

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
<code>project_id</code>	A unique identifier for the proposed project. Example: p036502
<code>project_title</code>	Title of the project. Examples: Art Will Make You Happy! First Grade Fun
<code>project_grade_category</code>	Grade level of students for which the project is targeted. One of the following enumerated values: Grades PreK-2 Grades 3-5 Grades 6-8 Grades 9-12
<code>project_subject_categories</code>	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 Math & Science Music & The Arts Special Needs Warmth
<code>project_subject_subcategories</code>	Examples: Music & The Arts Literacy & Language, Math & Science
<code>school_state</code>	State where school is located (Two-letter U.S. postal code (https://en.wikipedia.org/wiki/List_of_U.S._state_abbreviations#Postal_codes)). Example: WY
<code>project_resource_summary</code>	One or more (comma-separated) subject subcategories for the project. Examples: Literacy Literature & Writing, Social Sciences
<code>project_essay_1</code>	An explanation of the resources needed for the project. Example: My students need hands on literacy materials to manage sensory needs!
<code>project_essay_2</code>	First application essay*
<code>project_essay_3</code>	Second application essay*
<code>project_essay_4</code>	Third application essay*
<code>project_submitted_datetime</code>	Fourth application essay*
<code>teacher_id</code>	Datetime when project application was submitted. Example: 2016-04-28 12:43:56.245
<code>teacher_prefix</code>	A unique identifier for the teacher of the proposed project. Example: bdf8baa8fedef6bfeec7ae4ff1c15c56
<code>teacher_number_of_previously_posted_projects</code>	Teacher's title. One of the following enumerated values: nan Dr. Mr. Mrs. Ms. Teacher.

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

Note: Many projects require multiple resources. The `id` value corresponds to a `project_id` 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
<code>project_is_approved</code>	A binary flag indicating whether DonorsChoose approved the project. A value of <code>0</code> indicates the project was not approved, and a value of <code>1</code> indicates the project was approved.

Notes on the Essay Data

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

- `__project_essay_1__`: "Introduce us to your classroom"
- `__project_essay_2__`: "Tell us more about your students"
- `__project_essay_3__`: "Describe how your students will use the materials you're requesting"
- `__project_essay_3__`: "Close by sharing why your project will make a difference"

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

- `__project_essay_1__`: "Describe your students: What makes your students special? Specific details about their background, your neighborhood, and your school are all helpful."
- `__project_essay_2__`: "About your project: How will these materials make a difference in your students' learning and improve their school lives?"

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

```
In [1]: %matplotlib inline
import warnings
warnings.filterwarnings("ignore")

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

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

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

from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle

from tqdm import tqdm
import os

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 [2]: project_data = pd.read_csv('../train_data.csv')
resource_data = pd.read_csv('../resources.csv')
```

```
In [3]: print("Number of data points in train data", project_data.shape)
print('-'*50)
print("The attributes of data :", project_data.columns.values)
```

Number of data points in train data (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 [4]: print("Number of data points in train data", resource_data.shape)
print(resource_data.columns.values)
resource_data.head(2)
```

```
Number of data points in train data (1541272, 4)
['id' 'description' 'quantity' 'price']
```

Out[4]:

	id	description	quantity	price
0	p233245	LC652 - Lakeshore Double-Space Mobile Drying Rack	1	149.00
1	p069063	Bouncy Bands for Desks (Blue support pipes)	3	14.95

1.2 Preprocessing Categorical Data

1.2.1 preprocessing project_subject_categories

```
In [5]: categories = 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 categories:
    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 & Hunger"]
        if 'The' in j.split(): # this will split each of the category based on space "Math & Science"=> "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 placing all the ' ' (space) with '' (empty) ex: "Math & Science"=> "Math&Science"
        temp+=j.strip()+" " # " abc ".strip() will return "abc", remove the trailing spaces
        temp = temp.replace('&', '_') # we are replacing the & value into _
    cat_list.append(temp.strip())

project_data['clean_categories'] = cat_list
project_data.drop(['project_subject_categories'], axis=1, inplace=True)

from collections import Counter
my_counter = Counter()
for word in project_data['clean_categories'].values:
    my_counter.update(word.split())

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

```
In [6]: sorted_cat_dict.keys()
```

```
Out[6]: dict_keys(['Warmth', 'Care_Hunger', 'History_Civics', 'Music_Arts', 'AppliedLearning', 'SpecialNeeds', 'Health_Sports', 'Math_Science', 'Literacy_Language'])
```

1.2.2 preprocessing of project_subject_subcategories

```
In [7]: sub_categories = 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_categories:
    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 & Hunger"]
        if 'The' in j.split(): # this will split each of the category based on space "Math & Science"=> "Math", "&",
"Science"
            j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i.e removing 'Th
e')
        j = j.replace(' ','') # we are placing all the ' '(space) with ''(empty) ex:"Math & Science"=>"Math&Scienc
e"
        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]))
```

```
In [8]: sorted_sub_cat_dict.keys()
```

```
Out[8]: dict_keys(['Economics', 'CommunityService', 'Financialliteracy', 'ParentInvolvement', 'Extracurricular', 'Civics_G
overnment', 'ForeignLanguages', 'NutritionEducation', 'Warmth', 'Care_Hunger', 'SocialSciences', 'PerformingArts',
'CharacterEducation', 'TeamSports', 'Other', 'College_CareerPrep', 'Music', 'History_Geography', 'Health_LifeScien
ce', 'EarlyDevelopment', 'ESL', 'Gym_Fitness', 'EnvironmentalScience', 'VisualArts', 'Health_Wellness', 'AppliedSc
iences', 'SpecialNeeds', 'Literature_Writing', 'Mathematics', 'Literacy'])
```

1.2.3 preprocessing of School State

```
In [9]: project_data['school_state'].unique()
```

```
Out[9]: array(['IN', 'FL', 'AZ', 'KY', 'TX', 'CT', 'GA', 'SC', 'NC', 'CA', 'NY',
'OK', 'MA', 'NV', 'OH', 'PA', 'AL', 'LA', 'VA', 'AR', 'WA', 'WV',
'ID', 'TN', 'MS', 'CO', 'UT', 'IL', 'MI', 'HI', 'IA', 'RI', 'NJ',
'MO', 'DE', 'MN', 'ME', 'WY', 'ND', 'OR', 'AK', 'MD', 'WI', 'SD',
'NE', 'NM', 'DC', 'KS', 'MT', 'NH', 'VT'], dtype=object)
```

```
In [10]: project_data['school_state'][project_data['school_state'].isnull()==True]
```

```
Out[10]: Series([], Name: school_state, dtype: object)
```

```
In [11]: # count of all the words in corpus python: https://stackoverflow.com/a/22898595/4084039
my_counter = Counter()
for word in project_data['school_state'].values:
    my_counter.update(word.split())

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

```
In [12]: sorted_school_state_dict.keys()
```

```
Out[12]: dict_keys(['VT', 'WY', 'ND', 'MT', 'RI', 'SD', 'NE', 'DE', 'AK', 'NH', 'WV', 'ME', 'HI', 'DC', 'NM', 'KS', 'IA',
'ID', 'AR', 'CO', 'MN', 'OR', 'KY', 'MS', 'NV', 'MD', 'CT', 'TN', 'UT', 'AL', 'WI', 'VA', 'AZ', 'NJ', 'OK', 'WA',
'MA', 'LA', 'OH', 'MO', 'IN', 'PA', 'MI', 'SC', 'GA', 'IL', 'NC', 'FL', 'NY', 'TX', 'CA'])
```

1.2.4 preprocessing of Teacher Prefix

```
In [13]: project_data.groupby(['teacher_prefix'])['teacher_prefix'].count()
```

```
Out[13]: teacher_prefix
Dr.      13
Mr.     10648
Mrs.     57269
Ms.      38955
Teacher  2360
Name: teacher_prefix, dtype: int64
```

```
In [14]: project_data['teacher_prefix'][project_data['teacher_prefix'].isnull()==True]
```

```
Out[14]: 7820      NaN
30368      NaN
57654      NaN
Name: teacher_prefix, dtype: object
```

```
In [15]: project_data['teacher_prefix'].fillna(project_data['teacher_prefix'].mode()[0],inplace=True)
```

```
In [16]: project_data['teacher_prefix'][project_data['teacher_prefix'].isnull()==True]
```

```
Out[16]: Series([], Name: teacher_prefix, dtype: object)
```

```
In [17]: project_data['teacher_prefix'].unique()
```

```
Out[17]: array(['Mrs.', 'Mr.', 'Ms.', 'Teacher', 'Dr.'], dtype=object)
```

```
In [18]: teacher_prefix = list(project_data['teacher_prefix'].values)

teacher_prefix_list = []
for i in teacher_prefix:
    temp = ""
    temp = i.split('.')
    temp = i.replace('.', '')
    teacher_prefix_list.append(temp)

project_data['clean_teacher_prefix'] = teacher_prefix_list
project_data.drop(['teacher_prefix'], 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_teacher_prefix'].values:
    my_counter.update(word.split())

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

```
In [19]: sorted_teacher_prefix_dict.keys()
```

```
Out[19]: dict_keys(['Dr', 'Teacher', 'Mr', 'Ms', 'Mrs'])
```

```
In [20]: project_data.groupby(['clean_teacher_prefix'])['clean_teacher_prefix'].count()
```

```
Out[20]: clean_teacher_prefix
Dr      13
Mr      10648
Mrs      57272
Ms      38955
Teacher  2360
Name: clean_teacher_prefix, dtype: int64
```

1.2.5 preprocessing of Project Grade Category

```
In [21]: project_data.groupby(['project_grade_category'])['project_grade_category'].count()
```

```
Out[21]: project_grade_category
Grades 3-5      37137
Grades 6-8      16923
Grades 9-12     10963
Grades PreK-2   44225
Name: project_grade_category, dtype: int64
```

```
In [22]: project_data['project_grade_category'][project_data['project_grade_category'].isnull()==True]
```

```
Out[22]: Series([], Name: project_grade_category, dtype: object)
```

```
In [23]: project_grade_category = list(project_data['project_grade_category'].values)

project_grade_category_list = []
for i in project_grade_category:
    temp = ""
    temp = i.split(' ')
    temp = i.replace('Grades ', '')
    project_grade_category_list.append(temp)

project_data['clean_project_grade_category'] = project_grade_category_list
project_data.drop(['project_grade_category'], 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_project_grade_category'].values:
    my_counter.update(word.split())

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

```
In [24]: sorted_project_grade_category_dict.keys()
```

```
Out[24]: dict_keys(['9-12', '6-8', '3-5', 'PreK-2'])
```

```
In [25]: project_data.groupby(['clean_project_grade_category'])['clean_project_grade_category'].count()
```

```
Out[25]: clean_project_grade_category
3-5      37137
6-8      16923
9-12     10963
PreK-2   44225
Name: clean_project_grade_category, dtype: int64
```

```
In [ ]:
```

1.3 Text preprocessing

```
In [26]: # merge two column text dataframe:
project_data["essay"] = project_data["project_essay_1"].map(str) + \
    project_data["project_essay_2"].map(str) + \
    project_data["project_essay_3"].map(str) + \
    project_data["project_essay_4"].map(str)
```

```
In [27]: project_data.head(2)
```

```
Out[27]:
```

	Unnamed: 0	id	teacher_id	school_state	project_submitted_datetime	project_title	project_essay_1	project_essay_2	project_essay_3	project_essay_4
0	160221	p253737	c90749f5d961ff158d4b4d1e7dc665fc	IN	2016-12-05 13:43:57	Educational Support for English Learners at Home	My students are English learners that are work...	"The limit of your language are the limit of your thinking"		
1	140945	p258326	897464ce9ddc600bcd1151f324dd63a	FL	2016-10-25 09:22:10	Wanted: Projector for Hungry Learners	Our students arrive to our school eager to learn...	The project need for school is very important		

```
In [28]: ##### 1.4.2.3 Using Pretrained Models: TFIDF weighted W2V
```

```
In [29]: # printing some random reviews
print(project_data['essay'].values[0])
print("="*50)
print(project_data['essay'].values[150])
print("="*50)
print(project_data['essay'].values[1000])
print("="*50)
print(project_data['essay'].values[20000])
print("="*50)
print(project_data['essay'].values[99999])
print("="*50)
```


My students are English learners that are working on English as their second or third languages. We are a melting pot of refugees, immigrants, and native-born Americans bringing the gift of language to our school. We have over 24 languages represented in our English Learner program with students at every level of mastery. We also have over 40 countries represented with the families within our school. Each student brings a wealth of knowledge and experiences to us that open our eyes to new cultures, beliefs, and respect. "The limits of your language are the limits of your world." -Ludwig Wittgenstein Our English learner's have a strong support system at home that helps for more resources. Many times our parents are learning to read and speak English along side of their children. Sometimes this creates barriers for parents to be able to help their child learn phonetics, letter recognition, and other reading skills. By providing these dvd's and players, students are able to continue their mastery of the English language even if no one at home is able to assist. All families with students within the Level 1 proficiency status, will be offered to be a part of this program. These educational videos will be specially chosen by the English Learner Teacher and will be sent home regularly to watch. The videos are to help the child develop early reading skills. Parents that do not have access to a dvd player will have the opportunity to check out a dvd player to use for the year. The plan is to use these videos and educational dvd's for the years to come for other EL students.

The 51 fifth grade students that will cycle through my classroom this year all love learning, at least most of the time. At our school, 97.3% of the students receive free or reduced price lunch. Of the 560 students, 97.3% are minority students. The school has a vibrant community that loves to get together and celebrate. Around Halloween there is a whole school parade to show off the beautiful costumes that students wear. On Cinco de Mayo we put on a big festival with crafts made by the students, dances, and games. At the end of the year the school hosts a carnival to celebrate the hard work put in during the school year, with a dunk tank being the most popular activity. My students will use these five brightly colored Hokki stools in place of regular, stationary, 4-legged chairs. As I will only have a total of ten in the classroom and not enough for each student to have an individual one, they will be used in a variety of ways. During independent reading time they will be used as special chairs students will each use on occasion. I will utilize them in place of chairs at my small group tables during math and reading times. The rest of the day they will be used by the students who need the highest amount of movement in their life in order to stay focused on school. Whenever asked what the classroom is missing, my students always say more Hokki Stools. They can't get their fill of the 5 stools we already have. When the students are sitting in group with me on the Hokki Stools, they are always moving, but at the same time doing their work. Anytime the students get to pick where they can sit, the Hokki Stools are the first to be taken. There are always students who head over to the kidney table to get one of the stools who are disappointed as there are not enough of them. We ask a lot of students to sit for 7 hours a day. The Hokki stools will be a compromise that allow my students to do desk work and move at the same time. These stools will help students to meet their 60 minutes a day of movement by allowing them to activate their core muscles for balance while they sit. For many of my students, these chairs will take away the barrier that exists in schools for a child who can't sit still.

How do you remember your days of school? Was it in a sterile environment with plain walls, rows of desks, and a teacher in front of the room? A typical day in our room is nothing like that. I work hard to create a warm inviting themed room for my students look forward to coming to each day. My class is made up of 28 wonderfully unique boys and girls of mixed races in Arkansas. They attend a Title I school, which means there is a high enough percentage of free and reduced-price lunch to qualify. Our school is an "open classroom" concept, which is very unique as there are no walls separating the classrooms. These 9 and 10 year-old students are very eager learners; they are like sponges, absorbing all the information and experiences and keep on wanting more. With these resources such as the comfy red throw pillows and the whimsical nautical hanging decor and the blue fish nets, I will be able to help create the mood in our classroom setting to be one of a themed nautical environment. Creating a classroom environment is very important in the success in each and every child's education. The nautical photo props will be used with each child as they step foot into our classroom for the first time on Meet the Teacher evening. I'll take pictures of each child with them, have them developed, and then hung in our classroom ready for their first day of 4th grade. This kind gesture will set the tone before even the first day of school! The nautical thank you cards will be used throughout the year by the students as they create thank you cards to their team groups. Your generous donations will help me to help make our classroom a fun, inviting, learning environment from day one. It costs lost of money out of my own pocket on resources to get our classroom ready. Please consider helping with this project to make our new school year a very successful one. Thank you!

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

The mediocre teacher tells. The good teacher explains. The superior teacher demonstrates. The great teacher inspires. -William A. Ward My school has 803 students which is makeup is 97.6% African-American, making up the largest segment of the student body. A typical school in Dallas is made up of 23.2% African-American students. Most of the students are on free or reduced lunch. We aren't receiving doctors, lawyers, or engineers children from rich backgrounds or neighborhoods. As an educator I am inspiring minds of young children and we focus not only on academics but one smart, effective, efficient, and disciplined students with good character. In our classroom we can utilize the Bluetooth for swift transitions during class. I use a speaker which doesn't amplify the sound enough to receive the message. Due to the volume of my speaker my students can't hear videos or books clearly and it isn't making the lessons as meaningful. But with the bluetooth speaker my students will be able to hear and I can stop, pause and replay it at any time. The cart will allow me to have more room for storage of things that are needed for the day and has an extra part to it I can use. The table top chart has all of the letter, words and pictures for students to learn about different letters and it is more accessible.

```
In [30]: # 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 [31]: sent = decontracted(project_data['essay'].values[20000])
print(sent)
print("="*50)
```

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

=====

```
In [32]: # \r \n \t remove from string python: http://texthandler.com/info/remove-Line-breaks-python/
sent = sent.replace('\r', ' ')
sent = sent.replace('\n', ' ')
sent = sent.replace('\t', ' ')
print(sent)
```

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

```
In [33]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
print(sent)
```

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

```
In [34]: # 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', 'afte
r', \
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'furt
her', \
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'm
ore', \
            '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', 'r
e', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "doesn't", 'hadn', \
            \
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn', "mightn't", 'mustn', \
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn', "wasn't", 'weren', "we
ren't", \
            'won', "won't", 'wouldn', "wouldn't"]
```

```
In [35]: # Combining all the above students
from tqdm import tqdm
preprocessed_essays = []
# tqdm is for printing the status bar
for sentence in tqdm(project_data['essay'].values):
    sent = decontracted(sentence)
    sent = sent.replace('\\r', ' ')
    sent = sent.replace('\\n', ' ')
    sent = sent.replace('\\t', ' ')
    sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
    # https://gist.github.com/sebleier/554280
    sent = ' '.join(e for e in sent.split() if e not in stopwords)
    preprocessed_essays.append(sent.lower().strip())
```

```
In [36]: # after preprocessing
preprocessed_essays[20000]
```

```
Out[36]: 'my kindergarten students varied disabilities ranging speech language delays cognitive delays gross fine motor del
ays autism they eager beavers always strive work hardest working past limitations the materials ones i seek studen
ts i teach title i school students receive free reduced price lunch despite disabilities limitations students love
coming school come eager learn explore have ever felt like ants pants needed groove move meeting this kids feel ti
me the want able move learn say wobble chairs answer i love develop core enhances gross motor turn fine motor skill
ls they also want learn games kids not want sit worksheets they want learn count jumping playing physical engageme
nt key success the number toss color shape mats make happen my students forget work fun 6 year old deserves nanna
n'
```

```
In [37]: project_data['preprocessed_essays'] = preprocessed_essays
project_data.drop(['essay'], axis=1, inplace=True)
```

1.4 Preprocessing of `project_title`

```
In [38]: # similarly you can preprocess the titles also
```

```
In [39]: project_data['project title'][2000:2010]
```

```
Out[39]: 2000          Steady Stools for Active Learning
          2001          Classroom Supplies
          2002  Kindergarten Students Deserve Quality Books a...
          2003          Listen to Understand!
          2004          iPads to iGnite Learning
          2005          Tablets For Learning
          2006          Go P.E.!
          2007          Making Learning Fun!
          2008  Empowerment Through Silk Screen Designed Tee S...
          2009          Let's Play Together!
          Name: project title, dtype: object
```

```
In [40]: # Combining all the above statements
from tqdm import tqdm
preprocessed_titles = []
# tqdm is for printing the status bar
for sentence in tqdm(project_data['project_title'].values):
    sent = decontracted(sentence)
    sent = sent.replace('\\r', ' ')
    sent = sent.replace('\\\"', ' ')
    sent = sent.replace('\\n', ' ')
    sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
    # https://gist.github.com/sebleier/554280
    sent = ' '.join(e for e in sent.split() if e not in stopwords)
    preprocessed_titles.append(sent.lower().strip())
```

```
In [41]: preprocessed_titles[2000:2010]
```

```
In [42]: project_data['preprocessed_titles'] = preprocessed_titles
project_data.drop(['project_title'], axis=1, inplace=True)
```

```
In [43]: project_data.columns
```

we are going to consider

1.5.1 Vectorizing Categorical data

```
# we use count vectorizer to convert the values into one from sklearn.feature_extraction.text import CountVectorizer
vectorizer = CountVectorizer(vocabulary=list(sorted_cat_dict.keys()), lowercase=False, binary=True)
categories_one_hot = vectorizer.fit_transform(project_data[\"clean_categories\"].values)
print(vectorizer.get_feature_names())
print(\"Shape of matrix after one hot encoding\", categories_one_hot.shape)
# we use count vectorizer to convert the values into one
vectorizer = CountVectorizer(vocabulary=list(sorted_sub_cat_dict.keys()), lowercase=False, binary=True)
sub_categories_one_hot = vectorizer.fit_transform(project_data[\"clean_subcategories\"].values)
```

```
print(vectorizer.get_feature_names()) print("Shape of matrix after one hot encoding ", sub_categories_one_hot.shape) # you can do the similar thing with state, teacher_prefix and project_grade_category also
```

1.5.2 Vectorizing Text data

1.5.2.1 Bag of words

We are considering only the words which appeared in at least 10 documents (rows or projects).
vectorizer = CountVectorizer(min_df=10) text_bow = vectorizer.fit_transform(preprocessed_essays) print("Shape of matrix after one hot encoding ", text_bow.shape) # you can vectorize the title also # before you vectorize the title make sure you preprocess it

1.5.2.2 TFIDF vectorizer

```
from sklearn.feature_extraction.text import TfidfVectorizer vectorizer = TfidfVectorizer(min_df=10) text_tfidf = vectorizer.fit_transform(preprocessed_essays) print("Shape of matrix after one hot encoding ", text_tfidf.shape)
```

1.5.2.3 Using Pretrained Models: Avg W2V

```
# 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 preprocod_texts: words.extend(i.split(' ')) for i in preprocod_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), "(" + str(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-save-and-load-variables-in-python/ import pickle with open('glove_vectors', 'wb') as f: pickle.dump(words_courpus, f) # stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-save-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()) # average Word2Vec # compute average word2vec for each review. avg_w2v_vectors = []; # the avg-w2v for each sentence/review is stored in this list for sentence in tqdm(preprocessed_essays): # for each review/sentence vector = np.zeros(300) # as word vectors are of zero length cnt_words = 0; # num of words with a valid vector in the sentence/review for word in sentence.split(): # for each word in a review/sentence if word in glove_words: vector += model[word] cnt_words += 1 if cnt_words != 0: vector /= cnt_words avg_w2v_vectors.append(vector) print(len(avg_w2v_vectors)) print(len(avg_w2v_vectors[0]))
```

1.5.2.3 Using Pretrained Models: TFIDF weighted W2V

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"] tfidf_model = TfidfVectorizer() tfidf_model.fit(preprocessed_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()) # average Word2Vec # compute average word2vec for each review. tfidf_w2v_vectors = []; # the avg-w2v for each sentence/review is stored in this list for sentence in tqdm(preprocessed_essays): # for each review/sentence vector = np.zeros(300) # as word vectors are of zero length tf_idf_weight = 0; # num of words with a valid vector in the sentence/review for word in sentence.split(): # for each word in a review/sentence if (word in glove_words) and (word in tfidf_words): vec = model[word] # getting the vector for each word # here we are multiplying idf value(dictionary[word]) and the tf value((sentence.count(word)/len(sentence.split())))) tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf 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.append(vector) print(len(tfidf_w2v_vectors)) print(len(tfidf_w2v_vectors[0])) # Similarly you can vectorize for title also
```

1.5.3 Vectorizing Numerical features

```
price_data = resource_data.groupby("id").agg({'price':'sum', 'quantity':'sum'}).reset_index() project_data = pd.merge(project_data, price_data, on='id', how='left') # check this one: https://www.youtube.com/watch?v=0HOqOcln3Z4&t=530s # standardization sklearn: https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html from sklearn.preprocessing import StandardScaler # price_standardized = standardScaler.fit(project_data['price'].values) # this will rise the error # ValueError: Expected 2D array, got 1D array instead: array=[725.05 213.03 329. ... 399.287.73 5.5 ]. # Reshape your data either using array.reshape(-1, 1) price_scalar = StandardScaler() price_scalar.fit(project_data['price'].values.reshape(-1,1)) # finding the mean and standard deviation of this data print(f"Mean : {price_scalar.mean_[0]}, Standard deviation : {np.sqrt(price_scalar.var_[0])}") # Now standardize the data with above maen and variance. price_standardized = price_scalar.transform(project_data['price'].values.reshape(-1, 1)) price_standardized
```

1.5.4 Merging all the above features

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

```
print(categories_one_hot.shape) print(sub_categories_one_hot.shape) print(text_bow.shape) print(price_standardized.shape) # 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 matrix :) X = hstack((categories_one_hot, sub_categories_one_hot, text_bow, price_standardized)) X.shape
```

In []:

1.6 Merging Numerical data in Resources to project_data

```
In [44]: price_data = resource_data.groupby('id').agg({'price':'sum', 'quantity':'sum'}).reset_index()
project_data = pd.merge(project_data, price_data, on='id', how='left')
```

```
In [ ]:
```

```
In [ ]:
```

Computing Sentiment Scores

```
In [45]: 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 with the biggest e
nthusiasm \
for learning my students learn in many different ways using all of our senses and multiple intelligences i use a wi
de range\
of techniques to help all my students succeed students in my class come from a variety of different backgrounds whi
ch makes\
for wonderful sharing of experiences and cultures including native americans our school is a caring community of su
ccessful \
learners which can be seen through collaborative student project based learning in and out of the classroom kinderg
arteners \
in my class love to work with hands on materials and have many different opportunities to practice a skill before i
t is\
mastered having the social skills to work cooperatively with friends is a crucial aspect of the kindergarten curric
ulum\
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 h
ealthy \
food for snack time my students will have a grounded appreciation for the work that went into making the food and k
nowledge \
of where the ingredients came from as well as how it is healthy for their bodies this project would expand our lear
ning of \
nutrition and agricultural cooking recipes by having us peel our own apples to make homemade applesauce make our ow
n bread \
and mix up healthy plants from our classroom garden in the spring we will also create our own cookbooks to be print
ed and \
shared with families students will gain math and literature skills as well as a life long enjoyment for healthy coo
king \
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,
```

```
In [ ]:
```

Assignment 9: RF and GBDT

Response Coding: Example



The response label 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, 0.5]

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

- **Set 1:** categorical (instead of one hot encoding, try [response coding](https://www.appliedaiaicourse.com/course/applied-ai-course-online/lessons/handling-categorical-and-numerical-features/)): use probability values), numerical features + project_title(BOW) + preprocessed_eassay (BOW)
- **Set 2:** categorical (instead of one hot encoding, try [response coding](https://www.appliedaiaicourse.com/course/applied-ai-course-online/lessons/handling-categorical-and-numerical-features/)): use probability values), numerical features + project_title(TFIDF)+ preprocessed_eassay (TFIDF)
- **Set 3:** categorical (instead of one hot encoding, try [response coding](https://www.appliedaiaicourse.com/course/applied-ai-course-online/lessons/handling-categorical-and-numerical-features/)): use probability values), numerical features + project_title(AVG W2V)+ preprocessed_eassay (AVG W2V). Here for this set take **20K** datapoints only.
- **Set 4:** categorical (instead of one hot encoding, try [response coding](https://www.appliedaiaicourse.com/course/applied-ai-course-online/lessons/handling-categorical-and-numerical-features/)): use probability values), numerical features + project_title(TFIDF W2V)+ preprocessed_eassay (TFIDF W2V). Here for this set take **20K** datapoints only.

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](https://www.appliedaiaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value
- Find the best hyper paramter using simple cross validation data
- You can write your own for loops to do this task

3. Representation of results

- You need to plot the performance of model both on train data and cross validation data for each hyper parameter, like shown in the figure



with X-axis as **n_estimators**, Y-axis as **max_depth**, and Z-axis as **AUC Score**, we have given the notebook which explains how to plot this 3d plot, you can find it in the same drive [3d_scatter_plot.ipynb](#)

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](https://seaborn.pydata.org/generated/seaborn.heatmap.html) with rows as **n_estimators**, columns as **max_depth**, and values inside the cell representing **AUC Score**

- You can choose either of the plotting techniques: 3d plot or heat map
- Once after you found the best hyper parameter, you need to train your model with it, and find the AUC on test data and plot the ROC curve on both train and test.



- Along with plotting ROC curve, you need to print the [confusion matrix](https://www.appliedaiaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tpr-fpr-fnr-fnr-1/) 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](http://zetcode.com/python/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](https://soundcloud.com/applied-ai-course/leakage-bow-and-tfidf).

2. Random Forest and GBDT

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

```
In [46]: # 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
```

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
- Essay : text data

- quantity : numerical
- teacher_number_of_previously_posted_projects : numerical
- price : numerical

```
In [47]: data1 = project_data.drop(['Unnamed: 0', 'id', 'project_submitted_datetime', 'project_essay_1', 'project_essay_2', 'project_essay_3', 'project_essay_4', 'project_resource_summary', 'teacher_id'], axis = 1)
```

```
In [48]: data1.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 109248 entries, 0 to 109247
Data columns (total 11 columns):
school_state                109248 non-null object
teacher_number_of_previously_posted_projects  109248 non-null int64
project_is_approved         109248 non-null int64
clean_categories            109248 non-null object
clean_subcategories         109248 non-null object
clean_teacher_prefix        109248 non-null object
clean_project_grade_category 109248 non-null object
preprocessed_essays         109248 non-null object
preprocessed_titles         109248 non-null object
price                      109248 non-null float64
quantity                   109248 non-null int64
dtypes: float64(1), int64(3), object(7)
memory usage: 10.0+ MB
```

```
In [49]: data1 = data1[:45000]
```

```
In [50]: y = data1['project_is_approved'].values
X = data1.drop(['project_is_approved'], axis=1)
X.head(1)
```

```
Out[50]:
```

	school_state	teacher_number_of_previously_posted_projects	clean_categories	clean_subcategories	clean_teacher_prefix	clean_project_grade
0	IN	0	Literacy_Language	ESL Literacy	Mrs	

```
In [51]: # train test split

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, stratify = y)
```

```
In [52]: X.shape
```

```
Out[52]: (45000, 10)
```

```
In [53]: y.shape
```

```
Out[53]: (45000,)
```

2.2 Make Data Model Ready: encoding numerical, categorical features


```
In [54]: # 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
```

2.2.1 Numerical features

1. teacher_number_of_previously_posted_projects
2. price
3. quantity

2.2.1.1 Teacher number of previously posted projects

```
In [55]: from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
# normalizer.fit(X_train['price'].values)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96 96.01 ... 368.98 80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature
# array.reshape(1, -1) if it contains a single sample.
normalizer.fit(X_train['teacher_number_of_previously_posted_projects'].values.reshape(1,-1))

X_train_TPPP_norm = normalizer.transform(X_train['teacher_number_of_previously_posted_projects'].values.reshape(1,-1))
X_test_TPPP_norm = normalizer.transform(X_test['teacher_number_of_previously_posted_projects'].values.reshape(1,-1))

print("After vectorizations")
print(X_train_TPPP_norm.shape, y_train.shape)
print(X_test_TPPP_norm.shape, y_test.shape)
print("=*100)
```

```
After vectorizations
(1, 30150) (30150,)
(1, 14850) (14850,)
=====
```

```
In [56]: print("Transpose of teacher number of previously posted projects")

X_train_TPPP_norm = X_train_TPPP_norm.transpose()
X_test_TPPP_norm = X_test_TPPP_norm.transpose()

print("After transpose")
print(X_train_TPPP_norm.shape, y_train.shape)
print(X_test_TPPP_norm.shape, y_test.shape)
print("=*100)
```

```
Transpose of teacher number of previously posted projects
After transpose
(30150, 1) (30150,)
(14850, 1) (14850,)
=====
```

2.2.1.2 price

```
In [57]: from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
# normalizer.fit(X_train['price'].values)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96 96.01 ... 368.98 80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature
# array.reshape(1, -1) if it contains a single sample.
normalizer.fit(X_train['price'].values.reshape(1,-1))

X_train_price_norm = normalizer.transform(X_train['price'].values.reshape(1,-1))
X_test_price_norm = normalizer.transform(X_test['price'].values.reshape(1,-1))

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

```
After vectorizations
(1, 30150) (30150,)
(1, 14850) (14850,)
=====
```

```
In [58]: print("Transpose of price")

X_train_price_norm = X_train_price_norm.transpose()
X_test_price_norm = X_test_price_norm.transpose()

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

```
Transpose of price
After vectorizations
(30150, 1) (30150,)
(14850, 1) (14850,)
=====
```

2.2.1.3 quantity

```
In [59]: from sklearn.preprocessing import Normalizer
normalizer = Normalizer()
# normalizer.fit(X_train['price'].values)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96 96.01 ... 368.98 80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature
# array.reshape(1, -1) if it contains a single sample.
normalizer.fit(X_train['quantity'].values.reshape(1,-1))

X_train_quantity_norm = normalizer.transform(X_train['quantity'].values.reshape(1,-1))
X_test_quantity_norm = normalizer.transform(X_test['quantity'].values.reshape(1,-1))

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

```
After vectorizations
(1, 30150) (30150,)
(1, 14850) (14850,)
=====
```

```
In [60]: print("Transpose of Quantity")

X_train_quantity_norm = X_train_quantity_norm.transpose()
X_test_quantity_norm = X_test_quantity_norm.transpose()

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

```
Transpose of Quantity
After vectorizations
(30150, 1) (30150,)
(14850, 1) (14850,)
=====
```

In []:

2.2.2 Categorical Data

Categorical Features for vectorization

1. Clean Categories
2. Clean Sub Categories
3. School State
4. Teacher Prefix
5. Project grade category

In the below function, I have considered all the unique features and calculated the pos and neg pos of that particular unique value

```
In [61]: def response(features,label):
df = pd.DataFrame({'A':features.values.tolist(),'label':label.tolist()})
l = len(features.values.tolist())
df1 = pd.DataFrame(np.nan, index=range(0,l),columns=['x','y'])
abc = df['A'].unique()

for i in tqdm(range(0,len(abc))):

    count_neg = 0
    count_pos = 0

    for j in range(0,len(df)):

        if((abc[i] == df.A[j]) and df.label[j] == 0):
            count_neg = count_neg+1
            #print(i,df.A[j],df.label[j],count_neg)
        elif((abc[i] == df.A[j]) and df.label[j] == 1):
            count_pos = count_pos+1
            #print(i,df.A[j],df.label[j],count_pos)

    prob_neg = count_neg/(count_neg+count_pos)
    prob_pos = count_pos/(count_neg+count_pos)

    c = count_neg+count_pos

    for p in range(0,len(df)):
        if((abc[i] == df.A[p]) and (c>1)):
            df1.iloc[p,0]=prob_neg
            df1.iloc[p,1]=prob_pos
        elif((abc[i] == df.A[p]) and (c==1)):
            df1.iloc[p,0]= 0.5
            df1.iloc[p,1]= 0.5
        print('unique feature = ' + df.A[p])

    print('Feature = ' + abc[i])
    print('Prob neg = ' + str(prob_neg) + '      Prob pos = ' + str(prob_pos))
    print('count neg = ' + str(count_neg) + '      count pos = ' + str(count_pos) + '      sum = '+str(c))

    return df1
```

```
""" b=count_neg+count_pos print('Feature = ' + i) print('Prob neg =' + str(prob_neg) + 'Prob pos =' + str(prob_pos)) print('count neg =' + str(count_neg) + 'count pos =' + str(count_pos) + 'sum = '+str(b)) """
```

In []:

2.2.2.1 Teacher Prefix

```
In [62]: X_train['clean_teacher_prefix'].value_counts()
```

```
Out[62]: Mrs      15767  
Ms       10853  
Mr       2857  
Teacher   671  
Dr         2  
Name: clean_teacher_prefix, dtype: int64
```

```
In [63]: response_clean_teacher_prefix = response(X_train['clean_teacher_prefix'],y_train)
```

```
20%|██████████| 1/5 [00:15<01:00, 15.15  
s/it]
```

```
Feature = Mrs  
Prob neg = 0.14955286357582293 Prob pos = 0.8504471364241771  
count neg = 2358 count pos = 13409 sum = 15767
```

```
40%|██████████| 2/5 [00:26<00:42, 14.01  
s/it]
```

```
Feature = Ms  
Prob neg = 0.15562517276329127 Prob pos = 0.8443748272367088  
count neg = 1689 count pos = 9164 sum = 10853
```

```
60%|██████████| 3/5 [00:32<00:23, 11.54  
s/it]
```

```
Feature = Mr  
Prob neg = 0.16100805040252011 Prob pos = 0.8389919495974799  
count neg = 460 count pos = 2397 sum = 2857
```

```
80%|██████████| 4/5 [00:36<00:09, 9.29  
s/it]
```

```
Feature = Teacher  
Prob neg = 0.20268256333830104 Prob pos = 0.797317436661699  
count neg = 136 count pos = 535 sum = 671
```

```
100%|██████████| 5/5 [00:39<00:00, 7.99  
s/it]
```

```
Feature = Dr  
Prob neg = 0.5 Prob pos = 0.5  
count neg = 1 count pos = 1 sum = 2
```

```
In [64]: X_train['clean_teacher_prefix'][600:620]
```

```
Out[64]: 12675 Mrs  
11670 Mrs  
25900 Ms  
8749 Mr  
7880 Ms  
27154 Mrs  
18622 Ms  
3458 Mr  
23508 Ms  
40992 Mrs  
24134 Mr  
35064 Ms  
39518 Mrs  
33881 Ms  
3255 Mrs  
35516 Mrs  
6537 Mrs  
37970 Teacher  
39198 Ms  
14886 Teacher  
Name: clean_teacher_prefix, dtype: object
```

In [65]: response_clean_teacher_prefix[600:620]

Out[65]:

	x	y
600	0.149553	0.850447
601	0.149553	0.850447
602	0.155625	0.844375
603	0.161008	0.838992
604	0.155625	0.844375
605	0.149553	0.850447
606	0.155625	0.844375
607	0.161008	0.838992
608	0.155625	0.844375
609	0.149553	0.850447
610	0.161008	0.838992
611	0.155625	0.844375
612	0.149553	0.850447
613	0.155625	0.844375
614	0.149553	0.850447
615	0.149553	0.850447
616	0.149553	0.850447
617	0.202683	0.797317
618	0.155625	0.844375
619	0.202683	0.797317

In []:

2.2.2.2 Clean categories

```
In [66]: X_train.clean_categories.value_counts()
```

```
Out[66]: Literacy_Language          6554
Math_Science          4641
Literacy_Language Math_Science    4009
Health_Sports         2808
Music_Arts            1397
SpecialNeeds          1204
Literacy_Language SpecialNeeds    1113
AppliedLearning       1012
Math_Science Literacy_Language     632
AppliedLearning Literacy_Language   626
Math_Science SpecialNeeds          554
History_Civics         518
Math_Science Music_Arts           476
Literacy_Language Music_Arts       465
History_Civics Literacy_Language    409
AppliedLearning SpecialNeeds       402
Health_Sports SpecialNeeds         385
Warmth_Care_Hunger     367
Math_Science AppliedLearning       347
AppliedLearning Math_Science       269
Literacy_Language History_Civics    223
Health_Sports Literacy_Language     213
AppliedLearning Music_Arts         211
Math_Science History_Civics        173
Literacy_Language AppliedLearning   171
AppliedLearning Health_Sports       150
Math_Science Health_Sports         121
History_Civics Math_Science         107
SpecialNeeds Music_Arts            88
History_Civics Music_Arts           87
Health_Sports Math_Science          67
History_Civics SpecialNeeds         66
Health_Sports AppliedLearning       62
AppliedLearning History_Civics       48
Health_Sports Music_Arts            42
Music_Arts SpecialNeeds            36
Literacy_Language Health_Sports     21
History_Civics AppliedLearning       12
Health_Sports History_Civics        11
SpecialNeeds Health_Sports         10
Health_Sports Warmth_Care_Hunger     8
Music_Arts Health_Sports            7
AppliedLearning Warmth_Care_Hunger    6
Music_Arts History_Civics           5
Math_Science Warmth_Care_Hunger      5
History_Civics Health_Sports         4
SpecialNeeds Warmth_Care_Hunger      3
Literacy_Language Warmth_Care_Hunger  2
Music_Arts AppliedLearning           2
Music_Arts Warmth_Care_Hunger        1
Name: clean_categories, dtype: int64
```

```
In [67]: response_clean_categories = response(X_train['clean_categories'],y_train)
```

2% ■■	1/50 [00:09<07:52, 9.65
s/it]	
Feature = Literacy_Language	
Prob neg = 0.13411657003356728 Prob pos = 0.8658834299664327	
count neg = 879 count pos = 5675 sum = 6554	
4% ■■■	2/50 [00:14<06:34, 8.21
s/it]	
Feature = Literacy_Language SpecialNeeds	
Prob neg = 0.14734950584007186 Prob pos = 0.8526504941599281	
count neg = 164 count pos = 949 sum = 1113	
6% ■■■■	3/50 [00:19<05:37, 7.18
s/it]	
Feature = SpecialNeeds	
Prob neg = 0.18687707641196014 Prob pos = 0.8131229235880398	
count neg = 225 count pos = 979 sum = 1204	
8% ■■■■■	4/50 [00:26<05:33, 7.26
s/it]	
Feature = Math_Science	
Prob neg = 0.18336565395388923 Prob pos = 0.8166343460461107	
count neg = 851 count pos = 3790 sum = 4641	
10% ■■■■■■	5/50 [00:32<05:11, 6.92
s/it]	
Feature = Health_Sports	
Prob neg = 0.150997150997151 Prob pos = 0.8490028490028491	
count neg = 424 count pos = 2384 sum = 2808	
12% ■■■■■■■	6/50 [00:38<04:41, 6.40
s/it]	
Feature = AppliedLearning	
Prob neg = 0.1956521739130435 Prob pos = 0.8043478260869565	
count neg = 198 count pos = 814 sum = 1012	
14% ■■■■■■■■	7/50 [00:43<04:16, 5.98
s/it]	
Feature = Health_Sports SpecialNeeds	
Prob neg = 0.14545454545454545 Prob pos = 0.8545454545454545	
count neg = 56 count pos = 329 sum = 385	
16% ■■■■■■■■■	8/50 [00:47<03:48, 5.44
s/it]	
Feature = Literacy_Language Music_Arts	
Prob neg = 0.18064516129032257 Prob pos = 0.8193548387096774	
count neg = 84 count pos = 381 sum = 465	
18% ■■■■■■■■■	9/50 [00:51<03:23, 4.96
s/it]	
Feature = Warmth_Care_Hunger	
Prob neg = 0.06267029972752043 Prob pos = 0.9373297002724795	
count neg = 23 count pos = 344 sum = 367	
20% ■■■■■■■■■■	10/50 [00:54<03:02, 4.56
s/it]	
Feature = SpecialNeeds Music_Arts	
Prob neg = 0.20454545454545456 Prob pos = 0.7954545454545454	
count neg = 18 count pos = 70 sum = 88	
22% ■■■■■■■■■■■	11/50 [01:01<03:24, 5.24
s/it]	
Feature = Literacy_Language Math_Science	
Prob neg = 0.13394861561486654 Prob pos = 0.8660513843851334	
count neg = 537 count pos = 3472 sum = 4009	
24% ■■■■■■■■■■■■	12/50 [01:05<03:07, 4.94
s/it]	
Feature = Math_Science Literacy_Language	
Prob neg = 0.14082278481012658 Prob pos = 0.8591772151898734	
count neg = 89 count pos = 543 sum = 632	
26% ■■■■■■■■■■■■■	13/50 [01:10<02:59, 4.85
s/it]	
Feature = Music_Arts	
Prob neg = 0.1388690050107373 Prob pos = 0.8611309949892627	
count neg = 194 count pos = 1203 sum = 1397	

Feature	Prob neg	Prob pos	count neg	count pos	sum	Percentage	Time	Score
AppliedLearning Health_Sports	0.1533333333333332	0.8466666666666667	23	127	150	30%	14/50 [01:14<02:41,	4.48
AppliedLearning History_Civics	0.1875	0.8125	9	39	48	32%	15/50 [01:17<02:28,	4.24
Math_Science SpecialNeeds	0.18411552346570398	0.8158844765342961	102	452	554	34%	16/50 [01:21<02:22,	4.18
Health_Sports Literacy_Language	0.18779342723004694	0.812206572769953	40	173	213	36%	17/50 [01:25<02:12,	4.02
History_Civics	0.16795366795366795	0.832046332046332	87	431	518	38%	18/50 [01:29<02:08,	4.01
Literacy_Language History_Civics	0.11210762331838565	0.8878923766816144	25	198	223	40%	19/50 [01:33<02:01,	3.93
Math_Science Health_Sports	0.21487603305785125	0.7851239669421488	26	95	121	42%	20/50 [01:37<01:58,	3.94
AppliedLearning Literacy_Language	0.1501597444089457	0.8498402555910544	94	532	626	44%	21/50 [01:41<01:55,	3.98
History_Civics Literacy_Language	0.08557457212713937	0.9144254278728606	35	374	409	46%	22/50 [01:45<01:50,	3.95
History_Civics SpecialNeeds	0.22727272727272727	0.7727272727272727	15	51	66	48%	23/50 [01:48<01:43,	3.84
Math_Science AppliedLearning	0.1585014409221902	0.8414985590778098	55	292	347	50%	24/50 [01:52<01:39,	3.82
Math_Science Music_Arts	0.16596638655462184	0.8340336134453782	79	397	476	52%	25/50 [01:56<01:35,	3.84
unique feature = Music_Arts Warmth Care_Hunger	1.0	0.0	1	0	1	52%	26/50 [01:59<01:29,	3.73

Percentage	Feature	Prob neg	Prob pos	count neg	count pos	sum	Score	Time
80%	Health_Sports Warmth Care_Hunger	0.0	1.0	0	8	8	40/50	[02:51<00:35, 3.55
82%	Health_Sports AppliedLearning	0.16129032258064516	0.8387096774193549	10	52	62	41/50	[02:54<00:31, 3.54
84%	History_Civics AppliedLearning	0.3333333333333333	0.6666666666666666	4	8	12	42/50	[02:58<00:28, 3.53
86%	History_Civics Music_Arts	0.14942528735632185	0.8505747126436781	13	74	87	43/50	[03:02<00:26, 3.72
88%	Music_Arts AppliedLearning	0.0	1.0	0	2	2	44/50	[03:05<00:22, 3.67
90%	Literacy_Language Health_Sports	0.23809523809523808	0.7619047619047619	5	16	21	45/50	[03:09<00:18, 3.62
92%	History_Civics Health_Sports	0.0	1.0	0	4	4	46/50	[03:12<00:14, 3.60
94%	AppliedLearning Warmth Care_Hunger	0.3333333333333333	0.6666666666666666	2	4	6	47/50	[03:16<00:10, 3.60
96%	Literacy_Language Warmth Care_Hunger	0.0	1.0	0	2	2	48/50	[03:20<00:07, 3.56
98%	SpecialNeeds Health_Sports	0.4	0.6	4	6	10	49/50	[03:23<00:03, 3.53
100%	Music_Arts Health_Sports	0.2857142857142857	0.7142857142857143	2	5	7	50/50	[03:28<00:00, 4.17

```
In [68]: response_clean_categories.count()
```

```
Out[68]: x      30150
          y      30150
          dtype: int64
```

2.2.2.3 Clean Sub categories

```
In [69]: X_train.clean_subcategories.value_counts()
```

```
Out[69]: Literacy 2671
Literacy Mathematics 2302
Literature_Writing Mathematics 1607
Literacy Literature_Writing 1516
Mathematics 1445
SpecialNeeds 1204
Literature_Writing 1198
Health_Wellness 968
AppliedSciences Mathematics 945
Literacy SpecialNeeds 686
AppliedSciences 674
Gym_Fitness Health_Wellness 654
ESL Literacy 634
VisualArts 580
Music 386
Literature_Writing SpecialNeeds 373
Warmth Care_Hunger 367
Gym_Fitness 340
Mathematics SpecialNeeds 337
Health_Wellness SpecialNeeds 332
EnvironmentalScience 331
TeamSports 280
Music PerformingArts 263
AppliedSciences EnvironmentalScience 251
EarlyDevelopment 247
EnvironmentalScience Health_LifeScience 247
EnvironmentalScience Mathematics 241
Health_Wellness NutritionEducation 234
Other 225
ESL Literature_Writing 217
...
TeamSports VisualArts 1
Other PerformingArts 1
Mathematics Warmth Care_Hunger 1
Literature_Writing Warmth Care_Hunger 1
CharacterEducation Economics 1
Economics Music 1
FinancialLiteracy History_Geography 1
Civics_Government Extracurricular 1
CommunityService Gym_Fitness 1
FinancialLiteracy Health_Wellness 1
EnvironmentalScience ForeignLanguages 1
CharacterEducation FinancialLiteracy 1
EnvironmentalScience FinancialLiteracy 1
Economics Literature_Writing 1
ForeignLanguages PerformingArts 1
Other TeamSports 1
ForeignLanguages Gym_Fitness 1
Civics_Government TeamSports 1
Civics_Government PerformingArts 1
EarlyDevelopment NutritionEducation 1
CommunityService PerformingArts 1
CommunityService History_Geography 1
NutritionEducation VisualArts 1
Gym_Fitness Health_LifeScience 1
Extracurricular Health_LifeScience 1
History_Geography ParentInvolvement 1
CommunityService Other 1
Extracurricular ForeignLanguages 1
College_CareerPrep Gym_Fitness 1
FinancialLiteracy Other 1
Name: clean_subcategories, Length: 362, dtype: int64
```

```
In [70]: response_clean_subcategories = response(X_train['clean_subcategories'],y_train)
```

0% s/it]	1/362 [00:07<43:42, 7.26
Feature = Literacy Prob neg = 0.11718457506551853 Prob pos = 0.8828154249344815 count neg = 313 count pos = 2358 sum = 2671	
1% s/it]	2/362 [00:11<37:48, 6.30
Feature = Literacy SpecialNeeds Prob neg = 0.13994169096209913 Prob pos = 0.8600583090379009 count neg = 96 count pos = 590 sum = 686	
1% s/it]	3/362 [00:16<35:37, 5.95
Feature = SpecialNeeds Prob neg = 0.18687707641196014 Prob pos = 0.8131229235880398 count neg = 225 count pos = 979 sum = 1204	
1% s/it]	4/362 [00:20<32:05, 5.38
Feature = AppliedSciences Prob neg = 0.20474777448071216 Prob pos = 0.7952522255192879 count neg = 138 count pos = 536 sum = 674	
1% s/it]	5/362 [00:24<29:51, 5.02
Feature = Gym_Fitness Health_Wellness Prob neg = 0.11314984709480122 Prob pos = 0.8868501529051988 count neg = 74 count pos = 580 sum = 654	
2% s/it]	6/362 [00:28<28:04, 4.73
Feature = ESL Literacy Prob neg = 0.14353312302839116 Prob pos = 0.8564668769716088 count neg = 91 count pos = 543 sum = 634	
2% s/it]	7/362 [00:32<25:49, 4.36
Feature = Extracurricular Prob neg = 0.17857142857142858 Prob pos = 0.8214285714285714 count neg = 5 count pos = 23 sum = 28	
2% s/it]	8/362 [00:36<24:47, 4.20
Feature = TeamSports Prob neg = 0.17857142857142858 Prob pos = 0.8214285714285714 count neg = 50 count pos = 230 sum = 280	
2% s/it]	9/362 [00:40<25:00, 4.25
Feature = Health_Wellness Prob neg = 0.13636363636363635 Prob pos = 0.8636363636363636 count neg = 132 count pos = 836 sum = 968	
3% s/it]	10/362 [00:44<24:10, 4.12
Feature = Health_Wellness SpecialNeeds Prob neg = 0.14156626506024098 Prob pos = 0.858433734939759 count neg = 47 count pos = 285 sum = 332	
3% s/it]	11/362 [00:47<23:16, 3.98
Feature = Literacy PerformingArts Prob neg = 0.14285714285714285 Prob pos = 0.8571428571428571 count neg = 4 count pos = 24 sum = 28	
3% s/it]	12/362 [00:51<22:58, 3.94
Feature = Warmth Care_Hunger Prob neg = 0.06267029972752043 Prob pos = 0.9373297002724795 count neg = 23 count pos = 344 sum = 367	
4% s/it]	13/362 [00:56<23:27, 4.03
Feature = AppliedSciences Mathematics Prob neg = 0.182010582010582 Prob pos = 0.817989417989418 count neg = 172 count pos = 773 sum = 945	

4%|■■■■
s/it] | 14/362 [00:59<22:45, 3.92

Feature = SpecialNeeds VisualArts
Prob neg = 0.20454545454545456 Prob pos = 0.795454545454545454
count neg = 18 count pos = 70 sum = 88

4%|■■■■
s/it] | 15/362 [01:03<22:20, 3.86

Feature = EarlyDevelopment
Prob neg = 0.2145748987854251 Prob pos = 0.7854251012145749
count neg = 53 count pos = 194 sum = 247

4%|■■■■
s/it] | 16/362 [01:08<24:47, 4.30

Feature = Literacy Mathematics
Prob neg = 0.1272806255430061 Prob pos = 0.8727193744569939
count neg = 293 count pos = 2009 sum = 2302

5%|■■■■
s/it] | 17/362 [01:13<25:48, 4.49

Feature = Mathematics
Prob neg = 0.17301038062283736 Prob pos = 0.8269896193771626
count neg = 250 count pos = 1195 sum = 1445

5%|■■■■
s/it] | 18/362 [01:17<24:23, 4.25

Feature = Health_LifeScience Literature_Writing
Prob neg = 0.10638297872340426 Prob pos = 0.8936170212765957
count neg = 5 count pos = 42 sum = 47

5%|■■■■
s/it] | 19/362 [01:22<25:25, 4.45

Feature = Music
Prob neg = 0.09844559585492228 Prob pos = 0.9015544041450777
count neg = 38 count pos = 348 sum = 386

6%|■■■■
s/it] | 20/362 [01:26<24:29, 4.30

Feature = Literature_Writing SpecialNeeds
Prob neg = 0.16890080428954424 Prob pos = 0.8310991957104558
count neg = 63 count pos = 310 sum = 373

6%|■■■■
s/it] | 21/362 [01:30<25:07, 4.42

Feature = Literacy Literature_Writing
Prob neg = 0.13192612137203166 Prob pos = 0.8680738786279684
count neg = 200 count pos = 1316 sum = 1516

6%|■■■■
s/it] | 22/362 [01:36<26:15, 4.63

Feature = Literature_Writing
Prob neg = 0.15025041736227046 Prob pos = 0.8497495826377296
count neg = 180 count pos = 1018 sum = 1198

6%|■■■■
s/it] | 23/362 [01:39<24:23, 4.32

Feature = Health_Wellness TeamSports
Prob neg = 0.21428571428571427 Prob pos = 0.7857142857142857
count neg = 18 count pos = 66 sum = 84

7%|■■■■
s/it] | 24/362 [01:43<23:30, 4.17

Feature = Gym_Fitness
Prob neg = 0.16176470588235295 Prob pos = 0.8382352941176471
count neg = 55 count pos = 285 sum = 340

7%|■■■■
s/it] | 25/362 [01:47<22:53, 4.07

Feature = ESL Literature_Writing
Prob neg = 0.18433179723502305 Prob pos = 0.815668202764977
count neg = 40 count pos = 177 sum = 217

7%|■■■■
s/it] | 26/362 [01:50<22:03, 3.94

Feature = Health_LifeScience Mathematics
Prob neg = 0.19548872180451127 Prob pos = 0.8045112781954887
count neg = 26 count pos = 107 sum = 133

7% ██████ s/it]	27/362 [01:54<21:16, 3.81
Feature = Literature_Writing Music Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 13 sum = 13	
8% ██████ s/it]	28/362 [01:58<22:10, 3.98
Feature = EarlyDevelopment Health_Wellness Prob neg = 0.1323529411764706 Prob pos = 0.8676470588235294 count neg = 9 count pos = 59 sum = 68	
8% ██████ s/it]	29/362 [02:03<22:27, 4.05
Feature = EnvironmentalScience Health_LifeScience Prob neg = 0.1862348178137652 Prob pos = 0.8137651821862348 count neg = 46 count pos = 201 sum = 247	
8% ██████ s/it]	30/362 [02:06<22:09, 4.01
Feature = College_CareerPrep SocialSciences Prob neg = 0.2222222222222222 Prob pos = 0.7777777777777778 count neg = 2 count pos = 7 sum = 9	
9% ██████ s/it]	31/362 [02:10<21:43, 3.94
Feature = PerformingArts Prob neg = 0.11538461538461539 Prob pos = 0.8846153846153846 count neg = 15 count pos = 115 sum = 130	
9% ██████ s/it]	32/362 [02:14<21:11, 3.85
Feature = EnvironmentalScience SpecialNeeds Prob neg = 0.1346153846153846 Prob pos = 0.8653846153846154 count neg = 7 count pos = 45 sum = 52	
9% ██████ s/it]	33/362 [02:18<21:21, 3.89
Feature = AppliedSciences Literacy Prob neg = 0.15337423312883436 Prob pos = 0.8466257668711656 count neg = 25 count pos = 138 sum = 163	
9% ██████ s/it]	34/362 [02:21<20:52, 3.82
Feature = Literacy VisualArts Prob neg = 0.19205298013245034 Prob pos = 0.8079470198675497 count neg = 29 count pos = 122 sum = 151	
10% ██████ s/it]	35/362 [02:25<20:34, 3.78
Feature = Health_Wellness Literacy Prob neg = 0.1984732824427481 Prob pos = 0.8015267175572519 count neg = 26 count pos = 105 sum = 131	
10% ██████ s/it]	36/362 [02:29<20:39, 3.80
Feature = SocialSciences Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334 count neg = 9 count pos = 45 sum = 54	
10% ██████ s/it]	37/362 [02:33<20:24, 3.77
Feature = Literature_Writing VisualArts Prob neg = 0.20786516853932585 Prob pos = 0.7921348314606742 count neg = 37 count pos = 141 sum = 178	
10% ██████ s/it]	38/362 [02:36<20:14, 3.75
Feature = Other Prob neg = 0.1511111111111111 Prob pos = 0.8488888888888889 count neg = 34 count pos = 191 sum = 225	
11% ██████ s/it]	39/362 [02:40<20:40, 3.84
Feature = AppliedSciences Health_LifeScience Prob neg = 0.175 Prob pos = 0.825 count neg = 28 count pos = 132 sum = 160	

11% ■■■■■■■ s/it]	40/362 [02:44<20:23, 3.80
Feature = College_CareerPrep Prob neg = 0.19387755102040816 Prob pos = 0.8061224489795918 count neg = 19 count pos = 79 sum = 98	
11% ■■■■■■■ s/it]	41/362 [02:48<20:52, 3.90
Feature = EnvironmentalScience Prob neg = 0.18429003021148035 Prob pos = 0.8157099697885196 count neg = 61 count pos = 270 sum = 331	
12% ■■■■■■■ s/it]	42/362 [02:55<25:25, 4.77
Feature = Literature_Writing Mathematics Prob neg = 0.1431238332296204 Prob pos = 0.8568761667703796 count neg = 230 count pos = 1377 sum = 1607	
12% ■■■■■■■ s/it]	43/362 [02:59<24:27, 4.60
Feature = Health_Wellness NutritionEducation Prob neg = 0.1581196581196581 Prob pos = 0.8418803418803419 count neg = 37 count pos = 197 sum = 234	
12% ■■■■■■■ s/it]	44/362 [03:04<24:04, 4.54
Feature = Music PerformingArts Prob neg = 0.11406844106463879 Prob pos = 0.8859315589353612 count neg = 30 count pos = 233 sum = 263	
12% ■■■■■■■ s/it]	45/362 [03:08<22:57, 4.35
Feature = Literature_Writing SocialSciences Prob neg = 0.1 Prob pos = 0.9 count neg = 10 count pos = 90 sum = 100	
13% ■■■■■■■ s/it]	46/362 [03:11<21:53, 4.16
Feature = History_Geography Prob neg = 0.2012987012987013 Prob pos = 0.7987012987012987 count neg = 31 count pos = 123 sum = 154	
13% ■■■■■■■ s/it]	47/362 [03:15<21:19, 4.06
Feature = Health_LifeScience Prob neg = 0.1588785046728972 Prob pos = 0.8411214953271028 count neg = 34 count pos = 180 sum = 214	
13% ■■■■■■■ s/it]	48/362 [03:19<20:42, 3.96
Feature = AppliedSciences EnvironmentalScience Prob neg = 0.2151394422310757 Prob pos = 0.7848605577689243 count neg = 54 count pos = 197 sum = 251	
14% ■■■■■■■ s/it]	49/362 [03:22<19:55, 3.82
Feature = AppliedSciences Health_Wellness Prob neg = 0.15384615384615385 Prob pos = 0.8461538461538461 count neg = 2 count pos = 11 sum = 13	
14% ■■■■■■■ s/it]	50/362 [03:26<19:28, 3.75
Feature = CharacterEducation Literature_Writing Prob neg = 0.23076923076923078 Prob pos = 0.7692307692307693 count neg = 12 count pos = 40 sum = 52	
14% ■■■■■■■ s/it]	51/362 [03:30<19:14, 3.71
Feature = History_Geography Literature_Writing Prob neg = 0.10493827160493827 Prob pos = 0.8950617283950617 count neg = 17 count pos = 145 sum = 162	
14% ■■■■■■■ s/it]	52/362 [03:34<19:50, 3.84
Feature = SocialSciences SpecialNeeds Prob neg = 0.21428571428571427 Prob pos = 0.7857142857142857 count neg = 3 count pos = 11 sum = 14	

15%|██████████
s/it] | 53/362 [03:37<19:25, 3.77

Feature = ForeignLanguages
Prob neg = 0.22330097087378642 Prob pos = 0.7766990291262136
count neg = 23 count pos = 80 sum = 103

15%|██████████
s/it] | 54/362 [03:41<19:01, 3.71

Feature = CharacterEducation Literacy
Prob neg = 0.09278350515463918 Prob pos = 0.9072164948453608
count neg = 9 count pos = 88 sum = 97

15%|██████████
s/it] | 55/362 [03:45<18:51, 3.68

Feature = EnvironmentalScience Mathematics
Prob neg = 0.17427385892116182 Prob pos = 0.8257261410788381
count neg = 42 count pos = 199 sum = 241

15%|██████████
s/it] | 56/362 [03:48<18:51, 3.70

Feature = NutritionEducation
Prob neg = 0.28205128205128205 Prob pos = 0.717948717948718
count neg = 22 count pos = 56 sum = 78

16%|██████████
s/it] | 57/362 [03:52<18:28, 3.63

Feature = Civics_Government FinancialLiteracy
Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334
count neg = 1 count pos = 5 sum = 6

16%|██████████
s/it] | 58/362 [03:55<18:26, 3.64

Feature = AppliedSciences College_CareerPrep
Prob neg = 0.15 Prob pos = 0.85
count neg = 18 count pos = 102 sum = 120

16%|██████████
s/it] | 59/362 [03:59<18:16, 3.62

Feature = Mathematics VisualArts
Prob neg = 0.16556291390728478 Prob pos = 0.8344370860927153
count neg = 25 count pos = 126 sum = 151

17%|██████████
s/it] | 60/362 [04:03<18:11, 3.61

Feature = CharacterEducation EarlyDevelopment
Prob neg = 0.34285714285714286 Prob pos = 0.6571428571428571
count neg = 12 count pos = 23 sum = 35

17%|██████████
s/it] | 61/362 [04:06<18:34, 3.70

Feature = EnvironmentalScience Literacy
Prob neg = 0.1440677966101695 Prob pos = 0.8559322033898306
count neg = 17 count pos = 101 sum = 118

17%|██████████
s/it] | 62/362 [04:10<18:16, 3.65

Feature = CommunityService Health_Wellness
Prob neg = 0.2 Prob pos = 0.8
count neg = 1 count pos = 4 sum = 5

17%|██████████
s/it] | 63/362 [04:14<18:13, 3.66

Feature = CharacterEducation
Prob neg = 0.22340425531914893 Prob pos = 0.776595744680851
count neg = 21 count pos = 73 sum = 94

18%|██████████
s/it] | 64/362 [04:17<18:05, 3.64

Feature = Civics_Government History_Geography
Prob neg = 0.14705882352941177 Prob pos = 0.8529411764705882
count neg = 10 count pos = 58 sum = 68

18%|██████████
s/it] | 65/362 [04:21<17:56, 3.63

Feature = EarlyDevelopment Other
Prob neg = 0.06521739130434782 Prob pos = 0.9347826086956522
count neg = 3 count pos = 43 sum = 46

18% ██████████ s/it]	66/362 [04:24<17:52, 3.62
Feature = EnvironmentalScience Literature_Writing Prob neg = 0.14457831325301204 Prob pos = 0.8554216867469879 count neg = 12 count pos = 71 sum = 83	
19% ██████████ s/it]	67/362 [04:28<17:33, 3.57
Feature = Mathematics Other Prob neg = 0.15384615384615385 Prob pos = 0.8461538461538461 count neg = 4 count pos = 22 sum = 26 unique feature = VisualArts Warmth Care_Hunger	
19% ██████████ s/it]	68/362 [04:31<17:21, 3.54
Feature = VisualArts Warmth Care_Hunger Prob neg = 1.0 Prob pos = 0.0 count neg = 1 count pos = 0 sum = 1	
19% ██████████ s/it]	69/362 [04:35<17:32, 3.59
Feature = EarlyDevelopment SpecialNeeds Prob neg = 0.16097560975609757 Prob pos = 0.8390243902439024 count neg = 33 count pos = 172 sum = 205	
19% ██████████ s/it]	70/362 [04:39<17:23, 3.57
Feature = EnvironmentalScience VisualArts Prob neg = 0.19117647058823528 Prob pos = 0.8088235294117647 count neg = 13 count pos = 55 sum = 68	
20% ██████████ s/it]	71/362 [04:42<17:28, 3.60
Feature = History_Geography Literacy Prob neg = 0.05732484076433121 Prob pos = 0.9426751592356688 count neg = 9 count pos = 148 sum = 157	
20% ██████████ s/it]	72/362 [04:46<17:19, 3.59
Feature = EarlyDevelopment Music Prob neg = 0.25 Prob pos = 0.75 count neg = 1 count pos = 3 sum = 4	
20% ██████████ s/it]	73/362 [04:49<17:15, 3.58
Feature = AppliedSciences Literature_Writing Prob neg = 0.15517241379310345 Prob pos = 0.8448275862068966 count neg = 18 count pos = 98 sum = 116	
20% ██████████ s/it]	74/362 [04:53<17:10, 3.58
Feature = College_CareerPrep Literature_Writing Prob neg = 0.11111111111111111 Prob pos = 0.8888888888888888 count neg = 10 count pos = 80 sum = 90	
21% ██████████ s/it]	75/362 [04:57<17:35, 3.68
Feature = VisualArts Prob neg = 0.1706896551724138 Prob pos = 0.8293103448275863 count neg = 99 count pos = 481 sum = 580	
21% ██████████ s/it]	76/362 [05:01<17:29, 3.67
Feature = AppliedSciences SpecialNeeds Prob neg = 0.15 Prob pos = 0.85 count neg = 18 count pos = 102 sum = 120	
21% ██████████ s/it]	77/362 [05:04<17:21, 3.65
Feature = Music SpecialNeeds Prob neg = 0.029411764705882353 Prob pos = 0.9705882352941176 count neg = 1 count pos = 33 sum = 34	
22% ██████████ s/it]	78/362 [05:09<19:23, 4.10
Feature = College_CareerPrep Literacy Prob neg = 0.12857142857142856 Prob pos = 0.8714285714285714 count neg = 9 count pos = 61 sum = 70	

22% ████████████████████ s/it]	79/362 [05:15<20:58, 4.45
Feature = CharacterEducation VisualArts Prob neg = 0.125 Prob pos = 0.875 count neg = 3 count pos = 21 sum = 24	
22% ████████████████████ s/it]	80/362 [05:18<19:51, 4.23
Feature = College_CareerPrep PerformingArts Prob neg = 0.4 Prob pos = 0.6 count neg = 4 count pos = 6 sum = 10	
22% ████████████████████ s/it]	81/362 [05:22<18:48, 4.02
Feature = CommunityService Prob neg = 0.2 Prob pos = 0.8 count neg = 3 count pos = 12 sum = 15	
23% ████████████████████ s/it]	82/362 [05:25<18:02, 3.87
Feature = AppliedSciences ParentInvolvement Prob neg = 0.15789473684210525 Prob pos = 0.8421052631578947 count neg = 3 count pos = 16 sum = 19	
23% ████████████████████ s/it]	83/362 [05:29<17:28, 3.76
Feature = CharacterEducation CommunityService Prob neg = 0.2857142857142857 Prob pos = 0.7142857142857143 count neg = 6 count pos = 15 sum = 21	
23% ████████████████████ s/it]	84/362 [05:33<18:04, 3.90
Feature = CharacterEducation Mathematics Prob neg = 0.10344827586206896 Prob pos = 0.896551724137931 count neg = 3 count pos = 26 sum = 29	
23% ████████████████████ s/it]	85/362 [05:37<17:36, 3.81
Feature = History_Geography SocialSciences Prob neg = 0.1511627906976744 Prob pos = 0.8488372093023255 count neg = 13 count pos = 73 sum = 86	
24% ████████████████████ s/it]	86/362 [05:40<17:09, 3.73
Feature = EarlyDevelopment Literature_Writing Prob neg = 0.20270270270270271 Prob pos = 0.7972972972972973 count neg = 15 count pos = 59 sum = 74	
24% ████████████████████ s/it]	87/362 [05:44<16:49, 3.67
Feature = History_Geography SpecialNeeds Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334 count neg = 5 count pos = 25 sum = 30	
24% ████████████████████ s/it]	88/362 [05:48<16:58, 3.72
Feature = Mathematics SpecialNeeds Prob neg = 0.19881305637982197 Prob pos = 0.8011869436201781 count neg = 67 count pos = 270 sum = 337	
25% ████████████████████ s/it]	89/362 [05:51<16:28, 3.62
Feature = AppliedSciences Music Prob neg = 0.19047619047619047 Prob pos = 0.8095238095238095 count neg = 4 count pos = 17 sum = 21	
25% ████████████████████ s/it]	90/362 [05:55<16:26, 3.63
Feature = EarlyDevelopment Literacy Prob neg = 0.15463917525773196 Prob pos = 0.845360824742268 count neg = 30 count pos = 164 sum = 194	
25% ████████████████████ s/it]	91/362 [05:58<16:16, 3.60
Feature = Civics_Government Literature_Writing Prob neg = 0.16129032258064516 Prob pos = 0.8387096774193549 count neg = 5 count pos = 26 sum = 31	

Feature	Prob neg	Prob pos	count neg	count pos	sum	Time	Score
Health_LifeScience SpecialNeeds	0.2222222222222222	0.7777777777777778	10	35	45	105/362 [06:48<15:17,	3.57
AppliedSciences EarlyDevelopment	0.21153846153846154	0.7884615384615384	11	41	52	106/362 [06:51<15:14,	3.57
FinancialLiteracy Mathematics	0.11627906976744186	0.8837209302325582	5	38	43	107/362 [06:55<15:09,	3.57
Economics Mathematics	0.0	1.0	0	8	8	108/362 [06:58<15:00,	3.55
EnvironmentalScience SocialSciences	0.22727272727272727	0.7727272727272727	5	17	22	109/362 [07:02<14:50,	3.52
Extracurricular SpecialNeeds	0.2857142857142857	0.7142857142857143	2	5	7	110/362 [07:05<14:38,	3.49
EarlyDevelopment NutritionEducation	0.0	1.0	0	1	1	111/362 [07:09<14:34,	3.48
SpecialNeeds Warmth Care_Hunger	0.3333333333333333	0.6666666666666666	1	2	3	112/362 [07:12<14:28,	3.47
Health_LifeScience Literacy	0.075	0.925	6	74	80	113/362 [07:16<14:31,	3.50
Mathematics ParentInvolvement	0.2	0.8	4	16	20	114/362 [07:19<14:27,	3.50
FinancialLiteracy	0.20689655172413793	0.7931034482758621	12	46	58	115/362 [07:23<14:23,	3.50
CharacterEducation College_CareerPrep	0.14814814814814814	0.8518518518518519	4	23	27	116/362 [07:26<14:18,	3.49
Other SpecialNeeds	0.1797752808988764	0.8202247191011236	16	73	89	117/362 [07:30<14:28,	3.55

Feature	Prob neg	Prob pos	count neg	count pos	sum	unique feature	Percentage	Time	Score
Health_LifeScience NutritionEducation	0.4	0.6	8	12	20		43%	157/362 [09:52<12:07,	3.55
ESL EnvironmentalScience	0.1111111111111111	0.8888888888888888	1	8	9		44%	158/362 [09:56<12:02,	3.54
FinancialLiteracy Other	0.0	1.0	0	1	1		44%	159/362 [09:59<12:03,	3.56
FinancialLiteracy SocialSciences	0.0	1.0	0	1	1		44%	160/362 [10:03<11:56,	3.55
FinancialLiteracy SocialSciences	0.0	1.0	0	1	1		44%	161/362 [10:06<11:48,	3.52
Gym_Fitness NutritionEducation	0.14285714285714285	0.8571428571428571	2	12	14		45%	162/362 [10:10<11:42,	3.51
History_Geography VisualArts	0.16	0.84	8	42	50		45%	163/362 [10:13<11:39,	3.51
EarlyDevelopment VisualArts	0.23684210526315788	0.7631578947368421	9	29	38		45%	164/362 [10:18<12:51,	3.90
Civics_Government ESL	0.0	1.0	0	1	1		46%	165/362 [10:23<14:02,	4.27
Civics_Government Extracurricular	1.0	0.0	1	0	1		46%	166/362 [10:27<13:42,	4.20
AppliedSciences SocialSciences	0.07142857142857142	0.9285714285714286	1	13	14		46%	167/362 [10:31<12:57,	3.99
History_Geography ParentInvolvement	0.0	1.0	0	1	1		46%	168/362 [10:34<12:23,	3.83
Extracurricular PerformingArts	0.0	1.0	0	8	8		47%	169/362 [10:38<11:58,	3.72

Feature = Music ParentInvolvement Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 2 sum = 2	
47% ██████████████████████████████████████ s/it]	170/362 [10:41<11:42, 3.66
Feature = AppliedSciences History_Geography Prob neg = 0.22727272727272727 Prob pos = 0.7727272727272727 count neg = 5 count pos = 17 sum = 22	
47% ██████████████████████████████████████ s/it]	171/362 [10:45<11:38, 3.66
Feature = Gym_Fitness Literacy Prob neg = 0.5 Prob pos = 0.5 count neg = 4 count pos = 4 sum = 8	
48% ██████████████████████████████████████ s/it]	172/362 [10:49<11:32, 3.65
Feature = SocialSciences VisualArts Prob neg = 0.05263157894736842 Prob pos = 0.9473684210526315 count neg = 1 count pos = 18 sum = 19	
48% ██████████████████████████████████████ s/it]	173/362 [10:52<11:22, 3.61
Feature = Extracurricular Literature_Writing Prob neg = 0.1 Prob pos = 0.9 count neg = 1 count pos = 9 sum = 10	
48% ██████████████████████████████████████ s/it]	174/362 [10:56<11:19, 3.61
Feature = Civics_Government SocialSciences Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 25 sum = 25	
48% ██████████████████████████████████████ s/it]	175/362 [10:59<11:07, 3.57
Feature = Economics Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 13 sum = 13	
49% ██████████████████████████████████████ s/it]	176/362 [11:03<11:02, 3.56
Feature = CharacterEducation SpecialNeeds Prob neg = 0.13725490196078433 Prob pos = 0.8627450980392157 count neg = 7 count pos = 44 sum = 51	
49% ██████████████████████████████████████ s/it]	177/362 [11:06<11:00, 3.57
Feature = Literacy NutritionEducation Prob neg = 0.5 Prob pos = 0.5 count neg = 1 count pos = 1 sum = 2	
49% ██████████████████████████████████████ s/it]	178/362 [11:10<10:58, 3.58
Feature = ESL SpecialNeeds Prob neg = 0.10204081632653061 Prob pos = 0.8979591836734694 count neg = 5 count pos = 44 sum = 49	
49% ██████████████████████████████████████ s/it]	179/362 [11:13<10:49, 3.55
Feature = College_CareerPrep Health_LifeScience Prob neg = 0.1 Prob pos = 0.9 count neg = 1 count pos = 9 sum = 10	
50% ██████████████████████████████████████ s/it]	180/362 [11:17<10:47, 3.56
Feature = College_CareerPrep ForeignLanguages Prob neg = 0.2 Prob pos = 0.8 count neg = 1 count pos = 4 sum = 5	
50% ██████████████████████████████████████ s/it]	181/362 [11:21<10:43, 3.56
Feature = Civics_Government Health_LifeScience Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 4 sum = 4	
50% ██████████████████████████████████████ s/it]	182/362 [11:24<10:39, 3.55

Feature = CharacterEducation Extracurricular Prob neg = 0.3125 Prob pos = 0.6875 count neg = 5 count pos = 11 sum = 16	
51% ██████████████████████████████████████ s/it]	183/362 [11:28<10:38, 3.56
Feature = Economics FinancialLiteracy Prob neg = 0.3125 Prob pos = 0.6875 count neg = 5 count pos = 11 sum = 16	
51% ██████████████████████████████████████ s/it]	184/362 [11:31<10:41, 3.61
Feature = CommunityService NutritionEducation Prob neg = 1.0 Prob pos = 0.0 count neg = 2 count pos = 0 sum = 2	
51% ██████████████████████████████████████ s/it]	185/362 [11:35<11:01, 3.74
Feature = ForeignLanguages Literature_Writing Prob neg = 0.17391304347826086 Prob pos = 0.8260869565217391 count neg = 4 count pos = 19 sum = 23	
51% ██████████████████████████████████████ s/it]	186/362 [11:39<10:44, 3.66
Feature = ParentInvolvement SpecialNeeds Prob neg = 0.25 Prob pos = 0.75 count neg = 2 count pos = 6 sum = 8	
52% ██████████████████████████████████████ s/it]	187/362 [11:42<10:35, 3.63
Feature = Literacy Music Prob neg = 0.125 Prob pos = 0.875 count neg = 5 count pos = 35 sum = 40	
52% ██████████████████████████████████████ s/it]	188/362 [11:46<10:28, 3.61
Feature = Extracurricular Mathematics Prob neg = 0.23529411764705882 Prob pos = 0.7647058823529411 count neg = 4 count pos = 13 sum = 17	
52% ██████████████████████████████████████ s/it]	189/362 [11:50<10:23, 3.61
Feature = CharacterEducation Health_Wellness Prob neg = 0.10344827586206896 Prob pos = 0.896551724137931 count neg = 3 count pos = 26 sum = 29	
52% ██████████████████████████████████████ s/it]	190/362 [11:53<10:17, 3.59
Feature = EarlyDevelopment Extracurricular Prob neg = 0.6666666666666666 Prob pos = 0.3333333333333333 count neg = 2 count pos = 1 sum = 3	
53% ██████████████████████████████████████ s/it]	191/362 [11:57<10:08, 3.56
Feature = Civics_Government Economics Prob neg = 0.09090909090909091 Prob pos = 0.9090909090909091 count neg = 1 count pos = 10 sum = 11	
53% ██████████████████████████████████████ s/it]	192/362 [12:00<10:03, 3.55
Feature = NutritionEducation TeamSports Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666 count neg = 1 count pos = 2 sum = 3	
53% ██████████████████████████████████████ s/it]	193/362 [12:04<09:58, 3.54
Feature = Mathematics TeamSports Prob neg = 0.5 Prob pos = 0.5 count neg = 1 count pos = 1 sum = 2	
54% ██████████████████████████████████████ s/it]	194/362 [12:07<09:49, 3.51
Feature = CommunityService Extracurricular Prob neg = 0.2222222222222222 Prob pos = 0.7777777777777778 count neg = 2 count pos = 7 sum = 9	
54% ██████████████████████████████████████ s/it]	195/362 [12:11<09:38, 3.47

```
54% ██████████ | 197/362 [12:18<09:34, 3.48  
s/it]
```

```
55% ██████████ | 199/362 [12:25<09:31, 3.50  
s/it]
```

```
55% ██████████ | 200/362 [12:28<09:29, 3.52  
s/it]
```

```
s/it] | ██████████| 201/362 [12:32<09:26,   3.52
```

56% ██████████ | 202/362 [12:35<09:21, 3.51
s/it]

```
s/it] ██████████ | 203/362 [12:39<09:17,   3.51
```

```
56% ██████████ | 204/362 [12:42<09:15, 3.52  
s/it]
```

```
57% ████████████████████████████████████████████████████████████████████████████ | 205/362 [12:46<09:12, 3.52
```

```
s/it]
```

```
s/it| ██████████ | 206/362 [12:49<09:11, 3.53
```

```
s/it| ██████████ 57% | 207/362 [12:53<09:10, 3.55
```

[illegible]

```
Feature = Economics EnvironmentalScience
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 3 sum = 3

61%|███████████████████████████████████████ | 222/362 [13:46<08:28, 3.63
s/it]

Feature = College_CareerPrep Other
Prob neg = 0.23076923076923078 Prob pos = 0.7692307692307693
count neg = 6 count pos = 20 sum = 26

62%|███████████████████████████████████████ | 223/362 [13:50<08:22, 3.61
s/it]

Feature = CharacterEducation ParentInvolvement
Prob neg = 0.25 Prob pos = 0.75
count neg = 3 count pos = 9 sum = 12

62%|███████████████████████████████████████ | 224/362 [13:53<08:11, 3.56
s/it]

Feature = AppliedSciences TeamSports
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 5 sum = 5

62%|███████████████████████████████████████ | 225/362 [13:57<08:03, 3.53
s/it]

Feature = History_Geography Other
Prob neg = 0.4 Prob pos = 0.6
count neg = 2 count pos = 3 sum = 5
unique feature = ForeignLanguages Gym_Fitness

62%|███████████████████████████████████████ | 226/362 [14:01<08:03, 3.56
s/it]

Feature = ForeignLanguages Gym_Fitness
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 1 sum = 1

63%|███████████████████████████████████████ | 227/362 [14:04<07:57, 3.54
s/it]

Feature = CharacterEducation Music
Prob neg = 0.25 Prob pos = 0.75
count neg = 1 count pos = 3 sum = 4
unique feature = Civics_Government NutritionEducation

63%|███████████████████████████████████████ | 228/362 [14:08<07:52, 3.52
s/it]

Feature = Civics_Government NutritionEducation
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 1 sum = 1

63%|███████████████████████████████████████ | 229/362 [14:11<07:49, 3.53
s/it]

Feature = EarlyDevelopment SocialSciences
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 3 sum = 3

64%|███████████████████████████████████████ | 230/362 [14:15<07:46, 3.54
s/it]

Feature = Health_Wellness PerformingArts
Prob neg = 0.25 Prob pos = 0.75
count neg = 1 count pos = 3 sum = 4

64%|███████████████████████████████████████ | 231/362 [14:18<07:42, 3.53
s/it]

Feature = EarlyDevelopment Warmth Care_Hunger
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2

64%|███████████████████████████████████████ | 232/362 [14:22<07:38, 3.53
s/it]

Feature = FinancialLiteracy Literature_Writing
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666
count neg = 1 count pos = 2 sum = 3

64%|███████████████████████████████████████ | 233/362 [14:25<07:32, 3.51
s/it]

Feature = CommunityService ParentInvolvement
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 3 sum = 3
unique feature = Literature_Writing Warmth Care_Hunger
```

		234/362 [14:29<07:32,	3.53
<hr/>			
Feature = Literature_Writing Warmth Care_Hunger Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 1 sum = 1			
65% ██████████████████ s/]it]		235/362 [14:32<07:30,	3.55
<hr/>			
Feature = CharacterEducation ForeignLanguages Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 3 sum = 3			
65% ██████████████████ s/]it]		236/362 [14:36<07:28,	3.56
<hr/>			
Feature = Civics_Government Prob neg = 0.25 Prob pos = 0.75 count neg = 4 count pos = 12 sum = 16			
65% ██████████████████ s/]it]		237/362 [14:39<07:21,	3.53
<hr/>			
Feature = ESL Other Prob neg = 0.5 Prob pos = 0.5 count neg = 1 count pos = 1 sum = 2 unique feature = College_CareerPrep Gym_Fitness			
66% ██████████████████ s/]it]		238/362 [14:43<07:17,	3.53
<hr/>			
Feature = College_CareerPrep Gym_Fitness Prob neg = 1.0 Prob pos = 0.0 count neg = 1 count pos = 0 sum = 1			
66% ██████████████████ s/]it]		239/362 [14:46<07:15,	3.54
<hr/>			
Feature = Extracurricular Health_Wellness Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 4 sum = 4			
66% ██████████████████ s/]it]		240/362 [14:50<07:10,	3.53
<hr/>			
Feature = ForeignLanguages Health_Wellness Prob neg = 0.5 Prob pos = 0.5 count neg = 1 count pos = 1 sum = 2			
67% ██████████████████ s/]it]		241/362 [14:53<07:04,	3.51
<hr/>			
Feature = ESL PerformingArts Prob neg = 0.5 Prob pos = 0.5 count neg = 2 count pos = 2 sum = 4			
67% ██████████████████ s/]it]		242/362 [14:57<07:01,	3.51
<hr/>			
Feature = ForeignLanguages SocialSciences Prob neg = 0.5 Prob pos = 0.5 count neg = 1 count pos = 1 sum = 2			
67% ██████████████████ s/]it]		243/362 [15:00<06:58,	3.51
<hr/>			
Feature = EarlyDevelopment FinancialLiteracy Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 2 sum = 2			
67% ██████████████████ s/]it]		244/362 [15:04<06:55,	3.52
<hr/>			
Feature = NutritionEducation Other Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 3 sum = 3			
68% ██████████████████ s/]it]		245/362 [15:08<06:53,	3.54
<hr/>			
Feature = ParentInvolvement PerformingArts Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 2 sum = 2 unique feature = Civics_Government TeamSports			
68% ██████████████████ s/]it]		246/362 [15:11<06:49,	3.53
<hr/>			
Feature = Civics_Government TeamSports Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 1 sum = 1			


```

68%|███████████████████████████████████████████████████████████████████████████████| 247/362 [15:14<06:42, 3.50
s/it]

Feature = ESL_Health_LifeScience
Prob neg = 0.18181818181818182 Prob pos = 0.8181818181818182
count neg = 2 count pos = 9 sum = 11

69%|███████████████████████████████████████████████████████████████████████████████| 248/362 [15:18<06:40, 3.51
s/it]

Feature = EarlyDevelopment_EnvironmentalScience
Prob neg = 0.21428571428571427 Prob pos = 0.7857142857142857
count neg = 3 count pos = 11 sum = 14

69%|███████████████████████████████████████████████████████████████████████████████| 249/362 [15:21<06:33, 3.48
s/it]

Feature = Other_ParentInvolvement
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 3 sum = 3

69%|███████████████████████████████████████████████████████████████████████████████| 250/362 [15:25<06:30, 3.48
s/it]

Feature = ForeignLanguages_Mathematics
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 11 sum = 11

69%|███████████████████████████████████████████████████████████████████████████████| 251/362 [15:30<07:24, 4.01
s/it]

Feature = College_CareerPrep_Health_Wellness
Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334
count neg = 1 count pos = 5 sum = 6

70%|███████████████████████████████████████████████████████████████████████████████| 252/362 [15:36<08:13, 4.49
s/it]

Feature = CharacterEducation_TeamSports
Prob neg = 0.75 Prob pos = 0.25
count neg = 3 count pos = 1 sum = 4

70%|███████████████████████████████████████████████████████████████████████████████| 253/362 [15:39<07:40, 4.22
s/it]

Feature = Health_LifeScience_Music
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 5 sum = 5

70%|███████████████████████████████████████████████████████████████████████████████| 254/362 [15:43<07:12, 4.01
s/it]

Feature = ForeignLanguages_SpecialNeeds
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 5 sum = 5

70%|███████████████████████████████████████████████████████████████████████████████| 255/362 [15:46<06:55, 3.88
s/it]

Feature = EarlyDevelopment_Gym_Fitness
Prob neg = 0.11111111111111111 Prob pos = 0.8888888888888888
count neg = 1 count pos = 8 sum = 9

71%|███████████████████████████████████████████████████████████████████████████████| 256/362 [15:50<06:40, 3.78
s/it]

Feature = ParentInvolvement
Prob neg = 0.4444444444444444 Prob pos = 0.5555555555555556
count neg = 4 count pos = 5 sum = 9

71%|███████████████████████████████████████████████████████████████████████████████| 257/362 [15:54<06:29, 3.71
s/it]

Feature = College_CareerPrep_NutritionEducation
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2
unique feature = AppliedSciences_Warmth_Care_Hunger

71%|███████████████████████████████████████████████████████████████████████████████| 258/362 [15:57<06:19, 3.64
s/it]

Feature = AppliedSciences_Warmth_Care_Hunger
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 1 sum = 1

72%|███████████████████████████████████████████████████████████████████████████████| 259/362 [16:01<06:13, 3.62
s/it]

Feature = Economics_History_Geography
Prob neg = 0.14285714285714285 Prob pos = 0.8571428571428571
count neg = 1 count pos = 6 sum = 7

```

Feature	Prob neg	Prob pos	count neg	count pos	sum	72%	s/it]
EnvironmentalScience ParentInvolvement	0.0	1.0	0	5	5		260/362 [16:04<06:10, 3.63
AppliedSciences Gym_Fitness	0.4	0.6	2	3	5		261/362 [16:08<06:03, 3.60
Extracurricular Gym_Fitness	0.0	1.0	0	2	2		262/362 [16:12<06:10, 3.70
AppliedSciences CharacterEducation	0.15384615384615385	0.8461538461538461	2	11	13		263/362 [16:15<06:07, 3.72
ParentInvolvement VisualArts	0.11111111111111111	0.8888888888888888	1	8	9		264/362 [16:19<05:59, 3.66
Other Warmth Care_Hunger	0.0	1.0	0	1	1		265/362 [16:23<05:51, 3.62
Extracurricular NutritionEducation	1.0	0.0	1	0	1		266/362 [16:26<05:48, 3.63
ESL SocialSciences	0.4	0.6	2	3	5		267/362 [16:30<05:43, 3.62
Gym_Fitness Mathematics	0.14285714285714285	0.8571428571428571	1	6	7		268/362 [16:33<05:39, 3.61
CommunityService Music	0.0	1.0	0	1	1		269/362 [16:37<05:35, 3.60
Economics Literacy	0.0	1.0	0	3	3		270/362 [16:40<05:29, 3.58
ESL Health_Wellness	0.16666666666666666	0.8333333333333334	1	5	6		271/362 [16:44<05:22, 3.54
							272/362 [16:48<05:21, 3.58

Feature = Civics_Government EnvironmentalScience	
Prob neg = 0.2857142857142857 Prob pos = 0.7142857142857143	
count neg = 2 count pos = 5 sum = 7	
75% ███	273/362 [16:51<05:16, 3.55
s/it]	
Feature = ESL VisualArts	
Prob neg = 0.3 Prob pos = 0.7	
count neg = 3 count pos = 7 sum = 10	
76% ███	274/362 [16:55<05:11, 3.54
s/it]	
Feature = SpecialNeeds TeamSports	
Prob neg = 0.4 Prob pos = 0.6	
count neg = 4 count pos = 6 sum = 10	
76% ███	275/362 [16:58<05:06, 3.52
s/it]	
Feature = Health_LifeScience TeamSports	
Prob neg = 0.0 Prob pos = 1.0	
count neg = 0 count pos = 3 sum = 3	
76% ███	276/362 [17:02<05:20, 3.73
s/it]	
Feature = ParentInvolvement SocialSciences	
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666	
count neg = 1 count pos = 2 sum = 3	
77% ███	277/362 [17:06<05:12, 3.67
s/it]	
Feature = Civics_Government SpecialNeeds	
Prob neg = 0.5 Prob pos = 0.5	
count neg = 2 count pos = 2 sum = 4	
77% ███	278/362 [17:09<05:04, 3.63
s/it]	
Feature = AppliedSciences CommunityService	
Prob neg = 0.2857142857142857 Prob pos = 0.7142857142857143	
count neg = 2 count pos = 5 sum = 7	
77% ███	279/362 [17:13<04:57, 3.59
s/it]	
Feature = Extracurricular History_Geography	
Prob neg = 0.0 Prob pos = 1.0	
count neg = 0 count pos = 2 sum = 2	
77% ███	280/362 [17:16<04:52, 3.57
s/it]	
Feature = CommunityService Mathematics	
Prob neg = 0.4 Prob pos = 0.6	
count neg = 2 count pos = 3 sum = 5	
78% ███	281/362 [17:20<04:48, 3.56
s/it]	
Feature = CharacterEducation SocialSciences	
Prob neg = 0.2857142857142857 Prob pos = 0.7142857142857143	
count neg = 2 count pos = 5 sum = 7	
78% ███	282/362 [17:23<04:43, 3.54
s/it]	
Feature = Literature_Writing TeamSports	
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666	
count neg = 1 count pos = 2 sum = 3	
78% ███	283/362 [17:27<04:37, 3.52
s/it]	
Feature = History_Geography Music	
Prob neg = 0.0 Prob pos = 1.0	
count neg = 0 count pos = 4 sum = 4	
78% ███	284/362 [17:30<04:33, 3.51
s/it]	
Feature = Music TeamSports	
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666	
count neg = 1 count pos = 2 sum = 3	
79% ███	285/362 [17:35<04:49, 3.76
s/it]	

```
Feature = ForeignLanguages History_Geography
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 5      sum = 5
unique feature = Music SocialSciences
```

```
Feature = Music SocialSciences
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
Feature = ForeignLanguages VisualArts
Prob neg = 0.2      Prob pos = 0.8
count neg = 1      count pos = 4      sum = 5
```

```
Feature = EnvironmentalScience NutritionEducation
Prob neg = 0.5      Prob pos = 0.5
count neg = 5      count pos = 5      sum = 10
```

```
Feature = Mathematics PerformingArts
Prob neg = 0.25      Prob pos = 0.75
count neg = 1      count pos = 3      sum = 4
```

```
Feature = EnvironmentalScience Other
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666
count neg = 1 count pos = 2 sum = 3
```

```
Feature = FinancialLiteracy SpecialNeeds
Prob neg = 0.23529411764705882      Prob pos = 0.7647058823529411
count neg = 4      count pos = 13      sum = 17
```

```
Feature = Gym_Fitness PerformingArts
Prob neg = 1.0      Prob pos = 0.0
count neg = 2      count pos = 0      sum = 2
```

```
Feature = EarlyDevelopment PerformingArts
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 5      sum = 5
```

```
Feature = Civics_Government CommunityService
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666
count neg = 1 count pos = 2 sum = 3
```

```
Feature = EarlyDevelopment Health_LifeScience
Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334
count neg = 1 count pos = 5 sum = 6
```

```
Feature = EnvironmentalScience Extracurricular
Prob neg = 0.5      Prob pos = 0.5
count neg = 1      count pos = 1      sum = 2
unique feature = Civics Government PerformingArts
```

```
Feature = Civics_Government PerformingArts
Prob neg = 1.0      Prob pos = 0.0
count neg = 1      count pos = 0      sum = 1
```

Feature	Prob neg	Prob pos	count neg	count pos	sum	83%	
CommunityService SocialSciences	0.5	0.5	1	1	2		299/362 [18:24<03:42, 3.54
Civics_Government Mathematics	0.2	0.8	1	4	5		300/362 [18:27<03:36, 3.49
NutritionEducation SocialSciences	0.0	1.0	0	2	2		301/362 [18:31<03:32, 3.48
ForeignLanguages Health_LifeScience	0.0	1.0	0	3	3		302/362 [18:35<03:31, 3.52
Economics SpecialNeeds	1.0	0.0	1	0	1		303/362 [18:38<03:27, 3.52
Gym_Fitness Other	0.0	1.0	0	4	4		304/362 [18:42<03:24, 3.53
College_CareerPrep ParentInvolvement	0.2	0.8	2	8	10		305/362 [18:45<03:23, 3.56
ESL Gym_Fitness	1.0	0.0	1	0	1		306/362 [18:49<03:19, 3.56
Economics SocialSciences	0.0	1.0	0	2	2		307/362 [18:52<03:13, 3.51
CommunityService Health_LifeScience	0.0	1.0	0	3	3		308/362 [18:56<03:10, 3.53
AppliedSciences ForeignLanguages	0.6666666666666666	0.3333333333333333	2	1	3		309/362 [18:59<03:07, 3.54
CommunityService Economics	0.0	1.0	0	2	2		310/362 [19:03<03:03, 3.53
EnvironmentalScience ForeignLanguages	0.0	1.0	0	1	1		

```

      86%|███████████████████████████████████████| | 311/362 [19:06<03:00,  3.53
s/it]

Feature = ForeignLanguages Music
Prob neg = 0.0    Prob pos = 1.0
count neg = 0     count pos = 2       sum = 2
unique feature = Extracurricular Health_LifeScience


      86%|███████████████████████████████████████| | 312/362 [19:10<02:55,  3.51
s/it]

Feature = Extracurricular Health_LifeScience
Prob neg = 1.0    Prob pos = 0.0
count neg = 1     count pos = 0       sum = 1


      86%|███████████████████████████████████████| | 313/362 [19:13<02:52,  3.52
s/it]

Feature = CharacterEducation Gym_Fitness
Prob neg = 0.0    Prob pos = 1.0
count neg = 0     count pos = 2       sum = 2
unique feature = ESL Extracurricular


      87%|███████████████████████████████████████| | 314/362 [19:17<02:49,  3.53
s/it]

Feature = ESL Extracurricular
Prob neg = 0.0    Prob pos = 1.0
count neg = 0     count pos = 1       sum = 1


      87%|███████████████████████████████████████| | 315/362 [19:20<02:45,  3.53
s/it]

Feature = Mathematics NutritionEducation
Prob neg = 0.0    Prob pos = 1.0
count neg = 0     count pos = 2       sum = 2
unique feature = Health_LifeScience ParentInvolvement


      87%|███████████████████████████████████████| | 316/362 [19:24<02:42,  3.53
s/it]

Feature = Health_LifeScience ParentInvolvement
Prob neg = 0.0    Prob pos = 1.0
count neg = 0     count pos = 1       sum = 1


      88%|███████████████████████████████████████| | 317/362 [19:28<02:38,  3.53
s/it]

Feature = CharacterEducation Health_LifeScience
Prob neg = 0.5    Prob pos = 0.5
count neg = 2     count pos = 2       sum = 4


      88%|███████████████████████████████████████| | 318/362 [19:31<02:38,  3.60
s/it]

Feature = PerformingArts TeamSports
Prob neg = 0.25   Prob pos = 0.75
count neg = 1     count pos = 3       sum = 4
unique feature = FinancialLiteracy Health_Wellness


      88%|███████████████████████████████████████| | 319/362 [19:35<02:42,  3.77
s/it]

Feature = FinancialLiteracy Health_Wellness
Prob neg = 0.0    Prob pos = 1.0
count neg = 0     count pos = 1       sum = 1
unique feature = Other TeamSports


      88%|███████████████████████████████████████| | 320/362 [19:39<02:35,  3.71
s/it]

Feature = Other TeamSports
Prob neg = 0.0    Prob pos = 1.0
count neg = 0     count pos = 1       sum = 1


      89%|███████████████████████████████████████| | 321/362 [19:43<02:29,  3.65
s/it]

Feature = Health_Wellness ParentInvolvement
Prob neg = 0.5    Prob pos = 0.5
count neg = 1     count pos = 1       sum = 2


      89%|███████████████████████████████████████| | 322/362 [19:46<02:25,  3.63
s/it]

Feature = Health_LifeScience Other
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666
count neg = 1     count pos = 2       sum = 3


      89%|███████████████████████████████████████| | 323/362 [19:50<02:20,  3.61
s/it]
```

```
Feature = CharacterEducation EnvironmentalScience
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 2      sum = 2
```

```
Feature = ESL ParentInvolvement
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 3      sum = 3
unique feature = CommunityService FinancialLiteracy
```

```
Feature = CommunityService FinancialLiteracy
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
unique feature = Extracurricular ForeignLanguages
```

```
Feature = Extracurricular ForeignLanguages
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
unique feature = Literacy Warmth Care_Hunger
```

```
Feature = Literacy Warmth Care_Hunger
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
Feature = FinancialLiteracy Literacy
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 5      sum = 5
unique feature = CommunityService ESL
```

```
Feature = CommunityService ESL
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
Feature = College_CareerPrep History_Geography
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666
count neg = 1 count pos = 2 sum = 3
unique feature = Economics Music
```

```
Feature = Economics Music
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
92% | 332/362 [20:21<01:45, 3.51
s/it]
```

```
Feature = EnvironmentalScience PerformingArts
Prob neg = 0.5      Prob pos = 0.5
count neg = 1      count pos = 1      sum = 2
unique feature = Other PerformingArts
```

```

Feature = Other PerformingArts
Prob neg = 1.0      Prob pos = 0.0
count neg = 1      count pos = 0      sum = 1
unique feature = FinancialLiteracy History Geography

```

```
Feature = FinancialLiteracy History_Geography
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```



```
Feature = CharacterEducation Warmth Care_Hunger
Prob neg = 1.0      Prob pos = 0.0
count neg = 2      count pos = 0      sum = 2
unique feature = AppliedSciences NutritionEducation
```

```
Feature = AppliedSciences NutritionEducation
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
Feature = CharacterEducation Civics_Government
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 2      sum = 2
unique feature = EnvironmentalScience Warmth Care_Hunger
```

```
Feature = EnvironmentalScience Warmth Care_Hunger
Prob neg = 1.0      Prob pos = 0.0
count neg = 1      count pos = 0      sum = 1
unique feature = CommunityService Gym_Fitness
```

```
Feature = CommunityService Gym_Fitness
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
unique feature = CommunityService Other
```

```
Feature = CommunityService Other
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
unique feature = ForeignLanguages PerformingArts
```

```
Feature = ForeignLanguages PerformingArts
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
unique feature = NutritionEducation VisualArts
```

```
Feature = NutritionEducation VisualArts
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
Feature = CharacterEducation History_Geography
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 2      sum = 2
```

```
unique feature = CommunityService_History_Geography
Feature = CommunityService_History_Geography
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
unique feature = ParentInvolvement TeamSports
Feature = ParentInvolvement TeamSports
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
unique feature = Mathematics Warmth Care_Hunger
Feature = Mathematics Warmth Care_Hunger
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

2.2.2.4 School State

```
In [72]: X_train.school_state.value_counts()
```

```
Out[72]: CA      4244
TX      2058
NY      2040
FL      1684
NC      1430
IL      1190
SC      1115
GA      1099
MI       901
PA       853
IN       704
OH       689
MO       684
LA       679
MA       643
WA       643
OK       641
NJ       616
AZ       598
VA       549
WI       497
AL       481
CT       480
UT       478
TN       470
MD       390
NV       387
KY       365
MS       355
OR       349
MN       340
CO       306
AR       257
IA       192
KS       181
ID       177
ME       154
NM       148
DC       147
HI       146
WV       122
DE       102
NE        95
AK        90
SD        83
RI        79
NH        72
MT        62
ND        33
WY        29
VT        23
Name: school_state, dtype: int64
```

```
In [73]: response_school_state = response(X_train['school_state'],y_train)
```

```

2%|██████| 1/51 [00:04<03:23, 4.07
s/it]

Feature = MO
Prob neg = 0.12719298245614036 Prob pos = 0.8728070175438597
count neg = 87 count pos = 597 sum = 684

4%|██████| 2/51 [00:08<03:31, 4.33
s/it]

Feature = NY
Prob neg = 0.15 Prob pos = 0.85
count neg = 306 count pos = 1734 sum = 2040

6%|██████| 3/51 [00:15<03:57, 4.95
s/it]

Feature = CA
Prob neg = 0.14255419415645618 Prob pos = 0.8574458058435438
count neg = 605 count pos = 3639 sum = 4244

8%|██████| 4/51 [00:19<03:39, 4.67
s/it]

Feature = IN
Prob neg = 0.171875 Prob pos = 0.828125
count neg = 121 count pos = 583 sum = 704

10%|██████| 5/51 [00:24<03:39, 4.78
s/it]

Feature = TX
Prob neg = 0.19387755102040816 Prob pos = 0.8061224489795918
count neg = 399 count pos = 1659 sum = 2058

12%|██████| 6/51 [00:28<03:21, 4.48
s/it]

Feature = AR
Prob neg = 0.16731517509727625 Prob pos = 0.8326848249027238
count neg = 43 count pos = 214 sum = 257

14%|██████| 7/51 [00:32<03:17, 4.49
s/it]

Feature = NC
Prob neg = 0.13356643356643358 Prob pos = 0.8664335664335664
count neg = 191 count pos = 1239 sum = 1430

16%|██████| 8/51 [00:36<03:05, 4.32
s/it]

Feature = CT
Prob neg = 0.11666666666666667 Prob pos = 0.8833333333333333
count neg = 56 count pos = 424 sum = 480

18%|██████| 9/51 [00:40<02:51, 4.09
s/it]

Feature = MT
Prob neg = 0.24193548387096775 Prob pos = 0.7580645161290323
count neg = 15 count pos = 47 sum = 62

20%|██████| 10/51 [00:43<02:43, 3.99
s/it]

Feature = MS
Prob neg = 0.19718309859154928 Prob pos = 0.8028169014084507
count neg = 70 count pos = 285 sum = 355

22%|██████| 11/51 [00:47<02:37, 3.94
s/it]

Feature = NV
Prob neg = 0.12919896640826872 Prob pos = 0.8708010335917312
count neg = 50 count pos = 337 sum = 387

24%|██████| 12/51 [00:52<02:37, 4.03
s/it]

Feature = MI
Prob neg = 0.16870144284128746 Prob pos = 0.8312985571587126
count neg = 152 count pos = 749 sum = 901

25%|██████| 13/51 [00:56<02:33, 4.04
s/it]

Feature = MA
Prob neg = 0.14307931570762053 Prob pos = 0.8569206842923794
count neg = 92 count pos = 551 sum = 643

```

27% ██████████ s/it]	14/51 [00:59<02:27, 3.99
Feature = TN Prob neg = 0.14893617021276595 Prob pos = 0.851063829787234 count neg = 70 count pos = 400 sum = 470	
29% ██████████ s/it]	15/51 [01:03<02:19, 3.86
Feature = KS Prob neg = 0.11602209944751381 Prob pos = 0.8839779005524862 count neg = 21 count pos = 160 sum = 181	
31% ██████████ s/it]	16/51 [01:08<02:21, 4.05
Feature = IL Prob neg = 0.15126050420168066 Prob pos = 0.8487394957983193 count neg = 180 count pos = 1010 sum = 1190	
33% ██████████ s/it]	17/51 [01:12<02:24, 4.24
Feature = FL Prob neg = 0.18171021377672208 Prob pos = 0.8182897862232779 count neg = 306 count pos = 1378 sum = 1684	
35% ██████████ s/it]	18/51 [01:17<02:21, 4.28
Feature = GA Prob neg = 0.1492265696087352 Prob pos = 0.8507734303912647 count neg = 164 count pos = 935 sum = 1099	
37% ██████████ s/it]	19/51 [01:21<02:18, 4.31
Feature = UT Prob neg = 0.1694560669456067 Prob pos = 0.8305439330543933 count neg = 81 count pos = 397 sum = 478	
39% ██████████ s/it]	20/51 [01:25<02:09, 4.19
Feature = IA Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334 count neg = 32 count pos = 160 sum = 192	
41% ██████████ s/it]	21/51 [01:29<02:05, 4.17
Feature = OH Prob neg = 0.11175616835994194 Prob pos = 0.888243831640058 count neg = 77 count pos = 612 sum = 689	
43% ██████████ s/it]	22/51 [01:33<01:56, 4.01
Feature = DC Prob neg = 0.19727891156462585 Prob pos = 0.8027210884353742 count neg = 29 count pos = 118 sum = 147	
45% ██████████ s/it]	23/51 [01:37<01:52, 4.02
Feature = AZ Prob neg = 0.1588628762541806 Prob pos = 0.8411371237458194 count neg = 95 count pos = 503 sum = 598	
47% ██████████ s/it]	24/51 [01:40<01:46, 3.93
Feature = KY Prob neg = 0.12876712328767123 Prob pos = 0.8712328767123287 count neg = 47 count pos = 318 sum = 365	
49% ██████████ s/it]	25/51 [01:44<01:42, 3.96
Feature = LA Prob neg = 0.17673048600883653 Prob pos = 0.8232695139911634 count neg = 120 count pos = 559 sum = 679	
51% ██████████ s/it]	26/51 [01:48<01:38, 3.96
Feature = VA Prob neg = 0.14754098360655737 Prob pos = 0.8524590163934426 count neg = 81 count pos = 468 sum = 549	

53%|███████████████████████████████████████
s/it] | 27/51 [01:52<01:35, 3.98

Feature = WA
Prob neg = 0.104199066874028 Prob pos = 0.895800933125972
count neg = 67 count pos = 576 sum = 643

55%|███████████████████████████████████████
s/it] | 28/51 [01:56<01:31, 3.96

Feature = AL
Prob neg = 0.14553014553014554 Prob pos = 0.8544698544698545
count neg = 70 count pos = 411 sum = 481

57%|███████████████████████████████████████
s/it] | 29/51 [02:01<01:29, 4.07

Feature = SC
Prob neg = 0.14708520179372198 Prob pos = 0.852914798206278
count neg = 164 count pos = 951 sum = 1115

59%|███████████████████████████████████████
s/it] | 30/51 [02:04<01:23, 3.98

Feature = MN
Prob neg = 0.15588235294117647 Prob pos = 0.8441176470588235
count neg = 53 count pos = 287 sum = 340

61%|███████████████████████████████████████
s/it] | 31/51 [02:08<01:19, 3.98

Feature = NJ
Prob neg = 0.19318181818181818 Prob pos = 0.8068181818181818
count neg = 119 count pos = 497 sum = 616

63%|███████████████████████████████████████
s/it] | 32/51 [02:12<01:15, 4.00

Feature = PA
Prob neg = 0.14419695193434937 Prob pos = 0.8558030480656507
count neg = 123 count pos = 730 sum = 853

65%|███████████████████████████████████████
s/it] | 33/51 [02:16<01:10, 3.92

Feature = OR
Prob neg = 0.17191977077363896 Prob pos = 0.828080229226361
count neg = 60 count pos = 289 sum = 349

67%|███████████████████████████████████████
s/it] | 34/51 [02:20<01:05, 3.83

Feature = AK
Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334
count neg = 15 count pos = 75 sum = 90

69%|███████████████████████████████████████
s/it] | 35/51 [02:24<01:01, 3.84

Feature = MD
Prob neg = 0.1641025641025641 Prob pos = 0.8358974358974359
count neg = 64 count pos = 326 sum = 390

71%|███████████████████████████████████████
s/it] | 36/51 [02:27<00:57, 3.80

Feature = CO
Prob neg = 0.16013071895424835 Prob pos = 0.8398692810457516
count neg = 49 count pos = 257 sum = 306

73%|███████████████████████████████████████
s/it] | 37/51 [02:31<00:51, 3.71

Feature = WY
Prob neg = 0.20689655172413793 Prob pos = 0.7931034482758621
count neg = 6 count pos = 23 sum = 29

75%|███████████████████████████████████████
s/it] | 38/51 [02:35<00:48, 3.69

Feature = WV
Prob neg = 0.14754098360655737 Prob pos = 0.8524590163934426
count neg = 18 count pos = 104 sum = 122

76%|███████████████████████████████████████
s/it] | 39/51 [02:38<00:44, 3.67

Feature = ID
Prob neg = 0.2033898305084746 Prob pos = 0.7966101694915254
count neg = 36 count pos = 141 sum = 177

78%		40/51	[02:44<00:48,	4.40
s/it]				
Feature = NH				
Prob neg = 0.1388888888888889 Prob pos = 0.8611111111111112				
count neg = 10 count pos = 62 sum = 72				
80%		41/51	[02:49<00:43,	4.38
s/it]				
Feature = OK				
Prob neg = 0.14664586583463338 Prob pos = 0.8533541341653667				
count neg = 94 count pos = 547 sum = 641				
82%		42/51	[02:53<00:38,	4.25
s/it]				
Feature = DE				
Prob neg = 0.11764705882352941 Prob pos = 0.8823529411764706				
count neg = 12 count pos = 90 sum = 102				
84%		43/51	[02:57<00:34,	4.30
s/it]				
Feature = ME				
Prob neg = 0.16233766233766234 Prob pos = 0.8376623376623377				
count neg = 25 count pos = 129 sum = 154				
86%		44/51	[03:01<00:30,	4.31
s/it]				
Feature = SD				
Prob neg = 0.13253012048192772 Prob pos = 0.8674698795180723				
count neg = 11 count pos = 72 sum = 83				
88%		45/51	[03:05<00:25,	4.21
s/it]				
Feature = NM				
Prob neg = 0.12162162162162163 Prob pos = 0.8783783783783784				
count neg = 18 count pos = 130 sum = 148				
90%		46/51	[03:09<00:20,	4.17
s/it]				
Feature = WI				
Prob neg = 0.16096579476861167 Prob pos = 0.8390342052313883				
count neg = 80 count pos = 417 sum = 497				
92%		47/51	[03:15<00:18,	4.56
s/it]				
Feature = HI				
Prob neg = 0.1506849315068493 Prob pos = 0.8493150684931506				
count neg = 22 count pos = 124 sum = 146				
94%		48/51	[03:19<00:13,	4.35
s/it]				
Feature = NE				
Prob neg = 0.16842105263157894 Prob pos = 0.8315789473684211				
count neg = 16 count pos = 79 sum = 95				
96%		49/51	[03:23<00:08,	4.37
s/it]				
Feature = ND				
Prob neg = 0.09090909090909091 Prob pos = 0.9090909090909091				
count neg = 3 count pos = 30 sum = 33				
98%		50/51	[03:27<00:04,	4.13
s/it]				
Feature = VT				
Prob neg = 0.21739130434782608 Prob pos = 0.782608695652174				
count neg = 5 count pos = 18 sum = 23				
100%		51/51	[03:30<00:00,	4.13
s/it]				
Feature = RI				
Prob neg = 0.17721518987341772 Prob pos = 0.8227848101265823				
count neg = 14 count pos = 65 sum = 79				

```
In [74]: response_school_state.count()
```

```
Out[74]: x      30150
          y      30150
          dtype: int64
```


2.2.2.5 Project Grade category

```
In [75]: X_train.clean_project_grade_category.value_counts()
```

```
Out[75]: PreK-2      12293
        3-5        10205
        6-8         4609
        9-12        3043
        Name: clean_project_grade_category, dtype: int64
```

```
In [76]: response_clean_project_grade_category = response(X_train['clean_project_grade_category'],y_train)
```

```

25%|██████████          | 1/4 [00:15<00:45, 15.05
s/it]

```

```
Feature = 3-5
Prob neg = 0.1464968152866242    Prob pos = 0.8535031847133758
count neg = 1495    count pos = 8710    sum = 10205
```

```
s/it] | 2/4 [00:27<00:28, 14.37
```

```
Feature = PreK-2
Prob neg = 0.15569836492312697      Prob pos = 0.8443016350768731
count neg = 1914      count pos = 10379      sum = 12293
```

75% | 3/4 [00:37<00:13, 13.04 s/it]

```
Feature = 6-8
Prob neg = 0.1612063354306791    Prob pos = 0.8387936645693209
count neg = 743    count pos = 3866    sum = 4609
```

[illegible]

```
Feature = 9-12
Prob neg = 0.1616825501150181    Prob pos = 0.8383174498849819
count neg = 492    count pos = 2551    sum = 3043
```

```
In [77]: response_clean_project_grade_category.count()
```

```
Out[77]: x      30150
         y      30150
         dtype: int64
```

In []:

2.2.3 Categorical data on test data

2.2.3.1 Teacher Prefix

```
In [78]: X_test['clean_teacher_prefix'].value_counts()
```

```
Out[78]: Mrs      7760
         Ms       5293
         Mr       1497
         Teacher   300
         Name: clean_teacher_prefix, dtype: int64
```

```
In [79]: response_test_clean_teacher_prefix = response(X_test['clean_teacher_prefix'], y_test)
```

```
25% ██████████ | 1/4 [00:06<00:18, 6.23  
s/it]
```

```
Feature = Ms
Prob neg = 0.1581333837143397      Prob pos = 0.8418666162856603
count neg = 837      count pos = 4456      sum = 5293
```

Feature = Mrs
 Prob neg = 0.1497422680412371 Prob pos = 0.8502577319587629
 count neg = 1162 count pos = 6598 sum = 7760

```
Feature = Mr
Prob neg = 0.15297261189044756      Prob pos = 0.8470273881095525
count neg = 229      count pos = 1268      sum = 1497
```

```
Feature = Teacher
Prob neg = 0.2    Prob pos = 0.8
count neg = 60    count pos = 240    sum = 300
```

```
In [80]: X_test['clean_teacher_prefix'][600:620]
```

```
Out[80]: 10814      Ms
          34836      Mrs
          23369      Mrs
          19844      Mrs
          30087      Mrs
          24425      Mrs
          34891      Mrs
          11869      Ms
          8159       Mrs
          3422       Mrs
          6422       Mrs
          9980       Ms
          6503       Mrs
          17339      Mrs
          31160      Mrs
          8132       Ms
          31308      Ms
          40351      Mrs
          20484      Mrs
          33180      Mrs
          Name: clean_teacher_prefix, dtype: object
```

In [81]: response_test_clean_teacher_prefix[600:620]

Out[81]:

	x	y
600	0.158133	0.841867
601	0.149742	0.850258
602	0.149742	0.850258
603	0.149742	0.850258
604	0.149742	0.850258
605	0.149742	0.850258
606	0.149742	0.850258
607	0.158133	0.841867
608	0.149742	0.850258
609	0.149742	0.850258
610	0.149742	0.850258
611	0.158133	0.841867
612	0.149742	0.850258
613	0.149742	0.850258
614	0.149742	0.850258
615	0.158133	0.841867
616	0.158133	0.841867
617	0.149742	0.850258
618	0.149742	0.850258
619	0.149742	0.850258

In []:

2.2.3.2 Clean categories

```
In [82]: X_test.clean_categories.value_counts()
```

```
Out[82]: Literacy_Language      3232
Math_Science      2305
Literacy_Language Math_Science  2025
Health_Sports     1437
Music_Arts        715
AppliedLearning   540
SpecialNeeds      538
Literacy_Language SpecialNeeds  517
Math_Science Literacy_Language  296
AppliedLearning Literacy_Language 291
Literacy_Language Music_Arts      247
Math_Science SpecialNeeds         240
History_Civics      234
Math_Science Music_Arts          217
AppliedLearning SpecialNeeds      208
Warmth Care_Hunger  189
History_Civics Literacy_Language  185
Health_Sports SpecialNeeds        179
Math_Science AppliedLearning      159
AppliedLearning Math_Science       142
AppliedLearning Music_Arts         120
Health_Sports Literacy_Language    117
Literacy_Language History_Civics   104
Literacy_Language AppliedLearning   82
Math_Science History_Civics        81
AppliedLearning Health_Sports       78
History_Civics Math_Science        50
Math_Science Health_Sports         47
History_Civics Music_Arts          38
Health_Sports Math_Science         36
SpecialNeeds Music_Arts            35
History_Civics SpecialNeeds        29
Health_Sports AppliedLearning       27
Music_Arts SpecialNeeds            22
AppliedLearning History_Civics      21
Health_Sports Music_Arts           14
Health_Sports History_Civics        10
History_Civics AppliedLearning      10
Literacy_Language Health_Sports      9
Health_Sports Warmth Care_Hunger     4
Music_Arts History_Civics           4
History_Civics Health_Sports         3
SpecialNeeds Warmth Care_Hunger     3
SpecialNeeds Health_Sports          3
AppliedLearning Warmth Care_Hunger   2
Math_Science Warmth Care_Hunger     2
Music_Arts Health_Sports            2
Music_Arts AppliedLearning          1
Name: clean_categories, dtype: int64
```

```
In [83]: response_test_clean_categories = response(X_test['clean_categories'],y_test)
```

2% ■■	1/48 [00:04<03:14, 4.14
s/it]	
Feature = Literacy_Language	
Prob neg = 0.13675742574257427	Prob pos = 0.8632425742574258
count neg = 442	count pos = 2790 sum = 3232
4% ■■■	2/48 [00:05<02:39, 3.46
s/it]	
Feature = History_Civics Literacy_Language	
Prob neg = 0.07567567567567568	Prob pos = 0.9243243243243243
count neg = 14	count pos = 171 sum = 185
6% ■■■■	3/48 [00:09<02:41, 3.58
s/it]	
Feature = Literacy_Language Math_Science	
Prob neg = 0.13530864197530865	Prob pos = 0.8646913580246913
count neg = 274	count pos = 1751 sum = 2025
8% ■■■■■	4/48 [00:15<03:01, 4.11
s/it]	
Feature = Health_Sports	
Prob neg = 0.16353514265831592	Prob pos = 0.8364648573416841
count neg = 235	count pos = 1202 sum = 1437
10% ■■■■■■	5/48 [00:20<03:09, 4.40
s/it]	
Feature = AppliedLearning Music_Arts	
Prob neg = 0.16666666666666666	Prob pos = 0.8333333333333334
count neg = 20	count pos = 100 sum = 120
12% ■■■■■■■	6/48 [00:25<03:19, 4.75
s/it]	
Feature = Warmth Care_Hunger	
Prob neg = 0.09523809523809523	Prob pos = 0.9047619047619048
count neg = 18	count pos = 171 sum = 189
15% ■■■■■■■	7/48 [00:28<02:47, 4.08
s/it]	
Feature = Music_Arts	
Prob neg = 0.14965034965034965	Prob pos = 0.8503496503496504
count neg = 107	count pos = 608 sum = 715
17% ■■■■■■■■	8/48 [00:30<02:21, 3.54
s/it]	
Feature = Literacy_Language SpecialNeeds	
Prob neg = 0.13539651837524178	Prob pos = 0.8646034816247582
count neg = 70	count pos = 447 sum = 517
19% ■■■■■■■■	9/48 [00:34<02:17, 3.54
s/it]	
Feature = SpecialNeeds	
Prob neg = 0.19516728624535315	Prob pos = 0.8048327137546468
count neg = 105	count pos = 433 sum = 538
21% ■■■■■■■■■	10/48 [00:37<02:15, 3.57
s/it]	
Feature = Math_Science	
Prob neg = 0.17136659436008678	Prob pos = 0.8286334056399133
count neg = 395	count pos = 1910 sum = 2305
23% ■■■■■■■■■	11/48 [00:39<01:52, 3.04
s/it]	
Feature = Health_Sports AppliedLearning	
Prob neg = 0.22222222222222222	Prob pos = 0.7777777777777778
count neg = 6	count pos = 21 sum = 27
25% ■■■■■■■■■	12/48 [00:41<01:37, 2.72
s/it]	
Feature = Math_Science Literacy_Language	
Prob neg = 0.11148648648648649	Prob pos = 0.8885135135135135
count neg = 33	count pos = 263 sum = 296
27% ■■■■■■■■■	13/48 [00:43<01:26, 2.48
s/it]	
Feature = History_Civics	
Prob neg = 0.19658119658119658	Prob pos = 0.8034188034188035
count neg = 46	count pos = 188 sum = 234


```
In [84]: response_test_clean_categories.count()
```

```
Out[84]: x    14850
          y    14850
          dtype: int64
```

2.2.3.3 Clean Sub categories

```
In [85]: X_test.clean_subcategories.value_counts()
```

```
Out[85]: Literacy 1296
Literacy Mathematics 1131
Literature_Writing Mathematics 843
Literacy Literature_Writing 771
Mathematics 749
Literature_Writing 625
SpecialNeeds 538
Health_Wellness 538
AppliedSciences Mathematics 453
AppliedSciences 335
Literacy SpecialNeeds 325
VisualArts 307
ESL Literacy 302
Gym_Fitness Health_Wellness 291
Music 213
Warmth Care_Hunger 189
Literature_Writing SpecialNeeds 168
Mathematics SpecialNeeds 161
Health_Wellness SpecialNeeds 156
Gym_Fitness 150
EnvironmentalScience Health_LifeScience 144
TeamSports 142
EnvironmentalScience 135
AppliedSciences EnvironmentalScience 134
EarlyDevelopment 123
Music PerformingArts 120
Other 118
Health_LifeScience 117
EarlyDevelopment SpecialNeeds 111
Literature_Writing VisualArts 105
...
College_CareerPrep Warmth Care_Hunger 1
Civics_Government Economics 1
College_CareerPrep ESL 1
Civics_Government FinancialLiteracy 1
EarlyDevelopment TeamSports 1
Extracurricular SpecialNeeds 1
EnvironmentalScience PerformingArts 1
Gym_Fitness SocialSciences 1
FinancialLiteracy ForeignLanguages 1
Literacy TeamSports 1
AppliedSciences Economics 1
TeamSports VisualArts 1
CommunityService Economics 1
ESL Music 1
ESL Extracurricular 1
Civics_Government TeamSports 1
CommunityService ParentInvolvement 1
ForeignLanguages Other 1
ESL PerformingArts 1
Extracurricular ParentInvolvement 1
History_Geography ParentInvolvement 1
CommunityService PerformingArts 1
Health_LifeScience Music 1
AppliedSciences FinancialLiteracy 1
Music Other 1
CharacterEducation NutritionEducation 1
EnvironmentalScience TeamSports 1
CharacterEducation PerformingArts 1
Gym_Fitness Literature_Writing 1
FinancialLiteracy Other 1
Name: clean_subcategories, Length: 314, dtype: int64
```

```
In [86]: response_test_clean_subcategories = response(X_test['clean_subcategories'],y_test)
```

0%	1/314 [00:03<17:47, 3.41
s/it]	
Feature = Literacy	
Prob neg = 0.11882716049382716	Prob pos = 0.8811728395061729
count neg = 154	count pos = 1142 sum = 1296
1%	2/314 [00:05<15:26, 2.97
s/it]	
Feature = History_Geography Literature_Writing	
Prob neg = 0.12790697674418605	Prob pos = 0.872093023255814
count neg = 11	count pos = 75 sum = 86
1%	3/314 [00:09<17:41, 3.41
s/it]	
Feature = Literacy Mathematics	
Prob neg = 0.13704686118479223	Prob pos = 0.8629531388152077
count neg = 155	count pos = 976 sum = 1131
1%	4/314 [00:13<18:49, 3.64
s/it]	
Feature = Gym_Fitness Health_Wellness	
Prob neg = 0.13745704467353953	Prob pos = 0.8625429553264605
count neg = 40	count pos = 251 sum = 291
2%	5/314 [00:16<16:21, 3.18
s/it]	
Feature = Extracurricular VisualArts	
Prob neg = 0.2	Prob pos = 0.8
count neg = 3	count pos = 12 sum = 15
2%	6/314 [00:19<15:58, 3.11
s/it]	
Feature = Warmth Care_Hunger	
Prob neg = 0.09523809523809523	Prob pos = 0.9047619047619048
count neg = 18	count pos = 171 sum = 189
2%	7/314 [00:25<20:23, 3.98
s/it]	
Feature = Literature_Writing	
Prob neg = 0.176	Prob pos = 0.824
count neg = 110	count pos = 515 sum = 625
3%	8/314 [00:27<18:41, 3.66
s/it]	
Feature = ESL Literacy	
Prob neg = 0.13245033112582782	Prob pos = 0.8675496688741722
count neg = 40	count pos = 262 sum = 302
3%	9/314 [00:30<16:39, 3.28
s/it]	
Feature = Health_Wellness NutritionEducation	
Prob neg = 0.17475728155339806	Prob pos = 0.8252427184466019
count neg = 18	count pos = 85 sum = 103
3%	10/314 [00:32<15:31, 3.06
s/it]	
Feature = Gym_Fitness TeamSports	
Prob neg = 0.23232323232323232	Prob pos = 0.7676767676767676
count neg = 23	count pos = 76 sum = 99
4%	11/314 [00:36<15:33, 3.08
s/it]	
Feature = Health_Wellness	
Prob neg = 0.14312267657992564	Prob pos = 0.8568773234200744
count neg = 77	count pos = 461 sum = 538
4%	12/314 [00:39<15:36, 3.10
s/it]	
Feature = VisualArts	
Prob neg = 0.1791530944625407	Prob pos = 0.8208469055374593
count neg = 55	count pos = 252 sum = 307
4%	13/314 [00:42<16:02, 3.20
s/it]	
Feature = Literacy Literature_Writing	
Prob neg = 0.14007782101167315	Prob pos = 0.8599221789883269
count neg = 108	count pos = 663 sum = 771

4% ■■■■ s/it]	14/314 [00:46<16:38, 3.33
Feature = Literacy SpecialNeeds Prob neg = 0.10461538461538461 Prob pos = 0.8953846153846153 count neg = 34 count pos = 291 sum = 325	
5% ■■■■ s/it]	15/314 [00:49<16:33, 3.32
Feature = NutritionEducation Prob neg = 0.16279069767441862 Prob pos = 0.8372093023255814 count neg = 7 count pos = 36 sum = 43	
5% ■■■■ s/it]	16/314 [00:52<16:27, 3.31
Feature = SpecialNeeds Prob neg = 0.19516728624535315 Prob pos = 0.8048327137546468 count neg = 105 count pos = 433 sum = 538	
5% ■■■■ s/it]	17/314 [00:56<16:24, 3.31
Feature = AppliedSciences Mathematics Prob neg = 0.1390728476821192 Prob pos = 0.8609271523178808 count neg = 63 count pos = 390 sum = 453	
6% ■■■■ s/it]	18/314 [00:59<15:50, 3.21
Feature = Health_Wellness Other Prob neg = 0.17391304347826086 Prob pos = 0.8260869565217391 count neg = 4 count pos = 19 sum = 23	
6% ■■■■ s/it]	19/314 [01:01<15:10, 3.09
Feature = AppliedSciences ESL Prob neg = 0.11764705882352941 Prob pos = 0.8823529411764706 count neg = 2 count pos = 15 sum = 17	
6% ■■■■ s/it]	20/314 [01:05<15:13, 3.11
Feature = Literature_Writing Mathematics Prob neg = 0.1257413997627521 Prob pos = 0.8742586002372479 count neg = 106 count pos = 737 sum = 843	
7% ■■■■ s/it]	21/314 [01:07<14:45, 3.02
Feature = History_Geography Prob neg = 0.2571428571428571 Prob pos = 0.7428571428571429 count neg = 18 count pos = 52 sum = 70	
7% ■■■■ s/it]	22/314 [01:11<14:53, 3.06
Feature = Mathematics Prob neg = 0.17489986648865152 Prob pos = 0.8251001335113485 count neg = 131 count pos = 618 sum = 749	
7% ■■■■ s/it]	23/314 [01:13<13:31, 2.79
Feature = Literacy VisualArts Prob neg = 0.1506849315068493 Prob pos = 0.8493150684931506 count neg = 11 count pos = 62 sum = 73	
8% ■■■■ s/it]	24/314 [01:15<12:27, 2.58
Feature = Health_Wellness Mathematics Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666 count neg = 8 count pos = 16 sum = 24	
8% ■■■■ s/it]	25/314 [01:17<11:33, 2.40
Feature = Health_LifeScience Literature_Writing Prob neg = 0.041666666666666664 Prob pos = 0.9583333333333334 count neg = 1 count pos = 23 sum = 24	
8% ■■■■ s/it]	26/314 [01:19<11:31, 2.40
Feature = Gym_Fitness Prob neg = 0.2133333333333333 Prob pos = 0.7866666666666666 count neg = 32 count pos = 118 sum = 150	

9%|███████
s/it] | 27/314 [01:21<11:00, 2.30

Feature = Music
Prob neg = 0.13615023474178403 Prob pos = 0.863849765258216
count neg = 29 count pos = 184 sum = 213

9%|███████
s/it] | 28/314 [01:24<10:58, 2.30

Feature = History_Geography Mathematics
Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334
count neg = 3 count pos = 15 sum = 18

9%|███████
s/it] | 29/314 [01:26<10:38, 2.24

Feature = AppliedSciences
Prob neg = 0.1761194029850746 Prob pos = 0.8238805970149253
count neg = 59 count pos = 276 sum = 335

10%|███████
s/it] | 30/314 [01:27<09:58, 2.11

Feature = ESL Literature_Writing
Prob neg = 0.09278350515463918 Prob pos = 0.9072164948453608
count neg = 9 count pos = 88 sum = 97

10%|███████
s/it] | 31/314 [01:29<09:30, 2.02

Feature = College_CareerPrep Literacy
Prob neg = 0.1 Prob pos = 0.9
count neg = 3 count pos = 27 sum = 30

10%|███████
s/it] | 32/314 [01:31<09:14, 1.97

Feature = Literature_Writing VisualArts
Prob neg = 0.18095238095238095 Prob pos = 0.819047619047619
count neg = 19 count pos = 86 sum = 105

11%|███████
s/it] | 33/314 [01:33<09:21, 2.00

Feature = College_CareerPrep SpecialNeeds
Prob neg = 0.30434782608695654 Prob pos = 0.6956521739130435
count neg = 7 count pos = 16 sum = 23

11%|███████
s/it] | 34/314 [01:35<09:10, 1.97

Feature = EnvironmentalScience
Prob neg = 0.15555555555555556 Prob pos = 0.8444444444444444
count neg = 21 count pos = 114 sum = 135

11%|███████
s/it] | 35/314 [01:37<08:50, 1.90

Feature = College_CareerPrep Literature_Writing
Prob neg = 0.175 Prob pos = 0.825
count neg = 7 count pos = 33 sum = 40

11%|███████
s/it] | 36/314 [01:39<08:46, 1.89

Feature = EarlyDevelopment
Prob neg = 0.16260162601626016 Prob pos = 0.8373983739837398
count neg = 20 count pos = 103 sum = 123

12%|███████
s/it] | 37/314 [01:41<08:38, 1.87

Feature = Other
Prob neg = 0.211864406779661 Prob pos = 0.788135593220339
count neg = 25 count pos = 93 sum = 118

12%|███████
s/it] | 38/314 [01:42<08:32, 1.86

Feature = PerformingArts
Prob neg = 0.11320754716981132 Prob pos = 0.8867924528301887
count neg = 6 count pos = 47 sum = 53

12%|███████
s/it] | 39/314 [01:44<08:26, 1.84

Feature = AppliedSciences CharacterEducation
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666
count neg = 2 count pos = 4 sum = 6

13%|██████████
s/it] | 40/314 [01:46<08:16, 1.81

Feature = Mathematics Other
Prob neg = 0.090909090909091 Prob pos = 0.90909090909091
count neg = 1 count pos = 10 sum = 11

13%|██████████
s/it] | 41/314 [01:48<08:13, 1.81

Feature = EarlyDevelopment Literacy
Prob neg = 0.17307692307692307 Prob pos = 0.8269230769230769
count neg = 18 count pos = 86 sum = 104

13%|██████████
s/it] | 42/314 [01:50<08:15, 1.82

Feature = Health_LifeScience
Prob neg = 0.19658119658119658 Prob pos = 0.8034188034188035
count neg = 23 count pos = 94 sum = 117

14%|██████████
s/it] | 43/314 [01:51<08:14, 1.82

Feature = Literature_Writing SpecialNeeds
Prob neg = 0.18452380952380953 Prob pos = 0.8154761904761905
count neg = 31 count pos = 137 sum = 168

14%|██████████
s/it] | 44/314 [01:53<08:08, 1.81

Feature = History_Geography SocialSciences
Prob neg = 0.15909090909091 Prob pos = 0.840909090909091
count neg = 7 count pos = 37 sum = 44

14%|██████████
s/it] | 45/314 [01:55<08:07, 1.81

Feature = Music PerformingArts
Prob neg = 0.09166666666666666 Prob pos = 0.9083333333333333
count neg = 11 count pos = 109 sum = 120

15%|██████████
s/it] | 46/314 [01:57<07:57, 1.78

Feature = ForeignLanguages Health_Wellness
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 3 sum = 3

15%|██████████
s/it] | 47/314 [01:58<07:53, 1.77

Feature = AppliedSciences History_Geography
Prob neg = 0.2 Prob pos = 0.8
count neg = 2 count pos = 8 sum = 10

15%|██████████
s/it] | 48/314 [02:00<07:58, 1.80

Feature = Literacy SocialSciences
Prob neg = 0.15517241379310345 Prob pos = 0.8448275862068966
count neg = 9 count pos = 49 sum = 58

16%|██████████
s/it] | 49/314 [02:02<07:54, 1.79

Feature = EnvironmentalScience SpecialNeeds
Prob neg = 0.22727272727272727 Prob pos = 0.7727272727272727
count neg = 5 count pos = 17 sum = 22

16%|██████████
s/it] | 50/314 [02:04<08:03, 1.83

Feature = Mathematics SpecialNeeds
Prob neg = 0.2111801242236025 Prob pos = 0.7888198757763976
count neg = 34 count pos = 127 sum = 161

16%|██████████
s/it] | 51/314 [02:06<07:51, 1.79

Feature = Civics_Government SocialSciences
Prob neg = 0.15384615384615385 Prob pos = 0.8461538461538461
count neg = 2 count pos = 11 sum = 13

17%|██████████
s/it] | 52/314 [02:08<07:54, 1.81

Feature = Health_Wellness SpecialNeeds
Prob neg = 0.1346153846153846 Prob pos = 0.8653846153846154
count neg = 21 count pos = 135 sum = 156

17% ██████████ s/it]	53/314 [02:09<07:46, 1.79
Feature = Other SpecialNeeds Prob neg = 0.20408163265306123 Prob pos = 0.7959183673469388 count neg = 10 count pos = 39 sum = 49	
17% ██████████ s/it]	54/314 [02:11<07:41, 1.77
Feature = College_CareerPrep Health_LifeScience Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 4 sum = 4	
18% ██████████ s/it]	55/314 [02:14<08:37, 2.00
Feature = ESL SpecialNeeds Prob neg = 0.20833333333333334 Prob pos = 0.7916666666666666 count neg = 5 count pos = 19 sum = 24	
18% ██████████ s/it]	56/314 [02:16<09:21, 2.18
Feature = CharacterEducation College_CareerPrep Prob neg = 0.18181818181818182 Prob pos = 0.8181818181818182 count neg = 2 count pos = 9 sum = 11	
18% ██████████ s/it]	57/314 [02:19<09:41, 2.26
Feature = College_CareerPrep Extracurricular Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 8 sum = 8	
18% ██████████ s/it]	58/314 [02:21<10:04, 2.36
Feature = Health_LifeScience Mathematics Prob neg = 0.189873417721519 Prob pos = 0.810126582278481 count neg = 15 count pos = 64 sum = 79	
19% ██████████ s/it]	59/314 [02:23<09:40, 2.28
Feature = Health_Wellness Literature_Writing Prob neg = 0.15789473684210525 Prob pos = 0.8421052631578947 count neg = 6 count pos = 32 sum = 38	
19% ██████████ s/it]	60/314 [02:25<09:02, 2.13
Feature = ForeignLanguages Literacy Prob neg = 0.13333333333333333 Prob pos = 0.8666666666666667 count neg = 4 count pos = 26 sum = 30	
19% ██████████ s/it]	61/314 [02:27<08:27, 2.01
Feature = EarlyDevelopment Mathematics Prob neg = 0.18181818181818182 Prob pos = 0.8181818181818182 count neg = 8 count pos = 36 sum = 44	
20% ██████████ s/it]	62/314 [02:29<08:08, 1.94
Feature = Extracurricular PerformingArts Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 4 sum = 4	
20% ██████████ s/it]	63/314 [02:30<07:56, 1.90
Feature = Health_LifeScience Literacy Prob neg = 0.10526315789473684 Prob pos = 0.8947368421052632 count neg = 4 count pos = 34 sum = 38	
20% ██████████ s/it]	64/314 [02:32<07:43, 1.85
Feature = AppliedSciences VisualArts Prob neg = 0.1414141414141414 Prob pos = 0.8585858585858586 count neg = 14 count pos = 85 sum = 99	
21% ██████████ s/it]	65/314 [02:34<07:38, 1.84
Feature = History_Geography Literacy Prob neg = 0.014925373134328358 Prob pos = 0.9850746268656716 count neg = 1 count pos = 66 sum = 67	

21%|███████████
s/it] | 66/314 [02:36<07:29, 1.81

Feature = Mathematics Music
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 6 sum = 6

21%|███████████
s/it] | 67/314 [02:37<07:23, 1.80

Feature = AppliedSciences Health_LifeScience
Prob neg = 0.13432835820895522 Prob pos = 0.8656716417910447
count neg = 9 count pos = 58 sum = 67

22%|███████████
s/it] | 68/314 [02:39<07:13, 1.76

Feature = Economics FinancialLiteracy
Prob neg = 0.3076923076923077 Prob pos = 0.6923076923076923
count neg = 4 count pos = 9 sum = 13

22%|███████████
s/it] | 69/314 [02:41<07:17, 1.79

Feature = EnvironmentalScience Health_LifeScience
Prob neg = 0.22916666666666666 Prob pos = 0.7708333333333334
count neg = 33 count pos = 111 sum = 144

22%|███████████
s/it] | 70/314 [02:43<07:11, 1.77

Feature = EarlyDevelopment EnvironmentalScience
Prob neg = 0.4 Prob pos = 0.6
count neg = 2 count pos = 3 sum = 5

23%|███████████
s/it] | 71/314 [02:44<07:09, 1.77

Feature = CharacterEducation
Prob neg = 0.23529411764705882 Prob pos = 0.7647058823529411
count neg = 12 count pos = 39 sum = 51

23%|███████████
s/it] | 72/314 [02:46<07:27, 1.85

Feature = History_Geography VisualArts
Prob neg = 0.1 Prob pos = 0.9
count neg = 2 count pos = 18 sum = 20

23%|███████████
s/it] | 73/314 [02:49<08:02, 2.00

Feature = Other VisualArts
Prob neg = 0.25 Prob pos = 0.75
count neg = 2 count pos = 6 sum = 8

24%|███████████
s/it] | 74/314 [02:51<07:45, 1.94

Feature = AppliedSciences Literacy
Prob neg = 0.15789473684210525 Prob pos = 0.8421052631578947
count neg = 12 count pos = 64 sum = 76
unique feature = Civics_Government Health_Wellness

24%|███████████
s/it] | 75/314 [02:52<07:30, 1.88

Feature = Civics_Government Health_Wellness
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 1 sum = 1

24%|███████████
s/it] | 76/314 [02:54<07:28, 1.88

Feature = Health_Wellness TeamSports
Prob neg = 0.15254237288135594 Prob pos = 0.847457627118644
count neg = 9 count pos = 50 sum = 59

25%|███████████
s/it] | 77/314 [02:56<07:20, 1.86

Feature = EarlyDevelopment Health_Wellness
Prob neg = 0.10810810810810811 Prob pos = 0.8918918918918919
count neg = 4 count pos = 33 sum = 37

25%|███████████
s/it] | 78/314 [02:58<07:16, 1.85

Feature = TeamSports
Prob neg = 0.18309859154929578 Prob pos = 0.8169014084507042
count neg = 26 count pos = 116 sum = 142

25% ████████████████████ s/it]	79/314 [03:00<07:11, 1.84
Feature = EnvironmentalScience History_Geography Prob neg = 0.16 Prob pos = 0.84 count neg = 4 count pos = 21 sum = 25	
25% ████████████████████ s/it]	80/314 [03:01<07:04, 1.81
Feature = EnvironmentalScience Literature_Writing Prob neg = 0.11428571428571428 Prob pos = 0.8857142857142857 count neg = 4 count pos = 31 sum = 35	
26% ████████████████████ s/it]	81/314 [03:03<07:01, 1.81
Feature = Health_Wellness Literacy Prob neg = 0.12162162162162163 Prob pos = 0.8783783783783784 count neg = 9 count pos = 65 sum = 74	
26% ████████████████████ s/it]	82/314 [03:05<06:52, 1.78
Feature = EarlyDevelopment VisualArts Prob neg = 0.2916666666666667 Prob pos = 0.7083333333333334 count neg = 7 count pos = 17 sum = 24	
26% ████████████████████ s/it]	83/314 [03:07<06:49, 1.77
Feature = FinancialLiteracy Prob neg = 0.11764705882352941 Prob pos = 0.8823529411764706 count neg = 2 count pos = 15 sum = 17	
27% ████████████████████ s/it]	84/314 [03:08<06:45, 1.76
Feature = College_CareerPrep Mathematics Prob neg = 0.23255813953488372 Prob pos = 0.7674418604651163 count neg = 10 count pos = 33 sum = 43	
27% ████████████████████ s/it]	85/314 [03:10<06:42, 1.76
Feature = SpecialNeeds VisualArts Prob neg = 0.14285714285714285 Prob pos = 0.8571428571428571 count neg = 5 count pos = 30 sum = 35	
27% ████████████████████ s/it]	86/314 [03:12<06:34, 1.73
Feature = ESL EnvironmentalScience Prob neg = 0.4 Prob pos = 0.6 count neg = 2 count pos = 3 sum = 5	
28% ████████████████████ s/it]	87/314 [03:14<06:32, 1.73
Feature = CharacterEducation Gym_Fitness Prob neg = 0.6666666666666666 Prob pos = 0.3333333333333333 count neg = 2 count pos = 1 sum = 3	
28% ████████████████████ s/it]	88/314 [03:15<06:29, 1.72
Feature = CharacterEducation Literacy Prob neg = 0.2 Prob pos = 0.8 count neg = 9 count pos = 36 sum = 45	
28% ████████████████████ s/it]	89/314 [03:17<06:28, 1.72
Feature = FinancialLiteracy Mathematics Prob neg = 0.15789473684210525 Prob pos = 0.8421052631578947 count neg = 3 count pos = 16 sum = 19	
29% ████████████████████ s/it]	90/314 [03:19<06:35, 1.76
Feature = Gym_Fitness SpecialNeeds Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334 count neg = 3 count pos = 15 sum = 18	
29% ████████████████████ s/it]	91/314 [03:21<06:28, 1.74
Feature = CharacterEducation Literature_Writing Prob neg = 0.08695652173913043 Prob pos = 0.9130434782608695 count neg = 2 count pos = 21 sum = 23	

29%|███████████
s/it] | 92/314 [03:22<06:28, 1.75

Feature = Literature_Writing SocialSciences
Prob neg = 0.10526315789473684 Prob pos = 0.8947368421052632
count neg = 4 count pos = 34 sum = 38

30%|███████████
s/it] | 93/314 [03:24<06:28, 1.76

Feature = Extracurricular Health_LifeScience
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2

30%|███████████
s/it] | 94/314 [03:26<06:29, 1.77

Feature = CharacterEducation EarlyDevelopment
Prob neg = 0.23529411764705882 Prob pos = 0.7647058823529411
count neg = 8 count pos = 26 sum = 34

30%|███████████
s/it] | 95/314 [03:28<06:26, 1.77

Feature = Literacy ParentInvolvement
Prob neg = 0.125 Prob pos = 0.875
count neg = 3 count pos = 21 sum = 24

31%|███████████
s/it] | 96/314 [03:30<06:30, 1.79

Feature = EnvironmentalScience Mathematics
Prob neg = 0.14130434782608695 Prob pos = 0.8586956521739131
count neg = 13 count pos = 79 sum = 92

31%|███████████
s/it] | 97/314 [03:31<06:22, 1.76

Feature = AppliedSciences SocialSciences
Prob neg = 0.1111111111111111 Prob pos = 0.8888888888888888
count neg = 1 count pos = 8 sum = 9

31%|███████████
s/it] | 98/314 [03:33<06:23, 1.78

Feature = ForeignLanguages
Prob neg = 0.1333333333333333 Prob pos = 0.8666666666666667
count neg = 4 count pos = 26 sum = 30

32%|███████████
s/it] | 99/314 [03:35<06:16, 1.75

Feature = EnvironmentalScience ForeignLanguages
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2

32%|███████████
s/it] | 100/314 [03:37<06:16, 1.76

Feature = Health_LifeScience SpecialNeeds
Prob neg = 0.06666666666666667 Prob pos = 0.9333333333333333
count neg = 1 count pos = 14 sum = 15

32%|███████████
s/it] | 101/314 [03:39<06:54, 1.94

Feature = CharacterEducation Health_Wellness
Prob neg = 0.2727272727272727 Prob pos = 0.7272727272727273
count neg = 3 count pos = 8 sum = 11

32%|███████████
s/it] | 102/314 [03:41<06:35, 1.86

Feature = College_CareerPrep VisualArts
Prob neg = 0.03225806451612903 Prob pos = 0.967741935483871
count neg = 1 count pos = 30 sum = 31

33%|███████████
s/it] | 103/314 [03:42<06:23, 1.82

Feature = AppliedSciences EarlyDevelopment
Prob neg = 0.18181818181818182 Prob pos = 0.8181818181818182
count neg = 4 count pos = 18 sum = 22

33%|███████████
s/it] | 104/314 [03:44<06:25, 1.83

Feature = AppliedSciences EnvironmentalScience
Prob neg = 0.208955223880597 Prob pos = 0.7910447761194029
count neg = 28 count pos = 106 sum = 134

```

33%|███████████| | 105/314 [03:46<06:20, 1.82
s/it]

Feature = AppliedSciences SpecialNeeds
Prob neg = 0.11904761904761904 Prob pos = 0.8809523809523809
count neg = 5 count pos = 37 sum = 42

34%|███████████| | 106/314 [03:48<06:17, 1.81
s/it]

Feature = College_CareerPrep
Prob neg = 0.19642857142857142 Prob pos = 0.8035714285714286
count neg = 11 count pos = 45 sum = 56

34%|███████████| | 107/314 [03:50<06:13, 1.80
s/it]

Feature = EnvironmentalScience Literacy
Prob neg = 0.11764705882352941 Prob pos = 0.8823529411764706
count neg = 6 count pos = 45 sum = 51

34%|███████████| | 108/314 [03:52<06:27, 1.88
s/it]

Feature = Extracurricular Literacy
Prob neg = 0.375 Prob pos = 0.625
count neg = 3 count pos = 5 sum = 8

35%|███████████| | 109/314 [03:54<06:47, 1.99
s/it]

Feature = Gym_Fitness Literacy
Prob neg = 0.25 Prob pos = 0.75
count neg = 1 count pos = 3 sum = 4

35%|███████████| | 110/314 [03:56<07:07, 2.09
s/it]

Feature = Literacy Other
Prob neg = 0.17391304347826086 Prob pos = 0.8260869565217391
count neg = 4 count pos = 19 sum = 23

35%|███████████| | 111/314 [03:59<07:24, 2.19
s/it]

Feature = Health_LifeScience ParentInvolvement
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2

36%|███████████| | 112/314 [04:01<07:40, 2.28
s/it]

Feature = ESL
Prob neg = 0.125 Prob pos = 0.875
count neg = 8 count pos = 56 sum = 64

36%|███████████| | 113/314 [04:04<07:48, 2.33
s/it]

Feature = Mathematics VisualArts
Prob neg = 0.1896551724137931 Prob pos = 0.8103448275862069
count neg = 11 count pos = 47 sum = 58

36%|███████████| | 114/314 [04:06<07:52, 2.36
s/it]

Feature = ForeignLanguages History_Geography
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2

37%|███████████| | 115/314 [04:08<07:48, 2.35
s/it]

Feature = Literature_Writing Music
Prob neg = 0.1 Prob pos = 0.9
count neg = 1 count pos = 9 sum = 10

37%|███████████| | 116/314 [04:10<07:17, 2.21
s/it]

Feature = CommunityService VisualArts
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 4 sum = 4

37%|███████████| | 117/314 [04:12<06:46, 2.06
s/it]

Feature = College_CareerPrep EnvironmentalScience
Prob neg = 0.25 Prob pos = 0.75
count neg = 1 count pos = 3 sum = 4

```

```

38%|███████████████████████| | 118/314 [04:14<06:29, 1.99
s/it]

Feature = CharacterEducation CommunityService
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 8 sum = 8

38%|███████████████████████| | 119/314 [04:15<06:12, 1.91
s/it]

Feature = EarlyDevelopment Literature_Writing
Prob neg = 0.10714285714285714 Prob pos = 0.8928571428571429
count neg = 3 count pos = 25 sum = 28

38%|███████████████████████| | 120/314 [04:17<05:59, 1.85
s/it]

Feature = CharacterEducation Mathematics
Prob neg = 0.3 Prob pos = 0.7
count neg = 3 count pos = 7 sum = 10

39%|███████████████████████| | 121/314 [04:19<05:50, 1.82
s/it]

Feature = AppliedSciences Other
Prob neg = 0.05555555555555555 Prob pos = 0.9444444444444444
count neg = 1 count pos = 17 sum = 18

39%|███████████████████████| | 122/314 [04:21<05:44, 1.79
s/it]

Feature = AppliedSciences College_CareerPrep
Prob neg = 0.18333333333333332 Prob pos = 0.8166666666666667
count neg = 11 count pos = 49 sum = 60

39%|███████████████████████| | 123/314 [04:22<05:39, 1.78
s/it]

Feature = Extracurricular Other
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 6 sum = 6

39%|███████████████████████| | 124/314 [04:24<05:34, 1.76
s/it]

Feature = Literature_Writing PerformingArts
Prob neg = 0.2 Prob pos = 0.8
count neg = 3 count pos = 12 sum = 15

40%|███████████████████████| | 125/314 [04:26<05:30, 1.75
s/it]

Feature = Civics_Government College_CareerPrep
Prob neg = 0.2 Prob pos = 0.8
count neg = 1 count pos = 4 sum = 5
unique feature = Extracurricular History_Geography

40%|███████████████████████| | 126/314 [04:28<05:27, 1.74
s/it]

Feature = Extracurricular History_Geography
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 1 sum = 1

40%|███████████████████████| | 127/314 [04:29<05:23, 1.73
s/it]

Feature = Gym_Fitness Mathematics
Prob neg = 0.3 Prob pos = 0.7
count neg = 3 count pos = 7 sum = 10

41%|███████████████████████| | 128/314 [04:31<05:20, 1.72
s/it]

Feature = Civics_Government Literacy
Prob neg = 0.06666666666666667 Prob pos = 0.9333333333333333
count neg = 1 count pos = 14 sum = 15

41%|███████████████████████| | 129/314 [04:33<05:21, 1.74
s/it]

Feature = AppliedSciences Literature_Writing
Prob neg = 0.07692307692307693 Prob pos = 0.9230769230769231
count neg = 4 count pos = 48 sum = 52

41%|███████████████████████| | 130/314 [04:34<05:16, 1.72
s/it]

Feature = SocialSciences
Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334
count neg = 4 count pos = 20 sum = 24

```

42% ██████████████████████████████████████ s/it]		131/314 [04:36<05:12,	1.71
Feature = Health_Wellness History_Geography Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 3 sum = 3			
42% ██████████████████████████████████████ s/it]		132/314 [04:38<05:14,	1.73
Feature = Mathematics TeamSports Prob neg = 0.5 Prob pos = 0.5 count neg = 1 count pos = 1 sum = 2			
42% ██████████████████████████████████████ s/it]		133/314 [04:40<05:20,	1.77
Feature = Extracurricular Prob neg = 0.1875 Prob pos = 0.8125 count neg = 3 count pos = 13 sum = 16			
43% ██████████████████████████████████████ s/it]		134/314 [04:42<05:21,	1.79
Feature = EarlyDevelopment SpecialNeeds Prob neg = 0.18018018018018017 Prob pos = 0.8198198198198198 count neg = 20 count pos = 91 sum = 111			
43% ██████████████████████████████████████ s/it]		135/314 [04:43<05:16,	1.77
Feature = CommunityService Prob neg = 0.18181818181818182 Prob pos = 0.8181818181818182 count neg = 2 count pos = 9 sum = 11			
43% ██████████████████████████████████████ s/it]		136/314 [04:45<05:14,	1.77
Feature = CommunityService Health_Wellness Prob neg = 0.5 Prob pos = 0.5 count neg = 1 count pos = 1 sum = 2			
44% ██████████████████████████████████████ s/it]		137/314 [04:47<05:39,	1.92
Feature = Extracurricular Music Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666 count neg = 1 count pos = 2 sum = 3			
44% ██████████████████████████████████████ s/it]		138/314 [04:49<05:49,	1.99
Feature = Literature_Writing Other Prob neg = 0.07142857142857142 Prob pos = 0.9285714285714286 count neg = 1 count pos = 13 sum = 14			
44% ██████████████████████████████████████ s/it]		139/314 [04:51<05:35,	1.92
Feature = Extracurricular Health_Wellness Prob neg = 0.5 Prob pos = 0.5 count neg = 1 count pos = 1 sum = 2			
45% ██████████████████████████████████████ s/it]		140/314 [04:53<05:22,	1.85
Feature = Literature_Writing ParentInvolvement Prob neg = 0.1 Prob pos = 0.9 count neg = 1 count pos = 9 sum = 10			
45% ██████████████████████████████████████ s/it]		141/314 [04:55<05:16,	1.83
Feature = CharacterEducation Music Prob neg = 0.2 Prob pos = 0.8 count neg = 1 count pos = 4 sum = 5			
45% ██████████████████████████████████████ s/it]		142/314 [04:56<05:10,	1.81
Feature = Economics Mathematics Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 7 sum = 7			
46% ██████████████████████████████████████ s/it]		143/314 [04:58<05:05,	1.78
Feature = Music SpecialNeeds Prob neg = 0.06666666666666667 Prob pos = 0.9333333333333333 count neg = 1 count pos = 14 sum = 15			

46% ██████████████████████████████████████ s/it]		144/314 [05:00<05:06,	1.81
Feature = Health_LifeScience Health_Wellness Prob neg = 0.21052631578947367 Prob pos = 0.7894736842105263 count neg = 4 count pos = 15 sum = 19			
46% ██████████████████████████████████████ s/it]		145/314 [05:02<05:03,	1.78
Feature = ESL VisualArts Prob neg = 0.0 Prob pos = 1.0 count neg = 0 count pos = 7 sum = 7			
46% ██████████████████████████████████████ s/it]		146/314 [05:04<04:58,	1.78
Feature = CharacterEducation Other Prob neg = 0.1875 Prob pos = 0.8125 count neg = 3 count pos = 13 sum = 16			
47% ██████████████████████████████████████ s/it]		147/314 [05:05<04:53,	1.76
Feature = AppliedSciences Extracurricular Prob neg = 0.1 Prob pos = 0.9 count neg = 1 count pos = 9 sum = 10			
47% ██████████████████████████████████████ s/it]		148/314 [05:07<04:51,	1.75
Feature = CharacterEducation SpecialNeeds Prob neg = 0.30434782608695654 Prob pos = 0.6956521739130435 count neg = 7 count pos = 16 sum = 23			
47% ██████████████████████████████████████ s/it]		149/314 [05:09<04:42,	1.71
Feature = ESL EarlyDevelopment Prob neg = 0.125 Prob pos = 0.875 count neg = 1 count pos = 7 sum = 8			
48% ██████████████████████████████████████ s/it]		150/314 [05:10<04:41,	1.72
Feature = CharacterEducation EnvironmentalScience Prob neg = 0.25 Prob pos = 0.75 count neg = 1 count pos = 3 sum = 4			
48% ██████████████████████████████████████ s/it]		151/314 [05:12<04:41,	1.73
Feature = ESL Mathematics Prob neg = 0.16216216216216217 Prob pos = 0.8378378378378378 count neg = 6 count pos = 31 sum = 37			
48% ██████████████████████████████████████ s/it]		152/314 [05:14<04:41,	1.74
Feature = Civics_Government Health_LifeScience Prob neg = 0.25 Prob pos = 0.75 count neg = 1 count pos = 3 sum = 4			
49% ██████████████████████████████████████ s/it]		153/314 [05:16<04:44,	1.76
Feature = ESL ForeignLanguages Prob neg = 0.2 Prob pos = 0.8 count neg = 1 count pos = 4 sum = 5			
49% ██████████████████████████████████████ s/it]		154/314 [05:18<04:53,	1.84
Feature = Gym_Fitness NutritionEducation Prob neg = 0.25 Prob pos = 0.75 count neg = 3 count pos = 9 sum = 12			
49% ██████████████████████████████████████ s/it]		155/314 [05:20<05:15,	1.98
Feature = Civics_Government SpecialNeeds Prob neg = 0.2 Prob pos = 0.8 count neg = 1 count pos = 4 sum = 5			
50% ██████████████████████████████████████ s/it]		156/314 [05:22<05:00,	1.90
Feature = Mathematics SocialSciences Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666 count neg = 3 count pos = 6 sum = 9 unique feature = History Geography ParentInvolvement			

Feature	Prob neg	Prob pos	count neg	count pos	sum	Percentage	Time	Score
History_Geography ParentInvolvement	0.0	1.0	0	1	1	50%	157/314 [05:23<04:49,	1.84
Health_LifeScience VisualArts	0.26666666666666666	0.7333333333333333	4	11	15	50%	158/314 [05:25<04:41,	1.81
Literacy Music	0.06666666666666667	0.9333333333333333	1	14	15	51%	159/314 [05:27<04:38,	1.80
NutritionEducation SpecialNeeds	0.2	0.8	1	4	5	51%	160/314 [05:29<04:35,	1.79
CharacterEducation TeamSports	0.0	1.0	0	5	5	51%	161/314 [05:30<04:29,	1.76
Civics_Government Literature_Writing	0.0	1.0	0	11	11	52%	162/314 [05:32<04:23,	1.74
FinancialLiteracy SpecialNeeds	0.0	1.0	0	2	2	52%	163/314 [05:34<04:21,	1.73
ForeignLanguages VisualArts	0.5	0.5	1	1	2	52%	164/314 [05:36<04:20,	1.74
Civics_Government History_Geography	0.20833333333333334	0.7916666666666666	5	19	24	53%	165/314 [05:37<04:18,	1.74
EarlyDevelopment PerformingArts	0.0	1.0	0	2	2	53%	166/314 [05:39<04:17,	1.74
AppliedSciences Gym_Fitness	0.0	1.0	0	4	4	54%	167/314 [05:41<04:14,	1.73
College_CareerPrep EarlyDevelopment	0.0	1.0	0	3	3	54%	168/314 [05:42<04:12,	1.73
ESL Health_LifeScience	0.75	0.25	3	1	4	54%	169/314 [05:44<04:11,	1.73

| 170/314 [05:46<04:09, 1.73
s/]it]

Feature = Extracurricular Literature_Writing
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 4 sum = 4

| 171/314 [05:48<04:08, 1.74
s/]it]

Feature = EnvironmentalScience SocialSciences
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 9 sum = 9

| 172/314 [05:49<04:07, 1.74
s/]it]

Feature = FinancialLiteracy History_Geography
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2
unique feature = FinancialLiteracy ForeignLanguages

| 173/314 [05:51<04:03, 1.72
s/]it]

Feature = FinancialLiteracy ForeignLanguages
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 1 sum = 1

| 174/314 [05:53<04:00, 1.71
s/]it]

Feature = Mathematics ParentInvolvement
Prob neg = 0.0833333333333333 Prob pos = 0.9166666666666666
count neg = 1 count pos = 11 sum = 12

| 175/314 [05:54<03:58, 1.72
s/]it]

Feature = AppliedSciences ParentInvolvement
Prob neg = 0.125 Prob pos = 0.875
count neg = 1 count pos = 7 sum = 8

| 176/314 [05:56<03:59, 1.73
s/]it]

Feature = CharacterEducation Health_LifeScience
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 4 sum = 4

| 177/314 [05:58<03:55, 1.72
s/]it]

Feature = EarlyDevelopment NutritionEducation
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 4 sum = 4

| 178/314 [06:00<03:57, 1.75
s/]it]

Feature = ForeignLanguages Literature_Writing
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666
count neg = 4 count pos = 8 sum = 12

| 179/314 [06:02<03:57, 1.76
s/]it]

Feature = EnvironmentalScience Gym_Fitness
Prob neg = 0.5 Prob pos = 0.5
count neg = 1 count pos = 1 sum = 2

| 180/314 [06:03<03:57, 1.77
s/]it]

Feature = EarlyDevelopment Extracurricular
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 3 sum = 3
unique feature = ParentInvolvement PerformingArts

| 181/314 [06:05<03:55, 1.77
s/]it]

Feature = ParentInvolvement PerformingArts
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 1 sum = 1

| 182/314 [06:07<03:52, 1.76
s/]it]

```
Feature = History_Geography_SpecialNeeds
Prob neg = 0.3125      Prob pos = 0.6875
count neg = 5      count pos = 11      sum = 16
unique feature = ESL Music
```

```
58% ██████████ | 183/314 [06:09<03:49, 1.75  
s/it]
```

```
Feature = ESL Music
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
s/it] ██████████ | 184/314 [06:10<03:52, 1.79
```

```
Feature = Health_Wellness Warmth Care_Hunger
Prob neg = 0.25      Prob pos = 0.75
count neg = 1      count pos = 3      sum = 4
```

```
s/it] | 185/314 [06:12<03:48, 1.77
```

```
Feature = Music SocialSciences
Prob neg = 0.5      Prob pos = 0.5
count neg = 2       count pos = 2      sum = 4
```

```
s/it] | ██████████ 59% | 186/314 [06:14<03:46, 1.77
```

```
Feature = Extracurricular Mathematics
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 8      sum = 8
```

```
s/it] | 60% ██████████ | 187/314 [06:16<03:41, 1.74
```

```
Feature = CommunityService EnvironmentalScience
Prob neg = 0.2      Prob pos = 0.8
count neg = 1      count pos = 4      sum = 5
```

```
60% ██████████ | 188/314 [06:17<03:38, 1.73
```

s/it]

```
Feature = AppliedSciences Health_Wellness
Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334
count neg = 1 count pos = 5 sum = 6
```

```
60% ██████████ | 189/314 [06:19<03:35, 1.72  
s/it]
```

```
Feature = College_CareerPrep ParentInvolvement
Prob neg = 0.5      Prob pos = 0.5
count neg = 2      count pos = 2      sum = 4
```

```
s/it] | 61% ██████████ | 190/314 [06:21<03:33, 1.72
```

```
Feature = CharacterEducation ParentInvolvement
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 4      sum = 4
```

```
61% ██████████ | 191/314 [06:22<03:28, 1.70  
s/it]
```

```
Feature = SpecialNeeds Warmth Care_Hunger
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 3      sum = 3
```

[illegible]

```
Feature = ParentInvolvement
Prob neg = 0.2      Prob pos = 0.8
count neg = 1      count pos = 4      sum = 5
```

```
61% | 193/314 [06:26<03:27, 1.72
s/it]
```

```
Feature = EnvironmentalScience VisualArts
Prob neg = 0.13043478260869565      Prob pos = 0.8695652173913043
count neg = 3      count pos = 20      sum = 23
```

```
s/it] | 62% ██████████ | 194/314 [06:28<03:26, 1.72
```

```
Feature = Civics_Government
Prob neg = 0.2727272727272727      Prob pos = 0.7272727272727273
count neg = 3      count pos = 8      sum = 11
```

```
62% | 195/314 [06:29<03:25, 1.72
s/it]
```



```
Feature = EarlyDevelopment Other
Prob neg = 0.2608695652173913    Prob pos = 0.7391304347826086
count neg = 6      count pos = 17    sum = 23
```

[illegible]

```
Feature = CharacterEducation VisualArts
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666
count neg = 3 count pos = 6 sum = 9
```

s/it] 67%

```
Feature = Other TeamSports
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 3      sum = 3
```

[illegible]

```
Feature = Health_Wellness SocialSciences
Prob neg = 0.4      Prob pos = 0.6
count neg = 2      count pos = 3      sum = 5
unique feature = ESL Gym_Fitness
```

[illegible]

```
Feature = ESL Gym_Fitness
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

[illegible]

```
Feature = College_CareerPrep PerformingArts
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 2      sum = 2
```

[illegible]

```
Feature = Civics_Government VisualArts
Prob neg = 0.25      Prob pos = 0.75
count neg = 1      count pos = 3      sum = 4
```

[illegible]

```
Feature = Economics SocialSciences
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 3      sum = 3
```

[illegible]

```
Feature = Other ParentInvolvement
Prob neg = 0.5      Prob pos = 0.5
count neg = 1      count pos = 1      sum = 2
unique feature = Extracurricular TeamSports
```

69%| ██████████
s/it]

```
Feature = Extracurricular TeamSports
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

[illegible]

```
Feature = SocialSciences VisualArts
Prob neg = 0.166666666666666666 Prob pos = 0.833333333333333333
count neg = 1 count pos = 5 sum = 6
```

70%|
s/it]

```
Feature = PerformingArts SpecialNeeds
Prob neg = 0.2857142857142857    Prob pos = 0.7142857142857143
count neg = 2    count pos = 5    sum = 7
unique feature = EnvironmentalScience TeamSports
```

70%| ██████████
s/it]

```
Feature = EnvironmentalScience TeamSports
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```

70%|███████████████████████████████████████| 221/314 [07:15<02:39, 1.71
s/it]

Feature = College_CareerPrep Health_Wellness
Prob neg = 0.5 Prob pos = 0.5
count neg = 2 count pos = 2 sum = 4

71%|███████████████████████████████████████| 222/314 [07:16<02:36, 1.70
s/it]

Feature = Health_LifeScience NutritionEducation
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2

71%|███████████████████████████████████████| 223/314 [07:18<02:34, 1.70
s/it]

Feature = EarlyDevelopment Health_LifeScience
Prob neg = 0.3333333333333333 Prob pos = 0.6666666666666666
count neg = 2 count pos = 4 sum = 6

71%|███████████████████████████████████████| 224/314 [07:20<02:33, 1.71
s/it]

Feature = AppliedSciences PerformingArts
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2

72%|███████████████████████████████████████| 225/314 [07:22<02:32, 1.71
s/it]

Feature = Gym_Fitness Health_LifeScience
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 2 sum = 2
unique feature = CharacterEducation PerformingArts

72%|███████████████████████████████████████| 226/314 [07:24<02:44, 1.87
s/it]

Feature = CharacterEducation PerformingArts
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 1 sum = 1

72%|███████████████████████████████████████| 227/314 [07:26<03:00, 2.07
s/it]

Feature = Gym_Fitness PerformingArts
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 4 sum = 4

73%|███████████████████████████████████████| 228/314 [07:29<03:14, 2.27
s/it]

Feature = Economics
Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334
count neg = 1 count pos = 5 sum = 6

73%|███████████████████████████████████████| 229/314 [07:32<03:27, 2.44
s/it]

Feature = NutritionEducation Other
Prob neg = 0.5 Prob pos = 0.5
count neg = 1 count pos = 1 sum = 2

73%|███████████████████████████████████████| 230/314 [07:34<03:08, 2.25
s/it]

Feature = ESL_History_Geography
Prob neg = 0.16666666666666666 Prob pos = 0.8333333333333334
count neg = 1 count pos = 5 sum = 6
unique feature = EarlyDevelopment Warmth Care_Hunger

74%|███████████████████████████████████████| 231/314 [07:36<02:54, 2.10
s/it]

Feature = EarlyDevelopment Warmth Care_Hunger
Prob neg = 0.0 Prob pos = 1.0
count neg = 0 count pos = 1 sum = 1

74%|███████████████████████████████████████| 232/314 [07:37<02:43, 2.00
s/it]

Feature = College_CareerPrep CommunityService
Prob neg = 0.14285714285714285 Prob pos = 0.8571428571428571
count neg = 1 count pos = 6 sum = 7

74%|███████████████████████████████████████| 233/314 [07:39<02:34, 1.91
s/it]

Feature = ForeignLanguages Mathematics
Prob neg = 0.4 Prob pos = 0.6
count neg = 2 count pos = 3 sum = 5

```

Feature	Prob neg	Prob pos	count neg	count pos	sum	unique feature	Percentage	Time	Score
EarlyDevelopment Music	0.0	1.0	0	3	3		75%	234/314 [07:41<02:28,	1.85
Economics History_Geography	0.0	1.0	0	5	5		75%	235/314 [07:42<02:21,	1.79
College_CareerPrep Other	0.3333333333333333	0.6666666666666666	5	10	15	FinancialLiteracy VisualArts	75%	236/314 [07:44<02:19,	1.79
FinancialLiteracy VisualArts	0.0	1.0	0	1	1		76%	237/314 [07:46<02:17,	1.78
History_Geography Music	0.2	0.8	1	4	5		76%	238/314 [07:48<02:13,	1.76
CharacterEducation Extracurricular	0.1111111111111111	0.8888888888888888	1	8	9		76%	239/314 [07:49<02:11,	1.75
Health_Wellness Music	0.0	1.0	0	2	2		77%	240/314 [07:51<02:09,	1.75
SpecialNeeds TeamSports	0.0	1.0	0	3	3	ESL PerformingArts	77%	241/314 [07:53<02:06,	1.73
ESL PerformingArts	0.0	1.0	0	1	1	Extracurricular ParentInvolvement	77%	242/314 [07:54<02:03,	1.71
Extracurricular ParentInvolvement	0.0	1.0	0	1	1	Extracurricular SocialSciences	78%	243/314 [07:56<02:01,	1.71
Extracurricular SocialSciences	0.0	1.0	0	1	1		78%	244/314 [07:58<01:59,	1.71
Health_Wellness VisualArts	0.5	0.5	2	2	4		78%	245/314 [08:00<02:00,	1.75
							78%	246/314 [08:01<01:58,	1.74

[illegible]

```
Feature = Civics_Government EnvironmentalScience
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
unique feature = Economics SpecialNeeds
```

82% [s/it]

| 259/314 [08:24<01:34, 1.72

```
Feature = Economics SpecialNeeds
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
unique feature = Civics_Government Mathematics
```

83% [s/it]

| 260/314 [08:25<01:33, 1.73

```
Feature = Civics_Government Mathematics
Prob neg = 1.0      Prob pos = 0.0
count neg = 1      count pos = 0      sum = 1
```

83% [s/it]

| 261/314 [08:27<01:31, 1.73

```
Feature = Economics Literacy
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 2      sum = 2
```

83%  s/it]

| 262/314 [08:29<01:29, 1.73

```
Feature = AppliedSciences CommunityService
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 3      sum = 3
```

84% s/it]

| 263/314 [08:31<01:27, 1.72

```
Feature = College_CareerPrep History_Geography
Prob neg = 0.5      Prob pos = 0.5
count neg = 1      count pos = 1      sum = 2
unique feature = ForeignLanguages Other
```

s/it] 84%

| 264/314 [08:32<01:26, 1.72

```
Feature = ForeignLanguages Other
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

s/it] 84%

| 265/314 [08:34<01:24, 1.72

```
Feature = Health_LifeScience History_Geography
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 4      sum = 4
unique feature = CommunityService Literacy
```

s/it] 85%

| 266/314 [08:36<01:22, 1.73

```
Feature = CommunityService Literacy
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

85% | s/it]

| 267/314 [08:38<01:21, 1.73

```
Feature = CommunityService History_Geography
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 3      sum = 3
unique feature = CharacterEducation History_Geography
```

s/it] 85%

| 268/314 [08:39<01:19, 1.72

```
Feature = CharacterEducation History_Geography
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

s/it] 86%

| 269/314 [08:41<01:18, 1.74

```
Feature = EarlyDevelopment ParentInvolvement
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 2      sum = 2
```

s/it] 86%

| 270/314 [08:43<01:16, 1.73

```
Feature = AppliedSciences Civics_Government
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 4      sum = 4
```


Iteration	Feature	Prob neg	Prob pos	count neg	count pos	sum	unique feature	Time (s)	Score
86%	Other SocialSciences	0.0	1.0	0	2	2		271/314 [08:45<01:16,	1.78
87%	History_Geography PerformingArts	0.0	1.0	0	2	2		272/314 [08:48<01:32,	2.21
87%	CommunityService ParentInvolvement	0.0	1.0	0	2	2		273/314 [08:50<01:36,	2.34
87%	CommunityService ParentInvolvement	0.0	1.0	0	1	1		274/314 [08:53<01:31,	2.29
87%	Civics_Government Economics	0.0	1.0	0	1	1		274/314 [08:53<01:31,	2.29
88%	Civics_Government Economics	0.0	1.0	0	1	1		275/314 [08:55<01:25,	2.19
88%	EnvironmentalScience PerformingArts	0.0	1.0	0	1	1		276/314 [08:57<01:20,	2.11
88%	Health_Wellness PerformingArts	0.0	1.0	0	2	2		277/314 [08:58<01:14,	2.03
88%	CharacterEducation ForeignLanguages	1.0	0.0	1	0	1		277/314 [08:58<01:14,	2.03
89%	CharacterEducation ForeignLanguages	0.0	1.0	0	1	1		278/314 [09:00<01:12,	2.01
89%	Literature_Writing TeamSports	0.0	1.0	0	1	1		278/314 [09:00<01:12,	2.01
89%	Literature_Writing TeamSports	0.0	1.0	0	1	1		279/314 [09:02<01:09,	1.99
89%	Mathematics Warmth Care_Hunger	1.0	0.0	1	0	1		279/314 [09:02<01:09,	1.99
89%	EarlyDevelopment TeamSports	0.0	1.0	0	1	1		280/314 [09:04<01:07,	1.98
89%	EarlyDevelopment TeamSports	0.0	1.0	0	1	1		281/314 [09:06<01:04,	1.96
89%	FinancialLiteracy Health_Wellness	0.0	1.0	0	1	1		281/314 [09:06<01:04,	1.96
90%	FinancialLiteracy Health_Wellness	0.0	1.0	0	1	1		282/314 [09:08<01:01,	1.93
90%	AppliedSciences Economics	1.0	0.0	1	0	1		282/314 [09:08<01:01,	1.93


```
Feature = Economics Literature_Writing
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
unique feature = ESL Extracurricular
```

```
Feature = ESL Extracurricular
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
Feature = College_CareerPrep NutritionEducation
Prob neg = 0.5      Prob pos = 0.5
count neg = 1      count pos = 1      sum = 2
unique feature = CommunityService Economics
```

```
Feature = CommunityService Economics
Prob neg = 1.0      Prob pos = 0.0
count neg = 1      count pos = 0      sum = 1
unique feature = Gym_Fitness Other
```

```
Feature = Gym_Fitness Other
Prob neg = 1.0      Prob pos = 0.0
count neg = 1      count pos = 0      sum = 1
unique feature = Gym_Fitness History_Geography
```

```
Feature = Gym_Fitness History_Geography
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
unique feature = Gym_Fitness Music
```

```
Feature = Gym_Fitness Music
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
unique feature = AppliedSciences FinancialLiteracy
Feature = AppliedSciences FinancialLiteracy
Prob neg = 1.0      Prob pos = 0.0
count neg = 1      count pos = 0      sum = 1
```

```
unique feature = Civics_Government FinancialLiteracy
Feature = Civics_Government FinancialLiteracy
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
unique feature = ESL ParentInvolvement
Feature = ESL ParentInvolvement
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
unique feature = Extracurricular SpecialNeeds
Feature = Extracurricular SpecialNeeds
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
unique feature = Music Other
Feature = Music Other
Prob neg = 0.0      Prob pos = 1.0
count neg = 0      count pos = 1      sum = 1
```

```
98%|███████████████████████████████████████████████████████████████████████████████ | 307/314 [09:53<00:12, 1.83  
s/it]  
  
unique feature = College_CareerPrep Warmth Care_Hunger  
Feature = College_CareerPrep Warmth Care_Hunger  
Prob neg = 0.0 Prob pos = 1.0  
count neg = 0 count pos = 1 sum = 1  
  
98%|███████████████████████████████████████████████████████████████████████████████ | 308/314 [09:54<00:11, 1.84  
s/it]  
  
unique feature = Civics_Government TeamSports  
Feature = Civics_Government TeamSports  
Prob neg = 0.0 Prob pos = 1.0  
count neg = 0 count pos = 1 sum = 1  
  
98%|███████████████████████████████████████████████████████████████████████████████ | 309/314 [09:56<00:09, 1.81  
s/it]  
  
unique feature = Gym_Fitness SocialSciences  
Feature = Gym_Fitness SocialSciences  
Prob neg = 0.0 Prob pos = 1.0  
count neg = 0 count pos = 1 sum = 1  
  
99%|███████████████████████████████████████████████████████████████████████████████ | 310/314 [09:58<00:07, 1.79  
s/it]  
  
unique feature = CommunityService PerformingArts  
Feature = CommunityService PerformingArts  
Prob neg = 0.0 Prob pos = 1.0  
count neg = 0 count pos = 1 sum = 1  
  
99%|███████████████████████████████████████████████████████████████████████████████ | 311/314 [10:00<00:05, 1.82  
s/it]  
  
unique feature = EarlyDevelopment SocialSciences  
Feature = EarlyDevelopment SocialSciences  
Prob neg = 1.0 Prob pos = 0.0  
count neg = 1 count pos = 0 sum = 1  
  
99%|███████████████████████████████████████████████████████████████████████████████ | 312/314 [10:02<00:03, 1.80  
s/it]  
  
unique feature = TeamSports VisualArts  
Feature = TeamSports VisualArts  
Prob neg = 0.0 Prob pos = 1.0  
count neg = 0 count pos = 1 sum = 1  
  
100%|███████████████████████████████████████████████████████████████████████████████ | 313/314 [10:03<00:01, 1.81  
s/it]  
  
unique feature = AppliedSciences ForeignLanguages  
Feature = AppliedSciences ForeignLanguages  
Prob neg = 0.0 Prob pos = 1.0  
count neg = 0 count pos = 1 sum = 1  
  
100%|███████████████████████████████████████████████████████████████████████████████ | 314/314 [10:05<00:00, 1.93  
s/it]  
  
unique feature = Gym_Fitness Literature_Writing  
Feature = Gym_Fitness Literature_Writing  
Prob neg = 0.0 Prob pos = 1.0  
count neg = 0 count pos = 1 sum = 1
```

```
In [87]: response_test_clean_subcategories.count()
```

```
Out[87]: x      14850
         y      14850
         dtype: int64
```

2.2.3.4 School State

```
In [88]: X_test.school_state.value_counts()
```

```
Out[88]: CA      2078  
        NY     1020  
        TX      946  
        FL      853  
        NC      677  
        IL      593  
        GA      539  
        SC      523  
        MI      430  
        PA      415  
        OH      377  
        WA      350  
        IN      350  
        MO      346  
        MA      326  
        LA      315  
        OK      312  
        NJ      304  
        AZ      300  
        VA      286  
        WI      255  
        TN      235  
        UT      230  
        CT      226  
        AL      223  
        NV      213  
        MD      199  
        KY      190  
        CO      171  
        MS      169  
        OR      169  
        MN      159  
        AR      131  
        ID       99  
        IA       84  
        DC       79  
        KS       77  
        WV       75  
        NM       68  
        HI       66  
        NH       53  
        ME       50  
        AK       47  
        SD       45  
        DE       42  
        RI       40  
        NE       37  
        MT       36  
        ND       24  
        WY       12  
        VT        6  
Name: school_state, dtype: int64
```

```
In [89]: response_test_school_state = response(X_test['school_state'],y_test)
```

```

2%|██████| 1/51 [00:02<01:46, 2.14
s/it]

Feature = OH
Prob neg = 0.14058355437665782 Prob pos = 0.8594164456233422
count neg = 53 count pos = 324 sum = 377

4%|██████| 2/51 [00:04<01:49, 2.24
s/it]

Feature = TX
Prob neg = 0.20190274841437633 Prob pos = 0.7980972515856237
count neg = 191 count pos = 755 sum = 946

6%|██████| 3/51 [00:06<01:43, 2.16
s/it]

Feature = OK
Prob neg = 0.17307692307692307 Prob pos = 0.8269230769230769
count neg = 54 count pos = 258 sum = 312

8%|██████| 4/51 [00:08<01:42, 2.19
s/it]

Feature = GA
Prob neg = 0.20222634508348794 Prob pos = 0.7977736549165121
count neg = 109 count pos = 430 sum = 539

10%|██████| 5/51 [00:10<01:38, 2.14
s/it]

Feature = OR
Prob neg = 0.20118343195266272 Prob pos = 0.7988165680473372
count neg = 34 count pos = 135 sum = 169

12%|██████| 6/51 [00:12<01:35, 2.11
s/it]

Feature = MA
Prob neg = 0.147239263803681 Prob pos = 0.852760736196319
count neg = 48 count pos = 278 sum = 326

14%|██████| 7/51 [00:15<01:37, 2.21
s/it]

Feature = FL
Prob neg = 0.17233294255568582 Prob pos = 0.8276670574443142
count neg = 147 count pos = 706 sum = 853

16%|██████| 8/51 [00:17<01:34, 2.20
s/it]

Feature = SC
Prob neg = 0.1491395793499044 Prob pos = 0.8508604206500956
count neg = 78 count pos = 445 sum = 523

18%|██████| 9/51 [00:19<01:30, 2.15
s/it]

Feature = NJ
Prob neg = 0.1611842105263158 Prob pos = 0.8388157894736842
count neg = 49 count pos = 255 sum = 304

20%|██████| 10/51 [00:22<01:43, 2.52
s/it]

Feature = CA
Prob neg = 0.14485081809432146 Prob pos = 0.8551491819056786
count neg = 301 count pos = 1777 sum = 2078

22%|██████| 11/51 [00:24<01:32, 2.32
s/it]

Feature = KY
Prob neg = 0.12631578947368421 Prob pos = 0.8736842105263158
count neg = 24 count pos = 166 sum = 190

24%|██████| 12/51 [00:26<01:26, 2.22
s/it]

Feature = MS
Prob neg = 0.09467455621301775 Prob pos = 0.9053254437869822
count neg = 16 count pos = 153 sum = 169

25%|██████| 13/51 [00:28<01:21, 2.15
s/it]

Feature = CT
Prob neg = 0.11504424778761062 Prob pos = 0.8849557522123894
count neg = 26 count pos = 200 sum = 226

```



```
In [90]: response_test_school_state.count()
```

```
Out[90]: x      14850
          y      14850
          dtype: int64
```

2.2.2.5 Project Grade category

```
In [91]: X_test.clean_project_grade_category.value_counts()
```

```
Out[91]: PreK-2      5958  
        3-5        5117  
        6-8       2338  
        9-12      1437  
        Name: clean_project_grade_category, dtype: int64
```

```
In [92]: response_test_clean_project_grade_category = response(X_test['clean_project_grade_category'],y_test)
```

```
25%|██████████| 1/4 [00:06<00:20, 6.71 s/it]
```

```
Feature = PreK-2  
Prob neg = 0.15256797583081572    Prob pos = 0.8474320241691843  
count neg = 909    count pos = 5049    sum = 5958
```

```
50%|██████████| 2/4 [00:12<00:12, 6.49 s/it]
```

```
Feature = 3-5  
Prob neg = 0.146765683017393    Prob pos = 0.853234316982607  
count neg = 751    count pos = 4366    sum = 5117
```

```
75%|██████████| 3/4 [00:16<00:05, 5.77 s/it]
```

```
Feature = 6-8  
Prob neg = 0.16167664670658682    Prob pos = 0.8383233532934131  
count neg = 378    count pos = 1960    sum = 2338
```

```
100%|██████████| 4/4 [00:20<00:00, 5.08 s/it]
```

```
Feature = 9-12  
Prob neg = 0.17397355601948503    Prob pos = 0.826026443980515  
count neg = 250    count pos = 1187    sum = 1437
```

```
In [93]: response_test_clean_project_grade_category.count()
```

```
Out[93]: x      14850  
        y      14850  
        dtype: int64
```

```
In [ ]:
```

```
In [ ]:
```

2.3 Make Data Model Ready: encoding eassay, and project_title

```
In [94]: # 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
```

Ecoding Essay and Project title

- 2.3.1 BOW
- 2.3.2 TFIDF
- 2.3.3 AVG W2V
- 2.3.4 TFIDF W2V

2.3.1 BOW Essays and Title

2.3.1.1 BOW Essay

```
In [95]: print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)

print("="*100)

vectorizer = CountVectorizer(min_df=10, max_features=5000)
vectorizer.fit(X_train['preprocessed_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['preprocessed_essays'].values)
X_test_essay_bow = vectorizer.transform(X_test['preprocessed_essays'].values)

print("After vectorizations")
print(X_train_essay_bow.shape, y_train.shape)
print(X_test_essay_bow.shape, y_test.shape)
print("="*100)

(30150, 10) (30150,)
(14850, 10) (14850,)
=====
After vectorizations
(30150, 5000) (30150,)
(14850, 5000) (14850,)
=====
```

2.3.1.2 BOW Title

```
In [96]: print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)

print("="*100)

vectorizer = CountVectorizer(min_df=10, max_features=5000)
vectorizer.fit(X_train['preprocessed_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['preprocessed_titles'].values)
X_test_title_bow = vectorizer.transform(X_test['preprocessed_titles'].values)

print("After vectorizations")
print(X_train_title_bow.shape, y_train.shape)
print(X_test_title_bow.shape, y_test.shape)
print("="*100)

(30150, 10) (30150,)
(14850, 10) (14850,)
=====
After vectorizations
(30150, 1512) (30150,)
(14850, 1512) (14850,)
=====
```

2.3.2 TF IDF Essay and Title

2.3.2.1 TF IDF Essay

```
In [97]: from sklearn.feature_extraction.text import TfidfVectorizer

print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)

print("="*100)

vectorizer = TfidfVectorizer(min_df=10, max_features=5000)
vectorizer.fit(X_train['preprocessed_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['preprocessed_essays'].values)
X_test_essay_tfidf = vectorizer.transform(X_test['preprocessed_essays'].values)

print("After vectorizations")
print(X_train_essay_tfidf.shape, y_train.shape)
print(X_test_essay_tfidf.shape, y_test.shape)
print("="*100)

(30150, 10) (30150,)
(14850, 10) (14850,)
=====
After vectorizations
(30150, 5000) (30150,)
(14850, 5000) (14850,)
=====
```

2.3.2.2 TF IDF Title

```
In [98]: print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)

print("="*100)

vectorizer = TfidfVectorizer(min_df=10, max_features=5000)
vectorizer.fit(X_train['preprocessed_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['preprocessed_titles'].values)
X_test_title_tfidf = vectorizer.transform(X_test['preprocessed_titles'].values)

print("After vectorizations")
print(X_train_title_tfidf.shape, y_train.shape)
print(X_test_title_tfidf.shape, y_test.shape)
print("="*100)

(30150, 10) (30150,)
(14850, 10) (14850,)
=====
After vectorizations
(30150, 1512) (30150,)
(14850, 1512) (14850,)
=====
```

2.3.3 AVG W2V Essay and Title

2.3.3.1 AVG W2V Essay

```
In [99]: # stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-save-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 [100]: # average Word2Vec
# compute average word2vec for each review.
avg_w2v_vectors_train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_train['preprocessed_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_train.append(vector)

print(len(avg_w2v_vectors_train))
print(len(avg_w2v_vectors_train[0]))
print(avg_w2v_vectors_train[0])
```

30150

300

[6.03663703e-02 1.80357668e-02 3.15515758e-03 -1.04732678e-01
-1.79821898e-02 9.56745273e-03 -3.02265479e+00 1.32809467e-01
-8.69166121e-03 -2.74705697e-02 5.51042855e-02 6.59065341e-02
1.57215642e-01 -2.28268739e-02 -3.40212103e-02 -2.29368303e-03
4.55836364e-02 -5.95546461e-02 5.92127194e-02 7.38102200e-03
7.48897327e-02 4.64619152e-02 -7.62177612e-02 3.14140000e-04
-4.22899273e-02 -3.39375394e-03 9.68373842e-02 -8.95884752e-02
-6.50876739e-02 -5.10648576e-02 -1.77028622e-01 -4.59837964e-02
2.07798091e-02 1.60771218e-02 -1.64737788e-02 -1.83907582e-02
-7.14229091e-04 -7.54712121e-03 -3.63153080e-02 -6.69749376e-02
-9.37662294e-02 8.21647636e-03 -3.69618503e-03 -1.14859694e-01
-6.20851236e-03 5.34671030e-02 2.33277945e-02 -5.25274559e-02
-1.87031879e-03 -7.81031067e-02 7.88129576e-03 -3.04058097e-02
5.54023709e-02 7.59857212e-03 -8.58008606e-03 -6.15183030e-04
1.15562213e-01 1.28996752e-02 -7.54857739e-02 4.64970788e-02
-3.97331855e-02 1.66540970e-02 4.83183661e-02 -4.83502424e-04
-1.13768747e-01 5.96814627e-02 7.99450036e-02 -3.85320782e-02
1.51412053e-01 -1.25391520e-01 -4.03803784e-02 -7.22552000e-03
3.20000885e-02 -5.68933248e-02 7.12134788e-03 -1.31873590e-01
1.90602921e-02 1.01376697e-02 6.63501188e-02 -2.30053576e-02
1.11786321e-02 -3.87882630e-01 4.98287130e-02 -5.71177436e-02
-7.35391564e-02 -9.79018061e-04 1.44921036e-01 -7.30829745e-02
8.78723109e-02 -1.82733219e-02 6.99676835e-02 -7.86330848e-03
3.60461848e-02 9.41429539e-02 -2.29369636e-03 -3.01215024e-01
-2.19216030e+00 -9.21735030e-03 4.79848315e-02 6.35802406e-02
-8.35392215e-02 1.68145527e-02 1.13495926e-01 -1.71403636e-04
5.09827406e-02 -2.59182164e-02 5.40112036e-02 -1.69917625e-01
-1.02474612e-03 3.02922933e-02 -9.46909091e-04 6.73906424e-03
3.75585573e-02 1.73469830e-01 -7.99429697e-03 2.66149727e-02
-8.14717035e-02 7.50661230e-02 7.80216863e-02 3.17567842e-02
2.17011776e-02 6.37558223e-02 -1.53692533e-03 -1.25898069e-01
8.69042339e-02 3.81207067e-02 8.82430573e-02 -3.62061012e-02
4.53016738e-02 1.40823108e-01 6.65890581e-02 1.81422055e-02
4.03704479e-02 -5.57535855e-02 3.47837339e-02 -2.64621532e-02
2.00530463e-01 -3.03405067e-02 1.05881362e-01 3.25648363e-01
7.74697891e-02 -1.69235706e-02 1.88543527e-02 -4.64030273e-02
1.15922584e-02 -9.28436364e-03 6.41507142e-02 -3.38219758e-02
1.03772382e-01 2.87533873e-02 -4.38730909e-03 -2.75668976e-02
3.97403509e-02 -6.67318909e-03 3.89856781e-02 -8.68695758e-03
-1.23950960e-02 -9.02351935e-02 -8.93452944e-02 2.86166570e-02
4.40412733e-02 -1.57587697e-04 7.58013000e-02 3.35279739e-02
-1.89131630e-02 9.46441642e-02 -6.63584309e-02 3.69610933e-02
1.16869763e-01 -5.36030319e-02 -1.48890061e-02 -2.84750715e-02
-6.63892412e-02 -1.04390782e-01 -8.49304115e-03 6.69286053e-02
2.30175150e-02 7.69093939e-04 -7.53266093e-02 -8.66918424e-02
1.65817059e-02 2.53495826e-01 -1.82576606e-02 -4.42825600e-02
-6.30473430e-02 -7.12471145e-02 -3.06051758e-03 -1.08713487e-01
1.24510255e-01 -4.30205352e-02 -1.27755333e-02 -9.36726358e-02
-6.72364381e-02 -6.81140127e-02 -2.47674303e-03 -1.48399400e-01
-4.13821152e-02 5.72004139e-02 -2.05502103e-02 -2.34503461e-02
8.69174085e-02 -3.21559321e-02 4.11321976e-03 7.45151833e-02
-4.43542394e-02 1.11177139e-02 6.30421303e-02 -9.25360842e-02
1.23839197e-01 3.17541073e-02 -1.11802988e-02 3.88824370e-02
2.62183648e-02 -1.22908156e-01 -9.22959104e-03 3.35727073e-02
-3.95522588e-02 -7.85739182e-02 -3.89616782e-02 2.35474675e-02
-1.21659675e-01 -4.06486285e-02 -5.34570796e-02 -9.06211624e-02
-2.32337142e+00 1.78750618e-01 3.87736236e-02 3.66324455e-02
-3.29713885e-02 -1.08320028e-01 -4.07908242e-03 -2.69775297e-02
-2.29992976e-02 -3.13711018e-02 -4.92665758e-02 8.06624671e-02
9.00577176e-02 -5.77090339e-02 1.42843103e-02 6.46711152e-02
-6.17939697e-03 5.13598001e-02 -1.97439287e-01 -4.33795091e-03
-6.40560630e-02 8.94114848e-03 -8.70763879e-03 -1.18347839e-01
-5.80593199e-02 -1.01852168e-02 -1.05146364e-02 1.03923228e-01
8.57433624e-02 -1.74722194e-02 9.89866827e-02 -3.94328970e-02
7.17072764e-02 -9.90313297e-02 2.55794727e-02 -4.63229230e-02
-1.45581552e-02 1.04945352e-02 4.91588618e-02 3.49634933e-03
6.89065109e-02 -1.13079510e-01 -9.55692515e-02 1.99901133e-02
6.25565030e-03 2.11005641e-02 -2.03946733e-02 -2.71862265e-02
-6.12519079e-02 3.08580655e-02 -5.98302994e-02 8.31249915e-02
9.66705503e-02 5.64963924e-02 -3.19526897e-02 2.80629105e-02
1.02855123e-01 -4.66336545e-03 -5.33676732e-02 9.66969891e-02
8.35056406e-03 9.09357376e-02 6.48731576e-03 -3.05745394e-03
4.34447406e-02 -2.69240073e-02 2.19264891e-02 -2.12284418e-02
-4.80163242e-02 -7.89752091e-02 3.29369612e-02 1.58385248e-02
4.95401897e-02 8.76077006e-02 7.06253455e-02 -1.82354550e-02]


```
In [102]: # average Word2Vec
# compute average word2vec for each review.
avg_w2v_vectors_train_title = []; # the avg-w2v for each sentence/review is stored in this List
for sentence in tqdm(X_train['preprocessed_titles'].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_train_title.append(vector)

print(len(avg_w2v_vectors_train_title))
print(len(avg_w2v_vectors_train_title[0]))
print(avg_w2v_vectors_train_title[0])
```

```
100%|██████████████████████████████████████████████████████████████████████████| 30150/30150 [00:01<00:00, 15614.98  
it/s]
```

30150

300

-2.798525000e-02	-2.625052500e-01	2.710475000e+00	8.273500000e-02
1.735475000e-01	1.208475000e-01	9.433150000e-02	3.367475000e-01
-2.450000000e-03	-2.377812500e-01	-7.597477500e-02	-2.609970000e-01
1.231825000e-01	1.254375000e-02	2.674280000e-01	-2.252475000e-02
1.114800000e-01	-1.800112500e-01	-2.323232500e-01	-4.689725000e-01
1.009500000e-02	-1.216650000e-01	-2.466300000e-02	-2.099515000e-01
-2.263175000e-01	-3.437985000e-01	-3.526677500e-02	-3.809575000e-01
-1.860840000e-01	2.700817500e-01	-1.449452500e-01	-1.175618000e-01
3.754825000e-01	1.620925000e-02	-2.685750000e-01	-2.891716580e-01
8.564000000e-03	3.823200000e-01	-1.692612500e-01	-4.971750000e-02
5.872375000e-02	-3.569600000e-02	1.108985000e-01	-1.068400000e-01
-1.473275000e-02	-1.835450500e-01	-1.018195000e-01	-1.226275000e-01
-9.169672500e-02	-2.826150000e-01	1.546605000e-01	-3.609500000e-01
-2.554752500e-01	-3.317975000e-02	-2.623080000e-01	-3.353500000e-01
-8.213200000e-02	-2.139880000e-01	2.681708500e-01	-7.274677500e-02
-4.180375000e-01	1.360500000e-01	-1.243321000e-01	3.770047500e-02
1.005045000e-01	2.902135000e-01	-2.521722500e-01	-1.514275000e-02
-2.165265000e-02	-7.961000000e-02	-9.481750000e-02	-5.601750000e-02
-1.424572500e-01	-4.269050000e-01	2.265625000e-01	1.466575000e-02
-3.543750000e-02	-3.244665000e-01	1.306550000e-01	1.287300000e-02
-3.384600000e-02	-1.603300000e-02	-3.293472500e-02	-3.232400000e-02
1.230999500e-01	-1.078822500e-01	-8.861125000e-02	2.092215000e-01
-1.689550000e-01	3.111000000e-03	-1.679370000e-01	-9.845000000e-02
-2.611600000e+00	4.797392500e-02	4.307400000e-02	1.704870000e-01
2.809000000e-02	-8.556300000e-02	-1.647655000e-01	-1.490107500e-01
2.599350000e-02	4.657550000e-02	3.082750000e-02	-1.303360000e-01
8.293250000e-02	9.137200000e-02	-2.503400000e-02	1.587650000e-01
2.655340000e-01	2.621340000e-01	1.145625250e-01	-2.442925000e-02
8.626550000e-02	-7.743500000e-03	3.509755000e-02	4.308500000e-02
-2.749807450e-01	1.754807500e-02	3.598250000e-02	-4.635475000e-02
-6.262802500e-02	-6.806500000e-02	-1.027750000e-01	-4.575350000e-02
-1.180272500e-01	7.146700000e-02	6.271750000e-02	-8.739000000e-02
-1.367190000e-01	1.416472500e-01	1.143395000e-01	-1.007307500e-01
4.004850000e-01	-2.808150000e-03	6.395050000e-02	5.257762500e-01
1.403752500e-01	1.224380000e-01	2.058545000e-01	1.072975000e-01
-8.767500000e-03	6.076400000e-02	9.018130000e-02	-2.007137700e-01
1.901950000e-01	-2.025250000e-03	-5.826250000e-02	1.082794750e-01
-1.962150000e-02	-2.091692500e-01	3.746325000e-02	-1.071325000e-01
1.111952500e-01	-2.062730000e-01	-3.996875000e-02	-6.254250000e-03
-1.733850000e-02	1.084160000e-01	2.768780000e-01	1.443897500e-01
7.903500000e-02	1.698105000e-01	3.249672500e-02	-2.492050000e-02
-3.277000000e-02	-2.948692500e-01	2.892000000e-02	3.327250000e-01
-6.614150000e-02	-2.474255000e-01	2.441440000e-01	-3.519775000e-02
-2.613175000e-01	-3.395625000e-02	-1.692330000e-01	-1.780387500e-01
-9.283500000e-02	1.759947500e-01	3.201000000e-02	-2.410277500e-01
4.701000000e-02	-1.000900000e-01	6.254185750e-02	3.294050000e-01
-2.113500000e-01	-1.352142500e-01	2.361300000e-01	1.266302500e-01
1.325437500e-01	-8.974025000e-02	1.632775000e-02	8.405200000e-02
-8.195500000e-02	-9.616600000e-02	2.926522500e-01	

```
In [103]: avg_w2v_vectors_test_title = []; # the avg-w2v for each sentence/review is stored in this List
for sentence in tqdm(X_test['preprocessed_titles'].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_test_title.append(vector)
```

2.3.4 TF IDF W2V Essay and Title

```
In [104]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model = TfidfVectorizer()
tfidf_model.fit(X_train['preprocessed_essays'].values)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model.get_feature_names(), list(tfidf_model.idf_)))
tfidf_words = set(tfidf_model.get_feature_names())
```

```
100%|██████████████████████████████████████████████████████████████████████████| 30150/30150 [02:45<00:00, 182.38  
it/s]
```

30150
300

```
In [106]: tfidf_w2v_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_test['preprocessed_essays'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf_idf_weight = 0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf_words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf value((sentence.count(word)/len(sentence.split())))
            tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf 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_test.append(vector)
```

```
100%|██████████████████████████████████████████████████████████████| 14850/14850 [01:21<00:00, 181.19  
it/s]
```

2.3.4.2 TF IDF W2V Title

```
In [107]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model = TfidfVectorizer()
tfidf_model.fit(X_train['preprocessed_titles'].values)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model.get_feature_names(), list(tfidf_model.idf_)))
tfidf_words = set(tfidf_model.get_feature_names())
```

```
In [108]: # average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_train_title = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_train['preprocessed_titles'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf_idf_weight = 0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf_words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf value((sentence.count(word)/len(sentence.split())))
            tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf 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_train_title.append(vector)

print(len(tfidf_w2v_vectors_train_title))
print(len(tfidf_w2v_vectors_train_title[0]))
```

```
100%|██████████████████████████████████████████████████████████████████████████| 30150/30150 [00:02<00:00, 11582.62  
it/s]
```

30150
300

```
In [109]: tfidf_w2v_vectors_test_title = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X_test['preprocessed_titles'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf_idf_weight = 0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove_words) and (word in tfidf_words):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf value((sentence.count(word)/len(sentence.split())))
            tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tfidf 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_test_title.append(vector)
```

```
100%|██████████████████████████████████████████████████████████████████████████████████| 14850/14850 [00:01<00:00, 10696.65
it/s]
```

In []:

Concatinating all the features

1. SET 1 BOW

```
In [110]: # merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_tr_BOW = hstack((X_train_essay_bow, X_train_title_bow, response_clean_teacher_prefix, response_clean_categories,
response_clean_subcategories, response_school_state, response_clean_project_grade_category, X_train_price_norm, X_train_quantity_norm, X_train_TPPP_norm)).tocsr()
X_te_BOW = hstack((X_test_essay_bow, X_test_title_bow, response_test_clean_teacher_prefix, response_test_clean_categories,
response_test_clean_subcategories, response_test_school_state, response_test_clean_project_grade_category,
X_test_price_norm, X_test_quantity_norm, X_test_TPPP_norm)).tocsr()

print("Final Data matrix")
print(X_tr_BOW.shape, y_train.shape)
print(X_te_BOW.shape, y_test.shape)
print("="*100)
```

```
Final Data matrix
(30150, 6525) (30150,)
(14850, 6525) (14850,)
=====
```

2. SET 2 TF IDF

```
In [111]: # merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_tr_TFIDF = hstack((X_train_essay_tfidf, X_train_title_tfidf, response_clean_teacher_prefix, response_clean_categories, response_clean_subcategories, response_school_state, response_clean_project_grade_category, X_train_price_norm, X_train_quantity_norm, X_train_TPPP_norm)).tocsr()
X_te_TFIDF = hstack((X_test_essay_tfidf, X_test_title_tfidf, response_test_clean_teacher_prefix, response_test_clean_categories, response_test_clean_subcategories, response_test_school_state, response_test_clean_project_grade_category, X_test_price_norm, X_test_quantity_norm, X_test_TPPP_norm)).tocsr()

print("Final Data matrix")
print(X_tr_TFIDF.shape, y_train.shape)
print(X_te_TFIDF.shape, y_test.shape)
print("=="*100)

Final Data matrix
(30150, 6525) (30150,)
(14850, 6525) (14850,)
=====
```

3. SET 3 AVG W2V

```
In [112]: # merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_tr_AVG_W2V = hstack((avg_w2v_vectors_train, avg_w2v_vectors_train_title, response_clean_teacher_prefix, response_clean_categories, response_clean_subcategories, response_school_state, response_clean_project_grade_category, X_train_price_norm, X_train_quantity_norm, X_train_TPPP_norm)).tocsr()
X_te_AVG_W2V = hstack((avg_w2v_vectors_test, avg_w2v_vectors_test_title, response_test_clean_teacher_prefix, response_test_clean_categories, response_test_clean_subcategories, response_test_school_state, response_test_clean_project_grade_category, X_test_price_norm, X_test_quantity_norm, X_test_TPPP_norm)).tocsr()

print("Final Data matrix")
print(X_tr_AVG_W2V.shape, y_train.shape)
print(X_te_AVG_W2V.shape, y_test.shape)
print("=="*100)

Final Data matrix
(30150, 613) (30150,)
(14850, 613) (14850,)
=====
```

4. SET 4 TF IDF W2V

```
In [113]: # merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack
X_tr_TFIDF_W2V = hstack((tfidf_w2v_vectors_train, tfidf_w2v_vectors_train_title, response_clean_teacher_prefix, response_clean_categories, response_clean_subcategories, response_school_state, response_clean_project_grade_category, X_train_price_norm, X_train_quantity_norm, X_train_TPPP_norm)).tocsr()
X_te_TFIDF_W2V = hstack((tfidf_w2v_vectors_test, tfidf_w2v_vectors_test_title, response_test_clean_teacher_prefix, response_test_clean_categories, response_test_clean_subcategories, response_test_school_state, response_test_clean_project_grade_category, X_test_price_norm, X_test_quantity_norm, X_test_TPPP_norm)).tocsr()

print("Final Data matrix")
print(X_tr_TFIDF_W2V.shape, y_train.shape)
print(X_te_TFIDF_W2V.shape, y_test.shape)
print("=="*100)

Final Data matrix
(30150, 613) (30150,)
(14850, 613) (14850,)
=====
```

In []:

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 instructions

2.4.1 Applying Random Forests on BOW, SET 1

```
In [114]: # Please write all the code with proper documentation
```

```
In [115]: import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
#from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import learning_curve, GridSearchCV

#n_estimators = [10, 50, 100, 150, 200, 300, 500, 1000], max_depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]

clf = RandomForestClassifier(class_weight='balanced')
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]}
set1 = GridSearchCV(clf, parameters, cv=5, scoring='roc_auc', return_train_score=True)
set1.fit(X_tr_BOW, y_train)
```

```
Out[115]: GridSearchCV(cv=5, error_score='raise',
    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=10, n_jobs=1, oob_score=False, random_state=None,
    verbose=0, warm_start=False),
    fit_params=None, iid=True, n_jobs=1,
    param_grid={'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]},
    pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
    scoring='roc_auc', verbose=0)
```

```
In [116]: print(set1.cv_results_)
```

```

{'mean_fit_time': array([ 0.30039654, 0.76196179, 1.16388173, 1.65357752, 2.11833329,
    3.03269095, 5.13307285, 0.32014251, 0.83456836, 1.37073483,
    1.93741269, 2.67723908, 3.66857982, 6.78026919, 0.34447908,
    0.93489819, 1.65238781, 2.35250893, 3.11966391, 4.54365506,
    7.66848507, 0.39594169, 1.08011932, 2.00563493, 2.98980455,
    3.75256476, 6.13100371, 10.2737278 , 0.42626829, 1.2666254 ,
    2.4989182 , 3.61453395, 5.47934685, 7.45108247, 11.59040475,
    0.49188375, 1.77365808, 2.94013567, 4.23926253, 5.65127959,
    8.34588046, 13.91457443, 0.54893265, 2.05709791, 3.52457409,
    5.15321312, 6.79782233, 10.33734798, 16.7803257 ]), 'std_fit_time': array([0.01544335, 0.09463311, 0.0121
4413, 0.01040326, 0.04945349,
    0.02188057, 0.44005595, 0.01291144, 0.06704364, 0.02319137,
    0.02294358, 0.28697989, 0.05286355, 1.03527446, 0.00794287,
    0.02064697, 0.02722317, 0.01676522, 0.0458745 , 0.04600046,
    0.42041819, 0.02389264, 0.02297892, 0.03882294, 0.18203374,
    0.04311213, 0.6611406 , 0.75031686, 0.00622063, 0.01130101,
    0.19263915, 0.14951075, 0.39591793, 0.79206606, 0.56643555,
    0.01573947, 0.21517587, 0.02626613, 0.06511739, 0.06147806,
    0.10251301, 0.39722547, 0.02940678, 0.21438413, 0.16910524,
    0.07485575, 0.09816269, 0.28602237, 0.07702868]), 'mean_score_time': array([0.07839932, 0.23517275, 0.38377
967, 0.56010218, 0.7426373 ,
    1.10145521, 1.87518606, 0.07360382, 0.2451509 , 0.41470599,
    0.58205199, 0.84634461, 1.10823836, 1.9647665 , 0.07480011,
    0.21702118, 0.40831704, 0.58665013, 0.76336074, 1.12540669,
    1.96096306, 0.07680798, 0.24376206, 0.40652876, 0.61118116,
    0.77294283, 1.15851083, 2.13589387, 0.08078456, 0.21962142,
    0.39574938, 0.59741845, 0.84773355, 1.1966095 , 1.93602996,
    0.07958989, 0.2760632 , 0.41410851, 0.59961176, 0.78271523,
    1.1936101 , 1.90971589, 0.07561226, 0.26928129, 0.42446604,
    0.60538855, 0.79068618, 1.16848536, 2.0028511 ]), 'std_score_time': array([0.01078722, 0.01946526, 0.008151
53, 0.01581277, 0.01555876,
    0.01049177, 0.14368557, 0.00222379, 0.03250394, 0.00559259,
    0.00796629, 0.08992769, 0.00424927, 0.20665757, 0.00260214,
    0.00376453, 0.01175971, 0.01117457, 0.00925067, 0.00866283,
    0.17616381, 0.00554566, 0.00361278, 0.0143411 , 0.04366763,
    0.00790213, 0.04642407, 0.31901821, 0.00567733, 0.01103875,
    0.01072507, 0.01199905, 0.06230652, 0.07650343, 0.11972388,
    0.00498334, 0.040904 , 0.01236756, 0.01326521, 0.012801 ,
    0.05993139, 0.009699 , 0.00230998, 0.03115082, 0.01744232,
    0.01553268, 0.01493261, 0.00739234, 0.19816856]), 'param_max_depth': masked_array(data=[2, 2, 2, 2, 2, 2,
2, 3, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4,
    4, 4, 4, 5, 5, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 6, 7,
    7, 7, 7, 7, 7, 7, 8, 8, 8, 8, 8, 8, 8],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'param_n_estimators': masked_array(data=[10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
150, 200,
    300, 500, 10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
    150, 200, 300, 500, 10, 50, 100, 150, 200, 300, 500,
    10, 50, 100, 150, 200, 300, 500, 10, 50, 100, 150, 200,
    300, 500],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'params': [{'max_depth': 2, 'n_estimators': 10}, {'max_depth': 2, 'n_estimators': 50},
{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 2, 'n_estimators': 150}, {'max_depth': 2, 'n_estimators': 20
0}, {'max_depth': 2, 'n_estimators': 300}, {'max_depth': 2, 'n_estimators': 500}, {'max_depth': 3, 'n_estimators':
10}, {'max_depth': 3, 'n_estimators': 50}, {'max_depth': 3, 'n_estimators': 100}, {'max_depth': 3, 'n_estimators':
150}, {'max_depth': 3, 'n_estimators': 200}, {'max_depth': 3, 'n_estimators': 300}, {'max_depth': 3, 'n_estimator
s': 500}, {'max_depth': 4, 'n_estimators': 10}, {'max_depth': 4, 'n_estimators': 50}, {'max_depth': 4, 'n_estimato
rs': 100}, {'max_depth': 4, 'n_estimators': 150}, {'max_depth': 4, 'n_estimators': 200}, {'max_depth': 4, 'n_estim
ators': 300}, {'max_depth': 4, 'n_estimators': 500}, {'max_depth': 5, 'n_estimators': 10}, {'max_depth': 5, 'n_est
imators': 50}, {'max_depth': 5, 'n_estimators': 100}, {'max_depth': 5, 'n_estimators': 150}, {'max_depth': 5, 'n_e
stimators': 200}, {'max_depth': 5, 'n_estimators': 300}, {'max_depth': 5, 'n_estimators': 500}, {'max_depth': 6,
'n_estimators': 10}, {'max_depth': 6, 'n_estimators': 50}, {'max_depth': 6, 'n_estimators': 100}, {'max_depth': 6,
'n_estimators': 150}, {'max_depth': 6, 'n_estimators': 200}, {'max_depth': 6, 'n_estimators': 300}, {'max_depth':
6, 'n_estimators': 500}, {'max_depth': 7, 'n_estimators': 10}, {'max_depth': 7, 'n_estimators': 50}, {'max_depth':
7, 'n_estimators': 100}, {'max_depth': 7, 'n_estimators': 150}, {'max_depth': 7, 'n_estimators': 200}, {'max_dept
h': 7, 'n_estimators': 300}, {'max_depth': 7, 'n_estimators': 500}, {'max_depth': 8, 'n_estimators': 10}, {'max_de
pth': 8, 'n_estimators': 50}, {'max_depth': 8, 'n_estimators': 100}, {'max_depth': 8, 'n_estimators': 150}, {'max
depth': 8, 'n_estimators': 200}, {'max_depth': 8, 'n_estimators': 300}, {'max_depth': 8, 'n_estimators': 500}], 's
plit0_test_score': array([0.58237942, 0.65504505, 0.67011174, 0.66637516, 0.68577045,
    0.68434675, 0.6829028 , 0.62614051, 0.64818963, 0.68131959,
    0.69144796, 0.68824991, 0.69318792, 0.69597351, 0.63297936,
    0.67340611, 0.68587974, 0.6917311 , 0.67949672, 0.69093696,
    0.69870635, 0.62393048, 0.68201478, 0.68732391, 0.69299487,

```


0.69080405, 0.69916354, 0.69791137, 0.64480687, 0.67899099,
0.6965383 , 0.69535786, 0.6950973 , 0.70094634, 0.70187697,
0.64313526, 0.68601224, 0.69970956, 0.70374015, 0.70026887,
0.69734678, 0.70076574, 0.62825729, 0.69358689, 0.69608512,
0.70168034, 0.70029483, 0.70763317, 0.70547441]], 'split1_test_score': array([0.57461474, 0.65424296, 0.672
93671, 0.66336578, 0.67474201,
0.67614763, 0.67186894, 0.63112997, 0.68552157, 0.66904039,
0.67593935, 0.66059104, 0.68872352, 0.69112707, 0.62446672,
0.68176843, 0.66881945, 0.69729231, 0.68837723, 0.69221763,
0.68982569, 0.61533957, 0.67455568, 0.70736737, 0.67627825,
0.68548876, 0.69906933, 0.6900939 , 0.64198075, 0.66426854,
0.66943099, 0.69460451, 0.68176991, 0.68904765, 0.69095994,
0.67085212, 0.67535925, 0.69329512, 0.68954567, 0.69614751,
0.69896614, 0.70159949, 0.64204859, 0.68308584, 0.69543678,
0.69496557, 0.71237346, 0.70191138, 0.70458926]], 'split2_test_score': array([0.6151851 , 0.66553098, 0.691
99184, 0.68199 , 0.70051905,
0.69328267, 0.70098921, 0.6473632 , 0.68847515, 0.68683909,
0.69227567, 0.69830521, 0.7016955 , 0.70162186, 0.61735885,
0.68439925, 0.69266099, 0.69715999, 0.69908304, 0.7107374 ,
0.70742223, 0.64473175, 0.69350804, 0.70545614, 0.70666804,
0.71699738, 0.71589796, 0.70843472, 0.64523525, 0.69009369,
0.69297204, 0.70584822, 0.71035608, 0.71701469, 0.71411207,
0.66999769, 0.69697282, 0.70824037, 0.71081295, 0.71102249,
0.72053877, 0.72263464, 0.65105842, 0.7089378 , 0.70947359,
0.70501721, 0.71266129, 0.71607247, 0.72436967]], 'split3_test_score': array([0.56888347, 0.68961066, 0.678
4406 , 0.69153139, 0.68983635,
0.70038526, 0.69555548, 0.6085974 , 0.68795361, 0.69758584,
0.69917948, 0.69106007, 0.69084683, 0.69935969, 0.65217135,
0.67862725, 0.69838065, 0.70478973, 0.69445574, 0.69855696,
0.70749145, 0.61334593, 0.67415948, 0.69916809, 0.71153021,
0.70444143, 0.70588831, 0.70902854, 0.66013724, 0.68970636,
0.70112469, 0.7013336 , 0.71348597, 0.70847545, 0.71146395,
0.63410992, 0.69842877, 0.6971104 , 0.71581545, 0.71337202,
0.7138293 , 0.7118516 , 0.65130858, 0.70033567, 0.70921445,
0.71723394 , 0.71999116, 0.71563376, 0.71101827]], 'split4_test_score': array([0.59707 , 0.68917595, 0.674
23498, 0.68943526, 0.68014871,
0.6957603 , 0.68005027, 0.64957186, 0.6965265 , 0.68643382,
0.68517435, 0.6884502 , 0.69991284, 0.69463412, 0.63806655,
0.67498449, 0.70039787, 0.70024366, 0.69041187, 0.70580756,
0.69974384, 0.6344189 , 0.6912461 , 0.69512908, 0.70244488,
0.70342677, 0.71070264, 0.70505128, 0.65789606, 0.68806108,
0.71732977, 0.71436086, 0.71151131, 0.70662594, 0.70593135,
0.66397774, 0.69907502, 0.70720624, 0.70422994, 0.71523142,
0.71240257, 0.71758453, 0.64944944, 0.71151976, 0.70949852,
0.70796041, 0.71971119, 0.71771297, 0.72045014]], 'mean_test_score': array([0.58762606, 0.67071999, 0.67754
304, 0.67853875, 0.6862035 ,
0.68998414, 0.68627343, 0.63255981, 0.68133169, 0.68424358,
0.68880357, 0.68533128, 0.6948731 , 0.69654329, 0.6330084 ,
0.67863705, 0.68922726, 0.69824307, 0.69036456, 0.69965081,
0.70063788, 0.62635298, 0.68309651, 0.69888866, 0.69798294,
0.70023126, 0.70614397, 0.70210373, 0.6500108 , 0.68222383,
0.69547847, 0.70230038, 0.70244357, 0.70442182, 0.70486872,
0.65641386, 0.69116919, 0.70111209, 0.70482881, 0.70720797,
0.70861621, 0.71088664, 0.64442376, 0.6994926 , 0.70394125,
0.70537129, 0.71300574, 0.71179242, 0.71317985]], 'std_test_score': array([0.01671398, 0.01575809, 0.007706
7 , 0.01164157, 0.00879023,
0.00866783, 0.01058569, 0.01500639, 0.0169815 , 0.00926539,
0.00781494, 0.01289548, 0.0050756 , 0.00366138, 0.01192199,
0.00409182, 0.01138441, 0.00427435, 0.00655486, 0.00765773,
0.00654878, 0.01182519, 0.00810915, 0.00725253, 0.01244864,
0.01109294, 0.00655391, 0.00719077, 0.00747108, 0.0098472 ,
0.01546064, 0.00729912, 0.01223217, 0.00925544, 0.00815441,
0.01499335, 0.00922419, 0.00577981, 0.00885025, 0.00758161,
0.00898669, 0.00863136, 0.00876028, 0.01037898, 0.00668351,
0.00734104, 0.00715352, 0.00605077, 0.00794877]], 'rank_test_score': array([49, 42, 41, 40, 33, 29, 32, 47,
38, 35, 31, 34, 26, 24, 46, 39, 30,
22, 28, 19, 17, 48, 36, 21, 23, 18, 7, 15, 44, 37, 25, 14, 13, 11,
9, 43, 27, 16, 10, 6, 5, 4, 45, 20, 12, 8, 2, 3, 1]), 'split0_train_score': array([0.61063298, 0.68
568082, 0.70710099, 0.7134753 , 0.72957268,
0.73082774, 0.71982317, 0.64506074, 0.70499323, 0.73504981,
0.73642614, 0.73535155, 0.74578915, 0.74866442, 0.66898936,
0.73947778, 0.74031541, 0.75851967, 0.74181156, 0.75215325,
0.76363423, 0.68896402, 0.75702892, 0.76427522, 0.76828077,
0.7712031 , 0.78016388, 0.77612007, 0.71741321, 0.77517386,
0.78914935, 0.78962952, 0.78832924, 0.79917645, 0.79972507,
0.73025324, 0.79213589, 0.8068392 , 0.81351553, 0.81007572,
0.80890845, 0.81233177, 0.72904998, 0.80797205, 0.83742839,
0.83277557, 0.83667881, 0.84307698, 0.84024205]], 'split1_train_score': array([0.60594531, 0.71721729, 0.71
737011, 0.70973782, 0.71597721,
0.72580396, 0.71985085, 0.65418753, 0.73191496, 0.72206015,
0.73349837, 0.7223375 , 0.74483584, 0.74560841, 0.67057901,
0.74765952, 0.73753901, 0.76017911, 0.75374631, 0.76042648,
0.7587017 , 0.68601167, 0.7526542 , 0.78366576, 0.76646151,
0.7686037 , 0.78104612, 0.78196193, 0.70910204, 0.76374945,
0.76472328, 0.79641863, 0.78364421, 0.79219439, 0.79575506,
0.73938554, 0.78780702, 0.81264327, 0.80982009, 0.81818144,
0.81674533, 0.82327162, 0.74754803, 0.81403003, 0.83229004,

```

0.83536258, 0.84826925, 0.83912574, 0.84372332]), 'split2_train_score': array([0.62151625, 0.6909055 , 0.71
276295, 0.69939357, 0.72608048,
0.71931899, 0.72573164, 0.6558565 , 0.71704863, 0.71865885,
0.72235679, 0.73208655, 0.72716787, 0.73663301, 0.65425533,
0.74135952, 0.74495147, 0.74885555, 0.75271005, 0.76102938,
0.75384447, 0.6938198 , 0.75292968, 0.77094886, 0.77785319,
0.78279534, 0.77862617, 0.77086339, 0.71200799, 0.76550354,
0.77766344, 0.78984261, 0.79257847, 0.79995814, 0.79526997,
0.744249 , 0.79548929, 0.80078454, 0.80709369, 0.81164472,
0.82138659, 0.82507015, 0.74752612, 0.82355801, 0.83526133,
0.82368585, 0.82954003, 0.83593019, 0.84266518]), 'split3_train_score': array([0.58805423, 0.7151461 , 0.70
91642 , 0.71942282, 0.71596671,
0.72823369, 0.72066075, 0.64099231, 0.72315823, 0.73829481,
0.73675321, 0.72878874, 0.73165192, 0.74273115, 0.68266332,
0.72883714, 0.75597696, 0.75950451, 0.75200723, 0.75386468,
0.76239286, 0.67781549, 0.74489106, 0.77102428, 0.77562941,
0.77358074, 0.77672026, 0.78226008, 0.71781751, 0.77653416,
0.78220196, 0.79030041, 0.79700108, 0.7979946 , 0.80238995,
0.71720291, 0.79528829, 0.78973512, 0.81730772, 0.81341961,
0.82053797, 0.81760038, 0.73774689, 0.81169747, 0.8311764 ,
0.84537245, 0.83858753, 0.83578499, 0.83643461]), 'split4_train_score': array([0.61042075, 0.70462791, 0.70
366281, 0.70952046, 0.70517572,
0.72128471, 0.70609934, 0.66703567, 0.72927049, 0.71992543,
0.72311515, 0.71958851, 0.7364624 , 0.73079756, 0.68000087,
0.72105592, 0.75481306, 0.75152687, 0.73447793, 0.75831945,
0.75262189, 0.68214847, 0.75100883, 0.7559404 , 0.76705072,
0.7664622 , 0.77319261, 0.77179282, 0.7094158 , 0.7716319 ,
0.79229329, 0.79361691, 0.79245902, 0.791356 , 0.78825569,
0.72660307, 0.79192138, 0.80097113, 0.79976389, 0.80979669,
0.81379553, 0.81853584, 0.7463991 , 0.81655893, 0.82574085,
0.83369267, 0.83200726, 0.84105192, 0.84352518]), 'mean_train_score': array([0.6073139 , 0.70271552, 0.7100
1221, 0.71030999, 0.71855456,
0.72509382, 0.71843315, 0.65262655, 0.72127711, 0.72679781,
0.73042993, 0.72763057, 0.73718144, 0.74088691, 0.67129758,
0.73567797, 0.74671918, 0.75571714, 0.74695062, 0.75715865,
0.75823903, 0.68575189, 0.75170254, 0.7691709 , 0.77105512,
0.77252902, 0.77794981, 0.77659966, 0.71315131, 0.77051858,
0.78120627, 0.79196161, 0.7908024 , 0.79613592, 0.79627915,
0.73153875, 0.79252837, 0.80219465, 0.80950018, 0.81262364,
0.81627478, 0.81936195, 0.74165402, 0.8147633 , 0.8323794 ,
0.83417782, 0.83701657, 0.83899396, 0.84131807]), 'std_train_score': array([0.01091039, 0.01263436, 0.00471
624, 0.00652965, 0.00860664,
0.00426847, 0.00654668, 0.00908943, 0.00962955, 0.00819993,
0.00638804, 0.00589071, 0.007267 , 0.00641988, 0.01001209,
0.00949608, 0.00747832, 0.00462055, 0.00757495, 0.00354719,
0.00441454, 0.00550359, 0.00394105, 0.00911823, 0.00473226,
0.00566526, 0.00279605, 0.00483807, 0.00378405, 0.00510039,
0.00970821, 0.00265682, 0.00450952, 0.0036247 , 0.00479344,
0.00953575, 0.00279992, 0.00760882, 0.00596271, 0.00306478,
0.00458118, 0.00449618, 0.00729197, 0.00522742, 0.00398305,
0.00691385, 0.00648377, 0.00284983, 0.00273778])}]

```

```

In [117]: import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(set1.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max().unstack()
max_scores1

```

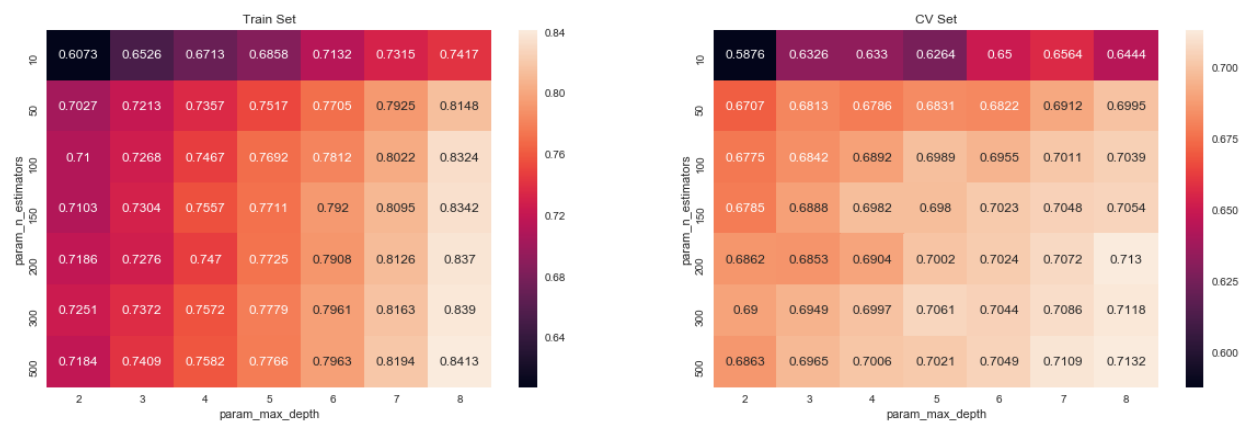
Out[117]:

	mean_fit_time							mean_score_time				...	std_test_score	
param_max_depth	2	3	4	5	6	7	8	2	3	4	...	6	7	
param_n_estimators														
10	0.300397	0.320143	0.344479	0.395942	0.426268	0.491884	0.548933	0.078399	0.073604	0.074800	...	0.007471	0.007471	
50	0.761962	0.834568	0.934898	1.080119	1.266625	1.773658	2.057098	0.235173	0.245151	0.217021	...	0.009847	0.009847	
100	1.163882	1.370735	1.652388	2.005635	2.498918	2.940136	3.524574	0.383780	0.414706	0.408317	...	0.015461	0.015461	
150	1.653578	1.937413	2.352509	2.989805	3.614534	4.239263	5.153213	0.560102	0.582052	0.586650	...	0.007299	0.007299	
200	2.118333	2.677239	3.119664	3.752565	5.479347	5.651280	6.797822	0.742637	0.846345	0.763361	...	0.012232	0.012232	
300	3.032691	3.668580	4.543655	6.131004	7.451082	8.345880	10.337348	1.101455	1.108238	1.125407	...	0.009255	0.009255	
500	5.133073	6.780269	7.668485	10.273728	11.590405	13.914574	16.780326	1.875186	1.964767	1.960963	...	0.008154	0.008154	

7 rows × 140 columns



```
In [118]: fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set_title('CV Set')
plt.show()
```



```
In [119]: print(set1.best_estimator_)

RandomForestClassifier(bootstrap=True, class_weight='balanced',
                        criterion='gini', max_depth=8, 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=500, n_jobs=1, oob_score=False, random_state=None,
                        verbose=0, warm_start=False)
```

Training our model with best Hyperparameters

```
In [123]: def pred_prob(clf, data):
y_pred = []
y_pred = clf.predict_proba(data)[:,:1]
return y_pred
```

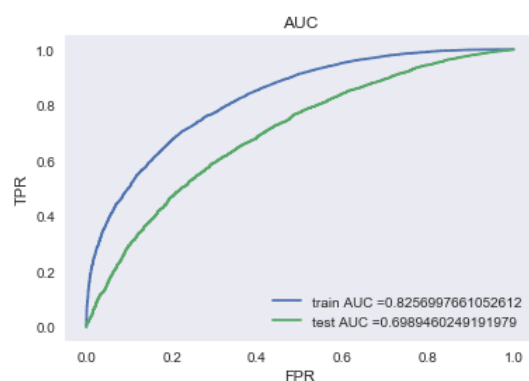
```
In [124]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
model = RandomForestClassifier(max_depth = 8, n_estimators = 500)

model.fit(X_tr_BOW, y_train)

y_train_pred = pred_prob(model,X_tr_BOW)
y_test_pred = pred_prob(model,X_te_BOW)

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

plt.close
plt.plot(train_fpr, train_tpr, label="train AUC =" +str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC =" +str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



Confusion Matrix

```
In [128]: # we are writing our own function for predict, with defined threshold
# we will pick a threshold that will give the least fpr
def find_best_threshold(threshold, fpr, tpr):
    t = threshold[np.argmax(tpr*(1-fpr))]
    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
    print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for threshold", np.round(t,3))
    return t

def predict_with_best_t(proba, threshold):
    predictions = []
    for i in proba:
        if i>=threshold:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

```
In [129]: #our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

```
the maximum value of tpr*(1-fpr) 0.5474011181642218 for threshold 0.842
Train confusion matrix
[[ 3603  1041]
 [ 7510 17996]]
```

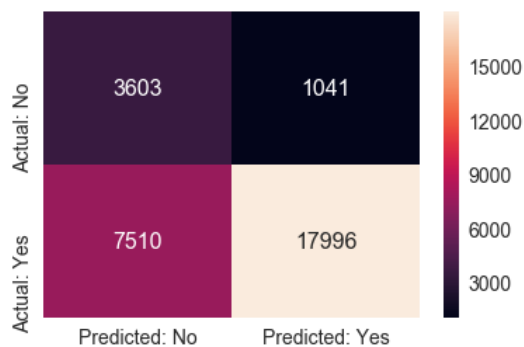
```
In [130]: #Plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

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

Train data confusion matrix

Out[130]: <matplotlib.axes._subplots.AxesSubplot at 0x2c385fae588>



```
In [131]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

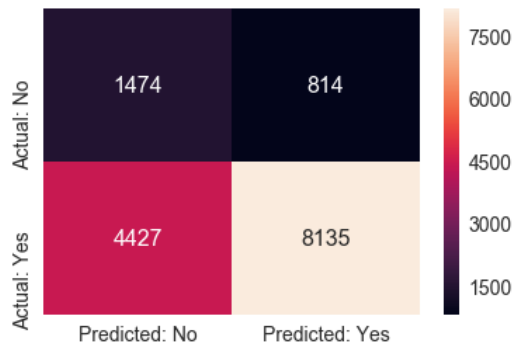
```
Test confusion matrix
[[1474  814]
 [4427 8135]]
```

```
In [132]: print("Test data confusion matrix")

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

Test data confusion matrix

```
Out[132]: <matplotlib.axes._subplots.AxesSubplot at 0x2c387735b38>
```



```
In [ ]:
```

2.4.2 Applying Random Forests on TFIDF, SET 2

```
In [120]: # Please write all the code with proper documentation
```

```
In [133]: import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
#from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import learning_curve, GridSearchCV

#n_estimators = [10, 50, 100, 150, 200, 300, 500, 1000], max_depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]

clf = RandomForestClassifier(class_weight='balanced')
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]}
set2 = GridSearchCV(clf, parameters, cv=5, scoring='roc_auc',return_train_score=True)
set2.fit(X_tr_TFIDF, y_train)
```

```
Out[133]: GridSearchCV(cv=5, error_score='raise',
    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=10, n_jobs=1, oob_score=False, random_state=None,
    verbose=0, warm_start=False),
    fit_params=None, iid=True, n_jobs=1,
    param_grid={'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]},
    pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
    scoring='roc_auc', verbose=0)
```

```
In [134]: print(set2.cv_results_)
```

```

{'mean_fit_time': array([ 0.4076952 , 1.16727767, 2.33196354, 2.99558949, 4.33202219,
    6.12521901, 8.74461374, 0.41348557, 1.26003013, 2.41334519,
    3.40130334, 4.52350416, 6.89954138, 10.94352593, 0.47871876,
    1.59712043, 3.07917299, 4.48262038, 5.70853405, 8.80983176,
    14.35780282, 0.53516898, 1.92305918, 3.59339061, 5.25654263,
    6.9629869 , 10.73708758, 17.41343155, 0.59839835, 2.28629332,
    4.34577675, 6.44795704, 8.79827929, 12.69524107, 21.16878352,
    0.71409078, 2.73548579, 5.46937947, 7.78020101, 10.12671895,
    15.4546618 , 25.24667745, 0.80145645, 3.15077386, 6.1425745 ,
    9.15171776, 12.40321641, 18.29309244, 30.39770827]), 'std_fit_time': array([0.03426796, 0.10991101, 0.4289
0565, 0.32914913, 0.96496716,
    0.39070317, 0.98083958, 0.00865933, 0.03619819, 0.13269056,
    0.02942185, 0.06110721, 0.30598282, 0.06592688, 0.01072289,
    0.04126672, 0.27238769, 0.29023146, 0.09511772, 0.67350047,
    0.73882345, 0.01824359, 0.01835603, 0.0452354 , 0.07094357,
    0.03529302, 0.64508143, 0.20238695, 0.01526869, 0.04073326,
    0.05727095, 0.07431261, 0.56928563, 0.11789221, 0.29433771,
    0.02821585, 0.04611296, 0.63831395, 0.24261047, 0.09772049,
    0.3099549 , 0.28404538, 0.02695052, 0.03359468, 0.07774381,
    0.14437869, 0.80986628, 0.45156134, 0.70846613]), 'mean_score_time': array([0.08577895, 0.23397527, 0.48689
885, 0.59521046, 0.83756695,
    1.31388655, 1.91907697, 0.07360592, 0.21383619, 0.39116917,
    0.56488934, 0.73864627, 1.16848254, 1.78823404, 0.0728066 ,
    0.21043925, 0.39952569, 0.57388611, 0.75897889, 1.10804491,
    1.82232957, 0.07640367, 0.21502481, 0.38358307, 0.5764607 ,
    0.75437703, 1.23828921, 1.84148369, 0.08158398, 0.2162137 ,
    0.40013971, 0.58205853, 0.80305362, 1.12839026, 1.84648285,
    0.07580528, 0.23039155, 0.42546425, 0.59720473, 0.79788871,
    1.1485425 , 1.99766521, 0.07460899, 0.21843281, 0.4186738 ,
    0.60320325, 0.78670444, 1.18283672, 1.93124361]), 'std_score_time': array([0.01157176, 0.01626087, 0.061260
88, 0.03529074, 0.17191734,
    0.10463615, 0.22980543, 0.00353423, 0.01205511, 0.02066354,
    0.01307506, 0.01609905, 0.12901427, 0.02237808, 0.00165247,
    0.00333691, 0.01847885, 0.01654094, 0.00535666, 0.00966887,
    0.03971036, 0.00868121, 0.00586762, 0.00430178, 0.01712395,
    0.01326911, 0.19766863, 0.02038736, 0.01459346, 0.00395011,
    0.01537596, 0.01490048, 0.05482295, 0.00232832, 0.0201999 ,
    0.00269176, 0.01502625, 0.04319615, 0.0134722 , 0.06676378,
    0.00204233, 0.2230724 , 0.00116982, 0.00166821, 0.01713371,
    0.01350076, 0.01469486, 0.01866192, 0.01305054]), 'param_max_depth': masked_array(data=[2, 2, 2, 2, 2, 2,
2, 3, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4, 4,
    4, 4, 4, 5, 5, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 6, 7,
    7, 7, 7, 7, 7, 7, 8, 8, 8, 8, 8, 8, 8],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'param_n_estimators': masked_array(data=[10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
150, 200,
    300, 500, 10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
    150, 200, 300, 500, 10, 50, 100, 150, 200, 300, 500,
    10, 50, 100, 150, 200, 300, 500, 10, 50, 100, 150, 200,
    300, 500],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'params': [{'max_depth': 2, 'n_estimators': 10}, {'max_depth': 2, 'n_estimators': 50},
{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 2, 'n_estimators': 150}, {'max_depth': 2, 'n_estimators': 20
0}, {'max_depth': 2, 'n_estimators': 300}, {'max_depth': 2, 'n_estimators': 500}, {'max_depth': 3, 'n_estimators':
10}, {'max_depth': 3, 'n_estimators': 50}, {'max_depth': 3, 'n_estimators': 100}, {'max_depth': 3, 'n_estimators':
150}, {'max_depth': 3, 'n_estimators': 200}, {'max_depth': 3, 'n_estimators': 300}, {'max_depth': 3, 'n_estimator
s': 500}, {'max_depth': 4, 'n_estimators': 10}, {'max_depth': 4, 'n_estimators': 50}, {'max_depth': 4, 'n_estimato
rs': 100}, {'max_depth': 4, 'n_estimators': 150}, {'max_depth': 4, 'n_estimators': 200}, {'max_depth': 4, 'n_estim
ators': 300}, {'max_depth': 4, 'n_estimators': 500}, {'max_depth': 5, 'n_estimators': 10}, {'max_depth': 5, 'n_est
imators': 50}, {'max_depth': 5, 'n_estimators': 100}, {'max_depth': 5, 'n_estimators': 150}, {'max_depth': 5, 'n_e
stimators': 200}, {'max_depth': 5, 'n_estimators': 300}, {'max_depth': 5, 'n_estimators': 500}, {'max_depth': 6,
'n_estimators': 10}, {'max_depth': 6, 'n_estimators': 50}, {'max_depth': 6, 'n_estimators': 100}, {'max_depth': 6,
'n_estimators': 150}, {'max_depth': 6, 'n_estimators': 200}, {'max_depth': 6, 'n_estimators': 300}, {'max_depth':
6, 'n_estimators': 500}, {'max_depth': 7, 'n_estimators': 10}, {'max_depth': 7, 'n_estimators': 50}, {'max_depth':
7, 'n_estimators': 100}, {'max_depth': 7, 'n_estimators': 150}, {'max_depth': 7, 'n_estimators': 200}, {'max_dept
h': 7, 'n_estimators': 300}, {'max_depth': 7, 'n_estimators': 500}, {'max_depth': 8, 'n_estimators': 10}, {'max_de
pth': 8, 'n_estimators': 50}, {'max_depth': 8, 'n_estimators': 100}, {'max_depth': 8, 'n_estimators': 150}, {'max
depth': 8, 'n_estimators': 200}, {'max_depth': 8, 'n_estimators': 300}, {'max_depth': 8, 'n_estimators': 500}], 's
plit0_test_score': array([0.60709112, 0.65996608, 0.65693607, 0.68059994, 0.68070058,
    0.68307791, 0.69690689, 0.62285036, 0.67148492, 0.69363183,
    0.6822842 , 0.69013228, 0.69554796, 0.69453335, 0.6197751 ,
    0.67387618, 0.70328844, 0.69725606, 0.69188554, 0.70285403,
    0.7049784 , 0.66059037, 0.69065108, 0.69690562, 0.70197297,

```

0.70596073, 0.69216023, 0.70327325, 0.64122915, 0.66919197,
0.69564301, 0.70034061, 0.70562506, 0.70379711, 0.70655422,
0.62901313, 0.67718563, 0.6896504 , 0.69939436, 0.71296762,
0.70969172, 0.70673165, 0.64653754, 0.70666435, 0.70582063,
0.70637552, 0.70458239, 0.70825599, 0.71399742]], 'split1_test_score': array([0.58874365, 0.64744581, 0.673
15459, 0.67797319, 0.67833214,
0.67892194, 0.67948305, 0.62217523, 0.67969629, 0.66181287,
0.68390545, 0.68859944, 0.68122272, 0.69203784, 0.62051574,
0.65313097, 0.68652024, 0.68819217, 0.69321619, 0.68671839,
0.69473577, 0.60940741, 0.69302058, 0.68665149, 0.69501263,
0.68698765, 0.69729378, 0.69593058, 0.63872499, 0.67732134,
0.68508824, 0.69615869, 0.7024153 , 0.6996853 , 0.69575754,
0.66625057, 0.68789758, 0.69198699, 0.69519938, 0.69486618,
0.70242438, 0.7020477 , 0.63824565, 0.6989731 , 0.69134928,
0.70382683, 0.7087464 , 0.70417502, 0.70218719]], 'split2_test_score': array([0.59439716, 0.6910779 , 0.703
17161, 0.7067554 , 0.69571681,
0.69720199, 0.70971943, 0.65026951, 0.67574078, 0.6931531 ,
0.70674717, 0.70006303, 0.71220211, 0.71786933, 0.63608647,
0.68817887, 0.7031486 , 0.70137243, 0.71061775, 0.70304352,
0.71761188, 0.64479801, 0.69276714, 0.69424556, 0.71760576,
0.7105671 , 0.71413676, 0.71947774, 0.65195684, 0.69185657,
0.7001831 , 0.71396098, 0.71521699, 0.71516128, 0.71813459,
0.63088856, 0.69326705, 0.710121 , 0.72050859, 0.71834054,
0.72205834, 0.72236981, 0.62816415, 0.7178248 , 0.72803155,
0.72165086, 0.71754457, 0.72771712, 0.72631846]], 'split3_test_score': array([0.62586137, 0.67015026, 0.693
23191, 0.69269613, 0.68409717,
0.68567857, 0.69358823, 0.60156148, 0.66102565, 0.68852083,
0.70071488, 0.69486059, 0.69882496, 0.6985519 , 0.61282914,
0.67747486, 0.69760356, 0.69230268, 0.70535685, 0.70180439,
0.70282532, 0.6280656 , 0.69317473, 0.6917077 , 0.70110485,
0.70594022, 0.70706898, 0.70824649, 0.64167234, 0.67828856,
0.70221968, 0.69972919, 0.70835116, 0.70373061, 0.70370887,
0.65365927, 0.68828132, 0.69646763, 0.71471307, 0.70905639,
0.71261044, 0.71300927, 0.64855695, 0.69696427, 0.70351705,
0.7034318 , 0.71356658, 0.7128759 , 0.7142657]), 'split4_test_score': array([0.62961518, 0.67965555, 0.681
4555 , 0.68989008, 0.69278315,
0.69203237, 0.69505958, 0.62636288, 0.66868143, 0.7013299 ,
0.70362049, 0.6971011 , 0.69668114, 0.69994622, 0.62379102,
0.68627898, 0.69443703, 0.68676527, 0.70802294, 0.71122549,
0.70520317, 0.62770653, 0.68874785, 0.7024472 , 0.70592839,
0.71084925, 0.70736489, 0.71099037, 0.63516472, 0.69338965,
0.69579853, 0.70898645, 0.71803893, 0.71273888, 0.71012509,
0.63877456, 0.70305497, 0.69512993, 0.71054146, 0.71562435,
0.71375668, 0.71772671, 0.64983803, 0.6996868 , 0.71250799,
0.71824363, 0.71743032, 0.72112762, 0.71949106]], 'mean_test_score': array([0.60914095, 0.66965847, 0.68158
912, 0.68958264, 0.68632557,
0.68738226, 0.6949515 , 0.62464378, 0.67132591, 0.68768945,
0.69545373, 0.69415106, 0.69689574, 0.70058755, 0.62259936,
0.67578756, 0.69699987, 0.69317807, 0.70181932, 0.70112888,
0.7050709 , 0.63411468, 0.69167234, 0.69439133, 0.70432479,
0.70406083, 0.70360443, 0.70758343, 0.64174981, 0.68200882,
0.69578651, 0.7038349 , 0.70992907, 0.70702234, 0.70685594,
0.64371689, 0.68993645, 0.69667101, 0.708071 , 0.71017093,
0.71210818, 0.71237666, 0.64226836, 0.7040229 , 0.70824508,
0.71070533, 0.71237362, 0.7148299 , 0.71525178]], 'std_test_score': array([0.01634826, 0.01514146, 0.016002
44, 0.01019974, 0.00678816,
0.00649703, 0.0096235 , 0.01550313, 0.00636659, 0.01357563,
0.01028333, 0.00426919, 0.00985407, 0.00908815, 0.00763018,
0.01251733, 0.00623079, 0.00548677, 0.00776035, 0.00795846,
0.00733703, 0.01733961, 0.0017244 , 0.00525999, 0.00750429,
0.00879821, 0.00784713, 0.00784716, 0.00560297, 0.00923679,
0.00591928, 0.00658885, 0.00585141, 0.00589894, 0.00736292,
0.01422563, 0.00839841, 0.0071352 , 0.00944339, 0.00824352,
0.00634967, 0.00731355, 0.00812621, 0.00763668, 0.01202809,
0.00768882, 0.00505169, 0.00855924, 0.00792048]], 'rank_test_score': array([49, 42, 39, 34, 37, 36, 28, 47,
41, 35, 27, 30, 24, 22, 48, 40, 23,
31, 20, 21, 14, 46, 32, 29, 15, 16, 19, 11, 45, 38, 26, 18, 8, 12,
13, 43, 33, 25, 10, 7, 5, 3, 44, 17, 9, 6, 4, 2, 1]), 'split0_train_score': array([0.62199605, 0.69
261902, 0.68940337, 0.72635312, 0.72421576,
0.73409359, 0.73854176, 0.67774106, 0.73229192, 0.75344117,
0.73678583, 0.75087438, 0.75460314, 0.74756329, 0.67645014,
0.74815777, 0.76944217, 0.76228239, 0.77660589, 0.77872616,
0.77898032, 0.71293973, 0.77061531, 0.78849306, 0.78914537,
0.79709075, 0.78803312, 0.79761429, 0.72733945, 0.786192 ,
0.80817274, 0.80753997, 0.80622257, 0.81458778, 0.81930834,
0.73134805, 0.80578292, 0.82516592, 0.83077874, 0.84052 ,
0.83883212, 0.84086225, 0.76089089, 0.84535067, 0.85254283,
0.85204931, 0.85844889, 0.86626734, 0.86688577]], 'split1_train_score': array([0.62453712, 0.69335799, 0.72
090997, 0.73006822, 0.72854897,
0.72995487, 0.72993784, 0.66615993, 0.73497106, 0.72238187,
0.75677394, 0.751959 , 0.74877772, 0.75700919, 0.67523135,
0.73234443, 0.76502255, 0.77049551, 0.77270212, 0.76790238,
0.77709756, 0.6762487 , 0.77896886, 0.78181271, 0.79517713,
0.78676542, 0.79333332, 0.79591088, 0.7333879 , 0.79329065,
0.80209381, 0.80764523, 0.81775922, 0.81606141, 0.81923979,
0.74598757, 0.8119533 , 0.8343064 , 0.83383883, 0.83042749,
0.84385102, 0.84032646, 0.76925082, 0.84421782, 0.85708232,


```

0.85606177, 0.86761899, 0.86320359, 0.86406942]), 'split2_train_score': array([0.63098364, 0.70712902, 0.74
00121 , 0.73440031, 0.72557712,
0.72263284, 0.74029989, 0.6609549 , 0.71599755, 0.73314332,
0.74834906, 0.74511224, 0.75496787, 0.75956017, 0.68892432,
0.75244354, 0.75939353, 0.77028313, 0.77229345, 0.76353787,
0.77435741, 0.70009032, 0.77151613, 0.77775752, 0.78831656,
0.79251616, 0.79324541, 0.79872303, 0.7333589 , 0.78784354,
0.80174299, 0.81121928, 0.80987413, 0.81325254, 0.81293827,
0.7396951 , 0.80234983, 0.8342375 , 0.83715094, 0.83718056,
0.84246733, 0.83887843, 0.76532908, 0.84828381, 0.85197397,
0.85702519, 0.8550176 , 0.86772284, 0.86306047]), 'split3_train_score': array([0.62968306, 0.70906232, 0.72
155135, 0.73239791, 0.73511138,
0.72647108, 0.73901672, 0.64243619, 0.70642736, 0.74234572,
0.75394139, 0.75321507, 0.75669579, 0.75792526, 0.65875534,
0.74148965, 0.77147353, 0.75882053, 0.77807228, 0.77994764,
0.77551701, 0.69738135, 0.778255 , 0.78094718, 0.79671174,
0.79698148, 0.79497481, 0.7963314 , 0.72941207, 0.78449631,
0.80664346, 0.80627666, 0.81412453, 0.81690928, 0.81362102,
0.75318134, 0.80216046, 0.82665405, 0.84051381, 0.84065786,
0.83852529, 0.84281595, 0.77729483, 0.83952171, 0.84569749,
0.85491012, 0.85894536, 0.86021393, 0.86637146]), 'split4_train_score': array([0.64319485, 0.7080278 , 0.71
516836, 0.72551947, 0.72998474,
0.72633209, 0.73134827, 0.64544982, 0.71214277, 0.73611941,
0.74740496, 0.74558508, 0.74553179, 0.7457128 , 0.67221592,
0.76307981, 0.75114309, 0.75764058, 0.77024032, 0.77437152,
0.7724447 , 0.70209531, 0.76965853, 0.78153244, 0.79012895,
0.79374822, 0.78902169, 0.79675477, 0.70569387, 0.78818538,
0.79265755, 0.81138987, 0.8194473 , 0.81087346, 0.81169534,
0.72996193, 0.81720015, 0.81686934, 0.83406652, 0.84072599,
0.83329994, 0.84236391, 0.76586877, 0.83577256, 0.85498912,
0.85691263, 0.85646319, 0.86181142, 0.85868766]), 'mean_train_score': array([0.63007894, 0.70203923, 0.7174
0903, 0.72974781, 0.72868759,
0.7278969 , 0.7358289 , 0.65854838, 0.72036613, 0.7374863 ,
0.74865104, 0.74934915, 0.75211526, 0.75355414, 0.67431541,
0.74750304, 0.76329498, 0.76390443, 0.77398281, 0.77289711,
0.7756794 , 0.69775108, 0.77380277, 0.78210858, 0.79189595,
0.79342041, 0.79172167, 0.79706688, 0.72583844, 0.78800158,
0.80226211, 0.8088142 , 0.81348555, 0.81433689, 0.81536055,
0.74003479, 0.80788933, 0.82744664, 0.83526977, 0.83790238,
0.83939514, 0.8410494 , 0.76772688, 0.84262932, 0.85245714,
0.8553918 , 0.85929881, 0.86384382, 0.86381496]), 'std_train_score': array([0.00733549, 0.00741885, 0.01630
737, 0.00341099, 0.00381154,
0.00386849, 0.00429633, 0.01313972, 0.01128296, 0.01026689,
0.00687599, 0.00335269, 0.00423767, 0.00573574, 0.00964717,
0.01032877, 0.00735596, 0.00551077, 0.00290188, 0.00629927,
0.00224252, 0.01197939, 0.00397679, 0.00350604, 0.00338993,
0.003778 , 0.00269805, 0.00100172, 0.01033808, 0.00295278,
0.00541622, 0.00209035, 0.00489915, 0.0021366 , 0.00325456,
0.00877844, 0.00585064, 0.00649432, 0.00330767, 0.0039702 ,
0.00367473, 0.00142264, 0.00547359, 0.00444015, 0.00384023,
0.00183489, 0.00439186, 0.00277982, 0.00292878])}]

```

```

In [135]: import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(set2.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max().unstack()
max_scores1

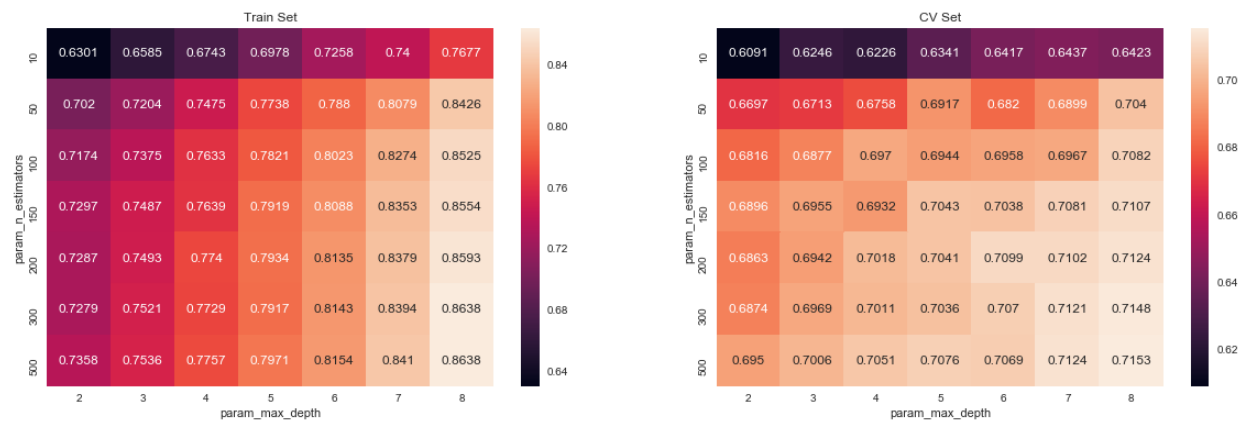
```

Out[135]:

	mean_fit_time							mean_score_time			...	std_test_sc
param_max_depth	2	3	4	5	6	7	8	2	3	4	...	6
param_n_estimators												
10	0.407695	0.413486	0.478719	0.535169	0.598398	0.714091	0.801456	0.085779	0.073606	0.072807	...	0.005603
50	1.167278	1.260030	1.597120	1.923059	2.286293	2.735486	3.150774	0.233975	0.213836	0.210439	...	0.009237
100	2.331964	2.413345	3.079173	3.593391	4.345777	5.469379	6.142575	0.486899	0.391169	0.399526	...	0.005919
150	2.995589	3.401303	4.482620	5.256543	6.447957	7.780201	9.151718	0.595210	0.564889	0.573886	...	0.006589
200	4.332022	4.523504	5.708534	6.962987	8.798279	10.126719	12.403216	0.837567	0.738646	0.758979	...	0.005851
300	6.125219	6.899541	8.809832	10.737088	12.695241	15.454662	18.293092	1.313887	1.168483	1.108045	...	0.005899
500	8.744614	10.943526	14.357803	17.413432	21.168784	25.246677	30.397708	1.919077	1.788234	1.822330	...	0.007363

7 rows × 140 columns

```
In [136]: fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set_title('CV Set')
plt.show()
```



```
In [137]: print(set2.best_estimator_)

RandomForestClassifier(bootstrap=True, class_weight='balanced',
                        criterion='gini', max_depth=8, 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=500, n_jobs=1, oob_score=False, random_state=None,
                        verbose=0, warm_start=False)
```

Training our model with best Hyperparameters

```
In [138]: def pred_prob(clf, data):
y_pred = []
y_pred = clf.predict_proba(data)[:,:1]
return y_pred
```

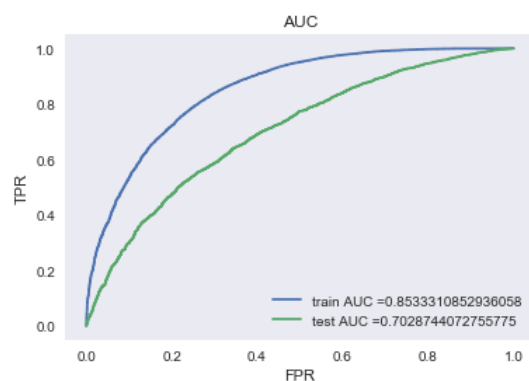
```
In [140]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
model = RandomForestClassifier(max_depth = 8, n_estimators = 500)

model.fit(X_tr_TFIDF, y_train)

y_train_pred = pred_prob(model,X_tr_TFIDF)
y_test_pred = pred_prob(model,X_te_TFIDF)

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

plt.close
plt.plot(train_fpr, train_tpr, label="train AUC =" +str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC =" +str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



Confusion Matrix

```
In [141]: #our objective here is to make auc the maximum
#so we find the best threshold that will give the Least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of $tpr \cdot (1 - fpr)$ 0.5926446990264167 for threshold 0.841
Train confusion matrix
[[3469 1175]
 [5270 20236]]

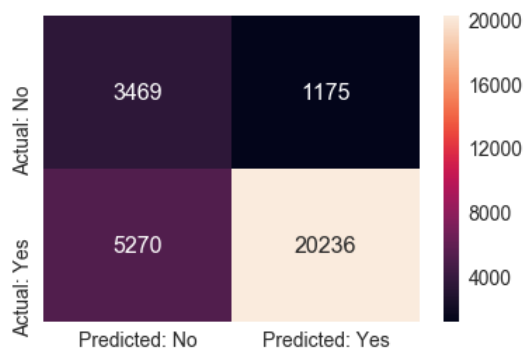
```
In [142]: # https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

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

Train data confusion matrix

Out[142]: <matplotlib.axes._subplots.AxesSubplot at 0x2c387733e80>



```
In [143]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

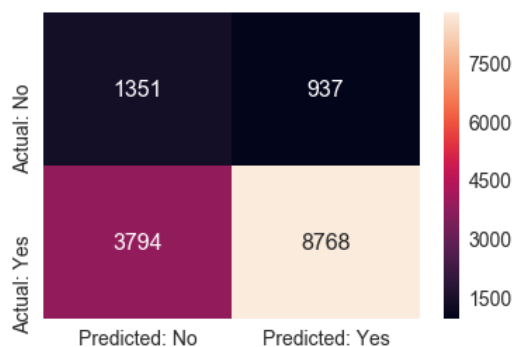
Test confusion matrix
[[1351 937]
 [3794 8768]]

```
In [144]: print("Test data confusion matrix")

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

Test data confusion matrix

Out[144]: <matplotlib.axes._subplots.AxesSubplot at 0x2c387733438>



In []:

2.4.3 Applying Random Forests on AVG W2V, SET 3

In []: # Please write all the code with proper documentation

```
In [145]: import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
#from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import learning_curve, GridSearchCV

#n_estimators = [10, 50, 100, 150, 200, 300, 500, 1000], max_depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]

clf = RandomForestClassifier(class_weight='balanced')
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]}
set3 = GridSearchCV(clf, parameters, cv=5, scoring='roc_auc', return_train_score=True)
set3.fit(X_tr_AVG_W2V, y_train)
```

```
Out[145]: GridSearchCV(cv=5, error_score='raise',
    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=10, n_jobs=1, oob_score=False, random_state=None,
    verbose=0, warm_start=False),
    fit_params=None, iid=True, n_jobs=1,
    param_grid={'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]},
    pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
    scoring='roc_auc', verbose=0)
```

```
In [146]: print(set3.cv_results_)
```

```

{'mean_fit_time': array([ 3.73062325, 13.32516446, 25.57221727, 33.69788375,
    41.92189856, 60.54669194, 99.69279761, 4.06591187,
    16.30799503, 31.07567439, 46.57105794, 61.64554644,
    92.21979003, 153.77058063, 5.51824231, 22.29996467,
    43.26291308, 65.49645438, 88.41017094, 128.48839798,
    213.09653106, 6.65020905, 29.62936335, 57.91731505,
    86.75618744, 115.32339101, 185.9726584 , 286.61373773,
    8.31237168, 38.32829809, 76.14577565, 114.00532498,
    152.73555007, 229.14879632, 381.00829735, 10.5434124 ,
    49.14317856, 97.81561079, 146.13300571, 196.76520405,
    291.58683152, 484.32141342, 12.91427064, 61.29288054,
    121.27448444, 180.93973322, 242.88846173, 364.30078444,
    606.01726732]), 'std_fit_time': array([ 0.46871538, 0.94828071, 1.6721416 , 2.05765362, 1.95092412,
    1.23487479, 1.11740305, 0.29004007, 0.74801564, 0.07524828,
    0.78092064, 0.45758603, 0.8748903 , 0.824161 , 0.69650726,
    0.37874563, 0.19436051, 0.75199033, 2.63021382, 1.31256689,
    0.82624271, 0.13649627, 0.66789174, 0.7844865 , 0.93759825,
    1.53875575, 25.72804289, 0.56307094, 0.05390959, 0.86349005,
    1.12045847, 2.65580884, 1.02227508, 1.05258202, 4.35531515,
    0.12423184, 0.91764252, 0.97585077, 1.13059805, 3.27768592,
    0.83730496, 2.10063469, 0.17608668, 0.9915423 , 0.94019382,
    1.31081392, 0.97941753, 1.55535882, 2.50909234]), 'mean_score_time': array([0.43264499, 0.89720206, 1.4
7086325, 1.76807261, 2.16500397,
    3.10249586, 5.19471078, 0.31894779, 0.69912319, 1.17266507,
    1.64579749, 2.12611423, 3.10389242, 5.41352496, 0.31795282,
    0.73343873, 1.20457859, 1.66813121, 2.27929773, 3.12106166,
    5.26392646, 0.33011689, 0.70511503, 1.18901477, 1.68050752,
    2.16042938, 3.15616808, 5.10474176, 0.3165544 , 0.70391197,
    1.24286914, 1.61387749, 2.30143914, 3.23315587, 5.29284568,
    0.31295619, 0.72206225, 1.2428925 , 1.77187657, 2.33735733,
    3.2967833 , 5.47077117, 0.33051081, 0.73264065, 1.24945831,
    1.74273496, 2.30264359, 3.29320908, 5.32076492]), 'std_score_time': array([0.0963797 , 0.07375091, 0.129240
07, 0.10906159, 0.07975843,
    0.08687339, 0.42801299, 0.01892752, 0.01032365, 0.01000217,
    0.02256441, 0.0107869 , 0.02361238, 0.78216354, 0.01134418,
    0.07193042, 0.04774801, 0.01823479, 0.18517518, 0.03122215,
    0.30411509, 0.02837078, 0.00993368, 0.01550209, 0.01824914,
    0.01663906, 0.02906525, 0.06053538, 0.01355238, 0.01538633,
    0.10891573, 0.20514628, 0.20089182, 0.02100894, 0.18498651,
    0.01024336, 0.01236752, 0.02474342, 0.06167748, 0.16855486,
    0.08634432, 0.17034525, 0.01551989, 0.01122304, 0.02398037,
    0.00280214, 0.10672358, 0.0313729 , 0.05331423]), 'param_max_depth': masked_array(data=[2, 2, 2, 2, 2, 2,
2, 3, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4,
    4, 4, 4, 5, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 7,
    7, 7, 7, 7, 7, 8, 8, 8, 8, 8, 8, 8],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'param_n_estimators': masked_array(data=[10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
150, 200,
    300, 500, 10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
    150, 200, 300, 500, 10, 50,
    100, 150, 200, 300, 500, 10, 50, 100, 150, 200,
    300, 500],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'params': [{'max_depth': 2, 'n_estimators': 10}, {'max_depth': 2, 'n_estimators': 50},
{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 2, 'n_estimators': 150}, {'max_depth': 2, 'n_estimators': 20
0}, {'max_depth': 2, 'n_estimators': 300}, {'max_depth': 2, 'n_estimators': 500}, {'max_depth': 3, 'n_estimators':
10}, {'max_depth': 3, 'n_estimators': 50}, {'max_depth': 3, 'n_estimators': 100}, {'max_depth': 3, 'n_estimators':
150}, {'max_depth': 3, 'n_estimators': 200}, {'max_depth': 3, 'n_estimators': 300}, {'max_depth': 3, 'n_estimator
s': 500}, {'max_depth': 4, 'n_estimators': 10}, {'max_depth': 4, 'n_estimators': 50}, {'max_depth': 4, 'n_estimato
rs': 100}, {'max_depth': 4, 'n_estimators': 150}, {'max_depth': 4, 'n_estimators': 200}, {'max_depth': 4, 'n_estim
ators': 300}, {'max_depth': 4, 'n_estimators': 500}, {'max_depth': 5, 'n_estimators': 10}, {'max_depth': 5, 'n_est
imators': 50}, {'max_depth': 5, 'n_estimators': 100}, {'max_depth': 5, 'n_estimators': 150}, {'max_depth': 5, 'n_e
stimators': 200}, {'max_depth': 5, 'n_estimators': 300}, {'max_depth': 5, 'n_estimators': 500}, {'max_depth': 6,
'n_estimators': 10}, {'max_depth': 6, 'n_estimators': 50}, {'max_depth': 6, 'n_estimators': 100}, {'max_depth': 6,
'n_estimators': 150}, {'max_depth': 6, 'n_estimators': 200}, {'max_depth': 6, 'n_estimators': 300}, {'max_depth':
6, 'n_estimators': 500}, {'max_depth': 7, 'n_estimators': 10}, {'max_depth': 7, 'n_estimators': 50}, {'max_depth':
7, 'n_estimators': 100}, {'max_depth': 7, 'n_estimators': 150}, {'max_depth': 7, 'n_estimators': 200}, {'max_dept
h': 7, 'n_estimators': 300}, {'max_depth': 7, 'n_estimators': 500}, {'max_depth': 8, 'n_estimators': 10}, {'max_de
pth': 8, 'n_estimators': 50}, {'max_depth': 8, 'n_estimators': 100}, {'max_depth': 8, 'n_estimators': 150}, {'max
depth': 8, 'n_estimators': 200}, {'max_depth': 8, 'n_estimators': 300}, {'max_depth': 8, 'n_estimators': 500}], 's
plit0_test_score': array([0.63610115, 0.6869933 , 0.68486661, 0.69110068, 0.68178143,
    0.68837333, 0.68944469, 0.66675746, 0.69036288, 0.69557412,
    0.69425739, 0.68701524, 0.69769997, 0.69635454, 0.65939126,

```

0.68491704, 0.69845866, 0.7016968 , 0.70094971, 0.69878272,
0.70136345, 0.67315262, 0.69344342, 0.70289538, 0.6996929 ,
0.70043492, 0.70206053, 0.7034165 , 0.6757345 , 0.7060563 ,
0.69800357, 0.70335321, 0.70627298, 0.70510203, 0.70796083,
0.65024206, 0.69314446, 0.69789069, 0.70463998, 0.70051361,
0.70751102, 0.70918916, 0.64080487, 0.69017785, 0.69290753,
0.70335891, 0.6990148 , 0.70544213, 0.70724602]], 'split1_test_score': array([0.62741861, 0.67582709, 0.667
89369, 0.67741039, 0.67344253,
0.67613602, 0.67382955, 0.65175806, 0.67061525, 0.67845601,
0.68567741, 0.68195223, 0.68358998, 0.6852368 , 0.65587015,
0.68123201, 0.68064727, 0.68956846, 0.68268743, 0.68553054,
0.68746224, 0.67216711, 0.67998339, 0.69213512, 0.69074301,
0.69006774, 0.6911009 , 0.69280386, 0.64957482, 0.68397003,
0.69190005, 0.69140055, 0.69455408, 0.69453614, 0.69747125,
0.64226996, 0.67862651, 0.69222713, 0.69439644, 0.69682215,
0.69691141, 0.69515697, 0.65355154, 0.68178721, 0.68634825,
0.69720958, 0.69339008, 0.69586305, 0.69819]), 'split2_test_score': array([0.64858544, 0.69111462, 0.697
2003 , 0.68939626, 0.69700342,
0.70081934, 0.69455598, 0.65857399, 0.71021512, 0.6955577 ,
0.70418008, 0.70850394, 0.70663639, 0.70533818, 0.65842511,
0.69734126, 0.70682546, 0.70615652, 0.70770289, 0.70921361,
0.7058689 , 0.67066948, 0.70151297, 0.70963523, 0.71458582,
0.71307553, 0.71541218, 0.71472805, 0.66269199, 0.6975506 ,
0.70934317, 0.71686001, 0.71279297, 0.71531849, 0.71643585,
0.67509378, 0.70499611, 0.71051097, 0.71370459, 0.71582452,
0.71301644, 0.71894132, 0.64833823, 0.7053922 , 0.70908024,
0.70512779, 0.71390506, 0.71732489, 0.71551305]), 'split3_test_score': array([0.63751646, 0.68057657, 0.686
86209, 0.68409432, 0.68668694,
0.68930215, 0.68860957, 0.66063462, 0.69638533, 0.69059677,
0.69381128, 0.69616502, 0.6976253 , 0.69661218, 0.6722511 ,
0.6966278 , 0.68942644, 0.69907777, 0.70439786, 0.70081512,
0.70498598, 0.6643713 , 0.69508227, 0.70740303, 0.70915557,
0.70458672, 0.70666973, 0.71059749, 0.6671414 , 0.70229164,
0.70943286, 0.70560427, 0.71095243, 0.70674549, 0.71162074,
0.64778619, 0.70437612, 0.70475238, 0.70328134, 0.70588325,
0.71116134, 0.71033857, 0.6447692 , 0.69117223, 0.70751086,
0.71244098, 0.70816525, 0.70908446, 0.71027674]), 'split4_test_score': array([0.63168648, 0.67160344, 0.699
70666, 0.69202012, 0.69741079,
0.68903959, 0.69308545, 0.66955748, 0.69021139, 0.69388609,
0.6993826 , 0.70292463, 0.69723968, 0.70244213, 0.67112665,
0.69297433, 0.70323453, 0.69844507, 0.70570869, 0.70659975,
0.70919284, 0.65551929, 0.70369527, 0.70744855, 0.71075419,
0.71062617, 0.71487969, 0.71123837, 0.67388895, 0.7007815 ,
0.701974 , 0.71506559, 0.71717851, 0.71713647, 0.71462239,
0.66618002, 0.70211343, 0.71191543, 0.71501658, 0.71332193,
0.71660983, 0.71966006, 0.6490787 , 0.70092895, 0.71074384,
0.71494792, 0.71519044, 0.71895998, 0.71818617]), 'mean_test_score': array([0.63626178, 0.68122351, 0.68730
538, 0.68680432, 0.6872645 ,
0.68873406, 0.68790493, 0.66145623, 0.691558 , 0.69081419,
0.69546158, 0.69531168, 0.69655828, 0.69719656, 0.66341246,
0.69061822, 0.69571831, 0.69898903, 0.70028916, 0.70018809,
0.70177442, 0.66717655, 0.69474312, 0.70390331, 0.70498593,
0.70375788, 0.70602418, 0.70655659, 0.66580639, 0.69813019,
0.7021306 , 0.70645634, 0.70834983, 0.70776732, 0.70962199,
0.65631387, 0.69665103, 0.70345886, 0.70620744, 0.70647267,
0.70904171, 0.71065687, 0.64730823, 0.69389133, 0.70131755,
0.70661665, 0.70593259, 0.70933446, 0.70988203]), 'std_test_score': array([0.0071078 , 0.00711618, 0.011266
18, 0.00544004, 0.0091567 ,
0.00781423, 0.00737637, 0.00627318, 0.01275329, 0.00644001,
0.00618527, 0.00979825, 0.00738446, 0.00689759, 0.00686372,
0.00644165, 0.00952983, 0.00543612, 0.00907159, 0.00824348,
0.00757773, 0.00658125, 0.008314 , 0.00627974, 0.00864515,
0.00816254, 0.00900417, 0.00779765, 0.00936852, 0.00758981,
0.00673896, 0.00915835, 0.00773414, 0.00809938, 0.00672047,
0.01230313, 0.00996325, 0.00748423, 0.00754075, 0.00725752,
0.00673863, 0.0088564 , 0.00428769, 0.00836045, 0.00982117,
0.00639759, 0.00847841, 0.00840448, 0.00699235]), 'rank_test_score': array([49, 42, 39, 41, 40, 37, 38, 46,
34, 35, 30, 31, 28, 26, 45, 36, 29,
24, 22, 23, 20, 43, 32, 16, 15, 17, 13, 9, 44, 25, 19, 11, 6, 7,
3, 47, 27, 18, 12, 10, 5, 1, 48, 33, 21, 8, 14, 4, 2]), 'split0_train_score': array([0.66364709, 0.71
38774 , 0.71283148, 0.72180735, 0.71310233,
0.71667777, 0.72059565, 0.70149002, 0.72580386, 0.7375143 ,
0.7361672 , 0.73008994, 0.74138487, 0.73812959, 0.71078282,
0.75425496, 0.76272026, 0.76516625, 0.76647352, 0.76512323,
0.76638417, 0.7514201 , 0.79158955, 0.79783071, 0.79733806,
0.80207676, 0.80340369, 0.80698442, 0.7974557 , 0.844013 ,
0.844691 , 0.85256955, 0.85243691, 0.85458251, 0.85483721,
0.83345418, 0.89701565, 0.9020852 , 0.90246731, 0.9050249 ,
0.90635939, 0.9088287 , 0.87541317, 0.9385451 , 0.94485469,
0.94741036, 0.94972686, 0.95151787, 0.9530801]), 'split1_train_score': array([0.66047507, 0.70876092, 0.70
752867, 0.71586727, 0.71449483,
0.71661421, 0.71292916, 0.70326151, 0.72248798, 0.73218205,
0.73785337, 0.73384733, 0.7386269 , 0.73909411, 0.71830649,
0.75227495, 0.75965912, 0.76386609, 0.76242682, 0.76467112,
0.76495272, 0.75607755, 0.78553101, 0.80005765, 0.79979761,
0.80037342, 0.80277553, 0.80463241, 0.79486654, 0.83734598,
0.84306219, 0.84468481, 0.84998246, 0.85146176, 0.85244371,

```

0.83169803, 0.88535032, 0.89821605, 0.90357681, 0.90363985,
0.90444963, 0.9049147 , 0.88040459, 0.9373195 , 0.94437776,
0.94819441, 0.9507175 , 0.95126645, 0.95208128]], 'split2_train_score': array([0.65882608, 0.71368526, 0.71
238546, 0.70482392, 0.71381609,
0.71751177, 0.713851 , 0.68784827, 0.73515631, 0.72773324,
0.73134683, 0.73808064, 0.73768763, 0.73851251, 0.70371042,
0.75090839, 0.76091826, 0.76248484, 0.76538729, 0.765286 ,
0.76242811, 0.7498334 , 0.78767221, 0.80200072, 0.80295762,
0.80228947, 0.80350416, 0.80438628, 0.79408625, 0.83630793,
0.84681669, 0.85192651, 0.85074253, 0.85280983, 0.85444084,
0.83442446, 0.88877092, 0.9022733 , 0.90389166, 0.90412418,
0.90552647, 0.90701497, 0.87404027, 0.93646803, 0.94741945,
0.95185846, 0.95195233, 0.95185515, 0.95312406]), 'split3_train_score': array([0.65832276, 0.71036832, 0.71
142205, 0.71013214, 0.71253773,
0.71398904, 0.7128005 , 0.70281393, 0.73058804, 0.72903862,
0.73546226, 0.73403023, 0.73615265, 0.73665525, 0.71416587,
0.7564818 , 0.75246933, 0.75955025, 0.76464216, 0.76192491,
0.76561417, 0.75285278, 0.79172076, 0.7980515 , 0.80280585,
0.7974574 , 0.80122337, 0.80327662, 0.78610772, 0.83699254,
0.85006546, 0.85094227, 0.8500859 , 0.84940617, 0.85389873,
0.83824803, 0.89092621, 0.90057769, 0.90380211, 0.90418237,
0.90740474, 0.90796608, 0.89033023, 0.93631721, 0.94661412,
0.94820036, 0.95027359, 0.95325439, 0.95378183]), 'split4_train_score': array([0.66011317, 0.68705572, 0.71
277743, 0.70823878, 0.71203725,
0.70897882, 0.71102431, 0.6918687 , 0.71893966, 0.725421 ,
0.72606004, 0.73004135, 0.72858542, 0.73335005, 0.71077676,
0.74905214, 0.75941142, 0.75137612, 0.75843031, 0.76157965,
0.76306724, 0.74501035, 0.78818519, 0.79434547, 0.79675803,
0.79732779, 0.79939781, 0.80145671, 0.78110743, 0.83641192,
0.84136515, 0.84499697, 0.84980276, 0.84886618, 0.84971257,
0.84103537, 0.88720685, 0.89474628, 0.90041932, 0.9003604 ,
0.90473653, 0.90598569, 0.88095832, 0.93581123, 0.94493436,
0.94999632, 0.94909904, 0.95155438, 0.9518798 ]), 'mean_train_score': array([0.66027683, 0.70674952, 0.7113
8902, 0.71217389, 0.71319765,
0.71475432, 0.71424012, 0.69745649, 0.72659517, 0.73037784,
0.73337794, 0.7332179 , 0.73648749, 0.7371483 , 0.71154847,
0.75259445, 0.75903568, 0.76048871, 0.76347202, 0.76371698,
0.76448928, 0.75103884, 0.78893974, 0.79845721, 0.79993143,
0.79990497, 0.80206091, 0.80414729, 0.79072473, 0.83821427,
0.8452001 , 0.84902402, 0.85061011, 0.85142529, 0.85306661,
0.83577201, 0.88985399, 0.8995797 , 0.90283144, 0.90346634,
0.90569535, 0.90694203, 0.88022932, 0.93689221, 0.94564008,
0.94913198, 0.95035387, 0.95188965, 0.95278941]), 'std_train_score': array([0.00186267, 0.01003891, 0.00199
523, 0.00600201, 0.00087821,
0.00312104, 0.00330686, 0.00635942, 0.00575045, 0.0041843 ,
0.00423865, 0.00298586, 0.00430248, 0.00206301, 0.00479872,
0.00258308, 0.00348617, 0.00492322, 0.00284808, 0.00162046,
0.00150608, 0.00365021, 0.00238961, 0.0025527 , 0.00261664,
0.00215659, 0.00156143, 0.00180771, 0.00612486, 0.00292419,
0.00302727, 0.00345603, 0.00096699, 0.0021219 , 0.00186298,
0.00339468, 0.0040225 , 0.00281959, 0.00130941, 0.00161565,
0.00108283, 0.00138839, 0.00572871, 0.00095851, 0.00116818,
0.00160572, 0.00096555, 0.00070749, 0.00070855])}]

```

```

In [159]: import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(set3.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max().unstack()
max_scores1

```

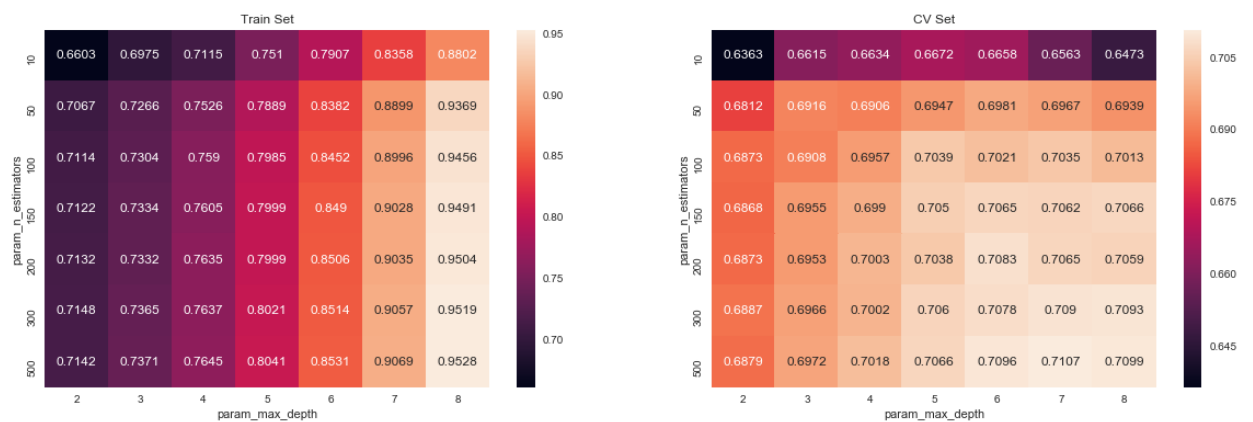
Out[159]:

param_max_depth	mean_fit_time							mean_score_time			...	std
	2	3	4	5	6	7	8	2	3	4	...	6
param_n_estimators												
10	3.730623	4.065912	5.518242	6.650209	8.312372	10.543412	12.914271	0.432645	0.318948	0.317953	...	0.0
50	13.325164	16.307995	22.299965	29.629363	38.328298	49.143179	61.292881	0.897202	0.699123	0.733439	...	0.0
100	25.572217	31.075674	43.262913	57.917315	76.145776	97.815611	121.274484	1.470863	1.172665	1.204579	...	0.0
150	33.697884	46.571058	65.496454	86.756187	114.005325	146.133006	180.939733	1.768073	1.645797	1.668131	...	0.0
200	41.921899	61.645546	88.410171	115.323391	152.735550	196.765204	242.888462	2.165004	2.126114	2.279298	...	0.0
300	60.546692	92.219790	128.488398	185.972658	229.148796	291.586832	364.300784	3.102496	3.103892	3.121062	...	0.0
500	99.692798	153.770581	213.096531	286.613738	381.008297	484.321413	606.017267	5.194711	5.413525	5.263926	...	0.0

7 rows × 140 columns




```
In [160]: fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set_title('CV Set')
plt.show()
```



```
In [162]: print(set3.best_estimator_)

RandomForestClassifier(bootstrap=True, class_weight='balanced',
                        criterion='gini', max_depth=7, 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=500, n_jobs=1, oob_score=False, random_state=None,
                        verbose=0, warm_start=False)
```

Training our model with best Hyperparameters

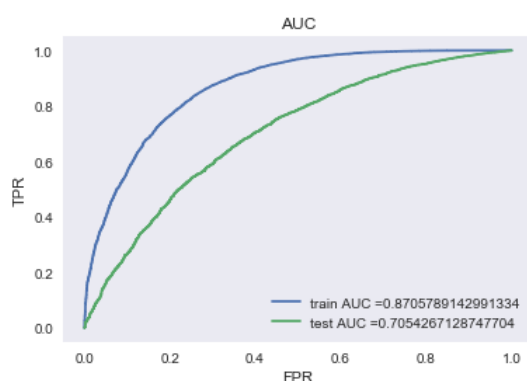
```
In [150]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
model = RandomForestClassifier(max_depth = 7, n_estimators = 500)

model.fit(X_tr_AVG_W2V, y_train)

y_train_pred = pred_prob(model,X_tr_AVG_W2V)
y_test_pred = pred_prob(model,X_te_AVG_W2V)

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

plt.close
plt.plot(train_fpr, train_tpr, label="train AUC =" +str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC =" +str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



Confusion matrix

```
In [151]: #our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of $tpr \cdot (1 - fpr)$ 0.6217242934107549 for threshold 0.831
Train confusion matrix
[[3461 1183]
[4228 21278]]

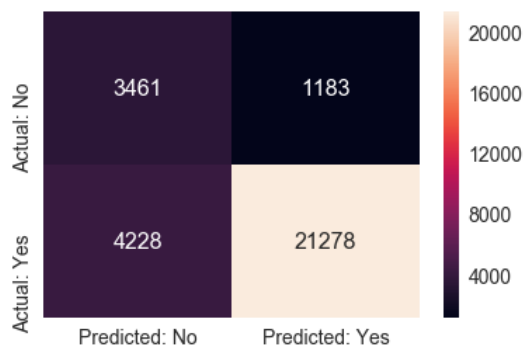
```
In [152]: #plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

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

Train data confusion matrix

Out[152]: <matplotlib.axes._subplots.AxesSubplot at 0x2c387725630>



```
In [153]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

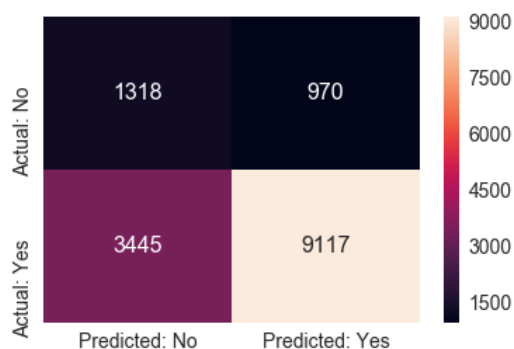
Test confusion matrix
[[1318 970]
[3445 9117]]

```
In [154]: print("Test data confusion matrix")

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

Test data confusion matrix

Out[154]: <matplotlib.axes._subplots.AxesSubplot at 0x2c38752fd30>



In []:

2.4.4 Applying Random Forests on TFIDF W2V, SET 4

```
In [155]: # Please write all the code with proper documentation
```

```
In [156]: import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
#from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import learning_curve, GridSearchCV

#n_estimators = [10, 50, 100, 150, 200, 300, 500, 1000], max_depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]

clf = RandomForestClassifier(class_weight='balanced')
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]}
set4 = GridSearchCV(clf, parameters, cv=5, scoring='roc_auc', return_train_score=True)
set4.fit(X_tr_TFIDF_W2V, y_train)
```

```
Out[156]: GridSearchCV(cv=5, error_score='raise',
    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=10, n_jobs=1, oob_score=False, random_state=None,
    verbose=0, warm_start=False),
    fit_params=None, iid=True, n_jobs=1,
    param_grid={'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]},
    pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
    scoring='roc_auc', verbose=0)
```

```
In [157]: print(set4.cv_results_)
```

```
[{'mean_fit_time': array([ 3.37656288, 10.6826333 , 20.47025652, 30.79544525,
    40.52462788, 60.3326427 , 104.0308053 , 3.88859434,
    16.65785251, 34.24960699, 54.64071875, 74.67776875,
    122.55498152, 206.21353583, 6.43122153, 29.2857357 ,
    60.86756506, 74.09678359, 90.94179354, 128.84166279,
    212.76262474, 6.85785995, 29.63774123, 58.11718302,
    87.6504045 , 114.88916621, 172.28625979, 284.34959168,
    8.3546576 , 38.32970505, 75.07503328, 112.3206285 ,
    149.93225298, 224.23852587, 373.22491245, 10.34992142,
    48.8280076 , 96.95551763, 144.45628934, 192.09070592,
    289.58498349, 488.22677097, 13.24418283, 61.58411808,
    122.79661183, 182.61325154, 246.40206442, 366.70414157,
    608.54800487]), 'std_fit_time': array([4.28545541e-01, 7.61170269e-02, 5.90249980e-02, 7.99001322e-01,
    8.90242182e-01, 8.71740600e-01, 7.91750712e+00, 1.16674431e-02,
    7.28747650e-01, 2.26865342e+00, 4.61617486e+00, 3.48773115e+00,
    7.14010361e+00, 1.19057430e+01, 2.21140056e-01, 1.69020244e+00,
    1.87773033e+00, 5.64744887e+00, 3.56865319e+00, 9.10843284e-01,
    6.51808558e-01, 4.90771691e-01, 1.00180000e+00, 6.42902104e-01,
    2.09860041e+00, 9.63375966e-01, 1.25906308e+00, 3.58010075e+00,
    8.66561950e-02, 7.37421187e-01, 8.33439082e-01, 8.93958631e-01,
    7.41448110e-01, 3.00439923e-01, 8.97358049e-01, 9.96862699e-02,
    9.58495140e-01, 1.77353620e+00, 1.52469492e+00, 1.03095950e+00,
    2.47810716e+00, 1.13793768e+00, 7.65855530e-01, 3.86180498e-01,
    1.53431913e+00, 1.53774178e+00, 5.12089202e+00, 4.70079336e+00,
    1.42538533e+00]), 'mean_score_time': array([0.34108763, 0.70411696, 1.17226534, 1.65158348, 2.12052798,
    3.07357922, 4.9950346 , 0.33211946, 0.74061933, 1.40205269,
    1.81175551, 2.3819171 , 4.02391467, 6.37122655, 0.39280996,
    0.95877771, 1.63521338, 1.80209165, 2.14700336, 3.12722216,
    5.06106601, 0.32493229, 0.71369162, 1.24388118, 1.68648815,
    2.18754344, 3.26906638, 5.12469568, 0.3187479 , 0.71309357,
    1.20658002, 1.70383019, 2.20170531, 3.25928626, 5.22523341,
    0.32075152, 0.72705679, 1.22872148, 1.72837906, 2.32199097,
    3.29917164, 5.41452093, 0.32015142, 0.77851014, 1.25683856,
    1.76468863, 2.34473109, 3.35881925, 5.37662187]), 'std_score_time': array([0.03874087, 0.00591467, 0.017914
    64, 0.02724038, 0.01600061,
    0.02083997, 0.04578612, 0.01495054, 0.05211174, 0.18115562,
    0.10471114, 0.12188756, 0.52108004, 0.44387613, 0.04177432,
    0.0704989 , 0.1013927 , 0.06076347, 0.12855792, 0.02017844,
    0.04936749, 0.02439235, 0.0131341 , 0.08006261, 0.01698248,
    0.01031206, 0.2474431 , 0.0221704 , 0.01329948, 0.00986708,
    0.00363261, 0.00825937, 0.02207959, 0.15445154, 0.06385135,
    0.01039855, 0.00790376, 0.02043356, 0.01399096, 0.17366591,
    0.08822745, 0.2090541 , 0.00754415, 0.06737551, 0.01233435,
    0.01034942, 0.10759653, 0.10994987, 0.05945013]), 'param_max_depth': masked_array(data=[2, 2, 2, 2, 2, 2,
    2, 3, 3, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4,
    4, 4, 4, 5, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 7,
    7, 7, 7, 7, 7, 8, 8, 8, 8, 8, 8]),
    mask=[False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False],
    fill_value='?'),
    dtype=object), 'param_n_estimators': masked_array(data=[10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
    150, 200,
    300, 500, 10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
    150, 200, 300, 500, 10, 50, 100, 150, 200,
    300, 500],
    mask=[False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False],
    fill_value='?'),
    dtype=object), 'params': [{'max_depth': 2, 'n_estimators': 10}, {'max_depth': 2, 'n_estimators': 50},
{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 2, 'n_estimators': 150}, {'max_depth': 2, 'n_estimators': 200}, {'max_depth': 2, 'n_estimators': 300}, {'max_depth': 2, 'n_estimators': 500}, {'max_depth': 3, 'n_estimators': 10}, {'max_depth': 3, 'n_estimators': 50}, {'max_depth': 3, 'n_estimators': 100}, {'max_depth': 3, 'n_estimators': 150}, {'max_depth': 3, 'n_estimators': 200}, {'max_depth': 3, 'n_estimators': 300}, {'max_depth': 3, 'n_estimators': 500}, {'max_depth': 4, 'n_estimators': 10}, {'max_depth': 4, 'n_estimators': 50}, {'max_depth': 4, 'n_estimators': 100}, {'max_depth': 4, 'n_estimators': 150}, {'max_depth': 4, 'n_estimators': 200}, {'max_depth': 4, 'n_estimators': 300}, {'max_depth': 4, 'n_estimators': 500}, {'max_depth': 5, 'n_estimators': 10}, {'max_depth': 5, 'n_estimators': 50}, {'max_depth': 5, 'n_estimators': 100}, {'max_depth': 5, 'n_estimators': 150}, {'max_depth': 5, 'n_estimators': 200}, {'max_depth': 5, 'n_estimators': 300}, {'max_depth': 5, 'n_estimators': 500}, {'max_depth': 6, 'n_estimators': 10}, {'max_depth': 6, 'n_estimators': 50}, {'max_depth': 6, 'n_estimators': 100}, {'max_depth': 6, 'n_estimators': 150}, {'max_depth': 6, 'n_estimators': 200}, {'max_depth': 6, 'n_estimators': 300}, {'max_depth': 6, 'n_estimators': 500}, {'max_depth': 7, 'n_estimators': 10}, {'max_depth': 7, 'n_estimators': 50}, {'max_depth': 7, 'n_estimators': 100}, {'max_depth': 7, 'n_estimators': 150}, {'max_depth': 7, 'n_estimators': 200}, {'max_depth': 7, 'n_estimators': 300}, {'max_depth': 7, 'n_estimators': 500}, {'max_depth': 8, 'n_estimators': 10}, {'max_depth': 8, 'n_estimators': 50}, {'max_depth': 8, 'n_estimators': 100}, {'max_depth': 8, 'n_estimators': 150}, {'max_depth': 8, 'n_estimators': 200}, {'max_depth': 8, 'n_estimators': 300}, {'max_depth': 8, 'n_estimators': 500}], 'split0_test_score': array([0.64216591, 0.67874014, 0.68367267, 0.6770
```

0.68504848, 0.68487505, 0.66158926, 0.67681704, 0.69147286,
0.68521937, 0.68842987, 0.68843262, 0.68985231, 0.65958346,
0.68055732, 0.68787077, 0.69124183, 0.69153404, 0.69227416,
0.69570514, 0.66024584, 0.68966053, 0.69111313, 0.69630095,
0.69340776, 0.69819619, 0.69484687, 0.66313196, 0.6882172 ,
0.69670013, 0.69779428, 0.69404303, 0.69397341, 0.6977698 ,
0.65150584, 0.68323741, 0.69285204, 0.69451162, 0.69306344,
0.69922325, 0.69577877, 0.64541534, 0.67682253, 0.69299952,
0.69418143, 0.69694908, 0.69301323, 0.69809492]], 'split1_test_score': array([0.65248377, 0.65829554, 0.660
40112, 0.66382328, 0.66712494,
0.65977418, 0.6720922 , 0.65132863, 0.67430962, 0.66657797,
0.67141334, 0.67213694, 0.67185037, 0.66998155, 0.66800691,
0.6713245 , 0.67516891, 0.67596953, 0.6725594 , 0.68100664,
0.68057446, 0.66210872, 0.67682565, 0.67773769, 0.68174564,
0.68235254, 0.68107712, 0.6819383 , 0.64250345, 0.67104996,
0.67795356, 0.68381725, 0.68434966, 0.68019082, 0.68428656,
0.65318879, 0.66978277, 0.68361699, 0.68953955, 0.68172032,
0.68221854, 0.68621868, 0.63866284, 0.67490766, 0.67764125,
0.67960397, 0.68294804, 0.68549213, 0.68368198]], 'split2_test_score': array([0.65031657, 0.69834615, 0.692
86484, 0.69356016, 0.69440488,
0.69777365, 0.69906827, 0.67379156, 0.6974014 , 0.7058537 ,
0.70373672, 0.70409968, 0.70247523, 0.70490262, 0.67602703,
0.70591933, 0.70570557, 0.70991146, 0.71285185, 0.70648888,
0.70902347, 0.6796888 , 0.702375 , 0.70272234, 0.71038499,
0.71158128, 0.71246947, 0.710703 , 0.66931451, 0.70616771,
0.70711562, 0.71379153, 0.71466432, 0.71324583, 0.71343342,
0.67130445, 0.7094797 , 0.7076991 , 0.71069456, 0.71180306,
0.71290207, 0.71585744, 0.66456924, 0.69561869, 0.70895637,
0.71055339, 0.71258005, 0.71068697, 0.71275583]], 'split3_test_score': array([0.65603802, 0.66939132, 0.687
47933, 0.68236119, 0.68615496,
0.68996602, 0.68862814, 0.64253194, 0.6923548 , 0.69162508,
0.68775408, 0.69501178, 0.69282074, 0.69430465, 0.6547683 ,
0.6960536 , 0.69730349, 0.69750143, 0.6998959 , 0.69596392,
0.69790617, 0.66941675, 0.69559653, 0.69925165, 0.70503283,
0.7000586 , 0.69938924, 0.70330793, 0.65941375, 0.6945315 ,
0.69751472, 0.70404798, 0.70291057, 0.7024708 , 0.70520333,
0.66651846, 0.69713699, 0.69743622, 0.70366603, 0.7049193 ,
0.70473592, 0.70394965, 0.66599386, 0.69345402, 0.70010292,
0.69615785, 0.70188437, 0.70086365, 0.70302051]], 'split4_test_score': array([0.64902018, 0.67503688, 0.689
17986, 0.68977389, 0.6923146 ,
0.69082951, 0.68922971, 0.65288584, 0.68354709, 0.68651579,
0.69120363, 0.6945135 , 0.69406058, 0.69526999, 0.66559866,
0.69672022, 0.70191084, 0.70734208, 0.69866583, 0.70343036,
0.69802954, 0.66393971, 0.69455448, 0.70163981, 0.69830607,
0.70473546, 0.70670178, 0.70764902, 0.66168229, 0.69849218,
0.70355246, 0.7065575 , 0.70645377, 0.70821222, 0.70898666,
0.66974803, 0.70129969, 0.7086664 , 0.70740165, 0.70933015,
0.70856162, 0.70872872, 0.66313992, 0.6936516 , 0.7037992 ,
0.70565482, 0.70618527, 0.71172214, 0.7110755]), 'mean_test_score': array([0.65000466, 0.67596213, 0.68271
938, 0.68132007, 0.68567559,
0.68467818, 0.68677853, 0.65642574, 0.68488577, 0.68840924,
0.68786523, 0.69083815, 0.68992772, 0.69086204, 0.66479667,
0.69011446, 0.69359145, 0.69639273, 0.69510117, 0.69583242,
0.69624768, 0.66707984, 0.69180227, 0.69449257, 0.69835403,
0.69842675, 0.69956648, 0.6996886 , 0.65920924, 0.69169137,
0.69656707, 0.70120142, 0.70048386, 0.69961814, 0.70193558,
0.66245251, 0.69218672, 0.69805363, 0.70116225, 0.70016671,
0.70152797, 0.70210622, 0.65555565, 0.68689034, 0.69669949,
0.69722991, 0.70010906, 0.700355 , 0.70172532]], 'std_test_score': array([0.0045841 , 0.01315221, 0.011544
11, 0.01045413, 0.00971532,
0.01309681, 0.00871525, 0.01058097, 0.00884522, 0.01268249,
0.01039929, 0.010605 , 0.01011844, 0.0115363 , 0.00727764,
0.01243473, 0.01097136, 0.01222699, 0.01320332, 0.00898625,
0.00911142, 0.00701041, 0.00851633, 0.00931237, 0.00968924,
0.00999072, 0.01059393, 0.01035658, 0.00897493, 0.01184917,
0.0100741 , 0.01009075, 0.01043467, 0.01163603, 0.01021208,
0.00841155, 0.01406148, 0.00939687, 0.00794208, 0.01124883,
0.01065168, 0.01028398, 0.01127761, 0.00905467, 0.01085468,
0.01067333, 0.01000079, 0.01010954, 0.01048337]], 'rank_test_score': array([49, 42, 40, 41, 37, 39, 36, 47,
38, 33, 34, 30, 32, 29, 44, 31, 25,
20, 23, 22, 21, 43, 27, 24, 15, 14, 13, 11, 46, 28, 19, 5, 7, 12,
2, 45, 26, 16, 6, 9, 4, 1, 48, 35, 18, 17, 10, 8, 3]), 'split0_train_score': array([0.67680809, 0.70
510608, 0.71476884, 0.70832104, 0.71593459,
0.71082422, 0.71264009, 0.69110755, 0.72456599, 0.73299337,
0.72895633, 0.72981627, 0.73285217, 0.7323845 , 0.71677938,
0.74539533, 0.75276707, 0.75584443, 0.75635276, 0.75513614,
0.75873966, 0.73941213, 0.78307697, 0.78785957, 0.79034149,
0.79027098, 0.79088088, 0.7929642 , 0.79024024, 0.82227393,
0.83626629, 0.83883337, 0.83709092, 0.83815196, 0.83975092,
0.83079817, 0.87836695, 0.88645488, 0.88484418, 0.88704505,
0.88937218, 0.8937839 , 0.85872241, 0.9306449 , 0.93320532,
0.93472471, 0.93687206, 0.9387218 , 0.94001493]], 'split1_train_score': array([0.68242793, 0.69712027, 0.70
495431, 0.70660405, 0.70960032,
0.70624489, 0.71377799, 0.69588581, 0.72007043, 0.72401875,
0.72227014, 0.72629077, 0.72854231, 0.72743375, 0.7262144 ,
0.74179556, 0.7511875 , 0.75384292, 0.75054962, 0.75597264,
0.7554835 , 0.7507691 , 0.77488194, 0.78589458, 0.78684703,

```

0.78873709, 0.78917651, 0.79182465, 0.77722909, 0.82665945,
0.83402367, 0.83468557, 0.83607344, 0.83801115, 0.83880279,
0.83695976, 0.87800286, 0.88126901, 0.88704211, 0.88625737,
0.8866281 , 0.89036201, 0.86188917, 0.92569637, 0.93187126,
0.93489264, 0.93394814, 0.93591907, 0.93777366]), 'split2_train_score': array([0.66680359, 0.7058891 , 0.70
192592, 0.70647298, 0.70808766,
0.70707178, 0.70982968, 0.69464582, 0.71938802, 0.73007025,
0.72774948, 0.72520243, 0.72852166, 0.72891788, 0.710762 ,
0.7454056 , 0.74894973, 0.75284713, 0.75748633, 0.75222856,
0.75384511, 0.74578748, 0.77987898, 0.78415743, 0.79087195,
0.78845584, 0.79020799, 0.79131388, 0.77944 , 0.82615291,
0.83168668, 0.83341903, 0.83815231, 0.83764324, 0.83865244,
0.82737574, 0.87844686, 0.88481289, 0.88749982, 0.88963228,
0.89280932, 0.89306127, 0.866116 , 0.92423195, 0.93374649,
0.93676496, 0.94067677, 0.94006914, 0.94226045]), 'split3_train_score': array([0.67702321, 0.69670492, 0.70
924384, 0.70355341, 0.7086803 ,
0.70958166, 0.71021617, 0.67329221, 0.72037252, 0.72311903,
0.72251394, 0.72944448, 0.72992372, 0.73052327, 0.70822748,
0.75048448, 0.75159763, 0.75243523, 0.75664843, 0.75348583,
0.75519609, 0.74937739, 0.78329305, 0.786155 , 0.78991606,
0.79023207, 0.79085018, 0.79286969, 0.77679072, 0.82744854,
0.83271117, 0.83518555, 0.83396944, 0.83830264, 0.83824098,
0.83059174, 0.87953934, 0.8865623 , 0.88607784, 0.89022103,
0.89040928, 0.89084456, 0.87467705, 0.92611811, 0.93411461,
0.93432032, 0.93873454, 0.93863088, 0.93937345]), 'split4_train_score': array([0.65561299, 0.69620168, 0.70
506971, 0.70949607, 0.70610422,
0.70913535, 0.70645907, 0.68305044, 0.71423573, 0.71539159,
0.72109855, 0.72270973, 0.72223133, 0.72504094, 0.71150929,
0.74487785, 0.75046462, 0.7536886 , 0.75055892, 0.75214007,
0.75071352, 0.74613728, 0.77928449, 0.78504957, 0.78216638,
0.78733216, 0.78753671, 0.78825559, 0.77821811, 0.82558859,
0.82917479, 0.83592857, 0.83434377, 0.83628873, 0.83663199,
0.83205744, 0.87351428, 0.88403063, 0.88744837, 0.88668058,
0.88963048, 0.89031503, 0.86627813, 0.92104818, 0.92986195,
0.93373531, 0.93647775, 0.93696506, 0.93806028]), 'mean_train_score': array([0.67173516, 0.70020441, 0.7071
9253, 0.70688951, 0.70968142,
0.70857158, 0.7105846 , 0.68759636, 0.71972654, 0.7251186 ,
0.72451769, 0.72669274, 0.72841424, 0.72886007, 0.71469851,
0.74559177, 0.75099331, 0.75373166, 0.75431921, 0.75379265,
0.75479558, 0.74629668, 0.78008309, 0.78582323, 0.78802858,
0.78900563, 0.78973045, 0.7914456 , 0.78038363, 0.82562468,
0.83277252, 0.83561042, 0.83592598, 0.83767954, 0.83841582,
0.83155657, 0.87757406, 0.88462594, 0.88658247, 0.88796726,
0.88976987, 0.89167335, 0.86553655, 0.9255479 , 0.93255993,
0.93488759, 0.93734185, 0.93806119, 0.93949655]), 'std_train_score': array([0.00951082, 0.00433872, 0.00444
661, 0.00201137, 0.00333009,
0.00167782, 0.00253568, 0.00843816, 0.003293 , 0.00610497,
0.00319071, 0.00266741, 0.00347074, 0.00252235, 0.00639511,
0.00279044, 0.00126529, 0.00117823, 0.00309648, 0.00153811,
0.00259831, 0.00392874, 0.0030659 , 0.00123574, 0.00324833,
0.00112073, 0.00125894, 0.00171297, 0.00501184, 0.00178354,
0.00236213, 0.00180703, 0.00159166, 0.00072898, 0.00101989,
0.00311226, 0.00209373, 0.00193664, 0.00100786, 0.00162982,
0.00198471, 0.00145824, 0.00536974, 0.00310824, 0.00154886,
0.00101987, 0.00226035, 0.00145486, 0.00160961]))}

```

```

In [158]: import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(set4.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max().unstack()
max_scores1

```

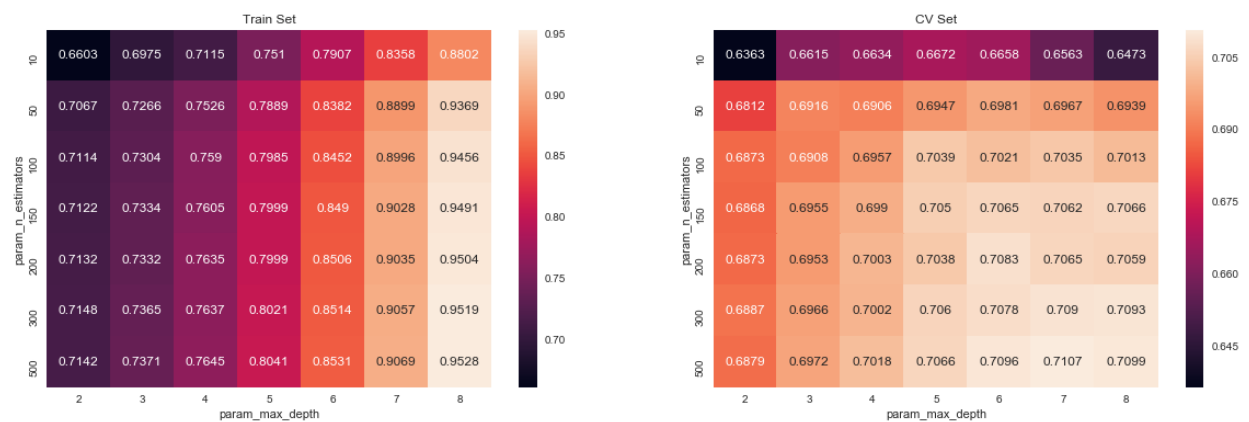
Out[158]:

	mean_fit_time							mean_score_time			...	st
param_max_depth	2	3	4	5	6	7	8	2	3	4	...	6
param_n_estimators												
10	3.376563	3.888594	6.431222	6.857860	8.354658	10.349921	13.244183	0.341088	0.332119	0.392810	...	0.
50	10.682633	16.657853	29.285736	29.637741	38.329705	48.828008	61.584118	0.704117	0.740619	0.958778	...	0
100	20.470257	34.249607	60.867565	58.117183	75.075033	96.955518	122.796612	1.172265	1.402053	1.635213	...	0.
150	30.795445	54.640719	74.096784	87.650405	112.320628	144.456289	182.613252	1.651583	1.811756	1.802092	...	0.
200	40.524628	74.677769	90.941794	114.889166	149.932253	192.090706	246.402064	2.120528	2.381917	2.147003	...	0.
300	60.332643	122.554982	128.841663	172.286260	224.238526	289.584983	366.704142	3.073579	4.023915	3.127222	...	0
500	104.030805	206.213536	212.762625	284.349592	373.224912	488.226771	608.548005	4.995035	6.371227	5.061066	...	0.

7 rows × 140 columns



```
In [161]: fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set_title('CV Set')
plt.show()
```



```
In [163]: print(set4.best_estimator_)

RandomForestClassifier(bootstrap=True, class_weight='balanced',
                        criterion='gini', max_depth=7, 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=500, n_jobs=1, oob_score=False, random_state=None,
                        verbose=0, warm_start=False)
```

Training our model with best Hyperparameters

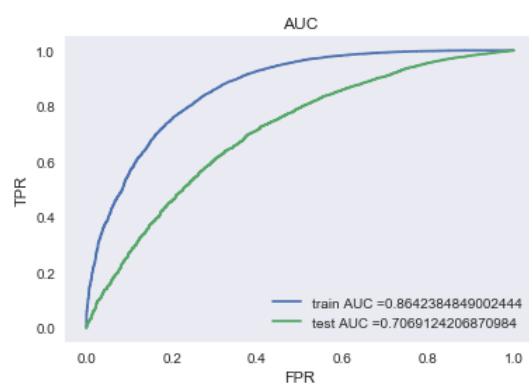
```
In [164]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
model = RandomForestClassifier(max_depth = 7, n_estimators = 500)

model.fit(X_tr_TFIDF_W2V, y_train)

y_train_pred = pred_prob(model,X_tr_TFIDF_W2V)
y_test_pred = pred_prob(model,X_te_TFIDF_W2V)

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

plt.close
plt.plot(train_fpr, train_tpr, label="train AUC =" +str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC =" +str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



Confusion matrix


```
In [165]: #our objective here is to make auc the maximum
#so we find the best threshold that will give the Least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of $tpr \cdot (1 - fpr)$ 0.6081086931429486 for threshold 0.829
Train confusion matrix
[[3467 1177]
[4730 20776]]

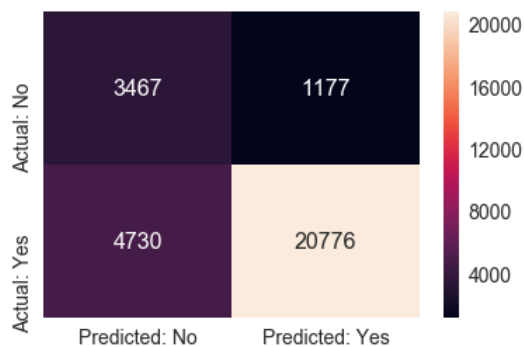
```
In [166]: #plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

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

Train data confusion matrix

Out[166]: <matplotlib.axes._subplots.AxesSubplot at 0x2c38803d4a8>



```
In [167]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

Test confusion matrix
[[1364 924]
[3550 9012]]

```
In [168]: print("Test data confusion matrix")

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

Test data confusion matrix

Out[168]: <matplotlib.axes._subplots.AxesSubplot at 0x2c3877257b8>



In []:

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 instructions

2.5.1 Applying XGBOOST on BOW, SET 1

```
In [ ]: # Please write all the code with proper documentation
```

```
In [169]: import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
#from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import learning_curve, GridSearchCV
from xgboost import XGBClassifier

#n_estimators = [10, 50, 100, 150, 200, 300, 500, 1000], max_depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]

clf = XGBClassifier(class_weight='balanced')
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]}
set1 = GridSearchCV(clf, parameters, cv=5, scoring='roc_auc', return_train_score=True)
set1.fit(X_tr_BOW, y_train)
```

```
Out[169]: GridSearchCV(cv=5, error_score='raise',
    estimator=XGBClassifier(base_score=None, booster=None, class_weight='balanced',
    colsample_bylevel=None, colsample_bynode=None,
    colsample_bytree=None, gamma=None, gpu_id=None,
    importance_type='gain', interaction_constraints=None,
    learning_rate=None, max_delta_step=None, max_pos_weight=None, subsample=None,
    tree_method=None, validate_parameters=False, verbosity=None),
    fit_params=None, iid=True, n_jobs=1,
    param_grid={'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]},
    pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
    scoring='roc_auc', verbose=0)
```

```
In [170]: print(set1.cv_results_)
```

```

{'mean_fit_time': array([ 3.84232435,  9.4050508 , 15.82866988, 21.06067882,
    26.64912529, 34.36430125, 56.76997375,  5.53260489,
    12.50954556, 20.48456411, 27.36482487, 35.95615177,
    48.30932741, 76.96787162,  5.36046486, 12.80814676,
    22.99769754, 36.17536006, 46.33272276, 57.97606778,
    92.10818729,  5.76398554, 14.74277344, 25.4407649 ,
    35.54414577, 48.21226854, 67.55414386, 110.30043049,
    6.45992465, 16.66363635, 29.25775747, 42.64794827,
    54.5114234 , 79.05179667, 134.42591381,  7.2611825 ,
    19.01634479, 33.01072145, 47.89072747, 61.83483906,
    91.06886082, 148.09894938,  7.66250825, 21.12650194,
    37.28249769, 53.64194818, 71.07831941, 102.64570122,
    170.23475337]), 'std_fit_time': array([0.17780663, 1.32991613, 1.06304874, 0.36050813, 0.67260309,
    1.53422994, 3.24083598, 0.44798178, 0.37321193, 0.52752653,
    0.70008059, 2.10946 , 0.83758651, 3.19180344, 0.31027575,
    0.2308999 , 1.47656834, 1.266332 , 1.7334592 , 1.52799013,
    4.60531698, 0.04582247, 0.10286461, 0.5862431 , 0.08336988,
    2.51786896, 0.58374843, 0.81783406, 0.02642007, 0.06874055,
    0.20818553, 2.43370309, 0.68152492, 0.53617639, 6.91093466,
    0.32190937, 0.68561591, 0.12532967, 0.59572382, 0.53990805,
    0.73856385, 0.67431298, 0.04050711, 0.45971951, 0.03439483,
    0.41141913, 2.21945913, 1.55042674, 5.96975473]), 'mean_score_time': array([0.53716273, 0.36542006, 0.38636
713, 0.40372071, 0.41588788,
    0.41768327, 0.45378752, 0.68297405, 0.41489062, 0.4105022 ,
    0.39713826, 0.38098149, 0.39235063, 0.4553843 , 0.6626286 ,
    0.33191242, 0.35485239, 0.42745709, 0.44181876, 0.37759113,
    0.42626023, 0.5176157 , 0.34348192, 0.35425315, 0.35784345,
    0.35784378, 0.40272341, 0.40152626, 0.52280216, 0.36063576,
    0.36342888, 0.34787006, 0.37779026, 0.37779007, 0.41568875,
    0.46395898, 0.3448781 , 0.35006428, 0.36642065, 0.36382709,
    0.40072918, 0.44899955, 0.43902607, 0.37579598, 0.35604782,
    0.36622157, 0.38596854, 0.43324242, 0.49547501]), 'std_score_time': array([0.06289507, 0.0411293 , 0.030931
01, 0.04550041, 0.03832209,
    0.11275861, 0.04649716, 0.08806942, 0.03624585, 0.03850083,
    0.034614 , 0.04403102, 0.04812245, 0.08912063, 0.16417198,
    0.00965704, 0.02562567, 0.02898556, 0.05780059, 0.03402475,
    0.04481413, 0.02473647, 0.02149801, 0.03215918, 0.02570295,
    0.04121549, 0.01172309, 0.03514652, 0.01640487, 0.02714934,
    0.05277592, 0.01314641, 0.02828196, 0.02034593, 0.05883918,
    0.00938615, 0.01882201, 0.01542562, 0.01558718, 0.00562139,
    0.02381505, 0.05132373, 0.0173822 , 0.0565113 , 0.02003667,
    0.01185837, 0.04013749, 0.02923177, 0.05533344]), 'param_max_depth': masked_array(data=[2, 2, 2, 2, 2, 2,
2, 3, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4,
    4, 4, 4, 5, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 7,
    7, 7, 7, 7, 7, 8, 8, 8, 8, 8, 8, 8],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'param_n_estimators': masked_array(data=[10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
150, 200,
    300, 500, 10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
    150, 200, 300, 500, 10, 50, 100, 150, 200, 300, 500,
    10, 50, 100, 150, 200, 300, 500, 10, 50, 100, 150, 200,
    300, 500],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'params': [{'max_depth': 2, 'n_estimators': 10}, {'max_depth': 2, 'n_estimators': 50},
{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 2, 'n_estimators': 150}, {'max_depth': 2, 'n_estimators': 20
0}, {'max_depth': 2, 'n_estimators': 300}, {'max_depth': 2, 'n_estimators': 500}, {'max_depth': 3, 'n_estimators':
10}, {'max_depth': 3, 'n_estimators': 50}, {'max_depth': 3, 'n_estimators': 100}, {'max_depth': 3, 'n_estimators':
150}, {'max_depth': 3, 'n_estimators': 200}, {'max_depth': 3, 'n_estimators': 300}, {'max_depth': 3, 'n_estimator
s': 500}, {'max_depth': 4, 'n_estimators': 10}, {'max_depth': 4, 'n_estimators': 50}, {'max_depth': 4, 'n_estimato
rs': 100}, {'max_depth': 4, 'n_estimators': 150}, {'max_depth': 4, 'n_estimators': 200}, {'max_depth': 4, 'n_estim
ators': 300}, {'max_depth': 4, 'n_estimators': 500}, {'max_depth': 5, 'n_estimators': 10}, {'max_depth': 5, 'n_est
imators': 50}, {'max_depth': 5, 'n_estimators': 100}, {'max_depth': 5, 'n_estimators': 150}, {'max_depth': 5, 'n_e
stimators': 200}, {'max_depth': 5, 'n_estimators': 300}, {'max_depth': 5, 'n_estimators': 500}, {'max_depth': 6,
'n_estimators': 10}, {'max_depth': 6, 'n_estimators': 50}, {'max_depth': 6, 'n_estimators': 100}, {'max_depth': 6,
'n_estimators': 150}, {'max_depth': 6, 'n_estimators': 200}, {'max_depth': 6, 'n_estimators': 300}, {'max_depth':
6, 'n_estimators': 500}, {'max_depth': 7, 'n_estimators': 10}, {'max_depth': 7, 'n_estimators': 50}, {'max_depth':
7, 'n_estimators': 100}, {'max_depth': 7, 'n_estimators': 150}, {'max_depth': 7, 'n_estimators': 200}, {'max_dept
h': 7, 'n_estimators': 300}, {'max_depth': 7, 'n_estimators': 500}, {'max_depth': 8, 'n_estimators': 10}, {'max_de
pth': 8, 'n_estimators': 50}, {'max_depth': 8, 'n_estimators': 100}, {'max_depth': 8, 'n_estimators': 150}, {'max
depth': 8, 'n_estimators': 200}, {'max_depth': 8, 'n_estimators': 300}, {'max_depth': 8, 'n_estimators': 500}], 's
plit0_test_score': array([0.68224433, 0.72594012, 0.73572395, 0.7345739 , 0.7364068 ,
    0.73710061, 0.72972291, 0.69293991, 0.73007694, 0.73187671,
    0.7325451 , 0.73073214, 0.72914577, 0.72473152, 0.70620905,

```

0.72811249, 0.73124904, 0.72428286, 0.72319515, 0.72249195,
0.72099419, 0.70543275, 0.73310905, 0.73085757, 0.72676116,
0.72260039, 0.71984192, 0.71764835, 0.71217718, 0.7209252 ,
0.71483301, 0.7121699 , 0.71350774, 0.71441031, 0.71557978,
0.69805009, 0.71442593, 0.71664482, 0.71749613, 0.71360553,
0.71572536, 0.70932989, 0.71080148, 0.71168412, 0.71223088,
0.70933685, 0.7103292 , 0.71559286, 0.71775954]], 'split1_test_score': array([0.68737467, 0.72928702, 0.736
94408, 0.73877017, 0.73840151,
0.73833852, 0.73572712, 0.69277495, 0.73256684, 0.73044986,
0.73138258, 0.72955112, 0.72981194, 0.72987483, 0.70458862,
0.73477899, 0.73066532, 0.7309387 , 0.72890581, 0.72558453,
0.72122723, 0.7074561 , 0.72558801, 0.73056772, 0.72953825,
0.72690722, 0.72519646, 0.72472661, 0.71083204, 0.72543249,
0.72398951, 0.72294242, 0.7209299 , 0.71750384, 0.71940895,
0.71492704, 0.71932507, 0.71355919, 0.71217657, 0.7108656 ,
0.71184369, 0.71423162, 0.71152831, 0.72150451, 0.71895937,
0.71324751, 0.71154583, 0.71245333, 0.7171776]), 'split2_test_score': array([0.69613369, 0.74384927, 0.756
31132, 0.75819047, 0.75771641,
0.75269281, 0.75068735, 0.71215083, 0.74408361, 0.75359725,
0.75337757, 0.7503513 , 0.74805907, 0.74157002, 0.71184274,
0.74672266, 0.75035151, 0.74804282, 0.74596804, 0.74514411,
0.73672736, 0.71378931, 0.74414323, 0.74160125, 0.74424694,
0.7415601 , 0.73985145, 0.73462653, 0.71286134, 0.73810998,
0.73565674, 0.73354472, 0.73048299, 0.72579618, 0.72424686,
0.71914517, 0.73363209, 0.73175092, 0.73235054, 0.7364505 ,
0.73392625, 0.73890797, 0.71278464, 0.7353363 , 0.73190708,
0.72751538, 0.73023937, 0.73171811, 0.73019938]], 'split3_test_score': array([0.67508081, 0.72142379, 0.732
32997, 0.7342412 , 0.73580488,
0.73479324, 0.73891831, 0.69204597, 0.73311487, 0.73491341,
0.73406204, 0.7325315 , 0.73592189, 0.73316678, 0.6958659 ,
0.73244519, 0.73582324, 0.73762442, 0.73803623, 0.73611392,
0.72855541, 0.69739782, 0.73015454, 0.73060792, 0.72706453,
0.72440554, 0.72396155, 0.72361284, 0.69972308, 0.72253747,
0.7205394 , 0.72249663, 0.72376319, 0.72161709, 0.71744813,
0.70642568, 0.73037959, 0.73075142, 0.72753047, 0.72637755,
0.72588344, 0.73108968, 0.70075255, 0.72916031, 0.72518401,
0.73096666, 0.73021668, 0.72724042, 0.72876105]], 'split4_test_score': array([0.68101896, 0.73959245, 0.747
08971, 0.7518383 , 0.754103 ,
0.75458761, 0.75063195, 0.70703365, 0.75017111, 0.75193135,
0.75281005, 0.75263291, 0.74543309, 0.74356828, 0.70787918,
0.73919023, 0.74246218, 0.73904774, 0.73844241, 0.73629769,
0.73538879, 0.71314321, 0.74579275, 0.74843464, 0.74628644,
0.74235169, 0.73465691, 0.729335 , 0.71435558, 0.73439148,
0.73351236, 0.73438366, 0.73019003, 0.72311643, 0.72176781,
0.71259375, 0.73726405, 0.73836139, 0.73789263, 0.73774803,
0.74011625, 0.74041823, 0.71301161, 0.73142648, 0.73521102,
0.73624192, 0.73408833, 0.7340407 , 0.73803596]], 'mean_test_score': array([0.68437053, 0.73201808, 0.74167
943, 0.74352223, 0.74448593,
0.74350198, 0.74113683, 0.69938859, 0.73800201, 0.74055305,
0.7408348 , 0.73915907, 0.73767381, 0.73458166, 0.70527704,
0.73624955, 0.73810989, 0.73598682, 0.73490902, 0.73312598,
0.72857812, 0.70744358, 0.73575709, 0.73641324, 0.73477882,
0.73156433, 0.72870117, 0.72598948, 0.70998977, 0.72827888,
0.72570559, 0.72510673, 0.72377422, 0.72048848, 0.7196901 ,
0.71022787, 0.72700459, 0.72621283, 0.72548859, 0.72500864,
0.72549819, 0.72679445, 0.70977564, 0.72582169, 0.72469771,
0.72346077, 0.72328309, 0.72420847, 0.72638603]], 'std_test_score': array([0.00706326, 0.00841408, 0.008816
66, 0.00972737, 0.00943591,
0.00837651, 0.00831674, 0.00849186, 0.00776261, 0.01008729,
0.01004638, 0.01013946, 0.00781879, 0.0070821 , 0.00528755,
0.00634335, 0.00743675, 0.00799857, 0.00797296, 0.00816573,
0.0066985 , 0.00596172, 0.00790996, 0.00735048, 0.00864079,
0.00859728, 0.00738972, 0.00570296, 0.00525743, 0.00676993,
0.00784637, 0.00819918, 0.00631937, 0.00405484, 0.00306865,
0.00734815, 0.00869227, 0.0094922 , 0.00944659, 0.01118153,
0.01064709, 0.01275656, 0.00458398, 0.008386 , 0.00837973,
0.01039171, 0.0101862 , 0.00865642, 0.00793857]], 'rank_test_score': array([49, 20, 4, 2, 1, 3, 5, 48,
10, 7, 6, 8, 11, 18, 47, 13, 9,
14, 16, 19, 23, 46, 15, 12, 17, 21, 22, 29, 44, 24, 31, 34, 38, 41,
42, 43, 25, 28, 33, 35, 32, 26, 45, 30, 36, 39, 40, 37, 27]), 'split0_train_score': array([0.6952915 , 0.76
848328, 0.8007226 , 0.82277427, 0.84025178,
0.86610881, 0.90380725, 0.72503745, 0.81028364, 0.85306492,
0.88295366, 0.90589098, 0.93558437, 0.96924016, 0.75317304,
0.85063053, 0.90123313, 0.93512771, 0.95347176, 0.97856737,
0.99535522, 0.78718526, 0.89865411, 0.94476757, 0.96980433,
0.98301726, 0.99485591, 0.99962516, 0.81525661, 0.93350242,
0.97093778, 0.98629808, 0.99483937, 0.99919062, 0.99999377,
0.8526611 , 0.9582356 , 0.98722312, 0.99673897, 0.99919882,
0.99996494, 0.99999996, 0.87764278, 0.97964276, 0.99648345,
0.99944958, 0.99992461, 0.99999979, 1.]), 'split1_train_score': array([0.70333386, 0.76801851, 0.79
947479, 0.82183499, 0.8382788 ,
0.86460117, 0.9036328 , 0.72893612, 0.80789175, 0.8521552 ,
0.87994222, 0.9015261 , 0.93408276, 0.96936957, 0.74952382,
0.85230331, 0.9015659 , 0.93110019, 0.9528519 , 0.97681781,
0.99460117, 0.7825595 , 0.89078275, 0.94071287, 0.96422949,
0.98086865, 0.99424337, 0.999646 , 0.82033869, 0.92977012,
0.97073545, 0.9859366 , 0.99326384, 0.9989732 , 0.99999256,

```

0.84522344, 0.95780251, 0.98621527, 0.99653519, 0.9989301 ,
0.99996339, 1. , 0.87602816, 0.97489431, 0.99391762,
0.99885524, 0.9998386 , 0.99999887, 1. ], 'split2_train_score': array([0.69882108, 0.7655466 , 0.79
571904, 0.81758143, 0.83429443,
0.86354541, 0.90321559, 0.72452771, 0.80372866, 0.84604136,
0.87376803, 0.89660997, 0.93056613, 0.96665871, 0.74770436,
0.84743744, 0.89684929, 0.9287299 , 0.94805392, 0.97349859,
0.99342639, 0.77409955, 0.88579297, 0.93575045, 0.96103401,
0.97830758, 0.99298197, 0.9995203 , 0.81225371, 0.92604573,
0.96686211, 0.98603791, 0.99377937, 0.99922508, 0.99998315,
0.84385097, 0.9537116 , 0.98312868, 0.99459078, 0.99835045,
0.99986428, 0.99999996, 0.87420579, 0.97393198, 0.99378933,
0.99899471, 0.99979387, 0.99999728, 0.99999999]), 'split3_train_score': array([0.69845139, 0.76630707, 0.79
748871, 0.81867267, 0.83555787,
0.86370662, 0.90520288, 0.72737804, 0.80772099, 0.85051675,
0.88030789, 0.90308476, 0.93424323, 0.9709756 , 0.7507415 ,
0.84892891, 0.9017088 , 0.93257922, 0.95064348, 0.97517321,
0.99461815, 0.78085523, 0.89083164, 0.94092988, 0.96510852,
0.98034148, 0.99384513, 0.99966588, 0.81281291, 0.92475088,
0.97006018, 0.98645373, 0.99467423, 0.99930298, 0.99999861,
0.84749234, 0.9586267 , 0.98731812, 0.9957925 , 0.99897678,
0.99996558, 1. , 0.87394488, 0.97574026, 0.99516033,
0.99917777, 0.99989386, 0.99999962, 1. ], 'split4_train_score': array([0.69570386, 0.76360829, 0.79
515657, 0.81758652, 0.83538085,
0.86214852, 0.90045136, 0.72388023, 0.80446913, 0.84862357,
0.88084412, 0.9034609 , 0.93332626, 0.96895315, 0.75339334,
0.85097895, 0.90030565, 0.93162656, 0.95350551, 0.9764327 ,
0.99461071, 0.77913905, 0.89513627, 0.9416217 , 0.96793027,
0.98141765, 0.99399772, 0.99943658, 0.81509546, 0.93198542,
0.97196221, 0.98941093, 0.99579439, 0.99941099, 0.99999385,
0.84833888, 0.96012859, 0.98684732, 0.99658119, 0.99917166,
0.99996955, 1. , 0.88374482, 0.97907312, 0.99454301,
0.99894172, 0.99984348, 0.99999876, 1. ], 'mean_train_score': array([0.69832034, 0.76639275, 0.7977
1234, 0.81968998, 0.83675275,
0.86402211, 0.90326197, 0.72595191, 0.80681883, 0.85008036,
0.87956318, 0.90211454, 0.93356055, 0.96903944, 0.75090721,
0.85005583, 0.90033256, 0.93183272, 0.95170531, 0.97609794,
0.99452233, 0.78076772, 0.89223955, 0.9407565 , 0.96562132,
0.98079053, 0.99398482, 0.99957878, 0.81515148, 0.92921092,
0.97011155, 0.98682745, 0.99447024, 0.99922057, 0.99999239,
0.84751335, 0.957701 , 0.9861465 , 0.99604773, 0.99892556,
0.99994555, 0.99999998, 0.87711329, 0.97665649, 0.99477875,
0.9990838 , 0.99985888, 0.99999886, 1. ], 'std_train_score': array([2.87830350e-03, 1.76010832e-03,
2.13181315e-03, 2.19177683e-03,
2.18747474e-03, 1.30588901e-03, 1.55587079e-03, 1.90240777e-03,
2.40998633e-03, 2.52343852e-03, 3.07955029e-03, 3.08746186e-03,
1.66469406e-03, 1.38371292e-03, 2.16860951e-03, 1.69466979e-03,
1.80887127e-03, 2.07946281e-03, 2.10408405e-03, 1.69352382e-03,
6.19352493e-04, 4.27831858e-03, 4.36349398e-03, 2.89584982e-03,
3.03553450e-03, 1.53129845e-03, 6.08446928e-04, 8.70583155e-05,
2.85612733e-03, 3.35672304e-03, 1.73541458e-03, 1.30470377e-03,
8.79087154e-04, 1.45022554e-04, 5.06074296e-06, 3.02780360e-03,
2.14296608e-03, 1.55787961e-03, 7.98483620e-04, 3.06147975e-04,
4.06867508e-05, 1.93884058e-08, 3.57568140e-03, 2.28585374e-03,
9.82617977e-04, 2.11182664e-04, 4.56462228e-05, 8.89490424e-07,
5.27672639e-09]})

```

```

In [171]: import seaborn as sns; sns.set()
max_scores1 = pd.DataFrame(set1.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max().unstack()
max_scores1

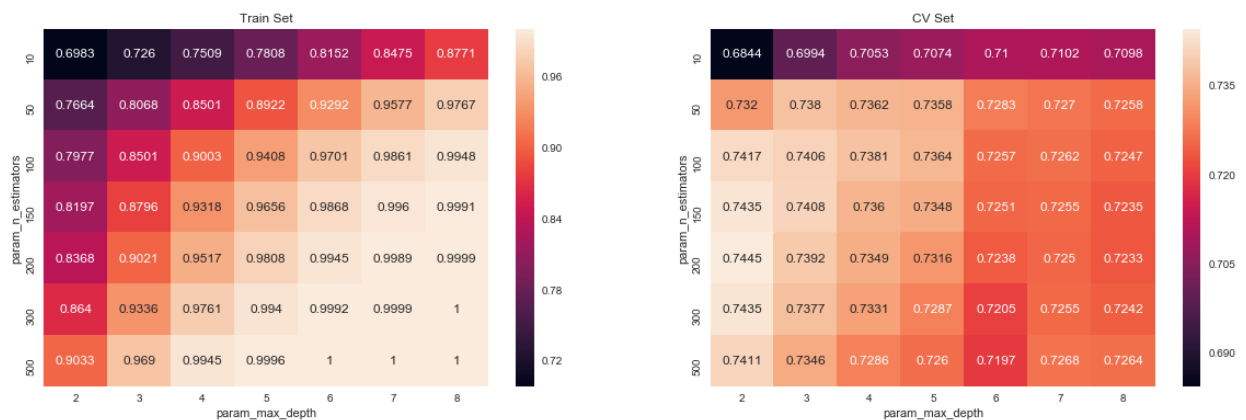
```

Out[171]:

	mean_fit_time							mean_score_time			...	std_t
param_max_depth	2	3	4	5	6	7	8	2	3	4	...	6
param_n_estimators												
10	3.842324	5.532605	5.360465	5.763986	6.459925	7.261182	7.662508	0.537163	0.682974	0.662629	...	0.005
50	9.405051	12.509546	12.808147	14.742773	16.663636	19.016345	21.126502	0.365420	0.414891	0.331912	...	0.006
100	15.828670	20.484564	22.997698	25.440765	29.257757	33.010721	37.282498	0.386367	0.410502	0.354852	...	0.007
150	21.060679	27.364825	36.175360	35.544146	42.647948	47.890727	53.641948	0.403721	0.397138	0.427457	...	0.008
200	26.649125	35.956152	46.332723	48.212269	54.511423	61.834839	71.078319	0.415888	0.380981	0.441819	...	0.006
300	34.364301	48.309327	57.976068	67.554144	79.051797	91.068861	102.645701	0.417683	0.392351	0.377591	...	0.004
500	56.769974	76.967872	92.108187	110.300430	134.425914	148.098949	170.234753	0.453788	0.455384	0.426260	...	0.003

7 rows × 140 columns

```
In [172]: fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores1.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores1.mean_test_score, annot = True, fmt='.4g', ax=ax[1])
ax[0].set_title('Train Set')
ax[1].set_title('CV Set')
plt.show()
```



```
In [173]: print(set1.best_estimator_)

XGBClassifier(base_score=0.5, booster=None, class_weight='balanced',
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              gamma=0, gpu_id=-1, importance_type='gain',
              interaction_constraints=None, learning_rate=0.300000012,
              max_delta_step=0, max_depth=2, min_child_weight=1, missing=nan,
              monotone_constraints=None, n_estimators=200, n_jobs=0,
              num_parallel_tree=1, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method=None, validate_parameters=False, verbosity=None)
```

```
In [174]: max_d = set1.best_params_['max_depth']
n_est = set1.best_params_['n_estimators']
```

Training our model with best Hyperparameters

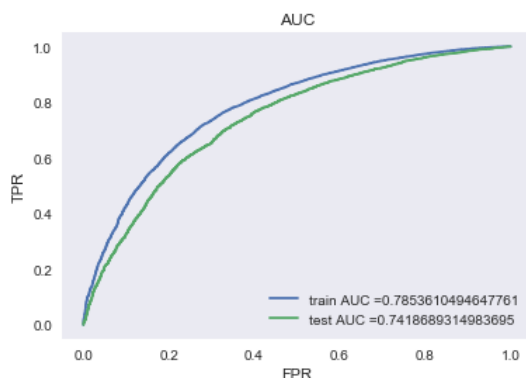
```
In [176]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import GradientBoostingClassifier
model = GradientBoostingClassifier(max_depth = max_d , n_estimators = n_est)

model.fit(X_tr_BOW, y_train)

y_train_pred = pred_prob(model,X_tr_BOW)
y_test_pred = pred_prob(model,X_te_BOW)

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

plt.close
plt.plot(train_fpr, train_tpr, label="train AUC =" +str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC =" +str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



Confusion matrix

```
In [177]: #our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of $tpr \cdot (1 - fpr)$ 0.5175654064068829 for threshold 0.835
Train confusion matrix
[[3344 1300]
 [7173 18333]]

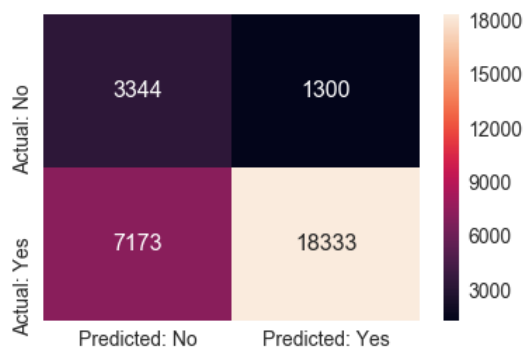
```
In [178]: #plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

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

Train data confusion matrix

Out[178]: <matplotlib.axes._subplots.AxesSubplot at 0x2c39885ff98>



```
In [179]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

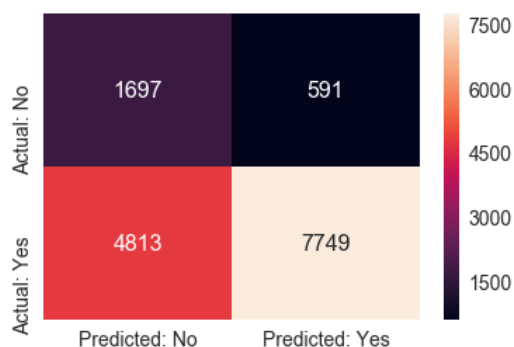
Test confusion matrix
[[1697 591]
 [4813 7749]]

```
In [180]: print("Test data confusion matrix")

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

Test data confusion matrix

Out[180]: <matplotlib.axes._subplots.AxesSubplot at 0x2c398915908>



2.5.2 Applying XGBOOST on TFIDF, SET 2

```
In [181]: # Please write all the code with proper documentation
```



```
In [182]: import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
#from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import learning_curve, GridSearchCV
from xgboost import XGBClassifier

#n_estimators = [10, 50, 100, 150, 200, 300, 500, 1000], max_depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]

clf = XGBClassifier(class_weight='balanced')
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]}
set2 = GridSearchCV(clf, parameters, cv=5, scoring='roc_auc', return_train_score=True)
set2.fit(X_tr_TFIDF, y_train)
```

```
Out[182]: GridSearchCV(cv=5, error_score='raise',
    estimator=XGBClassifier(base_score=None, booster=None, class_weight='balanced',
    colsample_bylevel=None, colsample_bynode=None,
    colsample_bytree=None, gamma=None, gpu_id=None,
    importance_type='gain', interaction_constraints=None,
    learning_rate=None, max_delta_step=None, max_leaf_child_weight=None, subsample=None,
    tree_method=None, validate_parameters=False, verbosity=None),
    fit_params=None, iid=True, n_jobs=1,
    param_grid={'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]},
    pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
    scoring='roc_auc', verbose=0)
```

```
In [183]: print(set2.cv_results_)
```

```
[{'mean_fit_time': array([ 6.20540586, 13.83320036, 22.98772478, 32.25374517,
41.3508182 , 60.7429595 , 97.63709579, 6.74635816,
17.86642041, 31.69723334, 44.96255884, 58.67149854,
85.64436684, 140.72287459, 7.88531289, 22.53992205,
40.19630489, 57.82875199, 75.5485651 , 111.54570079,
182.36112399, 8.8519269 , 26.83663163, 49.40268517,
70.68616858, 93.78479805, 137.17835402, 224.12025127,
9.82173362, 30.78866339, 57.03647065, 83.33414445,
109.27597022, 160.59712596, 266.09041381, 10.80829554,
34.94415107, 65.49804277, 95.55885291, 125.56760244,
186.67339268, 301.24061341, 11.49027114, 39.60847726,
73.93428206, 108.14539371, 141.31130099, 210.38079228,
339.7578095 ]), 'std_fit_time': array([0.63752742, 0.77116663, 0.36997205, 0.87610681, 0.62571369,
0.82293503, 0.61692052, 0.06869409, 0.61078798, 0.79114296,
0.56766296, 0.7120891 , 0.61699251, 1.34817852, 0.03359467,
0.30024141, 0.39802436, 0.55285794, 0.61131142, 0.97704933,
0.73735067, 0.05242002, 0.64925244, 0.69701516, 0.37649544,
2.46646631, 0.87172225, 2.09130183, 0.16485065, 0.0460857 ,
0.1899844 , 1.17133361, 1.34127467, 0.60288647, 5.09876577,
0.31970744, 0.21346953, 0.83639106, 0.66562088, 0.64371018,
1.25134913, 1.43857427, 0.07018854, 0.58008512, 1.63351462,
0.57791883, 0.61454973, 1.4633432 , 2.13381024]), 'mean_score_time': array([0.59002094, 0.32532997, 0.35185
995, 0.34447904, 0.36223173,
0.34088783, 0.35425239, 0.44580832, 0.32792373, 0.33051596,
0.35305624, 0.33929286, 0.34627433, 0.36701894, 0.39115438,
0.36422625, 0.36402726, 0.35485172, 0.36482458, 0.3456758 ,
0.38955855, 0.35525012, 0.33570228, 0.36442566, 0.34767108,
0.35345459, 0.40292244, 0.45298858, 0.36163301, 0.33590164,
0.35923939, 0.35744438, 0.36562223, 0.39933319, 0.45298896,
0.35983777, 0.33330832, 0.36801615, 0.35006375, 0.42386751,
0.40930591, 0.43344102, 0.33550296, 0.38118067, 0.37040954,
0.37360091, 0.40970483, 0.41848164, 0.45139341]), 'std_score_time': array([0.0795876 , 0.05722745, 0.016693
23, 0.02978408, 0.03834948,
0.01470399, 0.03791634, 0.02789018, 0.009128 , 0.01284364,
0.02268198, 0.00888461, 0.02931198, 0.01013171, 0.02384768,
0.03792209, 0.04371961, 0.02066594, 0.05199286, 0.01905538,
0.04323755, 0.02324789, 0.01521179, 0.02799362, 0.01127641,
0.00835823, 0.01528324, 0.06751092, 0.05387684, 0.02023757,
0.02466005, 0.01764575, 0.02317263, 0.03625511, 0.03329637,
0.07641519, 0.01060008, 0.02696178, 0.01355792, 0.04227539,
0.03384248, 0.04057439, 0.017892 , 0.04458161, 0.03073691,
0.03891718, 0.03517284, 0.03160522, 0.03500966]), 'param_max_depth': masked_array(data=[2, 2, 2, 2, 2, 2,
2, 3, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4,
4, 4, 4, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 6, 7,
7, 7, 7, 7, 7, 8, 8, 8, 8, 8, 8, 8],
mask=[False, False, False, False, False, False, False, False,
False, False, False, False, False, False, False, False, False,
False, False, False, False, False, False, False, False, False,
False, False, False, False, False, False, False, False,
False, False, False, False, False, False, False, False,
False],
fill_value='?'),
dtype=object), 'param_n_estimators': masked_array(data=[10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
150, 200,
300, 500, 10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
150, 200, 300, 500, 10, 50, 100, 150, 200, 300, 500,
10, 50, 100, 150, 200, 300, 500, 10, 50, 100, 150, 200,
300, 500],
mask=[False, False, False, False, False, False, False, False,
False, False, False, False, False, False, False, False, False,
False, False, False, False, False, False, False, False, False,
False, False, False, False, False, False, False, False,
False, False, False, False, False, False, False, False,
False, False, False, False, False, False, False, False,
False],
fill_value='?'),
dtype=object), 'params': [{'max_depth': 2, 'n_estimators': 10}, {'max_depth': 2, 'n_estimators': 50},
{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 2, 'n_estimators': 150}, {'max_depth': 2, 'n_estimators': 20
0}, {'max_depth': 2, 'n_estimators': 300}, {'max_depth': 2, 'n_estimators': 500}, {'max_depth': 3, 'n_estimators':
10}, {'max_depth': 3, 'n_estimators': 50}, {'max_depth': 3, 'n_estimators': 100}, {'max_depth': 3, 'n_estimators':
150}, {'max_depth': 3, 'n_estimators': 200}, {'max_depth': 3, 'n_estimators': 300}, {'max_depth': 3, 'n_estimator
s': 500}, {'max_depth': 4, 'n_estimators': 10}, {'max_depth': 4, 'n_estimators': 50}, {'max_depth': 4, 'n_estimato
rs': 100}, {'max_depth': 4, 'n_estimators': 150}, {'max_depth': 4, 'n_estimators': 200}, {'max_depth': 4, 'n_estim
ators': 300}, {'max_depth': 4, 'n_estimators': 500}, {'max_depth': 5, 'n_estimators': 10}, {'max_depth': 5, 'n_est
imators': 50}, {'max_depth': 5, 'n_estimators': 100}, {'max_depth': 5, 'n_estimators': 150}, {'max_depth': 5, 'n_e
stimators': 200}, {'max_depth': 5, 'n_estimators': 300}, {'max_depth': 5, 'n_estimators': 500}, {'max_depth': 6,
'n_estimators': 10}, {'max_depth': 6, 'n_estimators': 50}, {'max_depth': 6, 'n_estimators': 100}, {'max_depth': 6,
'n_estimators': 150}, {'max_depth': 6, 'n_estimators': 200}, {'max_depth': 6, 'n_estimators': 300}, {'max_depth':
6, 'n_estimators': 500}, {'max_depth': 7, 'n_estimators': 10}, {'max_depth': 7, 'n_estimators': 50}, {'max_depth':
7, 'n_estimators': 100}, {'max_depth': 7, 'n_estimators': 150}, {'max_depth': 7, 'n_estimators': 200}, {'max_dept
h': 7, 'n_estimators': 300}, {'max_depth': 7, 'n_estimators': 500}, {'max_depth': 8, 'n_estimators': 10}, {'max_de
pth': 8, 'n_estimators': 50}, {'max_depth': 8, 'n_estimators': 100}, {'max_depth': 8, 'n_estimators': 150}, {'max_
depth': 8, 'n_estimators': 200}, {'max_depth': 8, 'n_estimators': 300}, {'max_depth': 8, 'n_estimators': 500}], 's
plit0_test_score': array([0.68794135, 0.72667856, 0.7294019 , 0.7319129 , 0.73198452,
0.73058519, 0.72675767, 0.70464146, 0.72974032, 0.7319956 ,
0.73086136, 0.72876062, 0.72757491, 0.7211653 , 0.71096088,
```

0.72336763, 0.72656389, 0.72390025, 0.72199794, 0.71838014,
0.71507374, 0.71320909, 0.72721825, 0.72282119, 0.7196648 ,
0.71658901, 0.71307617, 0.70650601, 0.71194447, 0.73040575,
0.72514441, 0.72061095, 0.71842286, 0.71679778, 0.71308809,
0.71620745, 0.73173356, 0.72359496, 0.72414393, 0.72037444,
0.71479398, 0.71086625, 0.70491046, 0.7172747 , 0.71390744,
0.71059271, 0.70710235, 0.70571092, 0.70696932]], 'split1_test_score': array([0.6860429 , 0.73048816, 0.738
86671, 0.73772107, 0.73645989,
0.72920968, 0.73079868, 0.70354638, 0.73170735, 0.73157493,
0.72996293, 0.72841698, 0.72436197, 0.72140913, 0.70090459,
0.72623268, 0.72162321, 0.71694473, 0.71959644, 0.71696425,
0.71477331, 0.70474225, 0.72071856, 0.7209491 , 0.71768279,
0.7109538 , 0.70916707, 0.7041497 , 0.70403859, 0.71450616,
0.70736726, 0.70821484, 0.70801869, 0.70547734, 0.70896091,
0.70923608, 0.71757474, 0.71180855, 0.71078752, 0.70932671,
0.70998721, 0.71074394, 0.70428633, 0.71001127, 0.70768264,
0.70549011, 0.71050876, 0.71248931, 0.71616553]], 'split2_test_score': array([0.6956036 , 0.74306796, 0.748
58272, 0.74812469, 0.74880218,
0.74595507, 0.74644474, 0.70882131, 0.74652472, 0.74707159,
0.74433895, 0.74079525, 0.73896304, 0.73232491, 0.71880047,
0.74016017, 0.73927293, 0.74100954, 0.7418033 , 0.74064489,
0.73699726, 0.7157457 , 0.74008558, 0.73744389, 0.73617079,
0.73510386, 0.73187901, 0.72982745, 0.70993214, 0.73457768,
0.73068115, 0.73209922, 0.73243822, 0.73132898, 0.7288252 ,
0.72135068, 0.73838685, 0.73617786, 0.73627029, 0.73252168,
0.73196131, 0.73103018, 0.71590355, 0.72956178, 0.72663479,
0.72454661, 0.72558337, 0.73101013, 0.73346949]], 'split3_test_score': array([0.675967 , 0.72777832, 0.736
99589, 0.7392705 , 0.7404478 ,
0.74282708, 0.73711544, 0.69224559, 0.72621612, 0.73015707,
0.72794756, 0.72786653, 0.72967731, 0.72176692, 0.69785183,
0.72714145, 0.72850941, 0.72852302, 0.72999933, 0.72549569,
0.72191073, 0.69991669, 0.72739468, 0.71930988, 0.71778355,
0.71813976, 0.71551506, 0.71356774, 0.69872568, 0.71901307,
0.72009066, 0.71726095, 0.71757232, 0.71259387, 0.72028564,
0.70557737, 0.72015745, 0.72225786, 0.71945094, 0.71853078,
0.71490752, 0.72008201, 0.69672824, 0.7153628 , 0.71596178,
0.71211042, 0.71621312, 0.71624182, 0.71777448]], 'split4_test_score': array([0.68451895, 0.74019737, 0.744
02247, 0.74495915, 0.74402712,
0.74658778, 0.74525702, 0.70179201, 0.74385917, 0.74354388,
0.74160324, 0.74100582, 0.74256115, 0.74125689, 0.71263167,
0.73929237, 0.7301538 , 0.73121491, 0.73213036, 0.72990928,
0.72745836, 0.71713193, 0.73781161, 0.73844357, 0.7366283 ,
0.73604715, 0.73444218, 0.73515039, 0.71132572, 0.72706512,
0.72685672, 0.72297458, 0.72384651, 0.71979801, 0.72026413,
0.71566343, 0.72503522, 0.72157145, 0.72376645, 0.72172229,
0.72209778, 0.72277273, 0.70962632, 0.72349056, 0.72439111,
0.72778421, 0.72568608, 0.72685376, 0.73227887]], 'mean_test_score': array([0.68601487, 0.73364162, 0.73957
345, 0.74039723, 0.7403439 ,
0.73903243, 0.7372741 , 0.70220945, 0.73560907, 0.73686823,
0.73494245, 0.73336863, 0.73262718, 0.72758396, 0.70822983,
0.73123833, 0.72922453, 0.72831825, 0.72910514, 0.72627847,
0.72324227, 0.710149 , 0.73064538, 0.72779301, 0.72558548,
0.72336607, 0.72081519, 0.71783931, 0.70719334, 0.72511367,
0.72202798, 0.72023203, 0.72005954, 0.7171991 , 0.71828456,
0.71360702, 0.72657778, 0.7230822 , 0.72288384, 0.72049514,
0.71874932, 0.71909863, 0.70629083, 0.71914002, 0.7175352 ,
0.71610424, 0.71701812, 0.71846049, 0.7213307]), 'std_test_score': array([0.0063064 , 0.00670286, 0.006505
05, 0.0056736 , 0.00583255,
0.00757958, 0.00775096, 0.00549313, 0.00806354, 0.00700672,
0.00667885, 0.00615631, 0.00694774, 0.00803203, 0.0077451 ,
0.00704635, 0.00578283, 0.00797971, 0.007901 , 0.0085946 ,
0.00833312, 0.00668394, 0.00722938, 0.00836757, 0.00885839,
0.01025547, 0.01031256, 0.01246961, 0.00507554, 0.00736373,
0.008082 , 0.00776832, 0.00801771, 0.00854606, 0.00682592,
0.00555943, 0.00762489, 0.00776938, 0.00824221, 0.00741283,
0.00765439, 0.00767346, 0.00633869, 0.00676193, 0.00701644,
0.00856347, 0.00761371, 0.00928531, 0.01012721]], 'rank_test_score': array([49, 9, 3, 1, 2, 4, 5, 48,
7, 6, 8, 10, 11, 18, 45, 12, 14,
16, 15, 20, 24, 44, 13, 17, 21, 23, 29, 38, 46, 22, 27, 31, 32, 40,
37, 43, 19, 25, 26, 30, 35, 34, 47, 33, 39, 42, 41, 36, 28]), 'split0_train_score': array([0.7060963 , 0.78
227148, 0.81847065, 0.84662878, 0.86782471,
0.90066443, 0.94100651, 0.73911529, 0.83056136, 0.88203216,
0.91346902, 0.93661882, 0.9644383 , 0.99003457, 0.76526132,
0.87621169, 0.93064287, 0.95910481, 0.97626371, 0.99281292,
0.9995276 , 0.79976739, 0.91841608, 0.96060373, 0.98220792,
0.99198657, 0.99892231, 0.99999549, 0.838716 , 0.95042045,
0.9841931 , 0.99524042, 0.99850851, 0.99995511, 1. ,
0.87328542, 0.97551903, 0.99483036, 0.99911642, 0.99991028,
0.99999996, 1. , 0.90747754, 0.98761944, 0.99802707,
0.99979855, 0.99999474, 1. , 1. ,]), 'split1_train_score': array([0.70798278, 0.78025762, 0.81
982527, 0.84902834, 0.86958923,
0.90062873, 0.94110865, 0.73449807, 0.82771215, 0.88217257,
0.91051342, 0.93299889, 0.96147723, 0.98775055, 0.76345271,
0.87498055, 0.92860643, 0.95842141, 0.97461333, 0.99088433,
0.99927392, 0.80430593, 0.91856824, 0.96446864, 0.98479684,
0.99324788, 0.99893435, 0.99999406, 0.83002097, 0.95059865,
0.98551487, 0.99603265, 0.99891859, 0.99997145, 1. ,

```

0.87241914, 0.97430127, 0.99478722, 0.99904857, 0.99990519,
0.99999865, 1. , 0.90212386, 0.98490836, 0.99807237,
0.99982138, 0.99999388, 1. , 1. ], 'split2_train_score': array([0.70331516, 0.77692227, 0.81
774215, 0.84558403, 0.86581346,
0.89771491, 0.9400615 , 0.73316219, 0.82372001, 0.87797127,
0.90892708, 0.93160935, 0.96075091, 0.98816745, 0.76444192,
0.87491855, 0.92768964, 0.95578525, 0.97436686, 0.99173795,
0.99931696, 0.80304041, 0.9180666 , 0.96126936, 0.98229092,
0.99236867, 0.99854602, 0.99999098, 0.83757024, 0.95139257,
0.9840311 , 0.99458904, 0.99843302, 0.99991636, 1. ,
0.86870556, 0.97333662, 0.99402132, 0.99866877, 0.99984762,
0.99999993, 1. , 0.89906165, 0.98762029, 0.99826688,
0.99986844, 0.99999367, 0.99999999, 1. ], 'split3_train_score': array([0.70365233, 0.78257753, 0.82
023565, 0.8487298 , 0.87077524,
0.90224831, 0.94289419, 0.73773967, 0.83032315, 0.87814938,
0.91404717, 0.93636252, 0.96402458, 0.98969228, 0.76915647,
0.87631206, 0.92932494, 0.95638871, 0.97372495, 0.99077105,
0.99942194, 0.79835918, 0.91220569, 0.95997427, 0.9826133 ,
0.99181053, 0.99866354, 0.99999947 , 0.83729613, 0.95157323,
0.98396089, 0.99484768, 0.99860315, 0.99994959, 0.99999999,
0.86978496, 0.97088783, 0.99386166, 0.99879263, 0.99988258,
0.999999 , 1. , 0.90759684, 0.98666028, 0.99855825,
0.99989115, 0.99999441, 1. , 1. ], 'split4_train_score': array([0.70457988, 0.77862603, 0.81
796943, 0.84554649, 0.86795125,
0.90030409, 0.93904221, 0.73085821, 0.82697347, 0.87668126,
0.90874073, 0.93055839, 0.96142873, 0.98903115, 0.76235436,
0.87630558, 0.93033683, 0.95949649, 0.97567608, 0.99170949,
0.99928237, 0.79436468, 0.91374688, 0.96369077, 0.98287211,
0.9920378 , 0.99858486, 0.99998797, 0.83414824, 0.95067242,
0.98394148, 0.99478487, 0.99818742, 0.9998881 , 1. ,
0.8704519 , 0.97109398, 0.9947288 , 0.99880409, 0.999759 ,
0.99999722, 1. , 0.89813617, 0.98411346, 0.99752203,
0.99977887, 0.99999029, 1. , 1. ], 'mean_train_score': array([0.70512529, 0.78013099, 0.8188
4863, 0.84710349, 0.86839078,
0.90031209, 0.94082261, 0.73507469, 0.82785803, 0.87940133,
0.91113948, 0.93362959, 0.96242395, 0.9889352 , 0.76493336,
0.87574569, 0.92932014, 0.95783934, 0.97492899, 0.99158315,
0.99936456, 0.79996752, 0.9162007 , 0.96200135, 0.98295622,
0.99229029, 0.99873022, 0.99999264, 0.83555031, 0.95093146,
0.98432829, 0.99509893, 0.99853014, 0.99993612, 1. ,
0.87092939, 0.97302775, 0.99444587, 0.9988861 , 0.99986093,
0.99999883, 1. , 0.90287921, 0.98618437, 0.99808932,
0.99983168, 0.9999934 , 1. , 1. ], 'std_train_score': array([1.72347394e-03, 2.15146852e-03,
1.00177731e-03, 1.50388189e-03,
1.68986147e-03, 1.46415617e-03, 1.27720130e-03, 3.00657289e-03,
2.50246792e-03, 2.26328540e-03, 2.23258118e-03, 2.46234984e-03,
1.50368908e-03, 8.69921903e-04, 2.32496529e-03, 6.51307581e-04,
1.09098228e-03, 1.48391261e-03, 9.17056174e-04, 7.34861227e-04,
9.70685240e-05, 3.52939224e-03, 2.68239077e-03, 1.76294461e-03,
9.50277553e-04, 5.11722039e-04, 1.66176640e-04, 2.79107903e-06,
3.15242866e-03, 4.61189969e-04, 5.99863699e-04, 5.12564098e-04,
2.38154066e-04, 2.99565572e-05, 2.63836317e-09, 1.68839264e-03,
1.80235679e-03, 4.16159506e-04, 1.68603750e-04, 5.55522314e-05,
9.12052095e-07, 0.00000000e+00, 4.02595042e-03, 1.43280607e-03,
3.39823365e-04, 4.21432144e-05, 1.59797973e-06, 2.63836317e-09,
0.00000000e+00]})

```

```

In [184]: import seaborn as sns; sns.set()
max_scores2 = pd.DataFrame(set2.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max().unstack()
max_scores2

```

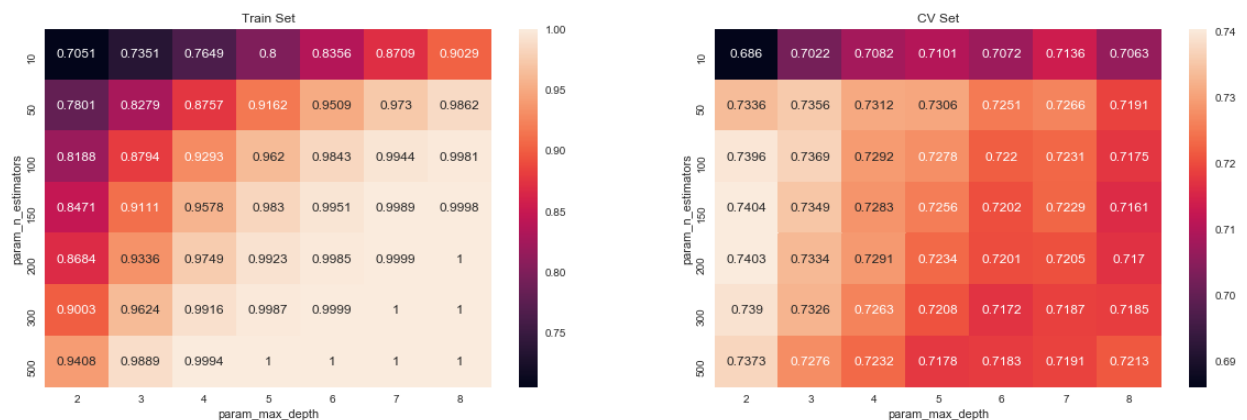
Out[184]:

	mean_fit_time							mean_score_time			...	std
param_max_depth	2	3	4	5	6	7	8	2	3	4	...	6
param_n_estimators												
10	6.205406	6.746358	7.885313	8.851927	9.821734	10.808296	11.490271	0.590021	0.445808	0.391154	...	0.0
50	13.833200	17.866420	22.539922	26.836632	30.788663	34.944151	39.608477	0.325330	0.327924	0.364226	...	0.0
100	22.987725	31.697233	40.196305	49.402685	57.036471	65.498043	73.934282	0.351860	0.330516	0.364027	...	0.0
150	32.253745	44.962559	57.828752	70.686169	83.334144	95.558853	108.145394	0.344479	0.353056	0.354852	...	0.0
200	41.350818	58.671499	75.548565	93.784798	109.275970	125.567602	141.311301	0.362232	0.339293	0.364825	...	0.0
300	60.742959	85.644367	111.545701	137.178354	160.597126	186.673393	210.380792	0.340888	0.346274	0.345676	...	0.0
500	97.637096	140.722875	182.361124	224.120251	266.090414	301.240613	339.757809	0.354252	0.367019	0.389559	...	0.0

7 rows × 140 columns



```
In [185]: fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores2.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores2.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 [186]: print(set2.best_estimator_)
```

```
XGBClassifier(base_score=0.5, booster=None, class_weight='balanced',
               colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
               gamma=0, gpu_id=-1, importance_type='gain',
               interaction_constraints=None, learning_rate=0.300000012,
               max_delta_step=0, max_depth=2, min_child_weight=1, missing=nan,
               monotone_constraints=None, n_estimators=150, n_jobs=0,
               num_parallel_tree=1, objective='binary:logistic', random_state=0,
               reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
               tree_method=None, validate_parameters=False, verbosity=None)
```

```
In [187]: max_d = set2.best_params_['max_depth']
n_est = set2.best_params_['n_estimators']
```

Training our model with best Hyperparameters

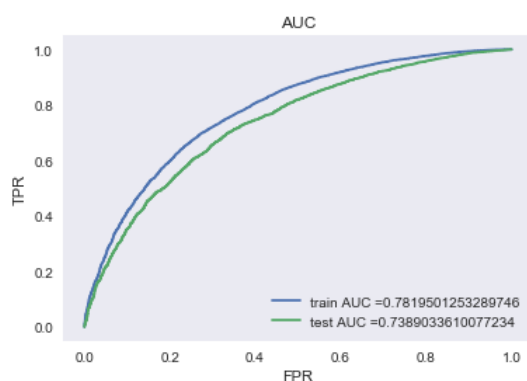
```
In [188]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import GradientBoostingClassifier
model = GradientBoostingClassifier(max_depth = max_d , n_estimators = n_est)

model.fit(X_tr_TFIDF, y_train)

y_train_pred = pred_prob(model,X_tr_TFIDF)
y_test_pred = pred_prob(model,X_te_TFIDF)

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

plt.close
plt.plot(train_fpr, train_tpr, label="train AUC =" +str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC =" +str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



Confusion matrix

```
In [189]: #our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of $tpr \cdot (1 - fpr)$ 0.5068760568606479 for threshold 0.842
Train confusion matrix
[[3373 1271]
 [7706 17800]]

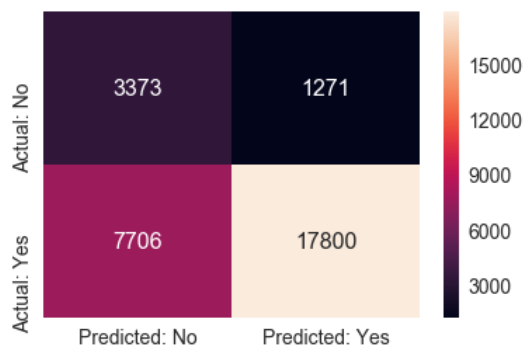
```
In [190]: #plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

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

Train data confusion matrix

Out[190]: <matplotlib.axes._subplots.AxesSubplot at 0x2c3880fe3c8>



```
In [191]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

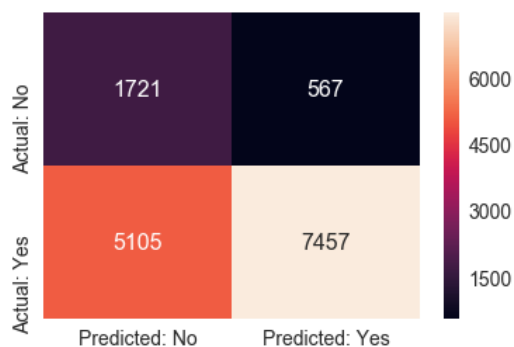
Test confusion matrix
[[1721 567]
 [5105 7457]]

```
In [192]: print("Test data confusion matrix")

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

Test data confusion matrix

Out[192]: <matplotlib.axes._subplots.AxesSubplot at 0x2c398aa9fd0>



In []:

2.5.3 Applying XGBOOST on AVG W2V, SET 3

```
In [193]: # Please write all the code with proper documentation
```

```
In [194]: import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
#from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import learning_curve, GridSearchCV
from xgboost import XGBClassifier

#n_estimators = [10, 50, 100, 150, 200, 300, 500, 1000], max_depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]

clf = XGBClassifier(class_weight='balanced')
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]}
set3 = GridSearchCV(clf, parameters, cv=5, scoring='roc_auc', return_train_score=True)
set3.fit(X_tr_AVG_W2V, y_train)
```

```
Out[194]: GridSearchCV(cv=5, error_score='raise',
    estimator=XGBClassifier(base_score=None, booster=None, class_weight='balanced',
    colsample_bylevel=None, colsample_bynode=None,
    colsample_bytree=None, gamma=None, gpu_id=None,
    importance_type='gain', interaction_constraints=None,
    learning_rate=None, max_delta_step=None, max_pos_weight=None, subsample=None,
    tree_method=None, validate_parameters=False, verbosity=None),
    fit_params=None, iid=True, n_jobs=1,
    param_grid={'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]},
    pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
    scoring='roc_auc', verbose=0)
```



```
In [195]: print(set3.cv_results_)
```

```

{'mean_fit_time': array([ 19.27864342,  47.58255305,  83.20867219, 117.41878643,
    152.62663283,  222.5114612,  359.90273104,  22.05920777,
    62.44948101,  114.03205285,  188.03859687, 2292.41762762,
    328.57044487,  552.16559982,  26.01861939,  80.92837677,
    149.83191419,  218.33452291,  283.53077412,  422.03069911,
    708.13122778,  29.21307554,  96.95731335, 184.58955021,
    270.58519268,  354.59493318,  529.50576563,  858.58774056,
    32.81963134,  114.82910514,  217.20094638,  319.71600556,
    422.60186582,  625.10689721, 1000.86305742,  35.77313313,
    132.08732744,  253.39576006,  368.35871034,  487.1687921 ,
    700.49232454, 1083.74441366,  38.56446152, 148.96623073,
    283.55569863,  412.61178131,  533.26013932,  758.98310766,
    1132.78866611]), 'std_fit_time': array([1.97872227e-01, 6.46769251e-01, 1.08047054e+00, 1.88429111e+00,
    1.29623262e+00, 1.81974236e+00, 1.93491423e+00, 1.44497880e-01,
    3.27315822e-01, 2.08912435e+00, 1.13704845e+01, 4.09543143e+03,
    7.29658578e+00, 1.80173758e+01, 7.30870471e-01, 5.59679249e-01,
    1.06440083e+00, 2.28994560e+00, 2.51637348e+00, 2.88975666e+00,
    1.71159745e+01, 4.49685894e-01, 8.29444065e-01, 8.86773500e-01,
    1.93835503e+00, 2.54843187e+00, 4.76653260e+00, 3.04810683e+00,
    7.73980331e-01, 1.45693686e+00, 1.73386781e+00, 9.02395369e-01,
    4.17519980e+00, 6.26485960e+00, 9.32291971e+00, 6.23596215e-01,
    1.88852042e+00, 1.64934077e+00, 1.12023914e+00, 4.55921952e+00,
    5.54393471e+00, 8.41964608e+00, 9.96083838e-01, 1.94495407e+00,
    2.55663404e+00, 5.24741476e+00, 3.16193724e+00, 8.92680471e+00,
    9.22849998e+00]), 'mean_score_time': array([1.9695334 , 2.03475981, 2.26434517, 2.11354818, 2.40676503,
    2.05390744, 2.09659333, 2.016608 , 2.14985151, 2.17059617,
    2.16401324, 2.36557651, 2.25098119, 2.48150959, 2.04832268,
    2.09041095, 2.12292352, 2.049719 , 2.31002336, 2.39320059,
    2.27990389, 2.20510364, 2.1841599 , 2.08841591, 2.21527696,
    2.25457101, 2.15563622, 2.42431746, 2.12611485, 2.10237947,
    2.25058298, 2.12192669, 2.09739223, 2.28489079, 2.28528986,
    2.12930727, 2.0772459 , 2.17877431, 2.43089981, 2.13489161,
    2.39240332, 2.62956944, 2.09619517, 2.3648756 , 2.0393476 ,
    2.18396053, 2.41873293, 2.32278862, 2.39778833]), 'std_score_time': array([0.07982026, 0.04019878, 0.240198
82, 0.14410187, 0.39084014,
    0.04384032, 0.20765519, 0.05098698, 0.28268421, 0.466258 ,
    0.05344305, 0.22315496, 0.39782543, 0.16326633, 0.06709399,
    0.1026334 , 0.12327277, 0.13679359, 0.50270965, 0.29202876,
    0.06528082, 0.18500394, 0.08352419, 0.07818048, 0.05193957,
    0.11335287, 0.12678698, 0.2451503 , 0.10397387, 0.06223898,
    0.37535307, 0.1148579 , 0.09207958, 0.24997949, 0.11908448,
    0.11737175, 0.15967505, 0.16501259, 0.33578261, 0.09353571,
    0.15258358, 0.41985474, 0.0331398 , 0.26136399, 0.04420457,
    0.05311776, 0.1633771 , 0.22297649, 0.18761129]), 'param_max_depth': masked_array(data=[2, 2, 2, 2, 2, 2,
2, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4,
    4, 4, 4, 5, 5, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 6, 7,
    7, 7, 7, 7, 7, 7, 8, 8, 8, 8, 8, 8, 8],
    mask=[False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'param_n_estimators': masked_array(data=[10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
150, 200,
    300, 500, 10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
    150, 200, 300, 500, 10, 50, 100, 150, 200, 300, 500,
    10, 50, 100, 150, 200, 300, 500, 10, 50, 100, 150, 200,
    300, 500],
    mask=[False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'params': [{'max_depth': 2, 'n_estimators': 10}, {'max_depth': 2, 'n_estimators': 50},
{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 2, 'n_estimators': 150}, {'max_depth': 2, 'n_estimators': 20
0}, {'max_depth': 2, 'n_estimators': 300}, {'max_depth': 2, 'n_estimators': 500}, {'max_depth': 3, 'n_estimators':
10}, {'max_depth': 3, 'n_estimators': 50}, {'max_depth': 3, 'n_estimators': 100}, {'max_depth': 3, 'n_estimators':
150}, {'max_depth': 3, 'n_estimators': 200}, {'max_depth': 3, 'n_estimators': 300}, {'max_depth': 3, 'n_estimator
s': 500}, {'max_depth': 4, 'n_estimators': 10}, {'max_depth': 4, 'n_estimators': 50}, {'max_depth': 4, 'n_estimato
rs': 100}, {'max_depth': 4, 'n_estimators': 150}, {'max_depth': 4, 'n_estimators': 200}, {'max_depth': 4, 'n_estim
ators': 300}, {'max_depth': 4, 'n_estimators': 500}, {'max_depth': 5, 'n_estimators': 10}, {'max_depth': 5, 'n_est
imators': 50}, {'max_depth': 5, 'n_estimators': 100}, {'max_depth': 5, 'n_estimators': 150}, {'max_depth': 5, 'n_e
stimators': 200}, {'max_depth': 5, 'n_estimators': 300}, {'max_depth': 5, 'n_estimators': 500}, {'max_depth': 6,
'n_estimators': 10}, {'max_depth': 6, 'n_estimators': 50}, {'max_depth': 6, 'n_estimators': 100}, {'max_depth': 6,
'n_estimators': 150}, {'max_depth': 6, 'n_estimators': 200}, {'max_depth': 6, 'n_estimators': 300}, {'max_depth':
6, 'n_estimators': 500}, {'max_depth': 7, 'n_estimators': 10}, {'max_depth': 7, 'n_estimators': 50}, {'max_depth':
7, 'n_estimators': 100}, {'max_depth': 7, 'n_estimators': 150}, {'max_depth': 7, 'n_estimators': 200}, {'max_dept
h': 7, 'n_estimators': 300}, {'max_depth': 7, 'n_estimators': 500}, {'max_depth': 8, 'n_estimators': 10}, {'max_de
pth': 8, 'n_estimators': 50}, {'max_depth': 8, 'n_estimators': 100}, {'max_depth': 8, 'n_estimators': 150}, {'max
depth': 8, 'n_estimators': 200}, {'max_depth': 8, 'n_estimators': 300}, {'max_depth': 8, 'n_estimators': 500}], 's
plit0_test_score': array([0.6795694 , 0.71585068, 0.71734738, 0.71737397, 0.71652688,

```

```

0.71292754, 0.70954899, 0.69644051, 0.72075051, 0.71828752,
0.71664629, 0.71671064, 0.71092026, 0.70559045, 0.70483757,
0.71584752, 0.70868217, 0.69804334, 0.69471743, 0.69146969,
0.69492208, 0.70192655, 0.70337716, 0.70440295, 0.69762707,
0.69474855, 0.69430064, 0.69798448, 0.69171622, 0.69176085,
0.6906169 , 0.69394724, 0.69710553, 0.69993289, 0.70060687,
0.68843768, 0.68802036, 0.68909257, 0.69225391, 0.69465382,
0.69978056, 0.70158276, 0.68707938, 0.69231984, 0.69856583,
0.70218722, 0.70536133, 0.70777654, 0.70953834]], 'split1_test_score': array([0.69207614, 0.72158491, 0.721
27133, 0.72040603, 0.7189906 ,
0.71807814, 0.71412959, 0.70019956, 0.71021586, 0.70867107,
0.70372354, 0.70252018, 0.69676106, 0.6927339 , 0.70657297,
0.70875991, 0.70356274, 0.70124771, 0.6997695 , 0.69949401,
0.70149292, 0.704301 , 0.69859938, 0.69375958, 0.68824703,
0.68943498, 0.68938497, 0.69993536, 0.70952824, 0.69676886,
0.69405807, 0.69478873, 0.699961 , 0.70614681, 0.71310159,
0.70072469, 0.68939225, 0.69252119, 0.6982188 , 0.69890716,
0.70140165, 0.70293104, 0.68863996, 0.68009386, 0.6856944 ,
0.69543235, 0.69815159, 0.70237236, 0.70377967]], 'split2_test_score': array([0.70037672, 0.73850185, 0.741
21043, 0.7404172 , 0.73848476,
0.7295201 , 0.72370885, 0.70546162, 0.73260346, 0.72856649,
0.72935392, 0.72652917, 0.72017939, 0.70819574, 0.71231068,
0.73154623, 0.73263173, 0.72076351, 0.71925301, 0.71700224,
0.71832925, 0.71465451, 0.70798841, 0.70224079, 0.70028471,
0.70397402, 0.70538587, 0.71045189, 0.71134504, 0.70615536,
0.70837342, 0.70652634, 0.70907982, 0.71608619, 0.71919582,
0.70458356, 0.71925353, 0.71426053, 0.71651836, 0.72050353,
0.72226894, 0.72424274, 0.6957186 , 0.70295763, 0.71085283,
0.71485603, 0.72071824, 0.7234609 , 0.72495273]], 'split3_test_score': array([0.69039809, 0.72729381, 0.730
48911, 0.73311613, 0.73188798,
0.73092171, 0.72632754, 0.70220354, 0.72533014, 0.72487486,
0.72049635, 0.71922979, 0.71337233, 0.70721037, 0.70162555,
0.7207788 , 0.71869612, 0.72033196, 0.71385906, 0.71753876,
0.71008365, 0.7056852 , 0.72623311, 0.71455638, 0.70754136,
0.70472632, 0.70908087, 0.71709076, 0.70354353, 0.71874887,
0.7131631 , 0.71296654, 0.71427076, 0.71745351, 0.72917054,
0.6947708 , 0.69568083, 0.69502434, 0.69986784, 0.70074189,
0.7072971 , 0.71491354, 0.70532878, 0.70273479, 0.70970065,
0.71479779, 0.71999686, 0.72530355, 0.72678461]], 'split4_test_score': array([0.69968501, 0.74233659, 0.747
96239, 0.74201 , 0.740705 ,
0.73291748, 0.72490128, 0.71235937, 0.73311289, 0.73177472,
0.73080097, 0.7269258 , 0.71868536, 0.71273223, 0.71608086,
0.73276496, 0.73074446, 0.72175651, 0.71962774, 0.71539408,
0.71269917, 0.72148769, 0.72016759, 0.70723973, 0.70210709,
0.70449791, 0.70976469, 0.71833954, 0.70385381, 0.70319915,
0.69881899, 0.70217797, 0.70535907, 0.71219703, 0.71882499,
0.70396134, 0.71159993, 0.71087249, 0.71428724, 0.72075867,
0.72471845, 0.72963814, 0.69834156, 0.70647363, 0.71502165,
0.72158128, 0.72441773, 0.72846982, 0.72988742]], 'mean_test_score': array([0.6924204 , 0.72911269, 0.73165
511, 0.73066385, 0.72931824,
0.72487233, 0.71972274, 0.70333239, 0.72440216, 0.72243448,
0.72020374, 0.71838278, 0.71198342, 0.7052923 , 0.70828515,
0.72193892, 0.71886271, 0.71242782, 0.70944452, 0.70817896,
0.70750483, 0.70961034, 0.71127257, 0.70443979, 0.6991613 ,
0.69947603, 0.7015829 , 0.70875973, 0.70399697, 0.70332624,
0.70100582, 0.70208109, 0.70515496, 0.71036288, 0.71617936,
0.6984951 , 0.7007886 , 0.7003535 , 0.7042285 , 0.70711215,
0.71109251, 0.71466071, 0.69502128, 0.69691548, 0.70396653,
0.70977029, 0.71372852, 0.71747595, 0.71898788]], 'std_test_score': array([0.00755583, 0.00998884, 0.011585
46, 0.0101166 , 0.00990527,
0.0078965 , 0.00665028, 0.00537775, 0.00846847, 0.0082148 ,
0.00980152, 0.00888224, 0.00832901, 0.006712 , 0.005218 ,
0.00918289, 0.01156301, 0.01049678, 0.0102947 , 0.01069747,
0.00831011, 0.00733673, 0.01036021, 0.00676887, 0.00635042,
0.00626399, 0.00823945, 0.00846194, 0.00686523, 0.0091941 ,
0.00852152, 0.0071779 , 0.00616969, 0.00652648, 0.00934755,
0.0061148 , 0.01246467, 0.01020403, 0.00949472, 0.01121306,
0.01045798, 0.01117866, 0.00665671, 0.009652 , 0.01063522,
0.00952582, 0.01014939, 0.01039374, 0.0103513 ]), 'rank_test_score': array([49, 
```

```

0.99999719, 1. , 1. , 0.86301543, 0.99104334,
0.99998154, 1. , 1. , 1. , 1. ,
0.90717215, 0.99976755, 1. , 1. , 1. ,
1. , 1. , 0.95747986, 0.99999923, 1. ,
1. , 1. , 1. , 1. , ]), 'split2_train_score': array([0.71846418, 0.77853479, 0.81
69577 , 0.84507854, 0.86626327,
0.9006545 , 0.9441765 , 0.74296381, 0.83393052, 0.89416409,
0.93290884, 0.95689001, 0.98288567, 0.99844545, 0.77702397,
0.8988115 , 0.96113296, 0.98720573, 0.99663809, 0.99990627,
1. , 0.81589748, 0.95648891, 0.99553818, 0.99979466,
0.99999723, 1. , 1. , 0.86762137, 0.99260471,
0.99998578, 1. , 1. , 1. , 1. ,
0.92638046, 0.99966788, 1. , 1. , 1. ,
1. , 1. , 0.95141994, 0.99999999, 1. ,
1. , 1. , 1. , 1. , ]), 'split3_train_score': array([0.71480899, 0.77906585, 0.81
691528, 0.84377444, 0.86580349,
0.90010471, 0.94352013, 0.74155755, 0.83131132, 0.89077731,
0.92841528, 0.95247855, 0.9808927 , 0.99824272, 0.77172829,
0.89642006, 0.95931877, 0.98550919, 0.99562008, 0.99984278,
1. , 0.81258282, 0.95931757, 0.99486323, 0.9997993 ,
0.99999926, 1. , 1. , 0.86643612, 0.99152833,
0.99997877, 1. , 1. , 1. , 1. ,
0.91322202, 0.9996217 , 1. , 1. , 1. ,
1. , 1. , 0.95223647, 1. , 1. ,
1. , 1. , 1. , 1. , ]), 'split4_train_score': array([0.71011708, 0.7766665 , 0.81
62679 , 0.84433997, 0.86628778,
0.90031945, 0.94303836, 0.74106027, 0.83354831, 0.89230807,
0.93003088, 0.95329151, 0.97949836, 0.99786983, 0.77495211,
0.89994562, 0.95912765, 0.9848093 , 0.9958365 , 0.99980102,
1. , 0.81286918, 0.95746336, 0.99468734, 0.99965559,
0.99999873, 1. , 1. , 0.86777079, 0.99172442,
0.99993886, 0.99999999, 1. , 1. , 1. ,
0.91657845, 0.99962156, 1. , 1. , 1. ,
1. , 1. , 0.95421494, 0.99999993, 1. ,
1. , 1. , 1. , 1. , ]), 'mean_train_score': array([0.71470271, 0.77947428, 0.8179
9822, 0.84623007, 0.86807184,
0.90221074, 0.9448783 , 0.7435588 , 0.83416391, 0.89365951,
0.93130161, 0.95513971, 0.9820269 , 0.99830655, 0.77407778,
0.89984395, 0.96035166, 0.98644582, 0.99626228, 0.99985924,
1. , 0.81527739, 0.95893394, 0.99528882, 0.999763 ,
0.99999701, 1. , 1. , 0.86595159, 0.9919363 ,
0.99997481, 1. , 1. , 1. , 1. ,
0.91507636, 0.99969349, 1. , 1. , 1. ,
1. , 1. , 0.95422639, 0.9999998 , 1. ,
1. , 1. , 1. , 1. , ]), 'std_train_score': array([2.82481606e-03, 2.00166785e-03,
1.82524124e-03, 2.45528480e-03,
2.46285779e-03, 2.27435993e-03, 1.70884966e-03, 2.17313363e-03,
1.75627548e-03, 1.92254920e-03, 1.78240415e-03, 1.87338995e-03,
1.58900496e-03, 2.40674378e-04, 1.80446074e-03, 2.58363508e-03,
1.33030894e-03, 1.23415839e-03, 4.76961860e-04, 5.27546228e-05,
0.00000000e+00, 2.17602257e-03, 1.73780000e-03, 4.44296954e-04,
5.47923585e-05, 2.35600844e-06, 0.00000000e+00, 0.00000000e+00,
1.79050408e-03, 6.58561415e-04, 1.83201867e-05, 5.27530637e-09,
0.00000000e+00, 0.00000000e+00, 4.96506831e-17, 6.40690439e-03,
7.14779822e-05, 0.00000000e+00, 0.00000000e+00, 4.96506831e-17,
4.96506831e-17, 0.00000000e+00, 2.22877304e-03, 2.88175368e-07,
0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
0.00000000e+00]})

```

```

In [196]: import seaborn as sns; sns.set()
max_scores3 = pd.DataFrame(set3.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max().unstack()
max_scores3

```

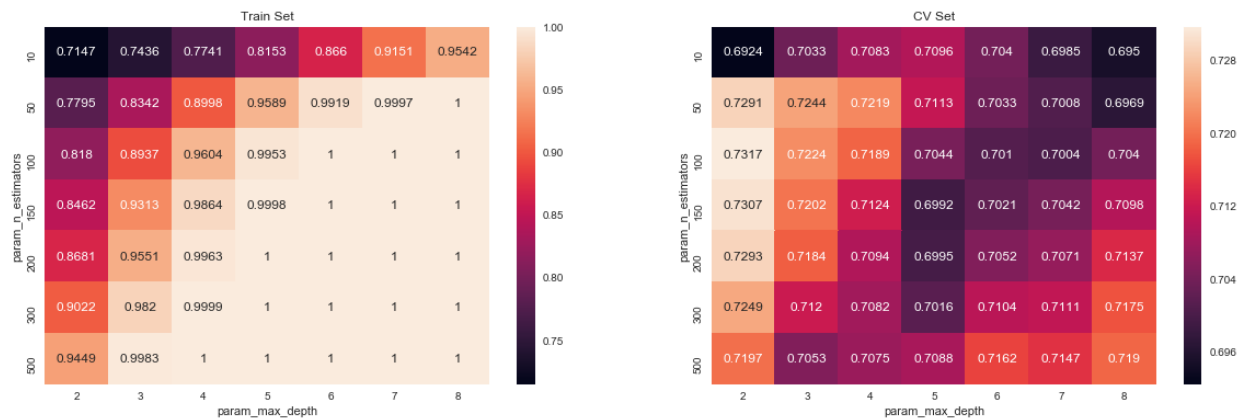
Out[196]:

	mean_fit_time							mean_score_time				..
param_max_depth	2	3	4	5	6	7	8	2	3	4	..	
param_n_estimators												
10	19.278643	22.059208	26.018619	29.213076	32.819631	35.773133	38.564462	1.969533	2.016608	2.048323	.	
50	47.582553	62.449481	80.928377	96.957313	114.829105	132.087367	148.966231	2.034760	2.149852	2.090411	.	
100	83.208672	114.032053	149.831914	184.589550	217.200946	253.395760	283.555699	2.264345	2.170596	2.122924	.	
150	117.418786	188.038597	218.334523	270.585193	319.716006	368.358710	412.611781	2.113548	2.164013	2.049719	.	
200	152.626633	2292.417628	283.530774	354.594933	422.601866	487.168792	533.260139	2.406765	2.365577	2.310023	.	
300	222.511146	328.570445	422.030699	529.505766	625.106897	700.492325	758.983108	2.053907	2.250981	2.393201	.	
500	359.902731	552.165600	708.131228	858.587741	1000.863057	1083.744414	1132.788666	2.096593	2.481510	2.279904	.	

7 rows × 140 columns



```
In [197]: fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores3.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores3.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 [198]: print(set3.best_estimator_)
```

```
XGBClassifier(base_score=0.5, booster=None, class_weight='balanced',
               colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
               gamma=0, gpu_id=-1, importance_type='gain',
               interaction_constraints=None, learning_rate=0.300000012,
               max_delta_step=0, max_depth=2, min_child_weight=1, missing=nan,
               monotone_constraints=None, n_estimators=100, n_jobs=0,
               num_parallel_tree=1, objective='binary:logistic', random_state=0,
               reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
               tree_method=None, validate_parameters=False, verbosity=None)
```

```
In [199]: max_d = set3.best_params_['max_depth']
n_est = set3.best_params_['n_estimators']
```

Training our model with best Hyperparameters

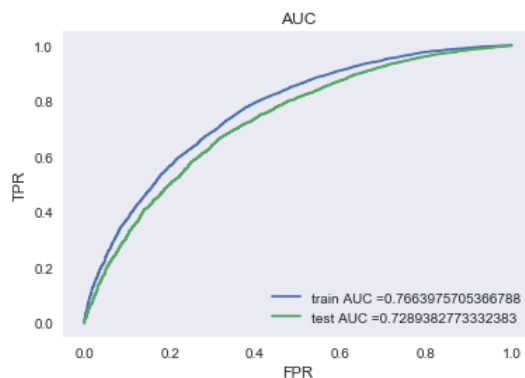
```
In [200]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import GradientBoostingClassifier
model = GradientBoostingClassifier(max_depth = max_d , n_estimators = n_est)

model.fit(X_tr_AVG_W2V, y_train)

y_train_pred = pred_prob(model,X_tr_AVG_W2V)
y_test_pred = pred_prob(model,X_te_AVG_W2V)

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

plt.close
plt.plot(train_fpr, train_tpr, label="train AUC =" +str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC =" +str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



Confusion Matrix

```
In [201]: #our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of $tpr \cdot (1 - fpr)$ 0.4875473727855019 for threshold 0.833
Train confusion matrix
[[3104 1540]
 [6901 18605]]

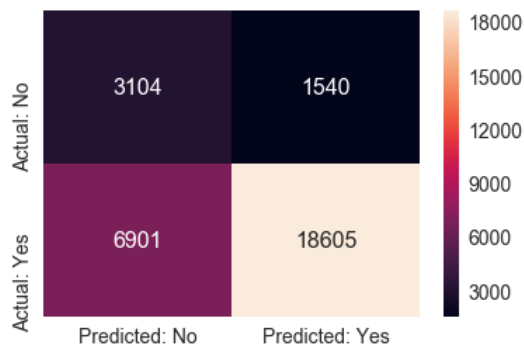
```
In [202]: #plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

print("Train data confusion matrix")

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

Train data confusion matrix

Out[202]: <matplotlib.axes._subplots.AxesSubplot at 0x2c387776908>



```
In [203]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

Test confusion matrix
[[1610 678]
 [4589 7973]]

```
In [204]: print("Test data confusion matrix")

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

Test data confusion matrix

Out[204]: <matplotlib.axes._subplots.AxesSubplot at 0x2c399700208>



In []:

2.5.4 Applying XGBOOST on TFIDF W2V, SET 4

```
In [205]: # Please write all the code with proper documentation
```

```
In [206]: import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
#from sklearn.grid_search import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import learning_curve, GridSearchCV
from xgboost import XGBClassifier

#n_estimators = [10, 50, 100, 150, 200, 300, 500, 1000], max_depth = [2, 3, 4, 5, 6, 7, 8, 9, 10]

clf = XGBClassifier(class_weight='balanced')
parameters = {'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]}
set4 = GridSearchCV(clf, parameters, cv=5, scoring='roc_auc', return_train_score=True)
set4.fit(X_tr_TFIDF_W2V, y_train)
```

```
Out[206]: GridSearchCV(cv=5, error_score='raise',
    estimator=XGBClassifier(base_score=None, booster=None, class_weight='balanced',
    colsample_bylevel=None, colsample_bynode=None,
    colsample_bytree=None, gamma=None, gpu_id=None,
    importance_type='gain', interaction_constraints=None,
    learning_rate=None, max_delta_step=None, max_leaf_nodes=None, min_child_weight=None,
    monotone_constraints=None, multi_output_support=None, n_estimators=None, num_parallel_tree=None,
    random_state=None, reg_alpha=None, reg_lambda=None, subsample=None, tree_method=None, validate_parameters=False, verbosity=None),
    fit_params=None, iid=True, n_jobs=1,
    param_grid={'n_estimators': [10, 50, 100, 150, 200, 300, 500], 'max_depth': [2, 3, 4, 5, 6, 7, 8]},
    pre_dispatch='2*n_jobs', refit=True, return_train_score=True,
    scoring='roc_auc', verbose=0)
```

```
In [207]: print(set4.cv_results_)
```



```

{'mean_fit_time': array([ 19.48469605,  47.37709379,  82.38368616, 117.45549631,
    152.82570796,  223.17537723,  364.70648417,  21.87948871,
    63.26101732, 113.89102201, 165.12381191, 215.84577818,
    317.34195538, 521.85424166,  25.21297317,  87.6785192 ,
    148.81962237, 213.88183031, 284.80376167, 417.31221271,
    687.81263161,  28.15589647,  96.4504694 , 179.76785836,
    263.8196857 , 350.34808912, 518.70107446, 851.94749875,
    31.75726542, 112.16903315, 213.44559708, 315.74820976,
    416.35995812, 616.97108469, 1080.4634304 ,  37.59964519,
    135.89665718, 265.12946591, 427.3624784 , 501.19556241,
    701.85629606, 1079.95056667,  38.20084052, 146.43100157,
    280.42188787, 404.2944171 , 520.81182227, 737.96790586,
    1112.16820283]), 'std_fit_time': array([ 0.87990155,  0.67554766,  0.87800321,  0.68479648,  1.26395711,
    1.255631 ,  2.12955455,  0.15179577,  1.14723398,  1.11731203,
    0.89650286,  1.54894116,  0.35618541,  0.99193942,  0.18782266,
    3.57858682,  3.99376175,  1.40019698,  7.69641303,  1.13376646,
    9.76110331,  0.09394966,  1.55599129,  1.01599922,  0.89939265,
    2.32307986,  3.68629812,  4.92156663,  0.78434713,  0.99538231,
    1.24833553,  1.40370846,  2.71878782,  4.47600035, 58.46508408,
    1.24910096,  1.8463043 , 11.48124605,  5.36493279, 17.01518503,
    2.74721682, 7.27209956,  0.72766792,  1.1738526 ,  0.62927718,
    1.27655574,  1.6668454 ,  4.42273192,  7.39657824]), 'mean_score_time': array([2.04872212, 1.97711358, 2.1
8974447, 2.09200687, 2.07405438,
    2.09360118, 2.14546332, 1.83589101, 2.13150129, 2.14107461,
    2.06487918, 2.13449254, 2.18834839, 2.23023748, 2.08681974,
    2.76739936, 2.1307024 , 2.19433198, 2.57730827, 2.16600804,
    2.24659257, 2.05769768, 2.12711234, 2.06288438, 2.16800265,
    2.11654115, 2.26494389, 2.16620822, 2.04253879, 2.16042371,
    2.04553089, 2.09061055, 2.05969229, 2.33495684, 2.78358364,
    2.31979885, 2.40053988, 2.42577863, 2.54554138, 2.55592947,
    2.32418566, 2.29865351, 2.16840172, 1.88057146, 2.04652767,
    2.05231204, 2.18455863, 2.20370755, 2.34453106]), 'std_score_time': array([0.08071707, 0.0668331 , 0.234292
98, 0.17621296, 0.07333855,
    0.05722508, 0.08834063, 0.21270177, 0.09781107, 0.19752583,
    0.07607414, 0.02414632, 0.11023049, 0.06722093, 0.10226557,
    0.55446561, 0.19742174, 0.25718024, 0.28679319, 0.19852832,
    0.14978657, 0.09389204, 0.12809204, 0.09041742, 0.20595451,
    0.07930981, 0.09726354, 0.06714613, 0.02709347, 0.17884472,
    0.07908531, 0.06105609, 0.12998758, 0.42577661, 0.23597305,
    0.20978276, 0.24312423, 0.36606399, 0.26080117, 0.18435587,
    0.08700867, 0.04693785, 0.19227844, 0.2297595 , 0.30073633,
    0.29791673, 0.0860337 , 0.19366605, 0.06578584]), 'param_max_depth': masked_array(data=[2, 2, 2, 2, 2, 2,
2, 3, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4,
    4, 4, 4, 5, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 7,
    7, 7, 7, 7, 7, 8, 8, 8, 8, 8, 8, 8],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'param_n_estimators': masked_array(data=[10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
150, 200,
    300, 500, 10, 50, 100, 150, 200, 300, 500, 10, 50, 100,
    150, 200, 300, 500, 10, 50, 100, 150, 200, 300, 500,
    10, 50, 100, 150, 200, 300, 500, 10, 50, 100, 150, 200,
    300, 500],
    mask=[False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False, False, False, False, False, False, False, False,
    False],
    fill_value='?'),
    dtype=object), 'params': [{'max_depth': 2, 'n_estimators': 10}, {'max_depth': 2, 'n_estimators': 50},
{'max_depth': 2, 'n_estimators': 100}, {'max_depth': 2, 'n_estimators': 150}, {'max_depth': 2, 'n_estimators': 20
0}, {'max_depth': 2, 'n_estimators': 300}, {'max_depth': 2, 'n_estimators': 500}, {'max_depth': 3, 'n_estimators':
10}, {'max_depth': 3, 'n_estimators': 50}, {'max_depth': 3, 'n_estimators': 100}, {'max_depth': 3, 'n_estimators':
150}, {'max_depth': 3, 'n_estimators': 200}, {'max_depth': 3, 'n_estimators': 300}, {'max_depth': 3, 'n_estimator
s': 500}, {'max_depth': 4, 'n_estimators': 10}, {'max_depth': 4, 'n_estimators': 50}, {'max_depth': 4, 'n_estimato
rs': 100}, {'max_depth': 4, 'n_estimators': 150}, {'max_depth': 4, 'n_estimators': 200}, {'max_depth': 4, 'n_estim
ators': 300}, {'max_depth': 4, 'n_estimators': 500}, {'max_depth': 5, 'n_estimators': 10}, {'max_depth': 5, 'n_est
imators': 50}, {'max_depth': 5, 'n_estimators': 100}, {'max_depth': 5, 'n_estimators': 150}, {'max_depth': 5, 'n_e
stimators': 200}, {'max_depth': 5, 'n_estimators': 300}, {'max_depth': 5, 'n_estimators': 500}, {'max_depth': 6,
'n_estimators': 10}, {'max_depth': 6, 'n_estimators': 50}, {'max_depth': 6, 'n_estimators': 100}, {'max_depth': 6,
'n_estimators': 150}, {'max_depth': 6, 'n_estimators': 200}, {'max_depth': 6, 'n_estimators': 300}, {'max_depth':
6, 'n_estimators': 500}, {'max_depth': 7, 'n_estimators': 10}, {'max_depth': 7, 'n_estimators': 50}, {'max_depth':
7, 'n_estimators': 100}, {'max_depth': 7, 'n_estimators': 150}, {'max_depth': 7, 'n_estimators': 200}, {'max_dept
h': 7, 'n_estimators': 300}, {'max_depth': 7, 'n_estimators': 500}, {'max_depth': 8, 'n_estimators': 10}, {'max_de
pth': 8, 'n_estimators': 50}, {'max_depth': 8, 'n_estimators': 100}, {'max_depth': 8, 'n_estimators': 150}, {'max
depth': 8, 'n_estimators': 200}, {'max_depth': 8, 'n_estimators': 300}, {'max_depth': 8, 'n_estimators': 500}], 's
plit0_test_score': array([0.69395832, 0.71810755, 0.71346892, 0.71132535, 0.71106531,
    0.70598562, 0.69861679, 0.69949078, 0.71196145, 0.70531101,
    0.70213543, 0.69872829, 0.69140038, 0.68162246, 0.69914266,

```

0.71090676, 0.6959426 , 0.68633261, 0.67948501, 0.68001679,
0.67896937, 0.70077966, 0.69362908, 0.68208925, 0.67661503,
0.67820541, 0.67775064, 0.68027956, 0.69605315, 0.68768353,
0.67998451, 0.67792206, 0.68120187, 0.68653885, 0.69068305,
0.69250687, 0.68206911, 0.67481736, 0.67909237, 0.68199484,
0.68219643, 0.6831277 , 0.67953712, 0.67352996, 0.68099363,
0.68067979, 0.68481935, 0.68744818, 0.6902748]), 'split1_test_score': array([0.68805943, 0.72035708, 0.720
4092 , 0.71932518, 0.71550271,
0.71005917, 0.70722852, 0.69638765, 0.70968039, 0.70791096,
0.70601514, 0.70160993, 0.70194409, 0.69621641, 0.70162523,
0.7071536 , 0.69926315, 0.70017825, 0.69415229, 0.69213238,
0.6950351 , 0.70124655, 0.69368308, 0.68795857, 0.68445675,
0.68353279, 0.68861812, 0.69452211, 0.68918007, 0.68084468,
0.68093014, 0.67713258, 0.68183406, 0.68812253, 0.69422573,
0.69175507, 0.68623293, 0.68493366, 0.68822445, 0.69304526,
0.69881969, 0.70065231, 0.67611144, 0.68652308, 0.69476658,
0.7012378 , 0.7032941 , 0.70401422, 0.70465636]), 'split2_test_score': array([0.70455064, 0.73889752, 0.736
96983, 0.73806219, 0.73704464,
0.73395157, 0.72675117, 0.7113787 , 0.73749791, 0.73415827,
0.73049988, 0.72887479, 0.71849354, 0.70594814, 0.71999454,
0.73184293, 0.72515436, 0.71895926, 0.70773687, 0.69506581,
0.69799195, 0.71445731, 0.71372158, 0.71101331, 0.7107623 ,
0.70243366, 0.70698373, 0.71326186, 0.70746908, 0.70675551,
0.7010349 , 0.6984256 , 0.6985424 , 0.7038377 , 0.70755856,
0.69847519, 0.70390058, 0.69968963, 0.70894814, 0.71036167,
0.71530541, 0.71873959, 0.68989058, 0.69765621, 0.70244421,
0.70580084, 0.70820365, 0.71098166, 0.71205186]), 'split3_test_score': array([0.68635912, 0.72576474, 0.726
46291, 0.72627615, 0.7251878 ,
0.72488224, 0.71729989, 0.69853048, 0.71897963, 0.71393703,
0.70664261, 0.70154895, 0.70141516, 0.69090951, 0.7016917 ,
0.71820053, 0.71769218, 0.71053039, 0.70803916, 0.70439712,
0.70123305, 0.69602163, 0.70923566, 0.7013356 , 0.69778947,
0.69458615, 0.69824602, 0.7012398 , 0.69785436, 0.68946938,
0.68885446, 0.69628721, 0.69738473, 0.70056875, 0.70371552,
0.68871814 , 0.6853211 , 0.693224 , 0.69784434, 0.70212747,
0.70022204, 0.7036521 , 0.69109869, 0.69016227, 0.70064556,
0.70209275, 0.70345279, 0.7071937 , 0.71023221]), 'split4_test_score': array([0.69532227, 0.73925815, 0.738
87674, 0.73606004, 0.73595673,
0.72823766, 0.72260362, 0.707549 , 0.73548491, 0.73478673,
0.72864104, 0.72109836, 0.71498373, 0.70535654, 0.71526754,
0.72847711, 0.71819029, 0.71578648, 0.71399117, 0.70758649,
0.70387451, 0.71575479, 0.7162376 , 0.7074289 , 0.70282101,
0.70786154, 0.70339519, 0.70760614, 0.69583487, 0.70561553,
0.69948506, 0.69892968, 0.70805061, 0.70756495, 0.7109103 ,
0.70654049, 0.68909451, 0.68797014, 0.69423159, 0.70063468,
0.70115045, 0.70499118, 0.69360238, 0.70444954, 0.70751393,
0.71552442, 0.71630531, 0.71590679, 0.72050158]), 'mean_test_score': array([0.69364991, 0.72847631, 0.72723
668, 0.72620896, 0.72495061,
0.72062252, 0.7144992 , 0.70266705, 0.72272008, 0.71921982,
0.71478594, 0.71037132, 0.7056466 , 0.69600982, 0.7075438 ,
0.7193156 , 0.71124778, 0.70635642, 0.70067975, 0.6958388 ,
0.69541997, 0.70565149, 0.70530065, 0.69796429, 0.69448804,
0.69332293, 0.69499789, 0.69938099, 0.69727831, 0.69407313,
0.69005717, 0.68973873, 0.69340184, 0.69732586, 0.70141796,
0.69559869, 0.68932341, 0.68812652, 0.69366768, 0.69763217,
0.69953817, 0.70223185, 0.68604758, 0.69046319, 0.6972719 ,
0.70106597, 0.703214 , 0.70510796, 0.70754236]), 'std_test_score': array([0.00642069, 0.00900704, 0.009664
35, 0.01006455, 0.01048363,
0.01076706, 0.01028378, 0.0057681 , 0.01167125, 0.01276504,
0.01218329, 0.0122279 , 0.00986725, 0.00915645, 0.00842062,
0.00959928, 0.01149811, 0.0118689 , 0.01243405, 0.00975646,
0.0087486 , 0.00794328, 0.00976944, 0.01116584, 0.01237176,
0.01113878, 0.01061068, 0.01142199, 0.00588812, 0.010306 ,
0.008895 , 0.01001375, 0.01038766, 0.00847139, 0.00774675,
0.00631908, 0.00762561, 0.00833153, 0.00993336, 0.00955895,
0.01051641, 0.01139876, 0.00690605, 0.01048544, 0.00910295,
0.01138578, 0.0103415 , 0.00968051, 0.01002029]), 'rank_test_score': array([41, 1, 2, 3, 4, 6, 10, 21,
5, 8, 9, 12, 17, 33, 13, 7, 11,
15, 25, 34, 36, 16, 18, 28, 38, 43, 37, 27, 31, 39, 45, 46, 42, 30,
23, 35, 47, 48, 40, 29, 26, 22, 49, 44, 32, 24, 20, 19, 14]), 'split0_train_score': array([0.71451286, 0.77
904834, 0.81819727, 0.84466455, 0.86648696,
0.89990607, 0.94453225, 0.74127991, 0.83226039, 0.89145469,
0.9297588 , 0.95303642, 0.9822931 , 0.99855967, 0.77372333,
0.89920479, 0.96112405, 0.98682374, 0.99655403, 0.99994475,
1. , 0.81616699, 0.95780666, 0.99606387, 0.99980673,
0.9999998 , 1. , 1. , 0.86189666, 0.99281108,
0.99997327, 1. , 1. , 1. , 1. ,
0.91707326, 0.99961694, 1. , 1. , 1. ,
1. , 1. , 0.95900738, 1. , 1. ,
1. , 1. , 1. , 1. , 1. ,]), 'split1_train_score': array([0.71484358, 0.77963573, 0.81
558084, 0.84448199, 0.86579238,
0.89906128, 0.94167678, 0.74078425, 0.83304802, 0.88927032,
0.92623826, 0.9511994 , 0.98057051, 0.99810786, 0.77345671,
0.89655948, 0.95933358, 0.98416974, 0.99556119, 0.99987168,
1. , 0.81721994, 0.95987974, 0.99486424, 0.99977276,
0.99999963, 1. , 1. , 0.87268482, 0.9923069 ,
0.99996023, 1. , 1. , 1. , 1. ,

```

0.92064803, 0.9997864, 1., 1., 1.,
1., 1., 0.96230299, 1., 1.,
1., 1., 1., 1., ], 'split2_train_score': array([0.71237402, 0.77475462, 0.80
980637, 0.8367689, 0.85865921,
0.893782, 0.93902028, 0.73304956, 0.82664083, 0.88347827,
0.92013324, 0.94827031, 0.97782929, 0.99792408, 0.76766856,
0.89473109, 0.95963654, 0.9874216, 0.99630616, 0.99990845,
1., 0.81330602, 0.9578445, 0.99529985, 0.99980444,
0.99999446, 1., 1., 0.86954316, 0.99014862,
0.99998434, 1., 1., 1., 1.,
0.91506876, 0.99975867, 1., 1., 1.,
1., 1., 0.95570732, 1., 1.,
1., 1., 1., 1., ], 'split3_train_score': array([0.71110998, 0.77845069, 0.81
395312, 0.83985987, 0.86163775,
0.8948691, 0.93990326, 0.74184056, 0.82811902, 0.88524879,
0.92350375, 0.95042936, 0.9807449, 0.99824743, 0.7723717,
0.89087095, 0.95854993, 0.98641276, 0.99630932, 0.99982632,
1., 0.81022696, 0.95724189, 0.99505976, 0.9997571,
0.99999938, 1., 1., 0.86075956, 0.9911833,
0.99998839, 1., 1., 1., 1.,
0.91783543, 0.99964286, 1., 1., 1.,
1., 1., 0.95482579, 0.99999982, 1.,
1., 1., 1., 1., ], 'split4_train_score': array([0.70906486, 0.77535367, 0.81
178455, 0.83969212, 0.8620944,
0.8953129, 0.93941314, 0.73490567, 0.82471515, 0.88309477,
0.92162076, 0.94742159, 0.97869221, 0.99769044, 0.76884441,
0.89384502, 0.9612552, 0.98625601, 0.99599612, 0.99989068,
1., 0.81260391, 0.95395875, 0.99424215, 0.9997804,
0.99999949, 1., 1., 0.86463324, 0.99088261,
0.99999054, 1., 1., 1., 1.,
0.91263698, 0.99971163, 1., 1., 1.,
1., 1., 0.95808246, 0.99999947, 1.,
1., 1., 1., 1., ], 'mean_train_score': array([0.71238106, 0.77744861, 0.8138
6443, 0.84109348, 0.86293414,
0.89658627, 0.94090914, 0.73837199, 0.82895668, 0.88650937,
0.92425096, 0.95007142, 0.980026, 0.9981059, 0.77121294,
0.89504227, 0.95997986, 0.98621677, 0.99614536, 0.99988838,
1., 0.81390476, 0.95734631, 0.99510597, 0.99978429,
0.99999855, 1., 1., 0.86590349, 0.9914665,
0.99997936, 1., 1., 1., 1.,
0.91665249, 0.9997033, 1., 1., 1.,
1., 1., 0.95798519, 0.99999986, 1.,
1., 1., 1., 1., ], 'std_train_score': array([2.15506039e-03, 1.99965925e-03,
2.91620398e-03, 3.04703694e-03,
2.87933555e-03, 2.43231617e-03, 2.02651154e-03, 3.65101486e-03,
3.21586360e-03, 3.30197153e-03, 3.42687924e-03, 2.02273726e-03,
1.58477584e-03, 2.93804298e-04, 2.48402284e-03, 2.77699953e-03,
1.05032424e-03, 1.10002890e-03, 3.41548585e-04, 3.92843115e-05,
0.00000000e+00, 2.51734265e-03, 1.91650103e-03, 5.93619086e-04,
1.89590610e-05, 2.05097865e-06, 0.00000000e+00, 4.96506831e-17,
4.54668998e-03, 9.66657656e-04, 1.12659233e-05, 0.00000000e+00,
0.00000000e+00, 4.96506831e-17, 0.00000000e+00, 2.68972896e-03,
6.50417130e-05, 0.00000000e+00, 0.00000000e+00, 4.96506831e-17,
0.00000000e+00, 0.00000000e+00, 2.64076641e-03, 2.05400553e-07,
0.00000000e+00, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
0.00000000e+00]))}

```

```

In [208]: import seaborn as sns; sns.set()
max_scores4 = pd.DataFrame(set4.cv_results_).groupby(['param_n_estimators', 'param_max_depth']).max().unstack()
max_scores4

```

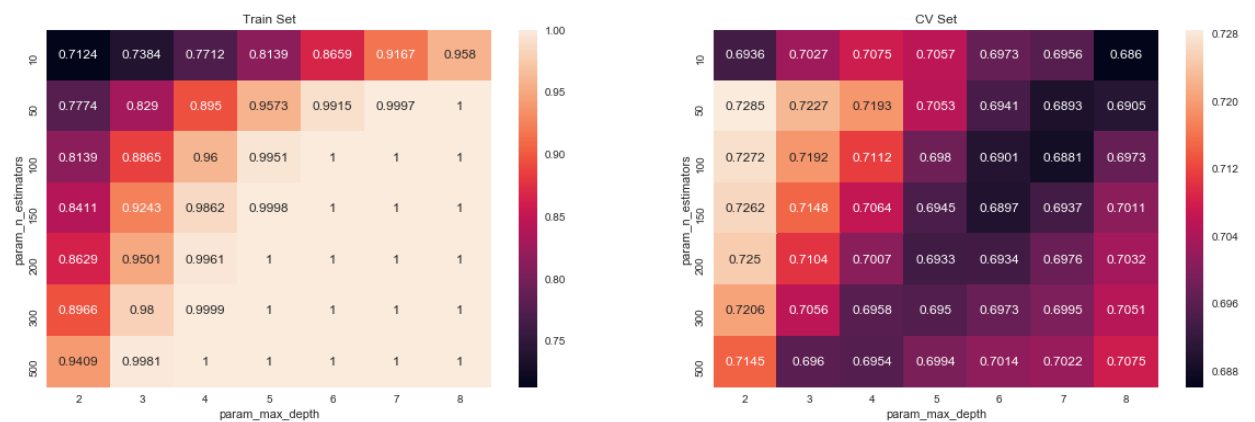
Out[208]:

	mean_fit_time							mean_score_time			...
param_max_depth	2	3	4	5	6	7	8	2	3	4	...
param_n_estimators											
10	19.484696	21.879489	25.212973	28.155896	31.757265	37.599645	38.200841	2.048722	1.835891	2.086820	...
50	47.377094	63.261017	87.678519	96.450469	112.169033	135.896657	146.431002	1.977114	2.131501	2.767399	...
100	82.383686	113.891022	148.819622	179.767858	213.445597	265.129466	280.421888	2.189744	2.141075	2.130702	...
150	117.455496	165.123812	213.881830	263.819686	315.748210	427.362478	404.294417	2.092007	2.064879	2.194332	...
200	152.825708	215.845778	284.803762	350.348089	416.359958	501.195562	520.811822	2.074054	2.134493	2.577308	...
300	223.175377	317.341955	417.312213	518.701074	616.971085	701.856296	737.967906	2.093601	2.188348	2.166008	...
500	364.706484	521.854242	687.812632	851.947499	1080.463430	1079.950567	1112.168203	2.145463	2.230237	2.246593	...

7 rows × 140 columns



```
In [209]: fig, ax = plt.subplots(1,2, figsize=(20,6))
sns.heatmap(max_scores4.mean_train_score, annot = True, fmt='.4g', ax=ax[0])
sns.heatmap(max_scores4.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 [210]: print(set4.best_estimator_)

XGBClassifier(base_score=0.5, booster=None, class_weight='balanced',
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              gamma=0, gpu_id=-1, importance_type='gain',
              interaction_constraints=None, learning_rate=0.300000012,
              max_delta_step=0, max_depth=2, min_child_weight=1, missing=nan,
              monotone_constraints=None, n_estimators=50, n_jobs=0,
              num_parallel_tree=1, objective='binary:logistic', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method=None, validate_parameters=False, verbosity=None)
```

```
In [211]: max_d = set4.best_params_['max_depth']
n_est = set4.best_params_['n_estimators']
```

Training our model with best Hyperparameters

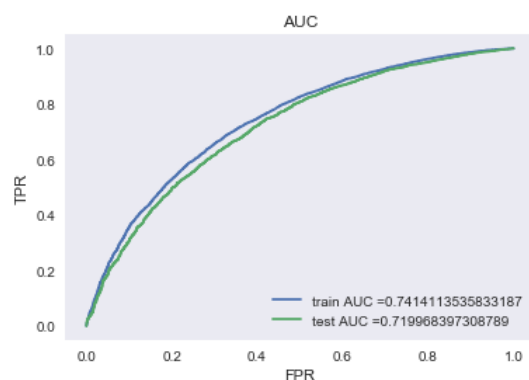
```
In [212]: # https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve.html#sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import GradientBoostingClassifier
model = GradientBoostingClassifier(max_depth = max_d , n_estimators = n_est)

model.fit(X_tr_TFIDF_W2V, y_train)

y_train_pred = pred_prob(model,X_tr_TFIDF_W2V)
y_test_pred = pred_prob(model,X_te_TFIDF_W2V)

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

plt.close
plt.plot(train_fpr, train_tpr, label="train AUC =" +str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC =" +str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("AUC")
plt.grid()
plt.show()
```



Confusion Matrix

```
In [213]: #our objective here is to make auc the maximum
#so we find the best threshold that will give the least fpr
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
```

the maximum value of $tpr \cdot (1 - fpr)$ 0.46242484499602293 for threshold 0.839
Train confusion matrix
[[3140 1504]
 [8062 17444]]

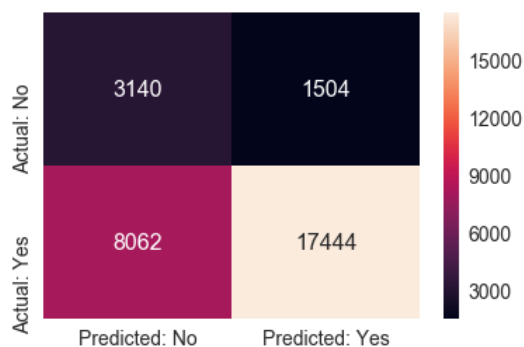
```
In [214]: #plotting confusion matrix using seaborn's heatmap
# https://stackoverflow.com/questions/35572000/how-can-i-plot-a-confusion-matrix

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

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

Train data confusion matrix

Out[214]: <matplotlib.axes._subplots.AxesSubplot at 0x2c399f1c8a8>



```
In [215]: print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

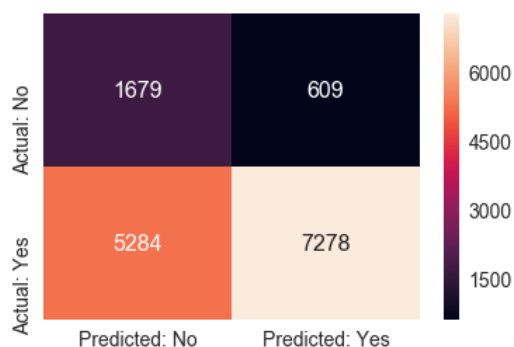
Test confusion matrix
[[1679 609]
 [5284 7278]]

```
In [216]: print("Test data confusion matrix")

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

Test data confusion matrix

Out[216]: <matplotlib.axes._subplots.AxesSubplot at 0x2c399eae00>



In []:

3. Conclusion

```
In [ ]: # Please compare all your models using Prettytable Library
```

```
In [217]: # Please compare all your models using Prettytable Library

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

from prettytable import PrettyTable

#If you get a ModuleNotFoundError error , install prettytable using: pip3 install prettytable

x = PrettyTable()
x.field_names = ["Vectorizer", "Model", "Hyperparameters(n_estimators,max_depth)", "Test AUC"]

x.add_row(["BOW", "RF", "(500, 8)", 0.698])
x.add_row(["TFIDF", "RF", "(500, 8)", 0.702])
x.add_row(["AVG W2V", "RF", "(500, 7)", 0.705])
x.add_row(["TFIDF W2V", "RF", "(500, 7)", 0.706])

x.add_row(["-----", "----", "-----", "-----"])

x.add_row(["BOW", "GBDT", "(200, 2)", 0.741])
x.add_row(["TFIDF", "GBDT", "(150, 2)", 0.738])
x.add_row(["AVG W2V", "GBDT", "(100, 2)", 0.728])
x.add_row(["TFIDF W2V", "GBDT", "(50, 2)", 0.719])

print(x)
```

Vectorizer	Model	Hyperparameters(n_estimators,max_depth)	Test AUC
BOW	RF	(500, 8)	0.698
TFIDF	RF	(500, 8)	0.702
AVG W2V	RF	(500, 7)	0.705
TFIDF W2V	RF	(500, 7)	0.706
-----	----	-----	-----
BOW	GBDT	(200, 2)	0.741
TFIDF	GBDT	(150, 2)	0.738
AVG W2V	GBDT	(100, 2)	0.728
TFIDF W2V	GBDT	(50, 2)	0.719

In []: