

Assignment:-

Applying Logistic Regression on Amazon fine Food Reviews analysis

Amazon Fine Food Reviews Analysis

Data Source: <https://www.kaggle.com/snap/amazon-fine-food-reviews> (<https://www.kaggle.com/snap/amazon-fine-food-reviews>)

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 - unique 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

1. Objective:

Given a review, determine whether the review is positive (Rating of 4 or 5) or negative (rating of 1 or 2). Use BoW, TF-IDF, Avg-Word2Vec, TF-IDF-Word2Vec to vectorise the reviews. Apply Logistic Regression Algorithm for Amazon fine food Reviews find right α using cross validation Get feature importance for positive class and Negative class

In [1]:

```
# Loading required libraries

import warnings
warnings.filterwarnings('ignore')

import numpy as np
import pandas as pd
import matplotlib
import sqlite3
import string
import gensim
import scipy
import nltk
import time
import seaborn as sns
from scipy import stats
from matplotlib import pyplot as plt

from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer

from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from sklearn.linear_model import LogisticRegression

from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve, roc_auc_score, auc
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_recall_fscore_support as prf1

from sklearn.model_selection import KFold
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score
```

1.1 Connecting SQL file

In [2]:

```
#Loading the data
con = sqlite3.connect('./final.sqlite')

data = pd.read_sql_query("""
SELECT *
FROM Reviews
""", con)
```

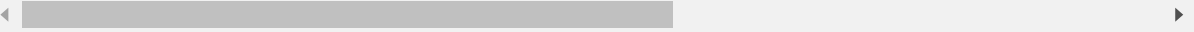
In [3]:

```
print(data.shape)
data.head()
```

(364171, 12)

Out[3]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Helpful
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
1	138688	150506	0006641040	A2IW4PEEKO2R0U	Tracy	1	
2	138689	150507	0006641040	A1S4A3IQ2MU7V4	sally sue "sally sue"	1	
3	138690	150508	0006641040	AZGXZ2UUK6X	Catherine Hallberg " (Kate)"	1	
4	138691	150509	0006641040	A3CMRKGE0P909G	Teresa	3	



1.2 Data Preprocessing

In [4]:

```
data.Score.value_counts()  
#i had done data preprocessing i had stored in final.sqlite now loaded this file no need to
```

Out[4]:

positive 307061
negative 57110
Name: Score, dtype: int64

1.3 Sorting the data

In [5]:

```
# Sorting the data according to the time-stamp  
sorted_data = data.sort_values('Time', axis=0, ascending=True, inplace=False, kind='quicksort')  
sorted_data.head()
```

Out[5]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpDenominator
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	1
30	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	3
424	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	1
330	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	2
423	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	1

1.4 Mapping

In [6]:

```
def partition(x):
    if x == 'positive':
        return 1
    return 0

#Preparing the filtered data
actualScore = sorted_data['Score']
positiveNegative = actualScore.map(partition)
sorted_data['Score'] = positiveNegative
sorted_data.head()
```

Out[6]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Help
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
30	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
424	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	
330	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	
423	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	

1.5 Taking First 150K Rows

In [7]:

```
# We will collect different 150000 rows without repetition from time_sorted_data dataframe
my_final = sorted_data[:150000]
print(my_final.shape)
my_final.head()
```

(150000, 12)

Out[7]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	Help
0	138706	150524	0006641040	ACITT7DI6IDDL	shari zychinski	0	
30	138683	150501	0006641040	AJ46FKXOVC7NR	Nicholas A Mesiano	2	
424	417839	451856	B00004CXX9	AIUWLEQ1ADEG5	Elizabeth Medina	0	
330	346055	374359	B00004CI84	A344SMIA5JECGM	Vincent P. Ross	1	
423	417838	451855	B00004CXX9	AJH6LUC1UT1ON	The Phantom of the Opera	0	



1.6 Splitting data into train and test based on time (70:30)

In [8]:

```
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_validate

x=my_final['CleanedText'].values
y=my_final['Score']

#Splitting data into train test and cross validation
x_train,x_test,y_train,y_test =train_test_split(x,y,test_size =0.3,random_state = 42)

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(105000,)
(45000,)
(105000,)
(45000,)
```

2. Techniques For Vectorization

Why we have to convert text to vector

By converting text to vector we can use whole power of linear algebra. we can find a plane to separate

In case of logistic regression to find important features, firstly we have to check multi collinearity between features, if

features are collinear then we should find important features using forward or backward feature selection.

If features are not correlated then we should use optimal vector, in which consist of weight for each feature.

Multi collinearity: which means very high inter correlation among the independent variables.

2.1 BOW

In [9]:

#Bow

```
from sklearn.feature_extraction.text import CountVectorizer
count_vect = CountVectorizer()
final_counts_Bow_tr= count_vect.fit_transform(x_train)# computing Bow
print("the type of count vectorizer ",type(final_counts_Bow_tr))
print("the shape of out text BOW vectorizer ",final_counts_Bow_tr.get_shape())
print("the number of unique words ", final_counts_Bow_tr.get_shape()[1])
final_counts_Bow_test= count_vect.transform(x_test)# computing Bow
print("the type of count vectorizer ",type(final_counts_Bow_test))
print("the shape of out text BOW vectorizer ",final_counts_Bow_test.get_shape())
```

```
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (105000, 38300)
the number of unique words 38300
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text BOW vectorizer (45000, 38300)
```

2.1.1 Standardizing Data

In [10]:

Data-preprocessing: Standardizing the data

```
from sklearn import preprocessing
standardized_data_train = preprocessing.normalize(final_counts_Bow_tr)
print(standardized_data_train.shape)
standardized_data_test = preprocessing.normalize(final_counts_Bow_test)
print(standardized_data_test.shape)
```

```
(105000, 38300)
(45000, 38300)
```

2.2 Applying Logistic Regression Algorithm

2.2.1 Gridsearch Cross Validation

2.2.1.1 Using L1 Regularization

In [15]:

```
# Finding the best parameters using Grid Search CV using 10-fold Cross-Validation in Logistic Regression

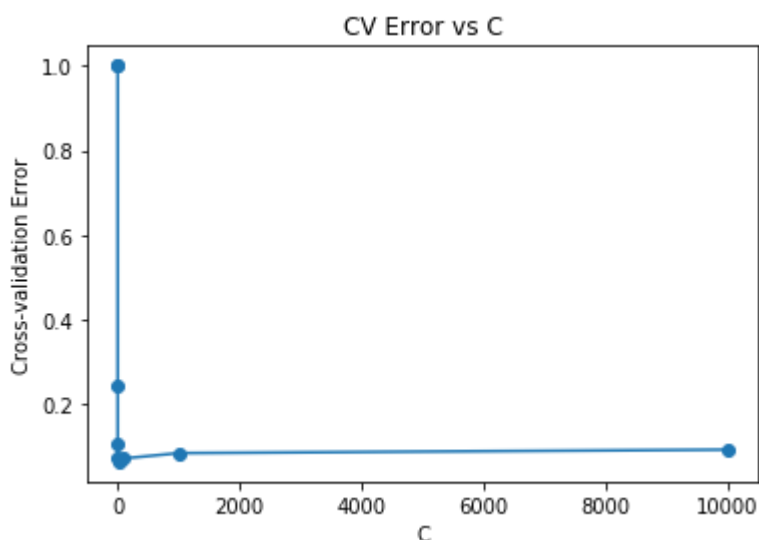
from sklearn.model_selection import GridSearchCV
tuned_parameters = [{'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}]
model = GridSearchCV(LogisticRegression(penalty='l1', class_weight='balanced'), tuned_parameters)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("Accuracy of the test model : ", model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is : LogisticRegression(C=10, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
Accuracy of the test model : 0.9360583243695472
```

Plotting a graph between C vs CV Error

In [21]:

```
score = model.cv_results_
score
plot_df = pd.DataFrame(score)
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")
plt.title("CV Error vs C")
plt.xlabel("C")
plt.ylabel("Cross-validation Error")
plt.show()
```



In [22]:

```
model.best_params_
```

Out[22]:

```
{'C': 10}
```

In [23]:

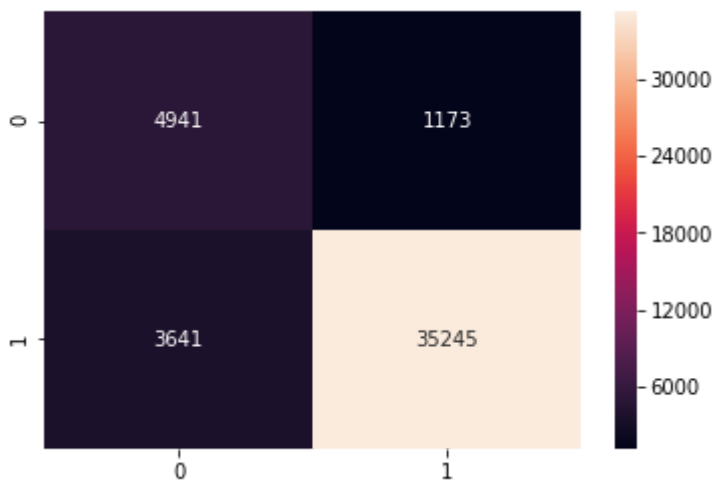
```
# Logistic Regression with Optimal value of C(1/Lambda)
lr = LogisticRegression(penalty='l1',class_weight='balanced', C=optimal_C, n_jobs=-1)
lr.fit(standardized_data_train,y_train)
pred_bow = lr.predict(standardized_data_test)
```

2.3 Confusion Matrix

In [24]:

```
cm_bow=confusion_matrix(y_test,pred_bow)
print("Confusion Matrix:")
sns.heatmap(cm_bow, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [25]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_bow.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 4941
false positives are 1173
false negatives are 3641
true positives are 35245
```

2.4 Calculating Accuracy, Error on test data, Precision, Recall, Classification Report

In [26]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_bow) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_bow = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_bow))

# evaluating precision
precision_score = precision_score(y_test, pred_bow)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_bow)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_bow)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 10.000 is 93.607245%

Test Error Logistic Regression classifier is 6.392755%

The Test Precision of the Logistic Regression classifier for C = 10.000 is 0.967791

The Test Recall of the Logistic Regression classifier for C = 10.000 is 0.906367

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.58	0.81	0.67	6114
1	0.97	0.91	0.94	38886
micro avg	0.89	0.89	0.89	45000
macro avg	0.77	0.86	0.80	45000
weighted avg	0.91	0.89	0.90	45000

2.5 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [27]:

```
import scipy as sp
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_

# Number of non zero elements in Standardized_train sparse matrix
no_of_non_zero = standardized_data_train.count_nonzero()

# Importing library to create a sparse matrix of epsilon
from scipy.sparse import csr_matrix

# Creating new sparse matrix with epsilon at same position of non-zero elements of standarda
x_train_indices = standardized_data_train.indices
x_train_indptr = standardized_data_train.indptr #CSR format index pointer array of the matr

# Creating a List of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = standardized_data_train.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,x_train_indices,x_train_indptr),shape=Shape,dtype=float)

# Add sparse_epsilon and X-standardized_data_train to get a new sparse matrix with epsilon
# non-zero element of standardized_data_train
epsilon_train = standardized_data_train + sparse_epsilon

print(standardized_data_train.shape)
print(epsilon_train.shape)
```

```
(105000, 38300)
(105000, 38300)
```

In [28]:

```

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
print("change_vector",change_vector)

# Sort this change_vector array after making all the elements positive in ascending order
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]

```

```

change_vector [ [-0.1873746   0.00267988  0.00070299 ...  0.07092126  0.00300
243
               0.02447227]]

```

Out[28]:

```

array([80.43086568, 68.34253473, 63.44736738, 62.67995684, 61.84514268,
       56.74291376, 48.17445131, 47.03001171, 47.00663241, 45.7840874 ,
       45.65869711, 45.54055911, 43.44398893, 42.32506811, 42.15079776,
       41.85722319, 40.20008194, 40.06860416, 39.52365714, 39.39666727])

```

In [29]:

```

absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,:-1]
top_index = sorted_absolute_index[0,0:20]

all_features = count_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t==> \t%f"%(all_features[j],weight_values[0,j]))

```

Top 20 features with their weight values :

mozzarella	==>	-81.221340
sonewher	==>	-69.028203
ov	==>	-64.114077
devault	==>	-63.686052
yadayadayada	==>	-63.632296
dcide	==>	-57.967970
gould	==>	-50.026035
disastr	==>	-49.416620
conceal	==>	48.887017
cucazza	==>	-47.661094
goodwil	==>	-46.443136
distrust	==>	-45.964719
robitussin	==>	-45.468910
coil	==>	-44.417557
differr	==>	-43.397257
lvoe	==>	-42.912444
yap	==>	-42.056988
sheat	==>	-40.935271
valentina	==>	-40.833585
allrecip	==>	-40.803531

2.7 Using L2 Regularization

In [31]:

```
# Finding the best parameters using Grid Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import GridSearchCV
tuned_parameters = [{'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}]
model = GridSearchCV(LogisticRegression(penalty='l2', class_weight='balanced'), tuned_parameters)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L2 Regularization", model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is :  LogisticRegression(C=100, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

```
Accuracy of model using L2 Regularization 0.9360205922938117
```

In [32]:

```
model.best_params_
```

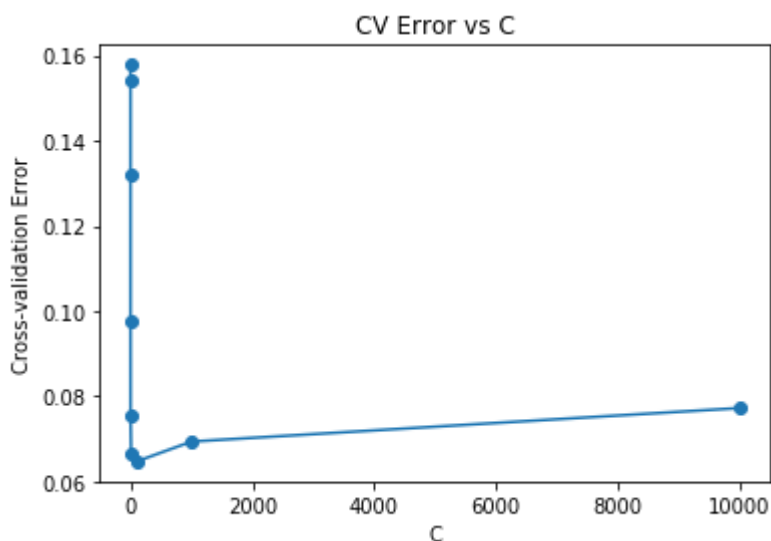
Out[32]:

```
{'C': 100}
```

Plotting a graph between C vs CV Error

In [33]:

```
score = model.cv_results_
score
plot_df = pd.DataFrame(score)
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")
plt.title("CV Error vs C")
plt.xlabel("C")
plt.ylabel("Cross-validation Error")
plt.show()
```



In [34]:

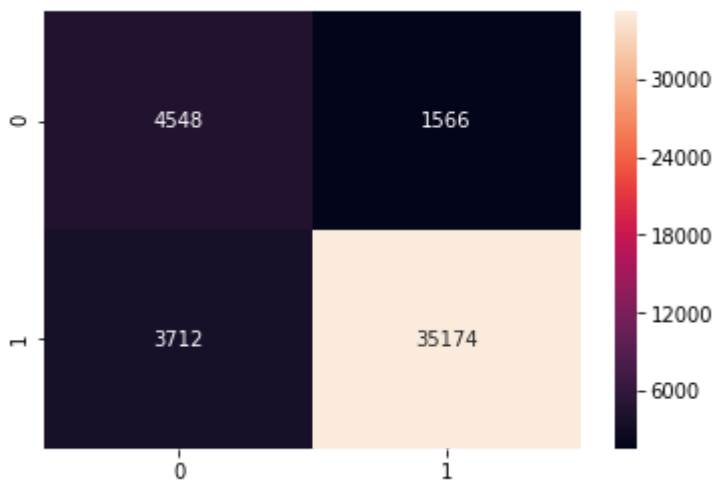
```
# Logistic Regression with Optimal value of C(1/Lambda)
lr = LogisticRegression(penalty='l1', C=optimal_C, class_weight='balanced', n_jobs=-1)
lr.fit(standardized_data_train, y_train)
pred_bow = lr.predict(standardized_data_test)
```

2.8 Confusion Matrix

In [35]:

```
cm_bow=confusion_matrix(y_test, pred_bow)
print("Confusion Matrix:")
sns.heatmap(cm_bow, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [36]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_bow.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true positives are {}")
```

```
true negitves are 4548
false positives are 1566
false negatives are 3712
true positives are 35174
```

2.9 Calculating Accuracy, Error on test data, Precision, Recall, Classification Report

In [37]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_bow) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_bow = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_bow))

# evaluating precision
precision_score = precision_score(y_test, pred_bow)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_bow)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_bow)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 100.000 is 93.020919%

Test Error Logistic Regression classifier is 6.979081%

The Test Precision of the Logistic Regression classifier for C = 100.000 is 0.957376

The Test Recall of the Logistic Regression classifier for C = 100.000 is 0.904541

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.55	0.74	0.63	6114
1	0.96	0.90	0.93	38886
micro avg	0.88	0.88	0.88	45000
macro avg	0.75	0.82	0.78	45000
weighted avg	0.90	0.88	0.89	45000

3.Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [38]:

```
import scipy as sp
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_

# Number of non zero elements in Standardized_train sparse matrix
no_of_non_zero = standardized_data_train.count_nonzero()

# Importing library to create a sparse matrix of epsilon
from scipy.sparse import csr_matrix

# Creating new sparse matrix with epsilon at same position of non-zero elements of standarda
x_train_indices = standardized_data_train.indices
x_train_indptr = standardized_data_train.indptr #CSR format index pointer array of the matr

# Creating a List of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = standardized_data_train.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,x_train_indices,x_train_indptr),shape=Shape,dtype=float)

# Add sparse_epsilon and X-standardized_data_train to get a new sparse matrix with epsilon
# non-zero element of standardized_data_train
epsilon_train = standardized_data_train + sparse_epsilon

print(standardized_data_train.shape)
print(epsilon_train.shape)
```

(105000, 38300)

(105000, 38300)

In [39]:

```
# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
print("change_vector",change_vector)

# Sort this change_vector array after making all the elements positive in ascending order
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

```
change_vector [ [-0.3867784    0.013296    0.00259353 ...  0.52455324  0.01590
12
               0.20404927]]
```

Out[39]:

```
array([279.88916404, 244.91940143, 243.18414983, 224.58891442,
       213.15402917, 184.8338223 , 182.25287213, 174.99382919,
       171.76343844, 169.23931672, 162.98911142, 162.7482134 ,
       161.09247776, 158.70466949, 157.13688115, 156.48302254,
       152.58759764, 151.56174503, 150.27188927, 149.85086208])
```

In [40]:

```

absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,:-1]
top_index = sorted_absolute_index[0,0:20]

all_features = count_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t==> \t%f"%(all_features[j],weight_values[0,j]))

```

Top 20 features with their weight values :

fishier	==>	-285.189896
corect	==>	-251.244529
reclin	==>	243.727351
uninari	==>	-236.927149
advantix	==>	-218.522241
conlus	==>	-188.172908
poem	==>	185.440551
jivalim	==>	-179.081780
goodwil	==>	-178.036782
sonewher	==>	-176.035821
mozzerela	==>	-170.565604
ridx	==>	-168.175897
hermosa	==>	-165.468684
anywh	==>	-164.294790
glimps	==>	-161.119542
crosswis	==>	-160.959288
opportunistic	==>	-156.879202
grainiest	==>	-156.172455
settlement	==>	155.095231
colicki	==>	154.755744

3.1 Randomized Search Cross Validation

3.1.1 Using L1 Regularization

In [43]:

```
# Finding the best parameters using Random Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import RandomizedSearchCV
param_distributions = {'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}
model = RandomizedSearchCV(LogisticRegression(penalty = 'l1', class_weight='balanced'), param_distributions, cv=10)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L1 Regularization", model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is :  LogisticRegression(C=100, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

```
Accuracy of model using L1 Regularization 0.9302091873165313
```

In [44]:

```
model.best_params_
```

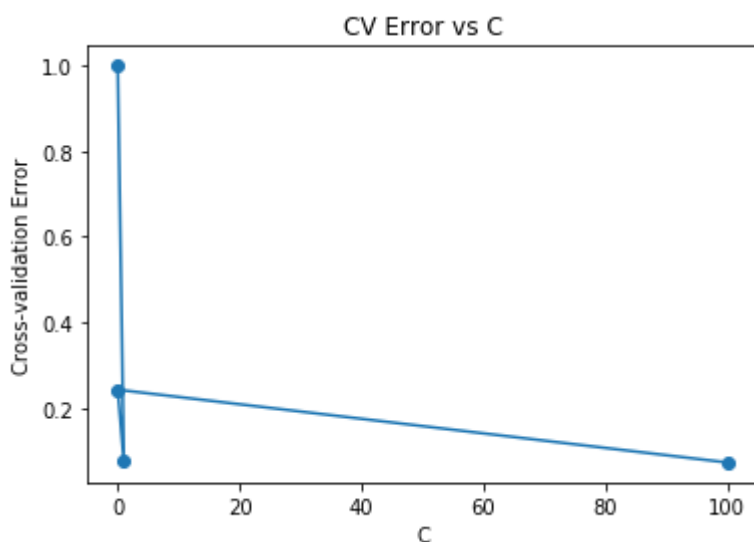
Out[44]:

```
{'C': 100}
```

Plotting a graph between C vs CV Error

In [45]:

```
score = model.cv_results_
score
plot_df = pd.DataFrame(score)
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")
plt.title("CV Error vs C")
plt.xlabel("C")
plt.ylabel("Cross-validation Error")
plt.show()
```



In [46]:

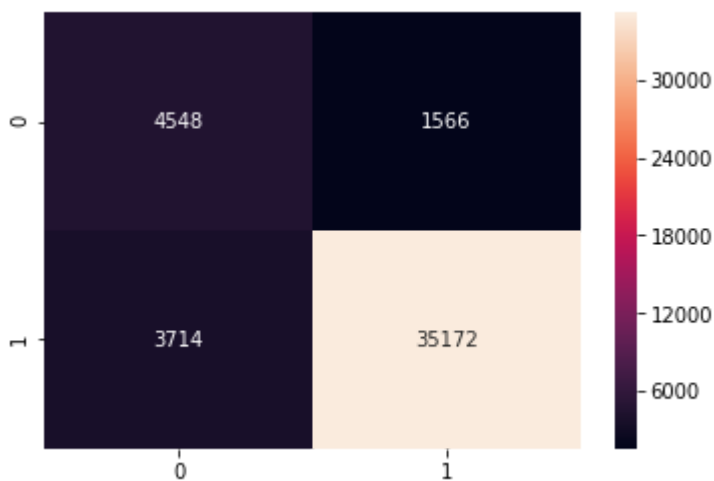
```
# Logistic Regression with Optimal value of C(1/Lambda)
lr = LogisticRegression(penalty='l1', C=optimal_C, class_weight='balanced', n_jobs=-1)
lr.fit(standardized_data_train, y_train)
pred_bow = lr.predict(standardized_data_test)
```

3.2 Confusion Matrix

In [47]:

```
cm_bow = confusion_matrix(y_test, pred_bow)
print("Confusion Matrix:")
sns.heatmap(cm_bow, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [48]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_bow.ravel()
(tn, fp, fn, tp)
print(" true negitives are {} \n false positives are {} \n false negatives are {} \n true positives are {}")
```

```
true negitives are 4548
false positives are 1566
false negatives are 3714
true positives are 35172
```

3.3 Calculating Accuracy, Error on test data, Precision, Recall, Classification Report

In [49]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_bow) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_bow = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_bow))

# evaluating precision
precision_score = precision_score(y_test, pred_bow)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_bow)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_bow)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 100.000 is 93.018089%

Test Error Logistic Regression classifier is 6.981911%

The Test Precision of the Logistic Regression classifier for C = 100.000 is 0.957374

The Test Recall of the Logistic Regression classifier for C = 100.000 is 0.904490

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.55	0.74	0.63	6114
1	0.96	0.90	0.93	38886
micro avg	0.88	0.88	0.88	45000
macro avg	0.75	0.82	0.78	45000
weighted avg	0.90	0.88	0.89	45000

3.4 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [50]:

```
import scipy as sp
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_

# Number of non zero elements in Standardized_train sparse matrix
no_of_non_zero = standardized_data_train.count_nonzero()

# Importing library to create a sparse matrix of epsilon
from scipy.sparse import csr_matrix

# Creating new sparse matrix with epsilon at same position of non-zero elements of standarda
x_train_indices = standardized_data_train.indices
x_train_indptr = standardized_data_train.indptr #CSR format index pointer array of the matr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = standardized_data_train.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,x_train_indices,x_train_indptr),shape=Shape,dtype=float)

# Add sparse_epsilon and X-standardized_data_train to get a new sparse matrix with epsilon
# non-zero element of standardized_data_train
epsilon_train = standardized_data_train + sparse_epsilon

print(standardized_data_train.shape)
print(epsilon_train.shape)
```

```
(105000, 38300)
(105000, 38300)
```


In [51]:

```
# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
print("change_vector",change_vector)

# Sort this change_vector array after making all the elements positive in ascending order
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

```
change_vector [[-0.38614634  0.01331118  0.00259891 ...  0.5272905  0.01586
398
               0.20437205]]
```

Out[51]:

```
array([279.89783694, 244.92999676, 243.273134 , 224.13152239,
       213.19758887, 184.79413525, 182.30110335, 174.95294991,
       171.72373889, 169.2394331 , 162.7680524 , 161.05276989,
       158.38835047, 157.22959459, 157.04489649, 156.51135248,
       152.63940584, 151.55381123, 150.24652117, 149.86025713])
```

In [52]:

```

absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,:-1]
top_index = sorted_absolute_index[0,0:20]

all_features = count_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t==> \t%f"%(all_features[j],weight_values[0,j]))

```

Top 20 features with their weight values :

fishier	==>	-285.206418
corect	==>	-251.268055
reclin	==>	243.816896
uninari	==>	-236.471964
advantix	==>	-218.572686
conlus	==>	-188.138885
poem	==>	185.488846
jivalim	==>	-179.050896
goodwil	==>	-178.002684
sonewher	==>	-176.042775
mozzerela	==>	-170.591002
ridx	==>	-168.138783
anywh	==>	-162.639048
glimps	==>	-161.218308
crosswis	==>	-160.997334
hermosa	==>	-160.879583
opportunistic	==>	-156.866545
grainiest	==>	-156.173835
settlement	==>	155.111289
colicki	==>	154.809600

3.5 Using L2 Regularization

In [53]:

```
# Finding the best parameters using Grid Search CV using 10-fold Cross-Validation in Logistic Regression
# Finding the best parameters using Random Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import RandomizedSearchCV
param_distributions = {'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}
model = RandomizedSearchCV(LogisticRegression(penalty='l2', class_weight='balanced'), param_distributions, cv=10, scoring='accuracy')
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L2 Regularization", model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is : LogisticRegression(C=100, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

```
Accuracy of model using L2 Regularization 0.9360205922938117
```

In [54]:

```
model.best_params_
```

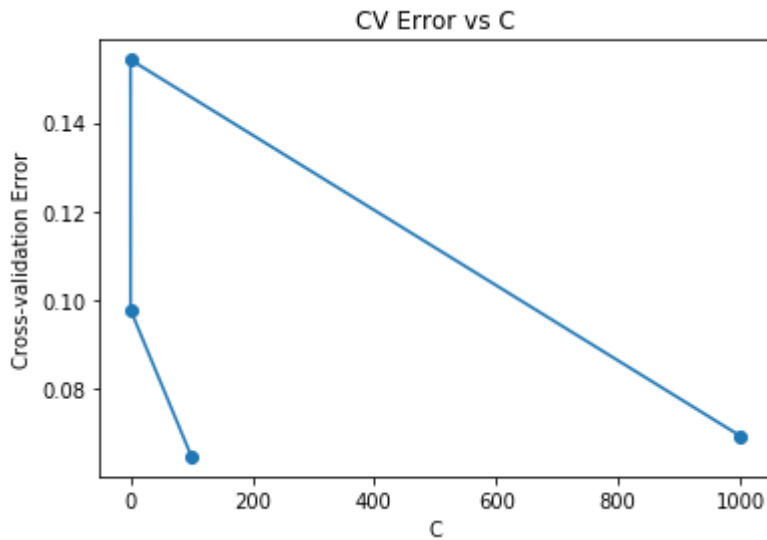
Out[54]:

```
{'C': 100}
```

Plotting a graph between C vs CV Error

In [55]:

```
score = model.cv_results_  
score  
plot_df = pd.DataFrame(score)  
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")  
plt.title("CV Error vs C")  
plt.xlabel("C")  
plt.ylabel("Cross-validation Error")  
plt.show()
```



In [56]:

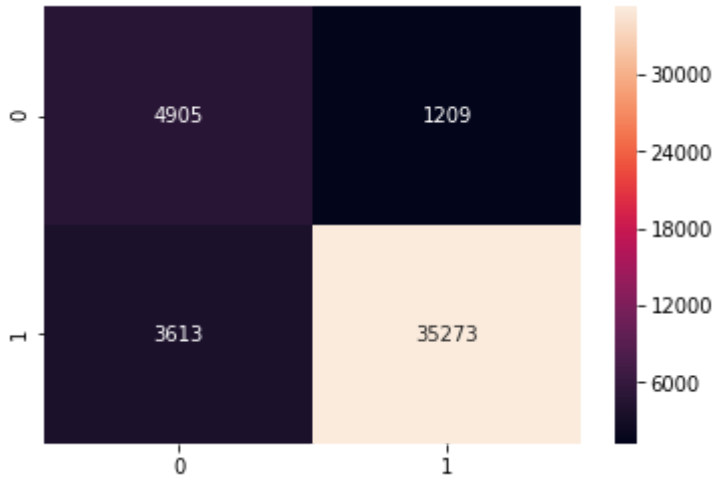
```
# Logistic Regression with Optimal value of C(1/Lambda)  
lr = LogisticRegression(penalty='l2', class_weight='balanced', C=optimal_C, n_jobs=-1)  
lr.fit(standardized_data_train, y_train)  
pred_bow = lr.predict(standardized_data_test)
```

3.6 Confusion Matrix

In [57]:

```
cm_bow=confusion_matrix(y_test,pred_bow)
print("Confusion Matrix:")
sns.heatmap(cm_bow, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [58]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_bow.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 4905
false positives are 1209
false negatives are 3613
true positives are 35273
```

3.7 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [59]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_bow) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_bow = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_bow))

# evaluating precision
precision_score = precision_score(y_test, pred_bow)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_bow)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_bow)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 100.000 is 93.602059%

Test Error Logistic Regression classifier is 6.397941%

The Test Precision of the Logistic Regression classifier for C = 100.000 is 0.966860

The Test Recall of the Logistic Regression classifier for C = 100.000 is 0.907087

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.58	0.80	0.67	6114
1	0.97	0.91	0.94	38886
micro avg	0.89	0.89	0.89	45000
macro avg	0.77	0.85	0.80	45000
weighted avg	0.91	0.89	0.90	45000

3.8 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [60]:

```
import scipy as sp
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_

# Number of non zero elements in Standardized_train sparse matrix
no_of_non_zero = standardized_data_train.count_nonzero()

# Importing library to create a sparse matrix of epsilon
from scipy.sparse import csr_matrix

# Creating new sparse matrix with epsilon at same position of non-zero elements of standarda
x_train_indices = standardized_data_train.indices
x_train_indptr = standardized_data_train.indptr #CSR format index pointer array of the matr

# Creating a List of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = standardized_data_train.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,x_train_indices,x_train_indptr),shape=Shape,dtype=float)

# Add sparse_epsilon and X-standardized_data_train to get a new sparse matrix with epsilon
# non-zero element of standardized_data_train
epsilon_train = standardized_data_train + sparse_epsilon

print(standardized_data_train.shape)
print(epsilon_train.shape)
```

```
(105000, 38300)
(105000, 38300)
```

In [61]:

```

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
print("change_vector",change_vector)

# Sort this change_vector array after making all the elements positive in ascending order
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]

change_vector [[ 0.08501586 -0.01889445 -0.00221554 ... -0.08913331 -0.02491
728
-0.1553935  ]]

```

Out[61]:

```

array([15.3546002 , 14.81342372, 14.24930477, 14.0817224 , 13.89300998,
       13.78803927, 12.40404504, 12.1563743 , 12.07690168, 11.91967391,
       11.40036526, 11.34016018, 11.33498141, 10.77895681, 10.76065832,
       10.63107242, 10.57098597, 10.36789833, 10.27637153,  9.95360835])

```


In [62]:

```

absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,:-1]
top_index = sorted_absolute_index[0,0:20]

all_features = count_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t==> \t%f"%(all_features[j],weight_values[0,j]))

```

Top 20 features with their weight values :

finnish	==>	-30.804405
yadayadayada	==>	-28.732250
compass	==>	-27.390156
sleepless	==>	-26.316562
skinnier	==>	-26.128913
worst	==>	-26.083704
cosmos	==>	-25.693283
coil	==>	-24.637455
nicknam	==>	-24.509341
avert	==>	-24.287710
abomin	==>	-23.418000
gould	==>	-22.707792
innard	==>	-22.500457
puberti	==>	-22.419660
dorothei	==>	-22.364858
riducul	==>	-22.072504
disastr	==>	-21.993514
downtown	==>	-21.979630
conceal	==>	21.906507
wunderbar	==>	-21.874626

4. TF-IDF

In [63]:

```
#tf-idf
from sklearn.feature_extraction.text import TfidfVectorizer
tf_idf_vect = TfidfVectorizer()

final_counts_tfidf_tr= tf_idf_vect.fit_transform(x_train)
print("the type of count vectorizer ",type(final_counts_tfidf_tr))
print("the shape of out text tfidf vectorizer ",final_counts_tfidf_tr.get_shape())
print("the number of unique words ", final_counts_tfidf_tr.get_shape()[1])
final_counts_tfidf_test= tf_idf_vect.transform(x_test)
print("the type of count vectorizer ",type(final_counts_tfidf_test))
print("the shape of out text tfidf vectorizer ",final_counts_tfidf_test.get_shape())
print("the number of unique words ", final_counts_tfidf_test.get_shape()[1])
```

```
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text tfidf vectorizer (105000, 38300)
the number of unique words 38300
the type of count vectorizer <class 'scipy.sparse.csr.csr_matrix'>
the shape of out text tfidf vectorizer (45000, 38300)
the number of unique words 38300
```

4.1 Standardizing Data

In [64]:

```
# Data-preprocessing: Standardizing the data
from sklearn import preprocessing
standardized_data_train = preprocessing.normalize(final_counts_tfidf_tr)
print(standardized_data_train.shape)
standardized_data_test = preprocessing.normalize(final_counts_tfidf_test)
print(standardized_data_test.shape)
```

```
(105000, 38300)
(45000, 38300)
```

4.2 Applying Logistic Regression Algorithm

4.2.1 Gridsearch Cross Validation

4.2.1.1 Using L1 Regularization

In [66]:

```
# Finding the best parameters using Grid Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import GridSearchCV
tuned_parameters = [{'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}]
model = GridSearchCV(LogisticRegression(penalty='l1', class_weight='balanced'), tuned_parameters)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L1 Regularization", model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is :  LogisticRegression(C=10, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

```
Accuracy of model using L1 Regularization 0.9351884979791957
```

In [67]:

```
model.best_params_
```

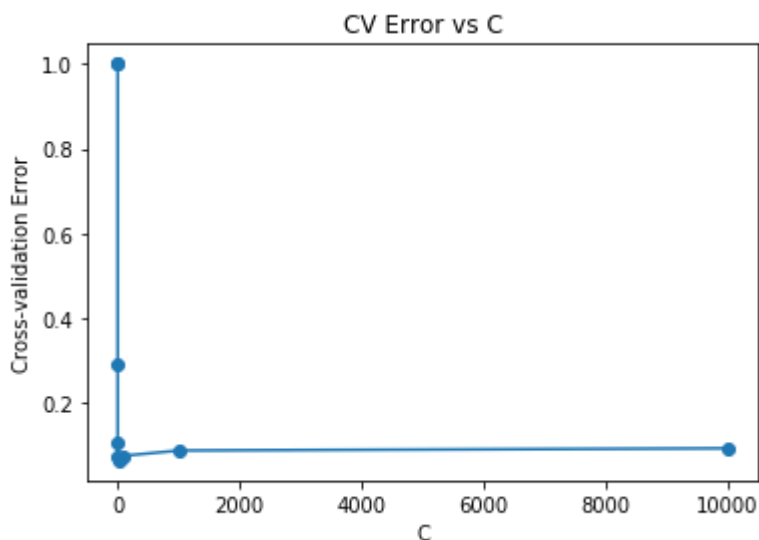
Out[67]:

```
{'C': 10}
```

Plotting a graph between C vs CV Error

In [68]:

```
score = model.cv_results_
score
plot_df = pd.DataFrame(score)
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")
plt.title("CV Error vs C")
plt.xlabel("C")
plt.ylabel("Cross-validation Error")
plt.show()
```



In [69]:

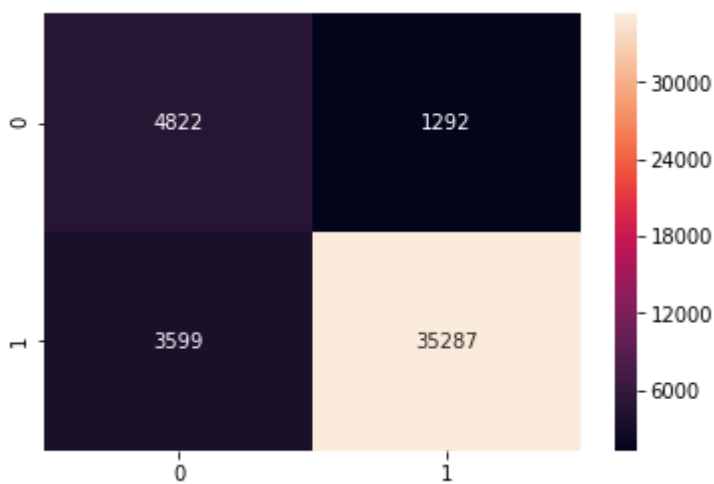
```
# Logistic Regression with Optimal value of C(1/Lambda)
lr = LogisticRegression(penalty='l1', class_weight='balanced', C=optimal_C, n_jobs=-1)
lr.fit(standardized_data_train, y_train)
pred_tfidf = lr.predict(standardized_data_test)
```

4.3 Confusion Matrix

In [70]:

```
cm_tfidf = confusion_matrix(y_test, pred_tfidf)
print("Confusion Matrix:")
sns.heatmap(cm_tfidf, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [71]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_tfidf.ravel()
(tn, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 4822
false positives are 1292
false negatives are 3599
true positives are 35287
```

4.4 Calculating Accuracy, Error on test data, Precision, Recall, Classification Report

In [72]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_tfidf) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_tfidf = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_tfidf))

# evaluating precision
precision_score = precision_score(y_test, pred_tfidf)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_tfidf)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_tfidf)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 10.000 is 93.518850%

Test Error Logistic Regression classifier is 6.481150%

The Test Precision of the Logistic Regression classifier for C = 10.000 is 0.964679

The Test Recall of the Logistic Regression classifier for C = 10.000 is 0.907447

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.57	0.79	0.66	6114
1	0.96	0.91	0.94	38886
micro avg	0.89	0.89	0.89	45000
macro avg	0.77	0.85	0.80	45000
weighted avg	0.91	0.89	0.90	45000

4.5 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [73]:

```
import scipy as sp
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_

# Number of non zero elements in Standardized_train sparse matrix
no_of_non_zero = standardized_data_train.count_nonzero()

# Importing library to create a sparse matrix of epsilon
from scipy.sparse import csr_matrix

# Creating new sparse matrix with epsilon at same position of non-zero elements of standarda
x_train_indices = standardized_data_train.indices
x_train_indptr = standardized_data_train.indptr #CSR format index pointer array of the matr

# Creating a List of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = standardized_data_train.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,x_train_indices,x_train_indptr),shape=Shape,dtype=float)

# Add sparse_epsilon and X-standardized_data_train to get a new sparse matrix with epsilon
# non-zero element of standardized_data_train
epsilon_train = standardized_data_train + sparse_epsilon

print(standardized_data_train.shape)
print(epsilon_train.shape)
```

```
(105000, 38300)
(105000, 38300)
```

In [74]:

```

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
print("change_vector",change_vector)

# Sort this change_vector array after making all the elements positive in ascending order
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]

change_vector [ [-0.27710367  0.00680627  0.00171921 ...  0.17550179  0.00778
236
               0.07935638]]

```

Out[74]:

```

array([47.28096945, 42.82660647, 39.69945422, 38.34484204, 36.99785103,
       35.19604317, 35.06539774, 33.58262556, 32.48656314, 32.03343388,
       31.50108337, 30.92770186, 29.19235448, 28.99190036, 28.76153169,
       28.68851382, 28.64328311, 28.5461175 , 28.50626186, 28.0785017 ])

```

In [75]:

```

absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,:-1]
top_index = sorted_absolute_index[0,0:20]

all_features = tf_idf_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t==> \t%f"%(all_features[j],weight_values[0,j]))

```

Top 20 features with their weight values :

corect	==>	-48.872809
mozzerela	==>	-44.468918
sonewher	==>	-41.609026
fishier	==>	-39.331064
goodwil	==>	-38.455216
ov	==>	-37.042570
jivalim	==>	-36.051134
devault	==>	-35.923801
yadayadayada	==>	-35.870142
ridx	==>	-33.457121
grainiest	==>	-32.592764
advantix	==>	-32.038224
insuffici	==>	-31.829199
voluntari	==>	-31.356050
merritt	==>	-31.162582
disstributor	==>	30.593466
opportunist	==>	-30.300442
pessimist	==>	-30.116889
dcide	==>	-29.952377
insignia	==>	-29.554033

4.6 Using L2 Regularization

In [76]:

```
# Finding the best parameters using Grid Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import GridSearchCV
tuned_parameters = [{'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}]
model = GridSearchCV(LogisticRegression(penalty='l2', class_weight='balanced'), tuned_parameters)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L2 Regularization", model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is :  LogisticRegression(C=10, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

```
Accuracy of model using L2 Regularization 0.9363146336594129
```

In [77]:

```
model.best_params_
```

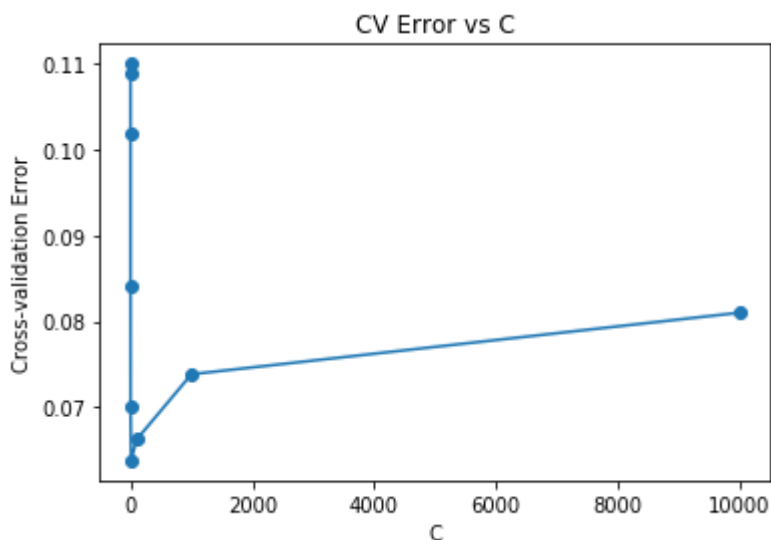
Out[77]:

```
{'C': 10}
```

Plotting a graph between C vs CV Error

In [78]:

```
score = model.cv_results_
score
plot_df = pd.DataFrame(score)
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")
plt.title("CV Error vs C")
plt.xlabel("C")
plt.ylabel("Cross-validation Error")
plt.show()
```



In [79]:

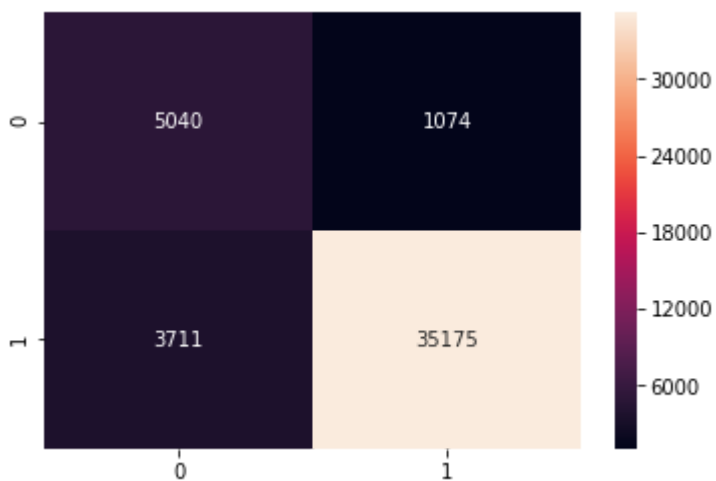
```
# Logistic Regression with Optimal value of C(1/Lambda)
lr = LogisticRegression(penalty='l2',class_weight='balanced', C=optimal_C, n_jobs=-1)
lr.fit(standardized_data_train,y_train)
pred_tfidf = lr.predict(standardized_data_test)
```

4.7 Confusion Matrix

In [80]:

```
cm_tfidf=confusion_matrix(y_test,pred_tfidf)
print("Confusion Matrix:")
sns.heatmap(cm_tfidf, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [81]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_tfidf.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true positives are {}")
```

```
true negitves are 5040
false positives are 1074
false negatives are 3711
true positives are 35175
```

4.8 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [82]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_tfidf) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_tfidf = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_tfidf))

# evaluating precision
precision_score = precision_score(y_test, pred_tfidf)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_tfidf)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_tfidf)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 10.000 is 93.631463%

Test Error Logistic Regression classifier is 6.368537%

The Test Precision of the Logistic Regression classifier for C = 10.000 is 0.970372

The Test Recall of the Logistic Regression classifier for C = 10.000 is 0.904567

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.58	0.82	0.68	6114
1	0.97	0.90	0.94	38886
micro avg	0.89	0.89	0.89	45000
macro avg	0.77	0.86	0.81	45000
weighted avg	0.92	0.89	0.90	45000

4.9 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [83]:

```
import scipy as sp
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_

# Number of non zero elements in Standardized_train sparse matrix
no_of_non_zero = standardized_data_train.count_nonzero()

# Importing library to create a sparse matrix of epsilon
from scipy.sparse import csr_matrix

# Creating new sparse matrix with epsilon at same position of non-zero elements of standarda
x_train_indices = standardized_data_train.indices
x_train_indptr = standardized_data_train.indptr #CSR format index pointer array of the matr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = standardized_data_train.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,x_train_indices,x_train_indptr),shape=Shape,dtype=float)

# Add sparse_epsilon and X-standardized_data_train to get a new sparse matrix with epsilon
# non-zero element of standardized_data_train
epsilon_train = standardized_data_train + sparse_epsilon

print(standardized_data_train.shape)
print(epsilon_train.shape)
```

(105000, 38300)

(105000, 38300)

In [84]:

```

# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
print("change_vector",change_vector)

# Sort this change_vector array after making all the elements positive in ascending order
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]

change_vector [[ 0.01708526 -0.00745136 -0.0015592  ... -0.04162235 -0.01324
496
-0.08478265]]

```

Out[84]:

```

array([5.70187706, 4.9461636 , 4.81924635, 4.69331995, 4.59300109,
        4.39143394, 4.38165593, 4.31749051, 4.30694245, 4.21006546,
        4.16142254, 4.01823138, 3.98269906, 3.96067984, 3.77184892,
        3.70826911, 3.69791019, 3.54576098, 3.54221151, 3.53803479])

```

In [85]:

```

absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,:-1]
top_index = sorted_absolute_index[0,0:20]

all_features = tf_idf_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t==> \t%f"%(all_features[j],weight_values[0,j]))

```

Top 20 features with their weight values :

worst	==>	-16.506950
great	==>	13.935663
delici	==>	13.480462
best	==>	12.510159
perfect	==>	12.193799
amaz	==>	11.647077
terribl	==>	-11.615033
love	==>	11.590019
disappoint	==>	-11.466183
skeptic	==>	10.841531
hook	==>	10.564131
beat	==>	10.195225
horribl	==>	-10.162381
addict	==>	9.747666
excel	==>	9.613231
finnish	==>	-9.521818
sleepless	==>	-9.335980
awesom	==>	9.327845
mediocr	==>	-9.293814
concept	==>	-9.088242

5. Randomized Search Cross Validation

5.1 Using L1 Regularization

In [86]:

```
# Finding the best parameters using Random Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import RandomizedSearchCV
param_distributions = {'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}
model = RandomizedSearchCV(LogisticRegression(penalty = 'l1', class_weight='balanced'), param_distributions, cv=10, scoring='accuracy')
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L1 Regularization", model.score(standardized_data_test, y_test))
```

The optimal value of C(1/lambda) is : LogisticRegression(C=10000, class_weight='balanced', dual=False, fit_intercept=True, intercept_scaling=1, max_iter=100, multi_class='warn', n_jobs=None, penalty='l1', random_state=None, solver='warn', tol=0.0001, verbose=0, warm_start=False)

Accuracy of model using L1 Regularization 0.9192951007657937

In [87]:

```
model.best_params_
```

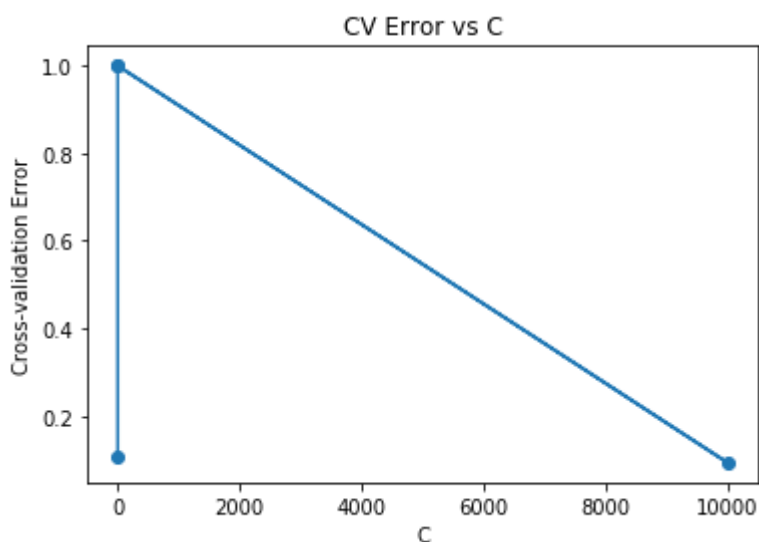
Out[87]:

```
{'C': 10000}
```

Plotting a graph between C vs CV Error

In [88]:

```
score = model.cv_results_
score
plot_df = pd.DataFrame(score)
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")
plt.title("CV Error vs C")
plt.xlabel("C")
plt.ylabel("Cross-validation Error")
plt.show()
```



In [89]:

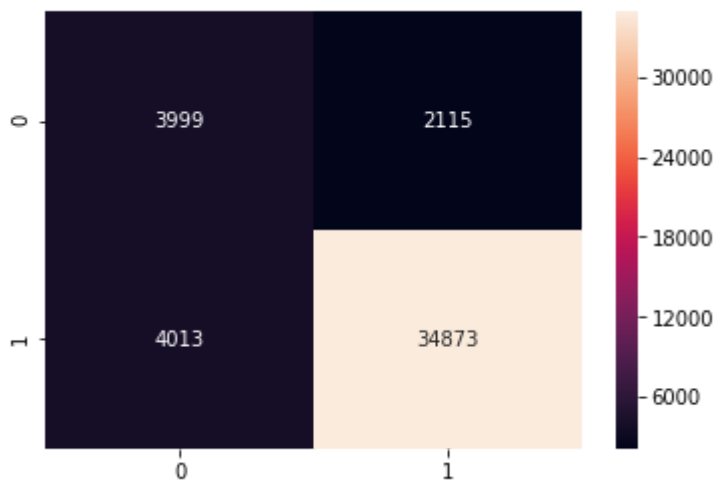
```
# Logistic Regression with Optimal value of C(1/Lambda)
lr = LogisticRegression(penalty='l1', C=optimal_C, class_weight='balanced', n_jobs=-1)
lr.fit(standardized_data_train, y_train)
pred_tfidf = lr.predict(standardized_data_test)
```

5.2 Confusion Matrix

In [90]:

```
cm_tfidf=confusion_matrix(y_test, pred_tfidf)
print("Confusion Matrix:")
sns.heatmap(cm_tfidf, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [91]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_tfidf.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 3999
false positives are 2115
false negatives are 4013
true positives are 34873
```

5.3 Calculating Accuracy, Error on test data, Precision, Recall, Classification Report

In [92]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_tfidf) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_tfidf = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_tfidf))

# evaluating precision
precision_score = precision_score(y_test, pred_tfidf)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_tfidf)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_tfidf)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 10000.000 is 91.923452%

Test Error Logistic Regression classifier is 8.076548%

The Test Precision of the Logistic Regression classifier for C = 10000.000 is 0.942819

The Test Recall of the Logistic Regression classifier for C = 10000.000 is 0.896801

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.50	0.65	0.57	6114
1	0.94	0.90	0.92	38886
micro avg	0.86	0.86	0.86	45000
macro avg	0.72	0.78	0.74	45000
weighted avg	0.88	0.86	0.87	45000

5.4 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [93]:

```
import scipy as sp
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_

# Number of non zero elements in Standardized_train sparse matrix
no_of_non_zero = standardized_data_train.count_nonzero()

# Importing library to create a sparse matrix of epsilon
from scipy.sparse import csr_matrix

# Creating new sparse matrix with epsilon at same position of non-zero elements of standarda
x_train_indices = standardized_data_train.indices
x_train_indptr = standardized_data_train.indptr #CSR format index pointer array of the matr

# Creating a list of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = standardized_data_train.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,x_train_indices,x_train_indptr),shape=Shape,dtype=float)

# Add sparse_epsilon and X-standardized_data_train to get a new sparse matrix with epsilon
# non-zero element of standardized_data_train
epsilon_train = standardized_data_train + sparse_epsilon

print(standardized_data_train.shape)
print(epsilon_train.shape)
```

```
(105000, 38300)
(105000, 38300)
```

In [94]:

```
# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
print("change_vector",change_vector)

# Sort this change_vector array after making all the elements positive in ascending order t
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

```
change_vector [[5.72958555 0.15190945 0.01363539 ... 1.68188796 0.31407761
2.41157368]]
```

Out[94]:

```
array([705.54878152, 545.72212982, 536.37754024, 470.86663565,
       419.71316906, 413.09228173, 397.85290011, 397.22695379,
       393.19836303, 365.0708472 , 360.41327023, 347.88514845,
       345.41022466, 342.87193146, 337.86331378, 334.88698489,
       333.11382585, 332.15545253, 329.02264881, 328.56727238])
```

In [95]:

```

absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,:-1]
top_index = sorted_absolute_index[0,0:20]

all_features = tf_idf_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t==> \t%f"%(all_features[j],weight_values[0,j]))

```

Top 20 features with their weight values :

hypothyroid	==>	718.963735
crohn	==>	573.121601
antihistamin	==>	549.200725
lingonberri	==>	481.851774
scald	==>	442.063725
kalocsai	==>	-423.824538
wfgf	==>	420.262767
piazza	==>	-419.366668
deglaz	==>	415.791976
dismantl	==>	-385.842543
misrepres	==>	-378.602006
aachen	==>	-378.119805
drakar	==>	-378.024980
reclin	==>	374.885015
advantix	==>	-373.630969
treacl	==>	372.488836
talleyrand	==>	365.259786
preffer	==>	360.788589
extravag	==>	-350.868300
spinachi	==>	340.726160

5.5 Using L2 Regularization

In [96]:

```
# Finding the best parameters using Random Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import RandomizedSearchCV
param_distributions = {'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}
model = RandomizedSearchCV(LogisticRegression(penalty = 'l2', class_weight='balanced'), param_distributions, cv=10, scoring='accuracy')
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L2 Regularization", model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is : LogisticRegression(C=100, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

```
Accuracy of model using L2 Regularization 0.933857913073428
```

In [97]:

```
model.best_params_
```

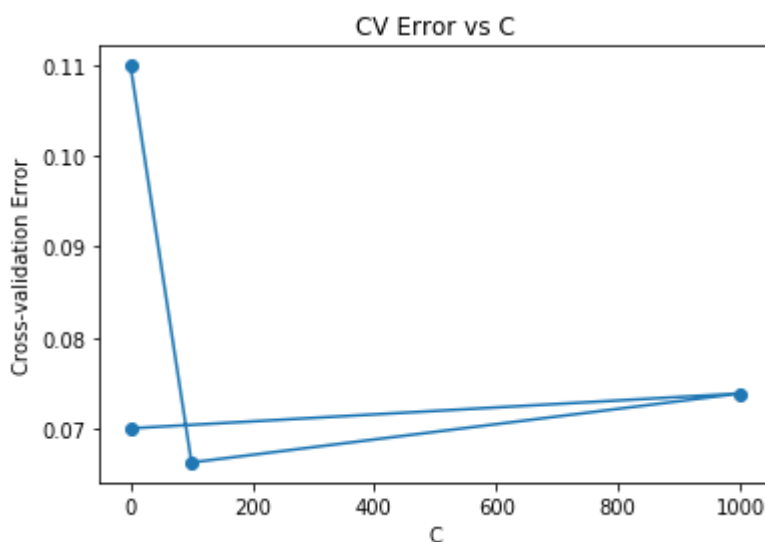
Out[97]:

```
{'C': 100}
```

Plotting a graph between C vs CV Error

In [98]:

```
score = model.cv_results_
score
plot_df = pd.DataFrame(score)
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")
plt.title("CV Error vs C")
plt.xlabel("C")
plt.ylabel("Cross-validation Error")
plt.show()
```



In [99]:

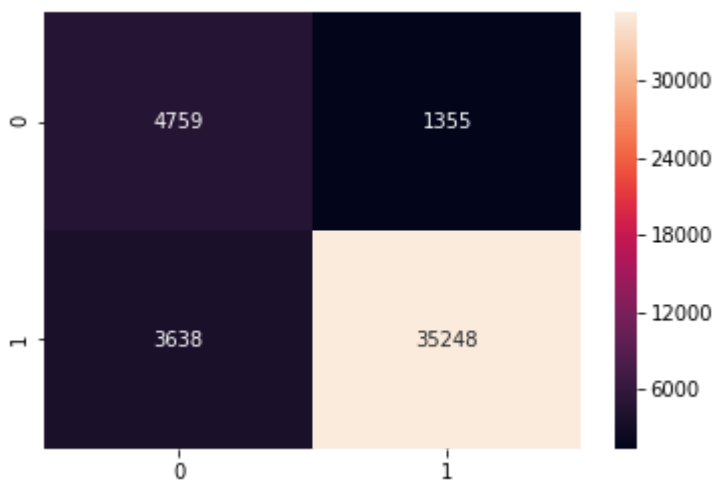
```
# Logistic Regression with Optimal value of C(1/Lambda)
lr = LogisticRegression(penalty='l2', class_weight='balanced',C=optimal_C, n_jobs=-1)
lr.fit(standardized_data_train,y_train)
pred_tfidf = lr.predict(standardized_data_test)
```

5.6 Confusion Matrix

In [100]:

```
cm_tfidf=confusion_matrix(y_test,pred_tfidf)
print("Confusion Matrix:")
sns.heatmap(cm_tfidf, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [101]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_tfidf.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true positives are {}")
```

```
true negitves are 4759
false positives are 1355
false negatives are 3638
true positives are 35248
```

5.7 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [102]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_tfidf) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_tfidf = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_tfidf))

# evaluating precision
precision_score = precision_score(y_test, pred_tfidf)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_tfidf)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_tfidf)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 100.000 is 93.385791%

Test Error Logistic Regression classifier is 6.614209%

The Test Precision of the Logistic Regression classifier for C = 100.000 is 0.962981

The Test Recall of the Logistic Regression classifier for C = 100.000 is 0.906444

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.57	0.78	0.66	6114
1	0.96	0.91	0.93	38886
micro avg	0.89	0.89	0.89	45000
macro avg	0.76	0.84	0.79	45000
weighted avg	0.91	0.89	0.90	45000

5.8 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [103]:

```
import scipy as sp
epsilon = sp.stats.distributions.norm.rvs(loc=0,scale=0.0001)
# Vector before the addition of epsilon
W_before_epsilon = lr.coef_

# Number of non zero elements in Standardized_train sparse matrix
no_of_non_zero = standardized_data_train.count_nonzero()

# Importing library to create a sparse matrix of epsilon
from scipy.sparse import csr_matrix

# Creating new sparse matrix with epsilon at same position of non-zero elements of standarda
x_train_indices = standardized_data_train.indices
x_train_indptr = standardized_data_train.indptr #CSR format index pointer array of the matr

# Creating a List of same element with repetition
data = [epsilon] * no_of_non_zero
Shape = standardized_data_train.shape

# Creating sparse matrix
sparse_epsilon = csr_matrix((data,x_train_indices,x_train_indptr),shape=Shape,dtype=float)

# Add sparse_epsilon and X-standardized_data_train to get a new sparse matrix with epsilon
# non-zero element of standardized_data_train
epsilon_train = standardized_data_train + sparse_epsilon

print(standardized_data_train.shape)
print(epsilon_train.shape)
```

```
(105000, 38300)
(105000, 38300)
```


In [104]:

```
# training Logistic Regression Classifier with epsilon_train
epsilon_lr = LogisticRegression(penalty='l2', C=optimal_C, n_jobs=-1)
epsilon_lr.fit(epsilon_train,y_train)

# Vector after the addition of epsilon
W_after_epsilon = epsilon_lr.coef_

# Change in vectors after adding epsilon
change_vector = W_after_epsilon - W_before_epsilon
print("change_vector",change_vector)

# Sort this change_vector array after making all the elements positive in ascending order
sorted_change_vector = np.sort(np.absolute(change_vector))[:,::-1]

sorted_change_vector[0,0:20]
```

```
change_vector [[ 0.08771318 -0.03604998  0.00046193 ...  0.02653029 -0.03382
972
               -0.2034842  ]]
```

Out[104]:

```
array([11.8980787 , 10.71434974,  9.88321025,  9.71325821,  9.26748008,
        9.17898238,  9.10531123,  8.88205754,  8.27490006,  8.18450277,
        8.18372848,  8.07494542,  7.94326188,  7.91036549,  7.55704613,
        7.4815967 ,  7.325322  ,  7.32500814,  7.15969046,  7.0403881 ])
```

In [105]:

```
absolute_weights = np.absolute(W_before_epsilon)
sorted_absolute_index = np.argsort(absolute_weights)[:,:-1]
top_index = sorted_absolute_index[0,0:20]

all_features = tf_idf_vect.get_feature_names()
weight_values = lr.coef_

# Top 20 features are
print("Top 20 features with their weight values :")

for j in top_index:
    print("%12s\t==> \t%f"%(all_features[j],weight_values[0,j]))
```

Top 20 features with their weight values :

yadayadayada	==>	-27.923918
ov	==>	-26.527925
mozzerela	==>	-24.951461
worst	==>	-23.527706
coil	==>	-20.754045
sonewher	==>	-20.435857
finnish	==>	-20.304019
distrust	==>	-20.243382
cystic	==>	-19.635566
conceal	==>	19.449148
compass	==>	-19.395615
skeptic	==>	19.341727
uninari	==>	-18.887920
statesid	==>	-18.872892
gould	==>	-18.790618
fishier	==>	-18.545537
allrecip	==>	-18.328219
eng	==>	-18.290134
disastr	==>	-18.207121
ransid	==>	-18.204572

6. WORD2VEC

In [106]:

```

from gensim.models import Word2Vec
# List of sentence in X_train text
sent_of_train=[]
for sent in x_train:
    sent_of_train.append(sent.split())

# List of sentence in X_test text
sent_of_test=[]
for sent in x_test:
    sent_of_test.append(sent.split())

# Train your own Word2Vec model using your own train text corpus
# min_count = 5 considers only words that occurred at least 5 times
w2v_model=Word2Vec(sent_of_train,min_count=5,size=50, workers=4)

w2v_words = list(w2v_model.wv.vocab)
print("number of words that occurred minimum 5 times ",len(w2v_words))

```

number of words that occurred minimum 5 times 12829

7. Avg Word2Vec

In [107]:

```

# compute average word2vec for each review for X_train .
train_vectors = [];
for sent in sent_of_train:
    sent_vec = np.zeros(50)
    cnt_words = 0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    train_vectors.append(sent_vec)

# compute average word2vec for each review for X_test .
test_vectors = [];
for sent in sent_of_test:
    sent_vec = np.zeros(50)
    cnt_words = 0;
    for word in sent: #
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    test_vectors.append(sent_vec)

```

7.1 Standardizing Data

In [108]:

```
# Data-preprocessing: Standardizing the data
from sklearn import preprocessing
standardized_data_train = preprocessing.normalize(train_vectors)
print(standardized_data_train.shape)
standardized_data_test = preprocessing.normalize(test_vectors)
print(standardized_data_test.shape)
```

(105000, 50)

(45000, 50)

7.2 Applying Logistic Regression Algorithm

7.2.1 Gridsearch Cross Validation

7.2.1.1 Using L1 Regularization

In [109]:

```
# Finding the best parameters using Grid Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import GridSearchCV
tuned_parameters = [{'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}]
model = GridSearchCV(LogisticRegression(penalty='l1', class_weight='balanced'), tuned_parameters)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L1 Regularization", model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is :  LogisticRegression(C=1000, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

Accuracy of model using L1 Regularization 0.888227108266073

In [110]:

```
model.best_params_
```

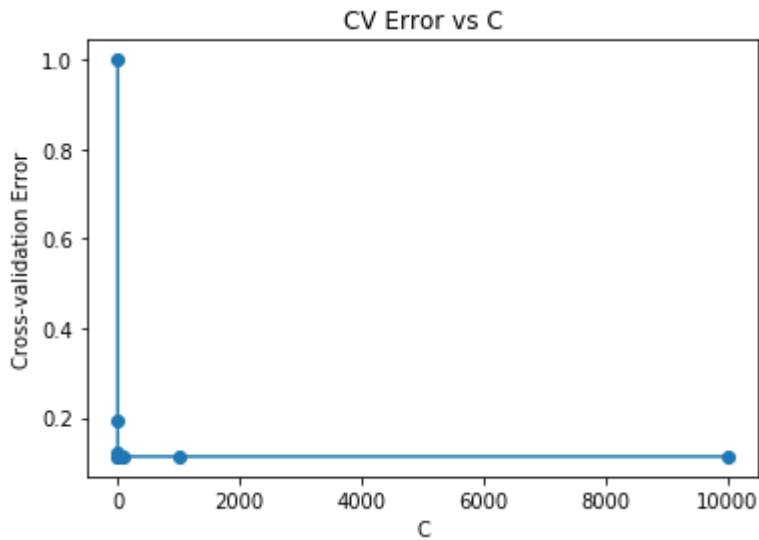
Out[110]:

```
{'C': 1000}
```

Plotting a graph between C vs CV Error

In [111]:

```
score = model.cv_results_  
score  
plot_df = pd.DataFrame(score)  
plt.plot(plot_df["param_C"], 1- plot_df["mean_test_score"], "-o")  
plt.title("CV Error vs C")  
plt.xlabel("C")  
plt.ylabel("Cross-validation Error")  
plt.show()
```



In [112]:

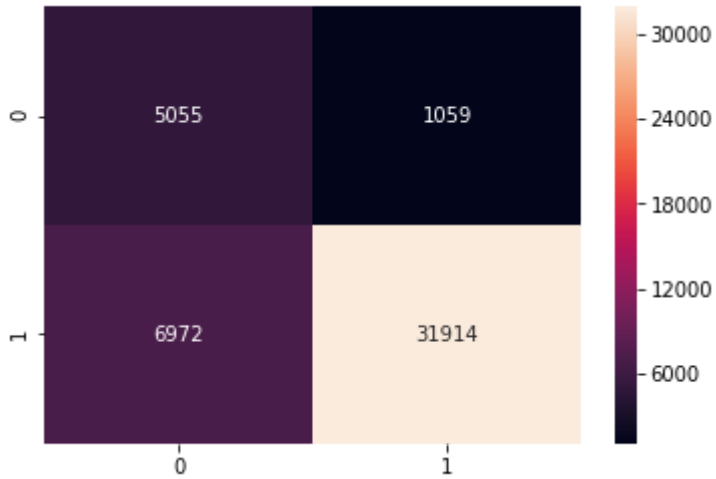
```
# Logistic Regression with Optimal value of C(1/Lambda)  
lr = LogisticRegression(penalty='l1', class_weight='balanced',C=optimal_C, n_jobs=-1)  
lr.fit(standardized_data_train,y_train)  
pred_avgw2v = lr.predict(standardized_data_test)
```

7.3 Confusion Matrix

In [113]:

```
cm_avgw2v=confusion_matrix(y_test,pred_avgw2v)
print("Confusion Matrix:")
sns.heatmap(cm_avgw2v, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [114]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_avgw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 5055
false positives are 1059
false negatives are 6972
true positives are 31914
```

7.4 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [115]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_avgw2v) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_avgw2v = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_avgw2v))

# evaluating precision
precision_score = precision_score(y_test, pred_avgw2v)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_avgw2v)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_avgw2v)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 1000.000 is 88.823947%

Test Error Logistic Regression classifier is 11.176053%

The Test Precision of the Logistic Regression classifier for C = 1000.000 is 0.967883

The Test Recall of the Logistic Regression classifier for C = 1000.000 is 0.820707

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.42	0.83	0.56	6114
1	0.97	0.82	0.89	38886
micro avg	0.82	0.82	0.82	45000
macro avg	0.69	0.82	0.72	45000
weighted avg	0.89	0.82	0.84	45000

7.5 Checking sparsity with increasing value of lambda(decreasing C)

In [116]:

```

lambda = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
for i in lambda[::-1]:
    lrr = LogisticRegression(penalty = 'l1', C = i)
    lrr.fit(standardized_data_train, y_train)
    print("lambda="+str(1/i)+" ; non-zeros="+str(np.count_nonzero(lrr.coef_)))

```

```

lambda=0.0001 ; non-zeros=50
lambda=0.001 ; non-zeros=50
lambda=0.01 ; non-zeros=50
lambda=0.1 ; non-zeros=50
lambda=1.0 ; non-zeros=50
lambda=10.0 ; non-zeros=47
lambda=100.0 ; non-zeros=22
lambda=1000.0 ; non-zeros=2
lambda=10000.0 ; non-zeros=0

```

In [117]:

```

lr = LogisticRegression(penalty='l2', C=0.01)
lr.fit(standardized_data_train, y_train)

```

Out[117]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [118]:

```

# Applying perturbation and checking if the coefficients differ too much
# Will not add noise to zeros

```

```

noise = np.random.normal(0 , 0.1 , 1)
print("Noise= "+str(noise[0]))
standardized_data_train.data = standardized_data_train.data + noise[0]

```

```
Noise= 0.0029464113914069215
```

In [119]:

```
# Fitting the new model on the transformed data
```

```

lr2 = LogisticRegression(penalty='l2', C=0.01)
lr2.fit(standardized_data_train, y_train)

```

Out[119]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```


In [120]:

```
# Calculating the percentage change between the old and new coefficients
count=0
for i in range(standardized_data_train.shape[1]):
    delta = abs((((lr.coef_[0][i] - lr2.coef_[0][i]) * 100)) / lr.coef_[0][i])
    if delta>40:
        count+=1

print("Number of features whose coefficients changed by more than 40% =",count)
```

Number of features whose coefficients changed by more than 40% = 0

Hence Number of Features whose coefficients changed by more than 40% is less these are less collinear
hence we cannot calculate feature importance

As weight vector values before and after perturbation changes significantly, then we can't use $|w|$ as feature importance measure.

7.6 Using L2 Regularization

In [122]:

```
# Finding the best parameters using Grid Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import GridSearchCV
tuned_parameters = [{'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**2, 10**3, 10**4]}]
model = GridSearchCV(LogisticRegression(penalty='l2', class_weight='balanced'), tuned_parameters)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L2 Regularization", model.score(standardized_data_test, y_test))
```

The optimal value of C(1/lambda) is : LogisticRegression(C=100, class_weight='balanced', dual=False, fit_intercept=True, intercept_scaling=1, max_iter=100, multi_class='warn', n_jobs=None, penalty='l2', random_state=None, solver='warn', tol=0.0001, verbose=0, warm_start=False)

Accuracy of model using L2 Regularization 0.8900891394296188

In [123]:

```
model.best_params_
```

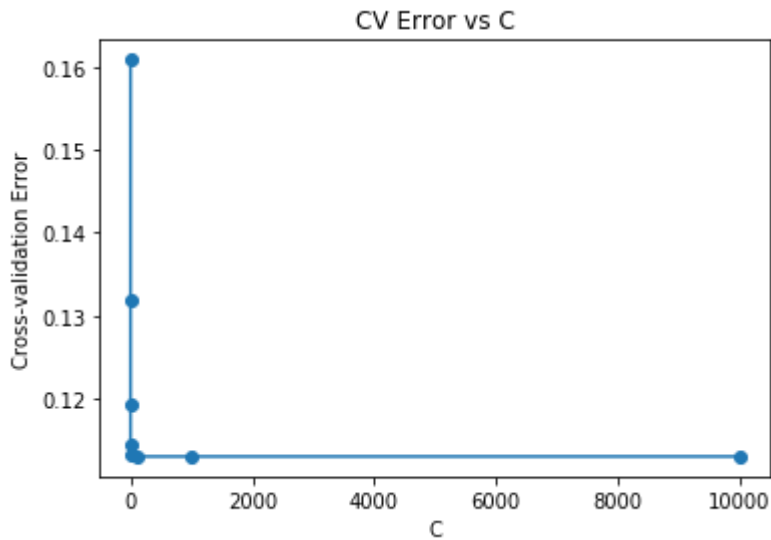
Out[123]:

```
{'C': 100}
```

Plotting a graph between C vs CV Error

In [124]:

```
score = model.cv_results_  
score  
plot_df = pd.DataFrame(score)  
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")  
plt.title("CV Error vs C")  
plt.xlabel("C")  
plt.ylabel("Cross-validation Error")  
plt.show()
```



In [125]:

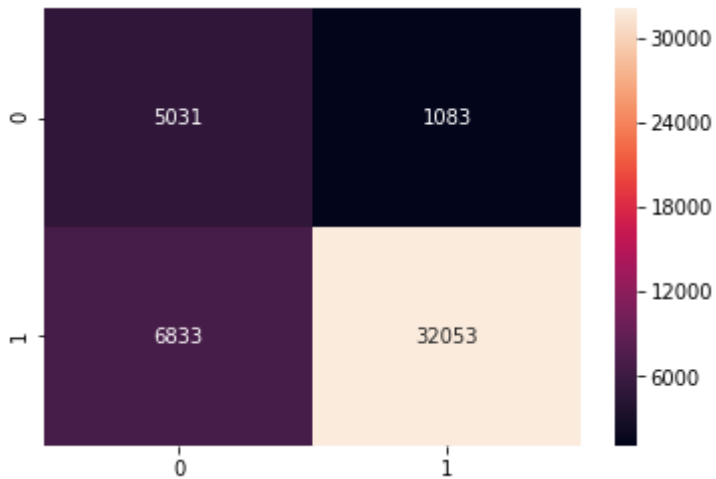
```
# Logistic Regression with Optimal value of C(1/Lambda)  
lr = LogisticRegression(penalty='l2', class_weight='balanced', C=optimal_C, n_jobs=-1)  
lr.fit(standardized_data_train, y_train)  
pred_avg2v = lr.predict(standardized_data_test)
```

7.7 Confusion Matrix

In [126]:

```
cm_avgw2v=confusion_matrix(y_test,pred_avgw2v)
print("Confusion Matrix:")
sns.heatmap(cm_avgw2v, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [127]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_avgw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 5031
false positives are 1083
false negatives are 6833
true positives are 32053
```

7.8 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [128]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_avgw2v) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_avgw2v = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_avgw2v))

# evaluating precision
precision_score = precision_score(y_test, pred_avgw2v)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_avgw2v)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_avgw2v)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 100.000 is 89.008914%

Test Error Logistic Regression classifier is 10.991086%

The Test Precision of the Logistic Regression classifier for C = 100.000 is 0.967317

The Test Recall of the Logistic Regression classifier for C = 100.000 is 0.824281

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.42	0.82	0.56	6114
1	0.97	0.82	0.89	38886
micro avg	0.82	0.82	0.82	45000
macro avg	0.70	0.82	0.72	45000
weighted avg	0.89	0.82	0.85	45000

7.9 Checking sparsity with increasing value of lambda(decreasing C)

In [129]:

```

lambda = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
for i in lambda[::-1]:
    lrr = LogisticRegression(penalty = 'l1', C = i)
    lrr.fit(standardized_data_train, y_train)
    print("lambda="+str(1/i)+" ; non-zeros="+str(np.count_nonzero(lrr.coef_)))

```

```

lambda=0.0001 ; non-zeros=50
lambda=0.001 ; non-zeros=50
lambda=0.01 ; non-zeros=50
lambda=0.1 ; non-zeros=50
lambda=1.0 ; non-zeros=50
lambda=10.0 ; non-zeros=47
lambda=100.0 ; non-zeros=22
lambda=1000.0 ; non-zeros=2
lambda=10000.0 ; non-zeros=0

```

In [130]:

```

lr = LogisticRegression(penalty='l2', C=0.01)
lr.fit(standardized_data_train, y_train)

```

Out[130]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [131]:

```

# Applying perturbation and checking if the coefficients differ too much
# Will not add noise to zeros

```

```

noise = np.random.normal(0 , 0.1 , 1)
print("Noise= "+str(noise[0]))
standardized_data_train.data = standardized_data_train.data + noise[0]

```

```
Noise= 0.08343477240791726
```

In [132]:

```
# Fitting the new model on the transformed data
```

```

lr2 = LogisticRegression(penalty='l2', C=0.01)
lr2.fit(standardized_data_train, y_train)

```

Out[132]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [133]:

```
# Calculating the percentage change between the old and new coefficients
count=0
for i in range(standardized_data_train.shape[1]):
    delta = abs((((lr.coef_[0][i] - lr2.coef_[0][i]) * 100))/ lr.coef_[0][i])
    if delta>40:
        count+=1

print("Number of features whose coefficients changed by more than 40% =",count)
```

Number of features whose coefficients changed by more than 40% = 10

Hence Number of Features whose coefficients changed by more than 40% is less these are less collinear
hence we cannot calculate feature importance

7.10 Randomized Search Cross Validation

7.10.1 Using L1 Regularization

In [134]:

```
# Finding the best parameters using Random Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import RandomizedSearchCV
param_distributions = {'C': [10**-4,10**-3, 10**-2,10**-1, 1, 10**1,10**2,10**3, 10**4]}
model = RandomizedSearchCV(LogisticRegression(penalty = 'l1',class_weight='balanced'), param_distributions, cv=10)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ",model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L1 Regularization",model.score(standardized_data_test, y_test))
```

The optimal value of C(1/lambda) is : LogisticRegression(C=1000, class_weight='balanced', dual=False, fit_intercept=True, intercept_scaling=1, max_iter=100, multi_class='warn', n_jobs=None, penalty='l1', random_state=None, solver='warn', tol=0.0001, verbose=0, warm_start=False)

Accuracy of model using L1 Regularization 0.9300732217573222

In [135]:

```
model.best_params_
```

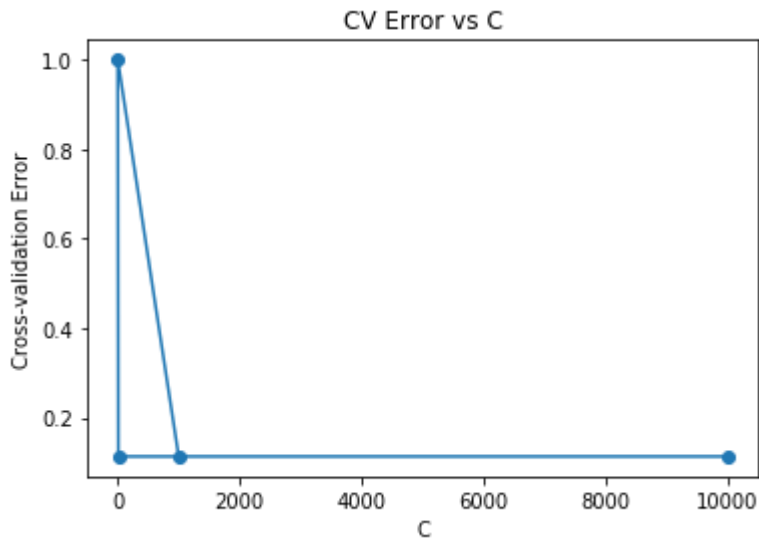
Out[135]:

```
{'C': 1000}
```

Plotting a graph between C vs CV Error

In [136]:

```
score = model.cv_results_  
score  
plot_df = pd.DataFrame(score)  
plt.plot(plot_df["param_C"], 1- plot_df["mean_test_score"], "-o")  
plt.title("CV Error vs C")  
plt.xlabel("C")  
plt.ylabel("Cross-validation Error")  
plt.show()
```



In [137]:

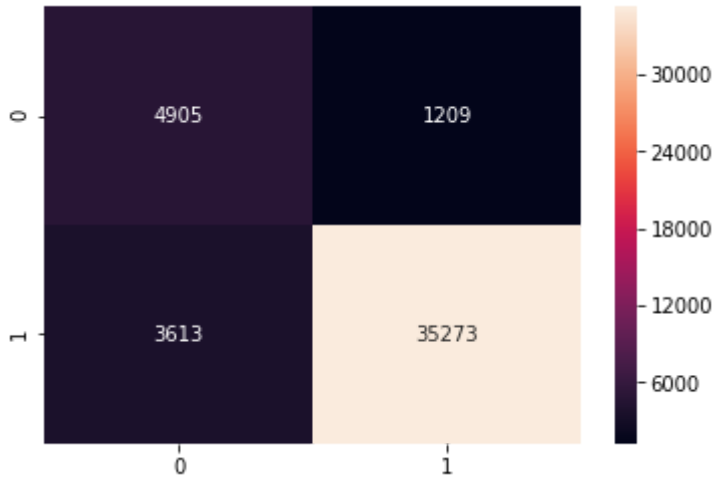
```
# Logistic Regression with Optimal value of C(1/Lambda)  
lr = LogisticRegression(penalty='l1',class_weight='balanced', C=optimal_C, n_jobs=-1)  
lr.fit(standardized_data_train,y_train)  
pred_avgw2v = lr.predict(standardized_data_test)
```

7.11 Confusion Matrix

In [138]:

```
cm_avgw2v=confusion_matrix(y_test,pred_avgw2v)
print("Confusion Matrix:")
sns.heatmap(cm_bow, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [139]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_avgw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 4092
false positives are 2022
false negatives are 3325
true positives are 35561
```

7.12 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [140]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_avgw2v) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_avgw2v = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_avgw2v))

# evaluating precision
precision_score = precision_score(y_test, pred_avgw2v)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_avgw2v)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_avgw2v)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 1000.000 is 93.007624%

Test Error Logistic Regression classifier is 6.992376%

The Test Precision of the Logistic Regression classifier for C = 1000.000 is 0.946199

The Test Recall of the Logistic Regression classifier for C = 1000.000 is 0.914494

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.55	0.67	0.60	6114
1	0.95	0.91	0.93	38886
micro avg	0.88	0.88	0.88	45000
macro avg	0.75	0.79	0.77	45000
weighted avg	0.89	0.88	0.89	45000

7.13 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [141]:

```

lambda = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
for i in lambda[::-1]:
    lrr = LogisticRegression(penalty = 'l1', C = i)
    lrr.fit(standardized_data_train, y_train)
    print("lambda="+str(1/i)+" ; non-zeros="+str(np.count_nonzero(lrr.coef_)))

```

```

lambda=0.0001 ; non-zeros=50
lambda=0.001 ; non-zeros=50
lambda=0.01 ; non-zeros=50
lambda=0.1 ; non-zeros=50
lambda=1.0 ; non-zeros=50
lambda=10.0 ; non-zeros=46
lambda=100.0 ; non-zeros=22
lambda=1000.0 ; non-zeros=2
lambda=10000.0 ; non-zeros=0

```

In [142]:

```

lr = LogisticRegression(penalty='l2', C=0.01)
lr.fit(standardized_data_train, y_train)

```

Out[142]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [143]:

```

# Applying perturbation and checking if the coefficients differ too much
# Will not add noise to zeros

```

```

noise = np.random.normal(0 , 0.1 , 1)
print("Noise= "+str(noise[0]))
standardized_data_train.data = standardized_data_train.data + noise[0]

```

```
Noise= 0.03855709270957694
```

In [144]:

```

# Fitting the new model on the transformed data

```

```

lr2 = LogisticRegression(penalty='l2', C=0.01)
lr2.fit(standardized_data_train.data, y_train)

```

Out[144]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [145]:

```
# Calculating the percentage change between the old and new coefficients
count=0
for i in range(standardized_data_train.shape[1]):
    delta = abs((((lr.coef_[0][i] - lr2.coef_[0][i]) * 100))/ lr.coef_[0][i])
    if delta>40:
        count+=1

print("Number of features whose coefficients changed by more than 40% =",count)
```

Number of features whose coefficients changed by more than 40% = 4

Hence Number of Features whose coefficients changed by more than 40% is less these are less collinear hence we cannot calculate feature importance

7.14 Using L2 Regularization

In [146]:

```
# Finding the best parameters using Random Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import RandomizedSearchCV
param_distributions = {'C': [10**-4,10**-3, 10**-2,10**-1, 1, 10**1,10**2,10**3, 10**4]}
model = RandomizedSearchCV(LogisticRegression(penalty = 'l2',class_weight='balanced'), param_distributions, cv=10)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ",model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L1 Regularization",model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is : LogisticRegression(C=10000, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l2', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

Accuracy of model using L1 Regularization 0.9384175502929749

In [147]:

```
model.best_params_
```

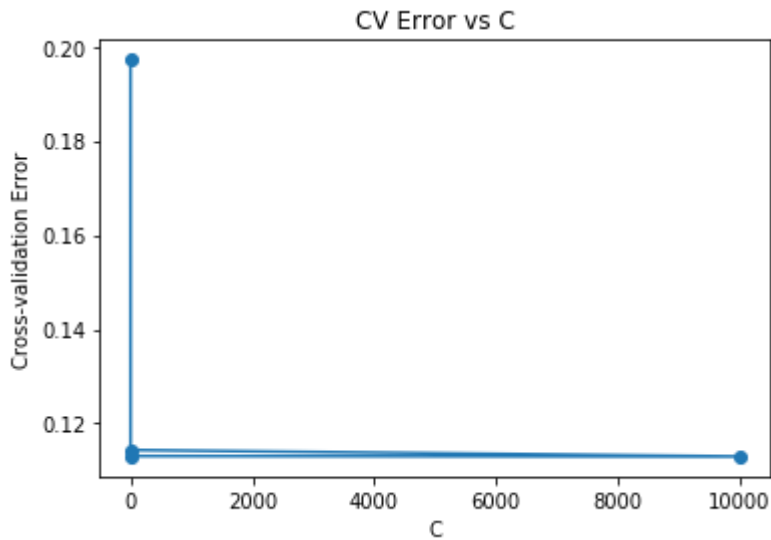
Out[147]:

```
{'C': 10000}
```

Plotting a graph between C vs CV Error

In [148]:

```
score = model.cv_results_  
score  
plot_df = pd.DataFrame(score)  
plt.plot(plot_df["param_C"], 1- plot_df["mean_test_score"], "-o")  
plt.title("CV Error vs C")  
plt.xlabel("C")  
plt.ylabel("Cross-validation Error")  
plt.show()
```



In [149]:

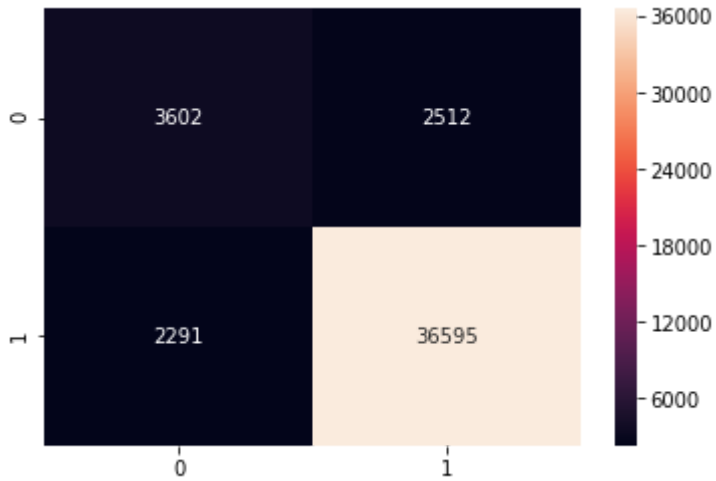
```
# Logistic Regression with Optimal value of C(1/Lambda)  
lr = LogisticRegression(penalty='l2', class_weight='balanced',C=optimal_C, n_jobs=-1)  
lr.fit(standardized_data_train,y_train)  
pred_avg2v = lr.predict(standardized_data_test)
```

7.15 Confusion Matrix

In [150]:

```
cm_avgw2v=confusion_matrix(y_test,pred_avgw2v)
print("Confusion Matrix:")
sns.heatmap(cm_avgw2v, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [151]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_avgw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 3602
false positives are 2512
false negatives are 2291
true positives are 36595
```

7.16 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [152]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_avgw2v) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_avgw2v = 100-f1score
print("\nTest Error  Logistic Regression classifier is  %f%%" % (test_error_avgw2v))

# evaluating precision
precision_score = precision_score(y_test, pred_avgw2v)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_avgw2v)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_avgw2v)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 10000.000 is 93.841755%

Test Error Logistic Regression classifier is 6.158245%

The Test Precision of the Logistic Regression classifier for C = 10000.000 is 0.935766

The Test Recall of the Logistic Regression classifier for C = 10000.000 is 0.941084

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.61	0.59	0.60	6114
1	0.94	0.94	0.94	38886
micro avg	0.89	0.89	0.89	45000
macro avg	0.77	0.77	0.77	45000
weighted avg	0.89	0.89	0.89	45000

7.17 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [153]:

```

lambda = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
for i in lambda[::-1]:
    lrr = LogisticRegression(penalty = 'l1', C = i)
    lrr.fit(standardized_data_train, y_train)
    print("lambda="+str(1/i)+" ; non-zeros="+str(np.count_nonzero(lrr.coef_)))

```

```

lambda=0.0001 ; non-zeros=50
lambda=0.001 ; non-zeros=50
lambda=0.01 ; non-zeros=50
lambda=0.1 ; non-zeros=50
lambda=1.0 ; non-zeros=50
lambda=10.0 ; non-zeros=47
lambda=100.0 ; non-zeros=23
lambda=1000.0 ; non-zeros=2
lambda=10000.0 ; non-zeros=0

```

In [154]:

```

lr = LogisticRegression(penalty='l2', C=0.01)
lr.fit(standardized_data_train, y_train)

```

Out[154]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [155]:

```

# Applying perturbation and checking if the coefficients differ too much
# Will not add noise to zeros

```

```

noise = np.random.normal(0 , 0.1 , 1)
print("Noise= "+str(noise[0]))
standardized_data_train.data = standardized_data_train.data + noise[0]

```

```
Noise= -0.05255630041709112
```

In [156]:

```
# Fitting the new model on the transformed data
```

```

lr2 = LogisticRegression(penalty='l2', C=0.01)
lr2.fit(standardized_data_train, y_train)

```

Out[156]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [157]:

```
# Calculating the percentage change between the old and new coefficients
count=0
for i in range(standardized_data_train.shape[1]):
    delta = abs((((lr.coef_[0][i] - lr2.coef_[0][i]) * 100))/ lr.coef_[0][i])
    if delta>40:
        count+=1

print("Number of features whose coefficients changed by more than 40% =",count)
```

Number of features whose coefficients changed by more than 40% = 6

Hence Number of Features whose coefficients changed by more than 40% is less these are less collinear
hence we cannot calculate feature importance

8.TFIDF-Word2Vec

In [158]:

```
#tf-idf weighted w2v

from sklearn.feature_extraction.text import TfidfVectorizer

tfidf2v_vect = TfidfVectorizer()
final_counts_tfidf2v_train= tfidf2v_vect.fit_transform(x_train)
print(type(final_counts_tfidf2v_train))
print(final_counts_tfidf2v_train.shape)

final_counts_tfidf2v_test= tfidf2v_vect.transform(x_test)
print(type(final_counts_tfidf2v_test))
print(final_counts_tfidf2v_test.shape)
```

```
<class 'scipy.sparse.csr.csr_matrix'>
(105000, 38300)
<class 'scipy.sparse.csr.csr_matrix'>
(45000, 38300)
```


In [159]:

```
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidfw2v_vect.get_feature_names(), list(tfidfw2v_vect.idf_)))

# TF-IDF weighted Word2Vec
tfidf_feat = tfidfw2v_vect.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and cell_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in sent_of_train: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            #
            tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors.append(sent_vec)
    row += 1

#Test case

tfidf_sent_vectors1 = []; # the tfidf-w2v for each sentence/review is stored in this list
row=0;
for sent in sent_of_test: # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            #
            tf_idf = tf_idf_matrix[row, tfidf_feat.index(word)]
            # to reduce the computation we are
            # dictionary[word] = idf value of word in whole courpus
            # sent.count(word) = tf valeus of word in this review
            tf_idf = dictionary[word]*(sent.count(word)/len(sent))
            sent_vec += (vec * tf_idf)
            weight_sum += tf_idf
    if weight_sum != 0:
        sent_vec /= weight_sum
    tfidf_sent_vectors1.append(sent_vec)
    row += 1
print(len(tfidf_sent_vectors))
print(len(tfidf_sent_vectors1))
```

105000

45000

8.1 Standardizing Data

In [160]:

```
# Data-preprocessing: Standardizing the data
from sklearn import preprocessing
standardized_data_train = preprocessing.normalize(tfidf_sent_vectors)
print(standardized_data_train.shape)
standardized_data_test = preprocessing.normalize(tfidf_sent_vectors1)
print(standardized_data_test.shape)
```

```
(105000, 50)
```

```
(45000, 50)
```

8.2 Applying Logistic Regression Algorithm

8.2.1 Gridsearch Cross Validation

8.2.1.1 Using L1 Regularization

In [161]:

```
# Finding the best parameters using Grid Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import GridSearchCV
tuned_parameters = [{'C': [10**-4, 10**-3, 10**-2, 10**-1, 1, 10**1, 10**2, 10**3, 10**4]}]
model = GridSearchCV(LogisticRegression(penalty='l1', class_weight='balanced'), tuned_parameters)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ", model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L1 Regularization", model.score(standardized_data_test, y_test))
```

```
The optimal value of C(1/lambda) is : LogisticRegression(C=1, class_weight='balanced', dual=False,
fit_intercept=True, intercept_scaling=1, max_iter=100,
multi_class='warn', n_jobs=None, penalty='l1', random_state=None,
solver='warn', tol=0.0001, verbose=0, warm_start=False)
```

```
Accuracy of model using L1 Regularization 0.868918918918919
```

In [162]:

```
model.best_params_
```

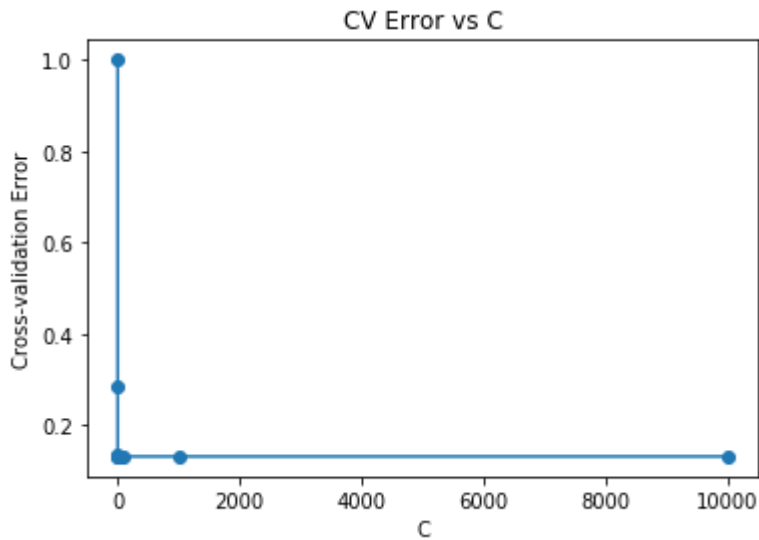
Out[162]:

```
{'C': 1}
```

Plotting a graph between C vs CV Error

In [163]:

```
score = model.cv_results_  
score  
plot_df = pd.DataFrame(score)  
plt.plot(plot_df["param_C"], 1- plot_df["mean_test_score"], "-o")  
plt.title("CV Error vs C")  
plt.xlabel("C")  
plt.ylabel("Cross-validation Error")  
plt.show()
```



In [164]:

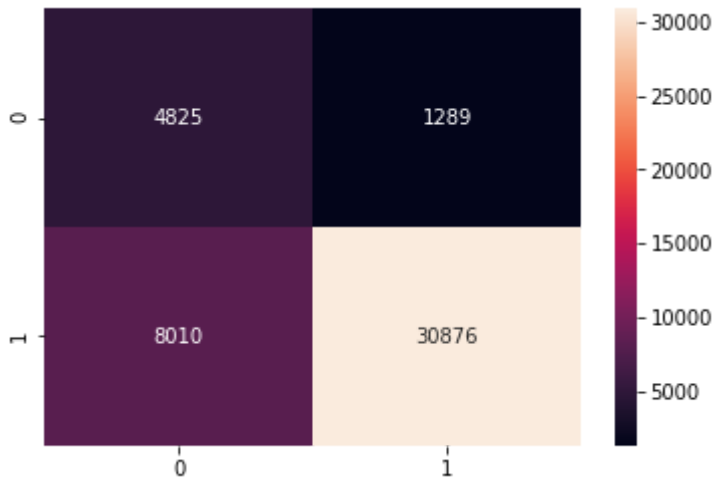
```
# Logistic Regression with Optimal value of C(1/Lambda)  
lr = LogisticRegression(penalty='l2',class_weight='balanced', C=optimal_C, n_jobs=-1)  
lr.fit(standardized_data_train,y_train)  
pred_tfidf2v = lr.predict(standardized_data_test)
```

8.3 Confusion Matrix

In [165]:

```
cm_tf1dfw2v=confusion_matrix(y_test,pred_tf1dfw2v)
print("Confusion Matrix:")
sns.heatmap(cm_tf1dfw2v, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [166]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_tf1dfw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 4825
false positives are 1289
false negatives are 8010
true positives are 30876
```

8.4 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [167]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_tfidf2v) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_tfidf2v = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_tfidf2v))

# evaluating precision
precision_score = precision_score(y_test, pred_tfidf2v)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_tfidf2v)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_tfidf2v)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 1.000 is 86.912218%

Test Error Logistic Regression classifier is 13.087782%

The Test Precision of the Logistic Regression classifier for C = 1.000 is 0.959925

The Test Recall of the Logistic Regression classifier for C = 1.000 is 0.794013

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.38	0.79	0.51	6114
1	0.96	0.79	0.87	38886
micro avg	0.79	0.79	0.79	45000
macro avg	0.67	0.79	0.69	45000
weighted avg	0.88	0.79	0.82	45000

8.5 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [168]:

```

lambda = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
for i in lambda[::-1]:
    lrr = LogisticRegression(penalty = 'l1', C = i)
    lrr.fit(standardized_data_train, y_train)
    print("lambda="+str(1/i)+" ; non-zeros="+str(np.count_nonzero(lrr.coef_)))

```

```

lambda=0.0001 ; non-zeros=50
lambda=0.001 ; non-zeros=50
lambda=0.01 ; non-zeros=50
lambda=0.1 ; non-zeros=50
lambda=1.0 ; non-zeros=50
lambda=10.0 ; non-zeros=47
lambda=100.0 ; non-zeros=23
lambda=1000.0 ; non-zeros=1
lambda=10000.0 ; non-zeros=0

```

In [169]:

```

lr = LogisticRegression(penalty='l2', C=0.01)
lr.fit(standardized_data_train, y_train)

```

Out[169]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [170]:

```

# Applying perturbation and checking if the coefficients differ too much
# Will not add noise to zeros

```

```

noise = np.random.normal(0 , 0.1 , 1)
print("Noise= "+str(noise[0]))
standardized_data_train.data = standardized_data_train.data + noise[0]

```

```
Noise= 0.12618696701812981
```

In [171]:

```

# Fitting the new model on the transformed data

```

```

lr2 = LogisticRegression(penalty='l2', C=0.01)
lr2.fit(standardized_data_train, y_train)

```

Out[171]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [172]:

```
# Calculating the percentage change between the old and new coefficients
count=0
for i in range(standardized_data_train.shape[1]):
    delta = abs((((lr.coef_[0][i] - lr2.coef_[0][i]) * 100))/ lr.coef_[0][i])
    if delta>40:
        count+=1

print("Number of features whose coefficients changed by more than 40% =",count)
```

Number of features whose coefficients changed by more than 40% = 15

Hence Number of Features whose coefficients changed by more than 40% is less these are less collinear
hence we cannot calculate feature importance

8.6 Using L2 Regularization

In [174]:

```
# Finding the best parameters using Grid Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import GridSearchCV
tuned_parameters = [{'C': [10**-5,10**-4,10**-3,10**-2,10**-1, 1, 10**2,10**3, 10**4]}]
model = GridSearchCV(LogisticRegression(penalty = 'l2',class_weight='balanced'), tuned_parameters)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ",model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L2 Regularization",model.score(standardized_data_test, y_test))
```

The optimal value of C(1/lambda) is : LogisticRegression(C=1, class_weight='balanced', dual=False, fit_intercept=True, intercept_scaling=1, max_iter=100, multi_class='warn', n_jobs=None, penalty='l2', random_state=None, solver='warn', tol=0.0001, verbose=0, warm_start=False)

Accuracy of model using L2 Regularization 0.9264148747721073

In [175]:

```
model.best_params_
```

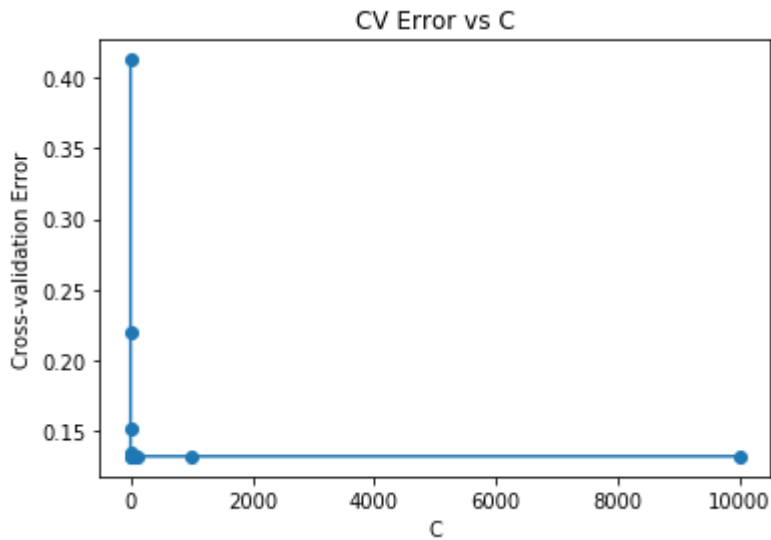
Out[175]:

```
{'C': 1}
```

Plotting a graph between C vs CV Error

In [176]:

```
score = model.cv_results_  
score  
plot_df = pd.DataFrame(score)  
plt.plot(plot_df["param_C"], 1- plot_df["mean_test_score"], "-o")  
plt.title("CV Error vs C")  
plt.xlabel("C")  
plt.ylabel("Cross-validation Error")  
plt.show()
```



In [177]:

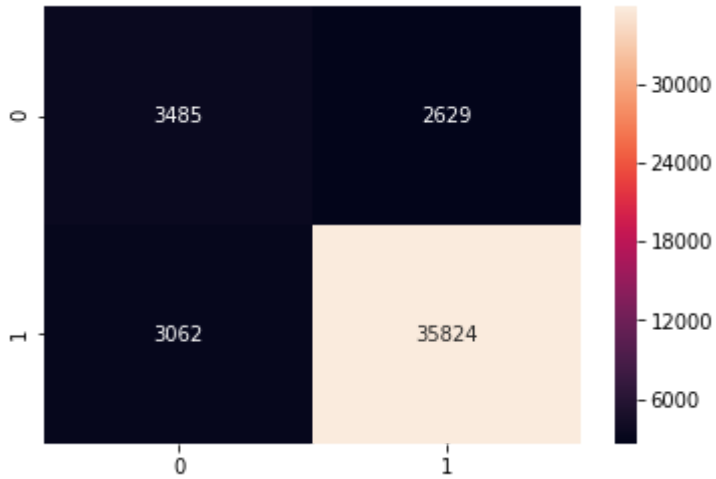
```
# Logistic Regression with Optimal value of C(1/Lambda)  
lr = LogisticRegression(penalty='l2',class_weight='balanced', C=optimal_C, n_jobs=-1)  
lr.fit(standardized_data_train,y_train)  
pred_tfidf2v = lr.predict(standardized_data_test)
```

8.7 Confusion Matrix

In [178]:

```
cm_tf1dfw2v=confusion_matrix(y_test,pred_tf1dfw2v)
print("Confusion Matrix:")
sns.heatmap(cm_tf1dfw2v, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [179]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_tf1dfw2v.ravel()
( tp, fp, fn, tn)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 3485
false positives are 2629
false negatives are 3062
true positives are 35824
```

8.8 Accuracy,Error on test data,Precision,Recall,Classification Report

In [180]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_tfidf2v) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_tfidf2v = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_tfidf2v))

# evaluating precision
precision_score = precision_score(y_test, pred_tfidf2v)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_tfidf2v)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_tfidf2v)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 1.000 is 92.641487%

Test Error Logistic Regression classifier is 7.358513%

The Test Precision of the Logistic Regression classifier for C = 1.000 is 0.931631

The Test Recall of the Logistic Regression classifier for C = 1.000 is 0.921257

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.53	0.57	0.55	6114
1	0.93	0.92	0.93	38886
micro avg	0.87	0.87	0.87	45000
macro avg	0.73	0.75	0.74	45000
weighted avg	0.88	0.87	0.88	45000

8.9 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [181]:

```

lambda = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
for i in lambda[::-1]:
    lrr = LogisticRegression(penalty = 'l1', C = i)
    lrr.fit(standardized_data_train, y_train)
    print("lambda="+str(1/i)+" ; non-zeros="+str(np.count_nonzero(lrr.coef_)))

```

```

lambda=0.0001 ; non-zeros=50
lambda=0.001 ; non-zeros=50
lambda=0.01 ; non-zeros=50
lambda=0.1 ; non-zeros=50
lambda=1.0 ; non-zeros=50
lambda=10.0 ; non-zeros=47
lambda=100.0 ; non-zeros=24
lambda=1000.0 ; non-zeros=2
lambda=10000.0 ; non-zeros=0

```

In [182]:

```

lr = LogisticRegression(penalty='l2', C=0.01)
lr.fit(standardized_data_train, y_train)

```

Out[182]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [183]:

```

# Applying perturbation and checking if the coefficients differ too much
# Will not add noise to zeros

```

```

noise = np.random.normal(0 , 0.1 , 1)
print("Noise= "+str(noise[0]))
standardized_data_train.data = standardized_data_train.data + noise[0]

```

```
Noise= 0.061524396794310335
```

In [184]:

```

# Fitting the new model on the transformed data

```

```

lr2 = LogisticRegression(penalty='l2', C=0.01)
lr2.fit(standardized_data_train, y_train)

```

Out[184]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [185]:

```
# Calculating the percentage change between the old and new coefficients
count=0
for i in range(standardized_data_train.shape[1]):
    delta = abs((((lr.coef_[0][i] - lr2.coef_[0][i]) * 100))/ lr.coef_[0][i])
    if delta>40:
        count+=1

print("Number of features whose coefficients changed by more than 40% =",count)
```

Number of features whose coefficients changed by more than 40% = 6

Hence Number of Features whose coefficients changed by more than 40% is less these are less collinear
hence we cannot calculate feature importance

9. Randomized Search Cross Validation

9.1 Using L1 Regularization

In [186]:

```
# Finding the best parameters using Random Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import RandomizedSearchCV
param_distributions = {'C': [10**-4,10**-3, 10**-2,10**-1, 1, 10**1,10**2,10**3, 10**4]}
model = RandomizedSearchCV(LogisticRegression(penalty = 'l1',class_weight='balanced'), param_distributions, cv=10)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ",model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L1 Regularization",model.score(standardized_data_test, y_test))
```

The optimal value of C(1/lambda) is : LogisticRegression(C=0.001, class_weight='balanced', dual=False, fit_intercept=True, intercept_scaling=1, max_iter=100, multi_class='warn', n_jobs=None, penalty='l1', random_state=None, solver='warn', tol=0.0001, verbose=0, warm_start=False)

Accuracy of model using L1 Regularization 0.8358122910181023

In [187]:

```
model.best_params_
```

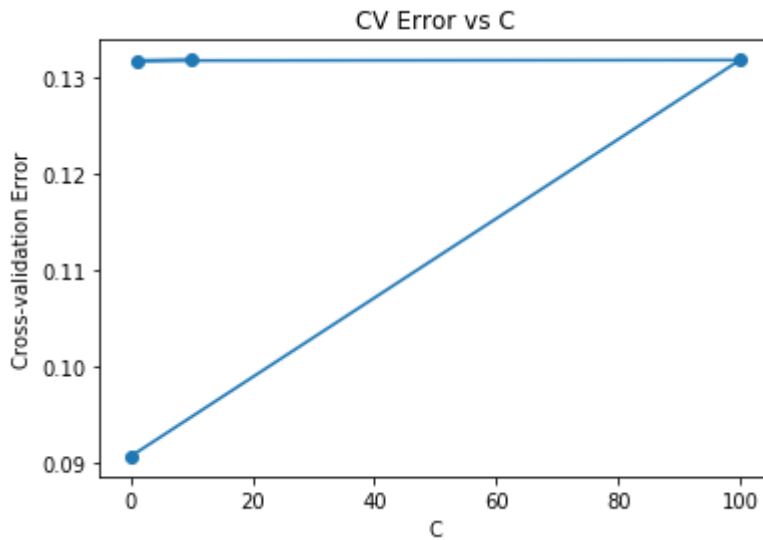
Out[187]:

```
{'C': 0.001}
```

Plotting a graph between C vs CV Error

In [188]:

```
score = model.cv_results_  
score  
plot_df = pd.DataFrame(score)  
plt.plot(plot_df["param_C"], 1 - plot_df["mean_test_score"], "-o")  
plt.title("CV Error vs C")  
plt.xlabel("C")  
plt.ylabel("Cross-validation Error")  
plt.show()
```



In [189]:

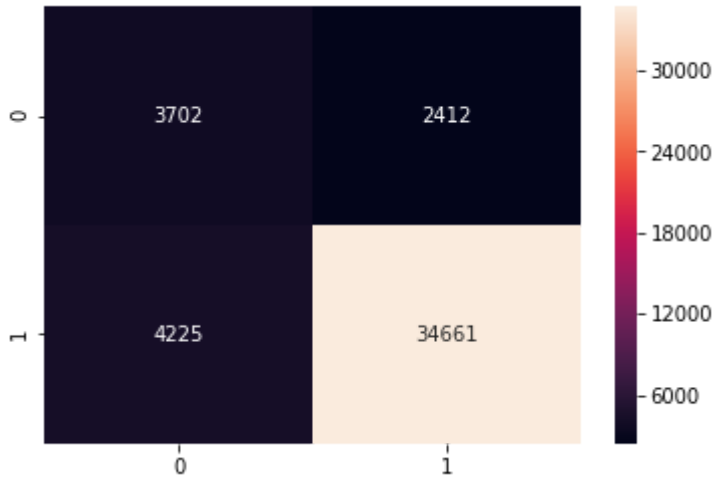
```
# Logistic Regression with Optimal value of C(1/Lambda)  
lr = LogisticRegression(penalty='l2', class_weight='balanced', C=optimal_C, n_jobs=-1)  
lr.fit(standardized_data_train, y_train)  
pred_tfidf2v = lr.predict(standardized_data_test)
```

9.2 Confusion Matrix

In [190]:

```
cm_tf1dfw2v=confusion_matrix(y_test,pred_tf1dfw2v)
print("Confusion Matrix:")
sns.heatmap(cm_tf1dfw2v, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [191]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_tf1dfw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 3702
false positives are 2412
false negatives are 4225
true positives are 34661
```

9.3 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [192]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_tfidf2v) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_tfidf2v = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_tfidf2v))

# evaluating precision
precision_score = precision_score(y_test, pred_tfidf2v)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_tfidf2v)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_tfidf2v)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 0.001 is 91.262392%

Test Error Logistic Regression classifier is 8.737608%

The Test Precision of the Logistic Regression classifier for C = 0.001 is 0.934939

The Test Recall of the Logistic Regression classifier for C = 0.001 is 0.891349

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.47	0.61	0.53	6114
1	0.93	0.89	0.91	38886
micro avg	0.85	0.85	0.85	45000
macro avg	0.70	0.75	0.72	45000
weighted avg	0.87	0.85	0.86	45000

9.4 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [193]:

```

lambda = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
for i in lambda[::-1]:
    lrr = LogisticRegression(penalty = 'l1', C = i)
    lrr.fit(standardized_data_train, y_train)
    print("lambda="+str(1/i)+" ; non-zeros="+str(np.count_nonzero(lrr.coef_)))

```

```

lambda=0.0001 ; non-zeros=50
lambda=0.001 ; non-zeros=50
lambda=0.01 ; non-zeros=50
lambda=0.1 ; non-zeros=50
lambda=1.0 ; non-zeros=50
lambda=10.0 ; non-zeros=48
lambda=100.0 ; non-zeros=25
lambda=1000.0 ; non-zeros=2
lambda=10000.0 ; non-zeros=0

```

In [194]:

```

lr = LogisticRegression(penalty='l2', C=0.01)
lr.fit(standardized_data_train, y_train)

```

Out[194]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [195]:

```

# Applying perturbation and checking if the coefficients differ too much
# Will not add noise to zeros

```

```

noise = np.random.normal(0 , 0.1 , 1)
print("Noise= "+str(noise[0]))
standardized_data_train.data = standardized_data_train.data + noise[0]

```

```
Noise= 0.2971801627396628
```

In [196]:

```

# Fitting the new model on the transformed data

```

```

lr2 = LogisticRegression(penalty='l2', C=0.01)
lr2.fit(standardized_data_train, y_train)

```

Out[196]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```


In [197]:

```
# Calculating the percentage change between the old and new coefficients
count=0
for i in range(standardized_data_train.shape[1]):
    delta = abs((((lr.coef_[0][i] - lr2.coef_[0][i]) * 100))/ lr.coef_[0][i])
    if delta>40:
        count+=1

print("Number of features whose coefficients changed by more than 40% =",count)
```

Number of features whose coefficients changed by more than 40% = 4

Hence Number of Features whose coefficients changed by more than 40% is less these are less collinear
hence we cannot calculate feature importance

9.5 Using L2 Regularization

In [198]:

```
# Finding the best parameters using Random Search CV using 10-fold Cross-Validation in Logistic Regression

from sklearn.model_selection import RandomizedSearchCV
param_distributions = {'C': [10**-4,10**-3, 10**-2,10**-1, 1, 10**1,10**2,10**3, 10**4]}
model = RandomizedSearchCV(LogisticRegression(penalty = 'l2',class_weight='balanced'), param_distributions, cv=10)
model.fit(standardized_data_train, y_train)
print("The optimal value of C(1/lambda) is : ",model.best_estimator_.C)
optimal_C = model.best_estimator_.C
print("\n Accuracy of model using L1 Regularization",model.score(standardized_data_test, y_test))
```

The optimal value of C(1/lambda) is : LogisticRegression(C=10, class_weight='balanced', dual=False, fit_intercept=True, intercept_scaling=1, max_iter=100, multi_class='warn', n_jobs=None, penalty='l2', random_state=None, solver='warn', tol=0.0001, verbose=0, warm_start=False)

Accuracy of model using L1 Regularization 0.9317876021143681

In [199]:

```
model.best_params_
```

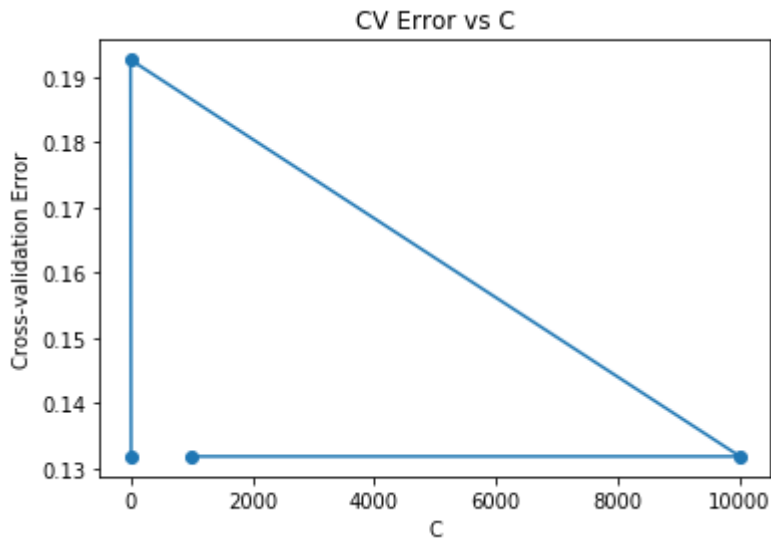
Out[199]:

```
{'C': 10}
```

Plotting a graph between C vs CV Error

In [200]:

```
score = model.cv_results_  
score  
plot_df = pd.DataFrame(score)  
plt.plot(plot_df["param_C"], 1- plot_df["mean_test_score"], "-o")  
plt.title("CV Error vs C")  
plt.xlabel("C")  
plt.ylabel("Cross-validation Error")  
plt.show()
```



In [201]:

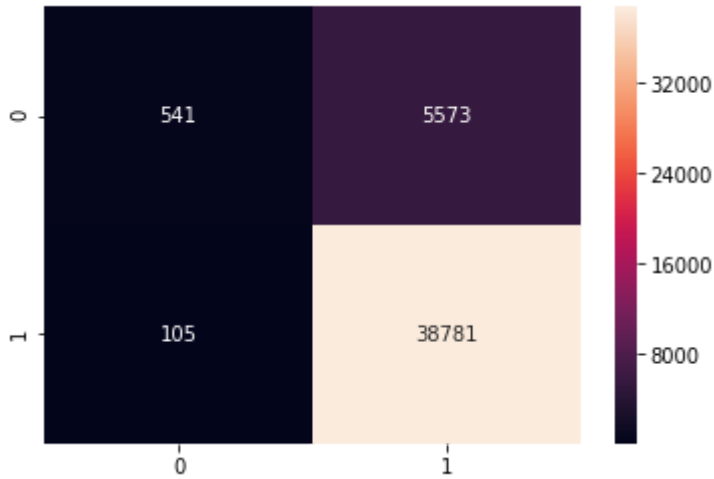
```
# Logistic Regression with Optimal value of C(1/Lambda)  
lr = LogisticRegression(penalty='l2',class_weight='balanced', C=optimal_C, n_jobs=-1)  
lr.fit(standardized_data_train,y_train)  
pred_tfidf2v = lr.predict(standardized_data_test)
```

9.6 Confusion Matrix

In [202]:

```
cm_tf1dfw2v=confusion_matrix(y_test,pred_tf1dfw2v)
print("Confusion Matrix:")
sns.heatmap(cm_tf1dfw2v, annot=True, fmt='d')
plt.show()
```

Confusion Matrix:



In [203]:

```
#finding out true negative , false positive , false negative and true positive
tn, fp, fn, tp = cm_tf1dfw2v.ravel()
( tp, fp, fn, tp)
print(" true negitves are {} \n false positives are {} \n false negatives are {} \n true pos
```

```
true negitves are 541
false positives are 5573
false negatives are 105
true positives are 38781
```

9.7 Calculating Accuracy,Error on test data,Precision,Recall,Classification Report

In [204]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import precision_score
from sklearn.metrics import classification_report

# evaluating accuracy
f1score = f1_score(y_test, pred_tfidf2v) * 100
print('\nThe Test Accuracy of the Logistic Regression classifier for C = %.3f is %f%%' % (C, f1score))

# Error on test data
test_error_tfidf2v = 100-f1score
print("\nTest Error Logistic Regression classifier is %f%%" % (test_error_tfidf2v))

# evaluating precision
precision_score = precision_score(y_test, pred_tfidf2v)
print('\nThe Test Precision of the Logistic Regression classifier for C = %.3f is %f' % (C, precision_score))

# evaluating recall
recall_score = recall_score(y_test, pred_tfidf2v)
print('\nThe Test Recall of the Logistic Regression classifier for C = %.3f is %f' % (C, recall_score))

# evaluating Classification report
classification_report = classification_report(y_test, pred_tfidf2v)
print('\nThe Test classification report of the Logistic regression classifier for C \n\n ', classification_report)
```

The Test Accuracy of the Logistic Regression classifier for C = 10.000 is 93.178760%

Test Error Logistic Regression classifier is 6.821240%

The Test Precision of the Logistic Regression classifier for C = 10.000 is 0.874352

The Test Recall of the Logistic Regression classifier for C = 10.000 is 0.997300

The Test classification report of the Logistic regression classifier for C

	precision	recall	f1-score	support
0	0.84	0.09	0.16	6114
1	0.87	1.00	0.93	38886
micro avg	0.87	0.87	0.87	45000
macro avg	0.86	0.54	0.55	45000
weighted avg	0.87	0.87	0.83	45000

9.8 Perturbation Test

Perturbation test means adding noise to one of the data point and comparing the difference b/w change in previous weights and New

weights to find of collinearity.

In [205]:

```

lambda = [0.0001, 0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]
for i in lambda[::-1]:
    lrr = LogisticRegression(penalty = 'l1', C = i)
    lrr.fit(standardized_data_train, y_train)
    print("lambda="+str(1/i)+" ; non-zeros="+str(np.count_nonzero(lrr.coef_)))

```

```

lambda=0.0001 ; non-zeros=50
lambda=0.001 ; non-zeros=50
lambda=0.01 ; non-zeros=50
lambda=0.1 ; non-zeros=50
lambda=1.0 ; non-zeros=50
lambda=10.0 ; non-zeros=45
lambda=100.0 ; non-zeros=25
lambda=1000.0 ; non-zeros=3
lambda=10000.0 ; non-zeros=0

```

In [206]:

```

lr = LogisticRegression(penalty='l2', C=0.01)
lr.fit(standardized_data_train, y_train)

```

Out[206]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [207]:

```

# Applying perturbation and checking if the coefficients differ too much
# Will not add noise to zeros

```

```

noise = np.random.normal(0 , 0.1 , 1)
print("Noise= "+str(noise[0]))
standardized_data_train.data = standardized_data_train.data + noise[0]

```

```
Noise= -0.14592227151454049
```

In [208]:

```
# Fitting the new model on the transformed data
```

```

lr2 = LogisticRegression(penalty='l2', C=0.01)
lr2.fit(standardized_data_train, y_train)

```

Out[208]:

```

LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
    intercept_scaling=1, max_iter=100, multi_class='warn',
    n_jobs=None, penalty='l2', random_state=None, solver='warn',
    tol=0.0001, verbose=0, warm_start=False)

```

In [209]:

```
# Calculating the percentage change between the old and new coefficients
count=0
for i in range(standardized_data_train.shape[1]):
    delta = abs((((lr.coef_[0][i] - lr2.coef_[0][i]) * 100)) / lr.coef_[0][i])
    if delta>40:
        count+=1

print("Number of features whose coefficients changed by more than 40% =",count)
```

Number of features whose coefficients changed by more than 40% = 0

Hence Number of Features whose coefficients changed by more than 40% is less these are less collinear
hence we cannot calculate feature importance

10.Conclusion

Model performance table

Model	Hyper parameter(c) with Random search	Regularizer	Test Error	Accuracy
Logistic Regression with Bow	100	L2	6.3979	93.602
Logistic Regression with Tfidf	100	L2	6.614209	93.385791
Logistic Regression with Avgw2v	1000	L2	6.1558245	93.841755
Logistic Regression with Tfidf2v	10	L2	6.821240	93.17876

Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or

more nominal, ordinal, interval or ratio-level independent variables.

Logistic regression is used to obtain odds ratio in the presence of more than one explanatory variable.

Logistic regression does not assume a linear relationship between the dependent variable and the independent variables, but it

does assume linear relationship between the logic of the explanatory variables and the response.

Independent variables can be even the power terms or some other nonlinear transformations of the original independent variables

The dependent variable does NOT need to be normally distributed, but it typically assumes a distribution from an exponential

family (e.g. binomial, Poisson, multinomial, normal,...); binary logistic regression assume binomial distribution of the

response

The goal of logistic regression is to correctly predict the category of outcome for individual cases using the most

parsimonious model. To accomplish this goal, a model is created that includes all predictor variables that are useful in

predicting the response variable.

Assumptions of Logistic Regression

- 1)logistic regression does not require a linear relationship between the dependent and independent variables.
- 2)Second, the error terms (residuals) do not need to be normally distributed.
- 3)Third, homoscedasticity is not required.
- 4)Finally, the dependent variable in logistic regression is not measured on an interval or ratio scale.

Steps Involved:-

- 1)Connecting SQL file
- 2)Data Preprocessing(Already i had done preprocessing no need to do again)
- 3)Sorting the data based on time
- 4)Mapping the data (i had changed my partition positive=1 and Negative=0)
- 5)Taking 1st 150K Rows (Due to low Ram)
- 6)Splitting data into train and test based on time (70:30)
- 7)Techniques For Vectorization Bow,TF-IDF,Avgword2vec,Tfidfword2vec
- 8)Standardizing Data and Applying Logistic Regression Algorithm
- 9)I calculated Accuracy,Error on Test Data, Confusion Matrix, Classification Report,Precision Score,Recall Score, F1-Score,Feature Importance,Log-Probabilities.
- 10)Performing perturbation test
- 11)Gettting Important Features
- 12)I Designed Model Performance Table
- 13)Conclusion

In []: