Assignment 5

October 1, 2018

0.1 Assignment 5: Apply Logistic regression to Amazon reviews dataset.

Given Dataset consists of reviews of fine foods from amazon. Reviews describe (1)product and user information, (2)ratings, and (3) a plain text review.Here, Logistic Regression algorithm is applied on amazon reviews datasets to predict whether a review is positive or negative.

Procedure to execute the above task is as follows:

- **Step1: Data Pre-processing is applied on given amazon reviews data-set.And Take sample of data from dataset because of computational limitations**
- **Step2: Time based splitting on train and test datasets.**
- **Step3: Apply Feature generation techniques(Bow,tfidf,avg w2v,tfidfw2v)**
- **Step4: Apply Logistic Regression algorithm using each technique.**
- **Step5: To find lambda using gridsearch cross-validation and random cross-validation**
- **Step5: L1 and L2 regularization**
- **Step6: L1 Regularization- Increase lambda hyperparameter to generate sparcity in dataset.** 1. Report Performance metric 2. Report Error 3. Report Sparcity in "W*"
- **Step6: Feature Importance for postive and Negative reviews** 1. Most Important Feature 2. Bar plot of top 15 Important Features.

0.2 Objective:

- To classify given reviews (positive (Rating of 4 or 5) & negative (rating of 1 or 2)) using Logistic regression algorithm.

```
In [1]: # All necessary module
        %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        #import  sys
        import re
        import math
        import sqlite3
        import pandas as pd
```

```python
import numpy as np
import pickle

from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV

import pytablewriter

from sklearn.linear_model import LogisticRegression
from scipy.stats import uniform
from sklearn.model_selection import RandomizedSearchCV

# modules for text processing
import nltk
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
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 f1_score
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score

#import scikitplot.metrics as skplt
from sklearn.metrics import classification_report,confusion_matrix,accuracy

from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer


# knn modules
# train-split data,accuracy-score,cross-validation modules
from sklearn.cross_validation import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

from collections import Counter
from sklearn.metrics import accuracy_score
from sklearn import cross_validation
from sklearn.preprocessing import StandardScaler
```

```
/usr/local/lib/python3.6/site-packages/sklearn/cross_validation.py:41: DeprecationW
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
In [2]: import zipfile
        archive = zipfile.ZipFile('/floyd/input/pri/Reviews.zip', 'r')
        csvfile = archive.open('Reviews.csv')
```

```
In [3]: # Reading CSV file and printing first five rows
        amz = pd.read_csv(csvfile ) # reviews.csv is  dataset file
        print(amz.head())
```

```
   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      5  1303862400
1                     0                       0      1  1346976000
2                     1                       1      4  1219017600
3                     3                       3      2  1307923200
4                     0                       0      5  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...
```

```
In [4]: # dimensions of dataset and columns name

        print(amz.shape)
        #print(amz1.shape)
        print(amz.columns)
```

```
(568454, 10)
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text'],
      dtype='object')
```

The amazon reviews datafile contains 568454 rows of entry and 10 columns.For given objective, processing of data is necessary."Score" and "text" columns is processed for required result.

Given reviews with Score>3 a positive rating, and reviews with a score<3 a negative rating. If score is equal to 3,it is considered as neutral score.

In [5]:
```python
# Processing
#Give reviews with Score>3 a positive rating, and reviews with a score<3 a

def score_part(x):
    if x < 3:
        return 'negative'
    return 'positive'

actualScore = amz['Score']
#print(actualScore)
New_score = actualScore.map(score_part)
#print(New_score)
amz['Score']=New_score

# If score is equal to 3,it is considered as neutral score.
```

In [6]:
```python
print(amz.shape)
amz.head(5)
```

```
(568454, 10)
```

Out[6]:
```
   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...
```

Data Pre-processing on raw data: Every datasets contains some unwanted data.Raw data is preprocessed by removing duplication.

```
In [7]: #Processing of ProductId
        #Sorting data according to ProductId in ascending order
        sorted_data=amz.sort_values('ProductId', axis=0, ascending=True, inplace=Fa
        #sorted_data.head() # printing sorted data
        # To check the duplications in raw data
        dupli=sorted_data[sorted_data.duplicated(["UserId","ProfileName","Time","Te
        print(dupli.head(5))
        # Remove Deduplication of entries
        final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Te
        final.shape
        #Checking to see how much % of data still remains
        (final['Id'].size*1.0)/(amz['Id'].size*1.0)*100
        final=final[final.HelpfulnessNumerator<=final.HelpfulnessDenominator]
        #Before starting the next phase of preprocessing lets see the number of ent
        print(final.shape)

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

```
            Id   ProductId          UserId  \
171222  171223  7310172001   AJD41FBJD9010
171153  171154  7310172001   AJD41FBJD9010
171151  171152  7310172001   AJD41FBJD9010
217443  217444  7310172101  A22FICU3LCG2J1
217444  217445  7310172101  A1LQV0PSM04DWI

                                             ProfileName  HelpfulnessNumerator  \
171222  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     1
171153  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     0
171151  N. Ferguson "Two, Daisy, Hannah, and Kitten"                     0
217443                                      C. Knapp                     1
217444                                  B. Feuerstein                    1

        HelpfulnessDenominator     Score        Time  \
171222                       1  positive  1233360000
171153                       0  positive  1233360000
171151                       0  positive  1233360000
217443                       1  positive  1275523200
217444                       1  positive  1274313600

                                                 Summary  \
171222  best dog treat-- great for training---  all do...
171153  best dog treat-- great for training---  all do...
171151  dogs LOVE it--  best treat for rewards and tra...
217443                               Can't resist this !
```

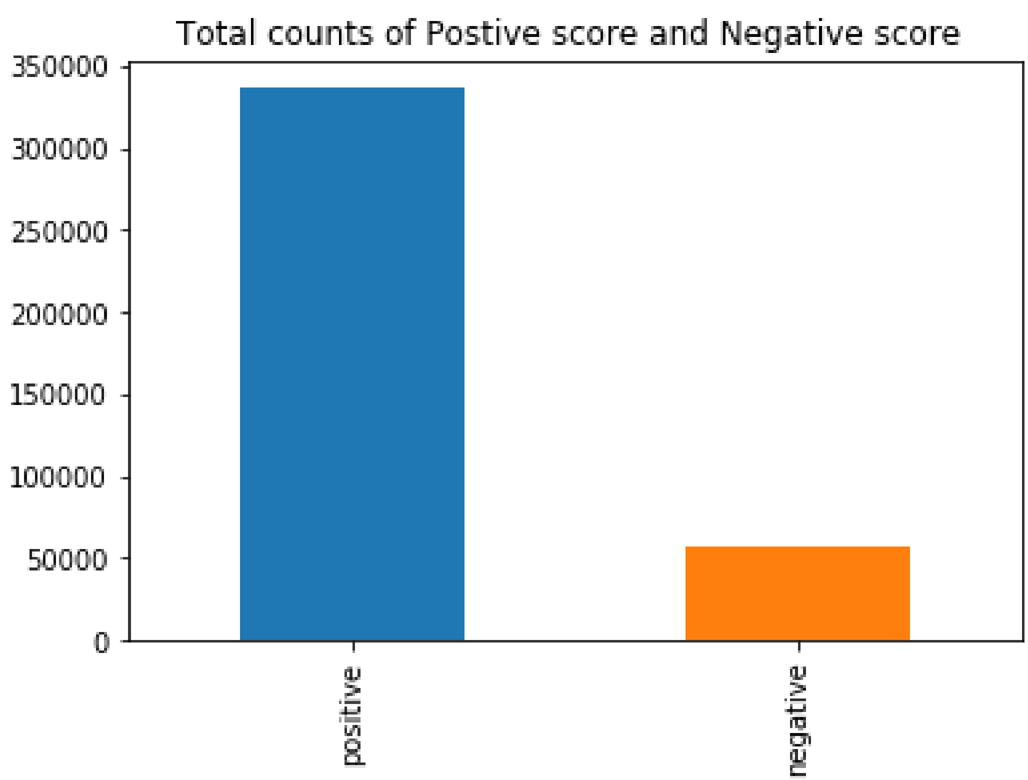
```
217444                          Freeze dried liver as dog treats

                                                              Text
171222  Freeze dried liver has a hypnotic effect on do...
171153  Freeze dried liver has a hypnotic effect on do...
171151  Freeze dried liver has a hypnotic effect on do...
217443  My dog can't resist these treats - I can get h...
217444  My little pupster loves these things. She is n...
(393931, 10)
```

```
Out[7]: positive    336824
        negative     57107
        Name: Score, dtype: int64
```

```
In [8]: a=final['Score'].value_counts().tolist()
        print('List of total counts Postive score and Negative score ==>',a)
        final['Score'].value_counts().plot(kind='bar')
        plt.title('Total counts of Postive score and Negative score ')
```

```
List of total counts Postive score and Negative score ==> [336824, 57107]
```

```
Out[8]: Text(0.5,1,'Total counts of Postive score and Negative score ')
```



observations

- The positive reviews is greater than negative reviews.It makes data imbalanced.
- From the bar plot ,it is seen that sampled datasets of review is imbalnced.

1 Text Preprocessing:

```
In [9]: import nltk
        nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
Out[9]: True
```

```
In [10]:
         stop = set(stopwords.words('english')) #set of stopwords
         sno = nltk.stem.SnowballStemmer('english') #initialising the snowball ste

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

cleaning html tags like" <.*?>" and punctuations like " r′[?|!|′|"|#]‘,r′′" from senetences

```
In [11]: #final = final.sample(frac=0.004,random_state=1)
         #print(final.shape)
```

```
In [12]: #Code for implementing step-by-step the checks mentioned in the pre-proces

         '''Pre processing of text data:It is cleaning and flitering text'''
         i=0
         str1=' '
         global final_string
         final_string=[]
         all_positive_words=[]
         all_negative_words=[]
         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 us
                                if(final['Score'].values)[i] == 'negative':
                                    all_negative_words.append(s) #list of all words us
                            else:
                                continue
                        else:
                            continue
                #print(filtered_sentence)
                str1 = b" ".join(filtered_sentence) #final string of cleaned words
                #print("***********************************************************

                final_string.append(str1)
                i+=1
            print('all_positive_words =',len(all_positive_words))
            print('all_negative_words =',len(all_negative_words))

            # Finding most frequently occuring Positive and Negative words

            freq_positive=nltk.FreqDist(all_positive_words)

            freq_negative=nltk.FreqDist(all_negative_words)

            print("\nMost Common Positive Words : ",freq_positive.most_common(20))

            print("\nMost Common Negative Words : ",freq_negative.most_common(20))
```

```
all_positive_words = 12908031
all_negative_words = 2338974

Most Common Positive Words :  [(b'like', 159742), (b'tast', 148220), (b'flavor', 12

Most Common Negative Words :  [(b'tast', 34433), (b'like', 32256), (b'product', 294
```

In [11]:
```
pickle_path_final_string='final_string.pkl'
final_string_unpkl=open(pickle_path_final_string,'rb')
final_string=pickle.load(final_string_unpkl)
```

In [12]:
```
final['CleanedText']=final_string
#adding a column of CleanedText which displays the data after pre-processi
Pre_Process_Data = final[['CleanedText','Score']]
```

```
X_Text=Pre_Process_Data ['CleanedText']

Y_Score =Pre_Process_Data ['Score'] # positive or negative score
print('\nPre_Process_Text_Data  X_Text=',X_Text.shape)
print('\nPre_Process_Score_Data Y_Score=',Y_Score.shape)
```

```
Pre_Process_Text_Data  X_Text= (393931,)

Pre_Process_Score_Data Y_Score= (393931,)
```

```
In [13]: # postive and negtive reviews from original datasets of amazon
         pos_final = final[final.Score == 'positive']# postive reviews
         pos_final = pos_final.sample(frac=0.3)
         print(pos_final.Score.value_counts())

         neg_final = final[final.Score == 'negative'] # negative reviews
         print(neg_final.Score.value_counts())
```

```
positive    101047
Name: Score, dtype: int64
negative    57107
Name: Score, dtype: int64
```

```
In [14]: final_pos_neg = pd.concat([pos_final,neg_final],axis=0)
         print(len(final_pos_neg))
         print(type(final_pos_neg))
         #print('final_pos_neg=',final_pos_neg['Score'])
```

```
158154
<class 'pandas.core.frame.DataFrame'>
```

```
In [15]: print(final_pos_neg.columns)
```

```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'CleanedText'],
      dtype='object')
```

1.0.1 Splitting Training and Testing dataset based on Time

```
In [16]: # splitting training and testing dataset
         #final_pos_neg= final_pos_neg.sample(frac=0.07,random_state=1)
         X1 = final_pos_neg[['Text','Time']].sort_values('Time',axis=0).drop('Time'
```

```
#50k data sample
X=X1[:40000]
print(X.shape)
Y1 = final_pos_neg[['Score','Time']].sort_values('Time',axis=0).drop('Time
#50k data sample
Y=Y1[:40000]
Y = Y['Score'].map(lambda x: 1 if x == 'positive' else 0).values
print(Y.shape)
## 70 % of data
tt =math.ceil(len(X)*.7)
print(tt)

X_train_data =  X[:tt]
X_train_data  = X_train_data
print('X_train_data ',X_train_data.shape)
X_test_data = X[tt:]
X_test_data = X_test_data
print('X_test_data ',X_test_data.shape )
Y_train_data = Y[:tt]
Y_train_data  = Y_train_data
print('Y_train_data ',Y_train_data.shape )
Y_test_data = Y[tt:]
Y_test_data= Y_test_data
print('Y_test_data ',Y_test_data .shape)
```

```
(40000, 1)
(40000,)
28000
X_train_data  (28000, 1)
X_test_data  (12000, 1)
Y_train_data  (28000,)
Y_test_data  (12000,)
```

Unix timestamp The column *Time* is based on unix timestamp.The unix time stamp is a way to track time as a running total of seconds and In time technically does not change no matter where you are located on the globe. This is very useful to computer systems for tracking and sorting dated information in dynamic and distributed applications both online and client side. https://www.unixtimestamp.com/

So here,time conversion is not necessary to process on amazon data.But following code will describe the date and time for human consideration.Time data is arranged according to year-month-day-hours-minute-seconds in descending order .

```
In [19]: # conversion of unix timestamp to human readable
         import datetime
         s=sorted_data['Time'].values.tolist() # convert pandas series into list
         print(len(s))
         ram=[]
```

```
for i in range(len(s)):

    #print(s[i])

    z=datetime.datetime.fromtimestamp(s[i]).strftime('%Y-%m-%d %H:%M:%S')
    # conversion formula of unix timestamp to yy-mm-dd-hh-mm-ss

    ram.append(z)
    #print(z)
print(ram[0:5])
```

```
568454
['2005-02-15 00:00:00', '2007-10-04 00:00:00', '2007-11-11 00:00:00', '2008-05-15 0
```

2 Optimal Lambda for Logistic Regression

In [20]:
```
models_performence = {
    'Model':[],
    'Vectorizer': [],
    'SearchCV':[],
    'Scoring Metrics': [],
    'Train_model_score': [],
    'Test_model_score': [],
    'best panalty': [],
    'Best lambda':[],
}

columns = ["Model","Vectorizer","SearchCV", "Scoring Metrics","Train_model
pd.DataFrame(models_performence, columns=columns)
```

Out[20]:
```
Empty DataFrame
Columns: [Model, Vectorizer, SearchCV, Scoring Metrics, Train_model_score,
Index: []
```

In [17]:
```
 # Time seris splitting Cross-Validation
tscv = TimeSeriesSplit(n_splits=10)
```

In [22]:
```
#  lambda_LR is function to calculate the lambda value using 'L2' for Log
def lambda_LR(X_train,y_train,X_test, y_test,vectorization):
    #  regularization penalty space
    penalty = ['l1']
    #  regularization hyperparameter distribution using uniform distribut
    C1 = uniform(loc=0, scale=4)
    C = np.logspace(0, 4, 10)
    #  hyperparameter options
```

```
hp1 =dict(C=C, penalty=penalty)
hp = dict(C=C1, penalty=penalty)
# Scoring options
d = ['accuracy','precision','recall','f1']

for i in range(len(d)):
    models_performence['Model'].append('Logistic Regression')
    models_performence['Vectorizer'].append(vectorization)
    models_performence['SearchCV'].append('GridSearchCV')
    #print('for GridSearchCV')
    p = d[i]
    models_performence['Scoring Metrics'].append(p)
    model1 = GridSearchCV(LogisticRegression(), hp1, scoring = p, cv=t
    best_model1=model1.fit(X_train, y_train)

    Test_model_score=model1.score(X_test, y_test)
    Train_model_score=model1.score(X_train, y_train)
    models_performence['Train_model_score'].append(Train_model_score.m
    models_performence['Test_model_score'].append(Test_model_score.mea

   # Reg1=best_model1.best_estimator_.get_params()['penalty']

    models_performence['best panalty'].append('l1')
    optimal_l1=best_model1.best_estimator_.get_params()['C']

    models_performence['Best lambda'].append(optimal_l1)



    #print('For RandomsearchCV')
    models_performence['Model'].append('Logistic Regression')
    models_performence['Vectorizer'].append(vectorization)

    models_performence['SearchCV'].append('RandomsearchCV')

    model2 = RandomizedSearchCV(LogisticRegression(),hp,scoring = p, c
    # Fit randomized search
    best_model2 = model2.fit(X_train,y_train)

    models_performence['Scoring Metrics'].append(p)
    #print(model2.best_estimator_)
    Test_model_score2=model2.score(X_test, y_test)
    Train_model_score=model2.score(X_train, y_train)
    models_performence['Train_model_score'].append(Train_model_score.m

    models_performence['Test_model_score'].append(Test_model_score2.me
    #Reg2=best_model2.best_estimator_.get_params()['penalty']
```

```
            models_performence['best panalty'].append('l1')
            optimal_l2=best_model2.best_estimator_.get_params()['C']


            models_performence['Best lambda'].append(optimal_l2)
```

```
In [23]: #  lambda_LR is function to calculate the lambda value using'L2' for Logis
        def lambda_LR1(X_train,y_train,X_test, y_test,vectorization):
            #  regularization penalty space
            penalty = ['l2']
            #  regularization hyperparameter distribution using uniform distributi
            C1 = uniform(loc=0, scale=4)
            C = np.logspace(0, 4, 10)
            #  hyperparameter options
            hp1 =dict(C=C, penalty=penalty)
            hp = dict(C=C1, penalty=penalty)
            # Scoring options
            d = ['accuracy','precision','recall','f1']

            for i in range(len(d)):
                models_performence['Model'].append('Logistic Regression')
                models_performence['Vectorizer'].append(vectorization)
                models_performence['SearchCV'].append('GridSearchCV')
                #print('for GridSearchCV')
                p = d[i]
                models_performence['Scoring Metrics'].append(p)
                model1 = GridSearchCV(LogisticRegression(), hp1, scoring = p, cv=t
                best_model1=model1.fit(X_train, y_train)

                Test_model_score=model1.score(X_test, y_test)
                Train_model_score=model1.score(X_train, y_train)
                models_performence['Train_model_score'].append(Train_model_score.m
                models_performence['Test_model_score'].append(Test_model_score.mea

                #Reg1=best_model1.best_estimator_.get_params()['penalty']

                models_performence['best panalty'].append('l2')
                optimal_l1=best_model1.best_estimator_.get_params()['C']

                models_performence['Best lambda'].append(optimal_l1)



                #print('For RandomsearchCV')
                models_performence['Model'].append('Logistic Regression')
```

```
        models_performence['Vectorizer'].append(vectorization)

        models_performence['SearchCV'].append('RandomsearchCV')

        model2 = RandomizedSearchCV(LogisticRegression(),hp,scoring = p, c
        # Fit randomized search
        best_model2 = model2.fit(X_train,y_train)

        models_performence['Scoring Metrics'].append(p)
        #print(model2.best_estimator_)
        Test_model_score2=model2.score(X_test, y_test)
        Train_model_score=model2.score(X_train, y_train)
        models_performence['Train_model_score'].append(Train_model_score.m

        models_performence['Test_model_score'].append(Test_model_score2.me
        #Reg2=best_model2.best_estimator_.get_params()['penalty']

        models_performence['best panalty'].append('l2')
        optimal_l2=best_model2.best_estimator_.get_params()['C']


        models_performence['Best lambda'].append(optimal_l2)
```

lambda_LR

- lambda_LR is function to calculate the optimal lambda value for Logistic Regression.
- GridsearchCV and RandomsearchCV method are used to obtain optimal lambda with L1&L2 penality,different scoring options(e.g,accuracy,precision,recall and F1-score) and broad range of lambda.
- Best parameter lambda and penalty for which model performs very well is obatained.

Pandas dataframe to markdown Table format

```
In [24]: # result_display  is function to convert dataframe into table format in Ma
         def result_display(df):
             writer = pytablewriter.MarkdownTableWriter()
             #writer.table_name = name
             writer.header_list = list(df.columns.values)
             writer.value_matrix = df.values.tolist()
             writer.write_table()
```

3 Methods to convert text into vector

Methods: * Bag of Words * Avg word2vec * Tf-idf * tf-idf weighted Word2Vec
Using above four method is used to convert text to numeric vector.

4 1. Bag of Words (BoW)

BOW for Training Data

```
In [25]: count_vect = CountVectorizer() #in scikit-learn
```

```
In [26]: #vector of train data
         data = count_vect.fit_transform(X_train_data.values.astype('U').ravel())
         data.get_shape()

         final_data = StandardScaler(with_mean=False).fit_transform(data )
         print(final_data.shape)
```

```
(28000, 33270)
```

Dumping & Loading Pickle file for training data (BOW)

```
In [27]: #Pickle file for training data
         pickle_path_BOW_train='X_train_data_BOW.pkl'
         X_train_data_BOW=open(pickle_path_BOW_train,'wb')
         pickle.dump(final_data ,X_train_data_BOW)
         X_train_data_BOW.close()
```

```
In [28]: pickle_path_BOW_train='X_train_data_BOW.pkl'
         unpickle_path1=open(pickle_path_BOW_train,'rb')
         final_data=pickle.load(unpickle_path1)
```

BOW for Testing Data

```
In [29]: final_data1=count_vect.transform(X_test_data.values.ravel())
         #print(final_data1)
         final_data_test = StandardScaler(with_mean=False).fit_transform(final_data
         print(final_data_test.shape)
```

```
(12000, 33270)
```

Dumping & Loading Pickle file for testing data (BOW)

```
In [30]: pickle_path_BOW_test='X_test_data_BOW.pkl'
         X_test_data_BOW=open(pickle_path_BOW_test,'wb')
         pickle.dump(final_data_test ,X_test_data_BOW)
         X_test_data_BOW.close()
```

```
In [31]: pickle_path_BOW_test='X_test_data_BOW.pkl'
         unpickle_path2=open(pickle_path_BOW_test,'rb')
         final_data_test=pickle.load(unpickle_path2)
```

Featured data of Bag of words is Standardization (mean=0 and std.dev=1).

```
In [17]: Train_data=Y_train_data
```

Optimal lambda using BOW (l1 regularization)

```
In [33]: # To get optimal lambda using BOW
         vectorization='BOW'
         optimal_lambda = lambda_LR(final_data ,Train_data,final_data_test,Y_test_d
```

Optimal lambda using BOW (l2 regularization)

```
In [34]: # To get optimal lambda using BOW

         vectorization='BOW'
         optimal_lambda = lambda_LR1(final_data ,Train_data,final_data_test,Y_test_
```

Dumping & loading model-performance in pickle format(BOW)

```
In [35]: pickle_path_BOW_lambda='optimal_lambda_BOW.pkl'
         optimal_lambda_BOW=open(pickle_path_BOW_lambda,'wb')
         pickle.dump(models_performence,optimal_lambda_BOW)
         optimal_lambda_BOW.close()
```

```
In [36]: pickle_path_BOW_lambda='optimal_lambda_BOW.pkl'
         unpickle_path11=open(pickle_path_BOW_lambda,'rb')
         models_performence22=pickle.load(unpickle_path11)
```

```
In [37]: columns = ["Model","Vectorizer","SearchCV", "Scoring Metrics","Train_model
         df=pd.DataFrame(models_performence22, columns=columns)
```

```
In [38]: result_display(df)
```

```
|       Model        |Vectorizer|   SearchCV    |Scoring Metrics|Train_model_score|Te
|--------------------|----------|---------------|---------------|----------------:|--
|Logistic Regression|BOW       |GridSearchCV   |accuracy       |           0.9993|
|Logistic Regression|BOW       |RandomsearchCV|accuracy       |           0.9917|
|Logistic Regression|BOW       |GridSearchCV   |precision      |           0.9993|
|Logistic Regression|BOW       |RandomsearchCV|precision      |           0.9912|
|Logistic Regression|BOW       |GridSearchCV   |recall         |           0.9997|
|Logistic Regression|BOW       |RandomsearchCV|recall         |           0.9983|
|Logistic Regression|BOW       |GridSearchCV   |f1             |           0.9995|
|Logistic Regression|BOW       |RandomsearchCV|f1             |           0.9995|
|Logistic Regression|BOW       |GridSearchCV   |accuracy       |           0.9999|
```

```
|Logistic Regression|BOW       |RandomsearchCV|accuracy       |             0.9997|
|Logistic Regression|BOW       |GridSearchCV  |precision      |             1.0000|
|Logistic Regression|BOW       |RandomsearchCV|precision      |             0.9938|
|Logistic Regression|BOW       |GridSearchCV  |recall         |             1.0000|
|Logistic Regression|BOW       |RandomsearchCV|recall         |             0.9990|
|Logistic Regression|BOW       |GridSearchCV  |f1             |             0.9999|
|Logistic Regression|BOW       |RandomsearchCV|f1             |             0.9999|
```

Model	Vectorizer	SearchCV	Scoring Metrics	Train_model_score	Test_model_score	best penalty	Best lambda
Logistic Regression	BOW	GridSearchCV	accuracy	0.9993	0.8206	l1	1.0000
Logistic Regression	BOW	RandomsearchCV	accuracy	0.9917	0.8477	l1	0.1599
Logistic Regression	BOW	GridSearchCV	precision	0.9993	0.8587	l1	1.0000
Logistic Regression	BOW	RandomsearchCV	precision	0.9912	0.8725	l1	0.1387
Logistic Regression	BOW	GridSearchCV	recall	0.9997	0.8791	l1	1.0000
Logistic Regression	BOW	RandomsearchCV	recall	0.9983	0.8933	l1	0.3494
Logistic Regression	BOW	GridSearchCV	f1	0.9995	0.8691	l1	1.0000
Logistic Regression	BOW	RandomsearchCV	f1	0.9995	0.8692	l1	0.9742
Logistic Regression	BOW	GridSearchCV	accuracy	0.9999	0.8016	l2	1.0000
Logistic Regression	BOW	RandomsearchCV	accuracy	0.9997	0.8082	l2	0.3761
Logistic Regression	BOW	GridSearchCV	precision	1.0000	0.8389	l2	21.5443
Logistic Regression	BOW	RandomsearchCV	precision	0.9938	0.8578	l2	0.0108
Logistic Regression	BOW	GridSearchCV	recall	1.0000	0.8688	l2	1.0000
Logistic Regression	BOW	RandomsearchCV	recall	0.9990	0.8934	l2	0.0497
Logistic Regression	BOW	GridSearchCV	f1	0.9999	0.8554	l2	1.0000
Logistic Regression	BOW	RandomsearchCV	f1	0.9999	0.8560	l2	0.8697

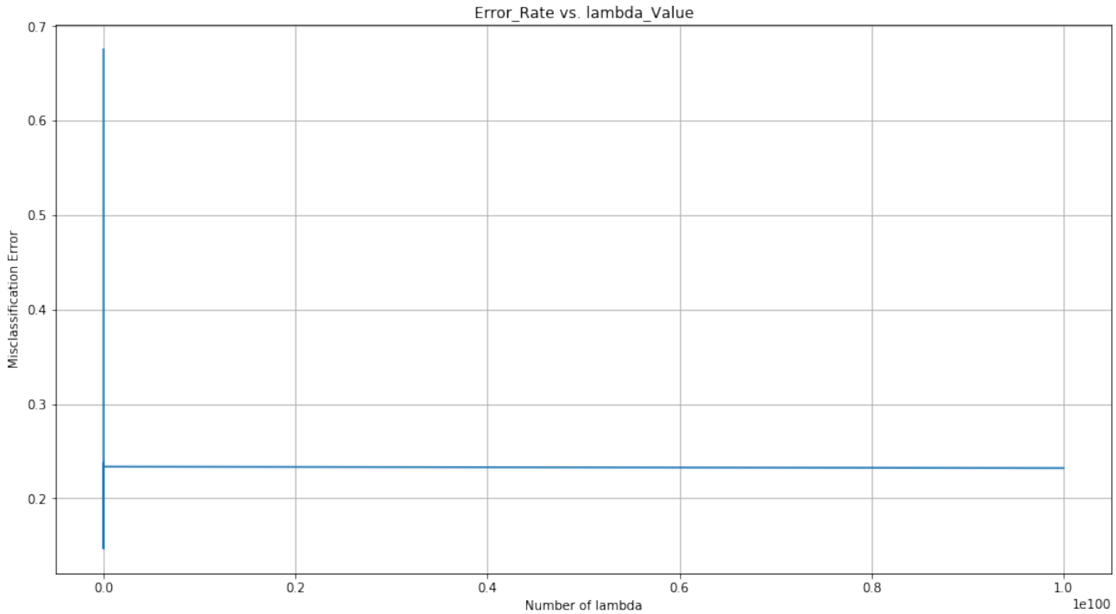
Above table describes the performance of model with different scoring techniques and regularization techniques with best Cross-validation search techniques.

5 L1 Regularization

Increase lambda hyperparameter to generate sparcity in dataset.

In [39]:
```
C2 = np.logspace(-50, 100, 50)
hp2= list(C2)
socore=[]
Sparsity=[]

for vect_data in range(len(hp2)):
    r=hp2[vect_data]
    clf = LogisticRegression(C=r, penalty='l1')
    clf.fit(final_data ,Train_data)
    w1 = clf.coef_
    #print(np.count_nonzero(w1))
    Sparsity.append(np.count_nonzero(w1))
    w = clf.coef_.ravel()
    model_score=clf.score(final_data_test,Y_test_data)
    socore.append(model_score)

MSE = [1 - x for x in socore]
global optimal_k
optimal_k = hp2[MSE.index(min(MSE))]
print('\nThe optimal number of lambda is %d.' % optimal_k)



  # plot misclassification error vs k
plt.figure(figsize=(15,8))
plt.plot(hp2, MSE)
plt.grid()
#for xy in zip(hp2, np.round(MSE,3)):
#    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.title('Error_Rate vs. lambda_Value')
plt.xlabel('Number of lambda')
plt.ylabel('Misclassification Error')
plt.show()

print("the misclassification error for each lambda_Value is : ", np.round

#print(socore)
print('Sparsity ==',Sparsity)
```

```
The optimal number of lambda is 0.
```




```
the misclassification error for each lambda_Value is :  [0.675 0.675 0.675 0.675 0.
 0.675 0.675 0.675 0.675 0.147 0.209 0.223 0.231 0.228 0.228 0.234 0.229
 0.232 0.231 0.231 0.235 0.23  0.235 0.23  0.23  0.234 0.231 0.229 0.234
 0.237 0.233 0.23  0.235 0.233 0.232 0.233 0.233 0.23  0.229 0.233 0.235
 0.234 0.232]
Sparsity == [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8247, 16627, 22818, 29
```

Observations:

- Sparsity of data increases as Increase in lambda hyperparameter.
- L1 regularization is used for calculating sparsityof datasets.
- The graph of error rate vs lambda value is shown above.

5.1 GridSearchCV with L2 regularization (BOW)

In [40]:
```
df=pd.DataFrame(models_performence22, columns=columns)
zx=df[df['best panalty'] == 'l2']
zx=zx[zx['SearchCV']=='GridSearchCV']
zx= zx.ix[zx['Test_model_score'].idxmax()]
print(zx)
lambdax=zx['Best lambda']

best_panalty=zx['best panalty']

Scoring_Metrics =zx['Scoring Metrics']
SearchCV=zx['SearchCV']
#print(SearchCV)
```

```
Model                  Logistic Regression
Vectorizer                             BOW
SearchCV                      GridSearchCV
Scoring Metrics                     recall
Train_model_score                        1
Test_model_score                  0.868846
best panalty                            l2
Best lambda                              1
Name: 12, dtype: object
```

In [41]:
```
#Best lambda and best penalty
hp1=dict(C=[lambdax], penalty=[best_panalty])
LR =GridSearchCV(LogisticRegression(), hp1, scoring =Scoring_Metrics, cv=t
LR.fit(final_data ,Train_data)

prediction1 = LR.predict(final_data_test)
```

In [42]:
```
#Training accuracy and training error
training_score=LR.score(final_data,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 1.0
training error is = 0.0
```

In [43]:
```
# Testing Accuracy and testing error for LogisticRegression model

Testing_score=round(accuracy_score(Y_test_data ,prediction1),5)
print("Accuracy for Logistic Regression model with Bag of words is = ",Tes
Testing_error=1-Testing_score
print("Testing error for Logistic Regression model with Bag of words is =
```

```
Accuracy for Logistic Regression model with Bag of words is =  0.80158
Testing error for Logistic Regression model with Bag of words is =  0.198420000000(
```

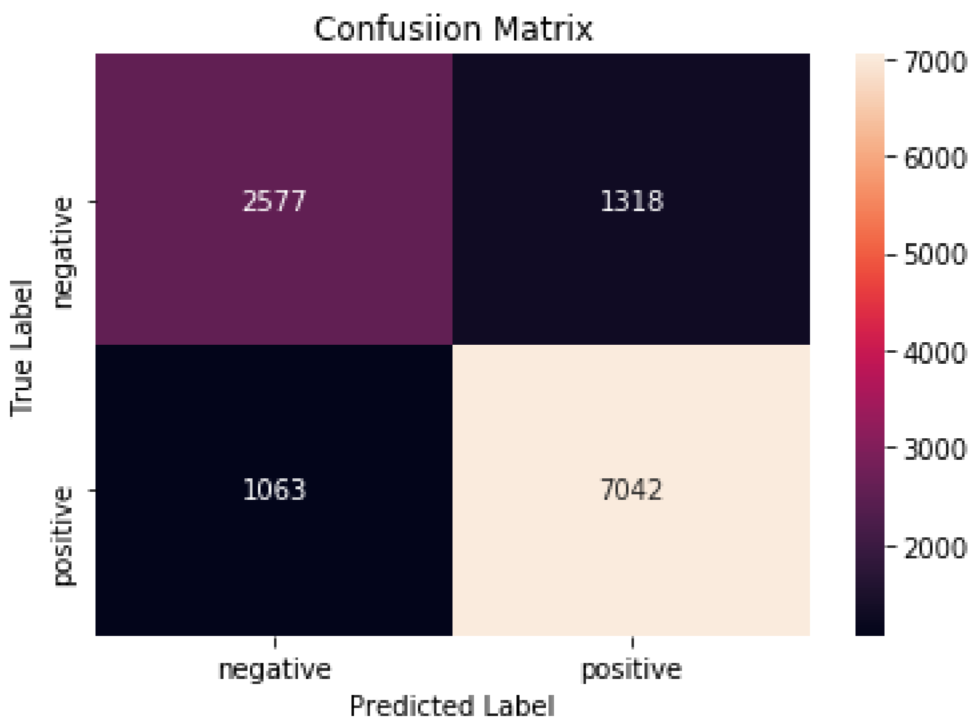
In [44]:
```
F1_score = round(f1_score(Y_test_data ,prediction1,average='macro'),5)*10(
recall = round(recall_score(Y_test_data,prediction1,average='macro'),5)*1(
precision = round(precision_score(Y_test_data ,prediction1,average='macro'
```

In [45]:
```
print(classification_report( Y_test_data,prediction1))
```

```
             precision    recall  f1-score   support

          0       0.71      0.66      0.68      3895
          1       0.84      0.87      0.86      8105
```

```
avg / total       0.80      0.80      0.80     12000
```

```
In [46]: cm = confusion_matrix(Y_test_data ,prediction1)
         label = ['negative', 'positive']
         df_conf = pd.DataFrame(cm, index = label, columns = label)
         sns.heatmap(df_conf, annot = True, fmt = "d")
         plt.title("Confusiion Matrix")
         plt.xlabel("Predicted Label")
         plt.ylabel("True Label")
         plt.show()
```




```
In [47]: models_performence1 = {
             'Model':['Logistic Regression'],
             'Vectorizer': ['BoW'],
             'SearchCV':[SearchCV],
             'Best penalty':[best_panalty],
             'Optimal lambda': [lambdax],
             'Training error':[training_error*100],
             'Test error':[Testing_error*100],
             'Accuracy':[Testing_score],
             'F1':[F1_score],
```

```
            'recall':[recall],
            'precision':[precision]


        }
```

```
In [48]: columns = ["Model","Vectorizer","SearchCV", "Best penalty","Optimal lambda
                    "Accuracy","F1","recall","precision",
                  ]
         df1=pd.DataFrame(models_performence1, columns=columns)
```

```
In [49]: result_display(df1)
```

```
|       Model       |Vectorizer|  SearchCV   |Best penalty|Optimal lambda|Training e
|-------------------|----------|-------------|------------|-------------:|----------
|Logistic Regression|BoW       |GridSearchCV|l2          |             1|
```

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	BoW	GridSearchCV	l2	1	0	19.84	0.8016	76.97	76.52	77.52

5.2 RandomsearchCV with L2 regularization (BOW)

```
In [50]: #RandomsearchCV
         zx=df[df['best panalty'] == 'l2']
         zx=zx[zx['SearchCV']=='RandomsearchCV']
         zx= zx.ix[zx['Test_model_score'].idxmax()]
         print(zx)
         lambdax=zx['Best lambda']

         best_panalty=zx['best panalty']

         Scoring_Metrics =zx['Scoring Metrics']
         SearchCV=zx['SearchCV']
         #print(SearchCV)
```

```
Model                    Logistic Regression
Vectorizer                               BOW
SearchCV                      RandomsearchCV
Scoring Metrics                       recall
Train_model_score                   0.999046
Test_model_score                    0.893399
best panalty                              l2
Best lambda                        0.0497333
```

```
Name: 13, dtype: object
```

```
In [51]: #Best lambda and best penalty
         C1 = uniform(loc=0, scale=lambdax)
         hp2=dict(C=C1, penalty=[best_panalty])
         LR2 =RandomizedSearchCV(LogisticRegression(), hp2, scoring =Scoring_Metric
         LR2.fit(final_data ,Train_data)

         prediction2 = LR2.predict(final_data_test)
         lambda_new=LR2.best_params_['C']
```

```
In [52]: #Training accuracy and training error
         training_score=LR2.score(final_data,Train_data)
         print('training accuracy=',training_score)
         training_error=1-training_score
         print('training error is =',training_error)
```

```
training accuracy= 0.9955312311709179
training error is = 0.004468768829082093
```

```
In [53]: # Testing Accuracy and testing error for LogisticRegression model

         Testing_score=round(accuracy_score(Y_test_data ,prediction2),5)
         print("Accuracy for Logistic Regression model with Bag of words is = ",Tes
         Testing_error=1-Testing_score
         print("Testing error for Logistic Regression model with Bag of words is =
```

```
Accuracy for Logistic Regression model with Bag of words is =  0.846
Testing error for Logistic Regression model with Bag of words is =  0.1540000000000
```

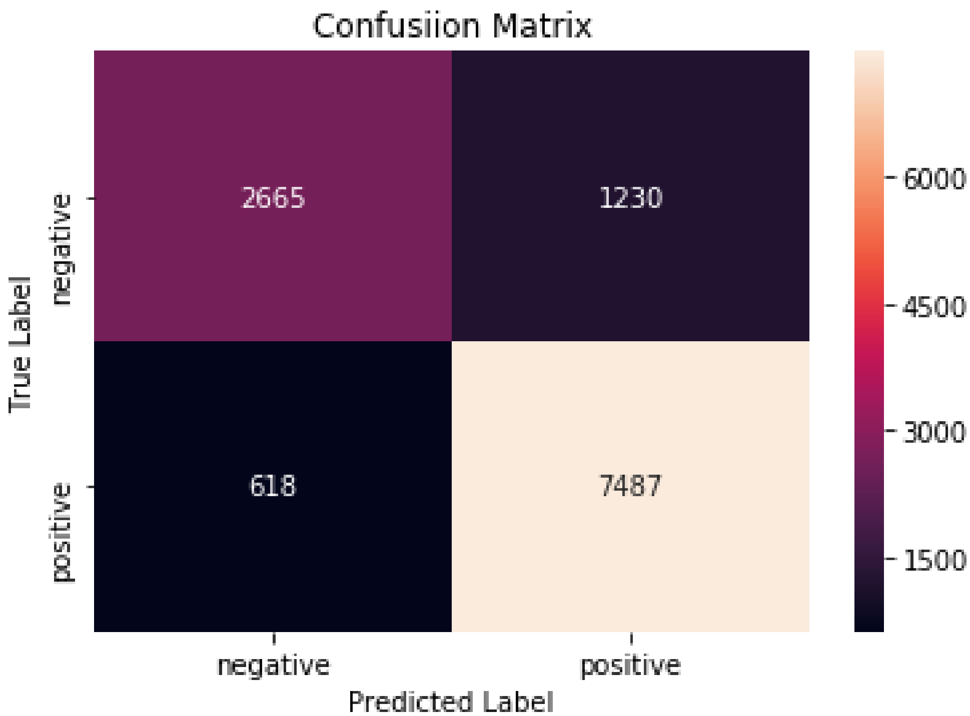
```
In [54]: F1_score = round(f1_score(Y_test_data ,prediction2,average='macro'),5)*100
         recall = round(recall_score(Y_test_data,prediction2,average='macro'),5)*10
         precision = round(precision_score(Y_test_data ,prediction2,average='macro'
```

```
In [55]: print(classification_report( Y_test_data,prediction2))
```

```
             precision    recall  f1-score   support

          0       0.81      0.68      0.74      3895
          1       0.86      0.92      0.89      8105

avg / total       0.84      0.85      0.84     12000
```

```
In [56]: cm = confusion_matrix(Y_test_data ,prediction2)
         label = ['negative', 'positive']
```

```
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



In [57]:
```
models_performence1['Model'].append('Logistic Regression')
models_performence1['Vectorizer'].append('BOW')
models_performence1['SearchCV'].append(SearchCV)
models_performence1['Best penalty'].append(best_panalty)
models_performence1[ 'Optimal lambda'].append(lambda_new)
models_performence1['Training error'].append(training_error*100)
models_performence1[ 'Test error'].append(Testing_error*100)
models_performence1[ 'Accuracy'].append(Testing_score)
models_performence1[ 'F1'].append(F1_score)
models_performence1['recall'].append(recall)
models_performence1[ 'precision'].append(precision)
```

In [58]:
```
columns = ["Model","Vectorizer","SearchCV", "Best penalty","Optimal lambda
            "Accuracy","F1","recall","precision",
           ]
df3=pd.DataFrame(models_performence1, columns=columns)
```

In [59]:
```
result_display(df3)
```

```
|       Model       |Vectorizer|    SearchCV    |Best penalty|Optimal lambda|Training
|-------------------|----------|---------------|------------|-------------:|--------
|Logistic Regression|BoW       |GridSearchCV   |l2          |        1.0000|
|Logistic Regression|BOW       |RandomsearchCV|l2          |        0.0042|
```

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	BoW	GridSearchCV	l2	1.0000	0.000	19.84	0.8016	76.97	76.52	77.52
Logistic Regression	BOW	RandomsearchCV	l2	0.0042	0.447	15.40	0.8460	81.63	80.40	83.53

5.3 GridSearchCV with L1 regularization (BOW)

```
In [60]: zx=df[df['best panalty'] == 'l1']
         zx=zx[zx['SearchCV']=='GridSearchCV']
         zx= zx.ix[zx['Test_model_score'].idxmax()]
         print(zx)
         lambdax=zx['Best lambda']

         best_panalty=zx['best panalty']

         Scoring_Metrics =zx['Scoring Metrics']
         SearchCV=zx['SearchCV']
         #print(SearchCV)
```

```
Model                    Logistic Regression
Vectorizer                               BOW
SearchCV                        GridSearchCV
Scoring Metrics                       recall
Train_model_score                   0.999749
Test_model_score                    0.879087
best panalty                              l1
Best lambda                                1
Name: 4, dtype: object
```

```
In [61]: hp3=dict(C=[lambdax], penalty=[best_panalty])

         LR3 =GridSearchCV(LogisticRegression(), hp3, scoring = Scoring_Metrics, cv

         LR3.fit(final_data ,Train_data)

         prediction3 = LR3.predict(final_data_test)
```

```
In [62]: #Training accuracy and training error
         training_score=LR3.score(final_data,Train_data)
         print('training accuracy=',training_score)
         training_error=1-training_score
         print('training error is =',training_error)
```

```
training accuracy= 0.9997489455713999
training error is = 0.00025105442860007265
```

```
In [63]: # Testing Accuracy and testing error for LogisticRegression model
         Testing_score=round(accuracy_score(Y_test_data ,prediction3),5)
         print("Accuracy for Logistic Regression model with Bag of words is = ",Tes
         Testing_error=1-Testing_score
         print("Testing error for Logistic Regression model with Bag of words is =
```

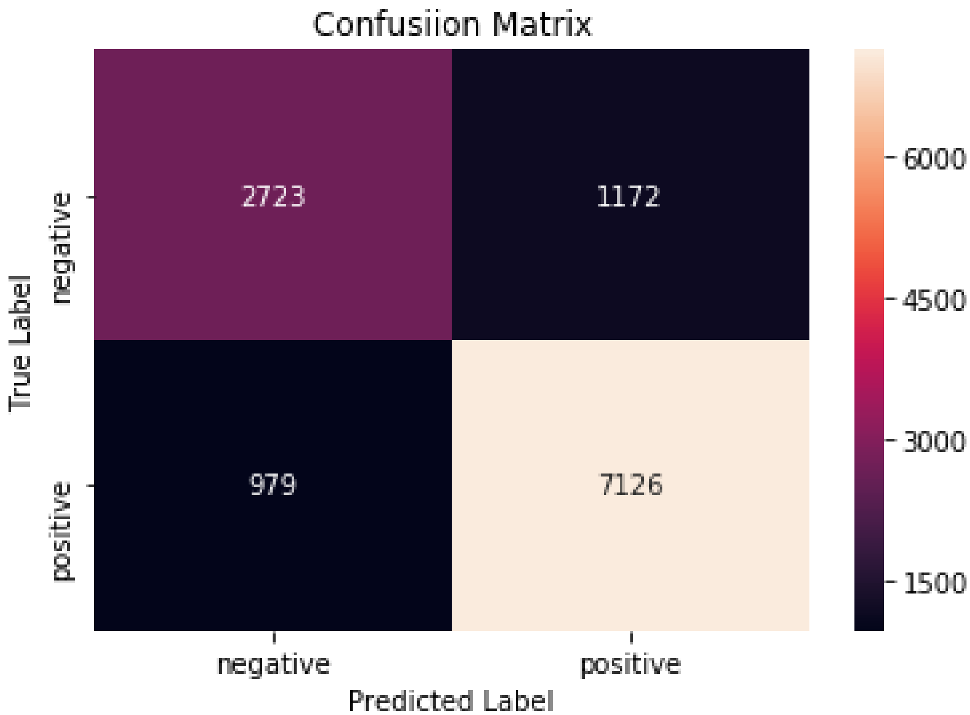
```
Accuracy for Logistic Regression model with Bag of words is =  0.82075
Testing error for Logistic Regression model with Bag of words is =  0.1792500000000
```

```
In [64]: F1_score = round(f1_score(Y_test_data ,prediction3,average='macro'),5)*100
         recall = round(recall_score(Y_test_data,prediction3,average='macro'),5)*10
         precision = round(precision_score(Y_test_data ,prediction3,average='macro'
```

```
In [65]: print(classification_report( Y_test_data,prediction3))
```

```
             precision    recall  f1-score   support

          0       0.74      0.70      0.72      3895
          1       0.86      0.88      0.87      8105

avg / total       0.82      0.82      0.82     12000
```

```
In [66]: cm = confusion_matrix(Y_test_data ,prediction3)
         label = ['negative', 'positive']
         df_conf = pd.DataFrame(cm, index = label, columns = label)
         sns.heatmap(df_conf, annot = True, fmt = "d")
         plt.title("Confusiion Matrix")
         plt.xlabel("Predicted Label")
         plt.ylabel("True Label")
         plt.show()
```




```
In [67]: models_performence1['Model'].append('Logistic Regression')
         models_performence1['Vectorizer'].append('BOW')
         models_performence1['SearchCV'].append(SearchCV)
         models_performence1['Best penalty'].append(best_panalty)
         models_performence1[ 'Optimal lambda'].append(lambdax)
         models_performence1['Training error'].append(training_error*100)
         models_performence1[ 'Test error'].append(Testing_error*100)
         models_performence1[ 'Accuracy'].append(Testing_score)
         models_performence1[ 'F1'].append(F1_score)
         models_performence1['recall'].append(recall)
         models_performence1[ 'precision'].append(precision)
```

```
In [68]: columns = ["Model","Vectorizer","SearchCV", "Best penalty","Optimal lambda
                     "Accuracy","F1","recall","precision",
                    ]
         df4=pd.DataFrame(models_performence1, columns=columns)
```

```
In [69]: result_display(df4)
```

```
|       Model        |Vectorizer|   SearchCV    |Best penalty|Optimal lambda|Training
|-------------------|----------|---------------|------------|-------------:|--------
|Logistic Regression|BoW       |GridSearchCV   |l2          |         1.000|
|Logistic Regression|BOW       |RandomsearchCV|l2          |         0.004|
|Logistic Regression|BOW       |GridSearchCV   |l1          |         1.000|
```

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	BoW	GridSearchCV	l2	1.000	0.0000	19.84	0.8016	76.97	76.52	77.52
Logistic Regression	BOW	RandomsearchCV	l2	0.004	0.4469	15.40	0.8460	81.63	80.40	83.53
Logistic Regression	BOW	GridSearchCV	l1	1.000	0.0251	17.92	0.8207	79.29	78.92	79.71

5.4 RandomsearchCV with L1 regularization (BOW)

```
In [70]: #RandomsearchCV

         zx=df[df['best panalty'] == 'l1']
         zx=zx[zx['SearchCV']=='RandomsearchCV']
         zx= zx.ix[zx['Test_model_score'].idxmax()]
         print(zx)
         lambdax=zx['Best lambda']

         best_panalty=zx['best panalty']

         Scoring_Metrics =zx['Scoring Metrics']
         SearchCV=zx['SearchCV']
         #print(SearchCV)
```

```
Model                    Logistic Regression
Vectorizer                               BOW
SearchCV                      RandomsearchCV
Scoring Metrics                       recall
Train_model_score                   0.998343
Test_model_score                    0.893276
best panalty                              l1
Best lambda                         0.349364
Name: 5, dtype: object
```

```
In [71]: #Best lambda and best penalty
         C1 = uniform(loc=0, scale=lambdax)
         hp4=dict(C=C1, penalty=[best_panalty])
         LR4 =RandomizedSearchCV(LogisticRegression(), hp2, scoring =Scoring_Metric
         LR4.fit(final_data ,Train_data)

         prediction4 = LR4.predict(final_data_test)
         lambda_new=LR4.best_params_['C']
```

In [72]:
```
#Training accuracy and training error
training_score=LR4.score(final_data,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.991765414741916
training error is = 0.008234585258083996
```

In [73]:
```
# Testing Accuracy and testing error for LogisticRegression model
Testing_score=round(accuracy_score(Y_test_data ,prediction4),5)
print("Accuracy for Logistic Regression model with Bag of words is = ",Tes
Testing_error=1-Testing_score
print("Testing error for Logistic Regression model with Bag of words is =
```

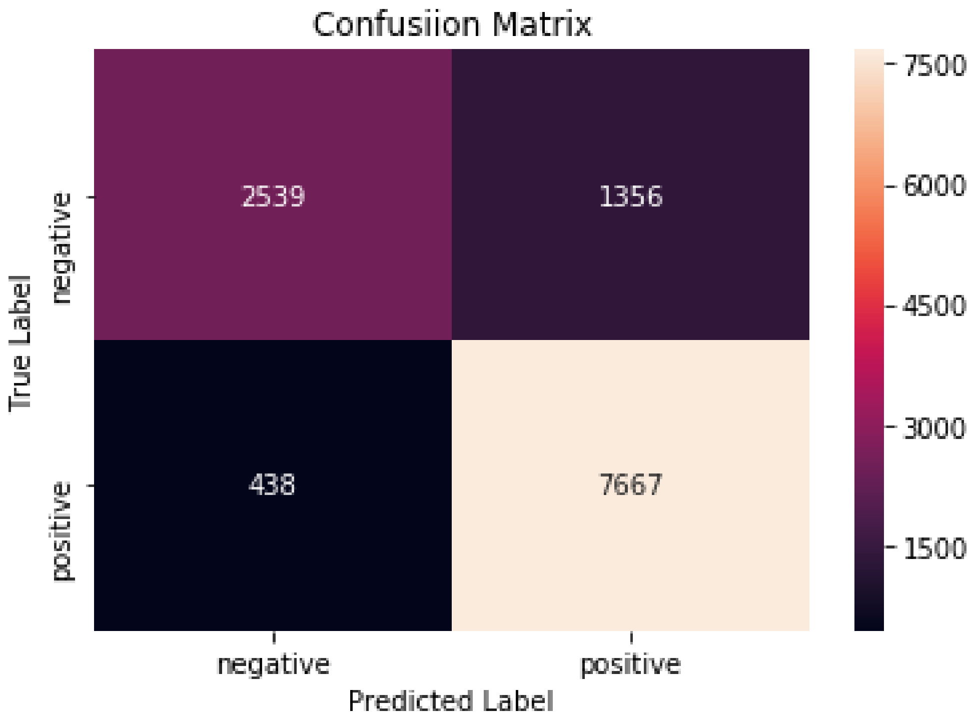
```
Accuracy for Logistic Regression model with Bag of words is =  0.8505
Testing error for Logistic Regression model with Bag of words is =  0.149499999999
```

In [74]:
```
F1_score = round(f1_score(Y_test_data ,prediction4,average='macro'),5)*10C
recall = round(recall_score(Y_test_data,prediction4,average='macro'),5)*1C
precision = round(precision_score(Y_test_data ,prediction4,average='macro'
```

In [75]:
```
print(classification_report( Y_test_data,prediction4))
```

```
             precision    recall  f1-score   support

          0       0.85      0.65      0.74      3895
          1       0.85      0.95      0.90      8105

avg / total       0.85      0.85      0.84     12000
```

In [76]:
```
cm = confusion_matrix(Y_test_data ,prediction4)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```




```
In [77]: models_performence1['Model'].append('Logistic Regression')
         models_performence1['Vectorizer'].append('BOW')
         models_performence1['SearchCV'].append(SearchCV)
         models_performence1['Best penalty'].append(best_panalty)
         models_performence1[ 'Optimal lambda'].append(lambda_new)
         models_performence1['Training error'].append(training_error*100)
         models_performence1[ 'Test error'].append(Testing_error*100)
         models_performence1[ 'Accuracy'].append(Testing_score)
         models_performence1[ 'F1'].append(F1_score)
         models_performence1['recall'].append(recall)
         models_performence1[ 'precision'].append(precision)
```

```
In [78]: columns = ["Model","Vectorizer","SearchCV", "Best penalty","Optimal lambda
                    "Accuracy","F1","recall","precision",
                   ]
         df5=pd.DataFrame(models_performence1, columns=columns)
```

```
In [79]: result_display(df5)
```

```
|       Model        |Vectorizer|   SearchCV    |Best penalty|Optimal lambda|Training
|-------------------|----------|---------------|------------|-------------:|--------
|Logistic Regression|BoW       |GridSearchCV   |l2          |        1.0000|        0
|Logistic Regression|BOW       |RandomsearchCV|l2          |        0.0042|        0
|Logistic Regression|BOW       |GridSearchCV   |l1          |        1.0000|        0
```

```
|Logistic Regression|BOW        |RandomsearchCV|l1             |         0.0005|        (
```

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	BoW	GridSearchCV	l2	1.0000	0.00000	19.84	0.8016	76.97	76.52	77.52
Logistic Regression	BOW	RandomsearchCV	l2	0.0042	0.44688	15.40	0.8460	81.63	80.40	83.53
Logistic Regression	BOW	GridSearchCV	l1	1.0000	0.02511	17.92	0.8207	79.29	78.92	79.71
Logistic Regression	BOW	RandomsearchCV	l1	0.0005	0.82346	14.95	0.8505	81.71	79.89	85.13

Dumping & Loading models_performence1 obtained by BOW

```
In [80]: pickle_path_BOW_final_result='optimal_lambda_BOW_final_result.pkl'
         optimal_lambda_BOW_final_result1=open(pickle_path_BOW_final_result,'wb')
         pickle.dump(models_performence1,optimal_lambda_BOW_final_result1)
         optimal_lambda_BOW_final_result1.close()
```

```
In [81]: pickle_path_BOW_final_result='optimal_lambda_BOW_final_result.pkl'
         unpickle_path_final=open(pickle_path_BOW_final_result,'rb')
         models_performence122=pickle.load(unpickle_path_final)
```

5.4.1 Observations:

- Logistic Regression with BOW using GridsearchCV & RandomSearchCV for L1 & L2 regularization techniques is used to get optimal lambda .
- Scoring metrics's values is good for Optimal Penalty l2 & randomsearchCV
- Training error is minimum here but test error is high compartively with training error.

6 2. tf-idf

```
In [82]: ##### TF-IDF for Training data
```

```
In [83]: models_performence = {
             'Model':[],
             'Vectorizer': [],
             'SearchCV':[],
             'Scoring Metrics': [],
             'Train_model_score': [],
             'Test_model_score': [],
             'best panalty': [],
             'Best lambda':[],
```

```
}

columns = ["Model","Vectorizer","SearchCV", "Scoring Metrics","Train_model
pd.DataFrame(models_performence, columns=columns)
```

```
Out[83]: Empty DataFrame
         Columns: [Model, Vectorizer, SearchCV, Scoring Metrics, Train_model_score,
         Index: []
```

```
In [18]: tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
         final_tf_idf = tf_idf_vect.fit_transform(X_train_data.values.astype('U').r
         final_tf_idf.get_shape()
```

```
Out[18]: (28000, 530093)
```

```
In [19]: features = tf_idf_vect.get_feature_names()
         len(features)
```

```
Out[19]: 530093
```

```
In [21]: final_tfidf_np = StandardScaler(with_mean=False).fit_transform(final_tf_ic
```

Dumping & Loading Pickle file for training data (TF-IDF)

```
In [26]: pickle_path_tfidf_train='X_train_data_tfidf.pkl'
         X_train_data_tfidf=open(pickle_path_tfidf_train,'wb')
         pickle.dump(final_tfidf_np ,X_train_data_tfidf)
         X_train_data_tfidf.close()
```

```
In [27]: pickle_path_tfidf_train='X_train_data_tfidf.pkl'
         unpickle_path5=open(pickle_path_tfidf_train,'rb')
         final_tfidf_np=pickle.load(unpickle_path5)
```

tf-idf For Testing datasets

```
In [22]: final_tf_idf_test = tf_idf_vect.transform(X_test_data.values.astype('U').r
         final_tf_idf_test.get_shape()
```

```
Out[22]: (12000, 530093)
```

```
In [23]: final_tfidf_np_test = StandardScaler(with_mean=False).fit_transform(final_
```

Dumping & Loading Pickle file for testing data(TF-IDF)

```
In [30]: pickle_path_tfidf_test='X_test_data_tfidf.pkl'
         X_test_data_tfidf=open(pickle_path_tfidf_test,'wb')
         pickle.dump(final_tfidf_np_test ,X_test_data_tfidf)
         X_test_data_tfidf.close()
```

In [31]:
```
pickle_path_tfidf_test='X_test_data_tfidf.pkl'
unpickle_path6=open(pickle_path_tfidf_test,'rb')
final_tfidf_np_test=pickle.load(unpickle_path6)
```

In [93]:
```
vectorization='TF-IDF'
optimal_lambda = lambda_LR(final_tfidf_np ,Train_data,final_tfidf_np_test,
```

In [94]:
```
vectorization='TF-IDF'
optimal_lambda = lambda_LR1(final_tfidf_np ,Train_data,final_tfidf_np_test
```

In [95]:
```
pickle_path_tfidf_lambda='optimal_lambda_tfidf.pkl'
optimal_lambda_tfidf=open(pickle_path_tfidf_lambda,'wb')
pickle.dump(models_performence,optimal_lambda_tfidf)
optimal_lambda_tfidf.close()
```

In [96]:
```
pickle_path_tfidf_lambda='optimal_lambda_tfidf.pkl'
unpickle_path232=open(pickle_path_tfidf_lambda,'rb')
models_performence232=pickle.load(unpickle_path232)
```

In [97]:
```
columns = ["Model","Vectorizer","SearchCV", "Scoring Metrics","Train_model
df6=pd.DataFrame(models_performence232, columns=columns)
```

In [98]:
```
result_display(df6)
```

```
|       Model       |Vectorizer|   SearchCV    |Scoring Metrics|Train_model_score|Te
|-------------------|----------|---------------|---------------|----------------:|--
|Logistic Regression|TF-IDF    |GridSearchCV   |accuracy       |                1|
|Logistic Regression|TF-IDF    |RandomsearchCV|accuracy       |                1|
|Logistic Regression|TF-IDF    |GridSearchCV   |precision      |                1|
|Logistic Regression|TF-IDF    |RandomsearchCV|precision      |                1|
|Logistic Regression|TF-IDF    |GridSearchCV   |recall         |                1|
|Logistic Regression|TF-IDF    |RandomsearchCV|recall         |                1|
|Logistic Regression|TF-IDF    |GridSearchCV   |f1             |                1|
|Logistic Regression|TF-IDF    |RandomsearchCV|f1             |                1|
|Logistic Regression|TF-IDF    |GridSearchCV   |accuracy       |                1|
|Logistic Regression|TF-IDF    |RandomsearchCV|accuracy       |                1|
|Logistic Regression|TF-IDF    |GridSearchCV   |precision      |                1|
|Logistic Regression|TF-IDF    |RandomsearchCV|precision      |                1|
|Logistic Regression|TF-IDF    |GridSearchCV   |recall         |                1|
|Logistic Regression|TF-IDF    |RandomsearchCV|recall         |                1|
|Logistic Regression|TF-IDF    |GridSearchCV   |f1             |                1|
|Logistic Regression|TF-IDF    |RandomsearchCV|f1             |                1|
```

Model	Vectorizer	SearchCV	Scoring Metrics	Train_model_score	Test_model_score	best penalty	Best lambda
Logistic Regression	TF-IDF	GridSearchCV	accuracy	1	0.8667	l1	2.7826
Logistic Regression	TF-IDF	RandomsearchCV	accuracy	1	0.8654	l1	3.9285
Logistic Regression	TF-IDF	GridSearchCV	precision	1	0.8669	l1	2.7826
Logistic Regression	TF-IDF	RandomsearchCV	precision	1	0.8673	l1	2.4854
Logistic Regression	TF-IDF	GridSearchCV	recall	1	0.9662	l1	59.9484
Logistic Regression	TF-IDF	RandomsearchCV	recall	1	0.9477	l1	2.9219
Logistic Regression	TF-IDF	GridSearchCV	f1	1	0.9057	l1	2.7826
Logistic Regression	TF-IDF	RandomsearchCV	f1	1	0.9044	l1	2.6000
Logistic Regression	TF-IDF	GridSearchCV	accuracy	1	0.8247	l2	10000.0000
Logistic Regression	TF-IDF	RandomsearchCV	accuracy	1	0.8225	l2	3.8382
Logistic Regression	TF-IDF	GridSearchCV	precision	1	0.8060	l2	10000.0000
Logistic Regression	TF-IDF	RandomsearchCV	precision	1	0.8028	l2	3.5410
Logistic Regression	TF-IDF	GridSearchCV	recall	1	0.9771	l2	1.0000
Logistic Regression	TF-IDF	RandomsearchCV	recall	1	0.9798	l2	0.0122
Logistic Regression	TF-IDF	GridSearchCV	f1	1	0.8825	l2	10000.0000
Logistic Regression	TF-IDF	RandomsearchCV	f1	1	0.8812	l2	3.9405

Above table shows the Performance of Logistic Regression using TF-IDF for various Cross-validation techniques,scoring techniques .

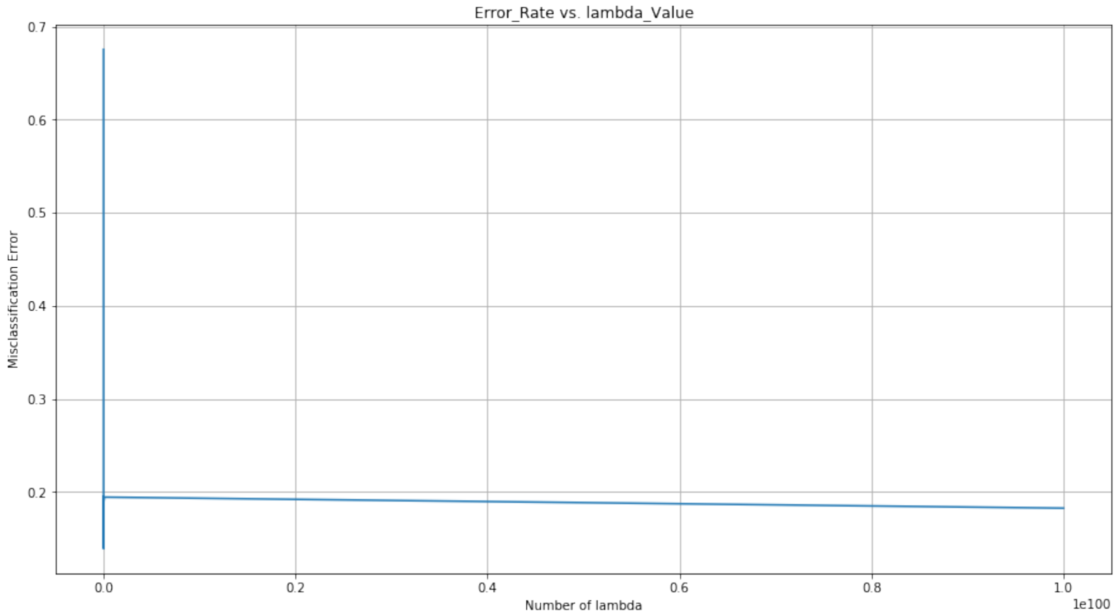
7 L1 Regularization

Increase lambda hyperparameter to generate sparcity in dataset.

```
In [99]: C2 = np.logspace(-50, 100, 50)
         hp2= list(C2)
         socore=[]
         Sparsity=[]
```

```python
    for vect_data in range(len(hp2)):
        r=hp2[vect_data]
        clf = LogisticRegression(C=r, penalty='l1')
        clf.fit(final_tfidf_np ,Train_data)
        w1 = clf.coef_
        #print(np.count_nonzero(w1))
        Sparsity.append(np.count_nonzero(w1))
        w = clf.coef_.ravel()
        model_score=clf.score(final_tfidf_np_test,Y_test_data)
        socore.append(model_score)

    MSE = [1 - x for x in socore]
    global optimal_k
    optimal_k = hp2[MSE.index(min(MSE))]
    print('\nThe optimal number of lambda is %d.' % optimal_k)



      # plot misclassification error vs k
    plt.figure(figsize=(15,8))
    plt.plot(hp2, MSE)
    plt.grid()
    #for xy in zip(hp2, np.round(MSE,3)):
    #    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
    plt.title('Error_Rate vs. lambda_Value')
    plt.xlabel('Number of lambda')
    plt.ylabel('Misclassification Error')
    plt.show()

    print("the misclassification error for each lambda_Value is : ", np.round(

    #print(socore)
    print('Sparsity ==',Sparsity)
```

```
The optimal number of lambda is 0.
```




```
the misclassification error for each lambda_Value is :  [0.675 0.675 0.675 0.675 0.
 0.675 0.675 0.675 0.675 0.139 0.15  0.189 0.191 0.191 0.184 0.188 0.189
 0.189 0.193 0.19  0.185 0.194 0.19  0.19  0.192 0.191 0.19  0.185 0.187
 0.192 0.188 0.188 0.189 0.19  0.19  0.188 0.188 0.192 0.188 0.195 0.189
 0.194 0.182]
Sparsity == [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 20775, 129532, 522482,
```

```
In [100]: df2=pd.DataFrame(models_performence232, columns=columns)
          #print(df2)
```

7.1 RandomsearchCV with L2 regularization (Tf-IDf)

```
In [101]: #L2 regularization

          zx=df2[df2['best panalty'] == 'l2']

          zx=zx[zx['SearchCV']=='RandomsearchCV']

          zx= zx.ix[zx['Test_model_score'].idxmax()]
          print(zx)
          lambdax=zx['Best lambda']

          best_panalty=zx['best panalty']

          Scoring_Metrics =zx['Scoring Metrics']
          SearchCV=zx['SearchCV']
```

```
Model                 Logistic Regression
Vectorizer                         TF-IDF
SearchCV                   RandomsearchCV
Scoring Metrics                    recall
Train_model_score                       1
Test_model_score                 0.979766
best panalty                           l2
Best lambda                     0.0122481
Name: 13, dtype: object
```

In [102]:
```
#Best lambda and best penalty
C1 = uniform(loc=0, scale=lambdax)
hp5=dict(C=C1, penalty=[best_panalty])
LR5 =RandomizedSearchCV(LogisticRegression(), hp5, scoring =Scoring_Metri
LR5.fit(final_data ,Train_data)

prediction5 = LR5.predict(final_data_test)
lambda_new=LR5.best_params_['C']
```

In [103]:
```
#Training accuracy and training error
training_score=LR5.score(final_data,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 0.991564571199036
training error is = 0.00843542880096404
```

In [104]:
```
# Testing Accuracy and testing error for knn model

Testing_score=round(accuracy_score(Y_test_data ,prediction5),5)
print("Accuracy for Logistic Regression model with Avg word2vec is = ",Te
Testing_error=1-Testing_score
print("Testing error for Logistic Regression model with Avg word2vec is =
```

```
Accuracy for Logistic Regression model with Avg word2vec is =  0.84908
Testing error for Logistic Regression model with Avg word2vec is =  0.150920000000
```

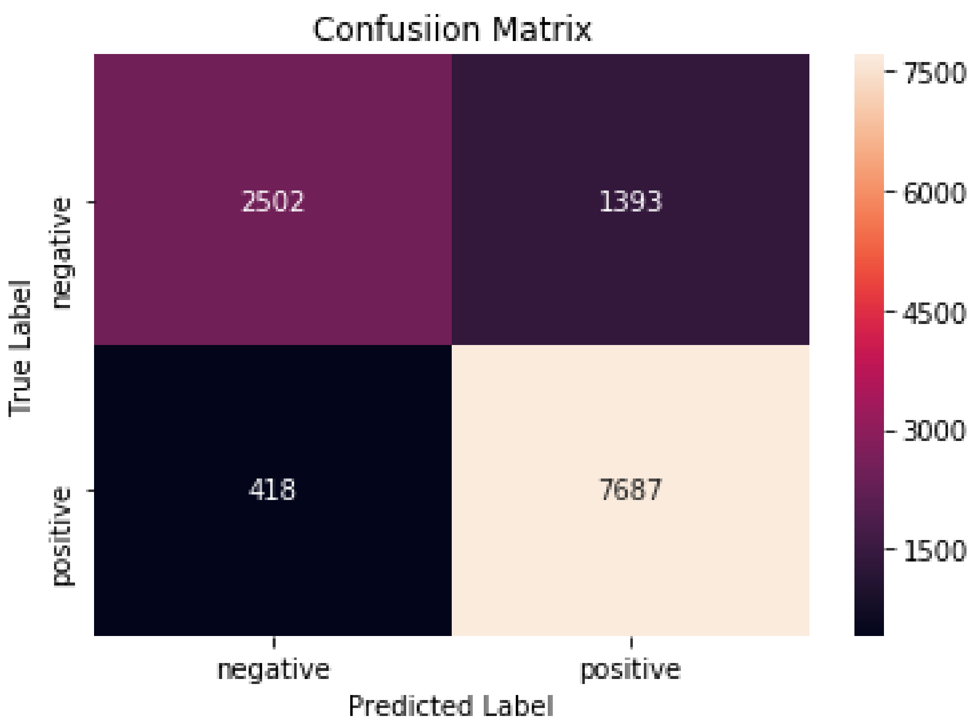
In [105]:
```
F1_score = round(f1_score(Y_test_data ,prediction5,average='macro'),5)*10
recall = round(recall_score(Y_test_data,prediction5,average='macro'),5)*1
precision = round(precision_score(Y_test_data ,prediction5,average='macro
```

In [106]:
```
print(classification_report( Y_test_data,prediction5))
```

```
             precision    recall  f1-score   support
```

```
           0       0.86      0.64      0.73      3895
           1       0.85      0.95      0.89      8105

avg / total        0.85      0.85      0.84     12000
```

```
In [107]: cm = confusion_matrix(Y_test_data ,prediction5)
          label = ['negative', 'positive']
          df_conf = pd.DataFrame(cm, index = label, columns = label)
          sns.heatmap(df_conf, annot = True, fmt = "d")
          plt.title("Confusiion Matrix")
          plt.xlabel("Predicted Label")
          plt.ylabel("True Label")
          plt.show()
```




```
In [108]: models_performence1['Model'].append('Logistic Regression')
          models_performence1['Vectorizer'].append('TF-IDF')
          models_performence1['SearchCV'].append(SearchCV)
          models_performence1['Best penalty'].append(best_panalty)
          models_performence1[ 'Optimal lambda'].append(lambda_new)
          models_performence1['Training error'].append(training_error*100)
          models_performence1[ 'Test error'].append(Testing_error*100)
          models_performence1[ 'Accuracy'].append(Testing_score)
```

```
models_performence1[ 'F1'].append(F1_score)
models_performence1['recall'].append(recall)
models_performence1[ 'precision'].append(precision)
```

```
In [109]: columns = ["Model","Vectorizer","SearchCV", "Best penalty","Optimal lambd
                      "Accuracy","F1","recall","precision",
                     ]
          df7=pd.DataFrame(models_performence1, columns=columns)
```

```
In [110]: result_display(df7)
```

```
|       Model        |Vectorizer|    SearchCV    |Best penalty|Optimal lambda|Training
|--------------------|----------|---------------|------------|-------------:|--------
|Logistic Regression|BoW       |GridSearchCV   |l2          |       1.00000|       0
|Logistic Regression|BOW       |RandomsearchCV|l2          |       0.00419|       0
|Logistic Regression|BOW       |GridSearchCV   |l1          |       1.00000|       0
|Logistic Regression|BOW       |RandomsearchCV|l1          |       0.00053|       0
|Logistic Regression|TF-IDF    |RandomsearchCV|l2          |       0.00041|       0
```

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	BoW	GridSearchCV	l2	1.00000	0.00000	19.84	0.8016	76.97	76.52	77.52
Logistic Regression	BOW	RandomsearchCV	l2	0.00419	0.44688	15.40	0.8460	81.63	80.40	83.53
Logistic Regression	BOW	GridSearchCV	l1	1.00000	0.02511	17.92	0.8207	79.29	78.92	79.71
Logistic Regression	BOW	RandomsearchCV	l1	0.00053	0.82346	14.95	0.8505	81.71	79.89	85.13
Logistic Regression	TF-IDF	RandomsearchCV	l2	0.00041	0.84354	15.09	0.8491	81.44	79.54	85.17

7.2 GridSearchCV with L2 regularization (Tf-IDf)

```
In [111]: zx=df[df['best panalty'] == 'l2']
          zx=zx[zx['SearchCV']=='GridSearchCV']
          zx= zx.ix[zx['Test_model_score'].idxmax()]
          print(zx)
          lambdax=zx['Best lambda']

          best_panalty=zx['best panalty']

          Scoring_Metrics =zx['Scoring Metrics']
          SearchCV=zx['SearchCV']
```

```
Model                  Logistic Regression
Vectorizer                             BOW
SearchCV                      GridSearchCV
Scoring Metrics                     recall
Train_model_score                        1
Test_model_score                  0.868846
best panalty                            l2
Best lambda                              1
Name: 12, dtype: object
```

In [112]:
```
#Best lambda and best penalty
hp6=dict(C=[lambdax], penalty=[best_panalty])
LR6 =GridSearchCV(LogisticRegression(), hp6, scoring =Scoring_Metrics, cv

LR6 .fit(final_tfidf_np ,Train_data)

prediction6 = LR6.predict(final_tfidf_np_test)
```

In [113]:
```
#Training accuracy and training error
training_score=LR6.score(final_tfidf_np,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 1.0
training error is = 0.0
```

In [114]:
```
# Testing Accuracy and testing error for knn model

Testing_score=round(accuracy_score(Y_test_data ,prediction6),5)
print("Accuracy for Logistic Regression model with Avg word2vec is = ",Te
Testing_error=1-Testing_score
print("Testing error for Logistic Regression model with Avg word2vec is =
```

```
Accuracy for Logistic Regression model with Avg word2vec is =  0.8195
Testing error for Logistic Regression model with Avg word2vec is =  0.1805
```

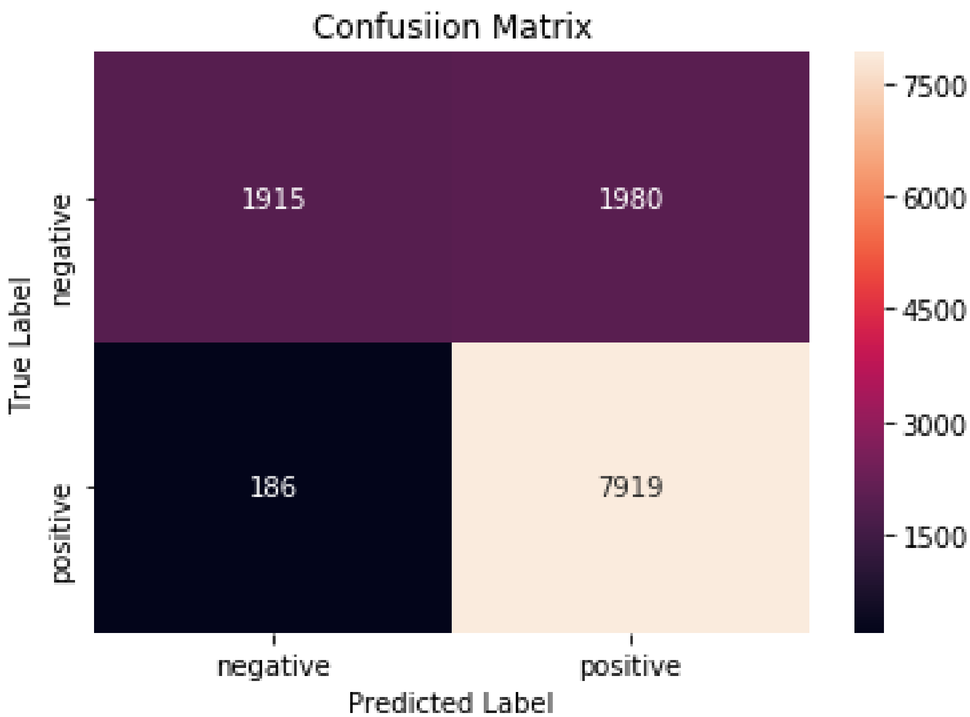
In [115]:
```
F1_score = round(f1_score(Y_test_data ,prediction6,average='macro'),5)*10
recall = round(recall_score(Y_test_data,prediction6,average='macro'),5)*1
precision = round(precision_score(Y_test_data ,prediction6,average='macro
```

In [116]:
```
print(classification_report( Y_test_data,prediction6))
```

```
             precision    recall  f1-score   support

          0       0.91      0.49      0.64      3895
```

```
          1       0.80      0.98      0.88      8105

avg / total       0.84      0.82      0.80     12000
```

```
In [117]: cm = confusion_matrix(Y_test_data ,prediction6)
          label = ['negative', 'positive']
          df_conf = pd.DataFrame(cm, index = label, columns = label)
          sns.heatmap(df_conf, annot = True, fmt = "d")
          plt.title("Confusiion Matrix")
          plt.xlabel("Predicted Label")
          plt.ylabel("True Label")
          plt.show()
```




```
In [118]: models_performence1['Model'].append('Logistic Regression')
          models_performence1['Vectorizer'].append('TF-IDF')
          models_performence1['SearchCV'].append(SearchCV)
          models_performence1['Best penalty'].append(best_panalty)
          models_performence1[ 'Optimal lambda'].append(lambdax)
          models_performence1['Training error'].append(training_error*100)
          models_performence1[ 'Test error'].append(Testing_error*100)
          models_performence1[ 'Accuracy'].append(Testing_score)
          models_performence1[ 'F1'].append(F1_score)
```

```
        models_performence1['recall'].append(recall)
        models_performence1[ 'precision'].append(precision)
```

```
In [119]: columns = ["Model","Vectorizer","SearchCV", "Best penalty","Optimal lamb
             "Accuracy","F1","recall","precision",
            ]
          df8=pd.DataFrame(models_performence1, columns=columns)
```

```
In [120]: result_display(df8)
```

```
|       Model       |Vectorizer|   SearchCV    |Best penalty|Optimal lambda|Training
|-------------------|----------|---------------|------------|-------------:|--------
|Logistic Regression|BoW       |GridSearchCV   |l2          |        1.0000|
|Logistic Regression|BOW       |RandomsearchCV|l2          |        0.0042|
|Logistic Regression|BOW       |GridSearchCV   |l1          |        1.0000|
|Logistic Regression|BOW       |RandomsearchCV|l1          |        0.0005|
|Logistic Regression|TF-IDF    |RandomsearchCV|l2          |        0.0004|
|Logistic Regression|TF-IDF    |GridSearchCV   |l2          |        1.0000|
```

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	BoW	GridSearchCV	l2	1.0000	0.0000	19.84	0.8016	76.97	76.52	77.52
Logistic Regression	BOW	RandomsearchCV	l2	0.0042	0.4469	15.40	0.8460	81.63	80.40	83.53
Logistic Regression	BOW	GridSearchCV	l1	1.0000	0.0251	17.92	0.8207	79.29	78.92	79.71
Logistic Regression	BOW	RandomsearchCV	l1	0.0005	0.8235	14.95	0.8505	81.71	79.89	85.13
Logistic Regression	TF-IDF	RandomsearchCV	l2	0.0004	0.8435	15.09	0.8491	81.44	79.54	85.17
Logistic Regression	TF-IDF	GridSearchCV	l2	1.0000	0.0000	18.05	0.8195	75.92	73.43	85.57

7.3 RandomsearchCV with L1 regularization (Tf-IDf)

```
In [121]: zx=df2[df2['best panalty'] == 'l1']
          zx=zx[zx['SearchCV']=='RandomsearchCV']
          zx= zx.ix[zx['Test_model_score'].idxmax()]
          print(zx)
          lambdax=zx['Best lambda']

          best_panalty=zx['best panalty']

          Scoring_Metrics =zx['Scoring Metrics']
```

```
         SearchCV=zx['SearchCV']
```

```
Model                  Logistic Regression
Vectorizer                          TF-IDF
SearchCV                    RandomsearchCV
Scoring Metrics                     recall
Train_model_score                        1
Test_model_score                  0.947687
best panalty                            l1
Best lambda                        2.92194
Name: 5, dtype: object
```

```
In [122]: #Best lambda and best penalty
          C1 = uniform(loc=0, scale=lambdax)
          hp7=dict(C=C1, penalty=[best_panalty])
          LR7 =RandomizedSearchCV(LogisticRegression(), hp7, scoring =Scoring_Metri

          LR7.fit(final_tfidf_np ,Train_data)

          prediction7 = LR7.predict(final_tfidf_np_test)
          lambda_new=LR7.best_params_['C']
```

```
In [123]: #Training accuracy and training error
          training_score=LR7.score(final_tfidf_np,Train_data)
          print('training accuracy=',training_score)
          training_error=1-training_score
          print('training error is =',training_error)
```

```
training accuracy= 1.0
training error is = 0.0
```

```
In [124]: # Testing Accuracy and testing error for knn model

          Testing_score=round(accuracy_score(Y_test_data ,prediction7),5)
          print("Accuracy for Logistic Regression model with Avg word2vec is = ",Te
          Testing_error=1-Testing_score
          print("Testing error for Logistic Regression model with Avg word2vec is =
```

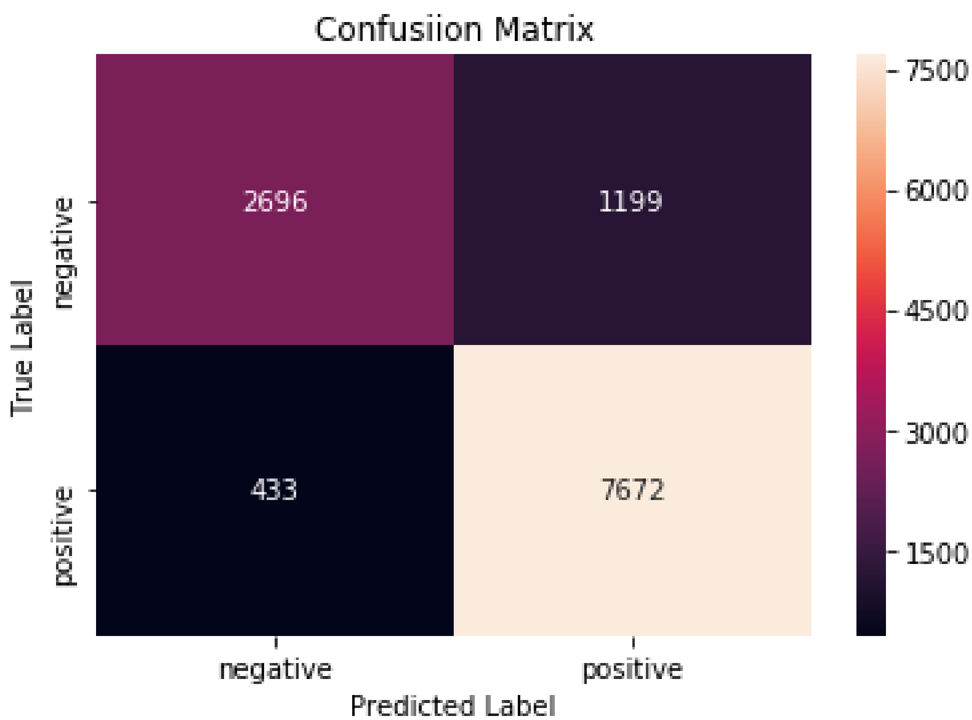
```
Accuracy for Logistic Regression model with Avg word2vec is =  0.864
Testing error for Logistic Regression model with Avg word2vec is =  0.136
```

```
In [125]: F1_score = round(f1_score(Y_test_data ,prediction7,average='macro'),5)*10
          recall = round(recall_score(Y_test_data,prediction7,average='macro'),5)*1
          precision = round(precision_score(Y_test_data ,prediction7,average='macro
```

```
In [126]: print(classification_report( Y_test_data,prediction7))
```

```
             precision    recall  f1-score   support

          0       0.86      0.69      0.77      3895
          1       0.86      0.95      0.90      8105

avg / total       0.86      0.86      0.86     12000
```

In [127]:
```
cm = confusion_matrix(Y_test_data ,prediction7)
label = ['negative', 'positive']
df_conf = pd.DataFrame(cm, index = label, columns = label)
sns.heatmap(df_conf, annot = True, fmt = "d")
plt.title("Confusiion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



In [128]:
```
models_performence1['Model'].append('Logistic Regression')
models_performence1['Vectorizer'].append('TF-IDF')
models_performence1['SearchCV'].append(SearchCV)
models_performence1['Best penalty'].append(best_panalty)
models_performence1[ 'Optimal lambda'].append(lambda_new)
models_performence1['Training error'].append(training_error*100)
```

```
        models_performence1[ 'Test error'].append(Testing_error*100)
        models_performence1[ 'Accuracy'].append(Testing_score)
        models_performence1[ 'F1'].append(F1_score)
        models_performence1['recall'].append(recall)
        models_performence1[ 'precision'].append(precision)
```

```
In [129]: columns = ["Model","Vectorizer","SearchCV", "Best penalty","Optimal lambd
                "Accuracy","F1","recall","precision",
              ]
          df9=pd.DataFrame(models_performence1, columns=columns)
```

```
In [130]: result_display(df9)
```

```
|       Model        |Vectorizer|    SearchCV    |Best penalty|Optimal lambda|Training
|--------------------|----------|---------------|------------|-------------:|--------
|Logistic Regression|BoW       |GridSearchCV   |l2          |        1.0000|
|Logistic Regression|BOW       |RandomsearchCV|l2          |        0.0042|
|Logistic Regression|BOW       |GridSearchCV   |l1          |        1.0000|
|Logistic Regression|BOW       |RandomsearchCV|l1          |        0.0005|
|Logistic Regression|TF-IDF    |RandomsearchCV|l2          |        0.0004|
|Logistic Regression|TF-IDF    |GridSearchCV   |l2          |        1.0000|
|Logistic Regression|TF-IDF    |RandomsearchCV|l1          |        2.8581|
```

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	BoW	GridSearchCV	l2	1.0000	0.0000	19.84	0.8016	76.97	76.52	77.52
Logistic Regression	BOW	RandomsearchCV	l2	0.0042	0.4469	15.40	0.8460	81.63	80.40	83.53
Logistic Regression	BOW	GridSearchCV	l1	1.0000	0.0251	17.92	0.8207	79.29	78.92	79.71
Logistic Regression	BOW	RandomsearchCV	l1	0.0005	0.8235	14.95	0.8505	81.71	79.89	85.13
Logistic Regression	TF-IDF	RandomsearchCV	l2	0.0004	0.8435	15.09	0.8491	81.44	79.54	85.17
Logistic Regression	TF-IDF	GridSearchCV	l2	1.0000	0.0000	18.05	0.8195	75.92	73.43	85.57
Logistic Regression	TF-IDF	RandomsearchCV	l1	2.8581	0.0000	13.60	0.8640	83.58	81.94	86.32

7.4 GridSearchCV with L1 regularization (Tf-IDf)

```
In [131]: zx=df2[df2['best panalty'] == 'l1']
          zx=zx[zx['SearchCV']=='GridSearchCV']
          zx= zx.ix[zx['Test_model_score'].idxmax()]
```

```
print(zx)
lambdax=zx['Best lambda']

best_panalty=zx['best panalty']

Scoring_Metrics =zx['Scoring Metrics']
SearchCV=zx['SearchCV']
```

```
Model                   Logistic Regression
Vectorizer                           TF-IDF
SearchCV                       GridSearchCV
Scoring Metrics                      recall
Train_model_score                         1
Test_model_score                   0.966194
best panalty                             l1
Best lambda                         59.9484
Name: 4, dtype: object
```

In [132]:
```
#Best lambda and best penalty

hp8=dict(C=[lambdax], penalty=[best_panalty])
LR8 =GridSearchCV(LogisticRegression(), hp8, scoring =Scoring_Metrics, cv

LR8.fit(final_tfidf_np ,Train_data)

prediction8 = LR8.predict(final_tfidf_np_test)
```

In [133]:
```
#Training accuracy and training error
training_score=LR8.score(final_tfidf_np,Train_data)
print('training accuracy=',training_score)
training_error=1-training_score
print('training error is =',training_error)
```

```
training accuracy= 1.0
training error is = 0.0
```

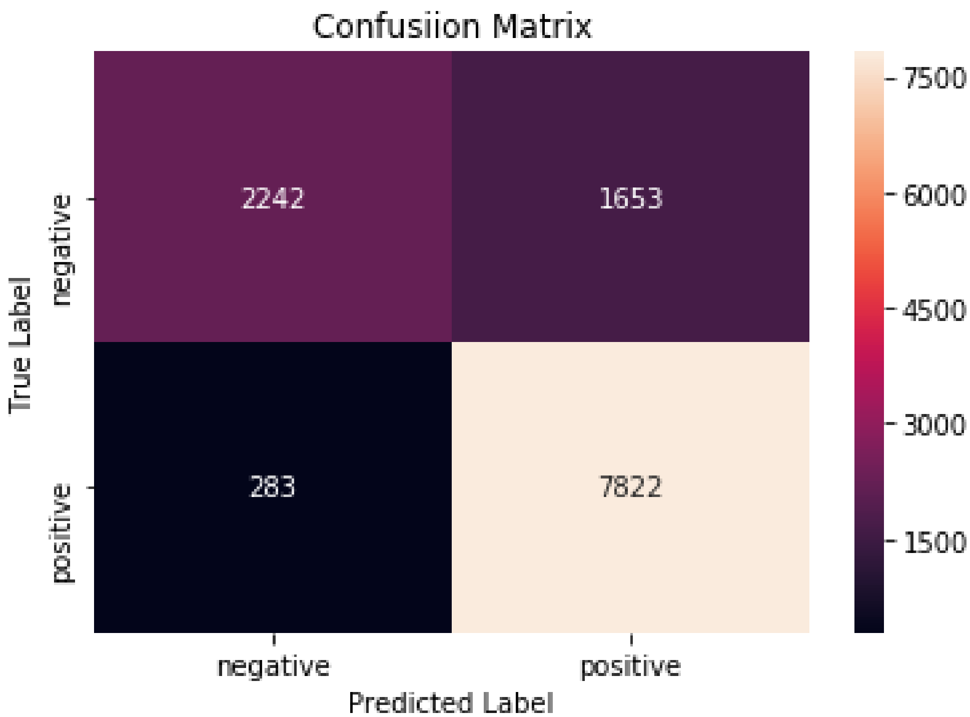
In [134]:
```
# Testing Accuracy and testing error for knn model

Testing_score=round(accuracy_score(Y_test_data ,prediction8),5)
print("Accuracy for Logistic Regression model with Avg word2vec is = ",Te
Testing_error=1-Testing_score
print("Testing error for Logistic Regression model with Avg word2vec is =
```

```
Accuracy for Logistic Regression model with Avg word2vec is =  0.83867
Testing error for Logistic Regression model with Avg word2vec is =  0.16132999999999
```

```
In [135]: F1_score = round(f1_score(Y_test_data ,prediction8,average='macro'),5)*10
          recall = round(recall_score(Y_test_data,prediction8,average='macro'),5)*1
          precision = round(precision_score(Y_test_data ,prediction8,average='macro
```

```
In [136]: print(classification_report( Y_test_data,prediction8))

             precision    recall  f1-score   support

          0       0.89      0.58      0.70      3895
          1       0.83      0.97      0.89      8105

avg / total       0.85      0.84      0.83     12000
```

```
In [137]: cm = confusion_matrix(Y_test_data ,prediction8)
          label = ['negative', 'positive']
          df_conf = pd.DataFrame(cm, index = label, columns = label)
          sns.heatmap(df_conf, annot = True, fmt = "d")
          plt.title("Confusiion Matrix")
          plt.xlabel("Predicted Label")
          plt.ylabel("True Label")
          plt.show()
```



```
In [138]: models_performence1['Model'].append('Logistic Regression')
          models_performence1['Vectorizer'].append('TF-IDF')
          models_performence1['SearchCV'].append(SearchCV)
          models_performence1['Best penalty'].append(best_panalty)
          models_performence1[ 'Optimal lambda'].append(lambdax)
          models_performence1['Training error'].append(training_error*100)
          models_performence1[ 'Test error'].append(Testing_error*100)
          models_performence1[ 'Accuracy'].append(Testing_score)
          models_performence1[ 'F1'].append(F1_score)
          models_performence1['recall'].append(recall)
          models_performence1[ 'precision'].append(precision)
```

```
In [139]: columns = ["Model","Vectorizer","SearchCV", "Best penalty","Optimal lamb
                      "Accuracy","F1","recall","precision",
                    ]
          df10=pd.DataFrame(models_performence1, columns=columns)
```

```
In [140]: result_display(df10)
```

```
|       Model       |Vectorizer|   SearchCV    |Best penalty|Optimal lambda|Trainin
|-------------------|----------|---------------|------------|-------------:|-------
|Logistic Regression|BoW       |GridSearchCV   |l2          |        1.0000|
|Logistic Regression|BOW       |RandomsearchCV|l2          |        0.0042|
|Logistic Regression|BOW       |GridSearchCV   |l1          |        1.0000|
|Logistic Regression|BOW       |RandomsearchCV|l1          |        0.0005|
|Logistic Regression|TF-IDF    |RandomsearchCV|l2          |        0.0004|
|Logistic Regression|TF-IDF    |GridSearchCV   |l2          |        1.0000|
|Logistic Regression|TF-IDF    |RandomsearchCV|l1          |        2.8581|
|Logistic Regression|TF-IDF    |GridSearchCV   |l1          |       59.9484|
```

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	BoW	GridSearchCV	l2	1.0000	0.0000	19.84	0.8016	76.97	76.52	77.52
Logistic Regression	BOW	RandomsearchCV	l2	0.0042	0.4469	15.40	0.8460	81.63	80.40	83.53
Logistic Regression	BOW	GridSearchCV	l1	1.0000	0.0251	17.92	0.8207	79.29	78.92	79.71
Logistic Regression	BOW	RandomsearchCV	l1	0.0005	0.8235	14.95	0.8505	81.71	79.89	85.13
Logistic Regression	TF-IDF	RandomsearchCV	l2	0.0004	0.8435	15.09	0.8491	81.44	79.54	85.17
Logistic Regression	TF-IDF	GridSearchCV	l2	1.0000	0.0000	18.05	0.8195	75.92	73.43	85.57
Logistic Regression	TF-IDF	RandomsearchCV	l1	2.8581	0.0000	13.60	0.8640	83.58	81.94	86.32

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	TF-IDF	GridSearchCV		59.9484	0.0000	16.13	0.8387	79.42	77.03	85.67

7.5 Feature Importance for Logistic Regression

Feature importance using count_vect

```
In [141]: model = LogisticRegression( random_state=0, class_weight='balanced')
          model.fit(final_data ,Train_data)
          # Calculate feature importances
          count_vect_feature=count_vect.get_feature_names()
          feature_importance = model.coef_[0]
          print(feature_importance)
```

```
[-6.98856785e-02  3.20812169e-02  6.86907874e-02 ... -1.16301296e-05
 -1.97800637e-05 -3.77890206e-04]
```

```
In [142]: Negative_Feature_Importance= feature_importance[-15:]
          print('Negative_Feature_Importanc',Negative_Feature_Importance)
          Positive_Feature_Importance= feature_importance[:15]
          print('Positive_Feature_Importance',Positive_Feature_Importance)
```

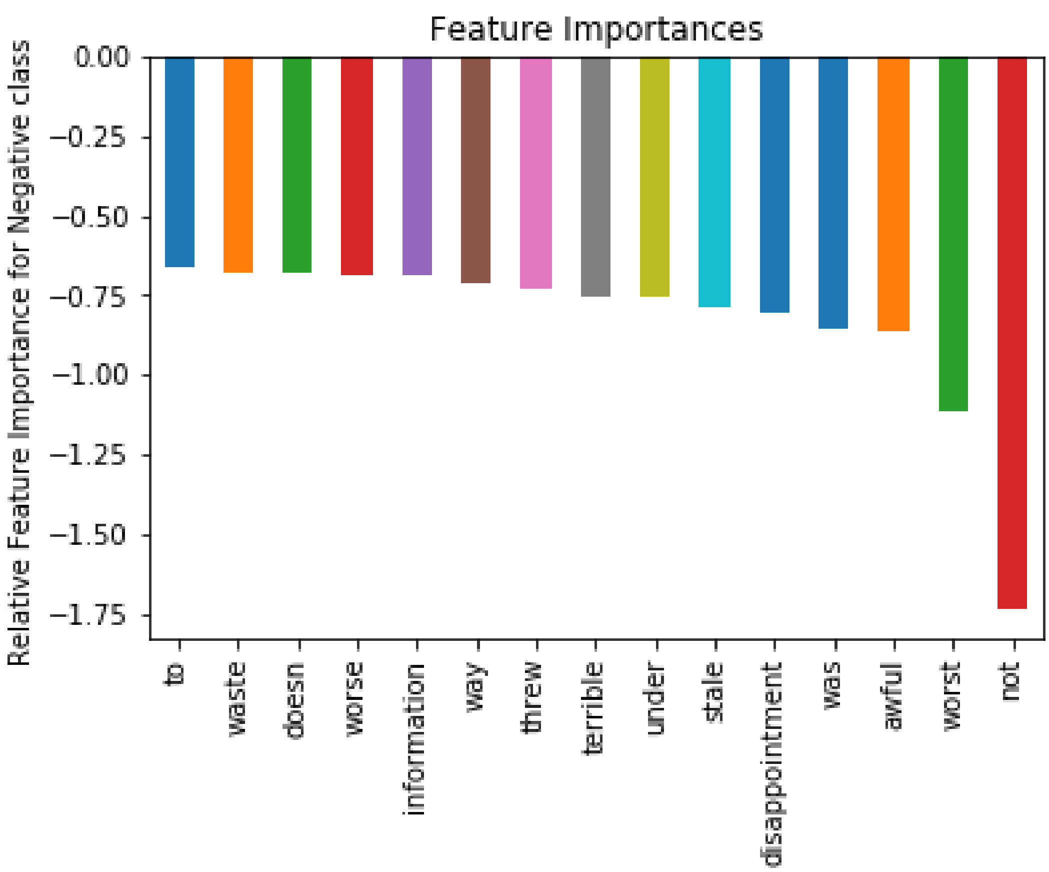
```
Negative_Feature_Importanc [ 1.27846516e-03 -8.72952486e-06 -2.72293848e-02 -5.0709
  2.14312914e-03  3.31203513e-02  5.10959783e-02  1.26563767e-01
  5.70493934e-02  4.62499125e-04 -2.63228160e-02  4.98604711e-03
 -1.16301296e-05 -1.97800637e-05 -3.77890206e-04]
Positive_Feature_Importance [-6.98856785e-02  3.20812169e-02  6.86907874e-02 -1.336
 -2.24748457e-05 -2.31786264e-05  1.33332202e-01 -2.16687646e-01
 -1.58712686e-06 -1.97722162e-01  1.17074106e-03  4.31862077e-03
  2.52835784e-02  8.86442954e-03 -1.02991746e-02]
```

```
In [143]: # Relative Feature Importance for Negative class using BOW
          feat_imp = pd.Series(feature_importance, count_vect_feature).sort_values
          print("Top 15 negative class feature",feat_imp[-15:])

          feat_imp[-15:].plot(kind='bar', title='Feature Importances')
          plt.ylabel('Relative Feature Importance for Negative class ')
```

```
Top 15 negative class feature to               -0.666154
waste               -0.674955
doesn               -0.678214
worse               -0.688182
information         -0.689716
way                 -0.711875
```

```
threw             -0.730362
terrible          -0.756894
under             -0.756945
stale             -0.787371
disappointment    -0.807016
was               -0.856012
awful             -0.865418
worst             -1.116509
not               -1.737925
dtype: float64
```

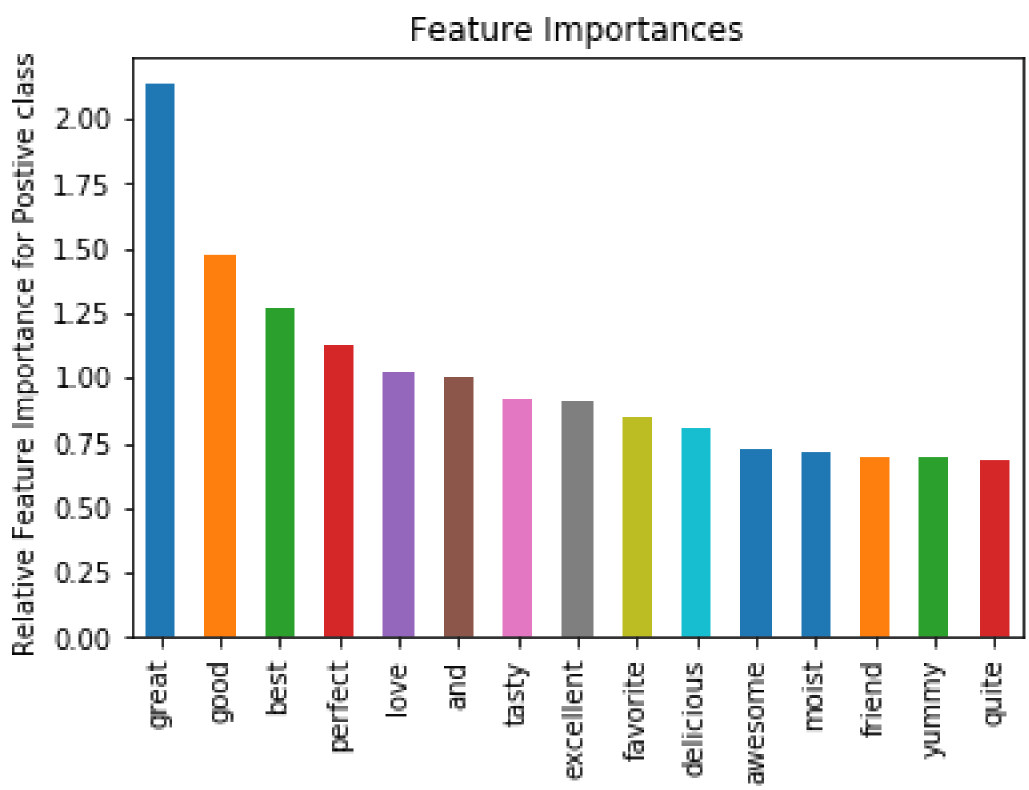
```
Out[143]: Text(0,0.5,'Relative Feature Importance for Negative class ')
```




```
In [144]: #Feature Importances for postive class using count_vect

          feat_imp = pd.Series(feature_importance, count_vect_feature).sort_values
          print("Top 15 postive class feature",feat_imp[:15])

          feat_imp[:15].plot(kind='bar', title='Feature Importances')
          plt.ylabel('Relative Feature Importance for Postive class ')
```

```
Top 15 postive class feature great       2.131231
good          1.479342
best          1.275140
perfect       1.129655
love          1.021882
and           1.005843
tasty         0.919905
excellent     0.914646
favorite      0.848755
delicious     0.804589
awesome       0.729551
moist         0.715587
friend        0.698840
yummy         0.695703
quite         0.683189
dtype: float64
```

Out[144]: Text(0,0.5,'Relative Feature Importance for Postive class ')



Feature importance using tf-idf -vect

```
In [24]: model = LogisticRegression(random_state=0, class_weight='balanced')
         model.fit(final_tfidf_np ,Train_data)
         tf_idf_feature=tf_idf_vect .get_feature_names()
         feature_importance = model.coef_[0]
         print(feature_importance)
```

```
[-0.01572257  0.00070768  0.0042909  ...  0.00199084  0.00199084
  0.00166962]
```

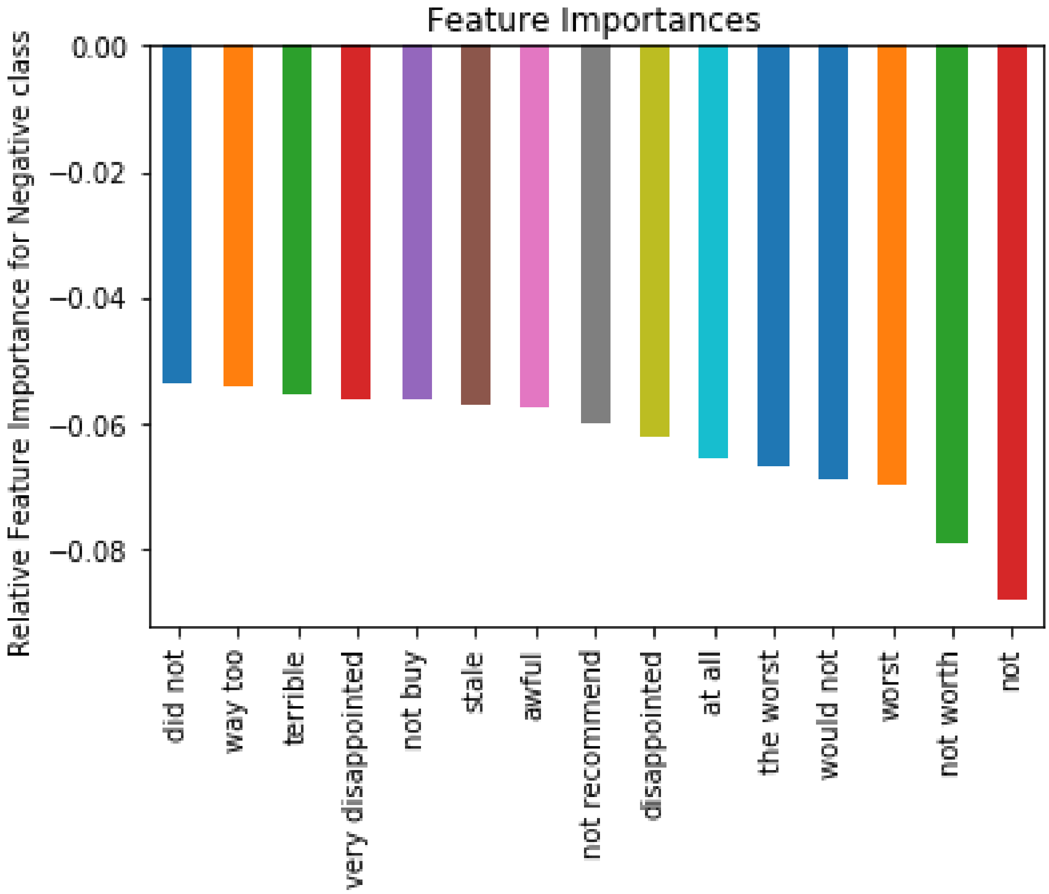
```
In [25]: Negative_Feature_Importance= feature_importance[-15:]
         print('Negative_Feature_Importance',Negative_Feature_Importance)
         Positive_Feature_Importance= feature_importance[:15]
         print('Positive_Feature_Importance',Positive_Feature_Importance)
```

```
Negative_Feature_Importance [ 0.00035824 -0.00379201  0.00235019 -0.00700736  0.000
  0.0004987   0.0004987  -0.00161642 -0.00161642  0.00279301  0.00279301
  0.00199084  0.00199084  0.00166962]
Positive_Feature_Importance [-1.57225749e-02  7.07681090e-04  4.29090014e-03 -2.184
 -8.80539569e-03  6.26167688e-04 -2.36090761e-03  1.81293314e-03
 -6.95264014e-03 -8.43264570e-03 -5.53123811e-05 -4.95346097e-03
  6.96913050e-05 -2.49085370e-03 -1.09552802e-03]
```

```
In [26]: # Relative Feature Importance for Negative class using tf_idf
         feat_imp = pd.Series(feature_importance,tf_idf_feature).sort_values(ascend
         print("Top 15 negative class feature",feat_imp[-15:])

         feat_imp[-15:].plot(kind='bar', title='Feature Importances')
         plt.ylabel('Relative Feature Importance for Negative class ')
```

```
Top 15 negative class feature did not            -0.053815
way too              -0.054299
terrible             -0.055495
very disappointed    -0.056223
not buy              -0.056270
stale                -0.056943
awful                -0.057589
not recommend        -0.060131
disappointed         -0.062147
at all               -0.065745
the worst            -0.066788
would not            -0.069012
worst                -0.069726
not worth            -0.079154
not                  -0.087908
dtype: float64
```

Out[26]: Text(0,0.5,'Relative Feature Importance for Negative class ')



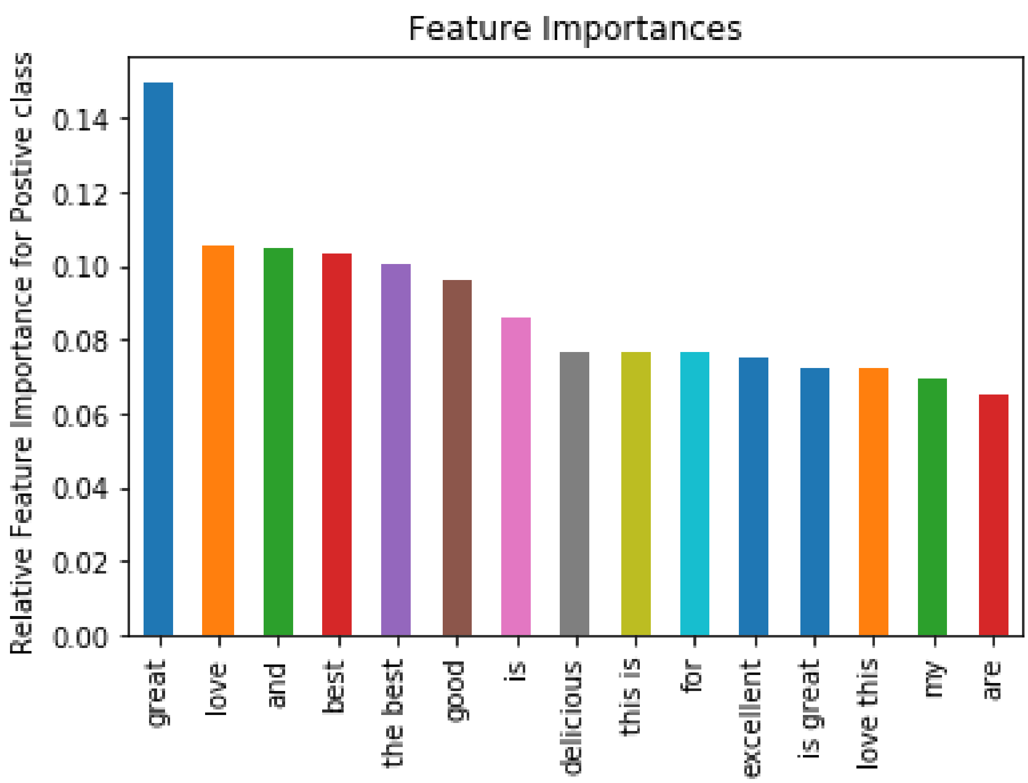
In [27]:

```
#Feature Importances for postive class using tf_idf

feat_imp = pd.Series(feature_importance, tf_idf_feature).sort_values(ascen
print("Top 15 postive class feature",feat_imp[:15])

feat_imp[:15].plot(kind='bar', title='Feature Importances')
plt.ylabel('Relative Feature Importance for Postive class ')
```

```
Top 15 postive class feature great        0.149660
love           0.105626
and            0.104531
best           0.103081
the best       0.100451
good           0.095941
is             0.085983
delicious      0.076961
this is        0.076417
```

```
for            0.076384
excellent      0.075110
is great       0.072469
love this      0.072014
my             0.069634
are            0.065415
dtype: float64
```

```
Out[27]: Text(0,0.5,'Relative Feature Importance for Postive class ')
```



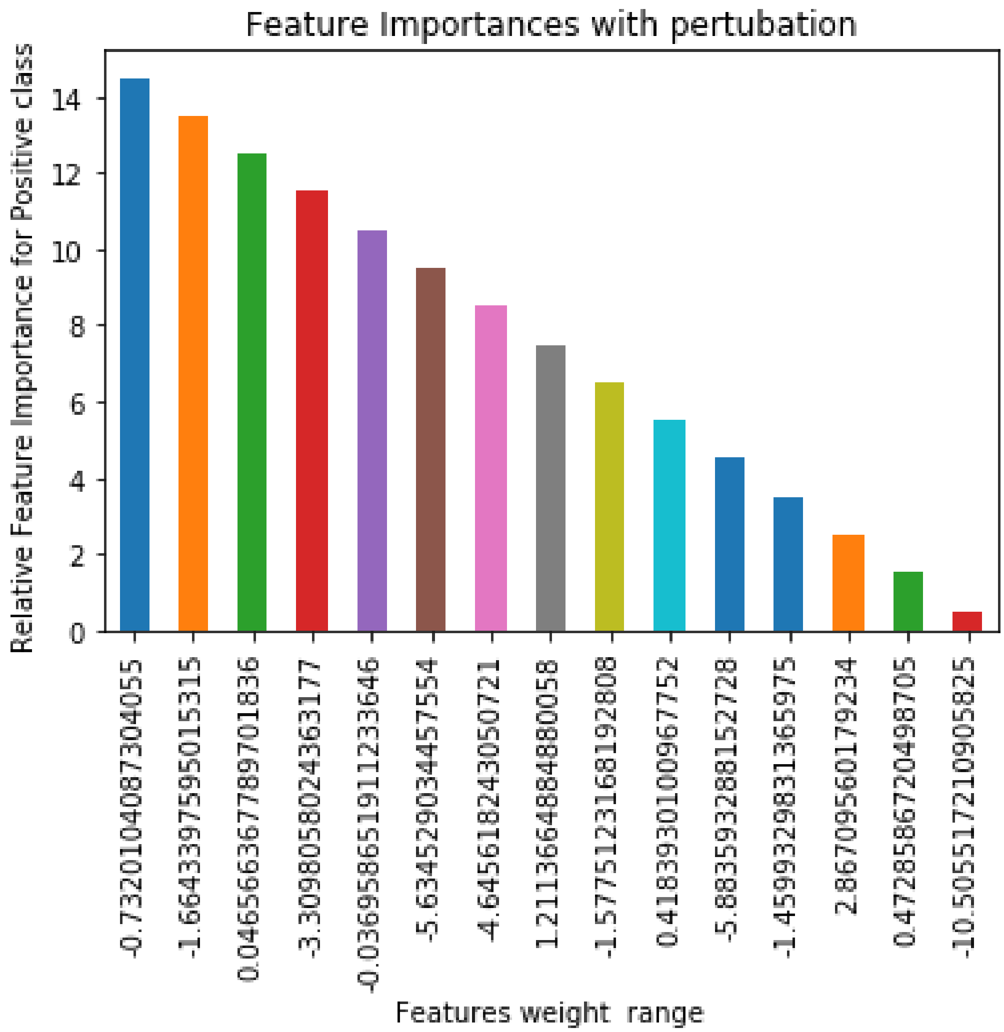
Observations

- Feature Importance for logistic regression using BOW and TF-IDF is as above.
- Top 15 features for postive words and negative words are printed.
- Graph is based on features weight vs relative feature importance.
- Top 15 Important Negative words which determines point belongs to negative class and Top 15 Important positive words which determines point belongs to positive class shows importance of words.

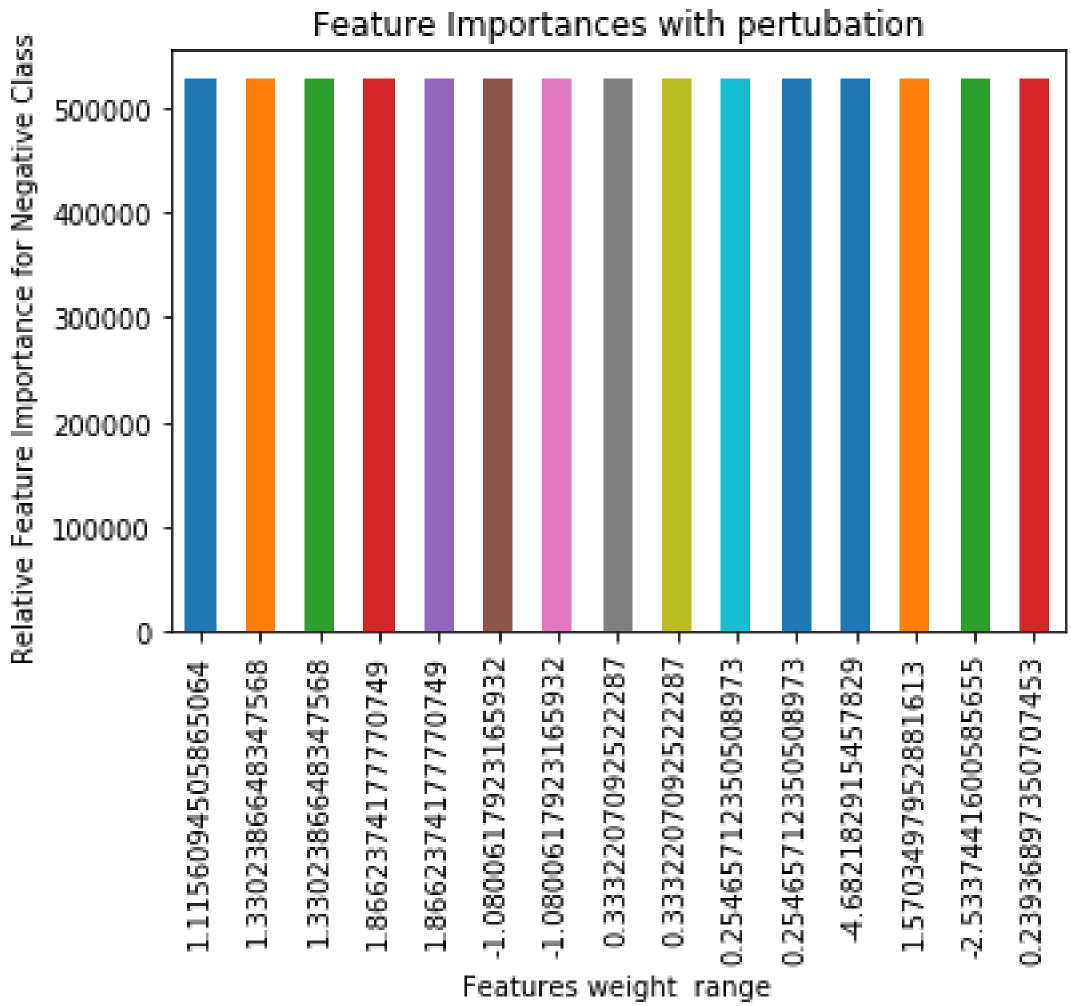
Use of Pertubation Techniques for postive class and negative class using tf-idf -vect

```
In [30]: # Use of Pertubation Techniques for postive class and negative class using
         feature_importance = 100.0 * (feature_importance / feature_importance.max
         # feature_importance# w

         pos = np.arange(feature_importance.shape[0]) + .5  # 0.5 is pertubation  w
         # pos is after adding small noise in weight
         print('Weight vector with pertubation',pos)
         print('original Weight vector',feature_importance)


         yy = [float(i) for i in feature_importance] #w

         #print(yy)
         vc=yy -pos
         print('Difference between w and w`',vc[:20])

         Pertub_pos = pd.Series(pos[:15],feature_importance[:15]).sort_values(ascen
         Pertub_pos.plot(kind='bar', title='Feature Importances with pertubation')
         plt.xlabel('Features weight  range')
         plt.ylabel('Relative Feature Importance for Positive class ')
         plt.show()

         Pertub_neg = pd.Series(pos[-15:],feature_importance[-15:]).sort_values(asc
         Pertub_neg.plot(kind='bar', title='Feature Importances with pertubation')
         plt.xlabel('Features weight  range')
         plt.ylabel('Relative Feature Importance for Negative Class ')
         plt.show()
```

```
Weight vector with pertubation [5.000000e-01 1.500000e+00 2.500000e+00 ... 5.300905
 5.300925e+05]
original Weight vector [-10.50551721   0.47285867   2.8670956  ...   1.33023866   1
   1.11560945]
Difference between w and w` [-11.00551721  -1.02714133   0.3670956   -4.95993298 -1
  -5.08160699  -8.07751232  -6.28863351 -13.14561824 -15.13452903
 -10.53695865 -14.8098058  -12.45343363 -15.16433976 -15.23201041
 -18.72835555 -21.19996661 -19.97548654 -22.67126371 -19.61690797]
```



Feature Importances with pertubation
Relative Feature Importance for Positive class
0
2
4
6
8
10
12
14
-0.7320104087304055
-1.6643397595015315
0.046566367789701836
-3.3098058024363177
-0.036958651911233646
-5.634529034457554
-4.645618243050721
1.2113664884880058
-1.5775123168192808
0.4183930100967752
-5.8835593288152728
-1.4599329831365975
2.86709560179234
0.4728586720498705
-10.505517210905825
Features weight range



Pertubation

- Pertubation Techniques for positive features and Negative features are used to check collinearity of features.
- If weight vector of features can change arbitrarily ,It means weight vector can not be used as feature Importance .
- Here,If Original weight vector and pertubated weight vector for respective features differ significantly,then we can't use weight vector (respective feature) for feature importance in particular class.
- In Feature Importance for positive class,["great" ,"love","and"] has high importance while ["are","love this","my"] has low importance and In pertubated Feature Importance, ["are" ,"my"] has low importance. This means that we can remove it's Importance from Positive class.
- Here,if positive feature or negative feature (words) are pertubated,then we can check whether a particular feature is important or not.

- All features are highly important in negative class. Also for pertubated Feature Importance ,all negative features are highly important so Feature .
- Importance for negative class doesn't change with small change in weight vector value.Finally,it is concluded that negative Feature Importance are highly important while positive Feature Importance are not.

8 Conclusions

Model	Vectorizer	SearchCV	Best penalty	Optimal lambda	Training error	Test error	Accuracy	F1	recall	precision
Logistic Regression	BoW	GridSearchCV	l2	1.0000	0.0000	19.84	0.8016	76.97	76.52	77.52
Logistic Regression	BOW	RandomsearchCV	l2	0.0042	0.4469	15.40	0.8460	81.63	80.40	83.53
Logistic Regression	BOW	GridSearchCV	l1	1.0000	0.0251	17.92	0.8207	79.29	78.92	79.71
Logistic Regression	BOW	RandomsearchCV	l1	0.0005	0.8235	14.95	0.8505	81.71	79.89	85.13
Logistic Regression	TF-IDF	RandomsearchCV	l2	0.0004	0.8435	15.09	0.8491	81.44	79.54	85.17
Logistic Regression	TF-IDF	GridSearchCV	l2	1.0000	0.0000	18.05	0.8195	75.92	73.43	85.57
Logistic Regression	TF-IDF	RandomsearchCV	l1	2.8581	0.0000	13.60	0.8640	83.58	81.94	86.32
Logistic Regression	TF-IDF	GridSearchCV	l1	59.9484	0.0000	16.13	0.8387	79.42	77.03	85.67

- Above Table shows the performance of trained and tested model with Logistic Regression.
- Confusion matrix and scoring metrics values for TF-IDF with RandomSearch CV & L1 regularization is comparatively best with other trained model.
- After comparing the developed models, Logistic Regression model with TF-IDF with RandomsearchCV ,l1 regularization works the best to predict the polarity of reviews among all models.

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In [ ]:
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