Amazon Fine Food Reviews Analysis

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews)

EDA: https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/ (https://nycdatascience.com/blog/student-works/amazon-fine-foods-visualization/)

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 Score/Rating. A rating of 4 or 5 can be cosnidered as a positive review. A rating of 1 or 2 can be considered as negative one. A review of rating 3 is considered nuetral and such reviews are ignored from our analysis. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

[1]. Reading Data

[1.1] 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 is 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 is above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [4]:
```
%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

from tqdm import tqdm
import os
```

```
C:\Users\sujpanda\Anaconda3\lib\site-packages\gensim\utils.py:1212: UserWarni
ng: detected Windows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [5]:
```
# using SQLite Table to read data.
con = sqlite3.connect('C:\\Users\\sujpanda\\Desktop\\applied\\database.sqlite'
)

# filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
# SELECT * FROM Reviews WHERE Score != 3 LIMIT 500000, will give top 500000 da
ta points
# you can change the number to any other number based on your computing power

# filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3
 LIMIT 500000""", con)
# for tsne assignment you can take 5k data points

filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 L
IMIT 50000""", con)

# Give reviews with Score>3 a positive rating(1), and reviews with a score<3 a
 negative rating(0).
def partition(x):
    if x < 3:
        return 0
    return 1

#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
print("Number of data points in our data", filtered_data.shape)
filtered_data.head(3)
```

```
Number of data points in our data (50000, 10)
```

Out[5]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfulne
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1

In [6]:
```
display = pd.read_sql_query("""
SELECT UserId, ProductId, ProfileName, Time, Score, Text, COUNT(*)
FROM Reviews
GROUP BY UserId
HAVING COUNT(*)>1
""", con)
```

In [7]:
```
print(display.shape)
display.head()
```

```
(80668, 7)
```

Out[7]:

	UserId	ProductId	ProfileName	Time	Score	Text	COL
0	#oc-R115TNMSPFT9I7	B007Y59HVM	Breyton	1331510400	2	Overall its just OK when considering the price...	2
1	#oc-R11D9D7SHXIJB9	B005HG9ET0	Louis E. Emory "hoppy"	1342396800	5	My wife has recurring extreme muscle spasms, u...	3
2	#oc-R11DNU2NBKQ23Z	B007Y59HVM	Kim Cieszykowski	1348531200	1	This coffee is horrible and unfortunately not ...	2
3	#oc-R11O5J5ZVQE25C	B005HG9ET0	Penguin Chick	1346889600	5	This will be the bottle that you grab from the...	3
4	#oc-R12KPBODL2B5ZD	B007OSBE1U	Christopher P. Presta	1348617600	1	I didnt like this coffee. Instead of telling y...	2

In [8]:
```
display[display['UserId']=='AZY10LLTJ71NX']
```

Out[8]:

	UserId	ProductId	ProfileName	Time	Score	Text
80638	AZY10LLTJ71NX	B006P7E5ZI	undertheshrine "undertheshrine"	1334707200	5	I was recommended to try green tea extract to ...

In [9]:
```
display['COUNT(*)'].sum()
```

Out[9]:
```
393063
```

[2] Exploratory Data Analysis

[2.1] Data Cleaning: Deduplication

It is observed (as shown in the table below) that the reviews data had many duplicate entries. Hence it was necessary to remove duplicates in order to get unbiased results for the analysis of the data. Following is an example:

In [10]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND UserId="AR5J8UI46CURR"
ORDER BY ProductID
""", con)
display.head()
```

Out[10]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpful
0	78445	B000HDL1RQ	AR5J8UI46CURR	Geetha Krishnan	2	2
1	138317	B000HDOPYC	AR5J8UI46CURR	Geetha Krishnan	2	2
2	138277	B000HDOPYM	AR5J8UI46CURR	Geetha Krishnan	2	2
3	73791	B000HDOPZG	AR5J8UI46CURR	Geetha Krishnan	2	2
4	155049	B000PAQ75C	AR5J8UI46CURR	Geetha Krishnan	2	2

As it can be seen above that same user has multiple reviews with same values for HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text and on doing analysis it was found that

ProductId=B000HDOPZG was Loacker Quadratini Vanilla Wafer Cookies, 8.82-Ounce Packages (Pack of 8)

ProductId=B000HDL1RQ was Loacker Quadratini Lemon Wafer Cookies, 8.82-Ounce Packages (Pack of 8) and so on

It was inferred after analysis that reviews with same parameters other than ProductId belonged to the same product just having different flavour or quantity. Hence in order to reduce redundancy it was decided to eliminate the rows having same parameters.

The method used for the same was that we first sort the data according to ProductId and then just keep the first similar product review and delelte the others. for eg. in the above just the review for ProductId=B000HDL1RQ remains. This method ensures that there is only one representative for each product and deduplication without sorting would lead to possibility of different representatives still existing for the same product.

```
In [11]: #Sorting data according to ProductId in ascending order
         sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inp
         lace=False, kind='quicksort', na_position='last')
```

```
In [12]: #Deduplication of entries
         final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"
         }, keep='first', inplace=False)
         final.shape

Out[12]: (46072, 10)
```

```
In [13]: #Checking to see how much % of data still remains
         (final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100

Out[13]: 92.144
```

Observation:- It was also seen that in two rows given below the value of HelpfulnessNumerator is greater than HelpfulnessDenominator which is not practically possible hence these two rows too are removed from calcualtions

In [14]:
```
display= pd.read_sql_query("""
SELECT *
FROM Reviews
WHERE Score != 3 AND Id=44737 OR Id=64422
ORDER BY ProductID
""", con)

display.head()
```

Out[14]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpfuln
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens "Jeanne"	3	1
1	44737	B001EQ55RW	A2V0I904FH7ABY	Ram	3	2

In [15]:
```
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
```

In [16]:
```
#Before starting the next phase of preprocessing lets see the number of entrie
s left
print(final.shape)

#How many positive and negative reviews are present in our dataset?
final['Score'].value_counts()
```

```
(46071, 10)
```

Out[16]:
```
1    38479
0     7592
Name: Score, dtype: int64
```

[3] Preprocessing

[3.1]. Preprocessing Review Text

Now that we have finished deduplication our data requires some preprocessing before we go on further with analysis and making the prediction model.

Hence in the Preprocessing phase we do the following in the order below:-

1. Begin by removing the html tags
2. Remove any punctuations or limited set of special characters like , or . or # etc.
3. Check if the word is made up of english letters and is not alpha-numeric
4. Check to see if the length of the word is greater than 2 (as it was researched that there is no adjective in 2-letters)
5. Convert the word to lowercase
6. Remove Stopwords
7. Finally Snowball Stemming the word (it was obsereved to be better than Porter Stemming)

After which we collect the words used to describe positive and negative reviews

In [17]:
```
# printing some random reviews
sent_0 = final['Text'].values[0]
print(sent_0)
print("="*50)

sent_1000 = final['Text'].values[10]
print(sent_1000)
print("="*50)

sent_1500 = final['Text'].values[15]
print(sent_1500)
print("="*50)

sent_4900 = final['Text'].values[49]
print(sent_4900)
print("="*50)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but t
hey are out there, but this one isnt.  Its too bad too because its a good pro
duct but I wont take any chances till they know what is going on with the chi
na imports.
==================================================
I've been trying to find the individual-pack option (at the affordable price)
for months now. I love having the ability to know exactly how much creamer
I'm using by counting the individual packets. (This product isn't available i
n my grocery store-- just by the coffee dispensers at local convenience store
s.) They're perfect for keeping at my desk at work~~I don't have to use the c
ommunity fridge, and it doesn't lump up in my coffee like the powdered versio
ns do. It's a little less convenient at home, though, where I'm accustomed to
using my refrigerated bottled versions~~opening the little packets one at a t
ime at 5 am can get annoying--but then again, I know exactly how much creamer
I'm adding to my coffee instead of dolloping in a random splash. (Now all I n
eed is someone to add the sugar-free versions of Coffee-Mate to the Amazon se
lection. Hint, hint. :) )
==================================================
This is another favorite in our house.  My cat doesn't want it more than 4 ti
mes a month or so, but he still wants it and licks the bowl clean.  It is fis
h, not his favorite, but he really likes his salmon and this one is outstandi
ng.  It's ground (why don't they make a sliced or bits version?), not his fav
orite either, but he does get it down pretty quickly.  Try this one - it's a
definite winner.
==================================================
My nine year old Dingo used to get smelly after a month on IAMS.  It's been t
hree months since his last bath (I just brush him) and no smell with Canidae!
  My 6mo old Chihuahua was on IAMS for puppies but kept sneeking the Canidae
from my Dingo.  So now he eats it too.  They scaf it down like crazy.  Buzz t
he Dingo's weight has improved without starving him.  This is the best dog fo
od.  The price is good here although I buy it at the pet store.
==================================================
```

In [18]:
```
# remove urls from text python: https://stackoverflow.com/a/40823105/4084039
sent_0 = re.sub(r"http\S+", "", sent_0)
sent_1000 = re.sub(r"http\S+", "", sent_1000)
sent_150 = re.sub(r"http\S+", "", sent_1500)
sent_4900 = re.sub(r"http\S+", "", sent_4900)

print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but t
hey are out there, but this one isnt.  Its too bad too because its a good pro
duct but I wont take any chances till they know what is going on with the chi
na imports.
```

In [19]:
```
# https://stackoverflow.com/questions/16206380/python-beautifulsoup-how-to-rem
ove-all-tags-from-an-element
from bs4 import BeautifulSoup

soup = BeautifulSoup(sent_0, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1000, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_1500, 'lxml')
text = soup.get_text()
print(text)
print("="*50)

soup = BeautifulSoup(sent_4900, 'lxml')
text = soup.get_text()
print(text)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but t
hey are out there, but this one isnt.  Its too bad too because its a good pro
duct but I wont take any chances till they know what is going on with the chi
na imports.
==================================================
I've been trying to find the individual-pack option (at the affordable price)
for months now. I love having the ability to know exactly how much creamer
I'm using by counting the individual packets. (This product isn't available i
n my grocery store-- just by the coffee dispensers at local convenience store
s.) They're perfect for keeping at my desk at work~~I don't have to use the c
ommunity fridge, and it doesn't lump up in my coffee like the powdered versio
ns do. It's a little less convenient at home, though, where I'm accustomed to
using my refrigerated bottled versions~~opening the little packets one at a t
ime at 5 am can get annoying--but then again, I know exactly how much creamer
I'm adding to my coffee instead of dolloping in a random splash. (Now all I n
eed is someone to add the sugar-free versions of Coffee-Mate to the Amazon se
lection. Hint, hint. :) )
==================================================
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mes a month or so, but he still wants it and licks the bowl clean.  It is fis
h, not his favorite, but he really likes his salmon and this one is outstandi
ng.  It's ground (why don't they make a sliced or bits version?), not his fav
orite either, but he does get it down pretty quickly.  Try this one - it's a
definite winner.
==================================================
My nine year old Dingo used to get smelly after a month on IAMS.  It's been t
hree months since his last bath (I just brush him) and no smell with Canidae!
  My 6mo old Chihuahua was on IAMS for puppies but kept sneeking the Canidae
from my Dingo.  So now he eats it too.  They scaf it down like crazy.  Buzz t
he Dingo's weight has improved without starving him.  This is the best dog fo
od.  The price is good here although I buy it at the pet store.
```

In [20]:
```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

In [21]:
```
sent_1500 = decontracted(sent_1500)
print(sent_1500)
print("="*50)
```

```
This is another favorite in our house.  My cat does not want it more than 4 t
imes a month or so, but he still wants it and licks the bowl clean.  It is fi
sh, not his favorite, but he really likes his salmon and this one is outstand
ing.  It is ground (why do not they make a sliced or bits version?), not his
favorite either, but he does get it down pretty quickly.  Try this one - it i
s a definite winner.
==================================================
```

In [22]:
```
#remove words with numbers python: https://stackoverflow.com/a/18082370/408403
9
sent_0 = re.sub("\S*\d\S*", "", sent_0).strip()
print(sent_0)
```

```
My dogs loves this chicken but its a product from China, so we wont be buying
it anymore.  Its very hard to find any chicken products made in the USA but t
hey are out there, but this one isnt.  Its too bad too because its a good pro
duct but I wont take any chances till they know what is going on with the chi
na imports.
```

In [23]:
```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent_1500 = re.sub('[^A-Za-z0-9]+', ' ', sent_1500)
print(sent_1500)
```

```
This is another favorite in our house My cat does not want it more than 4 tim
es a month or so but he still wants it and licks the bowl clean It is fish no
t his favorite but he really likes his salmon and this one is outstanding It
is ground why do not they make a sliced or bits version not his favorite eith
er but he does get it down pretty quickly Try this one it is a definite winne
r
```

In [24]:
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
# <br /><br /> ==> after the above steps, we are getting "br br"
# we are including them into stop words list
# instead of <br /> if we have <br/> these tags would have revmoved in the 1st
 step

stopwords= set(['br', 'the', 'i', 'me', 'my', 'myself', 'we', 'our', 'ours',
'ourselves', 'you', "you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he'
, 'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'it
self', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 't
hat', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have',
'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'becau
se', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into',
'through', 'during', 'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on',
'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'a
ll', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'tha
n', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "shoul
d've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn',
"didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'm
a', 'mightn', "mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shoul
dn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"])
```

In [25]:
```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_reviews = []
# tqdm is for printing the status bar
for sentance in tqdm(final['Text'].values):
    sentance = re.sub(r"http\S+", "", sentance)
    sentance = BeautifulSoup(sentance, 'lxml').get_text()
    sentance = decontracted(sentance)
    sentance = re.sub("\S*\d\S*", "", sentance).strip()
    sentance = re.sub('[^A-Za-z]+', ' ', sentance)
    # https://gist.github.com/sebleier/554280
    sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not i
n stopwords)
    preprocessed_reviews.append(sentance.strip())
```

```
100%|██████████| 46071/46071 [00:38<00:00, 1196.83it/s]
```

```
In [26]: preprocessed_reviews[15]
```

```
Out[26]: 'another favorite house cat not want times month still wants licks bowl clean
         fish not favorite really likes salmon one outstanding ground not make sliced
         bits version not favorite either get pretty quickly try one definite winner'
```

[3.2] Preprocessing Review Summary

```
In [27]: ## Similartly you can do preprocessing for review summary also.
         # Combining all the above stundents
         from tqdm import tqdm
         preprocessed_summary = []
         # tqdm is for printing the status bar
         for sentance in tqdm(final['Summary'].values):
             sentance = re.sub(r"http\S+", "", sentance)
             sentance = BeautifulSoup(sentance, 'lxml').get_text()
             sentance = decontracted(sentance)
             sentance = re.sub("\S*\d\S*", "", sentance).strip()
             sentance = re.sub('[^A-Za-z]+', ' ', sentance)
             # https://gist.github.com/sebleier/554280
             sentance = ' '.join(e.lower() for e in sentance.split() if e.lower() not i
         n stopwords)
             preprocessed_summary.append(sentance.strip())
```

```
 76%|███████▋  | 34822/46071 [00:15<00:04, 2498.73it/s]C:\Users\sujpanda\Anac
onda3\lib\site-packages\bs4\__init__.py:219: UserWarning: "b'...'" looks like
a filename, not markup. You should probably open this file and pass the fileh
andle into Beautiful Soup.
  ' Beautiful Soup.' % markup)
100%|██████████| 46071/46071 [00:21<00:00, 2102.01it/s]
```

Some Utility functions

In [28]:
```
def get_optimum_k(X_train,X_test,y_train,y_test,test_size,algorithm):

    f1_scores =[]

    max_accuracy = 0
    optimum_k = 0
    i = 0
    for i in range(1,30,2):
        # instantiate learning model (k = 30)
        knn = KNeighborsClassifier(n_neighbors=i,algorithm=algorithm)

        # fitting the model on crossvalidation train
        knn.fit(X_train, y_train)

        # predict the response on the crossvalidation train
        pred = knn.predict(X_test)

        # evaluate CV accuracy
        from sklearn.metrics import accuracy_score, f1_score, precision_score,
 recall_score, classification_report, confusion_matrix
        f1_score = f1_score(y_test, pred)*100
        f1_scores.append(f1_score)
        #acc = accuracy_score(y_cv, pred, normalize=True) * float(100)
        print('\nCV f1 score for k = %d is %d%%' % (i, f1_score))
        if int(f1_score) > max_accuracy:
            max_accuracy = int(f1_score)
            optimum_k = i

    print('\nCV with Max f1 score for k = %d is %d%%' % (optimum_k, max_accura
cy))
    print(f1_scores)
    MSE = [1 - x for x in f1_scores]
    myList = list(range(0,30))
    neighbors = list(filter(lambda x: x % 2 != 0, myList))
    # 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
))

    return optimum_k
```

In [29]:
```
def knn_results(optimum_n,algorithm_to_choose,X_train,X_test,y_train,y_test):
    # roc curve and auc
    from sklearn.datasets import make_classification
    from sklearn.neighbors import KNeighborsClassifier
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import roc_curve
    from sklearn.metrics import roc_auc_score
    from matplotlib import pyplot
    # ============================== KNN with k = optimal_k ==================
=============================
    # instantiate learning model k = optimal_k
    knn_optimal = KNeighborsClassifier(n_neighbors=optimum_n,algorithm=algorit
hm_to_choose)

    # fitting the model
    knn_optimal.fit(X_train, y_train)

    # 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%%' % (optimum
_n, acc))

    probs = knn_optimal.predict_proba(X_test)
    probs = probs[:, 1]
    # calculate AUC
    auc = roc_auc_score(y_test, probs)
    print('AUC: %.3f' % auc)
    # calculate roc curve
    fpr, tpr, thresholds = roc_curve(y_test, probs)
    # plot no skill
    pyplot.plot([0, 1], [0, 1], linestyle='--')
    # plot the roc curve for the model
    pyplot.plot(fpr, tpr, marker='.')
    # show the plot
    pyplot.show()
    from sklearn.metrics import confusion_matrix
    con_mat = confusion_matrix(y_test, pred, [0, 1])
    return con_mat
```

In [30]:
```
def showHeatMap(con_mat):
    class_label = ["negative", "positive"]
    df_cm = pd.DataFrame(con_mat, index = class_label, columns = class_label)
    sns.heatmap(df_cm, annot = True, fmt = "d")
    plt.title("Confusion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
```

[5.1] Applying KNN brute force

[5.1.1] Applying KNN brute force on BOW, SET 1

In [39]:
```
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
import warnings
warnings.filterwarnings("ignore")
```

In [40]:
```
print(final['Text'].shape)
```

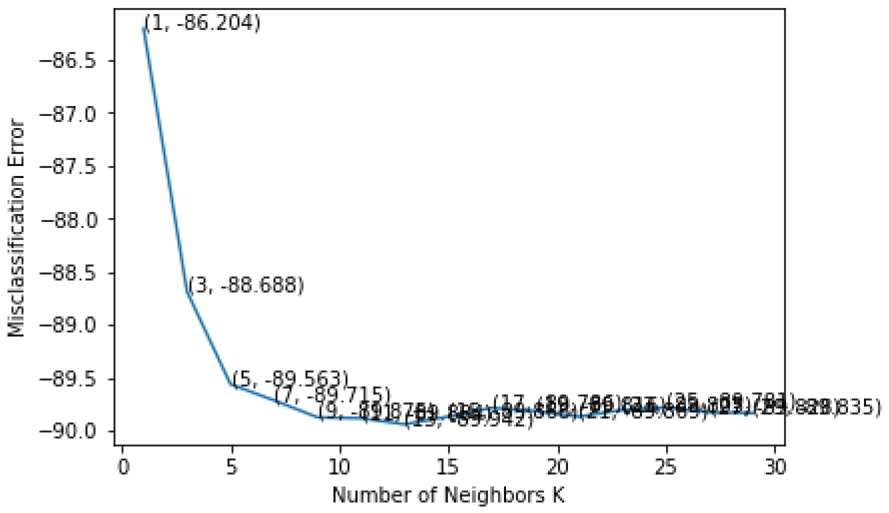
```
(46071,)
```

In [41]:
```
X_1, X_test, y_1, y_test = cross_validation.train_test_split(preprocessed_revi
ews, final['Score'], test_size=0.3, random_state=0)
```

Note: There is chance of data leakage in case we vectorize the whole dataset. To avoid that first split the data then fit_transform the trainging data and only transform the test data.

In [190]:
```
count_vect = CountVectorizer()
final_counts = count_vect.fit_transform(X_1)
final_test_count = count_vect.transform(X_test)

# split the train data set into cross validation train and cross validation te
st
X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(X_1, y_1, test_size
=0.3)

final_counts_tr_cv = count_vect.transform(X_tr)
final_test_count_cv = count_vect.transform(X_cv)

optimum_k=get_optimum_k(final_counts_tr_cv,final_test_count_cv,y_tr,y_cv,0.3,
'brute')
```

```
CV f1 score for k = 1 is 87%

CV f1 score for k = 3 is 89%

CV f1 score for k = 5 is 90%

CV f1 score for k = 7 is 90%

CV f1 score for k = 9 is 90%

CV f1 score for k = 11 is 90%

CV f1 score for k = 13 is 90%

CV f1 score for k = 15 is 90%

CV f1 score for k = 17 is 90%

CV f1 score for k = 19 is 90%

CV f1 score for k = 21 is 90%

CV f1 score for k = 23 is 90%

CV f1 score for k = 25 is 90%

CV f1 score for k = 27 is 90%

CV f1 score for k = 29 is 90%

CV with Max f1 score for k = 5 is 90%
[87.20396548558841, 89.68827782387106, 90.56295258117262, 90.71470075537479,
90.87536231884059, 90.88383399895817, 90.94169366034244, 90.8680816609797, 9
0.78620530298655, 90.81567857761357, 90.8692138981877, 90.8052607291186, 90.7
8120495820123, 90.82838531158126, 90.83472550262113]
```

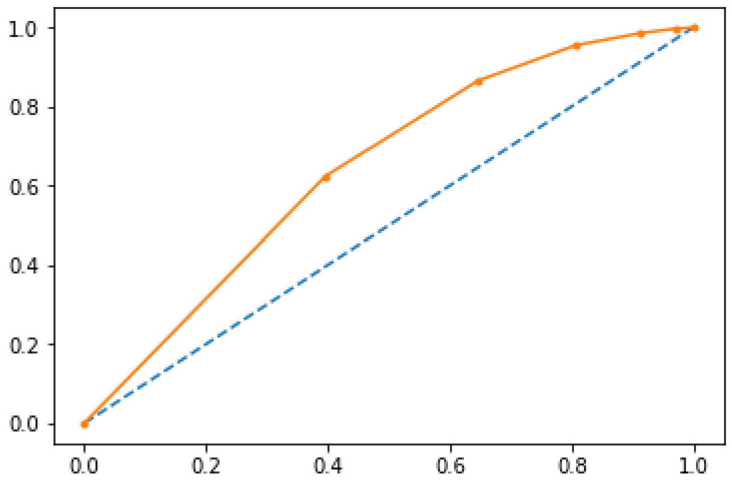


```
the misclassification error for each k value is :  [-86.204 -88.688 -89.563 -
89.715 -89.875 -89.884 -89.942 -89.868 -89.786
 -89.816 -89.869 -89.805 -89.781 -89.828 -89.835]
```

Observation: From the plot it is obivous that K=5 is the optimum value. After this if we change the K value it is not going to reduce the error further.

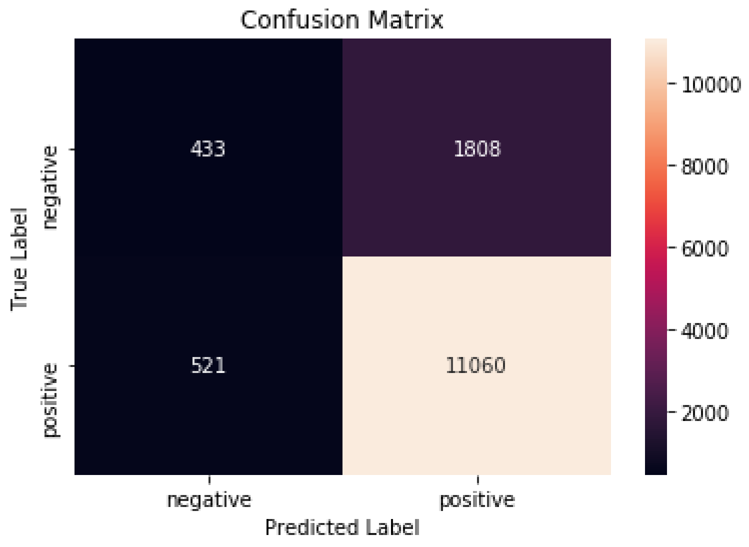
In [191]:
```
con_mat=knn_results(optimum_k,'brute',final_counts,final_test_count,y_1,y_test
)
```

```
The accuracy of the knn classifier for k = 5 is 83.150051%
AUC: 0.645
```



Observation: My AUC is 0.645 means my model is performing better than the dumb model.

In [192]:
```
showHeatMap(con_mat)
```



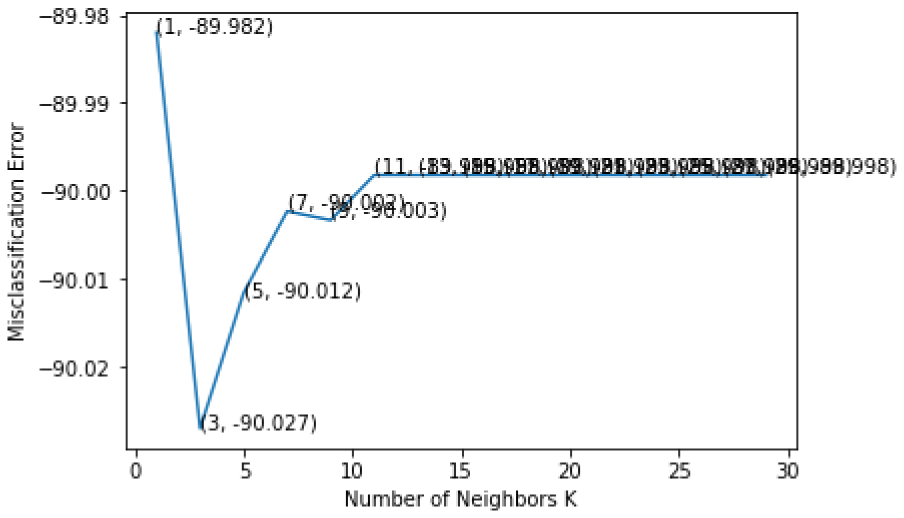
Observation : My model predicted 1808 + 521 = 2329 points wrongly.

[5.1.2] Applying KNN brute force on TFIDF, SET 2

In [193]:
```
X_1, X_test, y_1, y_test = cross_validation.train_test_split(preprocessed_revi
ews, final['Score'], test_size=0.3, random_state=0)
```

In [194]:
```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), min_df=10)
tf_idf_vect.fit(X_1)
final_tf_idf = tf_idf_vect.transform(X_1)
final_test_count = tf_idf_vect.transform(X_test)

# split the train data set into cross validation train and cross validation te
st
X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(X_1, y_1, test_size
=0.3)

final_counts_tr_cv = tf_idf_vect.transform(X_tr)
final_test_count_cv = tf_idf_vect.transform(X_cv)

optimum_k=get_optimum_k(final_counts_tr_cv,final_test_count_cv,y_tr,y_cv,0.3,
'brute')
```

```
CV f1 score for k = 1 is 90%

CV f1 score for k = 3 is 91%

CV f1 score for k = 5 is 91%

CV f1 score for k = 7 is 91%

CV f1 score for k = 9 is 91%

CV f1 score for k = 11 is 90%

CV f1 score for k = 13 is 90%

CV f1 score for k = 15 is 90%

CV f1 score for k = 17 is 90%

CV f1 score for k = 19 is 90%

CV f1 score for k = 21 is 90%

CV f1 score for k = 23 is 90%

CV f1 score for k = 25 is 90%

CV f1 score for k = 27 is 90%

CV f1 score for k = 29 is 90%

CV with Max f1 score for k = 3 is 91%
[90.98198656050596, 91.02694172021192, 91.01155255001409, 91.00230998929517,
91.0033237564081, 90.99819738621, 90.99819738621, 90.99819738621, 90.99819738
621, 90.99819738621, 90.99819738621, 90.99819738621, 90.99819738621, 90.99819
738621, 90.99819738621]
```

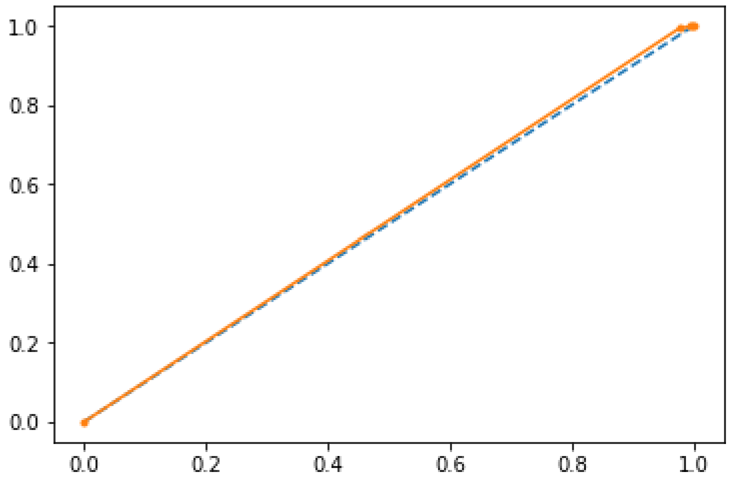


```
the misclassification error for each k value is :  [-89.982 -90.027 -90.012 -
90.002 -90.003 -89.998 -89.998 -89.998 -89.998
 -89.998 -89.998 -89.998 -89.998 -89.998 -89.998]
```

Observation: From the plot it is obivious that K = 3 is optimum with maximum accuracy.

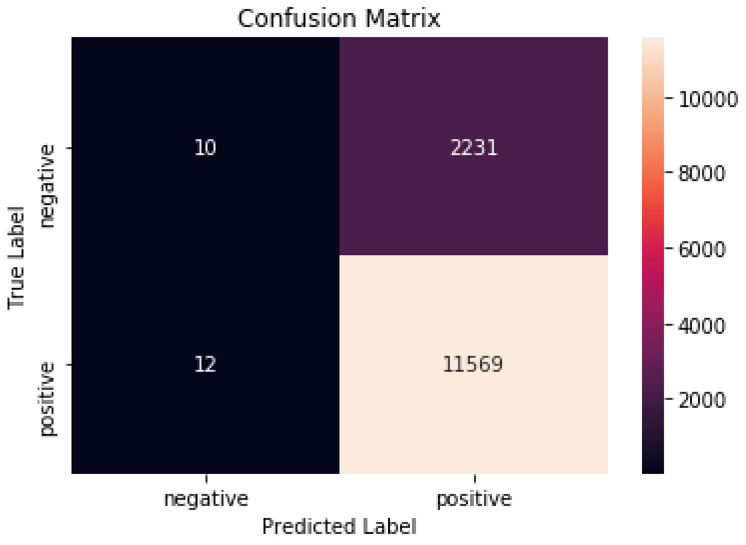
```
In [195]: con_mat=knn_results(optimum_k,'brute',final_tf_idf,final_test_count,y_1,y_test
)
```

```
The accuracy of the knn classifier for k = 3 is 83.772247%
AUC: 0.509
```



Observation : TFIDF model is as dumb as my dumb model and accuracy is very low.

```
In [196]: showHeatMap(con_mat)
```



Obseration: My model predict most of the negative points as positive (2231). So model is more biased towards +ve points.

[5.1.3] Applying KNN brute force on AVG W2V, SET 3

In [42]:
```
# split the data set into train and test
X_train, X_test, y_1, y_test = cross_validation.train_test_split(preprocessed_
reviews, final['Score'], test_size=0.3, random_state=0)
```

In [43]:
```
i=0
list_of_sentance=[]
for sentance in X_train:
    list_of_sentance.append(sentance.split())

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
    #print(w2v_model.wv.most_similar('great'))
    #print('='*50)
    #print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negati
ve300.bin', binary=True)
        #print(w2v_model.wv.most_similar('great'))
        #print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v =
 True, to train your own w2v ")

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])




# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this li
st
for sent in tqdm(list_of_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might
 need to change this to 300 if you use google's w2v
    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]))
```

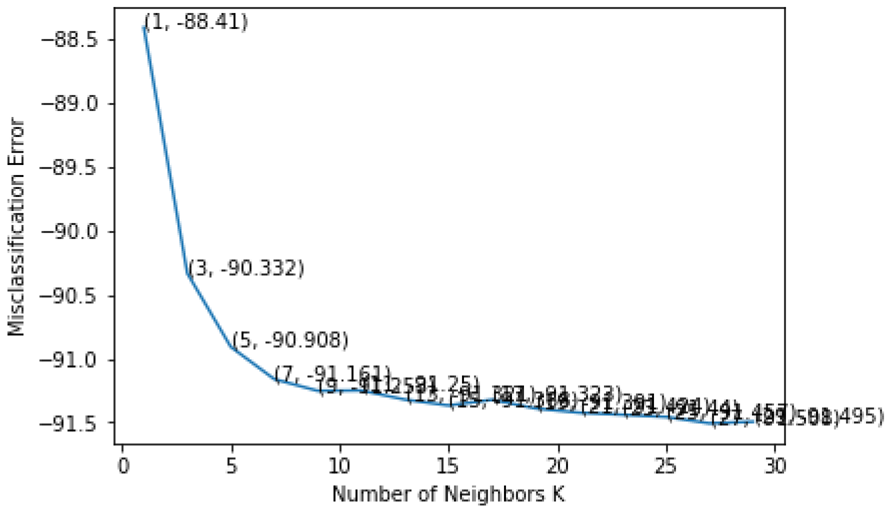
```
number of words that occured minimum 5 times  10772
sample words  ['three', 'cats', 'kitty', 'notoriously', 'fussy', 'eaters', 'a
lthough', 'eat', 'dry', 'food', 'not', 'especially', 'pleased', 'willing', 'k
it', 'n', 'favor', 'purina', 'products', 'one', 'two', 'things', 'going', 'pr
ice', 'right', 'dogs', 'also', 'give', 'paws', 'little', 'sneaks', 'hi', 'wou
ld', 'better', 'sweet', 'aftertaste', 'tastes', 'like', 'saccharin', 'bit',
'overpowering', 'excited', 'saw', 'vintage', 'cracker', 'jack', 'box', 'rea
d', 'review', 'arrived']

100%|██████████| 32249/32249 [01:41<00:00, 317.14it/s]

32249
50
```

In [44]:
```
#working with test data to get the sentence vector and traind the model with w
2vec
i=0
list_of_test_sentance=[]
for sentance in X_test:
    list_of_test_sentance.append(sentance.split())


is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_test_sentance,min_count=5,size=50, workers=4)
    #print(w2v_model.wv.most_similar('great'))
    #print('='*50)
    #print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negati
ve300.bin', binary=True)
        #print(w2v_model.wv.most_similar('great'))
        #print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v =
 True, to train your own w2v ")

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])

# average Word2Vec
# compute average word2vec for each review.
sent_test_vectors = []; # the avg-w2v for each sentence/review is stored in th
is list
for sent in tqdm(list_of_test_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might
 need to change this to 300 if you use google's w2v
    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_test_vectors.append(sent_vec)
print(len(sent_test_vectors))
print(len(sent_test_vectors[0]))
```

```
number of words that occured minimum 5 times  7102
sample words  ['wow', 'lobster', 'spreads', 'quite', 'treat', 'try', 'good',
'hard', 'cheese', 'mild', 'crackers', 'sweet', 'taste', 'delicious', 'melts',
'mouth', 'not', 'available', 'markets', 'dolce', 'coffee', 'maker', 'love',
'unfortunately', 'area', 'buy', 'flavored', 'coffees', 'thank', 'handling',
'machine', 'favorite', 'lungo', 'espresso', 'several', 'cups', 'day', 'many',
'miracle', 'health', 'products', 'know', 'real', 'enough', 'people', 'said',
'things', 'seeds', 'decided', 'jump']

100%|██████████| 13822/13822 [00:31<00:00, 434.58it/s]

13822
50
```

In [200]:
```
# split the train data set into cross validation train and cross validation te
st
X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(sent_vectors, y_1,
test_size=0.3)

optimum_k=get_optimum_k(X_tr,X_cv,y_tr,y_cv,0.3,'brute')
```

```
CV f1 score for k = 1 is 89%

CV f1 score for k = 3 is 91%

CV f1 score for k = 5 is 91%

CV f1 score for k = 7 is 92%

CV f1 score for k = 9 is 92%

CV f1 score for k = 11 is 92%

CV f1 score for k = 13 is 92%

CV f1 score for k = 15 is 92%

CV f1 score for k = 17 is 92%

CV f1 score for k = 19 is 92%

CV f1 score for k = 21 is 92%

CV f1 score for k = 23 is 92%

CV f1 score for k = 25 is 92%

CV f1 score for k = 27 is 92%

CV f1 score for k = 29 is 92%

CV with Max f1 score for k = 7 is 92%
[89.40972222222221, 91.33192389006342, 91.9083786854853, 92.16140726213823, 9
2.25293629137504, 92.25035494557501, 92.32131263648705, 92.3675369835563, 92.
32308960320263, 92.3909208514642, 92.42424242424242, 92.44032608058178, 92.45
736388677255, 92.50776170113055, 92.49516667643096]
```

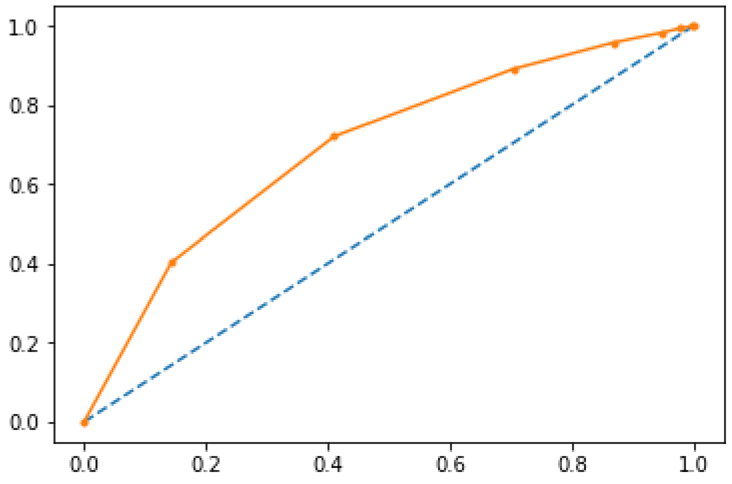


```
the misclassification error for each k value is :  [-88.41  -90.332 -90.908 -
91.161 -91.253 -91.25  -91.321 -91.368 -91.323
 -91.391 -91.424 -91.44  -91.457 -91.508 -91.495]
```

Observation: For k=7 gives most accuracy. After increasing k does not affect much.

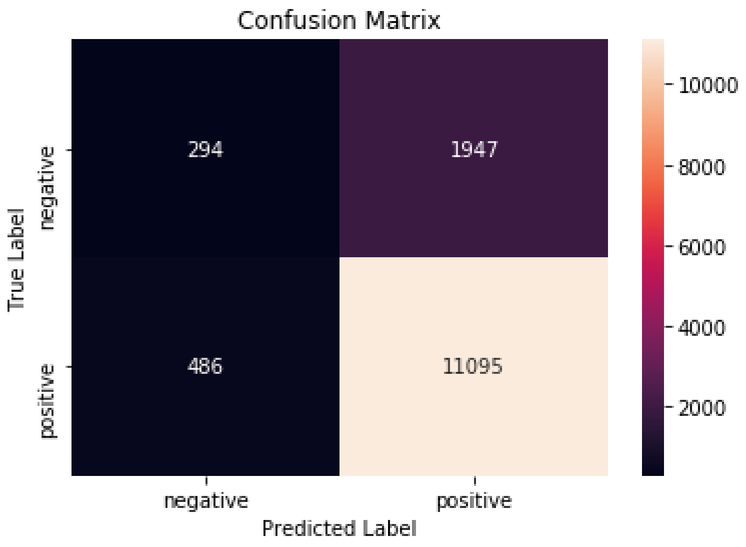
In [201]:
```
con_mat=knn_results(optimum_k,'brute',sent_vectors,sent_test_vectors,y_1,y_tes
t)
```

```
The accuracy of the knn classifier for k = 7 is 82.397627%
AUC: 0.696
```



Observation: My model preformed better in this case with auc of 0.696.

In [202]:
```
showHeatMap(con_mat)
```



Observation : My model misclassified 586 + 1947 data points.

[5.1.4] Applying KNN brute force on TFIDF W2V, SET 4

In [45]:
```
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
import warnings
warnings.filterwarnings("ignore")

X_train, X_test, y_1, y_test = cross_validation.train_test_split(preprocessed_
reviews, final['Score'], test_size=0.3, random_state=0)

model = TfidfVectorizer()
X_train = model.fit_transform(X_train)
X_test = model.transform(X_test)

dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [46]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in
 this list
row=0;
for sent in tqdm(list_of_sentance): # 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 and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            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
```

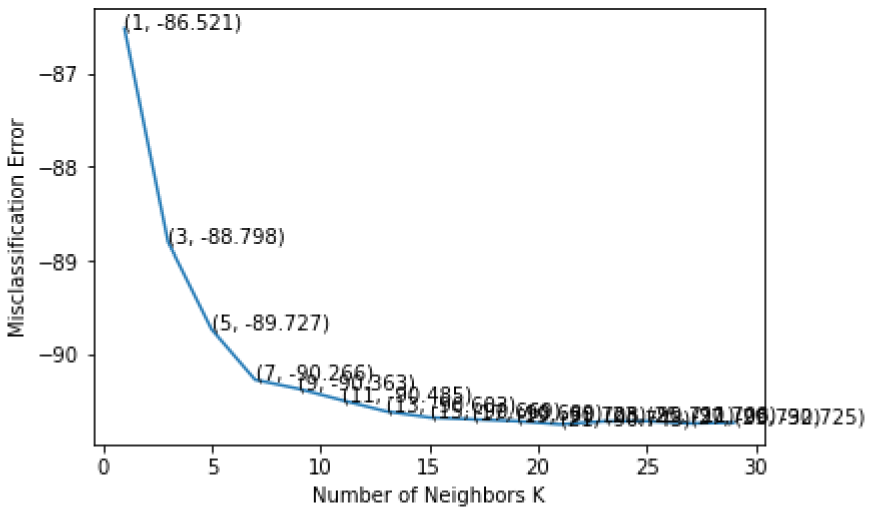
```
100%|██████████| 32249/32249 [22:02<00:00, 24.38it/s]
```

In [47]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_test_sent_vectors = []; # the tfidf-w2v for each sentence/review is stor
ed in this list
row=0;
for sent in tqdm(list_of_test_sentance): # 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 and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_test_sent_vectors.append(sent_vec)
    row += 1
```

```
100%|██████████| 13822/13822 [10:16<00:00, 22.42it/s]
```

In [48]:
```
# split the train data set into cross validation train and cross validation te
st
X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(tfidf_sent_vectors,
 y_1, test_size=0.3)

optimum_k=get_optimum_k(X_tr,X_cv,y_tr,y_cv,0.3,'brute')
```

```
CV f1 score for k = 1 is 87%

CV f1 score for k = 3 is 89%

CV f1 score for k = 5 is 90%

CV f1 score for k = 7 is 91%

CV f1 score for k = 9 is 91%

CV f1 score for k = 11 is 91%

CV f1 score for k = 13 is 91%

CV f1 score for k = 15 is 91%

CV f1 score for k = 17 is 91%

CV f1 score for k = 19 is 91%

CV f1 score for k = 21 is 91%

CV f1 score for k = 23 is 91%

CV f1 score for k = 25 is 91%

CV f1 score for k = 27 is 91%

CV f1 score for k = 29 is 91%

CV with Max f1 score for k = 7 is 91%
[87.5208603745596, 89.79762402244643, 90.72711215778628, 91.26622237811294, 9
1.36318754719174, 91.48517145505097, 91.60314160314161, 91.66906889593544, 9
1.6887302866352, 91.70832615066368, 91.74269811212487, 91.71061683100207, 91.
70821156380724, 91.73208044462268, 91.72536219435378]
```

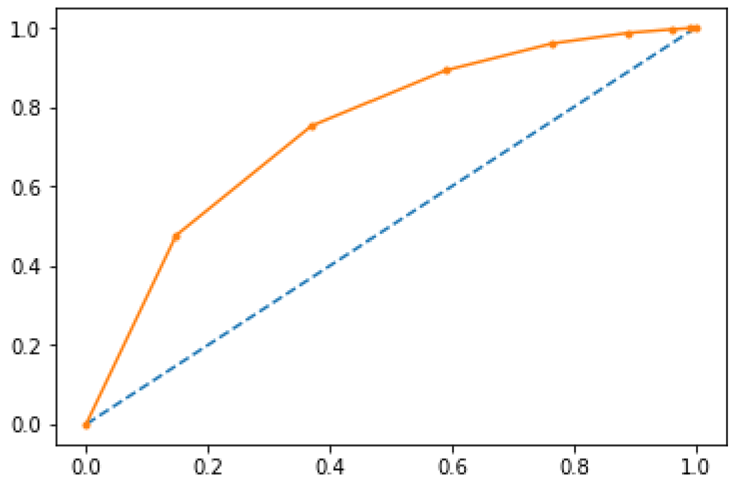


```
the misclassification error for each k value is :  [-86.521 -88.798 -89.727 -
90.266 -90.363 -90.485 -90.603 -90.669 -90.689
 -90.708 -90.743 -90.711 -90.708 -90.732 -90.725]
```

Observation: For k=7 gives most accuracy. After increasing k does not affect much.

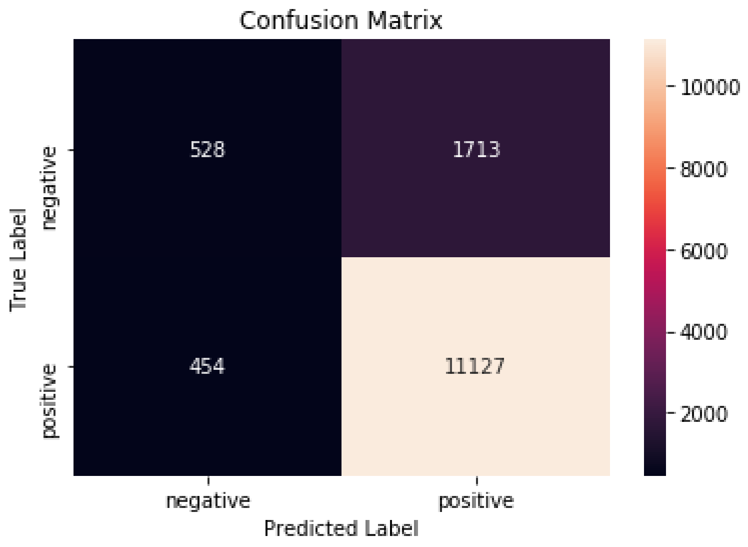
In [49]:
```
con_mat=knn_results(optimum_k,'brute',tfidf_sent_vectors,tfidf_test_sent_vecto
rs,y_1,y_test)
```

```
The accuracy of the knn classifier for k = 7 is 84.322095%
AUC: 0.746
```



Observation: My model preformed better in this case with auc of 0.746.

In [50]:
```
showHeatMap(con_mat)
```



Observation : My model misclassified 454 + 1713 data points. Better than w2vec.

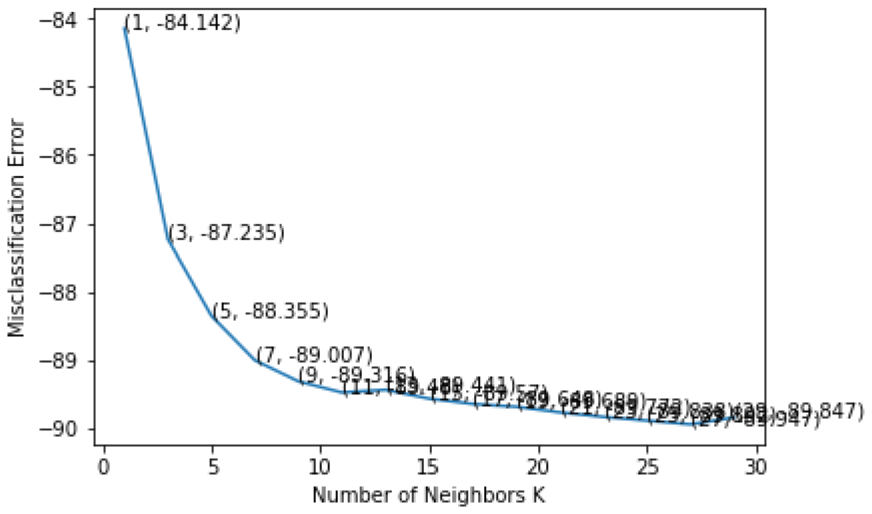
[5.2] Applying KNN kd-tree

[5.2.1] Applying KNN kd-tree on BOW, SET 5

In [51]:
```
# split the data set into train and test
X_1, X_test, y_1, y_test = cross_validation.train_test_split(preprocessed_revi
ews, final['Score'], test_size=0.3, random_state=0)
```

In [52]:
```
count_vect = CountVectorizer(min_df=10, max_features=500)
final_counts = count_vect.fit_transform(X_1)
final_test_count = count_vect.transform(X_test)

# split the train data set into cross validation train and cross validation te
st
X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(X_1, y_1, test_size
=0.3)

final_counts_tr_cv = count_vect.transform(X_tr)
final_test_count_cv = count_vect.transform(X_cv)

optimum_k=get_optimum_k(final_counts_tr_cv,final_test_count_cv,y_tr,y_cv,0.3,
'kd_tree')
```

```
CV f1 score for k = 1 is 85%

CV f1 score for k = 3 is 88%

CV f1 score for k = 5 is 89%

CV f1 score for k = 7 is 90%

CV f1 score for k = 9 is 90%

CV f1 score for k = 11 is 90%

CV f1 score for k = 13 is 90%

CV f1 score for k = 15 is 90%

CV f1 score for k = 17 is 90%

CV f1 score for k = 19 is 90%

CV f1 score for k = 21 is 90%

CV f1 score for k = 23 is 90%

CV f1 score for k = 25 is 90%

CV f1 score for k = 27 is 90%

CV f1 score for k = 29 is 90%

CV with Max f1 score for k = 7 is 90%
[85.14245649818344, 88.23529411764704, 89.35452793834297, 90.00716332378222,
90.31644063763979, 90.47957371225577, 90.44074205364527, 90.56981398634328, 9
0.64832774936814, 90.68935171604576, 90.77175313268533, 90.83786470209905, 9
0.89209557749605, 90.94729469444931, 90.84650837174027]
```

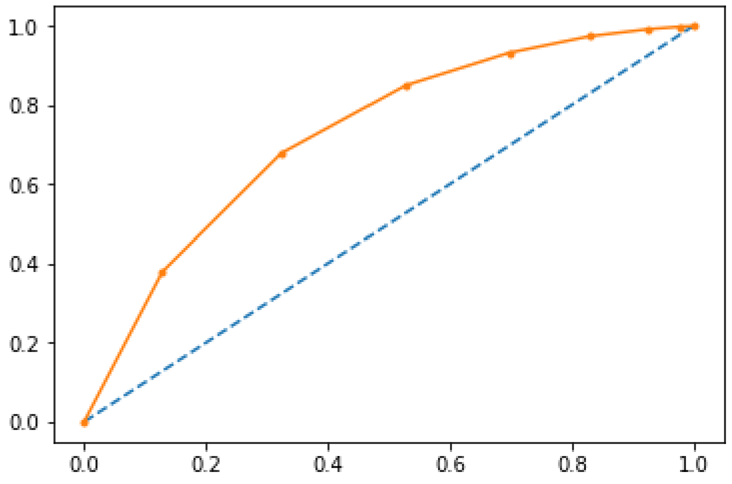


```
the misclassification error for each k value is :  [-84.142 -87.235 -88.355 -
89.007 -89.316 -89.48  -89.441 -89.57  -89.648
 -89.689 -89.772 -89.838 -89.892 -89.947 -89.847]
```

Observation: For k=7 gives most accuracy. After increasing k does not affect much.

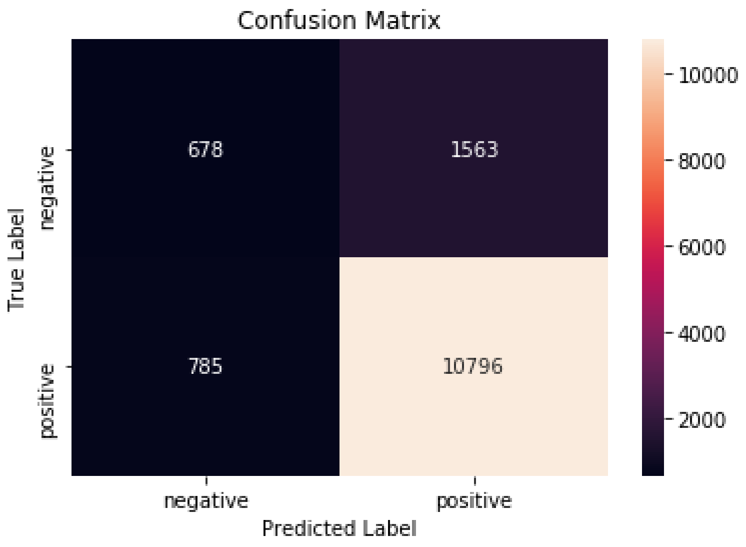
In [53]:
```
con_mat=knn_results(optimum_k,'kd_tree',final_counts,final_test_count,y_1,y_te
st)
```

```
The accuracy of the knn classifier for k = 7 is 83.012589%
AUC: 0.729
```



Observation: My model preformed better in this case with auc of 0.729.

In [54]:
```
showHeatMap(con_mat)
```



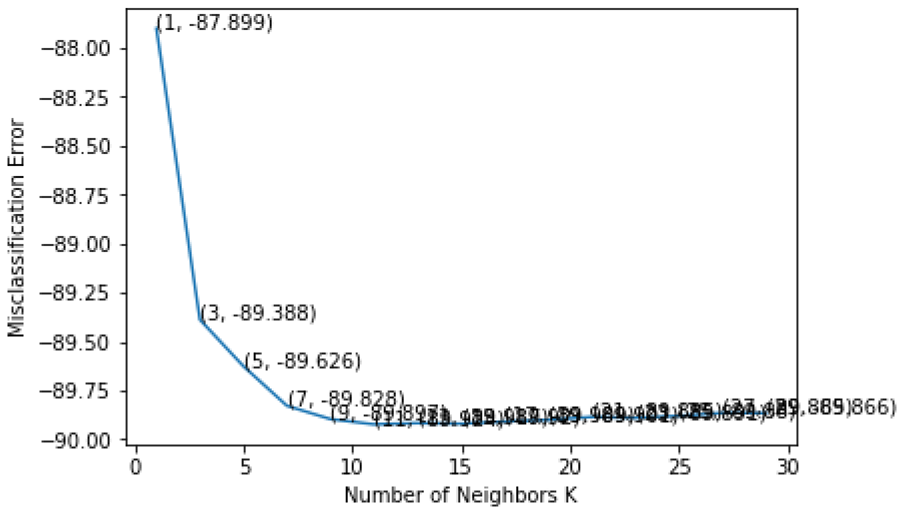
Observation : My model misclassified 785 + 1563 data points.

[5.2.2] Applying KNN kd-tree on TFIDF, SET 6

In [55]:
```
X_1, X_test, y_1, y_test = cross_validation.train_test_split(preprocessed_revi
ews, final['Score'], test_size=0.3, random_state=0)
```

In [56]:
```
tf_idf_vect = TfidfVectorizer(min_df=10, max_features=500)
tf_idf_vect.fit(X_1)
final_tf_idf = tf_idf_vect.transform(X_1)
final_test_count = tf_idf_vect.transform(X_test)

# split the train data set into cross validation train and cross validation te
st
X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(X_1, y_1, test_size
=0.3)

final_counts_tr_cv = tf_idf_vect.transform(X_tr)
final_test_count_cv = tf_idf_vect.transform(X_cv)

optimum_k=get_optimum_k(final_counts_tr_cv,final_test_count_cv,y_tr,y_cv,0.3,
'kd_tree')
```

```
CV f1 score for k = 1 is 88%

CV f1 score for k = 3 is 90%

CV f1 score for k = 5 is 90%

CV f1 score for k = 7 is 90%

CV f1 score for k = 9 is 90%

CV f1 score for k = 11 is 90%

CV f1 score for k = 13 is 90%

CV f1 score for k = 15 is 90%

CV f1 score for k = 17 is 90%

CV f1 score for k = 19 is 90%

CV f1 score for k = 21 is 90%

CV f1 score for k = 23 is 90%

CV f1 score for k = 25 is 90%

CV f1 score for k = 27 is 90%

CV f1 score for k = 29 is 90%

CV with Max f1 score for k = 3 is 90%
[88.89946460440214, 90.38772213247172, 90.62589474889768, 90.82840236686391,
90.89671601157052, 90.9235037653587, 90.91731704558308, 90.92039098254139, 9
0.90909090909092, 90.90088055994582, 90.88549015181444, 90.89061970877074, 9
0.88036117381489, 90.86497771257687, 90.8660084626234]
```

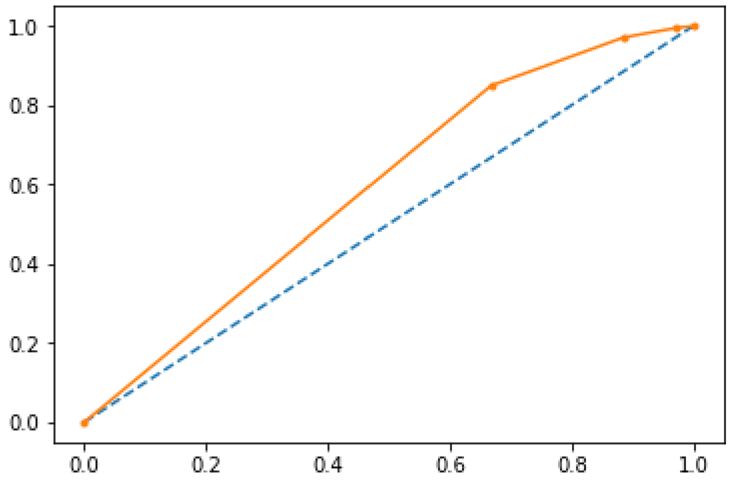


```
the misclassification error for each k value is :  [-87.899 -89.388 -89.626 -
89.828 -89.897 -89.924 -89.917 -89.92  -89.909
 -89.901 -89.885 -89.891 -89.88  -89.865 -89.866]
```

Observation: For k=3 gives most accuracy. After increasing k does not affect much.

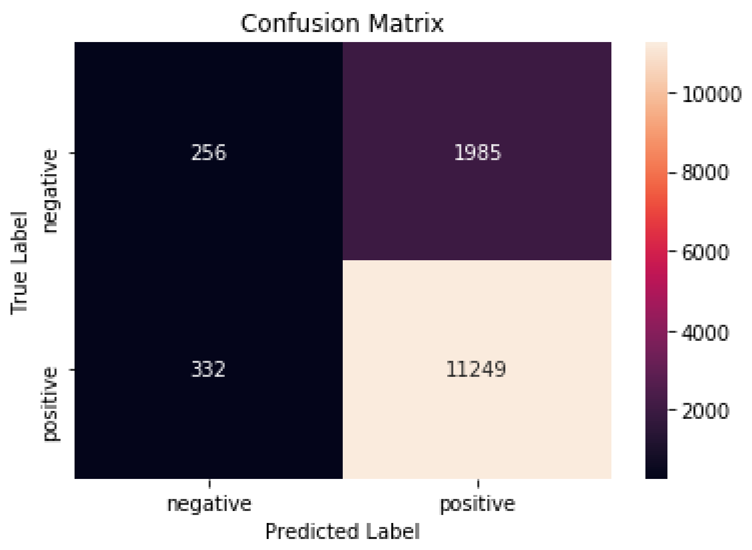
In [57]:
```
con_mat=knn_results(optimum_k,'kd_tree',final_tf_idf,final_test_count,y_1,y_te
st)
```

```
The accuracy of the knn classifier for k = 3 is 83.236869%
AUC: 0.595
```



Observation: My model preformed not much better than the dumb model with auc 0.595.

In [58]:
```
showHeatMap(con_mat)
```



Observation : 332 + 1985 points classifed wrongly.

[5.2.3] Applying KNN kd-tree on AVG W2V, SET 3

In [59]:
```
X_train, X_test, y_1, y_test = cross_validation.train_test_split(preprocessed_
reviews, final['Score'], test_size=0.3, random_state=0)
```

In [60]:
```
i=0
list_of_sentance=[]
for sentance in X_train:
    list_of_sentance.append(sentance.split())

is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_sentance,min_count=5,size=50, workers=4)
    #print(w2v_model.wv.most_similar('great'))
    #print('='*50)
    #print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negati
ve300.bin', binary=True)
        #print(w2v_model.wv.most_similar('great'))
        #print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v =
 True, to train your own w2v ")

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

```
number of words that occured minimum 5 times  10772
sample words  ['three', 'cats', 'kitty', 'notoriously', 'fussy', 'eaters', 'a
lthough', 'eat', 'dry', 'food', 'not', 'especially', 'pleased', 'willing', 'k
it', 'n', 'favor', 'purina', 'products', 'one', 'two', 'things', 'going', 'pr
ice', 'right', 'dogs', 'also', 'give', 'paws', 'little', 'sneaks', 'hi', 'wou
ld', 'better', 'sweet', 'aftertaste', 'tastes', 'like', 'saccharin', 'bit',
'overpowering', 'excited', 'saw', 'vintage', 'cracker', 'jack', 'box', 'rea
d', 'review', 'arrived']
```

```
In [61]: # average Word2Vec
         # compute average word2vec for each review.
         sent_vectors = []; # the avg-w2v for each sentence/review is stored in this li
         st
         for sent in tqdm(list_of_sentance): # for each review/sentence
             sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might
          need to change this to 300 if you use google's w2v
             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]))
```

```
100%|██████████| 32249/32249 [01:48<00:00, 298.29it/s]

32249
50
```

In [62]:
```
#working with test data to get the sentence vector and traind the model with w
2vec
i=0
list_of_test_sentance=[]
for sentance in X_test:
    list_of_test_sentance.append(sentance.split())


is_your_ram_gt_16g=False
want_to_use_google_w2v = False
want_to_train_w2v = True

if want_to_train_w2v:
    # min_count = 5 considers only words that occured atleast 5 times
    w2v_model=Word2Vec(list_of_test_sentance,min_count=5,size=50, workers=4)
    #print(w2v_model.wv.most_similar('great'))
    #print('='*50)
    #print(w2v_model.wv.most_similar('worst'))

elif want_to_use_google_w2v and is_your_ram_gt_16g:
    if os.path.isfile('GoogleNews-vectors-negative300.bin'):
        w2v_model=KeyedVectors.load_word2vec_format('GoogleNews-vectors-negati
ve300.bin', binary=True)
        #print(w2v_model.wv.most_similar('great'))
        #print(w2v_model.wv.most_similar('worst'))
    else:
        print("you don't have gogole's word2vec file, keep want_to_train_w2v =
 True, to train your own w2v ")

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
print("sample words ", w2v_words[0:50])
```

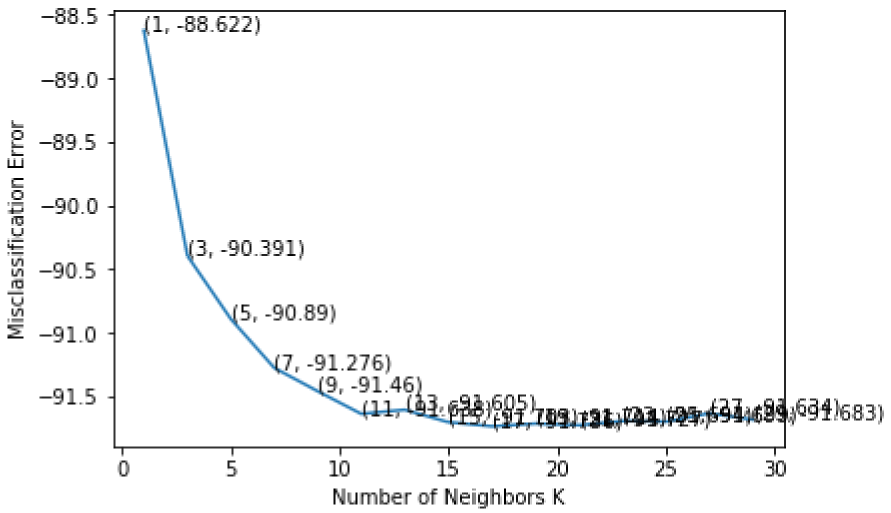
```
number of words that occured minimum 5 times  7102
sample words  ['wow', 'lobster', 'spreads', 'quite', 'treat', 'try', 'good',
'hard', 'cheese', 'mild', 'crackers', 'sweet', 'taste', 'delicious', 'melts',
'mouth', 'not', 'available', 'markets', 'dolce', 'coffee', 'maker', 'love',
'unfortunately', 'area', 'buy', 'flavored', 'coffees', 'thank', 'handling',
'machine', 'favorite', 'lungo', 'espresso', 'several', 'cups', 'day', 'many',
'miracle', 'health', 'products', 'know', 'real', 'enough', 'people', 'said',
'things', 'seeds', 'decided', 'jump']
```

In [63]:
```
# average Word2Vec
# compute average word2vec for each review.
sent_test_vectors = []; # the avg-w2v for each sentence/review is stored in th
is list
for sent in tqdm(list_of_test_sentance): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length 50, you might
 need to change this to 300 if you use google's w2v
    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_test_vectors.append(sent_vec)
print(len(sent_test_vectors))
print(len(sent_test_vectors[0]))
```

```
100%|██████████| 13822/13822 [00:37<00:00, 370.82it/s]

13822
50
```

In [64]:
```
# split the train data set into cross validation train and cross validation te
st
X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(sent_vectors, y_1,
test_size=0.3)

optimum_k=get_optimum_k(X_tr,X_cv,y_tr,y_cv,0.3,'kd_tree')
```

```
CV f1 score for k = 1 is 89%

CV f1 score for k = 3 is 91%

CV f1 score for k = 5 is 91%

CV f1 score for k = 7 is 92%

CV f1 score for k = 9 is 92%

CV f1 score for k = 11 is 92%

CV f1 score for k = 13 is 92%

CV f1 score for k = 15 is 92%

CV f1 score for k = 17 is 92%

CV f1 score for k = 19 is 92%

CV f1 score for k = 21 is 92%

CV f1 score for k = 23 is 92%

CV f1 score for k = 25 is 92%

CV f1 score for k = 27 is 92%

CV f1 score for k = 29 is 92%

CV with Max f1 score for k = 7 is 92%
[89.62246720453287, 91.39144558743908, 91.89028026237328, 92.27574750830566,
92.45952015128236, 92.63767430867406, 92.60548834464444, 92.70330704954691, 9
2.7360489757476, 92.71445358401881, 92.72705909998825, 92.69379617685, 92.698
93355209187, 92.6335498215435, 92.6832123624444]
```

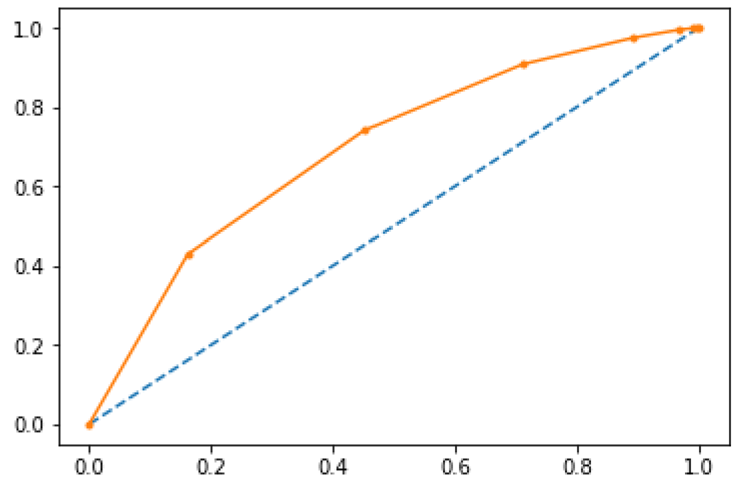


```
the misclassification error for each k value is :  [-88.622 -90.391 -90.89  -
91.276 -91.46  -91.638 -91.605 -91.703 -91.736
 -91.714 -91.727 -91.694 -91.699 -91.634 -91.683]
```

Observation: For k=7 gives most accuracy. After increasing k does not affect much.

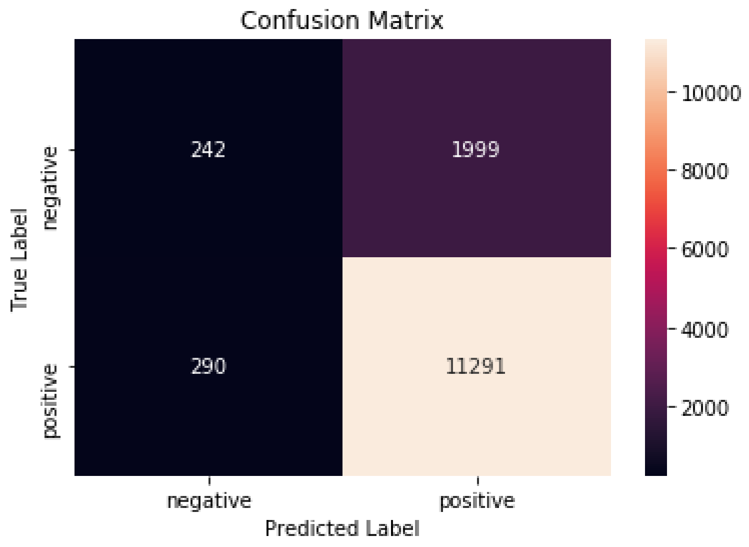
In [65]:
```
con_mat=knn_results(optimum_k,'kd_tree',sent_vectors,sent_test_vectors,y_1,y_t
est)
```

```
The accuracy of the knn classifier for k = 7 is 83.439444%
AUC: 0.695
```



Observation: My model predicted with auc 0.695.

In [66]:
```
showHeatMap(con_mat)
```



Observation : 290 + 1999 points classifed wrongly.

[5.2.4] Applying KNN kd-tree on TFIDF W2V, SET 4

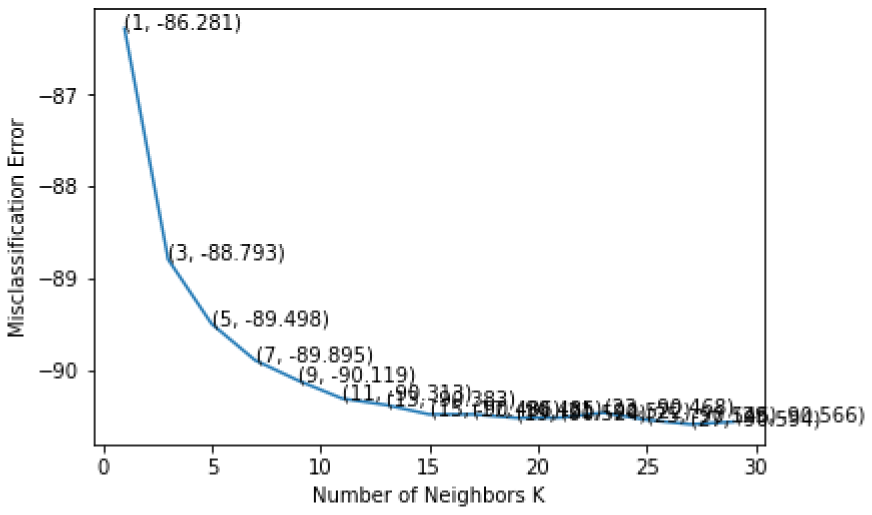
In [72]:
```
X_train, X_test, y_1, y_test = cross_validation.train_test_split(preprocessed_
reviews, final['Score'], test_size=0.3, random_state=0)

model = TfidfVectorizer()
X_train = model.fit_transform(X_train)

dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))

X_test = model.transform(X_test)
```

In [ ]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in
 this list
row=0;
for sent in tqdm(list_of_sentance): # 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 and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            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
```

In [ ]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val
 = tfidf

tfidf_test_sent_vectors = []; # the tfidf-w2v for each sentence/review is stor
ed in this list
row=0;
for sent in tqdm(list_of_test_sentance): # 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 and word in tfidf_feat:
            vec = w2v_model.wv[word]
#             tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_test_sent_vectors.append(sent_vec)
    row += 1
```

In [75]:
```
# split the train data set into cross validation train and cross validation te
st
X_tr, X_cv, y_tr, y_cv = cross_validation.train_test_split(tfidf_sent_vectors,
 y_1, test_size=0.3)

optimum_k=get_optimum_k(X_tr,X_cv,y_tr,y_cv,0.3,'kd_tree')
```

```
CV f1 score for k = 1 is 87%

CV f1 score for k = 3 is 89%

CV f1 score for k = 5 is 90%

CV f1 score for k = 7 is 90%

CV f1 score for k = 9 is 91%

CV f1 score for k = 11 is 91%

CV f1 score for k = 13 is 91%

CV f1 score for k = 15 is 91%

CV f1 score for k = 17 is 91%

CV f1 score for k = 19 is 91%

CV f1 score for k = 21 is 91%

CV f1 score for k = 23 is 91%

CV f1 score for k = 25 is 91%

CV f1 score for k = 27 is 91%

CV f1 score for k = 29 is 91%

CV with Max f1 score for k = 9 is 91%
[87.2813004094801, 89.7934750074828, 90.4978444457568, 90.8952514784238, 91.1
188811188811, 91.31292043609372, 91.3826031599051, 91.48567467652495, 91.4851
941467911, 91.52425340928707, 91.52152670000574, 91.46761598530088, 91.545658
03822534, 91.5944689884675, 91.56626506024097]
```

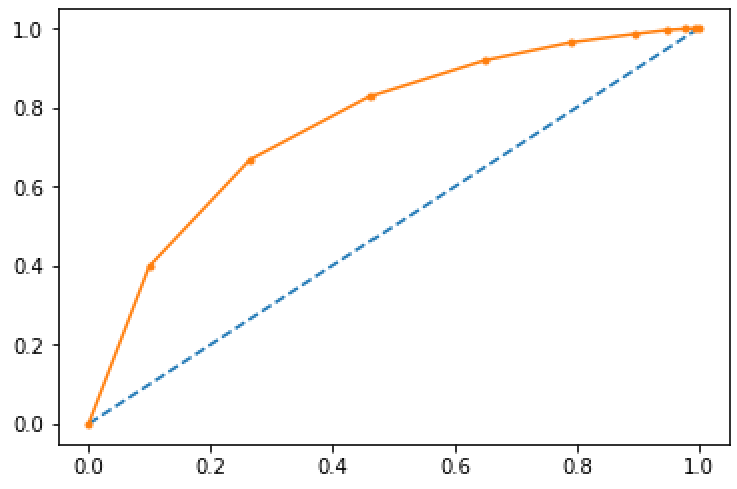


```
the misclassification error for each k value is :  [-86.281 -88.793 -89.498 -
89.895 -90.119 -90.313 -90.383 -90.486 -90.485
 -90.524 -90.522 -90.468 -90.546 -90.594 -90.566]
```

Observation: For k=9 gives most accuracy. After increasing k does not affect much.

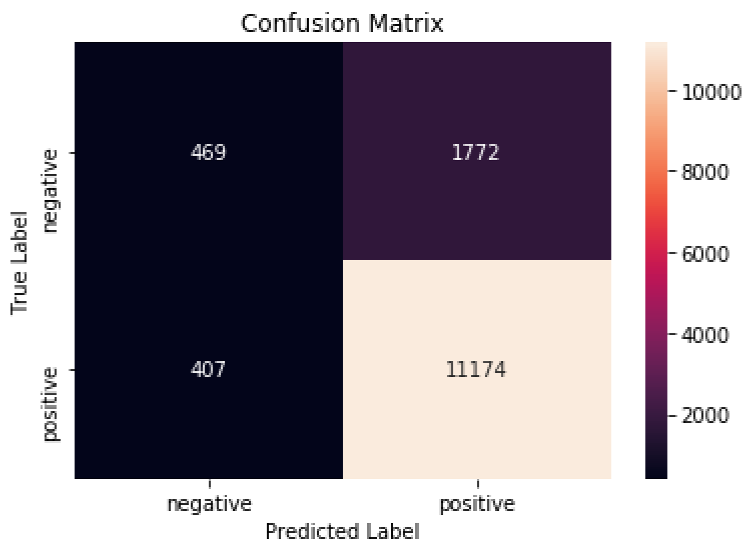
In [76]:
```
con_mat=knn_results(optimum_k,'kd_tree',tfidf_sent_vectors,tfidf_test_sent_vec
tors,y_1,y_test)
```

```
The accuracy of the knn classifier for k = 9 is 84.235277%
AUC: 0.759
```



Observation: My model predicted with auc 0.759.

In [77]:
```
showHeatMap(con_mat)
```



Observation : 407 + 1772 points classifed wrongly.

[6] Conclusions

Method	**No of samples**	**Algorithm**	**k value**	**accuray**	**AUC Score**
BOW	50000	brute	5	83	0.645
BOW	50000	kd_tree	7	83	0.729
TF-IDF	50000	brute	3	83	0.509
TF-IDF	50000	kd_tree	3	83	0.595
AVG W2VEC	50000	brute	7	82	0.696
AVG W2VEC	50000	kd_tree	7	83	0.695
TF_IDF AVG W2VEC	50000	brute	7	84	0.746
TF_IDF AVG W2VEC	50000	kd_tree	9	84	0.759