Amazon Food Review Dataset_Naive Bayes

June 14, 2018

1 Naive Bayes on Amazon Food Review dataset

1.1 Making predictions over amazon recommendation dataset

1.1.1 Predictions

The purpose of this analysis is to make up a prediction model where we will be able to predict whether a recommendation is positive or negative. In this analysis, we will not focus on the Score, but only the positive/negative sentiment of the recommendation.

To do so, we will work on Amazon's recommendation dataset, we will build a Term-doc incidence matrix using term frequency and inverse document frequency ponderation. When the data is ready, we will load it into predicitve algorithms, mainly in Naïve Bayesian.

In the end, we hope to find a "best" **Optimal score(alpha)** for predicting the recommendation's sentiment.

1.1.2 Loading the data

In order to load the data, we will use the SQLITE dataset where we will only fetch the Score and the recommendation summary.

As we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score id above 3, then the recommendation wil be set to "postive". Otherwise, it will be set to "negative".

The data will be split into an training set and a test set with a test set ratio of **0.3**

```
In [1]: %matplotlib inline

        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import TfidfVectorizer

        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from sklearn.metrics import roc_curve, auc
        from nltk.stem.porter import PorterStemmer

        #Using sqlite3 Table to read te data
        con=sqlite3.connect(r'D:\Machine Learning\Course Recordings\Assignments\Amazon Product

        filtered_data = pd.read_sql_query("""
        SELECT Score,Text
        FROM Reviews
        WHERE Score != 3
        """, con)

        # Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r

        actual_score=filtered_data['Score']

        filtered_data['Score']=filtered_data['Score'].apply(lambda x :'negatiave' if x <3 else
```

In [2]:
```
### Taking Random data instead of complete dataset.
filtered_data_sample=filtered_data.sample(40000, replace=True)
```

In [3]:
```
filtered_data_sample.head(5)
```

Out[3]:
```
           Score                                              Text
478770  positive  I love this stuff having grown up in Hong Kong...
210686  positive  So far, of all the decaf Kcups we have tried, ...
149016  positive  Oh my goodness.. This is indeed the best garli...
309285  positive  ...it would not dissolve fully.  Product from ...
46740   positive  This is a blend of beans from 3 regions and 3 ...
```

In [4]:
```
filtered_data_sample['Score'].value_counts()
```

Out[4]:
```
positive     33829
negatiave     6171
Name: Score, dtype: int64
```

1.2 Preprocessing the data

In [5]:
```
"""
# import nltk
stemmer = PorterStemmer()
from nltk.corpus import stopwords

def stem_tokens(tokens, stemmer):
    stemmed = []
    for item in tokens:
        stemmed.append(stemmer.stem(item))
    return stemmed
```

```
        def tokenize(text):
            tokens = nltk.word_tokenize(text)
            #tokens = [word for word in tokens if word not in stopwords.words('english')]
            stems = stem_tokens(tokens, stemmer)
            return ' '.join(stems)

        intab = string.punctuation
        outtab = "                                "
        trantab = str.maketrans(intab, outtab)
        """
```

```
Out[5]: '\n# import nltk\nstemmer = PorterStemmer()\nfrom nltk.corpus import stopwords\n\ndef s
```

```
In [6]: import re
        import nltk
        import string
        from nltk.corpus import stopwords
        from nltk.stem import PorterStemmer
        from nltk.stem.wordnet import WordNetLemmatizer

        stop=set(stopwords.words('english')) # set of stop words in english
        sno=nltk.stem.SnowballStemmer('english') # initilizing the snowballstemmer


        def cleanhtml(sentance): # function to clean th word of any html tag<>
            cleaner=re.compile('<.*?>')
            cleantext=re.sub(cleaner,' ',sentance)
            return cleantext

        def cleanpunc(sentance): # function to clean punctuation or special charactor
            cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentance)
            cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
            return  cleaned
        print(stop)
        print('******************************')
        print(sno.stem('tasty'))
```

```
{'haven', 'out', 'over', "isn't", 'didn', 'for', "that'll", 'about', 'both', 'hers', 'themselve
******************************
tasti
```

```
In [7]: #Code for implementing step-by-step the checks mentioned in the pre-processing phase
        # this code takes a while to run as it needs to run on 500k sentences.
        i=0
        str1=' '
        final_string=[]
        all_positive_words=[] # store words from +ve reviews here
        all_negative_words=[] # store words from -ve reviews here.
        s=''
        for sent in filtered_data_sample['Text'].values:
            filtered_sentence=[]
            #print(sent);
            sent=cleanhtml(sent) # remove HTMl tags
            for w in sent.split():
                for cleaned_words in cleanpunc(w).split():
                    if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                        if(cleaned_words.lower() not in stop):
                            s=(sno.stem(cleaned_words.lower())).encode('utf8')
                            filtered_sentence.append(s)
                            if (filtered_data_sample['Score'].values)[i] == 'positive':
                                all_positive_words.append(s) #list of all words used to descri
                            if(filtered_data_sample['Score'].values)[i] == 'negatiave':
                                all_negative_words.append(s) #list of all words used to descri
                        else:
                            continue
                    else:
                        continue
            #print(filtered_sentence)
            str1 = b" ".join(filtered_sentence) #final string of cleaned words
            #print("***********************************************************************")

            final_string.append(str1)
            i+=1
```

```
In [8]: filtered_data_sample['CleanedText']=final_string
```

```
In [9]: # Decoding

        filtered_data_sample['CleanedText'] = [i.decode() for i in filtered_data_sample['Cleane
```

```
In [10]: #filtered_data_sample.drop('Cleaned_text',axis=1,inplace=True)

         filtered_data_sample.head(5)
```

```
Out[10]:            Score                                               Text  \
         478770  positive  I love this stuff having grown up in Hong Kong...
         210686  positive  So far, of all the decaf Kcups we have tried, ...
         149016  positive  Oh my goodness.. This is indeed the best garli...
         309285  positive  ...it would not dissolve fully.  Product from ...
         46740   positive  This is a blend of beans from 3 regions and 3 ...

                                                        CleanedText
         478770  love stuff grown hong kong british coloni ate ...
         210686  far decaf kcup tri favorit wish automat order ...
         149016  good inde best garlic season made first becam ...
```

```
309285   would dissolv fulli product local groceri diss...
46740    blend bean region differ roast one contain pro...
```

```
In [11]: Text=filtered_data_sample['CleanedText']
         Score=filtered_data_sample['Score']
```

1.2.1 Splitting the data

```
In [13]: #BoW

         from sklearn.feature_extraction.text import CountVectorizer
         count_vect = CountVectorizer() #in scikit-learn
         final_counts = count_vect.fit_transform(Text)
```

```
In [16]: from sklearn.cross_validation import train_test_split
         from sklearn import cross_validation
         #X_1, X_test, y_train, y_test = train_test_split(Text, Score, test_size=0.3, random_s

         X_1, X_test, y_1, y_test = cross_validation.train_test_split(final_counts,Score, test_
```

```
In [17]: # split the train data set into cross validation train and cross validation test
         X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(X_1, y_1, test_size=0.3)
```

1.3 Applying Bernoulli Naïve Bayes learning method on Bag Of Words

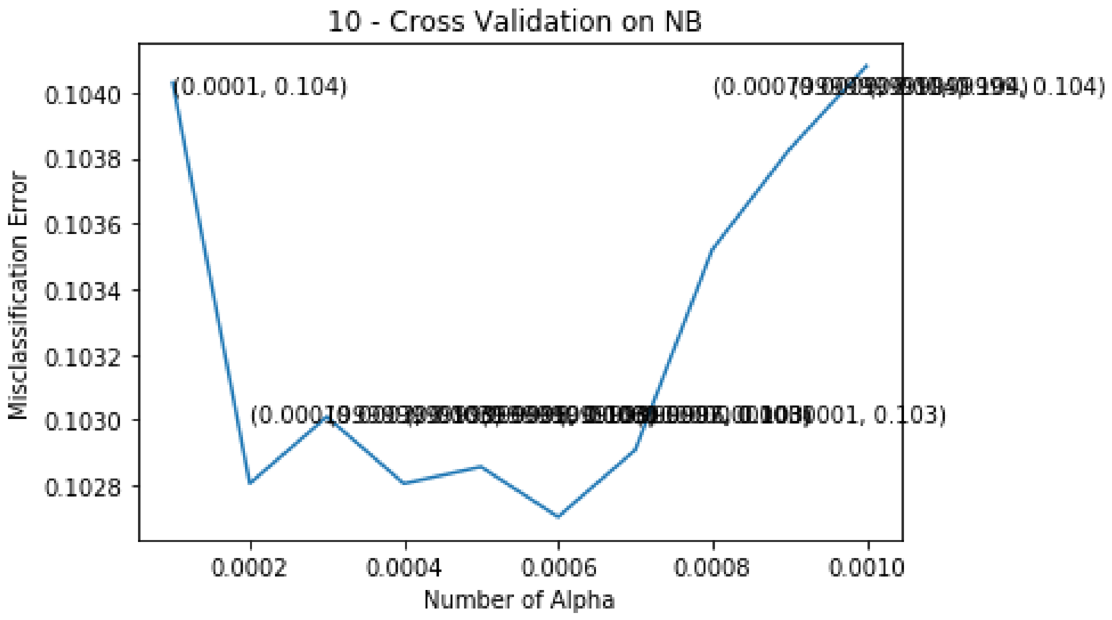
```
In [148]: from sklearn.naive_bayes import BernoulliNB
          from sklearn.metrics import accuracy_score

          NB_List=np.linspace(.0001,.001,5)
          for i in NB_List:

              NB = BernoulliNB(i)

              # fitting the model on crossvalidation train
              NB.fit(X_tr, y_tr)

              # predict the response on the crossvalidation train
              pred = NB.predict(X_cv)

              # evaluate CV accuracy
              acc = accuracy_score(y_cv, pred, normalize=True) * float(100)
              print('\nCV accuracy for Alpha = %.4f is %d%%' % (i, acc))

          NB = BernoulliNB(.0001)
          NB.fit(X_tr,y_tr)
          pred = NB.predict(X_test)
          acc = accuracy_score(y_test, pred, normalize=True) * float(100)
          print('\n****Test accuracy for Alpha = 1 is %d%%' % (acc))
```

```
CV accuracy for Alpha = 0.0001 is 88%

CV accuracy for Alpha = 0.0003 is 89%

CV accuracy for Alpha = 0.0006 is 89%

CV accuracy for Alpha = 0.0008 is 89%

CV accuracy for Alpha = 0.0010 is 89%

****Test accuracy for Alpha = 1 is 88%
```

```
In [149]: import numpy as np
          import pandas as pd
          import matplotlib.pyplot as plt
          from sklearn.cross_validation import train_test_split
          from sklearn.naive_bayes import BernoulliNB
          from sklearn.metrics import accuracy_score
          from sklearn.cross_validation import cross_val_score
          from collections import Counter
          from sklearn.metrics import accuracy_score
          from sklearn import cross_validation

          np.set_printoptions(precision=5)

          bow_myList=np.linspace(.0001,.001,10)


          # empty list that will hold cv scores
          cv_scores = []

          # perform 10-fold cross validation
          for i in bow_myList:
              NB = BernoulliNB(alpha=i)
              scores = cross_val_score(NB, X_tr, y_tr, cv=10, scoring='accuracy')
              cv_scores.append(scores.mean())

          # changing to misclassification error
          MSE = [1 - x for x in cv_scores]

          # determining best alpha
          optimal_alpha = bow_myList[MSE.index(min(MSE))]
          print('\nThe optimal number of neighbors is %.4f.' % optimal_alpha)

          # plot misclassification error vs k
          plt.plot(bow_myList, MSE)
```

```
for xy in zip(bow_myList, np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Number of Alpha')
plt.ylabel('Misclassification Error')
plt.title("10 - Cross Validation on NB ")
plt.show()

print("the misclassification error for each Alpha value is : ", np.round(MSE,3))
```

```
The optimal number of neighbors is 0.0006.
```



```
the misclassification error for each Alpha value is :  [0.104 0.103 0.103 0.103 0.103 0.103 0.
```

```
In [153]: NB_optimal = BernoulliNB(alpha=optimal_alpha)

          # fitting the model
          NB_optimal.fit(X_tr, y_tr)

          # predict the response
          pred_bow = NB_optimal.predict(X_test)

          # evaluate accuracy
```

```
        acc = accuracy_score(y_test, pred_bow) * 100
        print('\nThe accuracy of the NB classifier for alpha = %.4f is %f%%' % (optimal_alpha
```

```
The accuracy of the NB classifier for alpha = 0.0006 is 88.800000%
```

1.4 Observation:

As we noticed , we have got optimal Alpha for Naive Bayes which indicates Hyper-paramter or Laplace Smooth at 0.0006 is closer to 89% of Accuracy (Classified) and 11% are Mis-classified.

For given train data we have estimated 89% of accuracy on Test data using BagOfWords vectorizer on Naive Bayes (NB).

1.5 Important features which are +Ve and -Ve

```
In [21]: ## Finding top features from Bag Of Words
         import numpy as np
         neg_class_prob_sorted = NB_optimal.feature_log_prob_[0, :].argsort()
         pos_class_prob_sorted = NB_optimal.feature_log_prob_[1, :].argsort()

         print('Negative Words Scoring **************\n')
         print(np.take(count_vect.get_feature_names(), neg_class_prob_sorted[:10])) # np.take(
         print('\n')
         print('Positive Words Scoring **************\n')
         print(np.take(count_vect.get_feature_names(), pos_class_prob_sorted[:10]))
```

```
Negative Words Scoring **************

['aaaaaaarrrrrggghhh' 'nytim' 'nystatin' 'nylon' 'nyla' 'nye' 'nyc'
 'oakbrook' 'nyabon' 'nuwara']


Positive Words Scoring **************

['aaaaaaarrrrrggghhh' 'presen' 'preservat' 'preset' 'preson' 'pressiez'
 'esb' 'erythurb' 'presso' 'erythitol']
```

1.6 F1- score,Precision, Recall

```
In [154]: from sklearn import metrics
          print(metrics.classification_report(y_test, pred_bow, target_names = ["positive", "ne
```

```
              precision    recall  f1-score   support

   positive       0.72      0.50      0.59      1951
   negative       0.91      0.96      0.94     10049
```

```
avg / total       0.88      0.89      0.88     12000
```

1.6.1 Obervation:

Using Metrics from sklearn , as we notices above measurements which reprasents f1-Score which closer to 86% , recall is 87% ,Precision is 86% and Accuracy is closer to 87%.

As we observed , For given training set using BagOfWord vectiorization in Naive Bayes, we got 87% accuracy on test set.

Using **Bernoulli Naïve Bayes learning method on Naive Bayes**, we got optimal Alpha which indicates hypermeter would closer to **0.0001** .

Let's focus on confusion matrix of this model, which predicts TP,TN,FP,FN on a diagonals on the Matrix.

1.7 Confusion Matrix

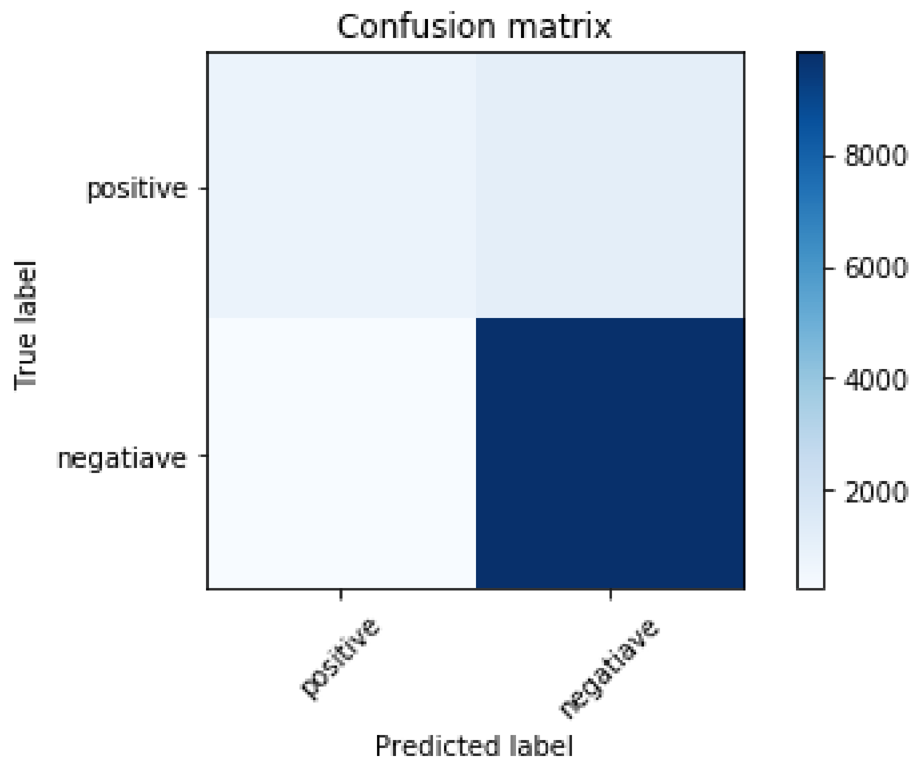
```
In [117]: confusion_matrix=cm_BoW
          FP = confusion_matrix.sum(axis=0) - np.diag(confusion_matrix)
          FN = confusion_matrix.sum(axis=1) - np.diag(confusion_matrix)
          TP = np.diag(confusion_matrix)
          TN = confusion_matrix.sum() - (FP + FN + TP)

          # Sensitivity, hit rate, recall, or true positive rate
          TPR = TP/(TP+FN)
          print('\n')

          print('TPR = ',TPR)
          # Specificity or true negative rate
          TNR = TN/(TN+FP)
          print('\n')

          print('TNR = ',TNR)
          # Precision or positive predictive value
          PPV = TP/(TP+FP)
          print('\n')

          print('Precision = ',PPV)
          # Negative predictive value
          NPV = TN/(TN+FN)
          print('\n')

          print('NPV(Negative Predictive Value) = ',NPV)

          # Fall out or false positive rate
          FPR = FP/(FP+TN)
          print('\n')
```

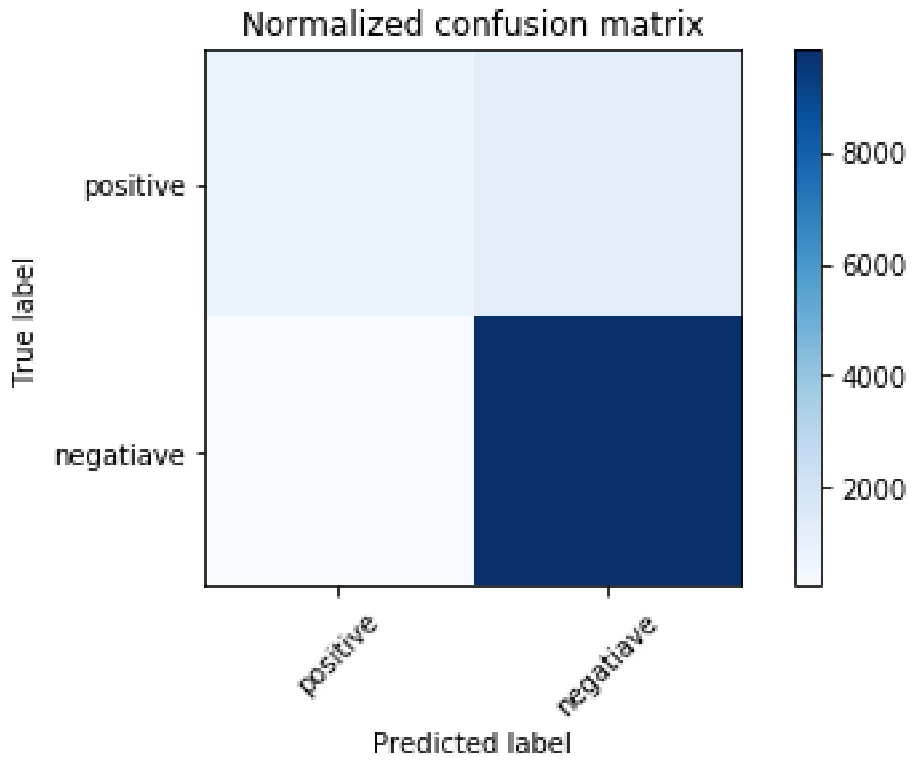
```
        print('FPR = ',FPR)
        # False negative rate
        FNR = FN/(TP+FN)
        print('\n')
        print('FNR = ',FNR)
        # False discovery rate
        print('\n')
        FDR = FP/(TP+FP)

        print('FDR = ',FDR)
        print('\n')
        # Overall accuracy
        ACC = (TP+TN)/(TP+FP+FN+TN)

        print('Accuracy = ',ACC)
```

```
TPR =  [0.41 0.98]


TNR =  [0.98 0.41]


Precision =  [0.78 0.89]


NPV(Negative Predictive Value) =  [0.89 0.78]


FPR =  [0.02 0.59]


FNR =  [0.59 0.02]


FDR =  [0.22 0.11]


Accuracy =  [0.89 0.89]
```

```
In [116]: from sklearn.metrics import confusion_matrix
          def plot_confusion_matrix(cm_BoW, title='Confusion matrix', cmap=plt.cm.Blues):
              plt.imshow(cm, interpolation='nearest', cmap=cmap)
              plt.title(title)
              plt.colorbar()
              tick_marks = np.arange(len(set(Score)))
```

```
    plt.xticks(tick_marks, set(Score), rotation=45)
    plt.yticks(tick_marks, set(Score))
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

# Compute confusion matrix
cm_BoW = confusion_matrix(y_test, pred)
np.set_printoptions(precision=2)
plt.figure()
plot_confusion_matrix(cm)

cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
plt.figure()
plot_confusion_matrix(cm_normalized, title='Normalized confusion matrix')

plt.show()
```





1.8 Naive Bayes Classification using TF-IDF vector

```
In [26]: # tif-idf

         from sklearn.feature_extraction.text import TfidfVectorizer
         tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))

         final_tf_idf = tf_idf_vect.fit_transform(Text)

In [28]: ## Splitting the data into Train and Test

         from sklearn.cross_validation import train_test_split
         from sklearn import cross_validation
         #X_1, X_test, y_train, y_test = train_test_split(Text, Score, test_size=0.3, random_s

         X_11, X_test, y_11, y_test = cross_validation.train_test_split(final_tf_idf,Score, te

         ## Split only train data into Train and test for Cross validation .

         # split the train data set into cross validation train and cross validation test
         X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(X_11, y_11, test_size=0.3)
```

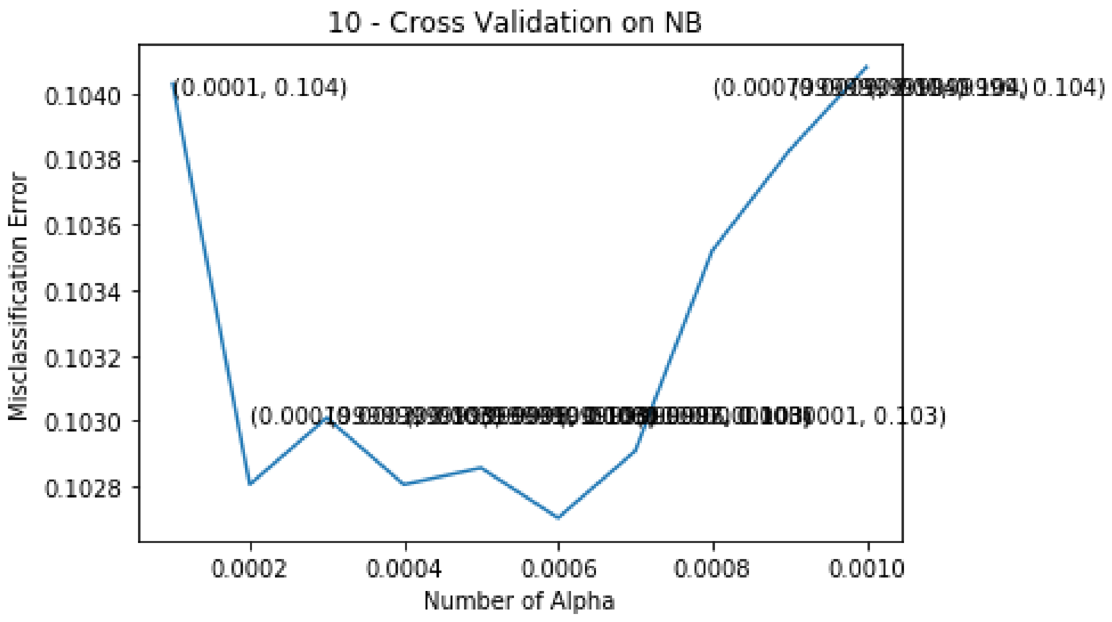
1.9 Applying Bernoulli Naïve Bayes learning method on TF-IDF

```
In [136]: from sklearn.naive_bayes import BernoulliNB
          from sklearn.metrics import accuracy_score

          np.set_printoptions(precision=5)

          myList=np.linspace(.0001,.001,10)

          for i in myList :


              NB = BernoulliNB(i)

              # fitting the model on crossvalidation train
              NB.fit(X_tr, y_tr)

              # predict the response on the crossvalidation train
              pred_tfidf = NB.predict(X_cv)

              # evaluate CV accuracy
              acc = accuracy_score(y_cv, pred_tfidf, normalize=True) * float(100)
              print('\nCV accuracy for Alpha = %.4f is %d%%' % (i, acc))

          NB = BernoulliNB(.0001)
          NB.fit(X_tr,y_tr)
          pred_tfidf = NB.predict(X_test)
          acc = accuracy_score(y_test, pred_tfidf, normalize=True) * float(100)
          print('\n****Test accuracy for Alpha = .0001 is %d%%' % (acc))
```

```
CV accuracy for Alpha = 0.0001 is 88%

CV accuracy for Alpha = 0.0002 is 89%

CV accuracy for Alpha = 0.0003 is 89%

CV accuracy for Alpha = 0.0004 is 89%

CV accuracy for Alpha = 0.0005 is 89%

CV accuracy for Alpha = 0.0006 is 89%

CV accuracy for Alpha = 0.0007 is 89%

CV accuracy for Alpha = 0.0008 is 89%

CV accuracy for Alpha = 0.0009 is 89%
CV accuracy for Alpha = 0.0010 is 89%

****Test accuracy for Alpha = .0001 is 88%
```

```
In [143]: import numpy as np
          import pandas as pd
          import matplotlib.pyplot as plt
          from sklearn.cross_validation import train_test_split
          from sklearn.naive_bayes import BernoulliNB
          from sklearn.metrics import accuracy_score
          from sklearn.cross_validation import cross_val_score
          from collections import Counter
          from sklearn.metrics import accuracy_score
          from sklearn import cross_validation

          np.set_printoptions(precision=5)

          myList=np.linspace(.0001,.001,10)


          # empty list that will hold cv scores
          cv_scores = []

          # perform 10-fold cross validation
          for i in myList:
              NB = BernoulliNB(alpha=i)
              scores = cross_val_score(NB, X_tr, y_tr, cv=10, scoring='accuracy')
              cv_scores.append(scores.mean())

          # changing to misclassification error
          MSE = [1 - x for x in cv_scores]

          # determining best alpha
          optimal_alpha = myList[MSE.index(min(MSE))]
          print('\nThe optimal number of neighbors is %.4f.' % optimal_alpha)

          # plot misclassification error vs k
          plt.plot(myList, MSE)

          for xy in zip(myList, np.round(MSE,3)):
              plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

          plt.xlabel('Number of Alpha')
          plt.ylabel('Misclassification Error')
          plt.title("10 - Cross Validation on NB ")
          plt.show()
          print("the misclassification error for each Alpha value is : ", np.round(MSE,3))
```

```
The optimal number of neighbors is 0.0006.
```



```
the misclassification error for each Alpha value is :  [0.104 0.103 0.103 0.103 0.103 0.103 0.1
```

```
In [145]: # ============================== NaiveBayes with Alpha = optimal_Alpha ============
          # instantiate learning model Alpha = optimal_alpha
          alpha_optimal = BernoulliNB(alpha=optimal_alpha)

          # fitting the model
          alpha_optimal.fit(X_tr, y_tr)

          # predict the response
          pred_tfidf = alpha_optimal.predict(X_test)

          # evaluate accuracy
          acc = accuracy_score(y_test,pred_tfidf) * 100
          print('\nThe accuracy of the NaiveBayes classifier for alpha = %.4f is %f%%' % (optin
```

```
The accuracy of the NaiveBayes classifier for alpha = 0.0006 is 88.800000%
```

1.10 Observation:

As we noticed , we have got optimal Alpha for Naive Bayes which indicates Hyper-paramter or Laplace Smooth at 0.0006 is closer to 89% of Accuracy (Classified) and 11% are Mis-classified.

For given train data we have estimated 89% of accuracy on Test data using TF-IDF vectorizer on Naive Bayes (NB).

1.11 Finding Important Features for +Ve and -Ve from TF-IDF vector

```
In [32]: ## Finding top features from TF-IDF
         import numpy as np
         neg_class_prob_sorted = NB_optimal.feature_log_prob_[0, :].argsort()
         pos_class_prob_sorted = NB_optimal.feature_log_prob_[1, :].argsort()

         print('Negative Words Scoring for Top 10 **************\n')
         print(np.take(tf_idf_vect.get_feature_names(), neg_class_prob_sorted[:10])) # np.take
         print('\n')
         print('Positive Words Scoring for Top 10 **************\n')
         print(np.take(tf_idf_vect.get_feature_names(), pos_class_prob_sorted[:10]))
```

```
Negative Words Scoring for Top 10 **************

['aaaaaaarrrrrggghhh' 'also harder' 'also hard' 'also happili'
 'also happi' 'also happen' 'also handi' 'also havent' 'also halo'
 'also hairbal']


Positive Words Scoring for Top 10 **************

['aaaaaaarrrrrggghhh' 'alway deposit' 'alway diet' 'alway differ'
 'alway dig' 'alway disappoint' 'advantag local' 'advantag littl'
 'alway dish' 'advantag lick']
```

1.12 F1- score,Precision, Recall

```
In [146]: from sklearn import metrics
          print(metrics.classification_report(y_test, pred_tfidf, target_names = ["positive", 
```

```
             precision    recall  f1-score   support

   positive       0.72      0.50      0.59      1951
   negative       0.91      0.96      0.94     10049

avg / total       0.88      0.89      0.88     12000
```

1.13 Obervation:

Using Metrics from sklearn , as we notices above measurements which reprasents f1-Score which closer to 88% , recall is 89% ,Precision is 88% and Accuracy is closer to 89%.

As we observed , For given training set using TF-IDF vectiorization in Naive Bayes, we got 88% accuracy on test set.

Using Bernoulli Naïve Bayes learning method on Naive Bayes, we got optimal Alpha which indicates hypermeter would closer to 0.0006 .

Let's focus on confusion matrix of this model, which predicts TP,TN,FP,FN on the Matrix.

1.14 Confusion Matrix

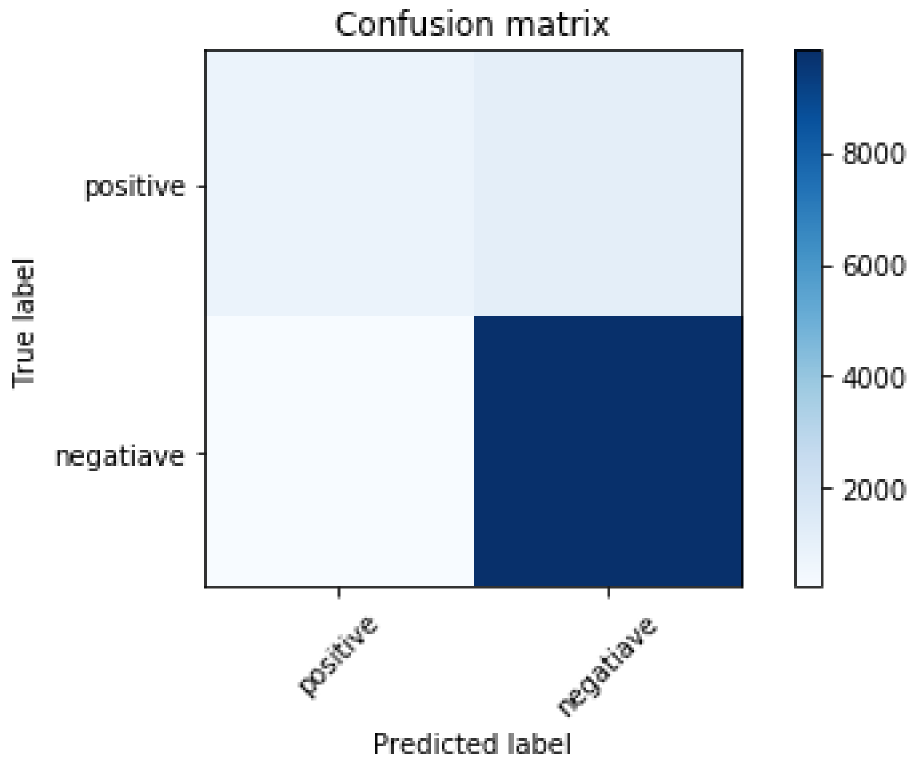
```
In [108]: confusion_matrix=cm
          FP = confusion_matrix.sum(axis=0) - np.diag(confusion_matrix)
          FN = confusion_matrix.sum(axis=1) - np.diag(confusion_matrix)
          TP = np.diag(confusion_matrix)
          TN = confusion_matrix.sum() - (FP + FN + TP)

          # Sensitivity, hit rate, recall, or true positive rate
          TPR = TP/(TP+FN)
          print('\n')

          print('TPR = ',TPR)
          # Specificity or true negative rate
          TNR = TN/(TN+FP)
          print('\n')

          print('TNR = ',TNR)
          # Precision or positive predictive value
          PPV = TP/(TP+FP)
          print('\n')

          print('Precision = ',PPV)
          # Negative predictive value
          NPV = TN/(TN+FN)
          print('\n')

          print('NPV(Negative Predictive Value) = ',NPV)

          # Fall out or false positive rate
          FPR = FP/(FP+TN)
          print('\n')

          print('FPR = ',FPR)
          # False negative rate
          FNR = FN/(TP+FN)
          print('\n')
          print('FNR = ',FNR)
```

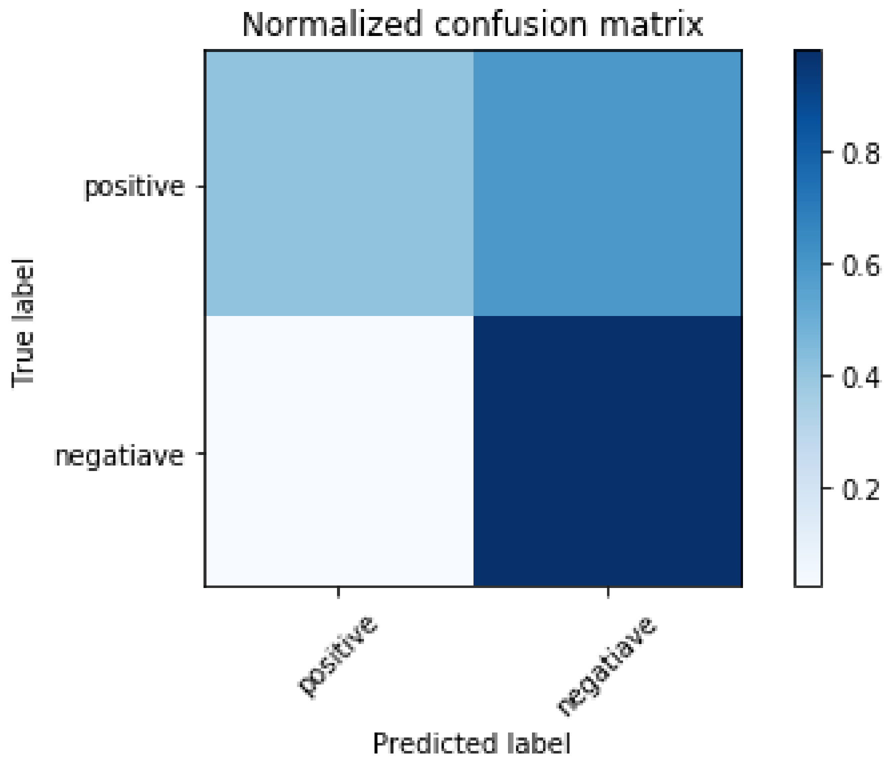
```
    # False discovery rate
    print('\n')
    FDR = FP/(TP+FP)

    print('FDR = ',FDR)
    print('\n')
    # Overall accuracy
    ACC = (TP+TN)/(TP+FP+FN+TN)

    print('Accuracy = ',ACC)
```

```
TPR =  [0.41 0.98]


TNR =  [0.98 0.41]


Precision =  [0.78 0.89]


NPV(Negative Predictive Value) =  [0.89 0.78]


FPR =  [0.02 0.59]


FNR =  [0.59 0.02]


FDR =  [0.22 0.11]


Accuracy =  [0.89 0.89]
```

```
In [114]: from sklearn.metrics import confusion_matrix
          def plot_confusion_matrix(cm, title='Confusion matrix', cmap=plt.cm.Blues):
              plt.imshow(cm, interpolation='nearest', cmap=cmap)
              plt.title(title)
              plt.colorbar()
              tick_marks = np.arange(len(set(Score)))
              plt.xticks(tick_marks, set(Score), rotation=45)
              plt.yticks(tick_marks, set(Score))

              plt.tight_layout()
              plt.ylabel('True label')
```

```
    plt.xlabel('Predicted label')

# Compute confusion matrix
cm = confusion_matrix(y_test, pred_tfidf)

np.set_printoptions(precision=2)
plt.figure()
plot_confusion_matrix(cm)

cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
plt.figure()
plot_confusion_matrix(cm_normalized, title='Normalized confusion matrix')

plt.show()
```





1.15 Conclusion:

We can assume that using BagOfWords and TF-IDF vectorizer has got Accuracy is closer to 89% for Hyper-paramter (alpa)which indicates Lapace Smooth.

If we look at F1-score which closer to Accuracy , it implies that for given train data we accomplished 89% accuracy on Test data

Naive Bayes , using Bernoulli Naïve Bayes we accomplished Laplace Smooth at 0.0006 which is called Optimal Hyper-parameter.