DSC-540-Topic2-Assignment-Final

August 18, 2021

[13]:
```
import struct
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
```

Data Preparation

[3]:
```
# This function is to read the binary training and test MNIST files
def read_idx(filename):
    with open(filename, 'rb') as f:
        zero, data_type, dims= struct.unpack('>HBB', f.read(4))
        shape= tuple(struct.unpack('>I', f.read(4))[0] for d in range(dims))
        return np.fromstring(f.read(), dtype=np.uint8).reshape(shape)
```

[4]:
```
# Let's load both the test and the training dataset with it.
raw_train=read_idx("train-images-idx3-ubyte")
raw_test=read_idx("t10k-images-idx3-ubyte")
```

```
<ipython-input-3-ad3cd2529e4f>:6: DeprecationWarning: The binary mode of
fromstring is deprecated, as it behaves surprisingly on unicode inputs. Use
frombuffer instead
  return np.fromstring(f.read(), dtype=np.uint8).reshape(shape)
```

The handwritten images are of 28 * 28 image format which need to be reshaped into a 2-D array for each images.

[5]:
```
# Let's flatten this trainining image dataset, i.e each entry would be of 28*28␣
↪long instead of 2d images.
train_data = np.reshape(raw_train, (60000, 28*28))
train_label = read_idx("train-labels-idx1-ubyte")
```

```
<ipython-input-3-ad3cd2529e4f>:6: DeprecationWarning: The binary mode of
fromstring is deprecated, as it behaves surprisingly on unicode inputs. Use
frombuffer instead
  return np.fromstring(f.read(), dtype=np.uint8).reshape(shape)
```

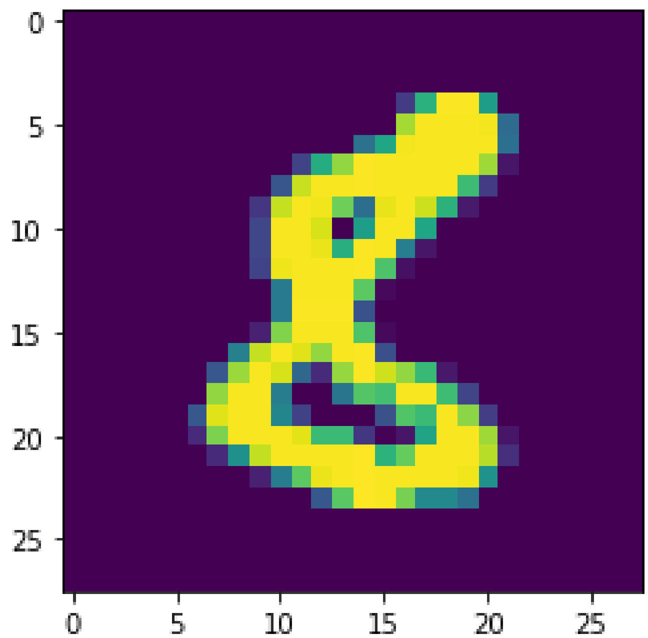
[6]:
```python
# Let's load the test datset and also the the label associated with it.

# Let's flatten this trainining image dataset, i.e each entry would be of 28*28␣
↪long instead of 2d images.
test_data = np.reshape(raw_test, (10000, 28*28))
test_label = read_idx("t10k-labels-idx1-ubyte")
```

```
<ipython-input-3-ad3cd2529e4f>:6: DeprecationWarning: The binary mode of
fromstring is deprecated, as it behaves surprisingly on unicode inputs. Use
frombuffer instead
  return np.fromstring(f.read(), dtype=np.uint8).reshape(shape)
```

[135]:
```python
# Let's see how the original data looks like from the binary input file look␣
↪like
plt.imshow(raw_train[46794])
```

[135]: `<matplotlib.image.AxesImage at 0x284f4393190>`



[8]:
```python
# The corresponding label for the above image can be given as follows
train_label[0]
```

[8]: 5

The image above is the number 5 and the label has the actual value in it.

[9]:
```
# Let's break the training dataset into two pieces namely the traing and the␣
↪validation set
trainData,valData,trainLabel,valLabel =␣
↪train_test_split(train_data,train_label,test_size=0.2,random_state=84)
```

[10]:
```
print("training data points: {}".format(len(trainData)))
print("validation data points: {}".format(len(valData)))
```

```
training data points: 48000
validation data points: 12000
```

K-Nearest Neighbor Classification Model

[328]:
```
# Let us create a model of Knearest Neighbors classifier and find out which␣
↪number of neighbors provides a better accurate fit.
# In order to do this we train the knn algorithm for different k values and␣
↪evaluate the accuracy score on the validation dataset

n_nei = np.arange(1,10,1)

for k in n_nei:
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(trainData,trainLabel)
    # Evaluate the model and calculate the accuracy
    score= model.score(valData, valLabel)
    print("k=%d, accuracy=%.2f%%" % (k, score * 100))
```

```
k=1, accuracy=97.42%
k=2, accuracy=96.88%
k=3, accuracy=97.50%
k=4, accuracy=97.26%
k=5, accuracy=97.27%
k=6, accuracy=97.22%
k=7, accuracy=97.09%
k=8, accuracy=97.01%
k=9, accuracy=96.89%
```

From above we can say that the model predicts with greater accuracy for k = 3 (97.5%). Hence we will build a model with k=3 and predict the results on the test dataset.

[405]:
```
# Let's build a model with k=3
model_f = KNeighborsClassifier(n_neighbors=3, p=2)
model_f.fit(trainData,trainLabel)
model_f
```

[405]:
```
KNeighborsClassifier(n_neighbors=3)
```

[103]:
```
# Now let's use the fitted model to predict the original test dataset.
pred_f = model_f.predict(test_data)
```

[104]:
```
# We can print the report of the predicted result as follows
print(classification_report(test_label,pred_f))
```

```
              precision    recall  f1-score   support

           0       0.96      0.99      0.98       980
           1       0.96      1.00      0.98      1135
           2       0.98      0.96      0.97      1032
           3       0.96      0.97      0.97      1010
           4       0.97      0.96      0.97       982
           5       0.97      0.96      0.97       892
           6       0.98      0.99      0.99       958
           7       0.96      0.96      0.96      1028
           8       0.99      0.93      0.96       974
           9       0.95      0.96      0.95      1009

    accuracy                           0.97     10000
   macro avg       0.97      0.97      0.97     10000
weighted avg       0.97      0.97      0.97     10000
```

From above we can say that number 8 has been predicted 99% right while 6 & 2 are predicted 98% right. The overall accuracy of the model is 97%

[105]:
```
# The distance between the Test data point and it's K nearest neighbors can be␣
↪given by the kneighbors function along with the k-neighbors
kneigh = model_f.kneighbors(test_data, return_distance=True)
# This will generate a tuple of 2 rows with 10000 entries in each row, one with␣
↪the 3 closest training data points and the other their corresponding␣
↪Euclidean distance.
```

[106]:
```
kneigh
# This represents a tuple for all 10000 test images and has two fields. The␣
↪first attribute provides the 3 closest neighbors for any specific datapoint␣
↪and the next attribute provides the corresponding euclidean distance with␣
↪respect to the data point from the test dataset to all it's 3 neighbors.
```

[106]:
```
(array([[ 676.58406721,  793.98677571,  862.67664858],
        [1162.9316403 , 1211.84446197, 1285.92845835],
        [ 321.66286699,  332.46353183,  341.04838366],
        …,
        [ 985.55415884, 1091.54157044, 1159.60036219],
        [1313.7682444 , 1335.91616503, 1378.28589197],
        [1014.89457581, 1226.16801459, 1350.13665975]]),
 array([[19297, 31432, 46794],
        [27727, 19003, 33558],
        [ 6947, 19056, 23293],
        …,
```

```
        [10536, 19423, 42489],
        [14748, 31059, 36296],
        [47870, 25599, 30564]], dtype=int64))
```

[148]:

```
# So for example the test data point 2 has three neighbors 6947, 19056 & 23293␣
↪(corresponding to Training dataset) and their corresponding elements are␣
↪provided below
x= kneigh[1]
y= kneigh[0]
print(x[2])
print(y[2])
```

```
[ 6947 19056 23293]
[321.66286699 332.46353183 341.04838366]
```

[396]:

```
# Here we will split the output of the kneighbors function as two 10000*3␣
↪arrays. One having the three neighbors of the test data point and the other␣
↪the corresponding euclidean distance from them.
kneigh_n = pd.DataFrame(list(kneigh)[1])
kneigh_e = pd.DataFrame(list(kneigh)[0])
```

[352]:

```
# Samples of 3 datapoints from test dataset and their 3 neighbors
kneigh_n[0:3]
```

[352]:

	0	1	2
0	19297	31432	46794
1	27727	19003	33558
2	6947	19056	23293

[353]:

```
# Samples of 3 datapoints from test dataset and their 3 neighbors' euclidean␣
↪distance from them
kneigh_e[0:3]
```

[353]:

	0	1	2
0	676.584067	793.986776	862.676649
1	1162.931640	1211.844462	1285.928458
2	321.662867	332.463532	341.048384

[22]:

```
# Calculate the Euclidean distance
def euc_dist(x1, x2):
    return np.sqrt(np.sum((x1-x2)**2))
```

[38]:

```
euc_dist(test_data[9999], train_data[9999])

# We can calculate the euclidean distance of all the data points from the test␣
↪dataset with respect to the training dataset using a simple loop statement␣
↪as shown below
```

```
# Note: Due to performance the below function has been commented out and the␣
↪Euclidean distance of one data point with respect to the test and training␣
↪dataset is show above.
#for i in range(len(test_data)):
#         dist = np.array([euc_dist(test_data[i], x_t) for x_t in
#         train_data])
```

[38]:

```
141.09571219565817
```

Most Popular Neighbor

In order to find the most famous neighbor for the test images, we will use the output of the kneighbor function (having k neighbors and their euclidean distance) and pick the 1st closest neighbor and see which had the most number of occurence.

[397]:

```
# We will use the neighbors array kneigh_n and get it's first neighbor to find␣
↪whihc is the most famous neighbor predicted by our knn model.
# In order to do that let's rename the first column of kneigh_ to a readable␣
↪name
kneigh_n = kneigh_n.rename(columns={0: 'c'})

kneigh_n

# The column c has the indices of the training label dataset and these are the␣
↪indices of the first neighbor.
```

[397]:

	c	1	2
0	19297	31432	46794
1	27727	19003	33558
2	6947	19056	23293
3	11230	476	10543
4	28745	18146	10246
…	…	…	…
9995	6308	39612	2669
9996	47811	23210	8364
9997	10536	19423	42489
9998	14748	31059	36296
9999	47870	25599	30564

[10000 rows x 3 columns]

[399]:

```
# Let's get the Training label and create a new column in the dataframe which␣
↪will hold the index value.
train_label_df=pd.DataFrame(train_label)
train_label_df['c'] = np.arange(train_label_df.shape[0])
train_label_df = train_label_df.rename(columns={0: 'Label'})
train_label_df
```

[399]:

```
       Label      c
0          5      0
1          0      1
2          4      2
3          1      3
4          9      4
…        …      …
59995      8  59995
59996      3  59996
59997      5  59997
59998      6  59998
59999      8  59999

[60000 rows x 2 columns]
```

[400]:

```
# Let's merge both datframes so that the final dataframe will have the neighbor␣
↪indices and the corresponding label values
kneigh_n_label=kneigh_n.merge(train_label_df, on='c')
kneigh_n_label

# Now we can see that the first neighbor's trainng inex is in column 'c' and␣
↪the corresponding column label is in column 'Label'
```

[400]:

```
          c      1      2  Label
0     19297  31432  46794      1
1     27727  19003  33558      5
2      6947  19056  23293      7
3      6947  19056  43510      7
4     11230    476  10543      2
…       …      …      …      …
9995  30254  32562   8472      3
9996  47168  35500  40098      7
9997   6308  39612   2669      4
9998  10536  19423  42489      5
9999  47870  25599  30564      9

[10000 rows x 4 columns]
```

[401]:

```
# In order to find the most famous nearest neighbor we can use the Counter␣
↪function from the collections package to see which is the most famous␣
↪predicted fisrt neighbor
from collections import Counter
Counter(kneigh_n_label['Label'])
```

[401]:

```
Counter({1: 1221,
         5: 893,
         7: 1006,
```

```
            2: 979,
            8: 954,
            0: 997,
            6: 949,
            9: 997,
            3: 1011,
            4: 993})
```

From above we can see that 1 has been predicted as the most common first neighbor by our knn model

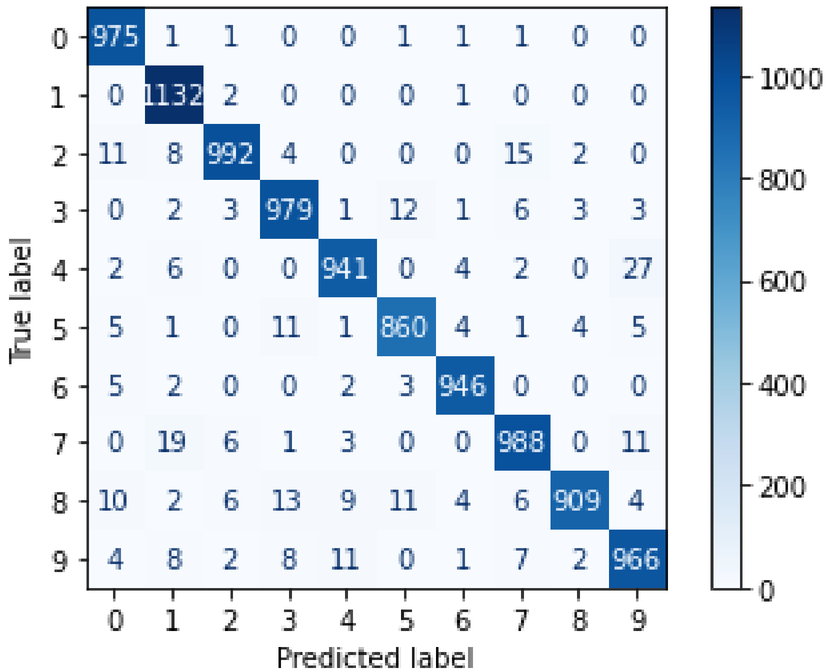
[402]:
```
# Similarly we can find the most predicted value in our predicted set by the␣
 ↪Counter function again
Counter(pred_f)
```

[402]:
```
Counter({7: 1026,
            2: 1012,
            1: 1181,
            0: 1012,
            4: 968,
            9: 1016,
            5: 887,
            6: 962,
            3: 1016,
            8: 920})
```

From above we can confirm that 1 has been predicted the most from the test dataset which coincides with the most number of nearest neighbors.

Confusion Matrix

[141]:
```
from sklearn.metrics import plot_confusion_matrix
plot_confusion_matrix(model_f, test_data, test_label,cmap=plt.cm.Blues)
plt.show()
```



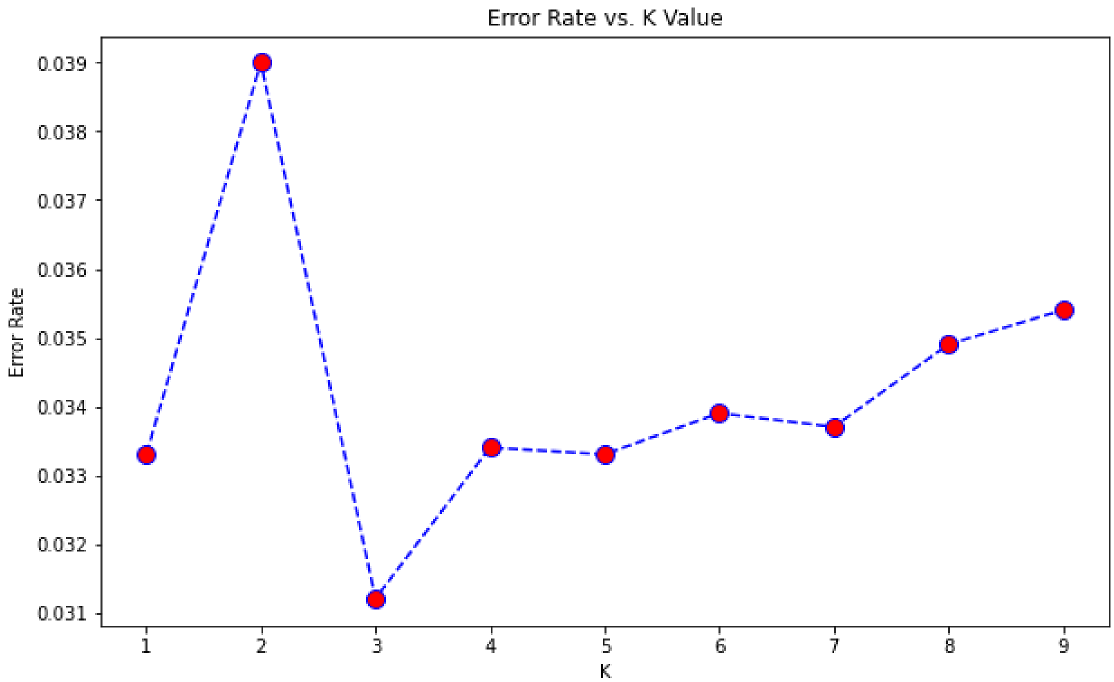
Error Rate Calculation

[144]:
```
error_rate = []
# Might take some time
for i in range(1,10):

    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(trainData,trainLabel)
    pred_i = knn.predict(test_data)
    error_rate.append(np.mean(pred_i != test_label))
```

[145]:
```
plt.figure(figsize=(10,6))
plt.plot(range(1,10),error_rate,color='blue', linestyle='dashed', marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
```

[145]:
```
Text(0, 0.5, 'Error Rate')
```



We can see above the error has been plotted for different k values. As portrayed above the error is the lowest at k=3 with an error rate of 0.0312.

Calculate the ROC for KNN

[199]:
```
knn_probs=model_f.predict_proba(test_data)
```

First we need to calculate the predictive probability of the knn model and then use the roc_auc_score from the scikit learn package to get the roc_auc_score

[208]:
```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import auc
```

[325]:
```
# Let's get the AUC for all the individual labels

for i in np.arange(0,10,1):
    fpr, tpr, threshold = roc_curve(test_label, knn_probs[:, i],pos_label=i)
    roc_auc = auc(fpr, tpr)
    print("label =",i, "auc =", roc_auc)
```

```
label = 0 auc = 0.9973163378433414
label = 1 auc = 0.9979642756869439
label = 2 auc = 0.9894021335117454
label = 3 auc = 0.9913556316699523
label = 4 auc = 0.9924075813071752
label = 5 auc = 0.9926645082133481
```

```
label = 6 auc = 0.9954374367080279
label = 7 auc = 0.989505016471478
label = 8 auc = 0.9863014376446598
label = 9 auc = 0.991255819193271
```

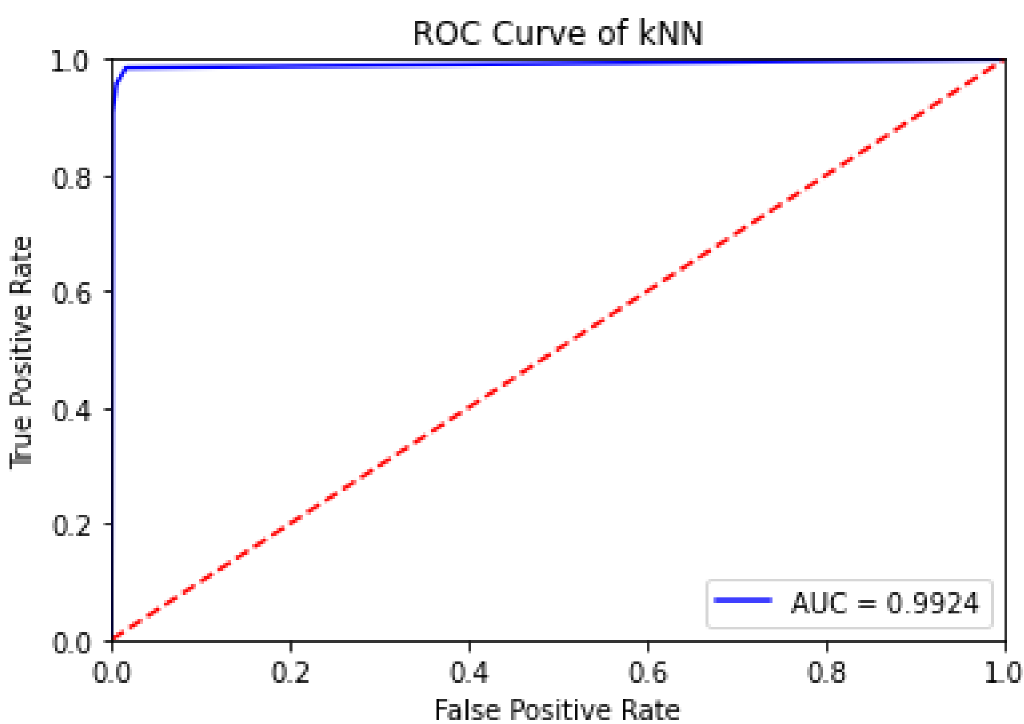
[326]:
```
# The overall Area under the curve can be given by the function roc_auc_curve
roc_auc_score=roc_auc_score(test_label, knn_probs,multi_class='ovr')
roc_auc_score
```

[326]:
```
0.9923610178249941
```

The AUC of the overaall model is close to 1 meaning the model is able to efficiently distinguish between the positive and negative classes accurately

We can plot the overall ROC curve for the model as shown below

[329]:
```
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.4f' % roc_auc_score)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve of kNN')
plt.show()
```



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