```
In [2]: %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        import seaborn as sns
        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 roc_curve, auc
        from nltk.stem.porter import PorterStemmer
        import re
        # Tutorial about Python regular expressions: https://pymotw.com/2/re/
        import string
        from nltk.corpus import stopwords
        from nltk.stem import PorterStemmer
        from nltk.stem.wordnet import WordNetLemmatizer
        from gensim.models import Word2Vec
        from gensim.models import KeyedVectors
        import pickle
        # using the SQLite Table to read data.
        con = sqlite3.connect('final.sqlite')
        #taking 5000 random reviews
        #sorting the data using time stamp
        finalDF = pd.read_sql_query(""" SELECT * FROM Reviews ORDER BY TIME ASC, RANDOM() L
        IMIT 5000 """, con)
        finalDF.head(10)
```

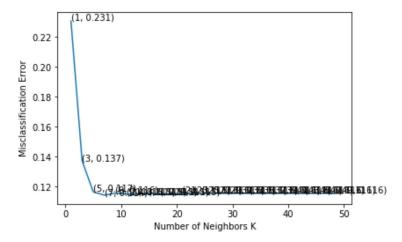
Out[2]:

	index	ld	ProductId	Userld	ProfileName	HelpfulnessNumerator	Helpfulnes
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0
1	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	2
2	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	0
3	346055	374359	B00004Cl84	A344SMIA5JECGM	Vincent P. Ross	1	2
4	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	0
5	346116	374422	B00004Cl84	A1048CYU0OV4O8	Judy L. Eans	2	2
6	346041	374343	B00004Cl84	A1B2IZU1JLZA6	Wes	19	23
7	70688	76882	B00002N8SM	A32DW342WBJ6BX	Buttersugar	0	0
8	346141	374450	B00004Cl84	ACJR7EQF9S6FP	Jeremy Robertson	2	3

2 of 20

```
In [3]: | #applying bag of words
         count_vect = CountVectorizer() #convert review text into sparse vectors
         bow_counts = count_vect.fit_transform(finalDF['CleanedText'].values)#return the val
         ues into matrix
         print("the type of count vectorizer ",type(bow_counts))
         print("the shape of out text BOW vectorizer ",bow_counts.get_shape())
         print("the number of unique words ", bow_counts.get_shape()[1])
         print(bow_counts[90])
         type(bow_counts)
         the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
         the shape of out text BOW vectorizer (5000, 11507)
         the number of unique words 11507
           (0, 8745)
                        1
           (0, 8052)
                         1
           (0, 3488)
                         1
           (0, 5964)
                         1
Out[3]: scipy.sparse.csr.csr_matrix
In [11]: from sklearn.cross_validation import train_test_split
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.metrics import accuracy_score
         from sklearn.cross_validation import cross_val_score
         from collections import Counter
         from sklearn.metrics import accuracy_score
         from sklearn import cross_validation
         # define column names
         # create design matrix X and target vector y
         X = bow_counts
         y = np.array(finalDF['Score']) # target function y consits score label
```

```
In [12]: from sklearn import cross_validation
         from sklearn.model_selection import TimeSeriesSplit
         #split the data set into train and test and test size=0.3
         X_1, X_test, y_1, y_test = cross_validation.train_test_split(X, y, test_size=0.3, r
         andom_state=0)
         # split the train data set into cross validation using time series split with 10 sp
         tscv=TimeSeriesSplit(n_splits=10)
         # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))
         # empty list that will hold cv scores
         cv_scores = []
         # perform 10-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k,algorithm='brute')# applying brute for
         ce technique.
             scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
             cv_scores.append(scores.mean())
         # changing to misclassification error
         MSE = [1 - x for x in cv_scores]
         \# finding better k
         optimal_k = neighbors[MSE.index(min(MSE))]
         print('\nThe optimal number of neighbors is %d.' % optimal_k)
         # plot misclassification error vs k
         plt.plot(neighbors, MSE)
         for xy in zip(neighbors, np.round(MSE,3)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Misclassification Error')
         plt.show()
         print("the misclassification error for each k value is : ", np.round(MSE,3))
```



the misclassification error for each k value is : $[0.231\ 0.137\ 0.117\ 0.114\ 0.116\ 0.115\ 0.115\ 0.115\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116$

```
In [13]: # instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

# fitting the model
knn_optimal.fit(X_1, y_1)

# predict the response
pred = knn_optimal.predict(X_test)

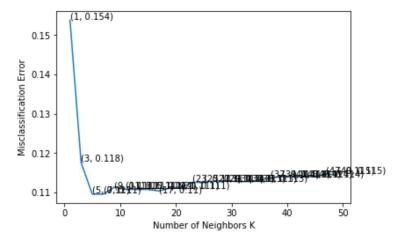
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%' % (optimal_k, acc))
```

The accuracy of the knn classifier for k = 7 is 86.800000%

```
In [14]: #Applying TFIDF on Knn
    tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))#converting review into sparse vect
    or
    final_tf_idf = tf_idf_vect.fit_transform(finalDF['CleanedText'].values)
    print("the type of count vectorizer ",type(final_tf_idf))
    print("the shape of out text TFIDF vectorizer ",final_tf_idf.get_shape())
    print("the number of unique words including both unigrams and bigrams ", final_tf_idf.get_shape()[1])
```

the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'> the shape of out text TFIDF vectorizer (5000, 152020) the number of unique words including both unigrams and bigrams 152020

```
In [15]: X = final_tf_idf
         y = np.array(finalDF['Score'])
         #split the data set into train and test and test size=0.3
         X_1, X_test, y_1, y_test = cross_validation.train_test_split(X, y, test_size=0.3, r
         andom_state=0)
         tscv=TimeSeriesSplit(n_splits=10) #applying time series split on the training data
         with 10 splits.
         # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))
         # empty list that will hold cv scores
         cv_scores = []
         # perform 10-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k,algorithm='brute')
             scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
             cv_scores.append(scores.mean())
         # changing to misclassification error
         MSE = [1 - x \text{ for } x \text{ in } cv\_scores]
         # determining best k
         optimal_k = neighbors[MSE.index(min(MSE))]
         print('\n The optimal number of neighbors is %d.' % optimal_k)
         # plot misclassification error vs k
         plt.plot(neighbors, MSE)
         for xy in zip(neighbors, np.round(MSE,3)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
         plt.xlabel('Number of Neighbors K')#adding x and y labels
         plt.ylabel('Misclassification Error')
         plt.show()
         print("the misclassification error for each k value is : ", np.round(MSE,3))
```



the misclassification error for each k value is : $[0.154\ 0.118\ 0.11\ 0.11\ 0.11$ 0.11 0.111 0.111 0.113 0.113 0.113 0.113 0.113 0.113 0.113 0.114 0.114 0.114 0.114 0.115 0.115]

```
In [16]: # instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

# fitting the model
knn_optimal.fit(X_1, y_1)

# predict the response
pred = knn_optimal.predict(X_test)

# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k, acc))
```

The accuracy of the knn classifier for k = 7 is 87.600000%

witti littl book make son laugh loud recit car drive along alway sing refrain he s learn whale india droop love new word book introduc silli classic book will be t son still abl recit memori colleg number of words that occured minimum 5 times 3833 sample words ['littl', 'book', 'make', 'son', 'laugh', 'loud', 'car', 'drive', 'along', 'alway', 'sing', 'hes', 'learn', 'india', 'love', 'new', 'word', 'intro duc', 'silli', 'classic', 'will', 'bet', 'still', 'abl', 'memori', 'colleg', 're memb', 'see', 'show', 'air', 'televis', 'year', 'ago', 'child', 'sister', 'later ', 'bought', 'day', 'thirti', 'someth', 'use', 'seri', 'song', 'student', 'teach ', 'turn', 'whole', 'school', 'purchas', 'children']

Out[18]: list

```
In [18]: # compute average word2vec for each review.
         sent_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 = w2v_model.wv[word]
                     sent_vec += vec
                     cnt_words += 1
             if cnt_words != 0:
                 sent_vec /= cnt_words
             sent_vectors.append(sent_vec)
         print(len(sent_vectors))
         print(len(sent_vectors[0]))
         type(sent_vectors)
         5000
         50
```

```
In [19]: X = sent_vectors
         y = np.array(finalDF['Score'])
         #split the data set into train and test with test size=0.3
         X_1, X_test, y_1, y_test = cross_validation.train_test_split(X, y, test_size=0.3, r
         andom_state=0)
         # split the train data set into cross validation using time series split with 10 sp
         tscv=TimeSeriesSplit(n_splits=10)
         # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))
         # empty list that will hold cv scores
         cv_scores = []
         # perform 10-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k,algorithm='brute')
             scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
             cv_scores.append(scores.mean())
         # changing to misclassification error
         MSE = [1 - x for x in cv_scores]
         # determining best k
         optimal_k = neighbors[MSE.index(min(MSE))]
         print('\n The optimal number of neighbors is $d.' % optimal_k)
         # plot misclassification error vs k
         plt.plot(neighbors, MSE)
         for xy in zip(neighbors, np.round(MSE,3)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Misclassification Error')
         plt.show()
         print("the misclassification error for each k value is : ", np.round(MSE,3))
```

```
(1, 0.195)
                                                                                              0.19
                                                                                              0.18
Misclassification Errol
                                                                                       0.17
                                                                                       0.16
                                                                                              0.15
                                                                                                                                                                                                                                                                                                                                                                                                                                                                          3, 0.147)
                                                                                                     0.14
                                                                                              0.13
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      (5, 0.128)
                                                                                              0.12
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                             1<sup>141</sup> 1<sup></sup>
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                  50
                                                                                                                                                                                                                                                                                                                     0
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    10
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    20
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      30
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                    Number of Neighbors K
```

the misclassification error for each k value is : $[0.195\ 0.147\ 0.128\ 0.123\ 0.12\ 0.118\ 0.118\ 0.117\ 0.115\ 0.116\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.116$

```
In [20]: # instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

# fitting the model
knn_optimal.fit(X_1, y_1)

# predict the response
pred = knn_optimal.predict(X_test)

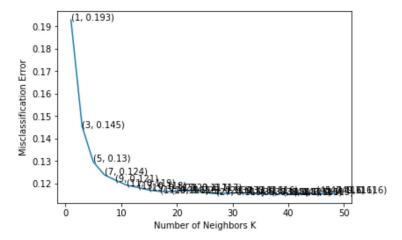
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k, acc))
```

The accuracy of the knn classifier for k = 29 is 86.600000%

```
In [21]: # TF-IDF weighted Word2Vec
         tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
         # final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfi
         df
         tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this
         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 = w2v_model.wv[word]
                     # obtain the tf_idfidf of a word in a sentence/review
                     tf_idf = final_tf_idf[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
         type(tfidf_feat)
```

Out[21]: list

```
In [23]: X = tfidf_sent_vectors
         y = np.array(finalDF['Score'])
         #split the data set into train and test with test size=0.3
         X_1, X_test, y_1, y_test = cross_validation.train_test_split(X, y, test_size=0.3, r
         andom_state=0)
         # split the train data set into cross validation using time series split with 10 sp
         tscv=TimeSeriesSplit(n_splits=10)
         # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))
         # empty list that will hold cv scores
         cv_scores = []
         # perform 10-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k,algorithm='brute')
             scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
             cv_scores.append(scores.mean())
         # changing to misclassification error
         MSE = [1 - x \text{ for } x \text{ in } cv\_scores]
         # determining best k
         optimal_k = neighbors[MSE.index(min(MSE))]
         print('\n The optimal number of neighbors is %d.' % optimal_k)
         # plot misclassification error vs k
         plt.plot(neighbors, MSE)
         for xy in zip(neighbors, np.round(MSE,3)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Misclassification Error')
         plt.show()
         print("the misclassification error for each k value is : ", np.round(MSE,3))
```



the misclassification error for each k value is : $[0.193\ 0.145\ 0.13\ 0.124\ 0.121\ 0.119\ 0.118\ 0.117\ 0.116\ 0.116\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.116\ 0.116$

```
In [24]: # instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

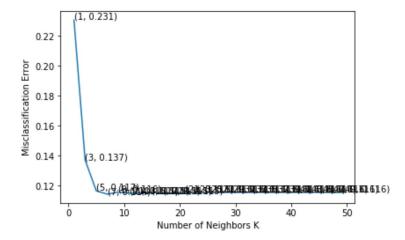
# fitting the model
knn_optimal.fit(X_1, y_1)

# predict the response
pred = knn_optimal.predict(X_test)

# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k, acc))
```

The accuracy of the knn classifier for k = 37 is 87.000000%

```
In [30]: from sklearn import cross_validation
         from sklearn.model_selection import TimeSeriesSplit
         X = bow_counts
         y = np.array(finalDF['Score']) # target function y consits score label
         #split the data set into train and test with test size=0.3
         X_1, X_test, y_1, y_test = cross_validation.train_test_split(X, y, test_size=0.3, r
         andom_state=0)
         # split the train data set into cross validation using time series split with 10 sp
         lits
         tscv=TimeSeriesSplit(n_splits=10)
         # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))
         # empty list that will hold cv scores
         cv_scores = []
         # perform 10-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree')
             scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
             cv_scores.append(scores.mean())
         # changing to misclassification error
         MSE = [1 - x for x in cv_scores]
         # determining best k
         optimal_k = neighbors[MSE.index(min(MSE))]
         \verb|print('\nThe optimal number of neighbors is $$d.' $$ optimal_k)|
         # plot misclassification error vs k
         plt.plot(neighbors, MSE)
         for xy in zip(neighbors, np.round(MSE,3)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Misclassification Error')
         plt.show()
         print("the misclassification error for each k value is : ", np.round(MSE,3))
```



the misclassification error for each k value is : $[0.231\ 0.137\ 0.117\ 0.114\ 0.116\ 0.115\ 0.115\ 0.115\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116\ 0.116$

```
In [31]: # instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

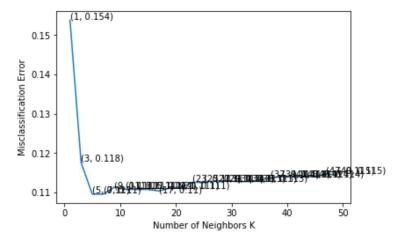
# fitting the model
knn_optimal.fit(X_1, y_1)

# predict the response
pred = knn_optimal.predict(X_test)

# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k, acc))
```

The accuracy of the knn classifier for k = 7 is 86.800000%

```
In [39]: X = final_tf_idf
         y = np.array(finalDF['Score'])
         #split the data set into train and test and test size=0.3
         X_1, X_test, y_1, y_test = cross_validation.train_test_split(X, y, test_size=0.3, r
         andom_state=0)
         # split the train data set into cross validation using time series split with 10 sp
         tscv=TimeSeriesSplit(n_splits=10)
         # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))
         # empty list that will hold cv scores
         cv_scores = []
         # perform 10-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree')
             scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
             cv_scores.append(scores.mean())
         # changing to misclassification error
         MSE = [1 - x \text{ for } x \text{ in } cv\_scores]
         # determining best k
         optimal_k = neighbors[MSE.index(min(MSE))]
         print('\n The optimal number of neighbors is %d.' % optimal_k)
         # plot misclassification error vs k
         plt.plot(neighbors, MSE)
         for xy in zip(neighbors, np.round(MSE,3)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Misclassification Error')
         plt.show()
         print("the misclassification error for each k value is : ", np.round(MSE,3))
```



the misclassification error for each k value is : [0.154 0.118 0.11 0.11 0.11 1 0.111 0.111 0.111 0.111 0.111 0.113 0.113 0.113 0.113 0.113 0.113 0.113 0.113 0.113 0.114 0.114 0.114 0.114 0.115 0.115]

```
In [40]: # instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

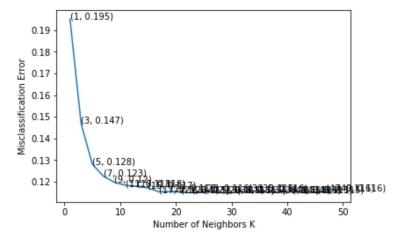
# fitting the model
knn_optimal.fit(X_1, y_1)

# predict the response
pred = knn_optimal.predict(X_test)

# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k, acc))
```

The accuracy of the knn classifier for k = 7 is 87.600000%

```
In [33]: X = sent_vectors
         y = np.array(finalDF['Score'])
         #split the data set into train and test and test size=0.3
         X_1, X_test, y_1, y_test = cross_validation.train_test_split(X, y, test_size=0.3, r
         andom_state=0)
         # split the train data set into cross validation using time series split with 10 sp
         tscv=TimeSeriesSplit(n_splits=10)
         # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))
         # empty list that will hold cv scores
         cv_scores = []
         # perform 10-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree')
             scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
             cv_scores.append(scores.mean())
         # changing to misclassification error
         MSE = [1 - x \text{ for } x \text{ in } cv\_scores]
         # determining best k
         optimal_k = neighbors[MSE.index(min(MSE))]
         print('\n The optimal number of neighbors is %d.' % optimal_k)
         # plot misclassification error vs k
         plt.plot(neighbors, MSE)
         for xy in zip(neighbors, np.round(MSE,3)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Misclassification Error')
         plt.show()
         print("the misclassification error for each k value is : ", np.round(MSE,3))
```



the misclassification error for each k value is : $[0.195\ 0.147\ 0.128\ 0.123\ 0.120\ 0.118\ 0.118\ 0.117\ 0.115\ 0.116\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.116$

```
In [34]: # instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

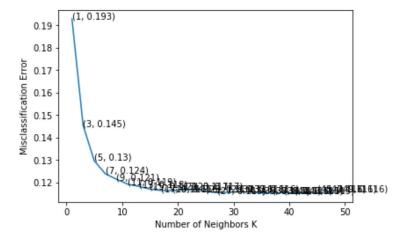
# fitting the model
knn_optimal.fit(X_1, y_1)

# predict the response
pred = knn_optimal.predict(X_test)

# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k, acc))
```

The accuracy of the knn classifier for k = 29 is 86.600000%

```
In [35]: X = tfidf_sent_vectors
         y = np.array(finalDF['Score'])
         #split the data set into train and test and test size=0.3
         X_1, X_test, y_1, y_test = cross_validation.train_test_split(X, y, test_size=0.3, r
         andom_state=0)
         # split the train data set into cross validation using time series split with 10 sp
         tscv=TimeSeriesSplit(n_splits=10)
         # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))
         # empty list that will hold cv scores
         cv_scores = []
         # perform 10-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k,algorithm='kd_tree')
             scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
             cv_scores.append(scores.mean())
         # changing to misclassification error
         MSE = [1 - x \text{ for } x \text{ in } cv\_scores]
         # determining best k
         optimal_k = neighbors[MSE.index(min(MSE))]
         print('\n The optimal number of neighbors is %d.' % optimal_k)
         # plot misclassification error vs k
         plt.plot(neighbors, MSE)
         for xy in zip(neighbors, np.round(MSE,3)):
             plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Misclassification Error')
         plt.show()
         print("the misclassification error for each k value is : ", np.round(MSE,3))
```



the misclassification error for each k value is : $[0.193\ 0.145\ 0.13\ 0.124\ 0.121\ 0.119\ 0.118\ 0.117\ 0.116\ 0.116\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.115\ 0.116\ 0.116$

```
In [36]: # instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k)

# fitting the model
knn_optimal.fit(X_1, y_1)

# predict the response
pred = knn_optimal.predict(X_test)

# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (optimal_k, acc))
```

The accuracy of the knn classifier for k = 37 is 87.000000%

In [41]: #Finally I observerd vectorization techniques with bruteforce and kd tree gives sam e accuracy with same k Value.