Part 5 - Logistic Regression

By Aziz Presswala

In [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import pickle
import os
import math
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.sparse import find
from tqdm import tqdm
from prettytable import PrettyTable

from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn import model_selection
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler

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

Splitting the Dataset into Train & Test

In [2]:
```
# Using the CleanedText column saved in final.sqlite db
con = sqlite3.connect('final.sqlite')
filtered_data = pd.read_sql_query("SELECT * FROM Reviews", con)
filtered_data.shape
```

Out[2]: (364171, 12)

In [3]:
```
# replacing all the 'positive' values of the Score attribute with 1
filtered_data['Score']=filtered_data['Score'].replace('positive',1)
```

In [4]:
```
# replacing all the 'neagtive' values of the Score attribute with 0
filtered_data['Score']=filtered_data['Score'].replace('negative',0)
```

In [5]:
```
#randomly selecting 100k points from the dataset
df=filtered_data.sample(100000)
```

In [6]:
```
#sort the dataset by timestamp
df = df.sort_values('Time')
#splitting the dataset into train(70%) & test(30%)
train_data = df[0:70000]
test_data = df[70000:100000]
```

Featurization

BAG OF WORDS

In [7]:
```
#applying fit transform on train datasset
count_vect = CountVectorizer(min_df=10)
x_train_bow = count_vect.fit_transform(train_data['CleanedText'].values
)
x_train_bow.shape
```

Out[7]: (70000, 7220)

In [8]:
```
#applying transform on test dataset
x_test_bow = count_vect.transform(test_data['CleanedText'].values)
x_test_bow.shape
```

Out[8]: (30000, 7220)

In [9]:
```
y_train_bow = train_data['Score']
y_test_bow = test_data['Score']
```

TF-IDF

In [10]:
```
#applying fit transform on train datasset
tf_idf_vect = TfidfVectorizer(min_df=10)
x_train_tfidf = tf_idf_vect.fit_transform(train_data['CleanedText'].val
ues)
x_train_tfidf.shape
```

Out[10]: (70000, 7205)

In [11]:
```
#applying transform on test dataset
x_test_tfidf = tf_idf_vect.transform(test_data['CleanedText'].values)
x_test_tfidf.shape
```

Out[11]: (30000, 7205)

In [12]:
```
y_train_tfidf = train_data['Score']
y_test_tfidf = test_data['Score']
```

Avg. Word2Vec

In [59]:
```
#training Word2Vec Model for train dataset
```

```
i=0
list_of_sent=[]
for sent in train_data['CleanedText'].values:
    list_of_sent.append(sent.split())
```

In [60]:
```
w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

In [61]:
```
X = w2v_model[w2v_model.wv.vocab]
```

In [62]:
```
#computing Avg Word2Vec for train dataset
w2v_words = list(w2v_model.wv.vocab)
sent_vectors = []; # the avg-w2v for each sentence/review is stored in
 this list
for sent in tqdm(list_of_sent): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|███████████████████████████████████████████████████████████████████
█████████| 70000/70000 [02:58<00:00, 393.20it/s]
```

```
70000
50
```

In [63]:
```
x_train_w2v = np.array(sent_vectors)
y_train_w2v = train_data['Score']
x_train_w2v.shape
```

Out[63]: (70000, 50)

In [64]:
```
#training Word2Vec Model for test dataset
i=0
list_of_sent1=[]
for sent in test_data['CleanedText'].values:
    list_of_sent1.append(sent.split())
```

In [65]:
```
#computing Avg Word2Vec for test dataset
w2v_words = list(w2v_model.wv.vocab)
sent_vectors = []; # the avg-w2v for each sentence/review is stored in
 this list
for sent in tqdm(list_of_sent1): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/re
view
    for word in sent: # for each word in a review/sentence
        if word in w2v_words:
            vec = w2v_model.wv[word]
            sent_vec += vec
            cnt_words += 1
    if cnt_words != 0:
        sent_vec /= cnt_words
    sent_vectors.append(sent_vec)
print(len(sent_vectors))
print(len(sent_vectors[0]))
```

```
100%|████████████████████████████████████████████████████████████████
█████████| 30000/30000 [01:14<00:00, 405.07it/s]
```

```
30000
50
```

In [66]:
```
x_test_w2v = np.array(sent_vectors)
y_test_w2v = test_data['Score']
x_test_w2v.shape
```

Out[66]: (30000, 50)

TFIDF - Word2Vec

In [75]:
```
# training model for training data
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(train_data['CleanedText'].values)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [76]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.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 tqdm(list_of_sent): # for each review/sentence
    sent_vec = np.zeros(50) # as word vectors are of zero length
    weight_sum =0; # num of words with a valid vector in the sentence/review
    for word in sent: # for each word in a review/sentence
        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
```

```
100%|██████████████████████████████████████████████████
██████████| 70000/70000 [03:03<00:00, 380.69it/s]
```

In [77]:
```
x_train_tfw2v = np.array(tfidf_sent_vectors)
y_train_tfw2v = train_data['Score']
x_train_tfw2v.shape
```

Out[77]: (70000, 50)

In [79]:
```
# training model for test dataset
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(test_data['CleanedText'].values)
# we are converting a dictionary with word as a key, and the idf as a v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [80]:
```
# TF-IDF weighted Word2Vec
tfidf_feat = model.get_feature_names() # tfidf words/col-names
# final_tf_idf is the sparse matrix with row= sentence, col=word and ce
ll_val = tfidf

tfidf_sent_vectors = []; # the tfidf-w2v for each sentence/review is st
ored in this list
row=0;
for sent in tqdm(list_of_sent1): # 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/r
eview
    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
```

```
100%|██████████| 30000/30000 [01:28<00:00, 338.80it/s]
```

In [81]:
```
x_test_tfw2v = np.array(tfidf_sent_vectors)
y_test_tfw2v = test_data['Score']
x_test_tfw2v.shape
```

Out[81]:
```
(30000, 50)
```

Applying Logistic Regression

Logistic Regression on BOW

Applying Logistic Regression with L1 regularization on BOW

In [10]:
```
# initializing Logistic Regression model with L1 regularisation
lr = LogisticRegression(penalty='l1')

# C values we need to try on classifier
C_values = [1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001,0.0005
,0.0001]
param_grid = {'C':[1000,500,100,50,10,5,1,0.5,0.1,0.05,0.01,0.005,0.001
,0.0005,0.0001]}

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(lr,param_grid,scoring='roc_auc',cv=10,return_train_
score=True)

gscv.fit(x_train_bow,y_train_bow)
```

```
print("Best C Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best C Value:  {'C': 0.5}
Best ROC AUC Score: 0.92936
```

In [11]:
```
# determining optimal C
optimal_C = gscv.best_params_['C']

#training the model using the optimal C
lrf = LogisticRegression(penalty='l1',C=optimal_C)
lrf.fit(x_train_bow,y_train_bow)

#predicting the class label using test data
y_pred = lrf.predict_proba(x_test_bow)[:,1]

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_bow, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,auc_score))
```

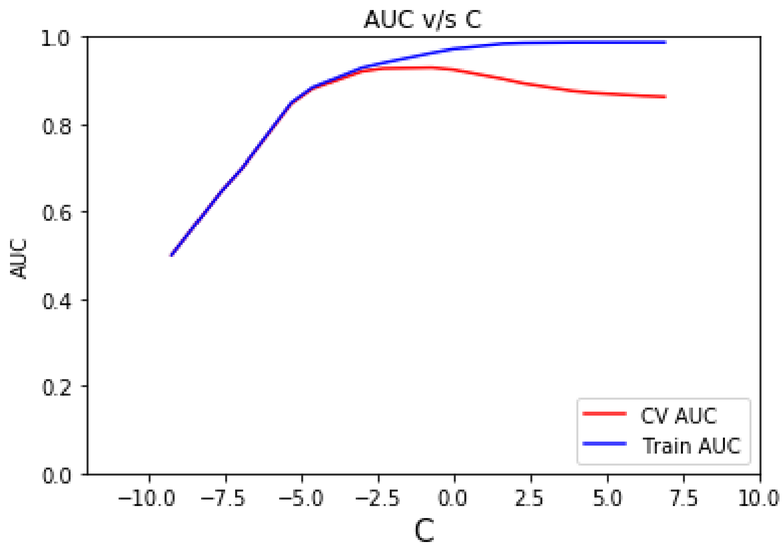
```
**** Test roc_auc_score for C = 0.500000 is 0.932319 ****
```

AUC vs C plot

In [16]:
```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in C_values]
print(log_alpha)
plt.xlim(-12,10)
plt.ylim(0.0,1.0)
plt.xlabel(r"C",fontsize=15)
plt.ylabel('AUC')
plt.title(r'AUC v/s C')
plt.plot(log_alpha, gscv.cv_results_['mean_test_score'], 'r', label='CV AUC')
plt.plot(log_alpha, gscv.cv_results_['mean_train_score'], 'b', label='Train AUC')
```

```
plt.legend(loc='lower right')
plt.show()
```

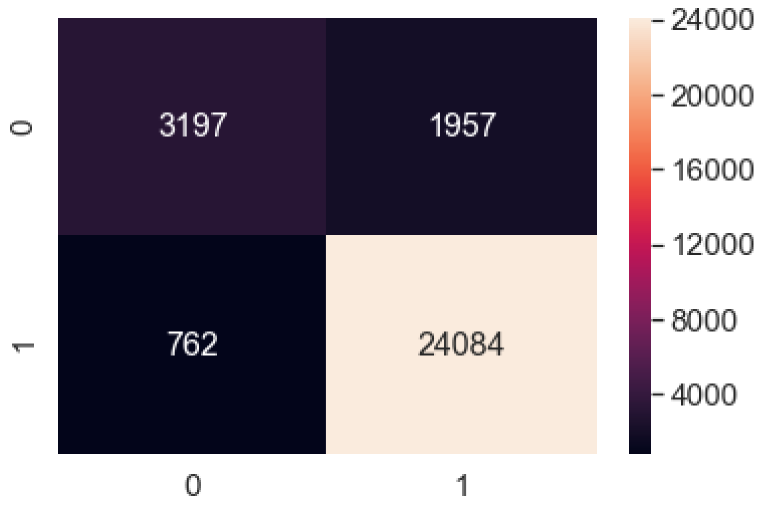
```
[6.907755278982137, 6.214608098422191, 4.605170185988092, 3.91202300542
8146, 2.302585092994046, 1.6094379124341003, 0.0, -0.6931471805599453,
-2.3025850929940455, -2.995732273553991, -4.605170185988091, -5.2983173
66548036, -6.907755278982137, -7.600902459542082, -9.210340371976182]
```



In [17]:
```
#plotting confusion matrix as heatmap
cm = confusion_matrix(y_test_bow, y_pred)
print(cm)
df_cm = pd.DataFrame(cm, range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

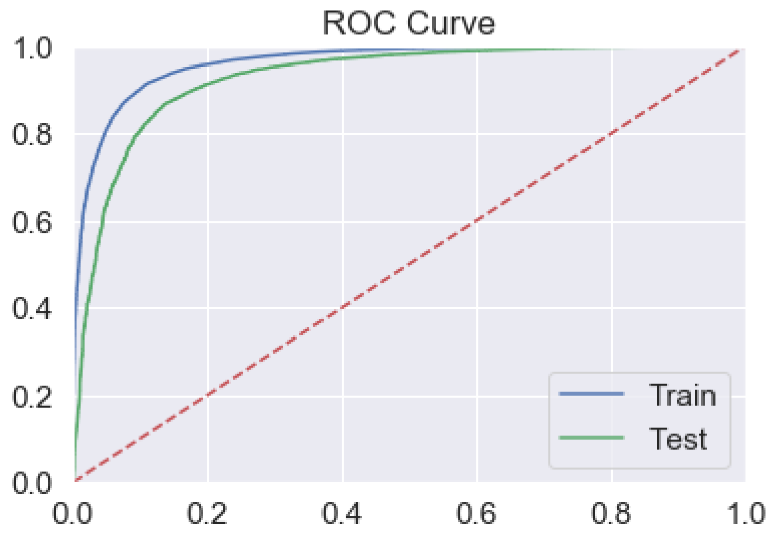
```
[[ 3197  1957]
 [  762 24084]]
```

Out[17]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x886618d550>
```



ROC Curve

In [18]:
```
# Plotting roc curve on Train Data
pred_train = lrf.predict_proba(x_train_bow)[:,1]
fpr, tpr, threshold = roc_curve(y_train_bow, pred_train)
plt.plot(fpr, tpr, 'b', label='Train')

# Plotting roc curve on Test Data
pred_test = lrf.predict_proba(x_test_bow)[:,1]
fpr, tpr, threshold = roc_curve(y_test_bow, pred_test)
plt.plot(fpr, tpr, 'g', label='Test')

plt.title('ROC Curve')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.legend(loc='lower right')
plt.show()
```



[1.1.1.1] Calculating sparsity on weight vector obtained using L1 regularization on BOW, SET 1

In [19]:
```
#Calculating sparsity on weight vector using optimal C value and L1 reg
ularization
lrf = LogisticRegression(C=optimal_C, penalty= 'l1')
lrf.fit(x_train_bow,y_train_bow)
pred = lrf.predict(x_test_bow)
print("Size of the weight vector:",len(lrf.coef_[0]))
print("No. of Non Zero weights:",np.count_nonzero(lrf.coef_))
print('Sparsity =', (len(lrf.coef_[0])-np.count_nonzero(lrf.coef_)))
```

```
Size of the weight vector: 7205
No. of Non Zero weights: 2608
Sparsity = 4597
```

Applying Logistic Regression with L2 regularization on BOW

In [41]:
```
# initializing Logistic Regression model with L2 regularisation
```

```
lr = LogisticRegression(penalty='l2',max_iter=1000)

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter & applying 1 fold CV
gscv = GridSearchCV(lr,param_grid,scoring='roc_auc',cv=2,return_train_s
core=True)

gscv.fit(x_train_bow,y_train_bow)

print("Best C Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best C Value:  {'C': 0.1}
Best ROC AUC Score: 0.87426
```

In [42]:

```
# determining optimal C
optimal_C = gscv.best_params_['C']

#training the model using the optimal C
lrf = LogisticRegression(penalty='l2',C=optimal_C)
lrf.fit(x_train_bow,y_train_bow)

#predicting the class label using test data
y_pred = lrf.predict(x_test_bow)

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_bow, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,au
c_score))
```

```
**** Test roc_auc_score for C = 0.100000 is 0.774518 ****
```

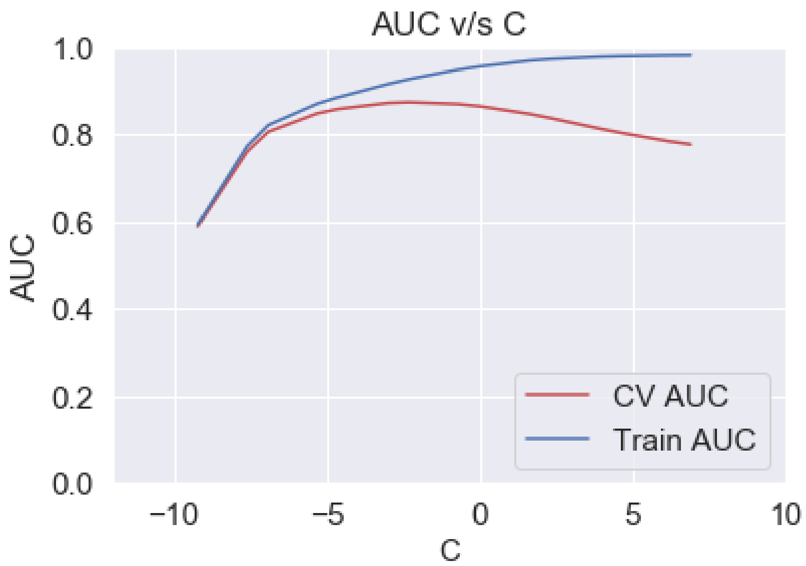
AUC vs C plot

In [43]:

```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in C_values]
print(log_alpha)
plt.xlim(-12,10)
```

```
plt.ylim(0.0,1.0)
plt.xlabel(r"C",fontsize=15)
plt.ylabel('AUC')
plt.title(r'AUC v/s C')
plt.plot(log_alpha, gscv.cv_results_['mean_test_score'], 'r', label='CV AUC')
plt.plot(log_alpha, gscv.cv_results_['mean_train_score'], 'b', label='Train AUC')
plt.legend(loc='lower right')
plt.show()
```

```
[6.907755278982137, 6.214608098422191, 4.605170185988092, 3.912023005428146, 2.302585092994046, 1.6094379124341003, 0.0, -0.6931471805599453, -2.3025850929940455, -2.995732273553991, -4.605170185988091, -5.298317366548036, -6.907755278982137, -7.600902459542082, -9.210340371976182]
```

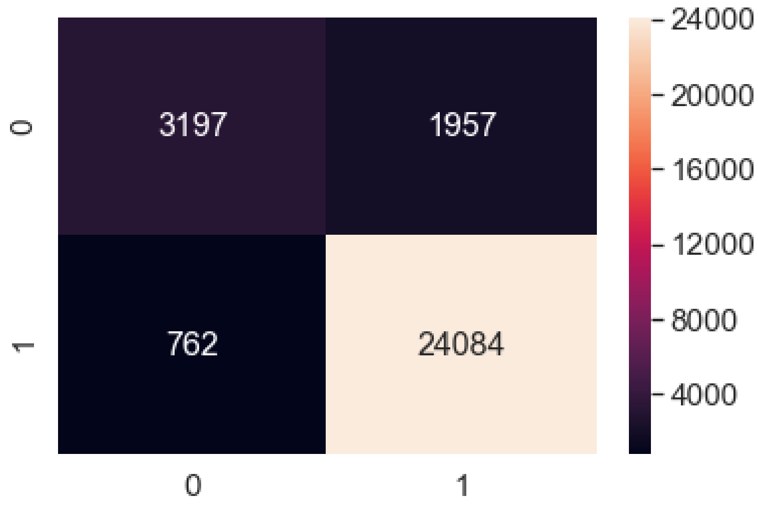


In [44]:
```
#plotting confusion matrix as heatmap
cm = confusion_matrix(y_test_bow, pred)
print(cm)
df_cm = pd.DataFrame(cm, range(2),range(2))
```

```
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
[[ 3197  1957]
 [  762 24084]]
```

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x8874b2e358>



Performing pertubation test (multicollinearity check) on BOW

In [20]:
```
# weight vector before adding noise
weight1 = lrf.coef_[0]
print(weight1[:50])
```

```
[ 0.          0.          0.          0.19961079  0.          0.
  0.          0.         -0.93373078  0.27533887  0.          0.
  0.          0.          0.          0.          0.         -0.2731258
4
  0.          0.         -0.57000398  0.          0.12731565  0.1347111
1
  0.          0.          0.          0.          0.          1.2841842
1
```

```
 0.          1.00466245  0.          0.         -0.28736664  0.
 0.79777289  0.         -0.11235233 -0.13702158  0.          0.
 0.16282287  0.         -0.25887163  0.54482719  0.          0.
 0.          0.08212421]
```

In [21]:
```
X_train_t = x_train_bow
#Random noise
epsilon = np.random.uniform(low=-0.0001, high=0.0001, size=(find(X_trai
n_t)[0].size,))

#Getting the postions(row and column) and value of non-zero datapoints
a,b,c = find(X_train_t)

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

In [22]:
```
#Training the model on the noise added dataset
lr = LogisticRegression(C= optimal_C, penalty= 'l1')
lr.fit(X_train_t,y_train_bow)
y_pred = lr.predict(x_test_bow)
print("Non Zero weights:",np.count_nonzero(lr.coef_))
```

```
Non Zero weights: 2423
```

In [23]:
```
# weight vector after adding noise
weight2 = lr.coef_[0]
print(weight2[:50])
```

```
[ 0.          0.          0.          0.27306786  0.          0.
  0.          0.         -0.56250695  0.37033967  0.          0.
  0.          0.          0.15584686  0.          0.         -0.1652630
6
  0.          0.         -0.98455298  0.64297284  0.          0.
  0.          0.          0.          0.          0.          0.2499672
9
  0.          0.28208293  0.          0.          0.          0.
  0.          0.         -0.11049378  0.          0.          0.
```

```
0.          -0.78722114 -0.32519839  0.35393533  0.          0.
0.          -0.02090544]
```

In [24]:
```
#adding a small value to both the weight vectors
val=10**-6
weight1+=val
weight2+=val
```

In [25]:
```
# calculating the percentage change
percent_change = abs((weight1 - weight2)/weight1) * 100
# no. of vectors that have a percentage change of more than 30%
print(percent_change[np.where(percent_change>30)].size)
```

```
2475
```

2475 features of 7205 have a percentage change greater than 30%. Hence the features are multicollinear.

Feature Importance on BOW

Top 10 important features of positive & negative class

In [42]:
```
#getting the feature names
feature_names = count_vect.get_feature_names()

#getting their corresponding log probabilities
coefs_with_fns = sorted(zip(lrf.coef_[0], feature_names))

#selecting the top 10 negative & positive features
top = zip(coefs_with_fns[:10], coefs_with_fns[:-(10 + 1):-1])
print("\t\t\tNegative\t\t\t\tPositive")
print("________________________________________________________________________________________________________")
for (coef_1, fn_1), (coef_2, fn_2) in top:
```

```
    print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, f
n_2))
```

```
                        Negative                                        Positiv
e
________________________________________________________________________
___________________________
        -2.4672 worst                                   2.3582  skeptic

        -1.9923 aw                                      2.1666  happier

        -1.9653 terribl                                 2.0430  hook

        -1.9143 threw                                   1.5808  yummi

        -1.9120 tasteless                               1.5784  uniqu

        -1.8529 yuck                                    1.5019  excel

        -1.6849 cancel                                  1.5008  amaz

        -1.6487 horribl                                 1.4916  awesom

        -1.6437 disappoint                              1.4478  delici

        -1.5628 bland                                   1.4238  addict
```

Logistic Regression on TFIDF

Applying Logistic Regression with L1 regularization on TFIDF

In [32]:
```
# initializing Logistic Regression model with L1 regularisation
lr = LogisticRegression(penalty='l1')

# using GridSearchCV to find the optimal value of C
```

```
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(lr,param_grid,scoring='roc_auc',cv=10,return_train_
score=True)

gscv.fit(x_train_tfidf,y_train_tfidf)

print("Best C Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best C Value:  {'C': 1}
Best ROC AUC Score: 0.94246
```

In [33]:

```
# determining optimal C
optimal_C = gscv.best_params_['C']

#training the model using the optimal C
lrf = LogisticRegression(penalty='l1',C=optimal_C)
lrf.fit(x_train_tfidf,y_train_tfidf)

#predicting the class label using test data
y_pred = lrf.predict(x_test_tfidf)

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_tfidf, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,au
c_score))
```

```
**** Test roc_auc_score for C = 1.000000 is 0.793112 ****
```

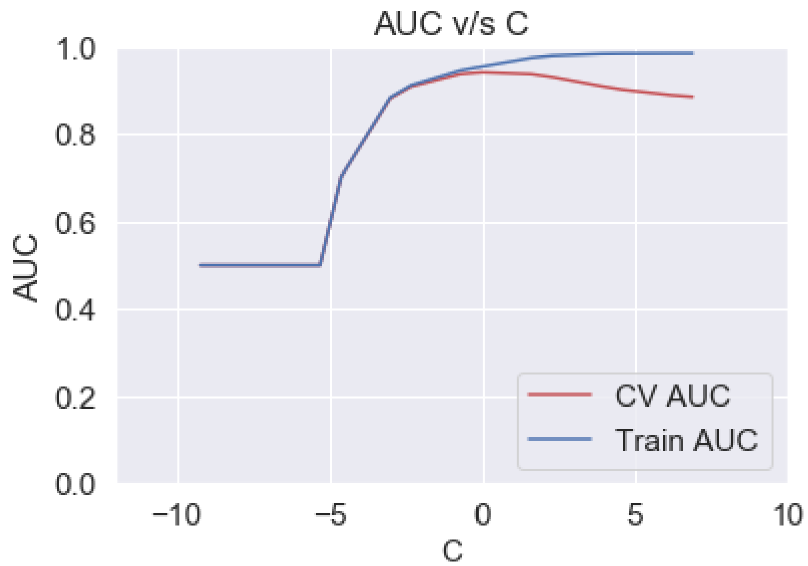
AUC vs C plot

In [34]:

```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in C_values]
print(log_alpha)
plt.xlim(-12,10)
plt.ylim(0.0,1.0)
plt.xlabel(r"C",fontsize=15)
plt.ylabel('AUC')
```

```
plt.title(r'AUC v/s C')
plt.plot(log_alpha, gscv.cv_results_['mean_test_score'], 'r', label='CV AUC')
plt.plot(log_alpha, gscv.cv_results_['mean_train_score'], 'b', label='Train AUC')
plt.legend(loc='lower right')
plt.show()
```

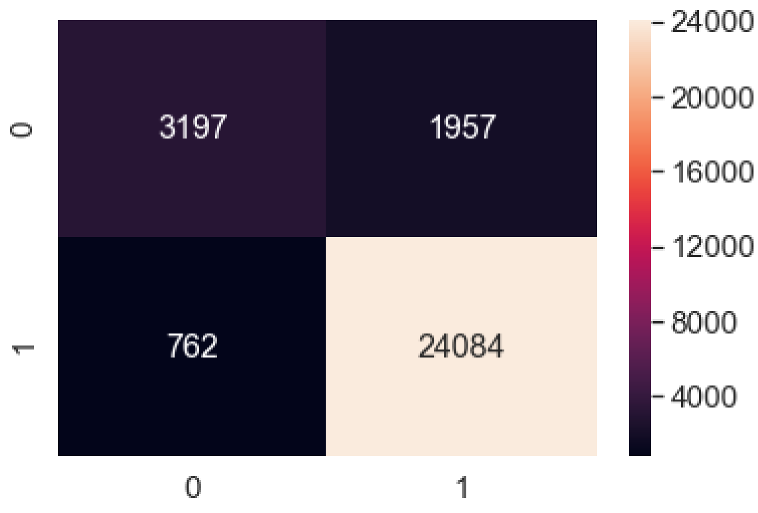
```
[6.907755278982137, 6.214608098422191, 4.605170185988092, 3.912023005428146, 2.302585092994046, 1.6094379124341003, 0.0, -0.6931471805599453, -2.3025850929940455, -2.995732273553991, -4.605170185988091, -5.298317366548036, -6.907755278982137, -7.600902459542082, -9.210340371976182]
```



In [35]:
```
#plotting confusion matrix as heatmap
cm = confusion_matrix(y_test_tfidf, pred)
print(cm)
df_cm = pd.DataFrame(cm, range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
[[ 3197  1957]
 [  762 24084]]
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x886a599630>



Applying Logistic Regression with L2 regularization on TFIDF

In [36]:
```
# initializing Logistic Regression model with L2 regularisation
lr = LogisticRegression(penalty='l2')

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(lr,param_grid,scoring='roc_auc',cv=10,return_train_
score=True)

gscv.fit(x_train_tfidf,y_train_tfidf)

print("Best C Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best C Value:  {'C': 1}
Best ROC AUC Score: 0.94428
```

In [37]:
```
# determining optimal C
```

```
optimal_C = gscv.best_params_['C']

#training the model using the optimal C
lrf = LogisticRegression(penalty='l2',C=optimal_C)
lrf.fit(x_train_tfidf,y_train_tfidf)

#predicting the class label using test data
y_pred = lrf.predict(x_test_tfidf)

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_tfidf, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,au
c_score))
```

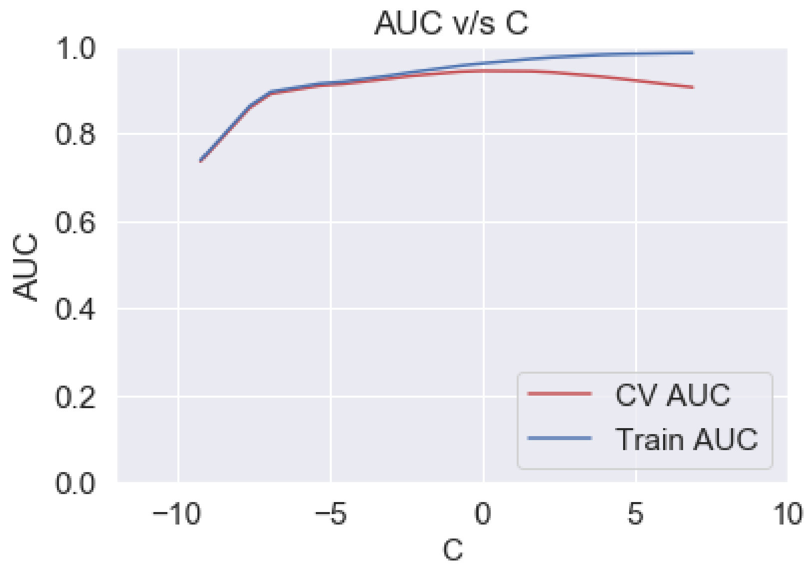
```
**** Test roc_auc_score for C = 1.000000 is 0.776427 ****
```

AUC vs C plot

In [38]:

```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in C_values]
print(log_alpha)
plt.xlim(-12,10)
plt.ylim(0.0,1.0)
plt.xlabel(r"C",fontsize=15)
plt.ylabel('AUC')
plt.title(r'AUC v/s C')
plt.plot(log_alpha, gscv.cv_results_['mean_test_score'], 'r', label='CV
 AUC')
plt.plot(log_alpha, gscv.cv_results_['mean_train_score'], 'b', label='T
rain AUC')
plt.legend(loc='lower right')
plt.show()
```

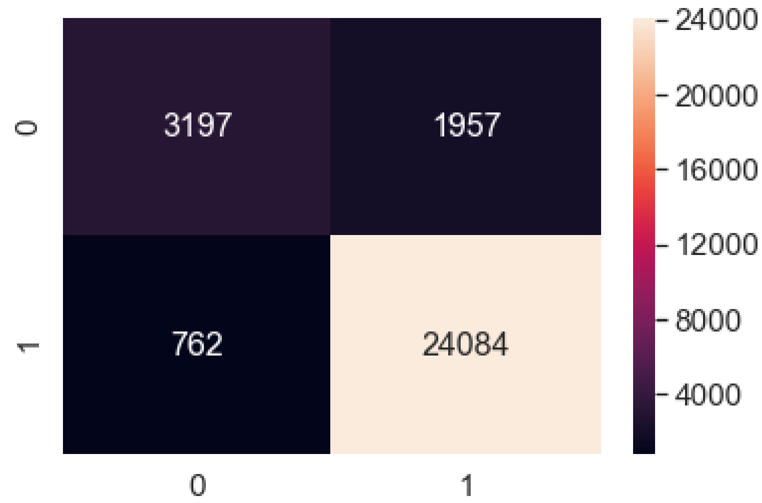
```
[6.907755278982137, 6.214608098422191, 4.605170185988092, 3.91202300542
8146, 2.302585092994046, 1.6094379124341003, 0.0, -0.6931471805599453,
-2.3025850929940455, -2.995732273553991, -4.605170185988091, -5.2983173
66548036, -6.907755278982137, -7.600902459542082, -9.210340371976182]
```



In [39]:
```
#plotting confusion matrix as heatmap
cm = confusion_matrix(y_test_tfidf, pred)
print(cm)
df_cm = pd.DataFrame(cm, range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
[[ 3197  1957]
 [  762 24084]]
```

Out[39]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x8873258668>
```



Feature Importance on TFIDF

Top 10 important features of positive & negative class

In [58]:
```
#getting the feature names
feature_names = tf_idf_vect.get_feature_names()

#getting their corresponding log probabilities
coefs_with_fns = sorted(zip(lrf.coef_[0], feature_names))

#selecting the top 10 negative & positive features
top = zip(coefs_with_fns[:10], coefs_with_fns[:-(10 + 1):-1])
print("\t\t\tNegative\t\t\t\tPositive")
print("__________________________________________________________________________________________________________________________________________________")
for (coef_1, fn_1), (coef_2, fn_2) in top:
    print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, f
n_2))
```

```
                        Negative                                        Positiv
e
```

-7.6603 disappoint	10.5891 great
-6.9781 worst	8.0863 best
-6.2206 terribl	7.7130 love
-5.9027 aw	7.1773 delici
-5.8746 horribl	6.7693 perfect
-5.1977 return	6.1566 excel
-5.1381 threw	5.6250 amaz
-4.7565 unfortun	5.4546 good
-4.7096 bland	5.1198 nice
-4.6534 stale	5.0755 favorit

Logistic Regression on AVG W2V

Applying Logistic Regression with L1 regularization on AVG W2V

In [67]:

```
# initializing Logistic Regression model with L1 regularisation
lr = LogisticRegression(penalty='l1')

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(lr,param_grid,scoring='roc_auc',cv=10,return_train_
score=True)
```

```
gscv.fit(x_train_w2v,y_train_w2v)

print("Best C Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best C Value:  {'C': 0.5}
Best ROC AUC Score: 0.90405
```

In [68]:

```
# determining optimal C
optimal_C = gscv.best_params_['C']

#training the model using the optimal C
lrf = LogisticRegression(penalty='l1',C=optimal_C)
lrf.fit(x_train_w2v,y_train_w2v)

#predicting the class label using test data
y_pred = lrf.predict(x_test_w2v)

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_w2v, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,au
c_score))
```

```
**** Test roc_auc_score for C = 0.500000 is 0.719229 ****
```

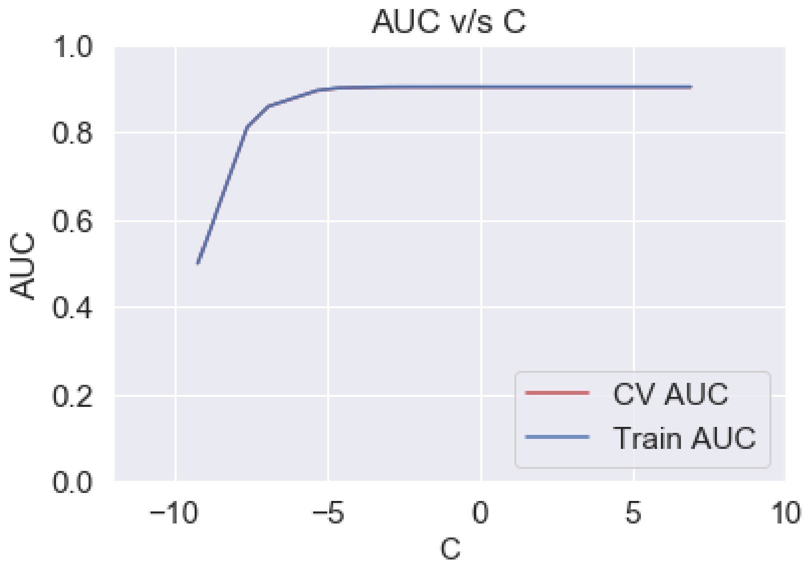
AUC vs C plot

In [69]:

```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in C_values]
print(log_alpha)
plt.xlim(-12,10)
plt.ylim(0.0,1.0)
plt.xlabel(r"C",fontsize=15)
plt.ylabel('AUC')
plt.title(r'AUC v/s C')
plt.plot(log_alpha, gscv.cv_results_['mean_test_score'], 'r', label='CV
 AUC')
plt.plot(log_alpha, gscv.cv_results_['mean_train_score'], 'b', label='T
```

```
rain AUC')
plt.legend(loc='lower right')
plt.show()
```

```
[6.907755278982137, 6.214608098422191, 4.605170185988092, 3.91202300542
8146, 2.302585092994046, 1.6094379124341003, 0.0, -0.6931471805599453,
-2.3025850929940455, -2.995732273553991, -4.605170185988091, -5.2983173
66548036, -6.907755278982137, -7.600902459542082, -9.210340371976182]
```



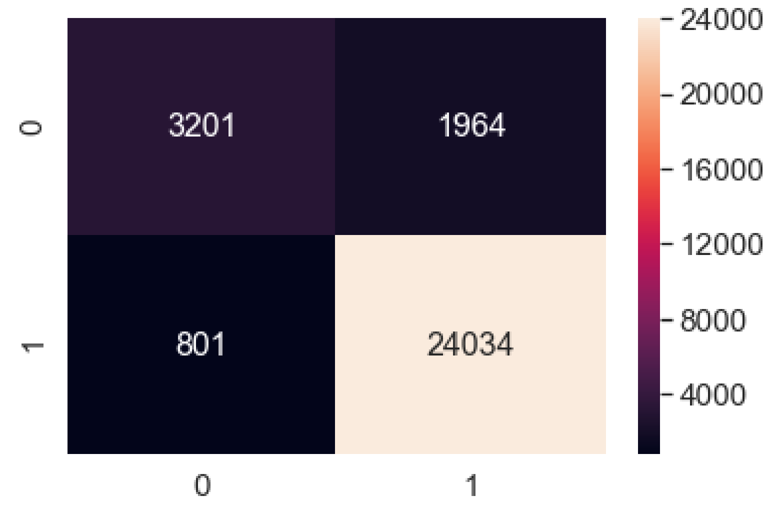
In [70]:

```
#plotting confusion matrix as heatmap
cm = confusion_matrix(y_test_w2v, pred)
print(cm)
df_cm = pd.DataFrame(cm, range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
[[ 3201  1964]
 [  801 24034]]
```

Out[70]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xa9c0438a20>
```



Applying Logistic Regression with L2 regularization on AVG W2V

In [71]:

```
# initializing Logistic Regression model with L2 regularisation
lr = LogisticRegression(penalty='l2')

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(lr,param_grid,scoring='roc_auc',cv=10,return_train_
score=True)

gscv.fit(x_train_w2v,y_train_w2v)

print("Best C Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best C Value:  {'C': 0.05}
Best ROC AUC Score: 0.90407
```

In [72]:

```
# determining optimal C
optimal_C = gscv.best_params_['C']
```

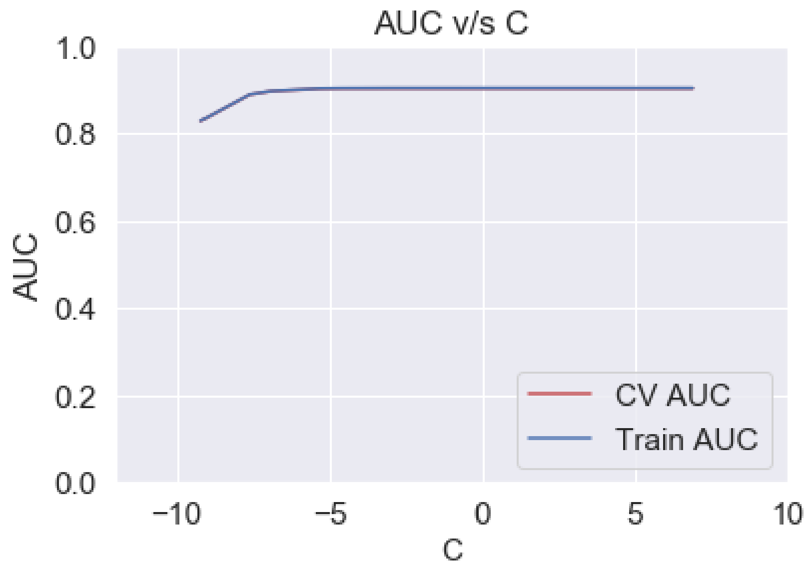
```
#training the model using the optimal C
lrf = LogisticRegression(penalty='l2',C=optimal_C)
lrf.fit(x_train_w2v,y_train_w2v)

#predicting the class label using test data
y_pred = lrf.predict(x_test_w2v)

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_w2v, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,auc_score))
```

```
**** Test roc_auc_score for C = 0.050000 is 0.715671 ****
```

AUC vs C plot

In [73]:
```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in C_values]
print(log_alpha)
plt.xlim(-12,10)
plt.ylim(0.0,1.0)
plt.xlabel(r"C",fontsize=15)
plt.ylabel('AUC')
plt.title(r'AUC v/s C')
plt.plot(log_alpha, gscv.cv_results_['mean_test_score'], 'r', label='CV AUC')
plt.plot(log_alpha, gscv.cv_results_['mean_train_score'], 'b', label='Train AUC')
plt.legend(loc='lower right')
plt.show()
```

```
[6.907755278982137, 6.214608098422191, 4.605170185988092, 3.912023005428146, 2.302585092994046, 1.6094379124341003, 0.0, -0.6931471805599453, -2.3025850929940455, -2.995732273553991, -4.605170185988091, -5.298317366548036, -6.907755278982137, -7.600902459542082, -9.210340371976182]
```



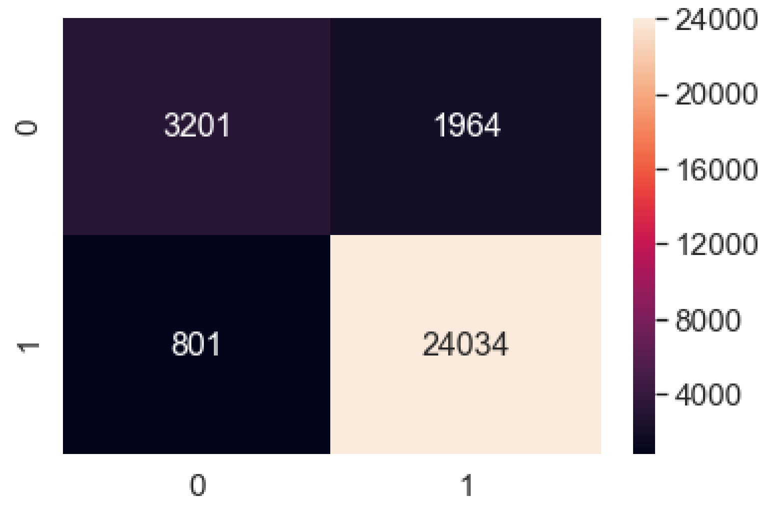
In [74]:

```
#plotting confusion matrix as heatmap
cm = confusion_matrix(y_test_w2v, pred)
print(cm)
df_cm = pd.DataFrame(cm, range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
[[ 3201  1964]
 [  801 24034]]
```

Out[74]:

```
<matplotlib.axes._subplots.AxesSubplot at 0xa9c0f46358>
```



Logistic Regression on TFIDF W2V

Applying Logistic Regression with L1 regularization on TFIDF W2V

In [82]:
```
# initializing Logistic Regression model with L1 regularisation
lr = LogisticRegression(penalty='l1')

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(lr,param_grid,scoring='roc_auc',cv=10,return_train_
score=True)

gscv.fit(x_train_tfw2v,y_train_tfw2v)

print("Best C Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best C Value:  {'C': 0.1}
Best ROC AUC Score: 0.87825
```

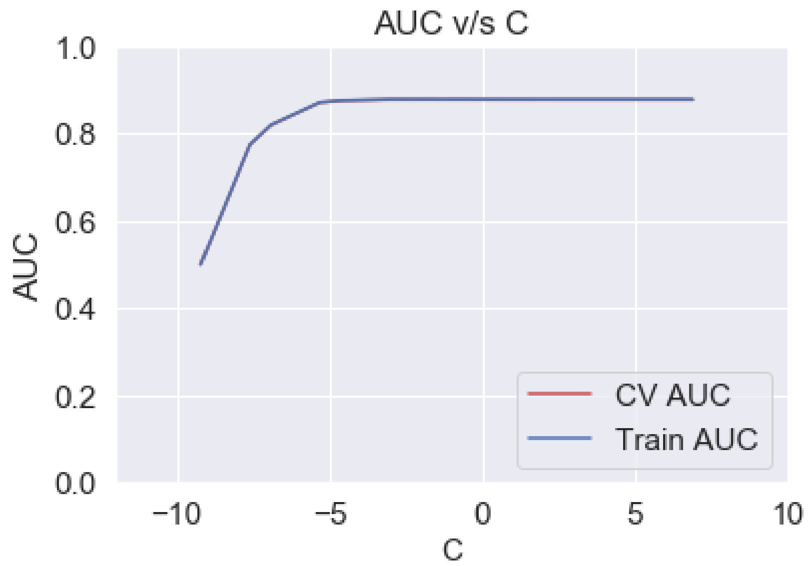
In [83]:
```
# determining optimal C
optimal_C = gscv.best_params_['C']

#training the model using the optimal C
lrf = LogisticRegression(penalty='l1',C=optimal_C)
lrf.fit(x_train_tfw2v,y_train_tfw2v)

#predicting the class label using test data
y_pred = lrf.predict(x_test_tfw2v)

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_tfw2v, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,au
c_score))
```

```
**** Test roc_auc_score for C = 0.100000 is 0.666148 ****
```

AUC vs C plot

In [84]:
```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in C_values]
print(log_alpha)
plt.xlim(-12,10)
plt.ylim(0.0,1.0)
plt.xlabel(r"C",fontsize=15)
plt.ylabel('AUC')
plt.title(r'AUC v/s C')
plt.plot(log_alpha, gscv.cv_results_['mean_test_score'], 'r', label='CV
 AUC')
plt.plot(log_alpha, gscv.cv_results_['mean_train_score'], 'b', label='T
rain AUC')
plt.legend(loc='lower right')
plt.show()
```

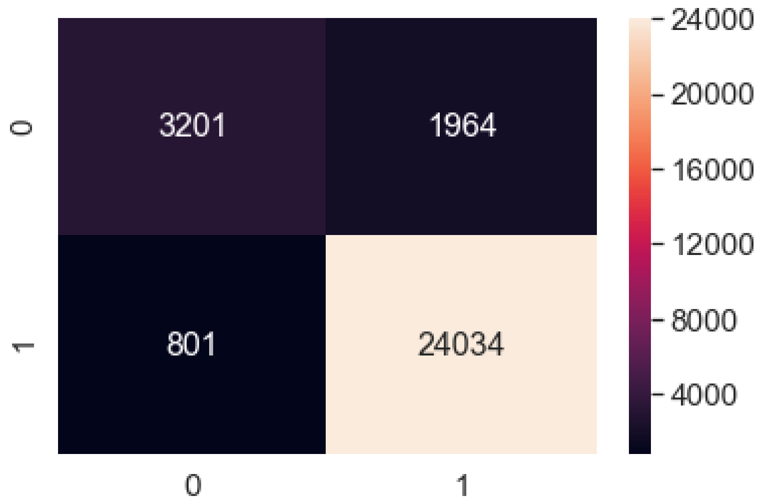
```
[6.907755278982137, 6.214608098422191, 4.605170185988092, 3.91202300542
8146, 2.302585092994046, 1.6094379124341003, 0.0, -0.6931471805599453,
-2.3025850929940455, -2.995732273553991, -4.605170185988091, -5.2983173
66548036, -6.907755278982137, -7.600902459542082, -9.210340371976182]
```



In [85]:
```
#plotting confusion matrix as heatmap
cm = confusion_matrix(y_test_tfw2v, pred)
print(cm)
df_cm = pd.DataFrame(cm, range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
[[ 3201  1964]
 [  801 24034]]
```

Out[85]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xa9c10187b8>
```



Applying Logistic Regression with L2 regularization on TFIDF W2V

In [86]:
```
# initializing Logistic Regression model with L2 regularisation
lr = LogisticRegression(penalty='l2')

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(lr,param_grid,scoring='roc_auc',cv=10,return_train_
score=True)

gscv.fit(x_train_tfw2v,y_train_tfw2v)

print("Best C Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best C Value:  {'C': 0.05}
Best ROC AUC Score: 0.87827
```

In [87]:
```
# determining optimal C
optimal_C = gscv.best_params_['C']
```

```
#training the model using the optimal C
lrf = LogisticRegression(penalty='l2',C=optimal_C)
lrf.fit(x_train_tfw2v,y_train_tfw2v)

#predicting the class label using test data
y_pred = lrf.predict(x_test_tfw2v)

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_tfw2v, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,au
c_score))
```

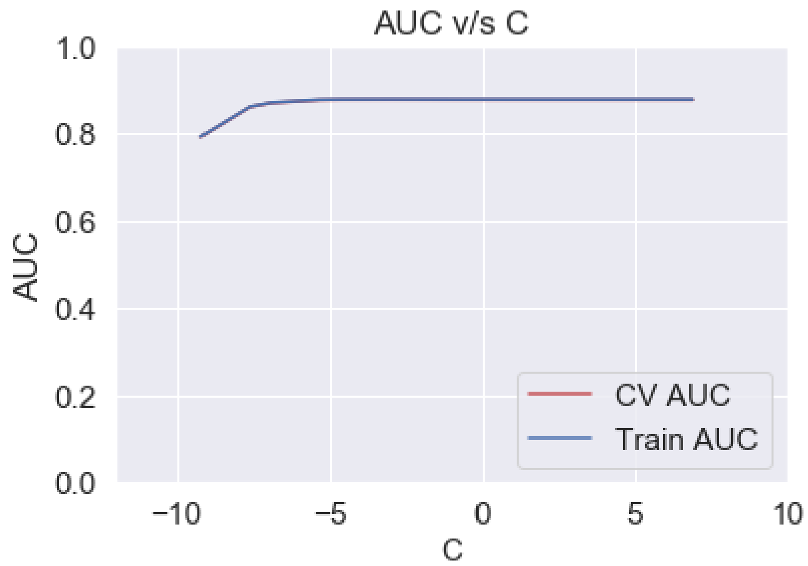
```
**** Test roc_auc_score for C = 0.050000 is 0.664893 ****
```

AUC vs C plot

In [88]:

```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in C_values]
print(log_alpha)
plt.xlim(-12,10)
plt.ylim(0.0,1.0)
plt.xlabel(r"C",fontsize=15)
plt.ylabel('AUC')
plt.title(r'AUC v/s C')
plt.plot(log_alpha, gscv.cv_results_['mean_test_score'], 'r', label='CV
 AUC')
plt.plot(log_alpha, gscv.cv_results_['mean_train_score'], 'b', label='T
rain AUC')
plt.legend(loc='lower right')
plt.show()
```

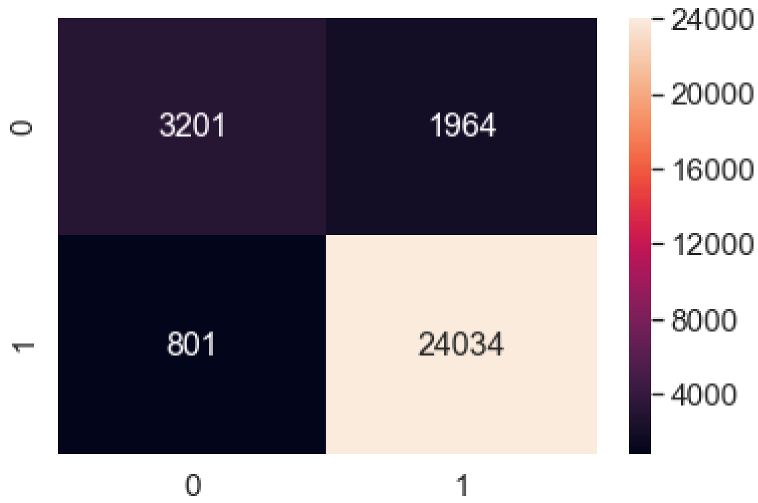
```
[6.907755278982137, 6.214608098422191, 4.605170185988092, 3.91202300542
8146, 2.302585092994046, 1.6094379124341003, 0.0, -0.6931471805599453,
-2.3025850929940455, -2.995732273553991, -4.605170185988091, -5.2983173
66548036, -6.907755278982137, -7.600902459542082, -9.210340371976182]
```



In [89]:
```
#plotting confusion matrix as heatmap
cm = confusion_matrix(y_test_tfw2v, pred)
print(cm)
df_cm = pd.DataFrame(cm, range(2),range(2))
sns.set(font_scale=1.4)
sns.heatmap(df_cm, annot=True,annot_kws={"size": 16}, fmt='g')
```

```
[[ 3201  1964]
 [  801 24034]]
```

Out[89]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xa9c11ef550>
```



Conclusion

In [45]:
```
# Summarizing the observations
x=PrettyTable()
x.field_names = ['Vectorizer','Penalty','C','AUC']
x.add_row(['BOW','L1','0.50','0.794813'])
x.add_row(['BOW','L2','0.10','0.774518'])
x.add_row(['Tfidf','L1','1.00','0.793112'])
x.add_row(['Tfidf','L2','1.00','0.776427'])
x.add_row(['Avg. Word2Vec','L1','0.50','0.719229'])
x.add_row(['Avg. Word2Vec','L2','0.05','0.715671'])
x.add_row(['Tfidf W2V','L1','0.10','0.666148'])
x.add_row(['Tfidf W2V','L2','0.05','0.664893'])
print(x)
```

```
+---------------+---------+------+----------+
|   Vectorizer  | Penalty |  C   |   AUC    |
+---------------+---------+------+----------+
|      BOW      |    L1   | 0.50 | 0.794813 |
|      BOW      |    L2   | 0.10 | 0.774518 |
|     Tfidf     |    L1   | 1.00 | 0.793112 |
```

Tfidf	L2	1.00	0.776427
Avg. Word2Vec	L1	0.50	0.719229
Avg. Word2Vec	L2	0.05	0.715671
Tfidf W2V	L1	0.10	0.666148
Tfidf W2V	L2	0.05	0.664893

Conclusions:-

1. From the above table, the performance of Logistic Regression using different vectorizers can be summed as follows - BoW > TFIDF > Avg. Word2Vec > TFIDF-W2V, with performance of BoW being the greatest in terms of AUC scores.
2. As proved in theory that L1 regularization increases sparsity, same was observed when BoW was implemented with L1 regularization.
3. Also, it was proved that the features were multicollinear when Pertubation Test was performed.