KNN on Amazon food reviews v1.1

May 10, 2018

0.1 K-NN for Amazon food reviews

```
In [1]: #importing required Modules
        %matplotlib inline
        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import pickle
        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 accuracy_score
        from sklearn.metrics import roc_curve, auc
        from nltk.stem.porter import PorterStemmer
        from sklearn.decomposition import TruncatedSVD
        from sklearn.preprocessing import StandardScaler
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.model_selection import TimeSeriesSplit
```

```
In [2]: #getting data
        conn = sqlite3.connect('final.sqlite')
        final_amazon = pd.read_sql_query("""
        SELECT *
        FROM Reviews
        """, conn)
```

```
In [5]: def cleanpunc(sentence):
            '''
            function to clean the word of any punctuation or special characters
            '''
            cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
            cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
```

```
            return  cleaned
        def cleanhtml(sentence):
            '''
            function to clean the word of any html-tags
            '''
            cleanr = re.compile('<.*?>')
            cleantext = re.sub(cleanr, ' ', sentence)
            return cleantext
```

In [3]:
```
#getting stop words
from nltk.corpus import stopwords
stop = set(stopwords.words('english'))
```

In [8]:
```
#Cleaning sentances
import re
from nltk.stem import WordNetLemmatizer
lem = WordNetLemmatizer()
from nltk.corpus import stopwords
stop = set(stopwords.words('english')) #set of stopwords
stop.remove('not')
stop.remove('very')
i=0
list_of_sent_clean=[]
for sent in final_amazon.CleanedTextBow.values:
    filtered_sentence=[]
    #sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            cleaned_words = cleaned_words.strip()
            if( (cleaned_words.isalpha()) & \
               (cleaned_words.lower() not in stop ) & \
                (len(cleaned_words)>2)):
                tmp = lem.lemmatize(cleaned_words.lower())
                filtered_sentence.append(tmp)
            else:
                continue
    list_of_sent_clean.append(' '.join(filtered_sentence))
```

In [9]:
```
#Cleaning summary text
import re
from nltk.stem import WordNetLemmatizer
lem = WordNetLemmatizer()
i=0
list_of_summary_clean=[]
for sent in final_amazon.Summary.values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
```

```
                for cleaned_words in cleanpunc(w).split():
                    if(cleaned_words.isalpha() & \
                       (cleaned_words.lower() not in stop) & \
                          (len(cleaned_words)>2)):
                        tmp = lem.lemmatize(cleaned_words.lower())
                        filtered_sentence.append(tmp)
                    else:
                        continue
            list_of_summary_clean.append(' '.join(filtered_sentence))
```

```
In [10]: #concatinating summary text and total text
         final_amazon['final_text']= list_of_summary_clean
         final_amazon['final_text'] = final_amazon['final_text'] + ' ' + list_of_sent_clean
```

```
In [11]: # store final table into an SQlLite table for future.
         conn = sqlite3.connect('final_clean.sqlite')
         c=conn.cursor()
         conn.text_factory = str
         final_amazon.to_sql('Reviews_final', conn, flavor=None, schema=None,
                             if_exists='replace', index=True,
                                    index_label=None, chunksize=None, dtype=None)
```

```
In [4]: conn = sqlite3.connect('final_clean.sqlite')
        final_review = pd.read_sql_query("""
        SELECT *
        FROM Reviews_final
        """, conn)
```

```
In [5]: #Sampling data
        s = final_review.sample(n=70000,random_state=0)
```

```
In [6]: s.drop('level_0',axis=1,inplace=True)
```

```
In [7]: #information about data
        s.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 70000 entries, 68546 to 359470
Data columns (total 14 columns):
index                     70000 non-null int64
Id                        70000 non-null int64
ProductId                 70000 non-null object
UserId                    70000 non-null object
ProfileName               70000 non-null object
HelpfulnessNumerator      70000 non-null int64
HelpfulnessDenominator    70000 non-null int64
Score                     70000 non-null object
Time                      70000 non-null int64
Summary                   70000 non-null object
```

```
Text                        70000 non-null object
CleanedText                 70000 non-null object
CleanedTextBow              70000 non-null object
final_text                  70000 non-null object
dtypes: int64(5), object(9)
memory usage: 8.0+ MB
```

```
In [8]: #SORT by time for TBS
        s = s.sort_values(by='Time')

In [9]: #changing lables to 1 or 0
        s.Score = s.Score.apply(lambda x:
                                1 if x == 'positive' else 0)

In [10]: #Converting to int8
         s.HelpfulnessNumerator = final_review.\
                                 HelpfulnessNumerator.astype(np.int8)
         s.HelpfulnessDenominator = final_review.\
                                 HelpfulnessDenominator.astype(np.int8)

In [11]: round(s.shape[0]*0.70) + round(s.shape[0]*0.30)

Out[11]: 70000

In [12]: #Splitting Dataframe for train and test
         train_df = s.iloc[:round(s.shape[0]*0.70),:]
         test_df = s.iloc[round(s.shape[0]*0.70):,:]

In [13]: #saving to disk
         train_df.to_csv('train_df_knn.csv')
         test_df.to_csv('test_df_knn.csv')

In [14]: print(train_df.shape)
         print(test_df.shape)

(49000, 14)
(21000, 14)
```

0.1.1 Bag of Words

```
In [20]: #traing scores for each k between 1-15 with brute alg
         list1 = list(range(1,16,2))
         list1.append(25)
         scores_train = []
         #CountVectorizer for BoW
         count_vect = CountVectorizer()
         final_counts_train = count_vect.fit_transform(
```

```
        train_df['final_text'].values)
        #sparce data so have to use bruteforce only so used brute force alg
        for k in list1:
            #knn instance
            model_knn = KNeighborsClassifier(n_neighbors=k,algorithm='brute')
            model_knn.fit(final_counts_train,train_df.Score)
            #Scoring training data
            score_train = model_knn.score(final_counts_train,train_df.Score)
            #Accuracy score
            #score_train = accuracy_score(train_df.Score,train_list)
            scores_train.append(score_train)
            print(score_train)
        #saving for further use
        pickle.dump(scores_train,open('scores_train1.p','wb'))
```

```
1.0
0.9128367346938776
0.8946326530612245
0.8851020408163265
0.8796938775510204
0.8756938775510205
0.8732040816326531
0.8705306122448979
0.8650612244897959
```

```
In [24]: #traing scores for each k between 1-15
         list1 = list(range(1,16,2))
         list1.append(25)
         scores_train = []
         #CountVectorizer for BoW
         count_vect = CountVectorizer(dtype=np.int8)
         final_counts_train = count_vect.fit_transform(
         train_df['final_text'].values)
         X = final_counts_train.toarray()
         for k in list1:
             #knn instance
             model_knn = KNeighborsClassifier(n_neighbors=k,
                                 algorithm='kd_tree',n_jobs=-1)
             model_knn.fit(X,train_df.Score)
             #Predicting training data
             train_list = model_knn.predict(X)
             #Accuracy score
             score_train = accuracy_score(train_df.Score,train_list)
             scores_train.append(score_train)
         #saving for further use
         pickle.dump(scores_train,open('scores_train.p','wb'))
```

```
In [25]: scores_train_brute = pickle.load(open('scores_train1.p','rb'))
```

```
scores_train_kdtree = pickle.load(open('scores_train.p','rb'))
```

In [26]:
```
print('train score corresponding to k value with kdtree ')
i = 0
for k in list1:
    print(k, ' ', scores_train_kdtree[i])
    i= i + 1
```

```
train score corresponding to k value with kdtree
1   1.0
3   0.9140408163265306
5   0.8932448979591837
7   0.8848163265306123
9   0.879
11   0.8758571428571429
13   0.8724897959183674
15   0.8704285714285714
25   0.865
```

In [27]:
```
print('train score corresponding to k value with brute ')
i = 0
for k in list1:
    print(k, ' ', scores_train_brute[i])
    i= i + 1
```

```
train score corresponding to k value with brute
1   1.0
3   0.9128367346938776
5   0.8946326530612245
7   0.8851020408163265
9   0.8796938775510204
11   0.8756938775510205
13   0.8732040816326531
15   0.8705306122448979
25   0.8650612244897959
```

In [23]:
```
#10 fold crossvalidation splits for Time series data
tscv_10 = TimeSeriesSplit(n_splits=10)
```

In [17]:
```
#time series data cross validation 10 fold
# with kd tree
scores_bow_cv = []
for k in list1:
    scores = []
    #10 fold cv
    for train_idx,test_idx in tscv_10.split(train_df):
        count_vect = CountVectorizer(dtype=np.int8)
```

```
            #train data
            X_train = train_df.iloc[train_idx]
            #test data
            X_test = train_df.iloc[test_idx]
            #bow wit train data
            final_counts_train = count_vect.fit_transform(
            #knn instance wit kd tree
            model_knn = KNeighborsClassifier(n_neighbors=k,
                                    algorithm='kd_tree',n_jobs=-1)
            model_knn.fit(X,X_train.Score)
            #bow transform for test data
            final_counts_test = count_vect.transform(
            X_test['final_text'].values)
            X_test_array = final_counts_test.toarray()
            #predicting test data
            test_list = model_knn.predict(X_test_array)
            #test accuracy for cv fold
            score = accuracy_score(X_test.Score,test_list)
            scores.append(score)
        scores_bow_cv.append(scores)
    #saving to disk for furter use
    pickle.dump(scores_bow_cv,open('scores_bow_cv.p','wb'))
```

In [14]:
```
#10 fold cv with brute force with sparse array
for k in list1:
    scores = []
    #10 fold cv
    for train_idx,test_idx in tscv_10.split(train_df):
        count_vect = CountVectorizer(dtype=np.int8)
        #train data
        X_train = train_df.iloc[train_idx]
        #test data
        X_test = train_df.iloc[test_idx]
        #bow wit train data
        final_counts_train = count_vect.fit_transform(
        X_train['final_text'].values)
        #knn instance wit kd tree
        model_knn = KNeighborsClassifier(n_neighbors=k,
                                algorithm='brute')
        model_knn.fit(final_counts_train,X_train.Score)
        #bow transform for test data
        final_counts_test = count_vect.transform(
        X_test['final_text'].values)
        #X_test_array = final_counts_test.toarray()
        #predicting test data
        test_list = model_knn.predict(final_counts_test)
        #test accuracy for cv fold
        score = accuracy_score(X_test.Score,test_list)
```

```
            scores.append(score)
        print(scores)
        scores_bow_cv.append(scores)
    #saving to disk for furter use
    pickle.dump(scores_bow_cv,open('scores_bow_cv_brute.p','wb'))
```

In [15]:
```
scores_bow_cv_kdtree = pickle.load(open('scores_bow_cv.p','rb'))
scores_bow_cv_brute = pickle.load(open('scores_bow_cv_brute.p','rb'))
```

In [18]:
```
#mean cv scores for kd tree
mean_cv_kdtree = np.array(scores_bow_cv_kdtree).mean(axis=1)
mean_cv_kdtree
```

Out[18]:
```
array([0.81082173, 0.84811405, 0.85071846, 0.84838348, 0.8473956 ,
       0.84694656, 0.84654243, 0.84631792, 0.84584643])
```

In [19]:
```
#mean cv scores for brute
mean_cv_brute = np.array(scores_bow_cv_brute).mean(axis=1)
mean_cv_brute
```

Out[19]:
```
array([0.83293669, 0.85532106, 0.85882353, 0.85951953, 0.85830714,
       0.85713965, 0.85675797, 0.85554558, 0.85348002])
```

In [20]:
```
#std with kd tree
std_cv_kdtree = np.array(scores_bow_cv_kdtree).std(axis=1)
std_cv_kdtree
```

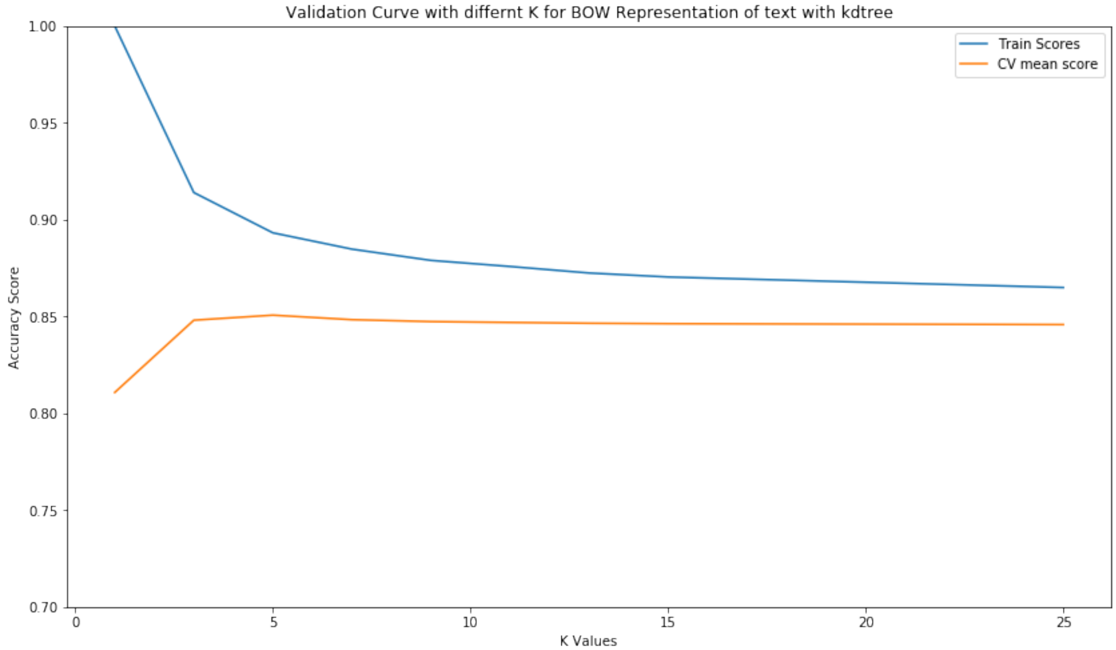
Out[20]:
```
array([0.01058437, 0.01332477, 0.01719177, 0.0185471 , 0.01898892,
       0.01911855, 0.01936252, 0.01954648, 0.01990145])
```

In [21]:
```
#std withsparse data brute force
std_cv_brute = np.array(scores_bow_cv_brute).std(axis=1)
std_cv_brute
```

Out[21]:
```
array([0.01165695, 0.01211861, 0.01383792, 0.01367679, 0.01415579,
       0.01509653, 0.01528598, 0.01539252, 0.01658215])
```

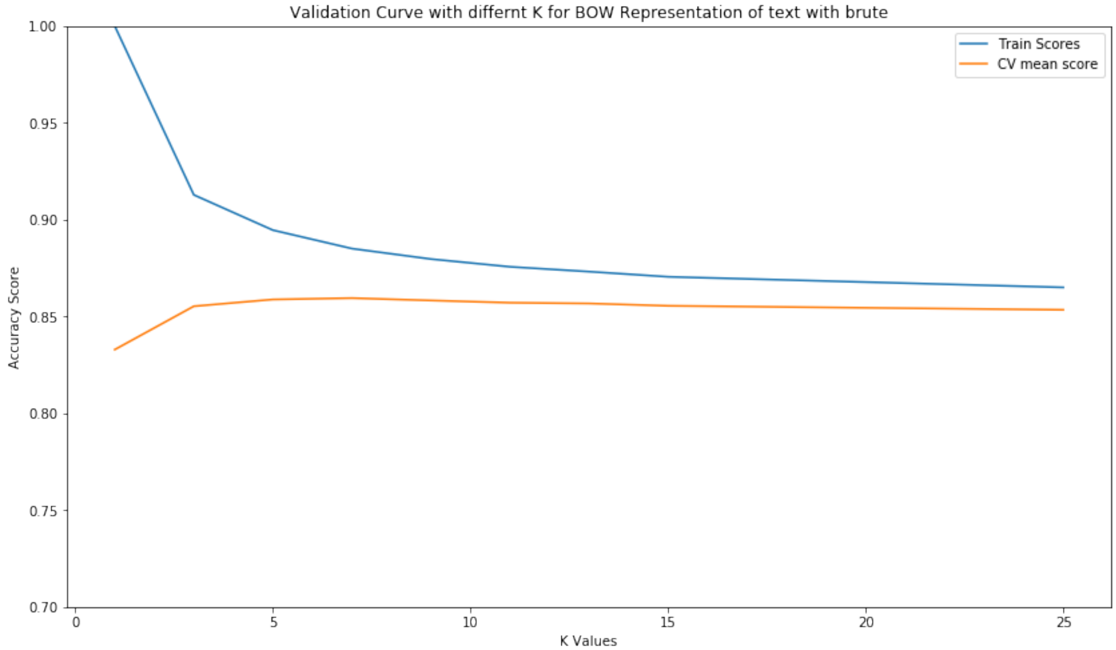
In [30]:
```
plt.figure(figsize=(14,8))
plt.plot(list1,
         scores_train_kdtree,label='Train Scores')
plt.plot(list1,
         mean_cv_kdtree,label = 'CV mean score')
plt.xlabel('K Values')
plt.ylabel('Accuracy Score')
plt.ylim(0.7,1)
plt.title('Validation Curve with diffrent K for BOW Representation of text with kdtree'
plt.legend()
```

Out[30]:
```
<matplotlib.legend.Legend at 0x14eb8acb1048>
```



In [31]:
```
list1 = list(range(1,16,2))
list1.append(25)
plt.figure(figsize=(14,8))
plt.plot(list1,
         scores_train_brute,label='Train Scores')
plt.plot(list1,
         mean_cv_brute,label = 'CV mean score')
plt.xlabel('K Values')
plt.ylabel('Accuracy Score')
plt.ylim(0.7,1)
plt.title('Validation Curve with differnt K for BOW Representation of text with brute')
plt.legend()
```

Out[31]: <matplotlib.legend.Legend at 0x14eb89268ba8>




```
In [34]: count_vect = CountVectorizer()
         final_counts_train = count_vect.fit_transform(
         train_df['final_text'].values)
         final_counts_test = count_vect.transform(
         test_df['final_text'].values)
```

```
In [137]: X = final_counts_train.toarray()
          X_test = final_counts_test.toarray()
          model_knn = KNeighborsClassifier(n_neighbors=5,
                                           algorithm='kd_tree',n_jobs=-1)
          model_knn.fit(X,train_df.Score)
          test_list = model_knn.predict(X_test)
          score = accuracy_score(test_df.Score,test_list)
          print('k = 5' , score)
```

```
k = 5 0.8494285714285714
```

```
In [35]: model_knn = KNeighborsClassifier(n_neighbors=7,algorithm='brute')
         model_knn.fit(final_counts_train,train_df.Score)
         #Scoring test data
         score_test = model_knn.score(final_counts_test,test_df.Score)
         print('k = 7',score_test)
```

```
k = 7 0.8496190476190476
```

Observation: with kdtree * For k = 5 the cv accuracy is high with mean 0.85071846 standard deviation of 0.01719177 for 10 fold cross validation. * For k > 5 the cv mean accuracy is decresing and train accuracy is also decresing. * Test accuracy for k =5 is 0.8494285714285714 with brute with kdtree * For k = 7 the cv accuracy is high with mean 0.85951953 standard deviation of 0.01367679 for 10 fold cross validation. * For k > 7 the cv mean accuracy is decresing and train accuracy is also decresing. * Test accuracy for k =7 is 0.8496190476190476

we can observe that for same k there is a increase in cv scores with brute force than kd tree.

0.1.2 TR-IDF:

```
In [17]: #k values
         list_tfidf = list(range(1,18,2))
         list_tfidf.extend([25,27,37,51,71,101])
```

```
In [18]: #train scores for different k values of tfidf representation
         scores_train_tfidf= []
         #tfidf
         tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
         final_tf_idf = tf_idf_vect.fit_transform(train_df['final_text'].values)
         #scaling sparse array
         scale = StandardScaler(with_mean=False)
         X = scale.fit_transform(final_tf_idf)
         for i in list_tfidf:
             #knn wit brute force algorithm
             model_knn = KNeighborsClassifier(n_neighbors=i,
                                     algorithm='brute',n_jobs=-1)
             model_knn.fit(X,train_df.Score)
             #predicting train scores
             test_list = model_knn.predict(X)
             #accuracy score
             score_train = accuracy_score(train_df.Score,test_list)
             scores_train_tfidf.append(score_train)
             print(k,score_train)
         pickle.dump(scores_train_tfidf,open('scores_train_tfidf.p','wb'))
```

```
1 1.0
3 0.8504897959183674
5 0.8499795918367347
7 0.8498571428571429
9 0.8498571428571429
11 0.8498571428571429
13 0.8498571428571429
15 0.8498571428571429
17 0.8498571428571429
25 0.8498571428571429
27 0.8498571428571429
37 0.8498571428571429
51 0.8498571428571429
```

```
71 0.8498571428571429
101 0.8498571428571429
```

```
In [19]: scores_train_tfidf = pickle.load(open('scores_train_tfidf.p','rb'))
         len(scores_train_tfidf)

Out[19]: 15

In [46]: #10 fold cv
         tscv_10 = TimeSeriesSplit(n_splits=10)
         scores_testcv_tfidf = []
         for i in list_tfidf:
             scores_test = []
             #for each fold
             for train_idx,test_idx in tscv_10.split(train_df):
                 tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
                 #train data
                 X_train = train_df.iloc[train_idx]
                 #cv data
                 X_test = train_df.iloc[test_idx]
                 #tfidf
                 final_tf_idf = tf_idf_vect.fit_transform(X_train['final_text'].values)
                 scale = StandardScaler(with_mean=False)
                 X = scale.fit_transform(final_tf_idf)
                 #knn
                 model_knn = KNeighborsClassifier(n_neighbors=i,
                                         algorithm='brute',n_jobs=-1)
                 model_knn.fit(X,X_train.Score)
                 #cv data tfidf representation
                 final_counts_test = tf_idf_vect.transform(
                 X_test['final_text'].values)
                 X_test_array = scale.transform(final_counts_test)
                 #prdicting cv data
                 test_list = model_knn.predict(X_test_array)
                 #accuracy of cv data
                 score_test = accuracy_score(X_test.Score,test_list)
                 scores_test.append(score_test)
             scores_testcv_tfidf.append(scores_test)
         pickle.dump(scores_testcv_tfidf,open('score_testcv_tfidf.p','wb'))

In [20]: scores_testcv_tfidf = pickle.load(open('score_testcv_tfidf.p','rb'))
         print(len(scores_testcv_tfidf))
         print(len(scores_testcv_tfidf[0]))

15
10
```

In [21]:
```
#mean cv sores
mean_cv = np.array(scores_testcv_tfidf).mean(axis=1)
mean_cv
```

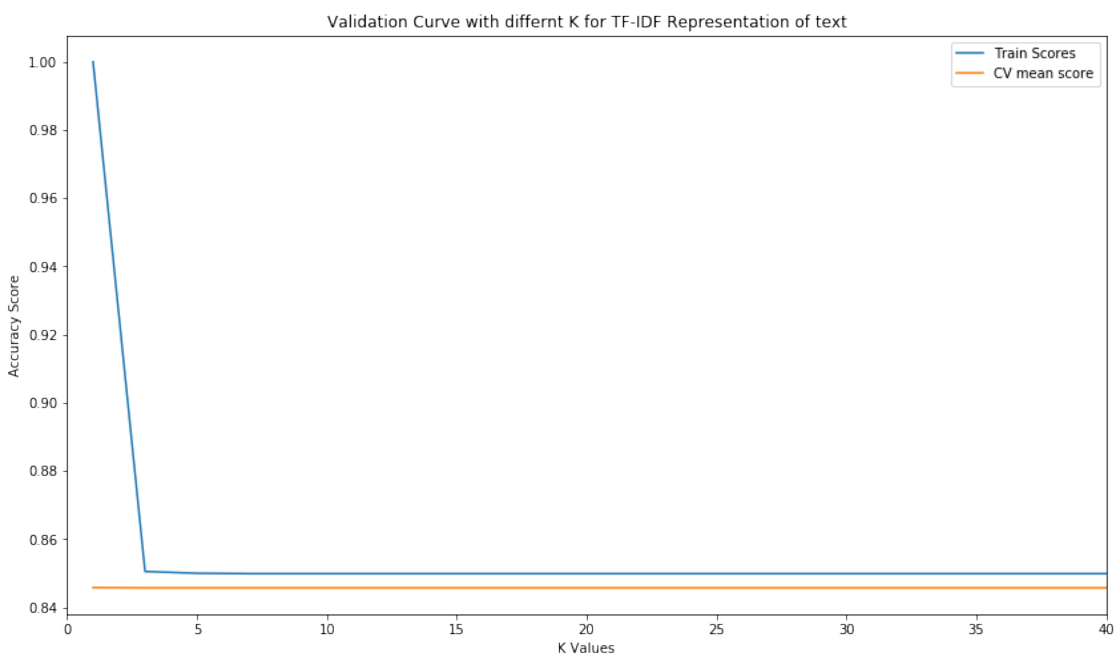
Out[21]:
```
array([0.84577907, 0.84568927, 0.84568927, 0.84568927, 0.84568927,
       0.84568927, 0.84568927, 0.84568927, 0.84568927, 0.84568927,
       0.84568927, 0.84568927, 0.84568927, 0.84568927, 0.84568927])
```

In [22]:
```
#standard deviation of cv scores
std_cv = np.array(scores_testcv_tfidf).std(axis=1)
std_cv
```

Out[22]:
```
array([0.01993593, 0.02002439, 0.02002439, 0.02002439, 0.02002439,
       0.02002439, 0.02002439, 0.02002439, 0.02002439, 0.02002439,
       0.02002439, 0.02002439, 0.02002439, 0.02002439, 0.02002439])
```

In [23]:
```
plt.figure(figsize=(14,8))
plt.plot(list_tfidf,
         scores_train_tfidf,label='Train Scores')
plt.plot(list_tfidf,
         mean_cv,label = 'CV mean score')
plt.xlabel('K Values')
plt.ylabel('Accuracy Score')
plt.xlim(0,40)
plt.title('Validation Curve with differnt K for TF-IDF Representation of text')
plt.legend()
```

Out[23]: <matplotlib.legend.Legend at 0x14cdfecf5320>



Observations:

- for k > 3 cv scores are same and for k > 5 the training scores are also same. so it is better to take k in range of 25-50 like that because if we take less value of k it may cause overfit. so i made optimal k as 25. if need of speed computation on test data we can prefer k as 5

```
In [83]: #test score for k = 25
         tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
         final_tf_idf = tf_idf_vect.fit_transform(train_df['final_text'].values)
         scale = StandardScaler(with_mean=False)
         X = scale.fit_transform(final_tf_idf)
         model_knn = KNeighborsClassifier(n_neighbors=25,
                               algorithm='brute',n_jobs=-1)
         model_knn.fit(X,train_df.Score)
         X_test =  tf_idf_vect.transform(test_df['final_text'].values)
         X_test = scale.transform(X_test)
         test_list = model_knn.predict(X_test)
         score_test = accuracy_score(test_df.Score,test_list)
         score_test
```

```
Out[83]: 0.8257619047619048
```

0.1.3 Word2Vec

```
In [16]: #importing
         from gensim.models import Word2Vec
         from gensim.models import KeyedVectors
         import pickle
         import gensim
```

```
In [85]: import gensim
         list_of_sent=[]
         for sent in final_review.final_text.values:
             list_of_sent.append(sent.split())
```

```
In [87]: #word2vec model
         w2v_model=gensim.models.Word2Vec(list_of_sent,min_count=5,size=50, workers=8)
```

```
In [88]: #saving to disk
         pickle.dump(w2v_model,open('w2v_model.p','wb'))
```

```
In [17]: w2v_model = pickle.load(open('w2v_model.p','rb'))
```

Avg Word2Vec

```
In [116]: # the avg-w2v for each sentence/review is stored in this list
          def avg_w2v(list_of_sent,model):
              '''
              Returns average of word vectors for
```

```
            each sentance with dimension of model given
            '''
            sent_vectors = []
            for sent in list_of_sent: # for each review/sentence
                doc = [word for word in sent if word in model.wv.vocab]
                if doc:
                    sent_vec = np.mean(model.wv[doc],axis=0)
                else:
                    sent_vec = np.zeros(50)
                sent_vectors.append(sent_vec)
            return sent_vectors
```

In [117]:
```
#avg word vectors
sent_vectors = avg_w2v(list_of_sent,w2v_model)
len(sent_vectors)
```

Out[117]: 364171

In [159]:
```
list_of_sent_train=[]
for sent in train_df.final_text.values:
    list_of_sent_train.append(sent.split())
```

In [148]:
```
#avg word2vec for
sent_vector_avgw2v = avg_w2v(list_of_sent_train,w2v_model)
```

In [149]:
```
#stacking columns
train_avgw2v = np.hstack((sent_vector_avgw2v,
            train_df[['HelpfulnessNumerator',
                      'HelpfulnessDenominator','Score']]))
column = list(range(0,50))
column.extend(['HelpfulnessNumerator','HelpfulnessDenominator','Score'])
train_df_avgw2v = pd.DataFrame(train_avgw2v,columns=column)
```

In [164]:
```
#saving
train_df_avgw2v.to_csv('train_df_avgw2v.csv',index=False)
```

In [4]:
```
train_df_avgw2v = pd.read_csv('train_df_avgw2v.csv')
```

In [166]:
```
#test data
list_of_sent_test=[]
for sent in test_df.final_text.values:
    list_of_sent_test.append(sent.split())
```

In [167]:
```
#test data avg word2vec
sent_vector_avgw2v = avg_w2v(list_of_sent_test,w2v_model)
```

In [168]:
```
#stacking for test data
test_avgw2v = np.hstack((sent_vector_avgw2v,
            test_df[['HelpfulnessNumerator',
```

```
                              'HelpfulnessDenominator','Score']]))
        column = list(range(0,50))
        column.extend(['HelpfulnessNumerator','HelpfulnessDenominator','Score'])
        test_df_avgw2v = pd.DataFrame(test_avgw2v,columns=column)
```

```
In [170]: test_df_avgw2v.to_csv('test_df_avgw2v.csv',index=False)
```

```
In [6]: test_df_avgw2v = pd.read_csv('test_df_avgw2v.csv')
```

```
In [38]: list_avgw2v = list(range(1,18,2))
         list_avgw2v.extend([25,35,45,55,95])
```

```
In [105]: #train scores for each k with avgword2vec
          scores_train_avgw2v = []
          #scaling
          scale = StandardScaler()
          X = scale.fit_transform(train_df_avgw2v.drop('Score',axis=1))
          for k in list_avgw2v:
              #knn with ball tree
              model_knn = KNeighborsClassifier(n_neighbors=k,
                                    algorithm='ball_tree',n_jobs=-1)
              model_knn.fit(X,train_df_avgw2v.Score)
              #train accuracy
              score_train = model_knn.score(X,train_df_avgw2v.Score)
              scores_train_avgw2v.append(score_train)
          pickle.dump(scores_train_avgw2v,open('scores_train_avgw2v.p','wb'))
```

```
In [34]: #loading
         scores_train_avgw2v = pickle.load(open('scores_train_avgw2v.p','rb'))
```

```
In [40]: print('train score corresponding to k value ')
         i = 0
         for k in list_avgw2v:
             print(k, ' ', scores_train_avgw2v[i])
             i= i + 1
```

```
train score corresponding to k value
1   1.0
3   0.9378775510204082
5   0.9230612244897959
7   0.9160204081632654
9   0.9118775510204081
11   0.908795918367347
13   0.9065918367346939
15   0.904469387755102
17   0.9033877551020408
25   0.898795918367347
35   0.8950816326530612
45   0.8921632653061224
```

```
55   0.8905714285714286
95   0.8862857142857142
```

```
In [90]: #10 fold cv
         tscv_10 = TimeSeriesSplit(n_splits=10)
         scores_avgw2v_cv = []
         for k in list_avgw2v:
             scores_test = []
             for train_idx,test_idx in tscv_10.split(train_df_avgw2v):
                 #train data
                 X_train = train_df_avgw2v.iloc[train_idx]
                 #cv data
                 X_test = train_df_avgw2v.iloc[test_idx]
                 #Scale
                 scale = StandardScaler()
                 X = scale.fit_transform(X_train.drop('Score',axis=1))
                 #knn
                 model_knn = KNeighborsClassifier(n_neighbors=45,
                                         algorithm='ball_tree',n_jobs=-1)
                 model_knn.fit(X,X_train.Score)
                 #cv data scaling
                 X_test_array = scale.transform(X_test.drop('Score',axis=1))
                 #predicting cv data
                 test_list = model_knn.predict(X_test_array)
                 #test accuracy
                 score_test = accuracy_score(X_test.Score,test_list)
                 scores_test.append(score_test)
             scores_avgw2v_cv.append(scores_test)
         pickle.dump(scores_avgw2v_cv,open('scores_avgw2v_cv.p','wb'))
```

```
In [41]: scores_avgw2v_cv = pickle.load(open('scores_avgw2v_cv.p','rb'))
```

```
In [42]: #mean cv scores
         mean_cv = np.array(scores_avgw2v_cv).mean(axis=1)
         mean_cv
```

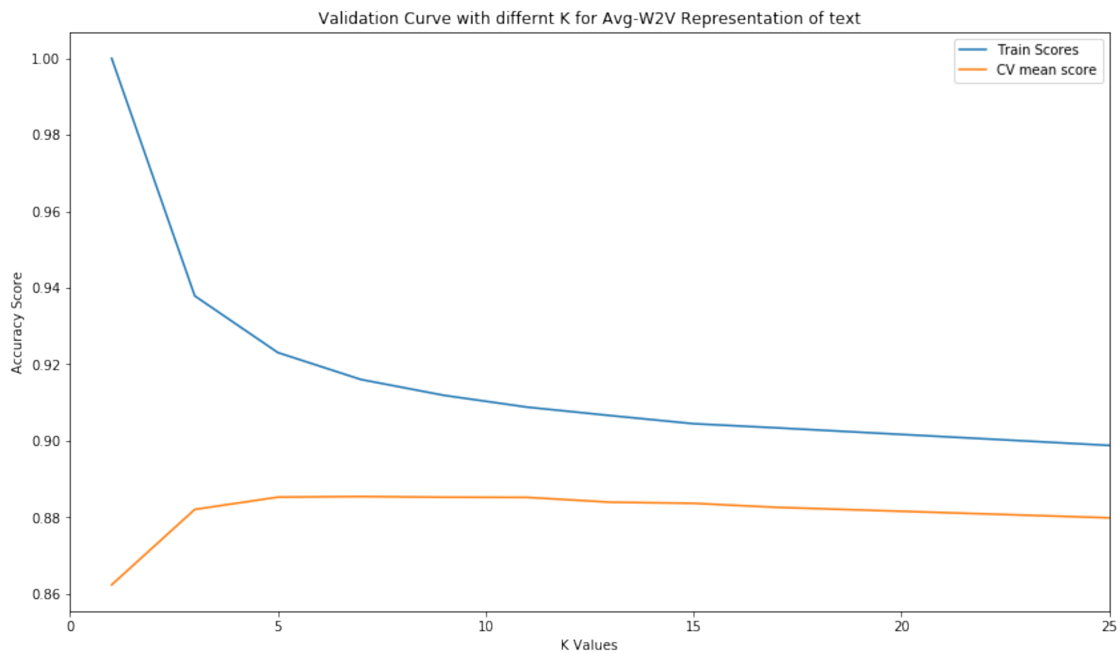
```
Out[42]: array([0.86234845, 0.88206107, 0.88527167, 0.88542883, 0.88524921,
                0.88520431, 0.88394701, 0.88365514, 0.88259991, 0.8798608 ,
                0.87723395, 0.87581949, 0.87462955, 0.86962281])
```

```
In [43]: #std of cv scores
         std_cv = np.array(scores_avgw2v_cv).std(axis=1)
         std_cv
```

```
Out[43]: array([0.01129099, 0.00897735, 0.00805013, 0.00777365, 0.00718627,
                0.00784851, 0.00829344, 0.00813781, 0.00821834, 0.00811899,
                0.009041  , 0.00941338, 0.00942074, 0.00990732])
```

In [45]:
```
plt.figure(figsize=(14,8))
plt.plot(list_avgw2v,
         scores_train_avgw2v,label='Train Scores')
plt.plot(list_avgw2v,
         mean_cv,label = 'CV mean score')
plt.xlabel('K Values')
plt.ylabel('Accuracy Score')
plt.xlim(0,25)
plt.title('Validation Curve with differnt K for Avg-W2V Representation of text')
plt.legend()
```

Out[45]:
```
<matplotlib.legend.Legend at 0x14fb0af539e8>
```



Observations:

- From above we can infer that 7 or 11 be optimal k. Train and test accureacy are below mentiond. after 11 cross validation accuracy is decresing and training also decresing.

In [46]:
```
#test scores
scale = StandardScaler()
X = scale.fit_transform(train_df_avgw2v.drop('Score',axis=1))
X_test = scale.transform(test_df_avgw2v.drop('Score',axis=1))
for k in [7,11]:
    model_knn = KNeighborsClassifier(n_neighbors=k,
                                     algorithm='ball_tree',n_jobs=-1)
    model_knn.fit(X,train_df.Score)
```

```
        score_test = model_knn.score(X_test,test_df.Score)
        score_train = model_knn.score(X,train_df.Score)
        print('k = ',k)
        print('Training Score',score_train)
        print('Testing Score',score_test)
```

```
k =  7
Training Score 0.9160204081632654
Testing Score 0.8811904761904762
k =  11
Training Score 0.908795918367347
Testing Score 0.8807142857142857
```

TF-IDF Weighted Word2Vec

In [16]:
```
import gensim
list_of_sent=[]
for sent in final_review.final_text.values:
    list_of_sent.append(sent.split())
```

In [19]:
```
#tf-idf
tf_idf_vect = TfidfVectorizer(ngram_range=(1,1))
final_tf_idf = tf_idf_vect.fit_transform(final_review.final_text.values)
```

In [56]:
```
#dict wit value as index
dict_tfidf = {k: v for v, k in enumerate(tf_idf_vect.get_feature_names())}
```

In [53]:
```
%%time
#time for for loop implementation
# TF-IDF weighted Word2Vec
tfidf_feat = tf_idf_vect.get_feature_names() # tfidf words/col-names
tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this lis
row=0;
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50,dtype=np.float64) # as word vectors are of zero length
    weight_sum =0.0; # num of words with a valid vector in the sentence/review
    for word in sent : # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tfidf = final_tf_idf[row, dict_tfidf[word]]
            sent_vec = sent_vec + vec*tfidf
            weight_sum = weight_sum + tfidf
        except:
            pass
    sent_vec = sent_vec/weight_sum
    tfidf_sent_vectors.append(sent_vec)
    row += 1
```

/glob/intel-python/versions/2018u2/intelpython3/lib/python3.6/site-packages/ipykernel_launcher.p

CPU times: user 6min 15s, sys: 22.8 s, total: 6min 38s
Wall time: 6min 12s

In [32]:
```
def tf_idf_W2V(w2v_model,tf_idf_vect,tf_idf_trans_arr,list_of_sent):
    import operator
    dict_tfidf = {k: v for v, k in enumerate(tf_idf_vect.get_feature_names())}
    sent_vectors = []
    i = 0
    for sent in list_of_sent: # for each review/sentence
        doc = [word for word in sent if word in w2v_model.wv.vocab]
        if doc:
            #itemgetter
            f = operator.itemgetter(*doc)
            try:
                #itemgetter from dict
                final = f(dict_tfidf)
                final = tf_idf_trans_arr[i,final]
                #converting to dense
                final = final.toarray()
                #converting to diagnol matrix for multiplication
                final= np.diag(final[0])
                sent_vec = np.dot(final,np.array(w2v_model.wv[doc]))
                #tfidf weighted word to vec
                sent_vec = np.sum(sent_vec,axis=0) / np.sum(final)
            except:
                sent_vec = np.zeros(50)
        else:
            sent_vec = np.zeros(50)
        sent_vectors.append(sent_vec)
        i = i+1
    return sent_vectors
```

In [49]:
```
#time for vectorized implementation
%time test = tf_idf_W2V(w2v_model,tf_idf_vect,final_tf_idf,list_of_sent)
```

CPU times: user 3min 58s, sys: 362 ms, total: 3min 58s
Wall time: 3min 58s

In [57]:
```
tfidf_sent_vectors[300]
```

Out[57]:
```
array([-0.50473002, -1.29254243, -1.14878999,  0.16220791, -1.57725931,
        0.33451035, -0.85590403, -0.99547177,  0.35920219,  0.35229029,
        0.48958326, -0.72000141, -0.63554757, -0.93693301, -0.48698263,
        0.47417588,  0.68699963,  1.06305276, -0.68265815, -1.3964433 ,
```

```
                 0.03462894, -0.5222669 ,  0.36551395,  0.44783677, -0.19720486,
                 0.23341387, -0.25774105,  0.80620439,  0.74853232, -0.14239912,
                -0.40646785, -0.18689983,  0.83903254,  0.07734973,  0.08818401,
                -0.3893744 , -0.26932468,  0.32558248, -1.17318695, -1.2369735 ,
                 0.42737041,  0.67004039, -0.13578889, -0.45484249,  0.9743006 ,
                 0.73795557,  0.69694404,  0.26626051,  0.05896904, -0.95720778])
```

```
In [58]: test[300]
```

```
Out[58]: array([-0.50473004, -1.29254244, -1.14879001,  0.16220793, -1.57725938,
                 0.33451035, -0.85590406, -0.99547177,  0.35920219,  0.3522903 ,
                 0.48958326, -0.72000142, -0.6355476 , -0.93693305, -0.48698265,
                 0.47417587,  0.68699964,  1.06305275, -0.68265816, -1.39644332,
                 0.03462894, -0.52226692,  0.36551395,  0.44783678, -0.19720486,
                 0.23341385, -0.25774106,  0.80620441,  0.74853235, -0.14239914,
                -0.40646785, -0.18689983,  0.8390326 ,  0.07734973,  0.088184  ,
                -0.3893744 , -0.2693247 ,  0.32558251, -1.17318696, -1.23697357,
                 0.42737042,  0.67004042, -0.13578887, -0.45484252,  0.97430062,
                 0.73795559,  0.69694405,  0.26626052,  0.05896904, -0.95720779])
```

Vectorized implementation is around 65% faster than normal for loop implementation. so i used vectorized implementation for claculating tfidf weighted word2vec. but this need more space than loop implementation.

```
In [18]: #list of k
         list_tfidf_w2v = list(range(1,26,2))
         list_tfidf_w2v.extend([35,45,95])
```

```
In [230]: print('train score corresponding to k value ')
          #tfidf instance
          tf_idf_vect = TfidfVectorizer(ngram_range=(1,1))
          final_tf_idf = tf_idf_vect.fit_transform(train_df['final_text'].values)
          list_of_sent = []
          #converting into list of words for each sentance of train
          for sent in train_df.final_text.values:
              list_of_sent.append(sent.split())
          #getting tfidf weighted word to vec
          X_train_fet = tf_idf_W2V(w2v_model,tf_idf_vect,final_tf_idf,list_of_sent)
          X_train_fet = np.hstack((X_train_fet,
                      train_df[['HelpfulnessNumerator',
                                'HelpfulnessDenominator']]))
          #scaling
          scale = StandardScaler()
          X = scale.fit_transform(X_train_fet)
          for k in list_tfidf_w2v:
              #knn with ball tree
              model_knn = KNeighborsClassifier(n_neighbors=k,
                                      algorithm='ball_tree',n_jobs=-1)
              model_knn.fit(X_train_fet,train_df.Score)
```

```
            #accuracy of train
            score_train = model_knn.score(X_train_fet,train_df.Score)
            scores_train.append(score_train)
            print(k, ' ', scores_train)
        #saving
        pickle.dump(scores_train,open('score_tfidfw2v_train1to19.p','wb'))
```

```
train score corresponding to k value
1   1.0
3   0.934734693877551
5   0.9206530612244898
7   0.9123877551020408
9   0.909
11   0.9058571428571428
13   0.9034489795918368
15   0.9009387755102041
17   0.9
19   0.8984489795918368
21   0.897673469387755
23   0.8967142857142857
25   0.8958571428571429
35   0.8929387755102041
45   0.8910204081632653
95   0.884
```

In [2]:
```
score_train_tfidf_w2v = pickle.load(open('score_train_tfidf_w2v.p','rb'))
```

In [223]:
```
#10 fold cv
tscv_10 = TimeSeriesSplit(n_splits=10)
score_cv_tfidf_w2v = []
for k in list_tfidf_w2v:
    scores_test = []
    #for each cv fold
    for train_idx,test_idx in tscv_10.split(train_df):
        #train data
        X_train = train_df.iloc[train_idx]
        #cv data
        X_test = train_df.iloc[test_idx]
        #tfidf
        tf_idf_vect = TfidfVectorizer(ngram_range=(1,1))
        final_tf_idf = tf_idf_vect.fit_transform(X_train['final_text'].values)
        list_of_sent = []
        for sent in X_train.final_text.values:
            list_of_sent.append(sent.split())
        #tfidf weighted word2vec
        X_train_fet = tf_idf_W2V(w2v_model,tf_idf_vect,
                                 final_tf_idf,list_of_sent)
```

```
                #stacking word vec and some other features
                X_train_fet = np.hstack((X_train_fet,
                        X_train[['HelpfulnessNumerator',
                              'HelpfulnessDenominator']]))
                #scaling
                scale = StandardScaler()
                X = scale.fit_transform(X_train_fet)
                #knn
                model_knn = KNeighborsClassifier(n_neighbors=21,
                                            algorithm='ball_tree',n_jobs=-1)
                model_knn.fit(X_train_fet,X_train.Score)
                #cv data transformation to tfidf
                final_tf_idf_test = tf_idf_vect.transform(X_test['final_text'].values)
                list_of_sent = []
                for sent in X_test.final_text.values:
                    list_of_sent.append(sent.split())
                #word2vec for cv data
                X_test_fet = tf_idf_W2V(w2v_model,tf_idf_vect,final_tf_idf_test,list_of_sent)
                X_train_fet = np.hstack((X_test_fet,
                        X_test[['HelpfulnessNumerator',
                              'HelpfulnessDenominator']]))
                X_test_array = scale.transform(X_train_fet)
                test_list = model_knn.predict(X_test_array)
                #accuracy of cv data
                score_test = accuracy_score(X_test.Score,test_list)
                scores_test.append(score_test)
            score_cv_tfidf_w2v.append(scores_test)
        pickle.dump(score_cv_tfidf_w2v,open('score_cv_tfidf_w2v.p','wb'))
```

In [3]:
```
score_cv_tfidf_w2v = pickle.load(open('score_cv_tfidf_w2v.p','rb'))
```

In [21]:
```
print(len(score_cv_tfidf_w2v))
print(len(score_cv_tfidf_w2v[0]))
```

```
16
10
```

In [239]:
```
#mean cv scores
mean_cv = np.array(score_cv_tfidf_w2v).mean(axis=1)
mean_cv
```

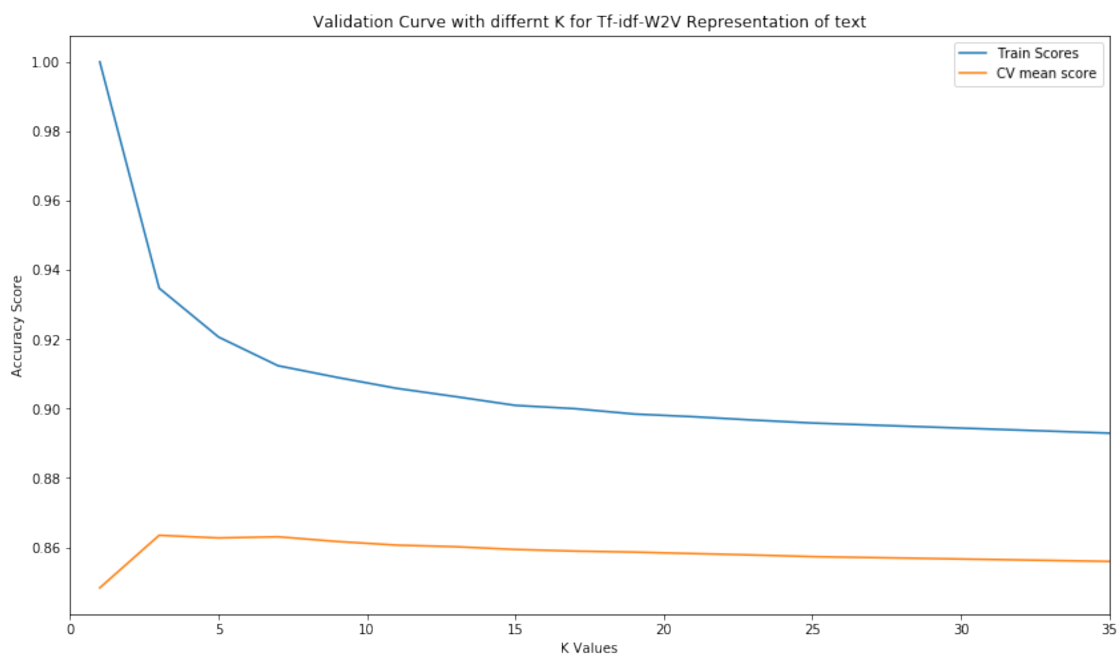
Out[239]:
```
array([0.84833857, 0.86349349, 0.86273013, 0.86306691, 0.86169735,
       0.86066457, 0.86019308, 0.85940727, 0.85893579, 0.85864392,
       0.85821733, 0.8578132 , 0.85734172, 0.85597216, 0.85480467,
       0.85215537])
```

In [4]:
```
std_cv = np.array(score_cv_tfidf_w2v).std(axis=1)
std_cv
```

Out[4]: array([0.01451891, 0.01193917, 0.01315763, 0.01381154, 0.01425322,
       0.01390058, 0.01384566, 0.01374618, 0.01385293, 0.01398445,
       0.01409291, 0.01398332, 0.01413468, 0.01445663, 0.01464605,
       0.01575441])

In [245]:
```
plt.figure(figsize=(14,8))
plt.plot(list_tfidf_w2v,
         score_train_tfidf_w2v,label='Train Scores')
plt.plot(list_tfidf_w2v,
         mean_cv,label = 'CV mean score')
plt.xlabel('K Values')
plt.ylabel('Accuracy Score')
plt.xlim(0,35)
plt.title('Validation Curve with differnt K for Tf-idf-W2V Representation of text')
plt.legend()
```

Out[245]: <matplotlib.legend.Legend at 0x14b7ac3a1fd0>



Observations: Cross validation score is maximum at 3,7 and after that cv score is decresing. below are the train and test scores for k = 3,7

In [34]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,1))
final_tf_idf = tf_idf_vect.fit_transform(train_df['final_text'].values)
list_of_sent = []
for sent in train_df.final_text.values:
    list_of_sent.append(sent.split())
```

```python
X_train_fet = tf_idf_W2V(w2v_model,tf_idf_vect,final_tf_idf,list_of_sent)
X_train_fet = np.hstack((X_train_fet,
            train_df[['HelpfulnessNumerator',
                      'HelpfulnessDenominator']]))
scale = StandardScaler()
X = scale.fit_transform(X_train_fet)
list_of_sent = []
for sent in test_df.final_text.values:
    list_of_sent.append(sent.split())
final_tf_idf_test = tf_idf_vect.transform(test_df['final_text'].values)
X_test_fet = tf_idf_W2V(w2v_model,tf_idf_vect,final_tf_idf_test,list_of_sent)
X_train_fet = np.hstack((X_test_fet,
                test_df[['HelpfulnessNumerator',
                      'HelpfulnessDenominator']]))
X_test_array = scale.transform(X_train_fet)
for k in [3,7]:
    model_knn = KNeighborsClassifier(n_neighbors=k,algorithm='ball_tree',n_jobs=-1)
    model_knn.fit(X_train_fet,train_df.Score)
    score_train = model_knn.score(X_train_fet,train_df.Score)
    test_score = model_knn.score(X_test_array,test_df.Score)
    print('k', k)
    print('Train Score',score_train)
    print('Test Score',test_score)
```

```
k 3
Train Score 0.934734693877551
Test Score 0.8553809523809524
k 7
Train Score 0.9123877551020408
Test Score 0.8570476190476191
```

Conclusions:

- For Bow representation of data got highest model mean cv accuracy of 0.8595 for k = 7 and test accuracy was 0.8496
- For TFIDF representation of data got highest model mean cv accuracy of 0.8457 for k = 25 and test accuracy was 0.8258
- For average word2vec representation of data got highest mean cv accuracy of 0.8854 for k = 7 and test accuracy was 0.8812
- For TF-IDF Weighted word2vec representation of data got highest mean cv accuracy of 0.8631 for k = 7 and test accuracy was 0.8571
  From above models, high accuracy model was average word2vec representation model and best k for that is 7 with mean cv accuracy of 0.8854
  observed that Training time is also less for average word2vec representation than others and used only 50 dimentional vector, and this is very less compared to others.