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	Descri
project_id	A unique identifier for the proposed project. Example: p03
	Title of the project. Exam
project_title	Art Will Make You Ha
	• First Grade
	Grade level of students for which the project is targeted. One of the following
<pre>project_grade_category</pre>	• Grades Pr
	• Grades • Grades
	• Grades
	One or more (comma-separated) subject categories for the project fro following enumerated list of va
	Applied Lear
	• Care & Hu • Health & Sp
	History & Ci
nnoiget subject estagonies	Literacy & LangMath & Sci
<pre>project_subject_categories</pre>	Music & TheSpecial N
	• Wa
	Exam
	• Music & The
	• MUSIC & THE
	• Literacy & Language, Math & Sci
school_state	
school_state	• Literacy & Language, Math & Sci State where school is located (<u>Two-letter U.S. postal</u> (https://en.wikipedia.org/wiki/List_of_U.S. state_abbreviations#Postal_co Example One or more (comma-separated) subject subcategories for the pr
school_state project_subject_subcategories	State where school is located (<u>Two-letter U.S. postal</u> (https://en.wikipedia.org/wiki/List_of_U.S. state_abbreviations#Postal_co Example One or more (comma-separated) subject subcategories for the present the p
	• Literacy & Language, Math & Sci State where school is located (<u>Two-letter U.S. postal</u> (https://en.wikipedia.org/wiki/List_of_U.S. state_abbreviations#Postal_co Example One or more (comma-separated) subject subcategories for the pr
	State where school is located (Two-letter U.S. postal (https://en.wikipedia.org/wiki/List_of_U.S. state_abbreviations#Postal_co
	State where school is located (Two-letter U.S. postal (https://en.wikipedia.org/wiki/List of U.S. state abbreviations#Postal co Example One or more (comma-separated) subject subcategories for the pr Exam Lite Literature & Writing, Social Scie An explanation of the resources needed for the project. Exan My students need hands on literacy materials to mar
project_subject_subcategories	State where school is located (Two-letter U.S. postal (https://en.wikipedia.org/wiki/List of U.S. state abbreviations#Postal co Example One or more (comma-separated) subject subcategories for the pr Exam Lite Literature & Writing, Social Scie
project_subject_subcategories	State where school is located (Two-letter U.S. postal (https://en.wikipedia.org/wiki/List of U.S. state abbreviations#Postal co Example One or more (comma-separated) subject subcategories for the pr Exam Lite Literature & Writing, Social Scie An explanation of the resources needed for the project. Exan My students need hands on literacy materials to mar
project_subject_subcategories project_resource_summary	State where school is located (Two-letter U.S. postal (https://en.wikipedia.org/wiki/List of U.S. state abbreviations#Postal co Example One or more (comma-separated) subject subcategories for the pr Exam Lite Literature & Writing, Social Scie An explanation of the resources needed for the project. Exan My students need hands on literacy materials to mar sensory ne
<pre>project_subject_subcategories project_resource_summary project_essay_1</pre>	State where school is located (Two-letter U.S. postal (https://en.wikipedia.org/wiki/List of U.S. state abbreviations#Postal co Example One or more (comma-separated) subject subcategories for the pr Exam Lite Literature & Writing, Social Scie An explanation of the resources needed for the project. Exan My students need hands on literacy materials to mar sensory ne First application e

Descri	Feature
Datetime when project application was submitted. Example: 2016-04 12:43:56	project_submitted_datetime
A unique identifier for the teacher of the proposed project. Exa l bdf8baa8fedef6bfeec7ae4ff1c1	teacher_id
Teacher's title. One of the following enumerated va	
•	
•	toochon mostiv
•	teacher_prefix
•	
•	
• Teac	

teacher_number_of_previously_posted_projects

Number of project applications previously submitted by the same tea

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

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

Note: Many projects require multiple resources. The 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

Project_is_approved

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

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

Notes on the Essay Data

project essay 4 will be NaN.

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

__project_essay_1:__ "Introduce us to your classroom"

__project_essay_2:__ "Tell us more about your students"

__project_essay_3:__ "Describe how your students will use the materials you're requesting"

__project_essay_3:__ "Close by sharing why your project will make a difference"

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

__project_essay_1:__ "Describe your students: What makes your students special? Specific details about their background, your neighborhood, and your school are all helpful."

__project_essay_2:__ "About your project: How will these materials make a difference in your students' learning and improve their school lives?"

For all projects with project_submitted_datetime of 2016-05-17 and later, the values of project_essay_3 and

```
In [1]: | %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        import sqlite3
        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn.feature extraction.text import CountVectorizer
        from sklearn.metrics import confusion matrix
        from sklearn import metrics
        from sklearn.metrics import roc_curve, auc
        from nltk.stem.porter import PorterStemmer
        import re
        # Tutorial about Python regular expressions: https://pymotw.com/2/re/
        import string
        from nltk.corpus import stopwords
        from nltk.stem import PorterStemmer
        from nltk.stem.wordnet import WordNetLemmatizer
        from gensim.models import Word2Vec
        from gensim.models import KeyedVectors
        import pickle
        from tqdm import tqdm
        import os
        from chart_studio import plotly
        import plotly.offline as offline
        import plotly.graph_objs as go
        offline.init notebook mode()
        from collections import Counter
```

1.1 Reading Data

```
In [3]:
        print("Number of data points in train data", project data.shape)
        print('-'*50)
        print("The attributes of data :", project data.columns.values)
        Number of data points in train data (80000, 17)
        The attributes of data : ['Unnamed: 0' 'id' 'teacher id' 'teacher prefix' 'sc
        hool state'
          'project submitted datetime' 'project grade category'
         'project_subject_categories' 'project_subject_subcategories'
          'project_title' 'project_essay_1' 'project_essay_2' 'project_essay_3'
          'project essay 4' 'project resource summary'
          'teacher_number_of_previously_posted_projects' 'project_is_approved']
In [4]: # how to replace elements in list python: https://stackoverflow.com/a/2582163/
        4084039
        cols = ['Date' if x=='project submitted datetime' else x for x in list(project
        data.columns)]
        #sort dataframe based on time pandas python: https://stackoverflow.com/a/49702
        492/4084039
        project_data['Date'] = pd.to_datetime(project_data['project_submitted_datetim
        e'])
        project_data.drop('project_submitted_datetime', axis=1, inplace=True)
        project data.sort values(by=['Date'], inplace=True)
        # how to reorder columns pandas python: https://stackoverflow.com/a/13148611/4
        084039
        project data = project data[cols]
        project data.head(2)
```

Out[4]:

	Unnamed: 0	id	teacher_id	teacher_prefix	school_state	
55660	8393	p205479	2bf07ba08945e5d8b2a3f269b2b3cfe5	Mrs.	CA	2 0 00:2
76127	37728	p043609	3f60494c61921b3b43ab61bdde2904df	Ms.	UT	2 0 00:3
4						•

1.2 preprocessing of project_subject_categories

```
In [6]: | catogories = list(project_data['project_subject_categories'].values)
        # remove special characters from list of strings python: https://stackoverflo
        w.com/a/47301924/4084039
        # https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
        # https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-fr
        om-a-string
        # https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-strin
        g-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 & Scienc
        e", "Warmth", "Care & Hunger"]
                if 'The' in j.split(): # this will split each of the catogory based on
        space "Math & Science"=> "Math", "&", "Science"
                    j=j.replace('The','') # if we have the words "The" we are going to
        replace it with ''(i.e removing 'The')
                j = j.replace(' ','') # we are placeing all the ' '(space) with ''(emp
        ty) ex: "Math & Science" => "Math&Science"
                temp+=j.strip()+" " #" abc ".strip() will return "abc", remove the tra
        iling spaces
                temp = temp.replace('&','_') # we are replacing the & value into
            cat list.append(temp.strip())
        project data['clean categories'] = cat list
        project_data.drop(['project_subject_categories'], axis=1, inplace=True)
        from collections import Counter
        my counter = Counter()
        for word in project data['clean categories'].values:
            my counter.update(word.split())
        cat_dict = dict(my_counter)
        sorted cat dict = dict(sorted(cat dict.items(), key=lambda kv: kv[1]))
```

1.3 preprocessing of project_subject_subcategories

```
In [7]:
        sub_catogories = list(project_data['project_subject_subcategories'].values)
        # remove special characters from list of strings python: https://stackoverflo
        w.com/a/47301924/4084039
        # https://www.geeksforgeeks.org/removing-stop-words-nltk-python/
        # https://stackoverflow.com/questions/23669024/how-to-strip-a-specific-word-fr
        om-a-string
        # https://stackoverflow.com/questions/8270092/remove-all-whitespace-in-a-strin
        g-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 & Scienc
        e", "Warmth", "Care & Hunger"]
                if 'The' in j.split(): # this will split each of the catogory based on
        space "Math & Science"=> "Math", "&", "Science"
                    j=j.replace('The','') # if we have the words "The" we are going to
        replace it with ''(i.e removing 'The')
                j = j.replace(' ','') # we are placeing all the ' '(space) with ''(emp
        ty) ex: "Math & Science" => "Math&Science"
                temp +=j.strip()+" "#" abc ".strip() will return "abc", remove the tra
        iling spaces
                temp = temp.replace('&',' ')
            sub cat list.append(temp.strip())
        project data['clean subcategories'] = sub cat list
        project_data.drop(['project_subject_subcategories'], axis=1, inplace=True)
        # count of all the words in corpus python: https://stackoverflow.com/a/2289859
        5/4084039
        my counter = Counter()
        for word in project data['clean subcategories'].values:
            my counter.update(word.split())
        sub cat dict = dict(my counter)
        sorted sub cat dict = dict(sorted(sub cat dict.items(), key=lambda kv: kv[1]))
```

1.3 Text preprocessing

<pre>In [9]: project_data.head(2)</pre>							
Out[9]:		Unnamed: 0	id	teacher_id	teacher_prefix	school_state	
	55660	8393	p205479	2bf07ba08945e5d8b2a3f269b2b3cfe5	Mrs.	CA	2 0 00:2
	76127	37728	p043609	3f60494c61921b3b43ab61bdde2904df	Ms.	UT	2 0 00:3
	4						•

1.4.2.3 Using Pretrained Models: TFIDF weighted W2V

```
In [10]: # printing some random reviews
    print(project_data['essay'].values[0])
    print("="*50)
    print(project_data['essay'].values[150])
    print(project_data['essay'].values[1000])
    print("="*50)
    print(project_data['essay'].values[20000])
    print("="*50)
    print(project_data['essay'].values[79999])
    print(project_data['essay'].values[79999])
```

I have been fortunate enough to use the Fairy Tale STEM kits in my classroom as well as the STEM journals, which my students really enjoyed. I would love to implement more of the Lakeshore STEM kits in my classroom for the next sch ool year as they provide excellent and engaging STEM lessons. My students come from a variety of backgrounds, including language and socioeconomic status. Many of them don't have a lot of experience in science and engineering and th ese kits give me the materials to provide these exciting opportunities for my students. Each month I try to do several science or STEM/STEAM projects. I wo uld use the kits and robot to help guide my science instruction in engaging a nd meaningful ways. I can adapt the kits to my current language arts pacing guide where we already teach some of the material in the kits like tall tales (Paul Bunyan) or Johnny Appleseed. The following units will be taught in the next school year where I will implement these kits: magnets, motion, sink vs. float, robots. I often get to these units and don't know If I am teaching th e right way or using the right materials. The kits will give me additional ideas, strategies, and lessons to prepare my students in science. It is challe nging to develop high quality science activities. These kits give me the mat erials I need to provide my students with science activities that will go alo ng with the curriculum in my classroom. Although I have some things (like ma gnets) in my classroom, I don't know how to use them effectively. The kits w ill provide me with the right amount of materials and show me how to use them in an appropriate way.

\"Why can't I play the drums, Mr. Reyes?\" I hear this one often. students to experience \"percussion\" as opposed to \"the drums.\" We need s ome percussion instruments in order to help make this dream come to fruition. We have a diverse population with almost entirely "minority students" in atte ndance, including many English Learners (several who barely speak any Englis h). We have great staff members that love the kids and support them in all as pects of their education. Students' safety is the primary interest at our sch ool. We hope to provide a well-rounded music education where band is "cool" and kids look forward to coming to class. We are finding ourselves in need of instruments to help keep the momentum of our program going. My students will b e able to experience more advanced pieces of music with this instrument. m asking for a high quality instrument so that it may be used and taken care of over time. Eventually, I'd love to start a percussion ensemble. estment will greatly help the percussion section at my school!My students com e from very troubled homes and they deal with stress that people shouldn't ha ve to experience. They know adversity more than the average person and have t o over come it in whatever ways they can manage. Music can be an amazing outl et for these kids. Your generous support could help change a life for a young troubled youth. Thank you for your help!

I have over 80 students on my ESL roster that need my services during the sch ool year. They come in at varying levels of English acquisition, so differenti ation is very important in my classroom. Technology is only becoming more important, so giving my students this chance to be hands-on is wonderful. My school has over 740 students; about 80% are of a minority group and roughly 60% of them are English Language Learners. There are more than 7 languages represented, some mainstream like Spanish or Vietnamese, and some indigenous like Mam. The neighborhood where my school is located is very low income, with some families being in poverty or homeless. With all of these things working against them, you will not meet a group of students who are more dedicated to learning. They are excited to try new things. My school works very hard to give the students as much access to print (good literature) and hands-on activities as we can. If my project is funded, my students will be able to use the iPad Minis during class time in several different ways. They will use them to look up wo

rds they don't understand, or to find synonyms and antonyms to help broaden their vocabularies. There are so many apps available that help English Language Learners practice and apply what they are learning in their classrooms. My students will be able to use these apps as hands-on practice when our lessons are complete, or as a reward for a job well done. As the majority of our students are low income, being able to work with technology in school can help them to become more future-ready. This project will make a difference in my classroom because it gives my students another avenue for learning. It gets technology into their hands that they don't have access to normally, making them more future-ready. It will give them a hands-on learning tool to make the mate rial more meaningful to them. It will give them a sense of ownership over the material and be an encouragement for learning a new language.

In my classroom, I have the opportunity to make a difference in the lives of children who face challenges associated with limited English language profici ency and socioeconomic status. Most of the students at my school walk into ou r classrooms after only being in the country for a few days-Imagine walking i nto a room and seeing a book for the first time.. or a pencil. A smiling teac her is talking to you in a language you don't understand-Many of our other st udents are homeless or being raised in a single parent household and receive a free lunch based on their socioeconomic status. These are the students I te ach every day.\r\nDespite these challenges, I believe that every single stude nt can learn, grow and accomplish amazing things. I can not control what happ ens outside of the classroom, however, I can certainly control what happens i nside the classroom. I will do everything in my power to give my students the best education and most positive and nurturing learning environment. I am hop eful to inspire our earliest learners to continue on a path to academic excel lence.My job is to not only teach my students how to read, but to also get th em excited about it! A major part in motivating the students is allowing them to choose where they sit in the classroom as they read-no one wants to sit at their desk every day! The problem with this, however, is our current classroo m library has two pillows and one bean bag. This makes the option of getting comfy while reading around the room very limited. \r\nDonations for this proj ect will allow more of my students the option to be comfortable while they re ad. My students will be able to sit on the soft pillows not only in the libra ry, but also around the room. My students will also enjoy the soft plush anim als to snuggle as they read. With your help, I can transform our reading time into something every student will enjoy!nannan

My first graders are eager to learn about the world around them. o school each day full of enthusiasm and genuinely love learning. \r\n\r\nOur diverse class includes students from a variety of cultural and economic backg Many come from homes where parents can't afford or simply don't know the importance of books, so it is important to me to provide an environment t hat is rich in literature so that students learn to love reading. students to be lifelong learners, and reading is the best way!I have used the se magazines in the past, and kids absolutely LOVE them!! The topics are of h igh interest for children and always correspond to real world issues that are important for kids to learn. The subscription also includes online resources such as videos, printable worksheets, and skill-based games. \r\n\r\nThese ma terials will expose students to rigorous and interesting nonfiction text that will spark their curiosity about the world around them. The topics allow me to teach the nonfiction text standards using interesting materials. They alw ays lead to engaging discussions and inspire students to find additional info rmation about the various topics.nannan

```
In [11]: # https://stackoverflow.com/a/47091490/4084039
import re

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

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

```
In [12]: sent = decontracted(project_data['essay'].values[20000])
    print(sent)
    print("="*50)
```

In my classroom, I have the opportunity to make a difference in the lives of children who face challenges associated with limited English language profici ency and socioeconomic status. Most of the students at my school walk into ou r classrooms after only being in the country for a few days-Imagine walking i nto a room and seeing a book for the first time.. or a pencil. A smiling teac her is talking to you in a language you do not understand-Many of our other s tudents are homeless or being raised in a single parent household and receive a free lunch based on their socioeconomic status. These are the students I te ach every day.\r\nDespite these challenges, I believe that every single stude nt can learn, grow and accomplish amazing things. I can not control what happ ens outside of the classroom, however, I can certainly control what happens i nside the classroom. I will do everything in my power to give my students the best education and most positive and nurturing learning environment. I am hop eful to inspire our earliest learners to continue on a path to academic excel lence.My job is to not only teach my students how to read, but to also get th em excited about it! A major part in motivating the students is allowing them to choose where they sit in the classroom as they read-no one wants to sit at their desk every day! The problem with this, however, is our current classroo m library has two pillows and one bean bag. This makes the option of getting comfy while reading around the room very limited. \r\nDonations for this proj ect will allow more of my students the option to be comfortable while they re ad. My students will be able to sit on the soft pillows not only in the libra ry, but also around the room. My students will also enjoy the soft plush anim als to snuggle as they read. With your help, I can transform our reading time into something every student will enjoy!nannan

```
In [13]: # \r \n \t remove from string python: http://texthandler.com/info/remove-line-
breaks-python/
sent = sent.replace('\\r', ' ')
sent = sent.replace('\\"', ' ')
print(sent)
```

In my classroom, I have the opportunity to make a difference in the lives of children who face challenges associated with limited English language profici ency and socioeconomic status. Most of the students at my school walk into ou r classrooms after only being in the country for a few days-Imagine walking i nto a room and seeing a book for the first time.. or a pencil. A smiling teac her is talking to you in a language you do not understand-Many of our other s tudents are homeless or being raised in a single parent household and receive a free lunch based on their socioeconomic status. These are the students I te ach every day. Despite these challenges, I believe that every single student can learn, grow and accomplish amazing things. I can not control what happens outside of the classroom, however, I can certainly control what happens insid e the classroom. I will do everything in my power to give my students the bes t education and most positive and nurturing learning environment. I am hopefu 1 to inspire our earliest learners to continue on a path to academic excellen ce.My job is to not only teach my students how to read, but to also get them excited about it! A major part in motivating the students is allowing them to choose where they sit in the classroom as they read-no one wants to sit at th eir desk every day! The problem with this, however, is our current classroom library has two pillows and one bean bag. This makes the option of getting co mfy while reading around the room very limited. Donations for this project will allow more of my students the option to be comfortable while they read. My students will be able to sit on the soft pillows not only in the library, but also around the room. My students will also enjoy the soft plush animals to snuggle as they read. With your help, I can transform our reading time int o something every student will enjoy!nannan

```
In [14]: #remove spacial character: https://stackoverflow.com/a/5843547/4084039
    sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
    print(sent)
```

In my classroom I have the opportunity to make a difference in the lives of c hildren who face challenges associated with limited English language proficie ncy and socioeconomic status Most of the students at my school walk into our classrooms after only being in the country for a few days Imagine walking int o a room and seeing a book for the first time or a pencil A smiling teacher i s talking to you in a language you do not understand Many of our other studen ts are homeless or being raised in a single parent household and receive a fr ee lunch based on their socioeconomic status These are the students I teach e very day Despite these challenges I believe that every single student can lea rn grow and accomplish amazing things I can not control what happens outside of the classroom however I can certainly control what happens inside the clas sroom I will do everything in my power to give my students the best education and most positive and nurturing learning environment I am hopeful to inspire our earliest learners to continue on a path to academic excellence My job is to not only teach my students how to read but to also get them excited about it A major part in motivating the students is allowing them to choose where t hey sit in the classroom as they read no one wants to sit at their desk every day The problem with this however is our current classroom library has two pi llows and one bean bag This makes the option of getting comfy while reading a round the room very limited Donations for this project will allow more of my students the option to be comfortable while they read My students will be abl e to sit on the soft pillows not only in the library but also around the room My students will also enjoy the soft plush animals to snuggle as they read Wi th your help I can transform our reading time into something every student wi 11 enjoy nannan

```
In [15]: # 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', 'it
         self', 'they', 'them', 'their',\
                     'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 't
         hat', "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', 'becau
         se', 'as', 'until', 'while', 'of', \
                    'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into',
         'off', 'over', 'under', 'again', 'further',\
                     'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'a
         11', 'any', 'both', 'each', 'few', 'more',\
                     'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so', 'tha
         n', 'too', 'very', \
                    's', 't', 'can', 'will', 'just', 'don', "don't", 'should', "shoul
         d've", 'now', 'd', 'll', 'm', 'o', 're', \
                    've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn',
         "didn't", 'doesn', "doesn't", 'hadn',\
                    "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't", 'm
         a', 'mightn', "mightn't", 'mustn',\
                    "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn', "shoul
         dn't", 'wasn', "wasn't", 'weren', "weren't", \
                     'won', "won't", 'wouldn', "wouldn't"]
```

```
In [16]: # Combining all the above stundents
    from tqdm import tqdm
    preprocessed_essays = []
    # tqdm is for printing the status bar
    for sentance in tqdm(project_data['essay'].values):
        sent = decontracted(sentance)
        sent = sent.replace('\\r', '')
        sent = sent.replace('\\r', '')
        sent = sent.replace('\\r', '')
        sent = re.sub('[^A-Za-z0-9]+', '', sent)
        # https://gist.github.com/sebleier/554280
        sent = ''.join(e for e in sent.split() if e.lower() not in stopwords)
        preprocessed_essays.append(sent.lower().strip())
```

```
100%| 80000/80000 [00:38<00:00, 2087.22it/s]
```

```
In [17]: # after preprocesing
preprocessed_essays[20000]
```

Out[17]: 'classroom opportunity make difference lives children face challenges associa ted limited english language proficiency socioeconomic status students school walk classrooms country days imagine walking room seeing book first time penc il smiling teacher talking language not understand many students homeless rai sed single parent household receive free lunch based socioeconomic status stu dents teach every day despite challenges believe every single student learn g row accomplish amazing things not control happens outside classroom however c ertainly control happens inside classroom everything power give students best education positive nurturing learning environment hopeful inspire earliest le arners continue path academic excellence job not teach students read also get excited major part motivating students allowing choose sit classroom read no one wants sit desk every day problem however current classroom library two pi llows one bean bag makes option getting comfy reading around room limited don ations project allow students option comfortable read students able sit soft pillows not library also around room students also enjoy soft plush animals s nuggle read help transform reading time something every student enjoy nannan'

1.4 Preprocessing of `project_title`

```
In [18]: # similarly you can preprocess the titles also
    def preprocess_text_func(text_data):
        sent = decontracted(text_data)
        sent = sent.replace('\\r', ' ')
        sent = sent.replace('\\"', ' ')
        sent = sent.replace('\\n', ' ')
        sent = re.sub('[^A-Za-z0-9]+', ' ', sent)
        sent = ' '.join(e for e in sent.split() if e not in stopwords)
        return sent.lower()
```

100%| **80000/80000** [00:01<00:00, 48061.09it/s]

```
In [20]: print(preprocessed_titles[5:12])
```

['breakout box ignite engagement', '21st century learning multimedia', 'ipad learners', 'a flexible classroom flexible minds', 'make powerful movies', 'ro bots taking 2nd grade', 'time kids to learn about science']

```
In [21]: print(project_data["project_title"].values[5:12])

['Breakout Box to Ignite Engagement!'
    '21st Century Learning with Multimedia' 'iPad for Learners'
    'A flexible classroom for flexible minds!' 'Make Powerful Movies!!'
    'Robots are Taking over 2nd Grade'
    'Time for Kids....To Learn About Science and more!']
```

1.5 Preparing data for models

we are going to consider

```
- school_state : categorical data
- clean_categories : categorical data
- clean_subcategories : categorical data
- project_grade_category : categorical data
- teacher_prefix : categorical data
- project_title : text data
- text : text data
- project_resource_summary: text data (optinal)
- quantity : numerical (optinal)
- teacher_number_of_previously_posted_projects : numerical
- price : numerical
```

1.5.1 Vectorizing Categorical data

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

```
In [23]: # we use count vectorizer to convert the values into one
         from sklearn.feature extraction.text import CountVectorizer
         vectorizer = CountVectorizer(vocabulary=list(sorted cat dict.keys()), lowercas
         e=False, binary=True)
         categories one hot = vectorizer.fit transform(project data['clean categories']
         .values)
         print(vectorizer.get feature names())
         print("Shape of matrix after one hot encodig ",categories one hot.shape)
         ['Warmth', 'Care_Hunger', 'History_Civics', 'Music_Arts', 'AppliedLearning',
         'SpecialNeeds', 'Health_Sports', 'Math_Science', 'Literacy_Language']
         Shape of matrix after one hot encodig (80000, 9)
In [24]: # we use count vectorizer to convert the values into one
         vectorizer = CountVectorizer(vocabulary=list(sorted_sub_cat_dict.keys()), lowe
         rcase=False, binary=True)
         sub categories one hot = vectorizer.fit transform(project data['clean subcateg
         ories'].values)
         print(vectorizer.get feature names())
         print("Shape of matrix after one hot encodig ", sub categories one hot.shape)
         ['Economics', 'CommunityService', 'FinancialLiteracy', 'ParentInvolvement',
         'Civics Government', 'Extracurricular', 'ForeignLanguages', 'NutritionEducati
         on', 'Warmth', 'Care_Hunger', 'SocialSciences', 'PerformingArts', 'CharacterE
         ducation', 'TeamSports', 'Other', 'College_CareerPrep', 'History_Geography',
         'Music', 'Health_LifeScience', 'EarlyDevelopment', 'ESL', 'Gym_Fitness', 'Env
         ironmentalScience', 'VisualArts', 'Health_Wellness', 'AppliedSciences', 'Spec
         ialNeeds', 'Literature_Writing', 'Mathematics', 'Literacy']
         Shape of matrix after one hot encodig (80000, 30)
In [25]: # you can do the similar thing with state, teacher prefix and project grade ca
         tegory also
         # function to perform one hot encoding
         def perform_one_hot_encoding(listdata, category,fillnan_value=""):
             vectorizer = CountVectorizer(vocabulary=listdata, lowercase=False, binary
         =True)
             vectorizer.fit(project data[category].fillna(fillnan value).values)
             print(vectorizer.get feature names())
             print("="*50)
             return vectorizer.transform(project data[category].fillna(fillnan value).v
         alues)
In [26]: # One hot encoding for school state
         countries list = sorted(project data["school state"].value counts().keys())
         school_state_one_hot = perform_one_hot_encoding(countries_list, "school_state"
         print("Shape of matrix after one hot encodig ",school_state_one_hot.shape)
         ['AK', 'AL', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL', 'GA', 'HI', 'I
         A', 'ID', 'IL', 'IN', 'KS', 'KY', 'LA', 'MA', 'MD', 'ME', 'MI', 'MN', 'MO',
         'MS', 'MT', 'NC', 'ND', 'NE', 'NH', 'NJ', 'NM', 'NV', 'NY', 'OH', 'OK', 'OR'
         'PA', 'RI', 'SC', 'SD', 'TN', 'TX', 'UT', 'VA', 'VT', 'WA', 'WI', 'WV', 'WY']
         Shape of matrix after one hot encodig (80000, 51)
```

```
In [27]: # Project_Grade_Category - replacing hyphens, spaces with Underscores
         project_data['project_grade_category'] = project_data['project_grade_category'
         ].map({'Grades PreK-2': 'Grades PreK 2',
          'Grades 6-8' : 'Grades_6_8',
         'Grades 3-5' : 'Grades 3 5',
          'Grades 9-12' : 'Grades_9_12'})
         project_data['teacher_prefix'] = project_data['teacher_prefix'].map({'Mrs.':
         'Mrs', 'Ms.': 'Ms', 'Mr.': 'Mr',
                                                                                'Teacher'
         : 'Teacher', 'Dr.' : 'Dr'})
         project data['project grade category'].head(5)
In [28]:
Out[28]: 55660
                  Grades_PreK_2
         76127
                     Grades 3 5
         51140
                  Grades PreK 2
         473
                  Grades PreK 2
         41558
                     Grades 3 5
         Name: project grade category, dtype: object
In [29]: project_data['teacher_prefix'].head(5)
Out[29]: 55660
                  Mrs
         76127
                   Ms
         51140
                  Mrs
         473
                  Mrs
         41558
                  Mrs
         Name: teacher_prefix, dtype: object
In [30]: | project_data['teacher_prefix'].isnull().values.any() # since there are null va
         lues replacing them with most common value Mrs
Out[30]: True
In [31]: project_data["teacher_prefix"].fillna("Mrs", inplace=True)
In [32]: project data['teacher prefix'].isnull().values.any() # No more Null Values
Out[32]: False
```

```
In [33]: # One hot encoding for teacher prefix
        teacher_prefix_list = sorted(project_data["teacher_prefix"].value_counts().key
        s())
        print (teacher prefix list)
        teacher prefix one hot = perform one hot encoding(teacher prefix list, "teache
        r_prefix", "Mrs.")
        print("Shape of matrix after one hot encodig ", teacher prefix one hot.shape)
        ['Dr', 'Mr', 'Mrs', 'Ms', 'Teacher']
        ['Dr', 'Mr', 'Mrs', 'Ms', 'Teacher']
        _____
        Shape of matrix after one hot encodig (80000, 5)
In [34]: # One hot encoding for project grade category
        grade list = sorted(project data["project grade category"].value counts().keys
        ())
        grade_one_hot = perform_one_hot_encoding(grade_list, "project_grade_category")
        print("Shape of matrix after one hot encodig ",grade one hot.shape)
        ['Grades 3 5', 'Grades 6 8', 'Grades 9 12', 'Grades PreK 2']
        _____
        Shape of matrix after one hot encodig (80000, 4)
```

1.5.2 Vectorizing Text data

1.5.2.1 Bag of words

```
In [35]: # We are considering only the words which appeared in at least 10 documents(ro
    ws or projects).
    vectorizer = CountVectorizer(min_df=10)
    text_bow = vectorizer.fit_transform(preprocessed_essays)
    print("Shape of matrix after one hot encodig ",text_bow.shape)

Shape of matrix after one hot encodig (80000, 14627)

In [36]: # you can vectorize the title also
    # before you vectorize the title make sure you preprocess it
    vectorizer_titles = CountVectorizer(min_df=10)
    text_bow_titles = vectorizer_titles.fit_transform(preprocessed_titles)
    print("Shape of matrix after one hot encodig ",text_bow_titles.shape)

Shape of matrix after one hot encodig (80000, 2740)
```

1.5.2.2 TFIDF vectorizer

```
In [37]: from sklearn.feature_extraction.text import TfidfVectorizer
    vectorizer = TfidfVectorizer(min_df=10)
    text_tfidf = vectorizer.fit_transform(preprocessed_essays)
    print("Shape of matrix after one hot encodig ",text_tfidf.shape)

Shape of matrix after one hot encodig (80000, 14627)

In [38]: # TFIDF Vectorizer for Preprocessed Title
    vectorizer_titles = TfidfVectorizer(min_df=10)
    text_tfidf_titles = vectorizer_titles.fit_transform(preprocessed_titles)
    print("Shape of matrix after one hot encodig ",text_tfidf_titles.shape)

Shape of matrix after one hot encodig (80000, 2740)
```

1.5.2.3 Using Pretrained Models: Avg W2V

```
In [ ]:
        # Reading glove vectors in python: https://stackoverflow.com/a/38230349/408403
        def loadGloveModel(gloveFile):
            print ("Loading Glove Model")
            f = open(gloveFile,'r', encoding="utf8")
            model = \{\}
            for line in tqdm(f):
                splitLine = line.split()
                word = splitLine[0]
                embedding = np.array([float(val) for val in splitLine[1:]])
                model[word] = embedding
            print ("Done.", len(model), " words loaded!")
            return model
        model = loadGloveModel('glove.42B.300d.txt')
        Output:
        Loading Glove Model
        1917495it [06:32, 4879.69it/s]
        Done. 1917495 words Loaded!
        # ============
        words = []
        for i in preproced texts:
            words.extend(i.split(' '))
        for i in preproced titles:
            words.extend(i.split(' '))
        print("all the words in the coupus", len(words))
        words = set(words)
        print("the unique words in the coupus", len(words))
        inter words = set(model.keys()).intersection(words)
        print("The number of words that are present in both glove vectors and our coup
        us", \
              len(inter words),"(",np.round(len(inter words)/len(words)*100,3),"%)")
        words_courpus = {}
        words glove = set(model.keys())
        for i in words:
            if i in words glove:
                words courpus[i] = model[i]
        print("word 2 vec length", len(words_courpus))
        # stronging variables into pickle files python: http://www.jessicayung.com/how
        -to-use-pickle-to-save-and-load-variables-in-python/
        import pickle
        with open('glove_vectors', 'wb') as f:
            pickle.dump(words courpus, f)
```

```
# stronging variables into pickle files python: http://www.jessicayung.com/how
In [39]:
         -to-use-pickle-to-save-and-load-variables-in-python/
         # make sure you have the glove vectors file
         with open('glove_vectors', 'rb') as f:
             model = pickle.load(f)
             glove words = set(model.keys())
In [40]: # average Word2Vec
         # compute average word2vec for each review.
         avg w2v vectors = []; # the avg-w2v for each sentence/review is stored in this
         list
         for sentence in tqdm(preprocessed essays): # for each review/sentence
             vector = np.zeros(300) # as word vectors are of zero length
             cnt words =0; # num of words with a valid vector in the sentence/review
             for word in sentence.split(): # for each word in a review/sentence
                 if word in glove words:
                     vector += model[word]
                     cnt words += 1
             if cnt_words != 0:
                 vector /= cnt words
             avg w2v vectors.append(vector)
         print(len(avg w2v vectors))
         print(len(avg w2v vectors[0]))
         100%
         | 80000/80000 [00:16<00:00, 4719.02it/s]
         80000
         300
         # average Word2Vec for Preprocessed Titles
In [41]:
         avg w2v vectors titles = []; # the avg-w2v for each project title is stored in
         this list
         for sentence in tqdm(preprocessed titles): # for each project title
             vector = np.zeros(300) # as word vectors are of zero length
             cnt words =0; # num of words with a valid vector in the sentence/review
             for word in sentence.split(): # for each word in a review/sentence
                 if word in glove words:
                     vector += model[word]
                     cnt words += 1
             if cnt_words != 0:
                 vector /= cnt words
             avg w2v vectors titles.append(vector)
         print(len(avg_w2v_vectors_titles))
         print(len(avg_w2v_vectors_titles[0]))
         100%
         ■| 80000/80000 [00:00<00:00, 81851.02it/s]
         80000
         300
```

1.5.2.3 Using Pretrained Models: TFIDF weighted W2V

tfidf model = TfidfVectorizer()

In [42]: # S = ["abc def pqr", "def def def abc", "pqr pqr def"]

```
tfidf model.fit(preprocessed essays)
         # we are converting a dictionary with word as a key, and the idf as a value
         dictionary = dict(zip(tfidf model.get feature names(), list(tfidf model.idf
         )))
         tfidf words = set(tfidf model.get feature names())
In [43]: # average Word2Vec
         # compute average word2vec for each review.
         tfidf w2v vectors = []; # the avg-w2v for each sentence/review is stored in th
         is list
         for sentence in tqdm(preprocessed essays): # for each review/sentence
             vector = np.zeros(300) # as word vectors are of zero length
             tf idf weight =0; # num of words with a valid vector in the sentence/revie
             for word in sentence.split(): # for each word in a review/sentence
                 if (word in glove words) and (word in tfidf words):
                     vec = model[word] # getting the vector for each word
                     # here we are multiplying idf value(dictionary[word]) and the tf v
         alue((sentence.count(word)/len(sentence.split())))
                     tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split
         ())) # getting the tfidf value for each word
                     vector += (vec * tf idf) # calculating tfidf weighted w2v
                     tf idf weight += tf idf
             if tf_idf_weight != 0:
                 vector /= tf_idf weight
             tfidf w2v vectors.append(vector)
         print(len(tfidf w2v vectors))
         print(len(tfidf_w2v_vectors[0]))
```

```
100%| 80000/80000 [01:58<00:00, 672.90it/s]
```

```
In [44]: # Similarly you can vectorize for title also
         tfidf w2v vectors titles = []; # the avg-w2v for each project title is stored
          in this list
         for sentence in tqdm(preprocessed titles): # for each project title
             vector = np.zeros(300) # as word vectors are of zero Length
             tf idf weight =0; # num of words with a valid vector in the sentence/revie
             for word in sentence.split(): # for each word in a review/sentence
                 if (word in glove words) and (word in tfidf words):
                     vec = model[word] # getting the vector for each word
                     # here we are multiplying idf value(dictionary[word]) and the tf v
         alue((sentence.count(word)/len(sentence.split())))
                     tf_idf = dictionary[word]*(sentence.count(word)/len(sentence.split
         ())) # getting the tfidf value for each word
                     vector += (vec * tf idf) # calculating tfidf weighted w2v
                     tf idf weight += tf idf
             if tf idf weight != 0:
                 vector /= tf idf weight
             tfidf_w2v_vectors_titles.append(vector)
         print(len(tfidf w2v vectors titles))
         print(len(tfidf_w2v_vectors_titles[0]))
```

```
100%| 80000/80000 [00:01<00:00, 40167.22it/s]
80000
300
```

1.5.3 Vectorizing Numerical features

```
In [45]: price_data = resource_data.groupby('id').agg({'price':'sum', 'quantity':'sum'
}).reset_index()
project_data = pd.merge(project_data, price_data, on='id', how='left')
```

```
In [46]: # check this one: https://www.youtube.com/watch?v=0HOqOcln3Z4&t=530s
         # standardization sklearn: https://scikit-learn.org/stable/modules/generated/s
         klearn.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 32
              ... 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 mea
         n and standard deviation of this data
         print(f"Mean : {price scalar.mean [0]}, Standard deviation : {np.sqrt(price sc
         alar.var_[0])}")
         # Now standardize the data with above maen and variance.
         price standardized = price scalar.transform(project data['price'].values.resha
         pe(-1, 1)
         Mean: 299.16610437500003, Standard deviation: 375.7800454521539
In [47]: price_standardized
Out[47]: array([[ 1.13333292],
                [-0.22921947],
                [ 0.07939191],
                [-0.08142025],
                [ 0.26567109],
                [-0.78148403]]
In [48]: # Vectorizing teacher number of previously posted projects
         teacher_number_of_previously_posted_projects_scalar = StandardScaler()
         teacher number of previously posted projects scalar.fit(project data['teacher
         number_of_previously_posted_projects'].values.reshape(-1,1)) # finding the mea
         n 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 sca
         lar.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 pr
         eviously posted projects'].values.reshape(-1, 1))
```

Mean : 11.214825, Standard deviation : 27.961699254862445

1.5.4 Merging all the above features

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

```
In [49]: | # Categorical
         print(school_state_one_hot.shape)
         print(categories one hot.shape)
         print(sub categories one hot.shape)
         print(teacher_prefix_one_hot.shape)
         print(grade one hot.shape)
         print(text_bow_titles.shape)
         print(text bow.shape)
         # Numerical
         print(price standardized.shape)
         print(teacher_number_of_previously_posted_projects_standardized.shape)
         (80000, 51)
         (80000, 9)
         (80000, 30)
         (80000, 5)
         (80000, 4)
         (80000, 2740)
         (80000, 14627)
         (80000, 1)
         (80000, 1)
In [50]: # merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
         from scipy.sparse import hstack
         # with the same hstack function we are concatinating a sparse matrix and a den
         se matirx :)
         X = hstack((school state one hot, categories one hot, sub categories one hot, t
         eacher prefix one hot,
                      grade one hot, text bow titles, text bow, price standardized,
                      teacher_number_of_previously_posted_projects_standardized))
         X.shape
Out[50]: (80000, 17468)
In [51]: X. class
Out[51]: scipy.sparse.coo.coo_matrix
```

Assignment 3: Apply KNN

1. [Task-1] Apply KNN(brute force version) on these feature sets

- Set 1: categorical, numerical features + project_title(BOW) + preprocessed_essay (BOW)
- Set 2: categorical, numerical features + project_title(TFIDF)+ preprocessed_essay (TFIDF)
- Set 3: categorical, numerical features + project_title(AVG W2V)+ preprocessed_essay (AVG W2V)
- Set 4: categorical, numerical features + project_title(TFIDF W2V)+ preprocessed_essay (TFIDF W2V)

2. Hyper paramter tuning to find best K

- Find the best hyper parameter which results in the maximum <u>AUC</u>
 (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/receiver-operating-characteristic-curve-roc-curve-and-auc-1/) value
- Find the best hyper paramter using k-fold cross validation (or) simple cross validation data
- Use gridsearch-cv or randomsearch-cv or write your own for loops to do this task

3. Representation of results

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



• Once you find the best hyper parameter, you need to train your model-M using the best hyper-param. Now, find the AUC on test data and plot the ROC curve on both train and test using model-M.



Along with plotting ROC curve, you need to print the <u>confusion matrix</u>
 (https://www.appliedaicourse.com/course/applied-ai-course-online/lessons/confusion-matrix-tpr-fpr-fnr-tnr-1/) with predicted and original labels of test data points



4. [Task-2]

Select top 2000 features from feature <u>Set 2 using `SelectKBest` (https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html</u>) and then apply KNN on top of these features

```
from sklearn.datasets import load_digits
from sklearn.feature_selection import SelectKBest, chi2
X, y = load_digits(return_X_y=True)
X.shape
X_new = SelectKBest(chi2, k=20).fit_transform(X, y)
X_new.shape
=======
output:
(1797, 64)
(1797, 20)
```

• Repeat the steps 2 and 3 on the data matrix after feature selection

5. Conclusion

• You need to summarize the results at the end of the notebook, summarize it in the table format. To print out a table please refer to this prettytable library link (http://zetcode.com/python/prettytable/)



Note: Data Leakage

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

2. K Nearest Neighbor

<pre>In [60]: Out[60]:</pre>	<pre>project_data.head(3)</pre>							
	Uni	named: 0	id	teacher_id	teacher_prefix	school_state	Date	
	0	8393	p205479	2bf07ba08945e5d8b2a3f269b2b3cfe5	Mrs	CA	2016- 04-27 00:27:36	
	1	37728	p043609	3f60494c61921b3b43ab61bdde2904df	Ms	UT	2016- 04-27 00:31:25	
	2	74477	p189804	4a97f3a390bfe21b99cf5e2b81981c73	Mrs	CA	2016- 04-27 00:46:53	
	4						+	

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

2.2 Make Data Model Ready: encoding numerical, categorical features

```
In [71]: # School State
        vectorizer = CountVectorizer()
        vectorizer.fit(X train['school state'].values) # fit has to happen only on tra
        in data
        # we use the fitted CountVectorizer to convert the text to vector
        X train state ohe = vectorizer.transform(X train['school state'].values)
        X cv state ohe = vectorizer.transform(X cv['school state'].values)
        X test state ohe = vectorizer.transform(X test['school state'].values)
        print("After vectorizations")
        print(X_train_state_ohe.shape, y_train.shape)
        print(X_cv_state_ohe.shape, y_cv.shape)
        print(X test state ohe.shape, y test.shape)
        print(vectorizer.get feature names())
        print("="*100)
        After vectorizations
        (35912, 51) (35912,)
        (17688, 51) (17688,)
        (26400, 51) (26400,)
        ['ak', 'al', 'ar', 'az', 'ca', 'co', 'ct', 'dc', 'de', 'fl', 'ga', 'hi', 'i
        a', 'id', 'il', 'in', 'ks', 'ky', 'la', 'ma', 'md', 'me', 'mi', 'mn', 'mo',
        'ms', 'mt', 'nc', 'nd', 'ne', 'nh', 'nj', 'nm', 'nv', 'ny', 'oh', 'ok', 'or',
         'pa', 'ri', 'sc', 'sd', 'tn', 'tx', 'ut', 'va', 'vt', 'wa', 'wi', 'wv', 'wy']
        ______
        In [72]: # teacher prefix
        vectorizer = CountVectorizer()
        vectorizer.fit(X train['teacher prefix'].values) # fit has to happen only on t
        rain data
        # we use the fitted CountVectorizer to convert the text to vector
        X_train_teacher_ohe = vectorizer.transform(X_train['teacher_prefix'].values)
        X cv teacher ohe = vectorizer.transform(X cv['teacher prefix'].values)
        X_test_teacher_ohe = vectorizer.transform(X_test['teacher_prefix'].values)
        print("After vectorizations")
        print(X_train_teacher_ohe.shape, y_train.shape)
        print(X cv teacher ohe.shape, y cv.shape)
        print(X test teacher ohe.shape, y test.shape)
        print(vectorizer.get feature names())
        print("="*100)
        After vectorizations
        (35912, 5) (35912,)
        (17688, 5) (17688,)
        (26400, 5) (26400,)
        ['dr', 'mr', 'mrs', 'ms', 'teacher']
        ______
        ==================
```

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```
In [73]: # project grade category
        vectorizer = CountVectorizer()
        vectorizer.fit(X train['project grade category'].values) # fit has to happen o
        nly on train data
        # we use the fitted CountVectorizer to convert the text to vector
        X train grade ohe = vectorizer.transform(X train['project grade category'].val
        ues)
        X cv grade ohe = vectorizer.transform(X cv['project grade category'].values)
        X_test_grade_ohe = vectorizer.transform(X_test['project_grade_category'].value
        s)
        print("After vectorizations")
        print(X train grade ohe.shape, y train.shape)
        print(X cv grade ohe.shape, y cv.shape)
        print(X_test_grade_ohe.shape, y_test.shape)
        print(vectorizer.get feature names())
        print("="*100)
        After vectorizations
        (35912, 4) (35912,)
        (17688, 4) (17688,)
        (26400, 4) (26400,)
        ['grades_3_5', 'grades_6_8', 'grades_9_12', 'grades_prek_2']
        ______
        In [77]: # categories
        vectorizer = CountVectorizer()
        vectorizer.fit(X train['clean categories'].values) # fit has to happen only on
        train data
        # we use the fitted CountVectorizer to convert the text to vector
        X_train_category_ohe = vectorizer.transform(X_train['clean_categories'].values
        X_cv_category_ohe = vectorizer.transform(X_cv['clean_categories'].values)
        X test category ohe = vectorizer.transform(X test['clean categories'].values)
        print("After vectorizations")
        print(X train category ohe.shape, y train.shape)
        print(X cv category ohe.shape, y cv.shape)
        print(X_test_category_ohe.shape, y_test.shape)
        print(vectorizer.get feature names())
        print("="*100)
        After vectorizations
        (35912, 9) (35912,)
        (17688, 9) (17688,)
        (26400, 9) (26400,)
        ['appliedlearning', 'care_hunger', 'health_sports', 'history_civics', 'litera
        cy language', 'math science', 'music arts', 'specialneeds', 'warmth']
         _____
```

```
In [78]: # sub categories
         vectorizer = CountVectorizer()
         vectorizer.fit(X train['clean subcategories'].values) # fit has to happen only
         on train data
         # we use the fitted CountVectorizer to convert the text to vector
         X train subcategory ohe = vectorizer.transform(X train['clean subcategories'].
         values)
         X cv subcategory ohe = vectorizer.transform(X cv['clean subcategories'].values
         X test subcategory ohe = vectorizer.transform(X test['clean subcategories'].va
         lues)
         print("After vectorizations")
         print(X train subcategory ohe.shape, y train.shape)
         print(X_cv_subcategory_ohe.shape, y_cv.shape)
         print(X test subcategory ohe.shape, y test.shape)
         print(vectorizer.get_feature_names())
         print("="*100)
         After vectorizations
         (35912, 30) (35912,)
```

```
After vectorizations
(35912, 30) (35912,)
(17688, 30) (17688,)
(26400, 30) (26400,)
['appliedsciences', 'care_hunger', 'charactereducation', 'civics_government',
'college_careerprep', 'communityservice', 'earlydevelopment', 'economics', 'e
nvironmentalscience', 'esl', 'extracurricular', 'financialliteracy', 'foreign
languages', 'gym_fitness', 'health_lifescience', 'health_wellness', 'history_
geography', 'literacy', 'literature_writing', 'mathematics', 'music', 'nutrit
ioneducation', 'other', 'parentinvolvement', 'performingarts', 'socialscience
s', 'specialneeds', 'teamsports', 'visualarts', 'warmth']
```

Encoding numerical features

```
In [81]: from sklearn.preprocessing import Normalizer
         normalizer = Normalizer()
         # normalizer.fit(X train['price'].values)
         # this will rise an error Expected 2D array, got 1D array instead:
         # array=[105.22 215.96 96.01 ... 368.98 80.53 709.67].
         # Reshape your data either using
         # array.reshape(-1, 1) if your data has a single feature
         # array.reshape(1, -1) if it contains a single sample.
         normalizer.fit(X train['price'].values.reshape(-1,1))
         X train price norm = normalizer.transform(X train['price'].values.reshape(-1,1
         ))
         X_cv_price_norm = normalizer.transform(X_cv['price'].values.reshape(-1,1))
         X test price norm = normalizer.transform(X test['price'].values.reshape(-1,1))
         print("After vectorizations")
         print(X train price norm.shape, y train.shape)
         print(X_cv_price_norm.shape, y_cv.shape)
         print(X_test_price_norm.shape, y_test.shape)
         print("="*100)
```

```
After vectorizations
(35912, 1) (35912,)
(17688, 1) (17688,)
(26400, 1) (26400,)
```

```
In [82]: # teacher previously posted projects
         normalizer = Normalizer()
         # normalizer.fit(X train['price'].values)
         # this will rise an error Expected 2D array, got 1D array instead:
         # array=[105.22 215.96 96.01 ... 368.98 80.53 709.67].
         # Reshape your data either using
         # array.reshape(-1, 1) if your data has a single feature
         # array.reshape(1, -1) if it contains a single sample.
         normalizer.fit(X train['teacher number of previously posted projects'].values.
         reshape(-1,1))
         X_train_teach_prev_norm = normalizer.transform(X_train['teacher_number_of_prev
         iously posted projects'].values.reshape(-1,1))
         X cv teach prev norm = normalizer.transform(X cv['teacher number of previously
         posted projects'].values.reshape(-1,1))
         X_test_teach_prev_norm = normalizer.transform(X_test['teacher_number_of_previo
         usly posted projects'].values.reshape(-1,1))
         print("After vectorizations")
         print(X train teach prev norm.shape, y train.shape)
         print(X cv teach prev norm.shape, y cv.shape)
         print(X_test_teach_prev_norm.shape, y_test.shape)
         print("="*100)
         After vectorizations
         (35912, 1) (35912,)
         (17688, 1) (17688,)
         (26400, 1) (26400,)
```

2.3 Make Data Model Ready: encoding essay, and project_title

```
In [67]: | print("After vectorizations")
        print(X_train_essay_bow.shape, y_train.shape)
        print(X cv essay bow.shape, y cv.shape)
        print(X test essay bow.shape, y test.shape)
        print("="*100)
        After vectorizations
        (35912, 5000) (35912,)
        (17688, 5000) (17688,)
        (26400, 5000) (26400,)
         _____
In [68]: # Preprocessing project title
        vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
        vectorizer.fit(X train['project title'].values) # fit has to happen only on tr
        ain data
Out[68]: CountVectorizer(analyzer='word', binary=False, decode error='strict',
                       dtype=<class 'numpy.int64'>, encoding='utf-8', input='conten
        t',
                       lowercase=True, max_df=1.0, max_features=5000, min_df=10,
                       ngram_range=(1, 4), preprocessor=None, stop_words=None,
                       strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                       tokenizer=None, vocabulary=None)
In [69]: # we use the fitted CountVectorizer to convert the text to vector
        X train pj title bow = vectorizer.transform(X train['project title'].values)
        X_cv_pj_title_bow = vectorizer.transform(X_cv['project_title'].values)
        X test pj title bow = vectorizer.transform(X test['project title'].values)
        print("After vectorizations")
In [70]:
        print(X_train_pj_title_bow.shape, y_train.shape)
        print(X_cv_pj_title_bow.shape, y_cv.shape)
        print(X_test_pj_title_bow.shape, y_test.shape)
        print("="*100)
        After vectorizations
        (35912, 4272) (35912,)
        (17688, 4272) (17688,)
        (26400, 4272) (26400,)
        _____
```

2.4 Appling KNN on different kind of featurization as mentioned in the instructions

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

2.4.1 Applying KNN brute force on BOW, SET 1

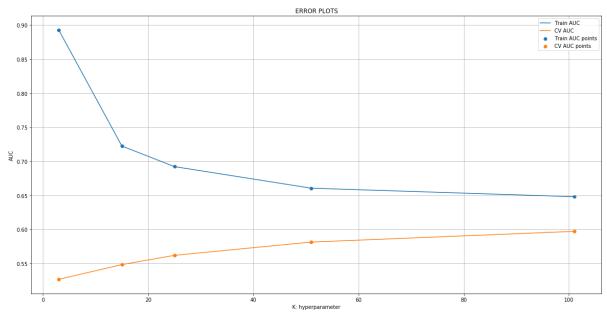
```
In [83]: | # concatinating all the features
         # merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
         from scipy.sparse import hstack
         X_tr = hstack((X_train_essay_bow, X_train_state_ohe, X_train_teacher_ohe,
                       X_train_grade_ohe, X_train_price_norm, X_train_category_ohe,
                       X_train_subcategory_ohe, X_train_teach_prev_norm,
                       X train pj title bow)).tocsr()
         X cr = hstack((X cv essay bow, X cv state ohe, X cv teacher ohe,
                       X_cv_grade_ohe, X_cv_category_ohe, X_cv_subcategory_ohe,
                       X_cv_price_norm, X_cv_teach_prev_norm, X_cv_pj_title_bow)).tocs
         r()
         X_te = hstack((X_test_essay_bow, X_test_state_ohe, X_test_teacher_ohe,
                       X test grade ohe, X test category ohe, X test subcategory ohe,
                       X_test_price_norm, X_test_teach_prev_norm,
                       X_test_pj_title_bow)).tocsr()
In [84]: | print("Final Data matrix - for set 1")
         print(X_tr.shape, y_train.shape)
         print(X cr.shape, y cv.shape)
         print(X te.shape, y test.shape)
         print("="*100)
         Final Data matrix - for set 1
         (35912, 9373) (35912,)
         (17688, 9373) (17688,)
         (26400, 9373) (26400,)
         ______
In [85]: # Since there was memory errors while trying with RandomizedSearchCV, trying t
         he for Loop approach
         def batch predict(clf, data):
             # roc auc score(y true, y score) the 2nd parameter should be probability e
         stimates of the positive class
             # not the predicted outputs
             y data pred = []
             tr loop = data.shape[0] - data.shape[0]%1000
             # consider you X tr shape is 49041, then your tr loop will be 49041 - 4904
         1\%1000 = 49000
             # in this for loop we will iterate unti the last 1000 multiplier
             for i in range(0, tr_loop, 1000):
                 y data pred.extend(clf.predict proba(data[i:i+1000])[:,1])
             # we will be predicting for the last data points
             if data.shape[0]%1000 !=0:
                 y data pred.extend(clf.predict proba(data[tr loop:])[:,1])
             return y_data_pred
```

```
In [86]:
         import matplotlib.pyplot as plt
         from sklearn.neighbors import KNeighborsClassifier
         from sklearn.metrics import roc_auc_score
In [87]: | train_auc = []
         cv auc = []
         K = [3, 15, 25, 51, 101]
         for i in tqdm(K):
             neigh = KNeighborsClassifier(n_neighbors=i, n_jobs=-1)
             neigh.fit(X_tr, y_train)
             y_train_pred = batch_predict(neigh, X_tr)
             y cv pred = batch predict(neigh, X cr)
             # roc_auc_score(y_true, y_score) the 2nd parameter should be probability e
         stimates of the positive class
             # not the predicted outputs
             train_auc.append(roc_auc_score(y_train,y_train_pred))
             cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
           0%|
         | 0/5 [00:00<?, ?it/s]
          20%
         | 1/5 [01:36<06:24, 96.09s/it]
          40%
         2/5 [03:18<04:53, 97.99s/it]
          60%
         | 3/5 [05:01<03:18, 99.38s/it]
          80%|
         4/5 [06:44<01:40, 100.46s/it]
         100%|
                    | 5/5 [08:27<00:00, 101.43s/it]
```

```
In [88]: plt.figure(figsize=(20,10))
    plt.plot(K, train_auc, label='Train AUC')
    plt.plot(K, cv_auc, label='CV AUC')

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

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



```
In [89]: # from the above error plot, we have max AUC for CV with least difference betw
een Train and CV AUCs at K=105
best_k = 105
```

Testing the performance on test data, plotting ROC Curves

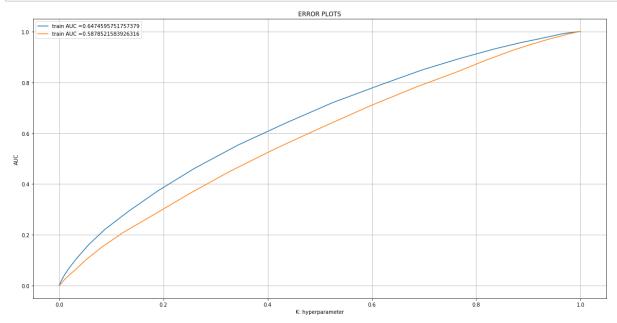
```
In [90]: from sklearn.metrics import roc_curve, auc

neigh = KNeighborsClassifier(n_neighbors=best_k, n_jobs=-1)
neigh.fit(X_tr, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability estim
ates of the positive class
# not the predicted outputs

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

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

```
In [91]: plt.figure(figsize=(20,10))
    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tp
    r)))
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
    plt.legend()
    plt.xlabel("K: hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.grid()
    plt.show()
```



The Blue plot in the Graph is Train AUC and Orange Plot is Test AUC. Initially the label was accidentally copy pasted as Train AUC for both. Since redrawing plot would require to re run entire ipynb and it takes up a lot of time. so documenting the information as a markdown.

```
In [92]:
         # we are writing our own function for predict, with defined thresould
         # we will pick a threshold that will give the least fpr
         def find_best_threshold(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 hi
         gh
             print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for threshol
         d", np.round(t,3))
             return t
         def predict with best t(proba, threshould):
             predictions = []
             for i in proba:
                 if i>=threshould:
                      predictions.append(1)
                 else:
                      predictions.append(0)
             return predictions
```

```
In [93]: print("="*100)
         from sklearn.metrics import confusion matrix
         best t = find best threshold(tr thresholds, train fpr, train tpr)
         print("Train confusion matrix")
         print(confusion matrix(y train, predict with best t(y train pred, best t)))
         print("Test confusion matrix")
         print(confusion matrix(y test, predict with best t(y test pred, best t)))
```

```
the maximum value of tpr*(1-fpr) 0.36356411719545345 for threshold 0.838
Train confusion matrix
[[ 3599 1880]
[13589 16844]]
Test confusion matrix
[[ 2342 1660]
 [10321 12077]]
```

2.4.2 Applying KNN brute force on TFIDF, SET 2

================

```
In [96]:
        # preprocessing TFIDF of Text Essays and Project Titles
        from sklearn.feature extraction.text import TfidfVectorizer
        vectorizer = TfidfVectorizer(min_df=10, ngram_range=(1,4), max_features=5000)
        vectorizer.fit(X_train["essay"].values)
        X train essay tfidf = vectorizer.transform(X train['essay'].values)
        X cv essay tfidf = vectorizer.transform(X cv['essay'].values)
        X test essay tfidf = vectorizer.transform(X test['essay'].values)
        print("Shape of Datamatrix after TFIDF Vectorization")
        print(X train essay tfidf.shape, y train.shape)
        print(X cv essay tfidf.shape, y cv.shape)
        print(X test essay tfidf.shape, y test.shape)
        print("="*100)
        Shape of Datamatrix after TFIDF Vectorization
        (35912, 5000) (35912,)
        (17688, 5000) (17688,)
        (26400, 5000) (26400,)
        ______
```

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csr()

```
In [97]: # Similarly you can vectorize for title also
         vectorizer titles = TfidfVectorizer(min df=10, ngram range=(1,4), max features
         =5000)
         vectorizer titles.fit(X train["project title"])
         X_train_pj_title_tfidf = vectorizer.transform(X_train['project_title'].values)
         X_cv_pj_title_tfidf = vectorizer.transform(X_cv['project_title'].values)
         X test pj title tfidf = vectorizer.transform(X test['project title'].values)
         print("Shape of Datamatrix after TFIDF Vectorization")
         print(X train pj title tfidf.shape, y train.shape)
         print(X_cv_pj_title_tfidf.shape, y_cv.shape)
         print(X_test_pj_title_tfidf.shape, y_test.shape)
         print("="*100)
         Shape of Datamatrix after TFIDF Vectorization
         (35912, 5000) (35912,)
         (17688, 5000) (17688,)
         (26400, 5000) (26400,)
         In [98]: # Concatinating all the features for Set 2
         X tr = hstack((X train essay tfidf, X train state ohe, X train teacher ohe,
                        X train grade ohe, X train price norm, X train category ohe,
                        X_train_subcategory_ohe, X_train_teach_prev_norm,
                        X train pj title tfidf)).tocsr()
         X_cr = hstack((X_cv_essay_tfidf, X_cv_state_ohe, X_cv_teacher_ohe,
                        X_cv_grade_ohe, X_cv_category_ohe, X_cv_subcategory_ohe,
```

X_te = hstack((X_test_essay_tfidf, X_test_state_ohe, X_test_teacher_ohe,

X_test_price_norm, X_test_teach_prev_norm,

X test pj title tfidf)).tocsr()

X cv price norm, X cv teach prev norm, X cv pj title tfidf)).to

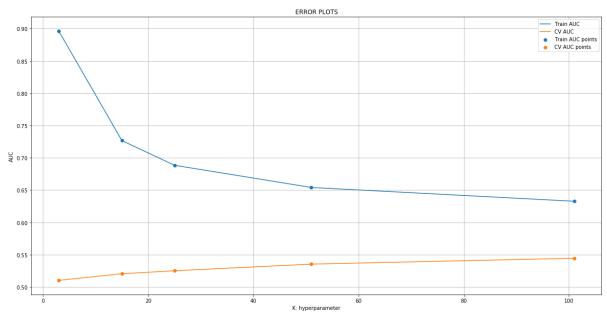
X_test_grade_ohe, X_test_category_ohe, X_test_subcategory_ohe,

```
In [99]: | train_auc = []
         cv_auc = []
         K = [3, 15, 25, 51, 101]
         for i in tqdm(K):
             neigh = KNeighborsClassifier(n_neighbors=i, n_jobs=-1)
             neigh.fit(X_tr, y_train)
             y_train_pred = batch_predict(neigh, X_tr)
             y_cv_pred = batch_predict(neigh, X_cr)
             # roc_auc_score(y_true, y_score) the 2nd parameter should be probability e
         stimates of the positive class
             # not the predicted outputs
             train_auc.append(roc_auc_score(y_train,y_train_pred))
             cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
           0%|
         | 0/5 [00:00<?, ?it/s]
          20%
         | 1/5 [01:35<06:22, 95.53s/it]
          40%
         | 2/5 [03:18<04:53, 97.89s/it]
          60%|
         | 3/5 [05:02<03:18, 99.49s/it]
          80%|
         | 4/5 [06:45<01:40, 100.61s/it]
         100%
                    | 5/5 [08:32<00:00, 102.45s/it]
```

```
In [100]: plt.figure(figsize=(20,10))
    plt.plot(K, train_auc, label='Train AUC')
    plt.plot(K, cv_auc, label='CV AUC')

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

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

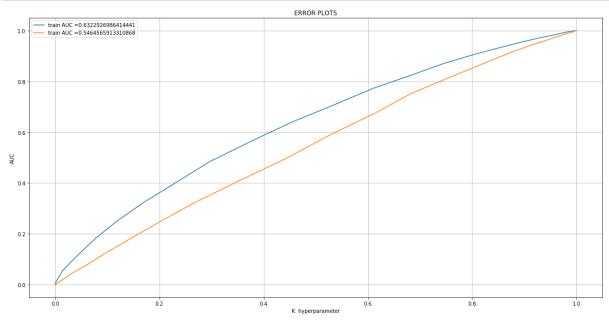


```
In [101]: best_k = 105
# Testing the performance of the model on test data, plotting ROC curves
neigh = KNeighborsClassifier(n_neighbors=best_k, n_jobs=-1)
neigh.fit(X_tr, y_train)

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

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

```
In [102]: plt.figure(figsize=(20,10))
    plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_tp
    r)))
    plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
    plt.legend()
    plt.xlabel("K: hyperparameter")
    plt.ylabel("AUC")
    plt.title("ERROR PLOTS")
    plt.grid()
    plt.show()
```



The Blue plot in the Graph is Train AUC and Orange Plot is Test AUC. Initially the label was accidentally copy pasted as Train AUC for both. Since redrawing plot would require to re run entire ipynb and it takes up a lot of time. so documenting the information as a markdown.

```
In [103]: # Confusion matrix
print("="*100)
    from sklearn.metrics import confusion_matrix
best_t = find_best_threshold(tr_thresholds, train_fpr, train_tpr)
print("Train confusion matrix")
print(confusion_matrix(y_train, predict_with_best_t(y_train_pred, best_t)))
print("Test confusion matrix")
print(confusion_matrix(y_test, predict_with_best_t(y_test_pred, best_t)))
```

the maximum value of tpr*(1-fpr) 0.35208438007015214 for threshold 0.857
Train confusion matrix
[[3437 2042]
 [13352 17081]]
Test confusion matrix
[[1898 2104]
 [9227 13171]]

2.4.3 Applying KNN brute force on AVG W2V, SET 3

```
In [104]: # Please write all the code with proper documentation
    # make sure you have the glove_vectors file
    with open('glove_vectors', 'rb') as f:
        model = pickle.load(f)
        glove_words = set(model.keys())
```

```
In [105]: # average Word2Vec
          # compute average word2vec for each review.
          avg_w2v_vectors_train = []; # the avg-w2v for each sentence/review is stored i
          n this list
          for sentence in tqdm(X_train['essay'].values): # for each review/sentence
              vector = np.zeros(300) # as word vectors are of zero length
              cnt words =0; # num of words with a valid vector in the sentence/review
              for word in sentence.split(): # for each word in a review/sentence
                  if word in glove words:
                      vector += model[word]
                      cnt words += 1
              if cnt_words != 0:
                  vector /= cnt_words
              avg w2v vectors train.append(vector)
          print(len(avg_w2v_vectors_train))
          print(len(avg_w2v_vectors_train[0]))
          print(avg_w2v_vectors_train[0])
```

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0%|
| 0/35912 [00:00<?, ?it/s]
 1%
304/35912 [00:00<00:11, 3017.95it/s]
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| 876/35912 [00:00<00:11, 2925.92it/s]
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| 1786/35912 [00:00<00:11, 2980.99it/s]
2069/35912 [00:00<00:11, 2927.37it/s]
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2380/35912 [00:00<00:11, 2973.47it/s]
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2661/35912 [00:00<00:11, 2845.31it/s]
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| 3884/35912 [00:01<00:10, 2954.11it/s]
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| 6303/35912 [00:02<00:10, 2875.95it/s]
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8095/35912 [00:02<00:09, 2932.74it/s]
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| 16604/35912 [00:05<00:07, 2753.13it/s]
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1.33784651e-02 -1.22021278e-01 7.16237646e-02 7.87142259e-02
-1.79656509e-02 -2.52493118e-02 -1.09611346e-01
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-4.44758121e-02 -3.36083245e-02 -1.01186310e-01
                                               3.02425453e-02
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-4.93174528e-02 3.68590708e-02 1.01812524e-01 1.16092321e-02]
```

```
In [106]: avg_w2v_vectors_cv = []; # the avg-w2v for each sentence/review is stored in t
his list
for sentence in tqdm(X_cv['essay'].values): # for each review/sentence
    vector = np.zeros(300) # as word vectors are of zero length
    cnt_words =0; # num of words with a valid vector in the sentence/review
    for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
    if cnt_words != 0:
        vector /= cnt_words
    avg_w2v_vectors_cv.append(vector)
```

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0%|
 0/17688 [00:00<?, ?it/s]
 2%
301/17688 [00:00<00:05, 2988.19it/s]
| 601/17688 [00:00<00:05, 2985.19it/s]
 5%
907/17688 [00:00<00:05, 3000.78it/s]
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 9%|
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3942/17688 [00:01<00:04, 3028.23it/s]
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4565/17688 [00:01<00:04, 3059.28it/s]
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4870/17688 [00:01<00:04, 3049.79it/s]
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| 5175/17688 [00:01<00:04, 3007.27it/s]
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| 5769/17688 [00:01<00:04, 2912.81it/s]
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6077/17688 [00:02<00:03, 2954.80it/s]
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6387/17688 [00:02<00:03, 2990.58it/s]
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6699/17688 [00:02<00:03, 3021.82it/s]
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7018/17688 [00:02<00:03, 3063.93it/s]
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| 7332/17688 [00:02<00:03, 3079.73it/s]
7641/17688 [00:02<00:03, 2903.14it/s]
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47%
8259/17688 [00:02<00:03, 2987.14it/s
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9178/17688 [00:03<00:02, 3023.04it/s]
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9488/17688 [00:03<00:02, 3039.18it/s]
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9798/17688 [00:03<00:02, 3050.58it/s]
| 10115/17688 [00:03<00:02, 3078.88it/s]
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| 10426/17688 [00:03<00:02, 3081.44it/s]
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| 10737/17688 [00:03<00:02, 3083.24it/s]
 62%
| 11049/17688 [00:03<00:02, 3087.47it/s]
 64%
| 11363/17688 [00:03<00:02, 3096.33it/s]
 66%||
| 11673/17688 [00:03<00:01, 3063.25it/s]
 68% II
| 11980/17688 [00:03<00:01, 3058.58it/s]
 70%
| 12304/17688 [00:04<00:01, 3104.30it/s]
 71%
| 12620/17688 [00:04<00:01, 3114.06it/s]
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| 12932/17688 [00:04<00:01, 3099.80it/s]
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| 13255/17688 [00:04<00:01, 3131.07it/s]
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| 13569/17688 [00:04<00:01, 3117.62it/s]
 78%
| 13881/17688 [00:04<00:01, 3102.26it/s]
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16380/17688 [00:05<00:00, 3024.42it/s]
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 96%
| 16998/17688 [00:05<00:00, 3038.18it/s]
17317/17688 [00:05<00:00, 3075.67it/s]
```

100%| 17688/17688 [00:05<00:00, 3041.55it/s]

```
In [107]: avg_w2v_vectors_test = []; # the avg-w2v for each sentence/review is stored in
    this list
    for sentence in tqdm(X_test['essay'].values): # for each review/sentence
        vector = np.zeros(300) # as word vectors are of zero length
        cnt_words =0; # num of words with a valid vector in the sentence/review
        for word in sentence.split(): # for each word in a review/sentence
        if word in glove_words:
            vector += model[word]
            cnt_words += 1
        if cnt_words != 0:
            vector /= cnt_words
        avg_w2v_vectors_test.append(vector)
```

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| 12031/26400 [00:03<00:04, 3123.76it/s]
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| 13583/26400 [00:04<00:04, 3065.32it/s]
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| 13907/26400 [00:04<00:04, 3109.16it/s]
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| 14221/26400 [00:04<00:03, 3111.59it/s]
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| 14859/26400 [00:04<00:03, 3140.40it/s]
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| 15176/26400 [00:04<00:03, 3142.38it/s]
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| 15802/26400 [00:05<00:03, 3096.80it/s]
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| 16112/26400 [00:05<00:03, 3072.65it/s]
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16420/26400 [00:05<00:03, 3067.95it/s]
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| 17033/26400 [00:05<00:03, 3012.47it/s]
| 17338/26400 [00:05<00:03, 3017.07it/s]
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21450/26400 [00:06<00:01, 3159.09it/s]
21767/26400 [00:07<00:01, 3155.45it/s]
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22083/26400 [00:07<00:01, 3140.55it/s]
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22712/26400 [00:07<00:01, 3093.80it/s]
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23022/26400 [00:07<00:01, 3079.71it/s]
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23331/26400 [00:07<00:00, 3076.07it/s]
 90%
23652/26400 [00:07<00:00, 3108.45it/s]
 91%||
23978/26400 [00:07<00:00, 3145.74it/s]
92%|
24296/26400 [00:07<00:00, 3149.09it/s]
 93%|
24612/26400 [00:08<00:00, 3136.14it/s]
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24926/26400 [00:08<00:00, 3130.44it/s]
96%
25249/26400 [00:08<00:00, 3152.80it/s]
| 25565/26400 [00:08<00:00, 3148.17it/s]
 98%
| 25880/26400 [00:08<00:00, 3113.95it/s]
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26400/26400 [00:08<00:00, 3074.05it/s]
```

```
In [108]: # avg w2v for project titles
          avg_w2v_vectors_pj_title_train = []; # the avg-w2v for each sentence/review is
          stored in this list
          for sentence in tqdm(X train['project title'].values): # for each review/sente
              vector = np.zeros(300) # as word vectors are of zero length
              cnt words =0; # num of words with a valid vector in the sentence/review
              for word in sentence.split(): # for each word in a review/sentence
                  if word in glove words:
                      vector += model[word]
                      cnt words += 1
              if cnt_words != 0:
                  vector /= cnt_words
              avg_w2v_vectors_pj_title_train.append(vector)
          print(len(avg_w2v_vectors_pj_title_train))
          print(len(avg_w2v_vectors_pj_title_train[0]))
          print(avg_w2v_vectors_pj_title_train[0])
```

35912 300

```
[-6.3004e-02 3.1239e-02 -1.8579e-01 4.4635e-02 -1.3728e-01 2.0852e-01
                        3.0234e-02 -5.0480e-01 1.8275e-01 -1.7641e-01
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 2.4091e-01 1.0702e-02 6.3483e-03 -5.2369e-03 -9.6554e-02 -6.0413e-02
 -9.9636e-02 -4.6387e-02 -4.1514e-01 1.3550e-01 6.4773e-02 -1.5405e-01
 -9.3040e-01 4.1329e-01 -6.9841e-02 -1.2174e-02 2.4677e-01 -3.4287e-01
 3.9454e-01 -2.0151e-01
                        3.9742e-01 -5.3066e-02 -4.7727e-01 -4.1655e-01
 3.5602e-01 2.1111e-01
                        1.0663e-01 -4.1312e-01 8.2616e-03 -3.8526e-01
 -1.6343e-01
            6.6813e-01 -1.9065e-01 3.3698e-01 -4.3189e-01 5.8042e-02
            3.4748e-01 6.4496e-02 2.2694e-03
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                                                2.0072e-01 2.2098e-01
 -3.0341e-01 -2.8312e-01 -3.1363e-01 5.3067e-01 -2.5296e-02 -1.5465e-01
 3.6343e-02 -4.6435e-01 2.3240e-01 1.8428e-01 -1.2815e-01 -1.3027e-02
 -1.9626e-01 -3.1234e-01 -7.1010e-02 -7.8771e-01 -2.9466e-01 -1.7576e-01
 6.7903e-02 -3.9181e-01 2.6900e-01 -6.8174e-01 2.5190e-01 -2.4059e-01
 2.7325e-01 -1.4917e-01 8.3279e-01 -3.0103e-01 -2.8582e-02 -3.3734e-01
 -2.9910e-01 -2.0228e-01 1.4101e-01 2.3135e-03 -2.7270e-01 -5.7234e-01
 -3.2172e+00 -4.6713e-01 -2.0993e-01 -4.8806e-01 4.9618e-01 7.8517e-02
 6.6969e-01 1.0868e-01 1.9829e-01 1.5625e-01 2.7715e-01
                                                           7.0318e-01
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             2.5801e-01 -3.4829e-01 -4.3414e-01
                                                9.9575e-02
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 9.8863e-02 6.2592e-03 -2.9063e-01 3.1175e-01 3.8153e-01 4.8195e-01
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                        6.9783e-02 7.0670e-02 -1.4149e-01
                                                            5.8837e-02
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                                                            6.1402e-01
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 -1.5517e-01 -3.5509e-01 -1.4373e-01 2.6160e-01 1.8030e-01 -3.8211e-02
 -3.8005e-01 -8.3100e-01 -3.3748e-01 3.7304e-02 -1.9378e-01 -5.4925e-01
 -7.3450e-02 1.3146e-01 -1.0388e+00 3.5216e-01 5.0045e-01 -1.7853e-01
 9.6374e-02 -9.7410e-02 6.3969e-01 -8.9913e-02
                                                1.7378e-01 -9.7138e-02
 -2.9316e-01 -1.9741e-02 -2.8150e-01 7.4473e-01 -2.2485e-01
                                                           1.9390e-01
 2.9590e-02 -4.0950e-02 7.4386e-02 -8.6166e-02 2.5382e-01
                                                           1.1339e-01
 1.1157e-01 7.2497e-01 -6.2336e-01 -7.8740e-02 -1.9173e-01
                                                            1.7641e-01
 6.7506e-02 -3.6622e-01 -5.8263e-02 1.7013e-01 5.0655e-01 1.4760e-01
 3.5870e-01 -2.2899e-01 1.1184e-01 -2.1720e-02 -2.2123e-01 -3.1221e-01
 -6.3867e-02 -2.2743e-01 -4.0240e-02 4.5925e-01 -4.4871e-02 4.3306e-02
 -3.1833e-01 1.7021e-01 -3.5768e+00 3.8211e-01 4.8462e-02 -1.0886e-01
 -1.6740e-01 1.1626e-01 3.4908e-02 2.2989e-01
                                                2.4380e-01 3.4586e-01
 1.5139e-01 6.6616e-01 -4.0853e-01 3.7251e-01 -6.9017e-01 -2.1990e-01
 4.4070e-01 -1.8349e-01 -3.1073e-01 1.8793e-01 -3.3471e-01 3.3364e-02
 3.1918e-02 -9.5115e-01 -1.7393e-01 -1.2559e-01 1.0029e-02 -1.4839e-02
 9.8882e-02 -1.7765e-01
                        1.9029e-02 -3.3748e-01 -4.4808e-01 -1.8664e-01
 7.2643e-02 1.9137e-01
                        9.5844e-01 -3.0384e-03 3.5579e-02 -1.8228e-01
 -5.5415e-01 -3.2349e-01 -3.7264e-01 3.3125e-01 5.4911e-01 1.5412e-01
 2.1926e-01 -1.5290e-01 -1.9009e-01 3.4024e-02 3.3934e-01
                                                            2.8025e-01
 1.0679e-01 2.9297e-01 -5.1538e-02 -4.7361e-02 -2.1209e-01
                                                            2.5042e-01
 -9.6005e-02
            1.8085e-01 1.4923e-01 4.3730e-01 -3.0703e-01
                                                            3.2686e-01
 9.3145e-02 2.9420e-01 -2.5635e-01 -3.2371e-01 -2.8559e-01 -5.0285e-01
 -6.1455e-02 -3.5492e-01 -2.7389e-01 -1.5301e-01 5.3436e-01 -1.3498e-01]
```

```
In [109]:
         avg w2v vectors pj title cv = []; # the avg-w2v for each sentence/review is st
          ored in this list
          for sentence in tqdm(X cv['project title'].values): # for each review/sentence
              vector = np.zeros(300) # as word vectors are of zero length
              cnt words =0; # num of words with a valid vector in the sentence/review
              for word in sentence.split(): # for each word in a review/sentence
                  if word in glove words:
                      vector += model[word]
                      cnt words += 1
              if cnt_words != 0:
                  vector /= cnt words
              avg_w2v_vectors_pj_title_cv.append(vector)
            0%|
          | 0/17688 [00:00<?, ?it/s]
          100%
          17688/17688 [00:00<00:00, 146571.93it/s]
In [110]:
         avg w2v vectors pj title test = []; # the avg-w2v for each sentence/review is
           stored in this list
          for sentence in tqdm(X_test['project_title'].values): # for each review/senten
              vector = np.zeros(300) # as word vectors are of zero Length
              cnt words =0; # num of words with a valid vector in the sentence/review
              for word in sentence.split(): # for each word in a review/sentence
                  if word in glove words:
                      vector += model[word]
                      cnt words += 1
              if cnt words != 0:
                  vector /= cnt words
              avg_w2v_vectors_pj_title_test.append(vector)
            0%|
          | 0/26400 [00:00<?, ?it/s]
          100%
          26400/26400 [00:00<00:00, 153010.79it/s]
```

```
In [111]: | X_tr = hstack((avg_w2v_vectors_train, X_train_state_ohe, X_train_teacher_ohe,
                         X_train_grade_ohe, X_train_category_ohe,
                         X train subcategory ohe, X train price norm,
                         X train teach prev norm, avg w2v vectors pj title train)).tocsr
          ()
          X_cr = hstack((avg_w2v_vectors_cv, X_cv_state_ohe, X_cv_teacher_ohe,
                         X cv grade ohe, X cv category ohe,
                         X_cv_subcategory_ohe, X_cv_price_norm,
                        X_cv_teach_prev_norm, avg_w2v_vectors_pj_title_cv)).tocsr()
          X_te = hstack((avg_w2v_vectors_test, X_test_state_ohe, X_test_teacher_ohe,
                         X_test_grade_ohe, X_test_category_ohe,
                         X_test_subcategory_ohe, X_test_price_norm,
                        X test teach prev norm, avg w2v vectors pj title test)).tocsr()
          print("Final Data matrix")
          print(X_tr.shape, y_train.shape)
          print(X_cr.shape, y_cv.shape)
          print(X te.shape, y test.shape)
          print("="*100)
```

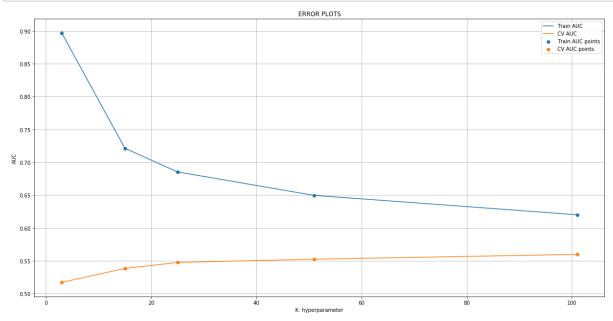
```
Final Data matrix
(35912, 701) (35912,)
(17688, 701) (17688,)
(26400, 701) (26400,)
```

```
In [112]: | train_auc = []
          cv_auc = []
          K = [3, 15, 25, 51, 101]
          for i in tqdm(K):
              neigh = KNeighborsClassifier(n_neighbors=i, n_jobs=-1)
              neigh.fit(X_tr, y_train)
              y_train_pred = batch_predict(neigh, X_tr)
              y_cv_pred = batch_predict(neigh, X_cr)
              # roc_auc_score(y_true, y_score) the 2nd parameter should be probability e
          stimates of the positive class
              # not the predicted outputs
              train_auc.append(roc_auc_score(y_train,y_train_pred))
              cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
            0%|
          | 0/5 [00:00<?, ?it/s]
           20%
          | 1/5 [07:11<28:46, 431.50s/it]
           40%
          | 2/5 [14:31<21:42, 434.18s/it]
           60%|
          | 3/5 [21:51<14:31, 435.65s/it]
           80%
          4/5 [29:10<07:16, 436.72s/it]
          100%
                     | 5/5 [36:30<00:00, 438.08s/it]
```

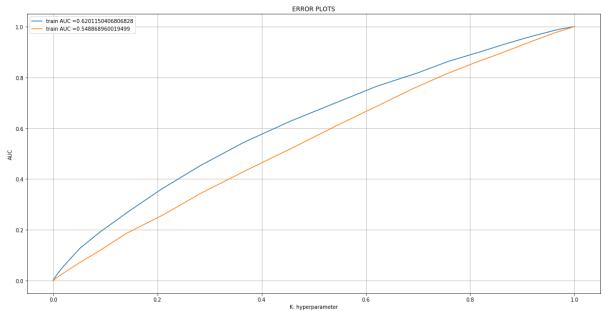
```
In [113]: plt.figure(figsize=(20,10))
    plt.plot(K, train_auc, label='Train AUC')
    plt.plot(K, cv_auc, label='CV AUC')

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

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



```
In [114]:
          best k = 101
          from sklearn.metrics import roc curve, auc
          neigh = KNeighborsClassifier(n neighbors=best k, n jobs=-1)
          neigh.fit(X_tr, y_train)
          # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estim
          ates of the positive class
          # not the predicted outputs
          y train pred = batch predict(neigh, X tr)
          y_test_pred = batch_predict(neigh, X_te)
          train fpr, train tpr, tr thresholds = roc curve(y train, y train pred)
          test fpr, test tpr, te thresholds = roc curve(y test, y test pred)
          plt.figure(figsize=(20,10))
          plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tp
          r)))
          plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
          plt.legend()
          plt.xlabel("K: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.grid()
          plt.show()
```



The Blue plot in the Graph is Train AUC and Orange Plot is Test AUC. Initially the label was accidentally copy pasted as Train AUC for both. Since redrawing plot would require to re run entire ipynb and it takes up a lot of time. so documenting the information as a markdown.

2.4.4 Applying KNN brute force on TFIDF W2V, SET 4

```
In [116]: | # 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 =0; # num of words with a valid vector in the sentence/revie
              for word in sentence.split(): # for each word in a review/sentence
                  if (word in glove_words) and (word in tfidf_words):
                      vec = model[word] # getting the vector for each word
                      # here we are multiplying idf value(dictionary[word]) and the tf v
          alue((sentence.count(word)/len(sentence.split())))
                      tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split
          ())) # getting the tfidf value for each word
                      vector += (vec * tf_idf) # calculating tfidf weighted w2v
                      tf idf weight += tf idf
              if tf_idf_weight != 0:
                  vector /= tf_idf_weight
              tfidf w2v vectors train.append(vector)
          print(len(tfidf w2v vectors train))
          print(len(tfidf w2v vectors train[0]))
```

```
0% l
 0/35912 [00:00<?, ?it/s]
28/35912 [00:00<02:09, 277.97it/s]
 0%|
 56/35912 [00:00<02:09, 276.33it/s]
 0%||
85/35912 [00:00<02:08, 278.89it/s]
 0%||
116/35912 [00:00<02:05, 284.60it/s]
 0% I
 145/35912 [00:00<02:06, 283.08it/s]
 0%|
| 172/35912 [00:00<02:08, 277.54it/s]
 1%|
 200/35912 [00:00<02:08, 277.67it/s]
 1%|
228/35912 [00:00<02:08, 276.92it/s]
 1%|
260/35912 [00:00<02:04, 285.71it/s]
 1%|
291/35912 [00:01<02:02, 291.17it/s]
 1%|
| 320/35912 [00:01<02:03, 288.45it/s]
 1%|
 349/35912 [00:01<02:03, 288.28it/s]
378/35912 [00:01<02:07, 278.24it/s]
407/35912 [00:01<02:06, 280.25it/s]
 1%
436/35912 [00:01<02:05, 281.69it/s]
 1%|
465/35912 [00:01<02:10, 272.37it/s]
 1%|
495/35912 [00:01<02:07, 277.22it/s]
 1%|
| 523/35912 [00:01<02:19, 253.39it/s]
 553/35912 [00:01<02:13, 264.57it/s]
 2%
| 588/35912 [00:02<02:03, 284.97it/s]
 2%
| 618/35912 [00:02<02:16, 258.22it/s]
 2%
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| 675/35912 [00:02<02:11, 268.58it/s]
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| 734/35912 [00:02<02:06, 278.46it/s]
 2%|
767/35912 [00:02<02:00, 290.82it/s]
 2%
 799/35912 [00:02<01:59, 294.28it/s]
 2%
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922/35912 [00:03<02:00, 289.30it/s]
 3%|
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982/35912 [00:03<01:58, 293.59it/s]
 3%|
| 1012/35912 [00:03<02:01, 286.42it/s]
 3%|
| 1043/35912 [00:03<01:59, 291.68it/s]
 3%|
| 1075/35912 [00:03<01:56, 298.17it/s]
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 1171/35912 [00:04<01:54, 304.61it/s]
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 4%||
| 1293/35912 [00:04<02:01, 285.18it/s]
 4%
| 1322/35912 [00:04<02:04, 277.00it/s]
 4%
| 1352/35912 [00:04<02:02, 282.14it/s]
 4%|
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| 1413/35912 [00:04<02:03, 278.33it/s]
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| 1603/35912 [00:05<01:51, 307.02it/s]
 5% | I
 1634/35912 [00:05<01:54, 300.13it/s]
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| 1665/35912 [00:05<01:54, 298.03it/s]
| 1695/35912 [00:05<01:59, 286.06it/s]
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| 1787/35912 [00:06<02:04, 273.46it/s]
 5%||
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 5%
| 1847/35912 [00:06<02:03, 275.04it/s]
  5%|
| 1875/35912 [00:06<02:04, 274.31it/s]
 5%
 1907/35912 [00:06<01:58, 286.02it/s]
1936/35912 [00:06<01:58, 286.58it/s]
 5%|
| 1972/35912 [00:06<01:51, 303.92it/s]
 6%
2003/35912 [00:07<01:56, 291.34it/s]
 6%|
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 6%|
2066/35912 [00:07<01:53, 298.80it/s]
2097/35912 [00:07<01:54, 294.57it/s]
 2130/35912 [00:07<01:51, 303.76it/s]
 6%
2161/35912 [00:07<01:59, 282.50it/s]
 6%|
2197/35912 [00:07<01:52, 300.70it/s]
2228/35912 [00:07<01:51, 302.78it/s]
2260/35912 [00:07<01:49, 306.22it/s]
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2291/35912 [00:07<01:49, 305.77it/s]
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2357/35912 [00:08<01:48, 308.20it/s]
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2389/35912 [00:08<01:58, 282.26it/s]
2419/35912 [00:08<01:56, 286.75it/s]
 7%
2454/35912 [00:08<01:50, 302.62it/s]
2485/35912 [00:08<01:51, 300.61it/s]
2516/35912 [00:08<01:55, 290.01it/s]
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 2582/35912 [00:08<01:50, 302.80it/s]
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2857/35912 [00:09<01:54, 288.81it/s]
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| 2916/35912 [00:10<01:58, 279.61it/s]
 2945/35912 [00:10<02:04, 265.80it/s]
 8%|
2972/35912 [00:10<02:04, 264.91it/s]
 8%|
3002/35912 [00:10<02:00, 273.99it/s]
| 3030/35912 [00:10<02:01, 269.62it/s]
| 3058/35912 [00:10<02:05, 261.43it/s]
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| 3125/35912 [00:10<01:52, 292.01it/s]
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| 3359/35912 [00:11<02:08, 252.55it/s]
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| 3533/35912 [00:12<02:00, 269.82it/s]
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3840/35912 [00:13<01:54, 279.94it/s]
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12%||
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| 5432/35912 [00:18<01:48, 282.08it/s]
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| 5524/35912 [00:19<01:43, 292.85it/s]
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| 5556/35912 [00:19<01:42, 296.56it/s]
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16%
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| 5650/35912 [00:19<01:44, 288.26it/s]
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| 6085/35912 [00:21<01:50, 269.40it/s]
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7782/35912 [00:26<01:34, 296.24it/s]
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| 8469/35912 [00:29<01:29, 307.06it/s]
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24%
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8593/35912 [00:29<01:34, 287.82it/s]
24%
| 8623/35912 [00:29<01:34, 289.90it/s]
24%
8658/35912 [00:29<01:29, 303.49it/s]
24%
8689/35912 [00:30<01:35, 286.23it/s]
24%||
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8749/35912 [00:30<01:34, 287.18it/s]
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9125/35912 [00:31<01:35, 280.36it/s]
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9213/35912 [00:31<01:34, 282.87it/s]
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26%
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9389/35912 [00:32<01:36, 275.57it/s]
26%
| 9424/35912 [00:32<01:30, 293.81it/s]
26%
9454/35912 [00:32<01:30, 293.28it/s]
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9484/35912 [00:32<01:33, 281.40it/s]
26%
9515/35912 [00:32<01:31, 288.01it/s]
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9547/35912 [00:33<01:29, 294.68it/s]
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| 9996/35912 [00:34<01:35, 271.14it/s]
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28%
| 10054/35912 [00:34<01:35, 269.57it/s]
28% II
| 10088/35912 [00:34<01:30, 286.90it/s]
28%
| 10118/35912 [00:35<01:32, 280.35it/s]
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28%
| 10206/35912 [00:35<01:37, 264.15it/s]
28% II
| 10233/35912 [00:35<01:37, 262.22it/s]
29%|
| 10265/35912 [00:35<01:32, 276.71it/s]
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| 10328/35912 [00:35<01:31, 279.22it/s]
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| 10505/35912 [00:36<01:34, 268.14it/s]
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| 10562/35912 [00:36<01:36, 263.41it/s]
| 10593/35912 [00:36<01:31, 275.31it/s]
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| 10777/35912 [00:37<01:24, 298.69it/s]
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| 10808/35912 [00:37<01:26, 291.19it/s]
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| 10839/35912 [00:37<01:25, 294.29it/s]
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| 10932/35912 [00:37<01:27, 284.25it/s]
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| 10961/35912 [00:38<01:36, 258.68it/s]
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| 10991/35912 [00:38<01:32, 269.30it/s]
31%||
| 11021/35912 [00:38<01:29, 277.27it/s]
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| 11302/35912 [00:39<01:26, 283.21it/s]
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| 11333/35912 [00:39<01:24, 290.15it/s]
32%|
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32% l l
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| 11750/35912 [00:40<01:17, 311.93it/s]
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| 11782/35912 [00:40<01:23, 289.84it/s]
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| 11905/35912 [00:41<01:20, 296.40it/s]
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| 12270/35912 [00:42<01:27, 271.73it/s]
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| 12333/35912 [00:42<01:21, 288.66it/s]
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| 12425/35912 [00:43<01:21, 289.54it/s]
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| 12542/35912 [00:43<01:25, 272.32it/s]
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| 13137/35912 [00:45<01:21, 279.37it/s]
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| 14901/35912 [00:51<01:09, 301.27it/s]
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| 14965/35912 [00:51<01:09, 300.86it/s]
42%II
| 14998/35912 [00:52<01:08, 307.56it/s]
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| 15030/35912 [00:52<01:07, 308.73it/s]
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| 15062/35912 [00:52<01:08, 303.41it/s]
| 15096/35912 [00:52<01:06, 312.90it/s]
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| 15159/35912 [00:52<01:13, 281.15it/s]
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15533/35912 [00:53<01:10, 287.69it/s]
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| 15804/35912 [00:54<01:08, 293.25it/s]
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| 15934/35912 [00:55<01:08, 290.91it/s]
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| 16089/35912 [00:55<01:07, 291.76it/s]
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| 16155/35912 [00:55<01:04, 306.60it/s]
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| 16495/35912 [00:57<01:12, 269.32it/s]
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16625/35912 [00:57<01:04, 299.90it/s<sup>-1</sup>
46%||
| 16657/35912 [00:57<01:03, 302.44it/s
| 16688/35912 [00:57<01:06, 289.57it/s
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| 16836/35912 [00:58<01:08, 279.54it/s]
| 16893/35912 [00:58<01:11, 264.78it/s]
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47%
| 16952/35912 [00:58<01:08, 275.51it/s]
47%||
| 16980/35912 [00:58<01:08, 275.43it/s]
| 17044/35912 [00:59<01:03, 295.47it/s]
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| 17077/35912 [00:59<01:02, 303.59it/s]
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| 17169/35912 [00:59<01:03, 293.72it/s]
| 17199/35912 [00:59<01:04, 291.51it/s]
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| 17324/35912 [01:00<01:02, 297.82it/s]
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| 17538/35912 [01:00<01:05, 278.65it/s]
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| 17653/35912 [01:01<01:07, 270.43it/s]
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| 17713/35912 [01:01<01:04, 280.05it/s]
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| 17743/35912 [01:01<01:03, 285.18it/s]
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| 17777/35912 [01:01<01:00, 299.10it/s]
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| 17808/35912 [01:01<01:00, 298.17it/s]
| 17838/35912 [01:01<01:01, 294.56it/s]
50%
| 17868/35912 [01:01<01:02, 287.90it/s]
50%
| 17897/35912 [01:02<01:04, 277.99it/s]
50% II
| 17929/35912 [01:02<01:02, 288.81it/s]
50%
| 17959/35912 [01:02<01:03, 283.23it/s]
| 17988/35912 [01:02<01:03, 283.78it/s]
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| 18017/35912 [01:02<01:06, 269.17it/s]
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| 18051/35912 [01:02<01:02, 285.15it/s]
50%
| 18087/35912 [01:02<00:59, 300.52it/s]
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| 18118/35912 [01:02<01:01, 288.34it/s]
| 18148/35912 [01:02<01:01, 291.12it/s]
| 18181/35912 [01:03<00:59, 298.73it/s]
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| 18212/35912 [01:03<00:58, 300.51it/s]
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| 18245/35912 [01:03<00:57, 306.44it/s]
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| 18337/35912 [01:03<01:03, 275.78it/s]
| 18371/35912 [01:03<01:00, 291.79it/s]
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| 18401/35912 [01:03<00:59, 292.72it/s]
51%
| 18431/35912 [01:03<01:00, 290.82it/s]
51%
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| 18556/35912 [01:04<01:01, 282.14it/s]
| 18588/35912 [01:04<00:59, 291.14it/s]
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52%
| 18652/35912 [01:04<00:57, 302.63it/s]
52%
18683/35912 [01:04<00:58, 294.64it/s]
52%
| 18718/35912 [01:04<00:55, 307.10it/s]
52% | I
| 18749/35912 [01:04<00:58, 295.89it/s]
52%
| 18779/35912 [01:05<01:01, 277.59it/s]
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| 18837/35912 [01:05<01:01, 277.09it/s]
53%
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| 18893/35912 [01:05<01:02, 272.93it/s]
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| 19111/35912 [01:06<00:57, 290.07it/s]
| 19141/35912 [01:06<00:59, 280.89it/s]
| 19170/35912 [01:06<01:02, 268.83it/s]
53%||
| 19198/35912 [01:06<01:02, 267.62it/s]
54%
19226/35912 [01:06<01:01, 270.64it/s]
54%||
| 19258/35912 [01:06<00:59, 280.26it/s]
54%
| 19287/35912 [01:06<00:59, 279.25it/s]
| 19317/35912 [01:06<00:58, 283.77it/s]
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| 19346/35912 [01:07<00:58, 280.87it/s]
| 19375/35912 [01:07<00:58, 281.30it/s]
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| 19404/35912 [01:07<00:58, 280.78it/s]
54%
| 19433/35912 [01:07<01:00, 271.02it/s]
54%
19461/35912 [01:07<01:01, 266.84it/s]
54%
| 19493/35912 [01:07<00:58, 278.83it/s]
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| 19526/35912 [01:07<00:56, 291.87it/s]
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19561/35912 [01:07<00:54, 302.62it/s]
| 19594/35912 [01:07<00:52, 309.70it/s]
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| 19626/35912 [01:08<00:55, 295.66it/s]
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| 19659/35912 [01:08<00:53, 302.90it/s]
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| 19722/35912 [01:08<00:55, 289.59it/s]
| 19752/35912 [01:08<00:56, 285.37it/s]
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| 19782/35912 [01:08<00:56, 286.52it/s]
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| 19811/35912 [01:08<00:58, 275.51it/s]
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| 19846/35912 [01:08<00:55, 291.56it/s]
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| 19876/35912 [01:08<00:54, 291.71it/s]
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| 19941/35912 [01:09<00:52, 305.69it/s]
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| 19972/35912 [01:09<00:52, 302.74it/s]
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20129/35912 [01:09<00:55, 285.11it/s]
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20160/35912 [01:09<00:54, 291.54it/s]
56%
20196/35912 [01:09<00:51, 307.81it/s]
56% II
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20383/35912 [01:10<00:52, 294.66it/s]
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20730/35912 [01:11<00:54, 280.16it/s]
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21017/35912 [01:12<00:51, 290.99it/s]
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21111/35912 [01:13<00:48, 303.71it/s]
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| 21202/35912 [01:13<00:50, 290.11it/s]
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21363/35912 [01:13<00:48, 301.58it/s]
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21487/35912 [01:14<00:48, 296.37it/s]
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22201/35912 [01:16<00:47, 290.81it/s]
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22261/35912 [01:17<00:47, 284.49it/s]
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22291/35912 [01:17<00:47, 287.54it/s]
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22356/35912 [01:17<00:44, 303.97it/s]
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24289/35912 [01:24<00:39, 292.10it/s]
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25745/35912 [01:28<00:33, 306.99it/s]
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26563/35912 [01:31<00:32, 291.14it/s]
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74%
26628/35912 [01:31<00:30, 306.23it/s]
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26659/35912 [01:32<00:30, 299.56it/s]
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26690/35912 [01:32<00:31, 295.97it/s]
74%
| 26720/35912 [01:32<00:32, 283.12it/s]
74%
26751/35912 [01:32<00:31, 288.47it/s]
75% I I
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26845/35912 [01:32<00:31, 290.19it/s]
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26879/35912 [01:32<00:30, 299.74it/s]
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27121/35912 [01:33<00:33, 263.12it/s]
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27207/35912 [01:34<00:31, 276.42it/s]
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78%
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27971/35912 [01:36<00:26, 303.16it/s]
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78%
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28314/35912 [01:37<00:26, 285.43it/s]
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28376/35912 [01:38<00:25, 293.50it/s]
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28407/35912 [01:38<00:25, 297.64it/s]
79%
28437/35912 [01:38<00:26, 283.38it/s]
79%
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AttributeError
                                    Traceback (most recent call last)
<ipython-input-116-77925bdae2d3> in <module>
    18 print(len(tfidf w2v vectors train))
    19 print(len(tfidf_w2v_vectors_train[0]))
---> 20 print(tfidf_w2v_vectors_train.shape)
AttributeError: 'list' object has no attribute 'shape'
```

localhost:8888/nbconvert/html/Assignment-2 t-SNE/Assignments DonorsChoose 2018/3 DonorsChoose KNN.jpynb?download=false

```
In [117]: # 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 =0; # num of words with a valid vector in the sentence/revie
              for word in sentence.split(): # for each word in a review/sentence
                  if (word in glove_words) and (word in tfidf_words):
                      vec = model[word] # getting the vector for each word
                      # here we are multiplying idf value(dictionary[word]) and the tf v
          alue((sentence.count(word)/len(sentence.split())))
                      tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split
          ())) # getting the tfidf value for each word
                      vector += (vec * tf_idf) # calculating tfidf weighted w2v
                      tf idf weight += tf idf
              if tf_idf_weight != 0:
                  vector /= tf_idf_weight
              tfidf w2v vectors cv.append(vector)
          print(len(tfidf w2v vectors cv))
          print(len(tfidf w2v vectors cv[0]))
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| 1026/17688 [00:03<00:54, 305.63it/s]
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| 1346/17688 [00:04<00:52, 308.86it/s]
 8%
| 1378/17688 [00:04<00:58, 280.42it/s]
| 1407/17688 [00:04<00:58, 277.76it/s]
 8%|
| 1440/17688 [00:04<00:55, 291.05it/s]
 8%|
| 1470/17688 [00:05<00:55, 292.19it/s]
| 1502/17688 [00:05<00:54, 298.55it/s]
 9%|
 1533/17688 [00:05<00:54, 297.80it/s]
| 1563/17688 [00:05<00:54, 296.90it/s]
| 1593/17688 [00:05<00:56, 283.75it/s]
 9%|
| 1625/17688 [00:05<00:54, 293.14it/s]
 9%|
| 1655/17688 [00:05<00:54, 291.96it/s]
10%
| 1685/17688 [00:05<00:55, 287.79it/s]
10%
| 1715/17688 [00:05<00:55, 289.89it/s]
10%
| 1745/17688 [00:05<00:54, 290.53it/s]
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10%
| 1775/17688 [00:06<00:57, 278.07it/s]
10%
| 1805/17688 [00:06<00:55, 283.72it/s]
10%
| 1834/17688 [00:06<00:55, 284.12it/s]
11%
| 1871/17688 [00:06<00:51, 304.84it/s]
11%
1904/17688 [00:06<00:52, 302.78it/s]
11%||
| 1935/17688 [00:06<00:52, 300.72it/s]
11%
| 1973/17688 [00:06<00:49, 318.60it/s]
11%
2006/17688 [00:06<00:50, 310.40it/s]
12%
2039/17688 [00:06<00:49, 315.37it/s]
12%
2071/17688 [00:07<00:50, 306.99it/s]
12%
2103/17688 [00:07<00:50, 309.22it/s]
12%
2135/17688 [00:07<00:51, 301.18it/s]
12%
2166/17688 [00:07<00:53, 292.84it/s]
2196/17688 [00:07<00:54, 286.74it/s]
13%
2225/17688 [00:07<00:55, 276.44it/s]
13%||
| 2257/17688 [00:07<00:53, 286.11it/s]
13%
2288/17688 [00:07<00:52, 291.45it/s]
13%
2318/17688 [00:07<00:55, 277.12it/s]
13%
2346/17688 [00:07<00:57, 267.08it/s]
2376/17688 [00:08<00:56, 268.96it/s]
14%
2404/17688 [00:08<00:56, 270.82it/s]
14%
2435/17688 [00:08<00:54, 279.42it/s]
14%
2467/17688 [00:08<00:52, 289.89it/s]
14%
2500/17688 [00:08<00:50, 298.64it/s]
14%
2533/17688 [00:08<00:49, 305.92it/s]
2564/17688 [00:08<00:52, 289.35it/s]
15%
2594/17688 [00:08<00:52, 287.66it/s]
15%
2623/17688 [00:08<00:53, 283.52it/s]
15%
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2652/17688 [00:09<00:53, 279.05it/s]
15%||
2681/17688 [00:09<00:54, 274.49it/s]
15%
2711/17688 [00:09<00:53, 279.53it/s]
16%
2743/17688 [00:09<00:51, 287.64it/s]
16%
2776/17688 [00:09<00:50, 293.80it/s]
2806/17688 [00:09<00:53, 279.38it/s]
16%
2835/17688 [00:09<00:53, 275.47it/s]
16%
2863/17688 [00:09<00:54, 272.20it/s]
16%
2891/17688 [00:09<00:55, 267.64it/s]
17%
2921/17688 [00:10<00:53, 275.27it/s]
17%
2954/17688 [00:10<00:51, 287.62it/s]
2987/17688 [00:10<00:49, 296.94it/s]
17%
| 3018/17688 [00:10<00:48, 300.10it/s]
17%
3050/17688 [00:10<00:48, 303.44it/s]
17%
3085/17688 [00:10<00:46, 313.74it/s]
18%||
| 3119/17688 [00:10<00:45, 317.83it/s]
18%
| 3151/17688 [00:10<00:46, 312.22it/s]
18%
| 3183/17688 [00:10<00:47, 305.76it/s]
18%||
3214/17688 [00:10<00:47, 303.66it/s]
18%
3246/17688 [00:11<00:47, 305.10it/s]
19%
3279/17688 [00:11<00:46, 310.64it/s]
19%
| 3312/17688 [00:11<00:45, 315.55it/s]
19%
3344/17688 [00:11<00:47, 299.37it/s]
19%
| 3375/17688 [00:11<00:48, 297.50it/s]
19%
| 3405/17688 [00:11<00:48, 295.84it/s]
19%
| 3435/17688 [00:11<00:49, 290.39it/s]
20%||
| 3465/17688 [00:11<00:49, 287.58it/s]
20%
| 3495/17688 [00:11<00:49, 288.90it/s]
3524/17688 [00:12<00:49, 286.05it/s]
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20%
| 3553/17688 [00:12<00:50, 279.17it/s]
| 3581/17688 [00:12<00:53, 261.66it/s]
20%
| 3611/17688 [00:12<00:51, 270.80it/s]
21%||
| 3644/17688 [00:12<00:49, 285.68it/s]
21%
3673/17688 [00:12<00:49, 280.54it/s]
21%
| 3704/17688 [00:12<00:48, 288.18it/s]
21%
| 3734/17688 [00:12<00:48, 287.65it/s]
21%
3763/17688 [00:12<00:48, 286.89it/s]
21%||
| 3792/17688 [00:12<00:48, 285.50it/s]
22%
3821/17688 [00:13<00:49, 279.61it/s]
22%
3851/17688 [00:13<00:48, 283.23it/s]
22%
| 3883/17688 [00:13<00:47, 291.95it/s]
22%
3913/17688 [00:13<00:48, 285.33it/s]
| 3942/17688 [00:13<00:48, 286.10it/s]
22%
3971/17688 [00:13<00:49, 276.81it/s]
23%
4000/17688 [00:13<00:49, 279.22it/s]
23%||
4029/17688 [00:13<00:50, 269.26it/s]
23%
4058/17688 [00:13<00:49, 274.59it/s]
23%
4094/17688 [00:14<00:46, 290.82it/s]
4124/17688 [00:14<00:46, 292.89it/s]
23%
4154/17688 [00:14<00:48, 278.03it/s]
24%
4184/17688 [00:14<00:47, 282.09it/s]
24%
4218/17688 [00:14<00:45, 294.40it/s]
24%
4248/17688 [00:14<00:46, 291.13it/s]
24%
| 4280/17688 [00:14<00:45, 297.79it/s]
4314/17688 [00:14<00:44, 302.13it/s]
25%
4345/17688 [00:14<00:43, 303.79it/s]
25%
| 4376/17688 [00:14<00:44, 302.30it/s]
25%||
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4407/17688 [00:15<00:44, 296.10it/s]
25%||
4437/17688 [00:15<00:46, 284.82it/s]
25%||
4472/17688 [00:15<00:44, 295.03it/s]
25%
4502/17688 [00:15<00:45, 291.56it/s]
26%
4532/17688 [00:15<00:44, 293.41it/s]
4562/17688 [00:15<00:44, 292.15it/s]
26%
4592/17688 [00:15<00:45, 285.46it/s]
26%
4627/17688 [00:15<00:43, 299.29it/s]
26%
4658/17688 [00:15<00:45, 285.96it/s]
26%
4687/17688 [00:16<00:47, 275.93it/s]
27%
4719/17688 [00:16<00:45, 285.72it/s]
27%
| 4748/17688 [00:16<00:47, 274.22it/s]
27%
4779/17688 [00:16<00:46, 280.42it/s]
27%
4813/17688 [00:16<00:43, 294.65it/s]
27%||
| 4846/17688 [00:16<00:42, 302.15it/s]
28%
4877/17688 [00:16<00:44, 286.98it/s]
28%
4910/17688 [00:16<00:43, 293.31it/s]
28%
4940/17688 [00:16<00:43, 292.08it/s]
28%
4970/17688 [00:17<00:45, 282.20it/s]
28%
4999/17688 [00:17<00:45, 276.60it/s]
28%
5030/17688 [00:17<00:44, 281.38it/s]
29%
| 5060/17688 [00:17<00:44, 285.31it/s]
29%
| 5093/17688 [00:17<00:42, 296.01it/s]
29%|
| 5123/17688 [00:17<00:42, 293.94it/s]
29%
| 5153/17688 [00:17<00:43, 290.82it/s]
29%
5183/17688 [00:17<00:42, 292.03it/s]
29%||
| 5213/17688 [00:17<00:42, 292.03it/s]
30%
| 5245/17688 [00:17<00:41, 298.45it/s]
5275/17688 [00:18<00:42, 290.48it/s]
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30%
| 5305/17688 [00:18<00:42, 291.80it/s]
| 5335/17688 [00:18<00:44, 275.06it/s]
30%
| 5365/17688 [00:18<00:43, 280.72it/s]
31%||
| 5395/17688 [00:18<00:43, 284.03it/s]
31%
5424/17688 [00:18<00:44, 277.82it/s]
31%||
| 5454/17688 [00:18<00:43, 283.53it/s]
31%
| 5486/17688 [00:18<00:41, 291.38it/s]
5516/17688 [00:18<00:43, 279.39it/s]
31%|
| 5545/17688 [00:19<00:43, 281.07it/s]
32%
| 5579/17688 [00:19<00:40, 295.92it/s]
32%|
5609/17688 [00:19<00:40, 294.75it/s]
32%
5643/17688 [00:19<00:39, 306.38it/s]
32%
| 5674/17688 [00:19<00:40, 294.60it/s]
| 5704/17688 [00:19<00:40, 295.56it/s]
32%
5734/17688 [00:19<00:40, 295.36it/s]
33%||
| 5764/17688 [00:19<00:41, 286.78it/s]
33% l
| 5794/17688 [00:19<00:41, 290.01it/s]
33%||
| 5825/17688 [00:19<00:40, 295.10it/s]
33%
| 5855/17688 [00:20<00:40, 289.10it/s]
| 5891/17688 [00:20<00:38, 305.90it/s]
33%
5924/17688 [00:20<00:38, 308.61it/s]
34%
| 5958/17688 [00:20<00:37, 315.00it/s]
34%
| 5990/17688 [00:20<00:38, 301.55it/s]
34%
| 6021/17688 [00:20<00:39, 298.99it/s]
34%
| 6055/17688 [00:20<00:37, 307.94it/s]
| 6086/17688 [00:20<00:38, 303.37it/s]
35%
6117/17688 [00:20<00:37, 304.67it/s]
35%|
6148/17688 [00:21<00:38, 296.84it/s]
35%||
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6178/17688 [00:21<00:39, 288.58it/s]
35%
6207/17688 [00:21<00:39, 287.52it/s]
35%
6239/17688 [00:21<00:38, 294.32it/s]
35%
6270/17688 [00:21<00:38, 297.37it/s]
36%||
| 6301/17688 [00:21<00:37, 300.41it/s]
6335/17688 [00:21<00:36, 307.29it/s]
36%
6366/17688 [00:21<00:37, 301.18it/s]
36%
6397/17688 [00:21<00:39, 286.37it/s]
36%
6430/17688 [00:21<00:38, 296.01it/s]
37%||
6460/17688 [00:22<00:38, 291.38it/s]
37% l
6490/17688 [00:22<00:39, 283.34it/s]
6519/17688 [00:22<00:40, 277.36it/s]
37%
| 6547/17688 [00:22<00:40, 277.54it/s]
37%
6579/17688 [00:22<00:38, 288.47it/s]
37%||
6609/17688 [00:22<00:38, 289.54it/s]
38%|
6641/17688 [00:22<00:37, 297.44it/s]
38%
6671/17688 [00:22<00:38, 289.82it/s]
38%
6705/17688 [00:22<00:36, 301.05it/s]
38%|
6737/17688 [00:23<00:36, 304.11it/s]
38%||
6768/17688 [00:23<00:35, 303.41it/s]
38%
6799/17688 [00:23<00:35, 302.92it/s]
39%
| 6830/17688 [00:23<00:36, 294.82it/s]
39%
6860/17688 [00:23<00:37, 291.42it/s]
39%|
6890/17688 [00:23<00:38, 278.62it/s]
39%
6923/17688 [00:23<00:37, 287.92it/s]
39%
6952/17688 [00:23<00:37, 286.21it/s]
39%||
| 6983/17688 [00:23<00:37, 289.09it/s]
40%|
7013/17688 [00:24<00:36, 290.81it/s]
7043/17688 [00:24<00:36, 288.66it/s]
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40%|
7072/17688 [00:24<00:37, 285.85it/s]
7103/17688 [00:24<00:36, 292.11it/s]
40%|
7133/17688 [00:24<00:36, 287.90it/s]
41%|
7168/17688 [00:24<00:34, 303.51it/s]
41%|
7199/17688 [00:24<00:35, 298.61it/s]
41%
7230/17688 [00:24<00:36, 288.71it/s]
41%||
7260/17688 [00:24<00:36, 286.39it/s]
41%
| 7289/17688 [00:24<00:37, 277.80it/s]
41%||
7322/17688 [00:25<00:35, 290.31it/s]
42%
| 7352/17688 [00:25<00:35, 290.83it/s]
42%
7382/17688 [00:25<00:35, 292.04it/s]
42%
7412/17688 [00:25<00:34, 293.75it/s]
42%
7442/17688 [00:25<00:35, 290.68it/s]
7472/17688 [00:25<00:35, 288.57it/s]
42%
| 7502/17688 [00:25<00:35, 289.61it/s]
43%
| 7535/17688 [00:25<00:34, 298.43it/s]
43%
7565/17688 [00:25<00:35, 285.51it/s]
43%
7594/17688 [00:26<00:35, 281.24it/s]
43%
7625/17688 [00:26<00:34, 287.87it/s]
7655/17688 [00:26<00:34, 289.14it/s]
43%
7685/17688 [00:26<00:34, 289.99it/s]
44%
7715/17688 [00:26<00:35, 279.28it/s]
44%
7744/17688 [00:26<00:37, 267.06it/s]
44%
| 7773/17688 [00:26<00:36, 272.99it/s]
44%
7801/17688 [00:26<00:36, 272.85it/s]
44%
7830/17688 [00:26<00:35, 274.85it/s
44%|
7864/17688 [00:26<00:34, 288.85it/s]
45%
7894/17688 [00:27<00:34, 285.64it/s
45%||
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7928/17688 [00:27<00:32, 299.48it/s]
45%
7959/17688 [00:27<00:34, 278.38it/s
45%||
7990/17688 [00:27<00:33, 286.60it/s]
45%
8022/17688 [00:27<00:32, 293.64it/s]
46%||
8056/17688 [00:27<00:31, 305.56it/s]
| 8088/17688 [00:27<00:31, 309.10it/s]
46%
8120/17688 [00:27<00:32, 292.05it/s]
46%||
8150/17688 [00:27<00:32, 292.88it/s]
46%
8180/17688 [00:28<00:33, 287.61it/s]
46%||
8214/17688 [00:28<00:31, 300.97it/s]
47%
8245/17688 [00:28<00:31, 295.20it/s]
8276/17688 [00:28<00:31, 298.86it/s]
47%
| 8307/17688 [00:28<00:31, 298.86it/s]
47%
8338/17688 [00:28<00:31,
                          300.57it/sl
47%|
8369/17688 [00:28<00:31, 292.46it/s]
48%
8403/17688 [00:28<00:30, 303.83it/s]
48%||
| 8434/17688 [00:28<00:30, 301.47it/s]
48%||
8465/17688 [00:28<00:32, 288.14it/s]
48%|
8496/17688 [00:29<00:31, 292.10it/s]
48%
8526/17688 [00:29<00:31,
                          290.39it/sl
48%|
8556/17688 [00:29<00:31, 292.58it/s]
49%||
8586/17688 [00:29<00:31, 289.05it/s]
49%||
| 8618/17688 [00:29<00:30, 297.08it/s]
49%|
8648/17688 [00:29<00:31,
                          286.26it/s]
49%||
8679/17688 [00:29<00:30, 291.57it/s]
49%
8711/17688 [00:29<00:30,
                          295.64it/sl
49%||
8741/17688 [00:29<00:30, 296.29it/s]
50%
8771/17688 [00:30<00:30, 291.57it/s]
8808/17688 [00:30<00:28, 308.47it/s]
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50% l
8840/17688 [00:30<00:30, 290.87it/s]
8870/17688 [00:30<00:30, 292.05it/s]
50%||
8900/17688 [00:30<00:30, 284.60it/s]
50%|
8929/17688 [00:30<00:31, 278.21it/s]
51%
8961/17688 [00:30<00:30, 287.42it/s]
51%
8990/17688 [00:30<00:32, 269.20it/s]
51%
9019/17688 [00:30<00:31, 273.77it/s]
51%
9050/17688 [00:31<00:30, 281.59it/s]
51%
9079/17688 [00:31<00:31, 270.05it/s]
51%
| 9109/17688 [00:31<00:30, 277.05it/s]
52%
9139/17688 [00:31<00:30, 282.17it/s]
52%||
9168/17688 [00:31<00:32, 264.50it/s]
52%
9198/17688 [00:31<00:31, 273.69it/s]
9226/17688 [00:31<00:31, 271.77it/s]
52%
9257/17688 [00:31<00:30, 279.37it/s]
52%
| 9286/17688 [00:31<00:30, 277.83it/s]
53%
9314/17688 [00:31<00:30, 277.87it/s]
53%
9344/17688 [00:32<00:29, 280.40it/s]
53%
9374/17688 [00:32<00:29, 282.99it/s]
9403/17688 [00:32<00:29, 277.92it/s]
53%
9431/17688 [00:32<00:30, 273.87it/s]
53%
9462/17688 [00:32<00:29, 279.40it/s]
54%
9496/17688 [00:32<00:28, 290.86it/s]
54%||
| 9526/17688 [00:32<00:28, 288.69it/s]
54%
9556/17688 [00:32<00:27, 290.53it/s]
54%
9592/17688 [00:32<00:26, 306.24it/s]
54%
9623/17688 [00:33<00:27, 288.74it/s]
55%
9653/17688 [00:33<00:28, 286.41it/s]
55%
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9686/17688 [00:33<00:27, 296.04it/s]
55%
9721/17688 [00:33<00:25, 307.35it/s]
55% II
9753/17688 [00:33<00:26, 302.48it/s]
55%
9784/17688 [00:33<00:27, 292.04it/s]
55% | I
9814/17688 [00:33<00:28, 276.73it/s]
9848/17688 [00:33<00:26, 291.79it/s]
56%
9879/17688 [00:33<00:26, 293.88it/s]
56%
9909/17688 [00:34<00:28, 275.57it/s]
56%
9940/17688 [00:34<00:27, 284.52it/s]
56%
9972/17688 [00:34<00:26, 293.71it/s]
57%
| 10002/17688 [00:34<00:26, 289.82it/s]
| 10032/17688 [00:34<00:27, 273.82it/s]
57%
| 10065/17688 [00:34<00:26, 287.25it/s]
57%
| 10095/17688 [00:34<00:26, 288.68it/s]
57% II
| 10125/17688 [00:34<00:26, 288.84it/s]
57%
| 10155/17688 [00:34<00:25, 289.80it/s]
58%
| 10185/17688 [00:34<00:25, 289.60it/s]
58%||
| 10215/17688 [00:35<00:26, 285.40it/s]
58%||
| 10251/17688 [00:35<00:24, 303.75it/s]
58% | I
10282/17688 [00:35<00:25, 292.01it/s]
58%
| 10312/17688 [00:35<00:25, 286.22it/s]
58%
| 10345/17688 [00:35<00:24, 295.90it/s]
59%|
10375/17688 [00:35<00:25, 281.49it/s]
59%|
| 10404/17688 [00:35<00:26, 277.70it/s]
59%|
| 10433/17688 [00:35<00:26, 271.26it/s]
59%
10461/17688 [00:35<00:27, 261.77it/s]
59% | I
| 10495/17688 [00:36<00:25, 279.98it/s]
59%
| 10524/17688 [00:36<00:25, 280.67it/s]
10555/17688 [00:36<00:24, 287.48it/s]
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60% l
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| 10615/17688 [00:36<00:24, 285.17it/s]
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| 10868/17688 [00:37<00:24, 272.92it/s]
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| 10896/17688 [00:37<00:24, 272.02it/s]
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62%
| 10956/17688 [00:37<00:23, 281.44it/s]
| 10988/17688 [00:37<00:23, 289.05it/s]
62%
| 11024/17688 [00:37<00:21, 306.64it/s]
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| 11056/17688 [00:37<00:22, 297.79it/s]
63% II
| 11087/17688 [00:38<00:22, 298.12it/s]
63%
| 11118/17688 [00:38<00:22, 296.64it/s]
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| 11148/17688 [00:38<00:22, 296.99it/s]
| 11178/17688 [00:38<00:23, 280.60it/s]
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| 11208/17688 [00:38<00:22, 284.74it/s]
64%
| 11239/17688 [00:38<00:22, 290.46it/s]
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| 11269/17688 [00:38<00:22, 280.36it/s]
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| 11333/17688 [00:38<00:21, 293.63it/s]
| 11363/17688 [00:39<00:21, 291.45it/s]
64%
| 11393/17688 [00:39<00:21, 292.45it/s]
65%
| 11423/17688 [00:39<00:21, 289.82it/s]
65% II
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11453/17688 [00:39<00:21, 284.71it/s]
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| 11482/17688 [00:39<00:22, 277.48it/s]
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| 11548/17688 [00:39<00:20, 300.95it/s]
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| 11579/17688 [00:39<00:20, 292.71it/s]
| 11609/17688 [00:39<00:21, 281.82it/s]
66%
| 11638/17688 [00:40<00:21, 278.72it/s]
66%
| 11667/17688 [00:40<00:21, 278.16it/s]
66%
| 11695/17688 [00:40<00:21, 274.05it/s]
66%
| 11726/17688 [00:40<00:21, 278.79it/s]
66%||
| 11754/17688 [00:40<00:21, 276.08it/s]
| 11783/17688 [00:40<00:21, 279.52it/s]
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| 11814/17688 [00:40<00:20, 282.72it/s]
67%
11845/17688 [00:40<00:20, 288.99it/s]
67%||
| 11874/17688 [00:40<00:20, 281.94it/s]
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| 11905/17688 [00:40<00:20, 288.41it/s]
67%
| 11934/17688 [00:41<00:20, 284.87it/s]
68%
| 11968/17688 [00:41<00:19, 298.07it/s]
68% l
| 12002/17688 [00:41<00:18, 307.24it/s]
68%
| 12037/17688 [00:41<00:17, 317.43it/s]
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| 12197/17688 [00:41<00:17, 311.49it/s]
69%
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69%
| 12260/17688 [00:42<00:18, 298.26it/s]
69%
| 12291/17688 [00:42<00:18, 293.37it/s]
| 12321/17688 [00:42<00:18, 290.42it/s]
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| 12384/17688 [00:42<00:17, 298.25it/s]
70%
| 12414/17688 [00:42<00:18, 292.87it/s]
70%
| 12450/17688 [00:42<00:17, 308.08it/s]
71%
12482/17688 [00:42<00:16, 307.32it/s]
71%||
| 12513/17688 [00:42<00:17, 290.23it/s]
71%
| 12543/17688 [00:43<00:17, 289.09it/s]
71%
| 12575/17688 [00:43<00:17, 296.29it/s]
71%
| 12605/17688 [00:43<00:17, 290.73it/s]
71%
| 12635/17688 [00:43<00:17, 289.44it/s]
72%
12669/17688 [00:43<00:16, 301.56it/s]
72%
| 12700/17688 [00:43<00:16, 294.76it/s]
72%
| 12730/17688 [00:43<00:18, 273.87it/s]
| 12758/17688 [00:43<00:18, 265.71it/s]
72%
| 12786/17688 [00:43<00:18, 268.50it/s]
72%
| 12818/17688 [00:44<00:17, 279.37it/s]
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| 12847/17688 [00:44<00:17, 276.22it/s]
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| 12875/17688 [00:44<00:18, 261.31it/s]
73%
| 12904/17688 [00:44<00:17, 268.02it/s]
| 12932/17688 [00:44<00:18, 261.83it/s]
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| 12961/17688 [00:44<00:17, 269.14it/s]
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| 13118/17688 [00:45<00:17, 268.00it/s]
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| 13152/17688 [00:45<00:15, 284.23it/s]
75%
| 13182/17688 [00:45<00:15, 281.70it/s]
75%
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| 13211/17688 [00:45<00:15, 282.70it/s]
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| 13243/17688 [00:45<00:15, 289.98it/s]
75%
| 13280/17688 [00:45<00:14, 304.95it/s]
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| 13342/17688 [00:45<00:15, 286.63it/s]
| 13372/17688 [00:46<00:15, 280.17it/s]
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| 13401/17688 [00:46<00:15, 278.39it/s]
76%
| 13430/17688 [00:46<00:15, 276.36it/s]
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| 13458/17688 [00:46<00:15, 276.03it/s]
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| 13486/17688 [00:46<00:15, 276.60it/s]
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77%||
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77%
| 13696/17688 [00:47<00:14, 275.47it/s]
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| 13726/17688 [00:47<00:14, 281.03it/s]
78%
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79%
| 14037/17688 [00:48<00:12, 296.44it/s]
| 14067/17688 [00:48<00:12, 288.31it/s]
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| 14155/17688 [00:48<00:12, 279.62it/s]
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| 14187/17688 [00:48<00:12, 287.70it/s]
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| 14252/17688 [00:49<00:11, 302.19it/s]
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| 14283/17688 [00:49<00:12, 277.03it/s]
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| 14921/17688 [00:51<00:09, 295.89it/s]
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| 14951/17688 [00:51<00:09, 293.01it/s]
85%||
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| 14981/17688 [00:51<00:09, 290.17it/s]
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| 15163/17688 [00:52<00:08, 294.62it/s]
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86%
| 15286/17688 [00:52<00:08, 298.62it/s]
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| 15381/17688 [00:52<00:07, 290.19it/s]
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| 15442/17688 [00:53<00:07, 294.43it/s]
| 15472/17688 [00:53<00:08, 274.42it/s]
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| 15816/17688 [00:54<00:06, 280.31it/s]
| 15851/17688 [00:54<00:06, 297.56it/s]
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| 15945/17688 [00:54<00:05, 300.87it/s]
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| 15976/17688 [00:54<00:05, 299.40it/s]
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| 16038/17688 [00:55<00:05, 295.72it/s]
91%
| 16068/17688 [00:55<00:05, 285.38it/s]
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| 16099/17688 [00:55<00:05, 289.30it/s]
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| 16129/17688 [00:55<00:05, 281.96it/s]
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| 16158/17688 [00:55<00:05, 274.09it/s]
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| 16188/17688 [00:55<00:05, 277.69it/s]
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| 16217/17688 [00:55<00:05, 280.68it/s]
92%
| 16251/17688 [00:55<00:04, 291.82it/s]
| 16283/17688 [00:56<00:04, 297.46it/s]
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| 16313/17688 [00:56<00:04, 294.08it/s]
92%|
| 16343/17688 [00:56<00:04, 278.78it/s]
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| 16372/17688 [00:56<00:04, 267.47it/s]
93%||
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| 16434/17688 [00:56<00:04, 279.88it/s]
| 16463/17688 [00:56<00:04, 281.42it/s]
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| 16492/17688 [00:56<00:04, 280.87it/s]
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| 16524/17688 [00:56<00:04, 290.98it/s]
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| 16555/17688 [00:56<00:03, 295.82it/s]
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| 16585/17688 [00:57<00:03, 286.26it/s]
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| 16614/17688 [00:57<00:03, 271.47it/s]
94%||
| 16642/17688 [00:57<00:03, 270.25it/s]
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| 16670/17688 [00:57<00:04, 247.97it/s]
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| 16699/17688 [00:57<00:03, 257.36it/s]
95%||
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| 16757/17688 [00:57<00:03, 266.56it/s]
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   | 17062/17688 [00:58<00:01, 325.01it/s]
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   | 17096/17688 [00:58<00:01, 326.78it/s]
97%
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  | | 17570/17688 [01:00<00:00, 278.51it/s]
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  | 17599/17688 [01:00<00:00, 276.45it/s]
100%
  | 17630/17688 [01:00<00:00, 284.37it/s]
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100%| 17659/17688 [01:00<00:00, 284.58it/s]
100%| 17688/17688 [01:00<00:00, 290.69it/s]

17688 300

```
In [118]: # 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 =0; # num of words with a valid vector in the sentence/revie
              for word in sentence.split(): # for each word in a review/sentence
                  if (word in glove_words) and (word in tfidf_words):
                      vec = model[word] # getting the vector for each word
                      # here we are multiplying idf value(dictionary[word]) and the tf v
          alue((sentence.count(word)/len(sentence.split())))
                      tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split
          ())) # getting the tfidf value for each word
                      vector += (vec * tf_idf) # calculating tfidf weighted w2v
                      tf idf weight += tf idf
              if tf_idf_weight != 0:
                  vector /= tf idf weight
              tfidf w2v vectors test.append(vector)
          print(len(tfidf w2v vectors test))
          print(len(tfidf w2v vectors test[0]))
```

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0% l
 0/26400 [00:00<?, ?it/s]
 0%|
27/26400 [00:00<01:39, 265.44it/s]
 0%||
 55/26400 [00:00<01:38, 267.54it/s]
 0%|
89/26400 [00:00<01:32, 285.29it/s]
 0%|
| 118/26400 [00:00<01:32, 285.22it/s]
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 1%|
| 172/26400 [00:00<01:35, 274.18it/s]
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265/26400 [00:00<01:31, 286.59it/s]
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| 330/26400 [00:01<01:30, 287.60it/s]
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| 395/26400 [00:01<01:26, 299.72it/s]
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425/26400 [00:01<01:28, 293.89it/s]
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455/26400 [00:01<01:30, 288.27it/s]
| 484/26400 [00:01<01:31, 283.94it/s]
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| 546/26400 [00:01<01:29, 288.93it/s]
 575/26400 [00:01<01:31, 281.90it/s]
 2%
609/26400 [00:02<01:27, 295.79it/s]
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| 639/26400 [00:02<01:27, 294.66it/s]
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 669/26400 [00:02<01:28, 289.62it/s]
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| 733/26400 [00:02<01:28, 290.60it/s]
| 763/26400 [00:02<01:27, 292.73it/s]
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793/26400 [00:02<01:29, 285.84it/s]
 3%|
822/26400 [00:02<01:36, 263.85it/s]
 3%|
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852/26400 [00:02<01:33, 272.46it/s]
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881/26400 [00:03<01:32, 276.12it/s]
909/26400 [00:03<01:32, 275.05it/s]
 4%||
937/26400 [00:03<01:34, 269.56it/s]
 4%
967/26400 [00:03<01:32, 275.93it/s]
996/26400 [00:03<01:31, 277.81it/s]
 4%|
| 1024/26400 [00:03<01:35, 266.77it/s]
 4%|
| 1053/26400 [00:03<01:32, 272.78it/s]
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1081/26400 [00:03<01:32, 272.72it/s]
 4%
| 1110/26400 [00:03<01:31, 277.08it/s]
| 1142/26400 [00:04<01:27, 287.37it/s]
 1171/26400 [00:04<01:30, 277.64it/s]
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| 1207/26400 [00:04<01:25, 293.91it/s]
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1237/26400 [00:04<01:27, 286.66it/s]
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| 1268/26400 [00:04<01:26, 290.19it/s]
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| 1298/26400 [00:04<01:33, 269.66it/s]
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| 1357/26400 [00:04<01:29, 279.78it/s]
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| 1484/26400 [00:05<01:27, 283.57it/s]
| 1513/26400 [00:05<01:28, 282.39it/s]
| 1542/26400 [00:05<01:27, 284.02it/s]
 6%|
| 1571/26400 [00:05<01:27, 282.68it/s]
 6%
| 1601/26400 [00:05<01:26, 286.24it/s]
 6%||
| 1630/26400 [00:05<01:26, 286.73it/s]
 6%|
| 1659/26400 [00:05<01:29, 277.23it/s]
1687/26400 [00:05<01:30, 274.20it/s]
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6%|
| 1715/26400 [00:06<01:30, 273.71it/s]
 1746/26400 [00:06<01:27, 281.56it/s]
| 1783/26400 [00:06<01:21, 302.03it/s]
| 1814/26400 [00:06<01:22, 297.62it/s]
 7%|
| 1850/26400 [00:06<01:18, 312.52it/s]
 7%|
| 1882/26400 [00:06<01:18, 311.31it/s]
 7%|
| 1914/26400 [00:06<01:19, 308.67it/s]
| 1946/26400 [00:06<01:21, 299.11it/s]
| 1977/26400 [00:06<01:23, 293.14it/s]
 8%|
2007/26400 [00:06<01:24, 289.39it/s]
2037/26400 [00:07<01:23, 290.22it/s]
 8% I I
| 2067/26400 [00:07<01:31, 266.78it/s]
2095/26400 [00:07<01:33, 259.56it/s]
 2125/26400 [00:07<01:30, 268.52it/s]
 8%|
2154/26400 [00:07<01:30, 267.25it/s]
 8%|
2181/26400 [00:07<01:30, 266.70it/s]
2212/26400 [00:07<01:27, 277.07it/s]
2242/26400 [00:07<01:25, 282.99it/s]
 9%|
 2275/26400 [00:07<01:21, 295.04it/s]
| 2305/26400 [00:08<01:22, 291.57it/s]
 9%||
2335/26400 [00:08<01:22, 292.56it/s]
 9%|
2365/26400 [00:08<01:24, 283.32it/s]
2394/26400 [00:08<01:25, 279.75it/s]
 9%|
2424/26400 [00:08<01:24, 284.13it/s]
2454/26400 [00:08<01:23, 288.10it/s]
2488/26400 [00:08<01:19, 300.54it/s]
10%|
2519/26400 [00:08<01:20, 294.92it/s]
10%
2549/26400 [00:08<01:27, 272.47it/s]
10%||
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2579/26400 [00:09<01:25, 279.59it/s]
10%
2609/26400 [00:09<01:23, 283.24it/s]
10%
2638/26400 [00:09<01:23, 283.79it/s]
10%
2667/26400 [00:09<01:24, 281.69it/s]
10%
2697/26400 [00:09<01:23, 285.53it/s]
2726/26400 [00:09<01:23, 283.71it/s]
10%|
2755/26400 [00:09<01:23, 282.47it/s]
11%
2787/26400 [00:09<01:22, 285.18it/s]
11%|
2817/26400 [00:09<01:21, 288.01it/s]
11%
2851/26400 [00:09<01:18, 299.70it/s]
11%
2882/26400 [00:10<01:27, 269.12it/s]
11%|
| 2914/26400 [00:10<01:23, 281.31it/s]
11%
2943/26400 [00:10<01:24, 276.00it/s]
11%|
2977/26400 [00:10<01:20, 291.22it/s]
11%||
3009/26400 [00:10<01:19, 294.57it/s]
12%
| 3041/26400 [00:10<01:17, 300.29it/s]
12%
3072/26400 [00:10<01:18, 299.00it/s]
12%
| 3103/26400 [00:10<01:19, 291.40it/s]
12%
| 3133/26400 [00:10<01:20, 287.41it/s]
12%
3162/26400 [00:11<01:25, 272.21it/s]
12%
| 3194/26400 [00:11<01:21, 284.42it/s]
12%
| 3223/26400 [00:11<01:21, 283.79it/s]
12%
3252/26400 [00:11<01:21, 285.01it/s]
12%
| 3281/26400 [00:11<01:23, 278.47it/s]
13%
3309/26400 [00:11<01:24, 273.42it/s]
13%
| 3340/26400 [00:11<01:22, 280.61it/s]
13%
| 3370/26400 [00:11<01:20, 285.56it/s]
13%
| 3399/26400 [00:11<01:21, 283.74it/s]
13%
3428/26400 [00:12<01:23, 275.27it/s]
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13%
| 3458/26400 [00:12<01:21, 281.67it/s]
3488/26400 [00:12<01:20, 284.70it/s]
13%
| 3517/26400 [00:12<01:21, 280.69it/s]
13%
| 3548/26400 [00:12<01:19, 287.49it/s]
14%
| 3577/26400 [00:12<01:19, 286.76it/s]
14%
| 3608/26400 [00:12<01:18, 291.11it/s]
14%
3639/26400 [00:12<01:18, 291.74it/s]
14%
| 3672/26400 [00:12<01:17, 293.62it/s]
14%
| 3702/26400 [00:12<01:20, 280.83it/s]
14%
| 3731/26400 [00:13<01:22, 274.11it/s]
14%
3762/26400 [00:13<01:20, 282.63it/s]
14%
| 3795/26400 [00:13<01:17, 292.43it/s]
14%
| 3825/26400 [00:13<01:18, 286.47it/s]
| 3854/26400 [00:13<01:21, 277.85it/s]
15%
| 3891/26400 [00:13<01:15, 299.03it/s]
15%
3922/26400 [00:13<01:21, 277.37it/s]
15%
3951/26400 [00:13<01:20, 280.45it/s]
15%||
3980/26400 [00:13<01:19, 282.64it/s]
15%
4009/26400 [00:14<01:21, 273.76it/s]
15%
4037/26400 [00:14<01:22, 270.25it/s]
15%
4065/26400 [00:14<01:24, 265.56it/s]
16%
4094/26400 [00:14<01:22, 271.89it/s]
16%
4127/26400 [00:14<01:18, 282.11it/s]
16%
4160/26400 [00:14<01:15, 294.37it/s]
16%
4192/26400 [00:14<01:15, 295.18it/s]
4222/26400 [00:14<01:16, 289.98it/s]
16%
4252/26400 [00:14<01:17, 286.44it/s]
16%
4281/26400 [00:15<01:20, 275.46it/s]
16%||
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4311/26400 [00:15<01:18, 281.02it/s]
16%
| 4346/26400 [00:15<01:14, 296.61it/s]
17%||
4376/26400 [00:15<01:15, 291.79it/s]
17%
4406/26400 [00:15<01:14, 293.57it/s]
17%
4436/26400 [00:15<01:15, 290.56it/s]
4471/26400 [00:15<01:11, 304.78it/s]
17%
4502/26400 [00:15<01:14, 294.38it/s]
17%
4532/26400 [00:15<01:16, 286.95it/s]
17%
4561/26400 [00:15<01:16, 285.54it/s]
17%
4592/26400 [00:16<01:14, 291.04it/s]
18%
4623/26400 [00:16<01:14, 294.18it/s]
18%
4653/26400 [00:16<01:17, 281.98it/s]
18%
4684/26400 [00:16<01:15, 287.64it/s]
18%
4714/26400 [00:16<01:15, 288.11it/s]
18%
4744/26400 [00:16<01:14, 290.12it/s]
18%
4779/26400 [00:16<01:11, 303.65it/s]
18%
4811/26400 [00:16<01:10, 307.72it/s]
18%
4842/26400 [00:16<01:10, 305.92it/s]
18%|
4873/26400 [00:16<01:11, 302.88it/s]
19%||
4904/26400 [00:17<01:11, 299.92it/s]
19%
4936/26400 [00:17<01:11, 299.07it/s]
19%
4966/26400 [00:17<01:13, 290.05it/s]
19%
4996/26400 [00:17<01:16, 278.53it/s]
19%||
| 5027/26400 [00:17<01:14, 285.12it/s]
19%
5061/26400 [00:17<01:11, 299.05it/s]
19%
5092/26400 [00:17<01:14, 285.02it/s]
19%||
| 5121/26400 [00:17<01:17, 275.32it/s]
20%
| 5156/26400 [00:17<01:12, 293.61it/s]
| 5190/26400 [00:18<01:09, 303.09it/s]
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20%
| 5222/26400 [00:18<01:09, 306.44it/s]
| 5253/26400 [00:18<01:11, 293.78it/s]
20%
| 5283/26400 [00:18<01:12, 290.71it/s]
20%
| 5313/26400 [00:18<01:13, 286.94it/s]
20%
| 5342/26400 [00:18<01:13, 286.38it/s]
20%
| 5376/26400 [00:18<01:10, 299.23it/s]
20%
| 5407/26400 [00:18<01:10, 295.71it/s]
21%
5441/26400 [00:18<01:08, 306.30it/s]
21%|
| 5474/26400 [00:19<01:06, 312.39it/s]
21%
| 5513/26400 [00:19<01:03, 330.77it/s]
21%
| 5547/26400 [00:19<01:03, 329.87it/s]
21%
| 5582/26400 [00:19<01:02, 334.00it/s]
21%
| 5616/26400 [00:19<01:08, 304.53it/s]
| 5648/26400 [00:19<01:09, 300.56it/s]
22%
| 5687/26400 [00:19<01:04, 320.59it/s]
22%
5720/26400 [00:19<01:05, 314.39it/s]
22%
| 5752/26400 [00:19<01:07, 304.59it/s]
22%||
5783/26400 [00:20<01:08, 301.09it/s]
22%
| 5814/26400 [00:20<01:08, 298.68it/s]
| 5847/26400 [00:20<01:07, 305.97it/s]
22%
| 5878/26400 [00:20<01:07, 304.70it/s]
22%
| 5909/26400 [00:20<01:07, 302.03it/s]
22%
| 5940/26400 [00:20<01:07, 301.09it/s]
23%
| 5971/26400 [00:20<01:08, 297.83it/s]
23%
| 6003/26400 [00:20<01:07, 300.96it/s]
6035/26400 [00:20<01:06, 304.91it/s]
23%
6067/26400 [00:20<01:06, 306.86it/s]
23%
| 6098/26400 [00:21<01:06, 304.42it/s]
23%||
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6129/26400 [00:21<01:07, 298.37it/s]
23%
| 6160/26400 [00:21<01:07, 300.26it/s]
23%
6191/26400 [00:21<01:06, 302.47it/s]
24%
6222/26400 [00:21<01:09, 291.22it/s]
24%
6252/26400 [00:21<01:09, 289.78it/s]
24%
6285/26400 [00:21<01:07, 299.36it/s]
24%|
6316/26400 [00:21<01:08, 294.96it/s]
24%
| 6346/26400 [00:21<01:07, 295.81it/s]
24%
6376/26400 [00:21<01:08, 292.95it/s]
24%||
6406/26400 [00:22<01:13, 272.77it/s]
24%
| 6434/26400 [00:22<01:14, 267.26it/s]
24%||
6465/26400 [00:22<01:12, 276.76it/s]
25%
| 6493/26400 [00:22<01:13, 269.92it/s]
25%
6521/26400 [00:22<01:14, 268.38it/s]
25%||
6548/26400 [00:22<01:16, 258.30it/s]
25%
| 6583/26400 [00:22<01:10, 279.84it/s]
25%
6612/26400 [00:22<01:11, 277.35it/s]
25%
6643/26400 [00:22<01:09, 285.84it/s]
25%||
6676/26400 [00:23<01:06, 297.20it/s]
25%||
6707/26400 [00:23<01:08, 288.58it/s]
26%
6739/26400 [00:23<01:06, 295.10it/s]
26%
| 6769/26400 [00:23<01:07, 290.75it/s]
26%
6799/26400 [00:23<01:07, 288.63it/s]
26%
6829/26400 [00:23<01:07, 291.32it/s]
26%
6859/26400 [00:23<01:08, 283.31it/s]
26%
6888/26400 [00:23<01:10, 274.98it/s]
26% II
| 6922/26400 [00:23<01:08, 285.32it/s]
26%
6953/26400 [00:24<01:06, 291.70it/s]
6983/26400 [00:24<01:06, 293.51it/s]
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27%
7013/26400 [00:24<01:07, 288.85it/s]
7043/26400 [00:24<01:06, 289.79it/s]
27%
| 7073/26400 [00:24<01:07, 287.14it/s]
27%
7104/26400 [00:24<01:06, 292.20it/s]
27%
7134/26400 [00:24<01:06, 291.31it/s]
27%
| 7168/26400 [00:24<01:03, 300.57it/s]
27%
| 7199/26400 [00:24<01:06, 290.80it/s]
27%
7230/26400 [00:24<01:04, 295.68it/s]
28%||
| 7260/26400 [00:25<01:05, 290.32it/s]
28%
7290/26400 [00:25<01:05, 291.68it/s]
28%
7320/26400 [00:25<01:07, 281.93it/s]
28%||
| 7349/26400 [00:25<01:08, 276.42it/s]
28%
7381/26400 [00:25<01:06, 287.63it/s]
28%
| 7414/26400 [00:25<01:04, 295.36it/s]
28%
7447/26400 [00:25<01:02, 304.35it/s]
28%
7478/26400 [00:25<01:05, 290.79it/s]
28% II
| 7508/26400 [00:25<01:06, 285.36it/s]
29%
| 7539/26400 [00:26<01:04, 290.91it/s]
29%
| 7569/26400 [00:26<01:05, 289.55it/s]
29%
| 7601/26400 [00:26<01:03, 297.47it/s]
29%
7631/26400 [00:26<01:05, 284.87it/s]
29%
| 7660/26400 [00:26<01:06, 280.02it/s]
29%
7692/26400 [00:26<01:05, 286.45it/s]
29%||
7721/26400 [00:26<01:06, 279.44it/s]
29%
| 7750/26400 [00:26<01:06, 281.93it/s]
7779/26400 [00:26<01:06, 278.00it/s]
30%
| 7807/26400 [00:27<01:07, 274.72it/s]
30%|
| 7840/26400 [00:27<01:04, 287.95it/s]
30% | I
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| 7870/26400 [00:27<01:06, 279.49it/s]
30%|
| 7899/26400 [00:27<01:08, 268.68it/s]
30%||
7934/26400 [00:27<01:04, 287.58it/s]
30%|
7964/26400 [00:27<01:03, 289.73it/s]
30%
| 7994/26400 [00:27<01:03, 287.92it/s]
8024/26400 [00:27<01:04, 283.43it/s]
31%
8054/26400 [00:27<01:03, 286.77it/s]
31%
8083/26400 [00:27<01:03, 287.11it/s]
31%|
8117/26400 [00:28<01:00, 300.58it/s]
31%||
8148/26400 [00:28<01:02, 292.44it/s]
31%||
| 8179/26400 [00:28<01:02, 292.68it/s]
31%||
8209/26400 [00:28<01:03, 285.82it/s]
31%
8241/26400 [00:28<01:01, 293.88it/s]
31%
8271/26400 [00:28<01:02, 289.93it/s]
31%||
8302/26400 [00:28<01:01, 293.38it/s]
32%
| 8333/26400 [00:28<01:00, 296.69it/s]
32%
8363/26400 [00:28<01:01, 295.29it/s]
32%
8393/26400 [00:29<01:06, 271.96it/s]
32%|
8421/26400 [00:29<01:07, 265.20it/s]
32%|
8452/26400 [00:29<01:04, 276.68it/s]
32%|
8484/26400 [00:29<01:02, 286.28it/s]
32%
| 8514/26400 [00:29<01:02, 287.14it/s]
32%
| 8549/26400 [00:29<00:59, 299.83it/s]
32%|
| 8580/26400 [00:29<01:01, 287.88it/s]
33%|
8611/26400 [00:29<01:01, 291.10it/s]
33%
8641/26400 [00:29<01:00, 293.09it/s]
33%||
8671/26400 [00:29<01:01, 289.39it/s]
33%|
| 8702/26400 [00:30<01:00, 293.81it/s]
8735/26400 [00:30<00:58, 303.21it/s]
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33%
8766/26400 [00:30<00:58, 301.02it/s]
8797/26400 [00:30<00:58, 302.13it/s]
33%|
| 8828/26400 [00:30<01:02, 279.23it/s]
34%
8857/26400 [00:30<01:03, 276.16it/s]
34%
8885/26400 [00:30<01:04, 272.67it/s]
34%
8913/26400 [00:30<01:04, 272.64it/s]
34%
| 8943/26400 [00:30<01:02, 278.96it/s]
34%
8976/26400 [00:31<00:59, 290.43it/s]
34%||
9006/26400 [00:31<01:03, 272.71it/s]
34%
| 9038/26400 [00:31<01:00, 284.81it/s]
34%
9067/26400 [00:31<01:01, 281.56it/s]
34%||
9102/26400 [00:31<00:58, 296.29it/s]
35%||
9133/26400 [00:31<00:59, 287.98it/s]
9163/26400 [00:31<01:00, 284.27it/s]
35%
9196/26400 [00:31<00:58, 295.22it/s]
35%
9226/26400 [00:31<00:59, 287.51it/s]
35% II
9255/26400 [00:32<00:59, 285.92it/s]
35%
9284/26400 [00:32<01:02, 275.92it/s]
35%
9315/26400 [00:32<01:00, 283.96it/s]
9344/26400 [00:32<01:04, 263.44it/s]
35%
9371/26400 [00:32<01:04, 263.26it/s]
36%
| 9401/26400 [00:32<01:02, 271.26it/s]
36%
9429/26400 [00:32<01:02, 272.46it/s]
36%
9457/26400 [00:32<01:04, 262.56it/s]
36%
9489/26400 [00:32<01:01, 276.26it/s]
9517/26400 [00:33<01:05, 257.01it/s]
36%
9548/26400 [00:33<01:02, 269.68it/s]
36%
9576/26400 [00:33<01:05, 256.45it/s]
36% l
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9608/26400 [00:33<01:01, 272.19it/s]
36%
| 9636/26400 [00:33<01:02, 269.95it/s]
37%
9669/26400 [00:33<00:58, 284.26it/s]
37%
9698/26400 [00:33<00:58, 284.51it/s]
37%
9731/26400 [00:33<00:56, 295.40it/s]
9761/26400 [00:33<00:56, 294.39it/s]
9791/26400 [00:33<00:56, 294.54it/s]
37%
9821/26400 [00:34<00:56, 294.65it/s]
37%
9853/26400 [00:34<00:55, 297.84it/s]
37%
9886/26400 [00:34<00:53, 306.19it/s]
38%||
9917/26400 [00:34<00:54, 304.85it/s]
9948/26400 [00:34<00:55, 297.81it/s]
38%
9978/26400 [00:34<00:59, 277.23it/s]
38%|
10009/26400 [00:34<00:57, 285.73it/s]
38%||
| 10040/26400 [00:34<00:57, 284.77it/s]
38%||
| 10069/26400 [00:34<00:57, 284.86it/s]
| 10100/26400 [00:35<00:56, 290.55it/s]
38%|
| 10132/26400 [00:35<00:54, 297.35it/s]
38%|
| 10162/26400 [00:35<00:54, 297.50it/s]
39%|
10192/26400 [00:35<00:55, 293.25it/s]
39%|
| 10222/26400 [00:35<00:57, 281.38it/s]
39%
| 10255/26400 [00:35<00:55, 291.49it/s]
39%
| 10285/26400 [00:35<00:56, 287.47it/s]
39%|
| 10320/26400 [00:35<00:53, 301.61it/s]
39%|
| 10351/26400 [00:35<00:54, 293.13it/s]
39%|
10383/26400 [00:35<00:53, 296.75it/s]
39%
| 10414/26400 [00:36<00:53, 299.97it/s]
40%
| 10445/26400 [00:36<00:53, 298.78it/s]
10475/26400 [00:36<00:54, 292.40it/s]
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40%
| 10505/26400 [00:36<00:55, 285.63it/s]
| 10534/26400 [00:36<00:56, 281.32it/s]
40%|
| 10563/26400 [00:36<00:55, 283.26it/s]
40%|
| 10592/26400 [00:36<00:57, 274.17it/s]
40%
10621/26400 [00:36<00:56, 278.15it/s]
40%
| 10652/26400 [00:36<00:55, 285.62it/s]
40%
| 10681/26400 [00:37<00:54, 286.30it/s]
41%
| 10710/26400 [00:37<00:54, 285.92it/s]
| 10743/26400 [00:37<00:52, 296.48it/s]
41%
| 10773/26400 [00:37<00:56, 274.91it/s]
41%|
| 10801/26400 [00:37<00:56, 274.20it/s]
41%||
| 10829/26400 [00:37<00:58, 268.22it/s]
41%
| 10860/26400 [00:37<00:56, 277.48it/s]
| 10888/26400 [00:37<00:57, 271.19it/s]
41%
| 10916/26400 [00:37<00:56, 272.39it/s]
41%
| 10949/26400 [00:37<00:53, 286.15it/s]
42%||
| 10979/26400 [00:38<00:54, 283.82it/s]
42%
| 11010/26400 [00:38<00:52, 290.60it/s]
42%
| 11041/26400 [00:38<00:52, 294.70it/s]
| 11073/26400 [00:38<00:51, 297.88it/s]
42%
| 11105/26400 [00:38<00:50, 301.84it/s]
42%
| 11138/26400 [00:38<00:49, 306.56it/s]
42%
| 11169/26400 [00:38<00:50, 300.68it/s]
42%
| 11200/26400 [00:38<00:52, 290.87it/s]
43%
| 11233/26400 [00:38<00:50, 300.99it/s]
| 11264/26400 [00:39<00:53, 283.90it/s]
43%
| 11298/26400 [00:39<00:50, 298.11it/s]
| 11329/26400 [00:39<00:50, 300.06it/s]
43%||
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| 11362/26400 [00:39<00:48, 306.97it/s]
43%
| 11393/26400 [00:39<00:49, 303.61it/s]
43%II
| 11424/26400 [00:39<00:51, 290.32it/s]
43%
| 11454/26400 [00:39<00:51, 291.68it/s]
44%||
| 11484/26400 [00:39<00:52, 284.34it/s]
44%
11546/26400 [00:40<00:52, 283.74it/s]
44%||
11575/26400 [00:40<00:53, 279.23it/s]
44%
11604/26400 [00:40<00:53, 278.53it/s]
44%||
| 11635/26400 [00:40<00:51, 285.12it/s]
44%
| 11664/26400 [00:40<00:52, 281.79it/s]
44%|
| 11693/26400 [00:40<00:53, 275.53it/s]
44%
| 11721/26400 [00:40<00:53, 273.83it/s]
45%
11754/26400 [00:40<00:50,
                          287.27it/s
45%
| 11783/26400 [00:40<00:51, 284.92it/s]
45%
| 11812/26400 [00:40<00:52, 276.83it/s]
11846/26400 [00:41<00:50, 289.63it/s]
45%||
| 11879/26400 [00:41<00:48, 297.64it/s]
45%
11910/26400 [00:41<00:48, 299.73it/s]
45%||
11941/26400 [00:41<00:49, 289.44it/s
45%
| 11974/26400 [00:41<00:48, 299.92it/s]
45%||
| 12005/26400 [00:41<00:49, 291.18it/s]
46%||
| 12064/26400 [00:41<00:52, 270.85it/s]
46%||
12092/26400 [00:41<00:53, 266.72it/s]
46%
12128/26400 [00:42<00:49, 288.00it/s
46%
| 12158/26400 [00:42<00:52, 271.21it/s
46%
| 12190/26400 [00:42<00:50, 283.66it/s]
| 12219/26400 [00:42<00:51, 275.21it/s]
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46% l
| 12247/26400 [00:42<00:52, 269.67it/s]
12280/26400 [00:42<00:49, 284.78it/s
47%||
| 12309/26400 [00:42<00:51, 275.95it/s]
47%
| 12341/26400 [00:42<00:49, 286.48it/s]
12371/26400 [00:42<00:49, 281.67it/s]
47%
| 12400/26400 [00:43<00:53, 262.05it/s]
47%
| 12428/26400 [00:43<00:52, 265.87it/s]
12460/26400 [00:43<00:50, 278.09it/s]
47%
| 12489/26400 [00:43<00:49, 280.15it/s]
47%
| 12519/26400 [00:43<00:48, 285.23it/s]
48%
| 12551/26400 [00:43<00:47, 293.44it/s]
48%||
| 12581/26400 [00:43<00:47, 290.47it/s]
48%|
| 12612/26400 [00:43<00:47, 292.94it/s]
| 12648/26400 [00:43<00:44, 309.70it/s]
48%||
12680/26400 [00:43<00:48, 285.40it/s]
48%
12710/26400 [00:44<00:49, 279.36it/s]
48%
| 12739/26400 [00:44<00:50, 268.59it/s]
48%
12768/26400 [00:44<00:49, 273.33it/s]
48%
| 12798/26400 [00:44<00:48, 280.24it/s]
49%||
| 12831/26400 [00:44<00:46, 289.87it/s]
49%|
12862/26400 [00:44<00:46, 290.87it/s]
49%|
| 12892/26400 [00:44<00:46, 292.07it/s]
49%
| 12922/26400 [00:44<00:47, 286.22it/s]
49%|
| 12951/26400 [00:44<00:48, 276.89it/s]
49%
| 13013/26400 [00:45<00:46, 289.19it/s]
49%
| 13043/26400 [00:45<00:46, 287.54it/s]
50% l
| 13072/26400 [00:45<00:46, 286.80it/s]
50%
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| 13101/26400 [00:45<00:48, 274.11it/s]
50%
| 13131/26400 [00:45<00:47, 280.84it/s]
50%
| 13160/26400 [00:45<00:48, 273.35it/s]
50%
| 13190/26400 [00:45<00:47, 275.63it/s]
50% II
| 13218/26400 [00:45<00:47, 275.52it/s]
| 13250/26400 [00:46<00:45, 286.17it/s]
50%|
| 13282/26400 [00:46<00:44, 293.33it/s]
50% | I
13317/26400 [00:46<00:42, 307.71it/s]
51%
| 13351/26400 [00:46<00:41, 314.34it/s]
51%||
| 13383/26400 [00:46<00:42, 309.85it/s]
51%
| 13415/26400 [00:46<00:43, 297.40it/s]
| 13445/26400 [00:46<00:44, 293.18it/s]
51%
| 13475/26400 [00:46<00:45, 283.72it/s]
51%
| 13504/26400 [00:46<00:48, 268.39it/s]
51%
| 13534/26400 [00:46<00:46, 275.83it/s]
51%
| 13563/26400 [00:47<00:46, 275.37it/s]
51%||
| 13595/26400 [00:47<00:45, 284.54it/s]
52%||
| 13624/26400 [00:47<00:45, 278.17it/s]
52%
| 13654/26400 [00:47<00:44, 283.79it/s]
52%
13685/26400 [00:47<00:43, 290.57it/s]
52%
| 13715/26400 [00:47<00:43, 291.86it/s]
52%||
| 13749/26400 [00:47<00:41, 304.21it/s]
52% | l
13781/26400 [00:47<00:41, 307.24it/s]
52%
| 13812/26400 [00:47<00:42, 293.47it/s]
52%
| 13842/26400 [00:48<00:43, 287.98it/s]
53%
13871/26400 [00:48<00:43, 287.96it/s]
53%
| 13903/26400 [00:48<00:42, 295.46it/s]
53%||
| 13935/26400 [00:48<00:41, 299.26it/s]
13966/26400 [00:48<00:42, 294.05it/s]
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53%||
| 13996/26400 [00:48<00:43, 288.38it/s]
14026/26400 [00:48<00:43, 282.93it/s]
53%||
| 14055/26400 [00:48<00:43, 284.40it/s]
53%
| 14084/26400 [00:48<00:43, 280.49it/s]
53%
14115/26400 [00:48<00:43, 284.98it/s]
54%
| 14146/26400 [00:49<00:42, 291.45it/s]
54%||
| 14176/26400 [00:49<00:42, 289.94it/s]
54%||
| 14206/26400 [00:49<00:42, 287.24it/s]
54%
| 14235/26400 [00:49<00:42, 284.90it/s]
54%
| 14266/26400 [00:49<00:41, 290.57it/s]
54%
14296/26400 [00:49<00:42, 286.03it/s]
54%||
| 14325/26400 [00:49<00:42, 285.74it/s]
54%
14361/26400 [00:49<00:40, 297.27it/s]
| 14391/26400 [00:49<00:42, 285.58it/s]
55%
| 14422/26400 [00:50<00:41, 290.25it/s]
55%
| 14452/26400 [00:50<00:41, 286.63it/s]
55%
| 14482/26400 [00:50<00:41, 285.77it/s]
55%
| 14511/26400 [00:50<00:42, 278.98it/s]
55%||
| 14539/26400 [00:50<00:42, 276.21it/s]
| 14575/26400 [00:50<00:39, 296.41it/s]
55%
14606/26400 [00:50<00:39, 298.00it/s]
55%||
14637/26400 [00:50<00:39, 298.26it/s]
56%
14668/26400 [00:50<00:40, 289.28it/s]
56%
14698/26400 [00:50<00:40, 287.61it/s]
56%||
| 14727/26400 [00:51<00:40, 285.15it/s]
| 14756/26400 [00:51<00:40, 285.97it/s]
56%
| 14785/26400 [00:51<00:41, 279.12it/s]
56%
| 14818/26400 [00:51<00:39, 292.09it/s]
56%
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| 14848/26400 [00:51<00:40, 283.81it/s]
56%
| 14879/26400 [00:51<00:40, 284.97it/s]
56%
| 14912/26400 [00:51<00:39, 293.39it/s]
57%
| 14944/26400 [00:51<00:38, 296.97it/s]
57% II
| 14974/26400 [00:51<00:40, 285.38it/s]
| 15006/26400 [00:52<00:38, 292.75it/s]
57%
| 15037/26400 [00:52<00:38, 297.09it/s]
57%
| 15067/26400 [00:52<00:39, 288.75it/s]
57%
| 15097/26400 [00:52<00:39, 289.73it/s]
57%||
| 15127/26400 [00:52<00:39, 284.65it/s]
57% II
| 15158/26400 [00:52<00:38, 290.39it/s]
58%||
| 15188/26400 [00:52<00:39, 280.31it/s]
58%
| 15219/26400 [00:52<00:39, 286.42it/s]
58%
15248/26400 [00:52<00:39, 284.34it/s]
58% | I
| 15277/26400 [00:53<00:39, 280.44it/s]
58%
| 15306/26400 [00:53<00:39, 280.19it/s]
58%||
| 15335/26400 [00:53<00:41, 266.17it/s]
58%||
| 15362/26400 [00:53<00:42, 260.57it/s]
58%||
| 15392/26400 [00:53<00:40, 268.55it/s]
58%||
15422/26400 [00:53<00:40, 272.94it/s]
59%
| 15450/26400 [00:53<00:41, 261.38it/s]
59%||
| 15477/26400 [00:53<00:41, 263.37it/s]
59%|
| 15504/26400 [00:53<00:42, 257.21it/s]
59%|
| 15534/26400 [00:53<00:40, 268.18it/s]
59%|
| 15562/26400 [00:54<00:40, 267.17it/s]
59%
15590/26400 [00:54<00:39, 270.32it/s]
59%||
| 15619/26400 [00:54<00:39, 274.58it/s]
59%
| 15650/26400 [00:54<00:37, 283.76it/s]
15679/26400 [00:54<00:37, 282.50it/s]
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60%
| 15708/26400 [00:54<00:37, 284.10it/s]
| 15739/26400 [00:54<00:36, 289.18it/s]
60%||
| 15773/26400 [00:54<00:35, 301.37it/s]
60% I
| 15804/26400 [00:54<00:37, 284.13it/s]
60%
15836/26400 [00:55<00:36, 292.62it/s]
60%
| 15870/26400 [00:55<00:34, 304.79it/s]
60%
| 15901/26400 [00:55<00:34, 301.23it/s]
60%
| 15932/26400 [00:55<00:34, 302.27it/s]
60% II
| 15964/26400 [00:55<00:34, 306.73it/s]
61%
| 15995/26400 [00:55<00:35, 293.97it/s]
61%
16025/26400 [00:55<00:35, 293.39it/s]
61%||
| 16055/26400 [00:55<00:36, 286.29it/s]
61%
| 16088/26400 [00:55<00:34, 295.95it/s]
| 16118/26400 [00:55<00:36, 284.72it/s]
61%
| 16147/26400 [00:56<00:36, 280.70it/s]
61%
16178/26400 [00:56<00:35, 285.92it/s]
61%||
| 16213/26400 [00:56<00:33, 301.19it/s]
62%
| 16244/26400 [00:56<00:33, 303.13it/s]
62%
| 16275/26400 [00:56<00:34, 291.64it/s]
| 16308/26400 [00:56<00:33, 301.57it/s]
62%
| 16339/26400 [00:56<00:33, 297.31it/s]
62%
| 16370/26400 [00:56<00:33, 298.63it/s]
62%
| 16401/26400 [00:56<00:33, 295.30it/s]
62%
| 16432/26400 [00:57<00:33, 298.93it/s]
62%
| 16462/26400 [00:57<00:35, 277.14it/s]
| 16491/26400 [00:57<00:36, 273.17it/s]
63%
| 16519/26400 [00:57<00:36, 272.99it/s]
63%
| 16552/26400 [00:57<00:34, 281.50it/s]
63% II
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16582/26400 [00:57<00:34, 286.20it/s]
63%||
| 16611/26400 [00:57<00:34, 280.08it/s]
63%
16640/26400 [00:57<00:36, 269.80it/s]
63%
| 16673/26400 [00:57<00:34, 284.88it/s]
63% II
| 16702/26400 [00:58<00:34, 284.94it/s]
| 16736/26400 [00:58<00:32, 298.91it/s]
64%
| 16767/26400 [00:58<00:33, 288.90it/s]
64%
| 16797/26400 [00:58<00:33, 285.71it/s]
64%
| 16826/26400 [00:58<00:33, 284.68it/s]
64%
| 16855/26400 [00:58<00:33, 284.80it/s]
64%||
| 16887/26400 [00:58<00:32, 293.12it/s]
64%||
| 16921/26400 [00:58<00:31, 304.34it/s]
64%
| 16952/26400 [00:58<00:31, 304.47it/s]
64%
16983/26400 [00:58<00:32, 292.51it/s]
64%||
| 17013/26400 [00:59<00:32, 285.70it/s]
65% II
| 17042/26400 [00:59<00:32, 285.52it/s]
65%
| 17071/26400 [00:59<00:35, 262.93it/s]
65%||
| 17098/26400 [00:59<00:35, 262.90it/s]
65% II
| 17127/26400 [00:59<00:34, 269.93it/s]
65%||
17157/26400 [00:59<00:33, 277.74it/s]
65%
| 17190/26400 [00:59<00:31, 287.99it/s]
65%
| 17221/26400 [00:59<00:31, 291.99it/s]
65%||
| 17251/26400 [00:59<00:32, 282.11it/s]
65%
| 17282/26400 [01:00<00:31, 289.36it/s]
66%
| 17312/26400 [01:00<00:32, 283.61it/s]
66%
17343/26400 [01:00<00:31, 289.63it/s]
66%
| 17373/26400 [01:00<00:31, 288.66it/s]
66%
| 17405/26400 [01:00<00:30, 295.99it/s]
| 17435/26400 [01:00<00:30, 293.06it/s]
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66%
| 17465/26400 [01:00<00:31, 285.27it/s]
| 17496/26400 [01:00<00:31, 286.82it/s]
66%
| 17526/26400 [01:00<00:30, 288.36it/s]
67%
| 17558/26400 [01:00<00:29, 295.76it/s]
67%
| 17588/26400 [01:01<00:30, 284.60it/s]
67%
| 17620/26400 [01:01<00:30, 291.37it/s]
67%
| 17650/26400 [01:01<00:30, 289.05it/s]
67%
| 17680/26400 [01:01<00:29, 291.63it/s]
| 17710/26400 [01:01<00:30, 282.70it/s]
67%
| 17739/26400 [01:01<00:31, 279.32it/s]
67%
| 17771/26400 [01:01<00:29, 289.83it/s]
67%
| 17801/26400 [01:01<00:30, 286.34it/s]
68%
| 17830/26400 [01:01<00:31, 275.40it/s]
| 17858/26400 [01:02<00:31, 270.57it/s]
68%
| 17886/26400 [01:02<00:31, 268.06it/s]
68%|
| 17919/26400 [01:02<00:29, 282.80it/s]
68%
| 17954/26400 [01:02<00:28, 297.23it/s]
68%
| 17985/26400 [01:02<00:28, 300.32it/s]
68%|
| 18016/26400 [01:02<00:28, 292.27it/s]
| 18046/26400 [01:02<00:29, 285.54it/s]
68%
| 18076/26400 [01:02<00:28, 288.25it/s]
69%|
| 18105/26400 [01:02<00:28, 286.48it/s]
69%
| 18137/26400 [01:02<00:27, 295.18it/s]
69%
| 18167/26400 [01:03<00:28, 291.66it/s]
69%
| 18197/26400 [01:03<00:29, 280.35it/s]
| 18226/26400 [01:03<00:29, 274.57it/s]
69%
| 18257/26400 [01:03<00:28, 283.75it/s]
69%
| 18289/26400 [01:03<00:27, 291.54it/s]
69%||
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| 18322/26400 [01:03<00:27, 297.43it/s]
70%
18353/26400 [01:03<00:26, 299.58it/s]
70% | I
| 18384/26400 [01:03<00:27, 290.97it/s]
70%|
| 18414/26400 [01:03<00:27, 290.43it/s]
70%
| 18445/26400 [01:04<00:27, 288.04it/s]
| 18476/26400 [01:04<00:26, 293.68it/s]
70%
| 18507/26400 [01:04<00:27, 291.89it/s]
70%
| 18537/26400 [01:04<00:27, 285.28it/s]
70%
18566/26400 [01:04<00:27, 280.28it/s]
70%
| 18597/26400 [01:04<00:27, 287.99it/s]
71%||
| 18629/26400 [01:04<00:26, 289.09it/s]
71%||
| 18658/26400 [01:04<00:27, 286.17it/s]
71%
| 18690/26400 [01:04<00:26, 293.33it/s]
71%
18723/26400 [01:05<00:25, 301.18it/s]
71%
| 18756/26400 [01:05<00:24, 307.79it/s]
71%||
| 18790/26400 [01:05<00:24, 314.40it/s]
71%
| 18822/26400 [01:05<00:25, 298.64it/s]
71%|
| 18853/26400 [01:05<00:25, 291.16it/s]
72%
| 18884/26400 [01:05<00:25, 295.10it/s]
72%
| 18914/26400 [01:05<00:27, 274.07it/s]
72%
| 18947/26400 [01:05<00:25, 287.45it/s]
72%
| 18977/26400 [01:05<00:26, 277.61it/s]
72%
| 19006/26400 [01:05<00:26, 279.01it/s]
72%
| 19039/26400 [01:06<00:25, 288.95it/s]
72%
| 19070/26400 [01:06<00:25, 291.85it/s]
72%
19102/26400 [01:06<00:24, 297.49it/s]
72%
| 19135/26400 [01:06<00:24, 300.91it/s]
73%
| 19166/26400 [01:06<00:25, 288.59it/s]
| 19196/26400 [01:06<00:25, 285.50it/s]
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73%|
| 19229/26400 [01:06<00:24, 295.34it/s]
| 19259/26400 [01:06<00:24, 291.79it/s]
73%
| 19291/26400 [01:06<00:24, 293.36it/s]
73%
| 19321/26400 [01:07<00:26, 263.00it/s]
73%
19349/26400 [01:07<00:26, 266.55it/s]
73%||
| 19377/26400 [01:07<00:27, 256.56it/s]
74%
| 19404/26400 [01:07<00:27, 252.62it/s]
74%
19435/26400 [01:07<00:26, 264.92it/s]
74%
| 19471/26400 [01:07<00:24, 286.51it/s]
74%
| 19504/26400 [01:07<00:23, 297.74it/s]
74%
| 19535/26400 [01:07<00:23, 295.53it/s]
74%
| 19566/26400 [01:07<00:23, 294.84it/s]
74%||
| 19596/26400 [01:08<00:23, 294.84it/s]
| 19626/26400 [01:08<00:23, 289.76it/s]
74%
| 19656/26400 [01:08<00:24, 279.90it/s]
75%
19687/26400 [01:08<00:23, 283.00it/s]
75%
| 19723/26400 [01:08<00:22, 299.59it/s]
75% l
| 19754/26400 [01:08<00:22, 300.24it/s]
75%
| 19785/26400 [01:08<00:22, 292.22it/s]
| 19815/26400 [01:08<00:23, 283.89it/s]
75%
| 19844/26400 [01:08<00:23, 283.40it/s]
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| 19873/26400 [01:09<00:22, 284.75it/s]
75%
| 19909/26400 [01:09<00:21, 301.72it/s]
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| 19940/26400 [01:09<00:21, 303.50it/s]
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| 19971/26400 [01:09<00:22, 283.89it/s]
| 20004/26400 [01:09<00:21, 292.59it/s]
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20034/26400 [01:09<00:21, 291.57it/s]
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20064/26400 [01:09<00:22, 282.67it/s]
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20093/26400 [01:09<00:22, 283.39it/s]
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20123/26400 [01:09<00:21, 286.75it/s]
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20152/26400 [01:09<00:23, 271.03it/s]
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20180/26400 [01:10<00:23, 269.15it/s]
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20209/26400 [01:10<00:22, 274.51it/s]
20241/26400 [01:10<00:21, 284.66it/s]
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20272/26400 [01:10<00:21, 291.21it/s]
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20302/26400 [01:10<00:21, 283.23it/s]
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20331/26400 [01:10<00:21, 278.88it/s]
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20360/26400 [01:10<00:22, 266.80it/s]
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20392/26400 [01:10<00:21, 277.36it/s]
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20423/26400 [01:10<00:20, 285.83it/s]
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20458/26400 [01:11<00:19, 301.89it/s]
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20491/26400 [01:11<00:19, 309.17it/s]
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20525/26400 [01:11<00:18, 317.17it/s]
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| 20558/26400 [01:11<00:19, 292.20it/s]
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20588/26400 [01:11<00:19, 292.18it/s]
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20623/26400 [01:11<00:18, 306.03it/s]
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20655/26400 [01:11<00:19, 289.34it/s]
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20685/26400 [01:11<00:20, 285.19it/s]
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20718/26400 [01:11<00:19, 294.34it/s]
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20748/26400 [01:12<00:19, 289.41it/s]
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20778/26400 [01:12<00:19, 287.70it/s]
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20807/26400 [01:12<00:19, 282.72it/s]
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| 20838/26400 [01:12<00:19, 288.18it/s]
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20868/26400 [01:12<00:19, 288.50it/s]
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20900/26400 [01:12<00:18, 294.22it/s]
79%
20930/26400 [01:12<00:19, 277.33it/s]
20961/26400 [01:12<00:19, 285.80it/s]
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80%|
20990/26400 [01:12<00:18, 286.43it/s]
21024/26400 [01:12<00:18, 298.48it/s]
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| 21055/26400 [01:13<00:18, 296.04it/s]
80%|
21086/26400 [01:13<00:17, 298.60it/s]
80%|
| 21119/26400 [01:13<00:17, 306.74it/s]
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| 21151/26400 [01:13<00:17, 308.16it/s]
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21182/26400 [01:13<00:17, 301.76it/s]
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21213/26400 [01:13<00:17, 297.43it/s]
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21244/26400 [01:13<00:17, 300.45it/s]
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| 21275/26400 [01:13<00:17, 289.10it/s]
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21309/26400 [01:13<00:16, 301.30it/s]
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21342/26400 [01:14<00:16, 308.71it/s]
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21374/26400 [01:14<00:16, 306.03it/s]
21405/26400 [01:14<00:17, 286.22it/s]
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21441/26400 [01:14<00:16, 302.87it/s]
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21472/26400 [01:14<00:16, 293.95it/s]
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21504/26400 [01:14<00:16, 299.86it/s]
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21535/26400 [01:14<00:16, 294.45it/s]
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21565/26400 [01:14<00:16, 286.18it/s]
21596/26400 [01:14<00:16, 292.33it/s]
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21627/26400 [01:14<00:16, 296.79it/s]
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21657/26400 [01:15<00:16, 296.22it/s]
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21687/26400 [01:15<00:16, 291.52it/s]
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21751/26400 [01:15<00:15, 290.86it/s]
21781/26400 [01:15<00:16, 281.40it/s]
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21810/26400 [01:15<00:16, 272.95it/s]
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21839/26400 [01:15<00:16, 276.48it/s]
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21867/26400 [01:15<00:16, 275.29it/s]
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21927/26400 [01:16<00:15, 282.52it/s]
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21956/26400 [01:16<00:15, 279.20it/s]
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21985/26400 [01:16<00:16, 271.49it/s]
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22198/26400 [01:17<00:14, 287.69it/s]
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22227/26400 [01:17<00:14, 281.90it/s]
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22256/26400 [01:17<00:14, 281.20it/s]
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22287/26400 [01:17<00:14, 287.87it/s]
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22345/26400 [01:17<00:14, 274.28it/s]
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22439/26400 [01:17<00:13, 293.88it/s]
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22528/26400 [01:18<00:13, 279.36it/s]
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22557/26400 [01:18<00:13, 277.83it/s]
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| 22585/26400 [01:18<00:14, 266.02it/s]
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22620/26400 [01:18<00:13, 285.44it/s]
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22650/26400 [01:18<00:14, 266.03it/s]
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22681/26400 [01:18<00:13, 275.84it/s]
22712/26400 [01:18<00:12, 283.92it/s]
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86%
22745/26400 [01:18<00:12, 294.17it/s]
| 22775/26400 [01:19<00:12, 291.82it/s]
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| 22806/26400 [01:19<00:12, 293.90it/s]
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22898/26400 [01:19<00:11, 292.43it/s]
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22928/26400 [01:19<00:12, 280.85it/s]
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22958/26400 [01:19<00:12, 285.74it/s]
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23107/26400 [01:20<00:11, 287.77it/s]
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23165/26400 [01:20<00:11, 281.24it/s]
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| 23194/26400 [01:20<00:12, 261.08it/s]
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23347/26400 [01:21<00:10, 278.97it/s]
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| 23376/26400 [01:21<00:10, 277.56it/s]
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23405/26400 [01:21<00:10, 278.97it/s]
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23554/26400 [01:21<00:09, 292.42it/s]
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23620/26400 [01:22<00:09, 305.56it/s]
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23651/26400 [01:22<00:08, 306.21it/s]
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23682/26400 [01:22<00:09, 298.70it/s]
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23712/26400 [01:22<00:09, 289.83it/s]
23747/26400 [01:22<00:08, 302.64it/s]
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23778/26400 [01:22<00:08, 299.75it/s]
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23812/26400 [01:22<00:08, 305.99it/s]
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23843/26400 [01:22<00:08, 304.72it/s]
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23905/26400 [01:22<00:08, 288.60it/s]
23936/26400 [01:23<00:08, 294.09it/s]
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23997/26400 [01:23<00:08, 294.23it/s]
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| 24057/26400 [01:23<00:08, 279.55it/s]
24091/26400 [01:23<00:07, 293.97it/s]
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24121/26400 [01:23<00:08, 279.49it/s]
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24152/26400 [01:23<00:07, 285.03it/s]
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24181/26400 [01:23<00:07, 279.30it/s]
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24210/26400 [01:24<00:07, 276.20it/s]
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24238/26400 [01:24<00:07, 275.91it/s]
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24266/26400 [01:24<00:08, 259.65it/s]
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| 24293/26400 [01:24<00:08, 262.11it/s]
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| 24325/26400 [01:24<00:07, 275.91it/s]
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24358/26400 [01:24<00:07, 282.94it/s]
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24389/26400 [01:24<00:06, 288.34it/s]
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24447/26400 [01:24<00:07, 272.31it/s]
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24475/26400 [01:25<00:07, 270.81it/s]
24508/26400 [01:25<00:06, 284.20it/s]
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24574/26400 [01:25<00:06, 295.60it/s]
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24604/26400 [01:25<00:06, 285.31it/s]
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24664/26400 [01:25<00:05, 291.56it/s]
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24698/26400 [01:25<00:05, 303.98it/s]
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24729/26400 [01:25<00:05, 293.02it/s]
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24759/26400 [01:25<00:05, 282.02it/s]
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24789/26400 [01:26<00:05, 286.58it/s]
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24818/26400 [01:26<00:05, 282.79it/s]
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24847/26400 [01:26<00:05, 274.62it/s]
24875/26400 [01:26<00:05, 275.63it/s]
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| 24930/26400 [01:26<00:05, 258.96it/s]
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24965/26400 [01:26<00:05, 277.72it/s]
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24994/26400 [01:26<00:05, 279.89it/s]
25024/26400 [01:26<00:04, 284.22it/s]
25053/26400 [01:27<00:04, 277.96it/s]
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25087/26400 [01:27<00:04, 292.74it/s]
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25117/26400 [01:27<00:04, 291.68it/s]
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25148/26400 [01:27<00:04, 293.80it/s]
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25178/26400 [01:27<00:04, 289.04it/s]
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25208/26400 [01:27<00:04, 287.44it/s]
25237/26400 [01:27<00:04, 285.04it/s]
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25269/26400 [01:27<00:03, 294.11it/s]
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25357/26400 [01:28<00:03, 273.69it/s]
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   25417/26400 [01:28<00:03, 284.51it/s]
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    25446/26400 [01:28<00:03, 264.48it/s]
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   25508/26400 [01:28<00:03, 283.36it/s]
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  25538/26400 [01:28<00:03, 286.72it/s]
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   25567/26400 [01:28<00:02, 285.38it/s]
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   25596/26400 [01:28<00:02, 279.53it/s]
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   25627/26400 [01:29<00:02, 287.44it/s]
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     25656/26400 [01:29<00:02, 285.88it/s]
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   25686/26400 [01:29<00:02, 287.70it/s]
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   25774/26400 [01:29<00:02, 275.87it/s]
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    25804/26400 [01:29<00:02, 279.74it/s]
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   25833/26400 [01:29<00:02, 278.09it/s]
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   25861/26400 [01:29<00:01, 276.41it/s]
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| | 25891/26400 [01:30<00:01, 281.71it/s]
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   25924/26400 [01:30<00:01, 292.51it/s]
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  | 25956/26400 [01:30<00:01, 299.63it/s]
   | 25987/26400 [01:30<00:01, 292.64it/s]
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   26017/26400 [01:30<00:01, 294.18it/s]
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   26047/26400 [01:30<00:01, 288.47it/s]
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1 26076/26400 [01:30<00:01, 279.97it/s]</pre>
 99%||
   26105/26400 [01:30<00:01, 271.24it/s]
   26138/26400 [01:30<00:00, 283.77it/s]
   26170/26400 [01:30<00:00, 292.38it/s]
```

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99% | 26200/26400 [01:31<00:00, 288.91it/s]
99% | 26230/26400 [01:31<00:00, 284.88it/s]
99% | 26265/26400 [01:31<00:00, 299.63it/s]
100% | 26296/26400 [01:31<00:00, 301.14it/s]
100% | 26330/26400 [01:31<00:00, 311.21it/s]
100% | 26362/26400 [01:31<00:00, 303.35it/s]
100% | 26362/26400 [01:31<00:00, 287.86it/s]
```

26400 300

```
In [119]: # preprocessing for Project_title with TFIDF Vectorization
    tfidf_model = TfidfVectorizer()
    tfidf_model.fit(X_train['project_title'])
    # we are converting a dictionary with word as a key, and the idf as a value
    dictionary = dict(zip(tfidf_model.get_feature_names(), list(tfidf_model.idf_
    )))
    tfidf_words = set(tfidf_model.get_feature_names())
```

```
In [120]: # average Word2Vec
          # compute average word2vec for each review.
          tfidf w2v vectors pj title train = []; # the avg-w2v for each sentence/review
           is stored in this list
          for sentence in tqdm(X_train['project_title']): # for each review/sentence
              vector = np.zeros(300) # as word vectors are of zero length
              tf_idf_weight =0; # num of words with a valid vector in the sentence/revie
              for word in sentence.split(): # for each word in a review/sentence
                  if (word in glove_words) and (word in tfidf_words):
                      vec = model[word] # getting the vector for each word
                      # here we are multiplying idf value(dictionary[word]) and the tf v
          alue((sentence.count(word)/len(sentence.split())))
                      tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split
          ())) # getting the tfidf value for each word
                      vector += (vec * tf_idf) # calculating tfidf weighted w2v
                      tf idf weight += tf idf
              if tf idf weight != 0:
                  vector /= tf_idf_weight
              tfidf w2v vectors pj title train.append(vector)
          print(len(tfidf_w2v_vectors_pj_title_train))
          print(len(tfidf w2v vectors pj title train[0]))
            0%|
          | 0/35912 [00:00<?, ?it/s]
           28%|
          | 10034/35912 [00:00<00:00, 99611.70it/s]
          | 19722/35912 [00:00<00:00, 98555.89it/s]
          100%
          ■| 35912/35912 [00:00<00:00, 97318.98it/s]
          35912
          300
```

```
In [121]: # average Word2Vec
          # compute average word2vec for each review.
          tfidf w2v vectors pj title cv = []; # the avg-w2v for each sentence/review is
           stored in this list
          for sentence in tqdm(X_cv['project_title']): # for each review/sentence
              vector = np.zeros(300) # as word vectors are of zero length
              tf_idf_weight =0; # num of words with a valid vector in the sentence/revie
              for word in sentence.split(): # for each word in a review/sentence
                  if (word in glove_words) and (word in tfidf_words):
                      vec = model[word] # getting the vector for each word
                      # here we are multiplying idf value(dictionary[word]) and the tf v
          alue((sentence.count(word)/len(sentence.split())))
                      tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split
          ())) # getting the tfidf value for each word
                      vector += (vec * tf_idf) # calculating tfidf weighted w2v
                      tf idf weight += tf idf
              if tf idf weight != 0:
                  vector /= tf_idf_weight
              tfidf w2v vectors pj title cv.append(vector)
          print(len(tfidf w2v vectors pj title cv))
          print(len(tfidf w2v vectors pj title cv[0]))
            0%|
```

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0%|
| 0/17688 [00:00<?, ?it/s]
| 100%| | 17688/17688 [00:00<00:00, 94340.56it/s]
| 17688
| 300
```

```
In [122]: # average Word2Vec
          # compute average word2vec for each review.
          tfidf w2v vectors pj title test = []; # the avg-w2v for each sentence/review i
          s stored in this list
          for sentence in tqdm(X_test['project_title']): # for each review/sentence
              vector = np.zeros(300) # as word vectors are of zero Length
              tf_idf_weight =0; # num of words with a valid vector in the sentence/revie
              for word in sentence.split(): # for each word in a review/sentence
                  if (word in glove_words) and (word in tfidf_words):
                      vec = model[word] # getting the vector for each word
                      # here we are multiplying idf value(dictionary[word]) and the tf v
          alue((sentence.count(word)/len(sentence.split())))
                      tf idf = dictionary[word]*(sentence.count(word)/len(sentence.split
          ())) # getting the tfidf value for each word
                      vector += (vec * tf_idf) # calculating tfidf weighted w2v
                      tf idf weight += tf idf
              if tf idf weight != 0:
                  vector /= tf_idf_weight
              tfidf w2v vectors pj title test.append(vector)
          print(len(tfidf_w2v_vectors_pj_title_test))
          print(len(tfidf w2v vectors pj title test[0]))
            0%|
          | 0/26400 [00:00<?, ?it/s]
           32%
          8398/26400 [00:00<00:00, 83384.07it/s]
          26400/26400 [00:00<00:00, 93872.79it/s]
          26400
          300
```

```
In [123]: # Concatinating all the features
          X_tr = hstack((tfidf_w2v_vectors_train, X_train_state_ohe, X_train_teacher_ohe
                         X train grade ohe, X train category ohe,
                         X_train_subcategory_ohe, X_train_price_norm,
                         X_train_teach_prev_norm, tfidf_w2v_vectors_pj_title_train)).toc
          sr()
          X_cr = hstack((tfidf_w2v_vectors_cv, X_cv_state_ohe, X_cv_teacher_ohe,
                         X_cv_grade_ohe,X_cv_category_ohe,
                         X cv subcategory ohe, X cv price norm,
                        X_cv_teach_prev_norm, tfidf_w2v_vectors_pj_title_cv)).tocsr()
          X te = hstack((tfidf w2v vectors test, X test state ohe, X test teacher ohe,
                         X test grade ohe, X test category ohe,
                         X_test_subcategory_ohe, X_test_price_norm,
                        X_test_teach_prev_norm, tfidf_w2v_vectors_pj_title_test)).tocsr
          ()
          print("Final Data matrix")
          print(X tr.shape, y train.shape)
          print(X_cr.shape, y_cv.shape)
          print(X te.shape, y test.shape)
          print("="*100)
```

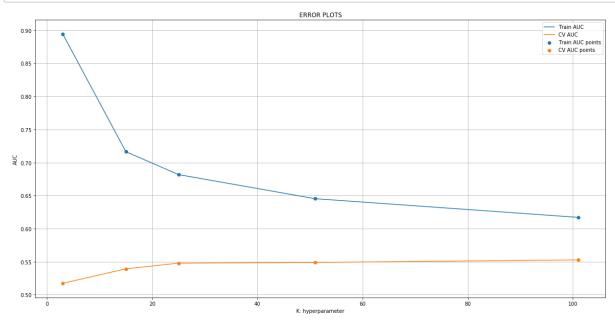
```
Final Data matrix
(35912, 701) (35912,)
(17688, 701) (17688,)
(26400, 701) (26400,)
```

```
In [124]: # Hyper parameter Tuning
          train auc = []
          cv_auc = []
          K = [3, 15, 25, 51, 101]
          for i in tqdm(K):
              neigh = KNeighborsClassifier(n_neighbors=i, n_jobs=-1)
              neigh.fit(X_tr, y_train)
              y_train_pred = batch_predict(neigh, X_tr)
              y_cv_pred = batch_predict(neigh, X_cr)
              # roc_auc_score(y_true, y_score) the 2nd parameter should be probability e
          stimates of the positive class
              # not the predicted outputs
              train_auc.append(roc_auc_score(y_train,y_train_pred))
              cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
            0%|
          | 0/5 [00:00<?, ?it/s]
           20%
          | 1/5 [07:01<28:04, 421.02s/it]
           40%
          2/5 [14:10<21:10, 423.59s/it]
           60%
          | 3/5 [21:23<14:12, 426.24s/it]
           80%
          4/5 [28:34<07:07, 427.76s/it]
          100%
                     || 5/5 [35:44<00:00, 428.98s/it]
```

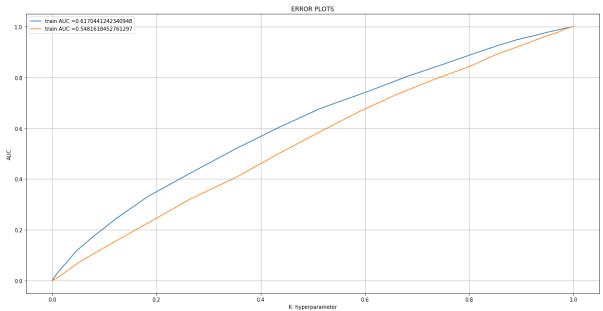
```
In [125]: plt.figure(figsize=(20,10))
    plt.plot(K, train_auc, label='Train AUC')
    plt.plot(K, cv_auc, label='CV AUC')

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

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



```
In [126]:
          best k = 101
          from sklearn.metrics import roc curve, auc
          neigh = KNeighborsClassifier(n_neighbors=best_k, n_jobs=-1)
          neigh.fit(X_tr, y_train)
          # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estim
          ates of the positive class
          # not the predicted outputs
          y train pred = batch predict(neigh, X tr)
          y_test_pred = batch_predict(neigh, X_te)
          train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)
          test fpr, test tpr, te thresholds = roc curve(y test, y test pred)
          plt.figure(figsize=(20,10))
          plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tp
          r)))
          plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
          plt.legend()
          plt.xlabel("K: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.grid()
          plt.show()
```



The Blue plot in the Graph is Train AUC and Orange Plot is Test AUC. Initially the label was accidentally copy pasted as Train AUC for both. Since redrawing plot would require to re run entire ipynb and it takes up a lot of time. so documenting the information as a markdown.

2.5 Feature selection with `SelectKBest`

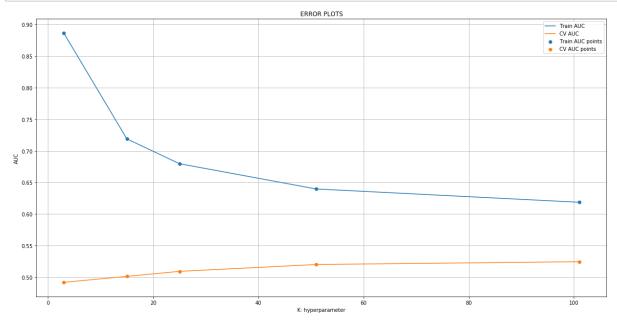
```
In [127]: # please write all the code with proper documentation, and proper titles for e
          ach subsection
          # go through documentations and blogs before you start coding
          # first figure out what to do, and then think about how to do.
          # reading and understanding error messages will be very much helpfull in debug
          ging your code
          # when you plot any graph make sure you use
              # a. Title, that describes your plot, this will be very helpful to the rea
          der
              # b. Legends if needed
              # c. X-axis label
              # d. Y-axis Label
          # Performing the Concatination of Features for Set-2
          X tr = hstack((X train essay tfidf, X train state ohe, X train teacher ohe,
                         X_train_grade_ohe, X_train_price_norm, X_train_category_ohe,
                         X_train_subcategory_ohe, X_train_teach_prev_norm,
                         X train pj title tfidf)).tocsr()
          X_cr = hstack((X_cv_essay_tfidf, X_cv_state_ohe, X_cv_teacher_ohe,
                         X cv grade ohe, X cv category ohe, X cv subcategory ohe,
                         X cv price norm, X cv teach prev norm, X cv pj title tfidf)).to
          csr()
          X te = hstack((X test essay tfidf, X test state ohe, X test teacher ohe,
                         X_test_grade_ohe, X_test_category_ohe, X_test_subcategory_ohe,
                         X test price norm, X test teach prev norm,
                         X test pj title tfidf)).tocsr()
In [128]: # importing necessary packages for Univariate feature selection
          from sklearn.feature selection import SelectKBest
          from sklearn.feature selection import chi2
In [129]:
          print ("shape before selecting top features")
          print (X tr.shape)
          print (X_cr.shape)
          print (X te.shape)
          shape before selecting top features
          (35912, 10101)
          (17688, 10101)
          (26400, 10101)
In [132]: # Selecting top 2000 features
          X tr new = SelectKBest(chi2, k=2000).fit transform(X tr, y train)
          print (X tr new.shape)
          (35912, 2000)
```

```
In [134]: X cr new = SelectKBest(chi2, k=2000).fit transform(X cr, y cv)
          print (X_cr_new.shape)
          X test new = SelectKBest(chi2, k=2000).fit transform(X te, y test)
          print (X test new.shape)
          (17688, 2000)
          (26400, 2000)
In [135]:
         # Hyperparameter Tuning and Error plots with Best 2000 features
          train auc = []
          cv_auc = []
          K = [3, 15, 25, 51, 101]
          for i in tqdm(K):
              neigh = KNeighborsClassifier(n neighbors=i, n jobs=-1)
              neigh.fit(X_tr_new, y_train)
              y_train_pred = batch_predict(neigh, X_tr_new)
              y_cv_pred = batch_predict(neigh, X_cr_new)
              # roc auc score(y true, y score) the 2nd parameter should be probability e
          stimates of the positive class
              # not the predicted outputs
              train_auc.append(roc_auc_score(y_train,y_train_pred))
              cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
            0%|
          | 0/5 [00:00<?, ?it/s]
           20%
          | 1/5 [00:50<03:22, 50.67s/it]
           40%
          2/5 [01:45<02:35, 51.86s/it]
           60%
          | 3/5 [02:39<01:45, 52.59s/it]
           80%
          4/5 [03:33<00:53, 53.09s/it]
          100%
                      | 5/5 [04:29<00:00, 53.83s/it]
```

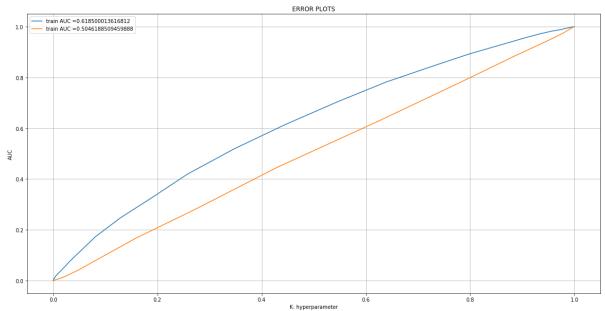
```
In [136]: plt.figure(figsize=(20,10))
    plt.plot(K, train_auc, label='Train AUC')
    plt.plot(K, cv_auc, label='CV AUC')

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

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



```
In [138]:
          best k = 101
          from sklearn.metrics import roc curve, auc
          neigh = KNeighborsClassifier(n_neighbors=best_k, n_jobs=-1)
          neigh.fit(X_tr_new, y_train)
          # roc_auc_score(y_true, y_score) the 2nd parameter should be probability estim
          ates of the positive class
          # not the predicted outputs
          y_train_pred = batch_predict(neigh, X_tr_new)
          y_test_pred = batch_predict(neigh, X_test_new)
          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.figure(figsize=(20,10))
          plt.plot(train fpr, train tpr, label="train AUC ="+str(auc(train fpr, train tp
          r)))
          plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_tpr)))
          plt.legend()
          plt.xlabel("K: hyperparameter")
          plt.ylabel("AUC")
          plt.title("ERROR PLOTS")
          plt.grid()
          plt.show()
```



The Blue plot in the Graph is Train AUC and Orange Plot is Test AUC. Initially the label was accidentally copy pasted as Train AUC for both. Since redrawing plot would require to re run entire ipynb and it takes up a lot of time. so documenting the information as a markdown.

3. Conclusions

```
In [141]: # Please compare all your models using Prettytable library
from prettytable import PrettyTable

#If you get a ModuleNotFoundError error , install prettytable using: pip3 inst
all prettytable

x = PrettyTable()
x.field_names = ["Vectorizer", "Model", "Hyperparameter", "Train AUC", "Test A
UC"]

x.add_row(["BOW","Brute",105,0.647,0.587])
x.add_row(["TFIDF","Brute",105,0.6322,0.546])
x.add_row(["W2V","Brute",101,0.620,0.548])
x.add_row(["TFIDF W2V","Brute",101,0.617,0.548])
print(x)
```

	L				L	_
			Hyperparameter		•	
•	BOW TFIDF W2V TFIDF W2V	Brute Brute Brute Brute	105 105 101 101	0.647 0.6322 0.62 0.617	0.587 0.546 0.548 0.548	
-	+	+			+	t

Summary: There was not a lot of difference in the AUC scores with all the features selected and top 2000 feature selection. With SelectionKBest the Train AUC was around 0.61 and Test AUC was around 0.50