DonorsChoose

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

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

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

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

About the DonorsChoose Data Set

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

Feature	Description				
project_id	A unique identifier for the proposed project. Example: p036502				
	Title of the project. Examples:				
project_title	Art Will Make You Happy!				
	• First Grade Fun				
	Grade level of students for which the project is targeted. One of the following enumerated values:				
project grade category	• Grades PreK-2				
project_grade_category	• Grades 3-5				
	• Grades 6-8				
	• Grades 9-12				
	One or more (comma-separated) subject categories for the project from the following enumerated list of values:				
	Applied Learning				
	• Care & Hunger				
	• Health & Sports				
	History & Civics				
	• Literacy & Language				
project_subject_categories	• Math & Science				
	• Music & The Arts				
	• Special Needs				
	• Warmth				
	Examples:				
	• Music & The Arts				
	• Literacy & Language, Math & Science				
school_state	State where school is located (<u>Two-letter U.S. postal code</u>). Example				
	One or more (comma-separated) subject subcategories for the project				
project_subject_subcategories	Examples:				
	• Literacy				

Feature	• Literature & Writing, Social Sciences Description				
project_resource_summary	An explanation of the resources needed for the project. Example: • My students need hands on literacy materials to manage sensory needs!				
project_essay_1	First application essay*				
project_essay_2	Second application essay*				
project_essay_3	Third application essay*				
project_essay_4	Fourth application essay*				
project_submitted_datetime	Datetime when project application was submitted. Example: 2016–04–28 12:43:56.245				
teacher_id	A unique identifier for the teacher of the proposed project. Example: bdf8baa8fedef6bfeec7ae4ff1c15c56				
teacher_prefix	Teacher's title. One of the following enumerated values: • nan • Dr. • Mr. • Mrs. • Ms. • Teacher.				
teacher_number_of_previously_posted_projects	Number of project applications previously submitted by the same teacher. Example: 2				

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

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

Feature	Description			
id	A project_id value from the train.csv file. Example: p036502			
description Desciption of the resource. Example: Tenor Saxophone Reeds, E				
quantity	Quantity of the resource required. Example: 3			
price	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
project is approved	A binary flag indicating whether DonorsChoose approved the project. A value of 0 indicates the project
project_is_approve	was not approved, and a value of 1 indicates the project was approved.

Notes on the Essay Data

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

- __project_essay_1:__ "Introduce us to your classroom"
- __project_essay_2:__ "Tell us more about your students"
- __project_essay_3:__ "Describe how your students will use the materials you're requesting"
- __project_essay_4:__ "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."

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 __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 plotly import plotly
import plotly.offline as offline
import plotly.graph_objs as go
offline.init notebook mode()
from collections import Counter
from google.colab import drive
drive.mount('/content/gdrive')
/usr/local/lib/python3.6/dist-packages/smart open/ssh.py:34: UserWarning: paramiko missing, openin
g SSH/SCP/SFTP paths will be disabled. `pip install paramiko` to suppress
 warnings.warn('paramiko missing, opening SSH/SCP/SFTP paths will be disabled. `pip install
paramiko` to suppress')
```

Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6 qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0% b&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fww ogleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fww ogleapis.com%2Fauth%2Fdrive.photos.photos.photos.photos.photos.photos.pho

```
Enter your authorization code:
.....
Mounted at /content/gdrive
```

1.1 Reading Data

```
In [0]:
```

```
project_data = pd.read_csv('gdrive/My Drive/train_data.csv')
```

```
In [0]:
project_data.columns

In [0]:
project_data[0:2000]['project_is_approved'].value_counts()

In [0]:
project_data[0:4000]['project_is_approved'].value_counts()

In [0]:
project_data[0:4000]['project_is_approved'].value_counts()

In [0]:
print("Number of data points in train data", project_data.shape)
print('-'*50)
print("The attributes of data :", project_data.columns.values)

In [0]:
print("Number of data points in train data", resource_data.shape)
print("Sumber of data points in train data", resource_data.shape)
print(resource_data.columns.values)
resource_data.head(2)
```

1.2 Data Analysis

```
# PROVIDE CITATIONS TO YOUR CODE IF YOU TAKE IT FROM ANOTHER WEBSITE.
# https://matplotlib.org/gallery/pie_and_polar_charts/pie_and_donut_labels.html#sphx-glr-gallery-p
ie-and-polar-charts-pie-and-donut-labels-py
y value counts = project data['project is approved'].value counts()
print("Number of projects thar are approved for funding ", y_value_counts[1], ", (",
(y_value_counts[1]/(y_value_counts[1]+y_value_counts[0]))*100,"%)")
print("Number of projects thar are not approved for funding ", y_value_counts[0], ", (",
(y\_value\_counts[0]/(y\_value\_counts[1]+y\_value\_counts[0]))*100,"%)")
fig, ax = plt.subplots(figsize=(6, 6), subplot kw=dict(aspect="equal"))
recipe = ["Accepted", "Not Accepted"]
data = [y_value_counts[1], y_value_counts[0]]
wedges, texts = ax.pie(data, wedgeprops=dict(width=0.5), startangle=-40)
bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
kw = dict(xycoords='data', textcoords='data', arrowprops=dict(arrowstyle="-"),
         bbox=bbox_props, zorder=0, va="center")
for i, p in enumerate(wedges):
   ang = (p.theta2 - p.theta1)/2. + p.theta1
    y = np.sin(np.deg2rad(ang))
    x = np.cos(np.deg2rad(ang))
   horizontalalignment = {-1: "right", 1: "left"}[int(np.sign(x))]
    connectionstyle = "angle, angleA=0, angleB={}".format(ang)
    kw["arrowprops"].update({"connectionstyle": connectionstyle})
    ax.annotate(recipe[i], xy=(x, y), xytext=(1.35*np.sign(x), 1.4*y),
                 horizontalalignment=horizontalalignment, **kw)
ax.set title("Nmber of projects that are Accepted and not accepted")
plt.show()
```

- 2.The above pie chart shows the percentage of projects which are approved in Blue which is 84.85830404217927 % and the percentage of projects which are not approved in Orange which is 15.141695957820739 %.\
- 3.We calculated approved and not approved projects using y_value_counts which gives details of no.of.projects submitted and how many of them are approved and not approved

1.2.1 Univariate Analysis: School State

In [0]:

```
# Pandas dataframe groupby count, mean: https://stackoverflow.com/a/19385591/4084039
temp = pd.DataFrame(project_data.groupby("school_state")
["project is approved"].apply(np.mean)).reset index()
# if you have data which contain only 0 and 1, then the mean = percentage (think about it)
temp.columns = ['state_code', 'num_proposals']
'''# How to plot US state heatmap: https://datascience.stackexchange.com/a/9620
scl = [[0.0, 'rgb(242,240,247)'], [0.2, 'rgb(218,218,235)'], [0.4, 'rgb(188,189,220)'], [0.4, 'rgb(1
                                [0.6, 'rgb(158,154,200)'],[0.8, 'rgb(117,107,177)'],[1.0, 'rgb(84,39,143)']]
data = [ dict(
                    type='choropleth',
                   colorscale = scl,
                    autocolorscale = False,
                    locations = temp['state_code'],
                    z = temp['num proposals'].astype(float),
                    locationmode = 'USA-states',
                    text = temp['state code'],
                   marker = dict(line = dict(color = 'rgb(255,255,255)', width = 2)),
                    colorbar = dict(title = "% of pro")
layout = dict(
                    title = 'Project Proposals % of Acceptance Rate by US States',
                    geo = dict(
                               scope='usa',
                               projection=dict( type='albers usa' ),
                               showlakes = True,
                               lakecolor = 'rgb(255, 255, 255)',
                    ),
fig = go.Figure(data=data, layout=layout)
offline.iplot(fig, filename='us-map-heat-map')
```

In [0]:

```
# https://www.csi.cuny.edu/sites/default/files/pdf/administration/ops/2letterstabbrev.pdf
temp.sort_values(by=['num_proposals'], inplace=True)
print("States with lowest % approvals")
print(temp.head(5))
print('='*50)
print("States with highest % approvals")
print(temp.tail(5))
```

```
#stacked bar plots matplotlib:
https://matplotlib.org/gallery/lines_bars_and_markers/bar_stacked.html

def stack_plot(data, xtick, col2='project_is_approved', col3='total'):
    ind = np.arange(data.shape[0])

    plt.figure(figsize=(20,5))
    pl = plt.bar(ind, data[col3].values)
    p2 = plt.bar(ind, data[col2].values)

    plt.ylabel('Projects')
    plt.title('Number of projects aproved vs rejected')
    plt.xticks(ind, list(data[xtick].values))
```

```
plt.legend((p1[0], p2[0]), ('total', 'accepted'))
plt.show()
```

```
def univariate barplots(data, col1, col2='project is approved', top=False):
   {\it \# Count number of zeros in data frame python: https://stackoverflow.com/a/51540521/4084039}
   temp = pd.DataFrame(project data.groupby(col1)[col2].agg(lambda x: x.eq(1).sum())).reset index(
    # Pandas dataframe grouby count: https://stackoverflow.com/a/19385591/4084039
   temp['total'] = pd.DataFrame(project data.groupby(col1)
[col2].agg({'total':'count'})).reset_index()['total']
   temp['Avg'] = pd.DataFrame(project data.groupby(col1)[col2].agg({'Avg':'mean'})).reset index()[
'Avg']
   temp.sort values(by=['total'],inplace=True, ascending=False)
   if top:
       temp = temp[0:top]
   stack plot(temp, xtick=col1, col2=col2, col3='total')
   print(temp.head(5))
   print("="*50)
   print(temp.tail(5))
univariate barplots(project data, 'school state', 'project is approved', False)
```

1.we calculated no.of.projects submitted per each state and calculated how many of them are approved and rejected from that state

2.we made a barplot of how many total projects are submitted from each state and how many are accepted and rejected from that state

- 3.We calculated acceptance rate which is perentage of projects submitted and accepted and rejected from particular state and we sorted the acceptance rate
- 1. projects from CA have been accepted and rejected more

SUMMARY: Every state has greater than 80% success rate in approval

1.2.2 Univariate Analysis: teacher_prefix

```
In [0]:
```

```
univariate_barplots(project_data, 'teacher_prefix', 'project_is_approved' , top=False)
```

- 1.based on the prefixe's of the teacher's who submitted projects, we calculated what are the total no.of.projects submitted by a teacher of particular prefix and what is the approval rate that that project is approved.
- 2.we calculated the approval rate of project acceptance of a teacher of a particular prefix
- 3.projects submitted by teacher of prefix-MRS are accepted more
- 4.no.of.projects approved and rejected by teacher of certain specific prefix

1.2.3 Univariate Analysis: project_grade_category

```
In [0]:
```

```
univariate_barplots(project_data, 'project_grade_category', 'project_is_approved', top=False)
```

1.we calculated the acceptance rate based on the grades of projects submitted and how many are accepted and rejected from that specific grade

2.projects from Grade preK-2 are submitted more

1.2.4 Univariate Analysis: project_subject_categories

```
In [0]:
```

```
catogories = list(project data['project subject categories'].values)
# remove special characters from list of strings python:
https://stackoverflow.com/a/47301924/4084039
# https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
# https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
# https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python
cat list = []
for i in catogories:
    temp = ""
    # consider we have text like this "Math & Science, Warmth, Care & Hunger"
    for j in i.split(','): # it will split it in three parts ["Math & Science", "Warmth", "Care & E
unger"
       if 'The' in j.split(): # this will split each of the catogory based on space "Math & Science
e"=> "Math", "&", "Science"
           j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i
.e removing 'The')
        j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math &
Science"=>"Math&Science"
       temp+=j.strip()+" " #" abc ".strip() will return "abc", remove the trailing spaces
        temp = temp.replace('&','_') # we are replacing the & value into
    cat list.append(temp.strip())
4
In [0]:
```

```
project data['clean categories'] = cat list
project_data.drop(['project subject categories'], axis=1, inplace=True)
project_data.head(2)
```

In [0]:

```
univariate barplots(project data, 'clean categories', 'project is approved', top=20)
```

- 1. projects from literacy language subcategories have been acceptd more
- 2. we calculated projects submitted of a specific sub-category
- 3. We calculated what are the total no.of.projets submitted from specific catgory and how many are accepted and rejected from that category

In [0]:

```
# count of all the words in corpus python: https://stackoverflow.com/a/22898595/4084039
from collections import Counter
my counter = Counter()
for word in project data['clean categories'].values:
   my counter.update(word.split())
```

In [0]:

```
# dict sort by value python: https://stackoverflow.com/a/613218/4084039
cat dict = dict(my counter)
sorted cat dict = dict(sorted(cat dict.items(), key=lambda kv: kv[1]))
ind = np.arange(len(sorted cat dict))
plt.figure(figsize=(20,5))
p1 = plt.bar(ind, list(sorted cat dict.values()))
plt.ylabel('Projects')
plt.title('% of projects aproved category wise')
plt.xticks(ind, list(sorted cat dict.keys()))
plt.show()
```

We calculated how many projected are approved from a specific categoryand we do plot how many are rejected and how many are submitted

```
In [0]:
```

```
for i, j in sorted_cat_dict.items():
    print("{:20} :{:10}".format(i,j))
```

1.2.5 Univariate Analysis: project_subject_subcategories

```
In [0]:
```

```
sub catogories = list(project data['project subject subcategories'].values)
# remove special characters from list of strings python:
https://stackoverflow.com/a/47301924/4084039
# https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
# https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-from-a-string
# https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-string-in-python
sub cat list = []
for i in sub catogories:
    temp = ""
    # consider we have text like this "Math & Science, Warmth, Care & Hunger"
    for j in i.split(','): # it will split it in three parts ["Math & Science", "Warmth", "Care & L
unger"1
        if 'The' in j.split(): # this will split each of the catogory based on space "Math & Science
e"=> "Math","&", "Science"
            j=j.replace('The','') # if we have the words "The" we are going to replace it with ''(i
.e removing 'The')
       j = j.replace(' ','') # we are placeing all the ' '(space) with ''(empty) ex:"Math &
Science"=>"Math&Science"
        temp +=j.strip()+" "#" abc ".strip() will return "abc", remove the trailing spaces
       temp = temp.replace('&',' ')
    sub cat list.append(temp.strip())
```

In [0]:

```
project_data['clean_subcategories'] = sub_cat_list
project_data.drop(['project_subject_subcategories'], axis=1, inplace=True)
project_data.head(2)
```

In [0]:

```
univariate_barplots(project_data, 'clean_subcategories', 'project_is_approved', top=50)
```

1. how many projects are submitted of a particular sub_category and how many are approved and rejected.

2.literacy sub_category are submitted more and are accepted more

```
In [0]:
```

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

```
# dict sort by value python: https://stackoverflow.com/a/613218/4084039
sub_cat_dict = dict(my_counter)
sorted_sub_cat_dict = dict(sorted(sub_cat_dict.items(), key=lambda kv: kv[1]))

ind = np.arange(len(sorted_sub_cat_dict))
plt.figure(figsize=(20,5))
pl = plt.bar(ind, list(sorted_sub_cat_dict.values()))

plt.ylabel('Projects')
plt.title('% of projects aproved state wise')
```

```
plt.xticks(ind, list(sorted_sub_cat_dict.keys()))
plt.show()
```

- 1. total no.of.projects approved for a specific sub_category
- 2. Literacy subcategory projects are accepted more

```
In [0]:
```

```
for i, j in sorted_sub_cat_dict.items():
    print("{:20} :{:10}".format(i,j))
```

1.2.6 Univariate Analysis: Text features (Title)

```
In [0]:
```

```
#How to calculate number of words in a string in DataFrame:
https://stackoverflow.com/a/37483537/4084039
word_count = project_data['project_title'].str.split().apply(len).value_counts()
word_dict = dict(word_count)
word_dict = dict(sorted(word_dict.items(), key=lambda kv: kv[1]))

ind = np.arange(len(word_dict))
plt.figure(figsize=(20,5))
pl = plt.bar(ind, list(word_dict.values()))

plt.ylabel('Numeber of projects')
plt.xlabel('Numeber words in project title')
plt.title('Words for each title of the project')
plt.xticks(ind, list(word_dict.keys()))
plt.show()
```

1.No.of.words in the project title and are the projects accepted based oon no.of.words in project title

2project title with more no.of.words are accepted more

```
In [0]:
```

```
approved_title_word_count = project_data[project_data['project_is_approved']==1]['project_title'].
str.split().apply(len)
approved_title_word_count = approved_title_word_count.values

rejected_title_word_count = project_data[project_data['project_is_approved']==0]['project_title'].
str.split().apply(len)
rejected_title_word_count = rejected_title_word_count.values
```

In [0]:

```
word_count_titles = project_data['project_title'].str.split().apply(len)
word_count_titles = word_count_titles.values
print(word_count_titles)
```

In [0]:

```
# https://glowingpython.blogspot.com/2012/09/boxplot-with-matplotlib.html
plt.boxplot([approved_title_word_count, rejected_title_word_count])
plt.xticks([1,2],('Approved Projects','Rejected Projects'))
plt.ylabel('Words in project title')
plt.grid()
plt.show()
```

We created a box plot for numerical data fo approved projects and rejected projects under project_title category

we found few outliers for approved projects and rejected projects

we found the lqr range for approved projects and rejected projects and found the range for approved projects under project title

category is High and the for rejected projects is low.

The mean for approved projects and rejected projects is Same though the IQR range is different.

In [0]:

```
plt.figure(figsize=(10,3))
sns.kdeplot(approved_title_word_count,label="Approved Projects", bw=0.6)
sns.kdeplot(rejected_title_word_count,label="Not Approved Projects", bw=0.6)
plt.legend()
plt.show()
```

We plotted the PDF curve for numerical data of approved projects and rejected projects under project_title category

the PDF for both is almost similar both approved and rejected projects Numerical data under project title category

The PDF will be calcuated based on the distribution of data which is Gaussian distribution for both approved and rejected projects numerical data under project_title category

Approved and rejected projects numerical data do follow gaussian distribution as the PDF for both is Gaussian curve

we can say whether the project will be accepted or rejected based on no.of.words present in the project title as PDF is almost same for both which gives the probability whither the project is accepted or rejected.

So we do need other few features To predict whether the project will be accepted or rejected

1.2.7 Univariate Analysis: Text features (Project Essay's)

In [0]:

In [0]:

In [0]:

```
word_count_essays = project_data['essay'].str.split().apply(len)
word_count_essays = word_count_essays.values
print(word_count_essays)
```

In [0]:

```
word_count_resource_summary = project_data['project_resource_summary'].str.split().apply(len)
word_count_resource_summary = word_count_resource_summary.values
print(word_count_resource_summary)
```

```
# https://glowingpython.blogspot.com/2012/09/boxplot-with-matplotlib.html
plt.boxplot([approved_word_count, rejected_word_count])
plt.title('Words for each essay of the project')
plt.xticks([1,2], ('Approved Projects', 'Rejected Projects'))
plt.ylabel('Words in project essays')
plt.grid()
plt.show()
```

We calculated boxplots for Approved projects and rejected projects on no.of.words present in essay

There are many outliers for both numerical data

The numerical data is whether the project is approved and rejected based on no.of.words present in the essay.

there many outliers for approved and rejected projects data on no.of.words present in essay

The IQR and median is almost similar for both approved and rejected data under no.of.words present in essay.

In [0]:

```
plt.figure(figsize=(10,3))
sns.distplot(approved_word_count, hist=False, label="Approved Projects")
sns.distplot(rejected_word_count, hist=False, label="Not Approved Projects")
plt.title('Words for each essay of the project')
plt.xlabel('Number of words in each eassay')
plt.legend()
plt.show()
```

We plotted the PDF curve for numerical data of approved projects and rejected projects under no.of.words present in the essay category.

the PDF for both is almost similar both approved and rejected projects Numerical data under no.of.words present in the essay category

The PDF will be calcuated based on the distribution of data which is Gaussian distribution for both approved and rejected projects numerical data under no.of.words present in the essay category

Approved and rejected projects numerical data under no.of.words present in the essay do follow gaussian distribution as the PDF for both is Gaussian curve

we cann say whether the project will be accepted or rejected based on no.of.words present in the essay as PDF is almost same for both which gives the probability whither the project is accepted or rejected.

So we do need other few features To predict whether the project will be accepted or rejected

1.2.8 Univariate Analysis: Cost per project

```
In [0]:
```

```
# we get the cost of the project using resource.csv file
resource_data.head(2)
```

```
In [0]:
```

```
# https://stackoverflow.com/questions/22407798/how-to-reset-a-dataframes-indexes-for-all-groups-in
-one-step
price_data = resource_data.groupby('id').agg({'price':'sum', 'quantity':'sum'}).reset_index()
price_data.head(2)
```

```
In [0]:
```

```
# join two dataframes in python:
project_data = pd.merge(project_data, price_data, on='id', how='left')
```

In [0]:

```
approved_price = project_data[project_data['project_is_approved']==1]['price'].values
rejected_price = project_data[project_data['project_is_approved']==0]['price'].values
```

```
# https://glowingpython.blogspot.com/2012/09/boxplot-with-matplotlib.html
plt.boxplot([approved_price, rejected_price])
plt.title('Box Plots of Cost per approved and not approved Projects')
plt.xticks([1,2],('Approved Projects','Rejected Projects'))
plt.vlabel('Price')
```

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

We calculated boxplots for Approved projects and rejected projects based on the price of project

There are many outliers for both numerical data for approved and rejected projects based on the price of project

The numerical data is whether the project is approved and rejected based on the price of project

there too many outliers for approved and rejected projects data based on the price of project and the IQR rane is too small for the data. As there are to many outliers in the data We could normalize and standard them to scale them under a certain range

The IQR and median is almost similar for both approved and rejected data based on the price of project.

In [0]:

```
plt.figure(figsize=(10,3))
sns.distplot(approved_price, hist=False, label="Approved Projects")
sns.distplot(rejected_price, hist=False, label="Not Approved Projects")
plt.title('Cost per approved and not approved Projects')
plt.xlabel('Cost of a project')
plt.legend()
plt.show()
```

We plotted the PDF curve for numerical data of approved projects and rejected projects based on the price of project and the plot do not follow PDF-Gaussian distribution as the graph increases and decreases linearly at a particular peak

the curve for both is almost similar both approved and rejected projects Numerical data based on the price of project

Approved and rejected projects numerical data based on the price of project do not follow gaussian distribution as the curve is linear .

we can say whether the project will be accepted or rejected based on the price of project as PDF which gives the probability whther the project is accepted or rejected but here the curve is linear, its difficult to calculate whether the project will be calculated or rejected.

So we do need other few features To predict whether the project will be accepted or rejected

In [0]:

```
# 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 = ["Percentile", "Approved Projects", "Not Approved Projects"]

for i in range(0,101,5):
    x.add_row([i,np.round(np.percentile(approved_price,i), 3), np.round(np.percentile(rejected_price,i), 3)])
print(x)
```

Here we created a table and calculated the percentiles for the approved and rejected data based on the price of project

We can say that the percentiles are larger for rejected projects as the price is high for rejected projects when compared to same percentile of approved projects

1.2.9 Univariate Analysis: teacher_number_of_previously_posted_projects

```
project_data['teacher_number_of_previously_posted_projects'].head(10)
approved_ppp = project_data[project_data['project_is_approved']==1]
['teacher_number_of_previously_posted_projects'].values
rejected_ppp = project_data[project_data['project_is_approved']==0]
['teacher_number_of_previously_posted_projects'].values
```

```
plt.boxplot([approved_ppp, rejected_ppp])
plt.title('Box Plots of Cost per approved and not approved Projects')
plt.xticks([1,2],('Approved Projects','Rejected Projects'))
plt.ylabel('teacher_number_of_previously_posted_projects')
plt.grid()
plt.show()
```

We calculated boxplots for Approved projects and rejected projects based on No.of.previously posted projects by a teacher

There are many outliers for both numerical data for approved and rejected projects based on No.of.previously posted projects by a teacher

The numerical data is whether the project is approved and rejected based on No.of.previously posted projects by a teacher

there too many outliers for approved and rejected projects data based on No.of.previously posted projects by a teacher and the IQR rane is too small for the data. As there are to many outliers in the data We could normalize and standard them to scale them under a certain range

The IQR and median is almost similar for both approved and rejected data No.of.previously posted projects by a teacher

```
In [0]:
```

```
x = PrettyTable()
x.field_names = ["Percentile", "Approved Projects", "Not Approved Projects"]

for i in range(0,101,5):
    x.add_row([i,np.round(np.percentile(approved_ppp,i), 3), np.round(np.percentile(rejected_ppp,i), 3)])
print(x)
```

Here we created a table and calculated the percentiles for the approved and rejected data No.of.previously posted projects by a teacher

The No.of.previously posted projects by a teacher are very less for a smaller range and more for a larger range

This means large no.of. teachers posted large no.of. projects previously and few no.of.teachers posted few no.of.projects previously.

```
In [0]:
```

```
plt.figure(figsize=(10,3))
sns.distplot(approved_ppp, hist=False, label="Approved Projects")
sns.distplot(rejected_ppp, hist=False, label="Not Approved Projects")
plt.title('Cost per approved and not approved Projects')
plt.xlabel('Cost of a project')
plt.legend()
plt.show()
```

We plotted the PDF curve for numerical data of approved projects and rejected projects No.of.previously posted projects by a teacher and the plot do not follow PDF-Gaussian distribution as the graph increases and decreases linearly at a particular peak

the curve for both is almost similar both approved and rejected projects Numerical data No.of.previously posted projects by a teacher

Approved and rejected projects numerical data No.of.previously posted projects by a teacher do not follow gaussian distribution as the curve is linear .

we can say whether the project will be accepted or rejected No.of.previously posted projects by a teacher as PDF which gives the probability whther the project is accepted or rejected but here the curve is linear, its difficult to calculate whether the project will be calculated or rejected.

So we do need other few features To predict whether the project will be accepted or rejected

1.2.10 Univariate Analysis: project_resource_summary

Please do this on your own based on the data analysis that was done in the above cells

Check if the presence of the numerical digits in the project_resource_summary effects the acceptance of the project or not. If you observe that presence of the numerical digits is helpful in the classification, please include it for further

process or you can ignore it.

```
In [0]:
```

```
k=project_data['project_resource_summary'].shape
n = k[0]
print(n)
b=project_data['project_resource_summary'][45]
print(b)
project_data['No.of.digits'] = 0
project_data.head(5)
```

In [0]:

CALCULATED ANALYSIS on NO.OF.DIGITS in THE PROJECT_RESOURCE_SUMMARY TEXT on 10000 points only as its taking HUGE TIME on my LAPTOP

```
In [0]:
```

```
project_data[:69999].to_pickle('gdrive/My Drive/naive_bayes_no.of.digits_original.pkl')
```

In [0]:

```
project_data = pd.read_pickle('gdrive/My Drive/naive_bayes_no.of.digits_original.pkl')
```

In [0]:

```
digits_project_resource_summary = project_data['No.of.digits']
```

In [0]:

```
rejected_np[:100]
```

As we can see the no.of.digits in the text are few and the text do contain any few digits

Approved np and rejected np is very sparse as we can see

```
In [0]:
```

```
plt.boxplot([approved_np[:49999], rejected_np[:49999]])
plt.title('Box Plots of No.of.digits in project_resource_summary per approved and not approved Projects')
plt.xticks([1,2],('Approved Projects','Rejected Projects'))
plt.ylabel('No.of.digits in project_resource_summary')
plt.grid()
plt.show()
```

FOR 10000 DATAPOINTS ONLY

The no.of.digits in No.of.digits in project_resource_summary text are few and very less, So we can IQR is almost zero and the text which has values are treated as outliers mostly for both approved and rejected projects

```
In [0]:
```

```
plt.figure(figsize=(10,3))
sns.distplot(approved_np, hist=False, label="Approved Projects")
sns.distplot(rejected_np, hist=False, label="Not Approved Projects")
plt.title('No.of.digits in project_resource_summary per approved and not approved Projects')
plt.xlabel('No.of.digits in project_resource_summary')
plt.legend()
plt.show()
```

This do not follow any gaussian distribution and the curve for approved and rejected is non-linear and non-symmetric and do have any local maximum and local minimum

we need to look for other features in the Project data and check whether other features data follow any distributions

1.3 Text preprocessing

1.3.1 Essay Text

```
In [0]:
```

```
project_data.shape
```

In [0]:

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

In [0]:

```
# 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 [0]:

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

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

```
print(sent)
```

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

In [0]:

```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
stopwords= ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've",
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his',
'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its', 'itself', 'they', 'them',
'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', "that'll",
'these', 'those', '
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having',
'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', '
while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during',
'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under'
, 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'why', 'how', 'all', 'any', 'both', '\epsilon
ach', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "should've", 'now', 'd', 'll'
, 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn', "didn't", 'doesn', "do
esn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'ma', 'mightn',
"mightn't", 'mustn',\
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shouldn't", 'wasn',
"wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't", "nan"]
4
```

In [0]:

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

In [0]:

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

1.3.2 Project title Text-Cleaning

```
# similarly you can preprocess the titles also
```

```
project_data['project_title'].values[50]

In [0]:

project_data['title'] = project_data['project_title'].map(str)
project_data['title'].values[0]

In [0]:

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

We are checking is decontracted applied to 20000th value of project title

```
In [0]:
```

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

we are replacing special characters in the project_title with space

```
In [0]:
```

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

we are replacing numerical charcaters in the text with space

```
In [0]:
```

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

```
In [0]:
```

```
preprocessed_titles[20000]
```

Resource_summary_Text

```
In [0]:
```

```
project_data['resources_summary'] = project_data['project_resource_summary'].map(str)
project_data['resources_summary'].values[0]
```

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

In [0]:

```
!pip install autocorrect
```

SpellingMistakes Count

Resource summary

In [0]:

```
from autocorrect import spell
  count_spellingmistake_resource = []
for i in tqdm(range(70000)):
    my_words = []
    my_words = preprocessed_resource_summary[i].split()
    my_words = list(set(my_words))
    count = 0
    for j in range(len(my_words)):

        if(my_words[j] != spell(my_words[j])):
            count += 1
        else:
            pass
            count_spellingmistake_resource.append(count)
```

Titles

```
from autocorrect import spell
count_spellingmistake_titles = []
for i in tqdm(range(70000)):

my_words = []

my_words = preprocessed_titles[i].split()
my_words = list(set(my_words))
count = 0
for i in range(len(my_words)):
```

```
if (my_words[j] != spell(my_words[j])):
    count += 1
    else:
        pass
count_spellingmistake_titles.append(count)
```

Essays

In [0]:

```
from autocorrect import spell
  count_spellingmistake_essays = []
  for i in tqdm(range(70000)):

    my_words = []

    my_words = preprocessed_essays[i].split()
    my_words = list(set(my_words))
    count = 0
    for j in range(len(my_words)):

        if(my_words[j] != spell(my_words[j])):
            count += 1
        else:
            pass
        count_spellingmistake_essays.append(count)
```

Sentimental Analysis of Essays

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

```
sauce make our own bread \
and mix up healthy plants from our classroom garden in the spring we will also create our own cook
books to be printed and \
shared with families students will gain math and literature skills as well as a life long enjoymen
t for healthy cooking \
nannan'
ss = sid.polarity_scores(for_sentiment)

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

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

```
ss = sid.polarity_scores(preprocessed_essays[5])
for k in ss:
    print(k,ss[k])
```

In [0]:

```
negative_polarity = []
neutrality_polarity = []
positive_polarity = []
compound_polarity = []

for i in range(70000):
    ss = sid.polarity_scores(preprocessed_essays[i])
    negative_polarity.append(ss['neg'])
    neutrality_polarity.append(ss['neu'])
    positive_polarity.append(ss['pos'])
    compound_polarity.append(ss['compound'])
```

In [0]:

```
negative_polarity = pd.Series(negative_polarity)
neutrality_polarity = pd.Series(neutrality_polarity)
positive_polarity = pd.Series(positive_polarity)
compound_polarity = pd.Series(compound_polarity)
```

In [0]:

```
count_spellingmistake_essays = pd.Series(count_spellingmistake_essays)
count_spellingmistake_titles = pd.Series(count_spellingmistake_titles)
count_spellingmistake_resource = pd.Series(count_spellingmistake_resource)
```

1. 4 Preparing data for models

```
In [0]:
```

```
project_data.columns
```

1.4.1 Vectorizing Categorical data

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

School state- One hot encoding

```
In [0]:
```

```
clean_categories = project_data['clean_categories'].values
clean_categories = pd.Series(clean_categories.ravel().tolist())
```

```
X = ['clean_categories']
```

Clean_Categories-One-Hot-Encoding

```
In [0]:
```

```
clean_subcategories = project_data['clean_subcategories'].values
clean_subcategories = pd.Series(clean_subcategories.ravel().tolist())
X = X + ['clean_subcategories']
```

Clean_SubCategories

```
In [0]:
```

```
project_grade_category = project_data['project_grade_category']
project_grade_category = pd.Series(project_grade_category.ravel().tolist())
X = X + ['project_grade_category']
```

Project_Grade_Category

```
In [0]:
```

```
school_state = project_data['school_state'].values
school_state = pd.Series(school_state.ravel().tolist())
X = X + ['school_state']
```

Teahcer_prefix-One Hot Encoding

```
In [0]:
```

```
project_data[project_data['teacher_prefix'].isnull()]
```

We contain nan values in the teacher_prefix column

```
In [0]:
```

```
#replacing nan values in pandas https://stackoverflow.com/questions/13295735/how-can-i-replace-
all-the-nan-values-with-zeros-in-a-column-of-a-pandas-datafra
project_data['teacher_prefix'].value_counts()
project_data['teacher_prefix'] = project_data['teacher_prefix'].fillna('Mrs.')
project_data['teacher_prefix'].isnull().any()
```

replaced nan values in teacher_prefix with "Mrs." as Mrs. is majority vote

```
In [0]:
```

```
teacher_prefix = project_data['teacher_prefix'].values
teacher_prefix = pd.Series(teacher_prefix.ravel().tolist())
X = X + ['teacher_prefix']
```

```
In [0]:
```

```
set5_categorical =
pd.concat([clean_categories,clean_subcategories,project_grade_category,school_state,teacher_prefix
],axis=1)
```

Vectorizing Numerical Features

```
In [0]:
```

```
# 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 = standardScalar.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 = pd.Series(price_standardized.ravel().tolist())
```

In [0]:

```
X = X + ['price_standardized']
```

teacher_number_of_previously_posted_projects

In [0]:

```
# 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 = standardScalar.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.
# Reshape your data either using array.reshape(-1, 1)
teacher number of previously posted projects scalar = StandardScaler()
teacher_number_of_previously_posted_projects_scalar.fit(project_data['teacher_number_of_previously_
osted projects'].values.reshape(-1,1)) # finding the mean and standard deviation of this data
print(f"Mean : {teacher_number_of_previously_posted_projects_scalar.mean_[0]}, Standard deviation
: {np.sqrt(teacher_number_of_previously_posted_projects_scalar.var_[0])}")
# Now standardize the data with above maen and variance.
teacher number_of_previously_posted_projects_standardized =
teacher number of previously posted projects scalar.transform(project data['teacher number of previ
ously posted projects'].values.reshape(-1, 1))
4
```

In [0]:

```
teacher_number_of_previously_posted_projects_standardized =
pd.Series(teacher_number_of_previously_posted_projects_standardized.ravel().tolist())
```

In [0]:

```
X = X + ['previously_posted_projects']
```

Quantity

```
# 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 = standardScalar.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.
7.3 5.5 1.
# Reshape your data either using array.reshape(-1, 1)
quantity scalar = StandardScaler()
quantity scalar.fit(resource data['quantity'][:109248].values.reshape(-1,1)) # finding the mean and
standard deviation of this data
print(f"Mean : {quantity_scalar.mean_[0]}, Standard deviation :
{np.sqrt(quantity scalar.var [0])}")
# Now standardize the data with above maen and variance.
quantity standardised = quantity scalar.transform(resource data['quantity']
[:109248].values.reshape(-1, 1))
In [0]:
quantity_standardised = pd.Series(quantity_standardised.ravel().tolist())
In [0]:
X = X + ['quantity standardised']
Digits in Resource_Summary
Words in Essays
In [0]:
from sklearn.preprocessing import StandardScaler
essays_scalar = StandardScaler()
essays scalar.fit(word count essays.reshape(-1,1)) # finding the mean and standard deviation of th
is data
print(f"Mean : {essays_scalar.mean_[0]}, Standard deviation : {np.sqrt(essays scalar.var [0])}")
# Now standardize the data with above maen and variance.
essays words_standardised = essays_scalar.transform(word_count_essays.reshape(-1, 1))
In [0]:
essays words standardised = pd.Series(essays words standardised.ravel().tolist())
```

```
Resource summary-No.of.Words
```

X = X + ['essays words standardised']

```
essays_scalar = StandardScaler()
essays_scalar.fit(word_count_resource_summary.reshape(-1,1)) # finding the mean and standard
deviation of this data
print(f"Mean : {essays_scalar.mean_[0]}, Standard deviation : {np.sqrt(essays_scalar.var_[0])}")
# Now standardize the data with above maen and variance.
summary_words_standardised = essays_scalar.transform(word_count_resource_summary.reshape(-1, 1))
```

```
In [0]:
summary words standardised = pd.Series(summary words standardised.ravel().tolist())
In [0]:
X = X + ['summary words standardised']
Titles-No.of.Words
In [0]:
titles scalar = StandardScaler()
titles_scalar.fit(word_count_titles.reshape(-1,1)) # finding the mean and standard deviation of th
print(f"Mean : {titles_scalar.mean_[0]}, Standard deviation : {np.sqrt(titles_scalar.var_[0])}")
# Now standardize the data with above maen and variance.
titles words standardised = titles scalar.transform(word count titles.reshape(-1, 1))
In [0]:
titles words standardised = pd.Series(titles words standardised.ravel().tolist())
In [0]:
X = X + ['titles words standardised']
Sentimental_score's of Essays
In [0]:
neutrality_scalar = StandardScaler()
neutrality scalar.fit(neutrality polarity.reshape(-1,1)) # finding the mean and standard deviation
of this data
print(f"Mean : {neutrality_scalar.mean_[0]}, Standard deviation :
{np.sqrt(neutrality scalar.var [0])}")
# Now standardize the data with above maen and variance.
neutrality polarity standardised = neutrality scalar.transform(neutrality polarity.reshape(-1, 1))
In [0]:
neutrality polarity standardised = pd.Series(neutrality polarity standardised.ravel().tolist())
In [0]:
X = X +['neutrality polarity standardised']
In [0]:
compound scalar = StandardScaler()
compound scalar.fit(compound polarity.reshape(-1,1)) # finding the mean and standard deviation of
print(f"Mean : {compound_scalar.mean_[0]}, Standard deviation :
{np.sqrt(compound scalar.var [0])}")
# Now standardize the data with above maen and variance.
compound polarity standardised = compound scalar.transform(compound polarity.reshape(-1, 1))
In [0]:
compound polarity standardised = pd.Series(compound polarity standardised.ravel().tolist())
```

```
In [0]:
X = X + ['compound polarity standardised']
In [0]:
positive scalar = StandardScaler()
positive_scalar.fit(positive_polarity.reshape(-1,1)) # finding the mean and standard deviation of
print(f"Mean : {positive_scalar.mean_[0]}, Standard deviation :
{np.sqrt(positive_scalar.var_[0])}")
# Now standardize the data with above maen and variance.
positive polarity standardised = positive_scalar.transform(positive_polarity.reshape(-1, 1))
In [0]:
positive polarity standardised = pd.Series(positive polarity standardised.ravel().tolist())
In [0]:
X = X + ['positive_polarity_standardised']
In [0]:
negative scalar = StandardScaler()
negative scalar.fit(negative polarity.reshape(-1,1)) # finding the mean and standard deviation of
this data
print(f"Mean : {negative_scalar.mean_[0]}, Standard deviation :
{np.sqrt(negative scalar.var [0])}")
# Now standardize the data with above maen and variance.
negative polarity standardised = negative scalar.transform(negative polarity.reshape(-1, 1))
In [0]:
negative polarity standardised = pd.Series(negative polarity standardised.ravel().tolist())
In [0]:
X = X + ['negative polarity standardised']
In [0]:
### Spelling Mistakes-Count in Essays
In [0]:
essays spelling scalar = StandardScaler()
essays_spelling_scalar.fit(count_spellingmistake_essays.reshape(-1,1))  # finding the mean and
standard deviation of this data
print(f"Mean : {essays_spelling_scalar.mean_[0]}, Standard deviation :
{np.sqrt(essays spelling scalar.var [0])}")
# Now standardize the data with above maen and variance.
spellingmistake essays = essays spelling scalar.transform(count spellingmistake essays.reshape(-1,
1))
spellingmistake essays = pd.Series(spellingmistake essays.ravel().tolist())
In [0]:
X = X + ['spellingmistake essays']
```

Spelling Mistakes-Count in Titles

```
In [0]:
titles spelling scalar = StandardScaler()
titles spelling scalar.fit(count spellingmistake titles.reshape(-1,1)) # finding the mean and
standard deviation of this data
print(f"Mean : {titles_spelling_scalar.mean_[0]}, Standard deviation :
{np.sqrt(titles spelling scalar.var [0])}")
# Now standardize the data with above maen and variance.
spellingmistake titles = titles spelling scalar.transform(count spellingmistake titles.reshape(-1,
In [0]:
spellingmistake titles = pd.Series(spellingmistake titles.ravel().tolist())
In [0]:
X = X + ['spellingmistake titles']
Spelling Mistakes-Count in Resource suumary
In [0]:
resource spelling scalar = StandardScaler()
resource_spelling_scalar.fit(count_spellingmistake_resource.reshape(-1,1)) # finding the mean and
standard deviation of this data
print(f"Mean : {resource_spelling_scalar.mean_[0]}, Standard deviation :
{np.sqrt(resource_spelling_scalar.var_[0])}")
# Now standardize the data with above maen and variance.
spellingmistake resource =
resource spelling scalar.transform(count spellingmistake resource.reshape(-1, 1))
spellingmistake resource = pd.Series(spellingmistake resource.ravel().tolist())
In [0]:
X = X + ['spellingmistake resource']
In [0]:
# 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 = standardScalar.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 1.
# Reshape your data either using array.reshape(-1, 1)
digits scalar = StandardScaler()
digits scalar.fit(digits project resource summary.values.reshape(-1,1)) # finding the mean and
standard deviation of this data
print(f"Mean : {digits scalar.mean [0]}, Standard deviation : {np.sqrt(digits scalar.var [0])}")
# Now standardize the data with above maen and variance.
digits standardised = digits scalar.transform(digits project resource summary.values.reshape(-1, 1)
```

```
digits_standardised = pd.Series(digits_standardised.ravel().tolist())
In [0]:
X = X + ['digits_standardised']
```

Similarity Between Essay_1 and Essay_2

```
In [0]:

X_features_cn = X

In [0]:

X_cat_num = X_features_cn
```

X-features cn conatains all feature-names of only categorial and Numerical-Features

we need to append this X_features_cn to BOW when performing BOW and to TFIDF when performing TFIDF

Converting each feature-vector to Dataframe

```
In [0]:
```

```
print(type(teacher prefix one hot))
teacher prefix one hot.shape
df = pd.DataFrame(teacher_prefix_one_hot.toarray().astype(np.float64))
type(df)
print(type(school state one hot))
school state one hot.shape
df1 = pd.DataFrame(school_state_one_hot.toarray().astype(np.float64))
type (df1)
print(type(sub_categories_one_hot))
sub categories one hot.shape
df2 = pd.DataFrame(sub categories one hot.toarray().astype(np.float64))
type (df2)
print(type(categories one hot))
categories one hot.shape
df3 = pd.DataFrame(categories one hot.toarray().astype(np.float64))
type (df3)
type(teacher_number_of_previously_posted_projects_standardized.tolist())
df4=teacher_number_of_previously_posted_projects_standardized.tolist()
type (df4)
type(price standardized.tolist())
df5=price standardized.tolist()
type (df5)
```

Combine all numerical and categorical features

```
In [0]:
```

```
set5_dataset =
pd.concat([set5_categorical,price_standardized[:69999],teacher_number_of_previously_posted_projects
standardized[:69999],quantity_standardised[:69999],essays_words_standardised[:69999],summary_words
_standardised[:69999],titles_words_standardised[:69999],neutrality_polarity_standardised[:69999],c
ompound_polarity_standardised[:69999],positive_polarity_standardised[:69999],negative_polarity_standardised[:69999],spellingmistake_essays[:69999],spellingmistake_titles[:69999],spellingmistake_resource[:69999],digits_standardised[:69999]],axis=1)
```

we are combining all the categorical and numerical features into a single X_cn Sparse Matrix

We are ignoring text features here

```
In [0]:
```

```
set5_dataset = set5_dataset[:69000]
```

In [0]:

```
set5_dataset.columns = X
```

Creating Datframe for X_cn as we need to concatenate text features into the dataframe

We can not add Text columns to Sparse matrix as the type of text is 'str and numerical columns as 'int'

dk is the dataframe conatining all categorical and numerical features

```
In [0]:
```

```
y = project_data['project_is_approved']
type(y)
```

Taking the output into a series-(y)

```
In [0]:
```

```
k =
pd.DataFrame({'preprocessed_essays':preprocessed_essays[:69999],'preprocessed_titles':preprocessed
titles[:69999],'preprocessed_resource_summary':preprocessed_resource_summary[:69999],'y':y[:69999]
})
```

k is the dataframe conatining all the text features and the output-(y) feature.

We should not be using hstack as the features are of strings and could not concatenate them

k is the dataframe conatining all text and output-y

dataset - contains all features

Dataset is the Dataframe containing all the features text, Categorical and Numerical Features

we need to vectorize the text features only after splitting Dataset into train,test,split

dataset conatins all features with text in raw format and also output-y

```
In [0]:
```

```
dataset = pd.concat([set5_dataset,k],axis=1)
dataset.to_pickle('gdrive/My Drive/dataset_RF.pkl')
```

In [0]:

```
dataset = pd.read_pickle('gdrive/My Drive/dataset_RF.pkl')
```

In [76]:

```
y = project_data['project_is_approved']
type(y)
```

Out[76]:

pandas.core.series.Series

```
In [0]:
```

```
X = dataset.columns
```

```
X_feature_dataset = X
```

X = Contains all the features-Names of the Dataset..We need to store them because when we convert them to sparse matrice's, We loose the column-Names

X needs to be stored in the order in which we are storing all the features(Numerical + Categorical)

Train-Test-Split of Dataset

In [0]:

```
from sklearn.model_selection import train_test_split
X_1, X_test, y_1, y_test = train_test_split(dataset[:69000], y[:69000], test_size=0.3,random_state=
0,stratify=y[:69000])
# split the train data set into cross validation train and cross validation test
X_train, X_cv, y_train, y_cv = train_test_split(X_1, y_1, test_size=0.3,random_state=0,stratify=y_1)
```

Split the essays into Train_test_split

We are splitting the dataset Randomly and by using stratify which means train and test-set contains equal no.of.y values

Stratify means train and test contain same proportion of 1 and 0 -samples or same ratio

while stratifying using cv, we need to stratify using y_train

X train = train set of essay after cross=validation

X_test = test set of essay

X_cv = cv set of essay

X 1 = train set before cross-Validation

Response Coding

In [86]:

```
# Clean_categories
z = X_train.groupby(['clean_categories'])['y'].value_counts() /
X_train.groupby(['clean_categories'])['y'].count()
z
```

Out[86]:

```
clean categories
AppliedLearning
                                   0.817117
                                0 0.182883
AppliedLearning Health Sports
                                 1
                                     0.809524
                                     0.190476
                               1
AppliedLearning History_Civics
                                     0.783333
                                     0.216667
AppliedLearning Literacy Language 1 0.880000
                                0
                                     0.120000
AppliedLearning Math Science
                                 1
                                0
                                     0.185185
AppliedLearning Music Arts
                                1
                                     0.807531
                                    0.192469
                                1 0.799136
AppliedLearning SpecialNeeds
                                     0.200864
AnnliedTearning Warmth Care Hunger 1
                                     0 200000
```

```
0.200000
whatempearming marmon care mander i
Health_Sports
                                    0.860583
                                 1
                                    0.139417
Health_Sports AppliedLearning
                                1 0.805556
                                0
                                     0.194444
Health_Sports History_Civics
                                      0.833333
                                0
                                     0.166667
                                1
Health_Sports Literacy_Language
                                    0.830827
                                0 0.169173
Health Sports Math Science
                                1 0.772152
                                 0
                                      0.227848
                                    0.851064
                                1
Health Sports Music Arts
                                0 0.148936
Health Sports SpecialNeeds
                                1 0.870192
                                0 0.129808
                                       . . .
Math_Science Health_Sports 0 0.204545
Math_Science History_Civics 1 0.829268
                                0 0.170732
Math_Science Literacy_Language
                                1 0.874433
                                     0.125567
                                0
                                1
0
Math Science Music Arts
                                      0.842742
                                     0.157258
Math_Science SpecialNeeds
                                1
                                     0.826958
                                    0.173042
                                0
Math Science Warmth Care Hunger
                                    0.666667
                                 1
                                      0.333333
Music Arts
                                 1
                                      0.855598
                                 Ω
                                     0.144402
                                0
Music Arts AppliedLearning
                                    0.500000
                                1 0.500000
Music_Arts Health_Sports
                                1 0.571429
                                0
1
                                      0.428571
                                    1.000000
Music_Arts History_Civics
Music_Arts SpecialNeeds
                                1
                                    0.880000
                                    0.120000
                                0
                                    1.000000
Music_Arts Warmth Care_Hunger
SpecialNeeds
                                 1
                                      0.815686
                                 0
                                      0.184314
                                1
SpecialNeeds Health Sports
                                     0.750000
                                    0.250000
SpecialNeeds Music Arts
                                1 0.815217
O 0.184783
SpecialNeeds Warmth Care_Hunger 1 1.000000
Warmth Care_Hunger 1 0.908277
                                0 0.091723
Name: y, Length: 95, dtype: float64
```

z= what is the probability such that data-point(x) belongs to y=1 and y=0 given x belongs to certain category of clean_categories.

but we need to ditribute this probabilities to all points which belongs certain and category and y=1 or y=0]

In [87]:

```
X_train=X_train.set_index(['clean_categories','y']).sort_index()
X_train.head()
```

Out[87]:

		clean_subcategories	project_grade_category	school_state	teacher_prefix	price_standardized	previo
clean_categories	у						
AppliedLearning	0	EarlyDevelopment	Grades PreK-2	NC	Ms.	0.498347	0.3184
	0	EarlyDevelopment	Grades PreK-2	PA	Ms.	1.303090	-0.401
	0	CharacterEducation Other	Grades 9-12	МТ	Mrs.	-0.625474	-0.365

		clean_subcategories	project_grade_category	school_state	teacher_prefix	price_standardized	previo
clean_categories	Ø	CharacterEducation	Grades 3-5	МО	Ms.	2.704927	-0.401
	0	EarlyDevelopment	Grades 3-5	GA	Mrs.	-0.576657	-0.365

5 rows × 26 columns

<u>+</u>

we are setting index as clean_categories and y and now we sorting the index such that clean_categories sort based on alphabetical order and ty from 0 to 1.

```
In [88]:
```

```
clean_categories_prob = pd.Series(z, index=X_train.index)
X_train = X_train.reset_index()
X_train.head()
```

Out[88]:

	clean_categories	у	clean_subcategories	project_grade_category	school_state	teacher_prefix	price_standardized	pre
0	AppliedLearning	0	EarlyDevelopment	Grades PreK-2	NC	Ms.	0.498347	0.3
1	AppliedLearning	0	EarlyDevelopment	Grades PreK-2	PA	Ms.	1.303090	-0.4
2	AppliedLearning	0	CharacterEducation Other	Grades 9-12	MT	Mrs.	-0.625474	-0.3
3	AppliedLearning	0	CharacterEducation	Grades 3-5	МО	Ms.	2.704927	-0.4
4	AppliedLearning	0	EarlyDevelopment	Grades 3-5	GA	Mrs.	-0.576657	-0.3

5 rows × 28 columns

z conatins probabilities and we need to match them with clean_categories and y, so we can make them index now,this clean_probabilities are formed

In [89]:

```
X_train.drop('clean_categories',axis=1,inplace=True)
X_train['clean_categories_Proba'] = clean_categories_prob.tolist()
X_train['clean_categories_Proba'].head()
```

Out[89]:

```
0  0.182883
1  0.182883
2  0.182883
3  0.182883
4  0.182883
Name: clean_categories_Proba, dtype: float64
```

Drop clean_Categories and replace them with probabilities as clean_categories_proba

```
In [90]:
```

```
x_y_1 = x_crain[x_crain['y']==1]['crean_categories_rroba']
X_y_0 = X_train[X_train['y']==0]['clean_categories_Proba']
X_train['clean_categories_Proba'] = X_y_1.add((1-X_y_0), fill_value=0)
X_train['clean_categories_Proba']
Out[90]:
0
         0.817117
1
         0.817117
2
         0.817117
         0.817117
3
         0.817117
5
        0.817117
         0.817117
6
         0.817117
        0.817117
8
        0.817117
9
10
        0.817117
         0.817117
11
12
         0.817117
13
         0.817117
        0.817117
14
15
        0.817117
16
         0.817117
17
         0.817117
18
         0.817117
19
        0.817117
20
        0.817117
21
         0.817117
         0.817117
22
23
         0.817117
24
         0.817117
25
         0.817117
26
         0.817117
27
         0.817117
28
         0.817117
29
         0.817117
33780
       0.908277
33781
         0.908277
33782
         0.908277
33783
         0.908277
33784
         0.908277
33785
         0.908277
33786
        0.908277
33787
         0.908277
33788
         0.908277
33789
         0.908277
33790
         0.908277
33791
        0.908277
33792
         0.908277
33793
         0.908277
33794
         0.908277
33795
         0.908277
33796
        0.908277
33797
        0.908277
33798
         0.908277
33799
         0.908277
33800
         0.908277
33801
         0.908277
         0.908277
33802
33803
         0.908277
33804
         0.908277
33805
         0.908277
33806
         0.908277
33807
         0.908277
33808
         0.908277
         0.908277
33809
Name: clean_categories_Proba, Length: 33810, dtype: float64
```

we are doing this because there are few probabilties such that y=0 and y=1, we need to cahnge the such that what is the probabiltiues usch that y=1, so we can subtract y=0 from 1 so that we can get all the probabiltiues which y=1.

```
In [0]:
```

```
# Clean SubCategories
z = X_{train.groupby(['clean_subcategories'])['y'].value counts() / 
X train.groupby(['clean subcategories'])['y'].count()
X_train=X_train.set_index(['clean_subcategories','y']).sort_index()
clean_subcategories_prob = pd.Series(z, index=X_train.index)
X_train = X_train.reset_index()
X_train.drop('clean_subcategories',axis=1,inplace=True)
X_train['clean_subcategories_Proba'] = clean_subcategories_prob.tolist()
X y 1 = X train[X train['y']==1]['clean subcategories Proba']
X y 0 = X train[X train['y']==0]['clean subcategories Proba']
X_train['clean_subcategories_Proba'] = X_y_1.add((1-X_y_0),fill_value=0)
In [0]:
#project grade category
z = X_train.groupby(['project_grade_category'])['y'].value_counts() /
X_train.groupby(['project_grade_category'])['y'].count()
X_train=X_train.set_index(['project_grade_category','y']).sort_index()
project_grade_category_prob = pd.Series(z, index=X_train.index)
X train = X train.reset index()
X_train.drop('project_grade_category',axis=1,inplace=True)
X_train['project_grade_category_proba'] = project_grade_category_prob.tolist()
X y 1 = X train[X train['y']==1]['project grade category proba']
X_y_0 = X_train[X_train['y']==0]['project_grade_category_proba']
X_train['project_grade_category_proba'] = X_y_1.add((1-X_y_0),fill_value=0)
In [0]:
# School State
z = X train.groupby(['school state'])['y'].value counts() / X train.groupby(['school state'])['y'].
count()
X_train=X_train.set_index(['school_state','y']).sort index()
school_state_prob = pd.Series(z, index=X_train.index)
X_train = X_train.reset_index()
X_train.drop('school_state',axis=1,inplace=True)
X_train['school_state_proba'] = school_state_prob.tolist()
X_y_1 = X_train[X_train['y']==1]['school_state_proba']
X_y_0 = X_train[X_train['y']==0]['school_state_proba']
X_train['school_state_proba'] = X_y_1.add((1-X_y_0),fill_value=0)
In [0]:
# Teacher Prefix
z = X train.groupby(['teacher prefix'])['y'].value counts() / X train.groupby(['teacher prefix'])[
'y'].count()
X_train=X_train.set_index(['teacher_prefix','y']).sort_index()
teacher_prefix_prob = pd.Series(z, index=X_train.index)
X_train = X_train.reset_index()
X train.drop('teacher_prefix',axis=1,inplace=True)
X train['teacher prefix proba'] = teacher prefix prob.tolist()
X_y_1 = X_train[X_train['y']==1]['teacher_prefix_proba']
X_y_0 = X_train[X_train['y']==0]['teacher_prefix_proba']
X train['teacher prefix proba'] = X y 1.add((1-X y 0), fill value=0)
In [0]:
X = X train.columns
In [0]:
y train = X train['y']
In [0]:
# Clean_categories
z = X cv.groupby(['clean categories'])['y'].value counts() / X cv.groupby(['clean categories'])['y
X cv=X cv.set index(['clean categories','y']).sort index()
clean categories prob = pd.Series(z, index=X cv.index)
```

```
X_cv = X_cv.reset_index()

X_cv.drop('clean_categories',axis=1,inplace=True)
X_cv['clean_categories_Proba'] = clean_categories_prob.tolist()
X_y_1 = X_cv[X_cv['y']==1]['clean_categories_Proba']
X_y_0 = X_cv[X_cv['y']==0]['clean_categories_Proba']
X_cv['clean_categories_Proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

```
# Clean_SubCategories
z = X_cv.groupby(['clean_subcategories'])['y'].value_counts() /
X_cv.groupby(['clean_subcategories'])['y'].count()
X_cv=X_cv.set_index(['clean_subcategories','y']).sort_index()
clean_subcategories_prob = pd.Series(z, index=X_cv.index)
X_cv = X_cv.reset_index()

X_cv.drop('clean_subcategories',axis=1,inplace=True)
X_cv['clean_subcategories_Proba'] = clean_subcategories_prob.tolist()
X_y_1 = X_cv[X_cv['y']==1]['clean_subcategories_Proba']
X_y_0 = X_cv[X_cv['y']==0]['clean_subcategories_Proba']
X_cv['clean_subcategories_Proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

In [0]:

```
#project_grade_category
z = X_cv.groupby(['project_grade_category'])['y'].value_counts() /
X_cv.groupby(['project_grade_category'])['y'].count()
X_cv=X_cv.set_index(['project_grade_category','y']).sort_index()
project_grade_category_prob = pd.Series(z, index=X_cv.index)
X_cv = X_cv.reset_index()
X_cv.drop('project_grade_category',axis=1,inplace=True)
X_cv['project_grade_category_proba'] = project_grade_category_prob.tolist()
X_y_1 = X_cv[X_cv['y']==1]['project_grade_category_proba']
X_y_0 = X_cv[X_cv['y']==0]['project_grade_category_proba']
X_cv['project_grade_category_proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

In [0]:

```
# School_State
z = X_cv.groupby(['school_state'])['y'].value_counts() / X_cv.groupby(['school_state'])['y'].count()

X_cv=X_cv.set_index(['school_state','y']).sort_index()
school_state_prob = pd.Series(z, index=X_cv.index)

X_cv = X_cv.reset_index()

X_cv.drop('school_state',axis=1,inplace=True)

X_cv['school_state_proba'] = school_state_prob.tolist()

X_y_1 = X_cv[X_cv['y']==1]['school_state_proba']

X_y_0 = X_cv[X_cv['y']==0]['school_state_proba']

X_cv['school_state_proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

In [0]:

```
# Teacher_Prefix
z = X_cv.groupby(['teacher_prefix'])['y'].value_counts() / X_cv.groupby(['teacher_prefix'])
['y'].count()
X_cv=X_cv.set_index(['teacher_prefix','y']).sort_index()
teacher_prefix_prob = pd.Series(z, index=X_cv.index)

X_cv = X_cv.reset_index()
X_cv.drop('teacher_prefix',axis=1,inplace=True)
X_cv['teacher_prefix_proba'] = teacher_prefix_prob.tolist()
X_y_1 = X_cv[X_cv['y']==1]['teacher_prefix_proba']
X_y_0 = X_cv[X_cv['y']==0]['teacher_prefix_proba']
X_cv['teacher_prefix_proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

```
y_cv = X_cv['y']
```

```
# Clean_categories
z = X_test.groupby(['clean_categories'])['y'].value_counts() /
X_test.groupby(['clean_categories'])['y'].count()
X_test=X_test.set_index(['clean_categories','y']).sort_index()
clean_categories_prob = pd.Series(z, index=X_test.index)
X_test = X_test.reset_index()

X_test.drop('clean_categories',axis=1,inplace=True)
X_test['clean_categories_Proba'] = clean_categories_prob.tolist()
X_y_1 = X_test[X_test['y']==1]['clean_categories_Proba']
X_y_0 = X_test[X_test['y']==0]['clean_categories_Proba']
X_test['clean_categories_Proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

```
# Clean_SubCategories
z = X_test.groupby(['clean_subcategories'])['y'].count()
X_test.groupby(['clean_subcategories'])['y'].count()
X_test=X_test.set_index(['clean_subcategories','y']).sort_index()
clean_subcategories_prob = pd.Series(z, index=X_test.index)
X_test = X_test.reset_index()

X_test.drop('clean_subcategories',axis=1,inplace=True)
X_test['clean_subcategories_Proba'] = clean_subcategories_prob.tolist()
X_y_1 = X_test[X_test['y']==1]['clean_subcategories_Proba']
X_y_0 = X_test[X_test['y']==0]['clean_subcategories_Proba']
X_test['clean_subcategories_Proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

In [0]:

```
#project_grade_category
z = X_test.groupby(['project_grade_category'])['y'].value_counts() / X_test.groupby(['project_grade_category'])['y'].count()
X_test=X_test.set_index(['project_grade_category','y']).sort_index()
project_grade_category_prob = pd.Series(z, index=X_test.index)
X_test = X_test.reset_index()
X_test.drop('project_grade_category',axis=1,inplace=True)
X_test['project_grade_category_proba'] = project_grade_category_prob.tolist()
X_y_1 = X_test[X_test['y']==1]['project_grade_category_proba']
X_y_0 = X_test[X_test['y']==0]['project_grade_category_proba']
X_test['project_grade_category_proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

In [0]:

```
# School_State
z = X_test.groupby(['school_state'])['y'].value_counts() / X_test.groupby(['school_state'])['y'].co
unt()
X_test=X_test.set_index(['school_state','y']).sort_index()
school_state_prob = pd.Series(z, index=X_test.index)
X_test = X_test.reset_index()
X_test.drop('school_state',axis=1,inplace=True)
X_test['school_state_proba'] = school_state_prob.tolist()
X_y_1 = X_test[X_test['y']==1]['school_state_proba']
X_y_0 = X_test[X_test['y']==0]['school_state_proba']
X_test['school_state_proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

```
# Teacher_Prefix
z = X_test.groupby(['teacher_prefix'])['y'].value_counts() / X_test.groupby(['teacher_prefix'])['y'].count()
X_test=X_test.set_index(['teacher_prefix','y']).sort_index()
teacher_prefix_prob = pd.Series(z, index=X_test.index)

X_test = X_test.reset_index()
X_test.drop('teacher_prefix',axis=1,inplace=True)
X_test['teacher_prefix_proba'] = teacher_prefix_prob.tolist()
X_y_1 = X_test[X_test['y']==1]['teacher_prefix_proba']
X_y_0 = X_test[X_test['y']==0]['teacher_prefix_proba']
X_test['teacher_prefix_proba'] = X_y_1.add((1-X_y_0),fill_value=0)
```

```
In [0]:

y_test = X_test['y']
```

1-BOW

1.1Vectorizers of train, test, split of only Raw test-Features

Essays_Vectorizers_BOW

```
In [0]:
```

```
X_train_essay = X_train[:]['preprocessed_essays']
X_cv_essay = X_cv[:]['preprocessed_essays']
X_test_essay = X_test[:]['preprocessed_essays']
```

In [0]:

```
# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer = CountVectorizer(min_df=10)
train_bow_essay = vectorizer.fit_transform(X_train_essay)
cv_bow_essay = vectorizer.transform(X_cv_essay)
test_bow_essay = vectorizer.transform(X_test_essay)
print(train_bow_essay.shape,cv_bow_essay.shape,test_bow_essay.shape)
```

```
(33810, 10476) (14490, 10476) (20700, 10476)
```

Vectorizing the train,test,cv sets of essays-Text features

min_df=10 means, we are using all the words present only in min of 10 documents

We need to fit the vectorizer with train set and then transform to cv,test using the same vectorizer

It is because test and cv should contain the same words as Train-set

```
In [0]:
```

```
X = X.tolist() + vectorizer.get_feature_names()
```

we are appending X = which contain BOW-features names of Essays to Categorical and Numerical-Features

Titles_Vectorizers_bow

```
In [0]:
```

```
X_train_titles = X_train[:]['preprocessed_titles']
X_cv_titles = X_cv[:]['preprocessed_titles']
X_test_titles = X_test[:]['preprocessed_titles']
X_1_titles = X_1[:]['preprocessed_titles']
```

In [0]:

```
vectorizer3 = CountVectorizer(min_df=10)
train_bow_titles = vectorizer3.fit_transform(X_train_titles)
bow_titles_cv = vectorizer3.transform(X_cv_titles)
test_bow_titles = vectorizer3.transform(X_test_titles)
```

Vectorizing the train,test,cv sets of titles-Text features

min_df=10 means, we are using all the words present only in min of 10 documents

Similar Vactorizing has to he done to Titles and titles are also the text vectors

```
In [0]:

X= X + vectorizer3.get_feature_names()

In [0]:

X_train_summary = X_train[:]['preprocessed_resource_summary']
X_cv_summary = X_cv[:]['preprocessed_resource_summary']
X_test_summary = X_test[:]['preprocessed_resource_summary']

In [0]:

vectorizer4 = CountVectorizer(min_df=10)
train_bow_summary = vectorizer4.fit_transform(X_train_summary)
bow_summary_cv = vectorizer4.transform(X_cv_summary)
test_bow_summary = vectorizer4.transform(X_test_summary)

In [0]:

X= X + vectorizer4.get_feature_names()
```

```
In [0]:
```

```
print(train_bow_essay.shape,test_bow_essay.shape,cv_bow_essay.shape)
print(train_bow_titles.shape,test_bow_titles.shape,bow_titles_cv.shape)
print(y_train.shape,y_test.shape,y_cv.shape)

(33810, 10476) (20700, 10476) (14490, 10476)
```

```
(33810, 10476) (20700, 10476) (14490, 10476)
(33810, 1639) (20700, 1639) (14490, 1639)
(33810,) (20700,) (14490,)
```

we are using BOW of the text here

As we need to use fit_transform for train of essays and titles and their respective test-set/cv-set should be transformed because they both should have the same no.of.features (train/test and 1/cv-sets).

When transforming CV,Test features, they should have same no.of features/vectorizers similar to Train-set

We need to vectorize the Each train and testset separately and fit the train data and then transform the test data

1.2Extract train, test of only numerical and categorical features

```
In [30]:
```

```
import scipy
X_train_cn =
X_train.drop(['y','preprocessed_essays','preprocessed_titles','preprocessed_resource_summary'],axi
s=1)
print(X_train_cn.shape)
X_train_cn = scipy.sparse.csr_matrix(X_train_cn)
print(X_train_cn.shape)

(33810, 24)
(33810, 24)
```

In [31]:

```
X_test_cn =
X_test.drop(['y','preprocessed_essays','preprocessed_titles','preprocessed_resource_summary'],axis
=1)
print(X_test_cn.shape)
X_test_cn = scipy.sparse.csr_matrix(X_test_cn)
print(X_test_cn.shape)
```

(20700, 24)

```
In [32]:

X_cv_cn =
   X_cv.drop(['y','preprocessed_essays','preprocessed_titles','preprocessed_resource_summary'],axis=1
)
print(X_cv_cn.shape)
   X_cv_cn = scipy.sparse.csr_matrix(X_cv_cn)
print(X_cv_cn.shape)

(14490, 24)
```

From the original TrainTest,Cv sets of dataset, we need to drop text of essays and Titles and replace them with Vectorizers of Text of Essays and Titles

We need to keep the Categorical and Numerical columns also along with the vectors of essays and titles

1.3-Train,test,cv sets of ALL features

```
In [0]:
```

(14490, 24)

```
from scipy.sparse import hstack
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler

X_train_bow = hstack((X_train_cn,train_bow_essay,train_bow_titles,train_bow_summary))
X_train_bow = X_train_bow.tocsr()
train_scalar = StandardScaler(with_mean = False)
X_train_bow = train_scalar.fit_transform(X_train_bow)
```

In [0]:

```
X_test_bow =hstack((X_test_cn,test_bow_essay,test_bow_titles,test_bow_summary))
X_test_bow = X_test_bow.tocsr()
test_scalar = StandardScaler(with_mean = False)
X_test_bow = test_scalar.fit_transform(X_test_bow)
```

In [0]:

```
X_cv_bow = hstack((X_cv_cn,cv_bow_essay,bow_titles_cv,bow_summary_cv))
X_cv_bow = X_cv_bow.tocsr()
cv_scalar = StandardScaler(with_mean = False)
X_cv_bow = cv_scalar.fit_transform(X_cv_bow)
```

Now using hstack concatenate all train sets of categorical,numerical,vectors of essays and vectors of titles -Features

Similarly concatenate all the test sets and cv sets with their respective features

Convert COO-matrix to CSR-Sparse matrix as the input gievn to the KNN should be of Sparse Matrix and Not Dataframe as DF taes more time to Run.

1.4-Applying Randdom Forest on BOW, SET 1

For one Estimator value, we are calculating models with different Depths and we will find the best Model.

```
In [0]:
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
```

```
from sklearn.model_selection import cross val score
from collections import Counter
from sklearn.metrics import accuracy score
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score
import matplotlib.pyplot as plt
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
```

1.5-AUC with trainset and CV-set using Dataset after CV-spliting

```
In [0]:
train auc = []
```

```
cv auc = []
estimator_values = [5, 10, 50, 100, 200, 500, 1000]
depth values = [2, 3, 4, 5, 6, 7, 8, 9, 10]
for j in tqdm(estimator_values):
  for i in depth values:
      neigh = RandomForestClassifier(n estimators=j, max depth=i,class weight="balanced")
     neigh.fit(X train_bow, y_train)
     # roc auc score(y true, y score) the 2nd parameter should be probability estimates of the po
sitive class
     # not the predicted outputs
     y train pred = []
      for k in range(0, X train bow.shape[0],1000):
         y_train_pred.extend(neigh.predict_proba(X_train_bow[k:k+1000])[:,1])
     y_cv_pred = []
      for k in range(0, X_cv_bow.shape[0],1000):
         y cv pred.extend(neigh.predict proba(X cv bow[k:k+1000])[:,1])
      train_auc.append(roc_auc_score(y_train,y_train_pred))
      cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
 0%|
               | 0/7 [00:00<?, ?it/s]
               1/7 [00:04<00:27, 4.64s/it]
14%1
29%|
               | 2/7 [00:11<00:26, 5.30s/it]
43%|
               | 3/7 [00:35<00:43, 10.84s/it]
               | 4/7 [01:20<01:03, 21.21s/it]
57%|
 71%
               | 5/7 [02:50<01:23, 41.68s/it]
               | 6/7 [06:23<01:33, 93.22s/it]
86%
               7/7 [13:31<00:00, 193.53s/it]
```

```
cv_auc_t = np.array(cv_auc).reshape(7,9).T
train_auc_t = np.array(train_auc).reshape(7,9).T
```

In [0]:

```
df cv = pd.DataFrame(cv auc t,columns=estimator values)
df cv.index = depth values
df cv
df train = pd.DataFrame(train auc t,columns=estimator values)
df_train.index = depth_values
df_train
```

Out[0]:

5 10 50	100 200	500 1000
---------	---------	----------

2	0.57705 \$	0.6179 35	0.6800 §5	0.724 300	0.731270	0.739 806	0.73 9606
3	0.611734	0.640761	0.706160	0.727680	0.749888	0.749243	0.756414
4	0.645062	0.656848	0.744035	0.755900	0.759500	0.763679	0.766450
5	0.648743	0.680902	0.748003	0.767211	0.773063	0.778334	0.783090
6	0.654763	0.701839	0.771026	0.780630	0.788488	0.794508	0.794430
7	0.660130	0.720624	0.782374	0.788125	0.801785	0.812221	0.813510
8	0.684067	0.723724	0.796471	0.817908	0.820728	0.833452	0.831753
9	0.694568	0.736933	0.815566	0.840234	0.842066	0.845787	0.849001
10	0.692495	0.747634	0.840962	0.850933	0.862798	0.865528	0.865338

Heat-Map TRAIN_AUC

```
X_Axis = n_Estimators
```

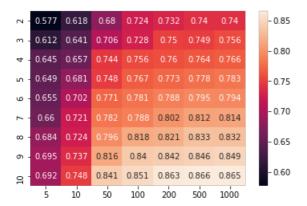
Y Axis = Depth

In [0]:

```
import seaborn as sns
sns.heatmap(df_train,annot=True,fmt='.3g')
```

Out[0]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f3c4bbe9550>



In [0]:

```
### Heat-Map-CV_AUC
```

In [0]:

```
import seaborn as sns
sns.heatmap(df_cv,annot=True,fmt='.3g')
```

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3c4ea9e4e0>

```
    N - 0.565
    0.609
    0.643
    0.691
    0.699
    0.701
    0.705

    M - 0.593
    0.616
    0.667
    0.694
    0.704
    0.706
    0.709
    -0.69

    M - 0.59
    0.597
    0.684
    0.7
    0.706
    0.709
    0.712

    M - 0.63
    0.639
    0.686
    0.692
    0.707
    0.708
    0.714
    -0.66

    M - 0.608
    0.644
    0.694
    0.697
    0.703
    0.712
    0.712
    -0.63

    M - 0.616
    0.628
    0.686
    0.704
    0.714
    0.716
    0.714
```

```
9 - 0.6 0.651 0.682 0.71 0.716 0.717 0.716

9 - 0.592 0.638 0.694 0.706 0.708 0.717 0.717

5 10 50 100 200 500 1000
```

The Best model is the model with highest CV_AUC and please check the hyperparameters of this model.

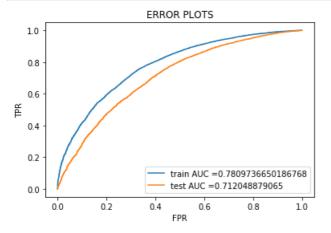
Please also check the TRAIN_AUC such that the model should not be overfitting, which means the train_auc should not be very high

Best_depth = 5 and best_N_Estimators = 75

1.7-ROC-Curve with optimal k for train and test-sets

In [0]:

```
from sklearn.metrics import roc curve, auc
neigh = RandomForestClassifier(n_estimators=1000, max_depth=5,class_weight="balanced")
neigh.fit(X train bow, y_train)
# roc auc score(y true, y score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs
y train pred = []
for k in range(0,X train bow.shape[0],1000):
 y_train_pred.extend(neigh.predict_proba(X_train_bow[k:k+1000])[:,1])
y test pred = []
for k in range(0, X_test_bow.shape[0],1000):
 y test pred.extend(neigh.predict proba(X test bow[k:k+1000])[:,1])
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train,y_train_pred )
test_fpr, test_tpr, te_thresholds = roc_curve(y_test,y_test_pred)
plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tpr)))
plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ERROR PLOTS")
plt.show()
print("="*100)
```



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

```
t = threshould[np.argmax(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))

predictions = []

for i in proba:
    if i>=t:
        predictions.append(1)
    else:
        predictions.append(0)

return predictions

import seaborn as sns

from sklearn.metrics import confusion_matrix

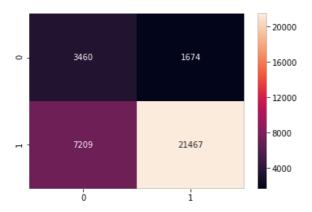
print("train Confusion Matrix")

cm_train=confusion_matrix(y_train,predict( y_train_pred, tr_thresholds, train_fpr, train_tpr))
sns.heatmap(cm_train,annot=True,fmt='.5g')
```

train Confusion Matrix the maximum value of tpr*(1-fpr) 0.5045137640024033 for threshold 0.498

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3c4e784588>



In [0]:

```
y_train.value_counts()
```

Out[0]:

1 28676 0 5134

Name: y, dtype: int64

In [0]:

```
print("Test confusion matrix")
cm=confusion_matrix(y_test, predict( y_test_pred, te_thresholds, test_fpr, test_tpr))
print(sns.heatmap(cm,annot=True,fmt='.5g'))
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.430261204856926 for threshold 0.494 AxesSubplot(0.125, 0.125; 0.62x0.755)



Gradient-Boosting with BOW using Train_auc and Cv_auc

4000

12337

```
In [0]:
train auc = []
cv auc = []
estimator_values = [5, 10, 50, 100, 200, 500, 1000]
depth values = [2, 3, 4, 5, 6, 7, 8, 9, 10]
for j in tqdm(estimator values):
  for i in depth_values:
     neigh = XGBClassifier(n_estimators=j, max_depth=i,class_weight="balanced")
     neigh.fit(X_train_bow, y_train)
      \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the po
sitive class
      # not the predicted outputs
      y train pred = []
      for k in range(0, X_train_bow.shape[0],1000):
          y_train_pred.extend(neigh.predict_proba(X_train_bow[k:k+1000])[:,1])
     y_cv_pred = []
      for k in range(0, X cv bow.shape[0],1000):
          y_cv_pred.extend(neigh.predict_proba(X_cv_bow[k:k+1000])[:,1])
      train_auc.append(roc_auc_score(y_train,y_train_pred))
      cv auc.append(roc_auc_score(y_cv, y_cv_pred))
```

```
0%| | 0/7 [00:00<?, ?it/s]

14%| | | 1/7 [00:55<05:33, 55.54s/it]

29%| | | 2/7 [02:13<05:11, 62.25s/it]

43%| | | 3/7 [06:19<07:49, 117.36s/it]

57%| | | 4/7 [13:48<10:50, 216.80s/it]

71%| | | 5/7 [27:48<13:27, 403.87s/it]

86%| | | 6/7 [1:01:30<14:49, 889.30s/it]

100%| | 7/7 [2:08:27<00:00, 1827.46s/it]
```

```
cv_auc_t = np.array(cv_auc).reshape(7,9).T
train_auc_t = np.array(train_auc).reshape(7,9).T
```

Tn [0]:

```
df_cv = pd.DataFrame(cv_auc_t,columns=estimator_values)
df_cv.index = depth_values
df_cv

df_train = pd.DataFrame(train_auc_t,columns=estimator_values)
df_train.index = depth_values
df_train
```

Out[0]:

5 2 0.652410		10	50	100	200	500	1000
2	0.652410	0.669098	0.728208	0.753750	0.779471	0.822711	0.864151
3	0.659628	0.682305	0.753001	0.783034	0.820071	0.878209	0.926833
4	0.684343	0.703859	0.780717	0.819945	0.863262	0.928498	0.969337
5	0.696097	0.723352	0.811526	0.858240	0.903465	0.959832	0.989991
6	0.721079	0.747494	0.852833	0.898437	0.939615	0.982644	0.997521
7	0.739332	0.783786	0.890362	0.934037	0.966462	0.993631	0.999661
8	0.767508	0.814100	0.926305	0.958996	0.982368	0.997989	0.999971
9	0.793246	0.836850	0.949633	0.976597	0.992526	0.999631	1.000000
10	0.811512	0.867143	0.969375	0.987900	0.997005	0.999951	1.000000

Heat_Map- Train_AUC

In [0]:

```
import seaborn as sns
sns.heatmap(df_train,annot=True,fmt='.3g')
```

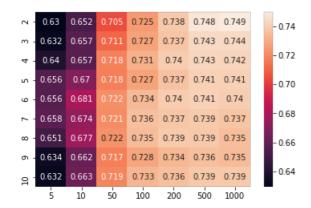
Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3c4b8ecd68>



Heat-Map- CV_AUC

```
import seaborn as sns
sns.heatmap(df_cv,annot=True,fmt='.3g')
Out[0]:
```

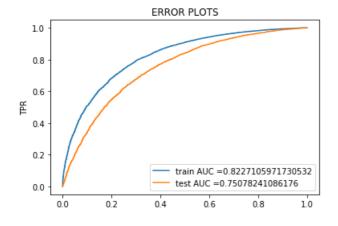


best_depth = 5

best_N_Estimators = 75

ROC-Curve with optimal_k for train and test-sets

```
from sklearn.metrics import roc curve, auc
neigh = XGBClassifier(n estimators=500, max depth=2,class weight="balanced")
neigh.fit(X_train_bow, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
# not the predicted outputs
y_train_pred = []
for k in range(0, X train bow.shape[0], 1000):
 y train pred.extend(neigh.predict proba(X train bow[k:k+1000])[:,1])
y_test_pred = []
for k in range(0, X test bow.shape[0],1000):
 y_test_pred.extend(neigh.predict_proba(X_test_bow[k:k+1000])[:,1])
train fpr, train tpr, tr thresholds = roc_curve(y_train,y_train_pred)
test fpr, test tpr, te thresholds = roc curve(y test,y test pred)
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ERROR PLOTS")
plt.show()
print("="*100)
```



•

4

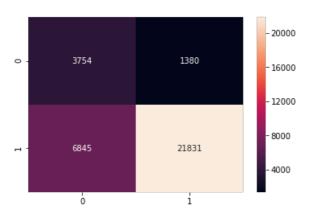
In [0]:

```
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr
def predict(proba, threshould, fpr, tpr):
    t = threshould[np.argmax(tpr*(1-fpr))]
    \# (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
     \texttt{print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for threshold", np.round(t,3))} \\
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
           predictions.append(0)
    return predictions
import seaborn as sns
from sklearn.metrics import confusion matrix
print("train Confusion Matrix")
cm_train=confusion_matrix(y_train,predict( y_train_pred, tr_thresholds, train_fpr, train_tpr))
sns.heatmap(cm train,annot=True,fmt='.5g')
```

train Confusion Matrix the maximum value of tpr*(1-fpr) 0.5566644177363441 for threshold 0.827

Out[0]:

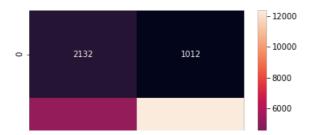
<matplotlib.axes._subplots.AxesSubplot at 0x7f3c4bdac4a8>

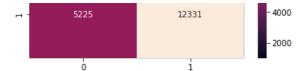


In [0]:

```
print("Test confusion matrix")
cm=confusion_matrix(y_test, predict( y_test_pred, te_thresholds, test_fpr, test_tpr))
print(sns.heatmap(cm,annot=True,fmt='.5g'))
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.476296498243063 for threshold 0.735 AxesSubplot($0.125, 0.125; 0.62 \times 0.755$)





2-TFIDF

We can use the same encoding of categorical variables here

2.1-Vectorizer of train, test, split with TFIDF-

```
In [0]:
```

```
X = X_train.columns
```

In [0]:

```
# We are considering only the words which appeared in at least 10 documents(rows or projects).
vectorizer3 = TfidfVectorizer(min_df=10)
train_tfidf_essay = vectorizer3.fit_transform(X_train_essay)
cv_tfidf_essay = vectorizer3.transform(X_cv_essay)
test_tfidf_essay = vectorizer3.transform(X_test_essay)
print(train_tfidf_essay.shape,cv_tfidf_essay.shape,test_tfidf_essay.shape)
```

(33810, 10476) (14490, 10476) (20700, 10476)

In [0]:

```
X= X.tolist() + vectorizer3.get_feature_names()
```

Vectorizing using TFIDF the train,test,cv sets of Essay-Text features

min_df=10 means, we are using all the words present only in min of 10 documents

In [0]:

```
vectorizer4 = TfidfVectorizer(min_df=10)
train_tfidf_titles = vectorizer4.fit_transform(X_train_titles)
tfidf_titles_cv = vectorizer4.transform(X_cv_titles)
test_tfidf_titles = vectorizer4.transform(X_test_titles)
```

In [0]:

```
X= X + vectorizer4.get_feature_names()
```

In [0]:

```
vectorizer5 = TfidfVectorizer(min_df=10)
train_tfidf_summary = vectorizer5.fit_transform(X_train_summary)
tfidf_summary_cv = vectorizer5.transform(X_cv_summary)
test_tfidf_summary = vectorizer5.transform(X_test_summary)
```

In [0]:

```
X = X + vectorizer5.get_feature_names()
```

we are using TFIDF of the text here

As we need to use fit_transform for train of essays and titles and their respective test-set/cv-set should be transformed because they both should have the same no.of.features (train/test and 1/cv-sets).

Whon transforming CV Test features \ they should have some no of features/vectorizers similar to Train set

vyrien transforming Cv, restreatures I, they should have same noton reatures/vectorizers similar to main-set

Vectorizing using TFIDF the train,test,cv sets of titles-Text features

min_df=10 means, we are using all the words present only in min of 10 documents

2.2-Train,test,cv sets of ALL features -Concatenating

```
In [0]:
```

```
from scipy.sparse import hstack
from sklearn import preprocessing

X_train_tfidf = hstack((X_train_cn, train_tfidf_essay, train_tfidf_titles, train_tfidf_summary))
X_train_tfidf = X_train_tfidf.tocsr()
train_scalar = StandardScaler(with_mean = False)
X_train_tfidf = train_scalar.fit_transform(X_train_tfidf)
```

In [0]:

```
X_test_tfidf =hstack((X_test_cn,test_tfidf_essay,test_tfidf_titles,test_tfidf_summary))
X_test_tfidf = X_test_tfidf.tocsr()
test_scalar = StandardScaler(with_mean = False)
X_test_tfidf = test_scalar.fit_transform(X_test_tfidf)
```

In [0]:

```
X_cv_tfidf = hstack((X_cv_cn,cv_tfidf_essay,tfidf_titles_cv,tfidf_summary_cv))
X_cv_tfidf = X_cv_tfidf.tocsr()
cv_scalar = StandardScaler(with_mean = False)
X_cv_tfidf = cv_scalar.fit_transform(X_cv_tfidf)
```

Now using hstack concatenate all train sets of categorical, numerical, vectors of essays and vectors of titles -Features

Similarly concatenate all the test sets and cv sets with their respective features

Convert COO-matrix to CSR-Sparse matrix as the input gievn to the KNN should be of Sparse Matrix and Not Dataframe

2.3-AUC with trainset and CV-set using Dataset after CV-spliting

```
train auc = []
cv_auc = []
estimator values = [5, 10, 50, 100, 200, 500, 1000]
depth_values = [2, 3, 4, 5, 6, 7, 8, 9, 10]
for j in tqdm(estimator values):
 for i in depth values:
     model tfidf = RandomForestClassifier(n estimators=j, max depth=i,class weight="balanced")
     model_tfidf.fit(X_train_tfidf, y_train)
     # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the po
sitive class
     # not the predicted outputs
     y_train_pred = []
      for k in range(0, X train tfidf.shape[0],100):
          y train pred.extend(model tfidf.predict proba(X train tfidf[k:k+100])[:,1])
     y cv pred = []
      for k in range(0, X cv tfidf.shape[0],100):
         y_cv_pred.extend(model_tfidf.predict_proba(X_cv_tfidf[k:k+100])[:,1])
```

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

```
0%| | 0/7 [00:00<?, ?it/s]

14%| | | 1/7 [00:08<00:50, 8.37s/it]

29%| | | 2/7 [00:21<00:48, 9.69s/it]

43%| | 3/7 [01:02<01:17, 19.31s/it]

57%| | 4/7 [02:24<01:53, 37.87s/it]

71%| | 5/7 [05:02<02:27, 73.97s/it]

86%| | 6/7 [11:31<02:48, 168.67s/it]

100%| | 7/7 [24:31<00:00, 351.85s/it]
```

In [0]:

```
cv_auc_t = np.array(cv_auc).reshape(7,9).T
train_auc_t = np.array(train_auc).reshape(7,9).T

df_cv = pd.DataFrame(cv_auc_t,columns=estimator_values)
df_cv.index = depth_values
df_cv

df_train = pd.DataFrame(train_auc_t,columns=estimator_values)
df_train.index = depth_values
df_train.
```

Out[0]:

	5	10	50	100	200	500	1000
2	0.597298	0.622420	0.709707	0.723709	0.731534	0.744051	0.744137
3	0.625633	0.637526	0.728524	0.745415	0.755582	0.759455	0.759771
4	0.596297	0.667129	0.747537	0.754032	0.771667	0.773621	0.775257
5	0.646986	0.698210	0.768353	0.781358	0.781392	0.794029	0.792316
6	0.673932	0.703243	0.780671	0.794842	0.805944	0.808849	0.810114
7	0.653388	0.720955	0.795804	0.811502	0.823003	0.827359	0.826291
8	0.687214	0.735563	0.824062	0.835977	0.837221	0.846419	0.851948
9	0.704676	0.764773	0.843384	0.853477	0.867546	0.867820	0.869552
10	0.723784	0.769793	0.863885	0.869240	0.882010	0.884822	0.887877

Heat_Map Train_AUC

```
import seaborn as sns
sns.heatmap(df_train,annot=True,fmt='.3g')
```

Out[0]: <matplotlib.axes. subplots.AxesSubplot at 0x7f3c4e7ac048> 0.597 0.622 0.71 0.724 0.732 0.744 0.744 - 0.85 0.626 0.638 0.729 0.745 0.756 0.759 0.76 0.596 0.667 0.748 0.754 0.772 0.774 0.775 - 0.80 0.647 0.698 0.768 0.781 0.781 0.794 0.792 - 0.75 0.674 0.703 0.781 0.795 0.806 0.809 0.81 0.653 0.721 0.796 0.812 0.823 0.827 0.826 - 0.70 0.687 0.736 0.824 0.836 0.837 0.846 0.852 - 0.65 0.705 0.765 0.843 0.853 0.868 0.868 0.87 0.724 0.77 0.864 0.869 0.882 0.885 0.888 - 0.60 ż 10 50 100 200 500 1000

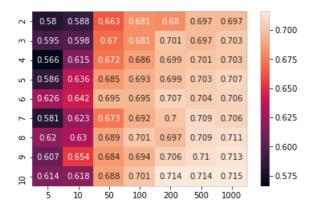
Heat_Map-CV_AUC

```
In [0]:
```

```
import seaborn as sns
sns.heatmap(df_cv,annot=True,fmt='.3g')
```

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3c4eefb0f0>



```
In [0]:
```

```
Best_depth = 10
```

In [0]:

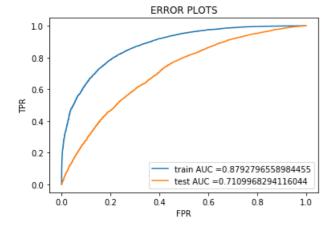
```
Best_n_Estiomators = 200
```

2.5-ROC-Curve with optimal_k for train and test-sets

```
from sklearn.metrics import roc_curve, auc

model_tfidf = RandomForestClassifier(n_estimators=200, max_depth=10,class_weight="balanced")
model_tfidf.fit(X_train_tfidf, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive class
# not the predicted outputs
" train_pred = []
```

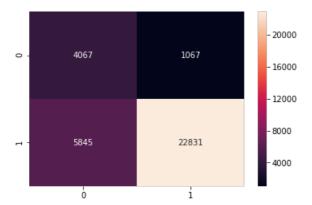
```
A_crain_brea = []
for k in range(0, X train tfidf.shape[0],100):
 y_train_pred.extend(model_tfidf.predict_proba(X_train_tfidf[k:k+100])[:,1])
y test pred = []
for k in range(0, X test tfidf.shape[0],100):
 y_test_pred.extend(model_tfidf.predict_proba(X_test_tfidf[k:k+100])[:,1])
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train,y_train_pred )
test fpr, test tpr, te thresholds = roc curve(y test,y test pred)
plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tpr)))
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ERROR PLOTS")
plt.show()
print("="*100)
```



```
In [0]:
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr
def predict(proba, threshould, fpr, tpr):
    t = threshould[np.argmax(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))
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
            predictions.append(0)
    return predictions
import seaborn as sns
from sklearn.metrics import confusion matrix
print("train Confusion Matrix")
cm_train=confusion_matrix(y_train,predict( y_train_pred, tr_thresholds, train_fpr, train_tpr))
sns.heatmap(cm train,annot=True,fmt='.5g')
```

train Confusion Matrix the maximum value of tpr*(1-fpr) 0.6307026712695112 for threshold 0.509

Out[0]:



In [0]:

```
y_train.value_counts()
```

Out[0]:

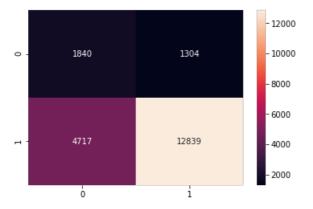
1 28676 0 5134

Name: y, dtype: int64

In [0]:

```
print("Test confusion matrix")
cm=confusion_matrix(y_test, predict( y_test_pred, te_thresholds, test_fpr, test_tpr))
print(sns.heatmap(cm,annot=True,fmt='.5g'))
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.427997184726795 for threshold 0.498 AxesSubplot(0.125, 0.125; 0.62x0.755)



In [0]:

```
y_test.value_counts()
```

Out[0]:

1 17556 0 3144

Name: y, dtype: int64

Gradient-Boosting with TFIDF

```
train_auc = []
cv_auc = []
```

```
estimator values = [5, 10, 50, 100, 200, 500, 1000]
depth values = [2, 3, 4, 5, 6, 7, 8, 9, 10]
for j in tqdm(estimator values):
  for i in depth values:
     model tfidf = XGBClassifier(n_estimators=j, max_depth=i,class_weight="balanced")
     model_tfidf.fit(X_train_tfidf, y_train)
     \# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the po
sitive class
     # not the predicted outputs
     y_train_pred = []
     for k in range(0, X train tfidf.shape[0], 100):
         y train pred.extend(model tfidf.predict proba(X train tfidf[k:k+100])[:,1])
     y cv pred = []
     for k in range(0, X cv tfidf.shape[0],100):
         y_cv_pred.extend(model_tfidf.predict_proba(X_cv_tfidf[k:k+100])[:,1])
     train_auc.append(roc_auc_score(y_train,y_train_pred))
     cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
 0%|
            | 0/7 [00:00<?, ?it/s]
             | 1/7 [01:37<09:44, 97.49s/it]
 14%|
              | 2/7 [04:00<09:15, 111.06s/it]
 29%|
              | 3/7 [12:32<15:25, 231.44s/it]
 43%|
 57%|
              | 4/7 [28:31<22:29, 449.84s/it]
 71%| | 5/7 [58:51<28:41, 860.89s/it]
 86%| | 6/7 [2:11:56<31:58, 1918.08s/it]
100%| 7/7 [4:36:15<00:00, 3940.16s/it]
```

In [0]:

```
cv_auc_t = np.array(cv_auc).reshape(7,9).T
train_auc_t = np.array(train_auc).reshape(7,9).T

df_cv = pd.DataFrame(cv_auc_t,columns=estimator_values)
df_cv.index = depth_values
df_cv

df_train = pd.DataFrame(train_auc_t,columns=estimator_values)
df_train.index = depth_values
df_train
```

Out[0]:

	5	10	50	100	200	500	1000
2	0.047054	0.674506	0.704070	0.764000	0.704544	0.046400	0.005700

_	0.047001	0.07 1000	0.731073	0.701020	0.731314	0.040100	4000
3	0.674888	10 0.689429	50 0.763897	100 0.799111	200 0.843257	500 0.909699	0.958999
4	0.677726	0.713794	0.798357	0.842271	0.891360	0.954508	0.988878
5	0.703925	0.730125	0.835376	0.882934	0.930766	0.981098	0.997937
6	0.724683	0.763335	0.876053	0.920761	0.960859	0.993698	0.999808
7	0.750245	0.787462	0.912554	0.952742	0.981004	0.998383	0.999993
8	0.771523	0.816916	0.941234	0.972830	0.991558	0.999754	1.000000
9	0.798657	0.851276	0.966012	0.987235	0.997288	0.999980	1.000000
10	0.826057	0.880859	0.981319	0.994218	0.999193	0.999999	1.000000

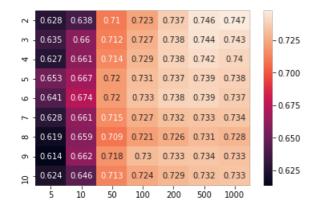
heat_Map Train_AUC

```
In [0]:
```

```
import seaborn as sns
sns.heatmap(df_cv,annot=True,fmt='.3g')
```

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3c4e326780>



Heat_Map-CV_AUC

In [0]:

```
import seaborn as sns
sns.heatmap(df_train,annot=True,fmt='.3g')
```

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f3c4e13d390>

```
- 0.648 0.672 0.732 0.762 0.792 0.846 0.896
                                                 - 0.96
0.675 0.689 0.764 0.799 0.843
                                     0.959
0.678 0.714 0.798 0.842 0.891 0.955 0.989
                                                 - 0.90
             0.835 0.883 0.931 0.981 0.998
                                                 - 0.84
0.725 0.763 0.876 0.921 0.961 0.994
                                        1
 0.75 0.787
                   0.953 0.981 0.998
                                        1
                                                 - 0.78
0.772 0.817 0.941 0.973 0.992
                                        1
                                                  0.72
0.799 0.851 0.966 0.987 0.997
                                        1
            0.981 0.994 0.999
                                                  0.66
```

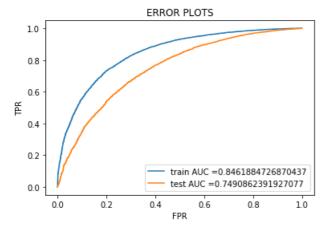
.

```
best_depth = 5
best_n estimators = 75
```

ROC-Curve with optimal_k for train and test-sets

In [0]:

```
from sklearn.metrics import roc curve, auc
model_tfidf = XGBClassifier(n_estimators=500, max_depth=2,class_weight="balanced")
model tfidf.fit(X train tfidf, y train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs
y_train_pred = []
for k in range(0, X train tfidf.shape[0],100):
 y_train_pred.extend(model_tfidf.predict_proba(X_train_tfidf[k:k+100])[:,1])
y test pred = []
for k in range(0, X test tfidf.shape[0],100):
 y_test_pred.extend(model_tfidf.predict_proba(X_test_tfidf[k:k+100])[:,1])
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train,y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test,y_test_pred)
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ERROR PLOTS")
plt.show()
```

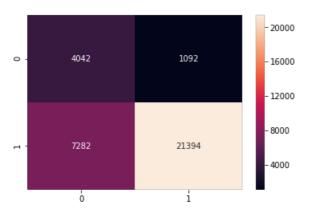


```
import seaborn as sns
from sklearn.metrics import confusion_matrix
print("train Confusion Matrix")
cm_train=confusion_matrix(y_train,predict( y_train_pred, tr_thresholds, train_fpr, train_tpr))
sns.heatmap(cm_train,annot=True,fmt='.5g')
```

train Confusion Matrix the maximum value of tpr*(1-fpr) 0.5873728449162392 for threshold 0.838

Out[0]:

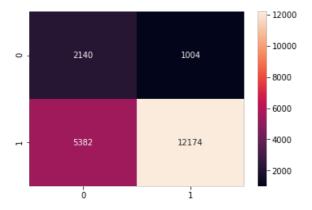
<matplotlib.axes. subplots.AxesSubplot at 0x7f3c4bdafda0>



In [0]:

```
print("Test confusion matrix")
cm=confusion_matrix(y_test, predict( y_test_pred, te_thresholds, test_fpr, test_tpr))
print(sns.heatmap(cm,annot=True,fmt='.5g'))
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.47199669889505164 for threshold 0.747 AxesSubplot(0.125, 0.125; 0.62x0.755)



In [0]:

```
# TFIDF-W2v
```

In [0]:

```
# stronging variables into pickle files python: http://www.jessicayung.com/how-to-use-pickle-to-sa
ve-and-load-variables-in-python/
# make sure you have the glove_vectors file
with open('gdrive/My Drive/glove_vectors', 'rb') as f:
    model = pickle.load(f)
    glove_words = set(model.keys())
```

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
```

```
tfidf_model_train = TfidfVectorizer()
tfidf_model_train.fit_transform(X_train_essay)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_train.get_feature_names(), list(tfidf_model_train.idf_)))
tfidf_words_train = set(tfidf_model_train.get_feature_names())
```

In [37]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm (X train essay): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight train =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_train):
           vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
           tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
           vector += (vec * tf idf) # calculating tfidf weighted w2v
           tf idf weight train += tf idf
    if tf_idf_weight_train != 0:
       vector /= tf idf weight train
    tfidf_w2v_vectors_train.append(vector)
100%| 33810/33810 [00:58<00:00, 573.32it/s]
```

In [0]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model_train_titles = TfidfVectorizer()
tfidf_model_train_titles.fit_transform(X_train_titles)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_train_titles.get_feature_names(), list(tfidf_model_train_titles.idf_)))
tfidf_words_train_titles = set(tfidf_model_train_titles.get_feature_names())
```

In [391:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors train titles = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train titles): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    \verb|tf_idf_weight_train_titles = 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 train titles):
             vec = model[word] # getting the vector for each word
             # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
             tf idf = dictionary[word] * (sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
             \texttt{vector} \; +\!\!= \; (\texttt{vec} \; * \; \texttt{tf\_idf}) \; \# \; \textit{calculating} \; \textit{tfidf} \; \textit{weighted} \; \textit{w2v}
             tf idf weight train titles += tf idf
    if tf idf weight train titles != 0:
        vector /= tf_idf_weight_train_titles
    tfidf w2v vectors train titles.append(vector)
print(len(tfidf w2v vectors train titles))
print(len(tfidf w2v vectors train titles[0]))
100%1
         | 33810/33810 [00:01<00:00, 27084.74it/s]
```

33810 300

```
tfidf_model_train = TfidfVectorizer()
tfidf_model_train.fit_transform(X_train_essay)

tfidf_model_train.transform(X_test_essay)

# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_train.get_feature_names(), list(tfidf_model_train.idf_)))
tfidf_words_test = set(tfidf_model_train.get_feature_names())
```

In [41]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X test essay): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight test =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 train):
           vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
           tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
           vector += (vec * tf_idf) # calculating tfidf weighted w2v
           tf idf weight test += tf idf
    if tf idf weight test != 0:
       vector /= tf idf weight test
    tfidf w2v vectors test.append(vector)
print(len(tfidf w2v vectors test))
print(len(tfidf w2v vectors test[0]))
100%| 20700/20700 [00:36<00:00, 562.73it/s]
```

20700 300

In [0]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model_train_titles = TfidfVectorizer()
tfidf_model_train_titles.fit_transform(X_train_titles)

tfidf_model_train_titles.transform(X_test_titles)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_train_titles.get_feature_names(), list(tfidf_model_train_titles.idf_)))
tfidf_words_test_titles = set(tfidf_model_train_titles.get_feature_names())
```

In [43]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors test titles = []; # the avg-w2v for each sentence/review is stored in this list
\textbf{for} \ \texttt{sentence} \ \textbf{in} \ \texttt{tqdm} \ (\texttt{X\_test\_titles}) : \ \textit{\# for each review/sentence}
    vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight test titles =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 train titles):
            vec = model[word] # getting the vector for each word
             # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
            tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
            vector += (vec * tf idf) # calculating tfidf weighted w2v
            tf_idf_weight_test_titles += tf_idf
    if tf_idf_weight_test_titles != 0:
        vector /= tf idf weight test titles
    tfidf_w2v_vectors_test_titles.append(vector)
print(len(tfidf_w2v_vectors_test_titles))
print(len(tfidf w2v vectors test titles[0]))
```

```
100%| 20700/20700 [00:00<00:00, 30581.44it/s]
20700
300
In [0]:
# S = ["abc def pgr", "def def def abc", "pgr pgr def"]
tfidf_model_train = TfidfVectorizer()
tfidf model train.fit transform(X train essay)
tfidf model train.transform(X cv essay)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf model train.get feature names(), list(tfidf model train.idf )))
tfidf words cv = set(tfidf model train.get feature names())
In [45]:
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors cv = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X cv essay): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight cv =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 train):
            vec = model[word] # getting the vector for each word
            \# here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
            tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
            vector += (vec * tf idf) # calculating tfidf weighted w2v
            tf idf weight cv += tf idf
    if tf idf weight cv != 0:
        vector /= tf idf weight cv
    tfidf w2v vectors cv.append(vector)
print(len(tfidf w2v vectors cv))
print(len(tfidf w2v vectors cv[0]))
100%| 14490/14490 [00:24<00:00, 579.97it/s]
14490
300
In [0]:
# S = ["abc def pgr", "def def def abc", "pgr pgr def"]
tfidf model 1 titles = TfidfVectorizer()
tfidf model 1 titles.fit transform(X train titles)
tfidf model 1 titles.transform(X cv titles)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf model 1 titles.get feature names(), list(tfidf model 1 titles.idf))))
tfidf words cv titles = set(tfidf model 1 titles.get feature names())
In [47]:
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors cv titles = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X cv titles): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight cv titles =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 train titles):
            vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
```

tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf

value((sentence.count(word)/len(sentence.split())))

idf value for each word

14490 300

In [0]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model_train = TfidfVectorizer()
tfidf_model_train.fit_transform(X_train_summary)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_train.get_feature_names(), list(tfidf_model_train.idf_)))
tfidf_words_train_summary = set(tfidf_model_train.get_feature_names())
```

In [49]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors train summary = []; # the avg-w2v for each sentence/review is stored in this lis
for sentence in tqdm(X train summary): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight train =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 thidf words train summary):
           vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
           tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
           vector += (vec * tf_idf) # calculating tfidf weighted w2v
           tf idf weight train += tf idf
    if tf idf weight train != 0:
       vector /= tf idf weight_train
    tfidf w2v vectors train summary.append(vector)
print(len(tfidf w2v vectors train summary))
print(len(tfidf w2v vectors train summary[0]))
100%| 33810/33810 [00:03<00:00, 10281.79it/s]
```

33810 300

In [0]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model_train = TfidfVectorizer()
tfidf_model_train.fit_transform(X_train_summary)

tfidf_model_train.transform(X_test_summary)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_train.get_feature_names(), list(tfidf_model_train.idf_)))
tfidf_words_test = set(tfidf_model_train.get_feature_names())
```

In [51]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf_w2v_vectors_test_summary = []; # the avg-w2v for each sentence/review is stored in this list
```

```
for sentence in tqdm(X test summary): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight test =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_train_summary):
           vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
           tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
           vector += (vec * tf idf) # calculating tfidf weighted w2v
           tf idf weight test += tf idf
    if tf_idf_weight_test != 0:
       vector /= tf_idf_weight_test
    tfidf w2v vectors test summary.append(vector)
100%| 20700/20700 [00:01<00:00, 10563.98it/s]
```

In [0]:

```
# S = ["abc def pqr", "def def def abc", "pqr pqr def"]
tfidf_model_1 = TfidfVectorizer()
tfidf_model_1.fit_transform(X_train_summary)
tfidf_model_1.transform(X_cv_summary)
# we are converting a dictionary with word as a key, and the idf as a value
dictionary = dict(zip(tfidf_model_1.get_feature_names(), list(tfidf_model_1.idf_)))
tfidf_words_cv = set(tfidf_model_1.get_feature_names())
```

In [53]:

```
# average Word2Vec
# compute average word2vec for each review.
tfidf w2v vectors cv summary = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm (X cv summary): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    tf idf weight cv =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 train summary):
           vec = model[word] # getting the vector for each word
            # here we are multiplying idf value(dictionary[word]) and the tf
value((sentence.count(word)/len(sentence.split())))
           tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split())) # getting the tf
idf value for each word
           vector += (vec * tf_idf) # calculating tfidf weighted w2v
           tf idf weight cv += tf idf
    if tf_idf_weight_cv != 0:
       vector /= tf_idf_weight_cv
    tfidf w2v vectors cv summary.append(vector)
print(len(tfidf w2v vectors cv summary))
print(len(tfidf w2v vectors cv summary[0]))
100%| 14490/14490 [00:01<00:00, 10074.80it/s]
```

14490 300

Concatenating All numerical and text features

```
from scipy.sparse import hstack
from sklearn.preprocessing import StandardScaler

X_train_tfidf_w2v = hstack((X_train_cn,tfidf_w2v_vectors_train,tfidf_w2v_vectors_train_titles,tfid
f_w2v_vectors_train_summary))
X_train_tfidf_w2v = X_train_tfidf_w2v.tocsr()
train_scalar = StandardScaler(with_mean = False)
X_train_tfidf_w2v = train_scalar.fit_transform(X_train_tfidf_w2v)
```

```
In [0]:
```

```
X_test_tfidf_w2v
=hstack((X_test_cn,tfidf_w2v_vectors_test,tfidf_w2v_vectors_test_titles,tfidf_w2v_vectors_test_summ
ary))
X_test_tfidf_w2v = X_test_tfidf_w2v.tocsr()
test_scalar = StandardScaler(with_mean = False)
X_test_tfidf_w2v = test_scalar.fit_transform(X_test_tfidf_w2v)
```

In [0]:

```
X_cv_tfidf_w2v=
hstack((X_cv_cn,tfidf_w2v_vectors_cv,tfidf_w2v_vectors_cv_titles,tfidf_w2v_vectors_cv_summary))
X_cv_tfidf_w2v = X_cv_tfidf_w2v.tocsr()
cv_scalar = StandardScaler(with_mean = False)
X_cv_tfidf_w2v = cv_scalar.fit_transform(X_cv_tfidf_w2v)

print(X_train_tfidf_w2v.shape,X_test_tfidf_w2v.shape,X_cv_tfidf_w2v.shape)

(33810, 924) (20700, 924) (14490, 924)
```

Random Forest for TFIDF

In [0]:

```
train auc = []
cv auc = []
estimator_values = [5, 10, 50, 100, 200, 500]
depth_values = [2, 3, 4, 5, 6, 7, 8, 9, 10]
for j in tqdm(estimator values):
  for i in depth values:
     model tfidf = RandomForestClassifier(n estimators=j, max depth=i,class weight="balanced")
     model_tfidf.fit(X_train_tfidf_w2v, y_train)
     # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the po
sitive class
     # not the predicted outputs
     y train pred = []
     for k in range(0,X train tfidf w2v.shape[0],1000):
         y_train_pred.extend(model_tfidf.predict_proba(X_train_tfidf_w2v[k:k+1000])[:,1])
     y_cv_pred = []
     for k in range(0, X cv tfidf w2v.shape[0],1000):
         y cv pred.extend(model tfidf.predict proba(X cv tfidf w2v[k:k+1000])[:,1])
     train_auc.append(roc_auc_score(y_train,y_train_pred))
     cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
100%| 6/6 [2:07:32<00:00, 1878.84s/it]
```

```
cv_auc_t = np.array(cv_auc).reshape(6,9).T
train_auc_t = np.array(train_auc).reshape(6,9).T

df_cv = pd.DataFrame(cv_auc_t,columns=estimator_values)
df_cv.index = depth_values
df_cv

df_train = pd.DataFrame(train_auc_t,columns=estimator_values)
```

```
df_train.index = depth_values
df_train
```

Out[0]:

	5	10	50	100	200	500
2	0.634570	0.652765	0.697827	0.704176	0.703836	0.707988
3	0.665614	0.684025	0.716505	0.727170	0.723168	0.727142
4	0.672474	0.717064	0.745018	0.745017	0.747351	0.747429
5	0.707046	0.737354	0.767023	0.774834	0.780642	0.781338
6	0.734554	0.771336	0.810551	0.819624	0.821587	0.824504
7	0.764397	0.812412	0.861134	0.870311	0.875852	0.876380
8	0.806376	0.860071	0.911885	0.921436	0.924759	0.926725
9	0.843954	0.911718	0.951186	0.960822	0.965525	0.967099
10	0.884985	0.930735	0.979499	0.984335	0.986759	0.988695

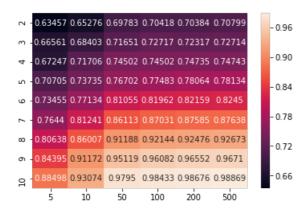
Heat_map Train_AUC

In [0]:

```
import seaborn as sns
sns.heatmap(df_train,annot=True,fmt='.5g')
```

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f58bc39e828>



Heat_Map-CV_AUC

In [0]:

```
import seaborn as sns
sns.heatmap(df_cv,annot=True,fmt='.5g')
```

Out[0]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f58bb84a710>

```
    ~ -0.60584 0.62817 0.66571 0.68037 0.67976 0.68441
    ~ -0.6383 0.65752 0.6834 0.69104 0.68636 0.69045
    ~ -0.62658 0.66408 0.68682 0.69207 0.69481 0.69065
    ~ -0.63778 0.65257 0.68807 0.69393 0.69624 0.69715
    ~ -0.62868 0.66071 0.68836 0.69338 0.69738 0.6996
    ~ - 0.6349 0.65076 0.68761 0.69641 0.70096 0.7005
    ~ - 0.64
```

```
∞ - 0.63091 0.65727 0.68378 0.69661 0.69602 0.70005

∞ - 0.60591 0.64771 0.68408 0.68842 0.6964 0.69853

⊝ - 0.62536 0.65326 0.67952 0.68964 0.69628 0.69999

5 10 50 100 200 500
```

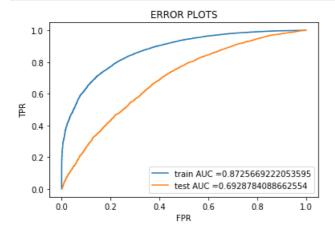
```
best_depth = 5
```

best_n_estimators = 50

ROC-Curve with optimal_k for train and test-sets

In [0]:

```
from sklearn.metrics import roc curve, auc
model tfidf = RandomForestClassifier(n estimators=200, max depth=7,class weight="balanced")
model_tfidf.fit(X_train_tfidf_w2v, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs
y_train_pred = []
for k in range(0, X_train_tfidf_w2v.shape[0],100):
 y train pred.extend(model tfidf.predict proba(X train tfidf w2v[k:k+100])[:,1])
y test pred = []
for k in range(0, X test tfidf w2v.shape[0],100):
 y_test_pred.extend(model_tfidf.predict_proba(X_test_tfidf_w2v[k:k+100])[:,1])
train fpr, train tpr, tr thresholds = roc curve(y train,y train pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test,y_test_pred)
plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tpr)))
plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ERROR PLOTS")
plt.show()
print("="*100)
```



.]:

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

```
t = threshould[np.argmax(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))

predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions

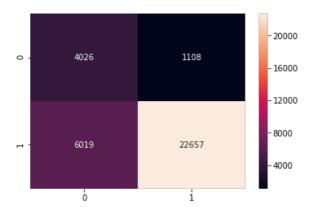
import seaborn as sns
from sklearn.metrics import confusion_matrix
print("train Confusion Matrix")

cm_train=confusion_matrix(y_train,predict( y_train_pred, tr_thresholds, train_fpr, train_tpr))
sns.heatmap(cm_train,annot=True,fmt='.5g')
```

train Confusion Matrix the maximum value of tpr*(1-fpr) 0.6195862042470331 for threshold 0.508

Out[0]:

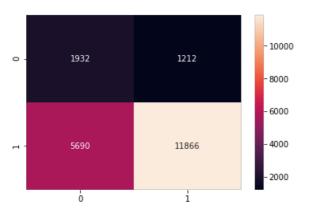
<matplotlib.axes._subplots.AxesSubplot at 0x7f58bbfb93c8>



In [0]:

```
print("Test confusion matrix")
cm=confusion_matrix(y_test, predict( y_test_pred, te_thresholds, test_fpr, test_tpr))
print(sns.heatmap(cm,annot=True,fmt='.5g'))
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.4153396155204111 for threshold 0.506 AxesSubplot(0.125, 0.125; 0.62x0.755)



Gradient-Boosting TFIDF

```
In [0]:
train auc = []
cv auc = []
estimator_values = [5, 10, 50, 100, 200, 500]
depth_values = [2, 3, 4, 5, 6, 7, 8, 9, 10]
for j in tqdm(estimator_values):
  for i in depth values:
     model_tfidf = XGBClassifier(n_estimators=j, max_depth=i,class_weight="balanced")
     model_tfidf.fit(X_train_tfidf_w2v, y_train)
     # roc auc score(y true, y score) the 2nd parameter should be probability estimates of the po
sitive class
     # not the predicted outputs
      y_train_pred = []
      for k in range(0, X_train_tfidf_w2v.shape[0],100):
         y_train_pred.extend(model_tfidf.predict_proba(X_train_tfidf_w2v[k:k+100])[:,1])
     y_cv_pred = []
      for k in range(0, X_cv_tfidf_w2v.shape[0],100):
          y cv pred.extend(model tfidf.predict proba(X cv tfidf w2v[k:k+100])[:,1])
      train_auc.append(roc_auc_score(y_train,y_train_pred))
```

100%| 6/6 [10:54:15<00:00, 9602.25s/it]

cv_auc.append(roc_auc_score(y_cv, y_cv_pred))

In [0]:

```
cv_auc_t = np.array(cv_auc).reshape(6,9).T

train_auc_t = np.array(train_auc).reshape(6,9).T

df_cv = pd.DataFrame(cv_auc_t,columns=estimator_values)
df_cv.index = depth_values
df_cv

df_train = pd.DataFrame(train_auc_t,columns=estimator_values)
df_train.index = depth_values
df_train
```

Out[0]:

	5	10	50	100	200	500
2	0.665593	0.688344	0.736403	0.763024	0.791598	0.843429
3	0.688685	0.705789	0.767901	0.803601	0.850719	0.932028
4	0.707175	0.732313	0.807504	0.858504	0.918022	0.987393
5	0.737923	0.768103	0.862096	0.919615	0.975259	0.999739
6	0.772526	0.805285	0.920523	0.971176	0.997419	1.000000
7	0.806921	0.850579	0.964018	0.995126	0.999976	1.000000
8	0.841389	0.901173	0.990963	0.999719	1.000000	1.000000
9	0.878628	0.934592	0.999080	0.999999	1.000000	1.000000
10	0.912496	0.961070	0.999977	1.000000	1.000000	1.000000

heat_map- Train_AUC

```
In [0]:
import seaborn as sns
sns.heatmap(df_train,annot=True,fmt='.5g')
Out[0]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f7822c299e8>
~ -0.66559 0.68834 0.7364 0.76302 0.7916 0.84343
                                                  -0.96
m - 0.68869 0.70579 0.7679 0.8036 0.85072 0.93203
   -0.70718 0.73231 0.8075 0.8585 0.91802 0.98739
                                                  - 0.90
u -0.73792 0.7681 0.8621 0.91961 0.97526 0.99974
   -0.77253 0.80528 0.92052 0.97118 0.99742
                                                  - 0.84
   -0.80692 0.85058 0.96402 0.99513 0.99998
                                        1
                                                  - 0.78
   -0.84139 0.90117 0.99096 0.99972 1
                                         1
    0.87863 0.93459 0.99908 1
                                         1
                                                  0.72
    0.9125 0.96107 0.99998
             10
                    50
                          100
                                 200
                                        500
```

Heat_map - CV_AUC

```
In [0]:
```

```
import seaborn as sns
sns.heatmap(df cv,annot=True,fmt='.5g')
Out[0]:
<matplotlib.axes. subplots.AxesSubplot at 0x7f7822a85550>

∼ -0.63717 0.66214 0.70659 0.72266 0.73206 0.73586

                                                   - 0.725
    0.65345 0.65829 0.71102 0.72403 0.72951 0.72589
                                                   -0.700
   - 0.61495 0.64801 0.7188 0.7284 0.72738 0.72128
 -0.62616 0.65684 0.71439 0.72152 0.71894 0.71365
                                                   - 0.675
 φ -0.62595 0.65194 0.70651 0.7162 0.71271 0.71093
                                                   -0.650
   -0.62664 0.64218 0.71006 0.71316 0.71061 0.7148
   -0.59224 0.61613 0.70015 0.70486 0.71046 0.71945
```

0.625

0.600

```
best depth = 5
best n estimators = 50
```

10

ROC-Curve with optimal k for train and test-sets

100 200

500

-0.61508 0.64703 0.70405 0.71355 0.71673 0.72686

0.58844 0.61926 0.6983 0.70768 0.71567 0.72543

50

```
from sklearn.metrics import roc_curve, auc
model_tfidf = XGBClassifier(n_estimators=50, max_depth=5,class_weight="balanced")
model tfidf.fit(X train tfidf w2v, y train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
class
# not the predicted outputs
y_train_pred = []
for k in range (0 Y train thidf w/2 chane [0] 1000).
```

```
y_train_pred.extend(model_tfidf.predict_proba(X_train_tfidf_w2v[k:k+1000])[:,1])

y_test_pred = []

for k in range(0, X_test_tfidf_w2v.shape[0],1000):
    y_test_pred.extend(model_tfidf.predict_proba(X_test_tfidf_w2v[k:k+1000])[:,1])

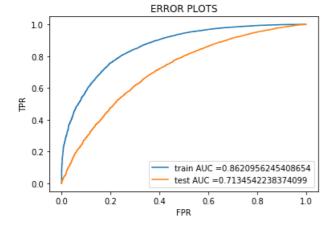
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train,y_train_pred))

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

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

plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))

plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ERROR PLOTS")
plt.title("ERROR PLOTS")
plt.show()
```



```
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr
def predict(proba, threshould, fpr, tpr):
    t = threshould[np.argmax(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))
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
import seaborn as sns
from sklearn.metrics import confusion matrix
print("train Confusion Matrix")
cm_train=confusion_matrix(y_train,predict( y_train_pred, tr_thresholds, train_fpr, train_tpr))
sns.heatmap(cm_train,annot=True,fmt='.5g')
```

```
In [0]:
```

```
print("Test confusion matrix")
cm=confusion_matrix(y_test, predict( y_test_pred, te_thresholds, test_fpr, test_tpr))
print(sns.heatmap(cm,annot=True,fmt='.5g'))
```

AVG W2V

In [54]:

```
# average Word2Vec
# compute average word2vec for each review.
avg_w2v_essays_vectors_train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train essay): # 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) and (word in tfidf_words_train):
           vector += model[word]
           cnt words += 1
    if cnt words != 0:
       vector /= cnt words
    avg w2v essays vectors train.append(vector)
print(len(avg w2v essays vectors train))
print(len(avg_w2v_essays_vectors_train[0]))
100%| 33810/33810 [00:09<00:00, 3546.29it/s]
33810
```

In [55]:

300

```
# average Word2Vec
# compute average word2vec for each review.
avg w2v titles vectors train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train titles): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    cnt words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
       if (word in glove words) and (word in tfidf words train titles):
           vector += model[word]
           cnt words += 1
    if cnt words != 0:
       vector /= cnt words
    avg_w2v_titles_vectors_train.append(vector)
print(len(avg_w2v_titles_vectors_train))
print(len(avg_w2v_titles_vectors_train[0]))
100%| 33810/33810 [00:00<00:00, 64001.91it/s]
```

33810 300

In [56]:

```
# average Word2Vec
# compute average word2vec for each review.
avg w2v essays vectors test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X test essay): # 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) and (word in tfidf words train):
           vector += model[word]
           cnt_words += 1
   if cnt words != 0:
       vector /= cnt_words
   avg_w2v_essays_vectors_test.append(vector)
print(len(avg w2v essays vectors test))
print(len(avg_w2v_essays_vectors_test[0]))
```

```
100%|| 20700/20700 [00:06<00:00, 3096.52it/s]
```

20700 300

In [57]:

```
# average Word2Vec
# compute average word2vec for each review.
avg w2v titles vectors test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X test titles): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    cnt words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
       if (word in glove_words) and (word in tfidf_words_train_titles):
           vector += model[word]
           cnt words += 1
    if cnt words != 0:
       vector /= cnt words
    avg_w2v_titles_vectors_test.append(vector)
print(len(avg_w2v_titles_vectors_test))
print(len(avg_w2v_titles_vectors_test[0]))
100%| 20700/20700 [00:00<00:00, 55067.66it/s]
20700
```

In [58]:

300

```
# average Word2Vec
# compute average word2vec for each review.
avg w2v essays vectors cv = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X cv essay): # 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) and (word in tfidf words train):
           vector += model[word]
           cnt_words += 1
    if cnt words != 0:
       vector /= cnt_words
    avg_w2v_essays_vectors_cv.append(vector)
print(len(avg w2v essays vectors cv))
print(len(avg_w2v_essays_vectors_cv[0]))
100%| | 14490/14490 [00:04<00:00, 3177.93it/s]
```

14490 300

In [59]:

```
print(len(avg_w2v_titles_vectors_cv[0]))

100%| 14490/14490 [00:00<00:00, 63278.58it/s]

14490
300
```

In [60]:

```
# average Word2Vec
# compute average word2vec for each review.
avg w2v summary vectors train = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X train summary): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    cnt words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
       if (word in glove_words) and (word in tfidf_words_train_summary):
           vector += model[word]
           cnt_words += 1
    if cnt words != 0:
       vector /= cnt_words
    avg_w2v_summary_vectors_train.append(vector)
print(len(avg_w2v_summary_vectors_train))
print(len(avg_w2v_summary_vectors_train[0]))
100%| 33810/33810 [00:01<00:00, 31008.80it/s]
```

In [61]:

33810 300

```
# average Word2Vec
# compute average word2vec for each review.
avg w2v summary vectors test = []; # the avg-w2v for each sentence/review is stored in this list
for sentence in tqdm(X test summary): # for each review/sentence
   vector = np.zeros(300) # as word vectors are of zero length
    cnt words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if (word in glove words) and (word in tfidf words train summary):
           vector += model[word]
           cnt_words += 1
    if cnt words != 0:
       vector /= cnt words
    avg_w2v_summary_vectors_test.append(vector)
print(len(avg_w2v_summary_vectors_test))
print(len(avg w2v summary vectors test[0]))
100%| 20700/20700 [00:00<00:00, 31184.44it/s]
```

20700 300

In [62]:

```
avg_w2v_summary_vectors_cv.append(vector)

print(len(avg_w2v_summary_vectors_cv))
print(len(avg_w2v_summary_vectors_cv[0]))

100%| | 14490/14490 [00:00<00:00, 31435.77it/s]
```

Conacatenating all features Numerical and Categorical

In [0]:

```
from scipy.sparse import hstack
from sklearn.preprocessing import StandardScaler

X_train_avg_w2v = hstack((X_train_cn,avg_w2v_essays_vectors_train,avg_w2v_titles_vectors_train,avg_w2v_summary_vectors_train))
X_train_avg_w2v = X_train_avg_w2v.tocsr()
train_scalar = StandardScaler(with_mean = False)
X_train_avg_w2v = train_scalar.fit_transform(X_train_avg_w2v)
```

In [0]:

```
X_cv_avg_w2v=
hstack((X_cv_cn,avg_w2v_essays_vectors_cv,avg_w2v_titles_vectors_cv,avg_w2v_summary_vectors_cv))
X_cv_avg_w2v = X_cv_avg_w2v.tocsr()
cv_scalar = StandardScaler(with_mean = False)
X_cv_avg_w2v = cv_scalar.fit_transform(X_cv_avg_w2v)
```

In [0]:

```
X_test_avg_w2v
=hstack((X_test_cn,avg_w2v_essays_vectors_test,avg_w2v_titles_vectors_test,avg_w2v_summary_vectors_test))
X_test_avg_w2v = X_test_avg_w2v.tocsr()
test_scalar = StandardScaler(with_mean = False)
X_test_avg_w2v = test_scalar.fit_transform(X_test_avg_w2v)
```

Random Forest

```
In [0]:
```

```
train_auc = []
cv_auc = []

estimator_values = [5, 10, 50, 100, 200, 500]
depth_values = [2, 3, 4, 5, 6, 7, 8, 9, 10]

for j in tqdm(estimator_values):

    for i in depth_values:
        model_avg_w2v = RandomForestClassifier(n_estimators=j, max_depth=i,class_weight="balanced")
        model_avg_w2v.fit(X_train_avg_w2v, y_train)
        # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the po
    sitive class
        # not the predicted outputs

        y_train_pred = []
        for k in range(0,X_train_avg_w2v.shape[0],100):
            y_train_pred.extend(model_avg_w2v.predict_proba(X_train_avg_w2v[k:k+100])[:,1])
        y_cv_pred = []
```

In [0]:

```
cv_auc_t = np.array(cv_auc).reshape(6,9).T
train_auc_t = np.array(train_auc).reshape(6,9).T

df_cv = pd.DataFrame(cv_auc_t,columns=estimator_values)
df_cv.index = depth_values
df_cv

df_train = pd.DataFrame(train_auc_t,columns=estimator_values)
df_train.index = depth_values
df_train
```

Out[0]:

	5	10	50	100	200	500
2	0.640799	0.659519	0.704403	0.708510	0.707882	0.715399
3	0.654874	0.685531	0.717716	0.729175	0.727148	0.731157
4	0.692136	0.707574	0.740910	0.744855	0.751770	0.755705
5	0.709447	0.725132	0.776641	0.784486	0.786348	0.789141
6	0.739988	0.768470	0.819318	0.828963	0.829643	0.833225
7	0.774656	0.811349	0.873764	0.879951	0.884853	0.889067
8	0.814683	0.869703	0.921009	0.933837	0.935840	0.939026
9	0.856077	0.905770	0.961856	0.967591	0.973332	0.974071
10	0.884267	0.942982	0.984851	0.989184	0.991714	0.992284

Heat_Map-Train_AUC

In [0]:

```
import seaborn as sns
sns.heatmap(df_train,annot=True,fmt='.5g')
```

Out[0]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f58bb811e48>

```
0.6408 0.65952 0.7044 0.70851 0.70788 0.7154
                                                        0.96
  0.65487 0.68553 0.71772 0.72918 0.72715 0.73116
                                                       - 0.90
   -0.69214 0.70757 0.74091 0.74486 0.75177 0.75571
- 0.70945 0.72513 0.77664 0.78449 0.78635 0.78914
                                                        - 0.84
   -0.73999 0.76847 0.81932 0.82896 0.82964 0.83323
  -0.77466 0.81135 0.87376 0.87995 0.88485 0.88907
                                                        - 0.78
  -0.81468 0.8697 0.92101 0.93384 0.93584 0.93903
                                                        - 0.72
  -0.85608 0.90577 0.96186 0.96759 0.97333 0.97407
    0.88427 0.94298 0.98485 0.98918 0.99171 0.99228
                                                        0.66
      5
             10
                     50
                          100
                                    200
                                            500
```

Heat Map-CV AUC

```
In [0]:
```

```
import seaborn as sns
sns.heatmap(df_cv,annot=True,fmt='.5g')
Out[0]:
<matplotlib.axes. subplots.AxesSubplot at 0x7f58bc1af9b0>
                                                    - 0.70
   - 0.60935 0.63881 0.67677 0.6841 0.68676 0.69129
   - 0.62674 0.64678 0.68529 0.69053 0.69066 0.69388
                                                     - 0.68
    0.6437 0.66138 0.6904 0.68763 0.6953 0.69671
 மு - 0.63306 0.65499 0.6937 0.69672 0.6995 0.70122
                                                    - 0.66
   -0.63156 0.64562 0.69116 0.6993 0.69958 0.70257
    0.63423 0.64102 0.69258 0.69182 0.70024 0.70326
                                                     - 0.64
 ∞ -0.62145 0.64316 0.6924 0.69382 0.69971 0.70356
   -0.60842 0.65213 0.68457 0.69409 0.70198 0.70307
                                                     0.62
    0.61674 0.63407 0.68902 0.69017 0.69281 0.70162
                           100
      Ś
             10
                                  200
                                          500
```

ROC-Curve with optimal_k for train and test-sets

In [0]:

max depth=5

n estimators = 60

```
from sklearn.metrics import roc curve, auc
model tfidf = RandomForestClassifier(n estimators=500, max depth=5,class weight="balanced")
model tfidf.fit(X train avg w2v, y train)
\# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estimates of the positive
# not the predicted outputs
y train pred = []
for k in range(0, X_train_avg_w2v.shape[0],100):
 y_train_pred.extend(model_tfidf.predict_proba(X_train_avg_w2v[k:k+100])[:,1])
y_test_pred = []
for k in range(0, X test avg w2v.shape[0],100):
 y test pred.extend(model tfidf.predict proba(X test avg w2v[k:k+100])[:,1])
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train,y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test,y_test_pred)
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tpr)))
plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ERROR PLOTS")
plt.show()
print("="*100)
```

```
0.8 - 0.6 0.6 0.8 0.0 0.2 0.4 0.6 0.8 1.0 FPR
```

4

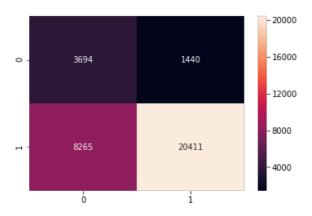
In [0]:

```
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr
def predict(proba, threshould, fpr, tpr):
    t = threshould[np.argmax(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))
    predictions = []
    for i in proba:
        if i>=t:
           predictions.append(1)
        else:
           predictions.append(0)
    return predictions
import seaborn as sns
from sklearn.metrics import confusion matrix
print("train Confusion Matrix")
cm_train=confusion_matrix(y_train,predict( y_train_pred, tr_thresholds, train_fpr, train_tpr))
sns.heatmap(cm_train,annot=True,fmt='.5g')
```

train Confusion Matrix the maximum value of tpr*(1-fpr) 0.5121376894186288 for threshold 0.507

Out[0]:

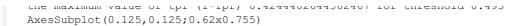
<matplotlib.axes. subplots.AxesSubplot at 0x7f58bc2fc2b0>



In [0]:

```
print("Test confusion matrix")
cm=confusion_matrix(y_test, predict( y_test_pred, te_thresholds, test_fpr, test_tpr))
print(sns.heatmap(cm,annot=True,fmt='.5g'))
```

Test confusion matrix the maximum value of thre (1-fnr) 0 (1/2/4/4/0.26/4/36/4/67) for threshold 0 (1/4/4/0.26/4/36/4/67)





Gradient-Boosting

In [66]:

```
train auc = []
cv auc = []
estimator_values = [5, 10, 50, 100, 200, 500]
depth_values = [2, 3, 4, 5, 6, 7, 8, 9, 10]
for j in tqdm(estimator values):
  for i in depth values:
     model_avg_w2v = XGBClassifier(n_estimators=j, max_depth=i,class_weight="balanced")
     model_avg_w2v.fit(X_train_avg_w2v, y_train)
     # roc auc score(y true, y score) the 2nd parameter should be probability estimates of the po
sitive class
     # not the predicted outputs
     y train pred = []
     for k in range(0,X train avg w2v.shape[0],1000):
         y_train_pred.extend(model_avg_w2v.predict_proba(X_train_avg_w2v[k:k+1000])[:,1])
     y_cv_pred = []
     for k in range(0, X_cv_avg_w2v.shape[0],1000):
         y_cv_pred.extend(model_avg_w2v.predict_proba(X_cv_avg_w2v[k:k+1000])[:,1])
     train_auc.append(roc_auc_score(y_train,y_train_pred))
     cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
100%| 6/6 [10:49:54<00:00, 9528.70s/it]
```

In [67]:

```
cv_auc_t = np.array(cv_auc).reshape(6,9).T
train_auc_t = np.array(train_auc).reshape(6,9).T

df_cv = pd.DataFrame(cv_auc_t,columns=estimator_values)
df_cv.index = depth_values
df_cv

df_train = pd.DataFrame(train_auc_t,columns=estimator_values)
df_train.index = depth_values
df_train.
```

	5	10	50	100	200	500
2	0.663820	0.676569	0.736907	0.764656	0.792420	0.846509
3	0.688277	0.699680	0.770801	0.806157	0.852741	0.930712
4	0.712439	0.731050	0.810805	0.858244	0.920996	0.986819
5	0.738667	0.771790	0.862357	0.921593	0.975786	0.999695
6	0.767304	0.810351	0.918602	0.969903	0.996596	1.000000
7	0.810475	0.857261	0.968209	0.994495	0.999945	1.000000
8	0.847671	0.900832	0.991348	0.999641	1.000000	1.000000
9	0.888586	0.939171	0.999323	0.999997	1.000000	1.000000
10	0.910258	0.962730	0.999949	1.000000	1.000000	1.000000

Heat_Map-train _AUC

```
In [68]:
import seaborn as sns
sns.heatmap(df train,annot=True,fmt='.5g')
Out[68]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f22ecb460f0>
 ~ -0.66382 0.67657 0.73691 0.76466 0.79242 0.84651
                                                    - 0.96
    -0.68828 0.69968 0.7708 0.80616 <mark>0.85274 0.93071</mark>
   -0.71244 0.73105 0.8108 0.85824 0.921 0.98682
                                                    - 0.90
 ம் - 0.73867 0.77179 <mark>0.86236</mark> 0.92159 0.97579 0.9997
                                                    - 0.84
 - 0.7673 0.81035 0.9186 0.9699 0.9966
                                          1
    0.81048 0.85726 0.96821 0.99449 0.99994
                                          1
                                                    - 0.78
    0.84767 0.90083 0.99135 0.99964
                                           1
    -0.88859 0.93917 0.99932 1
                                                    0.72
     0.91026 0.96273 0.99995 1
                                           1
             10
                    50 100 200
                                          500
```

Heat_Map-CV_AUC

0.6056 0.63929 0.69213 0.6983 0.70642 0.71912

```
In [69]:
import seaborn as sns
sns.heatmap(df cv,annot=True,fmt='.5g')
Out[69]:
<matplotlib.axes._subplots.AxesSubplot at 0x7f22ecb62d68>

∼ - 0.63348 0.65468 0.70831 0.72315 0.73376 0.73624

                                                      -0.725
    -0.65304 0.65675 0.70862 0.72737 0.73335 0.73277
    - 0.63825 <mark>0.66838 0.71529 0.72564 0.72422 0.72052</mark>
                                                      - 0.700
 ம் - 0.64527 0.67958 0.71434 0.72731 0.73192 0.72202
                                                      - 0.675
    -0.64509 <mark>0.68135</mark> 0.71299 0.72025 0.71613 0.71256
     0.6312 0.65689 0.70951 0.71963 0.72075 0.72066
                                                      - 0.650
    - 0.61254 0.64547 0.70779 0.71393 0.71633 0.72177
    0.6235 0.65945 0.71029 0.71371 0.71601 0.72439
```

0.625

5 10 50 100 200 500

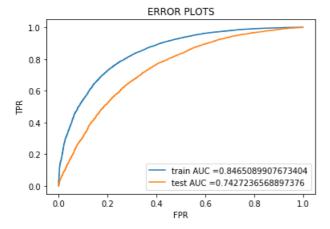
max_depth=5

n_estimators = 55

ROC-Curve with optimal_k for train and test-sets

In [70]:

```
from sklearn.metrics import roc curve, auc
model tfidf = XGBClassifier(n estimators=500, max depth=2,class weight="balanced")
model_tfidf.fit(X_train_avg_w2v, y_train)
# roc auc score(y true, y score) the 2nd parameter should be probability estimates of the positive
# not the predicted outputs
y train pred = []
for k in range(0, X_train_avg_w2v.shape[0],100):
 y train pred.extend(model tfidf.predict proba(X train avg w2v[k:k+100])[:,1])
y_test_pred = []
for k in range(0, X test avg w2v.shape[0],100):
 y test pred.extend(model tfidf.predict proba(X test avg w2v[k:k+100])[:,1])
train fpr, train tpr, tr thresholds = roc curve(y train,y train pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test,y_test_pred)
plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tpr)))
plt.plot(test fpr, test tpr, label="test AUC ="+str(auc(test fpr, test tpr)))
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ERROR PLOTS")
plt.show()
print("="*100)
```



T. [71]

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

    t = threshould[np.argmax(tpr*(1-fpr))]
# (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
```

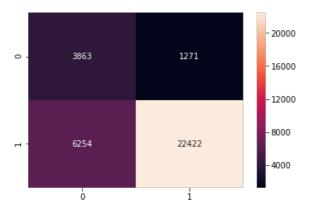
```
print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for threshold", np.round(t,3))
predictions = []
for i in proba:
    if i>=t:
        predictions.append(1)
    else:
        predictions.append(0)
return predictions

import seaborn as sns
from sklearn.metrics import confusion_matrix
print("train Confusion Matrix")
cm_train=confusion_matrix(y_train,predict( y_train_pred, tr_thresholds, train_fpr, train_tpr))
sns.heatmap(cm_train,annot=True,fmt='.5g')
```

train Confusion Matrix the maximum value of tpr*(1-fpr) 0.5883349119860578 for threshold 0.824

Out [71]:

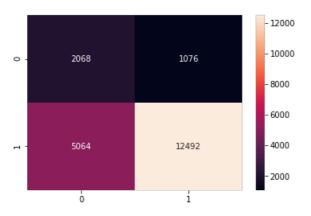
<matplotlib.axes._subplots.AxesSubplot at 0x7f22ecbfb208>



In [72]:

```
print("Test confusion matrix")
cm=confusion_matrix(y_test, predict( y_test_pred, te_thresholds, test_fpr, test_tpr))
print(sns.heatmap(cm,annot=True,fmt='.5g'))
```

Test confusion matrix the maximum value of tpr*(1-fpr) 0.4680307639327326 for threshold 0.732 AxesSubplot(0.125, 0.125; 0.62x0.755)



In [74]:

```
import numpy as np
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Model", "max_depth", "n_estimators", "Train-AUC", "Test-AUC"]
```

```
x.add_row(["BOW-Random-Forest",5,1000,0.780,0.712])
x.add_row(["BOW-Gradient-Boosting",2,1000,0.822,0.750])
x.add_row(["TFidf-Random-Forest",10,200,0.879,0.710])
x.add_row(["TFidf-Gradient-Boosting",2,500,0.846,0.749])
x.add_row(["TFidf-W2V-Random-Forest",7,200,0.773,0.684])
x.add_row(["TFidf-W2V-Gradient-Boosting",5,50,0.862,0.713])
x.add_row(["AVG-W2V-Random-Forest",5,500,0.789,0.702])
x.add_row(["AVG-W2V-Gradient-Boosting",2,500,0.846,0.742])
```

BOW-Gradient-Boosting 2 1000 0.822 0 TFidf-Random-Forest 10 200 0.879 0 TFidf-Gradient-Boosting 2 500 0.846 0.	1100	Test-AU	'	Train-AUC		n_estimators	h	max_dept	1	Model
TFidf-W2V-Gradient-Boosting 5 50 0.862 0.	0.712 0.75 0.71 0.749 0.684 0.713 0.702	0.75 0.71 0.749 0.684	+-	0.822 0.879 0.846 0.773 0.862	-+ 	1 1000 200 500 200 50	+ 	5 2 10 2 7 5	-+· 	BOW-Gradient-Boosting TFidf-Random-Forest TFidf-Gradient-Boosting TFidf-W2V-Random-Forest TFidf-W2V-Gradient-Boosting