Amazone Fine Food Review Analysis Logistic Regression

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

In [1]:
```
#import re
#import nltk
#import string
#import pickle
import sqlite3
import numpy as np
import pandas as pd
import seaborn as sns
import scikitplot.metrics as skplt
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn import metrics
from sklearn.model_selection import TimeSeriesSplit
#from nltk.corpus import stopwords
from sklearn.metrics import roc_curve,auc
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
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
from sklearn.linear_model import LogisticRegressionCV
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression
from wordcloud import WordCloud
import gensim
import warnings
warnings.filterwarnings("ignore")
from tqdm import tqdm
```

Loading Data

In [2]:
```
con = sqlite3.connect("final.sqlite")
final = pd.read_sql_query("""SELECT * FROM Reviews""",con)
```

Sorting data

In [3]:
```
final.sort_values("Time",ascending=True, inplace=True, kind='quicksort')
```

Replace Negative with 0 and Positive with 1

In [4]:
```
final['Score'].replace(['negative', 'positive'],[0,1],inplace=True)
```

In [5]:
```
final = final.to_csv("final.csv") #saving dataframe
```

In [6]:
```
final = pd.read_csv("final.csv") #retriving the sorted dataframe
```

In [7]:
```
final = final.iloc[:100000] #taking initial 100k points
```

Function

In [8]:
```
# defining LR function that does cross validation , plotting Misclassification
 Error v/s C, accuracy, test accuracy
# and confusion matrix
# this function takes 'algo', 'X_train', 'X_test', 'y_train', 'y_test' as argu
ments
def LR(search,X_train, X_test, y_train, y_test):


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

    #if(reg=='l1'):
    #    clf= 'l1'
    #elif(reg=='l2'):
    #    clf= 'l2'


    LR = LogisticRegression()
    param = {'C': [0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100, 150,
 200],'penalty':['l2','l1']} #params we need to try on classifier
    tscv = TimeSeriesSplit(n_splits=10) #For time based splitting

    if(search=="Grid"):
        CV=GridSearchCV(estimator=LR, param_grid=param, verbose=1, cv=tscv)
    elif(search=="Random"):
        CV=RandomizedSearchCV(estimator=LR, param_distributions=param, cv=tscv
,  verbose=1)

    #Finding the best k using Cross Validation

    gsv = CV
    gsv.fit(X_train,y_train)

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


    #plot error vs C
    x_1=[]
    x_2=[]
    y_1=[]
    y_2=[]
    for x in gsv.grid_scores_:
        if(x[0]['penalty']=='l1'):
            x_1.append(x[0]['C'])
            y_1.append(1-x[1])
        else:
            x_2.append(x[0]['C'])
            y_2.append(1-x[1])
    plt.plot(x_1,y_1, label='l1')
    plt.plot(x_2,y_2, label='l2')
    plt.xlabel('value of C')
```

```
    plt.ylabel('misclassification error')
    plt.title('C vs error')
    plt.legend()
    plt.show()

    #Testing Accuracy on Test data

    LR = LogisticRegression(C=gsv.best_params_['C'],penalty=gsv.best_params_[
'penalty'])
    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("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(LR.coef_))
    print("Confusion Matrix of test set:\n [ [TN  FP]\n [FN TP] ]\n")

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

    C = gsv.best_params_['C'] #for best C
    penalty = gsv.best_params_['penalty'] #for best penalty

    return C, penalty
```

Function for multiple sparsity

In [9]:
```
# sparsity increases as we increase lambda or decrease C when L1 Regularizer i
s used
# this function takes 'X_train', 'y_train','X_test','y_test' as arguments
def sparsity(X_train,y_train,X_test, y_test):

    w_change=[]
    C= [0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, 50, 100, 150]
    for x in C:
        LR=LogisticRegression(penalty='l1', C=x)
        LR.fit(X_train,y_train)
        accuracy = LR.predict(X_test)
        print('at C=',x)
        print('test error=',(1-accuracy_score(accuracy,y_test)))
        count=np.count_nonzero(LR.coef_)
        print('number of non zero element in w=', count)
        print('**********************************************')
        w_change.append(count)


    plt.figure(figsize=(6,6))
    plt.plot(C,w_change,color='green')
    plt.title('change in non zero element in W , when C changes')
    plt.xlabel('value of C')
    plt.ylabel('number of non zero element in W')
    plt.show()
```

Function for Feature Importance

In [10]:
```
#code borrowed from  https://stackoverflow.com/questions/11116697/how-to-get-m
ost-informative-features-for-scikit-learn-classifiers
def show_cloud(vectorizer, w, n=100):
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(w[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    positive = []
    negative = []
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        #print("\t%.4f\t%-15s\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))
        positive.append(fn_2)
        negative.append(fn_1)
    positive = ' '.join(positive)

    #wordcloud for postitve word

    wordcloud  = WordCloud(max_font_size=40).generate(positive)
    plt.figure()
    plt.title("wordcloud for positive class words")
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show()

    print('*****************************************************')

    negative = ' '.join(negative)

    #wordcloud for negative word

    wordcloud  = WordCloud(max_font_size=40).generate(negative)
    plt.figure()
    plt.title("wordcloud for negative class words")
    plt.imshow(wordcloud, interpolation="bilinear")
    plt.axis("off")
    plt.show()
```

1.Bag Of Word

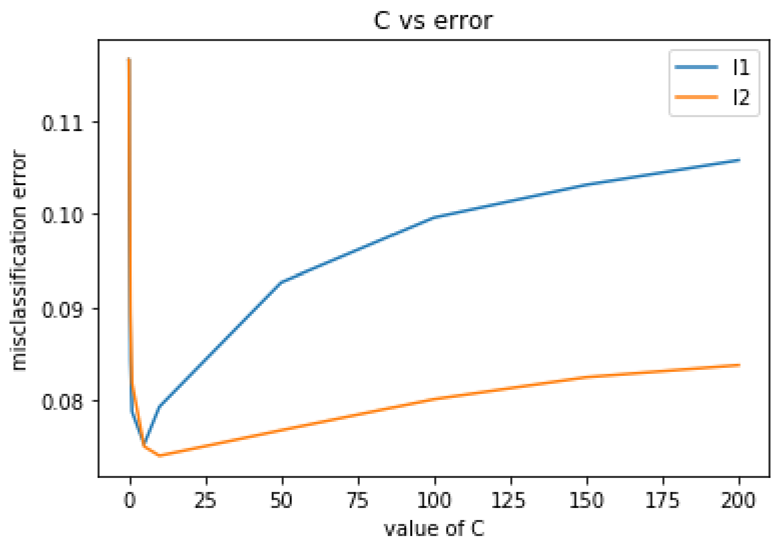
The bag-of-words model is a simplifying representation used in natural language processing and information retrieval(IR).Also known as the vector space model.The bag-of-words model is commonly used in methods of document classification where the occurrence of each word is used as a feature for training a classifier.OR Simply,Converting a collection of text documents to a matrix of token counts

In [11]:
```
X = final["CleanedText"] #taking cleandtext as X
y = final["Score"] #taking score as y
```

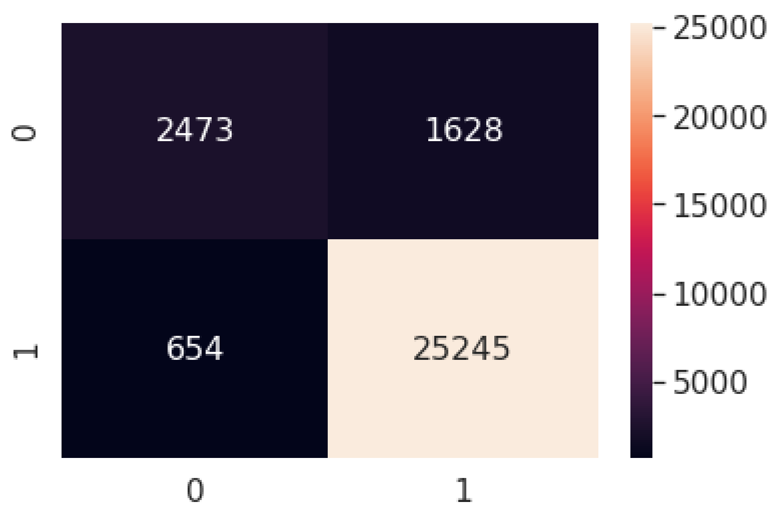
1.1 Grid

In [12]:
```
#Breaking into Train and test
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=0.7,shuffle
=False,random_state=0)

#Bag of Words
count = CountVectorizer()

X_train = count.fit_transform(X_train)

X_test = count.transform(X_test)

C, penalty = LR(search="Grid",X_train = X_train, X_test=X_test, y_train=y_trai
n, y_test=y_test)
```

```
Train Data Size:  (70000, 31377)
Test Data Size:  (30000, 31377)
Fitting 10 folds for each of 26 candidates, totalling 260 fits

[Parallel(n_jobs=1)]: Done 260 out of 260 | elapsed:  4.7min finished

Best HyperParameter:  {'C': 10, 'penalty': 'l2'}
Best Accuracy: 92.60%
```




```
Accuracy on test set: 92.393%
Precision on test set: 0.939
Recall on test set: 0.975
F1-Score on test set: 0.957
Non Zero weights: 31377
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```



In [13]:
```
#Normalize Data
X_train = preprocessing.normalize(X_train)

X_test = preprocessing.normalize(X_test)
```

1.1.1 Perturbation test

In [14]:
```
clf = LogisticRegression(C= C, penalty= penalty)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
w=clf.coef_
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: 92.393%
Non Zero weights: 31377
```

In [15]:
```
# for findind feature importance we need to check multicollinearity
# apply perturbation test for checking multicollinearity
# in perturbation test, we add some noise to the training data and the fit the model
# the w we will get after fittng the model, if it is significantly different than w which we get without any error adding then we will say it is multicollinear

X_train.data=X_train.data+np.random.normal(loc=0,scale=0.1,size=X_train.data.shape) #adding a noise with a very small value
```

In [16]:
```
#computing weight after perturbation weight
clf=LogisticRegression(C=C, penalty=penalty)
clf.fit(X_train,y_train)
w_=clf.coef_
print('number of non-zero element in w_=', np.count_nonzero(w_))
```

```
number of non-zero element in w_= 31377
```

In [17]:
```
#getting the number of elements in w which changes after perturbation test by more than 50%
w_delta=abs((w-w_)/w)*100
cnt=0
for i in range(len(w_delta[0])):
    if (w_delta[0][i]>30):
        cnt+=1
print('number of elements in w_delta,more than 30% =',cnt)
```

```
number of elements in w_delta,more than 30% = 24172
```

Observation-

- we have 31377 non zero elements in weight before perturbation
- after perturbation test, 24172 elements in weight before perturbation change by more than 30 %
- Thus we can say that elements weight are collinear

1.1.2 Word Cloud Feature Importance

In [18]:
```
clf = LogisticRegression(C = C, penalty = penalty)
clf.fit(X_train,y_train)
show_cloud(count, clf.coef_)
```

wordcloud for positive class words

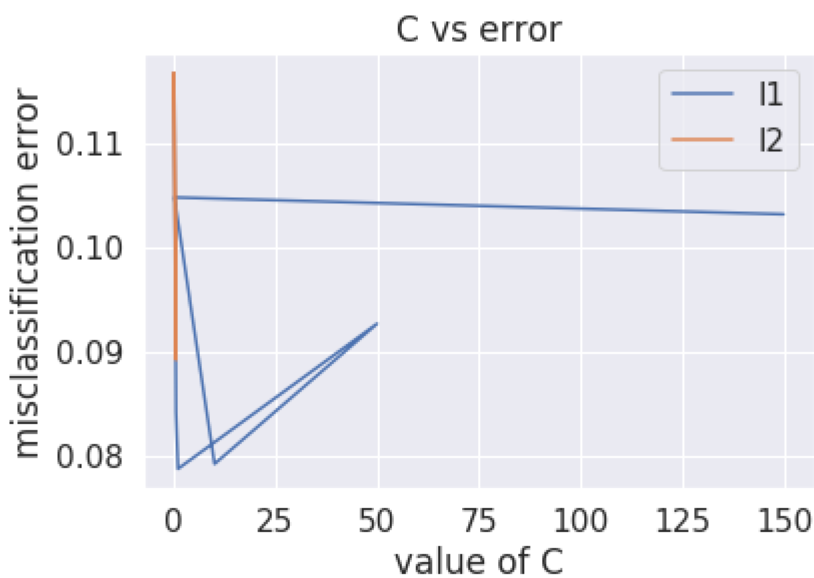
****

wordcloud for negative class words

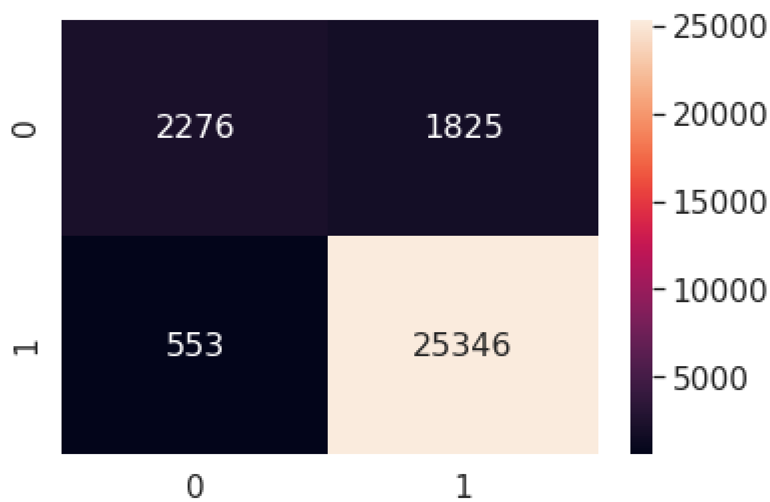
1.2 Random

In [19]:
```
#Breaking into Train and test
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=0.7,shuffle
=False,random_state=0)

#Bag of Words
count = CountVectorizer()

X_train = count.fit_transform(X_train)

X_test = count.transform(X_test)

C, penalty = LR(search="Random",X_train = X_train, X_test=X_test, y_train=y_tr
ain, y_test=y_test)
```

```
Train Data Size:  (70000, 31377)
Test Data Size:  (30000, 31377)
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': 'l1', 'C': 1}
Best Accuracy: 92.12%
```



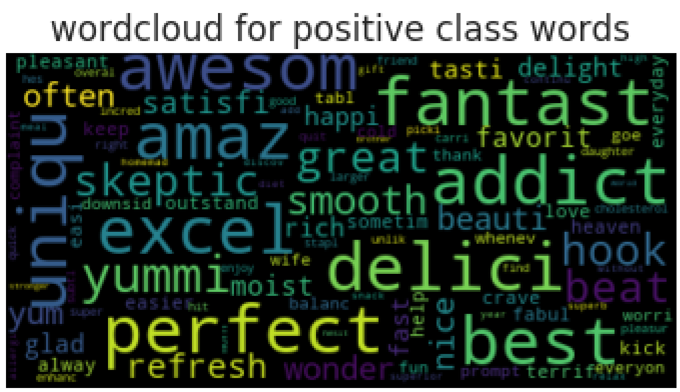

```
Accuracy on test set: 92.073%
Precision on test set: 0.933
Recall on test set: 0.979
F1-Score on test set: 0.955
Non Zero weights: 1012
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```



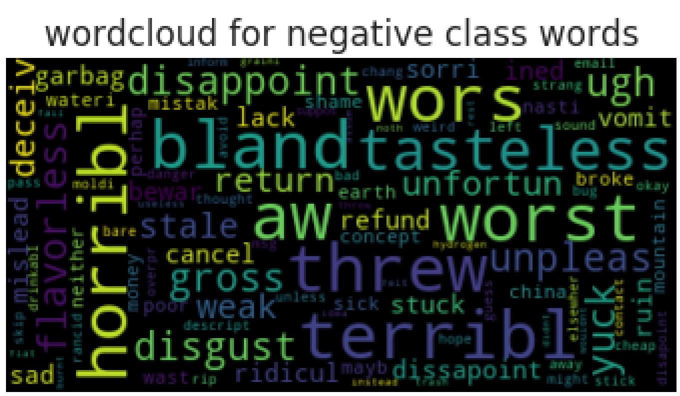
In [20]:
```
#Normalize Data
X_train = preprocessing.normalize(X_train)

X_test = preprocessing.normalize(X_test)
```

1.2.2 Word Cloud

In [21]:
```
clf = LogisticRegression(C = C, penalty = penalty)
clf.fit(X_train,y_train)
show_cloud(count, clf.coef_)
```



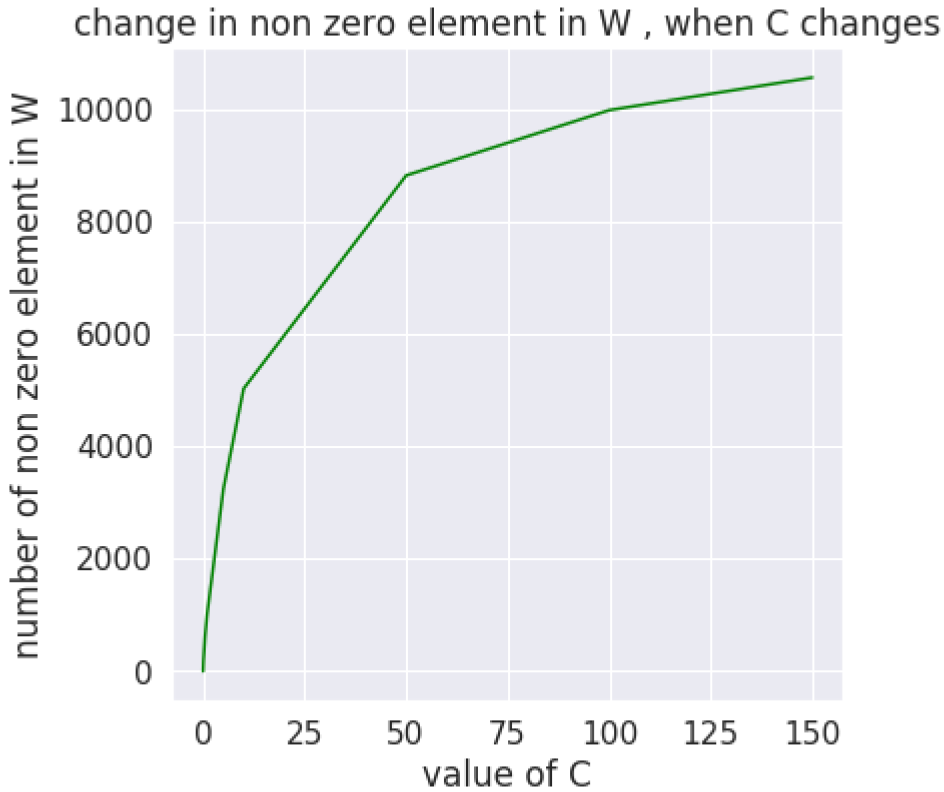

```
**************************************************
```



1.3 Sparsity

In [22]:
```
sparsity(X_train=X_train , y_train=y_train , X_test=X_test , y_test=y_test)
```

```
at C= 0.001
test error= 0.1367
number of non zero element in w= 0
***********************************************
at C= 0.005
test error= 0.1367
number of non zero element in w= 2
***********************************************
at C= 0.01
test error= 0.1367
number of non zero element in w= 10
***********************************************
at C= 0.05
test error= 0.119566666667
number of non zero element in w= 86
***********************************************
at C= 0.1
test error= 0.106766666667
number of non zero element in w= 181
***********************************************
at C= 0.5
test error= 0.0836666666667
number of non zero element in w= 626
***********************************************
at C= 1
test error= 0.0792666666667
number of non zero element in w= 1013
***********************************************
at C= 5
test error= 0.0764666666667
number of non zero element in w= 3238
***********************************************
at C= 10
test error= 0.0793333333333
number of non zero element in w= 5026
***********************************************
at C= 50
test error= 0.0937666666667
number of non zero element in w= 8816
***********************************************
at C= 100
test error= 0.102033333333
number of non zero element in w= 9977
***********************************************
at C= 150
test error= 0.105833333333
number of non zero element in w= 10557
***********************************************
```



Observation

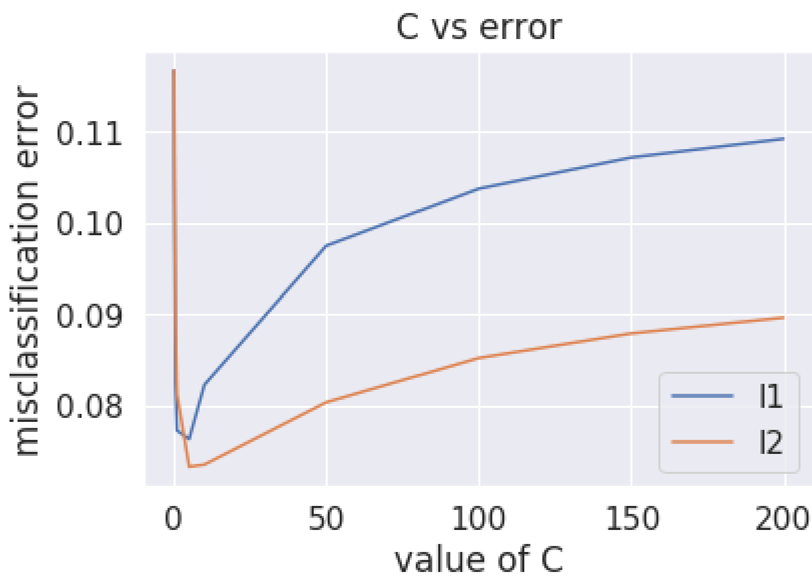
```
as we increase value of C(decreasing lambda) the sparsity decreases
```

2.TFIDF

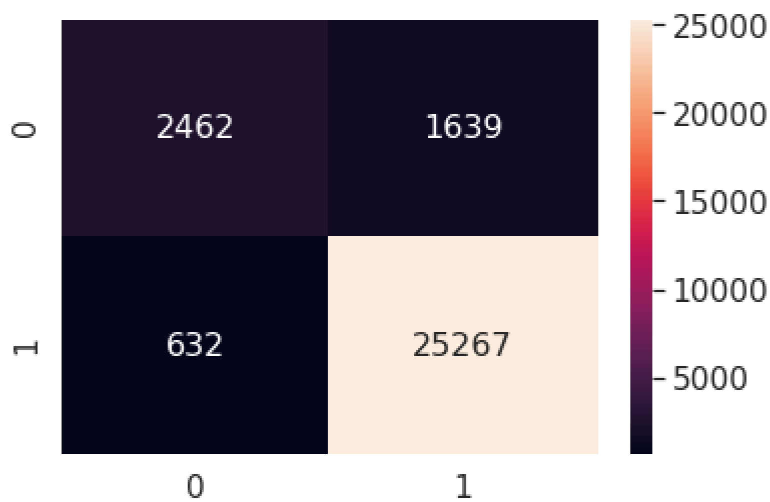
2.1 Grid

In [23]:
```
#Breaking into Train and test
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=0.7,shuffle
=False,random_state=0)

tfidf = TfidfVectorizer(ngram_range=(1,1), binary=True)

X_train = tfidf.fit_transform(X_train)

X_test = tfidf.transform(X_test)

C, penalty =LR(search="Grid",X_train = X_train, X_test=X_test, y_train=y_train
, y_test=y_test)
```

```
Train Data Size:  (70000, 31377)
Test Data Size:  (30000, 31377)
Fitting 10 folds for each of 26 candidates, totalling 260 fits

[Parallel(n_jobs=1)]: Done 260 out of 260 | elapsed:  4.0min finished

Best HyperParameter:  {'C': 5, 'penalty': 'l2'}
Best Accuracy: 92.67%
```




```
Accuracy on test set: 92.430%
Precision on test set: 0.939
Recall on test set: 0.976
F1-Score on test set: 0.957
Non Zero weights: 31377
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```



In [24]:
```
#Normalize Data
X_train = preprocessing.normalize(X_train)

X_test = preprocessing.normalize(X_test)
```

2.1.1 Perturbation test

In [25]:
```
clf = LogisticRegression(C= C, penalty= penalty)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
w=clf.coef_
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: 92.430%
Non Zero weights: 31377
```

In [26]:
```
X_train.data=X_train.data+np.random.normal(loc=0,scale=0.01,size=X_train.data.
shape) #adding a noise with a very small value
```

In [27]:
```
#computing weight after perturbation weight
clf=LogisticRegression(C=C, penalty=penalty)
clf.fit(X_train,y_train)
w_=clf.coef_
print('number of non-zero element in w_=', np.count_nonzero(w_))
```

```
number of non-zero element in w_= 31377
```

In [28]:
```
#getting the number of elements in w which changes after perturbation test by
 more than 50%
w_delta=abs((w-w_)/w)*100
cnt=0
for i in range(len(w_delta[0])):
    if (w_delta[0][i]>30):
        cnt+=1
print('number of elements in w_delta,more than 30% =',cnt)
```

```
number of elements in w_delta,more than 30% = 2114
```

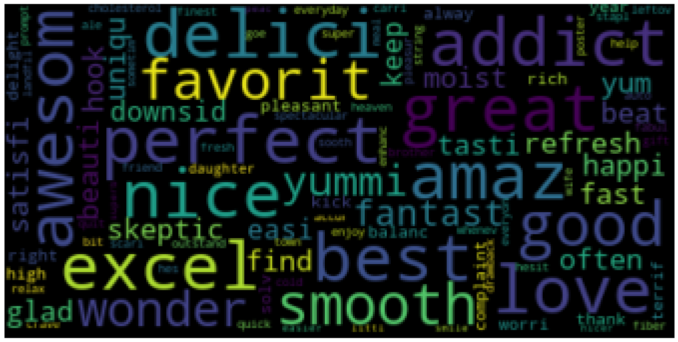
Observation-

- we have 31377 non zero elements in weight before perturbation
- after perturbation test, 2114 elements in weight before perturbation change by more than 30 %
- Thus we can say that the elements weight are collinear

2.1.2 Word Cloud Feature Importance

In [29]:
```
clf = LogisticRegression(C = C, penalty = penalty)
clf.fit(X_train,y_train)
show_cloud(count, clf.coef_)
```

wordcloud for positive class words



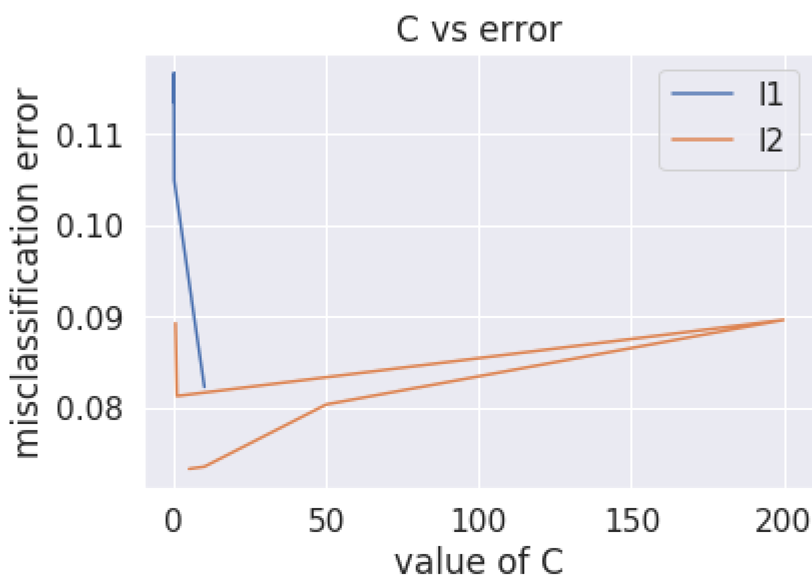
****

wordcloud for negative class words

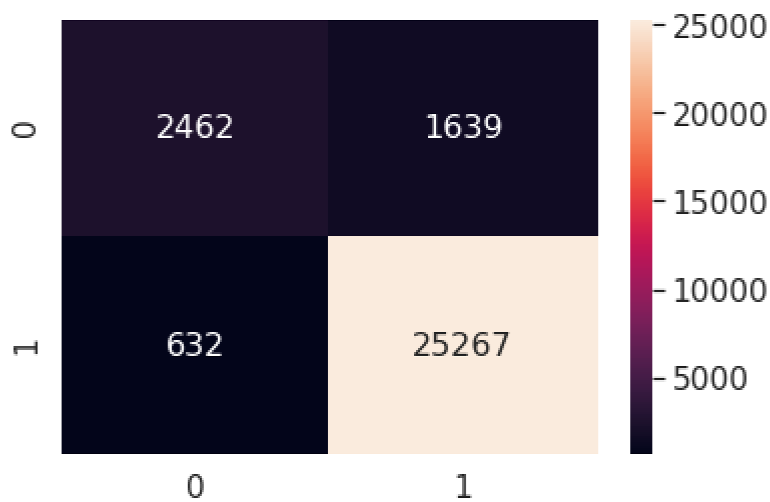
2.2 Random

In [30]:
```
#Breaking into Train and test
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=0.7,shuffle
=False,random_state=0)

tfidf = TfidfVectorizer(ngram_range=(1,1), binary=True)

X_train = tfidf.fit_transform(X_train)

X_test = tfidf.transform(X_test)

C, penalty = LR(search="Random",X_train = X_train, X_test=X_test, y_train=y_tr
ain, y_test=y_test)
```

```
Train Data Size:  (70000, 31377)
Test Data Size:  (30000, 31377)
Fitting 10 folds for each of 10 candidates, totalling 100 fits

[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  1.1min finished

Best HyperParameter:  {'penalty': 'l2', 'C': 5}
Best Accuracy: 92.67%
```




```
Accuracy on test set: 92.430%
Precision on test set: 0.939
Recall on test set: 0.976
F1-Score on test set: 0.957
Non Zero weights: 31377
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```



2.2.1 Word Cloud Feature Importance

In [31]:
```
clf = LogisticRegression(C = C, penalty = penalty)
clf.fit(X_train,y_train)
show_cloud(count, clf.coef_)
```

wordcloud for positive class words

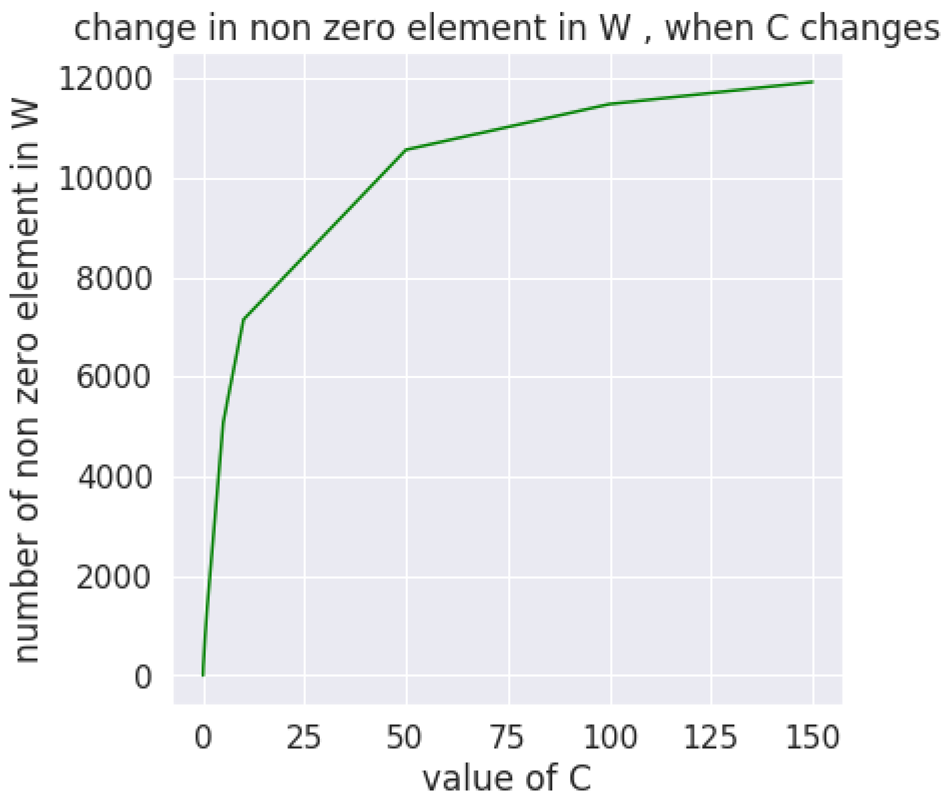
****

wordcloud for negative class words

2.3 Sparsity

In [32]:
```
sparsity(X_train=X_train , y_train=y_train , X_test=X_test , y_test=y_test)
```

```
at C= 0.001
test error= 0.1367
number of non zero element in w= 0
***********************************************
at C= 0.005
test error= 0.1367
number of non zero element in w= 0
***********************************************
at C= 0.01
test error= 0.1367
number of non zero element in w= 4
***********************************************
at C= 0.05
test error= 0.119633333333
number of non zero element in w= 80
***********************************************
at C= 0.1
test error= 0.105733333333
number of non zero element in w= 187
***********************************************
at C= 0.5
test error= 0.0814333333333
number of non zero element in w= 737
***********************************************
at C= 1
test error= 0.0782
number of non zero element in w= 1318
***********************************************
at C= 5
test error= 0.0791666666667
number of non zero element in w= 5086
***********************************************
at C= 10
test error= 0.0841666666667
number of non zero element in w= 7149
***********************************************
at C= 50
test error= 0.101533333333
number of non zero element in w= 10563
***********************************************
at C= 100
test error= 0.1095
number of non zero element in w= 11482
***********************************************
at C= 150
test error= 0.1136
number of non zero element in w= 11928
***********************************************
```



Observation-

- as we increase value of C(decreasing lambda) the sparsity decreases

3.AVG WORD2VEC

In [33]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=0.7,shuffle
=False,random_state=0)
```

In [34]:
```
#url for the GoogleNews word2vec model
url="https://s3.amazonaws.com/dl4j-distribution/GoogleNews-vectors-negative30
0.bin.gz"
```

In [35]:
```
import urllib
urllib.request.urlretrieve (url, "GoogleNews-vectors-negative300.bin.gz")
```

Out[35]:
```
('GoogleNews-vectors-negative300.bin.gz',
 <http.client.HTTPMessage at 0x3ffef3c5fbe0>)
```

In [36]:
```
# import modules & set up logging
import gensim, logging
logging.basicConfig(format='%(asctime)s : %(levelname)s : %(message)s', level=
logging.INFO)
```

In [37]:
```
#Loading the GoogleNews word2vec model(able to read bin.gz file directly, no n
eed to extract)
model = gensim.models.KeyedVectors.load_word2vec_format('GoogleNews-vectors-ne
gative300.bin.gz', binary=True)
```

```
2018-11-12 06:53:54,090 : INFO : loading projection weights from GoogleNews-v
ectors-negative300.bin.gz
2018-11-12 06:56:41,601 : INFO : loaded (3000000, 300) matrix from GoogleNews
-vectors-negative300.bin.gz
```

In [38]:
```
#getting the list of sentences in a 'list'
i=0

list_of_sentences=[]
for sent in X_train.values:
    filtered_sentence=[]
    for w in sent.split():
        #w=w.decode('utf-8')
        if (w==sent.split()[0]):
            w=w[2:]
        filtered_sentence.append(w.lower())
    list_of_sentences.append(filtered_sentence)

print(len(list_of_sentences))
```

```
70000
```

In [39]:
```
words=list(model.wv.vocab)
print(len(words))
```

```
3000000
```

In [40]:
```
#calculating avg word2vec
vectors=[];
for sentence in list_of_sentences:
    sentence_vector=np.zeros(300)
    count_vec=0;
    for word in sentence:
        try:
            vec=model.wv[word]
            sentence_vector+=vec
            count_vec+=1;
        except:
            pass
    sentence_vector/=count_vec
    vectors.append(sentence_vector)
```

In [41]:
```
z=list(np.unique(np.where(np.isnan(vectors))[0]))
z
```

Out[41]:
```
[]
```

In [42]:
```
vectors=np.delete(vectors, z, axis=0)
y_train_word=np.array(y_train)
y_train_word=np.delete(y_train_word, z, axis=0)
```

In [43]:
```
#calculating avg word2vec
x_test_word=[];
for sentence in X_test.values:
    sentence_vector=np.zeros(300)
    count_vec=0;
    for word in sentence.split():
        if(word==sentence.split()[0]):
            word=word[2:]

        try:
            vec=model.wv[word]
            sentence_vector+=vec
            count_vec+=1;
        except:
            pass
    sentence_vector/=count_vec
    x_test_word.append(sentence_vector)


print(len(x_test_word))
```

```
30000
```

In [44]:
```
#checking row containing nan value
z=list(np.unique(np.where(np.isnan(x_test_word))[0]))
z
```

Out[44]:
```
[]
```

In [45]:
```
#deleting row containing nan value
x_test_word=np.delete(x_test_word, z, axis=0)
y_test_word=np.array(y_test)
y_test_word=np.delete(y_test_word, z, axis=0)
```

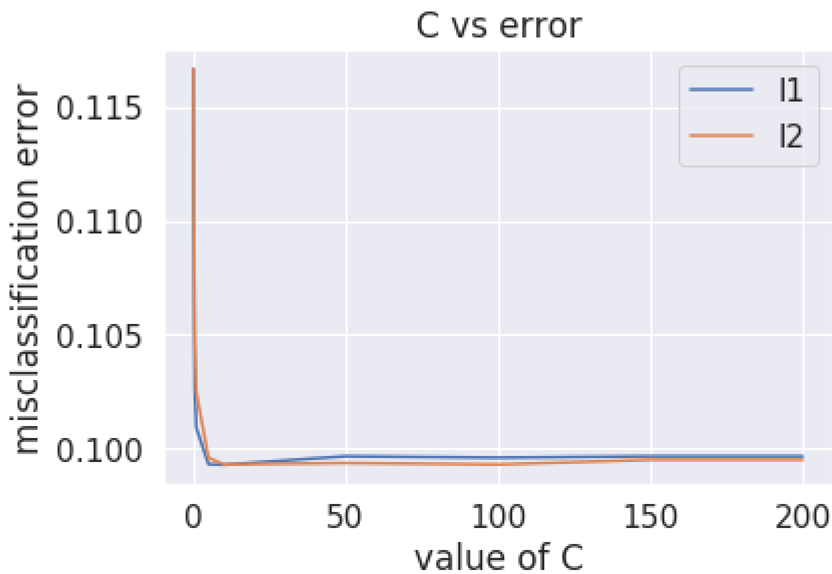
3.1 Grid

In [46]:
```
C, penalty = LR(search="Grid",X_train = vectors, X_test=x_test_word, y_train=y
_train, y_test=y_test)
```

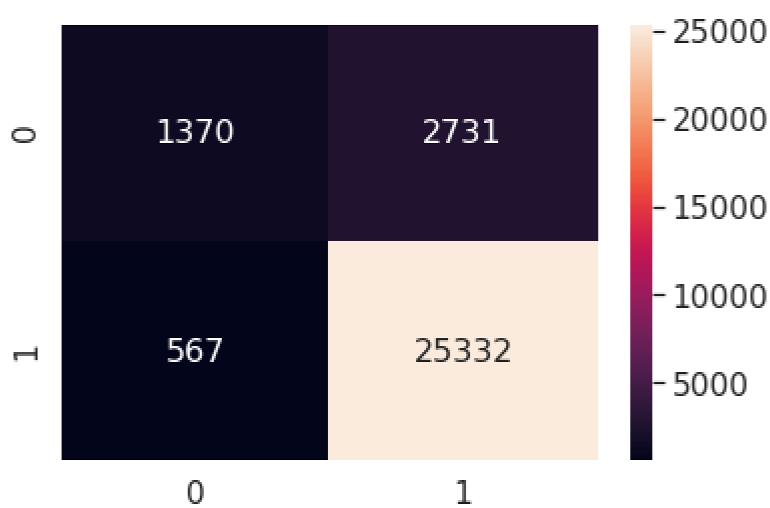
```
Train Data Size:  (70000, 300)
Test Data Size:  (30000, 300)
Fitting 10 folds for each of 26 candidates, totalling 260 fits
```

```
[Parallel(n_jobs=1)]: Done 260 out of 260 | elapsed: 31.5min finished
```

```
Best HyperParameter:  {'C': 10, 'penalty': 'l1'}
Best Accuracy: 90.07%
```




```
Accuracy on test set: 89.007%
Precision on test set: 0.903
Recall on test set: 0.978
F1-Score on test set: 0.939
Non Zero weights: 293
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```



In [47]:
```
#Normalize Data
X_train = preprocessing.normalize(vectors)

X_test = preprocessing.normalize(x_test_word)
```

3.1.1 Perturbation test

In [48]:
```
clf = LogisticRegression(C= C, penalty= penalty)
clf.fit(X_train,y_train)
y_pred = clf.predict(X_test)
w=clf.coef_
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: 89.010%
Non Zero weights: 293
```

In [49]:
```
X_train.data = X_train.data + np.random.normal(loc=0,scale=0.1,size=X_train.sh
ape) #adding a noise with a very small value
```

In [50]:
```
#computing weight after perturbation weight
clf=LogisticRegression(C=C, penalty=penalty)
clf.fit(X_train,y_train)
w_=clf.coef_
print('number of non-zero element in w_=', np.count_nonzero(w_))
```

```
number of non-zero element in w_= 298
```

In [51]:
```
#getting the number of elements in w which changes after perturbation test by
 more than 50%
w_delta=abs((w-w_)/w)*100
cnt=0
for i in range(len(w_delta[0])):
    if (w_delta[0][i]>30):
        cnt+=1
print('number of elements in w_delta,more than 30% =',cnt)
```

```
number of elements in w_delta,more than 30% = 290
```

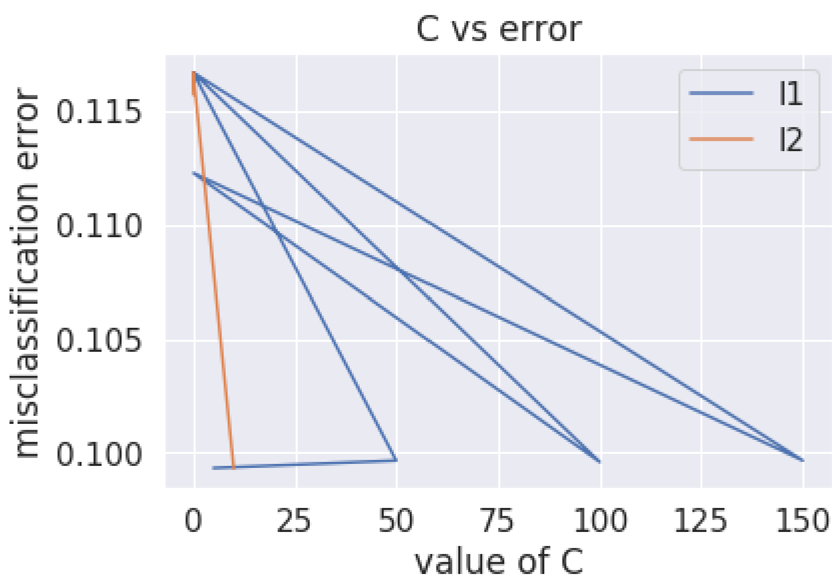
Observation-

- we have 300 non zero elements in weight before perturbation
- after perturbation test, 290 elements in weight before perturbation change by more than 30 %
- Thus we can say that elements weight are collinear

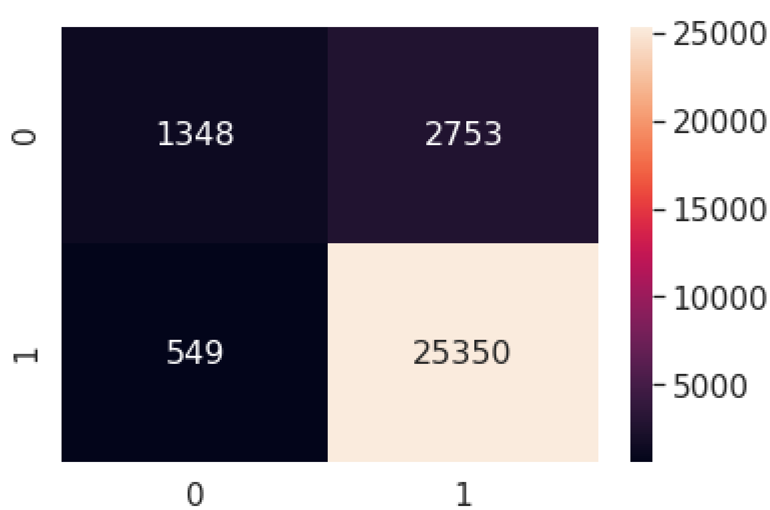
3.2 Random

In [52]:
```
C, penalty = LR(search="Random",X_train = vectors, X_test=x_test_word, y_train
=y_train, y_test=y_test)
```

```
Train Data Size:  (70000, 300)
Test Data Size:  (30000, 300)
Fitting 10 folds for each of 10 candidates, totalling 100 fits

[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed: 15.5min finished

Best HyperParameter:  {'penalty': 'l2', 'C': 10}
Best Accuracy: 90.07%
```



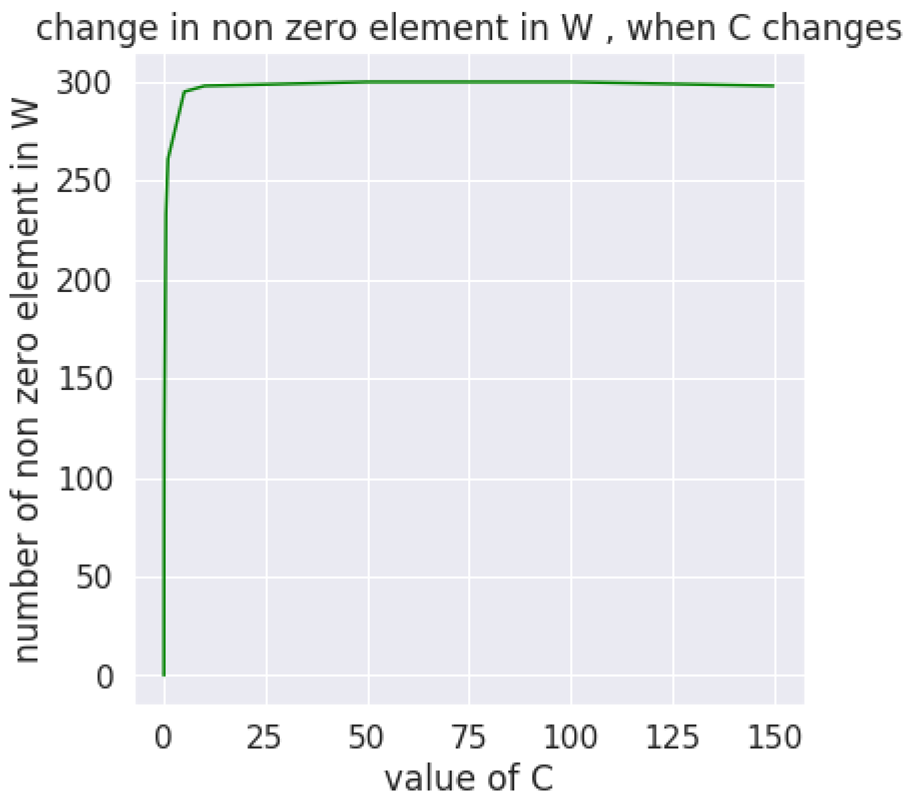

```
Accuracy on test set: 88.993%
Precision on test set: 0.902
Recall on test set: 0.979
F1-Score on test set: 0.939
Non Zero weights: 300
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```



3.3 Sparsity

In [53]:
```
sparsity(X_train = vectors, X_test= x_test_word, y_train=y_train, y_test=y_tes
t)
```

```
at C= 0.001
test error= 0.1367
number of non zero element in w= 0
***********************************************
at C= 0.005
test error= 0.1367
number of non zero element in w= 0
***********************************************
at C= 0.01
test error= 0.1367
number of non zero element in w= 7
***********************************************
at C= 0.05
test error= 0.131133333333
number of non zero element in w= 76
***********************************************
at C= 0.1
test error= 0.123733333333
number of non zero element in w= 125
***********************************************
at C= 0.5
test error= 0.115233333333
number of non zero element in w= 233
***********************************************
at C= 1
test error= 0.114066666667
number of non zero element in w= 261
***********************************************
at C= 5
test error= 0.113166666667
number of non zero element in w= 295
***********************************************
at C= 10
test error= 0.112733333333
number of non zero element in w= 298
***********************************************
at C= 50
test error= 0.112433333333
number of non zero element in w= 300
***********************************************
at C= 100
test error= 0.112433333333
number of non zero element in w= 300
***********************************************
at C= 150
test error= 0.112466666667
number of non zero element in w= 298
***********************************************
```



Observation-

- as we increase value of C(decreasing lambda) the sparsity decreases

4. TFDIF WORD2VEC

In [67]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=0.7,shuffle
=False,random_state=0)

tfidf=TfidfVectorizer(ngram_range=(1,1))
x_train_tfidf=tfidf.fit_transform(X_train.values)
x_test_tfidf=tfidf.transform(X_test.values)

#dictionary = dict(zip(tfidf.get_feature_names(), list(tfidf.idf_)))
```

In [68]:
```
features=tfidf.get_feature_names()
len(features)
```

Out[68]: 31377

In [79]:
```
#calculating tf-idf w2vec
tfidf_vectors = [];
row=0;
for sentence in list_of_sentences:
    sentence_vec = np.zeros(300)
    weight_sum =0;
    for word in sentence:
        try:
            vec = model.wv[word]
            tf_idf = x_train_tfidf[row, features.index(word)]
            sentence_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sentence_vec /= weight_sum
    tfidf_vectors.append(sentence_vec)
    row += 1

print(len(tfidf_vectors))
```

```
70000
```

In [81]:
```
z=list(np.unique(np.where(np.isnan(tfidf_vectors))[0]))
z
```

Out[81]:
```
[1622, 1695, 11064, 55871, 60700]
```

In [82]:
```
y_train_word=np.array(y_train)
y_train_word=np.delete(y_train_word, z, axis=0)
tfidf_vectors=np.delete(tfidf_vectors, z, axis=0)
```

In [83]:
```
print(len(tfidf_vectors))
```

```
69995
```

In [73]:
```
#calculating tf-idf w2vec
x_test_tf_word = [];
row=0;
for sentence in X_test.values:
    sentence_vec = np.zeros(300)
    weight_sum =0;
    for word in sentence.split():
        if(word==sentence.split()[0]):
            word=word[2:]

        try:
            vec = model.wv[word]
            tf_idf = x_test_tfidf[row, features.index(word)]
            sentence_vec += (vec * tf_idf)
            weight_sum += tf_idf
        except:
            pass
    sentence_vec /= weight_sum
    x_test_tf_word.append(sentence_vec)
    row += 1
```

In [74]:
```
print(len(x_test_tf_word))
```

30000

In [75]:
```
z=list(np.unique(np.where(np.isnan(x_test_tf_word))[0]))
z
```

Out[75]: []

In [76]:
```
x_test_tf_word=np.delete(x_test_tf_word, z , axis=0)
len(x_test_tf_word)
```

Out[76]: 30000

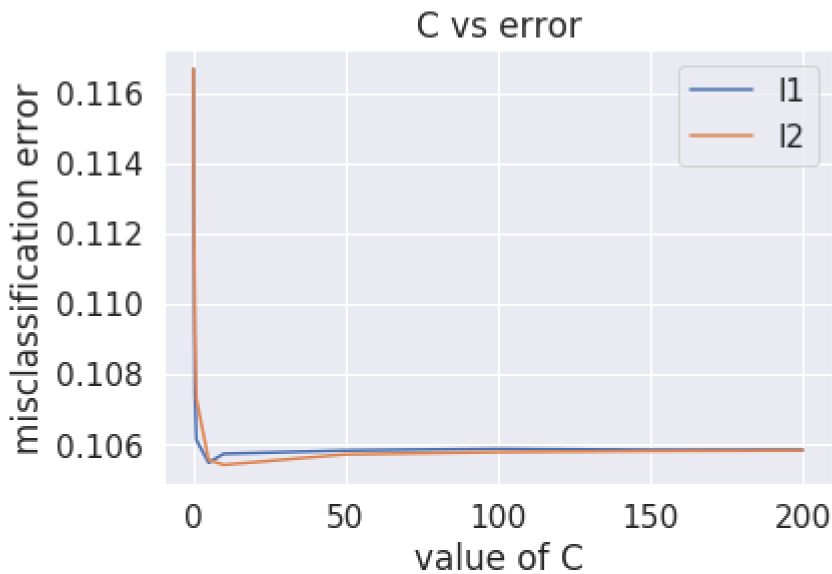
In [77]:
```
y_test_word=np.array(y_test)
y_test_word=np.delete(y_test_word, z, axis=0)
len(x_test_word)
```

Out[77]: 30000

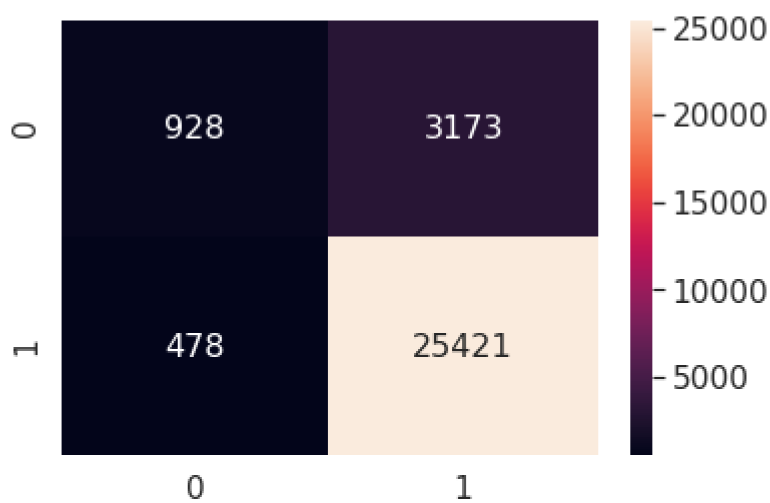
4.1 Grid

In [86]:
```
C, penalty = LR(search="Grid",X_train = tfidf_vectors, X_test = x_test_tf_word
, y_train = y_train_word, y_test = y_test)
```

```
Train Data Size:  (69995, 300)
Test Data Size:  (30000, 300)
Fitting 10 folds for each of 26 candidates, totalling 260 fits

[Parallel(n_jobs=1)]: Done 260 out of 260 | elapsed: 21.6min finished

Best HyperParameter:  {'C': 10, 'penalty': 'l2'}
Best Accuracy: 89.46%
```




```
Accuracy on test set: 87.830%
Precision on test set: 0.889
Recall on test set: 0.982
F1-Score on test set: 0.933
Non Zero weights: 300
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```



In [87]:
```
#Normalize Data
X_train = preprocessing.normalize(tfidf_vectors)

#Normalize Data
X_test = preprocessing.normalize(x_test_tf_word)
```

4.1.1 Perturbation test

In [88]:
```
clf = LogisticRegression(C = C, penalty = penalty)
clf.fit(X_train,y_train_word)
y_pred = clf.predict(X_test)
w=clf.coef_
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: 87.830%
Non Zero weights: 300
```

In [89]:
```
X_train.data=X_train.data+np.random.normal(loc=0,scale=0.1,size=X_train.data.s
hape) #adding a noise with a very small value
```

In [90]:
```
#computing weight after perturbation weight
clf=LogisticRegression(C=C, penalty=penalty)
clf.fit(X_train,y_train_word)
w_=clf.coef_
print('number of non-zero element in w_=', np.count_nonzero(w_))
```

```
number of non-zero element in w_= 300
```

In [91]:
```
#getting the number of elements in w which changes after perturbation test by
 more than 50%
w_delta=abs((w-w_)/w)*100
cnt=0
for i in range(len(w_delta[0])):
    if (w_delta[0][i]>50):
        cnt+=1
print('number of elements in w_delta,more than 50% =',cnt)
```

```
number of elements in w_delta,more than 50% = 272
```

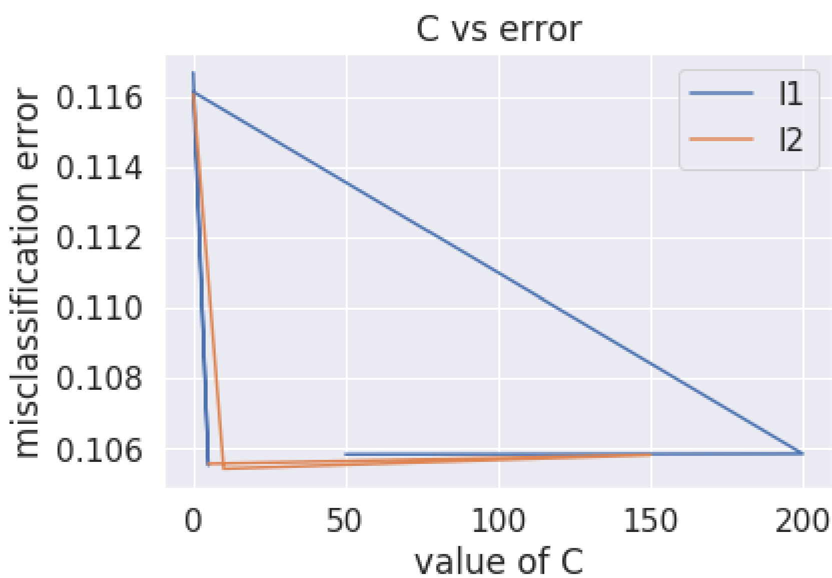
Observation-

- we have 300 non zero elements in weight before perturbation
- after perturbation test, 272 elements in weight before perturbation change by more than 30 %
- we can say that it is collinear

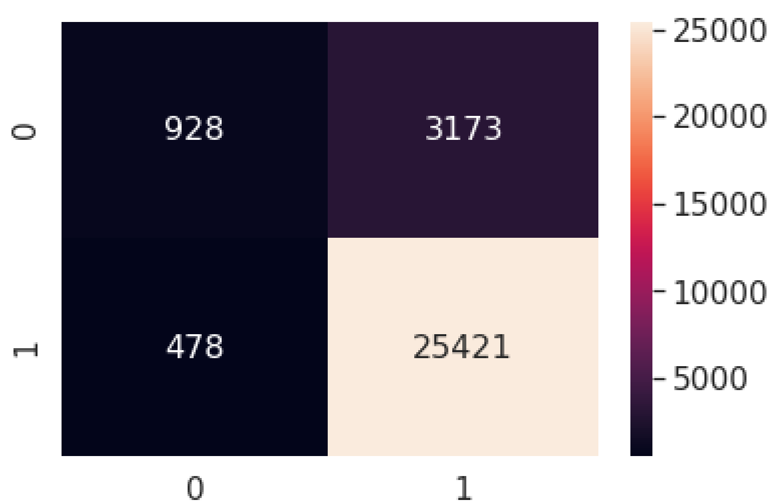
4.2 Random

In [92]:
```
C, penalty = LR(search="Random",X_train = tfidf_vectors, X_test = x_test_tf_wo
rd, y_train = y_train_word, y_test = y_test)
```

```
Train Data Size:  (69995, 300)
Test Data Size:  (30000, 300)
Fitting 10 folds for each of 10 candidates, totalling 100 fits

[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:  8.4min finished

Best HyperParameter:  {'penalty': 'l2', 'C': 10}
Best Accuracy: 89.46%
```



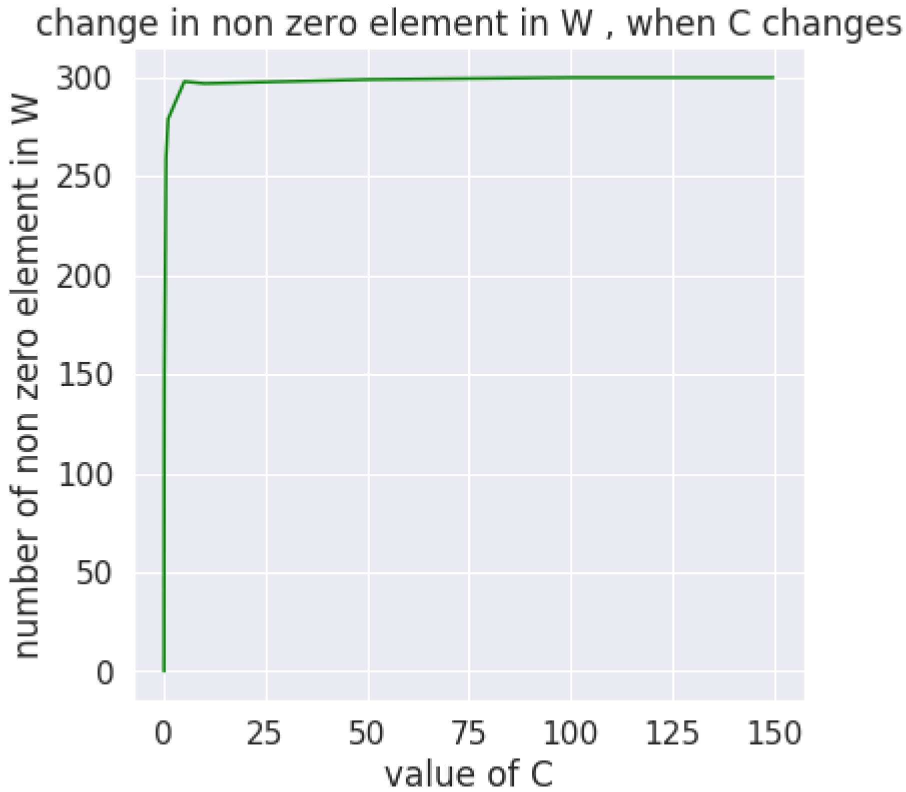

```
Accuracy on test set: 87.830%
Precision on test set: 0.889
Recall on test set: 0.982
F1-Score on test set: 0.933
Non Zero weights: 300
Confusion Matrix of test set:
 [ [TN  FP]
 [FN TP] ]
```



4.3 Sparsity

In [94]:
```
sparsity(X_train = tfidf_vectors, X_test = x_test_tf_word, y_train = y_train_w
ord, y_test = y_test)
```

```
at C= 0.001
test error= 0.1367
number of non zero element in w= 0
***********************************************
at C= 0.005
test error= 0.1367
number of non zero element in w= 0
***********************************************
at C= 0.01
test error= 0.1367
number of non zero element in w= 6
***********************************************
at C= 0.05
test error= 0.134666666667
number of non zero element in w= 102
***********************************************
at C= 0.1
test error= 0.1313
number of non zero element in w= 151
***********************************************
at C= 0.5
test error= 0.1262
number of non zero element in w= 259
***********************************************
at C= 1
test error= 0.125233333333
number of non zero element in w= 279
***********************************************
at C= 5
test error= 0.1251
number of non zero element in w= 298
***********************************************
at C= 10
test error= 0.125066666667
number of non zero element in w= 297
***********************************************
at C= 50
test error= 0.1251
number of non zero element in w= 299
***********************************************
at C= 100
test error= 0.125133333333
number of non zero element in w= 300
***********************************************
at C= 150
test error= 0.125133333333
number of non zero element in w= 300
***********************************************
```



Observation-

- as we increase value of C(decreasing lambda) the sparsity decreases

Performance Table

ALGORITHM	Search	C	Penalty	Accuracy	Precision	Recall	F1-Score
BOW	GRID	10	L2	92.393%	0.939	0.975	0.957
	RANDOM	1	L1	92.073%	0.933	0.979	0.955
TFIDF	GRID	5	L2	92.430%	0.939	0.976	0.957
	RANDOM	5	L2	92.430%	0.939	0.976	0.957
AVG W2V	GRID	10	L1	89.077%	0.903	0.978	0.939
	RANDOM	10	L2	88.993%	0.902	0.979	0.939
TFIDF W2v	GRID	10	L2	87.830%	0.889	0.982	0.933
	RANDOM	10	L2	87.830%	0.889	0.982	0.933

Observation

- we have taken amazon fine food review and applied logistic regression model using BoW, Tfidf, Avg word2vec and Tfidf word2vec.
- the Accuracy comes for tfidf and bag of words is fairly good.
- in the final table we can see that Logistic regression works well for BOW and TFIDF, but not good in case of avg word2vec and tfidf word2vec.
- we can conclude that logistic regression works fairly well if dimension is high