Experimenting NLP Techniques On Semantic Analysis

CS505 Fall 2023 Final Project

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Abstract:
Sentiment analysis using natural language processing (NLP) involves evaluating and interpreting subjective information in text data to understand the sentiments, opinions, or emotions expressed. This technique is widely used for analyzing social media posts, product reviews, and other user-generated content to gauge public opinion or customer sentiment. It typically involves processing and classifying text as positive, negative, or neutral. Advanced NLP models, including machine learning and deep learning approaches, are employed to capture the nuances of human language and sentiment accurately.

Our final project proposes a comparative study of text classification methods applied to Amazon Prime Video reviews. We aimed to combine the tools that we have learned during class to understand how these techniques impact on the performance of different models. We examined the effectiveness of text processing techniques such as stemming and lemmatization, oversampling with generating texts through a language model, and different transformer and neural network models (RNN, Roberta, BERT, GPT-2) on the accuracy. When deciding which path to proceed, we experimented with different tools on our dataset and gauged the value of the metrics like perplexity and accuracy. According to the values of the metrics, we proceeded the project with the tools that yield better results. Restating our purpose in other words, we didn’t strive to get the best accuracy possible by using different tools, yet our real aim was to compare effectiveness of the tools we have learned in the class.

Some results that we found are that transformer models yield higher accuracy with preprocessed text. And text generation with transformer models for oversampling is a good (increases accuracy and doesn’t harm the nature of the dataset) but inefficient way.

(NOTE: Final report is 12 pages. But this is because there are too many images below, not because of redundant analysis. Please consider all pages.)

Experiment Setup and Decision Flow:

Note: All the details of the explanations below can be found in MAIN.

The First look:

In the original dataset, there are nine features which are Id, ProductId, UserId, HelpfulnessNumerator, HelpfulnessDenominator, Time, Summary, Text, Score (label feature, labels are 1.0, 2.0, 3.0, 4.0, 5.0). Even though all of these features can be used to predict the score, only features that were used are Summary and Text for the sake of the aim of the project. Since the average word length of the texts in the Summary column is 4.84, we decided to combine Summary and Text columns and named the new column “Merged_Text” (4.84 is a low number such that it is difficult to make a sentiment analysis on it).

Dealing with Null Values:

There were 17470 null values in the label column, so we dropped all of them. And, there was one null value for each of the Summary and Text columns. We may have used imputation techniques in NLP for replacing two null values. But since this would have no impact on the performance, we just dropped them.

Problem Restatement: Compare the effectiveness of different techniques learned in the class on text classification.

During class, we have spent a large amount of time on language models. We learned that language models are used to create chat bots, predict the next word in a sentence and complete half sentences. When further exploring the dataset, we encountered imbalance classes. So we thought we could use language models in a way that is not mentioned in the class: using language models as a way of oversampling, in other words creating synthetic data for minority classes to be able to work on a balanced dataset (classes 1.0 and 2.0 are minority classes). Large language models like GPT-2 are known for their ability to generate texts near spoken language and we thought it would be interesting to observe the ability of GPT-2 in generating texts for bad reviews of the movies.

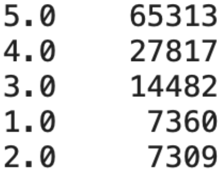
Before jumping into generating texts, it is essential to do text preprocessing because the reviews are written by users in an informal way. When working on text preprocessing, we thought the depth of the level of preprocessing shouldn’t be the same for text classification and text generation since they are two different tasks. So we made two different versions of text processing with different detailness for the sake of the nature of the task.

Preprocessing for Text Generation:

The use of the words in the text are important to reflect the sentiment. But the use of punctuation marks and capital letters are also important to catch the emotion of the text. So we just removed the punctuation marks that don’t hold any emotion like “#$%&()*+<=>@^_[]{|}~]+”. This was essential in terms of getting rid of weird use of punctuation marks as well like “&#34;type-casting&#34;”. Also we removed numbers in the text because numbers were also used in a weird way. We removed all possible HTML tags included in the text. We didn’t do any stemming and lemmatization because LLMs can be fine-tuned with texts without applying these. (see text_processing_lm() function in MAIN)

Oversampling:

We mentioned that there was a great imbalance between classes. We want to generate texts for the minority classes such as 1.0 and 2.0 but there should be a limit in the number of generated texts. For example, we can’t make the dataset balanced with generating texts in a way that all the classes have the same number of the majority class 5.0, i.e. we can’t generate 50k+ samples. So considering the training time we decided to make the dataset balanced by using 10k samples from each class. In order to do this, we approximately generated samples in sizes of ⅓ of their original sample size, i.e. oversampled classes 1.0 and 2.0 so that they both have 10k samples at the end.

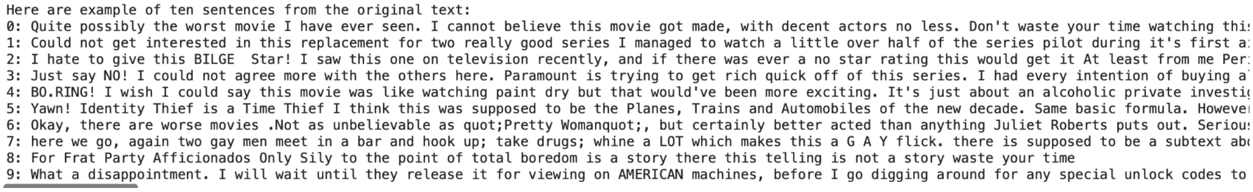


```
5.0    65313
4.0    27817
3.0    14482
1.0     7360
2.0     7309
```

We decided to use the GPT-2 model since it is more apt to generate texts than other transformers models like BERT due its decoder-only architecture.
We first extracted samples that belong to class 1.0 and then fine-tuned the pre-trained GPT-2 model with these samples to generate texts. The details can be found in Final_project_GPT2_for_oversample_class1.ipynb file.

We did the same thing for class 2.0. The details can be found in Final_project_GPT2_for_oversample_class2.ipynb file.

For class 1.0, here are the original reviews,



```
Here are example of ten sentences from the original text:
0: Quite possibly the worst movie I have ever seen. I cannot believe this movie got made, with decent actors no less. Don't waste your time watching thi
1: Could not get interested in this replacement for two really good series I managed to watch a little over half of the series pilot during it's first a
2: I hate to give this BILGE  Star! I saw this one on television recently, and if there was ever a no star rating this would get it At least from me Per
3: Just say NO! I could not agree more with the others here. Paramount is trying to get rich quick off of this series. I had every intention of buying a
4: BO.RING! I wish I could say this movie was like watching paint dry but that would've been more exciting. It's just about an alcoholic private investi
5: Yawn! Identity Thief is a Time Thief I think this was supposed to be the Planes, Trains and Automobiles of the new decade. Same basic formula. Howeve
6: Okay, there are worse movies .Not as unbelievable as quot;Pretty Womanquot;, but certainly better acted than anything Juliet Roberts puts out. Seriou
7: here we go, again two gay men meet in a bar and hook up; take drugs; whine a LOT which makes this a G A Y flick. there is supposed to be a subtext ab
8: For Frat Party Afficionados Only Sily to the point of total boredom is a story there this telling is not a story waste your time
9: What a disappointment. I will wait until they release it for viewing on AMERICAN machines, before I go digging around for any special unlock codes to
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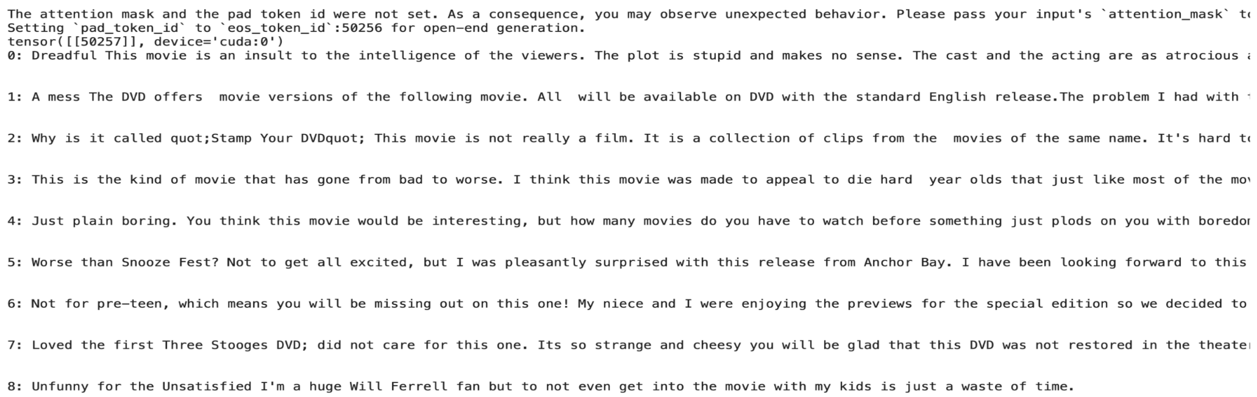
Here are the generated texts, (spot that there are grammatical and punctuation errors. But these are not very significant since we are going to perform additional text processing before text classification)



```
The attention mask and the pad token id were not set. As a consequence, you may observe unexpected behavior. Please pass your input's `attention_mask` t
Setting `pad_token_id` to `eos_token_id`:50256 for open-end generation.
tensor([[50257]], device='cuda:0')
0: Dreadful This movie is an insult to the intelligence of the viewers. The plot is stupid and makes no sense. The cast and the acting are as atrocious 

1: A mess The DVD offers  movie versions of the following movie. All  will be available on DVD with the standard English release.The problem I had with 

2: Why is it called quot;Stamp Your DVDquot; This movie is not really a film. It is a collection of clips from the  movies of the same name. It's hard t

3: This is the kind of movie that has gone from bad to worse. I think this movie was made to appeal to die hard  year olds that just like most of the mo

4: Just plain boring. You think this movie would be interesting, but how many movies do you have to watch before something just plods on you with boredo

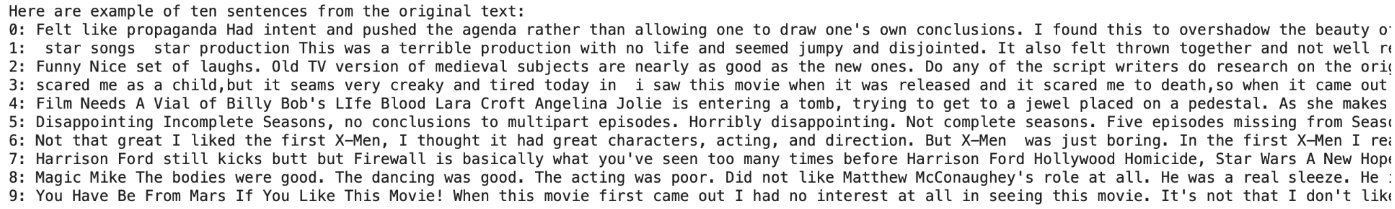
5: Worse than Snooze Fest? Not to get all excited, but I was pleasantly surprised with this release from Anchor Bay. I have been looking forward to this

6: Not for pre-teen, which means you will be missing out on this one! My niece and I were enjoying the previews for the special edition so we decided to

7: Loved the first Three Stooges DVD; did not care for this one. Its so strange and cheesy you will be glad that this DVD was not restored in the theate

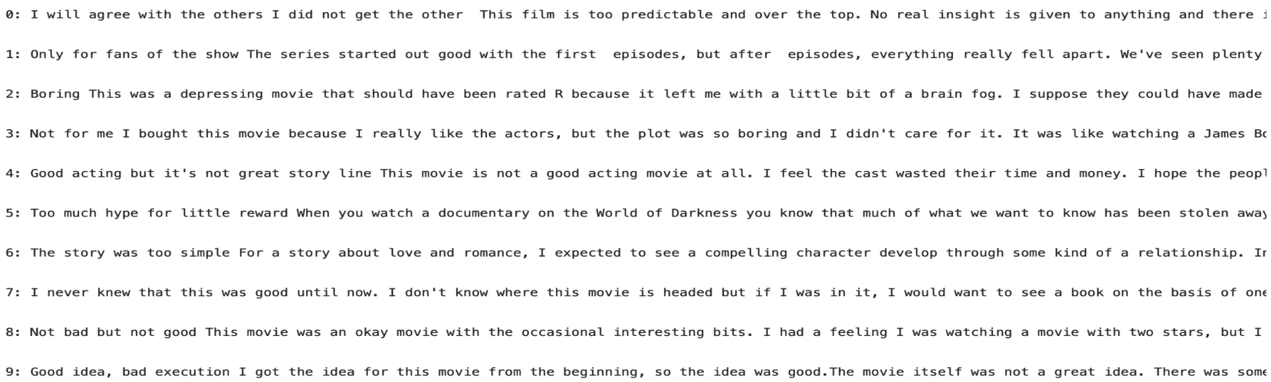
8: Unfunny for the Unsatisfied I'm a huge Will Ferrell fan but to not even get into the movie with my kids is just a waste of time.
```

For class 2.0, here are the original reviews,



```
Here are example of ten sentences from the original text:
0: Felt like propaganda Had intent and pushed the agenda rather than allowing one to draw one's own conclusions. I found this to overshadow the beauty o
1:  star songs  star production This was a terrible production with no life and seemed jumpy and disjointed. It also felt thrown together and not well r
2: Funny Nice set of laughs. Old TV version of medieval subjects are nearly as good as the new ones. Do any of the script writers do research on the ori
3: scared me as a child,but it seams very creaky and tired today in  i saw this movie when it was released and it scared me to death,so when it came out
4: Film Needs A Vial of Billy Bob's LIfe Blood Lara Croft Angelina Jolie is entering a tomb, trying to get to a jewel placed on a pedestal. As she makes
5: Disappointing Incomplete Seasons, no conclusions to multipart episodes. Horribly disappointing. Not complete seasons. Five episodes missing from Seas
6: Not that great I liked the first X-Men, I thought it had great characters, acting, and direction. But X-Men  was just boring. In the first X-Men I re
7: Harrison Ford still kicks butt but Firewall is basically what you've seen too many times before Harrison Ford Hollywood Homicide, Star Wars A New Hop
8: Magic Mike The bodies were good. The dancing was good. The acting was poor. Did not like Matthew McConaughey's role at all. He was a real sleeze. He
9: You Have Be From Mars If You Like This Movie! When this movie first came out I had no interest at all in seeing this movie. It's not that I don't lik
```

Here are the generated texts,



```
0: I will agree with the others I did not get the other  This film is too predictable and over the top. No real insight is given to anything and there

1: Only for fans of the show The series started out good with the first  episodes, but after  episodes, everything really fell apart. We've seen plenty

2: Boring This was a depressing movie that should have been rated R because it left me with a little bit of a brain fog. I suppose they could have made

3: Not for me I bought this movie because I really like the actors, but the plot was so boring and I didn't care for it. It was like watching a James B

4: Good acting but it's not great story line This movie is not a good acting movie at all. I feel the cast wasted their time and money. I hope the peop

5: Too much hype for little reward When you watch a documentary on the World of Darkness you know that much of what we want to know has been stolen awa

6: The story was too simple For a story about love and romance, I expected to see a compelling character develop through some kind of a relationship. I

7: I never knew that this was good until now. I don't know where this movie is headed but if I was in it, I would want to see a book on the basis of on

8: Not bad but not good This movie was an okay movie with the occasional interesting bits. I had a feeling I was watching a movie with two stars, but I

9: Good idea, bad execution I got the idea for this movie from the beginning, so the idea was good.The movie itself was not a great idea. There was som
```

During the training process, we wanted to make sure that the fine-tuned model grasps the tone of the texts properly but at the same time we don't want to fine-tuned the model in a way that the model generates very similar texts to the ones in the original text (we wanted to avoid overfitting). So we trained the model with epoch=2 and epoch=4 (not so large numbers that could result in overfitting) and compared their perplexity on the training text. While the perplexity of the model that was trained with epoch=2 is 45.56, the perplexity of the model that was trained with epoch=4 is 22.95.

Therefore, it is apparent that the model that was trained with epoch=4 creates more realistic texts. So I generated texts with this model.

Additionally, we want to be sure if the fine-tuned model is better than the pre-trained GPT-2 model. On class 1.0 texts, while the vanilla GPT-2's generated texts' perplexity is 46.47, our fine-tuned model's text's perplexity is 22.95. (All the details can be found under Fine-tuned model's perplexity section of MAIN)

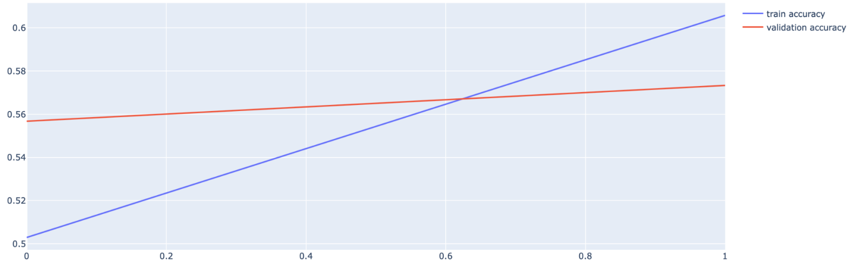
Text Classification:

Text Preprocessing for Text Classification:

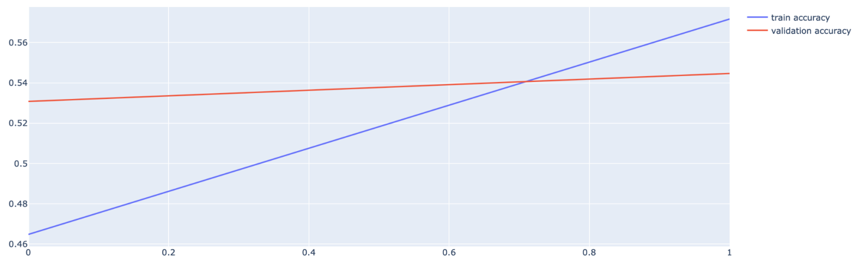
Before diving into the text classification task, we wondered how text preprocessing has an effect on the accuracy of our model. Here again, recalling the aim of our project, we wanted to analyze the effectiveness of the text preprocessing process. This is because the raw texts actually may contain information with its weird word capitalizations and use of punctuation marks. And we wondered whether the models that we are going to use are able to take advantage of this or not. To do this, we first fine-tuned the GPT-2 model (GPT2ForSequenceClassification) with the text that is not preprocessed and with the text that is preprocessed. For this task, by text preprocessing we meant lower-casing, stemming, lemmatization and getting rid of punctuation. (see text_processing() function in MAIN).
(You can observe the transformation of the text before and after text preprocessing under the Text Processing section in MAIN).

Results:

With epoch=2, with text preprocessing:



without text preprocessing:



The train and validation accuracies of the model that we trained with preprocessed text are 0.61 and 0.57 respectively. But the train and validation accuracies of the model that we trained without preprocessed text are 0.57 and 0.54 respectively.

Since there is an improvement in the accuracy when we do the text classification, we decided to train all the models with the text that are preprocessed.

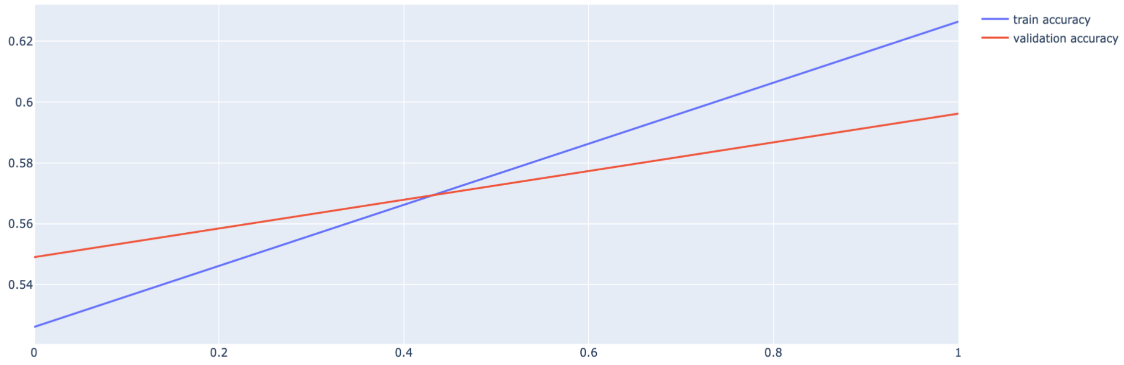
(Details regarding above findings can be found in gpt2_text_classification_notextproc.ipynb and gpt2_text_classification_textprocessed.ipynb)

Different Datasets Used in Text Processing:

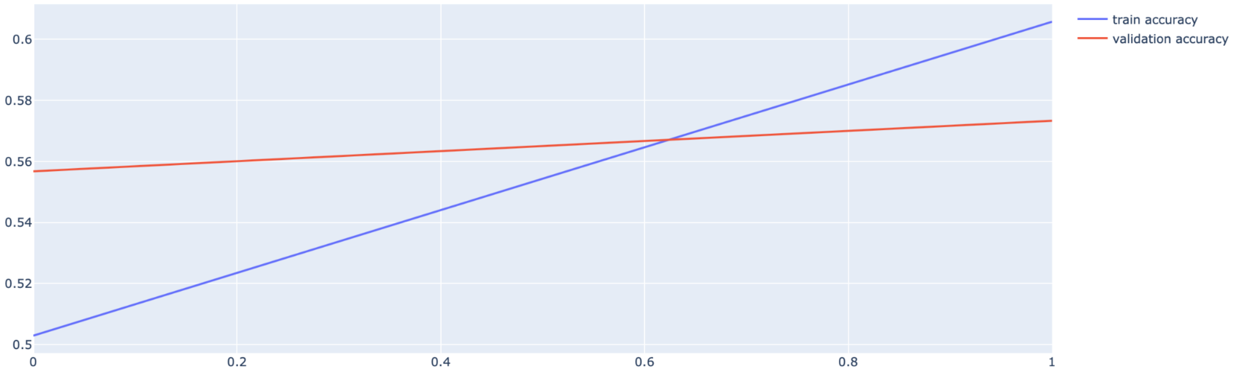
In order to understand the effect of oversampling, we decided to run each model with two datasets. One dataset is the one that is perfectly balanced (each class has 10k samples). The other dataset is the one that is not perfectly balanced but close to the first dataset. We decided to not make the second dataset perfectly balanced since otherwise each class has approximately 7k samples. And the accuracy of the models that are trained with less data may be expected to be smaller. To minimize this we prepared the dataset in a way that class 1.0 and class 2.0 have their original number of samples and the other classes have 10k samples. From now on we will mention the first dataset as “df_final” and the second dataset as “df_final_oversample”)

Results of GPT-2:

Accuracy of the model trained with df_final,



Accuracy of the model trained with df_final_oversample,

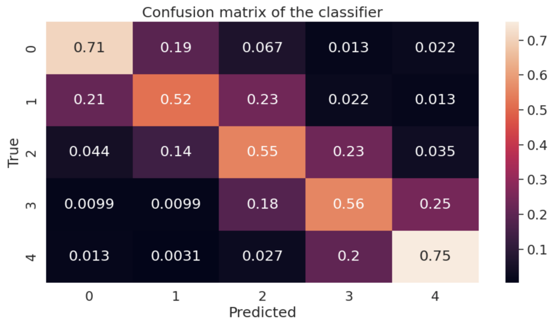


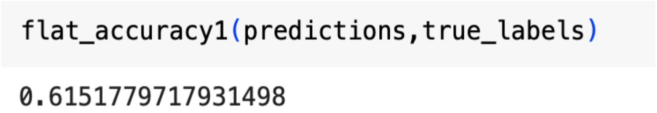
The train and validation accuracies of the model that we trained with df_final are 0.61 and 0.57 respectively. But the train and validation accuracies of the model that we trained with df_final_oversample are 0.63 and 0.60 respectively.
Therefore, the model that we trained with df_final_oversample yielded better accuracy results.

(Details regarding above findings can be found in gpt2_text_classification_oversample.ipynb and gpt2_text_classification_textprocessed.ipynb)

Results of Roberta:

Accuracy of the model trained with df_final,

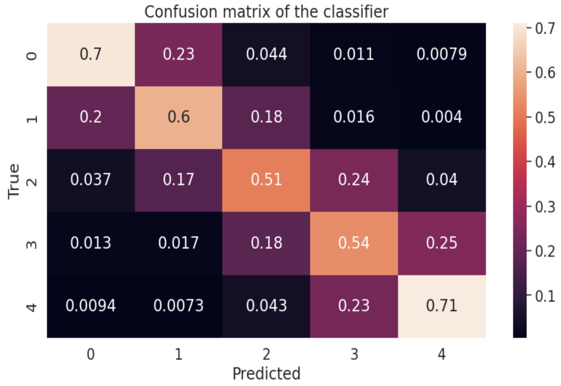


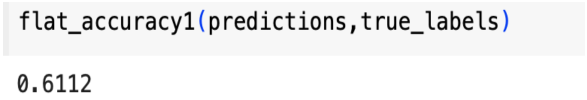


```
flat_accuracy1(predictions,true_labels)

0.6151779717931498
```

Accuracy of the model trained with df_final_oversample,





```
flat_accuracy1(predictions,true_labels)

0.6112
```

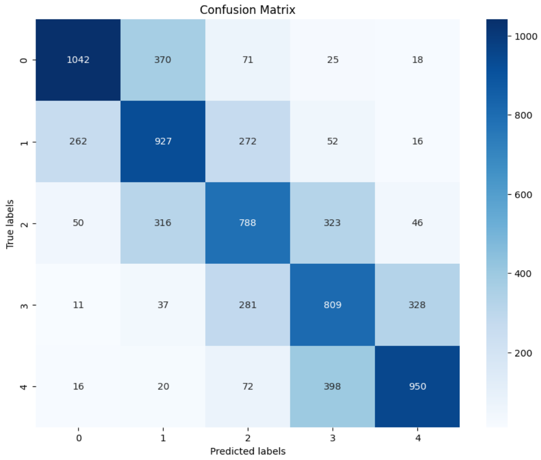
The accuracy of the model that we trained with df_final is 0.615. But the accuracy of the model that we trained with df_final_oversample is 0.611.

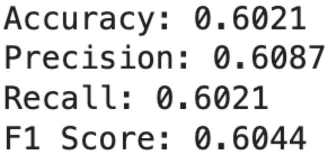
Therefore, both models have very similar accuracies. But from the heatmap we can observe that the accuracy of class 1.0 remained unchanged but the accuracy of class 2.0 improved from 0.54 to 0.6.

(Details regarding above findings can be found in roberta_text_classification_oversample_textproc.ipynb and roberta_text_classification_textproc.ipynb)

Results of BERT:

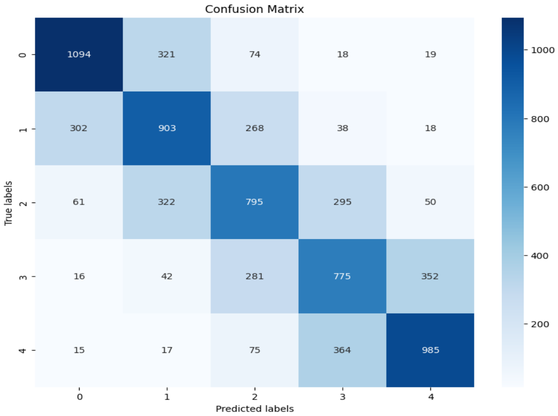
Accuracy of the model trained with df_final,

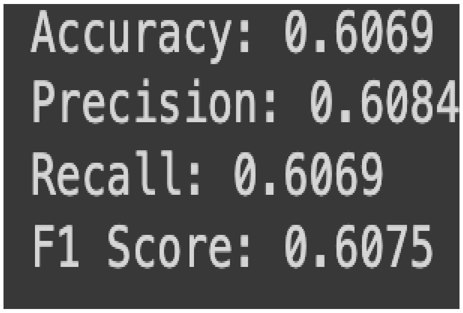




```
Accuracy: 0.6021
Precision: 0.6087
Recall: 0.6021
F1 Score: 0.6044
```

Accuracy of the model trained with df_final_oversample,





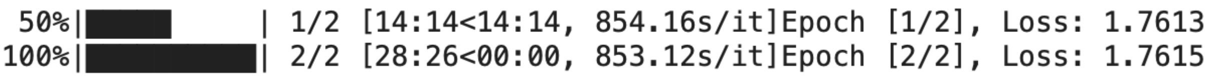
```
Accuracy: 0.6069
Precision: 0.6084
Recall: 0.6069
F1 Score: 0.6075
```

The accuracy of the model that we trained with df_final is 0.602. But the accuracy of the model that we trained with df_final_oversample is 0.606.

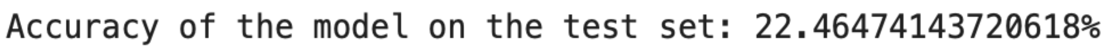
Therefore, both models have very similar accuracies. (Details regarding above findings can be found in RNN_and_BERT.ipynb)

Results of RNN:

Accuracy of the model trained with df_final,

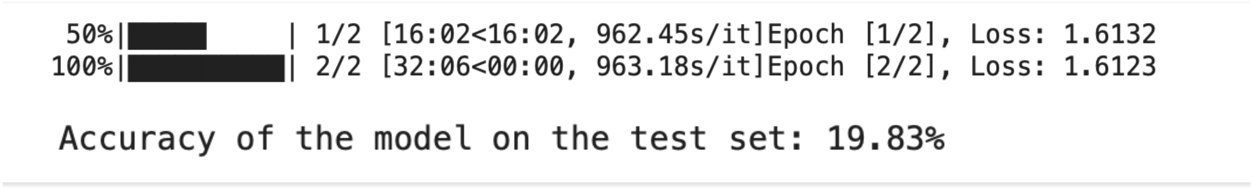


```
 50%|█████     | 1/2 [14:14<14:14, 854.16s/it]Epoch [1/2], Loss: 1.7613
100%|██████████| 2/2 [28:26<00:00, 853.12s/it]Epoch [2/2], Loss: 1.7615
```



```
Accuracy of the model on the test set: 22.46474143720618%
```

Accuracy of the model trained with df_final_oversample,



```
 50%|█████     | 1/2 [16:02<16:02, 962.45s/it]Epoch [1/2], Loss: 1.6132
100%|██████████| 2/2 [32:06<00:00, 963.18s/it]Epoch [2/2], Loss: 1.6123

 Accuracy of the model on the test set: 19.83%
```

The accuracy of the model that we trained with df_final is 0.22. But the accuracy of the model that we trained with df_final_oversample is 0.19.

(Details regarding above findings can be found in RNN_and_BERT.ipynb)

Conclusion:

Throughout the project we tried to experiment techniques and parameters as possible as we could.

We first experimented if we should fine-tune the GPT-2 for text generation with epoch=2 or epoch=4. From the perplexity results, we decided to train it with epoch=4. We also compared the perplexities of the vanilla GPT-2 and our fine-tuned model. And we concluded that our fine-tuned model generated better texts. Therefore, we oversampled the minority classes with this model.

Secondly, we experimented if we should do text preprocessing when dealing with text classification tasks. To do this, we fine-tuned the GPT-2 model with two texts: one with preprocessed and one without preprocessed. And the accuracy of the model that is fine-tuned with preprocessed text yielded better results. Therefore, we fine-tuned or trained our text classifiers with preprocessed text.

Thirdly, we fine-tuned/ trained RNN, Roberta, GPT-2 and BERT with two different datasets: one with perfectly balanced (oversampled with text generation) and the one with not oversampled. For most of the models, we got similar accuracy results (all around 0.61). We can infer two things from this: The generated text doesn't give any relevant information about the text. Or, we should do more text generation. For the first inference, even though the generated texts may not give additional information to the model, it didn't harm the accuracy of the model. So this oversampling technique, to some extent, can be a cure for imbalanced datasets without any harm. For the second inference, we only generated approximately 5k samples to a dataset with length

approximately 50k. The generated samples are not too much. So it was expected that the effect of this would reflect less on the accuracy. But, we can see slight improvements in the accuracy when we use the oversampled dataset such as in the fine-tuned GPT-2 model. So this can be a sign that if we generate more texts, we may improve the accuracy.
Again, our primary aim was not to boost the accuracy. Instead, our main goal was to play around with different techniques and parameters and compare their performance.

Future Work

As discussed above, more efficient models for text generation can be used because the runtime required to sample 2700 samples took about one and half hours. Secondly, more NN models can be used such as LSTM, Bidirectional LSTM and FFNN to make a better comparison of different NN models. Thirdly, different embedding techniques can be used for RNN such as GloVe and word2vec. As can be seen in RNN_and_BERT.ipnyb we tried to use word2vec embedding. But it took too much time to just do the embedding 2 hours+. So for future work we could do more text processing like removing stop words to shorten the text for creating faster embedding matrices. Lastly, more texts can be generated in order to better understand the effect of this oversampling technique on the accuracy.

Shared Responsibilities:

Can Erozer:

- Fine-tuned GPT-2 models and generated texts with different parameters
- Calculated the perplexity of the models and decided which models to use
- Decided the need of text processing by comparing it on a model
- Fine-tuned Roberta and GPT-2 and analyzed their results
- Wrote the decision flow, conclusion part and future work section

Jialu Li:

- Worked with text preprocessing tools
- Finding the project idea
- Implemented RNN. Worked with word2vec embeddings and tf-idf. Evaluated its results
- Fine-tuned BERT and evaluated the results
- Analyzed the findings from the models and wrote it to final report
- Wrote abstract and experiment setup section