04_deception_MNB_hints

October 27, 2019

```
In [1]: """
        n n n
       #IST 736 - Text Mining
        #Homework Hints 4
       #Multinomial Naive Bayes
       #feature tables
       #Counclusion
       # %%
       ###################
       ## Reading in and vectorizing
       ## various formats for text data
        ##
       ## This example shows what to do with
       ## a very poorly formatted and dirty
       ## csv file.
       ## Here is the name of the original
        ## file: deception_data_converted_final.csv
        ## Textmining Naive Bayes Example
       import pandas as pd
       import numpy as np
       import re
       from nltk.corpus import stopwords
       from sklearn.feature_extraction.text import CountVectorizer
       from sklearn.feature_extraction.text import TfidfVectorizer
       from sklearn import preprocessing
       from sklearn.model_selection import KFold
       from sklearn.naive_bayes import MultinomialNB
       from sklearn.metrics import confusion_matrix, accuracy_score, precision_recall_fscore_
       import matplotlib.pyplot as plt
       import copy
       from wordcloud import WordCloud
In [2]: # Here is some code to create a confusion matrix ...
        #Thanks to https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusio
```

```
def plot_confusion_matrix(y_true, y_pred, classes,
                          normalize=False,
                          title=None,
                          cmap=plt.cm.Blues):
    11 11 11
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    if not title:
        if normalize:
            title = 'Normalized confusion matrix'
        else:
            title = 'Confusion matrix, without normalization'
    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    # Only use the labels that appear in the data
    #classes = classes[unique_labels(y_true, y_pred)]
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
    fig, ax = plt.subplots()
    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.figure.colorbar(im, ax=ax)
    # We want to show all ticks...
    ax.set(xticks=np.arange(cm.shape[1]),
           yticks=np.arange(cm.shape[0]),
           # ... and label them with the respective list entries
           xticklabels=classes, yticklabels=classes,
           title=title,
           ylabel='True label',
           xlabel='Predicted label')
    # Rotate the tick labels and set their alignment.
    plt.setp(ax.get xticklabels(), rotation=45, ha="right",
             rotation_mode="anchor")
    # Loop over data dimensions and create text annotations.
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i, j], fmt),
                    ha="center", va="center",
                    color="white" if cm[i, j] > thresh else "black")
    fig.tight_layout()
    return ax
# %%
```

```
## Step 1: Read in the file
       ## We cannot read it in as csv because it is a mess
       ## One option is to convert it to text.
       RawfileName="deception data converted final.csv"
       FILE=open(RawfileName, "r")
       ## We are going to clean it and then write it back to csv!
       ## So, we need an empty csv file - let's make one....
       filename="CleanText.csv"
       NEWFILE=open(filename,"w")
       ## In the first row, create a column called Label and a column Text...
       ToWrite="Lie_Label,Senti_Label,Review\n"
       ## Write this to new empty cs v file
       NEWFILE.write(ToWrite)
       ## Close it up
       NEWFILE.close()
In [4]: ### Now, we have an empty csv file called CLeanText.csv
       ### Above we created the first row of column names: Label and Review
       ### Next, we will open this file for "a" or append - so we can
       ### add things to it from where we left off
        ### NOTE: If you open this file again with "w" it will write over
        ### whatever is in the file! USE "a"....
        ### This line of code opens the file for append and creates
        ### a variable (NEWFILE) that we can use to access and control the
        ### file.
       NEWFILE=open(filename, "a")
        ### We also will build a CLEAN dataframe.
        ### So for now, we need a blank one...
       MyFinalDF=pd.DataFrame()
        ####################################
        ## TMPORTANT
       ##
        ## Below, we will create a lot of
       ## prints and outputs that we want to see
        ## Let's write them all to a file so
        ## we can see what our code is doing
        OutputFile="MyOutputFile.txt"
       ## There are many ways to do this...
       ## I prefer to open the file with "w" to
       ## create it. Then, close and reopen with "a" to
       ## write to it.
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## You can also use with open, etc
        OUTFILE=open(OutputFile,"w")
        OUTFILE.close()
        OUTFILE=open(OutputFile, "a") ### REMEMBER to close this below....
In [5]: ###
        ### Let's go through it one row at a time....
        # %%
        #Get the nltk.corpus stopwords ready
        nltkstopwords = stopwords.words('english')
        nltkstopwords = [w for w in nltkstopwords if not w == 't']
        nltkstopwords = nltkstopwords + [w.replace("'", "") for w in nltkstopwords]
        # %%
        #Get the lengths while reading and tokenizing
        MyLength = []
        MyLengthOrig = []
        for row in FILE:
            RawRow="\n\nThe row is: " + row +"\n"
            OUTFILE.write(RawRow) ## I am going to write this later again for comp
            row=row.lstrip() ## strip all spaces from the left
            row=row.rstrip() ## strip all spaces from the right
            row=row.strip() ## strip all extra spaces in general
            row=row.replace(","," ")
            #print(row)
            ## Split up the row of text by space - TOKENIZE IT into a LIST
            Mylist=row.split(" ")
            #Use OrigList to get the original length
            OrigList = Mylist
            #print(Mylist)
            ## Now, we will clean this list (row)
            ## We will place the results (cleaned) into a new list
            ## Therefore, we need to build a new empty list...
            NewList=[]
            for word in Mylist:
                #print("The next word is: ", word)
                PlaceInOutputFile = "The next word BEFORE is: " + word + "\n"
                OUTFILE.write(PlaceInOutputFile)
                word=word.lower()
                word=word.lstrip()
                \#word=word.strip("\n")
                \#word=word.strip("\setminus n")
                word=word.replace(","," ")
                #for good measure, take out stopwords before and after general tokenization
                if word in nltkstopwords:
                    word = ''
```

```
#Replace any string that occurs more than two times in a row with that string
    word = re.sub(r''(.)\1\{2,\}", "\1", word, 1)
    word=word.replace(" ","")
    word=word.replace("_","")
    word=re.sub('\+', ' ',word)
    word=re.sub('.*\+\n', '',word)
    word=word.replace("\t","")
    word=word.replace("\r", "")
    word=word.replace(".","")
    word=word.replace("'", "")
    word=word.replace("(", "")
    word=word.replace(")", "")
    #word=word.replace("\'s","")
    word=word.lstrip()
    word=word.rstrip()
    word=word.strip()
    if word in nltkstopwords:
        word = ''
    #word.replace("\","")
    if word not in ["", "\\", """, """, "*", ":", ";"]:
        if len(word) >= 1:
            if not re.search(r'\d', word): ##remove digits
                NewList.append(word)
                PlaceInOutputFile = "The next word AFTER is: " + word + "\n"
                OUTFILE.write(PlaceInOutputFile)
#print(NewList)
#print(NewList[-1]) ## what is this??? Its the last element
## What is the last element?? Its the label!
NewList = [w for w in NewList if w not in nltkstopwords]
   ## Labels for our data set <-----!!!!!!!!!!!!!!!!!!!!!!!!!!!!
llabel=NewList[0]
if llabel == "f":
    llabel="truth"
elif llabel == "t":
    llabel="lie"
else:
    llabel="NEITHER f or t"
slabel=NewList[1]
if slabel == "n":
    slabel="neg"
```

```
elif slabel == "p":
   slabel="pos"
else:
   slabel="NEITHER n or p"
## -----
\label is: " + llabel + " "+ slabel +" "n"
OUTFILE.write(PlaceInOutputFile)
NewList.pop(0) ## removes first item
NewList.pop(0) ## removes first item
Text=" ".join(NewList)
\#PlaceInOutputFile = "\nThe text is: " + Text + "\n"
#OUTFILE.write(PlaceInOutputFile)
#print(Text)
#print("LABEL\n")
#print(label)
### More cleaning....
Text=Text.replace("\\n","")
Text=Text.strip("\\n")
Text=Text.replace("\\'","")
Text=Text.replace("\\","")
Text=Text.replace('"',"")
Text=Text.replace("'","")
Text=Text.replace("s'","")
Text=Text.lstrip()
#if len(Text) < 2:
 # print("SMALL", Text)
#print(type(Text))
#print(Text)
LastStopWords=Text.split(" ")
LastStopWords = [w for w in LastStopWords if w not in nltkstopwords]
Text = " ".join(LastStopWords)
## Create the string you want to write to the NEWFILE...
OriginalRow="ORIGINAL" + RawRow
OUTFILE.write(OriginalRow)
ToWrite=llabel+","+slabel+","+Text+"\n"
if "NEITHER" not in ToWrite:
    #Let's get the lengths of each tokenized review while we're here.
   MyLength.append(len(NewList))
    #Same for the original. Subtract two for the two labels
```

```
MyLengthOrig.append(len(OrigList) - 2)
                NEWFILE.write(ToWrite)
                OUTFILE.write(ToWrite)
        ## CLOSE files - always close files!
        FILE.close()
        NEWFILE.close()
        OUTFILE.close()
In [6]: ##########
        ## Read the new csv file you created into a DF or into CounterVectorizer
        ## recall that filename is CleanFile.csv - the file we just made
        ## Into DF
       MyTextDF=pd.read csv(filename)
        ## remove any rows with NA
        MyTextDF = MyTextDF.dropna(how='any',axis=0) ## axis 0 is rowwise
        print(MyTextDF.head())
        #print(MyTextDF["Label"])
        #print(MyTextDF.iloc[1,1])
 Lie_Label Senti_Label
                                                                    Review
0
      truth
                    neg mikes pizza high point ny service slow quality...
1
                    neg really like buffet restaurant marshall street ...
      truth
2
                    neg went shopping friend went dodo restaurant dinn...
      truth
                    neg olive oil garden disappointing expect good foo...
3
     truth
4
                    neg seven heaven restaurant never known superior s...
      truth
In [7]: ## KEEP THE LABELS!
       MyLieLabel = MyTextDF["Lie_Label"]
        MySentiLabel = MyTextDF["Senti_Label"]
        ## Remove the labels from the DF
        DF_noLabel= MyTextDF.drop(["Lie_Label"], axis=1) #axis 1 is column
        DF_noLabel= DF_noLabel.drop(["Senti_Label"], axis=1)
        #print(DF_noLabel.head())
        ## Create a list where each element in the list is a row from
        ## the file/DF
        print(DF noLabel.head())
        print("length: ", len(DF_noLabel))
                                              Review
O mikes pizza high point ny service slow quality...
1 really like buffet restaurant marshall street ...
2 went shopping friend went dodo restaurant dinn...
3 olive oil garden disappointing expect good foo...
4 seven heaven restaurant never known superior s...
length: 92
```

```
In [8]: # %% EDA
```

200

100

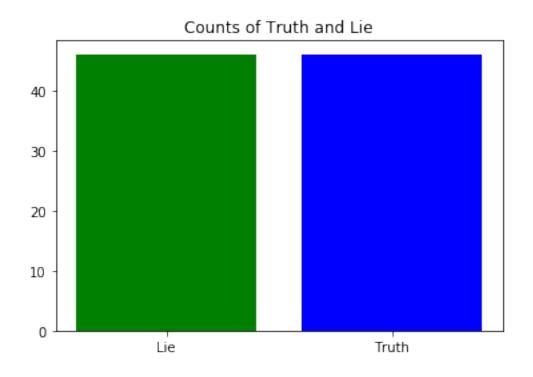
20

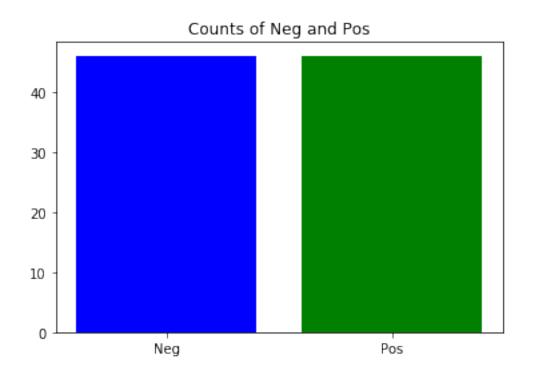
40

```
#Word count before and after.
  dat = {'x': np.arange(len(MyLength)),
          'y1': MyLengthOrig,
          'y2': MyLength}
  plt.plot(dat['x'], dat['y1'], label = 'Before Tokenization')
  plt.plot(dat['x'], dat['y2'], label = 'After Tokenization')
  plt.title('Number of Tokens')
  plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
  plt.show()
   #pos/neg & lie/truth ratios
  dat = [len(MyTextDF[(MyTextDF["Lie_Label"] == "truth")]),
          len(MyTextDF[(MyTextDF["Lie_Label"] == "lie")]),
          len(MyTextDF[(MyTextDF["Senti_Label"] == "neg")]),
          len(MyTextDF[(MyTextDF["Senti_Label"] == "pos")])]
  plt.bar(x = ['Truth', 'Lie'], height = dat[:1], color = ['b', 'g'])
  plt.title('Counts of Truth and Lie')
  plt.show()
  plt.bar(x = ['Neg', 'Pos'], height = dat[2:], color = ['b', 'g'])
  plt.title('Counts of Neg and Pos')
  plt.show()
   #Percent change in lengths
  pctChange = [(MyLengthOrig[i] - MyLength[i])/MyLengthOrig[i] for i in range(len(MyLengthOrig[i])
  print(np.mean(pctChange))
                   Number of Tokens
500
                                                           Before Tokenization
                                                           After Tokenization
400
300
```

60

80





```
In [9]: #Awesome. We have a clean dataset with all of the lower case, cleaned, tokenized revie
        #We also have the length of each tokenized review in MyLength
       print(DF_noLabel.head())
        print(MyLieLabel.head())
        print(MySentiLabel.head())
                                              Review
O mikes pizza high point ny service slow quality...
1 really like buffet restaurant marshall street ...
2 went shopping friend went dodo restaurant dinn...
3 olive oil garden disappointing expect good foo...
4 seven heaven restaurant never known superior s...
0
    truth
1
    truth
2
    truth
3
    truth
    truth
Name: Lie_Label, dtype: object
0
    neg
1
    neg
2
    neg
3
    neg
    neg
Name: Senti_Label, dtype: object
In [10]: #We will now get the datasets we want to experiment with. (all will be vectorized and
         #Counts
         #Normalized Counts
         #tfidf
         #Standardized Counts
         #Standardized Normalized Counts
         #Standardized tfidf
         #Standard name for vectorizers, fits, and DFs are as follows:
         #Vectorizer: vect<Type>Oriq
         #Fit: vect<Type>OrigFit
         #DF: vect<Type><Orig|Stand>DF
         #DF with label: vect<Type><Orig|Stand>DF<Lie|Senti>
         #Define function to put labels back on. df defaults to DF_noLabel, lab as string
         def add_labels(df, lab = ''):
             tmp = copy.deepcopy(df)
             if lab == "Lie LABEL":
                 tmp[lab] = MyLieLabel
```

```
tmp[lab] = MySentiLabel
             else:
                 print('Use either Lie LABEL or Senti LABEL')
                 return()
             return(tmp)
         #Use: #new = add_labels(df = original, lab = 'Lie LABEL')
         # %%
         ### BUILD the LIST that "content" in all vectorizers will expect
         MyList=[] #empty list
         for i in range(0,len(DF_noLabel)):
             NextText=DF_noLabel.iloc[i,0] ## what is this??
             ## PRINT TO FIND OUT!
             #print(MyTextDF.iloc[i,1])
             \#print("Review \#", i, "is: ", NextText, "\n\n")
             #print(type(NextText))
             ## This list is a collection of all the reviews. It will be HUGE
             MyList.append(NextText)
         ## see what this list looks like....
         print(MyList[0:4])
['mikes pizza high point ny service slow quality low would think would know least make good pi
In [11]: # %% COUNT VECTORIZER
         vectCountOrig = CountVectorizer(input="content")
         vectCountOrigFit = vectCountOrig.fit_transform(MyList)
         MyColumnNames=vectCountOrig.get_feature_names()
         #We can use MyColumnNames over and over again. As long as we keep using MyList
         vectCountOrigDF=pd.DataFrame(vectCountOrigFit.toarray(), columns = MyColumnNames)
         print(vectCountOrigDF.head(10))
         vectCountOrigDFLie = add_labels(vectCountOrigDF, 'Lie LABEL')
         vectCountOrigDFSenti = add_labels(vectCountOrigDF, 'Senti LABEL')
         print(vectCountOrigDFLie.head(10))
         print(vectCountOrigDFSenti.head(10))
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```

elif lab == "Senti LABEL":

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3	0		0	truth								
4	0		0	truth								
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5		0	0		0	0		0	1	0	0	
6		0	0		0	0		0	0	0	0	
7		0	0		1	0		0	0	0	0	
8		0	0		0	0	0	0	0	0	0	
8 9		0	0		0 0	0		0 1	0	0 1	0 0	

youll yuenan Senti LABEL 0 0 0 neg

```
1
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                   0
                                 neg
2
         0
                   0
                                 neg
3
         0
                   0
                                 neg
4
         0
                   0
                                 neg
5
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6
         0
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                                 neg
7
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                   0
                                 neg
8
         0
                   0
                                 neg
9
         0
                   0
                                 neg
```

[10 rows x 1344 columns]

```
In [12]: #%% NORMALIZED COUNT VECTORIZER
         #We will normalize based on MyLength which is the number of tokens
         vectCountNormOrigDF = copy.deepcopy(vectCountOrigDF)
         vectCountNormOrigDF["_length"] = MyLength
         for col in MyColumnNames:
             vectCountNormOrigDF[col] = vectCountNormOrigDF[col] / vectCountNormOrigDF._length
         vectCountNormOrigDF = vectCountNormOrigDF.drop('_length', axis = 1)
         print(vectCountNormOrigDF.head(10))
         #Nice!
         vectCountNormOrigDFLie = add_labels(vectCountNormOrigDF, 'Lie LABEL')
         vectCountNormOrigDFSenti = add labels(vectCountNormOrigDF, 'Senti LABEL')
            abruptly
                      absolutely
                                   acceptable
                                               accord
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[10 rows x 1343 columns]
In [13]: # %% TFIDF VECTORIZER
         # create the vectorizer
         vectTFIDFOrig = TfidfVectorizer(input = 'content')
         # tokenize and build vocab
         vectTFIDFOrigFit = vectTFIDFOrig.fit_transform(MyList)
         vectTFIDFOrigDF = pd.DataFrame(vectTFIDFOrigFit.toarray(), columns = MyColumnNames)
         print(vectTFIDFOrigDF.head(10))
         vectTFIDFOrigDFLie = add_labels(vectTFIDFOrigDF, 'Lie LABEL')
         vectTFIDFOrigDFSenti = add labels(vectTFIDFOrigDF, 'Senti LABEL')
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[10 rows x 1343 columns]
In [14]: # %% STANDARDIZED COUNT VECTORIZER
         vectCountStandDF = copy.deepcopy(vectCountOrigDF)
         scaler = preprocessing.MinMaxScaler()
         vectCountStandDF = pd.DataFrame(scaler.fit_transform(vectCountStandDF), columns = MyC
         print(vectCountStandDF.head())
         vectCountStandDFLie = add_labels(vectCountStandDF, 'Lie LABEL')
         vectCountStandDFSenti = add labels(vectCountStandDF, 'Senti LABEL')
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In [15]: # %% STANDARDIZED NORMALIZED COUNT VECTORIZER

```
vectCountNormStandDF = copy.deepcopy(vectCountNormOrigDF)
         scaler = preprocessing.MinMaxScaler()
         vectCountNormStandDF = pd.DataFrame(scaler.fit_transform(vectCountNormStandDF), column
         print(vectCountNormStandDF.head(10))
         vectCountNormStandDFLie = add_labels(vectCountNormStandDF, 'Lie LABEL')
         vectCountNormStandDFSenti = add_labels(vectCountNormStandDF, 'Senti LABEL')
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In [16]: # %% STANDARDIZED TFIDF VECTORIZER

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vectTFIDFStandDF = copy.deepcopy(vectTFIDFOrigDF)
         scaler = preprocessing.MinMaxScaler()
         vectTFIDFStandDF = pd.DataFrame(scaler.fit_transform(vectTFIDFStandDF), columns = MyC
         print(vectTFIDFStandDF.head(10))
         vectTFIDFStandDFLie = add_labels(vectTFIDFStandDF, 'Lie LABEL')
         vectTFIDFStandDFSenti = add_labels(vectTFIDFStandDF, 'Senti LABEL')
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```
In [17]: #Alright!!!
         #We have 12 datasets (6 vectorize methods, 2 label sets):
         list_of_DF_Lie = [vectCountOrigDFLie, vectCountNormOrigDFLie, vectTFIDFOrigDFLie, vec
         list_of_DF_Lie_Names = ['vectCountOrigDFLie', 'vectCountNormOrigDFLie', 'vectTFIDFOrigDFLie']
         list_of_DF_Senti = [vectCountOrigDFSenti, vectCountNormOrigDFSenti, vectTFIDFOrigDFSenti]
         list_of_DF_Senti_Names = ['vectCountOrigDFSenti', 'vectCountNormOrigDFSenti', 'vectTF
In [18]: #Separate the different possible labels indices for both labels because we have a sma
         TruthLie_ind = MyTextDF[(MyTextDF["Lie_Label"] == "truth")].index
         LieLie_ind = MyTextDF[(MyTextDF["Lie_Label"] == "lie")].index
         trainIndex_Lie = []
         testIndex_Lie = []
         trainIndex_LieT = []
         testIndex_LieT = []
         trainIndex_LieL = []
         testIndex_LieL = []
         #Get 10 folds
         kfLieT = KFold(n_splits = 10, shuffle = True)
         kfLieT.get_n_splits(TruthLie_ind)
         kfLieL = KFold(n_splits = 10, shuffle = True)
         kfLieL.get_n_splits(LieLie_ind)
         for train_index, test_index in kfLieT.split(TruthLie_ind):
             trainIndex_LieT.append(train_index)
             testIndex_LieT.append(test_index)
         for train_index, test_index in kfLieL.split(LieLie_ind):
             trainIndex_LieL.append(train_index)
             testIndex_LieL.append(test_index)
         for i in range(10):
             trainIndex_Lie.append(trainIndex_LieT[i] + trainIndex_LieL[i])
             testIndex_Lie.append(testIndex_LieT[i] + testIndex_LieL[i])
         #Repeat above for senti
         NegSent_ind = MyTextDF[(MyTextDF["Senti_Label"] == "neg")].index
         PosSent_ind = MyTextDF[(MyTextDF["Senti_Label"] == "pos")].index
```

```
trainIndex_Senti = []
         testIndex_Senti = []
         trainIndex_SentiN = []
         testIndex_SentiN = []
         trainIndex_SentiP = []
         testIndex_SentiP = []
         #Get 10 folds
         kfSentiN = KFold(n_splits = 10, shuffle = True)
         kfSentiN.get_n_splits(NegSent_ind)
         kfSentiP = KFold(n_splits = 10, shuffle = True)
         kfSentiP.get_n_splits(PosSent_ind)
         for train_index, test_index in kfSentiN.split(NegSent_ind):
             trainIndex_SentiN.append(train_index)
             testIndex_SentiN.append(test_index)
         for train_index, test_index in kfSentiP.split(PosSent_ind):
             trainIndex_SentiP.append(train_index)
             testIndex_SentiP.append(test_index)
         for i in range(10):
             trainIndex_Senti.append(trainIndex_SentiN[i] + trainIndex_SentiP[i])
             testIndex_Senti.append(testIndex_SentiN[i] + testIndex_SentiP[i])
In [19]: #Let's model with MNB!
         #We will iterate through all 10 folds for each dataset
         #We have our cross validation index list, so we can iterate through our CV list for e
         # %%
         ## Which Features will be most important????!?!
         #Define a function to produce a dictionary of features sorted by importance
         def feat_imp(train_df, model):
             featLogProb = []
             features = {}
             ind = 0
             for feats in train_df.columns:
                 ## the following line takes the difference of the log prob of feature given m
                 ## thus it measure the importance of the feature for classification.
                 featLogProb.append(abs(model.feature_log_prob_[1,ind] - model.feature_log_prob_
                 features[(feats)] = featLogProb[ind]
                 ind = ind + 1
```

```
for ki in range(len(sortedKeys)):
                 features2[sortedKeys[ki]] = sortedVals[ki]
             return(features2)
In [20]: # %% MULTINOMIAL NAIVE BAYES LIE
         \#https://scikit-learn.org/stable/modules/generated/sklearn.naive\_bayes.MultinomialNB.
         #For each metric, we have a dictionary where the keys are the experiment dataframes a
         cm_Lie = {}
         acc_Lie = {}
         prfs_Lie = {}
         #Also get the most important features for each run
         features_Lie = {}
         for loc in range(len(list_of_DF_Lie)):
             DF = list_of_DF_Lie[loc]
             name = list_of_DF_Lie_Names[loc]
             cm_Lie[name] = []
             acc_Lie[name] = []
             prfs_Lie[name] = []
             features_Lie[name] = []
             ind = 1
             for train_ind, test_ind in zip(trainIndex_Lie, testIndex_Lie):
                 train = DF.iloc[train_ind, ]
                 test = DF.iloc[test_ind, ]
                 #Remove labels
                 trainLabels = train["Lie LABEL"]
                 testLabels = test["Lie LABEL"]
                 train = train.drop(["Lie LABEL"], axis = 1)
                 test = test.drop(["Lie LABEL"], axis = 1)
                 #Create the modeler
                 MyModelNB= MultinomialNB()
                 MyModelNB.fit(train, trainLabels)
                 Prediction = MyModelNB.predict(test)
                 y_true = (testLabels).tolist()
                 y_predict = (Prediction).tolist()
                 labels =['lie', 'truth']
                 cm = confusion_matrix(y_true, y_predict, labels)
                 cm_Lie[name].append(cm)
                 acc = accuracy_score(y_true, y_predict)
                 acc_Lie[name].append(acc)
                 prfs = precision_recall_fscore_support(y_true, y_predict, pos_label = 'lie', a
```

sortedKeys = sorted(features, key = features.get, reverse = True)[:19]

sortedVals = sorted(features.values(), reverse = True)[:19]

features2 = {}

```
features_Lie[name].append(feat_imp(train, MyModelNB))
                 #Plot the confusion matrix
                  title = str('Confusion Matrix' + name + ' fold ' + str(ind))
         #
         #
                  cm_plot = plot_confusion_matrix(y_true = y_true, y_pred = y_predict, classes
         #
                  outpath = str('output/Lie/confmat/' + name + '_fold_' + str(ind) + '.png')
         #
                  plt.savefig(outpath, bbox_inches='tight')
         #
                  plt.clf()
         #
                  #Create a word cloud
         #
                  wc = WordCloud().generate_from_frequencies(features_Lie[name][ind - 1])
         #
                  plt.imshow(wc)
         #
                  plt.xticks(ticks = None)
                  plt.yticks(ticks = None)
         #
                  outpath = str('output/Lie/wordclouds/' + name + '_fold_' + str(ind) + '.png'.
                  plt.savefig(outpath, bbox_inches='tight')
                 ind += 1
C:\Users\jerem\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:1135: UndefinedMe
  'precision', 'predicted', average, warn_for)
In [25]: # %% MULTINOMIAL NAIVE BAYES SENTI
         \#https://scikit-learn.org/stable/modules/generated/sklearn.naive\_bayes.MultinomialNB.
         #For each metric, we have a dictionary where the keys are the experiment dataframes a
         cm_Senti = {}
         acc_Senti = {}
         prfs_Senti = {}
         #Also get the most important features for each run
         features_Senti = {}
         for loc in range(len(list_of_DF_Senti)):
             DF = list_of_DF_Senti[loc]
             name = list_of_DF_Senti_Names[loc]
             cm_Senti[name] = []
             acc_Senti[name] = []
             prfs_Senti[name] = []
             features_Senti[name] = []
             ind = 1
             for train_ind, test_ind in zip(trainIndex_Senti, testIndex_Senti):
                 train = DF.iloc[train_ind, ]
                 test = DF.iloc[test_ind, ]
                 #Remove labels
```

prfs_Lie[name].append(prfs)

```
#Create the modeler
                 MyModelNB= MultinomialNB()
                 MyModelNB.fit(train, trainLabels)
                 Prediction = MyModelNB.predict(test)
                 y_true = (testLabels).tolist()
                 y_predict = (Prediction).tolist()
                 labels =['neg', 'pos']
                 cm = confusion_matrix(y_true, y_predict, labels)
                 cm_Senti[name].append(cm)
                 acc = accuracy_score(y_true, y_predict)
                 acc_Senti[name].append(acc)
                 prfs = precision_recall_fscore_support(y_true, y_predict, pos_label = 'pos', a
                 prfs_Senti[name].append(prfs)
                 features_Senti[name].append(feat_imp(train, MyModelNB))
                 #Plot the confusion matrix
         #
                  title = str('Confusion Matrix' + name + ' fold ' + str(ind))
                  cm_plot = plot_confusion_matrix(y_true = y_true, y_pred = y_predict, classes
         #
                  outpath = str('output/Senti/confmat/' + name + '_fold_' + str(ind) + '.png')
                  plt.savefig(outpath, bbox_inches='tight')
         #
                 plt.clf()
         #
                  #Create a word cloud
                  wc = WordCloud().generate from frequencies(features Senti[name][ind - 1])
         #
                 plt.imshow(wc)
                 plt.xticks(ticks = None)
                 plt.yticks(ticks = None)
                 outpath = str('output/Senti/wordclouds/' + name + '_fold_' + str(ind) + '.pn
         #
                  plt.savefig(outpath, bbox_inches='tight')
                 ind += 1
C:\Users\jerem\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:1135: UndefinedMe
  'precision', 'predicted', average, warn_for)
In [27]: # Average across folds
         #Compare model performance
         # remember this list_of_DF_Lie_Names and list_of_DF_Senti_Names
         model_summary_Lie = {}
         model_summary_Senti = {}
         acc_Dict_Lie = {}
                                        23
```

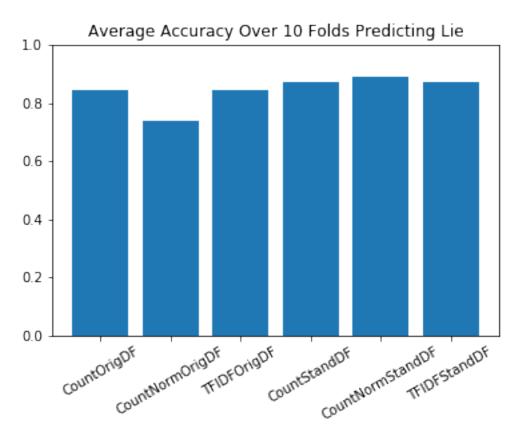
trainLabels = train["Senti LABEL"]
testLabels = test["Senti LABEL"]

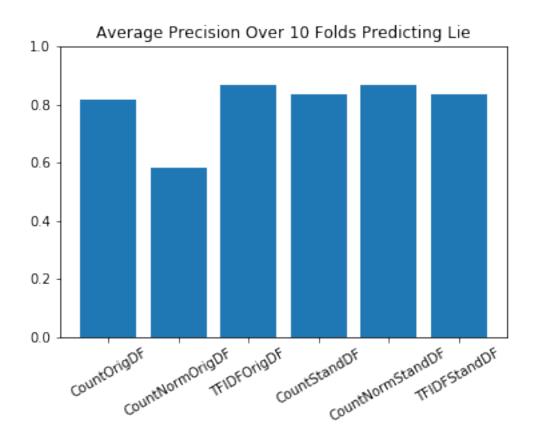
train = train.drop(["Senti LABEL"], axis = 1)
test = test.drop(["Senti LABEL"], axis = 1)

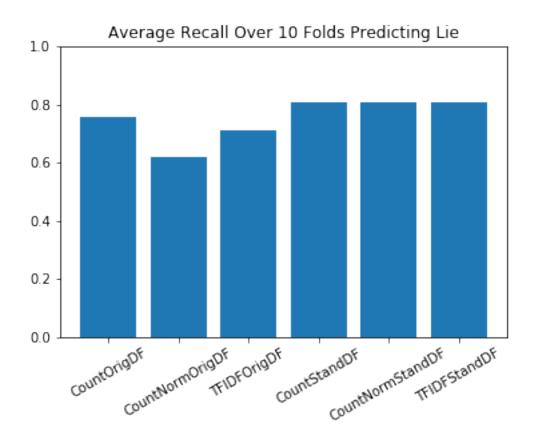
```
prec_Dict_Lie = {}
rec_Dict_Lie = {}
F1_Dict_Lie = {}
acc_Dict_Senti = {}
prec_Dict_Senti = {}
rec_Dict_Senti = {}
F1_Dict_Senti = {}
for name in list_of_DF_Lie_Names:
    newname = name.replace('vect', '').replace('Lie', '')
    model_summary_Lie[newname] = {}
    #accuracy
    a_avg = 0
    for a in acc_Lie[name]:
        a_avg += a
    a_avg = a_avg / 10
    model_summary_Lie[newname]['acc'] = a_avg
    acc_Dict_Lie[newname] = a_avg
    #precision, recall, F1
    p_avg = 0
    r_avg = 0
    F1_avg = 0
    for m in prfs_Lie[name]:
        p_avg += m[0]
        r_avg += m[1]
        F1_avg += m[2]
    p_avg = p_avg / 10
    r_avg = r_avg / 10
    F1_avg = F1_avg / 10
    model_summary_Lie[newname]['prec'] = p_avg
    model_summary_Lie[newname]['rec'] = r_avg
    model_summary_Lie[newname]['F1'] = F1_avg
    prec Dict Lie[newname] = p avg
    rec_Dict_Lie[newname] = r_avg
    F1_Dict_Lie[newname] = F1_avg
for name in list_of_DF_Senti_Names:
    newname = name.replace('vect', '').replace('Senti', '')
    model_summary_Senti[newname] = {}
    #accuracy
    a_avg = 0
    for a in acc_Senti[name]:
        a_avg += a
    a_avg = a_avg / 10
    model_summary_Senti[newname]['acc'] = a_avg
    acc_Dict_Senti[newname] = a_avg
```

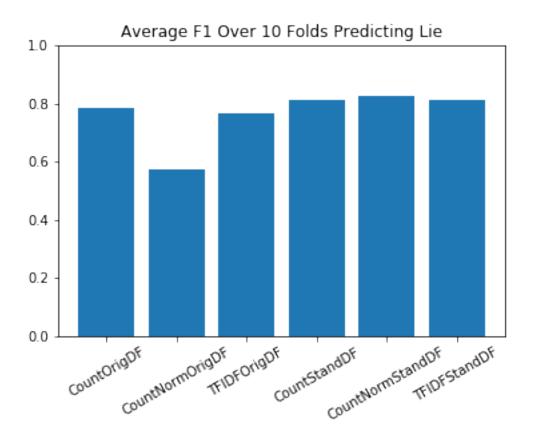
```
#precision, recall, F1
             p_avg = 0
             r_avg = 0
             F1 \text{ avg} = 0
             for m in prfs_Senti[name]:
                 p avg += m[0]
                 r_avg += m[1]
                 F1_avg += m[2]
             p_avg = p_avg / 10
             r_avg = r_avg / 10
             F1_avg = F1_avg / 10
             model_summary_Senti[newname]['prec'] = p_avg
             model_summary_Senti[newname]['rec'] = r_avg
             model_summary_Senti[newname]['F1'] = F1_avg
             prec_Dict_Senti[newname] = p_avg
             rec_Dict_Senti[newname] = r_avg
             F1_Dict_Senti[newname] = F1_avg
In [28]: # %%LIE PLOTS
         #Plot some of the metrics from above
         #Accuracy
         plt.bar(range(len(acc Dict Lie)), list(acc Dict Lie.values()), align='center')
         plt.xticks(range(len(acc_Dict_Lie)), list(acc_Dict_Lie.keys()))
         locs, labels = plt.xticks()
         plt.setp(labels, rotation=30)
         axes = plt.gca()
         axes.set_ylim([0,1])
         plt.title('Average Accuracy Over 10 Folds Predicting Lie')
         plt.show()
         plt.clf()
         #Precision
         plt.bar(range(len(prec_Dict_Lie)), list(prec_Dict_Lie.values()), align='center')
         plt.xticks(range(len(prec_Dict_Lie)), list(prec_Dict_Lie.keys()))
         locs, labels = plt.xticks()
         plt.setp(labels, rotation=30)
         axes = plt.gca()
         axes.set ylim([0,1])
         plt.title('Average Precision Over 10 Folds Predicting Lie')
         plt.show()
         plt.clf()
         #Recall
```

```
plt.bar(range(len(rec_Dict_Lie)), list(rec_Dict_Lie.values()), align='center')
plt.xticks(range(len(rec_Dict_Lie)), list(rec_Dict_Lie.keys()))
locs, labels = plt.xticks()
plt.setp(labels, rotation=30)
axes = plt.gca()
axes.set_ylim([0,1])
plt.title('Average Recall Over 10 Folds Predicting Lie')
plt.show()
plt.clf()
#F1
plt.bar(range(len(F1_Dict_Lie)), list(F1_Dict_Lie.values()), align='center')
plt.xticks(range(len(F1_Dict_Lie)), list(F1_Dict_Lie.keys()))
locs, labels = plt.xticks()
plt.setp(labels, rotation=30)
axes = plt.gca()
axes.set_ylim([0,1])
plt.title('Average F1 Over 10 Folds Predicting Lie')
plt.show()
plt.clf()
```









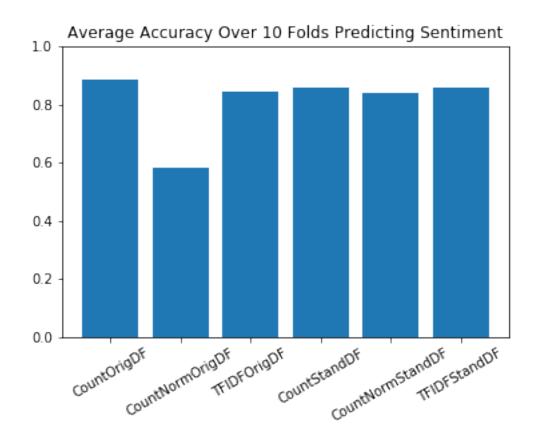
<matplotlib.figure.Figure at 0x1afca1d3c18>

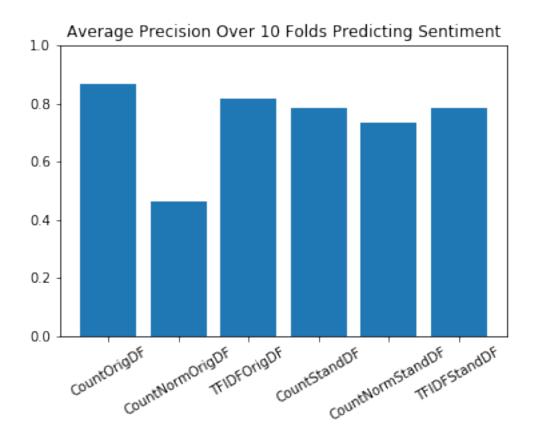
```
In [29]: # %%SENTI PLOTS

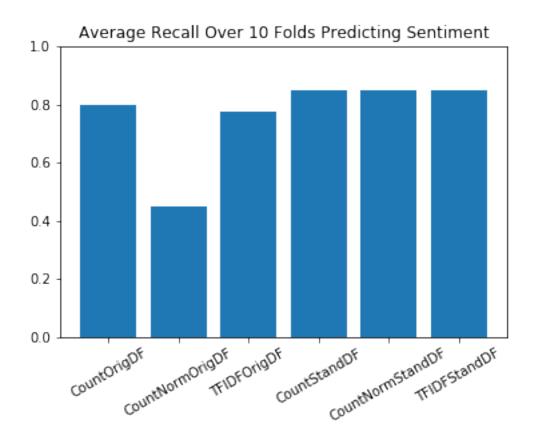
#Plot some of the metrics from above
#Accuracy
plt.bar(range(len(acc_Dict_Senti)), list(acc_Dict_Senti.values()), align='center')
plt.xticks(range(len(acc_Dict_Senti)), list(acc_Dict_Senti.keys()))
locs, labels = plt.xticks()
plt.setp(labels, rotation=30)
axes = plt.gca()
axes.set_ylim([0,1])
plt.title('Average Accuracy Over 10 Folds Predicting Sentiment')
plt.show()
plt.clf()

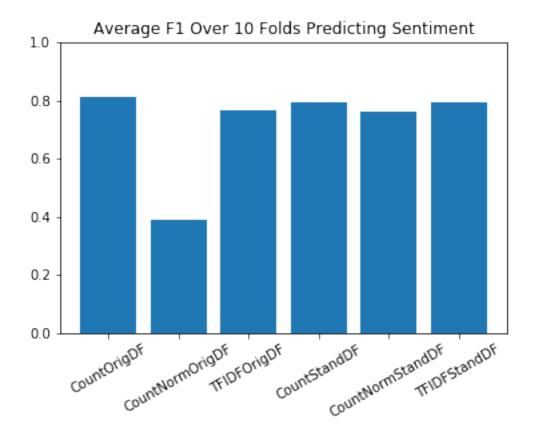
#Precision
plt.bar(range(len(prec_Dict_Senti)), list(prec_Dict_Senti.values()), align='center')
plt.xticks(range(len(prec_Dict_Senti)), list(prec_Dict_Senti.keys()))
```

```
locs, labels = plt.xticks()
plt.setp(labels, rotation=30)
axes = plt.gca()
axes.set_ylim([0,1])
plt.title('Average Precision Over 10 Folds Predicting Sentiment')
plt.show()
plt.clf()
#Recall
plt.bar(range(len(rec_Dict_Senti)), list(rec_Dict_Senti.values()), align='center')
plt.xticks(range(len(rec_Dict_Senti)), list(rec_Dict_Senti.keys()))
locs, labels = plt.xticks()
plt.setp(labels, rotation=30)
axes = plt.gca()
axes.set_ylim([0,1])
plt.title('Average Recall Over 10 Folds Predicting Sentiment')
plt.show()
plt.clf()
#F1
plt.bar(range(len(F1_Dict_Senti)), list(F1_Dict_Senti.values()), align='center')
plt.xticks(range(len(F1_Dict_Senti)), list(F1_Dict_Senti.keys()))
locs, labels = plt.xticks()
plt.setp(labels, rotation=30)
axes = plt.gca()
axes.set_ylim([0,1])
plt.title('Average F1 Over 10 Folds Predicting Sentiment')
plt.show()
plt.clf()
```









<matplotlib.figure.Figure at 0x1afc99c14e0>

```
In [35]: # %%
        features_dfs_Lie = {}
         features_dfs_Senti = {}
         #Get dataframes for each feature list
         for i in list_of_DF_Lie_Names:
             df = pd.DataFrame()
             dics = features_Lie[i]
             fold = 1
             for dic in dics:
                 col1 = 'fold_' + str(fold) + '_word'
                 col2 = 'fold_' + str(fold) + '_value'
                 sortedKeys = sorted(dic, key = dic.get, reverse = True)
                 sortedVals = sorted(dic.values(), reverse = True)
                 df[col1] = sortedKeys
                 df[col2] = sortedVals
                 fold += 1
```

```
features_dfs_Lie[i] = df

for i in list_of_DF_Senti_Names:
    df = pd.DataFrame()
    dics = features_Senti[i]
    fold = 1
    for dic in dics:
        col1 = 'fold_' + str(fold) + '_word'
        col2 = 'fold_' + str(fold) + '_value'
        sortedKeys = sorted(dic, key = dic.get, reverse = True)
        sortedVals = sorted(dic.values(), reverse = True)
        df[col1] = sortedKeys
        df[col2] = sortedVals
        fold += 1

features_dfs_Senti[i] = df
```