Part 6 - Support Vector Machines (SVM)

By Aziz Presswala

In [1]:

```
# importing libraries
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import sqlite3
import math
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 time import time
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.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_curve, auc, roc_auc_score

from gensim.models import Word2Vec
```

[1.0] 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]
```

In [7]:
```
#randomly selecting 20k points from the dataset for rbf kernel
df1=filtered_data.sample(20000)
```

In [8]:
```
#sort the dataset by timestamp
df1 = df1.sort_values('Time')
#splitting the dataset into train(70%) & test(30%)
train_data_rbf = df1[0:14000]
test_data_rbf = df1[14000:20000]
```

[2.0] Featurization

[2.1] BAG OF WORDS

For Linear Kernel

In [9]:
```
#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[9]: (70000, 7164)

In [10]:
```
#applying transform on test dataset
x_test_bow = count_vect.transform(test_data['CleanedText'].values)
x_test_bow.shape
```

Out[10]: (30000, 7164)

In [11]:
```
y_train_bow = train_data['Score']
y_test_bow = test_data['Score']
```

For RBF Kernel

In [25]:
```
#applying fit transform on train datasset
count_vect_rbf = CountVectorizer(min_df=10)
x_train_bow_rbf = count_vect_rbf.fit_transform(train_data_rbf['CleanedT
ext'].values)
x_train_bow_rbf.shape
```

Out[25]: (14000, 3337)

In [26]:
```
#applying fit transform on test dataset
x_test_bow_rbf = count_vect_rbf.transform(test_data_rbf['CleanedText'].
```

```
values)
x_test_bow_rbf.shape
```

Out[26]: (6000, 3337)

In [27]:
```
y_train_bow_rbf = train_data_rbf['Score']
y_test_bow_rbf = test_data_rbf['Score']
```

[2.2] TF-IDF

For Linear Kernel

In [18]:
```
#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[18]: (70000, 7164)

In [19]:
```
#applying transform on test dataset
x_test_tfidf = tf_idf_vect.transform(test_data['CleanedText'].values)
x_test_tfidf.shape
```

Out[19]: (30000, 7164)

In [20]:
```
y_train_tfidf = train_data['Score']
y_test_tfidf = test_data['Score']
```

For RBF Kernel

In [31]:
```
#applying fit transform on train datasset
tf_idf_vect_rbf = TfidfVectorizer(min_df=10)
x_train_tfidf_rbf = tf_idf_vect_rbf.fit_transform(train_data_rbf['Clean
```

```
edText'].values)
x_train_tfidf_rbf.shape
```

Out[31]: (14000, 3337)

In [32]:
```
#applying transform on test dataset
x_test_tfidf_rbf = tf_idf_vect_rbf.transform(test_data_rbf['CleanedTex
t'].values)
x_test_tfidf_rbf.shape
```

Out[32]: (6000, 3337)

In [33]:
```
y_train_tfidf_rbf = train_data_rbf['Score']
y_test_tfidf_rbf = test_data_rbf['Score']
```

[2.3] Avg. Word2Vec

For Linear Kernel

In [34]:
```
#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 [35]:
```
w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

In [36]:
```
X = w2v_model[w2v_model.wv.vocab]
```

In [37]:
```
#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 [02:19<00:00, 500.06it/s]
```

```
70000
50
```

In [38]:

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

Out[38]:

```
(70000, 50)
```

In [39]:

```
#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 [40]:

```
#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
```

```python
    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 [01:12<00:00, 415.77it/s]
```

```
30000
50
```

In [41]:

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

Out[41]:

```
(30000, 50)
```

For RBF Kernel

In [49]:

```python
#training Word2Vec Model for train dataset
i=0
list_of_sent=[]
for sent in train_data_rbf['CleanedText'].values:
    list_of_sent.append(sent.split())
```

In [50]:

```python
w2v_model=Word2Vec(list_of_sent,min_count=5,size=50, workers=4)
```

In [51]:

```python
X = w2v_model[w2v_model.wv.vocab]
```

In [52]:

```python
#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%|██████████████████████████████████████████████████
████████| 14000/14000 [00:19<00:00, 726.18it/s]
```

```
14000
50
```

In [53]:

```
x_train_w2v_rbf = np.array(sent_vectors)
y_train_w2v_rbf = train_data_rbf['Score']
x_train_w2v_rbf.shape
```

Out[53]:

```
(14000, 50)
```

In [54]:

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

In [55]:

```
#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%|██████████████████████████████████████████████████████████████████
███████████| 6000/6000 [00:08<00:00, 703.16it/s]
```

```
6000
50
```

In [56]:

```
x_test_w2v_rbf = np.array(sent_vectors)
y_test_w2v_rbf = test_data_rbf['Score']
x_test_w2v_rbf.shape
```

Out[56]:

```
(6000, 50)
```

[2.4] TFIDF - Word2Vec

For Linear Kernel

In [66]:

```
# 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 v
alue
dictionary = dict(zip(model.get_feature_names(), list(model.idf_)))
```

In [67]:

```
# 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_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/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%|██████████████████████████████████████
█████| 70000/70000 [02:48<00:00, 414.90it/s]
```

In [68]:

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

Out[68]:

```
(70000, 50)
```

In [69]:

```
# 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 [70]:

```
# 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 [01:19<00:00, 377.03it/s]
```

In [71]:

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

Out[71]: (30000, 50)

For RBF Kernel

In [72]:

```
# training model for training data
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(train_data_rbf['CleanedText'].value
s)
# 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 [62]:

```
# 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_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/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%|██████████████████████████████████████████████████████████████
█████████| 14000/14000 [00:24<00:00, 576.98it/s]
```

In [63]:
```
x_train_tfw2v_rbf = np.array(tfidf_sent_vectors)
y_train_tfw2v_rbf = train_data_rbf['Score']
x_train_tfw2v_rbf.shape
```

Out[63]:
```
(14000, 50)
```

In [64]:
```
# training model for test dataset
model = TfidfVectorizer()
tf_idf_matrix = model.fit_transform(test_data_rbf['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 [65]:
```
# 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%|████████████████████████████████████████████████████████████
██████████| 6000/6000 [00:10<00:00, 554.98it/s]
```

In [66]:
```
x_test_tfw2v_rbf = np.array(tfidf_sent_vectors)
y_test_tfw2v_rbf = test_data_rbf['Score']
x_test_tfw2v_rbf.shape
```

Out[66]:
```
(6000, 50)
```

[3.0] Applying SVM

[3.1] Linear SVM

[3.1.1] Applying Linear SVM on BOW (l1 reg.), SET 1

In [12]:
```
# initializing SGDClassifier model with L1 regularisation
sgdc = SGDClassifier(loss='hinge', penalty='l1', class_weight='balance
d')

# alpha values we need to try on classifier
alpha_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10*
*4]
param_grid = {'alpha':alpha_values}

# using GridSearchCV to find the optimal value of alpha
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(sgdc,param_grid,scoring='roc_auc',cv=10,return_trai
n_score=True,n_jobs=-1)
gscv.fit(x_train_bow,y_train_bow)
```

```
# getting the optimal value of alpha
print("Best alpha Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best alpha Value:  {'alpha': 0.0001}
Best ROC AUC Score: 0.91089
```

In [13]:

```
# determining optimal alpha
optimal_alpha = gscv.best_params_['alpha']

# calibrating the above results using CalibratedClassifierCV and traini
ng the model
ccv = CalibratedClassifierCV(gscv,cv='prefit')
ccv.fit(x_train_bow,y_train_bow)

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

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

```
**** Test roc_auc_score for alpha = 0.000100 is 0.907703 ****
```

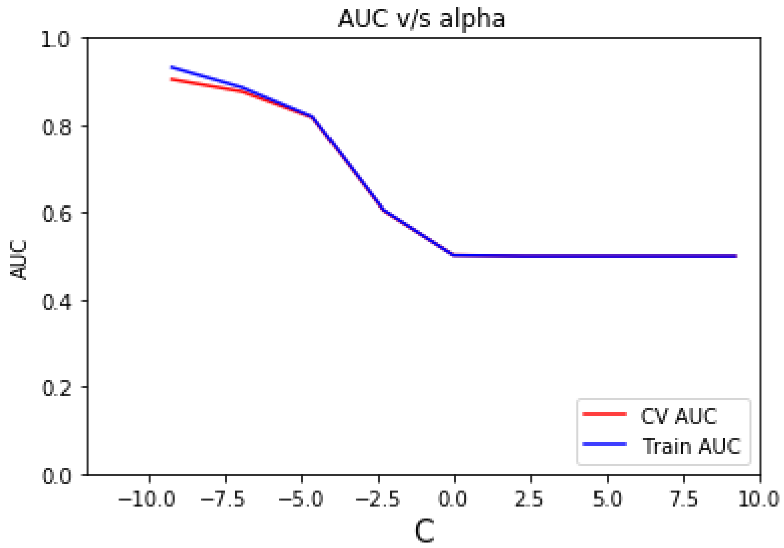
AUC vs alpha

In [14]:

```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in alpha_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 alpha')
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()
```

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.907755278982137, 9.210340371976184]
```

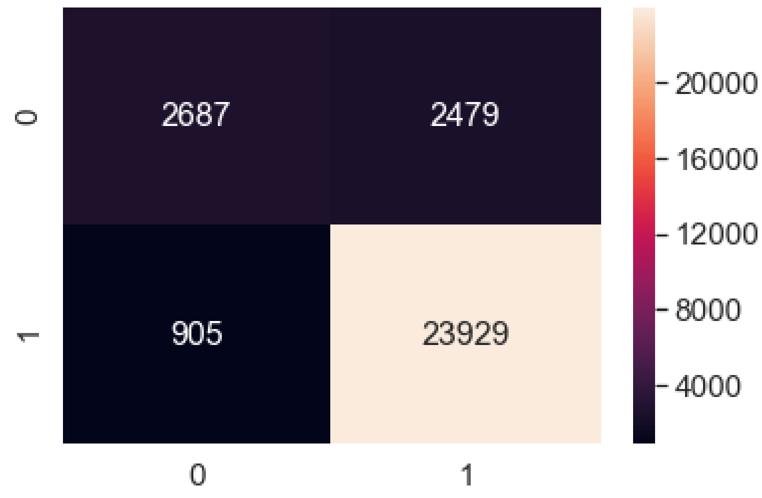


Confusion Matrix on Test Data

In [15]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_test_bow)
cm = confusion_matrix(y_test_bow, y_predict)
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')
```

```
[[ 2687  2479]
 [  905 23929]]
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1b0be125438>

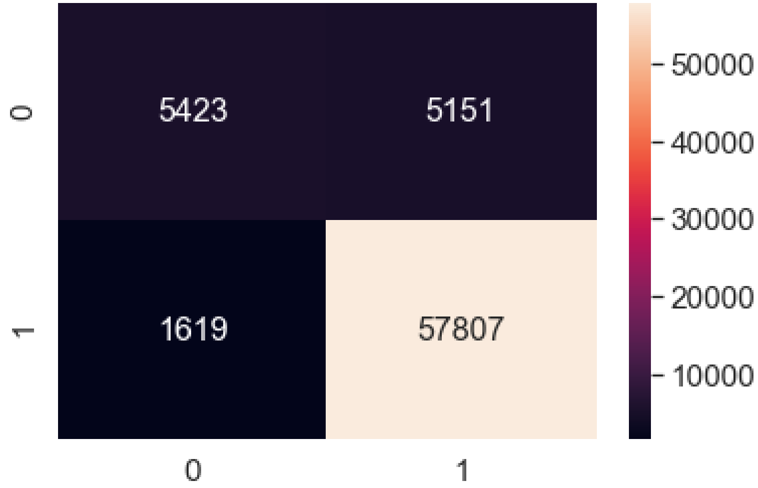


Confusion Matrix on Train Data

In [16]:
```python
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_train_bow)
cm = confusion_matrix(y_train_bow, y_predict)
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')
```

```
[[ 5423  5151]
 [ 1619 57807]]
```

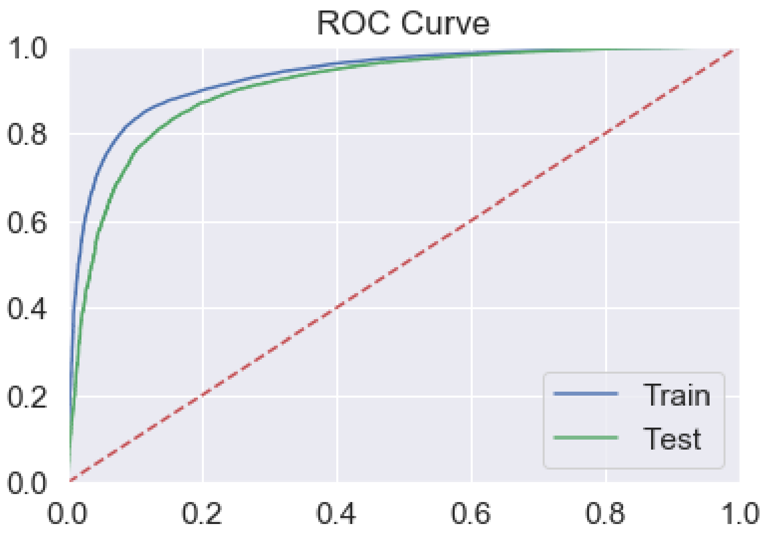
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1b0c5be6978>



ROC Curve

In [17]:

```
# Plotting roc curve on Train Data
pred_train = ccv.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 = ccv.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()
```



[3.1.2] Applying Linear SVM on BOW (l2 reg.), SET 1

In [18]:
```
# initializing SGDClassifier model with L2 regularisation
sgdc = SGDClassifier(loss='hinge', penalty='l2', class_weight='balance
d')

# alpha values we need to try on classifier
alpha_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10*
*4]
param_grid = {'alpha':alpha_values}

# using GridSearchCV to find the optimal value of alpha
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(sgdc,param_grid,scoring='roc_auc',cv=10,return_trai
n_score=True,n_jobs=-1)
gscv.fit(x_train_bow,y_train_bow)

# getting the optimal value of alpha
print("Best alpha Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best alpha value:  {'alpha': 0.001}
Best ROC AUC Score: 0.92749
```

In [19]:
```
# determining optimal alpha
optimal_alpha = gscv.best_params_['alpha']

# calibrating the above results using CalibratedClassifierCV and traini
ng the model
ccv = CalibratedClassifierCV(gscv,cv='prefit')
ccv.fit(x_train_bow,y_train_bow)

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

#determining the Test roc_auc_score for optimal alpha
auc_score = roc_auc_score(y_test_bow, y_pred)
print('\n**** Test roc_auc_score for alpha = %.5f is %f ****' % (optima
l_alpha,auc_score))
```

```
**** Test roc_auc_score for alpha = 0.00100 is 0.931857 ****
```

AUC vs alpha

In [20]:
```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in alpha_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 alpha')
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()
```

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
```

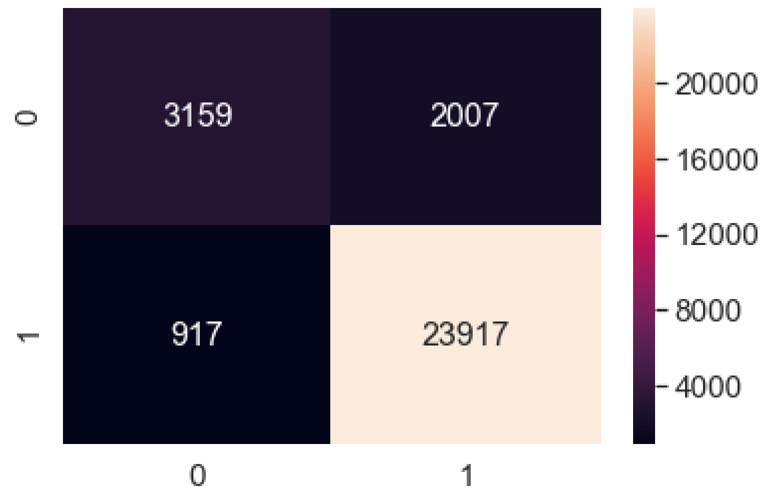
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.907755278982137, 9.210340371976184]

Confusion Matrix on Test Data

In [21]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_test_bow)
cm = confusion_matrix(y_test_bow, y_predict)
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')
```

```
[[ 3159  2007]
 [  917 23917]]
```

Out[21]: `<matplotlib.axes._subplots.AxesSubplot at 0x1b0aa849f28>`

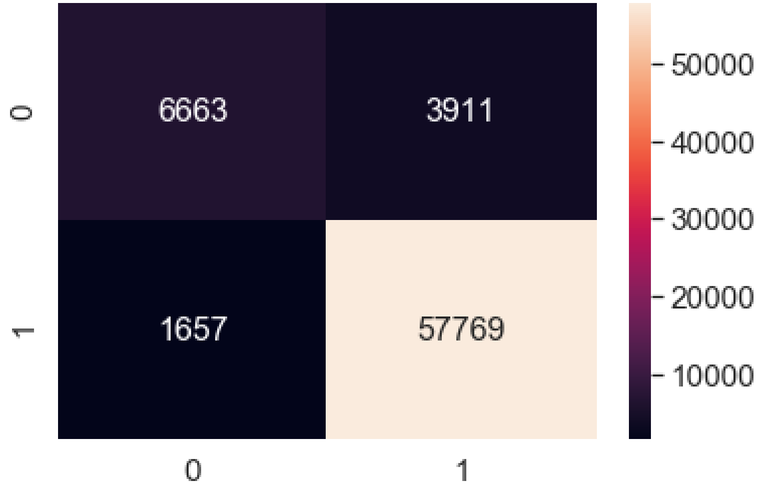


Confusion Matrix on Train Data

In [22]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_train_bow)
cm = confusion_matrix(y_train_bow, y_predict)
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')
```

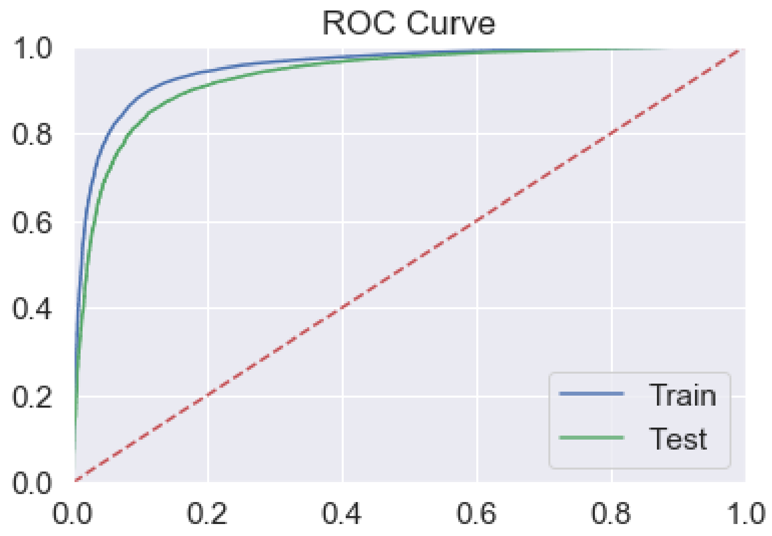
```
[[ 6663  3911]
 [ 1657 57769]]
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b0aee02828>
```



ROC Curve

In [23]:
```
# Plotting roc curve on Train Data
pred_train = ccv.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 = ccv.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()
```



Feature Importance

In [14]:
```
# Training the model with optimal alpha value to get the feature import
ance
clf = SGDClassifier(loss='hinge', penalty='l1', alpha=optimal_alpha)
clf.fit(x_train_bow,y_train_bow)
```

Out[14]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l1',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [15]:
```
feature_names = count_vect.get_feature_names()
coefs_with_fns = sorted(zip(clf.coef_[0], feature_names),reverse=True)
top = zip(coefs_with_fns[:10], coefs_with_fns[:-(10 + 1):-1])
print("\t\tPositive\t\t\t\tNegative")
print("________________________________________________________________
```

```
                                        ")
for (coef_1, fn_1), (coef_2, fn_2) in top:
    print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, f
n_2))
```

```
                Positive                                        Negative
________________________________________________________________________
___________________________
        47.8184 zevia                                           -51.6009
scone
        29.5217 blast                                           -41.3797
worst
        29.5180 communiti                                       -23.4885
aw
        24.8816 louisiana                                       -22.9970
rip
        24.7078 oro                                             -22.7622
terribl
        24.5689 qualita                                         -22.6392
foil
        24.2616 aerat                                           -22.3172
horribl
        23.4551 addict                                          -22.2651
canida
        22.7108 excel                                           -20.7548
lesson
        22.5032 refresh                                         -19.2569
disgust
```

[3.1.3] Applying Linear SVM on TFIDF (l1 reg.), SET 2

In [21]:
```
# initializing SGDClassifier model with L1 regularisation
sgdc = SGDClassifier(loss='hinge', penalty='l1', class_weight='balance
d')

# alpha values we need to try on classifier
alpha_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10*
*4]
```

```
param_grid = {'alpha': alpha_values}

# using GridSearchCV to find the optimal value of alpha
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(sgdc,param_grid,scoring='roc_auc',cv=10,return_trai
n_score=True)
gscv.fit(x_train_tfidf,y_train_tfidf)

# getting the optimal value of alpha
print("Best alpha Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best alpha Value:  {'alpha': 0.0001}
Best ROC AUC Score: 0.93541
```

In [22]:

```
# determining optimal alpha
optimal_alpha = gscv.best_params_['alpha']

# calibrating the above results using CalibratedClassifierCV and traini
ng the model
ccv = CalibratedClassifierCV(gscv,cv='prefit')
ccv.fit(x_train_tfidf,y_train_tfidf)

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

#determining the Test roc_auc_score for optimal alpha
auc_score = roc_auc_score(y_test_tfidf, y_pred)
print('\n**** Test roc_auc_score for C = %.5f is %f ****' % (optimal_al
pha,auc_score))
```

```
**** Test roc_auc_score for C = 0.00010 is 0.933137 ****
```

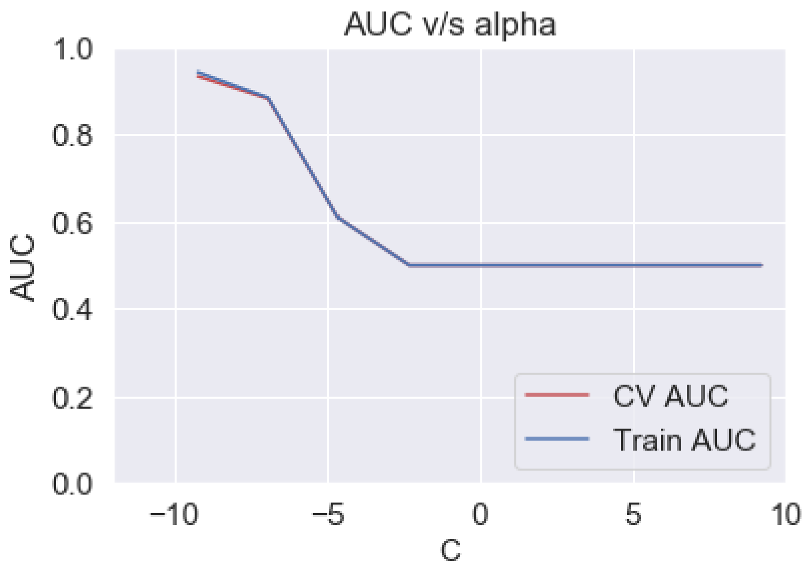
AUC vs alpha

In [31]:

```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in alpha_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 alpha')
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()
```

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.302585092994045 5, 0.0, 2.302585092994046, 4.605170185988092, 6.907755278982137, 9.210340371976184]
```



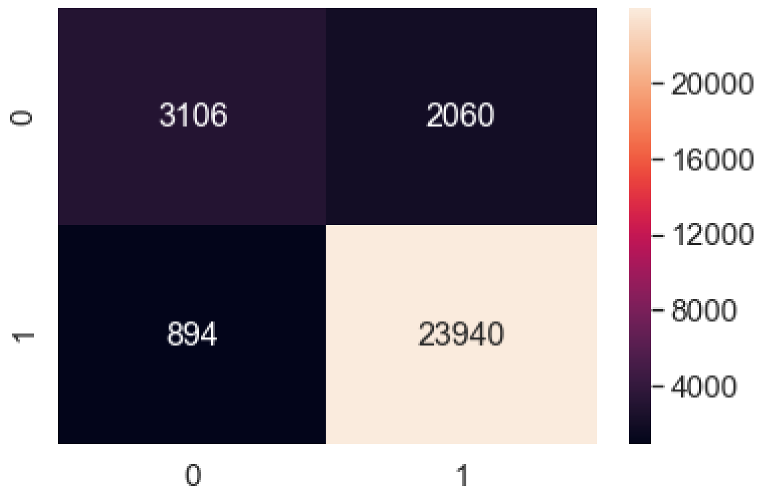
Confusion Matrix on Test Data

In [32]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_test_tfidf)
cm = confusion_matrix(y_test_tfidf, y_predict)
```

```
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')
```

```
[[ 3106  2060]
 [  894 23940]]
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x1b0c19dee48>

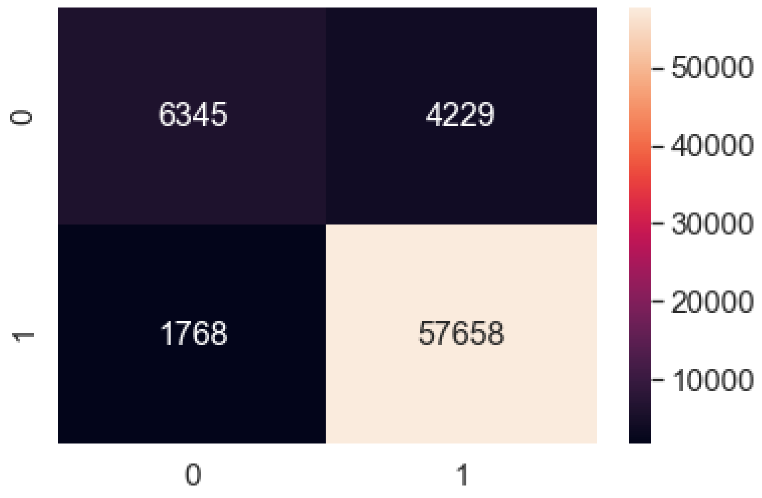


Confusion Matrix on Train Data

In [33]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_train_tfidf)
cm = confusion_matrix(y_train_tfidf, y_predict)
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')
```

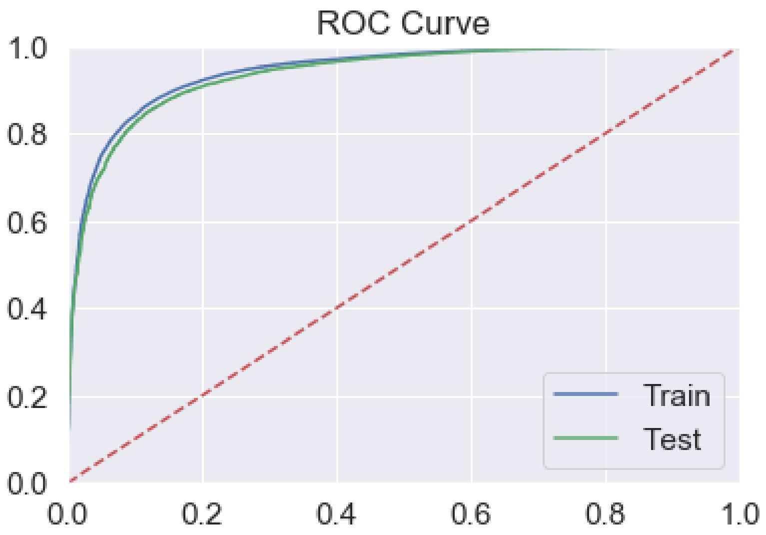
```
[[ 6345  4229]
 [ 1768 57658]]
```

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x1b0ab37f6d8>



ROC Curve

In [34]:
```
# Plotting roc curve on Train Data
pred_train = ccv.predict_proba(x_train_tfidf)[:,1]
fpr, tpr, threshold = roc_curve(y_train_tfidf, pred_train)
plt.plot(fpr, tpr, 'b', label='Train')

# Plotting roc curve on Test Data
pred_test = ccv.predict_proba(x_test_tfidf)[:,1]
fpr, tpr, threshold = roc_curve(y_test_tfidf, 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()
```



[3.1.4] Applying Linear SVM on TFIDF (l2 reg.), SET 2

In [18]:
```
# initializing SGDClassifier model with L2 regularisation
sgdc = SGDClassifier(loss='hinge', penalty='l2', class_weight='balance
d')

# alpha values we need to try on classifier
alpha_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10*
*4]
param_grid = {'alpha':alpha_values}

# using GridSearchCV to find the optimal value of alpha
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(sgdc,param_grid,scoring='roc_auc',cv=10,return_trai
n_score=True)
gscv.fit(x_train_tfidf,y_train_tfidf)

# getting the optimal value of alpha
print("Best alpha Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best alpha Value: {'alpha': 0.0001}
```

```
Best alpha value:  {'alpha': 0.0001}
Best ROC AUC Score: 0.94330
```

In [19]:
```
# determining optimal alpha
optimal_alpha = gscv.best_params_['alpha']

# calibrating the above results using CalibratedClassifierCV and traini
ng the model
ccv = CalibratedClassifierCV(gscv,cv='prefit')
ccv.fit(x_train_tfidf,y_train_tfidf)

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

#determining the Test roc_auc_score for optimal alpha
auc_score = roc_auc_score(y_test_tfidf, y_pred)
print('\n**** Test roc_auc_score for C = %.5f is %f ****' % (optimal_al
pha,auc_score))
```

```
**** Test roc_auc_score for C = 0.00010 is 0.943233 ****
```

In [20]:
```
# plotting AUC vs C on Train & Validation dataset
log_alpha=[math.log(x) for x in alpha_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 alpha')
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()
```

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.90775527898213
7, 9.210340371976184]
```

Confusion Matrix on Test Data

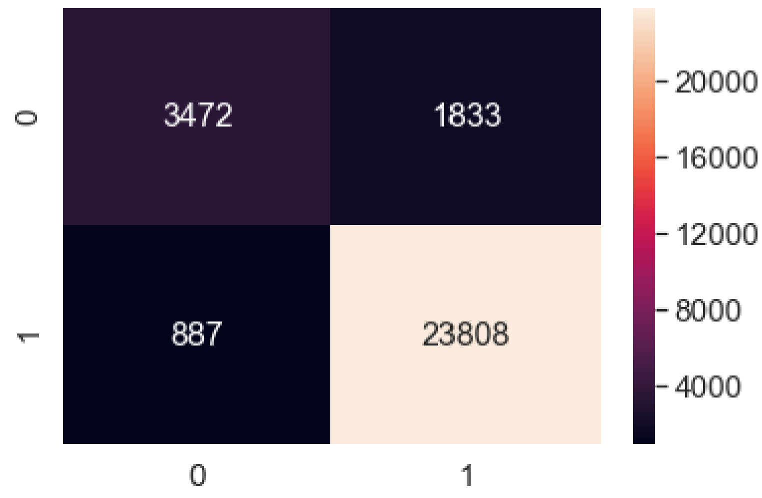
In [21]:

```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_test_tfidf)
cm = confusion_matrix(y_test_tfidf, y_predict)
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')
```

```
[[ 3472  1833]
 [  887 23808]]
```

Out[21]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x231cf234080>
```

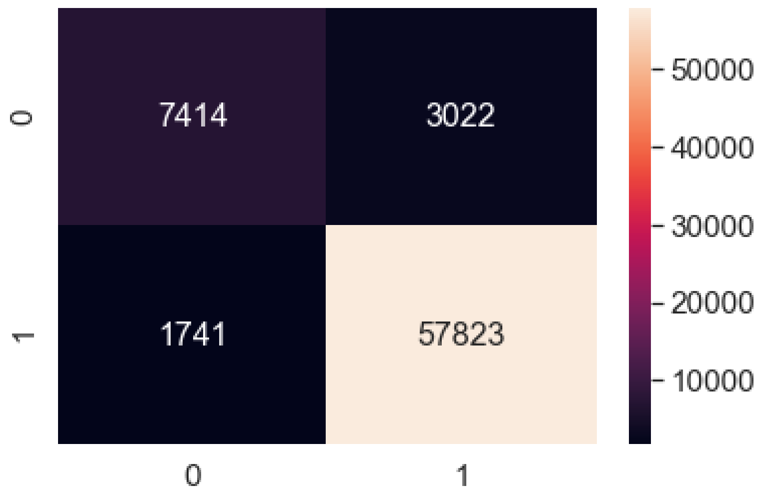


Confusion Matrix on Train Data

In [22]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_train_tfidf)
cm = confusion_matrix(y_train_tfidf, y_predict)
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')
```

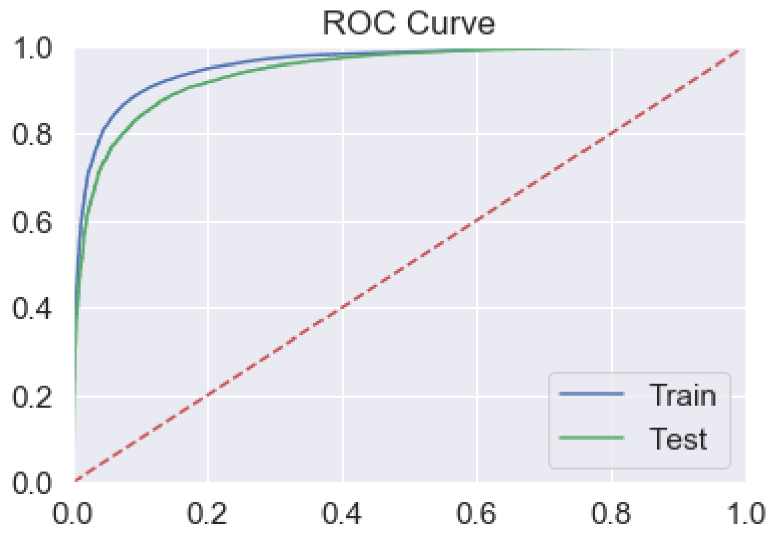
```
[[ 7414  3022]
 [ 1741 57823]]
```

Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x231d2e2d6d8>
```



ROC Curve

In [23]:
```
# Plotting roc curve on Train Data
pred_train = ccv.predict_proba(x_train_tfidf)[:,1]
fpr, tpr, threshold = roc_curve(y_train_tfidf, pred_train)
plt.plot(fpr, tpr, 'b', label='Train')

# Plotting roc curve on Test Data
pred_test = ccv.predict_proba(x_test_tfidf)[:,1]
fpr, tpr, threshold = roc_curve(y_test_tfidf, 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()
```



Feature Importance

In [23]:
```
# Training the model with optimal alpha value to get the feature import
ance
clf = SGDClassifier(loss='hinge', penalty='l1', alpha=optimal_alpha)
clf.fit(x_train_tfidf,y_train_tfidf)
```

Out[23]:
```
SGDClassifier(alpha=0.0001, average=False, class_weight=None,
       early_stopping=False, epsilon=0.1, eta0=0.0, fit_intercept=True,
       l1_ratio=0.15, learning_rate='optimal', loss='hinge', max_iter=N
one,
       n_iter=None, n_iter_no_change=5, n_jobs=None, penalty='l1',
       power_t=0.5, random_state=None, shuffle=True, tol=None,
       validation_fraction=0.1, verbose=0, warm_start=False)
```

In [24]:
```
feature_names = tf_idf_vect.get_feature_names()
coefs_with_fns = sorted(zip(clf.coef_[0], feature_names),reverse=True)
top = zip(coefs_with_fns[:10], coefs_with_fns[:-(10 + 1):-1])
print("\t\tPositive\t\t\t\tNegative")
print("_________________________________________________________________
```

```
_________________________________________")
for (coef_1, fn_1), (coef_2, fn_2) in top:
    print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, f
n_2))
```

```
                Positive                                        Negative
________________________________________________________________________
___________________________
        5.1297  great                                           -8.0417 worst
        5.0628  delici                                          -5.6084 aw
        4.5153  best                                            -5.4433 disappo
int
        3.8739  perfect                                         -5.0686 return
        3.6090  excel                                           -5.0151 terribl
        3.5547  love                                            -4.5465 horribl
        2.8356  amaz                                            -4.5168 disgust
        2.8086  nice                                            -4.2374 threw
        2.6004  good                                            -3.8006 gross
        2.5112  tasti                                           -3.7946 wast
```

[3.1.5] Applying Linear SVM on AVG W2V (l1 reg.), SET 3

In [54]:
```
# initializing SGDClassifier model with L1 regularisation
sgdc = SGDClassifier(loss='hinge', penalty='l1',class_weights)

# alpha values we need to try on classifier
alpha_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10*
*4]
param_grid = {'alpha':[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10
```

```
**3,10**4]}

# using GridSearchCV to find the optimal value of alpha
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(sgdc,param_grid,scoring='roc_auc',cv=10,return_trai
n_score=True)
gscv.fit(x_train_w2v,y_train_w2v)

# getting the optimal value of alpha
print("Best alpha Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best alpha Value:  {'alpha': 0.001}
Best ROC AUC Score: 0.89904
```

In [55]:

```
# determining optimal alpha
optimal_alpha = gscv.best_params_['alpha']

# calibrating the above results using CalibratedClassifierCV and traini
ng the model
ccv = CalibratedClassifierCV(gscv,cv='prefit')
ccv.fit(x_train_w2v,y_train_w2v)

#predicting the class label using test data
y_pred = ccv.predict_proba(x_test_w2v)[:,1]

#determining the Test roc_auc_score for optimal alpha
auc_score = roc_auc_score(y_test_w2v, y_pred)
print('\n**** Test roc_auc_score for C = %.5f is %f ****' % (optimal_al
pha,auc_score))
```

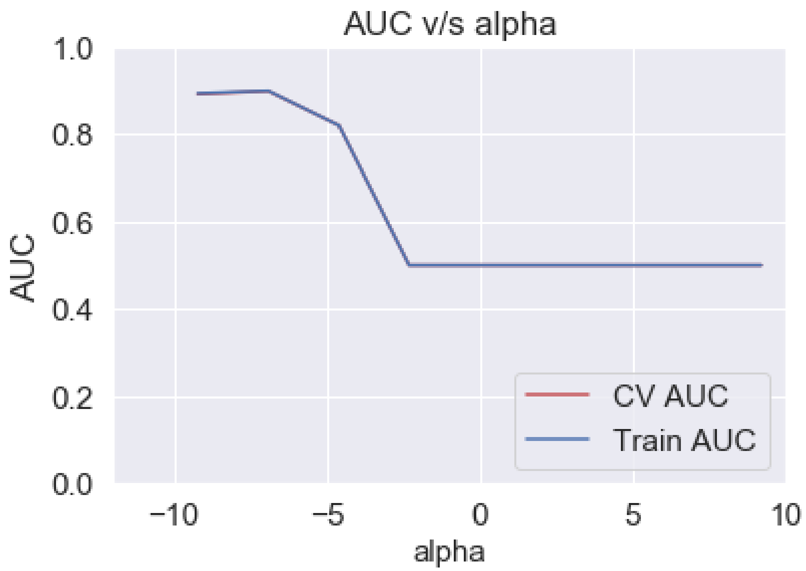
```
**** Test roc_auc_score for C = 0.00100 is 0.897834 ****
```

In [56]:

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

```
plt.ylabel('AUC')
plt.title('AUC v/s alpha')
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()
```

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.90775527898213
7, 9.210340371976184]
```



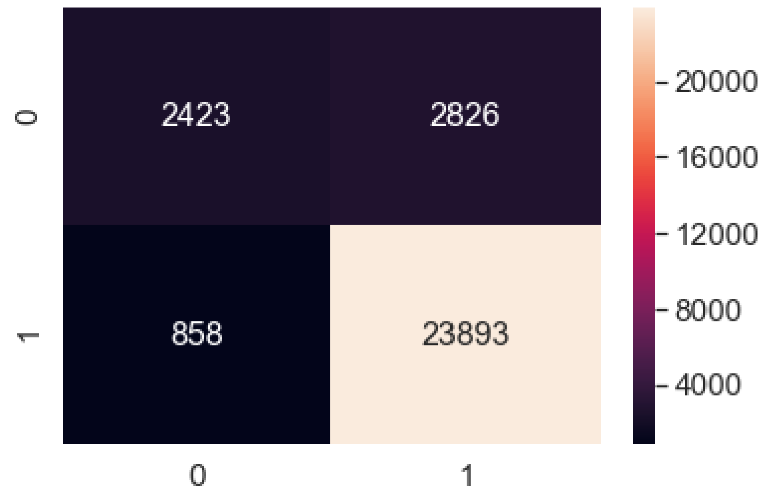
Confusion Matric on Test Data

In [57]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_test_w2v)
cm = confusion_matrix(y_test_w2v, y_predict)
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')
```

```
[[ 2423  2826]
 [  858 23893]]
```

Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x1f7935da240>

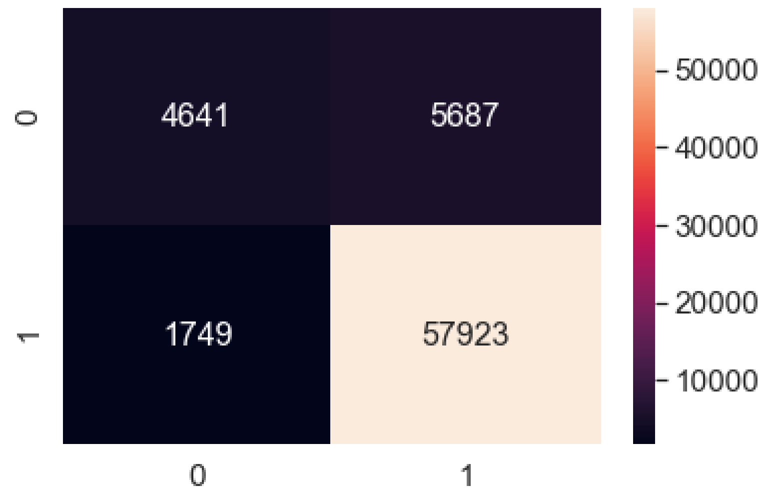


Confusion Matric on Train Data

In [59]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_train_w2v)
cm = confusion_matrix(y_train_w2v, y_predict)
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')
```

```
[[ 4641  5687]
 [ 1749 57923]]
```

Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x1f79a02f898>



[3.1.6] Applying Linear SVM on AVG W2V (l2 reg.), SET 3

In [60]:
```
# initializing SGDClassifier model with L2 regularisation
sgdc = SGDClassifier(loss='hinge', penalty='l2')

# alpha values we need to try on classifier
alpha_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]
param_grid = {'alpha':[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]}

# using GridSearchCV to find the optimal value of alpha
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(sgdc,param_grid,scoring='roc_auc',cv=10,return_train_score=True)
gscv.fit(x_train_w2v,y_train_w2v)

# getting the optimal value of alpha
print("Best alpha Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best alpha Value:  {'alpha': 0.001}
```

```
Best ROC AUC Score: 0.89941
```

In [61]:

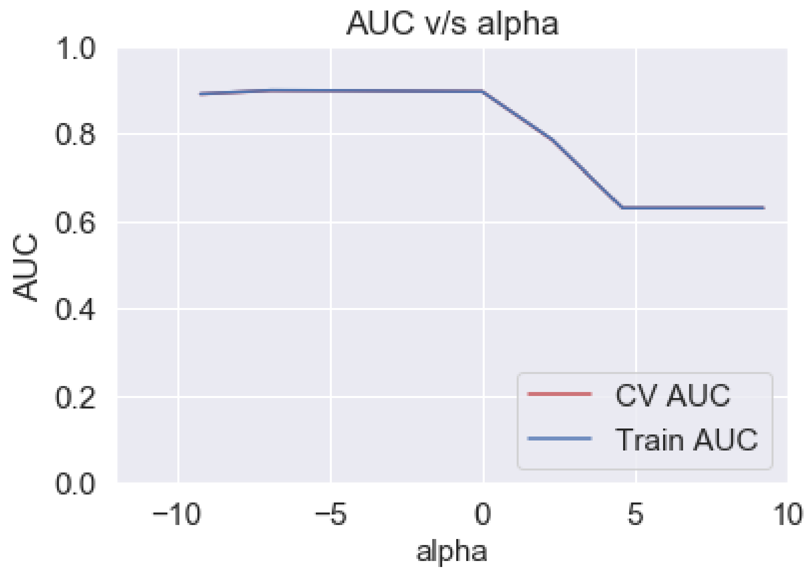
```
# determining optimal alpha
optimal_alpha = gscv.best_params_['alpha']

# calibrating the above results using CalibratedClassifierCV and traini
ng the model
ccv = CalibratedClassifierCV(gscv,cv='prefit')
ccv.fit(x_train_w2v,y_train_w2v)

#predicting the class label using test data
y_pred = ccv.predict_proba(x_test_w2v)[:,1]

#determining the Test roc_auc_score for optimal alpha
auc_score = roc_auc_score(y_test_w2v, y_pred)
print('\n**** Test roc_auc_score for C = %.5f is %f ****' % (optimal_al
pha,auc_score))
```

```
**** Test roc_auc_score for C = 0.00100 is 0.899219 ****
```

In [62]:

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

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.90775527898213
7, 9.210340371976184]
```

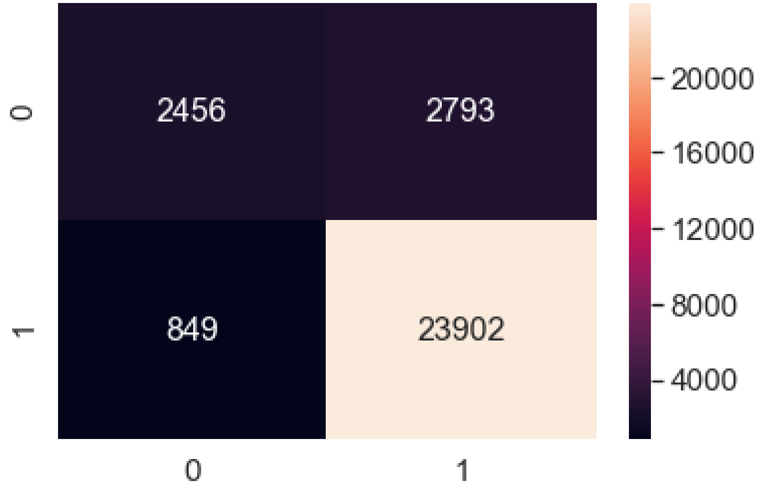


Confusion Matric on Test Data

In [63]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_test_w2v)
cm = confusion_matrix(y_test_w2v, y_predict)
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')
```

```
[[ 2456  2793]
 [  849 23902]]
```

Out[63]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f79a3323c8>
```

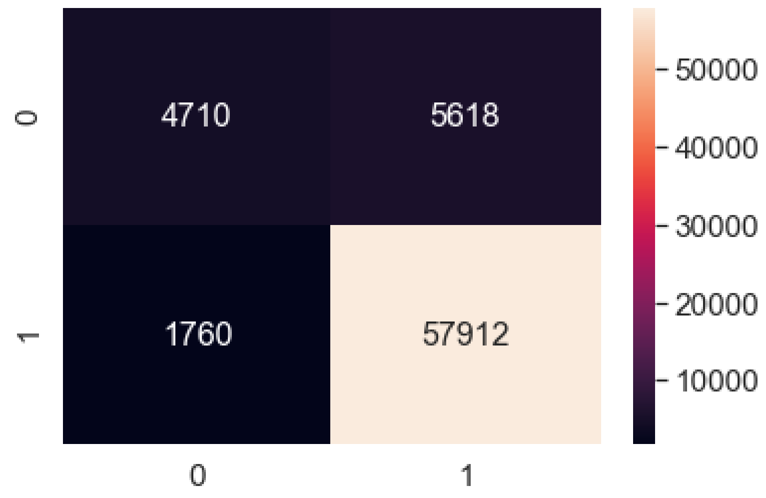


Confusion Matric on Train Data

In [64]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_train_w2v)
cm = confusion_matrix(y_train_w2v, y_predict)
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')
```

```
[[ 4710  5618]
 [ 1760 57912]]
```

Out[64]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f79a3fe3c8>
```



[3.1.7] Applying Linear SVM on TFIDF W2V (l1 reg.), SET 4

In [73]:
```
# initializing SGDClassifier model with L1 regularisation
sgdc = SGDClassifier(loss='hinge', penalty='l1')

# alpha values we need to try on classifier
alpha_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10*
*4]
param_grid = {'alpha':[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10
**3,10**4]}

# using GridSearchCV to find the optimal value of alpha
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(sgdc,param_grid,scoring='roc_auc',cv=10,return_trai
n_score=True)
gscv.fit(x_train_tfw2v,y_train_tfw2v)

# getting the optimal value of alpha
print("Best alpha Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best alpha Value:  {'alpha': 0.001}
```

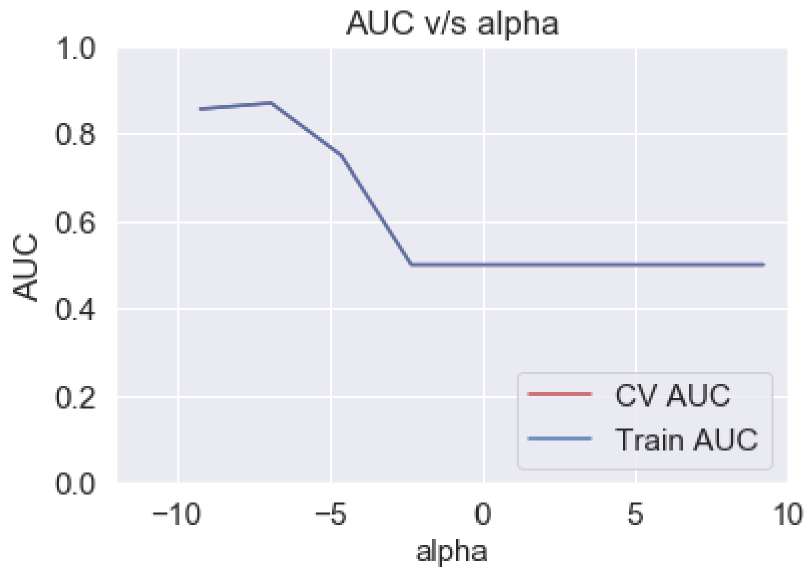
```
Best ROC AUC Score: 0.87024
```

In [74]:
```python
# determining optimal alpha
optimal_alpha = gscv.best_params_['alpha']

# calibrating the above results using CalibratedClassifierCV and traini
ng the model
ccv = CalibratedClassifierCV(gscv,cv='prefit')
ccv.fit(x_train_tfw2v,y_train_tfw2v)

#predicting the class label using test data
y_pred = ccv.predict_proba(x_test_tfw2v)[:,1]

#determining the Test roc_auc_score for optimal alpha
auc_score = roc_auc_score(y_test_tfw2v, y_pred)
print('\n**** Test roc_auc_score for C = %.5f is %f ****' % (optimal_al
pha,auc_score))
```

```
**** Test roc_auc_score for C = 0.00100 is 0.865229 ****
```

In [75]:
```python
# plotting AUC vs alpha on Train & Validation dataset
log_alpha=[math.log(x) for x in alpha_values]
print(log_alpha)
plt.xlim(-12,10)
plt.ylim(0.0,1.0)
plt.xlabel("alpha",fontsize=15)
plt.ylabel('AUC')
plt.title('AUC v/s alpha')
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()
```

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.90775527898213
7, 9.210340371976184]
```

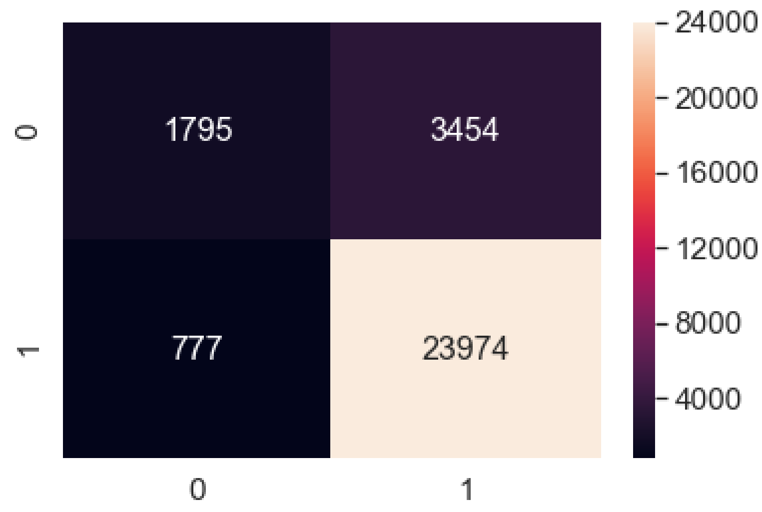


Confusion Matrix on Test Data

In [76]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_test_tfw2v)
cm = confusion_matrix(y_test_tfw2v, y_predict)
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')
```

```
[[ 1795  3454]
 [  777 23974]]
```

Out[76]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f79a6e87b8>
```

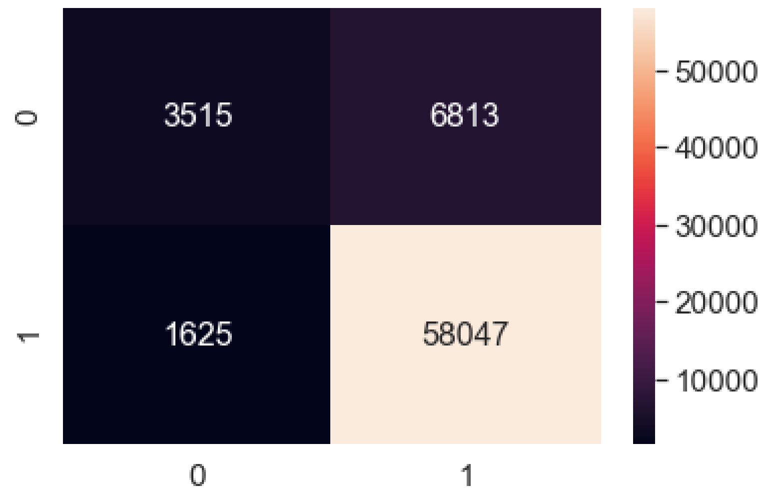


Confusion Matrix on Train Data

In [77]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_train_tfw2v)
cm = confusion_matrix(y_train_tfw2v, y_predict)
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')
```

```
[[ 3515  6813]
 [ 1625 58047]]
```

Out[77]: `<matplotlib.axes._subplots.AxesSubplot at 0x1f79a4f17f0>`



[3.1.8] Applying Linear SVM on TFIDF W2V (l2 reg.), SET 4

In [78]:
```
# initializing SGDClassifier model with L2 regularisation
sgdc = SGDClassifier(loss='hinge', penalty='l2')

# alpha values we need to try on classifier
alpha_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10*
*4]
param_grid = {'alpha':[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10
**3,10**4]}

# using GridSearchCV to find the optimal value of alpha
# using roc_auc as the scoring parameter & applying 10 fold CV
gscv = GridSearchCV(sgdc,param_grid,scoring='roc_auc',cv=10,return_trai
n_score=True)
gscv.fit(x_train_tfw2v,y_train_tfw2v)

# getting the optimal value of alpha
print("Best alpha Value: ",gscv.best_params_)
print("Best ROC AUC Score: %.5f"%(gscv.best_score_))
```

```
Best alpha Value:  {'alpha': 0.001}
```

```
Best ROC AUC Score: 0.87182
```

In [79]:

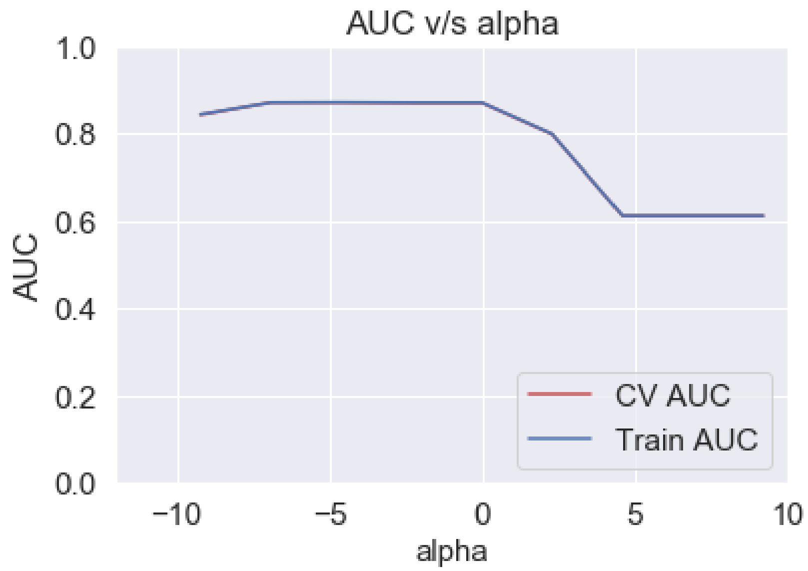
```
# determining optimal alpha
optimal_alpha = gscv.best_params_['alpha']

# calibrating the above results using CalibratedClassifierCV and traini
ng the model
ccv = CalibratedClassifierCV(gscv,cv='prefit')
ccv.fit(x_train_tfw2v,y_train_tfw2v)

#predicting the class label using test data
y_pred = ccv.predict_proba(x_test_tfw2v)[:,1]

#determining the Test roc_auc_score for optimal alpha
auc_score = roc_auc_score(y_test_tfw2v, y_pred)
print('\n**** Test roc_auc_score for C = %.5f is %f ****' % (optimal_al
pha,auc_score))
```

```
**** Test roc_auc_score for C = 0.00100 is 0.866762 ****
```

In [80]:

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

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.90775527898213
7, 9.210340371976184]
```

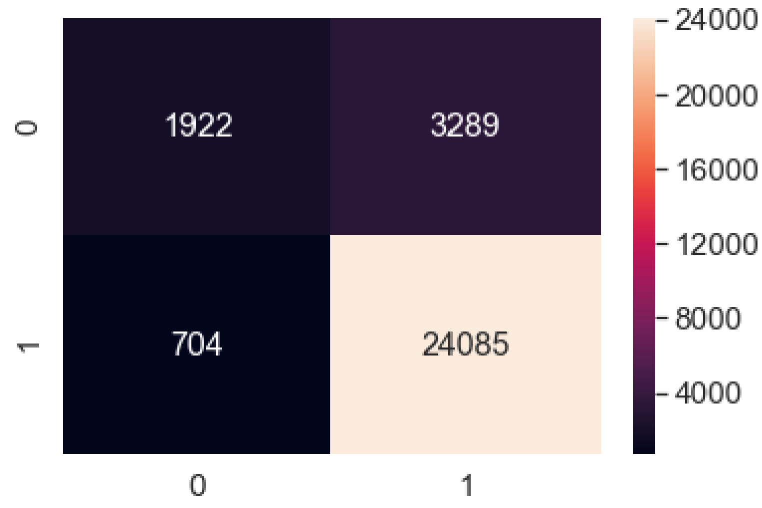


Confusion Matrix on Test Data

In [101]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_test_tfw2v)
cm = confusion_matrix(y_test_tfw2v, y_predict)
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')
```

```
[[ 1922  3289]
 [  704 24085]]
```

Out[101]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1b42bd7ba90>
```

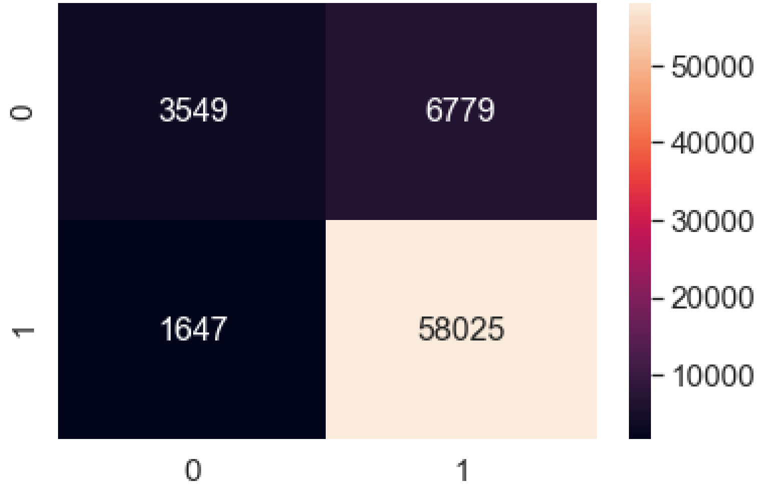


Confusion Matrix on Train Data

In [81]:
```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_train_tfw2v)
cm = confusion_matrix(y_train_tfw2v, y_predict)
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')
```

```
[[ 3549  6779]
 [ 1647 58025]]
```

Out[81]: `<matplotlib.axes._subplots.AxesSubplot at 0x1f79a65bbe0>`



[3.2] RBF SVM

[3.2.1] Applying RBF SVM on BOW, SET 1

In [82]:
```
# initializing SupportVectorClassifier model with RBF Kernel
svc = SVC(kernel='rbf')

# C values we need to try on classifier
C_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]
param_grid = {'C':[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,
10**4]}

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter
gscv = GridSearchCV(svc,param_grid,scoring='roc_auc', n_jobs=-1, return
_train_score=True)

gscv.fit(x_train_bow_rbf,y_train_bow_rbf)
```

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

```
Best C Value:  {'C': 100}
Best ROC AUC Score: 0.90546
```

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

#training the model using the optimal C
svc_clf = SVC(kernel='rbf', C=optimal_C, probability=True)
svc_clf.fit(x_train_bow_rbf,y_train_bow_rbf)

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

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

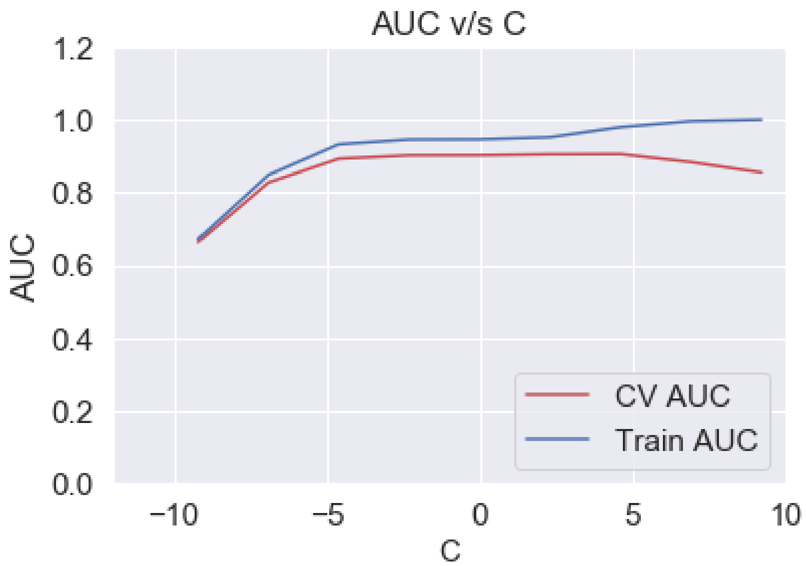
```
**** Test roc_auc_score for C = 100.000000 is 0.918736 ****
```

AUC vs C

In [84]:
```
# plotting AUC vs C on Train & Validation dataset
log_C=[math.log(x) for x in C_values]
print(log_C)
plt.xlim(-12,10)
plt.ylim(0.0,1.2)
plt.xlabel("C",fontsize=15)
plt.ylabel('AUC')
plt.title('AUC v/s C')
plt.plot(log_C, gscv.cv_results_['mean_test_score'], 'r', label='CV AUC')
plt.plot(log_C, gscv.cv_results_['mean_train_score'], 'b', label='Train AUC')
```

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

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.90775527898213
7, 9.210340371976184]
```

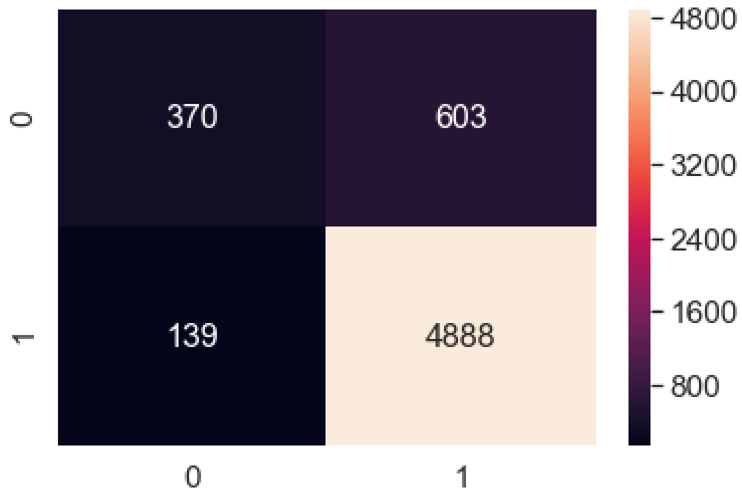


Confusion Matrix on Test Data

In [43]:
```
# plotting confusion matrix as heatmap
y_predict = svc_clf.predict(x_test_bow_rbf)
cm = confusion_matrix(y_test_bow_rbf, y_predict)
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')
```

```
[[ 370  603]
 [ 139 4888]]
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x1f1e14eb710>



Confusion Matrix on Train Data

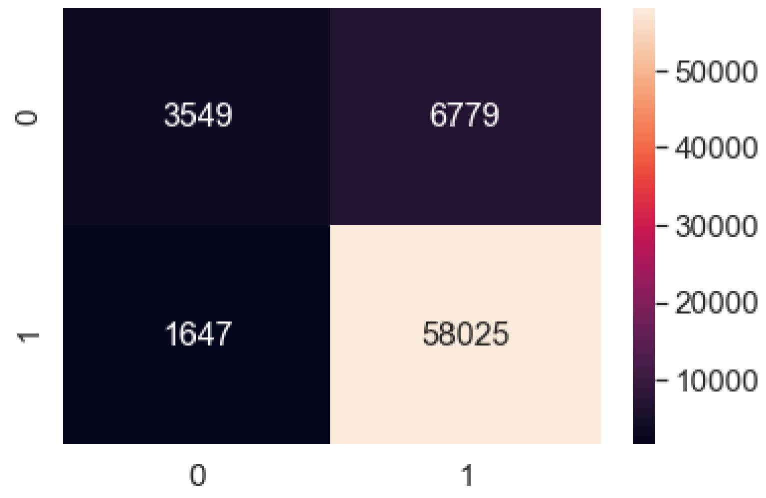
In [85]:

```
# plotting confusion matrix as heatmap
y_predict = ccv.predict(x_train_tfw2v)
cm = confusion_matrix(y_train_tfw2v, y_predict)
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')
```

```
[[ 3549  6779]
 [ 1647 58025]]
```

Out[85]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f79a89f518>
```



[3.2.2] Applying RBF SVM on TFIDF, SET 2

In [44]:
```
# initializing SupportVectorClassifier model with RBF Kernel
svc = SVC(kernel='rbf')

# C values we need to try on classifier
C_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]
param_grid = {'C':[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,
10**4]}

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter
gscv = GridSearchCV(svc, param_grid, scoring='roc_auc', n_jobs=-1, retu
rn_train_score=True)

gscv.fit(x_train_tfidf_rbf,y_train_tfidf_rbf)

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

```
Best C Value:  {'C': 100}
Best ROC AUC Score: 0.88825
```

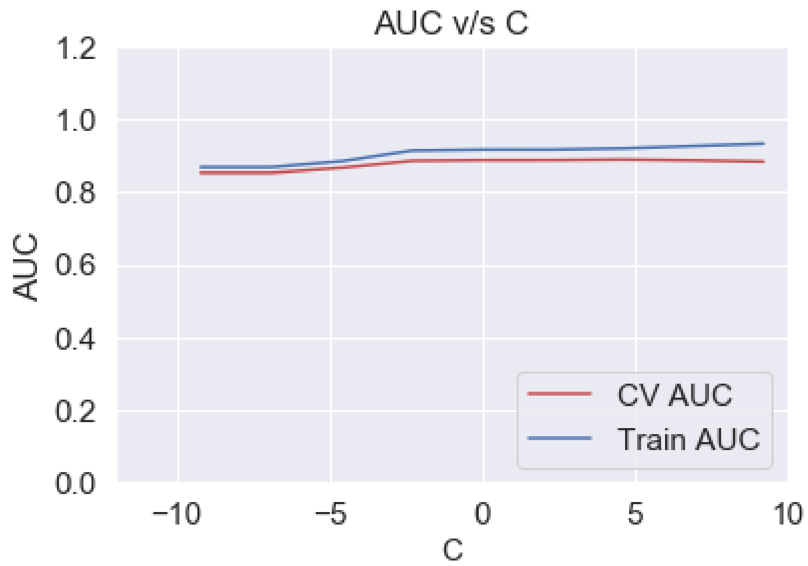
In [45]:
```
# determining optimal C
optimal_C = gscv.best_params_['C']

#training the model using the optimal C
svc_clf = SVC(kernel='rbf', C=optimal_C, probability=True)
svc_clf.fit(x_train_tfidf_rbf,y_train_tfidf_rbf)

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

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

```
**** Test roc_auc_score for C = 100.000000 is 0.888614 ****
```

AUC vs C

In [46]:
```
# plotting AUC vs C on Train & Validation dataset
log_C=[math.log(x) for x in C_values]
print(log_C)
plt.xlim(-12,10)
plt.ylim(0.0,1.2)
plt.xlabel("C",fontsize=15)
plt.ylabel('AUC')
plt.title('AUC v/s C')
plt.plot(log_C, gscv.cv_results_['mean_test_score'], 'r', label='CV AU
C')
plt.plot(log_C, gscv.cv_results_['mean_train_score'], 'b', label='Train
 AUC')
plt.legend(loc='lower right')
plt.show()
```

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.90775527898213
7, 9.210340371976184]
```

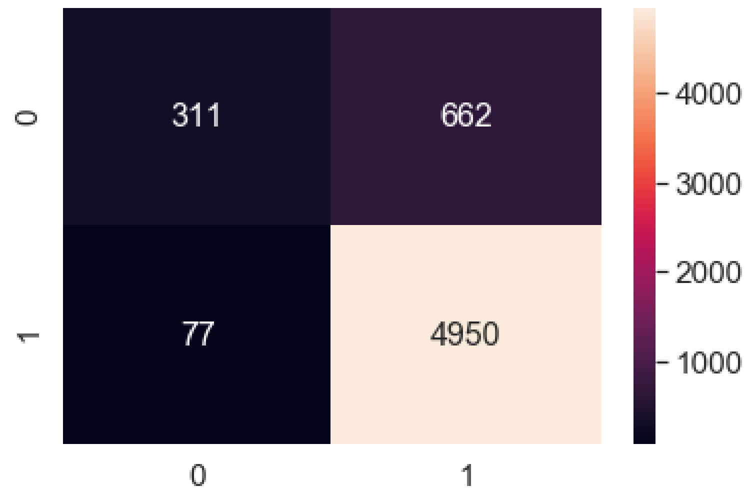


Confusion Matrix

In [47]:
```
# plotting confusion matrix as heatmap
y_predict = svc_clf.predict(x_test_tfidf_rbf)
cm = confusion_matrix(y_test_tfidf_rbf, y_predict)
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')
```

```
[[ 311  662]
 [  77 4950]]
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x1f1ded73f28>



[3.2.3] Applying RBF SVM on AVG W2V, SET 3

In [57]:
```
# initializing SupportVectorClassifier model with RBF Kernel
svc = SVC(kernel='rbf')

# C values we need to try on classifier
C_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]
param_grid = {'C':[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,
10**4]}

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter
gscv = GridSearchCV(svc, param_grid, scoring='roc_auc', n_jobs=-1, retu
rn_train_score=True)

gscv.fit(x_train_w2v_rbf,y_train_w2v_rbf)

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

```
Best C Value:  {'C': 10}
Best ROC AUC Score: 0.87154
```

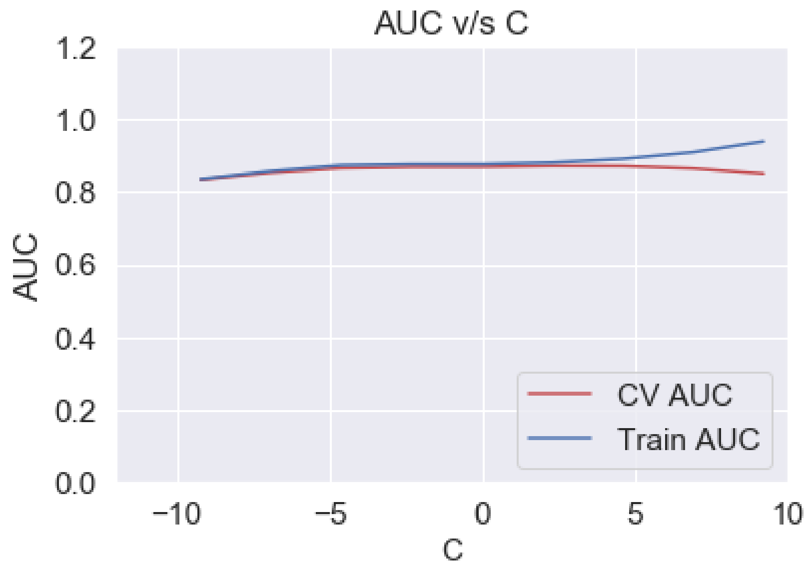
In [58]:
```
# determining optimal C
optimal_C = gscv.best_params_['C']

#training the model using the optimal C
svc_clf = SVC(kernel='rbf', C=optimal_C, probability=True)
svc_clf.fit(x_train_w2v_rbf,y_train_w2v_rbf)

#predicting the class label using test data
y_pred = svc_clf.predict_proba(x_test_w2v_rbf)[:,1]

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_w2v_rbf, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,au
c_score))
```

```
**** Test roc_auc_score for C = 10.000000 is 0.863734 ****
```

AUC vs C

In [59]:
```
# plotting AUC vs C on Train & Validation dataset
log_C=[math.log(x) for x in C_values]
print(log_C)
plt.xlim(-12,10)
plt.ylim(0.0,1.2)
plt.xlabel("C",fontsize=15)
plt.ylabel('AUC')
plt.title('AUC v/s C')
plt.plot(log_C, gscv.cv_results_['mean_test_score'], 'r', label='CV AU
C')
plt.plot(log_C, gscv.cv_results_['mean_train_score'], 'b', label='Train
 AUC')
plt.legend(loc='lower right')
plt.show()
```

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.90775527898213
7, 9.210340371976184]
```

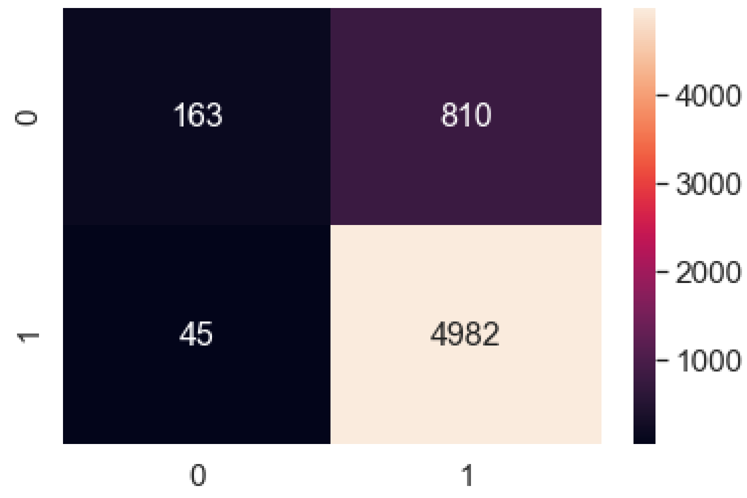


Confusion Matrix

In [60]:
```
# plotting confusion matrix as heatmap
y_predict = svc_clf.predict(x_test_w2v_rbf)
cm = confusion_matrix(y_test_w2v_rbf, y_predict)
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')
```

```
[[ 163  810]
 [  45 4982]]
```

Out[60]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f1da078ac8>
```



[3.2.4] Applying RBF SVM on TFIDF W2V, SET 4

In [68]:

```
# initializing SupportVectorClassifier model with RBF Kernel
svc = SVC(kernel='rbf')

# C values we need to try on classifier
C_values = [10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,10**4]
param_grid = {'C':[10**-4,10**-3,10**-2,10**-1,10**0,10**1,10**2,10**3,
10**4]}

# using GridSearchCV to find the optimal value of C
# using roc_auc as the scoring parameter
gscv = GridSearchCV(svc, param_grid, scoring='roc_auc', n_jobs=-1, retu
rn_train_score=True)

gscv.fit(x_train_tfw2v_rbf,y_train_tfw2v_rbf)

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

```
Best C Value:  {'C': 10}
Best ROC AUC Score: 0.84562
```

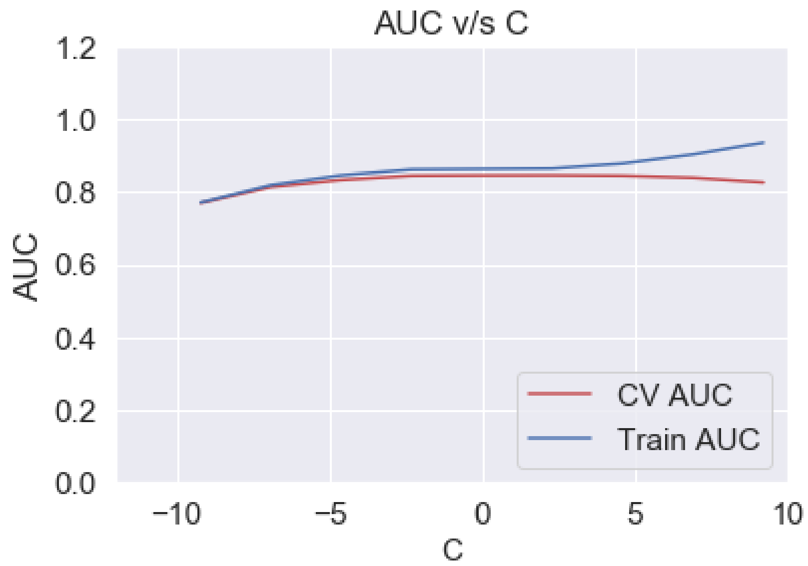
In [69]:
```
# determining optimal C
optimal_C = gscv.best_params_['C']

#training the model using the optimal C
svc_clf = SVC(kernel='rbf', C=optimal_C, probability=True)
svc_clf.fit(x_train_tfw2v_rbf,y_train_tfw2v_rbf)

#predicting the class label using test data
y_pred = svc_clf.predict_proba(x_test_tfw2v_rbf)[:,1]

#determining the Test roc_auc_score for optimal C
auc_score = roc_auc_score(y_test_tfw2v_rbf, y_pred)
print('\n**** Test roc_auc_score for C = %f is %f ****' % (optimal_C,au
c_score))
```

```
**** Test roc_auc_score for C = 10.000000 is 0.840449 ****
```

AUC vs C

In [70]:
```
# plotting AUC vs C on Train & Validation dataset
log_C=[math.log(x) for x in C_values]
print(log_C)
plt.xlim(-12,10)
plt.ylim(0.0,1.2)
plt.xlabel("C",fontsize=15)
plt.ylabel('AUC')
plt.title('AUC v/s C')
plt.plot(log_C, gscv.cv_results_['mean_test_score'], 'r', label='CV AU
C')
plt.plot(log_C, gscv.cv_results_['mean_train_score'], 'b', label='Train
 AUC')
plt.legend(loc='lower right')
plt.show()
```

```
[-9.210340371976182, -6.907755278982137, -4.605170185988091, -2.3025850
929940455, 0.0, 2.302585092994046, 4.605170185988092, 6.90775527898213
7, 9.210340371976184]
```

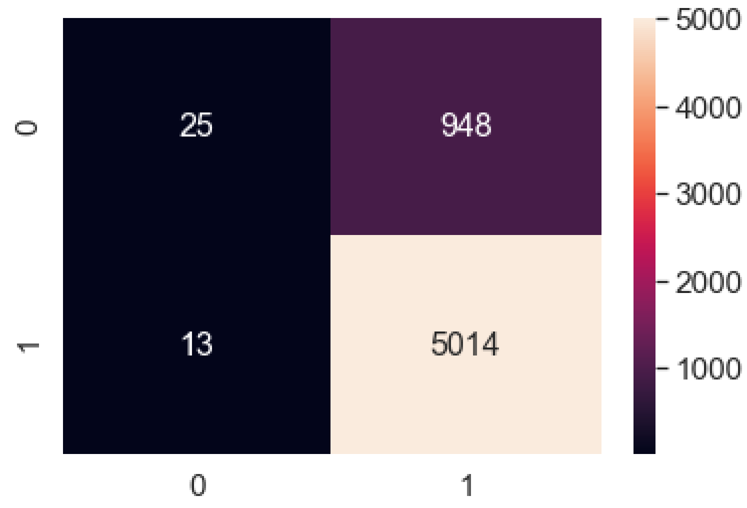


Confusion Matrix

In [71]:
```
# plotting confusion matrix as heatmap
y_predict = svc_clf.predict(x_test_tfw2v_rbf)
cm = confusion_matrix(y_test_tfw2v_rbf, y_predict)
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')
```

```
[[  25  948]
 [  13 5014]]
```

Out[71]: <matplotlib.axes._subplots.AxesSubplot at 0x1f1db4eb7b8>



[4.0] Conclusion

In [37]:

```
# Summarizing the observations
x=PrettyTable()
x.field_names = ['Vectorizer', 'Regularizer', 'Alpha', 'Train AUC', 'Te
st AUC']
x.add_row(['BOW', 'l1', '0.0001', '0.90528', '0.90802'])
x.add_row(['BOW', 'l2', '0.001', '0.92749', '0.93185'])
x.add_row(['TFIDF', 'l1', '0.0001', '0.93440', '0.93586'])
x.add_row(['TFIDF', 'l2', '0.0001', '0.94330', '0.94323'])
x.add_row(['Avg W2V', 'l1', '0.001', '0.89904', '0.90300'])
x.add_row(['Avg W2V', 'l2', '0.001', '0.89941', '0.90357'])
x.add_row(['TFIDF-W2V', 'l1', '0.001', '0.87024', '0.87130'])
x.add_row(['TFIDF-W2V', 'l2', '0.01', '0.87182', '0.87173'])
print('***** Observations for Linear SVM *****')
print(x)
```

```
***** Observations for Linear SVM *****
+------------+-------------+--------+-----------+----------+
| Vectorizer | Regularizer | Alpha  | Train AUC | Test AUC |
+------------+-------------+--------+-----------+----------+
|    BOW     |      l1     | 0.0001 |  0.90528  | 0.90802  |
```

```
|    BOW     |      l2      | 0.001  |  0.92749   | 0.93185  |
|   TFIDF    |      l1      | 0.0001 |  0.93440   | 0.93586  |
|   TFIDF    |      l2      | 0.0001 |  0.94330   | 0.94323  |
|  Avg W2V   |      l1      | 0.001  |  0.89904   | 0.90300  |
|  Avg W2V   |      l2      | 0.001  |  0.89941   | 0.90357  |
| TFIDF-W2V  |      l1      | 0.001  |  0.87024   | 0.87130  |
| TFIDF-W2V  |      l2      |  0.01  |  0.87182   | 0.87173  |
+------------+--------------+--------+------------+----------+
```

From the above table, we can draw the following conclusions:-

1. Bag of Words (BoW) & TFIDF Vectorizer perform better as compared to Avg Word2Vec & TFIDF Word2Vec.
2. Models trained with L2 regularization perform better than L1 regularization.

In [38]:

```
x=PrettyTable()
x.field_names = ['Vectorizer', 'C', 'Train AUC', 'Test AUC']
x.add_row(['BOW', '10', '0.90546', '0.88696'])
x.add_row(['TFIDF', '100', '0.88825', '0.88861'])
x.add_row(['Avg W2V', '10', '0.87154', '0.86373'])
x.add_row(['TFIDF-W2V', '10', '0.84562', '0.84044'])
print('*** Observations for RBF SVM ***')
print(x)
```

```
*** Observations for RBF SVM ***
+------------+-----+-----------+----------+
| Vectorizer |  C  | Train AUC | Test AUC |
+------------+-----+-----------+----------+
|    BOW     |  10 |  0.90546  | 0.88696  |
|   TFIDF    | 100 |  0.88825  | 0.88861  |
|  Avg W2V   |  10 |  0.87154  | 0.86373  |
| TFIDF-W2V  |  10 |  0.84562  | 0.84044  |
+------------+-----+-----------+----------+
```

From the above table, we can draw the following conclusions:-

1. Bag of Words (BoW) & TFIDF Vectorizer perform better as compared to Avg Word2Vec & TFIDF Word2Vec.
2. SVM using RBF Kernels have a significantly high training time as compared to Linear SVM's