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[1] Problem Statement :

- Time Based slicing(100k data points) to split Train Data(70%) and Test Data(30%).
- Appling ensemble models(both Random Forest and XGBoost) to find the optimal hyperparameters using 10 fold cv :
  1)Bag Of Words
  2)TF-IDF
  2)Average Word2Vec
  2)TF-IDF weighted Word2Vec
- Comparsion of various performance metrics obtained by various featurization models.

[2] Overview of Dataset :

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

[3] Loading the Data :

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".

In [1]:

```
#Importing the necessary Packages
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")


import time
from tqdm import tqdm
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from xgboost import XGBClassifier
from IPython.display import HTML
from collections import OrderedDict


from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
```

In [2]:

```
import pickle

#dumping an object to file object using dump method
def dumpfile(a,file_Name):
    fileObject = open(file_Name,"wb")
    pickle.dump(a,fileObject,protocol=2)
    fileObject.close()

#loading an object from file object using load method
def loadfile(file_Name):
    fileObject = open(file_Name,"rb")
    b = pickle.load(fileObject)
    return b
```

In [27]:

```
# using the SQLite Table to read data.
con = sqlite3.connect('database.sqlite')



#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 """, con)
```

In [7]:

```
# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative ra
ting.
def partition(x):
    if x < 3:
        return 'negative'
    return 'positive'

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
```

In [8]:

```
print("Number of datapoints: ",filtered_data.shape[0])
print("Number of attributes/features: ",filtered_data.shape[1])
HTML(filtered_data.head().to_html(index=False))
```

```
Number of datapoints:  525814
Number of attributes/features:  10
```

Out[8]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1
4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3
5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0

[4] Exploratory Data Analysis :

[4.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

Deduplication 1:- As can be seen below the same user has multiple reviews of the with the same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

In [9]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)

HTML(display.head().to_html(index=False))
```

Out[9]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfu
78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

In [10]:

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

In [11]:

```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
'first', inplace=False)
final.shape
```

Out[11]:

```
(364173, 10)
```

Deduplication 2:- 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 [51]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

HTML(display.head().to_html(index=False))
```

Out[51]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Help
64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [52]:

```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
print(final.shape)
```

```
(364171, 10)
```

Deduplication 3:- It was also seen that a same user has given different reviews for a same product at same time.I think it is normal for a user to give multiple reviews about a product,but that should be in diffrent time. So,all those rows with same user giving multiple reviews for a same product at same time are considered as duplicate and hence dropped.

In [53]:

```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId= "A8891HVRDJAM6"
ORDER BY ProductID
""", con)

HTML(display.head().to_html(index=False))
```

Out[53]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulne
86221	B000084E6V	A8891HVRDJAM6	Marfaux "Marfaux"	33	33
86236	B000084E6V	A8891HVRDJAM6	Marfaux "Marfaux"	3	3

In [54]:

```
final=final.drop_duplicates(subset={"ProductId","UserId","ProfileName","Time"}, keep='f
irst', inplace=False)
print(final.shape)
```

```
(363633, 10)
```

Deduplication 4:- It was also seen that in few rows with Ids from 150493 to 150529 contain reviews regarding books,not fine foods.So I think these should be also removed from the dataset. After looking at the productid column, it can be noticed that all the observations for fine foods start with B followed by numbers except for Ids from 150493 to 150529. I suppose the reviews for book ‘Chicken soup for the soul’ have gotten into the datset mistakenly as they contain the words “chicken soup.

In [55]:

```
display = final[final.ProductId == "0006641040"]
HTML(display.head().to_html(index=False))
```

Out[55]:

Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfu
150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	1
150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1
150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	1
150509	0006641040	A3CMRKGE0P909G	Teresa	3	4

In [56]:

```
final = final[final.ProductId != "0006641040"]
```

In [57]:

```
print("Percentage  of data still remaining : ",(final['Id'].size*1.0)/(filtered_data['I
d'].size*1.0)*100)

#Before starting the next phase of preprocessing lets see the number of entries left
print("Number of reviews left after Data Cleaning and Deduplication :")
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
Percentage  of data still remaining :  69.14973735959865
Number of reviews left after Data Cleaning and Deduplication :
(363599, 10)
```

Out[57]:

```
positive    306566
negative     57033
Name: Score, dtype: int64
```

Observation:-
It is an imbalanced dataset as the number of positive reviews are way high in number than negative reviews.

[5] Text Preprocessing Using NLTK :

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

1. Removal of HTML Tags
2. Removal of 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. Removal of Stopwords
7. Finally Snowball Stemming the word

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

[5.1] Using SQLite Table to load preprocessed data already saved in disk:

In [142]:

```
# using the SQLite Table to read data.
conn = sqlite3.connect('final.sqlite')

final = pd.read_sql_query(""" SELECT * FROM Reviews """,conn)
```

In [143]:

```
#Listing out the number of positive and negative reviews
final = final.reset_index(drop=True)
final['Score'].value_counts()
```

Out[143]:

```
positive    306566
negative     57033
Name: Score, dtype: int64
```

In [144]:

```
(final['Score'].value_counts()/len(final['Score']))*100
```

Out[144]:

```
positive    84.314313
negative    15.685687
Name: Score, dtype: float64
```

[6] Train and Test Split of Data :

Sorting the data by Time :

In [145]:

```
final = final.sample(n = 100000)

final=final.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort'
, na_position='last')
final.head()
```

Out[145]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNum
386	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0
225	346141	374450	B00004CI84	ACJR7EQF9S6FP	Jeremy Robertson	2
831	138017	149789	B00004S1C6	A1KXONFPU2XQ5K	Stephanie Manley	26
213	346115	374421	B00004CI84	A1FJOY14X3MUHE	Justin Howard	2
807	138000	149768	B00004S1C5	A7P76IGRZZBFJ	E. Thompson "Soooooper Genius"	18

Time Based Slicing :

- Diving the data to Train set(first 70% ie older data) and Test Set(last 30% ie recent data)

In [146]:

```
from sklearn.model_selection import train_test_split

X = final["CleanedText"].values
y = final["Score"].values
X_train,X_test,y_train,y_test = train_test_split(X, y, test_size = 0.3,shuffle = False)
```

In [29]:

```
print("Shape of X_train: ",X_train.shape)
print("Shape of y_train: ",y_train.shape)
print("Shape of X_test: ",X_test.shape)
print("Shape of y_test: ",y_test.shape)
```

```
Shape of X_train:  (70000,)
Shape of y_train:  (70000,)
Shape of X_test:  (30000,)
Shape of y_test:  (30000,)
```

[7] Ensemble Models :

[7.1] Random Forest(Bagging):

- Ensemeble model with concept of **Bootsrap Sampling,Feature Sampling and Aggregation of baselearners using majority vote**.
- Hyperparameter - **No of Baselearners(decission Trees)**
- Baselearners with **high varriance and low bias(fully grown trees)**
- Performing 10 fold cross validation(Grid Search) on Train data
- Finding the optimal hyperparameters
- Plotting between CV error/CV Accuracy and No of Baselearners
- Predicting on Test Data and plotting Confusion Matrix
- Reporting Performance Metrics

In [4]:

```
import warnings
warnings.filterwarnings('ignore')


from sklearn.model_selection import TimeSeriesSplit
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score as cv
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix,precision_score,recall_score,f1_score,clas
sification_report
from sklearn.model_selection import GridSearchCV

def RF_model(X_train,y_train):

    baselearners=[10,20,30,40,50,60,70,80,100]
    param_rf=dict(n_estimators=baselearners)

    #Cross validation using TimeSeriesSplit
    tscv = TimeSeriesSplit(n_splits=10)


    #using class_weight = "balanced_subsample" to balance the imbalanced nature on the
 bootstrap sample for every tree grown
    model = RandomForestClassifier(class_weight = "balanced_subsample")
    grid = GridSearchCV(model, param_rf, cv = tscv, scoring = 'f1_weighted')
    grid_estimator = grid.fit(X_train, y_train)

    #Finding the optimal hyperparameter
    optimal_baselearners = grid_estimator.best_params_

    #Finding the best score
    grid_mean_scores = [i.mean_validation_score for i in grid_estimator.grid_scores_]
    best_score = grid_estimator.best_score_

    #CV Scores
    print("\n\033[1mGrid Scores for Model is:\033[0m\n",grid_estimator.grid_scores_)
    print("\n\033[1mBest Parameters:\033[0m ",optimal_baselearners)
    print("\n\033[1mBest F1-Score:\033[0m {} ".format(np.round(best_score,3)))


    #Plot
    plt.figure(figsize = (10,6))
    plt.plot(baselearners,grid_mean_scores, 'g-o')
    for xy in zip(baselearners, np.round(grid_mean_scores,3)):
         plt.annotate('(%s %s)' % xy, xy = xy, textcoords = 'data')
    plt.title("CV F1-Score vs No of BaseLearners ", fontsize=20, fontweight='bold')
    plt.xlabel("BaseLearners", fontsize=16)
    plt.ylabel('CV F1-Score', fontsize=16)
    plt.grid('on')

    return grid_estimator
```

In [5]:

```
def RF_Test(X_test,y_test):
    y_pred = grid_estimator.predict(X_test)
    accuracy = accuracy_score(y_test,y_pred) * 100
    precision = precision_score(y_test,y_pred,average= 'weighted')
    recall = recall_score(y_test,y_pred,average= 'weighted')
    f1= f1_score(y_test,y_pred,average= 'weighted')
    MSE = (1 - (accuracy/100))
    cm = confusion_matrix(y_test, y_pred)
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
    cm_df = pd.DataFrame(cm,
                         index = ['negative','positive'],
                        columns = ['negative','positive'])
    sns.heatmap(cm_df, annot=True)
    plt.title('Confusion Matrix')
    plt.ylabel('Actual Label')
    plt.xlabel('Predicted Label')
    plt.show()

    print(cm)
    print("\n\033[1mTest Error :\033[0m {}".format(np.round(MSE,3)))
    print("\033[1mTest Accuracy :\033[0m {} %".format(np.round(accuracy,3)))
    print("\033[1mTrue Negative :\033[0m {}".format(tn))
    print("\033[1mFalse Positive :\033[0m {}".format(fp))
    print("\033[1mFalse Negative :\033[0m {}".format(fn))
    print("\033[1mTrue Positive :\033[0m {}".format(tp))
    print("\33[1mPrecission Score :\033[0m {}".format(np.round(precision,3)))
    print("\33[1mRecall Score :\033[0m {}".format(np.round(recall,3)))
    print("\33[1mF1 Score :\033[0m {}".format(np.round(f1,3)))
    print("\n\n")

    print('\33[1mClassification Report for Model is :\33[0m')
    classificationreport = classification_report(y_test, y_pred)
    print(classificationreport)
```

In [6]:

```
def featureimportance(X_train, y_train, d, vectorizer, n=20):
    clf = RandomForestClassifier(max_depth=d,class_weight="balanced")
    clf.fit(X_train,y_train)

    features=clf.feature_importances_
    index = np.argsort(features)[::-1][:n]

    names = vectorizer.get_feature_names()
    names = np.array(names)
    plt.figure(figsize=(20, 6))
    plt.bar(range(n),features[index])
    plt.xticks(range(n),names[index],rotation=90)
    plt.title("Feature Importance", fontsize=20,fontweight="bold")
    plt.grid('on')
    plt.show()
```

[7.2] XGBoost (Gradient Boosting):

- Ensemeble model with **Additive Combining of Baselearners with concept of fitting pseudo residuals obtained at the previous iteration**.
- Hyperparameter - **No of Baselearners(decission Trees), depth, Learningrate**
- Baselearners with **high bias and low varriance(shallow trees of very less depth)**
- Performing 10 fold cross validation(Grid Search) on Train data
- Finding the optimal hyperparameters
- Predicting on Test Data and plotting Confusion Matrix
- Reporting Performance Metrics

In [7]:

```
import warnings
warnings.filterwarnings('ignore')

import xgboost as xgb
from xgboost.sklearn import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV
import scipy.stats as st


#taking depth between range 1 to 5 for shallow trees(high bias)
param_gb = {"n_estimators":st.randint(3,200),
            "max_depth":st.randint(1,5),
            "learning_rate":st.uniform(0.05,0.5)
}


def XGB_model(X_train,y_train):

    #Cross validation using TimeSeriesSplit
    tscv = TimeSeriesSplit(n_splits=10)


    model = XGBClassifier()
    grid = RandomizedSearchCV(model, param_gb, cv = tscv, scoring = 'f1_weighted')
    random_estimator = grid.fit(X_train, y_train)

    #Finding the optimal hyperparameters
    optimal_hyperparameters = random_estimator.best_params_

    #Finding the best score
    grid_mean_scores = [i.mean_validation_score for i in random_estimator.grid_scores_]
    best_score = random_estimator.best_score_

    #CV Scores
    print("\n\033[1mGrid Scores for Model is:\033[0m\n",random_estimator.grid_scores_)
    print("\n\033[1mBest Parameters:\033[0m ",optimal_hyperparameters)
    print("\n\033[1mBest F1-Score:\033[0m {} ".format(np.round(best_score,3)))


    return random_estimator
```

In [8]:

```
def XGB_Test(X_test,y_test):
    y_pred = random_estimator.predict(X_test)
    accuracy = accuracy_score(y_test,y_pred) * 100
    precision = precision_score(y_test,y_pred,average= 'weighted')
    recall = recall_score(y_test,y_pred,average= 'weighted')
    f1= f1_score(y_test,y_pred,average= 'weighted')
    MSE = (1 - (accuracy/100))
    cm = confusion_matrix(y_test, y_pred)
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
    cm_df = pd.DataFrame(cm,
                         index = ['negative','positive'],
                        columns = ['negative','positive'])
    sns.heatmap(cm_df, annot=True)
    plt.title('Confusion Matrix')
    plt.ylabel('Actual Label')
    plt.xlabel('Predicted Label')
    plt.show()

    print(cm)
    print("\n\033[1mTest Error :\033[0m {}".format(np.round(MSE,3)))
    print("\033[1mTest Accuracy :\033[0m {} %".format(np.round(accuracy,3)))
    print("\033[1mTrue Negative :\033[0m {}".format(tn))
    print("\033[1mFalse Positive :\033[0m {}".format(fp))
    print("\033[1mFalse Negative :\033[0m {}".format(fn))
    print("\033[1mTrue Positive :\033[0m {}".format(tp))
    print("\33[1mPrecission Score :\033[0m {}".format(np.round(precision,3)))
    print("\33[1mRecall Score :\033[0m {}".format(np.round(recall,3)))
    print("\33[1mF1 Score :\033[0m {}".format(np.round(f1,3)))
    print("\n\n")

    print('\33[1mClassification Report for Model is :\33[0m')
    classificationreport = classification_report(y_test, y_pred)
    print(classificationreport)
```

[8] Featurization Methods :

[8.1] Bag Of Words(unigram) :

In [9]:

```
%%time
bow_unigram = CountVectorizer(min_df=0.0005)
X_train_bowuni = bow_unigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_bowuni))
print("The shape of text BOW vectorizer: ", X_train_bowuni.get_shape())
print("Number of unique word: ", X_train_bowuni.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text BOW vectorizer:  (70000, 3907)
Number of unique word:  3907
CPU times: user 3.18 s, sys: 8 ms, total: 3.19 s
Wall time: 3.19 s
```

In [10]:

```
%%time
X_test_bowuni = bow_unigram.transform(X_test)
print("The shape of text BOW vectorizer: ", X_test_bowuni.get_shape())
print("Number of unique word: ", X_test_bowuni.get_shape()[1])
```

```
The shape of text BOW vectorizer:  (30000, 3907)
Number of unique word:  3907
CPU times: user 1.52 s, sys: 8 ms, total: 1.53 s
Wall time: 1.53 s
```

In [11]:

```
print("Shape of Training Data: ",X_train_bowuni.shape)
print("Shape of Test Data: ",X_test_bowuni.shape)
```

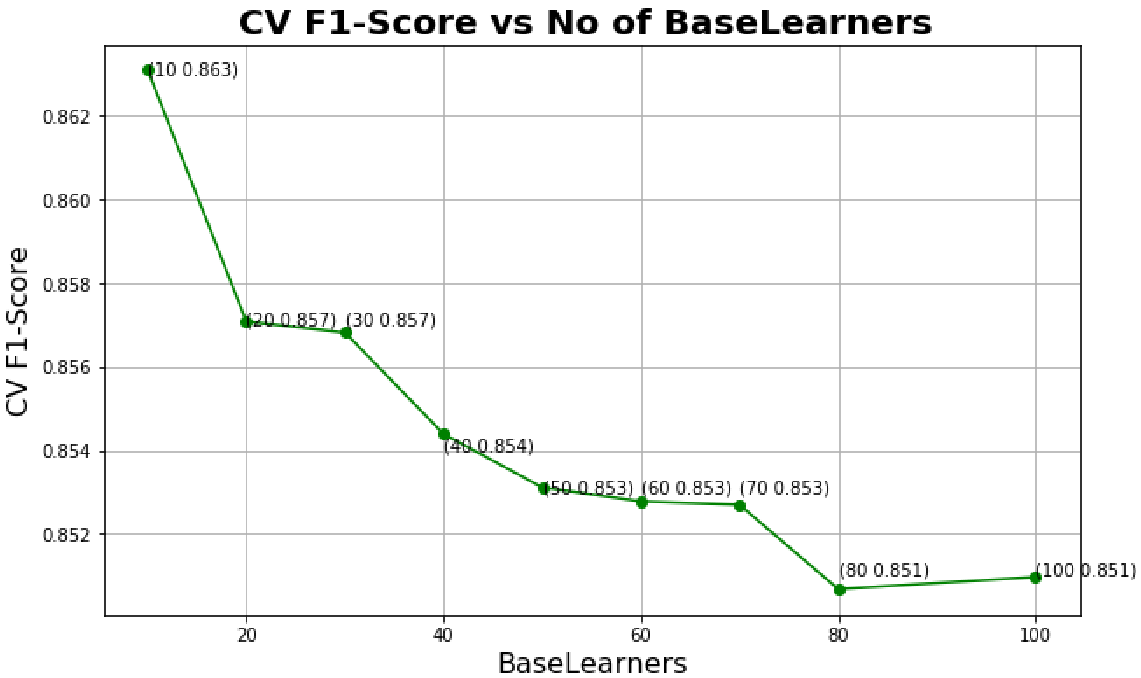
```
Shape of Training Data:  (70000, 3907)
Shape of Test Data:  (30000, 3907)
```

[8.1.1] Random Forest :

In [14]:

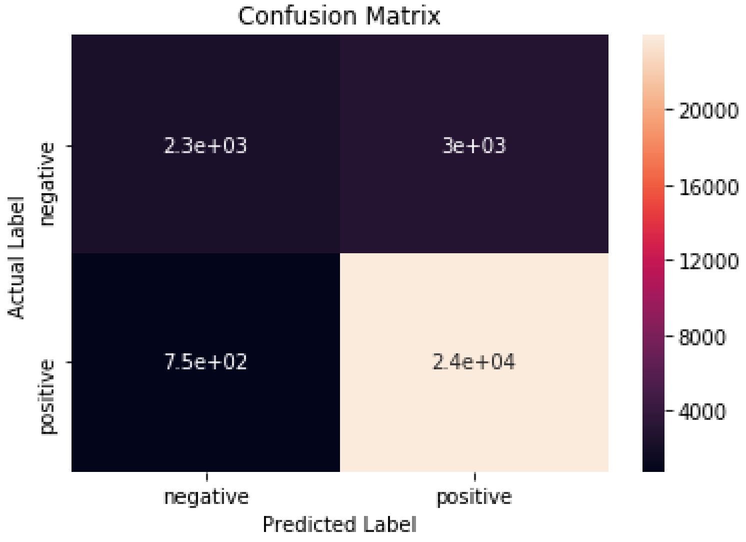
```
%%time
grid_estimator = RF_model(X_train_bowuni, y_train)
```

```
Grid Scores for Model is:
 [mean: 0.86308, std: 0.00795, params: {'n_estimators': 10}, mean: 0.8570
7, std: 0.00680, params: {'n_estimators': 20}, mean: 0.85681, std: 0.0084
1, params: {'n_estimators': 30}, mean: 0.85438, std: 0.00789, params: {'n_
estimators': 40}, mean: 0.85311, std: 0.00953, params: {'n_estimators': 5
0}, mean: 0.85277, std: 0.00818, params: {'n_estimators': 60}, mean: 0.852
69, std: 0.00963, params: {'n_estimators': 70}, mean: 0.85068, std: 0.0100
2, params: {'n_estimators': 80}, mean: 0.85096, std: 0.00982, params: {'n_
estimators': 100}]

Best Parameters:  {'n_estimators': 10}

Best F1-Score: 0.863
CPU times: user 1h 20s, sys: 668 ms, total: 1h 20s
Wall time: 1h 21s
```



In [15]:

```
%%time
RF_Test(X_test_bowuni,y_test)
```




```
[[ 2338  2958]
 [  746 23958]]
```

Test Error : 0.123
Test Accuracy : 87.653 %
True Negative : 2338
False Positive : 2958
False Negative : 746
True Positive : 23958
Precission Score : 0.867
Recall Score : 0.877
F1 Score : 0.863

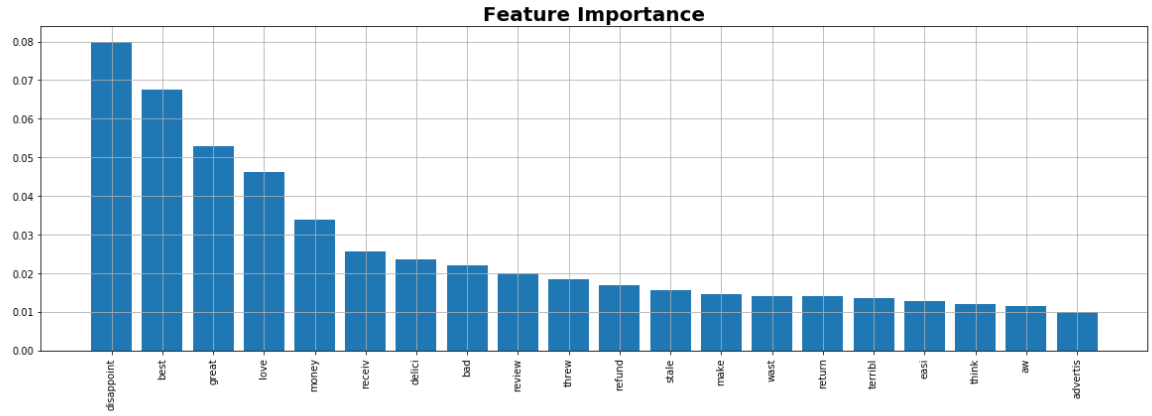
Classification Report for Model is :

```
             precision    recall  f1-score   support

   negative       0.76      0.44      0.56      5296
   positive       0.89      0.97      0.93     24704

avg / total       0.87      0.88      0.86     30000
```

CPU times: user 2.14 s, sys: 12 ms, total: 2.15 s
Wall time: 2.15 s

In [20]:

```
%%time
featureimportance(X_train_bowuni, y_train,10,bow_unigram)
```




```
CPU times: user 1.06 s, sys: 8 ms, total: 1.07 s
Wall time: 1.07 s
```

[8.1.2] XG Boost :

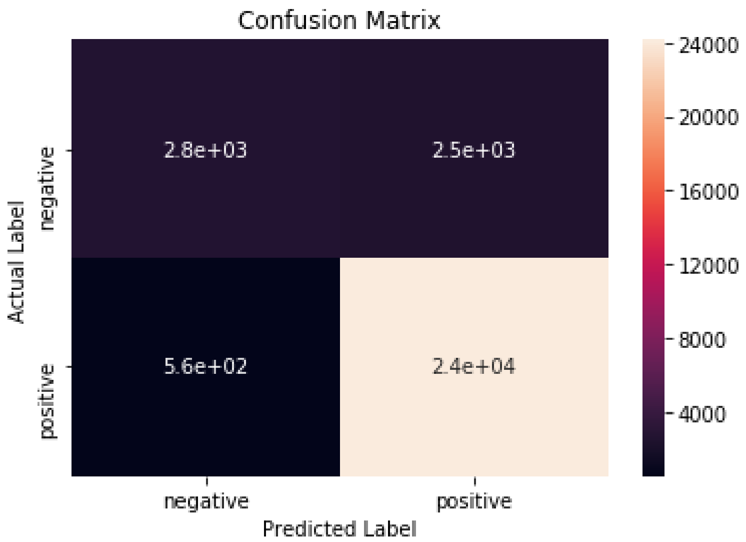
In [12]:

```
%%time
random_estimator = XGB_model(X_train_bowuni, y_train)
```

```
Grid Scores for Model is:
 [mean: 0.80644, std: 0.01509, params: {'learning_rate': 0.066683608366298
84, 'max_depth': 2, 'n_estimators': 108}, mean: 0.84430, std: 0.00891, par
ams: {'learning_rate': 0.06799300292669126, 'max_depth': 3, 'n_estimator
s': 180}, mean: 0.77916, std: 0.02652, params: {'learning_rate': 0.0654438
087041719, 'max_depth': 1, 'n_estimators': 16}, mean: 0.78029, std: 0.0258
0, params: {'learning_rate': 0.08886350897510405, 'max_depth': 2, 'n_estim
ators': 10}, mean: 0.78126, std: 0.02576, params: {'learning_rate': 0.2406
5436138139162, 'max_depth': 1, 'n_estimators': 14}, mean: 0.85244, std: 0.
01080, params: {'learning_rate': 0.4914024104034224, 'max_depth': 1, 'n_es
timators': 76}, mean: 0.86488, std: 0.00903, params: {'learning_rate': 0.4
803253730117049, 'max_depth': 3, 'n_estimators': 40}, mean: 0.87344, std:
 0.00735, params: {'learning_rate': 0.3860620927908864, 'max_depth': 4, 'n
_estimators': 53}, mean: 0.88192, std: 0.00710, params: {'learning_rate':
 0.3981686322300846, 'max_depth': 3, 'n_estimators': 101}, mean: 0.89162,
 std: 0.00722, params: {'learning_rate': 0.5450651968482602, 'max_depth':
 2, 'n_estimators': 180}]

Best Parameters:  {'learning_rate': 0.5450651968482602, 'max_depth': 2, 'n
_estimators': 180}

Best F1-Score: 0.892
CPU times: user 10min 35s, sys: 1.04 s, total: 10min 36s
Wall time: 10min 36s
```

In [13]:

```
%%time
XGB_Test(X_test_bowuni,y_test)
```




```
[[ 2761  2535]
 [  556 24148]]
```

Test Error : 0.103
Test Accuracy : 89.697 %
True Negative : 2761
False Positive : 2535
False Negative : 556
True Positive : 24148
Precission Score : 0.892
Recall Score : 0.897
F1 Score : 0.887

Classification Report for Model is :

```
             precision    recall  f1-score   support

   negative       0.83      0.52      0.64      5296
   positive       0.90      0.98      0.94     24704

avg / total       0.89      0.90      0.89     30000
```

```
CPU times: user 2.5 s, sys: 28 ms, total: 2.53 s
Wall time: 2.52 s
```

[8.2] Bag Of Words(bigram) :

In [9]:

```
%%time
bow_bigram = CountVectorizer(ngram_range=(1, 2),min_df=0.0005)
X_train_bowbi = bow_bigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_bowbi))
print("The shape of text BOW vectorizer: ", X_train_bowbi.get_shape())
print("Number of unique word: ", X_train_bowbi.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text BOW vectorizer:  (70000, 10992)
Number of unique word:  10992
CPU times: user 10.5 s, sys: 132 ms, total: 10.6 s
Wall time: 10.6 s
```

In [10]:

```
%%time
X_test_bowbi = bow_bigram.transform(X_test)
print("The shape of text BOW vectorizer: ", X_test_bowbi.get_shape())
print("Number of unique word: ", X_test_bowbi.get_shape()[1])
```

```
The shape of text BOW vectorizer:  (30000, 10992)
Number of unique word:  10992
CPU times: user 2.92 s, sys: 4 ms, total: 2.92 s
Wall time: 2.92 s
```

In [11]:

```
print("Shape of Training Data: ",X_train_bowbi.shape)
print("Shape of Test Data: ",X_test_bowbi.shape)
```

```
Shape of Training Data:  (70000, 10992)
Shape of Test Data:  (30000, 10992)
```

[8.2.1] Random Forest :

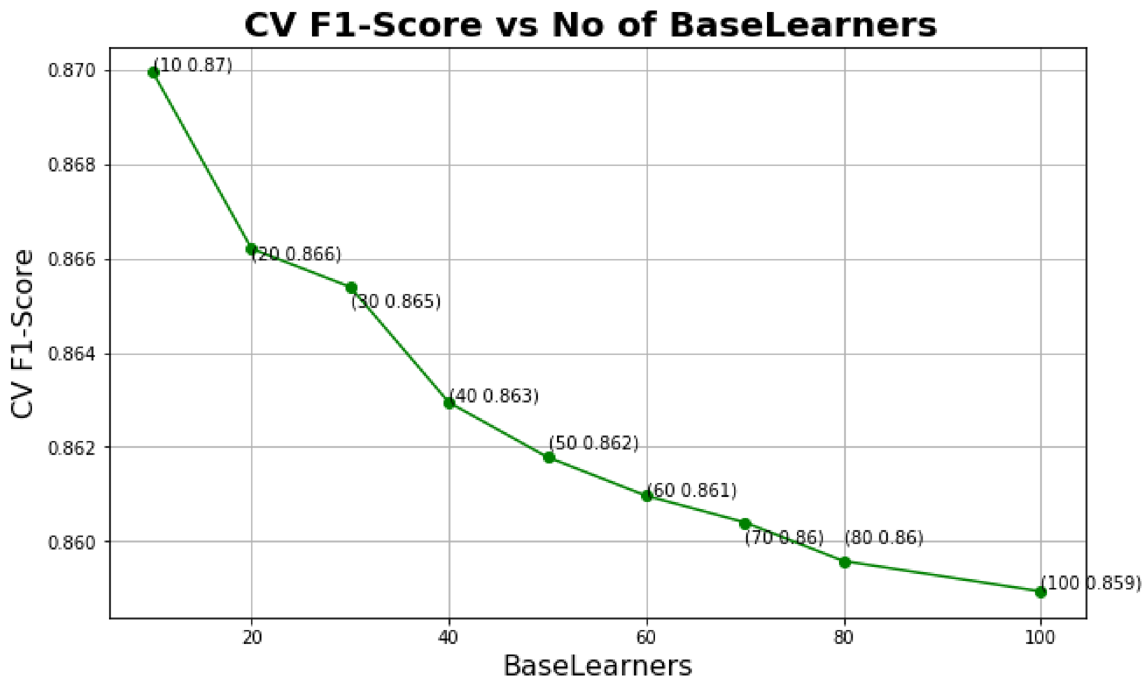
In [24]:

```
%%time
grid_estimator = RF_model(X_train_bowbi, y_train)
```

Grid Scores for Model is:
 [mean: 0.86993, std: 0.00702, params: {'n_estimators': 10}, mean: 0.86620, std: 0.00900, params: {'n_estimators': 20}, mean: 0.86539, std: 0.00993, params: {'n_estimators': 30}, mean: 0.86294, std: 0.00967, params: {'n_estimators': 40}, mean: 0.86178, std: 0.01020, params: {'n_estimators': 50}, mean: 0.86097, std: 0.00937, params: {'n_estimators': 60}, mean: 0.86040, std: 0.01030, params: {'n_estimators': 70}, mean: 0.85959, std: 0.01052, params: {'n_estimators': 80}, mean: 0.85894, std: 0.01117, params: {'n_estimators': 100}]

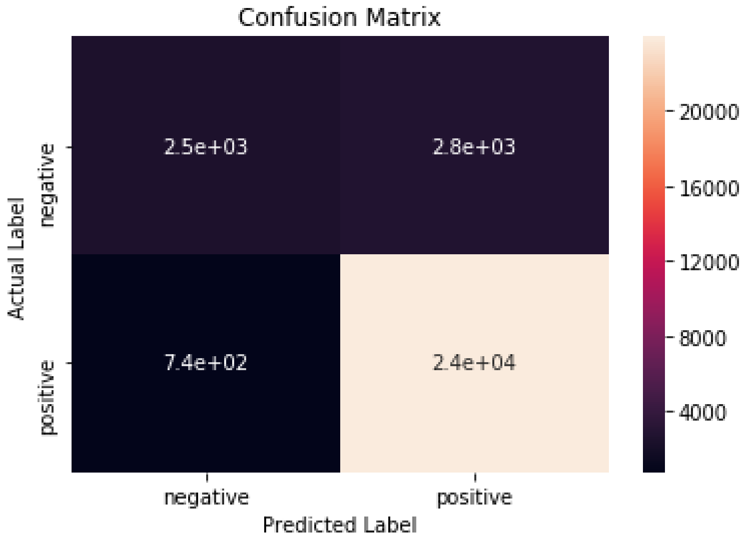
Best Parameters: {'n_estimators': 10}

Best F1-Score: 0.87
CPU times: user 1h 1min 43s, sys: 1.1 s, total: 1h 1min 44s
Wall time: 1h 1min 44s



In [25]:

```
%%time
RF_Test(X_test_bowbi,y_test)
```




```
[[ 2502  2794]
 [  744 23960]]
```

Test Error : 0.118
Test Accuracy : 88.207 %
True Negative : 2502
False Positive : 2794
False Negative : 744
True Positive : 23960
Precission Score : 0.874
Recall Score : 0.882
F1 Score : 0.87

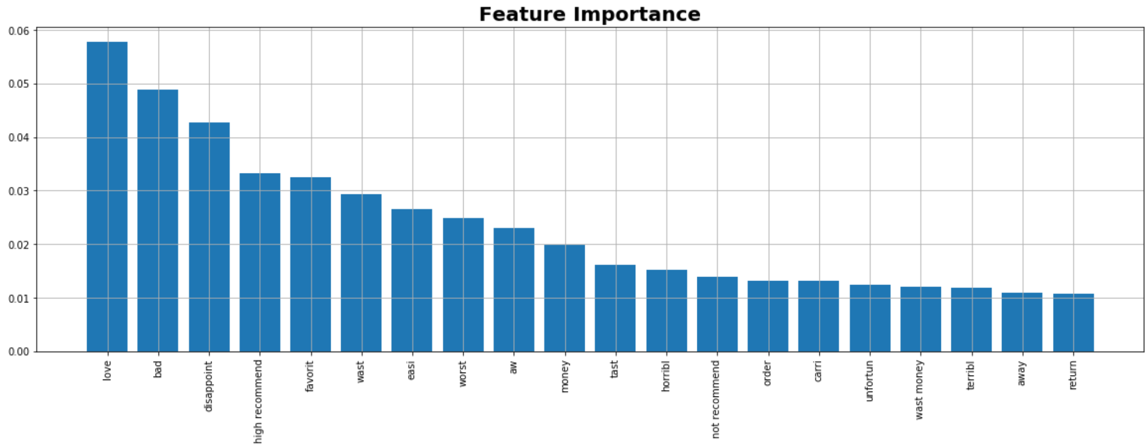
Classification Report for Model is :

	precision	recall	f1-score	support
negative	0.77	0.47	0.59	5296
positive	0.90	0.97	0.93	24704
avg / total	0.87	0.88	0.87	30000

CPU times: user 2.2 s, sys: 4 ms, total: 2.2 s
Wall time: 2.2 s

In [12]:

```
%%time
featureimportance(X_train_bowbi, y_train,10,bow_bigram)
```




```
CPU times: user 1.12 s, sys: 12 ms, total: 1.13 s
Wall time: 1.06 s
```

[8.2.2] XG Boost :

In [27]:

```
%%time
random_estimator = XGB_model(X_train_bowbi, y_train)
```

Grid Scores for Model is:

```
 [mean: 0.90417, std: 0.00660, params: {'learning_rate': 0.400235387812680
3, 'max_depth': 4, 'n_estimators': 193}, mean: 0.87037, std: 0.00681, para
ms: {'learning_rate': 0.08997932166986629, 'max_depth': 4, 'n_estimators':
 170}, mean: 0.89803, std: 0.00616, params: {'learning_rate': 0.2568979843
529595, 'max_depth': 4, 'n_estimators': 187}, mean: 0.90015, std: 0.00579,
 params: {'learning_rate': 0.5437151482553318, 'max_depth': 2, 'n_estimato
rs': 196}, mean: 0.87302, std: 0.00844, params: {'learning_rate': 0.540262
3804152094, 'max_depth': 2, 'n_estimators': 51}, mean: 0.80409, std: 0.017
97, params: {'learning_rate': 0.28608081689708253, 'max_depth': 4, 'n_esti
mators': 4}, mean: 0.84448, std: 0.00975, params: {'learning_rate': 0.2675
2627839555604, 'max_depth': 4, 'n_estimators': 24}, mean: 0.89964, std: 0.
00690, params: {'learning_rate': 0.5440893217185155, 'max_depth': 3, 'n_es
timators': 129}, mean: 0.89353, std: 0.00574, params: {'learning_rate': 0.
4630762654729691, 'max_depth': 3, 'n_estimators': 98}, mean: 0.82271, std:
 0.01152, params: {'learning_rate': 0.07324583630780253, 'max_depth': 3,
 'n_estimators': 83}]
```

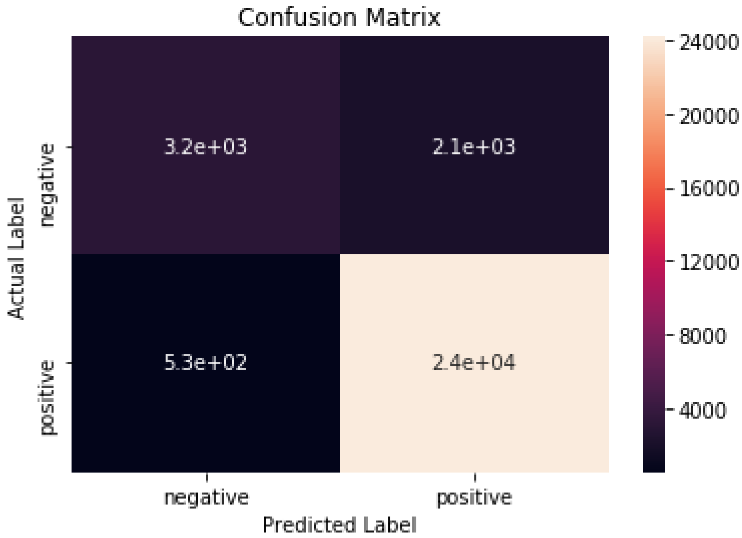
Best Parameters: {'learning_rate': 0.4002353878126803, 'max_depth': 4, 'n_estimators': 193}

Best F1-Score: 0.904

```
CPU times: user 23min 1s, sys: 1.33 s, total: 23min 3s
Wall time: 23min 3s
```

In [28]:

```
%%time
XGB_Test(X_test_bowbi,y_test)
```




```
[[ 3170  2126]
 [  533 24171]]
```

Test Error : 0.089
Test Accuracy : 91.137 %
True Negative : 3170
False Positive : 2126
False Negative : 533
True Positive : 24171
Precission Score : 0.908
Recall Score : 0.911
F1 Score : 0.905

Classification Report for Model is :

	precision	recall	f1-score	support
negative	0.86	0.60	0.70	5296
positive	0.92	0.98	0.95	24704
avg / total	0.91	0.91	0.90	30000

```
CPU times: user 2.68 s, sys: 8 ms, total: 2.69 s
Wall time: 2.69 s
```

[8.3] TF-IDF(unigram) :

In [13]:

```
%%time
tfidf_unigram = TfidfVectorizer(min_df = 0.0005)
X_train_tfidfuni = tfidf_unigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_tfidfuni))
print("The shape of text TFIDF vectorizer: ", X_train_tfidfuni.get_shape())
print("Number of unique word: ", X_train_tfidfuni.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text TFIDF vectorizer:  (70000, 3907)
Number of unique word:  3907
CPU times: user 3.26 s, sys: 0 ns, total: 3.26 s
Wall time: 3.26 s
```

In [14]:

```
%%time
X_test_tfidfuni = tfidf_unigram.transform(X_test)
print("The shape of text TFIDF vectorizer: ", X_test_tfidfuni.get_shape())
print("Number of unique word: ", X_test_tfidfuni.get_shape()[1])
```

```
The shape of text TFIDF vectorizer:  (30000, 3907)
Number of unique word:  3907
CPU times: user 1.54 s, sys: 4 ms, total: 1.54 s
Wall time: 1.54 s
```

In [15]:

```
print("Shape of Training Data: ",X_train_tfidfuni.shape)
print("Shape of Test Data: ",X_test_tfidfuni.shape)
```

```
Shape of Training Data:  (70000, 3907)
Shape of Test Data:  (30000, 3907)
```

[8.3.1] Random Forest :

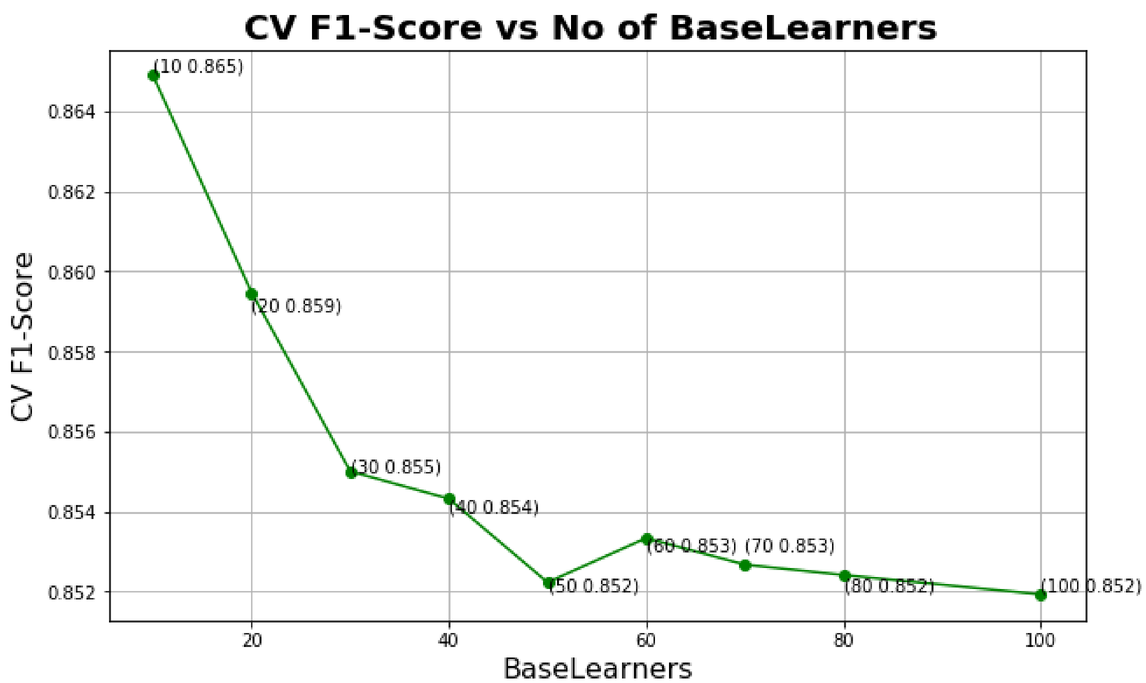
In [33]:

```
%%time
grid_estimator = RF_model(X_train_tfidfuni, y_train)
```

Grid Scores for Model is:
 [mean: 0.86489, std: 0.00728, params: {'n_estimators': 10}, mean: 0.85947, std: 0.00822, params: {'n_estimators': 20}, mean: 0.85500, std: 0.00761, params: {'n_estimators': 30}, mean: 0.85431, std: 0.00897, params: {'n_estimators': 40}, mean: 0.85223, std: 0.00864, params: {'n_estimators': 50}, mean: 0.85333, std: 0.00880, params: {'n_estimators': 60}, mean: 0.85267, std: 0.00916, params: {'n_estimators': 70}, mean: 0.85241, std: 0.00988, params: {'n_estimators': 80}, mean: 0.85192, std: 0.00774, params: {'n_estimators': 100}]

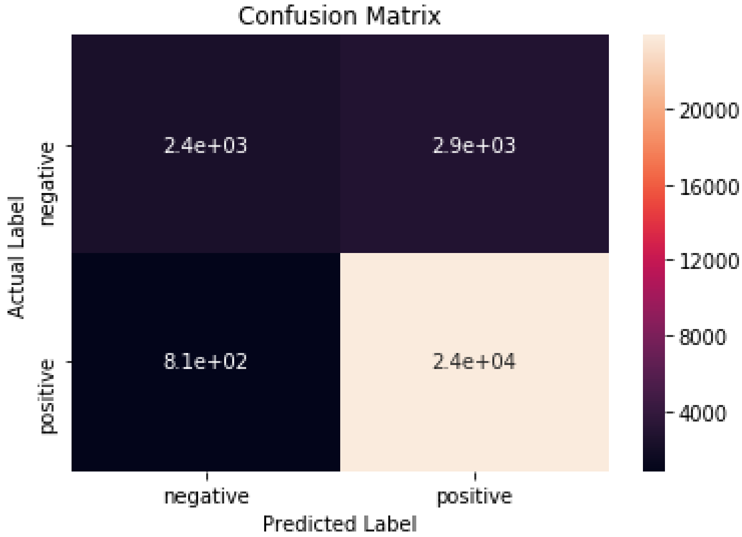
Best Parameters: {'n_estimators': 10}

Best F1-Score: 0.865
CPU times: user 54min 21s, sys: 344 ms, total: 54min 21s
Wall time: 54min 21s



In [34]:

```
%%time
RF_Test(X_test_tfidfuni,y_test)
```




```
[[ 2371  2925]
 [  809 23895]]
```

Test Error : 0.124
Test Accuracy : 87.553 %
True Negative : 2371
False Positive : 2925
False Negative : 809
True Positive : 23895
Precission Score : 0.865
Recall Score : 0.876
F1 Score : 0.863

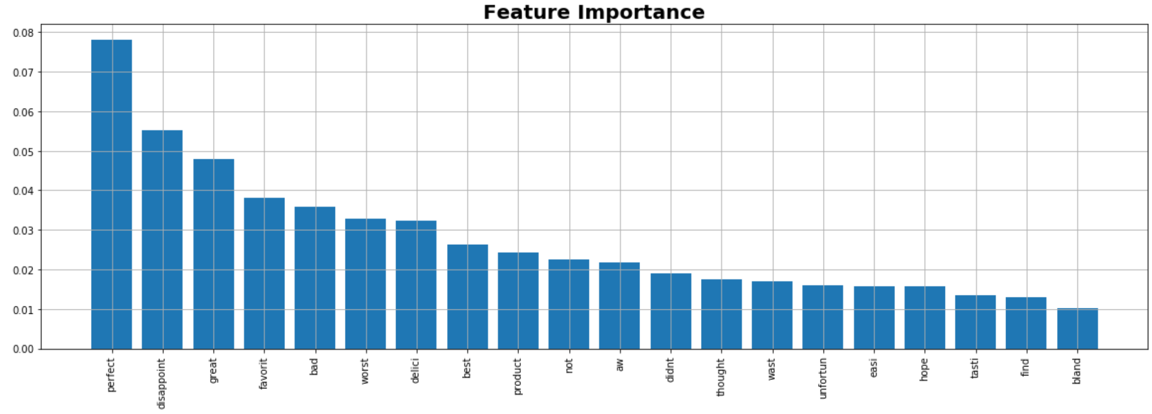
Classification Report for Model is :

	precision	recall	f1-score	support
negative	0.75	0.45	0.56	5296
positive	0.89	0.97	0.93	24704
avg / total	0.87	0.88	0.86	30000

```
CPU times: user 2.16 s, sys: 8 ms, total: 2.17 s
Wall time: 2.16 s
```

In [16]:

```
%%time
featureimportance(X_train_tfidfuni, y_train,10,tfidf_unigram)
```




```
CPU times: user 1.4 s, sys: 16 ms, total: 1.41 s
Wall time: 1.33 s
```

[8.3.2] XG Boost :

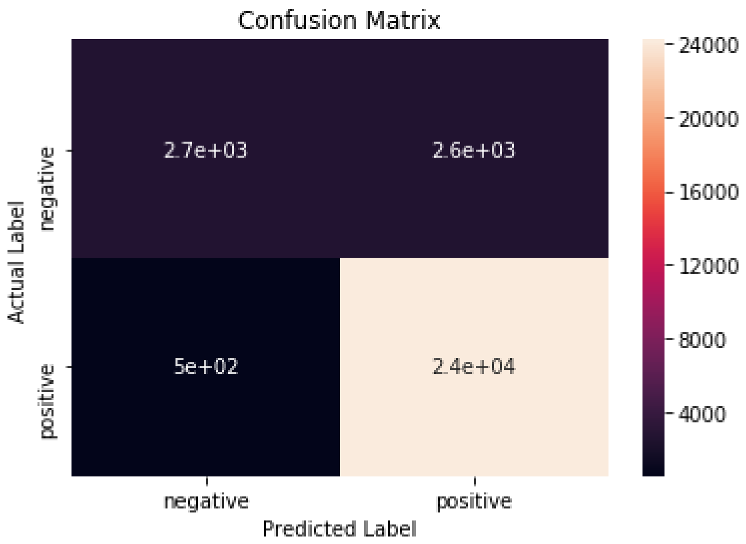
In [35]:

```
%%time
random_estimator = XGB_model(X_train_tfidfuni, y_train)
```

```
Grid Scores for Model is:
 [mean: 0.81616, std: 0.01485, params: {'learning_rate': 0.114681647693674
68, 'max_depth': 1, 'n_estimators': 156}, mean: 0.88597, std: 0.00745, par
ams: {'learning_rate': 0.37997386892353996, 'max_depth': 4, 'n_estimator
s': 95}, mean: 0.85434, std: 0.00881, params: {'learning_rate': 0.39043392
37898107, 'max_depth': 3, 'n_estimators': 34}, mean: 0.88564, std: 0.0079
0, params: {'learning_rate': 0.4138275398055624, 'max_depth': 2, 'n_estima
tors': 161}, mean: 0.87461, std: 0.00800, params: {'learning_rate': 0.1947
77008177086, 'max_depth': 3, 'n_estimators': 146}, mean: 0.80907, std: 0.0
1731, params: {'learning_rate': 0.28179495659688353, 'max_depth': 1, 'n_es
timators': 42}, mean: 0.88939, std: 0.00726, params: {'learning_rate': 0.3
423200842906201, 'max_depth': 4, 'n_estimators': 127}, mean: 0.87897, std:
 0.00733, params: {'learning_rate': 0.46615737176463273, 'max_depth': 2,
 'n_estimators': 98}, mean: 0.82245, std: 0.01411, params: {'learning_rat
e': 0.3277361134251982, 'max_depth': 1, 'n_estimators': 48}, mean: 0.8230
2, std: 0.01221, params: {'learning_rate': 0.055839713227799306, 'max_dept
h': 4, 'n_estimators': 92}]

Best Parameters:  {'learning_rate': 0.3423200842906201, 'max_depth': 4, 'n
_estimators': 127}

Best F1-Score: 0.889
CPU times: user 26min 23s, sys: 608 ms, total: 26min 24s
Wall time: 26min 24s
```

In [36]:

```
%%time
XGB_Test(X_test_tfidfuni,y_test)
```




```
[[ 2686  2610]
 [  497 24207]]

Test Error : 0.104
Test Accuracy : 89.643 %
True Negative : 2686
False Positive : 2610
False Negative : 497
True Positive : 24207
Precission Score : 0.892
Recall Score : 0.896
F1 Score : 0.886



Classification Report for Model is :
             precision    recall  f1-score   support

   negative       0.84      0.51      0.63      5296
   positive       0.90      0.98      0.94     24704

avg / total       0.89      0.90      0.89     30000

CPU times: user 2.47 s, sys: 16 ms, total: 2.48 s
Wall time: 2.48 s
```

[8.4] TF-IDF(bigram) :

In [17]:

```
%%time
tfidf_bigram = TfidfVectorizer(ngram_range=(1, 2),min_df = 0.0005)
X_train_tfidfbi = tfidf_bigram.fit_transform(X_train)
print("Type of Count Vectorizer: ",type(X_train_tfidfbi))
print("The shape of text TFIDF vectorizer: ", X_train_tfidfbi.get_shape())
print("Number of unique word: ", X_train_tfidfbi.get_shape()[1])
```

```
Type of Count Vectorizer:  <class 'scipy.sparse.csr.csr_matrix'>
The shape of text TFIDF vectorizer:  (70000, 10992)
Number of unique word:  10992
CPU times: user 10.5 s, sys: 136 ms, total: 10.7 s
Wall time: 10.7 s
```

In [18]:

```
%%time
X_test_tfidfbi = tfidf_bigram.transform(X_test)
print("The shape of text TFIDF vectorizer: ", X_test_tfidfbi.get_shape())
print("Number of unique word: ", X_test_tfidfbi.get_shape()[1])
```

```
The shape of text TFIDF vectorizer:  (30000, 10992)
Number of unique word:  10992
CPU times: user 2.98 s, sys: 0 ns, total: 2.98 s
Wall time: 2.97 s
```

In [19]:

```
print("Shape of Training Data: ",X_train_tfidfbi.shape)
print("Shape of Test Data: ",X_test_tfidfbi.shape)
```

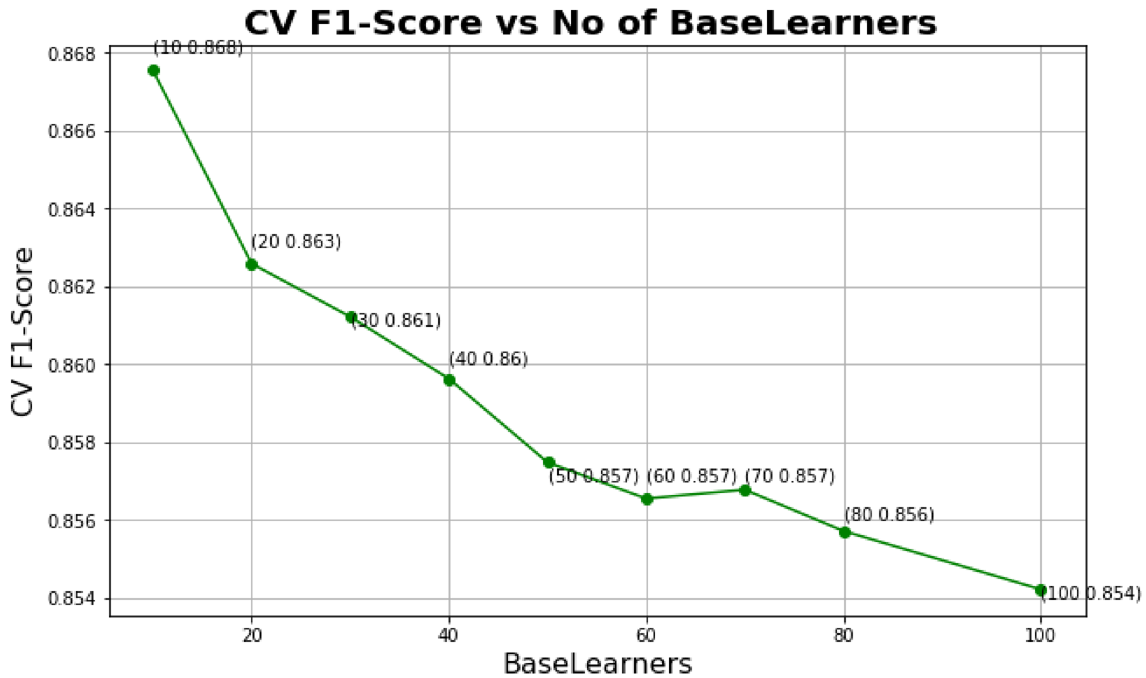
```
Shape of Training Data:  (70000, 10992)
Shape of Test Data:  (30000, 10992)
```

[8.4.1] Random Forest :

In [20]:

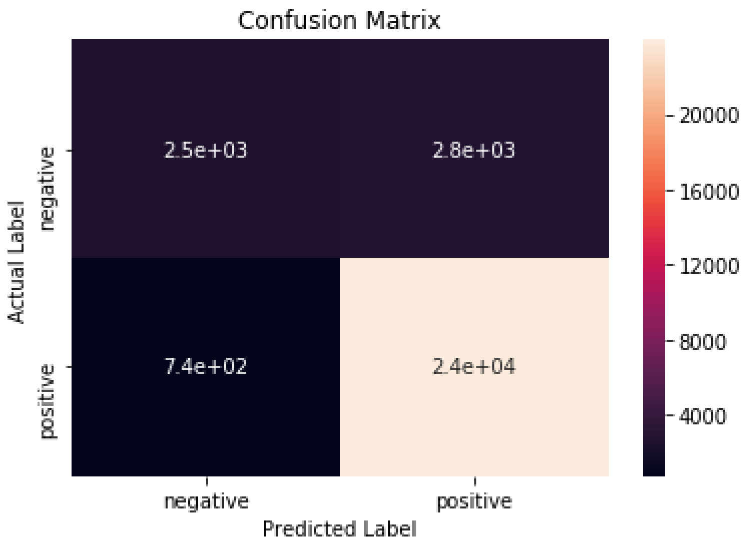
```
%%time
grid_estimator = RF_model(X_train_tfidfbi, y_train)
```

```
Grid Scores for Model is:
 [mean: 0.86754, std: 0.00797, params: {'n_estimators': 10}, mean: 0.8625
8, std: 0.00989, params: {'n_estimators': 20}, mean: 0.86121, std: 0.0094
2, params: {'n_estimators': 30}, mean: 0.85962, std: 0.00987, params: {'n_
estimators': 40}, mean: 0.85748, std: 0.01070, params: {'n_estimators': 5
0}, mean: 0.85655, std: 0.01271, params: {'n_estimators': 60}, mean: 0.856
77, std: 0.01187, params: {'n_estimators': 70}, mean: 0.85571, std: 0.0124
0, params: {'n_estimators': 80}, mean: 0.85422, std: 0.01166, params: {'n_
estimators': 100}]

Best Parameters:  {'n_estimators': 10}

Best F1-Score: 0.868
CPU times: user 55min 42s, sys: 328 ms, total: 55min 42s
Wall time: 55min 43s
```



In [21]:

```
%%time
RF_Test(X_test_tfidfbi,y_test)
```




```
[[ 2545  2751]
 [  735 23969]]
```

Test Error : 0.116
Test Accuracy : 88.38 %
True Negative : 2545
False Positive : 2751
False Negative : 735
True Positive : 23969
Precission Score : 0.876
Recall Score : 0.884
F1 Score : 0.872

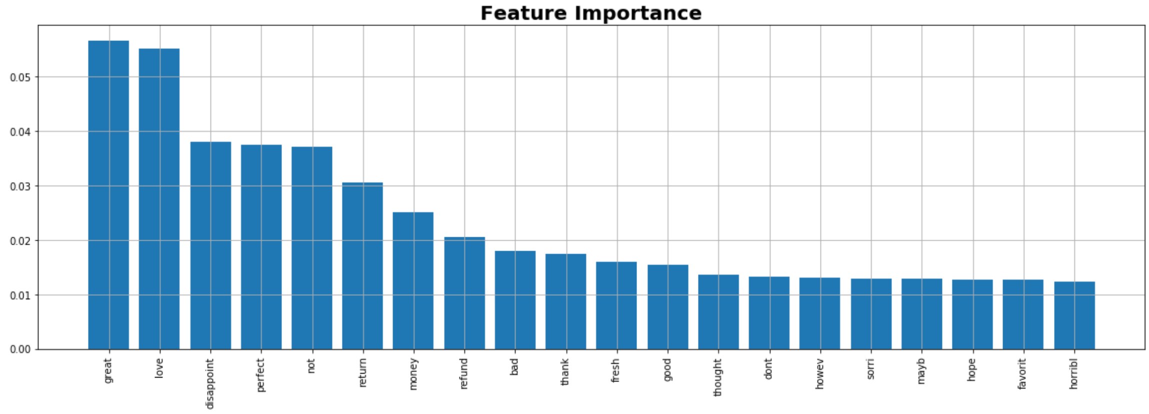
Classification Report for Model is :

	precision	recall	f1-score	support
negative	0.78	0.48	0.59	5296
positive	0.90	0.97	0.93	24704
avg / total	0.88	0.88	0.87	30000

```
CPU times: user 2.52 s, sys: 4 ms, total: 2.52 s
Wall time: 2.27 s
```

In [22]:

```
%%time
featureimportance(X_train_tfidfbi, y_train,10,tfidf_bigram)
```




```
CPU times: user 1.31 s, sys: 12 ms, total: 1.32 s
Wall time: 1.21 s
```

[8.4.2] XG Boost :

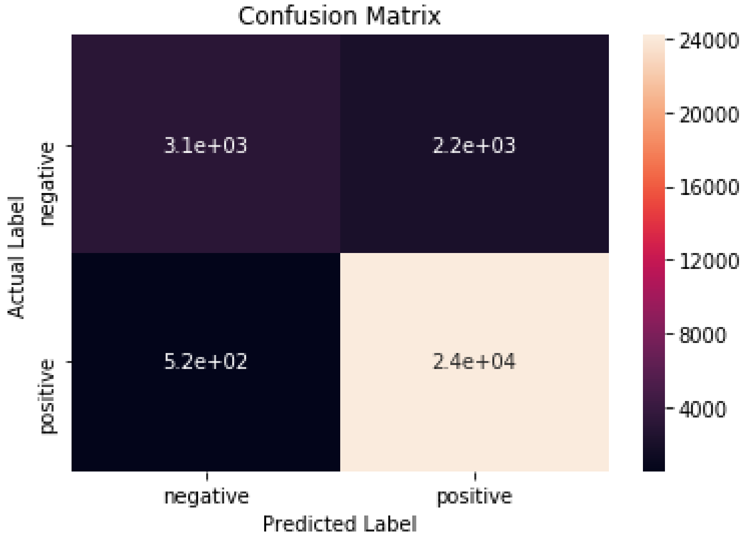
In [23]:

```
%%time
random_estimator = XGB_model(X_train_tfidfbi, y_train)
```

```
Grid Scores for Model is:
 [mean: 0.89753, std: 0.00809, params: {'learning_rate': 0.251789664419470
87, 'max_depth': 4, 'n_estimators': 180}, mean: 0.89441, std: 0.00709, par
ams: {'learning_rate': 0.32483875522951977, 'max_depth': 3, 'n_estimator
s': 153}, mean: 0.87425, std: 0.00901, params: {'learning_rate': 0.4683493
4918484555, 'max_depth': 1, 'n_estimators': 132}, mean: 0.89856, std: 0.00
827, params: {'learning_rate': 0.48519292400276026, 'max_depth': 3, 'n_est
imators': 128}, mean: 0.90252, std: 0.00699, params: {'learning_rate': 0.4
910869994505028, 'max_depth': 3, 'n_estimators': 171}, mean: 0.87139, std:
 0.00784, params: {'learning_rate': 0.3131972305306965, 'max_depth': 4, 'n
_estimators': 45}, mean: 0.82672, std: 0.01263, params: {'learning_rate':
 0.4488556702105684, 'max_depth': 4, 'n_estimators': 7}, mean: 0.87294, st
d: 0.00742, params: {'learning_rate': 0.4408239090832846, 'max_depth': 3,
 'n_estimators': 41}, mean: 0.88453, std: 0.00653, params: {'learning_rat
e': 0.38972032330992923, 'max_depth': 3, 'n_estimators': 76}, mean: 0.8543
9, std: 0.01019, params: {'learning_rate': 0.25173010380599353, 'max_dept
h': 2, 'n_estimators': 72}]

Best Parameters:  {'learning_rate': 0.4910869994505028, 'max_depth': 3, 'n
_estimators': 171}

Best F1-Score: 0.903
CPU times: user 37min 17s, sys: 1.48 s, total: 37min 18s
Wall time: 37min 18s
```

In [24]:

```
%%time
XGB_Test(X_test_tfidfbi,y_test)
```




```
[[ 3124  2172]
 [  515 24189]]

Test Error : 0.09
Test Accuracy : 91.043 %
True Negative : 3124
False Positive : 2172
False Negative : 515
True Positive : 24189
Precission Score : 0.907
Recall Score : 0.91
F1 Score : 0.904



Classification Report for Model is :
             precision    recall  f1-score   support

   negative       0.86      0.59      0.70      5296
   positive       0.92      0.98      0.95     24704

avg / total       0.91      0.91      0.90     30000

CPU times: user 2.65 s, sys: 12 ms, total: 2.66 s
Wall time: 2.65 s
```

[8.5] Average Word2Vec :

In [9]:

```
i=0
list_of_sent_train=[]
for sent in X_train:
    list_of_sent_train.append(sent.split())
```

In [10]:

```
print(X_train[0])
print("**************************************************************************")
print(list_of_sent_train[0])
```

```
beetlejuic excel funni movi keaton hilari wacki beetlejuic great special e
ffect help film think one best movi ever made sure youll agre good time wa
tch beetlejuic
************************************************************************
**
['beetlejuic', 'excel', 'funni', 'movi', 'keaton', 'hilari', 'wacki', 'bee
tlejuic', 'great', 'special', 'effect', 'help', 'film', 'think', 'one', 'b
est', 'movi', 'ever', 'made', 'sure', 'youll', 'agre', 'good', 'time', 'wa
tch', 'beetlejuic']
```

In [11]:

```
%%time
## Word2Vec Model considering only those words that occur atleast 5 times in the corpus
min_count = 5
w2v_model = Word2Vec(list_of_sent_train, min_count = min_count, size = 200, workers =
 4)
w2v_words = list(w2v_model.wv.vocab)
```

```
CPU times: user 58.2 s, sys: 100 ms, total: 58.3 s
Wall time: 16 s
```

In [12]:

```
w2v_words = list(w2v_model.wv.vocab)
```

In [13]:

```
i=0
list_of_sent_test=[]
for sent in X_test:
    list_of_sent_test.append(sent.split())
```

In [14]:

```
print(X_test[5])
print("**************************************************************************")
print(list_of_sent_test[5])
```

```
overpow point slight nauseat strawberri flavor smell chemic even though su
ppos natur
************************************************************************
**
['overpow', 'point', 'slight', 'nauseat', 'strawberri', 'flavor', 'smell',
'chemic', 'even', 'though', 'suppos', 'natur']
```

In [31]:

```
%%time
X_train_avgw2v = [] # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sent_train):
    sent_vec = np.zeros(200) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    X_train_avgw2v.append(sent_vec)
```

```
100%|██████████| 70000/70000 [01:45<00:00, 664.67it/s]

CPU times: user 1min 45s, sys: 1.66 s, total: 1min 46s
Wall time: 1min 45s
```

In [32]:

```
%%time
X_test_avgw2v = [] # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sent_test):
    sent_vec = np.zeros(200) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    X_test_avgw2v.append(sent_vec)
```

```
100%|██████████| 30000/30000 [00:48<00:00, 618.78it/s]

CPU times: user 48.4 s, sys: 820 ms, total: 49.2 s
Wall time: 48.5 s
```

In [33]:

```
#Checking NAN in test data if any
np.any(np.isnan(X_test_avgw2v))
```

Out[33]:

```
False
```

In [34]:

```
print("Number of rows in Train Data: ",len(X_train_avgw2v))
print("Number of features in Train Data: ",len(X_train_avgw2v[0]))
print("Number of rows in Test Data: ",len(X_test_avgw2v))
print("Number of features in Test Data: ",len(X_test_avgw2v[0]))
```

```
Number of rows in Train Data:  70000
Number of features in Train Data:  200
Number of rows in Test Data:  30000
Number of features in Test Data:  200
```

[8.5.1] Random Forest :

In [35]:

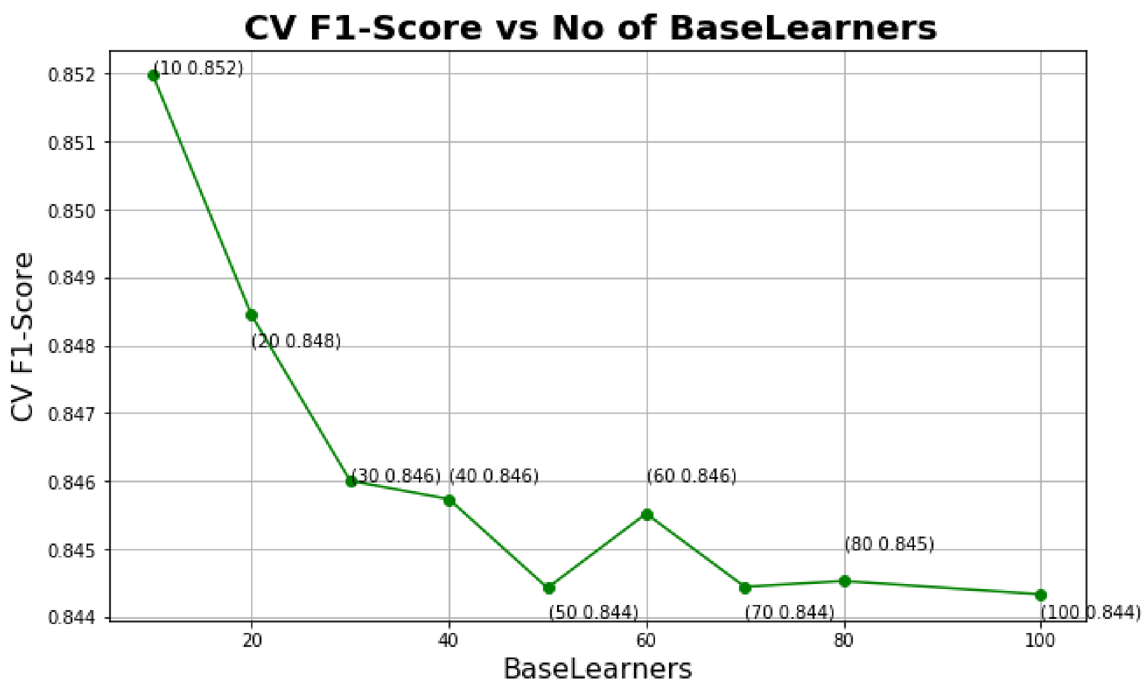
```
%%time
grid_estimator = RF_model(X_train_avgw2v,y_train)
```

Grid Scores for Model is:

```
 [mean: 0.85197, std: 0.00872, params: {'n_estimators': 10}, mean: 0.8484
4, std: 0.00917, params: {'n_estimators': 20}, mean: 0.84600, std: 0.0095
0, params: {'n_estimators': 30}, mean: 0.84573, std: 0.00938, params: {'n_
estimators': 40}, mean: 0.84443, std: 0.01044, params: {'n_estimators': 5
0}, mean: 0.84552, std: 0.00996, params: {'n_estimators': 60}, mean: 0.844
44, std: 0.01014, params: {'n_estimators': 70}, mean: 0.84453, std: 0.0106
6, params: {'n_estimators': 80}, mean: 0.84433, std: 0.00999, params: {'n_
estimators': 100}]
```

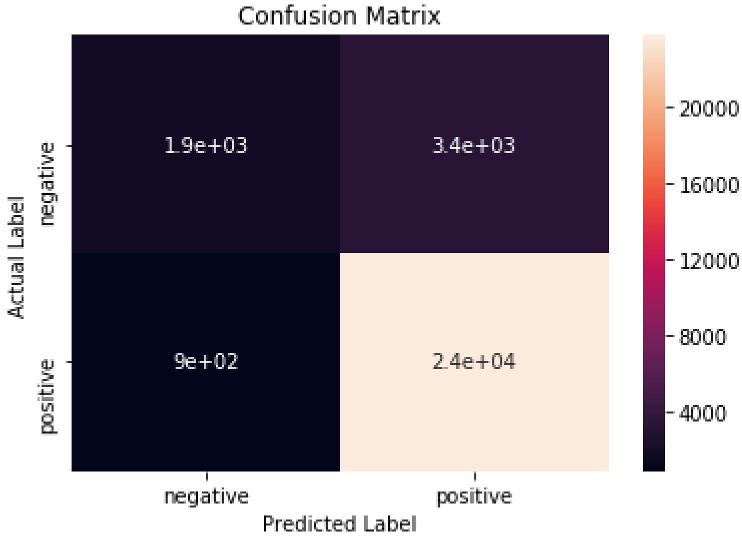
Best Parameters: {'n_estimators': 10}

Best F1-Score: 0.852
CPU times: user 49min 34s, sys: 504 ms, total: 49min 35s
Wall time: 49min 35s



In [36]:

```
%%time
RF_Test(X_test_avgw2v,y_test)
```




```
[[ 1940  3356]
 [  896 23808]]
```

Test Error : 0.142
Test Accuracy : 85.827 %
True Negative : 1940
False Positive : 3356
False Negative : 896
True Positive : 23808
Precission Score : 0.842
Recall Score : 0.858
F1 Score : 0.84

Classification Report for Model is :

	precision	recall	f1-score	support
negative	0.68	0.37	0.48	5296
positive	0.88	0.96	0.92	24704
avg / total	0.84	0.86	0.84	30000

CPU times: user 2.18 s, sys: 4 ms, total: 2.19 s
Wall time: 2.18 s

[8.5.2] XG Boost :

In [37]:

```
%%time
X_train_avgw2v = np.array(X_train_avgw2v)
X_test_avgw2v = np.array(X_test_avgw2v)
random_estimator = XGB_model(X_train_avgw2v,y_train)
```

Grid Scores for Model is:

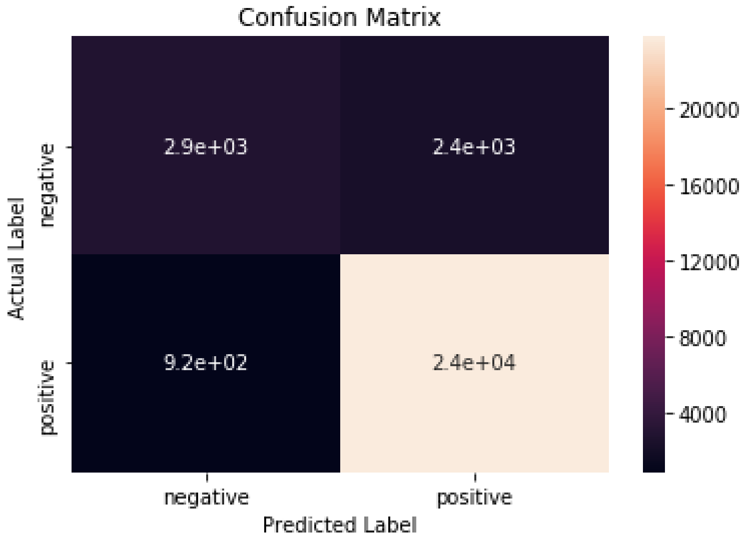
```
 [mean: 0.88798, std: 0.00615, params: {'learning_rate': 0.272167256109986
43, 'max_depth': 4, 'n_estimators': 83}, mean: 0.77916, std: 0.02652, para
ms: {'learning_rate': 0.05261647072918803, 'max_depth': 1, 'n_estimators':
 71}, mean: 0.88604, std: 0.00586, params: {'learning_rate': 0.50458908342
728, 'max_depth': 4, 'n_estimators': 79}, mean: 0.88755, std: 0.00750, par
ams: {'learning_rate': 0.4717464764704802, 'max_depth': 3, 'n_estimators':
 93}, mean: 0.85864, std: 0.01084, params: {'learning_rate': 0.12052289170
778548, 'max_depth': 3, 'n_estimators': 45}, mean: 0.89038, std: 0.00746,
 params: {'learning_rate': 0.3665145670483816, 'max_depth': 3, 'n_estimato
rs': 193}, mean: 0.86438, std: 0.01025, params: {'learning_rate': 0.112882
74464101562, 'max_depth': 2, 'n_estimators': 90}, mean: 0.88384, std: 0.00
695, params: {'learning_rate': 0.09655411544597182, 'max_depth': 4, 'n_est
imators': 119}, mean: 0.87150, std: 0.00832, params: {'learning_rate': 0.0
939622102210408, 'max_depth': 4, 'n_estimators': 66}, mean: 0.88996, std:
 0.00553, params: {'learning_rate': 0.1398577058254305, 'max_depth': 4, 'n
_estimators': 183}]
```

Best Parameters: {'learning_rate': 0.3665145670483816, 'max_depth': 3, 'n
_estimators': 193}

Best F1-Score: 0.89
CPU times: user 2h 3min 19s, sys: 3.44 s, total: 2h 3min 23s
Wall time: 2h 3min 23s

In [38]:

```
%%time
XGB_Test(X_test_avgw2v,y_test)
```




```
[[ 2936  2360]
 [  917 23787]]
```

Test Error : 0.109
Test Accuracy : 89.077 %
True Negative : 2936
False Positive : 2360
False Negative : 917
True Positive : 23787
Precission Score : 0.884
Recall Score : 0.891
F1 Score : 0.884

Classification Report for Model is :

```
             precision    recall  f1-score   support

   negative       0.76      0.55      0.64      5296
   positive       0.91      0.96      0.94     24704

avg / total       0.88      0.89      0.88     30000

CPU times: user 2.31 s, sys: 16 ms, total: 2.32 s
Wall time: 2.32 s
```

[8.6] TF-IDF Weighted Word2Vec :

In [15]:

```
%%time
tfidf = TfidfVectorizer(ngram_range=(1, 2))
tfidf_vectors = tfidf.fit_transform(X_train)
```

```
CPU times: user 11.1 s, sys: 212 ms, total: 11.3 s
Wall time: 11.3 s
```

In [16]:

```
dictionary = dict(zip(tfidf.get_feature_names(),list(tfidf.idf_)))
print(len(dictionary))
```

```
968796
```

In [17]:

```
%%time
tfidf_feat = tfidf.get_feature_names() # tfidf words/col-names
X_train_tfidfw2v = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in tqdm(list_of_sent_train):
    sent_vec = np.zeros(200)
    weight_sum =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*sent.count(word)
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    X_train_tfidfw2v.append(sent_vec)
    row += 1
```

```
100%|██████████| 70000/70000 [02:05<00:00, 557.10it/s]

CPU times: user 2min 7s, sys: 4.3 s, total: 2min 11s
Wall time: 2min 7s
```

In [18]:

```
%%time
X_test_tfidfw2v = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in tqdm(list_of_sent_test):
    sent_vec = np.zeros(200)
    weight_sum =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            tf_idf = dictionary[word]*sent.count(word)
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    X_test_tfidfw2v.append(sent_vec)
    row += 1
```

```
100%|██████████| 30000/30000 [00:57<00:00, 523.50it/s]

CPU times: user 57.3 s, sys: 2.32 s, total: 59.6 s
Wall time: 57.3 s
```

In [19]:

```
print("Number of rows in Train Data: ",len(X_train_tfidfw2v))
print("Number of features in Train Data: ",len(X_train_tfidfw2v[0]))
print("Number of rows in Test Data: ",len(X_test_tfidfw2v))
print("Number of features in Test Data: ",len(X_test_tfidfw2v[0]))
```

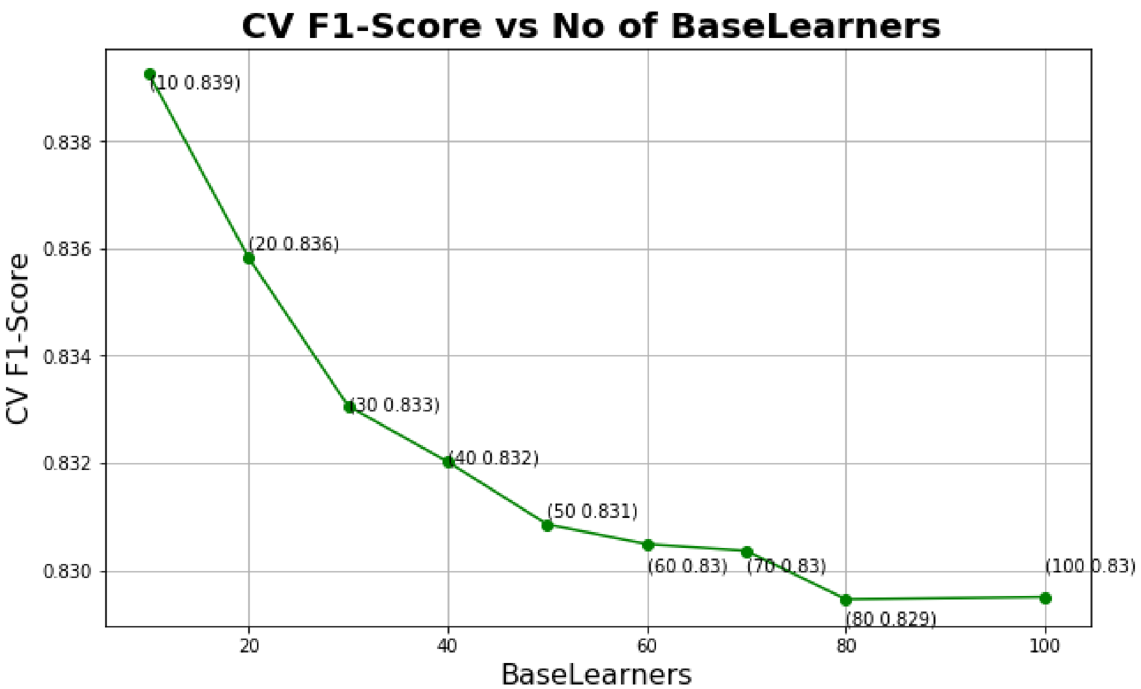
```
Number of rows in Train Data:  70000
Number of features in Train Data:  200
Number of rows in Test Data:  30000
Number of features in Test Data:  200
```

[8.6.1] Random Forest :

In [44]:

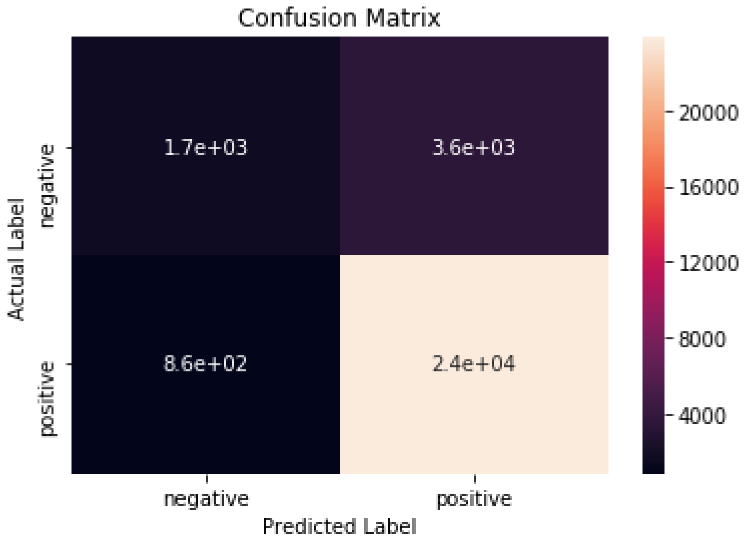
```
%%time
grid_estimator=RF_model(X_train_tfidfw2v,y_train)
```

```
Grid Scores for Model is:
 [mean: 0.83924, std: 0.01154, params: {'n_estimators': 10}, mean: 0.8358
2, std: 0.01151, params: {'n_estimators': 20}, mean: 0.83306, std: 0.0126
7, params: {'n_estimators': 30}, mean: 0.83202, std: 0.01220, params: {'n_
estimators': 40}, mean: 0.83085, std: 0.01232, params: {'n_estimators': 5
0}, mean: 0.83048, std: 0.01189, params: {'n_estimators': 60}, mean: 0.830
36, std: 0.01301, params: {'n_estimators': 70}, mean: 0.82946, std: 0.0120
7, params: {'n_estimators': 80}, mean: 0.82950, std: 0.01221, params: {'n_
estimators': 100}]

Best Parameters:  {'n_estimators': 10}

Best F1-Score: 0.839
CPU times: user 49min 46s, sys: 408 ms, total: 49min 47s
Wall time: 49min 47s
```



In [45]:

```
%%time
RF_Test(X_test_tfidfw2v, y_test)
```




```
[[ 1687  3609]
 [  855 23849]]
```

Test Error : 0.149
Test Accuracy : 85.12 %
True Negative : 1687
False Positive : 3609
False Negative : 855
True Positive : 23849
Precission Score : 0.832
Recall Score : 0.851
F1 Score : 0.829

Classification Report for Model is :

	precision	recall	f1-score	support
negative	0.66	0.32	0.43	5296
positive	0.87	0.97	0.91	24704
avg / total	0.83	0.85	0.83	30000

```
CPU times: user 2.18 s, sys: 20 ms, total: 2.2 s
Wall time: 2.2 s
```

[8.6.2] XG Boost :

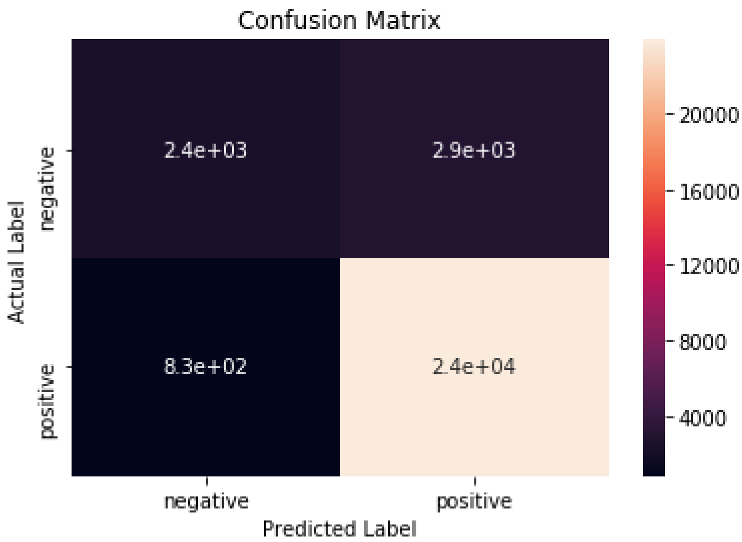
In [20]:

```
%%time
X_train_tfidfw2v = np.array(X_train_tfidfw2v)
X_test_tfidfw2v = np.array(X_test_tfidfw2v)
random_estimator=XGB_model(X_train_tfidfw2v,y_train)
```

```
Grid Scores for Model is:
 [mean: 0.84073, std: 0.01342, params: {'learning_rate': 0.523236888877684
4, 'max_depth': 3, 'n_estimators': 9}, mean: 0.83370, std: 0.01349, param
s: {'learning_rate': 0.37533771588509884, 'max_depth': 2, 'n_estimators':
 16}, mean: 0.86987, std: 0.00859, params: {'learning_rate': 0.31307003190
533916, 'max_depth': 2, 'n_estimators': 182}, mean: 0.83667, std: 0.01346,
 params: {'learning_rate': 0.31582975218074916, 'max_depth': 1, 'n_estimat
ors': 57}, mean: 0.86508, std: 0.00950, params: {'learning_rate': 0.226909
87966728288, 'max_depth': 2, 'n_estimators': 161}, mean: 0.86303, std: 0.0
1208, params: {'learning_rate': 0.5028992699476139, 'max_depth': 1, 'n_est
imators': 143}, mean: 0.87277, std: 0.00829, params: {'learning_rate': 0.3
4198272429360455, 'max_depth': 3, 'n_estimators': 134}, mean: 0.86996, st
d: 0.00904, params: {'learning_rate': 0.5246179731780988, 'max_depth': 2,
 'n_estimators': 123}, mean: 0.86506, std: 0.01017, params: {'learning_rat
e': 0.47481811163317117, 'max_depth': 2, 'n_estimators': 71}, mean: 0.8430
7, std: 0.01350, params: {'learning_rate': 0.41072519901734084, 'max_dept
h': 1, 'n_estimators': 50}]

Best Parameters:  {'learning_rate': 0.34198272429360455, 'max_depth': 3,
 'n_estimators': 134}

Best F1-Score: 0.873
CPU times: user 1h 6min 42s, sys: 3.14 s, total: 1h 6min 45s
Wall time: 1h 6min 45s
```

In [21]:

```
%%time
XGB_Test(X_test_tfidfw2v, y_test)
```




```
[[ 2387  2909]
 [  829 23875]]
```

Test Error : 0.125
Test Accuracy : 87.54 %
True Negative : 2387
False Positive : 2909
False Negative : 829
True Positive : 23875
Precission Score : 0.865
Recall Score : 0.875
F1 Score : 0.863

Classification Report for Model is :

	precision	recall	f1-score	support
negative	0.74	0.45	0.56	5296
positive	0.89	0.97	0.93	24704
avg / total	0.87	0.88	0.86	30000

```
CPU times: user 2.31 s, sys: 0 ns, total: 2.31 s
Wall time: 2.31 s
```

[9] Conclusion :

Random Forest(Bagging) :

Featurization Model	Accuracy	Precission	Recall	F1 score
BOW(unigram)	87.653 %	0.867	0.877	0.863
BOW(bigram)	88.207 %	0.874	0.882	0.887
TF-IDF(unigram)	87.553 %	0.865	0.876	0.863
TF-IDF(bigram)	88.38 %	0.876	0.884	0.872
Average Word2Vec	85.827 %	0.842	0.858	0.84
TF-IDF Weighted Word2Vec	85.12 %	0.832	0.851	0.829

XG Boost(Gradient Boosting) :

Featurization Model	Accuracy	Precission	Recall	F1 score
BOW(unigram)	89.697 %	0.892	0.897	0.887
BOW(bigram)	91.137 %	0.908	0.911	0.905
TF-IDF(unigram)	89.643 %	0.892	0.896	0.886
TF-IDF(bigram)	91.043 %	0.907	0.91	0.904
Average Word2Vec	89.077 %	0.884	0.891	0.884
TF-IDF Weighted Word2Vec	87.54 %	0.865	0.875	0.863

1 - It is observed that XGBoost(Gradient Boosting) performs fairly well in terms of performance metrics then RandomForest(Bootsrap sampling).

2 - Using BOW bigram and Tfidf bigram, XGboost gives best performance with F1 score of **0.905** and **0.904**.

3 - Run Time complexity of both Random Forest and XGBoost is superfast, hence can be used for low latency applications.