Assignment:-

Applying GBDT and RF on Amazon Fine Food Reviews Analysis

Amazon Fine Food Reviews Analysis

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

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454
Number of users: 256,059
Number of products: 74,258
Timespan: Oct 1999 - Oct 2012
Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

1. Objective:

Given a review, determine whether the review is positive Rating (4 or 5) or negative rating (1 or 2). Use BoW, TF-IDF, Avg-Word2Vec,TF-IDF-Word2Vec to vectorise the reviews. Apply GBDT and Random Forest Algorithm for Amazon fine food Reviews find right baselearners using cross validation Get feature importance for positive class and Negative class

In [1]:

```
# loading required libraries
import warnings
warnings.filterwarnings('ignore')

import numpy as np
import pandas as pd
import matplotlib
import sqlite3
import string
import gensim
import scipy
import nltk
import time
import seaborn as sns
from scipy import stats
from matplotlib import pyplot as plt

from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer

from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve, roc_auc_score, auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_recall_fscore_support as prf1

from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split
```

1.1 Connecting SQL file

In [2]:

```
#Loading the data
con = sqlite3.connect('./final.sqlite')

data = pd.read_sql_query("""
SELECT *
FROM Reviews
""", con)
```

In [3]:

```
print(data.shape)
data.head()
```

```
(364171, 12)
```

Out[3]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpful
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
1	138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	
2	138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	
3	138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	
4	138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3	

1.2 Data Preprocessing

In [4]:

```
data.Score.value_counts()
#i had done data preprocessing i had stored in final.sqlite now loaded this file no need to
```

Out[4]:

```
positive    307061
negative     57110
Name: Score, dtype: int64
```

1.3 Sorting the data

In [5]:

```
# Sorting the data according to the time-stamp
sorted_data = data.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksc
sorted_data.head()
```

Out[5]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Help
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
30	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
424	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	
330	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	
423	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	

1.4 Mapping

In [6]:

```
def partition(x):
    if x == 'positive':
        return 1
    return 0

#Preparing the filtered data
actualScore = sorted_data['Score']
positiveNegative = actualScore.map(partition)
sorted_data['Score'] = positiveNegative
sorted_data.head()
```

Out[6]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Help
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
30	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
424	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	
330	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	
423	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	

1.5 Taking First 150k rows

In [7]:

```
# We will collect different 150000 rows without repetition from time_sorted_data dataframe
my_final = sorted_data[:150000]
print(my_final.shape)
my_final.head()
```

(150000, 12)

Out[7]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Help
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
30	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
424	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	
330	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	
423	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	

1.6 Spliting data into train and test based on time (70:30)

In [8]:

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate


x=my_final['CleanedText'].values
y=my_final['Score']

#Splitting data into train test and cross validation
x_train,x_test,y_train,y_test =train_test_split(x,y,test_size =0.3,random_state = 42)

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(105000,)
(45000,)
(105000,)
(45000,)
```

2. Techniques For Vectorization

Why we have to convert text to vector

By converting text to vector we can use whole power of linear algebra.we can find a plane to seperate

2.1 BOW

In [9]:

```
#Bow

from sklearn.feature_extraction.text import CountVectorizer
count_vect = CountVectorizer()
final_counts_Bow_tr= count_vect.fit_transform(x_train)# computing Bow
print("the type of count vectorizer ",type(final_counts_Bow_tr))
print("the shape of out text BOW vectorizer ",final_counts_Bow_tr.get_shape())
print("the number of unique words ", final_counts_Bow_tr.get_shape()[1])
final_counts_Bow_test= count_vect.transform(x_test)# computing Bow
print("the type of count vectorizer ",type(final_counts_Bow_test))
print("the shape of out text BOW vectorizer ",final_counts_Bow_test.get_shape())
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (105000, 38300)
the number of unique words  38300
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer  (45000, 38300)
```

2.2 Normalizing Data

In [10]:

```
# Data-preprocessing: Normalizing Data

from sklearn import preprocessing
standardized_data_train = preprocessing.normalize(final_counts_Bow_tr)
print(standardized_data_train.shape)
standardized_data_test = preprocessing.normalize(final_counts_Bow_test)
print(standardized_data_test.shape)
```

```
(105000, 38300)
(45000, 38300)
```

2.3 Applying RandomForest Algorithm

In [11]:

```
#Gridsearch Cross Validation
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree

base_learners = [40,60,80,100,120]
depth=[3,5,7,9,11]
param_grid = {'n_estimators': base_learners,'max_depth':depth}
rf = RandomForestClassifier(min_samples_leaf=5,max_features='sqrt',criterion='gini',random_
model = GridSearchCV(rf, param_grid,scoring ='f1',cv=3 , n_jobs = -1,pre_dispatch=2)
model.fit(standardized_data_train,y_train)
print(model.best_score_, model.best_params_)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(standardized_data_test, y_test))

a = model.best_params_
optimal_estimator = a.get('n_estimators')
optimal_depth = a.get('max_depth')
```

```
0.9169864843830612 {'max_depth': 11, 'n_estimators': 120}
Model with best parameters :
 RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=11, max_features='sqrt',
            max_leaf_nodes=None, min_impurity_decrease=0.0,
            min_impurity_split=None, min_samples_leaf=5,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=120, n_jobs=None, oob_score=False,
            random_state=100, verbose=0, warm_start=False)
Accuracy of the model :  0.9161176281536236
```

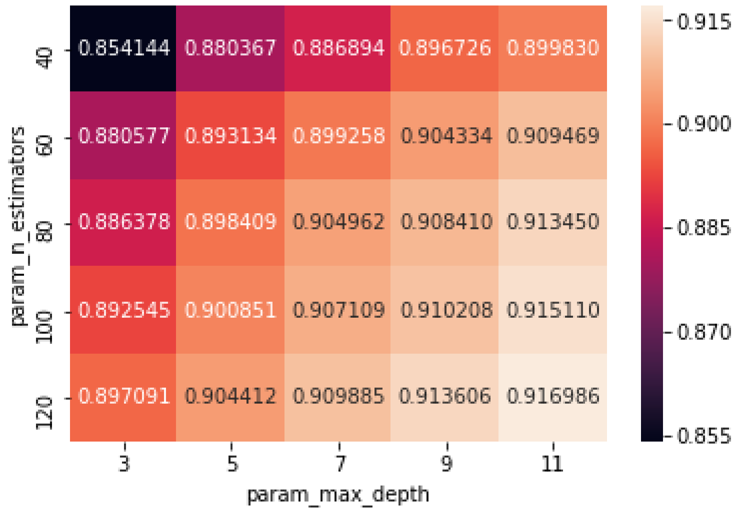
In [12]:

```
results = model.cv_results_
meanscore=results['mean_test_score']
```

Heatmap for plotting CV Scores

In [13]:

```
pvt =pd.pivot_table(pd.DataFrame(model.cv_results_),values='mean_test_score', index='param_
import seaborn as sns
ax = sns.heatmap(pvt,annot=True,fmt="f")
```



In [14]:

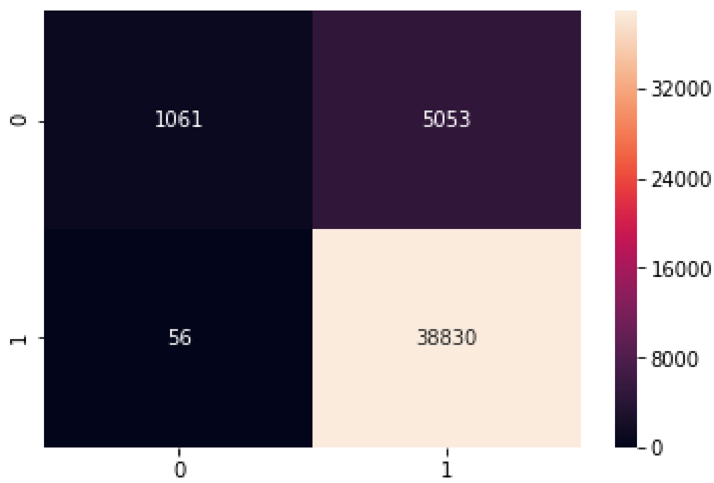
```
clf = RandomForestClassifier(n_estimators=optimal_estimator, class_weight ='balanced')
clf.fit(standardized_data_train,y_train)
y_pred = clf.predict(standardized_data_test)
```

2.4 Confusion Matrix

In [15]:

```
cm_bow=confusion_matrix(y_test,y_pred)
print("Confusion Matrix:")
sns.heatmap(cm_bow, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [16]:

```
#finding out  true negative , false positive , false negative and true positve
tn, fp, fn, tp = cm_bow.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {}\n true pos
```

```
 true negitves are 1061
 false positives are 5053
 false negatives are 56
 true positives are 38830
```

2.5 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [17]:

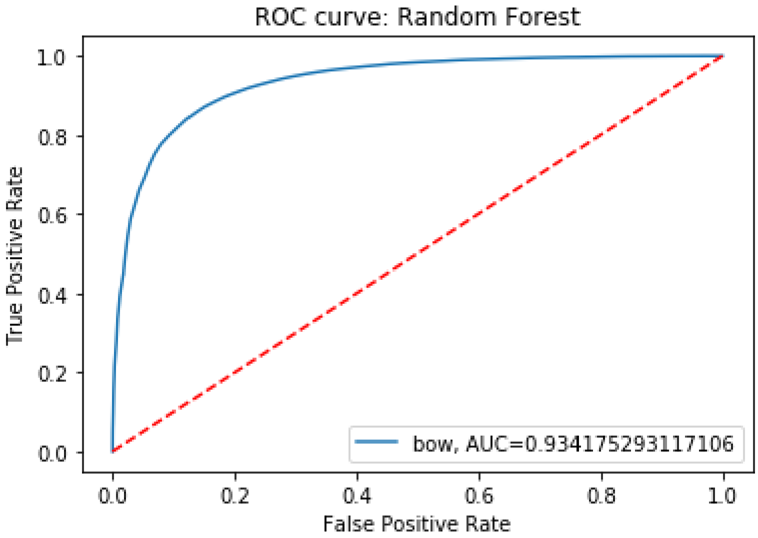
```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score

# evaluating accuracy
acc_bow = accuracy_score(y_test, y_pred) * 100
print('\nTest Accuracy of the RandomForest for base_learners ={}, depth ={} is accuracy {}'

# Error on test data
test_error_bow = 100-acc_bow
print("\nTest Error RandomForest for base learner and optimal_depth  is  %f%%" % (test_errc

# evaluating precision
precision_score = precision_score(y_test, y_pred)
print('\nThe Test Precision of the RandomForest for base_learners ={}, depth ={} is accurac

# evaluating recall
recall_score = recall_score(y_test, y_pred)
print('\nThe Test Recall of the RandomForest for base_learners ={}, depth ={} is accuracy {

# evaluating Classification Report
classification_report = classification_report(y_test, y_pred)
print('\nThe Test classification report for base learner and optimal_depth   \n\n ',(classi
```

```
Test Accuracy of the RandomForest for base_learners =120, depth =11 is accur
acy 88.64666666666666

Test Error RandomForest for base learner and optimal_depth  is  11.353333%

The Test Precision of the RandomForest for base_learners =120, depth =11 is
accuracy 0.8848529043137434

The Test Recall of the RandomForest for base_learners =120, depth =11 is acc
uracy 0.9985598930206244

The Test classification report for base learner and optimal_depth

                precision    recall  f1-score   support

           0       0.95      0.17      0.29      6114
           1       0.88      1.00      0.94     38886

   micro avg       0.89      0.89      0.89     45000
   macro avg       0.92      0.59      0.62     45000
weighted avg       0.89      0.89      0.85     45000
```

2.6 Plotting roc_auc curve

In [18]:

```
y_pred_proba = clf.predict_proba(standardized_data_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="bow, AUC="+str(auc))
plt.plot([0,1],[0,1],'r--')
plt.title('ROC curve: Random Forest')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



2.7 Top 25 words

In [19]:

```
words = count_vect.get_feature_names()
likelihood_df = pd.DataFrame(clf.feature_importances_.transpose(),columns=[ 'Score'],index=
top_25 = likelihood_df.sort_values(by='Score',ascending=False).iloc[:25]
top_25.reset_index(inplace=True)
top_words = top_25['index']
print(top_words)
```

```
0          great
1           love
2           best
3     disappoint
4         delici
5           good
6           tast
7        perfect
8          would
9        product
10           bad
11          find
12         excel
13          like
14         money
15       favorit
16          wast
17       thought
18           use
19         didnt
20          easi
21          make
22          nice
23        wonder
24        flavor
Name: index, dtype: object
```

In [20]:

```
from wordcloud import WordCloud

list_of_words_str = ' '.join(top_words)

wc = WordCloud(background_color="white", max_words=len(top_words),
               width=900, height=600, collocations=False)
wc.generate(list_of_words_str)
print ("\n\nWord Cloud for Important features")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

```
Word Cloud for Important features
```

3.Applying GBDT Algorithm

In [21]:

```
from sklearn.ensemble import GradientBoostingClassifier

Learning_rate = [0.05,0.1,0.2,0.3]
depth=[3,5,7,9,11]
param_grid = {'max_depth':depth, 'learning_rate':Learning_rate}
gb = GradientBoostingClassifier(loss='deviance',max_features='sqrt',subsample=0.1,n_estimat
model = GridSearchCV(gb, param_grid, scoring = 'f1', cv=3 , n_jobs = -1,pre_dispatch=2)
model.fit(standardized_data_train,y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(standardized_data_test, y_test))
a = model.best_params_
optimal_learningrate = a.get('learning_rate')
optimal_depth = a.get('max_depth')
```

```
Model with best parameters :
 GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=11,
              max_features='sqrt', max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              n_iter_no_change=None, presort='auto', random_state=None,
              subsample=0.1, tol=0.0001, validation_fraction=0.1,
              verbose=0, warm_start=False)
Accuracy of the model :  0.9409884855581576
```

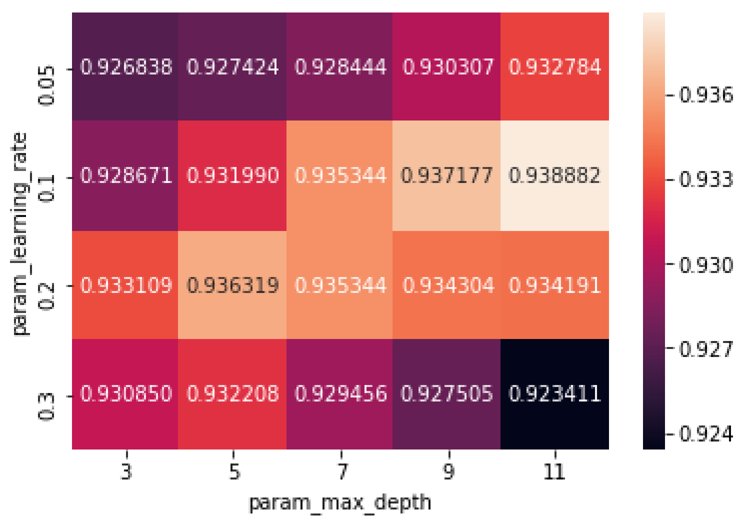
In [22]:

```
results = model.cv_results_
meanscore=results['mean_test_score']
```

Heatmap for plotting CV Scores

In [23]:

```
pvt =pd.pivot_table(pd.DataFrame(model.cv_results_),values='mean_test_score', index='param_
import seaborn as sns
ax = sns.heatmap(pvt,annot=True,fmt="f")
```



In [24]:

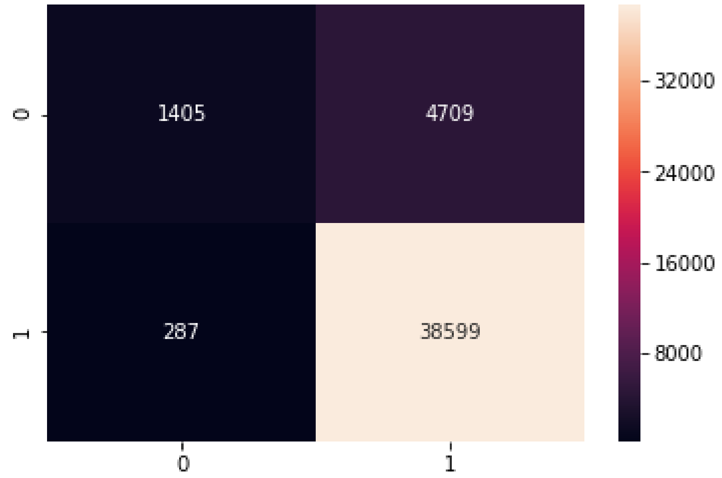
```
clf = GradientBoostingClassifier(max_depth=optimal_depth,learning_rate=optimal_learningrate
clf.fit(standardized_data_train,y_train)
y_pred = clf.predict(standardized_data_test)
```

3.1 Confusion Matrix

In [25]:

```
## Confusion Matrix:
cm_bow=confusion_matrix(y_test,y_pred)
print("Confusion Matrix:")
sns.heatmap(cm_bow, annot=True, fmt='d')
plt.show()
```

```
Confusion Matrix:
```



In [26]:

```
#finding out  true negative , false positive , false negative and true positve
tn, fp, fn, tp = cm_bow.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {}\n true pos
```

```
 true negitves are 1405
 false positives are 4709
 false negatives are 287
 true positives are 38599
```

3.2 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [27]:

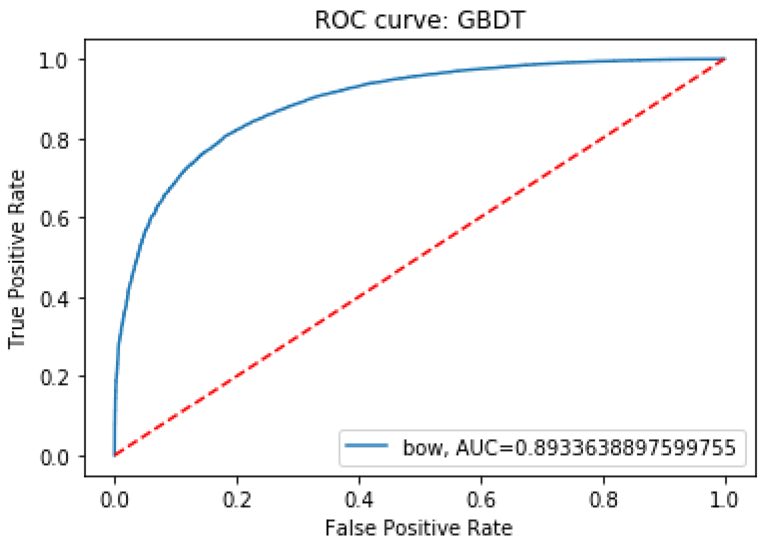
```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score

# evaluating accuracy
acc_bow = accuracy_score(y_test, y_pred) * 100
print('\nTest Accuracy of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.forma

# Error on test data
test_error_bow = 100-acc_bow
print("\nTest Error GBDT for maxdepth and Learning_rate is  %f%%" % (test_error_bow))

# evaluating precision
precision_score = precision_score(y_test, y_pred)
print('\nThe Test Precision of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.

# evaluating recall
recall_score = recall_score(y_test, y_pred)
print('\nThe Test Recall of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.for

# evaluating Classification Report
classification_report = classification_report(y_test, y_pred)
print('\nThe Test classification report for GBDT maxdepth and Learning_rate   \n\n ',(class
```

```
Test Accuracy of the GBDT for maxdepth=11, Learning_rate =0.1 is accuracy 8
8.89777777777778

Test Error GBDT for maxdepth and Learning_rate is  11.102222%

The Test Precision of the GBDT for maxdepth=11, Learning_rate =0.1 is accura
cy 0.8912672023644592

The Test Recall of the GBDT for maxdepth=11, Learning_rate =0.1 is accuracy
0.9926194517307

The Test classification report for GBDT maxdepth and Learning_rate

                precision    recall  f1-score   support

           0       0.83      0.23      0.36      6114
           1       0.89      0.99      0.94     38886

   micro avg       0.89      0.89      0.89     45000
   macro avg       0.86      0.61      0.65     45000
weighted avg       0.88      0.89      0.86     45000
```

3.3 Plotting roc_auc curve

In [28]:

```
y_pred_proba = clf.predict_proba(standardized_data_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="bow, AUC="+str(auc))
plt.plot([0,1],[0,1],'r--')
plt.title('ROC curve: GBDT')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



3.4 Top 25 words

In [29]:

```
words = count_vect.get_feature_names()
likelihood_df = pd.DataFrame(clf.feature_importances_.transpose(),columns=[ 'Score'],index=
top_25 = likelihood_df.sort_values(by='Score',ascending=False).iloc[:25]
top_25.reset_index(inplace=True)
top_words = top_25['index']
print(top_words)
```

```
0     disappoint
1          great
2        terribl
3           wast
4            bad
5          worst
6           love
7        horribl
8        thought
9           best
10          tast
11         would
12         threw
13         money
14            aw
15         didnt
16        return
17        delici
18         stale
19        receiv
20       wouldnt
21         gross
22          poor
23          list
24       product
Name: index, dtype: object
```

In [30]:

```
from wordcloud import WordCloud

list_of_words_str = ' '.join(top_words)

wc = WordCloud(background_color="white", max_words=len(top_words),
               width=900, height=600, collocations=False)
wc.generate(list_of_words_str)
print ("\n\nWord Cloud for Important features")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

```
Word Cloud for Important features
```

4. TF-IDF

In [31]:

```
#tf-idf
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vect = TfidfVectorizer()

final_counts_tfidf_tr= tf_idf_vect.fit_transform(x_train)
print("the type of count vectorizer ",type(final_counts_tfidf_tr))
print("the shape of out text tfidf vectorizer ",final_counts_tfidf_tr.get_shape())
print("the number of unique words ", final_counts_tfidf_tr.get_shape()[1])
final_counts_tfidf_test= tf_idf_vect.transform(x_test)
print("the type of count vectorizer ",type(final_counts_tfidf_test))
print("the shape of out text tfidf vectorizer ",final_counts_tfidf_test.get_shape())
print("the number of unique words ", final_counts_tfidf_test.get_shape()[1])
```

```
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text tfidf vectorizer  (105000, 38300)
the number of unique words  38300
the type of count vectorizer  <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text tfidf vectorizer  (45000, 38300)
the number of unique words  38300
```

4.1 Normalizing Data

In [32]:

```
# Data-preprocessing: Normalizing Data
from sklearn import preprocessing
standardized_data_train = preprocessing.normalize(final_counts_tfidf_tr)
print(standardized_data_train.shape)
standardized_data_test = preprocessing.normalize(final_counts_tfidf_test)
print(standardized_data_test.shape)
```

```
(105000, 38300)
(45000, 38300)
```

4.2 Applying RandomForest Algorithm

In [33]:

```
# Gridsearch Cross Validation

from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree

base_learners = [40,60,80,100,120]
depth=[3,5,7,9,11]
param_grid = {'n_estimators': base_learners,'max_depth':depth}
rf = RandomForestClassifier(min_samples_leaf=5,max_features='sqrt',criterion='gini',random_
model = GridSearchCV(rf, param_grid,scoring ='f1',cv=3 , n_jobs = -1,pre_dispatch=2)
model.fit(standardized_data_train,y_train)
print(model.best_score_, model.best_params_)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(standardized_data_test, y_test))

a = model.best_params_
optimal_estimator = a.get('n_estimators')
optimal_depth = a.get('max_depth')
```

```
0.9127876758692683 {'max_depth': 11, 'n_estimators': 120}
Model with best parameters :
 RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=11, max_features='sqrt',
            max_leaf_nodes=None, min_impurity_decrease=0.0,
            min_impurity_split=None, min_samples_leaf=5,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=120, n_jobs=None, oob_score=False,
            random_state=100, verbose=0, warm_start=False)
Accuracy of the model :  0.910332405876581
```

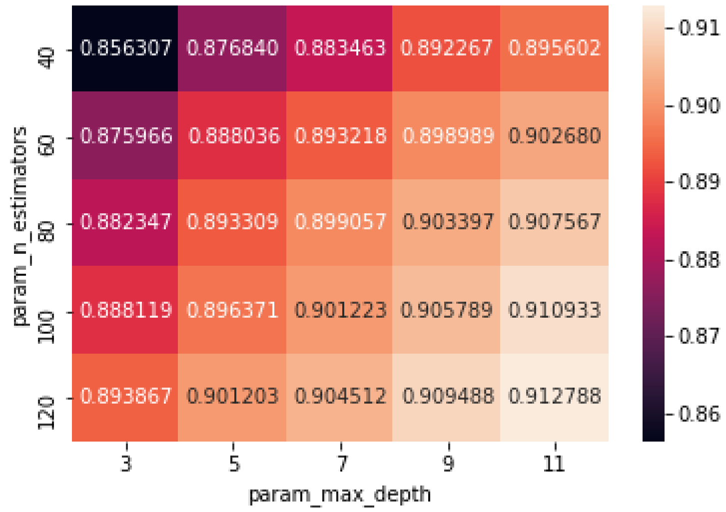
In [34]:

```
results = model.cv_results_
meanscore=results['mean_test_score']
```

Heatmap for Plotting CV Scores

In [35]:

```
pvt =pd.pivot_table(pd.DataFrame(model.cv_results_),values='mean_test_score', index='param_
import seaborn as sns
ax = sns.heatmap(pvt,annot=True,fmt="f")
```



In [36]:

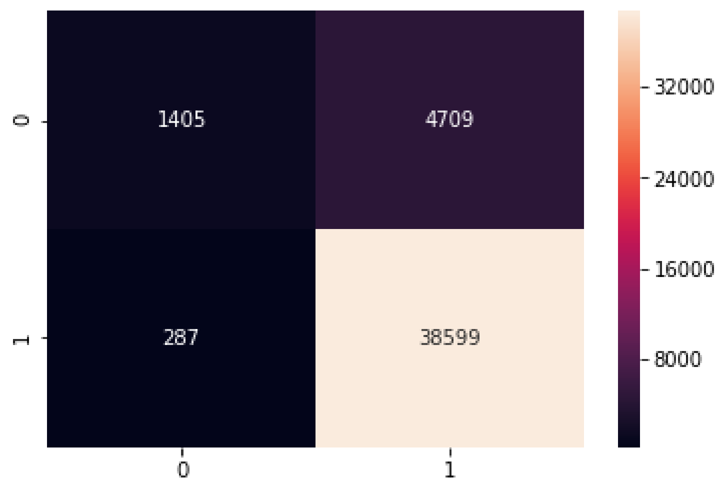
```
clf = RandomForestClassifier(n_estimators=optimal_estimator, class_weight ='balanced')
clf.fit(standardized_data_train,y_train)
y_pred = clf.predict(standardized_data_test)
```

4.3 Confusion Matrix

In [37]:

```
cm_tfidf=confusion_matrix(y_test,y_pred)
print("Confusion Matrix:")
sns.heatmap(cm_bow, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [38]:

```
#finding out  true negative , false positive , false negative and true positve
tn, fp, fn, tp = cm_tfidf.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {}\n true pos
```

```
 true negitves are 1139
 false positives are 4975
 false negatives are 67
 true positives are 38819
```

4.4 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [39]:

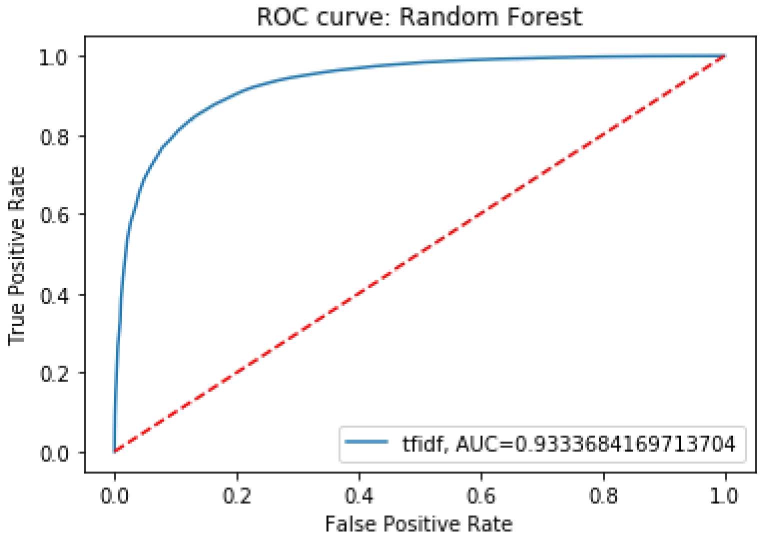
```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report


# evaluating accuracy
acc_tfidf = accuracy_score(y_test, y_pred) * 100
print('\nThe Test Accuracy of the RandomForest for base_learners ={}, depth ={} is accuracy

# Error on test data
test_error_tfidf = 100-acc_tfidf
print("\nTest Error of the RandomForest for optimal_depth  %f%%" % (test_error_tfidf))

# evaluating precision
precision_score = precision_score(y_test, y_pred)
print('\nThe Test Precision of the RandomForest for base_learners ={}, depth ={} is accurac

# evaluating recall
recall_score = recall_score(y_test, y_pred)
print('\nThe Test Recall of the RandomForest for base_learners ={}, depth ={} is accuracy {

# evaluating Classification report
classification_report = classification_report(y_test, y_pred)
print('\nThe Test classification report of the RandomForest for optimal_depth is \n\n ',(cl
```

```
The Test Accuracy of the RandomForest for base_learners =120, depth =11 is a
ccuracy 88.79555555555557

Test Error of the RandomForest for optimal_depth  11.204444%

The Test Precision of the RandomForest for base_learners =120, depth =11 is
accuracy 0.8863999634653149

The Test Recall of the RandomForest for base_learners =120, depth =11 is acc
uracy 0.9982770148639614

The Test classification report of the RandomForest for optimal_depth is

                precision    recall  f1-score   support

           0       0.94      0.19      0.31      6114
           1       0.89      1.00      0.94     38886

   micro avg       0.89      0.89      0.89     45000
   macro avg       0.92      0.59      0.63     45000
weighted avg       0.89      0.89      0.85     45000
```

4.5 Plotting roc_auc curve

In [40]:

```
y_pred_proba = clf.predict_proba(standardized_data_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="tfidf, AUC="+str(auc))
plt.plot([0,1],[0,1],'r--')
plt.title('ROC curve: Random Forest')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



4.6 Top 25 words

In [41]:

```
words = tf_idf_vect.get_feature_names()
likelihood_df = pd.DataFrame(clf.feature_importances_.transpose(),columns=[ 'Score'],index=
top_25 = likelihood_df.sort_values(by='Score',ascending=False).iloc[:25]
top_25.reset_index(inplace=True)
top_words = top_25['index']
print(top_words)
```

```
0          great
1           love
2           best
3     disappoint
4         delici
5           good
6            bad
7          would
8        perfect
9           tast
10       product
11          find
12         money
13       favorit
14          like
15           use
16       thought
17          make
18        return
19       terribl
20         excel
21          nice
22         didnt
23        wonder
24       horribl
Name: index, dtype: object
```

In [42]:

```
from wordcloud import WordCloud

list_of_words_str = ' '.join(top_words)

wc = WordCloud(background_color="white", max_words=len(top_words),
               width=900, height=600, collocations=False)
wc.generate(list_of_words_str)
print ("\n\nWord Cloud for Important features")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

```
Word Cloud for Important features
```

5.Applying GBDT Algorithm

In [43]:

```
from sklearn.ensemble import GradientBoostingClassifier

Learning_rate = [0.05,0.1,0.2,0.3]
depth=[3,5,7,9,11]
param_grid = {'max_depth':depth, 'learning_rate':Learning_rate}
gb = GradientBoostingClassifier(loss='deviance',max_features='sqrt',subsample=0.1,n_estimat
model = GridSearchCV(gb, param_grid, scoring = 'f1', cv=3 , n_jobs = -1,pre_dispatch=2)
model.fit(standardized_data_train,y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(standardized_data_test, y_test))
a = model.best_params_
optimal_learningrate = a.get('learning_rate')
optimal_depth = a.get('max_depth')
```

```
Model with best parameters :
 GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=11,
              max_features='sqrt', max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              n_iter_no_change=None, presort='auto', random_state=None,
              subsample=0.1, tol=0.0001, validation_fraction=0.1,
              verbose=0, warm_start=False)
Accuracy of the model :  0.9404039665716443
```

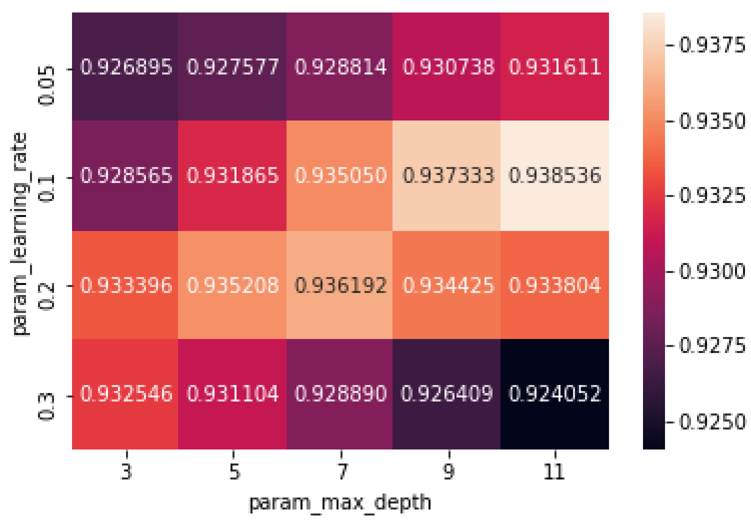
In [44]:

```
results = model.cv_results_
meanscore=results['mean_test_score']
```

Heatmap for plotting CV Scores

In [45]:

```
pvt =pd.pivot_table(pd.DataFrame(model.cv_results_),values='mean_test_score', index='param_
import seaborn as sns
ax = sns.heatmap(pvt,annot=True,fmt="f")
```



In [46]:

```
clf = GradientBoostingClassifier(max_depth=optimal_depth,learning_rate=optimal_learningrate
clf.fit(standardized_data_train,y_train)
y_pred = clf.predict(standardized_data_test)
```

5.1 Confusion Matrix

In [47]:

```
#finding out  true negative , false positive , false negative and true positve
tn, fp, fn, tp = cm_tfidf.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {}\n true pos
```

```
 true negitves are 1139
 false positives are 4975
 false negatives are 67
 true positives are 38819
```

5.2 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [48]:

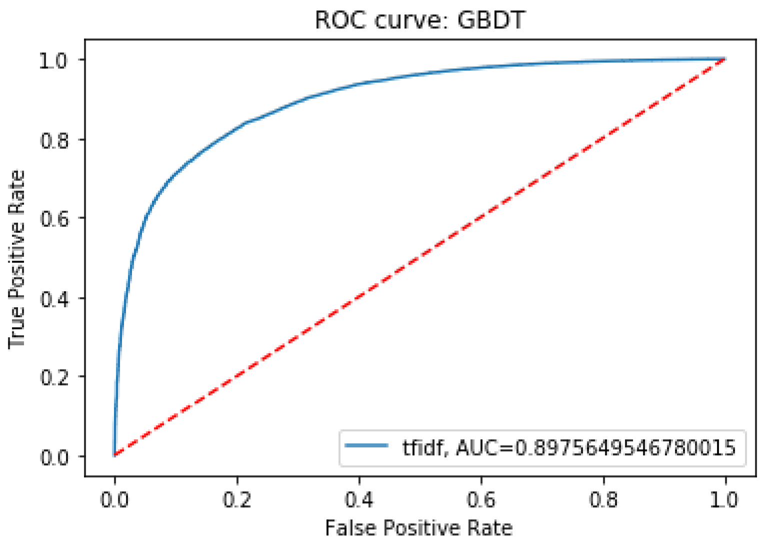
```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report


# evaluating accuracy
acc_tfidf = accuracy_score(y_test, y_pred) * 100
print('\nThe Test Accuracy of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.f

# Error on test data
test_error_tfidf = 100-acc_tfidf
print("\nTest Error of the GBDT for maxdepth and Learning_rate %f%%" % (test_error_tfidf))

# evaluating precision
precision_score = precision_score(y_test, y_pred)
print('\nThe Test Precision of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.

# evaluating recall
recall_score = recall_score(y_test, y_pred)
print('\nThe Test Recall of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.for

# evaluating Classification report
classification_report = classification_report(y_test, y_pred)
print('\nThe Test classification report of the GBDT for maxdepth and Learning_rate is \n\n
```

```
The Test Accuracy of the GBDT for maxdepth=11, Learning_rate =0.1 is accurac
y 88.95555555555555

Test Error of the GBDT for maxdepth and Learning_rate 11.044444%

The Test Precision of the GBDT for maxdepth=11, Learning_rate =0.1 is accura
cy 0.8913324410393686

The Test Recall of the GBDT for maxdepth=11, Learning_rate =0.1 is accuracy
0.9932880728282673

The Test classification report of the GBDT for maxdepth and Learning_rate is 


              precision    recall  f1-score   support

           0       0.84      0.23      0.36      6114
           1       0.89      0.99      0.94     38886

   micro avg       0.89      0.89      0.89     45000
   macro avg       0.87      0.61      0.65     45000
weighted avg       0.88      0.89      0.86     45000
```

5.3 Plotting roc_auc curve

In [49]:

```
y_pred_proba = clf.predict_proba(standardized_data_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="tfidf, AUC="+str(auc))
plt.plot([0,1],[0,1],'r--')
plt.title('ROC curve: GBDT')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



5.4 Top 25 words

In [50]:

```
words = tf_idf_vect.get_feature_names()
likelihood_df = pd.DataFrame(clf.feature_importances_.transpose(),columns=[ 'Score'],index=
top_25 = likelihood_df.sort_values(by='Score',ascending=False).iloc[:25]
top_25.reset_index(inplace=True)
top_words = top_25['index']
print(top_words)
```

```
0     disappoint
1          great
2            bad
3        horribl
4         return
5           best
6          threw
7           love
8        thought
9          didnt
10         money
11         would
12          wast
13            aw
14       terribl
15         stale
16        refund
17      unfortun
18         worst
19        delici
20          good
21        pictur
22         throw
23        receiv
24          mayb
Name: index, dtype: object
```

In [51]:

```
from wordcloud import WordCloud

list_of_words_str = ' '.join(top_words)

wc = WordCloud(background_color="white", max_words=len(top_words),
               width=900, height=600, collocations=False)
wc.generate(list_of_words_str)
print ("\n\nWord Cloud for Important features")
plt.imshow(wc, interpolation='bilinear')
plt.axis("off")
plt.show()
```

```
Word Cloud for Important features
```

6. WORD2VEC

In [52]:

```
from gensim.models import Word2Vec
# List of sentence in X_train text
sent_of_train=[]
for sent in x_train:
    sent_of_train.append(sent.split())

# List of sentence in X_est text
sent_of_test=[]
for sent in x_test:
    sent_of_test.append(sent.split())

# Train your own Word2Vec model using your own train text corpus
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(sent_of_train,min_count=5,size=50, workers=4)

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
```

```
number of words that occured minimum 5 times  12829
```

7. Avg Word2Vec

In [53]:

```
# compute average word2vec for each review for X_train .
train_vectors = [];
for sent in sent_of_train:
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    train_vectors.append(sent_vec)

# compute average word2vec for each review for X_test .
test_vectors = [];
for sent in sent_of_test:
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    test_vectors.append(sent_vec)
```

7.1 Standardizing Data

In [54]:

```
# Data-preprocessing: Normalizing Data

from sklearn import preprocessing
standardized_data_train = preprocessing.normalize(train_vectors)
print(standardized_data_train.shape)
standardized_data_test = preprocessing.normalize(test_vectors)
print(standardized_data_test.shape)
```

```
(105000, 50)
(45000, 50)
```

7.2 Applying RandomForest Algorithm

In [55]:

```
# Gridsearch Cross Validation
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree

base_learners = [40,60,80,100,120]
depth=[3,5,7,9,11]
param_grid = {'n_estimators': base_learners,'max_depth':depth}
rf = RandomForestClassifier(min_samples_leaf=5,max_features='sqrt',criterion='gini',random_
model = GridSearchCV(rf, param_grid,scoring ='f1',cv=3 , n_jobs = -1,pre_dispatch=2)
model.fit(standardized_data_train,y_train)
print(model.best_score_, model.best_params_)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(standardized_data_test, y_test))

a = model.best_params_
optimal_estimator = a.get('n_estimators')
optimal_depth = a.get('max_depth')
```

```
0.9235738058587347 {'max_depth': 11, 'n_estimators': 120}
Model with best parameters :
 RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=11, max_features='sqrt',
            max_leaf_nodes=None, min_impurity_decrease=0.0,
            min_impurity_split=None, min_samples_leaf=5,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=120, n_jobs=None, oob_score=False,
            random_state=100, verbose=0, warm_start=False)
Accuracy of the model :  0.9181707187599533
```

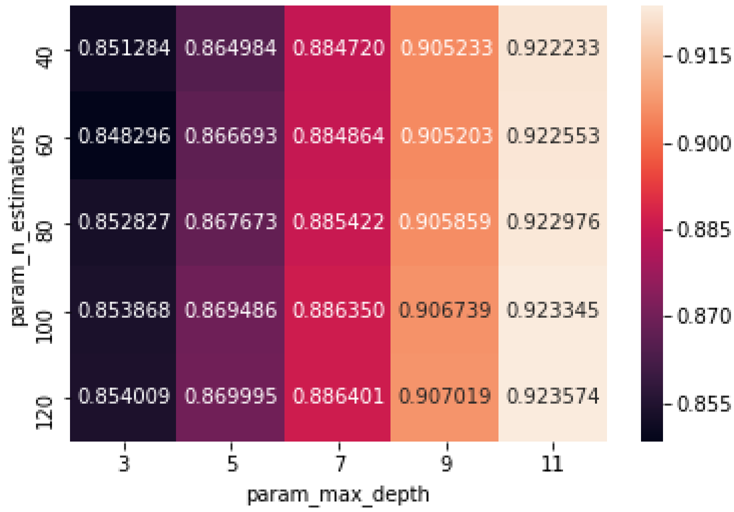
In [56]:

```
results = model.cv_results_
meanscore=results['mean_test_score']
```

Heatmap for plotting CV Scores

In [57]:

```
pvt =pd.pivot_table(pd.DataFrame(model.cv_results_),values='mean_test_score', index='param_
import seaborn as sns
ax = sns.heatmap(pvt,annot=True,fmt="f")
```



In [58]:

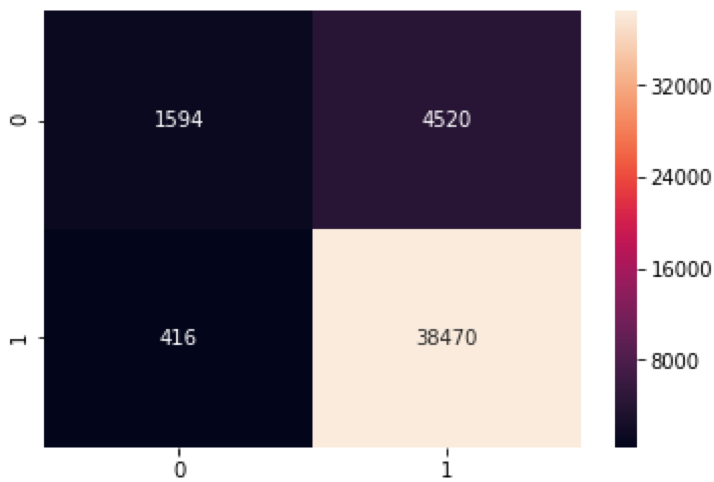
```
clf = RandomForestClassifier(n_estimators=optimal_estimator, class_weight ='balanced')
clf.fit(standardized_data_train,y_train)
y_pred = clf.predict(standardized_data_test)
```

7.3 Confusion Matrix

In [59]:

```
cm_avgw2v=confusion_matrix(y_test,y_pred)
print("Confusion Matrix:")
sns.heatmap(cm_avgw2v, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [60]:

```
#finding out  true negative , false positive , false negative and true positve
tn, fp, fn, tp = cm_avgw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {}\n true pos
```

```
 true negitves are 1594
 false positives are 4520
 false negatives are 416
 true positives are 38470
```

7.4 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [61]:

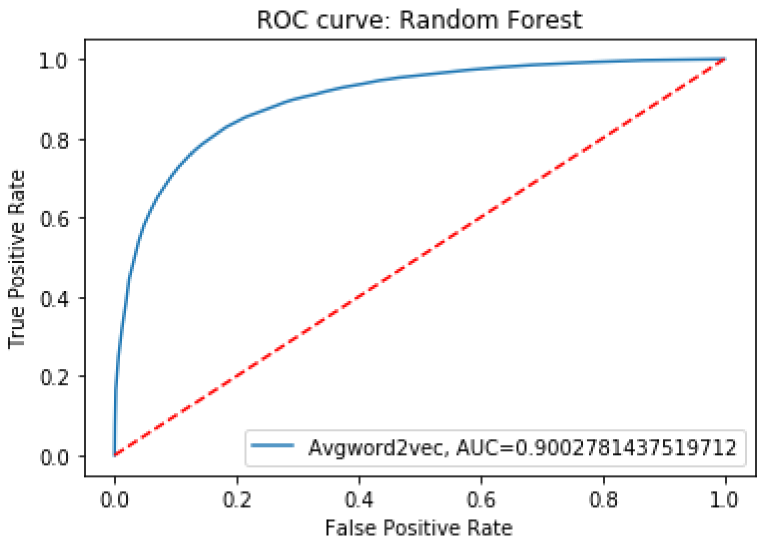
```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report


# evaluating accuracy
acc_avgw2v = accuracy_score(y_test, y_pred) * 100
print('\nThe Test Accuracy  of the RandomForest for base_learners ={}, depth ={} is accurac

# Error on test data
test_error_avgw2v = 100-acc_avgw2v
print("\nTest Error of the RandomForest for optimal_estimator,optimal_depth is  %f%%" % (te

# evaluating precision
precision_score = precision_score(y_test, y_pred)
print('\nThe Test Precision  of the RandomForest for base_learners ={}, depth ={} is accura

# evaluating recall
recall_score = recall_score(y_test, y_pred)
print('\nThe Test Recall  of the RandomForest for base_learners ={}, depth ={} is accuracy

# evaluating Classification report
classification_report = classification_report(y_test, y_pred)
print('\nThe Test classification report of the RandomForest for optimal_estimator,optimal_d
```

```
The Test Accuracy  of the RandomForest for base_learners =120, depth =11 is 
accuracy 89.03111111111112

Test Error of the RandomForest for optimal_estimator,optimal_depth is  10.96
8889%

The Test Precision  of the RandomForest for base_learners =120, depth =11 is 
accuracy 0.8948592695975809

The Test Recall  of the RandomForest for base_learners =120, depth =11 is ac
curacy 0.989302062438924

The Test classification report of the RandomForest for optimal_estimator,opt
imal_depth is 

              precision    recall  f1-score   support

           0       0.79      0.26      0.39      6114
           1       0.89      0.99      0.94     38886

   micro avg       0.89      0.89      0.89     45000
   macro avg       0.84      0.63      0.67     45000
weighted avg       0.88      0.89      0.87     45000
```

7.5 Plotting roc_auc curve

In [62]:

```
y_pred_proba = clf.predict_proba(standardized_data_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="Avgword2vec, AUC="+str(auc))
plt.plot([0,1],[0,1],'r--')
plt.title('ROC curve: Random Forest')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



8.Applying GBDT Algorithm

In [63]:

```
from sklearn.ensemble import GradientBoostingClassifier

Learning_rate = [0.05,0.1,0.2,0.3]
depth=[3,5,7,9,11]
param_grid = {'max_depth':depth, 'learning_rate':Learning_rate}
gb = GradientBoostingClassifier(loss='deviance',max_features='sqrt',subsample=0.1,n_estimat
model = GridSearchCV(gb, param_grid, scoring = 'f1', cv=3 , n_jobs = -1,pre_dispatch=2)
model.fit(standardized_data_train,y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(standardized_data_test, y_test))
a = model.best_params_
optimal_learningrate = a.get('learning_rate')
optimal_depth = a.get('max_depth')
```

```
Model with best parameters :
 GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.05, loss='deviance', max_depth=7,
              max_features='sqrt', max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              n_iter_no_change=None, presort='auto', random_state=None,
              subsample=0.1, tol=0.0001, validation_fraction=0.1,
              verbose=0, warm_start=False)
Accuracy of the model :  0.9425643440439163
```

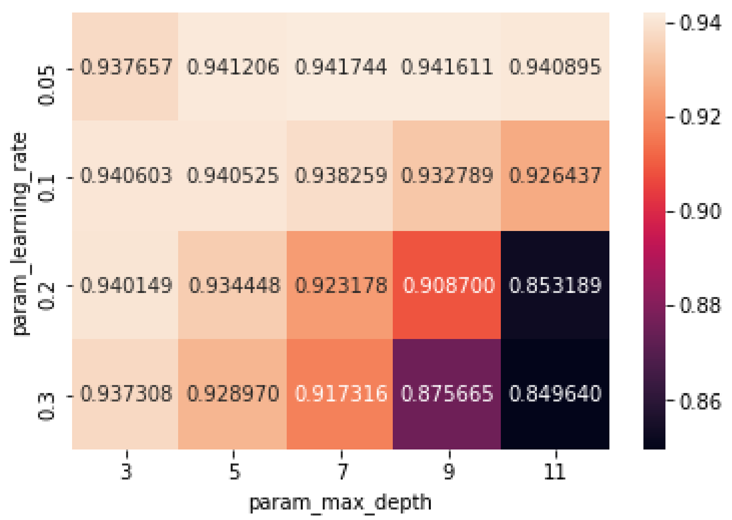
In [64]:

```
results = model.cv_results_
meanscore=results['mean_test_score']
```

Heatmap for plotting CV Scores

In [65]:

```
pvt =pd.pivot_table(pd.DataFrame(model.cv_results_),values='mean_test_score', index='param_
import seaborn as sns
ax = sns.heatmap(pvt,annot=True,fmt="f")
```



In [66]:

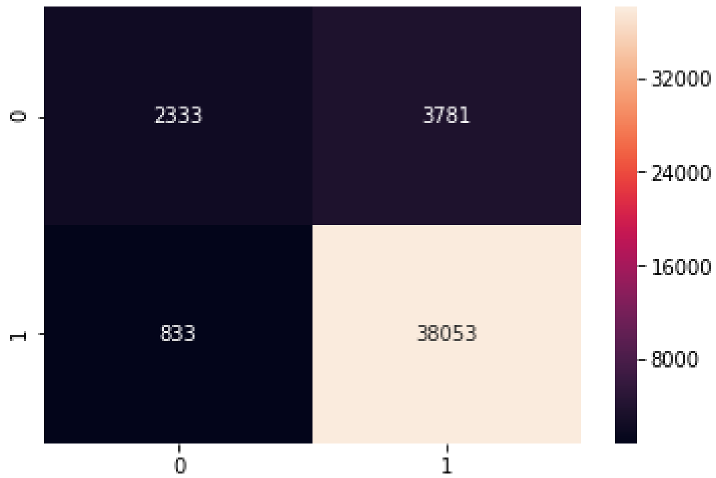
```
clf = GradientBoostingClassifier(max_depth=optimal_depth,learning_rate=optimal_learningrate
clf.fit(standardized_data_train,y_train)
y_pred = clf.predict(standardized_data_test)
```

8.1 Confusion Matrix

In [67]:

```
cm_avgw2v=confusion_matrix(y_test,y_pred)
print("Confusion Matrix:")
sns.heatmap(cm_avgw2v, annot=True, fmt='d')
plt.show()
```

```
Confusion Matrix:
```



In [68]:

```
#finding out  true negative , false positive , false negative and true positve
tn, fp, fn, tp = cm_avgw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {}\n true pos
```

```
 true negitves are 2333
 false positives are 3781
 false negatives are 833
 true positives are 38053
```

8.2 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [69]:

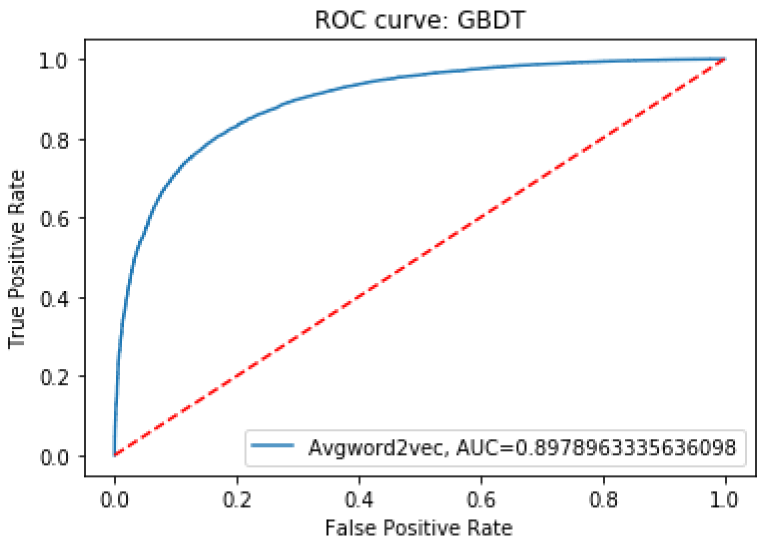
```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report


# evaluating accuracy
acc_avgw2v = accuracy_score(y_test, y_pred) * 100
print('\nThe Test Accuracy of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.f

# Error on test data
test_error_avgw2v = 100-acc_avgw2v
print("\nTest Error of the GBDT for maxdepth and Learning_rate is  %f%%" % (test_error_avgw

# evaluating precision
precision_score = precision_score(y_test, y_pred)
print('\nThe Test Precision of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.

# evaluating recall
recall_score = recall_score(y_test, y_pred)
print('\nThe Test Recall of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.for

# evaluating Classification report
classification_report = classification_report(y_test, y_pred)
print('\nThe Test classification report of the GBDT for maxdepth and Learning_rate \n\n ',(
```

```
The Test Accuracy of the GBDT for maxdepth=7, Learning_rate =0.05 is accurac
y 89.74666666666667

Test Error of the GBDT for maxdepth and Learning_rate is  10.253333%

The Test Precision of the GBDT for maxdepth=7, Learning_rate =0.05 is accura
cy 0.9096189702156141

The Test Recall of the GBDT for maxdepth=7, Learning_rate =0.05 is accuracy
0.9785784086817878

The Test classification report of the GBDT for maxdepth and Learning_rate

                precision    recall  f1-score   support

           0       0.74      0.38      0.50      6114
           1       0.91      0.98      0.94     38886

   micro avg       0.90      0.90      0.90     45000
   macro avg       0.82      0.68      0.72     45000
weighted avg       0.89      0.90      0.88     45000
```

8.3 Plotting roc_auc curve

In [70]:

```
y_pred_proba = clf.predict_proba(standardized_data_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="Avgword2vec, AUC="+str(auc))
plt.plot([0,1],[0,1],'r--')
plt.title('ROC curve: GBDT')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



9. TFIDF-Word2Vec

In [71]:

```
#tf-idf weighted w2v

from sklearn.feature_extraction.text import TfidfVectorizer

tfidfw2v_vect = TfidfVectorizer()
final_counts_tfidfw2v_train= tfidfw2v_vect.fit_transform(x_train)
print(type(final_counts_tfidfw2v_train))
print(final_counts_tfidfw2v_train.shape)

final_counts_tfidfw2v_test= tfidfw2v_vect.transform(x_test)
print(type(final_counts_tfidfw2v_test))
print(final_counts_tfidfw2v_test.shape)
```

```
<class 'scipy.sparse.csr.csr_matrix'>
(105000, 38300)
<class 'scipy.sparse.csr.csr_matrix'>
(45000, 38300)
```

In [72]:

```
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidfw2v_vect.get_feature_names(), list(tfidfw2v_vect.idf_)))


# TF-IDF weighted Word2Vec
tfidf_feat = tfidfw2v_vect.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in sent_of_train: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors.append(sent_vec)
    row += 1

#Test case

tfidf_sent_vectors1 = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in sent_of_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors1.append(sent_vec)
    row += 1
print(len(tfidf_sent_vectors))
print(len(tfidf_sent_vectors1))
```

```
105000
45000
```

9.1 Normalizing Data

In [73]:

```
# Data-preprocessing: Normalizing Data
from sklearn import preprocessing
standardized_data_train = preprocessing.normalize(tfidf_sent_vectors)
print(standardized_data_train.shape)
standardized_data_test = preprocessing.normalize(tfidf_sent_vectors1)
print(standardized_data_test.shape)
```

```
(105000, 50)
(45000, 50)
```

9.2 Applying RandomForest Algorithm

In [74]:

```
#Gridsearch Cross Validation

from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestClassifier
from sklearn import tree

base_learners = [40,60,80,100,120]
depth=[3,5,7,9,11]
param_grid = {'n_estimators': base_learners,'max_depth':depth}
rf = RandomForestClassifier(min_samples_leaf=5,max_features='sqrt',criterion='gini',random_
model = GridSearchCV(rf, param_grid,scoring ='f1',cv=3 , n_jobs = -1,pre_dispatch=2)
model.fit(standardized_data_train,y_train)
print(model.best_score_, model.best_params_)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(standardized_data_test, y_test))

a = model.best_params_
optimal_estimator = a.get('n_estimators')
optimal_depth = a.get('max_depth')
```

```
0.9196179232555778 {'max_depth': 11, 'n_estimators': 120}
Model with best parameters :
 RandomForestClassifier(bootstrap=True, class_weight='balanced',
            criterion='gini', max_depth=11, max_features='sqrt',
            max_leaf_nodes=None, min_impurity_decrease=0.0,
            min_impurity_split=None, min_samples_leaf=5,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=120, n_jobs=None, oob_score=False,
            random_state=100, verbose=0, warm_start=False)
Accuracy of the model :  0.9149292947964668
```

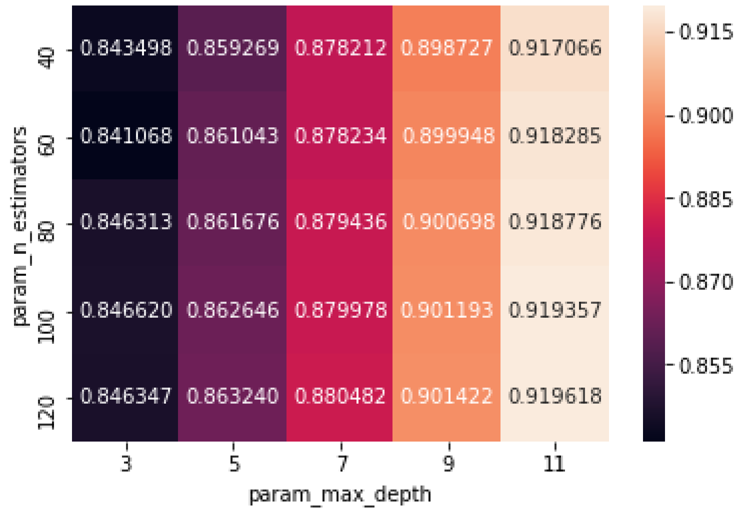
In [75]:

```
results = model.cv_results_
meanscore=results['mean_test_score']
```

Heatmap for Plotting CV Scores

In [76]:

```
pvt =pd.pivot_table(pd.DataFrame(model.cv_results_),values='mean_test_score', index='param_
import seaborn as sns
ax = sns.heatmap(pvt,annot=True,fmt="f")
```



In [77]:

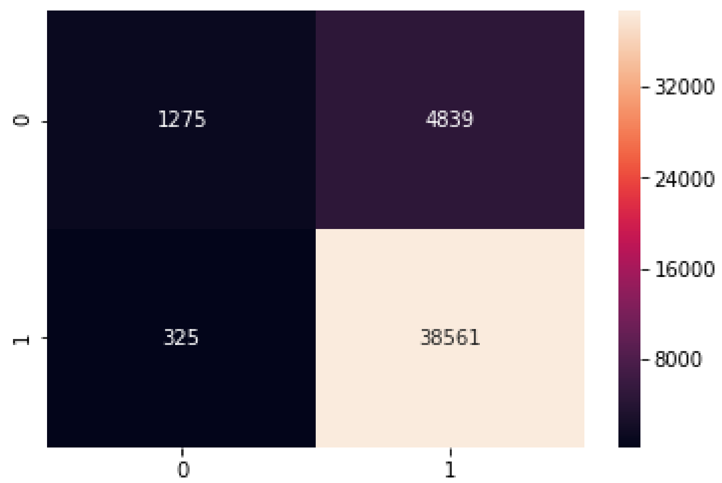
```
clf = RandomForestClassifier(n_estimators=optimal_estimator, class_weight ='balanced')
clf.fit(standardized_data_train,y_train)
y_pred = clf.predict(standardized_data_test)
```

9.3 Confusion Matrix

In [78]:

```
cm_tfidfw2v=confusion_matrix(y_test,y_pred)
print("Confusion Matrix:")
sns.heatmap(cm_tfidfw2v, annot=True, fmt='d')
plt.show()
```

```
Confusion Matrix:
```



In [79]:

```
#finding out  true negative , false positive , false negative and true positve
tn, fp, fn, tp = cm_tfidfw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {}\n true pos
```

```
 true negitves are 1275
 false positives are 4839
 false negatives are 325
 true positives are 38561
```

9.4 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [80]:

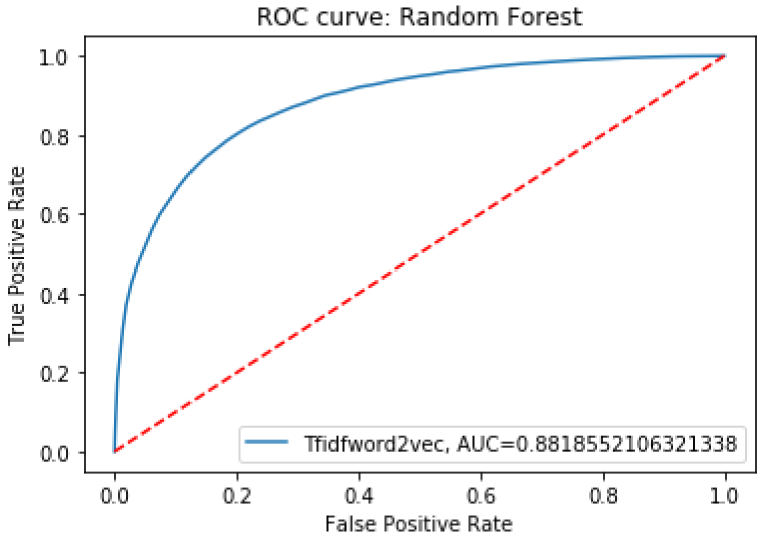
```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
acc_tfidfw2v = accuracy_score(y_test, y_pred) * 100
print('\nThe Test Accuracy of the RandomForest for base_learners ={}, depth ={} is accuracy

# Error on test data
test_error_tfidfw2v = 100-acc_tfidfw2v
print("\nTest Error of the RandomForest for maxdepth is  %f%%" % (test_error_tfidfw2v))

# evaluating precision
precision_score = precision_score(y_test, y_pred)
print('\nThe Test Precision of the RandomForest for base_learners ={}, depth ={} is accurac

# evaluating recall
recall_score = recall_score(y_test, y_pred)
print('\nThe Test Recall of the RandomForest for base_learners ={}, depth ={} is accuracy {

# evaluating Classification report
classification_report = classification_report(y_test, y_pred)
print('\nThe Test classification report of the RandomForest for maxdepth is \n\n ',(classif
```

```
The Test Accuracy of the RandomForest for base_learners =120, depth =11 is a
ccuracy 88.52444444444444

Test Error of the RandomForest for maxdepth is  11.475556%

The Test Precision of the RandomForest for base_learners =120, depth =11 is
accuracy 0.8885023041474654

The Test Recall of the RandomForest for base_learners =120, depth =11 is acc
uracy 0.9916422362804094

The Test classification report of the RandomForest for maxdepth is

                precision    recall  f1-score   support

           0       0.80      0.21      0.33      6114
           1       0.89      0.99      0.94     38886

   micro avg       0.89      0.89      0.89     45000
   macro avg       0.84      0.60      0.63     45000
weighted avg       0.88      0.89      0.85     45000
```

9.5 Plotting roc_auc curve

In [81]:

```
y_pred_proba = clf.predict_proba(standardized_data_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="Tfidfword2vec, AUC="+str(auc))
plt.plot([0,1],[0,1],'r--')
plt.title('ROC curve: Random Forest')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



10.Applying GBDT Algorithm

In [82]:

```
from sklearn.ensemble import GradientBoostingClassifier

Learning_rate = [0.05,0.1,0.2,0.3]
depth=[3,5,7,9,11]
param_grid = {'max_depth':depth, 'learning_rate':Learning_rate}
gb = GradientBoostingClassifier(loss='deviance',max_features='sqrt',subsample=0.1,n_estimat
model = GridSearchCV(gb, param_grid, scoring = 'f1', cv=3 , n_jobs = -1,pre_dispatch=2)
model.fit(standardized_data_train,y_train)
print("Model with best parameters :\n",model.best_estimator_)
print("Accuracy of the model : ",model.score(standardized_data_test, y_test))
a = model.best_params_
optimal_learningrate = a.get('learning_rate')
optimal_depth = a.get('max_depth')
```

```
Model with best parameters :
 GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.05, loss='deviance', max_depth=9,
              max_features='sqrt', max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              n_iter_no_change=None, presort='auto', random_state=None,
              subsample=0.1, tol=0.0001, validation_fraction=0.1,
              verbose=0, warm_start=False)
Accuracy of the model :  0.9384902258610256
```

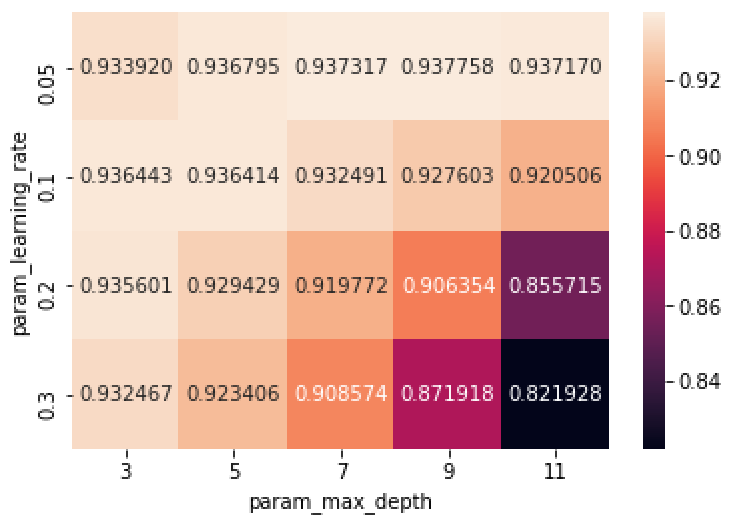
In [83]:

```
results = model.cv_results_
meanscore=results['mean_test_score']
```

Heatmap for plotting CV Scores

In [84]:

```
pvt =pd.pivot_table(pd.DataFrame(model.cv_results_),values='mean_test_score', index='param_
import seaborn as sns
ax = sns.heatmap(pvt,annot=True,fmt="f")
```



In [85]:

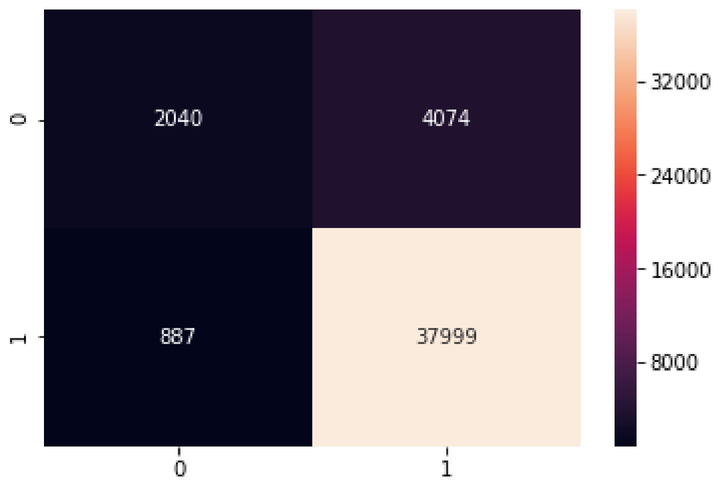
```
clf = GradientBoostingClassifier(max_depth=optimal_depth,learning_rate=optimal_learningrate
clf.fit(standardized_data_train,y_train)
y_pred = clf.predict(standardized_data_test)
```

10.1 Confusion Matrix

In [86]:

```
cm_tfidfw2v=confusion_matrix(y_test,y_pred)
print("Confusion Matrix:")
sns.heatmap(cm_tfidfw2v, annot=True, fmt='d')
plt.show()
```

```
Confusion Matrix:
```



In [87]:

```
#finding out  true negative , false positive , false negative and true positve
tn, fp, fn, tp = cm_tfidfw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {}\n true pos
```

```
 true negitves are 2040
 false positives are 4074
 false negatives are 887
 true positives are 37999
```

10.2 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [88]:

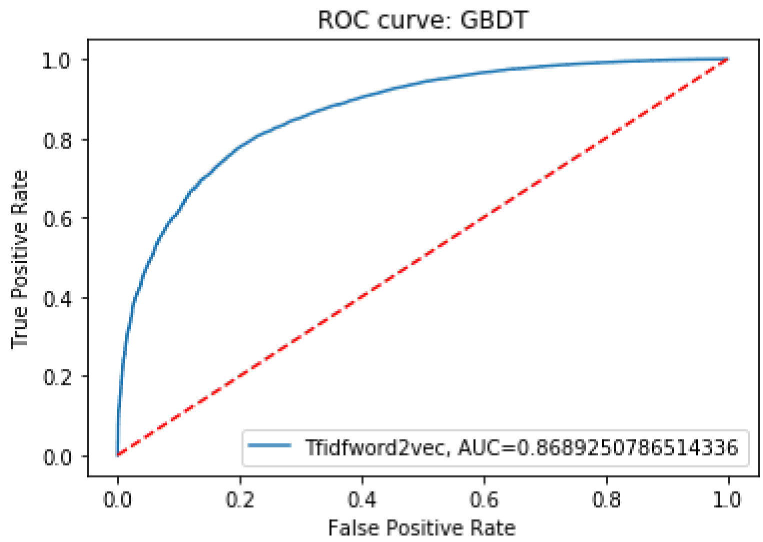
```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
acc_tfidfw2v = accuracy_score(y_test, y_pred) * 100
print('\nThe Test Accuracy of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.f

# Error on test data
test_error_tfidfw2v = 100-acc_tfidfw2v
print("\nTest Error of the GBDT for maxdepth and Learning_rate  %f%%" % (test_error_tfidfw2

# evaluating precision
precision_score = precision_score(y_test, y_pred)
print('\nThe Test Precision of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.

# evaluating recall
recall_score = recall_score(y_test, y_pred)
print('\nThe Test Recall of the GBDT for maxdepth={}, Learning_rate ={} is accuracy {}'.for

# evaluating Classification report
classification_report = classification_report(y_test, y_pred)
print('\nThe Test classification report of the GBDT for maxdepth and Learning_rate \n\n ',(
```

```
The Test Accuracy of the GBDT for maxdepth=9, Learning_rate =0.05 is accurac
y 88.97555555555556

Test Error of the GBDT for maxdepth and Learning_rate  11.024444%

The Test Precision of the GBDT for maxdepth=9, Learning_rate =0.05 is accura
cy 0.903168302711953

The Test Recall of the GBDT for maxdepth=9, Learning_rate =0.05 is accuracy
0.9771897340945327

The Test classification report of the GBDT for maxdepth and Learning_rate

                precision    recall  f1-score   support

           0       0.70      0.33      0.45      6114
           1       0.90      0.98      0.94     38886

   micro avg       0.89      0.89      0.89     45000
   macro avg       0.80      0.66      0.69     45000
weighted avg       0.88      0.89      0.87     45000
```

10.3 Plotting roc_auc curve

In [89]:

```
y_pred_proba = clf.predict_proba(standardized_data_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="Tfidfword2vec, AUC="+str(auc))
plt.plot([0,1],[0,1],'r--')
plt.title('ROC curve: GBDT')
plt.legend(loc='lower right')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



11. Conclusion

```
-----------------------------------------------------------------------------------------
-----------------------------
|
  Model Performance Table



-----------------------------------------------------------------------------------------
-----------------------------
|           Model                   |         Depth           | base learner | Test Error
  | Accuracy  |
|:----------------------------------:|:---------------------:|:------------:|:-----------
-:|:---------:|
| Random Forest with Bow            |          11             |   120        |11.353333
  |88.6466666 |
| Random Forest with Tfidf          |          11             |   120        |11.204444
  |88.7955555 |
| Random Forest with Avgw2v         |          11             |   120        |10.968889
  |89.0311111 |
| Random Forest with Tfidfw2v       |          11             |   120        |11.475556
  |88.5244444 |

-----------------------------------------------------------------------------------------
-----------------------------



-----------------------------------------------------------------------------------------
-----------------------------
|
```

Model Performance Table

Model	Depth	learning rate	Test Error	Accuracy
GBDT with Bow	11	0.1	11.102222	88.897777
GBDT with Tfidf	11	0.1	11.044444	88.955555
GBDT with Avgw2v	7	0.05	10.253333	89.746666
GBDT with Tfidfw2v	3	0.05	11.024444	88.975555

Steps Involved:-

1) Connecting SQL file

2) Data Preprocessing(Already i had done preprocessing no need to do again)

3) Sorting the data based on time

4) Taking 1st 150K Rows (Due to low Ram)

5) Spliting data into train and test based on time (70:30)

6) Techniques For Vectorization Bow,TF-IDF,word2vec,Avgword2vec,tfidfword2vec.

7) Normalizing Data

8) Applying Random Forest Algorithm

9) Introduced heatmap for cv_results vs max_deth vs base learner

10) I calculated Accuracy,Error on Test Data, Confusion Matrix,Precision Score,Recall Score,Classification Report,ROC_curve

11) Calculated top features and builded a word cloud

12) Applying GradientBoostingClassifier

13) Introduced heatmap for cv_results vs max_deth vs learning rate

12) I calculated Accuracy,Error on Test Data, Confusion Matrix,Precision Score,Recall Score,Classification Report,ROC_curve

13) Conclusion

In [ ]: