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## 1 LAB 8 : Classification

1. Support Vector Machines
2. K-Nearest Neighbors
3. Classification on MNIST Digit

```
[1]: import numpy as np
import matplotlib.pyplot as plt
import math
```

## 2 Support Vector Machines (SVM)

1. Try to maximize the margin of separation between data.
2. Instead of learning  $wx+b=0$  separating hyperplane directly (like logistic regression), SVM try to learn  $wx+b=0$ , such that, the margin between two hyperplanes  $wx+b=1$  and  $wx+b=-1$  (also known as support vectors) is maximum.
3. Margin between  $wx+b=1$  and  $wx+b=-1$  hyperplane is  $\frac{2}{||w||}$
4. we have a constraint optimization problem of maximizing  $\frac{2}{||w||}$ , with constraints  $wx+b \geq 1$  (for +ve class) and  $wx+b \leq -1$  (for -ve class).
5. As  $y_i = 1$  for +ve class and  $y_i = -1$  for -ve class, the constraint can be re-written as:

$$y(wx + b) \geq 1$$

6. Final optimization is (i.e to find w and b):

$$\min_{||w||} \frac{1}{2} ||w||,$$

$$y(wx + b) \geq 1, \forall \text{ data}$$

Acknowledgement:

<https://pythonprogramming.net/predictions-svm-machine-learning-tutorial/>

<https://medium.com/deep-math-machine-learning-ai/chapter-3-1-svm-from-scratch-in-python-86f93f853dc>

## 2.1 Data generation:

1. Generate 2D gaussian data with fixed mean and variance for 2 class.(var=Identity, class1: mean[-4,-4], class2: mean[1,1], No. of data 25 from each class)
2. create the label matrix
3. Plot the generated data

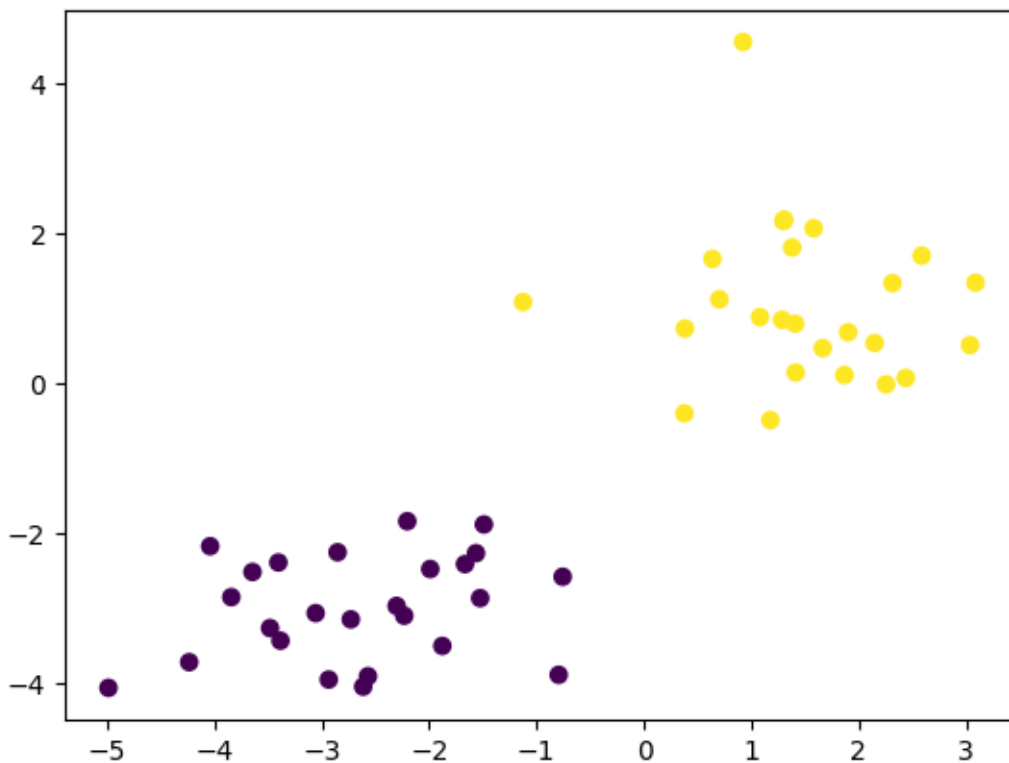
```
[2]: No_sample=50
mean1=np.array([-3,-3])
var1=np.array([[1,0],[0,1]])
mean2=np.array([1,1])
var2=var1
data1=np.random.multivariate_normal(mean1,var1,int(No_sample/2))
data2=np.random.multivariate_normal(mean2,var2,int(No_sample/2))
X=np.concatenate((data1,data2))
print(X.shape)
y=np.concatenate((-1*np.ones(data1.shape[0]),np.ones(data2.shape[0])))
print(y.shape)

plt.figure()
plt.scatter(X[:,0],X[:,1],marker='o',c=y)
```

(50, 2)

(50,)

[2]: <matplotlib.collections.PathCollection at 0x7f5e76bfba30>



Create a data dictionary, which contains both label and data points.

```
[3]: positiveX=[]
negativeX=[]
for i,v in enumerate(y):
    if v==1:
        negativeX.append(X[i])
    else:
        positiveX.append(X[i])

#our data dictionary
data_dict = {-1:np.array(negativeX), 1:np.array(positiveX)}
```

## 2.2 SVM training

1. create a search space for  $w$  (i.e  $w_1=w_2$ ),  $[0, 0.5*\max((\text{abs}(\text{feat})))]$  and for  $b$ ,  $[-\max((\text{abs}(\text{feat}))),\max((\text{abs}(\text{feat})))]$ , with appropriate step.
2. we will start with a higher step and find optimal  $w$  and  $b$ , then we will reduce the step and again re-evaluate the optimal one.
3. In each step, we will take transform of  $w$ ,  $[1,1]$ ,  $[-1,1]$ ,  $[1,-1]$  and  $[-1,-1]$  to search around the  $w$ .
4. In every pass (for a fixed step size) we will store all the  $w$ ,  $b$  and its corresponding  $\|w\|$ , which make the data correctly classified as per the condition  $y(wx + b) \geq 1$ .
5. Obtain the optimal hyperplane having minimum  $\|w\|$ .
6. Start with the optimal  $w$  and repeat the same (step 3,4 and 5) for a reduced step size.

```
[8]: class SVM:
    def __init__(self, data_dict) -> None:
        self.data_dict = data_dict
        self.w = []
        self.b = []
        self.max_feature_value=float('-inf')
        self.min_feature_value=float('+inf')
        self._min_max_fv(data_dict)
        self.learning_rate = [self.max_feature_value * 0.1, self.
↪max_feature_value * 0.01, self.max_feature_value * 0.001,]

    def _min_max_fv(self, data_dict):
        for yi in data_dict:
            if np.amax(data_dict[yi])>self.max_feature_value:
                self.max_feature_value=np.amax(data_dict[yi])

            if np.amin(data_dict[yi])<self.min_feature_value:
```

```

        self.min_feature_value=np.amin(data_dict[yi])

def train(self, data_dict):
    i=1
    w = []
    b = []

    length_Wvector = {}
    transforms = [[1,1],[-1,1],[-1,-1],[1,-1]]

    b_step_size = 2
    b_multiple = 5
    w_optimum = self.max_feature_value*0.5

    for lrate in self.learning_rate:

        w = np.array([w_optimum,w_optimum])
        optimized = False
        while not optimized:

            for b in np.arange(-1*(self.max_feature_value*b_step_size),
↪self.max_feature_value*b_step_size, lrate*b_multiple):
                for transformation in transforms:
                    w_t = w*transformation

                    correctly_classified = True

                    for yi in data_dict:
                        for xi in data_dict[yi]:
                            if yi*(np.dot(w_t,xi)+b) < 1: # we want ↪
↪yi*(np.dot(w_t,xi)+b) >= 1 for correct classification
                                correctly_classified = False

                    if correctly_classified:
                        length_Wvector[np.linalg.norm(w_t)] = [w_t,b]↪
↪#store w, b for minimum magnitude

                        if w[0] < 0:
                            optimized = True
                        else:
                            w = w - lrate

        norms = sorted([n for n in length_Wvector])

        minimum_wlength = length_Wvector[norms[0]]
        w = minimum_wlength[0]

```

```

        b = minimum_wlength[1]

        w_optimum = w[0]+lrate*2

    self.w = w
    self.b = b

    return w,b

```

## Training

```

[13]: # All the required variables
w=[] # Weights 2 dimensional vector
b=[] # Bias
SVC = SVM(data_dict)
w,b = SVC.train(data_dict)
print(w)
print(b)

```

```

[0.60693615 0.60693615]
1.02677167662862

```

## 2.3 Visualization of the SVM separating hyperplanes (after training)

```

[11]: def visualize(data_dict):

    plt.scatter(X[:,0],X[:,1],marker='o',c=y)

    # hyperplane = x.w+b
    # v = x.w+b
    # psu = 1
    # nsu = -1
    # dec = 0
    def hyperplane_value(x,w,b,v):
        return (-w[0]*x-b+v) / w[1]

    hyp_x_min = np.min([np.min(data_dict[1]),np.min(data_dict[-1])])
    hyp_x_max = np.max([np.max(data_dict[1]),np.max(data_dict[-1])])

    # (w.x+b) = 1
    # positive support vector hyperplane
    psv1 = hyperplane_value(hyp_x_min, w, b, 1)
    psv2 = hyperplane_value(hyp_x_max, w, b, 1)
    plt.plot([hyp_x_min,hyp_x_max],[psv1,psv2], 'k')

```

```

#  $(w \cdot x + b) = -1$ 
# negative support vector hyperplane
nsv1 = hyperplane_value(hyp_x_min, w, b, -1)
nsv2 = hyperplane_value(hyp_x_max, w, b, -1)
plt.plot([hyp_x_min, hyp_x_max], [nsv1, nsv2], 'k')

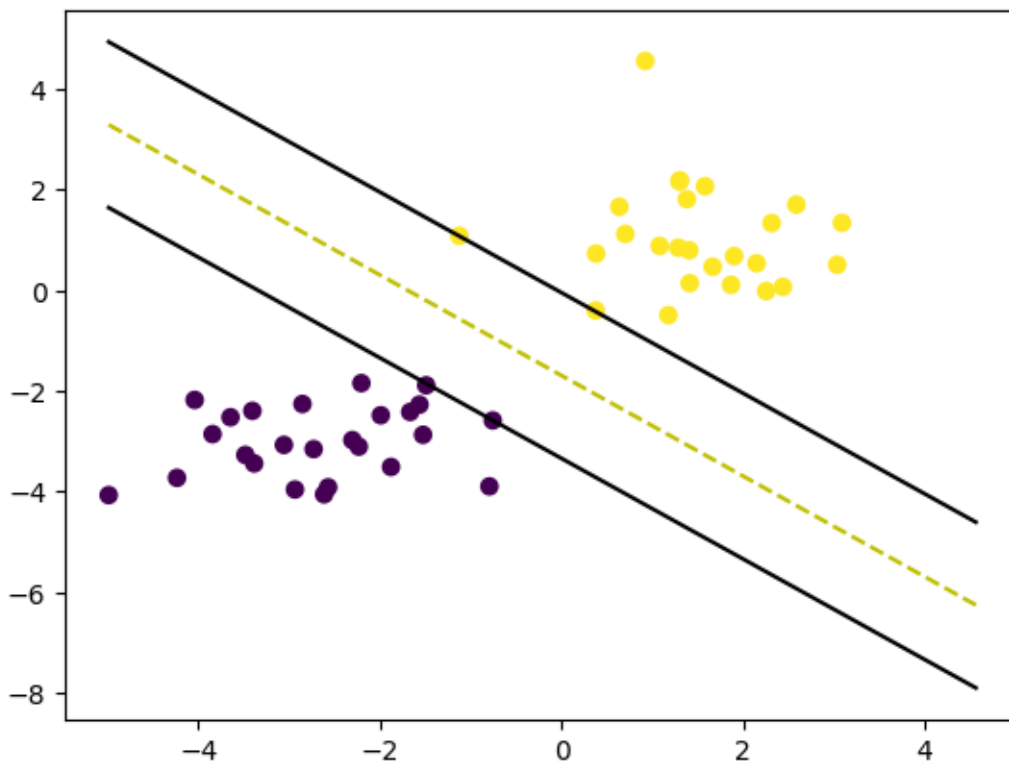
#  $(w \cdot x + b) = 0$ 
# positive support vector hyperplane
db1 = hyperplane_value(hyp_x_min, w, b, 0)
db2 = hyperplane_value(hyp_x_max, w, b, 0)
plt.plot([hyp_x_min, hyp_x_max], [db1, db2], 'y--')

```

```

[12]: fig = plt.figure()
      visualize(data_dict)

```



## Testing

```

[14]: def predict(data, w, b):
      y_pred = np.sign(np.dot(data, w) + b)

```

```
return y_pred
```

```
[15]: No_test_sample=40
data1=np.random.multivariate_normal(mean1,var1,int(No_test_sample/2))
data2=np.random.multivariate_normal(mean2,var2,int(No_test_sample/2))
test_data=np.concatenate((data1,data2))
y_gr=np.concatenate((-1*np.ones(data1.shape[0]),np.ones(data2.shape[0])))

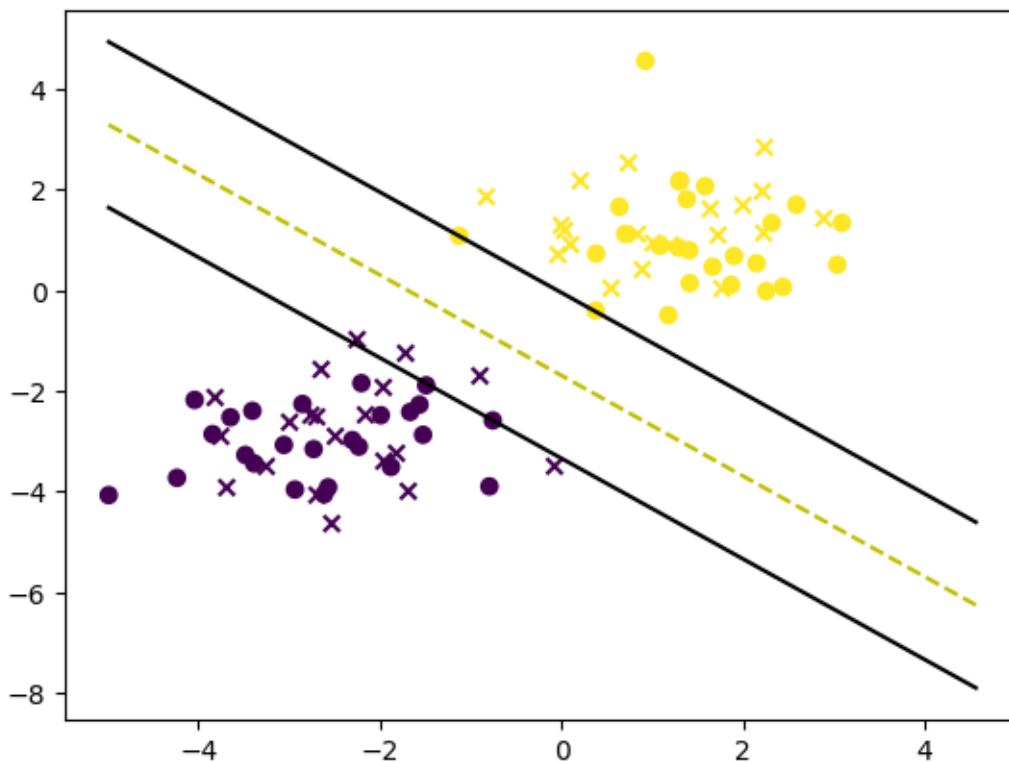
# evaluate with the trained model

y_pred=predict(test_data,w,b)
accuracy=(1-(np.abs(0.5*np.sum(y_pred-y_gr))/y_pred.shape[0]))*100
print('test accuracy=',accuracy)

# Visualization
plt.figure()
visualize(data_dict)
plt.scatter(test_data[:,0],test_data[:,1],marker='x',c=y_gr)
```

test accuracy= 100.0

```
[15]: <matplotlib.collections.PathCollection at 0x7f5e75edbd90>
```



Use the Sci-kit Learn Package and perform Classification on the above dataset using the SVM algorithm

```
[16]: from sklearn.svm import LinearSVC
      svm = LinearSVC()
      svm.fit(X,y)
      tr_Acc = svm.score(X,y)
      print('Train accuracy SVM =',tr_Acc*100)
```

Train accuracy SVM = 100.0

```
[14]: # svm testing
      from sklearn.metrics import confusion_matrix as conf_mat
      y_pred=svm.predict(test_data)
      svm_Acc=svm.score(test_data,y_gr)
      print('Test accuracy SVM=',svm_Acc*100)
      print('Confusion matrix=\n',conf_mat(y_gr,y_pred))
```

Test accuracy SVM= 100.0

Confusion matrix=

```
[[20  0]
 [ 0 20]]
```

### 3 K-Nearest Neighbours (KNN)

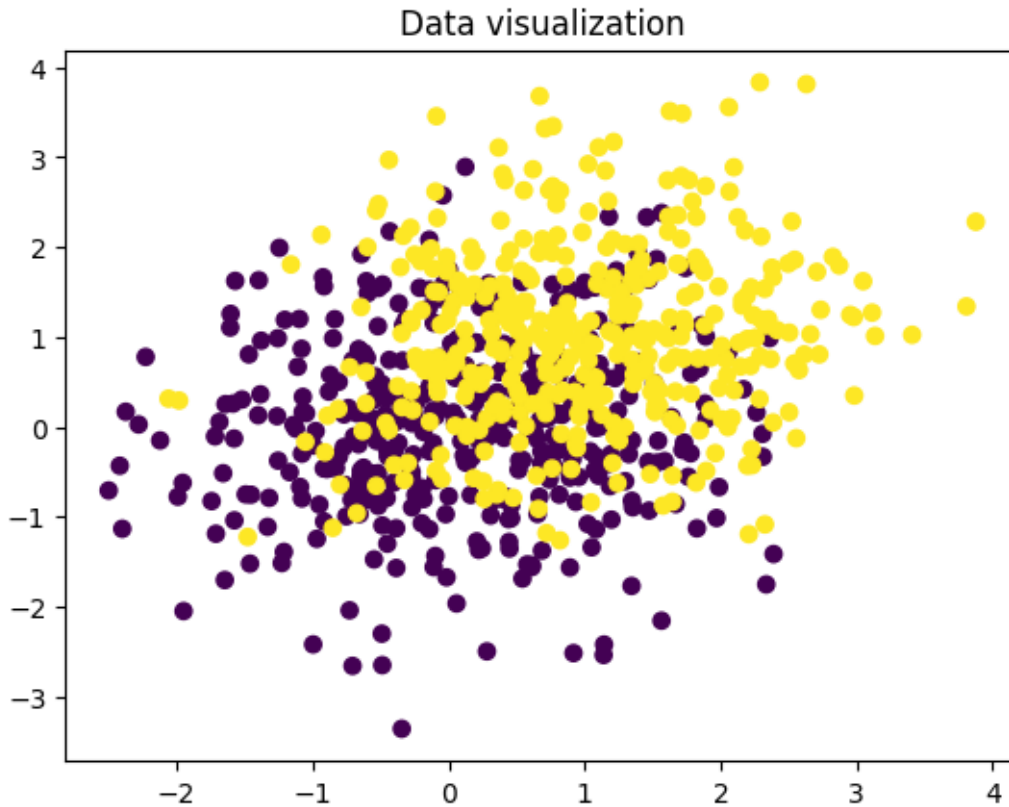
```
[17]: import numpy as np
      import matplotlib.pyplot as plt

      mean1=np.array([0,0])
      mean2=np.array([1,1])
      var=np.array([[1,0.1],[0.1,1]])
      np.random.seed(0)
      data1=np.random.multivariate_normal(mean1,var,500)
      data2=np.random.multivariate_normal(mean2,var,500)
      data_train=np.concatenate((data1[:-100,],data2[:-100]))
      label=np.concatenate((np.zeros(data1.shape[0]-100),np.ones(data2.shape[0]-100)))

      plt.figure()
      plt.scatter(data_train[:,0],data_train[:,1],c=label)
      plt.title('Data visualization')
```

```
[17]: Text(0.5, 1.0, 'Data visualization')
```





```
[18]: def euclidean_distance(row1, row2):
      return np.linalg.norm(row1-row2)
```

```
[22]: def get_neighbors(train,label_train, test_row, num_neighbors):
      distances = list()
      for i in range(train.shape[0]):
          train_row=train[i,:]
          label_row=label_train[i]
          dist = euclidean_distance(test_row, train_row)
          distances.append((train_row, dist,label_row))
      distances.sort(key=lambda tup: tup[1])
      neighbors = list()
      for i in range(num_neighbors):
          neighbors.append(distances[i])
      return neighbors
```

```
[23]: def predict_classification(neighbors):
      pred=list()
      for i in range(len(neighbors)):
          pred.append(neighbors[i][2])
      prediction = max(set(pred), key=pred.count)
```

```
return prediction
```

```
[24]: data_test=np.concatenate((data1[-100:],data2[-100:]))  
label_test=np.concatenate((np.zeros(100),np.ones(100)))
```

```
[25]: K=2  
  
pred_label=np.zeros(data_test.shape[0])  
for i in range(data_test.shape[0]):  
    neig=get_neighbors(data_train,label, data_test[i,:], K)  
    pred_label[i]=predict_classification(neig)  
  
accuracy=(len(np.where(pred_label==label_test)[0])/len(label_test))*100  
print('Testing Accuracy=',accuracy,'%')
```

Testing Accuracy= 65.5 %

Use the Sci-kit Learn Package and perform Classification on the above dataset using the K-Nearest Neighbour algorithm

```
[26]: from sklearn.neighbors import KNeighborsClassifier  
model = KNeighborsClassifier(n_neighbors=2)  
model.fit(data_train,label)  
pred_label = model.predict(data_test)  
  
accuracy=(len(np.where(pred_label==label_test)[0])/len(label_test))*100  
print('Testing Accuracy=',accuracy,'%')
```

Testing Accuracy= 65.5 %

## 4 Classification on MNIST Digit Data

1. Read MNIST data and perform train-test split
2. Select any 2 Classes and perform classification task using SVM, KNN and Logistic Regression algorithms with the help of Sci-Kit Learn tool
3. Report the train and test accuracy and also display the results using confusion matrix
4. Repeat steps 2 and 3 for all 10 Classes and tabulate the results

```
[23]: %pip install idx2numpy
```

Collecting idx2numpy

Downloading idx2numpy-1.2.3.tar.gz (6.8 kB)

Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages (from idx2numpy) (1.19.5)

Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from idx2numpy) (1.15.0)

Building wheels for collected packages: idx2numpy

Building wheel for idx2numpy (setup.py) ... done

Created wheel for idx2numpy: filename=idx2numpy-1.2.3-py3-none-any.whl

```
size=7919
sha256=fe3b197928ffeca37b34dc0e7f469cb48191e3629e835dd7e3db4ba3f455ef5
  Stored in directory: /root/.cache/pip/wheels/1a/ce/ad/d5e95a35cfe34149aade5e50
0f2edd535c0566d79e9a8e1d8a
Successfully built idx2numpy
Installing collected packages: idx2numpy
Successfully installed idx2numpy-1.2.3
```

```
[98]: import numpy as np
import matplotlib.pyplot as plt
from sklearn.utils import shuffle

file1='./t10k-images-idx3-ubyte'
file2='./t10k-labels-idx1-ubyte'

import idx2numpy

x_train= idx2numpy.convert_from_file(file1)
y_train= idx2numpy.convert_from_file(file2)
```

```
[99]: print(x_train.shape)
print(y_train.shape)
```

```
(10000, 28, 28)
(10000,)
```

```
[100]: indx1 = np.where(y_train == 1)[0]

indx4 = np.where(y_train == 4)[0]
```

```
[101]: x1 = x_train[indx1]
x4 = x_train[indx4]

y1 = y_train[indx1]
y2 = y_train[indx4]
```

```
[102]: X = []
for x in x1:
    X.append([x.flatten()])
for x in x4:
    X.append([x.flatten()])
X = np.concatenate(X)
print(X.shape)

Y = np.concatenate((y1,y2))
print(Y.shape)
```

(2117, 784)  
(2117,)

```
[103]: from PIL import Image
        for im in x1[:5]:
            img = Image.fromarray(im)
            img.show()
        for im in x4[:5]:
            img = Image.fromarray(im)
            img.show()
```



4

4

4

```
[104]: from sklearn.svm import SVC
       from sklearn.linear_model import LogisticRegression
       from sklearn.neighbors import KNeighborsClassifier
       from sklearn.preprocessing import StandardScaler
       from sklearn.pipeline import make_pipeline
```

```
[105]: from sklearn.model_selection import train_test_split
       from sklearn.metrics import accuracy_score
       from sklearn.metrics import confusion_matrix

       X_tr, X_tst, Y_tr, Y_tst = train_test_split(X,Y)
```

## 5 SVM

```
[106]: clf = make_pipeline(StandardScaler(), SVC())
       clf.fit(X=X_tr,y=Y_tr)
       print(f"Test accuracy is {clf.score(X_tr,Y_tr)}")
       y_pred = clf.predict(X_tst)
       print(f"Accuracy of this model is {accuracy_score(Y_tst,y_pred)*100}%")
       confusion_matrix(Y_tst,y_pred)
```

Test accuracy is 1.0

Accuracy of this model is 99.62264150943396%

```
[106]: array([[280,  2],
              [ 0, 248]])
```

## 6 Logistic

```
[107]: clf = make_pipeline(StandardScaler(), LogisticRegression())
        clf.fit(X=X_tr,y=Y_tr)
        print(f"Test accuracy is {clf.score(X_tr,Y_tr)}")
        y_pred = clf.predict(X_tst)
        print(f"Accuracy of this model is {accuracy_score(Y_tst,y_pred)*100}%")
        confusion_matrix(Y_tst,y_pred)
```

Test accuracy is 1.0

Accuracy of this model is 99.81132075471699%

```
[107]: array([[281,  1],
              [ 0, 248]])
```

## 7 Knn

```
[108]: clf = make_pipeline(StandardScaler(), KNeighborsClassifier())
        clf.fit(X=X_tr,y=Y_tr)
        print(f"Test accuracy is {clf.score(X_tr,Y_tr)}")
        y_pred = clf.predict(X_tst)
        print(f"Accuracy of this model is {accuracy_score(Y_tst,y_pred)*100}%")
        confusion_matrix(Y_tst,y_pred)
```

Test accuracy is 0.9899180844360429

Accuracy of this model is 99.43396226415095%

```
[108]: array([[282,  0],
              [ 3, 245]])
```

## 8 All 10 classes

### 8.1 Test train split

```
[112]: file1='./t10k-images-idx3-ubyte'
        file2='./t10k-labels-idx1-ubyte'

        import idx2numpy

        x_train= idx2numpy.convert_from_file(file1)
        y_train= idx2numpy.convert_from_file(file2)

        X = []
        Y = []

        for x in x_train:
```

```

X.append([x.flatten()])

X = np.concatenate(X)
print(X.shape)

Y = y_train
print(Y.shape)

X_tr, X_tst, Y_tr, Y_tst = train_test_split(X,Y

(10000, 784)
(10000,)

```

## 9 SVM

```

[113]: clf = make_pipeline(StandardScaler(), SVC())
clf.fit(X=X_tr,y=Y_tr)
print(f"Test accuracy is {clf.score(X_tr,Y_tr)}")
y_pred = clf.predict(X_tst)
print(f"Accuracy of this model is {accuracy_score(Y_tst,y_pred)*100}%")
confusion_matrix(Y_tst,y_pred)

```

Test accuracy is 0.9846666666666667  
Accuracy of this model is 93.32000000000001%

```

[113]: array([[207,  0,  6,  1,  0,  0,  0,  0,  0,  0],
 [ 0, 258,  1,  0,  0,  1,  1,  0,  0,  0],
 [ 2,  0, 242,  0,  1,  0,  1,  5,  4,  0],
 [ 0,  0,  9, 232,  1,  3,  1,  5,  3,  0],
 [ 0,  0,  5,  0, 232,  0,  1,  0,  1,  3],
 [ 1,  1,  5,  4,  0, 208,  8,  2,  1,  1],
 [ 2,  1, 10,  0,  1,  0, 231,  0,  1,  0],
 [ 1,  3,  8,  2,  3,  0,  0, 252,  0,  6],
 [ 2,  1,  5,  1,  2, 10,  2,  0, 226,  0],
 [ 4,  1,  5,  1,  6,  2,  0,  9,  0, 245]])

```

## 10 Logistic

```

[114]: clf = make_pipeline(StandardScaler(), LogisticRegression())
clf.fit(X=X_tr,y=Y_tr)
print(f"Test accuracy is {clf.score(X_tr,Y_tr)}")
y_pred = clf.predict(X_tst)
print(f"Accuracy of this model is {accuracy_score(Y_tst,y_pred)*100}%")
confusion_matrix(Y_tst,y_pred)

```

Test accuracy is 0.9998666666666667  
Accuracy of this model is 88.44%

```
/home/abhishekj/.local/lib/python3.9/site-
packages/sklearn/linear_model/_logistic.py:444: 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](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
n_iter_i = _check_optimize_result(
```

```
[114]: array([[205,  0,  3,  1,  1,  2,  2,  0,  0,  0],
 [ 0, 254,  1,  0,  0,  3,  0,  1,  2,  0],
 [ 3,  5, 211, 11,  1,  1,  3,  8, 10,  2],
 [ 0,  0,  8, 218,  2, 15,  0,  3,  8,  0],
 [ 0,  0,  6,  0, 217,  1,  1,  5,  2, 10],
 [ 1,  2,  3,  9,  3, 188,  7,  7,  9,  2],
 [ 3,  1,  5,  1,  2,  4, 229,  0,  1,  0],
 [ 1,  2,  4,  2,  8,  0,  1, 245,  2, 10],
 [ 4,  3,  4,  4,  4, 11,  4,  1, 209,  5],
 [ 4,  1,  2,  4, 14,  3,  0, 10,  0, 235]])
```

## 11 KNN

```
[115]: clf = make_pipeline(StandardScaler(), KNeighborsClassifier())
clf.fit(X=X_tr,y=Y_tr)
print(f"Test accuracy is {clf.score(X_tr,Y_tr)}")
y_pred = clf.predict(X_tst)
print(f"Accuracy of this model is {accuracy_score(Y_tst,y_pred)*100}%")
confusion_matrix(Y_tst,y_pred)
```

Test accuracy is 0.9410666666666667

Accuracy of this model is 91.36%

```
[115]: array([[211,  1,  1,  0,  0,  0,  0,  1,  0,  0],
 [ 0, 259,  1,  0,  0,  0,  1,  0,  0,  0],
 [ 8,  4, 224,  9,  0,  0,  1,  5,  3,  1],
 [ 0,  0,  1, 236,  3,  5,  0,  4,  3,  2],
 [ 0,  4,  4,  0, 227,  0,  0,  1,  0,  6],
 [ 5,  2,  1,  9,  2, 200,  7,  2,  1,  2],
 [ 7,  1,  2,  0,  0,  0, 235,  0,  1,  0],
 [ 0,  9,  2,  1,  3,  0,  0, 246,  0, 14],
 [ 7,  3,  4,  8,  3, 17,  0,  3, 204,  0],
 [ 3,  2,  0,  2,  9,  3,  0, 12,  0, 242]])
```