

In [1]:

```
#importing necessary packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
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
```

C:\Users\lenovo\Anaconda3\lib\site-packages\sklearn\cross\_validation.py:41: DeprecationWarning: This module was deprecated in version 0.18 in favor of the model\_selection module into which all the refactored classes and functions are moved. Also note that the interface of the new CV iterators are different from that of this module. This module will be removed in 0.20.

"This module will be removed in 0.20.", DeprecationWarning)

In [2]:

```
%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.metrics import
accuracy_score, precision_score, recall_score, confusion_matrix, classification_report, f1_score
import scikitplot as skplt

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\lenovo\Anaconda3\lib\site-packages\gensim\utils.py:1197: UserWarning: detected Windows; aliasing chunkize to chunkize\_serial  
warnings.warn("detected Windows; aliasing chunkize to chunkize\_serial")

In [78]:

```
# using the SQLite Table to read data.
con = sqlite3.connect('database.sqlite')

#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
filtered_data = pd.read_sql_query(""" SELECT * FROM Reviews WHERE Score != 3 """, con)
```

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

(525814, 10)

In [79]:

```
filtered_data.head(5)
```

Out[79]:

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

In [80]:

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

#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 (525814, 10)

Out[80]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	positive	1303862400	Good Quality Dog Food
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	negative	1346976000	Not as

		ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	AdvertiserSummary
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	positive	1219017600	"Delight' says it al

In [81]:

```
filtered_data['Score'].value_counts() #Data points in each class
```

Out[81]:

```
positive    443777
negative    82037
Name: Score, dtype: int64
```

In [82]:

```
#Sorting the data taking productid as the parameter
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
sorted_data.shape
```

Out[82]:

```
(525814, 10)
```

In [83]:

```
#Deleting the duplicates reviews which is created when user writed a review for the product, it automatically generates for the same product of different color etc
final = sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep='first', inplace=False)
final.shape
```

Out[83]:

```
(364173, 10)
```

In [84]:

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

Out[84]:

```
69.25890143662969
```

In [85]:

```
duplicate_data= pd.read_sql_query("""SELECT * FROM Reviews WHERE Score != 3 AND Id=44737 OR Id=64422 ORDER BY ProductID""", con)
print(duplicate_data)
```

	Id	ProductId	UserId	ProfileName	\
0	64422	B000MIDROQ	A161DK06JJMCYF	J. E. Stephens	"Jeanne"
1	44737	B001EQ55RW	A2V0I904FH7ABY		Ram
	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	\
0	3	1	5	1224892800	
1	3	2	4	1212883200	
	Summary	\			
0	Bought This for My Son at College				
1	Pure cocoa taste with crunchy almonds inside				

```
0 My son loves spaghetti so I didn't hesitate or...
1 It was almost a 'love at first bite' - the per...
```

In [86]:

```
#Dropping the data which has HelpfulnessNumerator<HelpfulnessDenominator which is impossible
final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
#Before starting the next phase of preprocessing lets see the number of entries left
print(final.shape)

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

```
(364171, 10)
```

Out[86]:

```
positive    307061
negative     57110
Name: Score, dtype: int64
```

In [87]:

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

Out[87]:

```
69.25852107399194
```

In [88]:

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

```
(364171, 10)
```

In [3]:

```
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
```

In [90]:

```
#Code for implementing step-by-step the checks mentioned in the pre-processing phase
# this code takes a while to run as it needs to run on 500k sentences.
from tqdm import tqdm
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 tqdm(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')
                    #print(cleaned_words.lower(),end=' ')
                    #print(s)
```

```

        filtered_sentence.append(s)
        if (final['Score'].values)[i] == 'positive':
            all_positive_words.append(s) #list of all words used to describe positive r
reviews
        if (final['Score'].values)[i] == 'negative':
            all_negative_words.append(s) #list of all words used to describe negative r
reviews 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

```

100% | 364171/364171  
[09:30<00:00, 638.72it/s]

In [91]:

```

final['CleanedText']=final_string #adding a column of CleanedText which displays the data after pr
e-processing of the review
final['CleanedText']=final['CleanedText'].str.decode("utf-8")
final.head(3)

```

Out[91]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	S
138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	0	positive	939340800	ed
138688	150506	0006641040	A2IW4PEEK02R0U	Tracy	1	1	positive	1194739200	bc
138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	1	positive	1191456000	s

In [92]:

```
final.shape
```

Out[92]:

(364171, 11)

In [93]:

```

# store final table into an SQLite table for future.
conn = sqlite3.connect('data_all_after_preprocess.sqlite')
c=conn.cursor()
conn.text_factory = str
final.to_sql('Reviews', conn, schema=None, if_exists='replace', index=False, index_label=None, chu
nksize=None, dtype=None)

```

In [94]:

```
#reading from Database
con = sqlite3.connect('data_all_after_preprocess.sqlite')
#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
data = pd.read_sql_query("""SELECT * FROM Reviews""", con)
print(data.shape)
```

```
(364171, 11)
```

In [95]:

```
data['Score'].value_counts()
```

Out[95]:

```
positive    307061
negative     57110
Name: Score, dtype: int64
```

In [96]:

```
final=data.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
```

In [97]:

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

```
(364171, 11)
```

In [98]:

```
final = final.head(60000)
print(final.shape)
```

```
(60000, 11)
```

In [99]:

```
# store final table into an SQLite table for future.
conn = sqlite3.connect('Data_60k_timebased.sqlite')
c=conn.cursor()
conn.text_factory = str
final.to_sql('Reviews', conn, schema=None, if_exists='replace', index=False, index_label=None, chunksize=None, dtype=None)
```

In [100]:

```
X_train_data = final[:40000]
X_cv_data = final[40000:50000]
X_test_data = final[50000:60000]
print(X_train_data.shape)
print(X_cv_data.shape)
print(X_test_data.shape)
```

```
(40000, 11)
```

```
(10000, 11)
```

```
(10000, 11)
```

In [101]:

```
# store final table into an SQLite table for future.
conn = sqlite3.connect('X_train_40k_timebased.sqlite')
c=conn.cursor()
conn.text_factory = str
X_train_data.to_sql('Reviews', conn, schema=None, if_exists='replace', index=False, index_label=None, chunksize=None, dtype=None)
```

In [102]:

```
# store final table into an SQLite table for future.
conn = sqlite3.connect('X_cv_10k_timebased.sqlite')
c=conn.cursor()
conn.text_factory = str
X_cv_data.to_sql('Reviews', conn, schema=None, if_exists='replace', index=False, index_label=None,
chunksizes=None, dtype=None)
```

In [103]:

```
# store final table into an SQLite table for future.
conn = sqlite3.connect('X_test_10k_timebased.sqlite')
c=conn.cursor()
conn.text_factory = str
X_test_data.to_sql('Reviews', conn, schema=None, if_exists='replace', index=False, index_label=None,
e, chunksizes=None, dtype=None)
```

In [5]:

```
#reading from Database
con = sqlite3.connect('X_train_40k_timebased.sqlite')
#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
X_train_data = pd.read_sql_query("""SELECT * FROM Reviews""", con)
print(X_train_data.shape)
```

(40000, 11)

In [6]:

```
#reading from Database
con = sqlite3.connect('X_cv_10k_timebased.sqlite')
#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
X_cv_data = pd.read_sql_query("""SELECT * FROM Reviews""", con)
print(X_cv_data.shape)
```

(10000, 11)

In [7]:

```
#reading from Database
con = sqlite3.connect('X_test_10k_timebased.sqlite')
#filtering only positive and negative reviews i.e.
# not taking into consideration those reviews with Score=3
X_test_data = pd.read_sql_query("""SELECT * FROM Reviews""", con)
print(X_test_data.shape)
```

(10000, 11)

In [8]:

```
y_train = X_train_data['Score']
y_cv = X_cv_data['Score']
y_test = X_test_data['Score']
print("Data")
print(X_train_data.shape)
print(X_cv_data.shape)
print(X_test_data.shape)
print("Label")
print(y_train.shape)
print(y_cv.shape)
print(y_test.shape)
```

Data  
(40000, 11)  
(10000, 11)

```
(10000, 11)
(10000, 11)
Label
(40000,)
(10000,)
(10000,)
```

## BOW

In [72]:

```
#count_vect = CountVectorizer(min_df = 50,max_features=2000)
X_train = count_vect.fit_transform(X_train_data['CleanedText'])
X_cv = count_vect.transform(X_cv_data['CleanedText'])
X_test = count_vect.transform(X_test_data['CleanedText'])
print(X_train.shape)
print(X_cv.shape)
print(X_test.shape)
```

```
(40000, 2000)
(10000, 2000)
(10000, 2000)
```

## BOW | BRUTE |

In [108]:

```
for i in tqdm(range(1,30,2)):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i,algorithm='brute')

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

    # predict the response on the crossvalidation data
    pred = knn.predict(X_cv)

    print("*****")
    print("For k = ",i)
    print('Accuracy = ', accuracy_score(y_cv, pred)*100)
    print("f1_score = ",np.round(f1_score(y_cv, pred, average='macro')*100))
    print("precision_score = ",np.round(precision_score(y_cv, pred, average='macro')*100))
    print("recall_score = ",np.round(recall_score(y_cv, pred, average='macro')*100))
```

0%| | C  
[00:00<?, ?it/s]

```
*****
For k = 1
Accuracy = 83.7
f1_score = 55.0
precision_score = 57.0
recall_score = 55.0
```

7%| | 1/15 [00:  
05:26, 23.35s/it]

```
*****
For k = 3
Accuracy = 85.35000000000001
f1_score = 55.0
precision_score = 58.0
recall_score = 54.0
```

13%| | 2/15 [00:  
05:04, 23.44s/it]







```

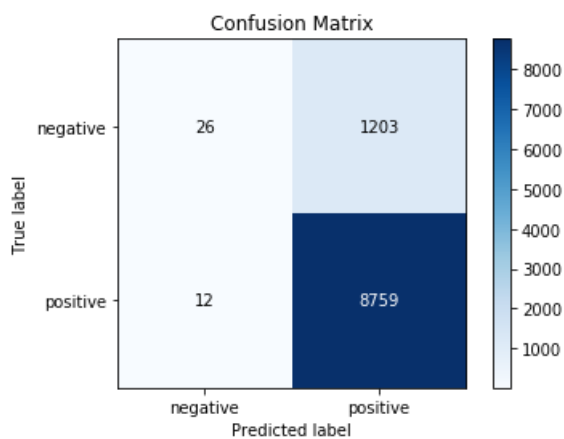
print("Best k = 11 ")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",np.round(f1_score(y_test, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_test, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_test, pred, average='macro')*100))
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()

```

```

***Test Data Report***
Best k = 11
Accuracy = 87.85
f1_score = 49.0
precision_score = 78.0
recall_score = 51.0

```



## BOW | KD\_TREE |

In [64]:

```

from sklearn.decomposition import TruncatedSVD
count_vect = CountVectorizer(min_df=50,max_features=2000)
train = count_vect.fit_transform(X_train_data['CleanedText'])
cv = count_vect.transform(X_cv_data['CleanedText'])
test = count_vect.transform(X_test_data['CleanedText'])
print(train.shape)
print(cv.shape)
print(test.shape)

```

```

(40000, 2000)
(10000, 2000)
(10000, 2000)

```

In [65]:

```

from sklearn.decomposition import TruncatedSVD
svd1 = TruncatedSVD(n_components=1999)
X_train = svd1.fit_transform(train)
len(X_train)

```

Out[65]:

```
40000
```

In [67]:

```

# initializing the pca
from sklearn import decomposition
pca = decomposition.PCA()
# PCA for dimensionality redcution (non-visualization)

pca.n_components = 1999
pca_data = pca.fit_transform(X_train)

percentage var explained = pca.explained_variance_ / np.sum(pca.explained_variance_):

```

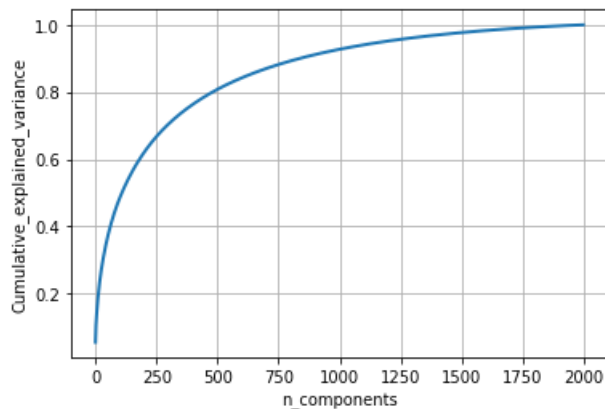
```
percentage_var_explained = percentage_var_explained_ / np.sum(pca.explained_variance_)

cum_var_explained = np.cumsum(percentage_var_explained)

# Plot the PCA spectrum
plt.figure(1, figsize=(6, 4))

plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()

# If we take 750-dimensions, approx. 90% of variance is explained.
```



In [68]:

```
svd = TruncatedSVD(n_components=750)
X_train = svd.fit_transform(train)
X_cv = svd.transform(cv)
X_test = svd.transform(test)
print(X_train.shape)
print(X_cv.shape)
print(X_test.shape)
```

```
(40000, 750)
(10000, 750)
(10000, 750)
```

In [69]:

```
for i in tqdm(range(1,30,2)):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i,algorithm='kd_tree')

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

    # predict the response on the crossvalidation data
    pred = knn.predict(X_cv)

    print("*****")
    print("For k = ",i)
    print('Accuracy = ', np.round(accuracy_score(y_cv, pred)*100))
    print("f1_score = ",np.round(f1_score(y_cv, pred, average='macro')*100))
    print("precision_score = ",np.round(precision_score(y_cv, pred, average='macro')*100))
    print("recall_score = ",np.round(recall_score(y_cv, pred, average='macro')*100))
```

```
0%|
[00:00<?, ?it/s]
```

```
*****
For k = 1
Accuracy = 82.0
f1_score = 57.0
```

```
f1_score = 57.0
precision_score = 57.0
recall_score = 57.0
```

7% | ██████████ | 1/15 [11:19<  
8:33, 679.53s/it]

```
*****
For k = 3
Accuracy = 86.0
f1_score = 57.0
precision_score = 63.0
recall_score = 56.0
```

13% | ██████████ | 2/15  
[22:53<2:28:08, 683.74s/it]

```
*****
For k = 5
Accuracy = 87.0
f1_score = 54.0
precision_score = 64.0
recall_score = 54.0
```

20% | ██████████ | 3/15  
[34:38<2:18:01, 690.17s/it]

```
*****
For k = 7
Accuracy = 88.0
f1_score = 53.0
precision_score = 67.0
recall_score = 53.0
```

27% | ██████████ | 4/15 [46:16<  
06:58, 692.59s/it]

```
*****
For k = 9
Accuracy = 88.0
f1_score = 52.0
precision_score = 72.0
recall_score = 53.0
```

33% | ██████████ | 5/15 [57:38<  
54:52, 689.27s/it]

```
*****
For k = 11
Accuracy = 88.0
f1_score = 52.0
precision_score = 74.0
recall_score = 52.0
```

40% | ██████████ | 6/15  
[1:09:04<1:43:16, 688.55s/it]

```
*****
For k = 13
Accuracy = 88.0
f1_score = 51.0
precision_score = 78.0
recall_score = 52.0
```

47% | ██████████ | 7/15  
[1:20:26<1:31:30, 686.32s/it]

```
*****
```

```
For k = 15
Accuracy = 88.0
f1_score = 50.0
precision_score = 78.0
recall_score = 52.0
```

```
53%|███████████| 8/15 [1:31:55<  
:20:11, 687.41s/it]
```

\*\*\*\*\*

```
For k = 17
Accuracy = 88.0
f1_score = 50.0
precision_score = 78.0
recall_score = 51.0
```

```
60%|███████████████████████████████████████████████████████████████████████████████          | 9/15 [1:43:20<
:08:38, 686.50s/it]
```

\*\*\*\*\*

```
For k = 19
Accuracy = 88.0
f1_score = 49.0
precision_score = 77.0
recall_score = 51.0
```

```
67%|███████████████████████████████████████████          | 10/15  
[1:55:00<57:32, 690.56s/it]
```

\*\*\*\*\*

```
For k = 21
Accuracy = 88.0
f1_score = 49.0
precision_score = 80.0
recall score = 51.0
```

[illegible]

\*\*\*\*\*

```
For k = 23
Accuracy = 88.0
f1_score = 49.0
precision_score = 84.0
recall_score = 51.0
```

```
80%|███████████          | 12/15 [2:18:0  
0<34:29, 689.88s/it]
```

\*\*\*\*\*

```
For k = 25
Accuracy = 88.0
f1_score = 48.0
precision_score = 81.0
recall_score = 51.0
```

[illegible]

\*\*\*\*\*

```
For k = 27
Accuracy = 88.0
f1_score = 48.0
precision_score = 85.0
recall score = 51.0
```

[illegible]

\*\*\*\*\*

```
For k = 29
Accuracy = 88.0
f1_score = 48.0
precision_score = 84.0
recall_score = 50.0
```

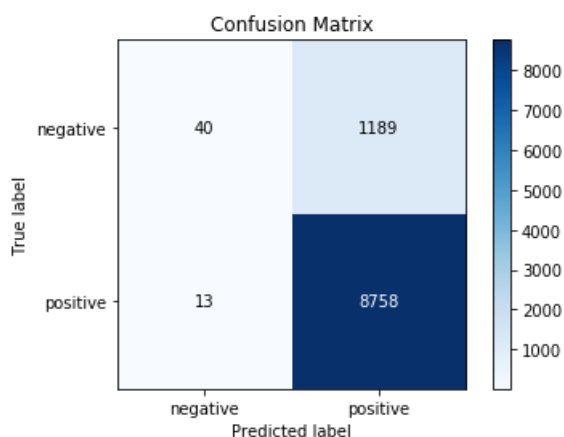
100% | 15/15  
[2:51:38<00:00, 678.79s/it]

In [71]:

```
knn = KNeighborsClassifier(n_neighbors=17,algorithm='kd_tree')
knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print("***Test Data Report***")
print("Best k = 17 ")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",np.round(f1_score(y_test, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_test, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_test, pred, average='macro')*100))
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Best k = 17
Accuracy = 87.98
f1_score = 50.0
precision_score = 82.0
recall_score = 52.0
```



## OBSERVATION :-

- BOW | BRUTE |
    - K = 11
    - f1\_score = 49.0
    - Accuracy = 87.85
  - BOW | KD\_TREE |
    - k = 17
    - f1\_score = 50.0
    - Accuracy = 87.98
- F1 Score is slightly larger in kd-tree as compared to brute force algorithm and also the accuracy is more as well

## TF - IDF

In [9]:

```
tf_idf_vect = TfidfVectorizer(min_df=50,max_features=2000)
X_train = tf_idf_vect.fit_transform(X_train_data['CleanedText'])
X_cv = tf_idf_vect.transform(X_cv_data['CleanedText'])
X_test = tf_idf_vect.transform(X_test_data['CleanedText'])
print(X_train.shape)
print(X_cv.shape)
print(X_test.shape)
```

```
(40000, 2000)
(10000, 2000)
(10000, 2000)
```

## TF - IDF | BRUTE |

In [10]:

```
for i in tqdm(range(1,30,2)):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i,algorithm='brute')

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

    # predict the response on the crossvalidation data
    pred = knn.predict(X_cv)

    print("*****")
    print("For k = ",i)
    print('Accuracy = ', accuracy_score(y_cv, pred)*100)
    print("f1_score = ",np.round(f1_score(y_cv, pred, average='macro')*100))
    print("precision_score = ",np.round(precision_score(y_cv, pred, average='macro')*100))
    print("recall_score = ",np.round(recall_score(y_cv, pred, average='macro')*100))
```

```
0%|          | C
[00:00<?, ?it/s]
```

```
*****
For k = 1
Accuracy = 87.11
f1_score = 50.0
precision_score = 59.0
recall_score = 52.0
```

```
7%|          | 1/15 [00:
04:36, 19.78s/it]
```

```
*****
For k = 3
Accuracy = 87.98
f1_score = 56.0
precision_score = 71.0
recall_score = 55.0
```

```
13%|          | 2/15 [00:
04:18, 19.87s/it]
```

```
*****
For k = 5
Accuracy = 88.44
f1_score = 56.0
precision_score = 78.0
recall_score = 55.0
```

```
20%|          | 3/15
[01:02<04:07, 20.63s/it]
```





[03:41<01:54, 22.90s/it]

```
*****
For k = 21
Accuracy = 88.64
f1_score = 54.0
precision_score = 91.0
recall_score = 54.0
```

73% | 11/15 [04:05<01:32, 23.12s/it]

```
*****
For k = 23
Accuracy = 88.59
f1_score = 53.0
precision_score = 91.0
recall_score = 53.0
```

80% | 12/15 [04:28<01:09, 23.17s/it]

```
*****
For k = 25
Accuracy = 88.46000000000001
f1_score = 52.0
precision_score = 90.0
recall_score = 53.0
```

87% | 13/15 [04:52<00:46, 23.44s/it]

```
*****
For k = 27
Accuracy = 88.5
f1_score = 53.0
precision_score = 92.0
recall_score = 53.0
```

93% | 14/15 [05:17<00:23, 23.81s/it]

```
*****
For k = 29
Accuracy = 88.41
f1_score = 52.0
precision_score = 90.0
recall_score = 53.0
```

100% | 15/15 [05:41<00:00, 24.03s/it]

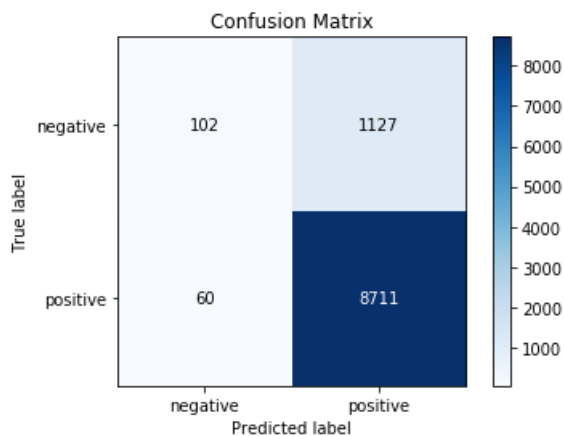
In [11]:

```
knn = KNeighborsClassifier(n_neighbors=7,algorithm='brute')
knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print("***Test Data Report***")
print("Best k = 7 ")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",np.round(f1_score(y_test, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_test, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_test, pred, average='macro')*100))
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Best k = 7
```

```
Accuracy = 88.13
f1_score = 54.0
precision_score = 76.0
recall_score = 54.0
```



## TF - IDF | KD\_TREE |

In [12]:

```
train = tf_idf_vect.fit_transform(X_train_data['CleanedText'])
cv = tf_idf_vect.transform(X_cv_data['CleanedText'])
test = tf_idf_vect.transform(X_test_data['CleanedText'])
print(train.shape)
print(cv.shape)
print(test.shape)
```

```
(40000, 2000)
(10000, 2000)
(10000, 2000)
```

In [13]:

```
from sklearn.decomposition import TruncatedSVD
svd1 = TruncatedSVD(n_components=1999)
X_train = svd1.fit_transform(train)
len(X_train)
```

Out[13]:

```
40000
```

In [14]:

```
# initializing the pca
from sklearn import decomposition
pca = decomposition.PCA()
# PCA for dimensionality reduction (non-visualization)

pca.n_components = 1999
pca_data = pca.fit_transform(X_train)

percentage_var_explained = pca.explained_variance_ / np.sum(pca.explained_variance_);

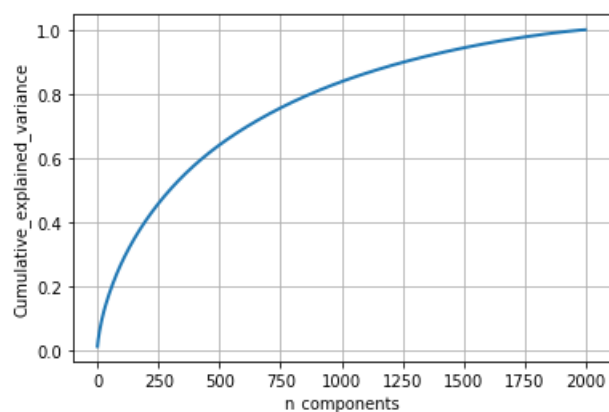
cum_var_explained = np.cumsum(percentage_var_explained)

# Plot the PCA spectrum
plt.figure(1, figsize=(6, 4))

plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative explained variance')
```

```
plt.show()
```

```
# If we take 1250-dimensions, approx. 90% of variance is explained.
```



In [15]:

```
svd = TruncatedSVD(n_components=1250)
X_train = svd.fit_transform(train)
X_cv = svd.transform(cv)
X_test = svd.transform(test)
print(X_train.shape)
print(X_cv.shape)
print(X_test.shape)
```

```
(40000, 1250)
(10000, 1250)
(10000, 1250)
```

In [16]:

```
for i in tqdm(range(1,30,2)):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i,algorithm='kd_tree')

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

    # predict the response on the crossvalidation data
    pred = knn.predict(X_cv)

    print("*****")
    print("For k = ",i)
    print('Accuracy = ', accuracy_score(y_cv, pred)*100)
    print("f1_score = ",np.round(f1_score(y_cv, pred, average='macro')*100))
    print("precision_score = ",np.round(precision_score(y_cv, pred, average='macro')*100))
    print("recall_score = ",np.round(recall_score(y_cv, pred, average='macro')*100))
```

```
0%|
[00:00<?, ?it/s]
```

```
*****
For k = 1
Accuracy = 85.92
f1_score = 53.0
precision_score = 58.0
recall_score = 53.0
```

```
7%|
:04, 1046.00s/it]
```

```
*****
For k = 3
Accuracy = 87.29
f1_score = 53.0
precision_score = 64.0
```

```
precision_score = 54.0
recall_score = 53.0
```

13%|██████████| 2/15  
[34:58<3:47:02, 1047.92s/it]

```
*****
For k = 5
Accuracy = 87.87
f1_score = 53.0
precision_score = 70.0
recall_score = 53.0
```

20%|██████████| 3/15  
[52:16<3:28:58, 1044.88s/it]

```
*****
For k = 7
Accuracy = 87.44
f1_score = 56.0
precision_score = 67.0
recall_score = 55.0
```

27%|██████████| 4/15 [1:10:51<3  
5:25, 1065.98s/it]

```
*****
For k = 9
Accuracy = 87.96000000000001
f1_score = 57.0
precision_score = 71.0
recall_score = 56.0
```

33%|██████████| 5/15 [1:29:45<3  
1:05, 1086.55s/it]

```
*****
For k = 11
Accuracy = 88.31
f1_score = 57.0
precision_score = 75.0
recall_score = 55.0
```

40%|██████████| 6/15  
[1:47:43<2:42:34, 1083.81s/it]

```
*****
For k = 13
Accuracy = 88.41
f1_score = 56.0
precision_score = 77.0
recall_score = 55.0
```

47%|██████████| 7/15  
[2:05:06<2:22:52, 1071.57s/it]

```
*****
For k = 15
Accuracy = 88.39
f1_score = 55.0
precision_score = 79.0
recall_score = 54.0
```

53%|██████████| 8/15 [2:22:39<2  
04:22, 1066.12s/it]

```
*****
For k = 17
Accuracy = 88.41
```

```
Accuracy = 88.41
f1_score = 53.0
precision_score = 82.0
recall_score = 53.0
```

```
60%|███████████          | 9/15 [2:40:04<1  
45:58, 1059.77s/it]
```

```
*****
For k = 19
Accuracy = 88.35
f1_score = 53.0
precision_score = 81.0
recall_score = 53.0
```

| 10/15

[2:57:26<1:27:52, 1054.45s/it]

```
*****
For k = 21
Accuracy = 88.49000000000001
f1_score = 53.0
precision_score = 87.0
recall_score = 53.0
```

```
73%|███████████████████████████████████████████████████████████████████████████████| 11/15  
[3:15:32<1:10:55, 1063.93s/it]
```

```
*****
For k = 23
Accuracy = 88.46000000000001
f1_score = 53.0
precision_score = 88.0
recall_score = 53.0
```

```
80%|███████████████████████████████████████████████████████████████████████████          | 12/15 [3:33:44]
<53:37, 1072.36s/it]
```

```
*****
For k = 25
Accuracy = 88.34
f1_score = 52.0
precision_score = 87.0
recall_score = 53.0
```

```
87%|███████████████████████████████████████████████████████████████████████████████          | 13/15 [3:51:51]
<35:53, 1076.73s/it]
```

```
*****
For k = 27
Accuracy = 88.31
f1_score = 51.0
precision_score = 88.0
recall_score = 52.0
```

```
93%|███████████████████████████████████████████████████████████████████          | 14/15  
[4:10:04<18:01, 1081.47s/it]
```

```
*****
For k = 29
Accuracy = 88.31
f1_score = 51.0
precision_score = 92.0
recall score = 52.0
```

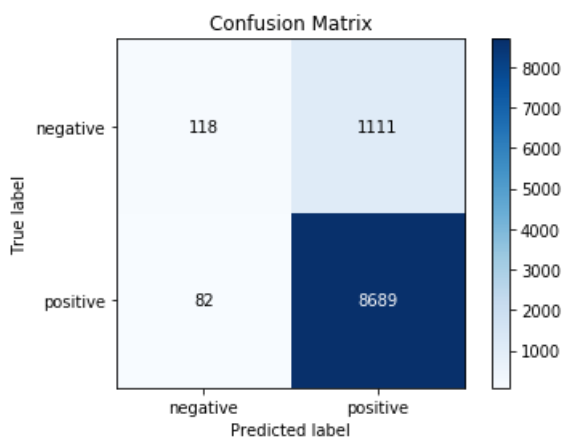
[illegible]

In [17]:

```
knn = KNeighborsClassifier(n_neighbors=13,algorithm='kd_tree')
knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print("***Test Data Report***")
print("Best k = 13 ")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",np.round(f1_score(y_test, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_test, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_test, pred, average='macro')*100))
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Best k = 13
Accuracy = 88.070000000000001
f1_score = 55.0
precision_score = 74.0
recall_score = 54.0
```



## OBSERVATION :-

- TF-IDF | BRUTE |
    1. K = 7
    2. f1\_score = 54.0
    3. Accuracy = 88.13
  - TF-IDF | KD\_TREE |
    1. k = 13
    2. f1\_score = 55.0
    3. Accuracy = 88.070000000000001
- F1 score is better in kd-tree as compared to brute force algorithm in TF-IDF

## W2VEC

In [19]:

```
import gensim
i=0
list_of_sent_train=[]
for sent in tqdm(X_train_data['Text'].values):
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()): # checking is the word is alphabet
                filtered_sentence.append(cleaned_words.lower()) # appending to the list
```

```

        filtered_sentence.append(cleaned_words.lower()) # appending to the list
    else:
        continue
list_of_sent_train.append(filtered_sentence)

```

```
100%|██████████████████████████████████████████████████████████████████████████████| 40000/40000  
[00:11<00:00, 3599.09it/s]
```

In [20]:

```
print(X_train_data['Text'].values[0])
print("*****")
print(list_of_sent_train[0])
```

```
this witty little book makes my son laugh at loud. i recite it in the car as we're driving along a
nd he always can sing the refrain. he's learned about whales, India, drooping roses: i love all t
he new words this book introduces and the silliness of it all. this is a classic book i am
willing to bet my son will STILL be able to recite from memory when he is in college
*****
['this', 'witty', 'little', 'book', 'makes', 'my', 'son', 'laugh', 'at', 'loud', 'i', 'recite', 'i
t', 'in', 'the', 'car', 'as', 'were', 'driving', 'along', 'and', 'he', 'always', 'can', 'sing', 't
he', 'refrain', 'hes', 'learned', 'about', 'whales', 'india', 'drooping', 'i', 'love', 'all', 'the
', 'new', 'words', 'this', 'book', 'introduces', 'and', 'the', 'silliness', 'of', 'it', 'all', 'th
is', 'is', 'a', 'classic', 'book', 'i', 'am', 'willing', 'to', 'bet', 'my', 'son', 'will',
'still', 'be', 'able', 'to', 'recite', 'from', 'memory', 'when', 'he', 'is', 'in', 'college']
```

In [21]:

```
w2v_model=gensim.models.Word2Vec(list of sent train,min count=5,size=50, workers=6)
```

In [22]:

```
words = list(w2v_model.wv.vocab)
print(len(words))
```

12405

In [23]:

```
w2v_model.wv.most_similar('good')
```

Out[23]:

```
[('great', 0.8216289281845093),
 ('decent', 0.7488343715667725),
 ('fine', 0.7407888174057007),
 ('fantastic', 0.7270007133483887),
 ('amazing', 0.7051384449005127),
 ('bad', 0.6884120106697083),
 ('yummy', 0.659767389294854),
 ('awesome', 0.6592874526977539),
 ('fabulous', 0.6558119058609009),
 ('ok', 0.6535512208938599)]
```

In [24]:

```
w2v_model.wv.most_similar('tasty')
```

Out[24]:

```
[('satisfying', 0.8282861709594727),
 ('filling', 0.8066790103912354),
 ('yummy', 0.7988016605377197),
 ('delicious', 0.7879558801651001),
 ('light', 0.7516793608665466),
 ('flavorful', 0.7407199144363403),
 ('crunchy', 0.7264057993888855),
 ('moist', 0.7226179242134094),
 ('nutritious', 0.7146416902542114),
 ('addicting', 0.6973412036895752)]
```



In [25]:

```
import gensim
i=0
list_of_sent_cv=[]
for sent in tqdm(X_cv_data['Text'].values):
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()): # checking is the word is alphabet
                filtered_sentence.append(cleaned_words.lower()) # appending to the list
            else:
                continue
    list_of_sent_cv.append(filtered_sentence)

100%|████████████████████████████████████████████████████████████████████████████████| 10000/10000
[00:03<00:00, 3187.41it/s]
```

In [26]:

```
import gensim
i=0
list_of_sent_test=[]
for sent in tqdm(X_test_data['Text'].values):
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()): # checking is the word is alphabet
                filtered_sentence.append(cleaned_words.lower()) # appending to the list
            else:
                continue
    list_of_sent_test.append(filtered_sentence)

100%|████████████████████████████████████████████████████████████████████████████████| 10000/10000
[00:02<00:00, 3620.47it/s]
```

## AVG - W2VEC

In [27]:

```
#TRAIN Data
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_train = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sent_train): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words = 0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors_train.append(sent_vec)
print(len(sent_vectors_train))
print(len(sent_vectors_train[0]))

100%|████████████████████████████████████████████████████████████████████████████████| 40000/40000
[00:14<00:00, 2720.57it/s]
```

40000  
50

```
#CV Data
# average Word2Vec
# compute average word2vec for each review.
sent_vectors_cv = []; # the avg-w2v for each sentence/review is stored in this list
for sent in tqdm(list_of_sent_cv): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words=0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors_cv.append(sent_vec)
print(len(sent_vectors_cv))
print(len(sent_vectors_cv[0]))
```

100%

10000/10000

[00:03<00:00, 2840.01it/s]

```
#TEST Data  
# average Word2Vec  
# compute average word2vec for each review.  
sentence_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list  
for sent in tqdm(list_of_sent_test):# for each review/sentence  
    sent_vec = np.zeros(50)# as word vectors are of zero length  
    cnt_words=0;# num of words with a valid vector in the sentence/review  
    for word in sent:# for each word in a review/sentence  
        try:  
            vec = w2v_model.wv[word]  
            sent_vec += vec  
            cnt_words += 1  
        except:  
            pass  
    sent_vec /= cnt_words  
    sentence_vectors_test.append(sent_vec)  
print(len(sentence_vectors_test))  
print(len(sentence_vectors_test[0]))
```

100% |██| 10000/10000  
[00:03<00:00, 2801.53it/s]

```
X_train = sent_vectors_train
X_cv = sent_vectors_cv
X_test = sent_vectors_test
```

```
for i in tqdm(range(1,30,2)):  
    # instantiate learning model (k = 30)  
    knn = KNeighborsClassifier(n_neighbors=i,algorithm='brute')  
  
    # fitting the model on train Data  
    knn.fit(X_train, y_train)
```

```
# predict the response on the crossvalidation data
pred = knn.predict(X_cv)

print("*****")
print("For k = ",i)
print('Accuracy = ', accuracy_score(y_cv, pred)*100)
print("f1_score = ",np.round(f1_score(y_cv, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_cv, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_cv, pred, average='macro')*100))
```

0%| | C  
[00:00<?, ?it/s]

```
*****
For k = 1
Accuracy = 85.17
f1_score = 61.0
precision_score = 63.0
recall_score = 60.0
```

7%| | 1/15 [00:  
02:25, 10.40s/it]

```
*****
For k = 3
Accuracy = 87.64
f1_score = 61.0
precision_score = 69.0
recall_score = 59.0
```

13%| | 2/15 [00:  
02:13, 10.29s/it]

```
*****
For k = 5
Accuracy = 88.12
f1_score = 60.0
precision_score = 72.0
recall_score = 58.0
```

20%| | 3/15  
[00:35<02:21, 11.82s/it]

```
*****
For k = 7
Accuracy = 88.5
f1_score = 60.0
precision_score = 75.0
recall_score = 57.0
```

27%| | 4/15 [00:  
<02:14, 12.26s/it]

```
*****
For k = 9
Accuracy = 88.56
f1_score = 59.0
precision_score = 76.0
recall_score = 57.0
```

33%| | 5/15 [01:  
<02:05, 12.59s/it]

```
*****
For k = 11
Accuracy = 88.58
f1_score = 58.0
precision_score = 77.0
```



```
f1_score = 56.0
precision_score = 80.0
recall_score = 55.0
```

87% | 13/15 [02:53<00:27, 13.64s/it]

```
*****
For k = 27
Accuracy = 88.5
f1_score = 55.0
precision_score = 80.0
recall_score = 55.0
```

93% | 14/15 [03:07<00:13, 13.86s/it]

```
*****
For k = 29
Accuracy = 88.46000000000001
f1_score = 55.0
precision_score = 80.0
recall_score = 54.0
```

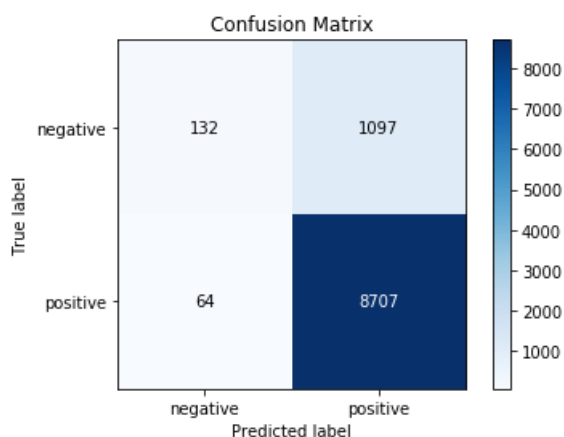
100% | 15/15 [03:22<00:00, 14.02s/it]

In [32]:

```
knn = KNeighborsClassifier(n_neighbors=17,algorithm='brute')
knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print("***Test Data Report***")
print("Best k = 17 ")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",np.round(f1_score(y_test, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_test, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_test, pred, average='macro')*100))
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Best k = 17
Accuracy = 88.39
f1_score = 56.0
precision_score = 78.0
recall_score = 55.0
```



## AVG - W2VEC | KD\_TREE |

In [33]:





80% | 12/15 [15:14<03:52, 77.40s/it]

```
*****
For k = 25
Accuracy = 88.55
f1_score = 56.0
precision_score = 80.0
recall_score = 55.0
```

87% | 13/15 [16:32<02:34, 77.38s/it]

```
*****
For k = 27
Accuracy = 88.5
f1_score = 55.0
precision_score = 80.0
recall_score = 55.0
```

93% | 14/15 [17:51<01:17, 77.88s/it]

```
*****
For k = 29
Accuracy = 88.46000000000001
f1_score = 55.0
precision_score = 80.0
recall_score = 54.0
```

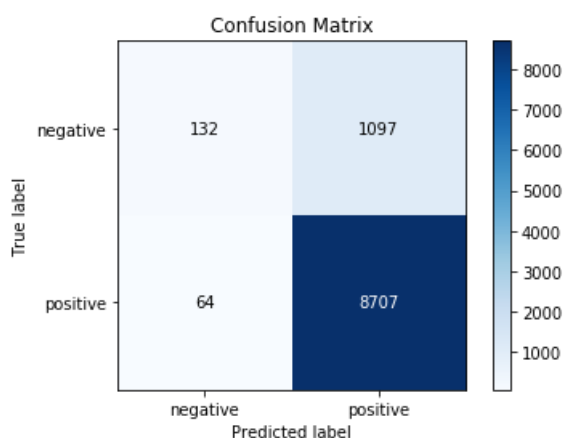
100% | 15/15 [19:09<00:00, 77.94s/it]

In [36]:

```
knn = KNeighborsClassifier(n_neighbors=17,algorithm='kd_tree')
knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print("***Test Data Report***")
print("Best k = 17 ")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",np.round(f1_score(y_test, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_test, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_test, pred, average='macro')*100))
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Best k = 17
Accuracy = 88.39
f1_score = 56.0
precision_score = 78.0
recall_score = 55.0
```





**OBSERVATION :-**

- AVG W2VEC | BRUTE |
  1. K = 17
  2. f1\_score = 56
  3. Accuracy = 88.39
- AVG W2VEC | KD\_TREE |
  1. k = 17
  2. f1\_score = 56
  3. Accuracy = 88.39
- Test data report for both the algorithms in AVG-W2VEC give similar results and K is same in both the cases as well

## TF - IDF W2VEC

In [37]:

```
tfidf_vect = TfidfVectorizer()
train_tfidf_w2v = tfidf_vect.fit_transform(X_train_data["CleanedText"])
cv_tfidf_w2v = tfidf_vect.transform(X_cv_data["CleanedText"])
test_tfidf_w2v = tfidf_vect.transform(X_test_data["CleanedText"])
print(train_tfidf_w2v.shape)
print(cv_tfidf_w2v.shape)
print(test_tfidf_w2v.shape)
```

(40000, 24413)  
(10000, 24413)  
(10000, 24413)

In [39]:

```
# TF-IDF weighted Word2Vec
tfidf_feat = tfidf_vect.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_train = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in tqdm(list_of_sent_train): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = train_tfidf_w2v[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors_train.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████████████████| 40000/40000 [30  
:23<00:00, 21.94it/s]
```

In [40]:

```
# TF-IDF weighted Word2Vec
tfidf_feat = tfidf_vect.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_cv = [] # the tfidf-w2v for each sentence/review is stored in this list
```

```
100%|██████████████████████████████████████████████████████████████████████████████| 10000/10000 [07  
:54<00:00, 19.53it/s]
```

```
# TF-IDF weighted Word2Vec
tfidf_feat = tfidf_vect.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_test = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in tqdm(list_of_sent_test): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            # obtain the tf_idf of a word in a sentence/review
            tf_idf = test_tfidf_w2v[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors_test.append(sent_vec)
    row += 1
```

```
100%|██████████████████████████████████████████████████████████████████████████████| 10000/10000 [07  
:38<00:00, 21.81it/s]
```

```
X_train = tfidf_sent_vectors_train
X_cv = tfidf_sent_vectors_cv
X_test = tfidf_sent_vectors_test
```

```
X_train = np.nan_to_num(X_train)
X_cv = np.nan_to_num(X_cv)
X_test = np.nan_to_num(X_test)
```

```
for i in tqdm(range(1,30,2)):
    # instantiate learning model (k = 30)
    knn = KNeighborsClassifier(n_neighbors=i,algorithm='brute')

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

```
# predict the response on the crossvalidation data
pred = knn.predict(X_cv)

print("*****")
print("For k = ",i)
print('Accuracy = ', accuracy_score(y_cv, pred)*100)
print("f1_score = ",np.round(f1_score(y_cv, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_cv, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_cv, pred, average='macro')*100))
```

0%| | C  
[00:00<?, ?it/s]

\*\*\*\*\*

For k = 1  
Accuracy = 82.0  
f1\_score = 57.0  
precision\_score = 57.0  
recall\_score = 57.0

7%| | 1/15 [00:  
02:36, 11.16s/it]

\*\*\*\*\*

For k = 3  
Accuracy = 86.0  
f1\_score = 57.0  
precision\_score = 62.0  
recall\_score = 56.0

13%| | 2/15 [00:  
02:24, 11.10s/it]

\*\*\*\*\*

For k = 5  
Accuracy = 87.0  
f1\_score = 56.0  
precision\_score = 66.0  
recall\_score = 55.0

20%| | 3/15  
[00:36<02:24, 12.03s/it]

\*\*\*\*\*

For k = 7  
Accuracy = 88.0  
f1\_score = 55.0  
precision\_score = 69.0  
recall\_score = 54.0

27%| | 4/15 [00:  
<02:19, 12.67s/it]

\*\*\*\*\*

For k = 9  
Accuracy = 88.0  
f1\_score = 55.0  
precision\_score = 72.0  
recall\_score = 54.0

33%| | 5/15 [01:  
<02:11, 13.18s/it]

\*\*\*\*\*

For k = 11  
Accuracy = 88.0  
f1\_score = 54.0  
precision\_score = 73.0  
recall\_score = 54.0



```
f1_score = 51.0
precision_score = 77.0
recall_score = 52.0
```

[illegible]

```
*****
For k = 27
Accuracy = 88.0
f1_score = 51.0
precision_score = 77.0
recall_score = 52.0
```

```
[03:09<00:13, 13.70s/it]
```

```
*****
For k = 29
Accuracy = 88.0
f1_score = 51.0
precision_score = 78.0
recall_score = 52.0
```

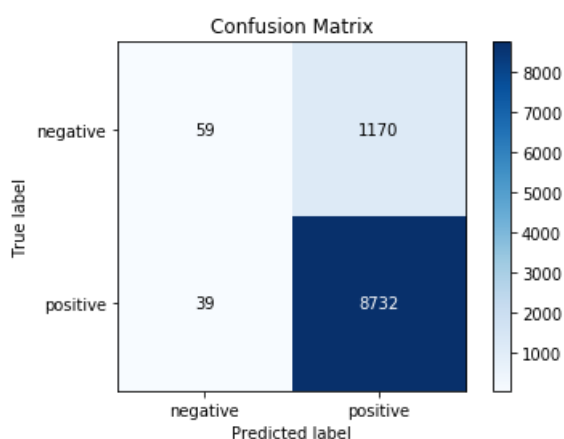
[illegible]

In [58]:

```
knn = KNeighborsClassifier(n_neighbors=21,algorithm='brute')
knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print("***Test Data Report***")
print("Best k = 21 ")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",np.round(f1_score(y_test, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_test, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_test, pred, average='macro')*100))
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Best k = 19
Accuracy = 88.0
f1_score = 51.0
precision_score = 74.0
recall score = 52.0
```



**TF-IDF - W2VEC | KD\_TREE |**

In [62]:

```
for i in tqdm(range(1,30,2)):  
    # instantiate learning model (k = 30)  
    knn = KNeighborsClassifier(n_neighbors=i,algorithm='kd_tree')  
  
    # fitting the model on train Data  
    knn.fit(X_train, y_train)  
  
    # predict the response on the crossvalidation data  
    pred = knn.predict(X_cv)  
  
    print("*****")  
    print("For k = ",i)  
    print('Accuracy = ', accuracy_score(y_cv, pred)*100)  
    print("f1_score = ",np.round(f1_score(y_cv, pred, average='macro')*100))  
    print("precision_score = ",np.round(precision_score(y_cv, pred, average='macro')*100))  
    print("recall score = ",np.round(recall_score(y_cv, pred, average='macro')*100))
```

```
0%|
[00:00<?, ?it/s]
```

\*\*\*\*\*

```
For k = 1
Accuracy = 82.0
f1_score = 57.0
precision_score = 57.0
recall score = 57.0
```

```
7%|██████████| 1/15 [01:17:04, 73.20s/it]
```

\*\*\*\*\*

```
For k = 3
Accuracy = 86.0
f1_score = 57.0
precision_score = 62.0
recall score = 56.0
```

```
13%|██████████| 2/15 [02:16:03, 74.10s/it]
```

\*\*\*\*\*

```
For k = 5
Accuracy = 87.0
f1_score = 56.0
precision_score = 66.0
recall score = 55.0
```

```
20%|██████████| 3/15
[03:40<14:40, 73.34s/it]
```

\*\*\*\*\*

```
For k = 7
Accuracy = 88.0
f1_score = 55.0
precision_score = 69.0
recall score = 54.0
```

```
27%|███████████          | 4/15 [05:  
<13:49, 75.38s/it]
```

\*\*\*\*\*

```
For k = 9
Accuracy = 88.0
f1_score = 55.0
precision_score = 72.0
recall score = 54.0
```

```
33%|███████████          | 5/15 [06:  
<12:46, 76.63s/it]
```



80% | 12/15 [15:07<03:46, 75.40s/it]

```
*****
For k = 25
Accuracy = 88.0
f1_score = 51.0
precision_score = 77.0
recall_score = 52.0
```

87% | 13/15 [16:22<02:30, 75.27s/it]

```
*****
For k = 27
Accuracy = 88.0
f1_score = 51.0
precision_score = 77.0
recall_score = 52.0
```

93% | 14/15 [17:37<01:15, 75.23s/it]

```
*****
For k = 29
Accuracy = 88.0
f1_score = 51.0
precision_score = 78.0
recall_score = 52.0
```

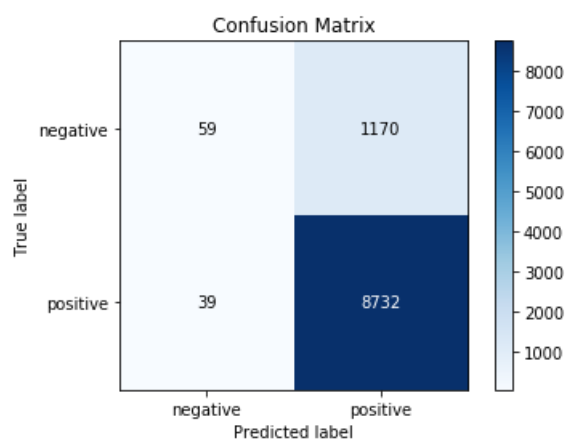
100% | 15/15 [18:52<00:00, 75.12s/it]

In [63]:

```
knn = KNeighborsClassifier(n_neighbors=21,algorithm='kd_tree')
knn.fit(X_train,y_train)
pred = knn.predict(X_test)

print("***Test Data Report***")
print("Best k = 21 ")
print('Accuracy = ', accuracy_score(y_test, pred)*100)
print("f1_score = ",np.round(f1_score(y_test, pred, average='macro')*100))
print("precision_score = ",np.round(precision_score(y_test, pred, average='macro')*100))
print("recall_score = ",np.round(recall_score(y_test, pred, average='macro')*100))
skplt.metrics.plot_confusion_matrix(y_test, pred)
plt.show()
```

```
***Test Data Report***
Best k = 21
Accuracy = 88.0
f1_score = 51.0
precision_score = 74.0
recall_score = 52.0
```





## OBSERVATION :-

- TF-IDF W2VEC | BRUTE |
    - K = 19
    - f1\_score = 51.0
    - Accuracy = 88.0
  - TF-IDF W2VEC | KD\_TREE |
    - K = 21
    - f1\_score = 51.0
    - Accuracy = 88.0
- Test data report for both the algorithms in TFIDF-W2VEC give similar results but k is Different in both cases

## RESULT

In [38]:

```
from IPython.display import HTML, display
import tabulate
table = [{"S.NO.", "MODEL || KNN ||", "Best K", "F1_SCORE", "Test Accuracy"},
         ["1", "BOW | brute |", "11", "49", "87.85"],
         ["2", "BOW | kd_tree |", "17", "50", "87.98"],
         ["3", "TF-IDF | brute |", "7", "54", "88.13"],
         ["4", "TF-IDF | kd_tree |", "13", "55", "88.07"],
         ["5", "AVG W2VEC | brute |", "17", "56", "88.39"],
         ["6", "AVG W2VEC | kd_tree |", "17", "56", "88.39"],
         ["7", "TF-IDF W2VEC | brute |", "19", "51.0", "88"],
         ["8", "TF-IDF W2VEC | kd_tree |", "21", "51.0", "88"]]
display(HTML(tabulate.tabulate(table, tablefmt='html')))
```

S.NO.	MODEL    KNN	Best K	F1_SCORE	Test Accuracy
1	BOW   brute	11	49	87.85
2	BOW   kd_tree	17	50	87.98
3	TF-IDF   brute	7	54	88.13
4	TF-IDF   kd_tree	13	55	88.07
5	AVG W2VEC   brute	17	56	88.39
6	AVG W2VEC   kd_tree	17	56	88.39
7	TF-IDF W2VEC   brute	19	51.0	88
8	TF-IDF W2VEC   kd_tree	21	51.0	88

## CONCLUSION

- AVG W2VEC(KD-TREE) & AVG W2VEC(BRUTE) gives the best accuracy rates among the models i.e 88.39
- BOW(BRUTE) gives the the least accuracy among the models.
- As amazon fine fodd reviews is a highly imbalanced dataset, so f1\_score, precision\_score, recall\_score plays major role in understanding the model performance rather than the accuracy rates, as we can see the the above results