Assignment 8

November 3, 2018

0.1 Assignment 8: Decision Trees on Amazon reviews data set [M]

Given Dataset consists of reviews of fine foods from amazon. Reviews describe (1)product and user information, (2)ratings, and (3) a plain text review.Here, decision Tree algorithm is applied on amazon reviews datasets to predict whether a review is positive or negative.

Procedure to execute the above task is as follows:

- **Step1: Data Pre-processing is applied on given amazon reviews data-set.And Take sample of data from dataset because of computational limitations**
- **Step2: Time based splitting on train and test datasets.**
- **Step3: Apply Feature generation techniques(avg w2v,tfidfw2v)**
- **Step4: Apply Decision Tree algorithm using each technique.**
- **Step5: To find C(1/lambda) and gamma(=1/sigma).**
- **Step6: Decision tree Feature Importance using BOW and TF-IDF**
- **Step7: Images of Decision tree in png format with verious vectorizations.**

0.2 Objective:

- To classify given reviews (positive (Rating of 4 or 5) & negative (rating of 1 or 2)) using Decision Trees algorithm.

```
In [1]: %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        import re
        import math

        import pandas as pd
        import numpy as np
        import pickle
        import graphviz
        # modules for text processing
        import nltk
        import string
```

```python
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn import preprocessing
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from tqdm import tqdm
import os
#import scikitplot.metrics as skplt
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score

from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

from sklearn.decomposition import TruncatedSVD
import pytablewriter

# train-split data,accuracy-score,cross-validation modules

from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.metrics import accuracy_score

from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import cross_validation
from sklearn.preprocessing import StandardScaler

from sklearn.model_selection  import GridSearchCV
from sklearn.svm import SVC
from scipy.stats import uniform
from sklearn.model_selection import RandomizedSearchCV
```

```
/usr/local/lib/python3.6/site-packages/sklearn/cross_validation.py:41: DeprecationWarning: This
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
In [2]: try:
            from StringIO import StringIO
        except ImportError:
            from io import StringIO
```

```
In [3]: import zipfile
        archive = zipfile.ZipFile('/floyd/input/pri/Reviews.zip', 'r')
        csvfile = archive.open('Reviews.csv')
```

```
In [4]: # Reading CSV file and printing first five rows
        amz = pd.read_csv(csvfile ) # reviews.csv is  dataset file
        print(amz.head())
```

```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

   HelpfulnessNumerator  HelpfulnessDenominator  Score        Time  \
0                     1                       1      5  1303862400
1                     0                       0      1  1346976000
2                     1                       1      4  1219017600
3                     3                       3      2  1307923200
4                     0                       0      5  1350777600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

```
In [5]: # dimensions of dataset and columns name

        print(amz.shape)
        #print(amz1.shape)
        print(amz.columns)
```

```
(568454, 10)
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
```

The amazon reviews datafile contains 568454 rows of entry and 10 columns.For given objective, processing of data is necessary."Score" and "text" columns is processed for required result.

Given reviews with Score>3 a positive rating, and reviews with a score<3 a negative rating. If score is equal to 3,it is considered as neutral score.

In [6]:
```
# Processing
#Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative rati

def score_part(x):
    if x < 3:
        return 'negative'
    return 'positive'

actualScore = amz['Score']
#print(actualScore)
New_score = actualScore.map(score_part)
#print(New_score)
amz['Score']=New_score

# If score is equal to 3,it is considered as neutral score.
```

In [7]:
```
print(amz.shape)
amz.head(5)
```

```
(568454, 10)
```

Out[7]:
```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

   HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
0                     1                       1  positive  1303862400
1                     0                       0  negative  1346976000
2                     1                       1  positive  1219017600
3                     3                       3  negative  1307923200
4                     0                       0  positive  1350777600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

Data Pre-processing on raw data: Every datasets contains some unwanted data.Raw data is preprocessed by removing duplication.

In [8]:
```
#Processing of ProductId
#Sorting data according to ProductId in ascending order
sorted_data=amz.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='qu
#sorted_data.head() # printing sorted data
# To check the duplications in raw data
dupli=sorted_data[sorted_data.duplicated(["UserId","ProfileName","Time","Text"])]
print(dupli.head(5))
# Remove Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='f
final.shape
#Checking to see how much % of data still remains
(final['Id'].size*1.0)/(amz['Id'].size*1.0)*100
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
            Id   ProductId          UserId  \
171222  171223  7310172001   AJD41FBJD9010
171153  171154  7310172001   AJD41FBJD9010
171151  171152  7310172001   AJD41FBJD9010
217443  217444  7310172101  A22FICU3LCG2J1
217444  217445  7310172101  A1LQV0PSM04DWI

                                          ProfileName  HelpfulnessNumerator  \
171222  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     1
171153  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     0
171151  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     0
217443                                      C. Knapp                     1
217444                                  B. Feuerstein                    1

        HelpfulnessDenominator     Score        Time  \
171222                       1  positive  1233360000
171153                       0  positive  1233360000
171151                       0  positive  1233360000
217443                       1  positive  1275523200
217444                       1  positive  1274313600

                                                 Summary  \
171222  best dog treat-- great for training---  all do...
171153  best dog treat-- great for training---  all do...
171151  dogs LOVE it--  best treat for rewards and tra...
217443                                Can't resist this !
```

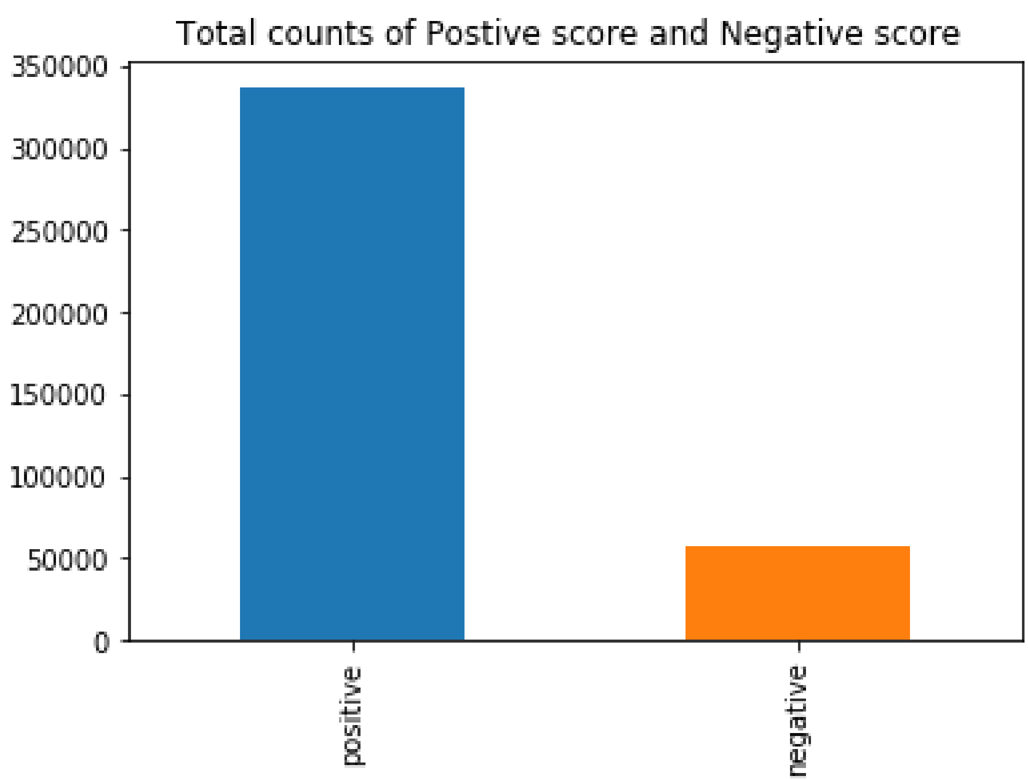
```
217444                   Freeze dried liver as dog treats

                                                    Text
171222  Freeze dried liver has a hypnotic effect on do...
171153  Freeze dried liver has a hypnotic effect on do...
171151  Freeze dried liver has a hypnotic effect on do...
217443  My dog can't resist these treats - I can get h...
217444  My little pupster loves these things. She is n...
(393931, 10)
```

Out[8]:
```
positive    336824
negative     57107
Name: Score, dtype: int64
```

In [9]:
```python
a=final['Score'].value_counts().tolist()
print('List of total counts Postive score and Negative score ==>',a)
final['Score'].value_counts().plot(kind='bar')
plt.title('Total counts of Postive score and Negative score ')
```

```
List of total counts Postive score and Negative score ==> [336824, 57107]
```

Out[9]:
```
Text(0.5,1,'Total counts of Postive score and Negative score ')
```



observations

- The positive reviews is greater than negative reviews.It makes data imbalanced.
- From the bar plot ,it is seen that sampled datasets of review is imbalnced.

1 Text Preprocessing:

In [10]:
```
import nltk
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

Out[10]: True

In [11]:
```

stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>$< /><')
    #cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special char
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
```

cleaning html tags like" <.*?>" and punctuations like " r'[?|!|'|"|#]',r''" from senetences

In [12]:
```
#final = final.sample(frac=0.004,random_state=1)
#print(final.shape)
```

In [13]:
```
#Code for implementing step-by-step the checks mentioned in the pre-processing phase.

'''Pre processing of text data:It is cleaning and flitering text'''
i=0
str1=' '
global final_string
final_string=[]
all_positive_words=[]
all_negative_words=[]
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTMl tags
```

```
            for w in sent.split():
                for cleaned_words in cleanpunc(w).split():
                    if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                        if(cleaned_words.lower() not in stop):
                            s=(sno.stem(cleaned_words.lower())).encode('utf8')
                            filtered_sentence.append(s)
                            if (final['Score'].values)[i] == 'positive':
                                all_positive_words.append(s) #list of all words used to describ
                            if(final['Score'].values)[i] == 'negative':
                                all_negative_words.append(s) #list of all words used to describ
                        else:
                            continue
                    else:
                        continue
            #print(filtered_sentence)
            str1 = b" ".join(filtered_sentence) #final string of cleaned words
            #print("***********************************************************************")

            final_string.append(str1)
            i+=1
        #print('all_positive_words =',len(all_positive_words))
        #print('all_negative_words =',len(all_negative_words))

        # Finding most frequently occuring Positive and Negative words

        freq_positive=nltk.FreqDist(all_positive_words)

        freq_negative=nltk.FreqDist(all_negative_words)

        #print("\nMost Common Positive Words : ",freq_positive.most_common(20))

        #print("\nMost Common Negative Words : ",freq_negative.most_common(20))
```

Dumping and loading Pre processing of text data in pickle file

```
In [14]: pickle_path_final_string='final_string.pkl'
         final_string_file=open(pickle_path_final_string,'wb')
         pickle.dump(final_string,final_string_file)
         final_string_file.close()
```

```
In [12]: pickle_path_final_string='final_string.pkl'
         final_string_unpkl=open(pickle_path_final_string,'rb')
         final_string=pickle.load(final_string_unpkl)
```

```
In [13]: final['CleanedText']=final_string
         #adding a column of CleanedText which displays the data after pre-processing of the rev
         Pre_Process_Data = final[['CleanedText','Score','Time']]
```

```
X_Text=Pre_Process_Data ['CleanedText']

Y_Score =Pre_Process_Data ['Score'] # positive or negative score
print('\nPre_Process_Text_Data  X_Text=',X_Text.shape)
print('\nPre_Process_Score_Data Y_Score=',Y_Score.shape)
```

```
Pre_Process_Text_Data  X_Text= (393931,)

Pre_Process_Score_Data Y_Score= (393931,)
```

```
In [14]: # postive and negtive reviews from original datasets of amazon
         pos_final = Pre_Process_Data[Pre_Process_Data .Score == 'positive']# postive reviews
         pos_final = pos_final.sample(frac=0.3)
         print(pos_final.Score.value_counts())

         neg_final = Pre_Process_Data [Pre_Process_Data .Score == 'negative'] # negative reviews
         print(neg_final.Score.value_counts())
```

```
positive    101047
Name: Score, dtype: int64
negative    57107
Name: Score, dtype: int64
```

```
In [15]: final_pos_neg = pd.concat([pos_final,neg_final],axis=0)
         print(len(final_pos_neg))
         print(type(final_pos_neg))
         #print('final_pos_neg=',final_pos_neg['Score'])
```

```
158154
<class 'pandas.core.frame.DataFrame'>
```

```
In [16]: print(final_pos_neg.columns)
```

```
Index(['CleanedText', 'Score', 'Time'], dtype='object')
```

1.0.1 Splitting Training and Testing dataset

```
In [17]: # splitting training and testing dataset (Time based splitting)

         X1 = final_pos_neg[['CleanedText','Time']].sort_values('Time',axis=0).drop('Time',axis=
         #40k data sample
         X=X1[:40000]

         print(X.shape)
```

```
Y1 = final_pos_neg[['Score','Time']].sort_values('Time',axis=0).drop('Time',axis=1)
#40k data sample
Y=Y1[:40000]
print(Y.shape)
## 70 % of data

X_train_data ,X_test_data,Y_train,Y_test  = train_test_split(X,
                                                              Y.values,

                                                            test_size=0.3,shuffle=False)




print('X_train_data ',X_train_data.shape)

print('X_test_data ',X_test_data.shape )

print('Y_train_data ',Y_train .shape)

print('Y_test_data ',Y_test .shape)
```

```
(40000, 1)
(40000, 1)
X_train_data  (28000, 1)
X_test_data  (12000, 1)
Y_train_data  (28000, 1)
Y_test_data  (12000, 1)
```

```
In [18]: Y_new = Y['Score'].map(lambda x: 1 if x == 'positive' else 0).values.ravel()
         # Y train and Test for sparse datasets

         y_train_new,y_test_new = train_test_split(Y_new,test_size=0.3,shuffle=False)
         print('y_train_new ',y_train_new.shape)

         print('y_test_new ',y_test_new .shape)
```

```
y_train_new  (28000,)
y_test_new  (12000,)
```

2 Optimal Depth of Tree for Decision Tree

```
In [19]:  # Time seris splitting Cross-Validation
         tscv = TimeSeriesSplit(n_splits=3)
```

```
In [20]: # Optimal_Depth_Tree is function to calculate the optimal depth value Decision Tree
         def Optimal_Depth_Tree(X_train,y_train):
```

```python
depthsize=list(range(3,25))
cv_scores = []
depth = []

# perform 10-fold cross validation
for k in range(len(depthsize)):
    #print(k)
    DT_clf = DecisionTreeClassifier(max_depth=depthsize[k],class_weight='balanced')
    scores = cross_val_score(DT_clf,
                             X_train,
                             y_train,
                             cv=tscv,
                             n_jobs=-1)
    cv_scores.append(scores.mean())
    depth.append(depthsize[k])

# changing to misclassification error

MSE = [1 - x for x in cv_scores]

# determining best depth
global optimal_depth
optimal_depth = depthsize[MSE.index(min(MSE))]
print('\nThe optimal depth_size is %d.' % optimal_depth)



  # plot misclassification error vs depth sizeof tree
fig4 = plt.figure( facecolor='g', edgecolor='k')
fig4.suptitle('Tree Depth vs CV Scores',
              fontsize=12)
plt.plot(depthsize, MSE,'*-')


for xy in zip(depthsize, np.round(MSE,3)):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')

plt.xlabel('Tree depthsize')
plt.ylabel('CV Scores')
plt.grid()
plt.show()

print("the misclassification error for each depth value is : ", np.round(MSE,5))

return optimal_depth
```

Pandas dataframe to markdown Table format

In [21]:
```
# result_display  is function to convert dataframe into table format in Markdown
def result_display(df):
    writer = pytablewriter.MarkdownTableWriter()
    writer.header_list = list(df.columns.values)
    writer.value_matrix = df.values.tolist()
    writer.write_table()
```

2.1 Decision Tree Image

In [22]:
```
import os
import io
import pydot

def decision_tree_image(classifier,features,name_png_format):

    os.environ["PATH"] += os.pathsep + 'C:/ProgramData/Anaconda3/pkgs/graphviz-2.38.0-4
    dotfile=io.StringIO()
    tree.export_graphviz(classifier, out_file=dotfile,
                                 feature_names=features,

                                 filled=True, rounded=True,
                                 special_characters=True)
    #graph = graphviz.Source(dot_data)
    (graph,)=pydot.graph_from_dot_data(dotfile.getvalue())
    graph.write_png(name_png_format)
```

Decision_tree_image is function to get image format of decision tree with verious Decision Tree classifier .

In [23]:
```
Train_data=y_train_new
Y_test_data=y_test_new
```

3 Methods to convert text into vector

Methods: * Bag of Words

- Avg word2vec
- TF-IDF
- tf-idf weighted Word2Vec

Using above Method is used to convert text to numeric vector as Bag of words & TF-IDF is high dimensional which results into bad decision tree.

4 1. Bag of Words (BoW)

BOW for Training Data

```
In [24]: count_vect = CountVectorizer() #in scikit-learn
         vect_Data = count_vect.fit_transform(X_train_data.values.ravel())
         print(vect_Data .shape)
```

```
(28000, 20535)
```

```
In [25]: # truncated SVD for dimesionality reduction for 100 dimensions
         svd = TruncatedSVD(n_components=100)

         final_data=svd.fit_transform(vect_Data )
         print("TruncatedSVD :",final_data.shape)
```

```
TruncatedSVD : (28000, 100)
```

BOW for Testing Data

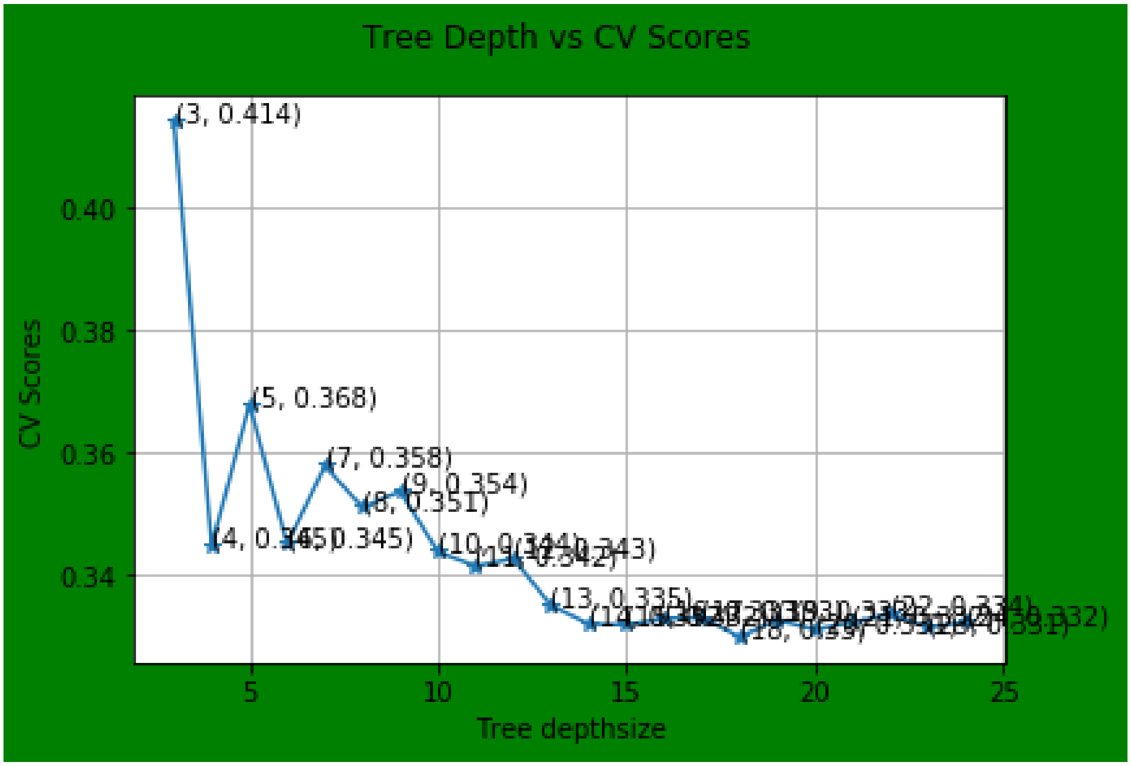
```
In [26]: #vector of test data
         vect_Data1= count_vect.transform(X_test_data.values.ravel())
         print(vect_Data1.shape)



         final_data_test=svd.transform(vect_Data1)
         print("TruncatedSVD :",final_data_test.shape)
```

```
(12000, 20535)
TruncatedSVD : (12000, 100)
```

4.1 Optimal Depth of tree using BOW

```
In [27]: Optimal_Depth_Tree1=Optimal_Depth_Tree(final_data ,Train_data)
```

```
The optimal depth_size is 18.
```




```
the misclassification error for each depth value is :  [0.41405 0.34486 0.36795 0.34505 0.35786
 0.34271 0.33505 0.33205 0.3319  0.33295 0.3331  0.32995 0.33267 0.33114
 0.33233 0.33367 0.33148 0.33238]
```

The optimal depth_size is 18 using BOW.

Decision Tree classifier for optimal depth

```
In [120]: # Decision Tree classifier for optimal depth using gini index
          DT_clf1 =DecisionTreeClassifier(criterion='gini',max_depth=optimal_depth,class_weight=
          DT_clf1.fit(final_data ,Train_data)
          prediction1= DT_clf1.predict(final_data_test)
```

```
In [122]: #Training accuracy and training error
          training_score=DT_clf1.score(final_data ,Train_data)
          print('training accuracy=',training_score)
          training_error=1-training_score
          print('training error is =',training_error)
```

```
training accuracy= 0.98075
training error is = 0.019249999999999
```

In [123]:
```
# Testing Accuracy and testing error for decision Tree model
Testing_score=round(accuracy_score(Y_test_data ,prediction1),5)
print("Accuracy for decision Tree  model with Avg word2vec is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for decision Tree  model with Avg word2vec is = ",Testing_error)
```

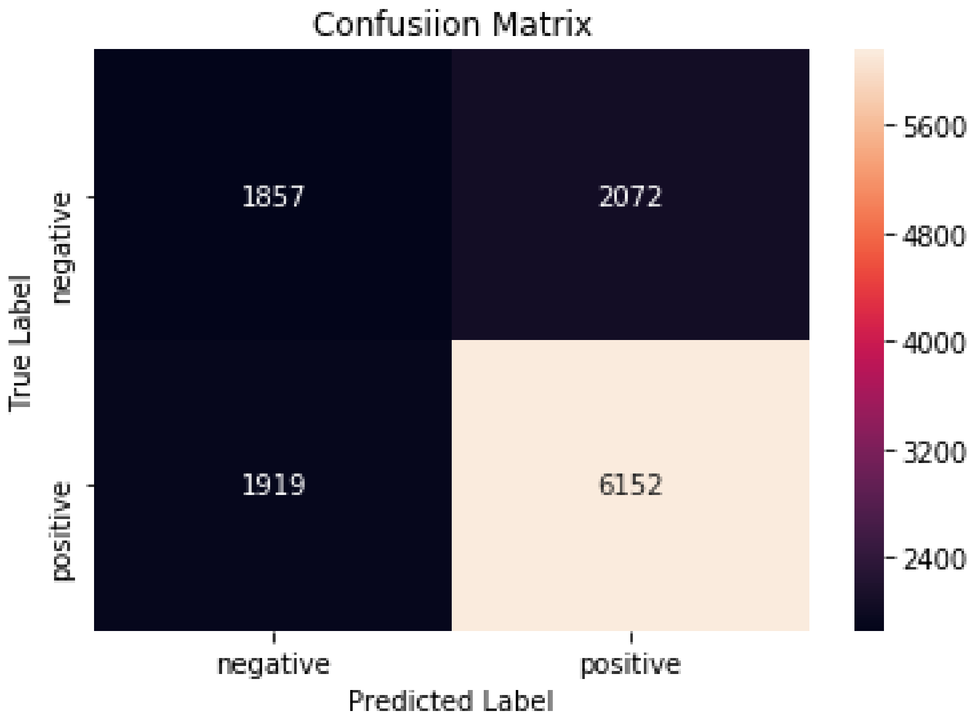
```
Accuracy for decision Tree  model with Avg word2vec is =  0.66742
Testing error for decision Tree  model with Avg word2vec is =  0.33258
```

In [124]:
```
F1_score = round(f1_score(Y_test_data ,prediction1,average='macro'),5)*100
recall = round(recall_score(Y_test_data,prediction1,average='macro'),5)*100
precision = round(precision_score(Y_test_data ,prediction1,average='macro'),5)*100
```

In [125]:
```
print(classification_report( Y_test_data,prediction1))
```

```
             precision    recall  f1-score   support

          0       0.49      0.47      0.48      3929
          1       0.75      0.76      0.76      8071

avg / total       0.66      0.67      0.67     12000
```

In [126]:
```
cm = confusion_matrix(Y_test_data ,prediction1)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```




```
In [127]: models_performence1 = {
              'Model':['Decision Tree'],
              'Vectorizer': ['BOW'],
              'Optimal Depthsize':[optimal_depth],
              'Training error':[training_error],
              'Test error':[Testing_error],
              'Accuracy':[Testing_score*100],
              'F1':[F1_score],
              'recall':[recall],
              'precision':[precision]


          }
```

```
In [128]: columns = ["Model","Vectorizer", "Optimal Depthsize", "Training error",  "Test error",
                      "Accuracy","F1","recall","precision",
                    ]
          df=pd.DataFrame(models_performence1, columns=columns)
          result_display(df)
```

```
|    Model    |Vectorizer|Optimal Depthsize|Training error|Test error|Accuracy| F1  |recall|prec
|-------------|----------|----------------:|-------------:|---------:|-------:|----:|-----:|----
|Decision Tree|BOW       |               18|       0.01925|    0.3326|   66.74|61.86| 61.74|
```

Model	Vectorizer	Optimal Depthsize	Training error	Test error	Accuracy	F1	recall	precision
Decision Tree	BOW	18	0.01925	0.3326	66.74	61.86	61.74	61.99

4.1.1 Observation:

- BOW is high dimensional vectorizer technique.
- Dimesional Reductionality is done using Trucated SVd .
- From confusion matrix ,TPR is too high.
- TNR,FPR,FNR is very low and almost similar.
- Precision value is only 61.99%..
- Since depth od tree is high ,model undergoes for overfitting.

5 2. Avg word2vec

Firstly, word2vec model is designed for amazon reviews using gensim module.

```
In [37]: import gensim
         list_sent=[]
         for text in tqdm(X_train_data.values.ravel()):
             filter_text=[]
             for i in text.split():
                 if(i.isalpha()):
                     filter_text.append(i.lower().decode("utf-8"))
                 else:
                     continue
             list_sent.append(filter_text)
         print(len(list_sent))
```

```
100%|??????????| 28000/28000 [00:00<00:00, 35378.97it/s]
```

```
28000
```

word2vec Model using Training Datasets

```
In [38]: w2v_model=gensim.models.Word2Vec(list_sent,min_count=5,size=100, workers=4)
         #this model is used in avg word2vec  .
```

```
In [39]: words = list(w2v_model.wv.vocab)
         print(len(words))
```

```
7183
```

```
In [40]: pickle_path_w2v_model='w2v_model.pkl'
         w2v_model_path=open(pickle_path_w2v_model,'wb')
         pickle.dump(w2v_model,w2v_model_path)
         w2v_model_path.close()
```

```
In [41]: pickle_path_w2v_model='w2v_model.pkl'
         unpickle_w2v_model=open(pickle_path_w2v_model,'rb')
         w2v_model=pickle.load(unpickle_w2v_model)
```

Avg Word2Vec

```
In [42]: #  For Training

         sent_vectors = []
         for sent in  tqdm(list_sent): # for each review/sentence
             sent_vec = np.zeros(100)
             cnt_words =0 # num of words with a valid vector in the sentence/review
             for word in sent:
                 try:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
                 except:
                     pass
             sent_vec /= cnt_words
             sent_vectors.append(sent_vec)


         print(len(sent_vectors))

         #print(sent_vectors[0:4])
```

```
100%|??????????| 28000/28000 [00:05<00:00, 5570.97it/s]

28000
```

```
In [43]: # Converting Nan value to zero in sent vectors.
         Sent_Nan = np.where(np.isnan(sent_vectors), 0, sent_vectors)
```

```
In [44]: # converting sent list to nd array
         Sent_final_vector = np.asarray(Sent_Nan )
         print(type(Sent_final_vector))
```

```
<class 'numpy.ndarray'>
```

```
In [45]: #  ForTesting
         # Words in test reviews
         list_sent_test=[]
         for text in tqdm(X_test_data.values.ravel()):
             filter_text=[]
             for i in text.split():
                 if(i.isalpha()):
                     filter_text.append(i.lower().decode("utf-8"))
                 else:
                     continue
             list_sent_test.append(filter_text)
         #print(len(list_sent_test))

         sent_vectors1 = []
         for sent in tqdm(list_sent_test): # for each review/sentence
             sent_vec = np.zeros(100)
             cnt_words =0 # num of words with a valid vector in the sentence/review
             for word in sent:
                 try:
                     vec = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
                 except:
                     pass
             sent_vec /= cnt_words
             sent_vectors1.append(sent_vec)


         print(len(sent_vectors1))

         #print(sent_vectors1)
         # Converting Nan value to zero in sent vectors.
         Sent_Nan1 = np.where(np.isnan(sent_vectors1), 0, sent_vectors1)

         # converting sent list to nd array
         Sent_final_vector1 = np.asarray(Sent_Nan1)
         print(type(Sent_final_vector1))
```

```
100%|??????????| 12000/12000 [00:00<00:00, 33979.17it/s]
100%|??????????| 12000/12000 [00:02<00:00, 5262.07it/s]
```

```
12000
```

```
<class 'numpy.ndarray'>
```

Dumping & Loading Pickle file for Avg word2vec

```
In [46]: pickle_path_AW2V_train='X_data_AW2V_train.pkl'
         X_data_AW2V_train=open(pickle_path_AW2V_train,'wb')
         pickle.dump(Sent_final_vector,X_data_AW2V_train)
         X_data_AW2V_train.close()

         pickle_path_AW2V_test='X_data_AW2V_test.pkl'
         X_data_AW2V_test=open(pickle_path_AW2V_test,'wb')
         pickle.dump(Sent_final_vector1,X_data_AW2V_test)
         X_data_AW2V_test.close()
```

```
In [47]: pickle_path_AW2V_train='X_data_AW2V_train.pkl'
         unpickle_path3_train=open(pickle_path_AW2V_train,'rb')
         Sent_final_vector=pickle.load(unpickle_path3_train)

         pickle_path_AW2V_test='X_data_AW2V_test.pkl'
         unpickle_path3_test=open(pickle_path_AW2V_test,'rb')
         Sent_final_vector1=pickle.load(unpickle_path3_test)
```

```
In [48]: # For Train
         final_w2v_count_Train=Sent_final_vector
         print(final_w2v_count_Train.shape)
```

```
(28000, 100)
```

```
In [49]: final_w2v_count_Test=Sent_final_vector1# For Test
         print(final_w2v_count_Test.shape)
```

```
(12000, 100)
```

for Training datasets ,avg word2vec

```
final_w2v_count_Train,
```

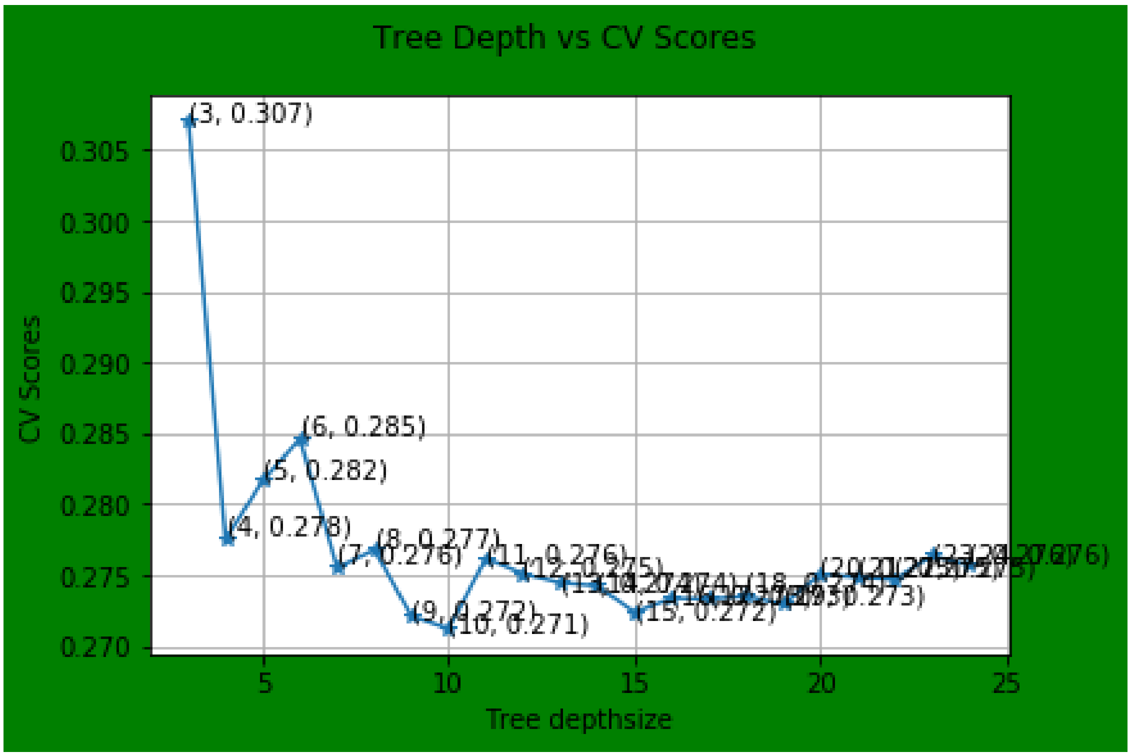
for testing datasets ,avg word2vec

```
final_w2v_count_Test,
```

5.1 Optimal Depth of tree using Avg word2vec

```
In [50]: Optimal_Depth_Tree1=Optimal_Depth_Tree(final_w2v_count_Train ,Train_data)
```

```
The optimal depth_size is 10.
```




```
the misclassification error for each depth value is :  [0.307    0.27752 0.28167 0.28462 0.27552
 0.2751  0.27448 0.27424 0.27238 0.27338 0.27333 0.27352 0.27295 0.2751
 0.27486 0.27471 0.27638 0.27571]
```

5.1.1 Observation

- The optimal depth_size is 12 using Avg word2vec featurization on Decision Tree model.
- The misclassification error for each depth value is 0.26348 and It is shown in above graph.

Decision Tree classifier for optimal depth

```
In [136]: # Decision Tree classifier for optimal depth using gini index
          DT_clf2 =DecisionTreeClassifier(criterion='gini',
                                          max_depth=optimal_depth,
                                          class_weight='balanced',
                                          random_state= 0)
```

```
DT_clf2.fit(final_w2v_count_Train ,Train_data)
prediction2= DT_clf2.predict(final_w2v_count_Test)
```

In [137]:
```
#Training accuracy and training error
training_score=DT_clf2.score(final_w2v_count_Train ,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.8420357142857143
training error is = 0.15796428571428567
```

In [138]:
```
# Testing Accuracy and testing error for decision Tree model
Testing_score=round(accuracy_score(Y_test_data ,prediction2),5)
print("Accuracy for decision Tree  model with Avg word2vec is = ",Testing_score)
Testing_error=1-Testing_score
print("Testing error for decision Tree  model with Avg word2vec is = ",Testing_error)
```

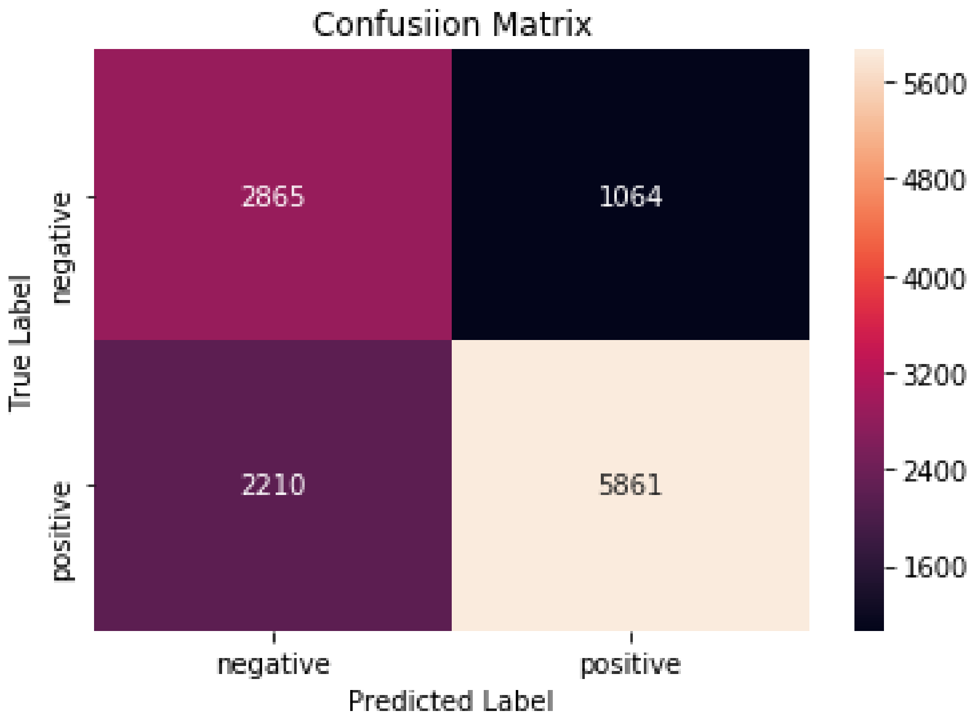
```
Accuracy for decision Tree  model with Avg word2vec is =  0.72717
Testing error for decision Tree  model with Avg word2vec is =  0.27283
```

In [139]:
```
F1_score = round(f1_score(Y_test_data ,prediction2,average='macro'),5)*100
recall = round(recall_score(Y_test_data,prediction2,average='macro'),5)*100
precision = round(precision_score(Y_test_data ,prediction2,average='macro'),5)*100
```

In [140]:
```
print(classification_report( Y_test_data,prediction2))
```

```
             precision    recall  f1-score   support

          0       0.56      0.73      0.64      3929
          1       0.85      0.73      0.78      8071

avg / total       0.75      0.73      0.73     12000
```

In [141]:
```
cm = confusion_matrix(Y_test_data ,prediction2)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```




```
In [142]: models_performence1['Model'].append('Decision Tree')
          models_performence1['Vectorizer'].append('Avg word2vec')
          models_performence1['Optimal Depthsize'].append(optimal_depth)
          models_performence1['Training error'].append(training_error)
          models_performence1[ 'Test error'].append(Testing_error)
          models_performence1[ 'Accuracy'].append(Testing_score*100)
          models_performence1[ 'F1'].append(F1_score)
          models_performence1['recall'].append(recall)
          models_performence1[ 'precision'].append(precision)
```

```
In [143]: columns = ["Model","Vectorizer", "Optimal Depthsize", "Training error",  "Test error",
                      "Accuracy","F1","recall","precision",
                    ]
          df2=pd.DataFrame(models_performence1, columns=columns)
          result_display(df2)
```

```
|    Model     | Vectorizer |Optimal Depthsize|Training error|Test error|Accuracy| F1  |recall|pr
|-------------|------------|-----------------:|-------------:|---------:|-------:|----:|-----:|--
|Decision Tree|BOW         |               18|       0.01925|    0.3326|   66.74|61.86| 61.74|
|Decision Tree|Avg word2vec|               10|       0.15796|    0.2728|   72.72|70.90| 72.77|
```

Model	Vectorizer	Optimal Depthsize	Training error	Test error	Accuracy	F1	recall	precision
Decision Tree	BOW	18	0.01925	0.3326	66.74	61.86	61.74	61.99
Decision Tree	Avg word2vec	10	0.15796	0.2728	72.72	70.90	72.77	70.54

5.1.2 Observation:

- Decision Tree for avg word2vec featurization work properly on Amazon reviews data set .
- All scoring metrics's results is best. F1 score is 70.90%
- Optimal depthsize is 10.
- From confusion matrix,TPR &TNR is high. It means model is working properly as comapred BOW.

6 3. TF-IDF

TF-IDF for Training data

```
In [60]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
         final_tf_idf11 = tf_idf_vect.fit_transform(X_train_data.values.ravel())
         final_tf_idf11.get_shape()
         tfidf_feat = tf_idf_vect.get_feature_names()
```

```
In [61]: final_tf_idf=svd.fit_transform(final_tf_idf11 )
         print("TruncatedSVD :",final_tf_idf.shape)
```

```
TruncatedSVD : (28000, 100)
```

Dumping & Loading Pickle file for training data (TF-IDF)

```
In [62]: pickle_path_tfidf_train='X_train_data_tfidf.pkl'
         X_train_data_tfidf=open(pickle_path_tfidf_train,'wb')
         pickle.dump(final_tf_idf ,X_train_data_tfidf)
         X_train_data_tfidf.close()
```

```
In [63]: pickle_path_tfidf_train='X_train_data_tfidf.pkl'
         unpickle_path5=open(pickle_path_tfidf_train,'rb')
         final_tf_idf=pickle.load(unpickle_path5)
```

```
In [64]: final_tfidf_np= final_tf_idf
         print("Train Data: ",final_tfidf_np.shape)

         warnings.filterwarnings("ignore")
```

```
Train Data:  (28000, 100)
```

```
In [65]: final_tf_idf_test1_svd = tf_idf_vect.transform(X_test_data.values.ravel())
         final_tf_idf_test1_svd.get_shape()
```

```
Out[65]: (12000, 493062)
```

```
In [66]: final_tf_idf_test=svd.transform(final_tf_idf_test1_svd)
         print("TruncatedSVD :",final_tf_idf_test.shape)
         #Normalize Data
         #X_sparse_tsvd = svd.fit(vect_Data1).transform(X_sparse)
```

```
TruncatedSVD : (12000, 100)
```

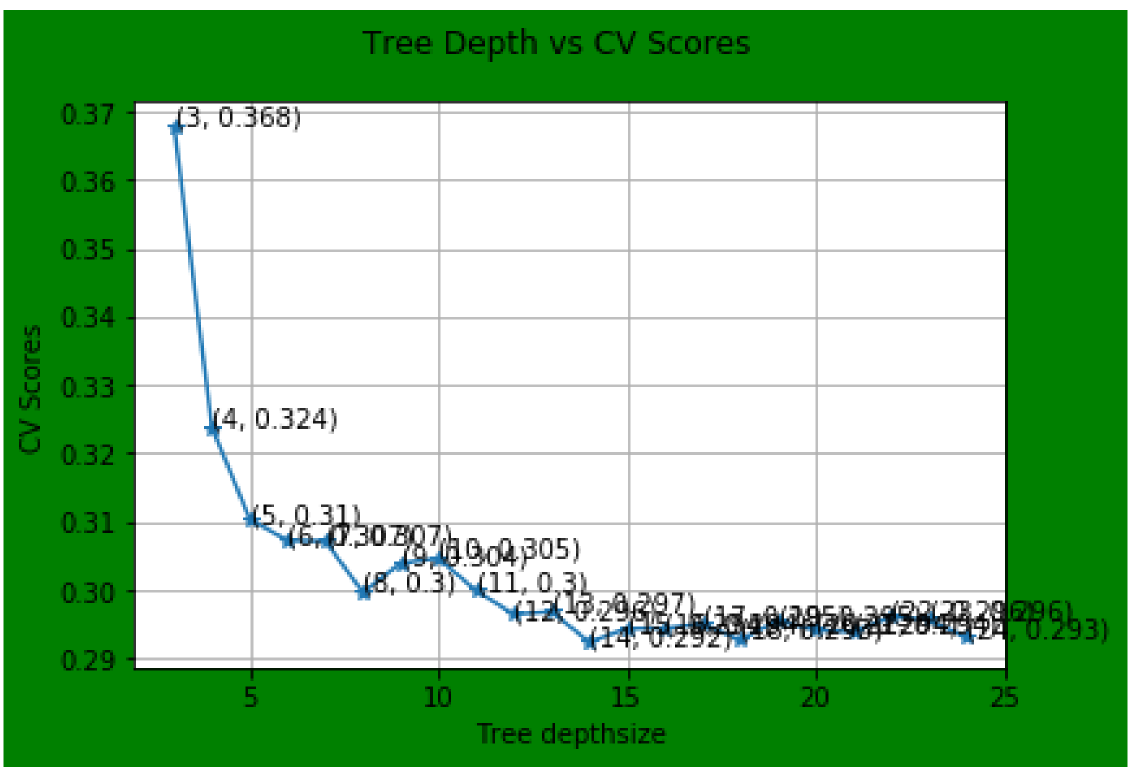
Dumping & Loading Pickle file for testing data(TF-IDF)

```
In [67]: pickle_path_tfidf_test='X_test_data_tfidf.pkl'
         X_test_data_tfidf=open(pickle_path_tfidf_test,'wb')
         pickle.dump(final_tf_idf_test ,X_test_data_tfidf)
         X_test_data_tfidf.close()
```

```
In [68]: pickle_path_tfidf_test='X_test_data_tfidf.pkl'
         unpickle_path6=open(pickle_path_tfidf_test,'rb')
         final_tfidf_np_test=pickle.load(unpickle_path6)
```

```
In [69]: Optimal_Depth_Tree1=Optimal_Depth_Tree(final_tfidf_np,Train_data)
```

```
The optimal depth_size is 14.
```



```
the misclassification error for each depth value is :  [0.36762 0.32371 0.31033 0.30724 0.30714
 0.29643 0.29681 0.29238 0.29433 0.29438 0.29505 0.29267 0.29548 0.2941
 0.29386 0.29605 0.29562 0.29305]
```

Decision Tree classifier for optimal depth

```
In [145]: DT_clf3 =DecisionTreeClassifier(criterion='gini',
                                          max_depth=optimal_depth,class_weight='balanced', rando
          DT_clf3.fit(final_tfidf_np,Train_data)
          prediction3= DT_clf3.predict(final_tfidf_np_test)
```

```
In [146]: #Training accuracy and training error
          training_score=DT_clf3.score(final_tfidf_np,Train_data)
          print('training accuracy=',training_score)
          training_error=1-training_score
          print('training error is =',training_error)
```

```
training accuracy= 0.9204285714285714
training error is = 0.07957142857142863
```

```
In [147]: # Testing Accuracy and testing error for knn model

          Testing_score=round(accuracy_score(Y_test_data ,prediction3),5)
          print("Accuracy for Decision tree model with TF-IDF weighted Word2Vec is = ",Testing_s
          Testing_error=1-Testing_score
          print("Testing error for decision Tree model withTF-IDF weighted Word2Vec is = ",Testi
```

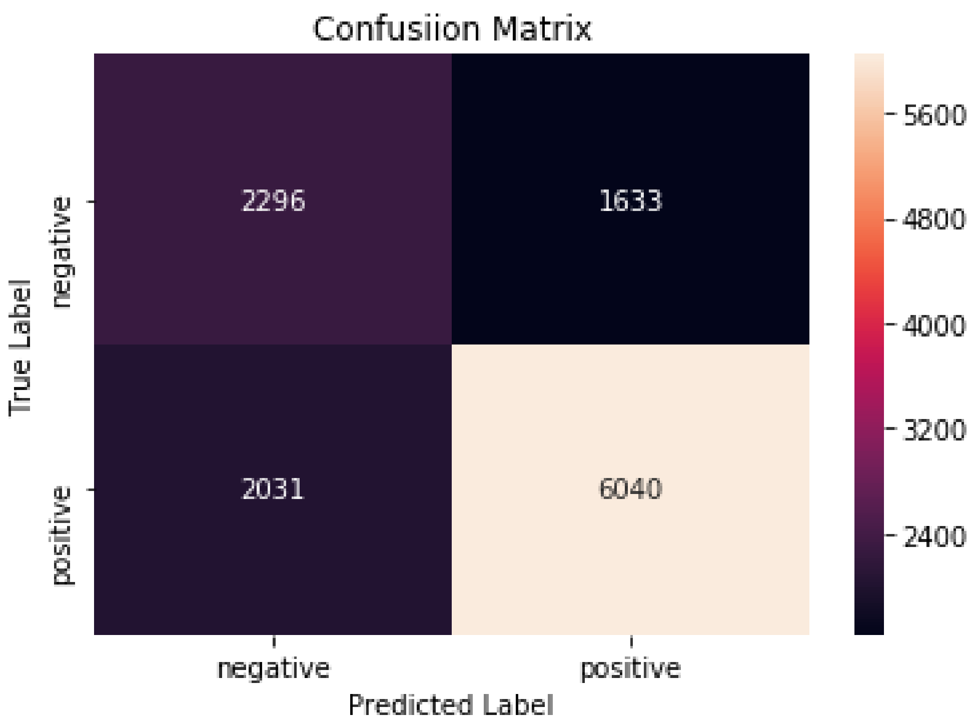
```
Accuracy for Decision tree model with TF-IDF weighted Word2Vec is =  0.69467
Testing error for decision Tree model withTF-IDF weighted Word2Vec is =  0.30533
```

```
In [148]: F1_score = round(f1_score(Y_test_data ,prediction3,average='macro'),5)*100
          recall = round(recall_score(Y_test_data,prediction3,average='macro'),5)*100
          precision = round(precision_score(Y_test_data ,prediction3,average='macro'),5)*100
```

```
In [149]: print(classification_report( Y_test_data,prediction3))
```

```
             precision    recall  f1-score   support

          0       0.53      0.58      0.56      3929
          1       0.79      0.75      0.77      8071

avg / total       0.70      0.69      0.70     12000
```

```
In [150]: cm = confusion_matrix(Y_test_data ,prediction3)
          label = ['negative', 'positive']
          df_conf = pd.DataFrame(cm, index = label, columns = label)
          sns.heatmap(df_conf, annot = True, fmt = "d")
          plt.title("Confusiion Matrix")
          plt.xlabel("Predicted Label")
          plt.ylabel("True Label")
          plt.show()
```




```
In [151]: models_performence1['Model'].append('Decision Tree')
          models_performence1['Vectorizer'].append('TF-IDF')
          models_performence1['Optimal Depthsize'].append(optimal_depth)
          models_performence1['Training error'].append(training_error)
          models_performence1[ 'Test error'].append(Testing_error)
          models_performence1[ 'Accuracy'].append(Testing_score*100)
          models_performence1[ 'F1'].append(F1_score)
          models_performence1['recall'].append(recall)
          models_performence1[ 'precision'].append(precision)
```

```
In [152]: columns = ["Model","Vectorizer", "Optimal Depthsize", "Training error",  "Test error",
                      "Accuracy","F1","recall","precision",
                    ]
          df3=pd.DataFrame(models_performence1, columns=columns)
          result_display(df3)
```

```
|    Model     | Vectorizer |Optimal Depthsize|Training error|Test error|Accuracy| F1  |recall|pr
|-------------|------------|----------------:|-------------:|---------:|-------:|----:|-----:|--
|Decision Tree|BOW         |               18|       0.01925|    0.3326|   66.74|61.86| 61.74|
|Decision Tree|Avg word2vec|               10|       0.15796|    0.2728|   72.72|70.90| 72.77|
|Decision Tree|TF-IDF      |               14|       0.07957|    0.3053|   69.47|66.17| 66.64|
```

Model	Vectorizer	Optimal Depthsize	Training error	Test error	Accuracy	F1	recall	precision
Decision Tree	BOW	18	0.01925	0.3326	66.74	61.86	61.74	61.99
Decision Tree	Avg word2vec	10	0.15796	0.2728	72.72	70.90	72.77	70.54
Decision Tree	TF-IDF	14	0.07957	0.3053	69.47	66.17	66.64	65.89

6.0.1 Observations:

- The optimal depth size of decision tree using TF-IDF is 14.
- from confusion matrix, FPR,FNR & TNR is too low and almost similar. It means model doesn't work properly.TPR is too high.

7 4.TF-IDF weighted Word2Vec

In [79]:
```
tfidf_feat = tf_idf_vect.get_feature_names()
w2v_words = list(w2v_model.wv.vocab)
dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))
```

In [80]:
```
list_of_sent=[]
for sent in tqdm(X_train_data.values.ravel()):
    list_of_sent.append(sent.decode("utf-8").split())
```

```
100%|??????????| 28000/28000 [00:00<00:00, 154692.47it/s]
```

In [81]:
```
# TF-IDF weighted Word2Vec
tfidf_feat =tf_idf_vect.get_feature_names() # tfidf words/col-names

tfidf_sent_vectors = [];
row=0;
for sent in tqdm(list_of_sent):
    sent_vec = np.zeros(100)
    weight_sum =0;
    for word in sent:
        if word in w2v_words:
```

```
                    vec = w2v_model.wv[word]
        #
                    tf_idf = dictionary[word]*sent.count(word)
                    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
```

```
100%|??????????| 28000/28000 [00:55<00:00, 504.22it/s]
```

```
In [82]: print(len(tfidf_sent_vectors))
```

```
28000
```

```
In [83]: #print(tfidf_sent_vectors[2])
         tfidf_sent_vectors_train  = np.where(np.isnan(tfidf_sent_vectors ), 0, tfidf_sent_vecto
         #print(tfidf_sent_vectors_train[2])
```

```
In [84]: tfidf_sent_vectors_train  = np.asarray(tfidf_sent_vectors_train )
         print(type(tfidf_sent_vectors))
```

```
<class 'list'>
```

Dumping & Loading Pickle file for trainText data (TF-IDF weighted word2vec)

```
In [85]: pickle_path_tfidf_weighted='X_data_tfidf_weighted.pkl'
         X_data_tfidf_weighted=open(pickle_path_tfidf_weighted,'wb')
         pickle.dump(tfidf_sent_vectors_train  ,X_data_tfidf_weighted)
         X_data_tfidf_weighted.close()
```

```
In [86]: pickle_path_tfidf_weighted='X_data_tfidf_weighted.pkl'
         unpickle_path7=open(pickle_path_tfidf_weighted,'rb')
         tfidf_sent_vectors_train =pickle.load(unpickle_path7)
```

```
In [87]: final_tfidf_w2v_np_train=tfidf_sent_vectors_train
```

For test Tf-idf weighted word2vec

```
In [88]: list_of_sent1=[]
         for sent in tqdm(X_test_data.values.ravel()):
             list_of_sent1.append(sent.decode("utf-8").split())
```

```
100%|??????????| 12000/12000 [00:00<00:00, 113486.60it/s]
```

```
In [89]: # TF-IDF weighted Word2Vec
         tfidf_feat =tf_idf_vect.get_feature_names() # tfidf words/col-names

         tfidf_sent_vectors1 = [];
         row=0;
         for sent in tqdm( list_of_sent1):
             sent_vec = np.zeros(100)
             weight_sum =0;
             for word in sent:
                 if word in w2v_words:
                     vec = w2v_model.wv[word]
         #
                     tf_idf = dictionary[word]*sent.count(word)
                     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

100%|??????????| 12000/12000 [00:24<00:00, 482.02it/s]
```

```
In [118]: #print(len(tfidf_sent_vectors1))
          #print(tfidf_sent_vectors1[2])
          tfidf_sent_vectors_test  = np.where(np.isnan(tfidf_sent_vectors1 ),
                                              0, tfidf_sent_vectors1 )
          #print(tfidf_sent_vectors_test[2])
          final_tfidf_w2v_np_test = np.asarray(tfidf_sent_vectors_test )
          #print(type(tfidf_sent_vectors1))
```

Dumping & Loading Pickle file for test Text data (TF-IDF weighted word2vec)

```
In [91]: pickle_path_tfidf_weighted1='X_data_tfidf_weighted_test.pkl'
         X_data_tfidf_weighted1=open(pickle_path_tfidf_weighted1,'wb')
         pickle.dump(final_tfidf_w2v_np_test  ,X_data_tfidf_weighted1)
         X_data_tfidf_weighted1.close()
```

```
In [92]: pickle_path_tfidf_weighted1='X_data_tfidf_weighted_test.pkl'
         unpickle_path71=open(pickle_path_tfidf_weighted1,'rb')
         final_tfidf_w2v_np_test1 =pickle.load(unpickle_path71)
```

```
In [93]: final_tfidf_w2v_np_test= final_tfidf_w2v_np_test1
```

for Training Data:

```
final_tfidf_w2v_np_train
```

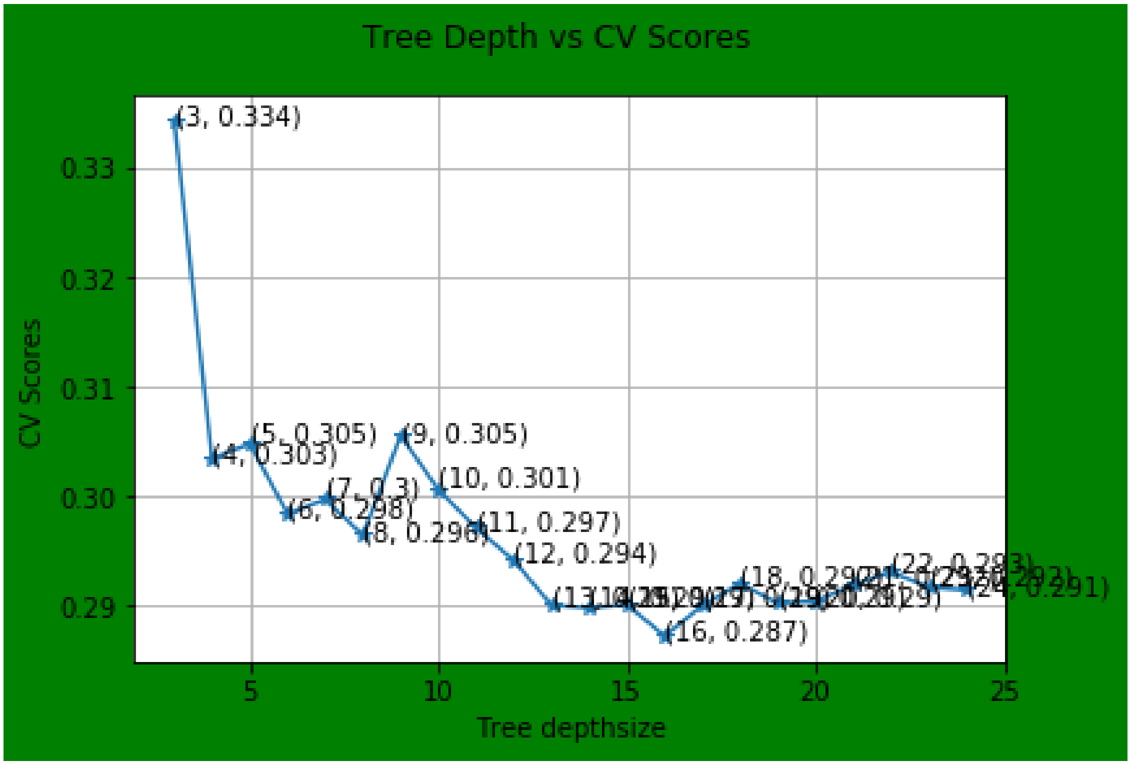
For testing data:

```
final_tfidf_w2v_np_test
```

7.1 Optimal Depth of tree using TF-IDF weighted Word2Vec

In [94]:
```
Optimal_Depth_Tree1=Optimal_Depth_Tree(final_tfidf_w2v_np_train,Train_data)
```

```
The optimal depth_size is 16.
```




```
the misclassification error for each depth value is :  [0.33419 0.30338 0.30471 0.29833 0.29962
 0.29405 0.28995 0.28971 0.29    0.28714 0.2899  0.29195 0.29014 0.29033
 0.29181 0.293   0.29162 0.29133]
```

Decision Tree classifier for optimal depth

In [154]:
```
DT_clf4 =DecisionTreeClassifier(criterion='gini',max_depth=optimal_depth,class_weight=
DT_clf4.fit(final_tfidf_w2v_np_train,Train_data)
prediction4= DT_clf4.predict(final_tfidf_w2v_np_test)
```

In [155]:
```
#Training accuracy and training error
training_score=DT_clf4.score(final_tfidf_w2v_np_train,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.9603928571428572
training error is = 0.03960714285714284
```

```
In [156]: # Testing Accuracy and testing error for knn model

          Testing_score=round(accuracy_score(Y_test_data ,prediction4),5)
          print("Accuracy for Decision tree model with TF-IDF weighted Word2Vec is = ",Testing_s
          Testing_error=1-Testing_score
          print("Testing error for decision Tree model withTF-IDF weighted Word2Vec is = ",Testi
```

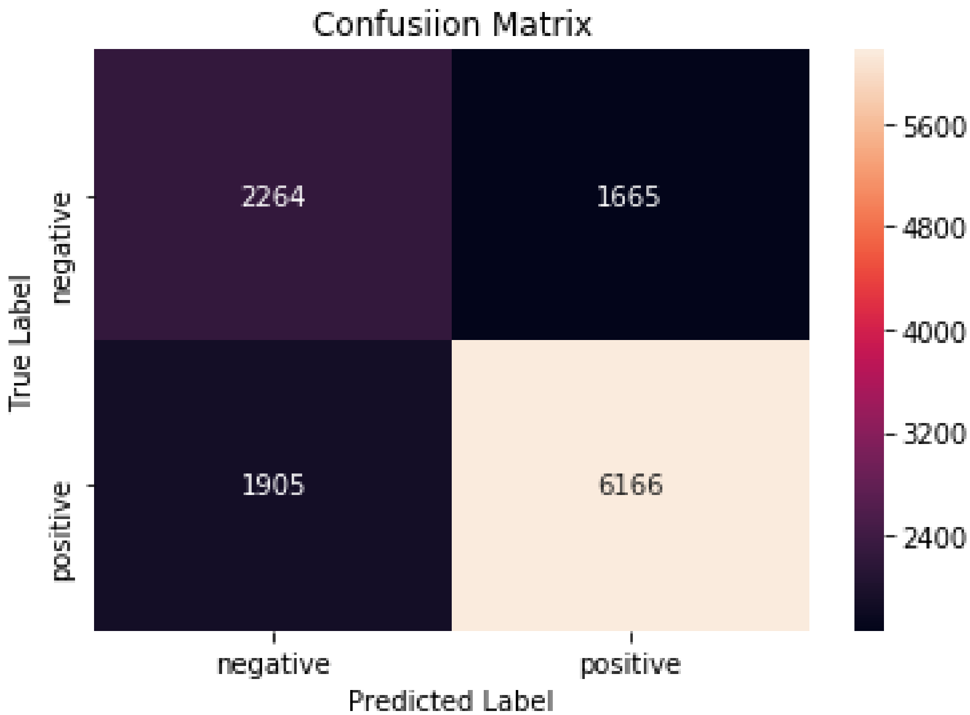
```
Accuracy for Decision tree model with TF-IDF weighted Word2Vec is =  0.7025
Testing error for decision Tree model withTF-IDF weighted Word2Vec is =  0.2975
```

```
In [157]: F1_score = round(f1_score(Y_test_data ,prediction4,average='macro'),5)*100
          recall = round(recall_score(Y_test_data,prediction4,average='macro'),5)*100
          precision = round(precision_score(Y_test_data ,prediction4,average='macro'),5)*100
```

```
In [158]: print(classification_report( Y_test_data,prediction4))
```

```
             precision    recall  f1-score   support

          0       0.54      0.58      0.56      3929
          1       0.79      0.76      0.78      8071

avg / total       0.71      0.70      0.70     12000
```

```
In [159]: cm = confusion_matrix(Y_test_data ,prediction4)
          label = ['negative', 'positive']
          df_conf = pd.DataFrame(cm, index = label, columns = label)
          sns.heatmap(df_conf, annot = True, fmt = "d")
          plt.title("Confusiion Matrix")
          plt.xlabel("Predicted Label")
          plt.ylabel("True Label")
          plt.show()
```




```
In [160]: models_performence1['Model'].append('Decision Tree')
          models_performence1['Vectorizer'].append('TF-IDF weighted word2vec')
          models_performence1['Optimal Depthsize'].append(optimal_depth)
          models_performence1['Training error'].append(training_error)
          models_performence1[ 'Test error'].append(Testing_error)
          models_performence1[ 'Accuracy'].append(Testing_score*100)
          models_performence1[ 'F1'].append(F1_score)
          models_performence1['recall'].append(recall)
          models_performence1[ 'precision'].append(precision)

In [161]: columns = ["Model","Vectorizer", "Optimal Depthsize", "Training error",  "Test error",
                        "Accuracy","F1","recall","precision",
                      ]
          df4=pd.DataFrame(models_performence1, columns=columns)
          result_display(df4)
```

```
|    Model    |        Vectorizer       |Optimal Depthsize|Training error|Test error|Accuracy| F1
|-------------|-------------------------|----------------:|-------------:|---------:|-------:|---
|Decision Tree|BOW                      |               18|       0.01925|    0.3326|   66.74|61.
|Decision Tree|Avg word2vec             |               10|       0.15796|    0.2728|   72.72|70.
|Decision Tree|TF-IDF                   |               14|       0.07957|    0.3053|   69.47|66.
|Decision Tree|TF-IDF weighted word2vec|               16|       0.03961|    0.2975|   70.25|66.
```

Model	Vectorizer	Optimal Depthsize	Training error	Test error	Accuracy	F1	recall	precision
Decision Tree	BOW	18	0.01925	0.3326	66.74	61.86	61.74	61.99
Decision Tree	Avg word2vec	10	0.15796	0.2728	72.72	70.90	72.77	70.54
Decision Tree	TF-IDF	14	0.07957	0.3053	69.47	66.17	66.64	65.89
Decision Tree	TF-IDF weighted word2vec	16	0.03961	0.2975	70.25	66.73	67.01	66.52

7.1.1 Observations:

- Though the dimesions od tf-idf weighted word2vec is low as comapred to BOW & TF_idf,results for decision tree is poor as seen in table.
- the optimal depth size is 16.

7.2 Feature Importance for Decision Tree

```
In [106]: def top_feats(row, features, top_n=15):
              topn_ids = np.argsort(row)[::-1][:top_n]
              names = np.array(features)
              print(names[topn_ids])
              top_feats = [(features[i], row[i]) for i in topn_ids]
              global df_feat
              df_feat = pd.DataFrame(top_feats,names[topn_ids])
              df_feat.columns = ['FEATURE', 'Feat_IMP_value']

              return df_feat
```

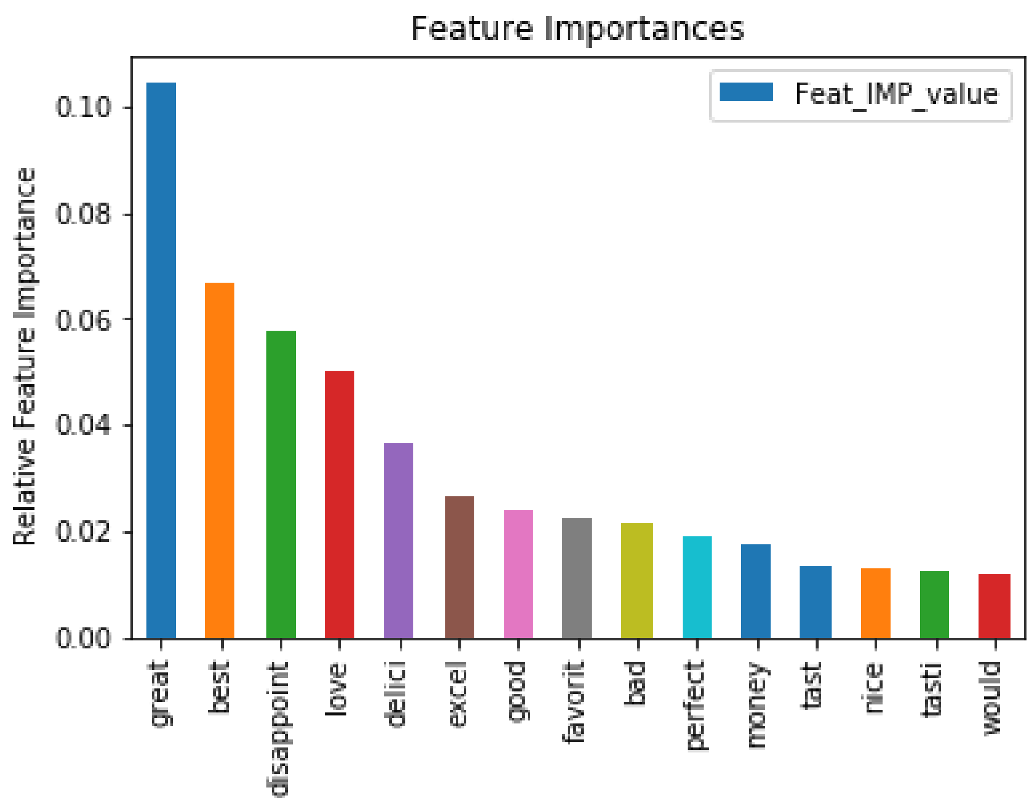
Feature importance using count_vect

```
In [132]: # Decision Tree classifier for optimal depth using gini index
          DT_clf11 =DecisionTreeClassifier(criterion='gini',max_depth=18,class_weight='balanced'
          data=count_vect.fit_transform(X_train_data.values.ravel())
          DT_clf11.fit(data ,Train_data)
          # Calculate feature importances
          count_vect_feature=count_vect.get_feature_names()
          feature_importance = DT_clf11.feature_importances_

In [133]: top_feat = top_feats(feature_importance,count_vect_feature,15)
          result_display(top_feat)
```

```
['great' 'best' 'disappoint' 'love' 'delici' 'excel' 'good' 'favorit'
 'bad' 'perfect' 'money' 'tast' 'nice' 'tasti' 'would']
| FEATURE  |Feat_IMP_value|
|----------|-------------:|
```

```
|great     |       0.10429|
|best      |       0.06659|
|disappoint|       0.05747|
|love      |       0.05009|
|delici    |       0.03636|
|excel     |       0.02647|
|good      |       0.02389|
|favorit   |       0.02266|
|bad       |       0.02165|
|perfect   |       0.01909|
|money     |       0.01729|
|tast      |       0.01323|
|nice      |       0.01306|
|tasti     |       0.01214|
|would     |       0.01170|
```

```
In [134]: df_feat.plot.bar(y='Feat_IMP_value',title='Feature Importances', rot=90)
          plt.ylabel('Relative Feature Importance  ')

Out[134]: Text(0,0.5,'Relative Feature Importance  ')
```



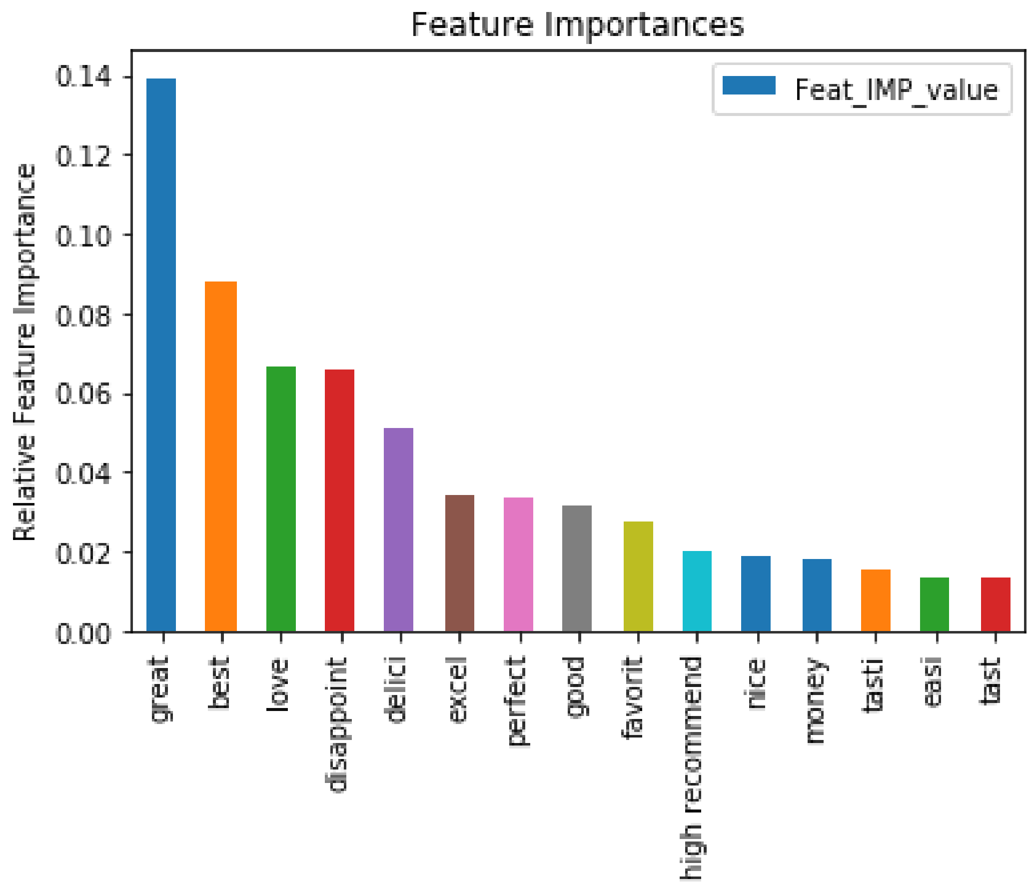
Feature importance using tf-idf -vect

```
In [162]: model =DecisionTreeClassifier(criterion='gini',max_depth=14,class_weight='balanced',ra
          final_tf_idf11 = tf_idf_vect.fit_transform(X_train_data.values.ravel())
          model.fit(final_tf_idf11 ,Train_data)
          tf_idf_feature=tf_idf_vect .get_feature_names()
          feature_importance1 = model.feature_importances_
```

```
In [163]: # Relative Feature Importance  using tf_idf
          top_feat1 = top_feats(feature_importance1,tf_idf_feature,15)
          result_display(top_feat1)
```

```
['great' 'best' 'love' 'disappoint' 'delici' 'excel' 'perfect' 'good'
 'favorit' 'high recommend' 'nice' 'money' 'tasti' 'easi' 'tast']
|   FEATURE    |Feat_IMP_value|
|--------------|-------------:|
|great         |       0.13924|
|best          |       0.08770|
|love          |       0.06648|
|disappoint    |       0.06602|
|delici        |       0.05085|
|excel         |       0.03439|
|perfect       |       0.03339|
|good          |       0.03134|
|favorit       |       0.02762|
|high recommend|       0.01984|
|nice          |       0.01898|
|money         |       0.01806|
|tasti         |       0.01545|
|easi          |       0.01347|
|tast          |       0.01299|
```

```
In [165]: df_feat.plot.bar(y='Feat_IMP_value',title='Feature Importances', rot=90)
          plt.ylabel('Relative Feature Importance  ')

Out[165]: Text(0,0.5,'Relative Feature Importance  ')
```



FEATURE_BOW	Feat_IMP_value_BOW	FEATURE_TFIDF	Feat_IMP_value_TFIDF
great	0.10429	great	0.13924
best	0.06659	best	0.08770
disappoint	0.05747	love	0.06648
love	0.05009	disappoint	0.06602
delici	0.03636	delici	0.05085
excel	0.02647	excel	0.03439
good	0.02389	perfect	0.03339
favorit	0.02266	good	0.03134
bad	0.02165	favorit	0.02762
perfect	0.01909	highrecomm	0.01984
money	0.01729	nice	0.01898
tast	0.01323	money	0.01806
nice	0.01306	tasti	0.01545
tasti	0.01214	easi	0.01347
would	0.01170	tast	0.01299

8 Decision Tree Image with all vectorization method

Decision Tree Classifier

- DT_clf1 using BOW
- DT_clf2 using Avg word2vec
- DT_clf3 Using TF-IDF
- DT_clf4 using TF-IDF weighted word2vec

```
In [166]: Classifier=[DT_clf1,DT_clf2,DT_clf3,DT_clf4]
```

Features_name

- features using BOW for Decision tree image using BOW & Avg word2vec:

  1. feature_importance

- Features using Tf-IDF for Decision tree image using TF-Idf & TF-IDF weighted word2vec:

  2.tf_idf_feature

```
In [167]: features=tf_idf_feature[:100]
```

name_png_format:

```
1. BOW_Decision_Tree.png
2. Avg word2vec.png
3. TF-IDF.png
4. TF-IDF weighted word2vec.png
```

```
In [168]: name_png_format=['BOW_Decision_Tree.png','Avg word2vec.png','TF-IDF.png','TF-IDF weigh
```

```
In [169]: for i in tqdm(range(4)):

              decision_tree_image(Classifier[i],features,name_png_format[i])

100%|??????????| 4/4 [03:17<00:00, 49.39s/it]
```

8.1 Observation:

Model	Vectorizer	Optimal Depthsize	Training error	Test error	Accuracy	F1	recall	precision
Decision Tree	BOW	18	0.01925	0.3326	66.74	61.86	61.74	61.99
Decision Tree	Avg word2vec	10	0.15796	0.2728	72.72	70.90	72.77	70.54
Decision Tree	TF-IDF	14	0.07957	0.3053	69.47	66.17	66.64	65.89
Decision Tree	TF-IDF weighted word2vec	16	0.03961	0.2975	70.25	66.73	67.01	66.52

- The results obtained after training and testing the amazon reviews datasets for Avg word2vecis best compared to other techniques.
- The Depth_size for BOW and TF-IDF is quite high (nearby max_size) ,it means model undergoes overfitting.
- The Depth_size for Tf-IDF weighted word2vec is too low,it means model undergoes underfitting
- Decision tree images with all feature geneation techniques is generated. And we can visually the decision tree.
- Feature importance using BOW and TF_IDF is shown as above.
- Decision Tree Model on amazon reviews datasets is classiefied all points as postive reviews.
- Here, decision tree on Amazon reviews datasets gives poor result as seen in above table.

```
In [ ]:
```

```
In [ ]:
```