Anmol_More

February 1, 2020

[1]:
```
import glob
import random
import math
import decimal
import re
import pandas as pd
import numpy as np

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]:

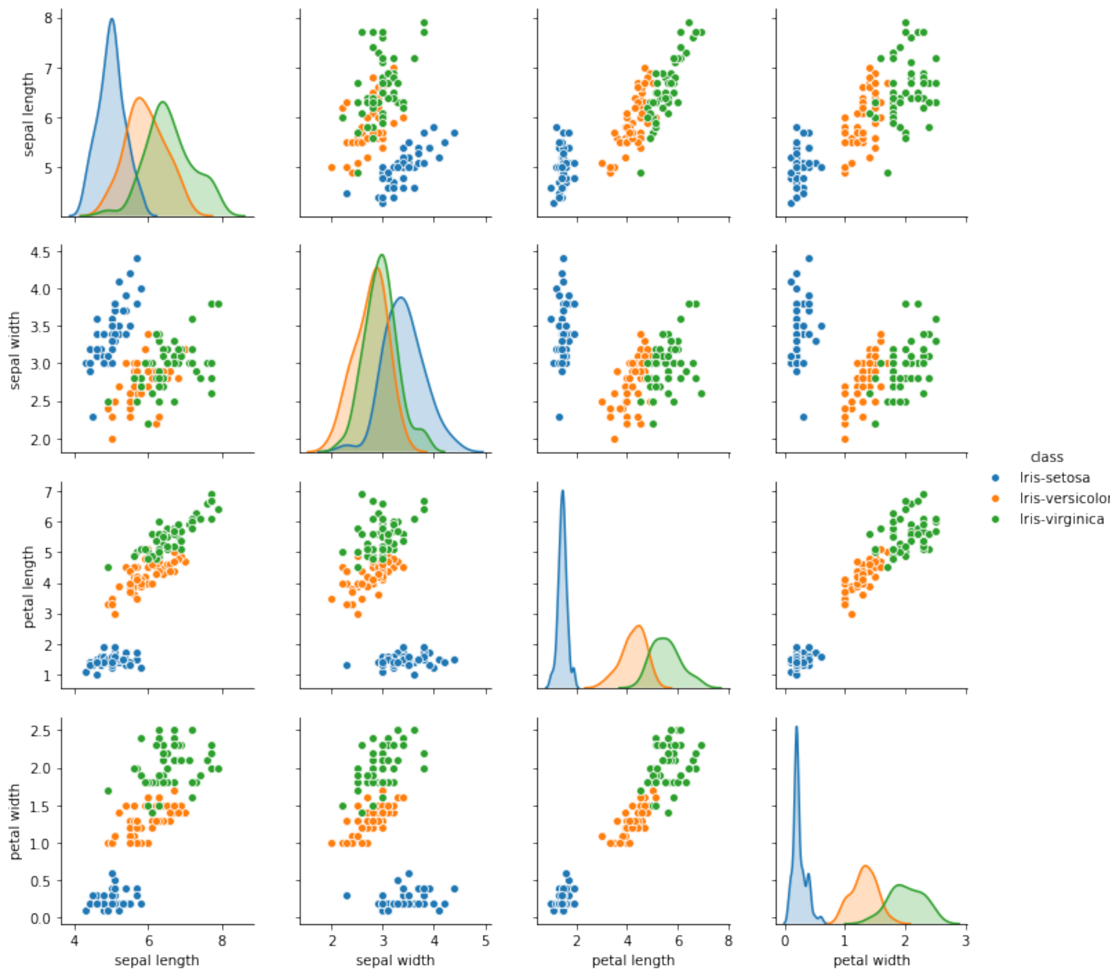
	sepal length	sepal width	petal length	petal width	class
48	5.3	3.7	1.5	0.2	Iris-setosa
67	5.8	2.7	4.1	1.0	Iris-versicolor
45	4.8	3.0	1.4	0.3	Iris-setosa
15	5.7	4.4	1.5	0.4	Iris-setosa
110	6.5	3.2	5.1	2.0	Iris-virginica

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

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 0x1a1f7c0610>



0.1.2 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)
```

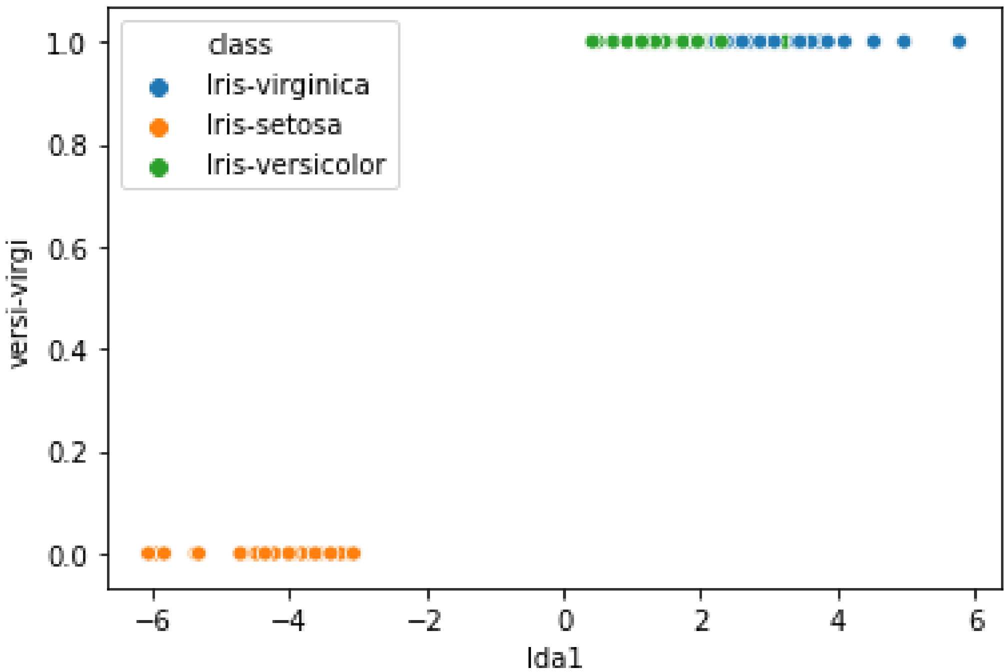
[5]:
```
     sepal length  sepal width  petal length  petal width            class  \
69            5.6          2.5           3.9          1.1  Iris-versicolor
113           5.7          2.5           5.0          2.0   Iris-virginica
63            6.1          2.9           4.7          1.4  Iris-versicolor
106           4.9          2.5           4.5          1.7   Iris-virginica
104           6.5          3.0           5.8          2.2   Iris-virginica

     versi-virgi
```

```
69             1
113            1
63             1
106            1
104            1
```

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

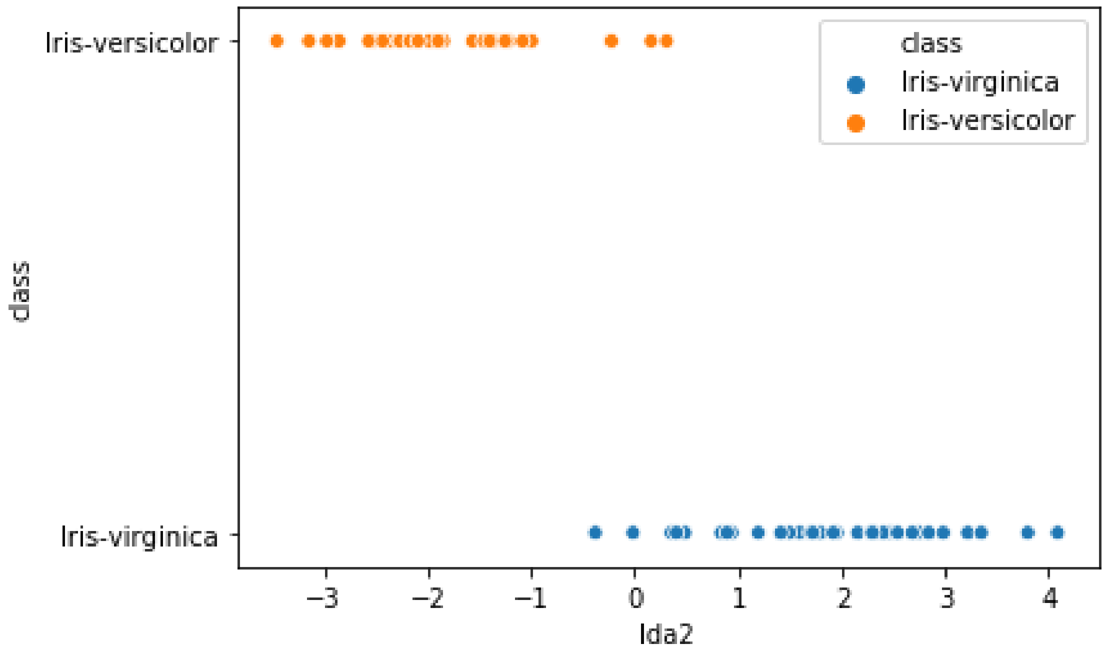
[7]:
```
#Ref https://scikit-learn.org/stable/auto_examples/decomposition/
 ↪plot_pca_vs_lda.html

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)
```

```
/Users/anmol/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:9:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  if __name__ == '__main__':
```



0.1.3 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)
```



0.1.4 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']])
```

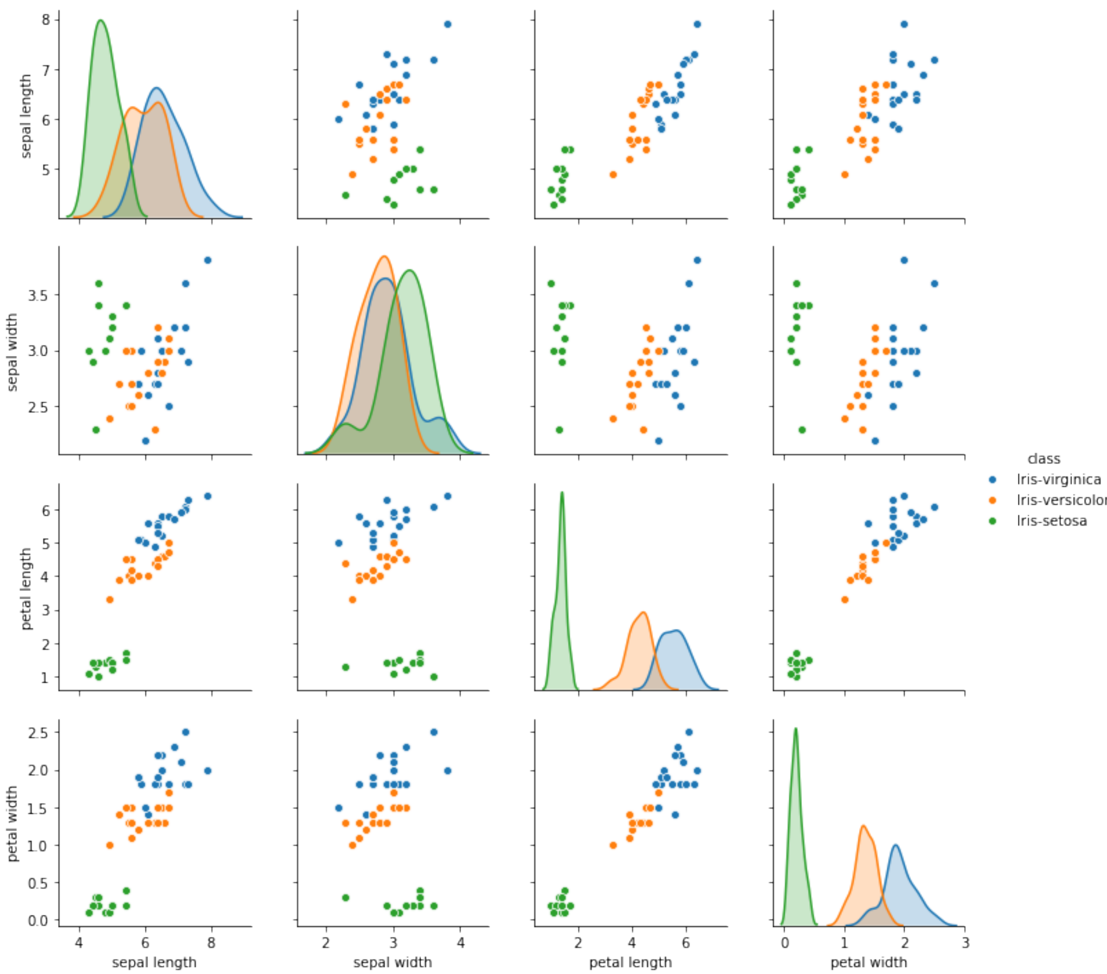
```
/Users/anmol/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
/Users/anmol/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

0.1.5 Comment on what you observed and did.

Plot how the original four features were classifying the data

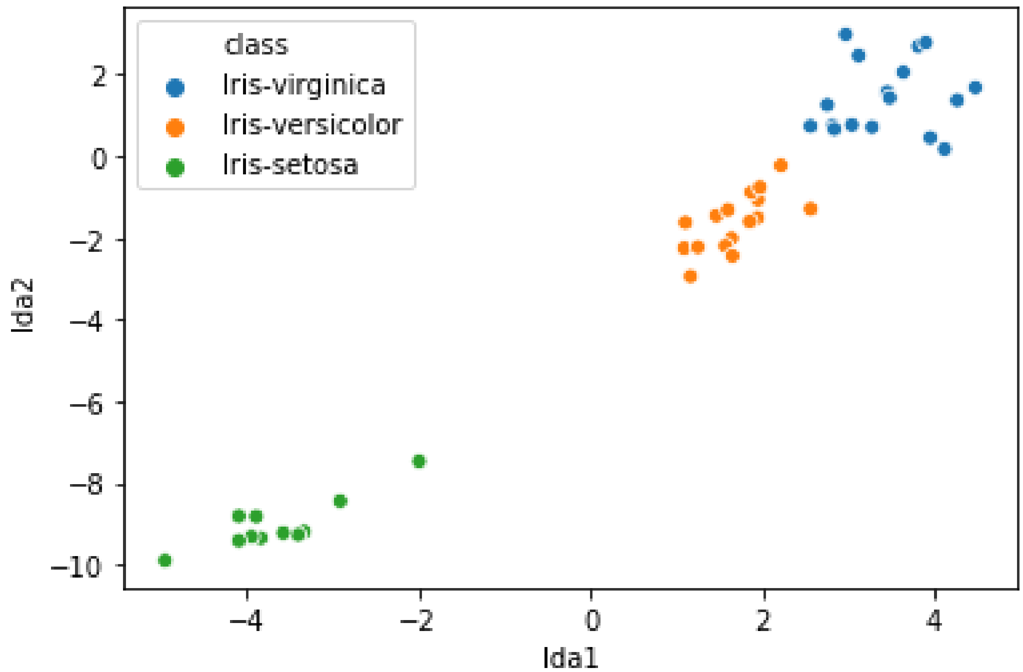
[10]:
```
sns.pairplot(hue='class', data=test[['sepal length', 'sepal width', 'petal␣
↪length', 'petal width', 'class']])
```

[10]: <seaborn.axisgrid.PairGrid at 0x1a218c5b10>



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

0.2.1 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]
```

0.2.2 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

0.2.3 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()
```

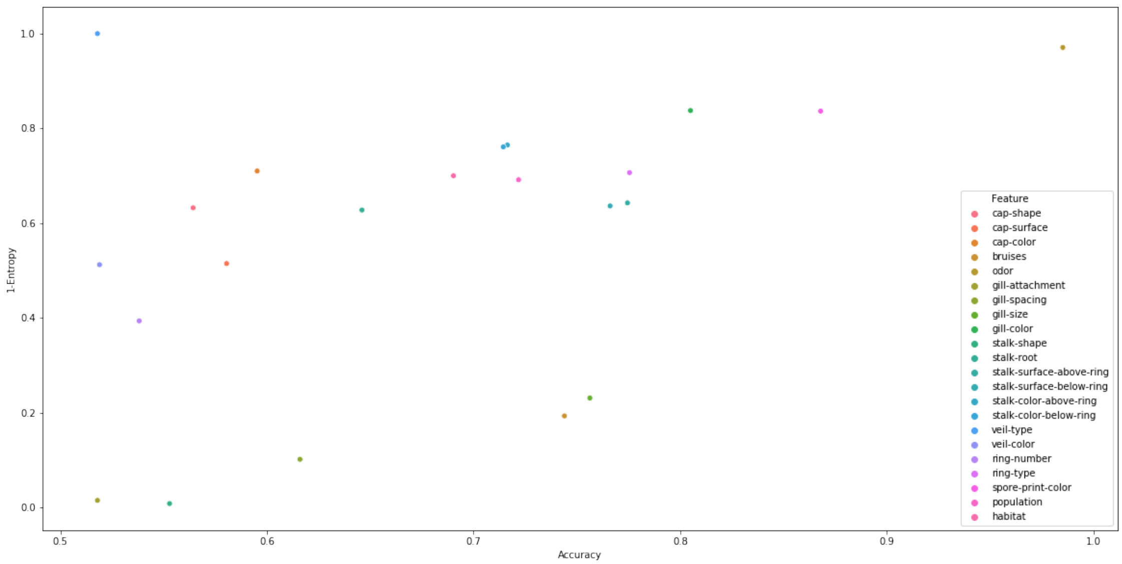
[15]:

	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

0.2.4 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)
```



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

[17]:
```python
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]:
```python
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']
```

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

[19]:
```python
#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)
```

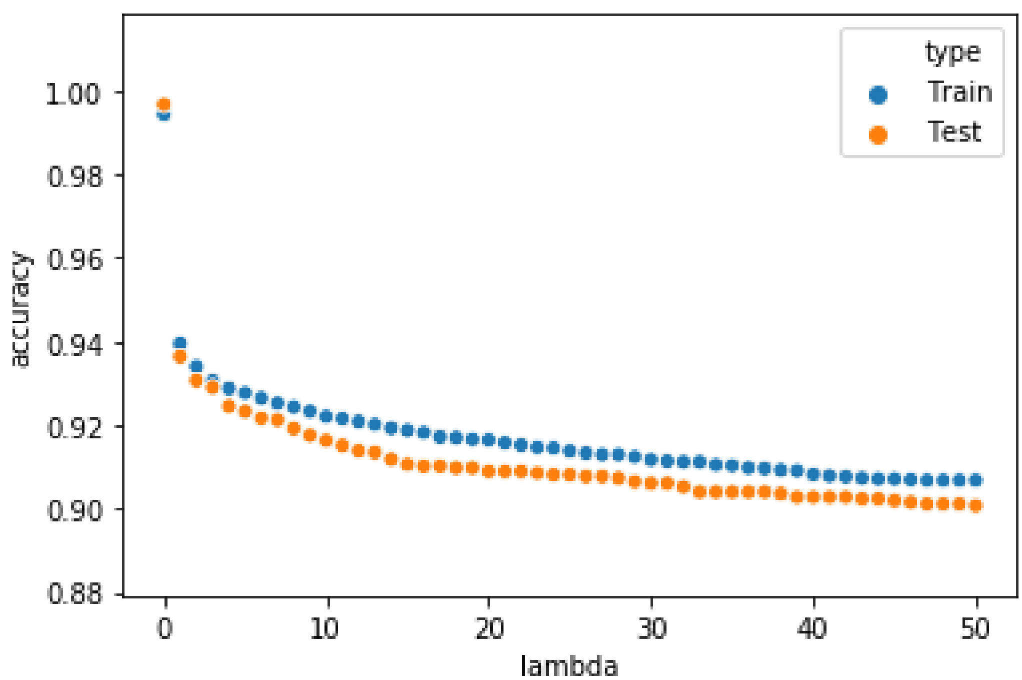
```
/Users/anmol/opt/anaconda3/lib/python3.7/site-
packages/sklearn/naive_bayes.py:485: UserWarning: alpha too small will result in
numeric errors, setting alpha = 1.0e-10
  'setting alpha = %.1e' % _ALPHA_MIN)
```

```
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
```

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

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

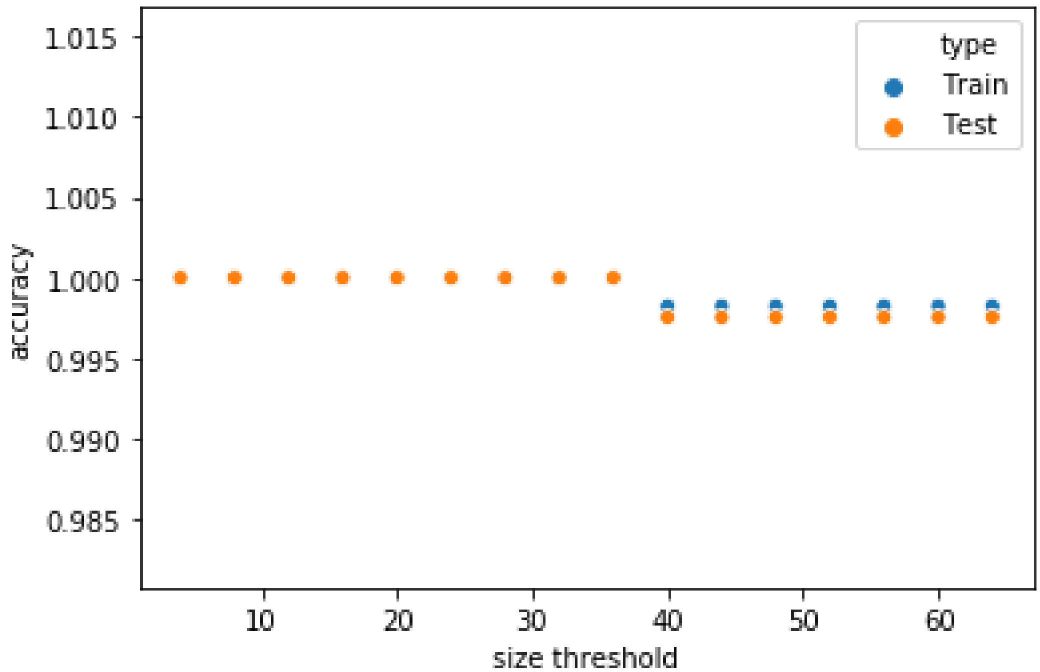


0.3.3 For decision tree classifier plot the Size Threshold (x axis) against training and test set accuracy.

[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))
```



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

[23]:
```
#Get summary of best tree at threshold of 36
dtc = DecisionTreeClassifier(min_samples_split=36)
dtc.fit(X_train, y_train)
dtc.get_depth()
```

[23]: 7

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

0.4.1 Take the MNIST dataset. Lets call it D0 dataset

[24]:
```
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']
```

[25]:
```
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
```

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

[26]:
```
pca = decomposition.PCA()
pca.n_components = n_components
pca_data = pca.fit_transform(mnist_data)
```

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

[27]:
```
model = LinearDiscriminantAnalysis(n_components=n_components)
model.fit(mnist_data, mnist_label.values.ravel())
mnist_fisher_proj_data = model.transform(mnist_data)
```

```
/Users/anmol/opt/anaconda3/lib/python3.7/site-
packages/sklearn/discriminant_analysis.py:388: UserWarning: Variables are
collinear.
  warnings.warn("Variables are collinear.")
```

0.4.4 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

[28]:
```
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
```

[29]:
```
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 :  0.756547619047619
Test set accuracy score :  0.756547619047619
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

    accuracy                           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 :  0.06119047619047619
Test set accuracy :  0.06119047619047619
Classification report :
              precision    recall  f1-score   support

           1       0.00      0.00      0.00       827
           0       0.05      0.06      0.05       931
           4       0.00      0.00      0.00       865
           7       0.00      0.00      0.00       844
           3       0.00      0.00      0.00       814
           5       0.01      0.02      0.02       720
           8       0.12      0.17      0.14       851
           9       0.00      0.00      0.00       915
           2       0.23      0.37      0.28       806
           6       0.00      0.00      0.00       827

    accuracy                           0.06      8400
   macro avg       0.04      0.06      0.05      8400
weighted avg       0.04      0.06      0.05      8400
```

```
(0.756547619047619, 0.06119047619047619)
```

```
/Users/anmol/opt/anaconda3/lib/python3.7/site-
packages/sklearn/mixture/base.py:265: ConvergenceWarning: Initialization 1 did
not converge. Try different init parameters, or increase max_iter, tol or check
for degenerate data.
```

```
% (init + 1), ConvergenceWarning)
```

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

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

[30]:
```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

    accuracy                           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 :  0.025595238095238095
Test set accuracy :  0.025595238095238095
Classification report :
              precision    recall  f1-score   support

           1       0.00      0.00      0.00       827
           0       0.00      0.00      0.00       931
           4       0.01      0.01      0.01       865
           7       0.00      0.00      0.00       844
           3       0.00      0.00      0.00       814
           5       0.16      0.16      0.16       720
           8       0.00      0.00      0.00       851
```

```
           9       0.02      0.03      0.03       915
           2       0.05      0.07      0.06       806
           6       0.01      0.01      0.01       827

    accuracy                           0.03      8400
   macro avg       0.03      0.03      0.03      8400
weighted avg       0.02      0.03      0.02      8400
```

```
(0.8776190476190476, 0.025595238095238095)
```

```
/Users/anmol/opt/anaconda3/lib/python3.7/site-
packages/sklearn/mixture/base.py:265: ConvergenceWarning: Initialization 1 did
not converge. Try different init parameters, or increase max_iter, tol or check
for degenerate data.
  % (init + 1), ConvergenceWarning)
```

0.4.6 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 0.019 - Fisher projection - test set accuracy is 0.108

0.5 P5 : MNIST KNN / Parzen window

0.5.1 Take the two datasets D1 and D2 from P4.

0.5.2 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

[31]:
```
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)
```

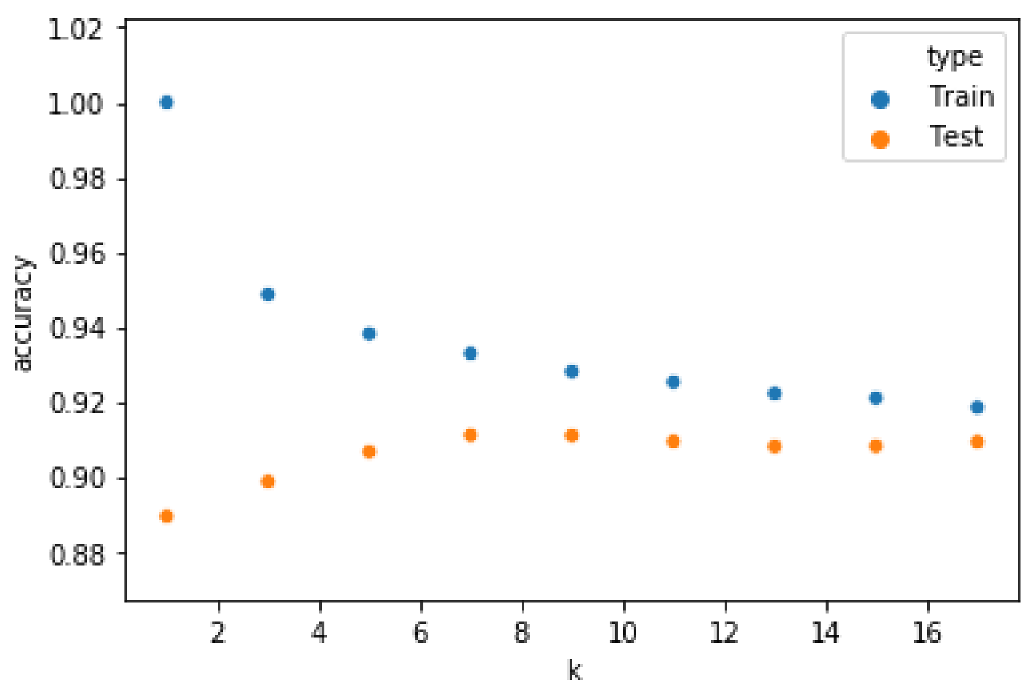
```
        df = df.append({'k' : i,'accuracy':test_score, 'type': 'Test'},␣
↪ignore_index=True)
        print(i, train_score, test_score)
    return df
```

kNN on PCA data (D1)

[32]:
```
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 0.8894
3 0.9487 0.8987
5 0.9382 0.9067
7 0.9329 0.9111
9 0.9281 0.911
11 0.9253 0.9094
13 0.9222 0.9081
15 0.921 0.9082
17 0.9185 0.9093
```

[32]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2227af90>

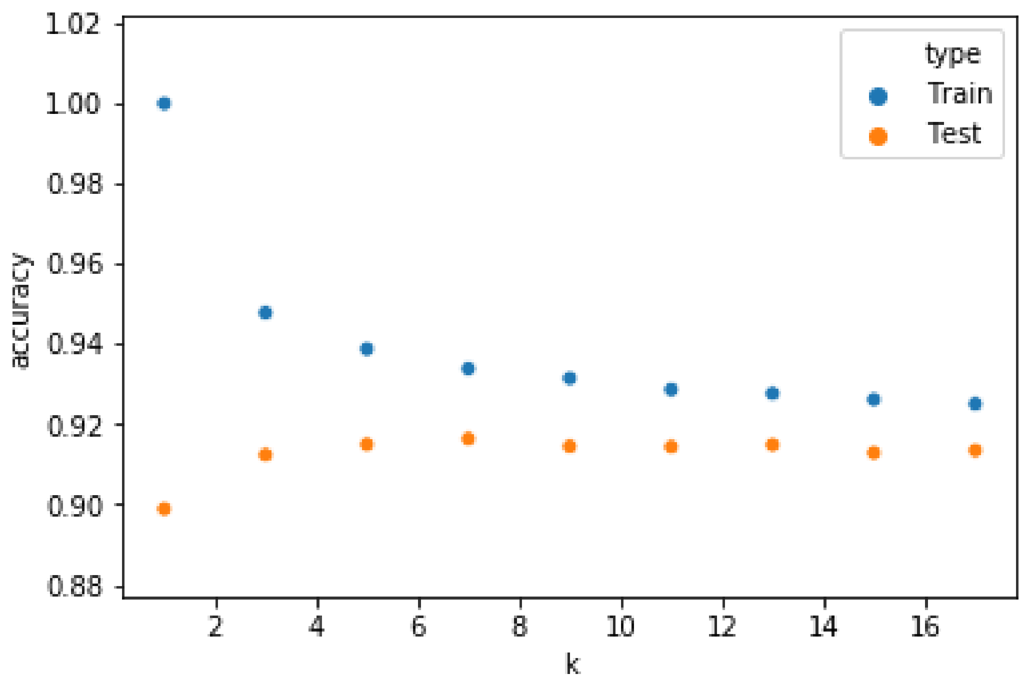


kNN on fisher projection data (D2)

[33]:
```
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
```

[33]: <matplotlib.axes._subplots.AxesSubplot at 0x1a272fd790>



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.

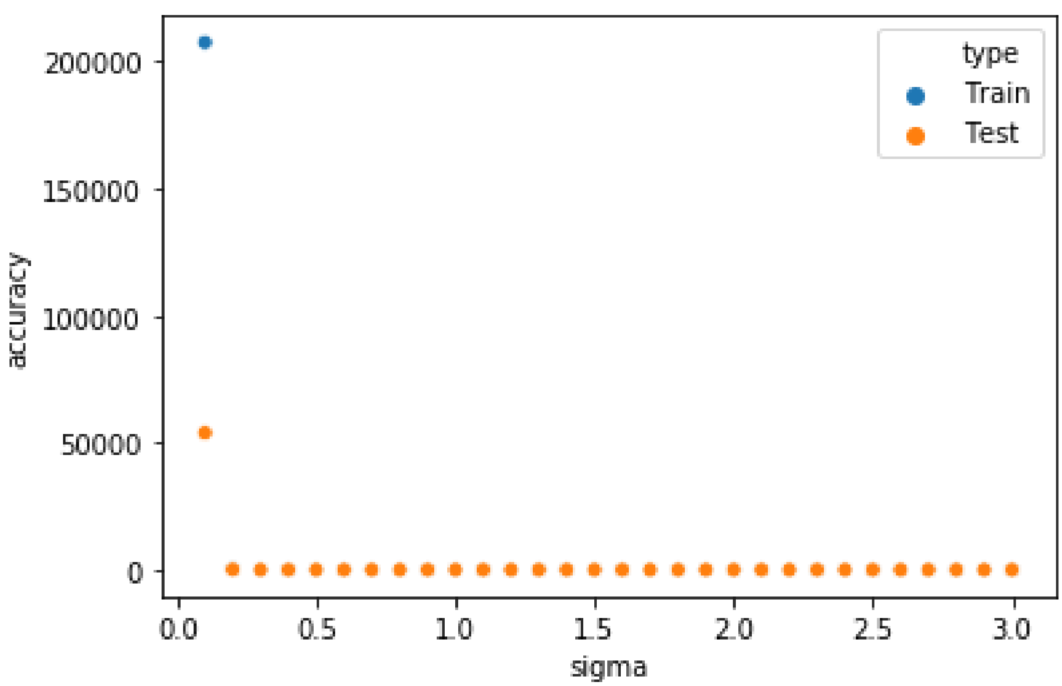
[34]:
```python
sigma_list = []
for i in np.arange(0.1, 3.1, 0.1) :
    sigma_list.append(round(i,1))
classes = np.sort(y_train.unique())

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
```

[35]:
```python
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 207607.48127078288 53865.39944951355
0.2 405.4833618569984 105.2058582998312
0.3 10.547552775023314 2.7366458085410637
0.4 0.7919596911269542 0.20548019199185866
0.5 0.10629503041064162 0.027579084518151026
0.6 0.020600689013717505 0.005345011344806806
```

```
0.7 0.005144706922253201 0.0013348348128957663
0.8 0.0015467962717323404 0.00040132849998410116
0.9 0.0005358711972272217 0.00013903601120464769
1.0 0.00020760748127078625 5.386539944951453e-05
1.1 8.804583836325039e-05 2.284418761922161e-05
1.2 4.023572072991727e-05 1.0439475282825914e-05
1.3 1.957730148010321e-05 5.079485372658026e-06
1.4 1.0048255707525901e-05 2.607099243937088e-06
1.5 5.4003470208120425e-06 1.4011626539730568e-06
1.6 3.0210864682272507e-06 7.838447265314619e-07
1.7 1.7506636209649984e-06 4.542234926592855e-07
1.8 1.0466234320844248e-06 2.7155470938408513e-07
1.9 6.433696812729857e-07 1.6692734126606283e-07
2.0 4.0548336185700884e-07 1.0520585829983457e-07
2.1 2.6137819043099633e-07 6.781663429841994e-08
2.2 1.719645280532261e-07 4.461755394379357e-08
2.3 1.1526367848362164e-07 2.9906071041065086e-08
2.4 7.85853920506213e-08 2.0389600161769797e-08
2.5 5.442305557025009e-08 1.4120491273293936e-08
2.6 3.8236916953327125e-08 9.920869868473012e-09
2.7 2.722507733715575e-08 7.0637611748541134e-09
2.8 1.962549942876185e-08 5.091990710814727e-09
2.9 1.4310704642810107e-08 3.713025259352586e-09
3.0 1.0547552775023744e-08 2.736645808541208e-09
```

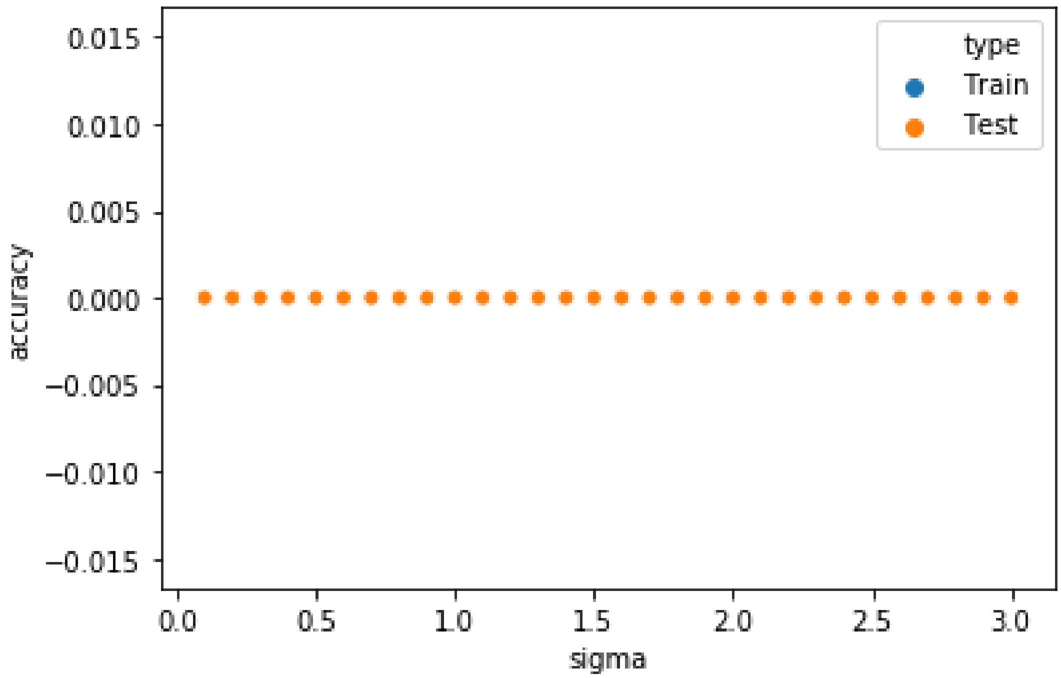
[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1a27371fd0>



[36]:
```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)
df = build_parzen_classifier(X_train, X_test, y_train, y_test)
sns.scatterplot(x="sigma", y='accuracy', hue='type', data=df)
```

```
0.1 0 0
0.2 2.1752105268263355e-155 0
0.3 2.689410168650887e-78 3.3933760029872144e-76
0.4 5.167705303549493e-47 2.8339405229216806e-50
0.5 5.356321942593302e-35 2.0741273381412824e-36
0.6 6.090299730156047e-28 1.2564696751956942e-28
0.7 1.9833720289582778e-24 5.821066248771212e-25
0.8 1.044703485742745e-22 2.800707136550076e-23
0.9 6.612105843952949e-21 1.6972442026723287e-21
1.0 2.2975123454076482e-20 5.9361953901670496e-21
1.1 4.750159232594671e-20 1.2086254193209371e-20
1.2 1.0255971294303331e-19 2.1481388563209358e-20
1.3 1.1320860398725435e-19 2.922963172492722e-20
1.4 9.540603576768931e-20 2.3938563385109085e-20
1.5 6.663863087528497e-20 1.6645402346820223e-20
1.6 4.675059711323352e-20 1.1879068272868309e-20
1.7 3.2177443458155434e-20 8.123941088589632e-21
1.8 2.2437413463061384e-20 5.796967479719207e-21
1.9 1.5403970919143272e-20 3.845776914008781e-21
2.0 1.0293767273075196e-20 2.559637423884564e-21
2.1 7.022007467041681e-21 1.7466196215580522e-21
2.2 4.764345435394489e-21 1.1890543813078467e-21
2.3 3.2501385537003576e-21 8.260158679674234e-22
2.4 3.192357336523302e-21 7.603643963292966e-22
2.5 4.259829357600479e-21 1.0354943608608742e-21
2.6 5.263630906415292e-21 1.3881437085825748e-21
2.7 5.625688368423628e-21 1.3540755847201077e-21
2.8 4.5571244526768026e-21 1.1442293255892184e-21
2.9 3.436902460224294e-21 8.67086827661017e-22
3.0 2.701874139114234e-21 6.971896234897026e-22
```

[36]: <matplotlib.axes._subplots.AxesSubplot at 0x1a22022290>



0.6 P6 : News group Text Classifier

[37]:
```
#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)
```

[37]:

	newsgroup	document_id
260	talk.religion.misc	83911
171	talk.religion.misc	83677
391	talk.religion.misc	84151
106	talk.religion.misc	83513
378	talk.religion.misc	84138

[38]:
```
#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
```

```python
#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
```

[38]:

	data	document
9	From: mathew <mathew@mantis.co.uk>\nSubject: A…	alt.atheism
3	Newsgroup: soc.religion.christian\ndocument_id…	soc.religion.christian
16	Newsgroup: rec.motorcycles\ndocument_id: 10172…	rec.motorcycles
1	Newsgroup: comp.sys.mac.hardware\ndocument_id:…	comp.sys.mac.hardware
0	Newsgroup: sci.crypt\ndocument_id: 14147\nFrom…	sci.crypt

[39]:

```
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.

[40]:
```
%%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 24.7 s, sys: 978 ms, total: 25.6 s
Wall time: 25.7 s
```

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

[41]:
```
word2vec.index = df.document
word2vec.sample(5)
```

[41]:
```
                          aaa  aaaa  aaaaa  aaaaaaaaaaaa  \
document
comp.os.ms-windows.misc     0     0      0             0
rec.sport.baseball          1     0      0             0
comp.windows.x              1     0      0             0
soc.religion.christian      0     0      0             0
talk.politics.mideast       0     0      0             0

                          aaaaaaaaaaaaaaaaaaaaaaaaaaaaauuuuuuuuuuuuuuuuuuuuuuuuuuuuugggggggggggggg
\
document
comp.os.ms-windows.misc                                                                     0
```

```
rec.sport.baseball                                                       0
comp.windows.x                                                           0
soc.religion.christian                                                   0
talk.politics.mideast                                                    0

                         aaaaagggghhhh  aaaaarrrrgh  aaaahhh  aaaall  \
document
comp.os.ms-windows.misc              1            0        0       0
rec.sport.baseball                   0            1        0       0
comp.windows.x                       0            0        0       0
soc.religion.christian               0            0        0       0
talk.politics.mideast                0            0        0       0

                         aaaarrgghhhh  …  zztop  zzum  zzvsi  zzx  zzy  zzz  \
document                               …
comp.os.ms-windows.misc             0  …      0     1      1    0    1    0
rec.sport.baseball                  0  …      0     0      0    0    0    0
comp.windows.x                      0  …      1     0      0    1    0    0
soc.religion.christian              0  …      0     0      0    0    0    0
talk.politics.mideast               1  …      0     0      0    0    0    0

                         zzzoh  zzzz  zzzzzz  zzzzzzt
document
comp.os.ms-windows.misc      1     0       0        0
rec.sport.baseball           0     0       1        1
comp.windows.x               0     0       0        0
soc.religion.christian       0     0       0        0
talk.politics.mideast        0     0       0        0

[5 rows x 112926 columns]
```

Dictionary : Sort this in descending order of document frequency

[42]:
```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.

[43]:
```python
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

[44]:
```
#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)]
word2vec_5k.index = df.document

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

[44]:
```
                          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]
```

[45]:

```
#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
```

```
/Users/anmol/opt/anaconda3/lib/python3.7/site-
packages/pandas/core/indexing.py:576: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self.obj[item_labels[indexer[info_axis]]] = value
```

[45]:

document	offer	third	world	later	late	\
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	

document	upon	last	difference	works	different	\
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]
```

[46]:
```
#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
```

[46]:
```
                              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)

[47]:
```
%%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 50.5 s, sys: 53.3 ms, total: 50.6 s
Wall time: 50.6 s
```

[48]:
```
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)
```

[49]:
```
#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
```

[49]:

```
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
```

[50]:

```
%%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)
```

```
/Users/anmol/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:19:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
15832
198752
CPU times: user 11min 37s, sys: 680 ms, total: 11min 38s
Wall time: 11min 38s
```

[51]:
```
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 + 1
    else :
        no_of_wrong_classifications_test = no_of_wrong_classifications + 1

print(no_of_correct_classifications_test)
print(no_of_wrong_classifications_test)
```

```
/Users/anmol/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:19:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

```
15833
198753
```

0.6.2 Summary text classification

[52]:
```python
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 :  0.07378393744233082
```