[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 Performed:

1. we need to work with 2 versions of KNN a. brute force b. kd tree
2. we suggest you not to go with GridsearchCV or k-fold as they take more time, use Simple Cross validation dataset to find the best hyperparameters, and use the test dataset report the final model performance
3. When we are working with the kd tree, we need to pass the dense matrix(constraint in the sklearn library) So, when you are working on BOW and TFIDF we need to convert these things into dense matrices.

   a. Using TruncatedSVD() this is exactly similar to PCA() and it can also accept sparse matrices and returns a dense matrix with lower dimensions i. Choosing the

n_components we need to follow the elbow method

b. Use max_features=2000(this can be changed according to your computing power) and min_df=50 (this can be changed according to your computing power) in Countvectorizer and then use .toarray() function to convert the sparse matrix to dense matrix.

4. 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.
5. For both of the algorithms, we can work with 10k(Due to less computing power because more data can cause the freezing state or hang your laptop if RAM is 4Gb) data points, Note that it will take more time you might need to wait.

In [1]:
```
import nltk
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.corpus import stopwords
import re
import string
import sqlite3
from sklearn.cross_validation import train_test_split
from sklearn.cross_validation import cross_val_score
from sklearn import cross_validation
from sklearn.metrics import accuracy_score
from sklearn.neighbors import KNeighborsClassifier
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: This module was deprecated in version 0.18 in favor of the model_selection module into which all the refactored classes and functions are moved. Also note that the interface of the new CV iterators are different from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [2]:
```
con = sqlite3.connect("./amazon-fine-food-reviews/database.sqlite")
data = pd.read_sql_query('''
SELECT *
FROM reviews
WHERE Score!=3
''', con)
data.shape
```

Out[2]:
```
(525814, 10)
```

Data cleaning

In [3]:
```
data['Score']  = data["Score"].apply(lambda x: 'positive' if x >= 4 els
e 'negative')
data.head(10)
print(data.shape)
```

```
(525814, 10)
```

In [4]:
```
data = data[data.HelpfulnessNumerator<=data.HelpfulnessDenominator]
print(data.shape)
```

```
(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 [5]:
```
sorted_data = data.sort_values('ProductId', inplace = False, axis =0, k
ind = 'quicksort', ascending = True, na_position = 'last')
sorted_data.head()
```

Out[5]:

	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 [6]:
```
sorted_data['Text'].values
```

Out[6]:
```
array([ "A charming, rhyming book that describes the circumstances unde
r which you eat (or don't) chicken soup with rice, month-by-month. This
sounds like the kind of thing kids would make up while they're out of r
ecess and sing over and over until they drive the teachers crazy. It's
cute and catchy and sounds really childlike but is skillfully writte
n.",
       "This is one of the best children's books ever written but it is
a mini version of the book and was not portrayed as one.  It is over pr
iced for the product.  I sent an email regarding my bewilderment  to Am
azon and got no response.",
       'My daughter loves all the "Really Rosie" books. She was introdu
ced to the Really Rosie CD performed by Carole King (also available on
Amazon!) on her 1st Birthday and now, a year later, she knows all the s
ongs. As far as the books go, we own: One Was Johnny, Alligators All Ar
ound, & Chicken Soup w/Rice. These books are well written with clever a
rt work by Maurice Sendak. Plus, they are really cheap!! Highly recomme
nded :)',
       ...,
       'The basket was the perfect sympathy gift when trying to express
how much you care and really provide resources to assist in the healing
process.',
       'Purchased this product at a local store in NY and my kids and i
love it. Its a quick easy meal. You can put in a toaster oven on toast
for 6 min. and its ready to eat.<br />strongly recommend',
       "I purchased this to send to my son who's away at college. It wa
s delivered right to his dorm room with very fast shipping. He loved it
so much he called me to thank me, and sadly, he hardly ever calls me an
ymore! If you want your kids to call home, and have some good snack to
get them through midterms then send them this."], dtype=object)
```

In [7]:
```
filtered_data = sorted_data.drop_duplicates(subset = {'UserId','Profile
Name','Time'} ,keep = 'first', inplace = False)
filtered_data.shape
```

Out[7]:
```
(328770, 10)
```

In [8]:
```
filtered_data['Score'].value_counts()
```

Out[8]:
```
positive    275650
```

```
negative     53120
Name: Score, dtype: int64
```

In [9]:
```
#text processing
final = filtered_data.copy()
#final = final.head(5000)
```

In [10]:
```
nltk.download('stopwords')
```

```
[nltk_data] Error loading stopwords: <urlopen error [Errno 11001]
[nltk_data]     getaddrinfo failed>
```

Out[10]:
```
False
```

In [11]:
```
stop = set(stopwords.words("english"))
print(stop)
```

```
{'my', 'i', 'so', 'most', 'me', 'same', 'himself', 'out', 'will', 'furt
her', 'your', 'here', 'was', 'these', 'm', 'ma', "hadn't", 'weren', "wo
n't", 'y', 'am', 'didn', 'isn', 'as', 'against', 'an', 'some', 'by',
's', 'if', 'more', "mustn't", 'myself', 'up', 'had', 'that', 'and', 'wh
ich', "couldn't", 'those', 'they', 'during', 'have', 'now', 'mightn',
"mightn't", 'to', 'both', 'when', 'because', 'there', 'being', 'but',
'his', "that'll", 'it', 'couldn', 'above', "don't", 'while', 'this', 'c
an', 'their', "didn't", 'shouldn', 'then', 'of', 'than', 'you', "yo
u'd", 'her', 'them', 'nor', 'hasn', 'themselves', "she's", 'mustn', 'do
wn', 'why', 'o', 'hers', 'how', 'own', 'under', "aren't", 'ours', 'onc
e', 'in', 'don', 're', 'ain', 'who', "weren't", 'been', 'hadn', "was
n't", 'with', 'all', 'wasn', 'at', "shan't", 'he', 'are', "doesn't", "h
asn't", 'very', 'be', 'whom', 'aren', 'below', "you've", 'our', 'into',
'does', 'or', 'doesn', "it's", "haven't", 'needn', 'did', 'after', 'onl
y', 'such', 'too', 'doing', 'we', 've', "you'll", 'over', 'itself', 'yo
urself', 'a', 'again', 'she', 'were', 'any', 'yours', 'do', 'just', "is
n't", 'few', "shouldn't", 'haven', 'about', 'other', 'for', 'between',
'each', 'd', 'll', "should've", 'should', 'on', "you're", 'no', 'befor
e', 'won', 'has', 'wouldn', 'where', 'herself', 'its', 'having', 'unti
l', 'theirs', 'is', 'not', 'off', 'yourselves', 'him', 'shan', 'ourselv
es', "needn't", 'through', 'from', "wouldn't", 'what', 'the', 't'}
```

In [12]:
```
st = PorterStemmer()
st.stem('burned')
```

Out[12]:
```
'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 [13]:
```
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 [14]:
```
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 [15]:
```
final['CleanedText'] = final_string
final.head()
```

Out[15]:

	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 [16]:
```
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
```

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

In [17]:
```
final = final.sort_values('Time',axis= 0,inplace = False , na_position
= 'last',ascending = True)
X = final['CleanedText'].values
X = list(X[:10001])
y = final['Score'].values
y =list(y[:10001])
del X[2543]
del y[2543]
```

In [18]:
```
# from sklearn.model_selection import TimeSeriesSplit
```

In [19]:
```
# tscv = TimeSeriesSplit(n_splits = int((100000 - 30000)/30000))
# for train_index , test_index in tscv.split(X):
#     X_train,X_test = X[train_index],X[test_index]
#     y_train,y_test = y[train_index],y[test_index]
```

In [20]:
```
X_train ,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.2,s
tratify = y)
```

In [21]:
```
# X_test = X_test[:3000]
# y_test = y_test[:3000]
```

In [22]:
```
len(X_train)
```

Out[22]: 8000

In [23]:
```
len(X_test)
```

Out[23]: 2000

KNN on BOW using brute and kd_tree algorithm

In [24]:
```
count_vect = CountVectorizer() #in scikit-learn
bow_train = count_vect.fit_transform(X_train)
bow_test = count_vect.transform(X_test)
#count_vect.get_feature_names()
```

In [25]:
```
# from scipy.sparse import csr_matrix
#bow_train = bow_train.todense()
#print(type(bow_train))
```

In [26]:
```
neighbors = list(np.arange(3,50,4))
```

In [27]:
```
#X_tr,X_test,y_tr,y_test = cross_validation.train_test_split(bow_X,bow_
y,test_size=0.3,random_state= 42)
import warnings
warnings.filterwarnings("ignore")

cv_scores = []
for n in neighbors:
    knn = KNeighborsClassifier(n_neighbors = n,algorithm = 'brute')
    #knn = KNeighborsClassifier(n_neighbors = n,algorithm = 'kd_tree',l
eaf_size = 30)
    cross_val = cross_val_score(knn,bow_train,y_train,cv = 5 , scoring
= 'accuracy')
    cv_scores.append(cross_val.mean())

MSE = [1-x for x in cv_scores]
optimal_n = neighbors[ MSE.index(min(MSE)) ]
knn_optimal = KNeighborsClassifier(n_neighbors = optimal_n,algorithm =
'brute')
knn_optimal.fit(bow_train,y_train)
pred = knn_optimal.predict(bow_test)
acc = accuracy_score(y_test,pred)*100

print("The accuracy for optimal k = {0} using brute is {1}".format(opti
mal_n,acc))
#print("The accuracy for optimal k = {0} using kd_tree is {1}".format(o
ptimal_n,acc))
```

```
The accuracy for optimal k = 7 using brute is 88.85
```

In [28]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

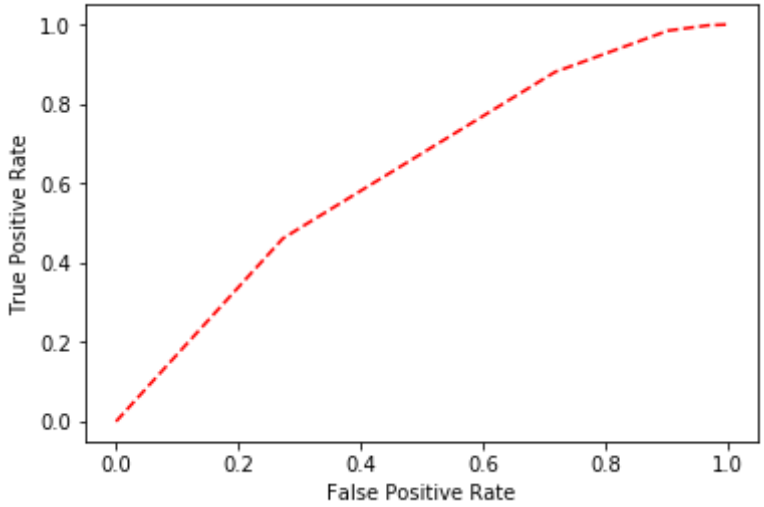
```
             precision    recall  f1-score   support

   negative       0.70      0.03      0.06       227
   positive       0.89      1.00      0.94      1773

avg / total       0.87      0.89      0.84      2000
```

In [29]:
```
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
0.998307952623
0.0308370044053


PRECISION SCORE
0.889447236181
0.7
```

In [30]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = knn_optimal.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()
```

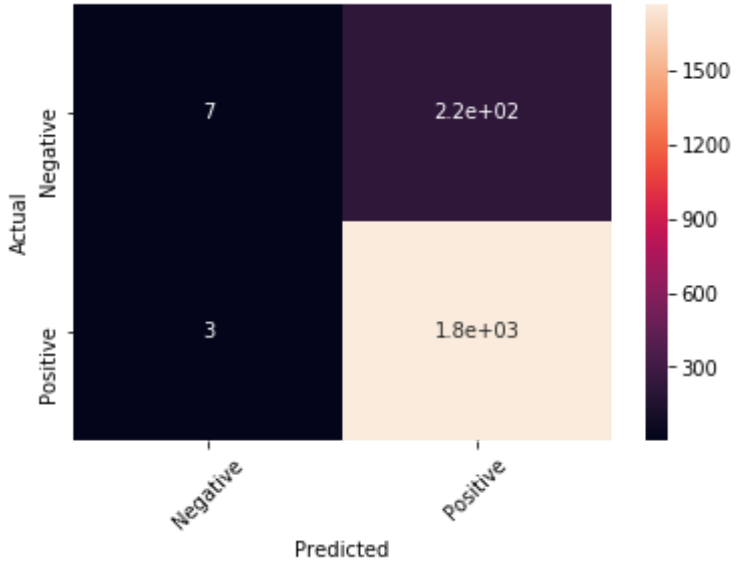


In [31]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.630396972701
```

In [32]:
```
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()
```

```
[[   7  220]
 [   3 1770]]
```



conclusion

Brute Algo

1. Optimal K = 7.
2. Accuracy = 88.85
3. AUC = 0.6303(approx)
4. TN = 7
5. TP = 1770

In [33]:
```
import warnings
warnings.filterwarnings("ignore")
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components = 200)
bow_tr = svd.fit_transform(bow_train)
bow_te = svd.transform(bow_test)
```

```
cv_scores = []
for n in neighbors:
    kn = KNeighborsClassifier(n_neighbors = n,algorithm = 'kd_tree',lea
f_size = 30)
    cross_val = cross_val_score(kn,bow_tr,y_train,cv = 2 , scoring = 'a
ccuracy')
    cv_scores.append(cross_val.mean())

MSE = [1-x for x in cv_scores]
optima_n = neighbors[ MSE.index(min(MSE)) ]
knn_optima = KNeighborsClassifier(n_neighbors = optima_n, algorithm =
'kd_tree',leaf_size = 30)
knn_optima.fit(bow_tr,y_train)
pred = knn_optima.predict(bow_te)
ac = accuracy_score(y_test,pred)*100
print("The accuracy for optimal k = {0} using kd_tree is {1}".format(op
tima_n,ac))
```

```
The accuracy for optimal k = 23 using kd_tree is 88.75
```

In [34]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

```
             precision    recall  f1-score   support

   negative       1.00      0.01      0.02       227
   positive       0.89      1.00      0.94      1773

avg / total       0.90      0.89      0.84      2000
```

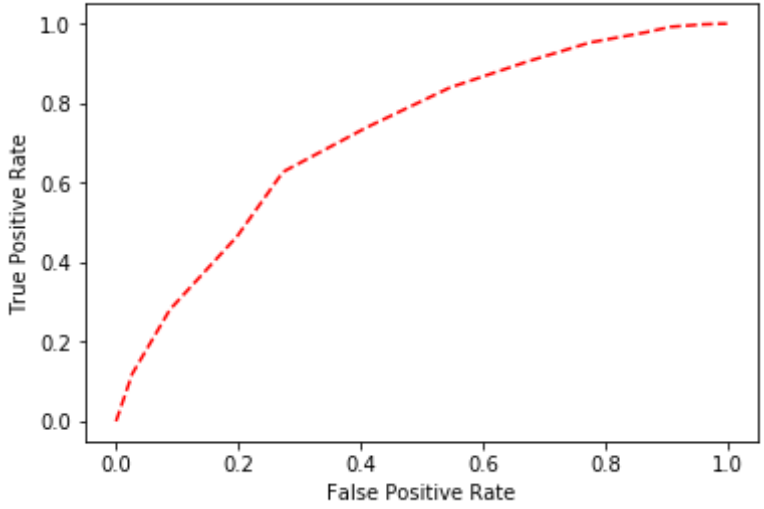
In [35]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
print('RECALL SCORE')
print(recall_score(y_test,pred,pos_label = 'positive'))
print(recall_score(y_test,pred,pos_label= 'negative') )
print('\n')
print('PRECISION SCORE')
```

```
print(precision_score(y_test,pred,pos_label = 'positive'))
print(precision_score(y_test,pred,pos_label = 'negative'))
```

```
RECALL SCORE
1.0
0.00881057268722


PRECISION SCORE
0.887387387387
1.0
```

In [36]:

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

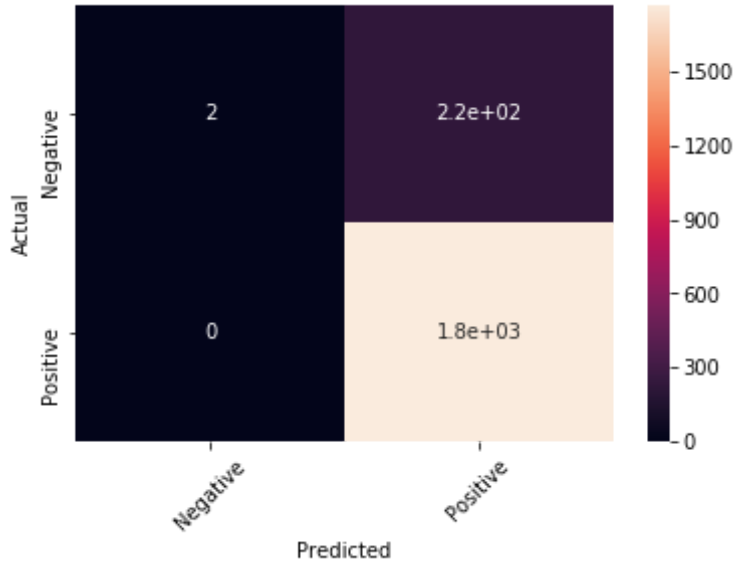


In [37]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.723115454281
```

In [38]:
```
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()
```

```
[[   2  225]
 [   0 1773]]
```



conclusion

Kd-tree Algo

1. Optimal K = 23
2. Accuracy = 88.75
3. AUC = 0.723(approx)
4. TN = 2
5. TP = 1773

KNN on TF-IDF using brute and kd_tree algorithms

In [39]:
```
tfidf_vect = TfidfVectorizer(ngram_range = (1,4))
tfidf_train = tfidf_vect.fit_transform(X_train)
tfidf_test = tfidf_vect.transform(X_test)
```

In [40]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler(with_mean = False)
X_tr= sc.fit_transform(tfidf_train)
X_te = sc.transform(tfidf_test)
```

In [41]:
```
#X_train, X_tes,y_train,y_tes = cross_validation.train_test_split(tfidf
_X,tfidf_y,test_size = 0.3 ,random_state = 42)
cv_scores = []
for i in neighbors:
    knn = KNeighborsClassifier(n_neighbors = i, algorithm = 'brute')
    cross_val = cross_val_score(knn, X_tr,y_train,cv = 5 , scoring = 'a
ccuracy')
    cv_scores.append(cross_val.mean())
MSE_tfidf = [1-x for x in cv_scores]
optimal_i = neighbors[MSE_tfidf.index(min(MSE_tfidf))]
knn_tfidf = KNeighborsClassifier(n_neighbors = optimal_i,algorithm = 'b
rute')
```

```
knn_tfidf.fit(X_tr, y_train)
pred = knn_tfidf.predict(X_te)
acc_tfidf = accuracy_score(y_test, pred)*100
print("The accuracy for k = {0} using brute is {1}".format(optimal_i,ac
c_tfidf))
```

```
The accuracy for k = 3 using brute is 88.64999999999999
```

In [42]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

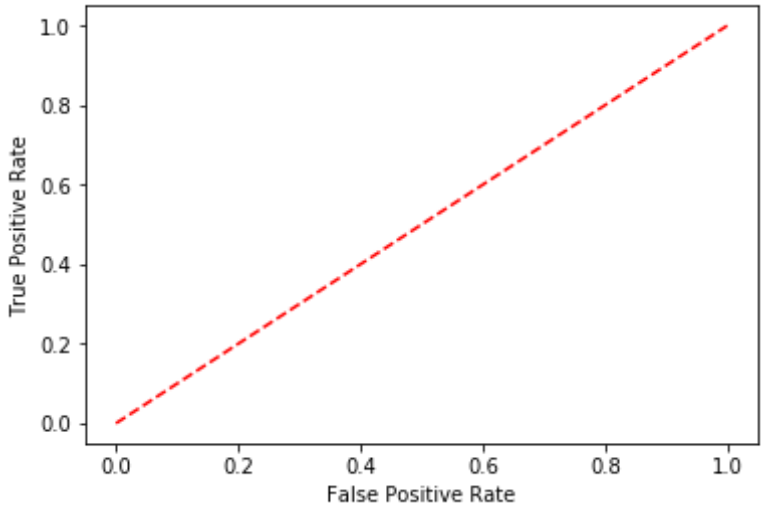
```
             precision    recall  f1-score   support

   negative       0.00      0.00      0.00       227
   positive       0.89      1.00      0.94      1773

avg / total       0.79      0.89      0.83      2000
```

In [43]:
```
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
1.0
0.0


PRECISION SCORE
0.8865
0.0
```

In [44]:
```
change = lambda x : 1 if x == 'positive' else 0
```

```
y_true = np.array([change(x) for x in y_test])
y_pred = knn_tfidf.predict_proba(X_te)[:,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()
```



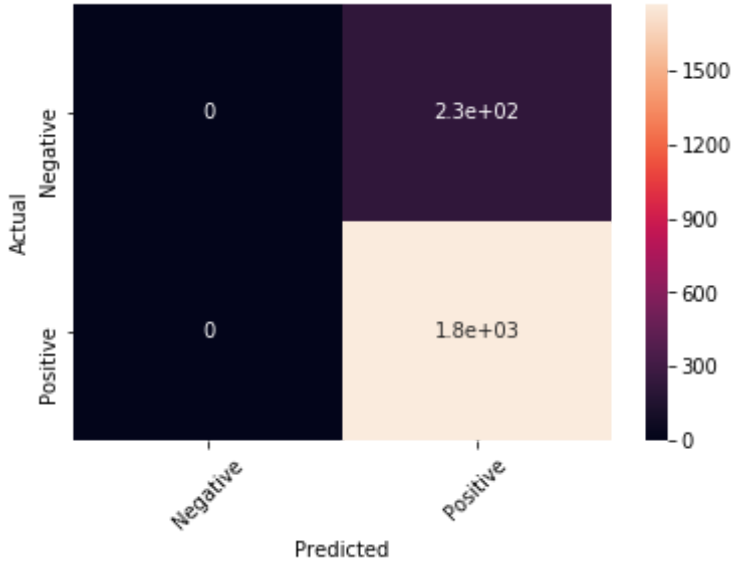
In [45]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.500282007896
```

In [46]:
```
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()
```

```
[[   0  227]
 [   0 1773]]
```



conclusion

Brute Algo

1. Optimal K = 3
2. Accuracy = 88.64
3. AUC = 0.5002(approx)
4. TN = 0
5. TP = 1773

In [47]:
```
import warnings
warnings.filterwarnings("ignore")
```

```
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components = 200)
tfidf_tr = svd.fit_transform(X_tr)
tfidf_te = svd.transform(X_te)
cv_scores = []
for i in neighbors:
    knn = KNeighborsClassifier(n_neighbors = i, algorithm = 'kd_tree',l
eaf_size = 35)
    cross_val = cross_val_score(knn, tfidf_tr,y_train,cv = 2 , scoring
= 'accuracy')
    cv_scores.append(cross_val.mean())
MSE_tfidf = [1-x for x in cv_scores]
optimal_i = neighbors[MSE_tfidf.index(min(MSE_tfidf))]
knn_tfidf = KNeighborsClassifier(n_neighbors = optimal_i,algorithm = 'k
d_tree',leaf_size = 35,n_jobs = -1)
knn_tfidf.fit(tfidf_tr, y_train)
pred = knn_tfidf.predict(tfidf_te)
acc_tfidf = accuracy_score(y_test, pred)*100
print("The accuracy for k = {0} using Kd_tree is {1}".format(optimal_i,
acc_tfidf))
```

```
The accuracy for k = 15 using Kd_tree is 88.64999999999999
```

In [48]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

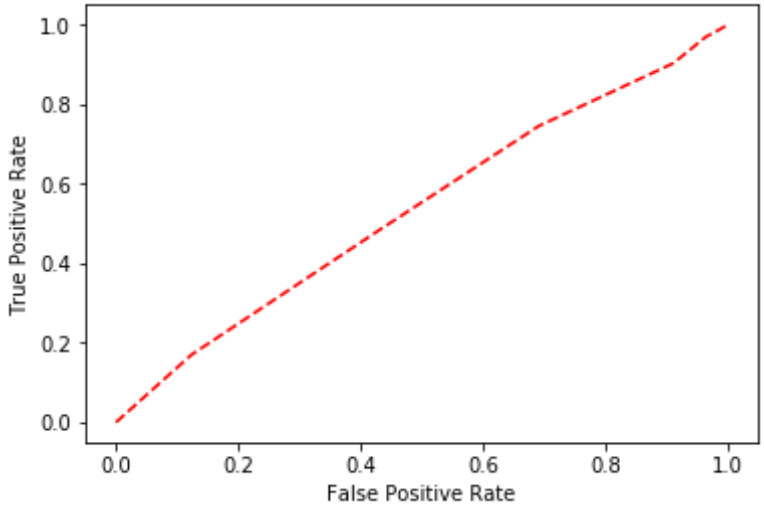
```
             precision    recall  f1-score   support

   negative       0.00      0.00      0.00       227
   positive       0.89      1.00      0.94      1773

avg / total       0.79      0.89      0.83      2000
```

In [49]:
```
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
1.0
0.0


PRECISION SCORE
0.8865
0.0
```

In [50]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = knn_tfidf.predict_proba(tfidf_te)[:,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()
```

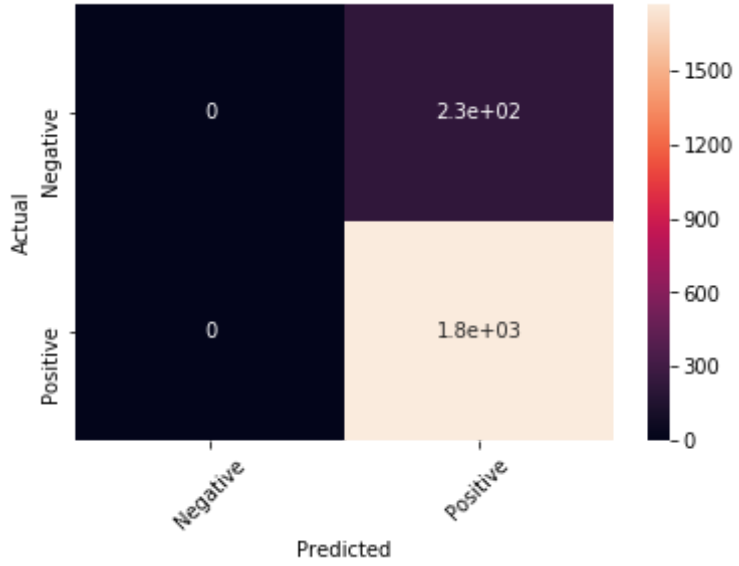


In [51]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.536774078132
```

In [52]:
```
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()
```

```
[[   0  227]
 [   0 1773]]
```



conclusion

Kd-tree Algo

1. Optimal K = 15
2. Accuracy = 88.65
3. AUC = 0.536(approx)
4. TN = 0
5. TP = 1773

KNN on avg W2V using brute and kd_tree algorithm

In [53]:
```
list_of_sent_train = []
for i in X_train:
```

```
    sent=[]
    for word in i.split():
        sent.append(word.decode('utf-8'))
    list_of_sent_train.append(sent)
#list_of_sent_train[2543]
```

In [54]:
```
from gensim.models import Word2Vec
import gensim
w2v_model=gensim.models.Word2Vec(list_of_sent_train,min_count=5,size=50
, workers=4)
sent_vectors_train = []
for sent in list_of_sent_train:
    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            #print(vec)
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
print(len(sent_vectors_train))
#print((sent_vectors_train[2543]))
```

```
8000
```

In [55]:
```
list_of_sent_test = []
for i in X_test:
    sent=[]
    for word in i.split():
        sent.append(word.decode('utf-8'))
    list_of_sent_test.append(sent)
```

In [56]:
```
from gensim.models import Word2Vec
```

```
import gensim
w2v_model=gensim.models.Word2Vec(list_of_sent_test,min_count=5,size=50,
 workers=4)
sent_vectors_test = []
for sent in list_of_sent_test:
    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            #print(vec)
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
```

```
2000
```

In [57]:

```
cv_scores = []
for i in neighbors:
    knn = KNeighborsClassifier(n_neighbors = i, algorithm = 'brute')
    cross_val = cross_val_score(knn, sent_vectors_train,y_train,cv = 5
, scoring = 'accuracy')
    cv_scores.append(cross_val.mean())
MSE = [1-x for x in cv_scores]
optimal_i = neighbors[MSE.index(min(MSE))]
knn = KNeighborsClassifier(n_neighbors = optimal_i,algorithm = 'brute')
knn.fit(sent_vectors_train, y_train)
pred = knn.predict(sent_vectors_test)
acc = accuracy_score(y_test, pred)*100
print("The accuracy for k = {0} using brute is {1}".format(optimal_i,ac
c))
```

```
The accuracy for k = 43 using brute is 88.64999999999999
```

In [58]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

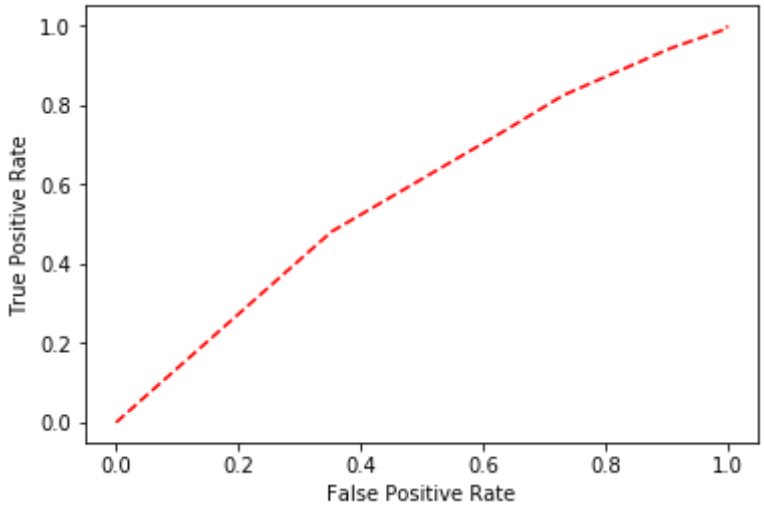
```
             precision    recall  f1-score   support

   negative       0.00      0.00      0.00       227
   positive       0.89      1.00      0.94      1773

avg / total       0.79      0.89      0.83      2000
```

In [59]:
```
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
1.0
0.0


PRECISION SCORE
0.8865
0.0
```

In [60]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = knn.predict_proba(sent_vectors_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()
```

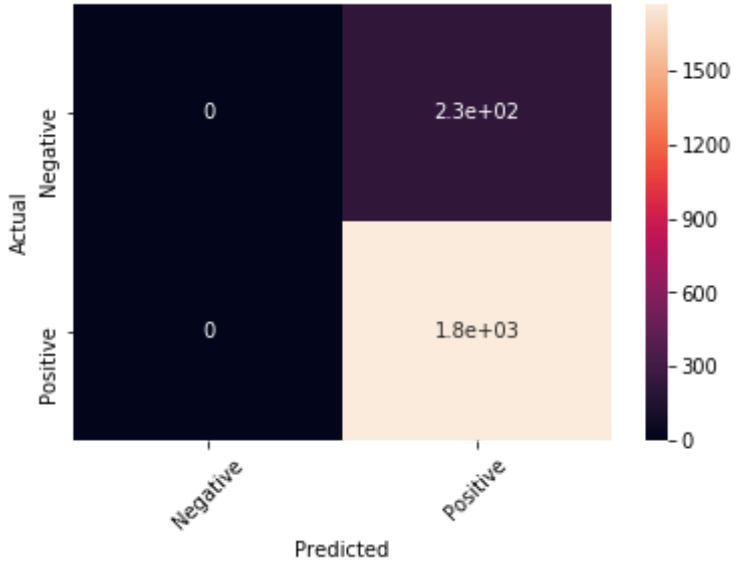


In [61]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.576564522661
```

In [62]:
```
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()
```

```
[[   0  227]
 [   0 1773]]
```



conclusion

Brute Algo

1. Optimal K = 43
2. Accuracy = 88.65
3. AUC = 0.576(approx)
4. TN = 0
5. TP = 1773

In [63]:
```
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components = 49)
sent_vectors_tr = svd.fit_transform(sent_vectors_train)
sent_vectors_te = svd.transform(sent_vectors_test)
cv_scores = []
for i in neighbors:
    knn = KNeighborsClassifier(n_neighbors = i, algorithm = 'kd_tree')
```

```
    cross_val = cross_val_score(knn, sent_vectors_tr,y_train,cv = 10 ,
scoring = 'accuracy')
    cv_scores.append(cross_val.mean())
MSE = [1-x for x in cv_scores]
optimal_i = neighbors[MSE.index(min(MSE))]
knn = KNeighborsClassifier(n_neighbors = optimal_i,algorithm = 'kd_tre
e')
knn.fit(sent_vectors_tr, y_train)
pred = knn.predict(sent_vectors_te)
acc = accuracy_score(y_test, pred)*100
print("The accuracy for k = {0} using Kd_tree is {1}".format(optimal_i,
acc))
```

```
The accuracy for k = 47 using Kd_tree is 88.64999999999999
```

In [64]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

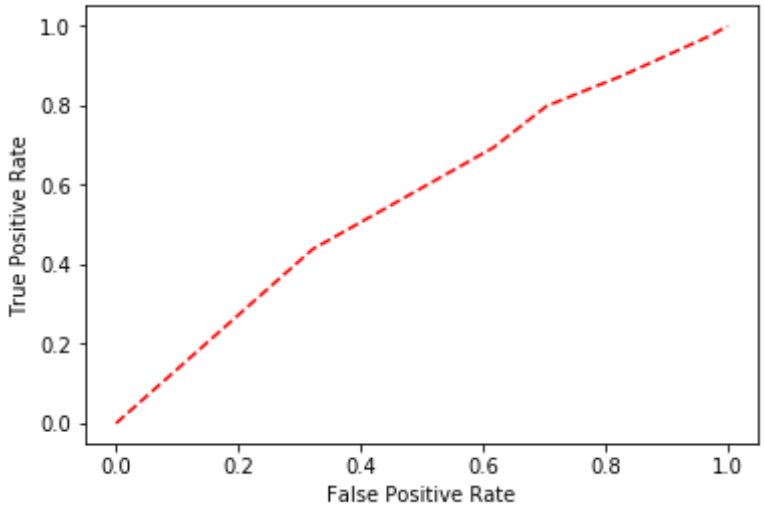
```
             precision    recall  f1-score   support

   negative       0.00      0.00      0.00       227
   positive       0.89      1.00      0.94      1773

avg / total       0.79      0.89      0.83      2000
```

In [65]:
```
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
1.0
0.0
```

```
PRECISION SCORE
0.8865
0.0
```

In [66]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = knn.predict_proba(sent_vectors_te)[:,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()
```

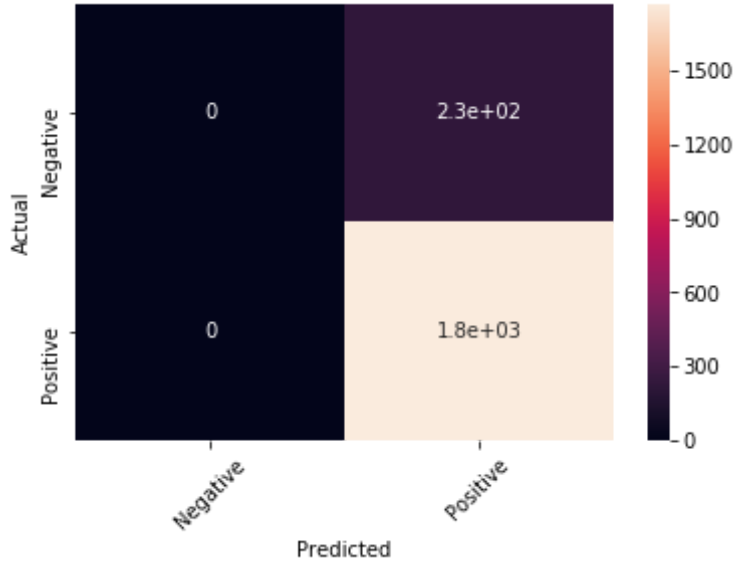


In [67]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.566552621183
```

In [68]:
```
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()
```

```
[[   0  227]
 [   0 1773]]
```



conclusion

Kd-tree Algo

1. Optimal K = 47

2. Accuracy = 88.649
3. AUC = 0.5665(approx)
4. TN = 0
5. TP = 1773

KNN on tf-idf w2v using kd_tree and brute algorithm

In [69]:
```
tf_idf_feat = tfidf_vect.get_feature_names()
tfidf_sent_vec_train = []
row = 0
for sent in list_of_sent_train:
    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            tfidf = tfidf_train[row,tf_idf_feat.index(word)]
            sent_vec += (vec*tfidf)
            weight_sum += tfidf
        except:
            pass
    sent_vec/= weight_sum
    tfidf_sent_vec_train.append(sent_vec)
    row += 1
```

In [70]:
```
tf_idf_feat = tfidf_vect.get_feature_names()
tfidf_sent_vec_test = []
row = 0
for sent in list_of_sent_test:
    sent_vec = np.zeros(50)
    weight_sum = 0
    for word in sent:
```

```
        try:
            vec = w2v_model.wv[word]
            tfidf = tfidf_test[row,tf_idf_feat.index(word)]
            sent_vec += (vec*tfidf)
            weight_sum += tfidf
        except:
            pass
    sent_vec/= weight_sum
    tfidf_sent_vec_test.append(sent_vec)
    row += 1
```

In [93]:
```
np.where(np.isnan(tfidf_sent_vec_train))
```

Out[93]:
```
(array([], dtype=int64), array([], dtype=int64))
```

In [92]:
```
del tfidf_sent_vec_train[7738]
```

In [94]:
```
del y_train[7738]
```

In [95]:
```
cv_scores = []
for i in neighbors:
    knn = KNeighborsClassifier(n_neighbors = i, algorithm = 'brute')
    cross_val = cross_val_score(knn, tfidf_sent_vec_train,y_train,cv =
5 , scoring = 'accuracy')
    cv_scores.append(cross_val.mean())
MSE = [1-x for x in cv_scores]
optimal_i = neighbors[MSE.index(min(MSE))]
knn = KNeighborsClassifier(n_neighbors = optimal_i,algorithm = 'brute')
knn.fit(tfidf_sent_vec_train, y_train)
pred = knn.predict(tfidf_sent_vec_test)
acc = accuracy_score(y_test, pred)*100
print("The accuracy for k = {0} using brute is {1}".format(optimal_i,ac
c))
```

```
The accuracy for k = 19 using brute is 88.64999999999999
```

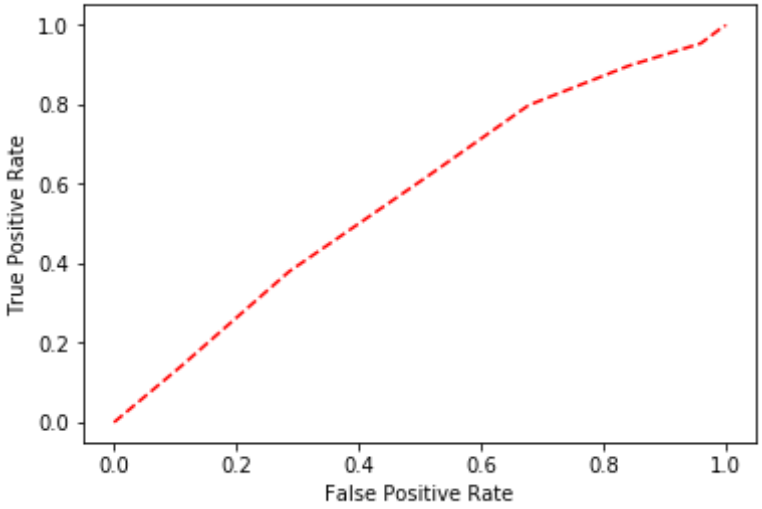
In [96]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

    negative       0.00      0.00      0.00       227
    positive       0.89      1.00      0.94      1773

avg / total       0.79      0.89      0.83      2000
```

In [97]:
```
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
1.0
0.0


PRECISION SCORE
0.8865
0.0
```

In [98]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = knn.predict_proba(tfidf_sent_vec_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()
```

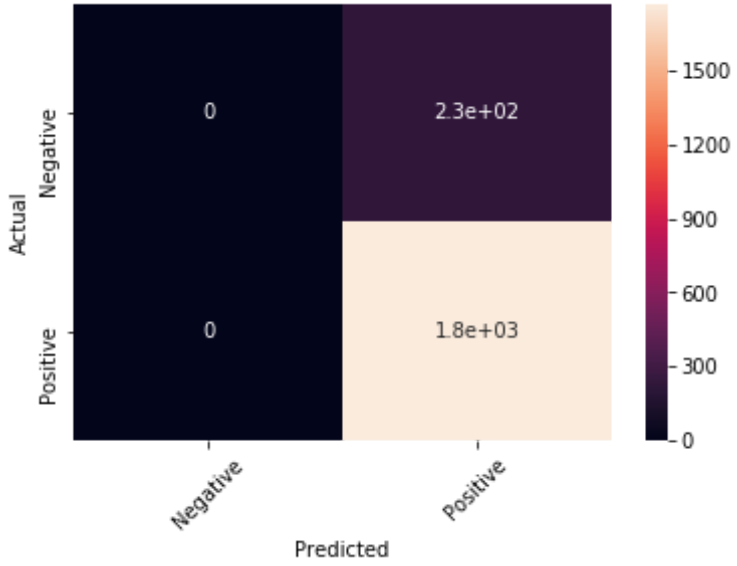


In [99]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.570554151728
```

In [100]:
```
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()
```

```
[[   0  227]
 [   0 1773]]
```



conclusion

Brute Algo

1. Optimal K = 19
2. Accuracy = 88.649
3. AUC = 0.5705(approx)
4. TN = 0
5. TP = 1773

In [101]:
```
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components = 49)
tfidf_sent_vec_tr = svd.fit_transform( tfidf_sent_vec_train)
tfidf_sent_vec_te = svd.transform( tfidf_sent_vec_test)
cv_scores = []
for i in neighbors:
    knn = KNeighborsClassifier(n_neighbors = i, algorithm = 'kd_tree')
```

```
    cross_val = cross_val_score(knn,  tfidf_sent_vec_tr,y_train,cv = 5
, scoring = 'accuracy')
    cv_scores.append(cross_val.mean())
MSE = [1-x for x in cv_scores]
optimal_i = neighbors[MSE.index(min(MSE))]
knn = KNeighborsClassifier(n_neighbors = optimal_i,algorithm = 'kd_tre
e')
knn.fit( tfidf_sent_vec_tr, y_train)
pred = knn.predict( tfidf_sent_vec_te)
acc = accuracy_score(y_test, pred)*100
print("The accuracy for k = {0} using Kd_tree is {1}".format(optimal_i,
acc))
```

```
The accuracy for k = 15 using Kd_tree is 88.6
```

In [102]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
```

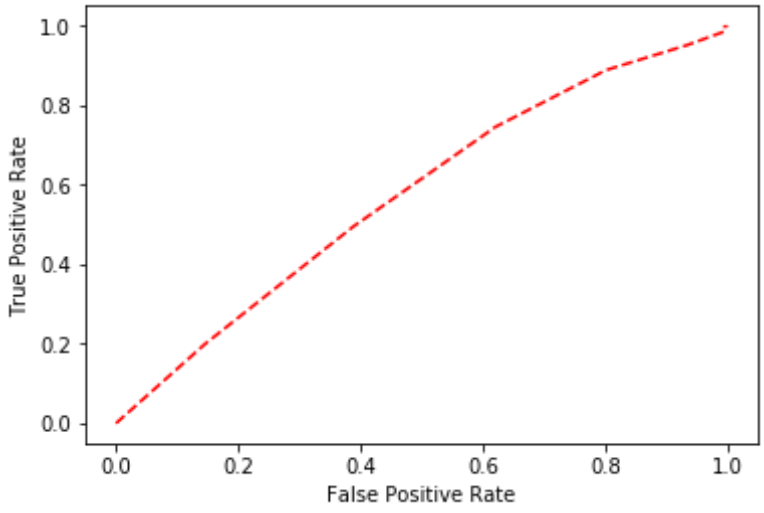
```
             precision    recall  f1-score   support

   negative       0.00      0.00      0.00       227
   positive       0.89      1.00      0.94      1773

avg / total       0.79      0.89      0.83      2000
```

In [103]:
```
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
0.999435984208
0.0
```

```
PRECISION SCORE
0.886443221611
0.0
```

In [104]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = knn.predict_proba( tfidf_sent_vec_te)[:,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()
```

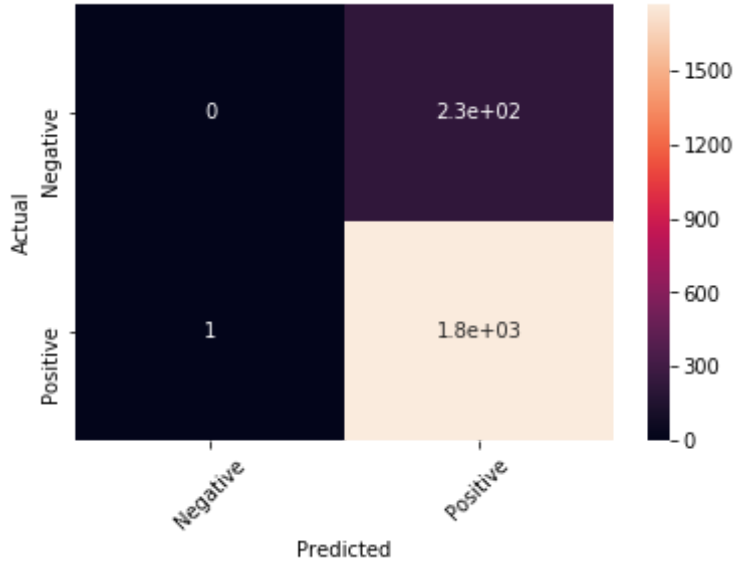


In [105]:
```
print(roc_auc_score(y_true,y_pred))
```

```
0.576373204529
```

In [106]:
```
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()
```

```
[[   0  227]
 [   1 1772]]
```



conclusion

kd-tree Algo

1. Optimal K = 15

2. Accuracy = 88.6
3. AUC = 0.5763(approx)
4. TN = 0
5. TP = 1772