OBJECTIVE

1. APPLYING RANDOM FOREST WITH TFIDF VECTORIZATION
   - FINDING THE BEST HYPERPARAMETER USING GRIDSEARCHCV WITH TRAIN DATA AND CROSS-VALIDATION DATA BY PLOTTING THE RESLUTS OF VAROIUS TRAIN DATA AND CROSS VALIDATION DATA
   - USING THE APROPRIATE VALUE OF HYPERPARAMETER ,TESTING ACCURACY ON TEST DATA USING F1-SCORE
   - PLOTTING THE CONFUSION MATRIX TO GET THE PRECISOIN ,RECALL VALUE WITH HELP OF HEATMAP
   - PRINTING THE TOP 30 MOST IMPORTANT FEATURES

In [0]:
```
from sklearn.model_selection import train_test_split          #importin
g 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 [4]:
```
from google.colab import drive
drive.mount('/content/gdrive')#geeting the content from the google driv
e
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remoun
t, 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 [6]:
```
# 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 [8]:
```
vectorizer=TfidfVectorizer(min_df=2)#building the vertorizer with word
 counts equal and more then 2
train_tfidf=vectorizer.fit_transform(x_train)#fitting the model on trai
ning data
print(train_tfidf.shape)
```

```
(70000, 16382)
```

In [9]:
```
test_tfidf=vectorizer.transform(x_test)#fitting the bow model on test d
ata
print("shape of x_test after tfidf vectorization ",test_tfidf.shape)
```

```
shape of x_test after tfidf vectorization  (30000, 16382)
```

In [0]:

```

```

In [10]:

```
#biudling 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':[21,3
0,35,40,45,50]}]
#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_jo
bs=-1)#building the gridsearchcv model
```

```
CPU times: user 4 µs, sys: 1 µs, total: 5 µs
Wall time: 7.63 µs
```

In [11]:

```
%%time
model.fit(train_tfidf, y_train)#fiitting the training data
```

```
CPU times: user 11.2 s, sys: 284 ms, total: 11.5 s
Wall time: 26min 40s
```

Out[11]:

```
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 [20]:
```
print(model.best_estimator_)#printing the best_estimator
```

```
RandomForestClassifier(bootstrap=True, class_weight={1: 0.5, 0: 0.5},
            criterion='gini', max_depth=73, 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=21, n_jobs=None, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
```

In [21]:
```
print(model.score(test_tfidf,y_test))#checking the score on test_Data
```

```
0.9376672494380418
```

In [22]:
```
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[22]:

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
0	8.207892	0.125787	0.942826	0.968657	61
1	11.751353	0.175003	0.942623	0.968801	61

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
2	13.598304	0.196765	0.942794	0.968604	61
3	15.517566	0.228227	0.942471	0.968346	61
4	17.657933	0.251955	0.942571	0.968759	61
5	19.466890	0.272821	0.942472	0.969249	61
6	8.745539	0.132947	0.942786	0.970711	64
7	12.032980	0.176906	0.943092	0.970263	64
8	14.123110	0.203084	0.942750	0.970345	64

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
9	16.386997	0.228492	0.942637	0.970659	64
10	18.190747	0.255849	0.942665	0.970313	64
11	20.558136	0.284757	0.942728	0.970934	64
12	9.144402	0.134296	0.943007	0.972365	68
13	12.795353	0.185571	0.942633	0.971862	68
14	15.200046	0.212584	0.942648	0.972416	68
15	17.023168	0.234259	0.942667	0.972219	68

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
16	19.363737	0.266417	0.942464	0.972856	68
17	21.581563	0.289683	0.942622	0.971730	68
18	9.801576	0.143186	0.943570	0.974136	73
19	14.160118	0.194498	0.943043	0.973793	73
20	16.824344	0.218368	0.943022	0.974422	73
21	18.932823	0.247959	0.943131	0.973988	73
22	21.523917	0.281439	0.942929	0.974456	73

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
23	24.093993	0.315355	0.942896	0.974129	73
24	10.646736	0.146012	0.943391	0.975058	77
25	15.027038	0.198350	0.943395	0.975380	77
26	17.612787	0.228716	0.943262	0.976097	77
27	19.867350	0.254089	0.943224	0.975760	77
28	22.579286	0.295588	0.943239	0.975469	77
29	24.659954	0.314257	0.943005	0.976081	77

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
30	10.896179	0.148836	0.943315	0.976295	80
31	15.231942	0.198558	0.943331	0.976448	80
32	17.803722	0.228328	0.943447	0.976752	80
33	20.242478	0.261301	0.943186	0.977049	80
34	22.851599	0.298497	0.943296	0.976556	80
35	23.545404	0.307550	0.943202	0.977062	80

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

In [25]:
```
test_score_heatmap
```

Out[25]:

param_n_estimators	21	30	35	40	45	50
param_max_depth						
61	5.72	5.74	5.72	5.75	5.74	5.75
64	5.72	5.69	5.72	5.74	5.73	5.73
68	5.70	5.74	5.74	5.73	5.75	5.74
73	5.64	5.70	5.70	5.69	5.71	5.71
77	5.66	5.66	5.67	5.68	5.68	5.70
80	5.67	5.67	5.66	5.68	5.67	5.68

In [26]:
```
import seaborn as sns
sns.heatmap(test_score_heatmap,annot=True,annot_kws={"size": 15}, fmt='g',linewidths=.3)
```

Out[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb8be172a58>
```

In [27]:
```
print(model.best_estimator_)#printing the best_estimator
```

```
RandomForestClassifier(bootstrap=True, class_weight={1: 0.5, 0: 0.5},
            criterion='gini', max_depth=73, 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=21, n_jobs=None, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
```

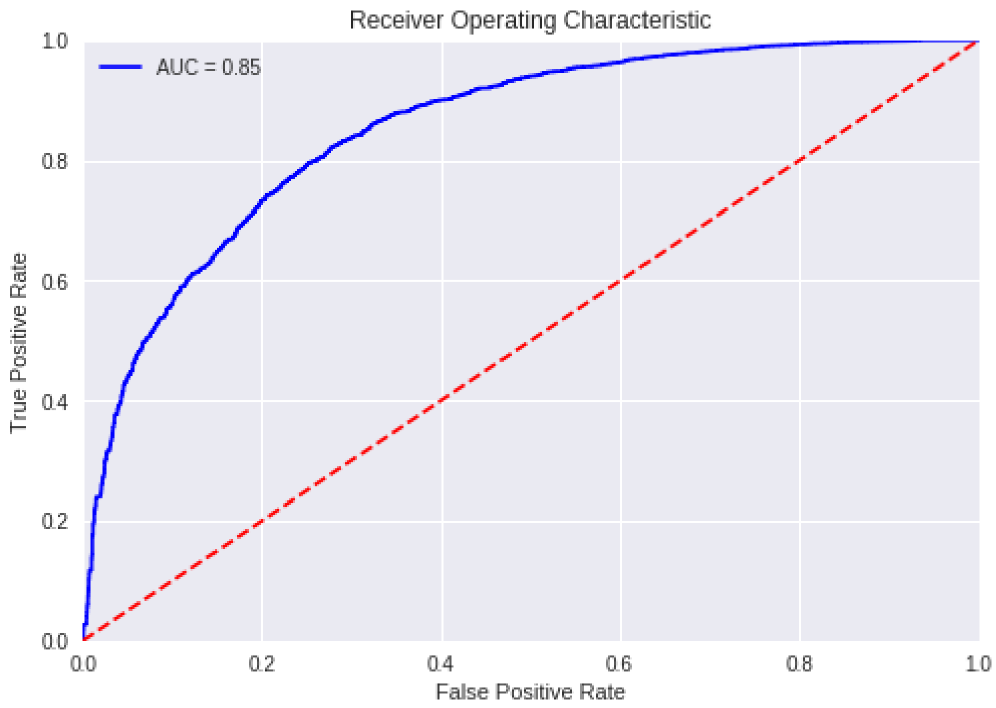
FROM THE ABOVE HEATMAPS RESULTS FOR CV DATA,WE FOUND THAT BEST HYPERPARAMETERS AS MAX_DEPTH=73 AND N_ESTIMATORS=21

PLOTTING THE ROC CURVE FOR GETTING AUC SCORE

In [29]:

```
rf=RandomForestClassifier(criterion='gini',class_weight={1:.5,0:.5},max
_depth=73 ,n_estimators=21)
rf.fit(train_tfidf,y_train)#fitting the model
probs = rf.predict_proba(test_tfidf)
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 [30]:
```
print('accuracy from the ROC curve is found as ',roc_auc*100)
```

```
accuracy from the ROC curve is found as  85.30101633953345
```

In [31]:
```
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 [32]:
```
print(top_features)#printing the top_features
top=list(top_features)
```

```
['return' 'refund' 'receiv' 'poor' 'gross' 'money' 'best' 'thought' 'ta
st'
```

```
'horribl' 'mayb' 'stale' 'love' 'threw' 'wast' 'bad' 'worst' 'terribl'
'aw' 'would' 'great' 'disappoint']
```

REPRESENTING TOP IMPORTANT FEATURES USING WORDCLOUD LIBRARY

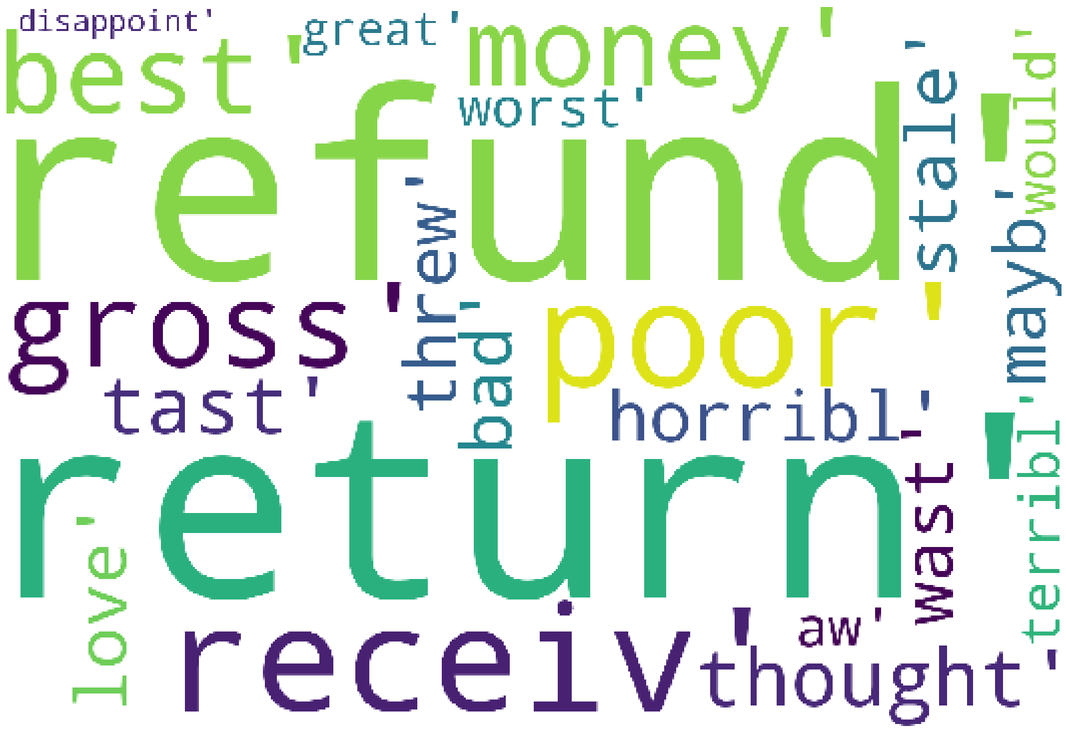
In [33]:

```
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 [34]:

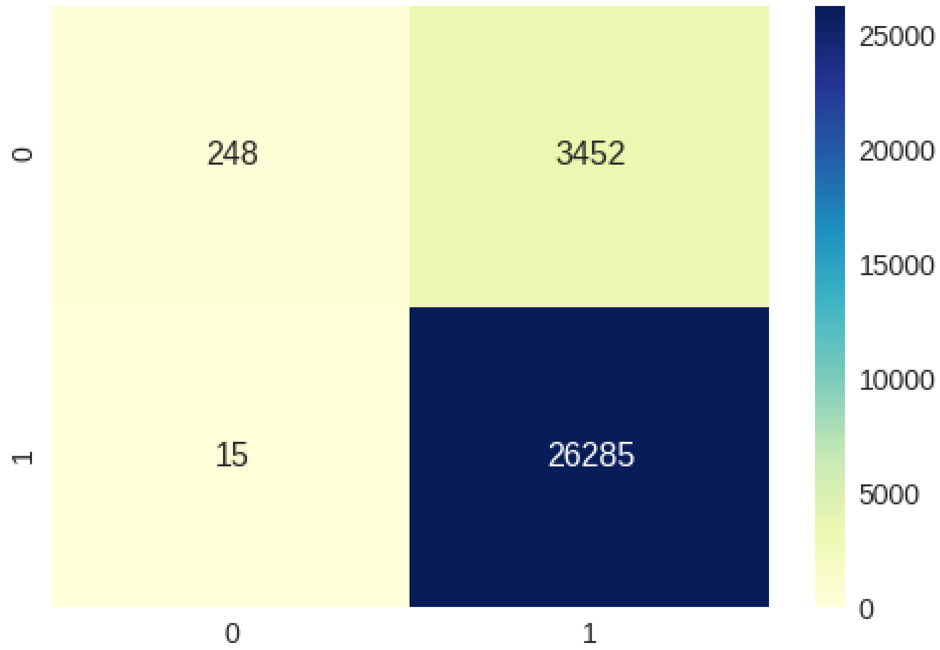
```
#Testing Accuracy on Test data
import seaborn as sns #importing seaborn as sns
from sklearn.metrics import *#importing varoious metrics from sklearn
#building the model
y_pred = rf.predict(test_tfidf)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*1
00))#printing accuracy
print("Precision 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))) #prin
ting 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="YlG
nBu")
```

```
Accuracy on test set: 88.443%
Precision on test set: 0.884
Recall on test set: 0.999
F1-Score on test set: 0.938
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[34]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb8b91d6e80>
```



BOW VECTORIZATION FOR RANDOM FOREST IS COMPLETED

OBJECTIVE

1. **APPLYING GBDT WITH TFIDF VECTORIZATION**
   - **FINDING THE BEST HYPERPARAMETER USING GRIDSEARCHCV WITH TRAIN DATA AND CROSS-VALIDATION DATA BY PLOTTING THE RESLUTS OF VAROIUS TRAIN DATA AND CROSS VALIDATION DATA**
   - **USING THE APROPRIATE VALUE OF HYPERPARAMETER ,TESTING ACCURACY ON TEST DATA USING F1-SCORE**
   - **PLOTTING THE CONFUSION MATRIX TO GET THE PRECISOIN ,RECALL VALUE WITH HELP OF HEATMAP**

- **PRINTING THE TOP 30 MOST IMPORTANT FEATURES**

In [35]:
```
from xgboost import XGBClassifier
#biudling 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':[21,3
0,35,40,45,50]}]
#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_jo
bs=-1)#building the gridsearchcv model
```

```
CPU times: user 3 µs, sys: 1 µs, total: 4 µs
Wall time: 6.91 µs
```

In [36]:
```
%%time
model.fit(train_tfidf, y_train)#fiitting the training data
```

```
CPU times: user 2min 51s, sys: 362 ms, total: 2min 51s
Wall time: 1h 12min 21s
```

Out[36]:
```
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 [43]:
```
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=30, 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 [60]:
```
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.head()#printing the dataframe
```

Out[60]:

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_de
0	14.193161	0.189327	0.946074	0.959469	11
1	20.153732	0.204038	0.947127	0.962851	11
2	23.310932	0.210168	0.947627	0.964501	11

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_de
3	26.559028	0.217920	0.947915	0.966236	11
4	29.652577	0.224765	0.948380	0.967831	11

5 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 [48]:

```
test_score_heatmap=results.pivot( 'param_max_depth' ,'param_n_estimator
s','cv_error_score'  )

test_score_heatmap
```

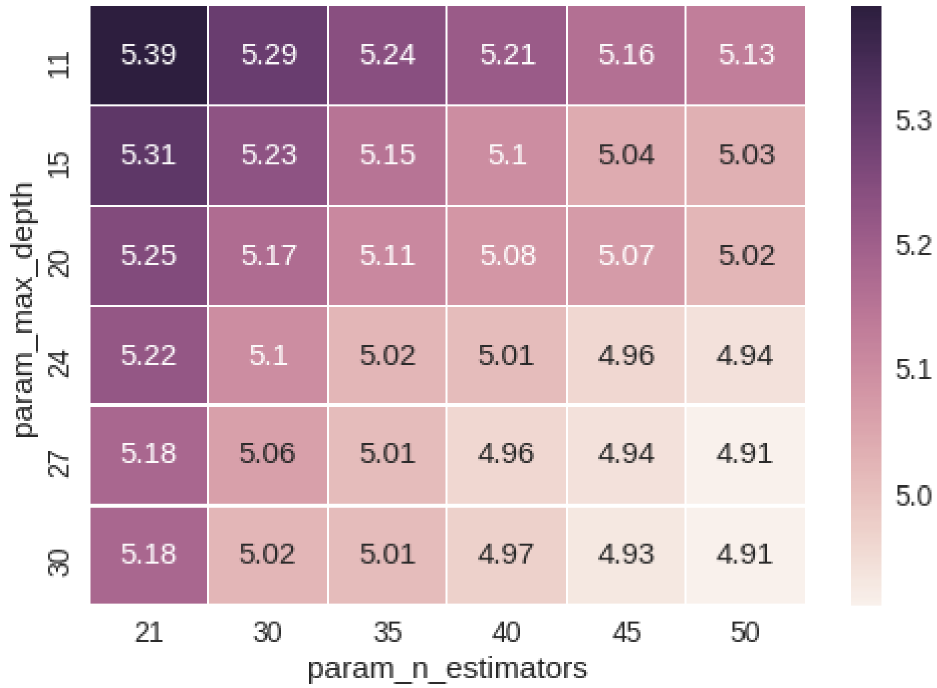
Out[48]:

param_n_estimators	21	30	35	40	45	50
param_max_depth						

param_n_estimators	21	30	35	40	45	50
param_max_depth						
11	5.39	5.29	5.24	5.21	5.16	5.13
15	5.31	5.23	5.15	5.10	5.04	5.03
20	5.25	5.17	5.11	5.08	5.07	5.02
24	5.22	5.10	5.02	5.01	4.96	4.94
27	5.18	5.06	5.01	4.96	4.94	4.91
30	5.18	5.02	5.01	4.97	4.93	4.91

In [49]:
```
import seaborn as sns
sns.heatmap(test_score_heatmap,annot=True,annot_kws={"size": 15}, fmt=
'g',linewidths=.3)
```

Out[49]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb8b81160b8>



In [50]:
```
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=30, 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=30 AND N_ESTIMATORS=50

PLOTTING THE ROC CURVE FOR GETTING AUC SCORE

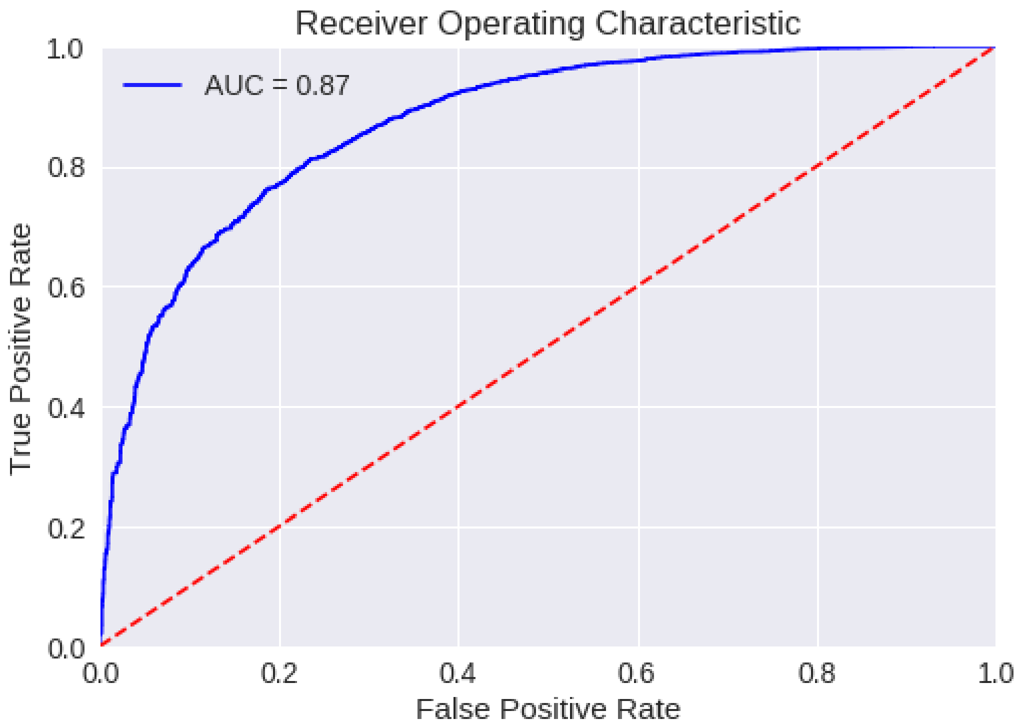
In [0]:

```
xg=XGBClassifier(n_jobs=-1,max_depth=30 ,n_estimators=50)
xg.fit(train_tfidf,y_train)#fitting the model
```

In [53]:

```
probs = xg.predict_proba(test_tfidf)
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 [54]:
```
print('accuracy from the ROC curve is found as ',roc_auc*100)
```

```
accuracy from the ROC curve is found as  87.37248689754394
```

In [55]:
```
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 [56]:
```
print(top_features)#printing the top_features
top=list(top_features)
```

```
['return' 'refund' 'receiv' 'poor' 'gross' 'money' 'best' 'thought' 'ta
```

```
st'
 'horribl' 'mayb' 'stale' 'love' 'threw' 'wast' 'bad' 'worst' 'terribl'
 'aw' 'would' 'great' 'disappoint']
```

REPRESENTING TOP IMPORTANT FEATURES USING WORDCLOUD LIBRARY

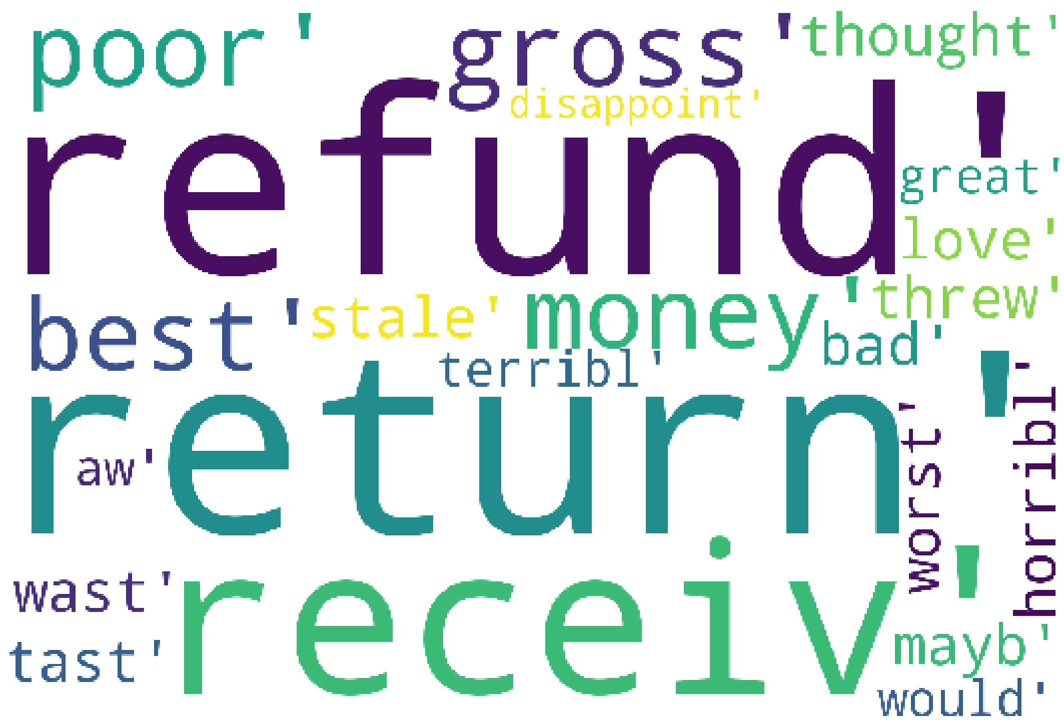
In [57]:

```
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()
```



In [59]:
```
y_pred = xg.predict(test_tfidf)
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')
```

```
Accuracy on test set: 90.110%
```

```
Precision on test set: 0.905
Recall on test set: 0.991
F1-Score on test set: 0.946
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[59]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fb8b7f11128>`