# **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!

Description	Feature
Description Fourth application essay	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. Mr. 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	<b>Desciption of the resource. 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, 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 [222]:

```
%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
import time
from tqdm import tqdm
import os
import pickle
from chart studio import plotly
import plotly.offline as offline
import plotly.graph_objs as go
offline.init notebook mode()
from collections import Counter
1.1 Reading Data
In [223]:
project data = pd.read csv('train data.csv')
```

```
resource_data = pd.read_csv('resources.csv')
In [224]:
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 (109248, 17)
The attributes of data: ['Unnamed: 0' 'id' 'teacher id' 'teacher prefix' 'school state'
 'project_submitted_datetime' 'project_grade_category'
 'project_subject_categories' 'project_subject_subcategories'
 'project title' 'project essay 1' 'project essay 2' 'project essay 3'
 'project essay 4' 'project resource summary'
 'teacher number of previously posted projects' 'project is approved']
In [225]:
# how to replace elements in list python: https://stackoverflow.com/a/2582163/4084039
cols = ['Date' if x=='project submitted datetime' else x for x in list(project data.columns)]
#sort dataframe based on time pandas python: https://stackoverflow.com/a/49702492/4084039
project_data['Date'] = pd.to_datetime(project_data['project_submitted_datetime'])
project data.drop('project submitted datetime', axis=1, inplace=True)
project data.sort values(by=['Date'], inplace=True)
# how to reorder columns pandas python: https://stackoverflow.com/a/13148611/4084039
project data = project data[cols]
project data.head(2)
```

```
Out[225]:
```

	Unnamed: 0	id	teacher_id	teacher_prefix	school_state	Date	project_grade_category	project_:
55660	8393	p205479	2bf07ba08945e5d8b2a3f269b2b3cfe5	Mrs.	CA	2016- 04-27 00:27:36	Grades PreK-2	
76127	37728	p043609	3f60494c61921b3b43ab61bdde2904df	Ms.	UT	2016- 04-27 00:31:25	Grades 3-5	
4								Þ

### In [226]:

```
print("Number of data points in train data", resource_data.shape)
print(resource_data.columns.values)
print(resource_data.head(2))

# https://stackoverflow.com/questions/22407798/how-to-reset-a-dataframes-indexes-for-all-groups-in
-one-step
price_data = resource_data.groupby('id').agg({'quantity':'sum', 'price':'sum'}).reset_index()

# Join two data frames
project_data = pd.merge(project_data, price_data, on='id', how='left')
project_data.head(5)
```

```
Number of data points in train data (1541272, 4)

['id' 'description' 'quantity' 'price']

id description quantity \
0 p233245 LC652 - Lakeshore Double-Space Mobile Drying Rack 1
1 p069063 Bouncy Bands for Desks (Blue support pipes) 3

price
0 149.00
1 14.95
```

## Out[226]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_state	Date	project_grade_category	project_subje
0	8393	p205479	2bf07ba08945e5d8b2a3f269b2b3cfe5	Mrs.	CA	2016- 04-27 00:27:36	Grades PreK-2	1
1	37728	p043609	3f60494c61921b3b43ab61bdde2904df	Ms.	UT	2016- 04-27 00:31:25	Grades 3-5	
2	74477	p189804	4a97f3a390bfe21b99cf5e2b81981c73	Mrs.	CA	2016- 04-27 00:46:53	Grades PreK-2	Litera
3	100660	p234804	cbc0e38f522143b86d372f8b43d4cff3	Mrs.	GA	2016- 04-27 00:53:00	Grades PreK-2	Al
4	33679	p137682	06f6e62e17de34fcf81020c77549e1d5	Mrs.	WA	2016- 04-27 01:05:25	Grades 3-5	Litera
4								Þ

# 1.2 preprocessing of project subject categories

```
In [227]:
```

```
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
mv 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]))
```

# 1.3 preprocessing of project subject subcategories

```
In [228]:
```

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

## 1.3 Text preprocessing

#### In [229]:

#### In [230]:

```
project_data.head(2)
```

## Out[230]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_state	Date	project_grade_category	project_title
0	8393	p205479	2bf07ba08945e5d8b2a3f269b2b3cfe5	Mrs.	CA	2016- 04-27 00:27:36	Grades PreK-2	Engineering STEAM into the Primary Classroom
1	37728	p043609	3f60494c61921b3b43ab61bdde2904df	Ms.	UT	2016- 04-27 00:31:25	Grades 3-5	Sensory Tools for Focus
4								·

#### In [231]:

```
#### 1.4.2.3 Using Pretrained Models: TFIDF weighted W2V
```

## In [232]:

```
# printing some random reviews
print(project_data['essay'].values[0])
print("="*50)
print(project_data['essay'].values[150])
print(project_data['essay'].values[1000])
print(project_data['essay'].values[20000])
print(project_data['essay'].values[20000])
print(project_data['essay'].values[99999])
print(project_data['essay'].values[99999])
print("="*50)
```

I have been fortunate enough to use the Fairy Tale STEM kits in my classroom as well as the STEM j ournals, which my students really enjoyed. I would love to implement more of the Lakeshore STEM k its in my classroom for the next school year as they provide excellent and engaging STEM lessons. My students come from a variety of backgrounds, including language and socioeconomic statu s. Many of them don't have a lot of experience in science and engineering and these kits give me the materials to provide these exciting opportunities for my students. Each month I try to do several science or STEM/STEAM projects. I would use the kits and robot to help guide my science i nstruction in engaging and meaningful ways. I can adapt the kits to my current language arts paci ng quide where we already teach some of the material in the kits like tall tales (Paul Bunyan) or Johnny Appleseed. The following units will be taught in the next school year where I will implement these kits: magnets, motion, sink vs. float, robots. I often get to these units and don 't know If I am teaching the right way or using the right materials. The kits will give me additional ideas, strategies, and lessons to prepare my students in science. It is challenging to d evelop high quality science activities. These kits give me the materials I need to provide my students with science activities that will go along with the curriculum in my classroom. Although I have some things (like magnets) in my classroom, I don't know how to use them effectively. The kits will provide me with the right amount of materials and show me how to use them in an appropriate way.

\_\_\_\_\_

I teach high school English to students with learning and behavioral disabilities. My students all vary in their ability level. However, the ultimate goal is to increase all students literacy level s. This includes their reading, writing, and communication levels. I teach a really dynamic group of students. However, my students face a lot of challenges. My students all live in poverty and in a dangerous reighborhood. Despite these challenges. I have students who have the the desire to def

a dangerous neighborhood. Despite these challenges, I have students who have the the desire to dereat these challenges. My students all have learning disabilities and currently all are performing below grade level. My students are visual learners and will benefit from a classroom that fulfills their preferred learning style. The materials I am requesting will allow my students to be prepared for the classroom with the necessary supplies. Too often I am challenged with students who come to school unprepared for class due to economic challenges. I want my students to be able to focus on learning and not how they will be able to get school supplies. The supplies will last all year. Students will be able to complete written assignments and maintain a classroom journal. The chart paper will be used to make learning more visual in class and to create posters to aid students in their learning. The students have access to a classroom printer. The toner will be used to print student work that is completed on the classroom Chromebooks.I want to try and remove all barriers for the students learning and create opportunities for learning. One of the biggest barriers is the students not having the resources to get pens, paper, and folders. My students will be able to increase their literacy skills because of this project.

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

\_\_\_\_\_

\"Life moves pretty fast. If you don't stop and look around once in awhile, you could miss it.\" from the movie, Ferris Bueller's Day Off. Think back...what do you remember about your grandparents? How amazing would it be to be able to flip through a book to see a day in their lives?My second graders are voracious readers! They love to read both fiction and nonfiction books . Their favorite characters include Pete the Cat, Fly Guy, Piggie and Elephant, and Mercy Watson. They also love to read about insects, space and plants. My students are hungry bookworms! My stude nts are eager to learn and read about the world around them. My kids love to be at school and are like little sponges absorbing everything around them. Their parents work long hours and usually do not see their children. My students are usually cared for by their grandparents or a family friend. Most of my students do not have someone who speaks English at home. Thus it is difficult f or my students to acquire language. Now think forward... wouldn't it mean a lot to your kids, nieces or nephews or grandchildren, to be able to see a day in your life today 30 years from now? Memories are so precious to us and being able to share these memories with future generations will be a rewarding experience. As part of our social studies curriculum, students will be learning ab out changes over time. Students will be studying photos to learn about how their community has ch anged over time. In particular, we will look at photos to study how the land, buildings, clothing, and schools have changed over time. As a culminating activity, my students will capture a slice of their history and preserve it through scrap booking. Key important events in their young lives will be documented with the date, location, and names. Students will be using photos from home and from school to create their second grade memories. Their scrap books will preserve their unique stories for future generations to enjoy. Your donation to this project will provide my second graders with an opportunity to learn about social studies in a fun and creative manner. Th rough their scrapbooks, children will share their story with others and have a historical document for the rest of their lives.

\"A person's a person, no matter how small.\" (Dr.Seuss) I teach the smallest students with the bi ggest enthusiasm for learning. My students learn in many different ways using all of our senses an d multiple intelligences. I use a wide range of techniques to help all my students succeed. \r\nSt udents in my class come from a variety of different backgrounds which makes for wonderful sharing of experiences and cultures, including Native Americans.\r\nOur school is a caring community of su ccessful learners which can be seen through collaborative student project based learning in and ou t of the classroom. Kindergarteners in my class love to work with hands-on materials and have many different opportunities to practice a skill before it is mastered. Having the social skills to wor k cooperatively with friends is a crucial aspect of the kindergarten curriculum. Montana is the perfect place to learn about agriculture and nutrition. My students love to role play in our pretend kitchen in the early childhood classroom. I have had several kids ask me, \"Can we try coo king with REAL food?\" I will take their idea and create \"Common Core Cooking Lessons\" where we learn important math and writing concepts while cooking delicious healthy food for snack time. My students will have a grounded appreciation for the work that went into making the food and knowled ge of where the ingredients came from as well as how it's healthy for their bodies. This project w ould expand our learning of nutrition and agricultural cooking recipes by having us peel our own a pples to make homemade applesauce, make our own bread, and mix up healthy plants from our classroo m garden in the spring. We will also create our own cookbooks to be printed and shared with famili es. \r\nStudents will gain math and literature skills as well as a life long enjoyment for healthy cooking.nannan

They are a social bunch who enjoy working in partners and working with groups. They are hard-working and eager to head to middle school next year. My job is to get them ready to make this transition and make it as smooth as possible. In order to do this, my students need to come to school every day and feel safe and ready to learn. Because they are getting ready to head to middle school, I give them lots of choice- choice on where to sit and work, the order to complete assignments, choice of projects, etc. Part of the students feeling safe is the ability for them to come into a welcoming, encouraging environment. My room is colorful and the atmosphere is casual. I want them to take ownership of the classroom because we ALL share it together. Because my time w ith them is limited, I want to ensure they get the most of this time and enjoy it to the best of their abilities. Currently, we have twenty-two desks of differing sizes, yet the desks are similar to the ones the students will use in middle school. We also have a kidney table with crates for sea ting. I allow my students to choose their own spots while they are working independently or in groups. More often than not, most of them move out of their desks and onto the crates. Believe it

or not, this has proven to be more successful than making them stay at their desks! It is because of this that I am looking toward the "Flexible Seating" option for my classroom.\r\n The students look forward to their work time so they can move around the room. I would like to get rid of the c

My classroom consists of twenty-two amazing sixth graders from different cultures and backgrounds.

onstricting desks and move toward more "fun" seating options. I am requesting various seating so my students have more options to sit. Currently, I have a stool and a papasan chair I inherited from the previous sixth-grade teacher as well as five milk crate seats I made, but I would like to give them more options and reduce the competition for the "good seats". I am also requesting two rugs as not only more seating options but to make the classroom more welcoming and appealing. In order for my students to be able to write and complete work without desks, I am requesting a class set of clipboards. Finally, due to curriculum that requires groups to work together, I am requesting tables that we can fold up when we are not using them to leave more room for our flexible seating options.\r\nI know that with more seating options, they will be that much more excited about coming to school! Thank you for your support in making my classroom one students will remember forever!nannan

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#### In [233]:

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

## In [234]:

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

\"A person is a person, no matter how small.\" (Dr.Seuss) I teach the smallest students with the b iggest enthusiasm for learning. My students learn in many different ways using all of our senses a nd multiple intelligences. I use a wide range of techniques to help all my students succeed. \r\nS tudents in my class come from a variety of different backgrounds which makes for wonderful sharing of experiences and cultures, including Native Americans.\r\nOur school is a caring community of su ccessful learners which can be seen through collaborative student project based learning in and ou t of the classroom. Kindergarteners in my class love to work with hands-on materials and have many different opportunities to practice a skill before it is mastered. Having the social skills to wor k cooperatively with friends is a crucial aspect of the kindergarten curriculum. Montana is the perfect place to learn about agriculture and nutrition. My students love to role play in our pretend kitchen in the early childhood classroom. I have had several kids ask me, \"Can we try coo king with REAL food?\" I will take their idea and create \"Common Core Cooking Lessons\" where we learn important math and writing concepts while cooking delicious healthy food for snack time. My students will have a grounded appreciation for the work that went into making the food and knowled ge of where the ingredients came from as well as how it is healthy for their bodies. This project would expand our learning of nutrition and agricultural cooking recipes by having us peel our own apples to make homemade applesauce, make our own bread, and mix up healthy plants from our classro om garden in the spring. We will also create our own cookbooks to be printed and shared with famil ies. \r\nStudents will gain math and literature skills as well as a life long enjoyment for health v cooking.nannan

\_\_\_\_\_

## In [235]:

```
# \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)
```

A person is a person, no matter how small. (Dr.Seuss) I teach the smallest students with the big gest enthusiasm for learning. My students learn in many different ways using all of our senses and

multiple intelligences. I use a wide range of techniques to help all my students succeed. Students in my class come from a variety of different backgrounds which makes for wonderful sharing of experiences and cultures, including Native Americans. Our school is a caring community of successful learners which can be seen through collaborative student project based learning in a nd out of the classroom. Kindergarteners in my class love to work with hands-on materials and have many different opportunities to practice a skill before it is mastered. Having the social skills t o work cooperatively with friends is a crucial aspect of the kindergarten curriculum. Montana is the perfect place to learn about agriculture and nutrition. My students love to role play in our p retend kitchen in the early childhood classroom. I have had several kids ask me, Can we try cooki ng with REAL food? I will take their idea and create Common Core Cooking Lessons where we learn important math and writing concepts while cooking delicious healthy food for snack time. My students will have a grounded appreciation for the work that went into making the food and knowled ge of where the ingredients came from as well as how it is healthy for their bodies. This project would expand our learning of nutrition and agricultural cooking recipes by having us peel our own apples to make homemade applesauce, make our own bread, and mix up healthy plants from our classro om garden in the spring. We will also create our own cookbooks to be printed and shared with famil ies. Students will gain math and literature skills as well as a life long enjoyment for healthy cooking.nannan

## In [236]:

```
#remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
print(sent)
```

A person is a person no matter how small Dr Seuss I teach the smallest students with the biggest enthusiasm for learning My students learn in many different ways using all of our senses and multi ple intelligences I use a wide range of techniques to help all my students succeed Students in my class come from a variety of different backgrounds which makes for wonderful sharing of experiences and cultures including Native Americans Our school is a caring community of successful learners which can be seen through collaborative student project based learning in and out of the classroom Kindergarteners in my class love to work with hands on materials and have many different opportunities to practice a skill before it is mastered Having the social skills to work cooperatively with friends is a crucial aspect of the kindergarten curriculum Montana is the perfect place to learn about agriculture and nutrition My students love to role play in our pretend kitchen in the early childhood classroom I have had several kids ask me Can we try cooking with REAL food I will take their idea and create Common Core Cooking Lessons where we learn important math and writing concepts while cooking delicious healthy food for snack time My students will have a grounded appreciation for the work that went into making the food and knowled qe of where the ingredients came from as well as how it is healthy for their bodies This project w ould expand our learning of nutrition and agricultural cooking recipes by having us peel our own a pples to make homemade applesauce make our own bread and mix up healthy plants from our classroom garden in the spring We will also create our own cookbooks to be printed and shared with families Students will gain math and literature skills as well as a life long enjoyment for healthy cooking nannan

## In [237]:

```
# 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',
```

In [238]:

```
# Create function that will filter sentance
def filterSentance(sentance):
    sent = decontracted(sentance)
    sent = sent.replace('\\r', ' ')
    sent = sent.replace('\\"', ' ')
    sent = sent.replace('\\n', ' ')
    sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
    sent = sent.lower()
    # https://gist.github.com/sebleier/554280
    sent = ' '.join(e for e in sent.split() if e not in stopwords)
    return sent.strip()
```

In [239]:

```
# 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):
        preprocessed_essays.append(filterSentance(sentance))
100%| 109248/109248 [01:09<00:00, 1576.94it/s]
```

In [240]:

```
# after preprocesing
preprocessed_essays[20000]
```

Out[240]:

'person person no matter small dr seuss teach smallest students biggest enthusiasm learning students learn many different ways using senses multiple intelligences use wide range techniques help students succeed students class come variety different backgrounds makes wonderful sharing experiences cultures including native americans school caring community successful learners seen collaborative student project based learning classroom kindergarteners class love work hands materials many different opportunities practice skill mastered social skills work cooperatively friends crucial aspect kindergarten curriculum montana perfect place learn agriculture nutrition students love role play pretend kitchen early childhood classroom several kids ask try cooking real food take id ea create common core cooking lessons learn important math writing concepts cooking delicious heal thy food snack time students grounded appreciation work went making food knowledge ingredients came e well healthy bodies project would expand learning nutrition agricultural cooking recipes us peel apples make homemade applesauce make bread mix healthy plants classroom garden spring also create cookbooks printed shared families students gain math literature skills well life long enjoyment he althy cooking nannan'

# 1.4 Preprocessing of `project\_title`

In [241]:

```
# similarly you can preprocess the titles also
# Combining all the above stundents
from tqdm import tqdm
preprocessed_titles = []
# tqdm is for printing the status bar
for sentance in tqdm(project_data['project_title'].values):
    preprocessed_titles.append(filterSentance(sentance))
100%| 109248/109248 [00:06<00:00, 18094.37it/s]
```

In [242]:

```
# after preprocessing
```

```
print(preprocessed titles[20000])
health nutritional cooking kindergarten
In [243]:
# similarly you can preprocess the project resource summary also
# Combining all the above stundents
from tqdm import tqdm
preprocessed resource summary = []
# tqdm is for printing the status bar
for sentance in tqdm(project data['project resource summary'].values):
    preprocessed_resource_summary.append(filterSentance(sentance))
100%| 109248/109248 [00:10<00:00, 10799.89it/s]
In [244]:
# after preprocessing
print(preprocessed resource summary[20000])
students need cooking supplies help us healthy learn nutrition mixer apple spiralizer kitchen
tools nutrition kit kid friendly healthy literature ink make cookbooks
In [245]:
# Preprocess teacher prefix
from tqdm import tqdm
preprocessed teacher prefix = []
# tqdm is for printing the status bar
for teacher prefix in tqdm(project data['teacher prefix'].values):
    teacher prefix = str(teacher prefix)
    clean teacher prefix = decontracted(teacher prefix)
    clean teacher prefix = clean teacher prefix.replace('\\r', ' ')
    clean_teacher_prefix = clean_teacher_prefix.replace('\\"', ' ')
    clean_teacher_prefix = clean_teacher_prefix.replace('\\n', ' ')
    clean teacher prefix = re.sub('[^A-Za-z0-9]+', ' ', clean teacher prefix)
    clean teacher_prefix = clean_teacher_prefix.lower()
    if clean teacher prefix in stopwords:
       continue
    preprocessed teacher prefix.append(clean teacher prefix.strip())
100%| 109248/109248 [00:02<00:00, 45904.99it/s]
In [246]:
preprocessed teacher prefix[0:10]
Out[246]:
['mrs', 'ms', 'mrs', 'mrs', 'mrs', 'mrs', 'mrs', 'ms', 'ms', 'ms']
In [247]:
# Preprocess project grade category
from tqdm import tqdm
preprocessed project grade category = []
# tqdm is for printing the status bar
for project_grade_category in tqdm(project_data['project_grade_category'].values):
    project grade category = str(project grade category)
    clean project grade category = decontracted(project grade category)
    clean project grade category = clean project grade category.replace('\\r', ' ')
    clean_project_grade_category = clean_project_grade_category.replace('\\"', ' ')
    {\tt clean\_project\_grade\_category:replace('\n', '')}
    clean_project_grade_category = re.sub('[^A-Za-z0-9]+', ' ', clean_project_grade_category)
    clean project grade category = clean project grade category.lower()
    if clean_project_grade_category in stopwords:
    clean_project_grade_category = clean_project_grade_category.strip()
```

```
wnitespace are creating problems because we are treating this as categorical reature
    preprocessed_project_grade_category.append(clean_project_grade_category.replace(' ', '_'))
          | 109248/109248 [00:01<00:00, 58878.88it/s]
In [248]:
preprocessed project grade category[0:10]
Out[248]:
['grades_prek 2',
 'grades 3 5',
 'grades_prek_2',
 'grades_prek_2',
 'grades 3 5',
 'grades_3_5',
 'grades_3_5',
 'grades 3 5',
 'grades_prek_2',
 'grades 3 5']
In [249]:
# Replace original columns with preprocessed column values
project_data['clean_essays'] = preprocessed_essays
project data['clean titles'] = preprocessed titles
project_data['project_resource_summary'] = preprocessed_resource_summary
project_data['teacher_prefix'] = preprocessed_teacher_prefix
project_data['project_grade_category'] = preprocessed_project_grade_category
# Drop essays column
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 [250]:
project data.head(5)
Out[250]:
   Unnamed:
                 id
                                        teacher id teacher prefix school state
                                                                             Date project grade category project title
          n
                                                                                                       Engineering
                                                                            2016-
                                                                                                       STEAM into
 0
       8393 p205479 2bf07ba08945e5d8b2a3f269b2b3cfe5
                                                                            04-27
                                                                                          grades_prek_2
                                                                                                       the Primary
                                                                          00:27:36
                                                                                                        Classroom
                                                                            2016-
                                                                                                         Sensory
       37728 p043609 3f60494c61921b3b43ab61bdde2904df
                                                                            04-27
                                                                                            grades_3_5
                                                                                                         Tools for
                                                                          00:31:25
                                                                                                           Focus
                                                                                                           Mobile
                                                                                                         Learning
                                                                            2016-
                                                                                                           with a
 2
      74477 p189804 4a97f3a390bfe21b99cf5e2b81981c73
                                                                            04 - 27
                                                                                          grades_prek_2
                                                           mrs
                                                                                                           Mobile
                                                                          00:46:53
                                                                                                         Listening
                                                                                                           Center
                                                                                                          Flexible
                                                                            2016-
                                                                                                        Seating for
      100660 p234804
                     cbc0e38f522143b86d372f8b43d4cff3
                                                                            04-27
                                                          mrs
                                                                       GΑ
                                                                                          grades_prek_2
                                                                                                          Flexible
                                                                          00:53:00
                                                                                                         Learning
                                                                                                      Going Deep:
                                                                            2016-
                                                                                                        The Art of
       33679 p137682 06f6e62e17de34fcf81020c77549e1d5
                                                                      WA
 4
                                                           mrs
                                                                            04-27
                                                                                            grades_3_5
```

Inner Thinking!

```
In [251]:
project_data.tail(5)
Out[251]:
        Unnamed:
                        id
                                                  teacher_id teacher_prefix school_state
                                                                                           Date project_grade_category project
                0
                                                                                                                           Na
                                                                                          2017-
                                                                                                                           F
 109243
            45036 p194916
                             29cf137e5a40b0f141d9fd7898303a5c
                                                                                          04-30
                                                                                                           grades_9_12
                                                                       mrs
                                                                                                                          Pro
                                                                                        23:11:45
                                                                                          2017-
                                                                                                                         Op
 109244
            12610 p162971
                             22fee80f2078c694c2d244d3ecb1c390
                                                                                   NM
                                                                                          04-30
                                                                                                         grades_prek_2
                                                                                                                        Organ
                                                                                        23:23:24
                                                                                                                           В
                                                                                          2017-
                                                                                                                         Agri
           179833 p096829 c8c81a73e29ae3bdd4140be8ad0bea00
                                                                                     IL
                                                                                                            grades_3_5
 109245
                                                                       mrs
                                                                                          04-30
                                                                                        23:25:42
                                                                                                                       Sustair
                                                                                          2017-
 109246
            13791 p184393
                             65545a295267ad9df99f26f25c978fd0
                                                                                    Н
                                                                                          04-30
                                                                                                           grades_9_12
                                                                      mrs
                                                                                                                           Μ
                                                                                        23:27:07
                                                                                                                           ٨
                                                                                          2017-
                                                                                                                           Ne
 109247
           124250 p028318
                              1fff5a88945be8b2c728c6a85c31930f
                                                                                    CA
                                                                                          04-30
                                                                                                         grades_prek_2
                                                                       mrs
                                                                                        23:45:08
In [252]:
print(set(preprocessed project grade category))
{'grades_3_5', 'grades_6_8', 'grades_9_12', 'grades_prek_2'}
In [253]:
project data['teacher prefix'] = project data['teacher prefix'].fillna('null')
In [254]:
project_data.head(2)
Out[254]:
   Unnamed:
                   id
                                             teacher_id teacher_prefix school_state
                                                                                     Date project_grade_category project_title
                                                                                                                  Engineering
                                                                                     2016-
                                                                                                                  STEAM into
0
        8393 p205479 2bf07ba08945e5d8b2a3f269b2b3cfe5
                                                                              CA
                                                                                    04-27
                                                                 mrs
                                                                                                   grades_prek_2
                                                                                                                  the Primary
                                                                                  00:27:36
                                                                                                                   Classroom
                                                                                     2016-
                                                                                                                     Sensory
                                                                              UΤ
       37728 p043609 3f60494c61921b3b43ab61bdde2904df
                                                                                                      grades_3_5
 1
                                                                 ms
                                                                                    04 - 27
                                                                                                                    Tools for
                                                                                  00:31:25
                                                                                                                      Focus
```

# 1.5 Preparing data for models

```
In [255]:
project_data.columns
Out[255]:
Index(['Unnamed: 0', 'id', 'teacher_id', 'teacher_prefix', 'school_state',
       'Date', 'project_grade_category', 'project_title',
       'project resource summary',
       'teacher_number_of_previously_posted_projects', 'project_is_approved',
       'quantity', 'price', 'clean categories', 'clean subcategories', 'essay',
       'clean essays', 'clean_titles'],
      dtype='object')
we are going to consider
      - school_state : categorical data
      - clean categories : categorical data
      - clean subcategories : categorical data
      - project grade category : categorical data
      - teacher_prefix : categorical data
      - project title : text data
      - text : text data
      - project_resource_summary: text data (optinal)
      - quantity : numerical (optinal)
      - teacher_number_of_previously_posted_projects : numerical
      - price : numerical
In [256]:
print(project data.shape)
# I am taking 30% of data points for my analysis
# AVGW2V and TFIDFW2V takes more time
# I am using macbook pro with 16GB of RAM but I didn't get AVGW2V result within 12 hrs for 50% of
data.
# So I switched to 30% of data
project_data = project_data.sample(frac=0.3)
print(project data.shape)
(109248, 18)
(32774, 18)
In [257]:
# Splitting data
y = project data['project is approved'].values
project_data.drop(['project_is_approved'], axis=1, inplace=True)
X = project data
project data.shape
Out [257]:
(32774, 17)
In [258]:
# Split Train, CV and Test data
from sklearn.model selection import train test split
Y train Y test v train v test = train test enlit(Y v test size=0 33 stratifv=v)
```

```
print('Train Data Set', X_train.shape, y_train.shape)
print('Cross Validate Data Set', X_cv.shape, y_cv.shape)
print('Test Data Set', X test.shape, y test.shape)
Train Data Set (14711, 17) (14711,)
Cross Validate Data Set (7247, 17) (7247,)
Test Data Set (10816, 17) (10816,)
In [259]:
# Commented code as per your suggestion
# # Handle imblanced data set
# from imblearn.over_sampling import RandomOverSampler
# from collections import Counter
# ros = RandomOverSampler(sampling strategy='minority', random state=42)
# X train, y train = ros.fit resample(X train, y train)
# print('Resampled Dataset Shape %s ' %Counter(y train))
# X train = pd.DataFrame(X train, columns=X.columns)
# X_train.head(2)
In [260]:
print('Train Data Set', X_train.shape, y_train.shape)
print('Cross Validate Data Set', X cv.shape, y cv.shape)
print('Test Data Set', X test.shape, y test.shape)
print('*'*100)
Train Data Set (14711, 17) (14711,)
Cross Validate Data Set (7247, 17) (7247,)
Test Data Set (10816, 17) (10816,)
4
```

 $\texttt{A\_ctain, A\_cesc, Y\_ctain, Y\_cesc - ctain\_cesc\_spitc(A, Y, cesc\_size=0.00, sctactiy=y)}$ 

X\_train, X\_cv, y\_train, y\_cv = train\_test\_split(X\_train, y\_train, test\_size=0.33, stratify=y\_train)

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

## 1.5.2 Vectorizing Text data

## 1.5.2.1 Bag of words

In [261]:

```
# # Sample code for bigram extraction using TFIDF
# from sklearn.feature_extraction.text import TfidfVectorizer
# corpus = [
# 'This is the first document.',
# 'This document is the second document.',
# 'And this is the third one.',
# 'Is this the first document?',
# ]
# vectorizer = TfidfVectorizer(ngram_range=(2,2))
# X = vectorizer.fit_transform(corpus)
# print(vectorizer.get_feature_names())
# print(X.shape)
```

## In [262]:

```
# - project_title : text data
print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)
print("*"*100)
```

```
# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vectorizer.fit(X_train['clean_titles'].values) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X train title bow = vectorizer.transform(X train['clean titles'].values)
X cv title bow = vectorizer.transform(X cv['clean titles'].values)
X_test_title_bow = vectorizer.transform(X_test['clean_titles'].values)
clean titles bow features = vectorizer.get feature names()
print("After vectorizations")
print(X train title bow.shape, y train.shape)
print(X cv_title_bow.shape, y_cv.shape)
print(X test title bow.shape, y test.shape)
# print(vectorizer.get feature names())
print("*"*100)
(14711, 17) (14711,)
(7247, 17) (7247,)
(10816, 17) (10816,)
After vectorizations
(14711, 1130) (14711,)
(7247, 1130) (7247,)
(10816, 1130) (10816,)
In [263]:
# - text : text data
print(X train.shape, y train.shape)
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)
print("*"*100)
\# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vectorizer.fit(X train['clean essays'].values) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X train essay bow = vectorizer.transform(X train['clean essays'].values)
X cv essay bow = vectorizer.transform(X cv['clean essays'].values)
X_test_essay_bow = vectorizer.transform(X_test['clean essays'].values)
easy_bow_features = vectorizer.get_feature_names()
print("After vectorizations")
print(X_train_essay_bow.shape, y_train.shape)
print(X cv essay bow.shape, y cv.shape)
print(X_test_essay_bow.shape, y_test.shape)
# print(vectorizer.get_feature_names())
print("*"*100)
(14711, 17) (14711,)
(7247, 17) (7247,)
(10816, 17) (10816,)
After vectorizations
(14711, 5000) (14711,)
(7247, 5000) (7247,)
(10816, 5000) (10816,)
In [264]:
# - project resource summary: text data (optinal)
print(X_train.shape, y_train.shape)
```

```
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)
print("*"*100)
# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vectorizer.fit(X train['project resource summary'].values) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X train project resource summary bow = vectorizer.transform(X train['project resource summary'].va
lues)
X cv project resource summary bow = vectorizer.transform(X cv['project resource summary'].values)
X test project resource summary bow =
vectorizer.transform(X test['project resource summary'].values)
project resource summary bow features = vectorizer.get feature names()
print("After vectorizations")
print(X train project resource summary bow.shape, y train.shape)
print(X_cv_project_resource_summary_bow.shape, y_cv.shape)
print(X test project resource summary bow.shape, y test.shape)
# print(vectorizer.get_feature_names())
print("*"*100)
(14711, 17) (14711,)
(7247, 17) (7247,)
(10816, 17) (10816,)
After vectorizations
(14711, 4134) (14711,)
(7247, 4134) (7247,)
(10816, 4134) (10816,)
```

#### 1.5.2.2 TFIDF vectorizer

(14711, 849) (14711,) (7247 849) (7247)

```
In [265]:
# - project title : text data
print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X test.shape, y test.shape)
print("*"*100)
from sklearn.feature_extraction.text import TfidfVectorizer
# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer = TfidfVectorizer(min df=10)
vectorizer.fit(X train['clean titles'].values) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X train title tfidf = vectorizer.transform(X train['clean titles'].values)
X cv title tfidf = vectorizer.transform(X cv['clean titles'].values)
X test title tfidf = vectorizer.transform(X test['clean titles'].values)
clean titles tfidf features = vectorizer.get feature names()
print("After vectorizations")
print(X train title tfidf.shape, y train.shape)
print(X_cv_title_tfidf.shape, y_cv.shape)
print(X cv title tfidf.shape, y test.shape)
print("*"*100)
(14711, 17) (14711,)
(7247, 17) (7247,)
(10816, 17) (10816,)
After vectorizations
```

```
(1471, 077) (1471,)
(7247, 849) (10816,)
In [266]:
# - text : text data
print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X test.shape, y_test.shape)
print("*"*100)
from sklearn.feature_extraction.text import TfidfVectorizer
# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer = TfidfVectorizer(min df=10)#, ngram range=(2,2), max features=5000
vectorizer.fit(X_train['clean_essays'].values) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X_train_essay_tfidf = vectorizer.transform(X train['clean essays'].values)
X cv essay tfidf = vectorizer.transform(X cv['clean essays'].values)
X test essay tfidf = vectorizer.transform(X test['clean essays'].values)
easy tfidf features = vectorizer.get feature names()
print("After vectorizations")
print(X train essay tfidf.shape, y train.shape)
print(X_cv_essay_tfidf.shape, y_cv.shape)
print(X test essay tfidf.shape, y test.shape)
print("*"*100)
(14711, 17) (14711,)
(7247, 17) (7247,)
(10816, 17) (10816,)
After vectorizations
(14711, 7337) (14711,)
(7247, 7337) (7247,)
(10816, 7337) (10816,)
In [267]:
# - project resource summary: text data (optinal)
print(X_train.shape, y_train.shape)
print(X_cv.shape, y_cv.shape)
print(X test.shape, y test.shape)
print("*"*100)
from sklearn.feature_extraction.text import TfidfVectorizer
# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer = TfidfVectorizer(min df=10)
vectorizer.fit(X train['project resource summary'].values) # fit has to happen only on train data
# we use the fitted CountVectorizer to convert the text to vector
X train project resource summary tfidf = vectorizer.transform(X train['project resource summary'].
values)
X cv project resource summary tfidf = vectorizer.transform(X cv['project resource summary'].values
X test project resource summary tfidf =
vectorizer.transform(X test['project resource summary'].values)
project resource summary tfidf features = vectorizer.get feature names()
print("After vectorizations")
print(X_train_project_resource_summary_tfidf.shape, y_train.shape)
print(X_cv_project_resource_summary_tfidf.shape, y_cv.shape)
print (X test project resource summary tfidf.shape, y test.shape)
print("*"*100)
```

### 1.5.2.3 Using Pretrained Models: Avg W2V

```
In [268]:
```

```
111
# 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)
. . .
```

```
loadGloveModel(gloveFile):\n print ("Loading Glove Model")\n f = open(gloveFile,\'r\',
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 =
loadGloveModel(\'glove.42B.300d.txt\')\n\n# ===========\nOutput:\n \nLoading G
love Model\n1917495it [06:32, 4879.69it/s]\nDone. 1917495 words loaded!\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),"
words_courpus[i] = model[i] \r
: 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'
4
                                                                     . ▶
```

## In [269]:

```
# 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())
```

#### In [270]:

```
# average Word2Vec for train text
# compute average word2vec for each review.
avg w2v vectors text train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train['clean essays'].values): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    cnt words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
       if word in glove words:
           vector += model[word]
           cnt words += 1
    if cnt_words != 0:
       vector /= cnt words
    avg_w2v_vectors_text_train.append(vector)
print(len(avg w2v vectors text train))
print(len(avg_w2v_vectors_text_train[0]))
100%| 14711/14711 [00:05<00:00, 2782.36it/s]
```

14711 300

## In [271]:

```
# average Word2Vec for CV text
# compute average word2vec for each review.
avg w2v vectors text cv = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_cv['clean_essays'].values): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    cnt words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
       if word in glove words:
           vector += model[word]
           cnt words += 1
    if cnt words != 0:
       vector /= cnt words
    avg w2v vectors text cv.append(vector)
print(len(avg_w2v_vectors_text_cv))
print(len(avg w2v vectors text cv[0]))
100%| 7247/7247 [00:02<00:00, 3336.93it/s]
```

```
7247
300
```

#### In [272]:

```
# average Word2Vec for test text
# compute average word2vec for each review.
avg_w2v_vectors_text_test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_test['clean_essays'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove words:
            vector += model[word]
            cnt words += 1
    if cnt words != 0:
       vector /= cnt_words
    avg w2v vectors text test.append(vector)
print(len(avg_w2v_vectors_text_test))
print(len(avg w2v vectors text test[0]))
100%| | 10816/10816 [00:04<00:00, 2324.49it/s]
10816
```

#### In [273]:

300

```
# Similarly you can vectorize for title also
# average Word2Vec
# compute average word2vec for each review.
avg w2v vectors title train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_train['clean_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
    avg w2v vectors title train.append(vector)
print(len(avg w2v vectors title train))
print(len(avg w2v vectors title train[0]))
100%| 14711/14711 [00:00<00:00, 32653.38it/s]
```

14711 300

### In [274]:

```
if cnt_words != 0:
    vector /= cnt_words
avg_w2v_vectors_title_cv.append(vector)

print(len(avg_w2v_vectors_title_cv))
print(len(avg_w2v_vectors_title_cv[0]))

100%| 7247/7247 [00:00<00:00, 58864.66it/s]</pre>
```

In [275]:

300

```
# Similarly you can vectorize for title also
# average Word2Vec
# compute average word2vec for each review.
avg w2v vectors title test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_test['clean_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
    avg w2v vectors title test.append(vector)
print(len(avg_w2v_vectors_title_test))
print(len(avg w2v vectors title test[0]))
100%| 10816/10816 [00:00<00:00, 38292.15it/s]
```

10816 300

In [276]:

```
# Similarly you can vectorize for project_resource_summary also
# average Word2Vec
# compute average word2vec for each review.
avg w2v vectors project resource summary train = []; # the avg-w2v for each sentence/review is sto
red in this list
for sentence in tqdm(X train['project resource summary']): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
       if word in glove words:
           vector += model[word]
           cnt words += 1
    if cnt words != 0:
       vector /= cnt_words
    avg w2v vectors project resource summary train.append(vector)
print(len(avg w2v vectors project resource summary train))
print(len(avg w2v vectors project resource summary train[0]))
100%| 14711/14711 [00:00<00:00, 26837.20it/s]
```

14711 300

In [277]:

```
# Similarly you can vectorize for project resource summary also
# average Word2Vec
# compute average word2vec for each review.
avg w2v vectors project resource summary cv = []; # the avg-w2v for each sentence/review is stored
in this list
for sentence in tqdm(X cv['project resource summary']): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
       if word in glove_words:
           vector += model[word]
           cnt words += 1
    if cnt_words != 0:
       vector /= cnt words
    avg_w2v_vectors_project_resource_summary_cv.append(vector)
print(len(avg w2v vectors project resource summary cv))
print(len(avg w2v vectors project resource summary cv[0]))
100%| 7247/7247 [00:00<00:00, 10577.49it/s]
7247
```

In [278]:

300

```
# Similarly you can vectorize for project resource summary also
# average Word2Vec
# compute average word2vec for each review.
avg_w2v_vectors_project_resource_summary_test = []; # the avg-w2v for each sentence/review is stor
ed in this list
for sentence in tqdm (X test['project resource summary']): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    cnt words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
           cnt words += 1
    if cnt words != 0:
       vector /= cnt words
    avg w2v vectors project resource summary test.append(vector)
print(len(avg w2v vectors project resource summary test))
print(len(avg w2v vectors project resource summary test[0]))
        10816/10816 [00:00<00:00, 11046.90it/s]
10816
```

1.5.2.3 Using Pretrained Models: TFIDF weighted W2V

```
In [279]:
```

300

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model = TfidfVectorizer()
tfidf_model.fit(X_train['clean_essays'])
# 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 [280]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_text_train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_train['clean_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
    tfidf_w2v_vectors_text_train.append(vector)
print(len(tfidf w2v vectors text train))
print(len(tfidf_w2v_vectors_text_train[0]))
        | 14711/14711 [00:49<00:00, 447.19it/s]
```

#### In [281]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors text cv = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_cv['clean_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
    tfidf_w2v_vectors_text_cv.append(vector)
print(len(tfidf_w2v_vectors_text_cv))
print(len(tfidf w2v vectors text cv[0]))
100%| 7247/7247 [00:17<00:00, 418.04it/s]
```

7247 300

## In [282]:

```
if tf idf weight != 0:
        vector /= tf idf weight
    tfidf_w2v_vectors_text_test.append(vector)
print(len(tfidf w2v vectors text test))
print(len(tfidf w2v vectors text test[0]))
100%| 10816/10816 [00:27<00:00, 390.96it/s]
10816
300
In [283]:
# S = ["abc def pgr", "def def def abc", "pgr pgr def"]
tfidf model = TfidfVectorizer()
tfidf model.fit(X train['clean 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 [284]:
# Similarly you can vectorize for title also
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors title train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train['clean 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
    tfidf w2v vectors title train.append(vector)
print(len(tfidf_w2v_vectors_title_train))
print(len(tfidf w2v vectors title train[0]))
100%| 14711/14711 [00:00<00:00, 25966.36it/s]
```

#### In [285]:

```
tf_idf_weight += tf_idf
if tf_idf_weight != 0:
    vector /= tf_idf_weight
    tfidf_w2v_vectors_title_cv.append(vector)

print(len(tfidf_w2v_vectors_title_cv))
print(len(tfidf_w2v_vectors_title_cv[0]))

100%| | 7247/7247 [00:00<00:00, 25684.01it/s]</pre>
```

```
In [286]:
```

```
# Similarly you can vectorize for title also
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_title_test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X test['clean 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
    tfidf w2v vectors title test.append(vector)
print(len(tfidf w2v vectors title test))
print(len(tfidf w2v vectors title test[0]))
100%| 100%| 10816/10816 [00:00<00:00, 30083.56it/s]
```

10816 300

### In [287]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model = TfidfVectorizer()
tfidf_model.fit(X_train['project_resource_summary'])
# 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 [288]:

```
# Similarly you can vectorize for title also
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_project_resource_summary_train = []; # the avg-w2v for each sentence/review is s
tored in this list
for sentence in tqdm(X_train['project_resource_summary']): # 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
```

#### In [289]:

```
# Similarly you can vectorize for title also
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_project_resource_summary_cv = []; # the avg-w2v for each sentence/review is stor
ed in this list
for sentence in tqdm(X cv['project resource summary']): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
   tf idf weight =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
       if (word in glove_words) and (word in tfidf_words):
           vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
           tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
           vector += (vec * tf_idf) # calculating tfidf weighted w2v
            tf idf weight += tf idf
    if tf_idf_weight != 0:
       vector /= tf idf weight
    tfidf w2v vectors project resource summary cv.append(vector)
print(len(tfidf w2v vectors project resource summary cv))
print(len(tfidf_w2v_vectors_project_resource_summary_cv[0]))
100%| 7247/7247 [00:00<00:00, 9948.22it/s]
```

7247 300

### In [290]:

```
# Similarly you can vectorize for title also
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors project resource summary test = []; # the avg-w2v for each sentence/review is st
ored in this list
for sentence in tqdm(X test['project resource summary']): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
   tf idf weight =0; # num of words with a valid vector in the sentence/review
   for word in sentence.split(): # for each word in a review/sentence
       if (word in glove_words) and (word in tfidf_words):
           vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
           tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
           vector += (vec * tf idf) # calculating tfidf weighted w2v
           tf idf weight += tf idf
   if tf idf weight != 0:
       vector /= tf idf weight
    tfidf w2v vectors project resource summary test.append(vector)
```

```
\verb|print(len(tfidf_w2v_vectors_project_resource_summary_test))| \\
print(len(tfidf w2v vectors project resource summary test[0]))
100%| | 10816/10816 [00:01<00:00, 7756.98it/s]
10816
300
1.5.3 Vectorizing Numerical features
In [291]:
# You no need to perform standardization/normalization on numerical data,
# because you will classify data by using gini impurity in decision tree classifier.
# - quantity : numerical (optional)
X train quantity norm = X train['quantity'].values.reshape(-1,1)
X cv quantity norm = X cv['quantity'].values.reshape(-1,1)
X test quantity norm = X test['quantity'].values.reshape(-1,1)
print("After vectorizations")
print(X_train_quantity_norm.shape, y_train.shape)
print(X_cv_quantity_norm.shape, y_cv.shape)
print(X_test_quantity_norm.shape, y_test.shape)
print("="*100)
After vectorizations
(14711, 1) (14711,)
(7247, 1) (7247,)
(10816, 1) (10816,)
In [292]:
# You no need to perform standardization/normalization on numerical data,
# because you will classify data by using gini impurity in decision tree classifier.
# One hot encoding of numerical feature
# - teacher number of previously posted projects : numerical
X_train_teacher_number_of_previously_posted_projects_norm =
X_train['teacher_number_of_previously_posted_projects'].values.reshape(-1,1)
X cv teacher number of previously posted projects norm =
X_cv['teacher_number_of_previously_posted_projects'].values.reshape(-1,1)
X test teacher number of previously posted projects norm =
X_test['teacher_number_of_previously_posted_projects'].values.reshape(-1,1)
print("After vectorizations")
print(X_train_teacher_number_of_previously_posted_projects_norm.shape, y_train.shape)
\verb|print(X_cv_teacher_number_of_previously_posted_projects_norm.shape, y_cv.shape)| \\
print(X test teacher number of previously posted projects norm.shape, y test.shape)
print("="*100)
After vectorizations
(14711, 1) (14711,)
(7247, 1) (7247,)
(10816, 1) (10816,)
In [293]:
# You no need to perform standardization/normalization on numerical data,
# because you will classify data by using gini impurity in decision tree classifier.
# - price : numerical
X train price norm = X train['price'].values.reshape(-1,1)
```

X\_cv\_price\_norm = X\_cv['price'].values.reshape(-1,1)
X test price norm = X test['price'].values.reshape(-1,1)

## 1.5.1 Vectorizing Categorical data

In [294]:

```
def calculate_proba_score_of_each_variable(data, classLabel):
    Function to return probability score
   Return Dict 'LA': { 'pos': 0.8267790262172284, 'neg': 0.17322097378277154}
    positive_score_dict = {}
    negative_score_dict = {}
    distinct feature = []
    # Collect negative and positive scores of a class label
    for i in range(len(data)):
        # Collect distinct features
        if(data[i] not in distinct_feature):
            distinct feature.append(data[i])
        if(1 == classLabel[i]):
            if (data[i] in positive_score_dict):
               positive score dict[data[i]] = positive score dict[data[i]] + 1
            else:
                positive score dict[data[i]] = 1
        else:
            if(data[i] in negative score dict):
               negative score dict[data[i]] = negative score dict[data[i]] + 1
            else:
                negative score dict[data[i]] = 1
     print (positive score dict, negative score dict)
    # Collect probability score
    prob score = {}
    for i in range(len(distinct feature)):
         print(distinct feature[i])
        pos_score = 0
       neg score = 0
        if (distinct feature[i] in positive score dict):
            pos_score = positive_score_dict[distinct_feature[i]]
        if (distinct feature[i] in negative score dict):
            neg score = negative score dict[distinct feature[i]]
       prob score[distinct feature[i]] = {"pos" : (pos score/(pos score+neg score)), "neg" : (neg
score/ (pos_score+neg_score))}
         print (prob score)
    return prob score
def convert_response_encoding(data, proba_score):
    Convert feature into response encoding
    Return Lists
    result pos = []
    result neg = []
    for i in range(len(data)):
        if((data[i] in proba score)):
            result pos.append(proba score[data[i]]['pos'])
            result neg.append(proba score[data[i]]['neg'])
        else: #handle missing data
           result_pos.append(0.5)
```

```
return [result_pos, result_neg]
```

#### In [295]:

```
# We are using response encoding instead of one hot encoding for categorical feature
from scipy.sparse import coo_matrix
# calculate response encoding on school state train data i.e. fit data
proba score train = calculate proba score of each variable(X train['school state'].values, y train
# transform train data
response encoding train pos, response encoding train neg = convert response encoding(X train['scho
ol_state'].values, proba_score_train)
response_encoding_train_pos = pd.DataFrame(response_encoding_train_pos)
response encoding train neg = pd.DataFrame (response encoding train neg)
# transform cv data
response encoding cv pos, response encoding cv neg = convert response encoding (X cv['school state'
].values, proba score train)
response encoding cv pos = pd.DataFrame(response encoding cv pos)
response encoding cv neg = pd.DataFrame(response encoding cv neg)
# transform test data
response_encoding_test_pos, response_encoding_test_neg =
convert response encoding(X test['school state'].values, proba score train)
response_encoding_test_pos = pd.DataFrame(response_encoding_test_pos)
response encoding test neg = pd.DataFrame(response encoding test neg)
# reshape data
X train school state pos = response encoding train pos.values.reshape(-1,1)
X_train_school_state_neg = response_encoding_train_neg.values.reshape(-1,1)
X cv school state pos = response encoding cv pos.values.reshape(-1,1)
X cv school state neg = response encoding cv neg.values.reshape(-1,1)
X_test_school_state_pos = response_encoding_test_pos.values.reshape(-1,1)
X test school state neg = response encoding test neg.values.reshape(-1,1)
# print data to do some verification
print(X train school state pos.shape, y train.shape)
print(X train school state neg.shape, y train.shape)
print(X cv school_state_pos.shape, y_cv.shape)
print(X_cv_school_state_neg.shape, y_cv.shape)
print(X_test_school_state_pos.shape, y_test.shape)
print(X test school state neg.shape, y test.shape)
print('*'*100)
print('train data positive')
print(X train school state pos[0:5])
print('*'*100)
print('train data negative')
print(X train school state neg[0:5])
print('*'*100)
print('cv data positive')
print(X cv school state pos[0:5])
print('*'*100)
print('cv data negative')
print(X_cv_school_state_neg[0:5])
print('*'*100)
print('test data positive')
print(X_test_school_state_pos[0:5])
print('*'*100)
print('test data negative')
print(X test school state neg[0:5])
print('*'*100)
X_train_school_state_pos = coo_matrix(X_train_school_state_pos)
X train school state neg = coo matrix(X train school state neg)
X_cv_school_state_pos = coo_matrix(X_cv_school_state_pos)
X cv school state neg = coo matrix(X cv school state neg)
X_test_school_state_pos = coo_matrix(X_test_school_state_pos)
```

```
|X_test_school_state_neg = coo_matrix(X_test_school_state_neg)
# print csr matrix shape
print(X_train_school_state_pos.shape, y_train.shape)
print(X_train_school_state_neg.shape, y_train.shape)
print(X_cv_school_state_pos.shape, y_cv.shape)
print(X_cv_school_state_neg.shape, y_cv.shape)
print(X_test_school_state_pos.shape, y_test.shape)
print(X_test_school_state_neg.shape, y_test.shape)
print('*'*100)
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
train data positive
[[0.84751773]
 [0.86019417]
 [0.84198113]
 [0.81569966]
 [0.84198113]]
train data negative
[[0.15248227]
 [0.13980583]
 [0.15801887]
 [0.18430034]
 [0.15801887]]
*************************
cv data positive
[[0.86019417]
 [0.87378641]
 [0.88663968]
 [0.86019417]
 [0.88059701]]
cv data negative
[[0.13980583]
 [0.12621359]
 [0.11336032]
 [0.13980583]
 [0.1194029911
test data positive
[[0.81672026]
 [0.8531746]
 [0.84198113]
 [0.7997936]
 [0.86019417]]
test data negative
[[0.18327974]
 [0.1468254]
 [0.15801887]
 [0.2002064]
 [0.13980583]]
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
```

**>** 

```
# We are using response encoding instead of one hot encoding for categorical feature
# - clean categories : categorical data
# calculate response encoding on clean categories train data i.e. fit data
proba score train = calculate proba score of each variable(X train['clean categories'].values,
y train)
# transform train data
response encoding train pos, response encoding train neg = convert response encoding (X train['clea
n categories'].values, proba score train)
response_encoding_train_pos = pd.DataFrame(response_encoding_train_pos)
response encoding train neg = pd.DataFrame (response encoding train neg)
# transform cv data
response encoding cv pos, response encoding cv neg =
convert response encoding(X cv['clean categories'].values, proba score train)
response encoding cv pos = pd.DataFrame(response encoding cv pos)
response_encoding_cv_neg = pd.DataFrame(response_encoding_cv_neg)
# transform test data
response_encoding_test_pos, response_encoding_test_neg =
convert response encoding(X test['clean categories'].values, proba score train)
response encoding test pos = pd.DataFrame(response encoding test pos)
response encoding test neg = pd.DataFrame(response encoding test neg)
# reshape data
X train clean categories pos = response encoding train pos.values.reshape(-1,1)
X_train_clean_categories_neg = response_encoding_train_neg.values.reshape(-1,1)
X cv clean categories pos = response encoding cv pos.values.reshape(-1,1)
X_cv_clean_categories_neg = response_encoding_cv_neg.values.reshape(-1,1)
X_test_clean_categories_pos = response_encoding_test_pos.values.reshape(-1,1)
X test clean categories neg = response encoding test neg.values.reshape(-1,1)
# print data to do some verification
print(X train clean categories pos.shape, y train.shape)
print(X train clean categories neg.shape, y train.shape)
print(X cv clean categories pos.shape, y cv.shape)
print(X_cv_clean_categories_neg.shape, y_cv.shape)
print(X_test_clean_categories_pos.shape, y_test.shape)
print(X test clean categories neg.shape, y test.shape)
print('*'*100)
print('train data positive')
print(X train clean categories pos[0:5])
print('*'*100)
print('train data negative')
print(X train clean categories neg[0:5])
print('*'*100)
print('cv data positive')
print(X cv clean categories pos[0:5])
print('*'*100)
print('cv data negative')
print(X cv clean categories neg[0:5])
print('*'*100)
print('test data positive')
print(X_test_clean_categories_pos[0:5])
print('*'*100)
print('test data negative')
print(X_test_clean_categories_neg[0:5])
print('*'*100)
X train clean categories pos = coo matrix(X train clean categories pos)
X_train_clean_categories_neg = coo_matrix(X_train_clean_categories_neg)
X_cv_clean_categories_pos = coo_matrix(X_cv_clean_categories_pos)
X cv clean categories neg = coo matrix(X cv clean categories neg)
X test clean categories pos = coo matrix(X test clean categories pos)
X test clean categories neg = coo matrix(X test clean categories neg)
# print csr matrix shape
print(X_train_clean_categories_pos.shape, y_train.shape)
print(X_train_clean_categories_neg.shape, y_train.shape)
print(X cv clean categories pos.shape. v cv.shape)
```

```
princting of the properties and prop
print(X_cv_clean_categories_neg.shape, y_cv.shape)
print(X_test_clean_categories_pos.shape, y_test.shape)
print(X_test_clean_categories_neg.shape, y_test.shape)
print('*'*100)
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
train data positive
[[0.84304933]
  [0.81161972]
  [0.84277879]
  [0.80555556]
 [0.81161972]]
*********************************
train data negative
[[0.15695067]
  [0.18838028]
  [0.15722121]
 [0.19444444]
 [0.18838028]]
******************
cv data positive
[[0.8676022]
  [0.88288288]
  [0.84277879]
  [0.82752458]
  [0.8676022 ]]
******************
cv data negative
[[0.1323978]
  [0.11711712]
  [0.15722121]
  [0.17247542]
  [0.1323978]]
**************************
test data positive
[[0.82608696]
  [0.82608696]
  [0.82608696]
   [0.86263455]
  [0.84277879]]
test data negative
[[0.17391304]
   [0.17391304]
  [0.17391304]
  [0.13736545]
 [0.15722121]]
 ******************
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
4
In [297]:
# We are using response encoding instead of one hot encoding for categorical feature
# - clean_categories : categorical data
{\it \# calculate response encoding on clean\_subcategories train \ data \ i.e. \ fit \ data}
```

```
proba score train = calculate proba score of each variable(X train['clean subcategories'].values,
y train)
# transform train data
response encoding train pos, response encoding train neg = convert response encoding (X train['clea
n subcategories'].values, proba score train)
response encoding train pos = pd.DataFrame(response encoding train pos)
response encoding train neg = pd.DataFrame (response encoding train neg)
# transform cv data
response_encoding_cv_pos, response_encoding_cv_neg =
convert response encoding(X cv['clean subcategories'].values, proba score train)
response encoding cv pos = pd.DataFrame(response encoding cv pos)
response encoding cv neg = pd.DataFrame(response encoding cv neg)
# transform test data
response encoding test pos, response encoding test neg =
convert response encoding(X test['clean subcategories'].values, proba score train)
response_encoding_test_pos = pd.DataFrame (response_encoding_test_pos)
response encoding test neg = pd.DataFrame(response encoding test neg)
# reshape data
X train clean subcategories pos = response encoding train pos.values.reshape(-1,1)
X_train_clean_subcategories_neg = response_encoding_train_neg.values.reshape(-1,1)
X_cv_clean_subcategories_pos = response_encoding_cv_pos.values.reshape(-1,1)
X_cv_clean_subcategories_neg = response_encoding_cv_neg.values.reshape(-1,1)
X_test_clean_subcategories_pos = response_encoding_test_pos.values.reshape(-1,1)
X test clean subcategories neg = response encoding test neg.values.reshape(-1,1)
# print data to do some verification
print(X_train_clean_subcategories_pos.shape, y_train.shape)
print (X train clean subcategories neg.shape, y train.shape)
print (X cv clean subcategories pos.shape, y cv.shape)
print(X cv clean subcategories_neg.shape, y_cv.shape)
print(X test clean subcategories pos.shape, y test.shape)
print(X test clean subcategories neg.shape, y test.shape)
print('*'*100)
print('train data positive')
print(X_train_clean_subcategories_pos[0:5])
print('*'*100)
print('train data negative')
print(X train clean subcategories neg[0:5])
print('*'*100)
print('cv data positive')
print(X cv clean subcategories pos[0:5])
print('*'*100)
print('cv data negative')
print(X cv clean subcategories neg[0:5])
print('*'*100)
print('test data positive')
print(X test clean subcategories pos[0:5])
print('*'*100)
print('test data negative')
print(X test clean subcategories neg[0:5])
print('*'*100)
X_train_clean_subcategories_pos = coo_matrix(X_train_clean_subcategories_pos)
X_train_clean_subcategories_neg = coo_matrix(X_train_clean_subcategories_neg)
X_cv_clean_subcategories_pos = coo_matrix(X_cv_clean_subcategories_pos)
X cv clean subcategories neg = coo matrix(X cv clean subcategories neg)
X test clean subcategories pos = coo matrix(X test clean subcategories pos)
X test clean subcategories neg = coo matrix(X test clean subcategories neg)
# print csr matrix shape
print(X train clean subcategories pos.shape, y train.shape)
print(X_train_clean_subcategories_neg.shape, y_train.shape)
print(X_cv_clean_subcategories_pos.shape, y_cv.shape)
print(X_cv_clean_subcategories_neg.shape, y_cv.shape)
print(X_test_clean_subcategories_pos.shape, y_test.shape)
print(X test clean subcategories neg.shape, y test.shape)
print('*'*100)
```

```
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
*******************
train data positive
[[0.72413793]
 [0.81161972]
 [0.8483965]
[0.80555556]
[0.81161972]]
                 *******************
train data negative
[[0.27586207]
 [0.18838028]
 [0.1516035]
 [0.19444444]
 [0.18838028]]
*************************
cv data positive
[[0.87652439]
 [0.93877551]
 [0.8483965]
[0.84563758]
[0.85669291]]
cv data negative
[[0.12347561]
[0.06122449]
 [0.1516035]
 [0.15436242]
 [0.14330709]]
test data positive
[[0.78787879]
 [0.81818182]
 [0.78787879]
[0.85882353]
[0.8483965]]
*******************************
test data negative
[[0.21212121]
[0.18181818]
 [0.21212121]
 [0.14117647]
 [0.1516035]]
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
In [298]:
# We are using response encoding instead of one hot encoding for categorical feature
# - project grade category : categorical data
# calculate response encoding on project_grade_category train data i.e. fit data
proba score train =
calculate proba score of each variable(X train['project grade category'].values, y train)
# transform train data
response encoding train pos, response encoding train neg = convert response encoding (X train['proj
ect grade category'].values, proba score train)
```

```
response encoding train pos = pd.DataFrame(response encoding train pos)
response encoding train neg = pd.DataFrame(response encoding train neg)
# transform cv data
response encoding cv pos, response encoding cv neg =
convert_response_encoding(X_cv['project_grade_category'].values, proba_score_train)
response_encoding_cv_pos = pd.DataFrame(response_encoding_cv_pos)
response_encoding_cv_neg = pd.DataFrame(response_encoding_cv_neg)
# transform test data
response encoding test pos, response encoding test neg =
convert_response_encoding(X_test['project_grade_category'].values, proba_score_train)
response_encoding_test_pos = pd.DataFrame (response_encoding_test_pos)
response_encoding_test_neg = pd.DataFrame (response_encoding_test_neg)
# reshape data
X_train_project_grade_category_pos = response_encoding_train_pos.values.reshape(-1,1)
X_train_project_grade_category_neg = response_encoding_train_neg.values.reshape(-1,1)
X_cv_project_grade_category_pos = response_encoding_cv_pos.values.reshape(-1,1)
X_cv_project_grade_category_neg = response_encoding_cv_neg.values.reshape(-1,1)
X_test_project_grade_category_pos = response_encoding_test_pos.values.reshape(-1,1)
X_test_project_grade_category_neg = response_encoding_test_neg.values.reshape(-1,1)
# print data to do some verification
print(X_train_project_grade_category_pos.shape, y_train.shape)
print(X_train_project_grade_category_neg.shape, y_train.shape)
print(X_cv_project_grade_category_pos.shape, y_cv.shape)
print(X_cv_project_grade_category_neg.shape, y_cv.shape)
print(X_test_project_grade_category_pos.shape, y_test.shape)
print(X test project grade category neg.shape, y test.shape)
print('*'*100)
print('train data positive')
print(X train project grade category pos[0:5])
print('*'*100)
print('train data negative')
print(X_train_project_grade_category_neg[0:5])
print('*'*100)
print('cv data positive')
print(X_cv_project_grade_category_pos[0:5])
print('*'*100)
print('cv data negative')
print(X_cv_project_grade_category_neg[0:5])
print('*'*100)
print('test data positive')
print(X_test_project_grade_category_pos[0:5])
print('*'*100)
print('test data negative')
print(X test_project_grade_category_neg[0:5])
print('*'*100)
X_train_project_grade_category_pos = coo_matrix(X_train_project_grade_category_pos)
X_train_project_grade_category_neg = coo_matrix(X_train_project_grade_category_neg)
X_cv_project_grade_category_pos = coo_matrix(X_cv_project_grade_category pos)
X_cv_project_grade_category_neg = coo_matrix(X_cv_project_grade_category_neg)
X_test_project_grade_category_pos = coo_matrix(X_test_project_grade_category_pos)
X_test_project_grade_category_neg = coo_matrix(X_test_project_grade_category_neg)
# print csr matrix shape
print(X_train_project_grade_category_pos.shape, y_train.shape)
print(X_train_project_grade_category_neg.shape, y_train.shape)
print(X_cv_project_grade_category_pos.shape, y_cv.shape)
print(X cv project grade category neg.shape, y cv.shape)
print(X_test_project_grade_category_pos.shape, y_test.shape)
print(X_test_project_grade_category_neg.shape, y_test.shape)
print('*'*100)
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
```

```
train data positive
[[0.83940972]
[0.84898711]
[0.8560804]
[0.84441398]
 [0.8560804]]
train data negative
[[0.16059028]
[0.15101289]
[0.1439196]
[0.15558602]
[0.1439196]]
*******************************
cv data positive
[[0.84898711]
[0.84898711]
[0.8560804]
[0.8560804]
[0.8560804]]
cv data negative
[[0.15101289]
[0.15101289]
 [0.1439196]
[0.1439196]
[0.1439196]]
               **********************
test data positive
[[0.8560804]
[0.8560804]
[0.83940972]
[0.8560804 ]
[0.83940972]]
test data negative
[[0.1439196]
[0.1439196 ]
 [0.16059028]
[0.1439196]
[0.16059028]]
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
In [299]:
# We are using response encoding instead of one hot encoding for categorical feature
# - teacher_prefix : categorical data
# calculate response encoding on teacher prefix train data i.e. fit data
proba_score_train = calculate_proba_score_of_each_variable(X_train['teacher_prefix'].values,
y_train)
# transform train data
response encoding train pos, response encoding train neg = convert response encoding(X train['teac
her prefix'].values, proba score train)
response_encoding_train_pos = pd.DataFrame(response_encoding_train_pos)
response encoding train neg = pd.DataFrame (response encoding train neg)
# transform cv data
response_encoding_cv_pos, response_encoding_cv_neg =
```

```
convert response encoding(x cv['teacher prefix'].values, propa score train)
response encoding cv pos = pd.DataFrame(response encoding cv pos)
response_encoding_cv_neg = pd.DataFrame(response_encoding_cv_neg)
# transform test data
response_encoding_test_pos, response_encoding_test_neg =
convert response encoding(X test['teacher prefix'].values, proba score train)
response_encoding_test_pos = pd.DataFrame (response_encoding_test_pos)
response encoding test neg = pd.DataFrame(response encoding test neg)
# reshape data
X train teacher prefix pos = response encoding train pos.values.reshape(-1,1)
X train teacher prefix neg = response encoding train neg.values.reshape(-1,1)
X cv teacher prefix pos = response encoding cv pos.values.reshape(-1,1)
X cv teacher prefix neg = response encoding cv neg.values.reshape(-1,1)
X_test_teacher_prefix_pos = response_encoding_test_pos.values.reshape(-1,1)
X_test_teacher_prefix_neg = response_encoding_test_neg.values.reshape(-1,1)
# print data to do some verification
print(X train teacher prefix pos.shape, y train.shape)
print(X_train_teacher_prefix_neg.shape, y_train.shape)
print(X_cv_teacher_prefix_pos.shape, y_cv.shape)
print(X_cv_teacher_prefix_neg.shape, y_cv.shape)
print(X_test_teacher_prefix_pos.shape, y_test.shape)
print(X test teacher prefix neg.shape, y test.shape)
print('*'*100)
print('train data positive')
print(X train teacher_prefix_pos[0:5])
print('*'*100)
print('train data negative')
print(X train teacher prefix neg[0:5])
print('*'*100)
print('cv data positive')
print(X_cv_teacher_prefix_pos[0:5])
print('*'*100)
print('cv data negative')
print(X_cv_teacher_prefix_neg[0:5])
print('*'*100)
print('test data positive')
print(X_test_teacher_prefix_pos[0:5])
print('*'*100)
print('test data negative')
print(X test teacher prefix neg[0:5])
print('*'*100)
X train teacher prefix pos = coo matrix(X train teacher prefix pos)
X_train_teacher_prefix_neg = coo_matrix(X_train_teacher_prefix_neg)
X_cv_teacher_prefix_pos = coo_matrix(X_cv_teacher_prefix_pos)
X_cv_teacher_prefix_neg = coo_matrix(X_cv_teacher_prefix_neg)
 test teacher prefix pos = coo matrix(X test teacher prefix pos)
X_test_teacher_prefix_neg = coo_matrix(X_test_teacher_prefix_neg)
# print csr matrix shape
print(X_train_teacher_prefix_pos.shape, y_train.shape)
print (X train teacher prefix neg.shape, y train.shape)
print(X_cv_teacher_prefix_pos.shape, y_cv.shape)
print(X cv teacher prefix neg.shape, y cv.shape)
print(X test teacher prefix pos.shape, y test.shape)
print(X_test_teacher_prefix_neg.shape, y_test.shape)
print('*'*100)
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
train data positive
[[0.8539633]
 [0.85095057]
 [0.85095057]
 [0.85095057]
```

```
[0.83367698]]
train data negative
[[0.1460367]
 [0.149049431
[0.14904943]
 [0.14904943]
[0.16632302]]
cv data positive
[[0.8539633]
[0.85095057]
 [0.8539633]
 [0.85095057]
 [0.8509505711
*************************
cv data negative
[[0.1460367]
 [0.14904943]
[0.1460367]
[0.14904943]
[0.1490494311
test data positive
[[0.85095057]
 [0.85095057]
 [0.8539633]
 [0.8539633]
 [0.83367698]]
test data negative
[[0.14904943]
 [0.14904943]
 [0.1460367]
[0.1460367]
 [0.16632302]]
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
```

#### 1.5.4 Merging all the above features

• we need to merge all the numerical vectors i.e catogorical, text, numerical vectors

```
In [300]:
```

```
# print(categories_one_hot.shape)
# print(sub_categories_one_hot.shape)
# print(text_bow.shape)
# print(price_standardized.shape)
print('Categorical Features')
print('*'*100)
print(X_train_school_state_pos.shape, y_train.shape)
print(X_train_school_state_neg.shape, y_train.shape)
print(X_cv_school_state_pos.shape, y_cv.shape)
print(X_cv_school_state_neg.shape, y_cv.shape)
print(X_test_school_state_neg.shape, y_test.shape)
print(X_test_school_state_neg.shape, y_test.shape)
print('*'*100)
print(X_train_clean_categories_pos.shape, y_train.shape)
print(X_train_clean_categories_neg.shape, y_train.shape)
```

```
print(X cv clean categories pos.shape, y cv.shape)
print(X_cv_clean_categories_neg.shape, y_cv.shape)
print(X_test_clean_categories_pos.shape, y_test.shape)
print(X test clean categories neg.shape, y test.shape)
print('*'*100)
print(X train clean subcategories pos.shape, y train.shape)
print(X train clean subcategories neg.shape, y train.shape)
print(X_cv_clean_subcategories_pos.shape, y_cv.shape)
print(X_cv_clean_subcategories_neg.shape, y_cv.shape)
print(X_test_clean_subcategories_pos.shape, y_test.shape)
print(X_test_clean_subcategories_neg.shape, y_test.shape)
print('*'*100)
print(X_train_project_grade_category_pos.shape, y_train.shape)
print(X_train_project_grade_category_neg.shape, y_train.shape)
print(X_cv_project_grade_category_pos.shape, y_cv.shape)
print(X_cv_project_grade_category_neg.shape, y_cv.shape)
print(X_test_project_grade_category_pos.shape, y_test.shape)
print(X_test_project_grade_category_neg.shape, y_test.shape)
print('*'*100)
print(X train teacher prefix pos.shape, y train.shape)
print(X_train_teacher_prefix_neg.shape, y_train.shape)
print(X_cv_teacher_prefix_pos.shape, y_cv.shape)
print(X_cv_teacher_prefix_neg.shape, y_cv.shape)
print(X_test_teacher_prefix_pos.shape, y_test.shape)
print(X_test_teacher_prefix_neg.shape, y_test.shape)
print('*'*100)
print('Text Encoding Features')
print('*'*100)
print(X_train_title_bow.shape, y_train.shape)
print(X cv title_bow.shape, y_cv.shape)
print(X test title bow.shape, y test.shape)
print('*'*100)
print(X_train_essay_bow.shape, y_train.shape)
print(X_cv_essay_bow.shape, y_cv.shape)
print(X test essay bow.shape, y test.shape)
print('*'*100)
print(X train project resource summary bow.shape, y train.shape)
print(X_cv_project_resource_summary_bow.shape, y_cv.shape)
print(X test project resource summary bow.shape, y test.shape)
print('*'*100)
print(X train_title_tfidf.shape, y_train.shape)
print(X cv title tfidf.shape, y cv.shape)
print(X_cv_title_tfidf.shape, y_test.shape)
print('*'*100)
print(X_train_essay_tfidf.shape, y_train.shape)
print(X_cv_essay_tfidf.shape, y_cv.shape)
print(X_test_essay_tfidf.shape, y_test.shape)
print('*'*100)
print(X_train_project_resource_summary_tfidf.shape, y_train.shape)
print(X cv project_resource_summary_tfidf.shape, y_cv.shape)
print(X test project resource summary tfidf.shape, y test.shape)
print('*'*100)
print(len(avg_w2v_vectors_text_train))
print(len(avg_w2v_vectors_text_train[0]))
print('*'*100)
print(len(avg_w2v_vectors_text_cv))
print(len(avg_w2v_vectors_text_cv[0]))
print('*'*100)
print(len(avg_w2v_vectors_text_test))
print(len(avg_w2v_vectors_text_test[0]))
print('*'*100)
print(len(avg_w2v_vectors_title_train))
print(len(avg w2v vectors title train[0]))
print('*'*100)
print(len(avg_w2v_vectors_title_cv))
print(len(avg w2v vectors title cv[0]))
print('*'*100)
print(len(avg w2v vectors title test))
print(len(avg_w2v_vectors_title_test[0]))
print('*'*100)
print(len(avg_w2v_vectors_project_resource_summary_train))
print(len(avg w2v vectors project resource summary train[0]))
print('*'*100)
print(len(avg_w2v_vectors_project_resource_summary_cv))
print(len(avg w2v vectors project resource summary cv[0]))
print('*'*100)
print(len(avg w2v vectors project resource summary test))
```

```
print(len(avg w2v vectors_project_resource_summary_test[0]))
print('*'*100)
print(len(tfidf w2v vectors text train))
print(len(tfidf w2v vectors text train[0]))
print('*'*100)
print(len(tfidf w2v vectors text cv))
print(len(tfidf w2v vectors text cv[0]))
print('*'*100)
print(len(tfidf w2v vectors text test))
print(len(tfidf_w2v_vectors_text_test[0]))
print('*'*100)
print(len(tfidf w2v vectors title train))
print(len(tfidf_w2v_vectors_title_train[0]))
print('*'*100)
print(len(tfidf w2v vectors title cv))
print(len(tfidf w2v vectors title cv[0]))
print('*'*100)
print(len(tfidf w2v vectors title test))
print(len(tfidf w2v vectors title test[0]))
print('*'*100)
print(len(tfidf w2v vectors project resource summary train))
print(len(tfidf_w2v_vectors_project_resource_summary_train[0]))
print('*'*100)
print(len(tfidf w2v vectors project resource summary cv))
print(len(tfidf_w2v_vectors_project_resource_summary_cv[0]))
print('*'*100)
print(len(tfidf_w2v_vectors_project_resource_summary_test))
print(len(tfidf_w2v_vectors_project_resource_summary_test[0]))
print('*'*100)
print('Numerical Features')
print('*'*100)
print(X train quantity norm.shape, y train.shape)
print(X_cv_quantity_norm.shape, y_cv.shape)
print(X test_quantity_norm.shape, y_test.shape)
print('*'*100)
\verb|print(X_train_teacher_number_of_previously_posted_projects_norm.shape, y_train.shape)| \\
print(X cv teacher number of previously posted projects norm.shape, y cv.shape)
print(X test teacher number of previously posted projects norm.shape, y test.shape)
print('*'*100)
print(X_train_price_norm.shape, y_train.shape)
print(X_cv_price_norm.shape, y_cv.shape)
print(X test_price_norm.shape, y_test.shape)
Categorical Features
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
******************
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
*****
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
```

```
(14711, 1) (14711,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(10816, 1) (10816,)
Text Encoding Features
(14711, 1130) (14711,)
(7247, 1130) (7247,)
(10816, 1130) (10816,)
(14711, 5000) (14711,)
(7247, 5000) (7247,)
(10816, 5000) (10816,)
(14711, 4134) (14711,)
(7247, 4134) (7247,)
(10816, 4134) (10816,)
(14711, 849) (14711,)
(7247, 849) (7247,)
(7247, 849) (10816,)
******
(14711, 7337) (14711,)
(7247, 7337) (7247,)
(10816, 7337) (10816,)
(14711, 1872) (14711,)
(7247, 1872) (7247,)
(10816, 1872) (10816,)
14711
300
7247
300
******************************
10816
300
*****
14711
7247
10816
300
14711
******
7247
300
10816
300
```

```
14711
7247
300
10816
300
*******************
300
7247
300
*****
10816
14711
300
72.47
300
10816
300
Numerical Features
(14711, 1) (14711,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(10816, 1) (10816,)
(14711, 1) (14711,)
(7247, 1) (7247,)
(10816, 1) (10816,)
4
In [301]:
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
# with the same hstack function we are concatinating a sparse matrix and a dense matirx :)
\# X = hstack((categories one hot, sub categories one hot, text bow, price standardized))
# X.shape
X train real = X train
X_cv_real = X_cv
X_test_real = X_test
X_train = hstack((X_train_school_state_pos, X_train_school_state_neg,
X_train_clean_categories_pos, X_train_clean_categories_neg, X_train_clean_subcategories_pos,
X_train_clean_subcategories_neg, X_train_project_grade_category_pos,
X_train_project_grade_category_neg, X_train_teacher_prefix_pos, X_train_teacher_prefix_neg,
X train title bow, X train essay bow, X train project resource summary bow, X train title tfidf, X
_train_essay_tfidf, X_train_project_resource_summary_tfidf, avg_w2v_vectors_text_train,
avg_w2v_vectors_title_train, avg_w2v_vectors_project_resource_summary_train,
tfidf w2v vectors text train, tfidf w2v vectors title train,
tfidf w2v vectors project resource summary train, X train quantity norm,
```

```
X_train_teacher_number_of_previously_posted_projects_norm, X_train_price_norm)).tocsr()
X cv = hstack((X cv school state pos, X cv school state neg, X cv clean categories pos,
X_cv_clean_categories_neg, X_cv_clean_subcategories_pos, X_cv_clean_subcategories_neg,
X_cv_project_grade_category_pos, X_cv_project_grade_category_neg, X_cv_teacher_prefix_pos,
X cv teacher prefix neg, X cv title bow, X cv essay bow, X cv project resource summary bow,
X cv title tfidf, X cv essay tfidf, X cv project resource summary tfidf, avg w2v vectors text cv,
avg_w2v_vectors_title_cv, avg_w2v_vectors_project_resource_summary_cv, tfidf_w2v_vectors_text_cv,
tfidf w2v vectors title cv, tfidf w2v vectors project resource summary cv, X cv quantity norm, X c
\verb|v_teacher_number_of_previously_posted_projects_norm, X_cv_price_norm)|).tocsr()|
X_test = hstack((X_test_school_state_pos, X_test_school_state_neg, X_test_clean_categories_pos,
X_test_clean_categories_neg, X_test_clean_subcategories_pos, X_test_clean_subcategories_neg, X_tes
t_project_grade_category_pos, X_test_project_grade_category_neg, X_test_teacher_prefix_pos,
X_test_teacher_prefix_neg, X_test_title_bow, X_test_essay_bow, X_test_project_resource_summary_bow
, X_test_title_tfidf, X_test_essay_tfidf, X_test_project_resource_summary_tfidf,
avg_w2v_vectors_text_test, avg_w2v_vectors_title_test,
avg w2v vectors project resource summary test, tfidf w2v vectors text test,
tfidf w2v vectors title test, tfidf w2v vectors project resource summary test,
X test quantity norm, X test teacher number of previously posted projects norm, X test price norm)
print(X train real.shape)
print(X_cv_real.shape)
print(X_test_real.shape)
print(X train.shape)
print(X_cv.shape)
print(X_test.shape)
(14711, 17)
(7247, 17)
```

**Computing Sentiment Scores** 

#### In [302]:

(10816, 17) (14711, 22135) (7247, 22135) (10816, 22135)

```
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
# import nltk
# nltk.download('vader lexicon')
sid = SentimentIntensityAnalyzer()
for sentiment = 'a person is a person no matter how small dr seuss i teach the smallest students w
ith the biggest enthusiasm \
for learning my students learn in many different ways using all of our senses and multiple intelli
gences i use a wide range\
of techniques to help all my students succeed students in my class come from a variety of differen
t backgrounds which makes\
for wonderful sharing of experiences and cultures including native americans our school is a carin
g community of successful \
learners which can be seen through collaborative student project based learning in and out of the
classroom kindergarteners \
in my class love to work with hands on materials and have many different opportunities to practice
a skill before it is\
mastered having the social skills to work cooperatively with friends is a crucial aspect of the ki
ndergarten curriculum\
montana is the perfect place to learn about agriculture and nutrition my students love to role pla
y in our pretend kitchen\
in the early childhood classroom i have had several kids ask me can we try cooking with real food
i will take their idea \
and create common core cooking lessons where we learn important math and writing concepts while co
oking delicious healthy \
food for snack time my students will have a grounded appreciation for the work that went into maki
ng the food and knowledge \
of where the ingredients came from as well as how it is healthy for their bodies this project woul
d expand our learning of \
nutrition and agricultural cooking recipes by having us peel our own apples to make homemade apple
sauce make our own bread \
and mix up healthy plants from our classroom garden in the spring we will also create our own cook
books to be printed and \
shared with families students will gain math and literature skills as well as a life long enjoymen
```

```
t for healthy cooking \
nannan'
ss = sid.polarity_scores(for_sentiment)

for k in ss:
    print('{0}: {1}, '.format(k, ss[k]), end='')

# we can use these 4 things as features/attributes (neg, neu, pos, compound)
# neg: 0.0, neu: 0.753, pos: 0.247, compound: 0.93
```

neg: 0.01, neu: 0.745, pos: 0.245, compound: 0.9975,

# **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 <u>response coding</u>: 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 <u>response coding</u>: 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  $\mathbf{n_{estimators}}$ , Y-axis as  $\mathbf{max_{depth}}$ , and Z-axis as  $\mathbf{AUC}$  Score, we have given the notebook which explains how to plot this 3d plot, you can find it in the same drive  $3d_{scatter_{plot.ipynb}}$ 

#### or

• 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 <u>confusion matrix</u> 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 link

#### Note: Data Leakage

- 1. There will be an issue of data-leakage if you vectorize the entire data and then split it into train/cv/test.
- 2. To avoid the issue of data-leakage, 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

Note: I already completed steps 2.1, 2.2 & 2.3 previously, So I didn't copy code in below cells.

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

```
In [303]:
```

```
# please write all the code with proper documentation, and proper titles for each subsection
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your code
# when you plot any graph make sure you use
# a. Title, that describes your plot, this will be very helpful to the reader
# b. Legends if needed
# c. X-axis label
# d. Y-axis label
```

# 2.2 Make Data Model Ready: encoding numerical, categorical features

```
In [304]:
```

```
# please write all the code with proper documentation, and proper titles for each subsection
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your code
# make sure you featurize train and test data separatly

# when you plot any graph make sure you use
# a. Title, that describes your plot, this will be very helpful to the reader
# b. Legends if needed
# c. X-axis label
# d. Y-axis label
```

# 2.3 Make Data Model Ready: encoding eassay, and project\_title

```
In [305]:
```

```
# please write all the code with proper documentation, and proper titles for each subsection
# go through documentations and blogs before you start coding
# first figure out what to do, and then think about how to do.
# reading and understanding error messages will be very much helpfull in debugging your code
# make sure you featurize train and test data separatly

# when you plot any graph make sure you use
# a. Title, that describes your plot, this will be very helpful to the reader
# b. Legends if needed
# c. X-axis label
# d. Y-axis label
```

#### In [306]:

```
#function to get heatmap confusion matrix

def get confusion matrix(clf.X te.v test):
```

```
y_pred = clf.predict(X_te)

df_cm = pd.DataFrame(confusion_matrix(y_test, y_pred), range(2), range(2))

df_cm.columns = ['Predicted NO', 'Predicted YES']

df_cm = df_cm.rename({0: 'Actual NO', 1: 'Actual YES'})

sns.set(font_scale=1.4) #for label size

sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}, fmt='g')
```

### In [307]:

```
# Collect bow features name
# print(10 + len(clean titles bow features) + len(easy bow features) +
len(project resource summary bow features) + 3)
feature_names_bow = ['school_state_pos', 'school_state_neg', 'clean_categories_pos',
'clean categories neg', 'clean subcategories pos', 'clean subcategories neg' \
               , 'project_grade_category_pos', 'project_grade_category_neg', 'teacher_prefix_pos',
'teacher_prefix_neg']
# append title bow
for i in clean titles bow features:
    feature_names_bow.append(i)
# append easy bow
for i in easy_bow_features:
   feature names bow.append(i)
# append project resource summary bow
for i in project resource summary bow features:
   feature_names_bow.append(i)
feature_names_bow.append('quantity')
feature_names_bow.append('teacher_number_of_previously_posted_projects_norm')
feature names bow.append('price')
len(feature names bow)
```

#### Out[307]:

10277

#### In [308]:

```
# Collect tfidf features name
# print(10 + len(clean titles tfidf features) + len(easy tfidf features) +
len(project_resource_summary_tfidf_features) + 3)
feature_names_tfidf = ['school_state_pos', 'school_state_neg', 'clean_categories_pos',
'clean_categories_neg', 'clean_subcategories_pos', 'clean_subcategories_neg'
               , 'project_grade_category_pos', 'project_grade_category_neg', 'teacher_prefix_pos',
'teacher_prefix_neg']
# append title tfidf
for i in clean titles tfidf features:
    feature names tfidf.append(i)
# append easy tfidf
for i in easy tfidf features:
   feature_names_tfidf.append(i)
# append project resource summary tfidf
for i in project resource summary tfidf features:
   feature_names_tfidf.append(i)
feature names tfidf.append('quantity')
feature_names_tfidf.append('teacher_number_of_previously_posted_projects_norm')
feature names tfidf.append('price')
len(feature names tfidf)
```

#### Out[308]:

# 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

## 2.4.1 Applying Random Forests on BOW, SET 1

```
In [309]:
```

```
%%time
# Please write all the code with proper documentation
# Prepare data for BOW
X train bow = hstack((X train school state pos, X train school state neg,
X train clean categories pos, X train clean categories neg, X train clean subcategories pos,
X train clean subcategories neg, X train project grade category pos,
X_train_project_grade_category_neg, X_train_teacher_prefix_pos, X_train_teacher_prefix_neg,
X_train_title_bow, X_train_essay_bow, X_train_project_resource_summary_bow, X_train_quantity_norm,
X train teacher number of previously posted projects norm, X train price norm)).tocsr()
X cv bow = hstack((X_cv_school_state_pos, X_cv_school_state_neg, X_cv_clean_categories_pos,
X cv clean categories neg, X cv clean subcategories pos, X cv clean subcategories neg,
X_cv_project_grade_category_pos, X_cv_project_grade_category_neg, X_cv_teacher_prefix_pos,
X_cv_teacher_prefix_neg, X_cv_title_bow, X_cv_essay_bow, X_cv_project_resource_summary_bow,
X cv quantity norm, X cv teacher number of previously posted projects norm, X cv price norm)).tocs
r()
X test bow = hstack((X test school state pos, X test school state neg, X test clean categories pos
, X test clean categories neg, X test clean subcategories pos, X test clean subcategories neg, X t
est_project_grade_category_pos, X_test_project_grade_category_neg, X_test_teacher_prefix_pos, X_t
est_teacher_prefix_neg, X_test_title_bow, X_test_essay_bow, X_test_project_resource_summary_bow, X
test quantity norm, X test teacher number of previously posted projects norm, X test price norm))
.tocsr()
print(X train bow.shape, y train.shape)
print(X_cv_bow.shape, y_cv.shape)
print(X test bow.shape, y test.shape)
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import learning curve, GridSearchCV
rf = RandomForestClassifier(class_weight='balanced', n jobs=-1)
parameters = {'n estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6, 7
, 8, 9, 10]}
clf=GridSearchCV(rf, parameters, cv=3, scoring='roc_auc', n jobs=-1, return train score=True)
clf.fit(X train bow, y train)
(14711, 10277) (14711,)
(7247, 10277) (7247,)
(10816, 10277) (10816,)
CPU times: user 23.9 s, sys: 925 ms, total: 24.9 s
Wall time: 9min 53s
Out[309]:
GridSearchCV(cv=3, error score='raise-deprecating',
             estimator=RandomForestClassifier(bootstrap=True,
                                              class weight='balanced',
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                                              max features='auto',
                                              max leaf nodes=None,
                                              min_impurity_decrease=0.0,
                                              min impurity split=None,
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```

```
iid='warn', n jobs=-1,
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               scoring='roc auc', verbose=0)
In [310]:
# Print results
clf.cv results
Out[310]:
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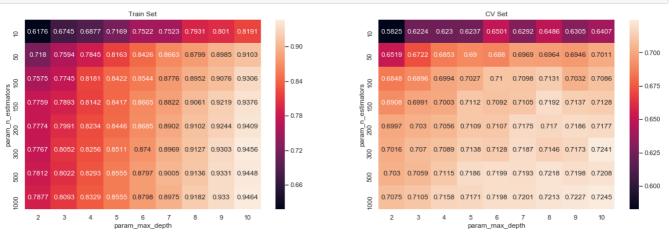
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       0.86835222, 0.88026838, 0.88207986, 0.88669388, 0.89004962,
       0.76194832, 0.8666889 , 0.88417163, 0.89326728, 0.8936308 ,
       0.90447324, 0.9067655 , 0.90522359, 0.79229216, 0.88495083,
       0.90069539, 0.90999917, 0.91563019, 0.92491707, 0.91833602,
       0.92440264,\ 0.80205913,\ 0.90062379,\ 0.90921071,\ 0.93068096,
       0.92896229, 0.93708418, 0.94291821, 0.94276876, 0.82188439,
       0.91497281, 0.94116484, 0.94386621, 0.94536301, 0.95113161,
       0.95102271, 0.95171609]),
'split2 train score': array([0.60869771, 0.71824877, 0.76818767, 0.76726308, 0.75949194,
        0.7798712 \ , \ 0.7724999 \ , \ 0.77523158, \ 0.65928635, \ 0.7565178 \ , \\
       0.77609177, 0.78362938, 0.78563485, 0.78946991, 0.79770509,
        \hbox{\tt 0.80229652, 0.6883342, 0.77605312, 0.80862693, 0.79968146, } 
       0.81609209, 0.81114918, 0.82380171, 0.8247185 , 0.71894756,
       0.81645435, 0.83672983, 0.84495193, 0.84126689, 0.84720672,
       0.84760543, 0.84287901, 0.76349454, 0.84298868, 0.84922998,
       \hbox{\tt 0.86591116, 0.85479501, 0.87022246, 0.87309871, 0.87392334,}\\
       0.74669796, 0.86331016, 0.86742601, 0.87163222, 0.8839839 ,
       0.89058689, 0.89485617, 0.8889091 , 0.80670103, 0.8656051 ,
       0.89475141, 0.89920549, 0.90366405, 0.90451209, 0.91034164,
       0.90980202, 0.80996729, 0.89650681, 0.90598849, 0.91329632,
       0.9156692 , 0.92088444, 0.92588026, 0.92344196, 0.82378383,
```

```
U.7120/300, U.72000373, U.73143342, U.733U37U0, U.7421/4U3,
       0.9407251 , 0.9413893 ]),
'mean_train_score': array([0.61763896, 0.7180059 , 0.7575448 , 0.77594177, 0.77741826,
       0.77674161, 0.78122523, 0.78772053, 0.67452644, 0.75935745,
       0.77446393, 0.78933993, 0.79910357, 0.80516897, 0.80223999,
       0.80933089,\ 0.68766804,\ 0.78454884,\ 0.81810442,\ 0.81422587,
       0.82336492,\ 0.82563165,\ 0.82934226,\ 0.8328743\ ,\ 0.71689968,
       0.8163207 , 0.84219262, 0.84168643, 0.8446367 , 0.85108826,
       0.85549678, 0.85549508, 0.75218518, 0.84260773, 0.85435003,
       0.8664568 , 0.86849448, 0.87404998, 0.87969857, 0.87982127,
       0.75232804,\ 0.8662831\ ,\ 0.8776085\ ,\ 0.88218086,\ 0.89023376,
       0.89689984,\ 0.90053619,\ 0.89752001,\ 0.79307618,\ 0.87994627,
       0.89516666, 0.90609586, 0.91017841, 0.91273647, 0.91358793,
       0.91818622, 0.80104989, 0.89851983, 0.90759915, 0.92191175,
       0.92439379, 0.9302961 , 0.9330919 , 0.93300526, 0.81908757,
       0.91032324, 0.93057444, 0.9375756, 0.94087727, 0.94563363,
       0.94478677, 0.9463543 ]),
'std_train_score': array([0.01951326, 0.00587223, 0.00988776, 0.00895259, 0.01662238,
       0.01563119, 0.01171188, 0.01121289, 0.01596657, 0.00825852,
       0.00768434, 0.00425068, 0.01061756, 0.01406394, 0.00603822,
       0.00632827, 0.00181581, 0.0103172 , 0.00798859, 0.01205953,
       0.00556161, 0.01153125, 0.00723379, 0.00734613, 0.00947351,
       0.00124442,\ 0.00402907,\ 0.00833356,\ 0.01233376,\ 0.00432363,
       0.00824352,\ 0.01073921,\ 0.00884181,\ 0.0055464\ ,\ 0.01047658,
       0.00137989, 0.01048822, 0.00568005, 0.00555724, 0.00726079,
       0.00683543, 0.00227985, 0.00729972, 0.00884066, 0.0044249,
       0.00573871, 0.00487745, 0.00669119, 0.01081878, 0.0102938 ,
       0.00435458,\ 0.00488656,\ 0.0049426\ ,\ 0.00878747,\ 0.00343211,
       0.00615462,\ 0.00772608,\ 0.00168198,\ 0.00131546,\ 0.00709808,
       0.00617151, 0.00686878, 0.00719723, 0.0078914 , 0.00535486,
       0.00503808, 0.00804021, 0.00507675, 0.00432187, 0.00393072,
       0.00447629, 0.00422522])}
```

#### In [311]:

```
# Find best hyper parameter max_depth and min_samples_split
import seaborn as sns; sns.set()
max_scores = pd.DataFrame(clf.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_scores.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores.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 [312]:

```
# Print params
print(clf.best_estimator_)
print(clf.score(X_train_bow, y_train))
print(clf.score(X_test_bow, y_test))
```

min\_samples\_split=2, min\_weight\_fraction\_leaf=0.0, n\_estimators=1000, n\_jobs=-1, oob\_score=False, random\_state=None, verbose=0, warm\_start=False)

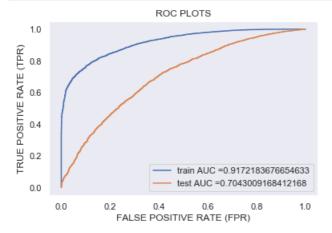
0.9172183676654633 0.7043009168412168

#### In [313]:

```
n_estimators = 1000
max_depth = 10
```

#### In [314]:

```
%%time
 # Create ROC Plot for Test Set
parameters = {'max_depth':[max_depth], 'n_estimators':[n_estimators]}
\verb|rf=GridSearchCV| (RandomForestClassifier(class\_weight="balanced", n_estimators=n_estimators, n_estimators=n_estimators, n_estimators=n_estimators, n_estimators=n_estimators, n_estimators=n_estimators, n_estimators=n_estimators=n_estimators, n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estimators=n_estim
max depth=max depth, n jobs=-1), parameters, cv=3, scoring='roc auc', n jobs=-1, return train score
=True)
rf.fit(X_train_bow, y_train);
y_train_pred = clf.predict_proba(X_train_bow)[:,1]
y test pred = clf.predict proba(X test bow)[:,1]
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("FALSE POSITIVE RATE (FPR)")
plt.ylabel("TRUE POSITIVE RATE (TPR)")
plt.title("ROC PLOTS")
plt.grid()
plt.show()
```



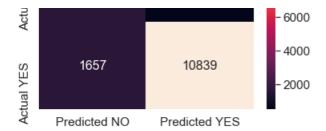
CPU times: user 43.5 s, sys: 828 ms, total: 44.4 s Wall time: 1min 1s

#### In [315]:

```
%%time
get_confusion_matrix(rf,X_train_bow,y_train)
```

```
CPU times: user 13.6 s, sys: 236 ms, total: 13.9 s Wall time: 8.6~\mathrm{s}
```





#### In [316]:

```
%%time
get_confusion_matrix(rf,X_test_bow,y_test)
```

CPU times: user 9.67 s, sys: 198 ms, total: 9.87 s

Wall time: 4.58 s



#### In [317]:

```
%%time
# Train a model on above hyperparameter to select best features
rf_feature_selection = RandomForestClassifier(class_weight='balanced', n_estimators=n_estimators,
max_depth=max_depth, n_jobs=-1)
rf_feature_selection.fit(X_train_bow, y_train)
rf_feature_selection.feature_importances_
```

CPU times: user 23.7 s, sys: 720 ms, total: 24.5 s

Wall time: 14.7 s

### Out[317]:

array([0.00727337, 0.00735108, 0.00681443, ..., 0.02060005, 0.01528153, 0.0187616])

#### In [318]:

```
# https://stackoverflow.com/questions/44101458/random-forest-feature-importance-chart-using-python
# Calculate feature importances
importances = rf_feature_selection.feature_importances_
# Sort feature importances in descending order
indices_pos = np.argsort(importances)[::-1]

# Sort feature importances in ascending order
indices_neg = np.argsort(importances)[::1]

# Rearrange feature names so they match the sorted feature importances for positive class
names_pos = [feature_names_bow[i] for i in indices_pos]

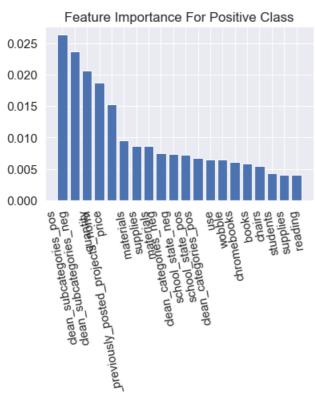
# Rearrange feature names so they match the sorted feature importances for negative class
names_neg = [feature_names_bow[i] for i in indices_neg]
```

```
# process for top n features n = 20
In [320]:
```

```
# collect n positive feature
# collect top n importance data
top 20 positive data = []
for i in indices pos:
    top 20 positive data.append(importances[i])
    if(len(top 20 positive data) >= n):
print(top_20_positive_data)
print("*"*100)
# collect top n importance label
top_20_positive_label = names_pos[0:n]
print(top_20_positive_label)
print("*"*100)
# Barplot: Add bars
plt.bar(range(n), top_20_positive_data)
# Add feature names as x-axis labels
plt.xticks(range(n), top 20 positive label , rotation=100, fontsize = 15)
# Create plot title
plt.title("Feature Importance For Positive Class")
# Show plot
plt.show()
```

[0.026331933336934253, 0.02367404044767679, 0.020600053746364436, 0.018761596183043544, 0.015281527149479437, 0.00950312097978943, 0.008707417849634224, 0.008680095032457615, 0.00756095544512088, 0.007351075024355123, 0.007273367841931229, 0.006814429376444725, 0.006535722830858892, 0.006458334187670129, 0.006106948856383575, 0.005915810175130168, 0.005507670244642196, 0.004302400424120888, 0.004135010950606783, 0.004073100735093452]

4

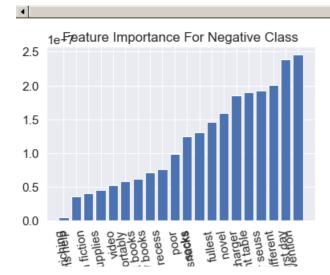


#### In [321]:

```
# collect n negative feature
# collect top n importance data
top 20 negative data = []
collect_neg_indices = []
for i in indices neg:
    if(importances[i] > 0):
        top_20_negative_data.append(importances[i])
        collect neg indices.append(i)
    if (len(top_20_negative_data) >= n):
       break;
print(top_20_negative_data)
print("*"*100)
# collect top n importance data
top 20 negative label = []
for i in collect_neg_indices:
    top_20_negative_label.append(names_neg[i])
print(top_20_negative_label)
print("*"*100)
# Barplot: Add bars
plt.bar(range(n), top 20 negative data)
# Add feature names as x-axis labels
plt.xticks(range(n), top_20_negative_label , rotation=100, fontsize = 15)
# Create plot title
plt.title("Feature Importance For Negative Class")
# Show plot
plt.show()
```

[4.724030407280267e-09, 3.5459442430600536e-08, 4.0799591018504394e-08, 4.530458336405595e-08, 5.2975635886083995e-08, 5.8481237432073735e-08, 6.17220916132652e-08, 7.16968200671659e-08, 7.566594213464851e-08, 9.865974997549917e-08, 1.246170478127686e-07, 1.3133319132394543e-07, 1.4675783834305262e-07, 1.589213448562151e-07, 1.8489239191015398e-07, 1.8999562174418277e-07, 1.923414231625342e-07, 2.0054795933282652e-07, 2.392824362049235e-07, 2.4565678820454505e-07]

['enriching', 'flexible seating options help', 'need non fiction', 'art supplies', 'video', 'comfortably', 'interest books', 'need new books', 'need recess', 'poor', 'socks', 'students need healthy snacks', 'fullest', 'novel', 'charger', 'light table', 'dr seuss', 'different', 'first day ', 'reading intervention']



# flexible seating opted art sinced non art sinterest interest need new need healthy? Udents need healthy?

#### 2.4.2 Applying Random Forests on TFIDF, SET 2

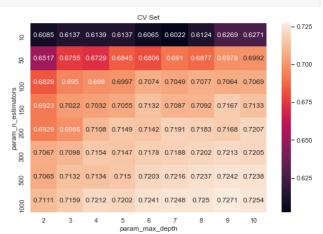
```
In [322]:
```

```
%%time
# Please write all the code with proper documentation
# Prepare data for TFIDF
X train tfidf = hstack((X train school state pos, X train school state neg,
X_train_clean_categories_pos, X_train_clean_categories_neg, X_train_clean_subcategories_pos,
X_train_clean_subcategories_neg, X_train_project_grade_category_pos,
X_train_project_grade_category_neg, X_train_teacher_prefix_pos, X_train_teacher_prefix_neg,
X_train_title_tfidf, X_train_essay_tfidf, X_train_project_resource_summary_tfidf,
X train quantity norm, X train teacher number of previously posted projects norm,
X train price norm)).tocsr()
X_cv_tfidf = hstack((X_cv_school_state_pos, X_cv_school_state_neg, X_cv_clean_categories_pos,
X cv clean categories neg, X cv clean subcategories pos, X cv clean subcategories neg,
X cv project_grade_category_pos, X_cv_project_grade_category_neg, X_cv_teacher_prefix_pos,
X cv teacher prefix neg, X cv title tfidf, X cv essay tfidf, X cv project resource summary tfidf,
X_cv_quantity_norm, X_cv_teacher_number_of_previously_posted_projects_norm, X_cv_price_norm)).tocs
X_test_tfidf = hstack((X_test_school_state_pos, X_test_school_state_neg,
X_test_clean_categories_pos, X_test_clean_categories_neg, X_test_clean_subcategories_pos,
X_test_clean_subcategories_neg, X_test_project_grade_category_pos,
X test project grade category neg, X test teacher prefix pos, X test teacher prefix neg,
X_test_title_tfidf, X_test_essay_tfidf, X_test_project_resource_summary_tfidf,
X_test_quantity_norm, X_test_teacher_number_of_previously_posted_projects_norm, X_test_price_norm)
).tocsr()
print(X train tfidf.shape)
print(X cv tfidf.shape)
print(X test tfidf.shape)
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import learning_curve, GridSearchCV
rf = RandomForestClassifier(class_weight='balanced', n_jobs=-1)
parameters = {'n estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6, 7
, 8, 9, 10]}
clf=GridSearchCV(rf, parameters, cv=3, scoring='roc_auc', n_jobs=-1, return_train_score=True)
clf.fit(X train tfidf, y train)
(14711, 10071)
(7247, 10071)
(10816, 10071)
CPU times: user 26.9 s, sys: 512 ms, total: 27.4 s
Wall time: 10min 49s
Out[322]:
GridSearchCV(cv=3, error score='raise-deprecating',
             estimator=RandomForestClassifier(bootstrap=True,
                                              class weight='balanced',
                                              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 iohs=-1
```

#### In [323]:

```
# Find best hyper parameter max_depth and min_samples_split
import seaborn as sns; sns.set()
max_scores = pd.DataFrame(clf.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_scores.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores.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 [324]:

```
# Print params
print(clf.best_estimator_)
print(clf.score(X_train_tfidf, y_train))
print(clf.score(X_test_tfidf, y_test))
```

0.9299142226641194 0.7091140809841328

#### In [325]:

```
n_estimators = 1000
max_depth = 10
```

#### In [326]:

```
# Create ROC Plot for Test Set
parameters = {'max_depth': [max_depth], 'n_estimators': [n_estimators]}
rf=GridSearchCV(RandomForestClassifier(class_weight='balanced', n_estimators=n_estimators,
max_depth=max_depth, n_jobs=-1), parameters, cv=3, scoring='roc_auc', n_jobs=-1, return_train_score
=True)
```

```
rf.fit(X_train_tfidf, y_train);

y_train_pred = clf.predict_proba(X_train_tfidf)[:,1]

y_test_pred = clf.predict_proba(X_test_tfidf)[:,1]

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()

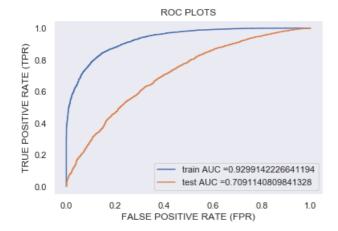
plt.xlabel("FALSE POSITIVE RATE (FPR)")

plt.ylabel("TRUE POSITIVE RATE (TPR)")

plt.title("ROC PLOTS")

plt.grid()

plt.show()
```



CPU times: user 40.2 s, sys: 726 ms, total: 40.9 s

Wall time: 46.8 s

#### In [327]:

```
%%time
get_confusion_matrix(rf,X_train_tfidf,y_train)
```

CPU times: user 8.24 s, sys: 121 ms, total: 8.36 s Wall time: 3.25 s  $\,$ 



#### In [328]:

```
%%time
get_confusion_matrix(rf,X_test_tfidf,y_test)
```

CPU times: user 6.38 s, sys: 114 ms, total: 6.49 s  $\,$ 

Wall time: 2.86 s



#### In [329]:

```
%%time
# Train a model on above hyperparameter to select best features
rf feature selection = RandomForestClassifier(class weight='balanced', n estimators=n estimators,
max_depth=max_depth, n_jobs=-1)
rf feature selection.fit(X train tfidf, y train)
rf feature selection.feature importances
CPU times: user 26.5 s, sys: 476 ms, total: 27 s
Wall time: 10.7 s
Out[329]:
array([0.00564628, 0.00633854, 0.00641493, ..., 0.01618556, 0.01078699,
       0.01696141])
In [330]:
\# https://stackoverflow.com/questions/44101458/random-forest-feature-importance-chart-using-python
# Calculate feature importances
importances = rf feature selection.feature importances
# Sort feature importances in descending order
indices_pos = np.argsort(importances)[::-1]
# Sort feature importances in asccending order
indices_neg = np.argsort(importances)[::1]
# Rearrange feature names so they match the sorted feature importances for positive class
names pos = [feature names tfidf[i] for i in indices pos]
# Rearrange feature names so they match the sorted feature importances for negative class
names neg = [feature names tfidf[i] for i in indices neg]
```

#### In [331]:

```
\# process for top n features n = 20
```

#### In [332]:

```
# collect top n importance data
top_20_positive_data = []
for i in indices_pos:
    top_20_positive_data.append(importances[i])
    if (len(top_20_positive_data) >= n):
        break;

print(top_20_positive_data)
print("*"*100)

# collect top n importance label
top_20_positive_label = names_pos[0:n]
print(top_20_positive_label)
```

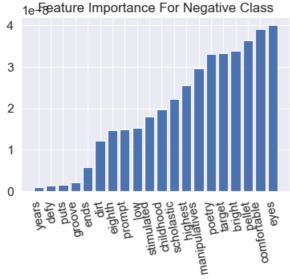
```
print("*"*100)
 # Barplot: Add bars
plt.bar(range(n), top_20_positive_data)
 # Add feature names as x-axis labels
plt.xticks(range(n), top_20_positive_label , rotation=100, fontsize = 15)
# Create plot title
plt.title("Feature Importance For Positive Class")
 # Show plot
plt.show()
0.012100496674058664,\ 0.010786992436094966,\ 0.010655334993992443,\ 0.009392511729585237,
0.008695271612570367,\ 0.007934021419129876,\ 0.006905389413091942,\ 0.00641493065688277,
0.005646276387120999, 0.005008126158841348, 0.004790594953613698, 0.004783900333657298]
['clean_subcategories_neg', 'clean_subcategories_pos', 'price', 'quantity', 'nannan', 'teacher_number_of_previously_posted_projects_norm', 'materials', 'materials', 'supplies',
'clean_categories_neg', 'supplies', 'clean_categories_pos', 'school_state_neg', 'chromebooks', 'us
e', 'chairs', 'school state pos', 'wobble', 'books', 'hands']
4
                            Feature Importance For Positive Class
   0.025
   0.020
   0.015
   0.010
   0.005
                                                     materials materials materials supplieg augment categories dean categories and categories are supplied and categori
                                                                                                   chool_state_pos
                                                                            dean_categories_neg
   0.000
                                 price price previously_posted_project@uaghter pannan teacher_number_of_previously_posted_project@uaghter price
                   dean_subcategories_neg
                                                                                            chromebooks
```

#### In [333]:

```
# collect n negative feature

# collect top n importance data
top_20_negative_data = []
collect_neg_indices = []
for i in indices_neg:
    if(importances[i] > 0):
        top_20_negative_data.append(importances[i])
        collect_neg_indices.append(i)
    if(len(top_20_negative_data) >= n):
```

```
break;
print(top 20 negative data)
print("*"*100)
 # collect top n importance data
top 20 negative label = []
for i in collect_neg_indices:
          top 20 negative label.append(names neg[i])
print(top 20 negative label)
print("*"*100)
 # Barplot: Add bars
plt.bar(range(n), top 20 negative data)
# Add feature names as x-axis labels
plt.xticks(range(n), top_20_negative_label , rotation=100, fontsize = 15)
 # Create plot title
plt.title("Feature Importance For Negative Class")
 # Show plot
plt.show()
[1.0100386983508363e-09, 1.4496355263582026e-09, 1.6814544047211648e-09, 2.1255451547281227e-09,
5.802882451658276 \\ e-09, \ 1.2254253098773021 \\ e-08, \ 1.4722914953300233 \\ e-08, \ 1.4973170716250735 \\ e-08, \ 1.497317071625073 \\ e-08, \ 1.497317071625070 \\ e-08, \ 1.497317071625070 \\ e-08, \ 1.497317071625070 \\ e-08, \ 1.497317071625070 \\ e-08, \ 1.497317070 \\ e-08, \ 1.4973170 \\ e-08, \ 1.
1.5254853225623342e-08, 1.794402183364072e-08, 1.9791987523195938e-08, 2.2276601282469166e-08,
2.5460615113996306e-08, 2.9529125076928686e-08, 3.2970829844695646e-08, 3.318136749488672e-08,
3.37809678788238e-08, 3.639388399454989e-08, 3.89090287699897e-08, 3.990171334115558e-08]
['years', 'defy', 'puts', 'groove', 'ends', 'dirt', 'eighth', 'prompt', 'low', 'stimulated',
'childhood', 'scholastic', 'highest', 'manipulatives', 'poetry', 'target', 'bright', 'pellet', 'co
mfortable', 'eyes']
         1e-Feature Importance For Negative Class
  4
  3
```



#### 2.4.3 Applying Random Forests on AVG W2V, SET 3

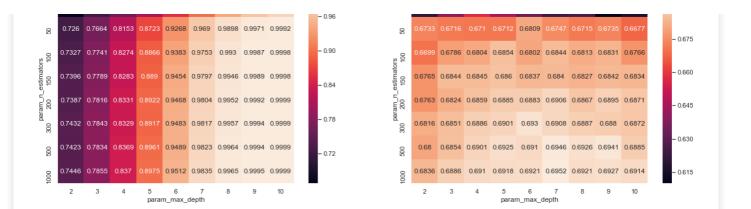
```
In [101]:
```

```
%%time
# Please write all the code with proper documentation
# Prepare data for AVGW2V
X_train_avgw2v = hstack((X_train_school_state_pos, X_train_school_state_neg,
X_train_clean_categories_pos, X_train_clean_categories_neg, X_train_clean_subcategories_pos,
X_train_clean_subcategories_neg, X_train_project_grade_category_pos,
X_train_project_grade_category_neg, X_train_teacher_prefix_pos, X_train_teacher_prefix_neg,
avg_w2v_vectors_text_train, avg_w2v_vectors_title_train,
avg_w2v_vectors_project_resource_summary_train, X_train_quantity_norm,
X_train_teacher_number_of_previously_posted_projects_norm, X_train_price_norm)).tocsr()
X_cv_avgw2v = hstack((X_cv_school_state_pos, X_cv_school_state_neg, X_cv_clean_categories_pos,
X_cv_clean_categories_neg, X_cv_clean_subcategories_pos, X_cv_clean_subcategories_neg,
```

```
{\tt X\_cv\_project\_grade\_category\_pos,\ X\_cv\_project\_grade\_category\_neg,\ X\_cv\_teacher\_prefix\_pos,\ X\_cv\_teacher\_prefix\_pos
X_cv_teacher_prefix_neg, avg_w2v_vectors_text_cv, avg_w2v_vectors_title_cv,
avg w2v vectors project resource summary cv, X cv quantity norm,
X_cv_teacher_number_of_previously_posted_projects_norm, X_cv_price_norm)).tocsr()
X test avgw2v = hstack((X test school state pos, X test school state neg,
X_test_clean_categories_pos, X_test_clean_categories_neg, X_test_clean_subcategories_pos,
X_test_clean_subcategories_neg, X_test_project_grade_category_pos,
X test project grade category neg, X test teacher prefix pos, X test teacher prefix neg,
avg w2v vectors text test, avg w2v vectors title test,
avg w2v vectors project resource summary test, X test quantity norm,
X_test_teacher_number_of_previously_posted_projects_norm, X_test_price_norm)).tocsr()
print(X_train_avgw2v.shape)
print(X cv avgw2v.shape)
print(X test avgw2v.shape)
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc auc score
from sklearn.model selection import learning curve, GridSearchCV
 rf = RandomForestClassifier(class weight='balanced', n jobs=-1)
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7
 , 8, 9, 101}
clf=GridSearchCV(rf, parameters, cv=3, scoring='roc_auc', n_jobs=-1, return_train_score=True)
clf.fit(X_train_avgw2v, y_train)
(14711, 913)
(7247, 913)
(10816, 913)
CPU times: user 7min 2s, sys: 1.7 s, total: 7min 4s
Wall time: 8h 58min 30s
Out[101]:
GridSearchCV(cv=3, error score='raise-deprecating',
                        estimator=RandomForestClassifier(bootstrap=True,
                                                                                     class_weight='balanced',
                                                                                     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=-1,
                                                                                      oob score=False,
                                                                                      random state=None, verbose=0,
                                                                                      warm_start=False),
                        iid='warn', n_jobs=-1,
                        param_grid={'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10],
                                               'n_estimators': [10, 50, 100, 150, 200, 300, 500,
                                                                               1000]},
                        pre dispatch='2*n jobs', refit=True, return train score=True,
                        scoring='roc_auc', verbose=0)
In [102]:
# Find best hyper parameter max depth and min samples split
import seaborn as sns; sns.set()
max_scores = pd.DataFrame(clf.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 scores.mean train score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores.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
```

0.6676 0.7222 0.7613 0.8061 0.8546 0.8996 0.9417 0.9653 0.9803

<u>9</u> 0.6203 0.64 0.6574 0.6456 0.6336 0.6239 0.6257 0.61 0.6163



#### In [103]:

```
# Print params
print(clf.best_estimator_)
print(clf.score(X_train_avgw2v, y_train))
print(clf.score(X_test_avgw2v, y_test))
```

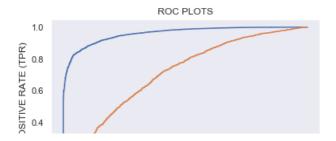
0.7023769060203968

#### In [105]:

```
n_estimators = 1000
max_depth = 7
```

#### In [106]:

```
%%time
# Create ROC Plot for Test Set
parameters = {'max depth':[max depth], 'n estimators':[n estimators]}
rf=GridSearchCV(RandomForestClassifier(class weight='balanced', n estimators=n estimators,
max depth=max depth, n jobs=-1), parameters, cv=3, scoring='roc auc', n jobs=-1, return train score
rf.fit(X_train_avgw2v, y_train);
y_train_pred = clf.predict_proba(X_train_avgw2v)[:,1]
y_test_pred = clf.predict_proba(X_test_avgw2v)[:,1]
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("FALSE POSITIVE RATE (FPR)")
plt.ylabel("TRUE POSITIVE RATE (TPR)")
plt.title("ROC PLOTS")
plt.grid()
plt.show()
```



CPU times: user 8min 1s, sys: 2.5 s, total: 8min 3s

Wall time: 6min 34s

#### In [107]:

```
%%time
get_confusion_matrix(rf,X_train_avgw2v,y_train)
```

CPU times: user 26.6 s, sys: 266 ms, total: 26.9 s  $\,$ 

Wall time: 7.99 s



#### In [108]:

```
%%time
get_confusion_matrix(rf,X_test_avgw2v,y_test)
```

CPU times: user 19.2 s, sys: 211 ms, total: 19.4 s

Wall time: 5.74 s



### 2.4.4 Applying Random Forests on TFIDF W2V, SET 4

# In [132]:

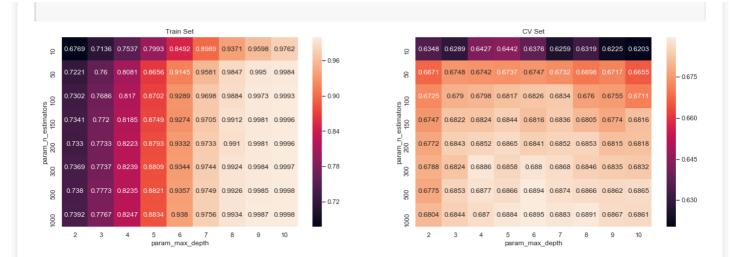
```
%%time
# Please write all the code with proper documentation
# Prepare data for TFIDFW2V
X_train_tfidfw2v = hstack((X_train_school_state_pos, X_train_school_state_neg, X_train_clean_categ
ories_pos, X_train_clean_categories_neg, X_train_clean_subcategories_pos,
X_train_clean_subcategories_neg, X_train_project_grade_category_pos,
X_train_project_grade_category_neg, X_train_teacher_prefix_neg,
```

```
tfidf_w2v_vectors_text_train, tfidf_w2v_vectors_title_train,
tfidf_w2v_vectors_project_resource_summary_train, X_train_quantity_norm,
X_train_teacher_number_of_previously_posted_projects_norm, X_train_price_norm)).tocsr()
X_cv_tfidfw2v = hstack((X_cv_school_state_pos, X_cv_school_state_neg, X_cv_clean_categories_pos,
X cv clean categories neg, X cv clean subcategories pos, X cv clean subcategories neg,
X_cv_project_grade_category_pos, X_cv_project_grade_category_neg, X_cv_teacher_prefix_pos,
X_cv_teacher_prefix_neg, tfidf_w2v_vectors_text_cv, tfidf_w2v_vectors_title_cv,
tfidf_w2v_vectors_project_resource_summary_cv, X_cv_quantity_norm,
X cv teacher number of previously posted projects norm, X cv price norm)).tocsr()
X test tfidfw2v = hstack((X test school state pos, X test school state neg,
X_test_clean_categories_pos, X_test_clean_categories_neg, X_test_clean_subcategories_pos,
X_test_clean_subcategories_neg, X_test_project_grade_category_pos,
{\tt X\_test\_project\_grade\_category\_neg,~X\_test\_teacher\_prefix\_pos,~X\_test\_teacher\_prefix\_neg,}
tfidf_w2v_vectors_text_test, tfidf_w2v_vectors_title_test,
tfidf_w2v_vectors_project_resource_summary_test, X_test_quantity_norm,
X_test_teacher_number_of_previously_posted_projects_norm, X_test_price_norm)).tocsr()
print(X train tfidfw2v.shape)
print(X cv tfidfw2v.shape)
print(X test tfidfw2v.shape)
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc auc score
from sklearn.model_selection import learning_curve, GridSearchCV
rf = RandomForestClassifier(class_weight='balanced', n_jobs=-1)
parameters = {'n_estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max_depth': [2, 3, 4, 5, 6, 7
, 8, 9, 101}
clf=GridSearchCV(rf, parameters, cv=3, scoring='roc auc', n jobs=-1, return train score=True)
clf.fit(X train tfidfw2v, y train)
4
(14711, 913)
(7247, 913)
(10816, 913)
CPU times: user 5min 27s, sys: 2.32 s, total: 5min 30s
Wall time: 3h 33min 1s
Out[132]:
GridSearchCV(cv=3, error score='raise-deprecating',
             estimator=RandomForestClassifier(bootstrap=True,
                                               class weight='balanced',
                                               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=-1,
                                               oob score=False,
                                               random state=None, verbose=0,
                                               warm_start=False),
             iid='warn', n jobs=-1,
             param grid={'max depth': [2, 3, 4, 5, 6, 7, 8, 9, 10],
                         'n_estimators': [10, 50, 100, 150, 200, 300, 500,
                                           1000]},
             pre dispatch='2*n jobs', refit=True, return train score=True,
             scoring='roc auc', verbose=0)
In [133]:
# Find best hyper parameter max depth and min samples split
import seaborn as sns; sns.set()
max_scores = pd.DataFrame(clf.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\_scores.mean\_train\_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max\_scores.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 [134]:

```
# Print params
print(clf.best_estimator_)
print(clf.score(X_train_tfidfw2v, y_train))
print(clf.score(X_test_tfidfw2v, y_test))
```

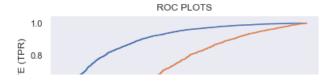
#### In [135]:

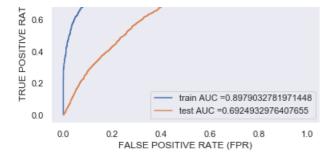
0.6924932976407655

```
n_estimators = 1000
max_depth = 6
```

#### In [136]:

```
%%time
# Create ROC Plot for Test Set
parameters = {'max depth':[max depth], 'n estimators':[n estimators]}
rf=GridSearchCV(RandomForestClassifier(class_weight='balanced', n_estimators=n_estimators,
\verb|max_depth=max_depth|, \verb|n_jobs=-1|, \verb|parameters|, \verb|cv=3|, \verb|scoring='roc_auc'|, \verb|n_jobs=-1|, return_train_score| \\
rf.fit(X_train_tfidfw2v, y_train);
y train pred = clf.predict proba(X train tfidfw2v)[:,1]
y_test_pred = clf.predict_proba(X_test_tfidfw2v)[:,1]
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("FALSE POSITIVE RATE (FPR)")
plt.ylabel("TRUE POSITIVE RATE (TPR)")
plt.title("ROC PLOTS")
plt.grid()
plt.show()
```





CPU times: user 6min 8s, sys: 1.14 s, total: 6min 10s Wall time: 5min 16s

#### In [137]:

```
%%time
get_confusion_matrix(rf,X_train_tfidfw2v,y_train)
```

CPU times: user 23 s, sys: 602 ms, total: 23.6 s Wall time:  $7.17~\mathrm{s}$ 



## In [138]:

```
%%time
get_confusion_matrix(rf,X_test_tfidfw2v,y_test)
```

CPU times: user 16.3 s, sys: 127 ms, total: 16.4 s Wall time: 4.48 s



# 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 [109]:

```
22time
# Please write all the code with proper documentation
# Prepare data for BOW
X train bow = hstack((X train school state pos, X train school state neg,
X_train_clean_categories_pos, X_train_clean_categories_neg, X_train_clean_subcategories_pos,
X_train_clean_subcategories_neg, X_train_project_grade_category_pos,
X train project grade_category_neg, X_train_teacher_prefix_pos, X_train_teacher_prefix_neg,
X_train_title_bow, X_train_essay_bow, X_train_project_resource_summary_bow, X_train_quantity_norm,
X_train_teacher_number_of_previously_posted_projects_norm, X_train_price_norm)).tocsr()
X cv bow = hstack((X cv school state pos, X cv school state neg, X cv clean categories pos,
X_cv_clean_categories_neg, X_cv_clean_subcategories_pos, X_cv_clean_subcategories_neg,
X_cv_project_grade_category_pos, X_cv_project_grade_category_neg, X_cv_teacher_prefix_pos,
X cv teacher prefix neg, X cv title bow, X cv essay bow, X cv project resource summary bow,
X cv quantity norm, X cv teacher number of previously posted projects norm, X cv price norm)).tocs
X test bow = hstack((X test school state pos, X test school state neg, X test clean categories pos
, X_test_clean_categories_neg, X_test_clean_subcategories_pos, X_test_clean_subcategories_neg, X_t
est_project_grade_category_pos, X_test_project_grade_category_neg, X_test_teacher_prefix_pos, X_t
est teacher prefix neg, X test title bow, X test essay bow, X test project resource summary bow, X
_test_quantity_norm, X_test_teacher_number_of_previously_posted_projects_norm, X_test_price_norm))
.tocsr()
print(X_train_bow.shape, y_train.shape)
print(X cv bow.shape, y cv.shape)
print(X_test_bow.shape, y_test.shape)
import matplotlib.pyplot as plt
from xgboost import XGBClassifier
from sklearn.metrics import roc auc score
from sklearn.model_selection import learning curve, GridSearchCV
xgb = XGBClassifier(class weight='balanced', n jobs=-1)
parameters = {'n estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6, 7
, 8, 9, 10]}
clf=GridSearchCV(xgb, parameters, cv=3, scoring='roc auc', n jobs=-1, return train score=True)
clf.fit(X_train_bow, y_train)
(14711, 10297) (14711,)
(7247, 10297) (7247,)
(10816, 10297) (10816,)
CPU times: user 57.1 s, sys: 582 ms, total: 57.7 s
Wall time: 2h 23min 51s
Out[109]:
GridSearchCV(cv=3, error score='raise-deprecating',
             estimator=XGBClassifier(base score=0.5, booster='gbtree',
                                     class_weight='balanced',
                                     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),
             iid='warn', n jobs=-1,
             param grid={'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10],
                         'n estimators': [10, 50, 100, 150, 200, 300, 500,
                                          1000]},
             pre dispatch='2*n jobs', refit=True, return train score=True,
             scoring='roc auc', verbose=0)
```

In [110]:

```
# print results
clf.cv_results_
```

```
Out[110]:
16.1352423 ,
                                                                          22.33804393.
           3.51865443,
                         12.71859105,
                                         20.17203482,
                                                        30.73062094,
                        61.84292674, 112.35918673, 220.19645007,
          45.76393096,
                        14.10237948, 28.95465748,
                                                       43.97654478,
           3.22812931.
                        84.12143501, 140.36739564, 310.88346863,
          60.53410061,
          4.75534431, 20.36359096, 40.32456072, 56.05845006, 74.82564855, 120.46896005, 190.72452331, 376.97966766,
           5.337744 ,
                        21.84740504,
                                        50.19408735,
                                                        65.1116937 ,
          90.90883255, 139.8322626, 220.12863731, 686.37745365,
           5.82620207,
                        26.77927597,
                                        54.03178104, 327.46429666,
         599.71170433, 137.82622568, 218.98402007, 436.53152227,
           6.00144076,
                         26.13107403,
                                         52.16250475,
                                                         75.72499569,
          96.38074795, 159.58858991, 264.78227202, 514.84462142,
                         31.306041 ,
                                        58.1673487 ,
           7.81324697,
                                                        85.18502744.
         114.28311698, 175.45543496, 287.90149951, 1010.950996
        7.26426832, 33.19498499, 63.13991769, 94.02897994, 1490.63741779, 173.30822619, 298.24340638, 465.73498829]),
 'std fit time': array([3.97627722e-02, 6.43154060e-02, 7.76635743e-01, 1.48273923e-01,
        5.89730316e-01, 7.66073703e-01, 1.05232813e+00, 2.17574003e+00,
        1.73217743e-01, 9.74821702e-01, 2.06681789e-01, 9.35245427e-01,
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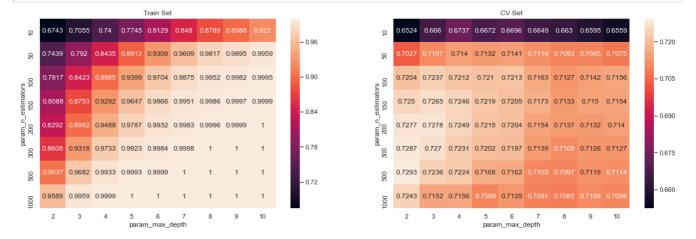
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       0.99976749, 0.99999838, 1.
                                            , 0.87055949, 0.98218003,
       0.99509106, 0.99857834, 0.99954721, 0.99996912, 1.
                 , 0.89587112, 0.99004346, 0.99815538, 0.99967137,
       1.
       0.99993038, 0.99999968, 1. , 1. , 0.92576463, 0.99633329, 0.99953522, 0.99991798, 0.99999003, 1. ,
             , 1. ]),
       1.
'mean train score': array([0.6743325 , 0.74394813, 0.78166208, 0.80882349, 0.8291509 ,
       0.86076856, 0.90367489, 0.9588635 , 0.70550456, 0.79203348,
       0.84226636, 0.87529987, 0.89924101, 0.93175126, 0.96821698, 0.99585309, 0.73998906, 0.84348981, 0.89852433, 0.92921448,
       0.94884971, 0.97332995, 0.99328076, 0.99989051, 0.77447229,
       0.89134497, 0.93990466, 0.96468435, 0.97867752, 0.99229844,
       0.9992932 , 0.99999992, 0.81289444, 0.93086711, 0.97041603,
       0.98664238, 0.99324465, 0.9983711 , 0.99994735, 1.
```

```
U.04/35/00, U.350005/1, U.50005/05, U.3501045, U.35000K42,
       0.99980745, 0.99999905, 1. , 0.87890764, 0.98173498, 0.99518596, 0.998613 , 0.99958823, 0.99997679, 1. ,
       1.
                , 0.89882171, 0.98949914, 0.9982423 , 0.99968623,
       0.99994103, 0.99999978, 1.
                                          , 1.
                                                      , 0.92197622,
        \hbox{\tt 0.99592591, 0.9995325 , 0.99992984, 0.99999281, 1.} 
       1.
                 , 1.
                             1),
'std train score': array([1.10240345e-02, 3.37120169e-03, 3.90224446e-03, 2.86327625e-03,
       2.36742845e-03, 2.06814117e-03, 1.34312992e-03, 5.22193545e-04,
       3.22344890e-03, 2.66560669e-03, 3.93472320e-03, 2.56980681e-03,
       2.80948222e-03, 1.64685310e-03, 5.44232239e-04, 5.72944695e-04,
       2.96178041e-03, 9.60625051e-04, 2.46990522e-03, 1.17979576e-03,
       1.53956619e-03, 1.88391470e-03, 4.05004304e-04, 2.78752266e-05, 5.68136638e-03, 2.34627514e-03, 2.72124555e-03, 1.03352957e-03,
       7.87039011e-04, 5.81192735e-04, 8.46041847e-05, 6.62159944e-08,
       3.32644959e-03, 3.86200062e-03, 1.41154727e-03, 7.95372341e-04,
       5.85097433e-03, 3.34576802e-03, 1.18350569e-03, 6.33081618e-04,
       2.64190699e-04, 2.83908299e-05, 5.05245539e-07, 0.00000000e+00,
       6.01712010e-03, 1.33233664e-03, 3.10150756e-04, 7.31404695e-05,
       2.91487818e-05, 5.42042447e-06, 0.00000000e+00, 0.00000000e+00,
       2.14513928e-03, 1.68182519e-03, 3.20799436e-04, 5.84600350e-05,
       1.40134272e-05, 1.01068625e-07, 0.00000000e+00, 0.00000000e+00,
       2.80362011e-03, 4.66083356e-04, 5.99233148e-05, 1.00616366e-05,
       1.96594172e-06, 0.00000000e+00, 0.0000000e+00, 0.0000000e+00])}
```

## In [111]:

```
# Find best hyper parameter max_depth and min_samples_split
import seaborn as sns; sns.set()
max_scores = pd.DataFrame(clf.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_scores.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores.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 [112]:

```
# Print params
print(clf.best_estimator_)
print(clf.score(X_train_bow, y_train))
print(clf.score(X_test_bow, y_test))
```

```
XGBClassifier(base_score=0.5, booster='gbtree', class_weight='balanced', colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=2, min_child_weight=1, missing=None, n_estimators=500, 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)
0.8705188919084077
```

0.070310031300407

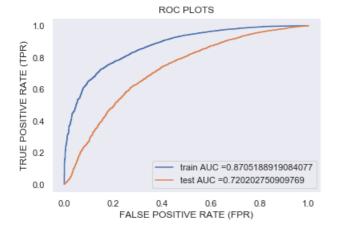
0.720202750909769

## In [334]:

```
n_estimators = 500
max_depth = 2
```

#### In [114]:

```
%%time
# Create ROC Plot for Test Set
parameters = {'max depth':[max depth], 'n estimators':[n estimators]}
xgb=GridSearchCV(XGBClassifier(class weight='balanced', n estimators=n estimators,
max_depth=max_depth, n_jobs=-1), parameters, cv=3, scoring='roc_auc', n_jobs=-1, return_train_score
xgb.fit(X_train_bow, y_train);
y train pred = clf.predict proba(X train bow)[:,1]
y_test_pred = clf.predict_proba(X_test_bow)[:,1]
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("FALSE POSITIVE RATE (FPR)")
plt.ylabel("TRUE POSITIVE RATE (TPR)")
plt.title("ROC PLOTS")
plt.grid()
plt.show()
```

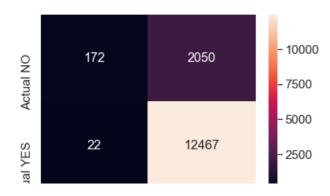


CPU times: user 51.3 s, sys: 394 ms, total: 51.7 s Wall time: 1min 55s

## In [115]:

```
%%time
get_confusion_matrix(xgb,X_train_bow,y_train)
```

CPU times: user 634 ms, sys: 30.5 ms, total: 665 ms Wall time: 672 ms  $\,$ 



팅 Predicted NO Predicted YES

## In [116]:

```
%%time
get_confusion_matrix(xgb,X_test_bow,y_test)
```

CPU times: user 484 ms, sys: 22 ms, total: 506 ms

Wall time: 509 ms



## In [336]:

```
from xgboost import XGBClassifier
# Train a model on above hyperparameter to select best features
xgb_feature_selection = XGBClassifier(class_weight='balanced', n_estimators=n_estimators,
max_depth=max_depth, n_jobs=-1)
xgb_feature_selection.fit(X_train_bow, y_train)
xgb_feature_selection.feature_importances_
CPU times: user 55.7 s, sys: 442 ms, total: 56.1 s
Wall time: 59.7 s
```

## Out[336]:

array([0.00349855, 0. , 0.00133162, ..., 0.00711722, 0.00464577, 0.00693135], dtype=float32)

## In [337]:

```
# https://stackoverflow.com/questions/44101458/random-forest-feature-importance-chart-using-python
# Calculate feature importances
importances = xgb_feature_selection.feature_importances_
# Sort feature importances in descending order
indices_pos = np.argsort(importances)[::-1]

# Sort feature importances in asccending order
indices_neg = np.argsort(importances)[::1]

# Rearrange feature names so they match the sorted feature importances for positive class
names_pos = [feature_names_bow[i] for i in indices_pos]

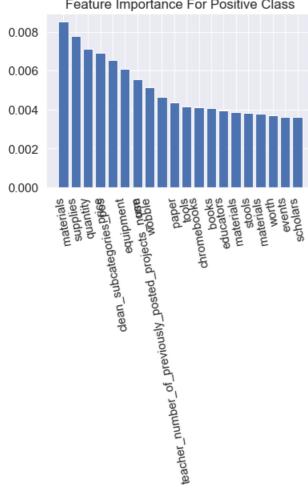
# Rearrange feature names so they match the sorted feature importances for negative class
names_neg = [feature_names_bow[i] for i in indices_neg]
```

## In [338]:

```
\# process for top n features n = 20
```

## In [339]:

```
# collect n positive feature
 # collect top n importance data
 top 20 positive data = []
 for i in indices_pos:
            top 20 positive data.append(importances[i])
            if(len(top 20 positive data) >= n):
                      break:
 print(top_20_positive_data)
print("*"*100)
 # collect top n importance label
 top 20 positive label = names pos[0:n]
 print(top_20_positive_label)
print("*"*100)
 # Barplot: Add bars
plt.bar(range(n), top 20 positive data)
 # Add feature names as x-axis labels
plt.xticks(range(n), top 20 positive label , rotation=100, fontsize = 15)
 # Create plot title
plt.title("Feature Importance For Positive Class")
 # Show plot
plt.show()
[0.0085176835,\ 0.007785931,\ 0.0071172155,\ 0.0069313548,\ 0.0065340674,\ 0.006097838,\ 0.00557561,\ 0.0069313548,\ 0.0065340674,\ 0.006097838,\ 0.00557561,\ 0.0069313548,\ 0.0065340674,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.00693148,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.0069313548,\ 0.00693148,\ 0.00693148,\ 0.00693148,\ 0.00693148,\ 0.00693148,\ 0.00693148,\ 0.00693148,\ 0.00693148,
0.0051340763,\ 0.004645771,\ 0.0043550604,\ 0.0041668196,\ 0.004128658,\ 0.0040737395,\ 0.0039688707,
0.0038815043,\ 0.0038250992,\ 0.0037717978,\ 0.0037215052,\ 0.0036201498,\ 0.0036098238]
['materials', 'supplies', 'quantity', 'price', 'clean_subcategories_pos', 'equipment', 'use', 'wob
ble', 'teacher_number_of_previously_posted_projects_norm', 'paper', 'tools', 'chromebooks', 'books', 'educators', 'materials', 'stools', 'materials', 'worth', 'events', 'scholars']
                           Feature Importance For Positive Class
   0.008
   0.006
   0.004
   0.002
```

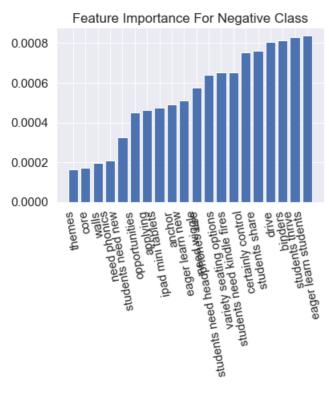


```
In [340]:
```

```
# collect n negative feature
# collect top n importance data
top_20_negative_data = []
collect_neg_indices = []
for i in indices neg:
    if (importances[i] > 0):
        top 20 negative data.append(importances[i])
        collect_neg_indices.append(i)
    if(len(top 20 negative data) >= n):
        break;
print(top 20 negative data)
print("*"*100)
# collect top n importance data
top 20 negative label = []
for i in collect_neg_indices:
    top 20 negative label.append(names neg[i])
print(top_20_negative_label)
print("*"*100)
# Barplot: Add bars
plt.bar(range(n), top_20_negative_data)
# Add feature names as x-axis labels
plt.xticks(range(n), top_20_negative_label , rotation=100, fontsize = 15)
# Create plot title
plt.title("Feature Importance For Negative Class")
# Show plot
plt.show()
[0.00016181421,\ 0.0001717893,\ 0.00019614046,\ 0.00020639696,\ 0.00032587635,\ 0.00044913276,
```

[0.00016181421, 0.0001717893, 0.00019614046, 0.00020639696, 0.00032587635, 0.00044913276, 0.00046302844, 0.0004734551, 0.0004897616, 0.00051184365, 0.0005776677, 0.0006421192, 0.0006526387, 0.0006545005, 0.0007516924, 0.0007634862, 0.0008068299, 0.00081551, 0.0008287739, 0.00083640416]

['themes', 'core', 'walls', 'need phonics', 'students need new', 'opportunities', 'applying', 'ipa d mini tablets', 'anchor', 'eager learn new', 'need wiggle', 'students need headphones use', 'variety seating options', 'students need kindle fires', 'certainly control', 'students share', 'd rive', 'binders', 'students thrive', 'eager learn students']



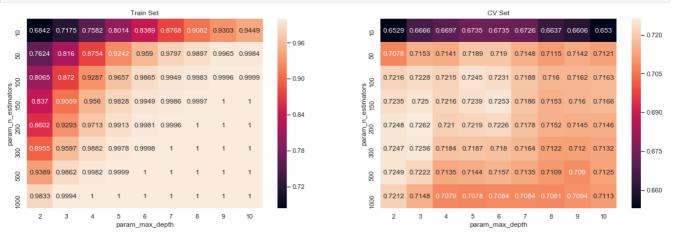
## 2.5.2 Applying XGBOOST on TFIDF, SET 2

```
In [117]:
%%time
# Please write all
```

```
# Please write all the code with proper documentation
 # Prepare data for TFIDF
X train tfidf = hstack((X train school state pos, X train school state neg,
X_train_clean_categories_pos, X_train_clean_categories_neg, X_train_clean_subcategories_pos,
X train clean subcategories_neg, X_train_project_grade_category_pos,
{\tt X\_train\_project\_grade\_category\_neg,~X\_train\_teacher\_prefix\_pos,~X\_train\_teacher\_prefix\_neg,}
{\tt X\_train\_title\_tfidf,\ X\_train\_essay\_tfidf,\ X\_train\_project\_resource\_summary\_tfidf,\ X\_train\_tfidf,\ X\_train\_tfidf,\ X\_train\_tfidf,\ X\_train\_tfidf,\ X\_trai
X train quantity norm, X train teacher number of previously posted projects norm,
X train price norm)).tocsr()
X cv tfidf = hstack((X cv school state pos, X cv school state neg, X cv clean categories pos,
X cv clean categories neg, X cv clean subcategories pos, X cv clean subcategories neg,
{\tt X\_cv\_project\_grade\_category\_pos,\ X\_cv\_project\_grade\_category\_neg,\ X\_cv\_teacher\_prefix\_pos,\ X\_cv\_teacher\_prefix\_pos
X_cv_teacher_prefix_neg, X_cv_title_tfidf, X_cv_essay_tfidf, X_cv_project_resource_summary_tfidf,
\label{thm:condition} \textbf{X}\_\texttt{cv}\_\texttt{quantity}\_\texttt{norm}, \ \textbf{X}\_\texttt{cv}\_\texttt{teacher}\_\texttt{number}\_\texttt{of}\_\texttt{previously}\_\texttt{posted}\_\texttt{projects}\_\texttt{norm}, \ \textbf{X}\_\texttt{cv}\_\texttt{price}\_\texttt{norm})). \texttt{tocs}
X test tfidf = hstack((X test school state pos, X test school state neg,
X_test_clean_categories_pos, X_test_clean_categories_neg, X_test_clean_subcategories_pos,
X_test_clean_subcategories_neg, X_test_project_grade_category_pos,
X test project grade category neg, X test teacher prefix pos, X test teacher prefix neg,
X_test_title_tfidf, X_test_essay_tfidf, X_test_project_resource_summary_tfidf,
X test quantity norm, X test teacher number of previously posted projects norm, X test price norm)
).tocsr()
print(X_train_tfidf.shape)
 print(X cv tfidf.shape)
print(X_test_tfidf.shape)
 import matplotlib.pyplot as plt
 from xgboost import XGBClassifier
 from sklearn.metrics import roc_auc_score
from sklearn.model_selection import learning curve, GridSearchCV
xgb = XGBClassifier(class_weight='balanced', n_jobs=-1)
parameters = {'n estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6, 7
 , 8, 9, 10]}
clf=GridSearchCV(xgb, parameters, cv=3, scoring='roc auc', n jobs=-1, return train score=True)
clf.fit(X train tfidf, y train)
(14711, 10072)
 (7247, 10072)
 (10816, 10072)
CPU times: user 37.8 s, sys: 410 ms, total: 38.2 s
Wall time: 22h 21min 12s
Out[117]:
GridSearchCV(cv=3, error score='raise-deprecating',
                                  estimator=XGBClassifier(base score=0.5, booster='gbtree',
                                                                                                  class weight='balanced',
                                                                                                 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),
                                  iid='warn', n jobs=-1,
                                  param grid={'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10],
                                                                  'n estimators': [10, 50, 100, 150, 200, 300, 500,
                                                                                                               1000]},
                                  pre dispatch='2*n jobs', refit=True, return train score=True,
                                  scoring='roc auc', verbose=0)
```

In [118]:

```
# Find best nyper parameter max_depth and min_samples_split
import seaborn as sns; sns.set()
max_scores = pd.DataFrame(clf.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_scores.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores.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 [119]:

```
# Print params
print(clf.best_estimator_)
print(clf.score(X_train_tfidf, y_train))
print(clf.score(X_test_tfidf, y_test))
```

0.8968451733475054 0.7184091200232278

## In [341]:

```
n_estimators = 200
max_depth = 3
```

## In [ ]:

```
%%time
# Create ROC Plot for Test Set
parameters = {'max_depth':[max_depth], 'n_estimators':[n_estimators]}
xgb=GridSearchCV(XGBClassifier(class_weight='balanced', n_estimators=n_estimators,
max_depth=max_depth, n_jobs=-1), parameters, cv=3, scoring='roc_auc', n_jobs=-1, return_train_score
=True)
xgb.fit(X_train_tfidf, y_train);
y train pred = clf.predict proba(X train tfidf)[:,1]
y test pred = clf.predict proba(X test tfidf)[:,1]
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("FALSE POSITIVE RATE (FPR)")
plt.ylabel("TRUE POSITIVE RATE (TPR)")
nl+ +i+le("ROC PLOTS")
```

```
plt.grid()
plt.show()
```

## In [125]:

```
%%time
get_confusion_matrix(xgb,X_train_tfidf,y_train)
```

CPU times: user 513 ms, sys: 24.2 ms, total: 538 ms

Wall time: 541 ms



## In [126]:

```
%%time
get_confusion_matrix(xgb,X_test_tfidf,y_test)
```

CPU times: user 431 ms, sys: 39.1 ms, total: 470 ms

Wall time: 494 ms



## In [342]:

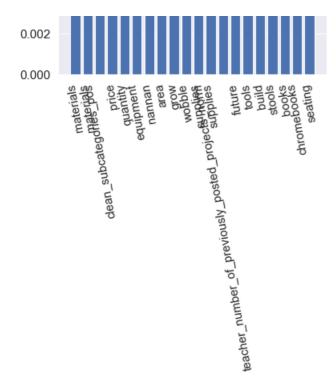
```
from xgboost import XGBClassifier
# Train a model on above hyperparameter to select best features
xgb_feature_selection = XGBClassifier(class_weight='balanced', n_estimators=n_estimators,
max_depth=max_depth, n_jobs=-1)
xgb_feature_selection.fit(X_train_tfidf, y_train)
xgb_feature_selection.feature_importances_
```

CPU times: user 47.8 s, sys: 425 ms, total: 48.2 s Wall time: 51.3 s  $\,$ 

## Out[342]:

```
array([0.00331598, 0. , 0.00140907, ..., 0.00608898, 0.00459591, 0.00659823], dtype=float32)
```

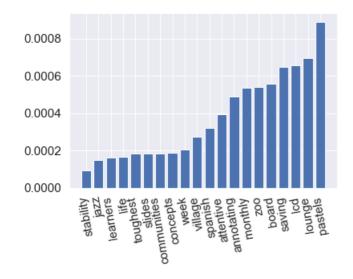
```
In [343]:
# https://stackoverflow.com/questions/44101458/random-forest-feature-importance-chart-using-python
# Calculate feature importances
importances = xgb feature selection.feature importances
# Sort feature importances in descending order
indices_pos = np.argsort(importances)[::-1]
# Sort feature importances in asccending order
indices neg = np.argsort(importances)[::1]
# Rearrange feature names so they match the sorted feature importances for positive class
names pos = [feature names tfidf[i] for i in indices pos]
# Rearrange feature names so they match the sorted feature importances for negative class
names neg = [feature names tfidf[i] for i in indices neg]
In [344]:
# process for top n features
In [345]:
# collect n positive feature
# collect top n importance data
top 20 positive data = []
for i in indices pos:
       top 20 positive_data.append(importances[i])
        if (len(top 20 positive data) >= n):
               break;
print(top_20_positive data)
print("*"*100)
# collect top n importance label
top_20_positive_label = names_pos[0:n]
print(top_20_positive_label)
print("*"*100)
# Barplot: Add bars
plt.bar(range(n), top 20 positive data)
# Add feature names as x-axis labels
plt.xticks(range(n), top 20 positive label , rotation=100, fontsize = 15)
# Create plot title
plt.title("Feature Importance For Positive Class")
# Show plot
plt.show()
0.0048559345, \ 0.004795042, \ 0.004702217, \ 0.00468814, \ 0.004605607, \ 0.004595907, \ 0.0045837476, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.0045907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.004595907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.0045907, \ 0.004
0.004491148, 0.0044378703, 0.004341614, 0.004304234, 0.004251539, 0.00422752]
['materials', 'materials', 'clean_subcategories_pos', 'price', 'quantity', 'equipment', 'nannan', 'area', 'grow', 'wobble', 'supplies',
'teacher_number_of_previously_posted_projects_norm', 'future', 'tools', 'build', 'stools',
'books', 'chromebooks', 'seating']
4
                   Feature Importance For Positive Class
 0.008
  0.006
  0.004
```



#### In [346]:

```
# collect n negative feature
# collect top n importance data
top 20 negative data = []
collect neg indices = []
for i in indices neg:
    if(importances[i] > 0):
        top 20 negative data.append(importances[i])
        collect neg indices.append(i)
    if (len(top 20 negative data) >= n):
        break;
print(top 20 negative data)
print("*"*100)
# collect top n importance data
top_20_negative_label = []
for i in collect_neg_indices:
    top 20 negative label.append(names neg[i])
print(top 20 negative label)
print("*"*100)
# Barplot: Add bars
plt.bar(range(n), top 20 negative data)
# Add feature names as x-axis labels
plt.xticks(range(n), top 20 negative label , rotation=100, fontsize = 15)
# Create plot title
plt.title("Feature Importance For Negative Class")
# Show plot
plt.show()
[9.292743e-05, 0.00015012757, 0.00016106894, 0.00016453672, 0.00018180761, 0.00018269985,
0.00018389258,\ 0.00018649247,\ 0.00020408655,\ 0.00027387298,\ 0.0003229957,\ 0.00039613864,
0.0004894801,\ 0.00053861097,\ 0.0005395893,\ 0.00055635575,\ 0.0006508971,\ 0.000658669,\ 0.0006948462,
0.0008917722]
['stability', 'jazz', 'learners', 'life', 'toughest', 'slides', 'communities', 'concepts', 'week',
'village', 'spanish', 'attentive', 'annotating', 'monthly', 'zoo', 'board', 'saving', 'lcd', 'lounge', 'pastels']
4
```

- | 33 ▶



## 2.5.3 Applying XGBOOST on AVG W2V, SET 3

GridSearchCV(cv=3, error score='raise-deprecating',

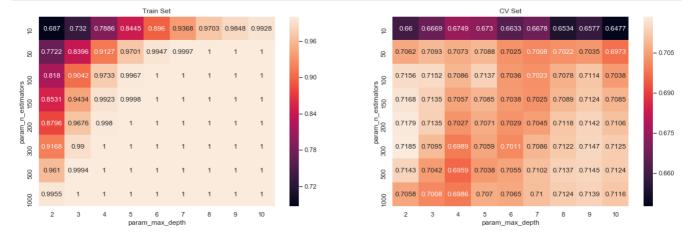
## In [120]:

```
%%time
# Please write all the code with proper documentation
# Prepare data for AVGW2V
X_train_avgw2v = hstack((X_train_school_state_pos, X_train_school_state_neg,
X_train_clean_categories_pos, X_train_clean_categories_neg, X_train_clean_subcategories_pos,
  _train_clean_subcategories_neg, X_train_project_grade_category_pos,
X_train_project_grade_category_neg, X_train_teacher_prefix_pos, X_train_teacher_prefix_neg,
avg w2v vectors text train, avg w2v vectors title train,
avg_w2v_vectors_project_resource_summary_train, X_train_quantity_norm,
{\tt X\_train\_teacher\_number\_of\_previously\_posted\_projects\_norm, \ {\tt X\_train\_price\_norm)).tocsr()}
X_cv_avgw2v = hstack((X_cv_school_state_pos, X_cv_school_state_neg, X_cv_clean_categories_pos,
X_cv_clean_categories_neg, X_cv_clean_subcategories_pos, X_cv_clean_subcategories_neg,
X cv project grade category pos, X cv project grade category neg, X cv teacher prefix pos,
X cv teacher prefix neg, avg w2v vectors text cv, avg w2v vectors title cv,
avg_w2v_vectors_project_resource_summary_cv, X_cv_quantity_norm,
X cv teacher number of previously posted projects norm, X cv price norm)).tocsr()
X_test_avgw2v = hstack((X_test_school_state_pos, X_test_school_state_neg,
X_test_clean_categories_pos, X_test_clean_categories_neg, X_test_clean_subcategories_pos,
X_test_clean_subcategories_neg, X_test_project_grade_category_pos,
{\tt X\_test\_project\_grade\_category\_neg,~X\_test\_teacher\_prefix\_pos,~X\_test\_teacher\_prefix\_neg,}
avg_w2v_vectors_text_test, avg_w2v_vectors_title_test,
avg_w2v_vectors_project_resource_summary_test, X_test_quantity_norm,
X_test_teacher_number_of_previously_posted_projects_norm, X_test_price_norm)).tocsr()
print(X_train_avgw2v.shape)
print(X cv avgw2v.shape)
print(X test avgw2v.shape)
import matplotlib.pyplot as plt
from xgboost import XGBClassifier
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import learning_curve, GridSearchCV
xgb = XGBClassifier(class_weight='balanced', n_jobs=-1)
parameters = { 'n estimators': [10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6, 7
, 8, 9, 10]}
clf=GridSearchCV(xgb, parameters, cv=3, scoring='roc auc', n jobs=-1, return train score=True)
clf.fit(X train avgw2v, y train)
(14711, 913)
(7247, 913)
(10816, 913)
CPU times: user 3min 43s, sys: 2.89 s, total: 3min 46s
Wall time: 1d 5h 58min 30s
Out[120]:
```

```
estimator=XGBClassifier(base score=0.5, booster='gbtree',
                        class_weight='balanced',
                        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),
iid='warn', n jobs=-1,
param_grid={'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10],
            'n estimators': [10, 50, 100, 150, 200, 300, 500,
                             1000]},
pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
scoring='roc auc', verbose=0)
```

## In [121]:

```
# Find best hyper parameter max_depth and min_samples_split
import seaborn as sns; sns.set()
max_scores = pd.DataFrame(clf.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_scores.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores.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 [122]:

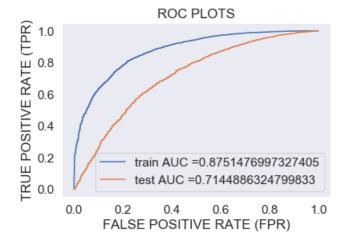
```
# Print params
print(clf.best_estimator_)
print(clf.score(X_train_avgw2v, y_train))
print(clf.score(X_test_avgw2v, y_test))
```

# 0.7144886324799833

## In [127]:

```
n_estimators = 300
max_depth = 2
```

```
%%time
# Create ROC Plot for Test Set
parameters = {'max_depth':[max_depth], 'n_estimators':[n_estimators]}
xqb=GridSearchCV(XGBClassifier(class weight='balanced', n estimators=n estimators,
max depth=max depth, n jobs=-1), parameters, cv=3, scoring='roc auc', n jobs=-1, return train score
=True)
xgb.fit(X train avgw2v, y train);
y_train_pred = clf.predict_proba(X_train_avgw2v)[:,1]
y test pred = clf.predict proba(X test avgw2v)[:,1]
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("FALSE POSITIVE RATE (FPR)")
plt.ylabel("TRUE POSITIVE RATE (TPR)")
plt.title("ROC PLOTS")
plt.grid()
plt.show()
```



CPU times: user 3min 29s, sys: 1.19 s, total: 3min 30s Wall time: 7min 30s

## In [129]:

```
%%time
get_confusion_matrix(xgb,X_train_avgw2v,y_train)
```

CPU times: user 3.23 s, sys: 210 ms, total: 3.44 s Wall time: 3.49 s  $\,$ 



## In [130]:

```
CPU times: user 2.53 s, sys: 135 ms, total: 2.66 s
Wall time: 3.08 s
                                              8000
            60
                             1573
9
                                              6000
Actual
                                              4000
            42
                             9141
                                              2000
Actual
       Predicted NO
                         Predicted YES
```

get confusion matrix(xgb,X test avgw2v,y test)

## 2.5.4 Applying XGBOOST on TFIDF W2V, SET 4

```
In [139]:
```

**66LIIII** 

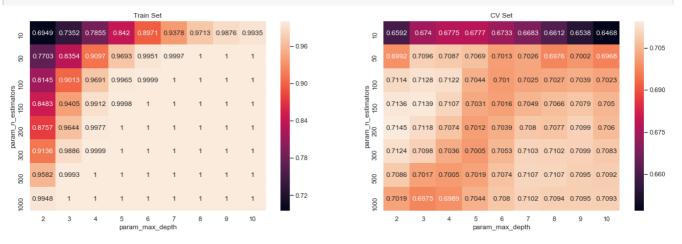
```
%%time
# Please write all the code with proper documentation
# Prepare data for TFIDFW2V
X train tfidfw2v = hstack((X train school state pos, X train school state neg, X train clean categ
ories_pos, X_train_clean_categories_neg, X_train_clean_subcategories_pos,
X train clean subcategories neg, X train project grade category pos,
X train project grade category neg, X train teacher prefix pos, X train teacher prefix neg,
tfidf w2v vectors text train, tfidf w2v vectors title train,
tfidf w2v vectors project resource summary train, X train quantity norm,
X_train_teacher_number_of_previously_posted_projects_norm, X_train_price_norm)).tocsr()
X_cv_tfidfw2v = hstack((X_cv_school_state_pos, X_cv_school_state_neg, X_cv_clean_categories_pos,
X_cv_clean_categories_neg, X_cv_clean_subcategories_pos, X_cv_clean_subcategories_neg,
X_cv_project_grade_category_pos, X_cv_project_grade_category_neg, X_cv_teacher_prefix_pos,
X cv teacher prefix neg, tfidf w2v vectors text cv, tfidf w2v vectors title cv,
tfidf_w2v_vectors_project_resource_summary_cv, X_cv_quantity_norm,
\label{thm:condition} X\_{cv\_teacher\_number\_of\_previously\_posted\_projects\_norm,\ X\_{cv\_price\_norm)).tocsr()}
X test tfidfw2v = hstack((X test school state pos, X test school state neg,
X_test_clean_categories_pos, X_test_clean_categories_neg, X_test_clean_subcategories_pos,
X_test_clean_subcategories_neg, X_test_project_grade_category_pos,
X test project grade category neg, X test teacher prefix pos, X test teacher prefix neg,
tfidf_w2v_vectors_text_test, tfidf_w2v_vectors_title_test,
tfidf w2v vectors project resource summary test, X test quantity norm,
X test teacher number of previously posted projects norm, X test price norm)).tocsr()
print(X_train_tfidfw2v.shape)
print(X_cv_tfidfw2v.shape)
print(X test tfidfw2v.shape)
import matplotlib.pyplot as plt
from xgboost import XGBClassifier
from sklearn.metrics import roc auc score
from sklearn.model selection import learning curve, GridSearchCV
xgb = XGBClassifier(class weight='balanced', n jobs=-1)
parameters = {'n estimators':[10, 50, 100, 150, 200, 300, 500, 1000], 'max depth': [2, 3, 4, 5, 6, 7
, 8, 9, 10]}
clf=GridSearchCV(xgb, parameters, cv=3, scoring='roc auc', n jobs=-1, return train score=True)
clf.fit(X train tfidfw2v, y train)
4
(14711, 913)
(7247, 913)
(10816, 913)
CPU times: user 2min 27s, sys: 1.97 s, total: 2min 29s
Wall time: 13h 31min 26s
```

```
Out[139]:
```

```
GridSearchCV(cv=3, error score='raise-deprecating',
             estimator=XGBClassifier(base score=0.5, booster='gbtree',
                                     class weight='balanced',
                                     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),
             iid='warn', n jobs=-1,
             param_grid={'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10],
                         'n_estimators': [10, 50, 100, 150, 200, 300, 500,
                                          1000]},
             pre dispatch='2*n jobs', refit=True, return train score=True,
             scoring='roc auc', verbose=0)
```

## In [140]:

```
# Find best hyper parameter max_depth and min_samples_split
import seaborn as sns; sns.set()
max_scores = pd.DataFrame(clf.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_scores.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores.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 [141]:

```
# Print params
print(clf.best_estimator_)
print(clf.score(X_train_tfidfw2v, y_train))
print(clf.score(X_test_tfidfw2v, y_test))
```

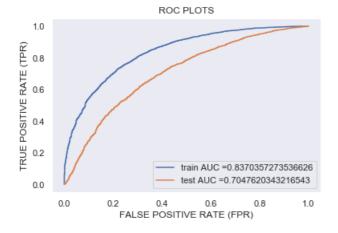
0.7047620343216543

## In [142]:

```
n_estimators = 200
max_depth = 2
```

## In [143]:

```
%%time
# Create ROC Plot for Test Set
parameters = {'max_depth':[max_depth], 'n_estimators':[n_estimators]}
max_depth=max_depth, n_jobs=-1), parameters, cv=3, scoring='roc_auc', n_jobs=-1, return_train_score
xgb.fit(X train tfidfw2v, y train);
y_train_pred = clf.predict_proba(X_train_tfidfw2v)[:,1]
y test pred = clf.predict proba(X test tfidfw2v)[:,1]
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("FALSE POSITIVE RATE (FPR)")
plt.ylabel("TRUE POSITIVE RATE (TPR)")
plt.title("ROC PLOTS")
plt.grid()
plt.show()
```



CPU times: user 2min 32s, sys: 1.55 s, total: 2min 34s Wall time: 5min 49s

## In [144]:

```
%%time
get_confusion_matrix(xgb,X_train_tfidfw2v,y_train)
```

CPU times: user 3.37 s, sys: 226 ms, total: 3.6 s

Wall time: 3.89 s



```
In [145]:
```

```
get_confusion_matrix(xgb,X_test_tfidfw2v,y_test)
```

```
CPU times: user 2.49 s, sys: 129 ms, total: 2.62 s
```

Wall time: 2.69 s



# 3. Conclusion

## In [348]:

```
# 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
x = PrettyTable()
x.field_names = ["Vectorizer", "Model", "N Estimators", "Max Depth", "AUC"]
x.add\_row(["Bag of Words", "Random Forest", 500, 10, 0.70])
x.add_row(["TFIDF", "Random Forest", 1000, 10, .71])
x.add_row(["AVG W2V", "Random Forest", 1000, 7, .70])
x.add row(["TFIDF W2V", "Random Forest", 1000, 6, .69])
x.add row(["Bag of Words", "XGBOOST", 500, 2, .72])
x.add_row(["TFIDF", "XGBOOST", 200, 3, .72])
x.add row(["AVG W2V", "XGBOOST", 300, 2, .71])
x.add row(["TFIDF W2V", "XGBOOST", 200, 2, 0.70])
print(x)
```

+   Vectorizer	·	N Estimators		
Bag of Words   TFIDF   AVG W2V   TFIDF W2V	Random Forest   Random Forest   Random Forest   Random Forest	+   500   1000	10 10 10 7 6	
Bag of Words   TFIDF   AVG W2V   TFIDF W2V	XGBOOST   XGBOOST   XGBOOST   XGBOOST	500   200   300   200	2 3 2 2	0.72     0.72     0.71     0.7

In [ ]: