[1] Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

Objective:

Given a review, determine whether the review is positive (Rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use the Score/Rating. A rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

Loading the data

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it easier to query the data and visualise the data efficiently.

Here 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 "positive". Otherwise, it will be set to "negative".

Task to be performed:

1. In this, We need to work with Only BOW and TFIDF.
2. We need to Give proper reasoning for choosing the particular versions of Naive Bayes
3. Choose different metric other than accuracy for choosing the best hyperparameter, which is apt for imbalanced datasets and accuracy sometimes gives us false conclusions about the model performance sometimes.
4. Do hyperparameter tuning or some feature engineering and make your model better by reducing the false positives (Ex: adding the length of the reviews, getting some features from the summary column)
5. We need to print the important features for each class, use model attributes to get the best features.

6. Avoid submitting the models which are more biased towards positive points. Try to improve if everything or most of the points are predicting as positive.

In [62]:
```
import numpy
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.naive_bayes import BernoulliNB
from sklearn.cross_validation import cross_val_score
from sklearn.cross_validation import train_test_split
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
import re
import sqlite3
```

In [63]:
```
con = sqlite3.connect("./amazon-fine-food-reviews/database.sqlite")
data = pd.read_sql_query('''
SELECT *
FROM REVIEWS
WHERE SCORE != 3''', con)
data.shape
```

Out[63]:
```
(525814, 10)
```

Data Cleaning

In [64]:
```
data = data[data.HelpfulnessNumerator <= data.HelpfulnessDenominator]
data.shape
```

Out[64]:
```
(525812, 10)
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [65]:

```
data['Score'] = data["Score"].apply(lambda x: "positive" if x > 3 else "negative")
sorted_data = data.sort_values('ProductId',axis = 0, inplace = False, kind = 'quicksort',ascending = True)
sorted_data.head()
```

Out[65]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
138693	150511	0006641040	A1C9K534BCI9GO	Laura Purdie Salas	0	0
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11	18
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1	2
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
138705	150523	0006641040	A2P4F2UO0UMP8C	Elizabeth A. Curry "Lovely Librarian"	0	0

In [66]:
```
filtered_data = sorted_data.drop_duplicates(subset = {'UserId','Profile
Name','Time'} ,keep = 'first', inplace = False)
filtered_data.shape
```

Out[66]:
```
(328770, 10)
```

In [67]:
```
filtered_data['Score'].value_counts()
```

Out[67]:
```
positive    275650
negative     53120
Name: Score, dtype: int64
```

In [68]:
```
final = filtered_data.copy()
```

In [69]:
```
import nltk
```

In [70]:
```
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to C:\Users\manish
[nltk_data]     dogra\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

Out[70]:
```
True
```

In [71]:
```
stop = set(stopwords.words("english"))
```

In [72]:
```
st = PorterStemmer()
```

```
st.stem('burned')
```

Out[72]: 'burn'

Text Preprocessing: Stemming, stop-word removal and Lemmatization.

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [73]:
```
def cleanhtml(sent):
    cleanr = re.compile('<.*?>')
    cleaned = re.sub(cleanr,' ',sent)
    return cleaned
def cleanpunc(sent):
    clean = re.sub(r'[?|!|$|#|\'|"|:]',r'',sent)
    clean = re.sub(r'[,|(|)|.|\|/]',r' ',clean)
    return clean
```

In [74]:
```
i=0
all_positive_reviews =[]
```

```
all_negative_reviews = []
final_string = []
stem_data = " "
for p in final['Text'].values:
    filtered_sens = []#filtered word
    p = cleanhtml(p)
    for w in p.split():
       # print(w)
        punc = cleanpunc(w)
        for s in punc.split():
            #print(w)
            if (s.isalpha()) & (len(s)>2):
                if s.lower() not in stop:
                    stem_data = (st.stem(s.lower())).encode('utf8')
                    #can we use lemmatizer and stemming altogether??
                    filtered_sens.append(stem_data)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_reviews.append(stem_data)
                    if (final['Score'].values)[i] == 'negative':
                        all_negative_reviews.append(stem_data)
                else:
                    continue
            else:
                continue
    #print(filtered_sens)
    str1 = b" ".join(filtered_sens)
    #print(str1)
    final_string.append(str1)
    i+=1
```

In [75]:

```
final['CleanedText'] = final_string
final.head()
```

Out[75]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
138693	150511	0006641040	A1C9K534BCI9GO	Laura Purdie Salas	0	0
138708	150526	0006641040	A3E9QZFE9KXH8J	R. Mitchell	11	18
138707	150525	0006641040	A2QID6VCFTY51R	Rick	1	2
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
138705	150523	0006641040	A2P4F2UO0UMP8C	Elizabeth A. Curry "Lovely Librarian"	0	0

In [76]:
```
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
from sklearn.feature_extraction.text import CountVectorizer
```

In [77]:
```
final = final.sort_values('Time',axis= 0,inplace = False , na_position
= 'last',ascending = True)
X = final['CleanedText'].values
X = X[:100000]
y = final['Score'].values
y = y[:100000]
```

In [78]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.2,st
ratify = y)
```

Naive bayes on Bow

In [79]:
```
count_vect = CountVectorizer(binary =True) #in scikit-learn
bow_train = count_vect.fit_transform(X_train)
bow_test = count_vect.transform(X_test)
#count_vect.get_feature_names()
```

In [80]:
```
import numpy as np
```

In [81]:
```
alp = [10**i for i in range(-3,4)]
```

In [82]:
```
cross_score = []
for alphas in alp:
    clf = BernoulliNB(alpha = alphas)
    cross_val = cross_val_score(clf,bow_train,y_train,cv=10,scoring =
'accuracy',n_jobs = -1)
    cross_score.append(cross_val.mean())
```

In [83]:
```
MSE = [1-x for x in cross_score]
optimal_alpha = alp[MSE.index(min(MSE))]
```

In [84]:
```
optimal_clf = BernoulliNB(alpha = optimal_alpha)
```

```
optimal_clf.fit(bow_train,y_train)
pred  = optimal_clf.predict(bow_test)
```

Accuracy

In [85]:
```
acc = accuracy_score(y_test,pred)*100
print("The accuracy for optimal alpha = {0} is {1}".format(optimal_alph
a,acc))
```

```
The accuracy for optimal alpha = 0.001 is 89.995
```

In [86]:
```
from sklearn.metrics import classification_report
#target_names = ['class 0', 'class 1']
print(classification_report(y_test,pred))
```

```
             precision    recall  f1-score   support

   negative       0.62      0.53      0.58      2541
   positive       0.93      0.95      0.94     17459

avg / total       0.89      0.90      0.90     20000
```

Recall , Precison and auc_score

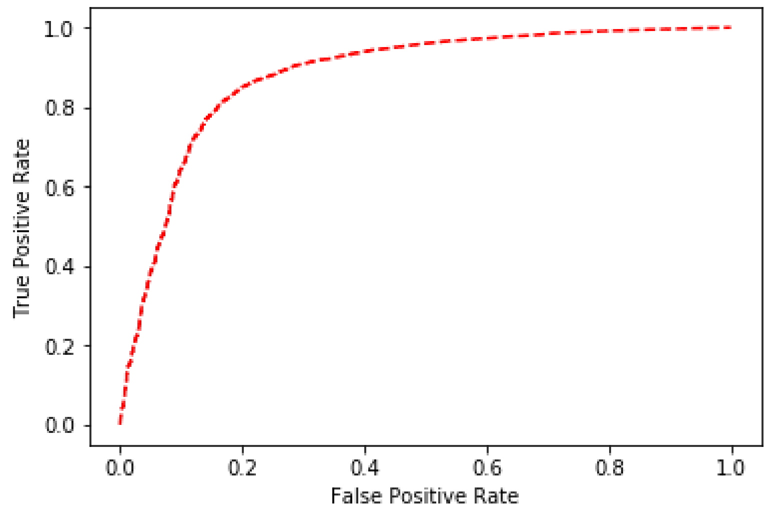
In [87]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
print('RECALL SCORE')
print(recall_score(y_test,pred,pos_label = 'positive'))
print(recall_score(y_test,pred,pos_label= 'negative') )
print('\n')
print('PRECISION SCORE')
print(precision_score(y_test,pred,pos_label = 'positive'))
print(precision_score(y_test,pred,pos_label = 'negative'))
```

```
RECALL SCORE
0.953090096798
0.534828807556


PRECISION SCORE
0.933677477275
0.623966942149
```

ROC Curve

In [88]:

```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred =optimal_clf.predict_proba(bow_test)[:,1]
#print(y_pred[:,1])

fpr,tpr,thresholds = roc_curve(y_true, y_pred)
plt.plot(fpr,tpr,'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```



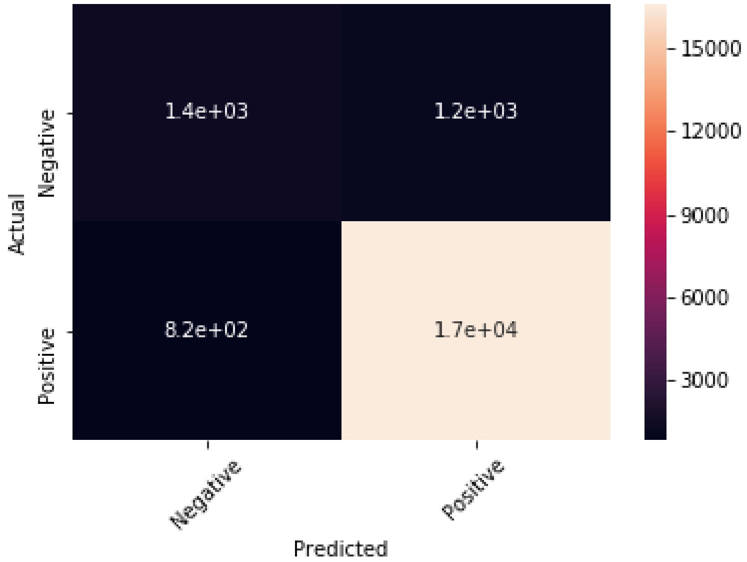
In [89]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.881352542626
```

Confusion Matrix

In [90]:
```
from sklearn.metrics import confusion_matrix
import seaborn as sns
confusion = confusion_matrix(y_test , pred)
print(confusion)
df_cm = pd.DataFrame(confusion , index = ['Negative','Positive'])
sns.heatmap(df_cm ,annot = True)
plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
[[ 1359  1182]
 [  819 16640]]
```



Important words(features)

In [91]:
```
neg_class = optimal_clf.feature_log_prob_[0,:].argsort()
pos_class = optimal_clf.feature_log_prob_[1,:].argsort()
print(np.take(count_vect.get_feature_names(), neg_class[::-1][:10]))
print(np.take(count_vect.get_feature_names(), pos_class[::-1][:10]))
```

```
['tast' 'like' 'product' 'one' 'would' 'tri' 'good' 'flavor' 'buy' 'ge
t']
['tast' 'like' 'great' 'good' 'love' 'flavor' 'one' 'use' 'tri' 'produc
t']
```

Multinomial NB on BOW

In [92]:
```
from sklearn.naive_bayes import MultinomialNB
alp = [10**i for i in range(-3,4)]
cross_score = []
```

```
for alphas in alp:
    clf = MultinomialNB(alpha = alphas)
    cross_val = cross_val_score(clf,bow_train,y_train,cv=10,scoring =
'accuracy',n_jobs = -1)
    cross_score.append(cross_val.mean())
```

In [93]:
```
MSE = [1-x for x in cross_score]
optimal_alpha = alp[MSE.index(min(MSE))]
optimal_clf = MultinomialNB(alpha = optimal_alpha)
optimal_clf.fit(bow_train,y_train)
pred  = optimal_clf.predict(bow_test)
```

Accuracy

In [94]:
```
acc = accuracy_score(y_test,pred)*100
print("The accuracy for optimal alpha = {0} is {1}".format(optimal_alph
a,acc))
```

```
The accuracy for optimal alpha = 1 is 91.64999999999999
```

In [95]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

```
             precision    recall  f1-score   support

   negative       0.73      0.55      0.63      2541
   positive       0.94      0.97      0.95     17459

avg / total       0.91      0.92      0.91     20000
```

Recall , Precison and auc_score

In [96]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
```

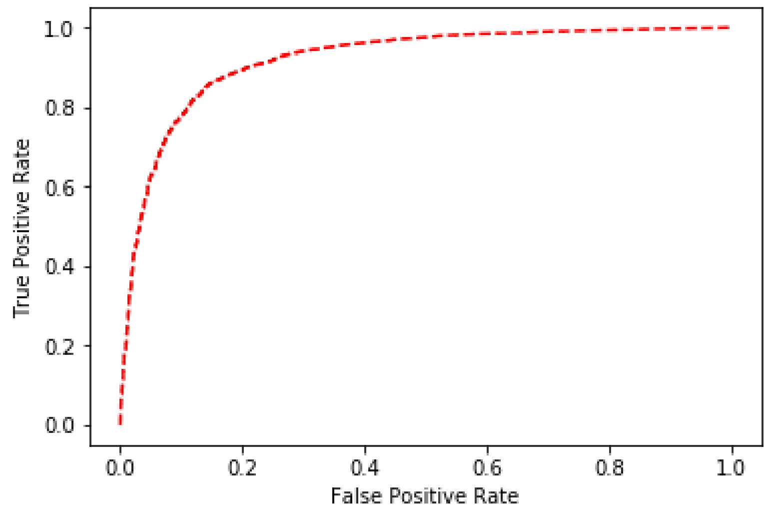
```
print('RECALL SCORE')
print(recall_score(y_test,pred,pos_label = 'positive'))
print(recall_score(y_test,pred,pos_label= 'negative') )
print('\n')
print('PRECISION SCORE')
print(precision_score(y_test,pred,pos_label = 'positive'))
print(precision_score(y_test,pred,pos_label = 'negative'))
```

```
RECALL SCORE
0.969986826279
0.548996458087


PRECISION SCORE
0.936618549859
0.726941115164
```

ROC Curve

In [97]:

```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred =optimal_clf.predict_proba(bow_test)[:,1]
fpr,tpr,thresholds = roc_curve(y_true, y_pred)
plt.plot(fpr,tpr,'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```



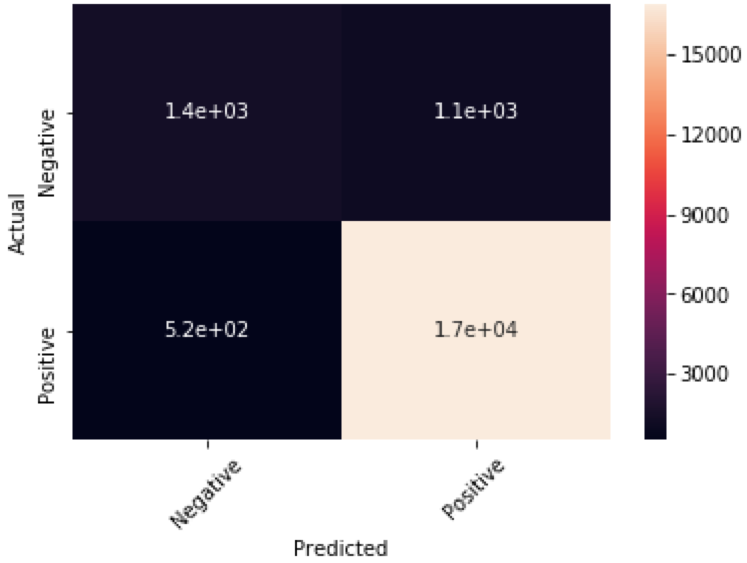
In [98]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.919729551795
```

Confusion Matrix

In [99]:
```
confusion = confusion_matrix(y_test , pred)
print(confusion)
df_cm = pd.DataFrame(confusion , index = ['Negative','Positive'])
sns.heatmap(df_cm ,annot = True)
plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
[[ 1395  1146]
 [  524 16935]]
```



Important words(features)

In [100]:
```
neg_class = optimal_clf.feature_log_prob_[0,:].argsort()
pos_class = optimal_clf.feature_log_prob_[1,:].argsort()
print(np.take(count_vect.get_feature_names(), neg_class[::-1][:10]))
print(np.take(count_vect.get_feature_names(), pos_class[::-1][:10]))
```

```
['tast' 'like' 'product' 'one' 'would' 'tri' 'good' 'flavor' 'buy' 'ge
t']
['tast' 'like' 'great' 'good' 'love' 'flavor' 'one' 'use' 'tri' 'produc
t']
```

Naive Bayes on Tf-idf

In [101]:
```
tfidf_vect = TfidfVectorizer(ngram_range = (1,2))
tfidf_train = tfidf_vect.fit_transform(X_train)
tfidf_test = tfidf_vect.transform(X_test)
```

In [102]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler(with_mean = False)
X_tr= sc.fit_transform(tfidf_train)
X_te = sc.transform(tfidf_test)
```

In [103]:
```
alp_1 = [10**i for i in range(-3,4)]
```

In [104]:
```
cross_score_1 = []
for alphas in alp_1:
    clf_1 = BernoulliNB(alpha = alphas)
    cross_val_1 = cross_val_score(clf_1,X_tr,y_train,cv=10,scoring = 'a
ccuracy',n_jobs = -1)
    cross_score_1.append(cross_val_1.mean())
```

In [105]:
```
MSE_1 = [1-x for x in cross_score_1]
opt_alpha = alp_1[MSE_1.index(min(MSE_1))]
```

In [106]:
```
opt_clf = BernoulliNB(alpha = opt_alpha)
opt_clf.fit(X_tr,y_train)
pred_1  = opt_clf.predict(X_te)
```

Accuracy

In [107]:
```
acc_1 = accuracy_score(y_test,pred_1)*100
print("The accuracy for optimal alpha = {0} is {1}".format(opt_alpha,ac
c_1))
```

```
The accuracy for optimal alpha = 0.001 is 90.0
```

In [109]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred_1))
```

```
             precision    recall  f1-score   support
```

```
   negative       0.86      0.25      0.39      2541
   positive       0.90      0.99      0.95     17459

avg / total       0.90      0.90      0.88     20000
```

Recall , Precision and auc_score

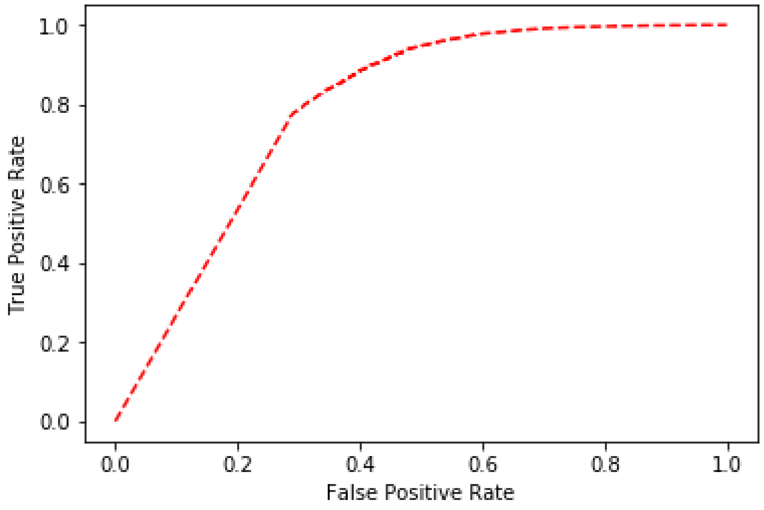
In [110]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
print('RECALL SCORE')
print(recall_score(y_test,pred_1,pos_label = 'positive'))
print(recall_score(y_test,pred_1,pos_label= 'negative') )
print('\n')
print('PRECISION SCORE')
print(precision_score(y_test,pred_1,pos_label = 'positive'))
print(precision_score(y_test,pred_1,pos_label = 'negative'))
```

```
RECALL SCORE
0.994043186895
0.253837072019


PRECISION SCORE
0.901511609787
0.861148197597
```

ROC Curve

In [111]:
```
change = lambda x : 1 if x == 'positive' else 0
tfidf_true = np.array([change(x) for x in y_test])
tfidf_pred =opt_clf.predict_proba(X_te)[:,1]
fpr,tpr,thresholds = roc_curve(tfidf_true, tfidf_pred)
plt.plot(fpr,tpr,'r--')
plt.ylabel('True Positive Rate')
```

```
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```



In [112]:

```
print(roc_auc_score(tfidf_true,tfidf_pred))
```

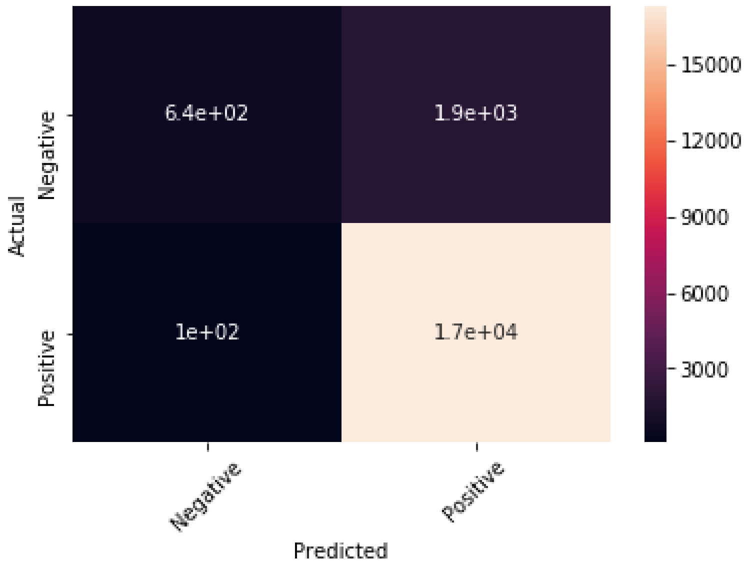
```
0.789832981162
```

confusion matrix

In [113]:

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
confusion = confusion_matrix(y_test , pred_1)
print(confusion)
df_cm = pd.DataFrame(confusion , index = ['Negative','Positive'])
sns.heatmap(df_cm ,annot = True)
plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
[[  645  1896]
 [  104 17355]]
```



Important Words (features)

In [114]:
```
ne_class = opt_clf.feature_log_prob_[0,:].argsort()
po_class = opt_clf.feature_log_prob_[1,:].argsort()
print(np.take(tfidf_vect.get_feature_names(), ne_class[::-1][:10]))
print(np.take(tfidf_vect.get_feature_names(), po_class[::-1][:10]))
```

```
['tast' 'like' 'product' 'one' 'would' 'tri' 'good' 'flavor' 'buy' 'ge
t']
['tast' 'like' 'great' 'good' 'love' 'flavor' 'one' 'use' 'tri' 'produc
t']
```

Multinomial NB on tfidf

In [115]:
```
from sklearn.naive_bayes import MultinomialNB
alp = [10**i for i in range(-3,4)]
cross_score = []
for alphas in alp:
    clf = MultinomialNB(alpha = alphas)
    cross_val = cross_val_score(clf,X_tr,y_train,cv=10,scoring = 'accur
acy',n_jobs = -1)
    cross_score.append(cross_val.mean())
```

In [116]:
```
MSE = [1-x for x in cross_score]
optimal_alpha = alp[MSE.index(min(MSE))]
optimal_clf = MultinomialNB(alpha = optimal_alpha)
optimal_clf.fit(X_tr,y_train)
pred  = optimal_clf.predict(X_te)
```

Accuracy

In [117]:
```
acc = accuracy_score(y_test,pred)*100
print("The accuracy for optimal alpha = {0} is {1}".format(optimal_alph
a,acc))
```

```
The accuracy for optimal alpha = 0.001 is 86.36
```

In [118]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

```
             precision    recall  f1-score   support

   negative       0.41      0.17      0.24      2541
   positive       0.89      0.96      0.93     17459

avg / total       0.83      0.86      0.84     20000
```

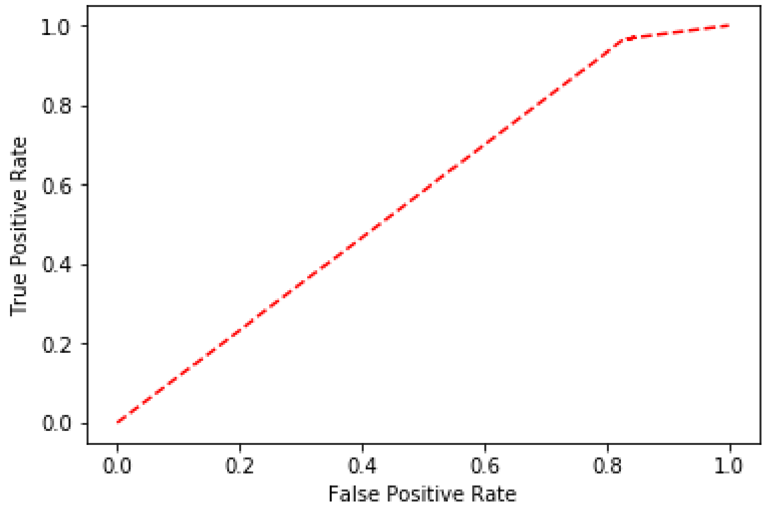
Recall , Precision and auc_score

In [119]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
print('RECALL SCORE')
print(recall_score(y_test,pred,pos_label = 'positive'))
print(recall_score(y_test,pred,pos_label= 'negative') )
print('\n')
print('PRECISION SCORE')
print(precision_score(y_test,pred,pos_label = 'positive'))
print(precision_score(y_test,pred,pos_label = 'negative'))
```

```
RECALL SCORE
0.964201844321
0.172373081464


PRECISION SCORE
0.888947562972
0.412041392286
```

ROC Curve

In [120]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred =optimal_clf.predict_proba(X_te)[:,1]
fpr,tpr,thresholds = roc_curve(y_true, y_pred)
plt.plot(fpr,tpr,'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```



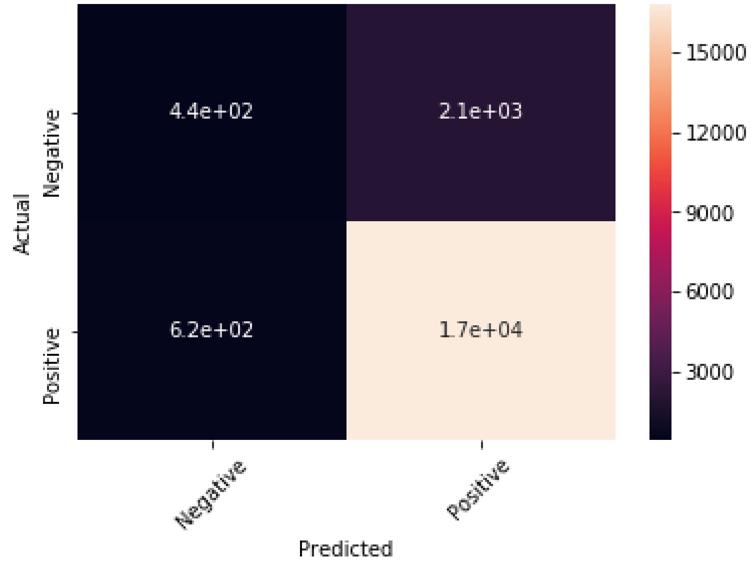
In [121]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.568656348728
```

confusion matrix

In [122]:
```
confusion = confusion_matrix(y_test , pred)
print(confusion)
df_cm = pd.DataFrame(confusion , index = ['Negative','Positive'])
sns.heatmap(df_cm ,annot = True)
plt.xticks([0.5,1.5],['Negative','Positive'],rotation = 45)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

```
[[  438  2103]
 [  625 16834]]
```



Important Words (features)

In [124]:
```
neg_class = optimal_clf.feature_log_prob_[0,:].argsort()
pos_class = optimal_clf.feature_log_prob_[1,:].argsort()
print(np.take(tfidf_vect.get_feature_names(), neg_class[::-1][:10]))
print(np.take(tfidf_vect.get_feature_names(), pos_class[::-1][:10]))
```

```
['tast' 'like' 'disappoint' 'product' 'would' 'one' 'bad' 'money' 'tri'
 'dont']
['great' 'tast' 'love' 'like' 'good' 'flavor' 'use' 'one' 'tri' 'make']
```

Report

Bernoulii NB on BOW

- Optimal alpha = 0.001

- Accuracy = 89.995
- Precision = 0.936(positive), 0.623(negative)
- Recall = 0.953 ,0.534
- AUC = 0.881
- TN = 1359
- TP = 16640

Bernoulii NB on TF-IDF

- Optimal alpha = .001
- Accuracy = 90.0
- Precision = 0.901, 0.861
- Recall = 0.994, 0.253
- AUC = 0.789
- TN = 645
- TP = 17355

Multinomial NB on BOW

- Optimal alpha = 1
- Accuracy = 91.649
- Precision = 0.936 , 0.726
- Recall = 0.969 , 0.548
- AUC = 0.919
- TN = 1395
- TP = 16935

Multinomial NB on TF-IDF

- Optimal alpha = .001
- Accuracy = 86.36
- Precision = .888, 0.412
- Recall = .964, 0.172
- AUC = 0.568
- TN = 438
- TP = 16834