Assignment-8: Apply Decision Tree On Amazon Fine Food Reviews DataSet ¶

Introduction

(i).A decision tree is a flowchart-like structure in which each internal node represents a “test” on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules.

Objective

To Predict the Polarity of Amazon Fine Food Review Using Decision Tree Algorithm.

Importing All Required Library

In [38]:
```
%matplotlib inline
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
import math

from sklearn.model_selection import GridSearchCV
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import classification_report
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import TimeSeriesSplit

from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import cross_val_score
from sklearn import preprocessing
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score

from gensim.models import Word2Vec
from gensim.models import KeyedVectors


import pickle


from tqdm import tqdm
import os
import warnings
warnings.filterwarnings("ignore")
```

Importing Amazon Fine Food Review Dataset

In [39]:
```
if os.path.isfile("final.sqlite"):
    conn=sqlite3.connect("final.sqlite")
    Data=pd.read_sql_query("select * from Reviews where Score!=3",conn)
    conn.close()
else :
    print("Error Importing the file")
```

In [40]:
```
# Printing some data of DataFrame

Data['Score'].value_counts()
```

Out[40]:
```
1    307061
0     57110
Name: Score, dtype: int64
```

Information About DataSet

In [41]:
```
print("\nNumber of Reviews: ",Data["Text"].count())
print("\nNumber of Users: ",len(Data["UserId"].unique())) # Unique returns 1-D
array of unique values of DataFrame.
print("\nNumber of Products: ",len(Data["ProductId"].unique()))
print("\nShape of Data: ", Data.shape)
print("\nColumn Name of DataSet : ",Data.columns)
print("\n\nNumber of Attributes/Columns in data: 12")
print("\nNumber of Positive Reviews : ", Data['Score'].value_counts()[1])
print("\nNumber of Negative Reviews : ", Data['Score'].value_counts()[0])
```

```
Number of Reviews:  364171

Number of Users:  243414

Number of Products:  65442

Shape of Data:  (364171, 12)

Column Name of DataSet :  Index(['index', 'Id', 'ProductId', 'UserId', 'Profi
leName',
       'HelpfulnessNumerator', 'HelpfulnessDenominator', 'Score', 'Time',
       'Summary', 'Text', 'CleanedText'],
      dtype='object')


Number of Attributes/Columns in data: 12

Number of Positive Reviews :  307061

Number of Negative Reviews :  57110
```

In [42]:
```
print("\nNumber of Reviews: ",Data["Text"].count())
```

```
Number of Reviews:  364171
```

Attribute Information About DataSet

1.Id - A unique value starts from 1

2.ProductId - A unique identifier for the product

3.UserId - A unqiue identifier for the user

4.ProfileName - Name of user profile

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 0 or 1

8.Time - Timestamp for the review

9.Summary - Brief summary of the review

10.Text - Text of the review

11.Cleaned Text - Text that only alphabets

In [43]:
```
# Sorting on the basis of Time Parameter
Data.sort_values('Time',inplace=True)
```

In [44]:
```
Data=Data.head(100000)
```

In [45]:
```
Y = Data['Score']
X = Data['CleanedText']
```

Splitting DataSet into Train and Test Data

In [46]:
```
from sklearn.model_selection import train_test_split
# X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33, sh
uffle=Flase): this is for time series split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.33,shuff
le=False) # this is random splitting

print("Shape of Train and Test Dataset for 100k points")
print(X_train.shape, Y_train.shape)
print(X_test.shape, Y_test.shape)
```

```
Shape of Train and Test Dataset for 100k points
(67000,) (67000,)
(33000,) (33000,)
```

Defining Some Function

Train Data Confusion Matrix Plot

In [47]:
```
def trainconfusionmatrix(model,X_train,y_train):
    print("Confusion Matrix for Train set")
    cm=confusion_matrix(y_train, model.predict(X_train))
    class_label = ["negative", "positive"]
    df_cm = pd.DataFrame(cm, index = class_label, columns = class_label)
    sns.heatmap(df_cm, annot = True, fmt = "d")
    plt.title("Train Confusiion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
```

Test Data Confusion Matrix Plot

In [48]:
```
def testconfusionmatrix(model,X_test,y_test):
    print("Confusion Matrix for Test set")
    cm=confusion_matrix(y_test, model.predict(X_test))
    class_label = ["negative", "positive"]
    df_cm = pd.DataFrame(cm, index = class_label, columns = class_label)
    sns.heatmap(df_cm, annot = True, fmt = "d")
    plt.title("Test Confusiion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
```

ROC-AUC Curve

In [49]:
```
def plot_auc_roc(model,X_train,X_test,y_train,y_test):
    train_fpr, train_tpr, thresholds = roc_curve(y_train,model.predict_proba(X
_train)[:,1])
    test_fpr, test_tpr, thresholds = roc_curve(y_test,model.predict_proba(X_te
st)[:,1])

    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, trai
n_tpr)))
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr
)))
    plt.legend()
    plt.xlabel("Hyperameter (C)")
    plt.ylabel("AUC")
    plt.title("ROC CURVE PLOTS")
    plt.show()
```

Plot

In [50]:
```
def plot(gsv):
    res=gsv.cv_results_
    cv_data=res['mean_test_score']
    train_data=res['mean_train_score']
    depth=[1, 1, 1, 1, 5, 5, 5, 5, 10, 10, 10, 10, 50, 50, 50, 50,
                    100, 100, 100, 100, 500, 500, 500, 500, 1000, 1000,
                    1000, 1000]


    plt.xlabel("Hyperparameter (Max_Depth)",fontsize=15)
    plt.ylabel("Mean_Score",fontsize=15)
    plt.title('Mean Score v/s Max_Depth',fontsize=15)
    plt.plot(depth,cv_data,label="Cross-Validation")
    plt.plot(depth,train_data,label="Train")
    plt.legend()
    plt.show()
```

GridSearchCV

In [51]:
```
def Grid_SearchCV(X_train,Y_train):

    param_grid= {'max_depth':[1,5,10,50,100,500,1000],
                 'min_samples_split':[5,10,100,500]
                }
    tscv = TimeSeriesSplit(n_splits=10)
    clf = DecisionTreeClassifier(class_weight='balanced')
    gsv=GridSearchCV(clf,param_grid, scoring = 'roc_auc', cv=tscv,n_jobs=-1,pr
e_dispatch=2)
    gsv.fit(X_train,Y_train)

    return gsv
```

30 Informative Feature

In [52]:
```
def show_30_informative_feature(vectorizer,model,n=30):


    Weights_Index = model.feature_importances_.argsort()
    length = len(Weights_Index)
    # For Negative Class
    neg_class=Weights_Index[:n]

    neg_feat=[vectorizer.get_feature_names()[x] for x in neg_class]
    neg_prob=[Weights_Index[x] for x in neg_class]

    neg_zip=list(zip(neg_feat,neg_prob))
    neg_zip.sort()

    # For Positive Class
    pos_class =  Weights_Index[-30:]

    pos_feat=[vectorizer.get_feature_names()[x] for x in pos_class]
    pos_prob=[Weights_Index[x] for x in pos_class]
    pos_zip=list(zip(pos_feat,pos_prob))
    pos_zip.sort()

    top=zip(pos_zip,neg_zip)

    print("{0:20}{1:55}{2:20}".format("S.N","Positive","Negative"))
    print("_"*90)
    i=1
    for (fn_1,coef_1), (fn_2,coef_2) in top:
        print("%d.\t\t%.3f\t%-30s\t\t%.3f\t%s" % (i,coef_1, fn_1, coef_2, fn_2
))
        i+=1
```

Bags of Words Vectorizer

In [17]:
```
vectorizer = CountVectorizer()
vectorizer.fit(X_train) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_bow = vectorizer.transform(X_train)
X_train_bow=preprocessing.normalize(X_train_bow)

X_test_bow = vectorizer.transform(X_test)
X_test_bow=preprocessing.normalize(X_test_bow)

print("Shape of Train and Test Data After vectorizations")
print(X_train_bow.shape, Y_train.shape)
print(X_test_bow.shape, Y_test.shape)
```

```
Shape of Train and Test Data After vectorizations
(67000, 30737) (67000,)
(33000, 30737) (33000,)
```

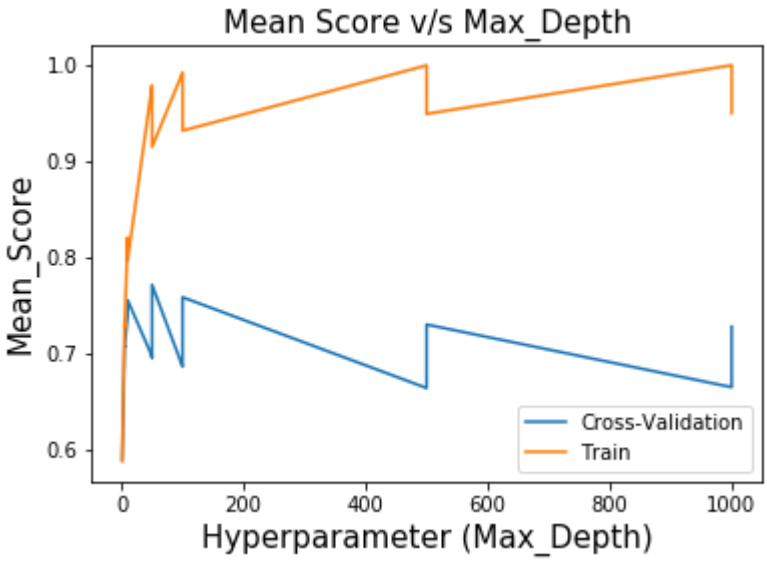
Finding the best value Of hyperparameter (Alpha)

In [18]:
```
gsv=Grid_SearchCV(X_train_bow,Y_train)

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'max_depth': 50, 'min_samples_split': 500}
Best Accuracy: 77.10%
```

Plot

In [19]:
```
plot(gsv)
```



Training the model

In [60]:
```
Best_Param=gsv.best_params_
depth=Best_Param['max_depth']
min_sample_split = Best_Param['min_samples_split']

Model_Bow=DecisionTreeClassifier(max_depth=depth,min_samples_split=min_sample_
split,class_weight="balanced")
Model_Bow.fit(X_train_bow,Y_train)
```

Out[60]:
```
DecisionTreeClassifier(class_weight='balanced', criterion='gini',
            max_depth=10, max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=500,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

In [44]:
```
from sklearn.externals import joblib
joblib.dump(Model_Bow,"BOW_Model.pkl")
```

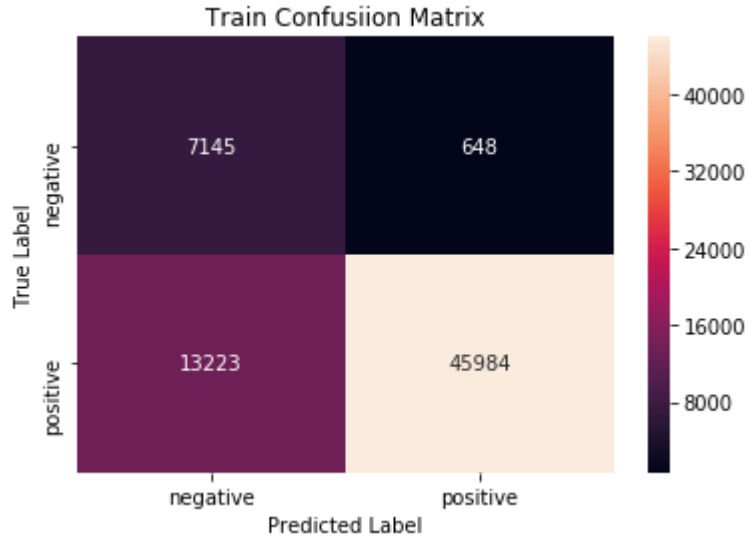
Out[44]: ['BOW_Model.pkl']

In [18]:
```
from sklearn.externals import joblib
Model_Bow=joblib.load("BOW_Model.pkl")
```

Evaluating the performance of model

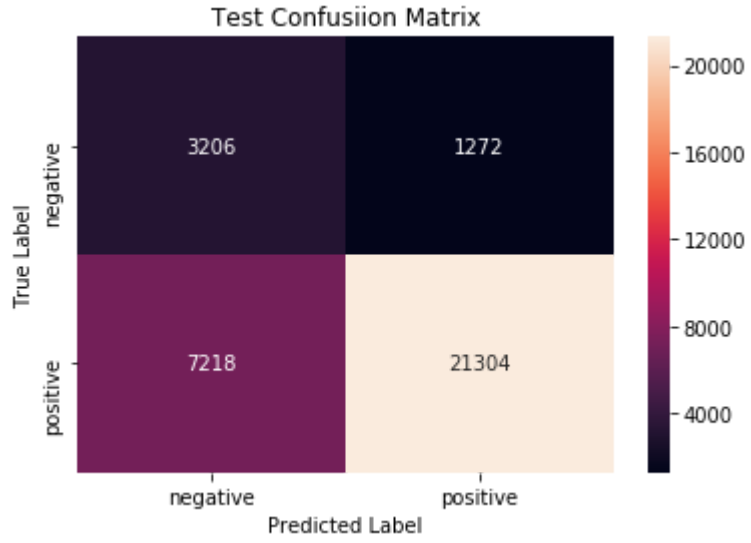
In [19]:
```
trainconfusionmatrix(Model_Bow,X_train_bow,Y_train)
```

```
Confusion Matrix for Train set
```

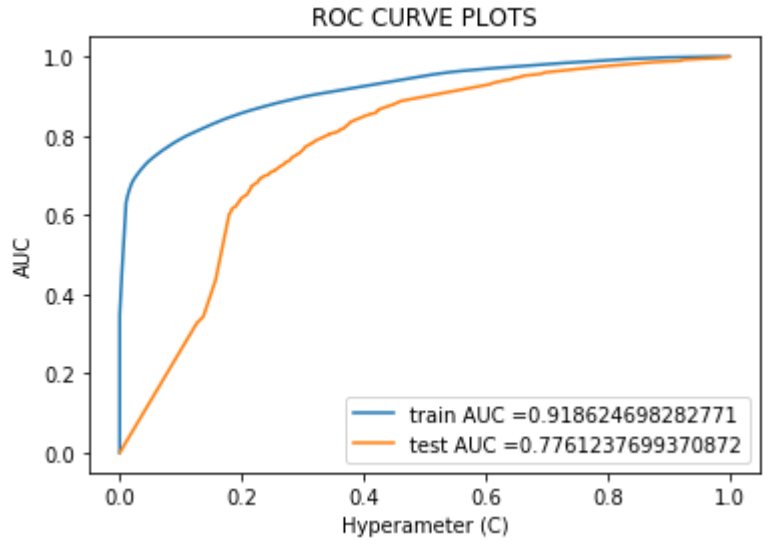


In [20]:
```
testconfusionmatrix(Model_Bow,X_test_bow,Y_test)
```

```
Confusion Matrix for Test set
```



In [21]:
```
plot_auc_roc_L(Model_Bow,X_train_bow,X_test_bow,Y_train,Y_test)
```



In [24]:
```
print("Classification Report: \n")
y_pred=Model_Bow.predict(X_test_bow)

print(classification_report(Y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.31      0.72      0.43      4478
           1       0.94      0.75      0.83     28522

   micro avg       0.74      0.74      0.74     33000
   macro avg       0.63      0.73      0.63     33000
weighted avg       0.86      0.74      0.78     33000
```

Displaying 30 most informative features

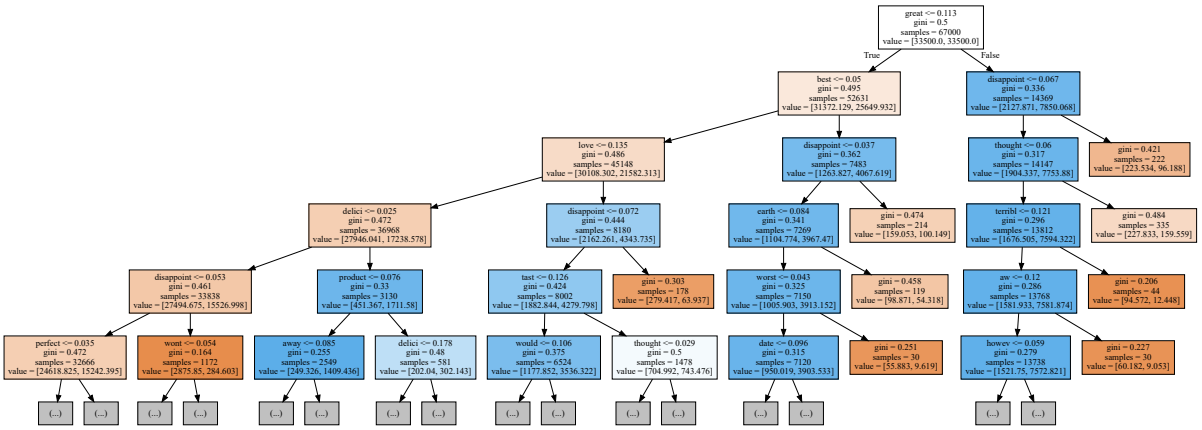
In [31]:
```
show_30_informative_feature(vectorizer,Model_Bow)
```

S.N	Positive		Negative
1.	19621.000	aw	0.000
aaa			
2.	19612.000	away	190.000
pkgs			
3.	19738.000	bad	189.000
pkirk			
4.	22766.000	best	188.000
pks			
5.	17382.000	delici	187.000
pkt			
6.	17892.000	disappoint	186.000
pkts			
7.	28778.000	easi	185.000
pku			
8.	27298.000	enjoy	184.000
pkwi			
9.	27608.000	excel	183.000
pla			
10.	30096.000	favorit	182.000
placat			
11.	30171.000	find	181.000
place			
12.	29401.000	good	180.000
placebo			
13.	24408.000	great	205.000
placement			
14.	23137.000	howev	206.000
placer			
15.	25386.000	keep	207.000
plack			
16.	5666.000	love	208.000
plactic			
17.	3968.000	mayb	234.000
plaesant			
18.	7149.000	money	233.000
plagu			
19.	6104.000	nice	232.000
plain			
20.	1629.000	perfect	231.000
plainer			
21.	3267.000	product	230.000
plak			
22.	13943.000	tast	229.000
plan			
23.	13929.000	tasti	228.000
plancha			
24.	9132.000	terribl	227.000
planck			
25.	8873.000	thought	226.000
plane			
26.	8297.000	unfortun	225.000
planet			
27.	10892.000	use	224.000

```
00      planetari
28.             10306.000       wonder                                  223.0
00      planett
29.             10371.000       worst                                   179.0
00      planetwond
30.             10169.000       would                                   222.0
00      plank
```

In [25]:
```
from sklearn.tree import export_graphviz
import graphviz

export_graphviz(Model_Bow,out_file="BOW.dot",feature_names=vectorizer.get_feat
ure_names(),filled=True,max_depth=5)
with open("BOW.dot") as f:
    dot_graph=f.read()
graphviz.Source(dot_graph)
```

Out[25]:



In [66]:
```
import os
os.environ["PATH"] += os.pathsep + 'C:/Program Files (x86)/Graphviz2.38/bin/'
```

TF-IDF Vectorizer

In [53]:
```
vectorizer_tfidf=TfidfVectorizer()
vectorizer_tfidf.fit(X_train)
```

Out[53]:
```
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.float64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), norm='l2', preprocessor=None, smooth_idf=True,
        stop_words=None, strip_accents=None, sublinear_tf=False,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, use_idf=True,
        vocabulary=None)
```

In [54]:
```
X_Train_Tfidf=vectorizer_tfidf.transform(X_train)
X_Train_Tfidf=preprocessing.normalize(X_Train_Tfidf)

X_Test_Tfidf=vectorizer_tfidf.transform(X_test)
X_Test_Tfidf=preprocessing.normalize(X_Test_Tfidf)
```

In [55]:
```
print("Shape of Train and Test Data After vectorizations")
print(X_Train_Tfidf.shape, Y_train.shape)
print(X_Test_Tfidf.shape, Y_test.shape)
```

```
Shape of Train and Test Data After vectorizations
(67000, 30737) (67000,)
(33000, 30737) (33000,)
```

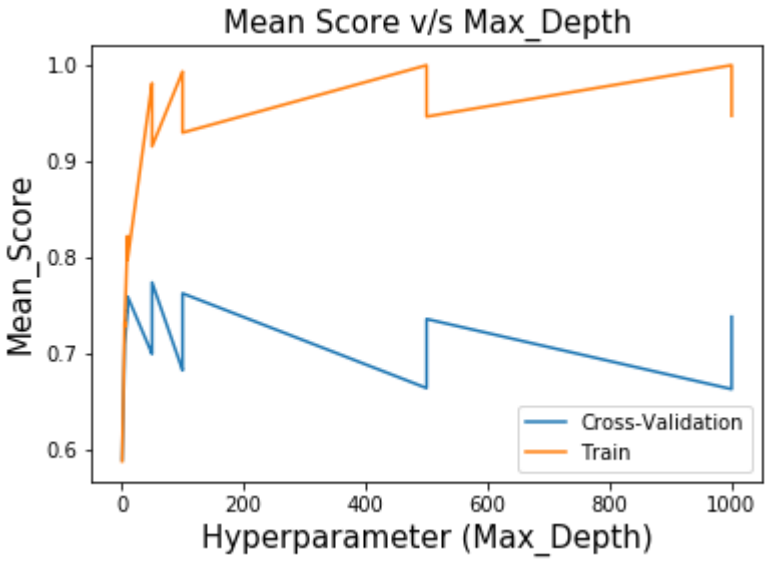
Finding the best value Of hyperparameter (Alpha)

In [56]:
```
gsv=Grid_SearchCV(X_Train_Tfidf,Y_train)

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'max_depth': 50, 'min_samples_split': 500}
Best Accuracy: 77.41%
```

Plot

In [57]:
```
plot(gsv)
```



Training the model

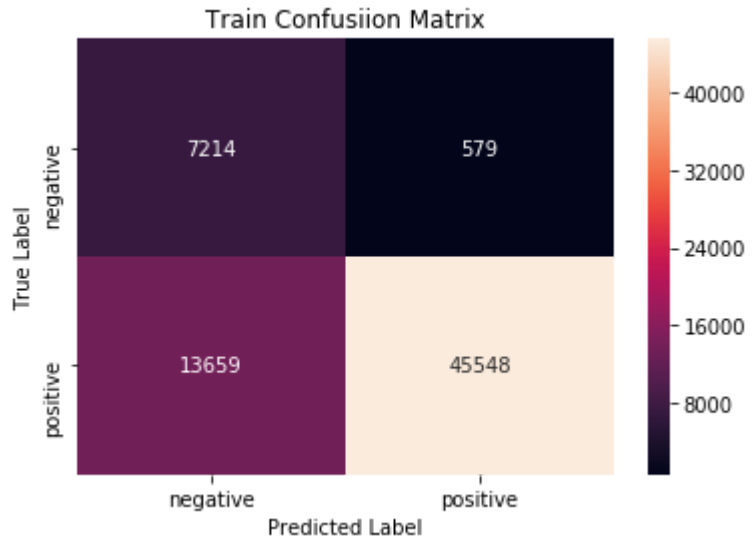
In [58]:
```
Best_Param=gsv.best_params_
depth=Best_Param['max_depth']
min_sample_split = Best_Param['min_samples_split']

Model_Tfidf=DecisionTreeClassifier(max_depth=depth,min_samples_split=min_sampl
e_split,class_weight="balanced")
Model_Tfidf.fit(X_Train_Tfidf,Y_train)
```

Out[58]:
```
DecisionTreeClassifier(class_weight='balanced', criterion='gini',
            max_depth=50, max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=500,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

Evaluating the performance of model

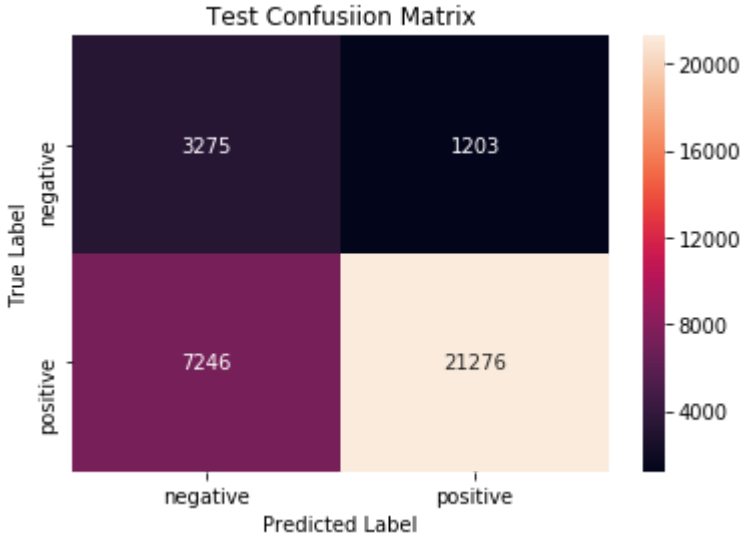
In [59]:
```
trainconfusionmatrix(Model_Tfidf,X_Train_Tfidf,Y_train)
```

```
Confusion Matrix for Train set
```

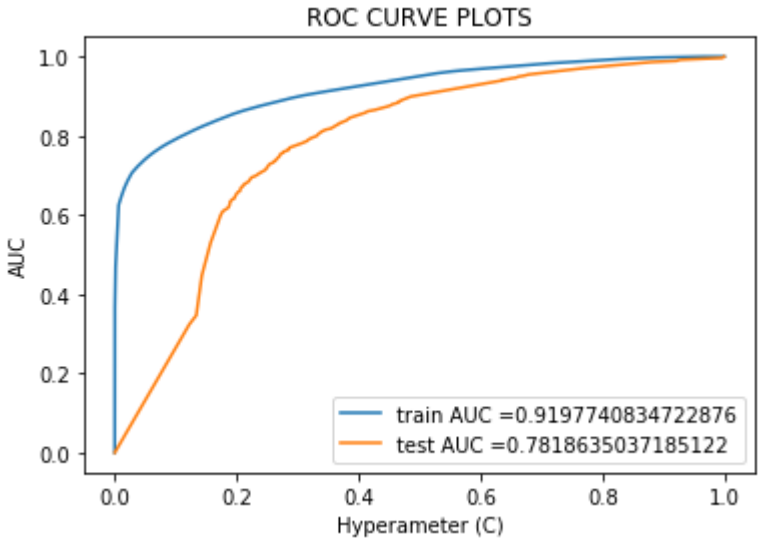


In [60]:
```
testconfusionmatrix(Model_Tfidf,X_Test_Tfidf,Y_test)
```

```
Confusion Matrix for Test set
```



In [62]:
```
plot_auc_roc(Model_Tfidf,X_Train_Tfidf,X_Test_Tfidf,Y_train,Y_test)
```



In [63]:
```
print("Classification Report: \n")
y_pred=Model_Tfidf.predict(X_Test_Tfidf)

print(classification_report(Y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.31      0.73      0.44      4478
           1       0.95      0.75      0.83     28522

   micro avg       0.74      0.74      0.74     33000
   macro avg       0.63      0.74      0.64     33000
weighted avg       0.86      0.74      0.78     33000
```

Displaying 30 most informative features

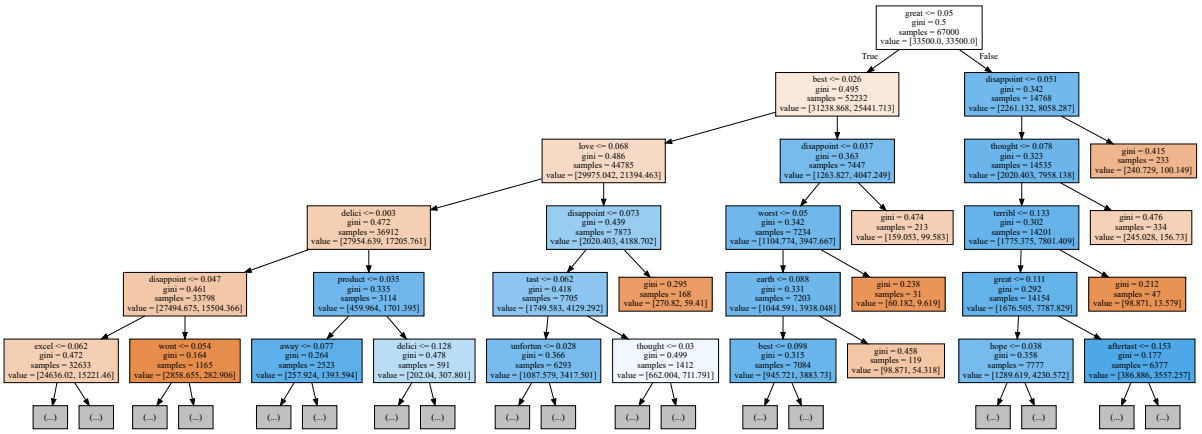
In [64]:
```
show_30_informative_feature(vectorizer_tfidf,Model_Tfidf)
```

S.N	Positive		Negative
1.	20573.000	alway	0.000
aaa			
2.	20606.000	amaz	185.000
pix			
3.	19609.000	aw	184.000
pixar			
4.	19600.000	away	183.000
pixi			
5.	19726.000	bad	182.000
pizaaz			
6.	22758.000	best	207.000
pizazz			
7.	17364.000	delici	208.000
pizel			
8.	17870.000	disappoint	209.000
pizell			
9.	28703.000	easi	210.000
pizza			
10.	27349.000	enjoy	237.000
pizzaz			
11.	27608.000	excel	236.000
pizzazz			
12.	30083.000	favorit	235.000
pizzeria			
13.	29855.000	find	234.000
pizzl			
14.	29478.000	good	232.000
pjs			
15.	24406.000	great	231.000
pjtip			
16.	23775.000	howev	230.000
pkg			
17.	25293.000	keep	229.000
pkgd			
18.	5625.000	love	228.000
pkgs			
19.	6076.000	nice	227.000
pkirk			
20.	1576.000	perfect	226.000
pks			
21.	3307.000	product	225.000
pkt			
22.	13963.000	tast	181.000
pkts			
23.	13949.000	tasti	224.000
pku			
24.	9115.000	terribl	222.000
pkwi			
25.	9529.000	thought	221.000
pla			
26.	8339.000	unfortun	220.000
placat			
27.	10792.000	use	219.000

```
00      place
28.             10400.000       wonder                                  218.0
00      placebo
29.             10161.000       worst                                   217.0
00      placement
30.             10187.000       would                                   216.0
00      placer
```

In [67]:
```
from sklearn.tree import export_graphviz
import graphviz

export_graphviz(Model_Tfidf,out_file="Tfidf.dot",feature_names=vectorizer_tfid
f.get_feature_names(),filled=True,max_depth=5)
with open("Tfidf.dot") as f:
    dot_graph=f.read()
graphviz.Source(dot_graph)
```

Out[67]:



Word To Vector

In [17]:
```
list_of_Train_sent=[]
list_of_Test_sent=[]

for sent in X_train:
    list_of_Train_sent.append(sent.split())

for sent in X_test:
    list_of_Test_sent.append(sent.split())
```

In [18]:
```
model=Word2Vec(list_of_Train_sent,min_count=5,size=50, workers=4)
```

Average Word To Vector

In [49]:
```
import numpy as np

Train_vectors = []
for sent in list_of_Train_sent:
    sent_vec = np.zeros(50)
    cnt_words = 0
    for word in sent:
        try:
            vec = model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    if cnt_words!=0:
        sent_vec /= cnt_words
    Train_vectors.append(sent_vec)
Train_vectors = np.nan_to_num(Train_vectors)
```

In [50]:
```
import numpy as np

Test_vectors=[]
for sent in list_of_Test_sent:
    sent_vec=np.zeros(50)
    cnt_words=0
    for word in sent:
        try:
            vec=model.wv[word]
            sent_vec+=vec
            cnt_words+=1
        except:
            pass
    if cnt_words!=0:
        sent_vec/=cnt_words
    Test_vectors.append(sent_vec)
Test_vectors=np.nan_to_num(Test_vectors)
```

In [51]:
```
print("Shape of Test Vectors : ",Test_vectors.shape)
```

```
Shape of Test Vectors :  (33000, 50)
```

In [52]:
```
X_Train_Awv=Train_vectors
X_Test_Awv=Test_vectors
```

In [53]:
```
print(X_Train_Awv.shape, Y_train.shape)
print(X_Test_Awv.shape, Y_test.shape)
```

```
(67000, 50) (67000,)
(33000, 50) (33000,)
```

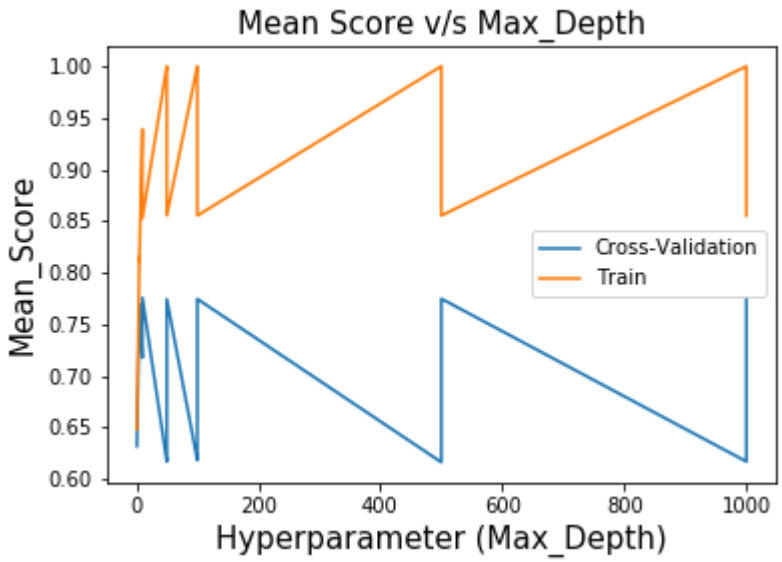
Finding the best value Of hyperparameter (Alpha)

In [54]:
```
gsv=Grid_SearchCV(X_Train_Awv,Y_train)

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'max_depth': 10, 'min_samples_split': 500}
Best Accuracy: 77.57%
```

Plot

In [55]:
```
plot(gsv)
```



Training Model

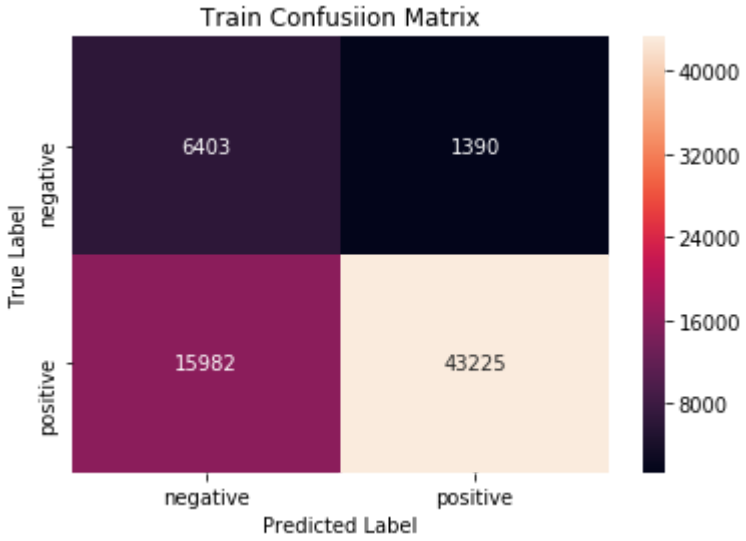
In [61]:
```
Best_Param=gsv.best_params_
depth=Best_Param['max_depth']
min_sample_split = Best_Param['min_samples_split']

Model_Awv=DecisionTreeClassifier(max_depth=depth,min_samples_split=min_sample_
split,class_weight="balanced")
Model_Awv.fit(X_Train_Awv,Y_train)
```

Out[61]:
```
DecisionTreeClassifier(class_weight='balanced', criterion='gini',
            max_depth=10, max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=500,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

Evaluating the performance of model

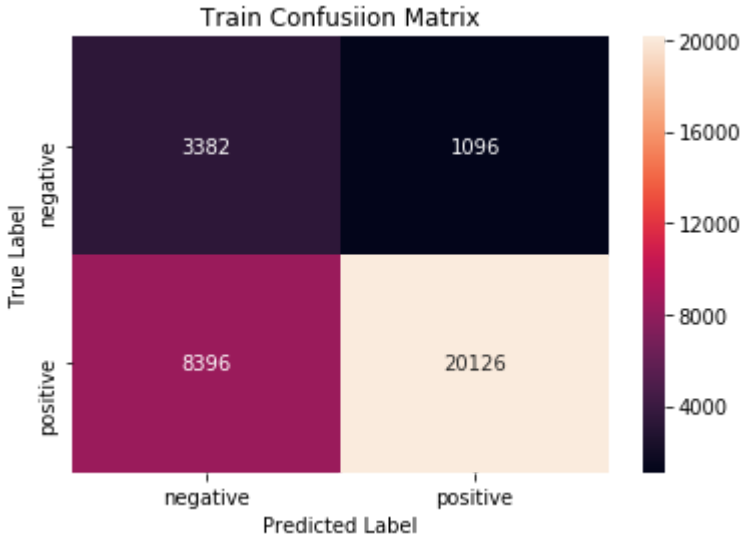
In [62]:
```
trainconfusionmatrix(Model_Awv,X_Train_Awv,Y_train)
```

Confusion Matrix for Train set

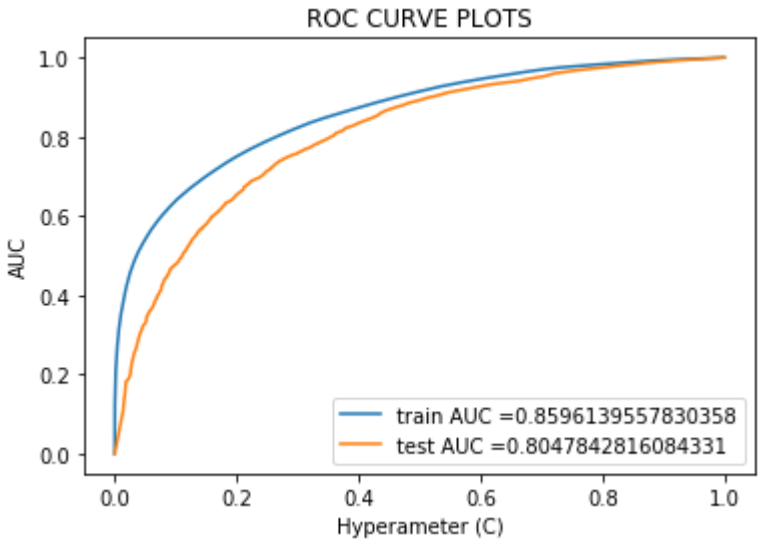


In [63]:
```
trainconfusionmatrix(Model_Awv,X_Test_Awv,Y_test)
```

Confusion Matrix for Train set



In [64]:
```
plot_auc_roc_L(Model_Awv,X_Train_Awv,X_Test_Awv,Y_train,Y_test)
```

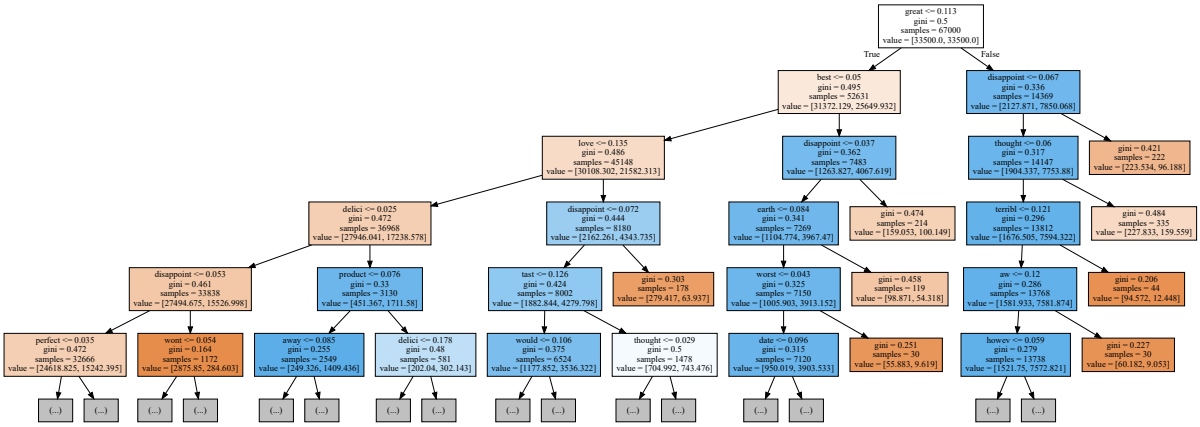


In [65]:
```
print("Classification Report: \n")
y_pred=Model_Awv.predict(X_Test_Awv)

print(classification_report(Y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.29      0.76      0.42      4478
           1       0.95      0.71      0.81     28522

   micro avg       0.71      0.71      0.71     33000
   macro avg       0.62      0.73      0.61     33000
weighted avg       0.86      0.71      0.76     33000
```

In [66]:
```
from sklearn.tree import export_graphviz
import graphviz

export_graphviz(Model_Awv,out_file="W2V.dot",feature_names=model.get_feature_n
ames(),filled=True,max_depth=5)
with open("W2V.dot") as f:
    dot_graph=f.read()
graphviz.Source(dot_graph)
```

Out[66]:



TF-IDF Word To Vector

In [19]:
```
TFIDF_Feature=vectorizer_tfidf.get_feature_names()
print(len(TFIDF_Feature))
print(TFIDF_Feature[0:20])
```

```
30737
['aaa', 'aaaaaaaaagghh', 'aaaaah', 'aaaaahhhhhhhhhhhhhhhh', 'aaaah', 'aaah',
'aachen', 'aad', 'aadp', 'aafco', 'aagh', 'aah', 'aahh', 'aand', 'aardvark',
'ab', 'aback', 'abandon', 'abaolut', 'abattoir']
```

In [20]:
```
w2v_words = list(model.wv.vocab)
print("Number of words that occured minimum 5 times ",len(w2v_words))
print("Sample words ", w2v_words[0:50])
```

```
Number of words that occured minimum 5 times  10488
Sample words  ['witti', 'littl', 'book', 'make', 'son', 'laugh', 'loud', 'ca
r', 'drive', 'along', 'alway', 'sing', 'refrain', 'hes', 'learn', 'whale', 'i
ndia', 'droop', 'love', 'new', 'word', 'introduc', 'silli', 'classic', 'wil
l', 'bet', 'still', 'abl', 'memori', 'colleg', 'rememb', 'see', 'show', 'ai
r', 'televis', 'year', 'ago', 'child', 'sister', 'later', 'bought', 'day', 't
hirti', 'someth', 'use', 'seri', 'song', 'student', 'teach', 'preschool']
```

In [21]:
```
from tqdm import tqdm
Train_TFIDF_W2V_Vectors=[]
row=0
for sent in tqdm(list_of_Train_sent):
    sent_vec=np.zeros(50)
    weight=0
    for word in sent:
        try :
            if word in TFIDF_Feature and word in w2v_words:

                w2v_vec=model.wv[word]
                tfidf_vec=X_Train_Tfidf[row,TFIDF_Feature.index(word)]
                sent_vec+=(w2v_vec*tfidf_vec)
                weight+=tfidf_vec

        except :
            pass
    if weight!=0:
        sent_vec/=weight
    Train_TFIDF_W2V_Vectors.append(sent_vec)
    row+=1
```

```
100%|████████████████████████████████████| 67000/67000 [25:17<00:00, 44.15it/
s]
```

In [22]:
```
Test_TFIDF_W2V_Vectors=[]
row=0
for sent in tqdm(list_of_Test_sent):
    sent_vec=np.zeros(50)
    weight=0

    for word in sent:
        try:
             if word in TFIDF_Feature and word in w2v_words:

                w2v_vec=model.wv[word]
                tfidf_vec=X_Test_Tfidf(row,TFIDF_Feature.index(word))
                sent_vec+=(w2v_vec*tfidf_vec)
                weight+=tfidf

        except :
            pass

    if weight!=0:
        sent_vec/=weight
    Test_TFIDF_W2V_Vectors.append(sent_vec)
    row+=1
```

```
100%|████████████████████████████████████| 33000/33000 [12:57<00:00, 42.42it/
s]
```

In [23]:
```
Train_TFIDF_W2V_Vectors = np.nan_to_num(Train_TFIDF_W2V_Vectors)
Test_TFIDF_W2V_Vectors = np.nan_to_num(Test_TFIDF_W2V_Vectors)
```

In [24]:
```
X_Train_TfidfW2v=Train_TFIDF_W2V_Vectors
X_Test_TfidfW2v=Test_TFIDF_W2V_Vectors
```

In [25]:
```
print(X_Train_TfidfW2v.shape, Y_train.shape)
print(X_Test_TfidfW2v.shape, Y_test.shape)
```

```
(67000, 50) (67000,)
(33000, 50) (33000,)
```

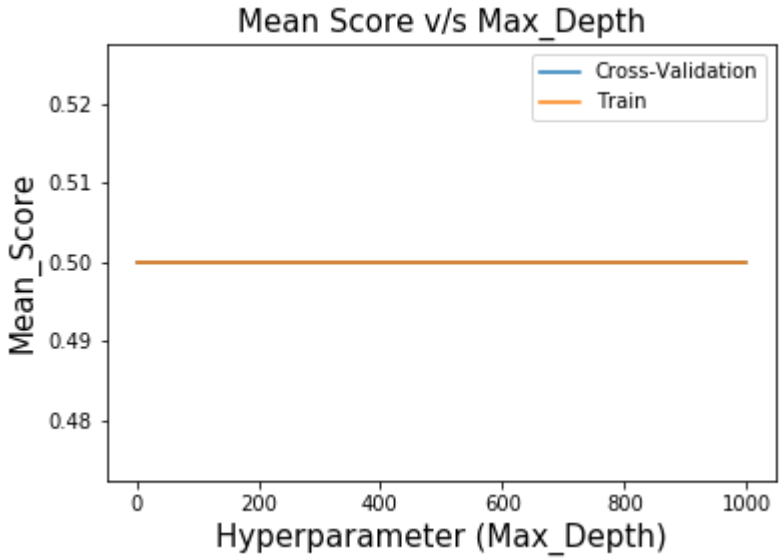
Finding the best value Of hyperparameter (Alpha)

In [26]:
```
gsv=Grid_SearchCV(X_Train_TfidfW2v,Y_train)

print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
Best HyperParameter:  {'max_depth': 1, 'min_samples_split': 5}
Best Accuracy: 50.00%
```

Plot

In [27]:
```
plot(gsv)
```



Training Model

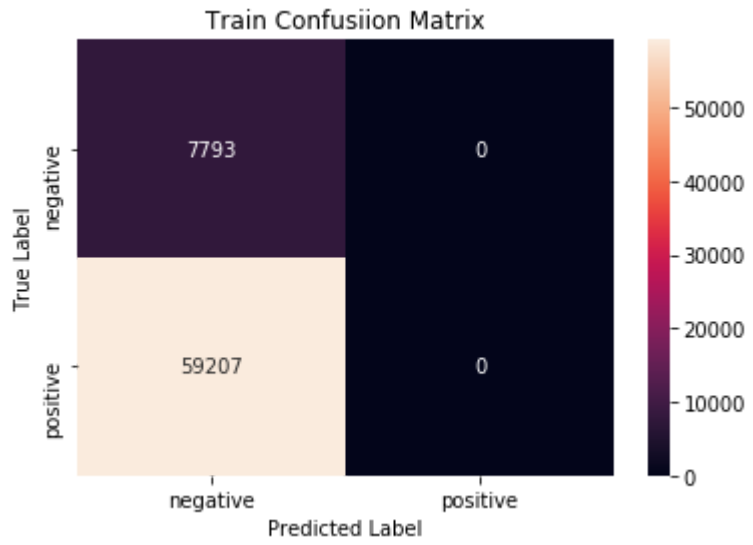
In [29]:
```
Best_Param=gsv.best_params_
depth=Best_Param['max_depth']
min_sample_split = Best_Param['min_samples_split']

Model_TfidfW2v=DecisionTreeClassifier(max_depth=depth,min_samples_split=min_sa
mple_split,class_weight="balanced")
Model_TfidfW2v.fit(X_Train_TfidfW2v,Y_train)
```

Out[29]:
```
DecisionTreeClassifier(class_weight='balanced', criterion='gini', max_depth=
1,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=5,
                       min_weight_fraction_leaf=0.0, presort=False, random_state=None,
                       splitter='best')
```

Evaluating the performance of model

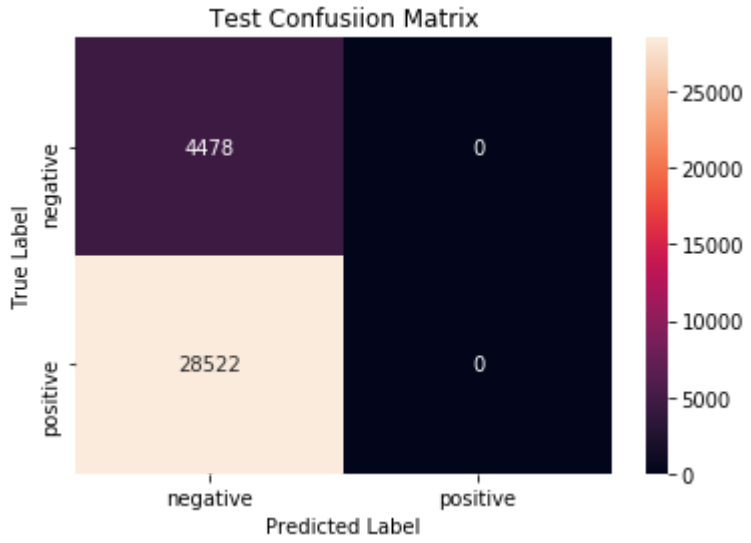
In [30]:
```
trainconfusionmatrix(Model_TfidfW2v,X_Train_TfidfW2v,Y_train)
```

```
Confusion Matrix for Train set
```

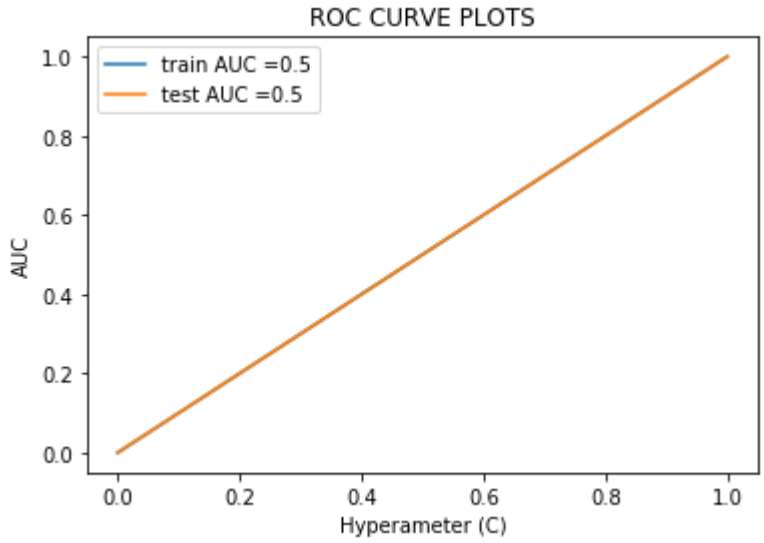


In [31]:
```
testconfusionmatrix(Model_TfidfW2v,X_Test_TfidfW2v,Y_test)
```

```
Confusion Matrix for Test set
```



In [34]:
```
plot_auc_roc(Model_TfidfW2v,X_Train_TfidfW2v,X_Test_TfidfW2v,Y_train,Y_test)
```



In [35]:
```
print("Classification Report: \n")
y_pred=Model_TfidfW2v.predict(X_Test_TfidfW2v)

print(classification_report(Y_test, y_pred))
```

```
Classification Report:

              precision    recall  f1-score   support

           0       0.14      1.00      0.24      4478
           1       0.00      0.00      0.00     28522

   micro avg       0.14      0.14      0.14     33000
   macro avg       0.07      0.50      0.12     33000
weighted avg       0.02      0.14      0.03     33000
```

Conclusion :

1. Report On different Vectorizer method.

In [1]:
```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Vectorizer", "Hyperparameter(Max_Depth)","Hyperparameter(Min
_Samples_Split)","Train AUC","Test AUC","F1-Score"]

x.add_row(["BOW",50,500,0.91,0.76,0.78])
x.add_row(["TF-IDF",50,500,0.91,0.78,0.78])
x.add_row(["Avg W2V",10,500,0.85,0.80,0.76])
x.add_row(["TF-IDF W2V",1,5,0.5,0.5,0.03])

print(x)
```

```
+------------+--------------------------+----------------------------------
+-----------+----------+----------+
| Vectorizer | Hyperparameter(Max_Depth) | Hyperparameter(Min_Samples_Split)
| Train AUC | Test AUC | F1-Score |
+------------+--------------------------+----------------------------------
+-----------+----------+----------+
|    BOW     |             50           |               500
|    0.91    |   0.76   |   0.78   |
|   TF-IDF   |             50           |               500
|    0.91    |   0.78   |   0.78   |
|  Avg W2V   |             10           |               500
|    0.85    |   0.8    |   0.76   |
| TF-IDF W2V |             1            |                5
|    0.5     |   0.5    |   0.03   |
+------------+--------------------------+----------------------------------
+-----------+----------+----------+
```

1. I have taken 100k points .

1. Model is performing very good in case of Average Word to Vector than others.

1. In case of TF-IDF W2V model is behaving like a dumb model.