Importing libraries

In [24]:

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

from sklearn import linear_model
import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer

import re
# Tutorial about Python regular expressions: https://pymotw.com/2/re/
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

warnings.filterwarnings("ignore")
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os

from plotly import plotly
import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
from collections import Counter

from prettytable import PrettyTable
from sklearn import decomposition
from sklearn.decomposition import TruncatedSVD
from sklearn.metrics import roc_curve, auc
from matplotlib import pyplot
from scipy.sparse import coo_matrix
from scipy.sparse import csr_matrix
from scipy.sparse import hstack
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import Normalizer
import itertools
```

1. Importing Data

In [3]:

```
X = pd.read_csv('DonorsChoose_processed.csv')
project_data = pd.read_csv('train_data.csv')
project_data=project_data[0:50000]
y = project_data['project_is_approved'].values
```

2. Splitting Data

In [4]:

```
# train test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, stratify=y)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33, stratify=y_train)

print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)
```

```
(22445, 11) (22445,)
(11055, 11) (11055,)
(16500, 11) (16500,)
```

3. Vectorizing data

3.1 BOW Vectorization of Clean_essay

In [5]:

```
from sklearn.feature_extraction.text import CountVectorizer
vec_essay = CountVectorizer(min_df=10,ngram_range=(2,2), max_features=5000)
vec_essay.fit(X_train['clean_essay'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_essay_bow = vec_essay.transform(X_train['clean_essay'].values)
X_cv_essay_bow = vec_essay.transform(X_cv['clean_essay'].values)
X_test_essay_bow = vec_essay.transform(X_test['clean_essay'].values)

print("After vectorizations")
print(X_train_essay_bow.shape, y_train.shape)
print(X_cv_essay_bow.shape, y_cv.shape)
print(X_test_essay_bow.shape, y_test.shape)
```

```
After vectorizations
(22445, 5000) (22445,)
(11055, 5000) (11055,)
(16500, 5000) (16500,)
```

- https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/handling-categorical-and-numerical-features/

3.2 one hot encoding the catogorical features: state

In [6]:

```
vec_state = CountVectorizer(min_df=10)
vec_state.fit(X_train['school_state'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_state_ohe = vec_state.transform(X_train['school_state'].values)
X_cv_state_ohe = vec_state.transform(X_cv['school_state'].values)
X_test_state_ohe = vec_state.transform(X_test['school_state'].values)

print("After vectorizations")
print(X_train_state_ohe.shape, y_train.shape)
print(X_cv_state_ohe.shape, y_cv.shape)
print(X_test_state_ohe.shape, y_test.shape)
print(vec_state.get_feature_names())
print("="*100)
```

```
After vectorizations
```

```
(16500, 50) (16500,)
['ak', 'al', 'ar', 'az', 'ca', 'co', 'ct', 'dc', 'de', 'fl', 'ga', 'hi', 'ia', 'id', 'il', 'in', 'k
s', 'ky', 'la', 'ma', 'md', 'me', 'mi', 'mn', 'mo', 'ms', 'mt', 'nc', 'nd', 'ne', 'nh', 'nj', 'nm',
'nv', 'ny', 'oh', 'ok', 'or', 'pa', 'ri', 'sc', 'sd', 'tn', 'tx', 'ut', 'va', 'wa', 'wi', 'wv', 'wy
']
==================================================================================================
```

3.3 one hot encoding the catogorical features: teacher_prefix

In [7]:

```
vec_tpre = CountVectorizer(min_df=10)
vec_tpre.fit(X_train['teacher_prefix'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_teacher_ohe = vec_tpre.transform(X_train['teacher_prefix'].values)
X_cv_teacher_ohe = vec_tpre.transform(X_cv['teacher_prefix'].values)
X_test_teacher_ohe = vec_tpre.transform(X_test['teacher_prefix'].values)

print("After vectorizations")
print(X_train_teacher_ohe.shape, y_train.shape)
print(X_cv_teacher_ohe.shape, y_cv.shape)
print(X_test_teacher_ohe.shape, y_test.shape)
print(vec_tpre.get_feature_names())
print("="*100)
```

```
After vectorizations
(22445, 4) (22445,)
(11055, 4) (11055,)
(16500, 4) (16500,)
['mr', 'mrs', 'ms', 'teacher']
==================================================================================================
```

3.4 one hot encoding the catogorical features: project_grade

In [8]:

```
vec_grade = CountVectorizer(min_df=10)
vec_grade.fit(X_train['project_grade_category'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_grade_ohe = vec_grade.transform(X_train['project_grade_category'].values)
X_cv_grade_ohe = vec_grade.transform(X_cv['project_grade_category'].values)
X_test_grade_ohe = vec_grade.transform(X_test['project_grade_category'].values)

print("After vectorizations")
print(X_train_grade_ohe.shape, y_train.shape)
print(X_cv_grade_ohe.shape, y_cv.shape)
print(X_test_grade_ohe.shape, y_test.shape)
print(vec_grade.get_feature_names())
print("="*100)
```

```
After vectorizations
(22445, 3) (22445,)
(11055, 3) (11055,)
(16500, 3) (16500,)
['12', 'grades', 'prek']
==================================================================================================
```

3.5 one hot encoding the catogorical features: project_title

In [9]:

```
# we use the fitted CountVectorizer to convert the text to vector
X_train_title_ohe = vec_title.transform(X_train['clean_title'].values)
X_cv_title_ohe = vec_title.transform(X_cv['clean_title'].values)
X_test_title_ohe = vec_title.transform(X_test['clean_title'].values)

print("After vectorizations")
print(X_train_title_ohe.shape, y_train.shape)
print(X_cv_title_ohe.shape, y_cv.shape)
print(X_test_title_ohe.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 7867) (22445,)
(11055, 7867) (11055,)
(16500, 7867) (16500,)
====================================================================================================
```

3.6 one hot encoding the catogorical features: project_category

In [10]:

```
vec_cate = CountVectorizer(min_df=10)
vec_cate.fit(X_train['clean_categories'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_category_ohe = vec_cate.transform(X_train['clean_categories'].values)
X_cv_category_ohe = vec_cate.transform(X_cv['clean_categories'].values)
X_test_category_ohe = vec_cate.transform(X_test['clean_title'].values)

print("After vectorizations")
print(X_train_category_ohe.shape, y_train.shape)
print(X_cv_category_ohe.shape, y_cv.shape)
print(X_test_category_ohe.shape, y_test.shape)
print(vec_cate.get_feature_names())
print("="*100)
```

```
After vectorizations
(22445, 9) (22445,)
(11055, 9) (11055,)
(16500, 9) (16500,)
['appliedlearning', 'care_hunger', 'health_sports', 'history_civics', 'literacy_language',
'math_science', 'music_arts', 'specialneeds', 'warmth']
====================================================================================================
```

3.7 one hot encoding the catogorical features: project_subcategory

In [11]:

```
vec_scate = CountVectorizer(min_df=10)
vec_scate.fit(X_train['clean_subcategories'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_subcategory_ohe = vec_scate.transform(X_train['clean_subcategories'].values)
X_cv_subcategory_ohe = vec_scate.transform(X_cv['clean_subcategories'].values)
X_test_subcategory_ohe = vec_scate.transform(X_test['clean_subcategories'].values)

print("After vectorizations")
print(X_train_subcategory_ohe.shape, y_train.shape)
print(X_cv_subcategory_ohe.shape, y_cv.shape)
print(X_test_subcategory_ohe.shape, y_test.shape)
print(vec_scate.get_feature_names())
print("="*100)
```

```
After vectorizations
(22445, 30) (22445,)
```

```
['appliedsciences', 'care_hunger', 'charactereducation', 'civics_government',
'college_careerprep', 'communityservice', 'earlydevelopment', 'economics', 'environmentalscience',
'esl', 'extracurricular', 'financialliteracy', 'foreignlanguages', 'gym_fitness',
'health_lifescience', 'health_wellness', 'history_geography', 'literacy', 'literature_writing', 'm
athematics', 'music', 'nutritioneducation', 'other', 'parentinvolvement', 'performingarts', 'socia
lsciences', 'specialneeds', 'teamsports', 'visualarts', 'warmth']
==================================================================================================
```

3.8 Normalizing the numerical features: Price

In [12]:

```
normalizer = Normalizer()
# normalizer.fit(X_train['price'].values)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96  96.01 ... 368.98  80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature
# array.reshape(1, -1)  if it contains a single sample.
normalizer.fit(X_train['price'].values.reshape(1,-1))

X_train_price_norm = normalizer.transform(X_train['price'].values.reshape(1,-1)).T
X_cv_price_norm = normalizer.transform(X_cv['price'].values.reshape(1,-1)).T
X_test_price_norm = normalizer.transform(X_test['price'].values.reshape(1,-1)).T

print("After vectorizations")
print(X_train_price_norm.shape, y_train.shape)
print(X_cv_price_norm.shape, y_cv.shape)
print(X_test_price_norm.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
==================================================================================================
```

3.9 Normalizing the numerical features: teacher no of previously posted projects

In [13]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X_train['teacher_number_of_previously_posted_projects'].values.reshape(1,-1))

X_train_post_norm = normalizer.transform(X_train['teacher_number_of_previously_posted_projects'].v
alues.reshape(1,-1)).T
X_cv_post_norm = normalizer.transform(X_cv['teacher_number_of_previously_posted_projects'].values.
reshape(1,-1)).T
X_test_post_norm =
normalizer.transform(X_test['teacher_number_of_previously_posted_projects'].values.reshape(1,-1)).T

print("After vectorizations")
print(X_train_post_norm.shape, y_train.shape)
print(X_cv_post_norm.shape, y_cv.shape)
print(X_test_post_norm.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
==================================================================================================
```

3.10 Normalizing the numerical features: resource summary

In [14]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X_train['Is_digit_present'].values.reshape(1,-1))

X_train_digit_norm = normalizer.transform(X_train['Is_digit_present'].values.reshape(1,-1)).T
X_cv_digit_norm = normalizer.transform(X_cv['Is_digit_present'].values.reshape(1,-1)).T
X_test_digit_norm = normalizer.transform(X_test['Is_digit_present'].values.reshape(1,-1)).T

print("After vectorizations")
print(X_train_digit_norm.shape, y_train.shape)
print(X_cv_digit_norm.shape, y_cv.shape)
print(X_test_digit_norm.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
====================================================================================================
```

3.11 Normalizing the numerical features: quantity

In [15]:

```
from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
normalizer.fit(X_train['quantity'].values.reshape(1,-1))

X_train_quantity_norm = normalizer.transform(X_train['quantity'].values.reshape(1,-1)).T
X_cv_quantity_norm = normalizer.transform(X_cv['quantity'].values.reshape(1,-1)).T
X_test_quantity_norm = normalizer.transform(X_test['quantity'].values.reshape(1,-1)).T

print("After vectorizations")
print(X_train_quantity_norm.shape, y_train.shape)
print(X_cv_quantity_norm.shape, y_cv.shape)
print(X_test_quantity_norm.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
====================================================================================================
```

Concatenation of all the vectorized data

In [16]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039

X_tr =
hstack((X_train_essay_bow,X_train_state_ohe,X_train_teacher_ohe,X_train_grade_ohe,X_train_title_ohe
,X_train_category_ohe,X_train_subcategory_ohe,X_train_price_norm,X_train_post_norm,X_train_digit_no
rm,X_train_quantity_norm))
X_cr = hstack((X_cv_essay_bow,X_cv_state_ohe,X_cv_teacher_ohe,X_cv_grade_ohe,X_cv_title_ohe,X_cv_ca
tegory_ohe,X_cv_subcategory_ohe,X_cv_price_norm,X_cv_post_norm,X_cv_digit_norm,X_cv_quantity_norm)
)
X_te =
hstack((X_test_essay_bow,X_test_state_ohe,X_test_teacher_ohe,X_test_grade_ohe,X_test_title_ohe,X_te
st_category_ohe,X_test_subcategory_ohe,X_test_price_norm,X_test_post_norm,X_test_digit_norm,X_test
_quantity_norm))

print("Final Data matrix")
```

```
print(X_te.shape, y_test.shape)
print("="*100)
```

```
Final Data matrix
(22445, 12967) (22445,)
(11055, 12967) (11055,)
(16500, 12967) (16500,)
====================================================================================================
```

Applying LinearSVM on BOW

In [33]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

SGD = linear_model.SGDClassifier(loss='hinge', learning_rate='optimal',
class_weight='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4],'penalty':['l1','l2']
}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

In [36]:

```
clf.best_params_
```

Out[36]:

```
{'alpha': 0.01, 'penalty': 'l2'}
```

As the best penalty is l2 , so we will use that and find the best alpha

In [17]:

```
SGD = linear_model.SGDClassifier(loss='hinge', penalty='l2', learning_rate='optimal', class_weight
='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4]}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

In [18]:

```
clf.best_params_
```

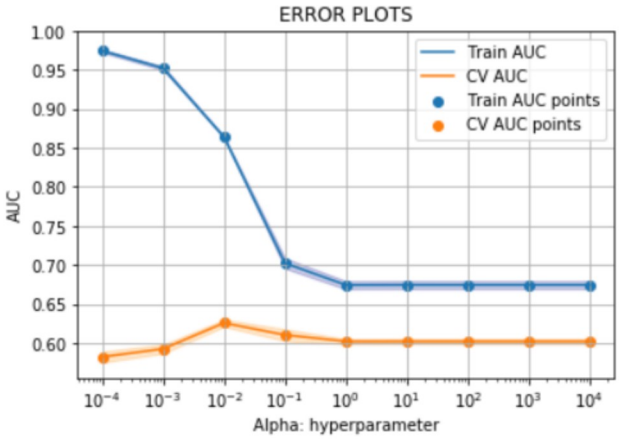
Out[18]:

```
{'alpha': 0.01}
```

In [42]:

```
plt.plot(parameters['alpha'], train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],train_auc - train_auc_std,train_auc +
```

```
plt.plot(parameters['alpha'], cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color=
'darkorange')

plt.scatter(parameters['alpha'], train_auc, label='Train AUC points')
plt.scatter(parameters['alpha'], cv_auc, label='CV AUC points')
pyplot.xscale('log')

plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



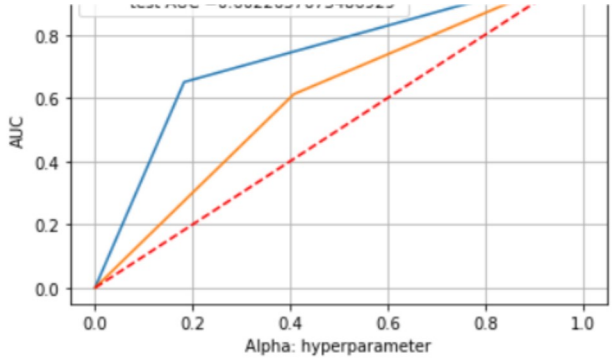
From the above graph we can see that for the value of alpha less than 0.01, it is over fitting the data and for the value of alpha more than 0.01, it is underfitting the data. So the best value of alpha will be 0.01 for this

In [47]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve

best_alpha = 0.01


SGD = linear_model.SGDClassifier(alpha=best_alpha, loss='hinge', penalty='l2', learning_rate='optim
al', class_weight='balanced',max_iter=2000, tol=1e-5)
SGD.fit(X_tr, y_train)

y_train_pred = SGD.predict(X_tr)

y_test_pred = SGD.predict(X_te)


train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)
```

In [49]:

```
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.plot([0, 1], [0, 1],'r--') #code copied from -https://stackoverflow.com/questions/25009284/how-
to-plot-roc-curve-in-python
plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



In [39]:

```
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr
def predict(proba, threshould, fpr, tpr):

    t = threshould[np.argmax(fpr*(1-tpr))]

    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high

    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for threshold", np.round(t,3))
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

In [52]:

```
from sklearn.metrics import confusion_matrix
train_conf=confusion_matrix(y_train, predict(y_train_pred, tr_thresholds, train_fpr, train_fpr))
test_conf=confusion_matrix(y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_fpr))
```

```
the maximum value of tpr*(1-fpr) 0.14937749163655656 for threshold 1
the maximum value of tpr*(1-fpr) 0.24148040547253397 for threshold 1
```

In [40]:

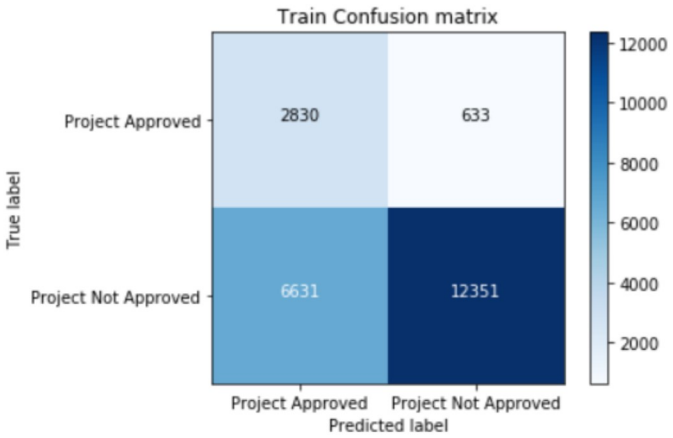
```
#sns heatmap confusion matrix -https://scikit-
learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
```

```
                horizontalalignment="center",
                color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
class_names=['Project Approved','Project Not Approved']
```

In [54]:

```
plot_confusion_matrix(train_conf, classes=class_names,
                      title='Train Confusion matrix')
```

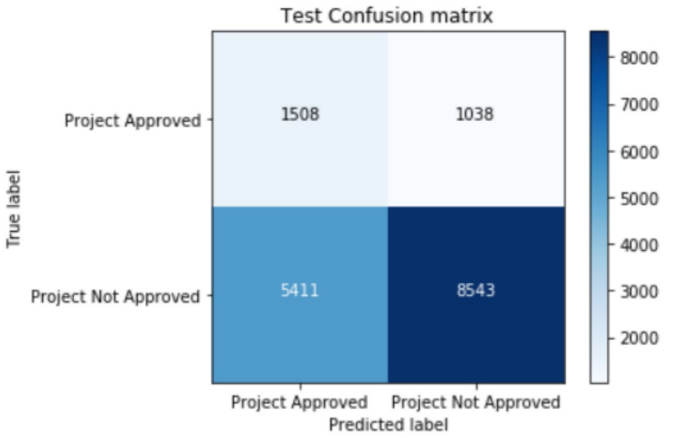
```
Confusion matrix, without normalization
[[ 2830   633]
 [ 6631 12351]]
```



In [55]:

```
plot_confusion_matrix(test_conf, classes=class_names,
                      title='Test Confusion matrix')
```

```
Confusion matrix, without normalization
[[1508 1038]
 [5411 8543]]
```



Conclusion

On applying LinearSVM BOW on DonorsChoose dataset with alpha value as 0.01 we got the AUC value of 0.60 on test data

TFIDF Vectorization of Clean_essay

In [19]:

```
vec_essay = TfidfVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vec_essay.fit(X_train['clean_essay'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_essay_tfidf = vec_essay.transform(X_train['clean_essay'].values)
X_cv_essay_tfidf = vec_essay.transform(X_cv['clean_essay'].values)
X_test_essay_tfidf = vec_essay.transform(X_test['clean_essay'].values)

print("After vectorizations")
print(X_train_essay_tfidf.shape, y_train.shape)
print(X_cv_essay_tfidf.shape, y_cv.shape)
print(X_test_essay_tfidf.shape, y_test.shape)
```

```
After vectorizations
(22445, 5000) (22445,)
(11055, 5000) (11055,)
(16500, 5000) (16500,)
```

TFIDF Vectorization of Clean_title

In [20]:

```
vec_title = TfidfVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vec_title.fit(X_train['clean_title'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_title_tfidf = vec_title.transform(X_train['clean_title'].values)
X_cv_title_tfidf = vec_title.transform(X_cv['clean_title'].values)
X_test_title_tfidf = vec_title.transform(X_test['clean_title'].values)

print("After vectorizations")
print(X_train_title_tfidf.shape, y_train.shape)
print(X_cv_title_tfidf.shape, y_cv.shape)
print(X_test_title_tfidf.shape, y_test.shape)
```

```
After vectorizations
(22445, 1682) (22445,)
(11055, 1682) (11055,)
(16500, 1682) (16500,)
```

Concatenation of all the vectorized data

In [21]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039

X_tr =
hstack((X_train_essay_tfidf,X_train_state_ohe,X_train_teacher_ohe,X_train_grade_ohe,X_train_title_t
fidf,X_train_category_ohe,X_train_subcategory_ohe,X_train_price_norm,X_train_post_norm,X_train_digi
t_norm,X_train_quantity_norm))
X_cr = hstack((X_cv_essay_tfidf,X_cv_state_ohe,X_cv_teacher_ohe,X_cv_grade_ohe,X_cv_title_tfidf,X_c
v_category_ohe,X_cv_subcategory_ohe,X_cv_price_norm,X_cv_post_norm,X_cv_digit_norm,X_cv_quantity_nc
rm))
X_te =
hstack((X_test_essay_tfidf,X_test_state_ohe,X_test_teacher_ohe,X_test_grade_ohe,X_test_title_tfidf
,X_test_category_ohe,X_test_subcategory_ohe,X_test_price_norm,X_test_post_norm,X_test_digit_norm,X
_test_quantity_norm))

print("Final Data matrix")
print(X_tr.shape, y_train.shape)
print(X_cr.shape, y_cv.shape)
print(X_te.shape, y_test.shape)
```

```
Final Data matrix
(22445, 6782) (22445,)
(11055, 6782) (11055,)
(16500, 6782) (16500,)
==========================================================================================================
```

In [59]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

SGD = linear_model.SGDClassifier(loss='hinge', learning_rate='optimal',
class_weight='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4],'penalty':['l1','l2']
}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

In [60]:

```
clf.best_params_
```

Out[60]:

```
{'alpha': 0.001, 'penalty': 'l2'}
```

As the best penalty is l2 , so we will use that and find the best alpha

In [22]:

```
SGD = linear_model.SGDClassifier(loss='hinge', penalty='l2', learning_rate='optimal', class_weight
='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4]}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

In [23]:

```
clf.best_params_
```

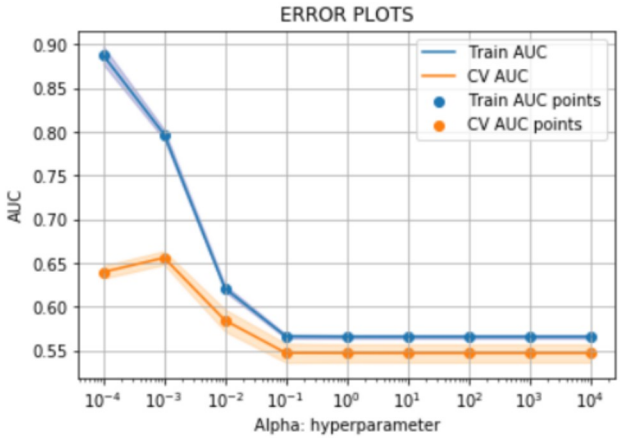
Out[23]:

```
{'alpha': 0.001}
```

In [62]:

```
plt.plot(parameters['alpha'], train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],train_auc - train_auc_std,train_auc +
train_auc_std,alpha=0.2,color='darkblue')

plt.plot(parameters['alpha'], cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color=
'darkorange')
```

```
pyplot.xscale('log')

plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



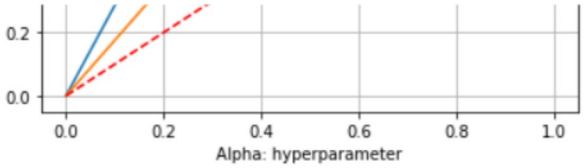
From the above graph we can see that for the value of alpha less than 0.001, it is over fitting the data and for the value of alpha more than 0.001, it is underfitting the data. So the best value of alpha will be 0.001 for this

In [63]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve

best_alpha = 0.001


SGD = linear_model.SGDClassifier(alpha=best_alpha, loss='hinge', penalty='l2', learning_rate='optim
al', class_weight='balanced',max_iter=2000, tol=1e-5)
SGD.fit(X_tr, y_train)

y_train_pred = SGD.predict(X_tr)

y_test_pred = SGD.predict(X_te)


train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)
```

In [64]:

```
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.plot([0, 1], [0, 1],'r--') #code copied from -https://stackoverflow.com/questions/25009284/how-
to-plot-roc-curve-in-python
plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



In [67]:

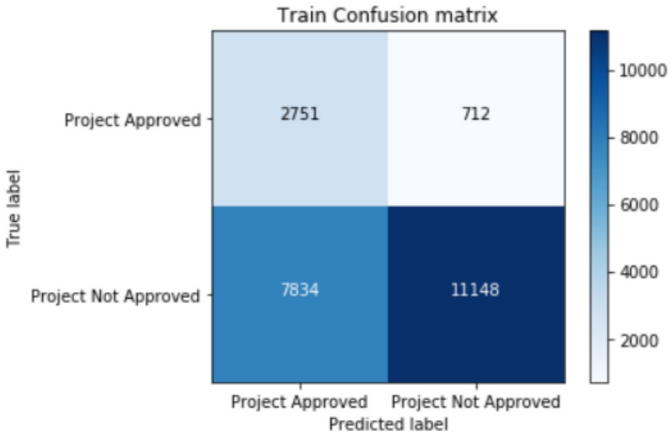
```
train_conf=confusion_matrix(y_train, predict(y_train_pred, tr_thresholds, train_fpr, train_fpr))
test_conf=confusion_matrix(y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_fpr))
```

```
the maximum value of tpr*(1-fpr) 0.16332986418279824 for threshold 1
the maximum value of tpr*(1-fpr) 0.2125046821130631 for threshold 1
```

In [68]:

```
plot_confusion_matrix(train_conf, classes=class_names,
                      title='Train Confusion matrix')
```

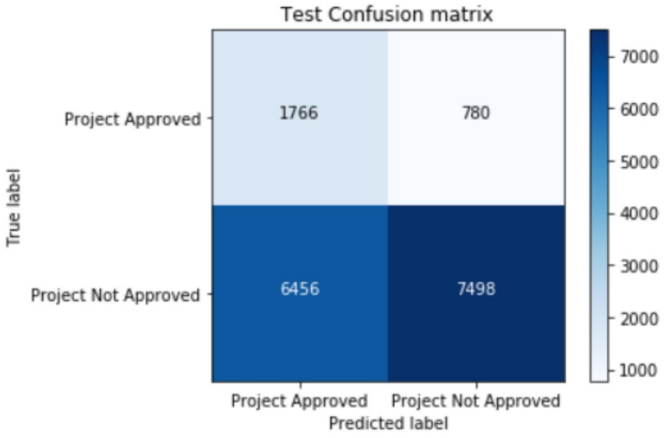
```
Confusion matrix, without normalization
[[ 2751   712]
 [ 7834 11148]]
```



In [69]:

```
plot_confusion_matrix(test_conf, classes=class_names,
                      title='Test Confusion matrix')
```

```
Confusion matrix, without normalization
[[1766  780]
 [6456 7498]]
```



On applying LinearSVM TFIDF on DonorsChoose dataset with alpha value as 0.001 we got the AUC value of 0.61 on test data

Applying LinearSVM on AVG W2V

AVG_W2V Vectorization of Clean_essay

In [70]:

```
# stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-sa
ve-and-load-variables-in-python/
# make sure you have the glove_vectors file

with open('glove_vectors.txt', 'rb') as f:
    model = pickle.load(f)
    glove_words =  set(model.keys())
```

In [71]:

```
# average Word2Vec
# compute average word2vec for each review.
avg_w2v_vectors_essay = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in X['clean_essay'].values: # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_essay.append(vector)
```

AVG_W2V Vectorization of Clean_title

In [72]:

```
# Similarly you can vectorize for title also
avg_w2v_vectors_title = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in X['clean_title'].values: # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_title.append(vector)
```

In [73]:

```
avg_w2v_vectors_title=csr_matrix(avg_w2v_vectors_title)
avg_w2v_vectors_essay=csr_matrix(avg_w2v_vectors_essay)
avg_w2v_vectors_title.shape
```

Out[73]:

```
(50000, 300)
```

In [74]:

```
#splitting avg_w2v_vectors_title into train and test
```

```
X_train_avg_title, X_cv_avg_title, y_train, y_cv = train_test_split(X_train_avg_t, y_train, test_si
ze=0.33, stratify=y_train)
```

In [75]:

```
#splitting avg_w2v_vectors_essay into train and test
X_train_avg_e, X_test_avg_e, y_train, y_test = train_test_split(avg_w2v_vectors_essay, y, test_size
=0.33, stratify=y)
X_train_avg_essay, X_cv_avg_essay, y_train, y_cv = train_test_split(X_train_avg_e, y_train, test_si
ze=0.33, stratify=y_train)
```

Concatenation of all the vectorized data

In [76]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039

X_tr =
hstack((X_train_avg_title,X_train_avg_essay,X_train_state_ohe,X_train_teacher_ohe,X_train_grade_ohe
,X_train_category_ohe,X_train_subcategory_ohe,X_train_price_norm,X_train_post_norm,X_train_digit_no
rm,X_train_quantity_norm))
X_cr = hstack((X_cv_avg_title,X_cv_avg_essay,X_cv_state_ohe,X_cv_teacher_ohe,X_cv_grade_ohe,X_cv_ca
tegory_ohe,X_cv_subcategory_ohe,X_cv_price_norm,X_cv_post_norm,X_cv_digit_norm,X_cv_quantity_norm)
)
X_te =
hstack((X_test_avg_t,X_test_avg_e,X_test_state_ohe,X_test_teacher_ohe,X_test_grade_ohe,X_test_categ
ory_ohe,X_test_subcategory_ohe,X_test_price_norm,X_test_post_norm,X_test_digit_norm,X_test_quantity
_norm))

print("Final Data matrix")
print(X_tr.shape, y_train.shape)
print(X_cr.shape, y_cv.shape)
print(X_te.shape, y_test.shape)
print("="*100)
```

```
Final Data matrix
(22445, 701) (22445,)
(11055, 701) (11055,)
(16500, 701) (16500,)
====================================================================================================
```

In [77]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

SGD = linear_model.SGDClassifier(loss='hinge', learning_rate='optimal',
class_weight='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4],'penalty':['l1','l2']
}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

In [78]:

```
clf.best_params_
```

Out[78]:

```
{'alpha': 0.001, 'penalty': 'l1'}
```

In [79]:

```
SGD = linear_model.SGDClassifier(loss='hinge', penalty='l1', learning_rate='optimal', class_weight
='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4]}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

In [80]:

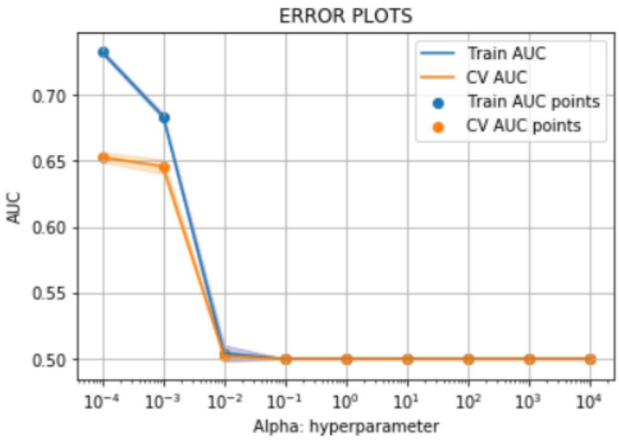
```
clf.best_params_
```

Out[80]:

```
{'alpha': 0.0001}
```

In [81]:

```
plt.plot(parameters['alpha'], train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],train_auc - train_auc_std,train_auc +
train_auc_std,alpha=0.2,color='darkblue')

plt.plot(parameters['alpha'], cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color=
'darkorange')

plt.scatter(parameters['alpha'], train_auc, label='Train AUC points')
plt.scatter(parameters['alpha'], cv_auc, label='CV AUC points')
pyplot.xscale('log')

plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



From the above graph we can see that for the value of alpha less than 0.0001, it is over fitting the data and for the value of alpha more than 0.0001, it is underfitting the data. So the best value of alpha will be 0.0001 for this

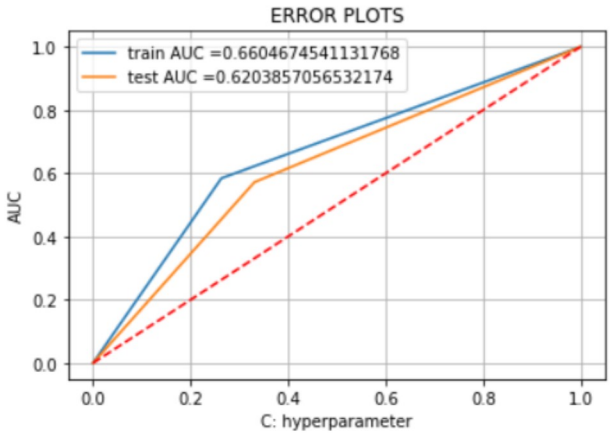
In [83]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
```

```
SGD = linear_model.SGDClassifier(alpha=best_alpha, loss='hinge', penalty='l1', learning_rate='optim
al', class_weight='balanced',max_iter=2000, tol=1e-5)
SGD.fit(X_tr, y_train)

y_train_pred = SGD.predict(X_tr)

y_test_pred = SGD.predict(X_te)


train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)
```

In [84]:

```
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.plot([0, 1], [0, 1],'r--') #code copied from -https://stackoverflow.com/questions/25009284/how-
to-plot-roc-curve-in-python
plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



In [86]:

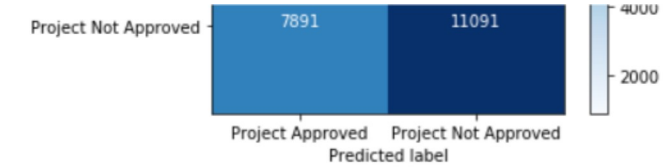
```
train_conf=confusion_matrix(y_train, predict(y_train_pred, tr_thresholds, train_fpr, train_fpr))
test_conf=confusion_matrix(y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_fpr))
```

```
the maximum value of tpr*(1-fpr) 0.19399936743107218 for threshold 1
the maximum value of tpr*(1-fpr) 0.22147536390894576 for threshold 1
```

In [87]:

```
plot_confusion_matrix(train_conf, classes=class_names,
                      title='Train Confusion matrix')
```

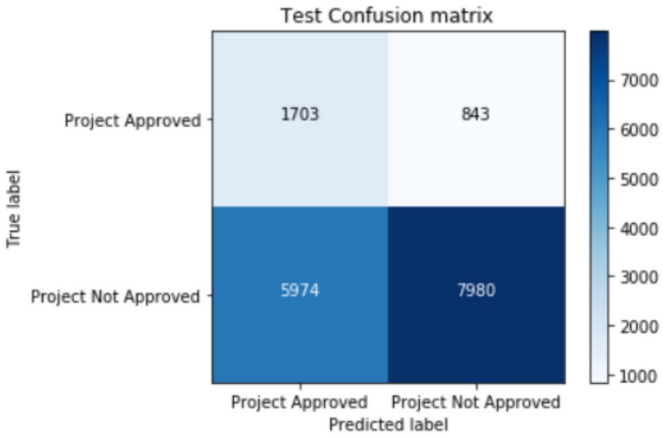
```
Confusion matrix, without normalization
[[ 2551   912]
 [ 7891 11091]]
```



In [88]:

```
plot_confusion_matrix(test_conf, classes=class_names,
                      title='Test Confusion matrix')
```

```
Confusion matrix, without normalization
[[1703  843]
 [5974 7980]]
```



Conclusion

On applying LinearSVM AVG W2V on DonorsChoose dataset with alpha value as 0.0001 we got the AUC value of 0.62 on test data

Applying LinearSVM on TFIDF W2V

TFIDF_W2V Vectorization of Clean_essay

In [89]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model = TfidfVectorizer()
tfidf_model.fit(X['clean_essay'].values)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model.get_feature_names(), list(tfidf_model.idf_)))
tfidf_words = set(tfidf_model.get_feature_names())
```

In [90]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_essay = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in X['clean_essay'].values: # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf_idf_weight =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf_words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
```

```
            vector += (vec * tf_idf) # calculating tfidf weighted w2v
            tf_idf_weight += tf_idf
    if tf_idf_weight != 0:
        vector /= tf_idf_weight
    tfidf_w2v_vectors_essay.append(vector)
```

TFIDF_W2V Vectorization of Clean_title

In [91]:

```
# Similarly you can vectorize for title also
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model = TfidfVectorizer()
tfidf_model.fit(X['clean_title'].values)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model.get_feature_names(), list(tfidf_model.idf_)))
tfidf_words = set(tfidf_model.get_feature_names())
```

In [92]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_title = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in X['clean_title'].values: # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf_idf_weight =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf_words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
            tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
            vector += (vec * tf_idf) # calculating tfidf weighted w2v
            tf_idf_weight += tf_idf
    if tf_idf_weight != 0:
        vector /= tf_idf_weight
    tfidf_w2v_vectors_title.append(vector)
```

In [93]:

```
tfidf_w2v_vectors_title=csr_matrix(tfidf_w2v_vectors_title)
tfidf_w2v_vectors_essay=csr_matrix(tfidf_w2v_vectors_essay)
tfidf_w2v_vectors_title.shape
```

Out[93]:

```
(50000, 300)
```

In [94]:

```
#splitting tfidf_w2v_vectors_title into train and test
X_train_tfidf_t, X_test_tfidf_t, y_train, y_test = train_test_split(tfidf_w2v_vectors_title, y, tes
t_size=0.33, stratify=y)
X_train_tfidf_title, X_cv_tfidf_title, y_train, y_cv = train_test_split(X_train_tfidf_t, y_train, t
est_size=0.33, stratify=y_train)
```

In [95]:

```
#splitting tfidf_w2v_vectors_title into train and test
X_train_tfidf_e, X_test_tfidf_e, y_train, y_test = train_test_split(tfidf_w2v_vectors_essay, y, tes
t_size=0.33, stratify=y)
X_train_tfidf_essay, X_cv_tfidf_essay, y_train, y_cv = train_test_split(X_train_tfidf_e, y_train, t
est_size=0.33, stratify=y_train)
```

Concatenation of all the vectorized data

In [96]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039

X_tr =
hstack((X_train_tfidf_essay,X_train_tfidf_title,X_train_state_ohe,X_train_teacher_ohe,X_train_grade
_ohe,X_train_category_ohe,X_train_subcategory_ohe,X_train_price_norm,X_train_post_norm,X_train_digi
t_norm,X_train_quantity_norm))
X_cr = hstack((X_cv_tfidf_essay,X_cv_tfidf_title,X_cv_state_ohe,X_cv_teacher_ohe,X_cv_grade_ohe,X_c
v_category_ohe,X_cv_subcategory_ohe,X_cv_price_norm,X_cv_post_norm,X_cv_digit_norm,X_cv_quantity_nc
rm))
X_te = hstack((X_test_tfidf_e,X_test_tfidf_t,X_test_state_ohe,X_test_teacher_ohe,X_test_grade_ohe,X
_test_category_ohe,X_test_subcategory_ohe,X_test_price_norm,X_test_post_norm,X_test_digit_norm,X_t
est_quantity_norm))

print("Final Data matrix")
print(X_tr.shape, y_train.shape)
print(X_cr.shape, y_cv.shape)
print(X_te.shape, y_test.shape)
print("="*100)
```

```
Final Data matrix
(22445, 701) (22445,)
(11055, 701) (11055,)
(16500, 701) (16500,)
====================================================================================================
```

In [97]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

SGD = linear_model.SGDClassifier(loss='hinge', learning_rate='optimal',
class_weight='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4],'penalty':['l1','l2']
}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

In [98]:

```
clf.best_params_
```

Out[98]:

```
{'alpha': 0.001, 'penalty': 'l1'}
```

As the best penalty is l1 , so we will use that and find the best alpha

In [99]:

```
SGD = linear_model.SGDClassifier(loss='hinge', penalty='l1', learning_rate='optimal', class_weight
='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4]}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

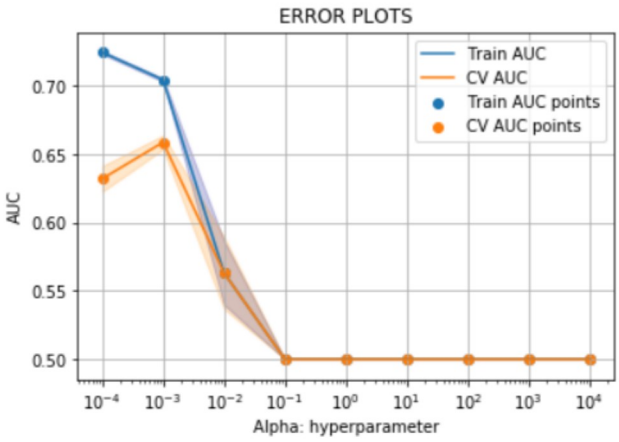
```
clf.best_params_
```

Out[100]:

```
{'alpha': 0.001}
```

In [101]:

```
plt.plot(parameters['alpha'], train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],train_auc - train_auc_std,train_auc +
train_auc_std,alpha=0.2,color='darkblue')

plt.plot(parameters['alpha'], cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color=
'darkorange')

plt.scatter(parameters['alpha'], train_auc, label='Train AUC points')
plt.scatter(parameters['alpha'], cv_auc, label='CV AUC points')
pyplot.xscale('log')

plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

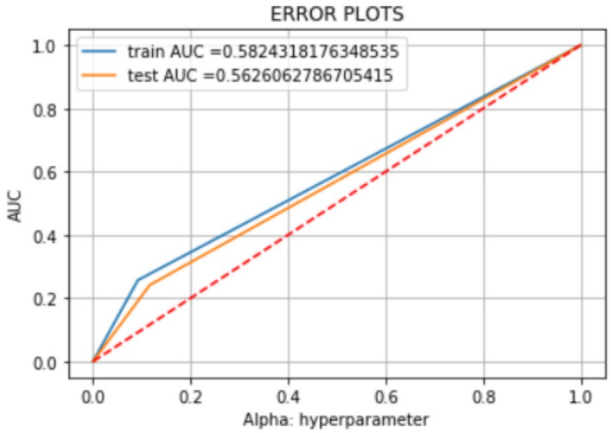


From the above graph we can see that for the value of alpha less than 0.001, it is over fitting the data and for the value of alpha more than 0.001, it is underfitting the data. So the best value of alpha will be 0.001 for this

In [102]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve

best_alpha = 0.001


SGD = linear_model.SGDClassifier(alpha=best_alpha, loss='hinge', penalty='l1', learning_rate='optim
al', class_weight='balanced',max_iter=2000, tol=1e-5)
SGD.fit(X_tr, y_train)

y_train_pred = SGD.predict(X_tr)

y_test_pred = SGD.predict(X_te)


train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)
```

```
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.plot([0, 1], [0, 1],'r--') #code copied from -https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



In [105]:

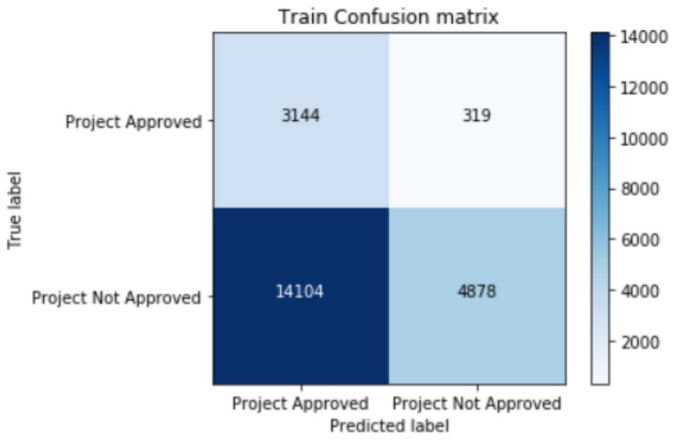
```
train_conf=confusion_matrix(y_train, predict(y_train_pred, tr_thresholds, train_fpr, train_fpr))
test_conf=confusion_matrix(y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_fpr))
```

```
the maximum value of tpr*(1-fpr) 0.08363118246278112 for threshold 1
the maximum value of tpr*(1-fpr) 0.10304551785250372 for threshold 1
```

In [106]:

```
plot_confusion_matrix(train_conf, classes=class_names,
                      title='Train Confusion matrix')
```

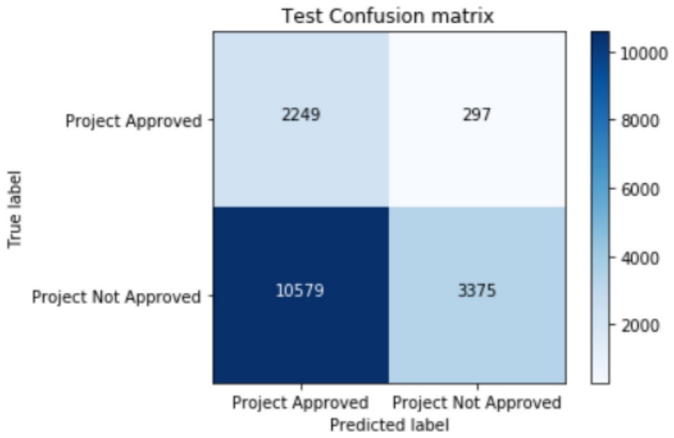
```
Confusion matrix, without normalization
[[ 3144   319]
 [14104  4878]]
```



In [107]:

```
plot_confusion_matrix(test_conf, classes=class_names,
                      title='Test Confusion matrix')
```

```
Confusion matrix, without normalization
[[ 2249   297]
```



Conclusion

On applying LinearSVM TFIDF W2V on DonorsChoose dataset with C value as 0.001 we got the AUC value of 0.56 on test data

LinearSVM with added Features `Set 5`

In [4]:

```
sub_title = list(X['clean_title'].values)
j=0
X['Title_Count']=0
for i in sub_title :
    count=1;
    for k in i:
        if(k==' '):
            count=count+1;
    X.loc[j,'Title_Count']=count
    j=j+1
```

In [5]:

```
sub_essay = list(X['clean_essay'].values)
j=0
X['Essay_Count']=0
for i in sub_essay :
    count=1;
    for k in i:
        if(k==' '):
            count=count+1;
    X.loc[j,'Essay_Count']=count
    j=j+1
```

In [6]:

```
#sentiment analysis python -- https://programminghistorian.org/en/lessons/sentiment-analysis
from nltk.sentiment.vader import SentimentIntensityAnalyzer
SIA = SentimentIntensityAnalyzer()
j=0
for i in sub_essay :
    scores = SIA.polarity_scores(i)
    X.loc[j,'Sentiment_Score']=scores['compound']
    j=j+1
```

In [7]:

```
X.tail(2)
```

	teacher_prefix	school_state	project_grade_category	teacher_number_of_previously_posted_projects	price	quar
49998	Mrs.	CT	Grades PreK-2	37	102.25	6
49999	Mrs.	KY	Grades PreK-2	0	505.43	41

Splitting Data

In [8]:

```
# train test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, stratify=y)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33, stratify=y_train)

print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)
```

```
(22445, 14) (22445,)
(11055, 14) (11055,)
(16500, 14) (16500,)
```

Normalizing the numerical features: Title_count

In [11]:

```
normalizer = Normalizer()
normalizer.fit(X_train['Title_Count'].values.reshape(1,-1))

X_train_tcount_norm = normalizer.transform(X_train['Title_Count'].values.reshape(1,-1)).T
X_cv_tcount_norm = normalizer.transform(X_cv['Title_Count'].values.reshape(1,-1)).T
X_test_tcount_norm = normalizer.transform(X_test['Title_Count'].values.reshape(1,-1)).T

print("After vectorizations")
print(X_train_tcount_norm.shape, y_train.shape)
print(X_cv_tcount_norm.shape, y_cv.shape)
print(X_test_tcount_norm.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
====================================================================================================
```

Normalizing the numerical features: Essay_count

In [12]:

```
normalizer = Normalizer()
normalizer.fit(X_train['Essay_Count'].values.reshape(1,-1))

X_train_ecount_norm = normalizer.transform(X_train['Essay_Count'].values.reshape(1,-1)).T
X_cv_ecount_norm = normalizer.transform(X_cv['Essay_Count'].values.reshape(1,-1)).T
```

```
print("After vectorizations")
print(X_train_ecount_norm.shape, y_train.shape)
print(X_cv_ecount_norm.shape, y_cv.shape)
print(X_test_ecount_norm.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
====================================================================================================
```

Normalizing the numerical features: Sentiment score

In [13]:

```
normalizer = Normalizer()
normalizer.fit(X_train['Sentiment_Score'].values.reshape(1,-1))

X_train_sent_norm = normalizer.transform(X_train['Sentiment_Score'].values.reshape(1,-1)).T
X_cv_sent_norm = normalizer.transform(X_cv['Sentiment_Score'].values.reshape(1,-1)).T
X_test_sent_norm = normalizer.transform(X_test['Sentiment_Score'].values.reshape(1,-1)).T

print("After vectorizations")
print(X_train_sent_norm.shape, y_train.shape)
print(X_cv_sent_norm.shape, y_cv.shape)
print(X_test_sent_norm.shape, y_test.shape)
print("="*100)
```

```
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
====================================================================================================
```

TFIDF vectorization of Clean Essay

In [14]:

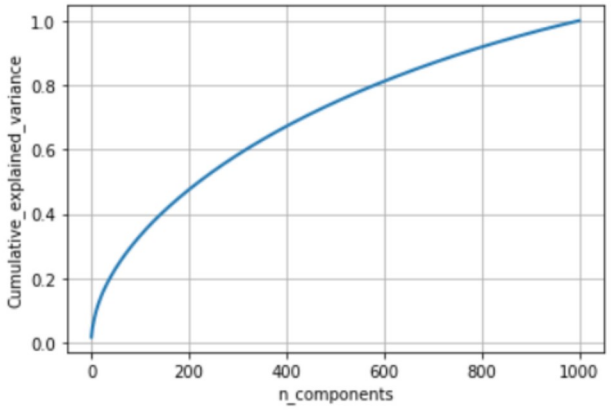
```
vec_essay = TfidfVectorizer(min_df=10)
vec_essay.fit(X_train['clean_essay'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_essay_tfidf = vec_essay.transform(X_train['clean_essay'].values)
X_cv_essay_tfidf = vec_essay.transform(X_cv['clean_essay'].values)
X_test_essay_tfidf = vec_essay.transform(X_test['clean_essay'].values)

print("After vectorizations")
print(X_train_essay_tfidf.shape, y_train.shape)
print(X_cv_essay_tfidf.shape, y_cv.shape)
print(X_test_essay_tfidf.shape, y_test.shape)
```

```
After vectorizations
(22445, 8799) (22445,)
(11055, 8799) (11055,)
(16500, 8799) (16500,)
```

In [16]:

```
pca = decomposition.PCA()
pca.n_components = 1000
pca_data = pca.fit_transform(X_train_essay_tfidf.todense())

percentage_var_explained = pca.explained_variance_ / np.sum(pca.explained_variance_);

cum_var_explained = np.cumsum(percentage_var_explained)
```

```
plt.figure(1, figsize=(6, 4))

plt.clf()
plt.plot(cum_var_explained, linewidth=2)
plt.axis('tight')
plt.grid()
plt.xlabel('n_components')
plt.ylabel('Cumulative_explained_variance')
plt.show()
```



from the above graph we can say that, we can choose 800 as the no of principal components as it explains more than 90% of the variance.

In [18]:

```
svd = TruncatedSVD(n_components=800, n_iter=7, random_state=42)
svd.fit(X_train_essay_tfidf)
X_train_essay_tfidf=svd.transform(X_train_essay_tfidf)
X_cv_essay_tfidf=svd.transform(X_cv_essay_tfidf)
X_test_essay_tfidf=svd.transform(X_test_essay_tfidf)

print("After vectorizations")
print(X_train_essay_tfidf.shape, y_train.shape)
print(X_cv_essay_tfidf.shape, y_cv.shape)
print(X_test_essay_tfidf.shape, y_test.shape)
```

```
After vectorizations
(22445, 800) (22445,)
(11055, 800) (11055,)
(16500, 800) (16500,)
```

Concatenation of all the vectorized data

In [30]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039

X_tr =
hstack((X_train_essay_tfidf,X_train_tcount_norm,X_train_ecount_norm,X_train_sent_norm,X_train_state
_ohe,X_train_teacher_ohe,X_train_grade_ohe,X_train_category_ohe,X_train_subcategory_ohe,X_train_pri
ce_norm,X_train_post_norm,X_train_digit_norm,X_train_quantity_norm))
X_cr = hstack((X_cv_essay_tfidf,X_cv_tcount_norm,X_cv_ecount_norm,X_cv_sent_norm,X_cv_state_ohe,X_c
v_teacher_ohe,X_cv_grade_ohe,X_cv_category_ohe,X_cv_subcategory_ohe,X_cv_price_norm,X_cv_post_norm
,X_cv_digit_norm,X_cv_quantity_norm))
X_te =
hstack((X_test_essay_tfidf,X_test_tcount_norm,X_test_ecount_norm,X_test_sent_norm,X_test_state_ohe
,X_test_teacher_ohe,X_test_grade_ohe,X_test_category_ohe,X_test_subcategory_ohe,X_test_price_norm,
X_test_post_norm,X_test_digit_norm,X_test_quantity_norm))

print("Final Data matrix")
print(X_tr.shape, y_train.shape)
print(X_cr.shape, y_cv.shape)
```

```
Final Data matrix
(22445, 904) (22445,)
(11055, 904) (11055,)
(16500, 904) (16500,)
==========================================================================================================
```

In [31]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

SGD = linear_model.SGDClassifier(loss='hinge', learning_rate='optimal',
class_weight='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4],'penalty':['l1','l2']
}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

In [32]:

```
clf.best_params_
```

Out[32]:

```
{'alpha': 0.0001, 'penalty': 'l1'}
```

As the best penalty is l1 , so we will use that and find the best alpha

In [33]:

```
SGD = linear_model.SGDClassifier(loss='hinge', penalty='l1', learning_rate='optimal', class_weight
='balanced',max_iter=2000, tol=1e-5)

parameters = {'alpha':[10**-4,10**-3,10**-2,10**-1,1,10**1,10**2,10**3,10**4]}
clf = GridSearchCV(SGD, parameters, cv=3, scoring='roc_auc')
clf.fit(X_tr, y_train)

train_auc= clf.cv_results_['mean_train_score']
train_auc_std= clf.cv_results_['std_train_score']
cv_auc = clf.cv_results_['mean_test_score']
cv_auc_std= clf.cv_results_['std_test_score']
```

In [34]:

```
clf.best_params_
```

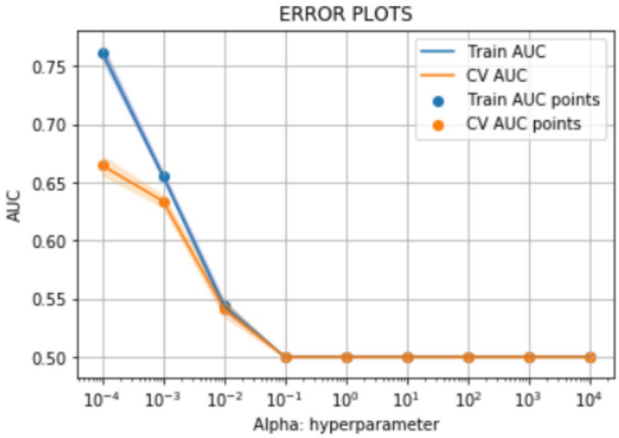
Out[34]:

```
{'alpha': 0.0001}
```

In [35]:

```
plt.plot(parameters['alpha'], train_auc, label='Train AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],train_auc - train_auc_std,train_auc +
train_auc_std,alpha=0.2,color='darkblue')

plt.plot(parameters['alpha'], cv_auc, label='CV AUC')
# this code is copied from here: https://stackoverflow.com/a/48803361/4084039
plt.gca().fill_between(parameters['alpha'],cv_auc - cv_auc_std,cv_auc + cv_auc_std,alpha=0.2,color=
'darkorange')
```

```
plt.scatter(parameters['alpha'], cv_auc, label='CV AUC points')
pyplot.xscale('log')

plt.legend()
plt.xlabel("Alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



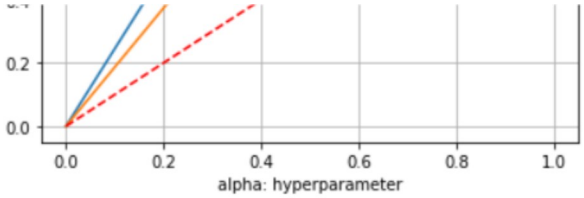
From the above graph we can see that for the value of alpha less than 0.0001, it is over fitting the data and for the value of alpha more than 0.0001, it is underfitting the data. So the best value of alpha will be 0.0001 for this

In [36]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve

best_alpha = 0.0001


SGD = linear_model.SGDClassifier(alpha=best_alpha, loss='hinge', penalty='l1', learning_rate='optim
al', class_weight='balanced',max_iter=2000, tol=1e-5)
SGD.fit(X_tr, y_train)

y_train_pred = SGD.predict(X_tr)

y_test_pred = SGD.predict(X_te)


train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)
```

In [37]:

```
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.plot([0, 1], [0, 1],'r--') #code copied from -https://stackoverflow.com/questions/25009284/how-
to-plot-roc-curve-in-python
plt.legend()
plt.xlabel("alpha: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



In [41]:

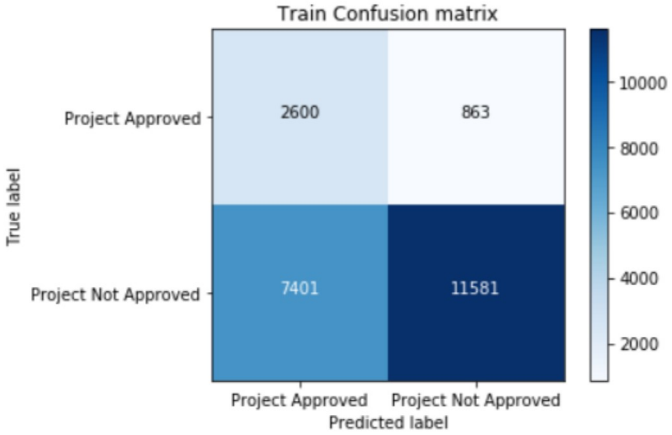
```
train_conf=confusion_matrix(y_train, predict(y_train_pred, tr_thresholds, train_fpr, train_fpr))
test_conf=confusion_matrix(y_test, predict(y_test_pred, tr_thresholds, test_fpr, test_fpr))
```

```
the maximum value of tpr*(1-fpr) 0.18710231481369527 for threshold 1
the maximum value of tpr*(1-fpr) 0.21931310701628912 for threshold 1
```

In [42]:

```
plot_confusion_matrix(train_conf, classes=class_names,
                      title='Train Confusion matrix')
```

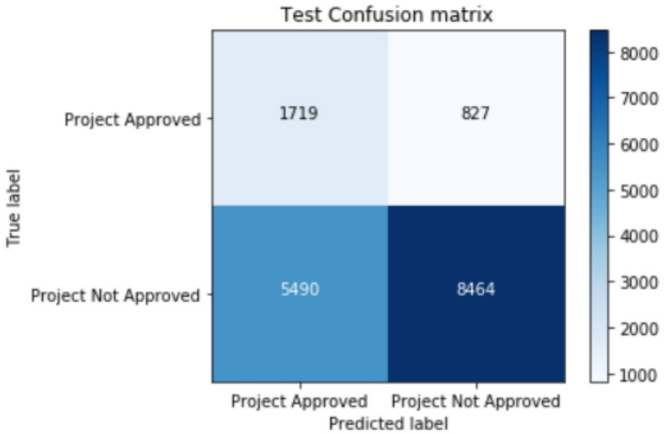
```
Confusion matrix, without normalization
[[ 2600   863]
 [ 7401 11581]]
```



In [43]:

```
plot_confusion_matrix(test_conf, classes=class_names,
                      title='Test Confusion matrix')
```

```
Confusion matrix, without normalization
[[1719  827]
 [5490 8464]]
```



Conclusion

On applying LinearSVM with added features on DonorsChoose dataset with C value as 0.0001 we got the AUC value of 0.64 on test data

In [25]:

```
#code copied from -http://zetcode.com/python/prettytable/

x = PrettyTable()
x.field_names = ["Vectorizer", "Hyper Parameter (alpha)","penalty", "AUC"]
x.add_row(["BOW",  0.01,"l2", 0.60])
x.add_row(["TFIDF",  0.001,"l2", 0.61])
x.add_row(["AVG W2V",  0.0001,"l1", 0.62])
x.add_row(["TFIDF W2V",  0.001,"l1", 0.56])
x.add_row(["Added features",  0.0001,"l1", 0.64])
print(x)
```

```
+---------------+------------------------+---------+------+
|   Vectorizer  | Hyper Parameter (alpha) | penalty | AUC  |
+---------------+------------------------+---------+------+
|      BOW      |          0.01          |    l2   | 0.6  |
|     TFIDF     |          0.001         |    l2   | 0.61 |
|    AVG W2V    |          0.0001        |    l1   | 0.62 |
|   TFIDF W2V   |          0.001         |    l1   | 0.56 |
| Added features |          0.0001        |    l1   | 0.64 |
+---------------+------------------------+---------+------+
```

Conclusion- The best vectorizer was found to be Added features while applying LinearSVM