

naiveBayes_AmazonFoodProductReview

November 21, 2018

Naive Bayes model implementation for Amazon food product reviews.

```
In [21]: import numpy as np
import pandas as pd
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
import sklearn
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import train_test_split
import sqlite3
import warnings
warnings.filterwarnings('ignore')
import string
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import cross_val_score
from sklearn import cross_validation
from sklearn.metrics import accuracy_score
from sklearn.decomposition import TruncatedSVD
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
import pickle
%matplotlib inline

In [2]: con = sqlite3.connect('/home/niranjan/Downloads/database.sqlite')
data = pd.read_sql_query('select * from Reviews where Score!=3 ',con)
data['Score'] = [1 if i > 3 else 0 for i in data['Score']]
#print(data.shape)

In [3]: data_sort = data.sort_values(by='ProductId',ascending=True, inplace=False, kind='quicksort')
data_groupby = data_sort[['ProductId', 'Score']].groupby('Score').count()
#print(data_groupby)

Removing duplicates data

In [4]: data_without_dup = data_sort.drop_duplicates(subset={'UserId', 'ProfileName', 'Time', 'Text'})
#print(data_without_dup.shape)
```

```
data_groupby = data_without_dup[['ProductId', 'Score']].groupby('Score').count()
#print(data_groupby)
```

```
In [5]: data_without_dup = data_without_dup[data_without_dup.HelpfulnessNumerator<=data_without_dup.HelpfulnessNumerator]
#print(data_without_dup.shape)
```

```
In [6]: import nltk
nltk.download('stopwords')
nltk.download('wordnet')
from nltk.corpus import stopwords
from nltk import WordNetLemmatizer
stop = set(stopwords.words('english'))
lemma = nltk.WordNetLemmatizer()
```

```
[nltk_data] Downloading package stopwords to
[nltk_data] /home/niranjana/nltk_data...
[nltk_data] Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /home/niranjana/nltk_data...
[nltk_data] Package wordnet is already up-to-date!
```

```
In [7]: import re
def cleanhtml(words):
    tag = re.compile(r'<.*>')
    cleanSent = re.sub(tag, '', words)
    return cleanSent

def PuncRemov(words):
    tag = re.compile(r'[^a-zA-Z]')
    cleanSent = re.sub(tag, '', words)
    return cleanSent

***-----data cleaning-----***
```

removal of html tags, symbols other than alphabets, stopwords and performing lemmatization as part of data pre-processing.

Lemmatization :- is the process of grouping together the inflected forms of a word so they can be analysed as a single item, identified by the word's lemma, or dictionary form.**

```
In [8]: final_string = []
str1 = ' '
positive_word = []
negative_word = []
i=0
```

```

for sen in data_without_dup['Text'].values:
    filtered_word = []
    sent = cleanhtml(sen)
    for word in sent.split():
        cleanWord = PuncRemov(word)
        for cleaned_words in cleanWord.split():
            if ((len(cleaned_words) > 2) & (cleaned_words.isalpha())):
                if (cleaned_words.islower() not in stop):
                    w = (lemma.lemmatize(cleaned_words.lower())).encode('utf8')
                    filtered_word.append(w)
                    if data_without_dup['Score'].values[i]=='positive':
                        positive_word.append(w)
                    else:
                        negative_word.append(w)
                else:
                    continue
            else:
                continue
        str1 = b" ".join(filtered_word)
        final_string.append(str1)
    i = i+1

```

```

In [9]: data_without_dup['cleaned_text'] = final_string
        data_without_dup['cleaned_text'] = data_without_dup['cleaned_text'].str.decode('utf8')

```

sorting data based on time in ascending order

```

In [10]: data_without_dup = data_without_dup.sort_values(by='Time',ascending=True,inplace=False)

In [11]: X = data_without_dup['cleaned_text']
        y = data_without_dup['Score']

In [87]: X_train= X[0:250000]
        y_train = y[0:250000]
        X_cv= X[250000:270000]
        y_cv = y[250000:270000]
        X_test = X[270000:290000]
        y_test = y[270000:290000]

```

BOW as Vectorizer

```

In [14]: count_vect = CountVectorizer()
        X_train_bow = count_vect.fit_transform(X_train)
        X_cv_bow = count_vect.transform(X_cv)
        X_test_bow = count_vect.transform(X_test)

```

Best alpha fit using Cross validation

```

In [38]: param = np.linspace(0,1,10000)
         #print(param)

         cv_scores = []
         for val in param:
             classifier = MultinomialNB(alpha=val)
             classifier.fit(X_train_bow,y_train)
             y_pred = classifier.predict(X_cv_bow)
             cv_scores.append(f1_score(y_pred,y_cv,average='micro'))

         #Determining optimal value of apha

         optimal_alpha = param[cv_scores.index(max(cv_scores))]
         print("optimal number of alpha is: ", optimal_alpha)

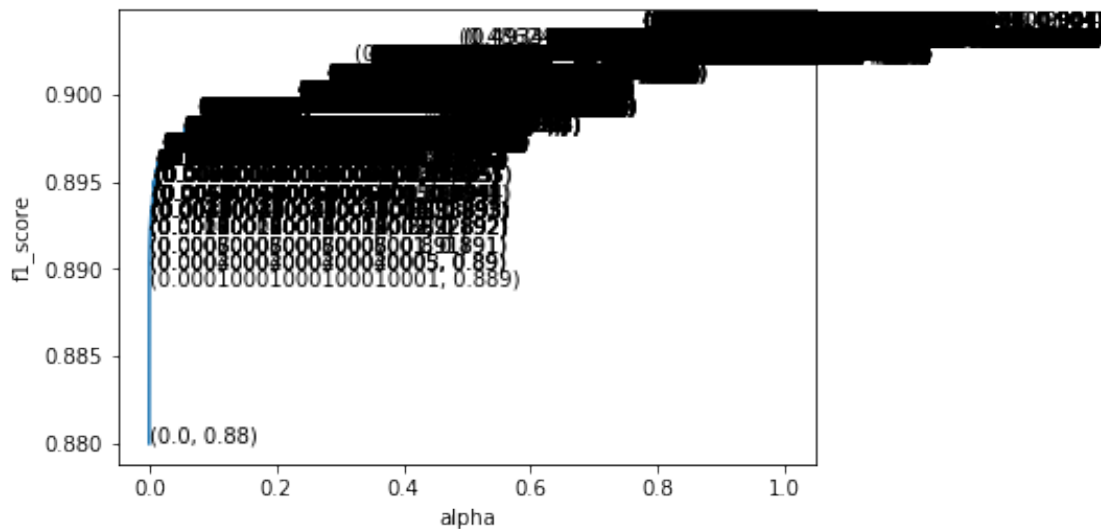
         plt.plot(param,cv_scores)

         for xy in zip(param, np.round(cv_scores,3)):
             plt.annotate('%s, %s' % xy, xy=xy, textcoords='data')
         plt.xlabel('alpha')
         plt.ylabel('f1_score')
         plt.show()

         #print("the f1_score for each alpha value is : ", np.round(cv_scores,3))

optimal number of alpha is:  0.7923792379237924

```



```

In [77]: clf = MultinomialNB(alpha=optimal_alpha)
         clf.fit(X_train_bow,y_train)
         pred = clf.predict(X_test_bow)
         # evaluate accuracy
         acc = f1_score(y_test, pred,average='micro')*100
         print("The accuracy of the multimonialNB classifier for alpha {a} is {b}%".format(a =
         print("-----")
         class_labels = clf.classes_
         feature_names =count_vect.get_feature_names()
         topn_class1 = sorted(zip(clf.predict_log_proba(X_test_bow)[: ,0], feature_names))[:10]
         topn_class2 = sorted(zip(clf.predict_log_proba(X_test_bow)[: ,1], feature_names))[:10]
         print("Important words in negative reviews")
         for coef, feat in topn_class1:
             print(class_labels[0], coef, feat)
         print("-----")
         print("Important words in positive reviews")
         for coef, feat in topn_class2:
             print(class_labels[1], coef, feat)
         tn,fp,fn,tp = confusion_matrix(y_test,pred).ravel()
         df = pd.DataFrame(confusion_matrix(y_test,pred))
         sns.heatmap(df,annot=True,fmt="d")
         plt.show()

```

The accuracy of the multimonialNB classifier for alpha 0.7923792379237924 is 90.405%

```

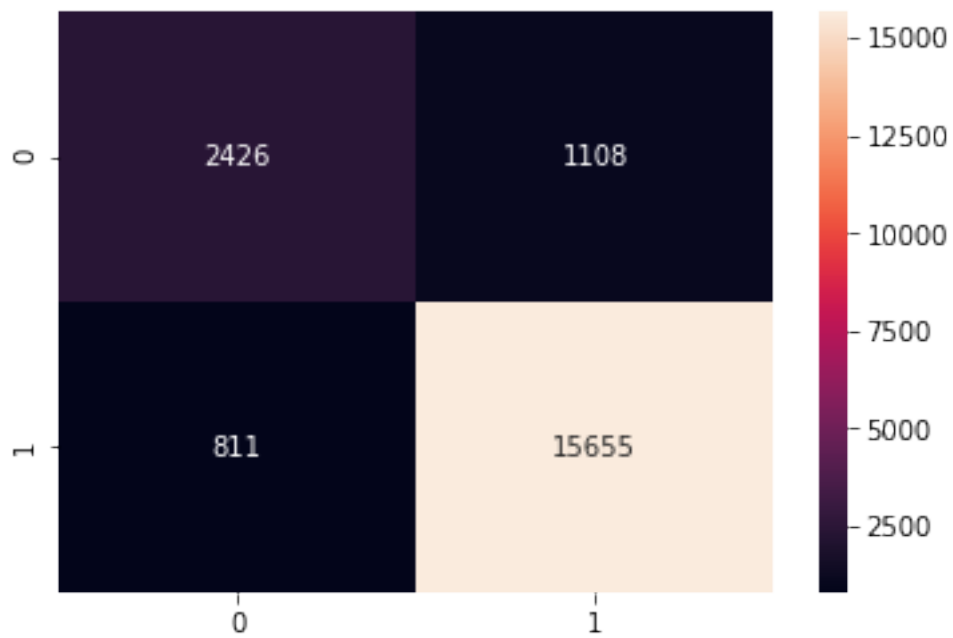
-----
Important words in negative reviews
0 -227.14954512541772 breakfastmorning
0 -193.00439882773208 bottler
0 -162.0512254941732 areeven
0 -111.79294854915304 barscookiescakesmeatloavesbr
0 -108.94069355239935 beetlj juice
0 -106.93009055314678 briannabr
0 -103.12694280755295 broccolihaters
0 -88.09768252082904 bitteracidic
0 -86.76064505100476 accountit
0 -83.78868009150756 amt

```

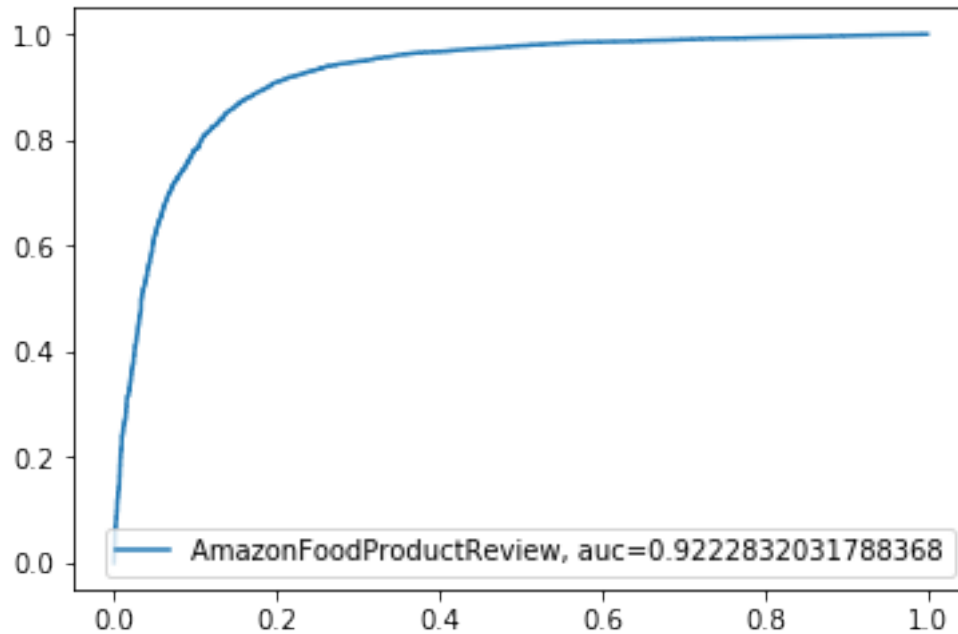
```

-----
Important words in positive reviews
1 -148.63024181920946 author
1 -148.13608061836158 attitudebr
1 -148.13608061836158 aux
1 -124.51900736951302 buyingmove
1 -121.91314757824148 attitude
1 -118.57365795156738 barsbr
1 -73.83664242421673 bjuice
1 -71.59713280601363 airfreshners
1 -63.17997228995955 agescons
1 -59.14661111178657 biy

```



```
In [78]: y_pred_proba = classifier.predict_proba(X_test_bow)[:,:1]
fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="AmazonFoodProductReview, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



```
In [73]: precision = (tp/tp+fp)
         recall = tp/fn+tp
         print("precision is :",precision)
         print("recall is :",recall)
```

```
precision is : 1109.0
recall is : 15674.303329223181
```

tf-idf as Vectorizer

```
In [88]: vec = TfidfVectorizer()

In [94]: tfidf_vect = CountVectorizer()
         X_train_tfidf = tfidf_vect.fit_transform(X_train)
         X_cv_tfidf = tfidf_vect.transform(X_cv)
         X_test_tfidf = tfidf_vect.transform(X_test)

In [95]: param = np.linspace(0,1,10000)
         #print(param)

         cv_scores = []
         for val in param:
             classifier = MultinomialNB(alpha=val)
             classifier.fit(X_train_tfidf,y_train)
             y_pred = classifier.predict(X_cv_tfidf)
```

```

cv_scores.append(f1_score(y_pred,y_cv,average='micro'))

#Determining optimal value of apha

optimal_alpha_tfidf = param[cv_scores.index(max(cv_scores))]
print("optimal number of alpha is: ", optimal_alpha_tfidf)

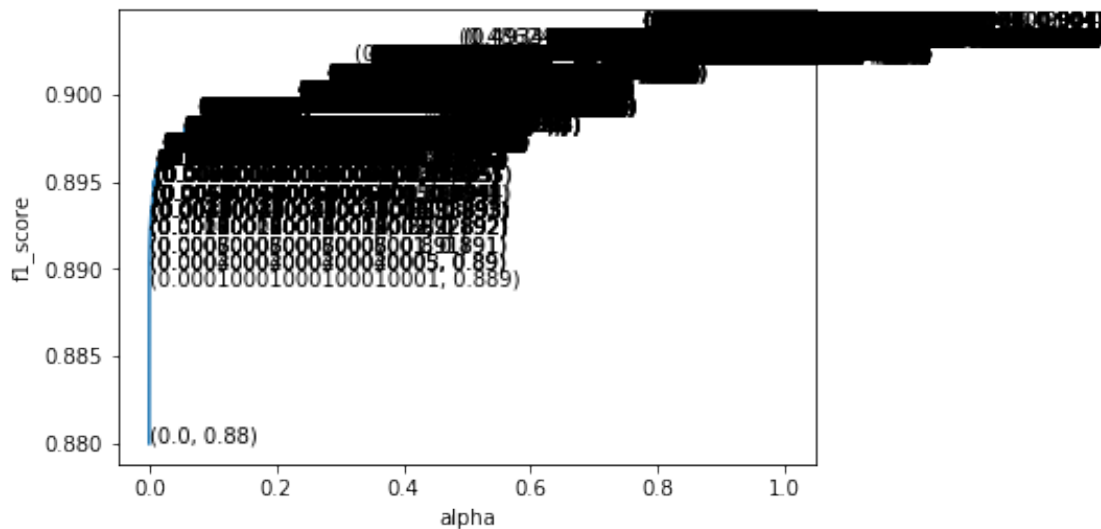
plt.plot(param,cv_scores)

for xy in zip(param, np.round(cv_scores,3)):
    plt.annotate('%s, %s' % xy, xy=xy, textcoords='data')
plt.xlabel('alpha')
plt.ylabel('f1_score')
plt.show()

print("the f1_score for each alpha value is : ", np.round(cv_scores,3))

```

optimal number of alpha is: 0.7923792379237924



the f1_score for each alpha value is : [0.88 0.889 0.89 ... 0.904 0.904 0.904]

```

In [96]: clf = MultinomialNB(alpha=optimal_alpha_tfidf)
         clf.fit(X_train_tfidf,y_train)
         pred = clf.predict(X_test_tfidf)
         # evaluate accuracy
         acc = f1_score(y_test, pred,average='micro')*100

```



```

print("The accuracy of the multinomialNB classifier for alpha {a} is {b}%".format(a =
print("-----")
class_labels = clf.classes_
feature_names = count_vect.get_feature_names()
topn_class1 = sorted(zip(clf.predict_log_proba(X_test_tfidf)[: ,0], feature_names))[:10]
topn_class2 = sorted(zip(clf.predict_log_proba(X_test_tfidf)[: ,1], feature_names))[:10]
print("Important words in negative reviews")
for coef, feat in topn_class1:
    print(class_labels[0], coef, feat)
print("-----")
print("Important words in positive reviews")
for coef, feat in topn_class2:
    print(class_labels[1], coef, feat)
tn,fp,fn,tp = confusion_matrix(y_test,pred).ravel()
df = pd.DataFrame(confusion_matrix(y_test,pred))
sns.heatmap(df,annot=True,fmt="d")
plt.show()

```

The accuracy of the multinomialNB classifier for alpha 0.7923792379237924 is 90.405%

```

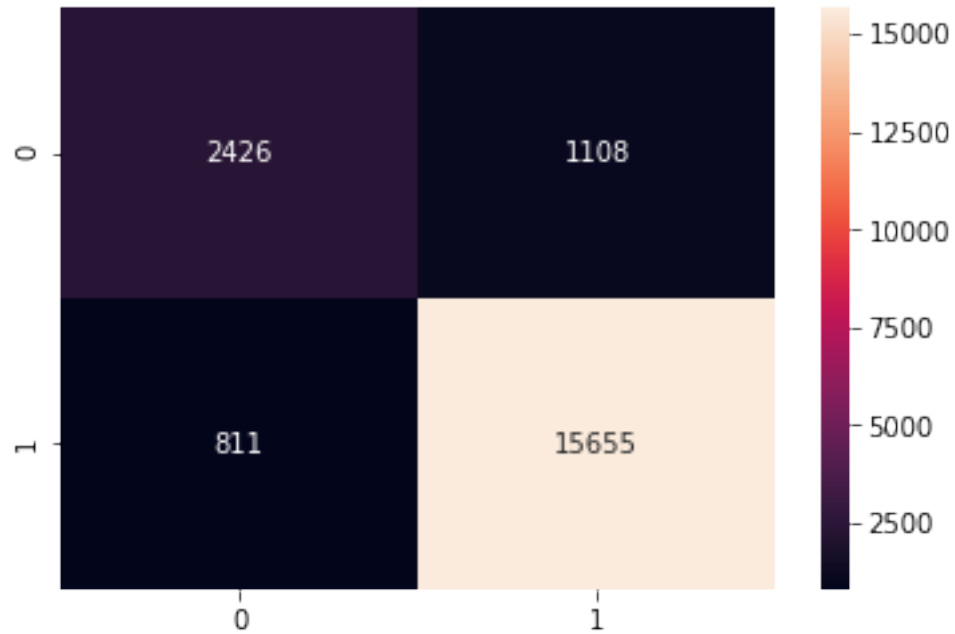
-----
Important words in negative reviews
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0 -88.09768252082904 bitteracidic
0 -86.76064505100476 accountit
0 -83.78868009150756 amt

```

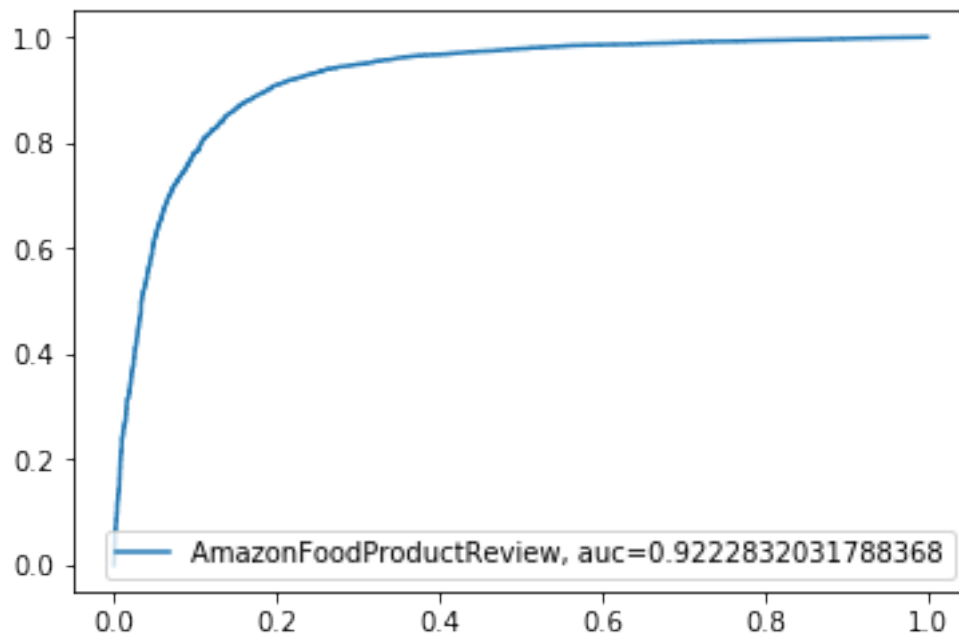
```

-----
Important words in positive reviews
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1 -71.59713280601363 airfreshners
1 -63.17997228995955 agescons
1 -59.14661111178657 biy

```



```
In [97]: y_pred_proba = classifier.predict_proba(X_test_tfidf)[::,1]
fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="AmazonFoodProductReview, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



```
In [98]: precision = (tp/tp+fp)
        recall = tp/fn+tp
        print("precision is :",precision)
        print("recall is :",recall)
```

```
precision is : 1109.0
recall is : 15674.303329223181
```

```
In [101]: from prettytable import PrettyTable
        x = PrettyTable()
        x.add_column("important_features_class_[0]",topn_class1)
        x.add_column("important_features_class_[1]",topn_class2)
        print(x)
        y = PrettyTable()
        y.field_names=["Vectorizer","Model","Alpha","f1_score","Precision","recall"]
        y.add_row(["BOW","MultinomialNB","0.7923792379237924","0.90405","1109.0","15674.303329223181"])
        y.add_row(["tfidf","MultinomialNB","0.7923792379237924","0.90405","1109.0","15674.303329223181"])
        print(y)
```

+-----+-----+-----+-----+-----+-----+			+-----+-----+-----+-----+-----+-----+		
important_features_class_[0]			important_features_class_[1]		
+-----+-----+-----+-----+-----+-----+			+-----+-----+-----+-----+-----+-----+		
(-227.14954512541772, 'breakfastmorning')			(-148.63024181920946, 'author')		
(-193.00439882773208, 'bottler')			(-148.13608061836158, 'attitudebr')		
(-162.0512254941732, 'areeven')			(-148.13608061836158, 'aux')		
(-111.79294854915304, 'barscookiescakesmeatloavesbr')			(-124.51900736951302, 'buyingmove')		
(-108.94069355239935, 'beetljuice')			(-121.91314757824148, 'attitude')		
(-106.93009055314678, 'briannabr')			(-118.57365795156738, 'barsbr')		
(-103.12694280755295, 'broccolihaters')			(-73.83664242421673, 'bjjuice')		
(-88.09768252082904, 'bitteracidic')			(-71.59713280601363, 'airfreshners')		
(-86.76064505100476, 'accountit')			(-63.17997228995955, 'agescons')		
(-83.78868009150756, 'amt')			(-59.14661111178657, 'biy')		
+-----+-----+-----+-----+-----+-----+			+-----+-----+-----+-----+-----+-----+		
+-----+-----+-----+-----+-----+-----+			+-----+-----+-----+-----+-----+-----+		
Vectorizer	Model	Alpha	f1_score	Precision	recall
+-----+-----+-----+-----+-----+-----+			+-----+-----+-----+-----+-----+-----+		
BOW	MultinomialNB	0.7923792379237924	0.90405	1109.0	15674.303329223181
tfidf	MultinomialNB	0.7923792379237924	0.90405	1109.0	15674.303329223181
+-----+-----+-----+-----+-----+-----+			+-----+-----+-----+-----+-----+-----+		