

# EE 5024 MLIP - Aakash (ME16B001)

January 27, 2020

## 0.1 K – NN Classification:

Download the Datasets from moodle and experiment with  $K = 1, 3, 5, 9$  and  $11$  for each of the following tasks.

### 0.1.1 Case I: MNIST dataset

For both train as well as test data the first digit in the  $i$ th row this the label (a number in the range 0-9) of the  $i$  sample. The next 784 ( $28 \times 28$ ) digits in the same row are the values of the pixels of the sample (image).

```
In [15]: from scipy.io import loadmat
import numpy as np
import matplotlib.pyplot as plt
import cv2
from scipy.spatial.distance import cdist

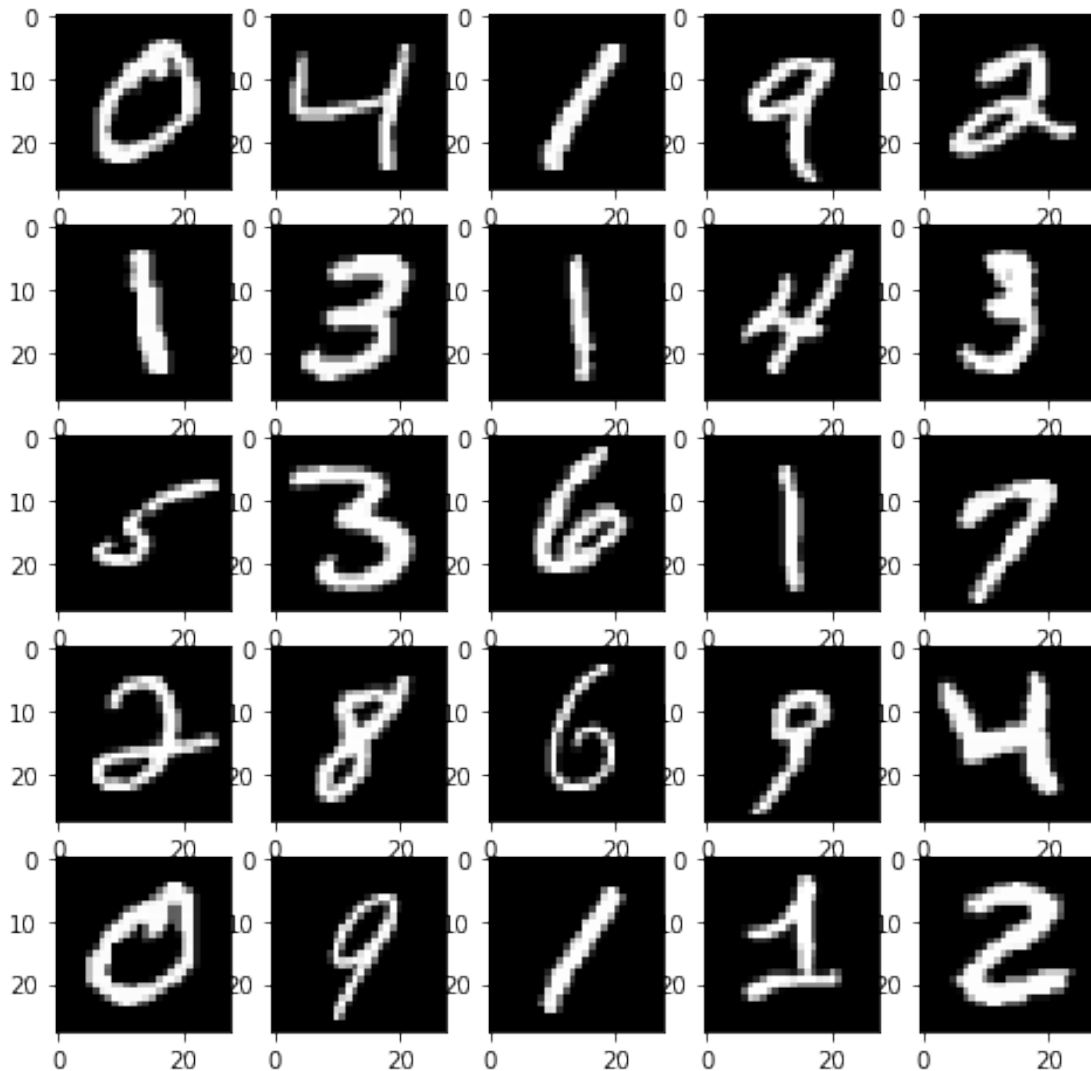
# load train data
train = loadmat('mnist_train.mat')
train=train['traindata']
print("MNIST train dataset size:",train.shape)
# load test data
test = loadmat('mnist_test.mat')
test=test['testdata']
print("MNIST test dataset size:",test.shape)

print("Visualizing the MNIST dataset")
fig=plt.figure(figsize=(8, 8))
columns = 5
rows = 5
for i in range(1, columns*rows +1):
    img=train[i][1:].reshape((28, 28))
    fig.add_subplot(rows, columns, i)
    plt.imshow(img,cmap='gray')
plt.show()
```

MNIST train dataset size: (5000, 785)

MNIST test dataset size: (500, 785)

Visualizing the MNIST dataset



Creating funtions for distance calculation and feature extraction

```
In [20]: def euclidean_distance(Xt,X):  
#     print(X.shape)  
#     print(Xt.shape)  
#     print(cdist(Xt, X).shape)  
    return cdist(Xt, X)  
  
# return histogram feature from the images  
def features(train,test):  
    # extract feature from train data  
    train_feature = np.zeros((5000, 256))
```

```

for j in range(train.shape[0]):
    feature = cv2.calcHist([train[j][:]], [0], None, [256], [0, 256])
    train_feature[j]=feature.reshape((1,256))

# extract feature from test data
test_feature = np.zeros((500, 256))
for j in range(test.shape[0]):
    feature = cv2.calcHist([test[j][:]], [0], None, [256], [0, 256])
    test_feature[j]=feature.reshape((1,256))
return train_feature,test_feature

```

Prediction function

```

In [21]: def predict(k, Xt, X, y):
    # Computing indices of k nearest neighbours of test image
    # print(Xt.shape, X.shape)
    distance = euclidean_distance(Xt, X)
    idx = np.argsort(distance)[: , :k]

    # Taking majority vote among the labels of knn
    y_pred = []
    for i in range(Xt.shape[0]):
        lab = y[idx[i]]
        sets, cnts = np.unique(lab, return_counts=True)
        y_pred.append(sets[np.argmax(cnts, axis = 0)])
    return y_pred

def result():
    accuracies = []
    ks = [1,3,5,9,11]
    for k in ks:
        y_pred = predict(k, test_feature, train_feature, train_labels)
        y_pred = np.array(y_pred)
        y_pred = y_pred.reshape((-1,1))
        # calculate the accuracy
        accuracy = np.mean(y_pred == test_labels)
        print ("k: ", k, "Accuracy:", accuracy)
        accuracies.append(accuracy)

    # plot k vs accuracy
    plt.scatter(ks, accuracies)
    plt.suptitle("k-Nearest Neighbours")
    plt.title("MNIST dataset")
    plt.xlabel('Value of k')
    plt.ylabel('Accuracy obtained')
    plt.show()

# datasets

```

```

train_labels = train[:,[0]].astype(int)
test_labels = test[:,[0]].astype(int)
train_feature = train[:,1:]
test_feature = test[:,1:]

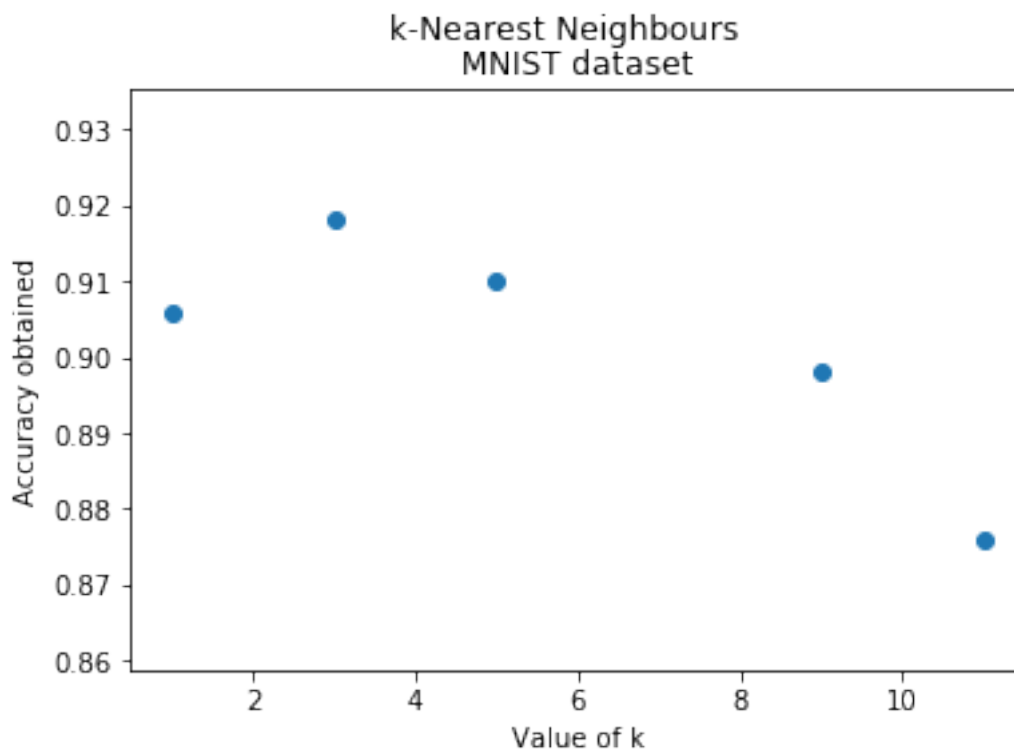
print("Dataset=MNIST, Feature Vector=Image pixels, Metric=Euclidian Distance")
result()

# histogram features
train_feature,test_feature = features(train_feature,test_feature)
print("Dataset=MNIST, Feature Vector=Histogram of Image, Metric=Euclidian Distance")
result()

```

Dataset=MNIST, Feature Vector=Image pixels, Metric=Euclidian Distance

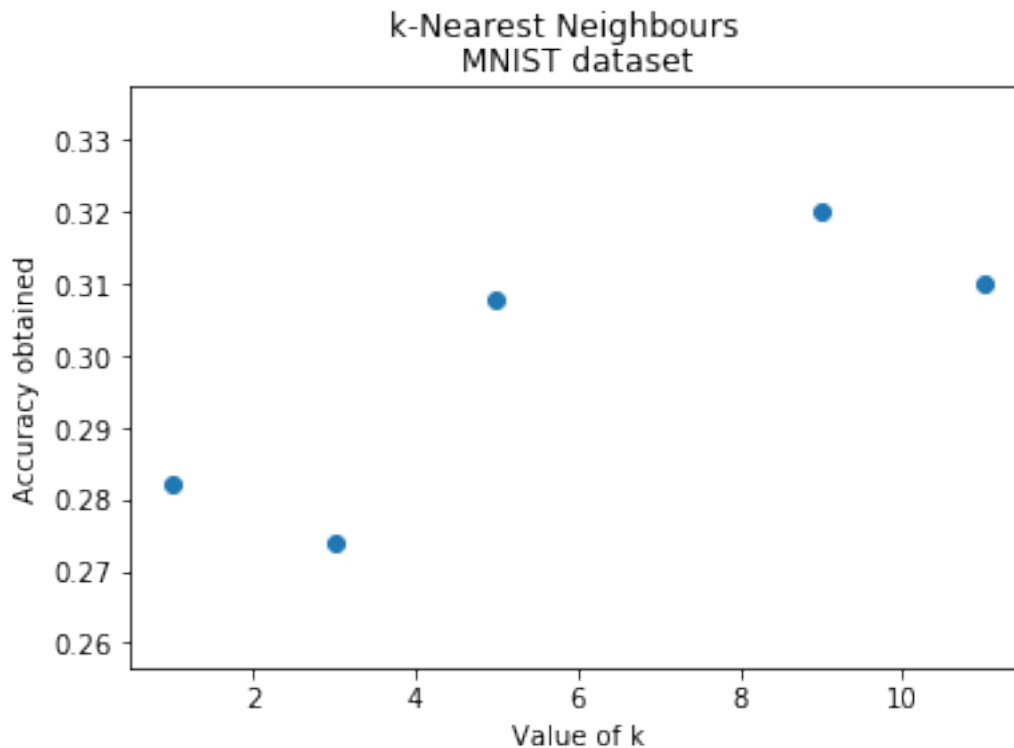
k: 1 Accuracy: 0.906  
k: 3 Accuracy: 0.918  
k: 5 Accuracy: 0.91  
k: 9 Accuracy: 0.898  
k: 11 Accuracy: 0.876



Dataset=MNIST, Feature Vector=Histogram of Image, Metric=Euclidian Distance

k: 1 Accuracy: 0.282

k: 3 Accuracy: 0.274  
k: 5 Accuracy: 0.308  
k: 9 Accuracy: 0.32  
k: 11 Accuracy: 0.31



The above results show that the pixel values when used as feature vector yield higher accuracies compared to choosing histogram of image as feature vector

### 0.1.2 Case II: CIFAR10 dataset

CIFAR10 contains 10 object classes. In both training as well as in test data each row stores a 32x32 color image. The first 1024 entries contain the red channel values, the next 1024 the green, and the final 1024 the blue.

```
In [35]: from scipy.io import loadmat
import numpy as np
import matplotlib.pyplot as plt
import cv2
from scipy.spatial.distance import cdist

# load train data
train = loadmat('CIFAR10_Train.mat')
train_labels = train['CIFAR10_Train_Labels']
```

```

train = train['CIFAR10_Train_Data']
print("CIFAR10 train dataset size:",train.shape)

# load test data
test = loadmat('CIFAR10_Test.mat')
test_labels = test['CIFAR10_Test_Labels']
test = test['CIFAR10_Test_Data']
print("CIFAR10 test dataset size:",test.shape)
print("testlbl",test_labels.shape)

# print(test_labels.shape)
print("Visualizing the CIFAR10 dataset")
fig=plt.figure(figsize=(8, 8))
columns = 5
rows = 5
for i in range(1, columns*rows +1):
    img=train[i][0:1024].reshape((32, 32))
    fig.add_subplot(rows, columns, i)
    plt.imshow(img,cmap='gray')
plt.show()

```

CIFAR10 train dataset size: (5000, 3072)

CIFAR10 test dataset size: (500, 3072)

testlbl (500, 1)

Visualizing the CIFAR10 dataset



Creating funtions for distance calculation and feature extraction

```
In [56]: # returns euclidean_distance vector
def euclidean_distance(Xt,X):
    return cdist(Xt, X)

# returns ncc distance vector
def ncc(Xt,X):
    return np.dot(Xt,np.transpose(X))/(np.linalg.norm(Xt)*np.linalg.norm(X))

# return histogram feature from the images (RGB channels)
def features(train,test):
    # extract feature from train data
    train_feature = np.zeros((5000, 768))
    for j in range(train.shape[0]):
```

```

        feature1 = cv2.calcHist([train[j][:1024]], [0], None, [256], [0, 256])
        feature2 = cv2.calcHist([train[j][1024:2048]], [0], None, [256], [0, 256])
        feature3 = cv2.calcHist([train[j][2048:]], [0], None, [256], [0, 256])
        feature = np.concatenate((feature1, feature2, feature3), axis=0)
        train_feature[j]=feature.reshape((1,768))

# extract feature from test data
test_feature = np.zeros((500, 768))
for j in range(test.shape[0]):
    feature1 = cv2.calcHist([test[j][:1024]], [0], None, [256], [0, 256])
    feature2 = cv2.calcHist([test[j][1024:2048]], [0], None, [256], [0, 256])
    feature3 = cv2.calcHist([test[j][2048:]], [0], None, [256], [0, 256])
    feature = np.concatenate((feature1, feature2, feature3), axis=0)
    test_feature[j]=feature.reshape((1,768))
return train_feature, test_feature

```

Prediction and accuracy calculation

```

In [57]: def predict(meteric,k, Xt, X, y):
        # calculate distance
        if meteric=="ncc":
            distance = ncc(Xt, X)
        elif meteric=="Eucledian":
            distance = euclidean_distance(Xt, X)

        # Computing indices of k nearest neighbours of test image
        idx = np.argsort(distance)[: , :k]

        # Taking majority vote among the labels of knn
        y_pred = []
        for i in range(Xt.shape[0]):
            lab = y[idx[i]]
            sets, cnts = np.unique(lab, return_counts=True)
            y_pred.append(sets[np.argmax(cnts, axis = 0)])
        return y_pred

def result(meteric):
    accuracies = []
    ks = [1,3,5,9,11]
    for k in ks:
        y_pred = predict(meteric,k, test_feature, train_feature, train_labels)
        y_pred = np.array(y_pred)
        y_pred = y_pred.reshape((-1,1))
        # calculate the accuracy
        accuracy = np.mean(y_pred == test_labels)
        print ("k: ", k, "Accuracy:", accuracy)
        accuracies.append(accuracy)

```



```

# plot k vs accuracy
plt.scatter(ks, accuracies)
plt.suptitle("k-Nearest Neighbours")
plt.title("MNIST dataset")
plt.xlabel('Value of k')
plt.ylabel('Accuracy obtained')
plt.show()

# extract histogram features
train_feature, test_feature = features(train, test)

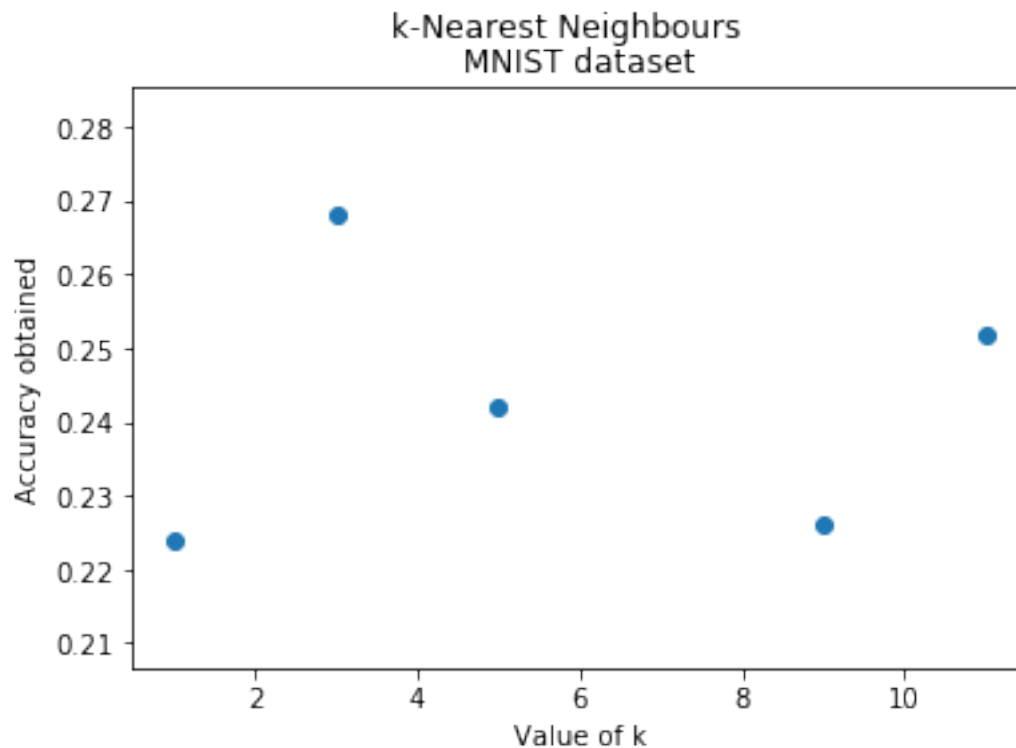
print("Dataset=CIFAR10, Feature Vector=Histogram of Image, Metric=Euclidian Distance")
meteric="Euclidian"
result(meteric)

print("Dataset=CIFAR10, Feature Vector=Histogram of Image, Metric=NCC")
meteric="ncc"
result(meteric)

```

Dataset=CIFAR10, Feature Vector=Histogram of Image, Metric=Euclidian Distance

k: 1 Accuracy: 0.224  
k: 3 Accuracy: 0.268  
k: 5 Accuracy: 0.242  
k: 9 Accuracy: 0.226  
k: 11 Accuracy: 0.252



Dataset=CIFAR10, Feature Vector=Histogram of Image, Metric=NCC

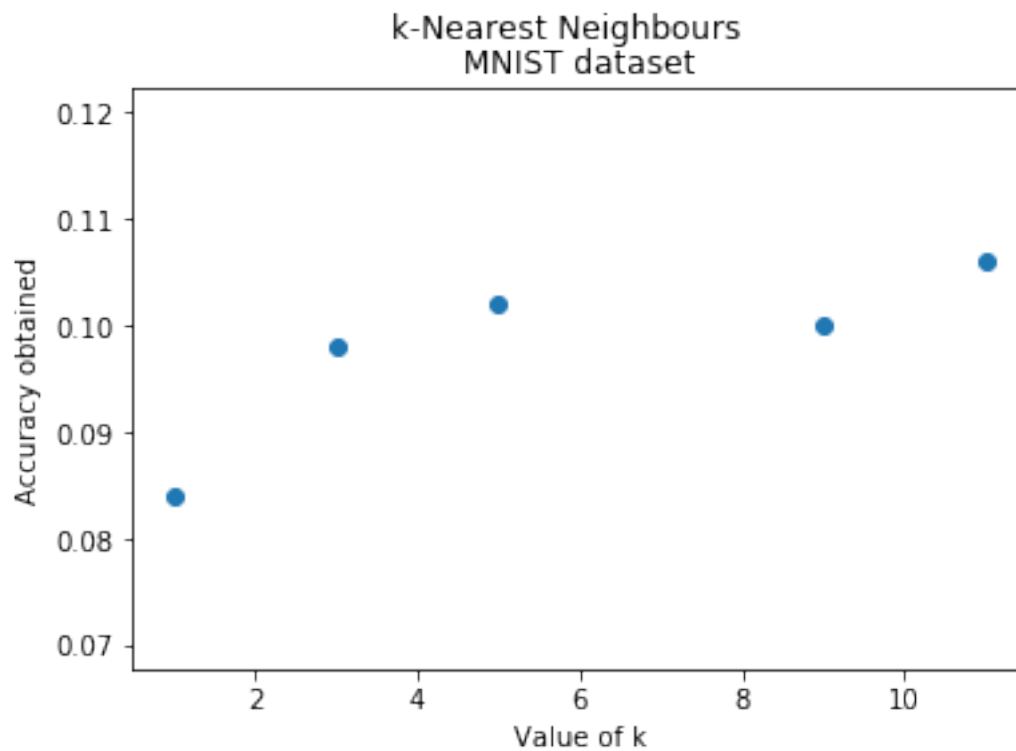
k: 1 Accuracy: 0.084

k: 3 Accuracy: 0.098

k: 5 Accuracy: 0.102

k: 9 Accuracy: 0.1

k: 11 Accuracy: 0.106



The accuracies for the CIFAR10 dataset are higher for the Euclidian metric compared to the NCC metric. Overall the kNN classification is unable to provide high (and usable) accuracies for classification.

(c) Aakash [nimrobotics.github.io](https://nimrobotics.github.io)