# **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. <b>Example:</b> p036502	
	Title of the project. Examples:	
<pre>project_title</pre>	• Art Will Make You Happy!	
	• First Grade Fun	
	Grade level of students for which the project is targeted. One of the following enumerated values:	
project grade category	• Grades PreK-2	
project_grade_category	• Grades 3-5	
	• 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	
. 3 = 3 = 3	<ul><li>Music &amp; The Arts</li><li>Special Needs</li></ul>	
	• 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. <b>Examples</b> :	
project subject subcategories	ene en mere (comma coparatou) eusjoch eusgenegenee ier mie projech <b>=numproe</b> r	
F3333		
	• Literature & Writing, Social Sciences	
	• Literature & Writing, Social Sciences	
	• Literature & Writing, Social Sciences  An explanation of the resources needed for the project. Example:	
<pre>project_resource_summary</pre>	• Literature & Writing, Social Sciences	
<pre>project_resource_summary project_essay_1</pre>	<ul> <li>Literacy</li> <li>Literature &amp; Writing, Social Sciences</li> <li>An explanation of the resources needed for the project. Example:</li> <li>My students need hands on literacy materials to manage sensory</li> </ul>	
	• Literacy • Literature & Writing, Social Sciences  An explanation of the resources needed for the project. Example: • 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. <b>Example:</b> 2016-04-28 12:43:56.245	<pre>project_submitted_datetime</pre>
A unique identifier for the teacher of the proposed project. <b>Example:</b> 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. <b>Example:</b> 2	teacher_number_of_previously_posted_projects

<sup>\*</sup> 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. <b>Example:</b> Tenor Saxophone Reeds, Box of 25
quantity	Quantity of the resource required. <b>Example:</b> 3
price	Price of the resource required. <b>Example:</b> 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
# 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
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
from tqdm import tqdm
import os
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',nrows=50000)
resource_data = pd.read_csv('resources.csv')
In [3]:
print("Number of data points in train data", project data.shape)
print('-'*50)
print("The attributes of data :", project data.columns.values)
```

# In [2]: project\_data = pd.read\_csv('train\_data.csv',nrows=50000) resource\_data = pd.read\_csv('resources.csv') In [3]: 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\_title' 'project\_essay\_2' 'project\_essay\_2' 'project\_essay\_3' 'project\_title' 'project\_essay\_2' 'project\_essay\_2' 'project\_essay\_3' 'project\_essay\_4' 'project\_resource\_summary' 'teacher\_number\_of\_previously\_posted\_projects' 'project\_is\_approved'] In [4]: 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']

	id	description	quantity	price	
<b>0</b> p2332	245	LC652 - Lakeshore Double-Space Mobile Drying Rack	1	149.00	
<b>1</b> p0690	063	Bouncy Bands for Desks (Blue support pipes)	3	14.95	

Out[4]:

# 1.2 preprocessing of project subject categories

In [5]:

```
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 & 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('&','_') # 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]))
4
```

# 1.3 preprocessing of project subject subcategories

```
In [6]:
```

```
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
In [7]:
# We need to get rid of The spaces between the text and the hyphens because they're special charac
#Rmoving multiple characters from a string in Python
#https://stackoverflow.com/questions/3411771/multiple-character-replace-with-python
project grade category = []
for i in range(len(project data)):
    a = project_data["project_grade_category"][i].replace(" ", "_").replace("-", "_")
    project grade category.append(a)
In [8]:
project_data.drop(['project_grade_category'], axis = 1, inplace = True)
project_data["project_grade_category"] = project_grade_category
print("After removing the special characters ,Column values: ")
np.unique(project_data["project_grade_category"].values)
After removing the special characters , Column values:
Out[8]:
array(['Grades 3 5', 'Grades 6 8', 'Grades 9 12', 'Grades PreK 2'],
     dtype=object)
In [9]:
#NaN values in techer prefix will create a problem while encoding, so we replace NaN values with th
e mode of that particular column
#removing dot(.) since it is a special character
mode_of_teacher_prefix = project_data['teacher prefix'].value counts().index[0]
project data['teacher prefix'] = project data['teacher prefix'].fillna(mode of teacher prefix)
In [10]:
prefixes = []
for i in range(len(project_data)):
    a = project_data["teacher_prefix"][i].replace(".", "")
    prefixes.append(a)
In [11]:
project data.drop(['teacher prefix'], axis = 1, inplace = True)
project data["teacher prefix"] = prefixes
print("After removing the special characters ,Column values: ")
np.unique(project data["teacher prefix"].values)
After removing the special characters , Column values:
Out[11]:
array(['Dr', 'Mr', 'Mrs', 'Ms', 'Teacher'], dtype=object)
```

# 1.3 Text preprocessing

```
In [12]:
```

# merge two column text dataframe:

### In [13]:

```
# 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"\'t", " not", phrase)
    phrase = re.sub(r"\'t", " not", 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"\'m", " am", phrase)
    return phrase
```

### In [14]:

```
sent = decontracted(project_data['essay'].values[20000])
print(sent)
print("="*50)
```

My kindergarten students have varied disabilities ranging from speech and language delays, cognitive delays, gross/fine motor delays, to autism. They are eager beavers and always strive to work their hardest working past their limitations. \r\n\r\nThe materials we have are the ones I seek out for my students. I teach in a Title I school where most of the students receive free or reduced price lunch. Despite their disabilities and limitations, my students love coming to school and come eager to learn and explore. Have you ever felt like you had ants in your pants and you needed to groove and move as you were in a meeting? This is how my kids feel all the time. The want to be able to move as they learn or so they say. Wobble chairs are the answer and I love then because they develop their core, which enhances gross motor and in Turn fine motor skills. \r\nThey also want to learn through games, my kids do not want to sit and do worksheets. They want to learn to count by jumping and playing. Physical engagement is the key to our success. The number toss and color and shape mats can make that happen. My students will forget they are doing work and just have the fun a 6 year old deserves.nannan

\_\_\_\_\_

### In [15]:

```
# \r \n \t remove from string python: http://texthandler.com/info/remove-line-breaks-python/
sent = sent.replace('\\r', ' ')
sent = sent.replace('\\"', ' ')
sent = sent.replace('\\n', ' ')
print(sent)
```

My kindergarten students have varied disabilities ranging from speech and language delays, cognitive delays, gross/fine motor delays, to autism. They are eager beavers and always strive to work their hardest working past their limitations. The materials we have are the ones I seek out for my students. I teach in a Title I school where most of the students receive free or reduced price lunch. Despite their disabilities and limitations, my students love coming to school and come eager to learn and explore. Have you ever felt like you had ants in your pants and you needed to groove and move as you were in a meeting? This is how my kids feel all the time. The want to be able to move as they learn or so they say. Wobble chairs are the answer and I love then because they develop their core, which enhances gross motor and in Turn fine motor skills. They also want to learn through games, my kids do not want to sit and do worksheets. They want to learn to count by jumping and playing. Physical engagement is the key to our success. The number toss and color and shape mats can make that happen. My students will forget they are doing work and just have the fun a 6 year old deserves.nannan

In [16]:

4

\_ ▶

```
#remove spacial character: nttps://stackoverilow.com/a/584354//4U84U39
sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
print(sent)
```

My kindergarten students have varied disabilities ranging from speech and language delays cognitive delays gross fine motor delays to autism They are eager beavers and always strive to work their hardest working past their limitations. The materials we have are the ones I seek out for my students I teach in a Title I school where most of the students receive free or reduced price lunch. Despite their disabilities and limitations my students love coming to school and come eager to learn and explore Have you ever felt like you had ants in your pants and you needed to groove and move as you were in a meeting This is how my kids feel all the time. The want to be able to move as the ey learn or so they say Wobble chairs are the answer and I love then because they develop their compared to the enhances gross motor and in Turn fine motor skills. They also want to learn through games my kids do not want to sit and do worksheets. They want to learn to count by jumping and playing Physical engagement is the key to our success. The number toss and color and shape mats can make that happen My students will forget they are doing work and just have the fun a 6 year old deserves nan nan

### In [17]:

```
# 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',
'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', '
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
esn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn',
"wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"]
4
```

### In [18]:

```
#convert all the words to lower case first and then remove the stopwords
for i in range(len(project_data['essay'].values)):
    project_data['essay'].values[i] = project_data['essay'].values[i].lower()
```

# In [19]:

```
# 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 = sent.replace('\\"', '')
    sent = sent.replace('\\n', '')
    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_essays_append(sent.lower().strip())
```

```
proprocessor cossips.appens.tomer.tomer.tomer.
100%| 50000/50000 [00:20<00:00, 2479.35it/s]
In [20]:
#creating a new column with the preprocessed essays and replacing it with the original columns
project data['preprocessed essays'] = preprocessed essays
project_data.drop(['project_essay_1'], axis=1, inplace=True)
project_data.drop(['project_essay_2'], axis=1, inplace=True)
project_data.drop(['project_essay_3'], axis=1, inplace=True)
project_data.drop(['project_essay_4'], axis=1, inplace=True)
In [21]:
essay word count=[]
for i in range(len(project data['preprocessed essays'])):
    essay word count.append(len(project data['preprocessed essays'][i].split()))
In [22]:
project_data['essay_word_count'] = essay_word count
1.4 Preprocessing of 'project title'
In [23]:
#convert all the words to lower case first and then remove the stopwords
for i in range(len(project data['project title'].values)):
    project_data['project_title'].values[i] = project_data['project_title'].values[i].lower()
In [24]:
# 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('\\"', ' ')
   sent = sent.replace('\\n', ' ')
   sent = sent.replace('nan',' ')
    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())
100%| 50000/50000 [00:00<00:00, 57706.82it/s]
In [25]:
#creating a new column with the preprocessed titles, useful for analysis
project data['preprocessed titles'] = preprocessed titles
In [26]:
title word count=[]
for i in range(len(project data['preprocessed titles'])):
    title word count.append(len(project data['preprocessed titles'][i].split()))
In [27]:
project_data['title_word_count'] = title_word_count
In [28]:
```

```
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
analyzer = SentimentIntensityAnalyzer()
neg=[];pos=[];neu=[]; compound = []
for i in tqdm(range(len(project data['preprocessed essays']))):
    sentiment scores = analyzer.polarity scores(project data['preprocessed essays'][i])
    neg.append(sentiment_scores['neg'])
    pos.append(sentiment_scores['pos'])
    neu.append(sentiment scores['neu'])
    compound.append(sentiment_scores['compound'])
100%| 50000/50000 [01:00<00:00, 832.18it/s]
In [29]:
#new columns indicating the sentiment score of each project essay
project data['neg'] = neg
project_data['neu'] = neu
project_data['pos'] = pos
project_data['compound'] = compound
Splitting data into Train and test: Stratified Sampling
In [30]:
# train test split
from sklearn.model_selection import train_test_split
project_data_train, project_data_test, y_train, y_test = train_test_split(project_data, project_dat
a['project_is_approved'], test_size=0.33, stratify = project_data['project_is_approved'])
In [31]:
print("Split ratio")
print('-'*50)
print('Train dataset:',len(project data train)/len(project data)*100,'%\n','size:',len(project data
_train))
print('Test dataset:',len(project data test)/len(project data)*100,'%\n','size:',len(project data t
est))
Split ratio
Train dataset: 67.0 %
size: 33500
Test dataset: 33.0 %
size: 16500
In [32]:
project_data_train.drop(['project_is_approved'], axis=1, inplace=True)
project_data_test.drop(['project_is_approved'], axis=1, inplace=True)
1.5 Preparing data for models
In [33]:
project_data.columns
Out[33]:
Index(['Unnamed: 0', 'id', 'teacher id', 'school state',
       'project_submitted_datetime', 'project_title',
```

'project\_resource\_summary',

```
'teacher_number_of_previously_posted_projects', 'project_is_approved',
    'clean_categories', 'clean_subcategories', 'project_grade_category',
    'teacher_prefix', 'essay', 'preprocessed_essays', 'essay_word_count',
    'preprocessed_titles', 'title_word_count', 'neg', 'neu', 'pos',
    'compound'],
    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
```

# Make Data Model Ready: vectorizing numerical, categorical features (with response coding)

# Make Data Model Ready: encoding eassay, and project title

- teacher\_number\_of\_previously\_posted\_projects : numerical

- project resource summary: text data (optinal)

### 1.5.2 Vectorizing Text data

- text : text data

- price : numerical

- quantity : numerical (optinal)

### 1.5.2.1 Bag of words

```
In [34]:
```

```
# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer_bow_essay = CountVectorizer(min_df=10)
vectorizer_bow_essay.fit(project_data_train['preprocessed_essays'].values)  #Fitting has to be on
Train data

train_essay_bow = vectorizer_bow_essay.transform(project_data_train['essay'].values)

test_essay_bow = vectorizer_bow_essay.transform(project_data_test['essay'].values)

print("Shape of train data matrix after one hot encoding ",train_essay_bow.shape)

print("Shape of test data matrix after one hot encoding ",test_essay_bow.shape)
```

Shape of train data matrix after one hot encoding (33500, 10329) Shape of test data matrix after one hot encoding (16500, 10329)

### In [35]:

```
# you can vectorize the title also
# before you vectorize the title make sure you preprocess it
vectorizer_bow_title = CountVectorizer(min_df=10)
vectorizer_bow_title.fit_transform(project_data_train['preprocessed_titles'].values) #Fitting has
s to be on Train data

train_title_bow = vectorizer_bow_title.transform(project_data_train['preprocessed_titles'].values)
test_title_bow = vectorizer_bow_title.transform(project_data_test['preprocessed_titles'].values)
```

```
print("Shape of train data matrix after one hot encoding ",train title bow.shape)
print("Shape of test data matrix after one hot encoding ", test title bow.shape)
Shape of train data matrix after one hot encoding (33500, 1538)
Shape of test data matrix after one hot encoding (16500, 1538)
1.5.2.2 TFIDF vectorizer
In [36]:
from sklearn.feature extraction.text import TfidfVectorizer
```

```
vectorizer_tfidf_essay = TfidfVectorizer(min_df=10)
vectorizer_tfidf_essay.fit(project_data_train['preprocessed_essays']) #Fitting has to be on
Train data
train essay tfidf = vectorizer tfidf essay.transform(project data train['preprocessed essays'].val
test essay tfidf =
vectorizer tfidf essay.transform(project data test['preprocessed essays'].values)
```

print ("Shape of train data matrix after one hot encoding ",train essay tfidf.shape)

print("Shape of test data matrix after one hot encoding ", test essay tfidf.shape)

Shape of train data matrix after one hot encoding (33500, 10329) Shape of test data matrix after one hot encoding (16500, 10329)

### In [37]:

```
vectorizer tfidf title = TfidfVectorizer(min df=10)
vectorizer_tfidf_title.fit(project_data_train['preprocessed_titles']) #Fitting has to be on
train_title_tfidf = vectorizer_tfidf_title.transform(project_data_train['preprocessed_titles'].val
ues)
test title tfidf =
vectorizer tfidf title.transform(project data test['preprocessed titles'].values)
print("Shape of train data matrix after one hot encoding ", train title tfidf.shape)
print("Shape of test data matrix after one hot encoding ", test title tfidf.shape)
```

Shape of train data matrix after one hot encoding (33500, 1538) Shape of test data matrix after one hot encoding (16500, 1538)

### 1.5.2.3 Using Pretrained Models: Avg W2V

### In [38]:

```
. . .
# Reading glove vectors in python: https://stackoverflow.com/a/38230349/4084039
def loadGloveModel(gloveFile):
   print ("Loading Glove Model")
   f = open(gloveFile,'r', encoding="utf8")
   model = \{\}
   for line in tqdm(f):
       splitLine = line.split()
       word = splitLine[0]
       embedding = np.array([float(val) for val in splitLine[1:]])
       model[word] = embedding
   print ("Done.",len(model)," words loaded!")
   return model
model = loadGloveModel('glove.42B.300d.txt')
```

```
Output:
Loading Glove Model
1917495it [06:32, 4879.69it/s]
Done. 1917495 words loaded!
 # ===============
 words = []
 for i in preproced texts:
      words.extend(i.split(' '))
for i in preproced_titles:
       words.extend(i.split(' '))
print("all the words in the coupus", len(words))
words = set(words)
print("the unique words in the coupus", len(words))
inter words = set(model.keys()).intersection(words)
print("The number of words that are present in both glove vectors and our coupus", \
           len(inter_words),"(",np.round(len(inter_words)/len(words)*100,3),"%)")
words courpus = {}
words_glove = set(model.keys())
for i in words:
       if i in words glove:
             words courpus[i] = model[i]
 print("word 2 vec length", len(words courpus))
 # stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-sa
ve-and-load-variables-in-python/
 import pickle
with open('glove_vectors', 'wb') as f:
      pickle.dump(words courpus, f)
 . . .
Out[38]:
encoding="utf8")\n model = {}\n for line in tqdm(f):\n
                                                                                                                       splitLine = line.split() \n
odel[word] = embedding\n
                                               print ("Done.",len(model)," words loaded!")\n return model\nmodel =
\label{loadGloveModel( 'glove.42B.300d.txt') } $$ n = = = --- nOutput: n $$ nLoading G $$ is a finite of the context of the 
love Model\n1917495it [06:32, 4879.69it/s]\nDone. 1917495 words loaded!\n\n#
=======\n\nwords = []\nfor i in preproced_texts:\n words.extend(i.split(\'\'))\n\nfor i in preproced_titles:\n words.extend(i.split(\'\'))\nprint("all the words in the
coupus", len(words))\nwords = set(words)\nprint("the unique words in the coupus",
len(words)) \n\ninter words = set(model.keys()).intersection(words) \nprint("The number of words tha
t are present in both glove vectors and our coupus", len(inter_words),"
```

In [39]:

4

```
# 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)
    glove_words = set(model.keys())
```

print("word 2 vec length", len(words\_courpus))\n\n# stronging variables into pickle files python
: http://www.jessicayung.com/how-to-use-pickle-to-save-and-load-variables-in-python/\n\nimport pic

kle\nwith open(\'glove vectors\', \'wb\') as f:\n pickle.dump(words courpus, f)\n\n\n'

words courpus[i] = model[i]\r.

### In [40]:

```
# average Word2Vec
# compute average word2vec for each review.
train_avg_w2v_essays = []; # the avg-w2v for each sentence/review is stored in this list
```

```
for sentence in tqdm(project_data_train['preprocessed_essays']): # 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
        train_avg_w2v_essays.append(vector)

print(len(train_avg_w2v_essays))
print(len(train_avg_w2v_essays[0]))
100%| 33500/33500 [00:06<00:00, 5499.96it/s]
```

33500 300

```
In [41]:
```

```
# average Word2Vec
# compute average word2vec for each review.
test avg w2v essays = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(project data test['preprocessed essays']): # 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
    test avg w2v essays.append(vector)
print(len(test_avg_w2v_essays))
print(len(test_avg_w2v_essays[0]))
100%| 100%| 16500/16500 [00:03<00:00, 5414.87it/s]
```

16500 300

### In [42]:

```
# average Word2Vec
# compute average word2vec for each review.
train_avg_w2v_titles = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(project_data_train['preprocessed_titles']): # 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
    train avg w2v titles.append(vector)
print(len(train avg w2v titles))
print(len(train_avg_w2v_titles[0]))
100%| 33500/33500 [00:00<00:00, 95552.04it/s]
```

### In [43]:

```
# average Word2Vec
# compute average word2vec for each review.
test avg w2v titles = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(project data test['preprocessed titles']): # 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
    test avg w2v titles.append(vector)
print(len(test_avg_w2v_titles))
print(len(test avg w2v titles[0]))
100%| 16500/16500 [00:00<00:00, 97571.52it/s]
16500
```

### 1.5.2.3 Using Pretrained Models: TFIDF weighted W2V

```
In [44]:
```

300

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model = TfidfVectorizer()
tfidf_model.fit(project_data_train['preprocessed_essays'].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 [45]:

```
# average Word2Vec
# compute average word2vec for each review.
train tfidf w2v essays = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(project data train['preprocessed essays']): # 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
    train tfidf w2v essays.append(vector)
print(len(train tfidf w2v essays))
print(len(train tfidf w2v essays[0]))
100%| 33500/33500 [00:42<00:00, 788.50it/s]
```

```
TIL [HO].
```

```
# average Word2Vec
# compute average word2vec for each review.
test tfidf w2v essays = []; # the avq-w2v for each sentence/review is stored in this list
for sentence in tqdm(project data test['preprocessed essays']): # 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
    test tfidf w2v essays.append(vector)
print(len(test tfidf w2v essays))
print(len(test tfidf w2v essays[0]))
100%| 100%| 16500/16500 [00:20<00:00, 803.77it/s]
```

16500 300

### In [47]:

```
# Similarly you can vectorize for title also
tfidf_model = TfidfVectorizer()
tfidf_model.fit(project_data_train['preprocessed_titles'])
# 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 [48]:

```
# average Word2Vec
# compute average word2vec for each review.
train tfidf w2v titles = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(project data train['preprocessed titles']): # 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
    train tfidf w2v titles.append(vector)
print(len(train tfidf w2v titles))
print(len(train tfidf w2v titles[0]))
100%| 33500/33500 [00:00<00:00, 47888.03it/s]
```

```
# average Word2Vec
# compute average word2vec for each review.
test tfidf w2v titles = []; # the avq-w2v for each sentence/review is stored in this list
for sentence in tqdm(project data test['preprocessed titles']): # 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
    test tfidf w2v titles.append(vector)
print(len(test tfidf w2v titles))
print(len(test tfidf w2v titles[0]))
100%| 16500/16500 [00:00<00:00, 46054.69it/s]
16500
300
```

### 1.5.3 Vectorizing Numerical features

```
In [50]:
```

```
In [51]:
project_data_train = pd.merge(project_data_train, price_data, on='id', how='left')
project_data_test = pd.merge(project_data_test, price_data, on='id', how='left')
```

price data = resource data.groupby('id').agg({'price':'sum', 'quantity':'sum'}).reset index()

### In [52]:

```
from sklearn.preprocessing import Normalizer
# normalizer.fit(X_train['price'].values)
# this will rise an error Expected 2D array, got 1D array instead:
# array.reshape(-1, 1) if your data has a single feature
# array.reshape(1, -1) if it contains a single sample.

normalizer = Normalizer()
normalizer.fit(project_data_train['price'].values.reshape(1,-1))

price_normalized_train = normalizer.transform(project_data_train['price'].values.reshape(1, -1))

price_normalized_test = normalizer.transform(project_data_test['price'].values.reshape(1, -1))
#reshaping again after normalization

price_normalized_train = price_normalized_train.reshape(-1, 1)
price_normalized_test = price_normalized_test.reshape(-1, 1)

print('After normalization')
print(price_normalized_test.shape)
```

```
After normalization (33500, 1) (16500, 1)
```

```
In [53]:
```

```
normalizer = Normalizer()
normalizer.fit(project data train['quantity'].values.reshape(1,-1))
quantity normalized train = normalizer.transform(project data train['quantity'].values.reshape(1, -
1))
quantity_normalized_test = normalizer.transform(project_data_test['quantity'].values.reshape(1, -1)
#reshaping again after normalization
quantity normalized train = quantity normalized train.reshape(-1,1)
quantity_normalized_test = quantity_normalized_test.reshape(-1,1)
print('After normalization')
print(quantity normalized train.shape)
print(quantity normalized test.shape)
After normalization
(33500, 1)
(16500, 1)
In [54]:
normalizer = Normalizer()
normalizer.fit(project data train['teacher number of previously posted projects'].values.reshape(1
,-1))
previously_posted_projects_normalized_train =
normalizer.transform(project_data_train['teacher_number_of_previously_posted_projects'].values.res
hape(1, -1))
previously posted projects normalized test =
normalizer.transform(project data test['teacher number of previously posted projects'].values.resh
ape(1, -1))
#reshaping again after normalization
previously posted projects normalized train = previously posted projects normalized train.reshape(
previously posted projects normalized test = previously posted projects normalized test.reshape(-1
,1)
print('After normalization')
print (previously posted projects normalized train.shape)
print(previously_posted_projects_normalized test.shape)
After normalization
(33500, 1)
(16500, 1)
In [55]:
normalizer = Normalizer()
normalizer.fit(project data train['essay word count'].values.reshape(-1,1))
essay word count normalized train = normalizer.transform(project data train['essay word count'].va
lues.reshape(1, -1))
essay word count normalized test = normalizer.transform(project data test['essay word count'].valu
es.reshape(1, -1))
#reshaping again after normalization
essay word count normalized train = essay word count normalized train.reshape(-1, 1)
essay_word_count_normalized_test = essay_word_count_normalized_test.reshape(-1, 1)
```

```
print('After normalization')
print(essay_word_count_normalized_train.shape)
print(essay word count normalized test.shape)
After normalization
(33500, 1)
(16500, 1)
In [56]:
normalizer = Normalizer()
normalizer.fit(project_data_train['title_word_count'].values.reshape(-1,1))
title word count normalized train = normalizer.transform(project data train['title word count'].va
lues.reshape(1, -1))
title word count normalized test = normalizer.transform(project data test['title word count'].valu
es.reshape(1, -1))
#reshaping again after normalization
title_word_count_normalized_train = title_word_count_normalized_train.reshape(-1, 1)
title_word_count_normalized_test = title_word_count_normalized_test.reshape(-1, 1)
print('After normalization')
print(title word count normalized train.shape)
print(title word count normalized test.shape)
After normalization
(33500, 1)
(16500, 1)
In [57]:
normalizer = Normalizer()
normalizer.fit(project data train['neg'].values.reshape(-1,1))
sent neg train = normalizer.transform(project data train['neg'].values.reshape(1, -1))
sent_neg_test = normalizer.transform(project_data_test['neg'].values.reshape(1, -1))
#reshaping again after normalization
sent neg train = sent neg train.reshape(-1,1)
sent neg test = sent neg test.reshape(-1,1)
print('After normalization')
print(sent neg train.shape)
print(sent_neg_test.shape)
After normalization
(33500, 1)
(16500, 1)
In [58]:
normalizer = Normalizer()
normalizer.fit(project data train['pos'].values.reshape(-1,1))
sent pos train = normalizer.transform(project data train['pos'].values.reshape(1, -1))
sent pos test = normalizer.transform(project data test['pos'].values.reshape(1. -1))
```

```
#reshaping again after normalization
sent_pos_train = sent_pos_train.reshape(-1,1)
sent pos test = sent pos test.reshape(-1,1)
print('After normalization')
print(sent pos train.shape)
print(sent pos test.shape)
After normalization
(33500, 1)
(16500, 1)
In [59]:
normalizer = Normalizer()
normalizer.fit(project_data_train['neu'].values.reshape(-1,1))
sent_neu_train = normalizer.transform(project_data_train['neu'].values.reshape(1, -1))
sent neu test = normalizer.transform(project data test['neu'].values.reshape(1, -1))
#reshaping again after normalization
sent neu train = sent neu train.reshape(-1,1)
sent_neu_test = sent_neu_test.reshape(-1,1)
print('After normalization')
print(sent neu train.shape)
print(sent_neu_test.shape)
After normalization
(33500, 1)
(16500, 1)
In [60]:
normalizer = Normalizer()
normalizer.fit(project_data_train['compound'].values.reshape(-1,1))
sent compound train = normalizer.transform(project data train['compound'].values.reshape(1, -1))
sent_compound_test = normalizer.transform(project_data_test['compound'].values.reshape(1, -1))
#reshaping again after normalization
sent compound train = sent compound train.reshape(-1,1)
sent_compound_test = sent_compound_test.reshape(-1,1)
print('After normalization')
print(sent compound train.shape)
print(sent_compound_test.shape)
After normalization
(33500, 1)
(16500, 1)
```

# **Response coding for Categorical Data**

I wrote my own function to calculate the response values for categorical features ( works for

```
both train and test data)
```

```
In [61]:
```

```
#https://stackoverflow.com/questions/11869910/pandas-filter-rows-of-dataframe-with-operator-chaini
def mask(df, key, value):
   return df[df[key] == value]
def get response(data, data label):
    cat_values = np.unique(data).tolist()
    df = pd.DataFrame({'feature':data.values.tolist(),'label':data label.values.tolist()})
    pd.DataFrame.mask = mask
    accep = {};reject={};prob neg = {};prob pos={}
    for i in cat values:
       count 0 = len(df.mask('feature', i).mask('label', 0))
       count 1 = len(df.mask('feature', i).mask('label', 1))
       total = count_0 + count_1
       prob_0 = count_0/total
       prob 1 = count 1/total
       accep[i] = count 1
       reject[i] = count 0
       prob neg[i] = prob 0
       prob_pos[i] = prob_1
    return prob neg, prob pos
In [62]:
cat 0 train = get response(project data train['clean categories'],y train)[0]
cat_1_train = get_response(project_data_train['clean_categories'],y_train)[1]
In [63]:
subcat 0 train = get response(project data train['clean subcategories'],y train)[0]
subcat 1 train = get response(project data train['clean subcategories'], y train)[1]
In [64]:
state_0_train = get_response(project_data_train['school_state'],y_train)[0]
state 1 train = get response(project data train['school state'],y train)[1]
In [65]:
prefix 0 train = get response(project data train['teacher prefix'],y train)[0]
prefix 1 train = get response(project data train['teacher prefix'],y train)[1]
In [66]:
grad cat 0 train = get response(project data train['project grade category'],y train)[0]
grad cat 1 train = get response(project data train['project grade category'], y train)[1]
In [67]:
cat 0 test = get response(project data test['clean categories'],y test)[0]
cat_1_test = get_response(project_data_test['clean_categories'], y_test)[1]
In [68]:
subcat_0_test = get_response(project_data_test['clean_subcategories'], y_test)[0]
subcat_1_test = get_response(project_data_test['clean_subcategories'], y_test)[1]
In [69]:
state_0_test = get_response(project_data_test['school_state'], y_test)[0]
```

state\_1\_test = get\_response(project\_data\_test['school\_state'], y\_test)[1]

```
In [70]:
prefix_0_test = get_response(project_data_test['teacher_prefix'],y_test)[0]
prefix_1_test = get_response(project_data_test['teacher_prefix'],y_test)[1]
In [71]:
grad_cat_0_test = get_response(project_data_test['project_grade_category'],y_test)[0]
grad cat 1 test = get response(project data test['project grade category'], y test)[1]
In [72]:
cat 0 train
Out[72]:
{'AppliedLearning': 0.19329896907216496,
 'AppliedLearning Health Sports': 0.14893617021276595,
 'AppliedLearning History Civics': 0.16363636363636364,
 'AppliedLearning Literacy_Language': 0.16400580551523947,
 'AppliedLearning Math Science': 0.1836734693877551,
 'AppliedLearning Music Arts': 0.18181818181818182,
 'AppliedLearning SpecialNeeds': 0.2018140589569161,
 'Health Sports': 0.148708254568368,
 'Health Sports AppliedLearning': 0.21875,
 'Health Sports History Civics': 0.0666666666666667,
 'Health Sports Literacy Language': 0.1910569105691057,
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DICETACATE WITCHING WATHER CATE HARINGE . V.V,

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'Civics Government EnvironmentalScience': 0.75,
'Civics Government FinancialLiteracy': 1.0,
'Civics Government Health LifeScience': 0.8571428571428571,
'Civics_Government Health_Wellness': 1.0,
'Civics_Government History_Geography': 0.8208955223880597,
'Civics Government Literacy': 0.94,
'Civics Government Literature Writing': 0.9032258064516129,
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'College CareerPrep EarlyDevelopment': 1.0,
'College CareerPrep Economics': 1.0,
'College CareerPrep EnvironmentalScience': 1.0,
'College_CareerPrep Extracurricular': 0.9230769230769231,
'College_CareerPrep FinancialLiteracy': 0.5,
'College CareerPrep ForeignLanguages': 0.6,
'College CareerPrep Gym Fitness': 0.0,
'College_CareerPrep History_Geography': 0.8,
'College CareerPrep Literature Writing': 0.83,
'College CareerPrep Mathematics': 0.8552631578947368,
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'College CareerPrep NutritionEducation': 0.5,
'College CareerPrep Other': 0.8518518518518519,
'College CareerPrep ParentInvolvement': 0.7692307692307693,
'College CareerPrep PerformingArts': 0.875,
'College CareerPrep SocialSciences': 0.7777777777778,
'College CareerPrep SpecialNeeds': 0.7073170731707317,
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'College_CareerPrep VisualArts': 0.8269230769230769,
'College CareerPrep Warmth Care Hunger': 1.0,
'CommunityService': 0.75,
'CommunityService ESL': 0.5,
'CommunityService EarlyDevelopment': 1.0,
'CommunityService Economics': 1.0,
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'CommunityService Extracurricular': 0.7142857142857143,
'CommunityService FinancialLiteracy': 1.0,
'CommunityService Gym Fitness': 1.0,
'CommunityService Health_LifeScience': 1.0,
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'CommunityService History Geography': 1.0,
'CommunityService Literacy': 1.0,
'CommunityService Literature Writing': 0.75,
'CommunityService Mathematics': 0.8,
'CommunityService Music': 1.0,
'CommunityService Other': 1.0,
'CommunityService ParentInvolvement': 1.0,
'CommunityService PerformingArts': 1.0,
'CommunityService SocialSciences': 0.0,
'CommunityService SpecialNeeds': 0.625,
'CommunityService VisualArts': 0.6428571428571429,
'ESL': 0.8473282442748091,
'ESL EarlyDevelopment': 0.8947368421052632,
'ESL EnvironmentalScience': 0.7,
'ESL Extracurricular': 1.0,
'ESL ForeignLanguages': 0.8571428571428571,
'ESL Gym Fitness': 0.5,
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'ESL History Geography': 0.833333333333334,
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'ESL Mathematics': 0.8313253012048193,
'ESL Music': 1.0,
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'ESL PerformingArts': 1.0,
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'ESL SpecialNeeds': 0.8181818181818182,
'ESL VisualArts': 0.7647058823529411,
'EarlyDevelopment': 0.8248175182481752,
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'EarlyDevelopment ForeignLanguages': 1.0,
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'EarlyDevelopment Health_LifeScience': 0.7272727272727273,
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'EnvironmentalScience Literacy': 0.8582677165354331,
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'EnvironmentalScience Mathematics': 0.83399209486166,
'EnvironmentalScience Music': 1.0,
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'EnvironmentalScience ParentInvolvement': 1.0,
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'Extracurricular Health LifeScience': 0.5,
'Extracurricular Health Wellness': 0.75,
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'Extracurricular NutritionEducation': 0.0,
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'FinancialLiteracy ForeignLanguages': 1.0,
'FinancialLiteracy Health LifeScience': 1.0,
'FinancialLiteracy Health_Wellness': 1.0,
'FinancialLiteracy History_Geography': 1.0,
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'FinancialLiteracy Literature Writing': 0.0,
'FinancialLiteracy Mathematics': 0.8695652173913043,
'FinancialLiteracy Other': 1.0,
'FinancialLiteracy ParentInvolvement': 1.0,
'FinancialLiteracy SocialSciences': 1.0,
'FinancialLiteracy SpecialNeeds': 0.8125,
'FinancialLiteracy VisualArts': 1.0,
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'ForeignLanguages Health Wellness': 0.75,
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'Gym Fitness TeamSports': 0.7967914438502673,
'Gym Fitness VisualArts': 1.0,
'Health LifeScience': 0.8432203389830508,
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'Health_LifeScience History_Geography': 0.8125,
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'Health LifeScience ParentInvolvement': 1.0,
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'Health Wellness Music': 0.9,
'Health Wellness NutritionEducation': 0.8353909465020576,
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'Health Wellness SpecialNeeds': 0.8614457831325302,
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'History_Geography VisualArts': 0.7959183673469388,
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'Literacy Music': 0.9302325581395349,
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'Literature Writing VisualArts': 0.806930693069307,
'Literature Writing Warmth Care Hunger': 1.0,
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'Mathematics NutritionEducation': 1.0,
'Mathematics Other': 0.7857142857142857,
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 'Mathematics PerformingArts': 1.0,
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 'Mathematics SpecialNeeds': 0.7923497267759563,
 'Mathematics TeamSports': 0.5,
 'Mathematics VisualArts': 0.7887323943661971,
 'Mathematics Warmth Care Hunger': 0.5,
 'Music': 0.8840262582056893,
 'Music Other': 0.5,
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 'Music SpecialNeeds': 0.966666666666667,
 'Music TeamSports': 1.0,
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 'NutritionEducation SpecialNeeds': 0.625,
 'NutritionEducation TeamSports': 1.0,
'NutritionEducation VisualArts': 0.5,
'Other': 0.8153846153846154,
 'Other ParentInvolvement': 0.8,
 'Other PerformingArts': 0.0,
 'Other SocialSciences': 1.0,
'Other SpecialNeeds': 0.7821782178217822,
'Other TeamSports': 1.0,
 'Other VisualArts': 0.8125,
 'Other Warmth Care Hunger': 1.0,
 'ParentInvolvement': 0.5454545454545454,
'ParentInvolvement PerformingArts': 1.0,
'ParentInvolvement SocialSciences': 0.8,
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 'ParentInvolvement TeamSports': 1.0,
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'PerformingArts': 0.8970588235294118,
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 'SpecialNeeds Warmth Care Hunger': 1.0,
 'TeamSports': 0.817629179331307,
 'TeamSports VisualArts': 0.5,
 'VisualArts': 0.835555555555556,
 'VisualArts Warmth Care Hunger': 0.0,
 'Warmth Care Hunger': 0.937046004842615}
In [77]:
subcat neg train = []
subcat pos train = []
for i in project_data_train['clean_subcategories']:
   subcat_neg_train.append(subcat_0_train[i])
   subcat pos train.append(subcat 1 train[i])
project data train['subcat 0'] = subcat neg train
project data train['subcat 1'] = subcat pos train
In [78]:
state 0 train
Out[78]:
{'AK': 0.1523809523809524,
 'AL': 0.15471698113207547,
 'AR': 0.18627450980392157,
 'AZ': 0.15109034267912771,
 'CA': 0.14046610169491525,
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'CO': 0.162534435261708,

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'CT': 0.10477941176470588,
'DC': 0.22093023255813954
'DE': 0.1320754716981132,
'FL': 0.1797872340425532,
'GA': 0.1630794701986755,
'HI': 0.17088607594936708,
'IA': 0.13658536585365855,
'TD': 0.19170984455958548.
'IL': 0.16310975609756098,
'IN': 0.16046213093709885,
'KS': 0.1092896174863388,
'KY': 0.12781954887218044,
'LA': 0.16759002770083103,
'MA': 0.16204986149584488,
'MD': 0.16997792494481237,
'ME': 0.14965986394557823,
'MN': 0.15873015873015872,
'MO': 0.13745271122320302,
'MS': 0.16470588235294117,
'MT': 0.21739130434782608,
'NC': 0.13966836734693877,
'ND': 0.07317073170731707,
'NE': 0.18478260869565216,
'NH': 0.09782608695652174,
'NJ': 0.17691154422788605,
'NM': 0.14450867052023122,
'NV': 0.1342281879194631,
'NY': 0.13895015438906044,
'OH': 0.11475409836065574,
'OK': 0.15988779803646563,
'OR': 0.18087855297157623,
'PA': 0.15817409766454352,
'RI': 0.14942528735632185,
'SC': 0.152777777777778,
'SD': 0.15306122448979592,
'TN': 0.15503875968992248,
'TX': 0.18664909969257795,
'UT': 0.16827852998065765,
'VA': 0.1430817610062893,
'VT': 0.23809523809523808,
'WA': 0.11869031377899045,
'WI': 0.16304347826086957,
'WV': 0.13548387096774195,
'WY': 0.20588235294117646}
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### In [79]:

### state 1 train

### Out[79]:

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{'AK': 0.8476190476190476,
 'AL': 0.8452830188679246,
 'AR': 0.8137254901960784.
 'AZ': 0.8489096573208723.
'CA': 0.8595338983050848,
'CO': 0.837465564738292,
 'CT': 0.8952205882352942,
 'DC': 0.7790697674418605,
 'DE': 0.8679245283018868,
'FL': 0.8202127659574469,
'GA': 0.8369205298013245,
 'HI': 0.8291139240506329,
 'IA': 0.8634146341463415,
 'ID': 0.8082901554404145,
 'TT.': 0.836890243902439.
'IN': 0.8395378690629012,
 'KS': 0.8907103825136612,
 'KY': 0.8721804511278195,
 'LA': 0.832409972299169,
 'MA': 0.8379501385041551,
 'MD': 0.8300220750551877,
 'ME': 0.8503401360544217,
 'MI': 0.833333333333334,
 IMMI. 0 0/10/00/10/00/10
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. ININ .: 0.04T70A04T70A04T9'
 'MO': 0.862547288776797,
 'MS': 0.8352941176470589,
 'MT': 0.782608695652174,
 'NC': 0.8603316326530612,
 'ND': 0.926829268292683,
 'NE': 0.8152173913043478,
 'NH': 0.9021739130434783,
 'NJ': 0.823088455772114,
 'NM': 0.8554913294797688,
 'NV': 0.8657718120805369,
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 'OH': 0.8852459016393442,
 'OK': 0.8401122019635343,
 'OR': 0.8191214470284238,
 'PA': 0.8418259023354565,
 'RI': 0.8505747126436781,
 'SC': 0.847222222222222,
 'SD': 0.8469387755102041,
 'TN': 0.8449612403100775,
 'TX': 0.8133509003074221,
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 'VA': 0.8569182389937107,
 'VT': 0.7619047619047619,
 'WA': 0.8813096862210096,
 'WI': 0.8369565217391305,
 'WV': 0.864516129032258,
 'WY': 0.7941176470588235}
In [80]:
state_neg_train = []
state_pos_train = []
for i in project data train['school state']:
    state_neg_train.append(state_0_train[i])
    state_pos_train.append(state_1_train[i])
project data train['state 0'] = state neg train
project_data_train['state_1'] = state_pos_train
In [81]:
prefix 0 train
Out[81]:
{'Dr': 0.5,
 'Mr': 0.16078551702976374,
 'Mrs': 0.14822666590271014,
 'Ms': 0.15854364915184113,
 'Teacher': 0.19971469329529243}
In [82]:
prefix 1 train
Out[82]:
{'Dr': 0.5,
 'Mr': 0.8392144829702363,
 'Mrs': 0.8517733340972898,
 'Ms': 0.8414563508481588,
 'Teacher': 0.8002853067047075}
In [83]:
prefix neg train = []
prefix_pos_train = []
for i in project_data_train['teacher_prefix']:
    prefix_neg_train.append(prefix_0_train[i])
    prefix_pos_train.append(prefix_1_train[i])
project data train['prefix 0'] = prefix neg train
project_data_train['prefix_1'] = prefix_pos_train
```

```
In [84]:
grad_cat 0 train
Out[84]:
{'Grades 3 5': 0.14883234576507495,
 'Grades_6_8': 0.16423712342079688,
'Grades_9_12': 0.17179951690821257,
 'Grades PreK 2': 0.15080710547652393}
In [85]:
grad cat 1 train
Out[85]:
{'Grades 3 5': 0.851167654234925,
 'Grades_6_8': 0.8357628765792031,
 'Grades_9_12': 0.8282004830917874,
 'Grades PreK 2': 0.8491928945234761}
In [86]:
grade neg train = []
grade pos train = []
for i in project data train['project grade category']:
    grade neg train.append(grad cat 0 train[i])
    grade_pos_train.append(grad_cat_1_train[i])
project_data_train['grade_0'] = grade_neg_train
project_data_train['grade_1'] = grade_pos_train
In [87]:
project data train.columns
Out[87]:
Index(['Unnamed: 0', 'id', 'teacher id', 'school state',
         'project submitted datetime', 'project title',
         'project_resource_summary',
         'teacher_number_of_previously_posted_projects', 'clean_categories', 'clean_subcategories', 'project_grade_category', 'teacher_prefix',
         'essay', 'preprocessed essays', 'essay word count',
         'preprocessed_titles', 'title_word_count', 'neg', 'neu', 'pos', 'compound', 'price', 'quantity', 'cat_0', 'cat_1', 'subcat_0', 'subcat_1', 'state_0', 'state_1', 'prefix_0', 'prefix_1', 'grade_0',
         'grade 1'],
       dtype='object')
In [88]:
project data train.head()
Out[88]:
```

_รเ	project_resource	project_title	project_submitted_datetime	school_state	teacher_id	id	Unnamed: 0	
	My students need and lear	reading is fundamental	2016-07-30 18:03:38	VA	79035a795a20edf0792b390535afde8d	p143868	150799	0
	My stu basketballs	character education through early morning bask	2016-12-23 15:23:35	СО	13465062735441af726acd10d7ed50ac	p057203	110848	1
	My stude trampolir	bounce and learn	2016-09-13 15:29:02	WI	21f2243d51d566e486a8f429af75d7dc	p037393	52340	2

........

```
My students ne
3 Unnameds p177980 17257472e5549a7bd0cba82635040b86 school_state project_submitted5datefine
                                                                            PHRIGESH4
                                                                                      projectiineourgees
                                                                             encouraging
                                                                                healthy
                                                                                eating
                                                                                      My students need a va
                                                    CA
      8722 p056227 d02a6876dee2ab709295b00bd3920859
                                                             2016-08-13 03:05:03
                                                                                through
                                                                                             examples c
                                                                               dramatic
5 rows × 33 columns
In [89]:
cat 0 test
Out[89]:
{'AppliedLearning': 0.1837837837837838,
 'AppliedLearning Health Sports': 0.19736842105263158,
 'AppliedLearning History Civics': 0.2608695652173913,
 'AppliedLearning Literacy_Language': 0.13069908814589665,
 'AppliedLearning Math Science': 0.20218579234972678,
 'AppliedLearning Music Arts': 0.22033898305084745,
 'AppliedLearning SpecialNeeds': 0.1774891774891775,
 'AppliedLearning Warmth Care Hunger': 0.5,
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 'Health_Sports AppliedLearning': 0.14285714285714285,
 'Health Sports History Civics': 0.1,
 'Health_Sports Literacy_Language': 0.15447154471544716,
 'Health Sports Music Arts': 0.27777777777778,
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 'Health Sports Warmth Care Hunger': 0.0,
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 'History_Civics AppliedLearning': 0.3,
 'History Civics Health Sports': 0.0,
 'History_Civics Literacy_Language': 0.083333333333333333,
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Out [90]:
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redecorate

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cat pos test = []
for i in project_data_test['clean_categories']:
   cat neg test.append(cat 0 test[i])
    cat pos test.append(cat 1 test[i])
project data test['cat 0'] = cat neg test
project data test['cat 1'] = cat pos test
In [92]:
subcat 0 test
Out[92]:
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'EnvironmentalScience Health LifeScience': 0.7769230769230769,
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'EnvironmentalScience History_Geography': 0.7391304347826086,
'FnwironmentalScience Titeracul. 0 8823520/1176/706
```

```
Environmentarscience biceracy . 0.0025529411/04/00,
'EnvironmentalScience Literature Writing': 0.8837209302325582,
'EnvironmentalScience Mathematics': 0.8257575757575758,
'EnvironmentalScience Music': 1.0,
'EnvironmentalScience NutritionEducation': 0.5,
'EnvironmentalScience Other': 0.0,
'EnvironmentalScience ParentInvolvement': 1.0,
'EnvironmentalScience SocialSciences': 0.8,
'EnvironmentalScience SpecialNeeds': 0.9130434782608695,
'EnvironmentalScience TeamSports': 1.0,
'EnvironmentalScience VisualArts': 0.8529411764705882,
'Extracurricular': 0.9473684210526315,
'Extracurricular Gym Fitness': 1.0,
'Extracurricular Health LifeScience': 0.5,
'Extracurricular Literature Writing': 1.0,
'Extracurricular Mathematics': 0.81818181818182,
'Extracurricular Music': 0.6,
'Extracurricular Other': 1.0,
'Extracurricular PerformingArts': 1.0,
'Extracurricular SpecialNeeds': 1.0,
'Extracurricular TeamSports': 1.0,
'Extracurricular VisualArts': 0.8823529411764706,
'FinancialLiteracy': 0.8636363636363636,
'FinancialLiteracy Health Wellness': 1.0,
'FinancialLiteracy History Geography': 1.0,
'FinancialLiteracy Literacy': 1.0,
'FinancialLiteracy Literature_Writing': 1.0,
'FinancialLiteracy Mathematics': 0.9047619047619048,
'FinancialLiteracy Other': 1.0,
'ForeignLanguages': 0.8076923076923077,
'ForeignLanguages Health_LifeScience': 1.0,
'ForeignLanguages Health Wellness': 1.0,
'ForeignLanguages History_Geography': 1.0,
'ForeignLanguages Literacy': 0.9069767441860465,
'ForeignLanguages Literature Writing': 0.6923076923076923,
'ForeignLanguages Mathematics': 0.5714285714285714,
'ForeignLanguages Music': 1.0,
'ForeignLanguages SocialSciences': 1.0,
'ForeignLanguages SpecialNeeds': 1.0,
'ForeignLanguages VisualArts': 0.0,
'Gym Fitness': 0.8238636363636364,
'Gym_Fitness Health_Wellness': 0.8475073313782991,
'Gym Fitness History Geography': 1.0,
'Gym Fitness Literacy': 0.5,
'Gym Fitness Literature Writing': 0.5,
'Gym Fitness Mathematics': 0.6,
'Gym Fitness Music': 1.0,
'Gym Fitness NutritionEducation': 0.9,
'Gym Fitness Other': 1.0,
'Gym Fitness ParentInvolvement': 1.0,
'Gym Fitness PerformingArts': 0.0,
'Gym Fitness SpecialNeeds': 0.8,
'Gym_Fitness TeamSports': 0.7528089887640449,
'Gym Fitness VisualArts': 0.0,
'Health LifeScience': 0.8201438848920863,
'Health LifeScience Health Wellness': 0.7307692307692307,
'Health LifeScience Literacy': 0.8529411764705882,
'Health LifeScience Literature Writing': 1.0,
'Health LifeScience Mathematics': 0.8082191780821918,
'Health LifeScience Music': 1.0,
'Health LifeScience NutritionEducation': 0.8,
'Health LifeScience ParentInvolvement': 1.0,
'Health_LifeScience SocialSciences': 0.9090909090909091,
'Health LifeScience SpecialNeeds': 0.77777777777778,
'Health LifeScience TeamSports': 1.0,
'Health LifeScience VisualArts': 0.7692307692307693,
'Health LifeScience Warmth Care Hunger': 1.0,
'Health Wellness': 0.8687615526802218,
'Health Wellness History Geography': 1.0,
'Health Wellness Literacy': 0.855072463768116,
'Health Wellness Literature Writing': 0.8913043478260869,
'Health Wellness Mathematics': 0.7906976744186046,
'Health_Wellness NutritionEducation': 0.832,
```

```
'Health Wellness ParentInvolvement': 1.0,
'Health Wellness PerformingArts': 1.0,
'Health Wellness SocialSciences': 0.5,
'Health Wellness SpecialNeeds': 0.8767123287671232,
'Health Wellness TeamSports': 0.7547169811320755,
'Health Wellness VisualArts': 1.0,
'Health Wellness Warmth Care Hunger': 1.0,
'History_Geography': 0.8390804597701149,
'History Geography Literacy': 0.9240506329113924,
'History_Geography Literature_Writing': 0.9080459770114943,
'History_Geography Mathematics': 0.8260869565217391,
'History_Geography Music': 0.5,
'History Geography Other': 0.5,
'History Geography PerformingArts': 1.0,
'History Geography SocialSciences': 0.7959183673469388,
'History Geography SpecialNeeds': 0.866666666666667,
'History Geography VisualArts': 0.8518518518518519,
'Literacy': 0.8733153638814016,
'Literacy Literature Writing': 0.8826945412311266,
'Literacy Mathematics': 0.8672768878718535,
'Literacy Music': 0.8333333333333334,
'Literacy Other': 0.9130434782608695,
'Literacy ParentInvolvement': 0.88,
'Literacy PerformingArts': 0.7333333333333333,
'Literacy SocialSciences': 0.9245283018867925,
'Literacy SpecialNeeds': 0.8594594594594595,
'Literacy TeamSports': 0.75,
'Literacy VisualArts': 0.8210526315789474,
'Literature Writing': 0.8361408882082695,
'Literature Writing Mathematics': 0.8600917431192661,
'Literature Writing Music': 1.0,
'Literature Writing Other': 0.8571428571428571,
'Literature Writing ParentInvolvement': 0.7777777777778,
'Literature Writing PerformingArts': 0.8333333333333334,
'Literature Writing SocialSciences': 0.8823529411764706,
'Literature Writing SpecialNeeds': 0.8652849740932642,
'Literature Writing VisualArts': 0.8073394495412844,
'Mathematics': 0.8370098039215687,
'Mathematics Music': 1.0,
'Mathematics Other': 0.833333333333334,
'Mathematics ParentInvolvement': 0.9285714285714286,
'Mathematics PerformingArts': 0.5,
'Mathematics SocialSciences': 0.8571428571428571,
'Mathematics SpecialNeeds': 0.8241758241758241.
'Mathematics VisualArts': 0.8539325842696629,
'Music': 0.8815165876777251,
'Music PerformingArts': 0.8543046357615894,
'Music SocialSciences': 0.5,
'Music TeamSports': 0.5,
'Music VisualArts': 0.5714285714285714,
'NutritionEducation': 0.7727272727272727,
'NutritionEducation Other': 1.0,
'NutritionEducation SocialSciences': 1.0,
'NutritionEducation SpecialNeeds': 0.8,
'NutritionEducation TeamSports': 0.0,
'Other': 0.85,
'Other SocialSciences': 1.0,
'Other SpecialNeeds': 0.8367346938775511,
'ParentInvolvement': 1.0,
'ParentInvolvement PerformingArts': 1.0,
'ParentInvolvement SpecialNeeds': 0.75,
'ParentInvolvement VisualArts': 0.8,
'PerformingArts': 0.859375,
'PerformingArts SocialSciences': 1.0,
'PerformingArts SpecialNeeds': 0.75,
'PerformingArts TeamSports': 1.0,
'PerformingArts VisualArts': 0.6,
'SocialSciences': 0.9090909090909091,
'SocialSciences SpecialNeeds': 0.6,
'SocialSciences VisualArts': 0.9,
'SpecialNeeds': 0.8112582781456954,
'SpecialNeeds TeamSports': 0.4,
'SpecialNeeds VisualArts': 0.82222222222222,
'SpecialNeeds Warmth Care_Hunger': 0.75,
```

```
'TeamSports': U./9452U54/9452U54,
 'VisualArts': 0.8110749185667753,
 'Warmth Care Hunger': 0.9015544041450777}
In [94]:
subcat neg test = []
subcat pos test = []
for i in project_data_test['clean_subcategories']:
    subcat neg test.append(subcat 0 test[i])
    subcat pos test.append(subcat 1 test[i])
project_data_test['subcat_0'] = subcat_neg_test
project data test['subcat 1'] = subcat pos test
In [95]:
state 0 test
Out[951:
'AL': 0.12692307692307692,
 'AR': 0.12857142857142856,
 'AZ': 0.17613636363636365,
 'CO': 0.17714285714285713,
 'CT': 0.14782608695652175,
 'DC': 0.2,
 'DE': 0.10204081632653061,
 'FL': 0.18039624608967675,
 'GA': 0.15645161290322582,
 'HI': 0.09876543209876543.
 'IA': 0.1881188118812,
 'ID': 0.2018348623853211,
 'IL': 0.1435114503816794,
 'IN': 0.15306122448979592,
 'KS': 0.14705882352941177,
 'KY': 0.13488372093023257,
 'LA': 0.17473118279569894,
 'MA': 0.12146892655367232,
 'MD': 0.11627906976744186,
 'ME': 0.2,
 'MI': 0.1517509727626459,
 'MN': 0.11797752808988764,
 'MO': 0.1447721179624665.
 'MS': 0.15028901734104047,
 'MT': 0.2702702702702703,
 'NC': 0.1489637305699482,
 'ND': 0.13636363636363635,
 'NE': 0.1346153846153846,
 'NH': 0.16326530612244897,
 'NJ': 0.17751479289940827,
 'NM': 0.09523809523809523,
 'NV': 0.14220183486238533,
 'NY': 0.15541740674955595,
 'OH': 0.13695090439276486,
 'OK': 0.1440443213296399,
 'OR': 0.1736842105263158,
 'PA': 0.11740041928721175,
 'RI': 0.15384615384615385,
 'SC': 0.12706270627062707,
 'SD': 0.13636363636363635,
 'TN': 0.15503875968992248,
 'TX': 0.21668264621284755,
 'UT': 0.15636363636363637,
 'VA': 0.15714285714285714,
 'VT': 0.18181818181818182,
 'WA': 0.0972972972972973,
 'WI': 0.1601423487544484,
 'WV': 0.14285714285714285,
 'WY': 0.11764705882352941}
In [96]:
```

```
state_1_test
Out[96]:
{'AK': 0.77083333333333334,
 'AL': 0.8730769230769231.
 'AR': 0.8714285714285714,
 'AZ': 0.8238636363636364,
 'CA': 0.8489583333333334,
 'CO': 0.8228571428571428,
 'CT': 0.8521739130434782,
 'DC': 0.8,
 'DE': 0.8979591836734694,
 'FL': 0.8196037539103233,
 'GA': 0.8435483870967742,
 'HI': 0.9012345679012346,
 'IA': 0.811881188119,
 'ID': 0.7981651376146789,
 'IL': 0.8564885496183207,
 'IN': 0.8469387755102041,
 'KS': 0.8529411764705882,
 'KY': 0.8651162790697674,
 'LA': 0.8252688172043011,
 'MA': 0.8785310734463276,
 'MD': 0.8837209302325582,
 'ME': 0.8,
 'MI': 0.8482490272373541,
 'MN': 0.8820224719101124,
 'MO': 0.8552278820375335,
 'MS': 0.8497109826589595,
 'MT': 0.7297297297297,
 'NC': 0.8510362694300518,
 'ND': 0.8636363636363636,
 'NE': 0.8653846153846154.
 'NH': 0.8367346938775511,
 'NJ': 0.8224852071005917,
 'NM': 0.9047619047619048.
 'NV': 0.8577981651376146,
 'NY': 0.844582593250444,
 'OH': 0.8630490956072352,
 'OK': 0.8559556786703602,
 'OR': 0.8263157894736842,
 'PA': 0.8825995807127882,
 'RI': 0.8461538461538461,
 'SC': 0.8729372937293729,
 'SD': 0.8636363636363636,
 'TN': 0.8449612403100775,
 'TX': 0.7833173537871524,
 'UT': 0.8436363636363636,
 'VA': 0.8428571428571429.
 'VT': 0.8181818181818182,
 'WA': 0.9027027027027027,
 'WI': 0.8398576512455516,
 'WV': 0.8571428571428571,
 'WY': 0.8823529411764706}
In [97]:
state neg test = []
state_pos_test = []
for i in project_data_test['school_state']:
    state neg test.append(state 0 test[i])
    state_pos_test.append(state_1_test[i])
project data test['state 0'] = state neg test
project data test['state 1'] = state pos test
In [98]:
prefix 0 test
Out[98]:
{'Mr': 0.16375,
 'Mrs': 0.15122568765105304,
 'Me' · N 153136216N3144761
```

```
T10 . U.IJJIJUZIUUJITT/UI,
 'Teacher': 0.205555555555555555555
In [99]:
prefix 1 test
Out[99]:
{'Mr': 0.83625,
 'Mrs': 0.848774312348947,
 'Ms': 0.8468637839685523,
 'Teacher': 0.79444444444444444)
In [100]:
prefix neg test = []
prefix_pos_test = []
for i in project_data_test['teacher_prefix']:
    prefix_neg_test.append(prefix_0_test[i])
    prefix_pos_test.append(prefix_1_test[i])
project_data_test['prefix_0'] = prefix_neg_test
project data test['prefix 1'] = prefix pos test
In [101]:
grad cat 0 test
Out[101]:
{'Grades 3 5': 0.1445739257101238,
 'Grades 6 8': 0.1543186180422265,
 'Grades 9 12': 0.16021765417170497,
 'Grades PreK 2': 0.16076455771225368}
In [102]:
grad cat 1 test
Out[102]:
{'Grades 3 5': 0.8554260742898762,
 'Grades 6 8': 0.8456813819577735,
 'Grades 9 12': 0.839782345828295,
 'Grades PreK 2': 0.8392354422877464}
In [103]:
grade neg test = []
grade pos test = []
for i in project_data_test['project_grade_category']:
    grade_neg_test.append(grad_cat_0_test[i])
     grade_pos_test.append(grad_cat_1_test[i])
project_data_test['grade_0'] = grade_neg_test
project data test['grade 1'] = grade pos test
In [104]:
project data test.columns
Out[104]:
Index(['Unnamed: 0', 'id', 'teacher id', 'school state',
        'project_submitted_datetime', 'project_title',
        'project resource summary',
        'teacher_number_of_previously_posted_projects', 'clean_categories', 'clean_subcategories', 'project_grade_category', 'teacher_prefix',
        'essay', 'preprocessed_essays', 'essay_word_count',
        'preprocessed_titles', 'title_word_count', 'neg', 'neu', 'pos',
'compound', 'price', 'quantity', 'cat_0', 'cat_1', 'subcat_0',
'subcat_1' 'state_0' 'state_1' 'prefix_0' 'prefix_1' 'grade_0'
```

```
'grade_1'],
dtype='object')
```

#### In [105]:

```
project_data_test.head()
```

#### Out[105]:

	Unnamed: 0	id	teacher_id	school_state	project_submitted_datetime	project_title	project_resource_s
(	<b>)</b> 11624	p199334	9ca29f5ac93bd54d86a17c068dc06be2	ОН	2017-01-07 13:37:32	we want to wobble while we learn!	My students ne option for sea
1	97849	p057423	a0920c721954b6332753616983e4ebdc	CA	2016-10-05 04:00:23	dry, dry, dry!!!	My students nε drying rack to
2	<b>2</b> 12662	p145706	2abc7240adb4199ebae24b35fb31cb17	NY	2016-11-02 11:43:29	everyone loves laminating!	My students ne laminated! Ma
3	<b>3</b> 12758	p238190	c04d98e5631410f9dadaa226163a500a	PA	2016-08-01 20:08:12	active bodies promote active minds	My students need Pedal Exerc
4	<b>4</b> 26057	p027307	3f031704f900c4a6893128abaca2ff98	CA	2016-09-01 05:33:15	a technologically advanced american history ex	My students nee mini and an Ar

#### 5 rows × 33 columns

#### In [106]:

```
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(project_data_train["cat_0"].values.reshape(-1,1)) #fit has to be done only on Train
cat 0 train normalized = normalizer.transform(project data train["cat 0"].values.reshape(1,-1))
cat_0_test_normalized = normalizer.transform(project_data_test["cat_0"].values.reshape(1,-1))
#reshaping after normalizing
cat 0 train_normalized = cat_0_train_normalized.reshape(-1,1)
cat 0 test normalized = cat 0 test normalized.reshape(-1,1)
print("After vectorizations")
print(cat_0_train_normalized.shape, y_train.shape)
print(cat_0_test_normalized.shape, y_test.shape)
4
```

After vectorizations (33500, 1) (33500,) (16500, 1) (16500,)

#### In [107]:

```
cat_0_train_normalized
```

#### Out[107]:

```
[0.00476633],
[0.0051798],
[0.00563073]])
```

#### In [108]:

```
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(project_data_train["cat_1"].values.reshape(-1,1)) #fit has to be done only on Trai
n data
cat_1_train_normalized = normalizer.transform(project_data_train["cat_1"].values.reshape(1,-1))
cat_1_test_normalized = normalizer.transform(project_data_test["cat_1"].values.reshape(1,-1))
#reshaping after normalizing
cat 1 train normalized = cat 1 train normalized.reshape(-1,1)
cat 1 test normalized = cat 1 test normalized.reshape(-1,1)
print("After vectorizations")
print(cat_1_train_normalized.shape, y_train.shape)
print(cat 1 test normalized.shape, y test.shape)
4
After vectorizations
```

After vectorizations (33500, 1) (33500,) (16500, 1) (16500,)

#### In [109]:

```
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(project_data_train["subcat_0"].values.reshape(-1,1)) #fit has to be done only on Tr
ain data
subcat_0_train_normalized = normalizer.transform(project_data_train["subcat_0"].values.reshape(1,-1
subcat 0 test normalized = normalizer.transform(project data test["subcat 0"].values.reshape(1,-1))
#reshaping after normalizing
subcat 0 train normalized = subcat 0 train normalized.reshape(-1,1)
subcat 0 test normalized = subcat 0 test normalized.reshape(-1,1)
print("After vectorizations")
print(subcat 0 train normalized.shape, y train.shape)
print(subcat_0_test_normalized.shape, y_test.shape)
```

After vectorizations (33500, 1) (33500,) (16500, 1) (16500,)

In [110]:

```
trom 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(project data train["subcat 1"].values.reshape(-1,1)) #fit has to be done only on Tr
ain data
subcat 1 train normalized = normalizer.transform(project data train["subcat 1"].values.reshape(1,-1
subcat 1 test normalized = normalizer.transform(project data test["subcat 1"].values.reshape(1,-1))
#reshaping after normalizing
subcat_1_train_normalized = subcat_1_train_normalized.reshape(-1,1)
subcat_1_test_normalized = subcat_1_test_normalized.reshape(-1,1)
print("After vectorizations")
print(subcat 1 train normalized.shape, y train.shape)
print(subcat 1 test normalized.shape, y test.shape)
4
After vectorizations
(33500, 1) (33500,)
(16500, 1) (16500,)
In [111]:
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(project_data_train["state_0"].values.reshape(-1,1)) #fit has to be done only on
Train data
state 0 train normalized = normalizer.transform(project data train["state 0"].values.reshape(1,-1))
state 0 test normalized = normalizer.transform(project data test["state 0"].values.reshape(1,-1))
#reshaping after normalizing
state 0 train normalized = state 0 train normalized.reshape(-1,1)
state 0 test normalized = state 0 test normalized.reshape(-1,1)
print("After vectorizations")
print(state 0 train normalized.shape, y train.shape)
print(state_0_test_normalized.shape, y_test.shape)
After vectorizations
(33500, 1) (33500,)
(16500, 1) (16500,)
In [112]:
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(project data train["state 1"].values.reshape(-1,1)) #fit has to be done only on
Train data
state 1 train normalized = normalizer.transform(project data train["state 1"].values.reshape(1,-1))
state 1 test normalized = normalizer.transform(project data test["state 1"].values.reshape(1,-1))
#reshaping after normalizing
state_1_train_normalized = state_1_train_normalized.reshape(-1,1)
state_1_test_normalized = state_1_test_normalized.reshape(-1,1)
print("After vectorizations")
print(state_1_train_normalized.shape, y_train.shape)
print(state 1 test normalized.shape, y test.shape)
After vectorizations
(33500, 1) (33500,)
(16500, 1) (16500,)
In [113]:
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(project data train["prefix 0"].values.reshape(-1,1)) #fit has to be done only on Tr
ain data
prefix 0 train normalized = normalizer.transform(project data train["prefix 0"].values.reshape(1,-1
prefix 0 test normalized = normalizer.transform(project data test["prefix 0"].values.reshape(1,-1))
#reshaping after normalizing
prefix 0 train normalized = prefix 0 train normalized.reshape(-1,1)
prefix 0 test normalized = prefix 0 test normalized.reshape(-1,1)
print("After vectorizations")
print(prefix_0_train_normalized.shape, y_train.shape)
print(prefix 0 test normalized.shape, y test.shape)
After vectorizations
(33500, 1) (33500,)
(16500, 1) (16500,)
In [114]:
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(project data train["prefix 1"].values.reshape(-1,1)) #fit has to be done only on Tr
ain data
prefix 1 train normalized = normalizer.transform(project data train["prefix 1"].values.reshape(1,-1
prefix_1_test_normalized = normalizer.transform(project_data_test["prefix_1"].values.reshape(1,-1))
```

#reshaping after normalizing

```
prefix 1_train_normalized = prefix_1_train_normalized.reshape(-1,1)
prefix 1 test normalized = prefix 1 test normalized.reshape(-1,1)
print("After vectorizations")
print(prefix 1 train normalized.shape, y train.shape)
print(prefix 1 test normalized.shape, y test.shape)
After vectorizations
(33500, 1) (33500,)
(16500, 1) (16500,)
In [115]:
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(project_data_train["grade_0"].values.reshape(-1,1)) #fit has to be done only on
Train data
grade 0 train normalized = normalizer.transform(project data train["grade 0"].values.reshape(1,-1))
grade 0 test normalized = normalizer.transform(project data test["grade 0"].values.reshape(1,-1))
#reshaping after normalizing
grade 0 train normalized = grade 0 train normalized.reshape(-1,1)
grade 0 test normalized = grade 0 test normalized.reshape(-1,1)
print("After vectorizations")
print(grade 0 train normalized.shape, y train.shape)
print(grade_0_test_normalized.shape, y_test.shape)
After vectorizations
(33500, 1) (33500,)
(16500, 1) (16500,)
In [116]:
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(project_data_train["grade_1"].values.reshape(-1,1)) #fit has to be done only on
Train data
grade_1_train_normalized = normalizer.transform(project_data_train["grade_1"].values.reshape(1,-1))
\verb|grade_1_test_normalized = normalizer.transform(project_data_test["grade_1"].values.reshape(1,-1))|
#reshaping after normalizing
grade 1 train normalized = grade 1 train normalized.reshape(-1,1)
grade 1 test normalized = grade 1 test normalized.reshape(-1,1)
print("After vectorizations")
print(grade 1 train normalized.shape, y train.shape)
print(grade 1 test normalized.shape, y test.shape)
```

```
After vectorizations (33500, 1) (33500,) (16500, 1) (16500,)
```

# **Assignment 9: RF and GBDT**

Response Coding: Example

The response tabel is built only on train dataset. For a category which is not there in train data and present in test data, we will encode them with default values Ex: in our test data if have State: D then we encode it as [0.5, 0.05]

### 1. Apply both Random Forrest and GBDT on these feature sets

- Set 1: categorical(instead of one hot encoding, try response coding: use probability values), numerical features + project\_title(BOW) + preprocessed\_eassay (BOW)
- Set 2: categorical(instead of one hot encoding, try <u>response coding</u>: use probability values), numerical features + project\_title(TFIDF)+ preprocessed\_eassay (TFIDF)
- Set 3: categorical(instead of one hot encoding, try response coding: use probability values), numerical features + project title(AVG W2V)+ preprocessed eassay (AVG W2V)
- Set 4: categorical(instead of one hot encoding, try <u>response coding</u>: use probability values), numerical features + project title(TFIDF W2V)+ preprocessed eassay (TFIDF W2V)

### 2. The hyper paramter tuning (Consider any two hyper parameters preferably n\_estimators, max\_depth)

- Consider the following range for hyperparameters **n\_estimators** = [10, 50, 100, 150, 200, 300, 500, 1000], **max\_depth** = [2, 3, 4, 5, 6, 7, 8, 9, 10]
- Find the best hyper parameter which will give the maximum AUC value
- find the best hyper paramter using k-fold cross validation/simple cross validation data
- use gridsearch cv or randomsearch cv or you can write your own for loops to do this task

#### 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

with X-axis as **n\_estimators**, Y-axis as **max\_depth**, and Z-axis as **AUC Score**, we have given the notebook which explains how to plot this 3d plot, you can find it in the same drive 3d\_scatter\_plot.ipynb



• 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

seaborn heat maps with rows as n\_estimators, columns as max\_depth, and values inside the cell representing AUC Score

- You can choose either of the plotting techniques: 3d plot or heat map
- 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 confusion matrix with predicted and original labels of test data points

#### 4. 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 <u>link</u>

#### 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. Random Forest and GBDT

# 2.4 Applying Random Forest

Apply Random Forest on different kind of featurization as mentioned in the instructions For Every model that you work on make sure you do the step 2 and step 3 of instrucations

min\_samples\_leaf=1, min\_samples\_split=2,

warm start=False)

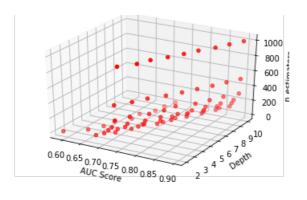
oob\_score=False, random\_state=None, verbose=0,

min weight fraction leaf=0.0, n estimators=1000, n jobs=None,

SET 1: categorical(instead of one hot encoding, try response coding(using probability values), numerical features + project\_title(BOW) + preprocessed\_eassay (BOW)

```
In [117]:
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_train = hstack((cat_0_train_normalized, cat_1_train_normalized, subcat_0_train_normalized,
subcat 1 train normalized, state 0 train normalized, state 1 train normalized,
grade 0 train normalized, grade 1 train normalized, prefix 0 train normalized,
prefix 1 train normalized, price normalized train, quantity_normalized_train,
previously posted projects normalized train, title word count normalized train,
essay word count normalized train, sent pos train, sent neg train, sent neu train, sent compound tr
ain, train_title_bow, train_essay_bow)).tocsr()
X test = hstack((cat 0 test normalized, cat 1 test normalized, subcat 0 test normalized, subcat 1
test normalized, state 0 test normalized, state 1 test normalized, grade 0 test normalized,
grade 1 test normalized, prefix 0 test normalized, prefix 1 test normalized, price normalized test
, quantity normalized test, previously posted projects normalized test,
title_word_count_normalized_test, essay_word_count_normalized_test, sent_pos_test, sent_neg_test,
sent new test, sent compound test, test title bow, test essay bow)).tocsr()
4
                                                                                                 •
In [118]:
print(X train.shape)
print(X test.shape)
(33500, 11886)
(16500, 11886)
In [119]:
# https://medium.com/@erikgreenj/k-neighbors-classifier-with-gridsearchcv-basics-3c445ddeb657
from sklearn.model selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
grid params = {'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6,
7, 8, 9, 10]}
gs = GridSearchCV(rf, grid_params, cv=3, scoring='roc_auc',n_jobs=-1)
gs results = gs.fit(X_train, y_train)
print(gs results.best score )
print(gs_results.best_estimator_)
print(gs results.best params )
0.6945542251837132
RandomForestClassifier(bootstrap=True, class weight=None, criterion='gini',
           max depth=10, max features='auto', max leaf nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
```

```
{'max depth': 10, 'n estimators': 1000}
In [120]:
#Output of GridSearchCV
print('Best score: ',gs results.best score )
print('k value with best score: ',gs results.best params )
print('='*75)
print('Train AUC scores')
print(gs.cv results_['mean_train_score'])
print('CV AUC scores')
print(gs.cv results ['mean test score'])
Best score: 0.6945542251837132
k value with best score: {'max depth': 10, 'n estimators': 1000}
_____
Train AUC scores
[0.58853489 0.67944103 0.70224551 0.71373403 0.72324539 0.73206266
 0.73070567 0.74079754 0.63323161 0.7087846 0.71508764 0.73566086
 0.74212832\ 0.748455 \qquad 0.75500214\ 0.76888324\ 0.65262022\ 0.72951518
 0.74816536\ 0.76415537\ 0.76730534\ 0.77773381\ 0.77336134\ 0.78126645
 0.65941007 \ 0.73720188 \ 0.77712411 \ 0.78575433 \ 0.7862262 \ 0.79528025
 0.79997579 \ 0.80404327 \ 0.68441132 \ 0.77095423 \ 0.79307966 \ 0.79552511
 0.81051242 0.80432755 0.82092999 0.82403399 0.68381901 0.78274149
 0.81342954 0.81690495 0.827263 0.83620188 0.83988294 0.84047833
 0.70530294 \ 0.79296768 \ 0.83342114 \ 0.83934473 \ 0.84335118 \ 0.85360487
 0.85949363 \ 0.86371645 \ 0.70874917 \ 0.81709163 \ 0.85098553 \ 0.85406452
 0.86339658 0.8701462 0.87665151 0.8797016 0.71852951 0.84103172
 CV AUC scores
[0.56819918 0.653053
                      0.65589413 0.66260294 0.67113425 0.68002796
 0.67564136 0.6802075 0.61200882 0.65510707 0.65467079 0.66978863
 0.67234144 \ 0.67770336 \ 0.68287778 \ 0.68968944 \ 0.61772203 \ 0.66286716
 0.66828335 0.67856104 0.67933769 0.68770159 0.68291505 0.68548756
 0.61995752 0.65581487 0.68236871 0.67957645 0.68107023 0.68771452
 0.68707406\ 0.68842762\ 0.63073385\ 0.66688596\ 0.67188535\ 0.67668718
 0.67895048 \ 0.68435864 \ 0.68907198 \ 0.68940834 \ 0.63183601 \ 0.66294838
 0.67601301 \ 0.6792186 \ 0.68525426 \ 0.68806438 \ 0.69207524 \ 0.69179155
 0.63309311 0.65540099 0.68479242 0.68145273 0.68609788 0.69088083
 0.68970752\ 0.69142257\ 0.63981271\ 0.66286219\ 0.67761845\ 0.68164653
 0.6870535 \quad 0.69145764 \quad 0.69051283 \quad 0.69338098 \quad 0.63089957 \quad 0.67357884
 0.67866074 0.68920971 0.68267953 0.6924755 0.6930018 0.69455423]
In [121]:
from mpl toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
                                                 #Train AUC Score
g1 = list(gs.cv_results_['mean_train_score'])
,8,8,8,8,8,8,9,9,9,9,9,9,9,10,10,10,10,10,10,10,10] #Depth
200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300,
500, 1000,10, 50, 100, 150, 200, 300, 500, 1000] #n estimators
ax.scatter(g1, g2, g3, c='r', marker='o')
ax.set xlabel('AUC Score')
ax.set_ylabel('Depth')
ax.set_zlabel('n_estimators')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
```



#### In [122]:

```
gs.cv results
```

```
Out[122]:
{'mean fit time': array([ 0.17462111,  0.40856457,  0.58339262,  0.85232123,  1.04593237,
          1.47726425, 2.33632247, 4.68881194, 0.20552675, 0.44023967,
         0.82226435, 0.97478596, 1.25126537, 1.82502675, 2.84294748,
         5.66242687, 0.17601903, 0.46765423, 0.78500279, 1.15159607,
         1.45887693, 2.26988689, 3.70074503, 7.23951705, 0.17746512,
         0.5901792 , 0.89494824,
4.24433303, 7.59056473,
                                     1.34517741,
0.18518265,
                                                    1.98432144, 2.47935406, 0.48118575, 0.96234846,
         1.49781354, 2.13988264, 2.65318576, 4.59198912, 8.92926455,
         0.20373297, 0.56341918, 1.08323995, 1.77550181, 2.33535647,
         3.30094258, 5.21841304, 10.07233485, 0.21428148, 0.62889576,
         1.15403533, 2.00249537, 2.70537345, 3.6570553, 5.83130646, l1.43976235, 0.23694142, 0.68791358, 1.28471979, 2.16474875,
         11.43976235,
          3.04585441, 3.88365841, 6.57448006, 12.7804269, 0.25987275,
         0.78368346, 1.45728461, 2.29497862, 3.47994582, 4.58132084,
         7.11564215, 13.28637314]),
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         0.10016718, 0.00459716, 0.01818824, 0.06806194, 0.07097189,
        0.15066619, 0.00230218, 0.02006647, 0.00249959, 0.0362854,
        0.00700026, 0.05573816, 0.05352439, 0.21271684, 0.00539201,
        0.09331323,\ 0.05436418,\ 0.03676741,\ 0.13766126,\ 0.06026132,
        0.04687898,\ 0.07339038,\ 0.00236114,\ 0.01738021,\ 0.07477928,
        0.0298644 , 0.1266079 , 0.02130385, 0.17483076, 0.41856709, 0.00587905, 0.00675271, 0.02672791, 0.11105147, 0.175308 ,
        0.0903708 , 0.24487577, 0.10669124, 0.00863109, 0.00402015,
        0.0324066 \ , \ 0.09863488, \ 0.10954041, \ 0.08214032, \ 0.06453391,
        0.11475233, 0.017111116, 0.04618761, 0.08338881, 0.121734
        0.18199975,\ 0.11892576,\ 0.15976988,\ 0.11900439,\ 0.00431042,
         0.05006792, 0.08093911, 0.03645672, 0.12624111, 0.1389107,
        0.07093896, 0.10056761]),
 'mean score time': array([0.09183033, 0.23396794, 0.49359441, 0.67618203, 0.96135314,
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        0.49911086,\ 0.74318647,\ 1.04970169,\ 1.28323523,\ 1.89941168,
        4.33605528, 0.07349984, 0.25159947, 0.48254212, 0.69990166, 0.92761819, 1.31597034, 2.13084769, 4.68985828, 0.07475654,
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        1.75203983, 4.19320019, 0.07297802, 0.21110948, 0.49284252,
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        1.08685795, 1.77962629, 4.18576535, 0.0698053 , 0.20343788,
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         1.7733314 , 2.94136747]),
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         0.01370748, 0.01494573, 0.06135446, 0.01575221, 0.07884723,
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        0.01316965, 0.02772838, 0.0378552 , 0.06834951, 0.09817869,
        0.03171482, 0.00873868, 0.0005124 , 0.00950221, 0.06917165,
        0.02409291, 0.0300763 , 0.06446047, 0.12981379, 0.29603213,
        0.00122575,\ 0.01723534,\ 0.04061798,\ 0.01593866,\ 0.08733722,
         0.05268183, \ 0.1369887 \ , \ 0.07527657, \ 0.00359333, \ 0.00674985, 
        0.0318702 , 0.0746036 , 0.11343016, 0.0932718 , 0.0721402 , 0.27897001 , 0.00131226 , 0.0059273 , 0.03919373 , 0.0748077
```

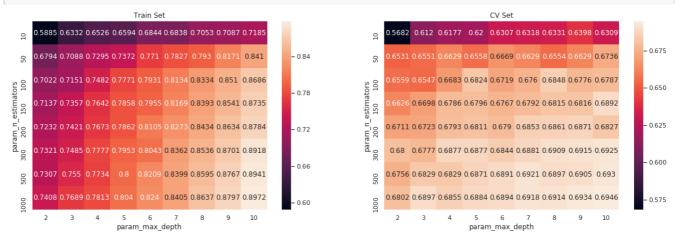
```
U.Z.OJ.OUI, U.UUIJIZZO, U.UUJUJZIJ, U.UJJIJJIJ, U.UIFOUII ,
       0.08053157, 0.03254355, 0.01934469, 0.06322226, 0.00436664,
       0.00683993, 0.01447174, 0.03529463, 0.07036967, 0.03613392,
       0.00458123, 0.06438854]),
'param_max_depth': masked_array(data=[2, 2, 2, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 3, 4, 4,
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                   8, 8, 9, 9, 9, 9, 9, 9, 9, 10, 10, 10, 10, 10, 10,
                   10, 10],
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                   False, False, False, False, False, False, False, False,
                   False, False, False, False, False, False, False,
                   False, False, False, False, False, False, False,
                   False, False, False, False, False, False, False,
                   False, False, False, False, False, False, False, False],
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                   150, 200, 300, 500, 1000, 10, 50, 100, 150, 200, 300,
                   500, 1000, 10, 50, 100, 150, 200, 300, 500, 1000, 10,
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                   200, 300, 500, 1000, 10, 50, 100, 150, 200, 300, 500,
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                   False, False, False, False, False, False, False, False],
       fill value='?',
            dtype=object),
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{'max depth': 6, 'n estimators': 100},
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{'max_depth': 6, 'n_estimators': 300},
{'max_depth': 6, 'n_estimators': 500},
```

```
\ max uepth . u, if estimators . iouus,
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{'max depth': 10, 'n estimators': 200},
{'max depth': 10, 'n estimators': 300},
{ 'max_depth': 10, 'n_estimators': 500},
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       0.67624655, 0.59280549, 0.64623333, 0.65886106, 0.66173347,
       0.67475079, 0.67577126, 0.67027765, 0.67446908, 0.60449854,
        \hbox{\tt 0.6457647 , 0.67812991, 0.66699791, 0.6684064 , 0.67411037, } 
       0.67307454, 0.6792232 , 0.60901528, 0.65151
                                                        , 0.65979309,
       0.6710526 , 0.66712715, 0.66901241, 0.68396102, 0.67621509,
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        \hbox{\tt 0.67697197, 0.6831138, 0.67764847, 0.61631284, 0.64755895, } 
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       0.6788096 , 0.62050437, 0.66451358, 0.67258149, 0.6598664 , 0.6672586 , 0.68340467, 0.6751693 , 0.68055296, 0.625094 ,
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       0.6856736 , 0.6822447 ]),
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        \hbox{0.66043207, 0.6792283, 0.67527203, 0.68172356, 0.67876154, } \\
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       0.62516937, 0.6770215 , 0.67984537, 0.67228017, 0.68129774,
       0.68329921, 0.68663414, 0.68669216, 0.63276941, 0.6493355,
       0.68465688, 0.68194314, 0.68193472, 0.68891739, 0.68610833,
       0.68809389, 0.64643822, 0.66371719, 0.6681623 , 0.69170438,
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       0.67119261, 0.68317485, 0.67891203, 0.69289746, 0.7027613 ,
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        \hbox{0.68547138, 0.6964045, 0.70151202, 0.70846732, 0.70764882, } 
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       0.70736565, 0.65249667, 0.66035558, 0.69211286, 0.69336986,
       0.7100798 , 0.70327119, 0.70529402, 0.71036272, 0.63433383,
       0.68975463, 0.68699479, 0.70548028, 0.69836 , 0.70852555,
       0 7061000
                   0 710166101
```

```
U. /U04U33 , U. /IUI00T3]),
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       0.67933769, 0.68770159, 0.68291505, 0.68548756, 0.61995752,
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       0.01116668, 0.02057049, 0.01242199, 0.00674469, 0.01302469,
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       49, 44, 39, 26, 15, 13, 66, 54, 45, 38, 24, 17, 5, 6, 65, 60, 25, 32, 22, 9, 11, 8, 64, 56, 43, 31, 21, 7, 10, 2, 67, 47, 40, 14, 29, 4, 3, 1], dtype=int32),
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```

```
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       \hbox{\tt 0.86979932, 0.86994248, 0.87404542, 0.87999032, 0.71686959,}\\
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 'std train score': array([0.00892459, 0.00082498, 0.00767496, 0.0077047 , 0.01183598,
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       0.00484104,\ 0.00151769,\ 0.00345264,\ 0.00336803,\ 0.00283977,
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       0.00566737, 0.00350092, 0.00195777, 0.0009706, 0.00873576,
       0.00232469, 0.00416612, 0.0019269 , 0.00703298, 0.0004936 ,
       0.00658362, 0.00262829])}
In [123]:
```

```
import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(gs.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max()
).unstack()[['mean_test_score', 'mean_train_score']]
fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train_Set')
ax[1].set_title('CV_Set')
plt.show()
```



#### In [124]:

```
gs_results.best_params_
```

#### Out[124]:

```
{'max_depth': 10, 'n_estimators': 1000}
```

```
. ولاحتا بند
```

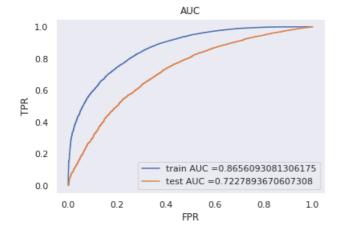
```
max_d = gs_results.best_params_['max_depth']
n_est = gs_results.best_params_['n_estimators']
```

#### In [126]:

```
def pred_prob(clf, data):
    y_pred = []
    y_pred = clf.predict_proba(data)[:,1]
    return y_pred
```

#### In [127]:

```
# https://scikit-
 learn.org/stable/modules/generated/sklearn.metrics.roc\_curve.html \# sklearn.metrics.roc\_curve.html \# sklearn.metrics.html \# sklearn.html \# sklearn.metrics.html \# sklearn.html \# sklearn.metrics.html
 from sklearn.metrics import roc curve, auc
model = RandomForestClassifier(max_depth = max_d, n_estimators = n_est)
model.fit(X train,y train)
y_train_pred = pred_prob(model, X_train)
y test pred = pred prob (model, X test)
 train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
 test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)
 plt.close
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.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



#### In [128]:

#### In [129]:

```
#our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of tpr\*(1-fpr) 0.5990830500929055 for threshold 0.838 Train confusion matrix [[ 3862 1306] [ 5619 22713]]

#### In [130]:

```
#plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

confusion_matrix_df_train = pd.DataFrame(confusion_matrix(y_train,
    predict_with_best_t(y_train_pred, best_t)), ['Actual: No','Actual: Yes'], ['Predicted:
    No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_train, annot=True,annot_kws={"size": 16}, fmt='g')
```

Train data confusion matrix

#### Out[130]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f90a2c55d30>



#### In [131]:

```
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

Test confusion matrix [[ 1255 1291] [ 2586 11368]]

#### In [132]:

```
print("Test data confusion matrix")

confusion_matrix_df_test = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_test_pred, b est_t)), ['Actual: No', 'Actual: Yes'], ['Predicted: No', 'Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_test, annot=True, annot_kws={"size": 16}, fmt='g')
```

Test data confusion matrix



# SET 2 categorical (with response coding), numerical features + project\_title(TFIDF)+ preprocessed\_eassay (TFIDF)

```
In [133]:
```

```
# Please write all the code with proper documentation
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X train = hstack((cat 0 train normalized, cat 1 train normalized, subcat 0 train normalized,
subcat 1 train normalized, state 0 train normalized, state 1 train normalized,
grade 0 train normalized, grade 1 train normalized, prefix 0 train normalized,
prefix 1 train normalized, price normalized train, quantity normalized train,
previously_posted_projects_normalized_train, title_word_count_normalized_train,
essay word count normalized train, sent pos train, sent neg train, sent neu train, sent compound tr
ain, train_title_tfidf, train_essay_tfidf)).tocsr()
X_test = hstack((cat_0_test_normalized, cat_1_test_normalized, subcat_0_test_normalized, subcat_1_
test normalized, state 0 test normalized, state 1 test normalized, grade 0 test normalized,
grade_1_test_normalized, prefix_0_test_normalized, prefix_1_test_normalized, price_normalized_test
, quantity\_normalized\_test, previously\_posted\_projects\_normalized\_test,
title_word_count_normalized_test, essay_word_count_normalized_test, sent_pos_test, sent_neg_test,
sent neu test, sent compound test, test title tfidf, test essay tfidf)).tocsr()
                                                                                                 1
```

#### In [134]:

```
print(X_train.shape)
print(X_test.shape)

(33500, 11886)
```

#### In [135]:

(16500, 11886)

```
# https://medium.com/@erikgreenj/k-neighbors-classifier-with-gridsearchcv-basics-3c445ddeb657

from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier()

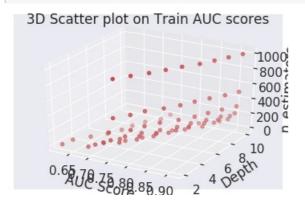
grid_params = {'n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth':[2, 3, 4, 5, 6, 7, 8, 9, 10]}

gs = GridSearchCV(rf, grid_params, cv=3, scoring='roc_auc',n_jobs=-1)
gs_results = gs.fit(X_train, y_train)
print(gs_results.best_score_)
print(gs_results.best_estimator_)
print(gs_results.best_params_)
```

#### 0.6993463225163405

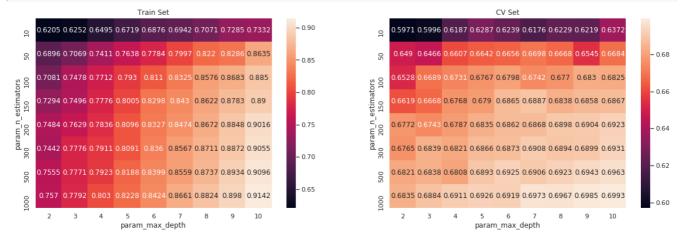
```
min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=1000, n_jobs=None,
           oob score=False, random_state=None, verbose=0,
           warm start=False)
{'max depth': 10, 'n estimators': 1000}
In [136]:
#Output of GridSearchCV
print('Best score: ',gs_results.best_score_)
print('k value with best score: ',gs_results.best_params_)
print('='*75)
print('Train AUC scores')
print(gs.cv results ['mean train score'])
print('CV AUC scores')
print(gs.cv_results_['mean_test_score'])
Best score: 0.6993463225163405
k value with best score: {'max_depth': 10, 'n_estimators': 1000}
______
Train AUC scores
[0.62054276 0.68964259 0.70806712 0.72935894 0.74839948 0.74419981
 0.75545765 \ 0.75703022 \ 0.62520024 \ 0.70694993 \ 0.74780455 \ 0.7495672
 0.76293286\ 0.77757226\ 0.77710342\ 0.77920006\ 0.64953316\ 0.74107092
 0.77119772 0.77762997 0.7835705 0.79109179 0.79230465 0.80304778
 0.67194971 0.76381961 0.79303772 0.80045827 0.80964932 0.80910508
 0.81876065 \ 0.82278297 \ 0.68764153 \ 0.77839127 \ 0.81097428 \ 0.8297809
 0.83270185 0.83604444 0.83987844 0.84239281 0.69416709 0.79966976
 0.83246064 0.84297722 0.84744121 0.85674806 0.85587531 0.86613062
 0.70714682 0.82199335 0.85762577 0.86215473 0.8671582 0.8710567
 0.87370296 0.88239591 0.72852792 0.82862873 0.868257 0.87826779
 0.88476812\ 0.88723934\ 0.89337032\ 0.89804785\ 0.73319916\ 0.86353169
 0.88502218 0.88996647 0.9016299 0.90550456 0.90964464 0.91419483
CV AUC scores
 [0.59709032 \ 0.64897489 \ 0.65283018 \ 0.66192487 \ 0.67722283 \ 0.67645755 
 0.68212417 0.68350964 0.59958842 0.64661354 0.66886342 0.66684349
 0.67429443 \ 0.68390446 \ 0.68378489 \ 0.68841621 \ 0.61867954 \ 0.66073068
 0.67311223 \ 0.67679362 \ 0.67868323 \ 0.6820571 \ 0.68078582 \ 0.69106643
 0.62871612 0.66422094 0.67669327 0.67896229 0.68352563 0.6866238
 0.68931881 \ 0.69255111 \ 0.62387034 \ 0.66564226 \ 0.67978501 \ 0.6865066
 0.68623153 \ 0.68730584 \ 0.6924547 \ \ 0.69192835 \ 0.61762407 \ 0.66979593
 0.67424565 0.68871457 0.68677485 0.69080886 0.6905532 0.69727695
 0.62292326 0.66678393 0.67696308 0.68376933 0.68984325 0.68935398
 0.69231944 0.69667254 0.62193992 0.65446518 0.6829541 0.68582945
  0.69041161 \ \ 0.68991146 \ \ 0.69430382 \ \ 0.69846896 \ \ 0.63718363 \ \ 0.66840856 
 In [137]:
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
```

```
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
```



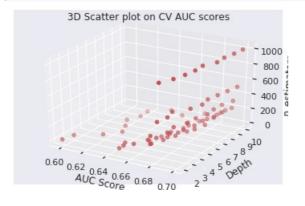
#### In [138]:

```
import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(gs.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max()
).unstack()[['mean_test_score', 'mean_train_score']]
fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train_Set')
ax[1].set_title('CV_Set')
plt.show()
```



### In [139]:

```
plt.title('3D Scatter plot on CV AUC scores')
plt.show()
```



#### In [140]:

```
gs_results.best_params_
```

#### Out[140]:

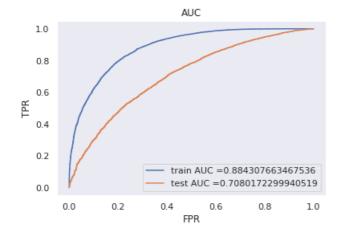
{'max depth': 10, 'n estimators': 1000}

#### In [141]:

```
max_d = gs_results.best_params_['max_depth']
n_est = gs_results.best_params_['n_estimators']
```

#### In [142]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc\_curve.html \# sklearn.metrics.roc\_curve.html \# sklearn.metrics.html \# sklearn.html \# sklearn.metrics.html \# sklearn.html \# sklea
from sklearn.metrics import roc curve, auc
model = RandomForestClassifier(max depth = max d, n estimators = n est)
model.fit(X_train,y_train)
y_train_pred = pred_prob(model, X_train)
y test pred = pred prob (model, X test)
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test fpr, test tpr, te thresholds = roc curve(y test, y test pred)
plt.close
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.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



#### In [143]:

```
#our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of tpr\*(1-fpr) 0.6387695744050311 for threshold 0.84 Train confusion matrix [[ 4011 1157] [ 5014 23318]]

#### In [144]:

```
#plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

confusion_matrix_df_train = pd.DataFrame(confusion_matrix(y_train,
    predict_with_best_t(y_train_pred, best_t)), ['Actual: No','Actual: Yes'],['Predicted:
No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_train, annot=True,annot_kws={"size": 16}, fmt='g')
```

Train data confusion matrix

#### Out[144]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f90a2640ba8>



### In [145]:

```
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

Test confusion matrix [[ 1305 1241] [ 3173 10781]]

# In [146]:

```
print("Test data confusion matrix")

confusion_matrix_df_test = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_test_pred, b est_t)), ['Actual: No', 'Actual: Yes'], ['Predicted: No', 'Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_test, annot=True, annot_kws={"size": 16}, fmt='g')
```

Test data confusion matrix

#### Out[146]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f90a2418c18>



# 2.4.3 Applying Random Forests on AVG W2V, SET 3

#### In [147]:

```
train_avg_w2v_essays_np = np.array(train_avg_w2v_essays)
train_avg_w2v_titles_np = np.array(train_avg_w2v_titles)
test_avg_w2v_essays_np = np.array(test_avg_w2v_essays)
test_avg_w2v_titles_np = np.array(test_avg_w2v_titles)
```

#### In [148]:

```
print(cat 0 train normalized.shape)
print(cat_1_train_normalized.shape)
print(subcat_0_train_normalized.shape)
print(subcat_1_train_normalized.shape)
print(state_0_train_normalized.shape)
print(state_1 train normalized.shape)
print(grade 0 train normalized.shape)
print(grade_1_train_normalized.shape)
print(prefix_0 train normalized.shape)
print(prefix 1 train normalized.shape)
print(price_normalized_train.shape)
print(quantity normalized train.shape)
print(previously_posted_projects_normalized_train.shape)
print(title_word_count_normalized_train.shape)
print(essay_word_count_normalized_train.shape)
print(sent_pos_train.shape)
print(sent_neg_train.shape)
print(sent neu train.shape)
print(sent_compound_train.shape)
print(train_avg_w2v_essays_np.shape)
print(train_avg_w2v_titles_np.shape)
```

```
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
(33500, 1)
```

```
(33500, 300)
(33500, 300)
```

#### In [149]:

```
#https://blog.csdn.net/w55100/article/details/90369779
# if you use hstack without converting it into to a sparse matrix first,
#it shows an error: blocks must be 2-D
from scipy.sparse import coo matrix, hstack
tr1 = coo_matrix(cat_0_train_normalized)
tr2 = coo_matrix(cat_1_train_normalized)
tr3 = coo_matrix(subcat_0_train_normalized)
tr4 = coo matrix(subcat 1 train normalized)
tr5 = coo_matrix(state_0_train_normalized)
tr6 = coo matrix(state 1 train normalized)
tr7 = coo_matrix(grade_0_train_normalized)
tr8 = coo_matrix(grade_1_train_normalized)
tr9 = coo matrix(prefix 0 train normalized)
tr10 = coo matrix(prefix 1 train normalized)
tr11 = coo matrix(price normalized train)
tr12 = coo matrix(quantity normalized train)
tr13 = coo_matrix(previously_posted_projects_normalized_train)
tr14 = coo matrix(title word count normalized train)
tr15 = coo matrix(essay word count normalized train)
tr16 = coo matrix(sent pos train)
tr17 = coo_matrix(sent_neg_train)
tr18 = coo_matrix(sent_neu_train)
tr19 = coo_matrix(sent_compound_train)
tr20 = coo_matrix(train_avg_w2v_essays_np)
tr21 = coo_matrix(train_avg_w2v_titles_np)
```

#### In [150]:

 $X_{train} = hstack([tr1,tr2,tr3,tr4,tr5,tr6,tr7,tr8,tr9,tr10,tr11,tr12,tr13,tr14,tr15,tr16,tr17,tr18,tr19,tr20,tr21]).tocsr()$ 

#### In [151]:

```
te1 = coo_matrix(cat_0_test_normalized)
te2 = coo matrix(cat 1 test normalized)
te3 = coo_matrix(subcat_0_test_normalized)
te4 = coo_matrix(subcat_1_test_normalized)
te5 = coo matrix(state 0 test normalized)
te6 = coo matrix(state 1 test normalized)
te7 = coo matrix(grade 0 test normalized)
te8 = coo matrix(grade 1 test normalized)
te9 = coo_matrix(prefix_0_test_normalized)
tel0 = coo matrix (prefix 1 test normalized)
tell = coo matrix(price normalized test)
tel2 = coo_matrix(quantity_normalized_test)
te13 = coo matrix(previously posted projects normalized test)
te14 = coo_matrix(title_word_count_normalized_test)
te15 = coo_matrix(essay_word_count_normalized_test)
tel6 = coo matrix(sent pos test)
te17 = coo_matrix(sent_neg_test)
tel8 = coo matrix(sent neu test)
te19 = coo matrix(sent compound test)
te20 = coo_matrix(test_avg_w2v_essays_np)
te21 = coo_matrix(test_avg_w2v_titles_np)
```

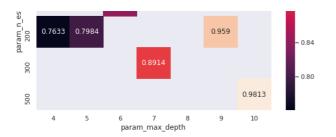
#### In [152]:

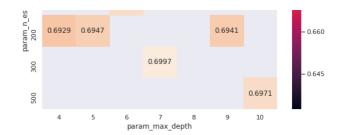
```
X_{\text{test}} = \text{hstack([te1,te2,te3,te4,te5,te6,te7,te8,te9,te10,te11,te12,te13,te14,te15,te16,te17,te18,te19,te20,te21]).tocsr()
```

#### In [153]:

```
print(X_train.shape)
print(X_test.shape)
```

```
(33500, 619)
(16500, 619)
In [154]:
from sklearn.model_selection import GridSearchCV
from scipy.stats import randint as sp randint
from sklearn.model_selection import RandomizedSearchCV
rf = RandomForestClassifier()
grid params = {'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6,
7, 8, 9, 101}
rs = RandomizedSearchCV(rf,grid params,cv=3, scoring='roc auc',n jobs=-1)
rs.fit(X train, y train)
Out[154]:
RandomizedSearchCV(cv=3, error score='raise-deprecating',
          estimator=RandomForestClassifier(bootstrap=True, class weight=None, criterion='gini',
            max depth=None, max features='auto', max leaf nodes=None,
            min impurity decrease=0.0, min impurity split=None,
            min samples leaf=1, min samples split=2,
            min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
            oob score=False, random state=None, verbose=0,
            warm start=False),
          fit params=None, iid='warn', n_iter=10, n_jobs=-1,
          param distributions={'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth'
: [2, 3, 4, 5, 6, 7, 8, 9, 10]},
          pre dispatch='2*n jobs', random state=None, refit=True,
          return train score='warn', scoring='roc auc', verbose=0)
4
In [155]:
print('Best score: ',rs.best score )
print('k value with best score: ',rs.best params )
print('='*75)
print('Train AUC scores')
print(rs.cv_results_['mean_train_score'])
print('CV AUC scores')
print(rs.cv_results_['mean_test_score'])
Best score: 0.6997477968139622
k value with best score: {'n estimators': 300, 'max depth': 7}
______
Train AUC scores
[0.84175025 0.83813186 0.95897765 0.76061834 0.89142588 0.90383558
0.98134637 0.79837164 0.88316523 0.76330023]
CV AUC scores
[0.69731014 0.64563891 0.69407684 0.69192079 0.6997478 0.63231555
 0.697081 0.69470458 0.69386893 0.69293507]
In [156]:
import seaborn as sns; sns.set()
max scores1 = pd.DataFrame(rs.cv results).groupby(['param n estimators', 'param max depth']).max(
).unstack()[['mean test score', 'mean train score']]
fig, ax = plt.subplots(1, 2, figsize=(20, 6))
sns.heatmap\,(max\_scores1.mean\_train\_score,\ annot\ =\ \textbf{True},\ fmt=\textbf{'}.4g\textbf{'},\ ax=ax\,[0])
sns.heatmap(max scores1.mean test score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set_title('CV Set')
plt.show()
                   Train Set
                                                                         CV Set
                         0.8381
  10
                                           - 0.96
                                                       10
                                                                                                 - 0.690
    0.7606
                                                          0.6919
                                                                         0.6939
  100
                                                       100
                                                                                                  0.675
                                                                    0.6973
```



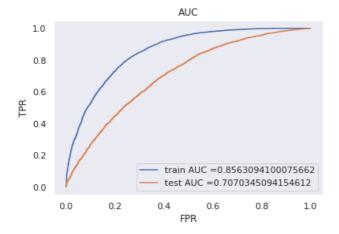


#### In [157]:

```
max_d = rs.best_params_['max_depth']
n_est = rs.best_params_['n_estimators']
```

#### In [158]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc curve.html#sklearn.metrics.roc curve
from sklearn.metrics import roc_curve, auc
model = RandomForestClassifier(max_depth = max_d, n_estimators = n_est)
model.fit(X_train,y_train)
y_train_pred = pred_prob(model, X_train)
y_test_pred = pred_prob (model, X_test)
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test fpr, test tpr, te thresholds = roc curve(y test, y test pred)
plt.close
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.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



#### In [159]:

```
#our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))

the maximum value of tpr*(1-fpr) 0.6017356835732354 for threshold 0.831
Train confusion matrix
[[ 3798 1370]
```

[ 5134 23198]]

\_\_\_\_\_\_\_.

```
#plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

confusion_matrix_df_train = pd.DataFrame(confusion_matrix(y_train,
    predict_with_best_t(y_train_pred, best_t)), ['Actual: No','Actual: Yes'],['Predicted:
    No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_train, annot=True,annot_kws={"size": 16}, fmt='g')
```

Train data confusion matrix

#### Out[160]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f90a298be80>



### In [161]:

```
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

Test confusion matrix [[ 1462 1084] [ 3748 10206]]

### In [162]:

```
print("Test data confusion matrix")

confusion_matrix_df_test = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_test_pred, b est_t)), ['Actual: No','Actual: Yes'], ['Predicted: No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_test, annot=True,annot_kws={"size": 16}, fmt='g')
```

Test data confusion matrix

#### Out[162]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f90a2903c18>



# 2.4.4 Applying Random Forests on TFIDF W2V, SET 4

### In [163]:

```
train_tfidf_w2v_essays_np = np.array(train_tfidf_w2v_essays)
train_tfidf_w2v_titles_np = np.array(train_tfidf_w2v_titles)
test_tfidf_w2v_essays_np = np.array(test_tfidf_w2v_essays)
test_tfidf_w2v_titles_np = np.array(test_tfidf_w2v_titles)
```

### In [164]:

```
#https://blog.csdn.net/w55100/article/details/90369779
# if you use hstack without converting it into to a sparse matrix first,
#it shows an error: blocks must be 2-D
from scipy.sparse import coo_matrix, hstack
tr1 = coo_matrix(cat_0_train_normalized)
tr2 = coo_matrix(cat_1_train_normalized)
tr3 = coo_matrix(subcat_0_train_normalized)
tr4 = coo matrix(subcat_1_train_normalized)
tr5 = coo matrix(state 0 train normalized)
tr6 = coo_matrix(state_1_train_normalized)
tr7 = coo_matrix(grade_0_train_normalized)
tr8 = coo matrix(grade 1 train normalized)
tr9 = coo matrix(prefix 0 train normalized)
tr10 = coo matrix(prefix 1 train normalized)
tr11 = coo matrix (price normalized train)
tr12 = coo_matrix(quantity_normalized_train)
tr13 = coo matrix (previously posted projects normalized train)
tr14 = coo matrix(title word count normalized train)
tr15 = coo matrix(essay word count normalized train)
tr16 = coo_matrix(sent_pos_train)
tr17 = coo_matrix(sent_neg_train)
tr18 = coo_matrix(sent_neu_train)
tr19 = coo matrix(sent compound train)
tr20 = coo_matrix(train_tfidf_w2v_essays_np)
tr21 = coo matrix(train tfidf w2v titles np)
```

### In [165]:

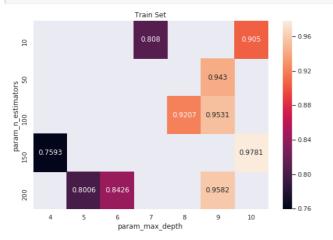
```
X_train = hstack([tr1,tr2,tr3,tr4,tr5,tr6,tr7,tr8,tr9,tr10,tr11,tr12,tr13,tr14,tr15,tr16,tr17,tr18,tr19,tr20,tr21]).tocsr()
```

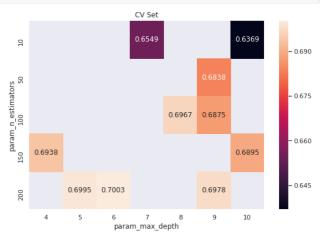
# In [166]:

```
tel = coo matrix(cat 0 test normalized)
te2 = coo_matrix(cat_1_test_normalized)
te3 = coo_matrix(subcat_0_test_normalized)
te4 = coo_matrix(subcat_1_test_normalized)
te5 = coo matrix(state 0 test normalized)
te6 = coo_matrix(state_1_test_normalized)
te7 = coo matrix(grade 0 test normalized)
te8 = coo_matrix(grade_1_test_normalized)
te9 = coo matrix(prefix_0_test_normalized)
te10 = coo_matrix(prefix_1_test_normalized)
tel1 = coo_matrix(price_normalized_test)
tel2 = coo matrix(quantity normalized test)
te13 = coo_matrix(previously_posted_projects_normalized_test)
te14 = coo_matrix(title_word_count_normalized_test)
te15 = coo_matrix(essay_word_count_normalized_test)
tel6 = coo matrix(sent pos test)
te17 = coo matrix(sent_neg_test)
tel8 = coo matrix(sent neu test)
te19 = coo_matrix(sent_compound_test)
te20 = coo_matrix(test_tfidf_w2v_essays_np)
te21 = coo matrix(test tfidf w2v titles np)
```

```
In [167]:
X \text{ test} = \text{hstack}([\text{te1}, \text{te2}, \text{te3}, \text{te4}, \text{te5}, \text{te6}, \text{te7}, \text{te8}, \text{te9}, \text{te10}, \text{te11}, \text{te12}, \text{te13}, \text{te14}, \text{te15}, \text{te16}, \text{te17}, \text{te18}, \text{te18}, \text{te19}, \text{te
e19, te20, te21]) .tocsr()
In [168]:
print(X train.shape)
print(X test.shape)
(33500, 619)
(16500, 619)
In [169]:
from sklearn.model selection import GridSearchCV
 from scipy.stats import randint as sp randint
from sklearn.model_selection import RandomizedSearchCV
rf = RandomForestClassifier()
grid params = {'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6,
 rs = RandomizedSearchCV(rf,grid params,cv=3, scoring='roc auc',n jobs=-1)
 rs.fit(X train, y train)
Out[169]:
RandomizedSearchCV(cv=3, error score='raise-deprecating',
                               \verb|estimator=RandomForestClassifier(bootstrap=True, class\_weight=None, criterion='gini', bootstrap=True, class\_weight=None, class_weight=None, class_weight=None, class_weight=None, class_weight
                                    max depth=None, max features='auto', max leaf nodes=None,
                                     min_impurity_decrease=0.0, min_impurity_split=None,
                                    min_samples_leaf=1, min_samples_split=2,
                                    min weight fraction leaf=0.0, n estimators='warn', n jobs=None,
                                     oob_score=False, random_state=None, verbose=0,
                                     warm start=False),
                               fit params=None, iid='warn', n iter=10, n jobs=-1,
                              param distributions={'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth'
: [2, 3, 4, 5, 6, 7, 8, 9, 10]},
                              pre dispatch='2*n jobs', random state=None, refit=True,
                               return train score='warn', scoring='roc auc', verbose=0)
4
                                                                                                                                                                                                                                                                                                      ▶
In [170]:
print('Best score: ',rs.best score )
print('k value with best score: ',rs.best_params_)
 print('='*75)
 print('Train AUC scores')
print(rs.cv results ['mean train score'])
print('CV AUC scores')
print(rs.cv_results_['mean_test_score'])
Best score: 0.7002994051565903
k value with best score: {'n_estimators': 200, 'max_depth': 6}
______
Train AUC scores
[0.90499463 \ 0.97805071 \ 0.94297009 \ 0.95821307 \ 0.80803184 \ 0.80055883
  0.92068165 0.84256625 0.75930702 0.95314876]
CV AUC scores
[0.63689366 0.68947082 0.68378449 0.69780267 0.65486867 0.69950839
   0.69673793 0.70029941 0.6938092 0.68754331]
In [171]:
import seaborn as sns; sns.set()
max scores1 = pd.DataFrame(rs.cv results).groupby(['param n estimators', 'param max depth']).max(
).unstack()[['mean_test_score', 'mean_train_score']]
fig, ax = plt.subplots(1,2, figsize=(20,6))
 sns.heatmap(max scores1.mean train score, annot = True, fmt='.4g', ax=ax[0])
 sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set title('Train Set')
```

```
ax[1].set_title('CV Set')
plt.show()
```



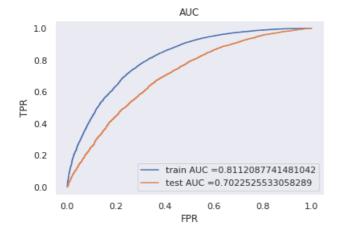


#### In [172]:

```
max_d = rs.best_params_['max_depth']
n_est = rs.best_params_['n_estimators']
```

#### In [173]:

```
# https://scikit-
 learn.org/stable/modules/generated/sklearn.metrics.roc\_curve.html \# sklearn.metrics.roc\_curve.html \# sklearn.metrics.html \# sklearn.html \# sklearn.metrics.html \# sklearn.html \# sklearn.metrics.html
 from sklearn.metrics import roc curve, auc
model = RandomForestClassifier(max_depth = max_d, n_estimators = n_est)
model.fit(X_train,y_train)
y_train_pred = pred_prob(model, X_train)
y test pred = pred prob (model, X test)
 train fpr, train tpr, tr thresholds = roc curve(y train, y train pred)
 test fpr, test tpr, te thresholds = roc curve(y test, y test pred)
plt.close
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.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



### In [174]:

```
#our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
```

```
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))

the maximum value of tpr*(1-fpr) 0.5430566086919842 for threshold 0.831
Train confusion matrix
[[ 3679  1489]
  [ 6719 21613]]
```

#### In [175]:

```
#plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

confusion_matrix_df_train = pd.DataFrame(confusion_matrix(y_train,
    predict_with_best_t(y_train_pred, best_t)), ['Actual: No','Actual: Yes'],['Predicted:
No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_train, annot=True,annot_kws={"size": 16}, fmt='g')
```

Train data confusion matrix

#### Out[175]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f90a249a9b0>



#### In [176]:

```
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

Test confusion matrix [[1519 1027] [4115 9839]]

### In [177]:

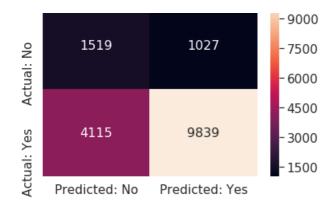
```
print("Test data confusion matrix")

confusion_matrix_df_test = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_test_pred, b est_t)), ['Actual: No', 'Actual: Yes'], ['Predicted: No', 'Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_test, annot=True, annot_kws={"size": 16}, fmt='g')
```

Test data confusion matrix

### Out[177]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f90a21af4e0>



# 2.5 Applying GBDT

Apply GBDT on different kind of featurization as mentioned in the instructions For Every model that you work on make sure you do the step 2 and step 3 of instrucations

# 2.5.1 Applying XGBOOST on BOW, SET 1

```
In [178]:
```

```
# Please write all the code with proper documentation
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_train = hstack((cat_0_train_normalized, cat_1_train_normalized, subcat_0_train_normalized,
subcat 1 train normalized, state 0 train normalized, state 1 train normalized,
grade 0 train normalized, grade 1 train normalized, prefix 0 train normalized,
prefix 1 train normalized, price normalized train, quantity normalized train,
previously posted projects normalized train, title word count normalized train,
essay word count normalized train, sent pos train, sent neg train, sent neu train, sent compound tr
ain, train_title_bow, train_essay_bow)).tocsr()
X_test = hstack((cat_0_test_normalized, cat_1_test_normalized, subcat_0_test_normalized, subcat_1_
test_normalized, state_0_test_normalized, state_1_test_normalized, grade_0_test_normalized,
grade 1 test normalized, prefix 0 test normalized, prefix 1 test normalized, price normalized test
, quantity_normalized_test, previously_posted_projects_normalized_test,
title_word_count_normalized_test, essay_word_count_normalized_test, sent_pos_test, sent_neg_test,
sent neu test, sent compound test, test title bow, test essay bow)).tocsr()
```

# In [179]:

```
from scipy.stats import randint as sp_randint
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier

gbdt = XGBClassifier()

grid_params = {'n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}

rs = RandomizedSearchCV(gbdt,grid_params ,cv=3, scoring='roc_auc',n_jobs=-1)
rs.fit(X_train, y_train)
```

# Out[179]:

..... , ....... 100 aac , voluce o,

#### In [180]:

```
print('Best score: ',rs.best score )
print('k value with best score: ',rs.best_params_)
print('='*75)
print('Train AUC scores')
print(rs.cv_results_['mean_train_score'])
print('CV AUC scores')
print(rs.cv results ['mean test score'])
```

Best score: 0.7445428354107052

k value with best score: {'n estimators': 300, 'max depth': 3}

\_\_\_\_\_\_

Train AUC scores

[0.97187364 0.94792116 0.98796361 0.999998029 0.86738756 0.99097955

0.9119555 0.8365766 0.95465996 0.86331461]

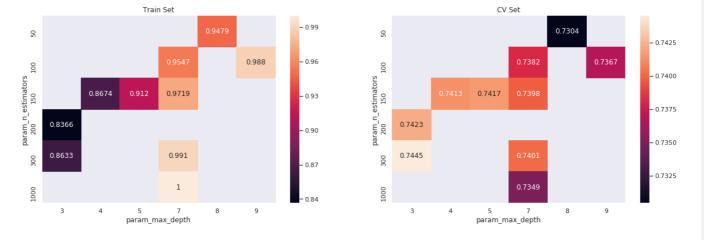
CV AUC scores

[0.73980478 0.73043996 0.73673138 0.73489207 0.74132502 0.74013574

0.7416625 0.74225172 0.73815023 0.74454284]

#### In [181]:

```
import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(rs.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max(
).unstack()[['mean test score', 'mean train score']]
fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max scores1.mean test score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set title('CV Set')
plt.show()
```



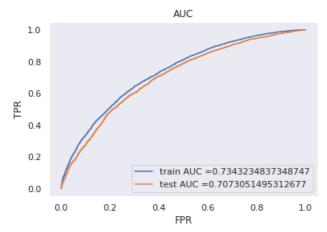
#### In [182]:

```
max_d = rs.best_params_['max_depth']
n_est = rs.best_params_['n_estimators']
```

### In [183]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc curve.html#sklearn.metrics.roc curve
from sklearn.metrics import roc curve, auc
model = RandomForestClassifier(max_depth = max_d, n_estimators = n_est)
model.fit(X train,y train)
y_train_pred = pred_prob(model, X_train)
y_test_pred = pred_prob (model, X_test)
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)
plt.close
```

```
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.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



#### In [184]:

```
#our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of tpr\*(1-fpr) 0.4505599025093441 for threshold 0.844 Train confusion matrix [[ 3620 1548] [10108 18224]]

# In [185]:

```
#plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

confusion_matrix_df_train = pd.DataFrame(confusion_matrix(y_train,
    predict_with_best_t(y_train_pred, best_t)), ['Actual: No','Actual: Yes'],['Predicted: No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_train, annot=True,annot_kws={"size": 16}, fmt='g')
```

Train data confusion matrix

### Out[185]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f90a21f2978>



Predicted: No Predicted: Yes

### In [186]:

```
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

Test confusion matrix [[1772 774] [5534 8420]]

#### In [187]:

```
print("Test data confusion matrix")

confusion_matrix_df_test = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_test_pred, b est_t)), ['Actual: No','Actual: Yes'], ['Predicted: No','Predicted: Yes'])

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

Test data confusion matrix

#### Out[187]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f90a29036d8>



# 2.5.2 Applying XGBOOST on TFIDF, SET 2

# In [188]:

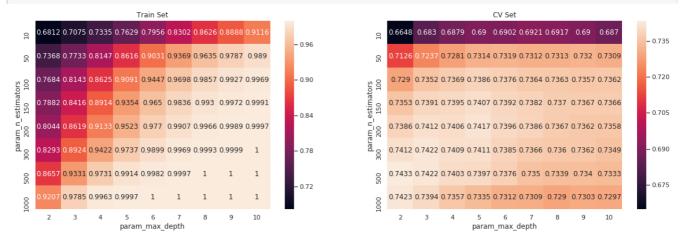
```
# Please write all the code with proper documentation
# Please write all the code with proper documentation
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X train = hstack((cat 0 train normalized, cat 1 train normalized, subcat 0 train normalized,
subcat 1 train normalized, state 0 train normalized, state 1 train normalized,
grade 0 train normalized, grade 1 train normalized, prefix 0 train normalized,
prefix_1_train_normalized, price_normalized_train, quantity_normalized_train,
previously posted projects normalized train, title word count normalized train,
essay word count normalized train, sent pos train, sent neg train, sent neu train, sent compound tr
ain, train_title_tfidf, train_essay_tfidf)).tocsr()
X test = hstack((cat 0 test normalized, cat 1 test normalized, subcat 0 test normalized, subcat 1
{\tt test\_normalized}, \ {\tt state\_0\_test\_normalized}, \ {\tt state\_1\_test\_normalized}, \ {\tt grade\_0\_test\_normalized}, \ {\tt mainimized}, \ {\tt grade\_0\_test\_normalized}, \ {\tt grade\_0\_test\_nor
grade_1_test_normalized, prefix_0_test_normalized, prefix_1_test_normalized, price_normalized_test
, quantity normalized test, previously posted projects normalized test,
title_word_count_normalized_test, essay_word_count_normalized_test, sent_pos_test, sent_neg_test,
sent new test, sent compound test, test title tfidf, test essay tfidf)).tocsr()
4
```

### In [189]:

from scipy.stats import randint as sp\_randint

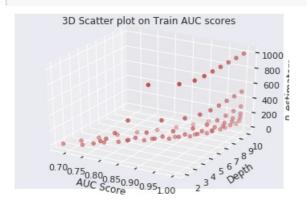
```
from sklearn.model selection import GridSearchCV
from xgboost import XGBClassifier
gbdt = XGBClassifier()
grid params = {'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6,
7, 8, 9, 10]}
gs = GridSearchCV(gbdt,grid params,cv=3, scoring='roc auc',n jobs=-1)
gs.fit(X train, y train)
Out[189]:
GridSearchCV(cv=3, error score='raise-deprecating',
       estimator=XGBClassifier(base score=0.5, booster='gbtree', colsample bylevel=1,
       colsample bynode=1, colsample bytree=1, gamma=0, learning rate=0.1,
       max_delta_step=0, max_depth=3, min_child_weight=1, missing=None,
       n estimators=100, n jobs=1, nthread=None,
       objective='binary:logistic', random state=0, reg alpha=0,
       reg lambda=1, scale pos weight=1, seed=None, silent=None,
       subsample=1, verbosity=1),
       fit params=None, iid='warn', n jobs=-1,
       param grid={'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4,
5, 6, 7, 8, 9, 10],
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring='roc auc', verbose=0)
In [190]:
print('Best score: ',qs.best score )
print('k value with best score: ',gs.best params )
print('='*75)
print('Train AUC scores')
print(gs.cv results ['mean train score'])
print('CV AUC scores')
print(gs.cv results ['mean test score'])
Best score: 0.7433302305643302
k value with best score: {'max_depth': 2, 'n_estimators': 500}
 _____
Train AUC scores
[0.68115019 0.73676062 0.76836407 0.78823845 0.80441724 0.82932553
 0.86570704 \ 0.92070117 \ 0.70752485 \ 0.77334008 \ 0.81427974 \ 0.84163643
 0.86192643 0.89244153 0.93309575 0.97849695 0.73352769 0.8147087
 0.86245649\ 0.89140106\ 0.91325322\ 0.94216504\ 0.97306833\ 0.99632215
 0.76286364 \ 0.86157073 \ 0.90911482 \ 0.93543796 \ 0.95234262 \ 0.97366148
 0.99141673 0.99972318 0.79560297 0.90306109 0.94469705 0.96498241
 0.97697677 0.98990733 0.99816021 0.99999035 0.83019117 0.93693913
 0.96981303 \ 0.9836378 \ 0.99072661 \ 0.99693097 \ 0.99974837 \ 0.99999993
 0.86260292 \ 0.96346486 \ 0.98571197 \ 0.99303822 \ 0.99659839 \ 0.99925442
 0.99998244 1.
                      0.88884922 0.97874784 0.9926957 0.99719582
                                           0.91157387 0.98900437
 0.99890029 0.99985403 0.99999928 1.
 0.99694603 0.99910166 0.99974033 0.99998617 0.99999998 1.
CV AUC scores
[0.66484381 0.71260835 0.72903438 0.73532406 0.7385961 0.74116106
 0.74333023 \ 0.74226007 \ 0.68301173 \ 0.72368573 \ 0.73517478 \ 0.73908484
 0.7411675 0.7421667 0.74216047 0.73937124 0.68793084 0.72805897
 0.73693765 0.73952553 0.74055945 0.74094694 0.74025206 0.73574681
 0.69001933 0.73141227 0.73861582 0.74066747 0.74173229 0.74114642
 0.73972829\ 0.73346807\ 0.69018755\ 0.73191118\ 0.73756961\ 0.73919831
 0.73956543\ 0.73852259\ 0.73762986\ 0.73121086\ 0.69208561\ 0.73124825
 0.73638432\ 0.73821942\ 0.73861821\ 0.73661982\ 0.73496519\ 0.73093021
 0.6917223 \quad 0.73134097 \quad 0.73633469 \quad 0.73698713 \quad 0.73666056 \quad 0.73598628
 0.73624823 \ 0.73616801 \ 0.73399777 \ 0.7303095 \ 0.6869721 \ 0.73093094
 0.73621124 0.73658562 0.73582606 0.73489962 0.7332812 0.72968985]
In [191]:
import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(gs.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max(
).unstack()[['mean test score', 'mean train score']]
fig, ax = plt.subplots(1, 2, figsize=(20, 6))
sns.heatmap(max scores1.mean train score, annot = True, fmt='.4g', ax=ax[0])
```

```
sns.heatmap(max_scoresl.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set_title('CV Set')
plt.show()
```



#### In [192]:

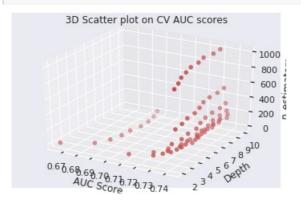
```
from mpl toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
fig = plt.figure()
ax = fig.add subplot(111, projection='3d')
g1 = list(gs.cv results ['mean train score'])
                                                     #Train AUC Score
,8,8,8,8,8,8,9,9,9,9,9,9,9,9,10,10,10,10,10,10,10,10] #Depth
g3 = [10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10, 50, 100, 150, 200, 300, 500, 1000,10,
50, 100, 150, 200, 300, 500, 1000, 10, 50, 100, 150, 200, 300, 500, 1000, 10, 50, 100, 150, 200, 300,
500, 1000,10, 50, 100, 150, 200, 300, 500, 1000] #n estimators
ax.scatter(g1, g2, g3, c='r', marker='o')
ax.set xlabel('AUC Score')
ax.set_ylabel('Depth')
ax.set zlabel('n estimators')
plt.title('3D Scatter plot on Train AUC scores')
plt.show()
```



#### In [193]:

```
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt

fig = plt.figure()
```



```
In [197]:
```

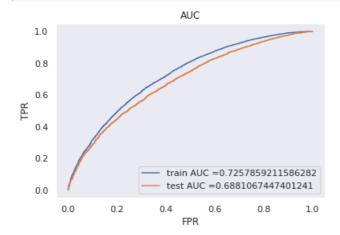
```
gs.best_params_
Out[197]:
{'max_depth': 2, 'n_estimators': 500}

In [198]:

max_d = gs.best_params_['max_depth']
n_est = gs.best_params_['n_estimators']
```

#### In [201]:

```
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc curve.html#sklearn.metrics.roc curve
from sklearn.metrics import roc curve, auc
model = RandomForestClassifier(max depth = max d, n estimators = n est)
model.fit(X_train,y_train)
y_train_pred = pred_prob(model, X_train)
y test pred = pred prob (model, X test)
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
test fpr, test tpr, te thresholds = roc curve(y test, y test pred)
plt.close
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.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



#### In [202]:

```
#our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of tpr\*(1-fpr) 0.4396031790131956 for threshold 0.845 Train confusion matrix [[ 3531 1637] [10103 18229]]

#### In [203]:

```
#plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

confusion_matrix_df_train = pd.DataFrame(confusion_matrix(y_train,
    predict_with_best_t(y_train_pred, best_t)), ['Actual: No','Actual: Yes'], ['Predicted:
    No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_train, annot=True,annot_kws={"size": 16}, fmt='g')
```

Train data confusion matrix

### Out[203]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f90a227aef0>



#### In [204]:

```
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

```
Test confusion matrix [[ 1230 1316] [ 3322 10632]]
```

#### In [205]:

```
print("Test data confusion matrix")

confusion_matrix_df_test = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_test_pred, b est_t)), ['Actual: No','Actual: Yes'], ['Predicted: No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_test, annot=True, annot_kws={"size": 16}, fmt='g')
```

Test data confusion matrix

#### Out [205]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f90a1c674a8>



# 2.5.3 Applying XGBOOST on AVG W2V, SET 3

### In [206]:

```
# Please write all the code with proper documentation
train_avg_w2v_essays_np = np.array(train_avg_w2v_essays)
train_avg_w2v_titles_np = np.array(train_avg_w2v_titles)
test_avg_w2v_essays_np = np.array(test_avg_w2v_essays)
test_avg_w2v_titles_np = np.array(test_avg_w2v_titles)
```

### In [207]:

```
#https://blog.csdn.net/w55100/article/details/90369779
# if you use hstack without converting it into to a sparse matrix first,
#it shows an error: blocks must be 2-D
from scipy.sparse import coo matrix, hstack
tr1 = coo_matrix(cat_0_train_normalized)
tr2 = coo_matrix(cat_1_train_normalized)
tr3 = coo_matrix(subcat_0_train_normalized)
tr4 = coo_matrix(subcat_1_train_normalized)
tr5 = coo matrix(state 0 train normalized)
tr6 = coo matrix(state 1 train normalized)
tr7 = coo_matrix(grade_0_train_normalized)
tr8 = coo_matrix(grade_1_train_normalized)
tr9 = coo matrix(prefix 0 train normalized)
tr10 = coo matrix(prefix 1 train normalized)
trl1 = coo matrix(price normalized train)
tr12 = coo_matrix(quantity_normalized_train)
tr13 = coo_matrix(previously_posted_projects_normalized_train)
tr14 = coo matrix(title word count normalized train)
tr15 = coo_matrix(essay_word_count_normalized_train)
tr16 = coo matrix(sent_pos_train)
tr17 = coo matrix(sent neg train)
tr18 = coo matrix(sent neu train)
```

```
tr19 = coo_matrix(sent_compound_train)
tr20 = coo matrix(train avg w2v essays np)
tr21 = coo_matrix(train_avg_w2v_titles_np)
X train = hstack([tr1,tr2,tr3,tr4,tr5,tr6,tr7,tr8,tr9,tr10,tr11,tr12,tr13,tr14,tr15,tr16,tr17,tr18,
tr19, tr20, tr21]).tocsr()
In [210]:
te1 = coo_matrix(cat_0_test_normalized)
te2 = coo matrix(cat 1 test normalized)
te3 = coo matrix(subcat 0 test normalized)
te4 = coo_matrix(subcat_1_test_normalized)
te5 = coo_matrix(state_0_test_normalized)
te6 = coo_matrix(state_1_test_normalized)
te7 = coo matrix(grade 0 test normalized)
te8 = coo matrix(grade 1 test normalized)
te9 = coo matrix(prefix 0 test normalized)
te10 = coo matrix(prefix 1 test normalized)
tell = coo matrix(price normalized test)
te12 = coo matrix(quantity normalized test)
te13 = coo_matrix(previously_posted_projects_normalized_test)
te14 = coo matrix(title word count normalized test)
te15 = coo_matrix(essay_word_count_normalized_test)
te16 = coo_matrix(sent_pos_test)
te17 = coo_matrix(sent_neg_test)
te18 = coo matrix(sent neu test)
te19 = coo matrix(sent compound_test)
te20 = coo matrix(test avg w2v essays np)
te21 = coo_matrix(test_avg_w2v_titles_np)
In [211]:
X \text{ test} = \text{hstack}([\text{te1}, \text{te2}, \text{te3}, \text{te4}, \text{te5}, \text{te6}, \text{te7}, \text{te8}, \text{te9}, \text{te10}, \text{te11}, \text{te12}, \text{te13}, \text{te14}, \text{te15}, \text{te16}, \text{te17}, \text{te18}, \text{te18}, \text{te19}, \text{te
e19, te20, te21]).tocsr()
In [212]:
from scipy.stats import randint as sp_randint
from sklearn.model selection import RandomizedSearchCV
from xgboost import XGBClassifier
gbdt = XGBClassifier()
grid params = {'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6,
rs = RandomizedSearchCV(qbdt,qrid params,cv=3, scoring='roc auc',n jobs=-1)
rs.fit(X train, y train)
Out[212]:
RandomizedSearchCV(cv=3, error_score='raise-deprecating',
                      estimator=XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
               colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1,
               max delta step=0, max depth=3, min child weight=1, missing=None,
               n_estimators=100, n_jobs=1, nthread=None,
               objective='binary:logistic', random_state=0, reg_alpha=0,
               reg lambda=1, scale pos weight=1, seed=None, silent=None,
               subsample=1, verbosity=1),
                     fit_params=None, iid='warn', n_iter=10, n_jobs=-1,
                     param distributions={'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth'
: [2, 3, 4, 5, 6, 7, 8, 9, 10]},
                     pre_dispatch='2*n_jobs', random_state=None, refit=True,
                      return_train_score='warn', scoring='roc_auc', verbose=0)
                                                                                                                                                                                                                    •
In [213]:
```

print('Best score: ',rs.best score )

nrint ('k walue with heet score ' re heet narame )

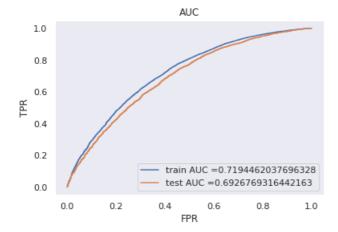
```
bitue/ v satue aten nese score. 'is:nese barams'
print('='*75)
print('Train AUC scores')
print(rs.cv_results_['mean_train_score'])
print('CV AUC scores')
print(rs.cv results ['mean test score'])
Best score: 0.7357391660102338
k value with best score: {'n estimators': 150, 'max depth': 3}
_____
Train AUC scores
[0.99859411 0.97690542 0.99718371 1.
                                                            1.
 0.8511252 0.87344236 0.82639463 0.92565958]
CV AUC scores
[0.72813414 \ 0.7323405 \ \ 0.72856256 \ 0.73014832 \ \ 0.72306499 \ \ 0.73296479
 0.73573917 0.69952303 0.70084636 0.73363487]
In [214]:
import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(rs.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max(
).unstack()[['mean_test_score', 'mean_train_score']]
fig, ax = plt.subplots(1, 2, figsize=(20, 6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max scores1.mean test score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set_title('CV Set')
plt.show()
                    Train Set
                                                                             CV Set
                                              - 0.99
                        0.8264
                                                                                 0.7008
                                                                                       0.6995
                                                                                                       0.728
                                              - 0.96
                              0.9986
                                                                                       0.7281
param_n_estimators
150 100
                                                         _n_estimators
150 100
                                              - 0.93
                                                                                                       0.720
           0.8511
                  0.9769
                                                                          0.7323
                                                                                 0.7286
                                                                    0.7357
                                              0.90
                                                                                                       0.712
                                                                                             0.733
                                      1
                                              0.87
                                                                                                       0.704
                                                                                       0.7301
                                1
                                                              0.7336
      2
                                      8
                                                               2
                                                                                               8
                 param_max_depth
                                                                          param_max_depth
In [215]:
rs.best params
Out[215]:
{'n estimators': 150, 'max depth': 3}
In [216]:
max d = rs.best params ['max depth']
n_est = rs.best_params_['n_estimators']
In [217]:
# https://scikit-
learn.org/stable/modules/generated/sklearn.metrics.roc curve.html#sklearn.metrics.roc curve
from sklearn.metrics import roc curve, auc
model = RandomForestClassifier(max_depth = max_d, n_estimators = n_est)
model.fit(X train,y train)
y train pred = pred prob (model, X train)
y test pred = pred prob(model, X test)
```

train for train to the thresholds - was asserted train or train model

```
train_ipr, train_tpr, tr_inresholds = roc_curve(y_train, y_train_pred)

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

plt.close
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.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



#### In [218]:

```
#our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of tpr\*(1-fpr) 0.4366130706278365 for threshold 0.841 Train confusion matrix [[ 3311 1857] [ 9024 19308]]

#### In [219]:

```
#plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

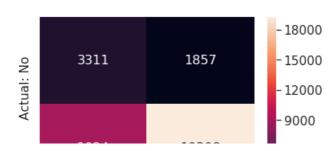
print("Train data confusion matrix")

confusion_matrix_df_train = pd.DataFrame(confusion_matrix(y_train,
    predict_with_best_t(y_train_pred, best_t)), ['Actual: No','Actual: Yes'],['Predicted: No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_train, annot=True,annot_kws={"size": 16}, fmt='g')
```

Train data confusion matrix

# Out[219]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f90a1bd7978>



```
9024 19308 - 6000 - 3000 Predicted: Yes
```

#### In [220]:

```
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

Test confusion matrix [[1579 967] [4821 9133]]

## In [221]:

```
print("Test data confusion matrix")
confusion_matrix_df_test = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_test_pred, b est_t)), ['Actual: No', 'Actual: Yes'], ['Predicted: No', 'Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_test, annot=True, annot_kws={"size": 16}, fmt='g')
```

Test data confusion matrix

#### Out[221]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f90a1b221d0>



# 2.5.4 Applying XGBOOST on TFIDF W2V, SET 4

### In [222]:

```
# Please write all the code with proper documentation
train_tfidf_w2v_essays_np = np.array(train_tfidf_w2v_essays)
train_tfidf_w2v_titles_np = np.array(train_tfidf_w2v_titles)
test_tfidf_w2v_essays_np = np.array(test_tfidf_w2v_essays)
test_tfidf_w2v_titles_np = np.array(test_tfidf_w2v_titles)
```

#### In [223]:

```
#https://blog.csdn.net/w55100/article/details/90369779
# if you use hstack without converting it into to a sparse matrix first,
#it shows an error: blocks must be 2-D

from scipy.sparse import coo_matrix, hstack
tr1 = coo_matrix(cat_0_train_normalized)
tr2 = coo_matrix(cat_1_train_normalized)
tr3 = coo_matrix(subcat_0_train_normalized)
tr4 = coo_matrix(subcat_1_train_normalized)
tr5 = coo_matrix(state_0_train_normalized)
tr6 = coo_matrix(state_1_train_normalized)
```

```
tr7 = coo_matrix(grade_0_train_normalized)
tr8 = coo_matrix(grade_1_train_normalized)
tr9 = coo_matrix(prefix_0_train_normalized)
tr10 = coo_matrix(prefix_1_train_normalized)
tr11 = coo_matrix(price_normalized_train)
tr12 = coo_matrix(quantity_normalized_train)
tr13 = coo_matrix(previously_posted_projects_normalized_train)
tr14 = coo_matrix(title_word_count_normalized_train)
tr15 = coo_matrix(essay_word_count_normalized_train)
tr16 = coo_matrix(sent_pos_train)
tr17 = coo_matrix(sent_neg_train)
tr18 = coo_matrix(sent_neg_train)
tr19 = coo_matrix(sent_neu_train)
tr20 = coo_matrix(train_tfidf_w2v_essays_np)
tr21 = coo_matrix(train_tfidf_w2v_titles_np)
```

### In [224]:

```
X_train = hstack([tr1,tr2,tr3,tr4,tr5,tr6,tr7,tr8,tr9,tr10,tr11,tr12,tr13,tr14,tr15,tr16,tr17,tr18,tr19,tr20,tr21]).tocsr()
```

#### In [225]:

```
tel = coo matrix(cat 0 test normalized)
te2 = coo matrix(cat 1 test normalized)
te3 = coo_matrix(subcat_0_test_normalized)
te4 = coo_matrix(subcat_1_test_normalized)
te5 = coo_matrix(state_0_test_normalized)
te6 = coo_matrix(state_1_test_normalized)
te7 = coo_matrix(grade_0_test_normalized)
te8 = coo matrix(grade 1 test normalized)
te9 = coo_matrix(prefix_0_test_normalized)
te10 = coo_matrix(prefix_1_test_normalized)
tell = coo matrix(price normalized test)
te12 = coo matrix(quantity normalized test)
tel3 = coo matrix(previously posted projects normalized test)
te14 = coo matrix(title word count normalized test)
te15 = coo_matrix(essay_word_count_normalized_test)
tel6 = coo matrix(sent pos test)
te17 = coo_matrix(sent_neg_test)
tel8 = coo matrix(sent neu test)
te19 = coo matrix(sent compound test)
te20 = coo_matrix(test_tfidf_w2v_essays_np)
te21 = coo_matrix(test_tfidf_w2v_titles_np)
```

#### In [226]:

```
X_test = hstack([te1,te2,te3,te4,te5,te6,te7,te8,te9,te10,te11,te12,te13,te14,te15,te16,te17,te18,te19,te20,te21]).tocsr()
```

### In [227]:

```
from scipy.stats import randint as sp_randint
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier

gbdt = XGBClassifier()

grid_params = {'n_estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}

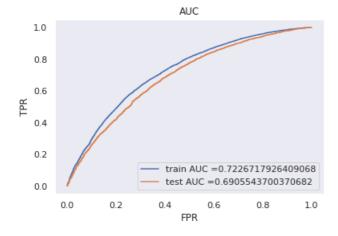
rs = RandomizedSearchCV(gbdt,grid_params ,cv=3, scoring='roc_auc',n_jobs=-1)
rs.fit(X_train, y_train)
```

### Out[227]:

```
rey_rambua-r, scare_pos_werginc-r, seed-none, stremc-none,
        subsample=1, verbosity=1),
           fit params=None, iid='warn', n_iter=10, n_jobs=-1,
          param distributions={'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth'
: [2, 3, 4, 5, 6, 7, 8, 9, 10]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
           return_train_score='warn', scoring='roc_auc', verbose=0)
                                                                                                         •
In [228]:
print('Best score: ',rs.best_score_)
print('k value with best score: ',rs.best params )
print('='*75)
print('Train AUC scores')
print(rs.cv results ['mean train score'])
print('CV AUC scores')
print(rs.cv_results_['mean_test_score'])
Best score: 0.736547312206274
k value with best score: {'n estimators': 100, 'max depth': 3}
Train AUC scores
[0.82991714 0.98885468 1.
                                     0.75100817 0.8194429 1.
 0.996027 1.
                         1.
                                     0.99876219]
CV AUC scores
[0.69965447 0.72589447 0.72509977 0.69844041 0.73654731 0.72613819
 0.72311922 0.72228901 0.72665804 0.72117126]
In [229]:
import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(rs.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max(
).unstack()[['mean_test_score', 'mean_train_score']]
fig, ax = plt.subplots(1, 2, figsize=(20, 6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set title('CV Set')
plt.show()
                                                                               CV Set
                    Train Set
                                                                                                        - 0.736
                                                                    0.6984
                                                                               0.6997
                                0.996
  20
                                                           20
                                               - 0.95
                                                                                                        - 0.728
     0.8194
                                                              0.7365
estimators
150 100
                                                          estimators
150 100
                                               - 0.90
                                       1
                                                                                                        - 0.720
am_n_e
                                                          am_n_e
                0.9889
                                               0.85
par?
300
                                                                                                        - 0.712
                0.9988
                                               0.80
  500
                                                           500
                                       10
                                                                                                10
                  param_max_depth
                                                                           param_max_depth
In [230]:
rs.best params
Out[230]:
{'n estimators': 100, 'max depth': 3}
In [231]:
max d = rs.best params ['max depth']
n_est = rs.best_params_['n_estimators']
```

```
In [232]:
```

```
learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc curve, auc
model = RandomForestClassifier(max_depth = max_d, n_estimators = n_est)
model.fit(X train, y train)
y_train_pred = pred_prob(model, X_train)
y test pred = pred prob (model, X test)
train fpr, train tpr, tr thresholds = roc curve (y train, y train pred)
test fpr, test tpr, te thresholds = roc curve(y test, y test pred)
plt.plot(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.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



### In [233]:

```
#our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of tpr\*(1-fpr) 0.4442493751663709 for threshold 0.84 Train confusion matrix [[ 3421 1747] [ 9318 19014]]

### In [234]:

```
#plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

confusion_matrix_df_train = pd.DataFrame(confusion_matrix(y_train,
    predict_with_best_t(y_train_pred, best_t)), ['Actual: No','Actual: Yes'], ['Predicted: No','Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_train, annot=True,annot_kws={"size": 16}, fmt='g')
```

Train data confusion matrix

#### Out[234]:

~macpiociin.ave3. \_ambioc3.vveanabioc ac ^vviinainionao



### In [235]:

```
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

Test confusion matrix [[1628 918] [4982 8972]]

### In [236]:

```
print("Test data confusion matrix")

confusion_matrix_df_test = pd.DataFrame(confusion_matrix(y_test, predict_with_best_t(y_test_pred, b est_t)), ['Actual: No', 'Actual: Yes'], ['Predicted: No', 'Predicted: Yes'])
sns.set(font_scale=1.4) #for label size
sns.heatmap(confusion_matrix_df_test, annot=True, annot_kws={"size": 16}, fmt='g')
```

Test data confusion matrix

### Out[236]:

<matplotlib.axes.\_subplots.AxesSubplot at 0x7f90a1ba3358>



# 3. Conclusion

## In [238]:

```
# Please compare all your models using Prettytable library
# Please compare all your models using Prettytable library
# 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", "Model", "Hyperparameters(n_estimators,max_depth)", "Test AUC"]

x.add_row(["BOW", "RF","(1000, 10)", 0.722])
x.add_row(["TFIDF", "RF", "(1000, 10)", 0.708])
x.add_row(["AVG W2V", "RF", "(300, 7)", 0.707])
x.add_row(["TFIDF W2V", "RF", "(200, 6)", 0.707])
x.add_row(["BOW", "GBDT", "(300, 3)", 0.707])
x.add_row(["TFIDF", "GBDT", "(500, 2)", 0.688])
x.add_row(["TFIDF W2V", "GBDT", "(150, 3)", 0.69])
x.add_row(["TFIDF W2V", "GBDT", "(100, 3)", 0.69])
print(x)
```

	+   Model   +	Hyperparameters(n_estimators,max_depth)	
BOW TFIDF AVG W2V TFIDF W2V	' RF     RF     RF     RF	(1000, 10) (1000, 10) (300, 7) (200, 6)	0.722   0.708   0.707   0.702
   BOW   TFIDF   AVG W2V   TFIDF W2V	   GBDT     GBDT     GBDT	(300, 3) (500, 2) (150, 3) (100, 3)	0.707   0.688   0.69   0.69