# 3.Logistic Regression - Multi Class

### November 9, 2021

Multi-Class Classification using Logistic Regression

We will predict hand-written digits. The dataset is available here https://scikit-learn.org/stable/auto\_examples/datasets/plot\_digits\_last\_image.html

```
[1]: # Import necessary package
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

### 0.0.1 Step 1: Load the dataset

```
[2]: # Load the dataset into pandas dataframe
from sklearn.datasets import load_digits
digits = load_digits()
```

```
[3]: # Dataset folder contains the following folders
dir(digits)
```

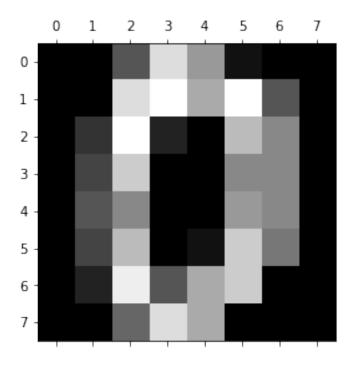
```
[3]: ['DESCR', 'data', 'feature_names', 'frame', 'images', 'target', 'target_names']
```

```
[4]: digits.data[0] # 64 values are used to represent an image (8x8 = 64 values as 1 D array) which \rightarrow is availale in data folder
```

```
[4]: array([ 0., 0., 5., 13., 9., 1., 0., 0., 0., 0., 13., 15., 10., 15., 5., 0., 0., 3., 15., 2., 0., 11., 8., 0., 0., 4., 12., 0., 0., 8., 8., 0., 0., 5., 8., 0., 0., 9., 8., 0., 0., 4., 11., 0., 1., 12., 7., 0., 0., 2., 14., 5., 10., 12., 0., 0., 0., 0., 6., 13., 10., 0., 0., 0.])
```

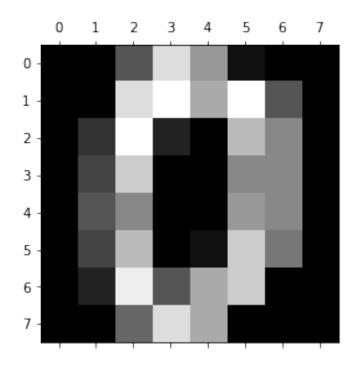
```
[5]: # Display the image of respective input from images folder
plt.gray()
plt.matshow(digits.images[0])
plt.show()
```

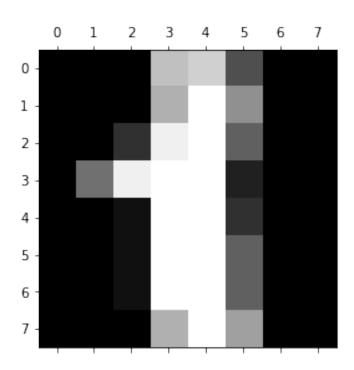
<Figure size 432x288 with 0 Axes>

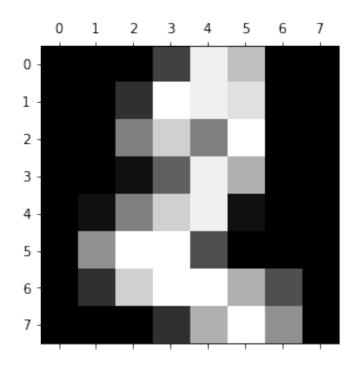


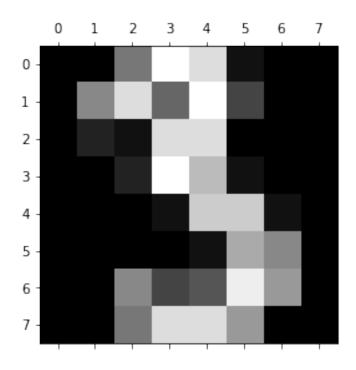
```
[6]: # Let us display 5 images
plt.gray()
for i in range(5):
    plt.matshow(digits.images[i])
    plt.show()
```

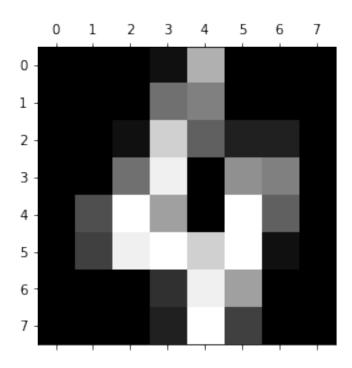
<Figure size 432x288 with 0 Axes>











[7]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

### 0.0.2 Step 2: Apply EDA

Any EDA techniques

## 0.0.3 Step 3. Pre-process and extract the features

It is already well loaded

## 0.0.4 Step 4. Split the data for training and testing

```
[8]: # Splitting dataset into training and testing set
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(digits.data, digits.target,
→test_size = 0.2)
```

### 0.0.5 Step 5. Training the model

### Fitting the model

```
[9]: from sklearn.linear model import LogisticRegression
      logistic_model = LogisticRegression()
      logistic_model.fit(x_train, y_train)
     C:\Users\Rathinaraja Jeyaraj\anaconda3\lib\site-
     packages\sklearn\linear_model\_logistic.py:762: 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(
 [9]: LogisticRegression()
[10]: y_train_pred = logistic_model.predict(x_train)
      y_train_pred
[10]: array([5, 3, 3, ..., 9, 4, 8])
[11]: train_predicted_prob = logistic_model.predict_proba(x_train)
      train_predicted_prob
      # each row contains probability for each digit
[11]: array([[1.65343039e-06, 1.88862528e-13, 9.47297093e-10, ...,
              4.21817324e-12, 1.78846051e-06, 6.06485540e-10],
             [8.65279130e-22, 2.78292795e-22, 1.56931565e-15, ...,
              4.49431750e-19, 2.03211969e-12, 7.58522283e-11],
             [3.02423565e-13, 9.05636296e-14, 7.17503083e-07, ...,
              1.43685765e-11, 3.02520639e-10, 8.97661248e-08],
             [3.30098358e-06, 4.36389257e-13, 2.40686173e-10, ...,
              3.88021625e-08, 6.15172902e-08, 9.98643455e-01],
             [3.30213100e-12, 1.92304116e-11, 1.00558877e-20, ...,
              3.10864231e-11, 1.50858926e-14, 1.23415495e-26],
             [8.98580572e-04, 4.23912326e-03, 2.21387617e-02, ...,
              3.55708497e-05, 9.72201161e-01, 3.07963485e-06]])
```

Performance score for logistic regression

```
[12]: out = logistic_model.score(x_train,y_train)
   Logistic_Train_RS = np.round(out,2)*100
   print("Performance score for training set :",Logistic_Train_RS,"%")
```

Performance score for training set : 100.0 %

Confusion matrix R2 score says the performance of logistic regression over simple probability that does not feature Age. We are interested to know how many has been correctly and wrongly classified.

```
[13]: from sklearn.metrics import confusion_matrix
    cm = confusion_matrix(y_train,y_train_pred)

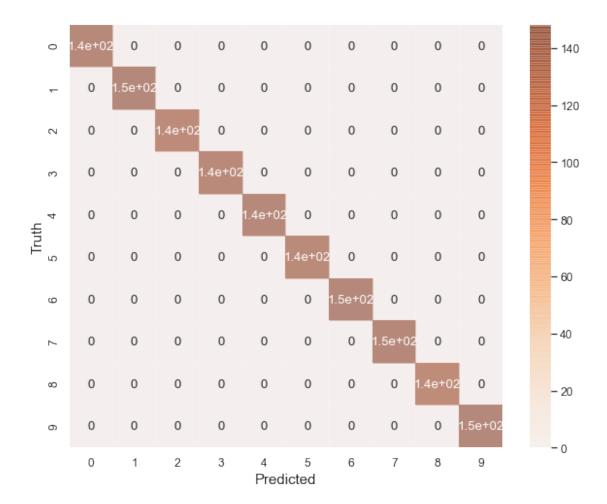
plt.figure(figsize = (10,8))
    sns.set(font_scale=1.1)

axes = plt.gca()
    axes.xaxis.label.set_size(15)
    axes.yaxis.label.set_size(15)

sns.heatmap(cm, annot=True,cmap=plt.cm.Oranges, alpha=0.5)

plt.xlabel('Predicted')
    plt.ylabel('Truth')
```

[13]: Text(64.5, 0.5, 'Truth')



## Precison, Recall, F1, Accuracy

[14]: # Total report
from sklearn import metrics
print(metrics.classification\_report(y\_train,y\_train\_pred))

	precision	recall	f1-score	support
0	1.00	1.00	1.00	144
1	1.00	1.00	1.00	148
2	1.00	1.00	1.00	139
3	1.00	1.00	1.00	143
4	1.00	1.00	1.00	145
5	1.00	1.00	1.00	141
6	1.00	1.00	1.00	147
7	1.00	1.00	1.00	146
8	1.00	1.00	1.00	137
9	1.00	1.00	1.00	147

```
1.00
                                  1.00
                                            1.00
                                                      1437
        macro avg
     weighted avg
                        1.00
                                  1.00
                                            1.00
                                                      1437
[15]: # Accuracy score
      temp = metrics.accuracy_score(y_train,y_train_pred)
      Logistic_Train_Accuracy = np.round(temp,2)*100
      print("Accuracy score : ",Logistic_Train_Accuracy,"%")
     Accuracy score: 100.0 %
[16]: # Precision score
      temp = metrics.precision_score(y_train,y_train_pred,average="macro")
      Logistic_Train_Precision = np.round(temp,2)*100
      print("Precision score : ",Logistic_Train_Precision,"%")
     Precision score: 100.0 %
[17]: # Recall score
      temp = metrics.recall_score(y_train,y_train_pred,average="macro")
      Logistic_Train_Recall = np.round(temp,2)*100
      print("Recall score : ",Logistic_Train_Recall,"%")
     Recall score: 100.0 %
[18]: # F1 score
      temp = metrics.f1_score(y_train,y_train_pred,average="macro")
      Logistic_Train_F1 = np.round(temp,2)*100
      print("F1 score : ",Logistic_Train_F1,"%")
     F1 score : 100.0 %
[19]: # Cohen Kappa score
      temp = metrics.cohen kappa score(y train,y train pred)
      Logistic_Train_CK = np.round(temp,2)*100
      print("Cohen Kappa score : ",Logistic_Train_CK,"%")
     Cohen Kappa score: 100.0 %
```

1.00

1437

**ROC** It should be plotted

accuracy

### 0.0.6 Step 6. Testing the model

```
[20]: # Predicting values for test input set
      y_test_pred = logistic_model.predict(x_test)
      y_test_pred
[20]: array([2, 7, 4, 7, 1, 9, 5, 1, 6, 4, 4, 0, 5, 4, 3, 4, 4, 6, 1, 4, 6, 2,
             3, 4, 9, 2, 3, 0, 5, 6, 2, 8, 7, 4, 2, 3, 2, 4, 0, 5, 9, 9, 7, 1,
             4, 1, 7, 0, 3, 5, 6, 3, 6, 1, 9, 7, 7, 7, 0, 2, 2, 4, 6, 3, 3, 3,
             7, 7, 3, 3, 9, 9, 1, 0, 8, 0, 3, 6, 8, 3, 9, 6, 0, 4, 8, 9, 5, 7,
             3, 7, 1, 8, 3, 3, 6, 6, 8, 2, 6, 6, 9, 6, 4, 9, 5, 8, 3, 8, 4, 5,
             1, 7, 5, 6, 0, 8, 8, 7, 2, 0, 2, 5, 2, 3, 5, 6, 6, 7, 0, 2, 8, 9,
             9, 2, 6, 9, 3, 2, 9, 0, 9, 4, 6, 8, 2, 3, 9, 4, 4, 0, 1, 5, 1, 0,
             7, 2, 7, 2, 8, 2, 9, 8, 9, 0, 8, 9, 1, 9, 9, 0, 6, 6, 3, 2, 8, 1,
             7, 2, 4, 9, 4, 9, 0, 3, 0, 1, 4, 4, 6, 5, 2, 3, 5, 3, 6, 0, 8, 2,
             5, 0, 3, 5, 5, 3, 1, 9, 4, 1, 1, 1, 8, 3, 5, 1, 9, 1, 2, 0, 2, 2,
             4, 9, 6, 8, 8, 5, 8, 1, 9, 8, 8, 8, 5, 8, 5, 8, 6, 6, 2, 1, 7, 8,
             4, 1, 3, 1, 3, 3, 5, 2, 4, 9, 8, 8, 4, 6, 6, 7, 8, 7, 7, 7, 1, 1,
             3, 5, 0, 0, 9, 7, 1, 0, 8, 4, 7, 8, 2, 2, 7, 1, 6, 7, 8, 9, 6, 3,
             3, 9, 0, 9, 5, 3, 8, 2, 0, 6, 2, 6, 1, 9, 0, 4, 8, 1, 7, 0, 8, 3,
             1, 0, 5, 7, 2, 2, 1, 5, 2, 0, 5, 9, 5, 1, 4, 4, 3, 7, 5, 4, 5, 8,
             9, 0, 3, 6, 7, 5, 6, 0, 7, 1, 5, 4, 8, 5, 6, 3, 2, 0, 1, 4, 5, 0,
             9, 5, 4, 2, 3, 1, 0, 5])
[21]: test_predicted_prob = logistic_model.predict_proba(x_test)
      test_predicted_prob
[21]: array([[2.61582464e-17, 6.36102953e-14, 9.99981368e-01, ...,
              6.32816723e-15, 8.43415735e-08, 2.54647447e-12],
             [1.12195460e-12, 3.38597251e-09, 1.84528603e-11, ...,
              9.99999974e-01, 8.18932749e-11, 5.37784237e-13],
             [4.70747557e-09, 1.17521732e-02, 3.25445044e-15, ...,
              2.42344059e-07, 2.83830434e-05, 9.41348585e-14],
             [2.41062240e-10, 9.99968965e-01, 4.12617874e-08, ...,
             1.63297882e-09, 2.99847610e-06, 2.69792678e-06],
             [9.99917021e-01, 3.42658903e-17, 9.61063241e-09, ...,
              3.61169708e-12, 8.27709068e-05, 9.43399890e-08],
             [1.50594596e-11, 6.48978633e-10, 1.04976291e-07, ...,
              3.57640245e-10, 1.07855157e-07, 1.05188150e-08]])
     Performance score for logistic regression
[22]: out = logistic model.score(x test,y test)
      Logistic_Test_RS = np.round(out,2)*100
```

print("Performance score for training set :",Logistic\_Test\_RS,"%")

Performance score for training set : 96.0 %

**Confusion matrix** R2 score says the performance of logistic regression over simple probability that does not feature Age. We are interested to know how many has been correctly and wrongly classified.

```
[23]: from sklearn.metrics import confusion_matrix
    cm = confusion_matrix(y_test,y_test_pred)

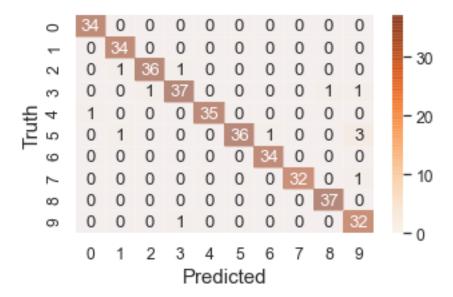
plt.figure(figsize = (5,3))
    sns.set(font_scale=1.1)

axes = plt.gca()
    axes.xaxis.label.set_size(15)
    axes.yaxis.label.set_size(15)

sns.heatmap(cm, annot=True,cmap=plt.cm.Oranges, alpha=0.5)

plt.xlabel('Predicted')
    plt.ylabel('Truth')
```

### [23]: Text(19.5, 0.5, 'Truth')



### Precison, Recall, F1, Accuracy

```
[24]: # Total report
from sklearn import metrics
print(metrics.classification_report(y_test,y_test_pred))
```

```
recall f1-score
                   precision
                                                    support
                0
                        0.97
                                   1.00
                                             0.99
                                                         34
                1
                        0.94
                                   1.00
                                             0.97
                                                         34
                2
                        0.97
                                   0.95
                                             0.96
                                                         38
                3
                        0.95
                                   0.93
                                             0.94
                                                         40
                4
                        1.00
                                   0.97
                                             0.99
                                                         36
                5
                         1.00
                                  0.88
                                             0.94
                                                         41
                6
                        0.97
                                  1.00
                                             0.99
                                                         34
                        1.00
                7
                                  0.97
                                             0.98
                                                         33
                        0.97
                                             0.99
                                                         37
                8
                                   1.00
                9
                        0.86
                                   0.97
                                             0.91
                                                         33
                                             0.96
                                                        360
         accuracy
                        0.96
                                   0.97
                                             0.96
                                                        360
        macro avg
     weighted avg
                        0.97
                                   0.96
                                             0.96
                                                        360
[25]: # Accuracy score
      temp = metrics.accuracy_score(y_test,y_test_pred)
      Logistic_Test_Accuracy = np.round(temp,2)*100
      print("Accuracy score : ",Logistic_Test_Accuracy,"%")
     Accuracy score: 96.0 %
[26]: # Precision score
      temp = metrics.precision_score(y_test,y_test_pred,average="macro")
      Logistic_Test_Precision = np.round(temp,2)*100
      print("Precision score : ",Logistic_Test_Precision,"%")
     Precision score: 96.0 %
[27]: # Recall score
      temp = metrics.recall_score(y_test,y_test_pred,average="macro")
      Logistic_Test_Recall = np.round(temp,2)*100
      print("Recall score : ",Logistic_Test_Recall,"%")
     Recall score: 97.0 %
[28]: # F1 score
      temp = metrics.f1_score(y_test,y_test_pred,average="macro")
      Logistic_Test_F1 = np.round(temp,2)*100
      print("F1 score : ",Logistic_Test_F1,"%")
     F1 score : 96.0 %
[29]: # Cohen Kappa score
      temp = metrics.cohen_kappa_score(y_test,y_test_pred)
```

```
Logistic_Test_CK = np.round(temp,2)*100
print("Cohen Kappa score : ",Logistic_Test_CK,"%")
```

Cohen Kappa score: 96.0 %

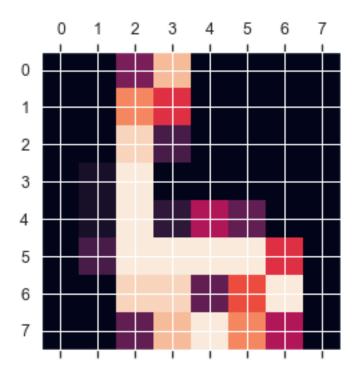
**ROC** It should be plotted

## 0.0.7 Step 7. Deploying model for prediction

## Prediction by passing individual input

[30]: plt.matshow(digits.images[67])

[30]: <matplotlib.image.AxesImage at 0x1f639ab8970>



```
[31]: digits.target[67]
```

[31]: 6

```
[32]: logistic_model.predict([digits.data[67]])
# giving the image index to the model, which will take the image as necessary

→ input
```

[32]: array([6])

```
[33]: logistic_model.predict(digits.data[0:5])
```

[33]: array([0, 1, 2, 3, 4])

#### 0.0.8 Step 8. Summary

```
[34]: print("
                     Logistic Regression
    print("======"")
    print("\t\tTraining phase
                               Testing phase ")
    print("======"")
    print("RS\t\t
                 ",Logistic_Train_RS,"%\t\t", Logistic_Test_RS,"%")
    print("Accuracy\t ",Logistic_Train_Accuracy,"%\t\t",_
     print("Precision\t
                      ",Logistic_Train_Precision,"%\t\t",_
     →Logistic_Test_Precision,"%")
    print("Recall\t\t ",Logistic_Train_Recall,"%\t\t", Logistic_Test_Recall,"%")
    print("F1\t\t ",Logistic_Train_F1,"%\t\t", Logistic_Test_F1,"%")
    print("CK\t\t
                  ",Logistic_Train_CK,"%\t\t", Logistic_Test_CK,"%")
    \#print("AUC \setminus t \setminus t \quad ", Logistic\_Train\_AUC, "\% \setminus t \setminus t", Logistic\_Test\_AUC, "\%")
```

Logistic Regression

	Training phase	Testing phase
RS	100.0 % 100.0 %	96.0 % 96.0 %
Accuracy Precision	100.0 %	96.0 %
Recall F1	100.0 % 100.0 %	97.0 % 96.0 %
CK	100.0 %	96.0 %