OBJECTIVE :

1. APPLYING DECISION TREE WITH TFIDF_AVG_WORD_2_VEC VECTORIZATION
   - FINDING THE BEST HYPERPARAMETER USING GRIDSEARCHCV WITH TRAIN DATA AND CROSS-VALIDATION DATA BY PLOTTING THE RESLUTS OF VAROIUS TRAIN DATA AND CROSS VALIDATION DATA
   - USING THE APROPRIATE VALUE OF HYPERPARAMETER ,TESTING ACCURACY ON TEST DATA USING F1-SCORE
   - PLOTTING THE CONFUSION MATRIX TO GET THE PRECISOIN ,RECALL VALUE WITH HELP OF HEATMAP #

In [0]:

```
from sklearn.model_selection import train_test_split          #importin
g the necessary libraries
from sklearn.model_selection import RandomizedSearchCV
from sklearn.datasets import *
from sklearn import naive_bayes
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
import numpy as np
import pandas as pd
from sklearn import *
import warnings
warnings.filterwarnings("ignore")
from sklearn.tree import DecisionTreeClassifier
from gensim.models import Word2Vec
from tqdm import tqdm
```

In [2]:

```
from google.colab import drive
drive.mount('/content/gdrive')#geeting the content from the google driv
e
```

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

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

In [4]:
```
# getting the counts of 0 and 1 in "SCORE" column to know whether it is
 unbalanced data or not
count_of_1=0
count_of_0=0
for i in final_processed_data['Score']:
   if i==1:
    count_of_1+=1
   else:
    count_of_0+=1
print(count_of_1)
print(count_of_0)
#it is an imbalanced dataset
```

```
88521
11479
```

In [0]:
```
#spliiting the data into train and test data
x_train,x_test,y_train,y_test=model_selection.train_test_split(final_pr
ocessed_data['CleanedText'].values,final_processed_data['Score'].values
,test_size=0.2,shuffle=False)
```

In [6]:
```
# Training my own Word2Vec model using your own text corpus
list_of_sent=[]
for sent in x_train:
 list_of_sent.append(sent.split())#splitting of sentences into words AN
D appending them to list
print(x_train[0])
print("*****************************************************************
*")
print(list_of_sent[0])
word_to_vector=Word2Vec(list_of_sent,min_count=5,size=100,workers=2)#co
nstructing my our word to vector
w_t_c_words=list(word_to_vector.wv.vocab)
print("*****************************************************************
```

```
*******")
print("sample words ", w_t_c_words[0:50])
```

```
witti littl book make son laugh loud recit car drive along alway sing r
efrain hes learn whale india droop love new word book introduc silli cl
assic book will bet son still abl recit memori colleg
*****************************************************************
['witti', 'littl', 'book', 'make', 'son', 'laugh', 'loud', 'recit', 'ca
r', 'drive', 'along', 'alway', 'sing', 'refrain', 'hes', 'learn', 'whal
e', 'india', 'droop', 'love', 'new', 'word', 'book', 'introduc', 'sill
i', 'classic', 'book', 'will', 'bet', 'son', 'still', 'abl', 'recit',
'memori', 'colleg']
***********************************************************************
sample words  ['witti', 'littl', 'book', 'make', 'son', 'laugh', 'lou
d', 'car', 'drive', 'along', 'alway', 'sing', 'refrain', 'hes', 'lear
n', 'india', 'droop', 'love', 'new', 'word', 'introduc', 'silli', 'clas
sic', 'will', 'bet', 'still', 'abl', 'memori', 'colleg', 'rememb', 'se
e', 'show', 'air', 'televis', 'year', 'ago', 'child', 'sister', 'late
r', 'bought', 'day', 'thirti', 'someth', 'use', 'seri', 'song', 'studen
t', 'teach', 'preschool', 'turn']
```

In [7]:

```
###### NOW STARTING TFIDF WORD TO VEC FOR TRAIN DATA###################
##############################################
#NOW STARTING TF-IDF WEIGHTED WORD-TO-VEC
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(x_train)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
train_tfidf_sent_vectors =[]# the tfidf-w2v for each sentence/review is
 stored in this list

for sent in tqdm(list_of_sent): # for each review/sentence
  sent_vec = np.zeros(100) # as word vectors are of zero length
  weight_sum =0; # num of words with a valid vector in the sentence/rev
iew
  for word in sent: # for each word in a review/sentence
   if word in w_t_c_words:
     vec = word_to_vector.wv[word]
```

```
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))# dictionary[word] = idf value of word in whole courpus
            sent_vec += (vec * tf_idf)# sent.count(word) = tf valeus of word in this review
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
        train_tfidf_sent_vectors.append(sent_vec)
```

```
100%|██████████| 80000/80000 [06:01<00:00, 221.25it/s]
```

In [8]:

```
from sklearn.preprocessing import StandardScaler #standarizing the training  data
x_train_data=StandardScaler( with_mean=False).fit_transform(train_tfidf_sent_vectors)
print(x_train_data.shape)
```

```
(80000, 100)
```

In [9]:

```
list_of_sent=[]
for sent in x_test:
 list_of_sent.append(sent.split())#splitting of sentences into words AND appending them to list
print(x_test[0])
print("*****************************************************************")
print(list_of_sent[0])
print('*******************************************************************')
```

```
hard find item dont buy mani either came stale got way quick classic nonetheless
*****************************************************************
['hard', 'find', 'item', 'dont', 'buy', 'mani', 'either', 'came', 'stale', 'got', 'way', 'quick', 'classic', 'nonetheless']
*******************************************************************
```

In [10]:

```
###### NOW STARTING TFIDF WORD TO VEC FOR TEST DATA##############################################################
```

```
#NOW STARTING TF-IDF WEIGHTED WORD-TO-VEC
model = TfidfVectorizer()
model.fit_transform(x_train)
model.transform(x_test)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
test_tfidf_sent_vectors =[]# the tfidf-w2v for each sentence/review is
 stored in this list

for sent in tqdm(list_of_sent): # for each review/sentence
  sent_vec = np.zeros(100) # as word vectors are of zero length
  weight_sum =0; # num of words with a valid vector in the sentence/rev
iew
  for word in sent: # for each word in a review/sentence
   if word in w_t_c_words:
     vec = word_to_vector.wv[word]
     tf_idf = dictionary[word]*(sent.count(word)/len(sent))# dictionary
[word] = idf value of word in whole courpus
     sent_vec += (vec * tf_idf)# sent.count(word) = tf valeus of word i
n this review
     weight_sum += tf_idf
  if weight_sum != 0:
   sent_vec /= weight_sum
   test_tfidf_sent_vectors.append(sent_vec)
```

```
100%|██████████| 20000/20000 [01:11<00:00, 278.93it/s]
```

In [11]:

```
from sklearn.preprocessing import StandardScaler #standarizing the trai
ning  data
x_test_data=StandardScaler( with_mean=False).fit_transform(test_tfidf_s
ent_vectors)
print(x_test_data.shape)
```

```
(20000, 100)
```

In [0]:

```
#using time series split method for cross-validation score
from sklearn.model_selection import TimeSeriesSplit
```

```
tscv = TimeSeriesSplit(n_splits=5)
from sklearn.tree import DecisionTreeClassifier
```

In [13]:
```
#biudling the model
dt=DecisionTreeClassifier(criterion='gini', splitter='best',class_weigh
t={1:.5,0:.5})
tuned_parameters=[{'max_depth':[5,7,10,15,50],'min_samples_split':[5,25
,50,100,500]}]
#applying the model of decision tree and using gridsearchcv to find the
 best hyper parameter
%time
from sklearn.model_selection import GridSearchCV
model = GridSearchCV(dt, tuned_parameters, scoring = 'f1', cv=tscv,n_jo
bs=-1)#building the gridsearchcv model
```

```
CPU times: user 4 µs, sys: 0 ns, total: 4 µs
Wall time: 7.63 µs
```

In [14]:
```
%%time
model.fit(x_train_data, y_train)#fiitting the training data
```

```
CPU times: user 6.86 s, sys: 192 ms, total: 7.05 s
Wall time: 8min 57s
```

Out[14]:
```
GridSearchCV(cv=TimeSeriesSplit(max_train_size=None, n_splits=5),
       error_score='raise-deprecating',
       estimator=DecisionTreeClassifier(class_weight={1: 0.5, 0: 0.5},
criterion='gini',
            max_depth=None, max_features=None, 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, presort=False, random_state=N
one,
            splitter='best'),
       fit_params=None, iid='warn', n_jobs=-1,
       param_grid=[{'max_depth': [5, 7, 10, 15, 50], 'min_samples_spli
t': [5, 25, 50, 100, 500]}],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='f1', verbose=0)
```

In [15]:
```
print(model.best_estimator_)#printing the best_estimato
```

```
DecisionTreeClassifier(class_weight={1: 0.5, 0: 0.5}, criterion='gini',
            max_depth=5, 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=N
one,
            splitter='best')
```

In [16]:
```
print(model.score(x_test_data,y_test))#checking the score on test_Data
```

```
0.9329527677909817
```

In [17]:
```
results=pd.DataFrame(model.cv_results_)# getting varoius cv_scores and
 train_scores various values of hyperparameter given as parameter and s
toring it in a dataframe
results#printing the dataframe
```

Out[17]:

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
0	4.132478	0.009768	0.937585	0.946900	5
1	4.105889	0.009138	0.937430	0.946765	5
2	4.139786	0.008752	0.937362	0.946650	5
3	4.058551	0.008469	0.937240	0.946428	5

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
4	4.117635	0.008721	0.936690	0.945307	5
5	5.432013	0.008839	0.936172	0.953498	7
6	5.316305	0.008714	0.935673	0.952984	7
7	5.264760	0.008701	0.934885	0.952249	7
8	5.237713	0.008728	0.934422	0.950722	7
9	5.165511	0.008650	0.934917	0.947014	7
10	7.174040	0.009269	0.930876	0.967702	10
11	7.218214	0.009001	0.928509	0.964584	10
12	7.207848	0.009181	0.927792	0.961782	10

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
13	7.180884	0.009166	0.929242	0.957397	10
14	6.808598	0.009503	0.933250	0.948300	10
15	10.085406	0.010208	0.920337	0.985736	15
16	11.559952	0.009817	0.916575	0.976040	15
17	9.972876	0.009822	0.917373	0.968841	15
18	9.681669	0.009514	0.921086	0.961204	15
19	10.510169	0.010767	0.930837	0.948867	15
20	15.320404	0.010648	0.902348	0.996597	50
21	14.876030	0.010496	0.904071	0.980798	50

	mean_fit_time	mean_score_time	mean_test_score	mean_train_score	param_max_d
22	16.624399	0.010361	0.909053	0.971764	50
23	14.655922	0.010256	0.915798	0.962880	50
24	12.567062	0.009214	0.929149	0.949205	50

25 rows × 22 columns

In [0]:
```
results['mean_train_score']=results['mean_train_score']*100
results['mean_test_score']=results['mean_test_score']*100
```

In [0]:
```
results=results.round(decimals=2)
```

PLOTTING THE HEATMAP WITH HYPERPARAMETERS FOR CV_DATA SCORE

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

In [21]:
```
test_score_heatmap
```

Out[21]:

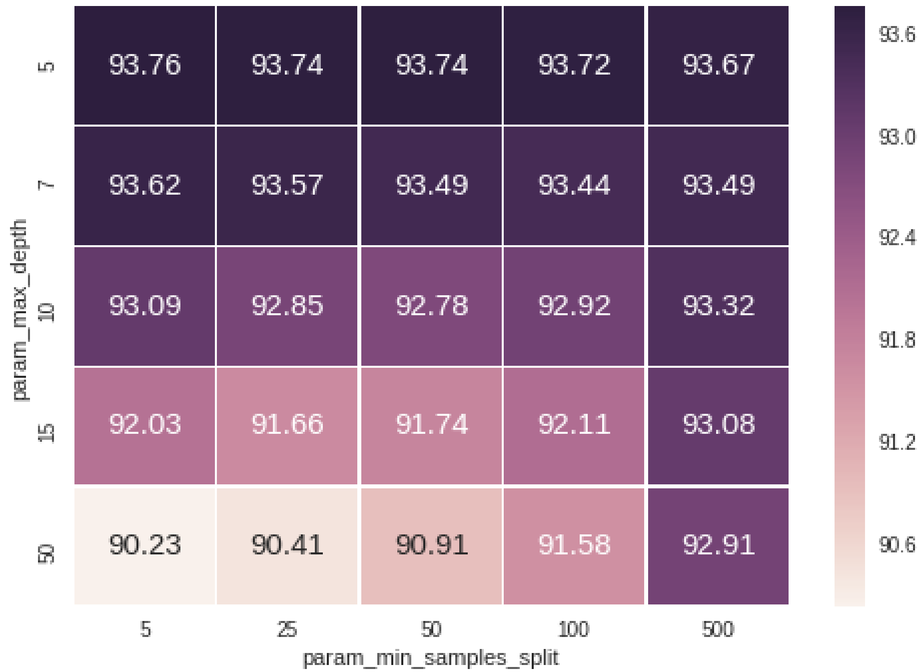
param_min_samples_split	5	25	50	100	500
param_max_depth					

param_min_samples_split	5	25	50	100	500
param_max_depth					
5	93.76	93.74	93.74	93.72	93.67
7	93.62	93.57	93.49	93.44	93.49
10	93.09	92.85	92.78	92.92	93.32
15	92.03	91.66	91.74	92.11	93.08
50	90.23	90.41	90.91	91.58	92.91

In [22]:

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

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe1316227b8>



In [23]:
```
print(model.best_estimator_)#printing the best_estimator
```

```
DecisionTreeClassifier(class_weight={1: 0.5, 0: 0.5}, criterion='gini',
            max_depth=5, 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=N
one,
            splitter='best')
```

From here,the best hyperparameter value is max_depth=5

In [24]:
```
dt=DecisionTreeClassifier(criterion='gini', splitter='best',class_weigh
t={1:.5,0:.5},min_samples_split=5,max_depth=5)
dt.fit(x_train_data,y_train)#fitting the model
```

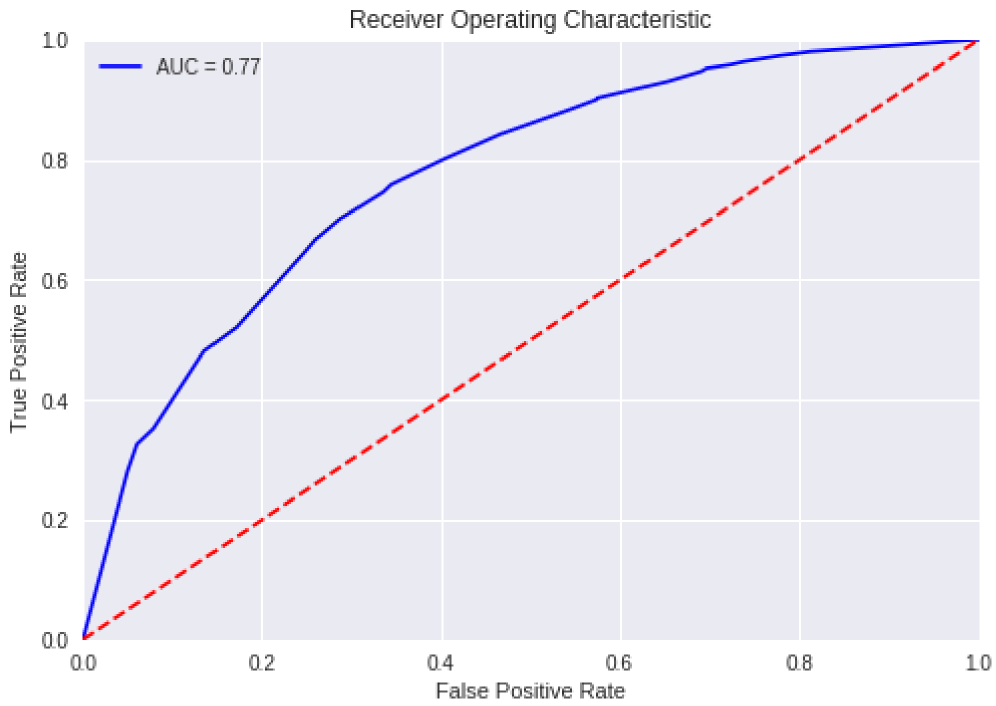
Out[24]:
```
DecisionTreeClassifier(class_weight={1: 0.5, 0: 0.5}, criterion='gini',
            max_depth=5, max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=5,
            min_weight_fraction_leaf=0.0, presort=False, random_state=N
one,
            splitter='best')
```

PLOTTING THE ROC CURVE FOR GETTING AUC SCORE

In [25]:
```
probs = model.predict_proba(x_test_data)
preds = probs[:,1]
fpr, tpr, threshold = metrics.roc_curve(y_test, preds)
roc_auc = metrics.auc(fpr, tpr)

#
```

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



In [26]:
```
print('FROM THE ABOVE PLOT,AUC_SCORE IS FOUND AS ',roc_auc*100)
```

```
FROM THE ABOVE PLOT,AUC_SCORE IS FOUND AS  77.36347212211996
```

TESTING OUR MODEL ON TEST DATA AND

CHECKING ITS PRECISION ,RECALL ,F1_FCORE

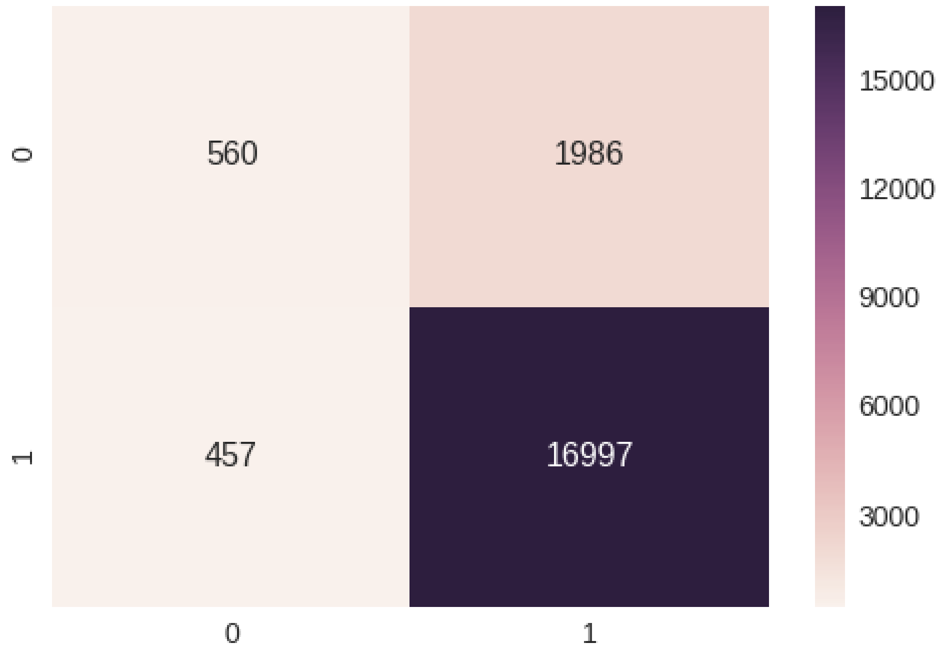
In [27]:

```
#Testing Accuracy on Test data
import seaborn as sns #importing seaborn as sns
from sklearn.metrics import *#importing varoius metrics from sklearn
y_pred = dt.predict(x_test_data)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*1
00))#printing accuracy
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
#printing precision score
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred))) #prin
ting recall
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2
)) #generating the heatmap for confusion matrix
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 87.785%
Precision on test set: 0.895
Recall on test set: 0.974
F1-Score on test set: 0.933
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe13056d978>
```



TFIDF_AVG WORD2 VECTORIZATION FOR DECISION TREE IS COMPLETED

In [0]:
```
# tfidf_avg word_2_vertorization is completed for decision_trees
```

TABULATING VAROIUS VECTORIZATION RESULTS WITH DIFFERENT ACCURACY SCORES

In [0]:
```
from tabulate import tabulate
```

In [29]:
```
table = [["BOW",10,89,98,93],["TF-IDF",10,89,98,93], ["AVG_WORD_2_VEC",
```

```
5,90,98,94],["TFIDF_AVG_WORD_2_VEC",5,88,98,93]]
print (tabulate(table))
```

```
-------------------  --  --  --  --
BOW                  10  89  98  93
TF-IDF               10  89  98  93
AVG_WORD_2_VEC        5  90  98  94
TFIDF_AVG_WORD_2_VEC  5  88  98  93
-------------------  --  --  --  --
```

In [30]:

```
headers=['VECTORIZATION','MAX_DEPTH','PRECISION','RECALL','F1_SCORE']
print (tabulate(table, headers, tablefmt="fancy_grid"))
```

```
╒══════════════════════╤═════════════╤═════════════╤══════════╤═══════
═════╕
│ VECTORIZATION        │   MAX_DEPTH │   PRECISION │   RECALL │   F1_SC
ORE │
╞══════════════════════╪═════════════╪═════════════╪══════════╪═══════
═════╡
│ BOW                  │          10 │          89 │       98 │
93 │
├──────────────────────┼─────────────┼─────────────┼──────────┼───────
─────┤
│ TF-IDF               │          10 │          89 │       98 │
93 │
├──────────────────────┼─────────────┼─────────────┼──────────┼───────
─────┤
│ AVG_WORD_2_VEC       │           5 │          90 │       98 │
94 │
├──────────────────────┼─────────────┼─────────────┼──────────┼───────
─────┤
│ TFIDF_AVG_WORD_2_VEC │           5 │          88 │       98 │
93 │
╘══════════════════════╧═════════════╧═════════════╧══════════╧═══════
═════╛
```

######DECISION TREE WITH ALL FOUR VECTORIZATION COMPLETED