DonorsChoose

DonorsChoose.org receives hundreds of thousands of project proposals each year for classroom projects in need of funding. Right now, a large number of volunteers is needed to manually screen each submission before it's approved to be posted on the DonorsChoose.org website.

Next year, DonorsChoose.org expects to receive close to 500,000 project proposals. As a result, there are three main problems they need to solve:

- How to scale current manual processes and resources to screen 500,000 projects so that they can be posted as quickly and as efficiently as possible
- · How to increase the consistency of project vetting across different volunteers to improve the experience for teachers
- How to focus volunteer time on the applications that need the most assistance

The goal of the competition is to predict whether or not a DonorsChoose.org project proposal submitted by a teacher will be approved, using the text of project descriptions as well as additional metadata about the project, teacher, and school. DonorsChoose.org can then use this information to identify projects most likely to need further review before approval.

About the DonorsChoose Data Set

The train.csv data set provided by DonorsChoose contains the following features:

Feature	Description	
project_id	A unique identifier for the proposed project. Example: p036502	
	Title of the project. Examples:	
project_title	• Art Will Make You Happy! • First Grade Fun	
	Grade level of students for which the project is targeted. One of the following enumerated values:	
<pre>project_grade_category</pre>	• Grades PreK-2 • Grades 3-5	
	• Grades 5-5 Grades 6-8	
	• Grades 9-12	
	One or more (comma-separated) subject categories for the project from the following enumerated list of values:	
	• Applied Learning	
	• Care & Hunger • Health & Sports	
	History & Civics	
	• Literacy & Language	
project subject categories	 Math & Science Music & The Arts 	
1 7 2 7 2 7	• Special Needs	
	• Warmth	
	Examples:	
	• Music & The Arts	
	• Literacy & Language, Math & Science	
school_state	State where school is located (Two-letter U.S. postal code). Example: WY	
	One or more (comma-separated) subject subcategories for the project. Examples :	
<pre>project_subject_subcategories</pre>	• Literacy	
	• Literature & Writing, Social Sciences	
	An explanation of the resources needed for the project. Example :	
<pre>project_resource_summary</pre>	My students need hands on literacy materials to manage sensory needs!	
<pre>project_resource_summary project_essay_1</pre>	My students need hands on literacy materials to manage sensory	
	My students need hands on literacy materials to manage sensory needs!	

e e	
Description Fourth application essay	Feature project_essay_4 _
Datetime when project application was submitted. Example: 2016-04-28 12:43:56.245	<pre>project_submitted_datetime</pre>
A unique identifier for the teacher of the proposed project. Example: bdf8baa8fedef6bfeec7ae4ff1c15c56	teacher_id
Teacher's title. One of the following enumerated values: nan Dr. Mrs. Mrs. Teacher.	teacher_prefix
Number of project applications previously submitted by the same teacher. Example: 2	teacher_number_of_previously_posted_projects

^{*} See the section **Notes on the Essay Data** for more details about these features.

Additionally, the resources.csv data set provides more data about the resources required for each project. Each line in this file represents a resource required by a project:

Feature	Description
id	A project_id value from the train.csv file. Example: p036502
description	Desciption of the resource. Example: Tenor Saxophone Reeds, Box of 25
quantity	Quantity of the resource required. Example: 3
price	Price of the resource required. Example: 9.95

Note: Many projects require multiple resources. The <code>id</code> value corresponds to a <code>project_id</code> in train.csv, so you use it as a key to retrieve all resources needed for a project:

The data set contains the following label (the value you will attempt to predict):

Label	Description
project is approved	A binary flag indicating whether DonorsChoose approved the project. A value of 0 indicates the project was not approved,
project_is_approved	and a value of 1 indicates the project was approved.

Notes on the Essay Data

Prior to May 17, 2016, the prompts for the essays were as follows:

- __project_essay_1:__ "Introduce us to your classroom"
- __project_essay_2:__ "Tell us more about your students"
- __project_essay_3:__ "Describe how your students will use the materials you're requesting"
- __project_essay_3:__ "Close by sharing why your project will make a difference"

Starting on May 17, 2016, the number of essays was reduced from 4 to 2, and the prompts for the first 2 essays were changed to the following:

- __project_essay_1:__ "Describe your students: What makes your students special? Specific details about their background, your neighborhood, and your school are all helpful."
- __project_essay_2:__ "About your project: How will these materials make a difference in your students' learning and improve their school lives?"

For all projects with project_submitted_datetime of 2016-05-17 and later, the values of project_essay_3 and project_essay_4 will be NaN.

In [1]:

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

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
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
```

1.1 Reading Data

```
In [2]:
project_data = pd.read_csv('train_data.csv')
resource_data = pd.read_csv('resources.csv')
In [3]:
project_data.shape
Out[3]:
(109248, 17)
In [4]:
project data=project data.sample(n=50000)
project data.shape
Out[4]:
(50000, 17)
In [5]:
project_data['project_is_approved'].value_counts()
Out[5]:
    42448
1
    7552
Name: project_is_approved, dtype: int64
In [6]:
resource data.shape
Out[6]:
(1541272, 4)
```

```
In [7]:
print("Number of data points in train data", project data.shape)
print('-'*50)
print("The attributes of data :", project data.columns.values)
Number of data points in train data (50000, 17)
The attributes of data: ['Unnamed: 0' 'id' 'teacher id' 'teacher prefix' 'school state'
 'project submitted datetime' 'project grade category'
 'project subject_categories' 'project_subject_subcategories'
 'project title' 'project essay 1' 'project essay 2' 'project essay 3'
 'project essay 4' 'project resource summary'
 'teacher_number_of_previously_posted_projects' 'project_is_approved']
In [8]:
# how to replace elements in list python: https://stackoverflow.com/a/2582163/4084039
cols = ['Date' if x=='project submitted datetime' else x for x in list(project data.columns)]
#sort dataframe based on time pandas python: https://stackoverflow.com/a/49702492/4084039
project_data['Date'] = pd.to_datetime(project_data['project_submitted_datetime'])
project data.drop('project submitted datetime', axis=1, inplace=True)
project data.sort values(by=['Date'], inplace=True)
# how to reorder columns pandas python: https://stackoverflow.com/a/13148611/4084039
project_data = project_data[cols]
project data.head(2)
Out[8]:
      Unnamed:
                    id
                                         teacher_id teacher_prefix school_state
                                                                            Date project_grade_category project_s
                                                                           2016-
  473
         100660 p234804 cbc0e38f522143b86d372f8b43d4cff3
                                                          Mrs.
                                                                     GΑ
                                                                           04-27
                                                                                        Grades PreK-2
                                                                         00:53:00
                                                                           2016-
23374
         72317 p087808 598621c141cda5fb184ee7e8ccdd3fcc
                                                          Ms.
                                                                      CA
                                                                           04-27
                                                                                        Grades PreK-2
                                                                         02:04:15
In [9]:
print("Number of data points in train data", resource data.shape)
print(resource data.columns.values)
resource data.head(2)
Number of data points in train data (1541272, 4)
['id' 'description' 'quantity' 'price']
Out[9]:
       id
                                       description quantity
                                                         price
              LC652 - Lakeshore Double-Space Mobile Drying
0 p233245
                                                      1 149.00
1 p069063
                Bouncy Bands for Desks (Blue support pipes)
                                                      3 14.95
```

1.2 preprocessing of project_subject_categories

```
print(project_data['project_subject_categories'].head(5))
                            Applied Learning
473
23374
                          Literacy & Language
7176
            Math & Science, Applied Learning
72593
          Literacy & Language, Math & Science
100222
                         Literacy & Language
Name: project subject categories, dtype: object
In [11]:
catogories = list(project data['project subject categories'].values)
# remove special characters from list of strings python:
https://stackoverflow.com/a/47301924/4084039
# https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
# https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
# https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python
cat list = []
for i in catogories:
   temp = ""
    # consider we have text like this "Math & Science, Warmth, Care & Hunger"
    for j in i.split(','): # it will split it in three parts ["Math & Science", "Warmth", "Care & L
unger"]
        if 'The' in j.split(): # this will split each of the catogory based on space "Math & Science"
e"=> "Math", "&", "Science"
            j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i
.e removing 'The')
       j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math &
Science"=>"Math&Science"
        temp+=j.strip()+" " #" abc ".strip() will return "abc", remove the trailing spaces
        temp = temp.replace('&','_') # we are replacing the & value into
    cat list.append(temp.strip())
project data['clean categories'] = cat list
project data.drop(['project subject categories'], axis=1, inplace=True)
from collections import Counter
my counter = Counter()
for word in project data['clean categories'].values:
   my_counter.update(word.split())
cat dict = dict(my counter)
sorted cat dict = dict(sorted(cat dict.items(), key=lambda kv: kv[1]))
                                                                                                |
In [12]:
print(project data['clean categories'].head(5))
473
                        AppliedLearning
23374
                      Literacy Language
7176
           Math Science AppliedLearning
72593
         Literacy_Language Math_Science
100222
                       Literacy Language
Name: clean_categories, dtype: object
1.3 preprocessing of project subject subcategories
```

```
In [13]:
```

```
In [14]:
```

```
sub catogories = list(project data['project subject subcategories'].values)
# remove special characters from list of strings python:
https://stackoverflow.com/a/47301924/4084039
# https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
# https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
# https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python
sub cat list = []
for i in sub catogories:
    temp = ""
    # consider we have text like this "Math & Science, Warmth, Care & Hunger"
    for j in i.split(','): # it will split it in three parts ["Math & Science", "Warmth", "Care & E
unger"]
       if 'The' in j.split(): # this will split each of the catogory based on space "Math & Science"
e"=> "Math","&", "Science"
            j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i
.e removing 'The')
       j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math &
Science"=>"Math&Science"
        temp +=j.strip()+" "#" abc ".strip() will return "abc", remove the trailing spaces
        temp = temp.replace('&',' ')
    sub_cat_list.append(temp.strip())
project_data['clean_subcategories'] = sub_cat_list
project_data.drop(['project_subject_subcategories'], axis=1, inplace=True)
# count of all the words in corpus python: https://stackoverflow.com/a/22898595/4084039
my counter = Counter()
for word in project data['clean subcategories'].values:
   my counter.update(word.split())
sub cat dict = dict(my counter)
sorted sub cat dict = dict(sorted(sub cat dict.items(), key=lambda kv: kv[1]))
4
                                                                                                 | b|
```

In [15]:

1.4 preprocessing of school_state

In [16]:

```
my_counter = Counter()
for word in project_data['school_state'].values:
    my_counter.update(word.split())

state_dict = dict(my_counter)
sorted_state_dict = dict(sorted(state_dict.items(), key=lambda kv: kv[1]))
```

In [17]:

```
1.5 preprocessing of project grade category
In [18]:
preproc = []
# tqdm is for printing the status bar
for sent in project_data['project_grade_category']:
   sent = sent.replace('Grades ', '')
sent = sent.replace('PreK-2', 'PreKto2')
    sent = sent.replace('3-5', '3to5')
   sent = sent.replace('6-8', '6to8')
   sent = sent.replace('9-12', '9to12')
    preproc.append(sent)
project data['project grade category']=preproc
In [19]:
my counter = Counter()
for word in project_data['project_grade_category'].values:
   my_counter.update(word.split())
grade_dict = dict(my_counter)
sorted_grade_dict = dict(sorted(grade_dict.items(), key=lambda kv: kv[1]))
In [20]:
print(project data['project grade category'].head(5))
        PreKto2
473
23374
         PreKto2
        PreKto2
7176
        PreKto2
72593
100222
           3to5
Name: project_grade_category, dtype: object
1.6 preprocessing of teacher prefix
In [21]:
print(type(project data['teacher prefix']))
<class 'pandas.core.series.Series'>
```

```
print(type(project_data['teacher_prefix']))

<class 'pandas.core.series.Series'>

In [22]:

project_data['teacher_prefix'] = project_data['teacher_prefix'].astype(str)
preproc = []
# tydm is for printing the status bar
for sent in project_data['teacher_prefix']:
    sent = sent.replace('Mr.', 'Mr')
    sent = sent.replace('Mrs.', 'Mrs')
    sent = sent.replace('Dr.', 'Dr')
    sent = sent.replace('Ms.', 'Ms')
    preproc.append(sent)
project_data['teacher_prefix']=preproc
```

```
#['Teacher', 'Mrs.', 'Dr.', 'Mr.', 'Ms.']
project_data['teacher_prefix']=project_data['teacher_prefix'].fillna('')
my_counter = Counter()
for word in project_data['teacher_prefix'].values:
    my_counter.update(word.split())

teacher_dict = dict(my_counter)
sorted_teacher_dict = dict(sorted(teacher_dict.items(), key=lambda kv: kv[1]))
```

In [23]:

1.3 Preprocessing of Essays

```
In [25]:
```

In [26]:

```
# https://stackoverflow.com/a/47091490/4084039
import re

def decontracted(phrase):
    # specific
    phrase = re.sub(r"won't", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

# general
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'t", " have", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'rm", " am", phrase)
    return phrase
```

In [27]:

```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
stopwords= ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've",
           "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his',
'himself', \
           'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
'their',\
           'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll",
'these', 'those', \
           'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having',
while', 'of', \
           'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during',
'before', 'after',\
           'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under'
, 'again', 'further',\
           'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', '\( \)
ach', 'few', 'more',\
           'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'very', \
           's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll'
, 'm', 'o', 're', \
           've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "do
           "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn',\
```

In [28]:

```
# Combining all the above stundents
from tqdm import tqdm
preprocessed_essays = []
# tqdm is for printing the status bar
for sentance in tqdm(project_data['essay'].values):
    sent = decontracted(sentance)
    sent = sent.replace('\\r', ' ')
    sent = sent.replace('\\"', ' ')
    sent = sent.replace('\\"', ' ')
    sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
    # https://gist.github.com/sebleier/554280
    sent = ' '.join(e for e in sent.split() if e.lower() not in stopwords)
    preprocessed_essays.append(sent.lower().strip())
```

In [29]:

```
# after preprocesing
preprocessed_essays[2000]
```

Out[29]:

'special education teacher small rural school district small 114 students grades 7 12 school school low income district majority students qualifying free reduced lunch programs three wonderful students autism need extra support technology bright learners need different form technology help successful classroom school purchased chromebooks students use classroom computers today learning working environment result school work done google classroom completely paper free way learning good equalizer special education students due amount electronic supports available computers three wond erful students students autism not able stay focused task online regular computer want right thing disability prevents pulling students computers not option three need access technology progress academically three need different type technology successful ipad pro comes still nice large screen students chromebooks gives additional controls able use guided access feature help focus guided access helps students autism attention sensory challenges stay task able limit ios device stay task disabling home button even restrict touch input certain areas screen wandering taps gestures distract learning ipad pro nice large screen keyboard help one students difficulty fine motor skills tremendously numerous ios apps would like use students help support educational social emotional development ipad pro would help please help special learners achieve full potential nannan'

```
In [30]:
```

```
project_data['essay']=preprocessed_essays
```

1.4 Preprocessing of `project_title`

In [31]:

```
# similarly you can preprocess the titles also
preprocessed_titles = []
# tqdm is for printing the status bar
for sentence in tqdm(project_data['project_title'].values):
    sent = decontracted(sentence)
    sent = sent.replace('\\r', '')
    sent = sent.replace('\\r', '')
    sent = sent.replace('\\r', '')
    sent = re.sub('[^A-Za-z0-9]+', '', sent)
# https://gist.github.com/sebleier/554280
    sent = ''.join(e for e in sent.split() if e not in stopwords)
    preprocessed_titles.append(sent.lower().strip())
```

```
In [32]:
```

```
project_data['project_title']=preprocessed_titles
```

Sentiment Analysis of essays

```
In [33]:
import nltk
nltk.downloader.download('vader lexicon')
from nltk.sentiment.vader import SentimentIntensityAnalyzer
analyser = SentimentIntensityAnalyzer()
neg = []
pos = []
neu = []
compound = []
for a in tqdm(project_data["essay"]) :
   b = analyser.polarity_scores(a)['neg']
    c = analyser.polarity_scores(a)['pos']
    d = analyser.polarity_scores(a)['neu']
    e = analyser.polarity_scores(a)['compound']
    neg.append(b)
    pos.append(c)
    neu.append(d)
    compound.append(e)
[nltk data] Downloading package vader lexicon to
[nltk_data] /home/samthekiller/nltk_data...
[nltk_data] Package vader_lexicon is already up-to-date!
100%| 50000/50000 [05:13<00:00, 159.67it/s]
In [34]:
project_data["pos"] = pos
```

```
In [35]:

project_data["neg"] = neg
```

```
In [36]:

project_data["neu"] = neu
```

```
In [37]:

project_data["compound"] = compound
```

Number of Words in Title

```
In [38]:

title_word_count = []

for a in project_data["project_title"] :
    b = len(a.split())
    title_word_count.append(b)

project_data["title_word_count"] = title_word_count
```

Number of Words in Essays

```
In [39]:
```

```
for a in project_data["essay"] :
    b = len(a.split())
    essay_word_count.append(b)

project_data["essay_word_count"] = essay_word_count
```

```
1.5 Preparing data for models
In [40]:
project data.columns
Out[40]:
Index(['Unnamed: 0', 'id', 'teacher_id', 'teacher_prefix', 'school_state',
        'Date', 'project_grade_category', 'project_title', 'project_essay_1',
        'project_essay_2', 'project_essay_3', 'project_essay_4',
        'project_resource_summary',
        'teacher_number_of_previously_posted_projects', 'project_is_approved',
        'clean categories', 'clean_subcategories', 'essay', 'pos', 'neg', 'neu',
        'compound', 'title_word_count', 'essay_word_count'],
      dtype='object')
we are going to consider
 school_state : categorical data
 clean_categories : categorical data
 · clean subcategories : categorical data
 • project_grade_category : categorical data
 · teacher prefix: categorical data
 · project title: text data
 · text: text data
 • project resource summary: text data (optinal)
 · quantity: numerical (optinal)
 • teacher number of previously posted projects : numerical
 · price: numerical
In [41]:
# 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', 'rb') as f:
    model = pickle.load(f,encoding = "ISO-8859-1")
```

Assignment 7: SVM

glove words = set(model.keys())

- 1. [Task-1] Apply Support Vector Machines(SGDClassifier with hinge loss: Linear SVM) on these feature sets
 - Set 1: categorical, numerical features + project_title(BOW) + preprocessed_eassay (BOW)
 - Set 2: categorical, numerical features + project_title(TFIDF)+ preprocessed_eassay (TFIDF)
 - Set 3: categorical, numerical features + project title(AVG W2V)+ preprocessed eassay (AVG W2V)
 - Set 4: categorical, numerical features + project_title(TFIDF W2V)+ preprocessed_eassay (TFIDF W2V)
- 2. The hyper paramter tuning (best alpha in range [10^-4 to 10^4], and the best penalty among 'I1', 'I2')
 - Find the best hyper parameter which will give the maximum AUC value
 - Find the best hyper paramter using k-fold cross validation or simple cross validation data
 - Use gridsearch cv or randomsearch cv or you can also write your own for loops to do this task of hyperparameter tuning
- 3. Representation of results

- You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown
 in the figure.
- Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.
- Along with plotting ROC curve, you need to print the <u>confusion matrix</u> with predicted and original labels of test data points. Please visualize your confusion matrices using <u>seaborn heatmaps</u>.
- 4. [Task-2] Apply the Support Vector Machines on these features by finding the best hyper paramter as suggested in step 2 and step 3
 - Consider these set of features Set 5:
 - school state : categorical data
 - clean_categories : categorical data
 - clean_subcategories : categorical data
 - project_grade_category :categorical data
 - teacher_prefix : categorical data
 - quantity : numerical data
 - teacher_number_of_previously_posted_projects : numerical data
 - price : numerical data
 - sentiment score's of each of the essay : numerical data
 - number of words in the title : numerical data
 - number of words in the combine essays : numerical data
 - Apply TruncatedSVD on <u>TfidfVectorizer</u> of essay text, choose the number of components (`n_components`) using <u>elbow method</u>: numerical data
 - Conclusion
 - You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table
 please refer to this prettytable library link

Note: Data Leakage

- 1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
- 2. To avoid the issue of data-leakag, make sure to split your data first and then vectorize it.
- 3. While vectorizing your data, apply the method fit_transform() on you train data, and apply the method transform() on cv/test data.
- 4. For more details please go through this link.

2. Support Vector Machines

2.1 Splitting data into Train and cross validation(or test): Stratified Sampling

```
In [42]:
y = project_data['project_is_approved']
print(y.shape)

(50000,)

In [43]:
project_data.drop(['project_is_approved'],axis=1,inplace=True)

In [44]:
X=project_data
```

print (X.shape)

```
In [45]:
#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)
2.2 Make Data Model Ready: encoding eassay, and project_title
In [46]:
print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)
print("="*100)
(22445, 23) (22445,)
(11055, 23) (11055,)
(16500, 23) (16500,)
Encoding of Text Data
In [47]:
from sklearn.feature extraction.text import CountVectorizer
BOW of Essay
In [48]:
vectorizer = CountVectorizer(min df=10,ngram range=(1,4), max features=5000)
In [49]:
vectorizer.fit(X train['essay'].values) # fit has to happen only on train data
Out[49]:
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=5000, min_df=10,
       ngram_range=(1, 4), preprocessor=None, stop_words=None,
        strip accents=None, token pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
In [50]:
# we use the fitted CountVectorizer to convert the text to vector
X_train_essay_bow = vectorizer.transform(X_train['essay'].values)
In [51]:
X cv essay bow = vectorizer.transform(X cv['essay'].values)
In [52]:
X test essay bow = vectorizer.transform(X test['essay'].values)
In [53]:
```

print("After vectorizations")

nrint (Y train essau how shane v train shane)

```
httiic/v_cratii_essal_nom.suahe, la_cratii.suahe)
print(X_cv_essay_bow.shape, y_cv.shape)
print(X test essay bow.shape, y test.shape)
print("="*100)
After vectorizations
(22445, 5000) (22445,)
(11055, 5000) (11055,)
(16500, 5000) (16500,)
BOW of Title
In [54]:
vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
In [55]:
vectorizer.fit(X train['project title'].values) # fit has to happen only on train data
Out[55]:
CountVectorizer(analyzer='word', binary=False, decode error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max df=1.0, max features=5000, min df=10,
        ngram_range=(1, 4), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
In [56]:
# we use the fitted CountVectorizer to convert the text to vector
X train title bow = vectorizer.transform(X train['project title'].values)
In [57]:
X cv title bow = vectorizer.transform(X cv['project title'].values)
In [58]:
X_test_title_bow = vectorizer.transform(X_test['project_title'].values)
In [59]:
print("After vectorizations")
print(X_train_title_bow.shape, y_train.shape)
print(X cv title bow.shape, y cv.shape)
print(X test title_bow.shape, y_test.shape)
print("="*100)
After vectorizations
(22445, 2004) (22445,)
(11055, 2004) (11055,)
(16500, 2004) (16500,)
TFIDF of Essay
In [60]:
vectorizer = TfidfVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
```

```
In [61]:
vectorizer.fit(X train['essay'].values) # fit has to happen only on train data
Out[61]:
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.float64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=5000, min_df=10,
        ngram range=(1, 4), norm='12', preprocessor=None, smooth idf=True,
        stop words=None, strip accents=None, sublinear tf=False,
        token pattern='(?u)\\b\\w\\b', tokenizer=None, use idf=True,
        vocabulary=None)
In [62]:
# we use the fitted CountVectorizer to convert the text to vector
X train essay tfidf = vectorizer.transform(X train['essay'].values)
In [63]:
X cv essay tfidf = vectorizer.transform(X cv['essay'].values)
In [64]:
X test essay tfidf = vectorizer.transform(X test['essay'].values)
In [65]:
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)
print("="*100)
After vectorizations
(22445, 5000) (22445,)
(11055, 5000) (11055,)
(16500, 5000) (16500,)
TFIDF of Title
In [66]:
vectorizer = TfidfVectorizer(min df=10,ngram range=(1,4), max features=5000)
vectorizer.fit(X train['project title'].values) # fit has to happen only on train data
Out [671:
TfidfVectorizer(analyzer='word', binary=False, decode error='strict',
        dtype=<class 'numpy.float64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=5000, min_df=10,
        ngram range=(1, 4), norm='12', preprocessor=None, smooth idf=True,
        stop_words=None, strip_accents=None, sublinear_tf=False,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, use_idf=True,
        vocabulary=None)
In [68]:
# we use the fitted CountVectorizer to convert the text to vector
X train title tfidf = vectorizer.transform(X train['project title'].values)
```

```
X_cv_title_tfidf = vectorizer.transform(X_cv['project_title'].values)
In [70]:
X_test_title_tfidf = vectorizer.transform(X_test['project_title'].values)
In [71]:
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)
print("="*100)
After vectorizations
(22445, 2004) (22445,)
(11055, 2004) (11055,)
(16500, 2004) (16500,)
Avg W2V of Essay
In [72]:
# average Word2Vec
# compute average word2vec for each essay.
avg w2v essay train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train['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_essay_train.append(vector)
print(len(avg w2v essay train))
print(len(avg w2v essay train[0]))
print(type(avg_w2v_essay_train))
100%| 22445/22445 [00:05<00:00, 3876.37it/s]
22445
300
<class 'list'>
In [73]:
# average Word2Vec
# compute average word2vec for each essay.
avg_w2v_essay_test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_test['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
```

In [69]:

if cnt words != 0:

print(len(avg_w2v_essay_test))

vector /= cnt_words
avg_w2v_essay_test.append(vector)

```
print(ten(avg_wzv_essay_test[0]))
print(type(avg_w2v_essay_test))

100%| 16500/16500 [00:04<00:00, 3793.06it/s]

16500
300
<class 'list'>
```

```
In [74]:
# average Word2Vec
# compute average word2vec for each essay.
avg w2v essay cv = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_cv['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_essay_cv.append(vector)
print(len(avg w2v essay cv))
print(len(avg w2v essay cv[0]))
print(type(avg_w2v_essay_cv))
100%| 100%| 11055/11055 [00:02<00:00, 3868.16it/s]
11055
300
<class 'list'>
```

Avg W2V of Title

In [75]:

```
# average Word2Vec
# compute average word2vec for each essay.
avg_w2v_title_train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train['project 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 title train.append(vector)
print(len(avg w2v title train))
print(len(avg_w2v_title_train[0]))
print(type(avg_w2v_title_train))
100%| 22445/22445 [00:00<00:00, 64788.21it/s]
22445
300
<class 'list'>
```

```
# average Word2Vec
# compute average word2vec for each essay.
avg w2v title test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X test['project 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 title test.append(vector)
print(len(avg w2v title test))
print(len(avg w2v title test[0]))
print(type(avg_w2v_title_test))
100%| 16500/16500 [00:00<00:00, 62770.59it/s]
16500
<class 'list'>
```

In [77]:

```
# average Word2Vec
# compute average word2vec for each essay.
avg_w2v_title_cv = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X cv['project 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_title_cv.append(vector)
print(len(avg w2v title cv))
print(len(avg w2v title cv[0]))
print(type(avg_w2v_title cv))
100%| 11055/11055 [00:00<00:00, 66241.65it/s]
11055
300
<class 'list'>
```

TFIDF-W2V of Essay

```
In [78]:
```

```
tfidf_model = TfidfVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
tfidf_model.fit(X_train['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 [79]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_train_essay = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_train['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())))
           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 train essay.append(vector)
print(len(tfidf w2v train essay))
print(len(tfidf w2v train essay[0]))
100%| 22445/22445 [00:36<00:00, 612.16it/s]
```

22445 300

In [80]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v test essay = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm (X test['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())))
           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 test essay.append(vector)
print(len(tfidf w2v test essay))
print(len(tfidf w2v test essay[0]))
100%| 16500/16500 [00:24<00:00, 667.19it/s]
```

16500 300

In [81]:

11055 300

TFIDF-W2V of Title

```
In [82]:
```

```
tfidf_model = TfidfVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
tfidf_model.fit(X_train['project_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 [83]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v train title = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train['project 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 train title.append(vector)
print(len(tfidf w2v train title))
print(len(tfidf w2v train title[0]))
100%| 22445/22445 [00:00<00:00, 30193.50it/s]
```

22445 300

In [84]:

```
tf_idf_weight += tf_idf
if tf_idf_weight != 0:
    vector /= tf_idf_weight
    tfidf_w2v_test_title.append(vector)

print(len(tfidf_w2v_test_title))
print(len(tfidf_w2v_test_title[0]))

100%| | 16500/16500 [00:00<00:00, 29088.69it/s]</pre>
```

```
In [85]:
```

```
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_cv_title = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X cv['project 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 cv title.append(vector)
print(len(tfidf w2v cv title))
print(len(tfidf_w2v_cv_title[0]))
100%| 11055/11055 [00:00<00:00, 25255.36it/s]
11055
300
```

2.3 Make Data Model Ready: encoding numerical and categorical features

Vectorizing Numerical features

```
In [86]:

price_data = resource_data.groupby('id').agg({'price':'sum', 'quantity':'sum'}).reset_index()

In [87]:

price_data.head(5)

Out[87]:
```

	id	price	quantity
0	p000001	459.56	7
1	p000002	515.89	21
2	p000003	298.97	4
3	p000004	1113.69	98
A	5000005	40E 00	0

```
4 μυυυυυο
            price quantity
In [88]:
X train=pd.merge(X train,price data,on='id',how='left')
X_test=pd.merge(X_test,price_data,on='id',how='left')
X_cv=pd.merge(X_cv,price_data,on='id',how='left')
In [89]:
X train=X train.fillna(0)
X cv=X cv.fillna(0)
X test=X test.fillna(0)
Normalizing the numerical features: Price
In [90]:
from sklearn.preprocessing import Normalizer
```

```
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))
X cv price norm = normalizer.transform(X cv['price'].values.reshape(-1,1))
X test price norm = normalizer.transform(X test['price'].values.reshape(-1,1))
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,)

Normalizing the numerical features: Number of previously posted projects

```
In [91]:
```

```
normalizer = Normalizer()
normalizer.fit(X train['teacher number of previously posted projects'].values.reshape(-1,1))
X train project norm = normalizer.transform(X train['teacher number of previously posted projects'
].values.reshape(-1,1))
X cv project norm = normalizer.transform(X cv['teacher number of previously posted projects'].valu
es.reshape(-1,1))
X test project norm = normalizer.transform(X test['teacher number of previously posted projects'].
values.reshape(-1,1))
print("After vectorizations")
print(X train project norm.shape, y train.shape)
print(X cv project norm.shape, y cv.shape)
print(X_test_project_norm.shape, y_test.shape)
print("="*100)
```

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

4 **▶**

Normalizing the numerical features: Title word Count

```
In [92]:
```

```
normalizer = Normalizer()
normalizer.fit(X_train['title_word_count'].values.reshape(-1,1))
X_train_title_norm = normalizer.transform(X_train['title_word_count'].values.reshape(-1,1))
X_cv_title_norm = normalizer.transform(X_cv['title_word_count'].values.reshape(-1,1))
X_test_title_norm = normalizer.transform(X_test['title_word_count'].values.reshape(-1,1))
print("After vectorizations")
print(X_train_title_norm.shape, y_train.shape)
print(X_cv_title_norm.shape, y_cv.shape)
print(X_test_title_norm.shape, y_test.shape)
print("="*100)
```

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

Normalizing the numerical features: Essay word Count

```
In [93]:
```

```
normalizer = Normalizer()
normalizer.fit(X_train['essay_word_count'].values.reshape(-1,1))
X_train_essay_norm = normalizer.transform(X_train['essay_word_count'].values.reshape(-1,1))
X_cv_essay_norm = normalizer.transform(X_cv['essay_word_count'].values.reshape(-1,1))
X_test_essay_norm = normalizer.transform(X_test['essay_word_count'].values.reshape(-1,1))
print("After vectorizations")
print(X_train_essay_norm.shape, y_train.shape)
print(X_cv_essay_norm.shape, y_cv.shape)
print(X_test_essay_norm.shape, y_test.shape)
print("="*100)
```

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

Normalizing the numerical features: Essay Sentiments-Positive

```
In [94]:
```

```
normalizer = Normalizer()
normalizer.fit(X_train['pos'].values.reshape(-1,1))
essay_sent_pos_train = normalizer.transform(X_train['pos'].values.reshape(-1,1))
essay_sent_pos_cv = normalizer.transform(X_cv['pos'].values.reshape(-1,1))
essay_sent_pos_test = normalizer.transform(X_test['pos'].values.reshape(-1,1))
print("After vectorizations")
print(essay_sent_pos_train.shape, y_train.shape)
print(essay_sent_pos_cv.shape, y_cv.shape)
print(essay_sent_pos_test.shape, y_test.shape)
print("="*100)
```

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

```
In [95]:
normalizer = Normalizer()
normalizer.fit(X train['neg'].values.reshape(-1,1))
essay sent neg train = normalizer.transform(X train['neg'].values.reshape(-1,1))
essay_sent_neg_cv = normalizer.transform(X_cv['neg'].values.reshape(-1,1))
essay_sent_neg_test = normalizer.transform(X_test['neg'].values.reshape(-1,1))
print("After vectorizations")
print(essay sent neg train.shape, y train.shape)
print(essay_sent_neg_cv.shape, y_cv.shape)
print(essay_sent_neg_test.shape, y_test.shape)
print("="*100)
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
______
Normalizing the numerical features: Essay Sentiments-Neutral
In [96]:
normalizer = Normalizer()
normalizer.fit(X train['neu'].values.reshape(-1,1))
essay sent neu train = normalizer.transform(X train['neu'].values.reshape(-1,1))
essay sent neu cv = normalizer.transform(X cv['neu'].values.reshape(-1,1))
essay sent neu test = normalizer.transform(X test['neu'].values.reshape(-1,1))
print("After vectorizations")
print(essay sent neu train.shape, y train.shape)
print(essay_sent_neu_cv.shape, y_cv.shape)
print(essay sent neu test.shape, y test.shape)
print("="*100)
After vectorizations
(22445, 1) (22445,)
(11055, 1) (11055,)
(16500, 1) (16500,)
Normalizing the numerical features: Essay Sentiments-Compound
In [97]:
normalizer = Normalizer()
normalizer.fit(X train['compound'].values.reshape(-1,1))
essay_sent_comp_train = normalizer.transform(X_train['compound'].values.reshape(-1,1))
essay sent comp cv = normalizer.transform(X cv['compound'].values.reshape(-1,1))
essay sent comp test = normalizer.transform(X test['compound'].values.reshape(-1,1))
print("After vectorizations")
print(essay_sent_comp_train.shape, y_train.shape)
print(essay_sent_comp_cv.shape, y_cv.shape)
```

```
print(essay sent comp test.shape, y test.shape)
print("="*100)
After vectorizations
(22445, 1) (22445,)
```

(11055, 1) (11055,) (16500, 1) (16500,)

Vectorizing Categorical features

- · school_state : categorical data
- alaan aataaariaa Laataaariaal data

```
    clean_categories : categorical data
    clean_subcategories : categorical data
    project_grade_category : categorical data
    teacher_prefix : categorical data
```

Vectorizing Categorical features: project grade category

```
In [98]:
from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(vocabulary=list(sorted grade dict.keys()), lowercase=False, binary=Tr
vectorizer.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 = vectorizer.transform(X train['project grade category'].values)
X_cv_grade_ohe = vectorizer.transform(X_cv['project_grade_category'].values)
X_test_grade_ohe = vectorizer.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(vectorizer.get feature names())
print("="*100)
After vectorizations
(22445, 4) (22445,)
(11055, 4) (11055,)
(16500, 4) (16500,)
['9to12', '6to8', '3to5', 'PreKto2']
_____
```

Vectorizing Categorical features: teacher prefix

```
In [100]:
vectorizer = CountVectorizer(vocabulary=list(sorted teacher dict.keys()), lowercase=False, binary=
True)
vectorizer.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 = vectorizer.transform(X train['teacher prefix'].values)
X cv teacher ohe = vectorizer.transform(X cv['teacher prefix'].values)
X_test_teacher_ohe = vectorizer.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(vectorizer.get feature names())
print("="*100)
After vectorizations
(22445, 6) (22445,)
(11055, 6) (11055,)
(16500, 6) (16500,)
['nan', 'Dr', 'Teacher', 'Mr', 'Ms', 'Mrs']
```

Vectorizing Categorical features: school state

```
vectorizer = CountVectorizer(vocabulary=list(sorted state dict.keys()), lowercase=False, binary=Tr
ue)
vectorizer.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 = vectorizer.transform(X train['school state'].values)
X cv state ohe = vectorizer.transform(X cv['school state'].values)
X test state ohe = vectorizer.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(vectorizer.get feature names())
print("="*100)
After vectorizations
(22445, 51) (22445,)
(11055, 51) (11055,)
(16500, 51) (16500,)
['WY', 'VT', 'ND', 'MT', 'SD', 'RI', 'NE', 'DE', 'AK', 'NH', 'ME', 'WV', 'HI', 'NM', 'DC', 'KS', 'I
A', 'ID', 'CO', 'AR', 'MN', 'OR', 'KY', 'NV', 'MS', 'MD', 'CT', 'UT', 'TN', 'AL', 'WI', 'VA', 'AZ',
'NJ', 'OK', 'MA', 'WA', 'LA', 'OH', 'MO', 'IN', 'PA', 'MI', 'SC', 'GA', 'IL', 'NC', 'FL', 'NY', 'TX
', 'CA'l
4
```

Vectorizing Categorical features: clean categories

In [102]:

```
vectorizer = CountVectorizer(vocabulary=list(sorted_cat_dict.keys()), lowercase=False, binary=True
)
vectorizer.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_cat_ohe = vectorizer.transform(X_train['clean_categories'].values)
X_cv_cat_ohe = vectorizer.transform(X_cv['clean_categories'].values)
X_test_cat_ohe = vectorizer.transform(X_test['clean_categories'].values)

print("After vectorizations")
print(X_train_cat_ohe.shape, y_train.shape)
print(X_cv_cat_ohe.shape, y_test.shape)
print(X_test_cat_ohe.shape, y_test.shape)
print(vectorizer.get_feature_names())
print("="*100)
After vectorizations
```

```
After vectorizations
(22445, 9) (22445,)
(11055, 9) (11055,)
(16500, 9) (16500,)
['Warmth', 'Care_Hunger', 'History_Civics', 'Music_Arts', 'AppliedLearning', 'SpecialNeeds',
'Health_Sports', 'Math_Science', 'Literacy_Language']
```

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Vectorizing Categorical features: clean subcategories

```
In [103]:
```

4

```
vectorizer = CountVectorizer(vocabulary=list(sorted_sub_cat_dict.keys()), lowercase=False, binary=
True)
vectorizer.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_sub_ohe = vectorizer.transform(X_train['clean_subcategories'].values)
X_cv_sub_ohe = vectorizer.transform(X_cv['clean_subcategories'].values)
X_test_sub_ohe = vectorizer.transform(X_test['clean_subcategories'].values)
print("After vectorizations")
print(X_train_sub_ohe_shape, v_train_shape)
```

```
print(X_cv_sub_ohe.shape, y_cv.shape)
print(X_test_sub_ohe.shape, y_test.shape)
print(vectorizer.get_feature_names())
print("="*100)

After vectorizations
(22445, 30) (22445,)
(11055, 30) (11055,)
(16500, 30) (16500,)
['Economics', 'CommunityService', 'FinancialLiteracy', 'ParentInvolvement', 'Civics_Government', 'Extracurricular', 'ForeignLanguages', 'NutritionEducation', 'Warmth', 'Care_Hunger', 'SocialSciences', 'PerformingArts', 'TeamSports', 'CharacterEducation', 'Other', 'College_CareerPrep', 'Music', 'History_Geography', 'EarlyDevelopment', 'Health_LifeScience', 'ESL', 'Gym_Fitness', 'EnvironmentalScience', 'VisualArts', 'Health_Wellness', 'AppliedSciences', 'SpecialNeeds', 'Literature_Writing', 'Mathematics', 'Literacy']
```

Applying SVM on BOW, SET 1

Creating Data Matrix

```
In [104]:
```

```
# Please write all the code with proper documentation
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_tr = hstack((X_train_essay_bow, X_train_title_bow, X_train_state_ohe, X_train_teacher_ohe,
X_train_grade_ohe,X_train_cat_ohe,X_train_sub_ohe, X_train_price_norm,X_train_project_norm)).tocsr
X cr = hstack((X cv essay bow, X cv title bow, X cv state ohe, X cv teacher ohe, X cv grade ohe, X cv
cat ohe, X cv sub ohe, X cv price norm, X cv project norm)).tocsr()
X te = hstack((X test essay bow, X test title bow, X test state ohe, X test teacher ohe, X test grad
e ohe, X test cat ohe, X test sub ohe, X test price norm, X test project norm)).tocsr()
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, 7106) (22445,)
(11055, 7106) (11055,)
(16500, 7106) (16500,)
```

11 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

```
In [105]:
```

```
def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
tive class
    # not the predicted outputs

y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your cr_loop will be 49041 - 49041%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
# we will be predicting for the last data points
```

```
y_data_pred.extend(c1f.pred1ct_proba(data[tr_100p:])[:,1])
return y_data_pred
```

```
In [106]:
```

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc auc score
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
train_auc = []
cv auc = []
log alphas=[]
parameters = { 'alpha': [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 1
0**4]}
for i in tqdm(parameters['alpha']):
   sgd = SGDClassifier(alpha=i, penalty='11', loss='hinge',random_state = 0 ,class_weight = 'balan
    clf_s = CalibratedClassifierCV(sgd, method='sigmoid')
    clf_s.fit(X_tr, y_train)
    y train pred = batch predict(clf s, X tr)
   y_cv_pred = batch_predict(clf_s, X_cr)
    train auc.append(roc auc score(y train, y train pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
100%| 11/11 [00:05<00:00, 2.32it/s]
```

In [107]:

 $[-6.0,\ -5.0,\ -4.0,\ -3.0,\ -2.0,\ -1.0,\ 0.0,\ 1.0,\ 2.0,\ 3.0,\ 4.0]$

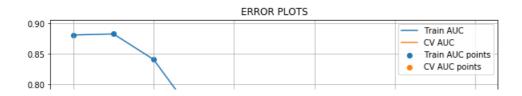
In [108]:

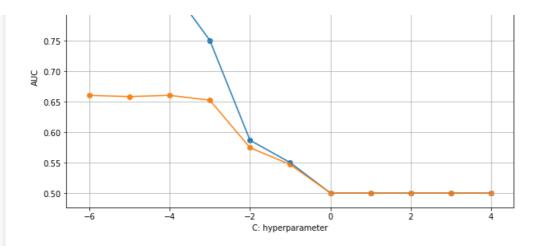
```
plt.clf()
plt.figure(figsize=(10,6))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

plt.legend()
plt.xlabel("C: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.color = '#FFFFFF'
plt.grid()
plt.show()
```

<Figure size 432x288 with 0 Axes>





In [109]:

```
best_k=0.0001
```

Train The Model

In [110]:

```
from sklearn.metrics import roc_curve, auc

neigh = SGDClassifier(alpha=best_k, penalty='ll', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')

clf_s = CalibratedClassifierCV(neigh, method='sigmoid')

clf_s.fit(X_tr, y_train)

# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class

# not the predicted outputs

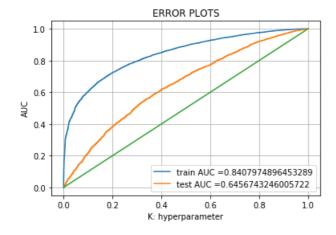
y_train_pred = batch_predict(clf_s, X_tr)
y_test_pred = batch_predict(clf_s, X_te)

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)

x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
```

In [111]:

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



Confusion Matrix

```
In [112]:
```

In [113]:

```
print("Train confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_fpr,train_fpr)),range(2),range(2))
sns.set(font_scale=1) #for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.24999991298370186 for threshold 0.803

Out[113]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f3553cf6198>



In [114]:

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix

the maximum value of tpr*(1-fpr) 0.25 for threshold 0.816

Out[114]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3553d277b8>



12 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

In [115]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc auc score
from sklearn.linear_model import SGDClassifier
from sklearn.model selection import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV
y true : array, shape = [n samples] or [n samples, n classes]
True binary labels or binary label indicators.
y score : array, shape = [n samples] or [n samples, n classes]
Target scores, can either be probability estimates of the positive class, confidence values, or no
n-thresholded measure of
decisions (as returned by "decision function" on some classifiers).
For binary y_true, y_score is supposed to be the score of the class with greater label.
train auc = []
cv auc = []
log_alphas=[]
parameters = {'alpha': [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 1
0**4]}
for i in tqdm(parameters['alpha']):
         sgd = SGDClassifier(alpha=i, penalty='12', loss='hinge',random state = 0 ,class weight = 'balan
ced')
         clf s = CalibratedClassifierCV(sgd, method='sigmoid')
        clf s.fit(X tr, y train)
         y_train_pred = batch_predict(clf_s, X_tr)
         y_cv_pred = batch_predict(clf s, X cr)
         \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive positive positive probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive positive probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability \# roc_auc_score(y_true, y_score(y_true, y_sco
tive class
         # not the predicted outputs
         train auc.append(roc auc score(y train, y train pred))
         cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
100%| 11/11 [00:03<00:00, 3.02it/s]
```

In [116]:

[-6 0 -5 0 -4 0 -3 0 -2 0 -1 0 0 0 1 0 2 0 3 0 4 0]

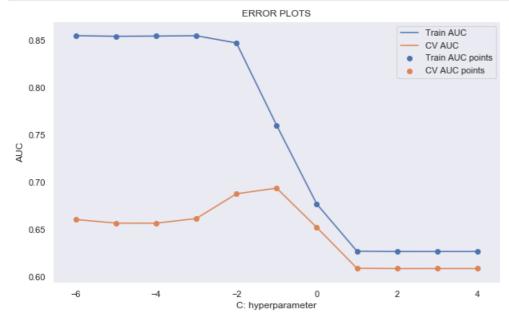
[0.0, 0.0, 3.0, 0.0, 2.0, 1.0, 0.0, 1.0, 2.0, 0.0, 3.0]

In [117]:

```
plt.figure(figsize=(10,6))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

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



In [118]:

```
best_k=0.1
```

Train The Model

In [119]:

```
from sklearn.metrics import roc_curve, auc

neigh = SGDClassifier(alpha=best_k, penalty='12', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')

clf_s = CalibratedClassifierCV(neigh, method='sigmoid')

clf_s.fit(X_tr, y_train)

# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class

# not the predicted outputs

y_train_pred = batch_predict(clf_s, X_tr)

y_test_pred = batch_predict(clf_s, X_te)

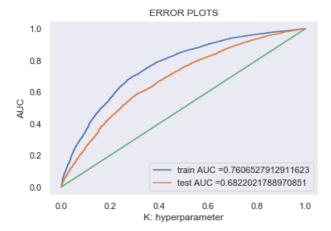
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)

test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
```

In [120]:

```
pit.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(x,x)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



Confusion Matrix

In [121]:

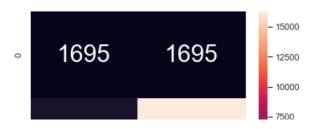
In [122]:

```
print("Train confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_fpr,train_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.784

Out[122]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f354bee15f8>





In [123]:

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.82

Out[123]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3553c2fa20>



12 regularizer gives better AUC score as compared to 11 regularizer. So we will use 12 regularizer

Applying SVM on TFIDF, SET 2

Creating Data Matrix

(11055, 7106) (11055,) (16500, 7106) (16500,)

```
In [124]:
```

```
# Please write all the code with proper documentation
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_tr = hstack((X_train_essay_tfidf,X_train_title_tfidf, X_train_state_ohe, X_train_teacher_ohe, X_t
rain grade ohe, X train cat ohe, X train sub ohe, X train price norm, X train project norm)).tocsr()
X_cr = hstack((X_cv_essay_tfidf, X_cv_title_tfidf, X_cv_state_ohe, X_cv_teacher_ohe, X_cv_grade_ohe,
X_cv_cat_ohe,X_cv_sub_ohe, X_cv_price_norm,X_cv_project_norm)).tocsr()
X_te = hstack((X_test_essay_tfidf,X_test_title_tfidf, X_test_state_ohe, X_test_teacher_ohe,
X_test_grade_ohe,X_test_cat_ohe,X_test_sub_ohe, X_test_price_norm,X_test_project_norm)).tocsr()
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, 7106) (22445,)
```

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11 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

```
def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
tive class
    # not the predicted outputs

y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your cr_loop will be 49041 - 49041%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    # we will be predicting for the last data points
    y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])
    return y_data_pred
```

In [126]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc auc score
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
train_auc = []
cv auc = []
log_alphas=[]
parameters = {'alpha': [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 1
for i in tqdm(parameters['alpha']):
   sgd = SGDClassifier(alpha=i, penalty='11', loss='hinge', random state = 0 ,class weight = 'balan
ced')
    clf s = CalibratedClassifierCV(sgd, method='sigmoid')
    clf s.fit(X tr, y train)
   y train pred = batch predict(clf s, X tr)
    y_cv_pred = batch_predict(clf_s, X_cr)
    train auc.append(roc auc score(y train, y train pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
100%| 11/11 [00:05<00:00, 2.29it/s]
```

In [127]:

```
for a in tqdm(parameters['alpha']):
    b = math.log10(a)
    log_alphas.append(b)
print(log_alphas)

100%| 11/11 [00:00<00:00, 11029.73it/s]

[-6.0, -5.0, -4.0, -3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0, 4.0]</pre>
```

```
In [128]:
```

```
plt.figure(figsize=(10,6))
plt.plot(log alphas, train auc. label='Train AUC')
```

```
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')

plt.scatter(log_alphas, cv_auc, label='CV AUC points')

plt.legend()

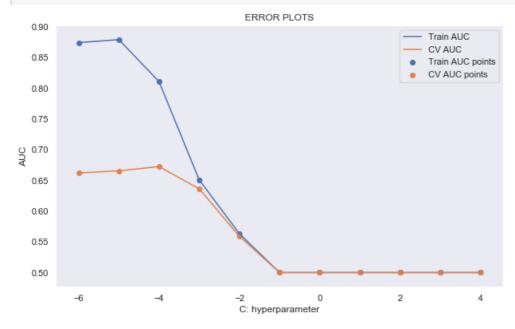
plt.xlabel("C: hyperparameter")

plt.ylabel("AUC")

plt.title("ERROR PLOTS")

plt.grid()

plt.show()
```



In [129]:

```
best_k=0.0001
```

Train The Model

In [130]:

```
from sklearn.metrics import roc_curve, auc

neigh = SGDClassifier(alpha=best_k, penalty='ll', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')

clf_s = CalibratedClassifierCV(neigh, method='sigmoid')

clf_s.fit(X_tr, y_train)

# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class

# not the predicted outputs

y_train_pred = batch_predict(clf_s, X_tr)

y_test_pred = batch_predict(clf_s, X_te)

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)

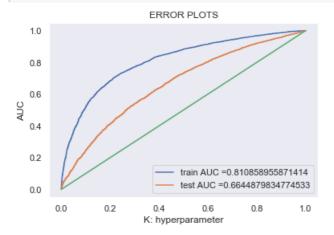
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
```

In [131]:

```
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(x,x)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
```





Confusion Matrix

In [132]:

```
# 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)
            predictions.append(0)
    return predictions
```

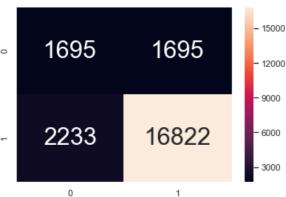
In [133]:

```
print("Train confusion matrix")
\verb|conf matr df_train_2=pd.DataFrame| (confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_tr
n fpr,train fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf matr df train 2,annot=True,annot kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.807

Out[133]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f354bf3e4e0>



```
In [134]:
```

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.821

Out[134]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f3553d1a048>



12 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

```
In [135]:
```

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc auc score
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
train_auc = []
cv auc = []
log alphas=[]
parameters = { 'alpha': [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 1
0**4]}
for i in tqdm(parameters['alpha']):
   sgd = SGDClassifier(alpha=i, penalty='12', loss='hinge',random_state = 0 ,class_weight = 'balan
ced')
   clf s = CalibratedClassifierCV(sgd, method='sigmoid')
   clf_s.fit(X_tr, y_train)
   y train pred = batch predict(clf s, X tr)
   y cv pred = batch predict(clf s, X cr)
    train auc.append(roc auc score(y train, y train pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
100%| 11/11 [00:04<00:00, 2.51it/s]
```

In [136]:

```
import math
for a in tqdm(parameters['alpha']):
    b = math.log10(a)
    log_alphas.append(b)
print(log_alphas)
```

```
100%| 11/11 [00:00<00:00, 14445.00it/s]
```

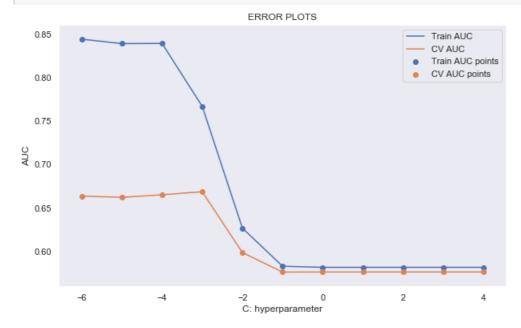
```
[-6.0, -5.0, -4.0, -3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0, 4.0]
```

In [137]:

```
plt.figure(figsize=(10,6))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

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



In [138]:

best k=0.001

Train The Model

In [139]:

```
from sklearn.metrics import roc_curve, auc

neigh = SGDClassifier(alpha=best_k, penalty='12', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')
clf_s = CalibratedClassifierCV(neigh, method='sigmoid')
clf_s.fit(X_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs

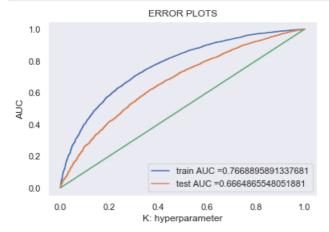
y_train_pred = batch_predict(clf_s, X_tr)
y_test_pred = batch_predict(clf_s, X_te)

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)

x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
```

In [140]:

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



Confusion Matrix

In [141]:

In [142]:

```
print("Train confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_fpr,train_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.796

Out[142]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3553981780>



In [143]:

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.826

Out[143]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3553d3c470>



I2 and I1 regularizers are performing equally good.

Applying SVM on AVG W2V, SET 3

Creating Data Matrix

In [144]:

```
# Please write all the code with proper documentation

# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_tr = hstack((avg_w2v_essay_train,avg_w2v_title_train, X_train_state_ohe, X_train_teacher_ohe, X_train_grade_ohe, X_train_cat_ohe, X_train_sub_ohe, X_train_price_norm, X_train_project_norm)).tocsr()
X_cr = hstack((avg_w2v_essay_cv,avg_w2v_title_cv, X_cv_state_ohe, X_cv_teacher_ohe, X_cv_grade_ohe, X_cv_cat_ohe, X_cv_sub_ohe, X_cv_price_norm, X_cv_project_norm)).tocsr()
X_te = hstack((avg_w2v_essay_test,avg_w2v_title_test, X_test_state_ohe, X_test_teacher_ohe, X_test_grade_ohe, X_test_cat_ohe, X_test_sub_ohe, X_test_price_norm, X_test_project_norm)).tocsr()
print("Final Data matrix")
print(X_tr.shape, y_train.shape)
print(X_cr.shape, y_train.shape)
print(X_te.shape, y_test.shape)
print("="*100)
```

Final Data matriv

```
(22445, 702) (22445,)
(11055, 702) (11055,)
(16500, 702) (16500,)
```

11 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

```
In [145]:
```

```
def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
tive class
    # not the predicted outputs

y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your cr_loop will be 49041 - 49041%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    # we will be predicting for the last data points
    y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])
    return y_data_pred
```

In [146]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc auc score
from sklearn.linear model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
train auc = []
cv auc = []
log_alphas=[]
parameters = \{ alpha': [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10
0**4]}
for i in tqdm(parameters['alpha']):
            sgd = SGDClassifier(alpha=i, penalty='11', loss='hinge',random_state = 0 ,class_weight = 'balan
ced')
             clf s = CalibratedClassifierCV(sgd, method='sigmoid')
             clf_s.fit(X_tr, y_train)
             y train pred = batch predict(clf s, X tr)
             y cv pred = batch predict(clf s, X cr)
              train auc.append(roc auc score(y train, y train pred))
              cv auc.append(roc auc score(y cv, y cv pred))
100%| 11/11 [00:22<00:00, 2.20s/it]
```

In [147]:

```
for a in tqdm(parameters['alpha']):
    b = math.log10(a)
    log_alphas.append(b)
print(log_alphas)

100%[ 11/11 [00:00<00:00, 48210.39it/s]

[-6.0, -5.0, -4.0, -3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0, 4.0]</pre>
```

In [148]:

```
plt.figure(figsize=(10,6))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

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

0.70 0.70 0.70 0.65 0.55 0.50 -6 -4 -2 0 2 4 C: hyperparameter

In [149]:

```
best_k=0.0012
```

Train The Model

In [150]:

```
from sklearn.metrics import roc_curve, auc
neigh = SGDClassifier(alpha=best_k, penalty='ll', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')
clf_s = CalibratedClassifierCV(neigh, method='sigmoid')
clf_s.fit(X_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs

y_train_pred = batch_predict(clf_s, X_tr)
y_test_pred = batch_predict(clf_s, X_te)

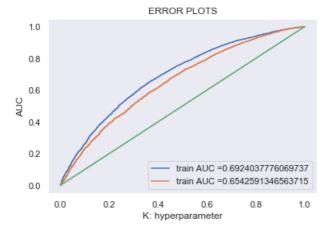
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
```

In [152]:

```
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test_tpr)))
plt.plot(x,x)
plt.legend()
plt.vlabel("K: hyperparameter")
```

```
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



Confusion Matrix

In [153]:

```
# 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
```

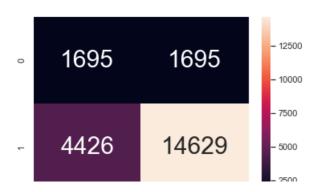
In [154]:

```
print("Train confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_fpr,train_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.817

Out[154]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3553ddfcc0>



0 1

In [155]:

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.843

Out[155]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3553a04860>



12 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

In [156]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
train auc = []
cv auc = []
log_alphas=[]
parameters = {'alpha': [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 1
0**4]}
for i in tqdm(parameters['alpha']):
   sgd = SGDClassifier(alpha=i, penalty='12', loss='hinge',random state = 0 ,class weight = 'balan
ced')
    clf_s = CalibratedClassifierCV(sgd, method='sigmoid')
   clf_s.fit(X_tr, y_train)
   y_train_pred = batch_predict(clf_s, X_tr)
    y_cv_pred = batch_predict(clf_s, X_cr)
    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
100%| 11/11 [00:12<00:00, 1.14s/it]
```

```
In [157]:
```

```
for a in tqdm(parameters['alpha']):
    b = math.log10(a)
```

```
log_alphas.append(b)
print(log_alphas)

100%| 11/11 [00:00<00:00, 18656.43it/s]

[-6.0, -5.0, -4.0, -3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0, 4.0]
```

In [158]:

```
plt.figure(figsize=(10,6))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

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

0.70 Train AUC CV AUC Train AUC points CV AUC points O.64 O.64 O.62 O.60 -6 -4 -2 C: hyperparameter

In [159]:

```
best_k=0.0012
```

Train The Model

In [160]:

```
from sklearn.metrics import roc_curve, auc

neigh = SGDClassifier(alpha=best_k, penalty='12', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')
clf_s = CalibratedClassifierCV(neigh, method='sigmoid')
clf_s.fit(X_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs

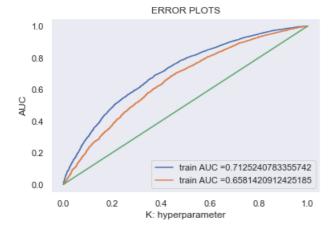
y_train_pred = batch_predict(clf_s, X_tr)
y_test_pred = batch_predict(clf_s, X_te)

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 [161]:

```
x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test_tpr)))
plt.plot(x,x)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



Confusion Matrix

In [162]:

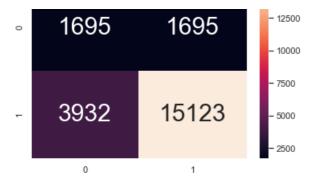
In [163]:

```
print("Train confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_fpr,train_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.813

Out[163]:

 ${\tt matplotlib.axes._subplots.AxesSubplot}$ at ${\tt 0x7f3553db6320}{\tt >}$



In [164]:

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix

the maximum value of tpr*(1-fpr) 0.25 for threshold 0.84

Out[164]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f35539dfd30>



12 and 11 regularizers perform almost same.

Applying SVM on TFIDF W2V, SET 4

Creating Data Matrix

```
In [165]:
```

```
# Please write all the code with proper documentation

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

from scipy.sparse import hstack

X tr = hstack((tfidf_w2v_train_essay,tfidf_w2v_train_title, X_train_state_ohe, X_train_teacher_ohe
, X_train_grade_ohe, X_train_cat_ohe, X_train_sub_ohe, X_train_price_norm, X_train_project_norm)).toc
sr()

X_cr = hstack((tfidf_w2v_cv_essay,tfidf_w2v_cv_title, X_cv_state_ohe, X_cv_teacher_ohe, X_cv_grade_ohe, X_cv_cat_ohe, X_cv_sub_ohe, X_cv_price_norm, X_cv_project_norm)).tocsr()

X_te = hstack((tfidf_w2v_test_essay,tfidf_w2v_test_title, X_test_state_ohe, X_test_teacher_ohe, X_test_grade_ohe, X_test_cat_ohe, X_test_sub_ohe, X_test_price_norm, X_test_project_norm)).tocsr()

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

11 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

```
def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
tive class
    # not the predicted outputs

y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your cr_loop will be 49041 - 49041%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    # we will be predicting for the last data points
    y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])
    return y_data_pred
```

import matplotlib.pyplot as plt
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV

cv_auc = []
log_alphas=[]
parameters = {'alpha': [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 1
0**4]}

for i in tqdm(parameters['alpha']):
 sgd = SGDClassifier(alpha=i, penalty='ll', loss='hinge',random_state = 0 ,class_weight = 'balan
ced')
 clf_s = CalibratedClassifierCV(sgd, method='sigmoid')
 clf_s.fit(X_tr, y_train)

y_cv_pred = batch_predict(clf_s, X_cr)

train_auc.append(roc_auc_score(y_train,y_train_pred))
cv_auc.append(roc_auc_score(y_cv, y_cv_pred))

100%| 11/11 [00:21<00:00, 2.13s/it]

y train pred = batch predict(clf s, X tr)

In [168]:

train auc = []

```
for a in tqdm(parameters['alpha']):
    b = math.log10(a)
    log_alphas.append(b)
print(log_alphas)

100%[ 11/11 [00:00<00:00, 34585.72it/s]

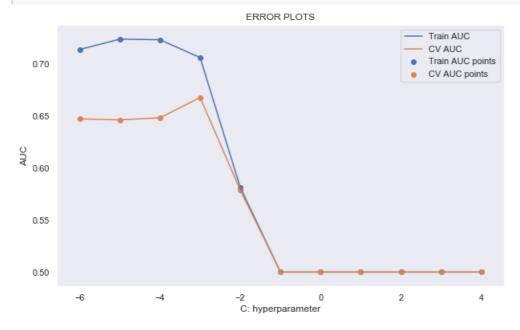
[-6.0, -5.0, -4.0, -3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0, 4.0]</pre>
```

In [169]:

```
plt.figure(figsize=(10,6))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

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



In [170]:

best_k=0.002

Train The Model

In [171]:

```
from sklearn.metrics import roc_curve, auc

neigh = SGDClassifier(alpha=best_k, penalty='11', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')
clf_s = CalibratedClassifierCV(neigh, method='sigmoid')
clf_s.fit(X_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs

y_train_pred = batch_predict(clf_s, X_tr)
y_test_pred = batch_predict(clf_s, X_te)

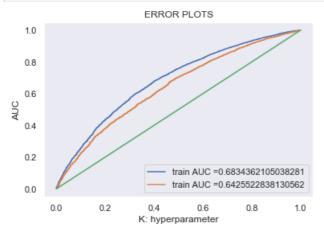
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
```

In [172]:

```
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test_tpr)))
```

```
plt.plot(x,x)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



Confusion Matrix

In [173]:

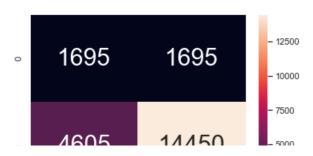
In [174]:

```
print("Train confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_fpr,train_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.823

Out[174]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3553a5b5c0>



In [175]:

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.844

Out[175]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3553c3a320>



12 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

In [176]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc auc score
from sklearn.linear_model import SGDClassifier
from sklearn.model selection import GridSearchCV
from sklearn.calibration import CalibratedClassifierCV
train auc = []
 cv auc = []
log_alphas=[]
parameters = \{ alpha': [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10
0**41}
for i in tqdm(parameters['alpha']):
            sgd = SGDClassifier(alpha=i, penalty='12', loss='hinge', random state = 0 ,class weight = 'balan
ced')
            clf_s = CalibratedClassifierCV(sgd, method='sigmoid')
             clf_s.fit(X_tr, y_train)
             y_train_pred = batch_predict(clf_s, X_tr)
             y_cv_pred = batch_predict(clf_s, X_cr)
             train_auc.append(roc_auc_score(y_train,y_train_pred))
             cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
100%| 11/11 [00:11<00:00, 1.08s/it]
```

```
In [177]:
```

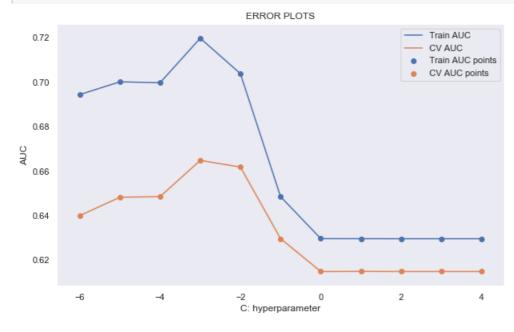
```
[-6.0, -5.0, -4.0, -3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0, 4.0]
```

In [178]:

```
plt.figure(figsize=(10,6))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

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



In [179]:

```
best k=0.001
```

Train The Model

```
In [180]:
```

```
from sklearn.metrics import roc_curve, auc

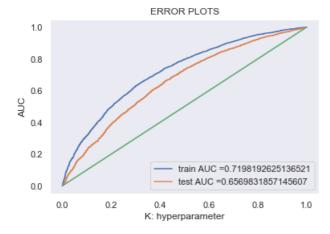
neigh = SGDClassifier(alpha=best_k, penalty='12', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')
clf_s = CalibratedClassifierCV(neigh, method='sigmoid')
clf_s.fit(X_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs
```

```
y_train_pred = batch_predict(clf_s, X_tr)
y_test_pred = batch_predict(clf_s, 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)
x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
```

In [181]:

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



12 regularizer is somewhat better than I1

Confusion Matrix

In [182]:

In [183]:

```
print("Train confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_fpr,train_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.812

Out[183]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3553990400>



In [184]:

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.835

Out[184]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f35538fb5f8>



I2 is better than I1

Set 5 : SVM on Categorical features, Numerical features & Essay Sentiments

Dimensionality Reduction of tfidf encoded essay feature

```
In [185]:
```

```
#X_train_essay_tfidf
```

In [188]:

```
from sklearn.decomposition import TruncatedSVD as TSVD

t_svd = TSVD(n_components = X_train_essay_tfidf.shape[1]-1)
```

```
t_svd.fit_transform(X_train_essay_tfidf)

percentage_var_explained = t_svd.explained_variance_ / np.sum(t_svd.explained_variance_);
    cum_var_explained = np.cumsum(percentage_var_explained)

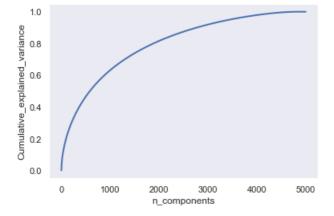
print(cum_var_explained)

[0.00202167 0.0119405 0.02054456 ... 1. 1. 1. ]
```

In [189]:

```
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()
```



Preserving 90% variance, we take 3300 points.

```
In [190]:
```

```
tsvd = TSVD(n_components = 3300)
X_train_essay_tfidf = tsvd.fit_transform(X_train_essay_tfidf)
X_test_essay_tfidf = tsvd.fit_transform(X_test_essay_tfidf)
X_cv_essay_tfidf = tsvd.fit_transform(X_cv_essay_tfidf)
```

Creating Data Matrix

In [192]:

```
X_tr = hstack((X_train_state_ohe, X_train_teacher_ohe,
X_train_grade_ohe,X_train_cat_ohe,X_train_sub_ohe,
X_train_price_norm,X_train_project_norm,X_train_title_norm,X_train_essay_norm,essay_sent_pos_train
,essay_sent_neg_train,essay_sent_neu_train,essay_sent_comp_train,X_train_essay_tfidf)).tocsr()
X_cr = hstack((X_cv_state_ohe, X_cv_teacher_ohe, X_cv_grade_ohe,X_cv_cat_ohe,X_cv_sub_ohe, X_cv_pri
ce_norm,X_cv_project_norm,X_cv_title_norm,X_cv_essay_norm,essay_sent_pos_cv,essay_sent_neg_cv,essa
y_sent_neu_cv,essay_sent_comp_cv,X_cv_essay_tfidf)).tocsr()
X_te = hstack((X_test_state_ohe, X_test_teacher_ohe, X_test_grade_ohe,X_test_cat_ohe,X_test_sub_ohe
, X_test_price_norm,X_test_project_norm,X_test_title_norm,X_test_essay_norm,essay_sent_pos_test,es
say_sent_neg_test,essay_sent_neu_test,essay_sent_comp_test,X_test_essay_tfidf)).tocsr()
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, 3408) (22445,)
```

```
(11055, 3408) (11055,)
(16500, 3408) (16500,)
```

√

11 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

```
In [193]:
```

```
def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
    tive class
    # not the predicted outputs

y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your cr_loop will be 49041 - 49041%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    # we will be predicting for the last data points
    y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])

return y_data_pred
```

In [194]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_auc_score
from sklearn.linear model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
train auc = []
cv auc = []
log_alphas=[]
parameters = \{ \text{'alpha': } [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-1, 10**-
for i in tqdm(parameters['alpha']):
             sgd = SGDClassifier(alpha=i, penalty='l1', loss='hinge', random state = 0 ,class weight = 'balan
ced')
             clf s = CalibratedClassifierCV(sgd, method='sigmoid')
              clf_s.fit(X_tr, y_train)
              y_train_pred = batch_predict(clf_s, X_tr)
              y_cv_pred = batch_predict(clf_s, X_cr)
              train_auc.append(roc_auc_score(y_train,y_train_pred))
              cv auc.append(roc auc score(y cv, y cv pred))
100%| 11/11 [02:02<00:00, 11.97s/it]
```

In [195]:

```
for a in tqdm(parameters['alpha']):
    b = math.log10(a)
    log_alphas.append(b)
print(log_alphas)

100%| 11/11 [00:00<00:00, 30096.11it/s]

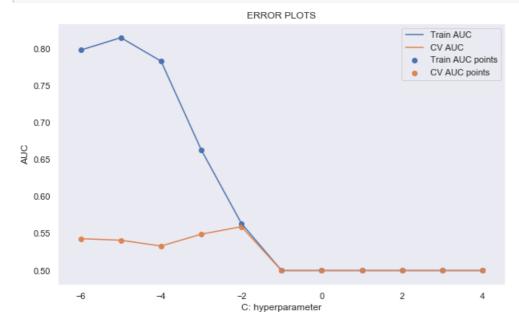
[-6.0, -5.0, -4.0, -3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0, 4.0]</pre>
```

```
In [196]:
```

```
plt.figure(figsize=(10,6))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

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



In [197]:

```
best_k=0.01
```

Train The Model

In [198]:

```
from sklearn.metrics import roc_curve, auc

neigh = SGDClassifier(alpha=best_k, penalty='ll', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')

clf_s = CalibratedClassifierCV(neigh, method='sigmoid')

clf_s.fit(X_tr, y_train)

# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class

# not the predicted outputs

y_train_pred = batch_predict(clf_s, X_tr)
y_test_pred = batch_predict(clf_s, X_te)

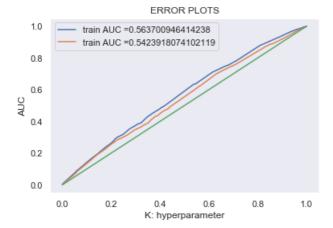
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
```

In [199]:

```
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test_tpr)))
plt.plot(x,x)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
```

```
plt.crute("ERROR PLOIS")
plt.grid()
plt.show()
```



Confusion Matrix

In [200]:

```
# 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 [201]:

```
print("Train confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_fpr,train_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.2490946824340199 for threshold 0.837

Out[201]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f354bfe9358>



In [202]:

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.24706524763673934 for threshold 0.841

Out[202]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f353bbe5390>



12 regularizer based Model

Hyperparameter Tuning: Simple for loop (if you are having memory limitations use this)

In [203]:

```
def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the posi
tive class
    # not the predicted outputs

y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your cr_loop will be 49041 - 49041%1000 = 49000
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    # we will be predicting for the last data points
    y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])
    return y_data_pred
```

In [204]:

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import SGDClassifier
from sklearn.calibration import CalibratedClassifierCV

train_auc = []
cv_auc = []
log_alphas=[]

parameters = {'alpha': [10**-6,10**-5,10**-4, 10**-3, 10**-2, 10**-1, 10**0, 10**1, 10**2, 10**3, 1 0**4]}

for i in tqdm(parameters['alpha']):
```

```
sgd = SGDClassifier(alpna=1, penalty='12', loss='ninge',random_state = 0 ,class_weight = 'balan'
ced')
    clf_s = CalibratedClassifierCV(sgd, method='sigmoid')
    clf_s.fit(X_tr, y_train)
    y_train_pred = batch_predict(clf_s, X_tr)
    y_cv_pred = batch_predict(clf_s, X_cr)

    train_auc.append(roc_auc_score(y_train,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
100%| 11/11 [01:00<00:00, 5.62s/it]
```

In [205]:

```
for a in tqdm(parameters['alpha']):
    b = math.log10(a)
    log_alphas.append(b)
print(log_alphas)
100%| 11/11 [00:00<00:00, 73233.88it/s]
```

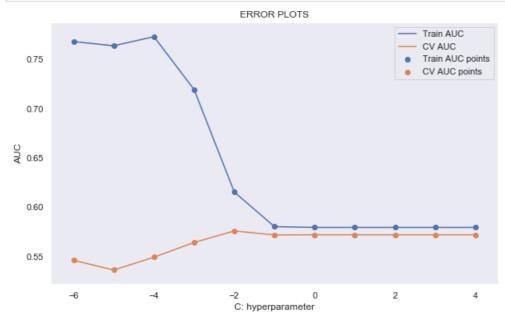
[-6.0, -5.0, -4.0, -3.0, -2.0, -1.0, 0.0, 1.0, 2.0, 3.0, 4.0]

In [206]:

```
plt.figure(figsize=(10,6))
plt.plot(log_alphas, train_auc, label='Train AUC')
plt.plot(log_alphas, cv_auc, label='CV AUC')

plt.scatter(log_alphas, train_auc, label='Train AUC points')
plt.scatter(log_alphas, cv_auc, label='CV AUC points')

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



In [207]:

```
best_k=0.01
```

In [208]:

```
from sklearn.metrics import roc_curve, auc

neigh = SGDClassifier(alpha=best_k, penalty='12', loss='hinge',random_state = 0 ,class_weight = 'b
alanced')

clf_s = CalibratedClassifierCV(neigh, method='sigmoid')

clf_s.fit(X_tr, y_train)

# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class

# not the predicted outputs

y_train_pred = batch_predict(clf_s, X_tr)

y_test_pred = batch_predict(clf_s, X_te)

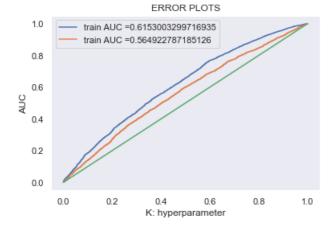
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)

test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

x=[0.0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1.0]
```

In [209]:

```
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="train AUC ="+str(auc(test_fpr, test_tpr)))
plt.plot(x,x)
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```



Confusion Matrix

In [210]:

print("Train confusion matrix")

```
print("Train confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_train,predict(y_train_pred,tr_thresholds,train_fpr,train_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Train confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.834

Out[212]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f350fa170b8>



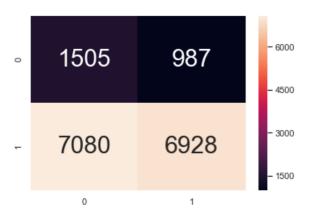
In [213]:

```
print("Test confusion matrix")
conf_matr_df_train_2=pd.DataFrame(confusion_matrix(y_test,predict(y_test_pred,tr_thresholds,test_fp
r,test_fpr)),range(2),range(2))
sns.set(font_scale=1)#for label size
sns.heatmap(conf_matr_df_train_2,annot=True,annot_kws={"size":30},fmt='g')
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.25 for threshold 0.857

Out[213]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3511486208>



12 regularizer performs just a bit better than I1.

3. Conclusions

In [215]:

http://zetcode.com/python/prettytable/

```
from prettytable import PrettyTable
#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable
x=PrettyTable()
x.field_names=["Vectorizer", "Regularizer", "AUC"]
x.add_row(["BOW", "L1", 0.65])
x.add_row(["BFIDF", "L2", 0.69])
x.add_row(["TFIDF", "L1", 0.66])
x.add_row(["TFIDF", "L1", 0.65])
x.add_row(["AVG W2V", "L1", 0.65])
x.add_row(["AVG W2V", "L2", 0.66])
x.add_row(["TFIDF W2V", "L1", 0.64])
x.add_row(["TFIDF W2V", "L2", 0.66])
x.add_row(["TRUNCATED TFIDF", "L1", 0.54])
x.add_row(["TRUNCATED TFIDF", "L2", 0.56])
print(x)
```

Vectorizer	Regularizer	AUC
BOW BOW TFIDF TFIDF AVG W2V AVG W2V TFIDF W2V TFIDF W2V TRUNCATED TFIDF	+	++ 0.65 0.69 0.66 0.67 0.65 0.66 0.64 0.66
TRUNCATED TFIDF	L2	0.56

INFERENCE:

- 1. L2 Regularizer is somewhat better than L1 Regularizer in all the cases.
- 2. If we use TRUNCATED TFIDF, the AUC score drops significantly. So, it is not a good model.