[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. Apply the random forest Classifier
2. Take any two hyperparameters and tune them
3. As we are having two hyperparameters to tune for representing the error plot you can use heat maps,example like this, rows representing one hyperparameter and columns representing other hyperparameter and the values in each representing the error metric value.
4. Get important features and represent them in a word cloud.

In [1]:
```
import numpy as np
import seaborn as sns
```

```python
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.cross_validation import train_test_split
from sklearn.cross_validation import cross_val_score
from sklearn.metrics import accuracy_score,precision_score,recall_score
,classification_report,confusion_matrix
from sklearn.metrics import roc_auc_score, roc_curve
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import GridSearchCV
import re
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
import sqlite3
```

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

In [2]:

```python
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]:

```python
data = data[data.HelpfulnessNumerator <= data.HelpfulnessDenominator]
```

```
data.shape
```

Out[3]: (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 [4]:
```
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[4]:

	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

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	He
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
138705	150523	0006641040	A2P4F2UO0UMP8C	Elizabeth A. Curry "Lovely Librarian"	0	0

In [5]:
```
filtered_data = sorted_data.drop_duplicates(subset = {'UserId','Profile
Name','Time'} ,keep = 'first', inplace = False)
filtered_data.shape
```

Out[5]: (328770, 10)

In [6]:
```
#filtered_data['Score'].value_counts()
final = filtered_data.copy()
```

In [7]:
```
import nltk
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[7]: True

In [8]:
```
stop = set(stopwords.words("english"))
st = PorterStemmer()
st.stem('burned')
```

Out[8]: '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 [9]:
```
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 [10]:
```
i=0
all_positive_reviews =[]
all_negative_reviews = []
final_string = []
```

```python
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 [11]:
```python
final['CleanedText'] = final_string
final.head()
```

Out[11]:

	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 [12]:
```
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 [13]:
```
X_train ,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.3,s
tratify = y)
```

In [14]:
```
count_vect = CountVectorizer()
bow_train = count_vect.fit_transform(X_train)
bow_test = count_vect.transform(X_test)
```

Random Forest on Bow

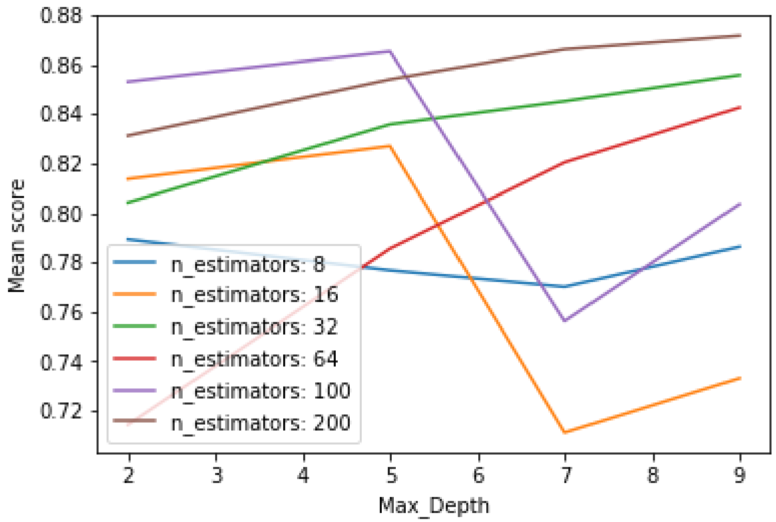
In [15]:
```
param_grid = {'n_estimators': [8, 16, 32, 64, 100, 200],'max_depth': [2
, 5, 7, 9]}
gd = GridSearchCV(RandomForestClassifier(class_weight = 'balanced'),par
am_grid,cv = 5,scoring = 'accuracy')
gd.fit(bow_train,y_train)
print(gd.best_estimator_)
pred = gd.predict(bow_test)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

```
RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=9, max_features='auto',
            max_leaf_nodes=None, min_impurity_decrease=0.0,
            min_impurity_split=None, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=200, n_jobs=1, oob_score=False, random_state=N
one,
            verbose=0, warm_start=False)
Accuracy is 87.3166666667
```

In [16]:
```
n_est = [8, 16, 32, 64, 100, 200]
max_dep = [2, 5, 7, 9]
```

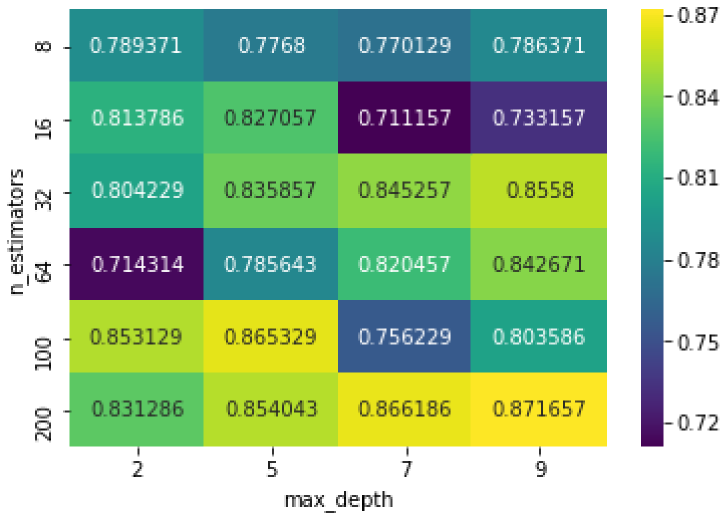
```python
scores = [x[1] for x in gd.grid_scores_]
scores = np.array(scores).reshape(len(n_est), len(max_dep))

for ind, i in enumerate(n_est):
    plt.plot(max_dep, scores[ind], label='n_estimators: ' + str(i))
plt.legend()
plt.xlabel('Max_Depth')
plt.ylabel('Mean score')
plt.show()
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\mode
l_selection\_search.py:761: DeprecationWarning: The grid_scores_ attrib
ute was deprecated in version 0.18 in favor of the more elaborate cv_re
sults_ attribute. The grid_scores_ attribute will not be available from
0.20
  DeprecationWarning)
```



In [17]:

```python
heat = pd.DataFrame(scores,columns = [2,5,7,9],index = [8, 16, 32, 64,
100, 200])
sns.heatmap(heat,annot = True,fmt="g", cmap='viridis')
plt.xlabel('max_depth')
plt.ylabel('n_estimators')
plt.show()
```



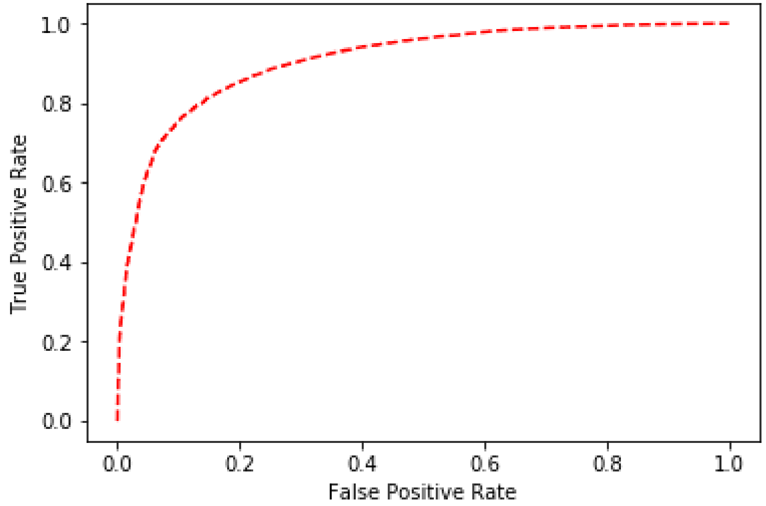
In [18]:

```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.50      0.73      0.59      3811
   positive       0.96      0.89      0.92     26189

avg / total       0.90      0.87      0.88     30000
```

```
Recall for positive 0.894154034136
Recall for negative 0.728942534768


Precision for postive 0.957750511247
Precision for negative 0.500540540541
```

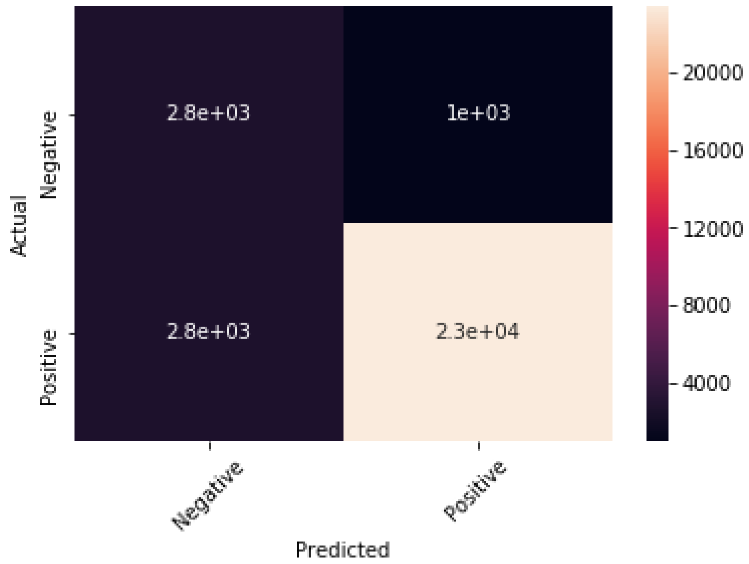
In [19]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = gd.predict_proba(bow_test)[:,1]
fpr,tpr,thresholds = roc_curve(y_true, y_pred)
plt.plot(fpr,tpr,'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```



In [20]:
```
print('ROC Score',roc_auc_score(y_true,y_pred))
print('\n')
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()
```

```
ROC Score 0.908012876625


[[ 2778  1033]
 [ 2772 23417]]
```



Top 10 important features of Random Forest

In [23]:
```
index = gd.best_estimator_.feature_importances_.argsort()[::-1]
top_10 = np.take(count_vect.get_feature_names(),index)
print(top_10)
```

```
['best' 'worst' 'disappoint' ..., 'peco' 'pecorino' 'aaa']
```

GBDT on Bow

In [24]:

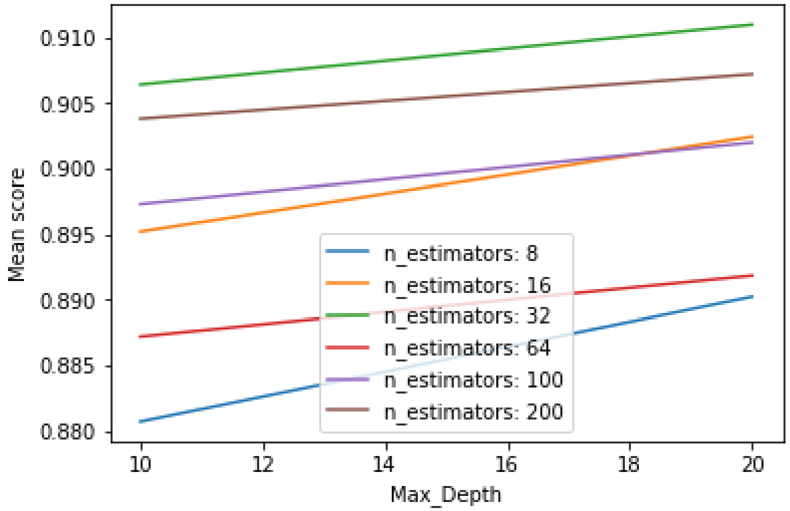
```
para_grid = {'n_estimators': [8, 16, 32, 64, 100, 200],'max_depth': [10
,20]}
ggd = GridSearchCV(GradientBoostingClassifier(),para_grid,cv = 5,scorin
g = 'accuracy')
ggd.fit(bow_train,y_train)
print(ggd.best_estimator_)
pred = ggd.predict(bow_test)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

```
GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=10,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=200,
              presort='auto', random_state=None, subsample=1.0, verbose
=0,
              warm_start=False)
Accuracy is 91.21
```

In [25]:

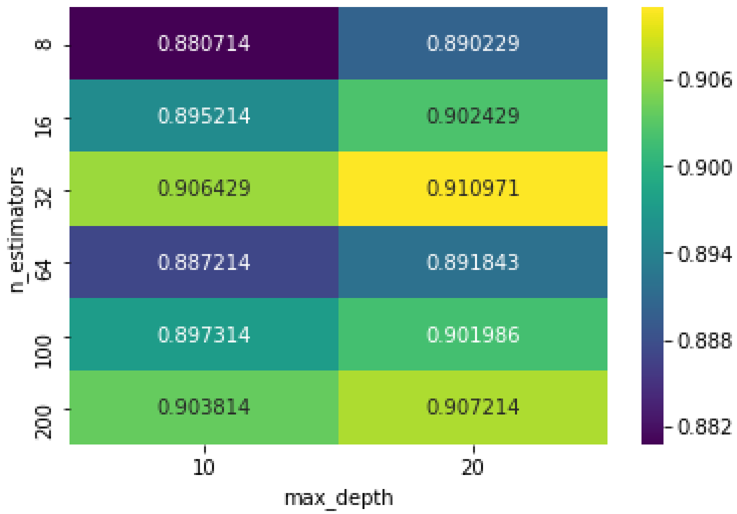
```
n_est = [8, 16, 32, 64, 100, 200]
max_dep = [ 10,20]
scores = [x[1] for x in ggd.grid_scores_]
scores = np.array(scores).reshape(len(n_est), len(max_dep))

for ind, i in enumerate(n_est):
    plt.plot(max_dep, scores[ind], label='n_estimators: ' + str(i))
plt.legend()
plt.xlabel('Max_Depth')
plt.ylabel('Mean score')
plt.show()
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\model_selection\_search.py:761: DeprecationWarning: The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



In [26]:

```
heat = pd.DataFrame(scores,columns = [ 10,20],index = [8, 16, 32, 64, 100, 200])
sns.heatmap(heat,annot = True,fmt="g", cmap='viridis')
plt.xlabel('max_depth')
plt.ylabel('n_estimators')
plt.show()
```



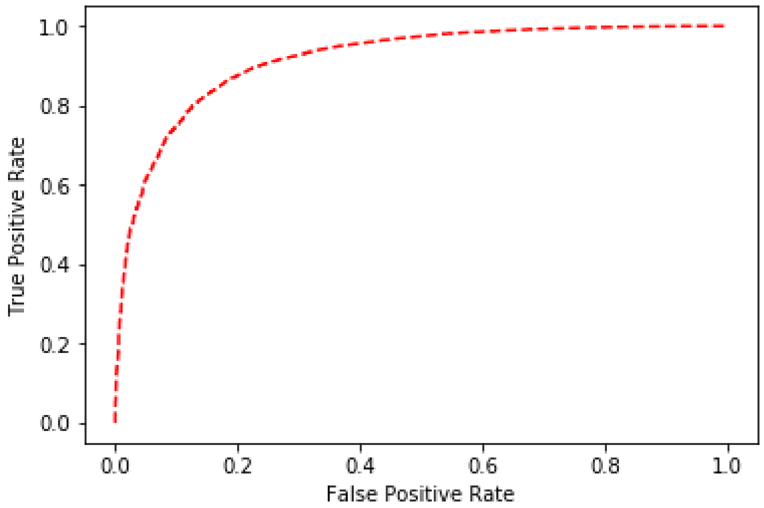
In [27]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.80      0.41      0.54      3811
   positive       0.92      0.98      0.95     26189

avg / total       0.90      0.91      0.90     30000
```

```
Recall for positive 0.984764595823
Recall for negative 0.412752558384


Precision for postive 0.920151277294
Precision for negative 0.797667342799
```

In [28]:

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

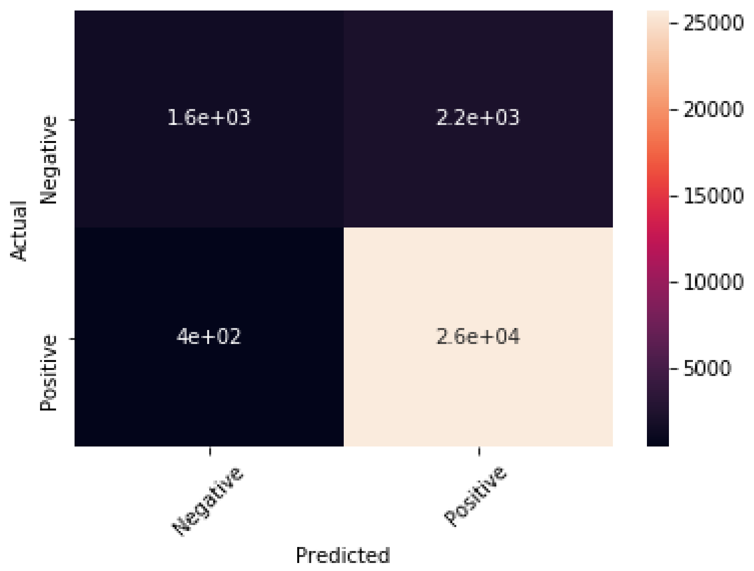


In [29]:

```
print('ROC Score',roc_auc_score(y_true,y_pred))
print('\n')
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()
```

```
ROC Score 0.916096376061


[[ 1573  2238]
 [  399 25790]]
```



Top 10 important features of GBDT

In [31]:
```
index = ggd.best_estimator_.feature_importances_.argsort()[::-1]
top_10 = np.take(count_vect.get_feature_names(),index)
print(top_10)
```

```
['great' 'disappoint' 'good' ..., 'parish' 'parisian' 'aaa']
```

Random Forest on Tfidf

In [32]:

```
tfidf_vect = TfidfVectorizer()
tfidf_train = tfidf_vect.fit_transform (X_train)
tfidf_test = tfidf_vect.transform(X_test)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler(with_mean = False)
X_tr = sc.fit_transform(tfidf_train)
X_te = sc.transform(tfidf_test)
gd_tf = GridSearchCV(RandomForestClassifier(class_weight = 'balanced'),
para_grid,cv = 5,scoring = 'accuracy')
gd_tf.fit(X_tr,y_train)
print(gd_tf.best_params_)
pred = gd_tf.predict(X_te)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

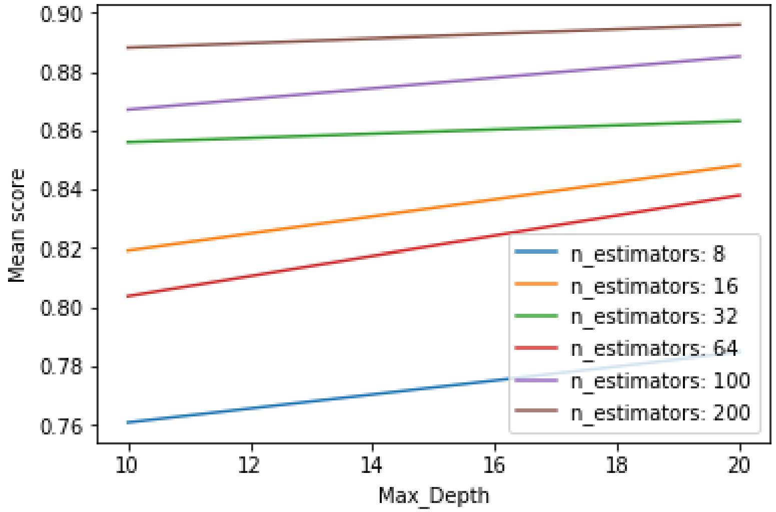
```
{'max_depth': 20, 'n_estimators': 200}
Accuracy is 89.4366666667
```

In [33]:

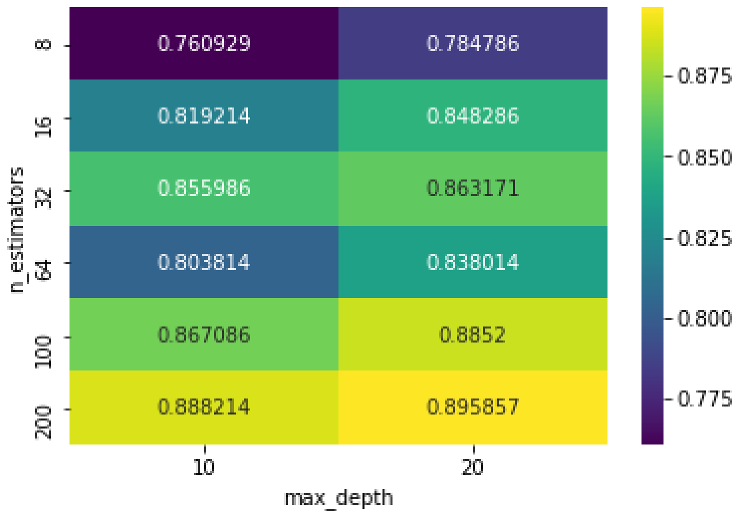
```
n_est = [8, 16, 32, 64, 100, 200]
max_dep = [ 10,20]
scores = [x[1] for x in gd_tf.grid_scores_]
scores = np.array(scores).reshape(len(n_est), len(max_dep))

for ind, i in enumerate(n_est):
    plt.plot(max_dep, scores[ind], label='n_estimators: ' + str(i))
plt.legend()
plt.xlabel('Max_Depth')
plt.ylabel('Mean score')
plt.show()
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\mode
l_selection\_search.py:761: DeprecationWarning: The grid_scores_ attrib
ute was deprecated in version 0.18 in favor of the more elaborate cv_re
sults_ attribute. The grid_scores_ attribute will not be available from
```

```
0.20
  DeprecationWarning)
```



In [34]:
```
heat = pd.DataFrame(scores,columns = [ 10,20],index = [8, 16, 32, 64, 1
00, 200])
sns.heatmap(heat,annot = True,fmt="g", cmap='viridis')
plt.xlabel('max_depth')
plt.ylabel('n_estimators')
plt.show()
```

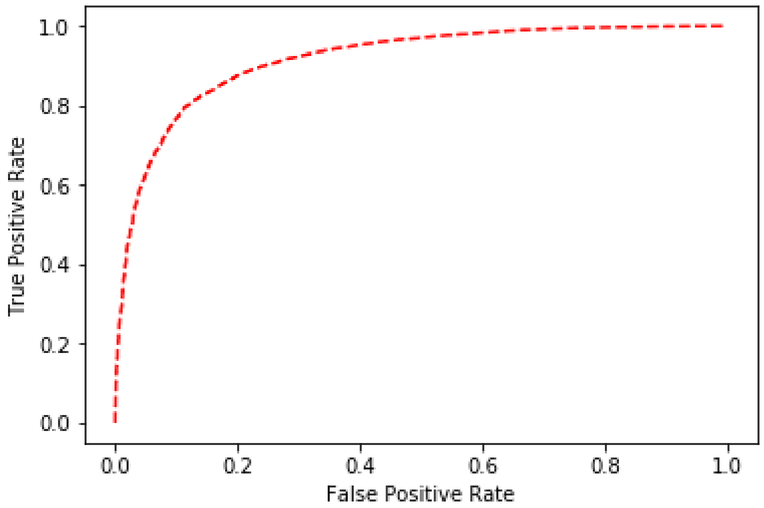


In [35]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.57      0.70      0.63      3811
   positive       0.96      0.92      0.94     26189

avg / total       0.91      0.89      0.90     30000
```

```
Recall for positive 0.922295620299
Recall for negative 0.702440304382


Precision for postive 0.955156596014
Precision for negative 0.568123938879
```

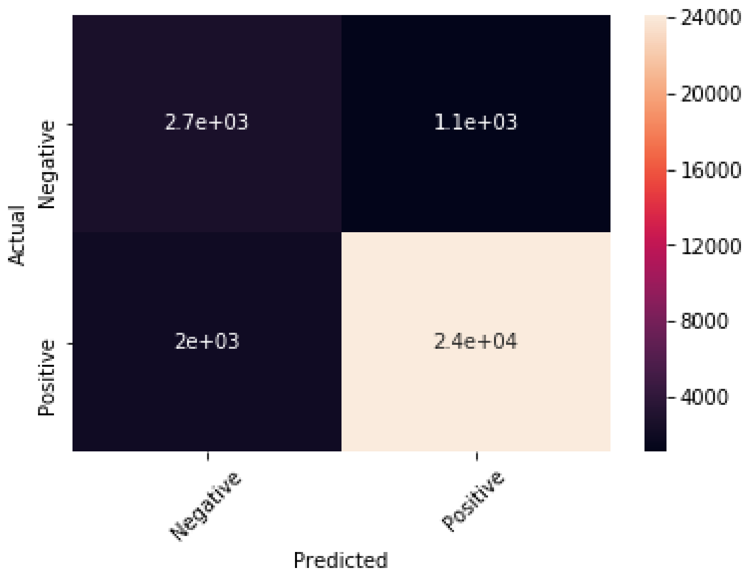
In [36]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = gd_tf.predict_proba(X_te)[:,1]
fpr,tpr,thresholds = roc_curve(y_true, y_pred)
plt.plot(fpr,tpr,'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```



In [37]:
```
print('ROC Score',roc_auc_score(y_true,y_pred))
print('\n')
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()
```

```
ROC Score 0.916330344306


[[ 2677  1134]
 [ 2035 24154]]
```



Top 10 important features of Random Forest

In [40]:
```
index = gd_tf.best_estimator_.feature_importances_.argsort()[::-1]
top_10 = np.take(tfidf_vect.get_feature_names(),index)
print(top_10)
```

```
['great' 'best' 'love' ..., 'orgi' 'orgini' 'aaa']
```

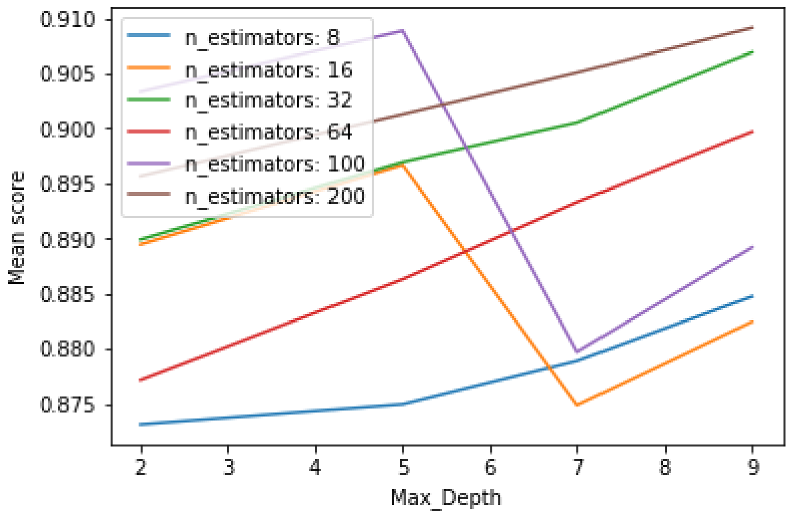
GBDT on Tfidf

In [41]:
```
para_grid = {'n_estimators': [8, 16, 32, 64, 100, 200],'max_depth': [2,
 5, 7, 9]}
ggd_tf = GridSearchCV(GradientBoostingClassifier(),para_grid,cv = 3,sco
ring = 'accuracy')
ggd_tf.fit(X_tr,y_train)
print(ggd_tf.best_params_)
pred = ggd_tf.predict(X_te)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

```
{'max_depth': 9, 'n_estimators': 200}
Accuracy is 91.1233333333
```

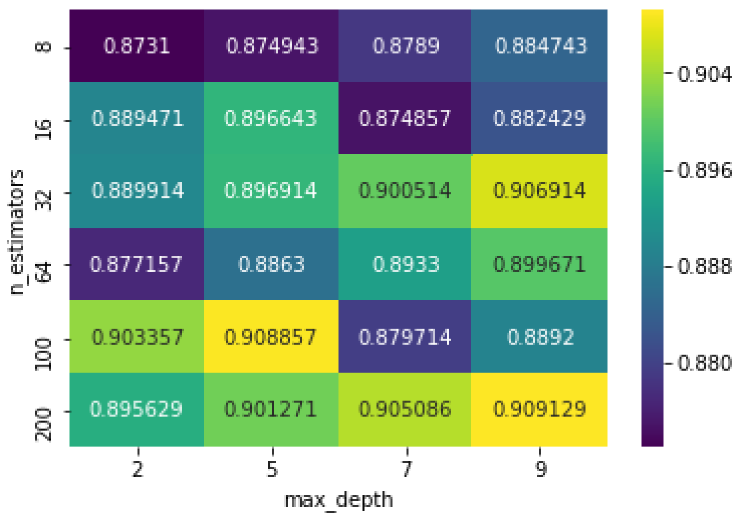
In [42]:
```
n_est = [8, 16, 32, 64, 100, 200]
max_dep =[2, 5, 7, 9]
scores = [x[1] for x in ggd_tf.grid_scores_]
scores = np.array(scores).reshape(len(n_est), len(max_dep))

for ind, i in enumerate(n_est):
    plt.plot(max_dep, scores[ind], label='n_estimators: ' + str(i))
plt.legend()
plt.xlabel('Max_Depth')
plt.ylabel('Mean score')
plt.show()
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\sklearn\mode
l_selection\_search.py:761: DeprecationWarning: The grid_scores_ attrib
ute was deprecated in version 0.18 in favor of the more elaborate cv_re
sults_ attribute. The grid_scores_ attribute will not be available from
0.20
  DeprecationWarning)
```



In [43]:

```
heat = pd.DataFrame(scores,columns = [2, 5, 7, 9],index = [8, 16, 32, 6
4, 100, 200])
sns.heatmap(heat,annot = True,fmt="g", cmap='viridis')
plt.xlabel('max_depth')
plt.ylabel('n_estimators')
plt.show()
```

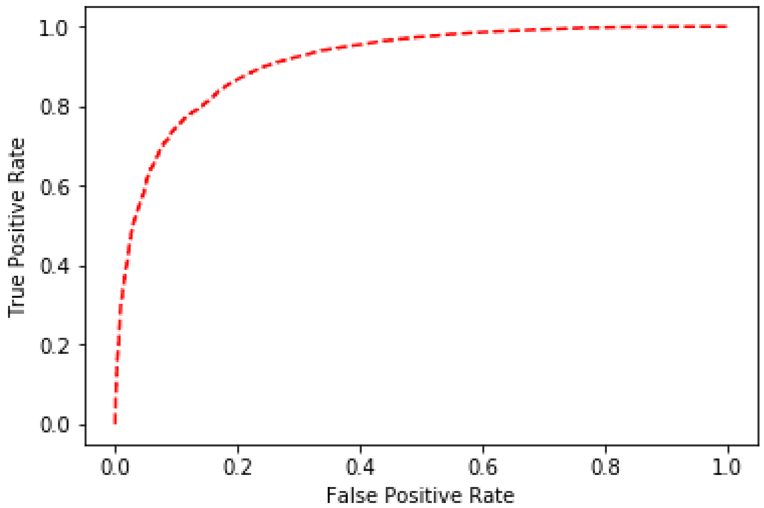


In [44]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.81      0.40      0.53      3811
   positive       0.92      0.99      0.95     26189

avg / total       0.90      0.91      0.90     30000



Recall for positive 0.986177402726
Recall for negative 0.396221464183


Precision for postive 0.918195392491
Precision for negative 0.806623931624
```

In [45]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = ggd_tf.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')
```

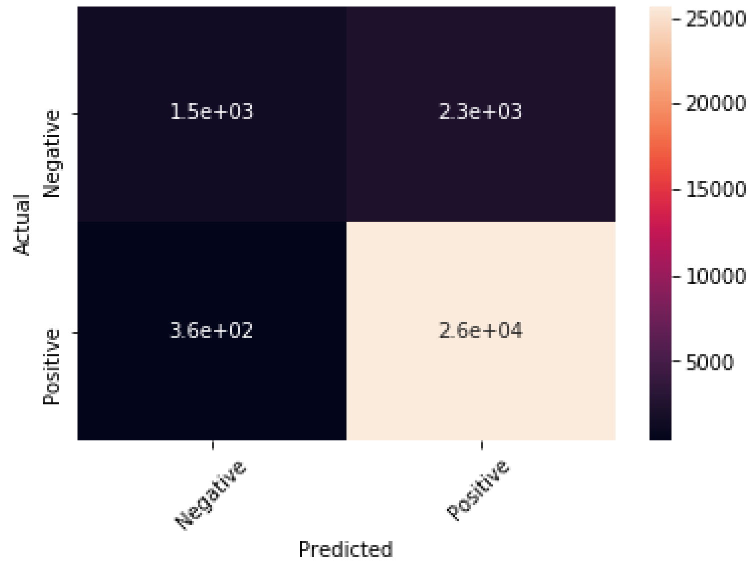
```
plt.legend()
plt.show()
```



In [46]:

```
print('ROC Score',roc_auc_score(y_true,y_pred))
print('\n')
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()
```

```
ROC Score 0.913903122267


[[ 1510  2301]
 [  362 25827]]
```



Top 10 important features of GBDT

In [47]:
```
index = ggd_tf.best_estimator_.feature_importances_.argsort()[::-1]
top_10 = np.take(tfidf_vect.get_feature_names(),index)
print(top_10)
```

```
['great' 'love' 'disappoint' ..., 'perchanc' 'perchas' 'aaa']
```

In [39]:
```
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)
```

In [40]:
```
from gensim.models import Word2Vec
w2v_model = 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_word = 0
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_word += 1
        except:
            pass
    sent_vec /= cnt_word
    sent_vectors_train.append(sent_vec)
print(len(sent_vectors_train))
```

```
C:\Users\manish dogra\Documents\anaconda\lib\site-packages\gensim\util
s.py:1197: UserWarning: detected Windows; aliasing chunkize to chunkize
_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_seria
l")
```

```
70000
```

In [41]:

```
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 [42]:

```
import warnings
warnings.filterwarnings("ignore")
from gensim.models import Word2Vec
w2v_model = 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_word = 0
    for word in sent:
```

```
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_word += 1
        except:
            pass
    sent_vec /= cnt_word
    sent_vectors_test.append(sent_vec)
print(len(sent_vectors_test))
```

```
30000
```

In [43]:
```
np.where(np.isnan(sent_vectors_test))
```

Out[43]:
```
(array([], dtype=int64), array([], dtype=int64))
```

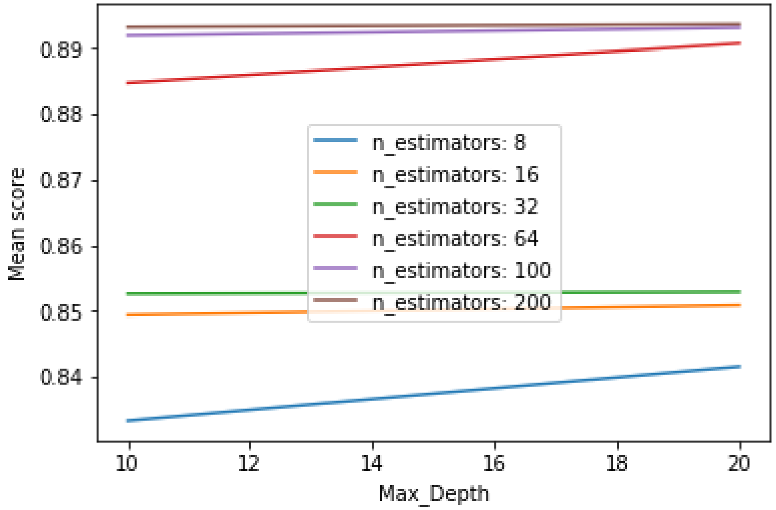
Random Forest on Avg W2vec

In [44]:
```
para_grid = {'n_estimators': [8, 16, 32, 64, 100, 200],'max_depth': [10
,20]}
sc = StandardScaler()
w2v_train = sc.fit_transform(sent_vectors_train)
w2v_test = sc.transform(sent_vectors_test)
gd_w2v = GridSearchCV(RandomForestClassifier(class_weight = 'balanced'
),para_grid,cv = 5,scoring = 'accuracy')
gd_w2v.fit(w2v_train,y_train)
print(gd_w2v.best_params_)
pred = gd_w2v.predict(w2v_test)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

```
{'max_depth': 20, 'n_estimators': 200}
Accuracy is 87.3
```

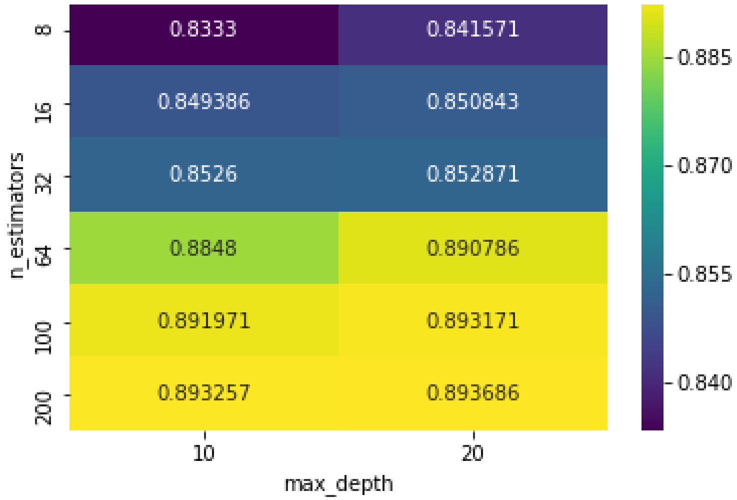
In [45]:
```
n_est = [8, 16, 32, 64, 100, 200]
max_dep = [ 10,20]
scores = [x[1] for x in gd_w2v.grid_scores_]
```

```python
scores = np.array(scores).reshape(len(n_est), len(max_dep))

for ind, i in enumerate(n_est):
    plt.plot(max_dep, scores[ind], label='n_estimators: ' + str(i))
plt.legend()
plt.xlabel('Max_Depth')
plt.ylabel('Mean score')
plt.show()
```



In [46]:

```python
heat = pd.DataFrame(scores,columns = [ 10,20],index = [8, 16, 32, 64, 1
00, 200])
sns.heatmap(heat,annot = True,fmt="g", cmap='viridis')
plt.xlabel('max_depth')
plt.ylabel('n_estimators')
plt.show()
```



In [47]:

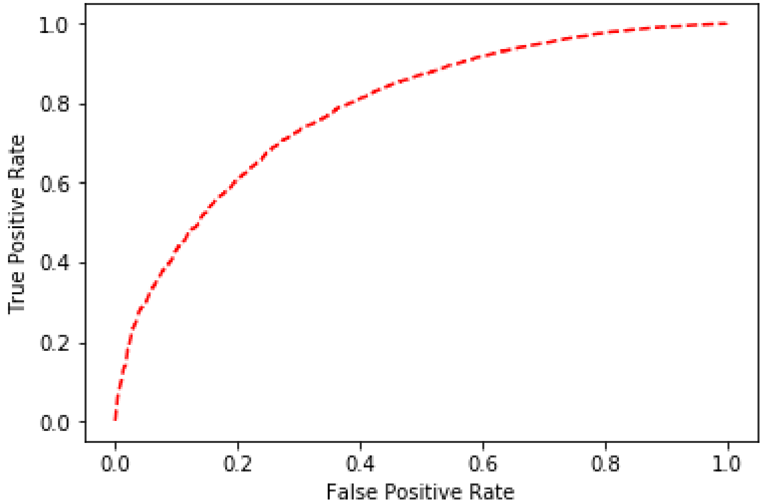
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.53      0.00      0.00      3811
   positive       0.87      1.00      0.93     26189

avg / total       0.83      0.87      0.81     30000
```

```
Recall for positive 0.999732712207
Recall for negative 0.00209918656521


Precision for postive 0.873169918292
Precision for negative 0.533333333333
```

In [48]:

```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = gd_w2v.predict_proba(w2v_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()
```

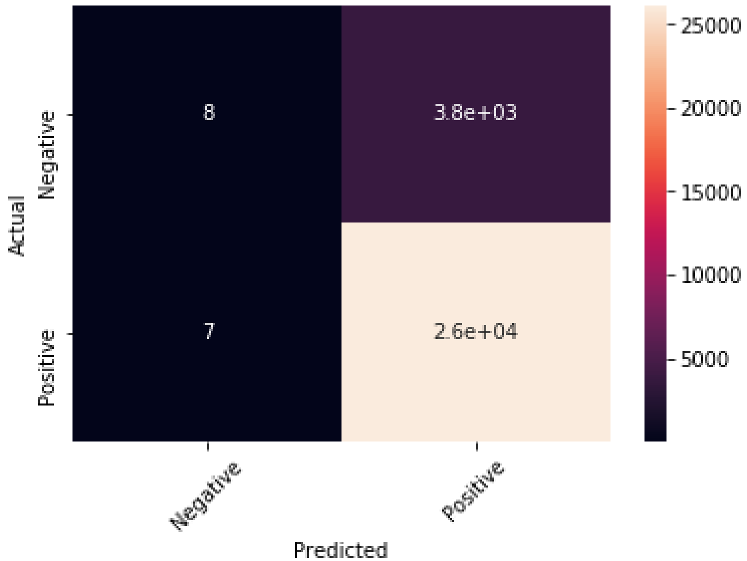


In [49]:

```
print('ROC Score',roc_auc_score(y_true,y_pred))
print('\n')
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()
```

```
ROC Score 0.787019246555


[[    8  3803]
 [    7 26182]]
```



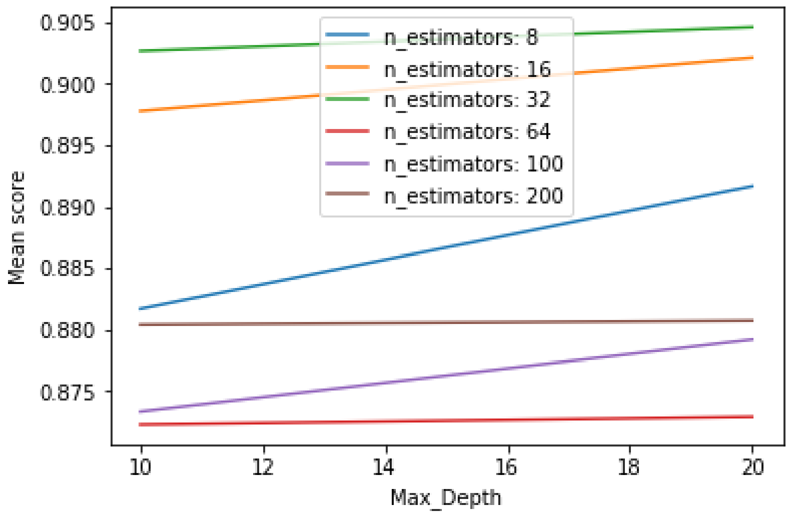
GBDT on Avg W2vec

In [50]:
```
ggd_w2v = GridSearchCV(GradientBoostingClassifier(),para_grid,cv = 5,sc
oring = 'accuracy')
ggd_w2v.fit(w2v_train,y_train)
print(ggd_w2v.best_params_)
pred = ggd_w2v.predict(w2v_test)
```

```
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

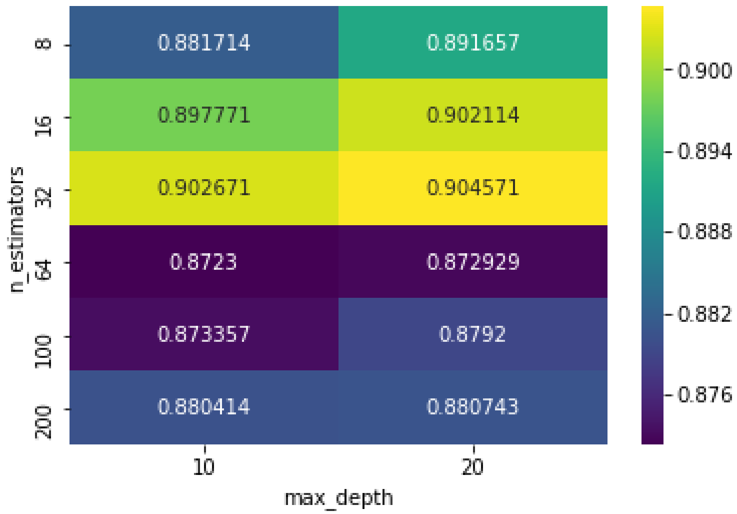
```
{'max_depth': 10, 'n_estimators': 200}
Accuracy is 87.5166666667
```

In [51]:
```
n_est = [8, 16, 32, 64, 100, 200]
max_dep = [ 10,20]
scores = [x[1] for x in ggd_w2v.grid_scores_]
scores = np.array(scores).reshape(len(n_est), len(max_dep))

for ind, i in enumerate(n_est):
    plt.plot(max_dep, scores[ind], label='n_estimators: ' + str(i))
plt.legend()
plt.xlabel('Max_Depth')
plt.ylabel('Mean score')
plt.show()
```



In [52]:
```
heat = pd.DataFrame(scores,columns = [ 10,20],index = [8, 16, 32, 64, 1
00, 200])
sns.heatmap(heat,annot = True,fmt="g", cmap='viridis')
plt.xlabel('max_depth')
```

```
plt.ylabel('n_estimators')
plt.show()
```

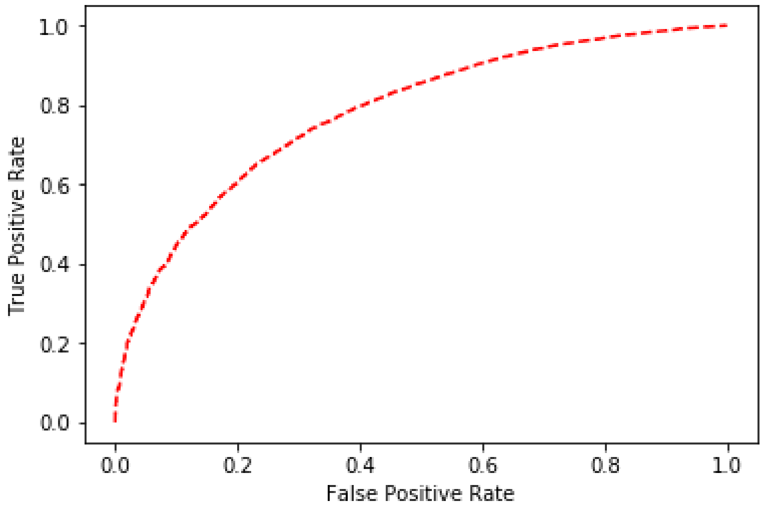


In [53]:
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
              precision    recall  f1-score   support

    negative       0.57      0.07      0.13      3811
    positive       0.88      0.99      0.93     26189
```

```
avg / total       0.84      0.88      0.83     30000



Recall for positive 0.992019550193
Recall for negative 0.072159538179


Precision for postive 0.880200569183
Precision for negative 0.568181818182
```

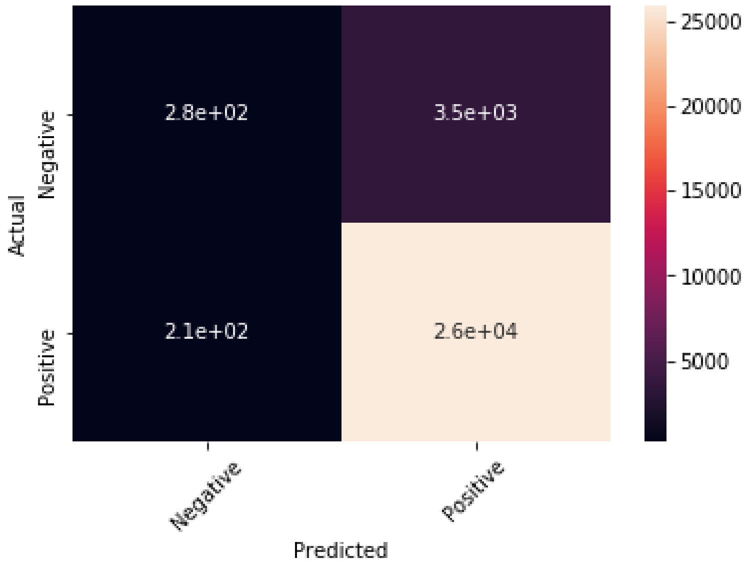
In [54]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = ggd_w2v.predict_proba(w2v_test)[:,1]
fpr,tpr,thresholds = roc_curve(y_true, y_pred)
plt.plot(fpr,tpr,'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.legend()
plt.show()
```



In [55]:
```
print('ROC Score',roc_auc_score(y_true,y_pred))
```

```
print('\n')
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()
```

```
ROC Score 0.781370669074


[[  275  3536]
 [  209 25980]]
```



In [56]:
```
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 [57]:
```
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 [58]:
```
np.where(np.isnan(tfidf_sent_vec_train))
```

Out[58]:
```
(array([16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718,
        16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718,
        16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718,
        16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718,
        16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718, 16718,
        16718, 16718, 16718, 16718, 16718], dtype=int64),
```

```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15,
16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32,
33,
        34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 4
9], dtype=int64))
```

In [61]:

```
y_tr = y_train
del tfidf_sent_vec_train[16718]
y_train = np.delete(y_train,16718)
```

Random Forest on Tfidf W2vec

In [62]:

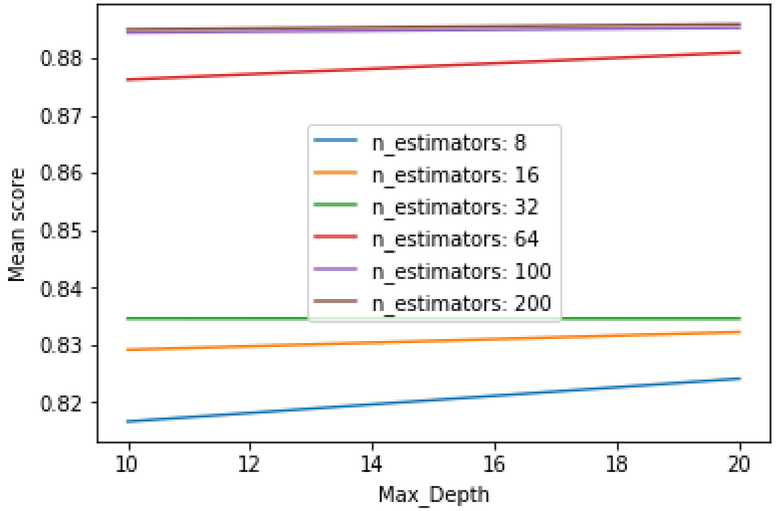
```
sc =  StandardScaler()
tfidf_w2v_train = sc.fit_transform(tfidf_sent_vec_train)
tfidf_w2v_test = sc.transform(tfidf_sent_vec_test)
gd_wtf = GridSearchCV(RandomForestClassifier(class_weight = 'balanced'
),para_grid,cv = 5,scoring = 'accuracy')
gd_wtf.fit(tfidf_w2v_train,y_train)
print(gd_wtf.best_params_)
pred = gd_wtf.predict(tfidf_w2v_test)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

```
{'max_depth': 20, 'n_estimators': 200}
Accuracy is 88.7066666667
```

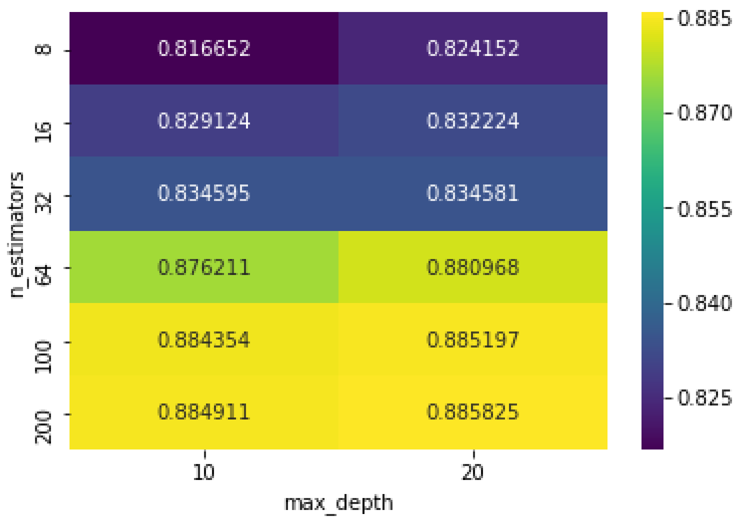
In [63]:

```
n_est = [8, 16, 32, 64, 100, 200]
max_dep = [ 10,20]
scores = [x[1] for x in gd_wtf.grid_scores_]
scores = np.array(scores).reshape(len(n_est), len(max_dep))

for ind, i in enumerate(n_est):
    plt.plot(max_dep, scores[ind], label='n_estimators: ' + str(i))
plt.legend()
plt.xlabel('Max_Depth')
```

```
plt.ylabel('Mean score')
plt.show()
```



In [64]:
```
heat = pd.DataFrame(scores,columns = [ 10,20],index = [8, 16, 32, 64, 1
00, 200])
sns.heatmap(heat,annot = True,fmt="g", cmap='viridis')
plt.xlabel('max_depth')
plt.ylabel('n_estimators')
plt.show()
```



In [65]:

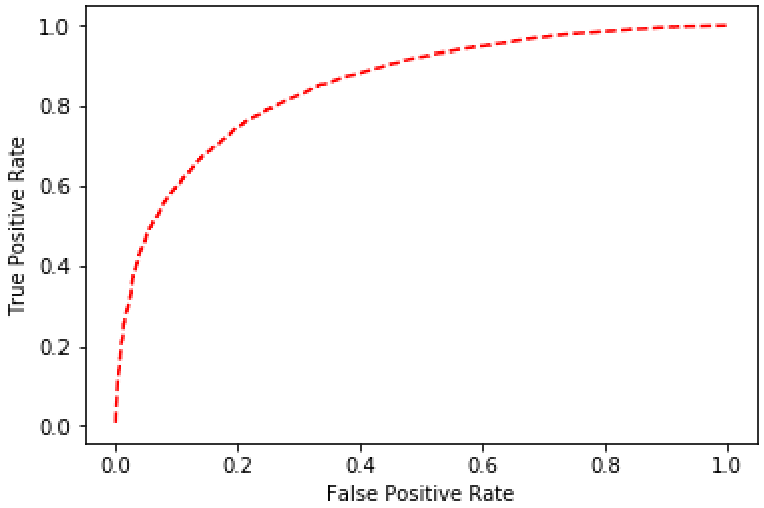
```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
             precision    recall  f1-score   support

   negative       0.62      0.28      0.38      3811
   positive       0.90      0.98      0.94     26189

avg / total       0.87      0.89      0.87     30000
```

```
Recall for positive 0.975714994845
Recall for negative 0.277879821569


Precision for postive 0.902773361597
Precision for negative 0.624778761062
```

In [66]:

```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = gd_wtf.predict_proba(tfidf_w2v_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()
```

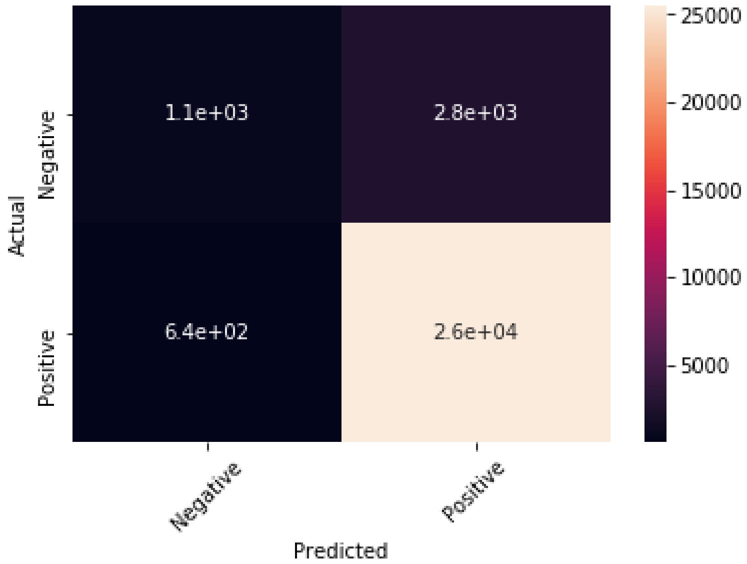


In [67]:

```
print('ROC Score',roc_auc_score(y_true,y_pred))
print('\n')
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()
```

```
ROC Score 0.852560674063


[[ 1059  2752]
 [  636 25553]]
```



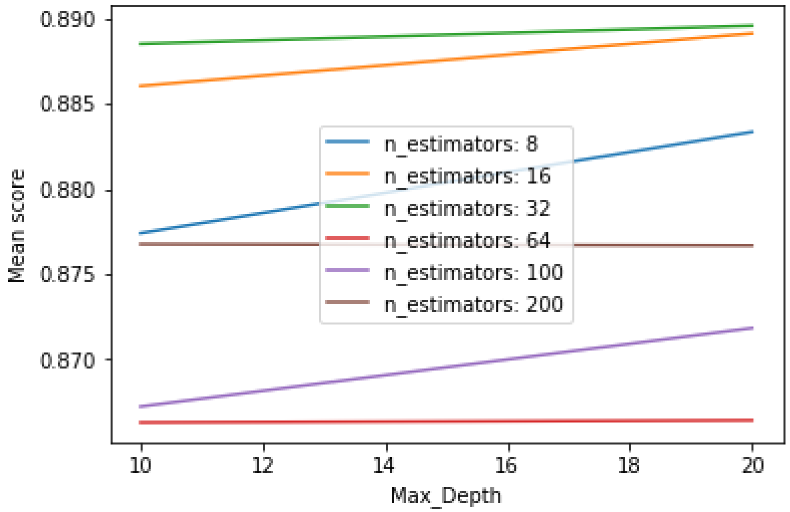
GBDT on Tfidf W2vec

In [68]:
```
ggd_wtf = GridSearchCV(GradientBoostingClassifier(),para_grid,cv = 3,sc
oring = 'accuracy')
ggd_wtf.fit(tfidf_w2v_train,y_train)
print(ggd_wtf.best_params_)
```

```
pred = ggd_wtf.predict(tfidf_w2v_test)
acc = accuracy_score(y_test,pred)
print('Accuracy is',acc*100)
```

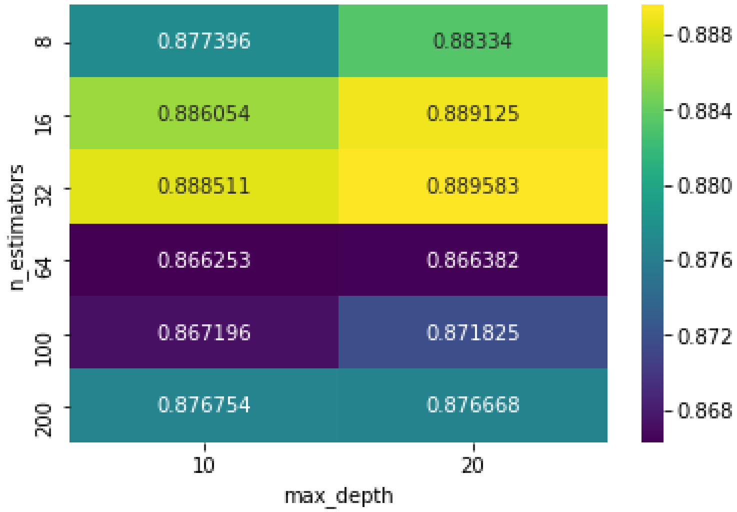
```
{'max_depth': 10, 'n_estimators': 200}
Accuracy is 89.1566666667
```

In [69]:
```
n_est = [8, 16, 32, 64, 100, 200]
max_dep = [ 10,20]
scores = [x[1] for x in ggd_wtf.grid_scores_]
scores = np.array(scores).reshape(len(n_est), len(max_dep))

for ind, i in enumerate(n_est):
    plt.plot(max_dep, scores[ind], label='n_estimators: ' + str(i))
plt.legend()
plt.xlabel('Max_Depth')
plt.ylabel('Mean score')
plt.show()
```



In [70]:
```
heat = pd.DataFrame(scores,columns = [ 10,20],index = [8, 16, 32, 64, 1
00, 200])
sns.heatmap(heat,annot = True,fmt="g", cmap='viridis')
```

```
plt.xlabel('max_depth')
plt.ylabel('n_estimators')
plt.show()
```



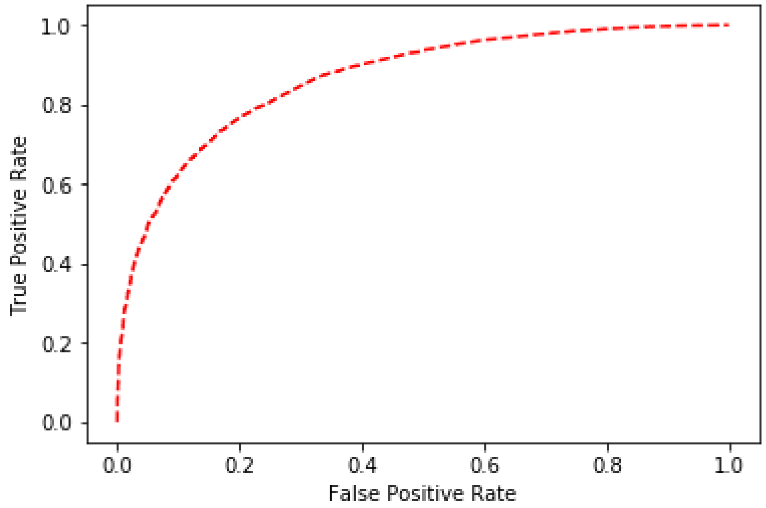
In [71]:

```
from sklearn.metrics import recall_score , precision_score , roc_auc_sc
ore ,roc_curve
from sklearn.metrics import classification_report
print(classification_report(y_test,pred))
print('\n')
print('Recall for positive',recall_score(y_test,pred,pos_label = 'posit
ive'))
print('Recall for negative',recall_score(y_test,pred,pos_label = 'negat
ive'))
print('\n')
print('Precision for postive',precision_score(y_test,pred,pos_label =
'positive'))
print('Precision for negative',precision_score(y_test,pred,pos_label =
'negative'))
```

```
              precision    recall  f1-score   support

    negative       0.66      0.30      0.41      3811
    positive       0.91      0.98      0.94     26189
```

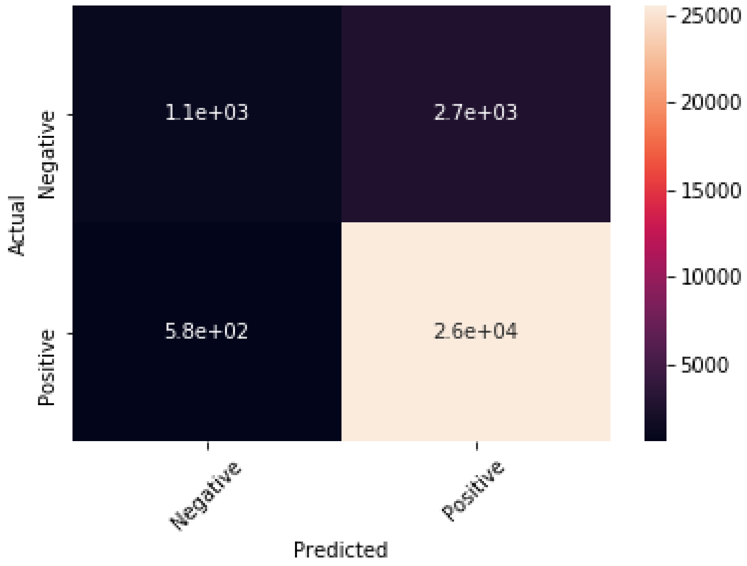
```
avg / total       0.87      0.89      0.87     30000


Recall for positive 0.977700561304
Recall for negative 0.299658882183


Precision for postive 0.905602320153
Precision for negative 0.661645422943
```

In [72]:
```
change = lambda x : 1 if x == 'positive' else 0
y_true = np.array([change(x) for x in y_test])
y_pred = ggd_wtf.predict_proba(tfidf_w2v_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 [73]:
```
print('ROC Score',roc_auc_score(y_true,y_pred))
print('\n')
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()
```

```
ROC Score 0.866378256623


[[ 1142  2669]
 [  584 25605]]
```



Result

RF on BOW

- Optimal max_depth = 9
- n_estimator = 200
- Accuracy = 86.89
- Precision = 0.96(positive), 0.49(negative)
- Recall = 0.89 ,0.73
- AUC = 0.905
- TN = 2790
- TP = 23278

GBDT on BOW

- Optimal max_depth = 10
- n_estimator = 200
- Accuracy = 91.38
- Precision = 0.92(positive), 0.82(negative)
- Recall = 0.99 ,0.41
- AUC = 0.918
- TN = 1579
- TP = 25837

R.F on Tfidf

- Optimal max_depth = 20
- n_estimator = 200
- Accuracy = 89.34
- Precision = 0.95(positive), 0.57(negative)
- Recall = 0.92 ,0.69
- AUC = 0.916
- TN = 2636
- TP = 24167

GBDT on Tfidf

- Optimal max_depth = 9
- n_estimator = 200
- Accuracy = 91.23

- Precision = 0.92(positive), 0.82(negative)
- Recall = 0.99 ,0.40
- AUC = 0.915
- TN = 1513
- TP = 25856

R.F on Avg-w2vec

- Optimal max_depth = 20
- n_estimator = 200
- Accuracy = 87.3
- Precision = 0.87(positive), 0.53(negative)
- Recall = 1.0 ,0.0
- AUC = 0.787
- TN = 8
- TP = 26182

GBDT on Avg-w2vec

- Optimal max_depth = 10
- n_estimator = 200
- Accuracy = 87.5
- Precision = 0.88(positive), 0.57(negative)
- Recall = 0.99 ,0.07
- AUC = 0.781
- TN = 275
- TP = 25980

R.F on Tfidf-w2vec

- Optimal max_depth = 20
- n_estimator = 200
- Accuracy = 88.70
- Precision = 0.90(positive), 0.62(negative)
- Recall = 0.98 ,0.28
- AUC = 0.85
- TN = 1059
- TP = 25553

GBDT on Tfidf-w2vec

- Optimal max_depth = 10
- n_estimator = 200
- Accuracy = 89.156
- Precision = 0.91(positive), 0.66(negative)
- Recall = 0.98 ,0.30
- AUC = 0.866
- TN = 1142
- TP = 25605