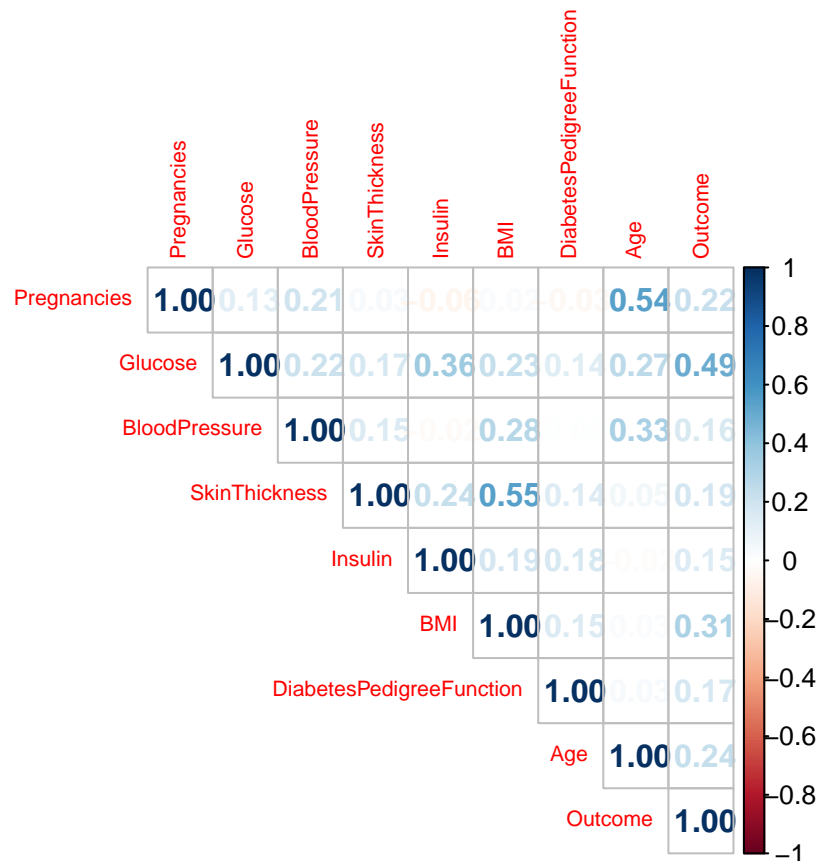
The Shapiro-Wilk tests shows that none of these variables has a normal distribution (mostly because outliers). The low p-values (all < 0.05) indicate strong evidence against the assumption of normality, thus we accept the null hypothesis of non-normality.

Although most of the variables didn't pass the normality test, we are still going to check the relationship between them.

## b) Find Correlation

### Correlation Plot

```
c <- cor(df)
corrplot(c, type = "upper", method = "number", tl.cex = 0.7)
```



Here we can see there are variables that have a quite strong relationship:

1. SkinThickness vs Insulin = obesity and the insulin resistant
2. Age vs Pregnancies
3. Glucose vs Outcomes = result of OGTT for people with diabetes
4. Glucose vs Insulin
5. BloodPressure vs Age
6. BMI vs Outcome

### Pearson's Correlation

```
correlation1 <- cor.test(df$Glucose, df$Outcome, method = "pearson")
correlation1
```

```
##
## Pearson's product-moment correlation
##
## data: df$Glucose and df$Outcome
## t = 15.679, df = 766, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
```

```
## 0.4374171 0.5446602
## sample estimates:
##      cor
## 0.4929084
```

Correlation Coefficient (cor): The test shows a statistically significant positive correlation between Glucose and Outcome, though the strength of the correlation is relatively strong (0.49).

Significance (p-value): The p-value of 2.2e-16 is very small (less than 0.05), suggesting strong evidence against the null hypothesis. Therefore, we reject the null hypothesis that there is no correlation between Glucose and Outcome.

Confidence Interval: We are 95% confident that the true population correlation coefficient falls between 0.4374171 and 0.5446602.

Conclusion:

There is a statistically significant, strong-positive correlation ( $r = 0.4929084$ ) between Glucose and Outcome. This suggests that as Glucose increases, there tends to be a significant increase in the Outcome. However, the correlation is strong, as the correlation coefficient is relatively close to one. In summary, while there is a statistically significant positive correlation between Glucose and Outcome, and so ( $r^2 = 0.24295015047576$ ), 24.3% variance of the Outcome can be explained by knowing the Glucose level. So, Glucose alone may not be a strong predictor of Outcome (diabetes). Other factors likely contribute more significantly to determining the outcome.

```
correlation2 <- cor.test(df$Insulin, df$Outcome, method = "pearson")
correlation2
```

```
##
## Pearson's product-moment correlation
##
## data: df$Insulin and df$Outcome
## t = 4.1548, df = 766, p-value = 3.622e-05
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## 0.07853781 0.21692327
## sample estimates:
##      cor
## 0.1484572
```

Correlation Coefficient (cor): The test shows a statistically significant positive correlation between Insulin and Outcome, though the strength of the correlation is relatively weak (0.1484572).

Significance (p-value): The p-value of 3.622e-05 is very small (less than 0.05), suggesting strong evidence against the null hypothesis. Therefore, we reject the null hypothesis that there is no correlation between Insulin and Outcome.

Confidence Interval: We are 95% confident that the true population correlation coefficient falls between 0.07853781 and 0.21692327.

Conclusion:

There is a statistically significant, weak-positive correlation ( $r = 0.1484572$ ) between Insulin and Outcome. This suggests that as Insulin increases, there tends to be a slight increase in the Outcome. However, the correlation is weak, as the correlation coefficient is relatively close to zero. In summary, while there is a statistically weak positive correlation between Insulin and Outcome, and so ( $r^2 = 0.02204118108884$ ), only 2.2% variance of the Outcome can be explained by knowing the Insulin level. So, Insulin alone may not be a strong predictor of Outcome (diabetes). Other factors likely contribute more significantly to determining the outcome.

```
correlation3 <- cor.test(df$BMI, df$Outcome, method = "pearson")
correlation3
```

```
##
## Pearson's product-moment correlation
##
## data: df$BMI and df$Outcome
## t = 9.097, df = 766, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## 0.2469654 0.3747208
## sample estimates:
## cor
## 0.3122541
```

Correlation Coefficient (cor): The test shows a statistically significant positive correlation between BMI and Outcome, though the strength of the correlation is relatively weak (0.3122541).

Significance (p-value): The p-value of 2.2e-16 is very small (less than 0.05), suggesting strong evidence against the null hypothesis. Therefore, we reject the null hypothesis that there is no correlation between BMI and Outcome.

Confidence Interval: We are 95% confident that the true population correlation coefficient falls between 0.2469654 and 0.3747208

Conclusion:

There is a statistically significant, weak-positive correlation ( $r = 0.3122541$ ) between BMI and Outcome. This suggests that as BMI increases, there tends to be a slight increase in the Outcome. However, the correlation is weak, as the correlation coefficient is relatively close to zero. In summary, while there is a statistically weak positive correlation between BMI and Outcome, and so ( $r^2 = 0.09757658500881$ ), only 9.8% variance of the Outcome can be explained by knowing the BMI level. So, BMI alone may not be a strong predictor of Outcome (diabetes). Other factors likely contribute more significantly to determining the outcome.

```
correlation4 <- cor.test(df$DiabetesPedigreeFunction, df$Outcome, method = "pearson")
correlation4
```

```
##
## Pearson's product-moment correlation
##
## data: df$DiabetesPedigreeFunction and df$Outcome
## t = 4.8858, df = 766, p-value = 1.255e-06
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## 0.1043836 0.2416168
## sample estimates:
## cor
## 0.1738441
```

Correlation Coefficient (cor): The test shows a statistically significant positive correlation between DiabetesPedigreeFunction and Outcome, though the strength of the correlation is relatively weak (0.174).

Significance (p-value): The p-value of 1.255e-06 is very small (less than 0.05), suggesting strong evidence against the null hypothesis. Therefore, we reject the null hypothesis that there is no correlation between DiabetesPedigreeFunction and Outcome.

Confidence Interval: This interval indicates that we are 95% confident that the true population correlation coefficient falls between 0.1043836 and 0.2416168.

Conclusion:

There is a statistically significant, weak-positive correlation ( $r = 0.1738441$ ) between DiabetesPedigreeFunction and Outcome. This suggests that as DiabetesPedigreeFunction increases, there tends to be a slight increase in the Outcome. However, the correlation is not strong, as the correlation coefficient is relatively close to zero. In summary, while there is a statistically weak positive correlation between DiabetesPedigreeFunction and Outcome, and so ( $r^2 = 0.03023773468$ ), only 3% variance of the Outcome can be explained by knowing the DiabetesPedigreeFunction level. So, DiabetesPedigreeFunction alone may not be a strong predictor of Outcome (diabetes). Other factors likely contribute more significantly to determining the outcome.

```
correlation5 <- cor.test(df$Outcome, df$BloodPressure, method = "pearson")
correlation5
```

```
##
## Pearson's product-moment correlation
##
## data: df$Outcome and df$BloodPressure
## t = 4.5721, df = 766, p-value = 5.63e-06
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## 0.0933180 0.2310663
## sample estimates:
## cor
## 0.1629863
```

Correlation Coefficient (cor): The test shows a statistically significant positive correlation between BloodPressure and Outcome, though the strength of the correlation is relatively weak (0.1629863).

Significance (p-value): The p-value of 1.255e-06 is very small (less than 0.05), suggesting strong evidence against the null hypothesis. Therefore, we reject the null hypothesis that there is no correlation between BloodPressure and Outcome.

Confidence Interval: This interval indicates that we are 95% confident that the true population correlation coefficient falls between 0.0933180 and 0.2310663.

Conclusion:

There is a statistically significant, weak-positive correlation ( $r = 0.1629863$ ) between BloodPressure and Outcome. This suggests that as BloodPressure increases, there tends to be a slight increase in the Outcome. However, the correlation is not strong, as the correlation coefficient is relatively close to zero. In summary, while there is a statistically weak positive correlation between BloodPressure and Outcome, and so ( $r^2 = 0.02654817969$ ), only 2.7% variance of the BloodPressure. can be explained by knowing the BloodPressure level. So, Outcome alone may not be a strong predictor of BloodPressure. Other factors likely contribute more significantly to determining the outcome.

### c) Check the Regression

```
# dependent(response) independent
regre <- lm(Outcome ~ DiabetesPedigreeFunction, data = df)
summary(regre)
```



```
##
## Call:
## lm(formula = Outcome ~ DiabetesPedigreeFunction, data = df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.8137 -0.3375 -0.2849  0.5963  0.7471
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.23087     0.02953   7.819 1.76e-14 ***
## DiabetesPedigreeFunction 0.25025     0.05122   4.886 1.25e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.47 on 766 degrees of freedom
## Multiple R-squared:  0.03022,    Adjusted R-squared:  0.02896
## F-statistic: 23.87 on 1 and 766 DF,  p-value: 1.255e-06
```

## 6. DISCUSSION

From the Pima Indians sample that took OGTT we gained knowledge, that there are two factors that influence diabetes.

OGTT results show the insulin resistance one person has, by looking at Glucose and Insulin levels after 2 hours (most effective). If a person has high glucose results, this indicates insulin failure in breaking down glucose into smaller substances for use by body cells. High insulin results also indicate that the insulin in the body has a delayed response and fails to break down glucose (the pancreas only produces insulin, but the insulin does not work properly).

Firstly, lifestyle took major parts in developing diabetes. People with higher BMI and SkinThickness tends to suffer from diabetes. People who have high body fat will also have high skin fold thickness. Most people that have obesity, tend to eat unhealthy and unbalanced food, consuming too much sugar and processed food. As a result, they are more likely to develop diabetes. Most people underestimate a healthy lifestyle and think that it is not important. Many people from a young age do not pay attention to the physical activity, eventhough the negative impacts can be felt from a young age, it is proven that diabetes begins to develop from the age of 35, and continues to develop in line with increasing age.

Second, heredity factor. People who have a history of diabetes in their family are more likely to develop diabetes. People who have a high DiabetesPedigreeFunction have more chance to grow probability of diabetes even with healthy lifestyle.

Why maintaining diabets is important? Diabetes can affect a person's blood pressure due to insulin resistance. This can cause worse complications such as inflammation and vascular damage.

## 7. CONCLUSION

From the analysis that we have conduct, We conclude that someone can get diabetes because of their daily lifestyle habits. Data have shown that people that have BMI levels of Overweight and Obesity are more likely to have diabetes. That's why it's really important to maintain a healthy lifestyle every day. However, there's also a chance that we can get diabetes due to family history. Genetic factor can increase the likelihood of developing diabetes, even with a healthy lifestyle. So, it's very important to check if we carry diabetes or not and let's also always maintain your glucose blood in normal level for avoiding any further complication.

For future research, I suggest looking deeper at lifestyle factors and their influence on diabetes, so that in the future there can be an efficient program to prevent diabetes from developing in people who already have hereditary factors.

## 8. REFERENCES

<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4418458/>  
<https://towardsdatascience.com/pima-indian-diabetes-prediction-7573698bd5fe>