Logistic Regression On Amazon Fine Food Reviews

This is my 5th assignment.

Objective:

```
 1. Apply the Logistic Regression algorithm on BOW,TF-IDF,Word2Vec, TF-IDF Word2
Vec
 2. Apply the both GridSearch and RandomSearch cross validation
 3. Evaluate differnet metrics such as precision ,recall,f1-score and plot the c
onfusion matrix
 4. Show how sparsity increase as lambda increase or C decreases with L1 regular
izer
 5. Use Pertubation to check for the multicolinerity of features
```

In [1]:

```
#Loading important Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import sqlite3 as sql
import seaborn as sns
from time import time
import random
import gensim
import warnings

from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score

warnings.filterwarnings("ignore")

%matplotlib inline

from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import TimeSeriesSplit
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
E:\PYTHON\lib\site-packages\gensim\utils.py:1209: UserWarning: detected Wi
ndows; aliasing chunkize to chunkize_serial
  warnings.warn("detected Windows; aliasing chunkize to chunkize_serial")
```

In [2]:

```
filtered_data=pd.read_csv('Reviews.csv')#displaying
filtered_data.head()
```

Out[2]:

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

In [3]:

```
#For setting positive/negative
filtered_data=pd.read_csv('Reviews.csv')
def partition(x):
    if x < 3:
        return 'negative'
    return 'positive'
#changing reviews with score less than 3 to be positive and vice-versa
actualScore = filtered_data['Score']
#pdb.set_trace()
positiveNegative = actualScore.map(partition)
#pdb.set_trace()
filtered_data['Score'] = positiveNegative
#print(filtered_data.head())#print 5 row
print(filtered_data.shape) #looking at the number of attributes and size of the data
filtered_data.head()
```

```
(568454, 10)
```

Out[3]:

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

In [4]:

```
#Sorting data according to ProductId in ascending order
sorted_data=filtered_data.sort_values('ProductId', axis=0, ascending=True,)
```

In [5]:

```
sorted_data=sorted_data[sorted_data.HelpfulnessNumerator<=sorted_data.HelpfulnessDenomi
nator]
print(sorted_data.shape)
```

```
(568452, 10)
```

In [6]:

```
#De-duplication of entries
final=sorted_data.drop_duplicates(subset={"UserId","ProfileName","Time","Text"}, keep=
'first', inplace=False)

print(final.shape)#shape

print((final['Id'].size*1.0)/(filtered_data['Id'].size*1.0)*100)#percentage

#get to know how much posive negative there in table
final['Score'].value_counts()
```

```
(393931, 10)
69.29865917031105
```

Out[6]:

```
positive    336824
negative     57107
Name: Score, dtype: int64
```

In [7]:

```
###Sorting as we want according to time series

n_samples = 150000
df_sample = final.sample(n_samples)

df_sample.sort_values('Time',inplace=True)
df_sample.head(5)
#print(df_sample.shape)
```

Out[7]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerato
150500	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2
451855	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0
451902	451903	B00004CXX9	A2DEE7F9XKP3ZR	jerome	0
1244	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7
1243	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10

In [8]:

```
import nltk
from nltk.corpus import stopwords
#nltk.download('stopwords')
stopwords = stopwords.words('english')#choosen the english language

from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.stem import PorterStemmer,SnowballStemmer

stop = set(stopwords.words('english')) #set of stopwords
porter = PorterStemmer()
snowball = SnowballStemmer('english')
#Text Preprocessing: Stemming, stop-word removal and Lemmatization
# find sentences containing HTML tags
import re#regular expression

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

```
0
In June<br />I saw a charming group<br />of roses all begin<br />to droop<
br />I pepped them up<br />with chicken soup!<br />Sprinkle once<br />spri
nkle twice<br />sprinkle chicken soup<br />with rice<br /><br />This is a
great book to teach children the months of the year. The repetition of the
phrases and the funny little stories with accompanying pictures make for a
n ideal bedtime read. This isn't nearly as good as some of Sendak's other
books (like Where the Wild Things are or Pierre: The Boy Who Didn't Care),
but it still carries his unique brand of charm.
```

In [9]:

```
%%time
#Code for implementing step-by-step the checks mentioned in the pre-processing phase
# this code takes a while to run as it needs to run on 500k sentences.
i=0
str1=' '
final_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''

final_150000 = df_sample.head(150000)#taking 150000 datapoints

def cleanhtml(sentence):
    cleanr = re.compile('<.*?>')
    cleantext = re.sub(cleanr, ' ', sentence)
    return cleantext

def cleanpunc(sentence):
    cleaned = re.sub(r'[?|!|\'|"|#]',r'',sentence)
    cleaned = re.sub(r'[.|,|)|(|\|/]',r' ',cleaned)
    return cleaned

    str1=[];

for sent in final_150000['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTMl tags
    sent=cleanpunc(sent)
    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=(snowball.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final_150000['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describ
e positive reviews
                    if(final_150000['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describ
e negative reviews reviews
                else:
                    continue
            else:
                continue
    #print(filtered_sentence)
    #str1 =b" ".join(filtered_sentence) #final string of cleaned words
    str1 =b' '.join(filtered_sentence).decode()
    #print("***********************************************************************")

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

Wall time: 7min 17s

In [10]:

```
#adding a column of CleanedText which displays the data after pre-processing of the rev
iew
final_150000['clean_text']=final_string

#final_50000=final_100000.head(150000)#taking 50k datapoints
print(final_150000.shape)
```

```
(150000, 11)
```

In [11]:

```
#Functions to save objects for later use and retireve it
import pickle
def SaveToFile(obj,filename):
    pickle.dump(obj,open(filename+".p","wb"))
def OpenFromFile(filename):
    temp = pickle.load(open(filename+".p","rb"))
    return temp
```

Bag Of Words Using Logistic Regression

In [13]:

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn import preprocessing
from sklearn.model_selection import train_test_split

from sklearn import preprocessing
X_train, X_test, y_train, y_test = train_test_split(final_150000['clean_text'].values,
                                                    final_150000['Score'].values ,test_
size=0.30,shuffle=False)
```

In [66]:

```
#Preprocessing data

#Preprocessing data

uni_gram = CountVectorizer()

uni_gram.fit(X_train)
X_train=uni_gram.transform(X_train)
X_test = uni_gram.transform(X_test)

X_train = preprocessing.normalize(X_train)
X_test = preprocessing.normalize(X_test)

print("Train Data Size: ",X_train.shape)
print("Test Data Size: ",X_test.shape)
```

```
Train Data Size:  (105000, 38523)
Test Data Size:  (45000, 25611)
```

In [67]:

```
from sklearn.model_selection import TimeSeriesSplit

tscv = TimeSeriesSplit(n_splits=10)
for train, cv in tscv.split(X_train):

    # print("%s %s" % (train, cv))
    print(X_train[train].shape, X_train[cv].shape)
```

```
(9550, 38523) (9545, 38523)
(19095, 38523) (9545, 38523)
(28640, 38523) (9545, 38523)
(38185, 38523) (9545, 38523)
(47730, 38523) (9545, 38523)
(57275, 38523) (9545, 38523)
(66820, 38523) (9545, 38523)
(76365, 38523) (9545, 38523)
(85910, 38523) (9545, 38523)
(95455, 38523) (9545, 38523)
```

Find the best C value

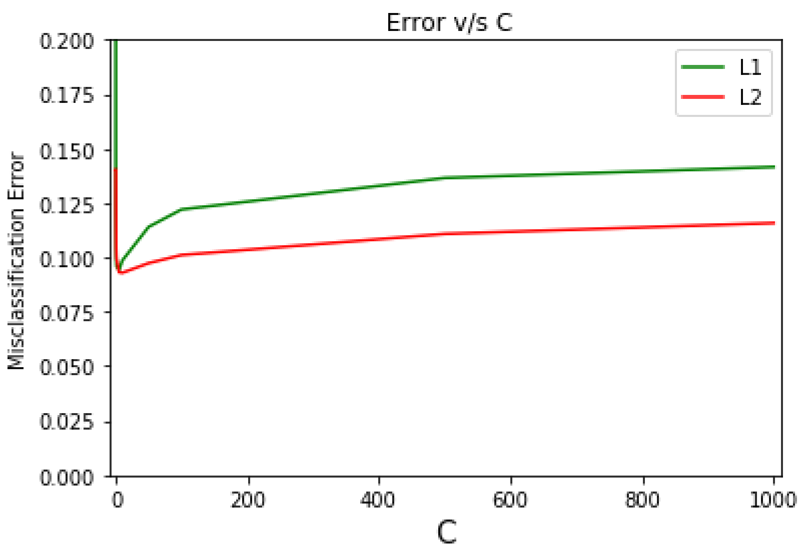
In [27]:

```
%%time
from sklearn.model_selection import GridSearchCV # Finding the best "Alpha" using forwa
rd chaining cross validation
from sklearn.linear_model import LogisticRegression

LR = LogisticRegression()
param_grid ={'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005
                  ,0.001,0.0005,0.0001],'penalty':['l1','l2']} #params we need to try o
n classifier

tscv = TimeSeriesSplit(n_splits=10) #For time based splitting

grid = GridSearchCV(LR, param_grid, cv=tscv, verbose=1)# instantiate the grid
grid.fit(X_train,y_train)

SaveToFile(grid,"LR-Uni-Gram")
print("Best HyperParameter: ",grid.best_params_)
print("Best Accuracy: %.2f%%"%(grid.best_score_*100))
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits

[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 25.9min finished

Best HyperParameter:  {'C': 10, 'penalty': 'l2'}
Best Accuracy: 90.71%
Wall time: 26min 7s
```

In [18]:

```
# plotting of L1 and L2 error
def error_vs_c(gsv):
    x1=[]
    y1=[]
    x2=[]
    y2=[]
    for a in gsv.grid_scores_:
        if (a[0]['penalty']) == 'l1':
            y1.append(1-a[1])
            x1.append(a[0]['C'])
        else:
            y2.append(1-a[1])
            x2.append(a[0]['C'])
    plt.xlim(-10,1010)
    plt.ylim(0,0.2)
    plt.xlabel("C",fontsize=15)
    plt.ylabel("Misclassification Error")
    plt.title(' Error v/s C')
    plt.plot(x1,y1,'g',label="L1")
    plt.plot(x2,y2,'r',label="L2")
    plt.legend()
    plt.show()
gscv = OpenFromFile("LR-Uni-Gram")
error_vs_c(gscv)
```



In [29]:

```
print(gscv.best_estimator_)
```

```
LogisticRegression(C=10, class_weight=None, dual=False, fit_intercept=Tru
e,
          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)
```

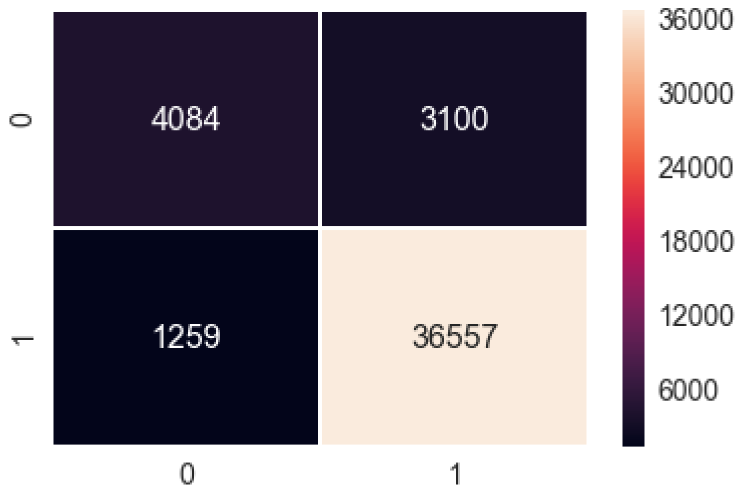
In [32]:

```
# testing accuracy on the best_estimator

LR = LogisticRegression(C=10,penalty='l2')
LR.fit(X_train,y_train)
y_pred = LR.predict(X_test)

print("Accuracy on test set: %0.2f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred, pos_label='positi
ve')*100))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred, pos_label='positive')*1
00))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred, pos_label='positive')*100
))
print("Non Zero weights:",np.count_nonzero(LR.coef_))

df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',linewidths=.5)
```

```
Accuracy on test set: 90.31%
Precision on test set: 92.183
Recall on test set: 96.671
F1-Score on test set: 94.374
Non Zero weights: 38523
```

Out[32]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x19e25f5ce48>
```



Show how sparsity decrease as if we increase the value of C

In [31]:

```
C_value = [1000,100,10,1,0.1,0.01,0.001,0.0001]
l1_value = ['l1','l1','l1','l1','l1','l1','l1','l1']
def sparsity_increase(i,j):
    LR = LogisticRegression(C=i,penalty=j)
    LR.fit(X_train,y_train)
    y_pred = LR.predict(X_test)
    print("C_value:",i)
    print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
    print("Non Zero weights:",np.count_nonzero(LR.coef_))
    print("-"*100)


for i,j in zip(C_value,l1_value):
    sparsity_increase(i,j)
```

```
C_value: 1000
Accuracy on test set: 86.416%
Non Zero weights: 20158
---------------------------------------------------------------------------
-------------------------
C_value: 100
Accuracy on test set: 87.867%
Non Zero weights: 15267
---------------------------------------------------------------------------
-------------------------
C_value: 10
Accuracy on test set: 89.929%
Non Zero weights: 6986
---------------------------------------------------------------------------
-------------------------
C_value: 1
Accuracy on test set: 90.227%
Non Zero weights: 1376
---------------------------------------------------------------------------
-------------------------
C_value: 0.1
Accuracy on test set: 88.393%
Non Zero weights: 262
---------------------------------------------------------------------------
-------------------------
C_value: 0.01
Accuracy on test set: 84.144%
Non Zero weights: 20
---------------------------------------------------------------------------
-------------------------
C_value: 0.001
Accuracy on test set: 84.036%
Non Zero weights: 0
---------------------------------------------------------------------------
-------------------------
C_value: 0.0001
Accuracy on test set: 84.036%
Non Zero weights: 0
---------------------------------------------------------------------------
-------------------------
```

```
Here we can see that with the increase of C values Non Zero Weight increases,
At C_value = 0.001 and 0.0001 and l1 regularizer we get 0 non zero weights.
That means sparsity is large and we dont have any non zero value.
```

Logistic Regression using RandomSearch cross validation for uni-gram

In [33]:

```
%%time
lr = LogisticRegression()

param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.000
1],'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gscv = RandomizedSearchCV(lr,param_grid,cv=tscv,verbose=1)
gscv.fit(X_train,y_train)
SaveToFile(gscv,"LR_RandomSearch-Uni-Gram")
print("Best HyperParameter: ",gscv.best_params_)
print("Best Accuracy: %.2f%%"%(gscv.best_score_*100))
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits

[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  8.7min finished

Best HyperParameter:  {'penalty': 'l2', 'C': 10}
Best Accuracy: 90.71%
Wall time: 8min 55s
```

In [36]:

```
#Function to plot Misclassification error against C
gscv = OpenFromFile("LR_RandomSearch-Uni-Gram")
error_vs_c(gscv)
```

In [35]:

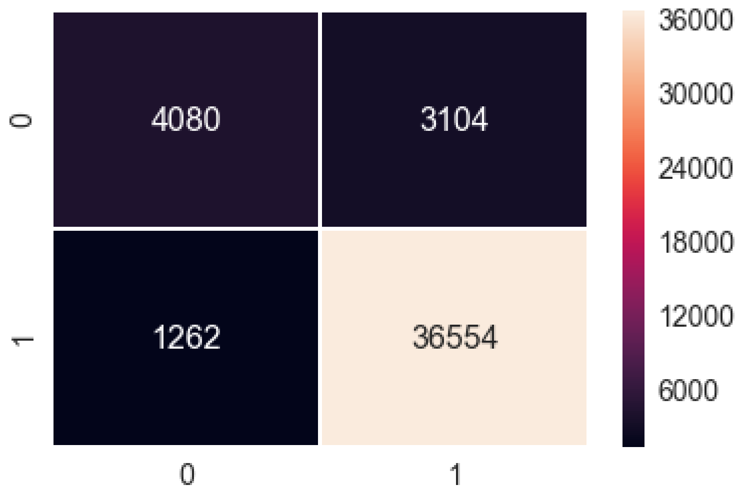
```
print(gscv.best_estimator_)
```

```
LogisticRegression(C=10, class_weight=None, dual=False, fit_intercept=Tru
e,
          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)
```

In [48]:

```
%%time
# testing accuracy on the best_estimator

LR = LogisticRegression(C=10,penalty='l2')
LR.fit(X_train,y_train)
y_pred = LR.predict(X_test)

print("Accuracy on test set: %0.2f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred, pos_label='positi
ve')*100))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred, pos_label='positive')*1
00))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred, pos_label='positive')*10
0))
print("Non Zero weights:",np.count_nonzero(LR.coef_))

df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',linewidths=.5)
```

```
Accuracy on test set: 90.30%
Precision on test set: 92.173
Recall on test set: 96.663
F1-Score on test set: 94.365
Non Zero weights: 38523
Wall time: 9.96 s
```



Perturbation Test

In [38]:

```
lr = LogisticRegression(C= 10, penalty= 'l2')
lr.fit(X_train,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
#print(dir(np))
#print(lr.coef_.size)
```

```
Accuracy on test set: 90.313%
Non Zero weights: 38523
```

In [39]:

```
from scipy.sparse import find
#Weights before adding random noise
weights1 = find(lr.coef_[0])[2]
print(weights1[:50])
```

```
[ 0.22959955  0.02769383  0.00654113  0.01785463  0.01785463  0.00654113
  0.00299281  0.0106362   0.00634867  0.00495284  0.05463248  0.05619479
  0.00530917 -1.06749079  0.01462368  0.01292867  0.10541176 -0.15542841
  0.11012422  0.19373848  0.00372414  0.00655134  0.17295654  0.00191956
  0.273013    0.12531101 -1.30802224  0.02479664  0.1105268  -0.54594398
  0.07473946 -1.68978546  0.40068942  0.01883747  0.13333569  0.15656358
  0.12240088 -0.54184479  1.07516448 -0.93276758  0.17495965  0.06166258
  0.02739986 -0.54089298  0.37617412 -0.26017884  0.09690935  0.21000545
  0.00319336 -0.73238522]
```

In [40]:

```
X_train_t = X_train
#Random noise
epsilon = np.random.uniform(low=-0.01, high=0.01, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
#print(X_train_t)
#print(epsilon)
```

In [41]:

```
lr = LogisticRegression(C= 10, penalty= 'l2')
lr.fit(X_train_t,y_train)#here is the change
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
```

```
Accuracy on test set: 90.298%
Non Zero weights: 38523
```

In [42]:

```
from scipy.sparse import find
#Weights after adding random noise
weights2 = find(lr.coef_[0])[2]
print(weights2[:50])
```

```
[ 0.24192824  0.03056787  0.00625709  0.02239777  0.02156479  0.00698248
  0.0031956   0.01063307  0.00755919  0.00606763  0.04407813  0.05275686
  0.00651099 -1.09837568  0.01646571  0.0151125   0.10120348 -0.18880752
  0.1153571   0.19401155  0.00399589  0.00644823  0.16108238  0.00185347
  0.29530647  0.13125347 -1.25165252  0.02785464  0.11110793 -0.51293364
  0.06505957 -1.71860612  0.40496988  0.01836217  0.13203888  0.16112345
  0.11684308 -0.55308113  1.02787996 -0.90887936  0.18031506  0.06249739
  0.02555603 -0.54759394  0.31722894 -0.2656791   0.09271546  0.22061393
  0.00298457 -0.73675312]
```

In [43]:

```
weights_diff = (abs(weights1 - weights2)/weights1) * 100
#print(weights_diff)
```

In [44]:

```
print(weights_diff[np.where(weights_diff > 30)].size)
```

```
911
```

weights_diff is 911 , SoThere is multi collinearity in this data

In [45]:

```
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")
    print("____________________________________________________________________________
____________________")
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(uni_gram,lr)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informativ
e-features-for-scikit-learn-classifiers
```

```
                                Positive
        Negative
__________________________________________________________________________
______________________
        -11.9491        worst                                   8.5708  aw
esom
        -10.4328        tasteless                               8.2752  ho
ok
        -9.8789 threw                                   8.2401  delici
        -9.8413 undrink                                 8.1334  beat
        -9.7391 disgust                                 7.5954  perfect
        -9.7223 aw                                      7.5620  addict
        -9.2114 horribl                                 7.4625  yum
        -8.7687 yuck                                    7.3716  worri
        -8.7128 terribl                                 7.3462  amaz
        -8.2059 gross                                   7.1507  best
        -7.7484 unapp                                   7.0583  heaven
        -7.6744 unaccept                                6.9828  uniqu
        -7.6144 disappoint                              6.9683  complaint
        -7.5041 refund                                  6.9484  fantast
        -7.2512 vomit                                   6.8881  yummi
        -7.2348 rancid                                  6.8358  solv
        -7.1865 skip                                    6.7729  excel
        -7.1184 june                                    6.7256  skeptic
        -7.0372 redeem                                  6.6689  downsid
        -7.0332 where                                   6.2354  terrif
        -6.9935 diarrhea                                6.1844  finest
        -6.9192 ined                                    6.1561  glad
        -6.9150 nasti                                   6.0937  great
        -6.9092 unpleas                                 6.0817  smooth
        -6.8995 flavorless                              5.9240  beauti
```

Logistic Regression TF-IDF

GridSearch

In [42]:

```
%%time
X_train, X_test, y_train, y_test = train_test_split(final_150000['clean_text'].values,
                                                    final_150000['Score'].values ,test_
size=0.30,shuffle=False)
tfidf = TfidfVectorizer(ngram_range=(1,2))
tfidf.fit(X_train)
X_train = tfidf.transform(X_train)

#Normalize Data
X_train = preprocessing.normalize(X_train)
print("Train Data Size: ",X_train.shape)
X_test = tfidf.transform(X_test)
#Normalize Data
X_test = preprocessing.normalize(X_test)
print("Test Data Size: ",X_test.shape)
```

```
Train Data Size:  (105000, 1308616)
Test Data Size:  (45000, 1308616)
Wall time: 39.1 s
```

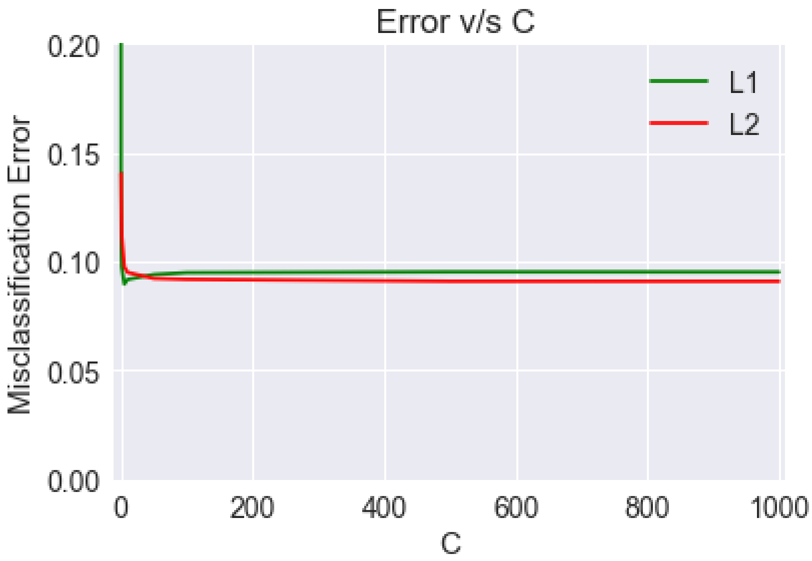
In [76]:

```
%%time
lr = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.000
1],'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gscv = GridSearchCV(lr,param_grid,cv=tscv,verbose=1)
gscv.fit(X_train,y_train)
SaveToFile(gscv,"LR-GridSearch-TF-IDF")
print("Best HyperParameter: ",gscv.best_params_)
print("Best Accuracy: %.2f%%"%(gscv.best_score_*100))
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits

[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 35.3min finished

Best HyperParameter:  {'C': 5, 'penalty': 'l1'}
Best Accuracy: 91.03%
Wall time: 35min 32s
```

In [77]:

```
gscv = OpenFromFile("LR-GridSearch-TF-IDF")
error_vs_c(gscv)
```



In [78]:

```
print(gscv.best_estimator_)
```

```
LogisticRegression(C=5, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

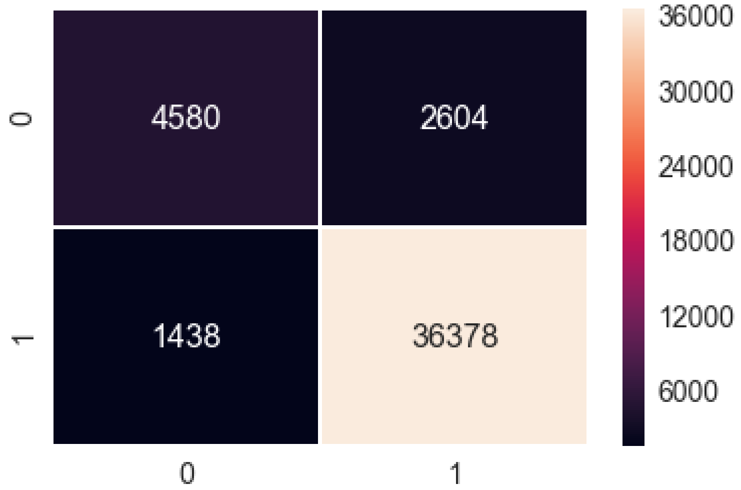
In [86]:

```
LR = LogisticRegression(C= 5, penalty= 'l1')
LR.fit(X_train,y_train)
y_pred = LR.predict(X_test)

print("Accuracy on test set: %0.2f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred, pos_label='positi
ve')*100))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred, pos_label='positive')*1
00))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred, pos_label='positive')*100
))
print("Non Zero weights:",np.count_nonzero(LR.coef_))

df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',linewidths=.5)
```

```
Accuracy on test set: 91.02%
Precision on test set: 93.320
Recall on test set: 96.197
F1-Score on test set: 94.737
Non Zero weights: 10553
```

Out[86]:

<matplotlib.axes._subplots.AxesSubplot at 0x19e3bde1c50>



Show how sparsity increases as we increase lambda (C=i/lamda) when L1 Regularizer is used

In [15]:

```
### Show how sparsity increase as if we increase the value of lamba
C_value = [1000,100,10,1,0.1,0.01,0.001,0.0001]
l1_value = ['l1','l1','l1','l1','l1','l1','l1','l1']
def sparsity_increase(i,j):
    lr = LogisticRegression(C=i,penalty=j)
    lr.fit(X_train,y_train)
    y_pred = lr.predict(X_test)
    print("C_value:",i)
    #print("C_value is: {} and l1_value is: {}".format(i,j))
    print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
    print("Non Zero weights:",np.count_nonzero(lr.coef_))
    print("-"*100)


for i,j in zip(C_value,l1_value):
    sparsity_increase(i,j)
```

```
C_value: 1000
Accuracy on test set: 90.209%
Non Zero weights: 31327
---------------------------------------------------------------------------
-------------------------
C_value: 100
Accuracy on test set: 90.124%
Non Zero weights: 23828
---------------------------------------------------------------------------
-------------------------
C_value: 10
Accuracy on test set: 90.540%
Non Zero weights: 16784
---------------------------------------------------------------------------
-------------------------
C_value: 1
Accuracy on test set: 90.442%
Non Zero weights: 1239
---------------------------------------------------------------------------
-------------------------
C_value: 0.1
Accuracy on test set: 87.358%
Non Zero weights: 131
---------------------------------------------------------------------------
-------------------------
C_value: 0.01
Accuracy on test set: 83.976%
Non Zero weights: 2
---------------------------------------------------------------------------
-------------------------
C_value: 0.001
Accuracy on test set: 83.976%
Non Zero weights: 0
---------------------------------------------------------------------------
-------------------------
C_value: 0.0001
Accuracy on test set: 83.976%
Non Zero weights: 0
---------------------------------------------------------------------------
-------------------------
```

Random Search

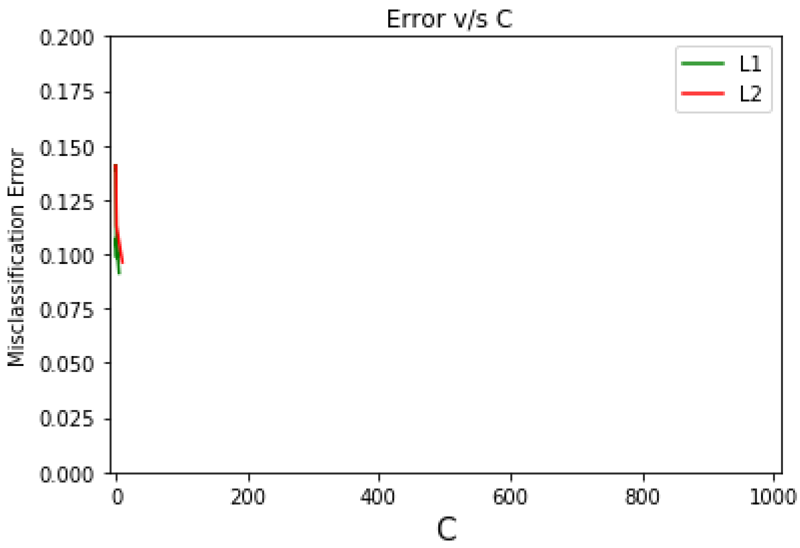
In [16]:

```
%%time
lr = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.0001]
              ,'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gscv = RandomizedSearchCV(lr,param_grid,cv=tscv,verbose=1)
gscv.fit(X_train,y_train)
SaveToFile(gscv,"LR-RandomSearch-TF_IDF")
print("Best HyperParameter: ",gscv.best_params_)
print("Best Accuracy: %.2f%%"%(gscv.best_score_*100))
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits

[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  7.3min finished

Best HyperParameter:  {'penalty': 'l1', 'C': 5}
Best Accuracy: 90.87%
Wall time: 7min 30s
```

In [19]:

```
gscv = OpenFromFile("LR-RandomSearch-TF_IDF")
error_vs_c(gscv)
```



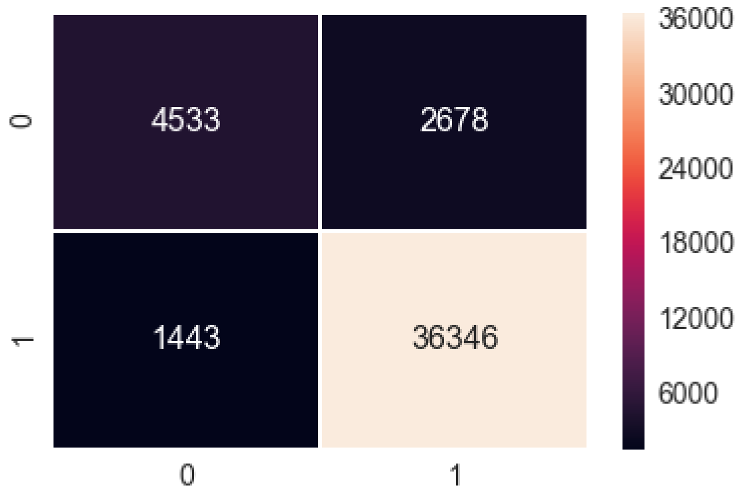
In [20]:

```
#Testing Accuracy on Test data

LR = LogisticRegression(C= 5, penalty= 'l1')
LR.fit(X_train,y_train)
y_pred = LR.predict(X_test)
print("Accuracy on test set: %0.2f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred, pos_label='positi
ve')*100))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred, pos_label='positive')*1
00))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred, pos_label='positive')*100
))
print("Non Zero weights:",np.count_nonzero(LR.coef_))
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',linewidths=.5)
```

```
Accuracy on test set: 90.84%
Precision on test set: 93.138
Recall on test set: 96.181
F1-Score on test set: 94.635
Non Zero weights: 10680
```

Out[20]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24e167d1668>
```



Perturbation Test

In [57]:

```
lr = LogisticRegression(C= 10, penalty= 'l1')
lr.fit(X_train,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
```

```
Accuracy on test set: 90.600%
Non Zero weights: 15468
```

In [61]:

```
from scipy.sparse import find
#Weights before adding random noise
weights1 = find(lr.coef_[0])[2]
#print(weights1[:50])
weightBefore=weights1[:15000]
#print(len(weightBefore))
```

In [62]:

```
X_train_t = X_train
#Random noise
epsilon = np.random.uniform(low=-0.01, high=0.01, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [63]:

```
lr = LogisticRegression(C=10, penalty= 'l1')
lr.fit(X_train_t,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
```

```
Accuracy on test set: 90.631%
Non Zero weights: 15589
```

In [64]:

```
from scipy.sparse import find
#Weights after adding random noise
weights2 = find(lr.coef_[0])[2]
#print(weights2[:50])
weightAfter=weights2[:15000]
```

In [65]:

```
weights_diff = (abs(weightAfter - weightBefore)/weightBefore) * 100
print(weights_diff[np.where(weights_diff > 30)].size)
```

```
5413
```

hence, weight diff is 5413 So There is multi collinear!!!!

In [66]:

```
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")
    print("________________________________________________________________________________________________")
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(tfidf,lr)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informative-features-for-scikit-learn-classifiers
```

```
                        Positive
        Negative
__________________________________________________________________________
______________________
        -45.4411        two star                                41.2952 hi
gh recommend
        -39.6636        great strength                          36.7070 fo
ur star
        -34.5574        diabet diabet                           32.0839 de
lici
        -34.3799        restaur know                            31.1237 go
od place
        -34.1253        oat roll                                30.2059 gr
eat
        -33.5921        get came                                29.8564 pl
easant surpris
        -33.0516        tri vacuum                              27.8280 in
iti unpleas
        -32.9782        sweet adult                             26.5075 wo
nt sorri
        -31.9411        limb perfect                            25.4264 am
az
        -31.6336        still energi                            25.2745 pe
rfect
        -31.4493        cool perfect                            24.9249 be
st
        -30.8957        want perfect                            24.2849 ol
d jordan
        -30.4316        violet flavour                          23.9483 co
rrect mistak
        -30.1363        worst                                   23.8293 co
uld wors
        -29.9191        still yet                               23.3753 ya
y
        -29.5042        fig arriv                               23.3627 wo
nt disappoint
        -29.3385        crunchi littl                           23.0562 ex
cel
        -29.1822        planter trail                           22.5292 lo
ve
        -28.5682        slight help                             22.5103 to
mato product
        -28.5352        less also                               22.3136 st
eal
        -28.2530        like chlorin                            21.6674 be
war dont
        -27.9570        cant someth                             21.4400 sa
lt jalapeno
        -27.6181        benefit dog                             20.7727 di
sappoint seem
        -27.5637        chewer year                             20.7269 le
ft aftertast
        -27.2743        deliveri superb                         20.4773 re
ceiv star
```

Logistic Regression Word2Vec(Avg)

In [67]:

```
# Train your own Word2Vec model using your own text corpus
import gensim
i=0
list_of_sent=[]
for sent in final_150000['clean_text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_of_sent.append(filtered_sentence)
```

In [68]:

```
len(list_of_sent)
```

Out[68]:

```
150000
```

In [69]:

```
#defining a word2vec model
w2v_model=gensim.models.Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
words=list(w2v_model.wv.vocab)
print(len(words))
```

```
15073
```

In [70]:

```
# 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
        try:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
        except:
            pass
    sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
150000
50
```

In [71]:

```
np.argwhere(np.isnan(sent_vectors))#checking for Nan fields
```

Out[71]:

```
array([], shape=(0, 2), dtype=int64)
```

In [73]:

```
%%time
#from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn import preprocessing
from sklearn.model_selection import train_test_split

X_train_AvgWord2Vec, X_test, y_train, y_test = train_test_split(sent_vectors,final_1500
00['Score'].values ,
                                                            test_size=0.30,shuffle=Fals
e)

X_train_AvgWord2Vec_final = preprocessing.normalize(X_train_AvgWord2Vec)
print("Train Data Size: ",X_train_AvgWord2Vec_final.shape)

X_test = preprocessing.normalize(X_test)
print("Test Data Size: ",X_test.shape)
```

```
Train Data Size:  (105000, 50)
Test Data Size:  (45000, 50)
Wall time: 406 ms
```

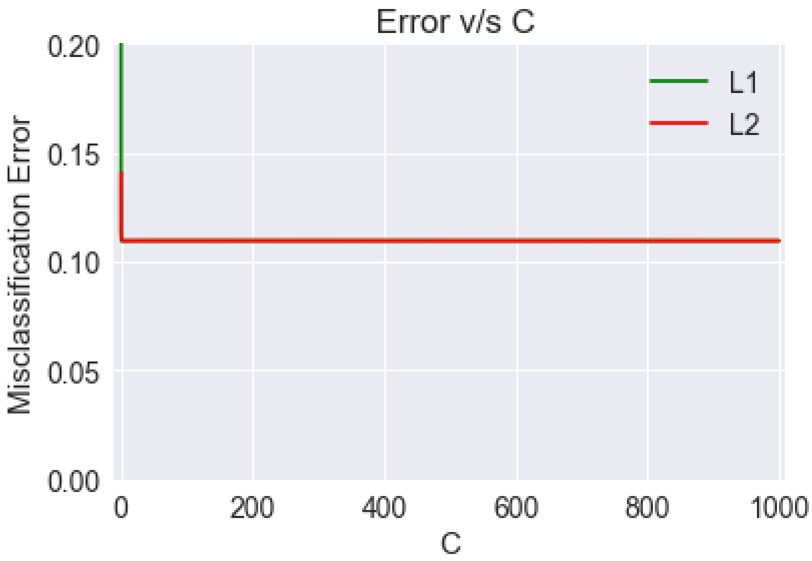
In [74]:

```
%%time
lr = LogisticRegression()

#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.000
1],'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gscv = GridSearchCV(lr,param_grid,cv=tscv,verbose=1)
gscv.fit(X_train_AvgWord2Vec_final,y_train)
SaveToFile(gscv,"LR-AvgWord2Vec")

print("Best HyperParameter: ",gscv.best_params_)
print("Best Accuracy: %.2f%%"%(gscv.best_score_*100))
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits

[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 10.9min finished

Best HyperParameter:  {'C': 1, 'penalty': 'l1'}
Best Accuracy: 89.06%
Wall time: 11min 3s
```

In [75]:

```
gscv = OpenFromFile("LR-AvgWord2Vec")
error_vs_c(gscv)
```



In [76]:

```
print(gscv.best_estimator_)
```

```
LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

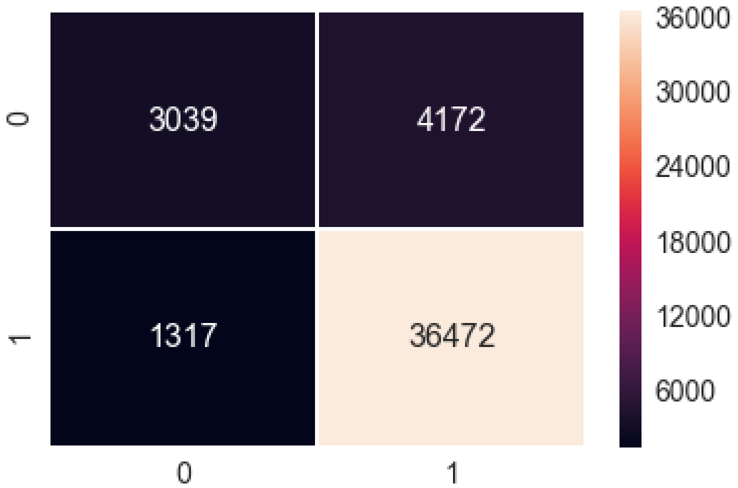
In [80]:

```
#Testing Accuracy on Test data with best hyper parametrs
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression(C= 1, penalty= 'l1')
lr.fit(X_train_AvgWord2Vec_final,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.2f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred, pos_label='positi
ve')*100))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred, pos_label='positive')*1
00))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred, pos_label='positive')*100
))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g', linewidths=.5)
```

```
Accuracy on test set: 87.80%
Precision on test set: 89.735
Recall on test set: 96.515
F1-Score on test set: 93.002
Non Zero weights: 50
```

Out[80]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24e1a9bcdd8>
```



Random Search AvgWord2Vec

In [77]:

```
%%time
lr = LogisticRegression()

param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.000
1],'penalty':['l1','l2']}

tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gscv = RandomizedSearchCV(lr,param_grid,cv=tscv,verbose=1)
gscv.fit(X_train_AvgWord2Vec_final,y_train)

SaveToFile(gscv,"LR-RandomSearch-AvgWord2Vec")

print("Best HyperParameter: ",gscv.best_params_)
print("Best Accuracy: %.2f%%"%(gscv.best_score_*100))
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits

[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  4.7min finished

Best HyperParameter:  {'penalty': 'l1', 'C': 1}
Best Accuracy: 89.06%
Wall time: 4min 55s
```

In [78]:

```
print(gscv.best_estimator_)
```

```
LogisticRegression(C=1, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

In [81]:

```
gscv = OpenFromFile("LR-RandomSearch-AvgWord2Vec")
error_vs_c(gscv)
```

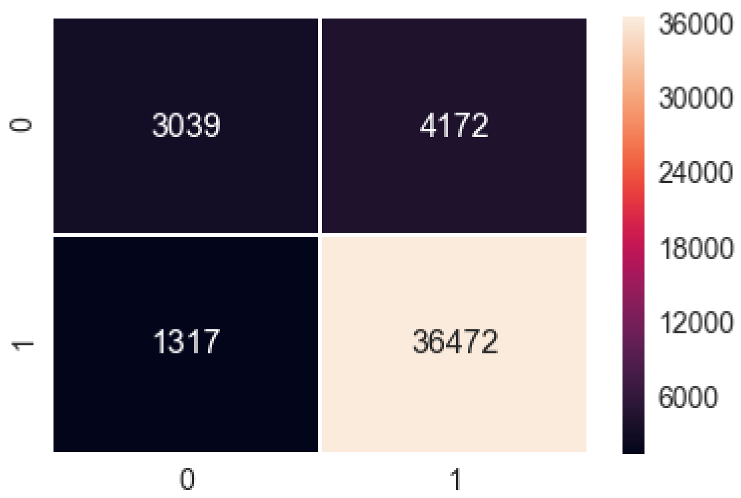
In [82]:

```
#Testing Accuracy on Test data with best hyper parametrs
from sklearn.linear_model import LogisticRegression

lr = LogisticRegression(C= 1, penalty= 'l1')
lr.fit(X_train_AvgWord2Vec_final,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.2f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred, pos_label='positi
ve')*100))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred, pos_label='positive')*1
00))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred, pos_label='positive')*100
))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',linewidths=.5)
```

```
Accuracy on test set: 87.80%
Precision on test set: 89.735
Recall on test set: 96.515
F1-Score on test set: 93.002
Non Zero weights: 50
```

Out[82]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x24e1aaa4208>
```



Perturbation Test

In [84]:

```
lr = LogisticRegression(C= 5, penalty= 'l1')
lr.fit(X_train_AvgWord2Vec_final,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
```

```
Accuracy on test set: 87.807%
Non Zero weights: 50
```

In [85]:

```
from scipy.sparse import find
#Weights before adding random noise
weights1 = find(lr.coef_[0])[2]
#print(weights1[:50])
print(len(weights2))
```

```
15589
```

In [87]:

```
X_train_t = X_train_AvgWord2Vec_final
#Random noise
epsilon = np.random.uniform(low=-0.01, high=0.01, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [88]:

```
lr = LogisticRegression(C= 5, penalty= 'l1')
lr.fit(X_train_t,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
```

```
Accuracy on test set: 87.793%
Non Zero weights: 50
```

In [89]:

```
weights2 = find(lr.coef_[0])[2]
print(weights2)
```

```
[-4.34900241  1.76867767  0.33333246  3.56636108  0.98012128  0.16709607
 -4.04869947  3.97330242 -4.61906939  0.40257605 -1.04850858 -0.90816507
  0.38303954  0.5806754   1.38053741 -2.80995933  0.3570581   1.75204251
  1.92276095  2.03041835  2.11604545 -0.68989182 -1.9768246  -0.15844519
 -0.64091827 -0.93381869 -1.40893477 -2.99523926 -4.38236244 -1.88402074
  1.81451336 -3.87562687  2.22155458  1.22219157  0.58076664  0.35743328
 -0.54735218 -0.34273084 -1.86643012  1.26418634  0.67847357 -2.07620699
  4.64500318 -0.39806912 -0.46781577 -0.11230673  4.39662317  0.11197016
  0.88200796 -2.39472743]
```

In [90]:

```
weights_diff = (abs(weights2 - weights1)/weights1) * 100
print(weights_diff[np.where(weights_diff > 30)].size)
```

```
1
```

We can see weightdiff is 1 , So its means theres is no multi Collinearity

In [91]:

```
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")
    print("________________________________________________________________________________________________")
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(tfidf,lr)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informative-features-for-scikit-learn-classifiers
```

```
                        Positive
        Negative
__________________________________________________________________________

______________________
        -4.6191 aaaaaahhhhhyaaaaaa                                  4.6450  aa
rrgghhhh
        -4.3824 aaf                                         4.3966  ab

        -4.3490 aaa                                         3.9733  aaaaaaarrr
rrggghhh back
        -4.0487 aaaaaaarrrrrggghhh                                  3.5664  aa
a job
        -3.8756 aafco approv                                2.2216  aafco dog

        -2.9952 aadp                                        2.1160  aaahhh sal
e
        -2.8100 aaaah favorit                               2.0304  aaahhh

        -2.3947 ab one                                      1.9228  aaah tast

        -2.0762 aah rest                                    1.8145  aafco

        -1.9768 aaahhhhhh drink                             1.7687  aaa aaa

        -1.8840 aaf hair                                    1.7520  aaah miss

        -1.8664 aah coffe                                   1.3805  aaaah

        -1.4089 aachen munich                               1.2642  aah handso
m
        -1.0485 aaaaah                                      1.2222  aafco larg

        -0.9338 aachen                                      0.9801  aaa spelt

        -0.9082 aaaaah satisfi                              0.8820  ab fine

        -0.6899 aaahhhhhh                                   0.6785  aah order

        -0.6409 aabsolut love                               0.5808  aafco requ
ir
        -0.5474 aafter luck                                 0.5807  aaaaahhhhh
hhhhhhhhhhh angel
        -0.4678 aarthur                                     0.4026  aaaaaahhhh
hyaaaaaa fire
        -0.3981 aarrgghhhh yorkiex                                  0.3830  aa
aaahhhhhhhhhhhhhhhh
        -0.3427 aah                                         0.3574  aafter

        -0.1584 aabsolut                                    0.3571  aaah

        -0.1123 aarthur whole                               0.3333  aaa hockey

        0.1120  ab diet                                     0.1671  aaaaaaaaag
ghh
```

Logistic Regression TF-IDF Word2Vec

GridSearch

In [92]:

```
# Train your own Word2Vec model using your own text corpus
import gensim
i=0
list_of_sent=[]
#final_20000 = final_50000.head(20000)
for sent in final_150000['clean_text'].values:
    filtered_sentence=[]
    sent=cleanhtml(sent)
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if(cleaned_words.isalpha()):
                filtered_sentence.append(cleaned_words.lower())
            else:
                continue
    list_of_sent.append(filtered_sentence)
```

In [93]:

```
%%time
# TF-IDF weighted Word2Vec
tfidf_feat = tfidf.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this lis
t
row=0;
for sent in list_of_sent: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        try:
            vec = w2v_model.wv[word]
            # obtain the tf_idfidf of a word in a sentence/review
            tf_idf = X_train_tfidf[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sent_vec /= weight_sum
    tfidf_sent_vectors.append(sent_vec)
    row += 1
print(len(tfidf_sent_vectors))
print(len(tfidf_sent_vectors[0]))
```

```
150000
50
Wall time: 34.9 s
```

In [94]:

```
np.argwhere(np.isnan(tfidf_sent_vectors))#checking for NaN values
```

Out[94]:

```
array([[     0,      0],
       [     0,      1],
       [     0,      2],
       ...,
       [149999,     47],
       [149999,     48],
       [149999,     49]], dtype=int64)
```

In [95]:

```
#Not shuffling the data as we want it on time basis
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(tfidf_sent_vectors,final_150000['Sc
ore'].values,
                                                    test_size=0.3,shuffle=False)
```

In [96]:

```
#resolving NaN issue
X_train=np.isnan(X_train)#for solving NaN issue
np.where(np.isnan(X_train))
np.nan_to_num(X_train)
X_test=np.isnan(X_test)
np.where(np.isnan(X_test))
np.nan_to_num(X_test)
```

Out[96]:

```
array([[ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       ...,
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True],
       [ True,  True,  True, ...,  True,  True,  True]])
```

In [97]:

```
print(np.argwhere(np.isnan(X_train)))#checking for NaN values
print(np.argwhere(np.isnan(X_test)))#checking for NaN values
print("We have Resolved the Nan Issue")
```

```
[]
[]
We have Resolved the Nan Issue
```

In [98]:

```
%%time
lr = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.000
1],'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gscv = GridSearchCV(lr,param_grid,cv=tscv,verbose=1)
gscv.fit(X_train,y_train)
SaveToFile(gscv,"LR GridSearch TF_IDF-WORD2VEC")
print("Best HyperParameter: ",gscv.best_params_)
print("Best Accuracy: %.2f%%"%(gscv.best_score_*100))
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits

[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed:  3.6min finished

Best HyperParameter:  {'C': 1000, 'penalty': 'l1'}
Best Accuracy: 85.92%
Wall time: 3min 39s
```

In [99]:

```
print(gscv.best_estimator_)
```

```
LogisticRegression(C=1000, class_weight=None, dual=False, fit_intercept=Tr
ue,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l1', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

In [100]:

```
gscv = OpenFromFile("LR GridSearch TF_IDF-WORD2VEC")
error_vs_c(gscv)
```

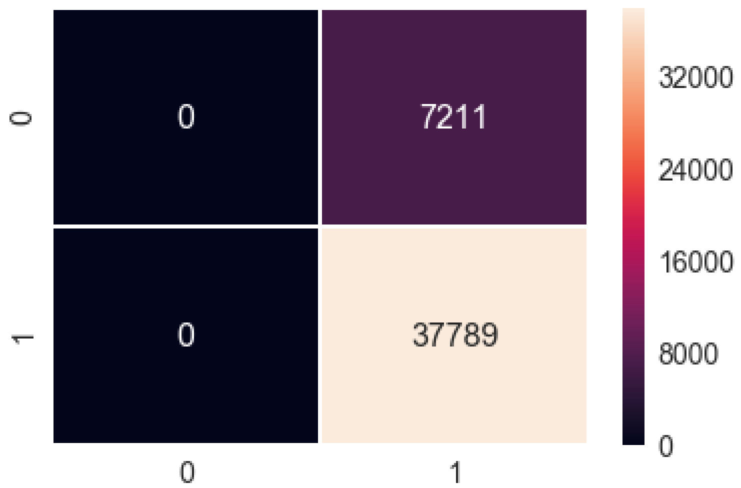
In [104]:

```
lr = LogisticRegression(C= 1000, penalty= 'l1')
lr.fit(X_train,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.2f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred, pos_label='positi
ve')*100))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred, pos_label='positive')*1
00))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred, pos_label='positive')*100
))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',linewidths=.5)
```

```
Accuracy on test set: 83.98%
Precision on test set: 83.976
Recall on test set: 100.000
F1-Score on test set: 91.290
Non Zero weights: 4
```

Out[104]:

<matplotlib.axes._subplots.AxesSubplot at 0x24e8ee88198>



RandomizedSearchCV

In [101]:

```
%%time
lr = LogisticRegression()
#params we need to try on classifier
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005,0.000
1],'penalty':['l1','l2']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gscv = RandomizedSearchCV(lr,param_grid,cv=tscv,verbose=1)
gscv.fit(X_train,y_train)
SaveToFile(gscv,"LR RandomSearch TF_IDF-WORD2VEC")
print("Best HyperParameter: ",gscv.best_params_)
print("Best Accuracy: %.2f%%"%(gscv.best_score_*100))
```

```
Fitting 10 folds for each of 10 candidates, totalling 100 fits

[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  1.3min finished


Best HyperParameter:  {'penalty': 'l2', 'C': 10}
Best Accuracy: 85.92%
Wall time: 1min 19s
```

In [102]:

```
print(gscv.best_estimator_)
```

```
LogisticRegression(C=10, class_weight=None, dual=False, fit_intercept=Tru
e,
          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)
```

In [103]:

```
gscv = OpenFromFile("LR RandomSearch TF_IDF-WORD2VEC")
error_vs_c(gscv)
```

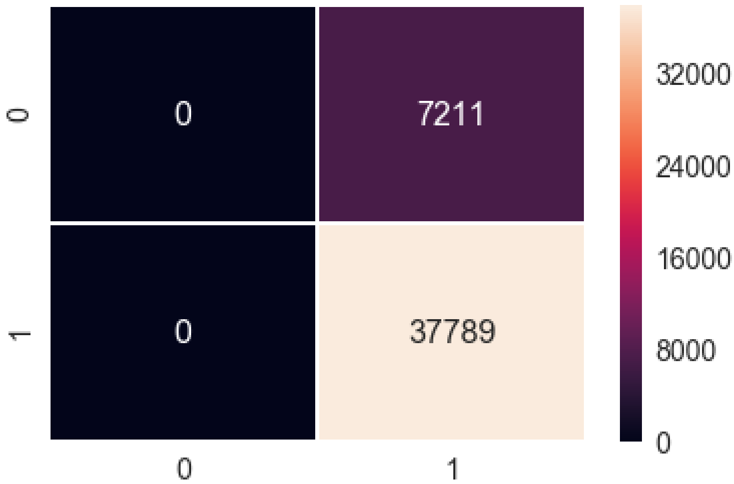
In [105]:

```
lr = LogisticRegression(C= 10, penalty= 'l2')
lr.fit(X_train,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.2f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred, pos_label='positi
ve')*100))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred, pos_label='positive')*1
00))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred, pos_label='positive')*100
))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)#for label size
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g',linewidths=.5)
```

```
Accuracy on test set: 83.98%
Precision on test set: 83.976
Recall on test set: 100.000
F1-Score on test set: 91.290
Non Zero weights: 50
```

Out[105]:

<matplotlib.axes._subplots.AxesSubplot at 0x24e8d53e748>



Perturbation Test

In [119]:

```
lr = LogisticRegression(C= 100, penalty= 'l1')
lr.fit(X_train,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
```

```
Accuracy on test set: 83.976%
Non Zero weights: 5
```

In [120]:

```
weights1 = find(lr.coef_[0])[2]
print(weights1[:50])
```

```
[3.41568429e-01 4.44866533e-02 7.25809153e-04 1.16931923e-12
 1.45051390e+00]
```

In [121]:

```
X_train_t = X_train
#Random noise
epsilon = np.random.uniform(low=-0.01, high=0.01, size=(find(X_train_t)[0].size,))
#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

#Introducing random noise to non-zero datapoints
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [122]:

```
lr = LogisticRegression(C= 100, penalty= 'l1')
lr.fit(X_train_t,y_train)
y_pred = lr.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(lr.coef_))
```

```
Accuracy on test set: 83.976%
Non Zero weights: 5
```

In [123]:

```
weights2 = find(lr.coef_[0])[2]
print(weights2[:50])
```

```
[3.41568429e-01 1.45051390e+00 7.25809153e-04 1.16931923e-12
 4.44866533e-02]
```

In [124]:

```
weights_diff = (abs(weights2 - weights1)/weights1) * 100
```

In [125]:

```
 print(weights_diff[np.where(weights_diff > 30)].size)
```

```
2
```

We can see weightdiff is 2 , So its means theres is no multi Collinearity

In [126]:

```
def show_most_informative_features(vectorizer, clf, n=25):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\t\t\tPositive\t\t\t\t\t\tNegative")
    print("_____________________________________________________________________________
____________________")
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(tfidf,lr)
#Code Reference:https://stackoverflow.com/questions/11116697/how-to-get-most-informativ
e-features-for-scikit-learn-classifiers
```

```
                Positive
        Negative

________________________________________________________________________

______________________
        0.0000  aaa                                     1.4505  aaahhh sal
e
        0.0000  aaa aaa                                 0.3416  aaaaaahhhh
hyaaaaaa fire
        0.0000  aaa hockey                              0.0445  aarthur wh
ole
        0.0000  aaa job                                 0.0007  aafco

        0.0000  aaa spelt                               0.0000  aah

        0.0000  aaaaaaaaagghh                           0.0000  ab one

        0.0000  aaaaaaarrrrrggghhh                              0.0000  ab
fine
        0.0000  aaaaaaarrrrrggghhh back                         0.0000  ab
diet
        0.0000  aaaaaahhhhhyaaaaaa                              0.0000  ab

        0.0000  aaaaah                                  0.0000  aarthur

        0.0000  aaaaah satisfi                          0.0000  aarrgghhhh
yorkiex
        0.0000  aaaaahhhhhhhhhhhhhhhh                           0.0000  aa
rrgghhhh
        0.0000  aaaaahhhhhhhhhhhhhhhh angel                             0.
0000    aah rest
        0.0000  aaaah                                   0.0000  aah order

        0.0000  aaaah favorit                           0.0000  aah handso
m
        0.0000  aaah                                    0.0000  aah coffe

        0.0000  aaah miss                               0.0000  aafter luc
k
        0.0000  aaah tast                               0.0000  aafter

        0.0000  aaahhh                                  0.0000  aafco requ
ir
        0.0000  aaahhhhhh                               0.0000  aafco larg

        0.0000  aaahhhhhh drink                         0.0000  aafco dog

        0.0000  aabsolut                                0.0000  aafco appr
ov
        0.0000  aabsolut love                           0.0000  aaf hair

        0.0000  aachen                                  0.0000  aaf

        0.0000  aachen munich                           0.0000  aadp
```

Analysis of Logistic Regression Model on 150k data points

Feature	**Algoritms**	**Accuracy**	**Precision**	**Recall**	**F1-Scores**	**Best Value for C**	**Penalty**
BOW	GridSearchCV	90.31	92.183	96.671	94.376	C=10	penalty='l2'
BOW	RandomSearchCV	90.30	92.173	96.663	94.365	C=10	penalty='l2'
TF-IDF	GridSearchCV	91.02	93.320	96.197	94.737	C=5	penalty='l1'
TF-IDF	RandomSearchCV	90.84	93.138	96.181	94.635	C=5	penalty='l1'
Word2Vec	GridSearchCV	87.80	89.735	96.515	93.002	C=1	penalty='l1'
Word2Vec	RandomSearchCV	87.80	89.735	96.515	93.002	C=1	penalty='l1'
TFIDF W2V	GridSearchCV	83.98	83.976	100	91.290	C=1000	penalty='l1'
TFIDF W2V	RandomSearchCV	83.98	83.976	100	91.290	C=10	penalty='l2'

Observation

```
- We did Bow,tf-idf,AvgWord2vec,and tfidf-word2vec on data points.
- TF-IDF using GridSearch has highest accuracy among all of them.
- We see that when C decreases (or lambda increases) the sparsity increases dras
tically,
  that mean L1 regularizer increase the sparsity in Logistic Regression.
- Multicolinearity is exits in this model.
```