assign1_q2

August 17, 2019

1 Assignment 1 : Question 2

1.1 Question

Consider the training dataset data.csv, which has 8 variables, as follows. “NumPreg”,“PlasmaGlucose”, “DiastolicBP”, “TricepSkin”, “BodyMassIndex” ,“Pedigree” “Age”, “Diabetic” The target is to fit a logistic regression model to predict the “Diabetic” variable based on the other 7 variables. In this connection, please answer the following questions, in given sequence. 1. Develop the best model to predict the categorical response variable “Diabetic” in case of the given dataset? Justify your choice for best model. 2. Suppose you have chosen a threshold t to classify P(Diabetic | X) > t as “Diabetic” = Yes. How would you choose the optimal threshold t such that the aforesaid classification achieves maximum accuracy for your best model? Justify your choice.

1.2 The Solution

1.2.1 Importing the Libraries

```
In [126]: import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
          import sklearn
          from sklearn.preprocessing import LabelEncoder
          from sklearn.model_selection import train_test_split
          from sklearn.linear_model import LogisticRegression
          from sklearn.metrics import confusion_matrix
          import seaborn as sn
```

1.2.2 Splitting the data into features and labels and encoding the labels

```
In [127]: df = pd.read_csv('data.csv')
          x = df.iloc[:,0:7].values
          y = df.iloc[:,7].values

          #encoding
          labelencoder_Y = LabelEncoder()
          y = labelencoder_Y.fit_transform(y) # All rows and first column i.e country column
          y
```

```
Out[127]: array([0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0,
                 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
                 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1,
                 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 0,
                 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0,
                 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0,
                 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1,
                 0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0,
                 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0,
                 0, 1])
```

1.2.3 Normalizing the features with Standard Scaler

```
In [128]: standard_scaler = sklearn.preprocessing.StandardScaler()
          x_scaled = standard_scaler.fit_transform(x)
          df_normalised_std = pd.DataFrame(x_scaled)
          df_normalised_std
```

```
Out[128]:            0         1         2         3         4         5         6
          0   0.425869 -1.202040 -0.284695 -0.103888 -0.345061 -0.315755 -0.740777
          1   1.021490  2.248642 -0.110035  0.323636 -1.179093 -0.971641  2.090800
          2   0.425869 -1.486959  0.937920  1.007674  0.570740 -0.994483  0.263976
          3  -1.063183  1.298913  0.413942  1.178684  2.549524 -0.658382 -0.558095
          4  -1.063183 -0.537230 -0.983331 -0.360403 -0.966497 -1.069534 -0.832118
          5   0.425869 -0.853806  0.413942 -0.189393  0.538033 -0.270072  1.816776
          6  -0.169752 -1.297013 -1.157991  0.152626  0.325436 -0.407122 -0.649436
          7  -0.765373  2.185326 -1.856628 -1.129946 -1.048265  0.633811 -0.740777
          8  -0.169752  0.570787  0.763261 -1.215451  0.014718 -0.850906  2.821529
          9  -0.467562  0.127580  0.588602  0.665655  1.797259  2.490522 -0.101389
          10 -1.063183  0.412499 -2.729924  0.494645  1.764552  5.962474  0.081294
          11  1.617110  0.950679  0.588602  0.067121 -0.230586 -0.968378  1.177388
          12 -0.765373  2.058696 -0.983331 -0.531413 -0.361414 -0.204809  2.456165
          13  2.510541 -1.012095 -0.808672 -1.899490 -0.770254  1.518114  1.086047
          14 -0.765373 -1.202040 -0.459354  1.948228  1.470187  1.488746 -0.284071
          15  0.128058 -0.790491  0.413942 -1.215451 -1.489812 -0.775854 -1.014801
          16 -0.765373 -0.473915 -0.983331 -1.813985 -1.130033  1.586640 -1.014801
          17  2.212731  0.602445  1.985875  0.323636  0.701569 -0.674698  1.725435
          18 -0.765373  0.792391 -0.284695 -0.018384 -0.492243 -0.364702  0.903364
          19 -1.063183  0.475814 -0.808672 -1.044441 -1.669701 -0.828064 -1.014801
          20 -0.467562 -0.790491 -0.110035 -1.129946 -1.947712 -0.736697 -0.466753
          21 -0.765373 -0.758833 -0.459354 -0.018384 -0.050696 -0.054706  0.903364
          22  0.128058 -1.297013  1.287239 -0.873432 -0.492243 -0.469121  0.172635
          23 -1.063183 -0.727176 -0.634013 -1.044441 -1.849590 -0.681224 -1.014801
          24 -0.765373 -1.170383 -0.284695  0.409141  0.865105 -0.195020 -0.740777
          25  1.617110  1.267255  1.112579 -0.702422 -0.246939  1.208119 -0.010048
          26 -0.765373 -0.790491 -1.157991 -1.642975 -1.130033  0.294447 -1.014801
          27 -1.063183  0.507472 -0.546683 -0.274898  1.682784 -0.097127 -0.740777
          28  0.425869 -0.505572  0.064624  1.178684  0.619801 -0.645330  0.081294
```

```
29  -0.467562 -0.442257  0.239283 -0.018384  0.014718  0.774125 -0.466753
..        ...       ...       ...       ...       ...       ...       ...
170  0.723679 -0.283969 -0.983331  0.836665  0.227315 -0.704066  0.720682
171  0.425869 -0.600545  0.064624 -0.018384  0.750630 -0.984693 -0.375412
172  1.021490  2.216984 -0.284695 -0.103888  0.587094  0.927491  0.812023
173  0.128058  1.900408  0.588602  0.836665  0.766983 -0.642066 -0.101389
174 -1.063183 -0.917122  1.199909 -0.360403  0.832397 -0.697539 -0.740777
175  1.021490  0.000950 -0.110035  0.323636 -1.113679 -0.978167  0.446658
176 -0.765373 -0.410600 -0.808672 -1.386461 -1.358983 -1.053219 -0.832118
177  1.021490  0.412499  1.636557  1.007674 -0.050696 -0.227651  0.629341
178  1.617110 -2.120112  0.763261  0.665655  0.080133 -1.190269  0.812023
179 -0.467562  1.045652  0.239283  0.494645  1.159469 -1.066271 -0.192730
180 -0.467562 -0.917122 -1.507309 -1.300956 -1.015558  0.937280 -0.923459
181  2.510541  0.507472  1.199909  0.323636  0.832397 -0.707329  0.812023
182 -1.063183 -0.220654 -0.459354  0.152626 -0.246939  0.105186 -0.923459
183  1.319300 -0.758833  0.239283  0.922170  1.159469  0.653389  0.994706
184  1.617110 -0.030708 -0.110035  1.264189  0.129193 -0.283124  0.720682
185 -1.063183  0.444157 -0.983331  0.494645  0.374497  0.238974 -1.014801
186  3.106162 -0.758833  0.588602 -0.360403  0.701569 -0.159126  1.268729
187  3.106162  1.615489 -0.808672  0.067121  0.210961 -0.811748  0.538000
188 -1.063183 -1.581932 -1.681968 -1.642975 -0.737547 -0.625751 -0.923459
189 -0.765373  0.285868  2.684512 -0.103888  0.080133 -0.739960  1.177388
190 -1.063183 -0.157338 -0.634013 -0.958937  0.423558  0.862229 -0.832118
191  0.425869  0.982336  1.112579  1.264189  1.044994  0.516339  0.172635
192 -0.765373  0.127580 -2.031287  1.349694  1.339359  0.496760 -0.740777
193 -0.467562 -0.378942 -0.284695 -0.616917  0.292729 -0.475648 -0.558095
194 -0.765373  0.507472  0.239283 -0.274898 -1.342629  1.198329 -0.832118
195 -0.467562  0.539129 -1.157991  0.409141 -1.130033  0.777388 -0.740777
196  1.021490  0.159238 -0.284695  1.691713  1.012287 -0.071022  0.994706
197 -1.063183 -0.568888 -0.110035  0.665655  1.159469  0.470655 -0.923459
198 -0.765373 -0.188996 -1.157991  0.580150  0.161900 -0.651856 -0.832118
199  1.319300  0.982336 -0.808672 -0.274898  0.276376  0.268342  1.268729

[200 rows x 7 columns]
```

1.2.4 Normalizing the features with Min-Max Scaler

```
In [129]: min_max_scaler = sklearn.preprocessing.MinMaxScaler()
          x_scaled_min_max = min_max_scaler.fit_transform(x)
          df_normalised_min_max = pd.DataFrame(x_scaled_min_max)
          df_normalised_min_max
```

```
Out[129]:         0         1         2         3         4         5         6
          0    0.357143  0.209790  0.416667  0.228261  0.404040  0.126645  0.071429
          1    0.500000  0.972028  0.444444  0.282609  0.232323  0.035406  0.809524
          2    0.357143  0.146853  0.611111  0.369565  0.592593  0.032229  0.333333
          3    0.000000  0.762238  0.527778  0.391304  1.000000  0.078983  0.119048
          4    0.000000  0.356643  0.305556  0.195652  0.276094  0.021788  0.047619
```

```
5    0.357143  0.286713  0.527778  0.217391  0.585859  0.133000  0.738095
6    0.214286  0.188811  0.277778  0.260870  0.542088  0.113936  0.095238
7    0.071429  0.958042  0.166667  0.097826  0.259259  0.258738  0.071429
8    0.214286  0.601399  0.583333  0.086957  0.478114  0.052202  1.000000
9    0.142857  0.503497  0.555556  0.326087  0.845118  0.517022  0.238095
10   0.000000  0.566434  0.027778  0.304348  0.838384  1.000000  0.285714
11   0.642857  0.685315  0.555556  0.250000  0.427609  0.035860  0.571429
12   0.071429  0.930070  0.305556  0.173913  0.400673  0.142079  0.904762
13   0.857143  0.251748  0.333333  0.000000  0.316498  0.381752  0.547619
14   0.071429  0.209790  0.388889  0.489130  0.777778  0.377667  0.190476
15   0.285714  0.300699  0.527778  0.086957  0.168350  0.062642  0.000000
16   0.071429  0.370629  0.305556  0.010870  0.242424  0.391285  0.000000
17   0.785714  0.608392  0.777778  0.282609  0.619529  0.076714  0.714286
18   0.071429  0.650350  0.416667  0.239130  0.373737  0.119837  0.500000
19   0.000000  0.580420  0.333333  0.108696  0.131313  0.055379  0.000000
20   0.142857  0.300699  0.444444  0.097826  0.074074  0.068089  0.142857
21   0.071429  0.307692  0.388889  0.239130  0.464646  0.162960  0.500000
22   0.285714  0.188811  0.666667  0.130435  0.373737  0.105311  0.309524
23   0.000000  0.314685  0.361111  0.108696  0.094276  0.075806  0.000000
24   0.071429  0.216783  0.416667  0.293478  0.653199  0.143441  0.071429
25   0.642857  0.755245  0.638889  0.152174  0.424242  0.338629  0.261905
26   0.071429  0.300699  0.277778  0.032609  0.242424  0.211530  0.000000
27   0.000000  0.587413  0.375000  0.206522  0.821549  0.157059  0.071429
28   0.357143  0.363636  0.472222  0.391304  0.602694  0.080799  0.285714
29   0.142857  0.377622  0.500000  0.239130  0.478114  0.278257  0.142857
..        ...       ...       ...       ...       ...       ...       ...
170  0.428571  0.412587  0.305556  0.347826  0.521886  0.072628  0.452381
171  0.357143  0.342657  0.472222  0.239130  0.629630  0.033591  0.166667
172  0.500000  0.965035  0.416667  0.228261  0.595960  0.299591  0.476190
173  0.285714  0.895105  0.555556  0.347826  0.632997  0.081253  0.238095
174  0.000000  0.272727  0.652778  0.195652  0.646465  0.073536  0.071429
175  0.500000  0.475524  0.444444  0.282609  0.245791  0.034498  0.380952
176  0.071429  0.384615  0.333333  0.065217  0.195286  0.024058  0.047619
177  0.500000  0.566434  0.722222  0.369565  0.464646  0.138901  0.428571
178  0.642857  0.006993  0.583333  0.326087  0.491582  0.004993  0.476190
179  0.142857  0.706294  0.500000  0.304348  0.713805  0.022242  0.214286
180  0.142857  0.272727  0.222222  0.076087  0.265993  0.300953  0.023810
181  0.857143  0.587413  0.652778  0.282609  0.646465  0.072174  0.476190
182  0.000000  0.426573  0.388889  0.260870  0.424242  0.185202  0.023810
183  0.571429  0.307692  0.500000  0.358696  0.713805  0.261462  0.523810
184  0.642857  0.468531  0.444444  0.402174  0.501684  0.131185  0.452381
185  0.000000  0.573427  0.305556  0.304348  0.552189  0.203813  0.000000
186  1.000000  0.307692  0.555556  0.195652  0.619529  0.148434  0.595238
187  1.000000  0.832168  0.333333  0.250000  0.518519  0.057649  0.404762
188  0.000000  0.125874  0.194444  0.032609  0.323232  0.083522  0.023810
189  0.071429  0.538462  0.888889  0.228261  0.491582  0.067635  0.571429
190  0.000000  0.440559  0.361111  0.119565  0.562290  0.290513  0.047619
191  0.357143  0.692308  0.638889  0.402174  0.690236  0.242397  0.309524
```

```
192  0.071429  0.503497  0.138889  0.413043  0.750842  0.239673  0.071429
193  0.142857  0.391608  0.416667  0.163043  0.535354  0.104403  0.119048
194  0.071429  0.587413  0.500000  0.206522  0.198653  0.337267  0.047619
195  0.142857  0.594406  0.277778  0.293478  0.242424  0.278711  0.071429
196  0.500000  0.510490  0.416667  0.456522  0.683502  0.160690  0.523810
197  0.000000  0.349650  0.444444  0.326087  0.713805  0.236042  0.023810
198  0.071429  0.433566  0.277778  0.315217  0.508418  0.079891  0.047619
199  0.571429  0.692308  0.333333  0.206522  0.531987  0.207898  0.595238

[200 rows x 7 columns]
```

1.2.5 Splitting into training and testing data(80:20)

In the training-testing split we use split ratio of 80:20 and random state = 31. A few random states were tried and best results were obtained at 31.

```
In [130]: x_train , x_test , y_train, y_test = train_test_split(x_scaled, y, test_size = 0.20,
```

1.2.6 Defining and training the Logistic Regression classifier

According to Scikit Documentation: The SAGA solver is often the best choice. Hence, SAGA was used as the solver.

```
In [131]: classifier = LogisticRegression(random_state=0, solver='saga')
          classifier.fit(x_train, y_train)

Out[131]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                             intercept_scaling=1, l1_ratio=None, max_iter=100,
                             multi_class='warn', n_jobs=None, penalty='l2',
                             random_state=0, solver='saga', tol=0.0001, verbose=0,
                             warm_start=False)
```

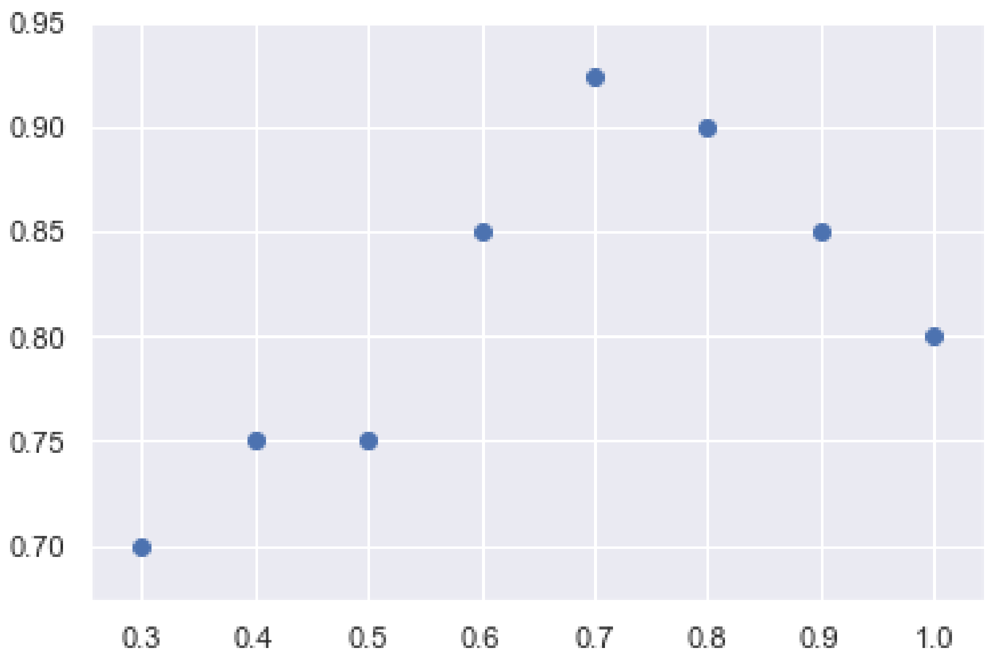
1.2.7 Prediciting the class for various thresholds and selecting the one with the best results

```
In [132]: plt_x = []
          plt_y = []

          threshold = 0.3

          while threshold <= 1.0:
              y_pred = np.where(classifier.predict_proba(x_test)[:, 1] >= threshold, 1, 0)
              cf_matrix = confusion_matrix(y_test, y_pred)
              plt_x.append(threshold)
              plt_y.append((cf_matrix[0][0] + cf_matrix[1][1]) / x_test.shape[0])
              threshold += 0.1

          corresponding_max_threshold = plt_x[plt_y.index(max(plt_y))]
          #     cf_matrix
```

1.2.8 Plotting the Training Accuracy v/s Threshold and predicting with the best threshold

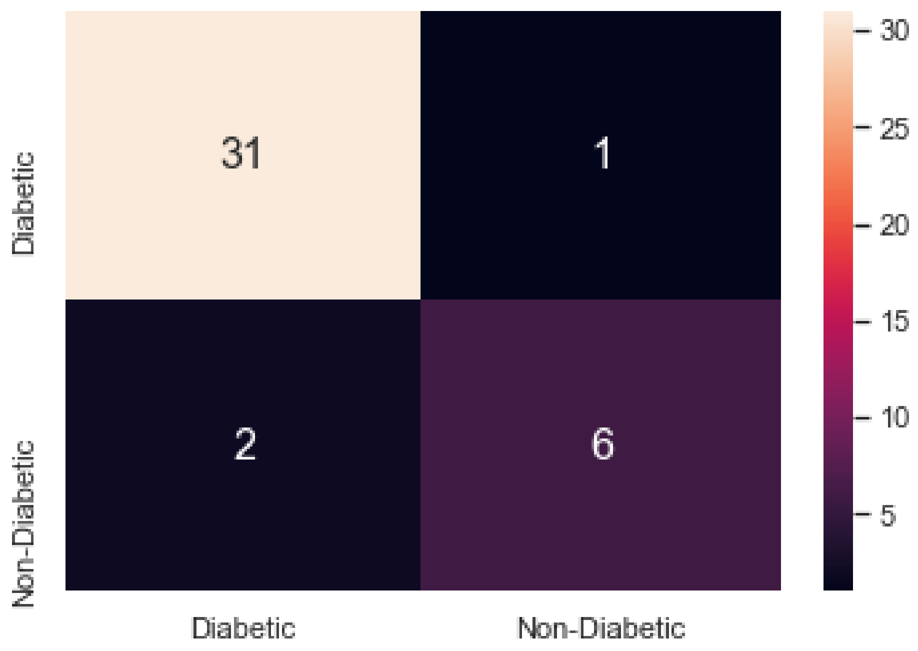
As we can see the threshold value where we get the maximum accuracy is 0.7 which is ~92.5%.

```
In [133]: %matplotlib inline

          y_pred = np.where(classifier.predict_proba(x_test)[:, 1] >= corresponding_max_thresho
          from sklearn.metrics import confusion_matrix
          cf_matrix = confusion_matrix(y_test, y_pred)

          plt.scatter(plt_x, plt_y)
          plt.show()
```



1.2.9 Heatmap of the class predictions

```
In [134]: %matplotlib inline

          labels = ['Diabetic', 'Non-Diabetic']
          df_cm = pd.DataFrame(cf_matrix, labels, labels)
          sn.set(font_scale=1)
          sn.heatmap(df_cm, annot=True, annot_kws={"size":16})
          plt.show()
```


Diabetic
Non-Diabetic
31
1
2
6
Diabetic
Non-Diabetic
30
25
20
15
10
5