2 LAB 8: Regression and Logistic Regression

- Regression
    - Linear Regression – Multiple Regression
- Logistic Regression – Multiclass classification Logistic Regression

```
try:
  from google.colab import drive
  %tensorflow_version 2.x
  COLAB = True
  print("Note: using Google CoLab")
except:
  print("Note: not using Google CoLab")
  COLAB = False

# Print your name and Roll No.
print('Name: Rohit Byas Sherwan')
print('Roll No. :181210043')

# Print the curent time
from datetime import datetime
print("Date Time :", datetime.now())
```

```
Note: using Google CoLab
Name: Rohit Byas Sherwan
Roll No. :181210043
Date Time : 2021-02-22 09:05:52.796377
```

```
import pandas as pd
import matplotlib.pyplot as plt
```

```
dataset=pd.read_csv('student_scores.csv')
dataset.shape
```

```
(25, 2)
```

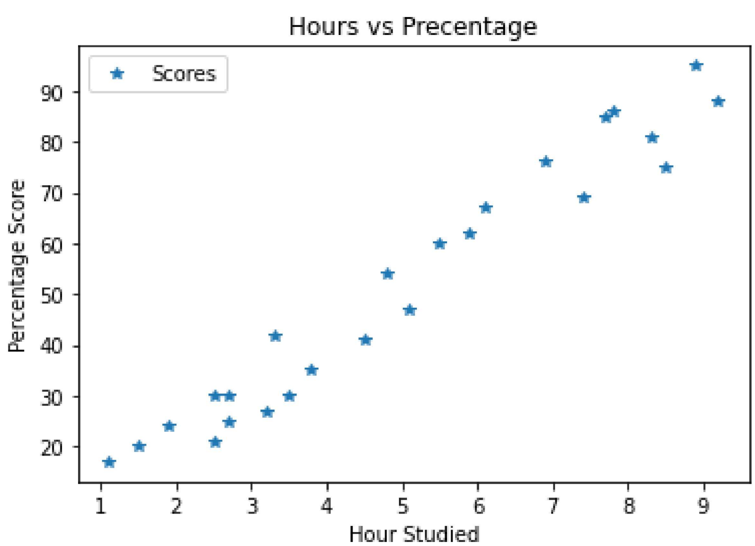
```
dataset.head()
```

Hours	Scores

```
dataset.describe()
```

	Hours	Scores
count	25.000000	25.000000
mean	5.012000	51.480000
std	2.525094	25.286887
min	1.100000	17.000000
25%	2.700000	30.000000
50%	4.800000	47.000000
75%	7.400000	75.000000
max	9.200000	95.000000

```
dataset.plot(x='Hours',y='Scores',style='*')
plt.title('Hours vs Precentage')
plt.xlabel('Hour Studied')
plt.ylabel('Percentage Score')
plt.show()
```



observation

From the graph above, we can clearly see that there is a positive linear relation between the number of hours studied and percentage of score.

```
# method to retrieve rows from a Data frame
x = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 1].values
```

```
import numpy as np
from sklearn.model_selection import train_test_split
```

```
?train_test_split
#Split arrays or matrices into random train and test subsets
```

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=0)
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

```
((20, 1), (5, 1), (20,), (5,))
```

observation

This script splits 80% of the data to training set while 20% of the data to test set. The test_size variable is where we actually specify the proportion of test set.

```
len(x_train),len(y_train)
```

```
(20, 20)
```

```
len(x_test), len(y_test)
```

```
(5, 5)
```

```
x_train
```

```
array([[3.8],
       [1.9],
       [7.8],
       [6.9],
       [1.1],
       [5.1],
       [7.7],
       [3.3],
       [8.3],
       [9.2],
       [6.1],
       [3.5],
       [2.7],
       [5.5],
       [2.7],
       [8.5],
       [2.5],
       [4.8],
       [8.9],
       [4.5]])
```

```
from sklearn.linear_model import LinearRegression


#traning the algorithm
regressor=LinearRegression()
regressor.fit(x_train,y_train)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

```
regressor.intercept_
```

```
2.018160041434662
```

```
regressor.coef_
```

```
array([9.91065648])
```

observation

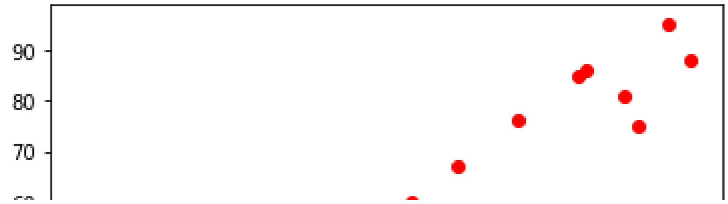
this tell that for every one unit of change in hours studied, the change in the score is about 9.91%

```
y_pred=regressor.predict(x_test)
```

```
df=pd.DataFrame({'Actual':y_test, 'Predicited':y_pred})
df
```

	Actual	Predicited
0	20	16.884145
1	27	33.732261
2	69	75.357018
3	30	26.794801
4	62	60.491033

```
#to see the relationship between the training data values
plt.scatter(x_train, y_train, c='red')
plt.show()
```

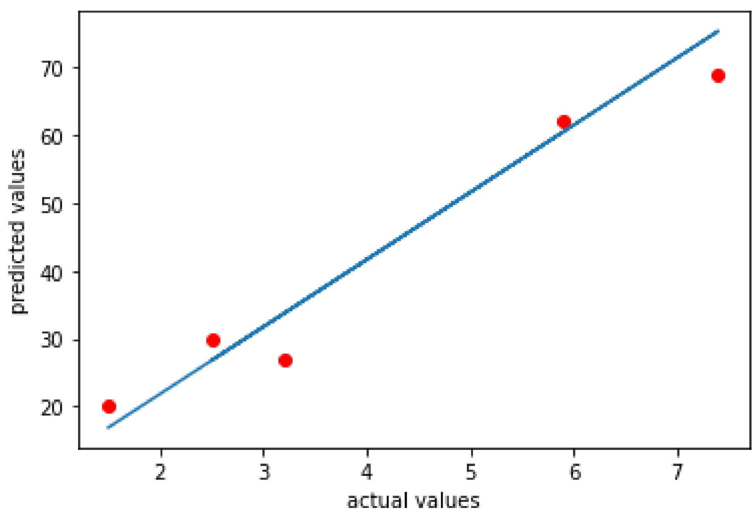


observation

we can see that, though our model is not very precise, the predicted percentages are close to the actual ones.

```
#to see the relationship between the predicted
#brain weight values using scattered graph
plt.plot(x_test,y_pred)
plt.scatter(x_test,y_test,c='red')
plt.xlabel('actual values')
plt.ylabel('predicted values')
```

```
Text(0, 0.5, 'predicted values')
```




```
from sklearn import metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,y_pred)))
```

```
Mean Absolute Error: 4.183859899002982
Mean Squared Error: 21.598769307217456
Root Mean Squared Error: 4.647447612100373
```

observation

we can see that Mean absolute error is less than 10%, so this model is good for prediction

5.2

```
# import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
dataset=pd.read_csv('petrol_consumption.csv')
dataset.shape
```

```
(48, 5)
```

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

```
dataset.head(5)
```

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol_Co
0	9.0	3571	1976	0.525	
1	9.0	4092	1250	0.572	
2	9.0	3865	1586	0.580	
3	7.5	4870	2351	0.529	
4	8.0	4399	431	0.544	

```
dataset.describe()
```

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)	Petrol
count	48.000000	48.000000	48.000000	48.000000	
mean	7.668333	4241.833333	5565.416667	0.570333	
std	0.950770	573.623768	3491.507166	0.055470	
min	5.000000	3063.000000	431.000000	0.451000	
25%	7.000000	3739.000000	3110.250000	0.529750	
50%	7.500000	4298.000000	4735.500000	0.564500	
75%	8.125000	4578.750000	7156.000000	0.595250	
max	10.000000	5342.000000	17782.000000	0.724000	

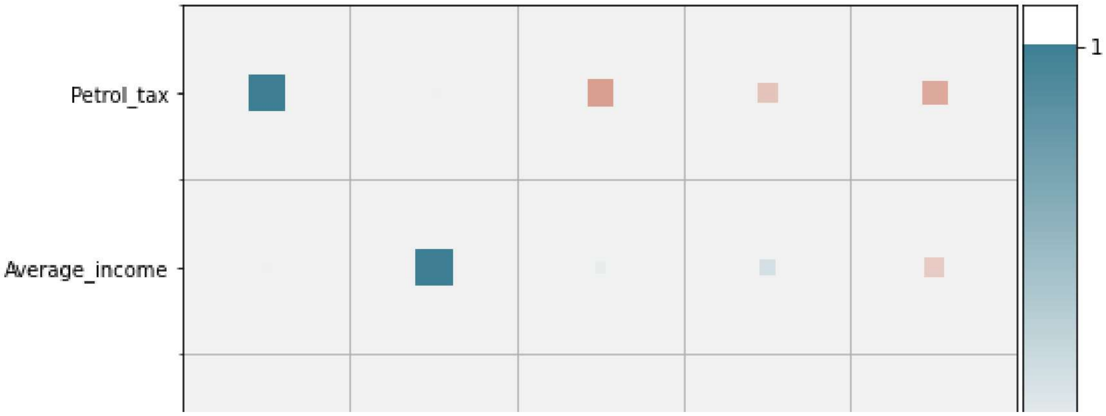
```
dataset.corr()
```

	Petrol_tax	Average_income	Paved_Highways	Population_Driv
Petrol_tax	1.000000	0.012665	-0.522130	
Average_income	0.012665	1.000000	0.050163	
Paved_Highways	-0.522130	0.050163	1.000000	

```
# install if you are using heatmapz for the first time
!pip install heatmapz
```

```
Collecting heatmapz
  Downloading https://files.pythonhosted.org/packages/26/5d/3928028fcb8de3bf09bb17975ca
Requirement already satisfied: pandas in /usr/local/lib/python3.6/dist-packages (from h
Requirement already satisfied: seaborn in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: matplotlib>=3.0.3 in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-packages (
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.6/dist-
Requirement already satisfied: numpy>=1.15.4 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: scipy>=1.0 in /usr/local/lib/python3.6/dist-packages (fr
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/l
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages (
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from
Installing collected packages: heatmapz
Successfully installed heatmapz-0.0.4
```

```
# Import the two methods from heatmap library
from heatmap import heatmap, corrplot
plt.figure(figsize=(8, 8))
corrplot(dataset.corr(), size_scale=300);
# Blue means positive, red means negative. The stronger the color, the larger the correlation
```




```
# load the data to input and output vairiable
X = dataset[['Petrol_tax', 'Average_income','Paved_Highways','Population_Driver_licence(%)']]
y = dataset['Petrol_Consumption']
```

```
# Split data into train, test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
```

```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((33, 4), (15, 4), (33,), (15,))
```

```
X_train
```

	Petrol_tax	Average_income	Paved_Highways	Population_Driver_licence(%)
2	9.00	3865	1586	0.580
46	7.00	4296	4083	0.623
18	7.00	4716	5915	0.724
15	7.00	4318	10340	0.586
28	8.00	4188	5975	0.563
22	9.00	4897	2449	0.511
16	7.00	4206	8508	0.572
41	7.00	3656	3985	0.563
20	7.00	4593	7834	0.663
42	7.00	4300	3635	0.603
8	8.00	4447	8577	0.529
13	7.00	4207	6580	0.545
25	9.00	3721	4746	0.544
5	10.00	5342	1333	0.571
17	7.00	3718	4725	0.540
35	6.58	3802	7834	0.629
14	7.00	4332	8159	0.608

```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

```
coeff_df = pd.DataFrame(regressor.coef_, X.columns, columns=['Coefficient'])
coeff_df
```

	Coefficient
Petrol_tax	-43.200216
Average_income	-0.067281
Paved_Highways	-0.005851
Population_Driver_licence(%)	1331.115701

9	7.00	4512	8507	0.552

```
y_pred = regressor.predict(X_test)
```

```
df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
```

```
df
```

	Actual	Predicted
29	534	468.315946
4	410	550.397078
26	577	590.639321
30	571	572.176794
32	577	649.893941
37	704	648.443789
34	487	515.198650
40	587	674.764637
7	467	503.476378
10	580	500.073610
11	471	417.315045
31	554	587.996148
33	628	624.508204
27	631	605.300526
47	524	563.470521

```
from sklearn import metrics
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Mean Absolute Error: 49.203756556631184
Mean Squared Error: 3673.2072706922686
Root Mean Squared Error: 60.60699027911111
```

observation

The value of root mean squared error is 60.07, which is greater than 10% of the mean value, this means that our algorithm was not very accurate but can still make reasonably good predictions.

PART 8.3: Logistic_Regression_using_Sklearn

```
# Run this cell if you are using scikit-learn for the first time
# ! pip install -U scikit-learn
```

```
import pandas as pd
```

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.metrics import plot_confusion_matrix
```

```
#predict whether a person is diabetic or not
dataset= pd.read_csv('sample_dataset.csv') # Dataset of diabities
```

```
dataset.head(5)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeF
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	

```
dataset.columns
```

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

```
independent_variables=['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
```

```
data= dataset[independent_variables] # Features
label= dataset.Outcome # Target variable
```

```
data.head(3)
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeF
0	6	148	72	35	0	33.6	
1	1	85	66	29	0	26.6	
2	8	183	64	0	0	23.3	

```
label.head(3)
```

```
0    1
1    0
```

```
2    1
Name: Outcome, dtype: int64
```

```
# split X and y into training and testing sets
train_data,test_data, train_label,test_label=train_test_split(data,label,test_size=0.20)
```

```
train_data.shape, test_data.shape, train_label.shape, test_label.shape
```

```
((614, 8), (154, 8), (614,), (154,))
```

```
# instantiate the model (using the default parameters)
regressor= LogisticRegression()
# fit the model with data
regressor.fit(train_data, train_label)
# predicting model's performancce on test data
predicted_test_label=regressor.predict(test_data)
```

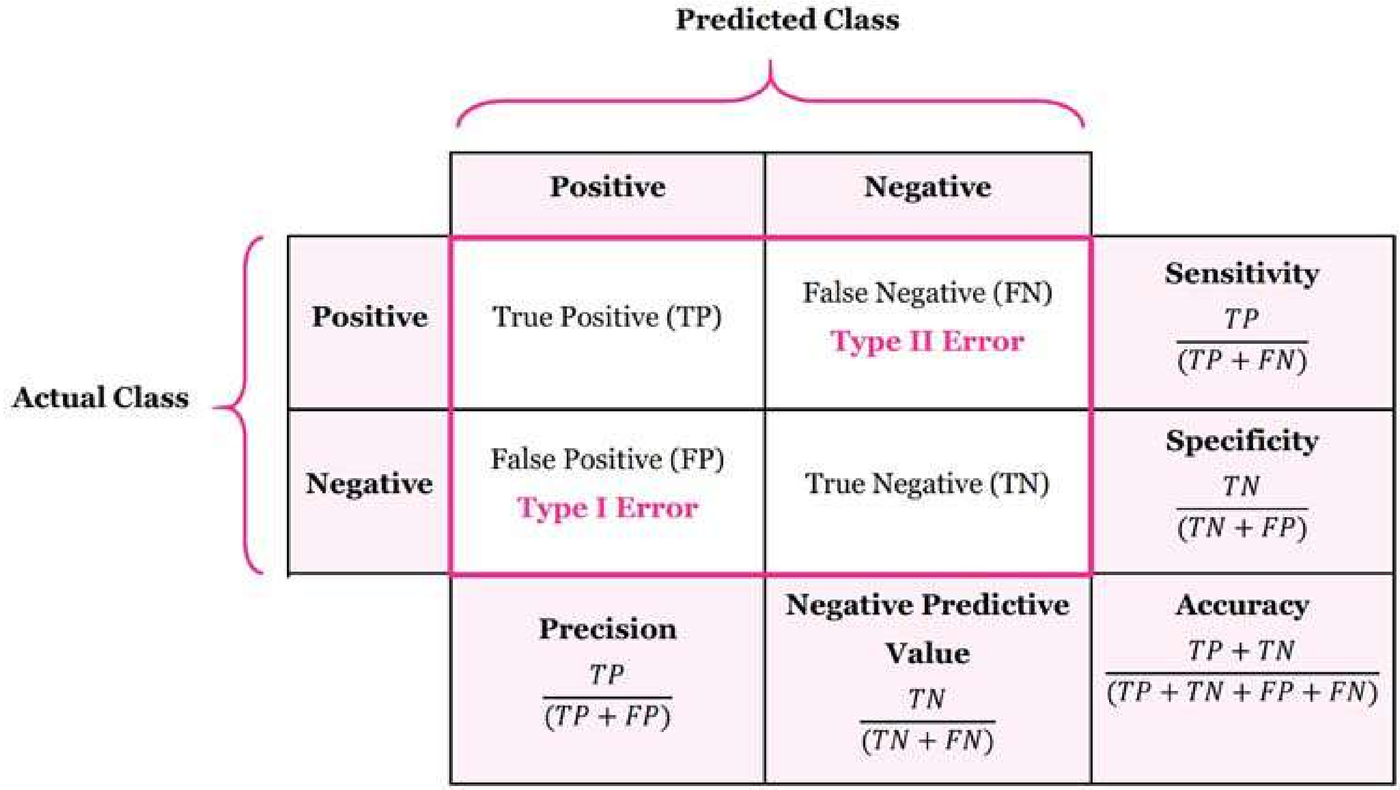
```
/usr/local/lib/python3.6/dist-packages/sklearn/linear_model/_logistic.py:940: Convergen
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
confusion_matrix= metrics.confusion_matrix(test_label, predicted_test_label)
confusion_matrix
```

```
array([[89,  6],
       [27, 32]])
```

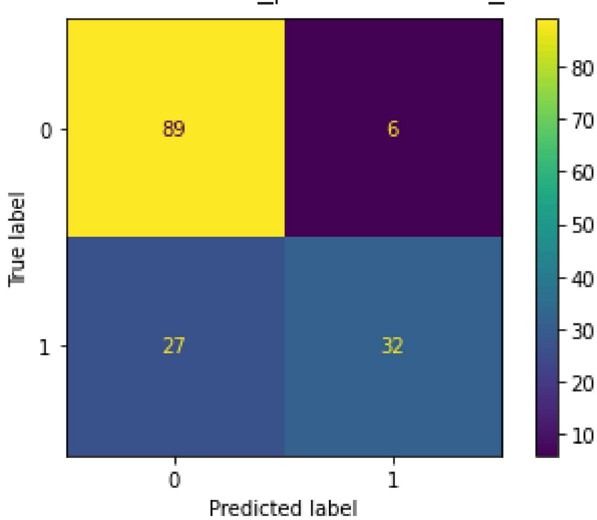
Evaluation Paramters : Confusion Matrix



	Positive	Negative	
Positive	True Positive (TP)	False Negative (FN) Type II Error	Sensitivity $\frac{TP}{(TP+FN)}$
Negative	False Positive (FP) Type I Error	True Negative (TN)	Specificity $\frac{TN}{(TN+FP)}$
	Precision $\frac{TP}{(TP+FP)}$	Negative Predictive Value $\frac{TN}{(TN+FN)}$	Accuracy $\frac{TP+TN}{(TP+TN+FP+FN)}$

```
plot_confusion_matrix(regressor, test_data, test_label)
# TruePositive , True Negative, False Positive, False Negative
```

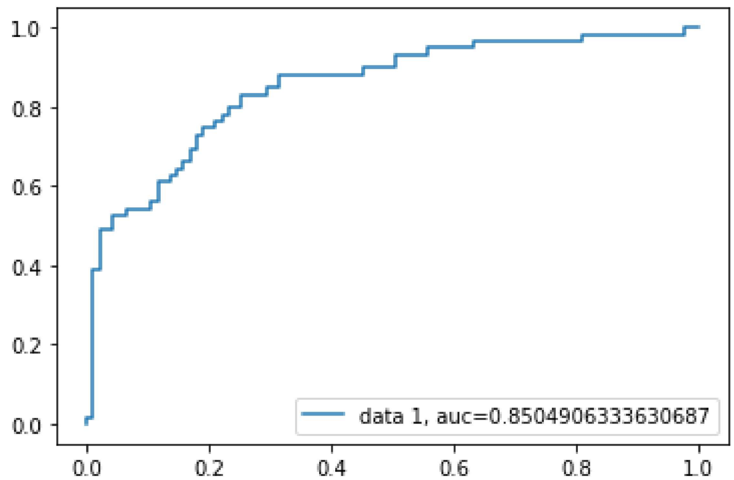
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f3cfc9ad780>
```




```
print("Accuracy:",metrics.accuracy_score(test_label, predicted_test_label))
print("Precision:",metrics.precision_score(test_label, predicted_test_label))
print("Recall:",metrics.recall_score(test_label, predicted_test_label))
```

```
Accuracy: 0.7857142857142857
Precision: 0.8421052631578947
Recall: 0.5423728813559322
```

```
test_predictions= regressor.predict_proba(test_data)[::,1]
fpr, tpr, _ = metrics.roc_curve(test_label, test_predictions)
auc = metrics.roc_auc_score(test_label, test_predictions)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



observation

1.Glucose level, BMI, pregnancies and diabetes pedigree function have significant influence on the model, specially glucose level and BMI

2.Blood pressure has a negative influence on the prediction i.e. higher blood pressure is correlated with a person not being diabetic.