Anmol_More

March 20, 2020

[1]:
```
import warnings
warnings.filterwarnings('ignore')

import glob
import random
import math
import decimal
import re
import pandas as pd
import numpy as np
import itertools

from sklearn import decomposition

from sklearn.model_selection import train_test_split
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.mixture import BayesianGaussianMixture
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import BernoulliNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.neighbors import KernelDensity
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn import metrics


from sklearn.feature_extraction.text import CountVectorizer

from nltk.corpus import stopwords
from nltk.stem import LancasterStemmer

import matplotlib.pyplot as plt
import seaborn as sns
```

set random seed

[2]:
```
#random seed in jupyter notebooks have scope of cell only and it's not␣
↪applicable for whole notebook
# so even after this we need to set random_state explicility
random.seed(11915043)
```

0.1 P1 : IRIS – HIERARCHICAL FISHER

[3]:
```
iris = pd.read_csv('DMG-2 Assignment Data Files/iris/iris.data', header=None,␣
↪names =
                   ['sepal length', 'sepal width', 'petal length', 'petal␣
↪width', 'class'])
iris.sample(5)
```

[3]:

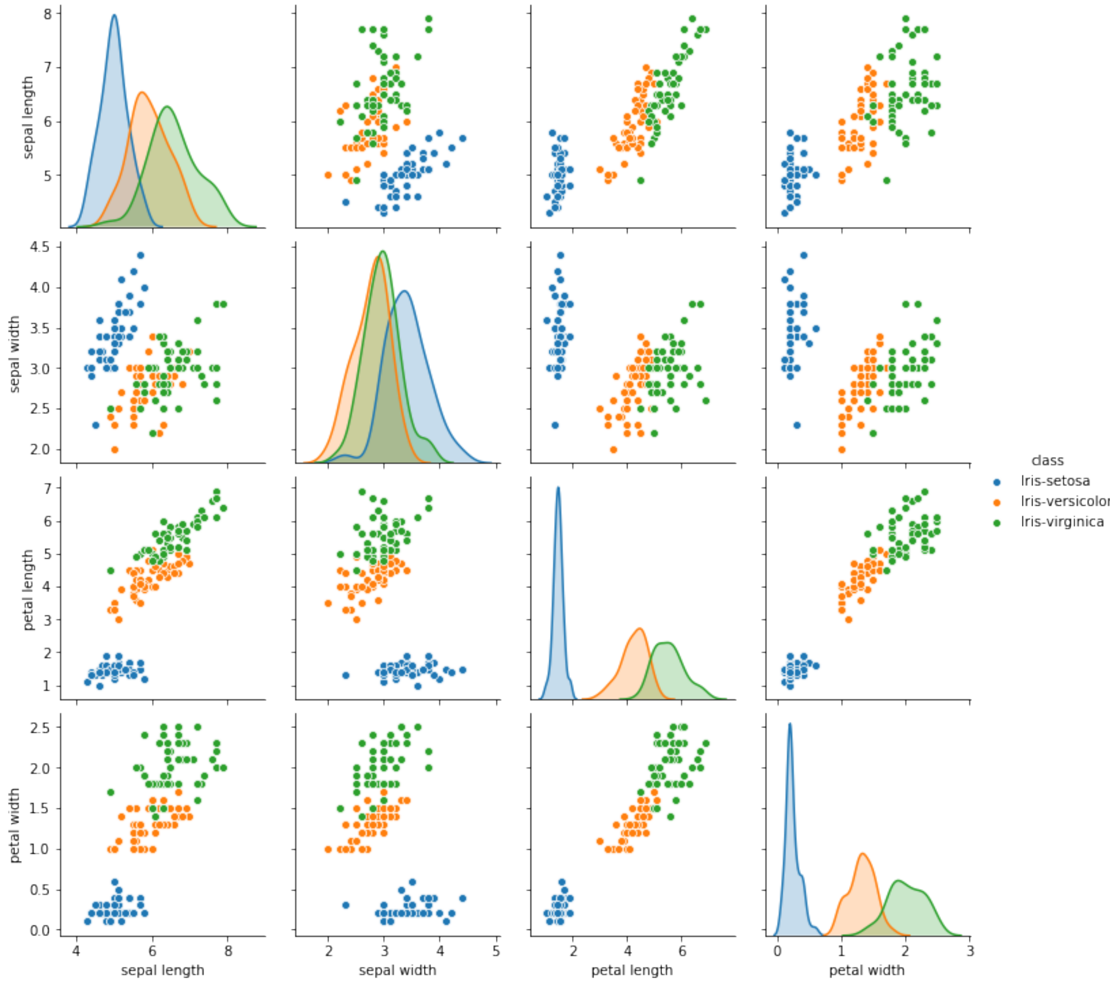
	sepal length	sepal width	petal length	petal width	class
129	7.2	3.0	5.8	1.6	Iris-virginica
108	6.7	2.5	5.8	1.8	Iris-virginica
132	6.4	2.8	5.6	2.2	Iris-virginica
32	5.2	4.1	1.5	0.1	Iris-setosa
40	5.0	3.5	1.3	0.3	Iris-setosa

Two classes in IRIS are more "similar" to each other. Find which ones using scatter plots. Lets say class 1 and class 2.

0.1.1 As seen in plots below 'Iris-versicolor' and 'Iris-virginica' are more similar to each other

[4]:
```
sns.pairplot(iris, hue = 'class')
```

[4]:
```
<seaborn.axisgrid.PairGrid at 0x12d3d0da0>
```



Lets create a "meta class" combining class 1 and class 2 (or whichever are the two most similar classes). Lets call it class 4.

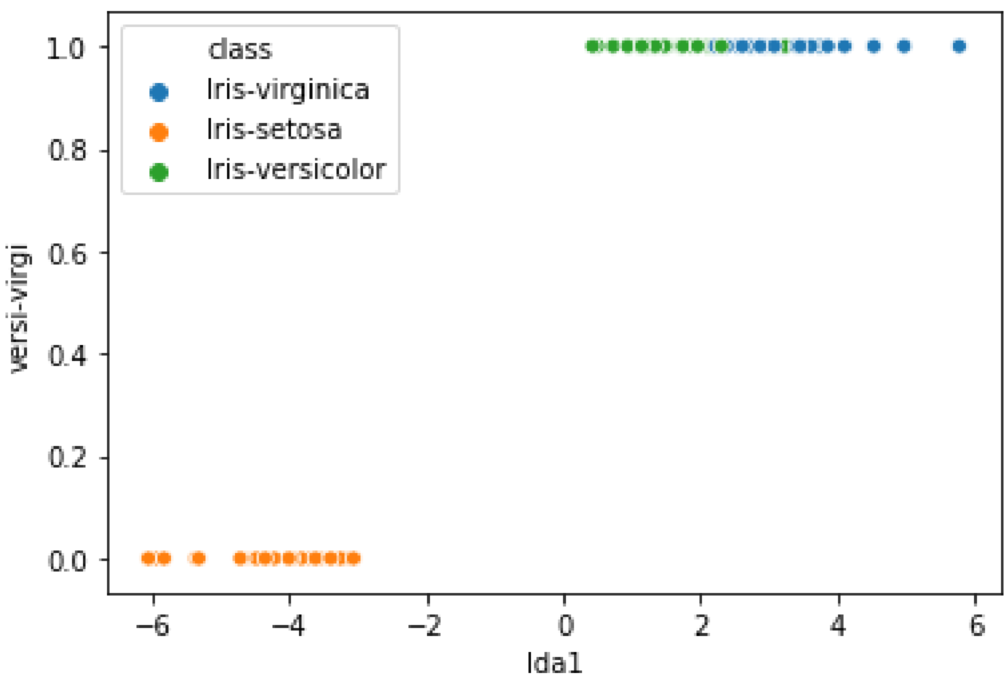
[5]:
```
iris['versi-virgi'] = np.where((iris['class'] == 'Iris-versicolor') |␣
↪(iris['class'] == 'Iris-virginica'), 1, 0)
iris.sample(5)
```

[5]:
```
     sepal length  sepal width  petal length  petal width            class  \
145           6.7          3.0           5.2          2.3   Iris-virginica
69            5.6          2.5           3.9          1.1  Iris-versicolor
63            6.1          2.9           4.7          1.4  Iris-versicolor
93            5.0          2.3           3.3          1.0  Iris-versicolor
51            6.4          3.2           4.5          1.5  Iris-versicolor

     versi-virgi
145            1
```

```
69             1
63             1
93             1
51             1
```

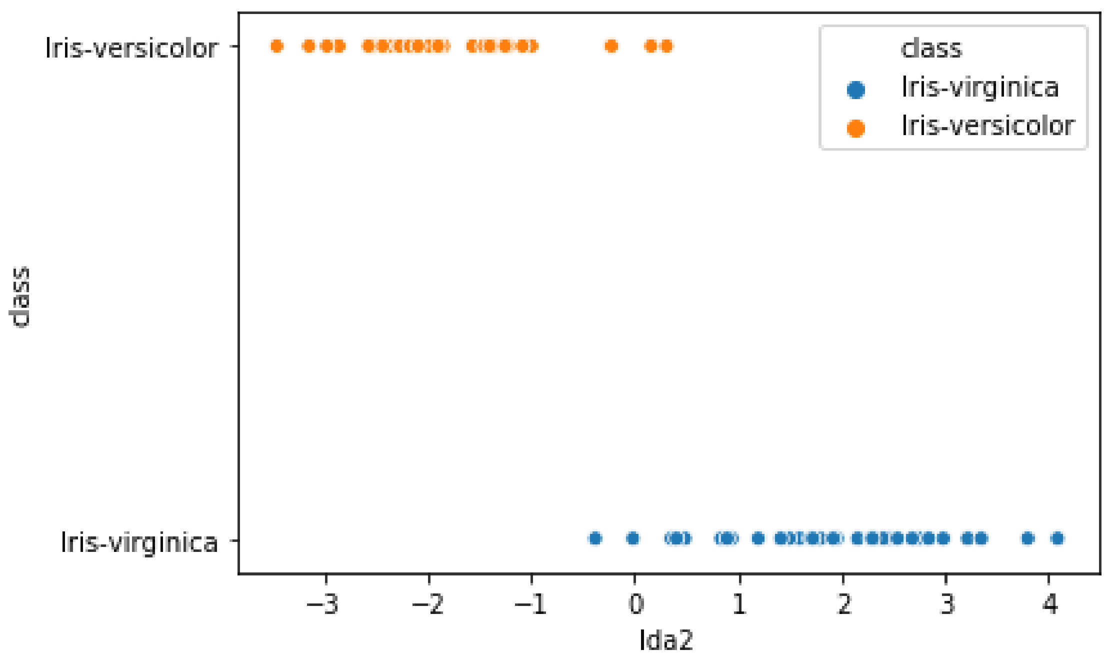
[6]:
```
train, test = train_test_split(iris, test_size=0.3, random_state=11915043)
```

[7]:
```
#Ref https://scikit-learn.org/stable/auto_examples/decomposition/
↪plot_pca_vs_lda.html

lda = LinearDiscriminantAnalysis()
features = ['sepal length', 'sepal width', 'petal length', 'petal width']
target = 'versi-virgi'

lda1 = lda.fit(train[features], train[target])
lda1_dis = lda1.transform(train[features])
train['lda1'] = lda1_dis

ax = sns.scatterplot(x="lda1", y="versi-virgi", hue="class", data=train)
```



Create the second Fisher projection by trying to discriminate class 1 from class 2 (the original two similar classes)

```
[8]: features = ['sepal length', 'sepal width', 'petal length', 'petal width']
target = 'class'

train = train[(train['class'] == 'Iris-versicolor') | (train['class'] ==␣
 ↪'Iris-virginica')]
lda = LinearDiscriminantAnalysis(n_components=1)
lda2 = lda.fit(train[features], train[target])
lda2_dis = lda2.transform(train[features])
train['lda2'] = lda2_dis

ax = sns.scatterplot(x="lda2", y="class", hue="class", data=train)
```



Now project the entire data in these two projections and color code the class points.

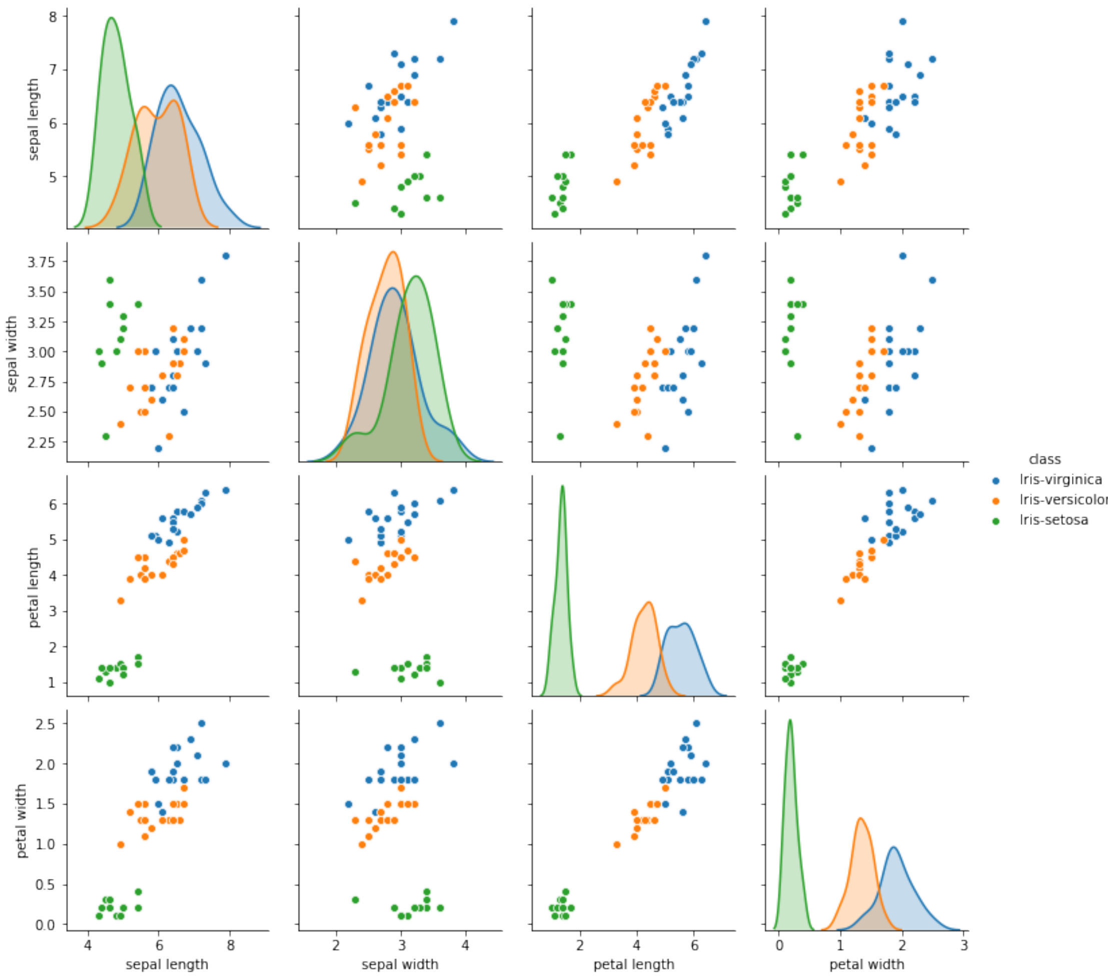
```
[9]: test['lda1'] = lda1.transform(test[['sepal length', 'sepal width', 'petal␣
 ↪length', 'petal width']])
test['lda2'] = lda2.transform(test[['sepal length', 'sepal width', 'petal␣
 ↪length', 'petal width']])
```

Comment on what you observed and did.

0.1.2 Plot how the original four features were classifying the data

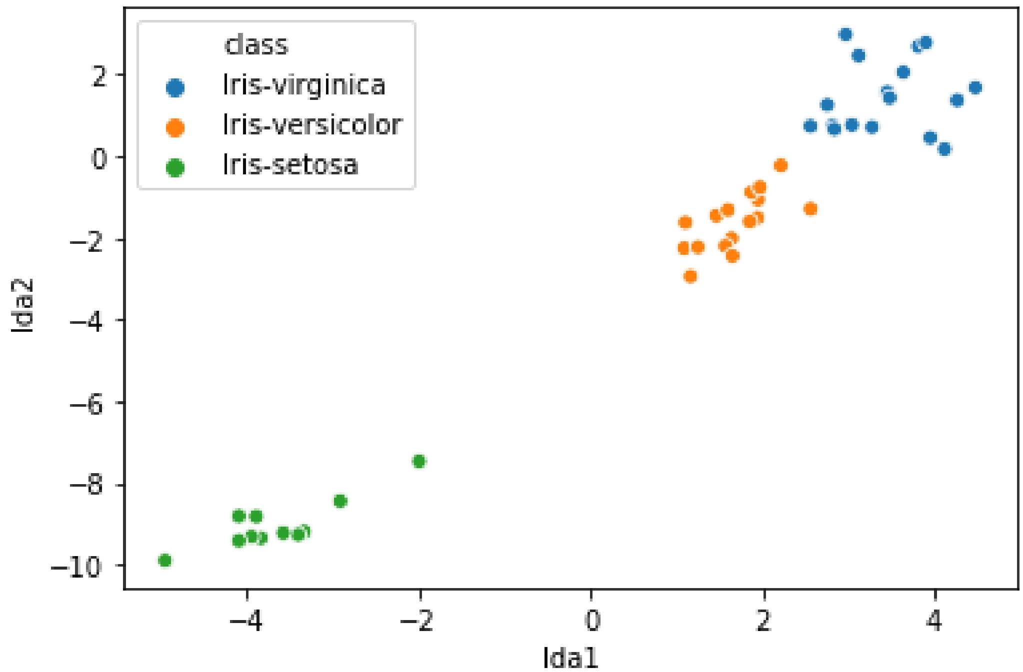
[10]:
```
sns.pairplot(hue='class', data=test[['sepal length', 'sepal width', 'petal␣
↪length', 'petal width', 'class']])
```

[10]: <seaborn.axisgrid.PairGrid at 0x13245a5f8>



0.1.3 We can clearly see the difference between all three classes ie. setosa, versicolor and vigginica using lda projections. Which was not clear earlier using original feature. Hence it's useful projection

[11]:
```
ax = sns.scatterplot(x="lda1", y="lda2", hue="class", data=test)
```



0.2 P2 : MUSHROOM information gain

Take the MUSHROOM training data. There are 20+ features and 2 classes. We want to find the BEST feature using the three purity measures: Accuracy, Gini Index, and Entropy.

[12]:
```
col_names = ['class',
             'cap-shape',
             'cap-surface',
             'cap-color',
             'bruises',
             'odor',
             'gill-attachment',
             'gill-spacing',
             'gill-size',
             'gill-color',
             'stalk-shape',
             'stalk-root',
             'stalk-surface-above-ring',
             'stalk-surface-below-ring',
             'stalk-color-above-ring',
             'stalk-color-below-ring',
             'veil-type',
             'veil-color',
```

```
             'ring-number',
             'ring-type',
             'spore-print-color',
             'population',
             'habitat']
mushroom = pd.read_csv('DMG-2 Assignment Data Files/Mushroom/agaricus-lepiota.
 ↪data',
                       index_col=None,
                       header=None,
                       names=col_names)
mushroom.head()
```

[12]:

```
  class cap-shape cap-surface cap-color bruises odor gill-attachment  \
0     p         x           s         n       t    p               f
1     e         x           s         y       t    a               f
2     e         b           s         w       t    l               f
3     p         x           y         w       t    p               f
4     e         x           s         g       f    n               f

  gill-spacing gill-size gill-color  … stalk-surface-below-ring  \
0            c         n          k  …                        s
1            c         b          k  …                        s
2            c         b          n  …                        s
3            c         n          n  …                        s
4            w         b          k  …                        s

  stalk-color-above-ring stalk-color-below-ring veil-type veil-color  \
0                      w                      w         p          w
1                      w                      w         p          w
2                      w                      w         p          w
3                      w                      w         p          w
4                      w                      w         p          w

  ring-number ring-type spore-print-color population habitat
0           o         p                 k          s       u
1           o         p                 n          n       g
2           o         p                 n          n       m
3           o         p                 k          s       u
4           o         e                 n          a       g

[5 rows x 23 columns]
```

0.2.1 Logic Used to Answer : For each feature, partition the data into k regions where k is the number of values the feature can take.

- Take one feature at a time from dataframe

- create a subset of data with that feature and class labels
- Groupby count to partition data into K features where k is no of values feature can take

Measure the Information gain due to each feature. Generate a table with the following columns:

- Feature_name
- Accuracy
- GINI index
- Entropy (NOTE: Use log_k for a feature with k values)

[13]:
```
#define a empty dataframe for result set
result_set = pd.DataFrame(columns = ['Feature', 'Accuracy', 'Gini',␣
↪'1-Entropy'])
result_set
```

[13]:
```
Empty DataFrame
Columns: [Feature, Accuracy, Gini, 1-Entropy]
Index: []
```

[14]:
```
#No. of rows
total_rows_data = mushroom.shape[0]

for column in col_names[1:] :
    df_feature_subset = mushroom[[column,'class']]
    feature_partition = df_feature_subset.groupby([column,'class']).size().
↪unstack(fill_value=0)

    #Ref : https://towardsdatascience.com/
↪gini-index-vs-information-entropy-7a7e4fed3fcb
    for index, row in feature_partition.iterrows():
        partition_total_sum = row['e'] + row['p']
        prob_e_class = row['e']/partition_total_sum
        prob_p_class = row['p']/partition_total_sum

        # calculate accuracy for each partition
        if(row['e'] > row['p']) :
            feature_partition.at[index,'Parition Accuracy'] = prob_e_class
        else :
            feature_partition.at[index,'Parition Accuracy'] = prob_p_class
        feature_partition.at[index,'Weighted Accuracy'] =␣
↪partition_total_sum*feature_partition.loc[index,'Parition Accuracy']/
↪total_rows_data

        #calculate gini index for each partition
        feature_partition.at[index,'Gini Index'] = prob_e_class**2 +␣
↪prob_p_class**2
```

```
        feature_partition.at[index,'Weighted Gini Index'] =␣
↪partition_total_sum*feature_partition.loc[index,'Gini Index']/total_rows_data

        #calculate entropy for each partition
        entropy = 0
        num_of_partitions = feature_partition.shape[0]
        if(num_of_partitions > 1) :
            #print(num_of_partitions)
            if(prob_e_class > 0) :
                entropy += prob_e_class*math.log(prob_e_class,␣
↪num_of_partitions)
            if(prob_p_class > 0) :
                entropy += prob_p_class*math.log(prob_p_class,␣
↪num_of_partitions)
        feature_partition.at[index,'Entropy'] = -1*entropy
        feature_partition.at[index,'Weighted Entropy'] =␣
↪partition_total_sum*feature_partition.loc[index,'Entropy']/total_rows_data
    print()
    print(feature_partition)

    result_set = result_set.append({'Feature' : column,
                        'Accuracy': feature_partition[['Weighted Accuracy']].
↪sum()[0].round(4),
                        'Gini' : feature_partition[['Weighted Gini Index']].
↪sum()[0].round(4),
                        '1-Entropy': 1-feature_partition[['Weighted Entropy']].
↪sum()[0].round(4)}, ignore_index=True)

result_set.head()
```

```
class         e     p  Parition Accuracy  Weighted Accuracy  Gini Index  \
cap-shape
b           404    48           0.893805           0.049729    0.810165
c             0     4           1.000000           0.000492    1.000000
f          1596  1556           0.506345           0.196455    0.500081
k           228   600           0.724638           0.073855    0.600924
s            32     0           1.000000           0.003939    1.000000
x          1948  1708           0.532823           0.239783    0.502155

class      Weighted Gini Index   Entropy  Weighted Entropy
cap-shape
b                     0.045076  0.188912          0.010511
c                     0.000492 -0.000000         -0.000000
f                     0.194024  0.386808          0.150076
k                     0.061246  0.328459          0.033477
s                     0.003939 -0.000000         -0.000000
```

x	0.225982	0.385649	0.173552

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index \
cap-surface					
f	1560	760	0.672414	0.192024	0.559453
g	0	4	1.000000	0.000492	1.000000
s	1144	1412	0.552426	0.173806	0.505497
y	1504	1740	0.536375	0.214180	0.502646

class	Weighted Gini Index	Entropy	Weighted Entropy
cap-surface			
f	0.159765	0.456221	0.130285
g	0.000492	-0.000000	-0.000000
s	0.159041	0.496028	0.156062
y	0.200712	0.498089	0.198892

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index \
cap-color					
b	48	120	0.714286	0.014771	0.591837
c	32	12	0.727273	0.003939	0.603306
e	624	876	0.584000	0.107829	0.514112
g	1032	808	0.560870	0.127031	0.507410
n	1264	1020	0.553415	0.155588	0.505706
p	56	88	0.611111	0.010832	0.524691
r	16	0	1.000000	0.001969	1.000000
u	16	0	1.000000	0.001969	1.000000
w	720	320	0.692308	0.088626	0.573964
y	400	672	0.626866	0.082718	0.532190

class	Weighted Gini Index	Entropy	Weighted Entropy
cap-color			
b	0.012239	0.259825	0.005373
c	0.003268	0.254476	0.001378
e	0.094925	0.294872	0.054445
g	0.114923	0.297804	0.067449
n	0.142175	0.298547	0.083934
p	0.009300	0.290217	0.005144
r	0.001969	-0.000000	-0.000000
u	0.001969	-0.000000	-0.000000
w	0.073476	0.268065	0.034317
y	0.070225	0.286896	0.037857

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index \
bruises					
f	1456	3292	0.693345	0.405219	0.574764
t	2752	624	0.815166	0.338749	0.698659

class	Weighted Gini Index	Entropy	Weighted Entropy

bruises			
f	0.335916	0.889275	0.519729
t	0.290334	0.690539	0.286960

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index	\
odor						
a	400	0	1.000000	0.049237	1.000000	
c	0	192	1.000000	0.023634	1.000000	
f	0	2160	1.000000	0.265879	1.000000	
l	400	0	1.000000	0.049237	1.000000	
m	0	36	1.000000	0.004431	1.000000	
n	3408	120	0.965986	0.419498	0.934287	
p	0	256	1.000000	0.031512	1.000000	
s	0	576	1.000000	0.070901	1.000000	
y	0	576	1.000000	0.070901	1.000000	

class	Weighted Gini Index	Entropy	Weighted Entropy
odor			
a	0.049237	-0.000000	-0.000000
c	0.023634	-0.000000	-0.000000
f	0.265879	-0.000000	-0.000000
l	0.049237	-0.000000	-0.000000
m	0.004431	-0.000000	-0.000000
n	0.405732	0.067553	0.029336
p	0.031512	-0.000000	-0.000000
s	0.070901	-0.000000	-0.000000
y	0.070901	-0.000000	-0.000000

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index	\
gill-attachment						
a	192	18	0.914286	0.023634	0.843265	
f	4016	3898	0.507455	0.494338	0.500111	

class	Weighted Gini Index	Entropy	Weighted Entropy
gill-attachment			
a	0.021798	0.422001	0.010908
f	0.487184	0.999840	0.973994

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index	\
gill-spacing						
c	3008	3804	0.558426	0.468242	0.506827	
w	1200	112	0.914634	0.147710	0.843843	

class	Weighted Gini Index	Entropy	Weighted Entropy
gill-spacing			
c	0.424976	0.990128	0.830225
w	0.136278	0.420809	0.067959

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index	\
gill-size						
b	3920	1692	0.698503	0.482521	0.578807	
n	288	2224	0.885350	0.273757	0.796990	

class	Weighted Gini Index	Entropy	Weighted Entropy
gill-size			
b	0.399836	0.883113	0.610048
n	0.246435	0.513783	0.158866

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index	\
gill-color						
b	0	1728	1.000000	0.212703	1.000000	
e	96	0	1.000000	0.011817	1.000000	
g	248	504	0.670213	0.062038	0.557945	
h	204	528	0.721311	0.064993	0.597958	
k	344	64	0.843137	0.042344	0.735486	
n	936	112	0.893130	0.115214	0.809102	
o	64	0	1.000000	0.007878	1.000000	
p	852	640	0.571046	0.104874	0.510095	
r	0	24	1.000000	0.002954	1.000000	
u	444	48	0.902439	0.054653	0.823914	
w	956	246	0.795341	0.117676	0.674453	
y	64	22	0.744186	0.007878	0.619254	

class	Weighted Gini Index	Entropy	Weighted Entropy
gill-color			
b	0.212703	-0.000000	-0.000000
e	0.011817	-0.000000	-0.000000
g	0.051646	0.255152	0.023618
h	0.053878	0.238122	0.021456
k	0.036937	0.174828	0.008780
n	0.104375	0.136794	0.017647
o	0.007878	-0.000000	-0.000000
p	0.093681	0.274867	0.050480
r	0.002954	-0.000000	-0.000000
u	0.049897	0.128653	0.007791
w	0.099790	0.203949	0.030176
y	0.006555	0.228835	0.002422

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index	\
stalk-shape						
e	1616	1900	0.540387	0.233875	0.503262	
t	2592	2016	0.562500	0.319055	0.507812	

class	Weighted Gini Index	Entropy	Weighted Entropy
stalk-shape			
e	0.217808	0.995289	0.430753

```
t                      0.288035  0.988699          0.560798

class          e     p  Parition Accuracy  Weighted Accuracy  Gini Index  \
stalk-root
?            720  1760           0.709677           0.216642    0.587929
b           1920  1856           0.508475           0.236337    0.500144
c            512    44           0.920863           0.063023    0.854252
e            864   256           0.771429           0.106352    0.647347
r            192     0           1.000000           0.023634    1.000000

class       Weighted Gini Index   Entropy  Weighted Entropy
stalk-root
?                      0.179476  0.374317          0.114267
b                      0.232465  0.430587          0.200135
c                      0.058464  0.171896          0.011764
e                      0.089245  0.333995          0.046046
r                      0.023634 -0.000000         -0.000000

class                        e     p  Parition Accuracy  Weighted Accuracy  \
stalk-surface-above-ring
f                          408   144           0.739130           0.050222
k                          144  2228           0.939292           0.274249
s                         3640  1536           0.703246           0.448055
y                           16     8           0.666667           0.001969

class                     Gini Index  Weighted Gini Index   Entropy  \
stalk-surface-above-ring
f                           0.614367             0.041744  0.414028
k                           0.885954             0.258676  0.165125
s                           0.582618             0.371200  0.438644
y                           0.555556             0.001641  0.459148

class                     Weighted Entropy
stalk-surface-above-ring
f                                 0.028132
k                                 0.048212
s                                 0.279471
y                                 0.001356

class                        e     p  Parition Accuracy  Weighted Accuracy  \
stalk-surface-below-ring
f                          456   144           0.760000           0.056130
k                          144  2160           0.937500           0.265879
s                         3400  1536           0.688817           0.418513
y                          208    76           0.732394           0.025603

class                     Gini Index  Weighted Gini Index   Entropy  \
stalk-surface-below-ring
```

```
f                             0.635200           0.046913  0.397520
k                             0.882812           0.250369  0.168645
s                             0.571304           0.347114  0.447267
y                             0.608014           0.021255  0.419004

class                    Weighted Entropy
stalk-surface-below-ring
f                                0.029359
k                                0.047828
s                                0.271752
y                                0.014648

class                      e     p  Parition Accuracy  Weighted Accuracy  \
stalk-color-above-ring
b                          0   432           1.000000           0.053176
c                          0    36           1.000000           0.004431
e                         96     0           1.000000           0.011817
g                        576     0           1.000000           0.070901
n                         16   432           0.964286           0.053176
o                        192     0           1.000000           0.023634
p                        576  1296           0.692308           0.159527
w                       2752  1712           0.616487           0.338749
y                          0     8           1.000000           0.000985

class                  Gini Index  Weighted Gini Index   Entropy  \
stalk-color-above-ring
b                        1.000000             0.053176 -0.000000
c                        1.000000             0.004431 -0.000000
e                        1.000000             0.011817 -0.000000
g                        1.000000             0.070901 -0.000000
n                        0.931122             0.051347  0.070123
o                        1.000000             0.023634 -0.000000
p                        0.573964             0.132258  0.280919
w                        0.527139             0.289654  0.302999
y                        1.000000             0.000985 -0.000000

class                  Weighted Entropy
stalk-color-above-ring
b                             -0.000000
c                             -0.000000
e                             -0.000000
g                             -0.000000
n                              0.003867
o                             -0.000000
p                              0.064732
w                              0.166493
y                             -0.000000
```

class	e	p	Parition Accuracy	Weighted Accuracy \
stalk-color-below-ring				
b	0	432	1.000000	0.053176
c	0	36	1.000000	0.004431
e	96	0	1.000000	0.011817
g	576	0	1.000000	0.070901
n	64	448	0.875000	0.055145
o	192	0	1.000000	0.023634
p	576	1296	0.692308	0.159527
w	2704	1680	0.616788	0.332841
y	0	24	1.000000	0.002954

class	Gini Index	Weighted Gini Index	Entropy \
stalk-color-below-ring			
b	1.000000	0.053176	-0.000000
c	1.000000	0.004431	-0.000000
e	1.000000	0.011817	-0.000000
g	1.000000	0.070901	-0.000000
n	0.781250	0.049237	0.171475
o	1.000000	0.023634	-0.000000
p	0.573964	0.132258	0.280919
w	0.527279	0.284539	0.302934
y	1.000000	0.002954	-0.000000

class	Weighted Entropy
stalk-color-below-ring	
b	-0.000000
c	-0.000000
e	-0.000000
g	-0.000000
n	0.010807
o	-0.000000
p	0.064732
w	0.163474
y	-0.000000

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index \
veil-type					
p	4208	3916	0.517971	0.517971	0.500646

class	Weighted Gini Index	Entropy	Weighted Entropy
veil-type			
p	0.500646	0.0	0.0

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index \
veil-color					
n	96	0	1.000000	0.011817	1.000000
o	96	0	1.000000	0.011817	1.000000

```
w           4016  3908           0.506815           0.494338    0.500093
y              0     8           1.000000           0.000985    1.000000

class       Weighted Gini Index   Entropy  Weighted Entropy
veil-color
n                      0.011817 -0.000000         -0.000000
o                      0.011817 -0.000000         -0.000000
w                      0.487781  0.499933          0.487625
y                      0.000985 -0.000000         -0.000000

class           e     p  Parition Accuracy  Weighted Accuracy  Gini Index  \
ring-number
n               0    36           1.000000           0.004431    1.000000
o            3680  3808           0.508547           0.468735    0.500146
t             528    72           0.880000           0.064993    0.788800

class        Weighted Gini Index   Entropy  Weighted Entropy
ring-number
n                       0.004431 -0.000000         -0.000000
o                       0.460991  0.630797          0.581414
t                       0.058257  0.333990          0.024667

class         e     p  Parition Accuracy  Weighted Accuracy  Gini Index  \
ring-type
e          1008  1768           0.636888           0.217627    0.537476
f            48     0           1.000000           0.005908    1.000000
l             0  1296           1.000000           0.159527    1.000000
n             0    36           1.000000           0.004431    1.000000
p          3152   816           0.794355           0.387986    0.673290

class      Weighted Gini Index   Entropy  Weighted Entropy
ring-type
e                     0.183658  0.407091          0.139105
f                     0.005908 -0.000000         -0.000000
l                     0.159527 -0.000000         -0.000000
n                     0.004431 -0.000000         -0.000000
p                     0.328854  0.315719          0.154206

class                 e     p  Parition Accuracy  Weighted Accuracy  \
spore-print-color
b                    48     0           1.000000           0.005908
h                    48  1584           0.970588           0.194978
k                  1648   224           0.880342           0.202856
n                  1744   224           0.886179           0.214673
o                    48     0           1.000000           0.005908
r                     0    72           1.000000           0.008863
u                    48     0           1.000000           0.005908
w                   576  1812           0.758794           0.223043
```

y	48	0	1.000000	0.005908

class	Gini Index	Weighted Gini Index	Entropy	Weighted Entropy
spore-print-color				
b	1.000000	0.005908	-0.000000	-0.000000
h	0.942907	0.189417	0.060390	0.012132
k	0.789320	0.181882	0.166684	0.038409
n	0.798268	0.193377	0.161308	0.039076
o	1.000000	0.005908	-0.000000	-0.000000
r	1.000000	0.008863	-0.000000	-0.000000
u	1.000000	0.005908	-0.000000	-0.000000
w	0.633949	0.186345	0.251438	0.073909
y	1.000000	0.005908	-0.000000	-0.000000

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index \
population					
a	384	0	1.000000	0.047267	1.000000
c	288	52	0.847059	0.035451	0.740900
n	400	0	1.000000	0.049237	1.000000
s	880	368	0.705128	0.108321	0.584155
v	1192	2848	0.704950	0.350566	0.584009
y	1064	648	0.621495	0.130970	0.529522

class	Weighted Gini Index	Entropy	Weighted Entropy
population			
a	0.047267	-0.000000	-0.000000
c	0.031008	0.238747	0.009992
n	0.049237	-0.000000	-0.000000
s	0.089737	0.338470	0.051995
v	0.290423	0.338556	0.168361
y	0.111588	0.370210	0.078016

class	e	p	Parition Accuracy	Weighted Accuracy	Gini Index \
habitat					
d	1880	1268	0.597205	0.231413	0.518897
g	1408	740	0.655493	0.173314	0.548356
l	240	592	0.711538	0.072871	0.589497
m	256	36	0.876712	0.031512	0.783824
p	136	1008	0.881119	0.124077	0.790503
u	96	272	0.739130	0.033481	0.614367
w	192	0	1.000000	0.023634	1.000000

class	Weighted Gini Index	Entropy	Weighted Entropy
habitat			
d	0.201070	0.346434	0.134241
g	0.144986	0.330940	0.087501
l	0.060372	0.308734	0.031618
m	0.028173	0.191902	0.006898

p	0.111317	0.187413	0.026391
u	0.027830	0.294959	0.013361
w	0.023634	-0.000000	-0.000000

[14]:

	Feature	Accuracy	Gini	1-Entropy
0	cap-shape	0.5643	0.5308	0.6324
1	cap-surface	0.5805	0.5200	0.5148
2	cap-color	0.5953	0.5245	0.7101
3	bruises	0.7440	0.6262	0.1933
4	odor	0.9852	0.9715	0.9707

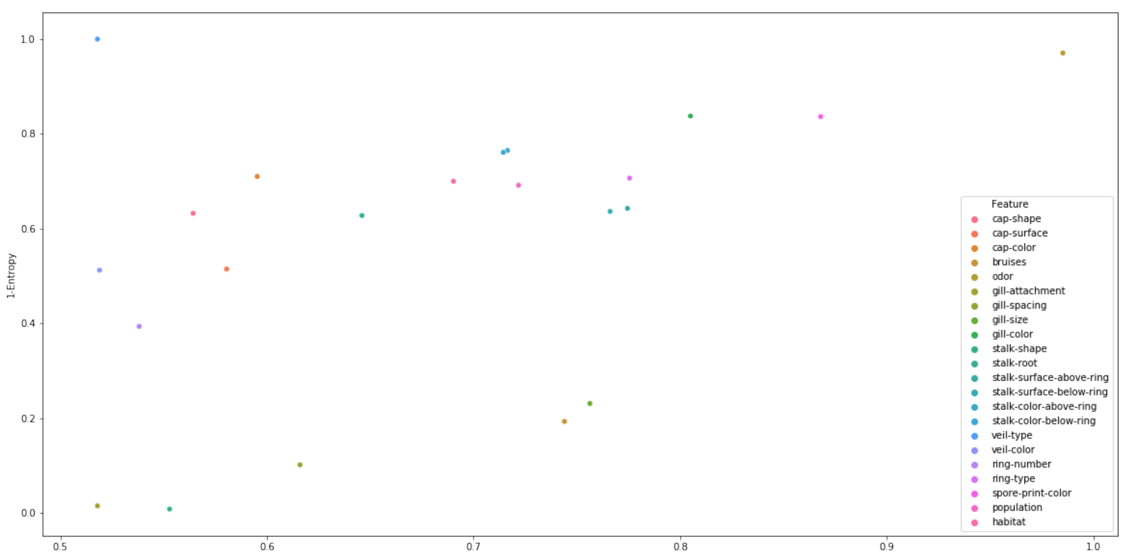
[15]:
```
result_set.tail()
```

[15]:

	Feature	Accuracy	Gini	1-Entropy
17	ring-number	0.5382	0.5237	0.3939
18	ring-type	0.7755	0.6824	0.7067
19	spore-print-color	0.8680	0.7835	0.8365
20	population	0.7218	0.6193	0.6916
21	habitat	0.6903	0.5974	0.7000

Plot accuracy vs. 1-Entropy scatter plot where each point is a feature. We can see that Accuracy and '1-Entropy' are curvi linear, as Accuracy increases '1-Entropy' also increases for that feature, however there are 5 features which are outlier to this trend

[16]:
```
fig, ax = plt.subplots(figsize=(20,10))
ax = sns.scatterplot(x='Accuracy', y='1-Entropy', hue='Feature',␣
↪data=result_set)
```



0.2.2 veil-type, odor, gill-color, spore-print-color are top features which alone can define the whole data

[17]:
```
result_set.sort_values(by='1-Entropy', ascending=False)
```

[17]:

	Feature	Accuracy	Gini	1-Entropy
15	veil-type	0.5180	0.5006	1.0000
4	odor	0.9852	0.9715	0.9707
8	gill-color	0.8050	0.7321	0.8376
19	spore-print-color	0.8680	0.7835	0.8365
13	stalk-color-above-ring	0.7164	0.6382	0.7649
14	stalk-color-below-ring	0.7144	0.6329	0.7610
2	cap-color	0.5953	0.5245	0.7101
18	ring-type	0.7755	0.6824	0.7067
21	habitat	0.6903	0.5974	0.7000
20	population	0.7218	0.6193	0.6916
11	stalk-surface-above-ring	0.7745	0.6733	0.6428
12	stalk-surface-below-ring	0.7661	0.6657	0.6364
0	cap-shape	0.5643	0.5308	0.6324
10	stalk-root	0.6460	0.5833	0.6278
1	cap-surface	0.5805	0.5200	0.5148
16	veil-color	0.5190	0.5124	0.5124
17	ring-number	0.5382	0.5237	0.3939
7	gill-size	0.7563	0.6463	0.2311
3	bruises	0.7440	0.6262	0.1933
6	gill-spacing	0.6160	0.5613	0.1018
5	gill-attachment	0.5180	0.5090	0.0151
9	stalk-shape	0.5529	0.5058	0.0084

0.3 P3 : MUSHROOM NB/DT

[18]:
```
col_names = ['class',
             'cap-shape',
             'cap-surface',
             'cap-color',
             'bruises',
             'odor',
             'gill-attachment',
             'gill-spacing',
             'gill-size',
             'gill-color',
             'stalk-shape',
             'stalk-root',
             'stalk-surface-above-ring',
             'stalk-surface-below-ring',
             'stalk-color-above-ring',
```

```
                'stalk-color-below-ring',
                'veil-type',
                'veil-color',
                'ring-number',
                'ring-type',
                'spore-print-color',
                'population',
                'habitat']
mushroom = pd.read_csv('DMG-2 Assignment Data Files/Mushroom/agaricus-lepiota.
 ↪data',
                       index_col=None,
                       header=None,
                       names=col_names)
mushroom.head()

X = mushroom.loc[:, mushroom.columns != 'class']
X = pd.get_dummies(X)
y = mushroom.loc[:, mushroom.columns == 'class']
```

Build Naive Bayes and Decision Tree classifiers on the MUSHROOM training dataset.

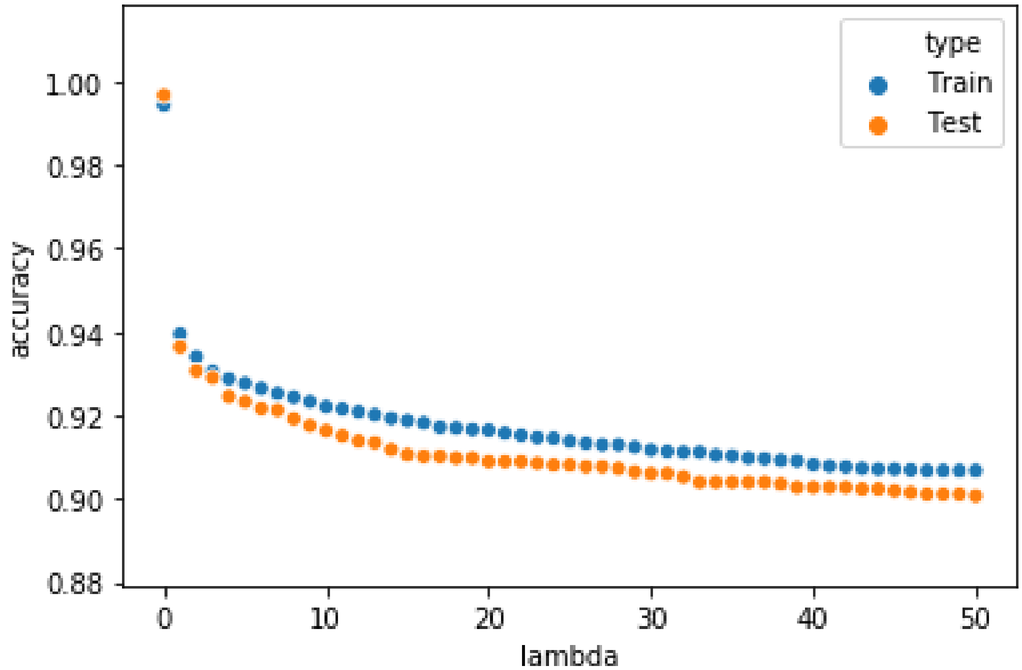
[19]:
```
#use a classic 70:30 split ratio
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=11915043)

df = pd.DataFrame(columns=['lambda','accuracy', 'type'])
for i in range(0,51) :
    nbc = BernoulliNB(alpha=i)
    nbc.fit(X_train, y_train.values.ravel())
    train_score = accuracy_score(y_train, nbc.predict(X_train))
    test_score = accuracy_score(y_test, nbc.predict(X_test))
    df = df.append({'lambda' : i,'accuracy':train_score, 'type': 'Train'},␣
 ↪ignore_index=True)
    df = df.append({'lambda' : i,'accuracy':test_score, 'type': 'Test'},␣
 ↪ignore_index=True)
    print(i, train_score, test_score)
```

```
0 0.9943721421034118 0.9967186218211649
1 0.9395005276116778 0.9364232977850697
2 0.934048540274358 0.9306808859721083
3 0.9305311290889905 0.9290401968826907
4 0.9287724234963067 0.9245283018867925
5 0.9277172001406965 0.9232977850697293
6 0.9264861062258178 0.9216570959803118
7 0.9252550123109391 0.9212469237079574
8 0.9243756595145972 0.9191960623461854
9 0.923320436158987 0.9175553732567678
```

```
10 0.9220893422441083 0.9163248564397046
11 0.9215617305663032 0.9150943396226415
12 0.9208582483292297 0.9138638228055783
13 0.9201547660921562 0.9134536505332239
14 0.9192754132958143 0.9118129614438064
15 0.9187478016180092 0.9105824446267432
16 0.918220189940204 0.9101722723543888
17 0.9171649665845938 0.9101722723543888
18 0.9169890960253254 0.9097621000820345
19 0.9166373549067885 0.9097621000820345
20 0.9164614843475202 0.9089417555373257
21 0.9157580021104467 0.9089417555373257
22 0.9152303904326415 0.9089417555373257
23 0.9147027787548364 0.9085315832649713
24 0.914526908195568 0.9081214109926169
25 0.9138234259584945 0.9081214109926169
26 0.9132958142806894 0.9077112387202625
27 0.9129440731621526 0.9077112387202625
28 0.9129440731621526 0.9073010664479081
29 0.9124164614843475 0.9064807219031994
30 0.911712979247274 0.906070549630845
31 0.9113612381287373 0.906070549630845
32 0.9111853675694689 0.9052502050861362
33 0.9111853675694689 0.904019688269073
34 0.9104818853323954 0.904019688269073
35 0.910306014773127 0.904019688269073
36 0.9097784030953219 0.904019688269073
37 0.9096025325360535 0.904019688269073
38 0.9092507914175167 0.9036095159967186
39 0.9090749208582484 0.9027891714520099
40 0.9081955680619065 0.9027891714520099
41 0.9078438269433696 0.9027891714520099
42 0.9076679563841012 0.9027891714520099
43 0.9073162152655645 0.9023789991796555
44 0.9071403447062961 0.9023789991796555
45 0.9071403447062961 0.9019688269073011
46 0.9069644741470277 0.9015586546349467
47 0.9067886035877594 0.9011484823625923
48 0.9067886035877594 0.9011484823625923
49 0.9067886035877594 0.9011484823625923
50 0.9067886035877594 0.9007383100902379
```

In Naïve Bayes classifier plot the value of lambda (x axis) for Laplacian smoothing against training and test set accuracy.

[20]:
```python
x = sns.scatterplot(x="lambda", y='accuracy', hue='type', data=df)
```



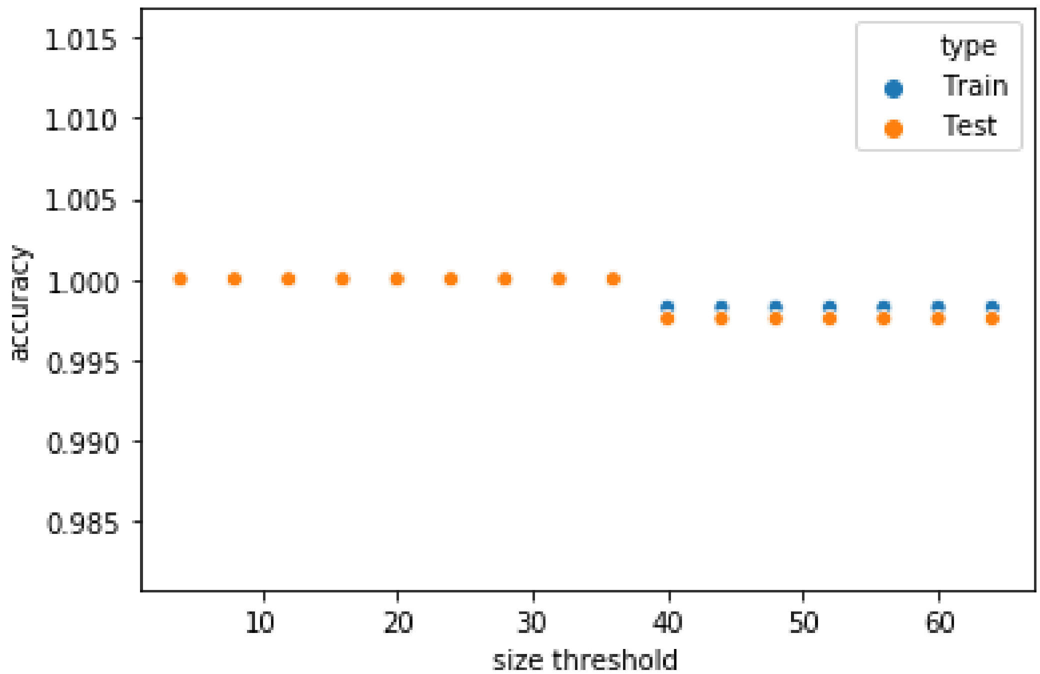
0.3.1 For decision tree classifier plot the Size Threshold (x axis) against training and test set accuracy.

[21]:
```
df = pd.DataFrame(columns=['size threshold','accuracy', 'type'])
for i in range(4,65,4) :
    dtc = DecisionTreeClassifier(min_samples_split=i)
    dtc.fit(X_train, y_train)
    train_score = accuracy_score(y_train, dtc.predict(X_train))
    test_score = accuracy_score(y_test, dtc.predict(X_test))
    df = df.append({'size threshold' : i,'accuracy':train_score, 'type':␣
 ↪'Train'}, ignore_index=True)
    df = df.append({'size threshold' : i,'accuracy':test_score, 'type':␣
 ↪'Test'}, ignore_index=True)
    print(i, train_score, test_score)
```

```
4 1.0 1.0
8 1.0 1.0
12 1.0 1.0
16 1.0 1.0
20 1.0 1.0
24 1.0 1.0
28 1.0 1.0
32 1.0 1.0
```

```
36 1.0 1.0
40 0.9982412944073162 0.9975389663658737
44 0.9982412944073162 0.9975389663658737
48 0.9982412944073162 0.9975389663658737
52 0.9982412944073162 0.9975389663658737
56 0.9982412944073162 0.9975389663658737
60 0.9982412944073162 0.9975389663658737
64 0.9982412944073162 0.9975389663658737
```

[22]:
```
ax = sns.scatterplot(x="size threshold", y='accuracy', hue='type', data=df)
#ax.set_xticks(range(0,68,4))
```



0.3.2 Find the best values of lambda and SizeThreshold where the test set accuracies starts to decrease.

Looking at plots above, we can say -

- Naive Bayes - Even with very small lambda value for smoothening we are getting best accuracy, ie lambda- 1.0e-10, since 0 is numerically not possible. The next best is lambda = 1
- Decision Tree Classifier - Best size threshold : 36

Comparision - - Naive bayes classifier are surprisingly giving better result on set set as lambda increases, compared to train set which creates doubt. - Decision Tree Classifier are performing better than Naive Bayes with a test set accuracy of 1 at size threshold of 36, just a depth of 8.

0.4 P4 : MNIST Bayesian

Take the MNIST dataset. Lets call it D0 dataset

[23]:
```
mnist = pd.read_csv('DMG-2 Assignment Data Files/MNIST/train.csv')
mnist.head()

mnist_data = mnist.loc[:, mnist.columns != 'label']
mnist_label = mnist.loc[:, mnist.columns == 'label']
```

[24]:
```
target_names = pd.Series(mnist.label.unique()).apply(str)
print(target_names)
n_components = 9
```

```
0    1
1    0
2    4
3    7
4    3
5    5
6    8
7    9
8    2
9    6
dtype: object
```

Do a 9 dimensional PCA projection . Lets call it D1 dataset

[25]:
```
pca = decomposition.PCA()
pca.n_components = n_components
pca_data = pca.fit_transform(mnist_data)
```

Do a 9 dimensional FISHER projection . Lets call it D2 dataset

[26]:
```
model = LinearDiscriminantAnalysis(n_components=n_components)
model.fit(mnist_data, mnist_label.values.ravel())
mnist_fisher_proj_data = model.transform(mnist_data)
```

Build a Bayesian classifier on D1 (single Gaussian per class)

- Diagonal Covariance matrix (i.e.set non diagonals to zero)
- Full Covariance matrix

Ref : #https://stats.stackexchange.com/questions/105140/gaussian-naive-bayes-really-equivalent-to-gmm-with-diagonal-covariance-matrices #https://scikit-learn.org/stable/modules/mixture.html#bgmm #https://www.programcreek.com/python/example/99731/sklear

[27]:
```
def build_classifier(X_train, X_test, y_train, y_test, n_gaussians,␣
 ↪target_names) :

    #Build bayesian classifier with diagnonal covariance matrix on fisher␣
 ↪projection data
    gnb_model = GaussianNB()
    gnb_model.fit(X_train, y_train)
    y_pred = gnb_model.predict(X_test)
    nb_diag_acc = accuracy_score(y_test, y_pred)
    print("Gaussian Naive Bayes diagonal matrix : ")
    print("Train set accuracy score : ", accuracy_score(y_test, y_pred))
    print("Test set accuracy score : ", nb_diag_acc)
    print("Classification report : ")
    print(classification_report(y_test, y_pred, target_names=target_names))

    #Build bayesian classifier with full covariance matrix on fisher projection␣
 ↪data
    bgm = BayesianGaussianMixture(
                n_components = n_gaussians,
                covariance_type='full')
    bgm.fit(X_train, y_train)
    y_pred = bgm.predict(X_test)
    #print(y_pred)
    #print(y_test)
    b_full_acc = accuracy_score(y_test, y_pred)
    print("\nBayesian Gaussian mixture full covariance matrix : ")
    print("Train set accuracy : ", accuracy_score(y_test, y_pred))
    print("Test set accuracy : ", b_full_acc)
    print("Classification report : ")
    print(classification_report(y_test, y_pred, target_names=target_names))

    #return test accuracies of both model
    return nb_diag_acc, b_full_acc
```

[28]:
```
X_train, X_test, y_train, y_test = train_test_split(pca_data, mnist['label'],␣
 ↪test_size=0.2, random_state=11915043)
print(build_classifier(X_train, X_test, y_train, y_test, 10, target_names))
```

```
Gaussian Naive Bayes diagonal matrix :
Train set accuracy score :  0.7566666666666667
Test set accuracy score :  0.7566666666666667
Classification report :
              precision    recall  f1-score   support

           1       0.89      0.83      0.86       827
           0       0.85      0.92      0.88       931
           4       0.83      0.74      0.78       865
```

```
           7       0.72      0.72      0.72       844
           3       0.64      0.69      0.66       814
           5       0.57      0.65      0.61       720
           8       0.87      0.84      0.86       851
           9       0.86      0.82      0.84       915
           2       0.70      0.73      0.72       806
           6       0.63      0.59      0.61       827

   micro avg       0.76      0.76      0.76      8400
   macro avg       0.76      0.75      0.75      8400
weighted avg       0.76      0.76      0.76      8400


Bayesian Gaussian mixture full covariance matrix :
Train set accuracy :  0.039285714285714285
Test set accuracy :  0.039285714285714285
Classification report :
              precision    recall  f1-score   support

           1       0.00      0.00      0.00       827
           0       0.00      0.00      0.00       931
           4       0.19      0.25      0.22       865
           7       0.00      0.00      0.00       844
           3       0.00      0.00      0.00       814
           5       0.00      0.00      0.00       720
           8       0.01      0.01      0.01       851
           9       0.07      0.06      0.07       915
           2       0.03      0.04      0.03       806
           6       0.01      0.01      0.01       827

   micro avg       0.04      0.04      0.04      8400
   macro avg       0.03      0.04      0.03      8400
weighted avg       0.03      0.04      0.04      8400

(0.7566666666666667, 0.039285714285714285)
```

0.4.1 Build a Bayesian classifier on D2 (single Gaussian per class)

- Diagonal Covariance matrix (i.e.set non diagonals to zero)
- Full Covariance matrix

[29]:
```python
X_train, X_test, y_train, y_test = train_test_split(mnist_fisher_proj_data,␣
 ↪mnist['label'], test_size=0.2,
                                                    random_state = 11915043)
print(build_classifier(X_train, X_test, y_train, y_test, 10, target_names))
```

```
Gaussian Naive Bayes diagonal matrix :
```

```
Train set accuracy score :  0.8776190476190476
Test set accuracy score :  0.8776190476190476
Classification report :
              precision    recall  f1-score   support

           1       0.95      0.93      0.94       827
           0       0.94      0.92      0.93       931
           4       0.86      0.86      0.86       865
           7       0.88      0.84      0.86       844
           3       0.90      0.88      0.89       814
           5       0.80      0.84      0.82       720
           8       0.93      0.91      0.92       851
           9       0.92      0.87      0.90       915
           2       0.77      0.83      0.80       806
           6       0.82      0.88      0.85       827

   micro avg       0.88      0.88      0.88      8400
   macro avg       0.88      0.88      0.88      8400
weighted avg       0.88      0.88      0.88      8400


Bayesian Gaussian mixture full covariance matrix :
Train set accuracy :  0.07964285714285714
Test set accuracy :  0.07964285714285714
Classification report :
              precision    recall  f1-score   support

           1       0.00      0.00      0.00       827
           0       0.00      0.00      0.00       931
           4       0.00      0.00      0.00       865
           7       0.00      0.00      0.00       844
           3       0.11      0.10      0.11       814
           5       0.02      0.02      0.02       720
           8       0.00      0.00      0.00       851
           9       0.02      0.02      0.02       915
           2       0.69      0.68      0.68       806
           6       0.00      0.00      0.00       827

   micro avg       0.08      0.08      0.08      8400
   macro avg       0.08      0.08      0.08      8400
weighted avg       0.08      0.08      0.08      8400

(0.8776190476190476, 0.07964285714285714)
```

0.4.2 Compare the test accuracies of the four classifiers and comment.

diagonal covariance matrix - - PCA projection - test set accuracy is 0.76 - Fisher projection - test set accuracy is 0.88

If we look at classification matrix for test set, we see that on PCA data, digits 7,3,5 are performing poorly which improves with f1score of 0.83-0.9 range when doing classification modeling on fisher projection data

full covariance matrix - - PCA projection - test set accuracy is 0.039 - Fisher projection - test set accuracy is 0.079

0.5 P5 : MNIST KNN / Parzen window

Take the two datasets D1 and D2 from P4.

Build k Nearest neighbors classifier with:

- K = 1, 3, 5, 7, 9, 11, 13, 15, 17
- Plot training and test accuracy with these values of k on x axis

[30]:
```
def build_knn(X_train, X_test, y_train, y_test) :
    df = pd.DataFrame(columns=['k','accuracy', 'type'])
    for i in range(1,18,2) :
        knn_model = KNeighborsClassifier(n_neighbors=i)
        knn_model.fit(X_train, y_train)
        train_score = round(accuracy_score(y_train, knn_model.
↪predict(X_train)),4)
        test_score = round(accuracy_score(y_test, knn_model.predict(X_test)),4)
        df = df.append({'k' : i,'accuracy':train_score, 'type': 'Train'},␣
↪ignore_index=True)
        df = df.append({'k' : i,'accuracy':test_score, 'type': 'Test'},␣
↪ignore_index=True)
        print(i, train_score, test_score)
    return df
```

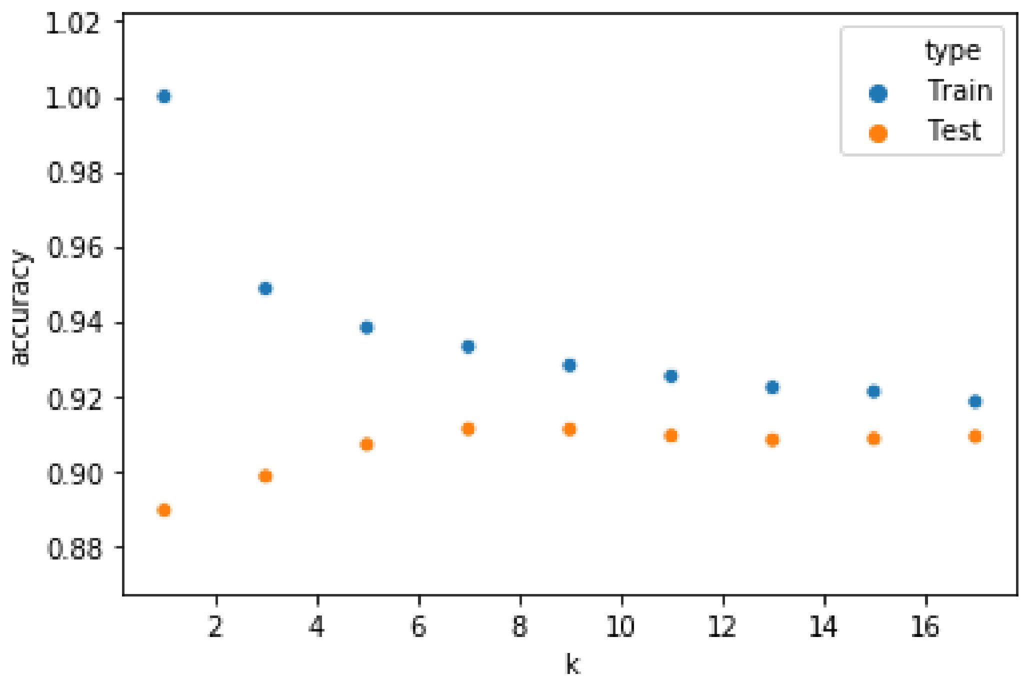
0.5.1 kNN on PCA data (D1)

[31]:
```
X_train, X_test, y_train, y_test = train_test_split(pca_data, mnist['label'],␣
↪test_size=0.2,
                                                    random_state=11915043)
df = build_knn(X_train, X_test, y_train, y_test)
sns.scatterplot(x="k", y='accuracy', hue='type', data=df)
```

```
1 1.0 0.8895
3 0.9487 0.8986
```

```
5 0.9383 0.9071
7 0.9332 0.9112
9 0.9282 0.9111
11 0.9253 0.9094
13 0.9223 0.9083
15 0.9212 0.9086
17 0.9185 0.9092
```

[31]: <matplotlib.axes._subplots.AxesSubplot at 0x107df6b38>



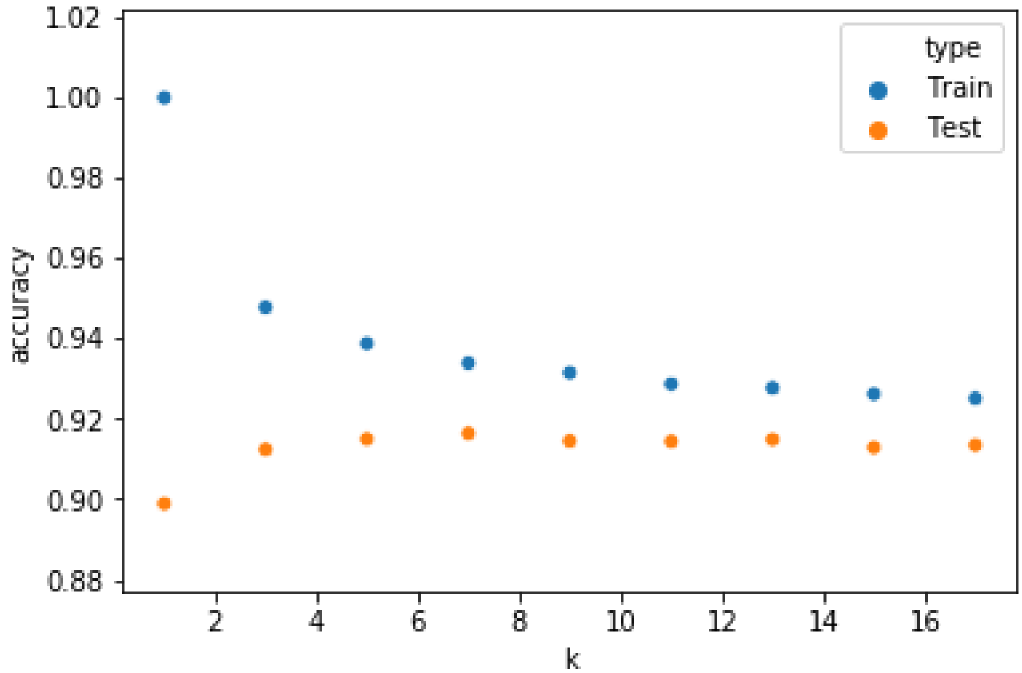
0.5.2 kNN on fisher projection data (D2)

[32]:
```
X_train, X_test, y_train, y_test = train_test_split(mnist_fisher_proj_data,␣
 ↪mnist['label'], test_size=0.2,
                                                    random_state=11915043)
df = build_knn(X_train, X_test, y_train, y_test)
sns.scatterplot(x="k", y='accuracy', hue='type', data=df)
```

```
1 1.0 0.8989
3 0.9478 0.9124
5 0.9388 0.915
7 0.9339 0.9164
9 0.9315 0.9145
11 0.9287 0.9144
```

```
13 0.9277 0.9149
15 0.9262 0.9129
17 0.9251 0.9135
```

[32]: <matplotlib.axes._subplots.AxesSubplot at 0x1331da748>



0.5.3 Build Parzen window classifier with:

- Sigma = 0.1, 0.2, 0.3, ..., 3.0
- Plot training and test accuracies with these values of sigma.

[33]:
```
sigma_list = []
for i in np.arange(0.1, 3.1, 0.1) :
    sigma_list.append(round(i,1))
classes = np.sort(y_train.unique())

def predict_accuracy(kde_models, X) :
    predict_accuracy = 0
    for model in kde_models :
        log_prob = model.score_samples(X)
        prob_X = np.sum(np.exp(log_prob))
        if(prob_X > predict_accuracy) :
            predict_accuracy = prob_X
    return predict_accuracy
```

```
#Adapted from : https://jakevdp.github.io/PythonDataScienceHandbook/05.
↪13-kernel-density-estimation.html
def build_parzen_classifier(X_train, X_test, y_train, y_test) :
    df = pd.DataFrame(columns=['sigma','accuracy', 'type'])
    for i in sigma_list :
        kde_models = []
        for class_label in classes :
            #print("kde for class : ", class_label)
            X = pca_data[mnist[mnist['label']==class_label].index]
            kde_model = KernelDensity(bandwidth=i, kernel='gaussian')
            kde_model.fit(X)
            kde_models.append(kde_model)
        train_score = predict_accuracy(kde_models, X_train)
        test_score = predict_accuracy(kde_models, X_test)

        df = df.append({'sigma' : i,'accuracy':train_score, 'type': 'Train'},␣
↪ignore_index=True)
        df = df.append({'sigma' : i,'accuracy':test_score, 'type': 'Test'},␣
↪ignore_index=True)
        print(i, train_score, test_score)
    return df
```

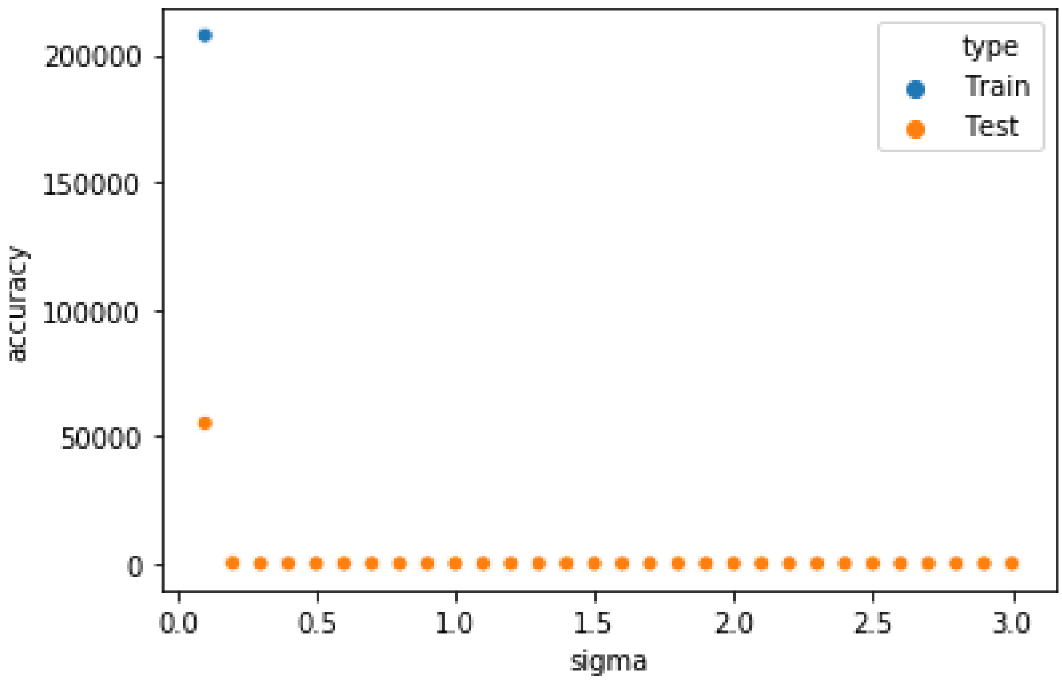
0.5.4 Parzen classifier pca data (D1)

[34]:
```
X_train, X_test, y_train, y_test = train_test_split(pca_data, mnist['label'],␣
↪test_size=0.2)
df = build_parzen_classifier(X_train, X_test, y_train, y_test)
sns.scatterplot(x="sigma", y='accuracy', hue='type', data=df)
```

```
0.1 207754.61222002213 55182.87807727062
0.2 405.77072699223174 107.77905874466936
0.3 10.555027801657433 2.8035806572814543
0.4 0.7925209511567064 0.2105059741106836
0.5 0.10637036145665202 0.028253633575562733
0.6 0.02061528867511225 0.005475743471252879
0.7 0.005148352964334133 0.0013674831614747896
0.8 0.0015478924827279522 0.00041114448068493083
0.9 0.0005362509679244791 0.0001424366538272371
1.0 0.00020775461222002624 5.518287807727167e-05
1.1 8.81082362484122e-05 2.340292716751003e-05
1.2 4.0264235693579006e-05 1.069481146729088e-05
1.3 1.9591175869083307e-05 5.20372307416721e-06
1.4 1.0055376883465235e-05 2.670865549755499e-06
1.5 5.404174234448712e-06 1.435433296528138e-06
1.6 3.023227505328069e-06 8.030165638377634e-07
```

```
1.7 1.7519043122867915e-06 4.653332170820048e-07
1.8 1.0473651717275167e-06 2.7819658950632485e-07
1.9 6.438256359011099e-07 1.7101017007182527e-07
2.0 4.057707269922448e-07 1.0777905874467283e-07
2.1 2.61563428559379e-07 6.947534224837816e-08
2.2 1.7208639892268248e-07 4.570884212404363e-08
2.3 1.1534536559009967e-07 3.06375352061773e-08
2.4 7.864108533902334e-08 2.088830364705304e-08
2.5 5.4461625065807907e-08 1.4465860390688683e-08
2.6 3.826401536930456e-08 1.0163521629233037e-08
2.7 2.724437168747127e-08 7.236531719110015e-09
2.8 1.9639407975518487e-08 5.2165342768663235e-09
2.9 1.4320846606604086e-08 3.803841097970922e-09
3.0 1.0555027801658002e-08 2.8035806572815842e-09
```

[34]: <matplotlib.axes._subplots.AxesSubplot at 0x132c523c8>



0.5.5 Parzen classifier fisher projection data (D2)

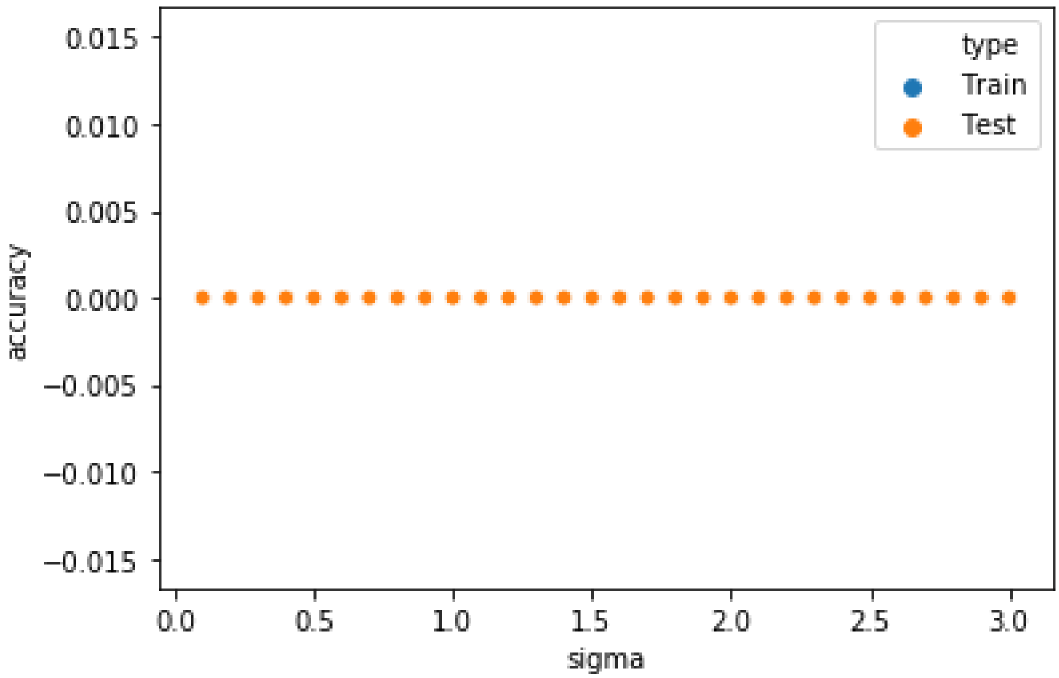
[35]:
```
X_train, X_test, y_train, y_test = train_test_split(mnist_fisher_proj_data,␣
↪mnist['label'],
                                                    test_size=0.2,␣
↪random_state=11915043)
```

```python
df = build_parzen_classifier(X_train, X_test, y_train, y_test)
sns.scatterplot(x="sigma", y='accuracy', hue='type', data=df)
df.head()
```

```
0.1 0 0
0.2 4.180604314400227e-155 3.543840697365687e-157
0.3 6.091418141662426e-76 1.3638441339754049e-75
0.4 5.267930823589812e-47 3.3559255760340885e-49
0.5 5.042714395219737e-35 3.1823008225772225e-36
0.6 6.150716102030815e-28 1.2420069253313746e-28
0.7 1.9709520103691598e-24 4.531913042507462e-25
0.8 1.07516288497189e-22 2.7973775751414435e-23
0.9 6.44480811786607e-21 1.6974634331313358e-21
1.0 2.3429241273765993e-20 5.7473293833950314e-21
1.1 4.6953043574132237e-20 1.1658997667946759e-20
1.2 1.0187639999347472e-19 2.224614840904473e-20
1.3 1.1307983573390784e-19 2.8060251543543405e-20
1.4 9.297822395785718e-20 2.4663560174089207e-20
1.5 6.697146630650185e-20 1.67465079055131e-20
1.6 4.687666163047527e-20 1.1486102723292086e-20
1.7 3.22484590879155e-20 7.81357174964774e-21
1.8 2.2439863653252653e-20 5.6836577302838945e-21
1.9 1.54019096548494e-20 3.867477967540979e-21
2.0 1.0292676869572286e-20 2.5014027591961316e-21
2.1 6.980582952396916e-21 1.747483697535453e-21
2.2 4.820208347431575e-21 1.1957552315702358e-21
2.3 3.301811640563048e-21 8.09597933434094e-22
2.4 3.1698827940898842e-21 7.646667584036535e-22
2.5 4.375235280018203e-21 9.548884252692902e-22
2.6 5.2850507609666405e-21 1.4044514115074316e-21
2.7 5.596003114749652e-21 1.3611020549821035e-21
2.8 4.596086960801872e-21 1.1358292875722011e-21
2.9 3.461832061992406e-21 8.905311146223086e-22
3.0 2.6686742974268377e-21 6.560534334527556e-22
```

[35]:

	sigma	accuracy	type
0	0.1	0	Train
1	0.1	0	Test
2	0.2	4.1806e-155	Train
3	0.2	3.54384e-157	Test
4	0.3	6.09142e-76	Train



Comment on the optimal k and optimal sigma and compare those classifiers across D1 and D2 and see which one has highest test accuracy. If we look at scatter plot for train and test set, we see that on fisher projection data we get marginal higher accuracy for K=9 on both train and test set, with k nearest neighbours

PCA data (D1) - - K nearest neighbour - test set accuracy is .91, for k=9

Fisher projection data (D2) - - K nearest neighbour - test set accuracy is 0.9145, for k=9

0.6 P6 : News group Text Classifier

[36]:
```
#check sample of categories and document nos.
#This file doesn't seem to be of any use, as all document Ids belong to same␣
↪newsgroup
categories = pd.read_csv("DMG-2 Assignment Data Files/Newsgroup/list.csv")
categories.sample(5)
```

[36]:

	newsgroup	document_id
203	talk.religion.misc	83781
227	talk.religion.misc	83830
102	talk.religion.misc	83509
362	talk.religion.misc	84121
32	talk.religion.misc	82801

[37]:

```python
#Ref :
#https://stackoverflow.com/questions/35672809/
↪how-to-read-a-list-of-txt-files-in-a-folder-in-python
#https://www.analyticsvidhya.com/blog/2018/10/
↪stepwise-guide-topic-modeling-latent-semantic-analysis/
#https://medium.com/@dobko_m/
↪nlp-text-data-cleaning-and-preprocessing-ea3ffe0406c1
#https://towardsdatascience.com/
↪nlp-extracting-the-main-topics-from-your-dataset-using-lda-in-minutes-21486f5aa925
#https://towardsdatascience.com/
↪machine-learning-nlp-text-classification-using-scikit-learn-python-and-nltk-c52b92a7c73a
#https://github.com/gokriznastic/20-newsgroups_text-classification/blob/master/
↪Multinomial%20Naive%20Bayes-%20BOW%20with%20TF.ipynb


#Read all documents one by one and create two dataframes
#One for finding probability and other for running naive bayes

df = pd.DataFrame(columns=['data','document'])
df_docs = pd.DataFrame(columns=['doc part','document'])
text_files = glob.glob("DMG-2 Assignment Data Files/Newsgroup/*.txt")

#read all text files and create a dataframe of whole dataset
for file in text_files :
    print("Reading file : ", file)
    category = file[file.rfind('/')+1:-4]
    with open(file, 'r', encoding='windows-1252') as current_file :
        data = current_file.read()
        df = df.append({'data':data, 'document': category}, ignore_index=True)

        #split each file at \n to create multiple documents from each data
        #this dataset will be used for naive bayes
        docs = data.split('\n\n')
        df_temp = pd.DataFrame(docs, columns=['doc part'])
        df_temp['document'] = category
        df_docs = df_docs.append(df_temp, ignore_index=True)

df.sample(5)
```

```
Reading file :  DMG-2 Assignment Data Files/Newsgroup/sci.crypt.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/comp.sys.mac.hardware.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/misc.forsale.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/soc.religion.christian.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/rec.sport.baseball.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/rec.sport.hockey.txt
Reading file :  DMG-2 Assignment Data
Files/Newsgroup/comp.sys.ibm.pc.hardware.txt
```

```
Reading file :  DMG-2 Assignment Data Files/Newsgroup/talk.politics.guns.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/rec.autos.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/alt.atheism.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/comp.os.ms-
windows.misc.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/sci.electronics.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/comp.windows.x.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/talk.religion.misc.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/talk.politics.mideast.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/sci.med.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/rec.motorcycles.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/comp.graphics.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/sci.space.txt
Reading file :  DMG-2 Assignment Data Files/Newsgroup/talk.politics.misc.txt
```

[37]:

	data	document
2	Newsgroup: misc.forsale\ndocument_id: 70337\nF…	misc.forsale
10	Newsgroup: comp.os.ms-windows.misc\ndocument_i…	comp.os.ms-windows.misc
14	Newsgroup: talk.politics.mideast\ndocument_id:…	talk.politics.mideast
3	Newsgroup: soc.religion.christian\ndocument_id…	soc.religion.christian
1	Newsgroup: comp.sys.mac.hardware\ndocument_id:…	comp.sys.mac.hardware

[38]:

```
stop_words = stopwords.words('english')

#important to add email ids to remove training bias, as documents contain␣
↪emails from specific sources
stop_words.
↪extend(["Newsgroup","document_id","From","Subject","document","umd","edu","wam","mri","com"

'''
Return cleaned array of words from data
'''
def clean_get_words(data, tokenize=False) :
    # replace all non alphabetical characters with space
    data = re.sub("[^a-zA-Z]", ' ', data)

    #convert data to lowercase
    data = data.lower()

    # remove all words less than 3 characters
    data = re.sub(r'\b\w{1,2}\b', '', data)

    # get all unique words from data
    words = re.sub("[^\w]", " ",  data).split()
    words = [word for word in words if word not in stop_words]

    #stemming at per DMG2 session 5 explaination before building NLP
```

```
    lancaster = LancasterStemmer()
    data = " ".join(words)
    lancaster.stem(data)

    #tokenize words are used during naive bayes
    if(tokenize) :
        return data.split(" ")

    return data
```

Build a Naïve Bayes Classifier on Newsgroup dataset

0.6.1 DICTIONARY :

- Compute the document frequency of all words (how many documents each word occurred in)
- Sort this in descending order of document frequency
- Pick the top 5000 and 10000 words as the dictionary.

[39]:
```
%%time

#clean each of the documents and get words from it
df['data'] = df['data'].map(clean_get_words)
#get unique words from each document
df['unique words data'] = df['data'].apply(lambda x: " ".join(set(x.split('␣
↪'))))

#create a count vector to create top 5k and 10k words
countVectorizer = CountVectorizer()
count_vec = countVectorizer.fit_transform(df['unique words data'])
word2vec = pd.DataFrame(count_vec.toarray(), columns=countVectorizer.
↪get_feature_names())
```

```
CPU times: user 26.9 s, sys: 982 ms, total: 27.9 s
Wall time: 28 s
```

Compute the document frequency of all words (how many documents each word occurred in)

[40]:
```
word2vec.index = df.document
word2vec.sample(5)
```

[40]:
```
                          aaa  aaaa  aaaaa  aaaaaaaaaaaa  \
document
soc.religion.christian      0     0      0             0
talk.politics.guns          1     0      0             0
talk.politics.misc          1     0      0             1
```

```
sci.space                  0     0      0             0
sci.med                    0     0      0             0

aaaaaaaaaaaaaaaaaaaaaaaaaaaaaauuuuuuuuuuuuuuuuuuuuuuuuuuuuuuuuugggggggggggggggg
\
document
soc.religion.christian                                                  0
talk.politics.guns                                                      0
talk.politics.misc                                                      0
sci.space                                                               0
sci.med                                                                 0

                        aaaaaggggghhhh  aaaaarrrrgh  aaaahhh  aaaall  \
document
soc.religion.christian               0            0        0       0
talk.politics.guns                   0            0        0       0
talk.politics.misc                   1            0        0       1
sci.space                            0            0        0       0
sci.med                              0            0        0       0

                        aaaarrgghhhh  …  zztop  zzum  zzvsi  zzx  zzy  zzz  \
document                              …
soc.religion.christian             0  …      0     0      0    0    0    0
talk.politics.guns                 0  …      0     0      0    0    0    0
talk.politics.misc                 0  …      0     0      0    0    0    0
sci.space                          0  …      0     0      0    0    0    0
sci.med                            0  …      0     0      0    0    0    1

                        zzzoh  zzzz  zzzzzz  zzzzzzt
document
soc.religion.christian      0     0       0        0
talk.politics.guns          0     0       0        0
talk.politics.misc          0     0       0        0
sci.space                   0     0       0        0
sci.med                     0     0       0        0

[5 rows x 112926 columns]
```

Dictionary : Sort this in descending order of document frequency

[41]:
```python
sum_matrix = word2vec.sum(axis=0)
term_document_frequency = sum_matrix.sort_values(ascending=False)
```

Dictionary : Pick the top 5000 and 10000 words as the dictionary.

[42]:

```
top_5k = term_document_frequency[:5000]
print(top_5k)
print()
top_10k = term_document_frequency[:10000]
print(top_10k)
```

```
offer             20
third             20
world             20
later             20
late              20
                  ..
eve               13
rank              13
anon              13
ranks             13
specifications    13
Length: 5000, dtype: int64

offer          20
third          20
world          20
later          20
late           20
               ..
perpetuate      7
api             7
listings        7
clay            7
diagnostics     7
Length: 10000, dtype: int64
```

Learn P(w|c) for all words and classes Done it for top 10k and top 5k words only

[43]:

```
#get all words in a given document, difference from above is set()
df['words'] = df['data'].apply(lambda x: " ".join(x.split(' ')))

#create a count vector to calculate probability of each word in given␣
 ↪document(class)
countVectorizer = CountVectorizer()
count_vec = countVectorizer.fit_transform(df['words'])
word2vec = pd.DataFrame(count_vec.toarray(), columns=countVectorizer.
 ↪get_feature_names())

#Take only top 5k and 10k words

word2vec_5k = word2vec[list(top_5k.index)]
```

```python
word2vec_5k.index = df.document

word2vec_10k = word2vec[list(top_10k.index)]
word2vec_10k.index = df.document
word2vec_10k
```

[43]:

```
                          offer  third  world  later  late  upon  last  \
document
sci.crypt                    34     60    232     94    68    92   186
comp.sys.mac.hardware        46     78    102     48    18    28   172
misc.forsale                668     12    130     14    18    24   128
soc.religion.christian       58     86    648    206    62   238   322
rec.sport.baseball           26    272    234     74    86    22   964
rec.sport.hockey             28    296    252    106   114    24   736
comp.sys.ibm.pc.hardware     34     66     74     58     6    20   172
talk.politics.guns           32     50    204    160    70    88   318
rec.autos                    70     44    144    128    60    18   270
alt.atheism                  30     75    582    150    30   264   204
comp.os.ms-windows.misc      34     28    204     50    26    14   112
sci.electronics              58     14     86     60    22    42   102
comp.windows.x               40     32    116    106    10    40   174
talk.religion.misc           34     56    384    132    52   148   154
talk.politics.mideast        38    256    922    360   118   224   612
sci.med                      36     32    236     84    38    64   232
rec.motorcycles              22     30    196    106    38    16   280
comp.graphics                70     47    252    100    22    51   234
sci.space                    50     70    378     92    82   100   286
talk.politics.misc           76    120    382     88    44   150   472

                          difference  works  different  …  slides  escaping  \
document                                                …
sci.crypt                         90     82        202  …       0         0
comp.sys.mac.hardware            150    208        132  …       2         0
misc.forsale                      12    144         28  …       0         0
soc.religion.christian           162    202        486  …       2         0
rec.sport.baseball                86     28        120  …       0         0
rec.sport.hockey                  54     32        126  …       0         4
comp.sys.ibm.pc.hardware         144    232        182  …       0         0
talk.politics.guns               150     64        230  …       0         4
rec.autos                         86     96        184  …       0         0
alt.atheism                      165    105        531  …       0         0
comp.os.ms-windows.misc           76    194        146  …       0         0
sci.electronics                   94    142        192  …       0         2
comp.windows.x                    82    252        228  …       8         4
talk.religion.misc                68     68        272  …       0         0
talk.politics.mideast            104     72        272  …       0        10
sci.med                          108    170        252  …       2         0
```

rec.motorcycles	102	66	94	…	10	4
comp.graphics	52	223	369	…	18	0
sci.space	60	72	252	…	4	0
talk.politics.misc	166	74	290	…	0	2

	perot	evolving	depletion	perpetuate	api \
document					
sci.crypt	0	4	0	2	10
comp.sys.mac.hardware	0	0	0	0	2
misc.forsale	0	0	0	0	2
soc.religion.christian	0	2	0	0	0
rec.sport.baseball	2	0	6	0	0
rec.sport.hockey	0	0	0	0	0
comp.sys.ibm.pc.hardware	0	0	0	0	0
talk.politics.guns	0	2	2	2	0
rec.autos	0	0	6	0	0
alt.atheism	3	6	6	3	0
comp.os.ms-windows.misc	0	0	0	0	32
sci.electronics	0	0	0	0	0
comp.windows.x	2	0	0	0	50
talk.religion.misc	6	0	0	2	0
talk.politics.mideast	0	0	0	2	0
sci.med	4	0	4	0	0
rec.motorcycles	0	0	0	0	0
comp.graphics	0	5	0	6	20
sci.space	12	4	6	0	2
talk.politics.misc	24	2	2	12	0

	listings	clay	diagnostics
document			
sci.crypt	0	0	0
comp.sys.mac.hardware	0	0	2
misc.forsale	0	4	8
soc.religion.christian	2	8	0
rec.sport.baseball	0	18	0
rec.sport.hockey	2	4	0
comp.sys.ibm.pc.hardware	0	0	16
talk.politics.guns	0	6	0
rec.autos	0	0	2
alt.atheism	0	0	0
comp.os.ms-windows.misc	0	0	6
sci.electronics	2	0	0
comp.windows.x	4	8	2
talk.religion.misc	0	0	0
talk.politics.mideast	0	2	0
sci.med	0	0	4
rec.motorcycles	6	0	0

```
comp.graphics                  8    0          0
sci.space                      4    0          0
talk.politics.misc             0    0          0

[20 rows x 10000 columns]
```

[44]:
```
#total no. of words in each document
word2vec_5k.loc[:,"sum"] = word2vec_5k.sum(axis=1)

#calculate probability P(w|C) for all words across all classes
df_prob = word2vec_5k.loc[:, word2vec_5k.columns != 'sum'].div(word2vec_5k.loc[:
↪,"sum"], axis=0)
df_prob
```

[44]:
```
                           offer     third     world     later      late  \
document
sci.crypt               0.000134  0.000236  0.000913  0.000370  0.000268
comp.sys.mac.hardware   0.000331  0.000562  0.000735  0.000346  0.000130
misc.forsale            0.006167  0.000111  0.001200  0.000129  0.000166
soc.religion.christian  0.000213  0.000315  0.002376  0.000755  0.000227
rec.sport.baseball      0.000153  0.001604  0.001380  0.000436  0.000507
rec.sport.hockey        0.000152  0.001606  0.001367  0.000575  0.000618
comp.sys.ibm.pc.hardware 0.000226 0.000439  0.000492  0.000385  0.000040
talk.politics.guns      0.000137  0.000213  0.000871  0.000683  0.000299
rec.autos               0.000436  0.000274  0.000898  0.000798  0.000374
alt.atheism             0.000102  0.000255  0.001982  0.000511  0.000102
comp.os.ms-windows.misc 0.000215  0.000177  0.001289  0.000316  0.000164
sci.electronics         0.000378  0.000091  0.000560  0.000391  0.000143
comp.windows.x          0.000192  0.000153  0.000556  0.000508  0.000048
talk.religion.misc      0.000208  0.000342  0.002346  0.000806  0.000318
talk.politics.mideast   0.000124  0.000834  0.003003  0.001172  0.000384
sci.med                 0.000169  0.000150  0.001107  0.000394  0.000178
rec.motorcycles         0.000154  0.000210  0.001369  0.000741  0.000265
comp.graphics           0.000278  0.000186  0.001000  0.000397  0.000087
sci.space               0.000221  0.000310  0.001674  0.000407  0.000363
talk.politics.misc      0.000297  0.000470  0.001495  0.000344  0.000172

                            upon      last  difference     works  different  \
document
sci.crypt               0.000362  0.000732    0.000354  0.000323   0.000795
comp.sys.mac.hardware   0.000202  0.001239    0.001081  0.001499   0.000951
misc.forsale            0.000222  0.001182    0.000111  0.001329   0.000259
soc.religion.christian  0.000873  0.001181    0.000594  0.000741   0.001782
rec.sport.baseball      0.000130  0.005684    0.000507  0.000165   0.000708
rec.sport.hockey        0.000130  0.003992    0.000293  0.000174   0.000683
comp.sys.ibm.pc.hardware 0.000133 0.001143    0.000957  0.001542   0.001209
talk.politics.guns      0.000376  0.001357    0.000640  0.000273   0.000982
```

rec.autos	0.000112	0.001684	0.000536	0.000599	0.001147
alt.atheism	0.000899	0.000695	0.000562	0.000358	0.001808
comp.os.ms-windows.misc	0.000088	0.000708	0.000480	0.001226	0.000923
sci.electronics	0.000273	0.000664	0.000612	0.000925	0.001250
comp.windows.x	0.000192	0.000834	0.000393	0.001208	0.001093
talk.religion.misc	0.000904	0.000941	0.000415	0.000415	0.001662
talk.politics.mideast	0.000730	0.001993	0.000339	0.000234	0.000886
sci.med	0.000300	0.001088	0.000506	0.000797	0.001182
rec.motorcycles	0.000112	0.001956	0.000713	0.000461	0.000657
comp.graphics	0.000202	0.000928	0.000206	0.000885	0.001464
sci.space	0.000443	0.001266	0.000266	0.000319	0.001116
talk.politics.misc	0.000587	0.001847	0.000650	0.000290	0.001135

	…	exclude	modules	mate	excluded	\
document	…					
sci.crypt	…	0.000008	0.000008	0.000024	0.000000	
comp.sys.mac.hardware	…	0.000014	0.000043	0.000000	0.000000	
misc.forsale	…	0.000000	0.000018	0.000018	0.000018	
soc.religion.christian	…	0.000095	0.000015	0.000037	0.000059	
rec.sport.baseball	…	0.000000	0.000000	0.000012	0.000012	
rec.sport.hockey	…	0.000011	0.000000	0.000000	0.000000	
comp.sys.ibm.pc.hardware	…	0.000013	0.000013	0.000000	0.000000	
talk.politics.guns	…	0.000000	0.000000	0.000009	0.000000	
rec.autos	…	0.000012	0.000012	0.000012	0.000062	
alt.atheism	…	0.000041	0.000000	0.000010	0.000051	
comp.os.ms-windows.misc	…	0.000013	0.000025	0.000038	0.000063	
sci.electronics	…	0.000000	0.000078	0.000000	0.000000	
comp.windows.x	…	0.000010	0.000038	0.000000	0.000019	
talk.religion.misc	…	0.000098	0.000000	0.000000	0.000024	
talk.politics.mideast	…	0.000020	0.000000	0.000007	0.000046	
sci.med	…	0.000000	0.000009	0.000009	0.000009	
rec.motorcycles	…	0.000014	0.000028	0.000014	0.000014	
comp.graphics	…	0.000000	0.000361	0.000000	0.000000	
sci.space	…	0.000000	0.000142	0.000009	0.000018	
talk.politics.misc	…	0.000016	0.000000	0.000031	0.000016	

	solving	eve	rank	anon	ranks	\
document						
sci.crypt	0.000031	0.000142	0.000008	0.000394	0.000000	
comp.sys.mac.hardware	0.000014	0.000014	0.000058	0.000000	0.000029	
misc.forsale	0.000055	0.000203	0.000000	0.000000	0.000000	
soc.religion.christian	0.000007	0.000213	0.000000	0.000000	0.000007	
rec.sport.baseball	0.000000	0.000000	0.000094	0.000012	0.000024	
rec.sport.hockey	0.000000	0.000011	0.000076	0.000000	0.000011	
comp.sys.ibm.pc.hardware	0.000013	0.000000	0.000013	0.000000	0.000013	
talk.politics.guns	0.000017	0.000009	0.000043	0.000068	0.000043	
rec.autos	0.000050	0.000025	0.000000	0.000000	0.000000	

```
alt.atheism                 0.000031  0.000072  0.000041  0.000010  0.000061
comp.os.ms-windows.misc     0.000000  0.000051  0.000000  0.000013  0.000013
sci.electronics             0.000013  0.000000  0.000000  0.000013  0.000000
comp.windows.x              0.000000  0.000029  0.000048  0.000067  0.000000
talk.religion.misc          0.000000  0.000195  0.000000  0.000000  0.000012
talk.politics.mideast       0.000052  0.000052  0.000013  0.000026  0.000046
sci.med                     0.000000  0.000000  0.000009  0.000009  0.000019
rec.motorcycles             0.000000  0.000000  0.000014  0.000028  0.000000
comp.graphics               0.000056  0.000056  0.000012  0.000024  0.000000
sci.space                   0.000027  0.000000  0.000000  0.000071  0.000009
talk.politics.misc          0.000055  0.000000  0.000031  0.000008  0.000008

                          specifications
document
sci.crypt                       0.000087
comp.sys.mac.hardware           0.000101
misc.forsale                    0.000074
soc.religion.christian          0.000007
rec.sport.baseball              0.000024
rec.sport.hockey                0.000000
comp.sys.ibm.pc.hardware        0.000186
talk.politics.guns              0.000000
rec.autos                       0.000037
alt.atheism                     0.000000
comp.os.ms-windows.misc         0.000051
sci.electronics                 0.000026
comp.windows.x                  0.000077
talk.religion.misc              0.000000
talk.politics.mideast           0.000000
sci.med                         0.000000
rec.motorcycles                 0.000014
comp.graphics                   0.000008
sci.space                       0.000018
talk.politics.misc              0.000000

[20 rows x 4999 columns]
```

[45]:
```python
#total no. of words in each document
word2vec_10k.loc[:,"sum"] = word2vec_10k.sum(axis=1)

#calculate probability P(w|C) for all words across all classes
df_prob = word2vec_10k.loc[:, word2vec_10k.columns != 'sum'].div(word2vec_10k.
 ↪loc[:,"sum"], axis=0)
df_prob
```

[45]:
```
                             offer     third     world     later      late  \
document
```

sci.crypt	0.000117	0.000206	0.000798	0.000323	0.000234
comp.sys.mac.hardware	0.000295	0.000500	0.000654	0.000308	0.000115
misc.forsale	0.005325	0.000096	0.001036	0.000112	0.000143
soc.religion.christian	0.000185	0.000274	0.002064	0.000656	0.000197
rec.sport.baseball	0.000138	0.001443	0.001242	0.000393	0.000456
rec.sport.hockey	0.000133	0.001405	0.001196	0.000503	0.000541
comp.sys.ibm.pc.hardware	0.000199	0.000386	0.000433	0.000340	0.000035
talk.politics.guns	0.000118	0.000184	0.000751	0.000589	0.000258
rec.autos	0.000387	0.000243	0.000796	0.000707	0.000332
alt.atheism	0.000089	0.000224	0.001736	0.000447	0.000089
comp.os.ms-windows.misc	0.000193	0.000159	0.001155	0.000283	0.000147
sci.electronics	0.000327	0.000079	0.000486	0.000339	0.000124
comp.windows.x	0.000168	0.000135	0.000488	0.000446	0.000042
talk.religion.misc	0.000181	0.000299	0.002049	0.000704	0.000277
talk.politics.mideast	0.000105	0.000706	0.002544	0.000993	0.000326
sci.med	0.000147	0.000131	0.000964	0.000343	0.000155
rec.motorcycles	0.000134	0.000183	0.001193	0.000645	0.000231
comp.graphics	0.000242	0.000163	0.000872	0.000346	0.000076
sci.space	0.000193	0.000271	0.001461	0.000356	0.000317
talk.politics.misc	0.000260	0.000411	0.001308	0.000301	0.000151

	upon	last	difference	works	different	\
document						
sci.crypt	0.000316	0.000640	0.000309	0.000282	0.000695	
comp.sys.mac.hardware	0.000180	0.001103	0.000962	0.001334	0.000846	
misc.forsale	0.000191	0.001020	0.000096	0.001148	0.000223	
soc.religion.christian	0.000758	0.001026	0.000516	0.000643	0.001548	
rec.sport.baseball	0.000117	0.005115	0.000456	0.000149	0.000637	
rec.sport.hockey	0.000114	0.003494	0.000256	0.000152	0.000598	
comp.sys.ibm.pc.hardware	0.000117	0.001007	0.000843	0.001359	0.001066	
talk.politics.guns	0.000324	0.001170	0.000552	0.000236	0.000847	
rec.autos	0.000099	0.001492	0.000475	0.000531	0.001017	
alt.atheism	0.000787	0.000608	0.000492	0.000313	0.001584	
comp.os.ms-windows.misc	0.000079	0.000634	0.000430	0.001099	0.000827	
sci.electronics	0.000237	0.000576	0.000531	0.000802	0.001084	
comp.windows.x	0.000168	0.000732	0.000345	0.001060	0.000959	
talk.religion.misc	0.000790	0.000822	0.000363	0.000363	0.001451	
talk.politics.mideast	0.000618	0.001689	0.000287	0.000199	0.000751	
sci.med	0.000261	0.000947	0.000441	0.000694	0.001029	
rec.motorcycles	0.000097	0.001704	0.000621	0.000402	0.000572	
comp.graphics	0.000176	0.000810	0.000180	0.000772	0.001277	
sci.space	0.000387	0.001105	0.000232	0.000278	0.000974	
talk.politics.misc	0.000514	0.001616	0.000568	0.000253	0.000993	

	…	slides	escaping	perot	evolving	\
document	…					
sci.crypt	…	0.000000	0.000000	0.000000	0.000014	

```
comp.sys.mac.hardware     …  0.000013  0.000000  0.000000  0.000000
misc.forsale              …  0.000000  0.000000  0.000000  0.000000
soc.religion.christian    …  0.000006  0.000000  0.000000  0.000006
rec.sport.baseball        …  0.000000  0.000000  0.000011  0.000000
rec.sport.hockey          …  0.000000  0.000019  0.000000  0.000000
comp.sys.ibm.pc.hardware  …  0.000000  0.000000  0.000000  0.000000
talk.politics.guns        …  0.000000  0.000015  0.000000  0.000007
rec.autos                 …  0.000000  0.000000  0.000000  0.000000
alt.atheism               …  0.000000  0.000000  0.000009  0.000018
comp.os.ms-windows.misc   …  0.000000  0.000000  0.000000  0.000000
sci.electronics           …  0.000000  0.000011  0.000000  0.000000
comp.windows.x            …  0.000034  0.000017  0.000008  0.000000
talk.religion.misc        …  0.000000  0.000000  0.000032  0.000000
talk.politics.mideast     …  0.000000  0.000028  0.000000  0.000000
sci.med                   …  0.000008  0.000000  0.000016  0.000000
rec.motorcycles           …  0.000061  0.000024  0.000000  0.000000
comp.graphics             …  0.000062  0.000000  0.000000  0.000017
sci.space                 …  0.000015  0.000000  0.000046  0.000015
talk.politics.misc        …  0.000000  0.000007  0.000082  0.000007

                          depletion  perpetuate       api  listings      clay  \
document
sci.crypt                  0.000000    0.000007  0.000034  0.000000  0.000000
comp.sys.mac.hardware      0.000000    0.000000  0.000013  0.000000  0.000000
misc.forsale               0.000000    0.000000  0.000016  0.000000  0.000032
soc.religion.christian     0.000000    0.000000  0.000000  0.000006  0.000025
rec.sport.baseball         0.000032    0.000000  0.000000  0.000000  0.000096
rec.sport.hockey           0.000000    0.000000  0.000000  0.000009  0.000019
comp.sys.ibm.pc.hardware   0.000000    0.000000  0.000000  0.000000  0.000000
talk.politics.guns         0.000007    0.000007  0.000000  0.000000  0.000022
rec.autos                  0.000033    0.000000  0.000000  0.000000  0.000000
alt.atheism                0.000018    0.000009  0.000000  0.000000  0.000000
comp.os.ms-windows.misc    0.000000    0.000000  0.000181  0.000000  0.000000
sci.electronics            0.000000    0.000000  0.000000  0.000011  0.000000
comp.windows.x             0.000000    0.000000  0.000210  0.000017  0.000034
talk.religion.misc         0.000000    0.000011  0.000000  0.000000  0.000000
talk.politics.mideast      0.000000    0.000006  0.000000  0.000000  0.000006
sci.med                    0.000016    0.000000  0.000000  0.000000  0.000000
rec.motorcycles            0.000000    0.000000  0.000000  0.000037  0.000000
comp.graphics              0.000000    0.000021  0.000069  0.000028  0.000000
sci.space                  0.000023    0.000000  0.000008  0.000015  0.000000
talk.politics.misc         0.000007    0.000041  0.000000  0.000000  0.000000

                          diagnostics
document
sci.crypt                    0.000000
comp.sys.mac.hardware        0.000013
```

```
misc.forsale                 0.000064
soc.religion.christian       0.000000
rec.sport.baseball           0.000000
rec.sport.hockey             0.000000
comp.sys.ibm.pc.hardware     0.000094
talk.politics.guns           0.000000
rec.autos                    0.000011
alt.atheism                  0.000000
comp.os.ms-windows.misc      0.000034
sci.electronics              0.000000
comp.windows.x               0.000008
talk.religion.misc           0.000000
talk.politics.mideast        0.000000
sci.med                      0.000016
rec.motorcycles              0.000000
comp.graphics                0.000000
sci.space                    0.000000
talk.politics.misc           0.000000

[20 rows x 9999 columns]
```

To run naive bayes, I have taken the whole dataset in original and do test train split

This Original document dataset is divided such that each new line is considered as new document (created above)

[46]:
```
%%time

#drop all rows which doesn't event even have a word with 3 characters
df_docs['doc part'] = df_docs['doc part'].map(clean_get_words)
print(df_docs.shape)
df_docs = df_docs[df_docs['doc part'].map(len) > 10]
print(df_docs.shape)
```

```
(300672, 2)
(268230, 2)
CPU times: user 51 s, sys: 147 ms, total: 51.2 s
Wall time: 51.3 s
```

[47]:
```
X = df_docs.loc[:, df_docs.columns == 'doc part']
y = df_docs.loc[:, df_docs.columns == 'document']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=11915043)
```

0.6.2 Prior class probabilities for each class

[48]:
```
#calculate prior probability of each class
prior_prob_class = round(y_train.document.value_counts()/y_train.document.
↪value_counts().sum(),4)
prior_prob_class
```

[48]:
```
alt.atheism                 0.0738
talk.politics.mideast       0.0727
comp.graphics               0.0723
soc.religion.christian      0.0598
sci.crypt                   0.0595
comp.windows.x              0.0545
sci.space                   0.0537
talk.politics.guns          0.0535
rec.sport.hockey            0.0492
sci.med                     0.0479
talk.politics.misc          0.0461
rec.sport.baseball          0.0441
misc.forsale                0.0414
comp.sys.ibm.pc.hardware    0.0410
rec.motorcycles             0.0408
comp.os.ms-windows.misc     0.0400
rec.autos                   0.0396
sci.electronics             0.0385
talk.religion.misc          0.0372
comp.sys.mac.hardware       0.0343
Name: document, dtype: float64
```

Build naive bayer classifier based on known class and prior probabilities

[49]:
```
%%time
#using slide 25, session 5 DMG2
def classify_naive_bayes(document, known_class) :
    index = 0
    lambda_smooth = 30
    total_words = 10000

    #get clean words for document
    words = clean_get_words(X_train['doc part'][index], True)

    #calculate laplascian smoothening probability
    laplacian_smooth_prob = (len(words) + lambda_smooth)/(len(words) +␣
↪total_words*lambda_smooth)

    #prior prob of class
```

```
    prior_class_prob = np.log(prior_prob_class[known_class])

    df_temp = df_prob.loc[:, df_prob.columns.isin(words)]
    unknown_word_count = len(words) - df_temp.shape[1]
    unkwnon_word_prob = unknown_word_count*laplacian_smooth_prob
    df_temp['unknown_words_prob'] = prior_prob_class*unknown_word_count

    high_prob_class = ((np.log(prior_prob_class) +
                        np.log(df_temp.sum(axis=1))).apply(math.exp)).
 ↪sort_values(ascending=False).index[0]
    if(known_class == high_prob_class) :
        return True
    else :
        return False

no_of_correct_classifications = 0
no_of_wrong_classifications = 0
for index, row in X_train.iterrows():
    if(classify_naive_bayes(row['doc part'], y_train.loc[index,'document'])) :
        no_of_correct_classifications = no_of_correct_classifications + 1
    else :
        no_of_wrong_classifications = no_of_wrong_classifications + 1

print(no_of_correct_classifications)
print(no_of_wrong_classifications)
```

```
15832
198752
CPU times: user 13min 57s, sys: 2.93 s, total: 14min
Wall time: 14min 3s
```

[50]:

```
no_of_correct_classifications_test = 0
no_of_wrong_classifications_test = 0
for index, row in X_test.iterrows():
    if(classify_naive_bayes(row['doc part'], y_test.loc[index,'document'])) :
        no_of_correct_classifications_test = no_of_correct_classifications_test␣
 ↪+ 1
    else :
        no_of_wrong_classifications_test = no_of_correct_classifications_test +␣
 ↪1

print(no_of_correct_classifications_test)
print(no_of_wrong_classifications_test)
```

```
3917
3918
```

0.6.3 Summary (Across classes probabilities) for text classification

Low train and test accuracy is because, I'm considering direct class comparision of highest probability class to orginal class, based on naive bayes classifier designed above instead of using actual naive bayes library

[51]:
```
print("Train set accuracy : ", no_of_correct_classifications/
 ↪(no_of_correct_classifications+no_of_wrong_classifications))
print("Test set accuracy : ", no_of_correct_classifications_test/
 ↪(no_of_correct_classifications_test+no_of_wrong_classifications_test))
```

```
Train set accuracy :  0.07377996495544868
Test set accuracy :  0.49993618379068283
```

0.7 P7: Pair-wise Classifier Features

0.7.1 Compute the fisher discriminant for that pair of classes

- https://colah.github.io/posts/2014-10-Visualizing-MNIST/

[52]:
```
mnist = pd.read_csv('DMG-2 Assignment Data Files/MNIST/train.csv')
mnist.head()

mnist_data = mnist.loc[:, mnist.columns != 'label']
mnist_label = mnist.loc[:, mnist.columns == 'label']
```

[53]:
```
target_names = pd.Series(mnist.label.unique()).apply(str)
features = mnist_data.columns

#create pair of unique sets
def get_class_pairs(target_names):
    pairs = list(itertools.combinations(target_names, 2))
    return pairs

all_pairs = get_class_pairs(target_names)
print(all_pairs)
```

```
[('1', '0'), ('1', '4'), ('1', '7'), ('1', '3'), ('1', '5'), ('1', '8'), ('1',
'9'), ('1', '2'), ('1', '6'), ('0', '4'), ('0', '7'), ('0', '3'), ('0', '5'),
('0', '8'), ('0', '9'), ('0', '2'), ('0', '6'), ('4', '7'), ('4', '3'), ('4',
'5'), ('4', '8'), ('4', '9'), ('4', '2'), ('4', '6'), ('7', '3'), ('7', '5'),
('7', '8'), ('7', '9'), ('7', '2'), ('7', '6'), ('3', '5'), ('3', '8'), ('3',
'9'), ('3', '2'), ('3', '6'), ('5', '8'), ('5', '9'), ('5', '2'), ('5', '6'),
('8', '9'), ('8', '2'), ('8', '6'), ('9', '2'), ('9', '6'), ('2', '6')]
```

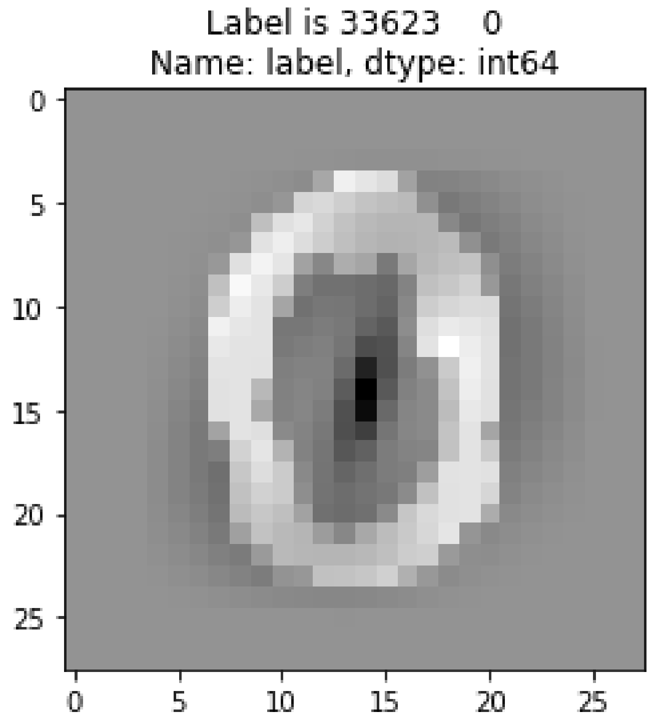
[54]:
```
#define placeholder dataframe for transformed data
mnist_transformed = pd.DataFrame()
```

[55]:

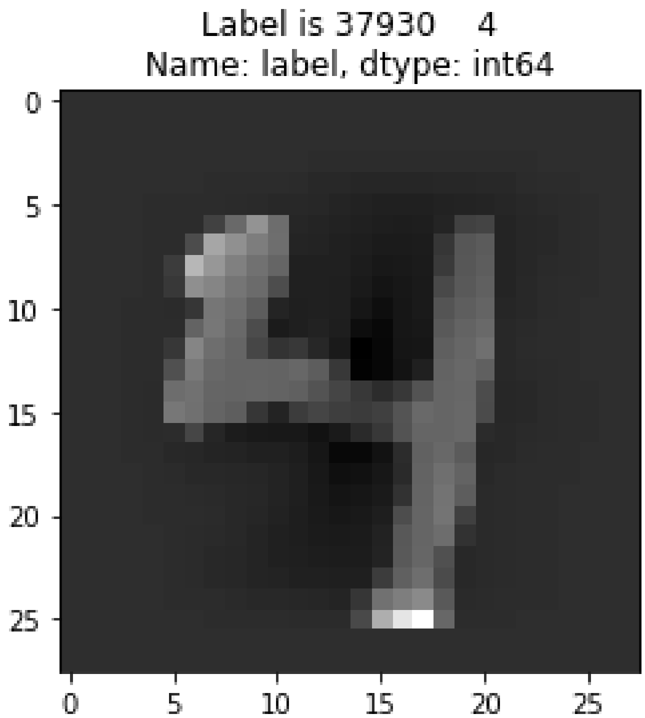
```
%%time

#iterate through all pairs one by one
for pair in all_pairs :
    print("Running LDA on pair : ", pair)
    first_class = int(pair[0])
    second_class = int(pair[1])

    #filter rows for pair of classes
    mnist_temp = mnist[(mnist.label == first_class) | (mnist.label ==␣
↪second_class)]
    mnist_data_temp = mnist_temp.loc[:, mnist_temp.columns != 'label']
    mnist_label_temp = mnist_temp.loc[:, mnist_temp.columns == 'label']

    #taking one pixel at a time, 784 features
    for feature in features :

        #calculate variance of first class
        mnist_temp_first_class_var = mnist_temp.loc[mnist_temp.label ==␣
↪first_class][feature].values.var()
        #calculate variance of first class
        mnist_temp_second_class_var = mnist_temp.loc[mnist_temp.label ==␣
↪second_class][feature].values.var()
        #calculate sum of variance
        sum_of_var = mnist_temp_first_class_var + mnist_temp_second_class_var

        #run LDA if sum of variance is not zero and transform that column data
        if(sum_of_var != 0) :
            #print(feature)
            pixel_data = mnist_temp.loc[:,feature].values.reshape(-1, 1)
            #print(pixel_data)
            model = LinearDiscriminantAnalysis()
            model.fit(pixel_data, mnist_label_temp.values.ravel())
            pixel_fisher_proj_data = model.transform(pixel_data)
            mnist_temp.loc[:,feature] = pixel_fisher_proj_data

    mnist_transformed = mnist_transformed.append(mnist_temp)

    #plot a sample image
    mnist_temp_sample = mnist_temp.sample(1)
    label = mnist_temp_sample.label
    pixels = mnist_temp_sample.iloc[:,1:]
    pixels = pixels.values.reshape((28, 28))

    # Plot image
    plt.title('Label is {label}'.format(label=label))
    plt.imshow(pixels, cmap='gray')
```

```
    plt.show()
```

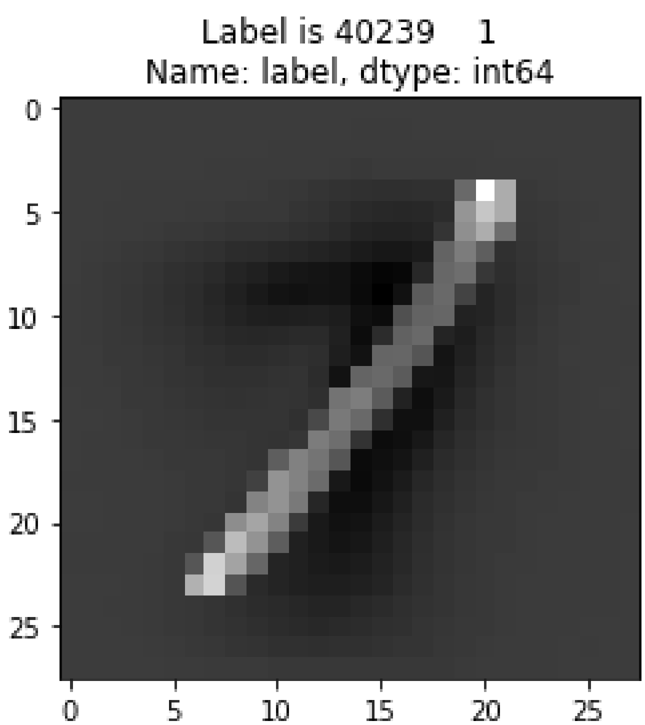
```
Running LDA on pair :  ('1', '0')
```



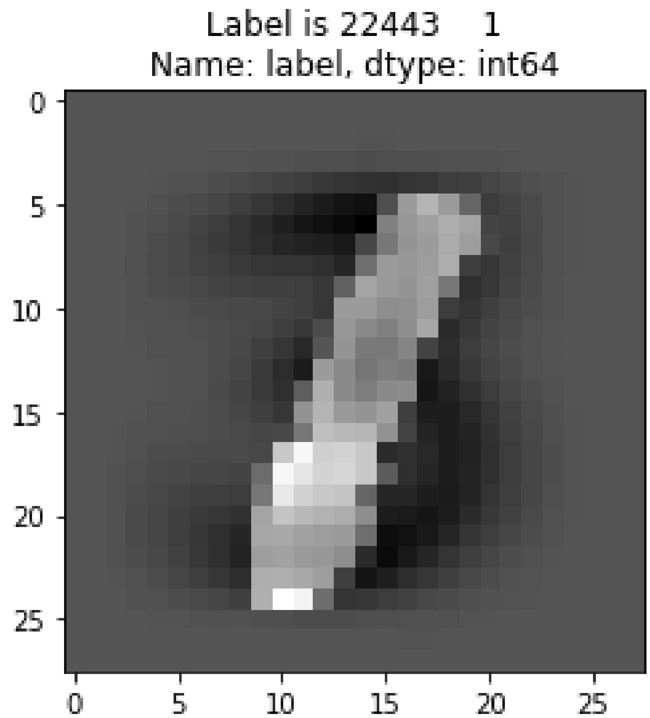

```
Running LDA on pair :  ('1', '4')
```



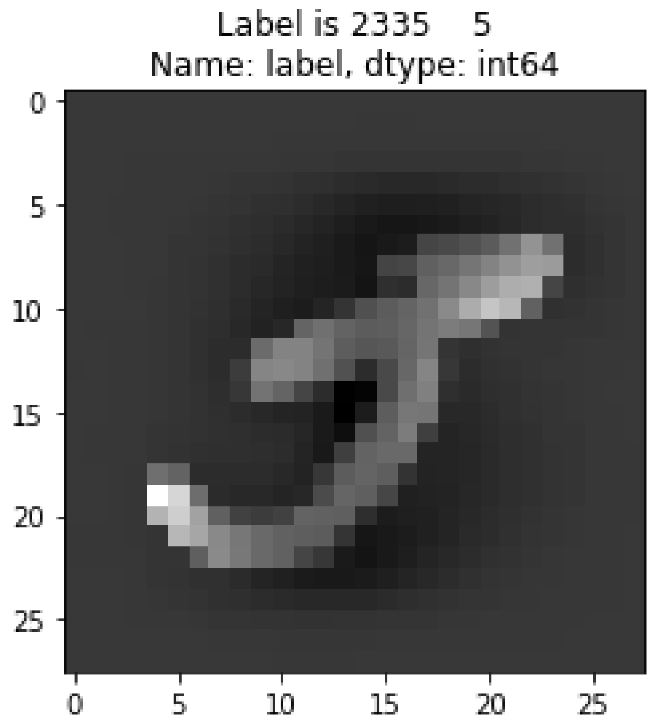

```
Running LDA on pair :  ('1', '7')
```



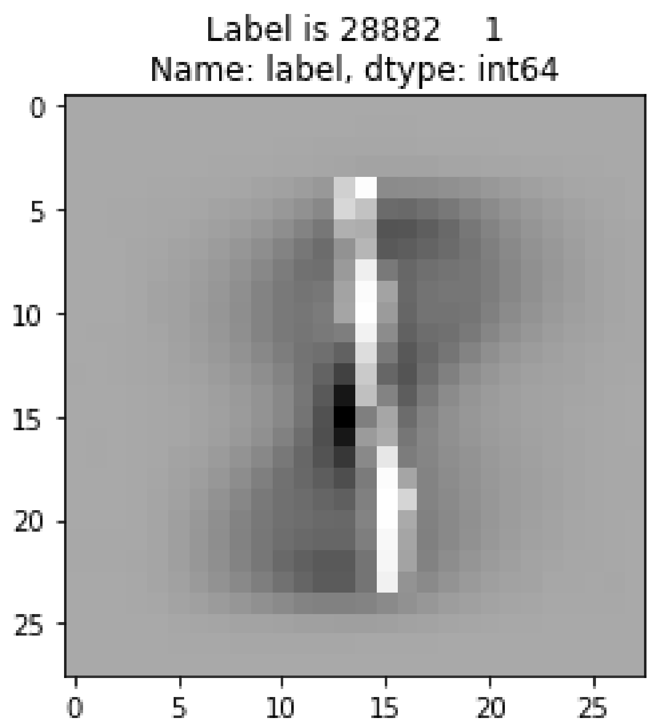
```
Running LDA on pair :  ('1', '3')
```



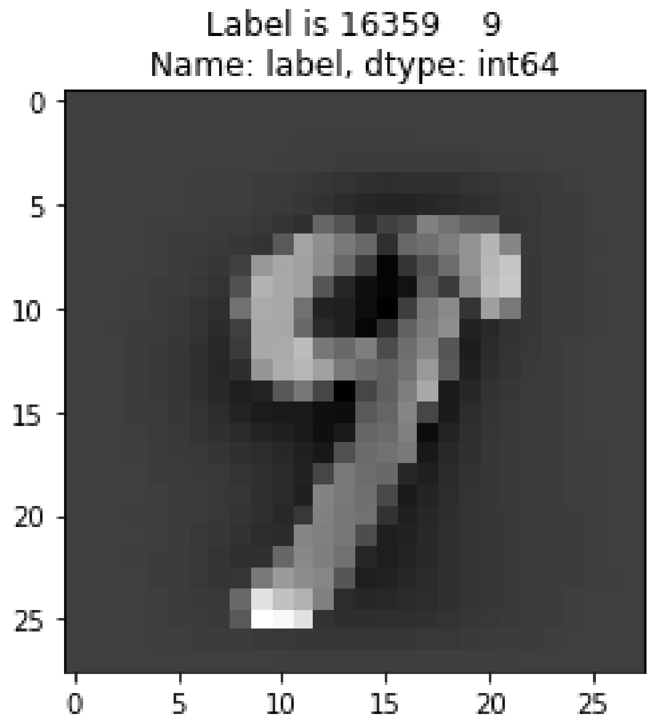

```
Running LDA on pair :  ('1', '5')
```



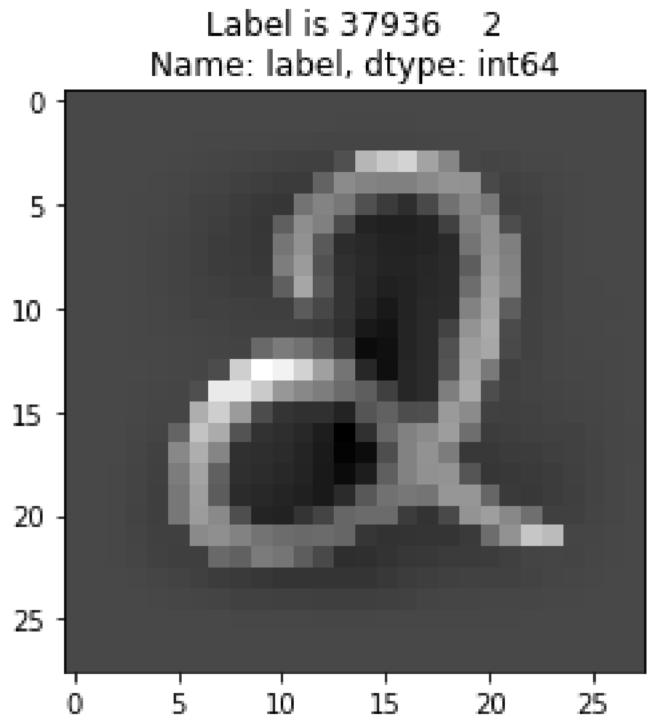
Running LDA on pair : ('1', '8')



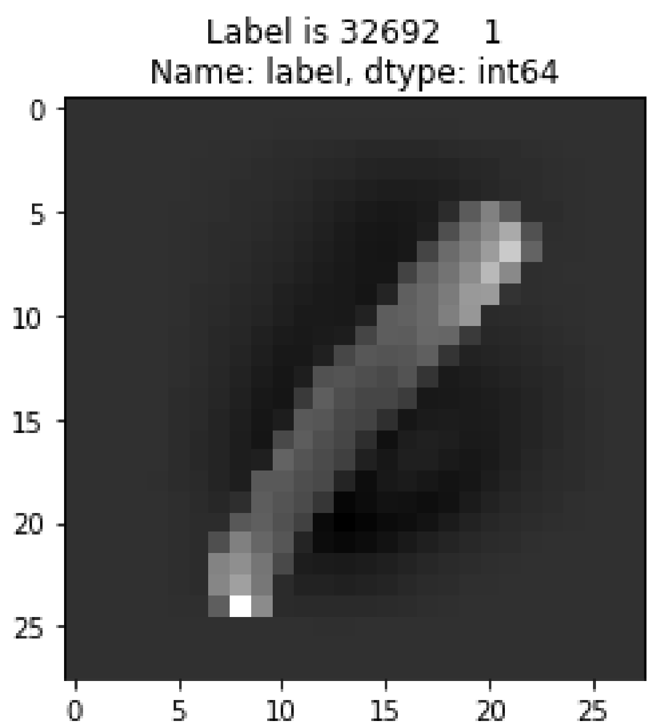
```
Running LDA on pair :  ('1', '9')
```



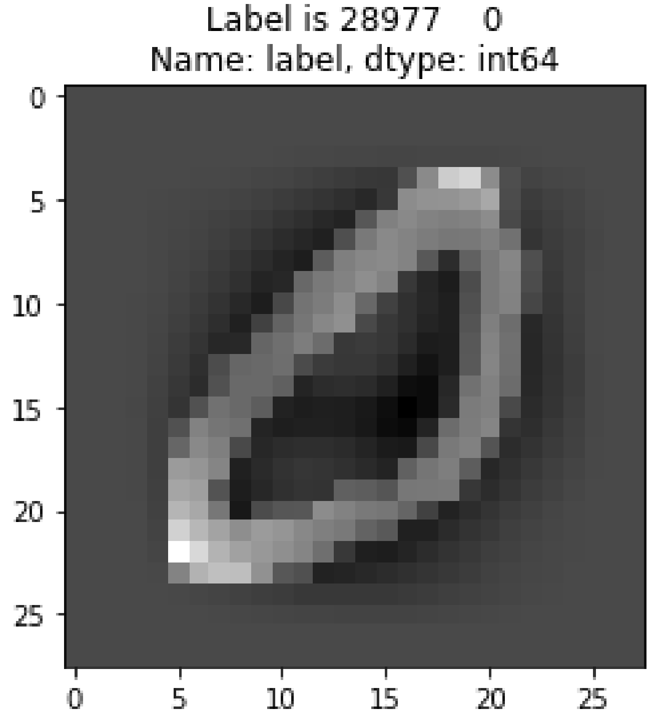

```
Running LDA on pair :  ('1', '2')
```



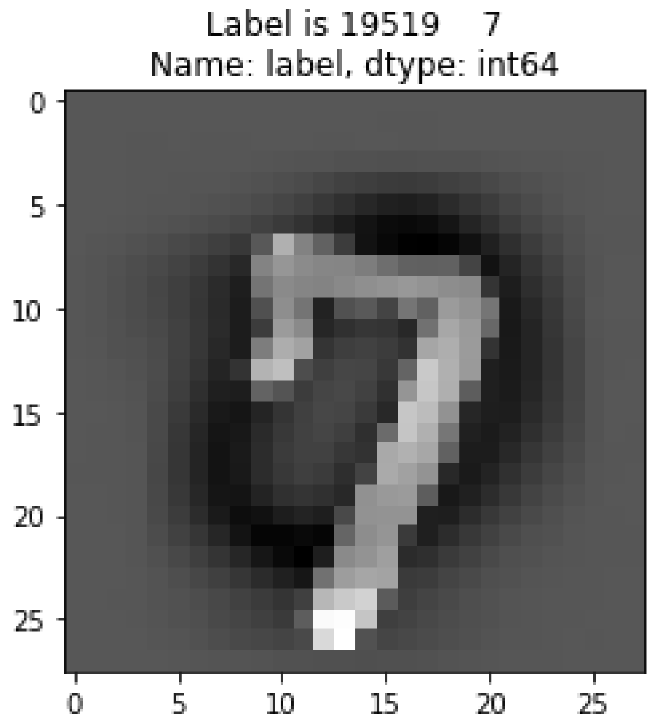

```
Running LDA on pair :  ('1', '6')
```



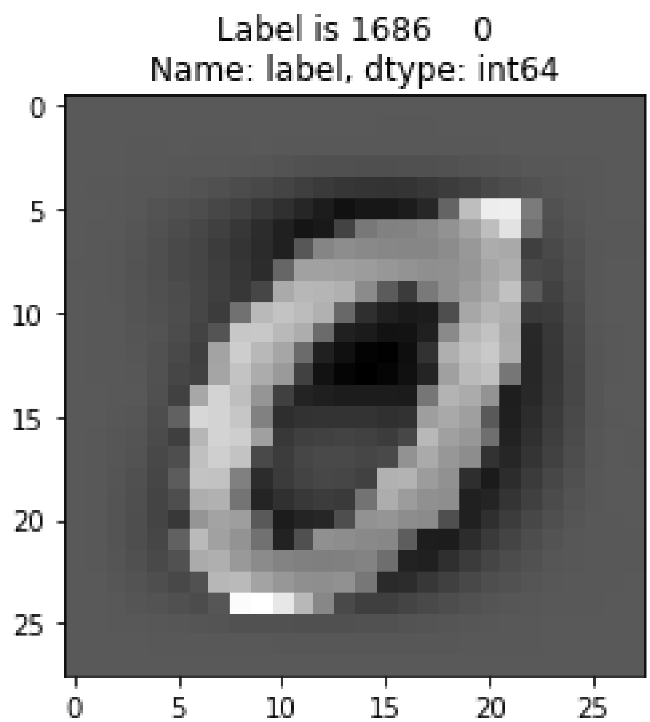
```
Running LDA on pair :  ('0', '4')
```



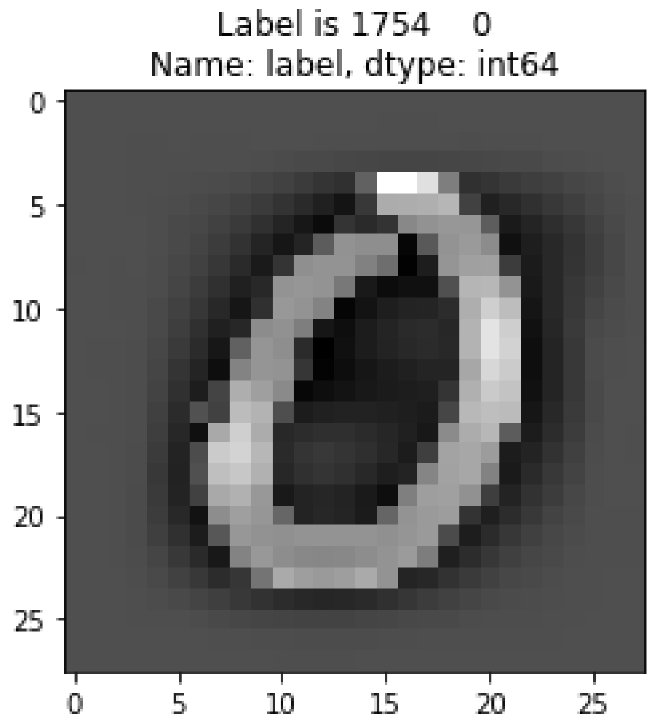

```
Running LDA on pair :  ('0', '7')
```



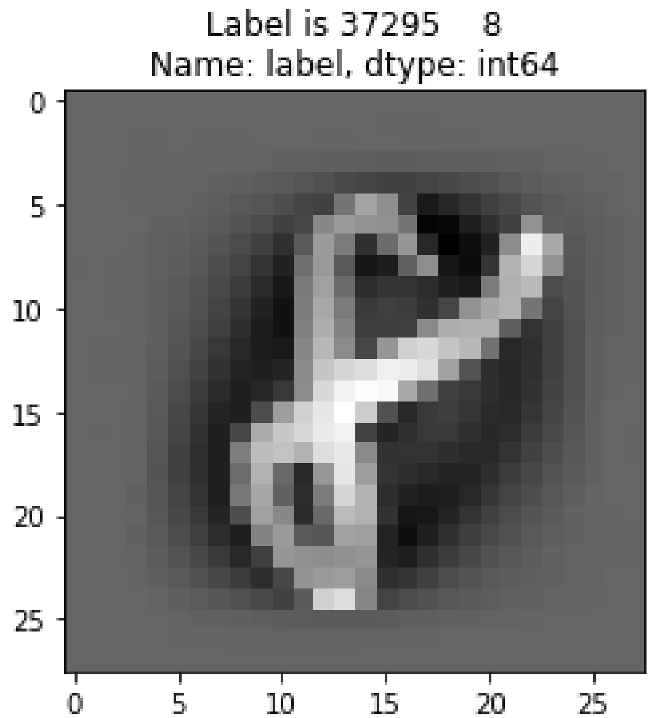
Running LDA on pair : ('0', '3')



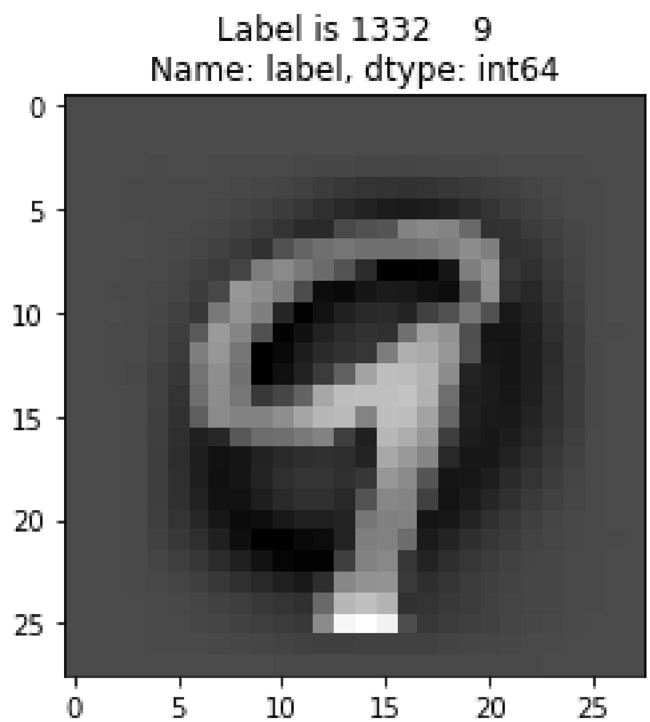
```
Running LDA on pair :  ('0', '5')
```



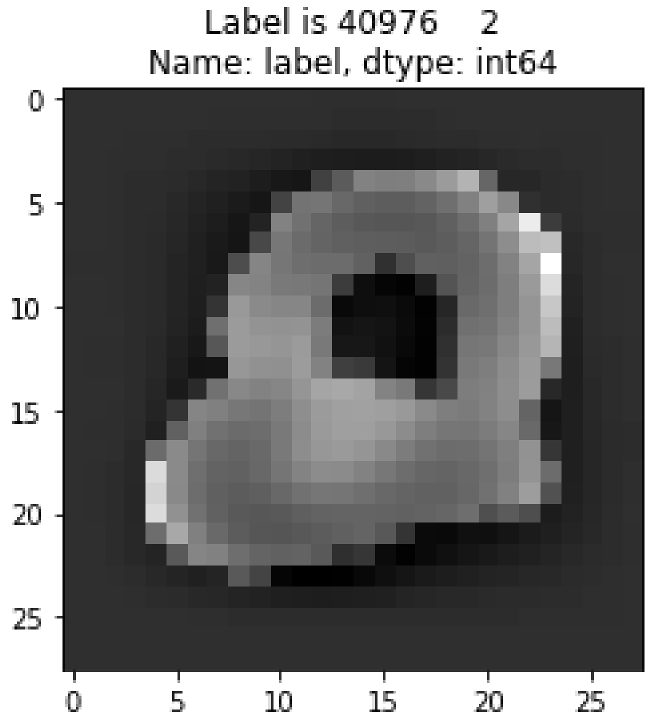

```
Running LDA on pair :  ('0', '8')
```



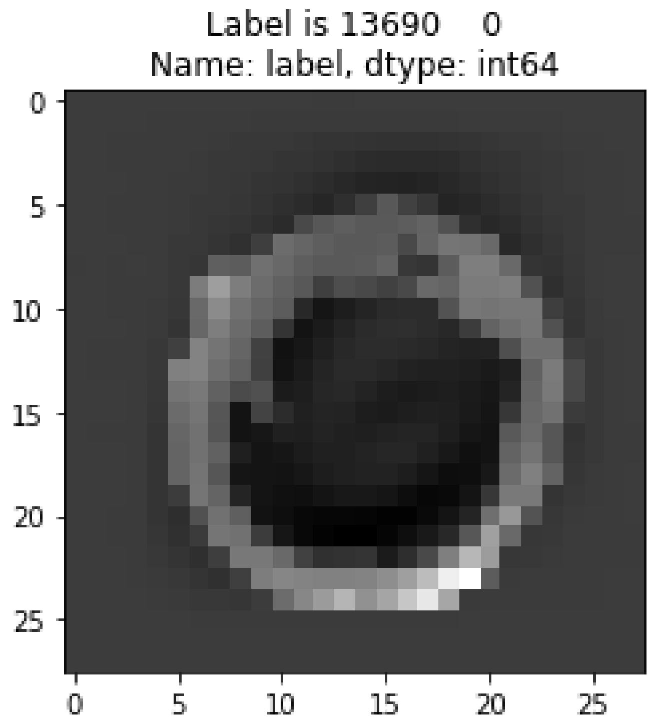

```
Running LDA on pair :  ('0', '9')
```



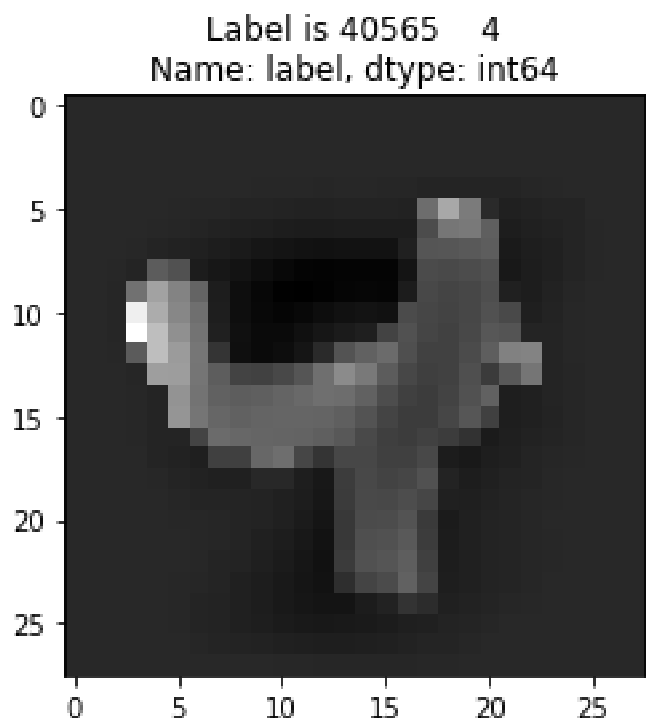
```
Running LDA on pair :  ('0', '2')
```



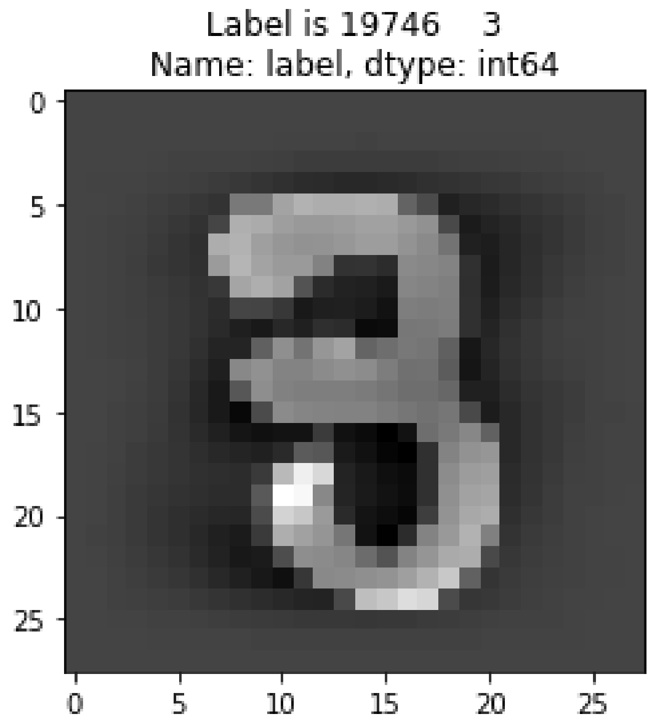

```
Running LDA on pair :  ('0', '6')
```



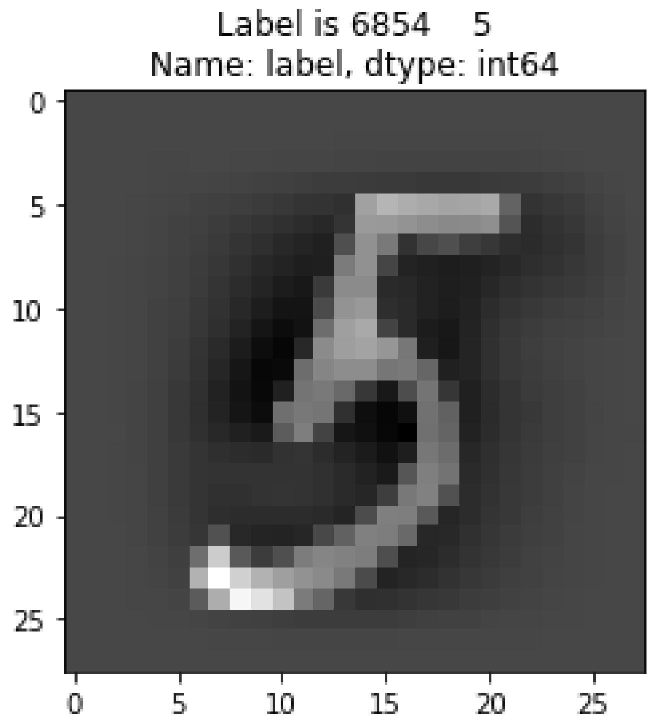

```
Running LDA on pair :  ('4', '7')
```



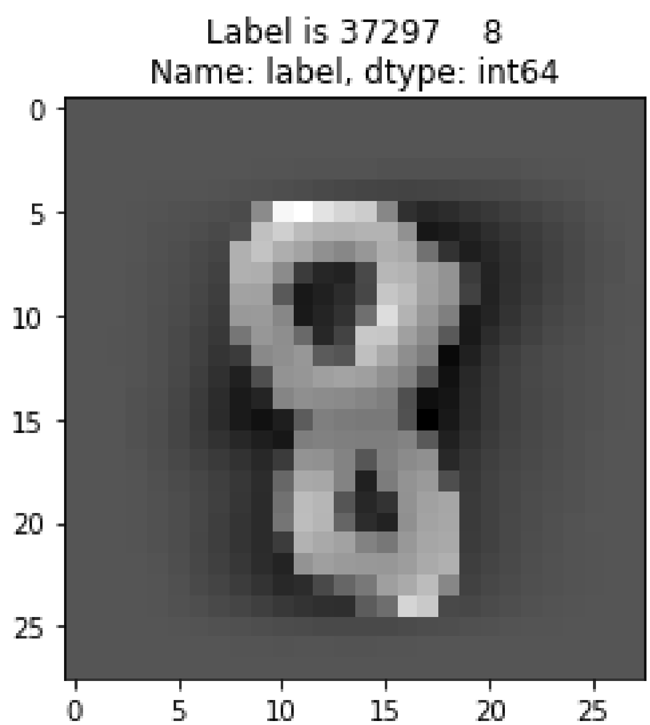
```
Running LDA on pair :  ('4', '3')
```



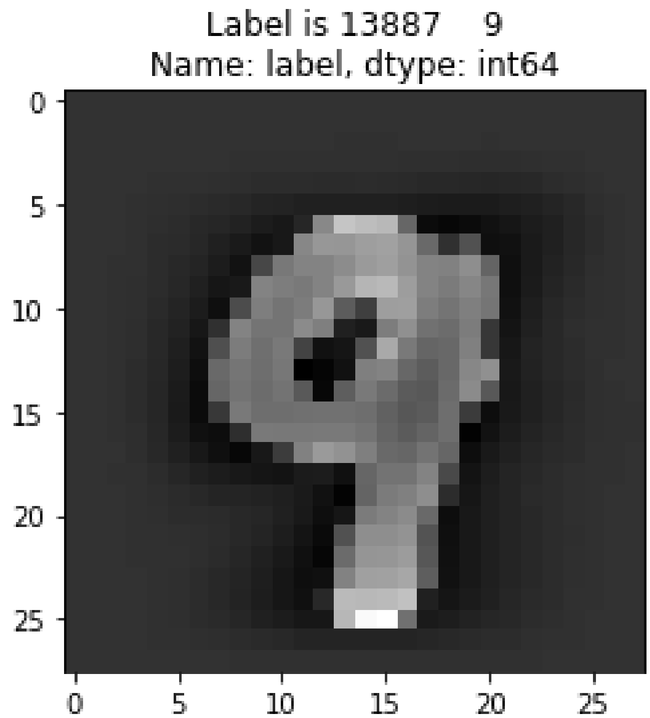

```
Running LDA on pair :  ('4', '5')
```



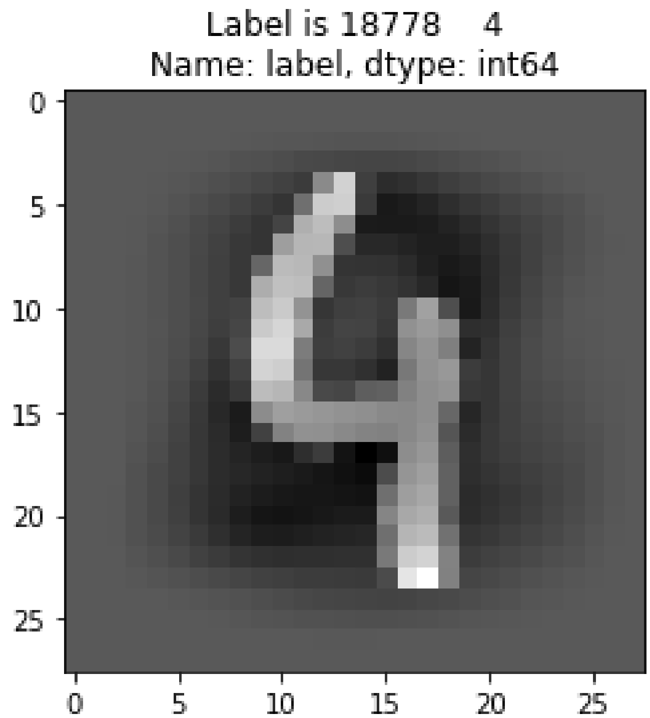

```
Running LDA on pair :  ('4', '8')
```



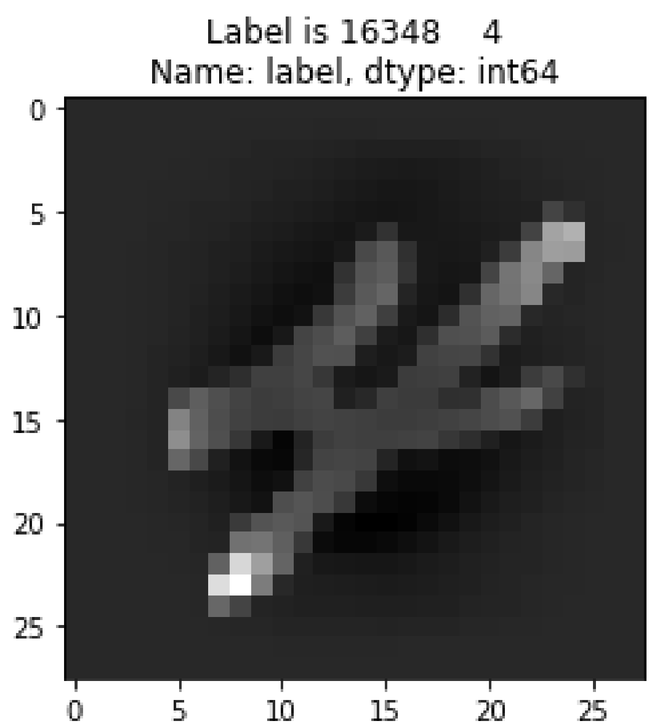
```
Running LDA on pair :  ('4', '9')
```



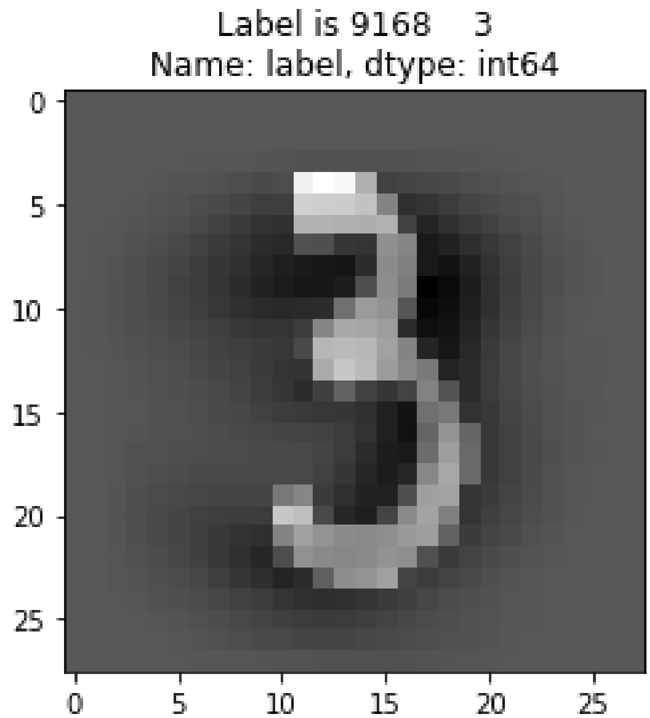

```
Running LDA on pair :  ('4', '2')
```



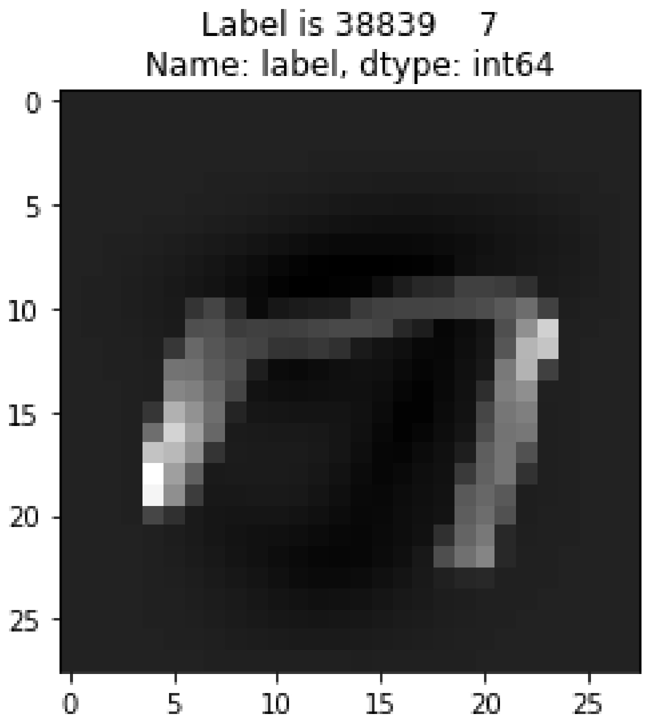
Running LDA on pair : ('4', '6')



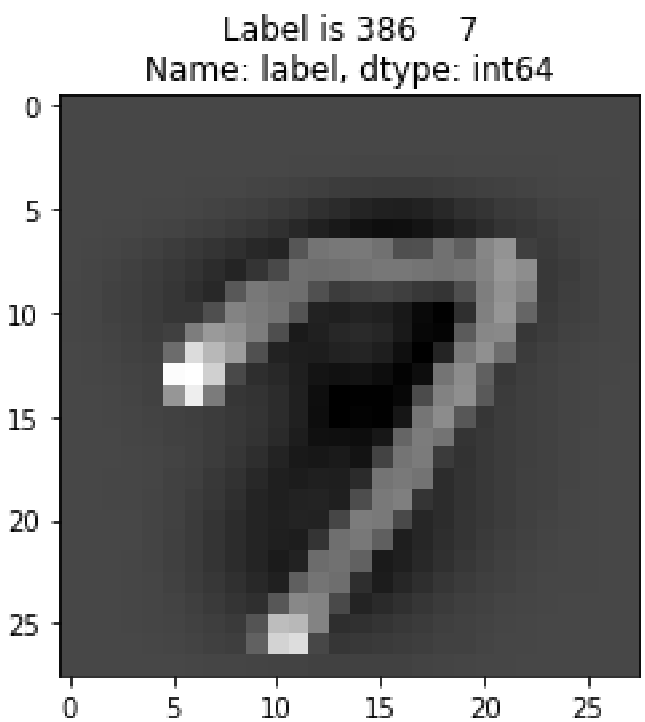
```
Running LDA on pair :  ('7', '3')
```



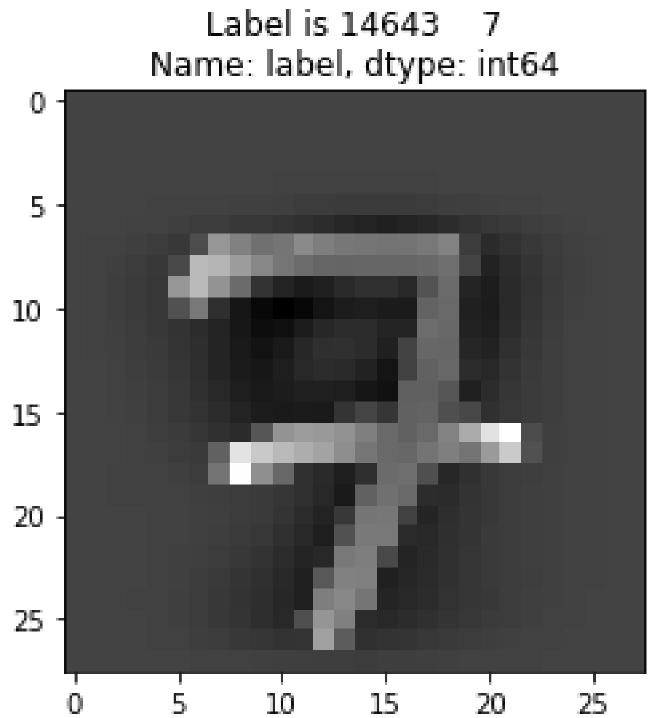

```
Running LDA on pair :  ('7', '5')
```



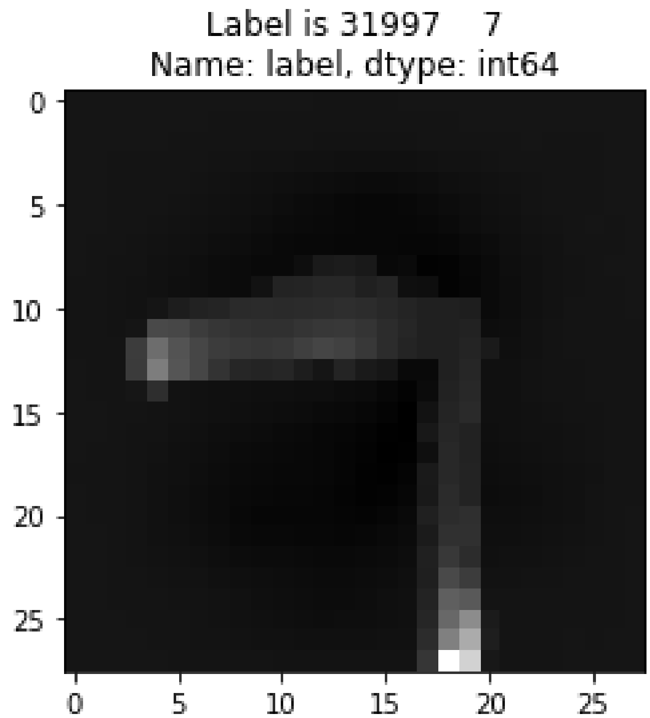

```
Running LDA on pair :  ('7', '8')
```



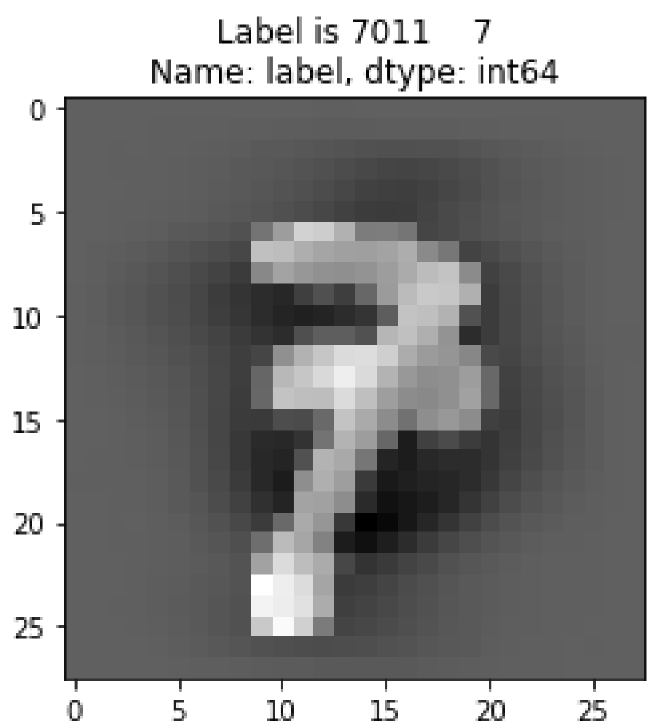
```
Running LDA on pair :  ('7', '9')
```



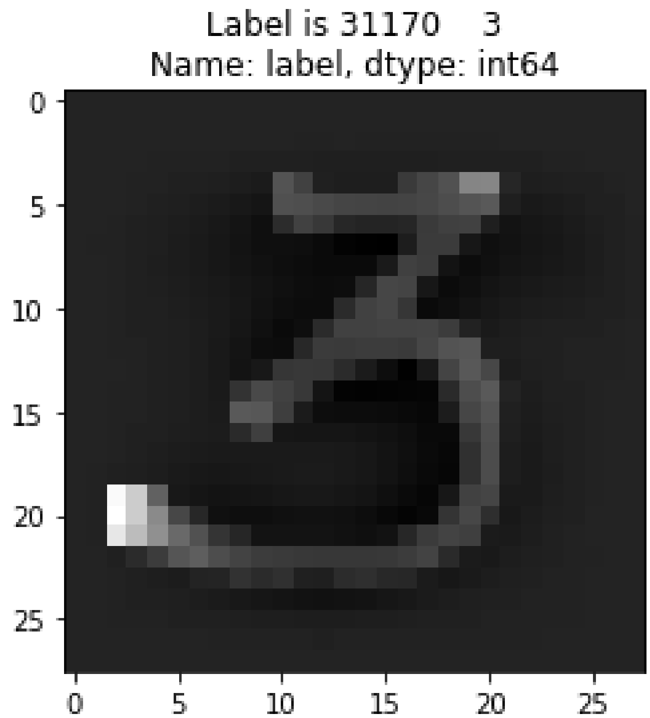

```
Running LDA on pair :  ('7', '2')
```



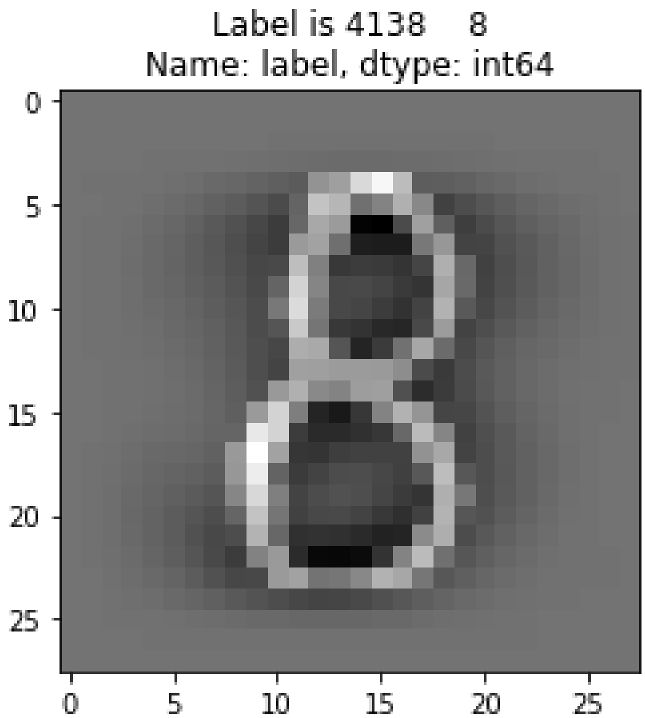

```
Running LDA on pair :  ('7', '6')
```



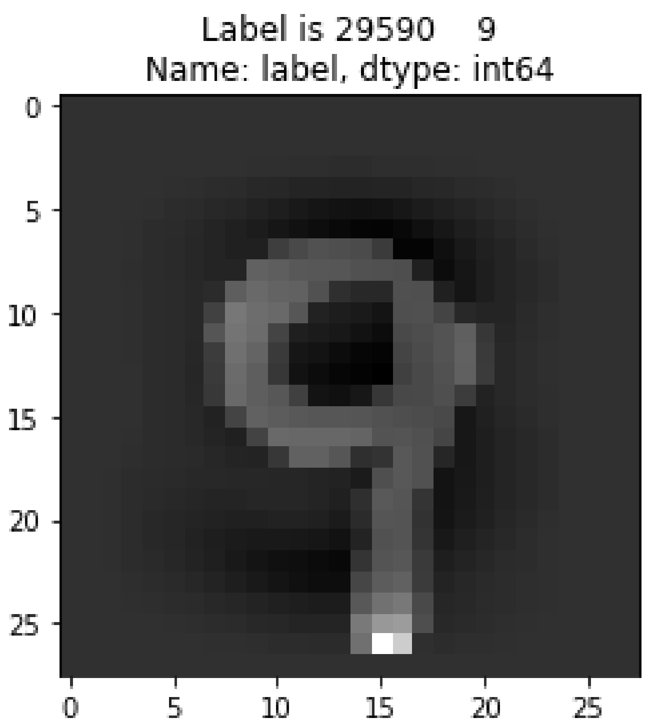
```
Running LDA on pair :  ('3', '5')
```



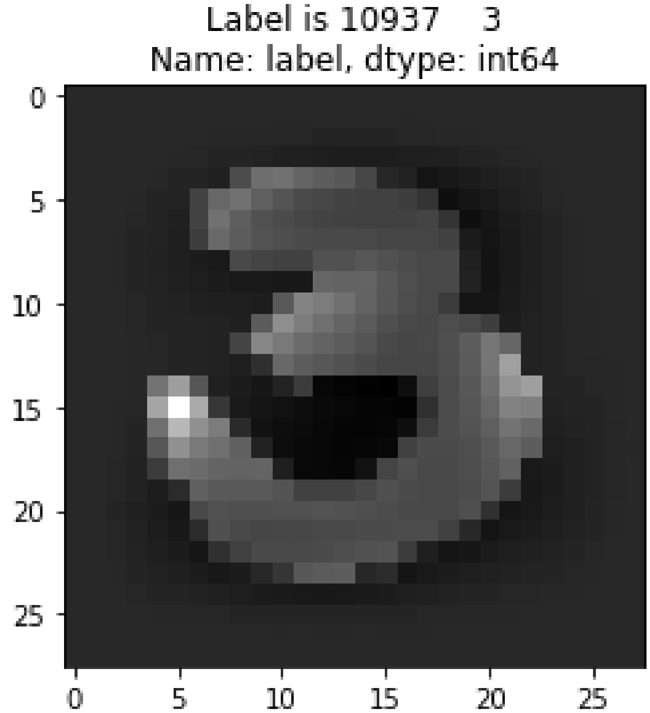

```
Running LDA on pair :  ('3', '8')
```



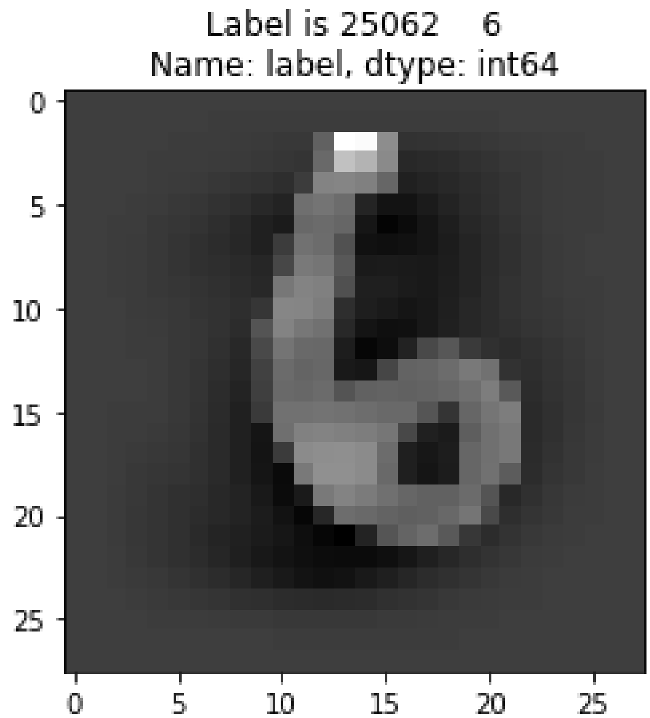

```
Running LDA on pair :  ('3', '9')
```



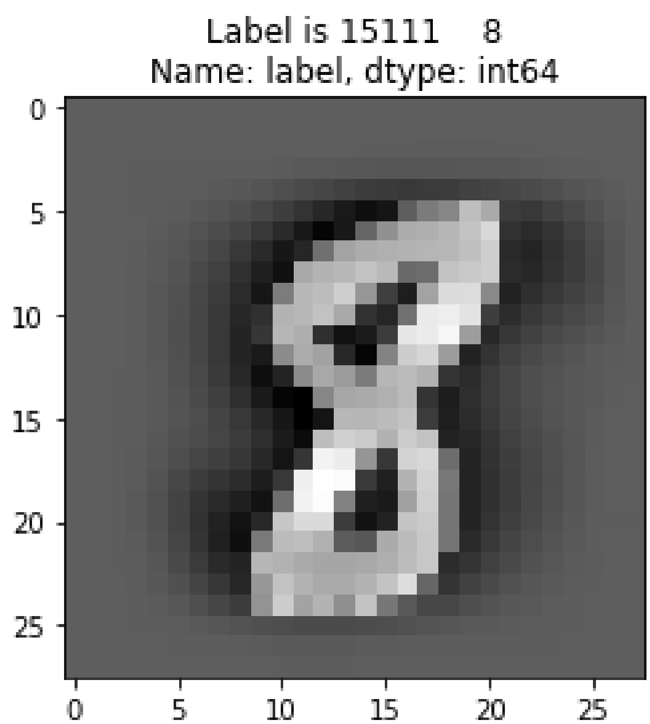
```
Running LDA on pair :  ('3', '2')
```



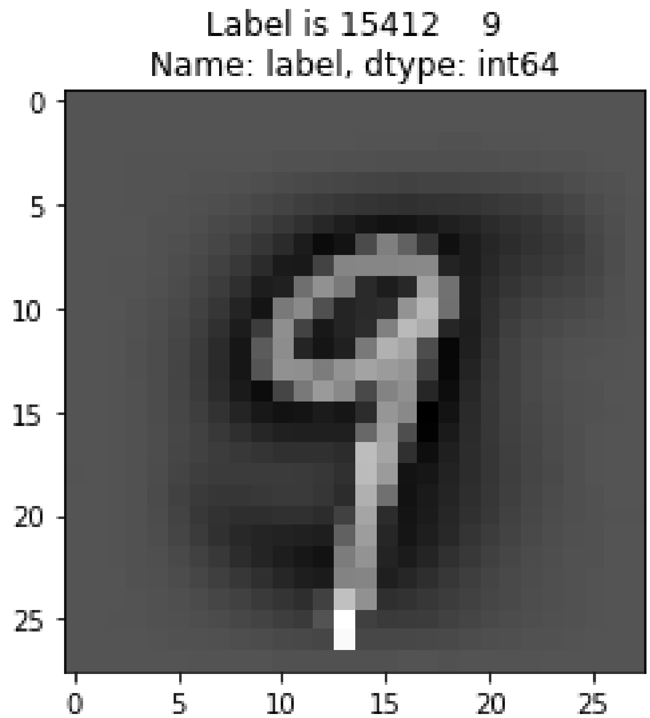

```
Running LDA on pair :  ('3', '6')
```



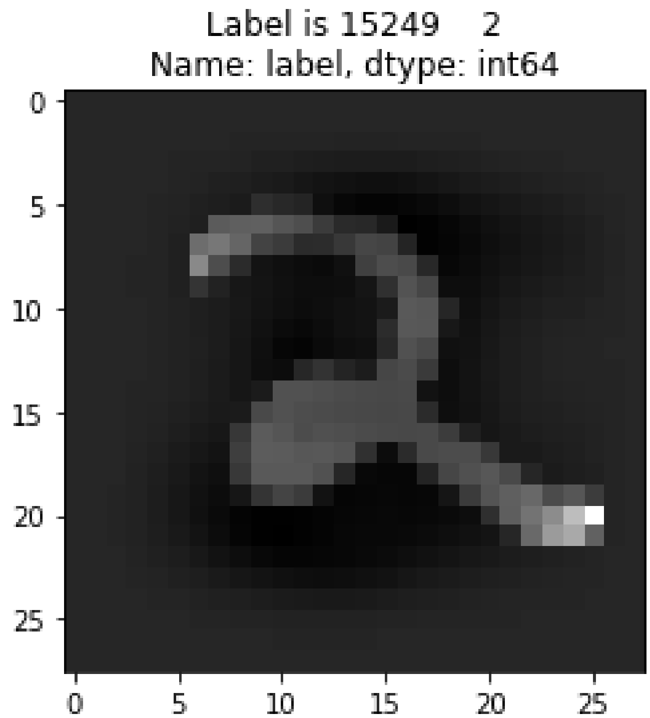

```
Running LDA on pair :  ('5', '8')
```



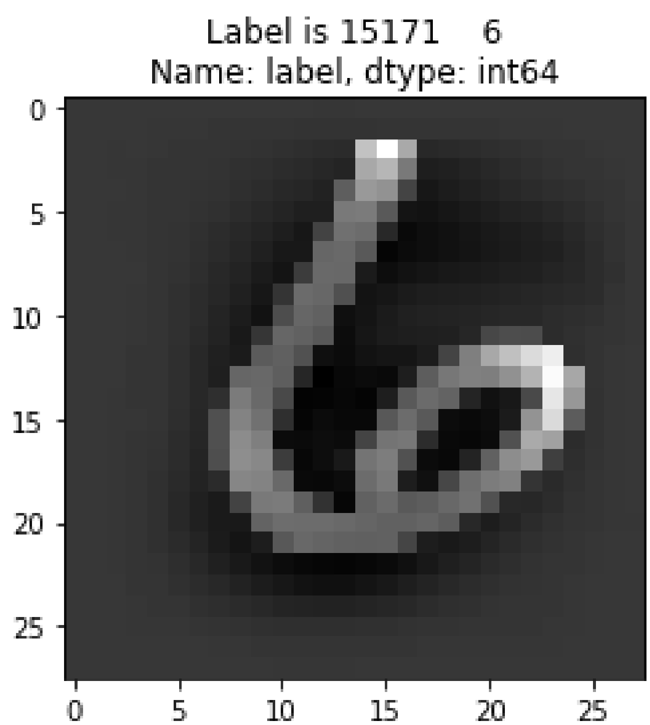
```
Running LDA on pair :  ('5', '9')
```



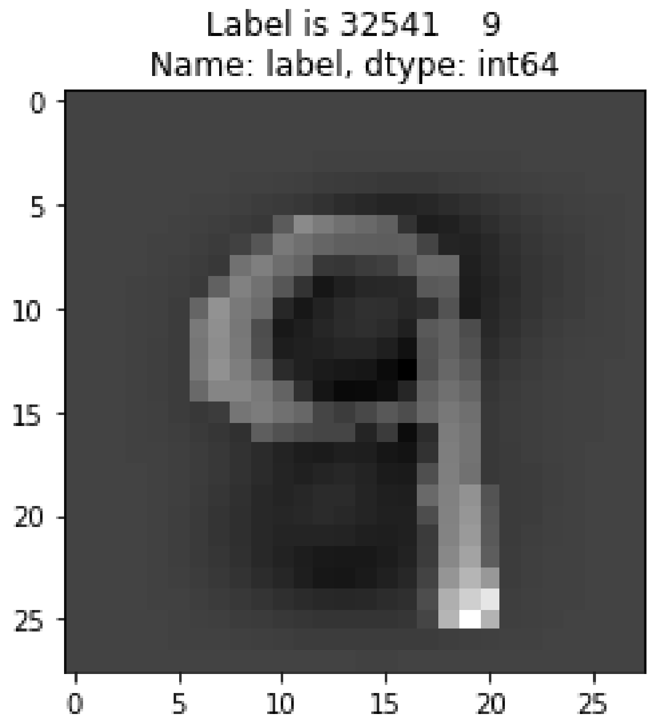

```
Running LDA on pair :  ('5', '2')
```



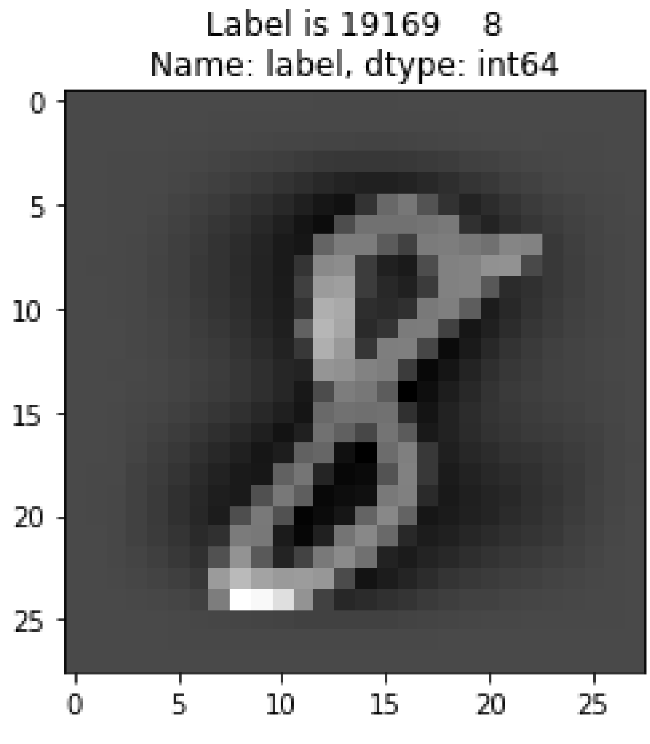

```
Running LDA on pair :  ('5', '6')
```



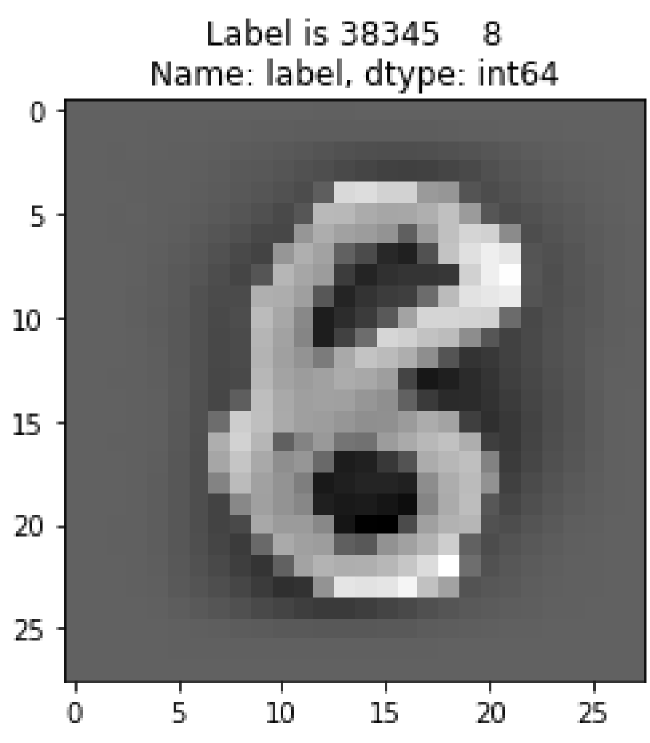
```
Running LDA on pair :  ('8', '9')
```



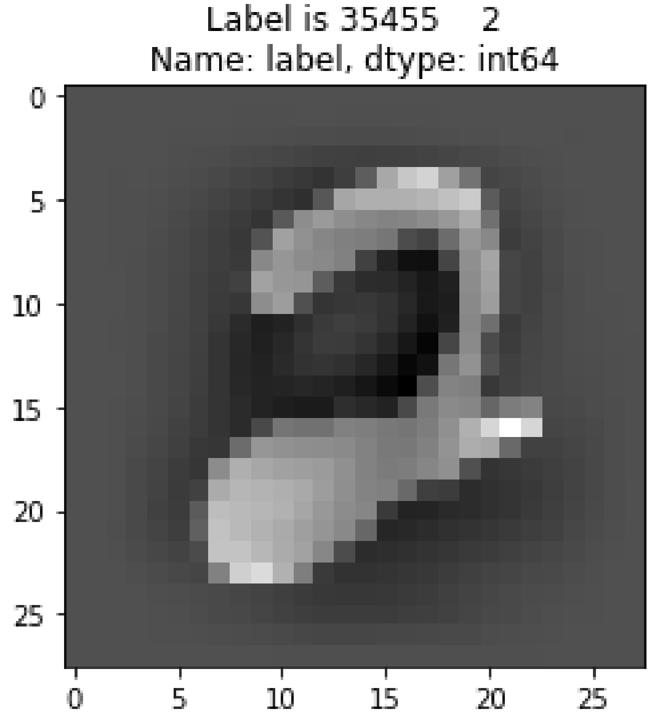

```
Running LDA on pair :  ('8', '2')
```



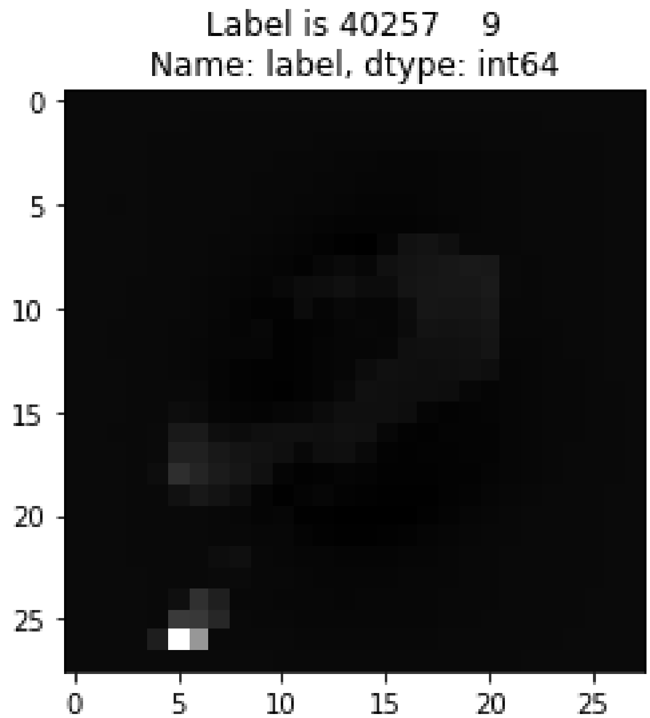

```
Running LDA on pair :  ('8', '6')
```



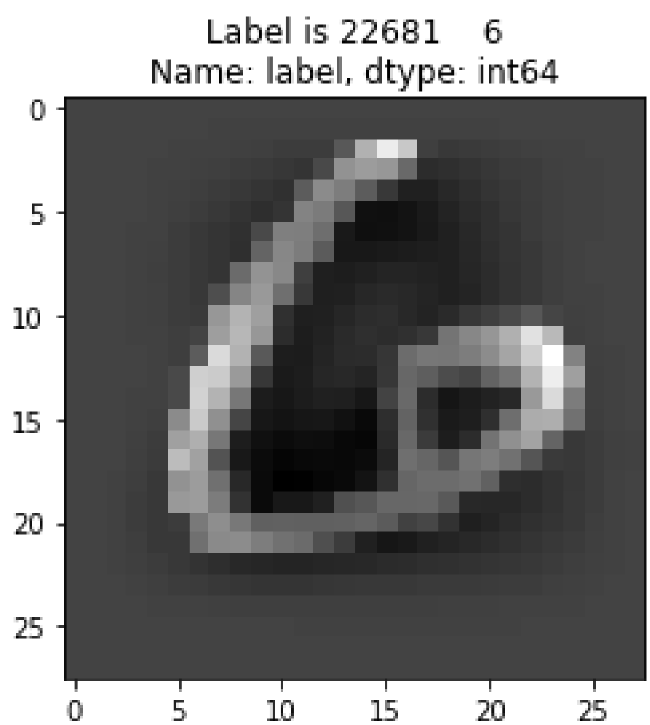
```
Running LDA on pair :  ('9', '2')
```




```
Running LDA on pair :  ('9', '6')
```




```
Running LDA on pair :  ('2', '6')
```



```
CPU times: user 19min 42s, sys: 6min 45s, total: 26min 27s
Wall time: 26min 45s
```

0.7.2 Comment on fisher discriminant for a few pairs of classes is learning to focus on different pixels in image

From above images we see that after fisher projection of pair of classes, the original class shows in foreground and and other class in pair goes in background with a little blur and darker background image

original image gets tilted positions in the angle of other class in pair

classes 0,2,3,5,8,9 dominate most images because they have overlapping whole area with most possible pairs

class pairs like (1,5), (7,5) resulted in complete black pixels because there is very minimal overlapping area between 5 and other numbers

class pairs like (9,2), (9,6) resulted in more grey pixels because there is very minimal overlapping area between 9 and 2 or 6 probably

Also, pairs which have comparable similar images like (1,7), (1,9) gets more white pixels in similar areas

[56]:
```
#Another way to visualize images, however matplot lib gives better images
from PIL import Image
import numpy as np

img = Image.fromarray(pixels, mode='L')
img.show()
```

0.8 P8 : Binary Heirarchical Classifier

Ref : - https://www.kaggle.com/nishan192/mnist-digit-recognition-using-svm

[57]:
```
mnist = pd.read_csv('DMG-2 Assignment Data Files/MNIST/train.csv')

#convert labels to strings, as we will have combined class names going forward␣
↪for tree building
mnist.label = mnist.label.apply(str)
#print(mnist.sample(5))
```

```
mnist_data = mnist.loc[:, mnist.columns != 'label']
mnist_label = mnist.loc[:, mnist.columns == 'label']
```

[58]:
```
#create pair of unique sets
def get_class_pairs(target_names):
    pairs = list(itertools.combinations(target_names, 2))
    return pairs
```

Steps followed :

Step 1 : Create all unique combination of pairs for all classes in data. Initially it will have 45 pairs for 10 set of classes

Step 2 : Run SVD for each pair of classes and get train and test set accuracy. Start with setting up highest accuracy as 100.

Step 3 : If test set accuracy is less than 100, choose that pair of classes being marked as lower accuracy.

Step 4 : Continue finding lowest accuracy pair, till all pairs are exhausted in current iteration. Also keep printing values if lower accuracy is found.

Step 5 : At end of iteration, pair with least accuracy is combined and mnist data is relabeled

Step 6 : Repeat Step 1-4, till no. of classes left in data is just 1.

[59]:
```
%%time

from sklearn.preprocessing import scale
from sklearn.svm import SVC

#mnist = mnist[(mnist.label == '1') | (mnist.label == '2') | (mnist.label ==␣
↪'3')]

#initially total classes will be 10 and pairs will be 45
target_names = pd.Series(mnist.label.unique())
pairs = get_class_pairs(target_names)
no_of_classes = target_names.shape[0]

# Consider first pair as minimum accuracy level to start with
lowest_acc_first_class = pairs[0][0]
lowest_acc_sec_class = pairs[0][1]

#define dataframe to store least accuracy classes in each iteration
df = pd.DataFrame(columns=['First Class', 'Second Class', 'Train Accuracy',␣
↪'Test Accuracy'])

print("Available class labels : ", target_names.values)
print()
```

```
while no_of_classes > 1 :
    highest_accuracy = 100
    print('................ Start with available class labels ................')
    print()
    print("All pairs in current iteration : ", pairs)
    for pair in pairs :
        first_class_in_pair = pair[0]
        second_class_in_pair = pair[1]
        mnist_temp = mnist[(mnist.label == first_class_in_pair) | (mnist.label␣
 ↪== second_class_in_pair)]
        #print(mnist_temp.shape)

        X = mnist_temp.loc[:, mnist_temp.columns != 'label'].astype(float)
        y = mnist_temp.loc[:, mnist_temp.columns == 'label']

        # feature scaling
        X_scaled = scale(X)
        # train test split
        X_train, X_test, y_train, y_test = train_test_split(X_scaled, y,␣
 ↪test_size = 0.2, random_state = 11915043)

        # linear SVM classifier
        model_linear_svm = SVC(kernel='linear')
        model_linear_svm.fit(X_train, y_train.values.ravel())
        train_accuracy = round(metrics.accuracy_score(y_true=y_train,␣
 ↪y_pred=model_linear_svm.predict(X_train)),3)
        y_pred = model_linear_svm.predict(X_test)
        test_accuracy = round(metrics.accuracy_score(y_true=y_test,␣
 ↪y_pred=y_pred),3)
        if(test_accuracy < highest_accuracy) :
            lowest_acc_first_class = first_class_in_pair
            lowest_acc_sec_class = second_class_in_pair
            highest_accuracy = test_accuracy
            print("Pair with lower accuracy in current iteration : (", pair[0],␣
 ↪"," , pair[1], "), ",
                  "Train accuracy : ", train_accuracy, ", Test Accuracy : "␣
 ↪,test_accuracy)

    df = df.append({'First Class':lowest_acc_first_class, 'Second Class' :
 ↪lowest_acc_sec_class,
                'Train Accuracy':train_accuracy, 'Test Accuracy':test_accuracy},␣
 ↪ignore_index=True)

    #Now, update the class labels
    updated_class_label = lowest_acc_first_class + '_' + lowest_acc_sec_class
    mnist.loc[(mnist.label == lowest_acc_first_class) |
```

```
            (mnist.label == lowest_acc_sec_class), 'label'] =␣
↪updated_class_label
    target_names = pd.Series(mnist.label.unique())
    no_of_classes = target_names.shape[0]
    print("Done with iteration, Updated class labels : ", target_names.values)
    print()
    pairs = get_class_pairs(target_names)
```

```
Available class labels :  ['1' '0' '4' '7' '3' '5' '8' '9' '2' '6']

… Start with available class labels …

All pairs in current iteration :  [('1', '0'), ('1', '4'), ('1', '7'), ('1',
'3'), ('1', '5'), ('1', '8'), ('1', '9'), ('1', '2'), ('1', '6'), ('0', '4'),
('0', '7'), ('0', '3'), ('0', '5'), ('0', '8'), ('0', '9'), ('0', '2'), ('0',
'6'), ('4', '7'), ('4', '3'), ('4', '5'), ('4', '8'), ('4', '9'), ('4', '2'),
('4', '6'), ('7', '3'), ('7', '5'), ('7', '8'), ('7', '9'), ('7', '2'), ('7',
'6'), ('3', '5'), ('3', '8'), ('3', '9'), ('3', '2'), ('3', '6'), ('5', '8'),
('5', '9'), ('5', '2'), ('5', '6'), ('8', '9'), ('8', '2'), ('8', '6'), ('9',
'2'), ('9', '6'), ('2', '6')]
Pair with lower accuracy in current iteration : ( 1 , 0 ),  Train accuracy :
1.0 , Test Accuracy :  0.998
Pair with lower accuracy in current iteration : ( 1 , 4 ),  Train accuracy :
1.0 , Test Accuracy :  0.997
Pair with lower accuracy in current iteration : ( 1 , 7 ),  Train accuracy :
1.0 , Test Accuracy :  0.995
Pair with lower accuracy in current iteration : ( 1 , 3 ),  Train accuracy :
1.0 , Test Accuracy :  0.988
Pair with lower accuracy in current iteration : ( 1 , 8 ),  Train accuracy :
1.0 , Test Accuracy :  0.979
Pair with lower accuracy in current iteration : ( 4 , 9 ),  Train accuracy :
0.996 , Test Accuracy :  0.959
Pair with lower accuracy in current iteration : ( 7 , 9 ),  Train accuracy :
0.988 , Test Accuracy :  0.954
Pair with lower accuracy in current iteration : ( 3 , 5 ),  Train accuracy :
0.991 , Test Accuracy :  0.942
Pair with lower accuracy in current iteration : ( 5 , 8 ),  Train accuracy :
0.996 , Test Accuracy :  0.939
Done with iteration, Updated class labels :  ['1' '0' '4' '7' '3' '5_8' '9' '2'
'6']

… Start with available class labels …

All pairs in current iteration :  [('1', '0'), ('1', '4'), ('1', '7'), ('1',
'3'), ('1', '5_8'), ('1', '9'), ('1', '2'), ('1', '6'), ('0', '4'), ('0', '7'),
('0', '3'), ('0', '5_8'), ('0', '9'), ('0', '2'), ('0', '6'), ('4', '7'), ('4',
'3'), ('4', '5_8'), ('4', '9'), ('4', '2'), ('4', '6'), ('7', '3'), ('7',
```

```
'5_8'), ('7', '9'), ('7', '2'), ('7', '6'), ('3', '5_8'), ('3', '9'), ('3',
'2'), ('3', '6'), ('5_8', '9'), ('5_8', '2'), ('5_8', '6'), ('9', '2'), ('9',
'6'), ('2', '6')]
Pair with lower accuracy in current iteration : ( 1 , 0 ),  Train accuracy :
1.0 , Test Accuracy :  0.998
Pair with lower accuracy in current iteration : ( 1 , 4 ),  Train accuracy :
1.0 , Test Accuracy :  0.997
Pair with lower accuracy in current iteration : ( 1 , 7 ),  Train accuracy :
1.0 , Test Accuracy :  0.995
Pair with lower accuracy in current iteration : ( 1 , 3 ),  Train accuracy :
1.0 , Test Accuracy :  0.988
Pair with lower accuracy in current iteration : ( 1 , 5_8 ),  Train accuracy :
1.0 , Test Accuracy :  0.972
Pair with lower accuracy in current iteration : ( 4 , 9 ),  Train accuracy :
0.996 , Test Accuracy :  0.959
Pair with lower accuracy in current iteration : ( 7 , 9 ),  Train accuracy :
0.988 , Test Accuracy :  0.954
Pair with lower accuracy in current iteration : ( 3 , 5_8 ),  Train accuracy :
0.969 , Test Accuracy :  0.944
Done with iteration, Updated class labels :  ['1' '0' '4' '7' '3_5_8' '9' '2'
'6']

… Start with available class labels …

All pairs in current iteration :  [('1', '0'), ('1', '4'), ('1', '7'), ('1',
'3_5_8'), ('1', '9'), ('1', '2'), ('1', '6'), ('0', '4'), ('0', '7'), ('0',
'3_5_8'), ('0', '9'), ('0', '2'), ('0', '6'), ('4', '7'), ('4', '3_5_8'), ('4',
'9'), ('4', '2'), ('4', '6'), ('7', '3_5_8'), ('7', '9'), ('7', '2'), ('7',
'6'), ('3_5_8', '9'), ('3_5_8', '2'), ('3_5_8', '6'), ('9', '2'), ('9', '6'),
('2', '6')]
Pair with lower accuracy in current iteration : ( 1 , 0 ),  Train accuracy :
1.0 , Test Accuracy :  0.998
Pair with lower accuracy in current iteration : ( 1 , 4 ),  Train accuracy :
1.0 , Test Accuracy :  0.997
Pair with lower accuracy in current iteration : ( 1 , 7 ),  Train accuracy :
1.0 , Test Accuracy :  0.995
Pair with lower accuracy in current iteration : ( 1 , 3_5_8 ),  Train accuracy :
1.0 , Test Accuracy :  0.98
Pair with lower accuracy in current iteration : ( 0 , 3_5_8 ),  Train accuracy :
1.0 , Test Accuracy :  0.977
Pair with lower accuracy in current iteration : ( 4 , 9 ),  Train accuracy :
0.996 , Test Accuracy :  0.959
Pair with lower accuracy in current iteration : ( 7 , 9 ),  Train accuracy :
0.988 , Test Accuracy :  0.954
Done with iteration, Updated class labels :  ['1' '0' '4' '7_9' '3_5_8' '2' '6']

… Start with available class labels …
```

```
All pairs in current iteration :  [('1', '0'), ('1', '4'), ('1', '7_9'), ('1',
'3_5_8'), ('1', '2'), ('1', '6'), ('0', '4'), ('0', '7_9'), ('0', '3_5_8'),
('0', '2'), ('0', '6'), ('4', '7_9'), ('4', '3_5_8'), ('4', '2'), ('4', '6'),
('7_9', '3_5_8'), ('7_9', '2'), ('7_9', '6'), ('3_5_8', '2'), ('3_5_8', '6'),
('2', '6')]
Pair with lower accuracy in current iteration : ( 1 , 0 ),  Train accuracy :
1.0 , Test Accuracy :  0.998
Pair with lower accuracy in current iteration : ( 1 , 4 ),  Train accuracy :
1.0 , Test Accuracy :  0.997
Pair with lower accuracy in current iteration : ( 1 , 7_9 ),  Train accuracy :
1.0 , Test Accuracy :  0.994
Pair with lower accuracy in current iteration : ( 1 , 3_5_8 ),  Train accuracy :
1.0 , Test Accuracy :  0.98
Pair with lower accuracy in current iteration : ( 0 , 3_5_8 ),  Train accuracy :
1.0 , Test Accuracy :  0.977
Pair with lower accuracy in current iteration : ( 4 , 7_9 ),  Train accuracy :
0.993 , Test Accuracy :  0.962
Pair with lower accuracy in current iteration : ( 3_5_8 , 2 ),  Train accuracy :
0.985 , Test Accuracy :  0.956
Done with iteration, Updated class labels :  ['1' '0' '4' '7_9' '3_5_8_2' '6']

… Start with available class labels …

All pairs in current iteration :  [('1', '0'), ('1', '4'), ('1', '7_9'), ('1',
'3_5_8_2'), ('1', '6'), ('0', '4'), ('0', '7_9'), ('0', '3_5_8_2'), ('0', '6'),
('4', '7_9'), ('4', '3_5_8_2'), ('4', '6'), ('7_9', '3_5_8_2'), ('7_9', '6'),
('3_5_8_2', '6')]
Pair with lower accuracy in current iteration : ( 1 , 0 ),  Train accuracy :
1.0 , Test Accuracy :  0.998
Pair with lower accuracy in current iteration : ( 1 , 4 ),  Train accuracy :
1.0 , Test Accuracy :  0.997
Pair with lower accuracy in current iteration : ( 1 , 7_9 ),  Train accuracy :
1.0 , Test Accuracy :  0.994
Pair with lower accuracy in current iteration : ( 1 , 3_5_8_2 ),  Train accuracy
:  0.998 , Test Accuracy :  0.985
Pair with lower accuracy in current iteration : ( 0 , 3_5_8_2 ),  Train accuracy
:  0.998 , Test Accuracy :  0.983
Pair with lower accuracy in current iteration : ( 4 , 7_9 ),  Train accuracy :
0.993 , Test Accuracy :  0.962
Done with iteration, Updated class labels :  ['1' '0' '4_7_9' '3_5_8_2' '6']

… Start with available class labels …

All pairs in current iteration :  [('1', '0'), ('1', '4_7_9'), ('1', '3_5_8_2'),
('1', '6'), ('0', '4_7_9'), ('0', '3_5_8_2'), ('0', '6'), ('4_7_9', '3_5_8_2'),
('4_7_9', '6'), ('3_5_8_2', '6')]
Pair with lower accuracy in current iteration : ( 1 , 0 ),  Train accuracy :
1.0 , Test Accuracy :  0.998
```

```
Pair with lower accuracy in current iteration : ( 1 , 4_7_9 ),  Train accuracy :
1.0 , Test Accuracy :  0.993
Pair with lower accuracy in current iteration : ( 1 , 3_5_8_2 ),  Train accuracy
:  0.998 , Test Accuracy :  0.985
Pair with lower accuracy in current iteration : ( 0 , 3_5_8_2 ),  Train accuracy
:  0.998 , Test Accuracy :  0.983
Pair with lower accuracy in current iteration : ( 4_7_9 , 3_5_8_2 ),  Train
accuracy :  0.981 , Test Accuracy :  0.972
Done with iteration, Updated class labels :  ['1' '0' '4_7_9_3_5_8_2' '6']

… Start with available class labels …

All pairs in current iteration :  [('1', '0'), ('1', '4_7_9_3_5_8_2'), ('1',
'6'), ('0', '4_7_9_3_5_8_2'), ('0', '6'), ('4_7_9_3_5_8_2', '6')]
Pair with lower accuracy in current iteration : ( 1 , 0 ),  Train accuracy :
1.0 , Test Accuracy :  0.998
Pair with lower accuracy in current iteration : ( 1 , 4_7_9_3_5_8_2 ),  Train
accuracy :  0.997 , Test Accuracy :  0.987
Pair with lower accuracy in current iteration : ( 0 , 6 ),  Train accuracy :
1.0 , Test Accuracy :  0.985
Pair with lower accuracy in current iteration : ( 4_7_9_3_5_8_2 , 6 ),  Train
accuracy :  0.993 , Test Accuracy :  0.981
Done with iteration, Updated class labels :  ['1' '0' '4_7_9_3_5_8_2_6']

… Start with available class labels …

All pairs in current iteration :  [('1', '0'), ('1', '4_7_9_3_5_8_2_6'), ('0',
'4_7_9_3_5_8_2_6')]
Pair with lower accuracy in current iteration : ( 1 , 0 ),  Train accuracy :
1.0 , Test Accuracy :  0.998
Pair with lower accuracy in current iteration : ( 1 , 4_7_9_3_5_8_2_6 ),  Train
accuracy :  0.998 , Test Accuracy :  0.987
Pair with lower accuracy in current iteration : ( 0 , 4_7_9_3_5_8_2_6 ),  Train
accuracy :  0.997 , Test Accuracy :  0.986
Done with iteration, Updated class labels :  ['1' '0_4_7_9_3_5_8_2_6']

… Start with available class labels …

All pairs in current iteration :  [('1', '0_4_7_9_3_5_8_2_6')]
Pair with lower accuracy in current iteration : ( 1 , 0_4_7_9_3_5_8_2_6 ),
Train accuracy :  0.998 , Test Accuracy :  0.988
Done with iteration, Updated class labels :  ['1_0_4_7_9_3_5_8_2_6']

CPU times: user 49min 22s, sys: 27.5 s, total: 49min 49s
Wall time: 49min 56s
```

[60]:

```python
#Code block taken directly from stackoverflow as it is released under CCA␣
↪license and appropriately cited here
#Ref : https://stackoverflow.com/questions/29586520/
↪can-one-get-hierarchical-graphs-from-networkx-with-python-3/29597209

import networkx as nx
import random

def hierarchy_pos(G, root=None, width=1., vert_gap = 0.2, vert_loc = 0, xcenter␣
↪= 0.5):

    '''
    From Joel's answer at https://stackoverflow.com/a/29597209/2966723.
    Licensed under Creative Commons Attribution-Share Alike

    If the graph is a tree this will return the positions to plot this in a
    hierarchical layout.

    G: the graph (must be a tree)

    root: the root node of current branch
    - if the tree is directed and this is not given,
      the root will be found and used
    - if the tree is directed and this is given, then
      the positions will be just for the descendants of this node.
    - if the tree is undirected and not given,
      then a random choice will be used.

    width: horizontal space allocated for this branch - avoids overlap with␣
↪other branches

    vert_gap: gap between levels of hierarchy

    vert_loc: vertical location of root

    xcenter: horizontal location of root
    '''
    if not nx.is_tree(G):
        raise TypeError('cannot use hierarchy_pos on a graph that is not a␣
↪tree')

    if root is None:
        if isinstance(G, nx.DiGraph):
            root = next(iter(nx.topological_sort(G)))  #allows back␣
↪compatibility with nx version 1.11
        else:
            root = random.choice(list(G.nodes))
```

```
    def _hierarchy_pos(G, root, width=1., vert_gap = 0.2, vert_loc = 0, xcenter␣
↪= 0.5, pos = None, parent = None):
        '''
        see hierarchy_pos docstring for most arguments

        pos: a dict saying where all nodes go if they have been assigned
        parent: parent of this branch. - only affects it if non-directed

        '''

        if pos is None:
            pos = {root:(xcenter,vert_loc)}
        else:
            pos[root] = (xcenter, vert_loc)
        children = list(G.neighbors(root))
        if not isinstance(G, nx.DiGraph) and parent is not None:
            children.remove(parent)
        if len(children)!=0:
            dx = width/len(children)
            nextx = xcenter - width/2 - dx/2
            for child in children:
                nextx += dx
                pos = _hierarchy_pos(G,child, width = dx, vert_gap = vert_gap,
                                    vert_loc = vert_loc-vert_gap, xcenter=nextx,
                                    pos=pos, parent = root)
        return pos


    return _hierarchy_pos(G, root, width, vert_gap, vert_loc, xcenter)
```

Prepare array from dataframe containing train and test accuracy to plot

[61]:
```
temp_items = []
for index, row in df.iterrows():
    combined = row['First Class'] + '_' + row['Second Class']
    temp_items.append((combined, row['First Class']))
    temp_items.append((combined, row['Second Class']))
    #print(row['First Class'], row['Second Class'])

df
```

[61]:

	First Class	Second Class	Train Accuracy	Test Accuracy
0	5	8	1.000	0.975
1	3	5_8	1.000	0.975
2	7	9	1.000	0.975
3	3_5_8	2	1.000	0.975

4	4	7_9	0.994	0.978
5	4_7_9	3_5_8_2	0.994	0.978
6	4_7_9_3_5_8_2	6	0.993	0.981
7	0	4_7_9_3_5_8_2_6	0.997	0.986
8	1	0_4_7_9_3_5_8_2_6	0.998	0.988

0.8.1 Plot Tree from dataframe of train and test accuracies at each level prepared above

[62]:

```python
import networkx as nx

graph = nx.Graph()
#add all combinations found at each level
graph.add_edges_from(temp_items)

#top node need to be specified to start the tree from data above
#then it takes a hierachy learned
pos = hierarchy_pos(graph,'1_0_4_7_9_3_5_8_2_6')
#increase graph size
plt.figure(3, figsize=(12,8))
nx.draw(graph, pos=pos, with_labels=True, node_size=10,font_size=12)
plt.show()
```