K- Nearest Neighbors on Amazon Food Reviews

In [59]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

# General Packages
import os
import sqlite3
import pandas as pd
import numpy as np
import string
import re
import nltk
import datetime
import time
from decimal import *

# Plotting Packages
import matplotlib.pyplot as plt
import seaborn as sns

# Packages for Tfidf
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

# Packages for BOW (Bag of words)
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc

# Packages for Text Preprocessing
from nltk.stem.porter import PorterStemmer
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer

#Packages for Word2vec, Average Word2vec & Tf-Idf Weighted Word2Vec
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

#Packages for plotting Tsne plot
from sklearn.manifold import TSNE

from sklearn.cross_validation import train_test_split
from sklearn.neighbors import KNeighborsClassifier
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
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import TimeSeriesSplit
from prettytable import PrettyTable
from prettytable import MSWORD_FRIENDLY
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import make_scorer, accuracy_score,average_precision_score
from sklearn.decomposition import TruncatedSVD
```

In [60]:
```
# Formaing Output using pretty table
Pretty = PrettyTable(["Model","Algorithm"," K ","TPR","TNR","Precision","Recall","F1-Score","FPR","FNR","PPV",
"NPV","Overall Accuracy (ACC)"])
Pretty.set_style(MSWORD_FRIENDLY)
print(Pretty)
```

```
| Model | Algorithm |  K  | TPR | TNR | Precision | Recall | F1-Score | FPR | FNR | PPV | NPV | Overall Accur
acy (ACC) |
```

Preprocessing Stage: Cleansed Stop Words, Punctuations & Html tags

In [61]:
```
#Connecting the Sqlite file after the Preprocessing Stage
#os.chdir('/Users/sujis/Downloads/AI/Sujit')
os.chdir('C:\Users\sujit.venkata\Downloads\Dev & Imp works\Applied AI')
con = sqlite3.connect('final.sqlite')
final= pd.read_sql_query(""" SELECT * FROM Reviews """, con)
```

In [62]:
```
final.head(1)
```

Out[62]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	positive	93934

In [63]:
```
final['Score'].value_counts()
```

Out[63]:
```
positive    307061
negative     57110
Name: Score, dtype: int64
```

Taking a Sample of 75000 records from the Dataset

In [64]:
```
# Taking 75K data points from the dataset
final_dataset=final.head(75000)
```

In [65]:
```
final_dataset['Score'].value_counts()
```

Out[65]:
```
positive    63939
negative    11061
Name: Score, dtype: int64
```

In [66]:
```
#Sorting the Dataframe with Date to apply Timebased Split
final_dataset=final_dataset.sort_values(by='Time',ascending=1)
```

In [67]:
```
# create design matrix X and target vector y
X = np.array(final_dataset.iloc[:, 0:12]) # end index is exclusive
Y = np.array(final_dataset['Score']) # showing you two ways of indexing a pandas df
```

In [68]:
```
#Time based split
tscv = TimeSeriesSplit(n_splits=5)
print(tscv)
```

```
TimeSeriesSplit(n_splits=5)
```

In [69]:
```
#Splitting the Dataset into Train set & Test set
for train_index, test_index in tscv.split(X):
   print("TRAIN:", train_index, "TEST:", test_index)
   X_train, X_test = X[train_index], X[test_index]
   Y_train, Y_test = Y[train_index], Y[test_index]
```

```
('TRAIN:', array([    0,     1,     2, ..., 12497, 12498, 12499], dtype=int64), 'TEST:', array([12500, 12501,
12502, ..., 24997, 24998, 24999], dtype=int64))
('TRAIN:', array([    0,     1,     2, ..., 24997, 24998, 24999], dtype=int64), 'TEST:', array([25000, 25001,
25002, ..., 37497, 37498, 37499], dtype=int64))
('TRAIN:', array([    0,     1,     2, ..., 37497, 37498, 37499], dtype=int64), 'TEST:', array([37500, 37501,
37502, ..., 49997, 49998, 49999], dtype=int64))
('TRAIN:', array([    0,     1,     2, ..., 49997, 49998, 49999], dtype=int64), 'TEST:', array([50000, 50001,
50002, ..., 62497, 62498, 62499], dtype=int64))
('TRAIN:', array([    0,     1,     2, ..., 62497, 62498, 62499], dtype=int64), 'TEST:', array([62500, 62501,
62502, ..., 74997, 74998, 74999], dtype=int64))
```

In [70]:
```
print(X_train.shape)
print(X_test.shape)
print('-------------------')
print(Y_train.shape)
print(Y_test.shape)
```

```
(62500L, 12L)
(12500L, 12L)
-------------------
(62500L,)
(12500L,)
```

In [71]:
```
# Converting X_Train, X_cv & X_test data is  to Dataframe for the ease of use
X_train_data=pd.DataFrame(X_train, columns=['index', 'Id', 'ProductId', 'UserId', 'ProfileName',
       'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score', 'Time',
       'Summary', 'Text', 'CleanedText'])

X_test_data=pd.DataFrame(X_test, columns=['index', 'Id', 'ProductId', 'UserId', 'ProfileName',
       'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score', 'Time',
       'Summary', 'Text', 'CleanedText'])
```

Bag of Words

In [72]:
```
# create the transform
vectorizer = CountVectorizer()
# tokenize and build vocab
vectorizer.fit(X_train_data['CleanedText'].values)
# Bag of Words : Train Data Set
Train_X_vector = vectorizer.transform(X_train_data['CleanedText'].values)
# summarize encoded vector
print(Train_X_vector.shape)
```

```
(62500, 30110)
```

In [73]:
```
#Test Data Set
Test_X_vector = vectorizer.transform(X_test_data['CleanedText'].values)
print(Test_X_vector.shape)
```

```
(12500, 30110)
```

In [74]:
```
print(Train_X_vector.shape)
print(Test_X_vector.shape)
print('-------------------')
print(Y_train.shape)
print(Y_test.shape)
```

```
(62500, 30110)
(12500, 30110)
-------------------
(62500L,)
(12500L,)
```

In [75]:
```
# 10 fold Cross Validation
cv_scores=[]
Params = list(np.arange(0.1,1,0.01))

for a in Params:
    nb = MultinomialNB(alpha=a)
    scores = cross_val_score(nb, Train_X_vector, Y_train, cv=10, scoring='accuracy')
    cv_scores.append(scores.mean())

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

In [76]:
```
# determining best k
optimal_alpha = Params[MSE.index(min(MSE))]
print('\nThe optimal alpha is %0.3f' % optimal_alpha)
```

```
The optimal alpha is 0.990
```

In [77]:
```
# plot misclassification error vs k
plt.plot(Params, MSE)

plt.xlabel('Alpha Parameters')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each Alpha value is : ", np.round(MSE,4))
```


```
('the misclassification error for each Alpha value is : ', array([ 0.1115,  0.1114,  0.1112,  0.1109,  0.111
1,  0.1111,  0.1112,
        0.1113,  0.1113,  0.1113,  0.1112,  0.1112,  0.1111,  0.1111,
        0.1109,  0.1109,  0.1107,  0.1108,  0.1106,  0.1105,  0.1104,
        0.1104,  0.1102,  0.1101,  0.1101,  0.1099,  0.1098,  0.1096,
        0.1094,  0.1093,  0.1092,  0.1091,  0.109 ,  0.1088,  0.1088,
        0.1087,  0.1085,  0.1082,  0.1081,  0.108 ,  0.108 ,  0.1078,
        0.1078,  0.1076,  0.1074,  0.1073,  0.1071,  0.107 ,  0.107 ,
        0.107 ,  0.107 ,  0.107 ,  0.1069,  0.1069,  0.1067,  0.1065,
        0.1065,  0.1063,  0.1062,  0.1063,  0.106 ,  0.1059,  0.1058,
        0.1058,  0.1057,  0.1054,  0.1052,  0.105 ,  0.105 ,  0.105 ,
        0.105 ,  0.1049,  0.1049,  0.1048,  0.1047,  0.1047,  0.1046,
        0.1045,  0.1044,  0.1043,  0.1042,  0.104 ,  0.104 ,  0.1039,
        0.1037,  0.1036,  0.1034,  0.1033,  0.1032,  0.1032]))
```

In [78]:
```
nb = BernoulliNB(alpha=optimal_alpha)
nb.fit(Train_X_vector,Y_train)
pred = nb.predict(Test_X_vector)
nb.predict_proba(Test_X_vector)
bag_test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\nThe accuracy of the Naive Bayes Classifier for Alpha = %0.3f is %0.2f%%' % (optimal_alpha, bag_test_a
cc))
#print('\n****Test accuracy for Alpha = 0.990 is %0.2f%%' % (bag_test_acc))
```

```
The accuracy of the Naive Bayes Classifier for Alpha = 0.990 is 85.10%
```

In [79]:
```
# Getting top Features using feature_log_prob
neg=np.take(vectorizer.get_feature_names(), (nb.feature_log_prob_[0, :].argsort())[:20]).tolist()
pos=np.take(vectorizer.get_feature_names(), (nb.feature_log_prob_[1, :].argsort())[:20]).tolist()
```

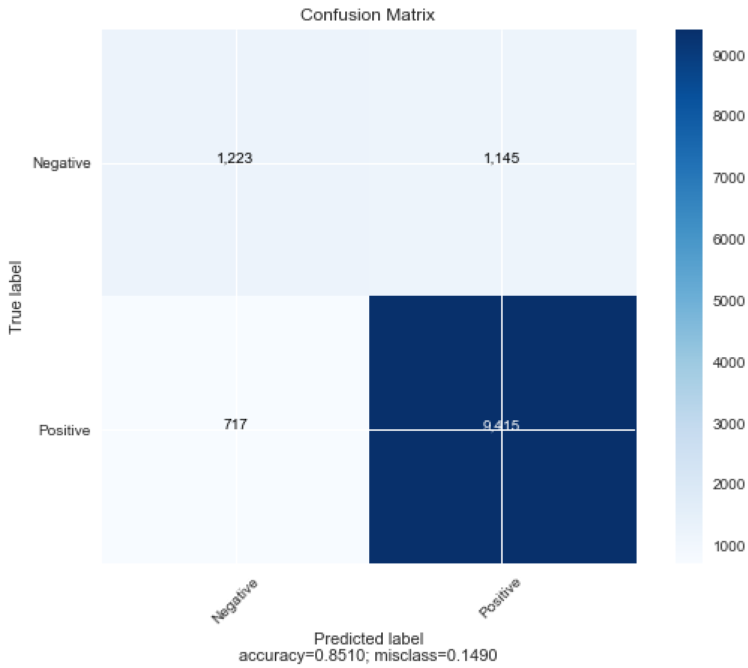
In [80]:
```
# Getting top Features using feature_count
def takefeature(elem):
    return elem[0]
def important_features(vectorizer,classifier,n=20):
    class_labels = classifier.classes_
    feature_names =vectorizer.get_feature_names()
    topn_class1 = sorted(zip(classifier.feature_count_[0], feature_names),key=takefeature,reverse=True)[:n]
    topn_class2 = sorted(zip(classifier.feature_count_[1], feature_names),key=takefeature,reverse=True)[:n]
    return topn_class1,topn_class2
```

In [81]:
```
neg_bw,pos_bw=important_features(vectorizer,nb,n=20)
```

In [82]:
```
Conf_matrix=confusion_matrix(Y_test, pred)
```

In [83]:
```
import numpy as np


def plot_confusion_matrix(cm,
                          target_names,
                          title='Confusion matrix',
                          cmap=None,
                          normalize=True):

    import matplotlib.pyplot as plt
    import numpy as np
    import itertools

    accuracy = np.trace(cm) / float(np.sum(cm))
    misclass = 1 - accuracy

    if cmap is None:
        cmap = plt.get_cmap('Blues')

    plt.figure(figsize=(8, 6))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()

    if target_names is not None:
        tick_marks = np.arange(len(target_names))
        plt.xticks(tick_marks, target_names, rotation=45)
        plt.yticks(tick_marks, target_names)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]


    thresh = cm.max() / 1.5 if normalize else cm.max() / 2
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        if normalize:
            plt.text(j, i, "{:0.4f}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")
        else:
            plt.text(j, i, "{:,}".format(cm[i, j]),
                     horizontalalignment="center",
                     color="white" if cm[i, j] > thresh else "black")


    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accuracy, misclass))
    plt.show()
```

In [84]:
```
plot_confusion_matrix(cm           = Conf_matrix,
                      normalize    = False,
                      target_names = ['Negative', 'Positive'],
                      title        = "Confusion Matrix")
```



In [85]:
```
Conf_matrix
```

Out[85]:
```
array([[1223, 1145],
       [ 717, 9415]])
```

In [86]:
```
TN,FP,FN,TP = Conf_matrix.ravel()
#confusion_matrix(Y_test, pred)
```

In [87]:
```
# Sensitivity, hit rate, recall, or true positive rate
TPR ='{0:.2%}'.format(Decimal(TP)/Decimal(TP+FN))
# Specificity or true negative rate
TNR ='{0:.2%}'.format(Decimal(TN)/Decimal(TN+FP))
# Fall out or false positive rate
FPR ='{0:.2%}'.format(Decimal(FP)/Decimal(FP+TN))
# False negative rate
FNR ='{0:.2%}'.format(Decimal(FN)/Decimal(TP+FN))
# Precision or positive predictive value
PPV ='{0:.2%}'.format(Decimal(TP)/Decimal(TP+FP))
# Negative predictive value
NPV ='{0:.2%}'.format(Decimal(TN)/Decimal(TN+FN))
# Overall accuracy
ACC ='{0:.2%}'.format(Decimal(TP+TN)/Decimal(TP+FP+FN+TN))
```

In [88]:
```
Recall=recall_score(Y_test, pred, average='micro')
```

In [89]:
```
Precision=precision_score(Y_test, pred, average='micro')
```

In [90]:
```
F1_Score=f1_score(Y_test, pred, average='weighted')
```

In [91]:
```
pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
```

Out[91]:

Predicted	negative	positive	All
True			
negative	1223	1145	2368
positive	717	9415	10132
All	1940	10560	12500

In [92]:
```
Pretty.add_row(["Bag of Words","10 fold - Cross Validation",optimal_alpha,TPR,TNR,'{0:.2f}'.format(Precision),
'{0:.2f}'.format(Recall),'{0:.2f}'.format(F1_Score),FPR,FNR,PPV,NPV,ACC])
```

In [93]:
```
print(Pretty)
```

```
|    Model     |         Algorithm          |  K   |  TPR   |  TNR   | Precision | Recall | F1-Score |  FPR
|  FNR  |  PPV   |  NPV   | Overall Accuracy (ACC) |
| Bag of Words | 10 fold - Cross Validation | 0.99 | 92.92% | 51.65% |    0.85   |  0.85  |   0.85   | 48.35%
| 7.08% | 89.16% | 63.04% |         85.10%         |
```

In [94]:
```
print(classification_report(Y_test, pred))
```

```
             precision    recall  f1-score   support

   negative       0.63      0.52      0.57      2368
   positive       0.89      0.93      0.91     10132

avg / total       0.84      0.85      0.85     12500
```

TF - IDF

In [95]:
```
tf_transformer = TfidfVectorizer(ngram_range=(1,2))
TF_vector=tf_transformer.fit(X_train_data['CleanedText'].values)
TF_train_Vector = TF_vector.transform(X_train_data['CleanedText'].values)
TF_train_Vector.shape
```

Out[95]: (62500, 885097)

In [96]:
```
TF_test_Vector = TF_vector.transform(X_test_data['CleanedText'].values)
TF_test_Vector.shape
```

Out[96]: (12500, 885097)

In [97]:
```
print(TF_train_Vector.shape)
print(TF_test_Vector.shape)
print('-------------------')
print(Y_train.shape)
print(Y_test.shape)
```

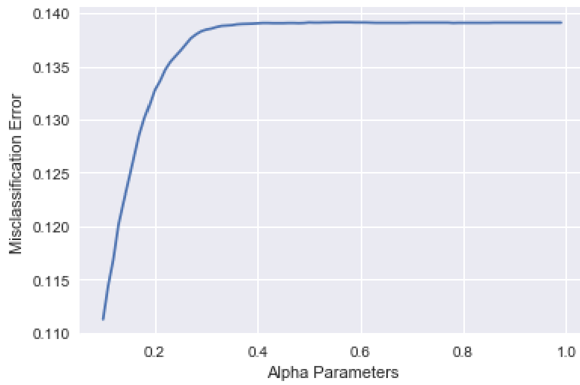
```
(62500, 885097)
(12500, 885097)
-------------------
(62500L,)
(12500L,)
```

In [98]:
```
# 10 fold Cross Validation
cv_scores=[]
Params = list(np.arange(0.1,1,0.01))

for a in Params:
    nb = MultinomialNB(alpha=a)
    scores = cross_val_score(nb, TF_train_Vector, Y_train, cv=10, scoring='accuracy')
    cv_scores.append(scores.mean())

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

In [99]:
```
# determining best k
optimal_alpha = Params[MSE.index(min(MSE))]
print('\nThe optimal alpha is %0.3f' % optimal_alpha)
```

```
The optimal alpha is 0.100
```

In [100]:
```
# plot misclassification error vs k
plt.plot(Params, MSE)

plt.xlabel('Alpha Parameters')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each Alpha value is : ", np.round(MSE,4))
```




```
('the misclassification error for each Alpha value is : ', array([ 0.1113,  0.1144,  0.1169,  0.1201,  0.122
3,  0.1244,  0.1264,
        0.1285,  0.1301,  0.1314,  0.1328,  0.1336,  0.1347,  0.1354,
        0.136 ,  0.1365,  0.1371,  0.1376,  0.138 ,  0.1383,  0.1384,
        0.1385,  0.1387,  0.1388,  0.1388,  0.1389,  0.1389,  0.139 ,
        0.139 ,  0.139 ,  0.139 ,  0.1391,  0.1391,  0.1391,  0.1391,
        0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,
        0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,
        0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,
        0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,
        0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,
        0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,
        0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391,
        0.1391,  0.1391,  0.1391,  0.1391,  0.1391,  0.1391]))
```

In [101]:
```
nb = BernoulliNB(alpha=optimal_alpha)
nb.fit(TF_train_Vector,Y_train)
pred = nb.predict(TF_test_Vector)
nb.predict_proba(TF_test_Vector)
bag_test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\nThe accuracy of the Naive Bayes Classifier for Alpha = %0.3f is %0.2f%%' % (optimal_alpha, bag_test_a
cc))
```

```
The accuracy of the Naive Bayes Classifier for Alpha = 0.100 is 88.02%
```

In [102]:
```
# Getting top Features using feature_log_prob
neg=np.take(tf_transformer.get_feature_names(), (nb.feature_log_prob_[0, :].argsort())[:20]).tolist()
pos=np.take(tf_transformer.get_feature_names(), (nb.feature_log_prob_[1, :].argsort())[:20]).tolist()
```

In [103]:
```
# Getting top Features using feature_count
def takefeature(elem):
    return elem[0]
def important_features(vectorizer,classifier,n=20):
    class_labels = classifier.classes_
    feature_names =vectorizer.get_feature_names()
    topn_class1 = sorted(zip(classifier.feature_count_[0], feature_names),key=takefeature,reverse=True)[:n]
    topn_class2 = sorted(zip(classifier.feature_count_[1], feature_names),key=takefeature,reverse=True)[:n]
    return topn_class1,topn_class2
```

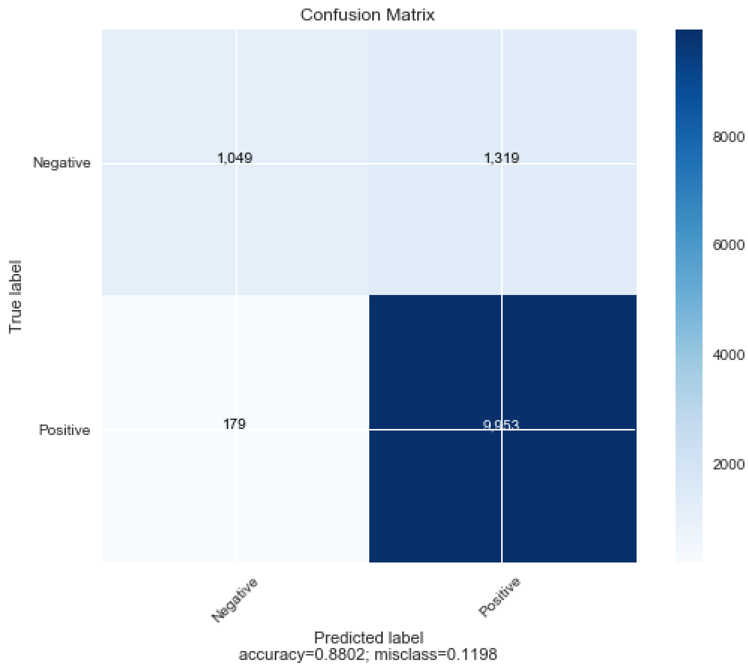
In [104]:
```
neg_tf,pos_tf=important_features(tf_transformer,nb,n=20)
```

In [105]:
```
Conf_matrix=confusion_matrix(Y_test, pred)
```

In [106]:
```
Conf_matrix
```

Out[106]:
```
array([[1049, 1319],
       [ 179, 9953]])
```

In [107]:
```
plot_confusion_matrix(cm           = Conf_matrix,
                      normalize    = False,
                      target_names = ['Negative', 'Positive'],
                      title        = "Confusion Matrix")
```



In [108]:
```
TN,FP,FN,TP = Conf_matrix.ravel()
#confusion_matrix(Y_test, pred)
```

In [109]:
```
# Sensitivity, hit rate, recall, or true positive rate
TPR ='{0:.2%}'.format(Decimal(TP)/Decimal(TP+FN))
# Specificity or true negative rate
TNR ='{0:.2%}'.format(Decimal(TN)/Decimal(TN+FP))
# Fall out or false positive rate
FPR ='{0:.2%}'.format(Decimal(FP)/Decimal(FP+TN))
# False negative rate
FNR ='{0:.2%}'.format(Decimal(FN)/Decimal(TP+FN))
# Precision or positive predictive value
PPV ='{0:.2%}'.format(Decimal(TP)/Decimal(TP+FP))
# Negative predictive value
NPV ='{0:.2%}'.format(Decimal(TN)/Decimal(TN+FN))
# Overall accuracy
ACC ='{0:.2%}'.format(Decimal(TP+TN)/Decimal(TP+FP+FN+TN))
```

In [110]:
```
Recall=recall_score(Y_test, pred, average='micro')
```

In [111]:
```
Precision=precision_score(Y_test, pred, average='micro')
```

In [112]:
```
F1_Score=f1_score(Y_test, pred, average='weighted')
```

In [113]:
```
pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
```

Out[113]:

Predicted	**negative**	**positive**	**All**
True			
negative	1049	1319	2368
positive	179	9953	10132
All	1228	11272	12500

In [114]:
```
Pretty.add_row(["TF - IDF","10 fold - Cross Validation",optimal_alpha,TPR,TNR,'{0:.2f}'.format(Precision),
'{0:.2f}'.format(Recall),'{0:.2f}'.format(F1_Score),FPR,FNR,PPV,NPV,ACC])
```

In [115]:
```
print(classification_report(Y_test, pred))
```

```
             precision    recall  f1-score   support

   negative       0.85      0.44      0.58      2368
   positive       0.88      0.98      0.93     10132

avg / total       0.88      0.88      0.86     12500
```

In [116]:
```
print(Pretty)
```

```
|    Model     |         Algorithm          |  K   |  TPR   |  TNR   | Precision | Recall | F1-Score |  FPR
|  FNR  |  PPV   |  NPV   | Overall Accuracy (ACC) |
| Bag of Words | 10 fold - Cross Validation | 0.99 | 92.92% | 51.65% |    0.85   |  0.85  |   0.85   | 48.35%
| 7.08% | 89.16% | 63.04% |         85.10%         |
|   TF - IDF   | 10 fold - Cross Validation | 0.1  | 98.23% | 44.30% |    0.88   |  0.88  |   0.86   | 55.70%
| 1.77% | 88.30% | 85.42% |         88.02%         |
```

In [120]:
```
print 'Top 20 Impotant Positive Features Identied using feature_count_'
```

```
Top 20 Impotant Positive Features Identied using feature_count_
```

In [161]:
```
Features = pd.DataFrame({'Class':[],'Model':[],'Feature Counts' : [], 'Feature':[]})
for each in pos_bw:
    Features = Features.append({'Class':'Positive','Model':'Bag of Words','Feature Counts': each[0],'Feature':
each[1]}, ignore_index=True)
for each in neg_bw:
    Features = Features.append({'Class':'Negative','Model':'Bag of Words','Feature Counts': each[0],'Feature':
each[1]}, ignore_index=True)
for each in pos_tf:
    Features = Features.append({'Class':'Positive','Model':'TF - IDF','Feature Counts': each[0],'Feature':each
[1]}, ignore_index=True)
for each in pos_tf:
    Features = Features.append({'Class':'Negative','Model':'TF - IDF','Feature Counts': each[0],'Feature':each
[1]}, ignore_index=True)
```

In [162]:
```
Features
```

Out[162]:

	Class	Feature	Feature Counts	Model
0	Positive	like	15110.0	Bag of Words
1	Positive	tast	14851.0	Bag of Words
2	Positive	love	14716.0	Bag of Words
3	Positive	great	14525.0	Bag of Words
4	Positive	good	14238.0	Bag of Words
5	Positive	use	12339.0	Bag of Words
6	Positive	one	11805.0	Bag of Words
7	Positive	flavor	11427.0	Bag of Words
8	Positive	product	10955.0	Bag of Words
9	Positive	tri	10884.0	Bag of Words
10	Positive	make	10573.0	Bag of Words
11	Positive	get	9508.0	Bag of Words
12	Positive	time	8144.0	Bag of Words
13	Positive	best	7836.0	Bag of Words
14	Positive	find	7595.0	Bag of Words
15	Positive	buy	7519.0	Bag of Words
16	Positive	tea	7343.0	Bag of Words
17	Positive	eat	7065.0	Bag of Words
18	Positive	amazon	7042.0	Bag of Words
19	Positive	realli	6936.0	Bag of Words
20	Negative	like	3022.0	Bag of Words
21	Negative	tast	2938.0	Bag of Words
22	Negative	product	2569.0	Bag of Words
23	Negative	one	2164.0	Bag of Words
24	Negative	would	1986.0	Bag of Words
25	Negative	tri	1881.0	Bag of Words
26	Negative	good	1744.0	Bag of Words
27	Negative	buy	1706.0	Bag of Words
28	Negative	get	1595.0	Bag of Words
29	Negative	flavor	1561.0	Bag of Words
...	...	...	...	...
50	Positive	make	10573.0	TF - IDF
51	Positive	get	9508.0	TF - IDF
52	Positive	time	8144.0	TF - IDF
53	Positive	best	7836.0	TF - IDF
54	Positive	find	7595.0	TF - IDF
55	Positive	buy	7519.0	TF - IDF
56	Positive	tea	7343.0	TF - IDF
57	Positive	eat	7065.0	TF - IDF
58	Positive	amazon	7042.0	TF - IDF
59	Positive	realli	6936.0	TF - IDF
60	Negative	like	15110.0	TF - IDF
61	Negative	tast	14851.0	TF - IDF

	Class	Feature	Feature Counts	Model
62	Negative	love	14716.0	TF - IDF
63	Negative	great	14525.0	TF - IDF
64	Negative	good	14238.0	TF - IDF
65	Negative	use	12339.0	TF - IDF
66	Negative	one	11805.0	TF - IDF
67	Negative	flavor	11427.0	TF - IDF
68	Negative	product	10955.0	TF - IDF
69	Negative	tri	10884.0	TF - IDF
70	Negative	make	10573.0	TF - IDF
71	Negative	get	9508.0	TF - IDF
72	Negative	time	8144.0	TF - IDF
73	Negative	best	7836.0	TF - IDF
74	Negative	find	7595.0	TF - IDF
75	Negative	buy	7519.0	TF - IDF
76	Negative	tea	7343.0	TF - IDF
77	Negative	eat	7065.0	TF - IDF
78	Negative	amazon	7042.0	TF - IDF
79	Negative	realli	6936.0	TF - IDF

80 rows × 4 columns

In [163]:
```
Features.to_csv('Features.csv',index=None)
```

Conclusion

We can conclude that the "TF-IDF Vectorized Multinomial Naive Bayes Classifier" achieved significantly good Precision and Probability rates & TPR,TNR compared to "Bag of Words Vectorized Multinomial Naive Bayes Classifier".