Import necessary libraries

In [1]:

```
import warnings
warnings.filterwarnings('ignore')
```

In [3]:

```
from sklearn.tree import DecisionTreeClassifier
import seaborn as sns
from sklearn.model_selection import TimeSeriesSplit
from scipy.sparse import *
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import *
import pickle
from tqdm import tqdm
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
import graphviz
from sklearn.tree import export_graphviz
from sklearn.externals import joblib
#from prettytable import PrettyTable
from wordcloud import WordCloud
```

Load preprocessed data

In [42]:

```
#Functions to save objects for later use and retireve it
def savetofile(obj,filename):
    pickle.dump(obj,open(filename+".pkl","wb"))
def openfromfile(filename):
    temp = pickle.load(open(filename+".pkl","rb"))
    return temp
y_train =openfromfile('y_train')
y_test =openfromfile('y_test')

count_vect =openfromfile('count_vect')
X_train_bigram = openfromfile('X_train_bigram')
X_test_bigram = openfromfile('X_test_bigram')

tf_idf_vect =openfromfile('tf_idf_vect')
X_train_tfidf =openfromfile('X_train_tfidf')
X_test_tfidf =openfromfile('X_test_tfidf')

avg_sent_vectors=openfromfile('avg_sent_vectors')
avg_sent_vectors_test=openfromfile('avg_sent_vectors_test')

tfidf_sent_vectors=openfromfile('tfidf_sent_vectors')
tfidf_sent_vectors_test=openfromfile('tfidf_sent_vectors_test')
```

Save and Load Model

In [4]:

```
def saveModeltofile(obj,filename):
    joblib.dump(obj,open(filename+".pkl","wb"))
def openModelfromfile(filename):
    temp = joblib.load(open(filename+".pkl","rb"))
    return temp
```

Standardizing data

In [44]:
```
def std_data(train,test,mean):
    scaler=StandardScaler(with_mean=mean)
    std_train=scaler.fit_transform(train)
    std_test=scaler.transform(test)
    return std_train, std_test
```

Observation:

1. In Decision Tree based algorithm we are not dealing with distance at all.
2. So, Data Standardization is not required for DecisionTree.

Decision Trees

Function for hyperparameter tunning using corss validation and error plot using heatmap:

In [45]:

```
# find Optimal value of hyperparam by TimeSeriesSplit and 10_fold_cross _validation
# using RandomizedSearchCV and GridSearchCV.
def DT_Classifier(x_train,y_train,TBS,params,searchMethod,vect):
    ''' FUNCTION FOR FINDING OPTIMAL VALUE OF HYPERPARAM AND DRAW HEATMAP WITH SCORE AND HYPERPARAM'''
    #INITIALIZE DECISION-TREE CLASSIFIER
    clf=DecisionTreeClassifier(class_weight='balanced',criterion='gini')
    # APPLY RANDOM OR GRID SEARCH FOR HYPERPARAMETER TUNNING
    if searchMethod=='grid':
        model=GridSearchCV(clf,\
                           cv=TBS,\
                           n_jobs=-1,\
                           param_grid=params,\
                           return_train_score=True,\
                           scoring=make_scorer(roc_auc_score,average='weighted'))
        model.fit(x_train,y_train)
    elif searchMethod=='random':
        model=RandomizedSearchCV(clf,\
                                 n_jobs=-1,\
                                 cv=TBS,\
                                 param_distributions=params,\
                                 n_iter=len(params['max_depth']),\
                                 return_train_score=True,\
                                 scoring=make_scorer(roc_auc_score,average='weighted'))
        model.fit(x_train,y_train)
    #PLOT THE PERFORMANCE OF MODEL ON CROSSVALIDATION DATA FOR EACH HYPERPARAM VALUE
    auc_results=[]
    auc_results.append(model.cv_results_['mean_test_score'])
    auc_results.append(model.cv_results_['mean_train_score'])
    data=['CV','Train'];i=0;
    plt.figure(figsize= (17,6))
    for auc in auc_results:
        auc=np.array(auc).reshape(len(params['min_samples_split']),len(params['max_depth']))
        cv_auc_df=pd.DataFrame(auc, np.array(params['min_samples_split']),np.array(params['max_depth']))
        cv_auc_df=cv_auc_df.round(4)
        plt.subplot(int('12'+str(i+1)))
        plt.title('Hyperparam Tunning %s-Data(%s)' %(data[i],vect))
        sns.set(font_scale=1.4)#for label size
        ax=sns.heatmap(cv_auc_df, annot=True,annot_kws={"size": 12}, fmt='g',)
        ax.set(xlabel='Depth-Values', ylabel='Min #Samples to split')
        i+=1
    plt.show()
    return model
```

Function which calculate performance on test data with optimal hyperparam :

In [175]:

```
# ============================== Decision Tree with optimal depth and optimalmin_samples_split=============

def test_performance(x_train,y_train,x_test,y_test,optimal,vect,summarize):
    '''FUNCTION FOR TEST PERFORMANCE(PLOT ROC CURVE FOR BOTH TRAIN AND TEST) WITH OPTIMAL HYPERPARAM'''
    #INITIALIZE DECISION TREE WITH OPTIMAL VALUE OF HYPERPARAMS
    clf=DecisionTreeClassifier(min_samples_split=optimal['min_samples_split'],\
                               max_depth=optimal['max_depth'],\
                               class_weight='balanced',\
                               criterion='gini')
    clf.fit(x_train,y_train)

    train_prob=clf.predict_proba(x_train)[:,1]
    test_prob=clf.predict_proba(x_test)[:,1]
    y_pred=clf.predict(x_test)

    fpr_test, tpr_test, threshold_test = roc_curve(y_test, test_prob,pos_label=1)
    fpr_train, tpr_train, threshold_train = roc_curve(y_train, train_prob,pos_label=1)
    auc_score_test=auc(fpr_test, tpr_test)
    auc_score_train=auc(fpr_train, tpr_train)

    f1=f1_score(y_test,y_pred,average='weighted')

    #ADD RESULTS TO PRETTY TABLE
    summarize.add_row([vect, optimal['max_depth'],optimal['min_samples_split'],\
                       '%.3f' %auc_score_test,'%.3f' %auc_score_train,'%.3f' %f1])

    plt.figure(1,figsize=(14,5))
    plt.subplot(121)
    plt.title('ROC Curve (%s)' %vect)
    #IDEAL ROC CURVE
    plt.plot([0,1],[0,1],'k--')
    #ROC CURVE OF TEST DATA
    plt.plot(fpr_test, tpr_test , 'b', label='Test_AUC= %.2f' %auc_score_test)
    #ROC CURVE OF TRAIN DATA
    plt.plot(fpr_train, tpr_train , 'g', label='Train_AUC= %.2f' %auc_score_train)
    plt.xlim([-0.1,1.1])
    plt.ylim([-0.1,1.1])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.grid(True)
    plt.legend(loc='lower right')

```

```
    #PLOT CONFUSION MATRIX USING HEATMAP
    plt.subplot(122)
    plt.title('Confusion-Matrix(Test Data)')
    df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), ['Negative','Positive'],['Negative','Positive'])
    sns.set(font_scale=1.4)#for label size
    sns.heatmap(df_cm,cmap='gist_earth', annot=True,annot_kws={"size": 16}, fmt='g')
    plt.show()
    return clf

```

Function which print top important features (feature importance):

In [5]:

```
def feature_importance(vectorizer,clf,n):
    '''FUNCTION FOR OVERALL FEATURE IMPORTANCE'''
    # FEATURE IMPORTANCES FROM DECISION TREE
    fe_importances = clf.feature_importances_

    # INDEX OF SORTED IMPORTANT FEATURES
    indices = np.argsort(fe_importances)[::-1][:n]

    # FEATURE NAMES
    names = vectorizer.get_feature_names()
    names=np.array(names)

    #WORDCLOUD PLOT
    wordcloud = WordCloud(max_font_size=50, max_words=100,collocations=False).\
    generate(str(names[indices]))
    plt.figure(1,figsize=(14,13))
    plt.title("WordCloud(Important Feature)")
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")

    #BAR CHART
    plt.figure(2,figsize=(13,8))
    sns.set(rc={'figure.figsize':(11.7,8.27)})
    plt.title("Feature Importance")
    # ADD BARS
    plt.bar(range(n), fe_importances[indices])
    # FEATURE NAMES ON X AXIS
    plt.xticks(range(n), names[indices], rotation=70)
    # Show plot
    plt.show()
```

Function for visualizing tree:

In [48]:

```
def visualizeDecisionTree(clf,vect,treeName):
    export_graphviz(clf, out_file=treeName+".dot",feature_names=vect.get_feature_names(),filled=True,proport
```

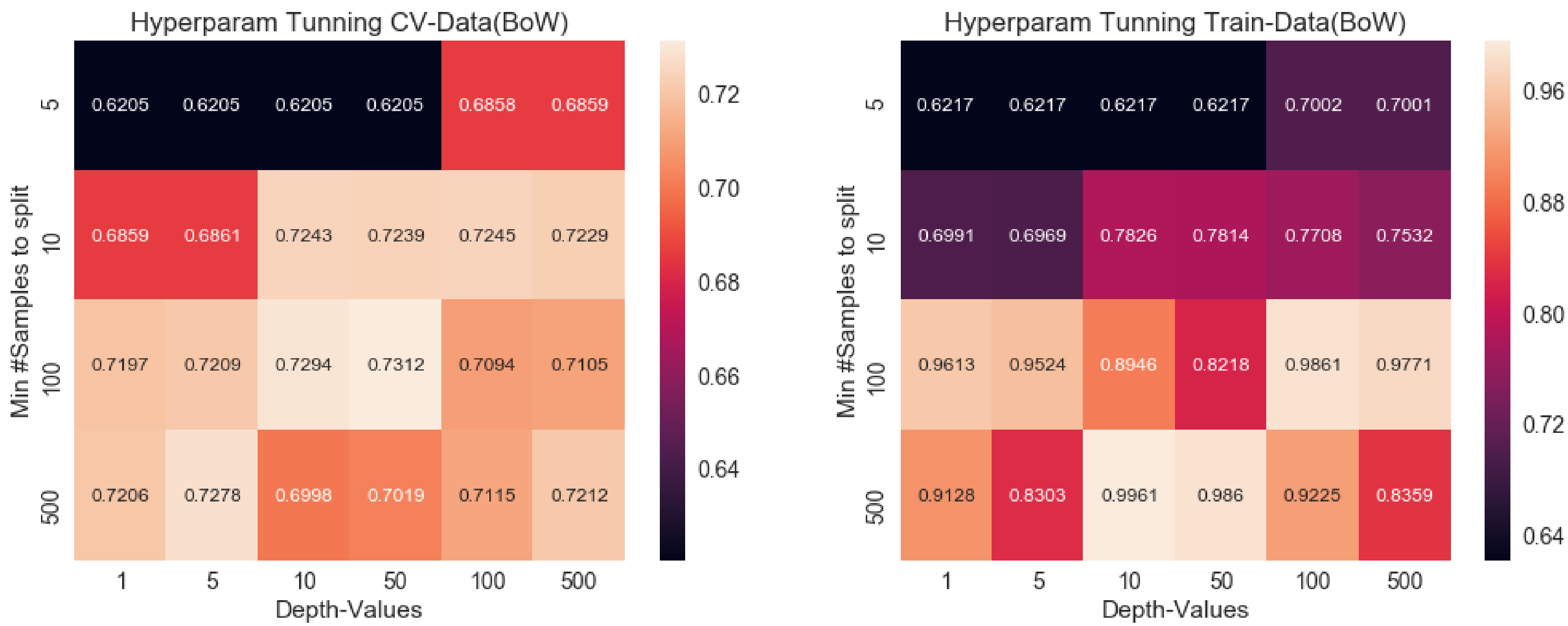
Initialization of common objects required for all vectorization:

In [102]:
```
#(best depth in range [1, 5, 10, 50, 100, 500], and the best min_samples_split in range [5, 10, 100, 500])
#VECTORIZER
vect=['BoW','TF-IDF','AVG-W2V','TFIDF-W2V']
#OBJECT FOR TIMESERIES CROSS VALIDATION
TBS=TimeSeriesSplit(n_splits=10)
#METHOD USE FOR HYPER PARAMETER TUNNING
searchMethod='grid'
#RANGE OF VALUES FOR HYPERPARAM
samples=[5, 10, 100, 500]
depth=[1, 5, 10, 50, 100, 500]
params={'max_depth':depth,'min_samples_split':samples}
#INITIALIZE PRETTY TABLE OBJECT
summarize = PrettyTable()
summarize.field_names = ['Vectorizer', 'Optimal-Depth', 'Optimal #Samples', 'Test(AUC)','Train(AUC)','Test(f
```

[1.1] Applying Decision Trees on BOW, SET 1

[1.1.1] Hyperparam tunning and plot Heatmap for hyperparam:

In [103]:
```
#TRAIN AND TEST DATA
train=X_train_bigram; test=X_test_bigram;
#HYPERPARAMS TUNNING
%time model=DT_Classifier(train,y_train,TBS,params,searchMethod,vect[0])
print(model.best_params_)
#SAVE CURRENT STATE OF MODEL
saveModeltofile(model,'model_bow_dt')
```




```
Wall time: 12min 8s
{'max_depth': 50, 'min_samples_split': 500}
```

Observation:

1. From the above heatmaps we pick optimal value of hyperparam such that our model is not overfit and underfit.
2. We pick optimal value of hyperparams:

    a. `max_depth=50`
    b. `min_smples_split=500`

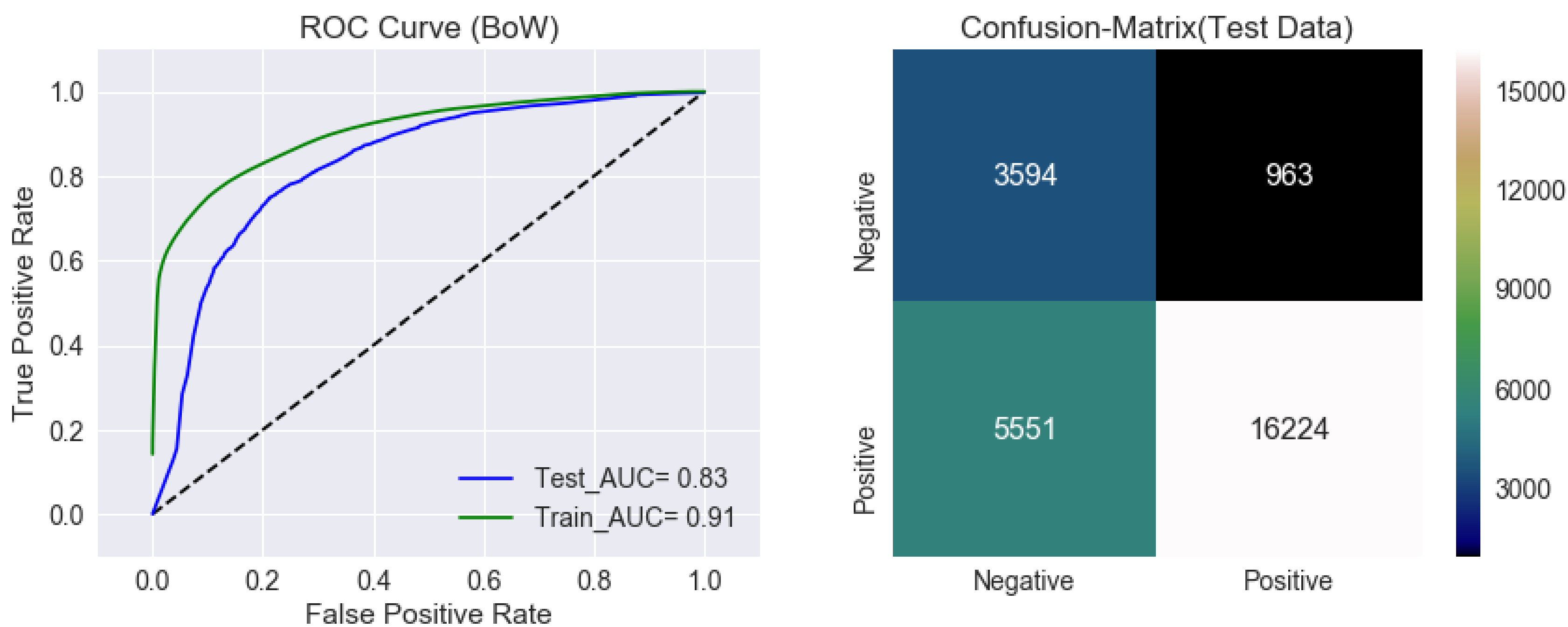
3. for those optimal hyperparam, model performance:

```
a. auc for crossvalidation data is .7019 and
b. auc for train data is .9860
```

In [140]:
```
best_params={'max_depth':50,'min_samples_split':500}
```

[1.1.2] Performance on test data with optimal value of hyperparam:

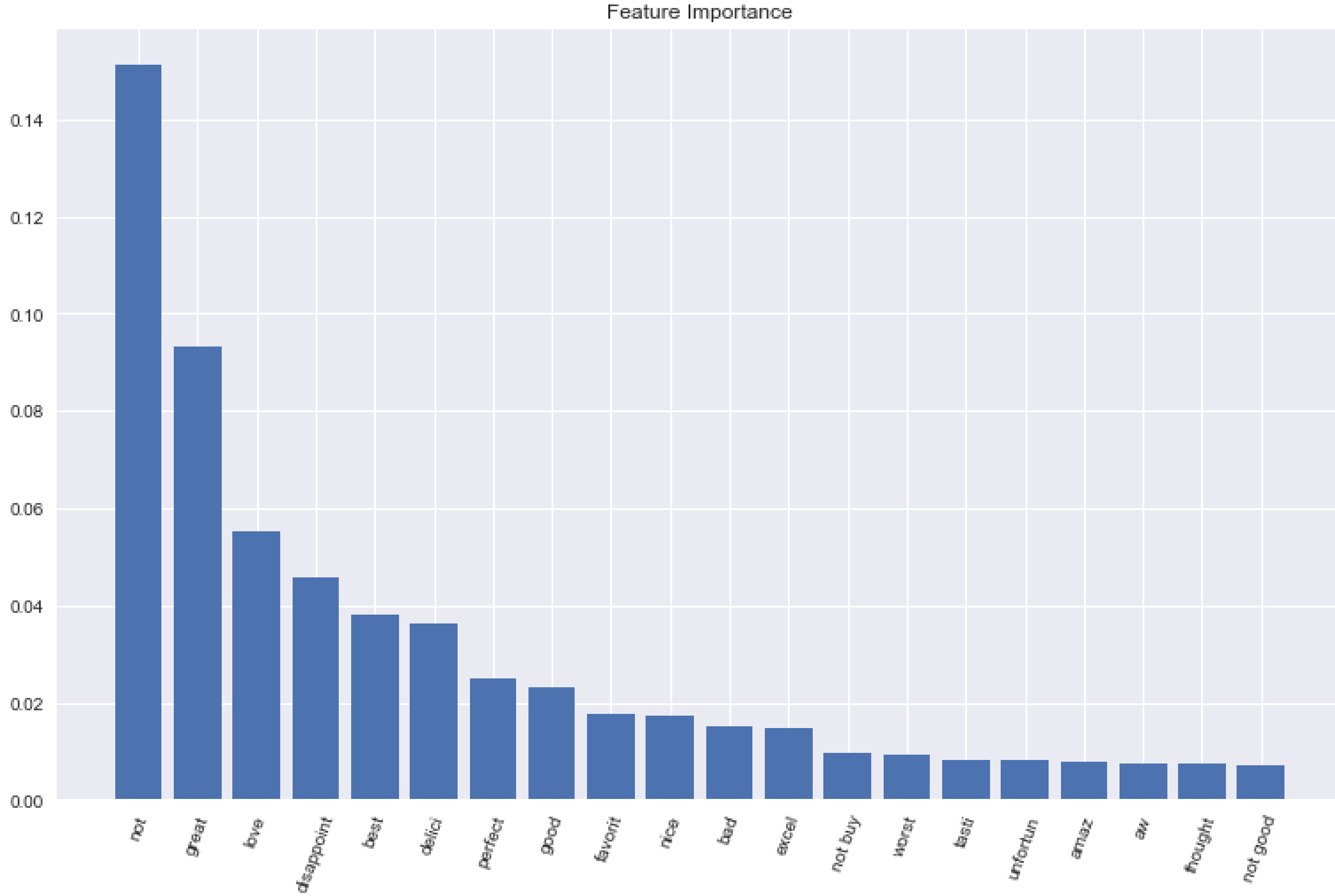
In [141]:
```
clf=test_performance(train,y_train,test,y_test,best_params,vect[0],summarize)
```



[1.1.3] Top 20 important features:

In [7]:
```
no_of_imp_features=20
feature_importance(count_vect,clf,no_of_imp_features)
```

WordCloud(Important Feature)



Observation:

1. Decision Tree give feature importance based on reduction in entroy or gini impurity due to a feature in whole Decision Tree.
2. We can't get class based feature importance in Decision Tree.

[1.1.5]Graphviz visualization of Decision Tree:

In [144]:
```
treeName='decision_bow'
visualizeDecisionTree(clf,count_vect,treeName)
with open(treeName+'.dot') as f:
    dot_graph = f.read()
graphviz.Source(dot_graph)
```

Out[144]: <graphviz.files.Source at 0x17862e10>

Note:

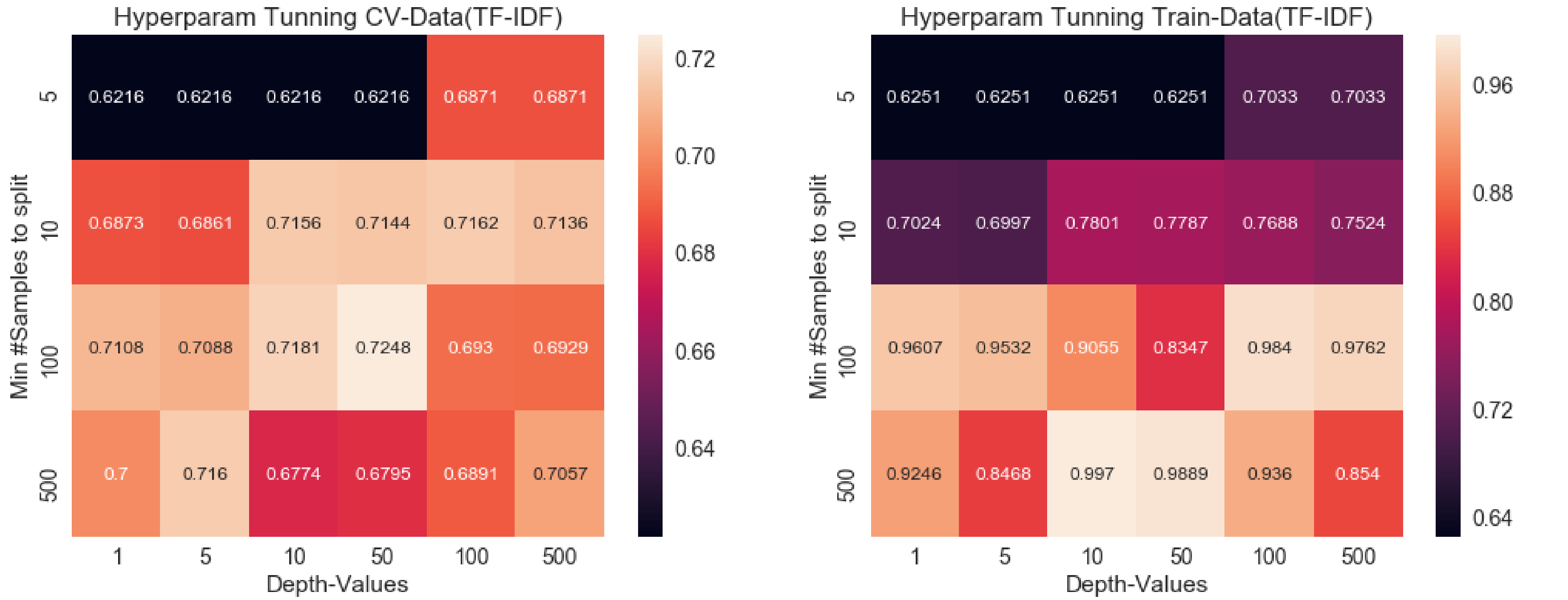
1. Please check the graph_bow.png to visualize the whole graph.

[2.1] Applying Decision Tree on TFIDF, SET 2

[2.1.1] Hyperparam tunning and plot Heatmap for hyperparam:

In [145]:

```
#TRAIN AND TEST DATA
train=X_train_tfidf; test=X_test_tfidf;
#HYPERPARAMS TUNNING
%time model=DT_Classifier(train,y_train,TBS,params,searchMethod,vect[1])
print(model.best_params_)
#SAVE CURRENT STATE OF MODEL
saveModeltofile(model,'model_tfidf_dt')
```




```
Wall time: 13min 25s
{'max_depth': 50, 'min_samples_split': 500}
```

Observation:

1. From the above heatmaps we pick optimal value of hyperparam such that our model is not overfit and underfit.
2. We pick optimal value of hyperparams:

    a. `max_depth=50`
    b. `min_smples_split=500`

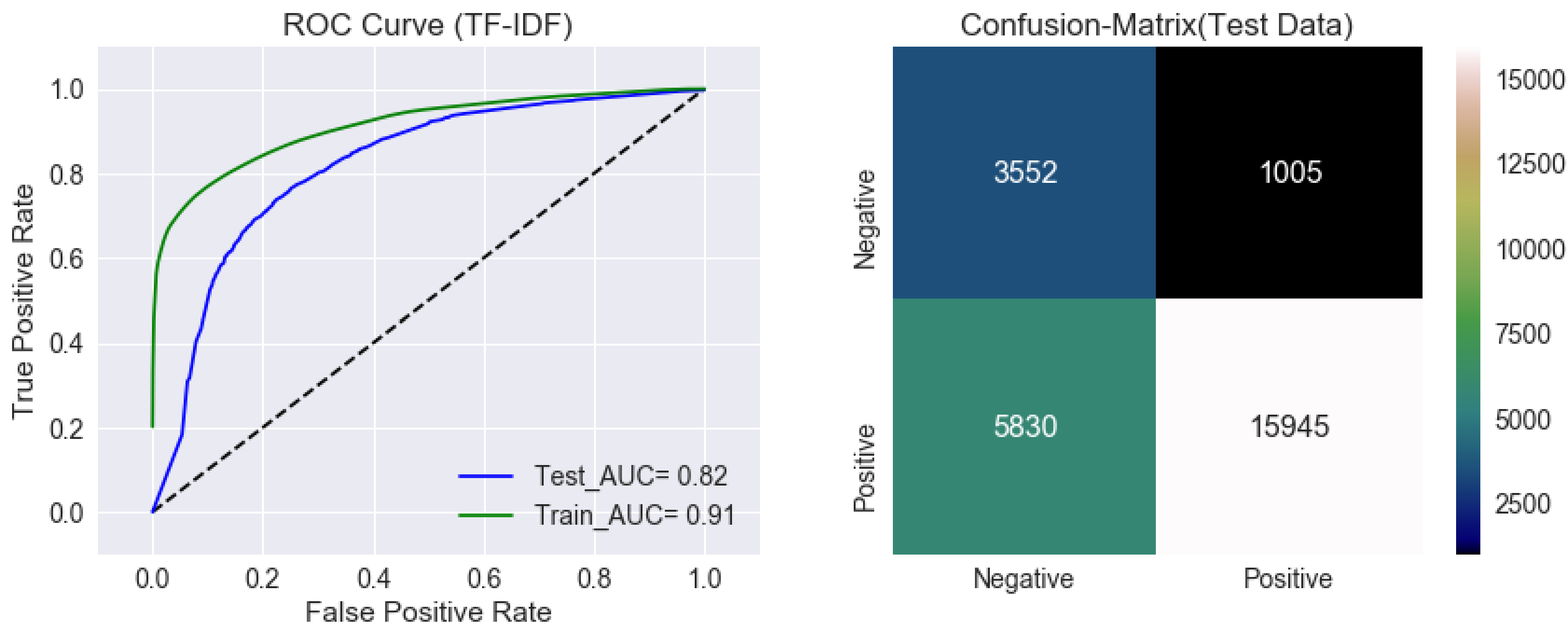
3. for those optimal hyperparam, model performance:

```
a. auc for crossvalidation data is .6795 and
b. auc for train data is .9889
```

In [161]:
```
best_params={'max_depth':50,'min_samples_split':500}
```

[2.1.2] Performance on test data with optimal value of hyperparam:

In [162]:
```
clf=test_performance(train,y_train,test,y_test,best_params,vect[1],summarize)
```

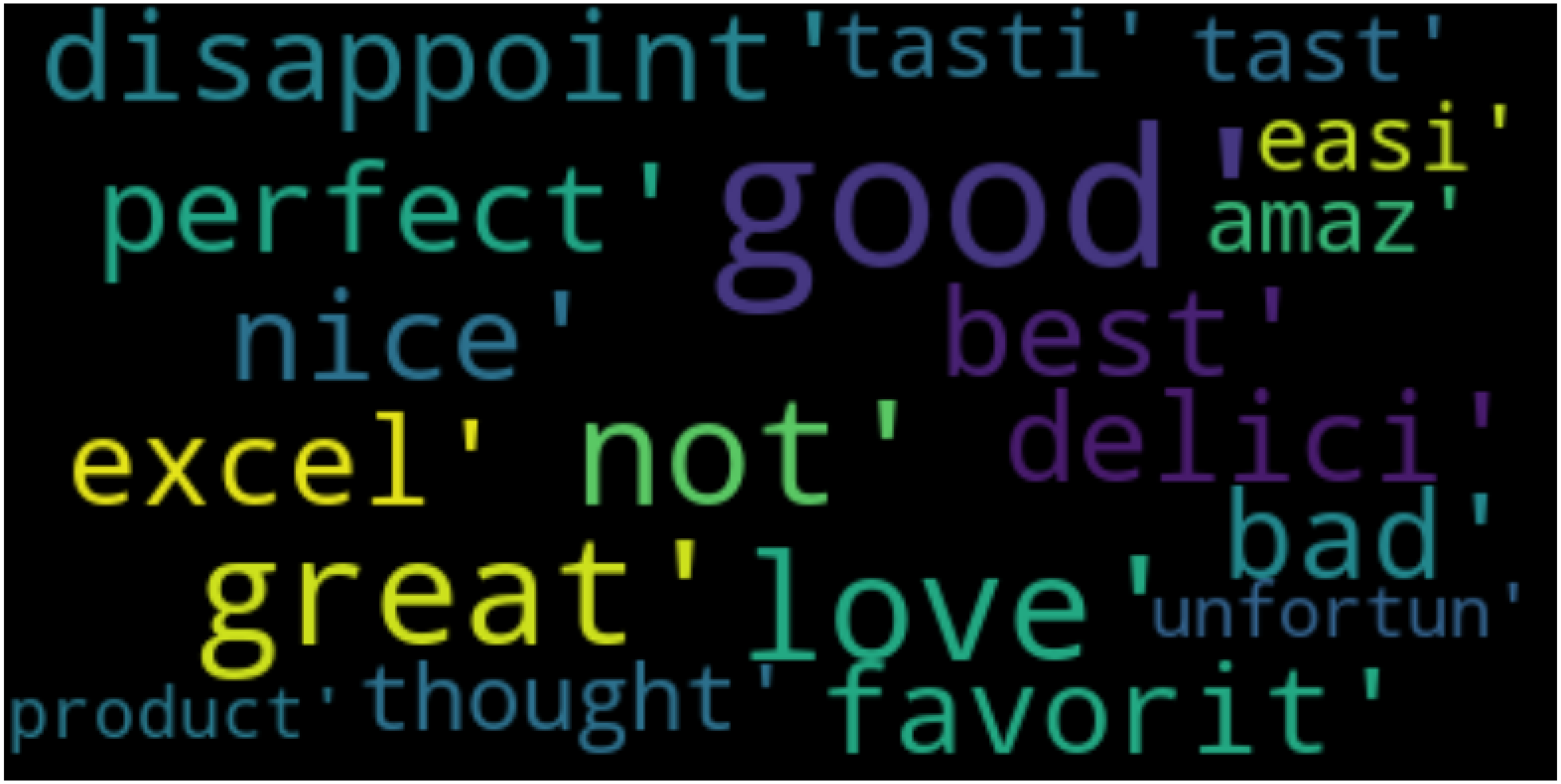


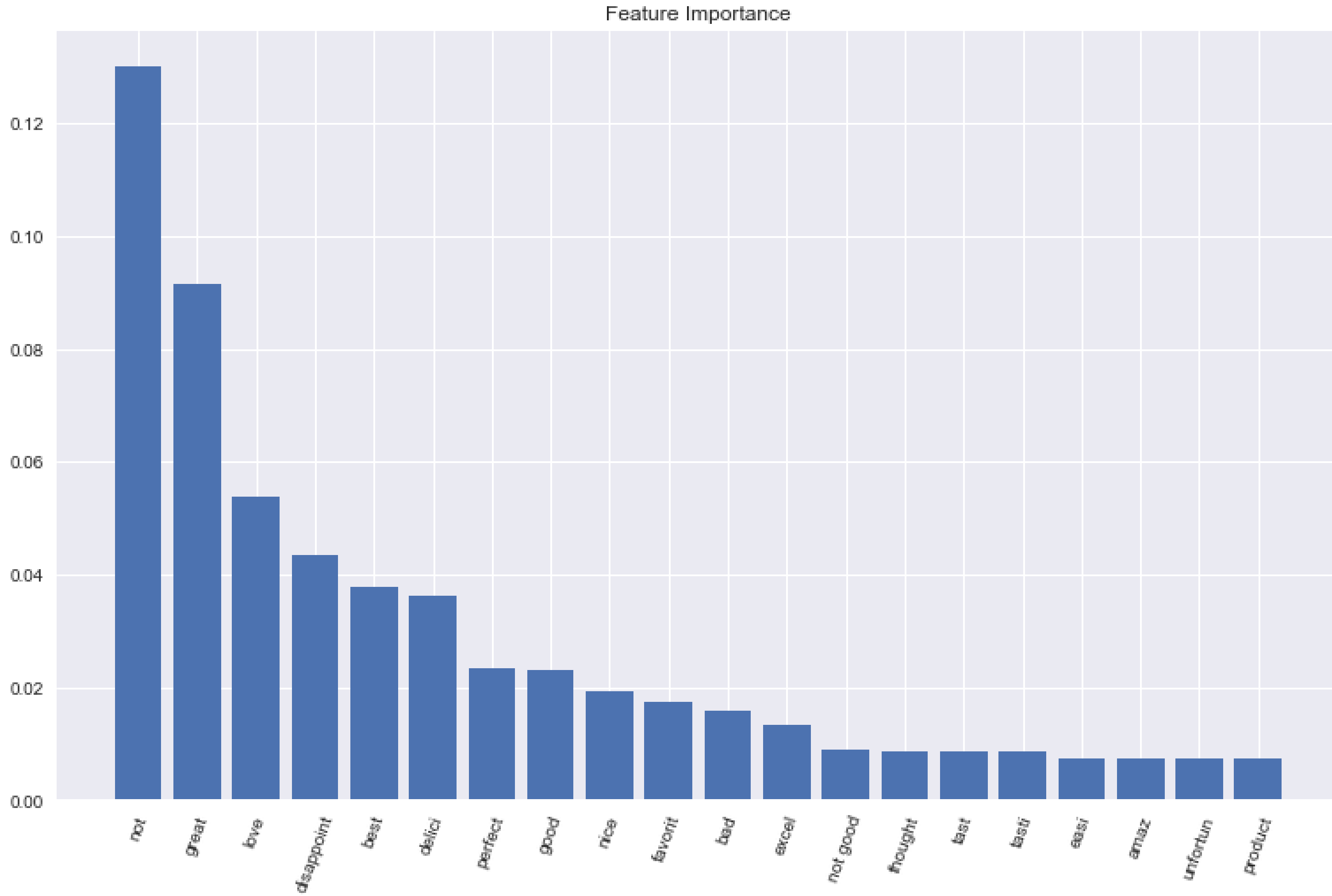
[2.1.3] Top 20 important features:

In [8]:

```
no_of_imp_features=20
feature_importance(tf_idf_vect,clf,no_of_imp_features)
```

WordCloud(Important Feature)





Observation:

1. Decision Tree give feature importance based on reduction in entroy or gini impurity due to a feature in whole Decision Tree.
2. We can't get class based feature importance in Decision Tree.

[2.1.4] Graphviz visualization of Decision Tree:

In [163]:
```
treeName='decision_tfidf'
visualizeDecisionTree(clf,tf_idf_vect,treeName)
with open(treeName+'.dot') as f:
    dot_graph = f.read()
graphviz.Source(dot_graph)
```

Out[163]: <graphviz.files.Source at 0x16fa9668>

Note:

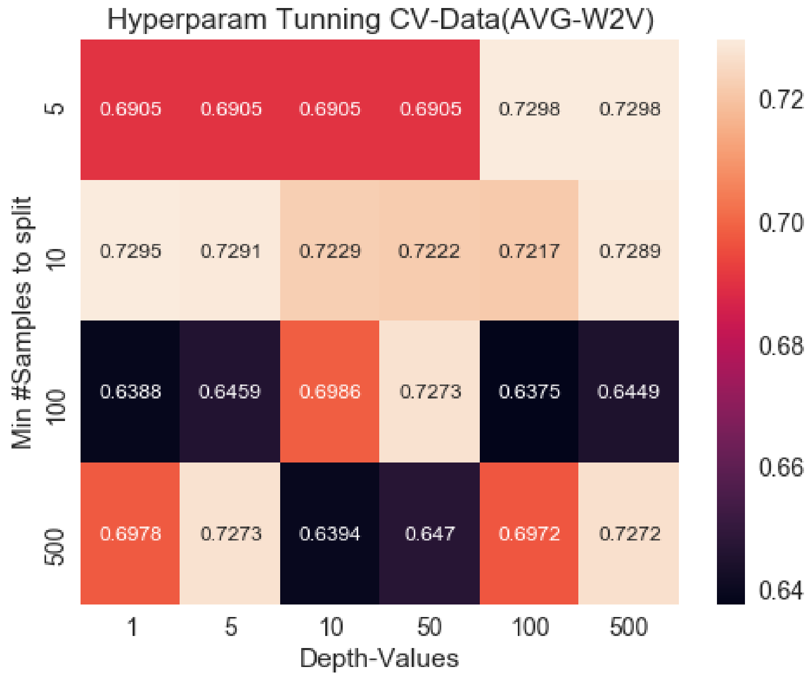
1. Please check the graph_tfidf.png to visualize the whole graph.

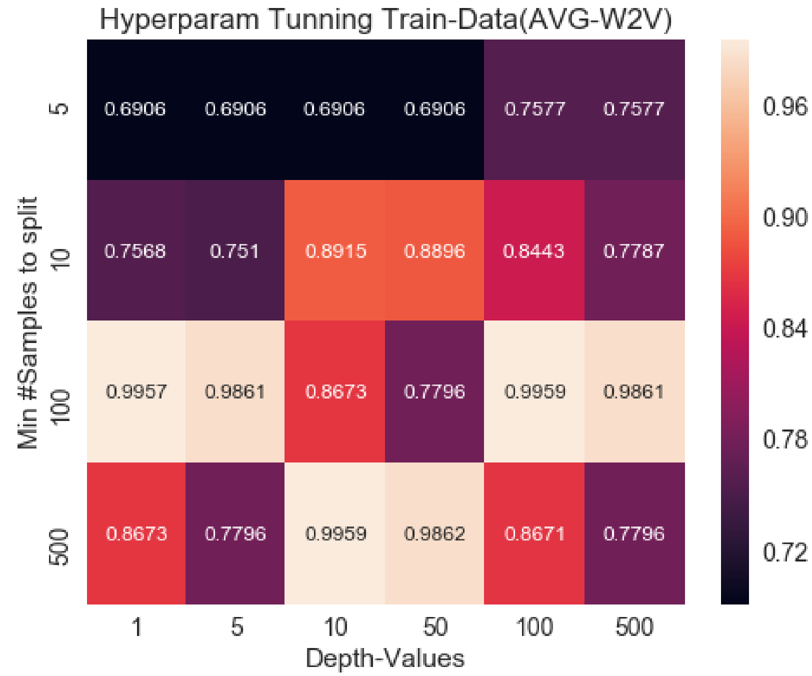
[3.1] Applying Decision Tree on AVG-W2V, SET 3

[3.1.1] Hyperparam tunning and plot Heatmap for hyperparam:

In [164]:

```
#TRAIN AND TEST DATA
train=avg_sent_vectors; test=avg_sent_vectors_test;
#HYPERPARAMS TUNNING
%time model=DT_Classifier(train,y_train,TBS,params,searchMethod,vect[2])
print(model.best_params_)
#SAVE CURRENT STATE OF MODEL
saveModeltofile(model,'model_avgw2v_dt')
```






```
Wall time: 6min 11s
{'max_depth': 5, 'min_samples_split': 5}
```

Observation:

1. From the above heatmaps we pick optimal value of hyperparam such that our model is not overfit and underfit.
2. We pick optimal value of hyperparams:

    a. `max_depth=5`

    b. `min_smples_split=5`

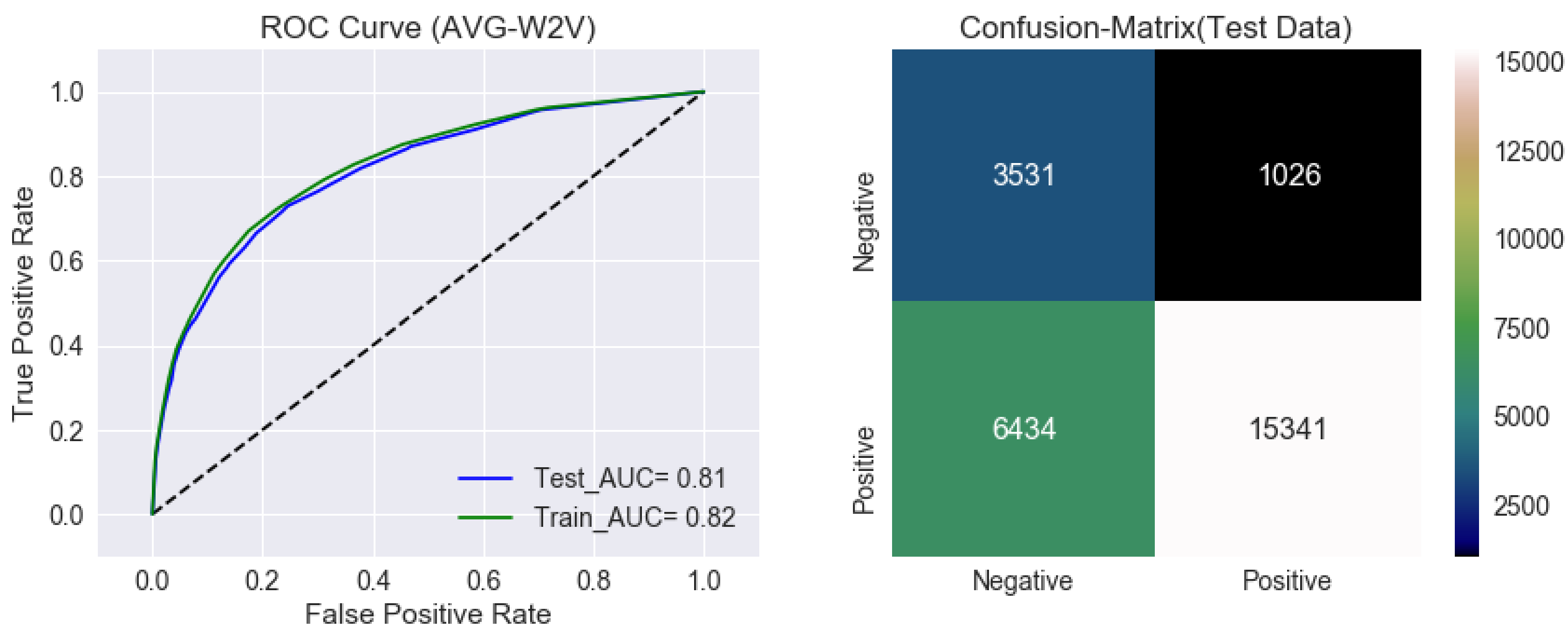
3. for those optimal hyperparam, model performance:

a. auc for crossvalidation data is .6905 and
b. auc for train data is .6906

In [173]:
```
best_params={'max_depth':5,'min_samples_split':5}
```

[3.1.2] Performance on test data with optimal value of hyperparam:

In [176]:
```
clf=test_performance(train,y_train,test,y_test,best_params,vect[2],summarize)
```

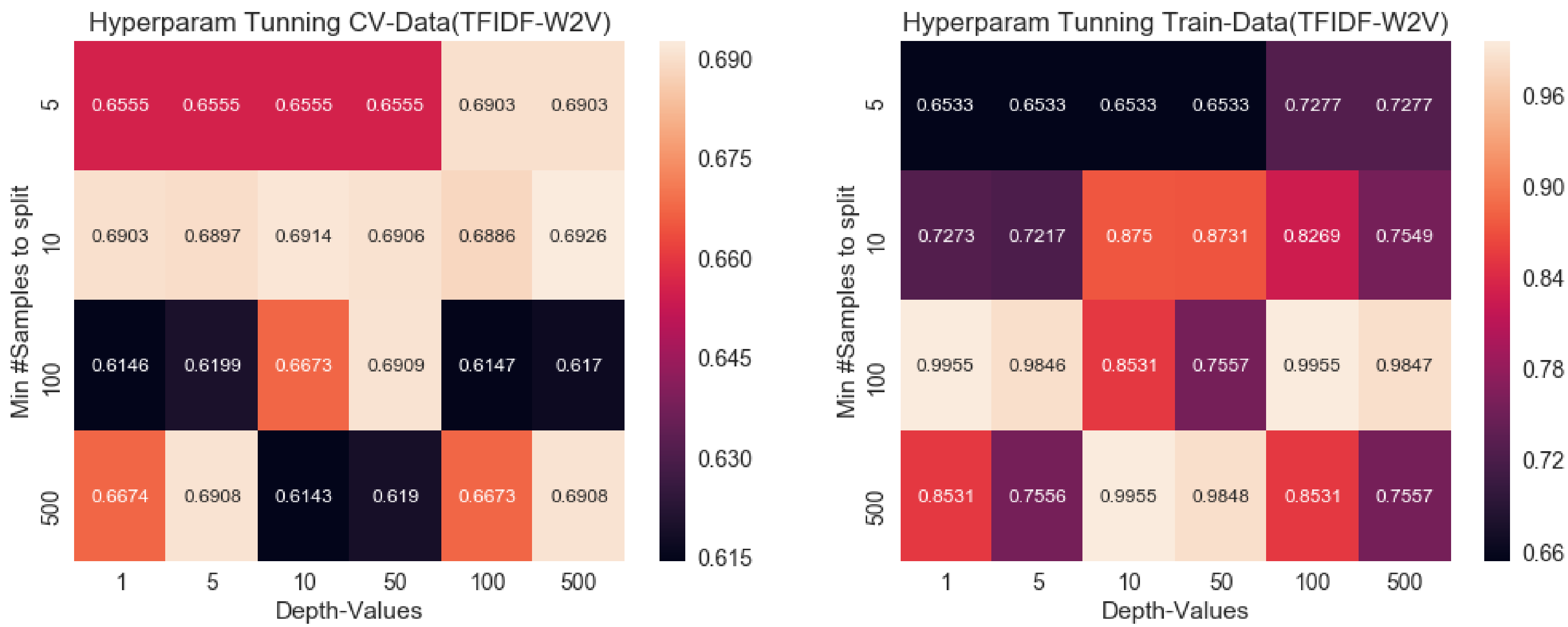


[4.1] Applying Decision Tree on TFIDF-W2V, SET 4

[4.1.1] Hyperparam tunning and plot Heatmap for hyperparam:

In [178]:

```
# TRAIN AND TEST DATA
train=tfidf_sent_vectors; test=tfidf_sent_vectors_test;
#HYPERPARAMS TUNNING
%time model=DT_Classifier(train,y_train,TBS,params,searchMethod,vect[3])
print(model.best_params_)
#SAVE CURRENT STATE OF MODEL
saveModeltofile(model,'model_tfidfw2v_dt')
```




```
Wall time: 6min 10s
{'max_depth': 10, 'min_samples_split': 500}
```

Observation:

1. From the above heatmaps we pick optimal value of hyperparam such that our model is not overfit and underfit.
2. We pick optimal value of hyperparams:

    a. `max_depth=10`
    b. `min_smples_split=500`

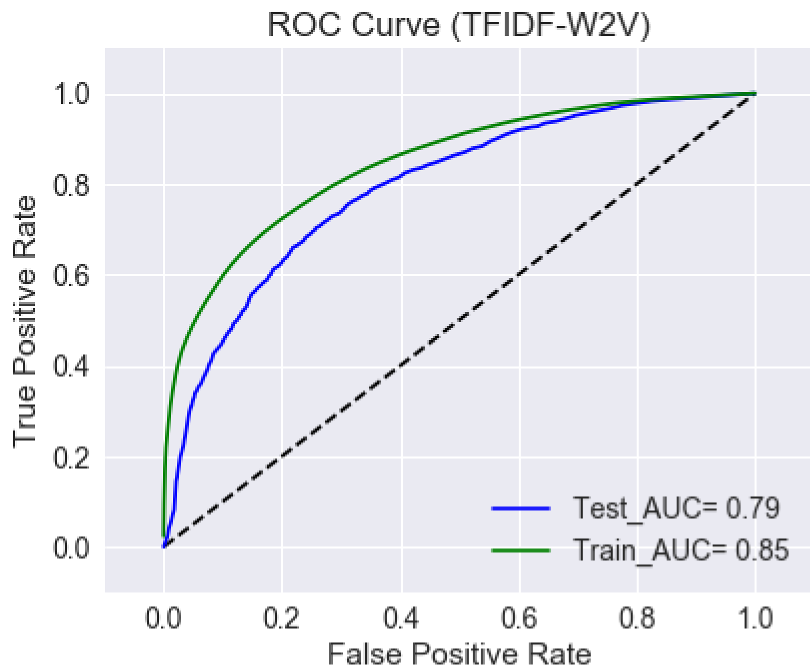
3. for those optimal hyperparam, model performance:

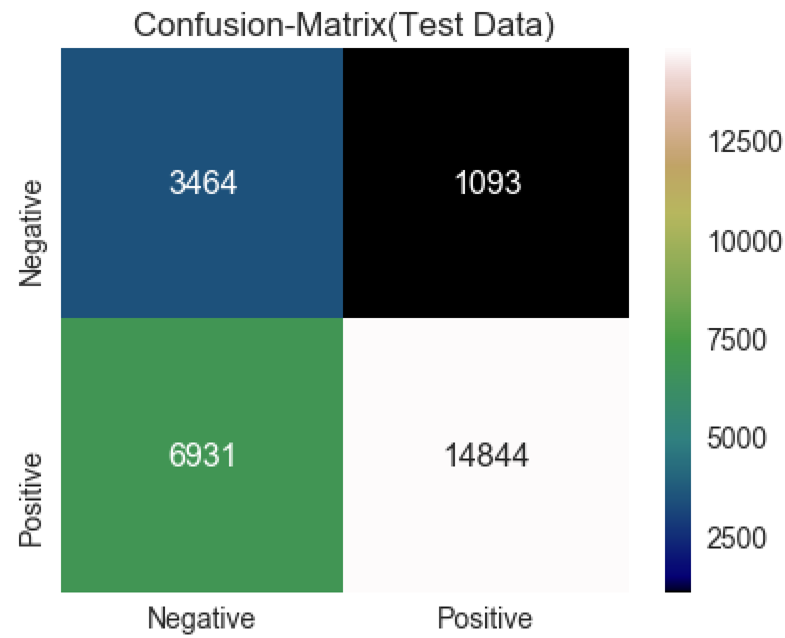
```
a. auc for crossvalidation data is .6143 and
b. auc for train data is .9955
```

In [179]:
```
best_params={'max_depth':10,'min_samples_split':500}
```

[4.1.2] Performance on test data with optimal value of hyperparam:

In [180]:
```
clf=test_performance(train,y_train,test,y_test,best_params,vect[3],summarize)
```





Observation:

1. We can't get feature importance in case of AVG-W2V and TFIDF-W2V vectorizer.
2. Because in case of AVG-W2V and TFIDF-W2V vectors the dimension of a vector is not representd by a feature.

Conclusion:

In [182]:
```
print(summarize)
```

Vectorizer	Optimal-Depth	Optimal #Samples	Test(AUC)	Train(AUC)	Test(f1-score)
BoW	50	500	0.828	0.905	0.779
TF-IDF	50	500	0.820	0.913	0.771
AVG-W2V	5	5	0.811	0.822	0.749
TFIDF-W2V	10	500	0.792	0.846	0.731

1. from the above table we can observe that the optimal performance is give by:

```
a. BoW vectorizer
b. f1-score=.779 and auc=.828
```

In [ ]:
```

```