NOTE:

1. RBF-SVM is implemented by using 40k data points. ¶

2. Linear-SVM is implemented by using 2 lakh data points.

Import necessary libraries

In [1]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [21]:
```
from sklearn.calibration import CalibratedClassifierCV,calibration_curve
import seaborn as sns
from sklearn.model_selection import TimeSeriesSplit
from scipy.sparse import *
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import *
import pickle
from tqdm import tqdm
from sklearn.model_selection import  cross_val_score
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.linear_model import SGDClassifier
from sklearn.svm import SVC
from sklearn.externals import joblib
from sklearn.model_selection import train_test_split
from prettytable import PrettyTable
%matplotlib inline
```

Load preprocessed data

In [3]:
```
#Functions to save objects for later use and retireve it
def savetofile(obj,filename):
    pickle.dump(obj,open(filename+".pkl","wb"))
def openfromfile(filename):
    temp = pickle.load(open(filename+".pkl","rb"))
    return temp

#DATA FOR LINEAR SVM
y_train =openfromfile('y_train')
y_test =openfromfile('y_test')

count_vect =openfromfile('count_vect')
X_train_bigram = openfromfile('X_train_bigram')
X_test_bigram = openfromfile('X_test_bigram')

tf_idf_vect =openfromfile('tf_idf_vect')
X_train_tfidf =openfromfile('X_train_tfidf')
X_test_tfidf =openfromfile('X_test_tfidf')

avg_sent_vectors=openfromfile('avg_sent_vectors')
avg_sent_vectors_test=openfromfile('avg_sent_vectors_test')

tfidf_sent_vectors=openfromfile('tfidf_sent_vectors')
tfidf_sent_vectors_test=openfromfile('tfidf_sent_vectors_test')

#DATA FOR RBF SVM
y_train_rbf =openfromfile('y_train_rbf')
y_test_rbf =openfromfile('y_test_rbf')

count_vect_rbf =openfromfile('count_vect_rbf')
X_train_bigram_rbf=openfromfile('X_train_bigram_rbf')
X_test_bigram_rbf=openfromfile('X_test_bigram_rbf')

tf_idf_vect_rbf =openfromfile('tf_idf_vect_rbf')
X_train_tfidf_rbf=openfromfile('X_train_tfidf_rbf')
X_test_tfidf_rbf=openfromfile('X_test_tfidf_rbf')

avg_sent_vectors_rbf=openfromfile('avg_sent_vectors_rbf')
avg_sent_vectors_test_rbf=openfromfile('avg_sent_vectors_test_rbf')

tfidf_sent_vectors_rbf=openfromfile('tfidf_sent_vectors_rbf')
```

```
tfidf_sent_vectors_test_rbf=openfromfile('tfidf_sent_vectors_test_rbf')
```

Samples Detail: (No. of samples taken)

In [100]:

```
print('No. of Training Samples (Linear-SVM):',X_train_bigram.shape[0])
print('No. of Training Samples (RBF-SVM):',X_train_bigram_rbf.shape[0])
print('No. of Test Samples (Linear-SVM):',X_test_bigram.shape[0])
print('No. of Test Samples (RBF-SVM):',X_test_bigram_rbf.shape[0])
```

```
No. of Training Samples (Linear-SVM): 112123
No. of Training Samples (RBF-SVM): 26190
No. of Test Samples (Linear-SVM): 48053
No. of Test Samples (RBF-SVM): 11225
```

Observation:

1. for linear svm all the preprcessing is done on 2 lakh reviews, after preprcessing we left with 1.60 lakh reviews.
2. for rbf svm all the preprcessing is done on 40k reviews, after preprcessing we left with 37.5k lakh reviews.

Save and Load Model:

In [4]:

```
def saveModeltofile(obj,filename):
    joblib.dump(obj,open(filename+".pkl","wb"))
def openModelfromfile(filename):
    temp = joblib.load(open(filename+".pkl","rb"))
    return temp
```

Standardizing data

In [5]:
```
def std_data(train,test,mean):
    scaler=StandardScaler(with_mean=mean)
    std_train=scaler.fit_transform(train)
    std_test=scaler.transform(test)
    return std_train, std_test
```

Support Vector Machine

Function for finding optimal value of hyperparameter and plot missclassification error vs hyperparam :

In [8]:
```
def SVM_Classifier(x_train,y_train,TBS,params,searchMethod,vect,kernel):
    ''' FUNCTION FOR FINDING OPTIMAL VALUE OF HYPERPARAM AND DRAW ERROR PLOT'''
    if kernel=='rbf':
        #INITIALIZE SVC CLASSIFIER WITH RBF-KERNEL
        clf=SVC(class_weight='balanced',kernel=kernel,decision_function_shape='ovr',verbose=3,cache_size=3000)
        hyper_name='C'
    elif kernel=='linear':
        #INITIALIZE SGDC OBJECT WITH HINGE LOSS
        clf=SGDClassifier(loss='hinge',penalty='l2',class_weight='balanced',random_state=1)
        hyper_name='alpha'
    # APPLY RANDOM OR GRID SEARCH FOR HYPERPARAMETER TUNNING
    if searchMethod=='grid':
        model=GridSearchCV(clf,\
                           cv=TBS,\
                           n_jobs=-1,\
                           param_grid=params,\
                           return_train_score=True,\
                           scoring=make_scorer(roc_auc_score,average='weighted'))
        model.fit(x_train,y_train)
    elif searchMethod=='random':
        model=RandomizedSearchCV(clf,\
                                 n_jobs=-1,\
                                 cv=TBS,\
                                 param_distributions=params,\
                                 n_iter=len(params[hyper_name]),\
                                 return_train_score=True,\
                                 scoring=make_scorer(roc_auc_score,average='weighted'))
        model.fit(x_train,y_train)

    #PLOT HYPERPARAM VS AUC VALUES(FOR BOTH CV AND TRAIN)
    train_auc= model.cv_results_['mean_train_score']
    train_auc_std= model.cv_results_['std_train_score']
    cv_auc = model.cv_results_['mean_test_score']
    cv_auc_std= model.cv_results_['std_test_score']
    plt.figure(1,figsize=(10,6))
    # HERE WE USE LOG FOR CLEAR VISUALIZATION OF ERROR PLOT
    plt.plot(np.log(params[hyper_name]), train_auc, label='Train AUC')
    # REFERENCE LINK: https://stackoverflow.com/a/48803361/4084039
    # gca(): get current axis
    plt.gca().fill_between(np.log(params[hyper_name]),train_auc - train_auc_std,train_auc + train_auc_std,alpha=0.2,
    plt.plot(np.log(params[hyper_name]), cv_auc, label='CV AUC')
```

```
    # REFERENCE LINK: https://stackoverflow.com/a/48803361/4084039
    plt.gca().fill_between(np.log(params[hyper_name]),cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color='darkc

    plt.title('ERROR PLOT (%s)' %vect)
    plt.xlabel('log(%s): Hyperparam' %hyper_name)
    plt.ylabel('AUC')
    plt.grid(True)
    plt.legend()
    plt.show()
    return model
```

Function for calibration of model and plot calibration curve:

In [9]:
```
def model_calibration(X_train,X_test,y_train,y_test,best_hyperparam,calibration_method,kernel):
    '''MODEL CALIBRATION AND DRAW CALIBRATION PLOT'''
    i=1;
    calibration_model={}
    #SPLIT DATA INTO TRAIN AND CROSS VALIDATION SET TO MAKE THE DATA DISJOINT
    x_tr,x_cv,y_tr,y_cv=train_test_split(X_train, y_train, test_size=0.3, shuffle=False)

    if kernel=='rbf':
        #INITIALIZE SVC WITH RBF KERNEL AND OPTIMAL VALUE OF HYPERPARAM
        clf=SVC(C=best_hyperparam['C'],\
                kernel=kernel,\
                class_weight='balanced',\
                decision_function_shape='ovr',\
                verbose=3,\
                cache_size=3000)
    elif kernel=='linear':
        #INITIALIZE SGDC WITH HINGE LOSS AND OPTIMAL VALUE OF HYPERPARAM
        clf=SGDClassifier(alpha=best_hyperparam['alpha'],\
                          class_weight='balanced',\
                          penalty=best_hyperparam['penalty'],\
                          loss='hinge',\
                          n_jobs=-1)
    clf.fit(x_tr,y_tr)
    #PREDICTED PROBABLITY BY A MODEL WITHOUT CALIBRATION
    test_pred_prob_uncalib=clf.decision_function(X_test)

    #NORMALIZE DECISION FUNCTION VALUES
    test_pred_prob_uncalib=\
    (test_pred_prob_uncalib-test_pred_prob_uncalib.min())/(test_pred_prob_uncalib.max()-test_pred_prob_uncalib.min()

    fop_uc,mop_uc=calibration_curve(y_test,test_pred_prob_uncalib, n_bins=7)
    for cal_method in calibration_method:
        # INITIALIZE CALIBRATION CLASSIFIER FOR BOTH SIGMOID AND ISOTONIC CALIBRATION
        calib_model=CalibratedClassifierCV(clf,cv='prefit',method=cal_method)
        calib_model.fit(x_cv,y_cv)
        calibration_model[cal_method]=calib_model
        test_pred_prob_calib = calib_model.predict_proba(X_test)[:,1]#y_calib
        fop_c,mop_c=calibration_curve(y_test,test_pred_prob_calib, n_bins=7)

        # IDEAL CALIBRATED PLOT
        plt.figure(1,figsize=(15,5))
```

```
        plt.subplot(int('12'+str(i)))
        plt.plot([0, 1], [0, 1], linestyle='--', color='black')
        # PLOT MODEL RELIABILITY PLOT
        plt.plot(mop_uc, fop_uc, marker='.',color='red',label='uncalibrated')
        plt.plot(mop_c, fop_c, marker='.',color='green',label='calibrated')
        plt.legend(loc='best')
        plt.title('Calibration Plots ({0})'.format(calibration_method[i-1]))
        i+=1
    plt.show()
    return calibration_model,clf
```

Function which calculate performance on test data with optimal hyperparam :

In [38]:

```
def test_performance(calib_model,clf,x_train,y_train,x_test,y_test,optimal_hyper,vect,summarize,kernel):
    '''PERFORMANCE ON TEST DATA AND PLOT ROC AND CONFUSION MATRIX WITH OPTIMAL HYPERPARAM'''

    data_used=['Test-Data','Train-Data']
    #PROBABILITY SCORE FOR TRAIN DATA
    calib_train_prob=calib_model.predict_proba(x_train)[:,1]
    #PROBABILITY SCORE FOR TEST DATA
    calib_test_prob=calib_model.predict_proba(x_test)[:,1]

    fpr_test, tpr_test, threshold_test = roc_curve(y_test, calib_test_prob,pos_label=1)
    fpr_train, tpr_train, threshold_train = roc_curve(y_train, calib_train_prob,pos_label=1)
    auc_score_test=auc(fpr_test, tpr_test)
    auc_score_train=auc(fpr_train, tpr_train)
    y_pred={} ; y_act={};
    y_pred[data_used[0]]=clf.predict(x_test)
    y_pred[data_used[1]]=clf.predict(x_train)
    y_act[data_used[0]]=y_test
    y_act[data_used[1]]=y_train
    f1=f1_score(y_test,y_pred[data_used[0]],average='weighted')
    if kernel=='linear':
        #ADD RESULTS TO PRETTY TABLE
        summarize.add_row([vect,kernel, optimal_hyper['penalty'],optimal_hyper['alpha'], '%.4f' %auc_score_test,'%.4
    elif kernel=='rbf':
        summarize.add_row([vect,kernel, optimal_hyper['C'], '%.4f' %auc_score_test,'%.4f' %f1])
    plt.figure(1,figsize=(14,7))
    plt.title('ROC Curve (%s)' %vect)
    #IDEAL ROC CURVE
    plt.plot([0,1],[0,1],'k--')
    #ROC CURVE OF TEST DATA
    plt.plot(fpr_test, tpr_test , 'b', label='Test_AUC= %.2f' %auc_score_test)
    #ROC CURVE OF TRAIN DATA
    plt.plot(fpr_train, tpr_train , 'g', label='Train_AUC= %.2f' %auc_score_train)
    plt.xlim([-0.1,1.1])
    plt.ylim([-0.1,1.1])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.grid(True)
    plt.legend(loc='lower right')

    plt.figure(2,figsize=(16,6))
    for k in range(2):
```

```
        #PLOT CONFUSION MATRIX USING HEATMAP
        plt.subplot(int('12'+str(k+1)))
        plt.title('Confusion-Matrix (%s)' %data_used[k])
        df_cm = pd.DataFrame(confusion_matrix(y_act[data_used[k]],y_pred[data_used[k]]), ['Negative','Positive'],['N
        sns.set(font_scale=1.4)#for label size
        sns.heatmap(df_cm,cmap='gist_earth', annot=True,annot_kws={"size": 16}, fmt='g')
    plt.show()
```

Function which print top important fetures and plot them using Bar plot :

In [17]:
```
#REFERENCE STACKOVERFLOW
def feature_importance(vectorizer,clf,n):
    '''TOP IMPORTANT FEATURE FOR BOTH POSITIVE AND NEGAVTIVE CLASS'''
    feature_names = vectorizer.get_feature_names()
    coefs_with_fns = sorted(zip(clf.coef_[0], feature_names))
    top = zip(coefs_with_fns[:n], coefs_with_fns[:-(n + 1):-1])
    print("\tNegative\t\t\t\tPositive\t\t")
    print("_"*75)
    for (coef_1, fn_1), (coef_2, fn_2) in top:
        print("\t%.4f\t%-15s\t\t\t\t%.4f\t%-15s" % (coef_1, fn_1, coef_2, fn_2))

    coef=sorted(clf.coef_[0],reverse=True)
    #STORE WEIGHT CORRESPONDING TO TOP POSITIVE AND NEGATIVE IMPORTANT FEATURES
    coef_p=coef[:n]
    coef_n=coef[:-(n + 1):-1]
    coef_np=coef_n+coef_p
    indices_n=np.argsort(clf.coef_[0])[:n]
    indices_p=np.argsort(clf.coef_[0])[::-1][:n]
    indices=list(indices_n)+list(indices_p)
    names = np.array(vectorizer.get_feature_names())
    #BAR CHART
    plt.figure(2,figsize=(13,6))
    sns.set(rc={'figure.figsize':(11.7,8.27)})
    plt.title("Feature Importance(top %d positive and negative class features)" % n)
    # ADD BARS
    plt.bar(range(2*n), coef_np)
    # ADD FEATURES NAME
    plt.xticks(range(2*n), names[indices], rotation=80)
    plt.show()
```

Initialization of common objects required for all vectorization:

In [18]:

```
#VECTORIZER
vect=['BoW','TF-IDF','AVG-W2V','TFIDF-W2V']
#OBJECT FOR TIMESERIES CROSS VALIDATION
TBS=TimeSeriesSplit(n_splits=10)
#METHOD USE FOR HYPER PARAMETER TUNNING(FOR FAST PERFORMANCE WE USE randomized)
searchMethod='random'
#RANGE OF VALUES(HYPERPARAM RBF)
c_ranges=[10**x for x in range(-4,5)] #np.logspace(-2,2,5)
params_rbf={'C':c_ranges}
#RANGE OF VALUES(HYPERPARAM LINEAR)
alpha_ranges=np.logspace(-5,5,11)
#REGULARIZER USED
penalty=['l1','l2']
params={'alpha':alpha_ranges,'penalty':penalty}
#KERNEL USED
kernel=['linear','rbf']
```

[1] Linear SVM

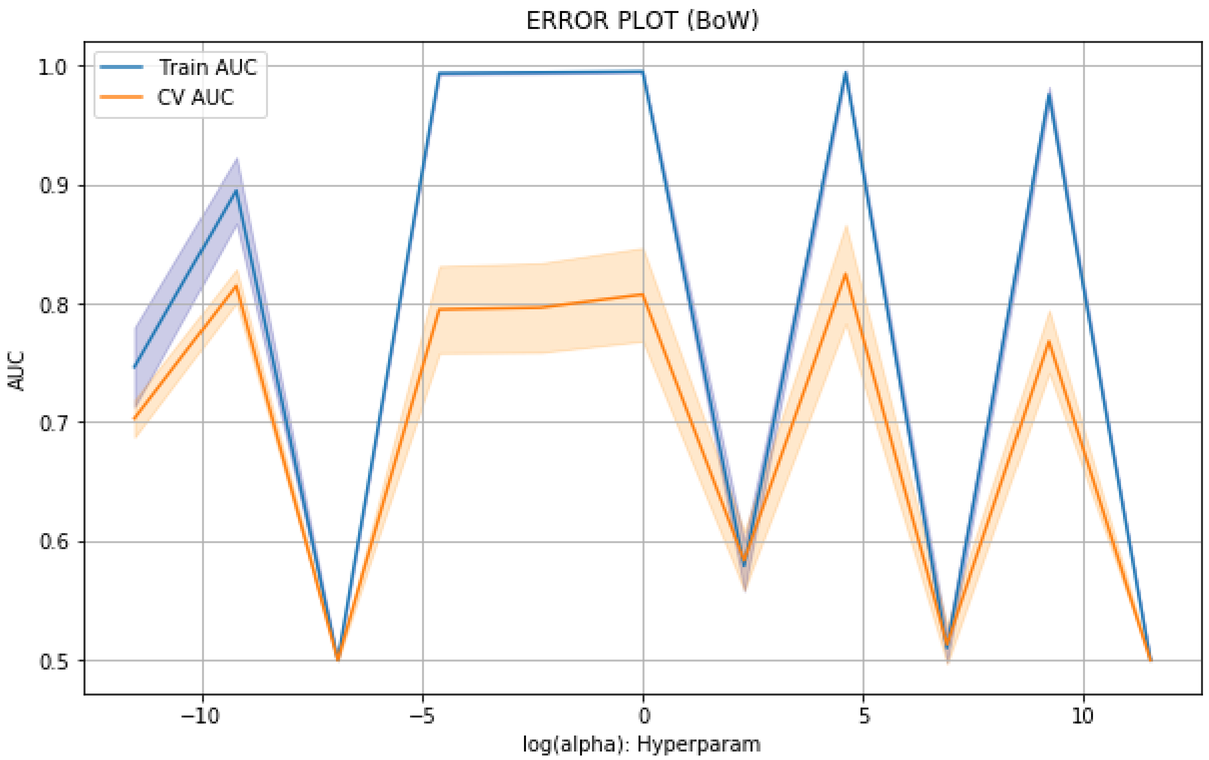
In [40]:

```
#INITIALIZE PRETTY TABLE OBJECT
summarize = PrettyTable()
summarize.field_names = ['Vectorizer', 'Kernel','Optimal-Penalty', 'Optimal-Alpha', 'Test(AUC)','Test(f1-score)']
```

[1.1] Applying Linear SVM on BOW, SET 1

[1.1.1] Hyperparam tunning and plot Hyperparam v/s Missclassification error:

In [22]:
```
#STANDARDIZE TRAIN AND TEST DATA
train, test=std_data(train=X_train_bigram,test=X_test_bigram,mean=False)
#HYPERPARAM TUNNING
%time model=SVM_Classifier(train,y_train,TBS,params,searchMethod,vect[0],kernel[0])
#PRINT OPTIMAL VALUE OF HYPERPARAM
print('Optimal value of hyperparam: ',model.best_params_)
#SAVE CURRENT STATE OF ML-MODEL FOR FUTURE USE
saveModeltofile(model,'model_bow_lsvm')
```

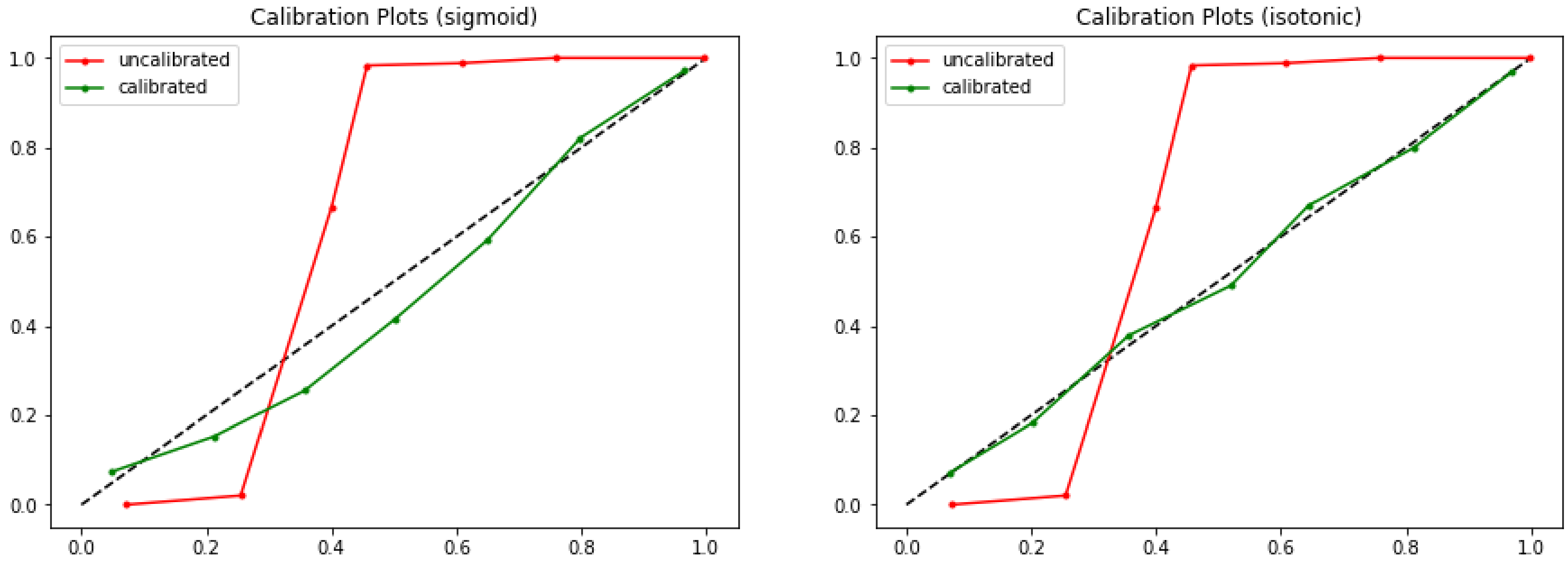



```
CPU times: user 21.1 s, sys: 608 ms, total: 21.7 s
Wall time: 22.9 s
Optimal value of hyperparam:  {'alpha': 1.0, 'penalty': 'l2'}
```

[1.1.2] Calibration of a model and plot calibration curve :

a. sigmoid
b. isotonic

In [23]:
```
calibration_method=['sigmoid','isotonic']
calib_model,clf=model_calibration(train,test,y_train,y_test,model.best_params_,calibration_method,kernel[0])
```



Observation:

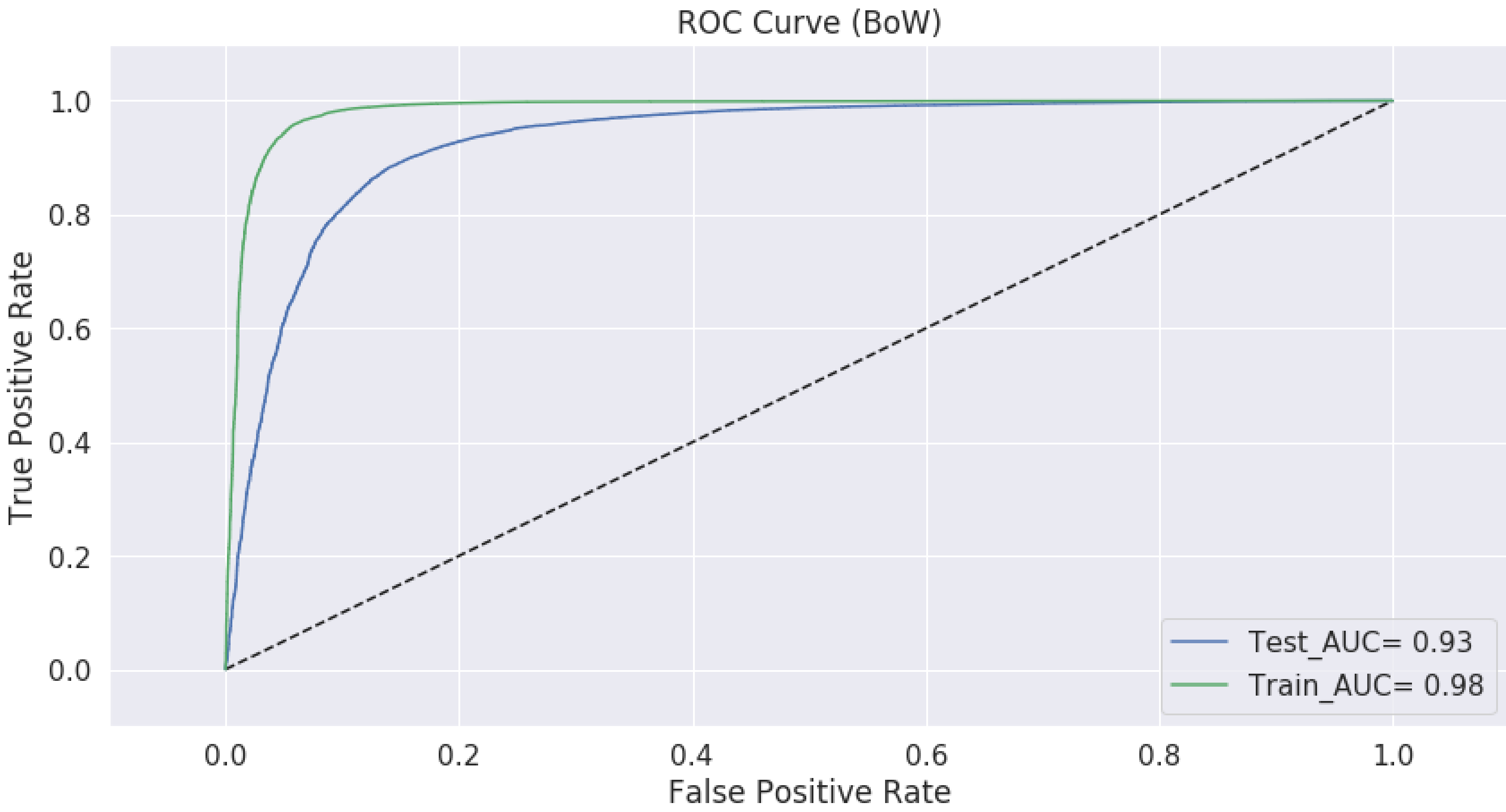
1. From the above plot we observe that the uncalibrated curve is looks like a sigmoidal curve so we choose sigmoidal calibration.

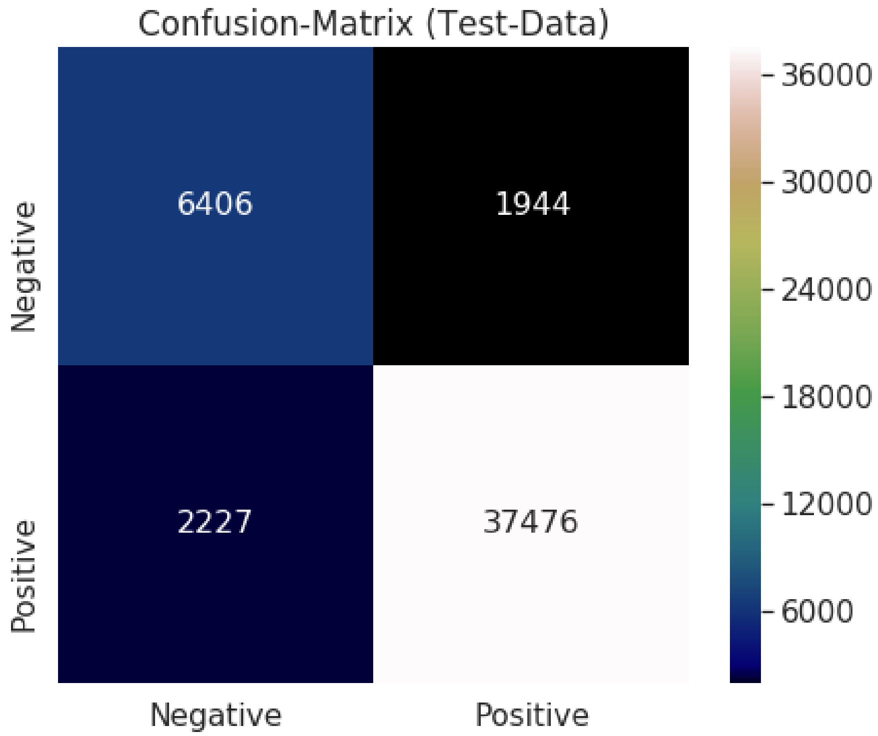
In [24]:
```
calib_mod=calib_model['sigmoid']
```

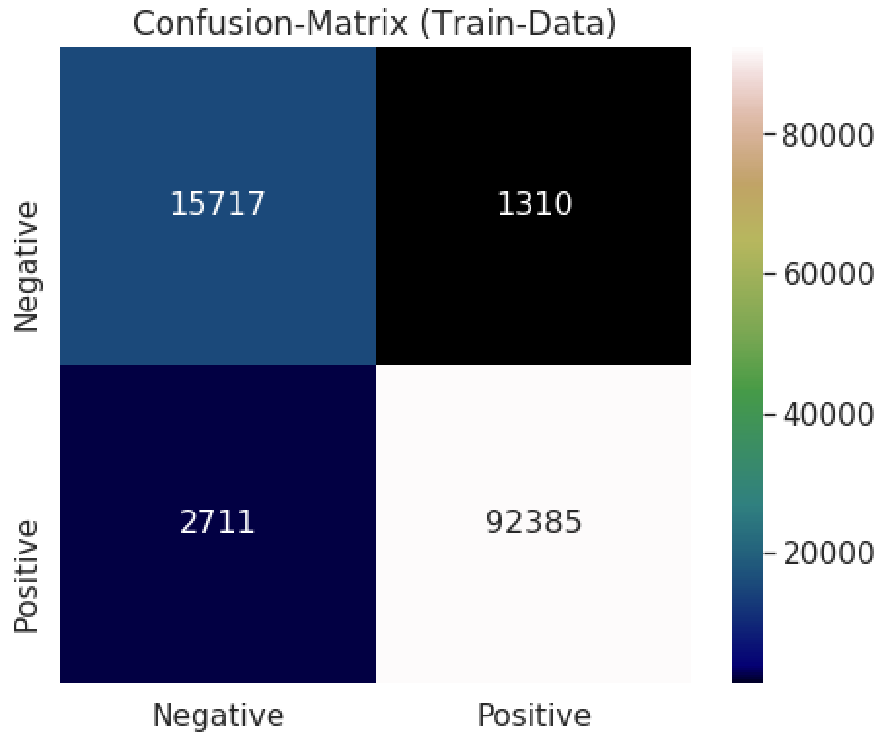
[1.1.3] Performance on test data with optimal value of hyperparam:

In [41]:

```
test_performance(calib_mod,clf,train,y_train,test,y_test,model.best_params_,vect[0],summarize,kernel[0])
```



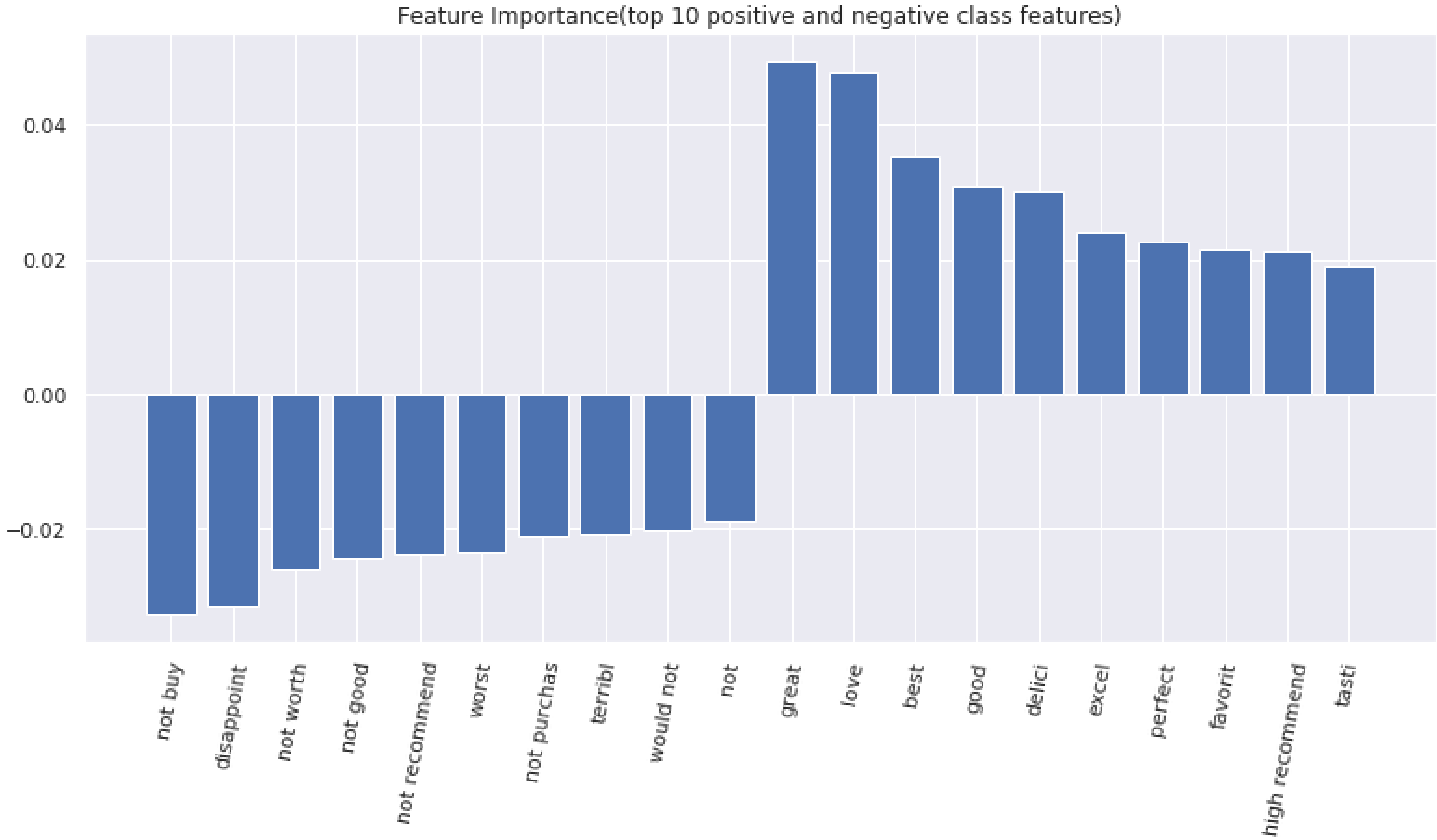




[1.1.4] Top 10 important features of positive and negative class from SET 1

In [42]:
```
no_of_imp_features=10
feature_importance(count_vect,clf,no_of_imp_features)
```

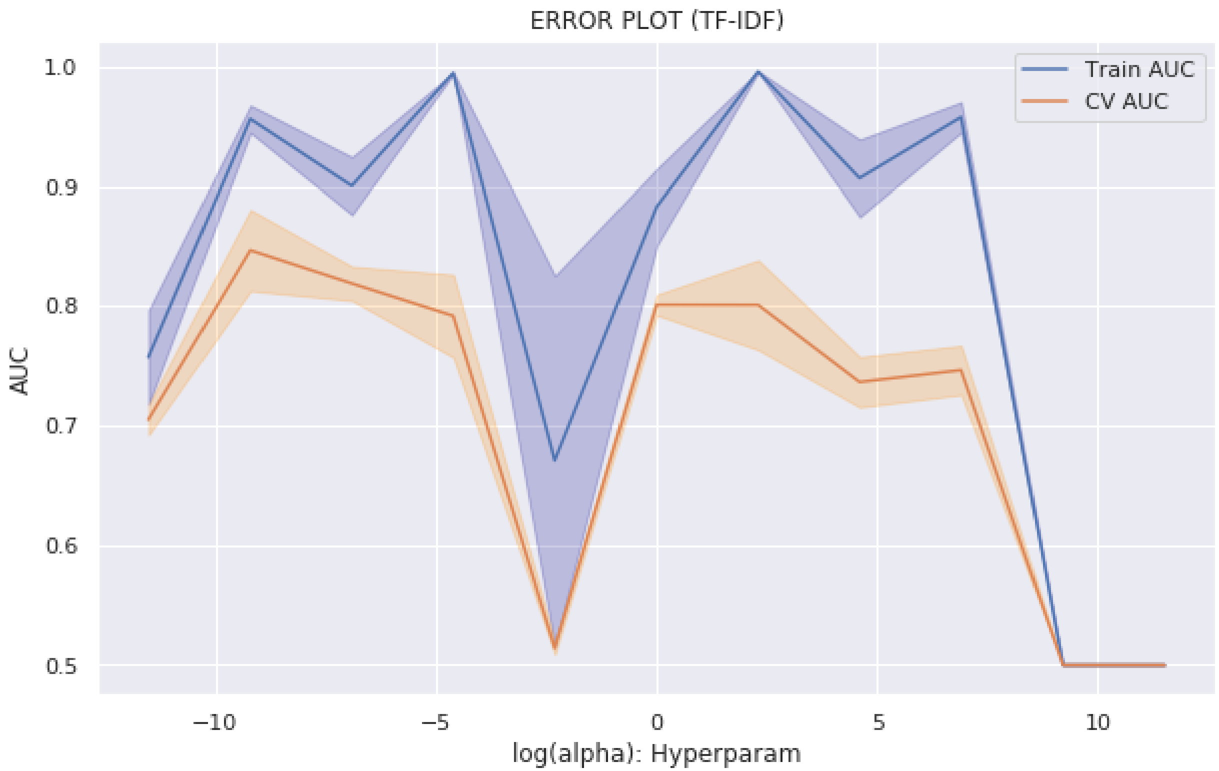
```
        Negative                                                Positive
________________________________________________________________________________
        -0.0327 not buy                                         0.0495  great
        -0.0316 disappoint                                      0.0477  love
        -0.0262 not worth                                       0.0354  best
        -0.0244 not good                                        0.0310  good
        -0.0238 not recommend                                   0.0301  delici
        -0.0235 worst                                           0.0241  excel
        -0.0210 not purchas                                     0.0226  perfect
        -0.0209 terribl                                         0.0215  favorit
        -0.0203 would not                                       0.0213  high recommend
        -0.0188 not                                             0.0190  tasti
```



[2.1] Applying Linear SVM on TFIDF, SET 2

[2.1.1] Hyperparam tunning and plot Hyperparam v/s Missclassification error:

In [43]:
```
#STANDARDIZE TRAIN AND TEST DATA
train, test=std_data(train=X_train_tfidf,test=X_test_tfidf,mean=False)
#HYPERPARAM TUNNING
%time model=SVM_Classifier(train,y_train,TBS,params,searchMethod,vect[1],kernel[0])
#PRINT OPTIMAL VALUE OF HYPERPARAM
print('Optimal value of hyperparam: ',model.best_params_)
#SAVE CURRENT STATE OF ML-MODEL FOR FUTURE USE
saveModeltofile(model,'model_tfidf_lsvm')
```



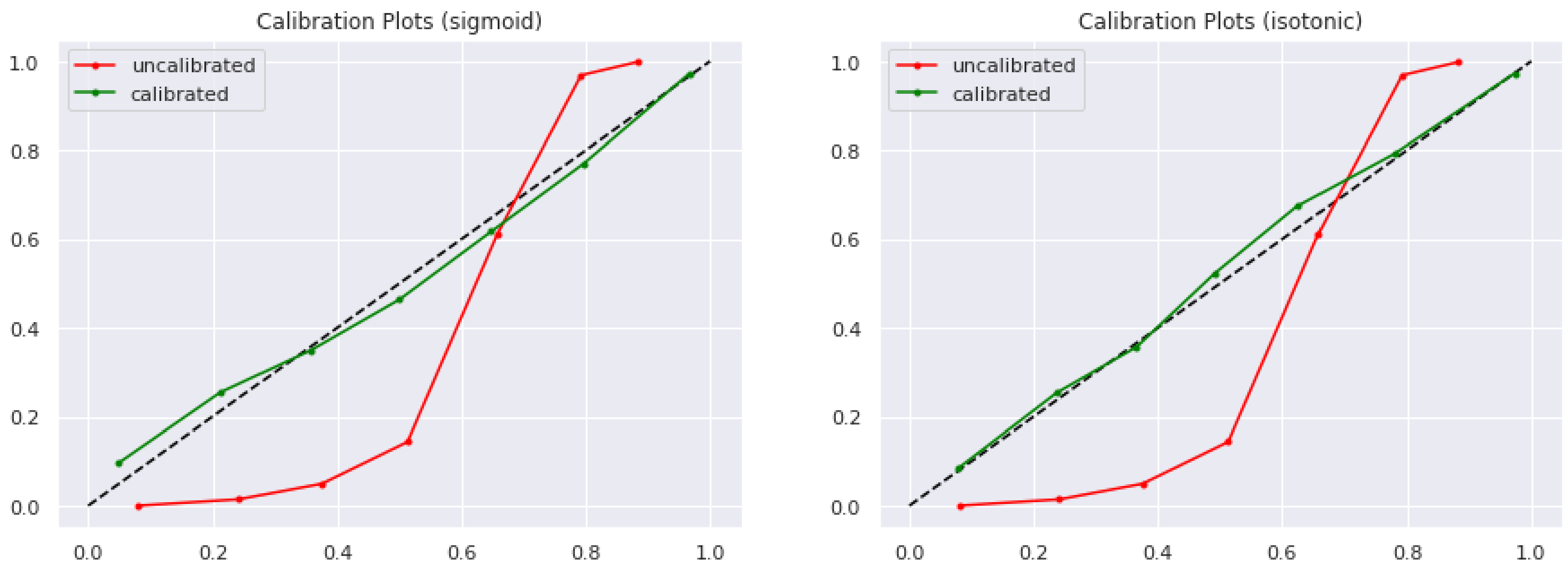

```
CPU times: user 21.3 s, sys: 616 ms, total: 21.9 s
Wall time: 23 s
Optimal value of hyperparam:  {'alpha': 10000.0, 'penalty': 'l2'}
```

[2.1.2] Calibration of a model and plot calibration curve :

```
a. sigmoid
b. isotonic
```

In [44]:

```
calibration_method=['sigmoid','isotonic']
calib_model,clf=model_calibration(train,test,y_train,y_test,model.best_params_,calibration_method,kernel[0])
```



Observation:

1. From the above plot we observe that the uncalibrated curve is looks like a sigmoidal curve so we choose sigmoidal calibration.

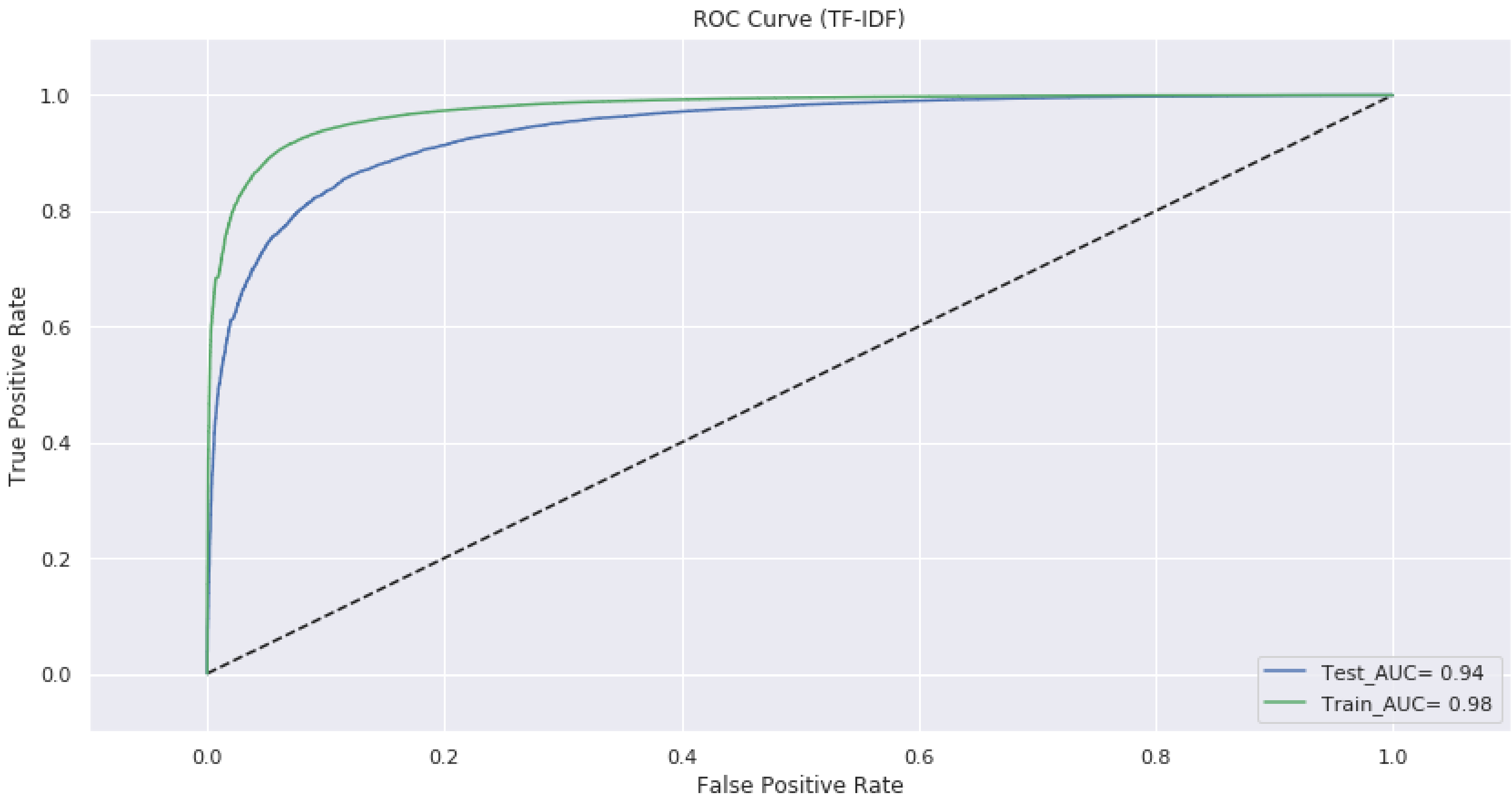
In [45]:

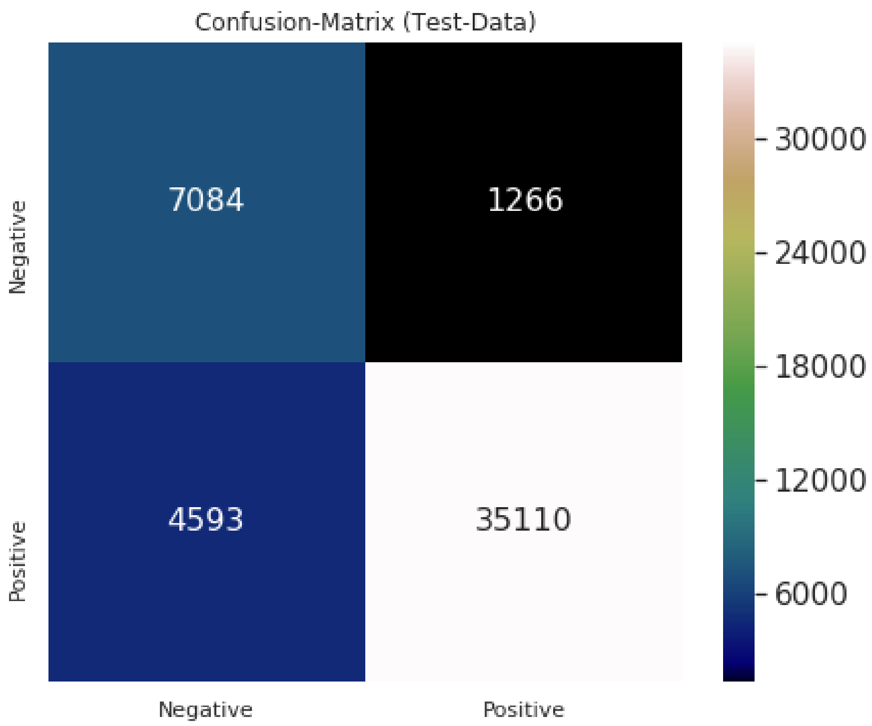
```
calib_mod=calib_model['sigmoid']
```

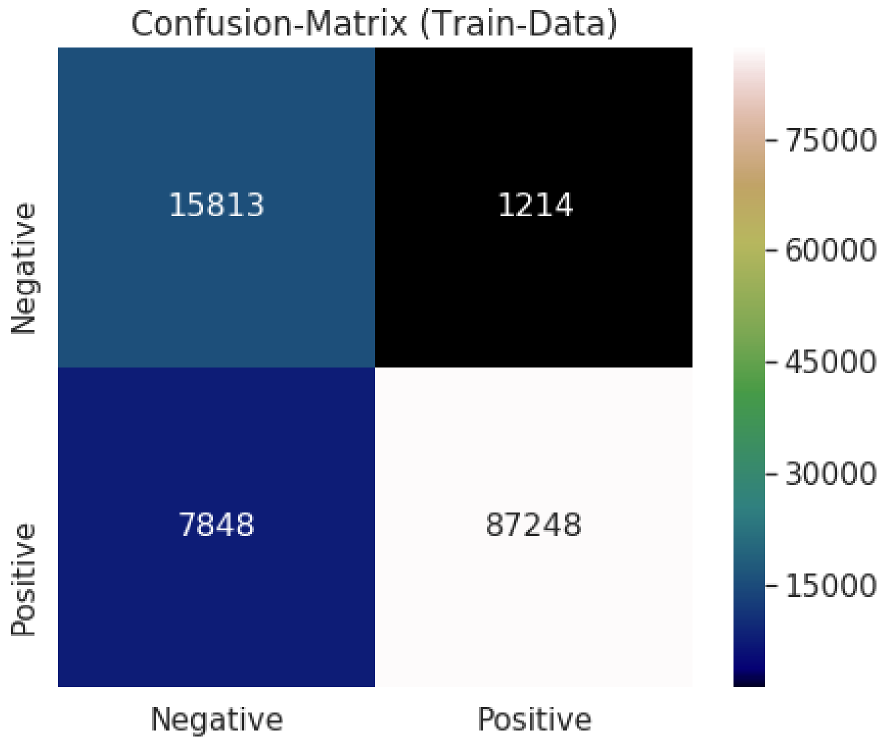
[2.1.3] Performance on test data with optimal value of hyperparam:

In [46]:

```
test_performance(calib_mod,clf,train,y_train,test,y_test,model.best_params_,vect[1],summarize,kernel[0])
```





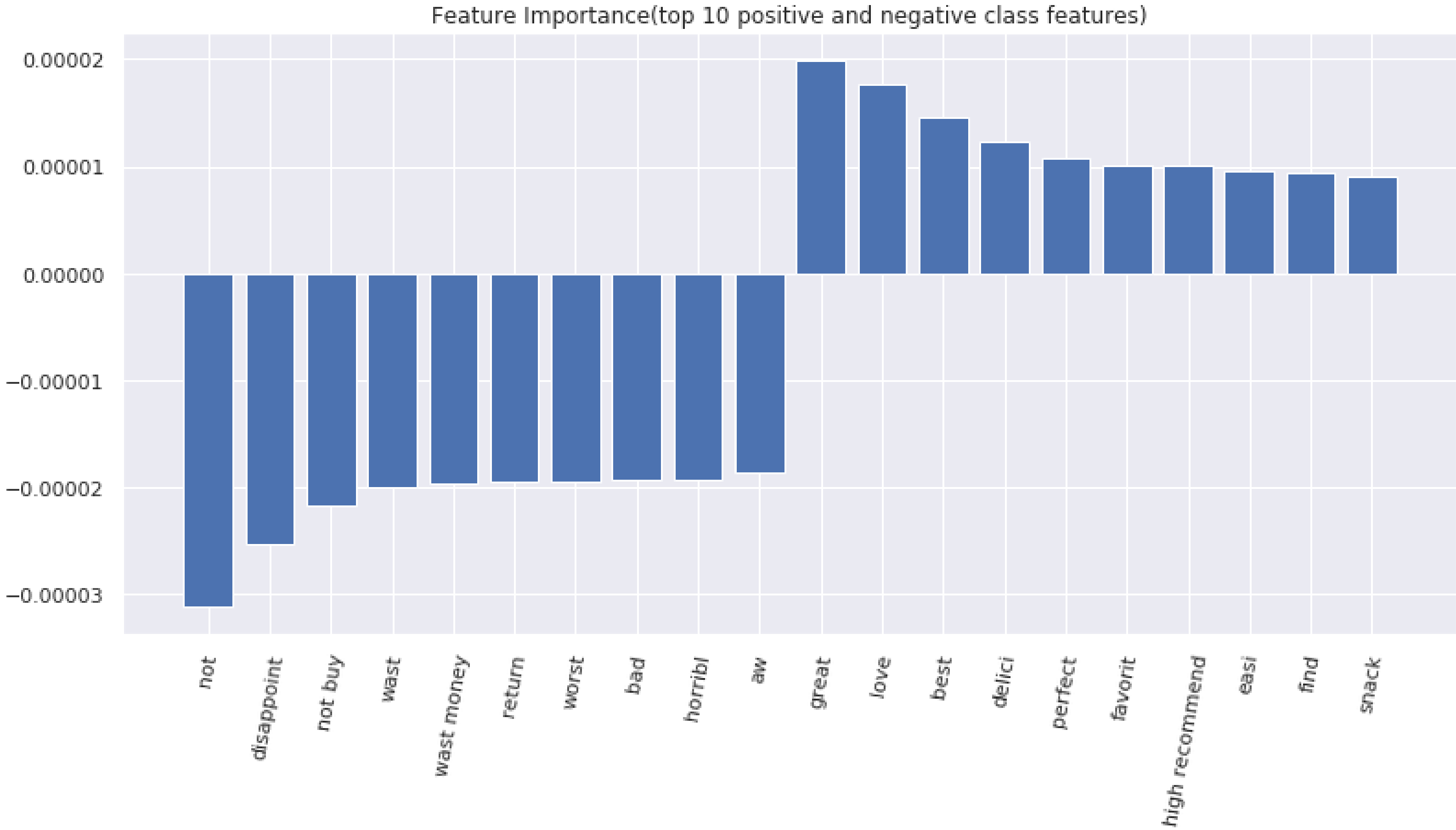


[2.1.4] Top 10 important features of positive and negative class from SET 2

In [47]:

```
no_of_imp_features=10
feature_importance(tf_idf_vect,clf,no_of_imp_features)
```

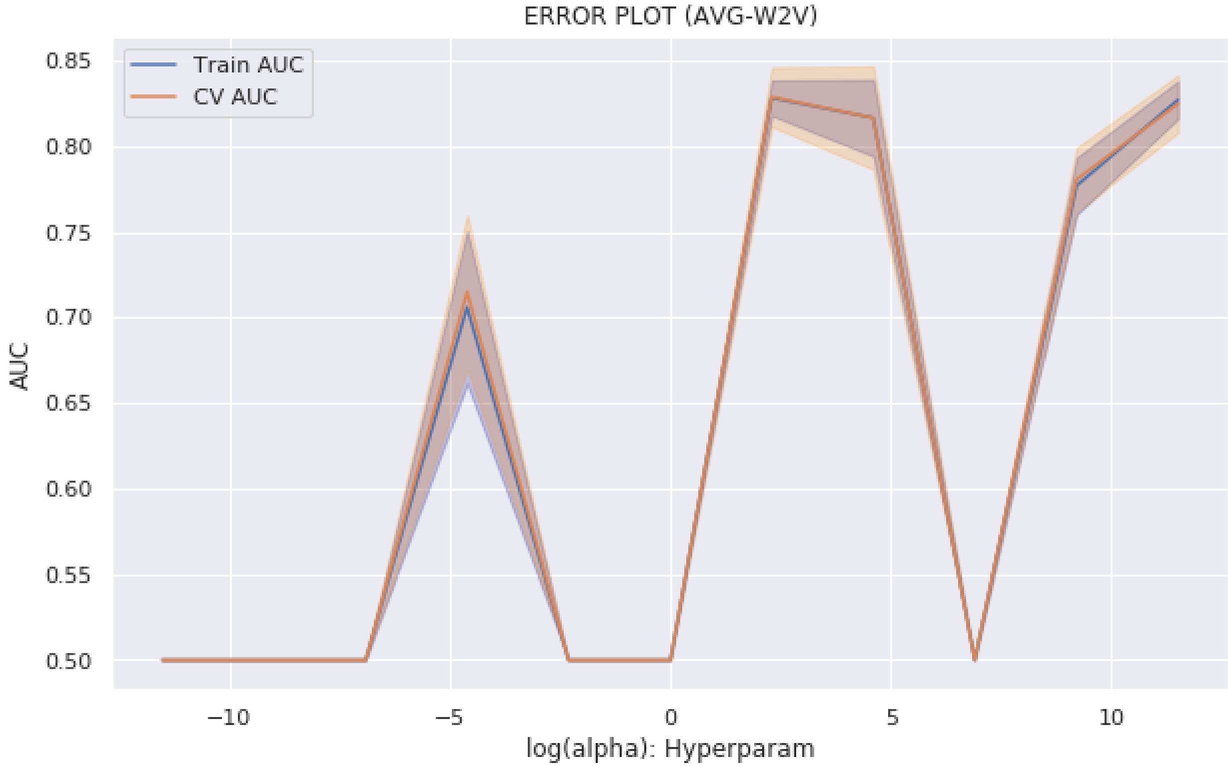
```
        Negative                                      Positive
________________________________________________________________________________
        -0.0000 not                                   0.0000  great
        -0.0000 disappoint                            0.0000  love
        -0.0000 not buy                               0.0000  best
        -0.0000 wast                                  0.0000  delici
        -0.0000 wast money                            0.0000  perfect
        -0.0000 return                                0.0000  favorit
        -0.0000 worst                                 0.0000  high recommend
        -0.0000 bad                                   0.0000  easi
        -0.0000 horribl                               0.0000  find
        -0.0000 aw                                    0.0000  snack
```



[3.1] Applying Linear SVM on AVG-W2V, SET 3

[3.1.1] Hyperparam tunning and draw Error plot:

In [48]:
```
#STANDARDIZE TRAIN AND TEST DATA
train, test=std_data(train=avg_sent_vectors,test=avg_sent_vectors_test,mean=True)
#HYPERPARAM TUNNING
%time model=SVM_Classifier(train,y_train,TBS,params,searchMethod,vect[2],kernel[0])
#PRINT OPTIMAL VALUE OF HYPERPARAM
print('Optimal value of hyperparam: ',model.best_params_)
#SAVE CURRENT STATE OF ML-MODEL FOR FUTURE USE
saveModeltofile(model,'model_avgw2v_lsvm')
```

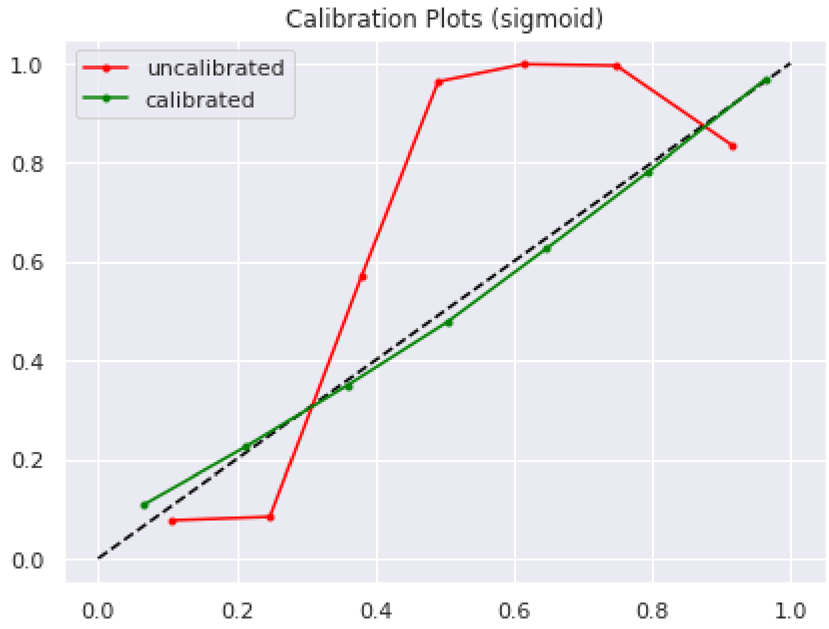


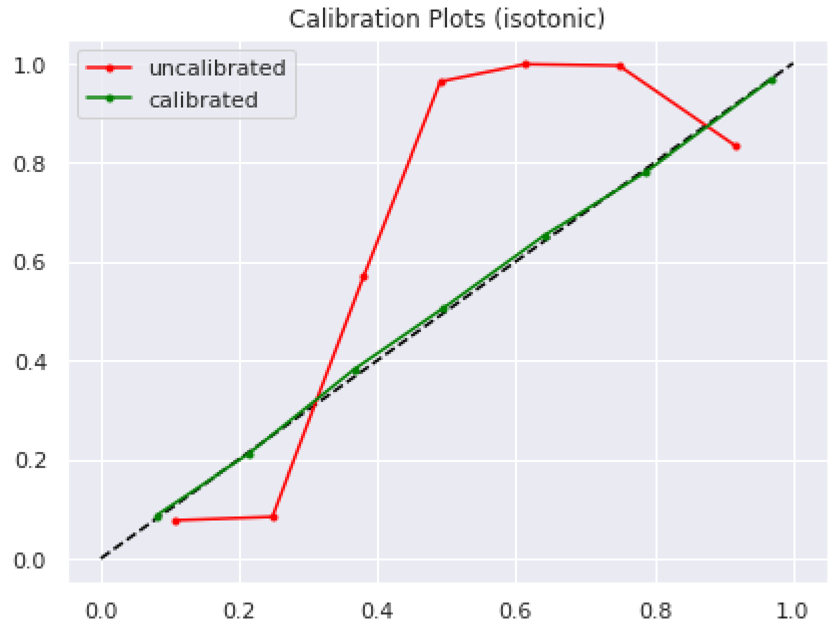

```
CPU times: user 21.7 s, sys: 568 ms, total: 22.3 s
Wall time: 22.9 s
Optimal value of hyperparam:  {'alpha': 0.01, 'penalty': 'l1'}
```

[3.1.2] Calibration of a model and plot calibration curve :

```
a. sigmoid
b. isotonic
```

In [49]:
```
calibration_method=['sigmoid','isotonic']
calib_model,clf=model_calibration(train,test,y_train,y_test,model.best_params_,calibration_method,kernel[0])
```





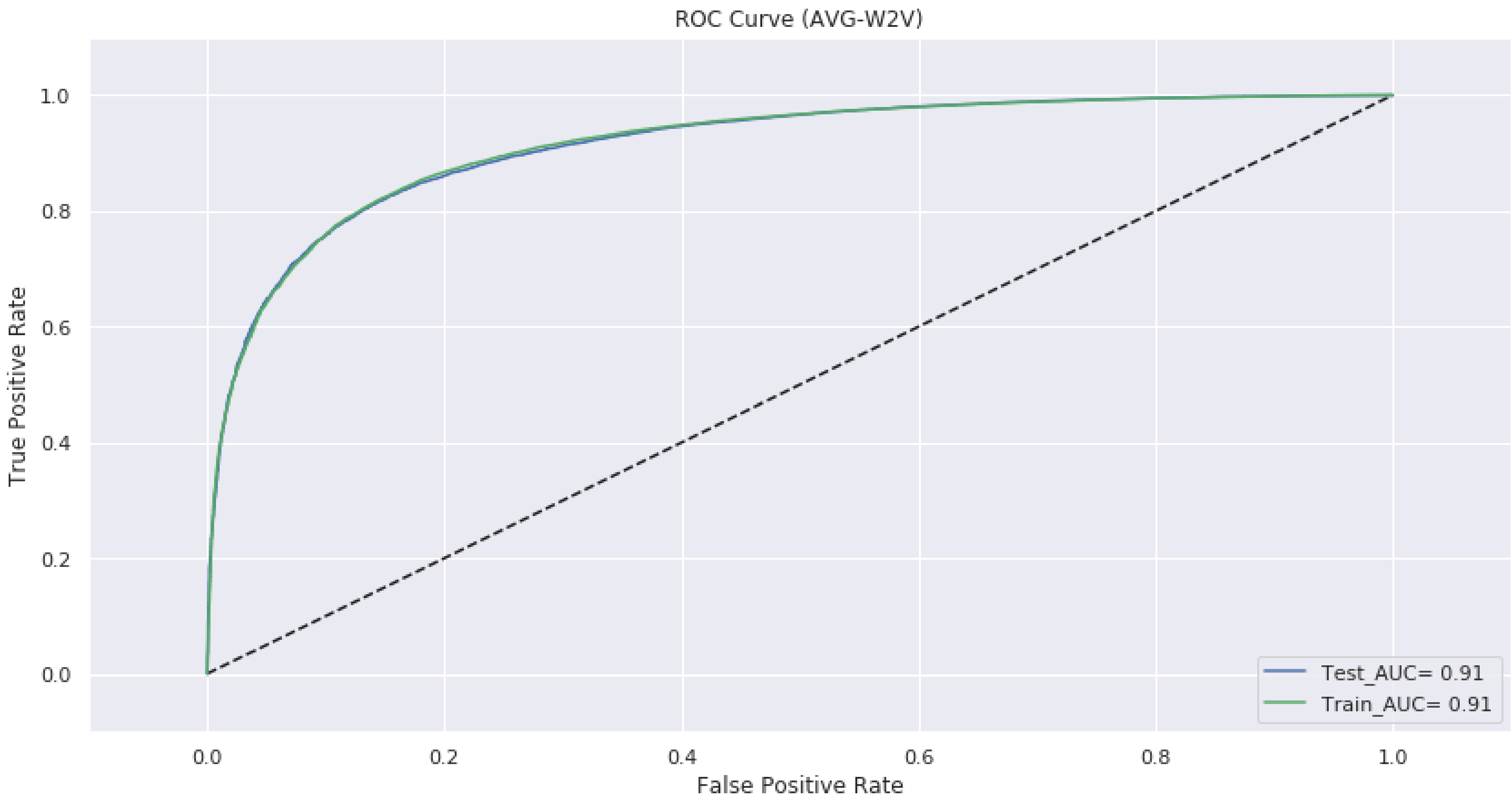
Observation:

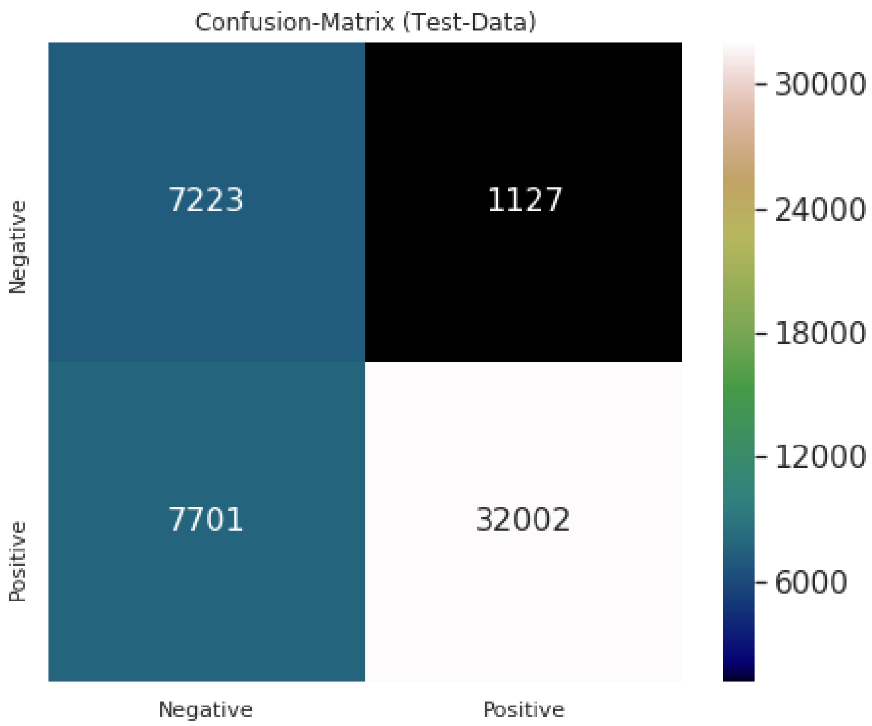
1. From the above plot we observe that the uncalibrated curve is almost looks like a sigmoidal curve so we choose sigmoidal calibration.

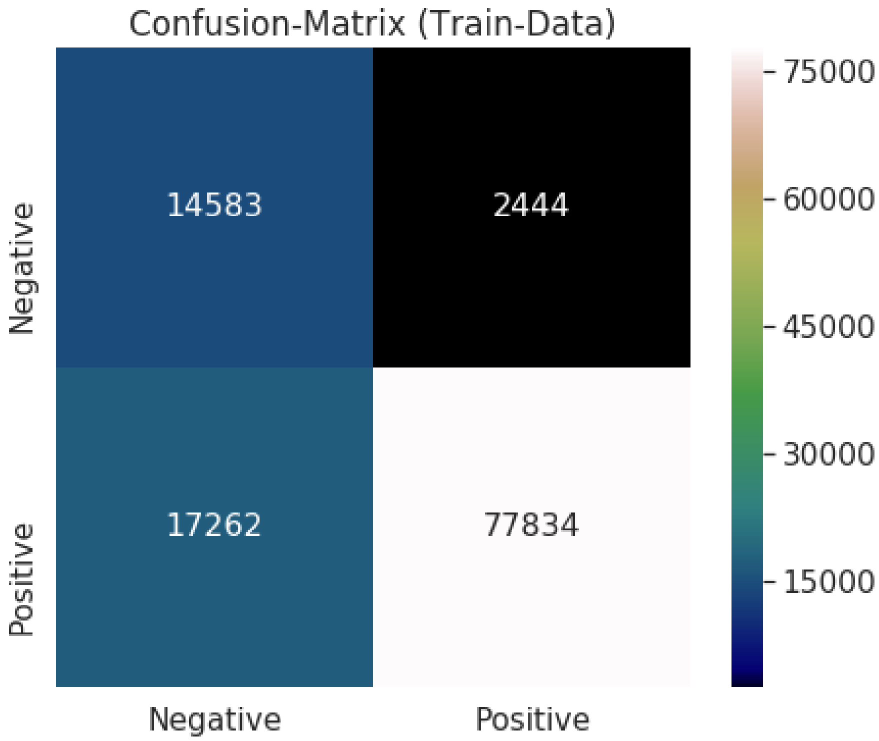
In [50]:
```
calib_mod=calib_model['sigmoid']
```

[3.1.3] Performance on test data with optimal value of hyperparam:

In [51]:
```
test_performance(calib_mod,clf,train,y_train,test,y_test,model.best_params_,vect[2],summarize,kernel[0])
```



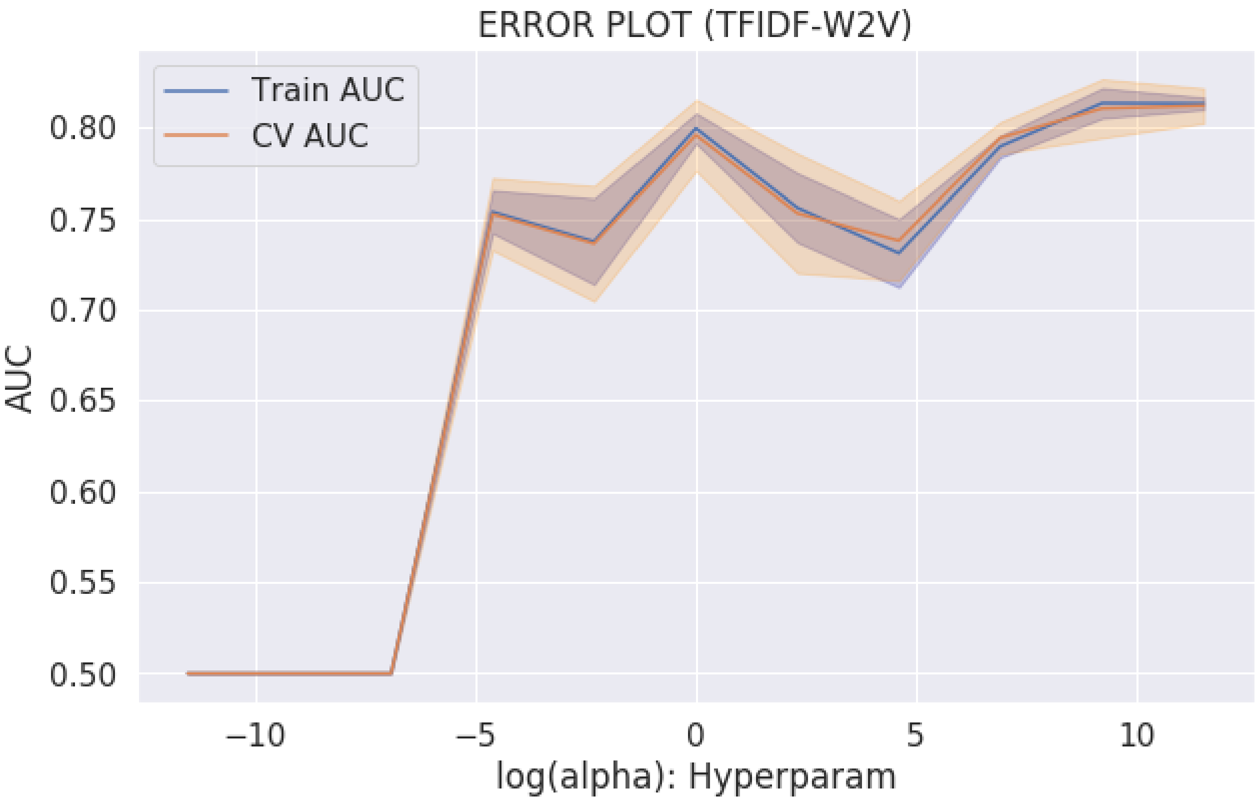




[4.1] Applying Linear SVM on TFIDF-W2V, SET 4

[4.1.1] Hyperparam tunning and plot Hyperparam v/s Missclassification error:

In [52]:
```
#STANDARDIZE TRAIN AND TEST DATA
train, test=std_data(train=tfidf_sent_vectors,test=tfidf_sent_vectors_test,mean=True)
#HYPERPARAM TUNNING
%time model=SVM_Classifier(train,y_train,TBS,params,searchMethod,vect[3],kernel[0])
#PRINT OPTIMAL VALUE OF HYPERPARAM
print('Optimal value of hyperparam: ',model.best_params_)
#SAVE CURRENT STATE OF ML-MODEL FOR FUTURE USE
saveModeltofile(model,'model_tfw2v_lsvm')
```

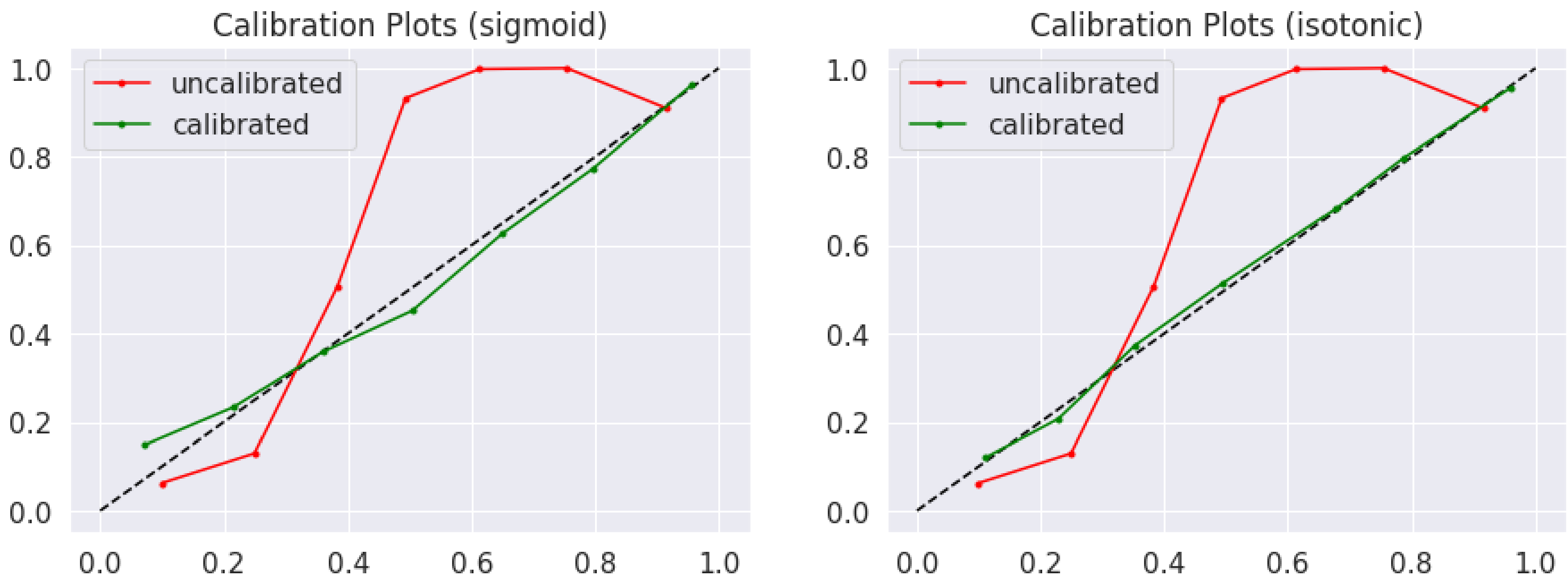



```
CPU times: user 21.4 s, sys: 588 ms, total: 22 s
Wall time: 22.2 s
Optimal value of hyperparam:  {'alpha': 0.1, 'penalty': 'l2'}
```

[4.1.2] Calibration of a model and plot calibration curve :

a. sigmoid
b. isotonic

In [53]:
```
calibration_method=['sigmoid','isotonic']
calib_model,clf=model_calibration(train,test,y_train,y_test,model.best_params_,calibration_method,kernel[0])
```



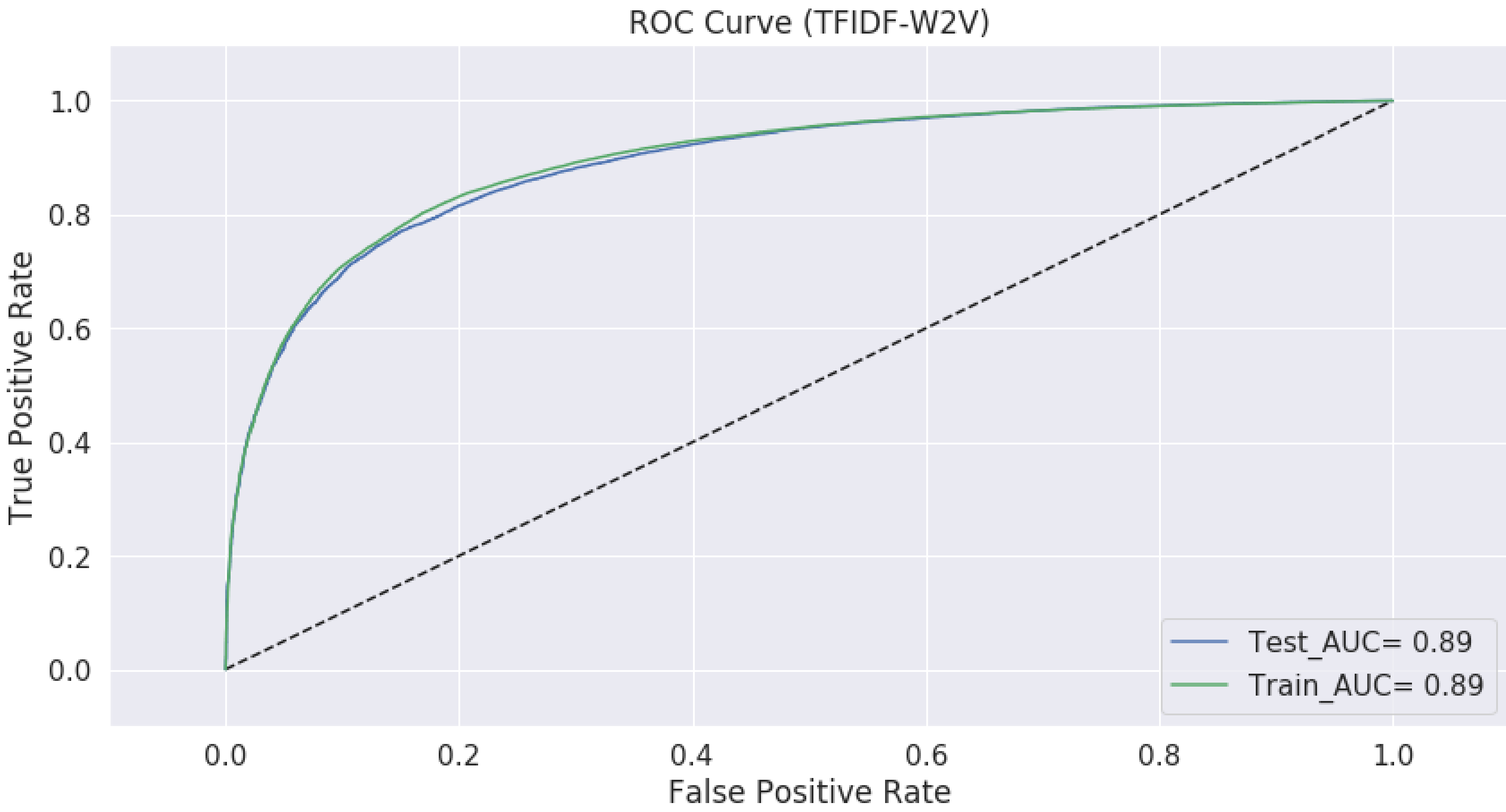
Observation:

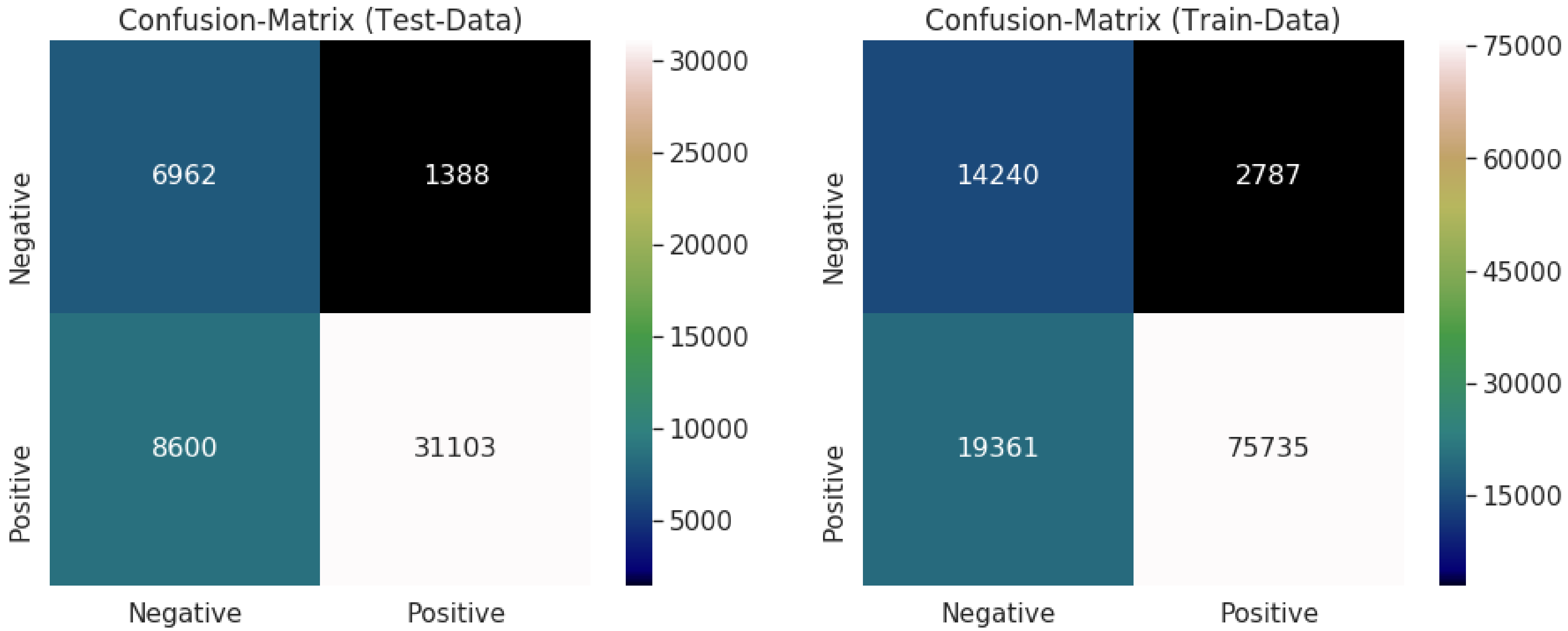
1. From the above plot we observe that the uncalibrated curve is almost looks like a sigmoidal curve so we choose sigmoidal calibration.

In [54]:
```
calib_mod=calib_model['sigmoid']
```

[4.1.3] Performance on test data with optimal value of hyperparam:

In [55]:
```
test_performance(calib_mod,clf,train,y_train,test,y_test,model.best_params_,vect[3],summarize,kernel[0])
```





Conclusion:

In [56]:
```
summary_linear=summarize
print(summarize)
```

Vectorizer	Kernel	Optimal-Penalty	Optimal-Alpha	Test(AUC)	Test(f1-score)
BoW	linear	l2	1.0	0.9314	0.9138
TF-IDF	linear	l2	10000.0	0.9422	0.8855
AVG-W2V	linear	l1	0.01	0.9140	0.8339
TFIDF-W2V	linear	l2	0.1	0.8905	0.8131

1. from the above table we can observe that the optimal performance is give by:

```
a. Bag of word vectorizer
b. f1-score=.9138 and auc=.9314
```

[2] RBF(Radial Basis Function) SVM

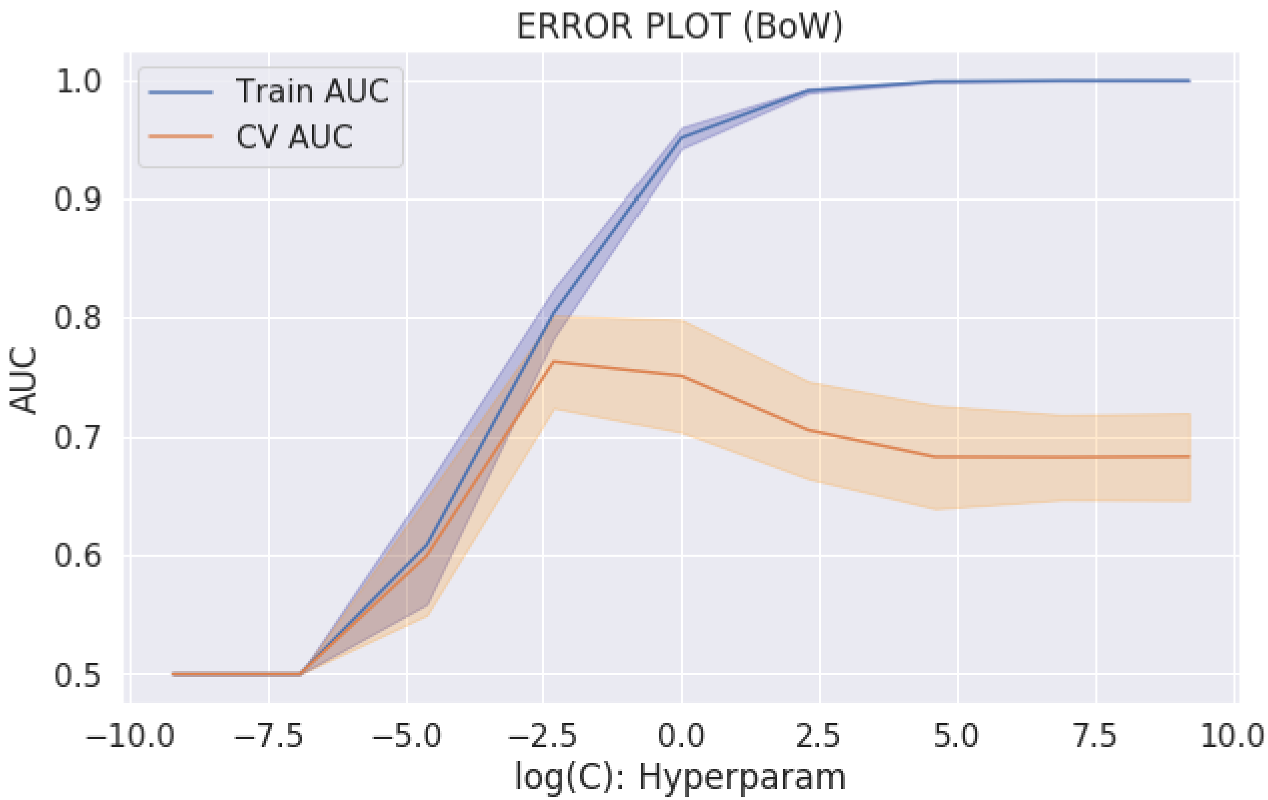
In [64]:
```
#INITIALIZE PRETTY TABLE OBJECT
summarize = PrettyTable()
summarize.field_names = ['Vectorizer', 'Kernel', 'Optimal-Alpha', 'Test(AUC)', 'Test(f1-score)']
```

[1.1] Applying RBF SVM on BOW, SET 1

[1.1.1] Hyperparam tunning and draw Error plot:

In [89]:
```
#STANDARDIZE TRAIN AND TEST DATA
train, test=std_data(train=X_train_bigram_rbf,test=X_test_bigram_rbf,mean=False)
#HYPERPARAM TUNNING
%time model=SVM_Classifier(train,y_train_rbf,TBS,params_rbf,searchMethod,vect[0],kernel[1])
#PRINT OPTIMAL VALUE OF HYPERPARAM
print('Optimal value of hyperparam: ',model.best_params_)
#SAVE CURRENT STATE OF ML-MODEL FOR FUTURE USE
saveModeltofile(model,'model_bow_rbfsvm')
```

```
[LibSVM]
```




```
CPU times: user 3min 30s, sys: 2.51 s, total: 3min 33s
Wall time: 19min 42s
Optimal value of hyperparam:  {'C': 0.1}
```

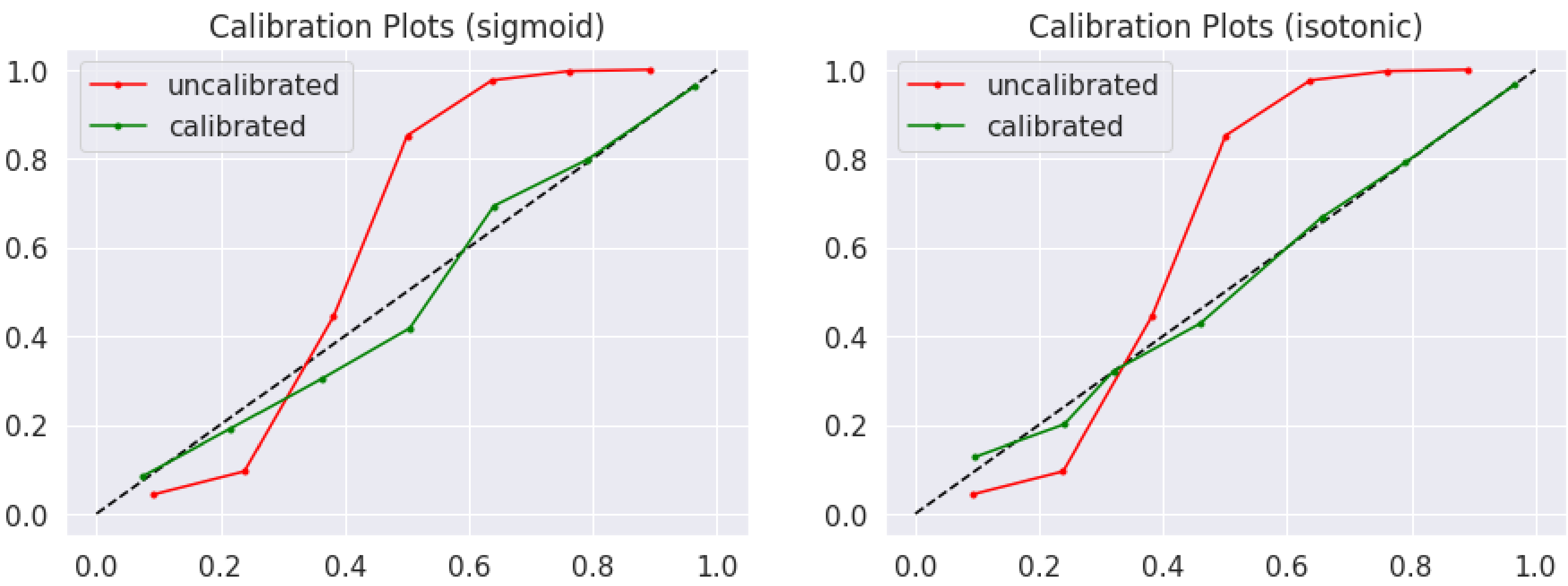
[1.1.2] Calibration of a model and plot calibration curve :

```
a. sigmoid
b. isotonic
```

In [90]:

```
calibration_method=['sigmoid','isotonic']
calib_model,clf=model_calibration(train,test,y_train_rbf,y_test_rbf,model.best_params_,calibration_method,kernel[1])
```

```
[LibSVM]
```



Observation:

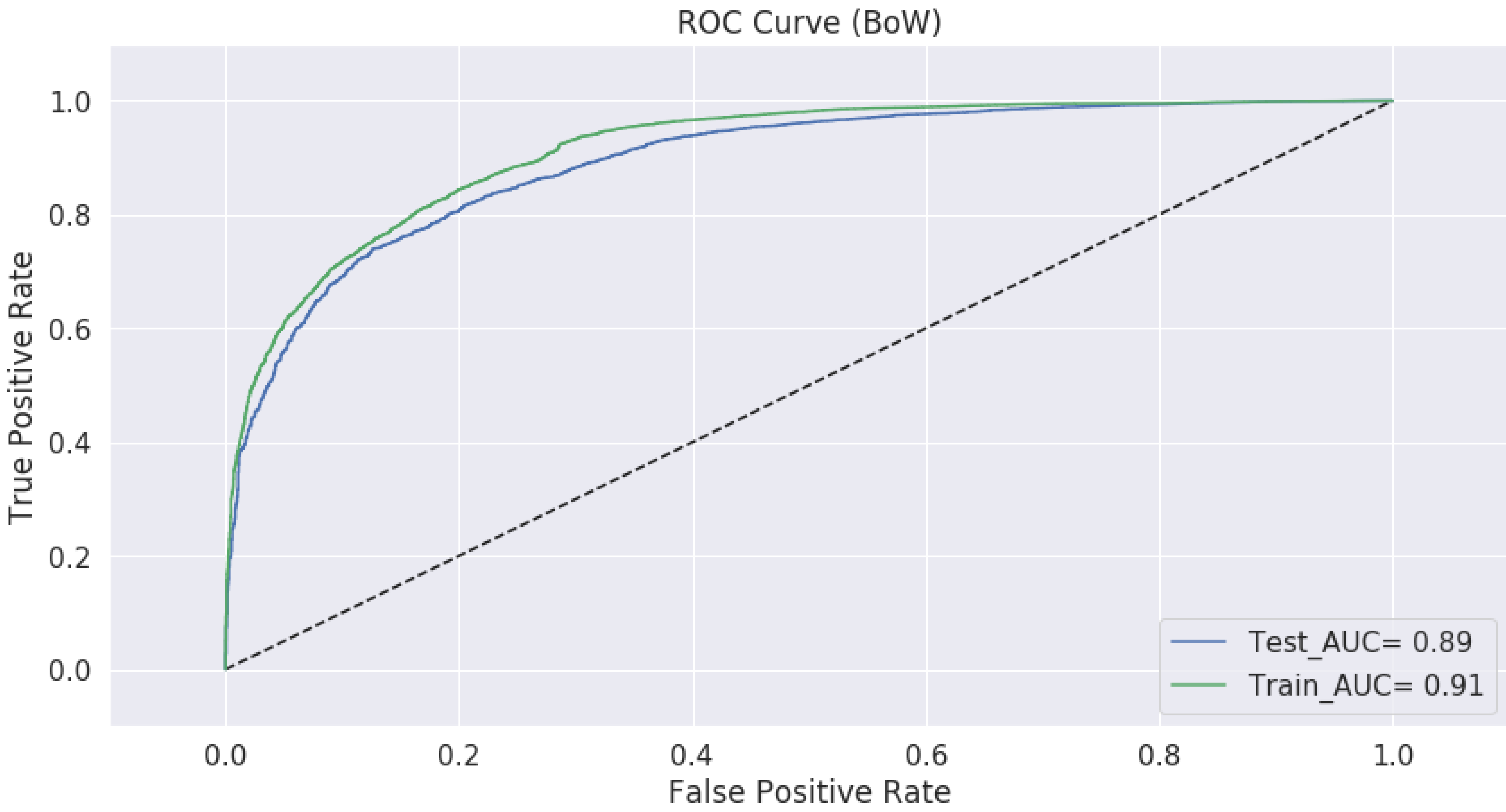
1. From the above plot we observe that the uncalibrated curve is looks like a sigmoidal curve so we choose sigmoidal calibration.

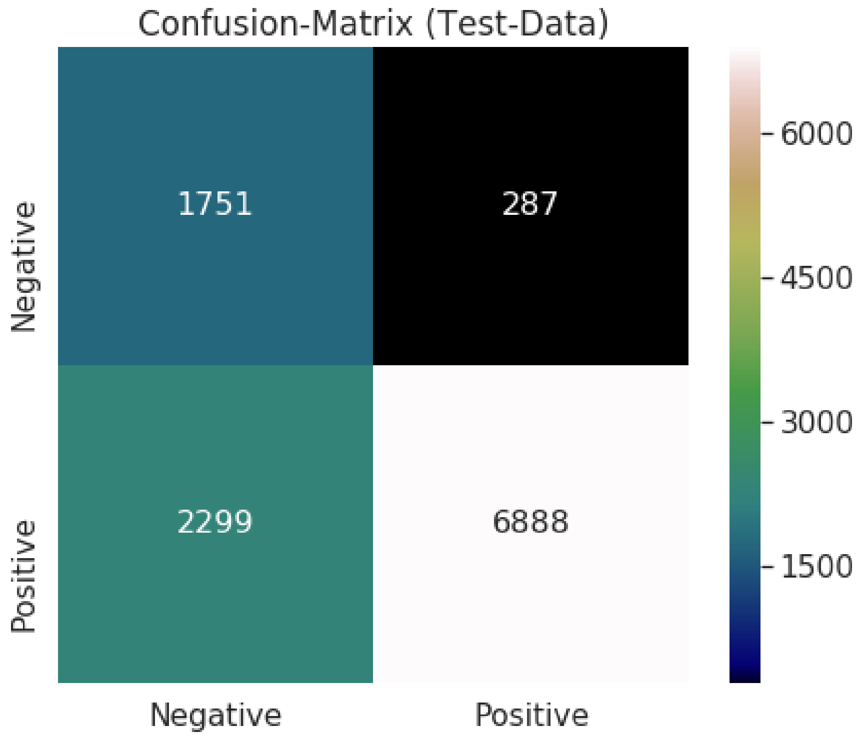
In [91]:

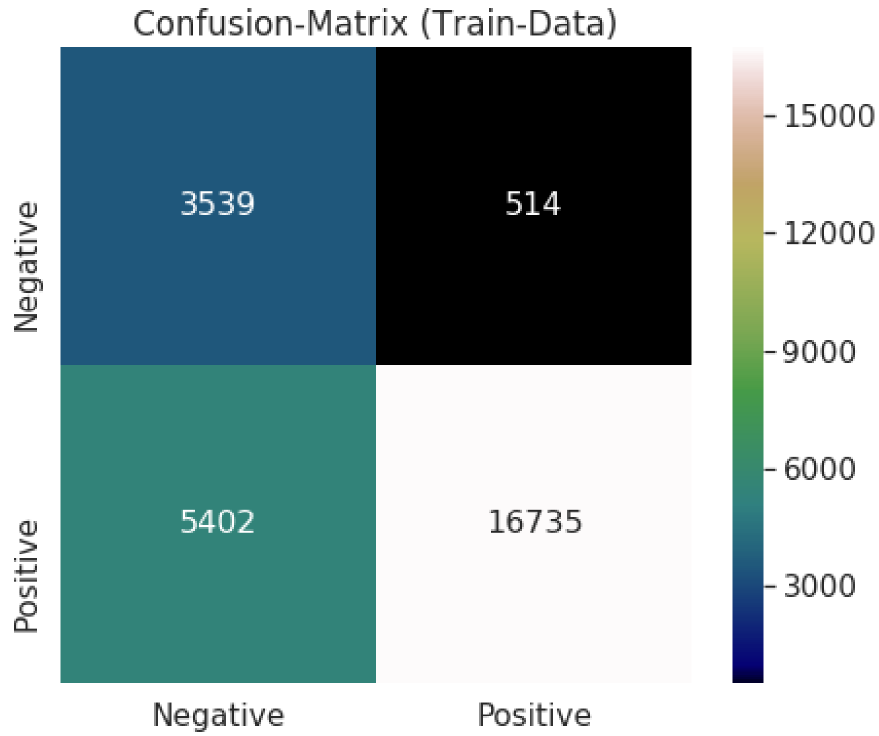
```
calib_mod=calib_model['sigmoid']
```

[1.1.3] Performance on test data with optimal value of hyperparam:

In [92]:
```
test_performance(calib_mod,clf,train,y_train_rbf,test,y_test_rbf,model.best_params_,vect[0],summarize,kernel[1])
```





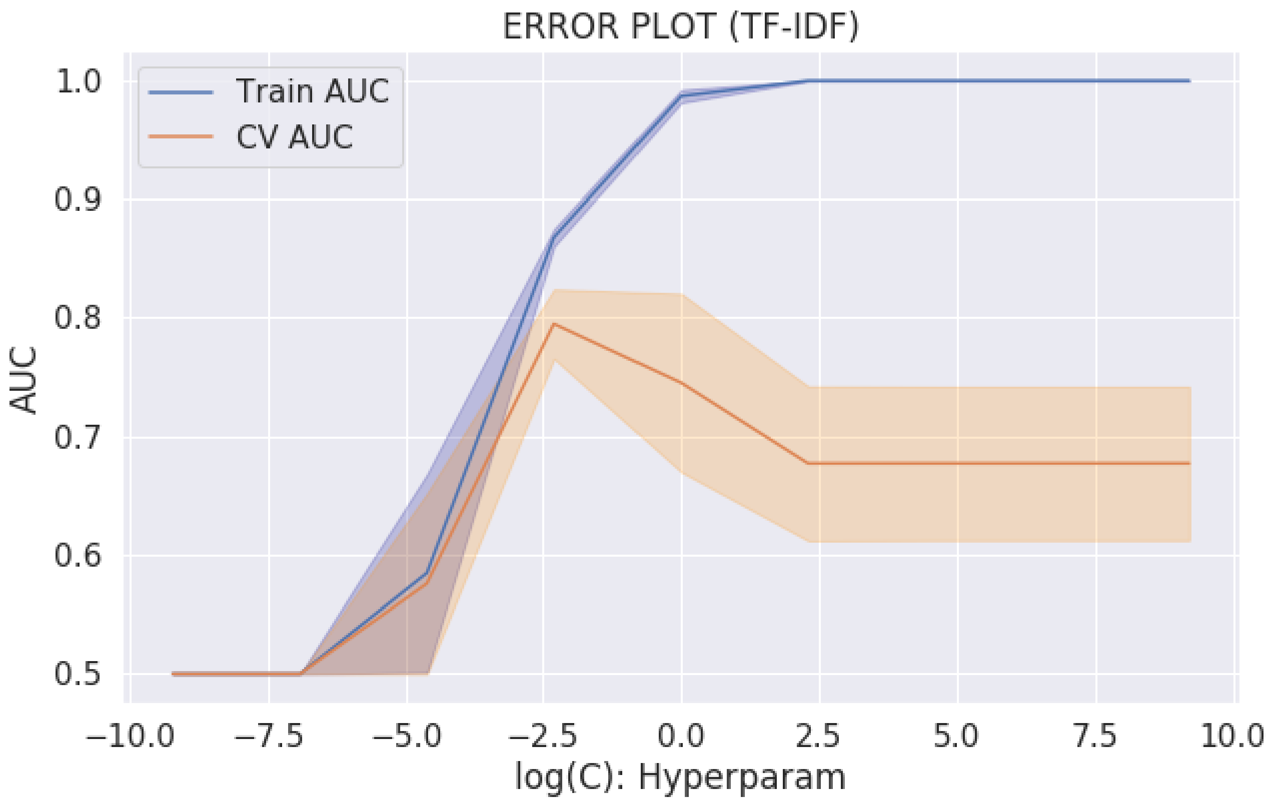


[2.1] Applying RBF SVM on TFIDF, SET 2

[2.1.1] Hyperparam tunning and draw Error plot:

In [93]:
```
#STANDARDIZE TRAIN AND TEST DATA
train, test=std_data(train=X_train_tfidf_rbf,test=X_test_tfidf_rbf,mean=False)
#HYPERPARAM TUNNING
%time model=SVM_Classifier(train,y_train_rbf,TBS,params_rbf,searchMethod,vect[1],kernel[1])
#PRINT OPTIMAL VALUE OF HYPERPARAM
print('Optimal value of hyperparam: ',model.best_params_)
#SAVE CURRENT STATE OF ML-MODEL FOR FUTURE USE
saveModeltofile(model,'model_tfidf_rbfsvm')
```

```
[LibSVM]
```




```
CPU times: user 3min 44s, sys: 5.38 s, total: 3min 49s
Wall time: 23min 40s
Optimal value of hyperparam:  {'C': 0.1}
```

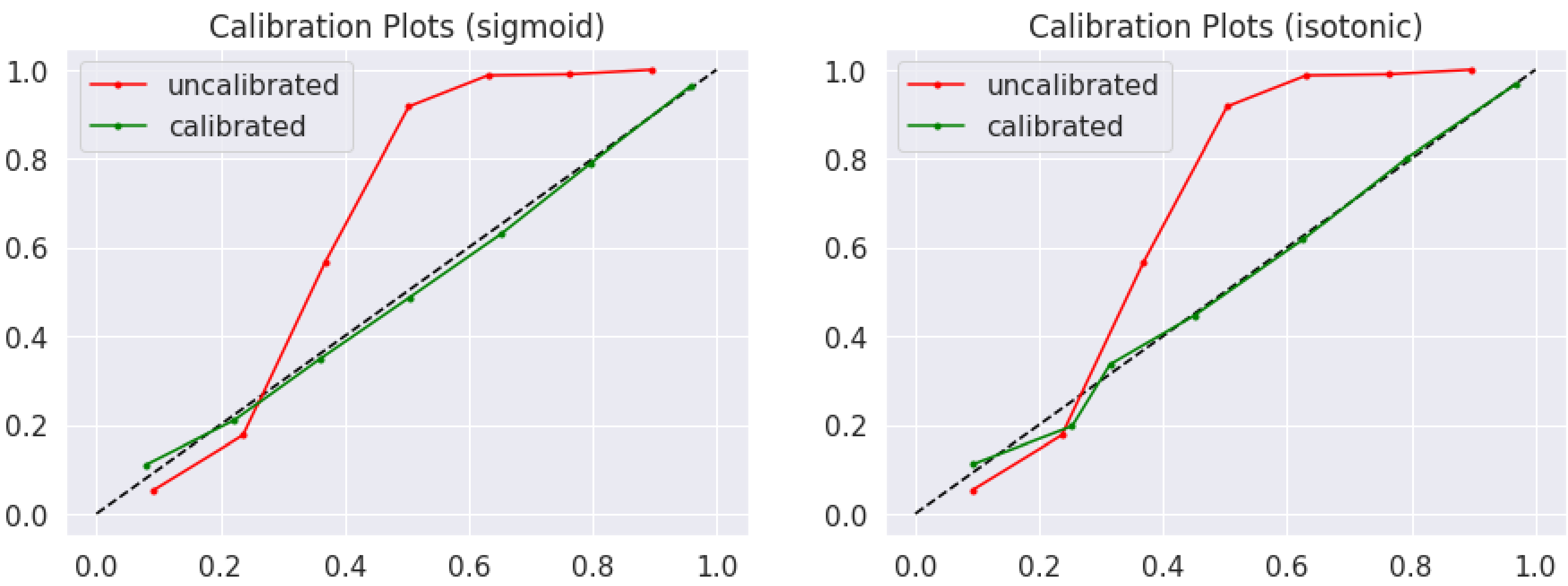
[2.1.2] Calibration of a model and plot calibration curve :

```
a. sigmoid
b. isotonic
```

In [68]:

```
calibration_method=['sigmoid','isotonic']
calib_model,clf=model_calibration(train,test,y_train_rbf,y_test_rbf,model.best_params_,calibration_method,kernel[1])
```

```
[LibSVM]
```



Observation:

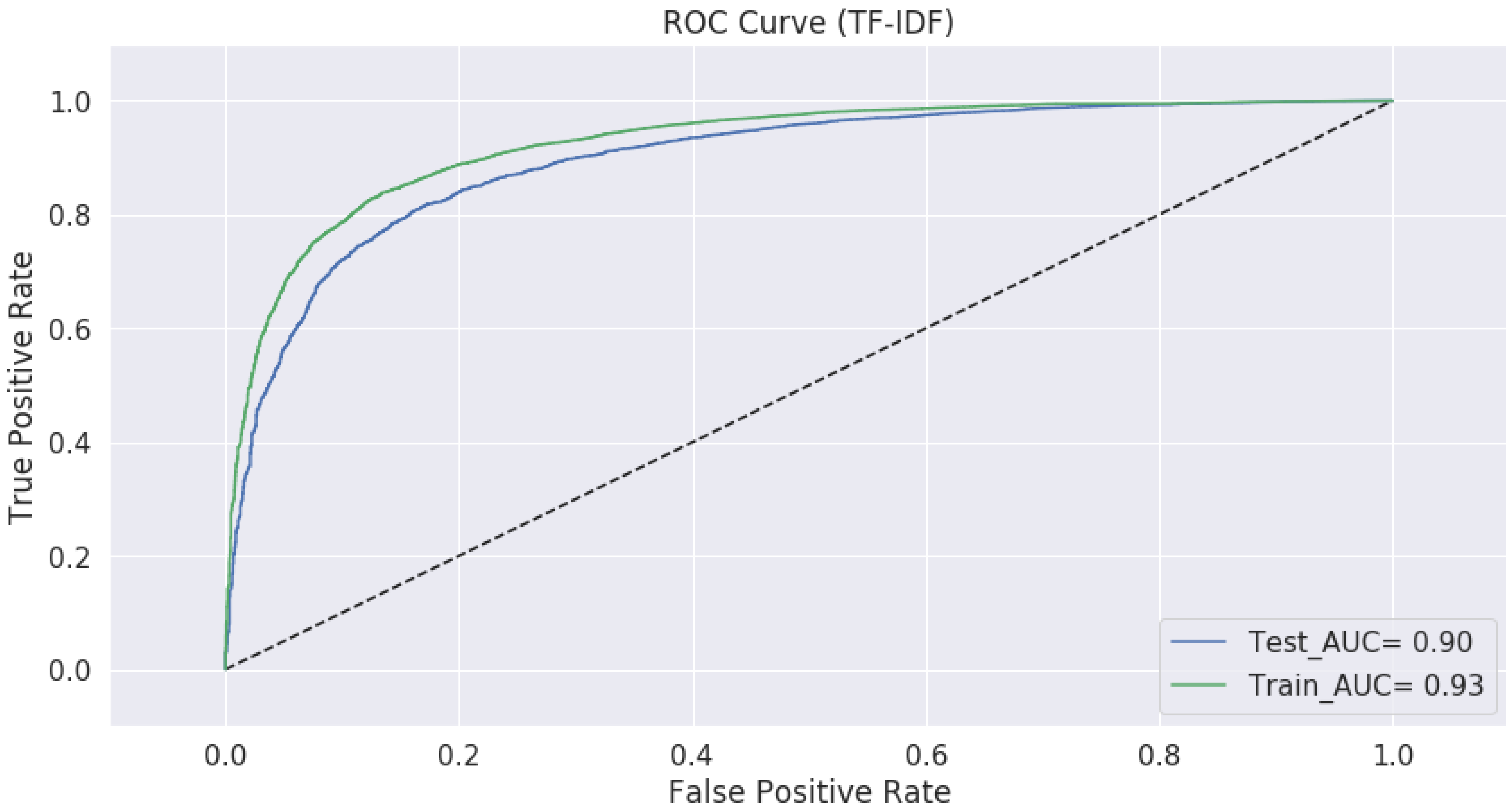
1. From the above plot we observe that the uncalibrated curve is looks like a sigmoidal curve so we choose sigmoidal calibration.

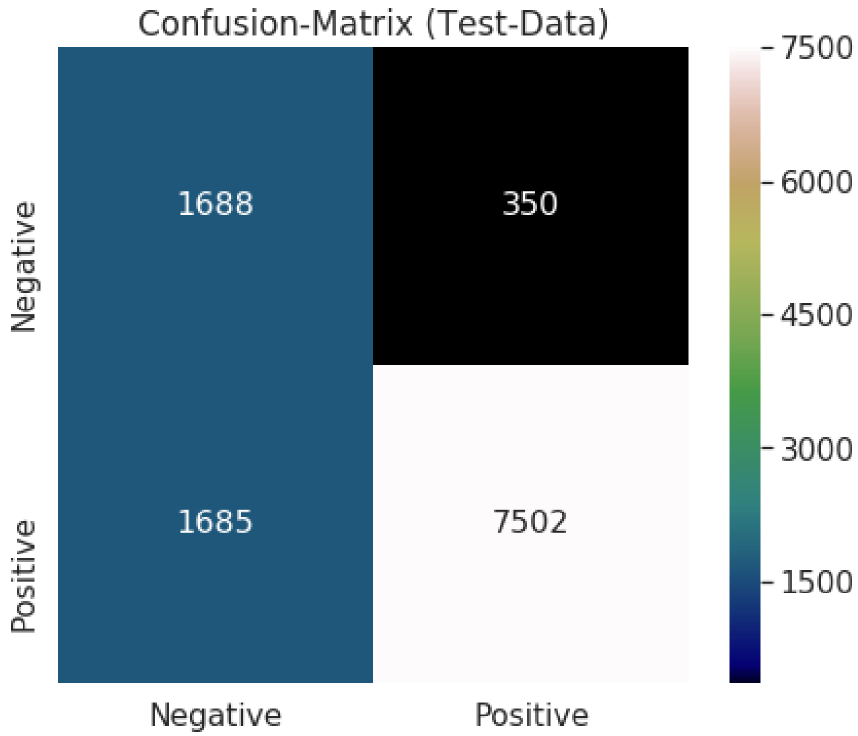
In [69]:

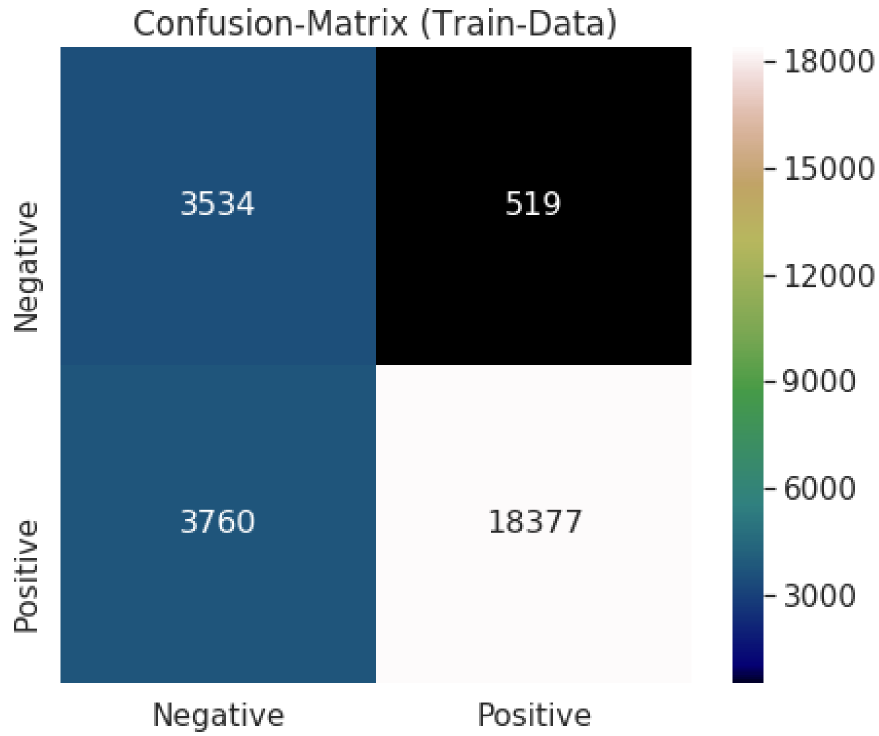
```
calib_mod=calib_model['sigmoid']
```

[2.1.3] Performance on test data with optimal value of hyperparam:

In [70]:
```
test_performance(calib_mod,clf,train,y_train_rbf,test,y_test_rbf,model.best_params_,vect[1],summarize,kernel[1])
```







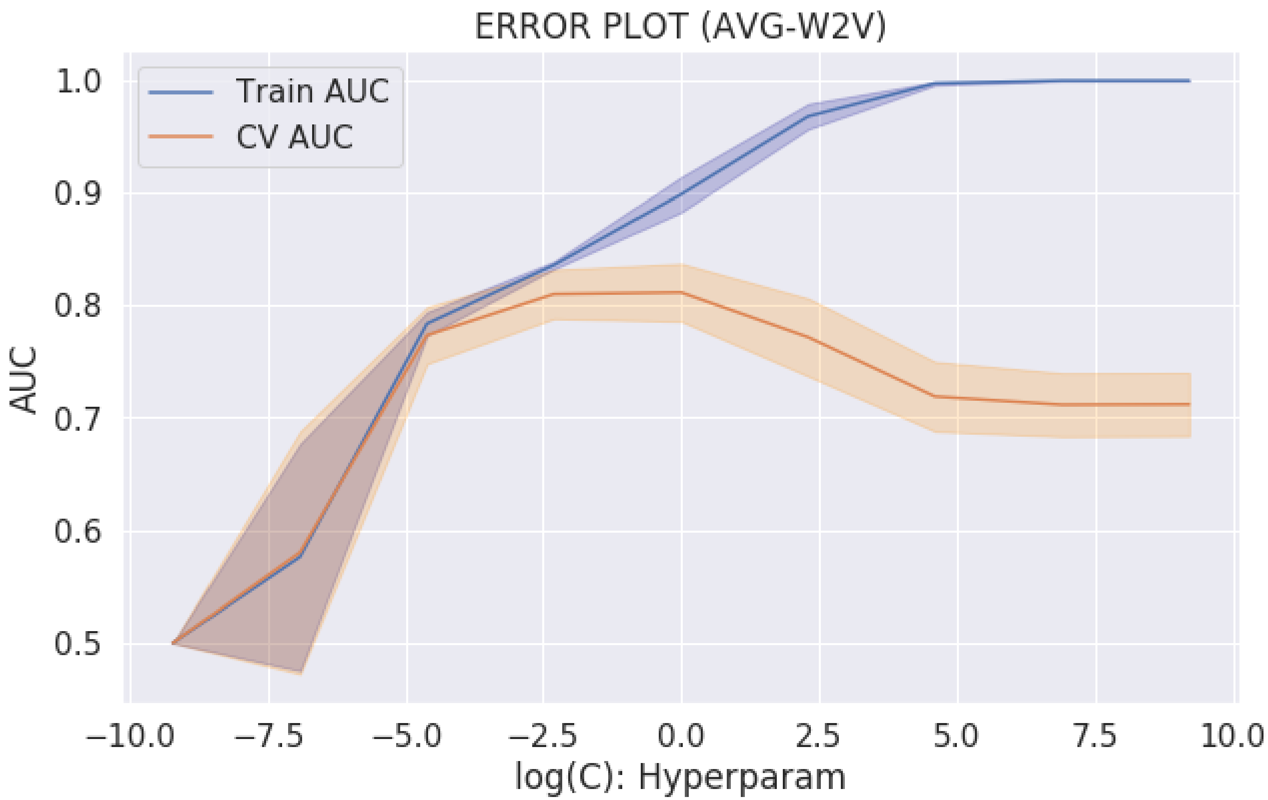
[3.1] Applying RBF SVM on AVG W2V, SET 3

[3.1.1] Hyperparam tunning and draw Error plot:

In [76]:

```
#STANDARDIZE TRAIN AND TEST DATA
train, test=std_data(train=avg_sent_vectors_rbf,test=avg_sent_vectors_test_rbf,mean=True)
#HYPERPARAM TUNNING
%time model=SVM_Classifier(train,y_train_rbf,TBS,params_rbf,searchMethod,vect[2],kernel[1])
#PRINT OPTIMAL VALUE OF HYPERPARAM
print('Optimal value of hyperparam: ',model.best_params_)
#SAVE CURRENT STATE OF ML-MODEL FOR FUTURE USE
saveModeltofile(model,'model_avgw2v_rbfsvm')
```

```
[LibSVM]
```



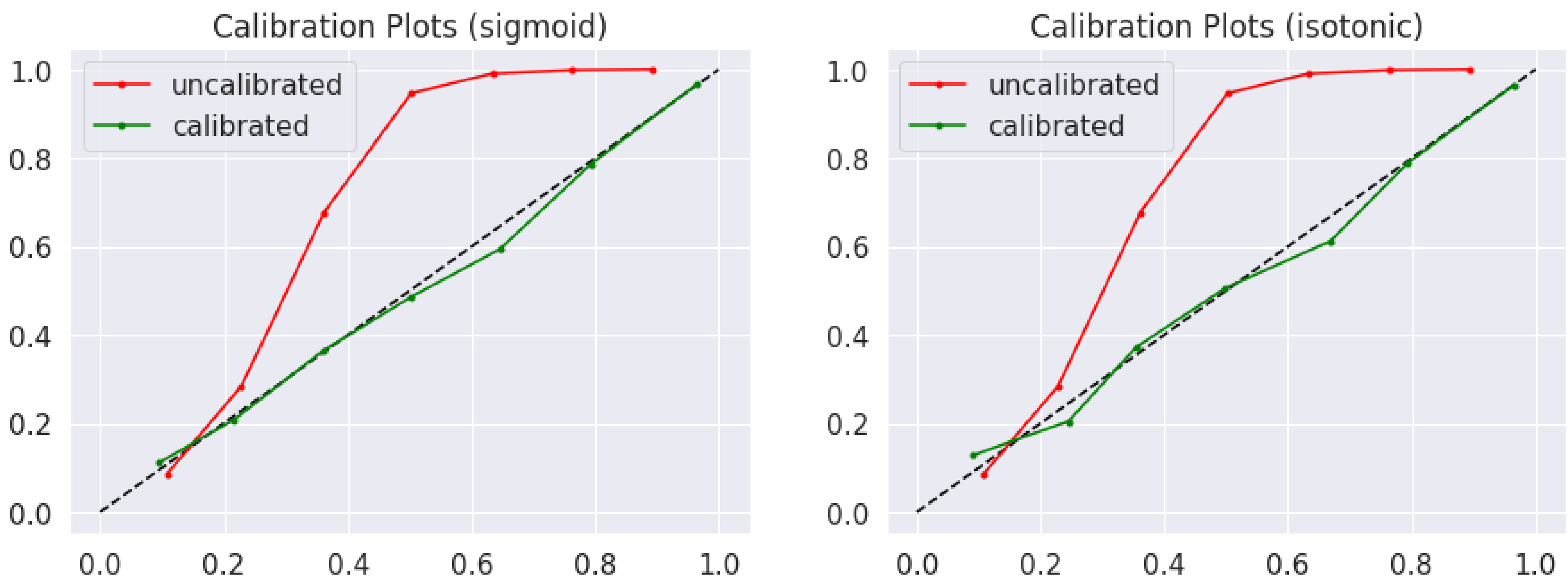

```
CPU times: user 1min 32s, sys: 1.5 s, total: 1min 34s
Wall time: 9min 52s
Optimal value of hyperparam:  {'C': 1}
```

[3.1.2] Calibration of a model and plot calibration curve :

```
a. sigmoid
b. isotonic
```

In [77]:
```
calibration_method=['sigmoid','isotonic']
calib_model,clf=model_calibration(train,test,y_train_rbf,y_test_rbf,model.best_params_,calibration_method,kernel[1])
```

```
[LibSVM]
```



Observation:

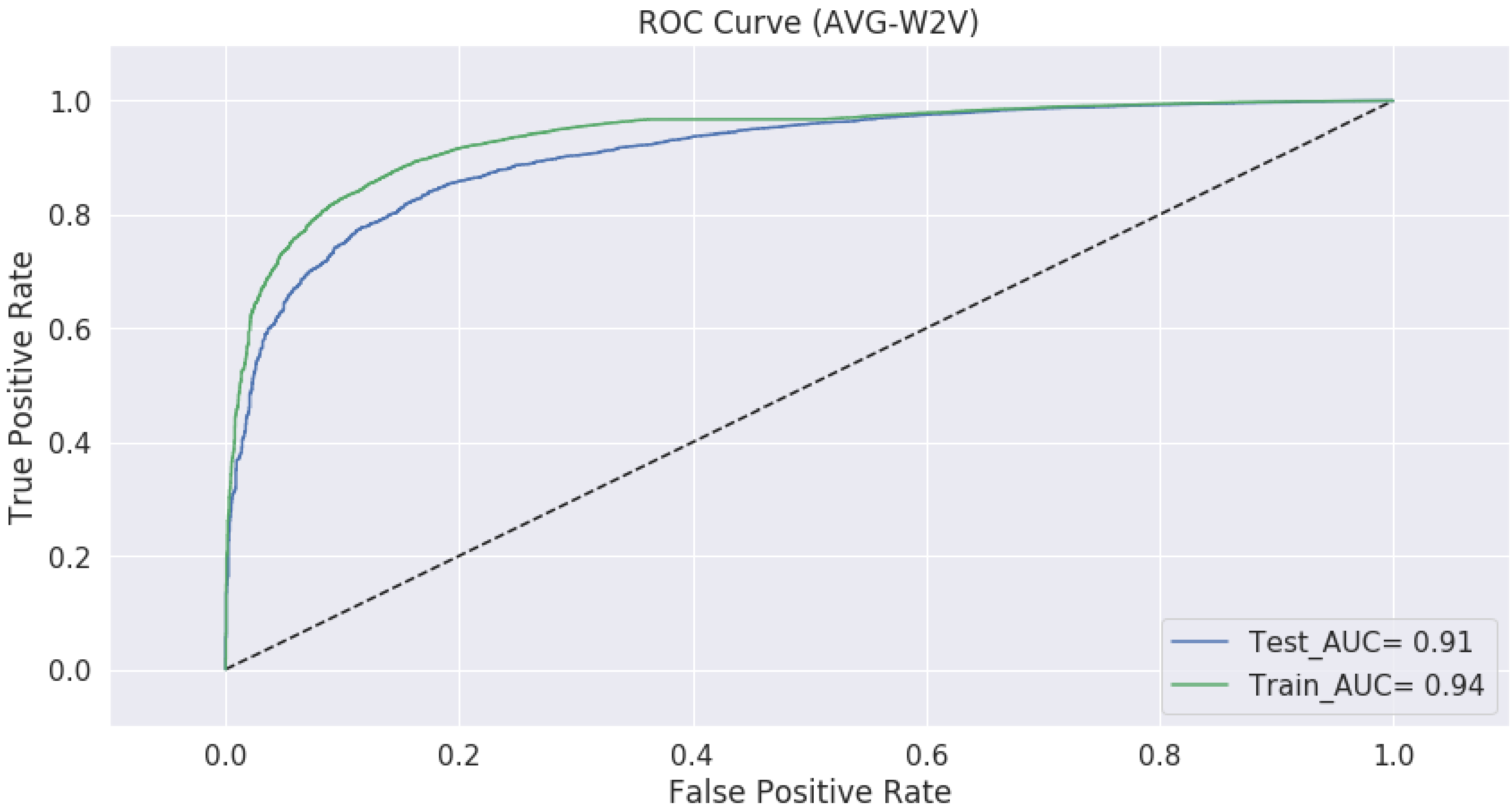
1. From the above plot we observe that the uncalibrated curve is looks like a sigmoidal curve so we choose sigmoidal calibration.

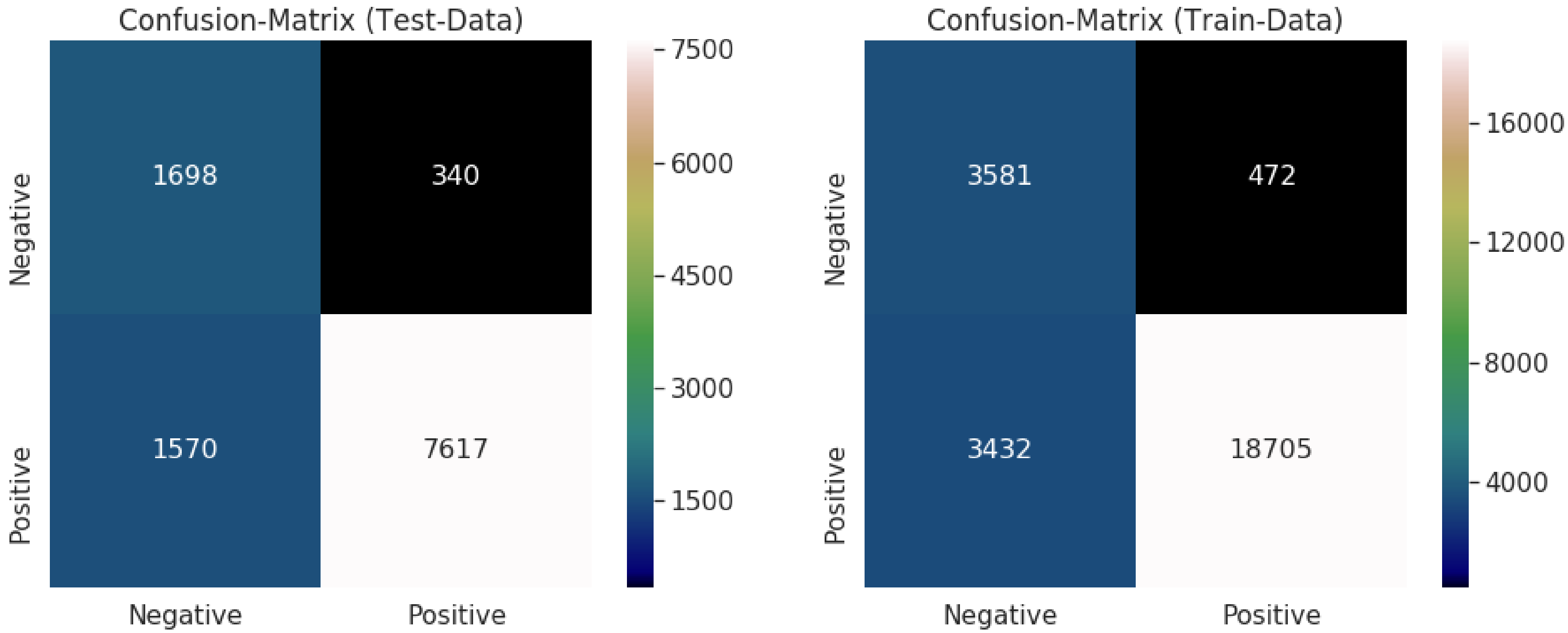
In [78]:
```
calib_mod=calib_model['sigmoid']
```

[3.1.3] Performance on test data with optimal value of hyperparam:

In [79]:

```
test_performance(calib_mod,clf,train,y_train_rbf,test,y_test_rbf,model.best_params_,vect[2],summarize,kernel[1])
```



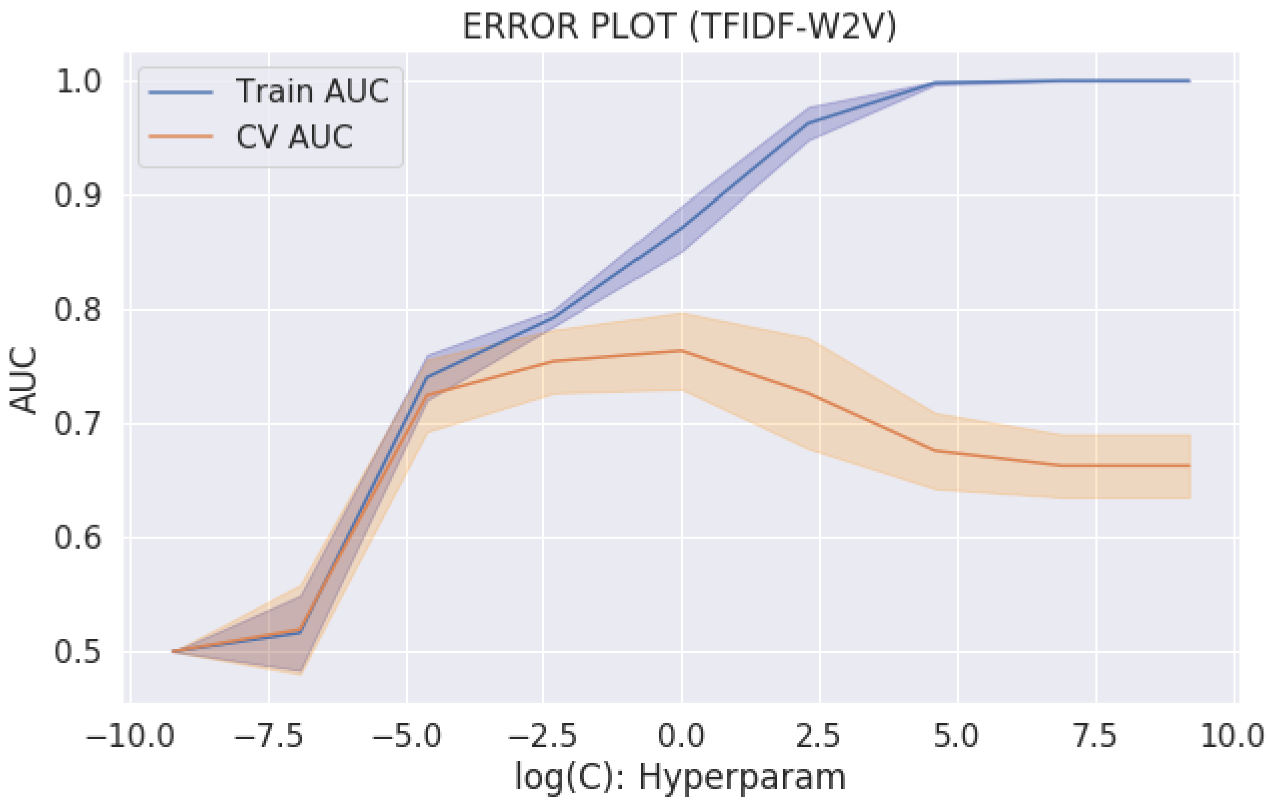


[4.1] Applying RBF SVM on TFIDF W2V, SET 4

[4.1.1] Hyperparam tunning and draw Error plot:

In [83]:
```
#STANDARDIZE TRAIN AND TEST DATA
train, test=std_data(train=tfidf_sent_vectors_rbf,test=tfidf_sent_vectors_test_rbf,mean=True)
#HYPERPARAM TUNNING
%time model=SVM_Classifier(train,y_train_rbf,TBS,params_rbf,searchMethod,vect[3],kernel[1])
#PRINT OPTIMAL VALUE OF HYPERPARAM
print('Optimal value of hyperparam: ',model.best_params_)
#SAVE CURRENT STATE OF ML-MODEL FOR FUTURE USE
saveModeltofile(model,'model_tfw2v_rbfsvm')
```

```
[LibSVM]
```



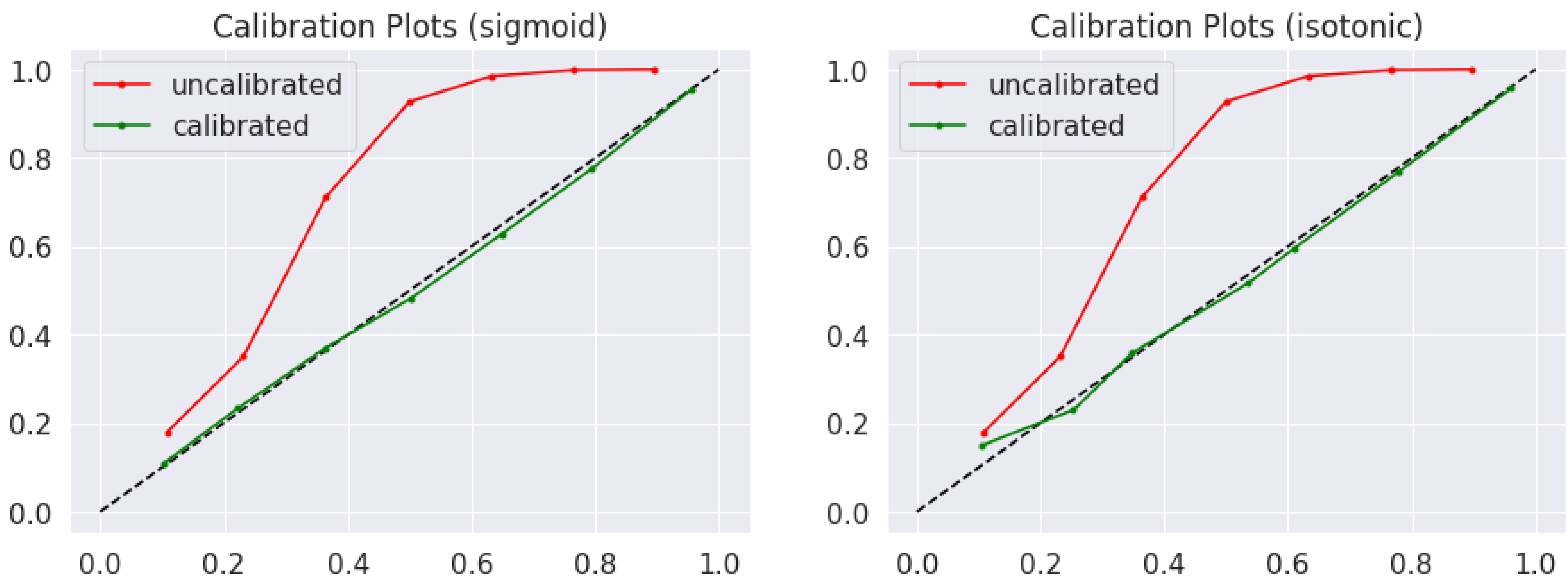

```
CPU times: user 1min 52s, sys: 2.28 s, total: 1min 54s
Wall time: 11min 13s
Optimal value of hyperparam:  {'C': 1}
```

[4.1.2] Calibration of a model and plot calibration curve :

```
a. sigmoid
b. isotonic
```

In [84]:
```
calibration_method=['sigmoid','isotonic']
calib_model,clf=model_calibration(train,test,y_train_rbf,y_test_rbf,model.best_params_,calibration_method,kernel[1])
```

```
[LibSVM]
```



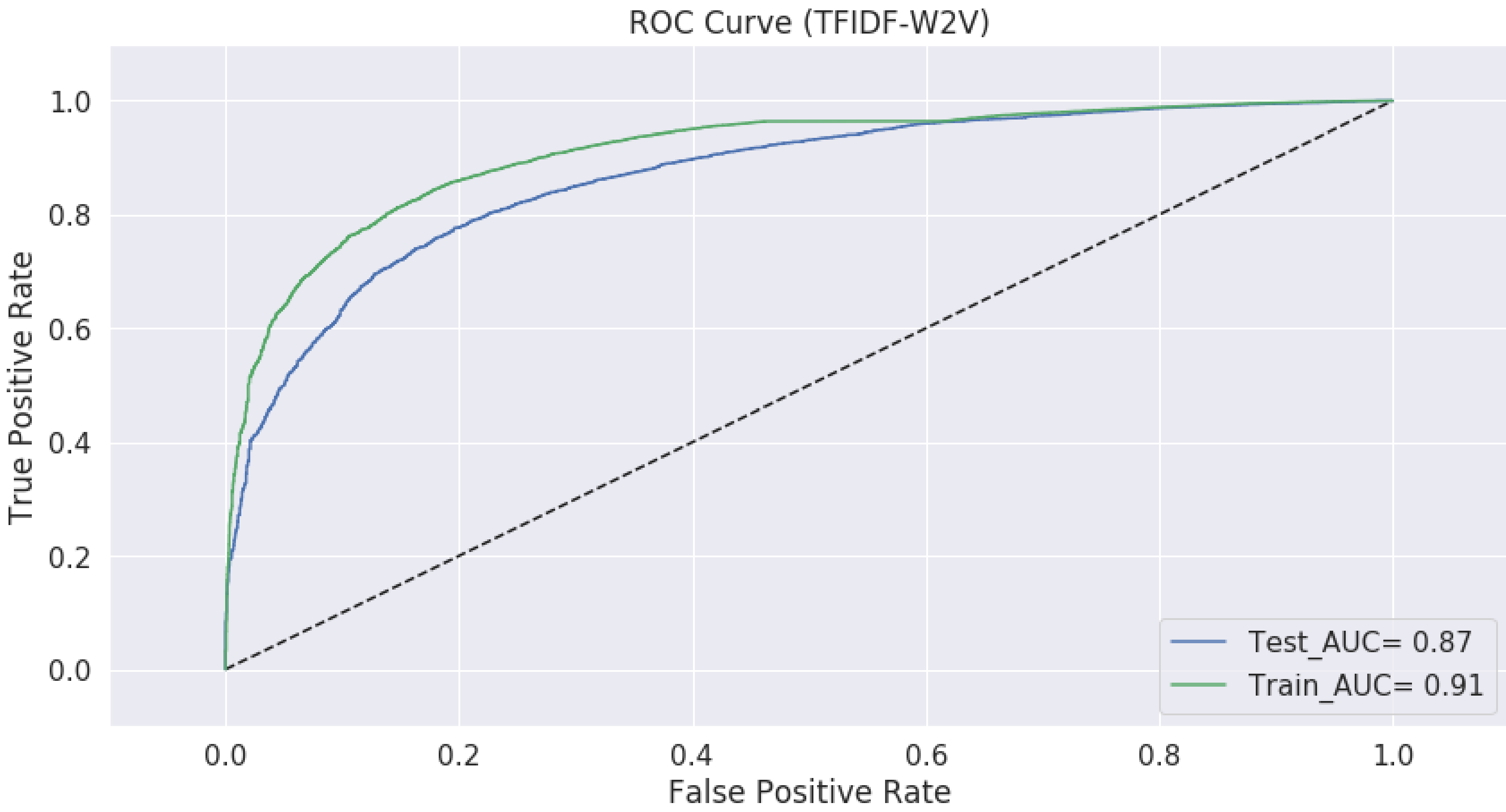
Observation:

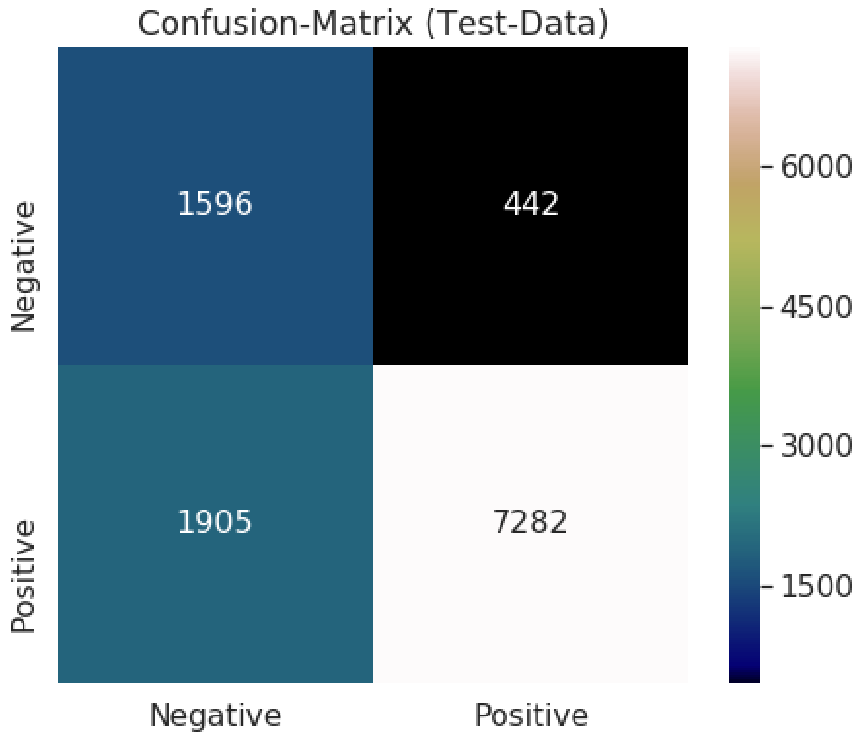
1. From the above plot we observe that the uncalibrated curve is looks like a sigmoidal curve so we choose sigmoidal calibration.

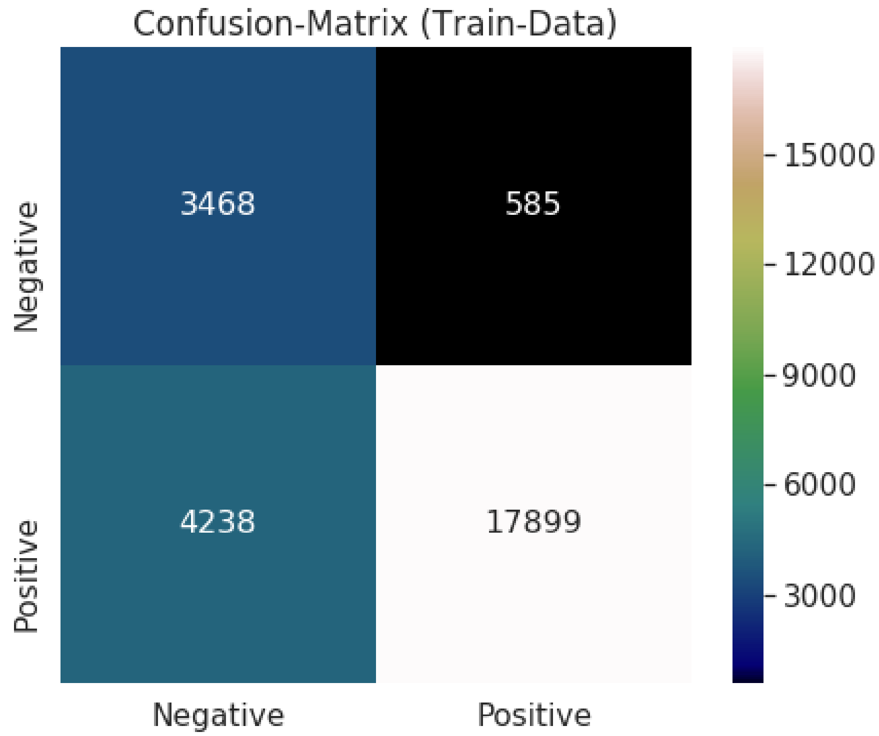
In [85]:
```
calib_mod=calib_model['sigmoid']
```

[4.1.3] Performance on test data with optimal value of hyperparam:

In [86]:
```
test_performance(calib_mod,clf,train,y_train_rbf,test,y_test_rbf,model.best_params_,vect[3],summarize,kernel[1])
```







Conclusion:

In [88]:

```
summary_rbf=summarize
print(summarize)
```

Vectorizer	Kernel	Optimal-Alpha	Test(AUC)	Test(f1-score)
BoW	rbf	0.1	0.8933	0.7935
TF-IDF	rbf	0.1	0.8974	0.8340
AVG-W2V	rbf	1	0.9086	0.8435
TFIDF-W2V	rbf	1	0.8676	0.8095

1. from the above table we can observe that the optimal performance is give by:

```
a. AVGW2V vectorizer
b. f1-score=.8435 and auc=.9086
```

Model performance summary for both RBF and LINEAR Kernel:

In [82]:

```
print('SVM with LINEAR KERNEL SUMMARY:\n',summary_linear)
print('SVM with RBF KERNEL SUMMARY:\n',summary_rbf)
```

```
SVM with LINEAR KERNEL SUMMARY:
 +------------+--------+----------------+---------------+-----------+----------------+
| Vectorizer | Kernel | Optimal-Penalty | Optimal-Alpha | Test(AUC) | Test(f1-score) |
+------------+--------+----------------+---------------+-----------+----------------+
|    BoW     | linear |       l2       |      1.0      |   0.9314  |     0.9138     |
|   TF-IDF   | linear |       l2       |    10000.0    |   0.9422  |     0.8855     |
|  AVG-W2V   | linear |       l1       |      0.01     |   0.9140  |     0.8339     |
| TFIDF-W2V  | linear |       l2       |      0.1      |   0.8905  |     0.8131     |
+------------+--------+----------------+---------------+-----------+----------------+
SVM with RBF KERNEL SUMMARY:
 +------------+--------+---------------+-----------+----------------+
| Vectorizer | Kernel | Optimal-Alpha | Test(AUC) | Test(f1-score) |
+------------+--------+---------------+-----------+----------------+
|    BoW     |  rbf   |      0.1      |   0.8933  |     0.7935     |
|   TF-IDF   |  rbf   |      0.1      |   0.8974  |     0.8340     |
| TFIDF-W2V  |  rbf   |       1       |   0.8676  |     0.8095     |
|  AVG-W2V   |  rbf   |       1       |   0.9086  |     0.8435     |
+------------+--------+---------------+-----------+----------------+
```

Reference Links:

1. https://machinelearningmastery.com/calibrated-classification-model-in-scikit-learn/ (https://machinelearningmastery.com/calibrated-classification-model-in-scikit-learn/)
2. https://www.appliedaicourse.com/ (https://www.appliedaicourse.com/)