Amazon Fine Food Reviews Analysis

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

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

1. Id
2. ProductId - unique identifier for the product
3. UserId - unqiue identifier for the user
4. ProfileName
5. HelpfulnessNumerator - number of users who found the review helpful
6. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
7. Score - rating between 1 and 5
8. Time - timestamp for the review
9. Summary - brief summary of the review
10. Text - text of the review

The dataset is available in two forms

1. .csv file
2. SQLite Database

In order to load the data, We have used the SQLITE dataset as it easier to query the data and visualise the data efficiently.

Loading the sqlite database and required libraries

In [3]:

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6
qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%
b&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.
2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fww
ogleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
··········
Mounted at /content/drive
```

In [4]:

```
!ls "/content/drive/My Drive"
```

```
database.sqlite
```

In [ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
import os
from sklearn.model_selection import train_test_split
from sklearn.grid_search import GridSearchCV
from sklearn.datasets import *
from sklearn.linear_model import LogisticRegression
```

In [6]:

```
import sqlite3
```

```
import sqlite3
con = sqlite3.connect('/content/drive/My Drive/database.sqlite')

filtered_data = pd.read_sql_query("""select * from Reviews WHERE Score != 3""",con)

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

Out[6]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	130386240
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	134697600
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	121901760
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	130792320
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	135077760

Partitioning the reviews into positive and negative by the use of score attribute

In [0]:

```
def partition(x):
    if x < 3:
        return 0
    else:
        return 1

actualScore = filtered_data['Score']
positiveNegative = actualScore.map(partition)
filtered_data['Score'] = positiveNegative
```

Data Cleaning : Deduplication

There may be same user who has multiple duplicate reviews with the same values of HelpfulnessNumerator, HelpfulnessDenominator, Score, Time, Summary and Text. So, in order to reduce redundancy it was decided to eliminate the rows having same parameters.¶

In [8]:

```
import datetime

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

sortedData = filtered_data.sort_values('ProductId',axis=0,kind="quicksort", ascending=True)
final = sortedData.drop_duplicates(subset={"UserId","ProfileName","Time","Text"},keep="first",inpla
ce=False)

final = final[final.HelpfulnessNumerator <= final.HelpfulnessDenominator]

#As data is huge, due to computation limitation we will randomly select data. we will try to pick
data in a way so that it doesn't make data imbalance problem
finalp = final[final.Score == 1]
finalp = finalp.sample(frac=0.3,random_state=1)

finaln = final[final.Score == 0]
finaln = finaln.sample(frac=0.8,random_state=1)

final = pd.concat([finalp,finaln],axis=0)

#sorting data by timestamp so that it can be devided in train and test dataset for time based slic
ing.
final = final.sort_values('Time',axis=0,kind="quicksort", ascending=True).reset_index(drop=True)


print(final.shape)
```

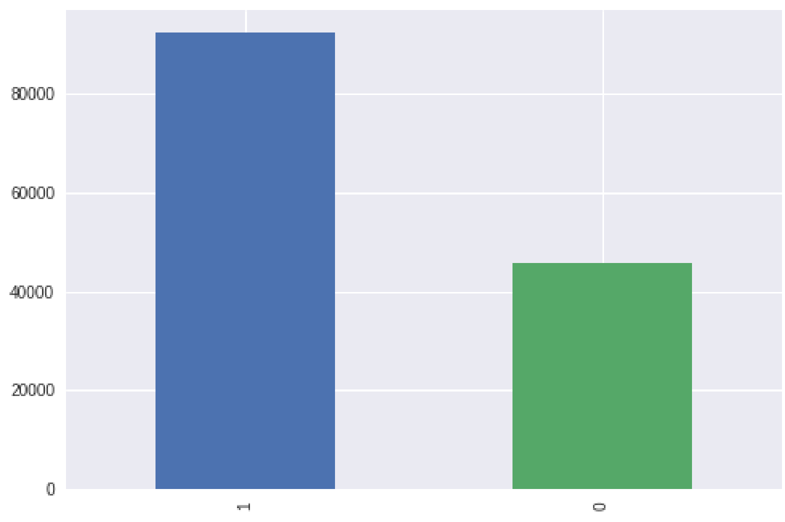
```
(137806, 10)
```

In [9]:

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

Out[9]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f38557c7a90>
```



We have taken unbalanced data of unequal number of positive and negative reviews.

In [0]:

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

Text Preprocessing: Stemming, stop-word removal and Lemmatization

In [11]:

```
import re
import string
```

```
import nltk
nltk.download("stopwords")
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

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

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

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_string=[]
all_positive_words=[] # store words from +ve reviews here
all_negative_words=[] # store words from -ve reviews here.
s=''
for sent in final['Text'].values:
    filtered_sentence=[]
    #print(sent);
    sent=cleanhtml(sent) # remove HTMl tags
    for w in sent.split():
        for cleaned_words in cleanpunc(w).split():
            if((cleaned_words.isalpha()) & (len(cleaned_words)>2)):
                if(cleaned_words.lower() not in stop):
                    s=(sno.stem(cleaned_words.lower())).encode('utf8')
                    filtered_sentence.append(s)
                    if (final['Score'].values)[i] == 'positive':
                        all_positive_words.append(s) #list of all words used to describe positive reviews
                    if(final['Score'].values)[i] == 'negative':
                        all_negative_words.append(s) #list of all words used to describe negative reviews reviews
                else:
                    continue
            else:
                continue
    str1 = b" ".join(filtered_sentence) #final string of cleaned words
    final_string.append(str1)
    i+=1
```

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

Feature generation techniques to convert Review texts to numeric vector.

Bag of Words (BoW) (uni-gram)

Splitting Data into Train and Test based on the ascending timestamp of the reviews.

In [0]:

```
import math
from sklearn import datasets
from  sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split

X = final_string
y = final['Score']
```

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

In [0]:

```
from sklearn.feature_extraction.text import CountVectorizer

count_vect = CountVectorizer()
final_bow_count1 = count_vect.fit_transform(X_train)
final_bow_count2 = count_vect.fit_transform(X_test)
```

In [0]:

```
from sklearn.preprocessing import StandardScaler

X_train = StandardScaler(with_mean=False).fit_transform(final_bow_count1)
X_test = StandardScaler(with_mean=False).transform(final_bow_count2)
```

In [15]:

```
from sklearn.model_selection import TimeSeriesSplit
tscv = TimeSeriesSplit(n_splits=10)
for train, cv in tscv.split(X_train):

    print(X_train[train].shape, X_train[cv].shape)
```

```
(8775, 44784) (8769, 44784)
(17544, 44784) (8769, 44784)
(26313, 44784) (8769, 44784)
(35082, 44784) (8769, 44784)
(43851, 44784) (8769, 44784)
(52620, 44784) (8769, 44784)
(61389, 44784) (8769, 44784)
(70158, 44784) (8769, 44784)
(78927, 44784) (8769, 44784)
(87696, 44784) (8769, 44784)
```

Finding the best "C" value and best regularizer [L1 or L2] using Grid Search CV

In [16]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
#parameters we need to find 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)
gsv = GridSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)

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

```
CPU times: user 4 µs, sys: 0 ns, total: 4 µs
Wall time: 9.78 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 14.4min finished
```

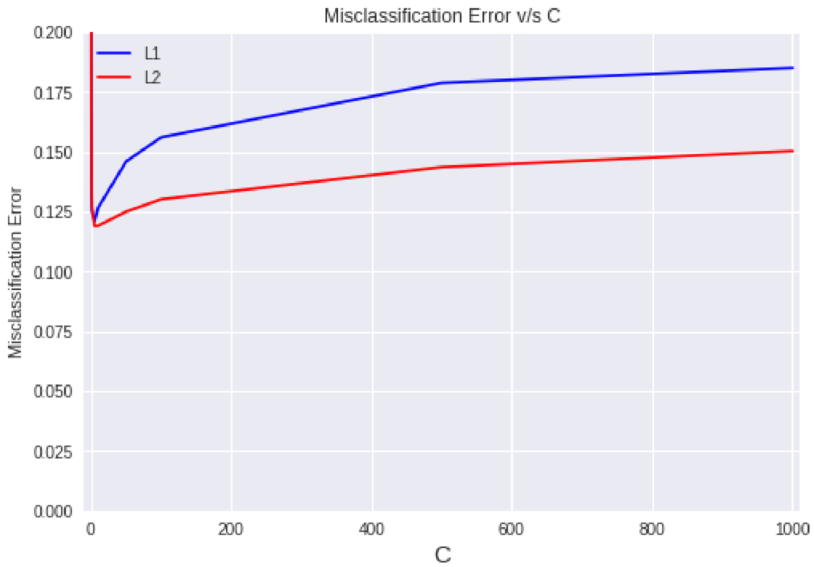
```
Best HyperParameter:  {'C': 5, 'penalty': 'l2'}
Best Accuracy: 88.10%
```

Function to plot Misclassification error against C

In [17]:

```
def plot_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('Misclassification Error v/s C')
    plt.plot(x1,y1,'b',label="L1")
    plt.plot(x2,y2,'r',label="L2")
    plt.legend()
    plt.show()

plot_error_vs_c(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



In [18]:

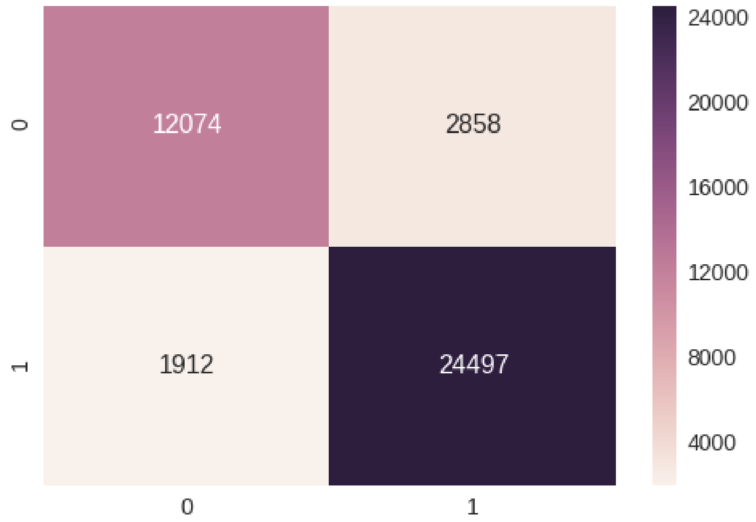
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
from sklearn.metrics import f1_score
from sklearn.metrics import recall_score

import seaborn as sns
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
```

```
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 88.462%
Precision on test set: 0.896
Recall on test set: 0.928
F1-Score on test set: 0.911
Non Zero weights: 37473
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f383e0de5c0>
```



Sparsity increases as we increase lambda or decrease C with L1 Regularizer.

In [19]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1000, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 83.561%
F1-Score on test set: 0.873
Non Zero weights: 22245
```

In [20]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 100, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 85.535%
F1-Score on test set: 0.888
```

```
Non Zero weights: 16773
```

In [21]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 87.983%
F1-Score on test set: 0.907
Non Zero weights: 7777
```

In [22]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.179%
F1-Score on test set: 0.909
Non Zero weights: 1634
```

In [23]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.1, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 85.610%
F1-Score on test set: 0.891
Non Zero weights: 357
```

In [24]:

```python
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.01, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 74.906%
F1-Score on test set: 0.828
Non Zero weights: 45
```

From the above results, we can observe that, the sparsity increases from 22245 non-zero weights(C=1000) to only 45 non-zero weights(C=0.01) with L1 Regularization.

Randomized Search CV to find optimal 'C' value and regularization parameters

In [25]:

In [25]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = 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']}
tscv = TimeSeriesSplit(n_splits=10)
gsv = RandomizedSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)

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

```
CPU times: user 4 µs, sys: 0 ns, total: 4 µs
Wall time: 10.3 µs
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed: 10.2min finished
```

```
Best HyperParameter:  {'penalty': 'l1', 'C': 1}
Best Accuracy: 87.49%
```

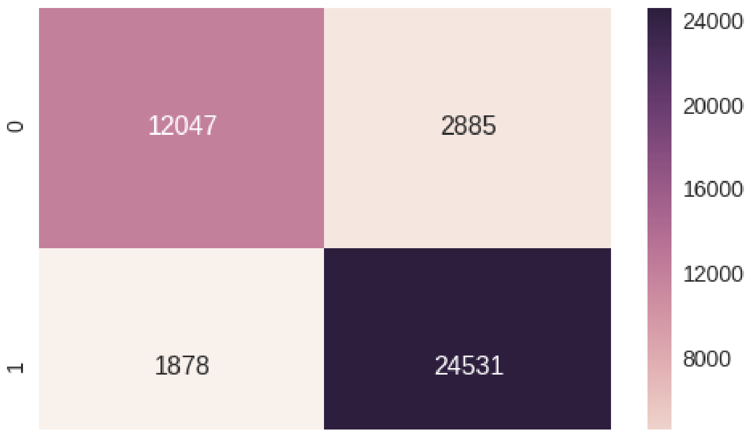
In [37]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
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')
```

```
Accuracy on test set: 88.479%
Precision on test set: 0.895
Recall on test set: 0.929
F1-Score on test set: 0.912
Non Zero weights: 37473
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f383c05e160>
```

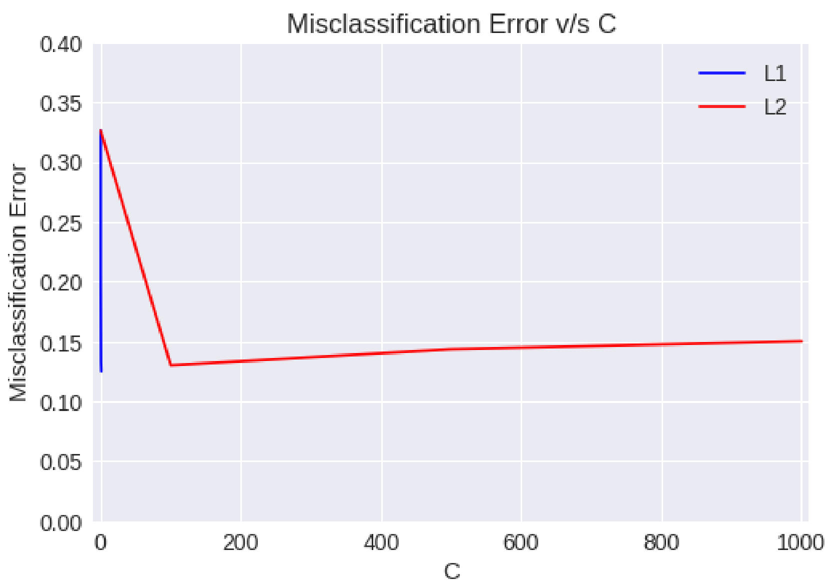


Function to plot Misclassification error against C

In [38]:

```
def plot_error_vs_c_r(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'])

    ind1 = np.argsort(x1)
    x1=np.array(x1)
    y1=np.array(y1)
    ind2 = np.argsort(x2)
    x2=np.array(x2)
    y2=np.array(y2)
    plt.xlim(-10,1010)
    plt.ylim(0,0.4)
    plt.xlabel("C",fontsize=15)
    plt.ylabel("Misclassification Error")
    plt.title('Misclassification Error v/s C')
    plt.plot(x1[ind1],y1[ind1],'b',label="L1")
    plt.plot(x2[ind2],y2[ind2],'r',label="L2")
    plt.legend()
    plt.show()

plot_error_vs_c_r(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



Perturbation Test

In [28]:

```
from sklearn.linear_model import LogisticRegression

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

```
Accuracy on test set: 88.462%
Non Zero weights: 37473
```

In [29]:

```
from scipy.sparse import find
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[ 6.18756387e-01  1.85705070e-01  1.32426472e-03  2.44996343e-02
  2.19201442e-03  4.17040376e-03 -9.29594140e-02 -3.16261522e-02
  4.17040376e-03  2.98182200e-01  5.38047331e-02  1.06477001e-01
  1.11423945e-01  5.61551667e-02  7.14083267e-04 -9.19048054e-01
 -1.44393910e-02  9.04678786e-02  6.66504302e-01  1.60291777e-02
 -4.27669024e-02  6.58026512e-01 -4.93371207e-01 -6.94667416e-01
  1.82063476e-02 -3.11226436e-01 -8.93647046e-01 -1.76883910e+00
  5.50919893e-02  7.41290549e-01  1.18941298e-01  1.69336398e-02
  4.56255350e-01 -3.65935920e-02 -3.81452653e-01  6.65831215e-01
  6.79501138e-01 -3.36451223e-01 -9.65760203e-01  5.73506171e-01
  1.44319397e+00 -5.45333647e-01 -3.17713929e+00  1.79860621e-01
 -1.55575073e-01  3.23146560e-04  2.98435890e-02  3.65054021e-02
 -4.05435107e-02 -4.17531443e-02]
```

In [0]:

```
X_train_t = X_train
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size,))
a,b,c = find(X_train_t)

X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [31]:

```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

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

```
Accuracy on test set: 88.462%
Non Zero weights: 37473
```

In [32]:

```
from scipy.sparse import find
weights2 = find(clf.coef_[0])[2]
print(weights2[:50])
```

```
[ 6.18384367e-01  1.85699425e-01  1.32354392e-03  2.45001179e-02
  2.19133399e-03  4.16829954e-03 -9.29766510e-02 -3.16051491e-02
  4.16873058e-03  2.98176807e-01  5.38613477e-02  1.06519685e-01
  1.11380902e-01  5.61559533e-02  7.13261525e-04 -9.19544370e-01
 -1.44285238e-02  9.05129497e-02  6.66587710e-01  1.60567962e-02
 -4.27369828e-02  6.58570306e-01 -4.93864332e-01 -6.95553148e-01
  1.82027619e-02 -3.11046331e-01 -8.93806985e-01 -1.76913175e+00
  5.51225944e-02  7.41374686e-01  1.18919536e-01  1.68892456e-02
  4.56166885e-01 -3.65524851e-02 -3.81493725e-01  6.66120391e-01
  6.79001693e-01 -3.36393293e-01 -9.64686853e-01  5.73520395e-01
  1.44258223e+00 -5.45217667e-01 -3.17779089e+00  1.79694730e-01
 -1.55740987e-01  3.23070245e-04  2.98418197e-02  3.62923799e-02
```

```
 -4.04371166e-02 -4.17242405e-02]
```

In [33]:

```
print(weights2.size)
```

```
37473
```

In [0]:

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

In [35]:

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

```
8
```

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

Top 25 Negative and Positive Features

In [39]:

```
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\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(count_vect,clf)
```

```
   Positive       Negative
_______________________________________________________________________________________________
 -14.9845 worst             9.4047 delici
 -11.4501 aw                9.0635 perfect
 -10.8000 terribl           8.7681 hook
 -10.0196 disgust           8.5961 addict
 -9.5982 threw             8.5661 excel
 -9.2981 disappoint        8.4470 skeptic
 -9.1852 tasteless         8.2187 amaz
 -9.0768 horribl           8.1304 yummi
 -8.5517 unpleas           8.0051 worri
 -8.4986 bland             7.6761 yum
 -8.4140 gross             7.5951 beat
 -7.9951 wors              7.5800 best
 -7.9178 yuck              7.4523 awesom
 -7.7482 unfortun          7.2594 fantast
 -7.5748 return            7.0864 great
 -7.5682 flavorless        7.0315 smooth
 -7.3902 undrink           6.6524 uniqu
 -7.2024 ugh               6.5815 complaint
 -7.1157 ruin              6.4480 terrif
 -7.0992 mediocr           6.2924 hesit
 -6.9902 disapoint         6.2344 heaven
 -6.9845 refund            6.1786 glad
 -6.8589 weak              6.1515 satisfi
 -6.8585 unaccept          6.0747 refresh
 -6.8421 sorri             5.9812 beauti
```

Observation:

1. Features are multi-collinear i.e. they are co-related, by pertubation test.
2. Unigram Featurization performs with accuracy of 88.4% and F1-Score of 0.912
3. Sparsity increases as we increase lambda or decrease C when L1 Regularizer is used

Bi-Gram

In [0]:

```
import math
from sklearn import datasets
from  sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split

X = final_string
y = final['Score']

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

In [0]:

```
from sklearn.feature_extraction.text import CountVectorizer

count_vect = CountVectorizer(ngram_range = (1,2))
final_bow_count1 = count_vect.fit_transform(X_train)
final_bow_count2 = count_vect.fit_transform(X_test)
```

In [0]:

```
from sklearn.preprocessing import StandardScaler

X_train = StandardScaler(with_mean=False).fit_transform(final_bow_count1)
X_test = StandardScaler(with_mean=False).transform(final_bow_count2)
```

Finding the best "C" value and best regularizer [L1 or L2] using Grid Search CV

In [49]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
#parameters 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
gsv = GridSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)

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

```
CPU times: user 6 µs, sys: 0 ns, total: 6 µs
Wall time: 13.4 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 31.4min finished
```

```
Best HyperParameter:  {'C': 50, 'penalty': 'l2'}
Best Accuracy: 89.34%
```

Function to plot Misclassification error against C

In [50]:

```
plot_error_vs_c(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```

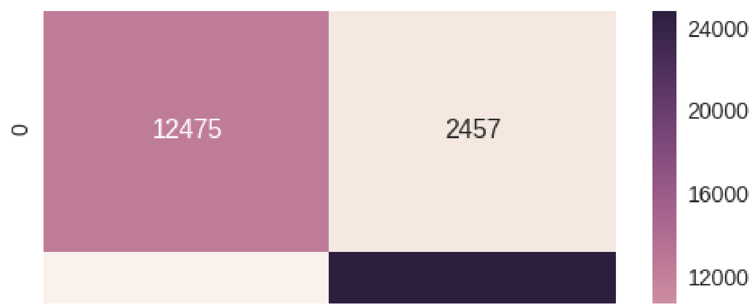
In [51]:

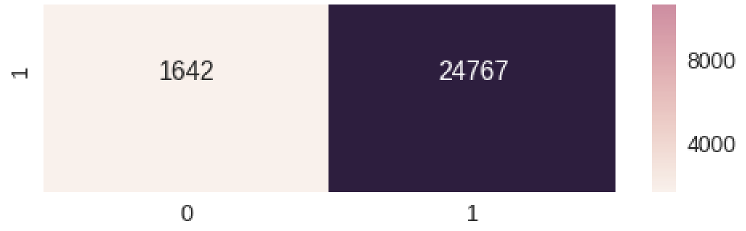
```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 100, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
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')
```

```
Accuracy on test set: 90.085%
Precision on test set: 0.910
Recall on test set: 0.938
F1-Score on test set: 0.924
Non Zero weights: 1250646
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[51]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f382bfb0a20>
```





In [54]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1000, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.815%
F1-Score on test set: 0.913
Non Zero weights: 29311
```

In [55]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 100, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.747%
F1-Score on test set: 0.913
Non Zero weights: 22913
```

In [56]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 89.432%
F1-Score on test set: 0.918
Non Zero weights: 15518
```

In [57]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.825%
F1-Score on test set: 0.914
Non Zero weights: 1743
```

In [58]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.1, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 85.095%
F1-Score on test set: 0.888
Non Zero weights: 303
```

In [59]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.01, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 71.735%
F1-Score on test set: 0.812
Non Zero weights: 28
```

Finding the best "C" value and best regularizer [L1 or L2] using Randomized Search CV

In [60]:

```
from sklearn.model_selection import TimeSeriesSplit
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = 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
gsv = RandomizedSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)

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

```
CPU times: user 6 µs, sys: 0 ns, total: 6 µs
Wall time: 13.1 µs
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  9.7min finished
```

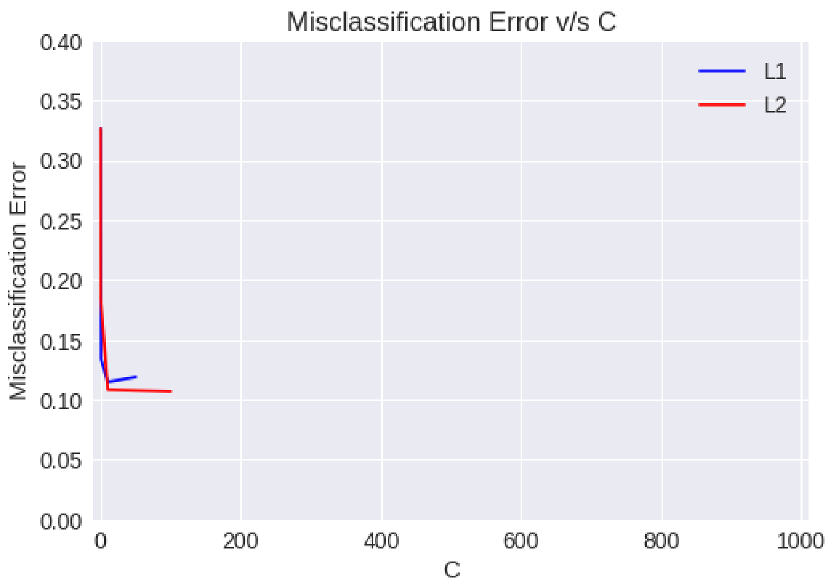
```
Best HyperParameter:  {'penalty': 'l2', 'C': 100}
Best Accuracy: 89.31%
```

Function to plot Misclassification error against C

In [61]:

```
plot_error_vs_c_r(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



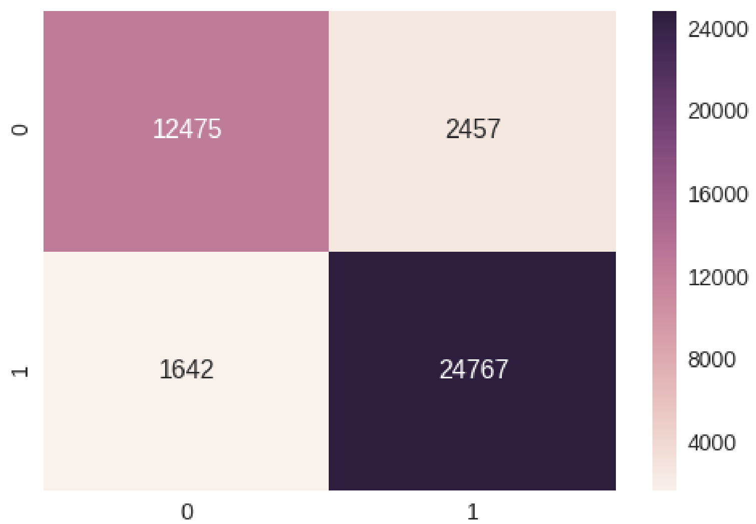
In [62]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 100, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
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')
```

```
Accuracy on test set: 90.085%
Precision on test set: 0.910
Recall on test set: 0.938
F1-Score on test set: 0.924
Non Zero weights: 1250646
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[62]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f384341b5c0>
```



Pertubation Test

In [63]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 500, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.037%
Non Zero weights: 1250646
```

In [64]:

```
from scipy.sparse import find
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[ 1.13320629e+00  1.13320629e+00  4.79728641e-01 -4.60824873e-02
  4.18514732e-01  7.81002606e-02  2.91961353e-02  3.30969336e-04
  1.68069233e-02  1.68069233e-02  3.48893548e-04  3.48893548e-04
  5.78008060e-03  5.78008060e-03 -1.50927102e-01 -1.50927102e-01
 -1.60335024e-01 -1.60335024e-01  5.78008060e-03  5.78008060e-03
  3.53787276e-01  3.53787276e-01  3.58490436e-02  3.58490436e-02
  1.36945320e-01  1.36945320e-01  2.46038384e-02  2.46038384e-02
  1.26720084e-01  5.18685459e-03  1.21533229e-01  4.03582876e-04
  4.03582876e-04 -9.28132986e-01 -7.82467616e-01 -1.45665370e-01
 -2.71726419e-01  3.99088273e-02  3.99088273e-02 -4.05907264e-01
  1.10667521e-01  8.76730032e-03 -6.50716310e-02  3.06256353e-01
  3.06256353e-01  8.49451111e-01  2.02849055e-03  8.44021881e-01
  3.40073995e-03  1.31064728e-03]
```

In [0]:

```
X_train_t = X_train
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size,))
a,b,c = find(X_train_t)

X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [66]:

```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

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

```
Accuracy on test set: 89.993%
Non Zero weights: 1250646
```

In [67]:

```
from scipy.sparse import find
weights2 = find(clf.coef_[0])[2]
print(weights2[:50])
```

```
[ 0.28631103  0.28647717  0.08655585 -0.03636776  0.08835174  0.02662309
  0.00790668  0.00042505  0.0179562   0.01795747  0.00047105  0.00047077
  0.00831836  0.00833144 -0.06900018 -0.06921521 -0.03606157 -0.03602566
  0.00833264  0.00832554  0.10866924  0.10863724  0.0247119   0.02475592
```

```
  0.04051669  0.0405553   0.01797194  0.01798842  0.05905442  0.00672441
  0.05232335  0.00051224  0.00051259 -0.32714536 -0.17436471 -0.1529727
 -0.0513378   0.01126877  0.01125957 -0.11404006  0.04389227  0.01132912
 -0.01501622  0.08039928  0.08030767  0.24901696  0.00301529  0.24076651
  0.00524678  0.00191099]
```

In [68]:

```
print(weights2.size)
```

```
1250646
```

In [0]:

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

In [70]:

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

```
634873
```

Top 25 Negative and Positive Features

In [71]:

```
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\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(bi_gram,clf)
```

```
   Positive       Negative
_________________________________________________________________________________________________
 -18.4032 worst                 14.9478 high recommend
 -13.8811 aw                    12.5891 delici
 -13.7633 terribl               12.5270 wont disappoint
 -13.0974 disappoint            11.8830 perfect
 -13.0468 two star              10.8539 excel
 -11.9320 disgust               10.5499 addict
 -11.5661 threw                 10.5027 hook
 -11.5414 horribl               10.2453 yummi
 -11.0929 bland                 10.1463 amaz
 -11.0069 tasteless              9.8808 even better
 -10.0707 unpleas                9.5970 awesom
 -9.9266 unfortun               9.5329 best
 -9.6113 wors                   9.3911 pleasant surpris
 -9.5448 weak                   9.3400 skeptic
 -9.4133 return                 9.0830 worri
 -9.3977 gross                  8.9233 yum
 -9.3932 wont buy               8.7629 fantast
 -9.0102 great review           8.7579 beat
 -8.8930 never buy              8.7288 great
 -8.8866 sorri                  8.4844 smooth
 -8.6220 yuck                   8.0840 right amount
 -8.5965 ruin                   8.0133 complaint
 -8.5838 sad                    7.9852 satisfi
 -8.5331 stale                  7.9022 well worth
 -8.4981 way sweet              7.8633 heaven
```

Observation:

1. Features are multi-collinear i.e. they are co-related, by pertubation test.
2. Bi-gram Featurization performs with accuracy of 90.08% and F1-Score of 0.924
3. Sparsity increases as we increase lambda or decrease C when L2 Regularizer is used

Tf-Idf Vectorizer

In [ ]:

```
import math
from sklearn import datasets
from  sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split

X = final_string
y = final['Score']

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

In [72]:

```
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vec = TfidfVectorizer()

final_tfidf_count1 = tf_idf_vec.fit_transform(X_train)
final_tfidf_count2 = tf_idf_vec.fit_transform(X_test)
```

```
Train Data Size:  (96464, 1250643)
Test Data Size:  (41342, 1250643)
CPU times: user 22.4 s, sys: 156 ms, total: 22.6 s
Wall time: 22.6 s
```

In [ ]:

```
from sklearn.preprocessing import StandardScaler

X_train = StandardScaler(with_mean=False).fit_transform(final_tfidf_count1)
X_test = StandardScaler(with_mean=False).transform(final_tfidf_count2)
```

Finding the best "C" value and best regularizer [L1 or L2] using Grid Search CV

In [73]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

clf = 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
gsv = GridSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)

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

```
CPU times: user 6 µs, sys: 0 ns, total: 6 µs
Wall time: 12.9 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 19.8min finished
```

```
Best HyperParameter:  {'C': 1000, 'penalty': 'l2'}
Best Accuracy: 89.25%
```

Function to plot Misclassification error against C

In [74]:

```
plot_error_vs_c(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```

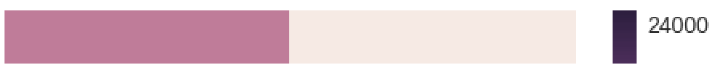
In [75]:

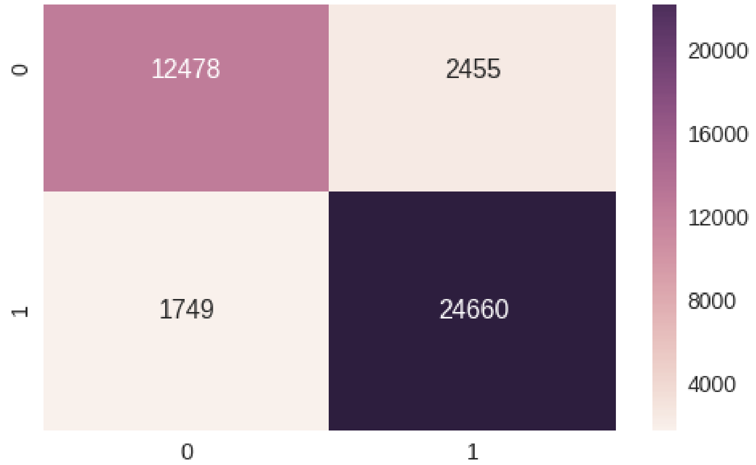
```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
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')
```

```
Accuracy on test set: 89.831%
Precision on test set: 0.909
Recall on test set: 0.934
F1-Score on test set: 0.921
Non Zero weights: 11797
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[75]:

```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x7f3827c07470&gt;
```





In [76]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1000, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 89.069%
F1-Score on test set: 0.915
Non Zero weights: 34779
```

In [77]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 100, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 89.031%
F1-Score on test set: 0.915
Non Zero weights: 25418
```

In [78]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 89.449%
F1-Score on test set: 0.918
Non Zero weights: 17945
```

In [79]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
```

```
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 88.876%
F1-Score on test set: 0.915
Non Zero weights: 1698
```

In [80]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.1, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 83.941%
F1-Score on test set: 0.881
Non Zero weights: 218
```

In [81]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 0.01, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 64.673%
F1-Score on test set: 0.783
Non Zero weights: 6
```

In [82]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression()
#parameters 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
gsv = RandomizedSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)

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

```
CPU times: user 5 µs, sys: 0 ns, total: 5 µs
Wall time: 10.3 µs
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  6.8min finished
```

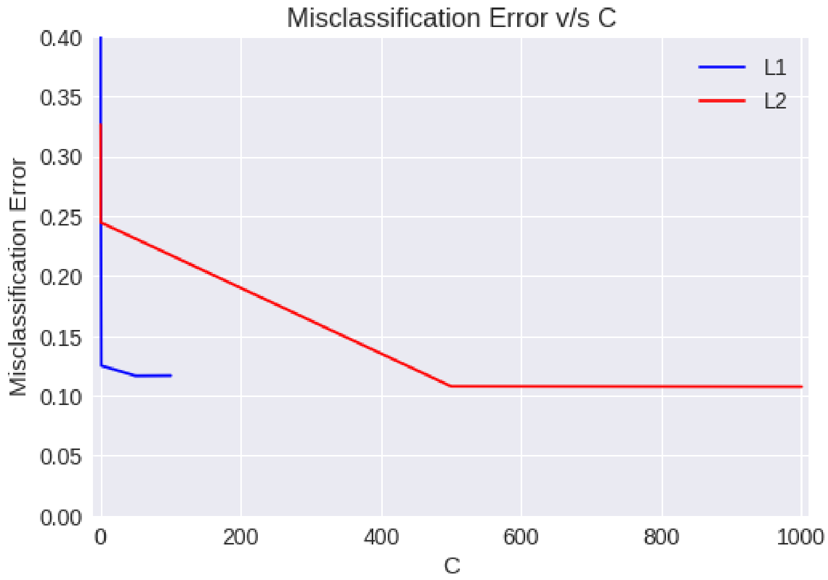
```
Best HyperParameter:  {'penalty': 'l2', 'C': 1000}
Best Accuracy: 89.25%
```

Function to plot Misclassification error against C

In [83]:

```
plot_error_vs_c_r(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



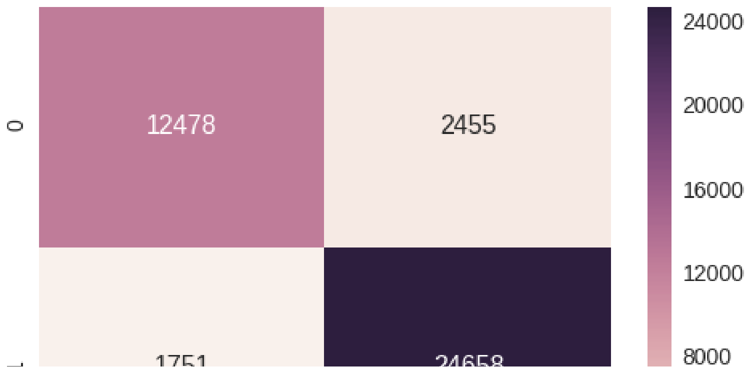
In [84]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l1')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
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')
```

```
Accuracy on test set: 89.826%
Precision on test set: 0.909
Recall on test set: 0.934
F1-Score on test set: 0.921
Non Zero weights: 11791
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[84]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3826ad5390>
```



Pertubation Test

In [85]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 500, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 90.158%
Non Zero weights: 1250643
```

In [86]:

```
from scipy.sparse import find
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[ 1.00509466e+00  1.00509466e+00  4.12847310e-01 -1.04698657e-01
  3.78991121e-01  1.31627941e-01  4.17360369e-02  1.54030648e-03
  6.17101063e-02  6.17101063e-02  1.34898674e-03  1.34898674e-03
  2.71839507e-02  2.71839507e-02 -2.57605671e-01 -2.57605671e-01
 -1.65807480e-01 -1.65807480e-01  2.71839507e-02  2.71839507e-02
  4.18748537e-01  4.18748537e-01  7.44057957e-02  7.44057957e-02
  1.27113527e-01  1.27113527e-01  5.18364714e-02  5.18364714e-02
  2.08682727e-01  2.61955744e-02  1.89923535e-01  1.01329639e-03
  1.01329639e-03 -1.04122093e+00 -7.04452770e-01 -3.73871940e-01
 -2.25957462e-01  4.58578204e-02  4.58578204e-02 -3.80843023e-01
  1.00298715e-01  2.04807055e-02 -7.09179389e-02  3.23756603e-01
  3.23756603e-01  7.55308195e-01  6.04529696e-03  7.90075294e-01
  6.39314724e-03  8.66767810e-03]
```

In [87]:

```
print(weights1[weights1<=0.0001])
```

```
[-0.10469866 -0.25760567 -0.25760567 ... -1.27981651 -0.37295155
 -1.45531383]
```

In [0]:

```
X_train_t = X_train
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size,))
a,b,c = find(X_train_t)

X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [89]:

```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

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

```
Accuracy on test set: 89.998%
```

```
Accuracy on test set: 89.998%
Non Zero weights: 1250643
```

In [90]:

```python
from scipy.sparse import find
weights2 = find(clf.coef_[0])[2]
print(weights2[:50])
```

```
[ 0.3247902   0.32453978  0.10467456 -0.05971542  0.10591561  0.05071104
  0.01656581  0.00127441  0.05064429  0.05064146  0.00149221  0.0014913
  0.02322372  0.02318837 -0.10417495 -0.10407558 -0.04699218 -0.04678544
  0.02320858  0.02321277  0.15344078  0.15332152  0.04288948  0.04283189
  0.05066988  0.05067962  0.03011144  0.03012415  0.09927833  0.02415531
  0.07864696  0.00111649  0.00111568 -0.42560924 -0.20370867 -0.23700423
 -0.05766986  0.01599901  0.01599103 -0.14146327  0.04944633  0.02400328
 -0.02348244  0.1015225   0.10150575  0.26278739  0.00794138  0.26374202
  0.00752928  0.01213404]
```

In [91]:

```python
print(weights2.size)
```

```
1250643
```

In [0]:

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

In [93]:

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

```
598435
```

Top 25 Negative and Positive Features

In [94]:

```python
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\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

show_most_informative_features(tfidf,clf)
```

```
   Positive      Negative
_______________________________________________________________________________________________
 -22.6276 disappoint          23.3992 great
 -20.0698 worst               21.3941 delici
 -16.4904 terribl             19.9136 best
 -15.8294 aw                  18.9423 perfect
 -13.6649 horribl             18.8337 love
 -13.1661 unfortun            16.6822 high recommend
 -13.0223 return              16.1760 excel
 -12.9197 bland               13.0896 amaz
 -12.5763 threw               13.0640 favorit
 -12.5523 disgust             12.9699 good
 -11.3975 weak                12.7737 nice
 -11.0395 tasteless           12.2593 yummi
 -11.0028 two star            12.0459 tasti
 -10.8574 stale               12.0045 addict
 -10.6144 wors                11.5526 awesom
```

```
-10.1106 sorri                10.9957 wont disappoint
-10.0493 gross                10.9308 smooth
-9.9154 unpleas               10.8738 wonder
-9.9112 wont buy              10.7825 happi
-9.7041 poor                  10.3118 hook
-9.6858 money                 10.1674 fantast
-9.5376 lack                  10.0306 thank
-9.3512 refund                9.7839 satisfi
-9.3260 sad                   9.7618 worri
-9.1536 bad                   9.7394 keep
```

Observation:

1. Features are multi-collinear i.e. they are co-related, by pertubation test.
2. Tf-Idf Featurization performs with accuracy of 89.8% and F1-Score of 0.921
3. Sparsity increases as we increase lambda or decrease C when L1 Regularizer is used

Average Word2Vec Vectorizer

In [0]:

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

In [0]:

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

    list_of_sent.append(filtered_sentence)
    final_string_for_tfidf.append((str1).strip())
```

In [0]:

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

In [0]:

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

In [0]:

```
import math
from sklearn import datasets
from sklearn.model_selection import train_test_split

X = sent_vectors
y = final['Score']

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

Finding the best "C" value and best regularizer [L1 or L2] using Grid Search CV

In [105]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression

clf = 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
gsv = GridSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)

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

```
CPU times: user 5 µs, sys: 0 ns, total: 5 µs
Wall time: 10 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 15.5min finished
```

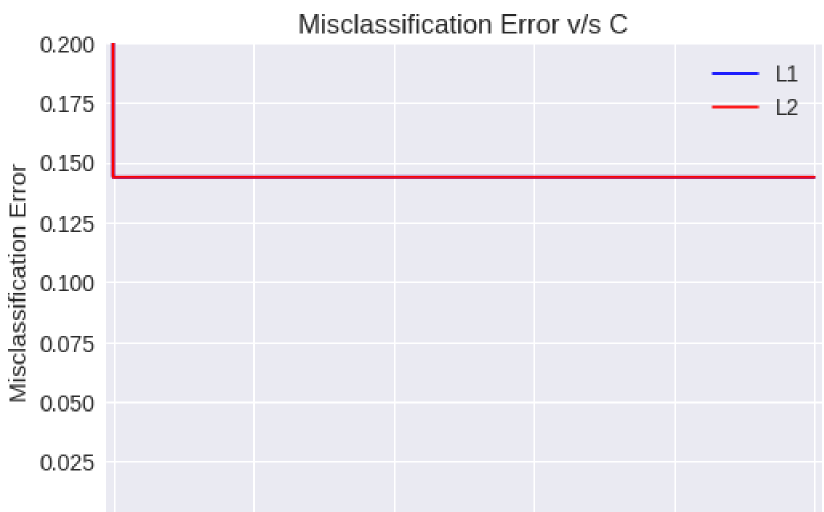
```
Best HyperParameter:  {'C': 1, 'penalty': 'l2'}
Best Accuracy: 85.62%
```

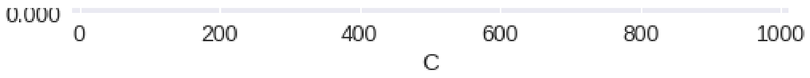
Function to plot Misclassification error against C

In [106]:

```
plot_error_vs_c(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```





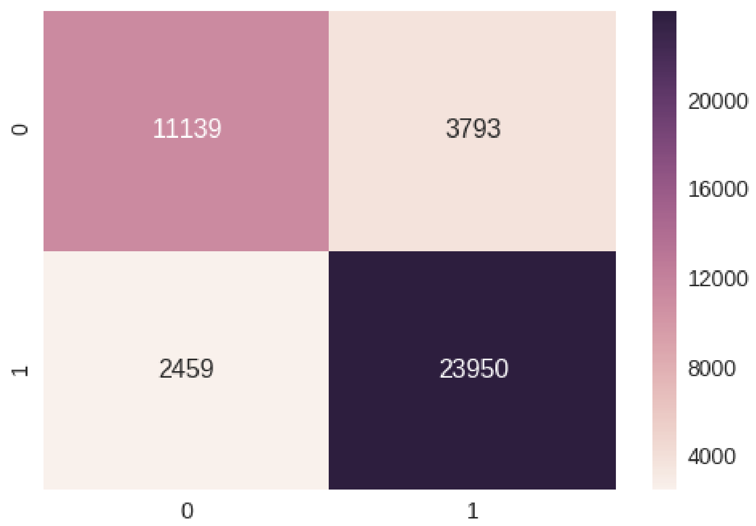
In [107]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 1000, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
Accuracy on test set: 84.877%
Precision on test set: 0.863
Recall on test set: 0.907
F1-Score on test set: 0.885
Non Zero weights: 50
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[107]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3832d42cf8>
```



Finding the best "C" value and best regularizer [L1 or L2] using Randomized Search CV

In [108]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = 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']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)

print("Best HyperParameter: ",gsv.best_params_)
```

```
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
CPU times: user 11 µs, sys: 0 ns, total: 11 µs
Wall time: 13.6 µs
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  5.5min finished
```

```
Best HyperParameter:  {'penalty': 'l2', 'C': 1}
Best Accuracy: 85.62%
```

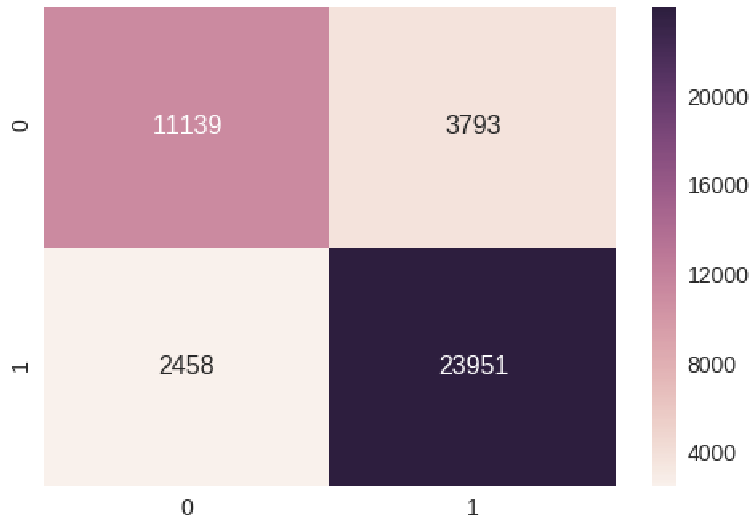
In [109]:

```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
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')
```

```
Accuracy on test set: 84.879%
Precision on test set: 0.863
Recall on test set: 0.907
F1-Score on test set: 0.885
Non Zero weights: 50
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[109]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3832b51048>
```



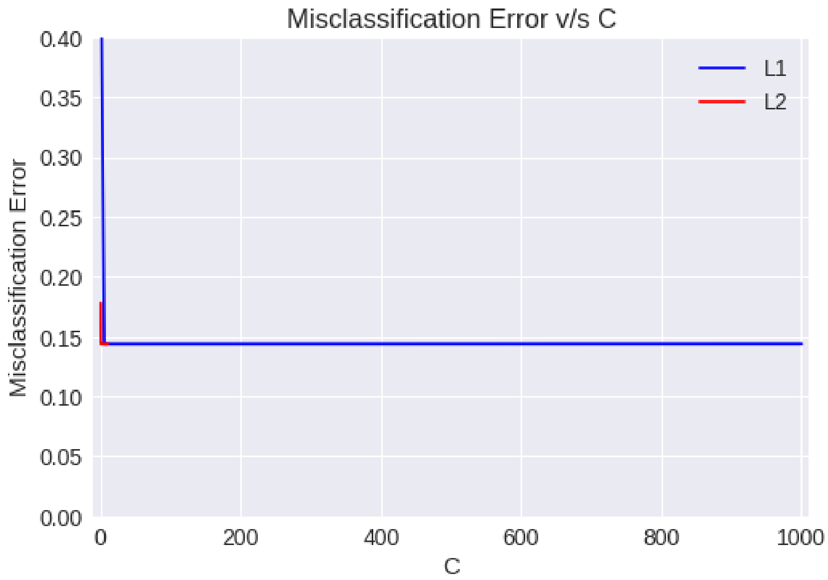
Function to plot Misclassification error against C

In [110]:

```
plot_error_vs_c_r(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
```

```
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



In [111]:

```
from sklearn.linear_model import LogisticRegression

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

```
Accuracy on test set: 84.879%
Non Zero weights: 50
```

In [112]:

```
from scipy.sparse import find
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[ 0.215303   -0.08421248  0.44742257  0.41708556  0.2095311  -0.65949407
  0.01187954  0.3948174   0.94517895  0.58840433  0.21126642 -0.38891501
 -1.23659635  1.64833703  0.1162524  -0.79080296 -0.32443373  0.18665229
 -0.28266221 -0.34966984 -1.05105844 -0.790018   -0.35806312 -0.75572728
  0.10842228 -0.34975354 -0.7637287  -0.12326595  1.01616732 -0.22713083
  0.51885008  0.6682174  -1.08583427  0.20464427  0.74865448  0.80875492
 -0.25958734 -0.41724779 -0.95983595 -0.08332266 -0.31138774  0.55521402
  0.25365556  0.23070857  0.8218135  -0.14952319 -0.53415395  0.38852245
 -0.72455825  0.21369857]
```

In [0]:

```
X_train_t = np.array(X_train)
epsilon = np.random.uniform(low=-0.01, high=0.01, size=(find(X_train_t)[0].size,))
a,b,c = find(X_train_t)

X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [122]:

```
#Training on train data having random noise
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
clf.fit(X_train_t,y_train)
y_pred = clf.predict(X_test)
```

```
y_pred = clf.predict(x_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 84.872%
Non Zero weights: 50
```

In [123]:

```
from scipy.sparse import find
weights2 = find(clf.coef_[0])[2]
print(weights2[:50])
```

```
[ 0.21305113 -0.08450643  0.4454418   0.42012933  0.21195646 -0.66990876
  0.00706347  0.39263436  0.95061488  0.58739876  0.21259696 -0.38814777
 -1.23410795  1.64547704  0.11539283 -0.78637485 -0.32110015  0.18821724
 -0.28010438 -0.35343375 -1.04767378 -0.78973893 -0.35509688 -0.75313933
  0.10720747 -0.34904896 -0.75995739 -0.12203038  1.00648818 -0.2301609
  0.51872395  0.67144219 -1.08367886  0.20881702  0.74580567  0.80902283
 -0.25966614 -0.41584445 -0.95662743 -0.07436878 -0.3118219   0.56058928
  0.2604125   0.22905283  0.8129459  -0.15396227 -0.53788449  0.39092572
 -0.7186704   0.20852634]
```

In [124]:

```
print(weights2.size)
```

```
50
```

In [0]:

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

In [126]:

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

```
1
```

Observation:

1. Features are multi-collinear i.e. they are co-related, by pertubation test.
2. Avg Word2Vec Featurization performs with accuracy of 84.87% and F1-Score of 0.885
3. Sparsity increases as we increase lambda or decrease C when L2 Regularizer is used

Tf-Idf Weighted Word2Vec

In [0]:

```
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vec_w = TfidfVectorizer()

final_tfidf_w = tf_idf_vec_w.fit_transform(final_string_for_tfidf)
```

In [0]:

```
tfidf_feat = tf_idf_vec_w.get_feature_names()
tfidf_sent_vectors = [];
row=0;
for sent in list_of_sent:
    sent_vec = np.zeros(50)
    weight_sum =0;
    for word in sent:
        try:
            vec = w2v_model.wv[word]
```

```
            tf_idf = final_tfidf_w[row, tfidf_feat.index(word)]
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except Exception as e:
            pass #print(e)

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

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

In [0]:

```
from sklearn import datasets
X = tfidf_sent_vectors
y = final['Score']

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

Finding the best "C" value and best regularizer [L1 or L2] using Grid Search CV

In [130]:

```
%time
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import TimeSeriesSplit

clf = 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']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = GridSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
CPU times: user 6 µs, sys: 0 ns, total: 6 µs
Wall time: 11.9 µs
Fitting 10 folds for each of 30 candidates, totalling 300 fits
```

```
[Parallel(n_jobs=1)]: Done 300 out of 300 | elapsed: 16.8min finished
```

```
Best HyperParameter:  {'C': 100, 'penalty': 'l1'}
Best Accuracy: 83.68%
```

In [131]:

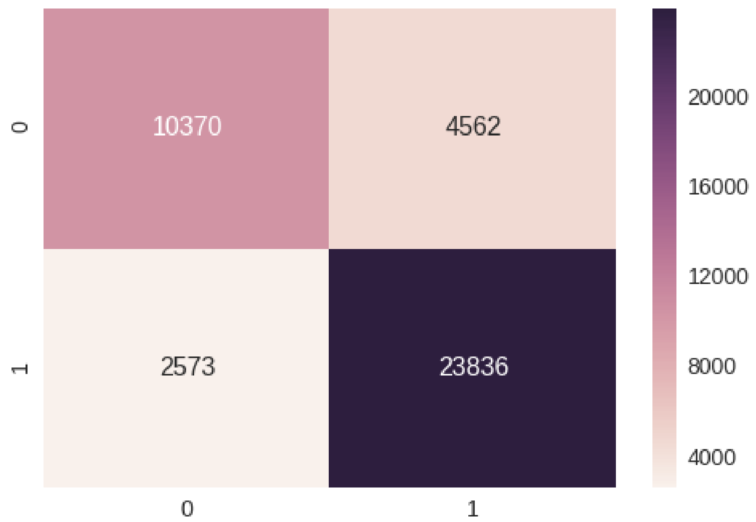
```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 10, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
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')
```

```
Accuracy on test set: 82.741%
```

```
Precision on test set: 0.839
Recall on test set: 0.903
F1-Score on test set: 0.870
Non Zero weights: 50
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[131]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f380a305320>
```

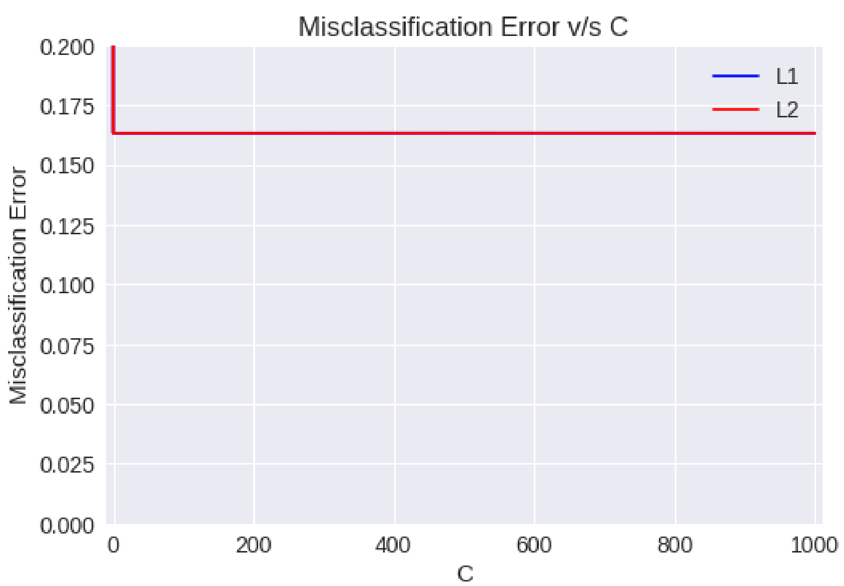


Function to plot Misclassification error against C

In [132]:

```
plot_error_vs_c(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



Finding the best "C" value and best regularizer [L1 or L2] using Randomized Search CV

In [133]:

```
%time
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

clf = 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']}
tscv = TimeSeriesSplit(n_splits=10) #For time based splitting
gsv = RandomizedSearchCV(clf,param_grid,cv=tscv,verbose=1)
gsv.fit(X_train,y_train)
print("Best HyperParameter: ",gsv.best_params_)
print("Best Accuracy: %.2f%%"%(gsv.best_score_*100))
```

```
CPU times: user 12 µs, sys: 0 ns, total: 12 µs
Wall time: 13.6 µs
Fitting 10 folds for each of 10 candidates, totalling 100 fits
```

```
[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  4.1min finished
```

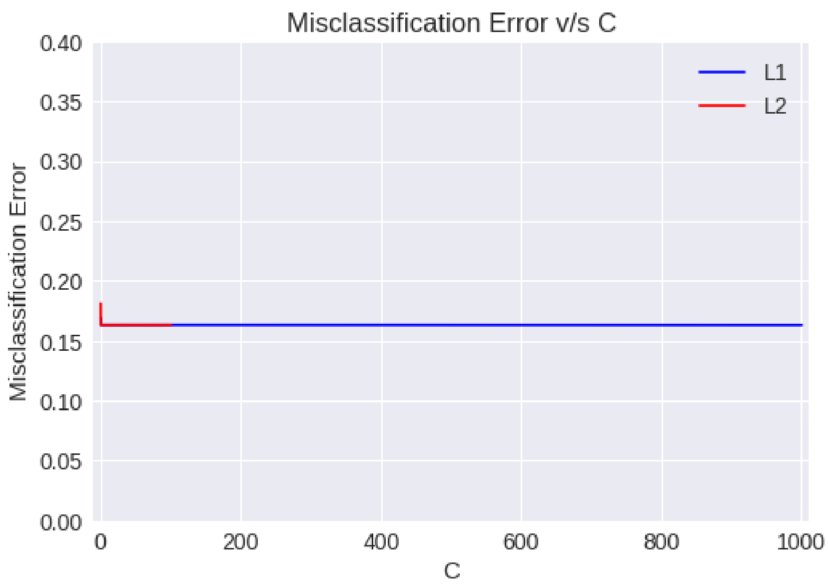
```
Best HyperParameter:  {'penalty': 'l1', 'C': 1000}
Best Accuracy: 83.68%
```

Function to plot Misclassification error against C

In [134]:

```
plot_error_vs_c_r(gsv)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_search.py:762: DeprecationWarning:
The grid_scores_ attribute was deprecated in version 0.18 in favor of the more elaborate
cv_results_ attribute. The grid_scores_ attribute will not be available from 0.20
  DeprecationWarning)
```



In [135]:

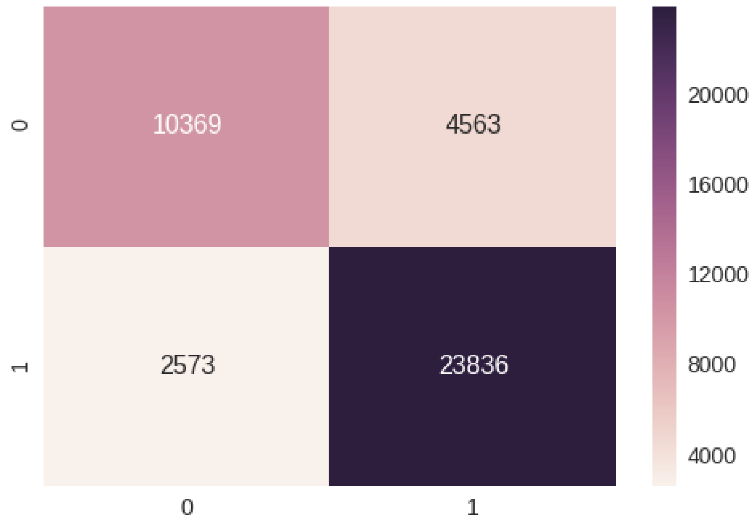
```
#Testing Accuracy on Test data
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Precision on test set: %0.3f"%(precision_score(y_test, y_pred)))
print("Recall on test set: %0.3f"%(recall_score(y_test, y_pred)))
print("F1-Score on test set: %0.3f"%(f1_score(y_test, y_pred)))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")
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')
```

```
Accuracy on test set: 82.739%
Precision on test set: 0.839
Recall on test set: 0.903
F1-Score on test set: 0.870
Non Zero weights: 50
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```

Out[135]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f380f158748>
```



In [136]:

```
from sklearn.linear_model import LogisticRegression

clf = LogisticRegression(C= 5, penalty= 'l2')
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
print("Accuracy on test set: %0.3f%%"%(accuracy_score(y_test, y_pred)*100))
print("Non Zero weights:",np.count_nonzero(clf.coef_))
```

```
Accuracy on test set: 82.739%
Non Zero weights: 50
```

In [137]:

```
from scipy.sparse import find
weights1 = find(clf.coef_[0])[2]
print(weights1[:50])
```

```
[ 0.21911647  0.17218338  0.75580931  0.42844329 -0.26931413 -1.12176646
  0.57481188  0.42517511  0.94820462  0.32483445  0.07420206 -0.58757913
 -0.1991115   0.74949686 -0.11049856 -0.31019213 -0.8074204  -0.05553134
 -0.12589457 -0.19398169 -0.5810513  -0.77270143 -0.49608794 -0.09951034
  0.32678439 -0.25988707 -0.15466491  0.00406681  0.74363131  0.13898376
  0.32661956  0.54448773 -0.66445505  0.82079135  0.65918674  0.57539719
  0.22632212  0.42655646 -1.1328619  -0.23919449  0.33666922  0.29416638
  0.00128143  0.00401115  1.24137491  0.02063452 -0.35755433  0.73314468
 -0.66995351 -0.07619673]
```

In [0]:

```
X_train_t = np.array(X_train)
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_train_t)[0].size))
a,b,c = find(X_train_t)
```

```
X_train_t[a,b] = epsilon + X_train_t[a,b]
```

In [139]:

```
#Predicting the output of test data.

from sklearn.linear_model import LogisticRegression

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

```
Accuracy on test set: 82.741%
Non Zero weights: 50
```

In [140]:

```
from scipy.sparse import find
weights2 = find(clf.coef_[0])[2]
print(weights2[:50])
```

```
[ 2.19181207e-01  1.72268796e-01  7.55960576e-01  4.28385986e-01
 -2.69361810e-01 -1.12157372e+00  5.74986489e-01  4.25271931e-01
  9.48168166e-01  3.24854422e-01  7.41520897e-02 -5.87808407e-01
 -1.99238164e-01  7.49595281e-01 -1.10491953e-01 -3.10318102e-01
 -8.07523748e-01 -5.56602047e-02 -1.25927340e-01 -1.93797580e-01
 -5.81178723e-01 -7.72786963e-01 -4.96357681e-01 -9.95965285e-02
  3.26920260e-01 -2.59921006e-01 -1.54812360e-01  4.09310942e-03
  7.43914903e-01  1.39119980e-01  3.26737282e-01  5.44391545e-01
 -6.64578232e-01  8.20674374e-01  6.59308959e-01  5.75473756e-01
  2.26357821e-01  4.26562683e-01 -1.13299444e+00 -2.39380697e-01
  3.36644078e-01  2.94034129e-01  1.07775941e-03  4.02741419e-03
  1.24181665e+00  2.08053424e-02 -3.57477032e-01  7.33176804e-01
 -6.70202583e-01 -7.59805053e-02]
```

In [144]:

```
print(weights2.size)
```

```
50
```

In [0]:

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

In [146]:

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

```
0
```

Observation:

1. Tf-Idf weighted Word2Vec Featurization performs with accuracy of 82.73% and F1-Score of 0.870.
2. Sparsity increases as we increase lambda or decrease C when L2 Regularizer is used.
3. Bigram Featurization performs best of all featurization techniques with accuracy of 90.08% and F1-Score of 0.924.
4. Logistic Regression works efficiently, on application on text data.