Build a logistic regression model to predict Diabetes

In [1]:
```
#Load the datset from sklearn
import pandas as pd
import numpy as np
from sklearn.datasets import load_diabetes

data=load_diabetes()
```

In [2]:
```
data
```

Out[2]:
```
{'data': array([[ 0.03807591,  0.05068012,  0.06169621, ..., -0.00259226,
          0.01990842, -0.01764613],
        [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
         -0.06832974, -0.09220405],
        [ 0.08529891,  0.05068012,  0.04445121, ..., -0.00259226,
          0.00286377, -0.02593034],
        ...,
        [ 0.04170844,  0.05068012, -0.01590626, ..., -0.01107952,
         -0.04687948,  0.01549073],
        [-0.04547248, -0.04464164,  0.03906215, ...,  0.02655962,
          0.04452837, -0.02593034],
        [-0.04547248, -0.04464164, -0.0730303 , ..., -0.03949338,
         -0.00421986,  0.00306441]]),
 'target': array([151.,  75., 141., 206., 135.,  97., 138.,  63., 110., 310., 10
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         87.,  65., 102., 265., 276., 252.,  90., 100.,  55.,  61.,  92.,
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         83., 128., 102., 302., 198.,  95.,  53., 134., 144., 232.,  81.,
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         77., 109., 272.,  60.,  54., 221.,  90., 311., 281., 182., 321.,
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        140., 189., 181., 209., 136., 261., 113., 131., 174., 257.,  55.,
         84.,  42., 146., 212., 233.,  91., 111., 152., 120.,  67., 310.,
         94., 183.,  66., 173.,  72.,  49.,  64.,  48., 178., 104., 132.,
        220.,  57.]),
 'frame': None,
 'DESCR': '.. _diabetes_dataset:\n\nDiabetes dataset\n----------------\n\nTen bas
eline variables, age, sex, body mass index, average blood\npressure, and six bloo
```

```
d serum measurements were obtained for each of n =\n442 diabetes patients, as wel
l as the response of interest, a\nquantitative measure of disease progression one
year after baseline.\n\n**Data Set Characteristics:**\n\n  :Number of Instances:
442\n\n  :Number of Attributes: First 10 columns are numeric predictive values\n
\n  :Target: Column 11 is a quantitative measure of disease progression one year
after baseline\n\n  :Attribute Information:\n      - age     age in years\n
- sex\n      - bmi     body mass index\n      - bp      average blood pressure\n
- s1      tc, total serum cholesterol\n      - s2      ldl, low-density lipoprote
ins\n      - s3      hdl, high-density lipoproteins\n      - s4      tch, total c
holesterol / HDL\n      - s5      ltg, possibly log of serum triglycerides level
\n      - s6      glu, blood sugar level\n\nNote: Each of these 10 feature variab
les have been mean centered and scaled by the standard deviation times `n_samples
` (i.e. the sum of squares of each column totals 1).\n\nSource URL:\nhttps://www
4.stat.ncsu.edu/~boos/var.select/diabetes.html\n\nFor more information see:\nBrad
ley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least Angl
e Regression," Annals of Statistics (with discussion), 407-499.\n(https://web.sta
nford.edu/~hastie/Papers/LARS/LeastAngle_2002.pdf)',
 'feature_names': ['age',
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  'bp',
  's1',
  's2',
  's3',
  's4',
  's5',
  's6'],
 'data_filename': 'C:\\ProgramData\\Anaconda3\\lib\\site-packages\\sklearn\\datas
ets\\data\\diabetes_data.csv.gz',
 'target_filename': 'C:\\ProgramData\\Anaconda3\\lib\\site-packages\\sklearn\\dat
asets\\data\\diabetes_target.csv.gz'}
```

In [3]:
```
data.feature_names
```

Out[3]:
```
['age', 'sex', 'bmi', 'bp', 's1', 's2', 's3', 's4', 's5', 's6']
```

In [4]:
```
data.DESCR
```

Out[4]:
```
'.. _diabetes_dataset:\n\nDiabetes dataset\n----------------\n\nTen baseline vari
ables, age, sex, body mass index, average blood\npressure, and six blood serum me
asurements were obtained for each of n =\n442 diabetes patients, as well as the r
esponse of interest, a\nquantitative measure of disease progression one year afte
r baseline.\n\n**Data Set Characteristics:**\n\n  :Number of Instances: 442\n\n
:Number of Attributes: First 10 columns are numeric predictive values\n\n  :Targe
t: Column 11 is a quantitative measure of disease progression one year after base
line\n\n  :Attribute Information:\n      - age     age in years\n      - sex\n
- bmi     body mass index\n      - bp      average blood pressure\n      - s1
tc, total serum cholesterol\n      - s2      ldl, low-density lipoproteins\n
- s3      hdl, high-density lipoproteins\n      - s4      tch, total cholesterol
/ HDL\n      - s5      ltg, possibly log of serum triglycerides level\n      - s6
glu, blood sugar level\n\nNote: Each of these 10 feature variables have been mean
centered and scaled by the standard deviation times `n_samples` (i.e. the sum of
squares of each column totals 1).\n\nSource URL:\nhttps://www4.stat.ncsu.edu/~boo
s/var.select/diabetes.html\n\nFor more information see:\nBradley Efron, Trevor Ha
stie, Iain Johnstone and Robert Tibshirani (2004) "Least Angle Regression," Annal
s of Statistics (with discussion), 407-499.\n(https://web.stanford.edu/~hastie/Pa
pers/LARS/LeastAngle_2002.pdf)'
```

In [5]:
```
#load diabetes.csv
diab=pd.read_csv("C:/1562_AIML/diabetes.csv")
```

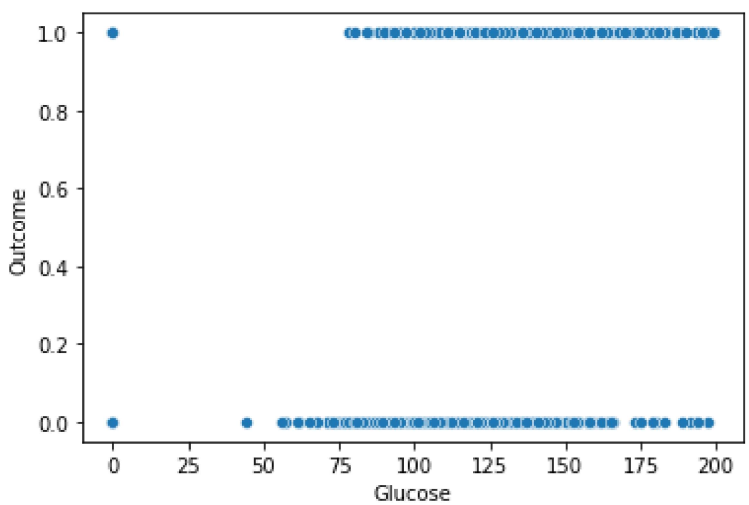
In [7]:
```
diab.head()
```

Out[7]:

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

In [14]:
```
#draw a scatter plot of glucose level against outcome
import seaborn as sns
sns.scatterplot(data=diab,x='Glucose', y='Outcome')
```

Out[14]: <AxesSubplot:xlabel='Glucose', ylabel='Outcome'>



In [10]:
```
diab.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
```

In [15]:
```
#prepare x and y
features=['Pregnancies','Glucose','BloodPressure','SkinThickness','Insulin','BMI',
x=diab[features]
y=diab.Outcome
```

In [17]:
```
#split the dataset in training and test dataset
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,train_size=0.8,random_state=100
```

In [23]:
```
#Build logistics regression model
from sklearn.linear_model import LogisticRegression
logr=LogisticRegression(max_iter=1000)

#train the model
logr.fit(x_train,y_train)

#test the model
y_pred=logr.predict(x_test)
```

In [25]:
```
#compute the accuracy of the model
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix

print("Accuracy score:",accuracy_score(y_test,y_pred))
```

```
Accuracy score: 0.7402597402597403
```

In [27]:
```
#print classification report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.77      0.85      0.81       101
           1       0.65      0.53      0.58        53

    accuracy                           0.74       154
   macro avg       0.71      0.69      0.70       154
weighted avg       0.73      0.74      0.73       154
```

In [30]:
```
print(confusion_matrix(y_test,y_pred))
```

```
[[86 15]
 [25 28]]
```

In [ ]: