# \*\* Homework 5 \*\*

#Modified by Mehul Motani from SKLearn

from sklearn import datasets, metrics

import matplotlib.pyplot as plt

In [1]: %matplotlib inline

import pandas as pd
import numpy as np

```
from sklearn.model selection import train test split
         from sklearn.preprocessing import StandardScaler
         from sklearn import svm, linear model
         from sklearn.naive_bayes import GaussianNB
         from sklearn.preprocessing import StandardScaler
         import time
In [2]: #plot the digits to find the hardest recognition one
         digits = datasets.load digits()
         #digits.data flattened image
         #digits.image 8x8 image
         #digits.target label
         print("digits.data.shape,digits.target.shape,digits.images.shape")
         print(digits.data.shape,digits.target.shape,digits.images.shape)
         _, axes = plt.subplots(nrows=1, ncols=10, figsize=(15, 3))
         for ax, image, label in zip(axes, digits.images, digits.target):
             ax.set_axis_off()
             ax.imshow(image, cmap=plt.cm.gray_r, interpolation="nearest")
             ax.set title("Training: %i" % label)
         digits.data.shape,digits.target.shape,digits.images.shape
         (1797, 64) (1797,) (1797, 8, 8)
         Training: 0 Training: 1 Training: 2 Training: 3 Training: 4
                                                                        Training: 8
                                                Training: 5
                                                        Training: 6
                                                                Training: 7
```

# \*\* SVM, Naïve Bayes and Logistic Regression classifiers \*\*

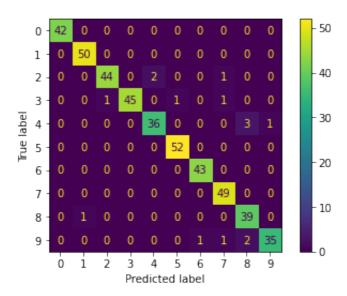
SVM needs standard normalization

```
In [3]: svc = svm.SVC()
        lr = linear_model.LogisticRegression(max_iter=5000)
        gnb = GaussianNB()
        # Split the data into 75% training and 25% test sets
        x_train, x_test, y_train, y_test = train_test_split(
           digits.data, digits.target, test_size=0.25, random_state=2, shuffle=T
        # Normalize the data set
        sc = StandardScaler()
        sc.fit(x train)
        X train = sc.transform(x train)
        X test = sc.transform(x test)
        # Classify
        for clf in [svc, lr, gnb]:
         y_pred=clf.fit(X_train, y_train).predict(X_test)
         print(metrics.accuracy_score(y_pred,y_test),clf)
         disp = metrics.ConfusionMatrixDisplay.from predictions(y_test, y_pred)
         disp.figure .suptitle("Confusion Matrix")
         print(f"Confusion matrix:\n{disp.confusion matrix}")
         plt.show()
          _, axes = plt.subplots(nrows=1, ncols=10, figsize=(15, 3))
         for ax, image, prediction in zip(axes, X test, y pred):
           ax.set_axis_off()
           image = image.reshape(8, 8)
           ax.imshow(image, cmap=plt.cm.gray_r, interpolation="nearest")
           ax.set_title(f"Prediction: {prediction}")
         plt.show()
         print(
           f"Classification report for classifier {clf}:\n"
           f"{metrics.classification_report(y_test, y_pred)}\n"
          )
        Confusion matrix:
        [[42 0 0 0 0
                        0
                           0 0 0 0]
        [050000000000]
            0 44 0 2 0 0 1 0 0]
        0
          0
            0
               1 45 0 1 0 1 0 0]
             0 0
                  0 36 0
                           0 0
          0
                                 3 11
        [ 0
            0 0 0 0 52 0 0 0 01
        0 ]
            0 0 0 0 0 43 0 0 01
          0
            0 0 0 0 0
                           0 49 0
                                    0]
        [ \ 0 \ 1 \ 0 \ 0 \ 0 \ 0 \ 0 \ 39
                                    0]
```

0 0 0 0 0 0

1 1

### Confusion Matrix



Prediction: 4 Prediction: 0 Prediction: 9 Prediction: 1 Prediction: 8 Prediction: 7 Prediction: 1 Prediction: 5 Prediction: 1 Prediction: 6





















Classification report for classifier SVC():

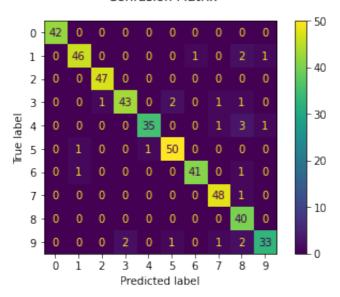
	precision	recall	f1-score	support
0	1.00	1.00	1.00	42
1	0.98	1.00	0.99	50
2	0.98	0.94	0.96	47
3	1.00	0.94	0.97	48
4	0.95	0.90	0.92	40
5	0.98	1.00	0.99	52
6	0.98	1.00	0.99	43
7	0.94	1.00	0.97	49
8	0.89	0.97	0.93	40
9	0.97	0.90	0.93	39
accuracy			0.97	450
macro avg	0.97	0.96	0.96	450
weighted avg	0.97	0.97	0.97	450
-				

# 

## Confusion matrix:

[[4	42	0	0	0	0	0	0	0	0	0]
[	0	46	0	0	0	0	1	0	2	1]
[	0	0	47	0	0	0	0	0	0	0]
[	0	0	1	43	0	2	0	1	1	0]
[	0	0	0	0	35	0	0	1	3	1]
[	0	1	0	0	1	50	0	0	0	0]
[	0	1	0	0	0	0	41	0	1	0]
[	0	0	0	0	0	0	0	48	1	0]
[	0	0	0	0	0	0	0	0	40	0]
Г	0	0	0	2	0	1	0	1	2	3311

### Confusion Matrix



Prediction: 4 Prediction: 0 Prediction: 9 Prediction: 1 Prediction: 8 Prediction: 7 Prediction: 1 Prediction: 5 Prediction: 1 Prediction: 6

Classification report for classifier LogisticRegression(max\_iter=5000):
 precision recall f1-score support

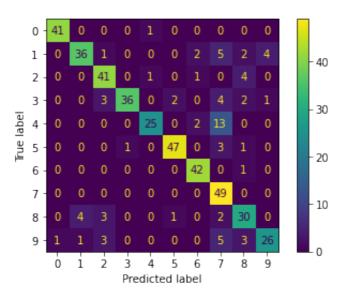
-				
•	1 00	1 00	1 00	4.0
0	1.00	1.00	1.00	42
1	0.96	0.92	0.94	50
2	0.98	1.00	0.99	47
3	0.96	0.90	0.92	48
4	0.97	0.88	0.92	40
5	0.94	0.96	0.95	52
6	0.98	0.95	0.96	43
7	0.94	0.98	0.96	49
8	0.80	1.00	0.89	40
9	0.94	0.85	0.89	39
accuracy			0.94	450
macro avg	0.95	0.94	0.94	450
weighted avg	0.95	0.94	0.94	450

# 0.828888888888889 GaussianNB()

### Confusion matrix:

[[4	11	0	0	0	1	0	0	0	0	0]
[	0	36	1	0	0	0	2	5	2	4]
[	0	0	41	0	1	0	1	0	4	0]
[	0	0	3	36	0	2	0	4	2	1]
[	0	0	0	0	25	0	2	13	0	0]
[	0	0	0	1	0	47	0	3	1	0]
[	0	0	0	0	0	0	42	0	1	0]
[	0	0	0	0	0	0	0	49	0	0]
[	0	4	3	0	0	1	0	2	30	0]
ſ	1	1	3	0	0	0	0	5	3	261

### Confusion Matrix



Prediction: 4 Prediction: 0 Prediction: 9 Prediction: 1 Prediction: 7 Prediction: 7 Prediction: 1 Prediction: 5 Prediction: 1 Prediction: 6

Classification report for classifier GaussianNB():

precision	recall	f1-score	support
0.98	0.98	0.98	42
0.88	0.72	0.79	50
0.80	0.87	0.84	47
0.97	0.75	0.85	48
0.93	0.62	0.75	40
0.94	0.90	0.92	52
0.89	0.98	0.93	43
0.60	1.00	0.75	49
0.70	0.75	0.72	40
0.84	0.67	0.74	39
		0.83	450
0.85	0.82	0.83	450
0.85	0.83	0.83	450
	0.98 0.88 0.80 0.97 0.93 0.94 0.89 0.60 0.70 0.84	0.98 0.98 0.88 0.72 0.80 0.87 0.97 0.75 0.93 0.62 0.94 0.90 0.89 0.98 0.60 1.00 0.70 0.75 0.84 0.67	0.98       0.98       0.98         0.88       0.72       0.79         0.80       0.87       0.84         0.97       0.75       0.85         0.93       0.62       0.75         0.94       0.90       0.92         0.89       0.98       0.93         0.60       1.00       0.75         0.70       0.75       0.72         0.84       0.67       0.74         0.83       0.85       0.82       0.83

```
In [4]: monte=100
        Accuracy=np.zeros([monte,3])
        for i in range(1,monte):
            # Split the data into 75% training and 25% test sets
            x_train, x_test, y_train, y_test = train_test_split(
            digits.data, digits.target, test_size=0.25, random_state=2, shuffle=T
            # Normalize the data set
            sc = StandardScaler()
            sc.fit(x train)
            X train = sc.transform(x train)
            X_test = sc.transform(x_test)
            for clf in [svc, lr, gnb]:
              y pred=clf.fit(X train, y train).predict(X test)
              Accuracy[i,k]=metrics.accuracy_score(y_pred,y_test)
              k+=1
        avg_SVC=np.mean(Accuracy[:,0])
        avg LoR=np.mean(Accuracy[:,1])
        avg GNB=np.mean(Accuracy[:,2])
        print("cycle%d"%monte+"times with average accuracy in SVC:%f"%avg SVC+
               " LogisticRegression:%f"%avg_LoR+" Gaussion:%f"%avg_GNB)
```

cycle100times with average accuracy in SVC:0.957000 LogisticRegression:0.935000 Gaussion:0.820600