| Technological Institute of the Philippines | Quezon City - Computer Engineering |
| --- | --- |
| Course Code: | CPE 019 |
| Code Title: | Emerging Technologies in CpE 2 |
| 2nd Semester | AY 2023-2024 |
| | |
| **Prelim Examination** | |
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| **Section** | CPE32S3 |
| **Date Performed**: | March 1, 2024 |
| **Date Submitted**: | March 6, 2024 |
| **Instructor**: | Engr. Roman Richard |

Choose any dataset applicable for classification and/or prediction analysis problems.

Show the application of the following algorithms:

** Linear Regression:**

**- Singular LR**

**- Multiple LR**

**- Polynomial LR**

**Logistic Regression**

**Decision Tree**

**Random Forest**

Provide Evaluation reports for all models

NOTE: Submit the github link that contains all files (pdf report, dataset and python notebooks).

```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

```
compFrame = pd.read_csv("/content/Advertising.csv")
```

```
# Display the information about the DataFrame
compFrame.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   TV         200 non-null    float64
 1   radio      200 non-null    float64
 2   newspaper  200 non-null    float64
 3   sales      200 non-null    float64
dtypes: float64(4)
memory usage: 6.4 KB
```

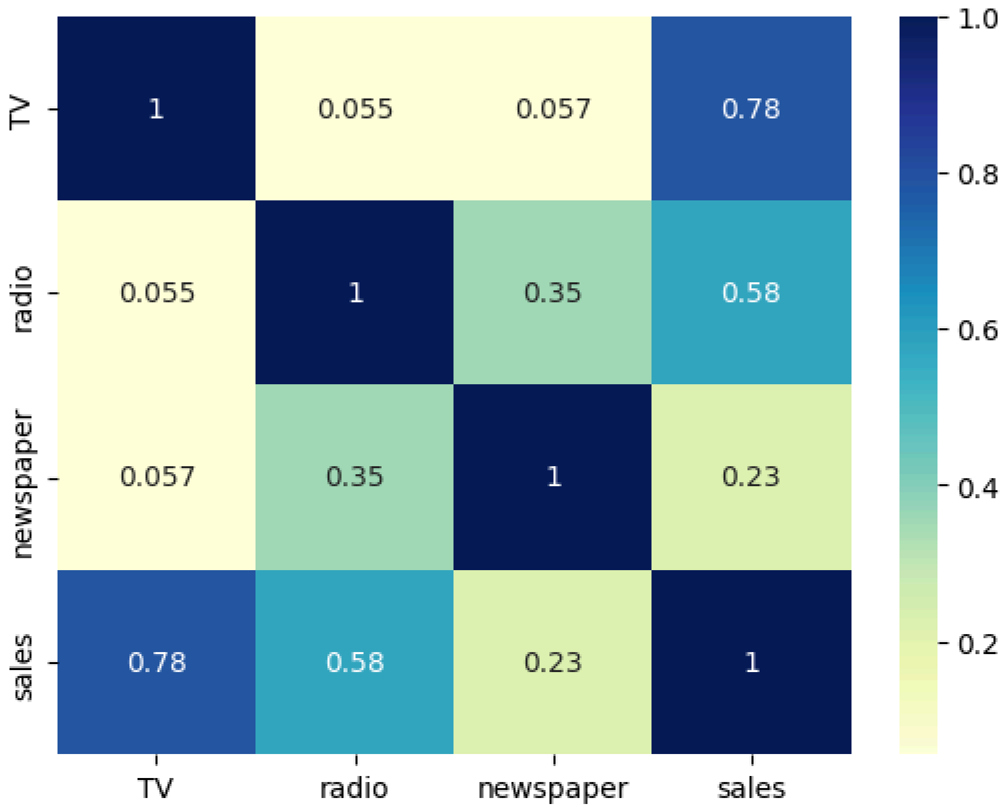
```
# Display first 5 rows
compFrame.head()
```

| | TV | radio | newspaper | sales |
|---|---|---|---|---|
| **0** | 230.1 | 37.8 | 69.2 | 22.1 |
| **1** | 44.5 | 39.3 | 45.1 | 10.4 |
| **2** | 17.2 | 45.9 | 69.3 | 9.3 |
| **3** | 151.5 | 41.3 | 58.5 | 18.5 |
| **4** | 180.8 | 10.8 | 58.4 | 12.9 |

```
# Display the summary statistics of the DataFrame
compFrame.describe()
```

| | TV | radio | newspaper | sales |
|---|---|---|---|---|
| **count** | 200.000000 | 200.000000 | 200.000000 | 200.000000 |
| **mean** | 147.042500 | 23.264000 | 30.554000 | 14.022500 |
| **std** | 85.854236 | 14.846809 | 21.778621 | 5.217457 |
| **min** | 0.700000 | 0.000000 | 0.300000 | 1.600000 |
| **25%** | 74.375000 | 9.975000 | 12.750000 | 10.375000 |
| **50%** | 149.750000 | 22.900000 | 25.750000 | 12.900000 |
| **75%** | 218.825000 | 36.525000 | 45.100000 | 17.400000 |
| **max** | 296.400000 | 49.600000 | 114.000000 | 27.000000 |

```
# Create a heatmap of the correlation matrix
sns.heatmap(compFrame.corr(),cmap='YlGnBu',annot=True)
plt.show()
```




```
# Calculate the correlation coefficients between the 'sales' column and all other columns ir
compFrame.corr()['sales']
```

```
TV           0.782224
radio        0.576223
newspaper    0.228299
```

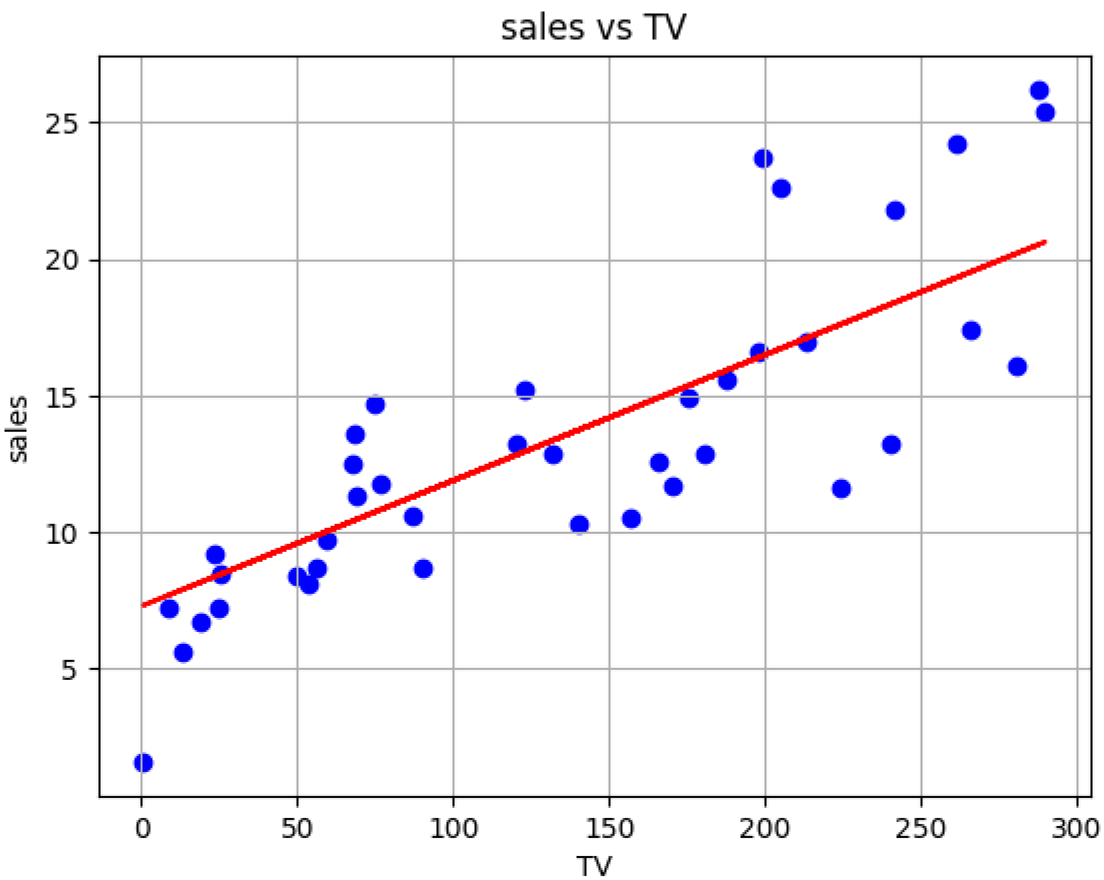
```
sales        1.000000
Name: sales, dtype: float64
```

# 1. Singular Linear Regression

Predicting sales revenue based on advertising spending through TV.

```
# Select independent and dependent variable
X = compFrame[['TV']]
y = compFrame['sales']

# Split the data into Train and Test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .2, random_state = 0)

# Fitting Singular Linear Regression to the Training set
model = LinearRegression()
model.fit(X_train, y_train)

# Get the coefficient value
print("Coefficients: ", model.coef_)

# Predicting the Test set results
y_pred = model.predict(X_test)

# Get the Mean Squared Error result
mse=mean_squared_error(y_test, y_pred)

# Get the R2_Score
r2 = r2_score(y_test, y_pred)

# Creating a DataFrame
new_data = pd.DataFrame({'TV': [500]})

# Making prediction using the trained model
predicted_sales = model.predict(new_data)

print("Predicted sales revenue when advertising spend on TV is 500:", predicted_sales[0])

print('Mean Squared Error: ', mse) # If the result is small values the model is better
print('R-squared: ', r2) # If the result is closer to 1 the model is better
plt.scatter(X_test,y_test, color = 'b')
plt.plot(X_test,y_pred, color = 'r')
plt.title('sales vs TV')
plt.xlabel('TV')
plt.ylabel('sales')
plt.grid(True)
```

```
Coefficients:  [0.04600779]
Predicted sales revenue when advertising spend on TV is 500: 30.296388575067947
Mean Squared Error:  10.18618193453022
R-squared:  0.6763151577939721
```




**Model Evaluation**

- Having a coefficients of 0.046 we can say that for every additional spent on TV advertising, we expect sales revenue to increase by about 0.046.
- Having a mean squared error of 10.18 where it indicates that, on average, the squared difference between the actual and predicted sales revenue values is about 10.186. But it says that if the value is closer to 1 it indicates better model performance.
- Having a r squared of 0.67 where model explains that approximately 67% of the variation in sales revenue based on TV spending alone.
- Based of the result we can conclude that there is a positive relationship between TV spending and sales revenue.

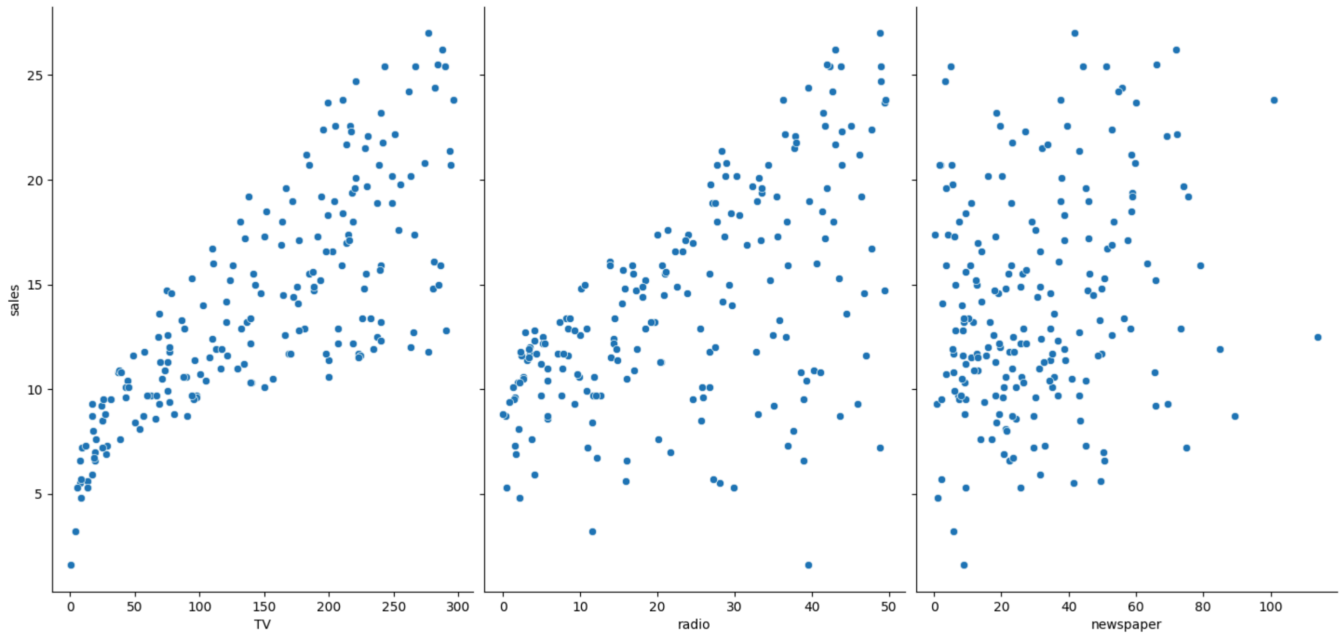
---

## 2. Multiple Linear Regression

---

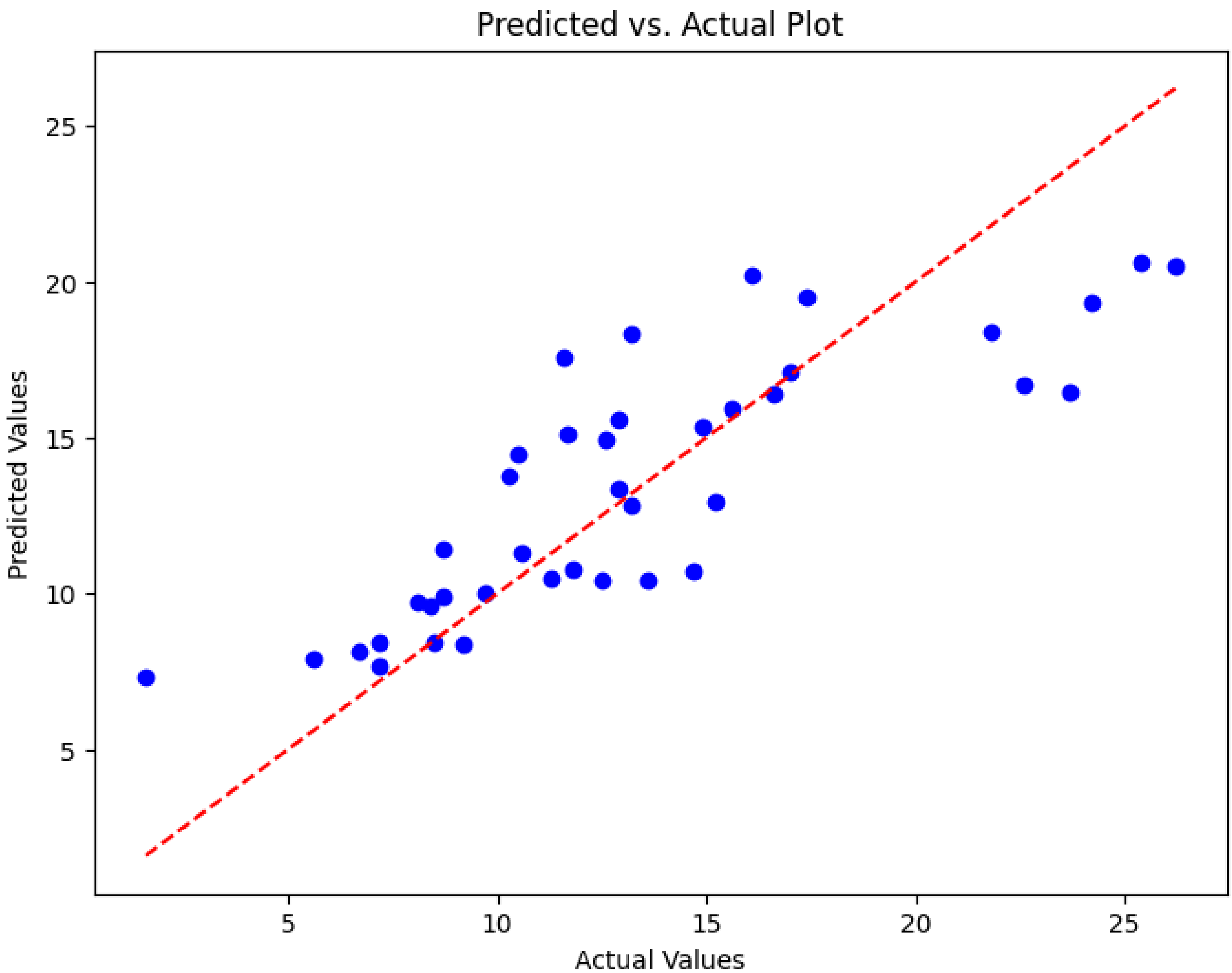
Predicting sales revenue based on advertising spending through media such as TV, radio, and newspaper.

```
#Relationship between Features and Response
sns.pairplot(compFrame, x_vars=['TV','radio','newspaper'], y_vars='sales', height=7, aspect=
```

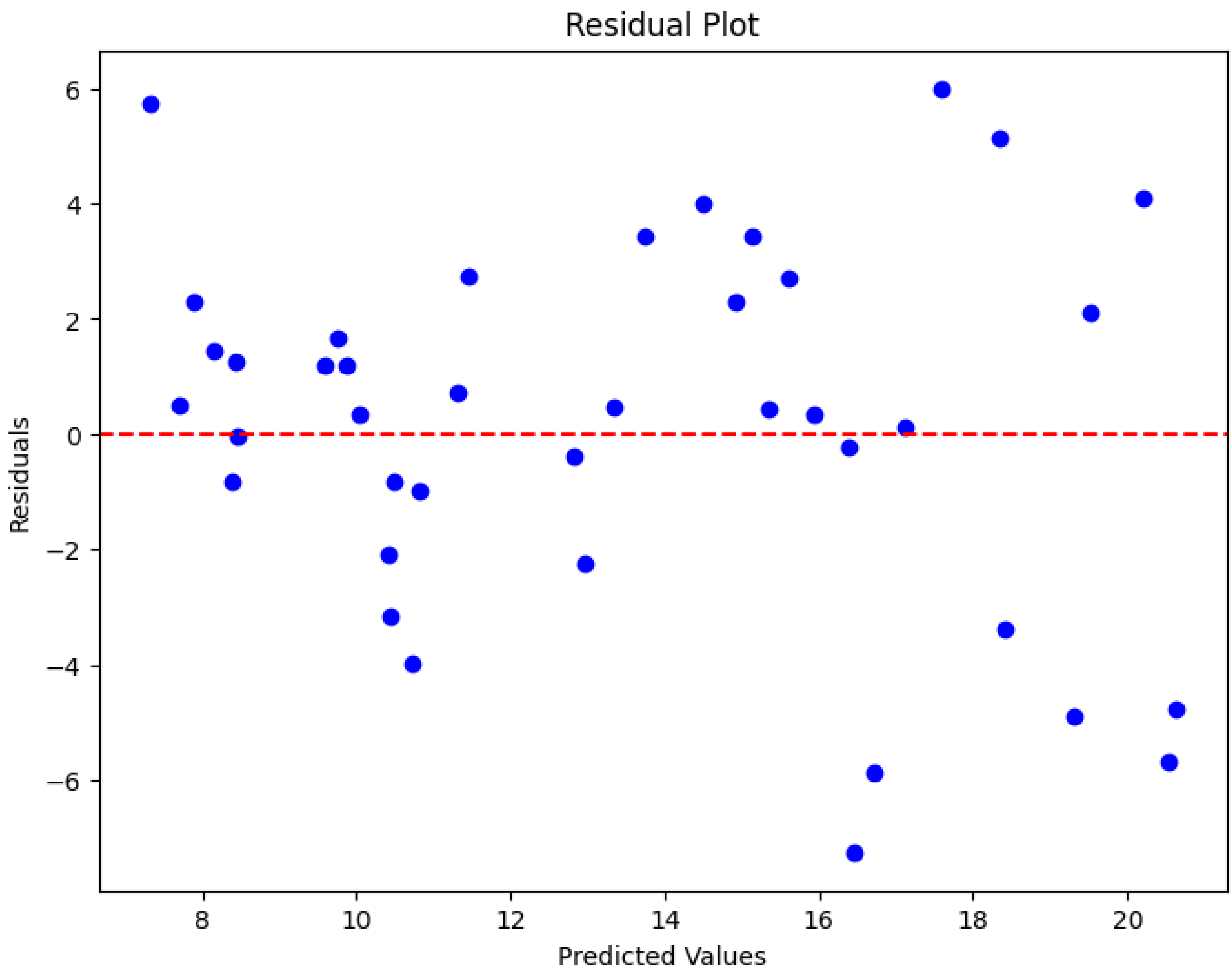


```
# Select independent and dependent variable
X = compFrame[['TV','radio', 'newspaper']]
y = compFrame['sales']

# Split the data into Train and Test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

# Fitting Singular Linear Regression to the Train set
model = LinearRegression()
model.fit(X_train, y_train)

# Get the coefficient value
print('Coefficient : ', model.coef_)

# Predicting the Train set results
y_pred_train = model.predict(X_train)

# Get the R2_Score
r2 = r2_score(y_train, y_pred_train)
print('R2_Score: ', r2)

# Predicting the Test set results
y_pred_test = model.predict(X_test)

# # Get the Mean Squared Error result
mse = mean_squared_error(y_test,y_pred_test)
print('MSE Score: ', mse)

# Creating a DataFrame
new_data = pd.DataFrame({'TV': [50], 'radio': [30], 'newspaper': [20]})

# Making prediction using the trained model
predicted_sales = model.predict(new_data)

print("Predicted sales revenue when advertising spend on TV is 50, radio is 30, and newspape

# Predicted vs. Actual plot
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], linestyle='--', color='
plt.title('Predicted vs. Actual Plot')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.show()
```

```
Coefficient :  [ 0.04458402  0.19649703 -0.00278146]
R2_Score:  0.9067114990146383
MSE Score:  4.402118291449685
Predicted sales revenue when advertising spend on TV is 50, radio is 30, and newspaper i
```




```
# Residual plot
plt.figure(figsize=(8, 6))
plt.scatter(y_pred, y_pred - y_test, color='blue')
plt.axhline(y=0,  linestyle='--', color='r')
plt.title('Residual Plot')
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.show()
```




**Model Evaluation**

- Having a coefficient values of [ 0.04458402 0.19649703 -0.00278146], in the first and second variable it has positive relationship since it has positive coefficient, while in the third variable it has negative relationship since the ouput is negative coefficient.
- Having a r squared of 0.90 that is approximately 90% of the variability in the dependent variable is explained by the independent variables included in the model.
- Having a mean squared error of 4.40 we can that the Multiple Linear Regression model we can say that it is better than the linear regression model since it give a lower values that is more closer to 1.
- We conclude, based on the provided coefficients, R-squared score, and MSE score, Multiple Linear Regression model appears to perform well.

# 3. Polynomial Regression

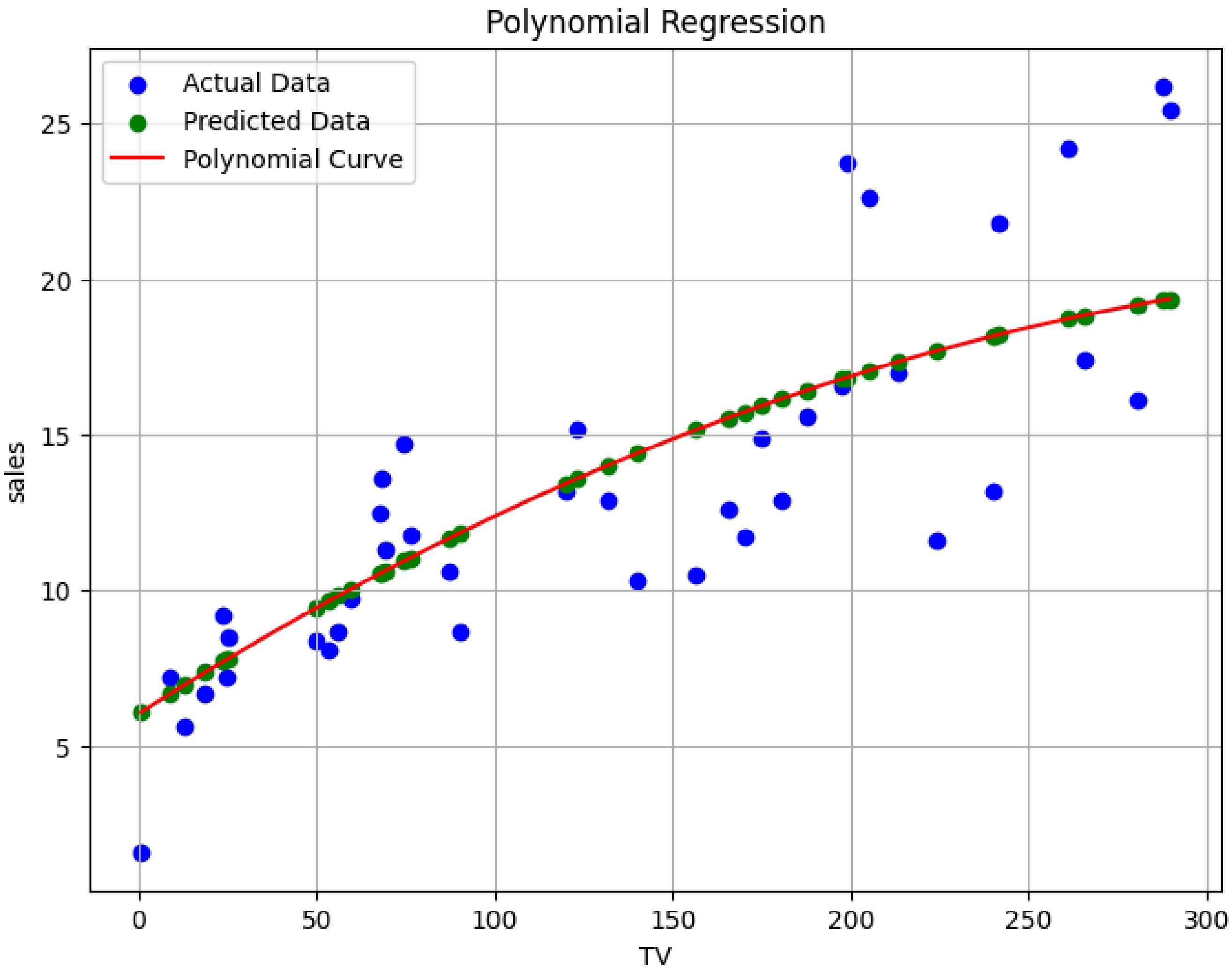
---

Predicting sales revenue based on advertising spending through TV using polynomial regression.

```
# Select independent and dependent variable
X = compFrame[['TV']]
y = compFrame['sales']

# Split the data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

# Apply PolynomialFeatures before scaling
poly = PolynomialFeatures(degree=2)
X_poly_train = poly.fit_transform(X_train)
X_poly_test = poly.transform(X_test)

scaler = StandardScaler()
X_train_scaler = scaler.fit_transform(X_poly_train)
X_test_scaler = scaler.transform(X_poly_test)

# Train Singular Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)
y_pred_simple = model.predict(X_test)

# Calculate MSE and R2 score for Singular Linear Regression
mse_simple = mean_squared_error(y_test, y_pred_simple)
r2_simple = r2_score(y_test, y_pred_simple)

# Train Polynomial Linear Regression model
poly_model = LinearRegression()
poly_model.fit(X_train_scaler, y_train)
y_pred = poly_model.predict(X_test_scaler)

# Calculate MSE and R2 score for Polynomial Regression
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Compare MSE and R2 score between PLR model and Simple Linear Regression model
print("Mean Squared Error for SLR:", mse_simple)
print("R2 Score for SLR:", r2_simple)
print("Mean Squared Error for PLR:", mse)
print("R2 Score for PLR:", r2)

# Get the coefficient value
print("Coefficients: ", poly_model.coef_)

# Get the intercept value
print('Intercept: ', poly_model.intercept_)

# Creating a DataFrame with a single data point for R&D Spend
new_data = pd.DataFrame({'TV': [50]})

# Making prediction using the trained model
predicted_sales = model.predict(new_data)
```

```
print("predict sales revenue when advertising spend on TV is 50:", predicted_sales[0])

# Plotting the Polynomial Curve
plt.figure(figsize=(8, 6))
plt.scatter(X_test, y_test, color='b', label='Actual Data')
plt.scatter(X_test, y_pred, color='g', label='Predicted Data')
x_values = np.linspace(min(X_test.values), max(X_test.values), 100).reshape(-1, 1)
x_poly_values = poly.transform(x_values)
x_poly_values_scaled = scaler.transform(x_poly_values)
y_poly_pred = poly_model.predict(x_poly_values_scaled)
plt.plot(x_values, y_poly_pred, color='r', label='Polynomial Curve')
plt.title('Polynomial Regression')
plt.xlabel('TV')
plt.ylabel('sales')
plt.legend()
plt.grid(True)
plt.show()
```

```
Mean Squared Error for SLR: 10.18618193453022
R2 Score for SLR: 0.6763151577939721
Mean Squared Error for PLR: 10.685507926293392
R2 Score for PLR: 0.660448147378093
Coefficients:  [ 0.          6.14894143 -2.32734841]
Intercept:  14.217500000000005
predict sales revenue when advertising spend on TV is 50: 9.592883253710221
```




### Model Evaluation

- As seen in the plotted graph we can say that Polynomial curve overlaid on the acutal and predicted data points, it shows that PLR model capture the underlying trend in the data reasonably well. In the graph PLR model can capture nonlinear relationships between the TV as an independent variable and sales as depedent variable. Also, it suggest that in capturing complex relationship between TV and sales PLR model is more suitable.

# Logistic, Decision Tree, and Random Forest Regressions

---

The first 28 cells are dedicated for data understanding, cleaning, and splitting.

```
#Step 1: Importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import classification_report

import warnings
warnings.filterwarnings('ignore')
```

```
#Step 2: Load the Dataset
diaFrame = pd.read_csv('/content/diabetes.csv')
```

```
#Step 3: Understanding the Variables

#3.1.1 - Head of the Dataset
diaFrame.head(5)
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFu |
|---|---|---|---|---|---|---|---|
| **0** | 6 | 148 | 72 | 35 | 0 | 33.6 | |
| **1** | 1 | 85 | 66 | 29 | 0 | 26.6 | |
| **2** | 8 | 183 | 64 | 0 | 0 | 23.3 | |
| **3** | 1 | 89 | 66 | 23 | 94 | 28.1 | |
| **4** | 0 | 137 | 40 | 35 | 168 | 43.1 | |

```
diaFrame.tail(5)
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigree |
|---|---|---|---|---|---|---|---|
| **763** | 10 | 101 | 76 | 48 | 180 | 32.9 | |
| **764** | 2 | 122 | 70 | 27 | 0 | 36.8 | |
| **765** | 5 | 121 | 72 | 23 | 112 | 26.2 | |
| **766** | 1 | 126 | 60 | 0 | 0 | 30.1 | |
| **767** | 1 | 93 | 70 | 31 | 0 | 30.4 | |

```
diaFrame.sample(5)
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigree |
|---|---|---|---|---|---|---|---|
| **310** | 6 | 80 | 66 | 30 | 0 | 26.2 | |
| **231** | 6 | 134 | 80 | 37 | 370 | 46.2 | |
| **520** | 2 | 68 | 70 | 32 | 66 | 25.0 | |
| **228** | 4 | 197 | 70 | 39 | 744 | 36.7 | |
| **238** | 9 | 164 | 84 | 21 | 0 | 30.8 | |

```
#3.1.2 - Shape of the Dataset
diaFrame.shape
```

```
(768, 9)
```

```
#3.1.3 - Type of the Dataset
diaFrame.dtypes
```

```
Pregnancies                   int64
Glucose                       int64
BloodPressure                 int64
SkinThickness                 int64
Insulin                       int64
BMI                         float64
DiabetesPedigreeFunction    float64
Age                           int64
Outcome                       int64
dtype: object
```

```
#3.1.4 - Info of the Dataset
diaFrame.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
```

```
 ---  ------                    --------------  -----
  0   Pregnancies               768 non-null    int64
  1   Glucose                   768 non-null    int64
  2   BloodPressure             768 non-null    int64
  3   SkinThickness             768 non-null    int64
  4   Insulin                   768 non-null    int64
  5   BMI                       768 non-null    float64
  6   DiabetesPedigreeFunction  768 non-null    float64
  7   Age                       768 non-null    int64
  8   Outcome                   768 non-null    int64
 dtypes: float64(2), int64(7)
 memory usage: 54.1 KB
```

```
#3.1.5 - Summary of the Dataset
diaFrame.describe()
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | Dia |
|---|---|---|---|---|---|---|---|
| **count** | 768.000000 | 768.000000 | 768.000000 | 768.000000 | 768.000000 | 768.000000 | |
| **mean** | 3.845052 | 120.894531 | 69.105469 | 20.536458 | 79.799479 | 31.992578 | |
| **std** | 3.369578 | 31.972618 | 19.355807 | 15.952218 | 115.244002 | 7.884160 | |
| **min** | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| **25%** | 1.000000 | 99.000000 | 62.000000 | 0.000000 | 0.000000 | 27.300000 | |
| **50%** | 3.000000 | 117.000000 | 72.000000 | 23.000000 | 30.500000 | 32.000000 | |
| **75%** | 6.000000 | 140.250000 | 80.000000 | 32.000000 | 127.250000 | 36.600000 | |
| **max** | 17.000000 | 199.000000 | 122.000000 | 99.000000 | 846.000000 | 67.100000 | |

By outputting the summary of the dataset, we can notice that the minimum values of the features for Pregnancy up to BMI has 0 values.

```
#3.2 - Data Cleaning
#3.2.1 - Drop the Duplicates
#Check first if there are any duplicates
diaFrame.shape
```

```
(768, 9)
```

```
diaFrame = diaFrame.drop_duplicates()
```

```
diaFrame.shape
```

```
(768, 9)
```

We can observe that there were no changes on the shape of the dataset, this only meaens that there were no duplicates on the dataset.

```
#3.2.2 - Check the NULL Values
diaFrame.isnull().sum()
```

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

The values are all 0, which means there is no NULL value in the dataset.

```
diaFrame.columns
```

```
Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
       'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
      dtype='object')
```

```
#Check the number of Zero values in the dataset
print('No. of zero values in Glucose ', diaFrame[diaFrame['Glucose']==0].shape[0])
print('No. of zero values in BloodPressure ', diaFrame[diaFrame['BloodPressure']==0].shape[6
print('No. of zero values in Insulin ', diaFrame[diaFrame['Insulin']==0].shape[0])
print('No. of zero values in SkinThickness ', diaFrame[diaFrame['SkinThickness']==0].shape[6
print('No. of zero values in BMI ', diaFrame[diaFrame['BMI']==0].shape[0])
```

```
No. of zero values in Glucose  5
No. of zero values in BloodPressure  35
No. of zero values in Insulin  374
No. of zero values in SkinThickness  227
No. of zero values in BMI  11
```

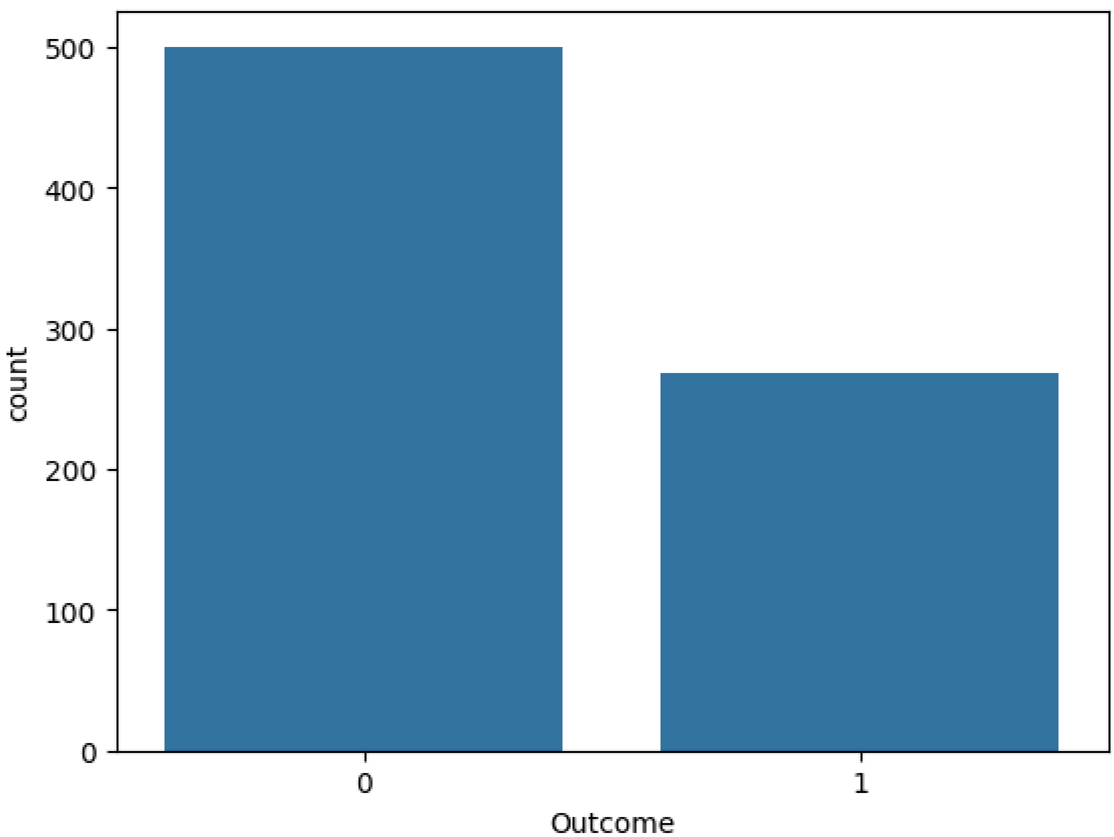
```
#Replace number of zero values with mean of that columns
diaFrame['Glucose']=diaFrame['Glucose'].replace(0,diaFrame['Glucose'].mean())
diaFrame['BloodPressure']=diaFrame['BloodPressure'].replace(0,diaFrame['BloodPressure'].mear
diaFrame['SkinThickness']=diaFrame['SkinThickness'].replace(0,diaFrame['SkinThickness'].mear
diaFrame['Insulin']=diaFrame['Insulin'].replace(0,diaFrame['Insulin'].mean())
diaFrame['BMI']=diaFrame['BMI'].replace(0,diaFrame['BMI'].mean())
```

```
diaFrame.describe()
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | Dia |
|---|---|---|---|---|---|---|---|
| **count** | 768.000000 | 768.000000 | 768.000000 | 768.000000 | 768.000000 | 768.000000 | |
| **mean** | 3.845052 | 121.681605 | 72.254807 | 26.606479 | 118.660163 | 32.450805 | |
| **std** | 3.369578 | 30.436016 | 12.115932 | 9.631241 | 93.080358 | 6.875374 | |
| **min** | 0.000000 | 44.000000 | 24.000000 | 7.000000 | 14.000000 | 18.200000 | |
| **25%** | 1.000000 | 99.750000 | 64.000000 | 20.536458 | 79.799479 | 27.500000 | |
| **50%** | 3.000000 | 117.000000 | 72.000000 | 23.000000 | 79.799479 | 32.000000 | |
| **75%** | 6.000000 | 140.250000 | 80.000000 | 32.000000 | 127.250000 | 36.600000 | |
| **max** | 17.000000 | 199.000000 | 122.000000 | 99.000000 | 846.000000 | 67.100000 | |

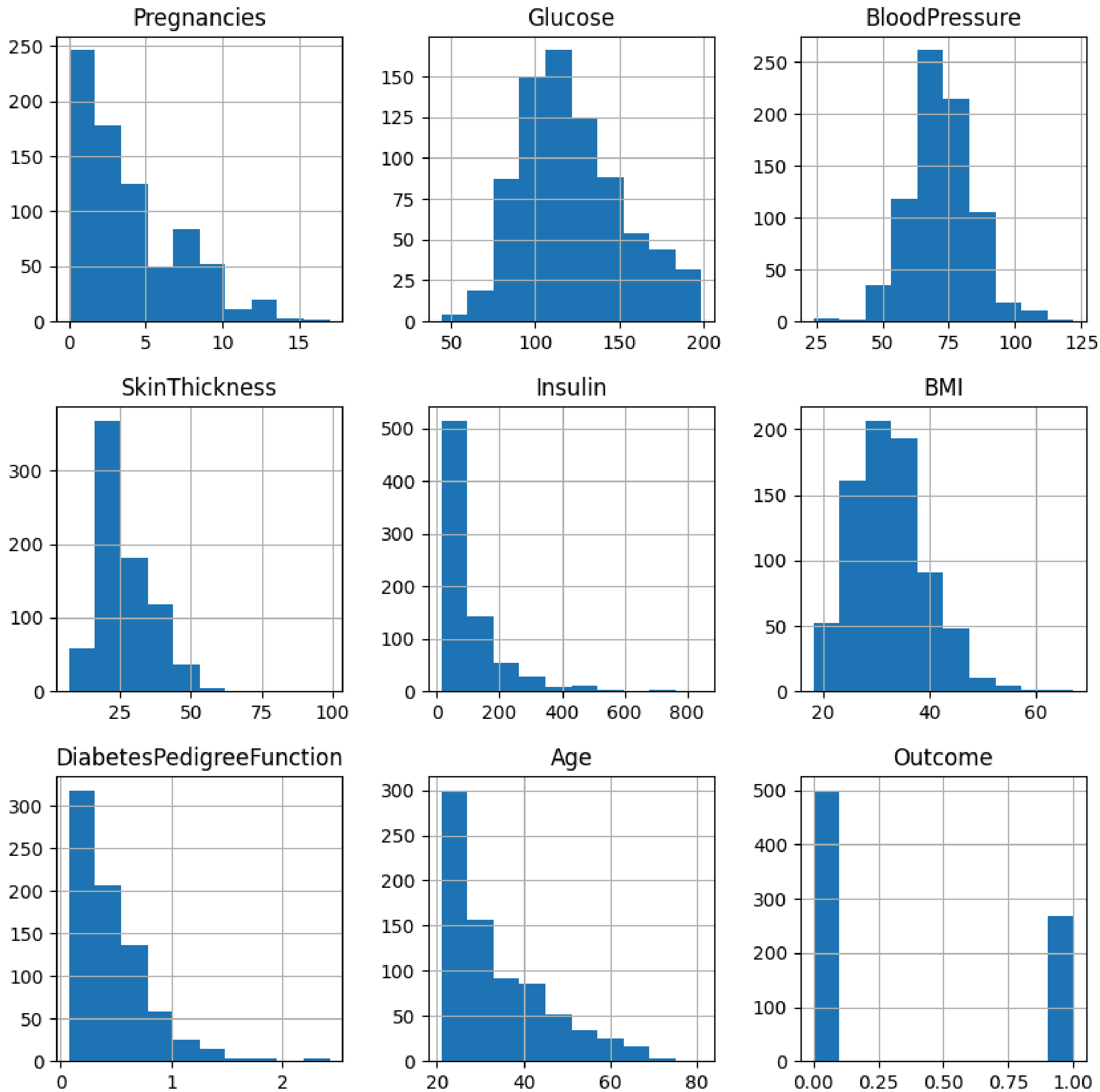
```
#create pie chart
sns.countplot(x='Outcome',data=diaFrame)
N,P = diaFrame['Outcome'].value_counts()
print("Negative (0) = ", N)
print("Positive (1) = ", P)
```

```
Negative (0) =  500
Positive (1) =  268
```



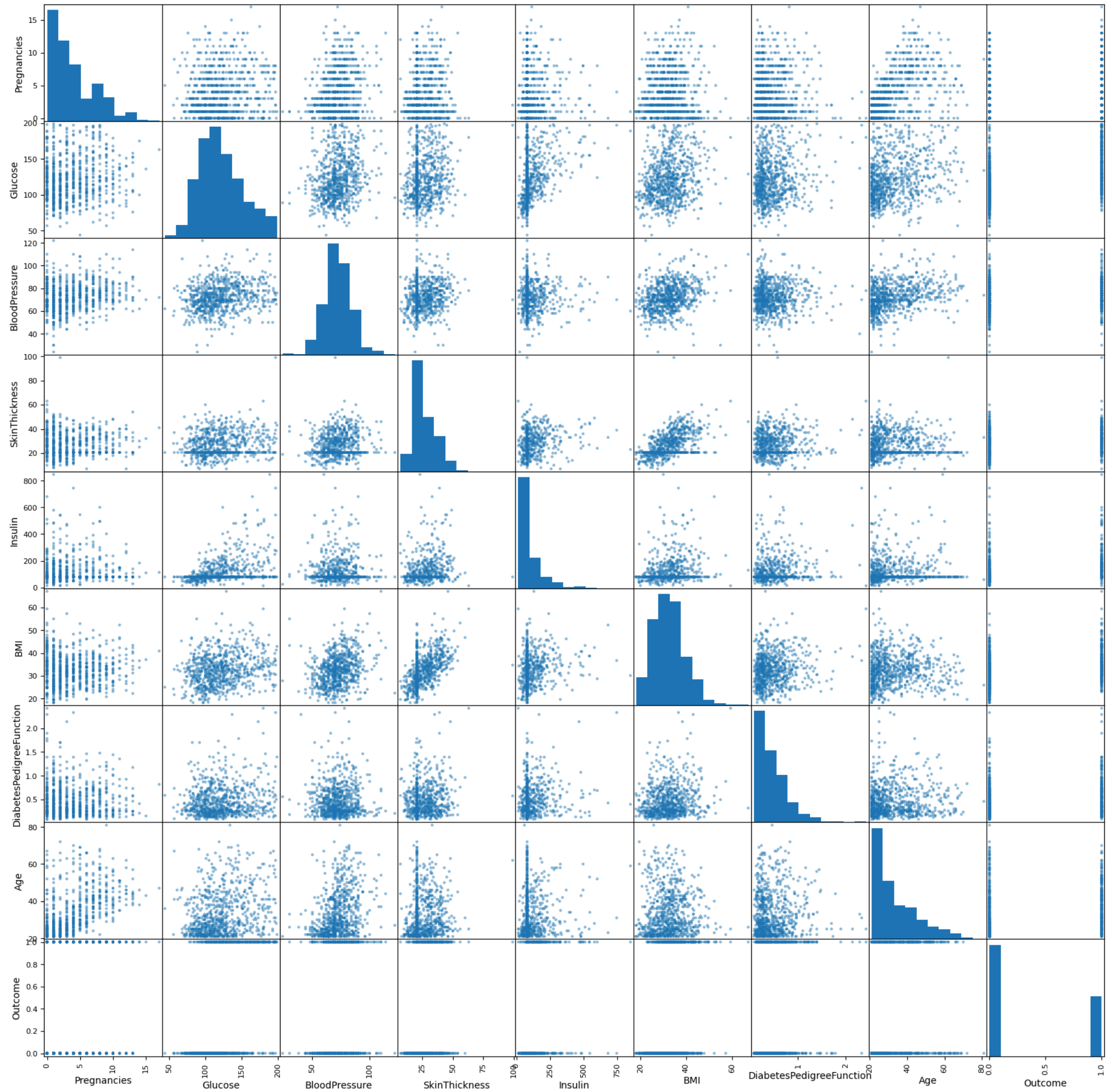
We can imply from this countplot generated from outcome that there is a greater population who doesn't have diabetes (0 value on outcome) than diabetes positive persons (1 value on outcome).

```
#4.2 Histograms
diaFrame.hist(bins=10, figsize=(10,10))
plt.show()
```

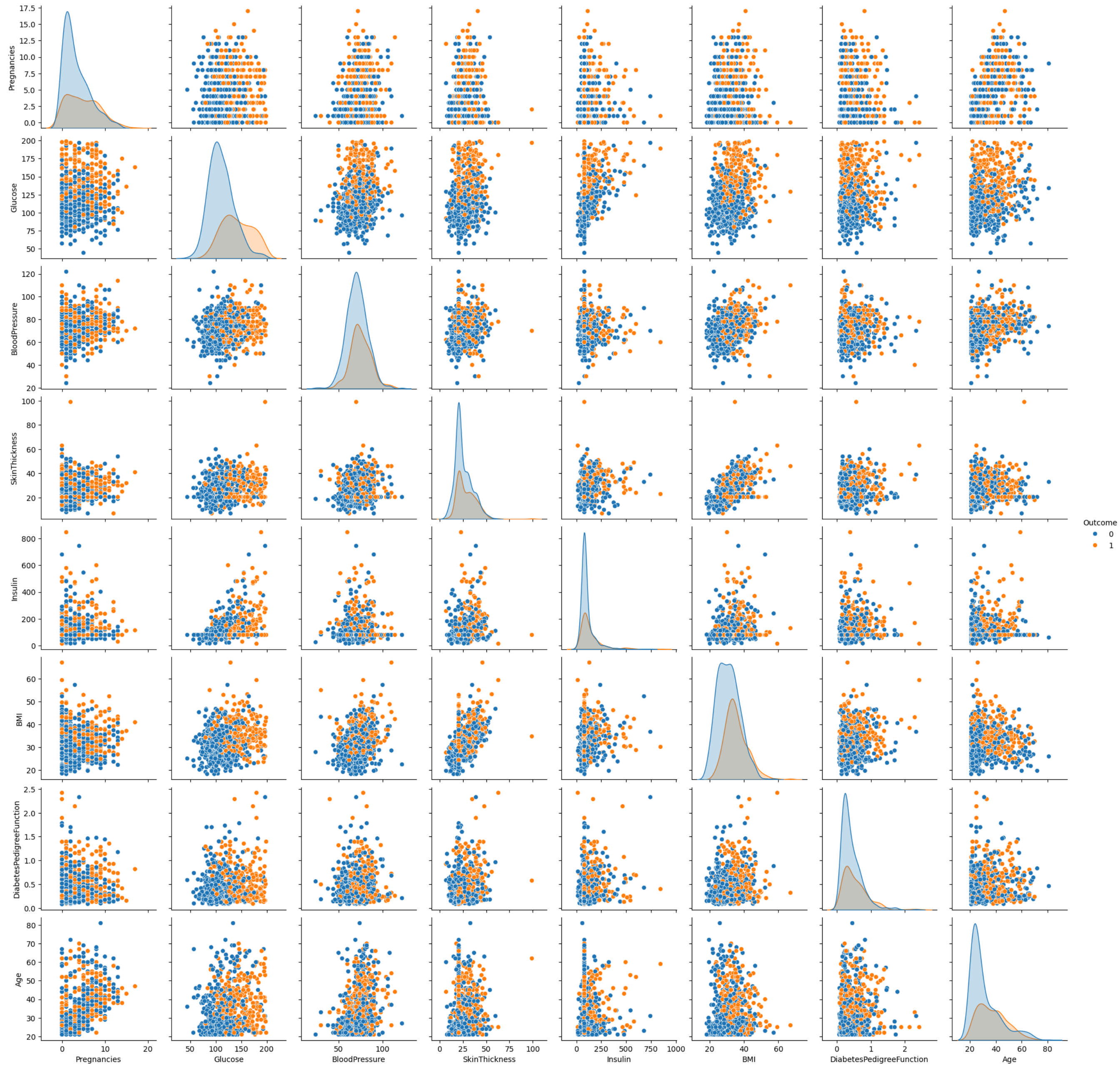



In the histplot, we can visualize the skewness of the data in the dataset features. We can also observe the normal distribustion figure with the BMI,Glucose, and BloodPressure.

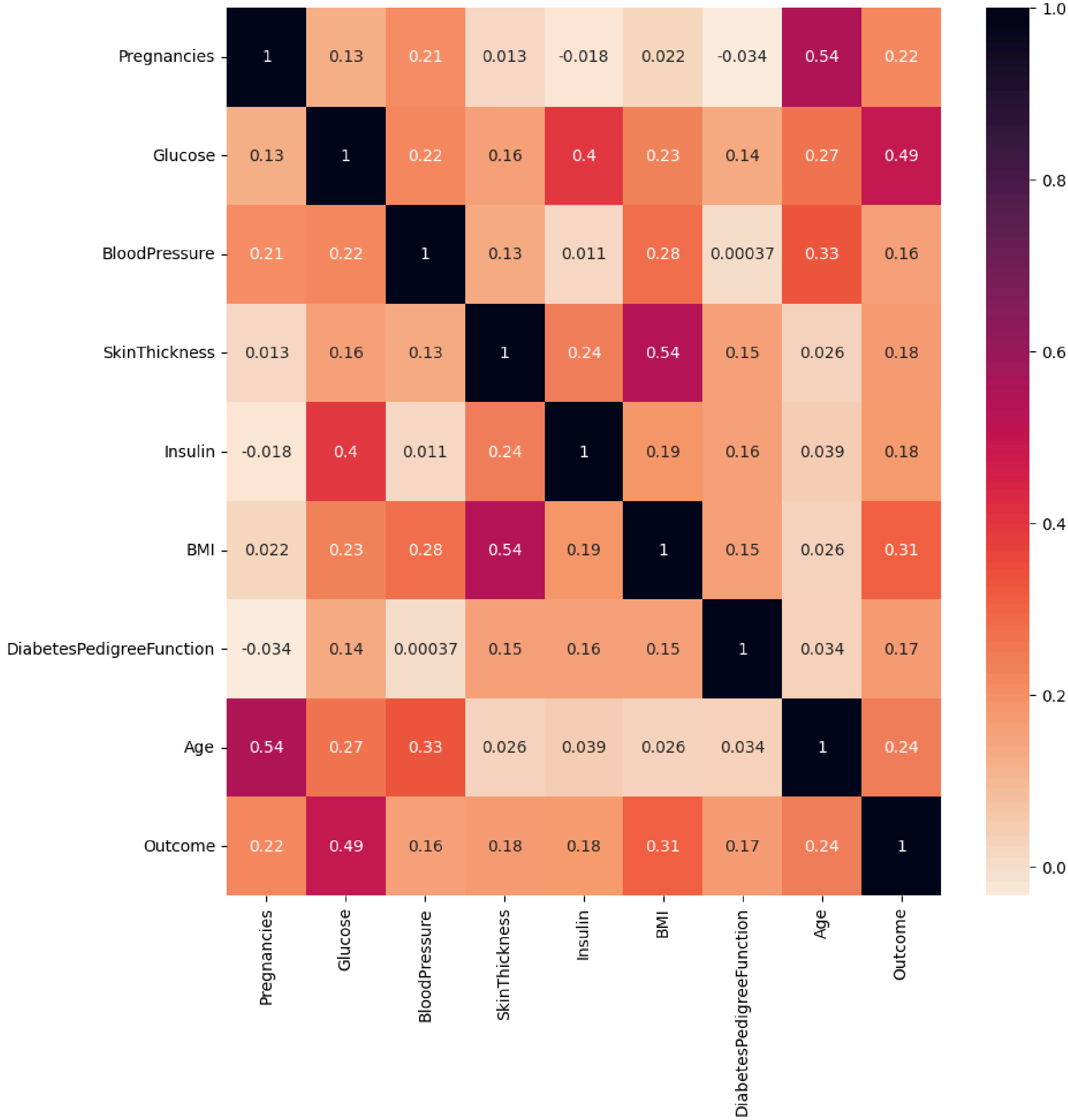
```
#4.3 Scatter Plot Matrix
scatter_matrix(diaFrame, figsize = (20,20));
```


Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome

```
sns.pairplot(data = diaFrame, hue = 'Outcome')
plt.show()
```


Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome
0
1

```
#4.5 Analyzing relationship between variables
corrD= diaFrame.corr()
top_corr_features = corrD.index
plt.figure(figsize = (10,10))

h = sns.heatmap(diaFrame[top_corr_features].corr(), annot=True, cmap=sns.color_palette("rock
```


Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome
1 0.13 0.21 0.013 -0.018 0.022 -0.034 0.54 0.22
0.13 1 0.22 0.16 0.4 0.23 0.14 0.27 0.49
0.21 0.22 1 0.13 0.011 0.28 0.00037 0.33 0.16
0.013 0.16 0.13 1 0.24 0.54 0.15 0.026 0.18
-0.018 0.4 0.011 0.24 1 0.19 0.16 0.039 0.18
0.022 0.23 0.28 0.54 0.19 1 0.15 0.026 0.31
-0.034 0.14 0.00037 0.15 0.16 0.15 1 0.034 0.17
0.54 0.27 0.33 0.026 0.039 0.026 0.034 1 0.24
0.22 0.49 0.16 0.18 0.18 0.31 0.17 0.24 1
1.0
0.8
0.6
0.4
0.2
0.0

In understanding the correlation analysis, we will be evaluating the correlation of the coefficients which will tell you how much one variable changes when the other one does. With the correlation output of the heatmap, we can see that there's a high correlation between 'Outcome' and the features 'Pregnancies', 'Glucose', 'BMI', and 'Age'. Therefore, we can use these features for prediction.

```
# Step 5: Splitting the dataframe to X & y

selected_feature = 'Outcome'
y = diaFrame[selected_feature]
X = diaFrame.drop(selected_feature, axis=1)
```

This codes removed the 'Outcome' Feature from the columns because we will be using the 'Outcome' as our independent variable and our remaining features as the dependent variable.

```
X.head()
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigree |
|---|---|---|---|---|---|---|---|
| **0** | 6 | 148.0 | 72.0 | 35.000000 | 79.799479 | 33.6 | |
| **1** | 1 | 85.0 | 66.0 | 29.000000 | 79.799479 | 26.6 | |
| **2** | 8 | 183.0 | 64.0 | 20.536458 | 79.799479 | 23.3 | |
| **3** | 1 | 89.0 | 66.0 | 23.000000 | 94.000000 | 28.1 | |
| **4** | 0 | 137.0 | 40.0 | 35.000000 | 168.000000 | 43.1 | |

```
y.head()
```

```
0    1
1    0
2    1
3    0
4    1
Name: Outcome, dtype: int64
```

Above, we just checked if the columns were successfully separated.

```
#Step 6: Apply Feature Scaling
#Applied Standard Scaler
scaler = StandardScaler()
scaler.fit(X)
SSX = scaler.transform(X)
```

```
#Step 7: Train Test Split
X_train, X_test, y_train, y_test = train_test_split(SSX, y, test_size = 0.3, random_state =
```

In the code above, we have splitted the train and test variables. Where we have divided the data into 70% for training and 30% for testing.

```
X_train.shape, y_train.shape
```

```
((537, 8), (537,))
```

```
X_test.shape, y_test.shape
```

```
((231, 8), (231,))
```

In the code above, we can see that the value of the train data is 537 while the test data is 231. That is the 70/30 ratio of the data.

## Step 8: Building the Classification Algorithms

---

# 4. Logistic Regression

---

```
#Step 8.1: Building the Logistic Regression
LogReg = LogisticRegression(solver='liblinear', multi_class='ovr')
LogReg.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression(multi_class='ovr', solver='liblinear')
```

```
# Prediction test using log reg
LogReg_prediction=LogReg.predict(X_test)
```