Tut+Lab Week 6 - Diabetes Dataset Analysis

1 Dataset

In this tutorial, we will practice the Logistic Regression classifier in diabetes analysis.

The dataset we use is Pima Indian Diabeters dataset. You can download data from the following link: https://www.kaggle.com/uciml/pima-indians-diabetes-database

Diabetes is a major problem in India. From 1971 to 2000, the number of diabetes incidence increased 10 times from 1.2% to 12.1%. As an estimation, in 2011, there are about 61.3 million people in the age of between 20 and 79 years living with diabetes. The estimation also predict that by 2030 this number will be close to 101,2 million people. Moreover, there are 77.2 million people reported to have prediabetes. In 2012, nearly 1 million people died due to diabetes. About 25 percent of citizens living in Chennai's urban slums are affected by diabetes. This number is nearly 7 per cent by three times of the national average. About 33 percent of the deaths in India involve people under 60 years old with non-communicable diseases. On average, Indian people suffer from diabetes 10 years before their Western countries. Changes in lifestyle lead to physical decreases Increased fat, sugar and activities activity calories and higher insulin cortisol levels Obesity and vulnerability. In 2011, India paid around $38 billion annually for dealing with diabetes problem.

For further information, please find in this article:

http://www.arogyaworld.org/wp-content/uploads/2010/10/ArogyaWorld_IndiaDiabetes_FactSheets_CGI2013_web.pdf

2 Dataset description

This dataset comes from the Diabetes and Digestive and Kidney Disease National Institutes. The purpose of this dataset is to diagnose whether or not a patient is diabetes, on the basis of certain diagnostic measures in the dataset. The selection of these instances from a larger database was subject to several restrictions. All patients are women from the Indian heritage of Pima, at least 21 years old.

The data sets comprise several variables of the medical predictor, and one objective variable, Outcome. The forecasting variables include the patient's number of pregnancies, BMI levels, insulin levels, age, etc.

3 Diabetes Data Analysis

3.1 Import and Loading dataset

[1]:
```python
import pandas as pd
```

[2]:
```python
# load dataset
diabetes_dataset = pd.read_csv("diabetes.csv", sep = ",")
```

[3]:
```python
diabetes_dataset
```

[3]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	\
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	
..	…	…	…	…	…	…	
763	10	101	76	48	180	32.9	
764	2	122	70	27	0	36.8	
765	5	121	72	23	112	26.2	
766	1	126	60	0	0	30.1	
767	1	93	70	31	0	30.4	

	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
..	…	…	…
763	0.171	63	0
764	0.340	27	0
765	0.245	30	0
766	0.349	47	1

```
767                    0.315   23       0

[768 rows x 9 columns]
```

[4]:
```
diabetes_dataset.shape
```

[4]:
```
(768, 9)
```

3.2 Explore of the data

[5]:
```
diabetes_dataset.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
```

3.3 Further analysis

Investigating the correlation between features.

- A large positive value (near to 1.0) indicates a strong positive correlation, i.e., if the value of one of the variables increases, the value of the other variable increases as well.
- A large negative value (near to -1.0) indicates a negative correlation, i.e., the value of one variable decreases with the other's increasing and vice-versa.
- A value near to 0 (both positive or negative) indicates no correlation between the two variables, and hence those variables are independent of each other.

[6]:
```
diabetes_dataset.corr()
```

[6]:
```
                          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               -0.081672 0.057328     0.207371      1.000000
```

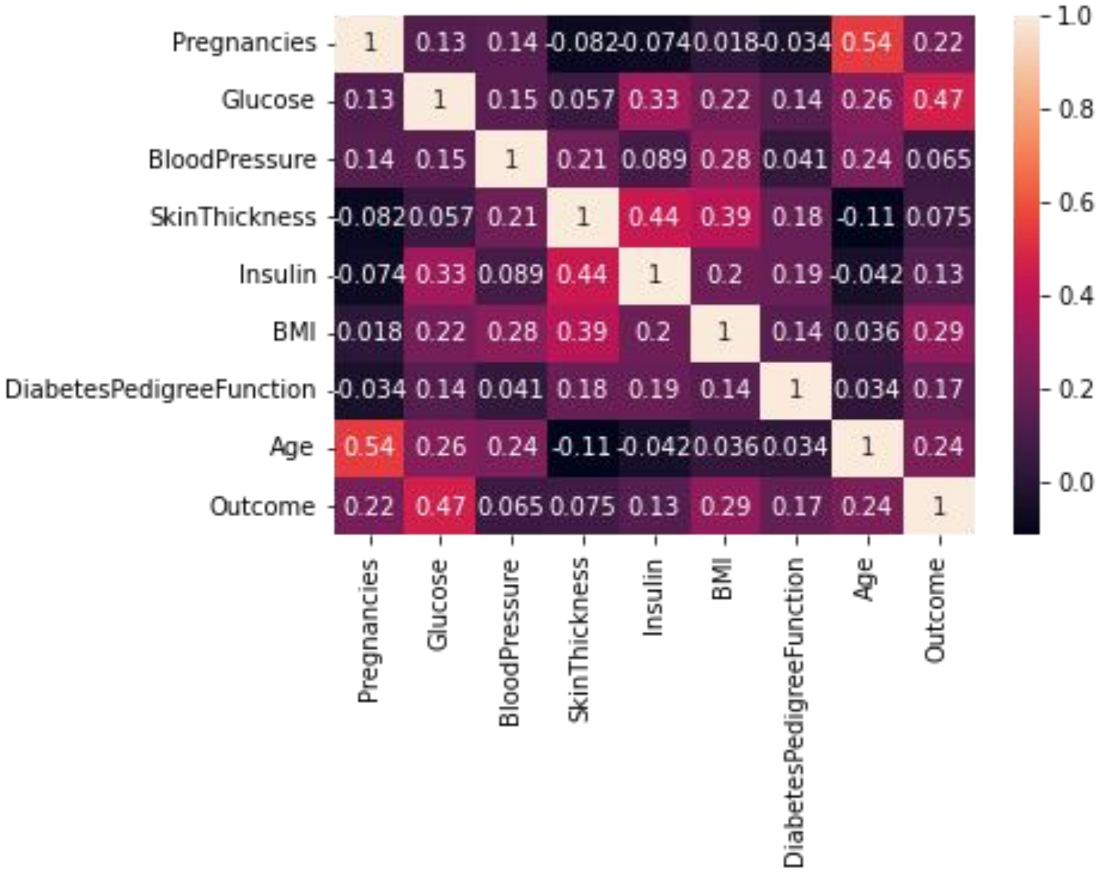
```
 Insulin                   -0.073535 0.331357     0.088933     0.436783
 BMI                        0.017683 0.221071     0.281805     0.392573
DiabetesPedigreeFunction   -0.033523 0.137337     0.041265     0.183928
 Age                        0.544341 0.263514     0.239528    -0.113970
 Outcome                    0.221898 0.466581     0.065068     0.074752

                          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

                              Age   Outcome
 Pregnancies      0.544341 0.221898
 Glucose                 0.263514 0.466581
 BloodPressure  0.239528  0.065068  SkinThickness -
 0.113970 0.074752
 Insulin                -0.042163 0.130548
 BMI                     0.036242 0.292695
 DiabetesPedigreeFunction 0.033561 0.173844
 Age                     1.000000 0.238356
 Outcome                 0.238356 1.000000
```

[7]:
```python
import seaborn as sn
import matplotlib.pyplot as plt

sn.heatmap(diabetes_dataset.corr(), annot=True)
plt.show()
```



From the heat map, it can be said that the diabetes outcome is dependent at most on Glucose, and at least on Blood Pressure and Skin Thickness.

As shown in the heat map, some of these features are highly correlated, e.g. Pregnancies and Age are highly correlated as they have coefficient that is high. Also, Insulin and SkinThickness are in a high correlation. The high correlation between features has implied to the results of the regression model that is based on the linear relationship between features.

4 Diabetes Classification from Logistic Regression

4.1 Feature Extraction

Here, you need to divide the given columns into a target or a dependent variable and feature vectors or independent variables.

[8]:
```
#Extract features and a target feature_columns = ['Pregnancies',
'Glucose', 'BloodPressure', 'SkinThickness',␣ ↪'Insulin', 'BMI',
'DiabetesPedigreeFunction', 'Age']
```

```
X = diabetes_dataset[feature_columns] # Features
y = diabetes_dataset.Outcome # Target
```

4.2 Splitting the Dataset

To understand model performance, the dataset is splitted into a training set and a test set with a ratio 3:1.

[9]:
```
# split X and y into training and testing datasets
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
↪25,random_state=0)
```

[10]:
```
X_train.shape
```

[10]:
```
(576, 8)
```

4.3 Build a Logistic Regression model and make a prediction

First, import the Logistic Regression module and create a Logistic Regression classifier object using LogisticRegression() function.

[11]:
```
# import the class
from sklearn.linear_model import LogisticRegression

# instantiate the model (using the default parameters)
lr = LogisticRegression(C = 10)
```

Then, fit your model on the train set using fit() and perform prediction on the test set using predict().

[12]:
```
# fit the model with the training data
lr.fit(X_train,y_train)

# Make a prediction for the testing data
y_pred=lr.predict(X_test)
```

```
C:\Users\nguye\anaconda3\lib\sitepackages\sklearn\linear_model\_logist
ic.py:763: ConvergenceWarning: lbfgs failed to converge (status=1):
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
  n_iter_i = _check_optimize_result(
```

4.4 Model Evaluation using Confusion Matrix

A confusion matrix is a table that is used to evaluate the performance of a classification model. You can also visualize the performance of an algorithm. The fundamental of a confusion matrix is the number of correct and incorrect predictions are summed up class-wise.

[13]:
```
# import the metrics class
from sklearn import metrics
from sklearn.metrics import classification_report

cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
print(cnf_matrix)
```

```
[[119  11]
 [ 26 36]]
```

Confusion Matrix Evaluation Metrics Let's evaluate the model using model evaluation metrics such as accuracy, precision, recall and F1-score.

[14]:
```
 print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred, average =␣
↪'weighted')) print("Recall:",metrics.recall_score(y_test,
y_pred, average = 'weighted')) print("F1-
score:",metrics.f1_score(y_test, y_pred, average = 'weighted'))
```

```
Accuracy: 0.8072916666666666
Precision: 0.8030157128882367
Recall: 0.8072916666666666
F1-score: 0.7992876007784263
```

Well, you got a classification rate of 81%, considered as good accuracy with 576 instances to train with.

Precision: Precision is about being precise, i.e., how accurate your model is. In other words, you can say, when a model makes a prediction, how often it is correct. In your prediction case, when your Logistic Regression model predicted patients are going to suffer from diabetes, that patients have 80% of the time.

Recall: If there are patients who have diabetes in the test set and your Logistic Regression model can identify it 81% of the time.

4.5 ROC Curve

Receiver Operating Characteristic(ROC) curve is a plot of the true positive rate against the false positive rate. It shows the tradeoff between sensitivity and specificity.

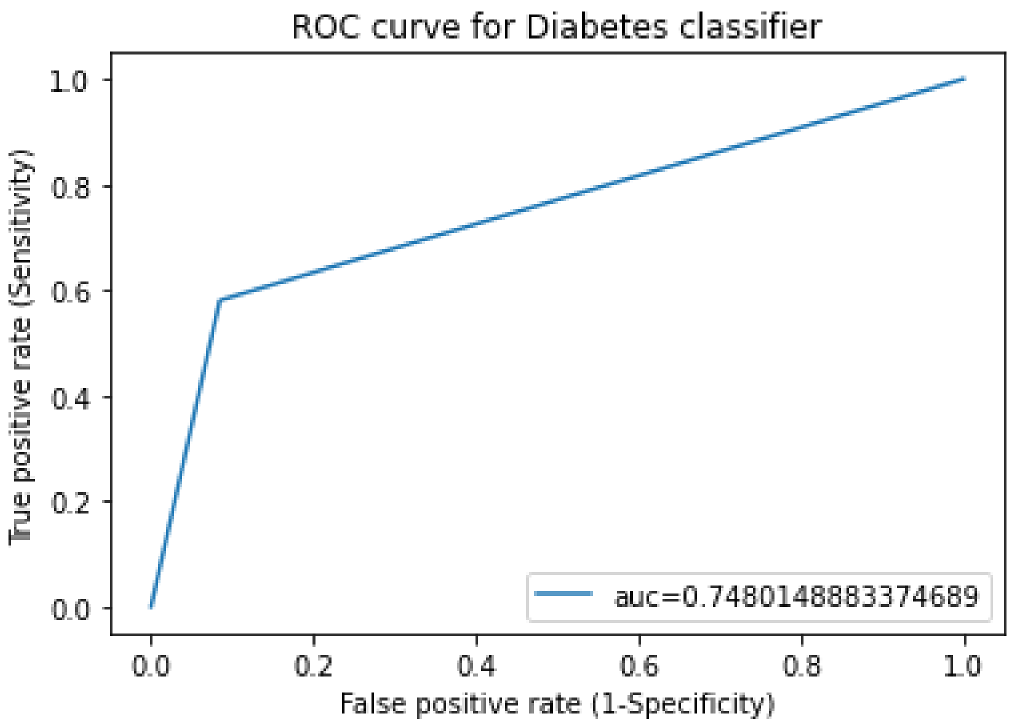
[15]:
```
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred)
auc = metrics.roc_auc_score(y_test, y_pred)

auc
```

[15]: 0.7480148883374689

AUC score for the case is nearly 75%. AUC score 1 represents perfect classifier, and 50% represents a worthless classifier. Now we plot the ROC curve.

[16]:
```
plt.plot(fpr,tpr,label="auc="+str(auc))
plt.title('ROC curve for Diabetes classifier ')
plt.xlabel('False positive rate (1-Specificity) ')
plt.ylabel('True positive rate (Sensitivity) ')
plt.legend(loc=4)
plt.show()
```



Display Misclassified rows with Predicted Labels

[17]:
```
index = 0
misclassifiedIndexes = []
for label, predict in zip(y_test, y_pred):
    if label != predict:
        misclassifiedIndexes.append(index)
    index +=1
```

[18]:
```
import numpy as np

np.array(misclassifiedIndexes).T
```

[18]:
```
array([ 21, 27, 36, 39, 47, 48, 49, 53, 57, 58, 59, 73, 77,
```

86, 94, 96, 99, 104, 105, 111, 113, 117, 127, 135, 137,

141, 144, 149, 156, 158, 164, 165, 172, 173, 180, 187, 188]) **4.6**

Find C to maximum the F1-score

[19]:
```
def linear_regression(c):
    lr = LogisticRegression(C = c, max_iter = 1000)
    fit_lr = lr.fit(X_train, y_train)
    predicted_lr = fit_lr.predict(X_test)
    cm_lr = metrics.confusion_matrix(y_test, predicted_lr)

    f1_sc = metrics.f1_score(y_test, predicted_lr, average = 'weighted')
    return f1_sc
```

[20]:
```
c = 0.0001
c_values = []
f1_values = []

while c < 1000:
    f1_sc = linear_regression(c)
    c_values.append(c)
    f1_values.append(f1_sc)
    c = c*10

f1_lr = pd.DataFrame({
    "c": c_values,
    "f1": f1_values
})
```

[21]:
```
f1_lr[f1_lr['f1'] == f1_lr['f1'].max()].c
```

[21]:
```
5     10.0
6    100.0
Name: c, dtype: float64
```

[22]:
```
f1_lr.sort_values('f1',ascending=False)
```

[22]:
```
          c        f1
5  10.0000  0.794545
6 100.0000  0.794545
3 0.1000 0.789817 4
1.0000   0.789817  2
0.0100   0.785102  1
0.0010  0.777589
 0   0.0001 0.741396
```

[ ]:

```

```