Assignment5_log_reg

December 21, 2018

In [37]:
```
# Importing libraries required for the assignments
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import pickle
import pprint

import sqlite3
import pandas as pd
import numpy as np
import nltk
import prettytable

import re
from wordcloud import WordCloud
from nltk.corpus import stopwords
from sklearn.feature_extraction.text import CountVectorizer
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import Normalizer
from sklearn.feature_extraction.text import TfidfVectorizer
from gensim.models import Word2Vec

from sklearn.model_selection import GridSearchCV

#from sklearn.neighbors import KNeighborsClassifier
#from sklearn import cross_validation
#from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,f1_score,make_scorer
#from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report
#from sklearn.naive_bayes import MultinomialNB,BernoulliNB,GaussianNB
from sklearn.linear_model import LogisticRegression
#from sklearn.decomposition import TruncatedSVD
```

In [8]:
```
pkl_file = open('data1.pkl', 'rb')
filtered_data = pickle.load(pkl_file)
```

```
#pprint.pprint(filtered_data)
pkl_file.close()
```

In [9]:
```
# Checking columns present in data

filtered_data.columns
```

Out[9]:
```
Index(['ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Time', 'Summary', 'Text', 'Sentiment',
       'CleanedText'],
      dtype='object')
```

In [10]:
```
# Time base sorting

filtered_data.sort_values('Time',inplace=True)
```

In [11]:
```
# Filtering only 100K data points for this assignments

filtered_100k=filtered_data.iloc[:100000,:]
```

In [12]:
```
filtered_100k.Time.head(20)
```

Out[12]:
```
61682     948672000
1130      961718400
1129      962236800
26503    1067040000
26502    1067040000
54376    1067472000
35508    1067558400
35655    1067644800
35654    1067904000
10388    1067990400
82577    1068076800
26501    1068076800
81533    1068422400
55130    1068940800
98503    1069027200
75316    1069113600
36417    1069459200
44110    1070668800
22710    1071100800
74752    1071705600
Name: Time, dtype: int64
```

In [13]:
```
filtered_100k.reset_index(inplace=True)
```

In [14]:
```
label=filtered_100k.Sentiment
```

In [15]:
```
# Dropping target column
filtered_100k.drop('Sentiment',axis=1,inplace=True)
```

In [16]:
```python
# Creating new label from reviews

filtered_100k['Tex_len']=filtered_100k.CleanedText.apply(lambda x:len(x.split(" ")))
```

In [17]:
```python
filtered_100k.Tex_len.head()
```

Out[17]:
```
0    28
1    17
2    36
3    10
4    15
Name: Tex_len, dtype: int64
```

In [18]:
```python
filtered_100k.drop('index',axis=1,inplace=True)
```

In [19]:
```python
filtered_100k.head()
```

Out[19]:
```
    ProductId          UserId    ProfileName  HelpfulnessNumerator  \
0  B00002N8SM  A32DW342WBJ6BX    Buttersugar                     0
1  B00002Z754  A29Z5PI9BW2PU3         Robbie                     7
2  B00002Z754  A3B8RCEI0FXFI6      B G Chase                    10
3  B00008RCMI  A284C7M23F0APC     A. Mendoza                     0
4  B00008RCMI  A19E94CF5O1LY7  Andrew Arnold                     0

   HelpfulnessDenominator        Time  \
0                       0   948672000
1                       7   961718400
2                      10   962236800
3                       0  1067040000
4                       0  1067040000

                                      Summary  \
0                      A sure death for flies
1                               Great Product
2                WOW Make your own 'slickers' !
3                     Best sugarless gum ever!
4  I've chewed this gum many times, but used?

                                                Text  \
0  I bought a few of these after my apartment was...
1  This was a really good idea and the final prod...
2  I just received my shipment and could hardly w...
3  I love this stuff. It is sugar-free so it does...
4  Nothing against the product, but it does bothe...

                                         CleanedText  Tex_len
0  bought apart infest fruit fli hour trap mani f...       28
1  realli good idea final product outstand use de...       17
2  receiv shipment could hard wait tri product lo...       36
```

```
3        love stuff rot gum tast good go buy gum get       10
4   noth product bother link top page buy use chew...       15
```

0.0.1 Train Test Split

```
In [20]: X_train, X_test, y_train, y_test = train_test_split(filtered_100k, label, test_size=0
```

```
In [21]: print(X_train.shape,len(y_train))
         print(X_test.shape,len(y_test))
```

```
(70000, 10) 70000
(30000, 10) 30000
```

0.0.2 Bag Of Words

```
In [22]: # Creating vectorizer

         count_vector=CountVectorizer(ngram_range=(1,2),dtype='float')
         vocab=count_vector.fit(X_train.CleanedText)

         bow_train=count_vector.transform(X_train.CleanedText)
         bow_test=count_vector.transform(X_test.CleanedText)
```

```
In [23]: #Data Scaling-Normilizer has given better result than Std scaler

         scaler = Normalizer()
         scaler.fit(bow_train)
         bow_train=scaler.transform(bow_train)
         bow_test=scaler.transform(bow_test)
```

```
In [20]: print(bow_train.get_shape())
         print(bow_test.get_shape())
```

```
(70000, 936298)
(30000, 936298)
```

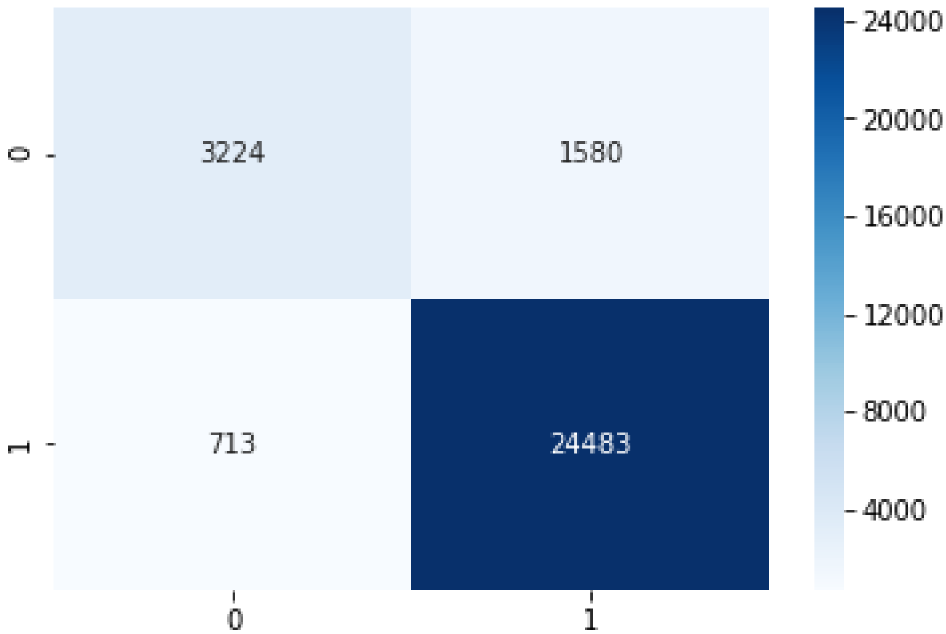
0.1 Applying Logistic Regression on Bag of word technique

```
In [21]: # Creating summary table to store summary of models
         summary_table = prettytable.PrettyTable(["Method","Model","Optimam C", "F-1 Score"])
         noise=.001
         # defining fait method and validation methods
         def fit_and_val_model(X_train,y_train,X_test,y_test,method,table=summary_table):

             #creating weighted f-1 scorer
             scorer=make_scorer(f1_score,average='weighted')
```

```
    #model fitting
    tuned_parameters = {'C': [10**-4, 10**-2,10**-1, 10**0, 10**1,10**2, 10**4]}
    model = GridSearchCV(LogisticRegression(), tuned_parameters, scoring = scorer, cv=
    model.fit(X_train, y_train)


    print(model.best_estimator_)
    print("\nThe model F-1 score is",model.score(X_test, y_test)*100)

    pred = model.predict(X_test)
    f1=f1_score(y_pred=pred,y_true=y_test,pos_label='Positive')
    score=f1*100

    print ("\n\nF-1 Scores on test data on optimal parameters is  {:.4f} %\n\n".forma
    #Add row to the summary table
    table.add_row([method,'Logistic_Reg',model.best_estimator_.C,score])

    # evaluate accuracy

    cnf_mtrx=confusion_matrix(y_true=y_test, y_pred=pred, labels=None, sample_weight=
    print(cnf_mtrx)
    # Heatmap to display
    sns.heatmap(cnf_mtrx,annot=True,cmap='Blues', fmt='g')
    plt.show()
    print (classification_report(y_test, pred))

    return model
```

```
In [22]: #Fitting Model for Bag of word
         model_bow=fit_and_val_model(bow_train,y_train,bow_test,y_test,"BOW")
```

```
LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)

The model F-1 score is 92.04224426562614


F-1 Scores on test data on optimal parameters is  95.5266 %


[[ 3224  1580]
 [  713 24483]]
```



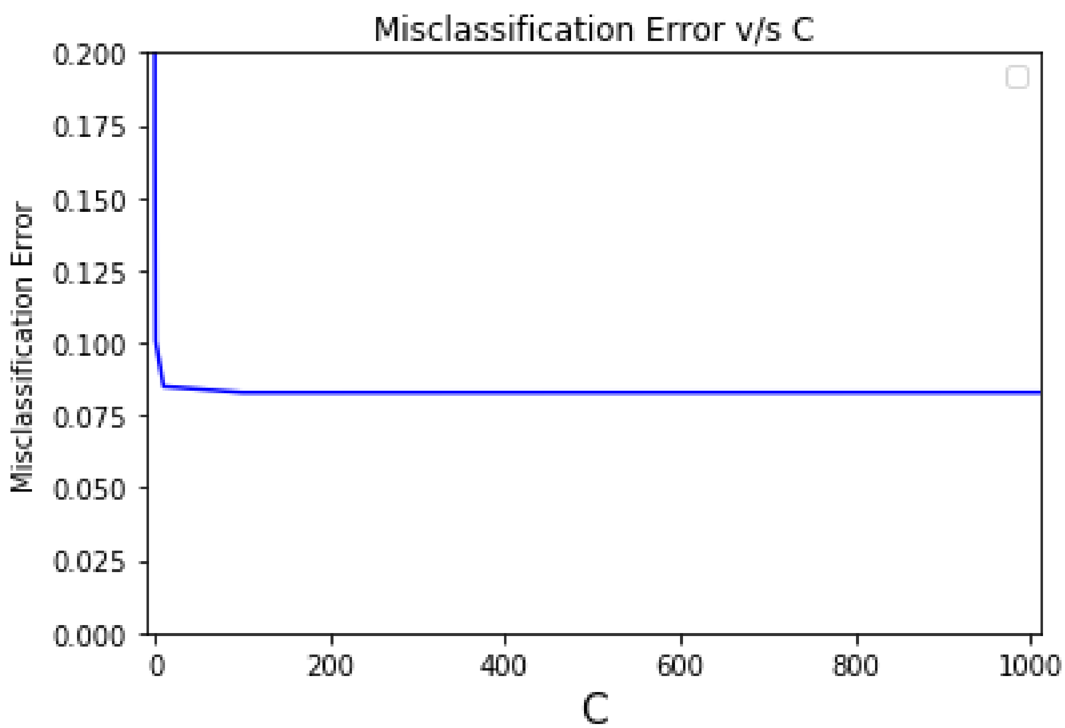

```
             precision    recall  f1-score   support

   Negative       0.82      0.67      0.74      4804
   Positive       0.94      0.97      0.96     25196

avg / total       0.92      0.92      0.92     30000
```

In [26]:
```
#Function to plot Misclassification error against C
def plot_error_vs_c_r(gsv):
    x1=[]
    y1=[]
    for a in gsv.grid_scores_:

            y1.append(1-a[1])
            x1.append(a[0]['C'])

    ind1 = np.argsort(x1)
    x1=np.array(x1)
    y1=np.array(y1)
    plt.xlim(-10,1010)
    plt.ylim(0,0.2)
    plt.xlabel("C",fontsize=15)
    plt.ylabel("Misclassification Error")
    plt.title('Misclassification Error v/s C')
```

```
        plt.plot(x1[ind1],y1[ind1],'b')
        plt.legend()
        plt.show()
```

In [27]: `plot_error_vs_c_r(model_bow)`

```
No handles with labels found to put in legend.
```



0.2 positive and Negative important features

In [67]:
```
w = count_vector.get_feature_names()
coef = model_bow.best_estimator_.coef_.tolist()[0]
coeff_df = pd.DataFrame({'Word' : w, 'Coefficient' : coef})
coeff_df = coeff_df.sort_values(['Coefficient', 'Word'], ascending=[0, 1])
print('')
print('-Top 20 positive-')
print(coeff_df.head(20).to_string(index=False))
print('')
print('-Top 20 negative-')
print(coeff_df.tail(20).to_string(index=False))
```

```
-Top 20 positive-
```

Coefficient	Word
18.080205	high recommend
15.494530	delici
15.145266	amaz
15.093377	perfect
14.007243	excel
13.576708	hook
12.814695	worri
12.389460	best
12.194448	skeptic
11.991574	pleasant surpris
11.951586	yummi
11.568554	beat
11.337003	nice
11.302593	even better
11.293159	well worth
11.220374	great
11.152751	drawback
11.148935	uniqu
10.947321	complaint
10.802550	five star

-Top 20 negative-

Coefficient	Word
-13.206646	weak
-13.535546	unpleas
-13.957391	return
-14.225451	never buy
-14.406827	unfortun
-14.564792	threw
-14.690462	shame
-14.712978	cancel
-14.798211	trash
-14.845801	undrink
-14.887052	want like
-15.334178	bland
-15.750716	disgust
-15.906526	tasteless
-16.301536	disappoint
-16.590034	horribl
-17.546100	aw
-18.707165	two star
-19.279446	terribl
-28.206905	worst

0.3 Pertubation Test

```
In [24]: noise=.001
         def fit_and_val(X_train,y_train,X_test,y_test,method):

             scorer=make_scorer(f1_score,average='weighted')
             tuned_parameters = {'C': [10**-4, 10**-2, 10**0, 10**2, 10**4]}
             model = GridSearchCV(LogisticRegression(), tuned_parameters, scoring = scorer, cv=
             model.fit(X_train, y_train)


             print(model.best_estimator_)
             print(model.score(X_test, y_test))
             w=model.best_estimator_.coef_
         #    print ("\nmodel performance is {:.4f}  %".format(scores*100))
             X_train.data=(X_train.data+noise)
             model.fit(X_train,y_train)
             w_noise=model.best_estimator_.coef_


             return w,w_noise
```

```
In [25]: wieght_vec,wieght_vec_noise=fit_and_val(bow_train,y_train,bow_test,y_test,"BOW")
```

```
LogisticRegression(C=100, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='warn',
          tol=0.0001, verbose=0, warm_start=False)
0.9204224426562614
```

```
In [32]: diff=(abs((wieght_vec-wieght_vec_noise)/(wieght_vec))*100)
```

```
In [33]: print(wieght_vec)
```

```
[[ 7.03119146e-04 -9.97335848e-01 -9.97335848e-01 ...  1.27624704e-02
  -3.57295615e-01 -3.57295615e-01]]
```

```
In [34]: print(wieght_vec_noise)
```

```
[[ 5.26089189e-04 -9.90273284e-01 -9.90273284e-01 ...  1.14379425e-02
  -3.53569524e-01 -3.53569524e-01]]
```

```
In [35]: print(diff[np.where(diff > 30)].size)
```

```
84223
```

84223 features have weight changes greater than 30%. Hence the features are multicollinear

```
In [46]: #Percentile check using elbow method


         for i in [0,10,20,30,40,50,60,70,80,90,99,100]:
             print (i,"\t",np.percentile(diff,i))
```

```
0            1.4695513016860096e-06
10            0.2189736010718234
20            0.43263692986461355
30            0.679063754344147
40            1.0250103302539102
50            1.6174555993307318
60            2.786294695032271
70            5.469606667249029
80            12.582727301552755
90            27.61731048417308
99            68.88447121865063
100            91574.81955658789
```

0.3.1 Since value changes dreastically between 99 percentile and 100th percentile , so checking between 99 to 100

```
In [47]: for i in [99.1,99.2,99.3,99.4,99.5,99.6,99.7,99.8,99.9,100]:
             print (i,"\t",np.percentile(diff,i))
```

```
99.1            69.97436319491256
99.2            71.10099062682309
99.3            72.44470278732685
99.4            73.51357381233778
99.5            74.65195359424874
99.6            75.99353850273316
99.7            77.25181503008362
99.8            78.4673873990905
99.9            83.40415660896264
100            91574.81955658789
```

```
In [57]: #Associating word with diff wiegt vector
         w = count_vector.get_feature_names()
         coef = diff[0]
         diff_df = pd.DataFrame({'Word' : w, 'Difference' : coef})
```

0.3.2 Printing words which has difference greater than 83.4 and there is 937 such words/feature

```
In [64]: print(diff_df.Word[diff_df.Difference > 83.4])
```

1300	absolut weird
3201	acid decaf
3316	acid ingredi
4631	actual bar
4651	actual best
4703	actual carri
5040	actual jerki
5069	actual lemon
5843	ad distil
6324	ad shot
7066	add herb
7815	addict candi
8495	addit get
8595	addit make
9452	admit defeat
9700	adolesc
10323	advanc stage
10651	advertis get
12532	aftertast found
12789	aftertast though
13108	agav syrup
15233	air obvious
15348	airedal
18812	almost equal
19284	almost sugar
19387	almost worth
19635	alon product
21238	also bite
24284	altogeth much
24341	altoid great
	...
909111	well start
909222	well thought
909368	well weird
909394	well within
910665	whatev
912480	whim groceri
912488	whim love
916017	window open
916981	wire fox
918056	within week
918554	without gum
919831	wonder came
920204	wonder item
921229	word expect
921952	work find
922275	work nespresso
924065	wors caffein

```
924293        wors thought
924947         worth onlin
925670        would dehydr
925970          would high
926791         would upset
927633      wrapper chocol
930557         year replac
932622           yet right
935148      zero complaint
935275          zero would
935566           zico pure
935738          zing sweet
935878       zipfizz total
Name: Word, Length: 937, dtype: object
```

0.4 Sparsity Check

```
In [57]: nbrs_list=[10**4,10**3, 10**2, 10,10**0, 10**-1]
         for C in nbrs_list:
             clf = LogisticRegression(C= C, penalty= 'l1')
             clf.fit(bow_train,y_train)
             y_pred = clf.predict(bow_test)
             print("\nFor C={:.4f}".format(C))
             print("F1-Score on test set: {:0.4f}%".format(f1_score(y_test, y_pred,pos_label='
             print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
For C=10000.0000
F1-Score on test set: 95.0864%
Non Zero weights: 37888

For C=1000.0000
F1-Score on test set: 94.7948%
Non Zero weights: 18192

For C=100.0000
F1-Score on test set: 94.8506%
Non Zero weights: 14458

For C=10.0000
F1-Score on test set: 95.1257%
Non Zero weights: 9588

For C=1.0000
F1-Score on test set: 95.1877%
Non Zero weights: 1066
```

```
For C=0.1000
F1-Score on test set: 93.5323%
Non Zero weights: 169
```

0.4.1 Here sparsity increases from 37888 non-zero weights For C=10000 to only 169 non-zero weightsFor C=0.1 when we use L1 Regularization

0.4.2 TF-IDF intialization and dimension creation

In [28]:
```
#craeting TF-IDF vectorizer

tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
filtered_tf_idf = tf_idf_vect.fit(X_train.CleanedText)
print("the type of count vectorizer ",type(filtered_tf_idf))
#print("the shape of out TF-IDF vectorizer ",filtered_tf_idf.get_shape())
```

```
the type of count vectorizer  <class 'sklearn.feature_extraction.text.TfidfVectorizer'>
```

In [29]:
```
tf_idf_train=tf_idf_vect.transform(X_train.CleanedText)
tf_idf_test=tf_idf_vect.transform(X_test.CleanedText)
```

In [30]:
```
#feature scaling

scaler = Normalizer()
scaler.fit(tf_idf_train)
tf_idf_train=scaler.transform(tf_idf_train)
tf_idf_test=scaler.transform(tf_idf_test)
```

In [25]:
```
print(tf_idf_train.get_shape())
print(tf_idf_test.get_shape())
```

```
(70000, 936298)
(30000, 936298)
```

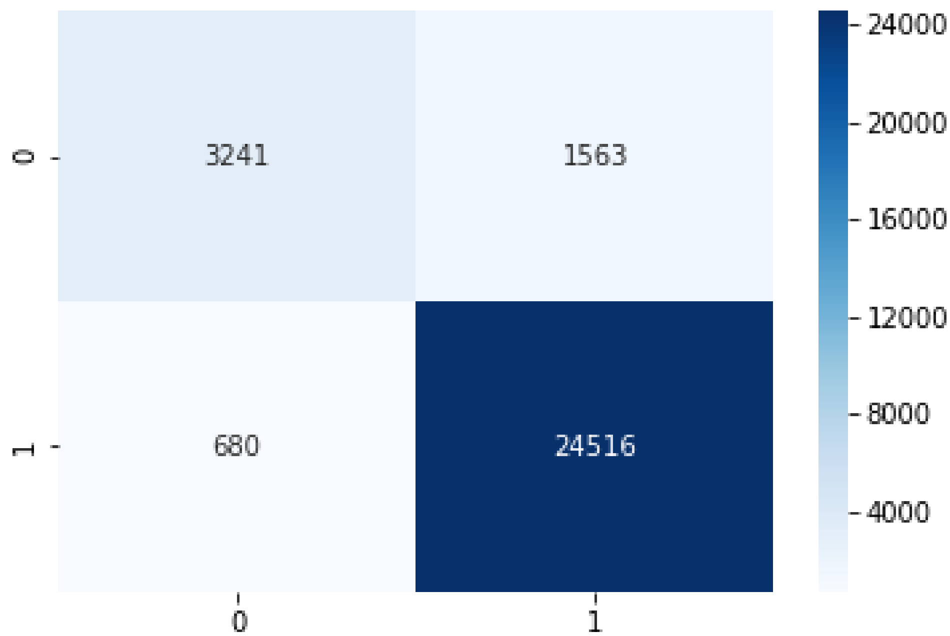
0.5 Applying logistic Regression on TF-IDF

In [31]:
```
#Fitting model against TF-IDF

Model=fit_and_val_model(tf_idf_train,y_train,tf_idf_test,y_test,"TF-IDF")
```

```
LogisticRegression(C=10000, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)

The model F-1 score is 92.20937849051664
```

```
F-1 Scores on test data on optimal parameters is  95.6255 %
```

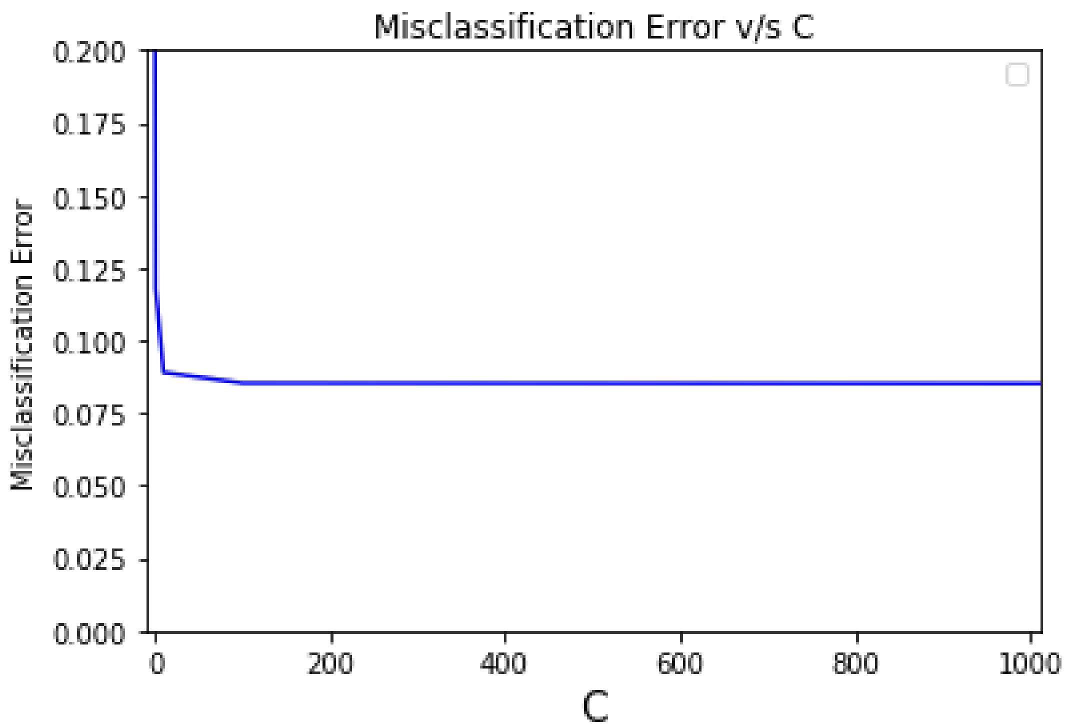
```
[[ 3241  1563]
 [  680 24516]]
```




```
             precision    recall  f1-score   support

   Negative       0.83      0.67      0.74      4804
   Positive       0.94      0.97      0.96     25196

avg / total       0.92      0.93      0.92     30000
```

In [32]: plot_error_vs_c_r(Model)

```
No handles with labels found to put in legend.
```



0.6 Positive and Negative important Feature

In [75]:
```
w = tf_idf_vect.get_feature_names()
coef  = Model.best_estimator_.coef_.tolist()[0]
coeff_df = pd.DataFrame({'Word' : w, 'Coefficient' : coef})
coeff_df = coeff_df.sort_values(['Coefficient', 'Word'], ascending=[0, 1])
print('')
print('-Top 20 positive-')
print(coeff_df.head(20).to_string(index=False))
print('')
print('-Top 20 negative-')
print(coeff_df.tail(20).to_string(index=False))
```

```
-Top 20 positive-
Coefficient             Word
  53.268579            great
  46.017515             best
  44.731027           delici
  43.958488             love
  43.533615          perfect
  36.770204            excel
  35.382622             nice
```

```
  35.075769  high recommend
  33.296421            amaz
  28.842241            good
  28.389148          wonder
  26.735957         favorit
  26.559487         without
  25.917003           thank
  24.634959           yummi
  24.273313          smooth
  24.203884           worri
  23.827254            hook
  23.821736            easi
  22.859229          awesom

-Top 20 negative-
Coefficient        Word
 -25.994713       shame
 -26.505790      cancel
 -26.827463   never buy
 -27.093618       trash
 -27.292348       sorri
 -27.433316        wast
 -28.324677        weak
 -28.547180       stale
 -28.644562   tasteless
 -30.108636    two star
 -30.139456     disgust
 -30.432148       threw
 -31.611178       bland
 -32.568419    unfortun
 -34.392851      return
 -35.923372     horribl
 -36.168662          aw
 -40.756866     terribl
 -48.189019  disappoint
 -54.754130       worst
```

0.7 Wieghted Word2Vec Model

In [33]:
```
#Creating sentence vector

list_of_sent=[]
for sent in filtered_100k.CleanedText:
    list_of_sent.append(sent.split())
#Word2vec model
w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
w2v_words = list(w2v_model.wv.vocab)
```

```
# average Word2Vec
# compute average word2vec for each review.
sent_vectors = []; # the avg-w2v for each sentence/review is stored in this list
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

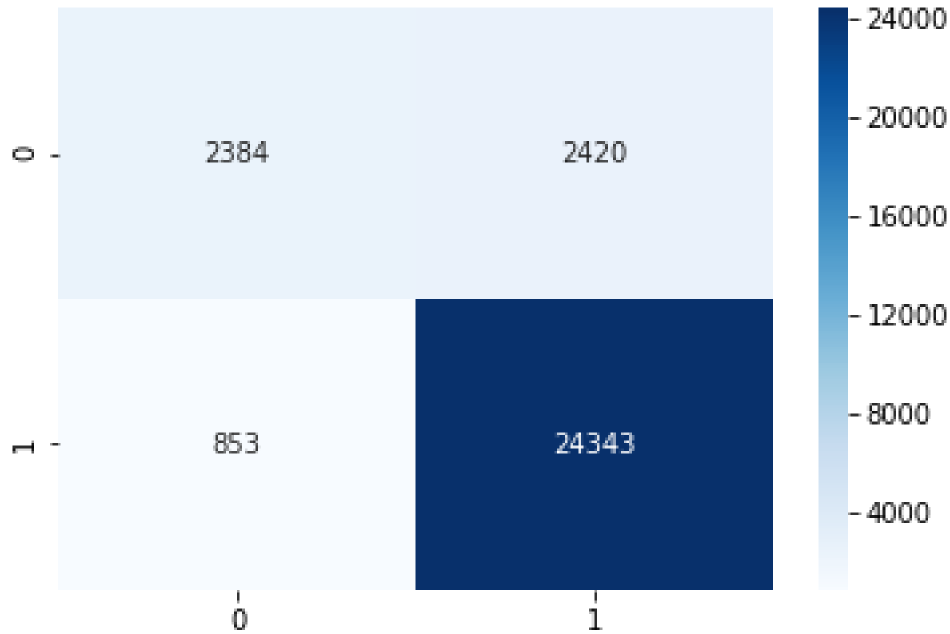
```
100000
50
```

In [34]:
```
#Train test split
w2v_train, w2v_test, y_train, y_test = train_test_split(sent_vectors, label, test_size
```

In [35]:
```
#Feature scaling
scaler = Normalizer()
scaler.fit(w2v_train)
w2v_train=scaler.transform(w2v_train)
w2v_test=scaler.transform(w2v_test)
```

In [36]:
```
#Fitting the model

Model=fit_and_val_model(w2v_train,y_train,w2v_test,y_test,"Wod2vec")
```

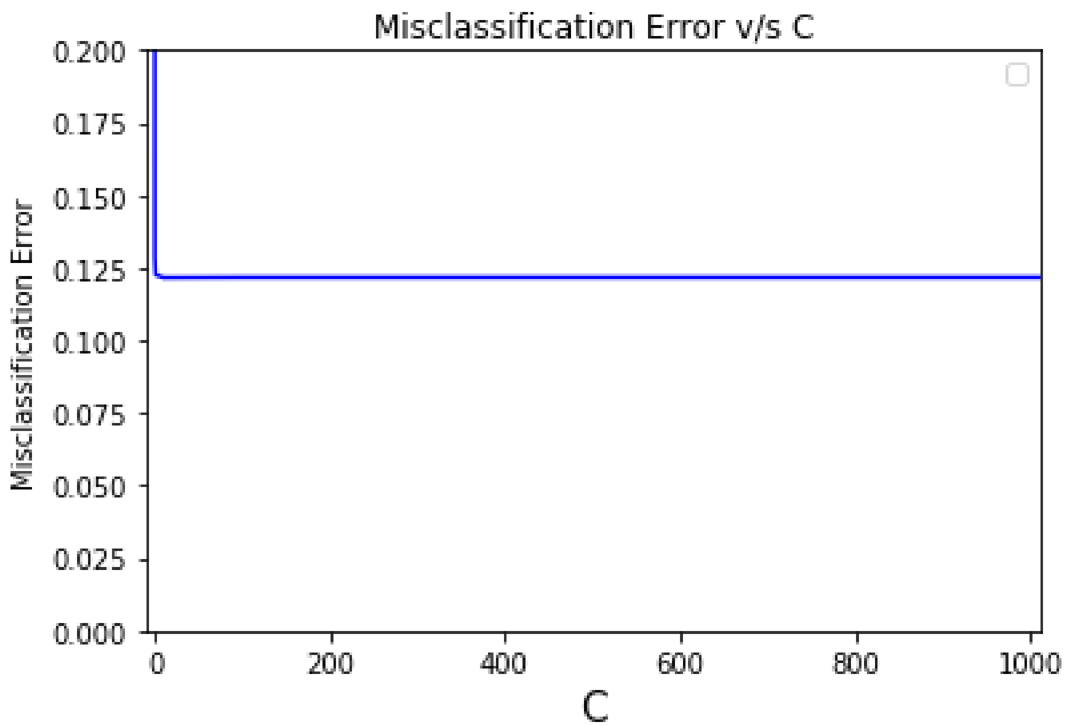
```
LogisticRegression(C=10, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)

The model F-1 score is 88.19146404613421


F-1 Scores on test data on optimal parameters is  93.7008 %


[[ 2384  2420]
 [  853 24343]]
```




```
             precision    recall  f1-score   support

   Negative       0.74      0.50      0.59      4804
   Positive       0.91      0.97      0.94     25196

avg / total       0.88      0.89      0.88     30000
```

In [37]: plot_error_vs_c_r(Model)

```
No handles with labels found to put in legend.
```



0.8 Wieghted TF-IDF

```
In [38]: #sentence vector creation
         list_of_sent_train=[]
         for sent in X_train.CleanedText:
             list_of_sent_train.append(sent.split())




         list_of_sent_test=[]
         for sent in X_test.CleanedText:
             list_of_sent_test.append(sent.split())

         w2v_model=Word2Vec(list_of_sent_train,min_count=5,size=50, workers=4)
         w2v_words = list(w2v_model.wv.vocab)

         len(w2v_words)

Out[38]: 10159

In [39]: #TF-IDF Vectorizer initialization
```

```
tf_idf_vect = TfidfVectorizer(ngram_range=(1,2))
filtered_tf_idf = tf_idf_vect.fit(X_train.CleanedText)
dictionary = dict(zip(tf_idf_vect.get_feature_names(), list(tf_idf_vect.idf_)))
print("the type of count vectorizer ",type(filtered_tf_idf))


tf_idf_train=tf_idf_vect.transform(X_train.CleanedText)
tf_idf_test=tf_idf_vect.transform(X_test.CleanedText)
```

```
the type of count vectorizer  <class 'sklearn.feature_extraction.text.TfidfVectorizer'>
```

In [40]:
```
#creating weighted TF-IDF


def w_tf_idf(X,word_vector,model,tfidf_feat,filtered_tf_idf):
    tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in th
#    row=0;
    for sent in X: # for each review/sentence
        sent_vec = np.zeros(50) # as word vectors are of zero length
        weight_sum =0; # num of words with a valid vector in the sentence/review
        for word in sent: # for each word in a review/sentence
            if word in word_vector:
                vec = model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
                tf_idf = dictionary[word]*sent.count(word)
                """tf_idf = filtered_tf_idf[row, tfidf_feat.index(word)]"""
                sent_vec += (vec * tf_idf)
                weight_sum += tf_idf
        if weight_sum != 0:
            sent_vec /= weight_sum
        tfidf_sent_vectors.append(sent_vec)
#        row += 1
    print(len(tfidf_sent_vectors))
    print(len(tfidf_sent_vectors[0]))
    return tfidf_sent_vectors
```

In [41]:
```
tfidf_feat = tf_idf_vect.get_feature_names()
tf_idf_sent_vectors_train=w_tf_idf(list_of_sent_train,w2v_words,w2v_model,tfidf_feat,t
tf_idf_sent_vectors_test=w_tf_idf(list_of_sent_test,w2v_words,w2v_model,tfidf_feat,tf_
```

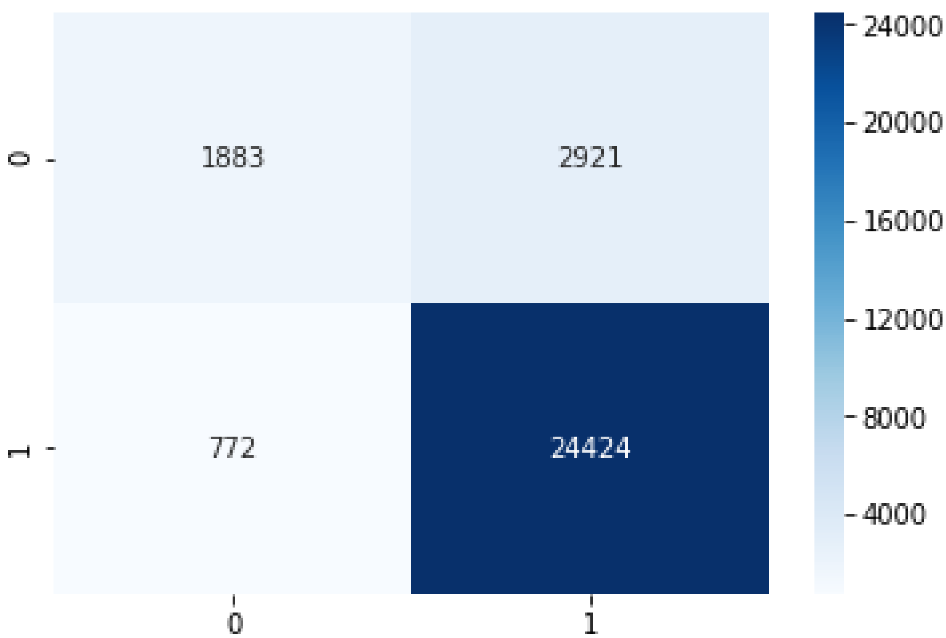
```
70000
50
30000
50
```

In [42]:
```
#Feature scaling
```

```
scaler = Normalizer()
scaler.fit(w2v_train)
tfidf_wieghted_train=scaler.transform(tf_idf_sent_vectors_train)
tfidf_wieghted_test=scaler.transform(tf_idf_sent_vectors_test)
```

In [43]:
```
# Model fitting

Model=fit_and_val_model(tfidf_wieghted_train,y_train,tfidf_wieghted_test,y_test,"Wiegh
```

```
LogisticRegression(C=10000, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)

The model F-1 score is 86.16844131988583


F-1 Scores on test data on optimal parameters is  92.9712 %


[[ 1883  2921]
 [  772 24424]]
```

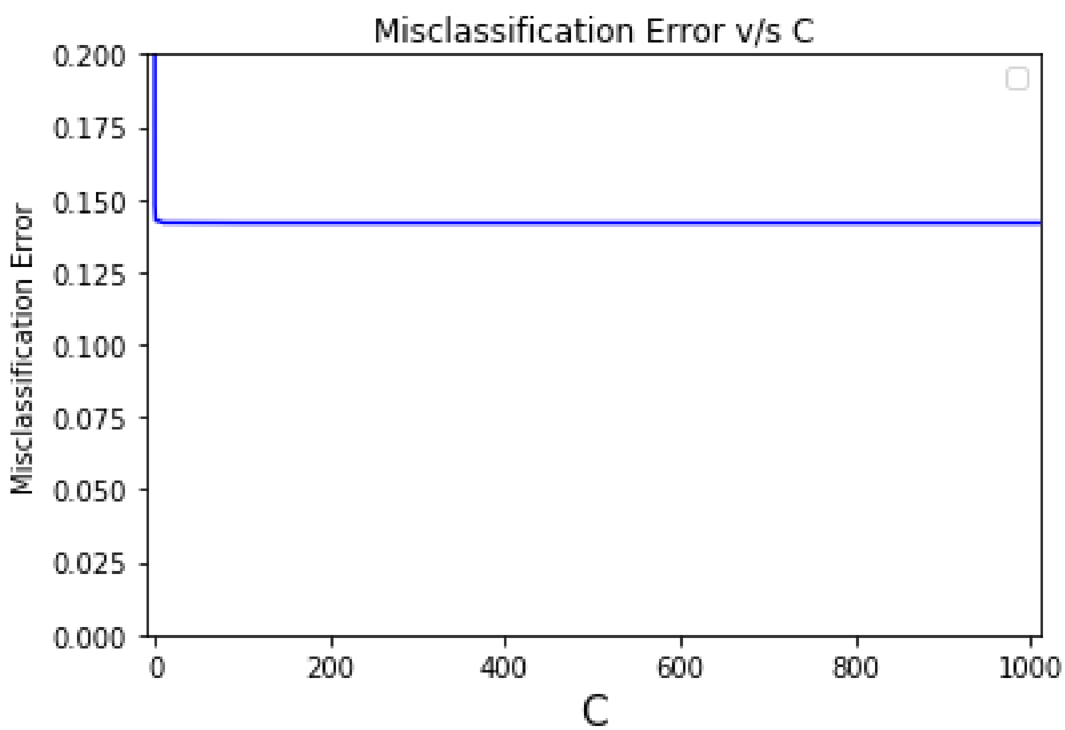



```
             precision    recall  f1-score   support
```

```
   Negative       0.71      0.39      0.50      4804
   Positive       0.89      0.97      0.93     25196

avg / total       0.86      0.88      0.86     30000
```

In [44]: plot_error_vs_c_r(Model)

```
No handles with labels found to put in legend.
```



In [45]: print(summary_table)

```
+-----------------+--------------+-----------+-------------------+
|      Method     |    Model     | Optimam C |     F-1 Score     |
+-----------------+--------------+-----------+-------------------+
|       BOW       | Logistic_Reg |    100    | 95.52663922433133 |
|      TF-IDF     | Logistic_Reg |   10000   | 95.62554851292052 |
|     Wod2vec     | Logistic_Reg |     10    | 93.70080255586136 |
| Wieghted TF-IDF | Logistic_Reg |   10000   | 92.97120344112217 |
+-----------------+--------------+-----------+-------------------+
```

0.8.1 Conclusion:BOW and TF-IDF has performed better than word2vec and weighted TF-IDF model for Logistic Regression