## Name: Viviyan Richards W

#Roll no:205229133

## Lab5. Diabetes Classification using Logistic Regression

Step1. [Understand Data]. Using Pandas, import "diabetes.csv" file and print properties such as head, shape, columns, dtype, info and value\_counts

```
In [2]: import pandas as pd
         data = pd.read csv('diabetes.csv')
         data.head()
Out[2]:
             Pregnancies
                        Glucose
                                 BloodPressure
                                               SkinThickness Insulin
                                                                     BMI DiabetesPedigreeFunction
          0
                      6
                             148
                                            72
                                                                     33.6
                                                                                           0.627
                      1
                              85
                                                          29
                                                                    26.6
          1
                                            66
                                                                  0
                                                                                           0.351
          2
                      8
                             183
                                            64
                                                          0
                                                                    23.3
                                                                                           0.672
                                                          23
                                                                    28.1
                                                                                           0.167
          3
                      1
                              89
                                            66
                                                                 94
                      0
                             137
                                            40
                                                          35
                                                                168 43.1
                                                                                           2.288
In [3]: data.shape
Out[3]: (768, 9)
In [4]: data.columns
Out[4]: Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
                 'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
                dtype='object')
In [5]: data.dtypes
Out[5]: Pregnancies
                                          int64
         Glucose
                                          int64
         BloodPressure
                                          int64
         SkinThickness
                                          int64
         Insulin
                                          int64
         BMI
                                        float64
         DiabetesPedigreeFunction
                                        float64
         Age
                                          int64
         Outcome
                                          int64
         dtype: object
```

```
In [6]: type(data)
Out[6]: pandas.core.frame.DataFrame
In [7]: 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
              Glucose
          1
                                         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
                                         768 non-null
                                                          int64
              Age
          8
              Outcome
                                         768 non-null
                                                          int64
        dtypes: float64(2), int64(7)
        memory usage: 54.1 KB
In [8]: data.value counts()
Out[8]: Pregnancies Glucose
                               BloodPressure SkinThickness
                                                                        BMI
                                                               Insulin
                                                                               DiabetesPedi
        greeFunction Age Outcome
                      57
                                               0
                                                               0
                                                                         21.7
                                                                               0.735
                                60
        67
              0
                         1
                      67
                                76
                                               0
                                                               0
                                                                         45.3
                                                                               0.194
        46
              0
                         1
                                108
                                               37
        5
                      103
                                                               0
                                                                         39.2 0.305
        65
              0
                         1
                                74
                                                               0
                                                                         28.8
                      104
                                               0
                                                                               0.153
        48
              0
                         1
                      105
                                72
                                               29
                                                               325
                                                                         36.9 0.159
        28
              0
                         1
         . .
        2
                      84
                                50
                                               23
                                                               76
                                                                         30.4 0.968
        21
              0
                         1
                      85
                                65
                                               0
                                                               0
                                                                         39.6
                                                                               0.930
        27
              0
                         1
                      87
                                               23
                                0
                                                               0
                                                                         28.9
                                                                               0.773
        25
              0
                         1
                                58
                                               16
                                                               52
                                                                         32.7
                                                                               0.166
        25
              0
                         1
        17
                      163
                                72
                                                               114
                                                                         40.9 0.817
                                               41
        47
        Length: 768, dtype: int64
```

Step2. [Build Logistic Regression Model]

## Prepare X matrix (8 feature columns) and y vector (ie., Outcome column)

```
In [9]: X=data.drop("Outcome", axis=1)
           y=data[["Outcome"]]
In [10]: X
Out[10]:
                                                                                 BMI
                                                                                       DiabetesPedigreeFunction
                  Pregnancies
                               Glucose
                                         BloodPressure
                                                         SkinThickness
                                                                         Insulin
               0
                            6
                                    148
                                                     72
                                                                     35
                                                                              0
                                                                                 33.6
                                                                                                           0.627
               1
                            1
                                                                     29
                                                                                 26.6
                                                                                                           0.351
                                     85
                                                     66
               2
                            8
                                                                      0
                                                                                 23.3
                                                                                                           0.672
                                    183
                                                     64
               3
                            1
                                     89
                                                                     23
                                                                                 28.1
                                                                                                           0.167
                                                     66
                                                                             94
                            0
                                    137
                                                     40
                                                                     35
                                                                            168
                                                                                 43.1
                                                                                                           2.288
                                     ...
                                                     ...
                                                                     ...
             763
                           10
                                    101
                                                     76
                                                                            180
                                                                                 32.9
                                                                                                           0.171
                                                                     48
             764
                            2
                                    122
                                                     70
                                                                     27
                                                                              0
                                                                                 36.8
                                                                                                           0.340
             765
                            5
                                                                            112 26.2
                                                     72
                                                                     23
                                                                                                           0.245
                                    121
             766
                                    126
                                                     60
                                                                      0
                                                                                 30.1
                                                                                                           0.349
            767
                             1
                                     93
                                                     70
                                                                     31
                                                                              0
                                                                                 30.4
                                                                                                           0.315
           768 rows × 8 columns
In [11]: y
Out[11]:
                  Outcome
               0
                         1
               1
                         0
               2
                         1
                         0
               3
               4
                         1
             763
                         0
             764
                         0
                         0
             765
             766
                         1
            767
                         0
```

Split dataset with stratified shuffle split for training and testing as X\_train, X\_test, y\_train, y\_test (use 25% test size).

768 rows × 1 columns

```
In [12]: from sklearn.model selection import StratifiedShuffleSplit
In [13]: |StratifiedShuffleSplit()
         shuffle = StratifiedShuffleSplit(n_splits=4, test_size=0.25,random_state=0)
In [14]: shuffle.get_n_splits(X,y)
Out[14]: 4
         Create LogisticRegression model, fit on training set and predict on test set
In [15]: import warnings
         warnings.filterwarnings('ignore')
In [16]: for train, test in shuffle.split(X, y):
            X train, X test = X.iloc[train], X.iloc[test]
            y_train, y_test = y.iloc[train], y.iloc[test]
In [17]: | from sklearn.linear_model import LogisticRegression
In [18]: | lmodel = LogisticRegression()
In [19]: |lmodel.fit(X_train,y_train)
Out[19]: LogisticRegression()
In [20]: |y_predict = lmodel.predict(X_test)
         y predict
Out[20]: array([0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0,
               0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
                1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
                0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0,
                0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
                1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0,
                0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0,
               0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0], dtype=int64)
In [21]: |lmodel.score(X train,y train)
Out[21]: 0.789930555555556
         Predict on a new sample
In [22]: new person = [[6, 200, 90, 10, 25, 23.3, 0.672, 42]]
```

## localhost:8888/notebooks/Downloads/PML\_LAB5.ipynb#205229116

```
In [23]: print(lmodel.predict(new_person))
```

[1]

## Step3. [Compute Classification Metrics]

#### Precision score

```
In [24]: from sklearn.metrics import precision_score
print(precision_score(y_test, y_predict))
```

0.6727272727272727

#### Recall score

```
In [25]: from sklearn.metrics import recall_score
print(recall_score(y_test, y_predict))
```

0.5522388059701493

## Accuracy score

#### Which is 75% Accurate

```
In [26]: from sklearn.metrics import accuracy_score
lor_ascore=accuracy_score(y_test, y_predict)
```

```
In [27]: lor_ascore
```

Out[27]: 0.75

## AUC score

## AUC is the percentage of the ROC plot that is underneath the curve:

```
In [28]: from sklearn.metrics import roc_auc_score
```

```
In [29]: print(roc_auc_score(y_test, y_predict))
```

0.7041194029850747

## Step4. [Understand Correlation]

## Create confusion matrix between y\_test and y\_pred and plot confusion matrix values in a Heatmap. Explain the meaning of the 4 numbers you get.

```
In [30]: from sklearn.metrics import confusion matrix
         cnf_matrix=confusion_matrix(y_test, y_predict)
         cnf matrix
Out[30]: array([[107,
                 [ 30, 37]], dtype=int64)
In [31]: cf_ac_score = accuracy_score(y_test, y_predict)
In [32]: cf ac score
Out[32]: 0.75
In [33]: import seaborn as sns
         sns.heatmap(confusion_matrix(y_test,y_predict) / len(y), cmap='YlGnBu', annot=Tru
Out[33]: <AxesSubplot:>
                     0.14
                                       0.023
                                                      0.10
                                                      - 0.08
                                                     -0.06
                    0.039
                                      0.048
                                                     -0.04
                      0
                                        1
```

X-axis is predicted value

Y-axis is real value

Step5. [Normalization using MinmaxScaler and rebuild LoR]

## Now, normalize your X\_train and X\_test values using MinmaxScaler

```
In [34]: from sklearn.preprocessing import MinMaxScaler
    scaler = MinMaxScaler()
    X_trained = scaler.fit_transform(X_train)
    X_tested = scaler.transform(X_test)
```

```
In [35]: X trained.shape
Out[35]: (576, 8)
In [36]: X tested.shape
Out[36]: (192, 8)
         Create a new LogisticRegression model, fit on normalized training set and predict on the
         normalized test set
In [37]: | from sklearn.linear_model import LogisticRegression
         lmodel1 = LogisticRegression()
In [38]: |lmodel1.fit(X trained, y train)
Out[38]: LogisticRegression()
In [39]: yn_predict = lmodel1.predict(X_tested)
        yn predict
Out[39]: array([0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0,
               0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
               1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0,
               0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0,
               0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
               1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0,
               0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0,
               0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0], dtype=int64)
In [40]: | lmodel1.score(X trained, y train)
Out[40]: 0.789930555555556
         Precision score
In [41]: from sklearn.metrics import precision score
         print(precision score(y test, yn predict))
         0.673469387755102
         Recall score
        from sklearn.metrics import recall score
         print(recall score(y test, yn predict))
         0.4925373134328358
```

#### Accuracy score

```
Which is 72% Accurate

In [43]: from sklearn.metrics import accuracy_score minmax_ascore=accuracy_score(y_test, yn_predict)

In [44]: minmax_ascore

Out[44]: 0.739583333333334

AUC score

AUC is the percentage of the ROC plot that is underneath the curve

In [45]: from sklearn.metrics import roc_auc_score

In [46]: lgr_auc=roc_auc_score(y_test, yn_predict) lgr_auc1=('LoR minmax, AUC=',lgr_auc) lgr_auc1

Out[46]: ('LoR minmax, AUC=', 0.6822686567164179)

Step6. [Normalization using StandardScaler and rebuild LoR]
```

```
PML_LAB5 - Jupyter Notebook
In [52]: ys predict = lmodel2.predict(Xs tested)
        ys predict
Out[52]: array([0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0,
               0, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1,
               1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0,
               0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0,
               0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0,
               1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0,
               0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0,
               0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0], dtype=int64)
In [53]: lmodel2.score(Xs_trained, y_train)
Out[53]: 0.7795138888888888
         Precision score
In [54]: from sklearn.metrics import precision score
         print(precision score(y test, ys predict))
         0.6851851851851852
         Recall score
In [55]: from sklearn.metrics import recall_score
         print(recall score(y test, ys predict))
         0.5522388059701493
         Accuracy score
         Which is 75% Accurate
In [56]: | from sklearn.metrics import accuracy_score
         ss_ascore=accuracy_score(y_test, ys_predict)
In [57]: |ss_ascore
```

#### **AUC** score

Out[57]: 0.7552083333333334

AUC is the percentage of the ROC plot that is underneath the curve

```
In [58]: from sklearn.metrics import roc_auc_score
In [59]: ss_auc=roc_auc_score(y_test, ys_predict)
    ss_auc1=('AUC=',ss_auc)
    ss_auc1
Out[59]: ('AUC=', 0.7081194029850746)
```

## Among the 3 models, which model gives better classification scores?

```
In [60]: print('StandardScaler:',ss_ascore)
print('MinmaxScaler:',minmax_ascore)
print('Logistic Regression Model:',lor_ascore)
```

StandardScaler: 0.7552083333333334 MinmaxScaler: 0.739583333333334 Logistic Regression Model: 0.75

## Step7. [Plot ROC curve]

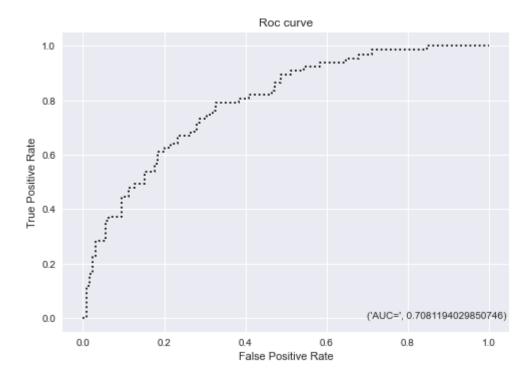
Plot ROC curve as shown below. You can use the MinmaxScaler scaled values of X\_test for computing predict\_proba() score.

```
In [61]: from sklearn.metrics import roc_curve

In [62]: predict_pb1 = lmodel1.predict_proba(X_tested)
    fpr1, tpr1, threshold1 = roc_curve(y_test,predict_pb1[:,1], pos_label=1)
```

```
In [63]: import matplotlib.pyplot as plt
    plt.style.use('seaborn')
    plt.annotate(xy=[0.7,0], s=ss_auc1)
    plt.plot(fpr1, tpr1, linestyle=':', color='black',label='Logistic Regression')
    plt.title('Roc curve')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
```

Out[63]: Text(0, 0.5, 'True Positive Rate')



Step8. [Comparison with KNN classifier].

# Create a KNN classifier with default values, fit on the scaled X using MinmaxScaler, predict and print classification metric scores.

```
In [64]: from sklearn.neighbors import KNeighborsClassifier
In [65]: lmodel3 = KNeighborsClassifier(n_neighbors=3)
In [66]: lmodel3.fit(X_trained,y_train)
Out[66]: KNeighborsClassifier(n_neighbors=3)
```

#### Precision score

```
In [68]: from sklearn.metrics import precision_score
print(precision_score(y_test, knn_y_predict))
```

0.6271186440677966

#### Recall score

```
In [69]: from sklearn.metrics import recall_score
print(recall_score(y_test, knn_y_predict))
```

0.5522388059701493

#### Accuracy score

```
In [70]: from sklearn.metrics import accuracy_score
kn_ascore=accuracy_score(y_test, knn_y_predict)
kn_ascore
```

Out[70]: 0.729166666666666

## **AUC score**

```
In [71]: from sklearn.metrics import roc_auc_score
kn_auc=roc_auc_score(y_test, knn_y_predict)
kn_auc1=('KNN minmax, AUC=',kn_auc)
kn_auc1
```

Out[71]: ('KNN minmax, AUC=', 0.6881194029850747)

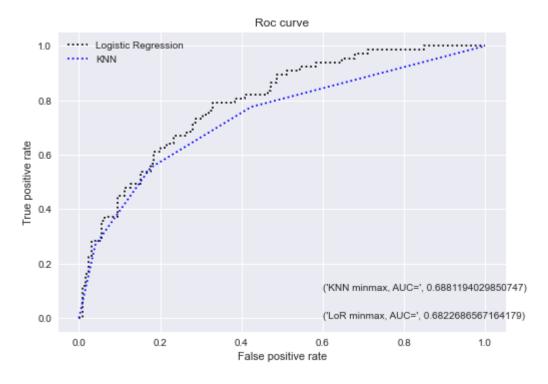
## Step9. [Update ROC curve]

Update your ROC curve, this time, with one more curve of KNN classifier,

```
In [72]: predict_pb2 = lmodel3.predict_proba(X_tested)
    fpr1,tpr1,threshold1 = roc_curve(y_test, predict_pb1[:,1],pos_label=1)
    fpr2,tpr2,threshold2 = roc_curve(y_test, predict_pb2[:,1],pos_label=1)
```

```
In [73]: plt.plot(fpr1,tpr1,linestyle=':',color='black',label='Logistic Regression')
    plt.plot(fpr2,tpr2,linestyle=':',color ='blue',label='KNN')
    plt.annotate(xy=[0.6,0.1], s=kn_auc1)
    plt.annotate(xy=[0.6,0], s=lgr_auc1)
    plt.legend(loc='best')
    plt.title('Roc curve')
    plt.xlabel('False positive rate')
    plt.ylabel('True positive rate')
```

Out[73]: Text(0, 0.5, 'True positive rate')



Step10. [Regularization]

In order to reduce overfitting of your data, you will use LogisticRegressionCV model with L1 and L2 regularization parameters. Create both models using the following statements

```
In [74]: from sklearn.linear_model import LogisticRegressionCV
In [75]: lmodel4 = LogisticRegressionCV(Cs=10, cv=4, penalty='l1', solver='liblinear')
lmodel5 = LogisticRegressionCV(Cs=10, cv=4, penalty='l2')
```

Perform fit using MinmaxScaler scaled values and predict

```
In [76]: |print(lmodel4.fit(X trained,y train))
     print(lmodel5.fit(X trained,y train))
     LogisticRegressionCV(cv=4, penalty='l1', solver='liblinear')
     LogisticRegressionCV(cv=4)
In [77]: | lr y predict1 = lmodel4.predict(X tested)
     lr y predict2 = lmodel5.predict(X tested)
     print('Logistic RegressionCV L1:\n',lr_y_predict1)
     print('-----
     print('Logistic RegressionCV L2:\n',lr_y_predict2)
     Logistic RegressionCV L1:
      0001000]
     Logistic RegressionCV L2:
      [0\ 0\ 1\ 1\ 0\ 1\ 1\ 0\ 0\ 1\ 1\ 0\ 0\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 0\ 0\ 0\ 0\ 0\ 0
      0 0 0 1 0 0 01
In [78]: from sklearn.metrics import roc auc score
     lrp auc=roc auc score(y test, lr y predict1)
     lrp1_auc=('LoR L1 minmax, AUC=',lrp_auc)
     lrp1 auc
Out[78]: ('LoR L1 minmax, AUC=', 0.6748059701492537)
In [79]: from sklearn.metrics import roc auc score
     lrp_auc2=roc_auc_score(y_test, lr_y_predict2)
     lrp2 auc=('LoR L2 minmax, AUC=',lrp auc2)
     lrp2 auc
Out[79]: ('LoR L2 minmax, AUC=', 0.6931940298507463)
```

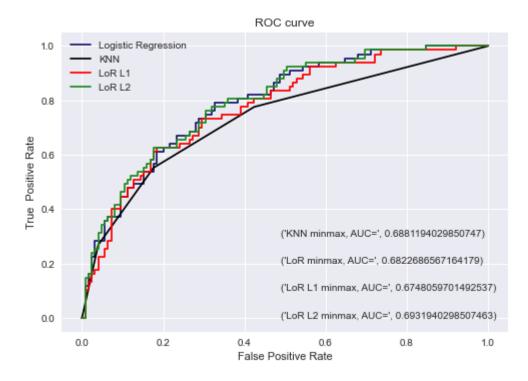
## Step11. [Update ROC curve]

#### Update your ROC curve, this time, with two more curves

```
In [80]: predict_pb3 = lmodel4.predict_proba(X_tested)
    predict_pb4 = lmodel5.predict_proba(X_tested)
    fpr1,tpr1,thresh1 = roc_curve(y_test, predict_pb1[:,1], pos_label=1)
    fpr2,tpr2,thresh2 = roc_curve(y_test, predict_pb2[:,1], pos_label=1)
    fpr3,tpr3,thresh3 = roc_curve(y_test, predict_pb3[:,1], pos_label=1)
    fpr4,tpr4,thresh4 = roc_curve(y_test, predict_pb4[:,1], pos_label=1)
```

```
In [90]: plt.plot(fpr1,tpr1,linestyle='-',color='midnightblue', label='Logistic Regressior
    plt.plot(fpr2,tpr2,linestyle='-',color='black', label='KNN')
    plt.plot(fpr3,tpr3,linestyle='-',color='red', label='LoR L1')
    plt.plot(fpr4,tpr4,linestyle='-',color='forestgreen', label='LoR L2')
    plt.annotate(xy=[0.49,0.3], s=kn_auc1)
    plt.annotate(xy=[0.49,0.2], s=lgr_auc1)
    plt.annotate(xy=[0.49,0.1], s=lrp1_auc)
    plt.annotate(xy=[0.49,0], s=lrp2_auc)
    plt.legend(loc='best')
    plt.title('ROC curve')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
```

Out[90]: Text(0, 0.5, 'True Positive Rate')



Logistic Regression L2 Minmax gives 69% of AUC score so this shows it is the best score