Assignment 9

November 12, 2018

0.1 Assignment 9: Apply GBDT and RF to Amazon reviews dataset. [M]

Given Dataset consists of reviews of fine foods from amazon. Reviews describe * (1) product and user information, * (2) ratings * (3) a plain text review.

Here, **GBDT(Gradient Boosting Decision Tree) and RF(Random Forest) algorithm** is applied on amazon reviews datasets to predict whether a review is positive or negative.

Procedure to execute the above task is as follows:

- **Step1: Data Pre-processing is applied on given amazon reviews data-set.**
- **Step2: Time based splitting on train and test datasets.**
- **Step3: Apply Feature generation techniques(BOW,TF-IDF,avg w2v,tfidfw2v)**
- **Step4: Apply GBDT(Gradient Boosting Decision Tree) algorithm using each technique.**
- **Step5: Apply RF(Random Forest) algorithm using each technique.**
- **Step6: To find Number of Base learners(m) using gridsearch cross-validation in case of RF(Random Forest) algorithm .**
- **Step7: To find Number of Base learners(m),depth,learning rate(v) using gridsearch cross-validation in case of RF(Random Forest) algorithm.**

0.2 Objective:

- **To classify given reviews (positive (Rating of 4 or 5) & negative (rating of 1 or 2)) using GBDT(Gradient Boosting Decision Tree) and RF(Random Forest) algorithm .**

```
In [1]: %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        import re
        import math
        import sqlite3
        import pandas as pd
        import numpy as np
        import pickle
        import graphviz
        import pydot
```

```python
# modules for text processing
import nltk
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification

from xgboost.sklearn import XGBClassifier
from xgboost import plot_tree
import xgboost as xgb


from sklearn.externals import joblib
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score

#import scikitplot.metrics as skplt
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score

from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer


# knn modules
# train-split data,accuracy-score,cross-validation modules
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.metrics import accuracy_score

from collections import Counter


from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import GridSearchCV
```

```python
from sklearn.svm import SVC
from scipy.stats import uniform
from sklearn.model_selection import RandomizedSearchCV
from tqdm import tqdm
import os
from sklearn.decomposition import TruncatedSVD
import pytablewriter
```

In [2]:
```python
try:
    from StringIO import StringIO
except ImportError:

    from io import StringIO
```

In [3]:
```python
import zipfile
archive = zipfile.ZipFile('/floyd/input/pri/Reviews.zip', 'r')
csvfile = archive.open('Reviews.csv')
```

In [4]:
```python
# Reading CSV file and printing first five rows
amz = pd.read_csv(csvfile ) # reviews.csv is  dataset file
print(amz.head())
```

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

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      5  1303862400
1                     0                       0      1  1346976000
2                     1                       1      4  1219017600
3                     3                       3      2  1307923200
4                     0                       0      5  1350777600

                Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

In [5]:
```python
# dimensions of dataset and columns name

print(amz.shape)
#print(amz1.shape)
print(amz.columns)
```

```
(568454, 10)
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
```

The amazon reviews datafile contains 568454 rows of entry and 10 columns.For given objective, processing of data is necessary."Score" and "text" columns is processed for required result.

Given reviews with Score>3 a positive rating, and reviews with a score<3 a negative rating. If score is equal to 3,it is considered as neutral score.

In [6]:
```
# Processing
#Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative rati

def score_part(x):
    if x < 3:
        return 'negative'
    return 'positive'

actualScore = amz['Score']
#print(actualScore)
New_score = actualScore.map(score_part)
#print(New_score)
amz['Score']=New_score

# If score is equal to 3,it is considered as neutral score.
```

In [7]:
```
print(amz.shape)
amz.head(5)
```

```
(568454, 10)
```

Out[7]:
```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

   HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
0                     1                       1  positive  1303862400
1                     0                       0  negative  1346976000
2                     1                       1  positive  1219017600
3                     3                       3  negative  1307923200
4                     0                       0  positive  1350777600
```

```
                  Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

Data Pre-processing on raw data: Every datasets contains some unwanted data.Raw data is preprocessed by removing duplication.

In [8]:
```
#Processing of ProductId
#Sorting data according to ProductId in ascending order
sorted_data=amz.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='qu
#sorted_data.head() # printing sorted data
# To check the duplications in raw data
dupli=sorted_data[sorted_data.duplicated(["UserId","ProfileName","Time","Text"])]
print(dupli.head(5))
# Remove Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='f
final.shape
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(amz['Id'].size*1.0)*100
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

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

```
            Id   ProductId          UserId  \
171222  171223  7310172001   AJD41FBJD9010
171153  171154  7310172001   AJD41FBJD9010
171151  171152  7310172001   AJD41FBJD9010
217443  217444  7310172101  A22FICU3LCG2J1
217444  217445  7310172101  A1LQV0PSM04DWI

                                        ProfileName  HelpfulnessNumerator  \
171222  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     1
171153  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     0
171151  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     0
217443                                    C. Knapp                     1
217444                               B. Feuerstein                     1

        HelpfulnessDenominator     Score        Time  \
171222                       1  positive  1233360000
171153                       0  positive  1233360000
171151                       0  positive  1233360000
```

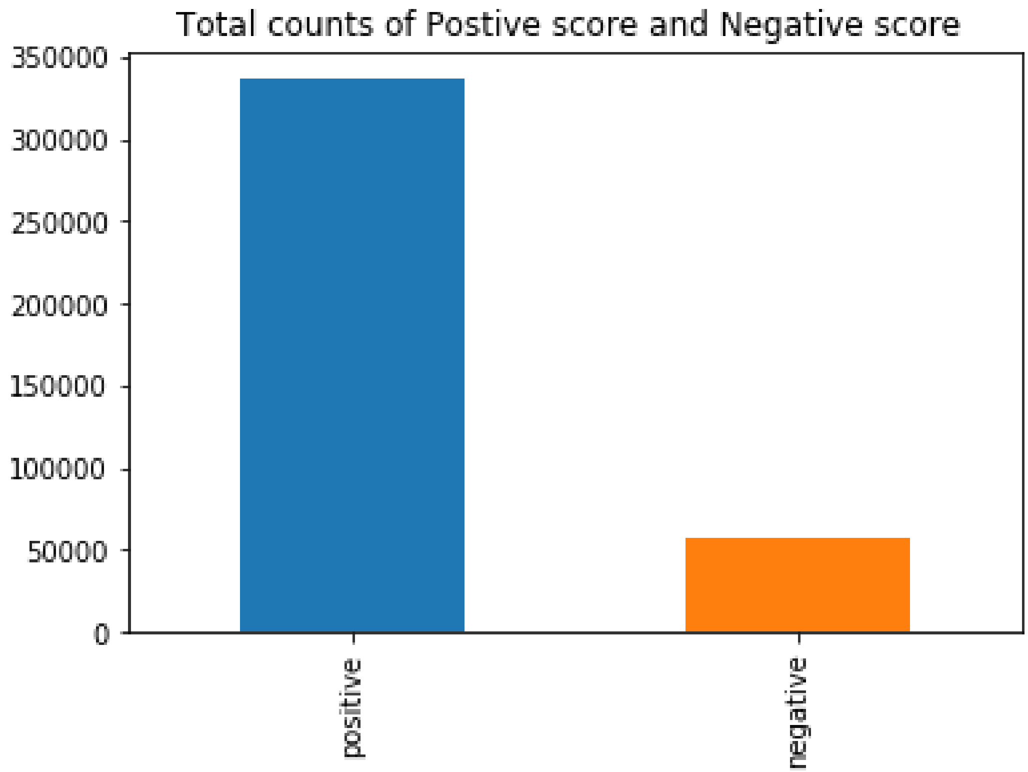
```
217443                        1  positive  1275523200
217444                        1  positive  1274313600

                                                  Summary  \
171222  best dog treat-- great for training---  all do...
171153  best dog treat-- great for training---  all do...
171151  dogs LOVE it--  best treat for rewards and tra...
217443                                Can't resist this !
217444                     Freeze dried liver as dog treats

                                                     Text
171222  Freeze dried liver has a hypnotic effect on do...
171153  Freeze dried liver has a hypnotic effect on do...
171151  Freeze dried liver has a hypnotic effect on do...
217443  My dog can't resist these treats - I can get h...
217444  My little pupster loves these things. She is n...
(393931, 10)
```

```
Out[8]: positive    336824
        negative     57107
        Name: Score, dtype: int64
```

```
In [9]: a=final['Score'].value_counts().tolist()
        print('List of total counts Postive score and Negative score ==>',a)
        final['Score'].value_counts().plot(kind='bar')
        plt.title('Total counts of Postive score and Negative score ')
```

```
List of total counts Postive score and Negative score ==> [336824, 57107]
```

```
Out[9]: Text(0.5,1,'Total counts of Postive score and Negative score ')
```



observations

- The positive reviews is greater than negative reviews.It makes data imbalanced.
- From the bar plot ,it is seen that sampled datasets of review is imbalnced.

1 Text Preprocessing:

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

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
Out[10]: True
```

```
In [11]:
         stop = set(stopwords.words('english')) #set of stopwords
         sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

         def cleanhtml(sentence): #function to clean the word of any html-tags
             cleanr = re.compile('<.*?>$< /><')
```

```
    #cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special char
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

cleaning html tags like" <.*?>" and punctuations like " r'[?|!|'|"|#]',r''" from senetences

In [12]:
```
#final = final.sample(frac=0.04,random_state=None)
#print(final.shape)
```

In [13]:
```
#Code for implementing step-by-step the checks mentioned in the pre-processing phase.

'''Pre processing of text data:It is cleaning and flitering text'''
i=0
str1=' '
global final_string
final_string=[]
all_positive_words=[]
all_negative_words=[]
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describ
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describ
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

    final_string.append(str1)
    i+=1
#print('all_positive_words =',len(all_positive_words))
```

```
#print('all_negative_words =',len(all_negative_words))

# Finding most frequently occuring Positive and Negative words

freq_positive=nltk.FreqDist(all_positive_words)

freq_negative=nltk.FreqDist(all_negative_words)

#print("\nMost Common Positive Words : ",freq_positive.most_common(20))

#print("\nMost Common Negative Words : ",freq_negative.most_common(20))
```

Dumping and loading Pre processing of text data in pickle file

```
In [14]: pickle_path_final_string='final_string.pkl'
         final_string_file=open(pickle_path_final_string,'wb')
         pickle.dump(final_string,final_string_file)
         final_string_file.close()
```

```
In [12]: pickle_path_final_string='final_string.pkl'
         final_string_unpkl=open(pickle_path_final_string,'rb')
         final_string=pickle.load(final_string_unpkl)
```

```
In [13]: final['CleanedText']=final_string
         #adding a column of CleanedText which displays the data after pre-processing of the rev
         Pre_Process_Data = final[['CleanedText','Score','Time']]

         X_Text=Pre_Process_Data ['CleanedText']

         Y_Score =Pre_Process_Data ['Score'] # positive or negative score
         print('\nPre_Process_Text_Data  X_Text=',X_Text.shape)
         print('\nPre_Process_Score_Data Y_Score=',Y_Score.shape)
```

```
Pre_Process_Text_Data  X_Text= (393931,)

Pre_Process_Score_Data Y_Score= (393931,)
```

```
In [14]: # postive and negtive reviews from original datasets of amazon
         pos_final = Pre_Process_Data[Pre_Process_Data .Score == 'positive']# postive reviews
         pos_final = pos_final.sample(frac=0.3)
         print(pos_final.Score.value_counts())

         neg_final = Pre_Process_Data [Pre_Process_Data .Score == 'negative'] # negative reviews
         print(neg_final.Score.value_counts())
```

```
positive    101047
Name: Score, dtype: int64
```

```
negative    57107
Name: Score, dtype: int64
```

```
In [15]: final_pos_neg = pd.concat([pos_final,neg_final],axis=0)
         print(len(final_pos_neg))
         print(type(final_pos_neg))
         #print('final_pos_neg=',final_pos_neg['Score'])
```

```
158154
<class 'pandas.core.frame.DataFrame'>
```

```
In [16]: print(final_pos_neg.columns)
```

```
Index(['CleanedText', 'Score', 'Time'], dtype='object')
```

1.0.1 Splitting Training and Testing dataset

```
In [17]: # splitting training and testing dataset (Time based splitting)

         X1 = final_pos_neg[['CleanedText','Time']].sort_values('Time',axis=0).drop('Time',axis=
         #40k data sample
         X=X1[:40000]

         print(X.shape)
         Y1 = final_pos_neg[['Score','Time']].sort_values('Time',axis=0).drop('Time',axis=1)
         #40k data sample
         Y=Y1[:40000]
         print(Y.shape)
         ## 70 % of data

         X_train_data ,X_test_data,Y_train_data,Y_test_data  = train_test_split(X,
                                                                 Y.values.ravel(),

                                                               test_size=0.3,shuffle=False)



         print('X_train_data ',X_train_data.shape)

         print('X_test_data ',X_test_data.shape )

         print('Y_train_data ',Y_train_data .shape)

         print('Y_test_data ',Y_test_data .shape)
```

```
(40000, 1)
(40000, 1)
```

```
X_train_data  (28000, 1)
X_test_data  (12000, 1)
Y_train_data  (28000,)
Y_test_data  (12000,)
```

```
In [18]: Y_new = Y['Score'].map(lambda x: 1 if x == 'positive' else 0).values.ravel()
         # Y train and Test for sparse datasets

         y_train_new,y_test_new = train_test_split(Y_new,test_size=0.3,shuffle=False)
         print('y_train_new ',y_train_new.shape)

         print('y_test_new ',y_test_new .shape)
```

```
y_train_new  (28000,)
y_test_new  (12000,)
```

```
In [19]: Train_data=y_train_new
         print(Train_data.shape)
```

```
(28000,)
```

2 Optimal Base_learners for Random Forests

```
In [20]:  # Time seris splitting Cross-Validation

         tscv = TimeSeriesSplit(n_splits=3)
```

```
In [21]: n_estimators=[100,150,200]
         Learning_rate=[0.1,0.001,0.6]
         Max_depth= [8,14,18]
```

```
In [22]: # Optimal_Base_learners is function to calculate the optimal Base_learners

         def Optimal_Base_learners(X_train,y_train):

             parameter_grid = dict(max_depth = Max_depth,n_estimators=n_estimators,
                                   max_features=['sqrt', 'log2'],
                           criterion=['gini',])


             random_forest = RandomForestClassifier( n_jobs =-1,
                                        class_weight='balanced' ,
                                        bootstrap=True,
                                        oob_score = True)
```

```
        RF_clf = GridSearchCV(estimator=random_forest,
                              param_grid=parameter_grid,
                              cv=tscv, n_jobs=-1)

        RF_clf.fit(X_train,y_train)
        optimal_estim=RF_clf.best_estimator_
        print("optimal_estim==",optimal_estim)
        global optimal_parameters_RF

        optimal_parameters_RF  =RF_clf.best_params_

        scores = cross_val_score(RF_clf, X_train, y_train, cv=tscv, n_jobs=-1)


        print('Mean of score:', np.mean(scores))
        print('Variance of scores:', np.var(scores))
        MSE = [1 - x for x in scores]

        print('\nThe optimal Best_parameters for Random Forest is === ',optimal_parameters_
         # plot misclassification error vs Number_Base_learners of Random Forests
        fig4 = plt.figure( facecolor='c', edgecolor='k')
        fig4.suptitle('Number_Base_learners vs CV Scores',
                      fontsize=12)

        plt.plot(n_estimators, MSE, color='green', marker='o', linestyle='dashed',
                    linewidth=2, markersize=12)

        for xy in zip(n_estimators, np.round(MSE,3)):
            plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

        plt.xlabel('Number of Base learners')
        plt.ylabel('CV Scores')
        plt.show()

        print("the misclassification error for each Base learners is : ", np.round(MSE,5))
```

Base_learners with different depth size

```
In [23]: # clf_perform_depth is function
         #to calculate the Base_learners with different depth size
         def clf_perform_depth(clf,X_train,y_train):

             # Parameters for model
             parameter_grid = dict(max_depth = Max_depth,
                                   n_estimators=n_estimators)
```

```
clf_CV = GridSearchCV(estimator=clf,
                      param_grid=parameter_grid,
                      cv=tscv, n_jobs=-1)

clf_CV_result=clf_CV.fit(X_train,y_train)

means =clf_CV_result.cv_results_['mean_test_score']
print(means)



# plot results
scores = np.array(means).reshape(len(Max_depth), len(n_estimators))
fig41 = plt.figure( facecolor='c', edgecolor='k')
fig41.suptitle('Number_Base_learners vs CV Scores',
              fontsize=12)
for i, value in enumerate(Max_depth):
    print(Max_depth)
    plt.plot(n_estimators, scores[i],
             linewidth=2, markersize=12,
             label='depth: ' + str(value))
plt.legend()
plt.grid()

plt.xlabel('n_estimators')
plt.ylabel('CV Scores')
```

3 Optimal Parameters for GBDT Algorithm

```
In [24]: # Optimal_BL_Depth_LR is function to calculate the optimal Base_learners,Depth Size,Lea
         def Optimal_BL_Depth_LR(X_train,y_train):
             parameter_grid = dict(learning_rate=Learning_rate,
                                   max_depth = Max_depth,
                                    n_estimators=n_estimators)



             GBDT_model = XGBClassifier()

             GBDT_clf = GridSearchCV(estimator=GBDT_model,
                                     param_grid=parameter_grid,
                                 n_jobs=-1,
                                 cv=tscv)
```

```
        GBDT_clf_result=GBDT_clf.fit(X_train,y_train)
        global Optimal_param_GBDT
        Optimal_estim_GBDT =GBDT_clf_result.best_estimator_
        Optimal_param_GBDT =GBDT_clf_result.best_params_
        print("Optimal_estim_GBDT===",Optimal_estim_GBDT)


        scores = cross_val_score(GBDT_clf_result, X_train, y_train, cv=tscv, n_jobs=-1)

        MSE =[1 - x for x in scores]

        print('\nThe optimal parameter for GBDT is ===' ,Optimal_param_GBDT )
        fig4 = plt.figure( facecolor='c', edgecolor='k')
        fig4.suptitle('Number_Base_learners vs CV Scores',
                      fontsize=12)

        plt.plot(n_estimators, MSE, color='green', marker='o', linestyle='dashed',
                    linewidth=2, markersize=12)

        for xy in zip(n_estimators, np.round(MSE,3)):
            plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

        plt.xlabel('Number of Base learners')
        plt.ylabel('CV Scores')
        plt.show()

        print("the misclassification error for each Base learners is : ", np.round(MSE,5))
```

Base_learners with different Learning Rate

```
In [24]: # Optimal_BL_Depth_LR is function to calculate
         #the optimal Base_learners,Depth Size,Learning Rate
         def GBDT_LR(Best_max_depth,X_train,y_train):


             parameter_grid = dict(learning_rate=Learning_rate,
                                   max_depth = [Best_max_depth,],
                                   n_estimators=n_estimators)

             GBDT_model = XGBClassifier()

             GBDT_clf = GridSearchCV(estimator=GBDT_model,
                                     param_grid=parameter_grid,

                                     cv=tscv,n_jobs=-1)
```

```
GBDT_clf_result=GBDT_clf.fit(X_train,y_train)

means = GBDT_clf_result.cv_results_['mean_test_score']

params = GBDT_clf_result.cv_results_['params']



scores1 = np.array(means).reshape(len(Learning_rate),len(n_estimators))
fig41 = plt.figure( facecolor='c', edgecolor='k')
fig41.suptitle('Number_Base_learners vs CV Scores',
              fontsize=12)
for i, value in tqdm(enumerate(Learning_rate)):
    plt.plot(n_estimators, scores1[i],
             linewidth=2, markersize=12,
             label='learning_rate: ' + str(value))
plt.legend()
plt.grid()
plt.xlabel('n_estimators')
plt.ylabel('Cv_Score')
```

```
In [25]: def roc_auc_plot(clf, Y_test_data,data_test):
             y_true = Y_test_data
             y_probas = clf.predict_proba(data_test)[:, 1]
             fpr_base, tpr_base, thresholds = roc_curve(y_true, [1 for thresholds in range(len(y
             False_postive_rate, True_negative_rate, thresholds = metrics.roc_curve(y_true, y_pr

             # Print ROC curve
             fig4 = plt.figure( facecolor='y', edgecolor='k',figsize = (8, 6))

             plt.rcParams['font.size'] = 16
             plt.plot(fpr_base, tpr_base, 'g', label = 'Base_model')
             plt.plot(False_postive_rate, True_negative_rate,'r', label = 'Test_model')

             plt.grid()
             plt.legend()
             plt.xlabel('False Positive Rate')
             plt.ylabel('True Positive Rate')
             plt.title('ROC Curves')
             plt.show()

             # Print AUC
             AUC = auc(False_postive_rate,True_negative_rate)
             print('AUC:', AUC)
```

Pandas dataframe to markdown Table format

```
In [26]: # result_display  is function to convert dataframe into table format in Markdown
         def result_display(df):
```

```
        writer = pytablewriter.MarkdownTableWriter()
        writer.header_list = list(df.columns.values)
        writer.value_matrix = df.values.tolist()
        writer.write_table()
```

3.1 Tree Image function for visualization of Random Forest

```
In [25]: import os
         import io
         import pydot

         def tree_image(classifier,features,name_png_format):

             os.environ["PATH"] += os.pathsep + 'C:/ProgramData/Anaconda3/pkgs/graphviz-2.38.0-4
             dotfile=io.StringIO()
             tree.export_graphviz(classifier, out_file=dotfile,
                                  feature_names=features,

                                  filled=True, rounded=True,
                                  special_characters=True)
             #graph = graphviz.Source(dot_data)
             (graph,)=pydot.graph_from_dot_data(dotfile.getvalue())
             graph.write_png(name_png_format)
```

4 Methods to convert text into vector

Methods:

- Avg word2vec
- tf-idf weighted Word2Vec
- Bag of words
- TF-IDF

5 1. Avg word2vec

Firstly, word2vec model is designed for amazon reviews using gensim module.

```
In [85]: import gensim
         list_sent=[]
         for text in tqdm(X_train_data.values.ravel()):
             filter_text=[]
             for i in text.split():
                 if(i.isalpha()):
                     filter_text.append(i.lower().decode("utf-8"))
                 else:
```

```
                continue
            list_sent.append(filter_text)
        print(len(list_sent))
```

```
100%|??????????| 28000/28000 [00:00<00:00, 33343.16it/s]
```

```
28000
```

word2vec Model using Training Datasets

```
In [86]: w2v_model=gensim.models.Word2Vec(list_sent,min_count=5,size=100, workers=4)
         #this model is used in avg word2vec   .
```

```
In [87]: pickle_path_w2v_model='w2v_model.pkl'
         w2v_model_path=open(pickle_path_w2v_model,'wb')
         pickle.dump(w2v_model,w2v_model_path)
         w2v_model_path.close()
```

```
In [27]: pickle_path_w2v_model='w2v_model.pkl'
         unpickle_w2v_model=open(pickle_path_w2v_model,'rb')
         w2v_model=pickle.load(unpickle_w2v_model)
```

```
In [28]: words = list(w2v_model.wv.vocab)
         print(len(words))
```

```
7235
```

Avg Word2Vec

```
In [90]: #  For Training


         sent_vectors = []
         for sent in  tqdm(list_sent): # for each review/sentence
             sent_vec = np.zeros(100)
             cnt_words =0 # num of words with a valid vector in the sentence/review
             for word in sent:
                 try:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
                 except:
                     pass
             sent_vec /= cnt_words
             sent_vectors.append(sent_vec)
```

```
print(len(sent_vectors))

#print(sent_vectors[0:4])
```

```
100%|??????????| 28000/28000 [00:05<00:00, 5525.10it/s]

28000
```

In [91]:
```
# Converting Nan value to zero in sent vectors.
Sent_Nan = np.where(np.isnan(sent_vectors), 0, sent_vectors)
```

In [92]:
```
# converting sent list to nd array
Sent_final_vector = np.asarray(Sent_Nan )
print(type(Sent_final_vector))
```

```
<class 'numpy.ndarray'>
```

In [93]:
```
#  ForTesting
# Words in test reviews
list_sent_test=[]
for text in tqdm(X_test_data.values.ravel()):
    filter_text=[]
    for i in text.split():
        if(i.isalpha()):
            filter_text.append(i.lower().decode("utf-8"))
        else:
            continue
    list_sent_test.append(filter_text)
#print(len(list_sent_test))

sent_vectors1 = []
for sent in tqdm(list_sent_test): # for each review/sentence
    sent_vec = np.zeros(100)
    cnt_words =0 # num of words with a valid vector in the sentence/review
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
```

```
            sent_vectors1.append(sent_vec)


    print(len(sent_vectors1))

    #print(sent_vectors1)
    # Converting Nan value to zero in sent vectors.
    Sent_Nan1 = np.where(np.isnan(sent_vectors1), 0, sent_vectors1)

    # converting sent list to nd array
    Sent_final_vector1 = np.asarray(Sent_Nan1)
    print(type(Sent_final_vector1))
```

```
100%|??????????| 12000/12000 [00:00<00:00, 31306.17it/s]
100%|??????????| 12000/12000 [00:02<00:00, 5293.12it/s]


12000
<class 'numpy.ndarray'>
```

Dumping & Loading Pickle file for Avg word2vec

```
In [94]: pickle_path_AW2V_train='X_data_AW2V_train.pkl'
         X_data_AW2V_train=open(pickle_path_AW2V_train,'wb')
         pickle.dump(Sent_final_vector,X_data_AW2V_train)
         X_data_AW2V_train.close()

         pickle_path_AW2V_test='X_data_AW2V_test.pkl'
         X_data_AW2V_test=open(pickle_path_AW2V_test,'wb')
         pickle.dump(Sent_final_vector1,X_data_AW2V_test)
         X_data_AW2V_test.close()
```

```
In [95]: pickle_path_AW2V_train='X_data_AW2V_train.pkl'
         unpickle_path3_train=open(pickle_path_AW2V_train,'rb')
         Sent_final_vector=pickle.load(unpickle_path3_train)

         pickle_path_AW2V_test='X_data_AW2V_test.pkl'
         unpickle_path3_test=open(pickle_path_AW2V_test,'rb')
         Sent_final_vector1=pickle.load(unpickle_path3_test)
```

```
In [96]: joblib.dump(Sent_final_vector, 'AW2V_train.joblib')
         joblib.dump(Sent_final_vector1, 'AW2V_test.joblib')

Out[96]: ['AW2V_test.joblib']
```

```
In [29]: final_w2v_count_Train = joblib.load('AW2V_train.joblib')
         final_w2v_count_Test = joblib.load('AW2V_test.joblib')
```

for Training datasets ,avg word2vec

```
final_w2v_count_Train,
```

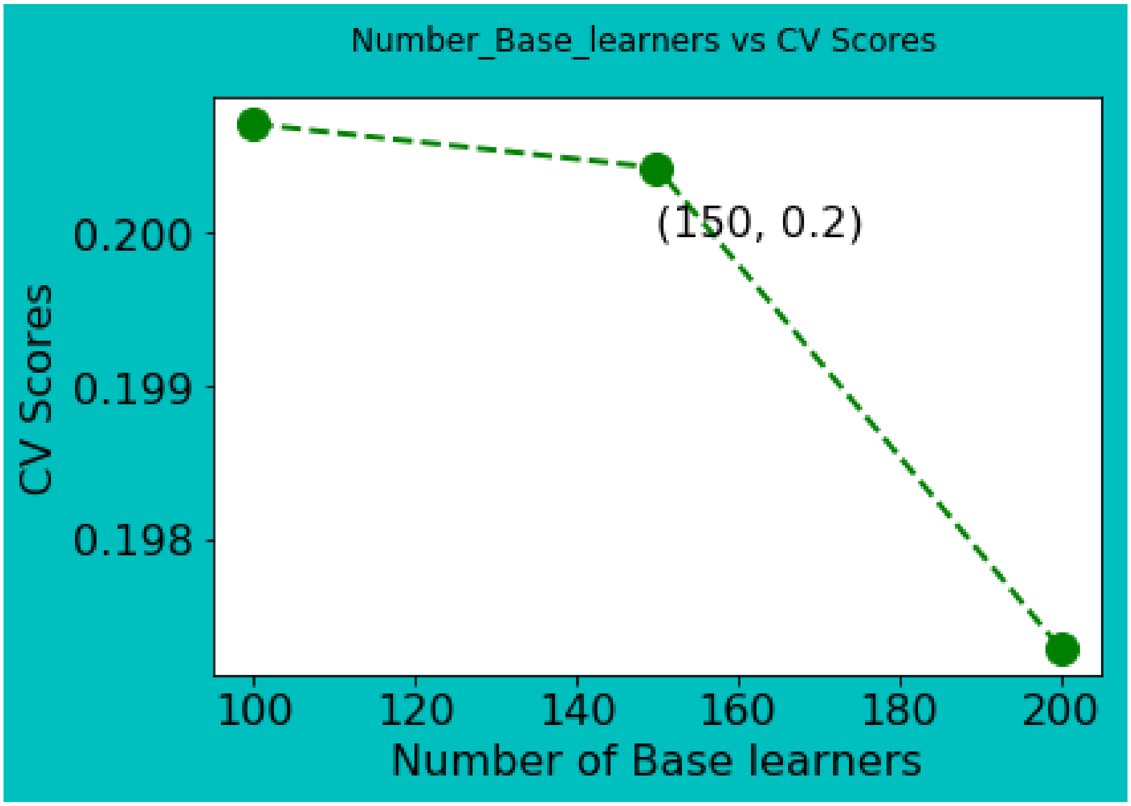
for testing datasets ,avg word2vec

```
final_w2v_count_Test,
```

5.1 Optimal Base_learners using Avg Word2Vec

```
In [61]: Optimal_Depth_Tree1=Optimal_Base_learners(final_w2v_count_Train ,Train_data)
```

```
optimal_estim== RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=14, max_features='sqrt',
            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=150, n_jobs=-1, oob_score=True, random_state=None,
            verbose=0, warm_start=False)
Mean of score: 0.8005238095238095
Variance of scores: 2.41269841269841e-06

The optimal Best_parameters for Random Forest is ===  {'criterion': 'gini', 'max_depth': 14, 'ma
```



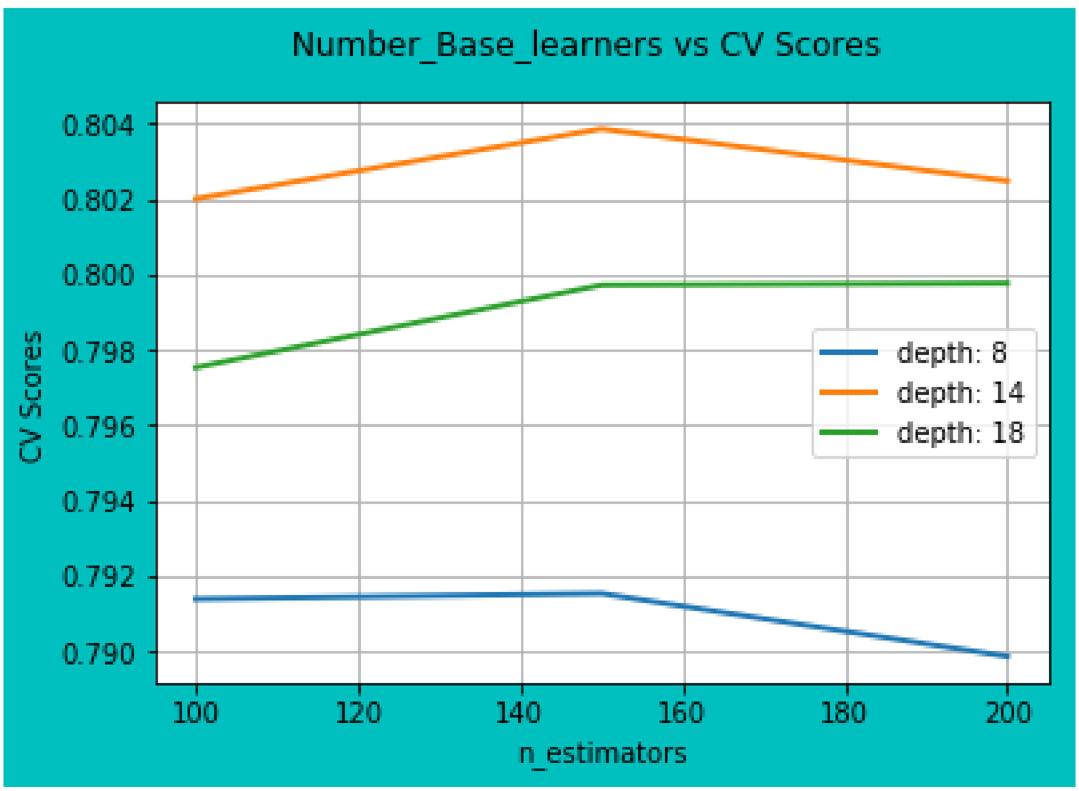
```
the misclassification error for each Base learners is :  [0.20071 0.20043 0.19729]
```

Base_learners graph with different depth size

```
In [30]: random_forest = RandomForestClassifier( n_jobs =-1,
                                                  class_weight='balanced' ,
                                                  bootstrap=True,
                                                  oob_score = True)
```

```
In [47]: clf_perform_depth(random_forest,final_w2v_count_Train ,Train_data)
```

```
[0.79138095 0.79152381 0.78985714 0.802      0.80385714 0.80247619
 0.79752381 0.79971429 0.7997619 ]
[8, 14, 18]
[8, 14, 18]
[8, 14, 18]
```



5.1.1 Observation

- The Base learner for random Forest=150 and depth size for Tree=14.
- As seen in the results , Misclassification Error is almost similar.
- The score of model vs Base Learners with respective their depth size is as shown in graph.

5.2 Random forest Model for optimal Parameters using Avg word2vec

```
In [100]: print("Best Parameters for Random Forest is ",optimal_parameters_RF)
          Best_criterion=optimal_parameters_RF.get('criterion')
          Best_max_features=optimal_parameters_RF.get('max_features')
          Best_n_estimators=optimal_parameters_RF.get('n_estimators')
          Best_max_depth=optimal_parameters_RF.get('max_depth')
```

```
Best Parameters for Random Forest is  {'criterion': 'gini', 'max_depth': 14, 'max_features': 'sq
```

```
In [101]: # Random forest classifier for optimal depth using gini index

          clf1 = RandomForestClassifier(n_estimators=Best_n_estimators,
                                        max_depth=Best_max_depth
                                        ,criterion=Best_criterion,
                                           max_features=Best_max_features,
                                        random_state=0,
                                        bootstrap=True,
                                        oob_score = True,
                                        n_jobs=-1)
          clf1.fit(final_w2v_count_Train,Train_data)
          RF1=clf1.fit(final_w2v_count_Train,Train_data)
```

```
In [102]: prediction1= clf1.predict(final_w2v_count_Test)
```

```
In [103]: #Training accuracy and training error
          training_score=clf1.score(final_w2v_count_Train ,Train_data)
          print('training accuracy=',training_score)
          training_error=1-training_score
          print('training error is =',training_error)
```

```
training accuracy= 0.9786071428571429
training error is = 0.021392857142857102
```

```
In [104]: # Testing Accuracy and testing error for Random Forest model
          Testing_score=round(accuracy_score(y_test_new ,prediction1),5)
          print("Accuracy for Random Forest  model with Avg word2vec is = ",Testing_score)
          Testing_error=1-Testing_score
          print("Testing error for Random Forest model with Avg word2vec is = ",Testing_error)
```

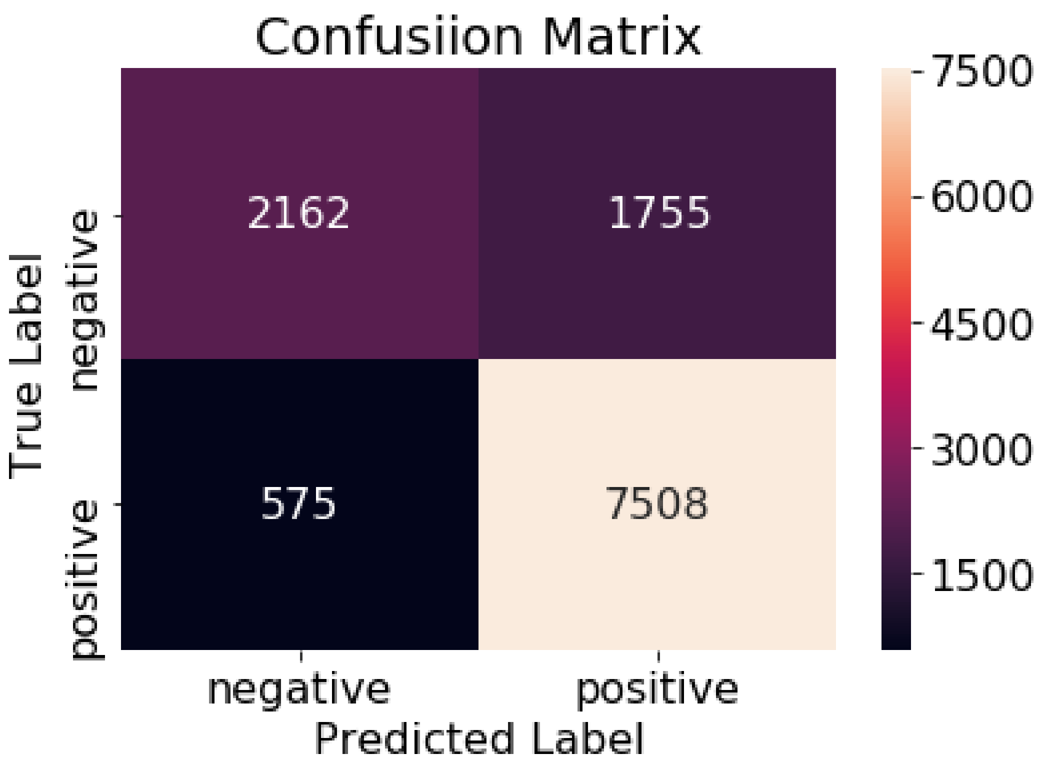
```
Accuracy for Random Forest  model with Avg word2vec is =  0.80583
Testing error for Random Forest model with Avg word2vec is =  0.19416999999999995
```

In [105]:
```
F1_score = round(f1_score(y_test_new ,prediction1,average='macro'),5)*100
recall = round(recall_score(y_test_new,prediction1,average='macro'),5)*100
precision = round(precision_score(y_test_new,prediction1,average='macro'),5)*100
```

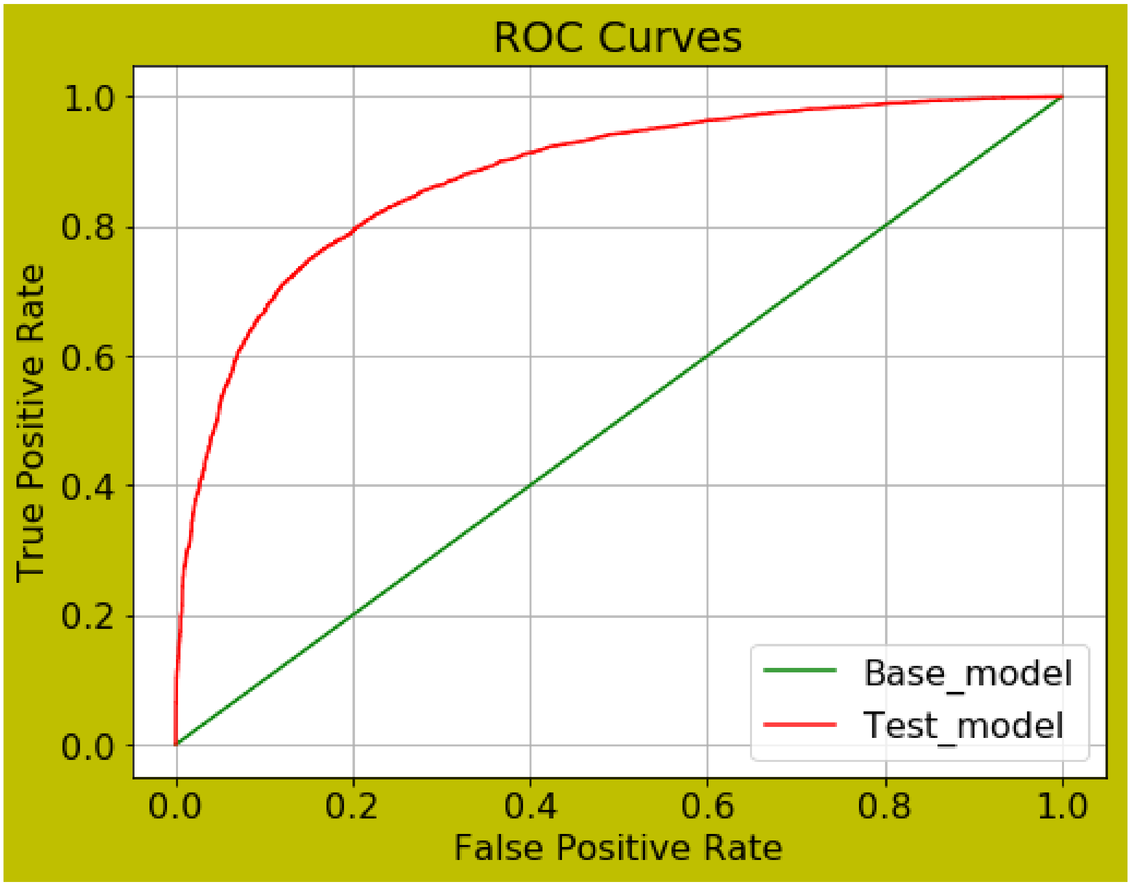
In [106]:
```
print(classification_report(y_test_new,prediction1))
```

```
             precision    recall  f1-score   support

          0       0.79      0.55      0.65      3917
          1       0.81      0.93      0.87      8083

avg / total       0.80      0.81      0.80     12000
```

In [107]:
```
cm = confusion_matrix(y_test_new ,prediction1)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



```
In [108]: roc_auc_plot(clf1,y_test_new,final_w2v_count_Test)
```




```
AUC: 0.878165725138325
```

```
In [109]: models_performence1 = {
              'Model':['Random Forest'],
              'Vectorizer': ['Avg word2vec'],
              'Optimal_Base_learners':[Best_n_estimators],
              'Best_criterion':[Best_criterion],
              'Best_max_features':[Best_max_features],
              'Best_max_depth':[Best_max_depth],
              'Training error':[training_error],
              'Test error':[Testing_error],
              'Accuracy':[Testing_score],
              'F1':[F1_score],
              'recall':[recall],
              'precision':[precision]


          }
```

```
In [110]: columns = ["Model","Vectorizer", "Optimal_Base_learners","Best_criterion","Best_max_fe
                     "Best_max_depth","Training error",  "Test error",
                      "Accuracy","F1","recall","precision",
                    ]
          df=pd.DataFrame(models_performence1, columns=columns)
          result_display(df)
```

```
|    Model    | Vectorizer |Optimal_Base_learners|Best_criterion|Best_max_features|Best_max_dept
|-------------|------------|--------------------:|--------------|-----------------|-------------
|Random Forest|Avg word2vec|                  150|gini          |sqrt             |            1
```

5.3 Observation

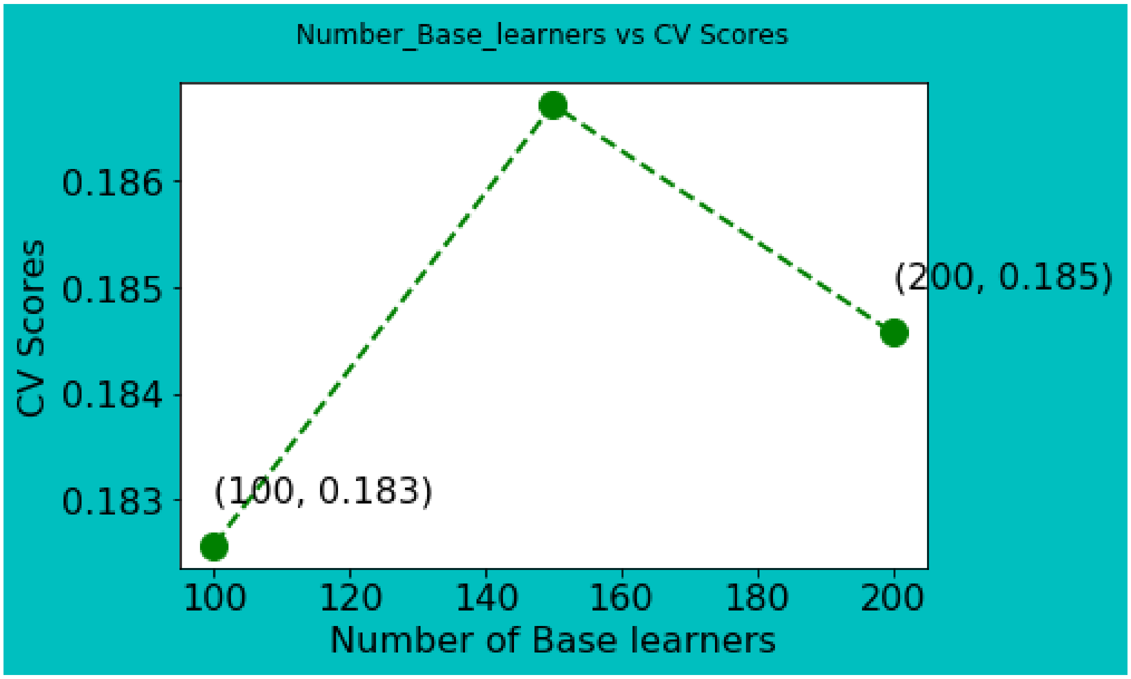
Model	Vectorizer	Optimal_Base_learners	Best_criterion	Best_max_features	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
Random Forest	Avg word2vec	150	gini	sqrt	14	0.02139	0.1942	0.8058	75.77	74.04	80.02

- For given random Forest model , AUC is 0.878.
- The ROC curve is as shown above.
- TPR & TNR is high and FPR & FNR is low as seen in confusion matrix.
- Random Forest for Avg word2vec works very well.

5.4 Optimal Base_learners,depth size & Learning Rate using Avg Word2Vec

```
In [73]: warnings.filterwarnings("ignore")
         Optimal_BL_Depth_LR(final_w2v_count_Train,Train_data)
```

```
Optimal_estim_GBDT=== XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=14, min_child_weight=1, missing=None, n_estimators=200,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)

The optimal parameter for GBDT is === {'learning_rate': 0.1, 'max_depth': 14, 'n_estimators': 20
```



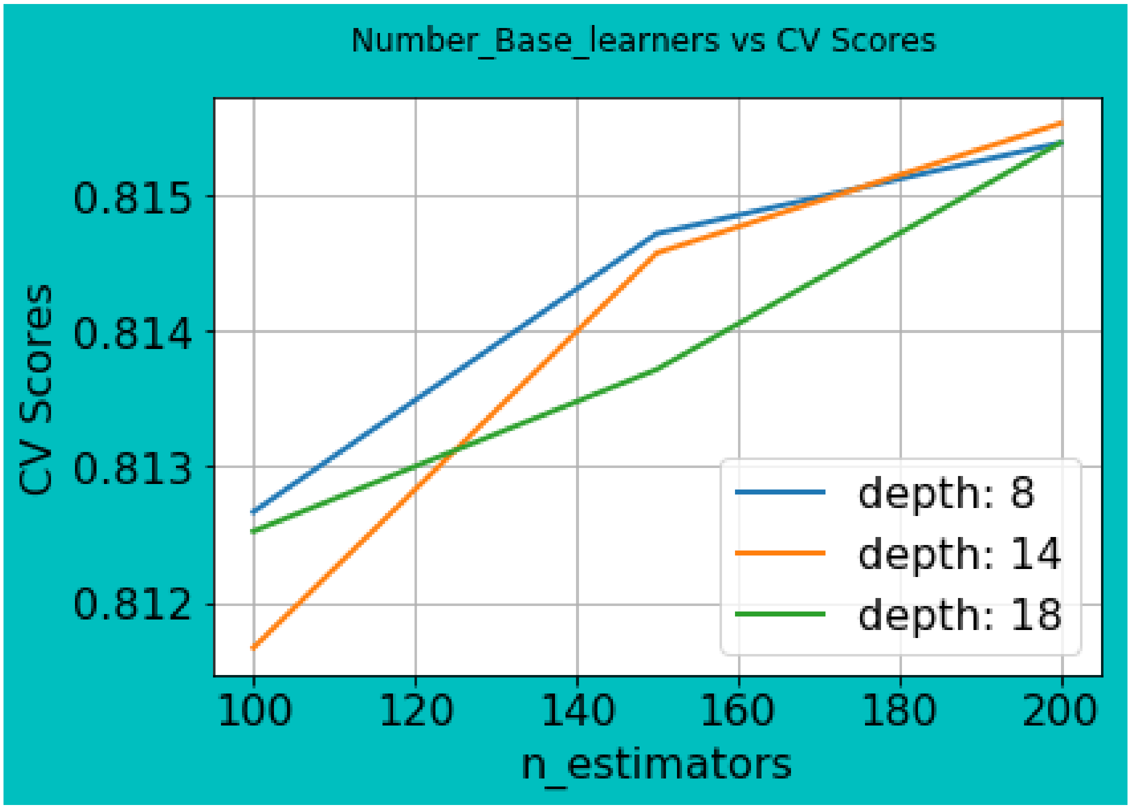

```
the misclassification error for each Base learners is :  [0.18257 0.18671 0.18457]
```

Base_learners graph with different depth size

```
In [31]: GBDT_model = XGBClassifier(class_weight='balanced' )
```

```
In [75]: clf_perform_depth(GBDT_model,final_w2v_count_Train ,Train_data)
```

```
[0.81266667 0.81471429 0.81538095 0.81166667 0.81457143 0.81552381
 0.81252381 0.81371429 0.81538095]
[8, 14, 18]
[8, 14, 18]
[8, 14, 18]
```

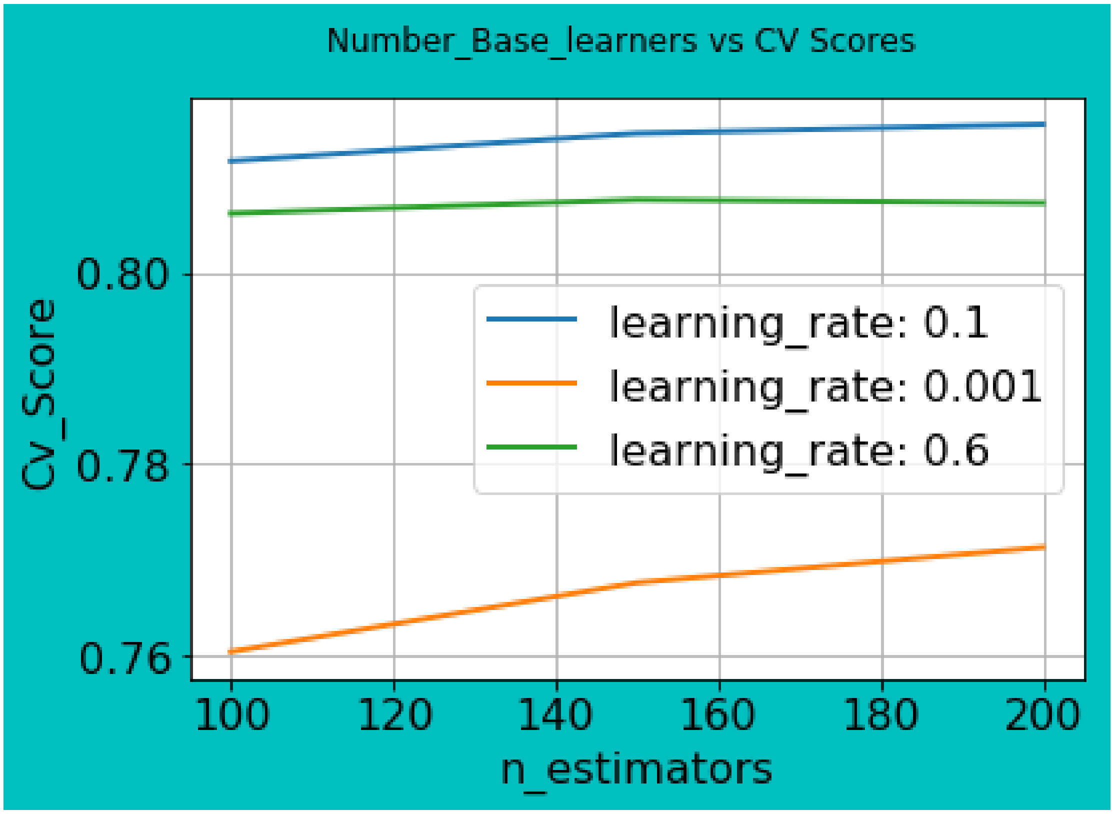



```
In [33]: print("Best Parameters for GBDT is ",Optimal_param_GBDT)

         Best_learning_rate=Optimal_param_GBDT.get('learning_rate')
         Best_n_estimators=Optimal_param_GBDT.get('n_estimators')
         Best_max_depth=Optimal_param_GBDT.get('max_depth')
```

```
Best Parameters for GBDT is  {'learning_rate': 0.1, 'max_depth': 14, 'n_estimators': 200}
```

```
In [76]: GBDT_LR(Best_max_depth,final_w2v_count_Train ,Train_data)
```

```
3it [00:00, 151.43it/s]
```



5.4.1 Observation

- The optimal Base Learners is 200 ,Depth size=14 & Learning_Rate=0.1
- Misclassification error in GBDT is almost similar as seen in graph .
- The graphs for Number of base learners Vs Score with different depth size and learning rate is seen

5.4.2 GBDT Model for optimal Parameters using Avg word2vec

In [34]:
```
# GBDT classifier for optimal depth using gini index
GBDT_clf1 = XGBClassifier(n_estimators=Best_n_estimators,
                          learning_rate=Best_learning_rate,
                            max_depth=Best_max_depth,
                          scoring="sqrt",
                          n_jobs=-1, verbose=1)
GBDT_clf1.fit(final_w2v_count_Train,Train_data)
```

Out[34]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=14, min_child_weight=1, missing=None, n_estimators=200,
       n_jobs=-1, nthread=None, objective='binary:logistic',
       random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
       scoring='sqrt', seed=None, silent=True, subsample=1, verbose=1)
```

In [35]:
```
prediction11= GBDT_clf1.predict(final_w2v_count_Test)
#print(prediction11)
```

```
/usr/local/lib/python3.6/site-packages/sklearn/preprocessing/label.py:151: DeprecationWarning: T
  if diff:
```

In [36]:
```
#Training accuracy and training error
training_score=GBDT_clf1.score(final_w2v_count_Train ,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.9995
training error is = 0.0004999999999999449
```

```
/usr/local/lib/python3.6/site-packages/sklearn/preprocessing/label.py:151: DeprecationWarning: T
  if diff:
```

In [37]:
```
# Testing Accuracy and testing error for GBDT model
Testing_score=round(accuracy_score(y_test_new ,prediction11),5)
print("Accuracy for GBDT  model with Avg word2vec is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for GBDT model with Avg word2vec is = ",Testing_error)
```

```
Accuracy for GBDT  model with Avg word2vec is =  0.66767
Testing error for GBDT model with Avg word2vec is =  0.33233
```

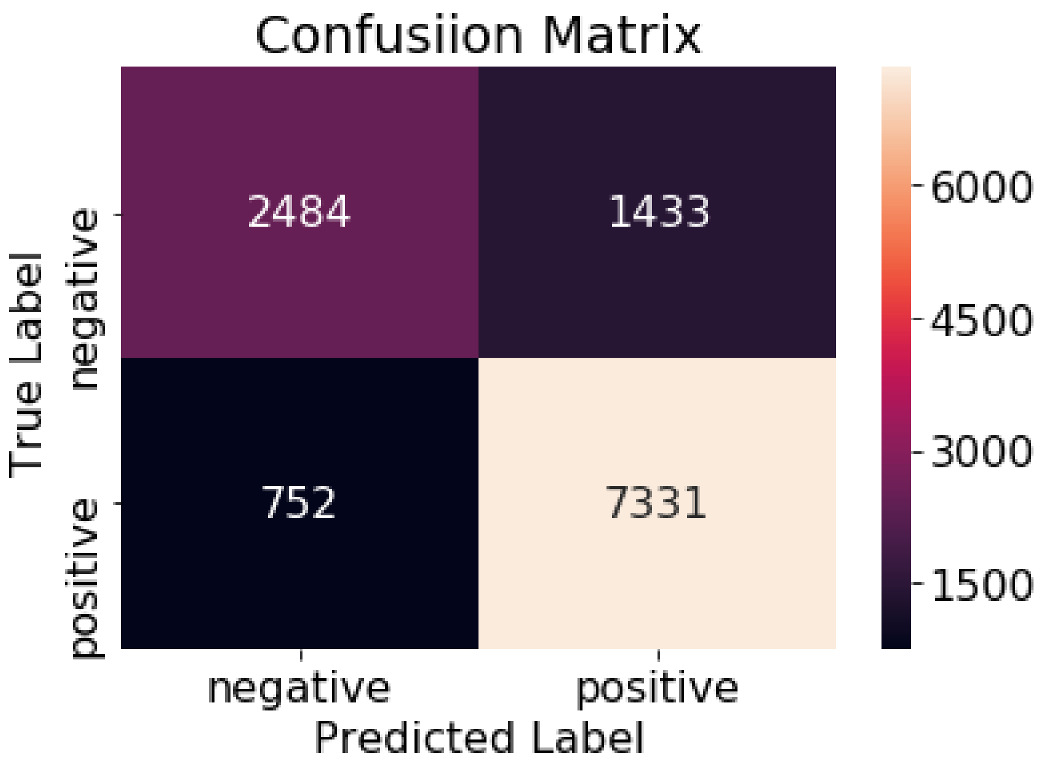
In [38]:
```
F1_score = round(f1_score(y_test_new ,prediction11,average='macro'),5)*100
recall = round(recall_score(y_test_new,prediction11,average='macro'),5)*100
precision = round(precision_score(y_test_new ,prediction11,average='macro'),5)*100
```

In [39]:
```
print(classification_report( y_test_new,prediction11))
```

```
             precision    recall  f1-score   support

          0       0.34      0.02      0.03      3932
          1       0.67      0.99      0.80      8068

avg / total       0.56      0.67      0.55     12000
```

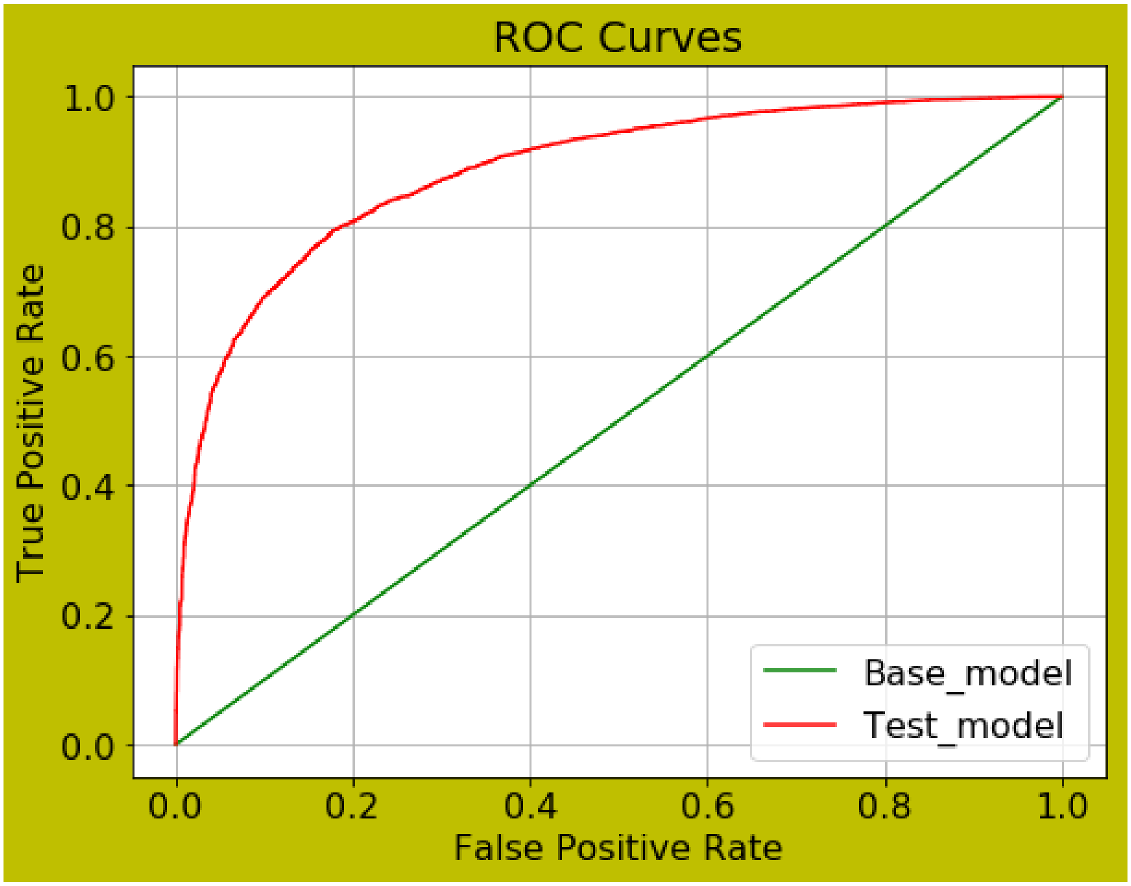
In [121]:
```
cm = confusion_matrix(y_test_new ,prediction11)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
```

```
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



5.4.3 ROC_AUC_plot

```
In [122]: roc_auc_plot(GBDT_clf1,y_test_new,final_w2v_count_Test)
```




```
AUC: 0.8863660848793337
```

```
In [123]: models_performence = {
              'Model':['GBDT'],
              'Vectorizer': ['Avg word2vec'],
              'Optimal_Base_learners':[Best_n_estimators],
              'Best_learning_rate':[Best_learning_rate],
              'Best_max_depth':[Best_max_depth],
              'Training error':[training_error],
              'Test error':[Testing_error],
              'Accuracy':[Testing_score],
              'F1':[F1_score],
              'recall':[recall],
              'precision':[precision]


          }
```

```
In [124]: columns = ["Model","Vectorizer", "Optimal_Base_learners","Best_learning_rate","Best_ma
                     "Training error",  "Test error",
```

```
                    "Accuracy","F1","recall","precision",
                  ]
        df1=pd.DataFrame(models_performence, columns=columns)
        result_display(df1)
```

```
|Model| Vectorizer |Optimal_Base_learners|Best_learning_rate|Best_max_depth|Training error|Test
|-----|------------|--------------------:|-----------------:|-------------:|-------------:|-----
|GBDT |Avg word2vec|                  200|               0.1|            14|      0.000071|    0
```

5.5 Observation:

Model	Vectorizer	Optimal_Base_learners	Best_learning_rate	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
GBDT	Avg word2vec	200	0.1	14	0.000071	0.1821	0.8179	78.24	77.06	80.20

- For given GBDT model AUC is 0.88
- Model performs well as TPR is too high and TNR is quite high and FPR &FNR is low as observered in Confusion Matrix.

6 2.TF-IDF weighted Word2Vec

```
In [40]: from sklearn.decomposition import TruncatedSVD

         svd = TruncatedSVD(n_components=100)

In [41]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
         final_tf_idf11 = tf_idf_vect.fit_transform(X_train_data.values.ravel())
         final_tf_idf11.get_shape()

Out[41]: (28000, 496181)

In [127]: final_tf_idf=svd.fit_transform(final_tf_idf11 )
          print("TruncatedSVD :",final_tf_idf.shape)

TruncatedSVD : (28000, 100)


In [59]: tfidf_feat = tf_idf_vect.get_feature_names()
         w2v_words = list(w2v_model.wv.vocab)
         dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))

In [129]: list_of_sent=[]
          for sent in tqdm(X_train_data.values.ravel()):
              list_of_sent.append(sent.decode("utf-8").split())
```

```
100%|??????????| 28000/28000 [00:00<00:00, 197925.22it/s]
```

```
In [130]: # TF-IDF weighted Word2Vec
          tfidf_feat =tf_idf_vect.get_feature_names() # tfidf words/col-names

          tfidf_sent_vectors = [];
          row=0;
          for sent in tqdm(list_of_sent):
              sent_vec = np.zeros(100)
              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
              tfidf_sent_vectors .append(sent_vec)
              row += 1
```

```
100%|??????????| 28000/28000 [00:55<00:00, 503.67it/s]
```

```
In [131]: print(len(tfidf_sent_vectors))
```

```
28000
```

```
In [132]: tfidf_sent_vectors_train  = np.where(np.isnan(tfidf_sent_vectors ), 0, tfidf_sent_vect
```

```
In [133]: tfidf_sent_vectors_train  = np.asarray(tfidf_sent_vectors_train )
          print(type(tfidf_sent_vectors))
```

```
<class 'list'>
```

Dumping & Loading Pickle file for trainText data (TF-IDF weighted word2vec)

```
In [134]: pickle_path_tfidf_weighted='X_data_tfidf_weighted.pkl'
          X_data_tfidf_weighted=open(pickle_path_tfidf_weighted,'wb')
          pickle.dump(tfidf_sent_vectors_train  ,X_data_tfidf_weighted)
          X_data_tfidf_weighted.close()
```

```
In [135]: pickle_path_tfidf_weighted='X_data_tfidf_weighted.pkl'
          unpickle_path7=open(pickle_path_tfidf_weighted,'rb')
          tfidf_sent_vectors_train =pickle.load(unpickle_path7)
```

In [136]:
```
final_tfidf_w2v_np_train=tfidf_sent_vectors_train
print(final_tfidf_w2v_np_train.shape)
```

```
(28000, 100)
```

For test Tf-idf weighted word2vec

In [137]:
```
list_of_sent1=[]
for sent in tqdm(X_test_data.values.ravel()):
    list_of_sent1.append(sent.decode("utf-8").split())
```

```
100%|??????????| 12000/12000 [00:00<00:00, 131725.14it/s]
```

In [138]:
```
# TF-IDF weighted Word2Vec
tfidf_feat =tf_idf_vect.get_feature_names() # tfidf words/col-names

tfidf_sent_vectors1 = [];
row=0;
for sent in tqdm(list_of_sent1):
    sent_vec = np.zeros(100)
    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
    tfidf_sent_vectors1 .append(sent_vec)
    row += 1
```

```
100%|??????????| 12000/12000 [00:26<00:00, 461.14it/s]
```

In [139]:
```
tfidf_sent_vectors_test  = np.where(np.isnan(tfidf_sent_vectors1 ),
                                    0, tfidf_sent_vectors1 )

final_tfidf_w2v_np_test = np.asarray(tfidf_sent_vectors_test )
```

Dumping & Loading Pickle file for test Text data (TF-IDF weighted word2vec)

In [140]:
```
pickle_path_tfidf_weighted1='X_data_tfidf_weighted_test.pkl'
X_data_tfidf_weighted1=open(pickle_path_tfidf_weighted1,'wb')
pickle.dump(final_tfidf_w2v_np_test  ,X_data_tfidf_weighted1)
X_data_tfidf_weighted1.close()
```

```
In [141]: pickle_path_tfidf_weighted1='X_data_tfidf_weighted_test.pkl'
          unpickle_path71=open(pickle_path_tfidf_weighted1,'rb')
          final_tfidf_w2v_np_test1 =pickle.load(unpickle_path71)
```

```
In [142]: final_tfidf_w2v_np_test=final_tfidf_w2v_np_test1
```

```
In [143]: joblib.dump(final_tfidf_w2v_np_train, 'tfidf_weighted_train.joblib')
          joblib.dump(final_tfidf_w2v_np_test, 'tfidf_weighted_test.joblib')
```

```
Out[143]: ['tfidf_weighted_test.joblib']
```

```
In [42]: final_tfidf_w2v_np_train = joblib.load('tfidf_weighted_train.joblib')
         final_tfidf_w2v_np_test = joblib.load('tfidf_weighted_test.joblib')
```

for Training Data:

```
final_tfidf_w2v_np_train
```

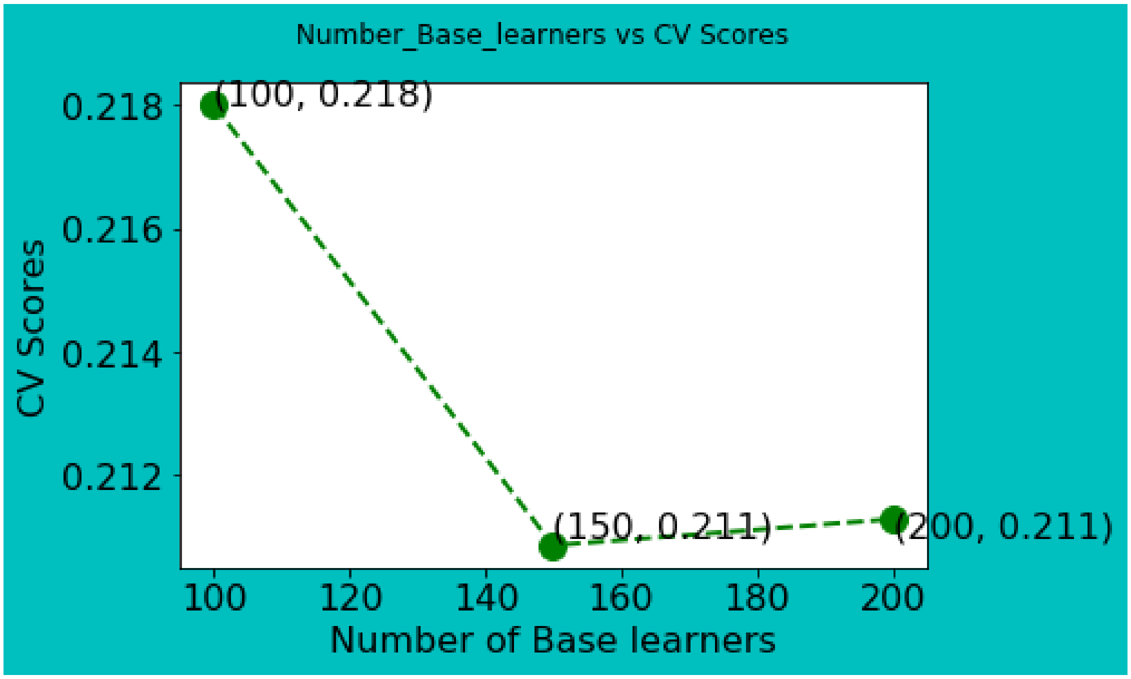
For testing data:

```
final_tfidf_w2v_np_test
```

6.1 Optimal Base_learners for Random Forest using TF-IDF weighted Word2Vec

```
In [110]: Optimal_Depth_Tree1=Optimal_Base_learners(final_tfidf_w2v_np_train ,Train_data)
```

```
optimal_estim== RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=14, max_features='log2',
            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=True, random_state=None,
            verbose=0, warm_start=False)
Mean of score: 0.7866190476190477
Variance of scores: 1.0698412698412597e-05

The optimal Best_parameters for Random Forest is ===  {'criterion': 'gini', 'max_depth': 14, 'ma
```



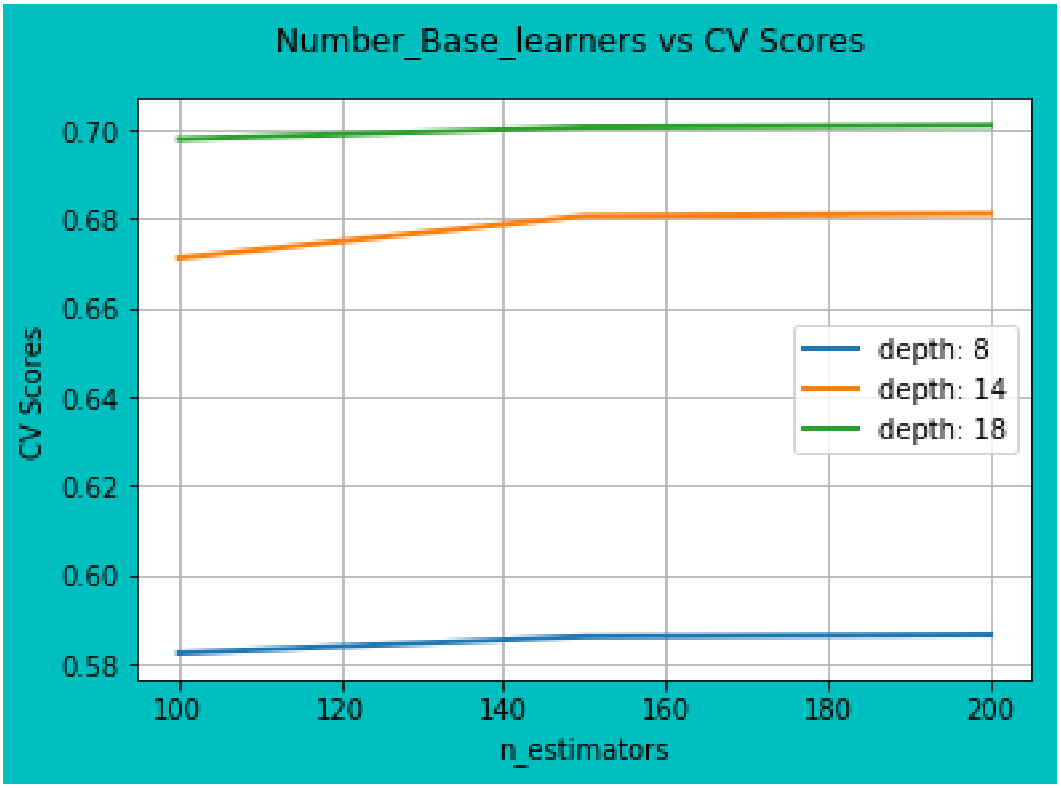

```
the misclassification error for each Base learners is :  [0.218   0.21086 0.21129]
```

Base_learners graph with different depth size

```
In [43]: random_forest = RandomForestClassifier( n_jobs =-1,
                                             class_weight='balanced' ,
                                             bootstrap=True,
                                             oob_score = True)
```

```
In [46]: clf_perform_depth(random_forest,final_tfidf_w2v_np_train ,Train_data)
```

```
[0.58238095 0.58609524 0.58657143 0.67119048 0.68057143 0.68114286
 0.69785714 0.70057143 0.701     ]
[8, 14, 18]
[8, 14, 18]
[8, 14, 18]
```



6.2 Random Forest for optimal Parametersusing TF-IDF weighted Word2Vec

In [146]:
```
optimal_parameters_RF={'criterion': 'gini', 'max_depth': 14, 'max_features': 'log2', '
```

In [147]:
```
#print("Best Parameters for Random Forest is ",optimal_parameters_RF)
Best_criterion=optimal_parameters_RF.get('criterion')
Best_max_features=optimal_parameters_RF.get('max_features')
Best_n_estimators=optimal_parameters_RF.get('n_estimators')
Best_max_depth=optimal_parameters_RF.get('max_depth')
```

In [148]:
```
RF_clf2 = RandomForestClassifier(n_estimators=Best_n_estimators,max_depth=Best_max_dep
                                max_features=Best_max_features, random_state=0,n_jobs=
RF_clf2.fit(final_tfidf_w2v_np_train,Train_data)
RF2=RF_clf2.fit(final_tfidf_w2v_np_train,Train_data)
```

In [149]:
```
prediction2= RF_clf2.predict(final_tfidf_w2v_np_test)
```

In [150]:
```
#Training accuracy and training error
training_score=RF_clf2.score(final_tfidf_w2v_np_train,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.9718214285714286
training error is = 0.028178571428571386
```

In [151]:
```
# Testing Accuracy and testing error for Random Forest model
Testing_score=round(accuracy_score(y_test_new ,prediction2),5)
print("Accuracy for Random Forest model with TF-IDF weighted Word2Vec is = ",Testing_s
Testing_error=1-Testing_score
print("Testing error for Random Forest model with TF-IDF weighted Word2Vec is = ",Test
```

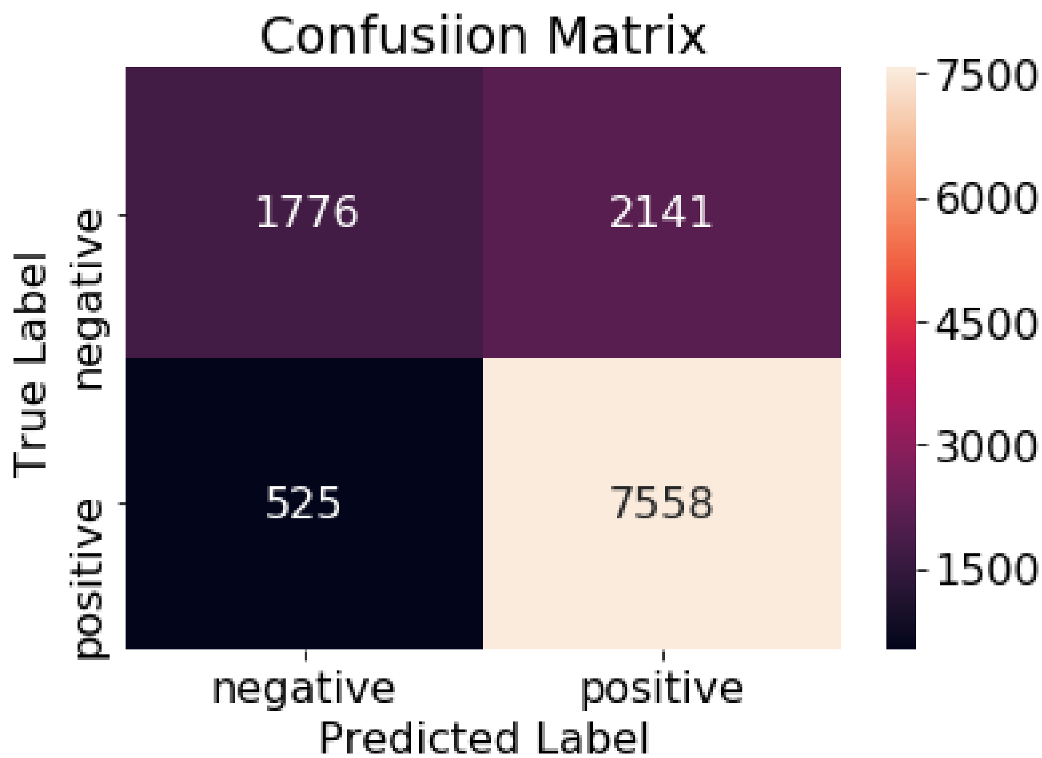
```
Accuracy for Random Forest model with TF-IDF weighted Word2Vec is =  0.77783
Testing error for Random Forest model with TF-IDF weighted Word2Vec is =  0.22216999999999998
```

In [152]:
```
F1_score = round(f1_score(y_test_new ,prediction2,average='macro'),5)*100
recall = round(recall_score(y_test_new,prediction2,average='macro'),5)*100
precision = round(precision_score(y_test_new ,prediction2,average='macro'),5)*100
```

In [153]:
```
print(classification_report( y_test_new,prediction2))
```

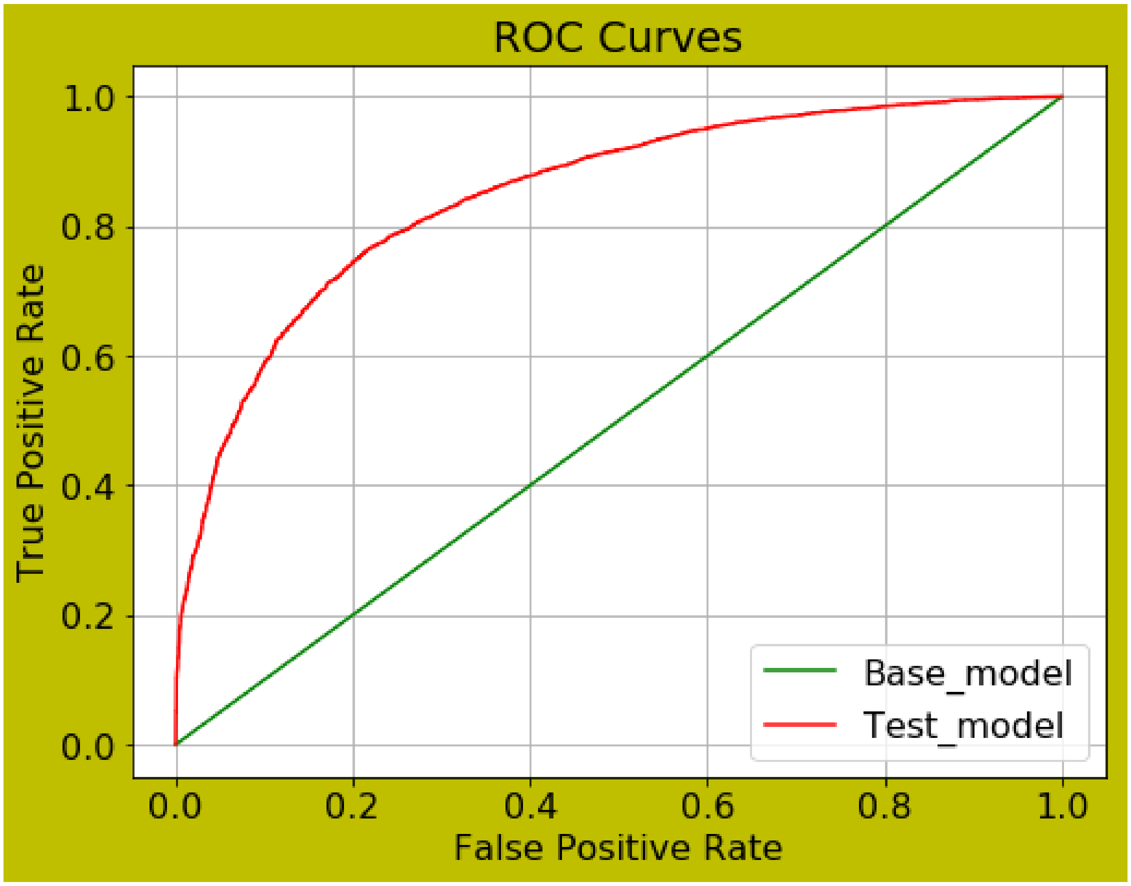
```
             precision    recall  f1-score   support

          0       0.77      0.45      0.57      3917
          1       0.78      0.94      0.85      8083

avg / total       0.78      0.78      0.76     12000
```

In [154]:
```
cm = confusion_matrix(y_test_new,prediction2)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



6.2.1 ROC_AUC_plot

```
In [155]: roc_auc_plot(RF_clf2,y_test_new,final_tfidf_w2v_np_test)
```




```
AUC: 0.8494367585521556
```

```
In [156]: models_performence1['Model'].append('Random Forest')
          models_performence1['Vectorizer'].append('TF-IDF weighted word2vec')
          models_performence1['Optimal_Base_learners'].append(Best_n_estimators)
          models_performence1['Best_criterion'].append(Best_criterion)
          models_performence1['Best_max_features'].append(Best_max_features)
          models_performence1['Best_max_depth'].append(Best_max_depth)
          models_performence1['Training error'].append(training_error)
          models_performence1[ 'Test error'].append(Testing_error)
          models_performence1[ 'Accuracy'].append(Testing_score)
          models_performence1[ 'F1'].append(F1_score)
          models_performence1['recall'].append(recall)
          models_performence1[ 'precision'].append(precision)
```

```
In [157]: columns = ["Model","Vectorizer", "Optimal_Base_learners","Best_criterion","Best_max_fe
                     "Best_max_depth","Training error",  "Test error",
                      "Accuracy","F1","recall","precision",
                    ]
```

```
df2=pd.DataFrame(models_performence1, columns=columns)
result_display(df2)
```

```
|    Model    |       Vectorizer       |Optimal_Base_learners|Best_criterion|Best_max_features|B
|-------------|------------------------|--------------------:|--------------|-----------------|-
|Random Forest|Avg word2vec            |                  150|gini          |sqrt             |
|Random Forest|TF-IDF weighted word2vec|                  200|gini          |log2             |
```

6.3 Observation:

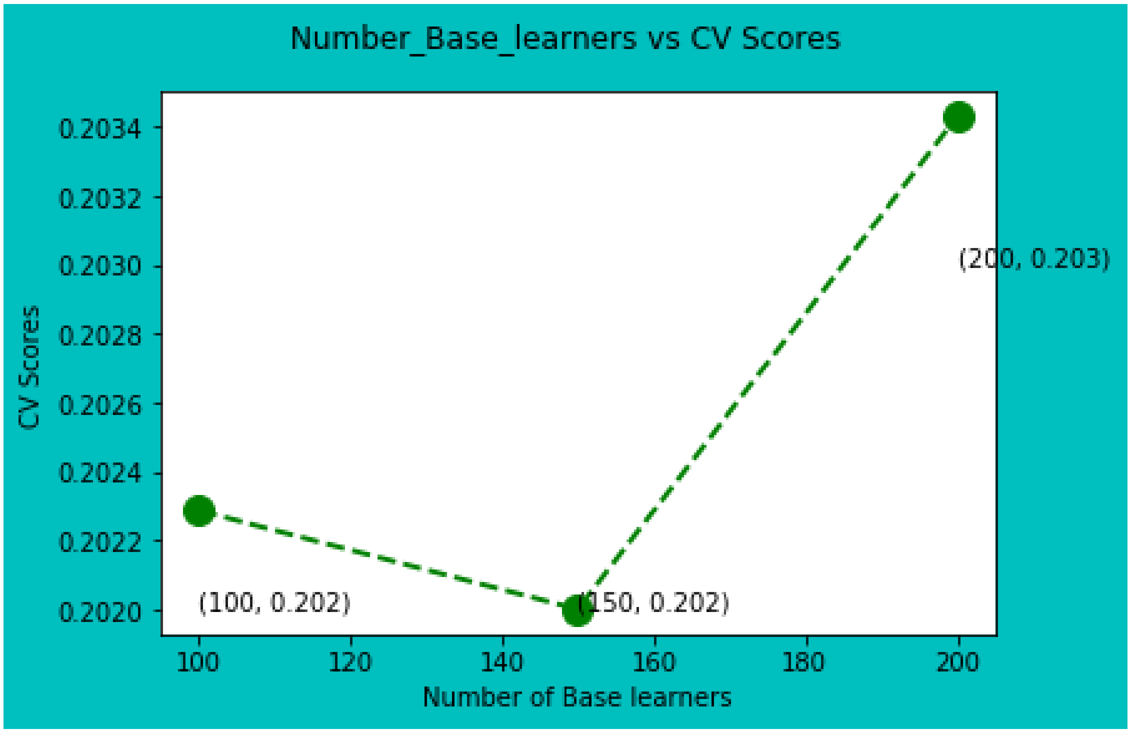
Model	Vectorizer	Optimal_Base_learners	Best_criterion	Best_max_features	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
Random Forest	Avg word2vec	150	gini	sqrt	14	0.02139	0.1942	0.8058	75.77	74.04	80.02
Random Forest	TF-IDF weighted word2vec	200	gini	log2	14	0.02818	0.2222	0.7778	71.07	69.42	77.55

- For given Random Forest , AUC is 0.849 .
- TPR is high and FPR & TNR is almost similar.But ROC graph & AUC is quite good.

6.4 Optimal Base_learners,depth size & Learning Rate using TF-IDF Avg Word2Vec

```
In [82]: warnings.filterwarnings("ignore")
         Optimal_BL_Depth_LR(final_tfidf_w2v_np_train,Train_data)
```

```
Optimal_estim_GBDT=== XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=8, min_child_weight=1, missing=None, n_estimators=200,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)

The optimal parameter for GBDT is === {'learning_rate': 0.1, 'max_depth': 8, 'n_estimators': 200
```

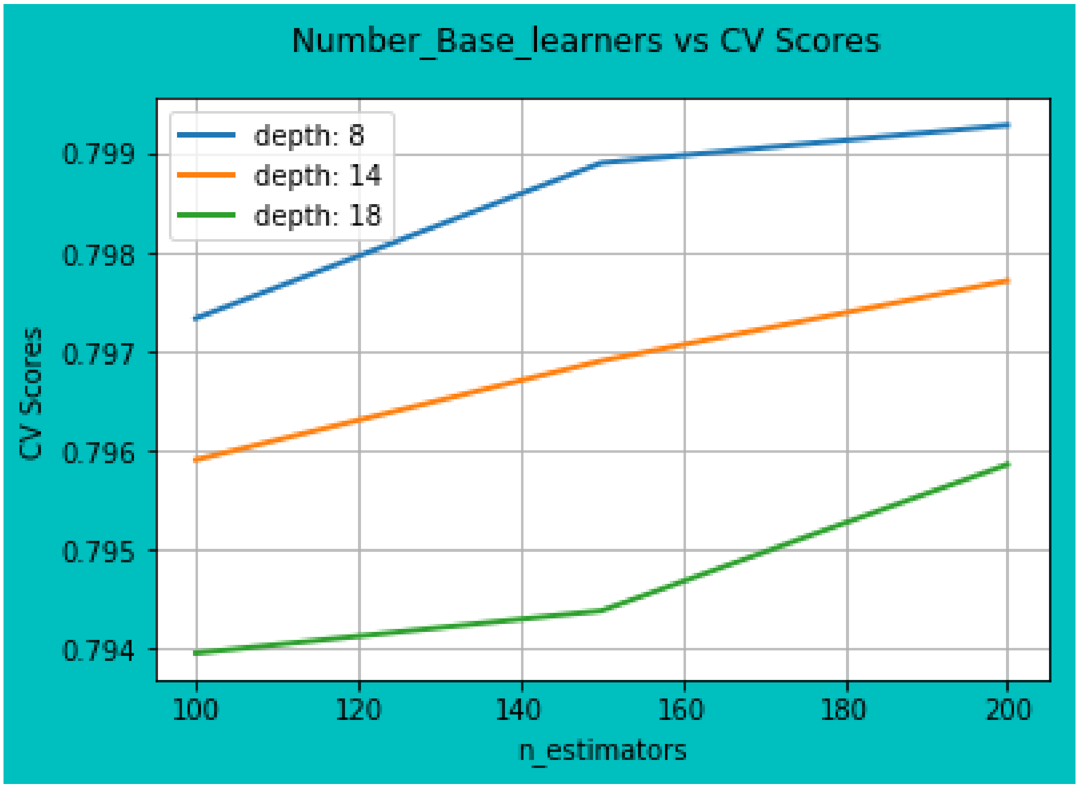



```
the misclassification error for each Base learners is :  [0.20229 0.202   0.20343]
```

Base_learners graph with different depth size

```
In [83]: clf_perform_depth(GBDT_model,final_tfidf_w2v_np_train ,Train_data)
```

```
[0.79733333 0.79890476 0.79928571 0.79590476 0.79690476 0.79771429
 0.79395238 0.79438095 0.79585714]
[8, 14, 18]
[8, 14, 18]
[8, 14, 18]
```



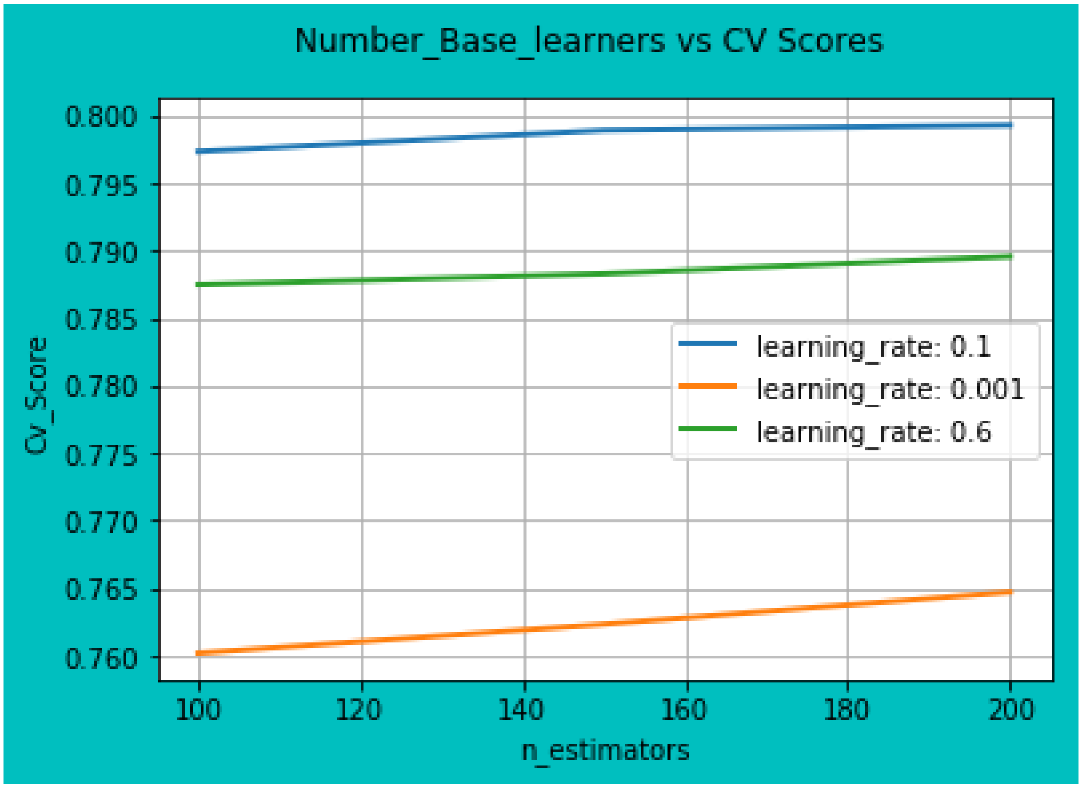
6.5 GBDT Model for optimal Parameters

```
In [45]: print("Best Parameters for GBDT is ",Optimal_param_GBDT)

         Best_learning_rate=Optimal_param_GBDT.get('learning_rate')
         Best_n_estimators=Optimal_param_GBDT.get('n_estimators')
         Best_max_depth=Optimal_param_GBDT.get('max_depth')
```

```
Best Parameters for GBDT is  {'learning_rate': 0.1, 'max_depth': 8, 'n_estimators': 200}
```

```
In [85]: GBDT_LR(Best_max_depth,final_tfidf_w2v_np_train ,Train_data)
```

```
3it [00:00, 149.60it/s]
```




```
In [46]: # GBDT classifier for optimal parametrs

         GBDT_clf12 = XGBClassifier(n_estimators=Best_n_estimators,
                                    learning_rate=Best_learning_rate,
                                         max_depth=Best_max_depth,
                                    scoring="sqrt",
                                   n_jobs=-1, cv=tscv, verbose=1)
         GBDT_clf12.fit(final_tfidf_w2v_np_train, Train_data)
```

```
Out[46]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                colsample_bytree=1,
                cv=TimeSeriesSplit(max_train_size=None, n_splits=3), gamma=0,
                learning_rate=0.1, max_delta_step=0, max_depth=8,
                min_child_weight=1, missing=None, n_estimators=200, n_jobs=-1,
                nthread=None, objective='binary:logistic', random_state=0,
                reg_alpha=0, reg_lambda=1, scale_pos_weight=1, scoring='sqrt',
                seed=None, silent=True, subsample=1, verbose=1)
```

```
In [161]: prediction12= GBDT_clf12.predict(final_tfidf_w2v_np_test)
```

```
/usr/local/lib/python3.6/site-packages/sklearn/preprocessing/label.py:151: DeprecationWarning: T
  if diff:
```

In [162]:
```
#Training accuracy and training error
training_score=GBDT_clf12.score(final_tfidf_w2v_np_train,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.99475
training error is = 0.005249999999999977
```

```
/usr/local/lib/python3.6/site-packages/sklearn/preprocessing/label.py:151: DeprecationWarning: T
  if diff:
```

In [163]:
```
# Testing Accuracy and testing error for GBDT model
Testing_score=round(accuracy_score(y_test_new,prediction12),5)
print("Accuracy for GBDT model with Avg word2vec is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for GBDT model with Avg word2vec is = ",Testing_error)
```

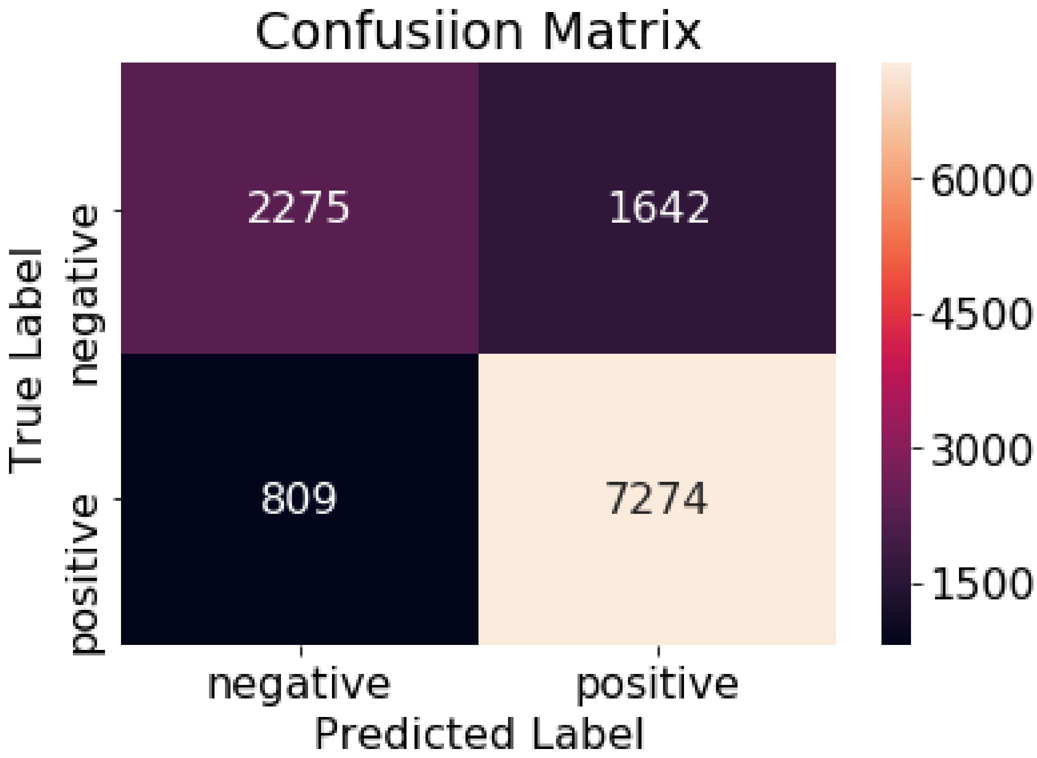
```
Accuracy for GBDT model with Avg word2vec is =  0.79575
Testing error for GBDT model with Avg word2vec is =  0.20425000000000004
```

In [164]:
```
F1_score = round(f1_score(y_test_new,prediction12,average='macro'),5)*100
recall = round(recall_score(y_test_new,prediction12,average='macro'),5)*100
precision = round(precision_score(y_test_new ,prediction12,average='macro'),5)*100
```

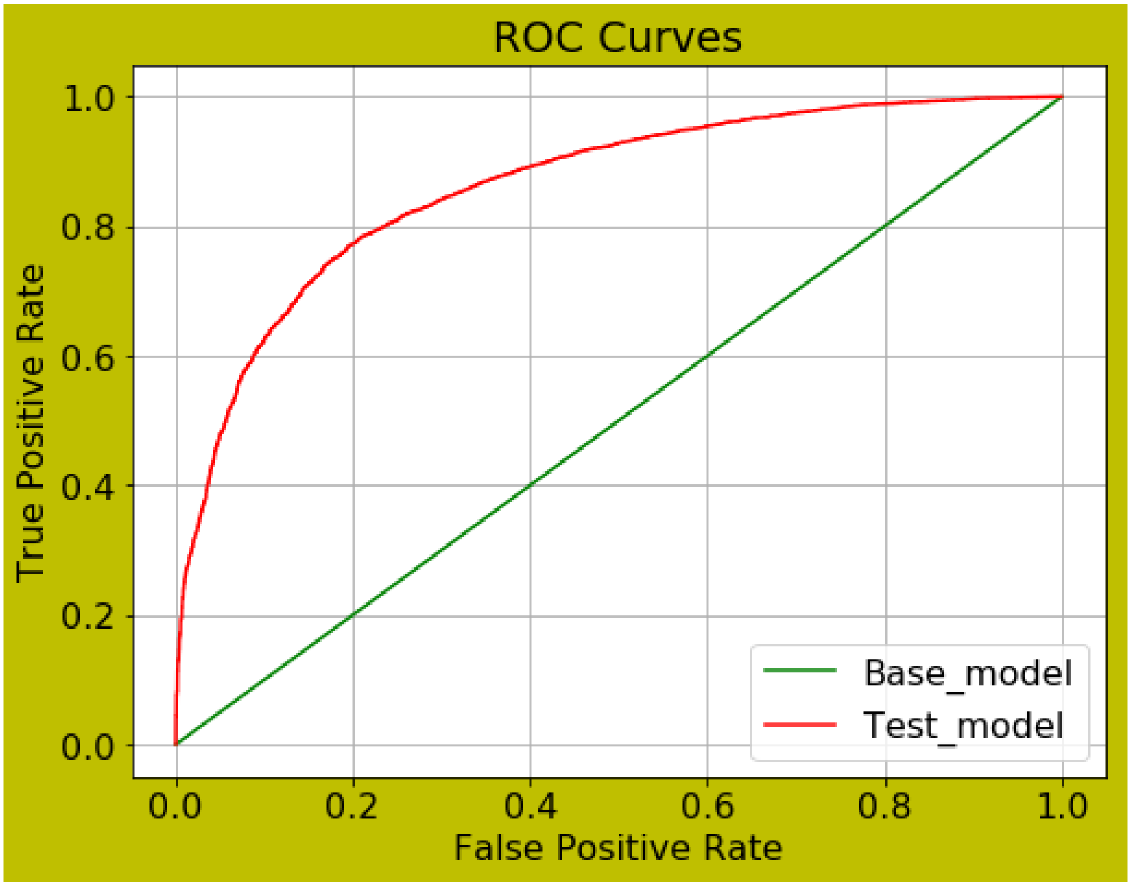
In [165]:
```
print(classification_report( y_test_new,prediction12))
```

```
             precision    recall  f1-score   support

          0       0.74      0.58      0.65      3917
          1       0.82      0.90      0.86      8083

avg / total       0.79      0.80      0.79     12000
```

In [166]:
```
cm = confusion_matrix(y_test_new,prediction12)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```




```
In [167]: roc_auc_plot(GBDT_clf12,y_test_new,final_tfidf_w2v_np_test)
```



AUC: 0.8622118945857585

```
In [168]: models_performence['Model'].append('GBDT')
          models_performence['Vectorizer'].append('TF-IDF weighted word2vec')
          models_performence['Optimal_Base_learners'].append(Best_n_estimators)
          models_performence['Best_learning_rate'].append(Best_learning_rate)
          models_performence['Best_max_depth'].append(Best_max_depth)
          models_performence['Training error'].append(training_error)
          models_performence[ 'Test error'].append(Testing_error)
          models_performence[ 'Accuracy'].append(Testing_score)
          models_performence[ 'F1'].append(F1_score)
          models_performence['recall'].append(recall)
          models_performence[ 'precision'].append(precision)
```

```
In [169]: columns = ["Model","Vectorizer", "Optimal_Base_learners","Best_learning_rate","Best_ma
                    "Training error",  "Test error",
                      "Accuracy","F1","recall","precision",
                    ]
          df4=pd.DataFrame(models_performence, columns=columns)
```

6.6 Observation

Model	Vectorizer	Optimal_Base_learners	Best_learning_rate	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
GBDT	Avg word2vec	200	0.1	14	0.000071	0.1821	0.8179	78.24	77.06	80.20
GBDT	TF-IDF weighted word2vec	200	0.1	8	0.005250	0.2043	0.7957	75.29	74.04	77.68

- ROC & AUC=0.862 for given GBDT model which is good comparatively GBDTusing Avg Word2vec model.
- TPR & TNR is high and FPR & FNR is low. It means model performs well.

7 3. Bag of Words (BoW)

BOW for Training Data

```
In [47]: count_vect = CountVectorizer() #in scikit-learn
         vect_Data = count_vect.fit_transform(X_train_data.values.ravel())
         print(vect_Data .shape)
```

```
(28000, 20694)
```

```
In [171]: # truncated SVD for dimesionality reduction for 100 dimensions
          svd = TruncatedSVD(n_components=100)

          final_data=svd.fit_transform(vect_Data )
          print("TruncatedSVD :",final_data.shape)
```

```
TruncatedSVD : (28000, 100)
```

Dumping & Loading Pickle file for training data (BOW)

```
In [172]: #Pickle file for training data
          import pickle
          pickle_path_BOW_train='X_train_data_BOW.pkl'
          X_train_data_BOW=open(pickle_path_BOW_train,'wb')
          pickle.dump(final_data ,X_train_data_BOW)
          X_train_data_BOW.close()
```

```
In [173]: pickle_path_BOW_train='X_train_data_BOW.pkl'
          unpickle_path1=open(pickle_path_BOW_train,'rb')
          final_data=pickle.load(unpickle_path1)
```

BOW for Testing Data

```
In [174]: #vector of test data
          vect_Data1= count_vect.transform(X_test_data.values.ravel())
          print(vect_Data1.shape)


          final_data_test=svd.transform(vect_Data1)
          print("TruncatedSVD :",final_data_test.shape)

(12000, 20835)
TruncatedSVD : (12000, 100)
```

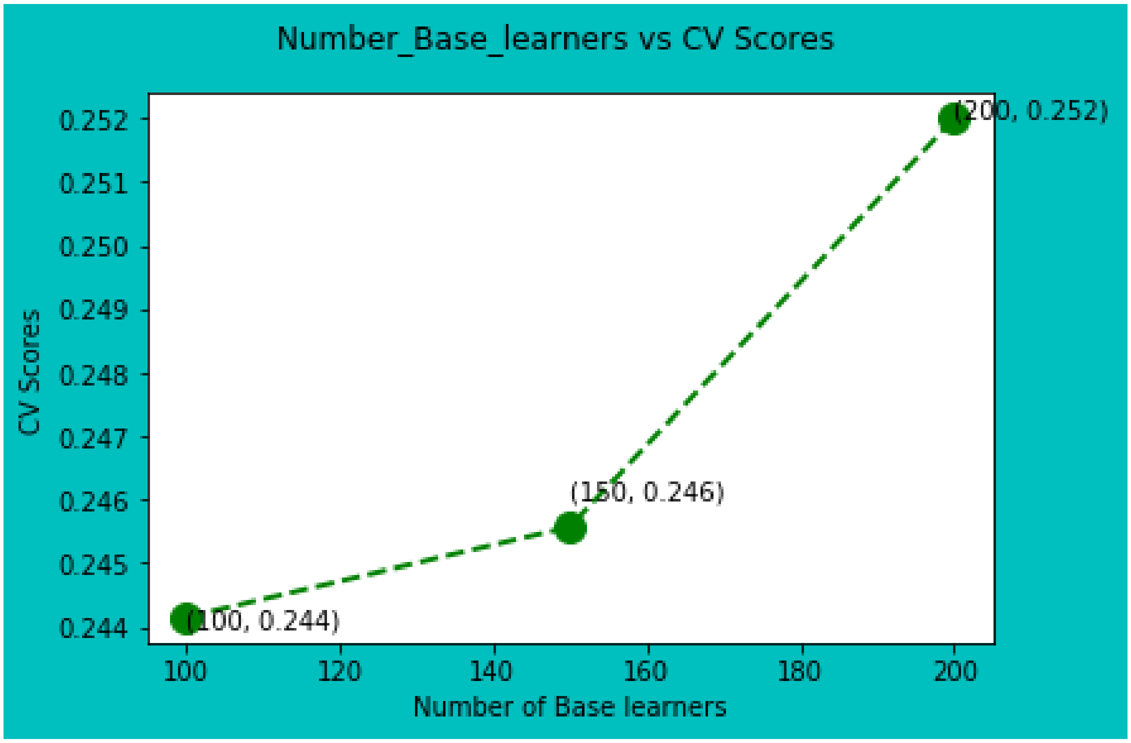
Dumping & Loading Pickle file for testing data (BOW)

```
In [175]: pickle_path_BOW_test='X_test_data_BOW.pkl'
          X_test_data_BOW=open(pickle_path_BOW_test,'wb')
          pickle.dump(final_data_test ,X_test_data_BOW)
          X_test_data_BOW.close()

In [176]: pickle_path_BOW_test='X_test_data_BOW.pkl'
          unpickle_path2=open(pickle_path_BOW_test,'rb')
          final_data_test=pickle.load(unpickle_path2)

In [177]: joblib.dump(final_data, 'BOW_train.joblib')

Out[177]: ['BOW_train.joblib']

In [178]: joblib.dump(final_data_test, 'BOW_test.joblib')

Out[178]: ['BOW_test.joblib']

In [48]: final_data = joblib.load('BOW_train.joblib')
         final_data_test = joblib.load('BOW_test.joblib')
```

7.1 Optimal Base_learners for Random Forest using BOW

```
In [48]: print(Train_data.shape)

(28000,)


In [78]: Optimal_Depth_Tree1=Optimal_Base_learners(final_data ,Train_data)

optimal_estim== RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=8, max_features='log2',
            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=150, n_jobs=-1, oob_score=True, random_state=None,
            verbose=0, warm_start=False)
Mean of score: 0.7527619047619046
Variance of scores: 1.1678004535147496e-05

The optimal Best_parameters for Random Forest is ===  {'criterion': 'gini', 'max_depth': 8, 'max
```

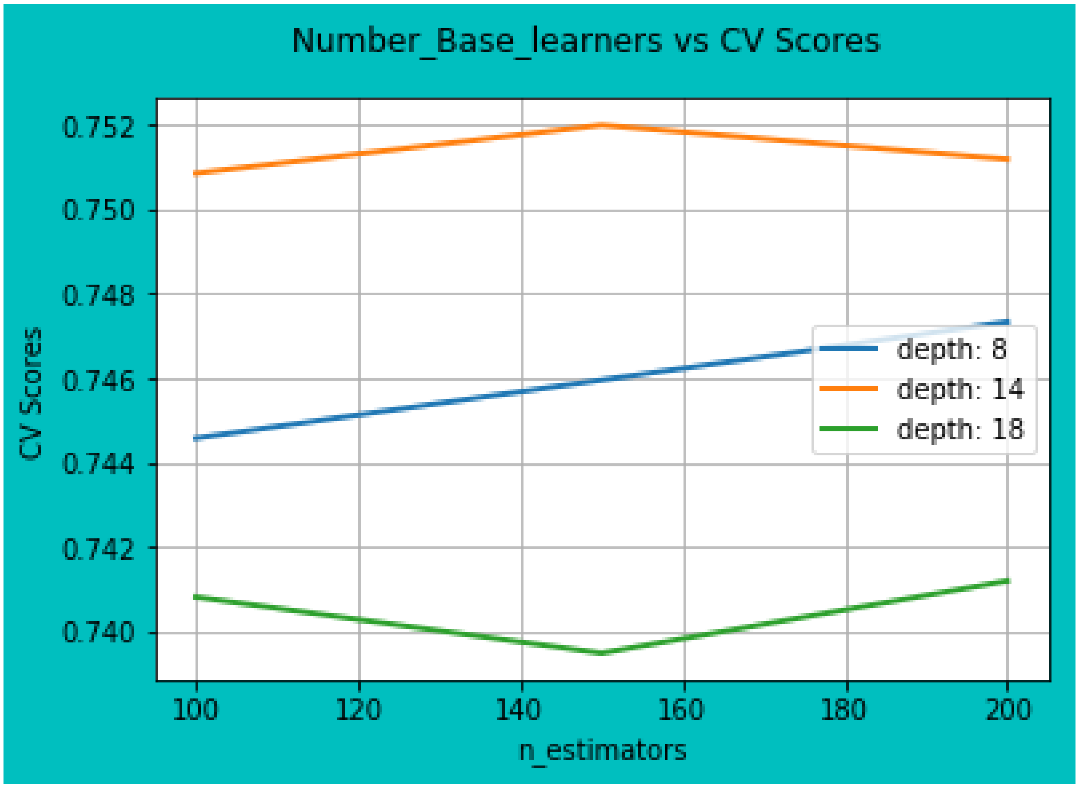



```
the misclassification error for each Base learners is :  [0.24414 0.24557 0.252  ]
```

Base_learners graph with different depth size

```
In [79]: clf_perform_depth(random_forest,final_data ,Train_data)
```

```
[0.74457143 0.74595238 0.74733333 0.75085714 0.752      0.75119048
 0.74080952 0.73947619 0.74119048]
[8, 14, 18]
[8, 14, 18]
[8, 14, 18]
```



7.2 Random Forest for optimal Parameters using BOW

In [182]:
```
print("Best Parameters for Random Forest is ",optimal_parameters_RF)
Best_criterion=optimal_parameters_RF.get('criterion')
Best_max_features=optimal_parameters_RF.get('max_features')
Best_n_estimators=optimal_parameters_RF.get('n_estimators')
Best_max_depth=optimal_parameters_RF.get('max_depth')
```

```
Best Parameters for Random Forest is  {'criterion': 'gini', 'max_depth': 8, 'max_features': 'log
```

In [183]:
```
RF_clf3 = RandomForestClassifier(n_estimators=Best_n_estimators,max_depth=Best_max_dep
                                max_features=Best_max_features, random_state=0,n_jobs=
RF_clf3.fit(final_data,Train_data)
RF3=RF_clf3.fit(final_data,Train_data)
```

In [184]:
```
prediction3= RF_clf3.predict(final_data_test)
```

In [185]:
```
#Training accuracy and training error
training_score=RF_clf3.score(final_data,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.73775
training error is = 0.26225
```

In [186]:
```python
# Testing Accuracy and testing error for Random Forest model

Testing_score=round(accuracy_score(y_test_new,prediction3),5)
print("Accuracy for Random Forest model with BOW is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for Random Forest model with BOW is = ",Testing_error)
```

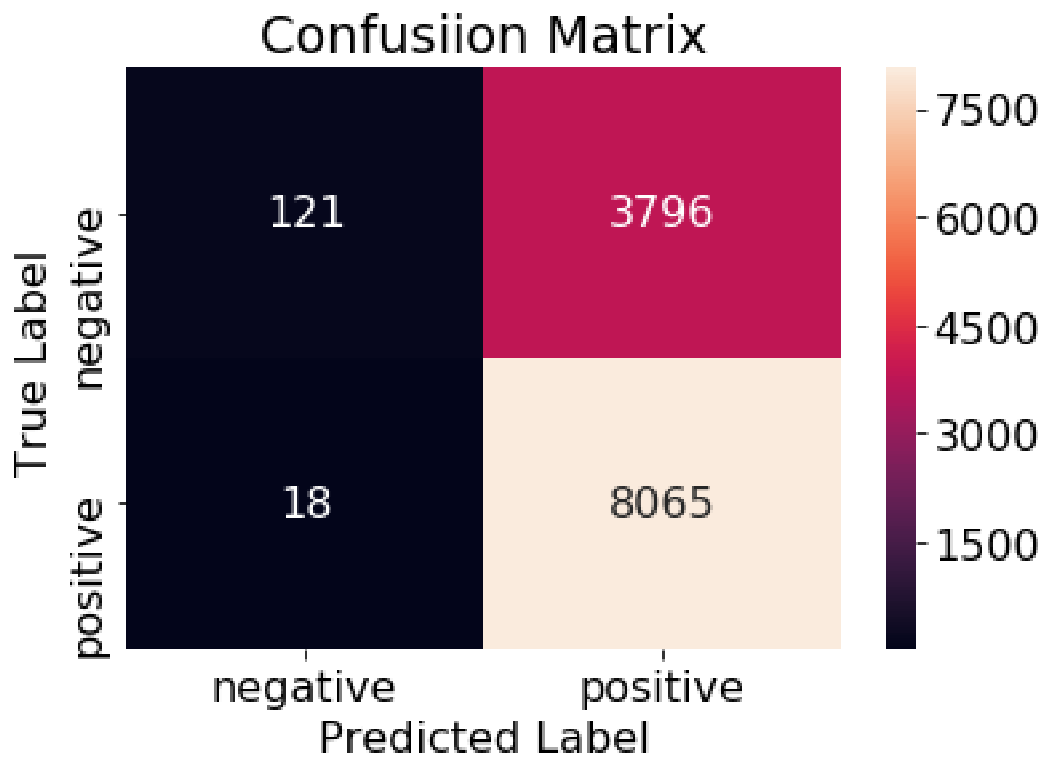
```
Accuracy for Random Forest model with BOW is =  0.68217
Testing error for Random Forest model with BOW is =  0.31782999999999995
```

In [187]:
```python
F1_score = round(f1_score(y_test_new,prediction3,average='macro'),5)*100
recall = round(recall_score(y_test_new,prediction3,average='macro'),5)*100
precision = round(precision_score(y_test_new ,prediction3,average='macro'),5)*100
```

In [188]:
```python
print(classification_report( y_test_new,prediction3))
```

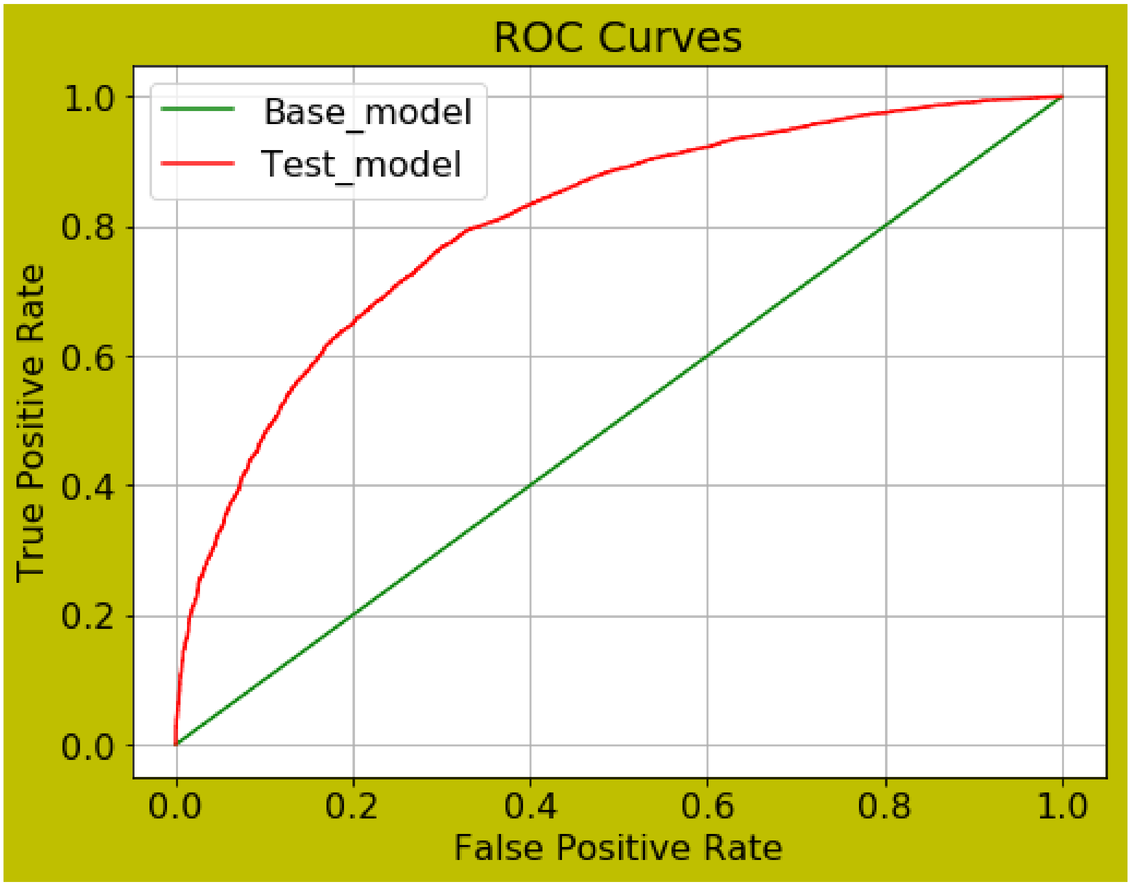
```
             precision    recall  f1-score   support

          0       0.87      0.03      0.06      3917
          1       0.68      1.00      0.81      8083

avg / total       0.74      0.68      0.56     12000
```

In [189]:
```python
cm = confusion_matrix(y_test_new ,prediction3)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



7.2.1 ROC_AUC_plot

```
In [190]: roc_auc_plot(RF_clf3,y_test_new,final_data_test)
```




```
AUC: 0.8057046229363208
```

```
In [191]: models_performence1['Model'].append('Random Forest')
          models_performence1['Vectorizer'].append('BOW')
          models_performence1['Optimal_Base_learners'].append(Best_n_estimators)
          models_performence1['Best_criterion'].append(Best_criterion)
          models_performence1['Best_max_features'].append(Best_max_features)
          models_performence1['Best_max_depth'].append(Best_max_depth)
          models_performence1['Training error'].append(training_error)
          models_performence1[ 'Test error'].append(Testing_error)
          models_performence1[ 'Accuracy'].append(Testing_score)
          models_performence1[ 'F1'].append(F1_score)
          models_performence1['recall'].append(recall)
          models_performence1[ 'precision'].append(precision)
```

```
In [192]: columns = ["Model","Vectorizer", "Optimal_Base_learners","Best_criterion","Best_max_fe
                      "Best_max_depth","Training error",  "Test error",
                       "Accuracy","F1","recall","precision",
                     ]
```

```
df5=pd.DataFrame(models_performence1, columns=columns)
result_display(df5)
```

```
|    Model     |        Vectorizer       |Optimal_Base_learners|Best_criterion|Best_max_features|B
|-------------|------------------------|--------------------:|--------------|-----------------|-
|Random Forest|Avg word2vec            |                  150|gini          |sqrt             |
|Random Forest|TF-IDF weighted word2vec|                  200|gini          |log2             |
|Random Forest|BOW                     |                  150|gini          |log2             |
```

7.3 Observation

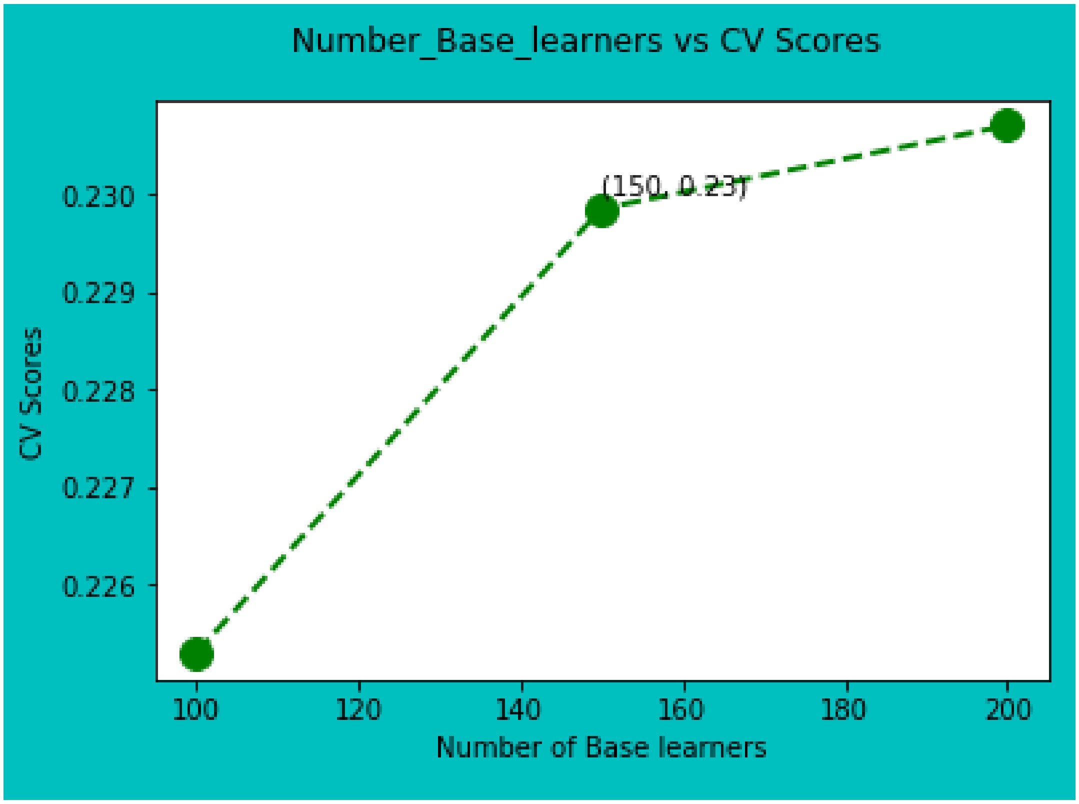
Model	Vectorizer	Optimal_Base_learners	Best_criterion	Best_max_features	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
Random Forest	Avg word2vec	150	gini	sqrt	14	0.02139	0.1942	0.8058	75.77	74.04	80.02
Random Forest	TF-IDF weighted word2vec	200	gini	log2	14	0.02818	0.2222	0.7778	71.07	69.42	77.55
Random Forest	BOW	150	gini	log2	8	0.26225	0.3178	0.6822	43.42	51.43	77.52

- The results for BOW is quite low as comapred Avgword2vec & TF-IDf weighted word2vec.
- From confusion matrix, It is observed that TPR & FPR is too high as compared to TNR &FNR.

7.4 Optimal Base_learners,depth size & Learning Rate using BOW

```
In [80]: warnings.filterwarnings("ignore")
         Optimal_BL_Depth_LR(final_data,Train_data)
```

```
Optimal_estim_GBDT=== XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=8, min_child_weight=1, missing=None, n_estimators=200,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)

The optimal parameter for GBDT is === {'learning_rate': 0.1, 'max_depth': 8, 'n_estimators': 200
```

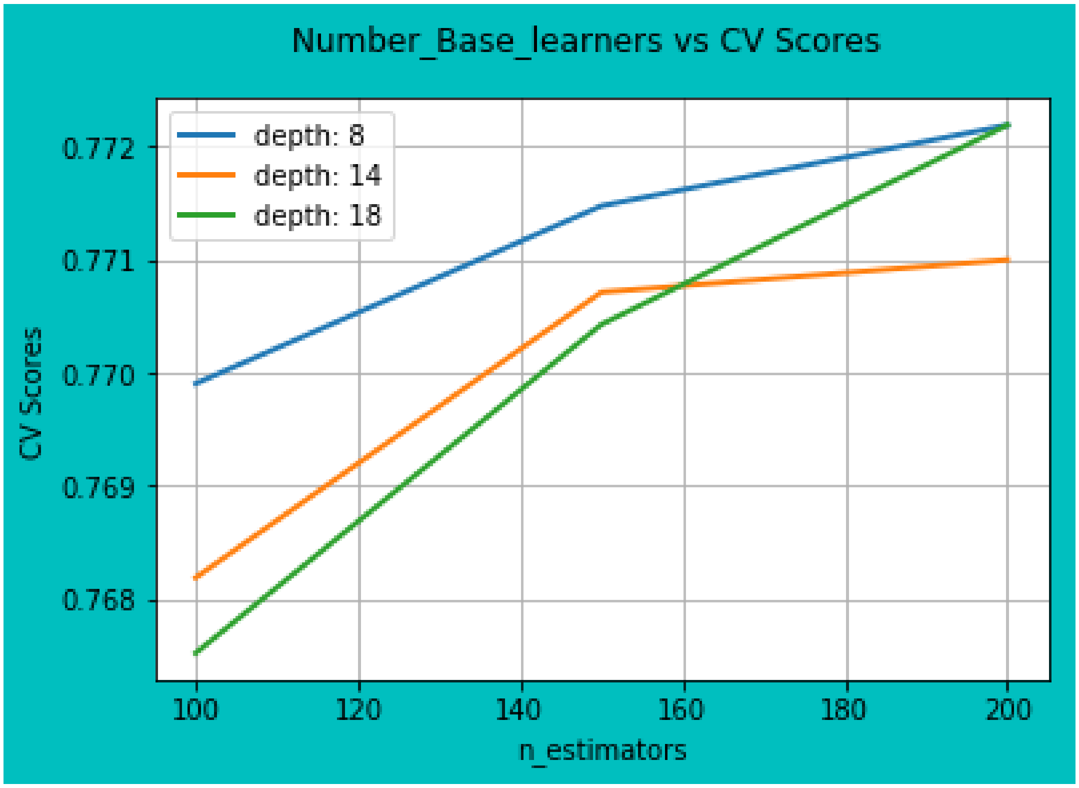



```
the misclassification error for each Base learners is :  [0.22529 0.22986 0.23071]
```

Base_learners graph with different depth size

```
In [81]: clf_perform_depth(GBDT_model,final_data,Train_data)
```

```
[0.76990476 0.77147619 0.77219048 0.76819048 0.77071429 0.771
 0.76752381 0.77042857 0.77219048]
[8, 14, 18]
[8, 14, 18]
[8, 14, 18]
```



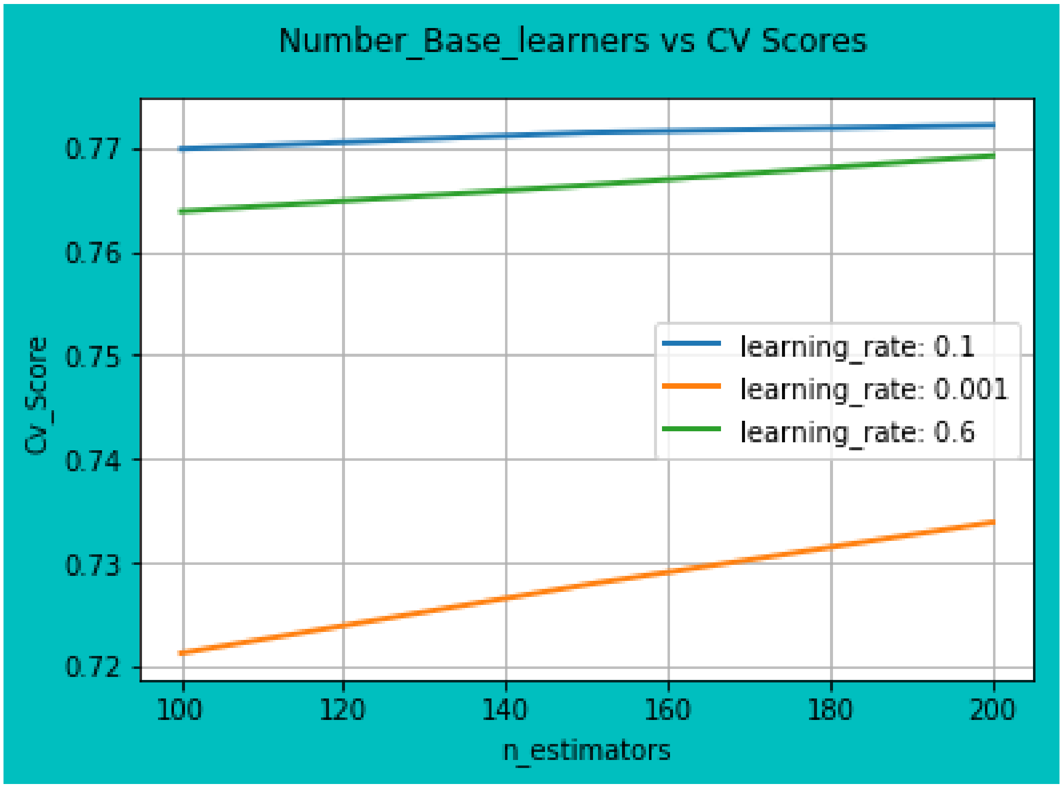
7.5 GBDT Model for optimal Parameters

```
In [50]: print("Best Parameters for GBDT is ",Optimal_param_GBDT)

         Best_learning_rate=Optimal_param_GBDT.get('learning_rate')
         Best_n_estimators=Optimal_param_GBDT.get('n_estimators')
         Best_max_depth=Optimal_param_GBDT.get('max_depth')
```

```
Best Parameters for GBDT is  {'learning_rate': 0.1, 'max_depth': 8, 'n_estimators': 200}
```

```
In [83]: GBDT_LR(Best_max_depth,final_data ,Train_data)
```

```
3it [00:00, 152.02it/s]
```



In [51]:
```
# GBDT classifier for optimal parametrs
GBDT_clf13 = XGBClassifier(n_estimators=Best_n_estimators,
                            learning_rate=Best_learning_rate,
                             max_depth=Best_max_depth,
                            scoring="sqrt",
                           n_jobs=-1, cv=tscv, verbose=1)
GBDT_clf13.fit(final_data, Train_data)
```

Out[51]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1,
       cv=TimeSeriesSplit(max_train_size=None, n_splits=3), gamma=0,
       learning_rate=0.1, max_delta_step=0, max_depth=8,
       min_child_weight=1, missing=None, n_estimators=200, n_jobs=-1,
       nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, scoring='sqrt',
       seed=None, silent=True, subsample=1, verbose=1)
```

In [196]:
```
prediction13= GBDT_clf13.predict(final_data_test)
```

```
/usr/local/lib/python3.6/site-packages/sklearn/preprocessing/label.py:151: DeprecationWarning: T
  if diff:
```

In [197]:
```
#Training accuracy and training error
training_score=GBDT_clf13.score(final_data,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.998
training error is = 0.0020000000000000018
```

```
/usr/local/lib/python3.6/site-packages/sklearn/preprocessing/label.py:151: DeprecationWarning: T
  if diff:
```

In [198]:
```
# Testing Accuracy and testing error for GBDT model
Testing_score=round(accuracy_score(y_test_new ,prediction13),5)
print("Accuracy for GBDT model with BOW is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for GBDT model with BOW is = ",Testing_error)
```

```
Accuracy for GBDT model with BOW is =  0.77383
Testing error for GBDT model with BOW is =  0.22616999999999998
```

In [199]:
```
# Testing Accuracy and testing error for GBDT model
Testing_score=round(accuracy_score(y_test_new,prediction13),5)
print("Accuracy for GBDT model with BOW is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for GBDT model with BOW is = ",Testing_error)
```

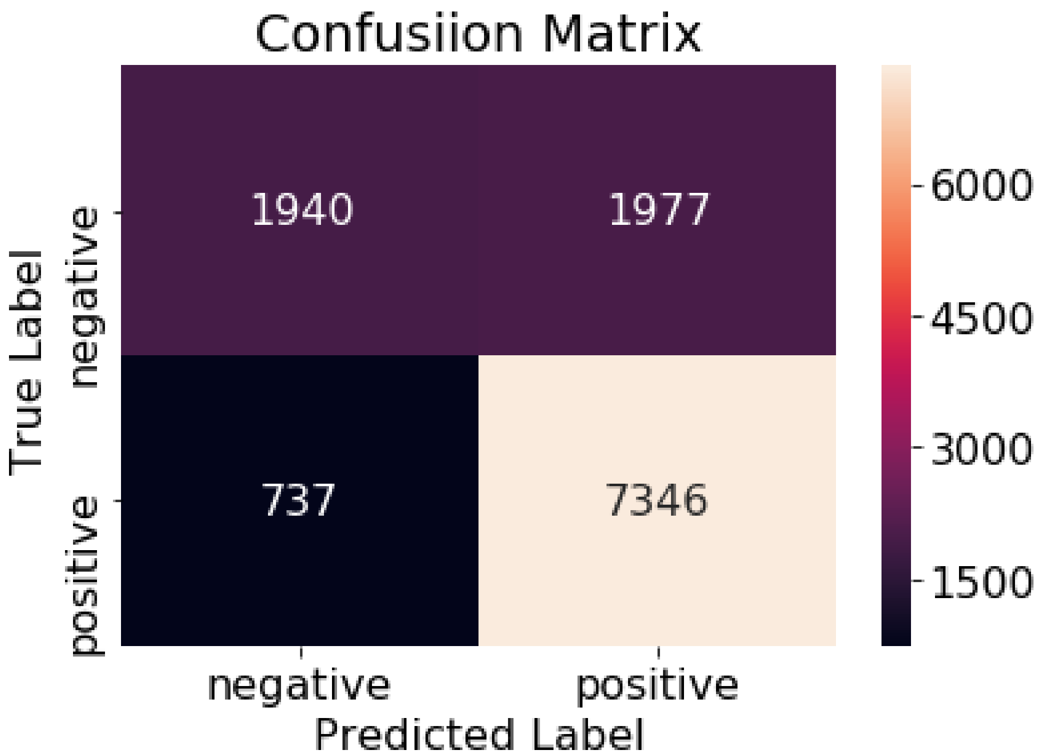
```
Accuracy for GBDT model with BOW is =  0.77383
Testing error for GBDT model with BOW is =  0.22616999999999998
```

In [200]:
```
F1_score = round(f1_score(y_test_new,prediction13,average='macro'),5)*100
recall = round(recall_score(y_test_new,prediction13,average='macro'),5)*100
precision = round(precision_score(y_test_new,prediction13,average='macro'),5)*100
```

In [201]:
```
print(classification_report( y_test_new,prediction13))
```

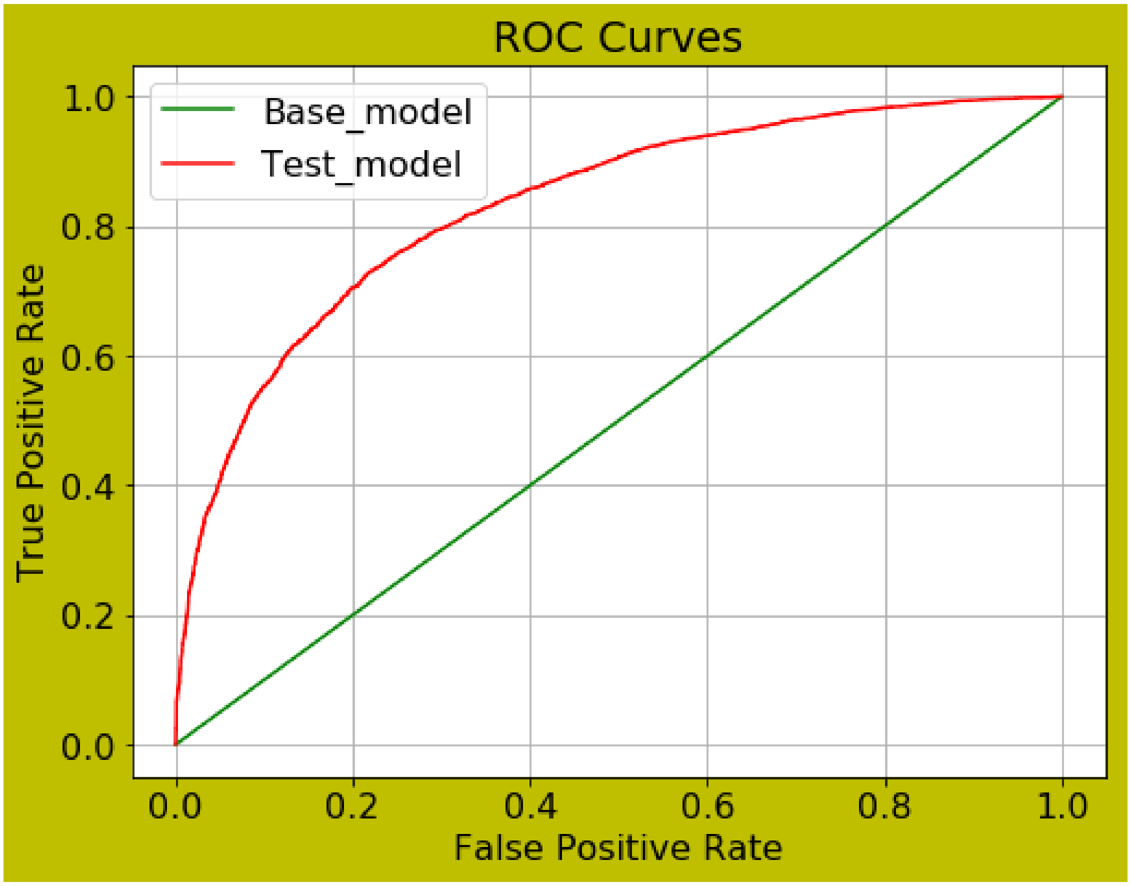
```
             precision    recall  f1-score   support

          0       0.72      0.50      0.59      3917
          1       0.79      0.91      0.84      8083

avg / total       0.77      0.77      0.76     12000
```

```
In [202]: cm = confusion_matrix(y_test_new,prediction13)
          label = ['negative', 'positive']
          df_conf = pd.DataFrame(cm, index = label, columns = label)
          sns.heatmap(df_conf, annot = True, fmt = "d")
          plt.title("Confusiion Matrix")
          plt.xlabel("Predicted Label")
          plt.ylabel("True Label")
          plt.show()
```



7.5.1 ROC_AUC_plot

```
In [203]: roc_auc_plot(GBDT_clf13,y_test_new,final_data_test)
```



AUC: 0.8321837948137701

In [204]:
```
models_performence['Model'].append('GBDT')
models_performence['Vectorizer'].append('BOW')
models_performence['Optimal_Base_learners'].append(Best_n_estimators)
models_performence['Best_learning_rate'].append(Best_learning_rate)
models_performence['Best_max_depth'].append(Best_max_depth)
models_performence['Training error'].append(training_error)
models_performence[ 'Test error'].append(Testing_error)
models_performence[ 'Accuracy'].append(Testing_score)
models_performence[ 'F1'].append(F1_score)
models_performence['recall'].append(recall)
models_performence[ 'precision'].append(precision)
```

In [205]:
```
columns = ["Model","Vectorizer", "Optimal_Base_learners","Best_learning_rate","Best_ma
           "Training error",  "Test error",
             "Accuracy","F1","recall","precision",
           ]
df6=pd.DataFrame(models_performence, columns=columns)
result_display(df6)
```

```
|Model|       Vectorizer       |Optimal_Base_learners|Best_learning_rate|Best_max_depth|Training
|-----|------------------------|--------------------:|-----------------:|-------------:|--------
|GBDT |Avg word2vec            |                  200|               0.1|            14|      0.
|GBDT |TF-IDF weighted word2vec|                  200|               0.1|             8|      0.
|GBDT |BOW                     |                  200|               0.1|             8|      0.
```

7.6 Observation

Model	Vectorizer	Optimal_Base_learners	Best_learning_rate	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
GBDT	Avg word2vec	200	0.1	14	0.000071	0.1821	0.8179	78.24	77.06	80.20
GBDT	TF-IDF weighted word2vec	200	0.1	8	0.005250	0.2043	0.7957	75.29	74.04	77.68
GBDT	BOW	200	0.1	8	0.002000	0.2262	0.7738	71.62	70.20	75.63

- From confusion matrix, It is seen that TPR is too high while TNR,FNR & FPR .
- The results for GBDT using BOW is low as comapred to Avg word2vec & TF-IDf weighted word2vec.

8 4. tf-idf

Dumping & Loading Pickle file for training data (TF-IDF)

```
In [206]: pickle_path_tfidf_train='X_train_data_tfidf.pkl'
          X_train_data_tfidf=open(pickle_path_tfidf_train,'wb')
          pickle.dump(final_tf_idf ,X_train_data_tfidf)
          X_train_data_tfidf.close()
```

```
In [52]: pickle_path_tfidf_train='X_train_data_tfidf.pkl'
         unpickle_path5=open(pickle_path_tfidf_train,'rb')
         final_tfidf_np=pickle.load(unpickle_path5)
```

```
In [53]: print("Train Data: ",final_tfidf_np.shape)


         warnings.filterwarnings("ignore")
```

```
Train Data:  (28000, 100)
```

tf-idf For Testing datasets

```
In [54]: final_tf_idf_test1_svd = tf_idf_vect.transform(X_test_data.values.ravel())
         final_tf_idf_test1_svd.get_shape()
```

Out[54]: (12000, 493904)

```
In [57]: final_tf_idf_test=svd.transform(final_tf_idf_test1_svd)

         print("TruncatedSVD :",final_tf_idf_test.shape)
         #Normalize Data
```

```
TruncatedSVD : (12000, 100)
```

Dumping & Loading Pickle file for testing data(TF-IDF)

```
In [213]: pickle_path_tfidf_test='X_test_data_tfidf.pkl'
          X_test_data_tfidf=open(pickle_path_tfidf_test,'wb')
          pickle.dump(final_tf_idf_test ,X_test_data_tfidf)
          X_test_data_tfidf.close()
```

```
In [214]: pickle_path_tfidf_test='X_test_data_tfidf.pkl'
          unpickle_path6=open(pickle_path_tfidf_test,'rb')
          final_tfidf_np_test=pickle.load(unpickle_path6)
```

```
In [215]: joblib.dump(final_tfidf_np, 'TFIDF_train.joblib')
          joblib.dump(final_tfidf_np_test, 'TFIDF_test.joblib')
```

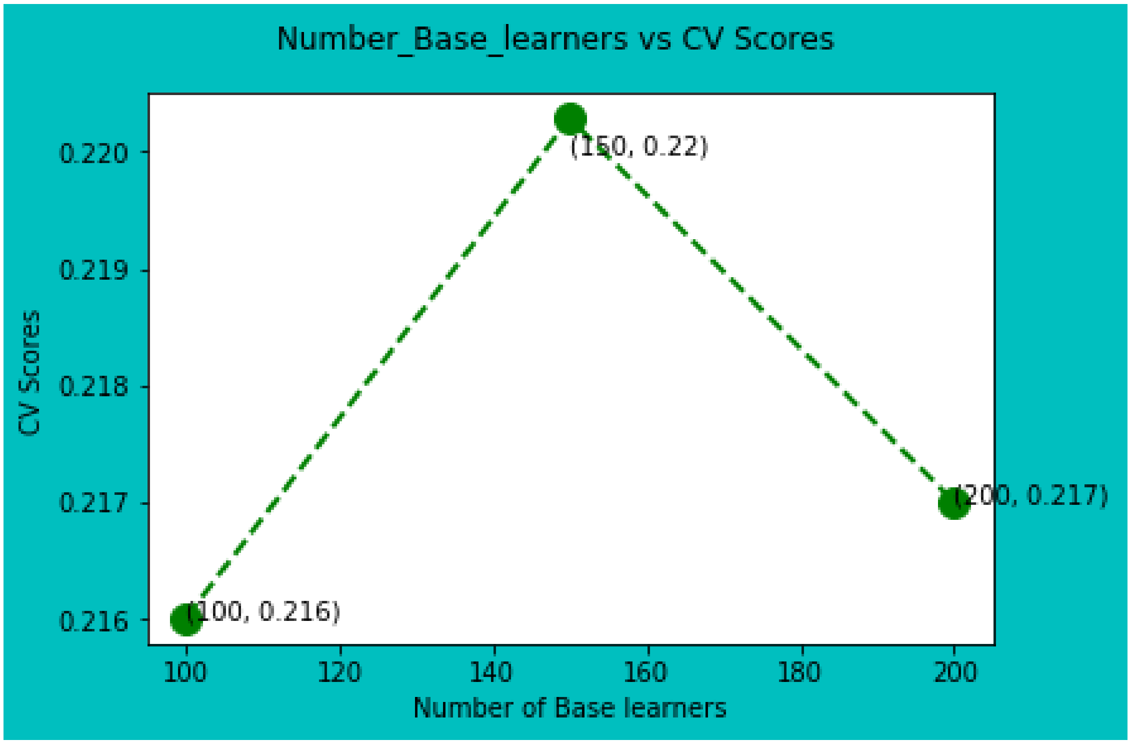
Out[215]: ['TFIDF_test.joblib']

```
In [52]: final_tfidf_np = joblib.load('TFIDF_train.joblib')
         final_tfidf_np_test = joblib.load('TFIDF_test.joblib')
```

8.1 Optimal Base_learners for Random Forest using TF-IDF

```
In [99]: Optimal_Depth_Tree1=Optimal_Base_learners(final_tfidf_np,Train_data)
```

```
optimal_estim== RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=14, max_features='sqrt',
            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=150, n_jobs=-1, oob_score=True, random_state=None,
            verbose=0, warm_start=False)
Mean of score: 0.7822380952380952
Variance of scores: 3.3514739229025806e-06

The optimal Best_parameters for Random Forest is ===  {'criterion': 'gini', 'max_depth': 14, 'ma
```

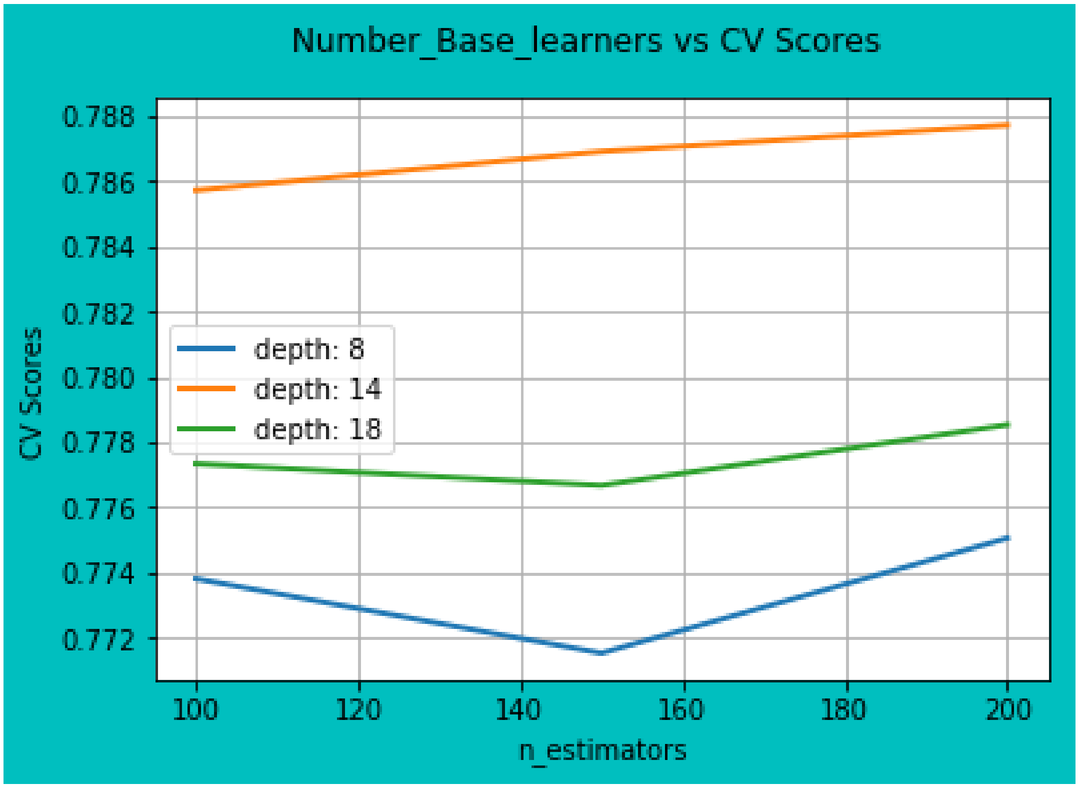



```
the misclassification error for each Base learners is :  [0.216   0.22029 0.217  ]
```

Base_learners graph with different depth size

```
In [100]: clf_perform_depth(random_forest,final_tfidf_np ,Train_data)
```

```
[0.77380952 0.77152381 0.77504762 0.78571429 0.78690476 0.78771429
 0.77733333 0.77666667 0.77852381]
[8, 14, 18]
[8, 14, 18]
[8, 14, 18]
```



8.2 Random Forest for optimal Parametersusing TF-IDF

In [218]:
```
print("Best Parameters for Random Forest is ",optimal_parameters_RF)
Best_criterion=optimal_parameters_RF.get('criterion')
Best_max_features=optimal_parameters_RF.get('max_features')
Best_n_estimators=optimal_parameters_RF.get('n_estimators')
Best_max_depth=optimal_parameters_RF.get('max_depth')
```

```
Best Parameters for Random Forest is  {'criterion': 'gini', 'max_depth': 14, 'max_features': 'sq
```

In [219]:
```
RF_clf4 = RandomForestClassifier(n_estimators=Best_n_estimators,max_depth=Best_max_dep
                                max_features=Best_max_features, random_state=0,n_jobs=
RF_clf4.fit(final_tfidf_np,Train_data)
RF4=RF_clf4.fit(final_tfidf_np,Train_data)
```

In [220]:
```
prediction4= RF_clf4.predict(final_tfidf_np_test)
```

In [221]:
```
#Training accuracy and training error
training_score=RF_clf4.score(final_tfidf_np,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.9704642857142857
training error is = 0.029535714285714332
```

In [222]:
```python
# Testing Accuracy and testing error for Random Forest model

Testing_score=round(accuracy_score(y_test_new ,prediction4),5)
print("Accuracy for Random Forest model with TF-IDF is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for Random Forest model with TF-IDF  is = ",Testing_error)
```

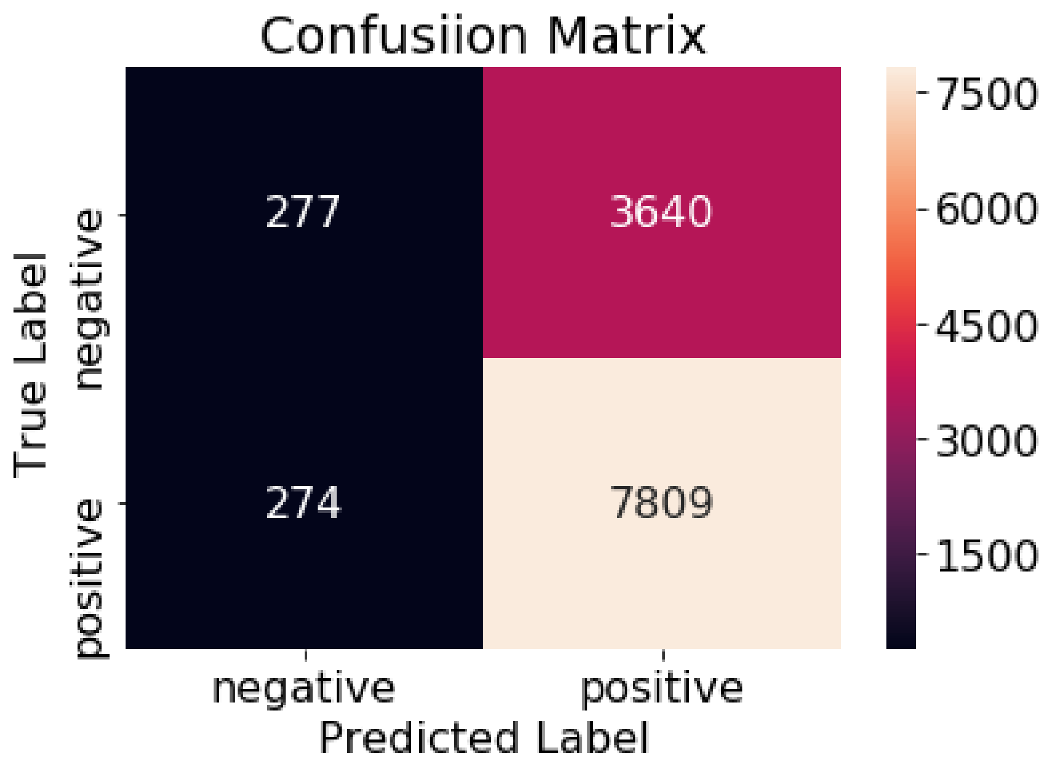
```
Accuracy for Random Forest model with TF-IDF is =  0.67383
Testing error for Random Forest model with TF-IDF  is =  0.32616999999999996
```

In [223]:
```python
F1_score = round(f1_score(y_test_new ,prediction4,average='macro'),5)*100
recall = round(recall_score(y_test_new,prediction4,average='macro'),5)*100
precision = round(precision_score(y_test_new ,prediction4,average='macro'),5)*100
```

In [224]:
```python
print(classification_report( y_test_new,prediction4))
```

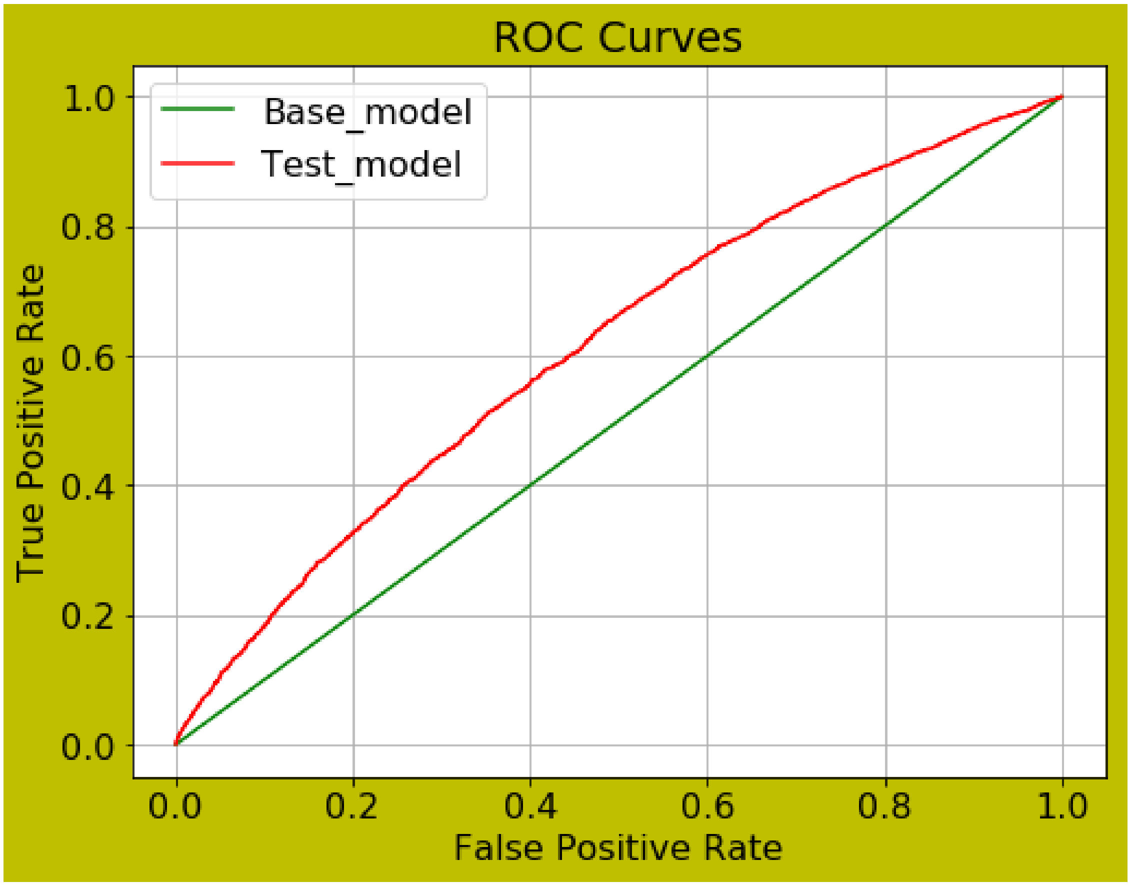
```
             precision    recall  f1-score   support

          0       0.50      0.07      0.12      3917
          1       0.68      0.97      0.80      8083

avg / total       0.62      0.67      0.58     12000
```

In [225]:
```python
cm = confusion_matrix(y_test_new,prediction4)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



8.2.1 ROC_AUC_plot

```
In [226]: roc_auc_plot(RF_clf4,y_test_new,final_tfidf_np_test)
```




```
AUC: 0.6125867945695272
```

In [227]:
```
models_performence1['Model'].append('Random Forest')
models_performence1['Vectorizer'].append('TF-IDF ')
models_performence1['Optimal_Base_learners'].append(Best_n_estimators)
models_performence1['Best_criterion'].append(Best_criterion)
models_performence1['Best_max_features'].append(Best_max_features)
models_performence1['Best_max_depth'].append(Best_max_depth)
models_performence1['Training error'].append(training_error)
models_performence1[ 'Test error'].append(Testing_error)
models_performence1[ 'Accuracy'].append(Testing_score)
models_performence1[ 'F1'].append(F1_score)
models_performence1['recall'].append(recall)
models_performence1[ 'precision'].append(precision)
```

In [228]:
```
columns = ["Model","Vectorizer", "Optimal_Base_learners","Best_criterion","Best_max_fe
           "Best_max_depth","Training error",  "Test error",
            "Accuracy","F1","recall","precision",
          ]
```

```
df7=pd.DataFrame(models_performence1, columns=columns)
result_display(df7)
```

```
|    Model    |       Vectorizer       |Optimal_Base_learners|Best_criterion|Best_max_features|B
|-------------|------------------------|--------------------:|--------------|-----------------|-
|Random Forest|Avg word2vec            |                  150|gini          |sqrt             |
|Random Forest|TF-IDF weighted word2vec|                  200|gini          |log2             |
|Random Forest|BOW                     |                  150|gini          |log2             |
|Random Forest|TF-IDF                  |                  150|gini          |sqrt             |
```

8.3 Observation

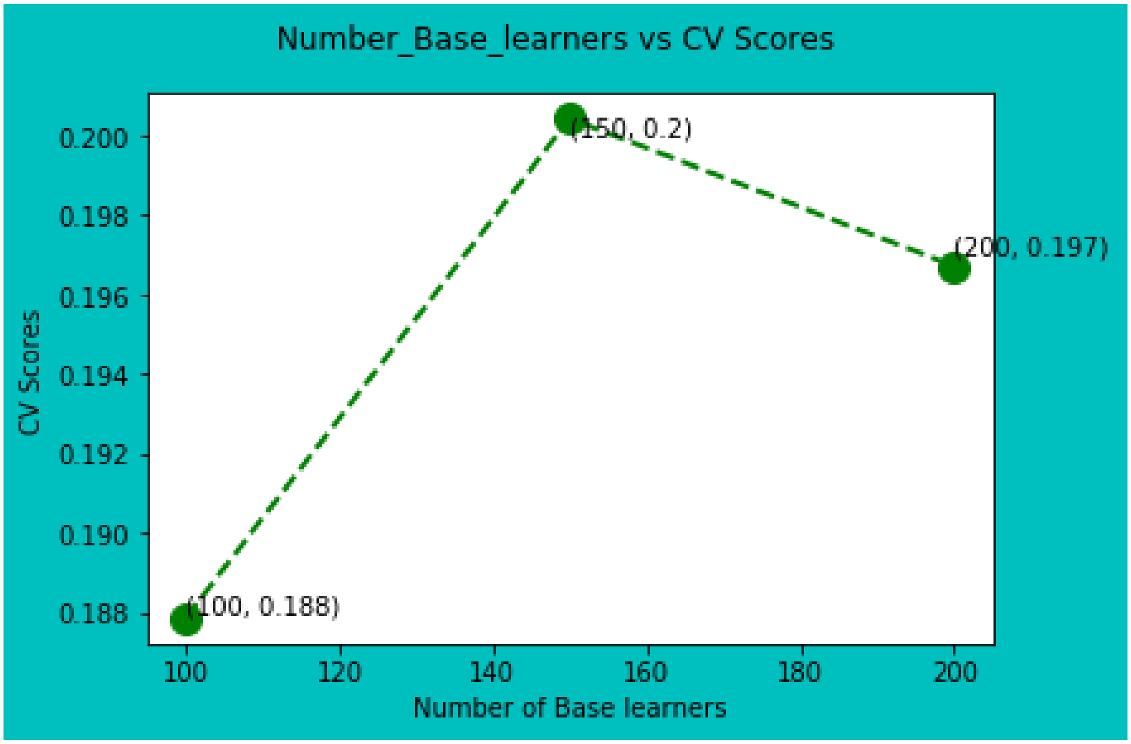
Model	Vectorizer	Optimal_Base_learners	Best_criterion	Best_max_features	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
Random Forest	Avg word2vec	150	gini	sqrt	14	0.02139	0.1942	0.8058	75.77	74.04	80.02
Random Forest	TF-IDF weighted word2vec	200	gini	log2	14	0.02818	0.2222	0.7778	71.07	69.42	77.55
Random Forest	BOW	150	gini	log2	8	0.26225	0.3178	0.6822	43.42	51.43	77.52
Random Forest	TF-IDF	150	gini	sqrt	14	0.02954	0.3262	0.6738	46.18	51.84	59.24

- For given Random Forest model, AUC is 0.612.
- TPR & FPR is high while TNR &FNR is quite low.
- the result obtained from Random Forest using TF_IDF is quite low comparatively to other random forest models.

8.4 Optimal Base_learners,depth size & Learning Rate using TF_IDF

```
In [102]: warnings.filterwarnings("ignore")
          Optimal_BL_Depth_LR(final_tfidf_np,Train_data)
```

```
Optimal_estim_GBDT=== XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0,
       max_depth=8, min_child_weight=1, missing=None, n_estimators=200,
       n_jobs=1, nthread=None, objective='binary:logistic', random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)

The optimal parameter for GBDT is === {'learning_rate': 0.1, 'max_depth': 8, 'n_estimators': 200
```

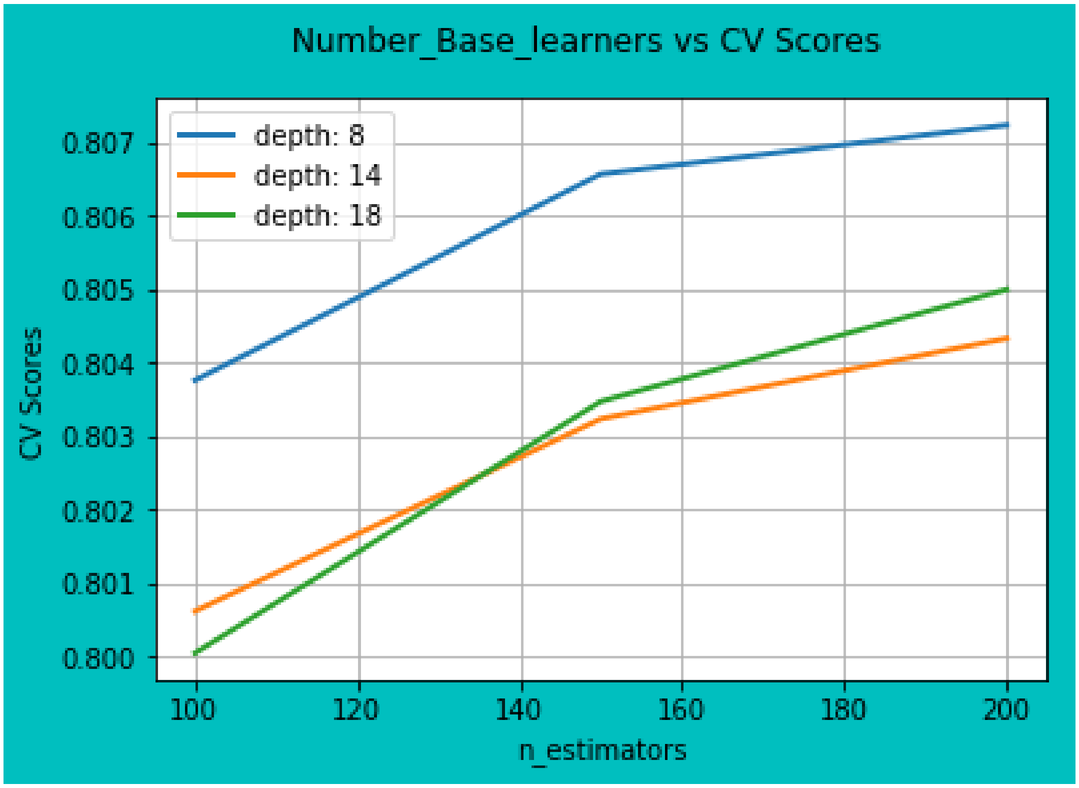



```
the misclassification error for each Base learners is :  [0.18786 0.20043 0.19671]
```

Base_learners graph with different depth size

```
In [103]: clf_perform_depth(GBDT_model,final_tfidf_np,Train_data)
```

```
[0.8037619  0.80657143 0.8072381  0.80061905 0.8032381  0.80433333
 0.80004762 0.80347619 0.805     ]
[8, 14, 18]
[8, 14, 18]
[8, 14, 18]
```



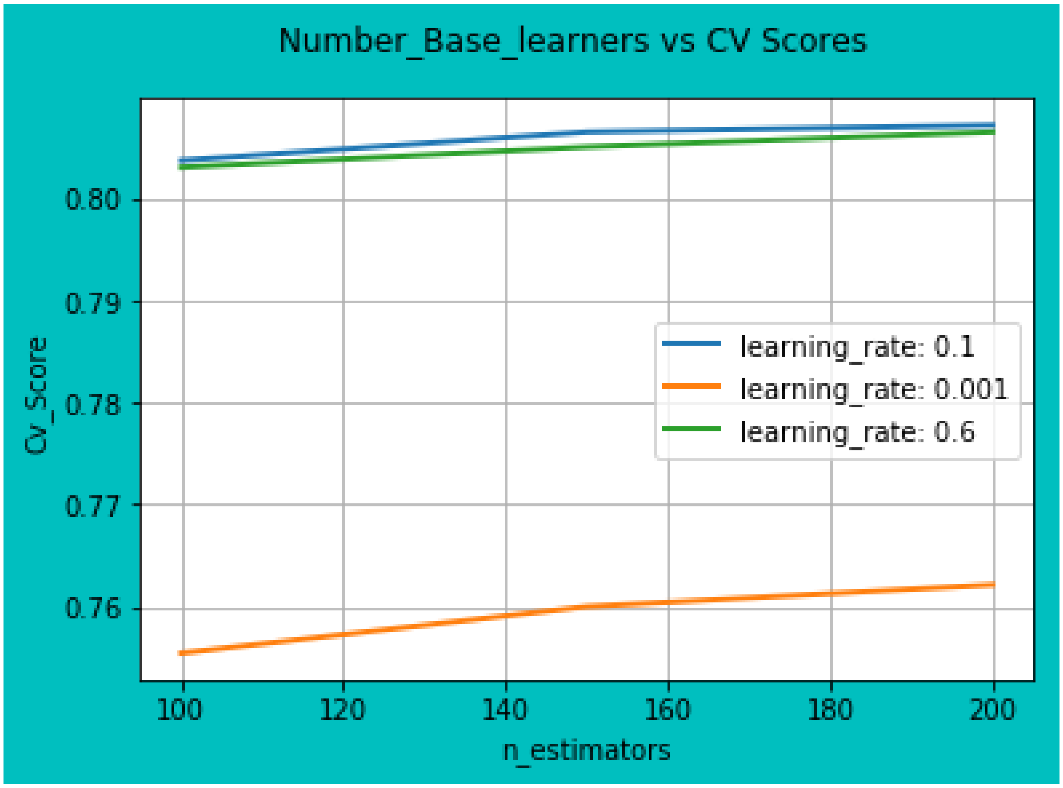
8.5 GBDT Model for optimal Parameters

```
In [54]: print("Best Parameters for GBDT is ",Optimal_param_GBDT)

         Best_learning_rate=Optimal_param_GBDT.get('learning_rate')
         Best_n_estimators=Optimal_param_GBDT.get('n_estimators')
         Best_max_depth=Optimal_param_GBDT.get('max_depth')
```

```
Best Parameters for GBDT is  {'learning_rate': 0.1, 'max_depth': 8, 'n_estimators': 200}
```

```
In [105]: GBDT_LR(Best_max_depth,final_tfidf_np ,Train_data)
```

```
3it [00:00, 155.77it/s]
```




```
In [55]: # GBDT classifier for optimal parametrs
         GBDT_clf14 = XGBClassifier(n_estimators=Best_n_estimators,learning_rate=Best_learning_r
                                          max_depth=Best_max_depth,scoring="sqrt",
                                    n_jobs=-1, cv=tscv, verbose=1)
         GBDT_clf14.fit(final_tfidf_np, Train_data)
```

```
Out[55]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                colsample_bytree=1,
                cv=TimeSeriesSplit(max_train_size=None, n_splits=3), gamma=0,
                learning_rate=0.1, max_delta_step=0, max_depth=8,
                min_child_weight=1, missing=None, n_estimators=200, n_jobs=-1,
                nthread=None, objective='binary:logistic', random_state=0,
                reg_alpha=0, reg_lambda=1, scale_pos_weight=1, scoring='sqrt',
                seed=None, silent=True, subsample=1, verbose=1)
```

```
In [232]: prediction14= GBDT_clf14.predict(final_tfidf_np_test)
```

```
In [233]: #Training accuracy and training error
          training_score=GBDT_clf14.score(final_tfidf_np,Train_data)
          print('training accuracy=',training_score)
          training_error=1-training_score
          print('training error is =',training_error)
```

```
training accuracy= 0.9987857142857143
training error is = 0.0012142857142857233
```

In [234]:
```python
# Testing Accuracy and testing error for GBDT model
Testing_score=round(accuracy_score(y_test_new ,prediction14),5)
print("Accuracy for GBDT model with Avg word2vec is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for GBDT model with Avg word2vec is = ",Testing_error)
```

```
Accuracy for GBDT model with Avg word2vec is =  0.66175
Testing error for GBDT model with Avg word2vec is =  0.33825000000000005
```

In [235]:
```python
# Testing Accuracy and testing error for GBDT model
Testing_score=round(accuracy_score(y_test_new ,prediction12),5)
print("Accuracy for GBDT model with TF-IDF is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for GBDT model with TF-IDF is = ",Testing_error)
```

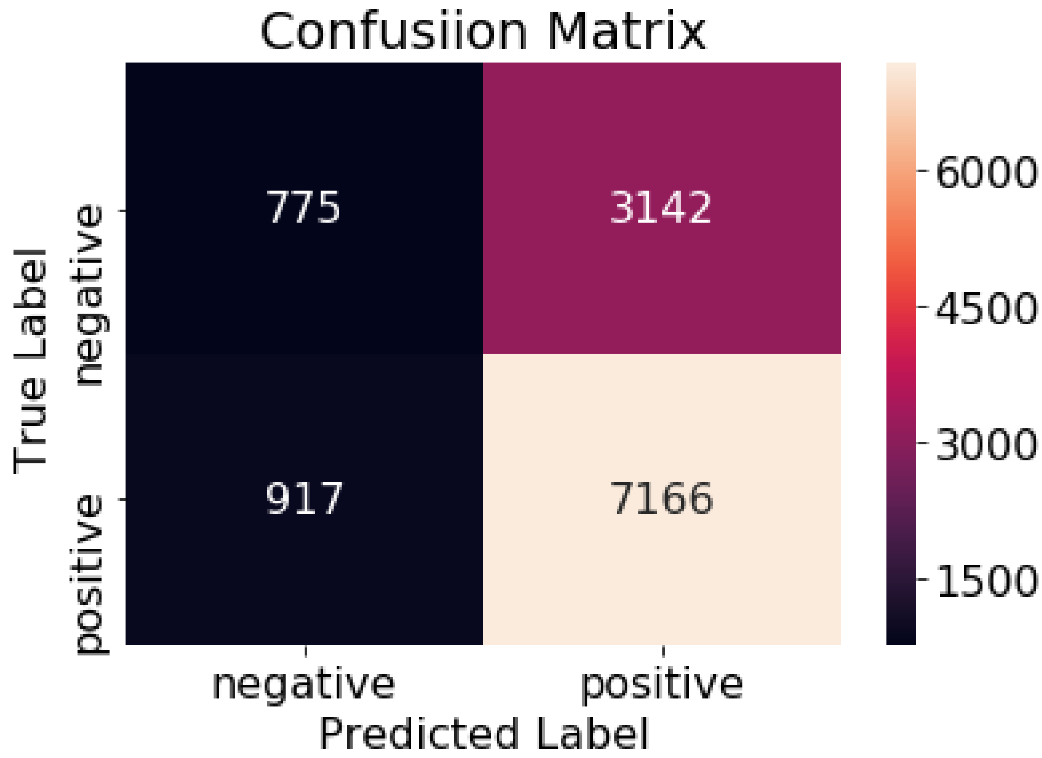
```
Accuracy for GBDT model with TF-IDF is =  0.79575
Testing error for GBDT model with TF-IDF is =  0.20425000000000004
```

In [236]:
```python
F1_score = round(f1_score(y_test_new ,prediction14,average='macro'),5)*100
recall = round(recall_score(y_test_new,prediction14,average='macro'),5)*100
precision = round(precision_score(y_test_new ,prediction14,average='macro'),5)*100
```

In [237]:
```python
print(classification_report(y_test_new,prediction14))
```

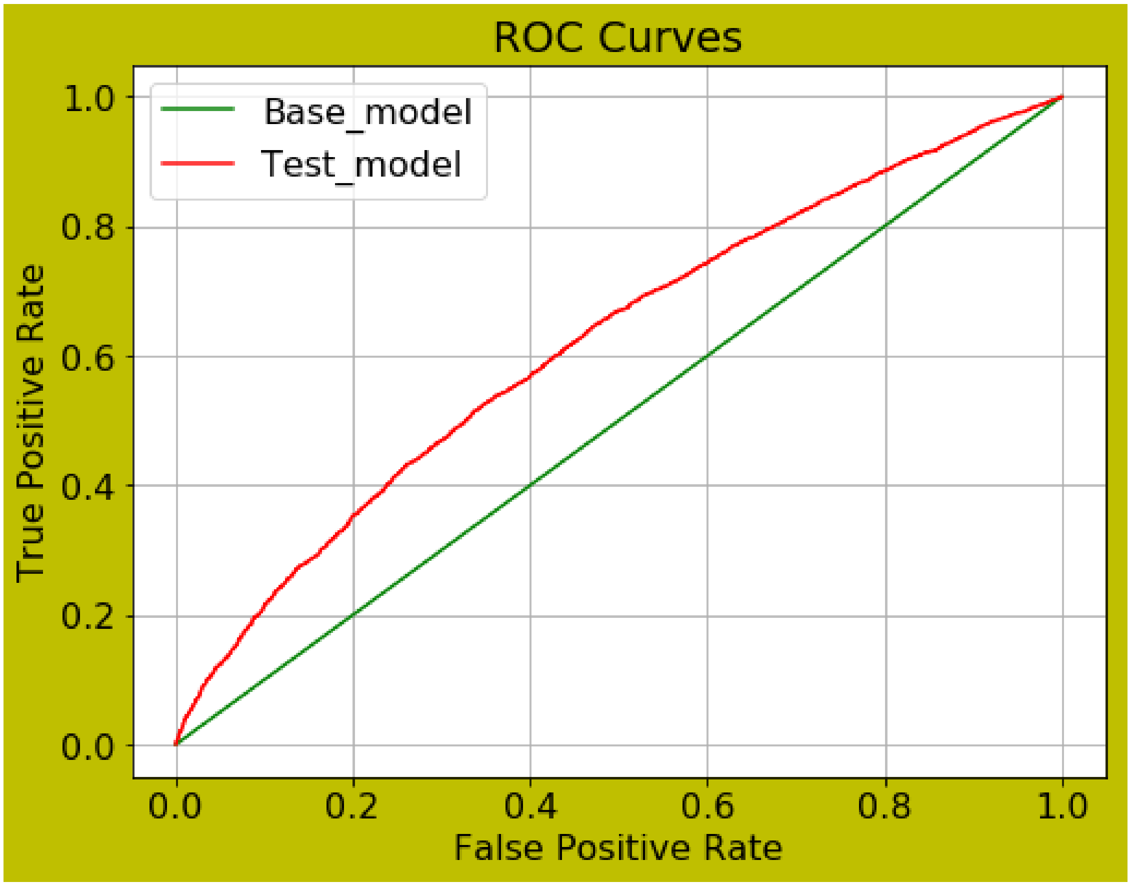
```
             precision    recall  f1-score   support

          0       0.46      0.20      0.28      3917
          1       0.70      0.89      0.78      8083

avg / total       0.62      0.66      0.62     12000
```

In [238]:
```python
cm = confusion_matrix(y_test_new ,prediction14)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



8.5.1 ROC_AUC_plot

In [239]:
```
roc_auc_plot(GBDT_clf14,y_test_new,final_tfidf_np_test)
```




```
AUC: 0.619135317140324
```

```
In [240]: models_performence['Model'].append('GBDT')
          models_performence['Vectorizer'].append('TF-IDF ')
          models_performence['Optimal_Base_learners'].append(Best_n_estimators)
          models_performence['Best_learning_rate'].append(Best_learning_rate)
          models_performence['Best_max_depth'].append(Best_max_depth)
          models_performence['Training error'].append(training_error)
          models_performence[ 'Test error'].append(Testing_error)
          models_performence[ 'Accuracy'].append(Testing_score)
          models_performence[ 'F1'].append(F1_score)
          models_performence['recall'].append(recall)
          models_performence[ 'precision'].append(precision)
```

```
In [241]: columns = ["Model","Vectorizer", "Optimal_Base_learners","Best_learning_rate","Best_ma
                    "Training error",  "Test error",
                      "Accuracy","F1","recall","precision",
                    ]
          df8=pd.DataFrame(models_performence, columns=columns)
          result_display(df8)
```

```
|Model|       Vectorizer       |Optimal_Base_learners|Best_learning_rate|Best_max_depth|Training
|-----|------------------------|--------------------:|-----------------:|-------------:|--------
|GBDT |Avg word2vec            |                  200|               0.1|            14|      0.
|GBDT |TF-IDF weighted word2vec|                  200|               0.1|             8|      0.
|GBDT |BOW                     |                  200|               0.1|             8|      0.
|GBDT |TF-IDF                  |                  200|               0.1|             8|      0.
```

8.6 Observation

Model	Vectorizer	Optimal_Base_learners	Best_learning_rate	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
GBDT	Avg word2vec	200	0.1	14	0.000071	0.1821	0.8179	78.24	77.06	80.20
GBDT	TF-IDF weighted word2vec	200	0.1	8	0.005250	0.2043	0.7957	75.29	74.04	77.68
GBDT	BOW	200	0.1	8	0.002000	0.2262	0.7738	71.62	70.20	75.63
GBDT	TF-IDF	200	0.1	8	0.001214	0.2043	0.7957	52.78	54.22	57.66

- For given GBDT model ,ROC curve is shown in graph and AUC is 0.619.
- The model variations with different depth size & learning rate can be seen Score Vs base learners graph.
- TPR & FPR is high while FNR & TNR is low as seen in confusion matrix.
- The results obtained from GBDT model using TF_IDF is quite low comparatively other GBDT models.

9 Feature Importance for Random Forest

In [56]:
```
# top_feats is function to get feature importance and print it
def top_feats(row, features, top_n=15):
    topn_ids = np.argsort(row)[::-1][:top_n]
    names = np.array(features)
    print(names[topn_ids])
    top_feats = [(features[i], row[i]) for i in topn_ids]
    global df_feat
    df_feat = pd.DataFrame(top_feats,names[topn_ids])
    df_feat.columns = ['FEATURE', 'Feat_IMP_value']

    return df_feat
```

9.1 Feature importance using count_vect

9.1.1 Feature importance for Random Forest

```
In [243]: data=count_vect.fit_transform(X_train_data.values.ravel())

          RF_clf311= RandomForestClassifier(n_estimators=100,max_depth=8,criterion='gini',
                                            max_features='sqrt', random_state=0,n_jobs=-1)
```

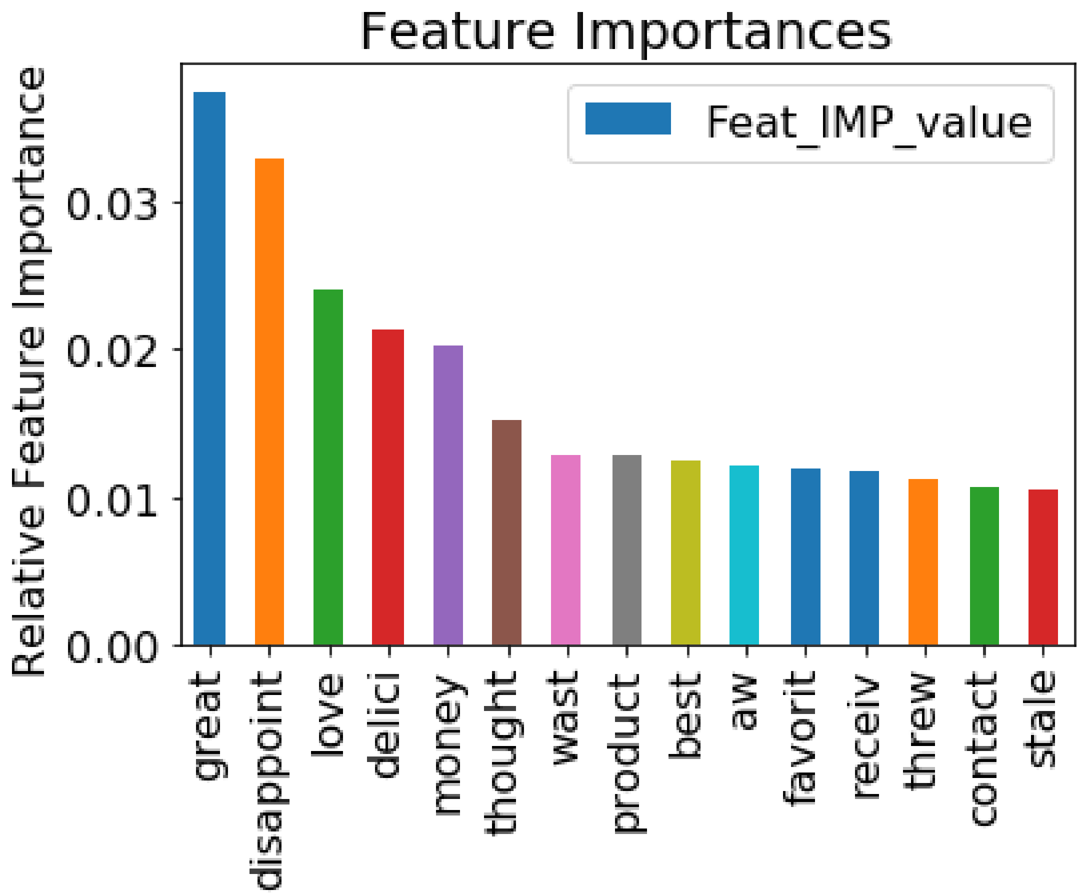
```
In [244]: RF_clf311.fit(data ,y_train_new)
          # Calculate feature importances
          count_vect_feature=count_vect.get_feature_names()

          feature_importance =RF_clf311.feature_importances_
          print(feature_importance)
```

```
[0. 0. 0. ... 0. 0. 0.]
```

```
In [245]: top_feat = top_feats(feature_importance,count_vect_feature,15)
          result_display(top_feat)
```

```
['great' 'disappoint' 'love' 'delici' 'money' 'thought' 'wast' 'product'
 'best' 'aw' 'favorit' 'receiv' 'threw' 'contact' 'stale']
| FEATURE  |Feat_IMP_value|
|----------|-------------:|
|great     |       0.03758|
|disappoint|       0.03291|
|love      |       0.02407|
|delici    |       0.02141|
|money     |       0.02023|
|thought   |       0.01517|
|wast      |       0.01284|
|product   |       0.01283|
|best      |       0.01243|
|aw        |       0.01213|
|favorit   |       0.01187|
|receiv    |       0.01177|
|threw     |       0.01115|
|contact   |       0.01067|
|stale     |       0.01039|
```

```
In [246]: df_feat.plot.bar(y='Feat_IMP_value',title='Feature Importances', rot=90)
          plt.ylabel('Relative Feature Importance  ')

Out[246]: Text(0,0.5,'Relative Feature Importance  ')
```



9.1.2 Feature importance for GBDT

```
In [247]: GBDT_clf1311 = XGBClassifier(n_estimators=100,
                                learning_rate=0.1,
                                 max_depth=8,
                                scoring="sqrt",
                               n_jobs=-1, cv=tscv, verbose=1)
```

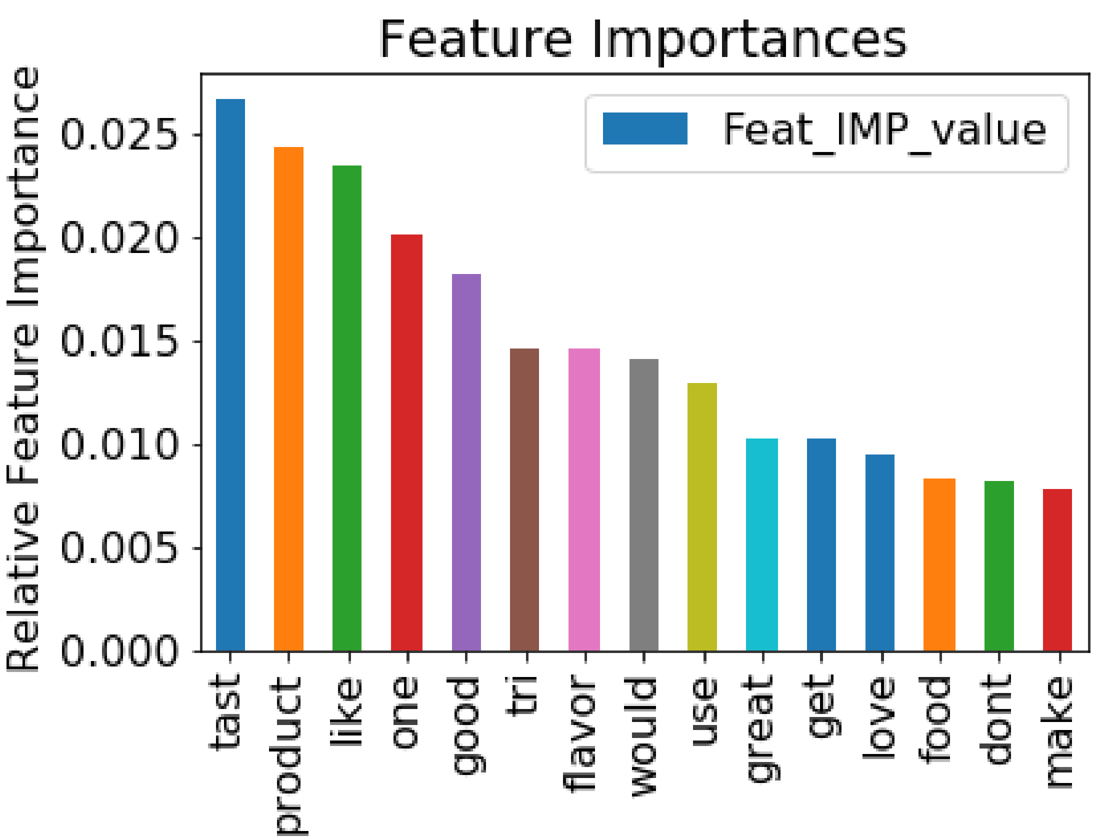
```
In [248]: GBDT_clf1311.fit(data ,y_train_new)
          # Calculate feature importances
          count_vect_feature=count_vect.get_feature_names()
          feature_importance =GBDT_clf1311.feature_importances_
```

```
In [249]: top_feat = top_feats(feature_importance,count_vect_feature,15)
          result_display(top_feat)
          df_feat.plot.bar(y='Feat_IMP_value',title='Feature Importances', rot=90)
          plt.ylabel('Relative Feature Importance ')
```

```
['tast' 'product' 'like' 'one' 'good' 'tri' 'flavor' 'would' 'use' 'great'
 'get' 'love' 'food' 'dont' 'make']
```

FEATURE	Feat_IMP_value
tast	0.026613
product	0.024357
like	0.023455
one	0.020147
good	0.018193
tri	0.014584
flavor	0.014584
would	0.014133
use	0.012930
great	0.010224
get	0.010224
love	0.009472
food	0.008269
dont	0.008119
make	0.007818

```
Out[249]: Text(0,0.5,'Relative Feature Importance ')
```



9.2 Feature importance using tf-idf -vect

9.2.1 Feature importance for Random Forest

In [250]:
```
final_tf_idf11 = tf_idf_vect.fit_transform(X_train_data.values.ravel())
```

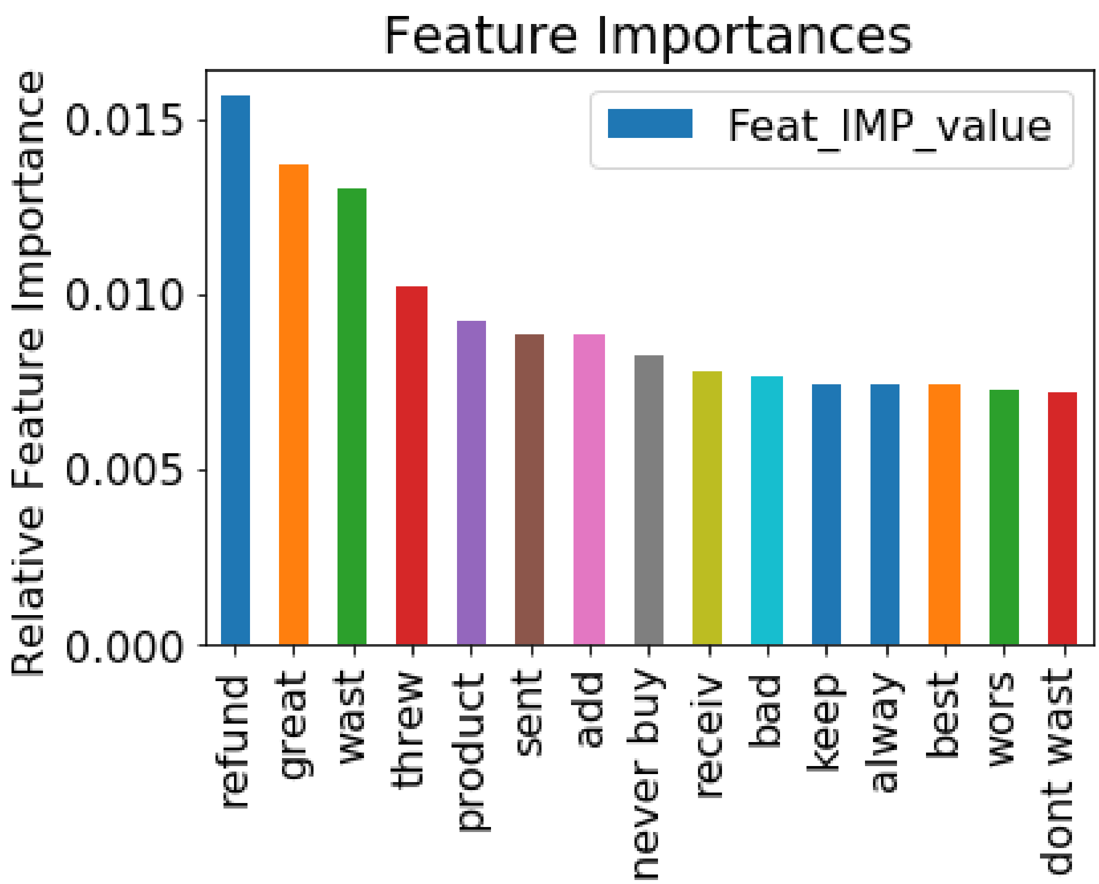
In [251]:
```
RF_clf411 = RandomForestClassifier(n_estimators=100,max_depth=8,criterion='gini',
                                   max_features=Best_max_features, random_state=0,n_jobs=
```

In [252]:
```
RF_clf411.fit(final_tf_idf11 ,y_train_new)
tf_idf_feature=tf_idf_vect .get_feature_names()
feature_importance1 = RF_clf411.feature_importances_
```

In [253]:
```
# Relative Feature Importance  using tf_idf
top_feat1 = top_feats(feature_importance1,tf_idf_feature,15)
result_display(top_feat1)
df_feat.plot.bar(y='Feat_IMP_value',title='Feature Importances', rot=90)
plt.ylabel('Relative Feature Importance  ')
```

```
['refund' 'great' 'wast' 'threw' 'product' 'sent' 'add' 'never buy'
 'receiv' 'bad' 'keep' 'alway' 'best' 'wors' 'dont wast']
| FEATURE |Feat_IMP_value|
|---------|-------------:|
|refund   |      0.015622|
|great    |      0.013658|
|wast     |      0.013036|
|threw    |      0.010216|
|product  |      0.009257|
|sent     |      0.008865|
|add      |      0.008831|
|never buy|      0.008272|
|receiv   |      0.007820|
|bad      |      0.007629|
|keep     |      0.007416|
|alway    |      0.007394|
|best     |      0.007390|
|wors     |      0.007251|
|dont wast|      0.007171|
```

Out[253]:
```
Text(0,0.5,'Relative Feature Importance  ')
```

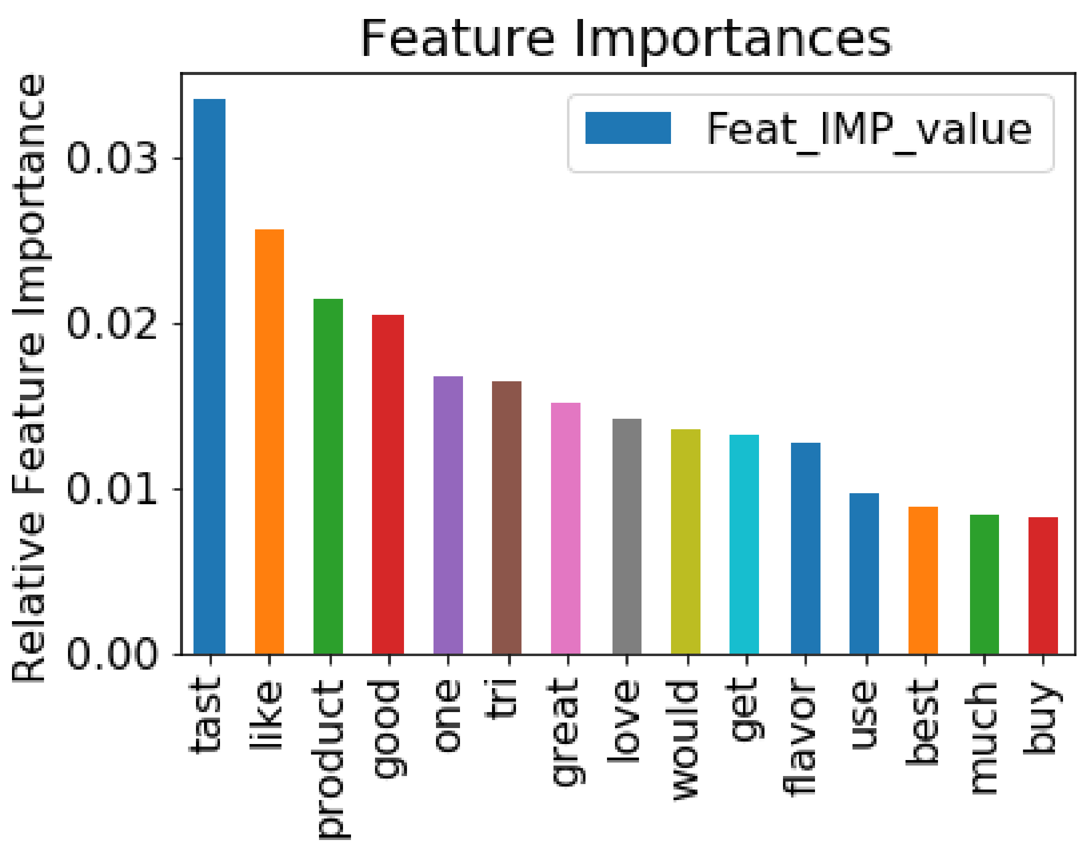


9.2.2 Feature importance for GBDT

```
In [254]: GBDT_clf1411 = XGBClassifier(n_estimators=Best_n_estimators,learning_rate=Best_learnin
                                                max_depth=Best_max_depth,scoring="sqrt",
                                          n_jobs=-1, cv=tscv, verbose=1)

In [255]: GBDT_clf1411.fit(final_tf_idf11 ,Train_data)
          tf_idf_feature=tf_idf_vect .get_feature_names()
          feature_importance1 =GBDT_clf1411.feature_importances_

In [256]: # Relative Feature Importance  using tf_idf
          top_feat1 = top_feats(feature_importance1,tf_idf_feature,15)
          result_display(top_feat1)
          df_feat.plot.bar(y='Feat_IMP_value',title='Feature Importances', rot=90)
          plt.ylabel('Relative Feature Importance  ')

['tast' 'like' 'product' 'good' 'one' 'tri' 'great' 'love' 'would' 'get'
 'flavor' 'use' 'best' 'much' 'buy']
|FEATURE|Feat_IMP_value|
|-------|-------------:|
```

```
|tast   |       0.033450|
|like   |       0.025605|
|product|       0.021355|
|good   |       0.020484|
|one    |       0.016670|
|tri    |       0.016343|
|great  |       0.015145|
|love   |       0.014164|
|would  |       0.013511|
|get    |       0.013184|
|flavor |       0.012639|
|use    |       0.009697|
|best   |       0.008825|
|much   |       0.008390|
|buy    |       0.008172|
```

```
Out[256]: Text(0,0.5,'Relative Feature Importance  ')
```



9.2.3 Random Forest Tree Image with all vectorization method

In [257]:
```
Classifier2=[RF1,RF2,RF3,RF4]
```

In [258]:
```
features2=tfidf_feat[:100]
```

In [259]:
```
name_png_format2=['RFAvg word2vec.png','RFTF-IDF weighted word2vec.png','RFBOW_Decisio
```

In [260]:
```
 for i in tqdm(range(4)):

    tree_image(Classifier2[i].estimators_[0],features2,name_png_format2[i])
```

```
100%|??????????| 4/4 [02:27<00:00, 36.84s/it]
```

9.2.4 GBDT Image with all vectorization method

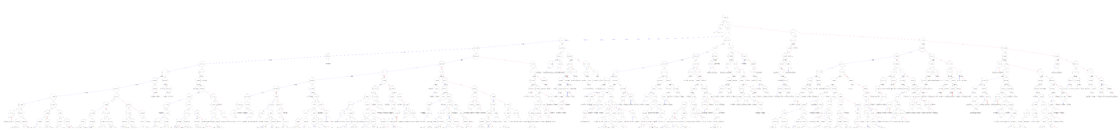
In [57]:
```
Classifier1=[GBDT_clf1,GBDT_clf12,GBDT_clf13,GBDT_clf14]
```

In [60]:
```
features1=tfidf_feat[:100]
```

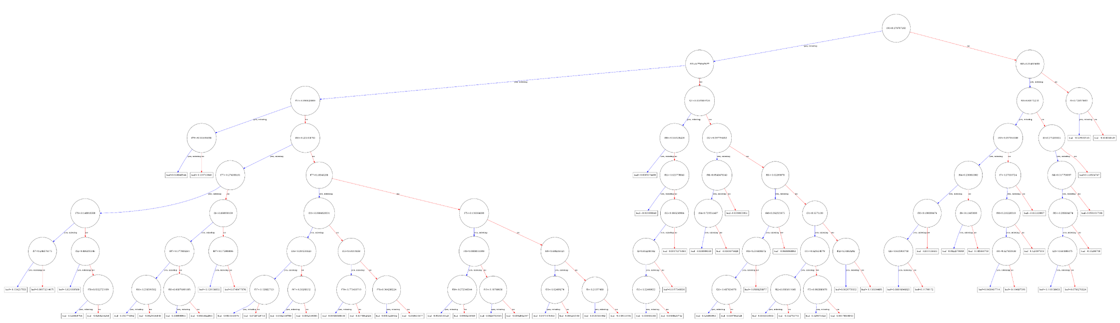
In [61]:
```
name_png_format1=['GBDTAvg word2vec.png','GBDTTF-IDF weighted word2vec.png','GBDTBOW_De
```

In [62]:
```
for i in tqdm(range(4)):

    fig, ax = plt.subplots(figsize=(100, 100))
    fif=plot_tree(Classifier1[i],num_trees=4, ax=ax)
    plt.savefig(name_png_format1[i])
    plt.show()
```

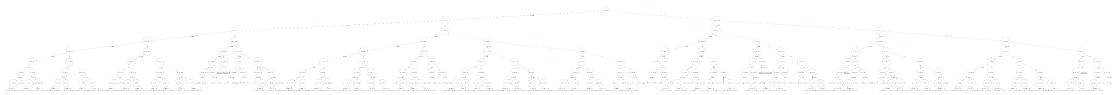
```
  0%|          | 0/4 [00:00<?, ?it/s]dot: graph is too large for cairo-renderer bitmaps. Scaling
```



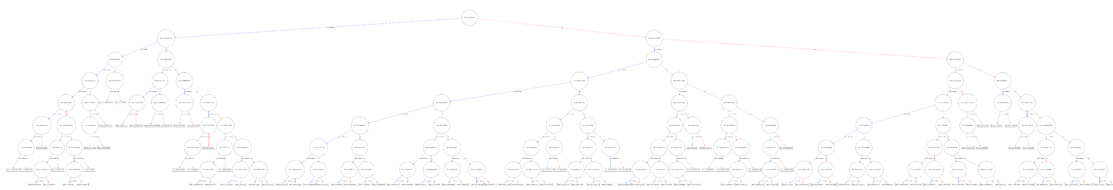
```
 25%|???       | 1/4 [00:37<01:53, 37.85s/it]
```



```
 50%|?????     | 2/4 [00:59<00:59, 29.92s/it]dot: graph is too large for cairo-renderer bitmaps.
```



```
 75%|????????  | 3/4 [01:32<00:30, 30.80s/it]
```



```
100%|??????????| 4/4 [01:58<00:00, 29.73s/it]
```

10 Observation

Model	Vectorizer	Optimal_Base_learners	Best_criterion	Best_max_features	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
Random Forest	Avg word2vec	150	gini	sqrt	14	0.02139	0.1942	0.8058	75.77	74.04	80.02
Random Forest	TF-IDF weighted word2vec	200	gini	log2	14	0.02818	0.2222	0.7778	71.07	69.42	77.55
Random Forest	BOW	150	gini	log2	8	0.26225	0.3178	0.6822	43.42	51.43	77.52
Random Forest	TF-IDF	150	gini	sqrt	14	0.02954	0.3262	0.6738	46.18	51.84	59.24

Model	Vectorizer	Optimal_Base_learners	Best_learning_rate	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
GBDT	Avg word2vec	200	0.1	14	0.000071	0.1821	0.8179	78.24	77.06	80.20

Model	Vectorizer	Optimal_Base_learners	Best_learning_rate	Best_max_depth	Training error	Test error	Accuracy	F1	recall	precision
GBDT	TF-IDF weighted word2vec	200	0.1	8	0.005250	0.2043	0.7957	75.29	74.04	77.68
GBDT	BOW	200	0.1	8	0.002000	0.2262	0.7738	71.62	70.20	75.63
GBDT	TF-IDF	200	0.1	8	0.001214	0.2043	0.7957	52.78	54.22	57.66

- The results obtained for Random Forest & GBDT model is shown in above table respectively.
- The Model performance with different depth size and learning rate is plotted in Score Vs Number of base learners graph.
- The ROC_AUC graph shows the actual performance of model.
- From the observation,It can be concluded that Random Forest model & GBDT model using Avg word2vec is best comapartively other models. And Random Forest Model & GBDT model Using TF_IDF performs bad.

```
In [ ]:
```