Assignment - 3 (Apply K-NN on Amazon reviews dataset)

September 5, 2018

1 OBJECTIVE :- Apply K-NN on Amazon Fine Food Reviews Dataset

2 Note :- I am completing this assignment with only 40K datapoints as my laptop got hang on 100K datapoints.

In [2]:
```
# Importing libraries
import warnings
warnings.filterwarnings("ignore")

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
%matplotlib inline
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 nltk.stem.porter import PorterStemmer

import 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
```

3 Loading Data

In [3]:
```
# using the SQLite Table to read data.
con1 = sqlite3.connect('database.sqlite')

# Eliminating neutral reviews i.e. those reviews with Score = 3
filtered_data = pd.read_sql_query(" SELECT * FROM Reviews WHERE Score != 3 ", con1)

# Give reviews with Score>3 a positive rating, and reviews with a score<3 a negative r
def polarity(x):
    if x < 3:
        return 'negative'
    return 'positive'

# Applying polarity function on Score column of filtered_data
filtered_data['Score'] = filtered_data['Score'].map(polarity)

print(filtered_data.shape)
filtered_data.head()
```

```
(525814, 10)
```

Out[3]:
```
   Id   ProductId          UserId                      ProfileName  \
0   1  B001E4KFG0  A3SGXH7AUHU8GW                       delmartian
1   2  B00813GRG4  A1D87F6ZCVE5NK                           dll pa
2   3  B000LQOCH0   ABXLMWJIXXAIN  Natalia Corres "Natalia Corres"
3   4  B000UA0QIQ  A395BORC6FGVXV                             Karl
4   5  B006K2ZZ7K  A1UQRSCLF8GW1T    Michael D. Bigham "M. Wassir"

   HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
0                     1                       1  positive  1303862400
1                     0                       0  negative  1346976000
2                     1                       1  positive  1219017600
3                     3                       3  negative  1307923200
4                     0                       0  positive  1350777600

                 Summary                                               Text
0  Good Quality Dog Food  I have bought several of the Vitality canned d...
1      Not as Advertised  Product arrived labeled as Jumbo Salted Peanut...
2  "Delight" says it all  This is a confection that has been around a fe...
3         Cough Medicine  If you are looking for the secret ingredient i...
4            Great taffy  Great taffy at a great price.  There was a wid...
```

4 Data Cleaning: Deduplication

In [4]:
```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=Fals
```

```
#Deduplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
print(final.shape)

#Checking to see how much % of data still remains
((final.shape[0]*1.0)/(filtered_data.shape[0]*1.0)*100)
```

```
(364173, 10)
```

Out[4]: 69.25890143662969

In [5]:
```
# Removing rows where HelpfulnessNumerator is greater than HelpfulnessDenominator
final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]

print(final.shape)
final[30:50]
```

```
(364171, 10)
```

Out[5]:

	Id	ProductId	UserId	\
138683	150501	0006641040	AJ46FKXOVC7NR	
138676	150493	0006641040	AMX0PJKV4PPNJ	
138682	150500	0006641040	A1IJKK6Q1GTEAY	
138681	150499	0006641040	A3E7R866M94L0C	
476617	515426	141278509X	AB1A5EGHHVA9M	
22621	24751	2734888454	A1C298ITT645B6	
22620	24750	2734888454	A13ISQV0U9GZIC	
284375	308077	2841233731	A3QD68O22M2XHQ	
157850	171161	7310172001	AFXMWPNS1BLU4	
157849	171160	7310172001	A74C7IARQEM1R	
157833	171144	7310172001	A1V5MY8V9AWUQB	
157832	171143	7310172001	A2SW060IW01VPX	
157837	171148	7310172001	A3TFTWTG2CC1GA	
157831	171142	7310172001	A2Z01AYFVQYG44	
157830	171141	7310172001	AZ40270J4JBZN	
157829	171140	7310172001	ADXXVGRCGQQUO	
157828	171139	7310172001	A13MS1JQG2ADOJ	
157827	171138	7310172001	A13LAE0YTXA11B	
157848	171159	7310172001	A16GY2RCF410DT	
157834	171145	7310172001	A1L8DNQYY69L2Z	

	ProfileName	\
138683	Nicholas A Mesiano	
138676	E. R. Bird "Ramseelbird"	
138682	A Customer	
138681	L. Barker "simienwolf"	

```
476617                                              CHelmic
22621                                     Hugh G. Pritchard
22620                                             Sandikaye
284375                                              LABRNTH
157850                                           H. Sandler
157849                                              stucker
157833                       Cheryl Sapper "champagne girl"
157832                                                  Sam
157837                                          J. Umphress
157831                               Cindy Rellie "Rellie"
157830  Zhinka Chunmee "gamer from way back in the 70's"
157829                                  Richard Pearlstein
157828                                          C. Perrone
157827                          Dita Vyslouzilova "dita"
157848                                                  LB
157834                                           R. Flores

        HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
138683                     2                       2  positive   940809600
138676                    71                      72  positive  1096416000
138682                     2                       2  positive  1009324800
138681                     2                       2  positive  1065830400
476617                     1                       1  positive  1332547200
22621                      0                       0  positive  1195948800
22620                      1                       1  negative  1192060800
284375                     0                       0  positive  1345852800
157850                     0                       0  positive  1229385600
157849                     0                       0  positive  1230076800
157833                     0                       0  positive  1244764800
157832                     0                       0  positive  1252022400
157837                     0                       0  positive  1240272000
157831                     0                       0  positive  1254960000
157830                     0                       0  positive  1264291200
157829                     0                       0  positive  1264377600
157828                     0                       0  positive  1265760000
157827                     0                       0  positive  1269216000
157848                     0                       0  positive  1231718400
157834                     0                       0  positive  1243728000

                                                  Summary  \
138683  This whole series is great way to spend time w...
138676  Read it once. Read it twice. Reading Chicken S...
138682                                It Was a favorite!
138681                                 Can't explain why
476617                                The best drink mix
22621                                  Dog Lover Delites
22620                                      made in china
284375                 Great recipe book for my babycook
```

```
157850                                    Excellent treats
157849                                     Sophie's Treats
157833                          THE BEST healthy dog treat!
157832                     My Alaskan Malamute Loves Them!!
157837                                    Best treat ever!
157831         my 12 year old maltese has always loved these
157830                    Dogs, Cats, Ferrets all love this
157829                                           5 snouts!
157828                                 Best dog treat ever
157827                           Great for puppy training
157848                                              Great!
157834                                     Terrific Treats

                                                     Text
138683  I can remember seeing the show when it aired o...
138676  These days, when a person says, "chicken soup"...
138682  This was a favorite book of mine when I was a ...
138681  This book has been a favorite of mine since I ...
476617  This product by Archer Farms is the best drink...
22621   Our dogs just love them.  I saw them in a pet ...
22620   My dogs loves this chicken but its a product f...
284375  This book is easy to read and the ingredients ...
157850  I have been feeding my greyhounds these treats...
157849  This is one product that my welsh terrier can ...
157833  This is the ONLY dog treat that my Lhasa Apso ...
157832  These liver treas are phenomenal. When i recei...
157837  This was the only treat my dog liked during ob...
157831  No waste , even if she is having a  day when s...
157830  I wanted a treat that was accepted and well li...
157829  My Westie loves these things!  She loves anyth...
157828  This is the only dog treat that my terrier wil...
157827  New puppy loves this, only treat he will pay a...
157848  My dog loves these treats!  We started using t...
157834  This is a great treat which all three of my do...
```

OBSERVATION :- Here books with ProductId - 0006641040 and 2841233731 are also there so we have to remove all these rows with these ProductIds from the data

In [6]:
```
final = final[final['ProductId'] != '2841233731']
final = final[final['ProductId'] != '0006641040']
final.shape
```

Out[6]:
```
(364136, 10)
```

5 Text Preprocessing: Stemming, stop-word removal and Lemmatization.

```
In [7]: #set of stopwords in English
        from nltk.corpus import stopwords
        stop = set(stopwords.words('english'))
        words_to_keep = set(('not'))
        stop -= words_to_keep
        #initialising the snowball stemmer
        sno = nltk.stem.SnowballStemmer('english')

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

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

In [8]: #Code for removing HTML tags , punctuations . Code for removing stopwords . Code for c
        # also greater than 2 . Code for stemmimg and also to convert them to lowercase letter
        i=0
        str1=' '
        final_string=[]
        all_positive_words=[] # store words from +ve reviews here
        all_negative_words=[] # store words from -ve reviews here.
        s=''
        for sent in final['Text'].values:
            filtered_sentence=[]
            #print(sent);
            sent=cleanhtml(sent) # remove HTMl tags
            for w in sent.split():
                for cleaned_words in cleanpunc(w).split():
                    if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                        if(cleaned_words.lower() not in stop):
                            s=(sno.stem(cleaned_words.lower())).encode('utf8')
                            filtered_sentence.append(s)
                            if (final['Score'].values)[i] == 'positive':
                                all_positive_words.append(s) #list of all words used to descri
                            if(final['Score'].values)[i] == 'negative':
                                all_negative_words.append(s) #list of all words used to descri
                        else:
                            continue
                    else:
```

```
                continue

        str1 = b" ".join(filtered_sentence) #final string of cleaned words


        final_string.append(str1)
        i+=1
```

```
In [9]: #adding a column of CleanedText which displays the data after pre-processing of the re
        final['CleanedText']=final_string
        final['CleanedText']=final['CleanedText'].str.decode("utf-8")
        #below the processed review can be seen in the CleanedText Column
        print('Shape of final',final.shape)
        final.head()
```

```
Shape of final (364136, 11)
```

```
Out[9]:              Id   ProductId          UserId        ProfileName  \
        476617  515426  141278509X   AB1A5EGHHVA9M            CHelmic
        22621    24751  2734888454  A1C298ITT645B6  Hugh G. Pritchard
        22620    24750  2734888454  A13ISQV0U9GZIC           Sandikaye
        157850  171161  7310172001   AFXMWPNS1BLU4         H. Sandler
        157849  171160  7310172001   A74C7IARQEM1R            stucker

                HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
        476617                     1                       1  positive  1332547200
        22621                      0                       0  positive  1195948800
        22620                      1                       1  negative  1192060800
        157850                     0                       0  positive  1229385600
        157849                     0                       0  positive  1230076800

                            Summary                                               Text  \
        476617  The best drink mix  This product by Archer Farms is the best drink...
        22621    Dog Lover Delites  Our dogs just love them.  I saw them in a pet ...
        22620        made in china  My dogs loves this chicken but its a product f...
        157850    Excellent treats  I have been feeding my greyhounds these treats...
        157849      Sophie's Treats  This is one product that my welsh terrier can ...

                                                      CleanedText
        476617  product archer farm best drink mix ever mix fl...
        22621   dog love saw pet store tag attach regard made ...
        22620   dog love chicken product china wont buy anymor...
        157850  feed greyhound treat year hound littl finicki ...
        157849  one product welsh terrier eat sophi food alerg...
```

6 Random Sampling Of Dataset

In [10]:
```
##Sorting data according to Time in ascending order for Time Based Splitting
time_sorted_data = final.sort_values('Time', axis=0, ascending=True, inplace=False, k

# Randomly selecting 40k datapoints

# We will collect diiferent 40k rows without repetition from time_sorted_data datafra
my_final = time_sorted_data.take(np.random.permutation(len(final))[:40000])
print(my_final.shape)
my_final.head()
```

```
(40000, 11)
```

Out[10]:
```
            Id   ProductId          UserId                       ProfileName  \
102985  111851  B000K0SH2Y   ANKCM346FMZZD                   Melissa Bernard
213868  231784  B0002W2F9K  A2W0OHJ0MZTQAI  OptimusPrimerib "OptimusPrimerib"
450464  487049  B000PDWBK0  A3G523R8W642DE                              vawn
256336  277898  B001E53WIW  A3UJO1INDG2XBF                           AMT1008
266640  289033  B00275QB0Y   AMBJQQSRCAOHS                     Scott_Andrews

        HelpfulnessNumerator  HelpfulnessDenominator     Score        Time  \
102985                     1                       1  positive  1335744000
213868                     0                       1  positive  1222300800
450464                     0                       0  positive  1324944000
256336                     0                       0  positive  1246406400
266640                     0                       0  positive  1322870400

                                  Summary  \
102985       My Favorite Chili Seasoning!
213868       Best Canned coffee out there
450464  Taste like movie theater popcorn.
256336                 excellent service
266640                     Love the taste

                                                     Text  \
102985  This chili seasoning is the best and it makes ...
213868  This is the finest coffee for caf&eacute; con ...
450464  I was really suprised at how good it tasted.  ...
256336  I am addicted to this tea - hot & iced - and h...
266640  Love the natural smoke flavor, adds great flav...

                                              CleanedText
102985  chili season best make make chili easi use veg...
213868  finest coffe con lech stovetop coffe make etc ...
450464  realli supris good tast kernel didnt pop defin...
256336  addict tea hot ice difficult time find price g...
266640  love natur smoke flavor add great flavor meat ...
```

```
In [11]: # Sample dataset
         my_final['Score'].value_counts()
```

```
Out[11]: positive    33674
         negative     6326
         Name: Score, dtype: int64
```

```
In [12]: # Original dataset
         final['Score'].value_counts()
```

```
Out[12]: positive    307028
         negative     57108
         Name: Score, dtype: int64
```

```
In [13]: # Ratio of positive reviews to negative reviews in Sample Dataset
         len(my_final[my_final['Score'] == 'positive'])/len(my_final[my_final['Score'] == 'nega
```

```
Out[13]: 5.323110970597534
```

```
In [14]: # Ratio of positive reviews to negative reviews in Original Dataset
         len(final[final['Score'] == 'positive'])/len(final[final['Score'] == 'negative'])
```

```
Out[14]: 5.37626952440989
```

OBSERVATION FOR RATIO : Ratio of positive reviews to negative reviews in Sample Dataset is approximately similar to ratio of positive reviews to negative reviews in Original Dataset

SPLITTING OF SAMPLE DATASET INTO TRAIN_DATA AND TEST_DATA

```
In [15]: from sklearn.model_selection import train_test_split


         x = my_final['CleanedText'].values
         y = my_final['Score']

         # split the data set into train and test
         X_train, X_test, Y_train, Y_test = train_test_split(x, y, test_size=0.3, random_state
```

7 (1). Bag of Words (BoW)

```
In [16]: #BoW
         count_vect = CountVectorizer(min_df = 50)
         X_train_vec = count_vect.fit_transform(X_train)
         X_test_vec = count_vect.transform(X_test)
         print("the type of count vectorizer :",type(X_train_vec))
         print("the shape of out text BOW vectorizer : ",X_train_vec.get_shape())
         print("the number of unique words :", X_train_vec.get_shape()[1])
```

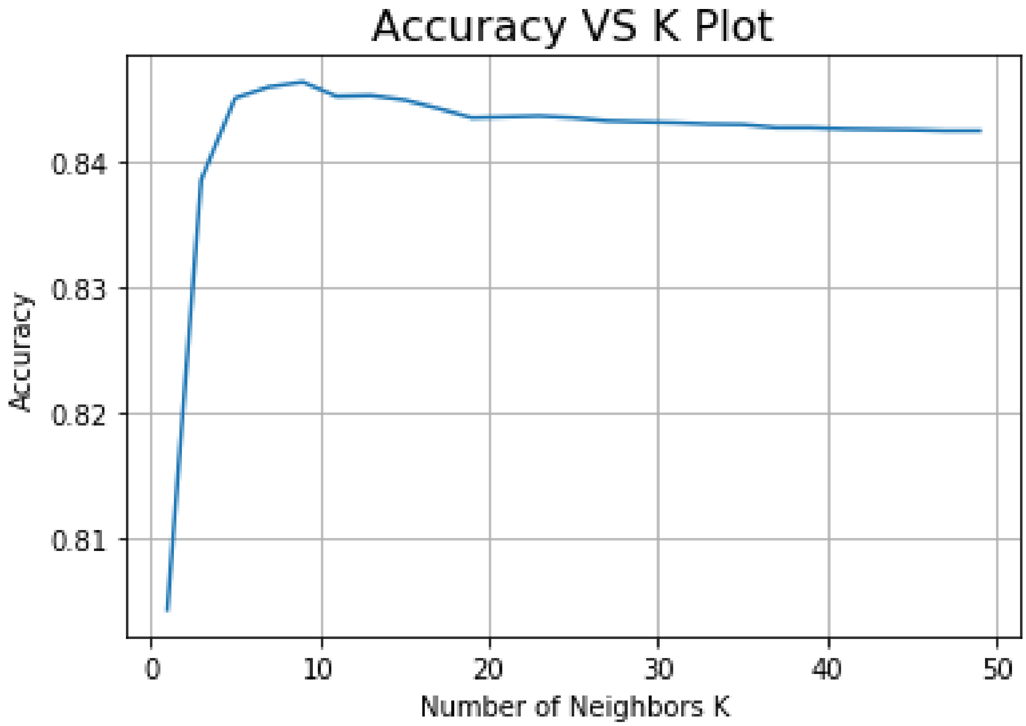
```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer :  (28000, 1988)
the number of unique words : 1988
```

8 3 Fold Cross-Validation (Brute force implementation)

In [17]:
```
# Importing libraries
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score,confusion_matrix
from sklearn.model_selection import cross_val_score

# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

# empty list that will hold cv scores
cv_scores = []

# perform 3-fold cross validation
for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors=k, algorithm='brute')
    scores = cross_val_score(knn, X_train_vec, Y_train, cv=3, scoring='accuracy', n_jo
    cv_scores.append(scores.mean())

# determining best k
optimal_k = neighbors[cv_scores.index(max(cv_scores))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)
```

```
The optimal number of neighbors is 9.
```

In [18]:
```
# plot accuracy vs k
plt.plot(neighbors, cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('Accuracy')
plt.title('Accuracy VS K Plot',size=16)
plt.grid()
plt.show()

print("\n Accuracy for each k value is : ", np.round(cv_scores,3))
```



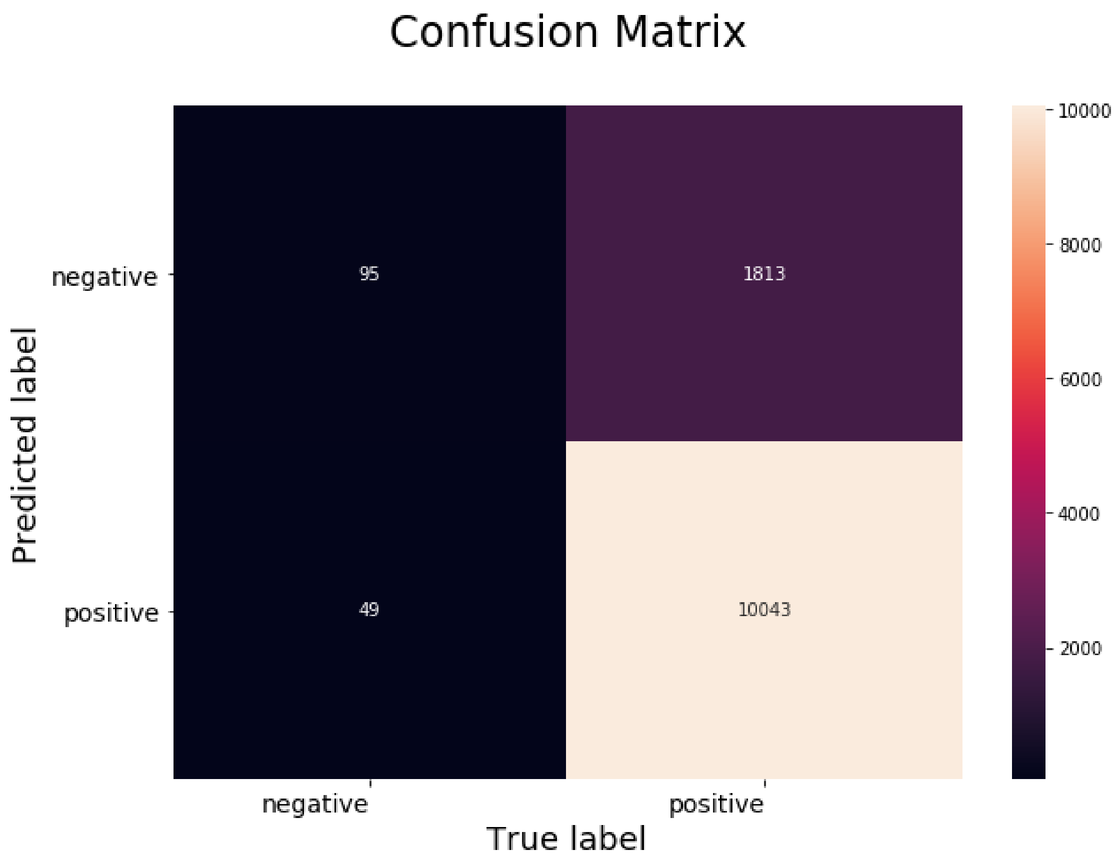

```
Accuracy for each k value is :  [0.804 0.839 0.845 0.846 0.846 0.845 0.845 0.845 0.844 0.844 0
0.844 0.843 0.843 0.843 0.843 0.843 0.843 0.843 0.843 0.843 0.843 0.843
0.843]
```

In [19]:
```
# ============================== KNN with k = optimal_k ==============================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k, algorithm='brute', n_jobs=-1

# fitting the model
knn_optimal.fit(X_train_vec, Y_train)

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

# evaluate accuracy
acc = accuracy_score(Y_test, pred) * 100
print('\nThe Test Accuracy of the K-NN classifier for k = %d is %f%%' % (optimal_k, ac

# Variables that will be used for  making table in Conclusion part of this assignment
bow_brute_K = optimal_k
bow_brute_train_acc = max(cv_scores)*100
bow_brute_test_acc = acc
```

```
The Test Accuracy of the K-NN classifier for k = 9 is 84.483333%
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [20]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, pred), index=class_names, columns=c
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

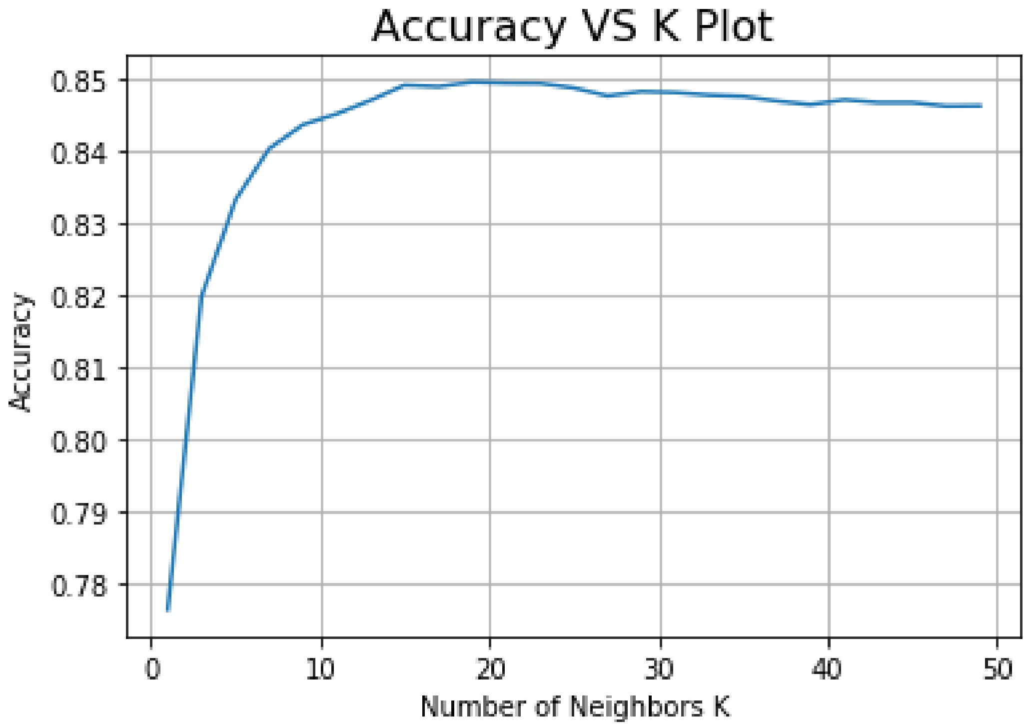


9 3 Fold Cross-Validation (kd_tree implementation)

```
In [21]: from sklearn.decomposition import TruncatedSVD
         svd = TruncatedSVD(n_components=100)
         X_train_vec_dense = svd.fit_transform(X_train_vec)
         X_test_vec_dense = svd.transform(X_test_vec)


         # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))

         # empty list that will hold cv scores
         cv_scores = []

         # perform 3-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
             scores = cross_val_score(knn, X_train_vec_dense, Y_train, cv=3, scoring='accuracy
             cv_scores.append(scores.mean())

         # determining best k
         optimal_k = neighbors[cv_scores.index(max(cv_scores))]
         print('\nThe optimal number of neighbors is %d.' % optimal_k)
```

```
The optimal number of neighbors is 19.
```

```
In [22]: # plot accuracy vs k
         plt.plot(neighbors, cv_scores)
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Accuracy')
         plt.title('Accuracy VS K Plot',size=16)
         plt.grid()
         plt.show()

         print("\n Accuracy for each k value is : ", np.round(cv_scores,3))
```



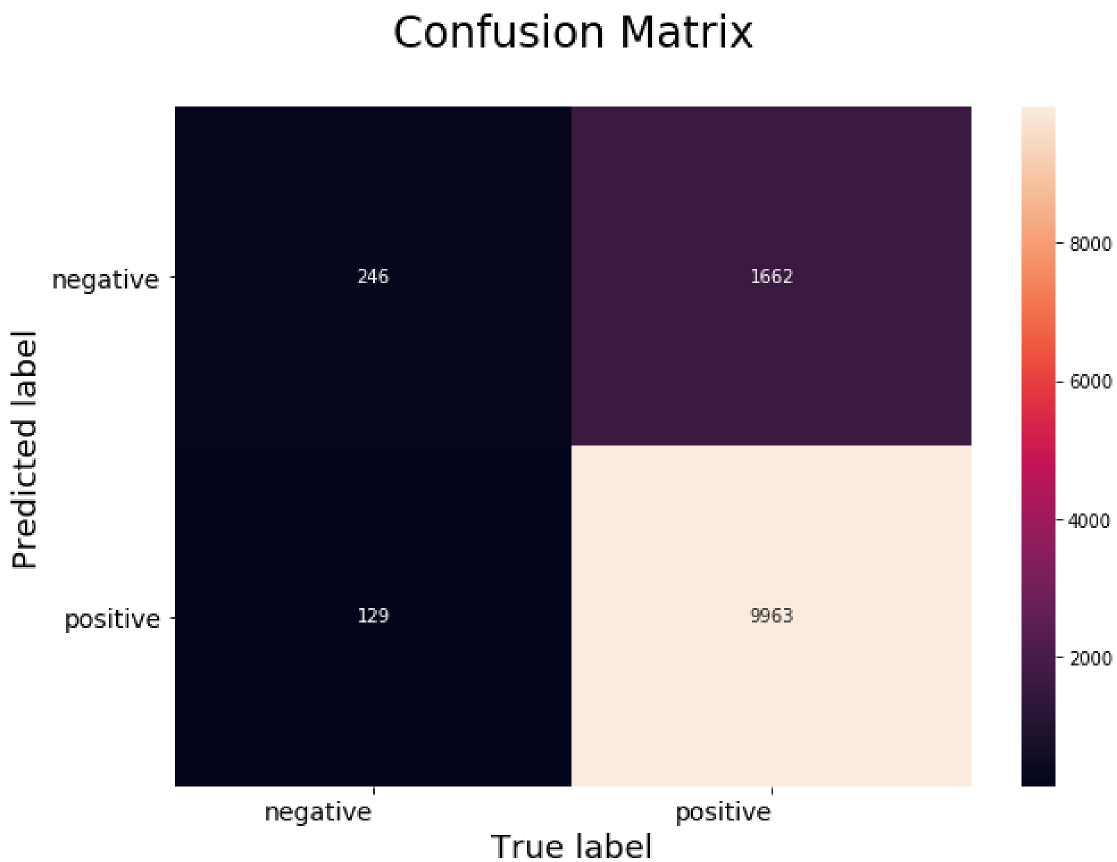

```
Accuracy for each k value is :  [0.776 0.82  0.833 0.84  0.844 0.845 0.847 0.849 0.849 0.85  0
0.849 0.848 0.848 0.848 0.848 0.848 0.847 0.846 0.847 0.847 0.847 0.846
0.846]
```

In [23]:
```
# ============================== KNN with k = optimal_k ==============================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k, algorithm='kd_tree', n_jobs=

# fitting the model
knn_optimal.fit(X_train_vec_dense, Y_train)

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

# evaluate accuracy
acc = accuracy_score(Y_test, pred) * 100
print('\nThe Test Accuracy of the K-NN classifier for k = %d is %f%%' % (optimal_k, ac

# Variables that will be used for  making table in Conclusion part of this assignment
bow_kdTree_K = optimal_k
bow_kdTree_train_acc = max(cv_scores)*100
bow_kdTree_test_acc = acc
```

```
The Test Accuracy of the K-NN classifier for k = 19 is 85.075000%
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [24]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, pred), index=class_names, columns=c
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



10 (2). TF-IDF

```
In [25]: tf_idf_vect = TfidfVectorizer(min_df=50)
         X_train_vec = tf_idf_vect.fit_transform(X_train)
         X_test_vec = tf_idf_vect.transform(X_test)
         print("the type of count vectorizer :",type(X_train_vec))
         print("the shape of out text TFIDF vectorizer : ",X_train_vec.get_shape())
         print("the number of unique words :", X_train_vec.get_shape()[1])
```

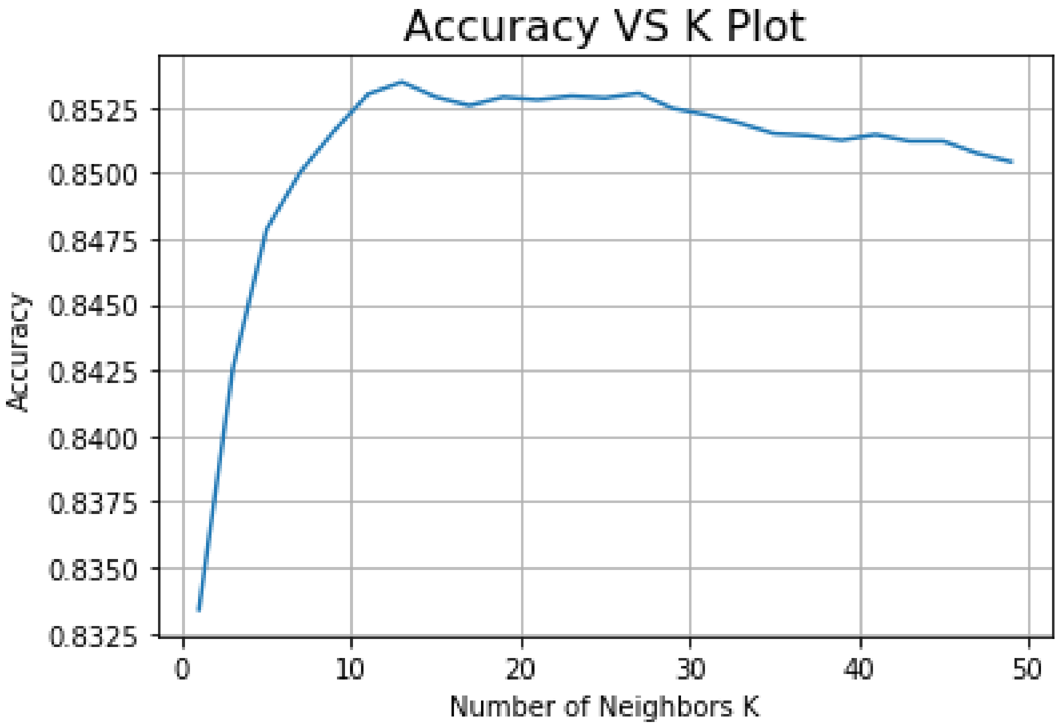
```
the type of count vectorizer : <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text TFIDF vectorizer :  (28000, 1988)
the number of unique words : 1988
```

11 3 Fold Cross-Validation (Brute force implementation)

```
In [26]: # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))

         # empty list that will hold cv scores
         cv_scores = []

         # perform 3-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k, algorithm='brute')
             scores = cross_val_score(knn, X_train_vec, Y_train, cv=3, scoring='accuracy', n_jo
             cv_scores.append(scores.mean())

         # determining best k
         optimal_k = neighbors[cv_scores.index(max(cv_scores))]
         print('\nThe optimal number of neighbors is %d.' % optimal_k)
```

```
The optimal number of neighbors is 13.
```

```
In [27]: # plot accuracy vs k
         plt.plot(neighbors, cv_scores)
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Accuracy')
         plt.title('Accuracy VS K Plot',size=16)
         plt.grid()
         plt.show()

         print("\n Accuracy for each k value is : ", np.round(cv_scores,3))
```



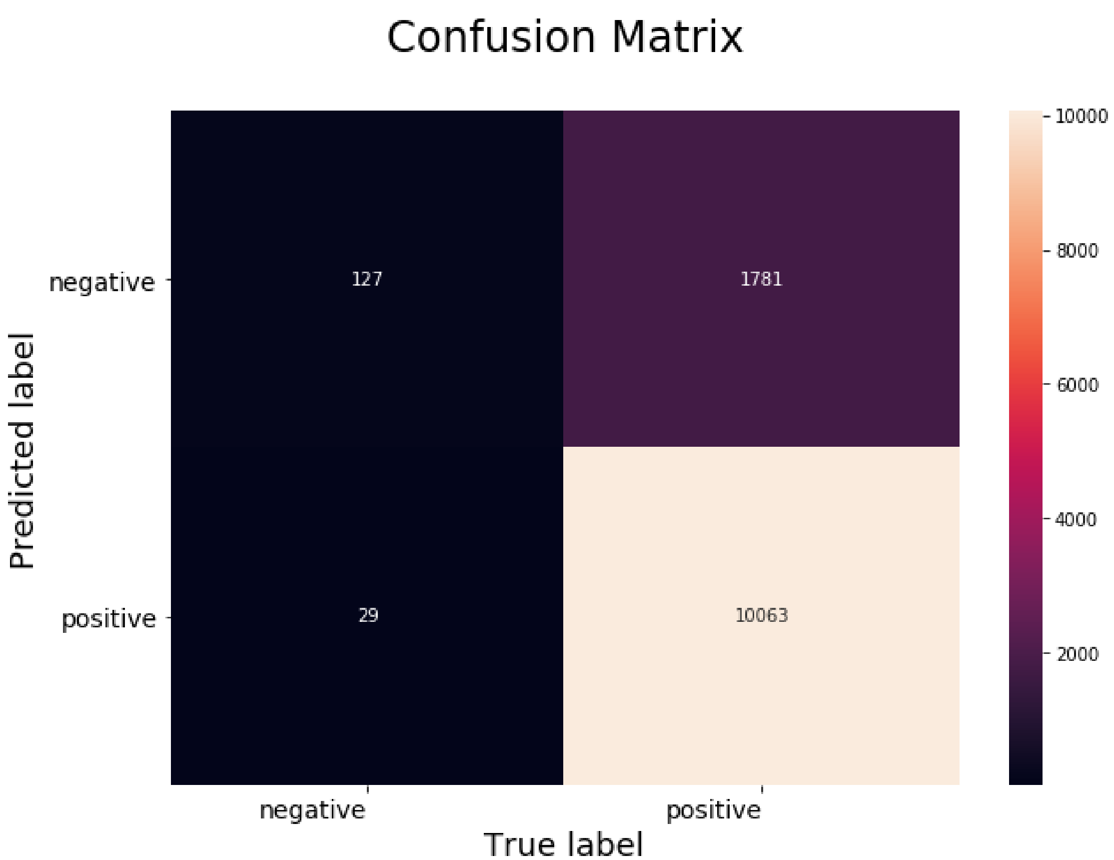

```
Accuracy for each k value is :  [0.833 0.843 0.848 0.85  0.852 0.853 0.853 0.853 0.853 0.853 0
0.853 0.853 0.852 0.852 0.852 0.851 0.851 0.851 0.851 0.851 0.851 0.851
0.85 ]
```

In [28]:
```
# =============================== KNN with k = optimal_k ===============================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k, algorithm='brute', n_jobs=-1

# fitting the model
knn_optimal.fit(X_train_vec, Y_train)

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

# evaluate accuracy
acc = accuracy_score(Y_test, pred) * 100
print('\nThe Test Accuracy of the K-NN classifier for k = %d is %f%%' % (optimal_k, ac

# Variables that will be used for  making table in Conclusion part of this assignment
tfidf_brute_K = optimal_k
tfidf_brute_train_acc = max(cv_scores)*100
tfidf_brute_test_acc = acc
```

```
The Test Accuracy of the K-NN classifier for k = 13 is 84.916667%
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [29]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, pred), index=class_names, columns=c
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

         # Setting tick labels for heatmap
         heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```

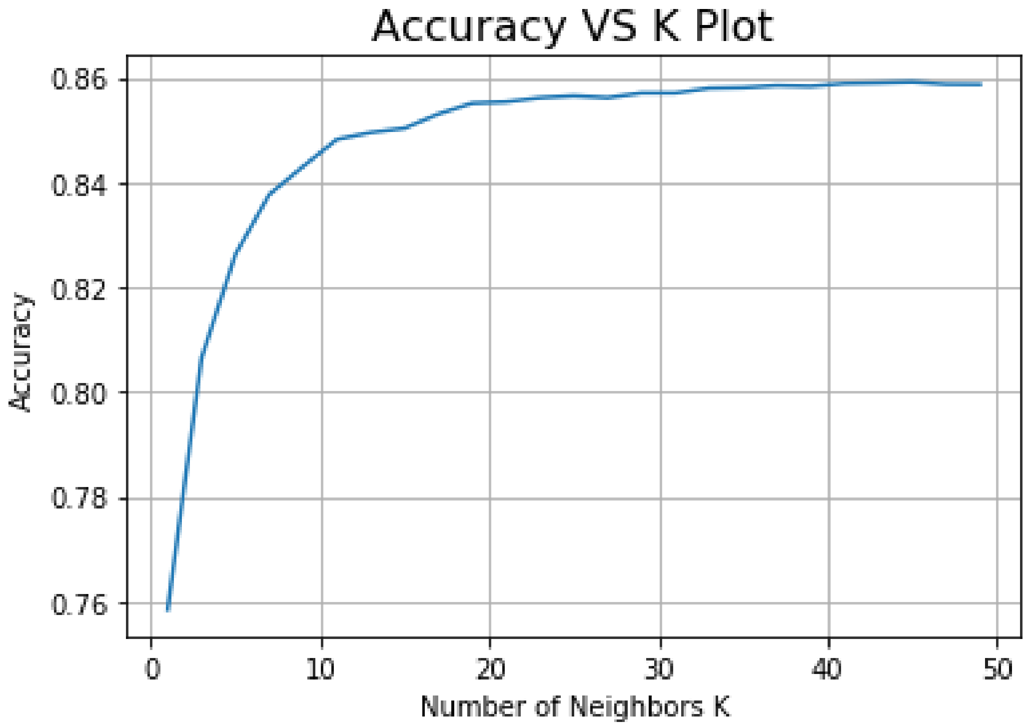


12 3 Fold Cross-Validation (kd_tree implementation)

In [30]:
```
svd = TruncatedSVD(n_components=100)
X_train_vec_dense = svd.fit_transform(X_train_vec)
X_test_vec_dense = svd.transform(X_test_vec)

# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

# empty list that will hold cv scores
cv_scores = []

# perform 3-fold cross validation
for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
    scores = cross_val_score(knn, X_train_vec_dense, Y_train, cv=3, scoring='accuracy
    cv_scores.append(scores.mean())

# determining best k
optimal_k = neighbors[cv_scores.index(max(cv_scores))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)
```

```
The optimal number of neighbors is 45.
```

In [31]:
```
# plot accuracy vs k
plt.plot(neighbors, cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('Accuracy')
plt.title('Accuracy VS K Plot',size=16)
plt.grid()
plt.show()

print("\n Accuracy for each k value is : ", np.round(cv_scores,3))
```



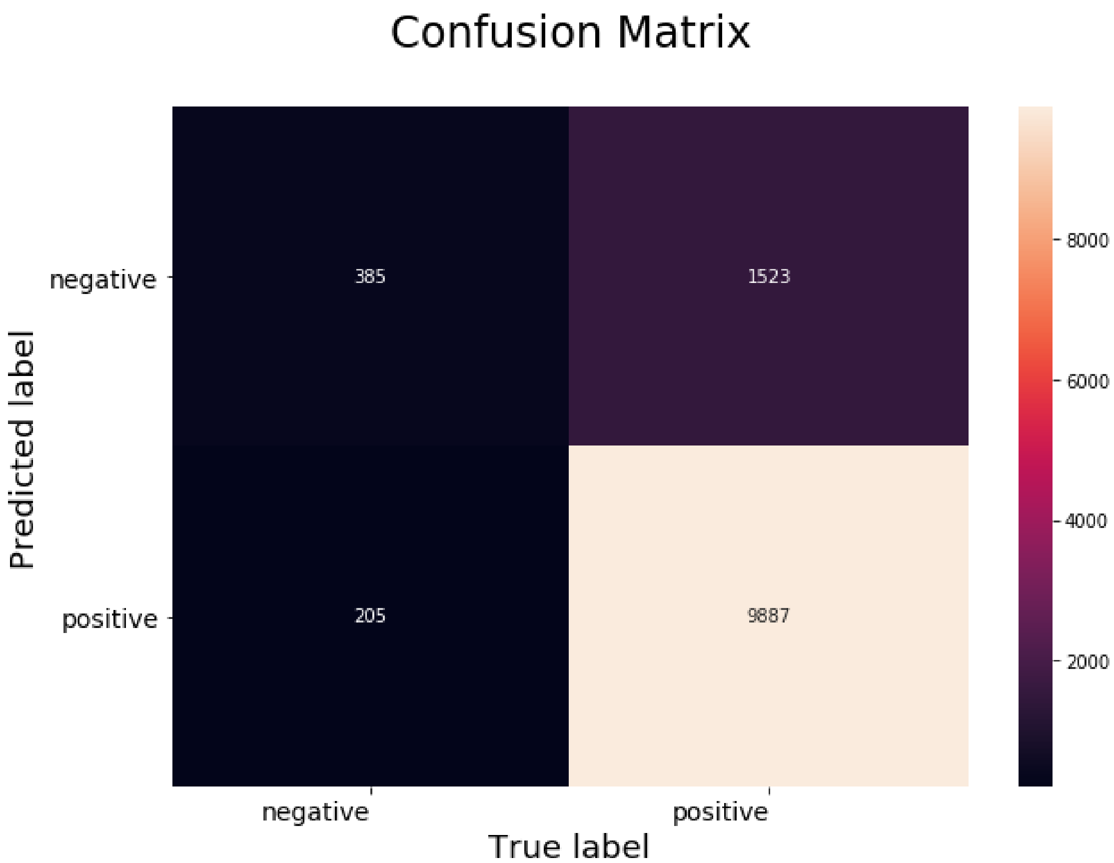

```
Accuracy for each k value is :  [0.758 0.806 0.826 0.838 0.843 0.848 0.85  0.85  0.853 0.855 0
0.857 0.856 0.857 0.857 0.858 0.858 0.858 0.858 0.859 0.859 0.859 0.859
0.859]
```

In [32]:
```
# ============================== KNN with k = optimal_k ==============================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k, algorithm='kd_tree', n_jobs=

# fitting the model
knn_optimal.fit(X_train_vec_dense, Y_train)

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

# evaluate accuracy
acc = accuracy_score(Y_test, pred) * 100
print('\nThe Test Accuracy of the K-NN classifier for k = %d is %f%%' % (optimal_k, ac

# Variables that will be used for  making table in Conclusion part of this assignment
tfidf_kdTree_K = optimal_k
tfidf_kdTree_train_acc = max(cv_scores)*100
tfidf_kdTree_test_acc = acc
```

```
The Test Accuracy of the K-NN classifier for k = 45 is 85.600000%
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [33]:
```
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, pred), index=class_names, columns=c
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```



13 Word2Vec

In [34]:
```
# List of sentence in X_train text
sent_of_train=[]
for sent in X_train:
    sent_of_train.append(sent.split())

# List of sentence in X_est text
sent_of_test=[]
for sent in X_test:
    sent_of_test.append(sent.split())

# Train your own Word2Vec model using your own train text corpus
# min_count = 5 considers only words that occured atleast 5 times
w2v_model=Word2Vec(sent_of_train,min_count=5,size=50, workers=4)

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occured minimum 5 times ",len(w2v_words))
```

```
number of words that occured minimum 5 times  7211
```

14 (3). Avg Word2Vec

In [35]:
```
# compute average word2vec for each review for X_train .
train_vectors = [];
for sent in sent_of_train:
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    train_vectors.append(sent_vec)

# compute average word2vec for each review for X_test .
test_vectors = [];
for sent in sent_of_test:
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
```

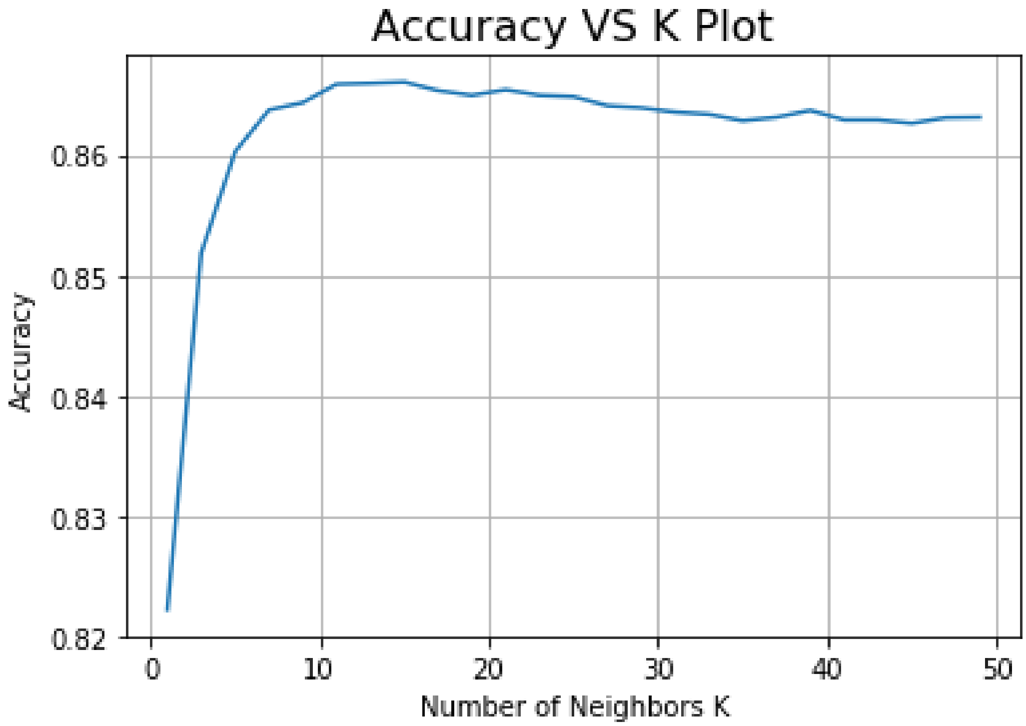
```
        if cnt_words != 0:
            sent_vec /= cnt_words
        test_vectors.append(sent_vec)
```

15 3 Fold Cross-Validation (Brute force implementation)

```
In [36]: # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))

         # empty list that will hold cv scores
         cv_scores = []

         # perform 3-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k, algorithm='brute')
             scores = cross_val_score(knn, train_vectors, Y_train, cv=3, scoring='accuracy', n_
             cv_scores.append(scores.mean())

         # determining best k
         optimal_k = neighbors[cv_scores.index(max(cv_scores))]
         print('\nThe optimal number of neighbors is %d.' % optimal_k)
```

```
The optimal number of neighbors is 15.
```

```
In [37]: # plot accuracy vs k
         plt.plot(neighbors, cv_scores)
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Accuracy')
         plt.title('Accuracy VS K Plot',size=16)
         plt.grid()
         plt.show()

         print("\n Accuracy for each k value is : ", np.round(cv_scores,3))
```



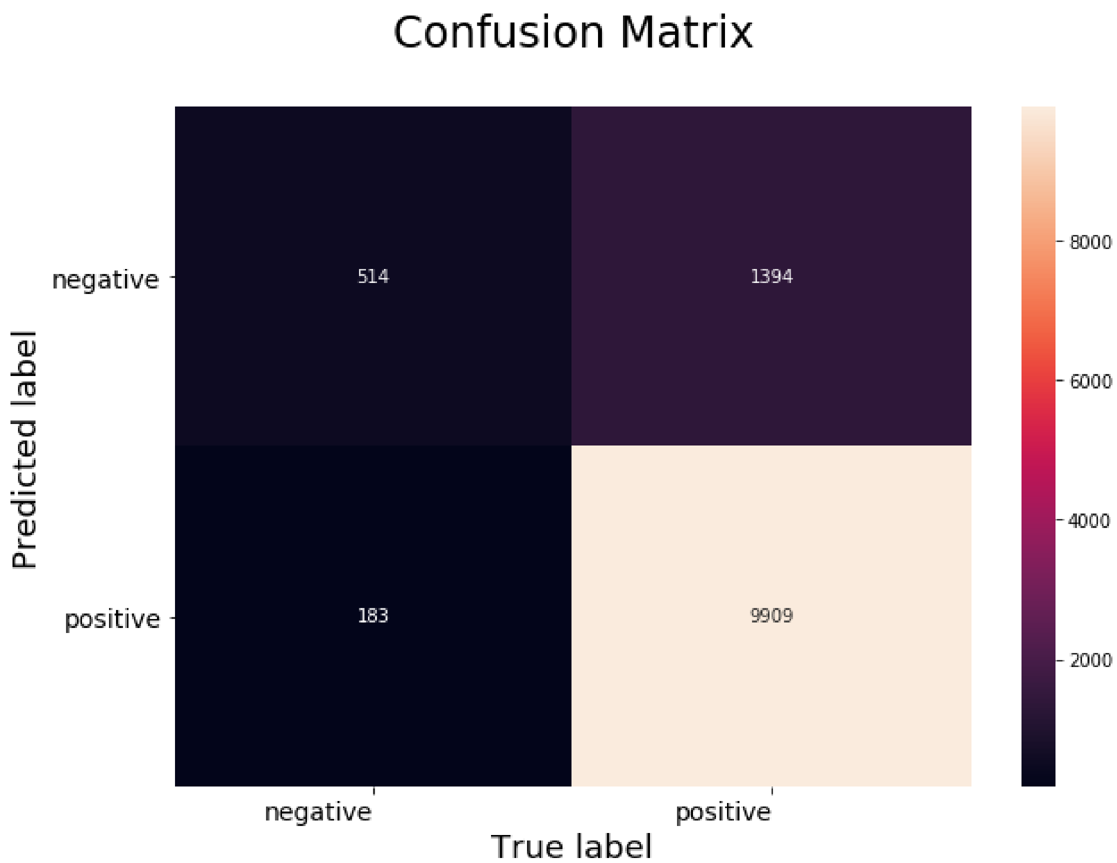

```
Accuracy for each k value is :  [0.822 0.852 0.86  0.864 0.864 0.866 0.866 0.866 0.865 0.865 0
0.865 0.864 0.864 0.864 0.863 0.863 0.863 0.864 0.863 0.863 0.863 0.863
0.863]
```

In [38]:
```
# =============================== KNN with k = optimal_k ===============================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k, algorithm='brute', n_jobs=-1

# fitting the model
knn_optimal.fit(train_vectors, Y_train)

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

# evaluate accuracy
acc = accuracy_score(Y_test, pred) * 100
print('\nThe Test Accuracy of the K-NN classifier for k = %d is %f%%' % (optimal_k, ac

# Variables that will be used for  making table in Conclusion part of this assignment
Avg_Word2Vec_brute_K = optimal_k
Avg_Word2Vec_brute_train_acc = max(cv_scores)*100
Avg_word2Vec_brute_test_acc = acc
```

```
The Test Accuracy of the K-NN classifier for k = 15 is 86.858333%
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

In [39]:
```python
# Code for drawing seaborn heatmaps
class_names = ['negative','positive']
df_heatmap = pd.DataFrame(confusion_matrix(Y_test, pred), index=class_names, columns=c
fig = plt.figure(figsize=(10,7))
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

# Setting tick labels for heatmap
heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
plt.ylabel('Predicted label',size=18)
plt.xlabel('True label',size=18)
plt.title("Confusion Matrix\n",size=24)
plt.show()
```

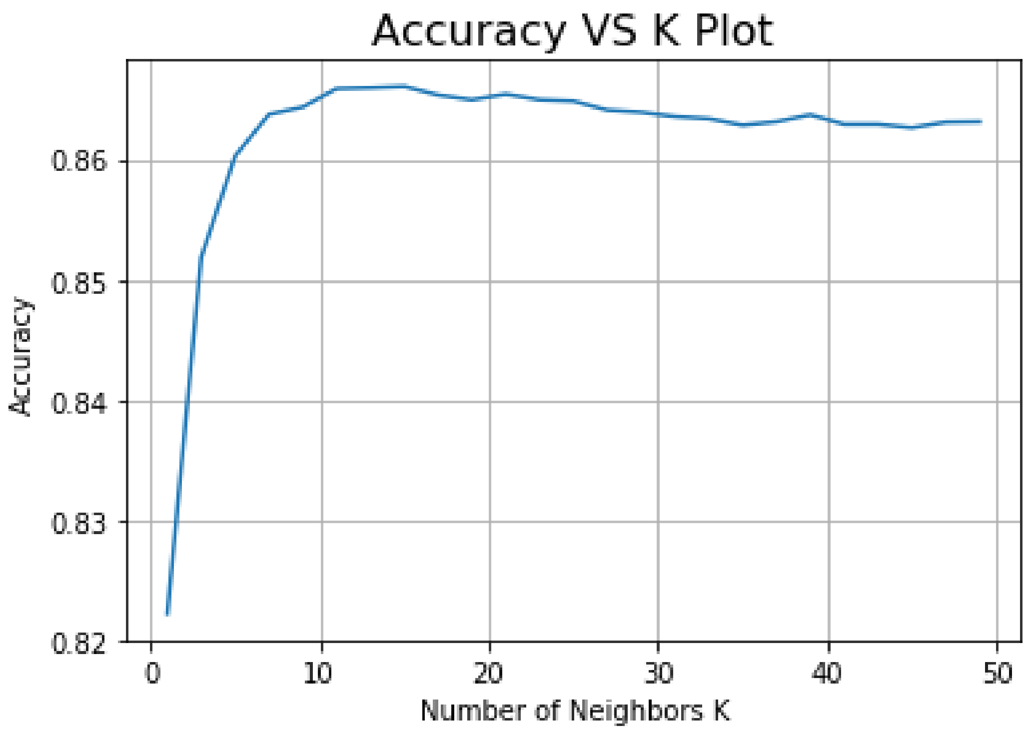


16 3 Fold Cross-Validation (kd_tree implementation)

In [40]:
```
# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

# empty list that will hold cv scores
cv_scores = []

# perform 3-fold cross validation
for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
    scores = cross_val_score(knn, train_vectors, Y_train, cv=3, scoring='accuracy', n
    cv_scores.append(scores.mean())

# determining best k
optimal_k = neighbors[cv_scores.index(max(cv_scores))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)
```

```
The optimal number of neighbors is 15.
```

In [41]:
```
# plot accuracy vs k
plt.plot(neighbors, cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('Accuracy')
plt.title('Accuracy VS K Plot',size=16)
plt.grid()
plt.show()

print("\n Accuracy for each k value is : ", np.round(cv_scores,3))
```



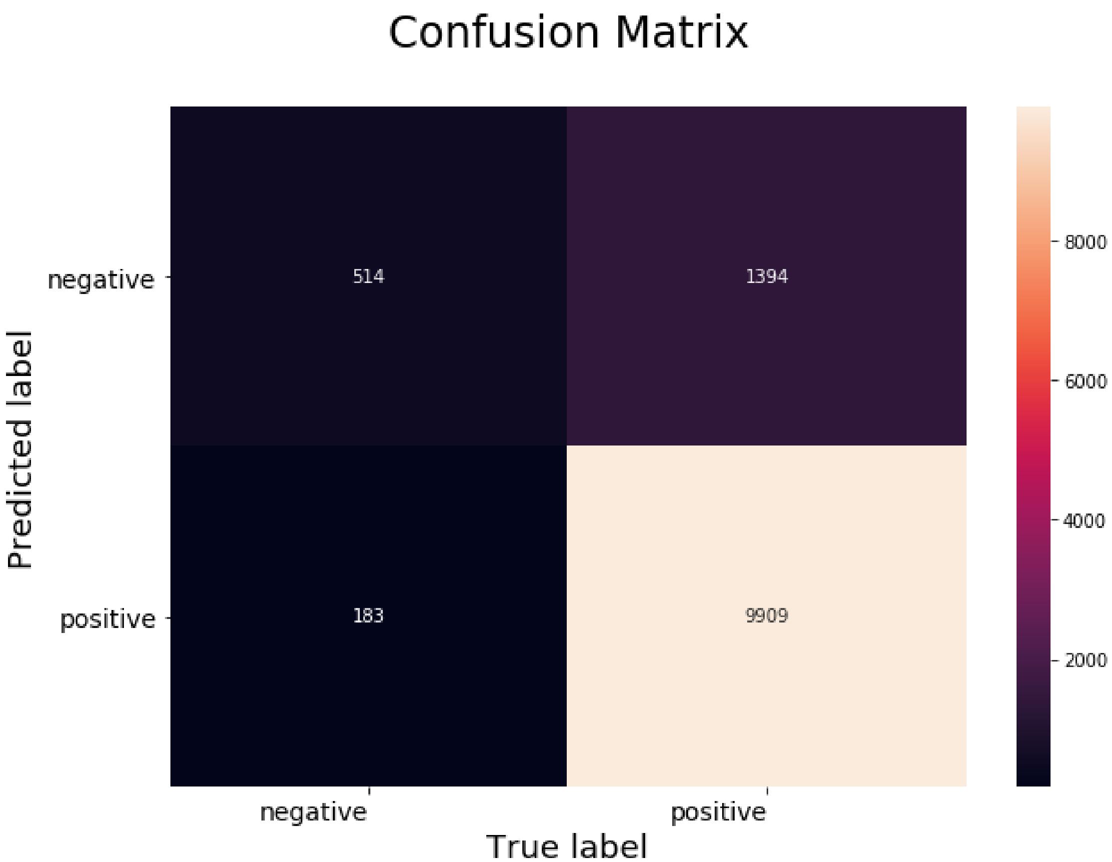

```
Accuracy for each k value is :  [0.822 0.852 0.86  0.864 0.864 0.866 0.866 0.866 0.865 0.865 (
0.865 0.864 0.864 0.864 0.863 0.863 0.863 0.864 0.863 0.863 0.863 0.863
0.863]
```

In [42]:
```
# ============================== KNN with k = optimal_k ==============================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k, algorithm='kd_tree', n_jobs=

# fitting the model
knn_optimal.fit(train_vectors, Y_train)

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

# evaluate accuracy
acc = accuracy_score(Y_test, pred) * 100
print('\nThe Test Accuracy of the K-NN classifier for k = %d is %f%%' % (optimal_k, ac

# Variables that will be used for  making table in Conclusion part of this assignment
Avg_Word2Vec_kdTree_K = optimal_k
Avg_Word2Vec_kdTree_train_acc = max(cv_scores)*100
Avg_Word2Vec_kdTree_test_acc = acc
```

```
The Test Accuracy of the K-NN classifier for k = 15 is 86.858333%
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [43]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, pred), index=class_names, columns=c
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

         # Setting tick labels for heatmap
         heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```



17 (4). TFIDF-Word2Vec

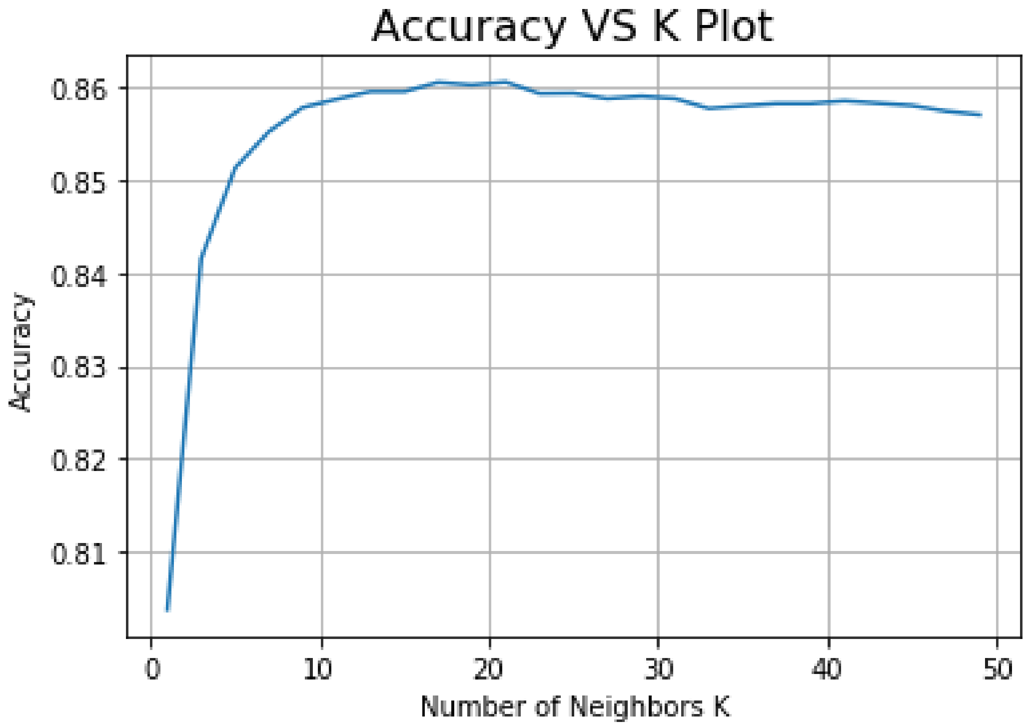
In [44]:
```
# TF-IDF weighted Word2Vec
tf_idf_vect = TfidfVectorizer()

# final_tf_idf1 is the sparse matrix with row= sentence, col=word and cell_val = tfid
final_tf_idf1 = tf_idf_vect.fit_transform(X_train)

# tfidf words/col-names
tfidf_feat = tf_idf_vect.get_feature_names()

# compute TFIDF Weighted Word2Vec for each review for X_test .
tfidf_test_vectors = [];
row=0;
for sent in sent_of_test:
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = final_tf_idf1[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_test_vectors.append(sent_vec)
    row += 1

# compute TFIDF Weighted Word2Vec for each review for X_train .
tfidf_train_vectors = [];
row=0;
for sent in sent_of_train:
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        if word in w2v_words:
            vec = w2v_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = final_tf_idf1[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_train_vectors.append(sent_vec)
    row += 1
```

18 3 Fold Cross-Validation (Brute force implementation)

```
In [45]: # creating odd list of K for KNN
         myList = list(range(0,50))
         neighbors = list(filter(lambda x: x % 2 != 0, myList))

         # empty list that will hold cv scores
         cv_scores = []

         # perform 3-fold cross validation
         for k in neighbors:
             knn = KNeighborsClassifier(n_neighbors=k, algorithm='brute')
             scores = cross_val_score(knn, tfidf_train_vectors, Y_train, cv=3, scoring='accura
             cv_scores.append(scores.mean())

         # determining best k
         optimal_k = neighbors[cv_scores.index(max(cv_scores))]
         print('\nThe optimal number of neighbors is %d.' % optimal_k)
```

```
The optimal number of neighbors is 21.
```

```
In [46]: # plot accuracy vs k
         plt.plot(neighbors, cv_scores)
         plt.xlabel('Number of Neighbors K')
         plt.ylabel('Accuracy')
         plt.title('Accuracy VS K Plot',size=16)
         plt.grid()
         plt.show()

         print("\n Accuracy for each k value is : ", np.round(cv_scores,3))
```



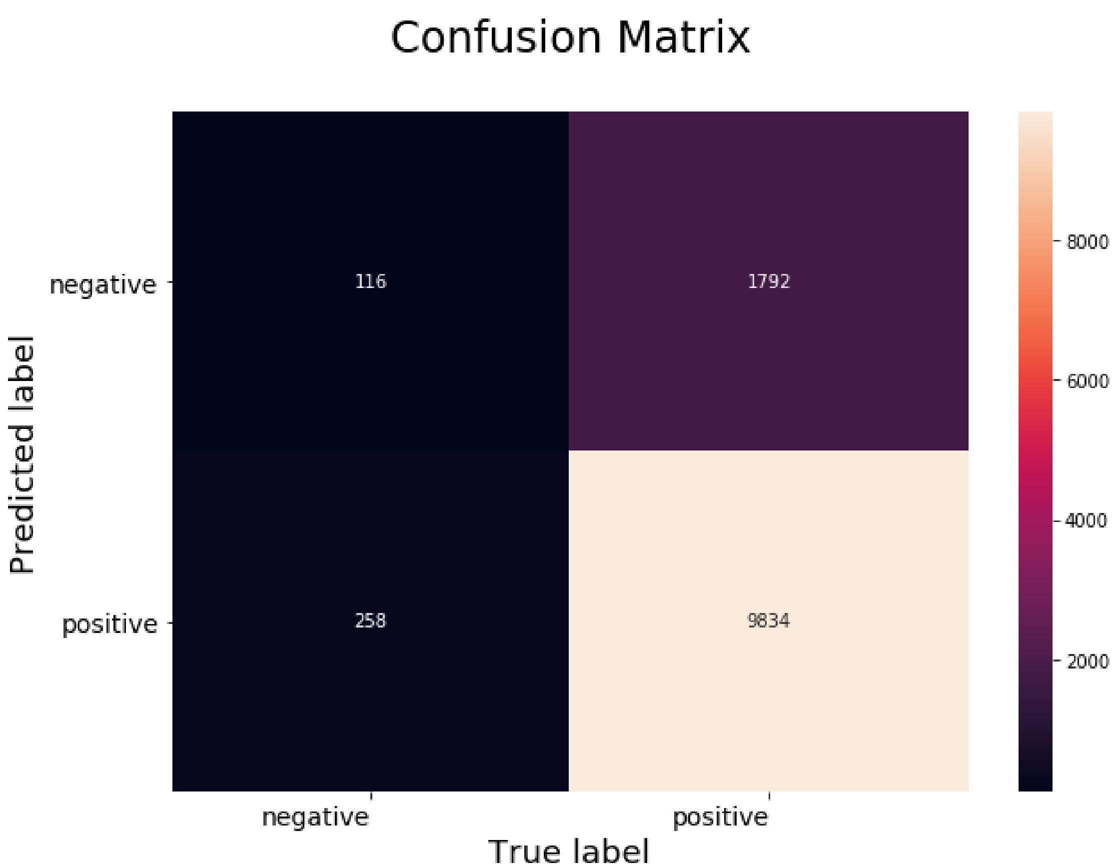

```
Accuracy for each k value is :  [0.804 0.842 0.851 0.855 0.858 0.859 0.86  0.86  0.861 0.86  0
0.859 0.859 0.859 0.859 0.858 0.858 0.858 0.858 0.859 0.858 0.858 0.857
0.857]
```

In [47]:
```
# ============================== KNN with k = optimal_k ==============================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k, algorithm='brute', n_jobs=-1

# fitting the model
knn_optimal.fit(tfidf_train_vectors, Y_train)

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

# evaluate accuracy
acc = accuracy_score(Y_test, pred) * 100
print('\nThe Test Accuracy of the K-NN classifier for k = %d is %f%%' % (optimal_k, ac

# Variables that will be used for  making table in Conclusion part of this assignment
TFIDF_Word2Vec_brute_K = optimal_k
TFIDF_Word2Vec_brute_train_acc = max(cv_scores)*100
TFIDF_word2Vec_brute_test_acc = acc
```

```
The Test Accuracy of the K-NN classifier for k = 21 is 82.916667%
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [48]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, pred), index=class_names, columns=c
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

         # Setting tick labels for heatmap
         heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```

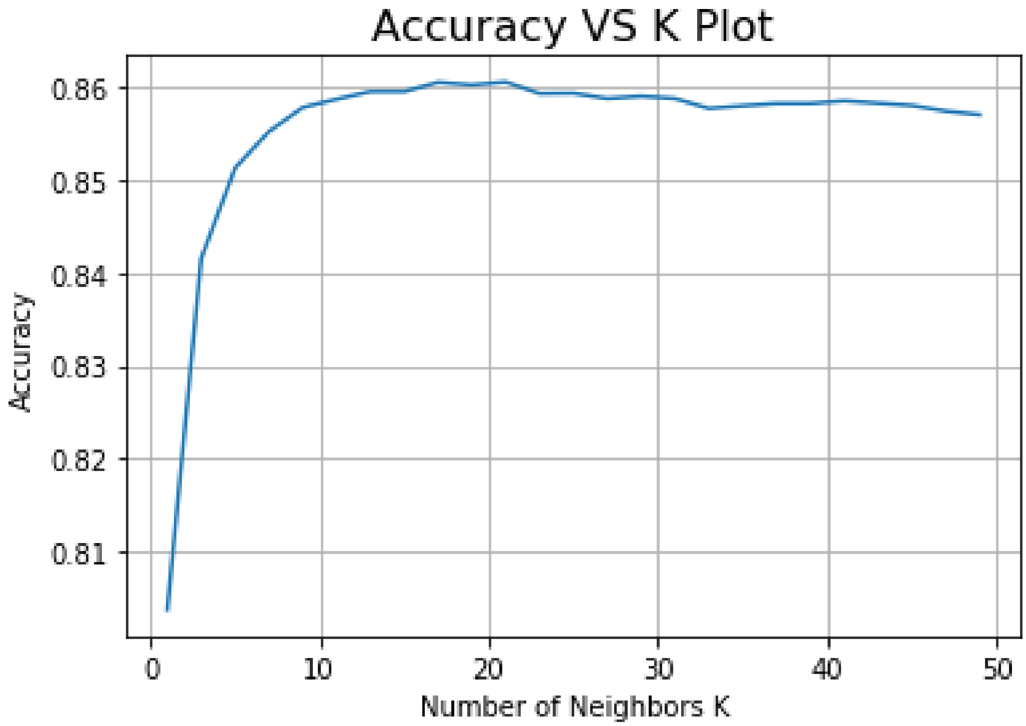


19 3 Fold Cross-Validation (kd_tree implementation)

In [49]:
```
# creating odd list of K for KNN
myList = list(range(0,50))
neighbors = list(filter(lambda x: x % 2 != 0, myList))

# empty list that will hold cv scores
cv_scores = []

# perform 3-fold cross validation
for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
    scores = cross_val_score(knn, tfidf_train_vectors, Y_train, cv=3, scoring='accura
    cv_scores.append(scores.mean())

# determining best k
optimal_k = neighbors[cv_scores.index(max(cv_scores))]
print('\nThe optimal number of neighbors is %d.' % optimal_k)
```

```
The optimal number of neighbors is 21.
```

In [50]:
```
# plot accuracy vs k
plt.plot(neighbors, cv_scores)
plt.xlabel('Number of Neighbors K')
plt.ylabel('Accuracy')
plt.title('Accuracy VS K Plot',size=16)
plt.grid()
plt.show()

print("\n Accuracy for each k value is : ", np.round(cv_scores,3))
```



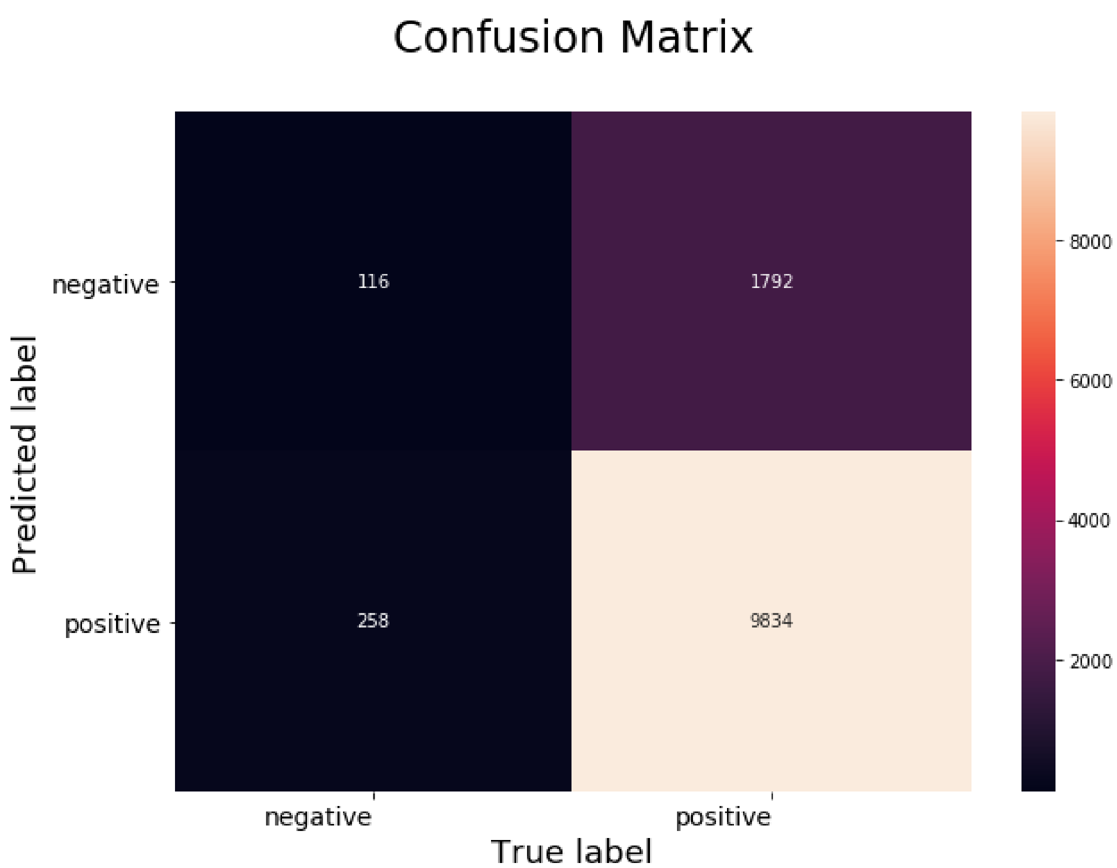

```
Accuracy for each k value is :  [0.804 0.842 0.851 0.855 0.858 0.859 0.86  0.86  0.861 0.86  0
0.859 0.859 0.859 0.859 0.858 0.858 0.858 0.858 0.859 0.858 0.858 0.857
0.857]
```

In [51]:
```
# ============================== KNN with k = optimal_k ==============================
# instantiate learning model k = optimal_k
knn_optimal = KNeighborsClassifier(n_neighbors=optimal_k, algorithm='kd_tree', n_jobs=

# fitting the model
knn_optimal.fit(tfidf_train_vectors, Y_train)

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

# evaluate accuracy
acc = accuracy_score(Y_test, pred) * 100
print('\nThe Test Accuracy of the K-NN classifier for k = %d is %f%%' % (optimal_k, ac

# Variables that will be used for  making table in Conclusion part of this assignment
TFIDF_Word2Vec_kdTree_K = optimal_k
TFIDF_Word2Vec_kdTree_train_acc = max(cv_scores)*100
TFIDF_Word2Vec_kdTree_test_acc = acc
```

```
The Test Accuracy of the K-NN classifier for k = 21 is 82.916667%
```

SEABORN HEATMAP FOR REPRESENTATION OF CONFUSION MATRIX :

```
In [52]: # Code for drawing seaborn heatmaps
         class_names = ['negative','positive']
         df_heatmap = pd.DataFrame(confusion_matrix(Y_test, pred), index=class_names, columns=c
         fig = plt.figure(figsize=(10,7))
         heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")

         # Setting tick labels for heatmap
         heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0, ha='right', f
         heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=0, ha='right', f
         plt.ylabel('Predicted label',size=18)
         plt.xlabel('True label',size=18)
         plt.title("Confusion Matrix\n",size=24)
         plt.show()
```



20 CONCLUSION :

21 (a). Procedure followed :

STEP 1 :- Text Preprocessing

STEP 2:- Sorting the dataset on the basis of time , then randomly selecting 40K datapoints from whole dataset and split these datapoints into train_data and test_data

STEP 3:- Training the vectorizer on train_data and later applying same vectorizer on both train_data and test_data to transform them into vectors

STEP 4:- Using KNN as an estimator in 3-Fold Cross-Validation in order to find optimal value of K .

STEP 5:- Draw "Accuracy VS K" plot

STEP 6:- Once , we get optimal value of K then train KNN again with this optimal K and make predictions on test_data

STEP 7:- Compute test accuracy using predicted values and ground truth values of test_data

STEP 8:- Plot Seaborn Heatmap for representation of Confusion Matrix

Repeat from STEP 3 to STEP 7 for each of these four vectorizers : Bag Of Words(BoW), TFIDF , Avg Word2Vec and TFIDF Word2Vec

22 (b). Table (Model Performances with their hyperparameters :

In [53]:
```
# Creating table using PrettyTable library
from prettytable import PrettyTable

names = ["KNN using 'brute' for BoW", "KNN using 'kdTree' for BoW", "KNN using 'brute
        "KNN using 'kdTree' for TFIDF", "KNN using 'brute' for Avg-Word2Vec", "KNN usi
        "KNN using 'brute' for TFIDF-Word2Vec", "KNN using 'kdTree' for TFIDF-Word2Vec

optimal_K = [bow_brute_K, bow_kdTree_K, tfidf_brute_K, tfidf_kdTree_K, Avg_Word2Vec_br
             TFIDF_Word2Vec_brute_K, TFIDF_Word2Vec_kdTree_K]

train_acc = [bow_brute_train_acc, bow_kdTree_train_acc, tfidf_brute_train_acc, tfidf_k
             Avg_Word2Vec_brute_train_acc, Avg_Word2Vec_kdTree_train_acc, TFIDF_Word2V
             TFIDF_Word2Vec_kdTree_train_acc]

test_acc = [bow_brute_test_acc, bow_kdTree_test_acc, tfidf_brute_test_acc, tfidf_kdTre
            Avg_word2Vec_brute_test_acc, Avg_Word2Vec_kdTree_test_acc, TFIDF_word2Vec_
            TFIDF_Word2Vec_kdTree_test_acc]

numbering = [1,2,3,4,5,6,7,8]

# Initializing prettytable
ptable = PrettyTable()

# Adding columns
ptable.add_column("S.NO.",numbering)
ptable.add_column("MODEL",names)
```

```python
ptable.add_column("Best K",optimal_K)
ptable.add_column("Training Accuracy",train_acc)
ptable.add_column("Test Accuracy",test_acc)

# Printing the Table
print(ptable)
```

```
+--------+-------------------------------------+--------+-------------------+-----------------
| S.NO. |                MODEL                | Best K | Training Accuracy |   Test Accuracy
+--------+-------------------------------------+--------+-------------------+-----------------
|   1    |       KNN using 'brute' for BoW     |   9    | 84.64286336414708 | 84.48333333333333
|   2    |       KNN using 'kdTree' for BoW    |   19   | 84.95713198858216 |      85.075
|   3    |      KNN using 'brute' for TFIDF    |   13   |  85.346414390277  | 84.91666666666666
|   4    |      KNN using 'kdTree' for TFIDF   |   45   | 85.91427842717621 |       85.6
|   5    |   KNN using 'brute' for Avg-Word2Vec |   15   |  86.6035585358501 | 86.85833333333333
|   6    |  KNN using 'kdTree' for Avg-Word2Vec |   15   |  86.6035585358501 | 86.85833333333333
|   7    |  KNN using 'brute' for TFIDF-Word2Vec |   21   | 86.06070648985852 | 82.91666666666666
|   8    | KNN using 'kdTree' for TFIDF-Word2Vec |   21   | 86.06070648985852 | 82.91666666666666
+--------+-------------------------------------+--------+-------------------+-----------------
```