K- Nearest Neighbors on Amazon Food Reviews

```
In [20]: %matplotlib inline
                                 import warnings
warnings.filterwarnings("ignore")
                                 # General Package
import os
import sqlite3
import pandas as
import numpy as n
import string
import re
import nltk
import datetime
import time
                                  # Plotting Packages
import matplotlib.pyplot as plt
import seaborn as sns
                                 # Packages for Tfidf
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
                                  # Packages for BOW (Bag of words)
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
                                  # Packages for Text Preprocessing
from nltk.stem.porter import PorterStemmer
from nltk.corpus import stopwords
from nltk.stem.wordnet import WordNetLemmatizer
                                 #Packages for Word2vec, Average Word2vec & Tf-Idf Weighted Word2Vec from gensim.models import Word2Vec from gensim.models import KeyedVectors import pickle
                                  #Packages for plotting Tsne plot
from sklearn.manifold import TSNE
                                from sklearn.manifold import TSNE

from sklearn.cross_validation import train_test_split
from sklearn.netrics import accuracy_score
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.medel_selection import TimeSeriesSplit
from prettytable import PrettyTable
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import from curve
 In [2]: # Formaing Output using pretty table
x = PrettyTable(["Model","Algorithm"," K ","TPR","TNR","Precision","Recall","F1-Score","FPR","FNR","PPV","NPV","Overall Accuracy (ACC)"])
from prettytable import MSWORD_FRIENDLY
x.set_style(MSWORD_FRIENDLY)
print(x)
                                 | Model | Algorithm | K | TPR | TNR | Precision | Recall | F1-Score | FPR | FNR | PPV | NPV | Overall Accuracy (ACC) |
```

Preprocessing Stage: Cleansed Stop Words, Punctuations & Html tags

```
In [3]: #Connecting the Sqlite file after the Preprocessing Stage
  os.chdir('/Users/sujis/Downloads/AI/Sujit')
  con = sqlite3.connect('final.sqlite')
  final= pd.read_sql_query(""" SELECT * FROM Reviews """, con)
In [4]: final.head(1)
Out[4]:
                                                                UserId ProfileName HelpfulnessNumerator HelpfulnessDenominator
                                   ld ProductId
                                                                                                                                                                                            EVERY book is educational this witty little book makes my son laugh at l... witti littl book make son laugh loud recit car...
               0 138706 150524 0006641040 ACITT7DI6IDDL shari zychinski
                                                                                                                                                       0 positive 939340800
In [5]: final['Score'].value_counts()
Out[5]: positive 307061
negative 57110
Name: Score, dtype: int64
```

Considering 50K data for KNN with 'Brute' Algorithm

```
In [209]: # Taking 75K data points from the dataset
final_dataset=final.head(50000)
In [210]: final_dataset['Score'].value_counts()
Out[210]: positive 42540
negative 7460
Name: Score, dtype: int64
In [211]: #Sorting the Dataframe with Date to apply Timebased Split
final_dataset=final_dataset.sort_values(by='Time',ascending=1)
In [212]: # create design matrix X and target vector y X = np.array(final_dataset.iloc[:, 0:12]) # end index is exclusive Y = np.array(final_dataset['Score']) # showing you two ways of indexing a pandas df
TimeSeriesSplit(max_train_size=None, n_splits=5)
TRAIN: [ 0 1 2 ... 8332 8333 8334] TEST: [ 8335 8336 8337 ... 16665 16666 16667]
TRAIN: [ 0 1 2 ... 16665 16666 16667] TEST: [ 16668 16669 16670 ... 24998 24999 25000]
TRAIN: [ 0 1 2 ... 24998 24999 25000] TEST: [ 25001 25002 25003 ... 33331 33332 33333]
TRAIN: [ 0 1 2 ... 33331 33332 33333] TEST: [ 33334 33335 33336 ... 41664 41665 41666]
TRAIN: [ 0 1 2 ... 41664 41665 41666] TEST: [ 41667 41668 41669 ... 49997 49998 49999]
```

```
In [215]: # Splitting the Train dataset into Cross Validation & Train Datasets
for train_index, test_index in tscv.split(X_tr):
    print("TRAIN:", train_index, "TEST:", test_index)
    X_train, X_cv = X[train_index], X[test_index]
    Y_train, Y_cv = Y[train_index], Y[test_index]
               TRAIN: [ 0 1 2 ... 6944 6945 6946] TEST: [ 6947 6948 6949 ... 13888 13889 13890]
TRAIN: [ 0 1 2 ... 13888 13889 13890] TEST: [ 13891 13892 13893 ... 20832 20833 20834]
TRAIN: [ 0 1 2 ... 20832 20833 20834] TEST: [ 20835 20836 20837 ... 27776 27777 27778]
TRAIN: [ 0 1 2 ... 27776 27777 27778] TEST: [ 27779 27780 27781 ... 34720 34721 34722]
TRAIN: [ 0 1 2 ... 34720 34721 34722] TEST: [ 34723 34724 34725 ... 41664 41665 41666]
(34723, 12)
(6944, 12)
(8333, 12)
                (34723,)
                (6944,)
(8333,)
```

Bag of Words

```
In [218]: # create the transform
    vectorizer = CountVectorizer()
    # tokenize and build vocab
    vectorizer.fit(X_train_data['CleanedText'].values)
    # Bag of Words: Train Data Set
    Train_X_vector = vectorizer.transform(X_train_data['CleanedText'].values)
    # summarize encoded vector
    print(Train_X_vector.shape)
                 (34723, 23935)
In [219]: # Cross Validation Data Set
CV_X_vector = vectorizer.transform(X_cv_data['CleanedText'].values)
print(CV_X_vector.shape)
                 (6944, 23935)
In [220]: #Test Data Set
    Test_X_vector = vectorizer.transform(X_test_data['CleanedText'].values)
    print(Test_X_vector.shape)
In [221]: print(Train_X_vector.shape)
    print(CV_X_vector.shape)
    print(Test_X_vector.shape)
                  print(
                   print(Y_train.shape)
                  print(Y_cv.shape)
print(Y_test.shape)
                  (34723, 23935)
                   (6944, 23935)
(8333, 23935)
                  (34723,)
In [222]: start_time_code = time.time()
for i in range(1,30,2):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i, algorithm="brute")
                            fitting the model on crossvalidation train nn.fit(Train_X_vector, Y_train)
                         pred = knn.predict(CV_X_vector)
                          # evaluate CV accuracy
                 bag_acc = accuracy_score(Y_cv, pred, normalize=True) * float(100) print('\nCV accuracy for k = %d is %0.1f%%' % (i, bag_acc)) end_time_code = time.time() print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                 CV accuracy for k = 1 is 77.0%
                  CV accuracy for k = 3 is 81.8%
                  CV accuracy for k = 5 is 82.7%
                  CV accuracy for k = 7 is 82.7%
                  CV accuracy for k = 9 is 82.7%
                 CV accuracy for k = 11 is 82.7%
                  CV accuracy for k = 13 is 82.7%
                  CV accuracy for k = 15 is 82.7%
                  CV accuracy for k = 17 is 82.6%
                 CV accuracy for k = 19 is 82.5%
                 CV accuracy for k = 21 is 82.5%
                  CV accuracy for k = 23 is 82.5%
                  CV accuracy for k = 25 is 82.5%
                  CV accuracy for k = 27 is 82.5%
                  CV accuracy for k = 29 is 82.6% Running Time for code execution 231.88899397850037 secs
In [223]: knn = KNeighborsClassifier(15,algorithm="brute")
knn.fit(Train_X_vector,Y_train)
pred = knn.predict(Test_X_vector)
bag_test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\n***Test accuracy for k = 15 is %0.2f%%' % (bag_test_acc))
                  ****Test accuracy for k = 15 is 81.70%
In [224]: Conf_matrix=confusion_matrix(Y_test, pred)
```

```
In [225]: Conf_matrix
In [226]: # Function for plotting Confusion Matrix
# Using this snipped of code copied from kaggle
import numpy as np
                 import matplotlib.pyplot as plt
import numpy as np
import itertools
                         accuracy = np.trace(cm) / float(np.sum(cm))
misclass = 1 - accuracy
                         if cmap is None:
    cmap = plt.get_cmap('Blues')
                         plt.figure(figsize=(8, 6))
plt.imshow(cm, interpolation='nearest', cmap=cmap)
plt.title(title)
plt.colorbar()
                         if target_names is not None:
    tick_marks = np.arange(len(target_names))
    plt.xticks(tick_marks, target_names, rotation=45)
    plt.yticks(tick_marks, target_names)
                         if normalize:
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                         plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label\naccuracy={:0.4f}; misclass={:0.4f}'.format(accuracy, misclass))
plt.show()
Confusion Matrix
                      Negative
                                                                                                                   4000
                   True label
                                                                                                                   3000
                                                                                                                   2000
                                                                                   6.779
                                                  Predicted label accuracy=0.8170; misclass=0.1830
In [228]: Conf_matrix
In [229]: TN,FP,FN,TP = Conf_matrix.ravel()
#confusion_matrix(Y_test, pred)
In [230]: # Sensitivity, hit rate, recall, or true positive rate

TPR = {0:.2} '.format( TP/(TP+FN))

# Specificity or true negative rate

TNR = '{0:.2} '.format( TN/(TN+FP))

# Fall out or false positive rate

FPR = '{0:.2} '.format( FP/(FP+TN))

# False negative rate

FNR = '{0:.2} '.format( FN/(TP+FN))

# Precision or positive predictive value

PPV = '{0:.2} '.format( TP/(TP+FP))

# Negative predictive value

NFV = '{0:.2} '.format( TN/(TN+FN))

# Overall accuracy
                  # Overall accuracy
ACC = '{0:.2%}'.format( (TP+TN)/(TP+FP+FN+TN))
In [231]: Recall=recall_score(Y_test, pred, average='micro')
In [232]: Precision=precision_score(Y_test, pred, average='micro')
In [233]: F1_Score=f1_score(Y_test, pred, average='weighted')
In [234]: pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
Out[234]:
                   Predicted negative positive All
                       True
                                       29 1520 1549
                                        5 6779 6784
                                      34 8299 8333
In [235]: x.add_row(("Bag of Words","Brute",15,TPR,TNR,'{0:.2f}'.format(Precision),'{0:.2f}'.format(Recall),'{0:.2f}'.format(Fl_Score),FPR,FNR,PPV,NPV,ACC])
In [236]: print(x)
                                                                Algorithm | kd_tree | Kd_tree | Kd_tree | Kd_tree | Kd_tree | Route
                                                                                               TPR | 99.07% | 99.09% | 98.25% | 99.34% | 99.93% |
                                                                                                                                                  Recall | F1-Score

0.82 | 0.76

0.83 | 0.77

0.83 | 0.79

0.83 | 0.77

0.82 | 0.74

        FPR
        FNR
        PPV
        NPV

        92.71%
        0.93%
        82.33%
        64.15%

        89.07%
        0.91%
        82.90%
        73.38%

        81.89%
        1.75%
        83.95%
        70.42%

        89.07%
        0.66%
        82.94%
        79.07%

        98.13%
        0.07%
        81.68%
        85.29%

                                                                                                                                                                                                                                                Overall Accuracy (ACC)
81.94%
82.64%
83.30%
                               Model
Bag of Words
TF - IDF
Average W2V
                                                                                       K |
17 |
13 |
11 |
                                                                                                               TNR
7.29%
10.93%
18.11%
                                                                                                                               Precision
0.82
0.83
0.83
                       TF - IDF Weighted W2V
Bag of Words
                                                                                        23 |
                                                                                                                10.93%
1.87%
```

```
29/10/2018
                                                                                            KNN -- Amazon Food Reviews
   In [237]: print(classification_report(Y_test, pred))
                            precision
                                                                 support
                                           0.82
              avg / total
                                 0.82
                                                      0.74
                                                                   8333
  TF - IDF
  Out[238]: (34723, 598035)
  Out[239]: (6944, 598035)
  In [240]: TF_test_Vector = TF_vector.transform(X_test_data['CleanedText'].values)
TF_test_Vector.shape
  Out[240]: (8333, 598035)
  (34723, 598035)
(6944, 598035)
(8333, 598035)
               (34723,)
              (6944,)
(8333,)
  In [242]: start_time_oode = time.time()
for i in range(1,30,2):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i, algorithm="brute")
                    fitting the model on crossvalidation train
                   knn.fit(TF_train_Vector, Y_train)
                   # predict the response on the crossvalidation train
pred = knn.predict(TF_cv_Vector)
              # evaluate CV accuracy
tf_acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
print('\ncV accuracy for k = %d is %0.2f%%' % (i, tf_acc))
end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
              CV accuracy for k = 1 is 80.04%
              CV accuracy for k = 3 is 83.19%
              CV accuracy for k = 5 is 83.60%
              CV accuracy for k = 7 is 83.81%
              CV accuracy for k = 11 is 83.80%
              CV accuracy for k = 13 is 83.74%
              CV accuracy for k = 15 is 83.60%
              CV accuracy for k = 17 is 83.50%
              CV accuracy for k = 19 is 83.40%
              CV accuracy for k = 21 is 83.40%
              CV accuracy for k = 23 is 83.35%
```

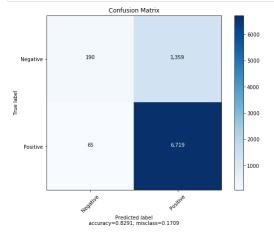
CV accuracy for k = 25 is 83.31% CV accuracy for k = 27 is 83.35% CV accuracy for k = 29 is 83.37% Running Time for code execution 213.33067083358765 secs

```
In [243]: knn = KNeighborsClassifier(11,algorithm="brute")
knn.fit(TF_train_Vector,Y_train)
pred = knn.predict(TF_test_Vector)
tf_test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\n***Test accuracy for k = 11 is %0.2f%%' % (tf_test_acc))
                          ****Test accuracy for k = 11 is 82.91%
```

```
In [244]: Conf_matrix=confusion_matrix(Y_test, pred)
In [245]: Conf_matrix
```

Out[245]: array([[190, 1359], [65, 6719]])

```
In [246]: plot_confusion_matrix(cm normalize
                                                           (cm = Conf_matrix,
normalize = False,
target_names = ['Negative', 'Positive'],
title = "Confusion Matrix')
```



```
In [247]: TN,FP,FN,TP = Conf_matrix.ravel()
#confusion matrix(Y test, pred)
```

```
29/10/2018
                                                                                                                                                                                                                                                                            KNN -- Amazon Food Reviews
        In [248]: # Sensitivity, hit rate, recall, or true positive rate
    TPR = '(0:.2%)'.format( TP/(TP+FN))
# Specificity or true negative rate
                                          TPR = '{0..2%}'.format( TP/(TP+FN))
# Specificity or true negative rate
TNR = '{0..2%}'.format( TN/(TN+FP))
# Fall out or false positive rate
FPR = '{0..2%}'.format( FP/(FP+TM))
# False negative rate
FNR = '{0..2%}'.format( FN/(TP+FN))
# Precision or positive predictive
PPV = '{0..2%}'.format( TP/(TP+FP))
# Negative predictive value
NPV = '{0..2%}'.format( TN/(TN+FN))
# Overall accuracy
                                          # Overall accuracy
ACC = '{0:.2%}'.format( (TP+TN)/(TP+FP+FN+TN))
         In [249]: Recall=recall_score(Y_test, pred, average='micro')
        In [250]: Precision=precision_score(Y_test, pred, average='micro')
         In [251]: F1_Score=f1_score(Y_test, pred, average='weighted')
         In [252]: pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
                                                      True
                                                                                 190
                                                                                                   1359 1549
                                                                                   65 6719 6784
                                                                            255 8078 8333
         In [253]: x.add_row(["TF - IDF", "Brute", 11, TPR, TNR, '{0:.2f}'.format(Precision), '{0:.2f}'.format(Recall), '{0:.2f}'.format(Fl_Score), FPR, FNR, PPV, NPV, ACC])
         In [254]: print(classification_report(Y_test, pred))
                                                                                                                            recall f1-score
                                                                                 precision
                                                                                                                                                                                            support
                                                                                                                         0.12
0.99
                                                  negative
positive
                                                                                                                          0.83
                                           avg / total
                                                                                                0.82
                                                                                                                                                             0.78
                                                                                                                                                                                                    8333
        In [255]: print(x)
                                                                                                                             Algorithm | kd_tree | Kd_t
                                                                                                                                                                                                                           TNR
7.29%
10.93%
18.11%
10.93%
                                                                                                                                                                                                                                                                                                                                                               FPR
92.71%
89.07%
81.89%
89.07%
98.13%
                                                                                                                                                                             K |
17 |
13 |
                                                                                                                                                                                                                                                                                                                                                                                                                                                                              Overall Accuracy (ACC)
                                                                                                                                                                                             TPR
99.07%
99.09%
98.25%
99.34%
                                                                                                                                                                                                                                                                                                                                                                                              FNR
0.93%
0.91%
1.75%
0.66%
                                                                                                                                                                                                                                                                                                                                                                                                                        PPV
82.33%
82.90%
83.95%
82.94%
                                                                                                                                                                                                                                                                                                                                  0.76
0.77
0.79
0.77
0.74
                                                                                                                                                                                                                                                                 0.82
0.83
0.83
                                                                                                                                                                                                                                                                                                  0.82
0.83
0.83
0.83
                                                                                                                                                                                                                                                                                                                                                                                                                                                    64.15%
73.38%
70.42%
79.07%
                                                                   Bag of Words
TF - IDF
                                                  rr - IDF
Average W2V
TF - IDF Weighted W2V
Bag of Words
TF - IDF
                                                                                                                                                                               11
23
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             83.30%
                                                                                                                                                                                                                                                                    0.83
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             82.84%
                                                                                                                                                                               15 |
11 |
                                                                                                                                                                                                                                                                                                    0.82
        Average W2V
         In [256]: # Train your own Word2Vec model using your own text corpus for Training Dataset
                                              list_of_sent=[]
for sent in X_train_data['CleanedText'].values:
    list_of_sent.append(sent.split())
                                           # min_count = 5 considers only words that occured atleast 5 times
Trained_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
                                          w2v_words = list(Trained_model.wv.vocab)
print("number of words that occurred minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
                                         number of words that occured minimum 5 times 8321 sample words ['littl', 'book', 'make', 'son', 'laugh', 'loud', 'car', 'drive', 'along', 'alway', 'sing', 'refrain', 'hes', 'learn', 'india', 'love', 'new', 'wo rd', 'introduc', 'silli', 'classic', 'will', 'bet', 'still', 'abl', 'memori', 'colleg', 'rememb', 'see', 'show', 'air', 'televis', 'year', 'ago', 'child', 'sist er', 'later', 'bought', 'day', 'thirti', 'someth', 'use', 'seri', 'song', 'student', 'teach', 'preschool', 'turn', 'whole', 'school']
      In [257]: # average Word2Vec
# compute average word2vec for each review.
start_time_code = time.time()
Trained_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent: # for each review/sentence
sent_vec = np.zeros(50) # as word vectors are of zero length
cnt_words = 0; # num of words with a valid vector in the sentence/review
for word in sent: # for each word in a review/sentence
if word in w2v_words:
    vec = Trained_model.wv[word]
    sent_vec += vec
    cnt_words += 1
if cnt_words != 0:
    sent_vec /= cnt_words
Trained_vectors.append(sent_vec)
print(len(Trained_vectors))
end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                                          34723
Running Time for code execution 62.595484018325806 secs
         In [258]: Train_X=Trained_vectors
         In [260]: # Train your own Word2Vec model using your own text corpus
                                          l=0
list_of_sent_cv=[]
for sent in X_cv_data['CleanedText'].values:
    list_of_sent_cv.append(sent.split())
```

```
Running Time for code execution 11.396867990493774 secs
```

```
In [262]: CV_X=Cv_vectors
```

```
In [264]: # Train your own Word2Vec model using your own text corpus
                 for sent in X_test_()
for sent in X_test_data('CleanedText').values:
    list_of_sent_test.append(sent.split())
```

```
8333 Running Time for code execution 14.642790079116821 secs
 In [266]: Test_X=test_vectors
               print(len(Tain_A))
print(len(Test_X))
print('---
print (Y_train.shape)
print(Y_cv.shape)
print(Y_test.shape)
                34723
                6944
8333
                (34723,)
                (6944,)
(8333,)
 In [268]: start_time_code = time.time()
for i in range(1,30,2):
    # instantiate learning model
                    # instantiate learning model (k = 30)
knn = KNeighborsClassifier(n_neighbors=i, algorithm="brute")
                     # fitting the model on crossvalidation train
knn.fit(Train_X, Y_train)
                     \begin{tabular}{ll} \# \ predict \ the \ response \ on \ the \ crossvalidation \ train \\ pred = \ knn.predict(CV\_X) \end{tabular}
               # evaluate CV accuracy
train_acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
print('\ncV accuracy for k = %d is %0.2f%%' % (i, train_acc))
end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
               CV accuracy for k = 1 is 80.17%
               CV accuracy for k = 3 is 83.45%
               CV accuracy for k = 5 is 84.12%
               CV accuracy for k = 7 is 84.48%
               CV accuracy for k = 9 is 84.59%
               CV accuracy for k = 11 is 84.53%
               CV accuracy for k = 13 is 84.48%
               CV accuracy for k = 15 is 84.48%
               CV accuracy for k = 17 is 84.56%
               CV accuracy for k = 19 is 84.52%
               CV accuracy for k = 21 is 84.45%
               CV accuracy for k = 23 is 84.36%
               CV accuracy for k = 25 is 84.38%
               CV accuracy for k = 27 is 84.25%
               CV accuracy for k=29 is 84.17\$ Running Time for code execution 105.32548975944519 secs
In [269]: # Since the train accuracy for k is the same from k=3 to k=29. so the smallest k at maximum accuracy is the best i.e. k=3
knn = KNeighborsClassifier(17,algorithm="brute")
knn.fit(Train X,Y_train)
pred = knn.predict(Test_X)
test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 17 is %0.2f%%' % (test_acc))
               ****Test accuracy for k = 17 is 83.96%
 In [270]: Conf_matrix=confusion_matrix(Y_test, pred)
 In [271]: Conf_matrix
 323
                                                                     1,226
                    Positive
                                          Predicted label 
accuracy=0.8396; misclass=0.1604
 In [273]: TN,FP,FN,TP = Conf_matrix.ravel()
#confusion_matrix(Y_test, pred)
```

```
In [274]: # Sensitivity, hit rate, recall, or true positive rate
TPR = {01.2%}'.format( TP/(TP+FN))
# Specificity or true negative rate
                     TPR = '{0:.2%}'.format( TP/(TP+FN))
# Specificity or true negative rate
TNR = '{0:.2%}'.format( TN/(TN+FP))
# Fall out or false positive rate
FPR = '{0:.2%}'.format( FP/(FP+TN))
# False negative rate
FNR = '{0:.2%}'.format( FN/(TP+FN))
# Precision or positive predictive
PPV = '{0:.2%}'.format( TN/(TP+FP))
# Negative predictive value
NPV = '{0:.2%}'.format( TN/(TN+FN))
# Overall accuracy
                      # Overall accuracy
ACC = '{0:.2%}'.format( (TP+TN)/(TP+FP+FN+TN))
In [275]: Recall=recall score(Y test, pred, average='micro')
In [276]: Precision=precision_score(Y_test, pred, average='micro')
In [277]: F1_Score=f1_score(Y_test, pred, average='weighted')
In [278]: pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
Out[278]:
                             True
                                              323
                                                          1226 1549
                                              111 6673 6784
                                              434
                                                        7899 8333
In [279]: x.add_row([" Average W2V", "Brute", 17, TPR, TNR, '{0:.2f}'.format(Precision), '{0:.2f}'.format(Recall), '{0:.2f}'.format(Fl_Score), FPR, FNR, PPV, NPV, ACC])
In [280]: print(classification_report(Y_test, pred))
                                              precision recall f1-score support
                                                                        0.84
                                                                                             0.80
                     avg / total
                                                       0.83
                                                                                                                       8333
In [281]: print(x)
                                                                           | Algorithm | kd_tree | Kd_tree | Kd_tree | Kd_tree | Brute | Brute | Brute | Brute |
                                                                                                                   TPR
99.07%
99.09%
98.25%
99.34%
99.93%
99.04%
98.36%
                                                                                                                                     TNR
7.29%
10.93%
18.11%
10.93%
1.87%
12.27%
20.85%
                                                                                                                                                                                 Recall
0.82
0.83
0.83
0.83
0.82
0.83
                                                                                                                                                                                                                         FPR | 92.71% | 89.07% | 81.89% | 89.07% | 98.13% | 87.73% | 79.15% |
                                                                                                                                                                                                                                            FNR
0.93%
0.91%
1.75%
0.66%
0.07%
0.96%
1.64%
                                                                                                                                                                                                                                                             PPV
82.33%
82.90%
83.95%
82.94%
81.68%
83.18%
84.48%
                                            Model
                                                                                                         K
17
                                                                                                                                                        Precision
                                                                                                                                                                                                                                                                                                  Overall Accuracy (ACC)
81.94%
                                                                                                                                                                                                                                                                               NPV
64.15%
73.38%
70.42%
79.07%
85.29%
74.51%
74.42%
                                    Model
Bag of Words
TF - IDF
Average W2V
IDF Weighted W2V
Bag of Words
TF - IDF
                                                                                                                                                              0.82
0.83
0.83
0.83
0.82
0.83
                                                                                                                                                                                                       0.76
0.77
0.79
0.77
0.74
0.78
0.80
                                                                                                                                                                                                                                                                                                                  81.94%
82.64%
83.30%
82.84%
81.70%
82.91%
83.96%
                                                                                                         13
11
23
15
11
```

TF-IDF weighted Word2Vec

```
In [26]: # TF-IDF weighted Word2Vec
tfidf_feat = TF_vector.get_feature_names() # tfidf words/col-names
 In [87]: # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
start_time_code = time.time()
tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
                         tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review
row=0;
for sent in list_of_sent: # for each review/sentence
sent_vec = np.zeros(50) # as word vectors are of zero length
weight_sum =0; # num of words with a valid vector in the sente
for word in sent: # for each word in a review/sentence
if word in w2v_words:
    vec = Trained_model.wv[word]
    # obtain the tf_idfidf of a word in a sentence/review
    tf_idf = TP_train_Vector[row, tfidf_feat.index(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
end_time_code = time.time()
                          end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                         Running Time for code execution 28771.18012213707 secs
  In [88]: Train X=tfidf sent vectors
 In [89]: df = pd.DataFrame.from_records(Train_X)
df.to_csv('TF-IDF_W2V_Train.csv',index=None)
In [282]: Train_X = pd.read_csv("TF-IDF_W2V_Train.csv")
In [116]: len(Train X)
Out[116]: 34723
 In [92]: # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
start_time_code = time.time()
tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
                        tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review row=0;

for sent in list_of_sent_cv: # for each review/sentence

sent_vec = np.zeros(50) # as word vectors are of zero length

weight_sum =0; # num of words with a valid vector in the sentence/review

for word in sent: # for each word in a review/sentence

if word in w2v_words:

vec = Trained_model.wv[word]

# obtain the tf_idfidf of a word in a sentence/review

tf_idf = TF_cv_vector[row, tfidf_feat.index(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

end time_code = time.time()
                          row += 1
end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                          Running Time for code execution 5836.9589948654175 secs
   In [93]: CV_X=tfidf_sent_vectors
  In [94]: df = pd.DataFrame.from_records(CV_X)
df.to_csv('TF-IDF_W2V_CV.csv',index=None)
In [283]: CV_X = pd.read_csv("TF-IDF_W2V_CV.csv")
```

```
In [27]: # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
start_time_code = time.time()
tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
                                tridg_sent_vectors = []; # the tridg_w2v for each sentence/review is stored if
row=0;
for sent in list_of_sent_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = Trained_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = TF_test_Vector[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
        row += 1
                                 row += 1
end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                                Running Time for code execution 7043.685368061066 secs
    In [28]: Test_X=tfidf_sent_vectors
   In [29]: df = pd.DataFrame.from_records(Test_X)
df.to_csv('TF-IDF_W2V_test.csv',index=None)
 In [284]: Test_X = pd.read_csv("TF-IDF_W2V_test.csv")
 In [285]: start_time_code = time.time()
for i in range(1,30,2):
    # instantiate learning model (k = 30)
knn = KNeighborsClassifier(n_neighbors=i, algorithm="brute")
                                                                                                                 on the crossvalidation train
                                            pred = knn.predict(CV X)
                                # evaluate CV accuracy
train_acc = accuracy_score(Y_ov, pred, normalize=True) * float(100)
print('\accuracy_score(Y_ov, p
                                CV accuracy for k = 1 is 80.11%
                                CV accuracy for k = 3 is 82.75%
                                CV accuracy for k = 5 is 83.55%
                                CV accuracy for k = 7 is 83.73%
                                CV accuracy for k = 9 is 83.94%
                               CV accuracy for k = 11 is 83.71%
                                CV accuracy for k = 13 is 83.67%
                                CV accuracy for k = 15 is 83.50%
                                CV accuracy for k = 17 is 83.53%
                               CV accuracy for k = 19 is 83.44%
                               CV accuracy for k = 21 is 83.48%
                                CV accuracy for k = 23 is 83.38%
                                CV accuracy for k = 25 is 83.45%
                                CV accuracy for k = 27 is 83.38%
                                CV accuracy for k = 29 is 83.41% Running Time for code execution 100.78603434562683 secs
In [286]: # Since the train accuracy for k is the same from k=3 to k=29. so the smallest k at maximum accuracy is the best i.e. k=3
knn = KNeighborsClassifier(9,algorithm="brute")
knn.fit(Train_X,Y_train)
pred = knn.predict(Test_X)
test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\n***Test accuracy for k = 9 is %0.2f%%' % (test_acc))
                                ****Test accuracy for k = 9 is 80.88%
In [287]: Conf_matrix=confusion_matrix(Y_test, pred)
 In [288]: Conf_matrix
Confusion Matrix
                                       Negative
                                                                                                                                                                                                          4000
                                                                                                                                                                                                          3000
                                                                                                                                                                                                         2000
                                                                                                                                                  6.708
                                                                                        Predicted label
accuracy=0.8088; misclass=0.1912
In [290]: TN,FP,FN,TP = Conf_matrix.ravel()
#confusion_matrix(Y_test, pred)
 In [291]: # Sensitivity, hit rate, recall, or true positive rate
TPR = {01.2%} .format( TP/(TP+FN))
# Specificity or true negative rate
TNR = {01.2%} .format( TN/(TM+FP))
                                TNR = '{0:.2%}'.format( TN/(TN+FP))
# Fall out or false positive rate
FPR = '{0:.2%}'.format( FP/(FP+TN))
# False negative rate
FNR = '{0:.2%}'.format( FN/(TP+FN))
# Precision or positive predictive value
PPV = '{0:.2%}'.format( TP/(TP+FP))
# Negative predictive value
NFV = '{0:.2%}'.format( TN/(TN+FN))
# Overall accuracy
```

Overall accuracy
ACC = '{0:.2%}'.format((TP+TN)/(TP+FP+FN+TN))

```
In [292]: Recall=recall_score(Y_test, pred, average='micro')
In [293]: Precision=precision score(Y test, pred, average='micro')
In [294]: F1_Score=f1_score(Y_test, pred, average='weighted')
In [295]: pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
Out[295]:
                         True
                                        32
                                                 1517 1549
                                       76 6708 6784
                                                8225 8333
                                      108
In [296]: x.add_row([" TF-IDF Weighted W2V ", "Brute", 17, TPR, TNR, '{0:.2f}'.format(Precision), '{0:.2f}'.format(Recall), '{0:.2f}'.format(F1_Score), FPR, FNR, PPV, NPV, ACC])
 In [297]: print(classification_report(Y_test, pred))
                                       precision recall f1-score
                                                                                               support
                  avg / total
                                            0.72
                                                            0.81
                                                                              0.73
                                                                                                    8333
In [298]: print(x)
                                                                Algorithm
kd_tree
Kd_tree
Kd_tree
Kd_tree
Brute
Brute
Brute
Brute
Brute
Brute
Brute
                                                                                       K
17
13
                                                                                                                                                                                                                                                   Overall Accuracy (ACC)
                                                                                                TPR
99.07%
99.09%
98.25%
99.34%
99.04%
98.36%
98.88%
                                                                                                                TNR
7.29%
10.93%
18.11%
10.93%
1.87%
12.27%
20.85%
2.07%
                                                                                                                                                                                      FPR | 92.71% | 89.07% | 81.89% | 89.07% | 98.13% | 87.73% | 79.15% | 97.93% |
                                                                                                                                                                                                                    PPV
82.33%
82.90%
83.95%
82.94%
81.68%
83.18%
84.48%
81.56%
                                                                                                                                                                                                                                   NPV
64.15%
73.38%
70.42%
79.07%
85.29%
74.51%
74.42%
29.63%
                      Model
Bag of Words
TF - IDF
Average W2V
TF - IDF Weighted W2V
Bag of Words
TF - IDF
Average W2V
TF-IDF Weighted W2V
                                                                                                                                                                                                     FNR
0.93%
0.91%
1.75%
0.66%
0.07%
0.96%
1.64%
                                                                                                                                     0.82
0.83
                                                                                                                                                      0.82
0.83
                                                                                                                                                                       0.76
0.77
0.79
0.77
0.74
0.78
0.80
0.73
                                                                                                                                                                                                                                                                 81.94%
82.64%
                                                                                                                                                      0.83
0.83
0.82
0.83
0.84
0.81
                                                                                        11
23
15
11
17
                                                                                                                                     0.83
                                                                                                                                                                                                                                                                  83.30%
82.84%
                                                                                                                                     0.83
0.82
0.83
0.84
0.81
```

Considering 30K data for KNN with 'kd_tree' Algorithm

```
In [6]: # Taking 75K data points from the dataset
final_dataset=final.head(30000)
  In [7]: final dataset['Score'].value counts()
 Out[7]: positive 25494
negative 4506
Name: Score, dtype: int64
  In [8]: #Sorting the Dataframe with Date to apply Timebased Split
final_dataset=final_dataset.sort_values(by='Time',ascending=1)
                  # create design matrix X and target vector y
X = np.array(final_dataset.iloc(:, 0:12]) # end index is exclusive
Y = np.array(final_dataset['Score']) # showing you two ways of indexing a pandas df
In [10]: #Time based split
tscv = TimeSeriesSplit(n_splits=5)
print(tscv)
                   {\tt TimeSeriesSplit(max\_train\_size=None,\ n\_splits=5)}
In [11]:
#Splitting the Dataset into Train set & Test set
for train_index, test_index in tscv.split(X):
    print("TRAIN:", train_index, "TEST:", test_index)
    X_tr, X_test = X[train_index], X[test_index]
    Y_tr, Y_test = Y[train_index], Y[test_index]
                   TRAIN: [ 0 1 2 ... 4997 4998 4999] TEST: [5000 5001 5002 ... 9997 9998 9999]
TRAIN: [ 0 1 2 ... 9997 9998 9999] TEST: [10000 10001 10002 ... 14997 14998 14999]
TRAIN: [ 0 1 2 ... 14997 14998 14999] TEST: [15000 15001 15002 ... 19997 19998 19999]
TRAIN: [ 0 1 2 ... 19997 19998 19999] TEST: [20000 20001 20002 ... 24997 24998 24999]
TRAIN: [ 0 1 2 ... 24997 24998 24999] TEST: [25000 25001 25002 ... 29997 29998 29999]
                    # Splitting the Train dataset into Cross Validation of
for train_index, test_index in tscv.split(X_tr):
    print("TRAIN:", train_index, "TEST:", test_index)
    X_train, X_cv = X[train_index], X[test_index]
    Y_train, Y_cv = Y[train_index], Y[test_index]
 In [12]:
                   TRAIN: [ 0 1 2 ... 4167 4168 4169] TEST: [4170 4171 4172 ... 8333 8334 8335]
TRAIN: [ 0 1 2 ... 8333 8334 8335] TEST: [8336 8337 8338 ... 12499 12500 12501]
TRAIN: [ 0 1 2 ... 12499 12500 12501] TEST: [12502 12503 12504 ... 16665 16666 16667]
TRAIN: [ 0 1 2 ... 16665 16666 16667] TEST: [1668 16669 16670 ... 20831 20832 20833]
TRAIN: [ 0 1 2 ... 20831 20832 20833] TEST: [20834 20835 20836 ... 24997 24998 24999]
print(
print(Y_train.shape)
print(Y_cv.shape)
print(Y_test.shape)
                    (20834, 12)
(4166, 12)
(5000, 12)
```

Bag of Words

```
In [118]: # create the transform
    vectorizer = CountVectorizer()
    # tokenize and build vocab
    vectorizer.fit(X_train_data['CleanedText'].values)
    # Baa of Words : Train Data Set
               # Bag of Words : Train Data Set
Train_X_vector = vectorizer.transform(X_train_data['CleanedText'].values)
               # summarize encoded vector
print(Train_X_vector.shape)
(4166, 19971)
```

```
In [120]: #Test Data Set
Test_X_vector = vectorizer.transform(X_test_data['CleanedText'].values)
               Test_X_vector = vectorizer
print(Test_X_vector.shape)
               (5000, 19971)
In [121]: print(Train_X_vector.shape)
    print(CV_X_vector.shape)
    print(Test_X_vector.shape)
              print(
print(Y_train.shape)
print(Y_cv.shape)
print(Y_test.shape)
               (20834, 19971)
(4166, 19971)
(5000, 19971)
In [122]: svd = TruncatedSVD(n_components=50)
In [123]: svd.fit(Train_X_vector)
Out[123]: TruncatedSVD(algorithm='randomized', n_components=50, n_iter=5, random_state=None, tol=0.0)
In [124]: TF_svd_Train=svd.transform(Train_X_vector)
In [125]: TF_svd_Train.shape
Out[125]: (20834, 50)
In [126]: TF_svd_CV=svd.transform(CV_X_vector)
In [127]: TF_svd_Test=svd.transform(Test_X_vector)
In [128]: start_time_code = time.time()
for i in range(1,30,2):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i, algorithm="kd_tree")
                     # fitting the model on crossvalidation train
knn.fit(TF_svd_Train, Y_train)
                    # predict the response on the crossvalidation train
pred = knn.predict(TF_svd_CV)
                     # evaluate CV accuracy
              bag_acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
print('\nCV accuracy for k = %d is %0.1f%%' % (i, bag_acc))
end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
              CV accuracy for k = 1 is 77.8%
              CV accuracy for k = 3 is 81.2%
               CV accuracy for k = 5 is 82.3%
               CV accuracy for k = 7 is 82.2%
              CV accuracy for k = 9 is 82.6%
              CV accuracy for k = 11 is 82.6%
              CV accuracy for k = 13 is 82.5%
               CV accuracy for k = 15 is 82.6%
              CV accuracy for k = 17 is 82.5%
              CV accuracy for k = 19 is 82.6%
              CV accuracy for k = 21 is 82.7%
              CV accuracy for k = 23 is 82.8%
               CV accuracy for k = 25 is 82.8%
               CV accuracy for k = 27 is 82.7%
               CV accuracy for k = 29 is 82.7% Running Time for code execution 174.01987504959106 secs
In [129]: knn = KNeighborsClassifier(17,algorithm="kd_tree")
knn.fit(TF_svd_Train,Y_train)
pred = knn.predict(TF_svd_Test)
bag_test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 17 is %0.2f%%' % (bag_test_acc))
               ****Test accuracy for k = 17 is 81.94%
In [130]: Conf_matrix=confusion_matrix(Y_test, pred)
In [131]: Conf_matrix
Out[131]: array([[ 68, 865], [ 38, 4029]])
Confusion Matrix
                  Negative
                                                                                               2000
                                                                                               1500
                                                                     4,029
                   Positive
                                                                                              1000
                                                                                               500
In [133]: TN,FP,FN,TP = Conf_matrix.ravel()
#confusion_matrix(Y_test, pred)
```

```
In [134]: # Sensitivity, hit rate, recall, or true positive rate
TPR ='{0:.2%}'.format( TP/(TP+FN))
# Specificity or true negative rate
                TPR = '{0..2%}'.format( TP/(TP+FN))

# Specificity or true negative rate
TNR = '{0..2%}'.format( TN/(TN+FP))

# Fall out or false positive rate
FPR = '{0..2%}'.format( FP/(FP+TN))

# False negative rate
FNR = '{0..2%}'.format( FN/(TP+FN))

# Precision or positive predictive value
PPV = '{0..2%}'.format( TP/(TP+FP))

# Negative predictive value
NPV = '{0..2%}'.format( TN/(TN+FN))

# Overall accuracy
ACC = '{0..2%}'.format( TP+TN)/(TP+FP+FN+
                # Overall accuracy
ACC = '{0:.2%}'.format( (TP+TN)/(TP+FP+FN+TN))
In [135]: Recall=recall_score(Y_test, pred, average='micro')
In [136]: Precision=precision_score(Y_test, pred, average='micro')
In [137]: F1_Score=f1_score(Y_test, pred, average='weighted')
In [138]: pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
                                   68
                                            865 933
                                  38 4029 4067
                                  106 4894 5000
In [139]: x.add_row(["Bag of Words", "kd_tree", 17, TPR, TNR, '{0:.2f}'.format(Precision), '{0:.2f}'.format(Recall), '{0:.2f}'.format(Fl_Score), FPR, FNR, PPV, NPV, ACC])
                | Model | Algorithm | K | TPR | TNR | Precision | Recall | F1-Score | FPR | FNR | PPV | NPV | Overall Accuracy (ACC) | Bag of Words | kd_tree | 17 | 99.07% | 7.29% | 0.82 | 0.82 | 0.76 | 92.71% | 0.93% | 82.33% | 64.15% | 81.94% |
 In [141]: print(classification_report(Y_test, pred))
                                 precision recall f1-score support
                avg / total
                                        0.79
                                                      0.82 0.76
                                                                                      5000
```

TF - IDF

```
In [143]: tf_transformer = TfidfVectorizer(ngram_range=(1,2))
    TF_vector=tf_transformer.fit(X_train_data['CleanedText'].values)
    TF_train_Vector = TF_vector.transform(X_train_data['CleanedText'].values)
    TF_train_Vector.shape
Out[143]: (20834, 427963)
In [144]: TF_cv_Vector = TF_vector.transform(X_cv_data['CleanedText'].values)
TF_cv_Vector.shape
Out[144]: (4166, 427963)
Out[145]: (5000, 427963)
print(
print(Y_train.shape)
print(Y_cv.shape)
print(Y_test.shape)
            (20834, 427963)
(4166, 427963)
(5000, 427963)
             (20834,)
            (4166,)
(5000,)
In [147]: svd = TruncatedSVD(n_components=20)
In [148]: svd.fit(TF_train_Vector)
Out[148]: TruncatedSVD(algorithm='randomized', n_components=20, n_iter=5, random_state=None, tol=0.0)
In [149]: TF_svd_Train=svd.transform(TF_train_Vector)
In [150]: TF_svd_Train.shape
Out[150]: (20834, 20)
In [151]: TF_svd_CV=svd.transform(TF_cv_Vector)
In [152]: TF_svd_Test=svd.transform(TF_test_Vector)
```

```
In [153]: start_time_code = time.time()
for i in range(1,30,2):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i, algorithm="kd_tree")
                      # fitting the model on crossvalidation train
knn.fit(TF_svd_Train, Y_train)
                         predict the response on the crossvalidation train
red = knn.predict(TF_svd_CV)
                       # evaluate CV accuracy
                # sevaluate tv acturacy
tf_acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
print('\aCV accuracy for k = %d is %0.2f%%' % (i, tf_acc))
end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                CV accuracy for k = 1 is 78.06%
                CV accuracy for k = 3 is 81.04%
                CV accuracy for k = 5 is 82.72%
                CV accuracy for k = 7 is 82.53%
                CV accuracy for k = 9 is 82.53%
                CV accuracy for k = 11 is 82.55%
                CV accuracy for k = 13 is 82.93%
                CV accuracy for k = 15 is 82.74%
                CV accuracy for k = 17 is 82.69%
                CV accuracy for k = 19 is 82.81%
                CV accuracy for k = 21 is 82.74%
                CV accuracy for k = 23 is 82.84%
                CV accuracy for k = 25 is 82.72%
                CV accuracy for k = 27 is 82.81%
                CV accuracy for k = 29 is 82.79% Running Time for code execution 46.00462007522583 secs
In [154]: knn = KNeighborsClassifier(17,algorithm="kd_tree")
knn.fit(TF_svd_Train,Y_train)
pred = knn.predict(TF_svd_Test)
tf_test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\n***Test accuracy for k = 17 is %0.2f%%' % (tf_test_acc))
                ****Test accuracy for k = 17 is 82.64%
In [155]: Conf_matrix=confusion_matrix(Y_test, pred)
In [156]: Conf_matrix
Out[156]: array([[ 102, 831], [ 37, 4030]])
102
                                                                            831
                 True label
                     Positive
                                                                                                       1000
                                                                                                       500
                                             Predicted label accuracy=0.8264; misclass=0.1736
In [158]: TN,FP,FN,TP = Conf_matrix.ravel()
#confusion_matrix(Y_test, pred)
In [159]: # Sensitivity, hit rate, recall, or true positive rate

TPR = '{0:.2%}'.format( TP/(TP+FN))

# Specificity or true negative rate

TNR = '{0:.2%}'.format( TN/(TN+FP))

# Fall out or false positive rate

FPR = '{0:.2%}'.format( FP/(FP+TN))

# False negative rate

FNR = '{0:.2%}'.format( FN/(TP+FN))

# Precision or positive predictive value

PPV = '{0:.2%}'.format( TP/(TP+FP))

# Negative predictive value

NPV = '{0:.2%}'.format( TN/(TN+FN))

# Overall accuracy

ACC = '{0:.2%}'.format( (TP+TN)/(TP+FP+FN+TN))
In [160]: Recall=recall_score(Y_test, pred, average='micro')
In [161]: Precision=precision_score(Y_test, pred, average='micro')
 In [162]: F1_Score=f1_score(Y_test, pred, average='weighted')
In [163]: pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
Out[163]:
                      True
                                   102
                                            831 933
                                   37
                                           4030 4067
                                  139
                                           4861 5000
In [164]: x.add_row([" TF - IDF ","Kd_tree",17,TPR,TNR,'{0:.2f}'.format(Precision),'{0:.2f}'.format(Recall),'{0:.2f}'.format(Fl_Score),FPR,FNR,PPV,NPV,ACC])
In [165]: print(classification_report(Y_test, pred))
                                   precision recall f1-score
                                                                                     support
                                                       0.83
                avg / total
                                          0.81
                                                                         0.77
                                                                                         5000
```

```
In [166]: print(x)
                          Model | Algorithm | K | TPR | TNR | Precision | Recall | F1-Score | FPR | FNR | PPV | NPV | Overall Accuracy (ACC)
Bag of Words | kd_tree | 17 | 99.07% | 7.29% | 0.82 | 0.82 | 0.76 | 92.71% | 0.93% | 82.33% | 64.15% | 81.94%
TF - IDF | Kd_tree | 13 | 99.09% | 10.93% | 0.83 | 0.83 | 0.77 | 89.07% | 0.91% | 82.90% | 73.38% | 82.64%
```

Average W2V

```
In [167]: # Train your own Word2Vec model using your own text corpus for Training Dataset
                                i=0
list_of_sent=[]
for sent in X_train_data['CleanedText'].values:
    list_of_sent.append(sent.split())
                                Trained_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
                                w2v_words = list(Trained_model.wv.vocab)
                              print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
                               number of words that occured minimum 5 times 6969 sample words ['littl', 'book', 'make', 'son', 'laugh', 'loud', 'car', 'drive', 'along', 'alway', 'sing', 'refrain', 'hes', 'learn', 'india', 'love', 'new', 'wo rd', 'introduc', 'sill', 'olassic', 'will', 'bet', 'still', 'abl', 'memori', 'colleg', 'rememb', 'see', 'show', 'air', 'televis', 'year', 'ago', 'child', 'sist er', 'later', 'bought', 'day', 'thirti', 'someth', 'use', 'seri', 'song', 'student', 'teach', 'turn', 'whole', 'school', 'purchas']
In [168]: # average Word2vec
# compute average word2vec for each review.
Trained_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent: # for each review/sentence
sent_vec = np.zeros(50) # as word vectors are of zero length
cnt_words = 0; # num of words with a valid vector in the sentence/review
for word in sent: # for each word in a review/sentence
if word in w2v_words:
    vec = Trained_model.wv[word]
    sent_vec += vec
    cnt_words += 1
if cnt_words != 0:
    sent_vec /= cnt_words
Trained_vectors.append(sent_vec)
print(len(Trained_vectors))
  In [169]: Train_X=Trained_vectors
  In [170]: # Train your own Word2Vec model using your own text corpus
                               l=0
list_of_sent_cv=[]
for sent in X_cv_data['CleanedText'].valuestist_of_sent_cv.append(sent.split())
                            # average Word2Vec
# compute average word2vec for each review.
Cv_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent_cv: # for each review/sentence
sent_vec = np.zeros(50) # as word vectors are of zero length
cnt_words = 0; # num of words with a valid vector in the sentence/review
for word in sent: # for each word in a review/sentence
if word in w2v_words:
    vec = Trained_model.wv[word]
    sent_vec += vec
    cnt_words != 0:
    sent_vec /= cnt_words
Cv_vectors.append(sent_vec)
print(len(Cv_vectors))
  In [171]: # average Word2Vec
# compute average
                               4166
  In [172]: CV_X=Cv_vectors
    In [173]: # Train your own Word2Vec model using your own text corpu
                                l=0
list_of_sent_test=[]
for sent in X_test_data['CleanedText'].values:
    list_of_sent_test.append(sent.split())
In [174]: # average Word2Vec
# compute average word2vec for each review.
test_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent_test: # for each review/sentence
sent_vec = np.zeros[50) # as word vectors are of zero length
cnt_words = 0; # num of words with a valid vector in the sentence/review
for word in sent: # for each word in a review/sentence
if word in w2v_words:
    vec = Trained_model.wv[word]
    sent_vec += vec
    cnt_words += 1
if cnt_words != 0:
    sent_vec /= cnt_words
test_vectors.append(sent_vec)
print(len(test_vectors))
  In [175]: Test_X=test_vectors
  In [176]: print (len(Train X))
                                print(len(CV_X))
print(len(Test_X))
                               print('------
print (Y_train.shape)
print(Y_cv.shape)
print(Y_test.shape)
                                20834
                                4166
5000
                                (20834,)
(4166,)
(5000,)
```

```
In [177]: start_time_code = time.time()
for i in range(1,30,2):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i, algorithm="kd_tree")
                      # fitting the model on crossvalidation train
knn.fit(Train_X, Y_train)
                         predict the response on the crossvalidation train
red = knn.predict(CV_X)
                # evaluate CV accuracy
train_acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
print('\nCV accuracy for k = %d is %0.2f%%' % (i, train_acc))
end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                CV accuracy for k = 1 is 79.28%
                CV accuracy for k = 3 is 82.45%
                CV accuracy for k = 5 is 83.39%
                CV accuracy for k = 7 is 83.27%
                CV accuracy for k = 9 is 83.22%
                CV accuracy for k = 11 is 83.44%
                CV accuracy for k = 13 is 83.34%
                CV accuracy for k = 15 is 83.41%
                CV accuracy for k = 17 is 83.39%
                CV accuracy for k = 19 is 83.27%
                CV accuracy for k = 21 is 83.34%
                CV accuracy for k = 23 is 83.37%
                CV accuracy for k = 25 is 83.29%
                CV accuracy for k = 27 is 83.29%
                CV accuracy for k = 29 is 83.27% Running Time for code execution 153.1801438331604 secs
In [178]: # Since the train accuracy for k is the same from k=3 to k=29. so the smallest k at maximum accuracy is the best i.e. k=3
knn = KNeighborsClassifier(11,algorithm="kd_tree")
knn.fit(Train X,Y_train)
pred = knn.predict(Test_X)
test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 11 is %0.2f%%' % (test_acc))
                ****Test accuracy for k = 11 is 83.30%
In [179]: Conf_matrix=confusion_matrix(Y_test, pred)
In [180]: Conf_matrix
Out[180]: array([[ 169, 764], [ 71, 3996]])
Confusion Matrix
                    Negative
                                            169
                 True label
                                                                                                       2000
                     Positive
                                                                                                       - 1000
                                             Predicted label accuracy=0.8330; misclass=0.1670
In [182]: TN,FP,FN,TP = Conf_matrix.ravel()
#confusion_matrix(Y_test, pred)
In [183]: # Sensitivity, hit rate, recall, or true positive rate

TPR = '{0:.2}' format( TP/(TP+FN))

# Specificity or true negative rate

TNR = '{0:.2}' format( TN/(TN+FP))

# Fall out or false positive rate

FPR = '{0:.2}' format( FP/(FP+TN))

# False negative rate

FNR = '{0:.2}' format( FN/(TP+FN))

# Precision or positive predictive value

PPV = '{0:.2}' format( TP/(TP+FP))

# Negative predictive value

NPY = '{0:.2}' format( TN/(TN+FN))

# Overall accuracy

ACC = '{0:.2}' format( (TP+TN)/(TP+FP+FN+TN))
                # Overall accuracy
ACC = '{0:.2%}'.format( (TP+TN)/(TP+FP+FN+TN))
In [184]: Recall=recall score(Y test, pred, average='micro')
In [185]: Precision=precision_score(Y_test, pred, average='micro')
In [186]: F1_Score=f1_score(Y_test, pred, average='weighted')
In [187]: pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
Out[187]:
                 Predicted negative positive All
                       True
                                   169
                                            764 933
                                   71 3996 4067
                                  240
                                          4760 5000
In [188]: x.add_row([" Average W2V ","Kd_tree",11,TPR,TNR,'{0:.2f}'.format(Precision),'{0:.2f}'.format(Recall),'{0:.2f}'.format(Fl_Score),FPR,FNR,PPV,NPV,ACC])
In [189]: print(classification_report(Y_test, pred))
                                   precision recall f1-score
                                                                                     support
                                                         0.18
                                                                         0.29
                                                                                         933
4067
                avg / total
                                          0.81
                                                       0.83
                                                                         0.79
                                                                                         5000
```

```
In [190]: print(x)

        FPR
        FNR
        PPV
        NPV
        Overall Accuracy (ACC)

        92.71%
        0.93%
        82.33%
        64.15%
        81.94%

        89.07%
        0.91%
        82.90%
        73.38%
        82.64%

        81.89%
        1.75%
        83.95%
        70.42%
        83.30%

        Model
        Algorithm
        K
        TPR
        TNR

        Bag of Words
        kd_tree
        17
        99.07%
        7.29%

        TF - IDF
        Kd_tree
        13
        99.09%
        10.93%

        Average W2V
        Kd_tree
        11
        98.25%
        18.11%
```

```
TF-IDF weighted Word2Vec
   In [53]:
                            tfidf feat = TF vector.get feature names() # tfidf words/col-names
   In [54]: # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
start_time_code = time.time()
tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
                            tridg_sent_vectors = []; # the tridg_wavv for each sentence/review is stored i
row=0;
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = Trained_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = TF_train_Vector[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
            row += 1
end_time_code = time.time()
                            row += 1 end_time_code = time.time() print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                            Running Time for code execution 13474.992048978806 secs
   In [55]: Train_X=tfidf_sent_vectors
   In [56]: df = pd.DataFrame.from_records(Train_X)
df.to_csv('TF-IDF_W2V_Train_kd.csv',index=None)
In [191]: Train_X = pd.read_csv("TF-IDF_W2V_Train_kd.csv")
   In [57]: # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
    start_time_code = time.time()
    tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
                                    idf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored iv=0;
r sent in list_of_sent_cv: # for each review/sentence
sent_vec = np.zeros(50) # as word vectors are of zero length
weight_sum =0; # num of words with a valid vector in the sentence/review
for word in sent: # for each word in a review/sentence
if word in w2v_words:
    vec = Trained_model.wv[word]
    # obtain the tf_idfidf of a word in a sentence/review
    tf_idf = TF_cv_Vector[row, tfidf_feat.index(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
it_ime_code = time.time()
                           row += 1 end_time_code = time.time() print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                            Running Time for code execution 2435.09094786644 secs
   In [58]: CV X=tfidf sent vectors
   In [59]: df = pd.DataFrame.from_records(CV_X)
df.to_csv('TF-IDF_W2V_CV_Kd.csv',index=None)
 In [192]: CV_X = pd.read_csv("TF-IDF_W2V_CV_Kd.csv")
   In [60]: # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf
start_time_code = time.time()
tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
                           tfidf_sent_vectors = []; # the tridr-wzv ror each sentence/review is stored row=0;
for sent in list_of_sent_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = Trained_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = TF_test_Vector[row, tfidf_feat.index(word)]
            sent_vec +e (vec * tf_idf)
            weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
            row += 1
end time code = time.time()
                             end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                            Running Time for code execution 2871.7937688827515 secs
   In [61]: Test_X=tfidf_sent_vectors
   In [62]: df = pd.DataFrame.from_records(Test_X)
df.to_csv('TF-IDF_W2V_Test_Kd.csv',index=None)
```

In [193]: Test_X = pd.read_csv("TF-IDF_W2V_Test_Kd.csv")

```
In [194]: start_time_code = time.time()
for i in range(1,30,2):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i, algorithm="kd_tree")
                       # fitting the model on crossvalidation train
knn.fit(Train_X, Y_train)
                          predict the response on the crossvalidation train
red = knn.predict(CV_X)
                # evaluate CV accuracy
train_acc = accuracy_score(Y_cv, pred, normalize=True) * float(100)
print('\nCV accuracy for k = %d is %0.2f%%' % (i, train_acc))
end_time_code = time.time()
print ("Running Time for code execution " + str(end_time_code - start_time_code) + " secs")
                CV accuracy for k = 1 is 77.87%
                CV accuracy for k = 3 is 81.06%
                CV accuracy for k = 5 is 82.53%
                CV accuracy for k = 7 is 82.67%
                CV accuracy for k = 9 is 83.37%
                CV accuracy for k = 11 is 83.15%
                CV accuracy for k = 13 is 83.08%
                CV accuracy for k = 15 is 82.89%
                CV accuracy for k = 17 is 82.89%
                CV accuracy for k = 19 is 82.93%
                CV accuracy for k = 21 is 82.89%
                CV accuracy for k = 23 is 82.93%
                CV accuracy for k = 25 is 82.91%
                CV accuracy for k = 27 is 83.03%
                CV accuracy for k = 29 is 82.86% Running Time for code execution 135.67332410812378 secs
In [195]: # Since the train accuracy for k is the same from k=3 to k=29. so the smallest k at maximum accuracy is the best i.e. k=3
knn = KNeighborsClassifier(23,algorithm="kd_tree")
knn.fit(Train X,Y_train)
pred = knn.predict(Test_X)
test_acc = accuracy_score(Y_test, pred, normalize=True) * float(100)
print('\n****Test accuracy for k = 23 is %0.2f%%' % (test_acc))
                ****Test accuracy for k = 23 is 82.84%
In [196]: Conf_matrix=confusion_matrix(Y_test, pred)
In [197]: Conf_matrix
In [198]: plot_confusion_matrix(cm normalize
                                                   (cm = Conf_matrix,
normalize = False,
target_names = ['Negative', 'Positive'],
title = "Confusion Matrix")
                                                     Confusion Matrix
                    Negative
                                             102
                                                                              831
                 True label
                                                                                                          2000
                                                                                                          1500
                     Positive
                                                                                                          1000
                                                                                                          500
                                              Predicted label accuracy=0.8284; misclass=0.1716
In [199]: TN,FP,FN,TP = Conf_matrix.ravel()
#confusion_matrix(Y_test, pred)
In [200]: # Sensitivity, hit rate, recall, or true positive rate

TPR = '{0:.2}' format( TP/(TP+FN))

# Specificity or true negative rate

TNR = '{0:.2}' format( TN/(TN+FP))

# Fall out or false positive rate

FPR = '{0:.2}' format( FP/(FP+TN))

# False negative rate

FNR = '{0:.2}' format( FN/(TP+FN))

# Precision or positive predictive value

PPV = '{0:.2}' format( TP/(TP+FP))

# Negative predictive value

NPY = '{0:.2}' format( TN/(TN+FN))

# Overall accuracy

ACC = '{0:.2}' format( (TP+TN)/(TP+FP+FN+TN))
                 # Overall accuracy
ACC = '{0:.2%}'.format( (TP+TN)/(TP+FP+FN+TN))
In [201]: Recall=recall score(Y test, pred, average='micro')
In [202]: Precision=precision_score(Y_test, pred, average='micro')
In [203]: F1_Score=f1_score(Y_test, pred, average='weighted')
In [204]: pd.crosstab(Y_test, pred, rownames=['True'], colnames=['Predicted'], margins=True)
Out[204]:
                  Predicted negative positive All
                       True
                                    102
                                             831 933
                                    27
                                            4040 4067
                                   129
                                            4871 5000
In [205]: x.add_row([" TF - IDF Weighted W2V ","Kd_tree",23,TPR,TNR,'{0:.2f}'.format(Precision),'{0:.2f}'.format(Recall),'{0:.2f}'.format(Fl_Score),FPR,FNR,PPV,NPV,ACC])
In [206]: print(classification_report(Y_test, pred))
                                    precision recall f1-score
                                                                                        support
                                                         0.11
                                                                           0.19
                                                                                            933
4067
                avg / total
                                           0.82
                                                         0.83
                                                                           0.77
                                                                                            5000
```

Model	Algorithm	K	TPR	TNR	Precision	Recall	F1-Score	FPR	FNR	PPV	NPV	Overall Accuracy (ACC)
Bag of Words	kd_tree	17	99.07%	7.29%	0.82	0.82	0.76	92.71%	0.93%	82.33%	64.15%	81.94%
TF - IDF	Kd_tree	13	99.09%	10.93%	0.83	0.83	0.77	89.07%	0.91%	82.90%	73.38%	82.64%
Average W2V	Kd_tree	11	98.25%	18.11%	0.83	0.83	0.79	81.89%	1.75%	83.95%	70.42%	83.30%
TF - IDF Weighted W2V	Kd_tree	23	99.34%	10.93%	0.83	0.83	0.77	89.07%	0.66%	82.94%	79.07%	82.84%
Bag of Words	Brute	15	99.93%	1.87%	0.82	0.82	0.74	98.13%	0.07%	81.68%	85.29%	81.70%
TF - IDF	Brute	11	99.04%	12.27%	0.83	0.83	0.78	87.73%	0.96%	83.18%	74.51%	82.91%
Average W2V	Brute	17	98.36%	20.85%	0.84	0.84	0.80	79.15%	1.64%	84.48%	74.42%	83.96%
TF-IDF Weighted W2V	Brute	17	98.88%	2.07%	0.81	0.81	0.73	97.93%	1.12%	81.56%	29.63%	80.88%

Conclusion

1. Of all the Word to vector conversion models, TF - IDF got more True Positive Rate and True Negative Rate in 'Brute' and 'Kd-tree'