

OBJECTIVE

1. APPLYING RANDOM FOREST WITH BOW VECTORIZATION

- FINDING THE BEST HYPERPARAMETER USING GRIDSEARCHCV WITH TRAIN DATA AND CROSS-VALIDATION DATA BY PLOTTING THE RESULTS OF VARIOUS TRAIN DATA AND CROSS VALIDATION DATA
- USING THE APPROPRIATE VALUE OF HYPERPARAMETER, TESTING ACCURACY ON TEST DATA USING F1-SCORE
- PLOTTING THE CONFUSION MATRIX TO GET THE PRECISION, RECALL VALUE WITH HELP OF HEATMAP
- PRINTING THE TOP 30 MOST IMPORTANT FEATURES

```
In [0]: from sklearn.model_selection import train_test_split          #importing the necessary libraries
from sklearn.model_selection import RandomizedSearchCV
from sklearn.datasets import *
from sklearn import naive_bayes
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
import pandas as pd
from sklearn import *
import warnings
warnings.filterwarnings("ignore")
from sklearn.ensemble import RandomForestClassifier
```

```
In [20]: from google.colab import drive
drive.mount('/content/gdrive')#getting the content from the google drive
```

Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive", force_remount=True).

```
In [0]: final_processed_data=pd.read_csv("gdrive/My Drive/final_new_data.csv")#  
loading the preprocessed data with 100k points into dataframe
```

```
In [22]: # getting the counts of 0 and 1 in "SCORE" column to know whether it is  
unbalanced data or not  
count_of_1=0  
count_of_0=0  
for i in final_processed_data['Score']:  
    if i==1:  
        count_of_1+=1  
    else:  
        count_of_0+=1  
print(count_of_1)  
print(count_of_0)  
#it is an imbalanced dataset  
  
88521  
11479
```

```
In [0]: #spliiting the data into train and test data  
x_train,x_test,y_train,y_test=model_selection.train_test_split(final_pr  
ocessed_data['CleanedText'].values,final_processed_data['Score'].values  
,test_size=0.3,shuffle=False)
```

```
In [92]: vectorizer=CountVectorizer(min_df=2)#building the vertorizer with word  
counts equal and more then 2  
train_bow=vectorizer.fit_transform(x_train)#fitting the model on traini  
ng data  
print(train_bow.shape)  
  
(70000, 16382)
```

```
In [93]: test_bow=vectorizer.transform(x_test)#fitting the bow model on test dat  
a  
print("shape of x_test after bow vectorization ",test_bow.shape)  
  
shape of x_test after bow vectorization (30000, 16382)
```

In [0]:

```
In [94]: #building the model
#using time series split method for cross-validation score
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=5)
rf=RandomForestClassifier(criterion='gini',class_weight={1:.5,0:.5})
tuned_parameters=[{'max_depth':[61,64,68,73,77,80], 'n_estimators':[21,30,35,40,45,50]}]
#applying the model of decision tree and using gridsearchcv to find the best hyper parameter
%%time
from sklearn.model_selection import GridSearchCV
model = GridSearchCV(rf, tuned_parameters, scoring = 'f1', cv=tscv,n_jobs=-1)#building the gridsearchcv model
```

CPU times: user 4 µs, sys: 0 ns, total: 4 µs
Wall time: 7.87 µs

```
In [95]: %%time
model.fit(train_bow, y_train)#fitting the training data
```

CPU times: user 18.7 s, sys: 208 ms, total: 18.9 s
Wall time: 25min 2s

```
Out[95]: GridSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=5),
                      error_score='raise-deprecating',
                      estimator=RandomForestClassifier(bootstrap=True, class_weight={1: 0.5, 0: 0.5},
                                                         criterion='gini', max_depth=None, max_features='auto',
                                                         max_leaf_nodes=None, min_impurity_decrease=0.0,
                                                         min_impurity_split=None, min_samples_leaf=1,
                                                         min_samples_split=2, min_weight_fraction_leaf=0.0,
                                                         n_estimators='warn', n_jobs=None, oob_score=False,
                                                         random_state=None, verbose=0, warm_start=False),
                      fit_params=None, iid='warn', n_jobs=-1,
                      param_grid=[{'max_depth': [61, 64, 68, 73, 77, 80], 'n_estimator
s': [21, 30, 35, 40, 45, 50]}],
```

```
pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
scoring='f1', verbose=0)
```

```
In [96]: print(model.best_estimator_)#printing the best_estimator
```

```
RandomForestClassifier(bootstrap=True, class_weight={1: 0.5, 0: 0.5},
                        criterion='gini', max_depth=77, max_features='auto',
                        max_leaf_nodes=None, min_impurity_decrease=0.0,
                        min_impurity_split=None, min_samples_leaf=1,
                        min_samples_split=2, min_weight_fraction_leaf=0.0,
                        n_estimators=35, n_jobs=None, oob_score=False,
                        random_state=None, verbose=0, warm_start=False)
```

```
In [106]: print(model.score(test_bow,y_test))#checking the score on test_Data
```

```
0.9380587825900744
```

```
In [107]: results=pd.DataFrame(model.cv_results_)# getting varoius cv_scores and
          train_scores various values of hyperparameter given as parameter and s
          toring it in a dataframe
          results#printing the dataframe
```

Out[107]:

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
0	7.693781	0.126196	0.943111	0.970668	61
1	10.929001	0.169017	0.942684	0.969995	61

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
2	12.851338	0.198344	0.942826	0.970563	61
3	14.822200	0.223285	0.942867	0.970194	61
4	16.404032	0.246995	0.942496	0.970630	61
5	18.451207	0.272454	0.942391	0.970166	61
6	8.061914	0.127674	0.942987	0.971677	64
7	11.573845	0.175007	0.942734	0.971318	64
8	13.473842	0.201682	0.942827	0.972150	64

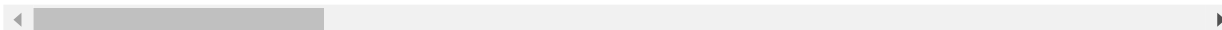
	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
9	15.423412	0.228173	0.943077	0.972066	64
10	17.217195	0.250988	0.942758	0.971803	64
11	19.453093	0.278592	0.942536	0.971756	64
12	8.525478	0.132627	0.943196	0.973631	68
13	12.238119	0.175908	0.943114	0.973612	68
14	14.318984	0.208440	0.943126	0.973527	68
15	16.243402	0.234396	0.943139	0.973558	68

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
16	18.247492	0.260157	0.943030	0.973599	68
17	20.666725	0.288669	0.942924	0.973688	68
18	9.186626	0.135550	0.943606	0.975151	73
19	13.311219	0.186319	0.943350	0.975634	73
20	15.180538	0.211716	0.943150	0.975475	73
21	17.508943	0.241048	0.943122	0.976006	73
22	19.411326	0.268782	0.943314	0.975545	73

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
23	21.840919	0.297235	0.943257	0.975653	73
24	9.778775	0.141616	0.943868	0.977652	77
25	13.969068	0.193177	0.943720	0.977494	77
26	16.430060	0.223109	0.944037	0.977108	77
27	18.301833	0.246289	0.943744	0.977534	77
28	20.481514	0.276714	0.943328	0.976954	77
29	22.827447	0.306357	0.943203	0.977366	77

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
30	9.886808	0.141406	0.944000	0.978311	80
31	14.167045	0.194468	0.943674	0.977792	80
32	16.406874	0.221186	0.943401	0.978075	80
33	18.961226	0.253323	0.943534	0.978649	80
34	21.339856	0.281226	0.943406	0.978393	80
35	22.205270	0.291927	0.943865	0.978379	80

36 rows × 22 columns



```
In [0]: results['mean_test_score']=results['mean_test_score']*100 #multiplying
        mean_test_score by 100
```

```
In [0]: results=results.round(decimals=2)# rounding off to 2 decimal places
results['cv_error_score']=100-results['mean_test_score']# generating a
new colum for getting cv_Errorscores and using it in pivottable
```

PLOTTING THE HEATMAP WITH HYPERPARAMETERS FOR CV_ERROR SCORE

```
In [0]: test_score_heatmap=results.pivot(          'param_max_depth'          , 'param
_n_estimators', 'cv_error_score' )
```

```
In [112]: test_score_heatmap
```

Out[112]:

param_n_estimators	21	30	35	40	45	50
param_max_depth						
61	5.69	5.73	5.72	5.71	5.75	5.76
64	5.70	5.73	5.72	5.69	5.72	5.75
68	5.68	5.69	5.69	5.69	5.70	5.71
73	5.64	5.66	5.68	5.69	5.67	5.67
77	5.61	5.63	5.60	5.63	5.67	5.68
80	5.60	5.63	5.66	5.65	5.66	5.61

```
In [113]: import seaborn as sns
sns.heatmap(test_score_heatmap,annot=True,annot_kws={"size": 15}, fmt=
'g',linewidths=.3)
```

Out[113]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7d024dd400>



In [114]: `print(model.best_estimator_)`*#printing the best_estimator*

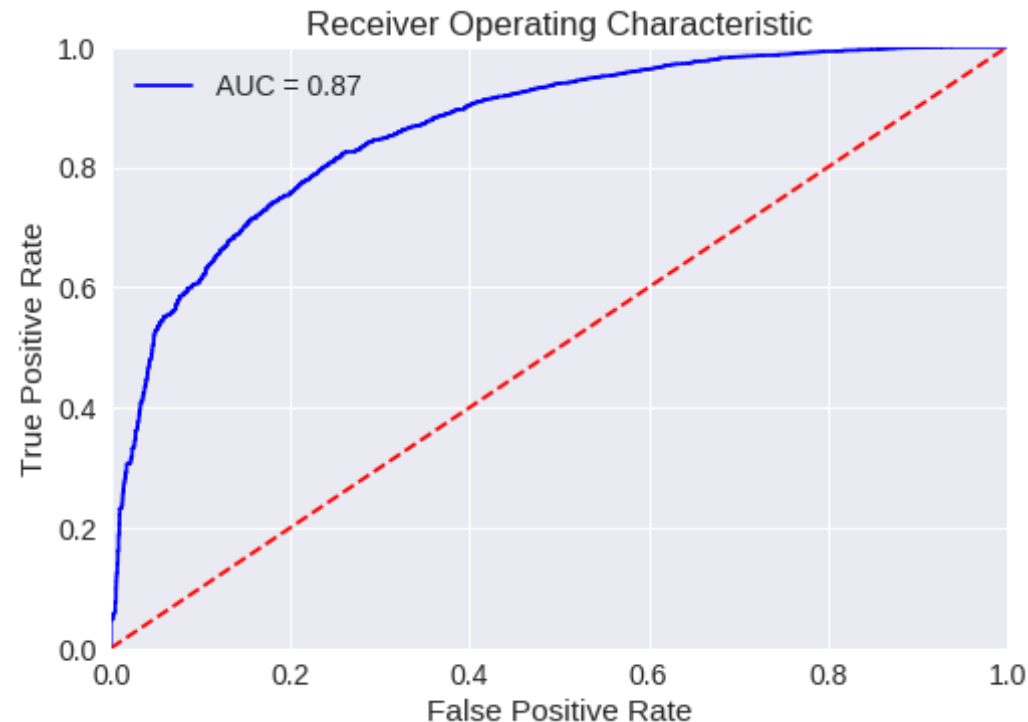
```
RandomForestClassifier(bootstrap=True, class_weight={1: 0.5, 0: 0.5},
                        criterion='gini', max_depth=77, max_features='auto',
                        max_leaf_nodes=None, min_impurity_decrease=0.0,
                        min_impurity_split=None, min_samples_leaf=1,
                        min_samples_split=2, min_weight_fraction_leaf=0.0,
                        n_estimators=35, n_jobs=None, oob_score=False,
                        random_state=None, verbose=0, warm_start=False)
```

FROM THE ABOVE HEATMAPS RESULTS FOR CV DATA, WE FOUND THAT BEST HYPERPARAMETERS AS MAX_DEPTH=77 AND MIN_SAMPLE_SPLIT=35

PLOTTING THE ROC CURVE FOR GETTING AUC SCORE

```
In [116]: rf=RandomForestClassifier(criterion='gini',class_weight={1:.5,0:.5},max
_depth=77 ,n_estimators=35)
rf.fit(train_bow,y_train)#fitting the model
probs = rf.predict_proba(test_bow)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
roc_auc = metrics.auc(fpr, tpr)

#
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'best')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



```
In [117]: print('accuracy from the ROC curve is found as ',roc_auc*100)
```

accuracy from the ROC curve is found as 86.5744784708663

```
In [118]: z=rf.feature_importances_
a=z.argsort()
print('shape of wieght vector is:',a.shape)
top_features=np.take(vectorizer.get_feature_names(),a[16360:])#taking l
ast features as they are of very high importance
```

shape of wieght vector is: (16382,)

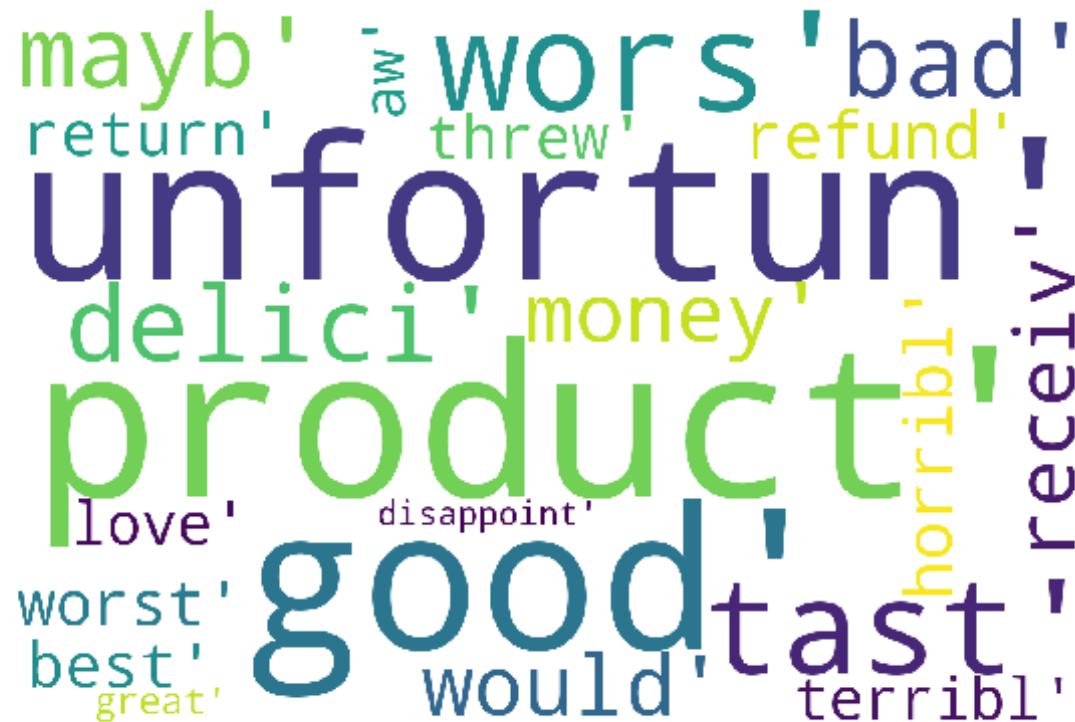
```
In [119]: print(top_features)#printing the top_features
top=list(top_features)
```

['product' 'unfortun' 'good' 'wors' 'tast' 'delici' 'bad' 'mayb' 'mone

```
y'  
'would' 'receiv' 'refund' 'horribl' 'return' 'worst' 'best' 'threw'  
'terribl' 'love' 'aw' 'great' 'disappoint']
```

REPRESENTING TOP IMPORTANT FEATURES USING WORDCLOUD LIBRARY

```
In [120]: from wordcloud import WordCloud #here we are printing the top features  
          using wordcloud library  
          import matplotlib.pyplot as plt  
          wordcloud = WordCloud(width = 1500, height = 1000,  
                                background_color = 'white',  
                                min_font_size = 10).generate(str(top))  
  
          # plot the WordCloud image  
          plt.figure(figsize = (8, 8), facecolor = None)  
          plt.imshow(wordcloud)  
          plt.axis("off")  
          plt.tight_layout(pad = 0)  
  
          plt.show()
```



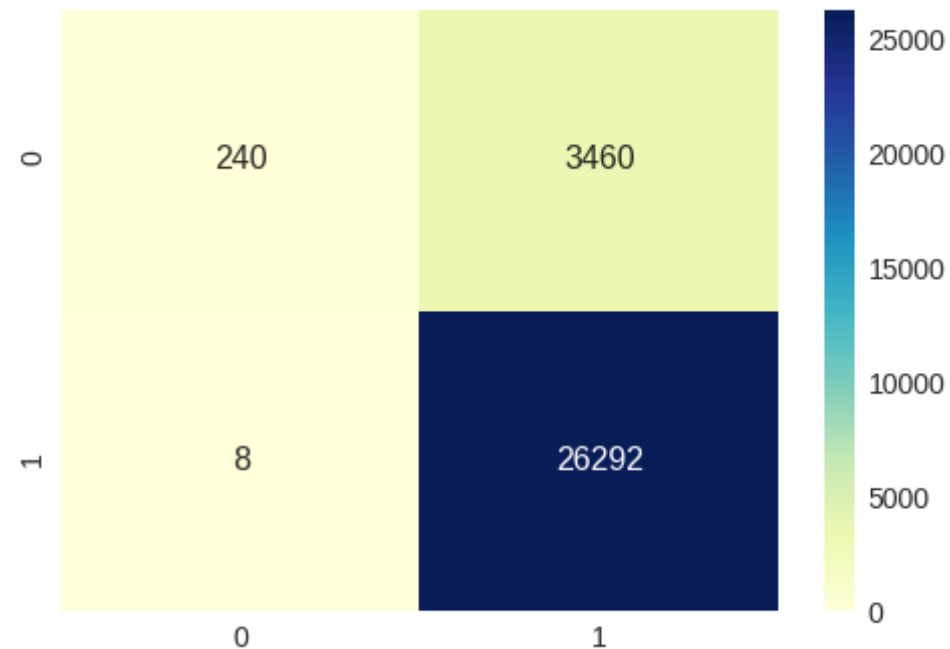
TESTING OUR MODEL ON TEST DATA AND CHECKING ITS PRECISION ,RECALL ,F1_FCORE

```
In [121]: #Testing Accuracy on Test data
import seaborn as sns #importing seaborn as sns
from sklearn.metrics import *#importing varoius metrics from sklearn
#building the model
y_pred = rf.predict(test_bow)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))#printing accuracy
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
```

```
#printing precision score
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred))) #printing recall
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Confusion Matrix of test set:\n [ [TN FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2)) #generating the heatmap for confusion matrix
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',cmap="YlGnBu")
```

```
Accuracy on test set: 88.440%
Precision on test set: 0.884
Recall on test set: 1.000
F1-Score on test set: 0.938
Confusion Matrix of test set:
 [ [TN FP]
  [FN TP] ]
```

```
Out[121]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7d023aa550>
```

BOW VECTORIZATION FOR RANDOM FOREST IS COMPLETED

OBJECTIVE

1. APPLYING GBDT WITH BOW VECTORIZATION

- FINDING THE BEST HYPERPARAMETER USING GRIDSEARCHCV WITH TRAIN DATA AND CROSS-VALIDATION DATA BY PLOTTING THE RESULTS OF VARIOUS TRAIN DATA AND CROSS VALIDATION DATA
- USING THE APPROPRIATE VALUE OF HYPERPARAMETER, TESTING ACCURACY ON TEST DATA USING F1-SCORE
- PLOTTING THE CONFUSION MATRIX TO GET THE PRECISION, RECALL VALUE WITH HELP OF HEATMAP

- PRINTING THE TOP 30 MOST IMPORTANT FEATURES

```
In [79]: from xgboost import XGBClassifier
#building the model
#using time series split method for cross-validation score
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=5)
xg=XGBClassifier(n_jobs=-1)
tuned_parameters=[{'max_depth': [11,15,20,24,27,30], 'n_estimators': [21,30,35,40,45,50]}]
#applying the model of decision tree and using gridsearchcv to find the best hyper parameter
%%time
from sklearn.model_selection import GridSearchCV
model = GridSearchCV(xg, tuned_parameters, scoring = 'f1', cv=tscv,n_jobs=-1)#building the gridsearchcv model
```

CPU times: user 4 µs, sys: 0 ns, total: 4 µs
Wall time: 7.87 µs

```
In [81]: %%time
model.fit(train_bow, y_train)#fitting the training data
```

CPU times: user 1min 37s, sys: 379 ms, total: 1min 38s
Wall time: 46min 2s

```
Out[81]: GridSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=5),
                    error_score='raise-deprecating',
                    estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsam
ple_bylevel=1,
                    colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=
0,
                    max_depth=3, min_child_weight=1, missing=None, n_estimators=100,
n_jobs=-1, nthread=None, objective='binary:logistic',
                    random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
                    seed=None, silent=True, subsample=1),
                    fit_params=None, iid='warn', n_jobs=-1,
                    param_grid=[{'max_depth': [11, 15, 20, 24, 27, 30], 'n_estimator
s': [21, 30, 35, 40, 45, 50]}],
```

```
pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',  
scoring='f1', verbose=0)
```

```
In [82]: print(model.best_estimator_)#printing the best_estimator
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,  
             colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=  
0,  
             max_depth=27, min_child_weight=1, missing=None, n_estimators=50,  
             n_jobs=-1, nthread=None, objective='binary:logistic',  
             random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,  
             seed=None, silent=True, subsample=1)
```

```
In [83]: results=pd.DataFrame(model.cv_results_)# getting varoius cv_scores and  
         train_scores various values of hyperparameter given as parameter and s  
         toring it in a dataframe  
         results#printing the dataframe
```

Out[83]:

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
0	8.378044	0.223508	0.945871	0.957951	11
1	11.744793	0.234820	0.946986	0.960688	11
2	13.630929	0.243391	0.947529	0.962423	11

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
3	15.404321	0.254485	0.948213	0.963805	11
4	17.146619	0.261241	0.948735	0.965392	11
5	19.081864	0.270164	0.949192	0.967105	11
6	11.781351	0.240545	0.947026	0.963850	15
7	16.268544	0.254496	0.948179	0.967263	15
8	18.858186	0.269509	0.948571	0.969465	15
9	21.280204	0.278331	0.949295	0.971127	15

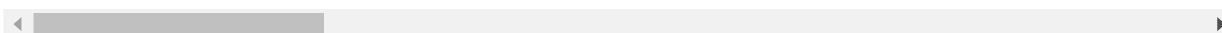
	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
10	24.122753	0.291332	0.949752	0.973010	15
11	26.368965	0.303199	0.950301	0.974599	15
12	15.796100	0.258495	0.947925	0.970377	20
13	22.099479	0.278792	0.948880	0.974037	20
14	25.815812	0.296917	0.949754	0.976184	20
15	29.185396	0.311018	0.950857	0.977981	20
16	32.608864	0.330868	0.951227	0.979562	20

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
17	36.093679	0.347879	0.951690	0.980947	20
18	19.114895	0.268711	0.948154	0.973932	24
19	26.965733	0.301868	0.949403	0.978179	24
20	31.717748	0.318615	0.950061	0.979911	24
21	35.838385	0.337649	0.950983	0.981705	24
22	39.751508	0.354716	0.951516	0.983142	24
23	43.892469	0.376672	0.951935	0.984425	24

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
24	21.777656	0.279111	0.948460	0.976372	27
25	30.553274	0.310690	0.949773	0.980333	27
26	35.477301	0.333657	0.950606	0.982152	27
27	40.452885	0.357649	0.951335	0.983875	27
28	45.264877	0.379433	0.952002	0.985435	27
29	49.976577	0.401949	0.952426	0.986562	27
30	24.410512	0.281754	0.948172	0.978369	30

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
31	33.874339	0.324059	0.949829	0.982440	30
32	39.416312	0.350812	0.950284	0.984381	30
33	44.859274	0.370497	0.951061	0.985891	30
34	50.118966	0.398341	0.951202	0.987295	30
35	51.189381	0.393930	0.951405	0.988397	30

36 rows × 22 columns



```
In [0]: results['mean_test_score']=results['mean_test_score']*100
results=results.round(decimals=2)
results['cv_error_score']=100-results['mean_test_score']
```


PLOTTING THE HEATMAP WITH HYPERPARAMETERS FOR CV_ERROR SCORE

```
In [85]: test_score_heatmap=results.pivot( 'param_max_depth' , 'param_n_estimators', 'cv_error_score' )
```

```
test_score_heatmap
```

Out[85]:

param_n_estimators	21	30	35	40	45	50
param_max_depth						
11	5.41	5.30	5.25	5.18	5.13	5.08
15	5.30	5.18	5.14	5.07	5.02	4.97
20	5.21	5.11	5.02	4.91	4.88	4.83
24	5.18	5.06	4.99	4.90	4.85	4.81
27	5.15	5.02	4.94	4.87	4.80	4.76
30	5.18	5.02	4.97	4.89	4.88	4.86

```
In [86]: import seaborn as sns
sns.heatmap(test_score_heatmap,annot=True,annot_kws={"size": 15}, fmt='g',linewidths=.3)
```

Out[86]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7d02f90a20>



In [87]: `print(model.best_estimator_)` *#printing the best_estimator*

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=
0,
              max_depth=27, min_child_weight=1, missing=None, n_estimators=50,
              n_jobs=-1, nthread=None, objective='binary:logistic',
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1,
              seed=None, silent=True, subsample=1)
```

FROM THE ABOVE HEATMAPS RESULTS FOR CV DATA, WE FOUND THAT BEST HYPERPARAMETERS AS MAX_DEPTH=27 AND N_ESTIMATORS=50

PLOTTING THE ROC CURVE FOR GETTING AUC SCORE

```
In [131]: xg=XGBClassifier(n_jobs=-1,max_depth=27 ,n_estimators=50)
xg.fit(train_bow,y_train)#fitting the model
probs = xg.predict_proba(test_bow)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
roc_auc = metrics.auc(fpr, tpr)

import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'best')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



```
In [132]: print('accuracy from the ROC curve is found as ',roc_auc*100)
```

accuracy from the ROC curve is found as 87.99880639194328

```
In [125]: z=rf.feature_importances_
a=z.argsort()
print('shape of wieght vector is:',a.shape)
top_features=np.take(vectorizer.get_feature_names(),a[16360:])#taking l
ast features as they are of very high importance
```

shape of wieght vector is: (16382,)

```
In [126]: print(top_features)#printing the top_features
top=list(top_features)
```

['product' 'unfortun' 'good' 'wors' 'tast' 'delici' 'bad' 'mayb' 'mone

```
y'  
'would' 'receiv' 'refund' 'horribl' 'return' 'worst' 'best' 'threw'  
'terribl' 'love' 'aw' 'great' 'disappoint']
```

REPRESENTING TOP IMPORTANT FEATURES USING WORDCLOUD LIBRARY

```
In [127]: from wordcloud import WordCloud #here we are printing the top features  
          using wordcloud library  
          import matplotlib.pyplot as plt  
          wordcloud = WordCloud(width = 1500, height = 1000,  
                                background_color = 'white',  
                                min_font_size = 10).generate(str(top))  
  
          # plot the WordCloud image  
          plt.figure(figsize = (8, 8), facecolor = None)  
          plt.imshow(wordcloud)  
          plt.axis("off")  
          plt.tight_layout(pad = 0)  
  
          plt.show()
```

horribl' money' refund'
 unfortun
 good' best' tast' disappoint'
 mayb' love' bad' return'
 product' worst' would' aw'
 great' worSdelici' receiv' threw'

```
In [133]: y_pred = xg.predict(test_bow)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))#printing accuracy
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
#printing precision score
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred))) #printing recall
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Confusion Matrix of test set:\n [ [TN FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2)) #generating the heatmap for confusion matrix
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',cmap="YlGnBu")
```

```
Accuracy on test set: 90.103%  
Precision on test set: 0.907  
Recall on test set: 0.988  
F1-Score on test set: 0.946  
Confusion Matrix of test set:  
[ [TN FP]  
  [FN TP] ]
```

Out[133]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7d023f4908>

