DMG2 Assignment : Problem 5

k-Nearest Neighbours Classifier, Parzen Window Classifier

In [1]:
```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn import preprocessing
from sklearn.neighbors import KernelDensity

sns.set_style('whitegrid')
```

In [2]:
```
DATA_DIR = '/home/jishnu/Documents/ISB/Term3/dmg2/assignments/hw_assignment
1/dmg2/datasets/mnist'
```

In [3]:
```
train = pd.DataFrame(columns=['V{}'.format(i) for i in range(1,785)] + ['lab
el'])
test = pd.DataFrame(columns=['V{}'.format(i) for i in range(1,785)] + ['labe
l'])
for num in range(10):
    # Consolidating training data
    temp_train =
pd.read_csv(os.path.join(DATA_DIR,'train{0}.csv'.format(num)),usecols=
['V{}'.format(i) for i in range(1,785)])
    temp_train['label'] = num
    train = train.append(temp_train,ignore_index=True)
    # Consolidating test data
    temp_test =
pd.read_csv(os.path.join(DATA_DIR,'test{0}.csv'.format(num)),usecols=
['V{}'.format(i) for i in range(1,785)])
    temp_test['label'] = num
    test = test.append(temp_test,ignore_index=True)
```

In [4]:
```
train.shape
```

Out[4]:
```
(36470, 785)
```

In [5]:
```
test.shape
```

Out[5]:
```
(24190, 785)
```

In [6]:
```
train[train.isnull().any(axis=1)].groupby(by='label')
['label'].value_counts()
```

Out[6]:
```
label  label
4      4         46
5      5        299
6      6          1
8      8         42
Name: label, dtype: int64
```

In [7]:
```
test[test.isnull().any(axis=1)].groupby(by='label')['label'].value_counts()
```

Out[7]:
```
label  label
4      4         35
5      5        203
6      6          4
8      8         30
Name: label, dtype: int64
```

There are missing values in both the training and test data. Shown above is the count of rows with missing values, and the associated labels.

In [8]:
```
train.groupby(by='label')['label'].value_counts()
```

Out[8]:
```
label  label
0      0        3567
1      1        4034
2      2        3582
3      3        3677
4      4        3567
5      5        3567
6      6        3567
7      7        3763
8      8        3567
9      9        3579
Name: label, dtype: int64
```

In [9]:
```
test.groupby(by='label')['label'].value_counts()
```

Out[9]:
```
label  label
0      0        2356
1      1        2708
2      2        2376
3      3        2454
4      4        2356
5      5        2356
6      6        2356
7      7        2502
8      8        2356
9      9        2370
Name: label, dtype: int64
```

Considering the number of complete data for each label, we can safely remove the rows with missing values for our analysis.

In [10]:
```
train = train.dropna()
test = test.dropna()
```

In [11]:
```
train.isnull().values.any()
```

Out[11]:
```
False
```

In [12]:
```
test.isnull().values.any()
```

Out[12]:
```
False
```

There are no missing values in the training and test data now

In [13]:
```
X_train = train.iloc[:,:784]
Y_train = train.iloc[:,784]

X_test = test.iloc[:,:784]
Y_test = test.iloc[:,784]
```

In [14]:
```
# Standardizing feature values
X_train = StandardScaler().fit_transform(X_train)
X_test = StandardScaler().fit_transform(X_test)
```

Applying PCA

In [15]:
```
# Applying PCA
pc = PCA(n_components=9).fit_transform(X_train)
d1_train = pd.DataFrame(data=pc,columns=['pc{0}'.format(i) for i in
range(1,10)])
d1_train['label'] = Y_train.values
d1_train.head(5)

pc = PCA(n_components=9).fit_transform(X_test)
d1_test = pd.DataFrame(data=pc,columns=['pc{0}'.format(i) for i in range(1,1
0)])
d1_test['label'] = Y_test.values
d1_test.head(5)
```

Out[15]:

	pc1	pc2	pc3	pc4	pc5	pc6	pc7	pc8	
0	1.751822	-6.389642	-2.021035	-2.694776	-6.429969	1.022368	-0.548045	5.235907	3.7857
1	5.884340	-7.690669	-2.390873	0.259680	-4.923272	-0.380960	0.317370	6.499910	3.0124
2	16.381102	5.663539	-1.865766	-3.369305	4.357549	-3.096304	-5.628728	-3.834695	2.3451
3	12.814328	-7.638465	-4.434865	-7.658347	-0.555438	-1.783533	-0.087714	1.804333	0.3498
4	11.123276	7.252622	5.007244	-0.333844	15.020188	-0.072097	-0.977431	-2.399776	-0.141

Applying Fisher LDA

In [16]:
```
fisher = LinearDiscriminantAnalysis(n_components=9).fit_transform(X_train,Y_
train.astype('int'))
d2_train = pd.DataFrame(data=fisher,columns=['f{0}'.format(i) for i in
range(1,10)])
d2_train['label'] = Y_train.values
d2_train.head(5)

fisher = LinearDiscriminantAnalysis(n_components=9).fit_transform(X_test,Y_t
est.astype('int'))
d2_test = pd.DataFrame(data=fisher,columns=['f{0}'.format(i) for i in
range(1,10)])
d2_test['label'] = Y_test.values
d2_test.head(5)
```

```
/home/jishnu/anaconda3/lib/python3.6/site-packages/sklearn/discriminant_anal
ysis.py:388: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
/home/jishnu/anaconda3/lib/python3.6/site-packages/sklearn/discriminant_anal
ysis.py:442: UserWarning: The priors do not sum to 1. Renormalizing
  UserWarning)
/home/jishnu/anaconda3/lib/python3.6/site-packages/sklearn/discriminant_anal
ysis.py:388: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")
```

Out[16]:

	f1	f2	f3	f4	f5	f6	f7	f8	
0	-2.833687	-1.079133	-0.845838	-0.764987	-0.484096	0.313129	-0.955681	-0.997196	1.07613
1	-3.849851	-3.435085	-1.935596	0.478846	-2.420500	-0.475621	0.572627	-0.989022	0.77908
2	-3.350865	-4.500847	-3.900589	-1.086583	-2.654538	-1.739049	-1.565408	-0.213139	-0.0240
3	-3.283216	-2.503597	-3.138834	-0.103059	-1.582149	-0.295842	1.330582	-3.239352	1.47333
4	-2.231976	-1.552025	-3.889057	-0.017441	-0.577388	-2.299944	-0.684894	0.945457	0.40414

k-Nearest Neighbors Classification

In [17]:
```
d1_train_X = d1_train.iloc[:,:9]
d1_train_Y = d1_train.iloc[:,9].astype('int')

d1_test_X = d1_test.iloc[:,:9]
d1_test_Y = d1_test.iloc[:,9].astype('int')

d2_train_X = d2_train.iloc[:,:9]
d2_train_Y = d2_train.iloc[:,9].astype('int')

d2_test_X = d2_test.iloc[:,:9]
d2_test_Y = d2_test.iloc[:,9].astype('int')
```

In [18]:
```
d1_knn = pd.DataFrame(columns=['k','acc_type','acc'])
d2_knn = pd.DataFrame(columns=['k','acc_type','acc'])
```

In [19]:
```
for k in range(1,18,2):
    knn1 = KNeighborsClassifier(n_neighbors=k).fit(d1_train_X,d1_train_Y)
    knn2 = KNeighborsClassifier(n_neighbors=k).fit(d2_train_X,d2_train_Y)
    d1_knn = d1_knn.append({'k' : k, 'acc_type' : 'training', 'acc' : np.rou
nd(knn1.score(d1_train_X,d1_train_Y),4)},ignore_index=True)
    d1_knn = d1_knn.append({'k' : k, 'acc_type' : 'test', 'acc' : np.round(k
nn1.score(d1_test_X,d1_test_Y),4)},ignore_index=True)
    d2_knn = d2_knn.append({'k' : k, 'acc_type' : 'training', 'acc' : np.rou
nd(knn2.score(d2_train_X,d2_train_Y),4)},ignore_index=True)
    d2_knn = d2_knn.append({'k' : k, 'acc_type' : 'test', 'acc' : np.round(k
nn2.score(d2_test_X,d2_test_Y),4)},ignore_index=True)
```

In [20]:
```
d1_knn.head()
```

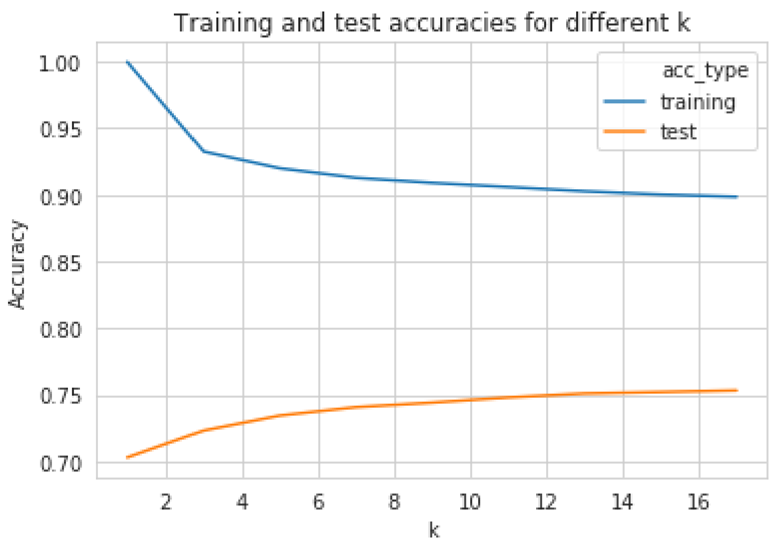
Out[20]:

	k	acc_type	acc
0	1	training	1.0000
1	1	test	0.7028
2	3	training	0.9326
3	3	test	0.7230
4	5	training	0.9200

Plotting training and test accuracy for kNN Classification

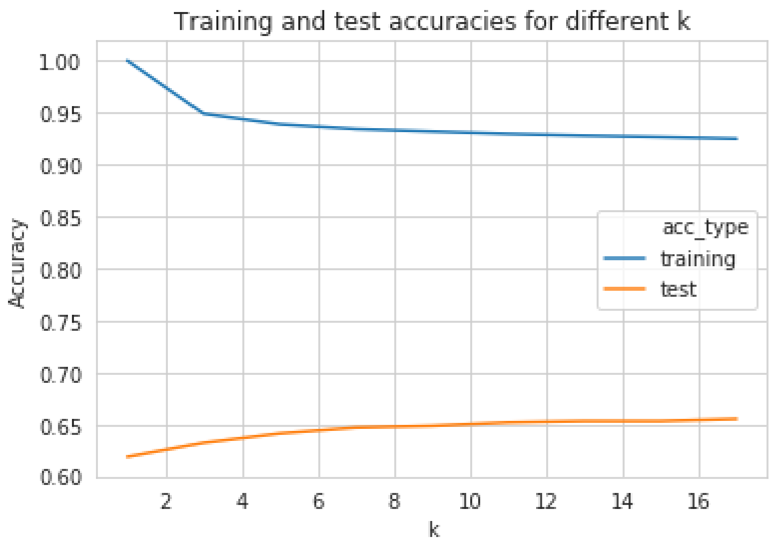
D1 Dataset

In [21]:
```
sns.lineplot(x='k',y='acc',hue='acc_type',data=d1_knn,ci=0,)
plt.title('Training and test accuracies for different k')
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.show();
```



D2 Dataset

In [22]:
```
sns.lineplot(x='k',y='acc',hue='acc_type',data=d2_knn,ci=0,)
plt.title('Training and test accuracies for different k')
plt.xlabel('k')
plt.ylabel('Accuracy')
plt.show();
```



The optimal k for both datasets is 8 when considering the test accuracies.

Parzen-Window Classification

For each data point in test set, find the kernel function of the form $exp(-(X_i - X_t)^2/2\sigma^2)/\sigma$

The distance function used in euclidean, and the sum of kernel function value is found for all training data for each class to come up with the score of the class.

This score is converted to a probaibility to find the predicted class with maximum probability

Sampling values from each class for better performance

In [23]:
```
d1_train.groupby('label', group_keys=False).count()
```

Out[23]:

	pc1	pc2	pc3	pc4	pc5	pc6	pc7	pc8	pc9
label									
0	3567	3567	3567	3567	3567	3567	3567	3567	3567
1	4034	4034	4034	4034	4034	4034	4034	4034	4034
2	3582	3582	3582	3582	3582	3582	3582	3582	3582
3	3677	3677	3677	3677	3677	3677	3677	3677	3677
4	3521	3521	3521	3521	3521	3521	3521	3521	3521
5	3268	3268	3268	3268	3268	3268	3268	3268	3268
6	3566	3566	3566	3566	3566	3566	3566	3566	3566
7	3763	3763	3763	3763	3763	3763	3763	3763	3763
8	3525	3525	3525	3525	3525	3525	3525	3525	3525
9	3579	3579	3579	3579	3579	3579	3579	3579	3579

In [24]:
```
d1_test.groupby('label', group_keys=False).count()
```

Out[24]:

	pc1	pc2	pc3	pc4	pc5	pc6	pc7	pc8	pc9
label									
0	2356	2356	2356	2356	2356	2356	2356	2356	2356
1	2708	2708	2708	2708	2708	2708	2708	2708	2708
2	2376	2376	2376	2376	2376	2376	2376	2376	2376
3	2454	2454	2454	2454	2454	2454	2454	2454	2454
4	2321	2321	2321	2321	2321	2321	2321	2321	2321
5	2153	2153	2153	2153	2153	2153	2153	2153	2153
6	2352	2352	2352	2352	2352	2352	2352	2352	2352
7	2502	2502	2502	2502	2502	2502	2502	2502	2502
8	2326	2326	2326	2326	2326	2326	2326	2326	2326
9	2370	2370	2370	2370	2370	2370	2370	2370	2370

There are around 3000 - 4000 data points for each class in train and 2000 - 3000 data points for each class in test. Let's sample 10 data points from each class

In [25]:
```
d1_train = d1_train.groupby('label', group_keys=False).apply(lambda x: x.sam
ple(min(len(x), 10)))
d1_test = d1_test.groupby('label', group_keys=False).apply(lambda x: x.sampl
e(min(len(x), 10)))

d2_train = d2_train.groupby('label', group_keys=False).apply(lambda x: x.sam
ple(min(len(x), 10)))
d2_test = d2_test.groupby('label', group_keys=False).apply(lambda x: x.sampl
e(min(len(x), 10)))

d1_train_X = d1_train.iloc[:,:9]
d1_train_Y = d1_train.iloc[:,9].astype('int')

d1_test_X = d1_test.iloc[:,:9]
d1_test_Y = d1_test.iloc[:,9].astype('int')

d2_train_X = d2_train.iloc[:,:9]
d2_train_Y = d2_train.iloc[:,9].astype('int')

d2_test_X = d2_test.iloc[:,:9]
d2_test_Y = d2_test.iloc[:,9].astype('int')
```

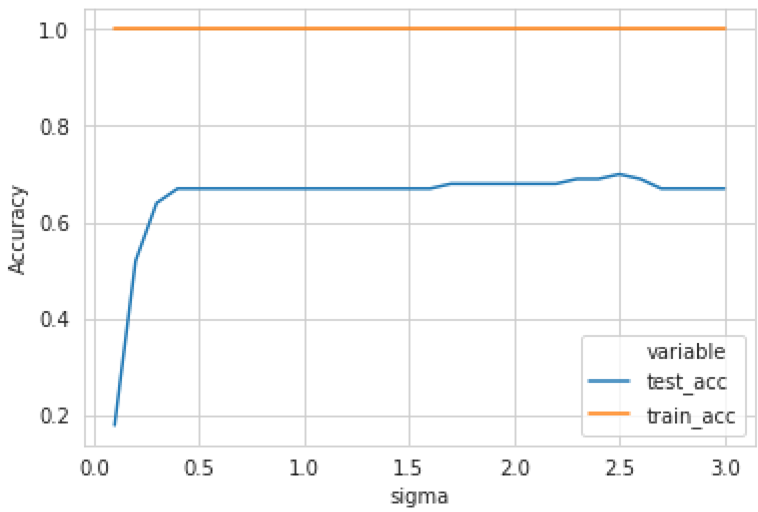
In [26]:
```
def d1_train_ker(row_x,row_y,sigma):
    dist = np.linalg.norm(row_x - row_y)
    kernel_fn = np.exp(-dist**2/(2*sigma**2)) / sigma
    return kernel_fn

def d1_ker(row,sigma):
    class_kernel_dict = dict()
    row_x = row
    for label in range(10):
        sum_ker_fn = 0
        d1_train_label = d1_train.loc[d1_train['label'] == label]
        kernel_fn = d1_train_label.apply(lambda row_y:d1_train_ker(row_x,row
_y[:9],sigma),axis=1)
        class_kernel_dict[label] = kernel_fn.sum()
    prediction = max(class_kernel_dict, key=class_kernel_dict.get)
    return prediction

def d2_ker(row,sigma):
    class_kernel_dict = dict()
    row_x = row
    for label in range(10):
        sum_ker_fn = 0
        d2_train_label = d2_train.loc[d2_train['label'] == label]
        kernel_fn = d2_train_label.apply(lambda row_y:d1_train_ker(row_x,row
_y[:9],sigma),axis=1)
        class_kernel_dict[label] = kernel_fn.sum()
    prediction = max(class_kernel_dict, key=class_kernel_dict.get)
    return prediction
```

In [27]:
```
parzen_acc = pd.DataFrame(columns=['sigma','train_acc','test_acc'])
for sigma in [x/10.0 for x in range(1,31,1)]:
    predicted_labels = d1_test_X.apply(lambda row:d1_ker(row,sigma),axis=1)
    test_acc_df = pd.DataFrame({'actual' : d1_test_Y,'predicted' : predicted
_labels})
    test_acc = np.round(test_acc_df.loc[test_acc_df['actual'] ==
test_acc_df['predicted']].shape[0] / test_acc_df.shape[0], 4)
    predicted_labels = d1_train_X.apply(lambda row:d1_ker(row,sigma),axis=1)
    train_acc_df = pd.DataFrame({'actual' : d1_train_Y,'predicted' : predict
ed_labels})
    train_acc = np.round(train_acc_df.loc[train_acc_df['actual'] == train_ac
c_df['predicted']].shape[0] / train_acc_df.shape[0], 4)
    parzen_acc = parzen_acc.append({'sigma' : sigma, 'train_acc' :
train_acc, 'test_acc' : test_acc},ignore_index=True)
    #print({'sigma' : sigma, 'train_acc' : train_acc, 'test_acc' : test_ac
c})
```

In [28]:
```
parzen_acc_d2 = pd.DataFrame(columns=['sigma','train_acc','test_acc'])
for sigma in [x/10.0 for x in range(1,31,1)]:
    predicted_labels = d2_test_X.apply(lambda row:d2_ker(row,sigma),axis=1)
    test_acc_df = pd.DataFrame({'actual' : d2_test_Y,'predicted' : predicted
_labels})
    test_acc = np.round(test_acc_df.loc[test_acc_df['actual'] ==
test_acc_df['predicted']].shape[0] / test_acc_df.shape[0], 4)
    predicted_labels = d2_train_X.apply(lambda row:d2_ker(row,sigma),axis=1)
    train_acc_df = pd.DataFrame({'actual' : d2_train_Y,'predicted' : predict
ed_labels})
    train_acc = np.round(train_acc_df.loc[train_acc_df['actual'] == train_ac
c_df['predicted']].shape[0] / train_acc_df.shape[0], 4)
    parzen_acc_d2 = parzen_acc_d2.append({'sigma' : sigma, 'train_acc' : tra
in_acc, 'test_acc' : test_acc},ignore_index=True)
    #print({'sigma' : sigma, 'train_acc' : train_acc, 'test_acc' : test_ac
c})
```

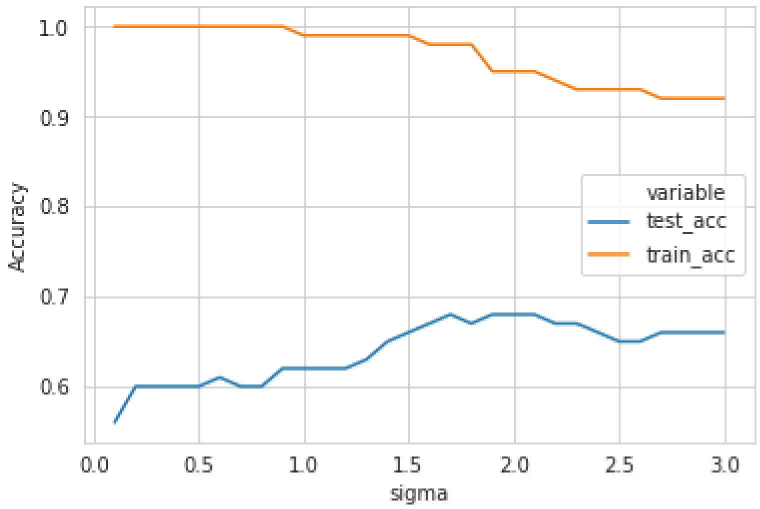
Plotting Train\Test Accuracy vs Sigma for D1 Dataset

In [29]:
```
sns.lineplot(x='sigma',y='value',hue='variable',data=parzen_acc.melt(id_vars=
['sigma'],value_vars=['test_acc','train_acc']))
plt.ylabel('Accuracy')
plt.show()
```



Plotting Train\Test Accuracy vs Sigma for D2 Dataset

In [30]:
```
sns.lineplot(x='sigma',y='value',hue='variable',data=parzen_acc_d2.melt(id_v
ars=['sigma'],value_vars=['test_acc','train_acc']))
plt.ylabel('Accuracy')
plt.show()
```



The optimal sigma is 0.5 for D1 dataset and 1.4 for D1 dataset.

It is seen that kNN classifier gives more test accuracies when compared to parzen window classifiers.

Google Form Answers

1) What's the test accuracy on D1 for k = 7 for kNN classifier?

In [32]:
```
d1_knn.loc[d1_knn['k'] == 7]
```

Out[32]:

	k	acc_type	acc
6	7	training	0.9128
7	7	test	0.7406

2) What's the test accuracy on D2 for k = 7 for kNN classifier?

In [33]:
```
d2_knn.loc[d2_knn['k'] == 7]
```

Out[33]:

	k	acc_type	acc
6	7	training	0.9340
7	7	test	0.6469

3) What's the test accuracy on D1 for sigma = 1 for Parzen Window classifier?

In [37]:
```
parzen_acc.loc[parzen_acc['sigma'] == 1.0]['test_acc']
```

Out[37]:
```
9    0.67
Name: test_acc, dtype: float64
```

4) What's the test accuracy on D2 for sigma = 1 for Parzen Window classifier?

In [38]:
```
parzen_acc_d2.loc[parzen_acc_d2['sigma'] == 1.0]['test_acc']
```

Out[38]:
```
9    0.62
Name: test_acc, dtype: float64
```