Assignment 3

October 13, 2018

0.1 Assignment 3:Apply k-NN 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 (3) a plain text review.

K-NN is used for classification and regression for data.Here, K-NN algorithm is applied on amazon reviews datasets to classify postive and negative reviews.

Procedure to execute the above task is as follows:

- Data Pre-processing is applied on given amazon reviews data-set.
- Take sample of data from dataset because of computational limitations
- apply Feature generation techniques(Bow,tfidf,avg w2v,tfidfw2v)
- Apply K-NN algorithm using each technique and find best accuracy

0.2 Objective:

- To classify given reviews (positive (Rating of 4 or 5) & negative (rating of 1 or 2)) using k-NN algorithm(brute force and kd tree).
- To train and test split data using Time based slicing
- To find optimal 'k' in knn using TimeSeriesSplit(Bow,tfidf,avg w2v,tfidfw2v)
- To calcuate Test accuracy:Best 'k'
- Comapare the results using brute force and kd tree

```
In [1]: %matplotlib inline
        import warnings

        warnings.filterwarnings("ignore")
```

```
In [2]: # All necessary module

        #import  sys
        import re
        import math
        import sqlite3
        import pandas as pd
        import numpy as np
        import pickle
        # modules for text processing
        import nltk
```

```
import string
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 scipy.sparse import csr_matrix
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.decomposition import TruncatedSVD
import pytablewriter
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

#import scikitplot.metrics as skplt
from sklearn.metrics import classification_report,confusion_matrix,accuracy

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


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

from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.neighbors import KNeighborsClassifier
from scipy.spatial import cKDTree
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
warnings.filterwarnings("ignore")
```

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

```
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)
        amz=amz.fillna(lambda x: x.median())
```

```
(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

        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=Fa

# To check the duplications in raw data
dupli=sorted_data[sorted_data.duplicated(["UserId","ProfileName","Time","Te
print(dupli.head(5))
# Remove Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Te
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 ent
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
```

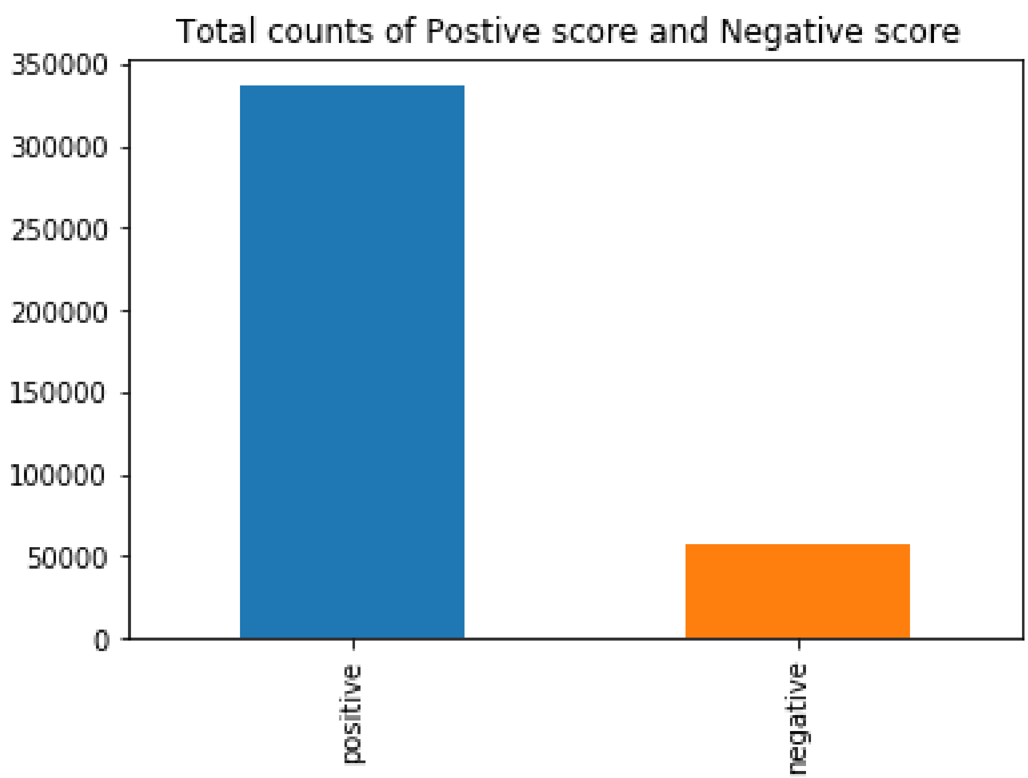
```
171222  Freeze dried liver has a hypnotic effect on do...
171153  Freeze dried liver has a hypnotic effect on do...
171151  Freeze dried liver has a hypnotic effect on do...
217443  My dog can't resist these treats - I can get h...
217444  My little pupster loves these things. She is n...
(393931,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

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

```
In [9]: 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 stem

         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
             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-proces

         '''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 us
                        if(final['Score'].values)[i] == 'negative':
                            all_negative_words.append(s) #list of all words us
                    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-processi
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']# posti
         pos_final = pos_final.sample(frac=0.3)
         print(pos_final.Score.value_counts())

         neg_final = Pre_Process_Data [Pre_Process_Data .Score == 'negative'] # neg
         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 based on Time

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

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

         print(X.shape)
```

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

X_train_data ,X_test_data,Y_train_data,Y_test_data  = train_test_split(X,
                                                     Y.values.ravel(),

                                                    test_size=0.3,shuffle=



print('X_train_data ',X_train_data.shape)

print('X_test_data ',X_test_data.shape )

print('Y_train_data ',Y_train_data .shape)

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

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

```
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=Fals
         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 K for KNN

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

In [20]: # k-optimal is function to calculate the optimal k value for knn
```

```
def k_optimal(X_train,X_test):
    print('opyimal k value')
    warnings.filterwarnings("ignore")

    My_List = list(range(2,20))
    neighbors = list(filter(lambda x: x % 2 != 0, My_List))
    algorithm=['kd_tree','brute']
    global optimal_k_list
    optimal_k_list=[]
    for algo in range(len(algorithm)):
        print('algorithm = ',algorithm[algo])

        test_error=[]
        train_error=[]
        cv_scores = []

        for i in range(len(neighbors)):
            hp1 =dict(n_neighbors=[neighbors[i],],algorithm=[algorithm[alg
            knn = KNeighborsClassifier(n_jobs=-1)
            model1 = GridSearchCV(knn, hp1,
                                  scoring ='f1',
                                  cv=tscv
                                  ,n_jobs= -1
                                  ,pre_dispatch=8)
            best_model1=model1.fit(X_train[algo], y_train_new)


            Train_score=model1.score(X_train[algo], y_train_new)

            train_error.append(1-Train_score)
            cv_scores.append(1-Train_score)
            Test_score=model1.score(X_test[algo],y_test_new)
            test_error.append(1-Test_score)



        MSE = [1 - x for x in cv_scores]

        # determining best k
        global optimal_k
        optimal_k = neighbors[MSE.index(min(MSE))]

        optimal_k_list.append(optimal_k)


        print('\nThe optimal number of neighbors is %d.' % optimal_k)

        fig = plt.figure( facecolor='y', edgecolor='k',figsize=(15,8))
```

```
        plt.semilogx(neighbors, MSE,'m*',linestyle='dashed', label='depths
        plt.legend(loc='lower left')


        for xy in zip(neighbors, np.round(MSE,3)):
            plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
        plt.title('Error_Rate vs. K_Value')
        plt.grid()
        plt.xlabel('Number of Neighbors K')
        plt.ylabel('Misclassification Error')
        plt.show()

        print("the misclassification error for each k value is : ", np.rou

        fig = plt.figure( facecolor='y', edgecolor='k')
        plt.semilogx(neighbors,train_error,'g*',linestyle='dashed', label=
        plt.semilogx(neighbors,test_error,'r*', linestyle='dashed',label='
        plt.legend(loc='lower left')
        plt.grid()

        plt.xlabel('K neighbors  ')
        plt.ylabel('Performance using '+str(algorithm[algo]))
        plt.show()
```

In [42]:
```
# k-optimal is function to calculate the optimal k value for knn
# using Multiprocessing
import multiprocessing as mp


def main():
    print("Started.")

    k_optimal(xtrain,xtest)
```

k-optimal is function to calculate the optimal k value for knn.

Pandas dataframe to markdown Table format

In [43]:
```
# result_display  is function to convert dataframe into table format in Ma
def result_display(df):
    writer = pytablewriter.MarkdownTableWriter()
    writer.header_list = list(df.columns.values)
    writer.value_matrix = df.values.tolist()
    writer.write_table()
```

3 Methods to convert text into vector

Methods: * Bag of Words * Avg word2vec * Tf-idf * tf-idf weighted Word2Vec
Using above four method is used to convert text to numeric vector.

4 1. Bag of Words (BoW)

BOW for Training Data

In [29]:
```
count_vect = CountVectorizer() #in scikit-learn
vect_Data = count_vect.fit_transform(X_train_data.values.ravel())
print(vect_Data .shape)
```

```
(28000, 20590)
```

In [30]:
```
# truncated SVD for dimesionality reduction for 100 dimensions
svd = TruncatedSVD(n_components=100,n_iter=7)

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

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

In [31]:
```
# StandardScaler
sc_data= StandardScaler(with_mean=False).fit_transform(Data )
final_data= preprocessing.normalize(sc_data)
print(final_data.shape)
#Normalize Data


warnings.filterwarnings("ignore")
```

```
(28000, 100)
```

Dumping & Loading Pickle file for training data (BOW)

In [32]:
```
#Pickle file for training data

pickle_path_BOW_train='X_train_data_BOW.pkl'
X_train_data_BOW=open(pickle_path_BOW_train,'wb')
pickle.dump(final_data ,X_train_data_BOW)
X_train_data_BOW.close()
```

In [33]:
```
pickle_path_BOW_train='X_train_data_BOW.pkl'
unpickle_path1=open(pickle_path_BOW_train,'rb')
final_data=pickle.load(unpickle_path1)
```

Sparse matrix for train Data (KD-Tree)

```
In [34]: final_data_sparse=csr_matrix(Data).todense()
         #final_data_sparse = preprocessing.normalize(final_data_sparse1)
         print("Train data Sparse:",final_data_sparse)
```

```
Train data Sparse: [[ 0.88923011 -0.23770002  0.15238884 ... -0.33439129 -0.1831011
   0.07761813]
 [ 0.52521297 -0.07851448  0.03767966 ...  0.19579533  0.12882225
  -0.18778595]
 [ 0.47455633 -0.1354722   0.06045515 ...  0.03616926 -0.02312829
   0.04665366]
 ...
 [ 0.94256057 -0.31561972 -0.02754873 ...  0.0648032  -0.18641765
   0.02396582]
 [ 1.21033516 -0.3813755   0.30442384 ... -0.21936339 -0.0671804
   0.05819784]
 [ 4.32335934 -1.38510882 -0.87885423 ... -0.27533609 -0.03328312
  -0.2384029 ]]
```

BOW for Testing Data

```
In [35]: vect_Data1= count_vect.transform(X_test_data.values.ravel())
         print(vect_Data1.shape)

         svd1 = svd.fit(vect_Data1)

         X_test=svd1.transform(vect_Data1)
         print("TruncatedSVD :",X_test.shape)
         #Normalize Data
         #X_sparse_tsvd = svd.fit(vect_Data1).transform(X_sparse)
```

```
(12000, 20590)
TruncatedSVD : (12000, 100)
```

```
In [36]: #final_data_test= bb.fit(data1 )
         final_data_test_f=StandardScaler(with_mean=False).fit(X_test)
         print(final_data_test_f)

         final_data_test1=final_data_test_f.transform(X_test)
         final_data_test= preprocessing.normalize(final_data_test1)
```

```
StandardScaler(copy=True, with_mean=False, with_std=True)
```

Dumping & Loading Pickle file for testing data (BOW)

```
In [37]: pickle_path_BOW_test='X_test_data_BOW.pkl'
         X_test_data_BOW=open(pickle_path_BOW_test,'wb')
         pickle.dump(final_data_test ,X_test_data_BOW)
         X_test_data_BOW.close()
```

```
In [38]: pickle_path_BOW_test='X_test_data_BOW.pkl'
         unpickle_path2=open(pickle_path_BOW_test,'rb')
         final_data_test=pickle.load(unpickle_path2)
```

```
In [ ]: ##### Sparse matrix for test data(KD-Tree)
```

```
In [39]: final_data_test_sparse=csr_matrix(final_data_test ).todense()
         #final_data_test_sparse= preprocessing.normalize(final_data_test_sparse)
         print("Test Data Sparse:",final_data_test_sparse.shape)
```

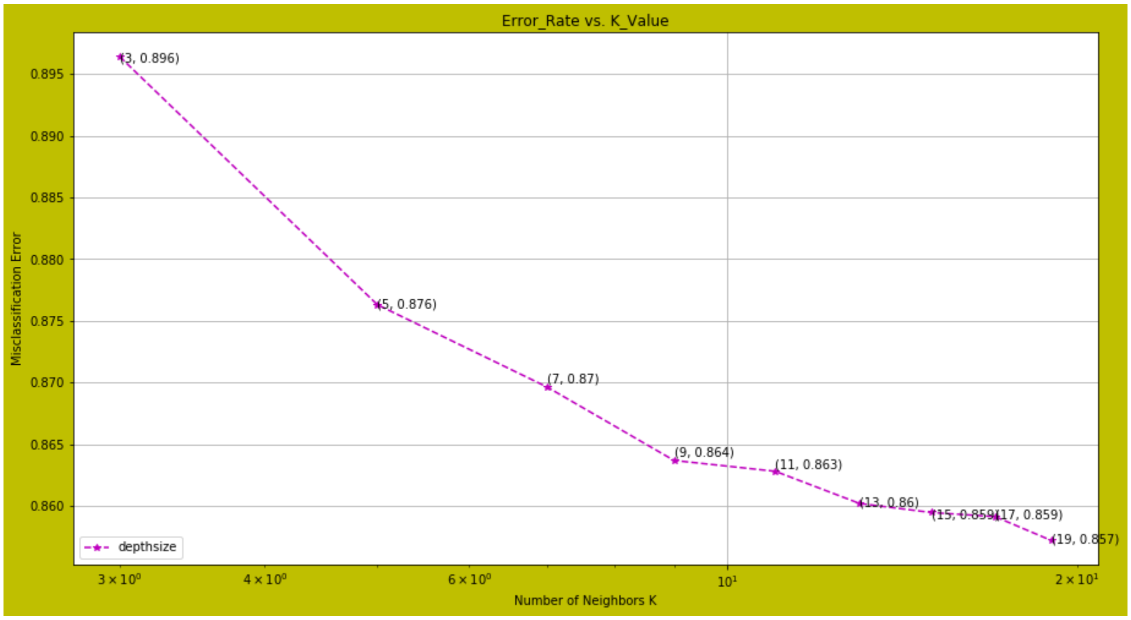
```
Test Data Sparse: (12000, 100)
```

Featured data of Bag of words is Standardization (mean=0 and std.dev=1).

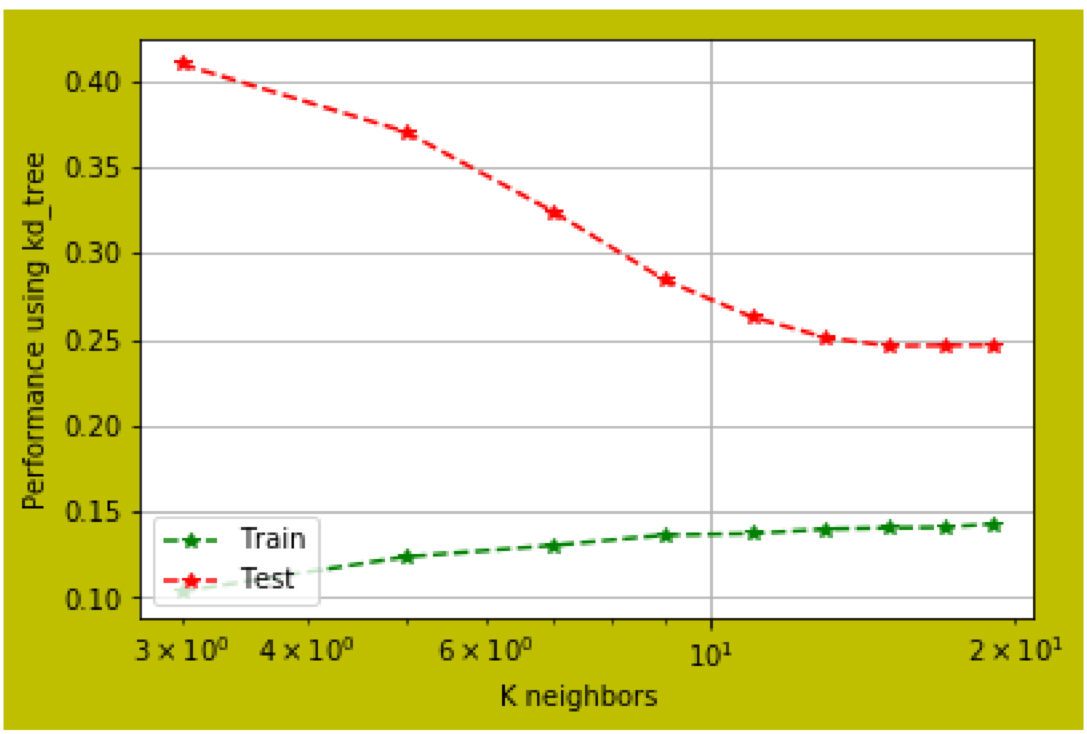
4.0.1 Optimal k using BOW

```
In [37]: # To get optimal k using BOW

         if __name__=='__main__':
             mp.freeze_support()

             xtrain=[final_data_sparse,final_data]
             xtest=[final_data_test_sparse,final_data_test]

             main()
```

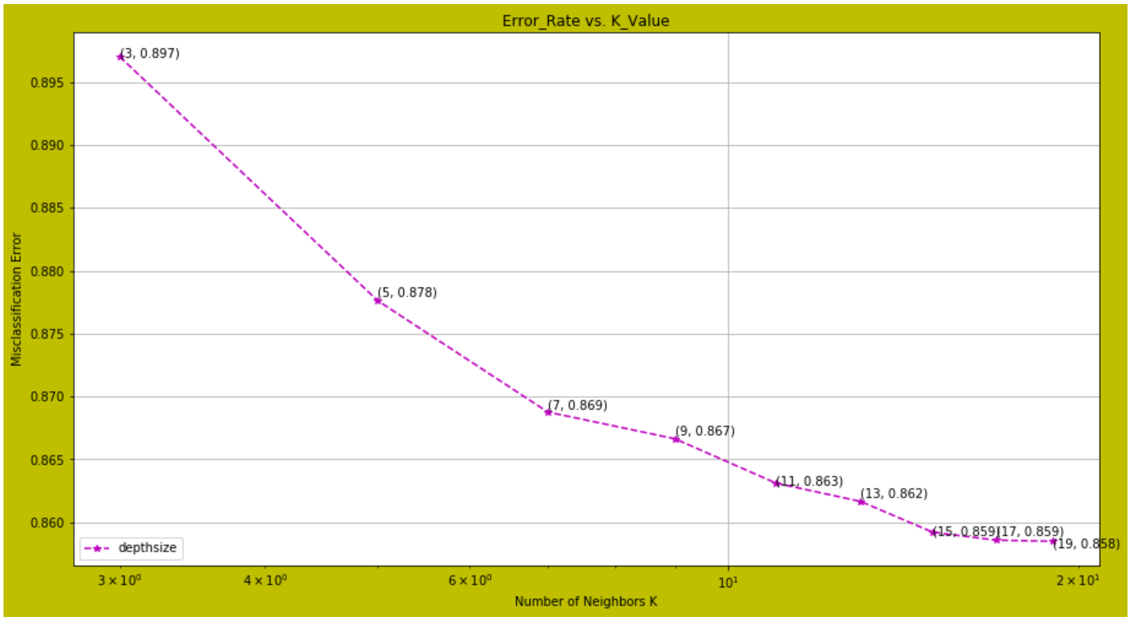
```
Started.
opyimal k value
algorithm =  kd_tree

The optimal number of neighbors is 19.
```



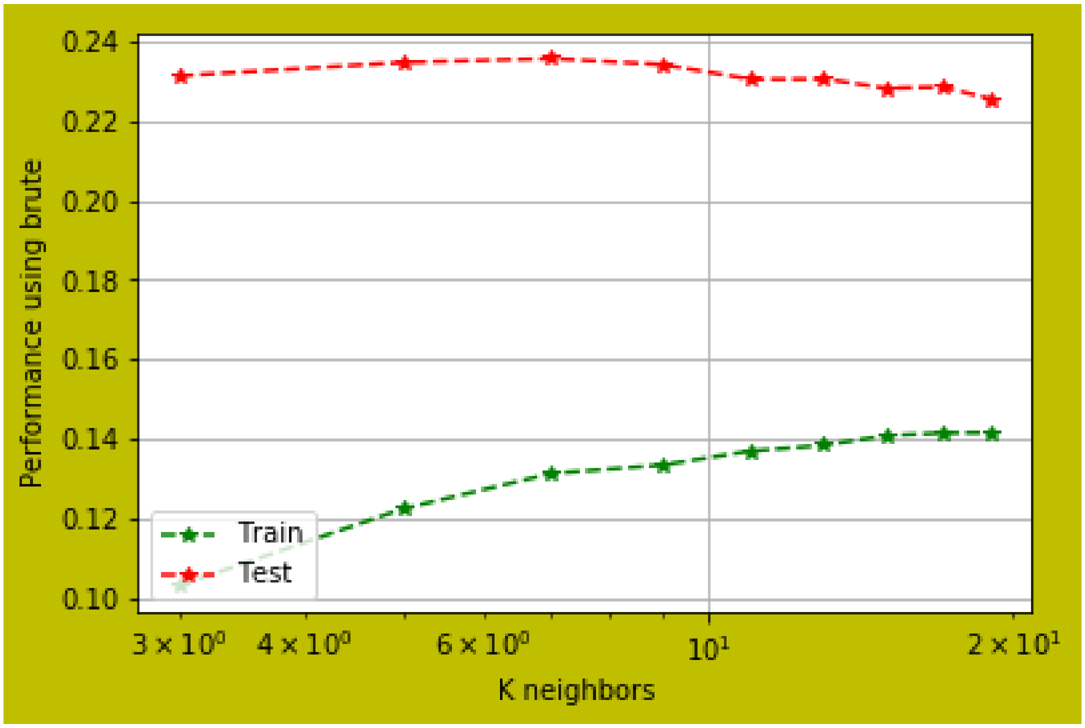

```
the misclassification error for each k value is :  [0.89642 0.87631 0.86964 0.86369
```



```
algorithm =  brute

The optimal number of neighbors is 19.
```




```
the misclassification error for each k value is :  [0.89705 0.87762 0.86877 0.86664
```



```
In [38]: print(optimal_k_list)

[19, 19]
```

Observations:

- The optimal number of neighbors is 19 for both KD_tree KNN and Brute KNN
- Error rate vs K value graph is shown as above.
- From the graph, misclassification error is low for higher k values.
- As k values increases from 1 to 20, MSE decreses and then remains constant.
- at k=19 , MSE is lower than other value for both the implementations.
- Training and testing error plot is shown for KD-Tree and Brute KNN.

4.1 Knn classifier for optimal k value

All techniques for Scoring metrics and confusion matrix are shown as below

```
In [26]: models_performence = {
             'Model':[],
             'Vectorizer': [],
             'algorithm':[],
             'Optimal k': [],
             'Train error':[],
             'Test error':[],
             'Accuracy':[],
             'F1':[],
             'recall':[],
             'precision':[]


         }
         columns = ["Model", "Vectorizer","algorithm","Optimal k", "Train error",
                     "Accuracy","F1","recall","precision",
                   ]
         pd.DataFrame(models_performence, columns=columns)

Out[26]: Empty DataFrame
         Columns: [Model, Vectorizer, algorithm, Optimal k, Train error, Test error
         Index: []
```

4.1.1 KNN Classifier

```
In [27]: #  Knn classifier
         def Knn_classifier_optimal_k(xtrain,ytrain,xtest,ytest,k,algo,vectorizatio
```

```
warnings.filterwarnings("ignore")

print(' Algorithm = '+str(algo))

models_performence['Model'].append('KNN')
models_performence['Vectorizer'].append(vectorization)
models_performence['algorithm'].append(algo)
models_performence['Optimal k'].append(k)
#
knn = KNeighborsClassifier(n_neighbors=k,
                           algorithm=algo,
                           metric='euclidean',
                           n_jobs=-1)

model=knn.fit(xtrain,ytrain)
prediction =  model.predict(xtest)

#Training accuracy and training error

training_score=knn.score(xtrain,ytrain)
print('training accuracy=',training_score)


training_error=1-training_score
print('training error is =',training_error)
models_performence['Train error'].append(training_error)

# Testing Accuracy and testing error for knn model

Testing_score=round(accuracy_score(ytest,prediction),5)
print("Accuracy for KNN model  is = ",Testing_score)
models_performence['Accuracy'].append(Testing_score)

Testing_error=1-Testing_score
print("Testing error for KNN model is = ",Testing_error)
models_performence['Test error'].append(Testing_error)

F1_score = round(f1_score(ytest ,prediction,average='macro'),5)*100
models_performence['F1'].append(F1_score)

recall = round(recall_score(ytest,prediction,average='macro'),5)*100
models_performence['recall'].append(recall)

precision = round(precision_score(ytest,prediction,average='macro'),5)
models_performence['precision'].append(precision)

print('\n')
print(classification_report( ytest,prediction))
```

```
    cm = confusion_matrix( ytest,prediction)
    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()
```

4.2 Knn classifier for optimal k value (BOW)

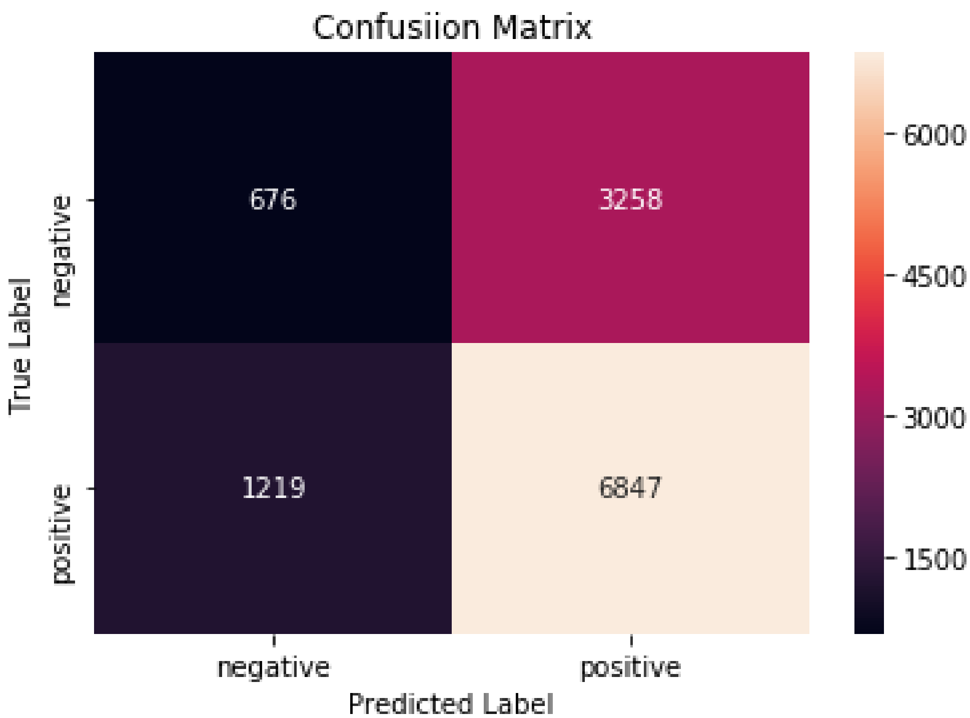
All techniques for Scoring metrics and confusion matrix are shown as below

```
In [41]: xtrain=[final_data_sparse,final_data]
         ytrain=[y_train_new,Y_train_data]

         xtest=[final_data_test_sparse,final_data_test]
         #xtest=final_data_test
         ytest=[y_test_new,Y_test_data]
         vectorization='BOW'

         k=optimal_k_list
```

```
In [42]: import multiprocessing as mp


         def main1():
             print("Started.")
             algorithm=['kd_tree','brute']

             for i in range(len(algorithm)):
                 algo=algorithm[i]
                 print("Algorithm is ="+str(algorithm)+" for optimal k ="+str(k[i])

                 Knn_classifier_optimal_k(xtrain[i],ytrain[i],xtest[i],ytest[i],k[i

         if __name__=='__main__':
             mp.freeze_support()
             main1()
```

```
Started.
Algorithm is =['kd_tree', 'brute'] for optimal k =19
 Algorithm = kd_tree
training accuracy= 0.7801785714285714
training error is = 0.2198214285714286
Accuracy for KNN model  is =  0.62692
Testing error for KNN model is =  0.37307999999999997
```

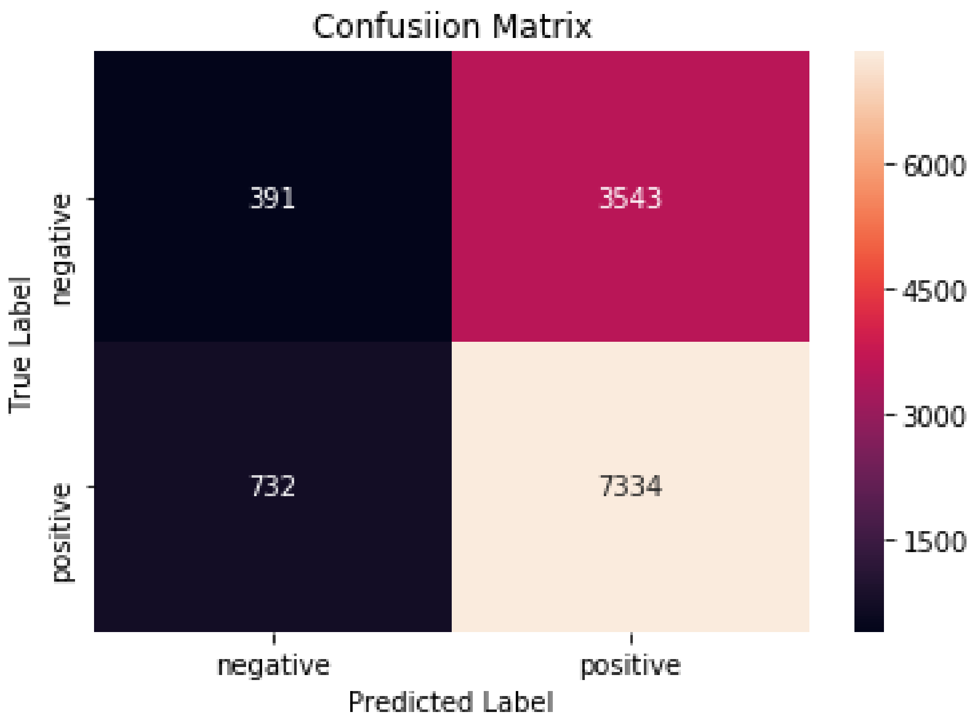
	precision	recall	f1-score	support
0	0.36	0.17	0.23	3934
1	0.68	0.85	0.75	8066
avg / total	0.57	0.63	0.58	12000




```
Algorithm is =['kd_tree', 'brute'] for optimal k =19
 Algorithm = brute
training accuracy= 0.7787857142857143
training error is = 0.2212142857142857
Accuracy for KNN model  is =  0.64375
Testing error for KNN model is =  0.35624999999999996
```

	precision	recall	f1-score	support
negative	0.35	0.10	0.15	3934
positive	0.67	0.91	0.77	8066

```
avg / total       0.57      0.64      0.57     12000
```




```
In [43]: df2=pd.DataFrame(models_performence, columns=columns)
         result_display(df2)
```

```
|Model|Vectorizer|algorithm|Optimal k|Train error|Test error|Accuracy| F1  |recall|
|-----|----------|---------|--------:|----------:|---------:|-------:|----:|-----:|
|KNN  |BOW       |kd_tree  |       19|     0.2198|    0.3731|  0.6269|49.28| 51.03|
|KNN  |BOW       |brute    |       19|     0.2212|    0.3562|  0.6437|46.45| 50.43|
```

Model	Vectorizer	algorithm	Optimal k	Train error	Test error	Accuracy	F1	recall	precision
KNN	BOW	kd_tree	19	0.2198	0.3731	0.6269	49.28	51.03	51.72
KNN	BOW	brute	19	0.2212	0.3562	0.6437	46.45	50.43	51.12

observations

- The optimal number of neighbors is 19 for both the algorithm.

- True postive rate is high(91%) for Brute force and 85% for KD-Tree.It means postive rating is higher as compared to negative rating which is good for amazon reviews .
- Confusion matrix and model performance is shown as above.
- FNR is higher in both Algorithm.
- KDTree Algorithm for KNN classifier is giving better performance as compared to brute Algorithm as seen in above table

5 2. Avg word2vec

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

In [44]:
```
import gensim
list_sent=[]
for text in 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))
```

```
28000
```

word2vec Model using Training Datasets

In [45]:
```
w2v_model=gensim.models.Word2Vec(list_sent,min_count=5,size=100, workers=4
#this model is used in avg word2vec   .
```

In [46]:
```
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 [47]:
```
pickle_path_w2v_model='w2v_model.pkl'
unpickle_w2v_model=open(pickle_path_w2v_model,'rb')
w2v_model=pickle.load(unpickle_w2v_model)
```

In [48]:
```
words = list(w2v_model.wv.vocab)
print(len(words))
#print(w2v_model['use'])
```

```
7263
```

Avg Word2Vec

```
In [49]: #  For Training

         sent_vectors = []
         for sent in 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])
```

```
28000
```

```
In [50]: # Converting Nan value to zero in sent vectors.
         Sent_Nan = np.where(np.isnan(sent_vectors), 0, sent_vectors)
```

```
In [51]: # converting sent list to nd array
         Sent_final_vector = np.asarray(Sent_Nan )
         print(type(Sent_final_vector))
```

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

```
In [52]: #  ForTesting
         # Words in test reviews
         list_sent_test=[]
         for text in 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 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))
```

```
12000
<class 'numpy.ndarray'>
```

Dumping & Loading Pickle file for Avg word2vec

In [53]:
```
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 [54]:
```
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_vecto1=pickle.load(unpickle_path3_test)
```

Standardscaler & normalizing training avg word2vec

```
In [55]: sc_data1= StandardScaler(with_mean=False).fit_transform(Sent_final_vector)
         # For Train
         final_w2v_count_Train=preprocessing.normalize(sc_data1)
         print(final_w2v_count_Train.shape)
```

```
(28000, 100)
```

Sparse Matrix for training Avg word2vec

```
In [56]: final_w2v_count_Train_sparse=csr_matrix(Sent_final_vector).todense()

         print("Train data Sparse:",final_w2v_count_Train_sparse.shape)
```

```
Train data Sparse: (28000, 100)
```

Standardscaler & normalizing testing avg word2vec

```
In [57]: sc_avgword2vec=StandardScaler(with_mean=False).fit(Sent_final_vector1)
         print(sc_avgword2vec)

         sc_avgword2vec1=sc_avgword2vec.transform(Sent_final_vector1)
```

```
StandardScaler(copy=True, with_mean=False, with_std=True)
```

```
In [58]: final_w2v_count_Test=preprocessing.normalize(sc_avgword2vec1)# For Test
         print(final_w2v_count_Test.shape)
```

```
(12000, 100)
```

```
In [59]: final_w2v_count_Test_sparse=csr_matrix(Sent_final_vector1).todense()

         print("Test Data Sparse:",final_w2v_count_Test_sparse.shape)
```

```
Test Data Sparse: (12000, 100)
```

for Training datasets ,avg word2vec

```
final_w2v_count_Train,
final_w2v_count_Train_sparse
```

for testing datasets ,avg word2vec

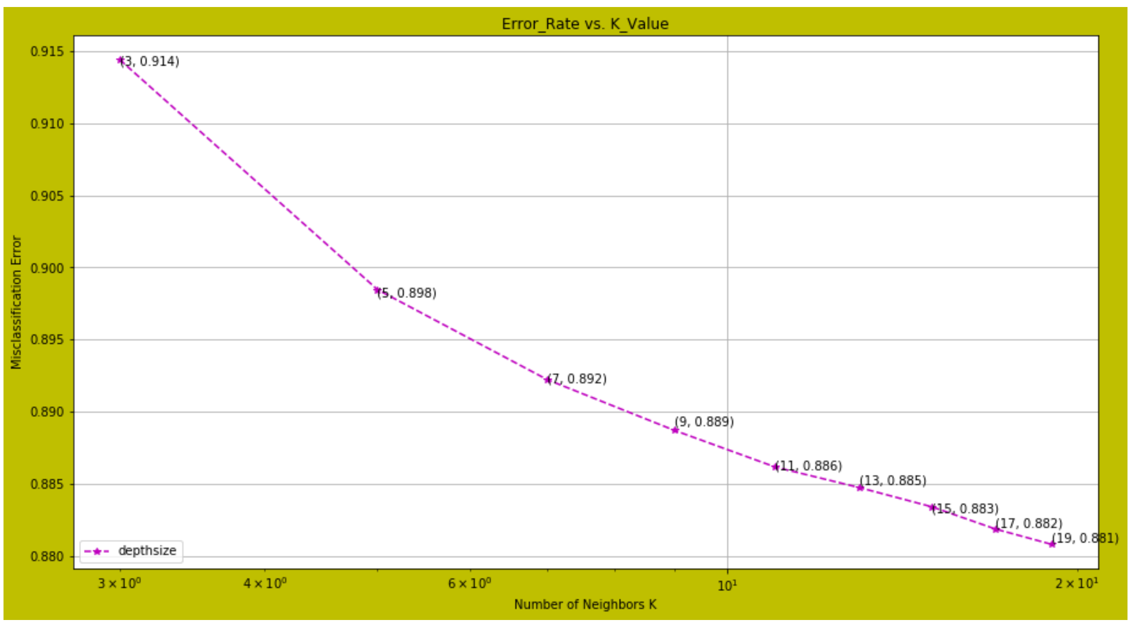
```
final_w2v_count_Test,
final_w2v_count_Test_sparse
```

5.0.1 Optimal k for Avg word2vec

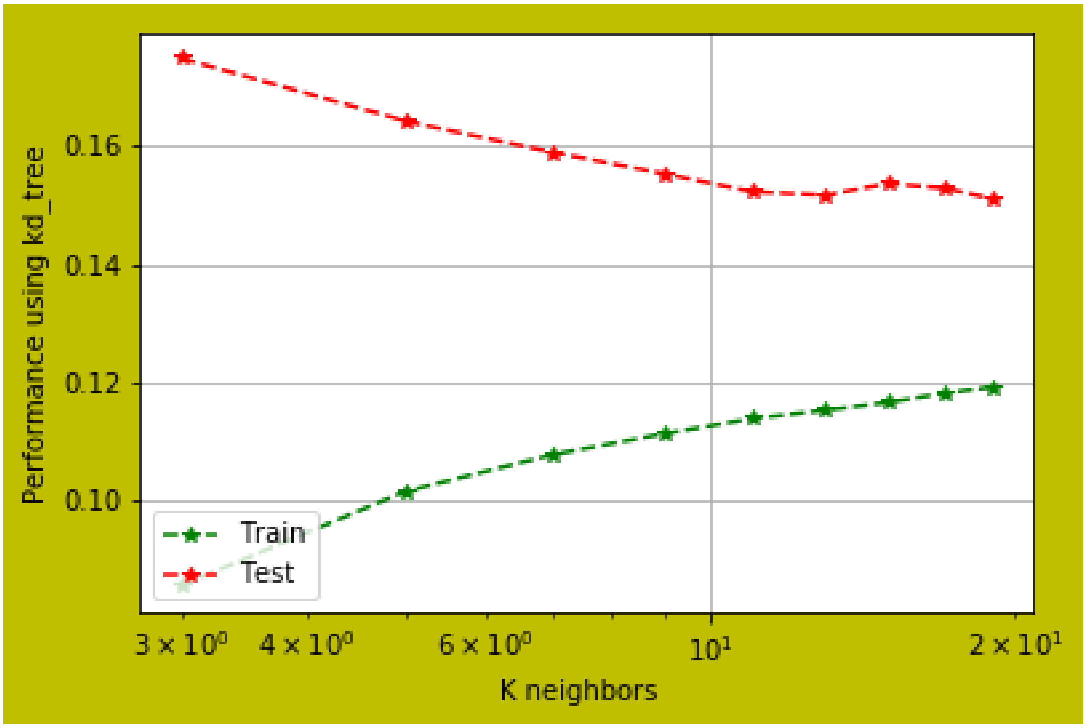
```
In [60]: # To get optimal k using  Avg word2vec
```

```
In [61]: if __name__=='__main__':
             mp.freeze_support()

             xtrain=[final_w2v_count_Train_sparse,final_w2v_count_Train]
             xtest=[final_w2v_count_Test_sparse,final_w2v_count_Test]

             main()
```

```
Started.
opyimal k value
algorithm =  kd_tree

The optimal number of neighbors is 19.
```

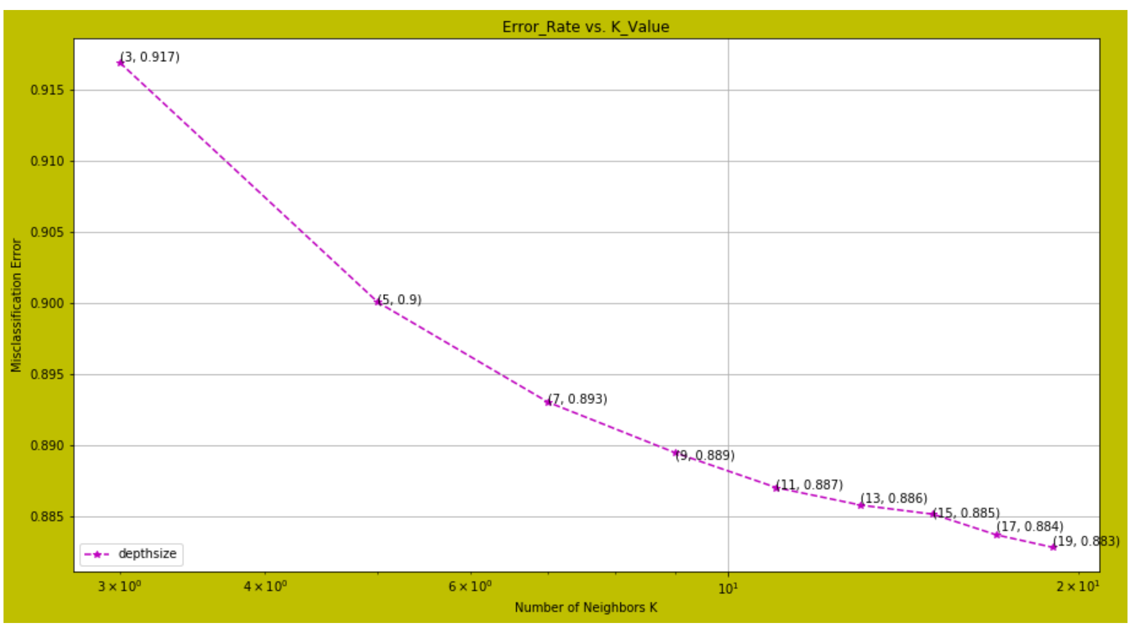



```
the misclassification error for each k value is :  [0.91441 0.89846 0.89222 0.88871
```

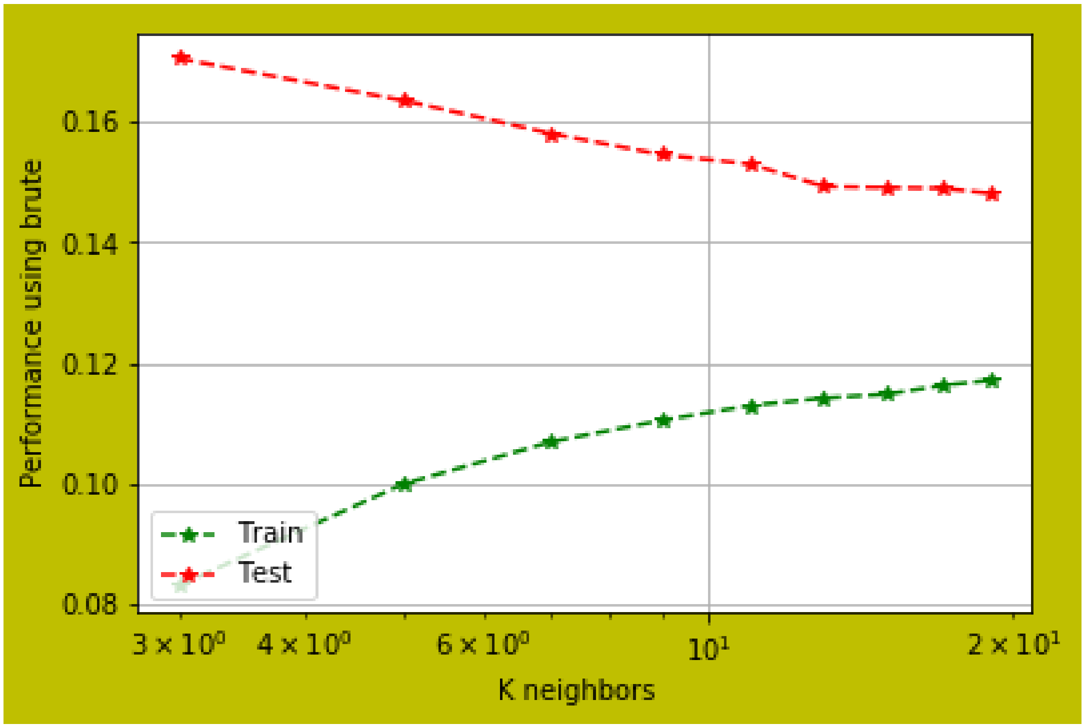


algorithm = brute

The optimal number of neighbors is 19.



```
the misclassification error for each k value is :  [0.91691 0.90007 0.89305 0.8895
```



Observations

- The optimal number of neighbors is 19 for avg word2vec for both the algorithm.
- MSE(Misclassification error) is descreasing when k values is increasing as seen in graph.
- In performance graph, lowest k value gives higest error in test datasets. As k value increase, testing error gets reduces but vice -versa in case of traing datasets.

5.1 Knn classifier for optimal k value (Avg word2vec)

All techniques for Scoring metrics and confusion matrix are shown as below

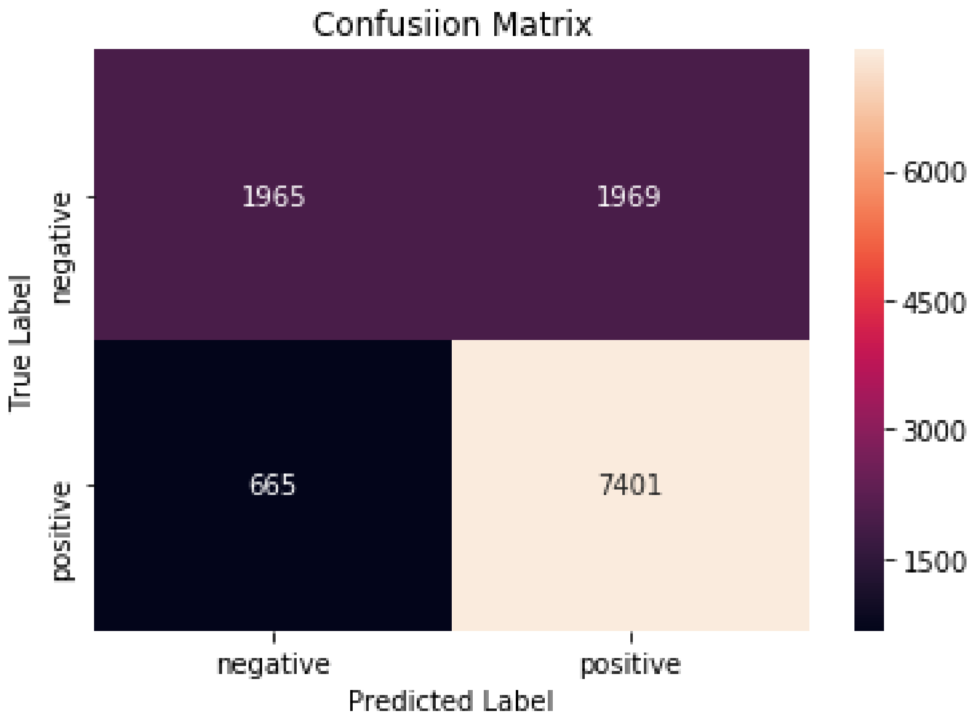
```
In [62]: k=optimal_k_list
         print(optimal_k_list)
```

```
[19, 19]
```

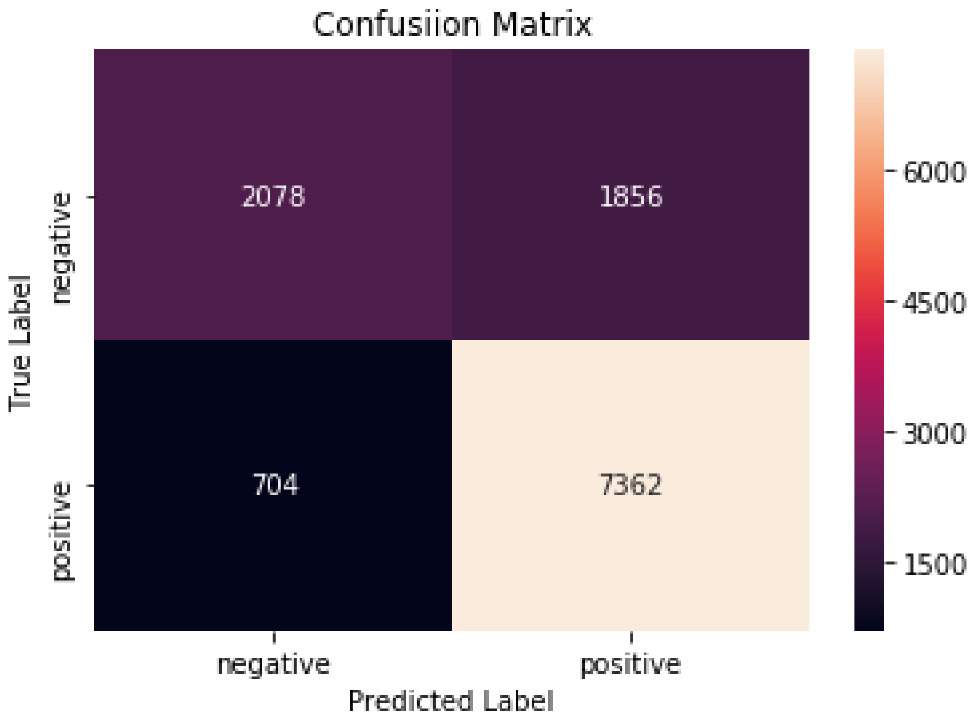
```
In [63]: xtrain=[final_w2v_count_Train_sparse,final_w2v_count_Train]
         ytrain=[y_train_new,Y_train_data]
         xtest=[final_w2v_count_Test_sparse,final_w2v_count_Test]
         ytest=[y_test_new,Y_test_data]
         vectorization='Avg word2vec'
```

```
In [64]: import multiprocessing as mp


         def main1():
             print("Started.")
             algorithm=['kd_tree','brute']

             for i in range(len(algorithm)):
                 algo=algorithm[i]
                 print("Algorithm is ="+str(algo)+" for optimal k ="+str(k[i]))

                 Knn_classifier_optimal_k(xtrain[i],ytrain[i],xtest[i],ytest[i],k[i

         if __name__=='__main__':
             mp.freeze_support()
             main1()
```

```
Started.
Algorithm is =kd_tree for optimal k =19
 Algorithm = kd_tree
training accuracy= 0.8197142857142857
training error is = 0.18028571428571427
Accuracy for KNN model  is =  0.7805
Testing error for KNN model is =  0.21950000000000003


             precision    recall  f1-score   support

          0       0.75      0.50      0.60      3934
          1       0.79      0.92      0.85      8066

avg / total       0.78      0.78      0.77     12000
```




```
Algorithm is =brute for optimal k =19
 Algorithm = brute
training accuracy= 0.8238571428571428
training error is = 0.17614285714285716
Accuracy for KNN model  is =  0.78667
Testing error for KNN model is =  0.21333000000000002


             precision    recall  f1-score   support

   negative       0.75      0.53      0.62      3934
   positive       0.80      0.91      0.85      8066

avg / total       0.78      0.79      0.78     12000
```




```
In [65]: df4=pd.DataFrame(models_performence, columns=columns)
         result_display(df4)
```

```
|Model| Vectorizer |algorithm|Optimal k|Train error|Test error|Accuracy| F1  |recal
|-----|------------|---------|--------:|----------:|---------:|-------:|----:|-----
|KNN  |BOW         |kd_tree  |       19|     0.2198|    0.3731|  0.6269|49.28| 51.0
|KNN  |BOW         |brute    |       19|     0.2212|    0.3562|  0.6437|46.45| 50.4
|KNN  |Avg word2vec|kd_tree  |       19|     0.1803|    0.2195|  0.7805|72.38| 70.8
|KNN  |Avg word2vec|brute    |       19|     0.1761|    0.2133|  0.7867|73.53| 72.0
```

Model	Vectorizer	algorithm	Optimal k	Train error	Test error	Accuracy	F1	recall	precision
KNN	BOW	kd_tree	19	0.2895	0.3299	0.6701	40.79	50.04	51.33
KNN	BOW	brute	19	0.2895	0.3299	0.6701	40.79	50.04	51.33
KNN	Avg word2vec	kd_tree	19	0.2875	0.3368	0.6632	42.09	49.98	49.82
KNN	Avg word2vec	brute	19	0.2875	0.3368	0.6632	42.09	49.98	49.82

observations

- The optimal number of neighbors is 19 for both the algorithm for avg word2vec model.
- True postive rate is high(91%) for Brute force and 92% for KD-Tree.It means postive rating is higher as compared to negative rating which is good for amazon reviews .
- Confusion matrix and model performance is shown as above.
- TNR and FNR is almost similar in both Algorithm.FNR is high.Almost 50% of negative (3934 negative words)are predicting as postive
- It means models performance is poor as negative reviews is showing as postive reviews.
- KDTree Algorithm for KNN classifier is giving better performance as compared to brute Algorithm as seen in above table

6 3. TF-IDF

```
In [66]: ##### 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]: features = tf_idf_vect.get_feature_names()
         len(features)
```

```
Out[61]: 493611
```

```
In [62]: 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 [70]: 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]: #StandardScaleing and normalizing training Tf-IDF
         sc_data2= StandardScaler(with_mean=False).fit_transform(final_tf_idf)
         final_tfidf_np= preprocessing.normalize(sc_data2)
         print("Train Data: ",final_tfidf_np.shape)


         warnings.filterwarnings("ignore")
```

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

```
In [73]: # Sparse matrix for Tf-IDF
         final_tf_idf_sparse=csr_matrix(final_tf_idf).todense()

         print("Train data Sparse:",final_tf_idf_sparse.shape)
```

```
Train data Sparse: (28000, 100)
```

tf-idf For Testing datasets

```
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, 493611)
```

```
In [66]: svd1 = svd.fit(final_tf_idf_test1_svd)

         final_tf_idf_test1=svd1.transform(final_tf_idf_test1_svd)
         print("TruncatedSVD :",final_tf_idf_test1.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 [76]: pickle_path_tfidf_test='X_test_data_tfidf.pkl'
         X_test_data_tfidf=open(pickle_path_tfidf_test,'wb')
         pickle.dump(final_tf_idf_test1 ,X_test_data_tfidf)
         X_test_data_tfidf.close()
```

```
In [67]: pickle_path_tfidf_test='X_test_data_tfidf.pkl'
         unpickle_path6=open(pickle_path_tfidf_test,'rb')
         final_tf_idf_test1=pickle.load(unpickle_path6)
```

```
In [68]: final_tf_idf_test1_f=StandardScaler(with_mean=False).fit(final_tf_idf_test
         print(final_tf_idf_test1_f)

         final_tf_idf_test11=final_tf_idf_test1_f.transform(final_tf_idf_test1 )
         #Normalize Data
         final_tfidf_np_test= preprocessing.normalize(final_tf_idf_test11)
         print("Test Data: ",final_tfidf_np_test.shape)
```

```
StandardScaler(copy=True, with_mean=False, with_std=True)
Test Data:  (12000, 100)
```

Sparse testing data for tf-idf

```
In [69]: final_tfidf_np_test_sparse=csr_matrix(final_tf_idf_test1).todense()

         print("Test Data Sparse:",final_tfidf_np_test_sparse.shape)
```

```
Test Data Sparse: (12000, 100)
```

For Training :

```
1.final_tfidf_np
2.final_tf_idf_sparse
```

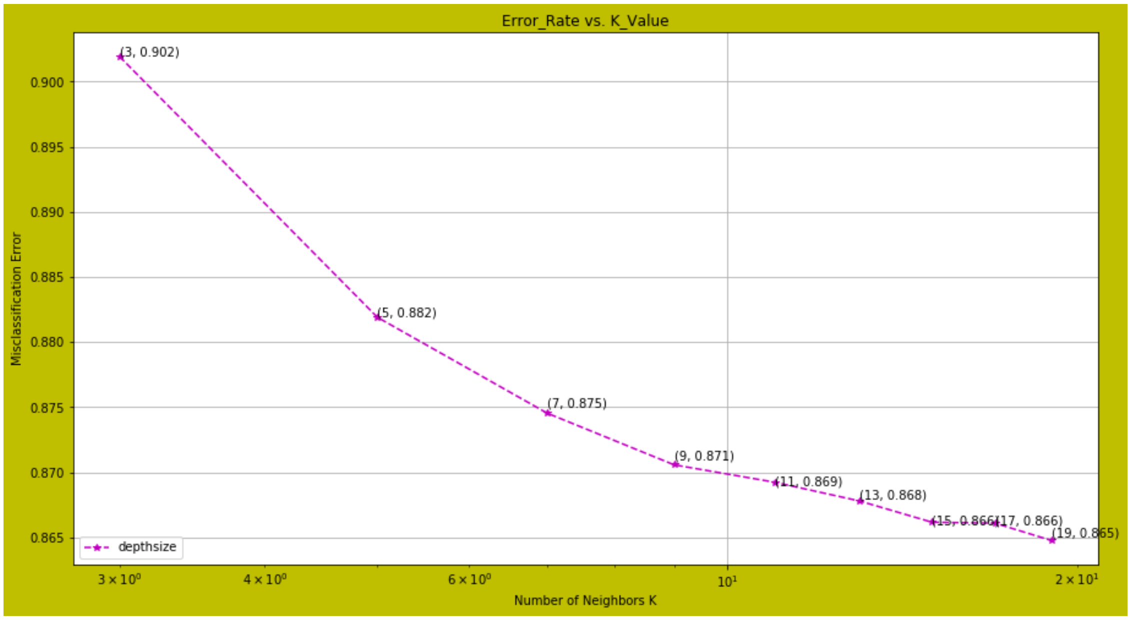
For Testing :

```
1.final_tfidf_np_test
2.final_tfidf_np_test_sparse
```

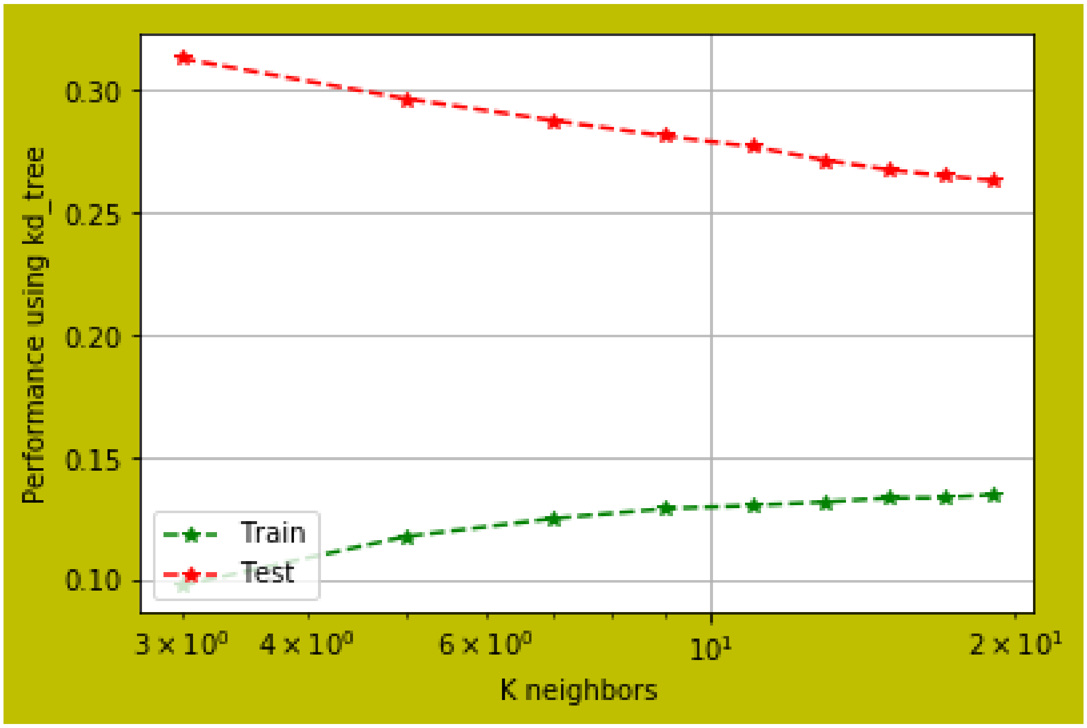
6.1 optimal k using TF-IDF

```
In [80]: # To get optimal k using TF-IDF
         if __name__=='__main__':
             mp.freeze_support()

             xtrain=[final_tf_idf_sparse,final_tfidf_np]

             xtest=[final_tfidf_np_test_sparse,final_tfidf_np_test]

             main()
```

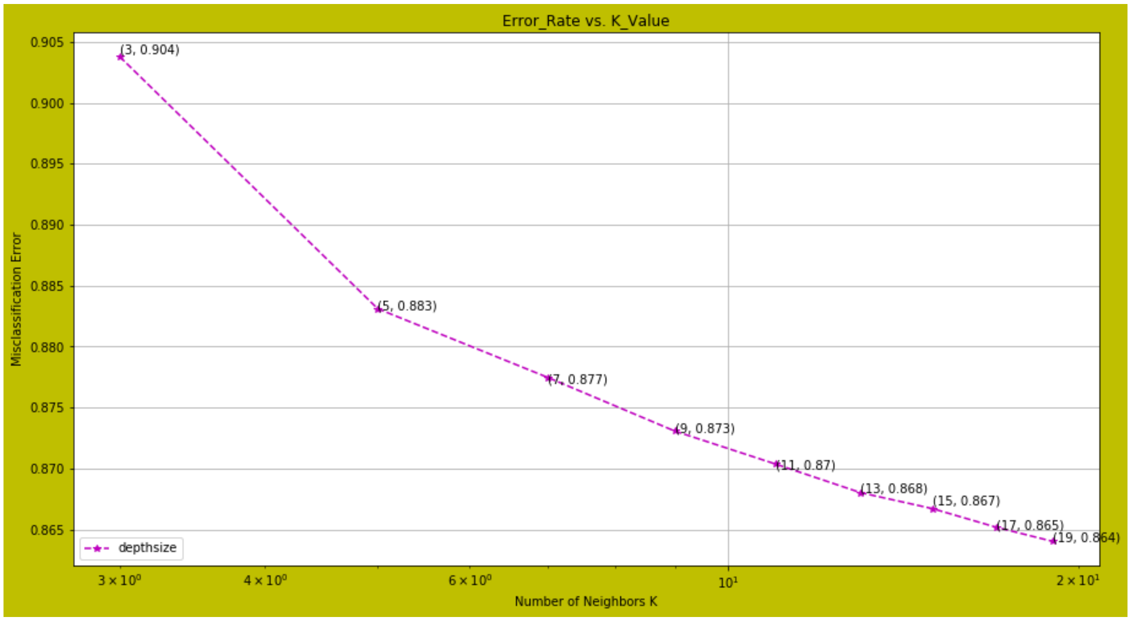
```
Started.
opyimal k value
algorithm =  kd_tree

The optimal number of neighbors is 19.
```



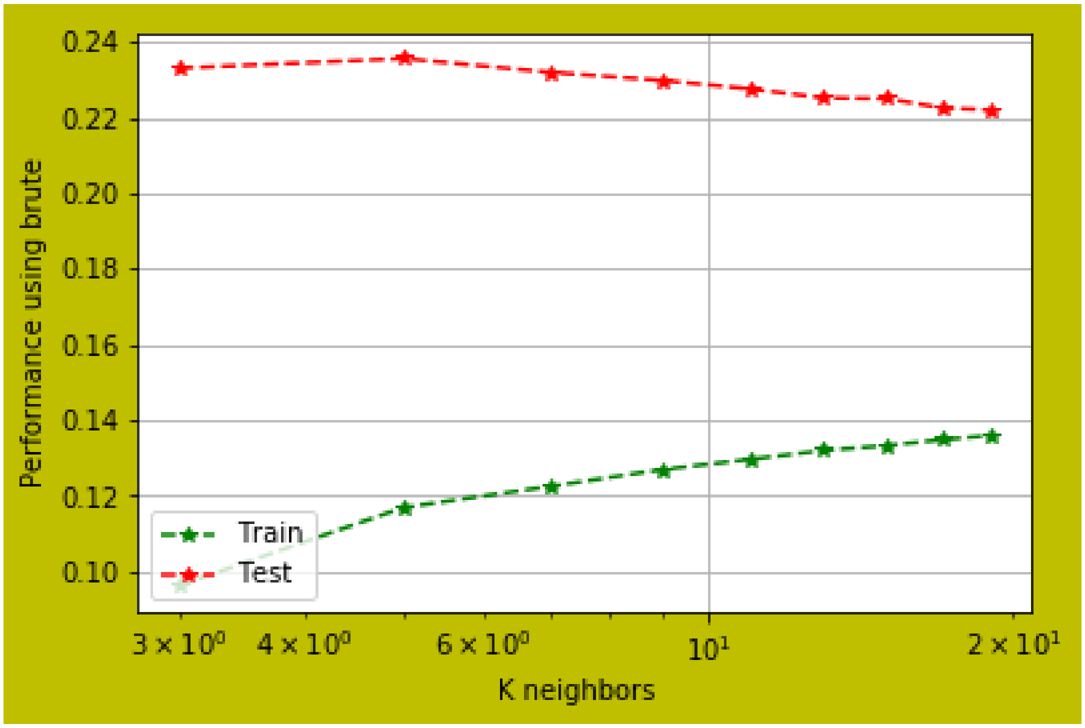

```
the misclassification error for each k value is :  [0.90194 0.88191 0.87455 0.87058
```



```
algorithm =  brute

The optimal number of neighbors is 19.
```




```
the misclassification error for each k value is :  [0.90378 0.88311 0.87747 0.87308
```



6.2 Knn classifier for optimal k value (TF-IDF)

All techniques for Scoring metrics and confusion matrix are shown as below

```
In [81]: k=optimal_k_list
         print(optimal_k_list)
```

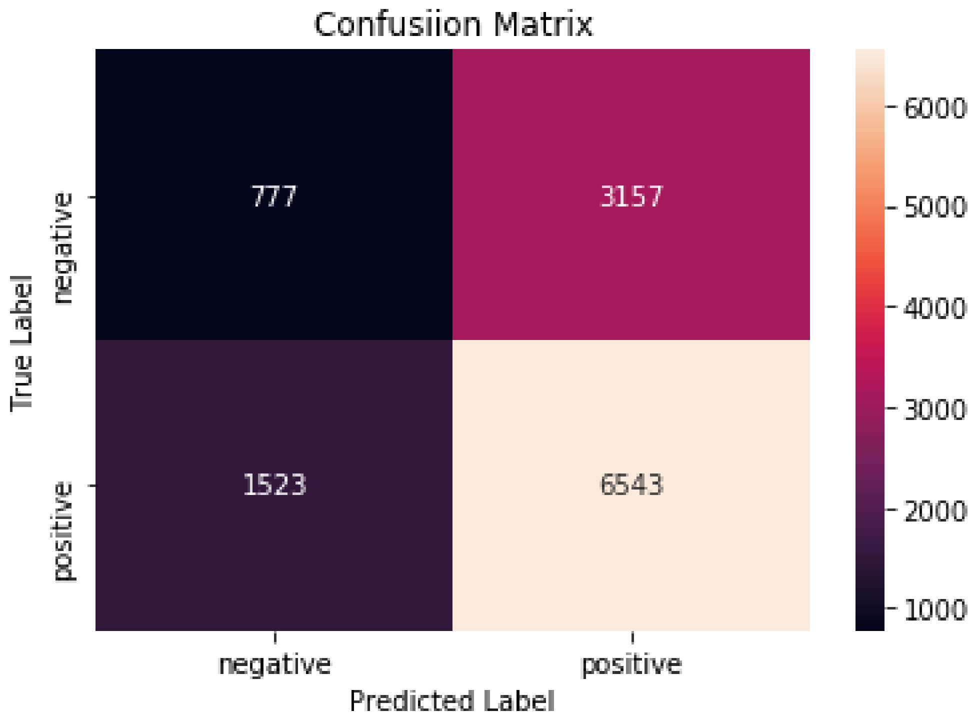
```
[19, 19]
```

```
In [82]: #KNN with Optimal K
         xtrain=[final_tf_idf_sparse,final_tfidf_np]
         ytrain=[y_train_new,Y_train_data]
         xtest=[final_tfidf_np_test_sparse,final_tfidf_np_test]
         ytest=[y_test_new,Y_test_data]
         vectorization=' TF-IDF'
```

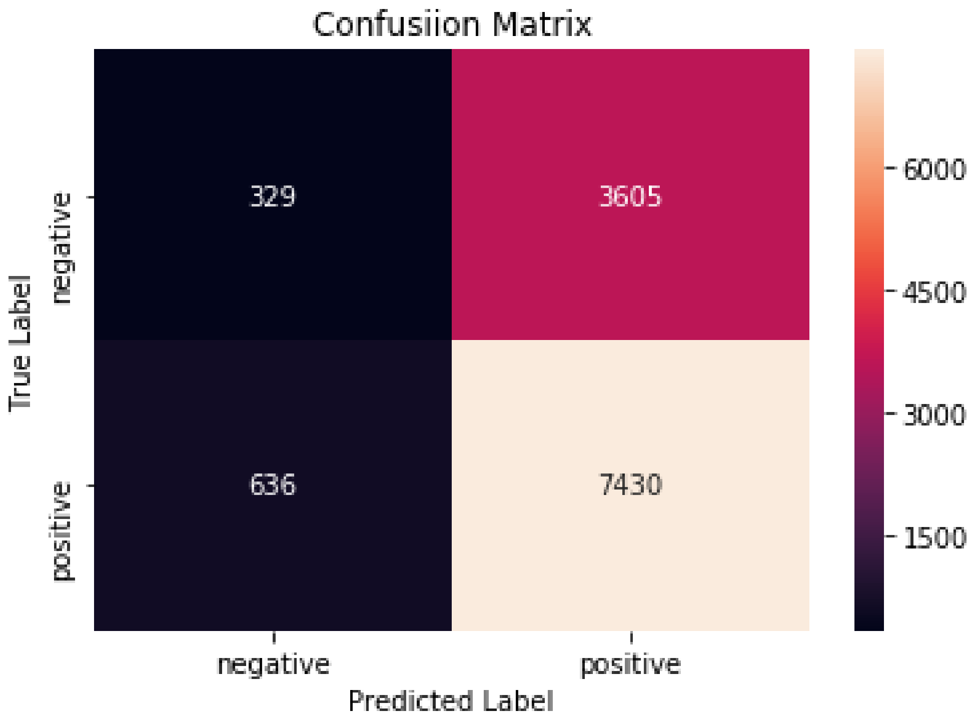
```
In [83]: import multiprocessing as mp


         def main1():
             print("Started.")
             algorithm=['kd_tree','brute']

             for i in range(len(algorithm)):
                 algo=algorithm[i]
                 print("Algorithm is ="+str(algo)+" for optimal k ="+str(k[i]))

                 Knn_classifier_optimal_k(xtrain[i],ytrain[i],xtest[i],ytest[i],k[i
         
         if __name__=='__main__':
             mp.freeze_support()
             main1()
```

```
Started.
Algorithm is =kd_tree for optimal k =19
 Algorithm = kd_tree
training accuracy= 0.7994285714285714
training error is = 0.20057142857142862
Accuracy for KNN model  is =  0.61
Testing error for KNN model is =  0.39


             precision    recall  f1-score   support
```

```
           0       0.34      0.20      0.25      3934
           1       0.67      0.81      0.74      8066

avg / total        0.56      0.61      0.58     12000
```




```
Algorithm is =brute for optimal k =19
 Algorithm = brute
training accuracy= 0.7911071428571429
training error is = 0.2088928571428571
Accuracy for KNN model  is =  0.64658
Testing error for KNN model is =  0.35341999999999996


             precision    recall  f1-score   support

   negative       0.34      0.08      0.13      3934
   positive       0.67      0.92      0.78      8066

avg / total       0.56      0.65      0.57     12000
```




```
In [84]: df6=pd.DataFrame(models_performence, columns=columns)
         result_display(df6)
```

```
|Model| Vectorizer |algorithm|Optimal k|Train error|Test error|Accuracy| F1  |recal
|-----|------------|---------|--------:|----------:|---------:|-------:|----:|-----
|KNN  |BOW         |kd_tree  |       19|     0.2198|    0.3731|  0.6269|49.28| 51.0
|KNN  |BOW         |brute    |       19|     0.2212|    0.3562|  0.6437|46.45| 50.4
|KNN  |Avg word2vec|kd_tree  |       19|     0.1803|    0.2195|  0.7805|72.38| 70.8
|KNN  |Avg word2vec|brute    |       19|     0.1761|    0.2133|  0.7867|73.53| 72.0
|KNN  | TF-IDF     |kd_tree  |       19|     0.2006|    0.3900|  0.6100|49.29| 50.4
|KNN  | TF-IDF     |brute    |       19|     0.2089|    0.3534|  0.6466|45.61| 50.2
```

```
In [85]: pickle_path111='df6.pkl'
         df61=open(pickle_path111,'wb')
         pickle.dump(df6,df61)
         df61.close()
```

```
In [44]: pickle_path111='df6.pkl'
         unpickle_path6=open(pickle_path111,'rb')
         df611=pickle.load(unpickle_path6)
```

```
In [45]: df6=pd.DataFrame(models_performence, columns=columns)
         result_display(df611)
```

```
|Model| Vectorizer |algorithm|Optimal k|Train error|Test error|Accuracy| F1  |recal
|-----|------------|---------|--------:|----------:|---------:|-------:|----:|-----
|KNN  |BOW         |kd_tree  |       19|     0.2198|    0.3731|  0.6269|49.28| 51.0
|KNN  |BOW         |brute    |       19|     0.2212|    0.3562|  0.6437|46.45| 50.4
|KNN  |Avg word2vec|kd_tree  |       19|     0.1803|    0.2195|  0.7805|72.38| 70.8
|KNN  |Avg word2vec|brute    |       19|     0.1761|    0.2133|  0.7867|73.53| 72.0
|KNN  | TF-IDF     |kd_tree  |       19|     0.2006|    0.3900|  0.6100|49.29| 50.4
|KNN  | TF-IDF     |brute    |       19|     0.2089|    0.3534|  0.6466|45.61| 50.2
```

Model	Vectorizer	algorithm	Optimal k	Train error	Test error	Accuracy	F1	recall	precision
KNN	BOW	kd_tree	19	0.2198	0.3731	0.6269	49.28	51.03	51.72
KNN	BOW	brute	19	0.2212	0.3562	0.6437	46.45	50.43	51.12
KNN	Avg word2vec	kd_tree	19	0.1803	0.2195	0.7805	72.38	70.85	76.85
KNN	Avg word2vec	brute	19	0.1761	0.2133	0.7867	73.53	72.05	77.28
KNN	TF-IDF	kd_tree	19	0.2006	0.3900	0.6100	49.29	50.43	50.62
KNN	TF-IDF	brute	19	0.2089	0.3534	0.6466	45.61	50.24	50.71

observations

- The optimal number of neighbors is 19 for both the algorithm for TF-IDf model.
- True postive rate is high(92%) for Brute force and 81% for KD-Tree.It means postive rating is higher as compared to negative rating which is good for amazon reviews .
- Confusion matrix and model performance is shown as above.
- KDTree Algorithm for KNN classifier is giving better performance as compared to brute Algorithm as seen in above table

7 4.TF-IDF weighted Word2Vec

```
In [70]: tfidf_feat = tf_idf_vect.get_feature_names()
```

```
In [71]: # TF-IDF weighted Word2Vec
         #tfidf_feat = tf_idf_vect.get_feature_names()

         tfidf_sent_vectors  = [];
         row=0;
         for sent in  X_train_data.values.ravel() :
             sent_vec = np.zeros(100)
             weight_sum =0;
             for word in sent:
```

```
                try:
                    vec = w2v_model.wv[word]

                    tfidf = final_tf_idf[row, tfidf_feat.index(word)]
                    sent_vec += (vec * tf_idf)
                    weight_sum += tf_idf
                except:
                    pass
            sent_vec /= weight_sum
            tfidf_sent_vectors .append(sent_vec)
            row += 1
```

```
In [72]: print(len(tfidf_sent_vectors))
```

```
28000
```

```
In [73]: print(tfidf_sent_vectors[2])
         tfidf_sent_vectors_train  = np.where(np.isnan(tfidf_sent_vectors ), 0, tfi
         print(tfidf_sent_vectors_train[2])
```

```
[nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan]
[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0.]
```

```
In [74]: 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 [75]: 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 [76]: 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 [77]: sc_data3= StandardScaler(with_mean=False).fit_transform(tfidf_sent_vectors
         final_tfidf_w2v_np_train=preprocessing.normalize(sc_data3)
```

For test Tf-idf weighted word2vec

```
In [78]: tfidf_sent_vectors1  = [];
         row=0;
         for sent in  X_test_data.values.ravel() :
             sent_vec = np.zeros(100)
             weight_sum =0;
             for word in sent:
                 try:
                     vec = w2v_model.wv[word]

                     tfidf = final_tf_idf_test1[row, tfidf_feat.index(word)]
                     sent_vec += (vec * tf_idf)
                     weight_sum += tf_idf
                 except:
                     pass
             sent_vec /= weight_sum
             tfidf_sent_vectors1 .append(sent_vec)
             row += 1
```

```
In [79]: 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))
```

```
12000
[nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan nan nan nan]
[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0.]
<class 'list'>
```

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

```
In [80]: 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 [81]: pickle_path_tfidf_weighted1='X_data_tfidf_weighted_test.pkl'
         unpickle_path71=open(pickle_path_tfidf_weighted1,'rb')
         final_tfidf_w2v_np_test =pickle.load(unpickle_path71)
```

```
In [82]: final_tfidf_np_test_sparse=csr_matrix(final_tf_idf_test1).todense()

         print("Test Data Sparse:",final_tfidf_np_test_sparse.shape)
```

```
Test Data Sparse: (12000, 100)
```

Sparse Matrix for Training And Testing TF-IDF weighted avg word2vec

```
In [83]: final_tfidf_w2v_np_train_sparse=csr_matrix(tfidf_sent_vectors_train).toden

         print("Train data Sparse:",final_tfidf_w2v_np_train_sparse.shape)
```

```
Train data Sparse: (28000, 100)
```

```
In [84]: final_tfidf_w2v_np_test_sparse=csr_matrix(tfidf_sent_vectors_test ).todens

         print("Test Data Sparse:",final_tfidf_w2v_np_test_sparse.shape)
```

```
Test Data Sparse: (12000, 100)
```

for Training Data:

```
1.final_tfidf_w2v_np_train_sparse
2.final_tfidf_w2v_np_train
```

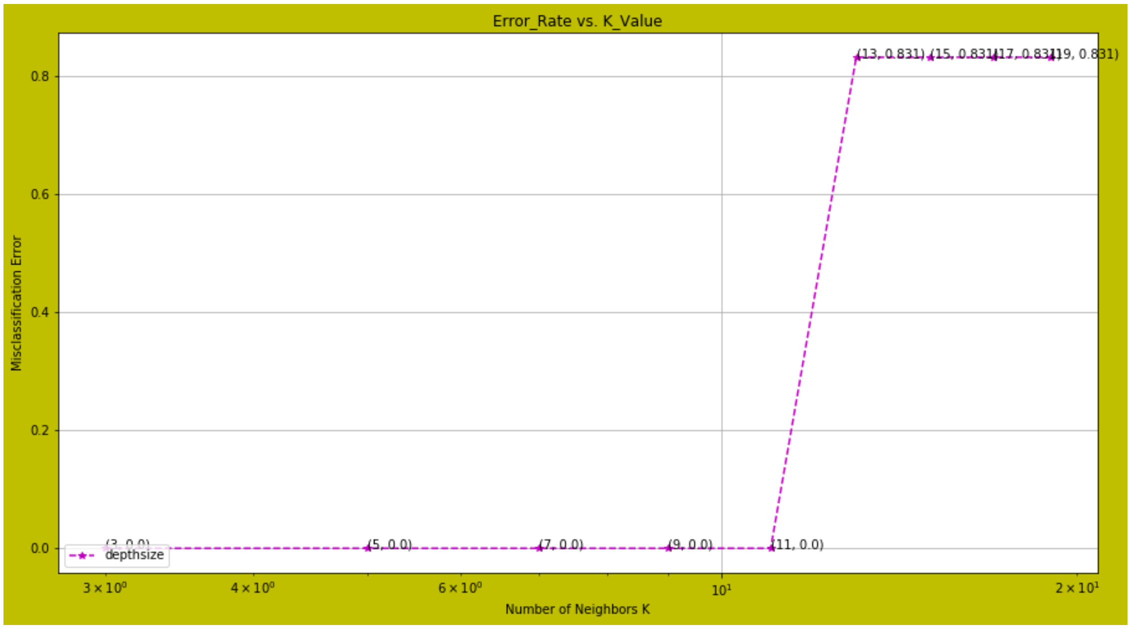
For testing data:

```
1.final_tfidf_w2v_np_test_sparse
2.final_tfidf_w2v_np_test
```

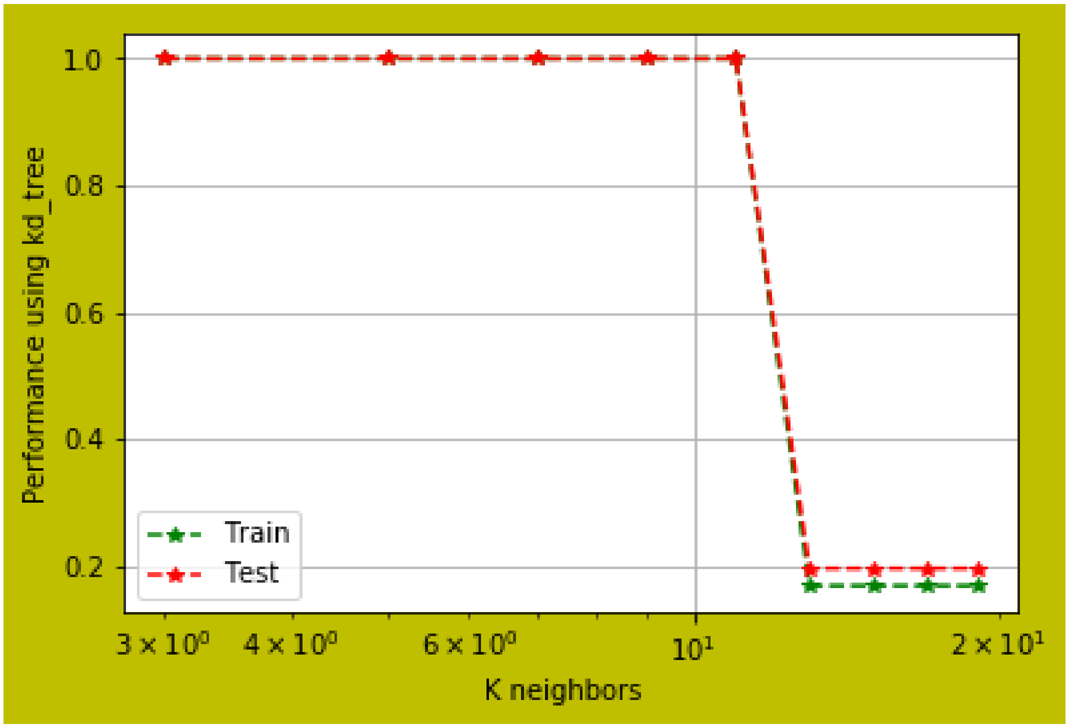
7.1 optimal k using TF-IDF weighted Word2Vec

```
In [85]: # To get optimal k using Tf-IDf weighted Word2Vec

         if __name__=='__main__':
             mp.freeze_support()
             xtrain=[final_tfidf_w2v_np_train_sparse,final_tfidf_w2v_np_train]
             xtest=[final_tfidf_w2v_np_test_sparse,final_tfidf_w2v_np_test]

             main()
```

```
Started.
opyimal k value
algorithm =  kd_tree

The optimal number of neighbors is 3.
```

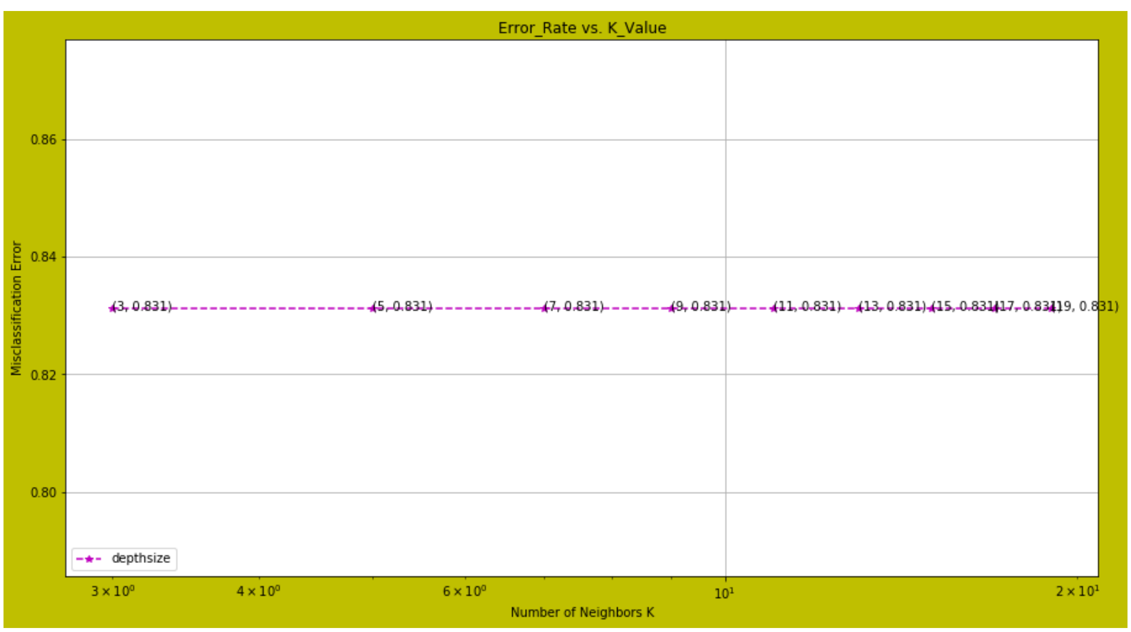



```
the misclassification error for each k value is :  [0.       0.       0.       0.
```

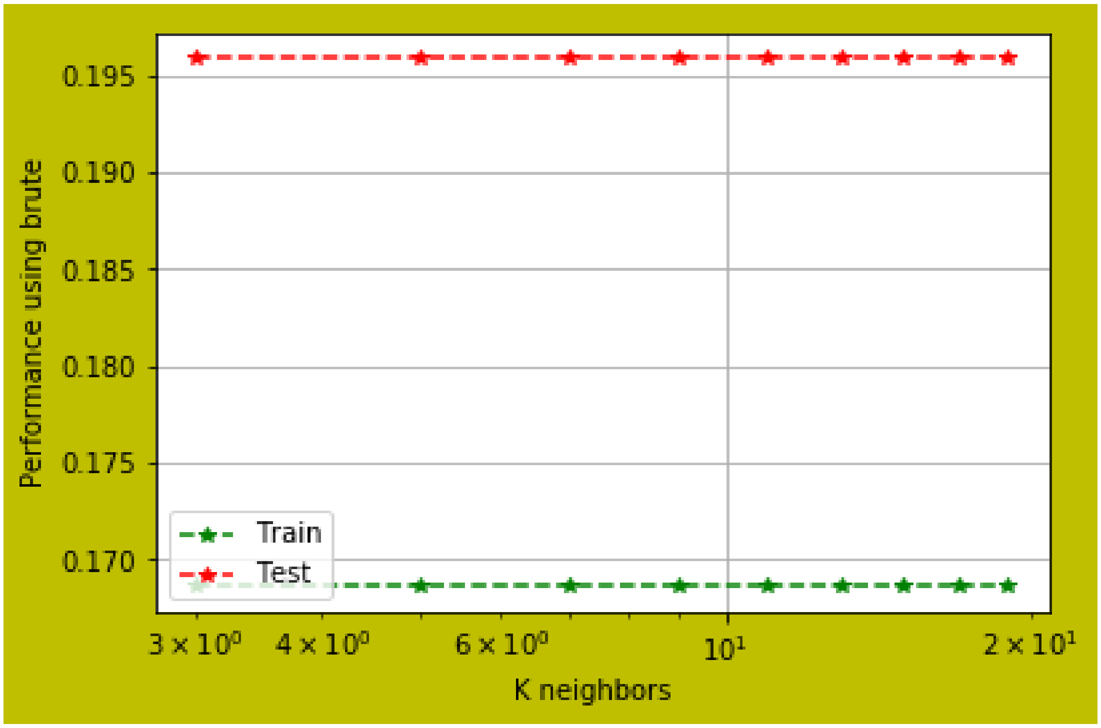


algorithm = brute

The optimal number of neighbors is 3.



```
the misclassification error for each k value is :  [0.83134 0.83134 0.83134 0.83134
```



Observations:

- The optimal number of neighbors is 3
- The graph is constant for all values of k
- MSE graph and performance graph for avg word2 vec and TF-IDF weighted word2vec is shown above.

7.2 Knn classifier for optimal k value (TF-IDF weighted word2vec)

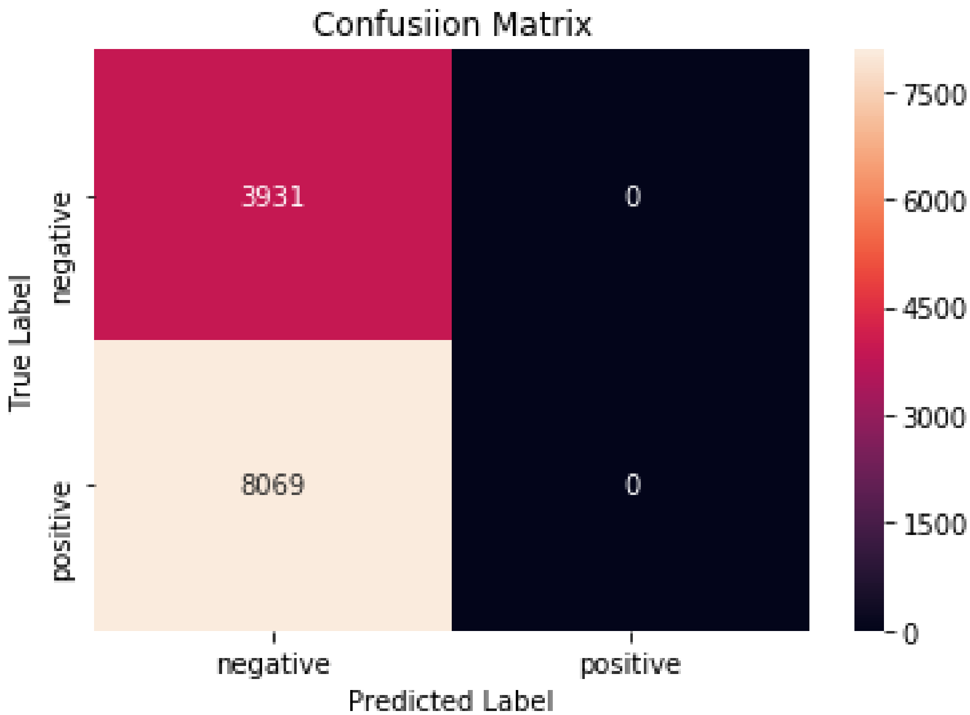
```
In [86]: k=optimal_k_list
         print(k)
```

```
[3, 3]
```

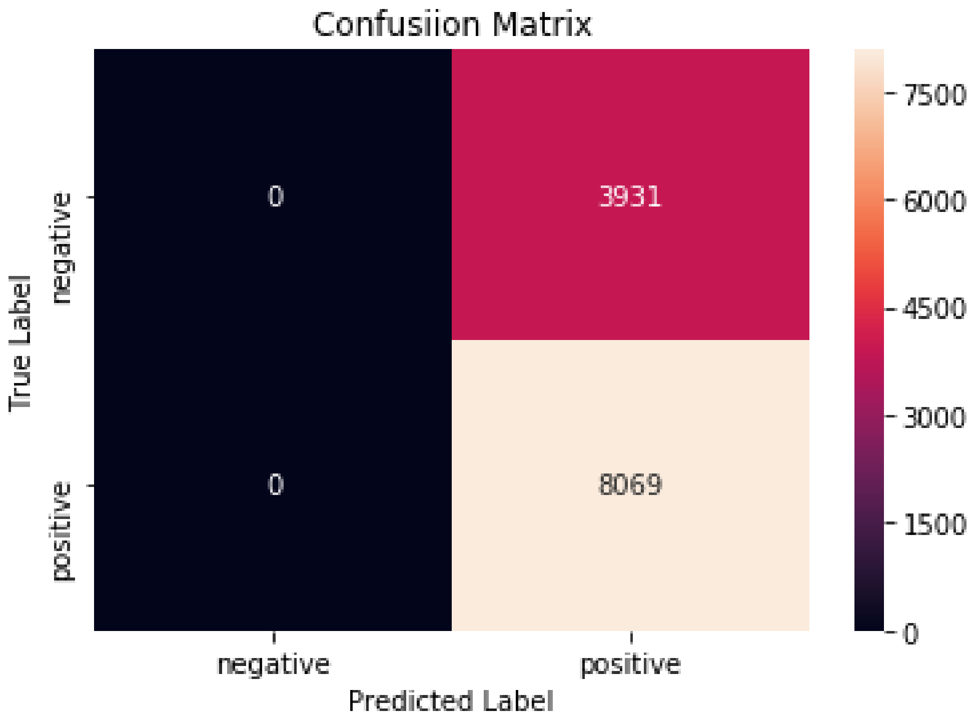
```
In [87]: #KNN with Optimal K
         xtrain=[final_tfidf_w2v_np_train_sparse,final_tfidf_w2v_np_train]
         ytrain=[y_train_new,Y_train_data]
         xtest=[final_tfidf_w2v_np_test_sparse,final_tfidf_w2v_np_test]
         ytest=[y_test_new,Y_test_data]


         vectorization=' TF-IDF weighted word2vec'
```

In [88]:
```
import multiprocessing as mp


def main1():
    print("Started.")
    algorithm=['kd_tree','brute']

    for i in range(len(algorithm)):
        algo=algorithm[i]
        print("Algorithm is ="+str(algo)+" for optimal k ="+str(k[i]))

        Knn_classifier_optimal_k(xtrain[i],ytrain[i],xtest[i],ytest[i],k[i

if __name__=='__main__':
    mp.freeze_support()
    main1()
```

```
Started.
Algorithm is =kd_tree for optimal k =3
 Algorithm = kd_tree
training accuracy= 0.28864285714285715
training error is = 0.7113571428571428
Accuracy for KNN model  is =  0.32758
Testing error for KNN model is =  0.67242


             precision    recall  f1-score   support

          0       0.33      1.00      0.49      3931
          1       0.00      0.00      0.00      8069

avg / total       0.11      0.33      0.16     12000
```




```
Algorithm is =brute for optimal k =3
 Algorithm = brute
training accuracy= 0.7113571428571429
training error is = 0.2886428571428571
Accuracy for KNN model  is =  0.67242
Testing error for KNN model is =  0.32758


             precision    recall  f1-score   support

   negative       0.00      0.00      0.00      3931
   positive       0.67      1.00      0.80      8069

avg / total       0.45      0.67      0.54     12000
```




```
In [89]: df8=pd.DataFrame(models_performence, columns=columns)
         result_display(df8)
```

```
|Model|       Vectorizer         |algorithm|Optimal k|Train error|Test error|Accurac
|-----|--------------------------|---------|--------:|----------:|---------:|-------
|KNN  | TF-IDF weighted word2vec|kd_tree  |        3|     0.7114|    0.6724|  0.327
|KNN  | TF-IDF weighted word2vec|brute    |        3|     0.2886|    0.3276|  0.672
```

```
In [90]: print(df8)
```

```
  Model                 Vectorizer algorithm  Optimal k  Train error  \
0   KNN   TF-IDF weighted word2vec   kd_tree          3     0.711357
1   KNN   TF-IDF weighted word2vec     brute          3     0.288643

   Test error  Accuracy     F1  recall  precision
0     0.67242   0.32758  24.675    50.0     16.379
1     0.32758   0.67242  40.206    50.0     33.621
```

8 Conclusions

Model	Vectorizer	algorithm	Optimal k	Train error	Test error	Accuracy	F1	recall	precision
KNN	BOW	kd_tree	19	0.2198	0.3731	0.6269	49.28	51.03	51.72
KNN	BOW	brute	19	0.2212	0.3562	0.6437	46.45	50.43	51.12
KNN	Avg word2vec	kd_tree	19	0.1803	0.2195	0.7805	72.38	70.85	76.85
KNN	Avg word2vec	brute	19	0.1761	0.2133	0.7867	73.53	72.05	77.28
KNN	TF-IDF	kd_tree	19	0.2006	0.3900	0.6100	49.29	50.43	50.62
KNN	TF-IDF	brute	19	0.2089	0.3534	0.6466	45.61	50.24	50.71
KNN	TF-IDF weighted word2vec	kd_tree	3	0.7114	0.6724	0.3276	24.67	50	16.38
KNN	TF-IDF weighted word2vec	brute	3	0.2886	0.3276	0.6724	40.21	50	33.62

- MSE(misclassification error) and optimal value of k is same for KdTree and Brute force in weighted tf-idf featurization technique.
- Training error for Tf-idf is low but testing error is too high in case of KDtree. In other vectorizer techniques training and testing error is quite similar.
- Model Tf-IDF weighted tf-idf using KDTree algorithm leads to overfitting.
- From above Table,It can be concluded that KNN model works best in case of Bag of words which is the best to predict the polarity of reviews among all models.
- All techniques for scoring metrics is good in case for BOW for given KNN model.
- The kd-tree and brute implementation of KNN for all featurization techniques gives relatively similar results.
- For getting K optimal values, f1 score and precision score metrics techniques doesnot work in KNN classifier. Only accuracy metrics gives relative optimal K-values.
- From all featurization techniques, BOW & Avg word2vec gives better results in both the implementations while Tf-IDF and TF-IDF weighted word2vec does not perform well.
- K-value for featurization techniques varies if dimesions(features) increases
- Avg word2vec for KNN(KDtree and Brute) performs very well for classifying given reviews (positive (Rating of 4 or 5) & negative (rating of 1 or 2))

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