Natural Language Processing, Sentiment Analysis, and Recommendation Modeling

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In this notebook, we will be walking through using Faiss Kmeans algorithm and Naive Bayes to classify and model sentiment on Tweets and Youtube comments all relating to interstellar travel and space.

Libraries

In [1]:
```
import faiss
import math
import pandas as pd
import numpy as np
from datetime import datetime

import scipy
from scipy.linalg import norm
from sklearn.preprocessing import MaxAbsScaler
from scipy.sparse import csr_matrix, coo_matrix, hstack, vstack

from textblob import TextBlob
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

from sklearn.decomposition import TruncatedSVD
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.metrics import silhouette_samples, confusion_matrix, plot_confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB, BernoulliNB, CategoricalNB
from sklearn.metrics import accuracy_score, roc_curve, auc, precision_score, recall_score, f1_score
from sklearn.metrics import classification_report
from sklearn.pipeline import Pipeline

%matplotlib inline
import matplotlib.pyplot as plt
from matplotlib import cm
```

Functions

In [2]:
```
def get_sentiment_an(df):
  """
  Given a pandas dataframe, this will shuffle it & get sentiment
  analysis values from TextBlob & VaderSentiment & assign columns inplac
e
  Will return completed dataframe & dataframe columns we'll be using for
  modeling as a coo_matrix.
                Columns returned:
  'polarity' : mean of text sentiment (TextBlob)
  'neg': negative sentiment value (VaderSentiment)
  'pos': positive sentiment value (VaderSentiment)
  'neu': neutral sentiment value (VaderSeniment)
  """
  # shuffling our dataframe so data is no longer sorted
  df = df.sample(frac = 1)
  df = df.reset_index().rename(columns={'index':'id'})
  # getting rid of all unnessecary columns
  df = df[['favorite_count', 'repost_count', 'text', 'id']]
  # feature generation using polarization
  df['polarity'] = df['text'].apply(lambda x:
                                   TextBlob(x).sentiment.polarity)
  # feature generation using intensity analyzer
  analyzer = SentimentIntensityAnalyzer()
  df['pol'] = ''
  for i in range(len(df)):
    sentence = df.at[i, 'text']
    df.at[i, 'pol'] = analyzer.polarity_scores(sentence)
  for i in range(len(df)):
    for h in ['neg', 'neu', 'pos']:
      df.at[i, h] = float(df['pol'][i][h])
  #turning our other variables into a matrix to combine our features
  maxab = MaxAbsScaler()
  drop = ['text', 'pol', 'id']
  hstack = maxab.fit_transform(coo_matrix(df.drop(labels=drop,  axis=1
)))
  return df, hstack
```

In [3]:
```
def word_transform(df):
  """
  Pass in a pandas dataframe and this will return a coo_matrix
  featuring the TFIDF vectorization of your text, with a maximum
  of 100 features of single words and 100 features of bigrams.
  """
  sing = TfidfVectorizer(max_features=100).fit_transform(df['text'])
  bi = TfidfVectorizer(ngram_range = (2, 2),
                       max_features=100).fit_transform(df['text'])
  vect = coo_matrix(np.append(bi.toarray(), sing.toarray(), axis=1))
  return vect
```

In [4]:
```
def svd_pca(vect, haystack):
    """
    Pass in your coo_matrix of your word vectors & the scaled
    features from your dataframe this will perform Principal Component
    Analysis in order to keep your most relevant 100 features, calculated
     in chunks to avoid RAM issues. It will return a numpy
     array containing all of the data for your model.
    """
    svd = TruncatedSVD(n_components=95, n_iter=250000,
                       random_state=0, algorithm='arpack').fit(vect)
    # splitting it so we never keep it all in RAM at once as an array
    splits = []
    shape = vect.shape[1]
    tbs = vect
    # since you cant directly index a matrix the easiest way is train_test
    # chose 50000 since my computer can handle it
    while shape > 50000:
        shape = shape - 50000
        # first, run through the whole matrix
        split1, split2 = train_test_split(tbs, random_state=0,
                                          train_size=shape)
        #all of our leftover rows (not in the 30k) are in split2
        tbs = split2
        # put the chunk of our matrix into a list to iterate over later
        splits.append(split1)
    # append the remainder (whatever was left < 30k) to the end of our lis
t
    splits.append(tbs)
    # start a new matrix by fit transforming our first chunk
    init = coo_matrix(svd.fit_transform(splits[0]))
    # start a loop that will fit transform and stack matricies together
    for item in splits[1:]:
        # fit transform will return it as a dense array
        init = vstack([init, coo_matrix(svd.fit_transform(item))])
    # combine our text matrix & our repost/favorite matrix
    return np.append(haystack.toarray(),
                     init.toarray(), axis=1).astype(np.float32)
```

In [5]:
```
def vect_and_stck(dataframe, first_run, drop_clust):
    """
    Pass in a DataFrame & this function will preprocess and return your
    dataframe & all of the columns nessecary to model as an array
    The first step is to get sentiment analysis scores,
    which is only nessecary the first time you run this, otherwise
    they can be turned to False to save time,
    sentiment analysis is followed by TDIDF vectorizaton on
    single words & bigrams, and lastly it ends with PCA to reduce
    our dimensions to a reasonable amount. Make drop_clust True to
    return a copy of your dataframe with no cluster column before
    rerunning your model on it.
    """
    if first_run == True:
      dataframe, haystack = get_sentiment_an(dataframe)
    else:
      clmn = ['neg', 'neu', 'pos', 'polarity',
              'repost_count', 'favorite_count']
      haystack = coo_matrix(dataframe[clmn])
    vect = word_transform(dataframe)
    if drop_clust == True:
      dataframe = dataframe.drop('cluster', 1)
    return svd_pca(vect, haystack), dataframe
```

In [6]:
```python
def plt_elbow(haystack, df, display):
    """
    Plots your clusters from k 1-5 and returns the best one as an int,
    if display is true it will display the elbow plot, if not it will
    just return your value.
    """
    max = 5
    K = range(1,max+1)
    # start numpy arrays to store results in
    inertias = np.zeros(max)
    diff = np.zeros(max)
    diff2 = np.zeros(max)
    diff3 = np.zeros(max)
    for k in K:
      kmeans, predictions = clusterizer(haystack, df, False)
      inertias[k - 1] = kmeans.obj[-1]
      # first difference
      if k > 1:
          diff[k - 1] = inertias[k - 1] - inertias[k - 2]
      # second difference
      elif k > 2:
          diff2[k - 1] = diff[k - 1] - diff[k - 2]
      # third difference
      elif k > 3:
          diff3[k - 1] = diff2[k - 1] - diff2[k - 2]
    # use differences & numpy argmin to determine best cluster
    elbow = np.argmin(diff3[3:]) + 3
    if display == True:
      print(f'Elbow {str(elbow)}')
      plt.plot(K, inertias, 'b*-')
      plt.plot(K[elbow], inertias[elbow], marker='o', markersize=12,
                  markeredgewidth=2, markeredgecolor='r')
      plt.ylabel('Inertia')
      plt.xlabel('K')
      plt.show()
    elbow = int(elbow)
    global findimb
    findimb += elbow - 1
    return elbow
```

In [7]:
```
def chunked_samples(dataframe, stack, fit_predict, drop):
  """
  Given your dataframe, feature array/matrix & predictions
  Computes Silhouette Scores using sklearn and chunking
  the data into sets of 75000 and returns a deep copy of
  your dataframe with the silhouette scores in the column
  'sil' Scores will not be perfect as this function chunks them, and
  therefore cannot get complete pairwise distances
  but without chunking silhouette scores cannot be run on
  any computer or service we can find and it will be pretty close.
  Use drop = True to calculate the z-score of your silhouette scores
  and get rid of the bottom 10%, assuming they're likely to be outliers.
  """
  start = 0
  clust = 75000
  for i in range(math.ceil(stack.shape[0]/75000)):
    df = dataframe[start:start+clust].reset_index(drop=True).copy()
    fp = np.ravel(fit_predict[start:start+clust][0:])
    if type(stack) != np.ndarray:
      hstk = stack.toarray()[start:start+clust][0:]
    else:
      hstk = stack[start:start+clust][0:]
    df['sil'] = silhouette_samples(hstk, fp)
    if i == 0:
      head = df
    else:
      head = head.append(df)
    if drop == True:
      mean = head['sil'].mean()
      std = head['sil'].std()
      head.reset_index(drop=True, inplace=True)
      for j in range(len(head)):
        head.at[j, 'silstd'] = (head.at[j, 'sil'] - mean)/std
      head = head.loc[head['silstd'] > -1.28].drop('silstd', 1)
    start += 75000
  return head.sample(frac=1).reset_index(drop=True).copy()
```

In [8]:
```
def quick_silhouette(dataframe, stack, fit_predict):
  """
  Pass in your dataframe, your feature array/matrix,
  & your predictions, and this will use chunked_samples
  to get your score & try to quickly form a matplotlib visual
  Scores won't be 100% accurate as you cannot get pairwise distances
  with chunking, but they use a sample size of 75,000 so they should
  be close, and the decrease in accuracy is well worth the 6-7 hours
  in speed it saves
  """
  _dataframe = chunked_samples(dataframe, stack, fit_predict, False)
  silhouette_vals = _dataframe['sil'].to_frame().to_numpy()
  labels = np.unique(fit_predict)
  y_ax_lower, y_ax_upper = 0, 0
  yticks = []
  for i, c in enumerate(labels):
    c_silhouette_vals = silhouette_vals[fit_predict == c]
    c_silhouette_vals.sort()
    y_ax_upper += len(c_silhouette_vals)
    color = cm.jet(float(i) / labels.shape[0])
    plt.barh(range(y_ax_lower, y_ax_upper), c_silhouette_vals,
             height=1.0, color=color)
    yticks.append((y_ax_lower + y_ax_upper) / 2.)
    y_ax_lower += len(c_silhouette_vals)
  plt.axvline(np.mean(silhouette_vals), color="red", linestyle="--")
  plt.yticks(yticks, labels + 1)
  plt.ylabel('Cluster')
  plt.xlabel('Silhouette Coefficient')
  plt.show()
```

In [9]:
```
def get_imb_clstr(dataframe):
  """
  Pass in your dataframe and get the cluster with the most values in it
  returned as an interger
  """
  clstr = dataframe['cluster'].value_counts()
  clstr = int(clstr.to_frame().reset_index()['index'][0])
  return clstr
```

In [10]:
```
def reset_clusters(new_predict, dataframe):
  """
  Pass in your new predictions and your dataframe
  and it will renumber all of your clusters.
  Be sure to use this before making visuals, if you don't
  clusters that have been reassigned will just appear to be missing.
  Edits your dataframe inplace. This is intentionally slower in
  the hopes of not crashing my ram by iterating over each line one by on
e
  """
  _clusters = [int(x) for x in np.unique(new_predict)]
  _range = list(range(len(_clusters)))
  to_rename = {}
  for num in _range:
    to_rename[_clusters[num]] = num
  for i in range(len(dataframe)):
    dataframe.at[i, 'cluster'] = to_rename[dataframe.at[i, 'cluster']]
```

In [11]:
```
def add_new_clst(df, dataframe, k, num_clust):
  """
  Pass in your new predictions and your dataframe
  and it will reassign the cluster you modeled to its new
  cluster assignments. Edits dataframe inplace.
  """
  for i in [x for x in df.index]:
    cluster = df.at[i, 'cluster'] + k + 1 * num_clust
    _id = df.at[i, 'id']
    index = dataframe.loc[dataframe['id'] == _id].index[0]
    dataframe.at[index, 'cluster'] = cluster
```

In [12]:
```
def clusterizer(matrix, dataframe, calc_k):
  """
  Pass in your feature array/matrix and your dataframe
  If you would like to have k be calculated for you using the
  elbow method with a maximum number of 5 clusters, do so by
  setting calc_k = True, otherwise, k will be 3
  """
  global k
  if calc_k == True:
    k = plt_elbow(matrix, dataframe, False)
  else:
    k = 3
  if type(matrix) != np.ndarray:
    matrix = matrix.toarray()
  shape = matrix.shape[0]
  kmeans = faiss.Kmeans(d = matrix.shape[1], k = k, nredo = 250,
                        update_index = True, seed = 42,
                        max_points_per_centroid = math.ceil(shape/k),
                        min_points_per_centroid = math.floor(shape/k),
                        niter = 20)
  kmeans.train(matrix)
  predict = kmeans.index.search(matrix, 1)[1]
  dataframe['cluster'] = predict
  return kmeans, predict
```

In [13]:
```
def get_slice(df, cluster):
  '''
  Pass in your dataframe and return just the values predicted to be in t
he
  largest cluster.
  '''
  return df.loc[df['cluster'] == cluster].reset_index(drop=True)
```

In [14]:
```
# def showconfusionmatrix(y_t, y_hat_t, title):
#     """
#     Plots confusion matrix for provided y_train, y_hat_train
#     OR y_test, y_hat_test
#     """
#     fig, ax = plot_confusion_matrix(confusion_matrix(y_t, y_hat_t))
#     ax.set_title(f'{title} Data')
#     ax.set_xticks([0, 1])
#     ax.set_xticklabels(['True', 'False'])
#     ax.set_yticks([0, 1])
#     ax.set_yticklabels(['True', 'False'])
#     ax.set_ylabel('Actual Data')
#     ax.set_xlabel('Predicted Data')
#     plt.show()
```

In [15]:

```python
def printreports(y_test, y_hat_test, y_train, y_hat_train):
    """
    Provided all input & predicted y values, prints classification
    report for training and testing data right next to each other"""
    print('                                                     ')
    print('                Testing Report:')
    report1 = classification_report(y_test, y_hat_test)
    print(report1)
    print('_____________________________________________________')
    print('                Training Report:')
    report2 = classification_report(y_train, y_hat_train)
    print(report2)
    print('_____________________________________________________')
```

In [16]:

```python
# creating a pipeline
def pipeline(name_of_pipeline, classifier, X_train, y_train, X_test, y_test):
    '''Creates and displays the pipeline classifiers along with the report of metrics'''
    name_of_pipeline = Pipeline([('classifier', classifier)])
    name_of_pipeline.fit(X_train, y_train)
    y_pred_test = name_of_pipeline.predict(X_test)
    y_pred_train = name_of_pipeline.predict(X_train)

    report = classification_report(y_test, y_pred_test, output_dict=True)
    df = pd.DataFrame(report).transpose()

    print(df)
    print('\n\n')
    print(name_of_pipeline.fit(X_train, y_train))
    print('\n\n')
    print('Training Accuracy: ', round(accuracy_score(y_train, y_pred_train),3))
    print('Testing Accuracy: ', round(accuracy_score(y_test, y_pred_test),3))
    print('\n\n')
    return
```

```
In [17]: def visualizing_confusionmatrix(name_of_pipeline, classifier, X_train, y
_train, X_test, y_test):
    '''Creates confusion matrices of the results from classifier'''
    fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(15,10))
    name_of_pipeline = Pipeline([('classifier', classifier)])
    name_of_pipeline.fit(X_train, y_train)
    y_pred_test = name_of_pipeline.predict(X_test)
    y_pred_train = name_of_pipeline.predict(X_train)

    #Plot Training Confusion Matrix
    plot_confusion_matrix(classifier, X_train, y_train, ax=axes[0,0],
                          display_labels=["0","1","2","3","4"])
    cm_train = confusion_matrix(y_train, y_pred_train)

    #Plot Normalized Training Confusion Matrix
    plot_confusion_matrix(classifier, X_train, y_train, ax=axes[1,0],
                          display_labels=["0","1","2","3","4"],
                          normalize='true')

    #Plot Test Confusion Matrix
    plot_confusion_matrix(classifier, X_test, y_test, ax=axes[0,1],
                          display_labels=["0","1","2","3","4"])
    cm_test = confusion_matrix(y_test, y_pred_test)

    #Plot Normalized Test Confusion Matrix
    plot_confusion_matrix(classifier, X_test, y_test, ax=axes[1,1],
                          display_labels=["0","1","2","3","4"],
                          normalize='true')

    axes[0,0].title.set_text(f'{classifier} Train')
    axes[0,1].title.set_text(f'{classifier} Test')
    axes[1,0].title.set_text(f'{classifier} Train')
    axes[1,1].title.set_text(f'{classifier} Test')

    plt.grid(False)
    plt.show()
    return
```

Unsupervised Learning | Model Setup

First, we begin by loading our data and preprocessing. Since our data has already been cleaned, tokenized, and lemmatized, the main focus is placed on feature generation and dimensionality reduction

```
In [18]: # open data, low_memory = False because we have some mixed dtype column
s,
# they aren't one's we use anyways so not worried sbout it
df = pd.read_csv("final_clean_6_word.csv", low_memory=False)
```

```
In [19]: # tokenize and preprocess our data, turning it into a matrix
matrix, df = vect_and_stck(df, True, False)
# taking an initial count to see how much we lose by the end
start = [len(df), datetime.now()]
```

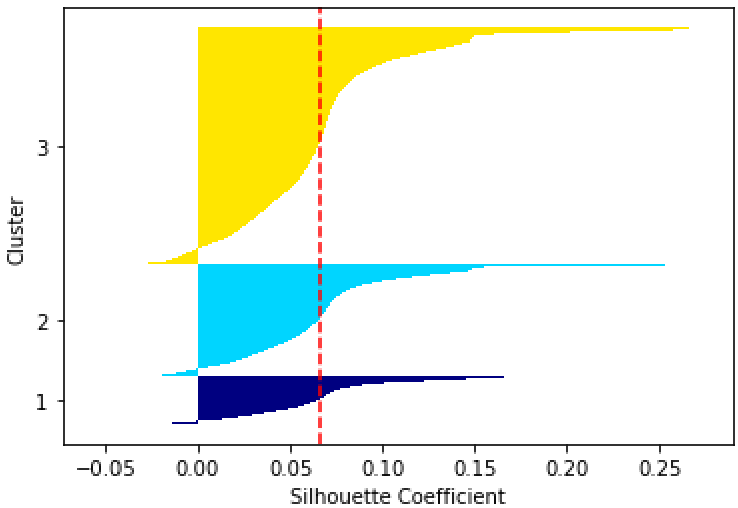
Unsupervised Model | First Edition

In [20]:
```
# start our model & make our initial predictions
first_means, predict = clusterizer(matrix, df, False)
```

Model Evaluation

In [21]:
```
# define a number to help us determine if any of our clusters has too ma
ny points in it
findimb = k
```

In [22]:
```
quick_silhouette(df, matrix, predict)
```



Unsupervised Model Refinement

In [34]:

```
k = 3
num_clust = k
cl = get_imb_clstr(df)
# if our largest cluster is too large, we break it down into more clusters
while len(get_slice(df, cl)) >= len(df)/num_clust-1 and num_clust <= 9:
    # dropping outliers and shuffling our data
    df = chunked_samples(df, matrix, predict, True)
    # processing our data without outliers
    matrix, df = vect_and_stck(df, False, True)
    # re-modeling our data with less outliers
    bttr_means, predict = clusterizer(matrix, df, False)
    # slicing our dataframe to get disproportionate cluster
    # cl = get_imb_clstr(df)
    slice_matrix, slice_df = vect_and_stck(get_slice(df, cl), False, True)
    # plugging our new k value into a new model optimized for our cluster
    clstr_means, clstr_pred = clusterizer(slice_matrix, slice_df, True)
    # updating our original datframe with our new clusters clusters
    add_new_clst(slice_df, df, k, num_clust)
    cl = get_imb_clstr(df)
    num_clust += k-1
```

```
---------------------------------------------------------------------------
----
ValueError                                Traceback (most recent call l
ast)
<ipython-input-34-b23d81ba1e0b> in <module>()
     12     # slicing our dataframe to get disproportionate cluster
     13     # cl = get_imb_clstr(df)
---> 14     slice_matrix, slice_df = vect_and_stck(get_slice(df, cl), F
alse, True)
     15     # plugging our new k value into a new model optimized for o
ur cluster
     16     clstr_means, clstr_pred = clusterizer(slice_matrix, slice_d
f, True)

<ipython-input-5-0eb41cd7dead> in vect_and_stck(dataframe, first_run, d
rop_clust)
     18              'repost_count', 'favorite_count']
     19     haystack = coo_matrix(dataframe[clmn])
---> 20   vect = word_transform(dataframe)
     21   if drop_clust == True:
     22     dataframe = dataframe.drop('cluster', 1)

<ipython-input-3-23e4b4f624a7> in word_transform(df)
      5   of 100 features of single words and 100 features of bigrams.
      6   """
----> 7   sing = TfidfVectorizer(max_features=100).fit_transform(df['te
xt'])
      8   bi = TfidfVectorizer(ngram_range = (2, 2),
      9                        max_features=100).fit_transform(df['tex
t'])

/Users/tlipman/opt/anaconda3/envs/learn-env/lib/python3.6/site-package
s/sklearn/feature_extraction/text.py in fit_transform(self, raw_documen
ts, y)
   1839         """
   1840         self._check_params()
-> 1841         X = super().fit_transform(raw_documents)
   1842         self._tfidf.fit(X)
   1843         # X is already a transformed view of raw_documents so

/Users/tlipman/opt/anaconda3/envs/learn-env/lib/python3.6/site-package
s/sklearn/feature_extraction/text.py in fit_transform(self, raw_documen
ts, y)
   1197
   1198         vocabulary, X = self._count_vocab(raw_documents,
-> 1199                                           self.fixed_vocabulary
_)
   1200
   1201         if self.binary:

/Users/tlipman/opt/anaconda3/envs/learn-env/lib/python3.6/site-package
s/sklearn/feature_extraction/text.py in _count_vocab(self, raw_document
s, fixed_vocab)
   1127             vocabulary = dict(vocabulary)
   1128             if not vocabulary:
-> 1129                 raise ValueError("empty vocabulary; perhaps the
documents only"
```

```
1130                                        " contain stop words")
1131

ValueError: empty vocabulary; perhaps the documents only contain stop w
ords
```

In [24]:
```
df = df.sample(frac = 1).reset_index(drop=True)
final_matrix, final_df = vect_and_stck(df, False, False)
final_clusters = np.ravel(final_df['cluster'].to_numpy())
reset_clusters(final_clusters, final_df)
```

Model Evaluation

In [25]:
```
final_clusters = final_df['cluster'].to_numpy()
# quick_silhouette(final_df, final_matrix, final_clusters)
```

In [26]:
```
end = [len(final_df), datetime.now()]
```

Bayesian Classification

In [27]:
```
from sklearn.pipeline import make_pipeline

gnb = make_pipeline(TfidfVectorizer(),  GaussianNB(var_smoothing=1e-20))
bnb = make_pipeline(TfidfVectorizer(), BernoulliNB())
```

In [28]:
```
categories = [x for x in final_df.columns]
```

In [29]:
```
X_train, X_test, y_train, y_test = train_test_split(final_matrix, final_
clusters, random_state=0)
print(f' {round(end[0]/start[0], 4)}% Unclassifiable')
time = end[1]-start[1]
print(f' Model took {time.total_seconds()/60} min to complete')
```

```
 0.8772% Unclassifiable
 Model took 66.84803643333333 min to complete
```

Model Evaluation

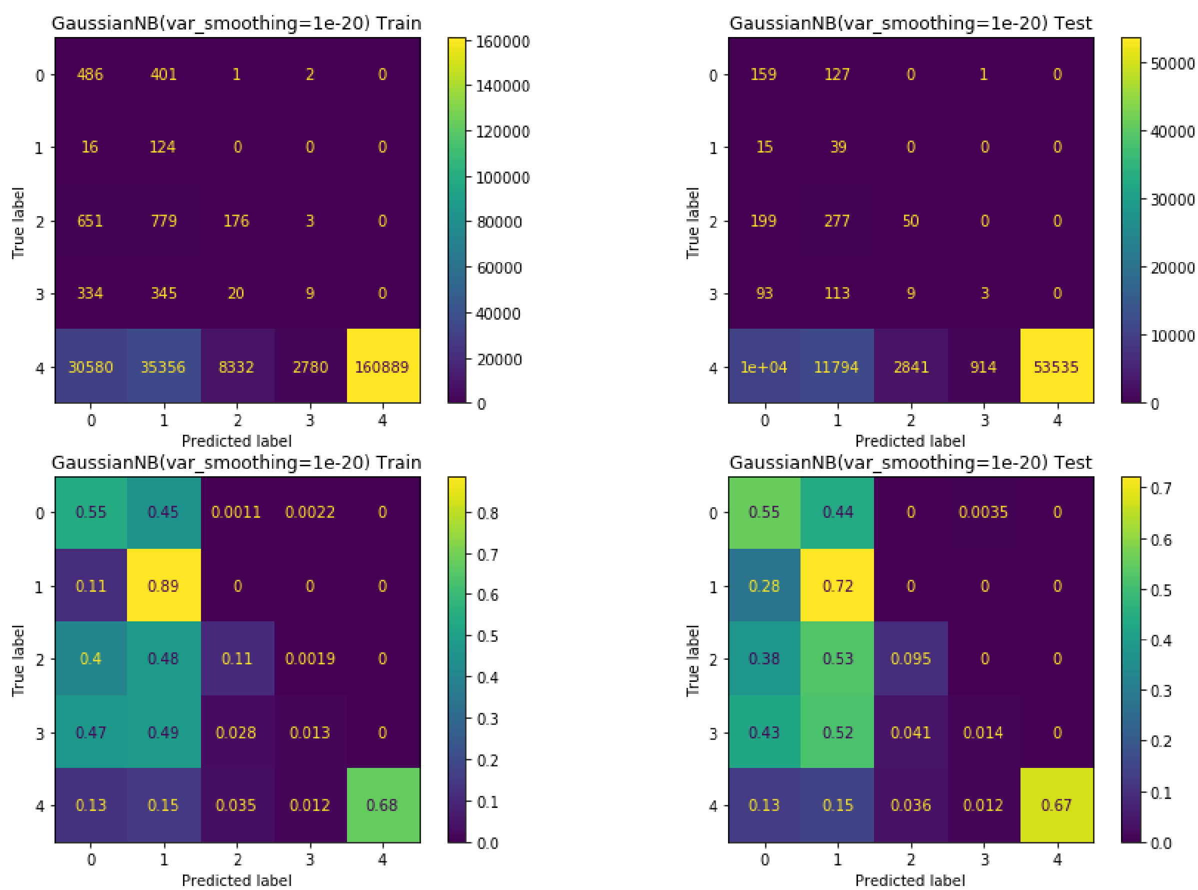
In [30]:

```
pipeline(gnb, GaussianNB(var_smoothing=1e-20), X_train, y_train, X_test,
y_test)
visualizing_confusionmatrix(gnb, GaussianNB(var_smoothing=1e-20), X_trai
n, y_train, X_test, y_test)
```

	precision	recall	f1-score	support
0	0.014825	0.554007	0.028878	287.000000
1	0.003158	0.722222	0.006288	54.000000
2	0.017241	0.095057	0.029189	526.000000
3	0.003268	0.013761	0.005282	218.000000
4	1.000000	0.674729	0.805777	79343.000000
accuracy	0.668747	0.668747	0.668747	0.668747
macro avg	0.207698	0.411955	0.175083	80428.000000
weighted avg	0.986686	0.668747	0.795219	80428.000000

```
Pipeline(steps=[('classifier', GaussianNB(var_smoothing=1e-20))])
```

```
Training Accuracy:  0.67
Testing Accuracy:  0.669
```

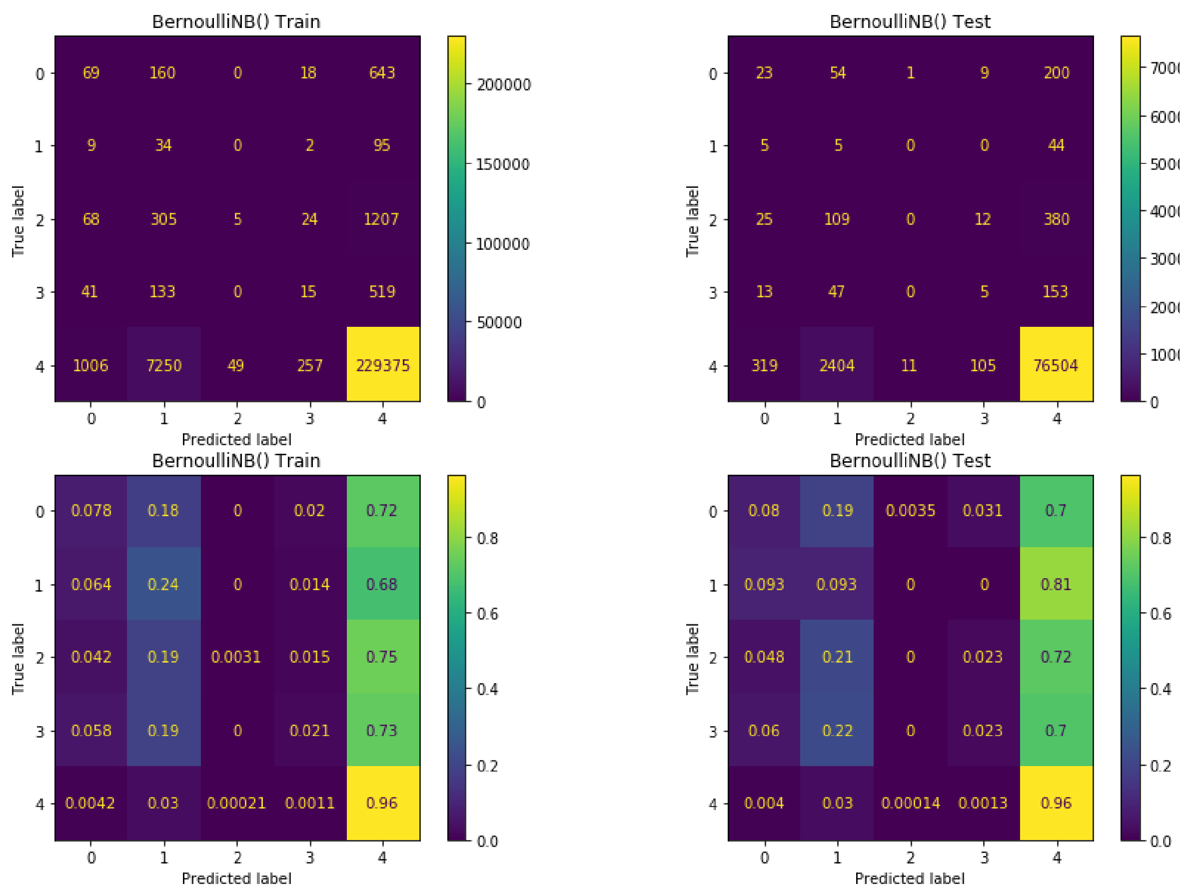


In [31]:
```
pipeline(bnb, BernoulliNB(), X_train, y_train, X_test, y_test)
visualizing_confusionmatrix(bnb, BernoulliNB(), X_train, y_train, X_test
, y_test)
```

	precision	recall	f1-score	support
0	0.059740	0.080139	0.068452	287.000000
1	0.001909	0.092593	0.003741	54.000000
2	0.000000	0.000000	0.000000	526.000000
3	0.038168	0.022936	0.028653	218.000000
4	0.989946	0.964219	0.976913	79343.000000
accuracy	0.951621	0.951621	0.951621	0.951621
macro avg	0.217953	0.231977	0.215552	80428.000000
weighted avg	0.976909	0.951621	0.964058	80428.000000

```
Pipeline(steps=[('classifier', BernoulliNB())])
```

```
Training Accuracy:  0.951
Testing Accuracy:  0.952
```



In [32]:
```
# gnb = GaussianNB(var_smoothing=1e-20)

# y_hat_test = gnb.fit(X_train, y_train).predict(X_test)
# y_hat_train = gnb.fit(X_train, y_train)
# showconfusionmatrix(y_test, y_hat_test, 'GNB')
# printreports(y_test, y_hat_test, y_train, y_hat_train)
```

In [33]:
```
# bnb = BernoulliNB()

# y_hat_test = bnb.fit(X_train, y_train).predict(X_test)
# y_hat_train = bnb.fit(X_train, )
# showconfusionmatrix(y_test, y_hat_test, 'BNB')
# printreports(y_test, y_hat_test, y_train, y_hat_train)
```