K-NN on Amazon Food Reviews Data Set

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

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 400 Number of users: 399 Number of products: 241 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

Id ProductId - unique identifier for the product, UserId - unqiue identifier for the user, ProfileName HelpfulnessNumerator - number of users who found the review helpful, HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not, Score - rating between 1 and 5, Time - timestamp for the review, Summary - brief summary of the review, Text - text of the review, Objective: Given a review, determine whether the review is positive (Rating of 4 or 5) or negative (rating of 1 or 2).

[Q] How to determine if a review is positive or negative?

[Ans] We could use the Score/Rating. A rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

Objective:

```
* Given a review determine whether a review is positive or negative, by appling KNN
algorithm and deciding the best Feature generation technique for given problem.
```

1. Loading the data

- The dataset is available in two forms

  1.csv file 2.SQLite Database

- I've processed 1000 points.
- I've cleaned the data on excel sheet and loaded the file as csv.file
- 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". I've Given reviews with Score>3 a positive rating, and reviews with a score<3 a negative rating.
- In order to reduce the redundancy, I've eliminated the rows having same parameters

In [4]:

```
%matplotlib inline

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 scikitplot.metrics as skplt
from sklearn.metrics import classification_report
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")

data = pd.read_csv("KNN Assignment.csv") #Loaded the data as csv.file

#looking at the number of attributes and size of the data

data.shape
data.head()
```

Out[4]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	Positive	13038
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	Negative	13469
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	Positive	1219C
3	4	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	Positive	13507
4	5	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	Positive	1342C

In [2]:

```
#Before starting the next phase of preprocessing lets see the number of entries left
data.shape
```

Out[2]:

```
(1000, 10)
```

In [3]:

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

Out[3]:

```
Positive     830
```

```
Negative     170
Name: Score, dtype: int64
```

2. Time Based Splitting

In [5]:

```
#Before we do Data Cleaning, we should sort our data
import datetime

data["Time"] = data["Time"].map(lambda t: datetime.datetime.fromtimestamp(int(t)).strftime('%Y-%m-%
d %H:%M:%S'))

#Here, I've sorted the data by 'ProductID' and deleted the duplicates
sortedData = data.sort_values('ProductId',axis=0,kind="quicksort", ascending=True)
final_data = sortedData.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},keep="first",
inplace=False)
```

In [6]:

```
#sorting the data by timestamp so that it can be divided into train and test dataset for time base
d slicing.
final = final_data.sort_values('Time',axis=0,kind="quicksort", ascending=True).reset_index(drop=Tru
e)
```

In [7]:

```
print(final.shape)
```

```
(1000, 10)
```

In [8]:

```
final.head()
```

Out[8]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
0	999	B000084E1U	A3DH85EYHW4AQH	Eric Hochman	1	1	Positive	2006-02-24 05:30:00
1	984	B002NVPPHC	A31YYS8JRQAZP8	Rena "Rena"	0	0	Positive	2006-08-19 05:30:00
2	905	B000CQG862	A3HXPEOW4KN19	Dawn Marakby	2	2	Positive	2006-09-15 05:30:00
3	580	B000G6MBX2	A4AYT6I29WTPY	Chip Lover "Leisa"	4	5	Positive	2006-09-18 05:30:00
								2006-

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
4	907	B000CQG862	AGV2SUHV9P471	M. Power	0	0	Positive	11-13 05:30:00

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

In [9]:

```
#find sentences containing html tags
import re
i=0;
for sent in final['Text'].values:
    if(len(re.findall('<.*?>', sent))):
        print(i)
        print(sent)
        break;
        i +=1;
```

```
0
McCann's Instant Oatmeal is great if you must have your oatmeal but can only scrape together two o
r three minutes to prepare it. There is no escaping the fact, however, that even the best instant
oatmeal is nowhere near as good as even a store brand of oatmeal requiring stovetop preparation.
Still, the McCann's is as good as it gets for instant oatmeal. It's even better than the organic,
all-natural brands I have tried.  All the varieties in the McCann's variety pack taste good.  It c
an be prepared in the microwave or by adding boiling water so it is convenient in the extreme when
time is an issue.<br /><br />McCann's use of actual cane sugar instead of high fructose corn syrup
helped me decide to buy this product.  Real sugar tastes better and is not as harmful as the other
stuff. One thing I do not like, though, is McCann's use of thickeners.  Oats plus water plus heat
should make a creamy, tasty oatmeal without the need for guar gum. But this is a convenience produ
ct.  Maybe the guar gum is why, after sitting in the bowl a while, the instant McCann's becomes to
o thick and gluey.
```

In [10]:

```
import re
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

stop = set(stopwords.words('english')) #set of stopwords
sno = nltk.stem.SnowballStemmer('english') #initialising the snowball stemmer

def cleanhtml(sentence): #function to clean the word of any html-tags
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext
def cleanpunc(sentence): #function to clean the word of any punctuation or special characters
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return  cleaned
print(stop)
print('************************************')
print(sno.stem('tasty'))
```

```
{'between', 'wasn', 'during', 'should', "doesn't", 'd', 'her', 'who', 'here', 'that', 'about', 'he
', 'hasn', 'be', "isn't", 'them', "needn't", 'you', 'yourself', 'ours', 'from', 'too', 'does', 'wh
ere', 'why', 'nor', "aren't", 'haven', "you'd", "don't", 'ma', 'but', 'at', 'with', 'we', 'for', "
didn't", "wasn't", 'mustn', 'o', 'out', 'will', 'were', "that'll", "weren't", 'these', 'doesn', "i
t's", 'because', 'now', 'above', 'mightn', 'don', 'it', 't', 'ain', 'are', 'other', 'm',
"haven't", 'its', 'any', 'doing', "shan't", 'down', 'whom', 'i', 'me', 'few', "she's", 'my', 'how'
, "you've", 'won', 'herself', 'while', 'same', 'very', 'such', 'and', 'if', 'most', 'the', 'just',
'when', 'needn', 'so', 've', 'is', 'as', 'to', 'y', "hadn't", 'being', 'those', 'can', 'having', '
against', 'him', "hasn't", 'theirs', 'they', 'off', 'an', 'once', 'through', 'their', 'into', 'the
mselves', 'weren', "couldn't", 'yours', 'myself', 'over', 'both', 'has', "should've", 'wouldn', "s
houldn't", 'all', 'by', 'again', 'on', "mustn't", 'your', 'own', 'll', 're', 'didn', "you'll",
'been', 'aren', 'itself', 'our', 'of', 'this', 'in', 'only', 'hadn', 'himself', 'each', 'then',
'no', 'a', 'which', 'until', 'below', 'couldn', 'or', 's', 'than', 'shouldn', 'do', 'shan',
'what', 'before', "won't", 'yourselves', 'further', 'more', 'some', 'under', 'there', 'his', 'had'
```

```
, 'up', 'was', 'not', "wouldn't", 'ourselves', 'after', "you're", 'hers', 'isn', 'did', 'am', 'hav
e', "mightn't", 'she'}
************************************
tasti
```

In [11]:

```python
#Code for implementing step-by-step the checks mentioned in the pre-processing phase

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 (data['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describe positive r
eviews
                    if(data['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describe negative r
eviews reviews
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    #print("***********************************************************************")

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

In [12]:

```python
final['CleanedText']=final_string #adding a column of CleanedText which displays the data after pr
e-processing of the review
```

In [13]:

```python
final.head(3) #below the processed review can be seen in the CleanedText Column
```

Out[13]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
0	999	B000084E1U	A3DH85EYHW4AQH	Eric Hochman	1	1	Positive	2006-02-24 05:30:00
1	984	B002NVPPHC	A31YYS8JRQAZP8	Rena "Rena"	0	0	Positive	2006-08-19 05:30:00
2	905	B000CQG862	A3HXPEOW4KN19	Dawn Marakby	2	2	Positive	2006-09-15

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
								05:30:00

In [14]:

```
final.shape
```

Out[14]:

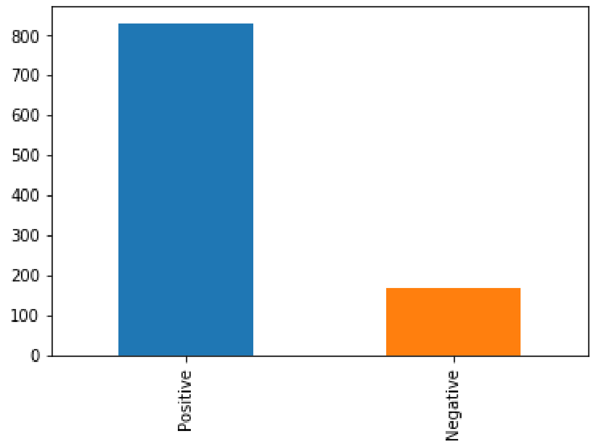
```
(1000, 11)
```

In [15]:

```
final['Score'].value_counts().plot(kind='bar')
```

Out[15]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x289f85e2e48>
```



Observations:- * I've performed the following Data preprocessing. > Removed Stop-words > Removed any punctuations or limited set of special characters like , or . or # etc. > Snowball Stemming the word (The goal of both stemming and lemmatization is to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form) > Converted the word to lowercase * I've added a column called 'CleanedText' which displays the data after pre-processing of the review. So,Now we have 1000 reviews with 11 columns * By observing the bar chart of the class label 'Score', we can say that there are about 80% of the reviews are positive and 20% are negative.

4. Building function to find optimal K for KNN

In [16]:

```
#kd_tree

from sklearn.cross_validation import cross_val_score

def find_optimal_k(X_train,y_train, myList):

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

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

    # perform 10-fold cross validation
    for k in neighbors:
        knn = KNeighborsClassifier(n_neighbors=k, algorithm='kd_tree')
        scores = cross_val_score(knn, X_train, y_train, cv=10, scoring='accuracy')
        cv_scores.append(scores.mean())

    # changing to misclassification error
    MSE = [1 - x for x in cv_scores]

    # determining best k
    optimal_k = neighbors[MSE.index(min(MSE))]
```

```
    print('\nThe optimal number of neighbors for Kd_Tree Algorithm is %d.' % optimal_k)

    plt.figure(figsize=(10,6))
    plt.plot(list(filter(lambda x: x % 2 != 0, myList)),MSE,color='red', linestyle='dashed', marker
='o',
             markerfacecolor='green', markersize=10)
    plt.title('Kd_Tree: Error Rate vs. K Value')
    plt.xlabel('K')
    plt.ylabel('Error Rate')

    print("the misclassification error for each k value is : ", np.round(MSE,3))

    return optimal_k
```

In [17]:

```
#brute

from sklearn.cross_validation import cross_val_score

def find_brute_optimal_k(X_train,y_train, myList):

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

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

    # perform 10-fold cross validation
    for k in neighbors:
        knn = KNeighborsClassifier(n_neighbors=k, algorithm='brute')
        scores = cross_val_score(knn, X_train, y_train, cv=10, scoring='accuracy')
        cv_scores.append(scores.mean())

    # changing to misclassification error
    MSE = [1 - x for x in cv_scores]

    # determining best k
    brute_optimal_k = neighbors[MSE.index(min(MSE))]
    print('\nThe optimal number of neighbors for Brute Force Algorithm is %d.' % brute_optimal_k)

    plt.figure(figsize=(10,6))
    plt.plot(list(filter(lambda x: x % 2 != 0, myList)),MSE,color='red', linestyle='dashed', marker
='o',
             markerfacecolor='green', markersize=10)
    plt.title('Brute Force: Error Rate vs. K Value')
    plt.xlabel('K')
    plt.ylabel('Error Rate')

    print("the misclassification error for each k value is : ", np.round(MSE,3))

    return brute_optimal_k
```

Observations:- * I've build a function to find optimal K for K-NN using two algorithms 'kd_tree' and 'brute force'. * I've created a odd list (myList) of K for K-NN and an empty list to hold cross validation scores (cv_scores) * I've performed 10-fold cross validation and appended the final scores to cv_scores list. * Here I got two optimal K values, optimal_k for kd_tree and brute_optimal_k for brute force. * I've also calculated the Misclassification Error for each K value.

5. Applying Feature Generation Techniques to Convert Text to Numeric Vector.

5.1 Applying KNN with Bag of Words

Generationg Bag of Words Vector Matrix for Reviews (BOW)

In [18]:

```
#BoW
count_vect = CountVectorizer() #in scikit-learn
```

```
final_counts = count_vect.fit_transform(final['Text'].values)
```

In [19]:

```
final_counts.get_shape()
```

Out[19]:

```
(1000, 6014)
```

In [20]:

```
import warnings
warnings.filterwarnings("ignore")

from sklearn.preprocessing import StandardScaler
final_bow_np = StandardScaler(with_mean=False).fit_transform(final_counts)
```

Splitting Data into Train and Test

In [21]:

```
#We already have sorted data by timestamp so we will use first 70% of data as Train with cross val
idation and next 30% for test
import math
from sklearn import datasets
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split

X = final_counts
y = final['Score']

X_train =  final_bow_np[:math.ceil(len(final)*.7)]
X_test = final_bow_np[math.ceil(len(final)*.7):]
y_train = y[:math.ceil(len(final)*.7)]
y_test =  y[math.ceil(len(final)*.7):]
```

Finding Optimal K by 10 fold Cross validation

In [22]:

```
myList = list(range(0,50))
optimal_k = find_optimal_k(X_train,y_train,myList)
```

```
The optimal number of neighbors for Kd_Tree Algorithm is 7.
the misclassification error for each k value is :  [0.397 0.234 0.163 0.16  0.16  0.16  0.16  0.16
0.16  0.16  0.16  0.16
 0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16
 0.16 ]
```

KNN with Kd_tree Optimal K

In [23]:

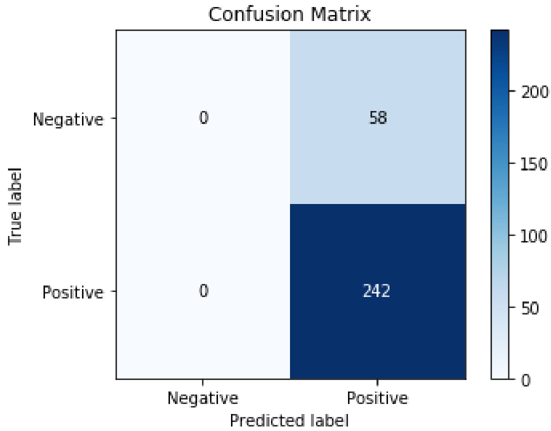
```
knn = KNeighborsClassifier(n_neighbors=optimal_k)
knn.fit(X_train, y_train)
pred = knn.predict(X_test)
```

In [24]:

```
skplt.plot_confusion_matrix(y_test ,pred)
```

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x289f89f99e8>
```



In [25]:

```
print(classification_report(y_test ,pred))
```

```
             precision    recall  f1-score   support

   Negative       0.00      0.00      0.00        58
   Positive       0.81      1.00      0.89       242

avg / total       0.65      0.81      0.72       300
```

In [26]:

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

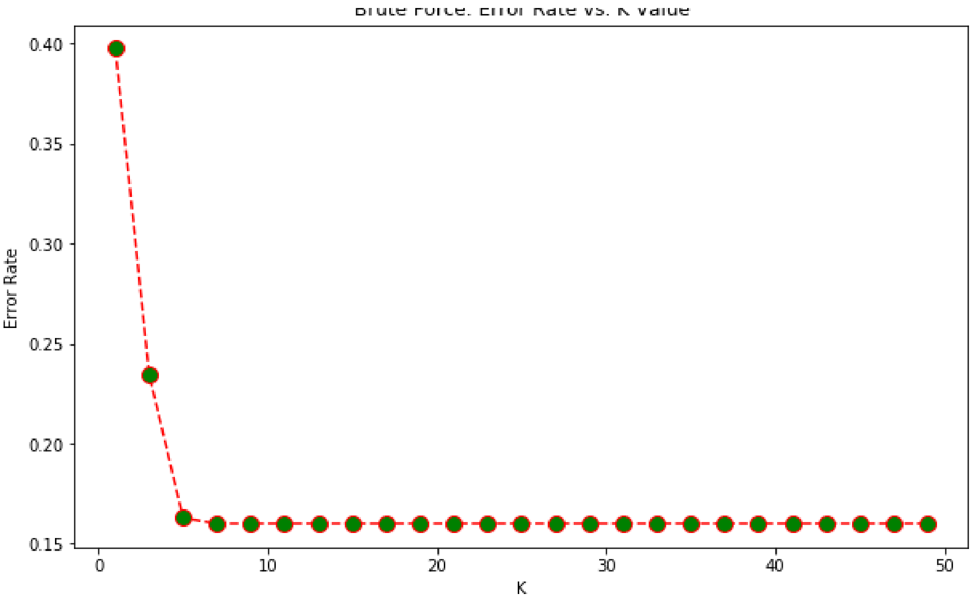
```
The accuracy of the knn classifier for kd_tree is k = 7 is 80.666667%
```

In [27]:

```
#Brute Force

myList = list(range(0,50))
brute_optimal_k = find_brute_optimal_k(X_train,y_train,myList)
```

```
The optimal number of neighbors for Brute Force Algorithm is 7.
the misclassification error for each k value is :  [0.397 0.234 0.163 0.16  0.16  0.16  0.16  0.16
0.16  0.16  0.16  0.16
 0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16
 0.16 ]
```



KNN with Brute Optimal K

In [28]:

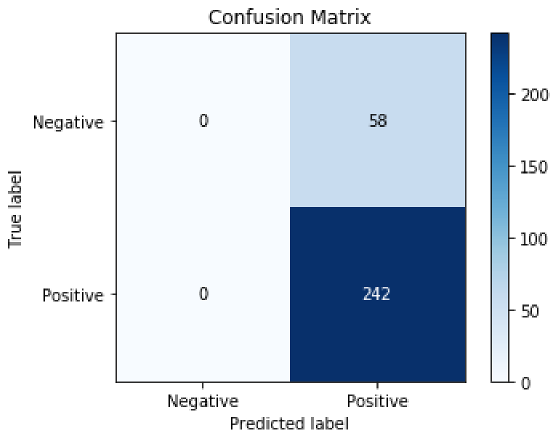
```
knn = KNeighborsClassifier(n_neighbors=brute_optimal_k)
knn.fit(X_train, y_train)
pred = knn.predict(X_test)
```

In [29]:

```
skplt.plot_confusion_matrix(y_test ,pred)
```

Out[29]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x289f89998d0>
```



In [30]:

```
print(classification_report(y_test ,pred))
```

```
             precision    recall  f1-score   support

   Negative       0.00      0.00      0.00        58
   Positive       0.81      1.00      0.89       242

avg / total       0.65      0.81      0.72       300
```

In [31]:

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

```
acc))
```

```
The accuracy of the knn classifier for Brute Force is k = 7 is 80.666667%
```

Observations:-

```
* I've applied Bag of Words (BOW) Feature Generation Technique to convert text to numeric ve
ctor.
* I've already sorted the data by Time, So here I've divided the data into three parts
        1. Train Data (49%)
        2. Data for Cross Validation (21%)
        3. Test Data (30)

* I've applied 10 fold cross validation to find the optimal K and applied both kd_tree and
brute force algorithms

* The optimal K value and test accuracy are same for both kd_tree and brute force
alogorithms.

        Bag of Words (BOW) optimal K value is 7 & Test Accuracy is 80.66667%
```

5.2 Applying KNN with TF-IDF

Generating TF-IDF Vector Matrix for Reviews

In [32]:

```python
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vec = TfidfVectorizer()#ngram_range=(2,2))

final_tfidf_count = tf_idf_vec.fit_transform(final_string)#final['Text'].values)

#print(final_string)
```

In [33]:

```python
final_tfidf_count.get_shape()
```

Out[33]:

```
(1000, 4091)
```

In [34]:

```python
from sklearn.preprocessing import StandardScaler

final_tfidf_np = StandardScaler(with_mean=False).fit_transform(final_tfidf_count )
```

Splitting Data into Train & Test

In [35]:

```python
from sklearn import datasets
from sklearn.neighbors import KNeighborsClassifier

from sklearn.model_selection import train_test_split

X = final_tfidf_count
y = final['Score']

X_train =  final_tfidf_count[:math.ceil(len(final)*.7)]
X_test = final_tfidf_count[math.ceil(len(final)*.7):]
y_train = y[:math.ceil(len(final)*.7)]
```

```
y_test =  y[math.ceil(len(final)*.7):]
```

Finding Optimal K by 10 fold Cross validation

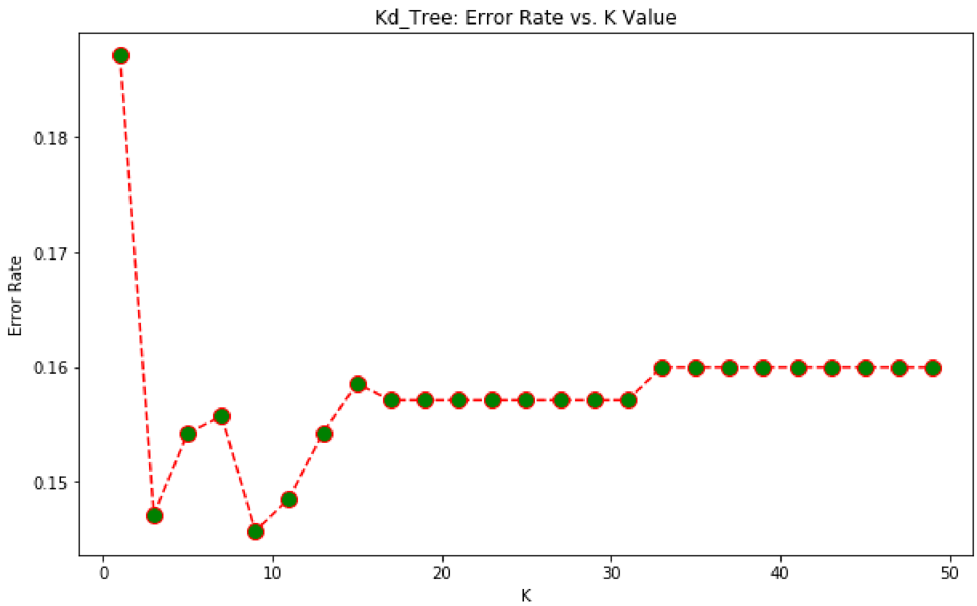
In [36]:

```
#Kd_Tree

myList = list(range(0,50))

tfidf_kd_optimal_k = find_optimal_k(X_train ,y_train,myList)
```

```
The optimal number of neighbors for Kd_Tree Algorithm is 9.
the misclassification error for each k value is :  [0.187 0.147 0.154 0.156 0.146 0.149 0.154 0.15
0.157 0.157 0.157 0.157
 0.157 0.157 0.157 0.157 0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16
 0.16 ]
```



KNN with Kd_Tree Optimal K

In [37]:

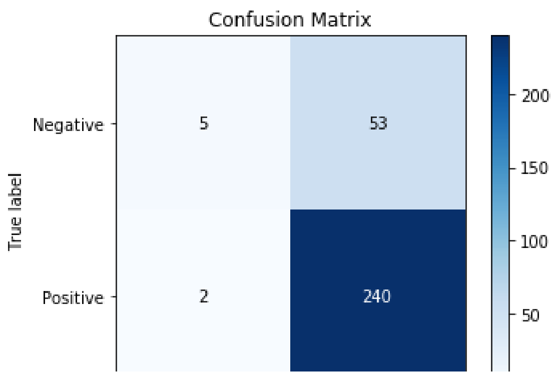
```
knn = KNeighborsClassifier(n_neighbors=tfidf_kd_optimal_k)
knn.fit(X_train, y_train)
pred = knn.predict(X_test)
```

In [38]:

```
skplt.plot_confusion_matrix(y_test ,pred)
```

Out[38]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x289f8a01a20>
```



In [39]:

```
print(classification_report(y_test ,pred))
```

```
             precision    recall  f1-score   support

   Negative       0.71      0.09      0.15        58
   Positive       0.82      0.99      0.90       242

avg / total       0.80      0.82      0.75       300
```

In [40]:

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

```
The accuracy of the knn classifier for Kd_Tree algorithm is k = 9 is 81.666667%
```

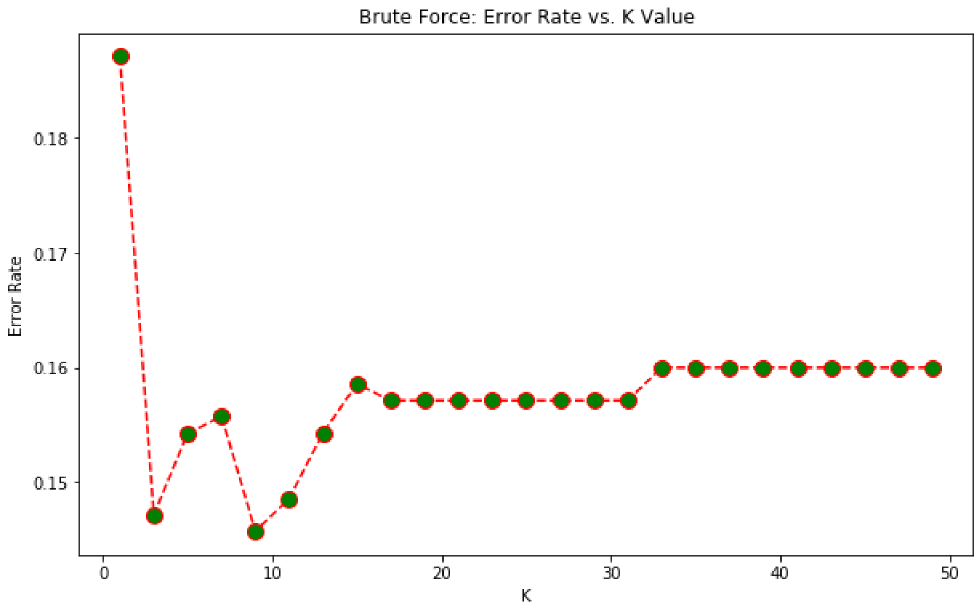
In [41]:

```
#Brute Force

myList = list(range(0,50))

tfidf_br_optimal_k = find_brute_optimal_k(X_train ,y_train,myList)
```

```
The optimal number of neighbors for Brute Force Algorithm is 9.
the misclassification error for each k value is :  [0.187 0.147 0.154 0.156 0.146 0.149 0.154 0.15
0.157 0.157 0.157 0.157
 0.157 0.157 0.157 0.157 0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16
 0.16 ]
```



K-NN with Brute Force Optimal K

In [42]:

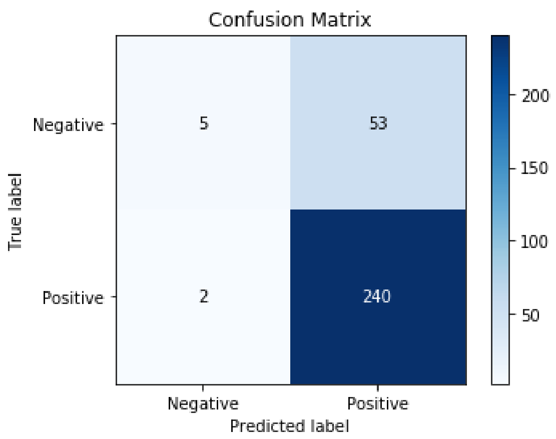
```
knn = KNeighborsClassifier(n_neighbors=tfidf_br_optimal_k)
knn.fit(X_train, y_train)
pred = knn.predict(X_test)
```

In [43]:

```
skplt.plot_confusion_matrix(y_test ,pred)
```

Out[43]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x289f8c38630>
```



In [44]:

```
print(classification_report(y_test ,pred))
```

```
             precision    recall  f1-score   support

   Negative       0.71      0.09      0.15        58
   Positive       0.82      0.99      0.90       242

avg / total       0.80      0.82      0.75       300
```

In [45]:

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

```
The accuracy of the knn classifier for Brute Force Algorithm is k = 9 is 81.666667%
```

Observations:-

```
* I've applied Term Frequency Inverse Document Frequency Feature Generation Technique to
convert text to numeric vector.
* I've already sorted the data by Time, So here I've divided the data into three parts
        1. Train Data (49%)
        2. Data for Cross Validation (21%)
        3. Test Data (30%)

* I've applied 10 fold cross validation to find the optimal K and applied both kd_tree and
brute force algorithms

* The optimal K value and test accuracy are same for both kd_tree and brute force
alogorithms.

        TF-IDF optimal K value is 9 & Test Accuracy is 81.6%
```

5.3 Appling KNN with Avg W2V

Generating W2V Vector Matrix for Reviews

In [46]:

```
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
```

In [47]:

```
import gensim
i=0
str1=''
list_of_sent=[]
for sent in final['Text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    str1 = ''
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (cleaned_words.lower() not in stop)):
                filtered_sentence.append(cleaned_words.lower())
                str1 += " "+cleaned_words.lower()
            else:
                continue
    #str1 = b" ".join(filtered_sentence) #final string of cleaned words

    list_of_sent.append(filtered_sentence)
```

In [48]:

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

In [49]:

```
sent_vectors = [];
for sent in list_of_sent:
    sent_vec = np.zeros(50)
    cnt_words =0;
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
```

In [50]:

```
from sklearn.preprocessing import StandardScaler

final_w2v_count = StandardScaler().fit_transform(sent_vectors)
```

Splitting Data into Train and Test

In [51]:

```
from sklearn import datasets
from sklearn.neighbors import KNeighborsClassifier

from sklearn.model_selection import train_test_split

X = sent_vectors
y = final['Score']

X_train =  sent_vectors[:math.ceil(len(final)*.7)]
X_test = sent_vectors[math.ceil(len(final)*.7):]
y_train = y[:math.ceil(len(final)*.7)]
y_test =  y[math.ceil(len(final)*.7):]
```

Finding Optimal K by 10 fold Cross validation

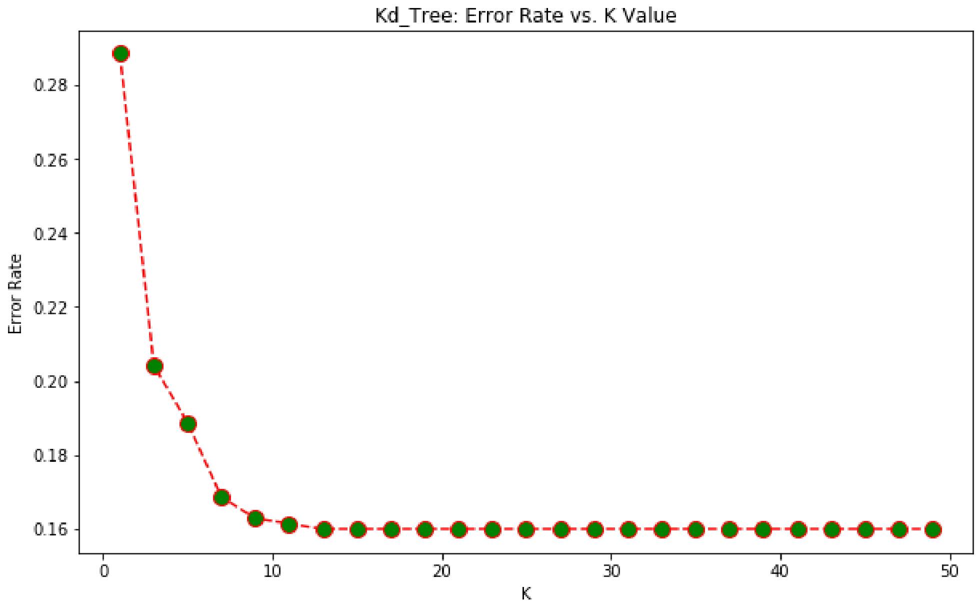
In [52]:

```
#Kd_tree

myList = list(range(0,40))

w2v_kd_optimal_k = find_optimal_k (X_train ,y_train,myList)
```

```
The optimal number of neighbors for Kd_Tree Algorithm is 13.
the misclassification error for each k value is :  [0.288 0.204 0.189 0.169 0.163 0.161 0.16  0.16
0.16  0.16  0.16  0.16
 0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16
 0.16 ]
```



KNN with Kd_Tree Optimal K

In [53]:

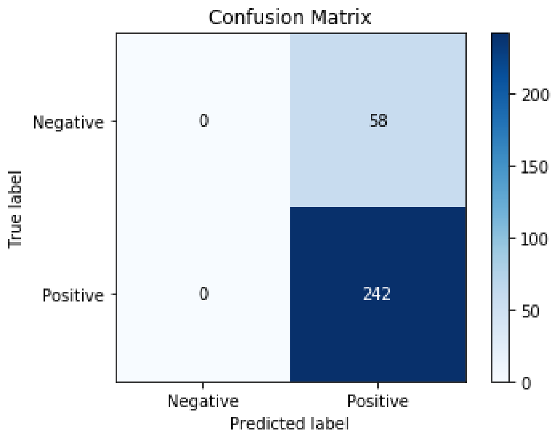
```
knn = KNeighborsClassifier(n_neighbors=w2v_kd_optimal_k)
knn.fit(X_train, y_train)
pred = knn.predict(X_test)
```

In [54]:

```
skplt.plot_confusion_matrix(y_test ,pred)
```

Out[54]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x289face6fd0>
```



In [55]:

```
print(classification_report(y_test ,pred))
```

```
             precision    recall  f1-score   support

   Negative       0.00      0.00      0.00        58
   Positive       0.81      1.00      0.89       242

avg / total       0.65      0.81      0.72       300
```

In [56]:

```
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for Kd_Tree Algorithm is k = %d is %f%%' %
(w2v_kd_optimal_k, acc))
```

```
The accuracy of the knn classifier for Kd_Tree Algorithm is k = 13 is 80.666667%
```

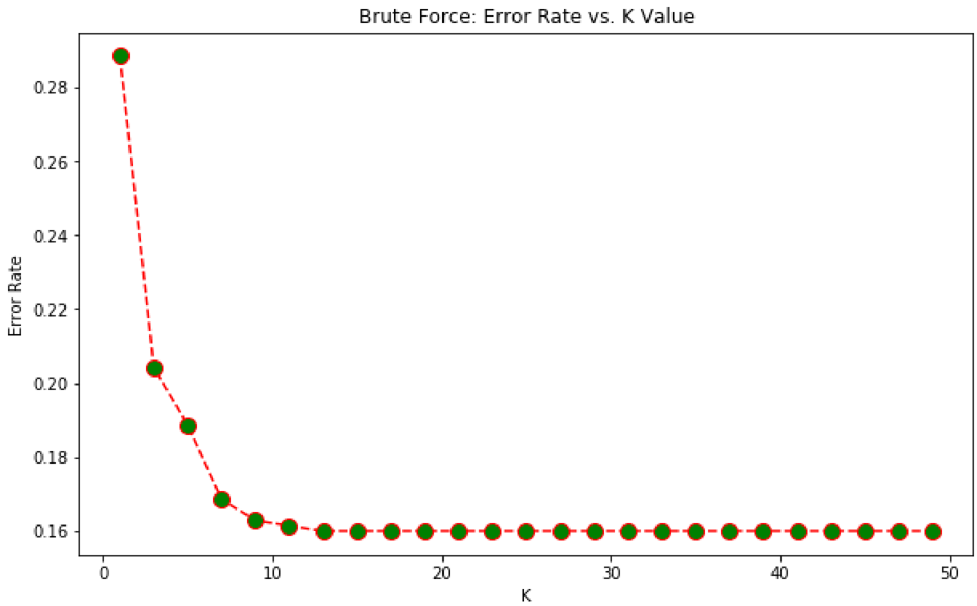
In [57]:

```
#Brute Force

myList = list(range(0,50))

w2v_br_optimal_k = find_brute_optimal_k (X_train ,y_train,myList)
```

```
The optimal number of neighbors for Brute Force Algorithm is 13.
the misclassification error for each k value is :  [0.288 0.204 0.189 0.169 0.163 0.161 0.16  0.16
0.16  0.16  0.16  0.16
 0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16
 0.16 ]
```



KNN with Brute Force Optimal K

In [58]:

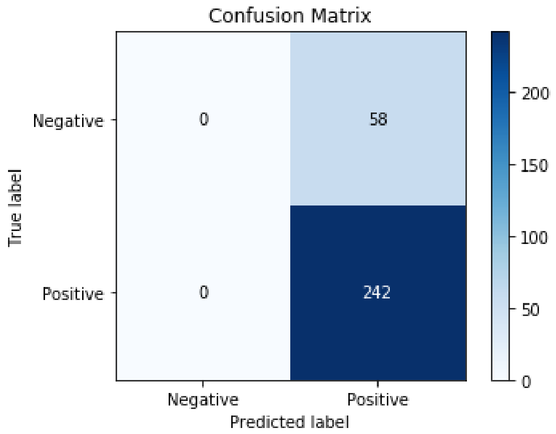
```
knn = KNeighborsClassifier(n_neighbors=w2v_br_optimal_k)
knn.fit(X_train, y_train)
pred = knn.predict(X_test)
```

In [59]:

```
skplt.plot_confusion_matrix(y_test ,pred)
```

Out[59]:

<matplotlib.axes._subplots.AxesSubplot at 0x289fab857b8>



In [60]:

```
print(classification_report(y_test ,pred))
```

```
             precision    recall  f1-score   support

   Negative       0.00      0.00      0.00        58
   Positive       0.81      1.00      0.89       242

avg / total       0.65      0.81      0.72       300
```

In [61]:

```
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for Brute Force Algorithm is k = %d is %f%%' %
(w2v_br_optimal_k, acc))
```

```
The accuracy of the knn classifier for Brute Force Algorithm is k = 13 is 80.666667%
```

Observations:-

```
   * I've first applied Word2Vec and computed the average w2v for each review and then coverte
   d the text to numeric vector.
   * I've already sorted the data by Time, So here I've divided the data into three parts
           1. Train Data (49%)
           2. Data for Cross Validation (21%)
           3. Test Data (30%)

   * I've applied 10 fold cross validation to find the optimal K and applied both kd_tree and
   brute force algorithms

   * The optimal K value and test accuracy are same for both kd_tree and brute force
   alogorithms.

           Word2Vec optimal K value is 13 & Test Accuracy is 80.6%
```

5.4 Appling KNN with tf-idf weighted W2V

Generating TF-IDF W2V Vector matrix for Reviews

In [77]:

```
import gensim
i=0
str1=''
final_string_for_tfidf = []
for sent in final['Text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    str1 = ''
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (cleaned_words.lower() not in stop)):
                filtered_sentence.append(cleaned_words.lower())
                str1 += " "+cleaned_words.lower()
            else:
                continue
    #str1 = b" ".join(filtered_sentence) #final string of cleaned words

    #final_string_for_tfidf.append(str1)
    final_string_for_tfidf.append((str1).strip())
```

In [78]:

```
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vec_w = TfidfVectorizer()#ngram_range=(2,2))

final_tfidf_w = tf_idf_vec_w.fit_transform(final_string_for_tfidf)
```

In [79]:

```
tfidf_feat = tf_idf_vec_w.get_feature_names()


tfidf_sent_vectors = [];
row=0;
for sent in list_of_sent:
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        try:
            vec = w2v_model.wv[word]
            tf_idf = final_tfidf_w[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except Exception as e:
            pass #print(e)

    try:
        sent_vec /= weight_sum
    except:
        print(e)

    tfidf_sent_vectors.append(sent_vec)
    row += 1
```

In [80]:

```
from sklearn.preprocessing import StandardScaler

final_tfidf_w2v_np = StandardScaler().fit_transform(tfidf_sent_vectors )
```

Finding Optimal K by 10 fold Cross validation

In [81]:

```
from sklearn import datasets
from sklearn.neighbors import KNeighborsClassifier


X = final_tfidf_w2v_np
y = final['Score']

X_train =  final_tfidf_w2v_np[:math.ceil(len(final)*.7)]
```

```
X_test = final_tfidf_w2v_np[math.ceil(len(final)*.7):]
y_train = y[:math.ceil(len(final)*.7)]
y_test =  y[math.ceil(len(final)*.7):]
```

Finding Optimal K by 10 fold Cross validation

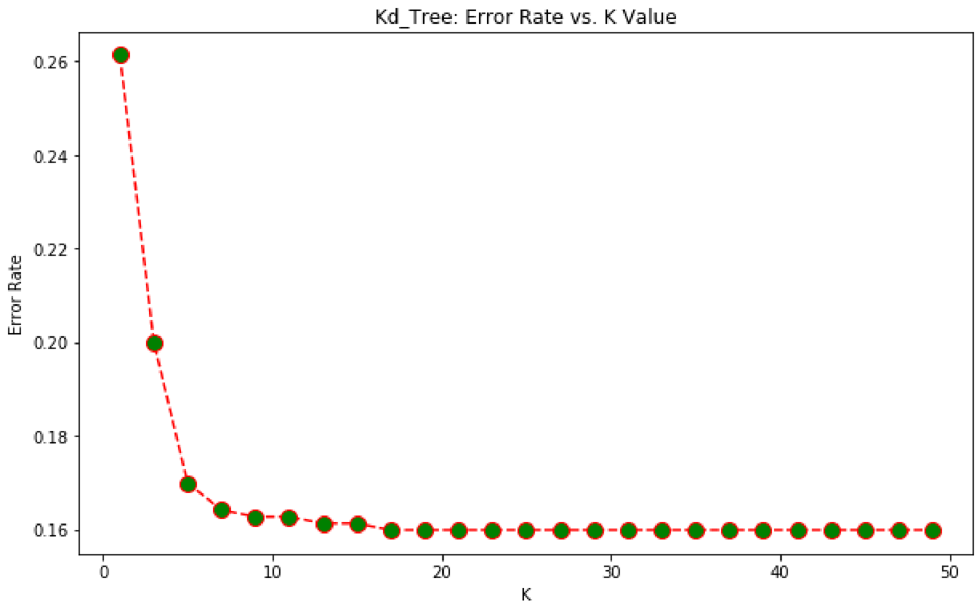
In [82]:

```
#Kd_tree

myList = list(range(0,40))

tfidf_w2v_optimal_k = find_optimal_k(X_train ,y_train,myList)
```

```
The optimal number of neighbors for Kd_Tree Algorithm is 17.
the misclassification error for each k value is :  [0.261 0.2   0.17  0.164 0.163 0.163 0.161 0.161
0.16  0.16  0.16  0.16
 0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16
 0.16 ]
```



KNN with Kd_tree Optimal K

In [83]:

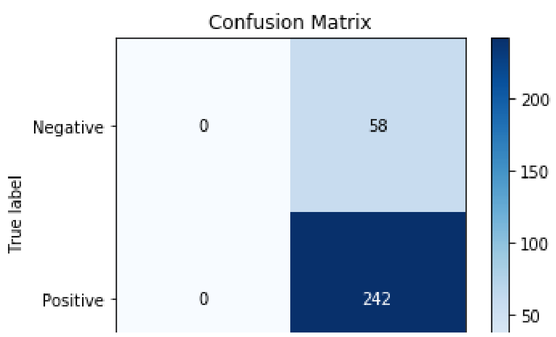
```
knn = KNeighborsClassifier(n_neighbors=tfidf_w2v_optimal_k)
knn.fit(X_train, y_train)
pred = knn.predict(X_test)
```

In [84]:

```
skplt.plot_confusion_matrix(y_test ,pred)
```

Out[84]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x289fb04b5f8>
```



In [85]:

```
print(classification_report(y_test ,pred))
```

```
             precision    recall  f1-score   support

   Negative       0.00      0.00      0.00        58
   Positive       0.81      1.00      0.89       242

avg / total       0.65      0.81      0.72       300
```

In [86]:

```
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for Kd_Tree Algorithm is k = %d is %f%%' %
(tfidf_w2v_optimal_k, acc))
```

```
The accuracy of the knn classifier for Kd_Tree Algorithm is k = 17 is 80.666667%
```

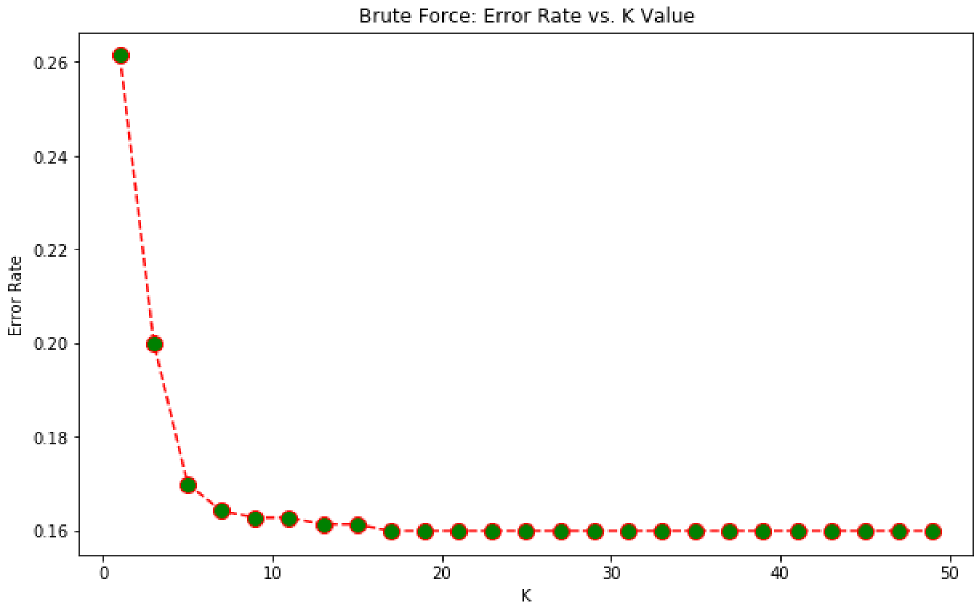
In [87]:

```
#Brute Force

myList = list(range(0,40))

tfidfbr_w2v_optimal_k = find_brute_optimal_k(X_train ,y_train,myList)
```

```
The optimal number of neighbors for Brute Force Algorithm is 17.
the misclassification error for each k value is :  [0.261 0.2   0.17  0.164 0.163 0.163 0.161 0.161
0.16  0.16  0.16  0.16
 0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16  0.16
 0.16 ]
```



KNN with Brute Force Optimal K

In [88]:

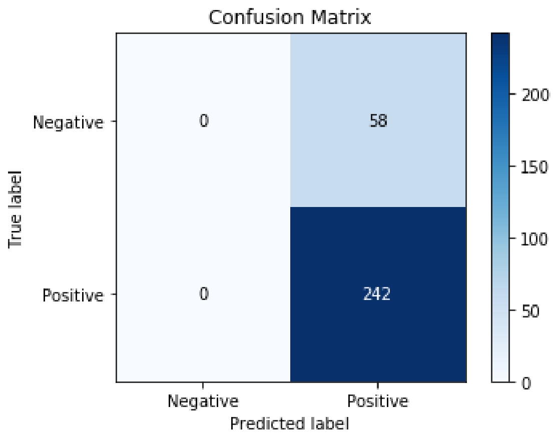
```
knn = KNeighborsClassifier(n_neighbors=tfidfbr_w2v_optimal_k)
knn.fit(X_train, y_train)
pred = knn.predict(X_test)
```

In [89]:

```
skplt.plot_confusion_matrix(y_test ,pred)
```

Out[89]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x289faf27a20>
```



In [90]:

```
print(classification_report(y_test ,pred))
```

```
             precision    recall  f1-score   support

   Negative       0.00      0.00      0.00        58
   Positive       0.81      1.00      0.89       242

avg / total       0.65      0.81      0.72       300
```

In [91]:

```
# evaluate accuracy
acc = accuracy_score(y_test, pred) * 100
print('\nThe accuracy of the knn classifier for k = %d is %f%%' % (tfidfbr_w2v_optimal_k, acc))
```

```
The accuracy of the knn classifier for k = 17 is 80.666667%
```

Observations:-

```
* I've applied TF-IDF Word2Vec Feature Generation Technique to convert text to numeric
vector.
* I've already sorted the data by Time, So here I've divided the data into three parts
        1. Train Data (49%)
        2. Data for Cross Validation (21%)
        3. Test Data (30%)

* I've applied 10 fold cross validation to find the optimal K and applied both kd_tree and
brute force algorithms

* The optimal K value and test accuracy are same for both kd_tree and brute force
alogorithms.

        Word2Vec optimal K value is 17 & Test Accuracy is 80.6%
```

6. Conclusion:

```
* The result of feature generation techniques and machine learning algorithms vary by
```

application. But by comparing the accuracy of all 4 developed models, KNN model with TF-IDF feature generation technique gives accuracy more than 81% which is the best to predict the polarity of reviews among all models. The best optimal K value is 9.

7. K-NN on Amazon Data set - Tabular Result

In [96]:

```
dataframe = pd.DataFrame(
{
    "Model": ['BOW','TF-IDF','WORD2VEC','AVG W2V'],
    "Hyper Parameter (K=)": [7,9,13,17],
    "Train Error (%)": [16,14,16,16],
    "Test Accuracy (%)": [80.6,81.6,80.6,80.6]
}
)
dataframe
```

Out[96]:

	Model	Hyper Parameter (K=)	Train Error (%)	Test Accuracy (%)
0	BOW	7	16	80.6
1	TF-IDF	9	14	81.6
2	WORD2VEC	13	16	80.6
3	AVG W2V	17	16	80.6