To understand the logistic Regression that includes non-linearity to linear regression

```
# 1.Load the basic libraries and packages\

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
```

```
# 2.    Load the dataset

data = pd.read_csv("https://raw.githubusercontent.com/nishithkotak/machine-learning/master/diabetes.csv")
data
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
103	1	81	72	18	40	26.6	0.283	24	0
104	2	85	65	0	0	39.6	0.930	27	0
105	1	126	56	29	152	28.7	0.801	21	0
106	1	96	122	0	0	22.4	0.207	27	0
107	4	144	58	28	140	29.5	0.287	37	0

108 rows × 9 columns

Next steps: Generate code with data | View recommended plots | New interactive sheet

```
# 3.    Analyze the dataset

data.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	108.00000	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000
mean	4.37037	118.194444	68.592593	19.120370	71.916667	30.870370	0.472815	33.833333	0.351852
std	3.56932	33.399160	22.038215	16.289276	123.098860	9.412373	0.371791	11.086322	0.479774
min	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	0.102000	21.000000	0.000000
25%	1.00000	98.500000	64.000000	0.000000	0.000000	25.300000	0.248000	24.750000	0.000000
50%	4.00000	113.500000	72.000000	20.000000	0.000000	31.350000	0.339500	31.000000	0.000000
75%	7.00000	139.500000	80.000000	32.000000	110.000000	37.225000	0.586250	41.000000	1.000000
max	15.00000	197.000000	122.000000	60.000000	846.000000	49.700000	2.288000	60.000000	1.000000

```
# 4.    Normalize the data

def Feature_Normalization(X):
  X = (X - np.mean(X , axis = 0)) / np.std(X , axis = 0)
  return X , np.mean(X , axis = 0) ,  np.std(X , axis = 0)
```

```
# 5.   Pre-process the data

x_train , x_test , y_train , y_test = train_test_split(x , y , test_size = 0.2 , random_state = 42)
```

```
# 6.   Visualize the Data

for feature in data.columns:
    sns.histplot(data[feature], kde=True)
    plt.show()
```

Show hidden output

```
# 7.Separate the feature and prediction value columns

x = data.iloc[: , :-1].values
y = data.iloc[: , -1].values
```

```
def Sigmoid(z):
    return 1 / (1 + np.exp(-z))
```

```
# 8.   Write the Hypothesis Function

def Hypothesis(theta, X):
    return Sigmoid(np.dot(X, theta))
```

```
# 9. Write the Cost Function

def Cost_function(theta, X, y):
    m = len(y)  # number of training examples
    h = Sigmoid(np.dot(X, theta))  # hypothesis (predicted probabilities)
    cost = (-1/m) * (np.dot(y.T, np.log(h)) + np.dot((1 - y).T, np.log(1 - h)))
    return cost
```

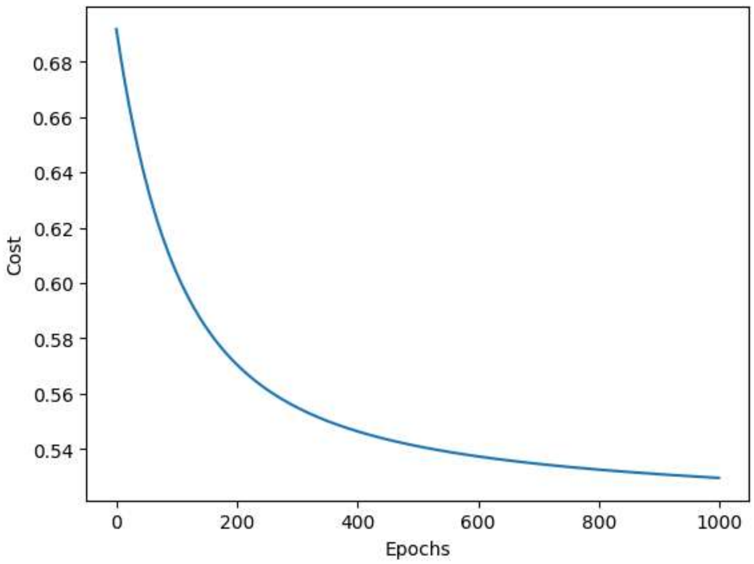
```
# 10.   Write the Gradient Descent optimization algorithm

def Gradient_Descent(X, y, theta_array, alpha, epochs):
    m = len(y)
    cost_history = []

    for i in range(epochs):
        h = Sigmoid(np.dot(X, theta_array))
        gradient = (1/m) * np.dot(X.T, (h - y))
        theta_array = theta_array - alpha * gradient
        cost = Cost_function(theta_array, X, y)
        cost_history.append(cost)

    return theta_array, cost_history
```

```
# 11.   Apply Feature Normalization technique over the data

x_train , train_mean , train_std = Feature_Normalization(x_train)
x_test , test_mean , test_std = Feature_Normalization(x_test)
```

```
# 12.   Apply the training over the dataset to minimize the loss

def Training(X, y, alpha, epochs):
    theta_array = np.zeros(X.shape[1])  # Initialize theta as a zero array with shape matching the number of features
    cost_history = []

    theta_array, cost_history = Gradient_Descent(X, y, theta_array, alpha, epochs)

    return theta_array, cost_history
```

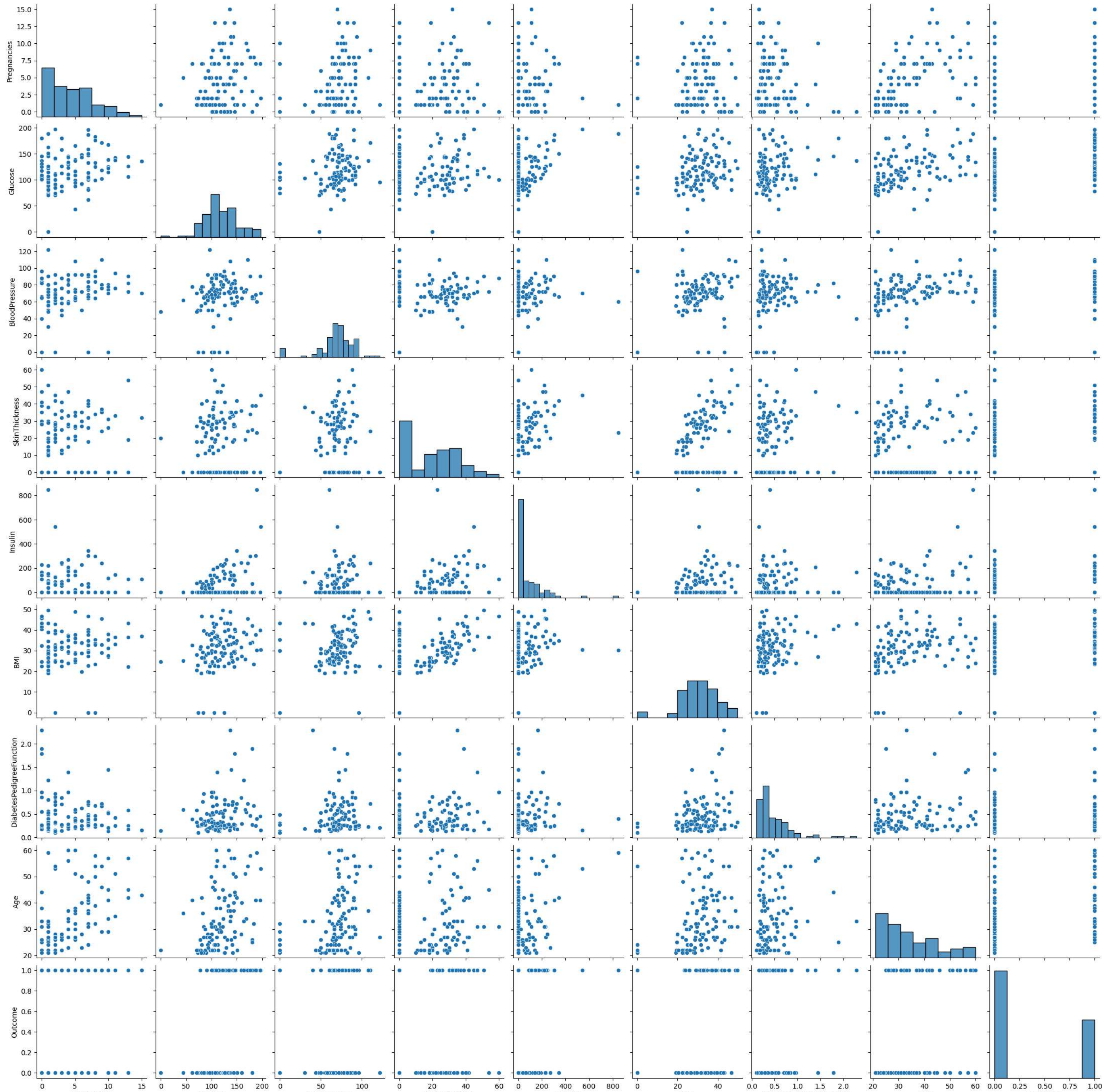
```
# Apply the Logistics Regression

alpha = 0.01
epochs = 1000
theta_array , cost_history = Training(x_train  , y_train , alpha , epochs)
```

```
# 13.   Observe the cost function vs iterations learning curve

x = np.arange(0, epochs)
plt.plot(x, cost_history)
plt.xlabel('Epochs')
plt.ylabel('Cost')
plt.show()
```



Results

```
# a.  Datapoints scattering

sns.pairplot(data)
plt.show()
```


Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome

```
# b.    Data Statistics before Normalization

data.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	108.00000	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000	108.000000
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75%	7.00000	139.500000	80.000000	32.000000	110.000000	37.225000	0.586250	41.000000	1.000000
max	15.00000	197.000000	122.000000	60.000000	846.000000	49.700000	2.288000	60.000000	1.000000

```
# c.    Data Statistics after Normalization

norm_data = Feature_Normalization(data)
norm_data = norm_data[0]  # Assuming norm_data[0] is the data array.
normalized_dataset = pd.DataFrame(norm_data , columns=data.columns)
normalized_dataset.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	
count	1.080000e+02	1.080000e+02	1.080000e+02	1.080000e+02	1.080000e+02	1.080000e+02	1.080000e+02	1.080000e+02	1.0
mean	2.634210e-17	3.186751e-17	-1.182182e-16	4.934325e-17	-9.457455e-17	3.340949e-18	2.672759e-17	-2.066248e-16	2.(
std	1.004662e+00	1.004662e+00	1.004662e+00	1.004662e+00	1.004662e+00	1.004662e+00	1.004662e+00	1.004662e+00	1.0
min	-1.230135e+00	-3.555343e+00	-3.126949e+00	-1.179273e+00	-5.869424e-01	-3.295055e+00	-1.002024e+00	-1.162979e+00	-
25%	-9.486633e-01	-5.924179e-01	-2.093637e-01	-1.179273e+00	-5.869424e-01	-5.945727e-01	-6.074995e-01	-8.231476e-01	-
50%	-1.042487e-01	-1.412110e-01	1.553344e-01	5.425229e-02	-5.869424e-	5.119492e-02	-3.602462e-01	-2.567617e-01	-

```
# d.    Learning Curve (Cost function vs iterations)

x = np.arange(0, epochs)
plt.plot(x, cost_history)
plt.xlabel('Epochs')
plt.ylabel('Cost')
plt.show()
```