RF and GBDT on Amazon reviews dataset

June 6, 2018

0.0.1 Random Forest and GBDT on Amazon reviews data set

```
In [1]: #importing required Modules
        %matplotlib inline
        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import pickle
        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.feature_extraction.text import CountVectorizer
        from sklearn.metrics import confusion_matrix
        from sklearn import metrics
        from sklearn.metrics import accuracy_score
        from sklearn.metrics import roc_curve, auc
        from nltk.stem.porter import PorterStemmer
        from sklearn.preprocessing import StandardScaler
        from sklearn.model_selection import TimeSeriesSplit
        from sklearn.metrics import precision_score
        from sklearn.metrics import recall_score
        from sklearn.metrics import confusion_matrix
        from sklearn.model_selection import GridSearchCV
        from sklearn.model_selection import RandomizedSearchCV
        from sklearn.model selection import ParameterGrid
        from sklearn.ensemble import RandomForestClassifier as RF
        import xgboost as xgb
        import warnings
        warnings.filterwarnings('ignore')
In [2]: conn = sqlite3.connect('final_clean_dt1.sqlite')
        final_review = pd.read_sql_query("""
        SELECT *
        FROM Reviews_final
        """, conn)
```

```
In [3]: #SORT by time for TBS
        final_review = final_review.sort_values(by='Time')
In [4]: final_review.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 364171 entries, 23 to 345187
Data columns (total 6 columns):
                          364171 non-null int64
index
HelpfulnessNumerator
                        364171 non-null int64
HelpfulnessDenominator 364171 non-null int64
Score
                          364171 non-null object
final text
                          364171 non-null object
Time
                          364171 non-null int64
dtypes: int64(4), object(2)
memory usage: 19.4+ MB
In [5]: #changing lables to 1 or 0
        final_review.Score = final_review.Score.apply(lambda x:
                             1 if x == 'positive' else 0)
In [6]: #Converting to int8
        final_review.HelpfulnessNumerator = final_review.\
                              HelpfulnessNumerator.astype(np.int8)
        final_review.HelpfulnessDenominator = final_review.\
                              HelpfulnessDenominator.astype(np.int8)
In [7]: #Splitting Dataframe for train and test
        train df = final review.iloc[:round(final review.shape[0]*0.70),:]
        test_df = final_review.iloc[round(final_review.shape[0]*0.70):,:]
In [8]: train df.to csv('train df dt.csv',index=False)
        test_df.to_csv('test_df_dt.csv',index=False)
In [8]: print(train_df.shape)
        print(test_df.shape)
(254920, 6)
(109251, 6)
Word2Vec
In [10]: #importing
         from gensim.models import Word2Vec
         from gensim.models import KeyedVectors
         import pickle
         import gensim
```

```
In [10]: import gensim
         list_of_sent=[]
         for sent in final_review.final_text.values:
             list_of_sent.append(sent.split())
In [12]: #word2vec model with 300 dim vector
         w2v_model_300=gensim.models.Word2Vec(list_of_sent,min_count=5,size=300, workers=8)
In []: pickle.dump(w2v_model_50,open('w2v_model_dt_50.p','wb'))
In [11]: w2v model 300 = pickle.load(open('w2v model dt 300.p','rb'))
Avg Word2Vec
In [11]: # the avg-w2v for each sentence/review is stored in this list
         def avg w2v(list of sent,model,d):
             Returns average of word vectors for
             each sentance with dimension of model given
             sent_vectors = []
             for sent in list_of_sent: # for each review/sentence
                 doc = [word for word in sent if word in model.wv.vocab]
                 if doc:
                     sent vec = np.mean(model.wv[doc],axis=0)
                 else:
                     sent_vec = np.zeros(d)
                 sent_vectors.append(sent_vec)
             return sent vectors
In [13]: list_of_sent_train=[]
         for sent in train df.final text.values:
             list_of_sent_train.append(sent.split())
In [15]: #avg word2vec for
         sent_vector_avgw2v_300 = avg_w2v(list_of_sent_train,w2v_model_300,300)
         #stacking columns
         train_avgw2v_300 = np.hstack((sent_vector_avgw2v_300,
                     train_df[['HelpfulnessNumerator','HelpfulnessDenominator','Score']]))
         column = list(range(0,300))
         column.extend(['HelpfulnessNumerator','HelpfulnessDenominator','Score'])
         train_df_avgw2v_300 = pd.DataFrame(train_avgw2v_300,columns=column)
In [15]: train_df_avgw2v_300.to_csv('train_df_avgw2v_300.csv',index=False)
In [16]: X_train = train_df_avgw2v_300.iloc[:round(train_df.shape[0]*0.70),:]
         X_test_cv = train_df_avgw2v_300.iloc[round(train_df.shape[0]*0.70):,:]
```

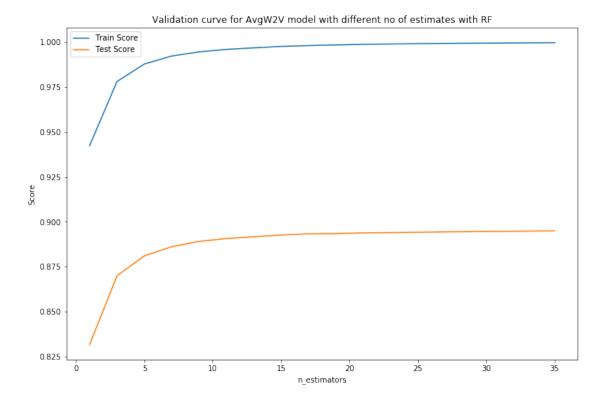
Random Forest

```
In [18]: #base model
         model = RF(n_jobs=-1,random_state=25).fit(X_train.drop('Score',axis=1),X_train.Score)
         train_score = model.score(X_train.drop('Score',axis=1),X_train.Score)
         #test score
         test_score = model.score(X_test_cv.drop('Score',axis=1),X_test_cv.Score)
         print('Train Score',train_score)
         print('Test Score',test_score)
Train Score 0.9969738405326041
Test Score 0.8889847795386788
In [26]: for i in range(1,20):
             model = RF(n_estimators=i,n_jobs=-1,random_state=25)
             model.fit(X_train.drop('Score',axis=1),X_train.Score)
             train_score = model.score(X_train.drop('Score',axis=1),X_train.Score)
             #test score
             test_score = model.score(X_test_cv.drop('Score',axis=1),X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 1 Train Score 0.9415558942861626 Test Score 0.8301035619017731
No of Estimators 2 Train Score 0.9352457913967407 Test Score 0.8022255348083058
No of Estimators 3 Train Score 0.9776400439353523 Test Score 0.8654610596788535
No of Estimators 4 Train Score 0.982403443096994 Test Score 0.8622312882472932
No of Estimators 5 Train Score 0.9876543901728273 Test Score 0.8755557299021915
No of Estimators 6 Train Score 0.9920199054044967 Test Score 0.8789554893038339
No of Estimators 7 Train Score 0.992031113402524 Test Score 0.881283016894189
No of Estimators 8 Train Score 0.9953038488265226 Test Score 0.8853627281761598
No of Estimators 9 Train Score 0.9945473089596736 Test Score 0.8842251163763796
No of Estimators 10 Train Score 0.9969738405326041 Test Score 0.8889847795386788
No of Estimators 11 Train Score 0.9958754567259196 Test Score 0.8864872639782415
No of Estimators 12 Train Score 0.9978648763757818 Test Score 0.8898085673936922
No of Estimators 13 Train Score 0.9970074645266862 Test Score 0.8875202677964329
No of Estimators 14 Train Score 0.9983131962968774 Test Score 0.8912992311313354
No of Estimators 15 Train Score 0.9976687364103024 Test Score 0.8883832836445421
No of Estimators 16 Train Score 0.9987391002219184 Test Score 0.8920837909932527
No of Estimators 17 Train Score 0.9981506803254803 Test Score 0.888801715570898
No of Estimators 18 Train Score 0.998985676178521 Test Score 0.8922799309587321
No of Estimators 19 Train Score 0.9984476922732062 Test Score 0.8891939955018567
In [47]: #grid search
         param_grid = {'n_estimators':[1,3,5,7,9,11,15,17,19,21,25,27,35]}
         model_grid_avgw2v = GridSearchCV(RF(n_jobs=-1,random_state=25),param_grid=param_grid,
                              cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
```

model_grid_avgw2v.fit(train_df_avgw2v_300.drop('Score',axis=1),train_df_avgw2v_300.Score')

```
In [50]: dict_scores = []
         idx = 0
         for i in model_grid_avgw2v.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['n_estimators'])
             dict_score.append(i[1])
             dict_score.append(i[2].std())
             dict_score.append(model_grid_avgw2v.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
             idx = idx + 1
         scores_df = pd.DataFrame(dict_scores,columns=['n_estimators','Test_score',
                                                         'Test_std', 'Train_score'])
In [55]: plt.figure(figsize=(12,8))
         plt.plot(scores_df.n_estimators,scores_df.Train_score,label='Train_Score')
         plt.plot(scores_df.n_estimators,scores_df.Test_score,label='Test Score')
         plt.title('Validation curve for AvgW2V model with different no of estimates with RF')
         plt.xlabel('n_estimators')
         plt.ylabel('Score')
         plt.legend()
```

Out[55]: <matplotlib.legend.Legend at 0x1541ace89a90>



In [56]: scores_df

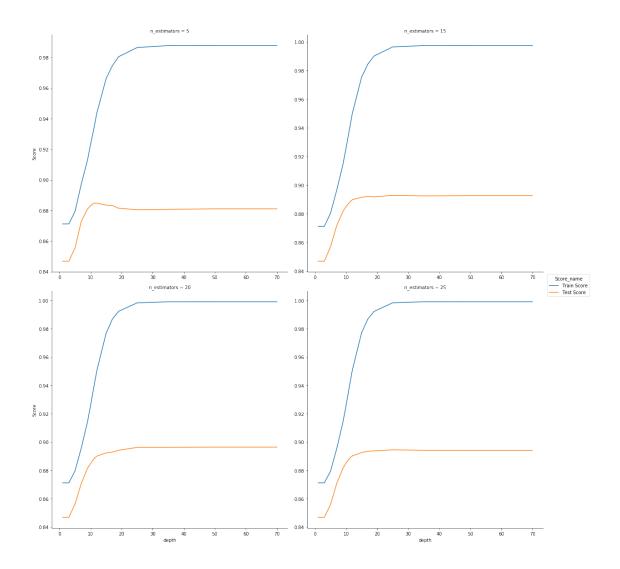
```
Out [56]:
             n_estimators Test_score Test_std Train_score
         0
                        1
                             0.831742 0.010920
                                                     0.942438
         1
                        3
                             0.870001
                                       0.009861
                                                     0.978063
         2
                        5
                             0.881069 0.008450
                                                     0.987786
         3
                        7
                             0.886157
                                       0.008190
                                                     0.992247
         4
                        9
                             0.889126 0.008104
                                                     0.994517
         5
                       11
                             0.890701 0.008086
                                                     0.995924
         6
                       15
                             0.892673 0.007981
                                                     0.997590
         7
                       17
                             0.893368 0.007743
                                                     0.998058
         8
                       19
                             0.893450 0.007841
                                                     0.998393
         9
                       21
                             0.893847
                                       0.007564
                                                     0.998735
         10
                       25
                                       0.007405
                             0.894179
                                                     0.999102
                       27
         11
                             0.894408 0.007433
                                                     0.999270
         12
                       35
                                       0.007525
                             0.894981
                                                     0.999662
```

We can observe that after no of estimates >15 there is no increment in test score. and that is also having some varince.

```
In [53]: print('with 15 estimaters')
         for i in range (1,20):
             model = RF(n_estimators=15,max_depth=i,n_jobs=-1,random_state=25)
             model.fit(X_train.drop('Score',axis=1),X_train.Score)
             #train score
             train_score = model.score(X_train.drop('Score',axis=1),X_train.Score)
             test_score = model.score(X_test_cv.drop('Score',axis=1),X_test_cv.Score)
             print('Deptha',i,'Train Score',train_score,'Test Score',test_score)
with 15 estimaters
Deptha 1 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Deptha 2 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Deptha 3 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Deptha 4 Train Score 0.8639349039474569 Test Score 0.83333333333333334
Deptha 5 Train Score 0.8719206025419739 Test Score 0.8425257597154663
Deptha 6 Train Score 0.8788247293268476 Test Score 0.8511166902034625
Deptha 7 Train Score 0.886177176032817 Test Score 0.8588707568387468
Deptha 8 Train Score 0.8944598865750599 Test Score 0.8674355353313458
Deptha 9 Train Score 0.9033534330097958 Test Score 0.8727836183900831
Deptha 10 Train Score 0.9147743829997086 Test Score 0.8787331973429573
Deptha 11 Train Score 0.9260160050211831 Test Score 0.880485381034573
Deptha 12 Train Score 0.9396113066284101 Test Score 0.8837020764684346
Deptha 13 Train Score 0.9517159444979938 Test Score 0.8841335843924891
Deptha 14 Train Score 0.9629127345273587 Test Score 0.8866441759506251
Deptha 15 Train Score 0.9702315572392459 Test Score 0.8867095559391182
Deptha 16 Train Score 0.9768610880724485 Test Score 0.887376431821748
Deptha 17 Train Score 0.9826556230526103 Test Score 0.8874025838171452
Deptha 18 Train Score 0.9864159063908005 Test Score 0.8874679638056384
Deptha 19 Train Score 0.988988141938087 Test Score 0.8861342120403787
```

```
In [54]: print('with 25 estimaters')
        for i in range(1,20):
            model = RF(n_estimators=25,max_depth=i,n_jobs=-1,random_state=25)
             model.fit(X_train.drop('Score',axis=1),X_train.Score)
             #train score
             train_score = model.score(X_train.drop('Score',axis=1),X_train.Score)
             test_score = model.score(X_test_cv.drop('Score',axis=1),X_test_cv.Score)
             print('Deptha',i,'Train Score',train_score,'Test Score',test_score)
with 25 estimaters
Deptha 1 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Deptha 2 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Deptha 3 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Deptha 4 Train Score 0.8630550761023066 Test Score 0.8325749254668131
Deptha 5 Train Score 0.8706316827688239 Test Score 0.8420550237983158
Deptha 6 Train Score 0.8776703055300262 Test Score 0.8509205502379832
Deptha 7 Train Score 0.8856279841294747 Test Score 0.8591061247973221
Deptha 8 Train Score 0.8937818026944028 Test Score 0.8674355353313458
Deptha 9 Train Score 0.9035383649772477 Test Score 0.8730974423348502
Deptha 10 Train Score 0.9145222030440923 Test Score 0.8788378053245463
Deptha 11 Train Score 0.9269518728564704 Test Score 0.881492232857367
Deptha 12 Train Score 0.9404855304745466 Test Score 0.8842381923740782
Deptha 13 Train Score 0.9533691242070341 Test Score 0.8860296040587897
Deptha 14 Train Score 0.9644818542511937 Test Score 0.8871149118677755
Deptha 15 Train Score 0.9721145009078478 Test Score 0.8879648517181861
Deptha 16 Train Score 0.9784806437874067 Test Score 0.8881348396882682
Deptha 17 Train Score 0.9844937347291027 Test Score 0.889115539515665
Deptha 18 Train Score 0.988085898096882 Test Score 0.8890501595271719
Deptha 19 Train Score 0.9907646096254287 Test Score 0.8891547675087609
In [16]: print('with 25 estimaters')
        for i in range(1,20):
             model = RF(n_estimators=25,max_depth=i,max_features='log2',n_jobs=-1,random_state
             model.fit(X_train.drop('Score',axis=1),X_train.Score)
             #train score
             train_score = model.score(X_train.drop('Score',axis=1),X_train.Score)
             #test score
             test_score = model.score(X_test_cv.drop('Score',axis=1),X_test_cv.Score)
             print('Deptha',i,'Train Score',train_score,'Test Score',test_score)
with 25 estimaters
Deptha 1 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Deptha 2 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Deptha 3 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Deptha 4 Train Score 0.8601746206092667 Test Score 0.8295543699984309
Deptha 5 Train Score 0.8634753760283338 Test Score 0.8325749254668131
```

```
Deptha 6 Train Score 0.8675382753132636 Test Score 0.8379622365186463
Deptha 7 Train Score 0.874408778104055 Test Score 0.8473377268685601
Deptha 8 Train Score 0.8830333325861335 Test Score 0.8554448454417072
Deptha 9 Train Score 0.8906939992378561 Test Score 0.861198284429102
Deptha 10 Train Score 0.9007251574723723 Test Score 0.8656702756420315
Deptha 11 Train Score 0.9132444912689696 Test Score 0.8699068988963858
Deptha 12 Train Score 0.9284033086010177 Test Score 0.8754118939275066
Deptha 13 Train Score 0.9422507901638609 Test Score 0.8781055494534233
Deptha 14 Train Score 0.9546132119880747 Test Score 0.8796092891887651
Deptha 15 Train Score 0.9666562058685078 Test Score 0.8806161410115592
Deptha 16 Train Score 0.9751126403801753 Test Score 0.8805376850253674
Deptha 17 Train Score 0.9825547510703638 Test Score 0.8841858883832836
Deptha 18 Train Score 0.9873517742260878 Test Score 0.8825121606778598
Deptha 19 Train Score 0.9912241375445517 Test Score 0.8822898687169831
In [76]: param_grid = {'n_estimators':[15,20,25],
                 'max_depth': [1,3,5,7,9,10,11,12,15,17,19,25,35,50,70]}
         model_grid_avgw2v_depth = GridSearchCV(RF(n_jobs=-1,
                             random_state=25),param_grid=param_grid,
                              cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
         model_grid_avgw2v_depth.fit(train_df_avgw2v_300.drop('Score',axis=1),
                                              train_df_avgw2v_300.Score)
In [77]: dict_scores = []
         idx = 0
         for i in model_grid_avgw2v_depth.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['n_estimators'])
             dict_score.append(i[0]['max_depth'])
             dict_score.append(i[1])
             dict_score.append(i[2].std())
             dict_score.append(model_grid_avgw2v_depth.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
             idx = idx + 1
         scores_df1 = pd.DataFrame(dict_scores,columns=['n_estimators','depth','Test_score',
                                                        'Test_std', 'Train_score'])
In [78]: scores_df_train = scores_df1.copy()
         scores_df_test = scores_df1.copy()
         scores_df_train['Score_name'] = 'Train Score'
         scores_df_test['Score_name'] = 'Test Score'
         scores_df_test['Score'] = scores_df_test['Test_score']
         scores_df_train['Score'] = scores_df_train['Train_score']
         final_df = scores_df_train.append(scores_df_test, ignore_index=True)
In [80]: g = sns.FacetGrid(final_df, col="n_estimators",col_wrap=2,
           hue="Score_name", sharex=False, sharey=False, size = 8).\
           map(plt.plot, 'depth', 'Score').add_legend()
```



We can observe that for each no of estimators, if depth is increasing, model is overfitting. and for 20 estimators with depth in with depth >25.

Out[85]:		$n_{estimators}$	depth	Test_score	${\sf Test_std}$	Train_score
5	58	20	70	0.896479	0.007020	0.999095
5	54	20	50	0.896479	0.007020	0.999095
5	50	20	35	0.896336	0.007000	0.999079
4	16	20	25	0.896263	0.006714	0.998319
4	17	25	25	0.894559	0.006800	0.998347

for Avg Word2vec best score got at $n_{ectimators} = 20$ and depth = 25 with mean cv of 0.896263.

```
for sent in train_df.final_text.values:
    list_of_sent_train.append(sent.split())
#avg word2vec for
sent_vector_avgw2v_300 = avg_w2v(list_of_sent_train,w2v_model_300,300)
#stacking columns
train avgw2v 300 = np.hstack((sent vector avgw2v 300,
            train df[['HelpfulnessNumerator','HelpfulnessDenominator']]))
column = list(range(0,300))
column.extend(['HelpfulnessNumerator','HelpfulnessDenominator'])
train_df_avgw2v_300 = pd.DataFrame(train_avgw2v_300,columns=column)
list_of_sent_test=[]
for sent in test_df.final_text.values:
    list_of_sent_test.append(sent.split())
#avg word2vec for
sent_vector_avgw2v_300_test = avg_w2v(list_of_sent_test,w2v_model_300,300)
#stacking columns
test_avgw2v_300 = np.hstack((sent_vector_avgw2v_300_test,
            test df[['HelpfulnessNumerator', 'HelpfulnessDenominator']]))
column = list(range(0,300))
column.extend(['HelpfulnessNumerator', 'HelpfulnessDenominator'])
test_df_avgw2v_300 = pd.DataFrame(test_avgw2v_300,columns=column)
model = RF(n_estimators=20,max_depth=25)
model.fit(train_df_avgw2v_300,train_df.Score)
#Predicting training data
train_list = model.predict(train_df_avgw2v_300)
#Accuracy score
score_train = accuracy_score(train_df.Score,train_list)
#predict test cv
test_list = model.predict(test_df_avgw2v_300)
#Accuracy score
score test = accuracy score(test df.Score,test list)
#precision
#precision
test_precision = precision_score(test_df.Score,test_list)
test_recall = recall_score(test_df.Score,test_list)
#confusion matrix
confusion_matrix_test = confusion_matrix(test_df.Score,test_list)
print("n_estimators=20,max_depth=25")
print('Train Score', score_train)
print('Test Score',score_test)
print('Test Precision',test_precision)
print('Test Recall',test_recall)
print('Test ConfusionMatrix',confusion_matrix_test)
```

XGBoost

```
In [20]: for i in range(0,100,10):
             model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
             model.fit(X_train.drop('Score',axis=1),X_train.Score)
             train_score = model.score(X_train.drop('Score',axis=1),X_train.Score)
             #test score
             test_score = model.score(X_test_cv.drop('Score',axis=1),X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 0 Train Score 0.1399878953621304 Test Score 0.17065484596474711
No of Estimators 10 Train Score 0.8844735603326533 Test Score 0.8588053768502537
No of Estimators 20 Train Score 0.8895563874380759 Test Score 0.8653302997018673
No of Estimators 30 Train Score 0.8968976261460178 Test Score 0.8743788901093154
No of Estimators 40 Train Score 0.9028658850956042 Test Score 0.8816883728228464
No of Estimators 50 Train Score 0.908088812176369 Test Score 0.8882263716721586
No of Estimators 60 Train Score 0.9120228194839838 Test Score 0.893365238767718
No of Estimators 70 Train Score 0.9152507229158727 Test Score 0.8973272660704011
No of Estimators 80 Train Score 0.9180919504158167 Test Score 0.9009623934306188
No of Estimators 90 Train Score 0.9202102620429938 Test Score 0.9035122129818505
In [26]: for i in range(80,150,10):
             model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
             model.fit(X_train.drop('Score',axis=1),X_train.Score)
             train_score = model.score(X_train.drop('Score',axis=1),X_train.Score)
             #test score
             test_score = model.score(X_test_cv.drop('Score',axis=1),X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 80 Train Score 0.9180919504158167 Test Score 0.9009623934306188
No of Estimators 90 Train Score 0.9202102620429938 Test Score 0.9035122129818505
No of Estimators 100 Train Score 0.9221380377037054 Test Score 0.9060620325330823
No of Estimators 110 Train Score 0.9242731613279236 Test Score 0.908232648151054
No of Estimators 120 Train Score 0.9259655690300599 Test Score 0.9101548198127517
No of Estimators 130 Train Score 0.9277028087243057 Test Score 0.911710863538888
No of Estimators 140 Train Score 0.9288572325211271 Test Score 0.9135676552120927
```

```
In [27]: for i in range(150,500,50):
             model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
             model.fit(X_train.drop('Score',axis=1),X_train.Score)
             train score = model.score(X train.drop('Score',axis=1),X train.Score)
             test score = model.score(X test cv.drop('Score',axis=1),X test cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 150 Train Score 0.9302470242765237 Test Score 0.9147444950049689
No of Estimators 200 Train Score 0.9353466633789872 Test Score 0.9194910821695695
No of Estimators 250 Train Score 0.9391237587142185 Test Score 0.9230216015481981
No of Estimators 300 Train Score 0.9419089462240254 Test Score 0.9252183691615671
No of Estimators 350 Train Score 0.944593261751586 Test Score 0.9268659448715937
No of Estimators 400 Train Score 0.9466779493846809 Test Score 0.9281996966368534
No of Estimators 450 Train Score 0.9484712290690637 Test Score 0.929363460432031
  We can obsever if no of estimators incresing then Test and Train scores also incresing.
In [32]: from scipy.stats import uniform
         eta1 = uniform.rvs(0,1,15,random_state=25)
         print('with 150 estimators')
         for i in eta1:
             model = xgb.XGBClassifier(learning_rate=i,n_estimators=150,n_jobs=-1)
             model.fit(X_train.drop('Score',axis=1),X_train.Score)
             #train score
             train_score = model.score(X_train.drop('Score',axis=1),X_train.Score)
             #test score
             test_score = model.score(X_test_cv.drop('Score',axis=1),X_test_cv.Score)
             print('Learning Rate',i,'Train Score',train_score,'Test Score',test_score)
with 150 estimators
Learning Rate 0.8701241366272119 Train Score 0.9562944116921835 Test Score 0.9261467649981694
Learning Rate 0.5822769286725598 Train Score 0.9537950281320751 Test Score 0.9289842564987708
Learning Rate 0.27883894070106907 Train Score 0.9459214095178319 Test Score 0.9268005648831006
Learning Rate 0.18591123209017923 Train Score 0.9403286185021631 Test Score 0.9236754014331293
Learning Rate 0.4111001279251132 Train Score 0.9502420927573917 Test Score 0.930161096291647
Learning Rate 0.11737554713471554 Train Score 0.933211539754769 Test Score 0.917699670484858
Learning Rate 0.684968744374135 Train Score 0.9552576718746497 Test Score 0.9287750405355929
Learning Rate 0.4376110596596504 Train Score 0.9507688686646791 Test Score 0.9294811444113186
Learning Rate 0.5562293251719702 Train Score 0.9528871802918563 Test Score 0.930056488310058
Learning Rate 0.3670803216193239 Train Score 0.9490092129743786 Test Score 0.9290234844918668
Learning Rate 0.40236572881420285 Train Score 0.9500459527919123 Test Score 0.9286573565563052
Learning Rate 0.11304070069439631 Train Score 0.9328192598238103 Test Score 0.9170589465976254
Learning Rate 0.44703084626748935 Train Score 0.9508529286498846 Test Score 0.9291019404780585
Learning Rate 0.5854451165110357 Train Score 0.9535092241823765 Test Score 0.9300695643077567
```

Learning Rate 0.16198510384493825 Train Score 0.9382831588621641 Test Score 0.9220016737277055

```
In [18]: #random search
         from scipy.stats import randint as sp_randint
         from scipy.stats import uniform
         np.random.seed(25)
         param_distributions = {'max_depth':sp_randint(3,5),'learning_rate':uniform(0,1),
                                 'n_estimators':sp_randint(50,700), 'subsample':uniform(0.7,0.3)
         model_random_avgw2v_depth = RandomizedSearchCV(xgb.XGBClassifier(n_jobs=-1,random_sta
                                                 param_distributions=param_distributions,n_iter
                                                 cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
         model_random_avgw2v_depth.fit(train_df_avgw2v_300.drop('Score',axis=1),train_df_avgw2v
In [23]: dict_scores = []
         idx = 0
         for i in model_random_avgw2v_depth.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['learning_rate'])
             dict_score.append(i[0]['max_depth'])
             dict_score.append(i[0]['n_estimators'])
             dict_score.append(i[0]['subsample'])
             dict_score.append(i[1])
             dict_score.append(i[2].std())
             dict_score.append(model_random_avgw2v_depth.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
             idx = idx + 1
         scores_df = pd.DataFrame(dict_scores,columns=['learning_rate','depth',
                  'n_estimators','subsample','Test_score','Test_std','Train_score'])
In [25]: scores_df.sort_values('Test_score',ascending=False)
Out [25]:
                                                                         Test_std \
             learning_rate
                            depth n_estimators
                                                 subsample Test_score
         13
                  0.510903
                                4
                                             576
                                                   0.927412
                                                               0.936679 0.003772
         2
                  0.437611
                                4
                                             550
                                                   0.810124
                                                               0.936248 0.003834
         28
                                3
                                             693
                                                               0.936002 0.004033
                  0.566830
                                                   0.937182
                                                               0.935876 0.003101
         4
                  0.406806
                                3
                                             354
                                                   0.797815
         3
                  0.402366
                                3
                                             309
                                                   0.859582
                                                               0.935630 0.003431
         6
                  0.481343
                                3
                                             353
                                                   0.843264
                                                               0.935540 0.003151
         5
                  0.699186
                                4
                                             612
                                                   0.950912
                                                               0.935052 0.005123
         16
                  0.076742
                                4
                                             458
                                                   0.903955
                                                               0.934621 0.003908
                                4
         18
                  0.719055
                                             672
                                                   0.818962
                                                               0.934254 0.004816
         10
                  0.456069
                                3
                                             221
                                                   0.857746
                                                               0.933883 0.003535
         17
                                4
                                             210
                                                               0.933775 0.003687
                  0.509213
                                                   0.880636
                                4
         26
                                             433
                                                               0.933684 0.004650
                  0.676561
                                                   0.898262
         7
                                4
                  0.631773
                                             452
                                                   0.793398
                                                               0.933123 0.003660
         8
                  0.605659
                                4
                                             285
                                                   0.831081
                                                               0.932722 0.004069
         24
                  0.766994
                                3
                                             521
                                                   0.841719
                                                               0.932118 0.004406
                                3
         21
                  0.650652
                                             549
                                                   0.705907
                                                               0.932001 0.004052
         12
                                3
                  0.903585
                                             613
                                                   0.987161
                                                               0.931829 0.004628
         20
                  0.842154
                                3
                                             633
                                                   0.898623
                                                               0.931639 0.005062
```

```
9
         0.281701
                        4
                                     107
                                           0.900884
                                                       0.930646
                                                                  0.004327
                        3
1
         0.185911
                                     186
                                           0.905491
                                                       0.930370
                                                                  0.005146
19
         0.825139
                        4
                                     579
                                           0.729381
                                                       0.930275
                                                                  0.004906
14
                        4
                                           0.726611
                                                       0.930142
         0.666186
                                     279
                                                                  0.004342
                        3
15
         0.641717
                                     117
                                           0.929946
                                                       0.929835
                                                                  0.003231
23
         0.836928
                        3
                                     382
                                           0.750712
                                                       0.928627
                                                                  0.004657
0
         0.870124
                        3
                                     193
                                           0.783652
                                                       0.928161
                                                                  0.003508
11
         0.559242
                        3
                                     64
                                           0.745576
                                                       0.926495
                                                                  0.004264
25
         0.215064
                        3
                                                       0.926353
                                     114
                                           0.927762
                                                                  0.005986
27
         0.094440
                        3
                                     243
                                           0.733825
                                                       0.926163
                                                                  0.005562
22
                        4
                                           0.749095
                                                       0.925982
         0.990475
                                     434
                                                                  0.005695
29
                        3
                                                       0.924394
         0.033683
                                     576
                                           0.810164
                                                                  0.006005
```

```
Train_score
       0.998045
13
2
       0.996316
28
       0.991577
4
       0.975302
3
       0.972967
6
       0.977620
5
       0.999616
16
       0.966540
18
       0.999800
10
       0.968635
17
       0.983310
26
       0.997391
7
       0.996940
8
       0.990600
24
       0.989528
21
       0.987656
12
       0.994322
20
       0.993807
9
       0.961340
1
       0.952671
19
       0.999448
14
       0.990129
15
       0.961299
23
       0.983342
0
       0.971065
11
       0.948061
25
       0.946190
27
       0.945670
22
       0.997964
29
       0.942891
```

We can observe from above that learning rate between 0.4-0.6 giving good score and if we are

incresing no of estimaters model efficiency is incresing.

```
In [37]: fig, axes = plt.subplots(6, 1,sharex=True,figsize=(15,15))
           for ax,i in zip(axes.ravel(),colm):
                ax.plot(range(0,30),scores_df[i])
                ax.set_ylabel(i)
                if i == 'Train Score':
                      ax.set_xlabel('Iteration no in random search')
                if i == 'learning_rate':
                      ax.set_title('iteration no vs params and scores')
                                            iteration no vs params and scores
        1.00
      ej 0.75
0.50
        4.00
      £ 3.50
        3.25
        600
       n estimators
000
500
       흥 0.9
       Sq 0.8
        0.7
       0.935
      Test score
       0.930
       0.925
      0.98
      E 0.96
```

```
xgb.XGBClassifier(n_jobs=-1,
                                              learning_rate=0.52,
                                              random_state=25),
                                              param_grid=param_grid,
                                      cv=TimeSeriesSplit(n_splits=10),
                                                  n_{jobs=-1}
         model_grid_avgw2v.fit(train_df_avgw2v_300.drop('Score',axis=1),
                                           train_df_avgw2v_300.Score)
In [30]: dict_scores = []
         idx = 0
         for i in model_grid_avgw2v_depth.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['n_estimators'])
             dict_score.append(i[0]['max_depth'])
             dict_score.append(i[0]['subsample'])
             dict_score.append(i[1])
             dict_score.append(i[2].std())
             dict_score.append(model_grid_avgw2v_depth.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
             idx = idx + 1
         scores_df = pd.DataFrame(dict_scores,columns=['n_estimators','depth',
                  'subsample','Test_score','Test_std','Train_score'])
In [32]: scores_df.sort_values('Test_score',ascending=False)
Out [32]:
             n_estimators
                           depth
                                   subsample Test_score
                                                          Test std
                                                                     Train_score
         7
                                5
                                        0.93
                                                0.939139
                      900
                                                           0.002537
                                                                        1.000000
                      900
                                5
         8
                                        1.00
                                                0.938992
                                                           0.002336
                                                                        1.000000
         4
                      800
                                5
                                        0.93
                                                           0.002644
                                                0.938897
                                                                        1.000000
                                5
         5
                      800
                                        1.00
                                                0.938690
                                                          0.002465
                                                                        1.000000
         13
                      800
                                7
                                        0.93
                                                0.938440
                                                          0.002398
                                                                        1.000000
                                7
         17
                      900
                                        1.00
                                                0.938435
                                                           0.002192
                                                                        1.000000
                                7
                                        0.93
         16
                      900
                                                0.938414
                                                           0.002297
                                                                        1.000000
                                7
         14
                      800
                                        1.00
                                                0.938289
                                                           0.002245
                                                                        1.000000
                                7
         12
                      800
                                        0.80
                                                0.937883
                                                           0.002347
                                                                        1.000000
         15
                      900
                                7
                                        0.80
                                                0.937823
                                                           0.002401
                                                                        1.000000
         6
                      900
                                5
                                        0.80
                                                0.937797
                                                           0.003259
                                                                        1.000000
                                5
         1
                      560
                                        0.93
                                                0.937754
                                                          0.003156
                                                                        0.999996
         10
                      560
                                7
                                        0.93
                                                0.937633
                                                           0.002251
                                                                        1.000000
                                7
                      560
         11
                                        1.00
                                                0.937594
                                                          0.002246
                                                                        1.000000
                                                                        0.999992
         2
                      560
                                5
                                        1.00
                                                          0.002853
                                                0.937421
         26
                                9
                      900
                                        1.00
                                                0.937361 0.002619
                                                                        1.000000
         3
                      800
                                5
                                        0.80
                                                0.937331 0.003446
                                                                        1.000000
         23
                      800
                                9
                                        1.00
                                                0.937223
                                                          0.002627
                                                                        1.000000
                      560
                                7
                                        0.80
         9
                                                0.937124 0.002138
                                                                        1.000000
         25
                      900
                                9
                                        0.93
                                                0.936925
                                                           0.002573
                                                                        1.000000
                      800
                                        0.93
         22
                                9
                                                0.936692 0.002666
                                                                        1.000000
```

20	560	9	1.00	0.936657	0.002620	1.000000
24	900	9	0.80	0.936537	0.002635	1.000000
21	800	9	0.80	0.936308	0.002734	1.000000
0	560	5	0.80	0.936278	0.003660	0.999995
19	560	9	0.93	0.935881	0.002666	1.000000
18	560	9	0.80	0.935687	0.002820	1.000000

Got best cv scores at no of estimators = 900, depth = 5, learning rate = 0.52 and subsample = 0.93 with mean cv score of 0.939139.

```
In [13]: #testscore
         list_of_sent_train=[]
         for sent in train_df.final_text.values:
             list_of_sent_train.append(sent.split())
         #avg word2vec for
         sent_vector_avgw2v_300 = avg_w2v(list_of_sent_train,w2v_model_300,300)
         #stacking columns
         train_avgw2v_300 = np.hstack((sent_vector_avgw2v_300,
                     train_df[['HelpfulnessNumerator','HelpfulnessDenominator']]))
         column = list(range(0,300))
         column.extend(['HelpfulnessNumerator', 'HelpfulnessDenominator'])
         train_df_avgw2v_300 = pd.DataFrame(train_avgw2v_300,columns=column)
         list_of_sent_test=[]
         for sent in test_df.final_text.values:
             list_of_sent_test.append(sent.split())
         #avg word2vec for
         sent_vector_avgw2v_300_test = avg_w2v(list_of_sent_test,w2v_model_300,300)
         #stacking columns
         test_avgw2v_300 = np.hstack((sent_vector_avgw2v_300_test,
                     test_df[['HelpfulnessNumerator', 'HelpfulnessDenominator']]))
         column = list(range(0,300))
         column.extend(['HelpfulnessNumerator', 'HelpfulnessDenominator'])
         test_df_avgw2v_300 = pd.DataFrame(test_avgw2v_300,columns=column)
         model = xgb.XGBClassifier(max_depth=5,learning_rate=0.52,n_estimators=900,
                                          n_jobs=-1,subsample=0.93,random_state=25)
         model.fit(train_df_avgw2v_300,train_df.Score)
         #Predicting training data
         train_list = model.predict(train_df_avgw2v_300)
         #Accuracy score
         score_train = accuracy_score(train_df.Score,train_list)
         #predict test cv
         test_list = model.predict(test_df_avgw2v_300)
         #Accuracy score
         score_test = accuracy_score(test_df.Score,test_list)
```

```
#precision
         #precision
         test_precision = precision_score(test_df.Score,test_list)
         test recall = recall score(test df.Score,test list)
         #confusion matrix
         confusion matrix test = confusion matrix(test df.Score,test list)
         print("""max_depth=5,learning_rate=0.52,n_estimators=900,subsample=0.93""")
         print('Train Score', score train)
         print('Test Score',score_test)
         print('Test Precision',test_precision)
         print('Test Recall',test_recall)
         print('Test ConfusionMatrix',confusion_matrix_test)
max_depth=5,learning_rate=0.52,n_estimators=900,subsample=0.93
Train Score 1.0
Test Score 0.9303164273095899
Test Precision 0.9402160582696143
Test Recall 0.9777425364858271
Test ConfusionMatrix [[13473 5606]
 [ 2007 88165]]
0.0.2 Tf-Idf Word2Vec
In [14]: from sklearn.base import BaseEstimator, TransformerMixin
         class TfidfWeightedWord2Vec(BaseEstimator, TransformerMixin):
             Class for Tfidf Weighted Word2Vec Calculations
             def __init__(self, word2vec):
                 self.word2vec = word2vec
                 self.word2weight = None
                 self.dim = word2vec.vector size
                 self.tfidf = None
             def fit(self, X, y=None):
                 tfidf = TfidfVectorizer()
                 tfidf.fit(X[:,0])
                 self.tfidf = tfidf
                 #print(self.word2vec.wv.vocab.keys())
                 return self
             def tf_idf_W2V(self,feature_names,tf_idf_trans_arr,list_of_sent):
                 tfidf weighted word2vec calculation
```

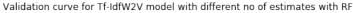
```
dict_tfidf = {k: v for v, k in enumerate(feature_names)}
                 sent_vectors = []
                 i = 0
                 for sent in list of sent: # for each review/sentence
                     doc = [word for word in sent if word in self.word2vec.wv.vocab.keys()]
                     if doc:
                         #itemgetter
                         f = operator.itemgetter(*doc)
                             #itemgetter from dict
                             final = f(dict_tfidf)
                             final = tf_idf_trans_arr[i,final]
                             #converting to dense
                             final = final.toarray()
                             #converting to diagnol matrix for multiplication
                             final= np.diag(final[0])
                             sent_vec = np.dot(final,np.array(self.word2vec.wv[doc]))
                             #tfidf weighted word to vec
                             sent vec = np.sum(sent vec,axis=0) / np.sum(final)
                         except:
                             sent_vec = np.zeros(self.dim)
                         sent_vec = np.zeros(self.dim)
                     sent_vectors.append(sent_vec)
                     i = i+1
                 return sent_vectors
             def transform(self, X):
                 #transform data
                 tf_idf_trans_arr = self.tfidf.transform(X[:,0])
                 feature_names = self.tfidf.get_feature_names()
                 list_of_sent = []
                 for sent in X[:,0]:
                     list of sent.append(sent.split())
                 temp_vec = self.tf_idf_W2V(feature_names,tf_idf_trans_arr,list_of_sent)
                 temp_vec= np.hstack((temp_vec,X[:,[1,2]]))
                 return temp_vec
In [14]: # For simple cv
         #Train data
         X_train = train_df.iloc[:round(train_df.shape[0]*0.70),:]
         X_test_cv = train_df.iloc[round(train_df.shape[0]*0.70):,:]
         #transforming to tfidf weighted word2vec
         tfidfvect_w2v = TfidfWeightedWord2Vec(w2v_model_300)
         tfidfvect_w2v.fit(X_train[['final_text','HelpfulnessNumerator',
                                    'HelpfulnessDenominator']].values)
         X_train_tfw2v = tfidfvect_w2v.transform(X_train[['final_text',
```

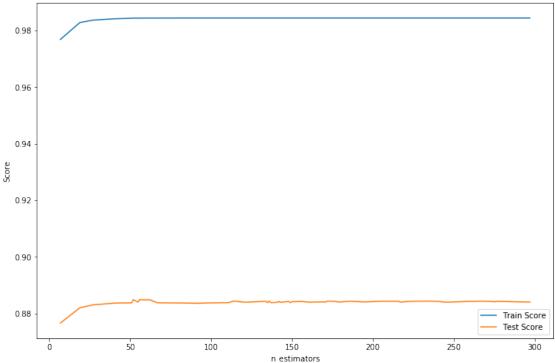
import operator

Random Forest

```
In [14]: #base model
         model = RF(n_jobs=-1,random_state=25).fit(X_train_tfw2v,X_train.Score)
         train_score = model.score(X_train_tfw2v, X_train.Score)
         #test score
         test_score = model.score(X_cv_tfw2v, X_test_cv.Score)
         print('Train Score',train_score)
         print('Test Score',test_score)
Train Score 0.9790018156956805
Test Score 0.8738950781944662
In [15]: for i in range(1,100,5):
             model = RF(n_estimators=i,n_jobs=-1,random_state=25)
             model.fit(X_train_tfw2v,X_train.Score)
             #train score
             train_score = model.score(X_train_tfw2v, X_train.Score)
             #test score
             test score = model.score(X cv tfw2v,X test cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 1 Train Score 0.9284873685862232 Test Score 0.8177336680788744
No of Estimators 6 Train Score 0.974675528457107 Test Score 0.8645980438307442
No of Estimators 11 Train Score 0.977847391898859 Test Score 0.8718682985511794
No of Estimators 16 Train Score 0.9804756674362826 Test Score 0.8768633296720539
No of Estimators 21 Train Score 0.9805148954293784 Test Score 0.8747319420471782
No of Estimators 26 Train Score 0.981316267288337 Test Score 0.8770463936398347
No of Estimators 31 Train Score 0.9813554952814328 Test Score 0.8756603378837805
No of Estimators 36 Train Score 0.9816188832350765 Test Score 0.8775171295569852
No of Estimators 41 Train Score 0.9816188832350765 Test Score 0.8759349338354516
No of Estimators 46 Train Score 0.9817365672143642 Test Score 0.8774648255661907
No of Estimators 51 Train Score 0.9817421712133778 Test Score 0.8756864898791777
No of Estimators 56 Train Score 0.9817813992064738 Test Score 0.8770594696375333
No of Estimators 61 Train Score 0.9817757952074601 Test Score 0.8755688058998902
No of Estimators 66 Train Score 0.9817926072045011 Test Score 0.877072545635232
No of Estimators 71 Train Score 0.9817926072045011 Test Score 0.8760003138239447
No of Estimators 76 Train Score 0.9817982112035148 Test Score 0.876967937653643
No of Estimators 81 Train Score 0.9817982112035148 Test Score 0.8759349338354516
No of Estimators 86 Train Score 0.9817982112035148 Test Score 0.8771902296145195
No of Estimators 91 Train Score 0.9818038152025286 Test Score 0.8762749097756158
No of Estimators 96 Train Score 0.9817982112035148 Test Score 0.8771379256237251
```

```
In [16]: #random search
         param_distributions = {'randomforestclassifier__n_estimators':sp_randint(5,300)}
         model_random_tfidfw2v = RandomizedSearchCV(make_pipeline(
                                   TfidfWeightedWord2Vec(w2v_model_300),
                                  RF(n_jobs=-1,random_state=25)),
                                 param_distributions=param_distributions,n_iter=60,
                                 cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
         model_random_tfidfw2v.fit(train_df_tfw2v,train_df.Score)
In [44]: dict scores = []
         idx = 0
         for i in model_random_tfidfw2v.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['randomforestclassifier_n_estimators'])
             dict_score.append(i[1])
             dict_score.append(i[2].std())
             dict_score.append(model_random_tfidfw2v.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
             idx = idx + 1
         scores_df = pd.DataFrame(dict_scores,columns=['n_estimators','Test_score',
                                                        'Test_std', 'Train_score'])
In [22]: scores_df = scores_df.sort_values('n_estimators')
        plt.figure(figsize=(12,8))
         plt.plot(scores_df.n_estimators,scores_df.Train_score,label='Train_Score')
         plt.plot(scores_df.n_estimators,scores_df.Test_score,label='Test Score')
         plt.title('Validation curve for Tf-IdfW2V model with different no of estimates with R
         plt.xlabel('n_estimators')
         plt.ylabel('Score')
         plt.legend()
Out[22]: <matplotlib.legend.Legend at 0x14850adf3048>
```





```
In [46]: #best scores
         scores_df.sort_values('Test_score',ascending=False).head(5)
Out [46]:
             n_{estimators}
                           Test_score
                                        Test_std
                                                  Train_score
         46
                       56
                              0.884962
                                        0.009991
                                                     0.984384
         35
                       62
                              0.884918
                                        0.010046
                                                     0.984405
         15
                       52
                             0.884914
                                        0.010177
                                                     0.984378
         58
                       58
                              0.884841
                                        0.010031
                                                     0.984390
         18
                      114
                             0.884448
                                       0.009929
                                                     0.984432
In [39]: param_distributions = {
             'randomforestclassifier__n_estimators':sp_randint(10,70),
             'randomforestclassifier__max_depth':sp_randint(3,30),
             'randomforestclassifier_min_samples_split':sp_randint(2,8),
             'randomforestclassifier__class_weight':[None,'balanced']}
         model_random_tfidfw2v = RandomizedSearchCV(make_pipeline(
                                    TfidfWeightedWord2Vec(w2v_model_300),
                                  RF(n_jobs=-1,random_state=25)),
                                  param_distributions=param_distributions,n_iter=100,
                                  cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
         model_random_tfidfw2v.fit(train_df_tfw2v,train_df.Score)
In [47]: dict_scores = []
         idx = 0
```

```
for i in model_random_tfidfw2v_all.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['randomforestclassifier__n_estimators'])
             dict_score.append(i[0]['randomforestclassifier__max_depth'])
             dict_score.append(i[0]['randomforestclassifier__min_samples_split'])
             dict_score.append(i[0]['randomforestclassifier__class_weight'])
             dict_score.append(i[1])
             dict_score.append(i[2].std())
             dict_score.append(model_random_tfidfw2v_all.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
             idx = idx + 1
         scores_df = pd.DataFrame(dict_scores,columns=['n_estimators','depth',
                  'min_samples_split','class_weight','Test_score','Test_std','Train_score'])
In [49]: scores_df.sort_values('Test_score',ascending=False).head(5)
Out [49]:
            n_estimators depth min_samples_split class_weight Test_score Test_std \
         0
                       64
                              29
                                                  7
                                                            None
                                                                    0.883093 0.010659
                                                  6
         55
                       49
                              28
                                                            None
                                                                    0.882808 0.010204
                       64
                              24
                                                  5
                                                            None
                                                                    0.881937 0.010730
         71
                       61
                              24
                                                  3
                                                            None 0.881906 0.010798
         44
                       23
                              26
                                                  4
                                                            None 0.881863 0.010971
             Train_score
                0.979521
         0
                0.980000
         55
                0.978783
         71
                0.980478
         44
                0.979109
```

We can observe that for no of estimators based on depth scores are changing and best score got at n_estimators at 56 and test cv is 0.884962

```
score_train = accuracy_score(train_df.Score,train_list)
         #predict test cv
         test_list = model.predict(X_cv_tfw2v)
         #Accuracy score
         score test = accuracy score(test df.Score,test list)
         #precision
         #precision
         test_precision = precision_score(test_df.Score,test_list)
         test_recall = recall_score(test_df.Score,test_list)
         #confusion matrix
         confusion_matrix_test = confusion_matrix(test_df.Score,test_list)
         print('n_estimators',56)
         print('Train Score', score_train)
         print('Test Score',score_test)
         print('Test Precision',test_precision)
         print('Test Recall',test_recall)
         print('Test ConfusionMatrix',confusion_matrix_test)
n_estimators 56
Train Score 0.9796524399811706
Test Score 0.8709485496700259
Test Precision 0.8726985900036254
Test Recall 0.9877234618285056
Test ConfusionMatrix [[ 6087 12992]
 [ 1107 89065]]
  Xg Boost
In [15]: X_train_tfw2v = X_train_tfw2v.astype(float)
         X_cv_tfw2v = X_cv_tfw2v.astype(float)
In [64]: for i in range(0,100,10):
             model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
             model.fit(X_train_tfw2v,X_train.Score)
             #train score
             train_score = model.score(X_train_tfw2v,X_train.Score)
             #test score
             test_score = model.score(X_cv_tfw2v, X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 0 Train Score 0.1399878953621304 Test Score 0.17065484596474711
No of Estimators 10 Train Score 0.8740277061711237 Test Score 0.84591244311941
No of Estimators 20 Train Score 0.8791217412745735 Test Score 0.8521627700193525
No of Estimators 30 Train Score 0.8847537602833382 Test Score 0.8581908049584184
No of Estimators 40 Train Score 0.8902961153078837 Test Score 0.8641142319158952
No of Estimators 50 Train Score 0.8953509224182377 Test Score 0.8695930749516189
```

```
No of Estimators 60 Train Score 0.8985956378471678 Test Score 0.8736989382289869
No of Estimators 70 Train Score 0.901431261348098 Test Score 0.8769810136513416
No of Estimators 80 Train Score 0.9036168209634395 Test Score 0.879818505151943
No of Estimators 90 Train Score 0.9063739884781781 Test Score 0.8818452847952298
In [23]: for i in range(100,500,50):
             model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
             model.fit(X_train_tfw2v,X_train.Score)
             #train score
             train_score = model.score(X_train_tfw2v,X_train.Score)
             test_score = model.score(X_cv_tfw2v,X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 100 Train Score 0.907831028221739 Test Score 0.883754380459229
No of Estimators 150 Train Score 0.9155925668557082 Test Score 0.8910115591819656
No of Estimators 200 Train Score 0.9202550940351034 Test Score 0.8957450703488676
No of Estimators 250 Train Score 0.9233316894936227 Test Score 0.8984779538678801
No of Estimators 300 Train Score 0.9258422810517586 Test Score 0.9008708614467283
No of Estimators 350 Train Score 0.9279942166730178 Test Score 0.902453057168262
No of Estimators 400 Train Score 0.929669812378113 Test Score 0.903878340917412
No of Estimators 450 Train Score 0.9312501400999753 Test Score 0.9051728646895758
In [25]: for i in range(500,1000,50):
             model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
             model.fit(X_train_tfw2v,X_train.Score)
             #train score
             train_score = model.score(X_train_tfw2v,X_train.Score)
             test_score = model.score(X_cv_tfw2v,X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 500 Train Score 0.9327239918405774 Test Score 0.9060881845284795
No of Estimators 550 Train Score 0.9341361995920289 Test Score 0.9069381243788901
No of Estimators 600 Train Score 0.9353410593799736 Test Score 0.9075396202730268
No of Estimators 650 Train Score 0.9363497792024389 Test Score 0.9080757361786704
No of Estimators 700 Train Score 0.9373584990249042 Test Score 0.9088733720382866
No of Estimators 750 Train Score 0.9381262468897805 Test Score 0.9091871959830535
No of Estimators 800 Train Score 0.9390284907309856 Test Score 0.9096840838956012
No of Estimators 850 Train Score 0.9398915065790948 Test Score 0.9101286678173545
No of Estimators 900 Train Score 0.940939454394656 Test Score 0.9106647837229981
No of Estimators 950 Train Score 0.9417856582457241 Test Score 0.9108216956953815
  With increase in no of estimatores test score is incresing.
In [26]: for i in range(500,1000,50):
             model = xgb.XGBClassifier(n_estimators=i,learning_rate=0.5,n_jobs=-1)
```

```
model.fit(X_train_tfw2v,X_train.Score)
             #train score
             train_score = model.score(X_train_tfw2v,X_train.Score)
             #test score
             test score = model.score(X cv tfw2v,X test cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 500 Train Score 0.9558012597789782 Test Score 0.9105732517391077
No of Estimators 550 Train Score 0.9579980273923472 Test Score 0.9108478476907788
No of Estimators 600 Train Score 0.9597016430925108 Test Score 0.9108478476907788
No of Estimators 650 Train Score 0.9616406267512497 Test Score 0.9110962916470526
No of Estimators 700 Train Score 0.9634283024366188 Test Score 0.9117762435273812
No of Estimators 750 Train Score 0.964918966174262 Test Score 0.9113447356033265
No of Estimators 800 Train Score 0.9664096299119052 Test Score 0.9115277995711073
No of Estimators 850 Train Score 0.9679171056465894 Test Score 0.9115408755688059
No of Estimators 900 Train Score 0.9692116294187533 Test Score 0.9122862074376274
No of Estimators 950 Train Score 0.9705397771849992 Test Score 0.9121031434698468
In [27]: for i in [700,900,950]:
             model = xgb.XGBClassifier(n_estimators=i,learning_rate=0.5,
                             n_jobs=-1,reg_alpha=0.2, reg_lambda=0.7)
             model.fit(X_train_tfw2v,X_train.Score)
             #train score
             train_score = model.score(X_train_tfw2v, X_train.Score)
             #test score
             test_score = model.score(X_cv_tfw2v,X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 700 Train Score 0.9641400103113582 Test Score 0.9118023955227784
No of Estimators 900 Train Score 0.9698560893053283 Test Score 0.912652335373189
No of Estimators 950 Train Score 0.9709376611149716 Test Score 0.9128877033317642
In [18]: for i in [700,900,950]:
             model = xgb.XGBClassifier(n_estimators=i,learning_rate=0.5,
                     max_depth=6,n_jobs=-1,reg_alpha=0.2, reg_lambda=0.7)
             model.fit(X_train_tfw2v,X_train.Score)
             #train score
             train_score = model.score(X_train_tfw2v, X_train.Score)
             #test score
             test_score = model.score(X_cv_tfw2v, X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 700 Train Score 0.9815628432449396 Test Score 0.9140383911292431
No of Estimators 900 Train Score 0.9816581112281724 Test Score 0.9146137350279826
No of Estimators 950 Train Score 0.9816973392212683 Test Score 0.9145222030440923
```

We can observe from initial simple cv that incresing the estimators are incresing test scores and there is impact of test scores with regularization and learning rate is also incresing the test score

```
In [16]: from xgboost import XGBClassifier
        param_distributions = {'xgbclassifier__n_estimators':sp_randint(600,1000),
                                'xgbclassifier_max_depth':sp_randint(3,10),
                                'xgbclassifier__learning_rate':uniform(0,1),
                                'xgbclassifier_subsample':uniform(0,1),
                                'xgbclassifier_reg_alpha':uniform(0,1),
                                'xgbclassifier_reg_lambda':uniform(0,1),
                               'xgbclassifier__colsample_bylevel':uniform(0.7,0.3)}
        model_random_tfidfw2v_xgb = RandomizedSearchCV(make_pipeline(
                                   TfidfWeightedWord2Vec(w2v_model_300),
                                     XGBClassifier(n_jobs=-1,random_state=25)),
                                 param_distributions=param_distributions,n_iter=30,
                                 cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
        model_random_tfidfw2v_xgb.fit(train_df_tfw2v,train_df.Score)
In [19]: dict_scores = []
        idx = 0
         for i in model_random_tfidfw2v_xgb.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['xgbclassifier__n_estimators'])
             dict_score.append(i[0]['xgbclassifier__max_depth'])
             dict_score.append(i[0]['xgbclassifier__subsample'])
             dict_score.append(i[0]['xgbclassifier__colsample_bylevel'])
             dict_score.append(i[0]['xgbclassifier__learning_rate'])
             dict_score.append(i[0]['xgbclassifier__reg_alpha'])
             dict_score.append(i[0]['xgbclassifier__reg_lambda'])
             dict_score.append(i[1])
             dict_score.append(i[2].std())
             dict_score.append(model_random_tfidfw2v_xgb.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
         scores_df = pd.DataFrame(dict_scores,columns=['n_estimators','depth',
                  'subsample', 'colsample_bylevel', 'learning_rate', 'reg_alpha',
                       'reg_lambda','Test_score','Test_std','Train_score'])
In [22]: scores_df.sort_values('Test_score', ascending=False).head()
Out [22]:
            n_estimators depth subsample colsample_bylevel learning_rate \
                                   0.994481
                                                      0.791814
                                                                     0.229976
         20
                      884
         6
                      906
                               5
                                 0.524254
                                                      0.885013
                                                                     0.151921
         3
                      903
                               7 0.849676
                                                      0.776976
                                                                     0.231515
                      667
                               3 0.960319
         21
                                                      0.737489
                                                                     0.351055
         19
                      894
                               3 0.328739
                                                      0.822887
                                                                     0.109562
             reg_alpha reg_lambda Test_score Test_std Train_score
        20
             0.998268 0.150014
                                      0.920558 0.006677
                                                           0.978847
```

```
6
    0.644862
               0.309258
                          0.920411 0.006462
                                               0.982022
                          0.919302 0.005702
3
    0.477546 0.631773
                                               0.984339
21
    0.323604 0.806417
                          0.919064 0.006489
                                               0.967847
19
    0.973815
               0.752860
                          0.918870 0.007118
                                               0.953416
```

from random search got good score at n_estimators = 884, depth = 4, subsample = 0.994481, colsample_bylevel=0.791814, learning_rate = 0.229976, reg_alpha = 0.998268, reg_lambda = 0.150014 and Test_score is 0.920558

```
In [24]: #testscore
         #transforming to tfidf weighted word2vec
         tfidfvect_w2v = TfidfWeightedWord2Vec(w2v_model_300)
         tfidfvect_w2v.fit(train_df[['final_text', 'HelpfulnessNumerator',
                                    'HelpfulnessDenominator']].values)
         X_train_tfw2v = tfidfvect_w2v.transform(train_df[['final_text',
                         'HelpfulnessNumerator', 'HelpfulnessDenominator']].values)
         X cv tfw2v = tfidfvect w2v.transform(test df[['final text',
                          'HelpfulnessNumerator', 'HelpfulnessDenominator']].values)
         model = xgb.XGBClassifier(n_estimators=884,max_depth=4,
                                    subsample=0.994481,
                                    colsample_bylevel=0.791814,
                                    learning_rate=0.229976,reg_alpha=0.998268,
                                    reg_lambda = 0.150014)
         model.fit(X_train_tfw2v,train_df.Score)
         #Predicting training data
         train_list = model.predict(X_train_tfw2v)
         #Accuracy score
         score_train = accuracy_score(train_df.Score,train_list)
         #predict test cv
         test list = model.predict(X cv tfw2v)
         #Accuracy score
         score test = accuracy score(test df.Score,test list)
         #precision
         #precision
         test_precision = precision_score(test_df.Score,test_list)
         #recall
         test_recall = recall_score(test_df.Score,test_list)
         #confusion matrix
         confusion_matrix_test = confusion_matrix(test_df.Score,test_list)
         print('Depth',9)
         print('Train Score', score_train)
         print('Test Score',score_test)
         print('Test Precision',test_precision)
         print('Test Recall',test_recall)
         print('Test ConfusionMatrix',confusion_matrix_test)
```

```
Train Score 0.9620547622783618
Test Score 0.9055477753064045
Test Precision 0.9101124749627652
Test Recall 0.9826110100696447
Test ConfusionMatrix [[10328 8751]
 [ 1568 88604]]
Bag of Words:
In [17]: #BoW with cleaned data and without stopwords
         #simple cv for train data
         scores_train = []
         from nltk.corpus import stopwords
         stop = set(stopwords.words('english'))
         stop.remove('not')
         stop.remove('very')
         #CountVectorizer for BoW
         count_vect = CountVectorizer(stop_words=list(stop),dtype=np.int8)
         X_train = train_df.iloc[:round(train_df.shape[0]*0.70),:]
         X_test_cv = train_df.iloc[round(train_df.shape[0]*0.70):,:]
         final_counts_train = count_vect.fit_transform(
                 X_train['final_text'].values)
         #test
         X_test = count_vect.transform(X_test_cv['final_text'].values)
  Random Forest:
In [16]: #base model
         model = RF(n_jobs=-1,random_state=25).fit(final_counts_train,X_train.Score)
         #train score
         train_score = model.score(final_counts_train, X_train.Score)
         #test score
         test_score = model.score(X_test, X_test_cv.Score)
         print('Train Score',train_score)
         print('Test Score',test_score)
Train Score 0.9972204164892067
Test Score 0.8877294837596108
In [17]: for i in range(1,20):
             model = RF(n_estimators=i,n_jobs=-1,random_state=25)
             model.fit(final_counts_train,X_train.Score)
             #train score
             train_score = model.score(final_counts_train,X_train.Score)
             test_score = model.score(X_test, X_test_cv.Score)
```

print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)

```
No of Estimators 1 Train Score 0.9418921342269844 Test Score 0.8236440190386527
No of Estimators 2 Train Score 0.9373136670327946 Test Score 0.7947199121292955
No of Estimators 3 Train Score 0.9773766559817085 Test Score 0.8608452324912391
No of Estimators 4 Train Score 0.9852726905920065 Test Score 0.8612505884198964
No of Estimators 5 Train Score 0.9875198941964987 Test Score 0.8727574663946859
No of Estimators 6 Train Score 0.9932191611934277 Test Score 0.8796877451749568
No of Estimators 7 Train Score 0.9916948734617023 Test Score 0.8778963334902453
No of Estimators 8 Train Score 0.9960323686983031 Test Score 0.8851404362152833
No of Estimators 9 Train Score 0.9943567729932079 Test Score 0.8803938490506825
No of Estimators 10 Train Score 0.9972204164892067 Test Score 0.8877294837596108
No of Estimators 11 Train Score 0.9958138127367689 Test Score 0.8814399288665725
No of Estimators 12 Train Score 0.9980498083432338 Test Score 0.8878863957319943
No of Estimators 13 Train Score 0.9968841765483849 Test Score 0.8812307129033945
No of Estimators 14 Train Score 0.9983972562820829 Test Score 0.8874287358125424
No of Estimators 15 Train Score 0.9975454484320011 Test Score 0.8811522569172028
No of Estimators 16 Train Score 0.9987559122189594 Test Score 0.8874287358125424
No of Estimators 17 Train Score 0.9981282643294255 Test Score 0.8819760447722161
No of Estimators 18 Train Score 0.9989352401873978 Test Score 0.88821329567446
No of Estimators 19 Train Score 0.9984757122682747 Test Score 0.8819760447722161
In [19]: print('with 14 estimators')
         for i in [5,8,10,20,25,30,50,100,200,300,400]:
             model = RF(n_estimators=14,max_depth=i,n_jobs=-1,random_state=25)
             model.fit(final_counts_train,X_train.Score)
             #train score
             train score = model.score(final counts train, X train.Score)
             #test score
             test_score = model.score(X_test, X_test_cv.Score)
             print('Depth',i,'Train Score',train_score,'Test Score',test_score)
with 14 estimators
Depth 5 Train Score 0.8600121046378696 Test Score 0.8293451540352529
Depth 8 Train Score 0.8600233126358969 Test Score 0.8293451540352529
Depth 10 Train Score 0.8600569366299792 Test Score 0.8293713060306501
Depth 20 Train Score 0.8624890722019233 Test Score 0.8304958418327318
Depth 25 Train Score 0.8648819797807715 Test Score 0.8318034416025942
Depth 30 Train Score 0.8687487391002219 Test Score 0.8338956012343742
Depth 50 Train Score 0.8927954988679923 Test Score 0.843127255609603
Depth 100 Train Score 0.9512171885857749 Test Score 0.8656310476489356
Depth 200 Train Score 0.9900136737575934 Test Score 0.8815183848527642
Depth 300 Train Score 0.9969794445316178 Test Score 0.8877556357550082
Depth 400 Train Score 0.9983019882988501 Test Score 0.8896778074167059
In [20]: print('with 14 estimators')
         for i in [400,500,600,700,800]:
             model = RF(n_estimators=14,max_depth=i,n_jobs=-1,random_state=25)
```

```
model.fit(final_counts_train,X_train.Score)
    #train score
    train_score = model.score(final_counts_train,X_train.Score)
    #test score
    test_score = model.score(X_test,X_test_cv.Score)
        print('Depth',i,'Train Score',train_score,'Test Score',test_score)

with 14 estimators
Depth 400 Train Score 0.9983019882988501 Test Score 0.8896778074167059
Depth 500 Train Score 0.9983356122929322 Test Score 0.887794863748104
Depth 600 Train Score 0.9983692362870145 Test Score 0.8885794236100214
Depth 700 Train Score 0.9983972562820829 Test Score 0.8874287358125424
Depth 800 Train Score 0.9983972562820829 Test Score 0.8874287358125424
```

We can observe that with increase in no of estimators score is incresing and with high variance base models score is increasing.

```
In [14]: param_distributions = {'randomforestclassifier_n_estimators':sp_randint(10,100),
                               'randomforestclassifier__max_depth':sp_randint(50,600)}
        model_random_bow = RandomizedSearchCV(make_pipeline(
                                CountVectorizer(stop_words=list(stop),dtype=np.int8),
                                RF(n_jobs=-1,random_state=25)),
                                param_distributions=param_distributions,
                                cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
        model_random_bow.fit(train_df['final_text'],train_df.Score)
In [18]: dict_scores = []
        idx = 0
        for i in model_random_bow.grid_scores_:
            dict score = []
            dict_score.append(i[0]['randomforestclassifier__n_estimators'])
            dict_score.append(i[0]['randomforestclassifier__max_depth'])
            dict_score.append(i[1])
            dict_score.append(i[2].std())
            dict_score.append(model_random_bow.cv_results_['mean_train_score'][idx])
            dict_scores.append(dict_score)
            idx = idx + 1
        scores_df = pd.DataFrame(dict_scores,columns=['n_estimators','depth',
                                        'Test_score', 'Test_std', 'Train_score'])
In [20]: scores_df.sort_values('Test_score',ascending=False).head(10)
Out [20]:
            n_estimators depth Test_score Test_std Train_score
        17
                            483
                                   0.891749 0.007396
                                                          0.999524
                      28
        49
                      26
                            434
                                   0.891680 0.007370
                                                          0.999376
        45
                      28
                            389 0.891253 0.007705
                                                          0.999268
                      34
                            479
                                   0.891046 0.007578
        37
                                                          0.999683
```

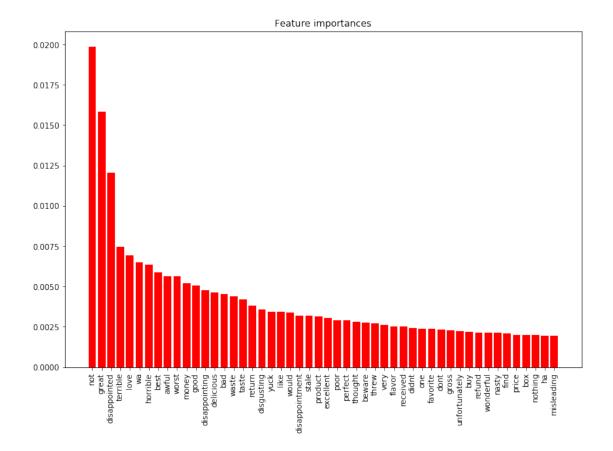
```
18
             40
                   404
                         0.890343 0.007515
                                                0.999657
             26
                   251
                         0.890006 0.008157
                                                0.996093
12
35
             54
                   564
                         0.889657 0.008277
                                                0.999923
13
             60
                   542
                         0.889411 0.008074
                                                0.999951
41
             66
                   567
                         0.889324 0.008297
                                                0.999961
15
             20
                   210
                         0.889212 0.008916
                                                0.992222
```

Best cv score got at no of estimators = 28, depth = 483 and Test cv score is 0.891749

```
In [18]: #Test scores
         from nltk.corpus import stopwords
         stop = set(stopwords.words('english'))
         stop.remove('not')
         stop.remove('very')
         #CountVectorizer for BoW
         count_vect = CountVectorizer(stop_words=list(stop),dtype=np.int8)
         final_counts_train = count_vect.fit_transform(
                 train_df['final_text'].values)
         #test
         X_test = count_vect.transform(test_df['final_text'].values)
         model = RF(n_estimators=28,max_depth=483)
         model.fit(final_counts_train,train_df.Score)
         #Predicting training data
         train_list = model.predict(final_counts_train)
         #Accuracy score
         score_train = accuracy_score(train_df.Score,train_list)
         #predict test cv
         test_list = model.predict(X_test)
         #Accuracy score
         score_test = accuracy_score(test_df.Score,test_list)
         #precision
         #precision
         test_precision = precision_score(test_df.Score,test_list)
         test_recall = recall_score(test_df.Score,test_list)
         #confusion matrix
         confusion_matrix_test = confusion_matrix(test_df.Score,test_list)
         print("n estimators=28,max depth=483")
         print('Train Score', score_train)
         print('Test Score',score_test)
         print('Test Precision',test_precision)
         print('Test Recall',test_recall)
         print('Test ConfusionMatrix',confusion_matrix_test)
n_estimators=28,max_depth=483
Train Score 0.9995606464773262
Test Score 0.8887058242029822
```

```
Test Precision 0.8856493153393643
Test Recall 0.9934236791908797
Test ConfusionMatrix [[ 7513 11566]
 [ 593 89579]]
In [25]: import operator
         importances = model.feature_importances_
         features = count_vect.get_feature_names()
         dict_feature = dict(zip(features,importances))
         sorted_feature = dict(sorted(dict_feature.items(), key=operator.itemgetter(1),reverse
In [29]: #To 100 features to seperate the data using Bag of words with RF
         list_feature = list(sorted_feature.keys())[0:100]
         list_fval = list(sorted_feature.values())[0:100]
         print(list_feature)
['not', 'great', 'disappointed', 'terrible', 'love', 'wa', 'horrible', 'best', 'awful', 'worst
In [35]: plt.figure(figsize=(12,8))
         plt.title("Feature importances")
         plt.bar(range(len(list_feature[0:50])),list_fval[0:50],
                color="r")
         plt.xticks(range(len(list_feature[0:50])),
                    list_feature[0:50],rotation = 90)
Out[35]: ([<matplotlib.axis.XTick at 0x153cdb9907b8>,
           <matplotlib.axis.XTick at 0x153cdbdfb208>,
           <matplotlib.axis.XTick at 0x153cda6c2400>,
           <matplotlib.axis.XTick at 0x153cd762fe10>,
           <matplotlib.axis.XTick at 0x153cdbd8f4e0>,
           <matplotlib.axis.XTick at 0x153cdbd8fb70>,
           <matplotlib.axis.XTick at 0x153cdbd6d240>,
           <matplotlib.axis.XTick at 0x153cdbd6d8d0>,
           <matplotlib.axis.XTick at 0x153cdbd6df60>,
           <matplotlib.axis.XTick at 0x153cd96c1630>,
           <matplotlib.axis.XTick at 0x153cd96c1cc0>,
           <matplotlib.axis.XTick at 0x153cd969a390>,
           <matplotlib.axis.XTick at 0x153cd969aa20>,
           <matplotlib.axis.XTick at 0x153cd591a0f0>,
           <matplotlib.axis.XTick at 0x153cd591a780>,
           <matplotlib.axis.XTick at 0x153cd591ae10>,
           <matplotlib.axis.XTick at 0x153cd48b44e0>,
           <matplotlib.axis.XTick at 0x153cd48b4b70>,
           <matplotlib.axis.XTick at 0x153cd48dc240>,
           <matplotlib.axis.XTick at 0x153cd48dc8d0>,
           <matplotlib.axis.XTick at 0x153cd48dcf60>,
           <matplotlib.axis.XTick at 0x153cd5fe3630>,
```

```
<matplotlib.axis.XTick at 0x153cd5fe3cc0>,
<matplotlib.axis.XTick at 0x153cd5fe1390>,
<matplotlib.axis.XTick at 0x153cd5fe1a20>,
<matplotlib.axis.XTick at 0x153cd92590f0>,
<matplotlib.axis.XTick at 0x153cd9259780>,
<matplotlib.axis.XTick at 0x153cd9259e10>,
<matplotlib.axis.XTick at 0x153cdacfa4e0>,
<matplotlib.axis.XTick at 0x153cdacfab70>,
<matplotlib.axis.XTick at 0x153cdacfe240>,
<matplotlib.axis.XTick at 0x153cdacfe8d0>,
<matplotlib.axis.XTick at 0x153cdacfef60>,
<matplotlib.axis.XTick at 0x153cd7a9e630>,
<matplotlib.axis.XTick at 0x153cd7a9ecc0>,
<matplotlib.axis.XTick at 0x153cd89de390>,
<matplotlib.axis.XTick at 0x153cd89dea20>,
<matplotlib.axis.XTick at 0x153cd8a030f0>,
<matplotlib.axis.XTick at 0x153cd8a03780>,
<matplotlib.axis.XTick at 0x153cd8a03e10>,
<matplotlib.axis.XTick at 0x153cd554f4a8>,
<matplotlib.axis.XTick at 0x153cd554fb38>,
<matplotlib.axis.XTick at 0x153cd5553208>,
<matplotlib.axis.XTick at 0x153cd5553898>,
<matplotlib.axis.XTick at 0x153cd5553f28>,
<matplotlib.axis.XTick at 0x153cd71da5f8>,
<matplotlib.axis.XTick at 0x153cd71dac88>,
<matplotlib.axis.XTick at 0x153cd71d3358>,
<matplotlib.axis.XTick at 0x153cd71d39e8>,
<matplotlib.axis.XTick at 0x153cdbd95128>],
<a list of 50 Text xticklabel objects>)
```



XGBoost

```
In [24]: #base model
    model = xgb.XGBClassifier(n_jobs=-1,random_state=25).fit(final_counts_train,X_train.S
    #train score
    train_score = model.score(final_counts_train,X_train.Score)
    #test score
    test_score = model.score(X_test,X_test_cv.Score)
    print('Train Score',train_score)
    print('Test Score',test_score)

Train Score 0.8965894062002645
Test Score 0.8765233537318897

In [29]: for i in range(0,100,10):
    model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
    model = model.fit(final_counts_train,X_train.Score)
    #train score
    train_score = model.score(final_counts_train,X_train.Score)
    #test score
```

```
test_score = model.score(X_test, X_test_cv.Score)
            print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 0 Train Score 0.1399878953621304 Test Score 0.17065484596474711
No of Estimators 10 Train Score 0.8616652843469099 Test Score 0.8314765416601286
No of Estimators 20 Train Score 0.8644224518616485 Test Score 0.8354516449605105
No of Estimators 30 Train Score 0.8701217188585775 Test Score 0.8432057115957947
No of Estimators 40 Train Score 0.8749467620093699 Test Score 0.8494168105026414
No of Estimators 50 Train Score 0.8794747932124364 Test Score 0.8547387415659815
No of Estimators 60 Train Score 0.8832911165407635 Test Score 0.8592368847743083
No of Estimators 70 Train Score 0.8868832799085428 Test Score 0.8644934358491553
No of Estimators 80 Train Score 0.8911759431530341 Test Score 0.8697107589309064
No of Estimators 90 Train Score 0.8940451906480464 Test Score 0.8735289502589048
In [28]: for i in range(50,500,50):
            model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
            model = model.fit(final_counts_train,X_train.Score)
             #train score
             train_score = model.score(final_counts_train,X_train.Score)
             test_score = model.score(X_test, X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 50 Train Score 0.8794747932124364 Test Score 0.8547387415659815
No of Estimators 100 Train Score 0.8965894062002645 Test Score 0.8765233537318897
No of Estimators 150 Train Score 0.9057799645827262 Test Score 0.8880040797112819
No of Estimators 200 Train Score 0.9116809755441483 Test Score 0.895731994351169
No of Estimators 250 Train Score 0.9159904507856806 Test Score 0.901093153407605
No of Estimators 300 Train Score 0.919470534173186 Test Score 0.9047936607563157
No of Estimators 350 Train Score 0.9223005536751026 Test Score 0.9079057482085883
No of Estimators 400 Train Score 0.9249064132164713 Test Score 0.9105732517391077
No of Estimators 450 Train Score 0.9269294568604156 Test Score 0.9127307913593807
In [30]: for i in range(500,1050,50):
            model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
             model = model.fit(final_counts_train,X_train.Score)
             #train score
             train_score = model.score(final_counts_train,X_train.Score)
             #test score
             test_score = model.score(X_test, X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 500 Train Score 0.9287059245477572 Test Score 0.9151498509336262
No of Estimators 550 Train Score 0.9303422922597565 Test Score 0.9166405146712694
No of Estimators 600 Train Score 0.9319058079845778 Test Score 0.9184319263559809
No of Estimators 650 Train Score 0.9331554997646321 Test Score 0.9198179821120351
No of Estimators 700 Train Score 0.9345172715249602 Test Score 0.920694073957843
```

```
No of Estimators 750 Train Score 0.9355820313375625 Test Score 0.9219493697369109
No of Estimators 800 Train Score 0.9368653471116989 Test Score 0.9226947016057325
No of Estimators 850 Train Score 0.93791329492726 Test Score 0.9238715413986087
No of Estimators 900 Train Score 0.9388883907556432 Test Score 0.9246822532559235
No of Estimators 950 Train Score 0.9397458026047387 Test Score 0.9253752811339505
No of Estimators 1000 Train Score 0.9407601264262178 Test Score 0.9262382969820597
In [31]: for i in [1200,1500,1750,2100]:
             model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
             model = model.fit(final_counts_train,X_train.Score)
             #train score
             train_score = model.score(final_counts_train, X_train.Score)
             #test score
             test_score = model.score(X_test, X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 1200 Train Score 0.9435397099370111 Test Score 0.9283043046184424
No of Estimators 1500 Train Score 0.9471150613077493 Test Score 0.9314817720592081
No of Estimators 1750 Train Score 0.9496424648629261 Test Score 0.9326455358543857
No of Estimators 2100 Train Score 0.9527190603214454 Test Score 0.9345284795229876
  even increase in estimators, test score alo increasing
In [12]: param_distributions = {'xgbclassifier_n_estimators':sp_randint(600,2000),
                                'xgbclassifier_max_depth':sp_randint(3,9),
                                'xgbclassifier__learning_rate':uniform(0,1),
                                'xgbclassifier_subsample':uniform(0,1),
                                'xgbclassifier_reg_alpha':uniform(0,1),
                                'xgbclassifier_reg_lambda':uniform(0,1),
                                'xgbclassifier__colsample_bylevel':uniform(0.7,0.3)}
         model_random_bow = RandomizedSearchCV(make_pipeline(CountVectorizer(stop_words=list(s
                                                              XGBClassifier(n_jobs=-1,random_state)
                                                param_distributions=param_distributions,n_iter
                                                cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
         model_random_bow.fit(train_df['final_text'],train_df.Score)
         pickle.dump(model_random_bow,open('model_random_bow_xgb.p','wb'))
In [16]: dict_scores = []
         idx = 0
         for i in model_random_bow_xgb.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['xgbclassifier__n_estimators'])
             dict_score.append(i[0]['xgbclassifier__max_depth'])
             dict_score.append(i[0]['xgbclassifier__subsample'])
             dict_score.append(i[0]['xgbclassifier__colsample_bylevel'])
             dict_score.append(i[0]['xgbclassifier__learning_rate'])
```

```
dict_score.append(i[0]['xgbclassifier__reg_alpha'])
              dict_score.append(i[0]['xgbclassifier__reg_lambda'])
              dict_score.append(i[1])
              dict_score.append(i[2].std())
              dict_score.append(model_random_bow_xgb.cv_results_['mean_train_score'][idx])
              dict_scores.append(dict_score)
              idx = idx + 1
         scores_df = pd.DataFrame(dict_scores,columns=['n_estimators','depth',
                   'subsample', 'colsample_bylevel', 'learning_rate', 'reg_alpha',
                         'reg_lambda','Test_score','Test_std','Train_score'])
In [17]: scores_df.sort_values('Test_score',ascending=False)
Out[17]:
                            depth
                                    subsample
                                                colsample_bylevel
             n_estimators
                                                                    learning_rate
         2
                      1825
                                 3
                                     0.836375
                                                          0.859582
                                                                          0.406806
         12
                                 3
                      1240
                                     0.660874
                                                          0.761028
                                                                          0.259216
         16
                      1763
                                     0.320007
                                                          0.952691
                                                                          0.177006
         7
                      1114
                                 6
                                     0.750906
                                                          0.990907
                                                                          0.666196
         23
                      1119
                                 3
                                     0.198074
                                                          0.713333
                                                                          0.293012
                                 5
         13
                       830
                                     0.790607
                                                          0.728332
                                                                          0.831163
                                 5
         5
                       614
                                     0.471378
                                                          0.857746
                                                                          0.559242
         9
                                 8
                      1615
                                     0.662077
                                                          0.947542
                                                                          0.712552
         10
                       655
                                 4
                                     0.725973
                                                          0.895196
                                                                          0.857754
         4
                      1681
                                     0.289804
                                                          0.831081
                                                                          0.281701
         3
                      1204
                                 5
                                     0.421004
                                                          0.844403
                                                                          0.516502
         20
                                 5
                                     0.806417
                      1730
                                                          0.745004
                                                                          0.994481
         24
                      1163
                                 5
                                     0.299572
                                                          0.712891
                                                                          0.383704
         8
                      1117
                                 3
                                     0.396542
                                                          0.822676
                                                                          0.593100
         18
                       891
                                 3
                                     0.747596
                                                          0.849763
                                                                          0.085110
         19
                      1822
                                 6
                                     0.998268
                                                          0.754903
                                                                          0.015087
         11
                      1905
                                 7
                                     0.310728
                                                          0.782047
                                                                          0.660684
         21
                      1091
                                 3
                                     0.119866
                                                          0.988096
                                                                          0.539474
         15
                      1885
                                 4
                                     0.353804
                                                          0.802320
                                                                          0.923763
                                 3
         14
                       830
                                     0.126974
                                                          0.710105
                                                                          0.795971
         0
                      1486
                                 8
                                     0.117376
                                                                          0.582277
                                                          0.961037
         22
                                 6
                       881
                                     0.074116
                                                          0.773796
                                                                          0.626783
                                 7
         6
                      1919
                                     0.053081
                                                          0.987161
                                                                          0.510903
         1
                                 7
                                     0.018730
                      1053
                                                          0.905491
                                                                          0.437611
         17
                       909
                                     0.023475
                                                          0.937474
                                                                          0.489521
             reg_alpha reg_lambda
                                      Test score
                                                   Test_std
                                                             Train score
         2
               0.699186
                           0.366395
                                        0.938228
                                                   0.003046
                                                                 0.981074
         12
              0.676561
                                                   0.002877
                           0.021376
                                        0.937136
                                                                 0.968227
         16
              0.958540
                           0.762318
                                        0.933874
                                                   0.004498
                                                                 0.986529
         7
               0.577135
                           0.121505
                                        0.931410
                                                   0.003405
                                                                 0.998340
         23
               0.588749
                           0.987940
                                        0.930107
                                                   0.004097
                                                                 0.956563
         13
               0.566830
                           0.174626
                                        0.929563
                                                   0.002793
                                                                 0.993391
         5
               0.151921
                           0.903585
                                        0.929356
                                                   0.003601
                                                                 0.980291
```

```
0.928485 0.003783
9
     0.210908
                 0.844187
                                                    0.999967
10
     0.990475
                 0.137572
                             0.928446 0.003519
                                                    0.983068
4
                             0.928329 0.003828
     0.669612
                 0.456069
                                                    0.996344
3
     0.034450
                 0.719930
                             0.928282 0.003205
                                                    0.989170
20
     0.531058
                 0.323604
                             0.927837 0.003633
                                                    0.999591
24
     0.434800
                 0.073235
                             0.927427 0.004114
                                                    0.980631
8
     0.719055
                 0.415219
                             0.927397 0.003359
                                                    0.970442
                             0.926340 0.004487
18
     0.109562
                 0.085703
                                                    0.944349
19
     0.582870
                 0.312620
                             0.921192 0.004684
                                                    0.945676
11
     0.215531
                 0.265331
                             0.912635 0.002424
                                                    0.992984
21
     0.801124
                 0.797099
                             0.905925 0.007794
                                                    0.934209
15
     0.345075
                 0.410529
                             0.905523 0.005715
                                                    0.960594
14
                             0.895935 0.008408
     0.507171
                 0.775050
                                                    0.919568
0
     0.185911
                 0.411100
                             0.877535 0.007569
                                                    0.911695
22
     0.063457
                 0.373199
                             0.873906 0.007535
                                                    0.895959
6
     0.666186
                 0.072758
                             0.859096 0.005541
                                                    0.883607
1
     0.761255
                 0.946506
                             0.857513 0.008010
                                                    0.878668
17
     0.637238
                 0.446780
                             0.851614 0.004864
                                                    0.871551
```

From above df we can observe that second row in the df i.e 12th index with 1240 estimators is giving max similar scores as 1825 estimators so for better time complexity n estimators coosen as 1240. and got good score at n_estimators = 1240, depth = 3, subsample = 0.660874, colsample_bylevel=0.761028, learning_rate = 0.259216, reg_alpha = 0.676561, reg_lambda = 0.021376 and Test_score is 0.937136

```
In [19]: param_distributions1 = {'xgbclassifier__n_estimators':sp_randint(600,2000),
                                 'xgbclassifier__max_depth':sp_randint(3,9)}
         model_random_bow1 = RandomizedSearchCV(make_pipeline(CountVectorizer(stop_words=list()))
                                                              XGBClassifier(n_jobs=-1,random_st
                                                 param_distributions=param_distributions1,n_ite
                                                 cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
         model_random_bow1.fit(train_df['final_text'],train_df.Score)
         pickle.dump(model_random_bow1,open('model_random_bow_xgb1.p','wb'))
In [21]: dict_scores = []
         idx = 0
         for i in model_random_bow1.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['xgbclassifier__n_estimators'])
             dict_score.append(i[0]['xgbclassifier__max_depth'])
             dict_score.append(i[1])
             dict_score.append(i[2].std())
             dict_score.append(model_random_bow1.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
             idx = idx + 1
         scores_df1 = pd.DataFrame(dict_scores,columns=['n_estimators','depth',
                         'Test_score', 'Test_std', 'Train_score'])
```

In [22]: scores_df1.sort_values('Test_score',ascending=False)

Out[22]:		n_estimators	depth	Test_score	Test_std	Train_score
	18	1978	7	0.938181	0.003358	0.987153
	5	1877	7	0.938030	0.003206	0.986398
	2	1486	8	0.937512	0.003099	0.986929
	19	1472	8	0.937508	0.003046	0.986764
	8	1712	6	0.937482	0.002863	0.980572
	3	1365	7	0.936951	0.002875	0.981748
	9	1452	6	0.936852	0.002762	0.977774
	15	1249	7	0.936610	0.003017	0.980420
	14	1581	5	0.936002	0.002954	0.972947
	6	1053	7	0.935682	0.003258	0.977682
	0	918	7	0.934914	0.002916	0.975334
	17	1204	5	0.934405	0.003269	0.967921
	10	731	8	0.934263	0.003227	0.976142
	12	1825	3	0.933279	0.002834	0.957562
	4	1780	3	0.933046	0.002852	0.957191
	11	1006	4	0.931207	0.003088	0.956341
	16	1428	3	0.930992	0.003162	0.953105
	1	743	5	0.930668	0.003390	0.958674
	7	767	4	0.928351	0.003608	0.951389
	13	709	3	0.923142	0.004575	0.940904

above model is better than this best model with estimators 1978, depth 7, because it is generalizing train and test data's well

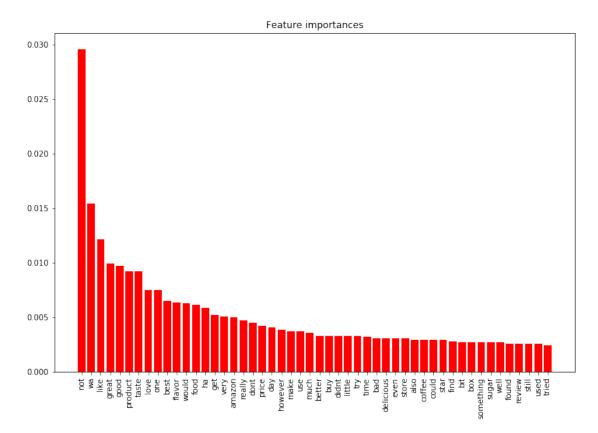
```
In [36]: #Test scores
         from nltk.corpus import stopwords
         stop = set(stopwords.words('english'))
         stop.remove('not')
         stop.remove('very')
         #CountVectorizer for BoW
         count_vect = CountVectorizer(stop_words=list(stop),dtype=np.int8)
         final_counts_train = count_vect.fit_transform(
                 train_df['final_text'].values)
         X_test = count_vect.transform(test_df['final_text'].values)
         model = xgb.XGBClassifier(max_depth=3,learning_rate=0.259216,
                                      n_estimators=1240,n_jobs=-1,
                                     subsample=0.660874,colsample_bylevel=0.761028,
                                     reg_alpha=0.676561,reg_lambda=0.021376)
         model.fit(final_counts_train,train_df.Score)
         #Predicting training data
         train_list = model.predict(final_counts_train)
         #Accuracy score
         score_train = accuracy_score(train_df.Score,train_list)
         #predict test cv
```

```
test_list = model.predict(X_test)
                    #Accuracy score
                   score_test = accuracy_score(test_df.Score,test_list)
                    #precision
                   #precision
                   test_precision = precision_score(test_df.Score,test_list)
                   test_recall = recall_score(test_df.Score,test_list)
                    #confusion matrix
                   confusion_matrix_test = confusion_matrix(test_df.Score,test_list)
                   print('''max_depth=3,learning rate=0.259216,n_estimators=1240,n_jobs=-1,
                   subsample=0.660874,colsample_bylevel=0.761028,reg_alpha=0.676561,
                   reg_lambda=0.021376''')
                   print('Train Score', score_train)
                   print('Test Score',score_test)
                   print('Test Precision',test_precision)
                   print('Test Recall',test_recall)
                   print('Test ConfusionMatrix',confusion_matrix_test)
max_depth=3,learning_rate=0.259216,n_estimators=1240,n_jobs=-1,
subsample=0.660874,colsample_bylevel=0.761028,reg_alpha=0.676561,
reg_lambda=0.021376
Train Score 0.956825670798682
Test Score 0.9375749421057931
Test Precision 0.949588987896179
Test Recall 0.9761899480991882
Test ConfusionMatrix [[14406 4673]
  [ 2147 88025]]
In [37]: import operator
                   importances = model.feature_importances_
                   features = count_vect.get_feature_names()
                   dict_feature = dict(zip(features,importances))
                   sorted_feature = dict(sorted(dict_feature.items(),
                                                               key=operator.itemgetter(1),reverse=True))
In [38]: #To 100 features to seperate the data using Bag of words with RF
                   list_feature = list(sorted_feature.keys())[0:100]
                   list_fval = list(sorted_feature.values())[0:100]
                   print(list_feature)
['not', 'wa', 'like', 'great', 'good', 'product', 'taste', 'love', 'one', 'best', 'flavor', 'wa', 'like', 'great', 'good', 'product', 'taste', 'love', 'one', 'best', 'flavor', 'wa', 'like', 'great', 'good', 'product', 'taste', 'love', 'one', 'best', 'flavor', 'wa', 'love', 'lov
In [39]: plt.figure(figsize=(12,8))
                   plt.title("Feature importances")
                   plt.bar(range(len(list_feature[0:50])),list_fval[0:50],
                                   color="r")
```

```
list_feature[0:50],rotation = 90)
Out[39]: ([<matplotlib.axis.XTick at 0x153cda7d6780>,
           <matplotlib.axis.XTick at 0x153cdacfad68>,
           <matplotlib.axis.XTick at 0x153cda7e5438>,
           <matplotlib.axis.XTick at 0x153cdab303c8>,
           <matplotlib.axis.XTick at 0x153cd7c5a320>,
           <matplotlib.axis.XTick at 0x153cd7c5a9b0>,
           <matplotlib.axis.XTick at 0x153cd7c4f080>,
           <matplotlib.axis.XTick at 0x153cd7c4f710>,
           <matplotlib.axis.XTick at 0x153cd7c4fda0>,
           <matplotlib.axis.XTick at 0x153cd9a71ba8>,
           <matplotlib.axis.XTick at 0x153cd9a71518>,
           <matplotlib.axis.XTick at 0x153cd9a901d0>,
           <matplotlib.axis.XTick at 0x153cd9a90860>,
           <matplotlib.axis.XTick at 0x153cd9a90ef0>,
           <matplotlib.axis.XTick at 0x153cdb38e5c0>,
           <matplotlib.axis.XTick at 0x153cdb38ec50>,
           <matplotlib.axis.XTick at 0x153cdb373cf8>,
           <matplotlib.axis.XTick at 0x153cdb373668>,
           <matplotlib.axis.XTick at 0x153cd4737080>,
           <matplotlib.axis.XTick at 0x153cd4737710>,
           <matplotlib.axis.XTick at 0x153cd4737da0>,
           <matplotlib.axis.XTick at 0x153cd6f7fba8>,
           <matplotlib.axis.XTick at 0x153cd6f7f518>,
           <matplotlib.axis.XTick at 0x153cd6f981d0>,
           <matplotlib.axis.XTick at 0x153cd6f98860>,
           <matplotlib.axis.XTick at 0x153cd6f98ef0>,
           <matplotlib.axis.XTick at 0x153cd4a3d5c0>,
           <matplotlib.axis.XTick at 0x153cd4a3dc50>,
           <matplotlib.axis.XTick at 0x153cd4a5c320>,
           <matplotlib.axis.XTick at 0x153cd4a5c9b0>,
           <matplotlib.axis.XTick at 0x153cd6c76080>,
           <matplotlib.axis.XTick at 0x153cd6c76710>,
           <matplotlib.axis.XTick at 0x153cd6c76da0>,
           <matplotlib.axis.XTick at 0x153cd6c74ba8>,
           <matplotlib.axis.XTick at 0x153cd6c74518>,
           <matplotlib.axis.XTick at 0x153cd53761d0>,
           <matplotlib.axis.XTick at 0x153cd5376860>,
           <matplotlib.axis.XTick at 0x153cd5376ef0>,
           <matplotlib.axis.XTick at 0x153cd53ab5c0>,
           <matplotlib.axis.XTick at 0x153cd53abc50>,
           <matplotlib.axis.XTick at 0x153cd4ab8320>,
           <matplotlib.axis.XTick at 0x153cd4ab89b0>,
           <matplotlib.axis.XTick at 0x153cd4ae2080>,
           <matplotlib.axis.XTick at 0x153cd4ae2710>,
           <matplotlib.axis.XTick at 0x153cd4ae2da0>,
```

plt.xticks(range(len(list_feature[0:50])),

```
<matplotlib.axis.XTick at 0x153cdb617ba8>,
<matplotlib.axis.XTick at 0x153cdb617518>,
<matplotlib.axis.XTick at 0x153cd74661d0>,
<matplotlib.axis.XTick at 0x153cd7466860>,
<matplotlib.axis.XTick at 0x153cd7466ef0>],
<a list of 50 Text xticklabel objects>)
```



Tf-Idf:

Random Forest

```
In [27]: for i in range(1,20):
             model = RF(n_estimators=i,n_jobs=-1,random_state=25)
             model.fit(final_counts_train,X_train.Score)
             #train score
             train score = model.score(final counts train, X train.Score)
             test_score = model.score(X_test, X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 1 Train Score 0.9434500459527919 Test Score 0.8208065275380512
No of Estimators 2 Train Score 0.9503541727376656 Test Score 0.8015325069302788
No of Estimators 3 Train Score 0.9757178722736545 Test Score 0.8582561849469115
No of Estimators 4 Train Score 0.9874246262132658 Test Score 0.86530414770647
No of Estimators 5 Train Score 0.9842135347784179 Test Score 0.8648464877870181
No of Estimators 6 Train Score 0.9929333572437291 Test Score 0.873659710235891
No of Estimators 7 Train Score 0.9885510300150188 Test Score 0.863421204037868
No of Estimators 8 Train Score 0.9948275089103584 Test Score 0.8727443903969873
No of Estimators 9 Train Score 0.9915323574903051 Test Score 0.861368272399184
No of Estimators 10 Train Score 0.9960828046894263 Test Score 0.8708483707306868
No of Estimators 11 Train Score 0.9935497971352357 Test Score 0.8614205763899786
No of Estimators 12 Train Score 0.9970635045168232 Test Score 0.8696192269470161
No of Estimators 13 Train Score 0.9951301248570981 Test Score 0.8600214446362258
No of Estimators 14 Train Score 0.9976295084172065 Test Score 0.8677493592761127
No of Estimators 15 Train Score 0.9961780726726592 Test Score 0.8599560646477327
No of Estimators 16 Train Score 0.9980386003452063 Test Score 0.8669124954234008
No of Estimators 17 Train Score 0.9968505525543028 Test Score 0.8593284167581986
No of Estimators 18 Train Score 0.9983468202909597 Test Score 0.8659056436006067
No of Estimators 19 Train Score 0.9974613884467957 Test Score 0.8594068727443904
In [28]: for i in [150,300,500]:
             model = RF(n_estimators=i,n_jobs=-1,random_state=25)
             model.fit(final_counts_train,X_train.Score)
             train_score = model.score(final_counts_train,X_train.Score)
             #test score
             test_score = model.score(X_test, X_test_cv.Score) VB
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 150 Train Score 0.9999943960009863 Test Score 0.8560463413358439
No of Estimators 300 Train Score 0.9999943960009863 Test Score 0.8549218055337622
No of Estimators 500 Train Score 0.9999943960009863 Test Score 0.8542810816465296
In [31]: #random search
         param_distributions = {'randomforestclassifier__n_estimators':sp_randint(1,50),
                                'randomforestclassifier__max_depth':sp_randint(10,150)}
         model_random_tfidf_rf = RandomizedSearchCV(make_pipeline(TfidfVectorizer(ngram_range=
```

```
RF(n_jobs=-1,random_state=25)),
                                                                                                      param_distributions=param_distributions,n_iter
                                                                                                      cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
                   model_random_tfidf_rf.fit(train_df['final_text'],train_df.Score)
                   pickle.dump(model_random_tfidf_rf,open('model_random_tfidf_rf.p','wb'))
In [44]: model_random_tfidf_rf.grid_scores_[0]
Out[44]: mean: 0.85523, std: 0.01842, params: {'randomforestclassifier_max_depth': 142, 'randomforestclassifier_max_depth': 142, 'randomforestclassifier_max_dep
In [45]: dict_scores = []
                   idx = 0
                   for i in model_random_tfidf_rf.grid_scores_:
                           dict_score = []
                           dict_score.append(i[0]['randomforestclassifier__n_estimators'])
                           dict_score.append(i[0]['randomforestclassifier__max_depth'])
                           dict_score.append(i[1])
                           dict_score.append(i[2].std())
                           dict_score.append(model_random_tfidf_rf.cv_results_['mean_train_score'][idx])
                           dict_scores.append(dict_score)
                           idx = idx + 1
                   scores_df1 = pd.DataFrame(dict_scores,columns=['n_estimators','depth',
                                                      'Test_score', 'Test_std', 'Train_score'])
In [46]: scores_df1.sort_values('Test_score',ascending=False)
Out [46]:
                           n_{estimators}
                                                         depth
                                                                      Test_score Test_std
                                                                                                                       Train_score
                   17
                                                   3
                                                              126
                                                                            0.860801
                                                                                                 0.016423
                                                                                                                              0.916165
                   36
                                                   6
                                                              105
                                                                            0.859692 0.019217
                                                                                                                              0.912101
                   2
                                                 29
                                                              146
                                                                            0.855562 0.018273
                                                                                                                              0.928623
                   3
                                                26
                                                              142
                                                                            0.855554 0.018274
                                                                                                                              0.925843
                   0
                                                27
                                                              142
                                                                            0.855230 0.018425
                                                                                                                              0.926185
                   38
                                                 38
                                                              149
                                                                            0.854565 0.018887
                                                                                                                              0.930270
                   31
                                                  4
                                                               63
                                                                            0.854518 0.020148
                                                                                                                              0.891385
                   37
                                                 20
                                                              120
                                                                            0.854099 0.018943
                                                                                                                              0.912255
                   10
                                                22
                                                              119
                                                                            0.853595 0.019060
                                                                                                                              0.911291
                   12
                                                 48
                                                              148
                                                                            0.853573 0.018661
                                                                                                                              0.929691
                   7
                                                  4
                                                                55
                                                                            0.853474 0.020593
                                                                                                                              0.887026
                   4
                                                 40
                                                              139
                                                                            0.853405 0.018838
                                                                                                                              0.923902
                   23
                                                 24
                                                                                                                              0.908702
                                                              116
                                                                            0.852801 0.019535
                   29
                                                 38
                                                              125
                                                                            0.852330 0.019519
                                                                                                                              0.913656
                   21
                                                 21
                                                              100
                                                                            0.851312 0.019907
                                                                                                                              0.899021
                   15
                                                31
                                                              108
                                                                                                                              0.902228
                                                                            0.850984 0.019731
                                                 44
                   16
                                                              114
                                                                            0.850535
                                                                                                 0.020016
                                                                                                                              0.905612
                                                 37
                   14
                                                              102
                                                                            0.850186 0.020033
                                                                                                                              0.897602
                   28
                                                47
                                                                98
                                                                            0.849197 0.020203
                                                                                                                              0.893931
                   35
                                                33
                                                                89
                                                                            0.848926 0.020388
                                                                                                                              0.888985
                   25
                                                27
                                                                81
                                                                            0.848727
                                                                                                 0.020194
                                                                                                                              0.885194
                                                 40
                   27
                                                                86
                                                                            0.848438 0.020199
                                                                                                                              0.886512
```

```
11
                       10
                              46
                                    0.847907 0.020621
                                                            0.874783
         20
                        3
                              21
                                    0.847838 0.020727
                                                            0.872820
         34
                        4
                              19
                                    0.847407 0.020747
                                                            0.872239
         9
                       48
                              58
                                    0.847057 0.020555
                                                            0.873843
         33
                       46
                              54
                                    0.847014 0.020589
                                                            0.873140
         26
                       15
                              25
                                    0.846897 0.020525
                                                            0.871390
                       49
         19
                              32
                                    0.846889 0.020509
                                                            0.871325
         18
                       10
                              15
                                    0.846884 0.020501
                                                            0.871232
                       47
         30
                              23
                                    0.846884 0.020505
                                                            0.871247
                       20
                              24
         22
                                    0.846880 0.020501
                                                            0.871268
         32
                       45
                              12
                                    0.846880 0.020501
                                                            0.871226
                       23
         8
                              11
                                    0.846880 0.020501
                                                            0.871226
         6
                       21
                              13
                                    0.846880 0.020501
                                                            0.871229
         5
                       25
                              13
                                                            0.871228
                                    0.846880 0.020501
         39
                       23
                              27
                                    0.846880 0.020501
                                                            0.871320
                        2
                             116
                                    0.845072 0.010422
                                                            0.925554
         13
In [12]: #random search
         param_distributions = {'randomforestclassifier_n_estimators':
                                       sp_randint(1,50)}
         model_random_tfidf_rf1 = RandomizedSearchCV(
                            make_pipeline(TfidfVectorizer(ngram_range=(1,2)),
                            RF(n_jobs=-1,random_state=25)),
                            param_distributions=param_distributions,n_iter=20,
                                cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
         model_random_tfidf_rf1.fit(train_df['final_text'],train_df.Score)
         pickle.dump(model_random_tfidf_rf1,open('model_random_tfidf_rf1.p','wb'))
In [15]: dict scores = []
         idx = 0
         for i in model_random_tfidf_rf1.grid_scores_:
             dict_score = []
             dict_score.append(i[0]['randomforestclassifier__n_estimators'])
             dict_score.append(i[1])
             dict_score.append(i[2].std())
             dict_score.append(model_random_tfidf_rf1.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
             idx = idx + 1
         scores_df = pd.DataFrame(dict_scores,columns=['n_estimators',
                         'Test_score', 'Test_std', 'Train_score'])
In [17]: scores_df = scores_df.sort_values('n_estimators')
In [21]: plt.figure(figsize=(12,8))
         plt.plot(scores_df.n_estimators,scores_df.Test_score,label='Test Score')
         plt.plot(scores_df.n_estimators,scores_df.Train_score,label='Train_Score')
```

0.848291 0.020515

0.848201 0.020624

0.878173

0.880570

24

1

15

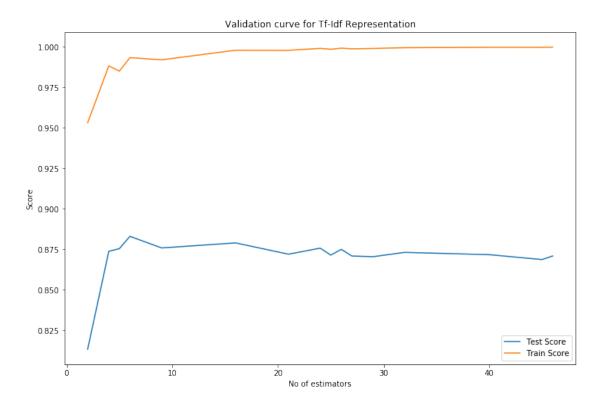
24

60

71

```
plt.title('Validation curve for Tf-Idf Representation')
plt.xlabel('No of estimators')
plt.ylabel('Score')
plt.legend()
```

Out[21]: <matplotlib.legend.Legend at 0x14c9e6254be0>



In [23]: scores_df.sort_values('Test_score',ascending=False).head(5)

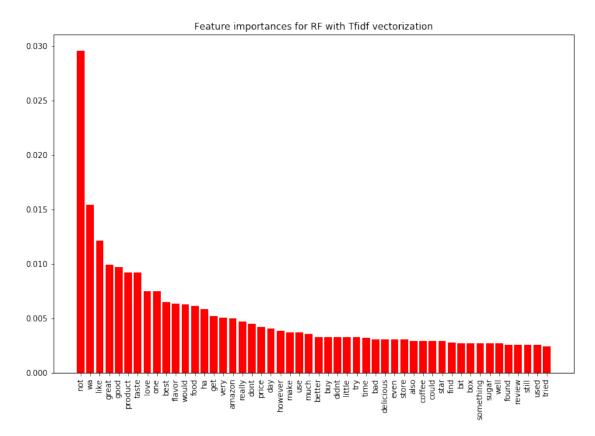
```
Out [23]:
             n_estimators
                           Test_score
                                        Test_std Train_score
         10
                              0.883076 0.010823
                        6
                                                     0.993331
         2
                       16
                              0.879002 0.011770
                                                     0.997926
                        9
         5
                              0.875895
                                        0.013146
                                                     0.992001
         3
                       24
                                                     0.999061
                              0.875766
                                       0.012165
         7
                        5
                              0.875455
                                       0.013131
                                                     0.985027
```

Got best cv score at n_estimators = 6 at max dept and mean cv score is 0.883076

```
#test
                    X_test = tf_idf_vect.transform(test_df['final_text'].values)
                    model = RF(n_estimators=6)
                    model.fit(final_counts_train,train_df.Score)
                     #Predicting training data
                    train list = model.predict(final counts train)
                     #Accuracy score
                    score_train = accuracy_score(train_df.Score,train_list)
                     #predict test cv
                     test_list = model.predict(X_test)
                     #Accuracy score
                     score_test = accuracy_score(test_df.Score,test_list)
                     #precision
                     #precision
                    test_precision = precision_score(test_df.Score,test_list)
                     #recall
                    test_recall = recall_score(test_df.Score,test_list)
                     #confusion matrix
                     confusion_matrix_test = confusion_matrix(test_df.Score,test_list)
                    print('n_estimators=6')
                    print('Train Score', score_train)
                    print('Test Score',score_test)
                    print('Test Precision',test_precision)
                    print('Test Recall',test_recall)
                    print('Test ConfusionMatrix',confusion_matrix_test)
n_estimators=6
Train Score 0.9927624352738114
Test Score 0.8698043953831086
Test Precision 0.8794440336537501
Test Recall 0.9760568690946192
Test ConfusionMatrix [[ 7014 12065]
  [ 2159 88013]]
In [42]: features = count_vect.get_feature_names()
                     dict_feature = dict(zip(features,importances))
                     sorted_feature = dict(sorted(dict_feature.items(),
                                                         key=operator.itemgetter(1),reverse=True))
In [43]: #To 100 features to seperate the data using Bag of words with RF
                    list_feature = list(sorted_feature.keys())[0:100]
                    list_fval = list(sorted_feature.values())[0:100]
                    print(list_feature)
['not', 'wa', 'like', 'great', 'good', 'product', 'taste', 'love', 'one', 'best', 'flavor', 'wa', 'like', 'great', 'good', 'product', 'taste', 'love', 'one', 'best', 'flavor', 'wa', 'like', 'great', 'good', 'product', 'taste', 'love', 'one', 'best', 'flavor', 'wa', 'like', 'great', 'good', 'product', 'taste', 'love', 'one', 'best', 'flavor', 'wa', 'love', 'great', 'great', 'good', 'product', 'taste', 'love', 'one', 'best', 'flavor', 'wa', 'great', '
```

```
In [45]: plt.figure(figsize=(12,8))
         plt.title("Feature importances for RF with Tfidf vectorization")
         plt.bar(range(len(list_feature[0:50])),list_fval[0:50],
                color="r")
         plt.xticks(range(len(list feature[0:50])),
                    list_feature[0:50],rotation = 90)
Out[45]: ([<matplotlib.axis.XTick at 0x153c7cb19438>,
           <matplotlib.axis.XTick at 0x153c8aa0aeb8>,
           <matplotlib.axis.XTick at 0x153cdb877828>,
           <matplotlib.axis.XTick at 0x153cd4d41898>,
           <matplotlib.axis.XTick at 0x153cd4d41f28>,
           <matplotlib.axis.XTick at 0x153cd8dbd5f8>,
           <matplotlib.axis.XTick at 0x153cd8dbdc88>,
           <matplotlib.axis.XTick at 0x153c619e9358>,
           <matplotlib.axis.XTick at 0x153c619e99e8>,
           <matplotlib.axis.XTick at 0x153c59d6f0b8>,
           <matplotlib.axis.XTick at 0x153c59d6f748>,
           <matplotlib.axis.XTick at 0x153c59d6fdd8>,
           <matplotlib.axis.XTick at 0x153cdae144a8>,
           <matplotlib.axis.XTick at 0x153cdae14b38>,
           <matplotlib.axis.XTick at 0x153cdae2b208>,
           <matplotlib.axis.XTick at 0x153cdae2b898>,
           <matplotlib.axis.XTick at 0x153cdae2bf28>,
           <matplotlib.axis.XTick at 0x153cdb7175f8>,
           <matplotlib.axis.XTick at 0x153cdb717c88>,
           <matplotlib.axis.XTick at 0x153cd3fd9358>,
           <matplotlib.axis.XTick at 0x153cd3fd99e8>,
           <matplotlib.axis.XTick at 0x153cd6ae50b8>,
           <matplotlib.axis.XTick at 0x153cd6ae5748>,
           <matplotlib.axis.XTick at 0x153cd6ae5dd8>,
           <matplotlib.axis.XTick at 0x153c7c5854a8>,
           <matplotlib.axis.XTick at 0x153c7c585b38>,
           <matplotlib.axis.XTick at 0x153c7c58f208>,
           <matplotlib.axis.XTick at 0x153c7c58f898>,
           <matplotlib.axis.XTick at 0x153c7c58ff28>,
           <matplotlib.axis.XTick at 0x153c6402b5f8>,
           <matplotlib.axis.XTick at 0x153c6402bc88>,
           <matplotlib.axis.XTick at 0x153c62732358>,
           <matplotlib.axis.XTick at 0x153c627329e8>,
           <matplotlib.axis.XTick at 0x153c536510b8>,
           <matplotlib.axis.XTick at 0x153c53651748>,
           <matplotlib.axis.XTick at 0x153c53651dd8>,
           <matplotlib.axis.XTick at 0x153c631b44a8>,
           <matplotlib.axis.XTick at 0x153c631b4b38>,
           <matplotlib.axis.XTick at 0x153c6319e208>,
           <matplotlib.axis.XTick at 0x153c6319e898>,
           <matplotlib.axis.XTick at 0x153c6319ef28>,
```

```
<matplotlib.axis.XTick at 0x153cd83b2c88>,
<matplotlib.axis.XTick at 0x153cd6d53358>,
<matplotlib.axis.XTick at 0x153cd6d53358>,
<matplotlib.axis.XTick at 0x153cd6d539e8>,
<matplotlib.axis.XTick at 0x153cd6d4e0b8>,
<matplotlib.axis.XTick at 0x153cd6d4e748>,
<matplotlib.axis.XTick at 0x153cd6d4edd8>,
<matplotlib.axis.XTick at 0x153cd5a534a8>,
<matplotlib.axis.XTick at 0x153cd5a534a8>,
<matplotlib.axis.XTick at 0x153c7f4d3320>],
<a list of 50 Text xticklabel objects>)
```



XGBoost:

```
In [16]: #base model
    model = xgb.XGBClassifier(n_jobs=-1,random_state=25).fit(final_counts_train,X_train.S.
    #train score
    train_score = model.score(final_counts_train,X_train.Score)
    #test score
    test_score = model.score(X_test,X_test_cv.Score)
    print('Train Score',train_score)
    print('Test Score',test_score)
```

```
Train Score 0.9028826970926453
Test Score 0.8865003399759401
```

```
In [17]: for i in range(0,100,10):
             model = xgb.XGBClassifier(n_estimators=i,n_jobs=-1)
             model = model.fit(final_counts_train,X_train.Score)
             #train score
             train_score = model.score(final_counts_train,X_train.Score)
             #test score
             test_score = model.score(X_test, X_test_cv.Score)
             print('No of Estimators',i,'Train Score',train_score,'Test Score',test_score)
No of Estimators 0 Train Score 0.1399878953621304 Test Score 0.17065484596474711
No of Estimators 10 Train Score 0.8626291721772656 Test Score 0.8329410534023746
No of Estimators 20 Train Score 0.8673925713389075 Test Score 0.8399105601757414
No of Estimators 30 Train Score 0.8716347985922754 Test Score 0.8461347350802866
No of Estimators 40 Train Score 0.8771883616148484 Test Score 0.8529865578743658
No of Estimators 50 Train Score 0.8829885005940239 Test Score 0.8608190804958419
No of Estimators 60 Train Score 0.8878079397458026 Test Score 0.8670955593911815
No of Estimators 70 Train Score 0.892061374997198 Test Score 0.8727966943877817
No of Estimators 80 Train Score 0.8962027302683194 Test Score 0.8783932214027931
No of Estimators 90 Train Score 0.8999910336015781 Test Score 0.8829567445996129
In [11]: from xgboost import XGBClassifier
         from scipy.stats import randint as sp_randint
         from scipy.stats import uniform
         from sklearn.pipeline import make_pipeline
         np.random.seed(25)
         param_distributions = {'xgbclassifier__n_estimators':sp_randint(200,900),
                                'xgbclassifier__max_depth':sp_randint(3,9),
                                'xgbclassifier_learning_rate':uniform(0,1),
                                'xgbclassifier_subsample':uniform(0,1),
                                'xgbclassifier_reg_alpha':uniform(0,1),
                                'xgbclassifier_reg_lambda':uniform(0,1),
                               'xgbclassifier__colsample_bylevel':uniform(0.7,0.3)}
         model_random_tfidf_xgb = RandomizedSearchCV(make_pipeline(TfidfVectorizer(ngram_range))
                                                             XGBClassifier(n_jobs=-1,random_state)
                                                param_distributions=param_distributions,n_iter
                                                cv=TimeSeriesSplit(n_splits=10),n_jobs=-1)
         model_random_tfidf_xgb.fit(train_df['final_text'],train_df.Score)
         pickle.dump(model_random_tfidf_xgb,open('model_random_tfidf_xgb.p','wb'))
In [14]: dict_scores = []
         idx = 0
         for i in model_random_tfidf_xgb.grid_scores_:
             dict_score = []
```

```
dict_score.append(i[0]['xgbclassifier__n_estimators'])
             dict_score.append(i[0]['xgbclassifier__max_depth'])
             dict_score.append(i[0]['xgbclassifier__subsample'])
             dict_score.append(i[0]['xgbclassifier__colsample_bylevel'])
             dict score.append(i[0]['xgbclassifier learning rate'])
             dict_score.append(i[0]['xgbclassifier__reg_alpha'])
             dict_score.append(i[0]['xgbclassifier__reg_lambda'])
             dict_score.append(i[1])
             dict score.append(i[2].std())
             dict_score.append(model_random_tfidf_xgb.cv_results_['mean_train_score'][idx])
             dict_scores.append(dict_score)
             idx = idx + 1
         scores_df = pd.DataFrame(dict_scores,columns=['n_estimators','depth',
                  'subsample', 'colsample_bylevel', 'learning_rate', 'reg_alpha',
                       'reg_lambda','Test_score','Test_std','Train_score'])
In [16]: scores_df.sort_values('Test_score', ascending=False).head(3)
Out [16]:
            n_estimators depth subsample colsample_bylevel learning_rate \
         2
                     759
                                  0.907128
                                                     0.859582
                                                                     0.406806
                     503
                                  0.849676
         3
                              7
                                                     0.776976
                                                                     0.231515
         5
                     371
                              5
                                  0.745284
                                                     0.900884
                                                                     0.456069
            reg_alpha reg_lambda Test_score Test_std Train_score
                         0.305770
         2
           0.362060
                                     0.944274 0.003011
                                                             0.983090
         3
            0.477546
                         0.631773
                                     0.942919 0.004053
                                                             0.991016
             0.525819
                         0.559242
                                     0.940904 0.003930
                                                             0.986590
  Got best cv score at n_estimators = 759, max_depth = 3,subample = 0.907128, colsam-
ple_bylevel = 0.859582, learning rate = 0.406806, reg_alpha = 0.362060, reg_lambda = 0.305770
and mean test cv is 0.944274
In [46]: #test scores
         #TFIDF with (1,2) gram with cleaned data
         #tfidf vec
         tf idf vect = TfidfVectorizer(ngram range=(1,2))
         final_counts_train = tf_idf_vect.fit_transform(
                 train_df['final_text'].values)
         #test
         X_test = tf_idf_vect.transform(test_df['final_text'].values)
         model = xgb.XGBClassifier(max_depth=3,learning_rate=0.406806,
                                    n_estimators=759,n_jobs=-1,
                                   subsample=0.907128,colsample_bylevel=0.859582,
                                     reg_alpha=0.362060,reg_lambda=0.305770)
         model.fit(final_counts_train,train_df.Score)
         #Predicting training data
         train_list = model.predict(final_counts_train)
         #Accuracy score
```

```
score test = accuracy score(test df.Score,test list)
         #precision
         #precision
         test_precision = precision_score(test_df.Score,test_list)
         test_recall = recall_score(test_df.Score,test_list)
         #confusion matrix
         confusion_matrix_test = confusion_matrix(test_df.Score,test_list)
         print('''max_depth=3,learning_rate=0.406806,
                  n_estimators=759,n_jobs=-1,
                  subsample=0.907128, colsample_bylevel=0.859582,
                  reg_alpha=0.362060,reg_lambda=0.305770''')
         print('Train Score', score_train)
         print('Test Score',score_test)
         print('Test Precision',test_precision)
         print('Test Recall',test recall)
         print('Test ConfusionMatrix',confusion_matrix_test)
max_depth=3,learning_rate=0.406806,
         n_estimators=759,n_jobs=-1,
         subsample=0.907128, colsample bylevel=0.859582,
         reg_alpha=0.362060,reg_lambda=0.305770
Train Score 0.9708889063235525
Test Score 0.9481926938883855
Test Precision 0.9579801877181193
Test Recall 0.9802266779044493
Test ConfusionMatrix [[15202 3877]
 [ 1783 88389]]
In [47]: import operator
         importances = model.feature_importances_
         features = count_vect.get_feature_names()
         dict_feature = dict(zip(features,importances))
         sorted_feature = dict(sorted(dict_feature.items(),
                             key=operator.itemgetter(1),reverse=True))
In [48]: #To 100 features to seperate the data using Bag of words with RF
         list_feature = list(sorted_feature.keys())[0:100]
         list_fval = list(sorted_feature.values())[0:100]
         print(list_feature)
['smartdogs', 'ovaltine', 'ambivalence', 'minuscule', 'grackle', 'everwhere', 'gent', 'adverti:
```

score_train = accuracy_score(train_df.Score,train_list)

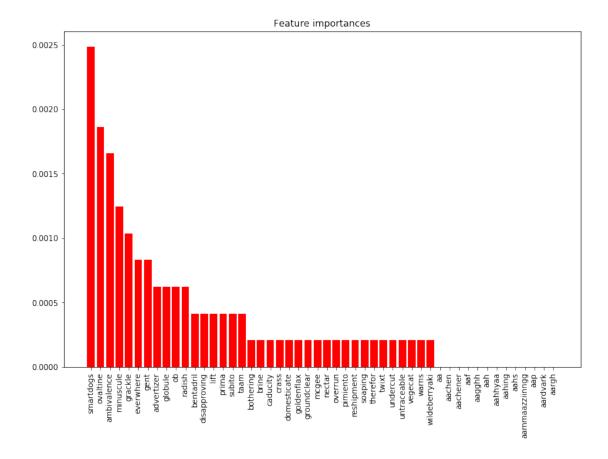
#predict test cv

#Accuracy score

test_list = model.predict(X_test)

```
In [49]: plt.figure(figsize=(12,8))
         plt.title("Feature importances")
         plt.bar(range(len(list_feature[0:50])),list_fval[0:50],
                color="r")
         plt.xticks(range(len(list feature[0:50])),
                    list_feature[0:50],rotation = 90)
Out[49]: ([<matplotlib.axis.XTick at 0x153cd6c32da0>,
           <matplotlib.axis.XTick at 0x153c60c5b8d0>,
           <matplotlib.axis.XTick at 0x153c3fac8e48>,
           <matplotlib.axis.XTick at 0x153c7b7544a8>,
           <matplotlib.axis.XTick at 0x153c7b754b38>,
           <matplotlib.axis.XTick at 0x153c7fe16208>,
           <matplotlib.axis.XTick at 0x153c7fe16898>,
           <matplotlib.axis.XTick at 0x153c7fe16f28>,
           <matplotlib.axis.XTick at 0x153cdc7e75f8>,
           <matplotlib.axis.XTick at 0x153cdc7e7c88>,
           <matplotlib.axis.XTick at 0x153cd8dfe358>,
           <matplotlib.axis.XTick at 0x153cd8dfe9e8>,
           <matplotlib.axis.XTick at 0x153cdc69f0b8>,
           <matplotlib.axis.XTick at 0x153cdc69f748>,
           <matplotlib.axis.XTick at 0x153cdc69fdd8>,
           <matplotlib.axis.XTick at 0x153cda3614a8>,
           <matplotlib.axis.XTick at 0x153cda361b38>,
           <matplotlib.axis.XTick at 0x153cd624d208>,
           <matplotlib.axis.XTick at 0x153cd624d898>,
           <matplotlib.axis.XTick at 0x153cd624df28>,
           <matplotlib.axis.XTick at 0x153cdbf2c5f8>,
           <matplotlib.axis.XTick at 0x153cdbf2cc88>,
           <matplotlib.axis.XTick at 0x153c7bb19358>,
           <matplotlib.axis.XTick at 0x153c7bb199e8>,
           <matplotlib.axis.XTick at 0x153cd7d0a0b8>,
           <matplotlib.axis.XTick at 0x153cd7d0a748>,
           <matplotlib.axis.XTick at 0x153cd7d0add8>,
           <matplotlib.axis.XTick at 0x153cda1504a8>,
           <matplotlib.axis.XTick at 0x153cda150b38>,
           <matplotlib.axis.XTick at 0x153cd4f0b208>,
           <matplotlib.axis.XTick at 0x153cd4f0b898>,
           <matplotlib.axis.XTick at 0x153cd4f0bf28>,
           <matplotlib.axis.XTick at 0x153cd4d745f8>,
           <matplotlib.axis.XTick at 0x153cd4d74c88>,
           <matplotlib.axis.XTick at 0x153c8a4fa358>,
           <matplotlib.axis.XTick at 0x153c8a4fa9e8>,
           <matplotlib.axis.XTick at 0x153c7c9480b8>,
           <matplotlib.axis.XTick at 0x153c7c948748>,
           <matplotlib.axis.XTick at 0x153c7c948dd8>,
           <matplotlib.axis.XTick at 0x153c7c3ff4a8>,
           <matplotlib.axis.XTick at 0x153c7c3ffb38>,
```

```
<matplotlib.axis.XTick at 0x153c7c7ec208>,
<matplotlib.axis.XTick at 0x153c7c7ec898>,
<matplotlib.axis.XTick at 0x153c7c7ecf28>,
<matplotlib.axis.XTick at 0x153cdb7cc5f8>,
<matplotlib.axis.XTick at 0x153cdb7ccc88>,
<matplotlib.axis.XTick at 0x153c8a9cb358>,
<matplotlib.axis.XTick at 0x153c8a9cb9e8>,
<matplotlib.axis.XTick at 0x153c7e2be0b8>,
<matplotlib.axis.XTick at 0x153c7e2be748>],
<a list of 50 Text xticklabel objects>)
```



Conclusions:

- 1. For RF with Avg Word2Vec Representation got good cv score at n_ectimators = 20 and depth = 25 with mean cv of 0.896263.
 - Train Score 0.997889533971442
 - Test Score 0.8889438082946609
 - Test Precision 0.8970036119448542
 - Test Recall 0.9777092667346848

• Test ConfusionMatrix

$$\begin{bmatrix}
8956 & 10123 \\
2010 & 88162
\end{bmatrix}$$
(1)

- 2. For XGBoost with Avg Word2Vec representation got best cv at no of estimators = 900, depth = 5, learning rate = 0.52 and subsample = 0.93 with mean cv score of 0.939139.
 - Train Score 1.0
 - Test Score 0.9303164273095899
 - Test Precision 0.9402160582696143
 - Test Recall 0.9777425364858271
 - Test ConfusionMatrix

$$\begin{bmatrix}
13473 & 5606 \\
2007 & 88165
\end{bmatrix}$$
(2)

- 3. For RF with Tf-Idf Word2Vec representation got best cv at at 56 and test cv is 0.884962.
 - Train Score 0.9796524399811706
 - Test Score 0.8709485496700259
 - Test Precision 0.8726985900036254
 - Test Recall 0.9877234618285056
 - Test ConfusionMatrix

$$\begin{bmatrix}
6087 & 12992 \\
1107 & 89065
\end{bmatrix}$$
(3)

- 4. For XGBoost with Tf-Idf Word2Vec representation got best cv at n_estimators = 884, depth = 4, subsample = 0.994481, colsample_bylevel=0.791814, learning_rate = 0.229976, reg_alpha = 0.998268, reg_lambda = 0.150014 and Test_score is 0.920558.
 - Train Score 0.9620547622783618
 - Test Score 0.9055477753064045
 - Test Precision 0.9101124749627652
 - Test Recall 0.9826110100696447
 - Test ConfusionMatrix

$$\begin{bmatrix}
10328 & 8751 \\
1568 & 88604
\end{bmatrix}$$
(4)

- 5. For RF with Bag of Words representation got best cv at no of estimators = 28, depth = 483 and Test cv score is 0.891749.
 - Train Score 0.9995606464773262
 - Test Score 0.8887058242029822
 - Test Precision 0.8856493153393643
 - Test Recall 0.9934236791908797
 - Test ConfusionMatrix

$$\begin{bmatrix}
7513 & 11566 \\
593 & 89579
\end{bmatrix}$$
(5)

- 6. For XGBoost with Bag of Words representation got best cv at n_estimators = 1240, depth = 3, subsample = 0.660874, colsample_bylevel=0.761028, learning_rate = 0.259216, reg_alpha = 0.676561, reg_lambda = 0.021376 and Test_score is 0.937136.
 - Train Score 0.956825670798682
 - Test Score 0.9375749421057931
 - Test Precision 0.949588987896179
 - Test Recall 0.9761899480991882
 - Test ConfusionMatrix

$$\begin{bmatrix}
14406 & 4673 \\
2147 & 88025
\end{bmatrix}$$
(6)

- 7. For RF with Tf-Idf vectorization got best cv at n_estimators = 6, max dept and mean cv score is 0.883076.
 - Train Score 0.9927624352738114
 - Test Score 0.8698043953831086
 - Test Precision 0.8794440336537501
 - Test Recall 0.9760568690946192
 - Test ConfusionMatrix

$$\begin{bmatrix}
7014 & 12065 \\
2159 & 88013
\end{bmatrix}$$
(7)

- 8. For XGBoost wit Tf-Idf vectorization got best cv at n_estimators = 759, max_depth = 3,sub-ample = 0.907128, colsample_bylevel = 0.859582, learning rate = 0.406806, reg_alpha = 0.362060, reg_lambda = 0.305770 and mean test cv is 0.944274.
 - Train Score 0.9708889063235525
 - Test Score 0.9481926938883855
 - Test Precision 0.9579801877181193
 - Test Recall 0.9802266779044493
 - Test ConfusionMatrix

$$\begin{bmatrix} 15202 & 3877 \\ 1783 & 88389 \end{bmatrix} \tag{8}$$