#import the liabrary

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt

import sklearn

import matplotlib.pyplot as plt

#load the dataset

dataset = pd.read_csv('/Users/shraddhalipane/Downloads/Project
2/Healthcare - Diabetes/health care diabetes.csv')

#know dataset

data=pd.read_csv('/Users/shraddhalipane/Downloads/Project 2/Healthcare
 Diabetes/health care diabetes.csv')

shape , info, describe , null values, neagtive values , head, tail

data.shape

(768, 9)

data.describe()

Glucose	BloodPressure	SkinThickness
768.000000	768.000000	768.000000
120.894531	69.105469	20.536458
31.972618	19.355807	15.952218
0.000000	0.000000	0.000000
99.000000	62.000000	0.000000
117.000000	72.000000	23.000000
140.250000	80.000000	32.000000
199.000000	122.000000	99.000000
	768.000000 120.894531 31.972618 0.000000 99.000000 117.000000 140.250000	768.000000 768.000000 120.894531 69.105469 31.972618 19.355807 0.000000 0.000000 99.000000 62.000000 117.000000 72.000000 140.250000 80.000000

	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.000000	768.000000	768.000000	768.000000
mean	31.992578	0.471876	33.240885	0.348958
std	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.078000	21.000000	0.000000
25%	27.300000	0.243750	24.000000	0.000000
50%	32.000000	0.372500	29.000000	0.000000
75%	36.600000	0.626250	41.000000	1.000000
max	67.100000	2.420000	81.000000	1.000000

data.isnull().sum()

Pregnancies	0
Glucose	0
BloodPressure	0
SkinThickness	0
Insulin	0
BMI	0
DiabetesPedigreeFunction	0
Age	0
Outcome	0
1	

dtype: int64

data.head()

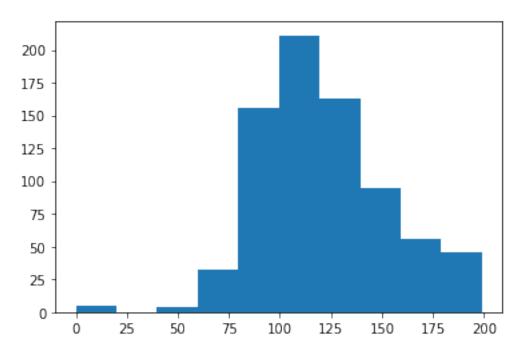
Pregnancies BMI \	Glucose	BloodPressure	SkinThickness	Insulin	
0 6	148	72	35	Θ	33.6
1 1	85	66	29	0	26.6
2 8	183	64	0	0	23.3
3 1	89	66	23	94	28.1
4 0	137	40	35	168	43.1

	DiabetesPedigreeFunction	Age	Outcome
0	0.627	50	1
1	0.351	31	0
2	0.672	32	1
3	0.167	21	0
4	2 288	33	1

data.info()

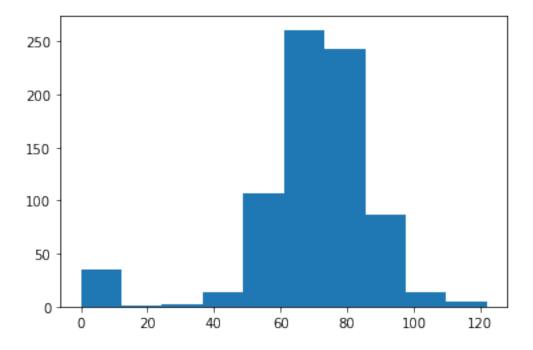
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):

		-	
#	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

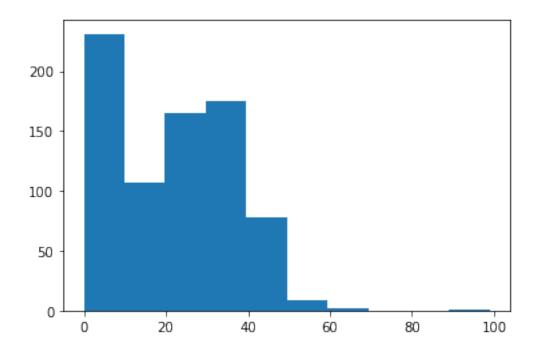


data['Glucose'].value_counts().head(7)

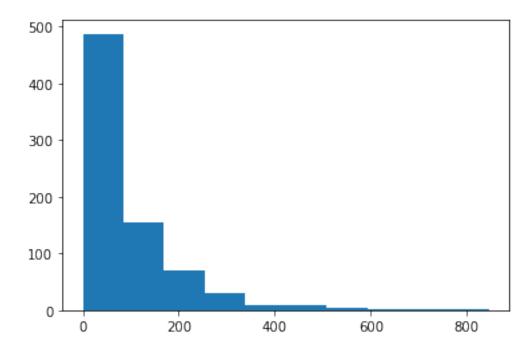
```
99
     17
     17
100
     14
111
129
     14
125
     14
106
     14
     13
112
Name: Glucose, dtype: int64
plt.hist(data['BloodPressure'])
(array([ 35.,
                                     73.2, 85.4, 97.6,
<BarContainer object of 10 artists>)
```



data['BloodPressure'].value_counts().head() Name: BloodPressure, dtype: int64 plt.hist(data['SkinThickness']) (array([231., 107., 165., 175., 78., 9., 2., 0., 0., 1.]), array([0. , 9.9, 19.8, 29.7, 39.6, 49.5, 59.4, 69.3, 79.2, 89.1, 99.]), <BarContainer object of 10 artists>)



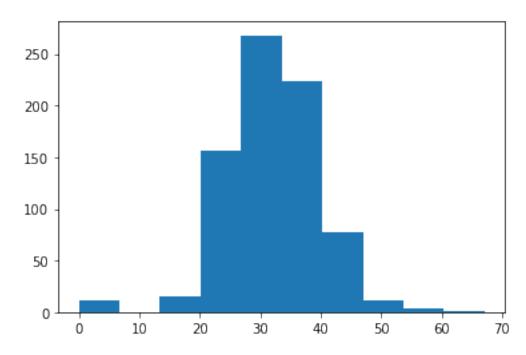
plt.hist(data['Insulin'])



plt.hist(data['BMI'])

(array([11., 0., 15., 156., 268., 224., 78., 12., 3., 1.]), array([0. , 6.71, 13.42, 20.13, 26.84, 33.55, 40.26, 46.97, 53.68,

60.39, 67.1]), <BarContainer object of 10 artists>)



data['Glucose'].value_counts()

```
99
       17
100
       17
111
       14
129
       14
125
       14
        1
191
177
        1
44
        1
62
        1
190
Name: Glucose, Length: 136, dtype: int64
```

data['BloodPressure'].value_counts()

70	57
74	52
78	45
68	45
72	44
64	43
80	40
76	39
60	37
0	35
62	34

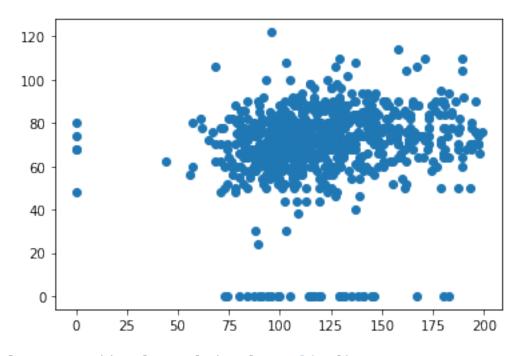
```
30
30
66
82
        25
88
        23
84
        22
90
86
        21
        21
58
50
        13
        12
56
52
        11
54
        11
75
         8
92
         8
7
6
6
5
4
65
85
94
48
96
44
         4 3 3 3 3 2 2 2 2 1 1
100
106
98
110
55
108
104
46
30
122
95
102
         1
61
         1
24
         1
38
          1
40
          1
114 1
Name: BloodPressure, dtype: int64
data['SkinThickness'].value_counts()
       227
0
32
        31
30
        27
27
        23
23
        22
        20
20
33
28
        20
18
        19
31
19
        18
39
        18
```

```
29
        17
40
        16
25
        16
26
        16
22
        16
37
        16
41
        15
        15
35
        14
36
15
        14
17
        14
        13
20
24
        12
42
        11
13
        11
21
        10
         8
46
34
         8
         7
12
         7
38
         6
6
11
43
16
         6
         6
45
14
         6 5 5 4 4 3 3 2 2 2 2 1
44
10
48
47
49
50
8
7
52
54
63
60
         1
56
         1
51
         1
99
         1
Name: SkinThickness, dtype: int64
data['Insulin'].value_counts()
0
        374
105
         11
130
          9
          9
140
          8
120
          1
73
```

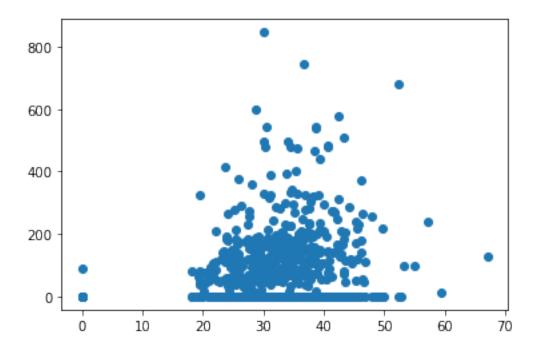
```
171
         1
255
         1
52
         1
112
         1
Name: Insulin, Length: 186, dtype: int64
data['BMI'].value_counts()
32.0
        13
31.6
        12
31.2
        12
0.0
        11
32.4
        10
36.7
         1
41.8
         1
42.6
         1
42.8
         1
46.3
         1
Name: BMI, Length: 248, dtype: int64
data.describe()
                                  BloodPressure
                                                  SkinThickness
       Pregnancies
                        Glucose
Insulin
                     768.000000
                                     768.000000
count
        768.000000
                                                     768.000000
768.000000
mean
          3.845052
                     120.894531
                                      69.105469
                                                      20.536458
79.799479
std
          3.369578
                      31.972618
                                      19.355807
                                                       15.952218
115.244002
                                       0.000000
                                                       0.000000
min
          0.000000
                       0.000000
0.000000
25%
          1.000000
                      99.000000
                                      62.000000
                                                       0.000000
0.000000
                     117.000000
                                      72,000000
50%
          3.000000
                                                      23,000000
30.500000
75%
                     140.250000
                                      80,000000
          6.000000
                                                      32.000000
127.250000
         17.000000
                     199.000000
                                     122.000000
                                                       99.000000
max
846.000000
               BMI
                    DiabetesPedigreeFunction
                                                        Age
                                                                Outcome
       768.000000
                                   768.000000
                                                768.000000
                                                             768.000000
count
mean
        31.992578
                                     0.471876
                                                 33.240885
                                                               0.348958
                                     0.331329
                                                 11.760232
std
         7.884160
                                                               0.476951
         0.00000
                                     0.078000
                                                 21.000000
                                                               0.00000
min
25%
        27.300000
                                     0.243750
                                                 24.000000
                                                               0.00000
50%
        32.000000
                                     0.372500
                                                 29.000000
                                                               0.00000
        36.600000
75%
                                     0.626250
                                                 41.000000
                                                               1.000000
max
        67.100000
                                     2.420000
                                                 81.000000
                                                               1.000000
```

```
data ['Outcome'].value_counts().head(7)

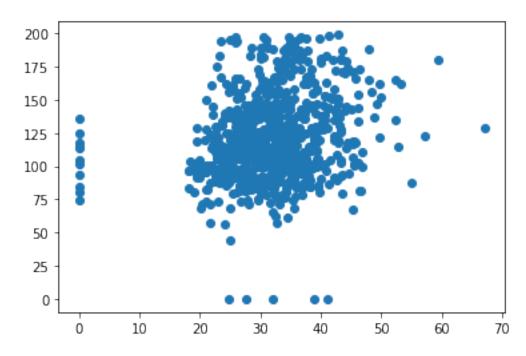
0    500
1    268
Name: Outcome, dtype: int64
plt.scatter(data['Glucose'],data['BloodPressure'])
<matplotlib.collections.PathCollection at 0x7fc5dd60d310>
```



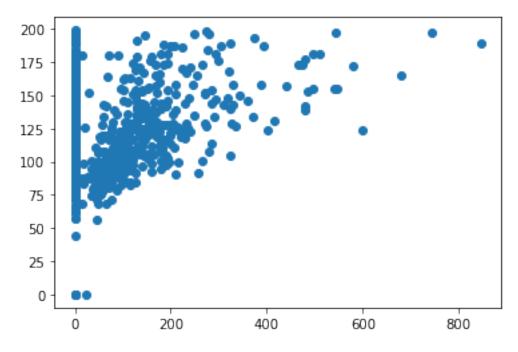
plt.scatter(data['BMI'],data['Insulin'])
<matplotlib.collections.PathCollection at 0x7fc5dd7e7e80>



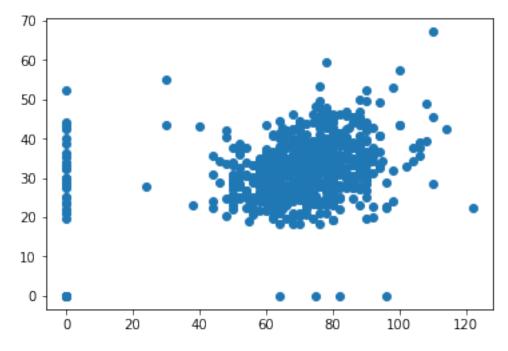
plt.scatter(data['BMI'],data['Glucose'])
<matplotlib.collections.PathCollection at 0x7fc5ca007910>



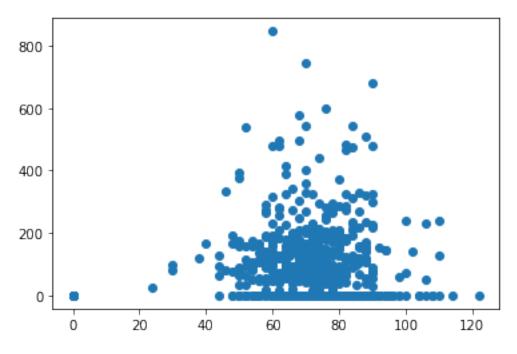
plt.scatter(data['Insulin'],data['Glucose'])
<matplotlib.collections.PathCollection at 0x7fc5b8215b20>



plt.scatter(data['BloodPressure'],data['BMI'])
<matplotlib.collections.PathCollection at 0x7fc5c9f4faf0>



plt.scatter(data['BloodPressure'],data['Insulin'])
<matplotlib.collections.PathCollection at 0x7fc5880b3e80>



#heatmap
data.corr()

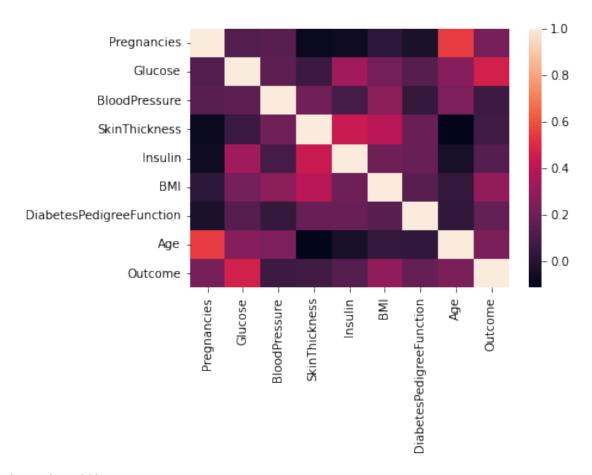
CkinThickness \	Pregnancies	Glucose	BloodPressure	
SkinThickness \ Pregnancies	1.000000	0.129459	0.141282	-
0.081672 Glucose	0.129459	1.000000	0.152590	
0.057328 BloodPressure	0.141282	0.152590	1.000000	
0.207371 SkinThickness 1.000000 Insulin 0.436783 BMI 0.392573 DiabetesPedigreeFunction 0.183928 Age 0.113970 Outcome 0.074752	-0.081672	0.057328	0.207371	
	-0.073535	0.331357	0.088933	
	0.017683	0.221071	0.281805	
	-0.033523	0.137337	0.041265	
	0.544341	0.263514	0.239528	-
	0.221898	0.466581	0.065068	

1	Insulin	BMI	DiabetesPedigreeFunction
\ Pregnancies	-0.073535	0.017683	-0.033523
Glucose	0.331357	0.221071	0.137337

BloodPressure	0.088933	0.281805	0.041265
SkinThickness	0.436783	0.392573	0.183928
Insulin	1.000000	0.197859	0.185071
BMI	0.197859	1.000000	0.140647
DiabetesPedigreeFunction	0.185071	0.140647	1.000000
Age	-0.042163	0.036242	0.033561
Outcome	0.130548	0.292695	0.173844
Pregnancies Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age Outcome	0.263514 0.239528 -0.113970 -0.042163 0.036242 0.033561	0.221898 0.466581 0.065068 0.074752 0.130548 0.292695 0.173844 0.238356	
import seaborn as sns			

sns.heatmap(data.corr())

<AxesSubplot:>



data.head()

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	
0 (148	72	35	0	33.6
1	. 85	66	29	0	26.6
2 8	183	64	0	Θ	23.3
3	. 89	66	23	94	28.1
4 6	137	40	35	168	43.1

	DiabetesPedigreeFunction	Age	Outcome
0	0.627	50	1
1	0.351	31	0
2	0.672	32	1
3	0.167	21	Θ
4	2.288	33	1

features=data.iloc[:,0:8].values

label=data.iloc[:,8].values

features

```
, 148.
array([[
                               72.
                                                33.6
                                                            0.627,
                                                                     50.
           6.
                                                                            ],
           1.
                     85.
                               66.
                                                26.6
                                                            0.351,
                                                                     31.
                                                                            ],
        [
           8.
                    183.
                               64.
                                                23.3
                                                            0.672,
                                                                     32.
                                                                            ],
                                         . . . ,
        [
           5.
                  , 121.
                               72.
                                                26.2
                                                            0.245,
                                                                     30.
                                                                            ],
                                       , ...,
                                                                            ],
                                                                     47.
            1.
                   126.
                               60.
                                                30.1
                                                            0.349,
                                         . . . ,
                                                                            ]])
            1.
                     93.
                               70.
                                       , ...,
                                                30.4
                                                            0.315,
                                                                     23.
label
array([1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0,
0,
        1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0,
1,
```

0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1,

0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,

0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1,

1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1,

1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,

0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0,

1,

0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1,

1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1,

1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0,

0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0,

0,

1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0,

0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1,

1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1,

0, 0, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,

0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0,

0,

0,

0,

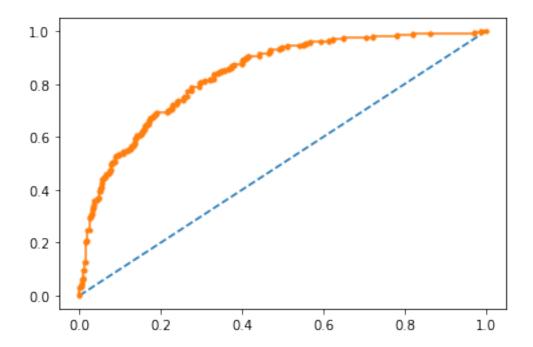
0,

1,

```
0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1,
0,
      0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0,
1,
      0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
0,
      1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0,
0,
      0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
0,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0,
0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0,
0,
      0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0,
0,
      0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0,
0,
      0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1,
0,
      0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1,
0,
      0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0,
0,
       1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0,
1,
      0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0,
1,
      0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1,
0,
      0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0,
0,
      0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1,
0,
       1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0])
from sklearn.model selection import train test split
X_train,X_test,y_train,y_test = train_test_split(features,
                                               label,
                                               test size=0.2,
                                               random_state =10)
from sklearn.linear model import LogisticRegression
classifier = LogisticRegression()
classifier.fit(X train,y train)
LogisticRegression()
print(classifier.score(X_train,y_train))
print(classifier.score(X test,y test))
```

```
0.7662337662337663
from sklearn.metrics import confusion matrix
cm = confusion matrix(label, classifier.predict(features))
array([[446, 54],
       [122, 146]])
from sklearn.metrics import classification report
print(classification report(label, classifier.predict(features)))
                           recall f1-score
              precision
                                              support
                             0.89
                                                  500
           0
                   0.79
                                       0.84
                   0.73
                             0.54
           1
                                       0.62
                                                  268
                                       0.77
                                                  768
    accuracy
                                       0.73
                                                  768
   macro avg
                   0.76
                             0.72
weighted avg
                   0.77
                             0.77
                                       0.76
                                                  768
from sklearn.metrics import roc curve
from sklearn.metrics import roc auc score
                                              #ROC Curve
probability = classifier.predict proba(features) # predict
probabilities
probability = probability[:, 1] # probability for positive outcomes
auc = roc auc score(label, probability) # calculating AUC
print('AUC: %.3f' % auc)
AUC: 0.837
fpr, tpr, thresholds = roc curve(label, probability) # ROC curve
calculation
plt.plot([0, 1], [0, 1], linestyle='--')
plt.plot(fpr, tpr, marker='.')
[<matplotlib.lines.Line2D at 0x7fc5dc5f20a0>]
```

0.7719869706840391



from sklearn.metrics import classification_report
print(classification_report)

<function classification_report at 0x7fc5dc29f940>

print(classifier.score(X_train,y_train))
print(classifier.score(X_test,y_test))

0.7719869706840391

0.7662337662337663

classification report

<function

sklearn.metrics._classification.classification_report(y_true, y_pred,
*, labels=None, target_names=None, sample_weight=None, digits=2,
output dict=False, zero division='warn')>

classifier.predict(X test)

 $1,\ 0,\ 0,\ 0,\ 1,\ 1,\ 1,\ 0,\ 0,\ 0,\ 0,\ 1,\ 0,\ 0,\ 1,\ 1,\ 0,\ 0,\ 0,\ 1,$ 0])

from sklearn.metrics import classification_report
print(classification_report)

<function classification_report at 0x7fc5dc29f940>