Amazon Fine Food Reviews Analysis- sentimental analysis using KNN Classifier

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon. Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10 Attribute Information: 1) Id 2) ProductId - unique identifier for the product 3) UserId - unqiue identifier for the user 4) ProfileName 5) HelpfulnessNumerator - number of users who found the review helpful 6) HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not 7) Score - rating between 1 and 5 8) Time - timestamp for the review 9) Summary - brief summary of the review 10) Text - text of the review Objective: Given a review, determine whether the review is positive (Rating of 4 or 5) or negative (rating of 1 or 2). [Q] How to determine if a review is positive or negative? [Ans] We could use the Score/Rating. A rating of 4 or 5 could be considered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

Loading the data The dataset is available in two forms 1).csv file 2)SQLite Database In order to load the data, We have used the SQLITE dataset as it easier to query the data and visualise the data efficiently. Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score id above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative". we will make postive label as 1 and negative score as 0 becoz we are taking F1_score as metric.

```
In [28]:
```

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load in
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read csv)
import sqlite3
import gensim
import re
import nltk
import matplotlib.pyplot as plt
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
import seaborn as sn
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature extraction.text import TfidfVectorizer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import log loss
from sklearn.metrics import accuracy score, fl score, confusion matrix, classification report
from sklearn.feature_extraction.text import CountVectorizer
# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list the files in the i
nput directory
# Any results you write to the current directory are saved as output.
```

In [4]:

```
data = pd.read_pickle("final_data.pkl")
data.shape

Out[4]:
(100000, 11)
```

Loading the data using sqlite**

```
In [3]:
```

```
con = sqlite3.connect("../input/database.sqlite")
data = pd.read_sql_query('select * from reviews where Score !=3',con)
data.head()
```

Out[3]:

	ld	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy
4									Þ

Data preprocessing

In [4]:

```
\#changing reviews score to postive if score is > 3 and negative if score less than 3
def change_labels(x):
    if x > 3:
       {f return} \ 1
   return 0
temp score = data['Score']
temp_score = temp_score.map(change_labels)
data['Score'] = temp score
data['Score'].head()
Out[4]:
0
1
     0
2
     1
4
    1
Name: Score, dtype: int64
```

Data Cleanising

In [5]:

```
#Removing Duplicates
print('Number of data points before removing duplicates',data.shape[0])
sorted_data=data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort',
na_position='last')
clean_data=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first',
inplace=False)
print('Number of data points after removing duplicates',clean_data.shape[0])
Number of data points before removing duplicates 525814
```

Number of data points after removing duplicates 364173

```
In [6]:
```

```
#removing rows whihch has HelpfulnessNumerator greater than HelpfulnessDenominator
clean_data=clean_data[clean_data['HelpfulnessNumerator']<=clean_data['HelpfulnessDenominator']]
print('Now the Number of data points are',clean_data.shape[0])</pre>
```

Now the Number of data points are 364171

looks like there are only 3 rows with HelpfulnessNumerator greater than HelpfulnessDenominator. Thats great !! Now lets go to the intresting part where we will clean the text reviews

In [7]:

```
#lets define some functions to clean the reviews

#to remove HTML Tags
def clean_html(x):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', x)
    return cleantext

# to remove unwanted charecteres like '!',',' etc.

def cleansen(x):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',x)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return cleaned

#stop words

stop_words = set(stopwords.words('english'))
#intialising stremming
stemmer = nltk.stem.SnowballStemmer('english')
```

In [8]:

```
import datetime
str1=' '
final string=[]
s=' '
start_time = datetime.datetime.now()
for sent in clean data['Text'].values:
    filtered sentence=[]
    sent=clean_html(sent) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleansen(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned words.lower() not in stop words):
                    s=(stemmer.stem(cleaned words.lower())).encode('utf8')
                    filtered sentence.append(s)
                else:
                    continue
            else:
                continue
    #print(filtered sentence)
    str1 = b" ".join(filtered sentence) #final string of cleaned words
    #print("***
    final string.append(str1)
clean data['CleanedText']=final string
print('Total time taken to clean the reviews',datetime.datetime.now()-start time)
```

Total time taken to clean the reviews 0:04:39.597683

In [9]:

```
clean_data['CleanedText'].head()
```

```
Out[9]:
          b'witti littl book make son laugh loud recit c...
138688
         b'grew read sendak book watch realli rosi movi...
        b'fun way children learn month year learn poem...
138689
138690
       b'great littl book read nice rhythm well good ...
138691
        b'book poetri month year goe month cute littl ...
Name: CleanedText, dtype: object
In [10]:
#lets take 100k points
final data = clean data.head(100000)
final data.shape
Out[10]:
(100000, 11)
```

Split the dataset randomly into three parts train, cross validation and test with 64%,16%, 20% of data respectively **

```
In [11]:
```

```
#noe lets split the data
from sklearn.model_selection import train_test_split
x,x_test,y,y_test = train_test_split(final_data['CleanedText'],final_data['Score'],train_size=0.8)
x_train,x_cv,y_train,y_cv = train_test_split(x,y,train_size=0.8)

/opt/conda/lib/python3.6/site-packages/sklearn/model_selection/_split.py:2179: FutureWarning: From version 0.21, test_size will always complement train_size unless both are specified.
FutureWarning)
```

Bag of Words (BoW) A commonly used model in methods of Text Classification. As part of the BOW model, a piece of text (sentence or a document) is represented as a bag or multiset of words, disregarding grammar and even word order and the frequency or occurrence of each word is used as a feature for training a classifier.

```
In [12]:
```

```
#Lets Vecotirize
#bagof words
bag_words = CountVectorizer()
x_train_bag= bag_words.fit_transform(x_train)
x_test_bag= bag_words.transform(x_test)
x_cv_bag= bag_words.transform(x_cv)

print('After vectorizing shape of x Train',x_train_bag.shape)
print('After vectorizing shape of x Test',x_test_bag.shape)
print('After vectorizing shape of x CV',x_cv_bag.shape)

After vectorizing shape of x Train (64000, 30264)
After vectorizing shape of x Test (20000, 30264)
After vectorizing shape of x CV (16000, 30264)
```

KNN Classifier

Classifier implementing the k-nearest neighbors vote. Here will be will be implementing using two Algoithms 1) Brute 2) KD_Tree

```
In [6]:
```

```
from sklearn.preprocessing import StandardScaler
def knn_brute(x_train,y_train,x_test,y_test,x_cv,y_cv):

k = [i for i in range(1,40,5)]

cv_f1_score_array=[]
train_f1_score_array=[]
stan_= StandardScaler(with_mean_= False)
```

```
Stall - Stalluaruscater (With Mean - Faise)
    x_train = stan.fit_transform(x_train)
    x cv = stan.transform(x_cv)
    for n in k:
        clf = KNeighborsClassifier(n neighbors = n,algorithm='brute')
        clf.fit(x train,y train)
        predict y = clf.predict(x cv)
        predict_y_t = clf.predict(x_train)
       cv f1 score array.append(f1 score(y cv, predict y))
       train_f1_score_array.append(f1_score(y_train, predict_y_t))
       print('For values of k = ', n, "The fl score is:", fl score(y cv, predict y))
    fig, ax = plt.subplots()
    ax.plot(k, train_f1_score_array,c='b',label ='Train f1_score')
    for i, txt in enumerate(np.round(train f1 score array,2)):
        ax.annotate((k[i],np.round(txt,2)), (k[i],train f1 score array[i]))
    ax.plot(k, cv_f1_score_array,c='g',label ='test f1_score')
    for i, txt in enumerate(np.round(cv f1 score array,2)):
        ax.annotate((k[i],np.round(txt,2)), (k[i],cv_f1_score_array[i]))
    plt.grid()
    plt.title("f1 score for each K ")
    plt.xlabel("K neighbors's")
    plt.ylabel("f1 Score")
   plt.legend()
   plt.show()
def knn kdtree(x train, y train, x test, y test, x cv, y cv):
    k = [i \text{ for } i \text{ in } range(1,40,6)]
    cv f1 score array=[]
    train_f1_score_array=[]
    for n in k:
       clf = KNeighborsClassifier(n neighbors = n,algorithm='kd tree')
       clf.fit(x_train,y_train)
       predict y = clf.predict(x cv)
       predict_y_t = clf.predict(x_train)
        cv_f1_score_array.append(f1_score(y_cv, predict_y))
        train_f1_score_array.append(f1_score(y_train, predict_y_t))
        print('For values of k = ', n, "The fl score is:", fl score(y cv, predict y))
    fig, ax = plt.subplots()
    ax.plot(k, train f1 score array,c='b',label ='Train logg error')
    for i, txt in enumerate(np.round(train_f1_score_array,2)):
        ax.annotate((k[i],np.round(txt,2)), (k[i],train_f1_score_array[i]))
    ax.plot(k, cv f1 score array,c='g',label ='CV logg error')
    for i, txt in enumerate(np.round(cv_f1_score_array,2)):
        ax.annotate((k[i],np.round(txt,2)), (k[i],cv_f1_score_array[i]))
    plt.grid()
    plt.title("f1 score for each K ")
    plt.xlabel("K neighbors's")
    plt.ylabel("f1 Score")
    plt.legend()
    plt.show()
```

In [7]:

```
import seaborn as sns
def best_knn_kdtree(x_train,y_train,x_test,y_test,x_cv,y_cv,best_k):
               clf_bag_best = KNeighborsClassifier(n_neighbors = best_k,algorithm='kd_tree')
               clf_bag_best.fit(x_train, y_train)
               predict_y_train = clf_bag_best.predict(x_train)
               print('For \ values \ of \ best \ k = ', \ best\_k, \ "The \ train \ f\_1score \ is:",f1\_score(y\_train, \ f\_1score) \ (y\_train, \ f\_1score) \ (y\_train
predict_y_train))
               predict_y_test = clf_bag_best.predict(x_test)
               print('For values of best k = ', best_k, "The test f1_score
is:",f1 score(y_test,predict_y_test))
              acc_t = accuracy_score(y_train,predict_y_train)
              print('Accuracy on train data is ',acc_t)
               acc = accuracy_score(y_test,predict_y_test)
               print('Accuracy on test data is ',acc)
               c 1 = confusion matrix(y train, predict y train)
               C = confusion_matrix(y_test, predict_y_test)
                                                                   "Confucion mot
```

```
plt.figure(figsize=(20,7))

sns.heatmap(c_1, annot=True, cmap="YlGnBu", fmt="d")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
print("-"*20, "Confusion matrix on test data", "-"*20)
plt.figure(figsize=(20,7))

sns.heatmap(C, annot=True, cmap="YlGnBu", fmt="d")
plt.xlabel('Predicted Class')
plt.ylabel('Original Class')
plt.show()
print(classification_report(y_test, predict_y_test))
return acc,acc_t,best_k
```

In [8]:

```
def best knn(x train,y train,x test,y test,x cv,y cv,best k):
    clf bag best = KNeighborsClassifier(n neighbors = best k,algorithm='brute')
    clf_bag_best.fit(x_train, y_train)
    predict_y_train = clf_bag_best.predict(x train)
    print('For values of best k = ', best k, "The train f 1score is:",f1 score(y train,
predict y train))
   predict y test = clf bag best.predict(x test)
   print('For values of best k = ', best k, "The test f1 score
is:",f1_score(y_test,predict_y_test))
   acc t = accuracy score(y train, predict y train)
    print('Accuracy on train data is ',acc t)
   acc = accuracy_score(y_test,predict_y_test)
   print('Accuracy on test data is ',acc)
    c_1 = confusion_matrix(y_train, predict_y_train)
    C = confusion_matrix(y_test, predict_y_test)
    print("-"*20, "Confusion matrix on train data", "-"*20)
   plt.figure(figsize=(20,7))
    sns.heatmap(c 1, annot=True, cmap="YlGnBu", fmt="d")
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
   plt.show()
   print("-"*20, "Confusion matrix on test data", "-"*20)
    plt.figure(figsize=(20,7))
    sns.heatmap(C, annot=True, cmap="YlGnBu", fmt="d")
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.show()
    print(classification report(y test, predict y test))
    return acc,acc_t,best_k
```

Brute

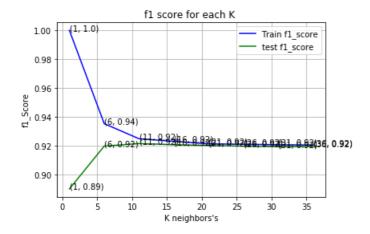
```
In [20]:
```

```
knn_brute(x_train_bag,y_train,x_test_bag,y_test,x_cv_bag,y_cv)

/opt/conda/lib/python3.6/site-packages/sklearn/utils/validation.py:595: DataConversionWarning: Dat a with input dtype int64 was converted to float64 by StandardScaler.
    warnings.warn(msg, DataConversionWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/validation.py:595: DataConversionWarning: Dat a with input dtype int64 was converted to float64 by StandardScaler.
    warnings.warn(msg, DataConversionWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/utils/validation.py:595: DataConversionWarning: Dat a with input dtype int64 was converted to float64 by StandardScaler.
    warnings.warn(msg, DataConversionWarning)

For values of k = 1 The fl score is: 0.8901534250522221
For values of k = 6 The fl score is: 0.9198300576836724
For values of k = 11 The fl score is: 0.9215726217152169
For values of k = 16 The fl score is: 0.920813559322034
```

```
For values of k = 21 The fl score is: 0.9202300405953991
For values of k = 26 The fl score is: 0.9197781385281385
For values of k = 31 The fl score is: 0.9193793732887131
For values of k = 36 The fl score is: 0.9194943896174125
```



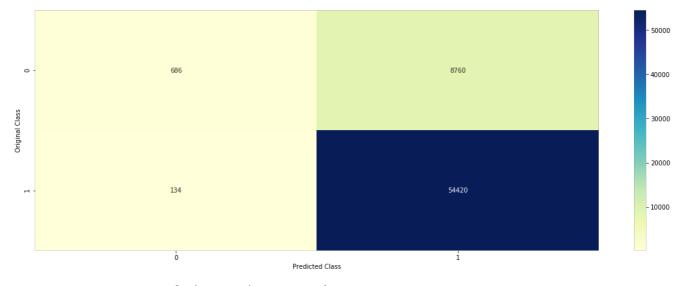
Seeing above plot we are can take K values as 11 as there is nout much difference in train and CV Scores

In [21]:

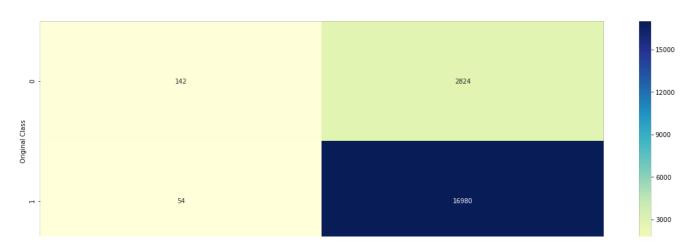
```
acc_bag_brute,acc_bagtest_brute,bestk_bag_brute=best_knn(x_train_bag,y_train,x_test_bag,y_test,x_cv
bag,y_cv,11)
```

For values of best k = 11 The train f_1score is: 0.9244568264052865 For values of best k = 11 The test f1_score is: 0.9218741516911885 Accuracy on train data is 0.86103125 Accuracy on test data is 0.8561

----- Confusion matrix on train data ------



----- Confusion matrix on test data -----



		Ü	Predicted Class			
		precision	recall	f1-score	support	
	0 1	0.72 0.86	0.05	0.09	2966 17034	
micro macro weighted	avg	0.86 0.79 0.84	0.86 0.52 0.86	0.86 0.51 0.80	20000 20000 20000	

we are getting 85% accuracy on test data. As we know that data imbalanced and Knn will be biased to majority class we are getting model slightly baised to postive points

Tf-Idf

In [22]:

```
#Now Tsne
#Lets Vecotirize
#bagof words

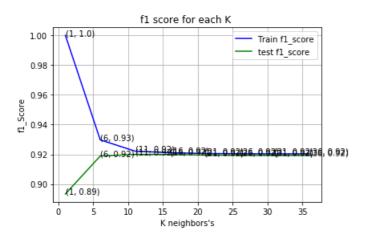
tfidf_words = TfidfVectorizer()
    x_train_tfidf= tfidf_words.fit_transform(x_train)
    x_test_tfidf= tfidf_words.transform(x_test)
    x_cv_tfidf= tfidf_words.transform(x_cv)
    print('After vectorizing shape of x Train',x_train_tfidf.shape)
    print('After vectorizing shape of x Test',x_test_tfidf.shape)
    print('After vectorizing shape of x CV',x_cv_tfidf.shape)

After vectorizing shape of x Train (64000, 30264)
After vectorizing shape of x Test (20000, 30264)
After vectorizing shape of x CV (16000, 30264)
```

In [23]:

```
knn_brute(x_train_tfidf,y_train,x_test_tfidf,y_test,x_cv_tfidf,y_cv)
```

```
For values of k = 1 The f1 score is: 0.8933705213473504 For values of k = 6 The f1 score is: 0.918863332533507 For values of k = 11 The f1 score is: 0.9199485722019218 For values of k = 16 The f1 score is: 0.9199296679515792 For values of k = 21 The f1 score is: 0.9194905233284908 For values of k = 26 The f1 score is: 0.9193352249695987 For values of k = 31 The f1 score is: 0.9192420711318269 For values of k = 36 The f1 score is: 0.9192110240475547
```



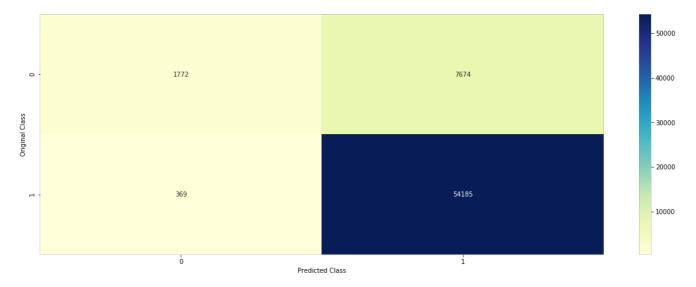
from above plot we can take k as 16

 $best_knn(x_train_tfidf,y_train,x_test_tfidf,y_test,x_cv_tfidf,y_cv,16)$

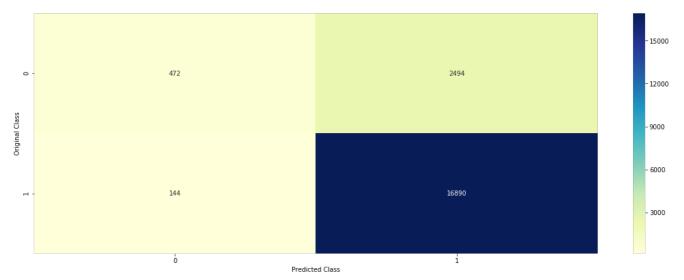
For values of best k = 16 The train f_1score is: 0.930909778117564 For values of best k = 16 The test f1_score is: 0.9275632928771487 Accuracy on train data is 0.874328125

Accuracy on test data is 0.8681

----- Confusion matrix on train data ------



----- Confusion matrix on test data -----



		precision	recall	f1-score	support
	0	0.77	0.16	0.26	2966
	1	0.87	0.99	0.93	17034
micro	avg	0.87	0.87	0.87	20000
macro		0.82	0.58	0.60	20000
weighted		0.86	0.87	0.83	20000

Out[24]:

(0.8681, 0.874328125, 16)

we are getting good accuracy than BOW

Avg Word2Vec One of the most naive but good ways to convert a sentence into a vector Convert all the words to vectors and then just take the avg of the vectors the resulting vector represent the sentence

```
import re

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

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
```

In [27]:

```
# Train your own Word2Vec model using your own train text corpus
import gensim
list_sent_train=[]
for sent in x_train:
    filtered_sentence=[]
    sent = sent.decode("utf-8")
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_sent_train.append(filtered_sentence)
```

In [28]:

```
w2v_model=gensim.models.Word2Vec(list_sent_train,min_count=5,size=50, workers=4)
```

In [32]:

64000 50

In [29]:

```
list sent test=[]
for sent in x_test:
    filtered sentence=[]
    sent = sent.decode('utf-8')
    sent=clean html(sent)
    for w in sent.split():
        for cleaned words in w.split():
            if(cleaned words.isalpha()):
                filtered sentence.append(cleaned words.lower())
            else:
                continue
    list_sent_test.append(filtered_sentence)
x_{test_avgw2v} = []; \# the avg-w2v for each sentence/review is stored in this list
for sent in list_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
```

20000 50

In [30]:

```
list sent cv=[]
for sent in x cv:
   filtered sentence=[]
    sent = sent.decode('utf-8')
    sent=clean_html(sent)
    for w in sent.split():
        for cleaned words in w.split():
            if(cleaned_words.isalpha()):
                filtered sentence.append(cleaned words.lower())
            else:
                continue
    list sent cv.append(filtered sentence)
x_cv_avgw^2v = []; # the avg-w^2v for each sentence/review is stored in this list
for sent in list_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
            vec = w2v model.wv[word]
            sent vec += vec
            cnt_words += 1
        except:
           pass
    sent_vec /= cnt_words
    x_cv_avgw2v.append(sent_vec)
print(len(x cv avgw2v))
print(len(x_cv_avgw2v[0]))
```

16000 50

In [33]:

```
knn_brute(x_train_avgw2v,y_train,x_test_avgw2v,y_test,x_cv_avgw2v,y_cv)
```

```
For values of k = 1 The f1 score is: 0.9118832371201394

For values of k = 6 The f1 score is: 0.930302487918382

For values of k = 11 The f1 score is: 0.9332866888228092

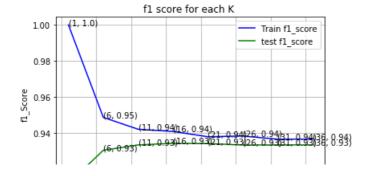
For values of k = 16 The f1 score is: 0.9341519031748816

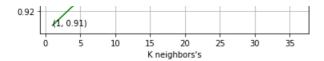
For values of k = 21 The f1 score is: 0.9340391446681062

For values of k = 26 The f1 score is: 0.9332124298120181

For values of k = 31 The f1 score is: 0.9332916623259367

For values of k = 36 The f1 score is: 0.9332962370452806
```





seeing above plot, we can take k as 26

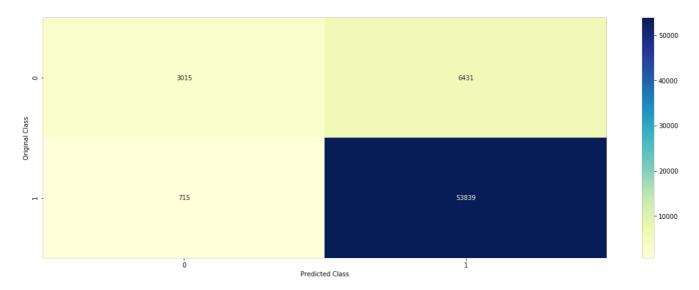
In [34]:

best_knn(x_train_avgw2v,y_train,x_test_avgw2v,y_test,x_cv_avgw2v,y_cv,26)

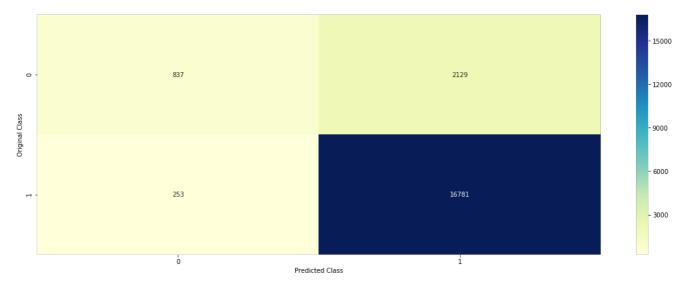
For values of best k = 26 The train f_1score is: 0.9377656239113774 For values of best k = 26 The test f1_score is: 0.9337302470509682 Accuracy on train data is 0.88834375

Accuracy on test data is 0.8809

----- Confusion matrix on train data



----- Confusion matrix on test data ------



		precision	recall	f1-score	support
	0	0.77	0.28	0.41	2966
	1	0.89	0.99	0.93	17034
micro	avg	0.88	0.88	0.88	20000
macro	avg	0.83	0.63	0.67	20000
weighted	avg	0.87	0.88	0.86	20000

Out[34]:

(0.8809, 0.88834375, 26)

Getting good accuracy than tfidf and BOW . model is also less biased

Tf-idf W2Vec Another way to covert sentence into vectors Take weighted sum of the vectors divided by the sum of all the tfidf's i.e. (tfidf(word) x w2v(word))/sum(tfidf's)

```
In [35]:
```

```
tfidf_feat = tfidf_words.get_feature_names() # tfidf words/col-names
# final tf idf is the sparse matrix with row = sentence, col = word and cell val = tfidf
x train tfidfwv= []; # the tfidf-w2v for each sentence/review is stored in this list
for sent in list sent train: # 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
        try:
            vec = w2v model.wv[word]
            # obtain the tf idfidf of a word in a sentence/review
            tfidf = final_tf_idf[row, tfidf_feat.index(word)]
            sent vec += (vec * tf idf)
            weight_sum += tf_idf
        except:
           pass
    sent vec /= weight sum
    x train tfidfwv.append(sent vec)
    row += 1
print('train shape',len(x train tfidfwv),len(x train tfidfwv[0]))
/opt/conda/lib/python3.6/site-packages/ipykernel launcher.py:18: RuntimeWarning: invalid value
encountered in true divide
```

train shape 64000 50

In [36]:

```
x test tfidfwv= []
for sent in list 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
        try:
            vec = w2v model.wv[word]
            # obtain the tf idfidf of a word in a sentence/review
            tfidf = final tf idf[row, tfidf feat.index(word)]
            sent vec += (vec * tf idf)
            weight_sum += tf_idf
        except:
           pass
    sent vec /= weight sum
    x_test_tfidfwv.append(sent_vec)
print('test shape',len(x test tfidfwv),len(x test tfidfwv[0]))
/opt/conda/lib/python3.6/site-packages/ipykernel launcher.py:14: RuntimeWarning: invalid value
encountered in true divide
```

test shape 20000 50

In [37]:

/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:14: RuntimeWarning: invalid value encountered in true divide

test shape 16000 50

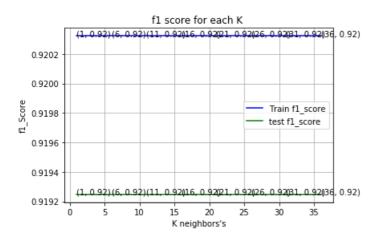
In [38]:

```
x_train_tfidfwv = np.nan_to_num(x_train_tfidfwv)
x_cv_tfidfwv = np.nan_to_num(x_cv_tfidfwv)
x_test_tfidfwv = np.nan_to_num(x_test_tfidfwv)
```

In [39]:

```
knn_brute(x_train_tfidfwv,y_train,x_test_tfidfwv,y_test,x_cv_tfidfwv,y_cv)
```

```
For values of k = 1 The f1 score is: 0.9192475260900401 For values of k = 6 The f1 score is: 0.9192475260900401 For values of k = 11 The f1 score is: 0.9192475260900401 For values of k = 16 The f1 score is: 0.9192475260900401 For values of k = 21 The f1 score is: 0.9192475260900401 For values of k = 26 The f1 score is: 0.9192475260900401 For values of k = 31 The f1 score is: 0.9192475260900401 For values of k = 36 The f1 score is: 0.9192475260900401
```



for all values of k we are getting same train and CV score .lets take k as 21

In [40]:

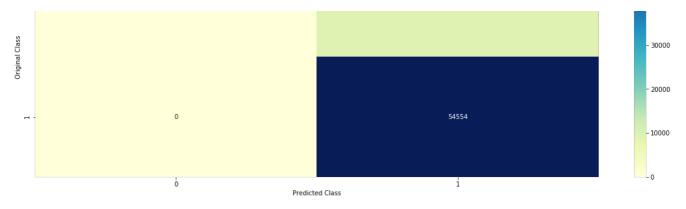
```
best_knn(x_train_tfidfwv,y_train,x_test_tfidfwv,y_test,x_cv_tfidfwv,y_cv,21)
```

9446

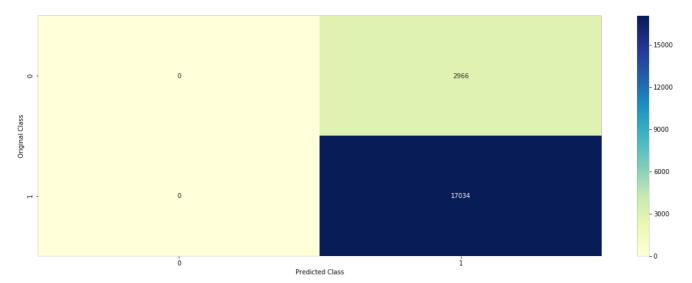
- 50000

0

40000



----- Confusion matrix on test data ------



		precision	recall	f1-score	support
	0 1	0.00 0.85	0.00	0.00 0.92	2966 17034
micro macro weighted	avg	0.85 0.43 0.73	0.85 0.50 0.85	0.85 0.46 0.78	20000 20000 20000

```
/opt/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples.
```

'precision', 'predicted', average, warn_for)

 $/ {\tt opt/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:} 1143:$

UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn_for)

/opt/conda/lib/python3.6/site-packages/sklearn/metrics/classification.py:1143:

UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn_for)

Out[40]:

(0.8517, 0.85240625, 21)

Model is dumb as predicntg all points as positive

KD Tree

taking top 20k points

```
sample data = clean data.head(20000)
sample data.shape
Out[41]:
```

(20000, 11)

In [9]:

```
#noe lets split the data
from sklearn.model_selection import train_test_split
x_s,x_test_s,y_s,y_test_s = train_test_split(sample_data['CleanedText'],sample_data['Score'],train_
x_train_s,x_cv_s,y_train_s,y_cv_s = train_test_split(x_s,y_s,train_size=0.8)
/usr/local/lib/python3.5/site-packages/sklearn/model_selection/_split.py:2026: FutureWarning: From
version 0.21, test_size will always complement train_size unless both are specified.
 FutureWarning)
```

In []:

Bag of Words

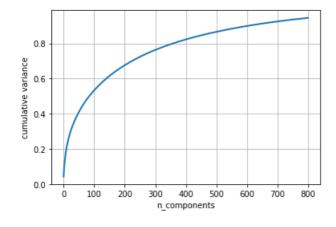
In [10]:

```
bag words con = CountVectorizer(max features=2000,min df=50)
x train bag c= bag words con.fit transform(x train s)
x test bag c= bag words con.transform(x test s)
x cv bag c= bag words con.transform(x cv s)
print('After vectorizing with 2000 features shape of x Train',x_train_bag_c.shape)
print('After vectorizing with 2000 features shape of x Test', x test bag c.shape)
print('After vectorizing with 2000 features shape of x CV',x cv bag c.shape)
```

After vectorizing with 2000 features shape of x Train (12800, 1309) After vectorizing with 2000 features shape of x Test (4000, 1309) After vectorizing with 2000 features shape of x CV (3200, 1309)

In [11]:

```
#converting to dense matrix using SVD
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n components=800)
svd.fit transform(x train bag c)
percentage var explained = svd.explained variance ratio
cum var explained = np.cumsum(percentage var explained)
plt.figure(1, figsize=(6, 4))
plt.clf()
plt.plot(cum var explained,linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n components')
plt.ylabel('cumulative variance')
plt.show()
```



from above plot we can see taking n components we are keeping more than 80% information. so taking n components as 400

In [12]:

```
svd_final = TruncatedSVD(n_components=400)
x_train_bag_c = svd_final.fit_transform(x_train_bag_c)

x_test_bag_c = svd_final.transform(x_test_bag_c)

x_cv_bag_c = svd_final.transform(x_cv_bag_c)
```

In []:

```
standardizing the data
```

In [13]:

```
from sklearn.preprocessing import StandardScaler
stand = StandardScaler()
x_train_bag_c = stand.fit_transform(x_train_bag_c)

x_test_bag_c = stand.transform(x_test_bag_c)

x_cv_bag_c = stand.transform(x_cv_bag_c)
```

In [14]:

```
knn_kdtree(x_train_bag_c,y_train_s,x_test_bag_c,y_test_s,x_cv_bag_c,y_cv_s)
```

```
For values of k = 1 The f1 score is: 0.8717002030644267

For values of k = 7 The f1 score is: 0.9170948955121617

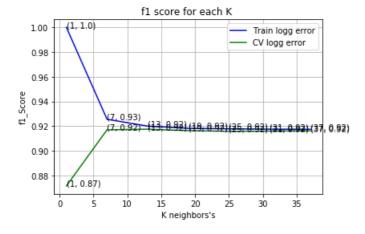
For values of k = 13 The f1 score is: 0.9175870858113849

For values of k = 19 The f1 score is: 0.9164402173913044

For values of k = 25 The f1 score is: 0.9158751696065129

For values of k = 31 The f1 score is: 0.9160590130574868

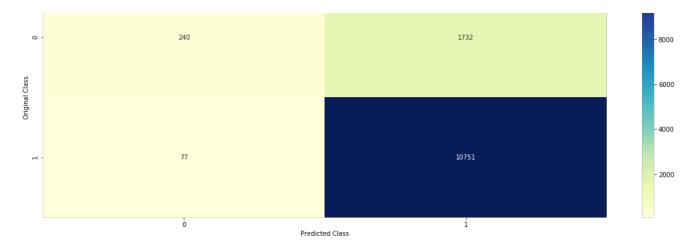
For values of k = 37 The f1 score is: 0.916271186440678
```



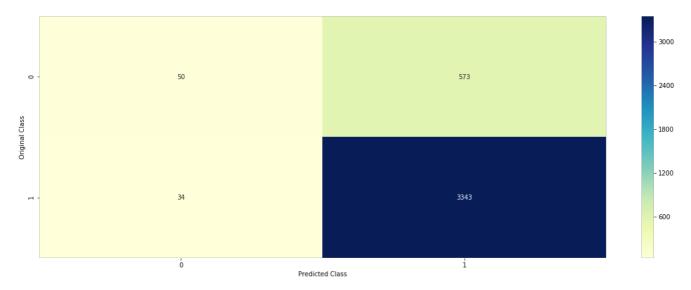
Taking K as 13

In [47]:

```
best_knn_kdtree(x_train_bag_c,y_train_s,x_test_bag_c,y_test_s,x_cv_bag_c,y_cv_s,13)
```



----- Confusion matrix on test data ------



		precision	recall	f1-score	support
	0 1	0.60 0.85	0.08	0.14 0.92	623 3377
micro macro weighted	avg	0.85 0.72 0.81	0.85 0.54 0.85	0.85 0.53 0.80	4000 4000 4000

Out[47]:

(0.84825, 0.858671875, 13)

we are getting 84.5 accuracy on test data

Tf-Idf

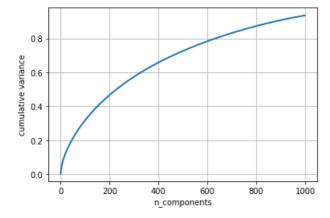
In [16]:

```
tfidf_words_con = TfidfVectorizer(max_features=2000,min_df=50)
x_train_tfidf_c = tfidf_words_con.fit_transform(x_train_s)
x_test_tfidf_c = tfidf_words_con.transform(x_test_s)
x_cv_tfidf_c = tfidf_words_con.transform(x_cv_s)
print('After vectorizing with 2000 features shape of x Train',x_train_tfidf_c.shape)
print('After vectorizing with 2000 features shape of x Test',x_test_tfidf_c.shape)
print('After vectorizing with 2000 features shape of x CV',x_cv_tfidf_c.shape)
```

After vectorizing with 2000 features shape of x Train (12800, 1309) After vectorizing with 2000 features shape of x Test (4000, 1309) After vectorizing with 2000 features shape of x CV (3200, 1309)

```
In [17]:
```

```
#converting to dense matrix using SVD
from sklearn.decomposition import TruncatedSVD
svd = TruncatedSVD(n_components=1000)
svd.fit_transform(x_train_tfidf_c)
percentage_var_explained = svd.explained_variance_ratio_
cum_var_explained = np.cumsum(percentage_var_explained)
plt.figure(1, figsize=(6, 4))
plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('cumulative variance')
plt.show()
```



from above plot we can see taking n components we are keeping more than 80% information. so taking n components as 650

In [18]:

```
svd_final = TruncatedSVD(n_components=650)
x_train_tfidf_c = svd_final.fit_transform(x_train_tfidf_c)
x_test_tfidf_c = svd_final.transform(x_test_tfidf_c)
x_cv_tfidf_c = svd_final.transform(x_cv_tfidf_c)
```

In [19]:

```
stand = StandardScaler()
x_train_tfidf_c = stand.fit_transform(x_train_tfidf_c)

x_test_tfidf_c = stand.transform(x_test_tfidf_c)

x_cv_tfidf_c = stand.transform(x_cv_tfidf_c)
```

In [20]:

```
knn_kdtree(x_train_tfidf_c,y_train_s,x_test_tfidf_c,y_test_s,x_cv_tfidf_c,y_cv_s)
```

```
For values of k = 1 The f1 score is: 0.9077695102958989

For values of k = 7 The f1 score is: 0.9170781542652818

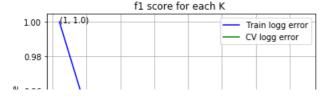
For values of k = 13 The f1 score is: 0.9169638308711157

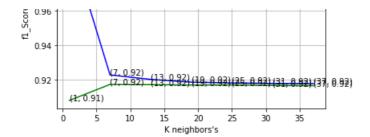
For values of k = 19 The f1 score is: 0.9167090754877014

For values of k = 25 The f1 score is: 0.9167655534836413

For values of k = 31 The f1 score is: 0.9164831441639845

For values of k = 37 The f1 score is: 0.9163279132791329
```





Taking K as 7

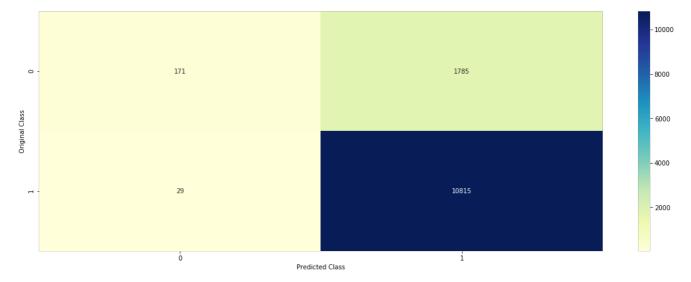
In [21]:

best_knn_kdtree(x_train_tfidf_c,y_train_s,x_test_tfidf_c,y_test_s,x_cv_tfidf_c,y_cv_s,7)

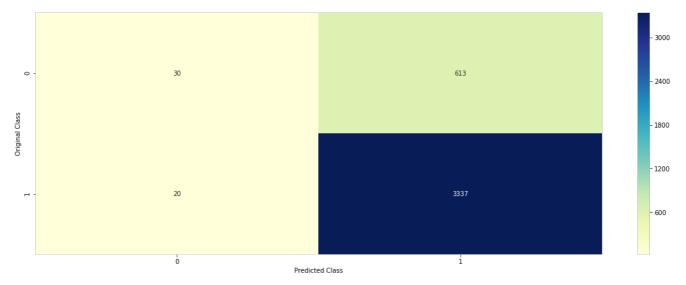
For values of best k = 7 The train f_1score is: 0.9226241255758403 For values of best k = 7 The test f1_score is: 0.9133707403859314 Accuracy on train data is 0.85828125

Accuracy on test data is 0.84175

----- Confusion matrix on train data -----



----- Confusion matrix on test data -----



support	f1-score	recall	precision	
643 3357	0.09 0.91	0.05	0.60 0.84	0 1
4000	0.78	0.84	0.81	avg / total

- . - - - -

```
Out[21]:
(0.84175, 0.85828125, 7)
We are getting 84.15 accuracy on test data
In [ ]:
AvgW2V
In [26]:
list sent train s=[]
for sent in x train s:
    filtered_sentence_s=[]
    sent = sent.decode('utf-8')
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned words in w.split():
            if(cleaned words.isalpha()):
                filtered sentence s.append(cleaned words.lower())
            else:
                continue
    list_sent_train_s.append(filtered_sentence_s)
In [29]:
w2v_model_s = gensim.models.Word2Vec(list_sent_train_s,min_count=5,size=50, workers=4)
In [30]:
x train avgw2v s= []; # the avg-w2v for each sentence/review is stored in this list
for sent in list sent train s: # 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
            vec = w2v model s.wv[word]
            sent vec += vec
            cnt words += 1
        except:
           pass
    sent_vec /= cnt_words
    x train avgw2v s.append(sent vec)
print(len(x train avgw2v s))
print(len(x_train_avgw2v_s[0]))
/usr/local/lib/python3.5/dist-packages/ipykernel launcher.py:12: RuntimeWarning: invalid value
encountered in true divide
 if sys.path[0] == '':
12800
50
In [31]:
list_sent_test_s=[]
for sent in x_test_s:
    filtered sentence=[]
    sent = sent.decode('utf-8')
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned words in w.split():
            if(cleaned words.isalpha()):
                filtered sentence.append(cleaned words.lower())
            else:
                continue
    list_sent_test_s.append(filtered_sentence)
x_test_avgw2v_s= []; # the avg-w2v for each sentence/review is stored in this list
for sent in list sent test s: # for each review/sentence
```

sent vec = nn zeros (50) # as word vectors are of zero length

4000 50

 $/usr/local/lib/python 3.5/dist-packages/ipykernel_launcher.py: 24: Runtime Warning: invalid value encountered in true_divide$

In [32]:

```
list_sent_cv_s=[]
for sent in x cv s:
   filtered_sentence=[]
   sent = sent.decode('utf-8')
    sent=cleanhtml(sent)
   for w in sent.split():
        for cleaned words in w.split():
            if(cleaned words.isalpha()):
               filtered_sentence.append(cleaned_words.lower())
            else:
                continue
   list_sent_cv_s.append(filtered_sentence)
x cv avgw2v s= []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_sent_cv_s: # 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
        try:
            vec = w2v model.wv[word]
            sent vec += vec
           cnt words += 1
        except:
            pass
    sent vec /= cnt words
    x cv avgw2v s.append(sent vec)
print(len(x cv avgw2v s))
print(len(x_cv_avgw2v_s[0]))
```

3200 50

 $/usr/local/lib/python 3.5/dist-packages/ipykernel_launcher.py: 24: Runtime Warning: invalid value encountered in true_divide$

In [34]:

```
x_train_avgw2v_s = np.nan_to_num(x_train_avgw2v_s)
x_test_avgw2v_s = np.nan_to_num(x_test_avgw2v_s)
x_cv_avgw2v_s = np.nan_to_num(x_cv_avgw2v_s)
```

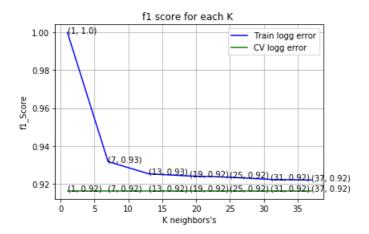
In [35]:

```
knn_kdtree(x_train_avgw2v_s,y_train_s,x_test_avgw2v_s,y_test_s,x_cv_avgw2v_s,y_cv_s)

For values of k = 1 The f1 score is: 0.9161727349703641
For values of k = 7 The f1 score is: 0.9161727349703641
For values of k = 13 The f1 score is: 0.9161727349703641
For values of k = 19 The f1 score is: 0.9161727349703641
```

For values of k = 25 The f1 score is: 0.9161727349703641

For values of k = 31 The f1 score is: 0.9161727349703641 For values of k = 37 The f1 score is: 0.9161727349703641

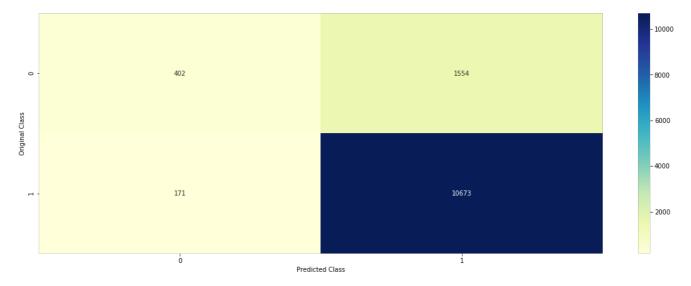


taking k as 13

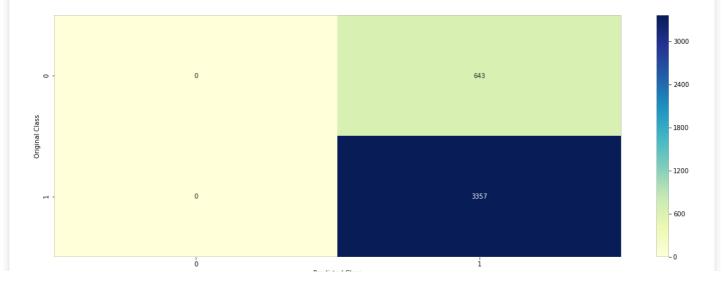
In [36]:

```
best_knn_kdtree(x_train_avgw2v_s,y_train_s,x_test_avgw2v_s,y_test_s,x_cv_avgw2v_s,y_cv_s,13)
```

For values of best k=13 The train f_1score is: 0.9252308092410386 For values of best k=13 The test f1_score is: 0.9126002446649449 Accuracy on train data is 0.865234375 Accuracy on test data is 0.83925 ------ Confusion matrix on train data ------



----- Confusion matrix on test data -----



Predicted Class

```
precision
                        recall f1-score support
          Ω
                 0.00
                           0.00
                                     0.00
          1
                 0.84
                           1.00
                                     0.91
                                               3357
avg / total
                 0.70
                           0.84
                                     0.77
                                               4000
```

```
/usr/local/lib/python3.5/site-packages/sklearn/metrics/classification.py:1135:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples.

'precision', 'predicted', average, warn for)
```

Out[36]:

```
(0.83925, 0.865234375, 13)
```

there is some difference in test and train accuracy but not much

In []:

```
Tf-idf W2Vec
```

In [37]:

```
tfidf feats = tfidf words con.get feature names() # tfidf words/col-names
# final tf idf is the sparse matrix with row= sentence, col=word and cell val = tfidf
x train tfidfwv s= []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in list sent train s: # 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
        try:
            vec = w2v model s.wv[word]
            # obtain the tf idfidf of a word in a sentence/review
            tfidf = final_tf_idf_s[row, tfidf_feats_s.index(word)]
            sent vec += (vec * tf idf)
           weight sum += tf idf
        except:
           pass
    sent vec /= weight_sum
    x train tfidfwv s.append(sent vec)
    row += 1
print('train shape',len(x train tfidfwv s),len(x train tfidfwv s[0]))
/usr/local/lib/python3.5/dist-packages/ipykernel launcher.py:18: RuntimeWarning: invalid value
encountered in true divide
```

train shape 12800 50

In [38]:

```
x_test_tfidfwv_s= []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in list_sent_test_s: # 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
        try:
        vec = w2v_model_s.wv[word]
        # obtain the tf_idfidf of a word in a sentence/review
        tfidf = final_tf_idf_t[row, tfidf_feats_s.index(word)]
        sent_vec += (vec * tf_idf)
        weight_sum += tf_idf
        except:
        pass
sent_vec /= weight_sum
x test tfidfwv s.append(sent vec)
```

```
row += 1
print('test shape',len(x_test_tfidfwv_s),len(x_test_tfidfwv_s[0]))

/usr/local/lib/python3.5/dist-packages/ipykernel_launcher.py:15: RuntimeWarning: invalid value encountered in true_divide
    from ipykernel import kernelapp as app
```

test shape 4000 50

In [39]:

```
x cv tfidfwv s= []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in list sent cv s: # 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
        try:
            vec = w2v_model_s.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tfidf = final tf idf cv[row, tfidf feats s.index(word)]
            sent_vec += (vec * tf idf)
            weight sum += tf idf
        except:
           pass
    sent vec /= weight sum
    x cv tfidfwv s.append(sent vec)
    row += 1
print('cv shape',len(x cv tfidfwv s),len(x cv tfidfwv s[0]))
/usr/local/lib/python3.5/dist-packages/ipykernel launcher.py:15: RuntimeWarning: invalid value
encountered in true divide
 from ipykernel import kernelapp as app
```

cv shape 3200 50

In [40]:

```
x_train_tfidfwv_s = np.nan_to_num(x_train_tfidfwv_s)
x_test_tfidfwv_s = np.nan_to_num(x_test_tfidfwv_s)
x_cv_tfidfwv_s = np.nan_to_num(x_cv_tfidfwv_s)
```

In [41]:

```
knn_kdtree(x_train_tfidfwv_s,y_train_s,x_test_tfidfwv_s,y_test_s,x_cv_tfidfwv_s,y_cv_s)
```

```
For values of k = 1 The f1 score is: 0.9161727349703641

For values of k = 7 The f1 score is: 0.9161727349703641

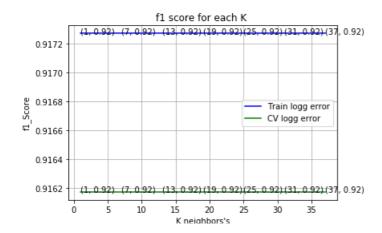
For values of k = 13 The f1 score is: 0.9161727349703641

For values of k = 19 The f1 score is: 0.9161727349703641

For values of k = 25 The f1 score is: 0.9161727349703641

For values of k = 31 The f1 score is: 0.9161727349703641

For values of k = 37 The f1 score is: 0.9161727349703641
```



.....g......

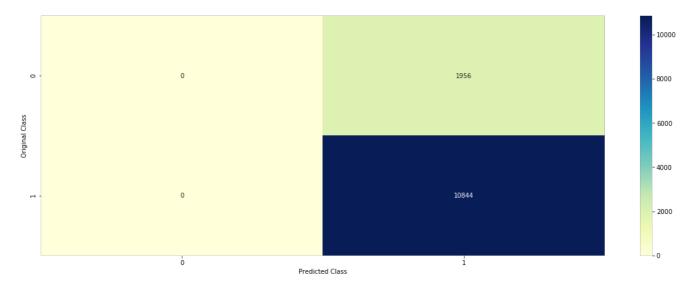
for all values of k we are getting same train and CV score .lets take k as 7

In [42]:

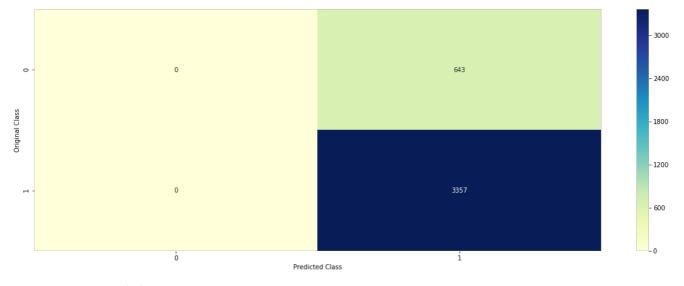
```
best_knn_kdtree(x_train_tfidfwv_s,y_train_s,x_test_tfidfwv_s,y_test_s,x_cv_tfidfwv_s,y_cv_s,7)
```

For values of best k = 7 The train f_1score is: 0.917272881069193 For values of best k = 7 The test f1_score is: 0.9126002446649449 Accuracy on train data is 0.8471875 Accuracy on test data is 0.83925

----- Confusion matrix on train data -----



----- Confusion matrix on test data -----



support	f1-score	recall	precision	
643	0.00	0.00	0.00	0
3357	0.91	1.00	0.84	1
4000	0.77	0.84	0.70	avg / total

Out[42]:

(0.83925, 0.8471875, 7)

In []:

Again a dumb model

```
In [ ]:
```

Performance Table

By looking above table we can say AVGW2V with brute is the best the model