

Exploring the Cause of Bias Towards Non-native Writers in GPT-Detector

{CSC3160} {Default} Project

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Abstract

A recent research from Stanford indicated that there is bias towards non-native English writers in almost all existing GPT-Detector. It is important to figure out the cause of such bias. In this project we made and validated two hypotheses about the cause of bias. In the end, we proposed some possible way to eliminate such bias.

1 Key Information to include

- I would like to give up 1% in poster session and move the remaining 4% to project report.

2 Introduction

The rapid adoption of generative large language models has brought about substantial advancements in digital communication, while simultaneously raising concerns regarding the potential misuse of AI-generated content.

Although numerous detection models have been proposed to differentiate between AI and human-generated content, a recent research paper [3] from Stanford suggested that those detectors may have bias towards non-native English writers. In another word, non-native writing samples are consistently misclassified as AI-generated, whereas native writing samples are accurately identified.

In order to eliminate such bias from detector, we need to understand how it is unintentionally generated in the training process.

We made two hypotheses for the cause of bias:

- The mismatch of dataset distribution leads to the bias of detector.
- The limited linguistic expressions in non-native writing leads to the bias of detector.

We tested the first hypothesis by fine-tuning the baseline model on two different essay datasets provided in [3]. One dataset was collected from US 8-th Grade Essay, which can be considered as good source of native writing samples. While another dataset was collected from non-native-authored TOEFL essays. The details of Experiment are described in 5. The result shows adding non-native-authored samples can effectively decrease the bias of detector.

We tested the second hypothesis by using the GLTR tools developed in [1] to test the essay written by non-native speaker and native speaker, and the result shows that non-native-authored essays tend to use more normal and repeated phrases and expressions. Additionally, in [3], researchers tried using ChatGPT to improve the word choices by prompts like "Make my linguistic expressions more complex.". We tested our fine-tuned model on their original-polished essay pairs in 5. The result validated the second hypothesis.

3 Related Work

3.1 Generated text detector

To my knowledge, existing detectors can be divided into two types.

First type is fine-tuning the pre-trained language model(which has the ability to extract features of text) on the dataset that contains human-written and AI-generated samples. One typical example is GPT-Detector proposed in [2], which is a pre-trained Roberta model[4] fine-tuned on a dataset containing the answers from human and ChatGPT to the same question. We use this model as our baseline.

Second type is using perplexity and burstiness of the text as a feature in inference. GPT Zero[5] is a typical example of this. Perplexity is a measurement of how well a language model like ChatGPT can predict the following word based on the previous ones. A low perplexity score means that the language model is confident at its predictions. Burstiness, is used to model the variation of perplexity through the whole passage. A low burstiness score means the perplexity score is stable.

3.2 Bias of Detector

The researchers from Stanford evaluated several commonly-used GPT-detector on native and non-native writing samples in [3]. Take the detector from Open AI as a example, 59% of non-native-authored essay is misclassified as AI-generated, while the number for native-authored essay is merely 8%.

4 Approach

As discussed in 2, the two hypotheses we want to test is:

- The mismatch of dataset distribution leads to the bias of detector.
- The limited linguistic expressions in non-native writing leads to the bias of detector.

We fine-tuned the pre-trained Roberta model[4] on a dataset[2] containing over 10000 pairs of answers from human and ChatGPT to the same question, and used this model as our baseline. We denoted it as M_{base} .

4.1 First Hypothesis

To test the first hypothesis, we further trained M_{base} on non-native-authored TOEFL essays and corresponding answers from ChatGPT by the same writing prompt. We denoted the trained model as M_1 . In order to better compare the result, we also trained M_{base} on same amount of native-authored US 8th grade essays and corresponding ChatGPT answers. We denoted the trained model as M_2 . We evaluated the three models, M_{base} , M_1 and M_2 on the test set composed of TOEFL essays and US 8th grade essays, the result are shown in 5.4.

4.2 Second Hypothesis

To test the second hypothesis, we feed a pair of essay sample from the dataset provided in [3] to the GLTR tool developed in[1]. GLTR computes the probability of being next word for every word in the vocabulary, and with those probabilities they can get the rank of true word in the whole vocabulary.

The result of GLTR is shown in 1 and 2. As we can see, native writing samples contain more word choices that ranked over 100 than the non-native-authored text. In another word, language model is less confident when making predictions on native-authored text. This result indicated that native-authored text may have higher perplexity for its rich word choices.

However, the influence of word choices richness on the detecting result is still unclear. Therefore, we used ChatGPT to improve the word choices of original TOEFL essays by prompts like "Make my words and expressions more flexible". We tested our models on the obtained dataset, and the result is shown in 5.4.

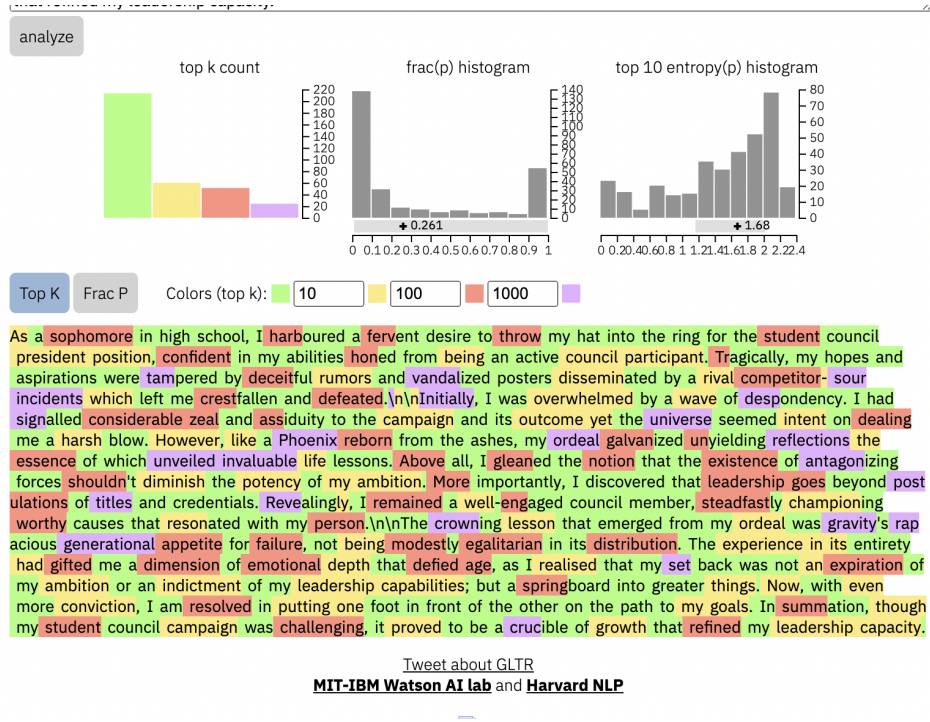


Figure 1: Evaluation Result of Native Sample

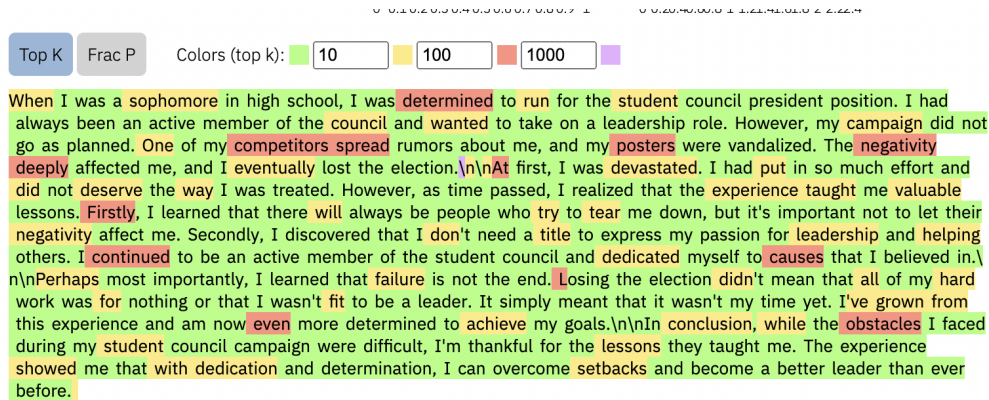


Figure 2: Evaluation Result of Non-Native Sample

5 Experiments

5.1 Data

The dataset we used to trained the M_{base} is H3C dataset proposed in [2]. The dataset contains tens of thousands of answer pairs from human and ChatGPT to the same questions. The dataset we used to trained the M_1 and M_2 are the essay dataset proposed in [3]. This dataset collected native and non-native writing samples as well as the ChatGPT answers to the same essay prompts. We listed some samples in AppendixA.

5.2 Evaluation method

To evaluate the performance of three models in indentifying AI-generated text as well as their possible bias towards non-native speaker, we choose two test dataset. One dataset is composed of TOEFL

essays from non-native writer, while another dataset is composed of US 8th grade essays from native writer. The test dataset is never seen by the model when training. We used misclassified rate as our metric.

5.3 Experimental details

In all training process, we adopt same setups to control the factors.

- Batch Size = 64
- Learning Rate = $2e-5$
- Epochs = 5
- Optimizer adopts AdamW as implemented in pytorch,

5.4 Results

5.4.1 Results for first hypothesis

Model	TOEFL Data	US Essay Data
M_{base}	56.5%	12.3%
M_1	27.2%	8.4%
M_2	54.2%	6.9%

Table 1: The misclassified rate for non-native and native samples

5.4.2 Results for second hypothesis

Model	TOEFL Data	ChatGPT-improved Data
M_{base}	56.5%	9.6%
M_1	27.2%	10.2%
M_2	54.2%	8.9%

Table 2: The misclassified rate for non-native and ChatGPT polished samples

6 Analysis

After training on the TOEFL essay data, the mis-classified rate1 of M_1 decreases from 56.5% to 27.2%, which is a grand improvement. This result validates the first hypothesis. We proved that by adding non-native writing samples to training set, the bias tend to decrease. Therefore, the mismatch of training dataset can be one possible cause of the bias in GPT-Detector.

We also noticed a small decrease (from 12.3% to 8.4%) in US 8th data, which is unexpected. We suppose it indicated that the model is underfit. In another word, the potential of model is not developed fully, and adding more data to the model can improve the power of model to the next level. We also noticed that the improvement of M_2 in US 8th data is bigger than in M_1 , which is expected, because the M_2 is trained on other samples of US 8th grade data, and therefore learnt more knowledge than M_1 , which is trained on TOFEL essays.

In the second table2, there is a significant decrease of misclassification rate when identifying the essay polished by ChatGPT, which proves our second hypothesis, which is, employing advanced word choices can bypass the detector. It can be concluded that the relatively simple and repeated linguistic expressions in non-native writing samples are the cause of biased behavior made by detector.

7 Conclusion

In this project, we made two hypothesis about the cause of bias in detector and proved them with experiment. The valuable lesson we learnt from this experience is that biased training dataset can lead

to biased model performance. Therefore, to make the model unbiased, we need to include training dataset from a large variety of topics. Although our model M_I has less bias than its predecessor M_{base} , the bias still exists. So future work can be adding more non-native data to the model. If the data is hard to acquire, some data augmentation techniques can be employed.

References

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- [2] Biyang Guo, Xin Zhang, Ziyuan Wang, Minqi Jiang, Jinran Nie, Yuxuan Ding, Jianwei Yue, and Yupeng Wu. How close is chatgpt to human experts? comparison corpus, evaluation, and detection. *arXiv preprint arXiv:2301.07597*, 2023.
- [3] Weixin Liang, Mert Yuksekgonul, Yining Mao, Eric Wu, and James Zou. Gpt detectors are biased against non-native english writers. *arXiv preprint arXiv:2304.02819*, 2023.
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- [5] Edward Tian. Gpt zero. <https://gptzero.me/>.

A Appendix (optional)

Some samples from the essay dataset are listed here:

A.1 Samples of TOEFL Essays

- I prefer to cook at home. First of all, it is cheaper and safer than the restaurant. Because I can buy the things needed for cooking, and I can make sure that they are clean and fresh. Second, making a good dinner helps me obtain a sense of achievement. On every Spring festival, I always make dinner for my whole family, they always think that the meal is delicious and we can chat freely around the table. I am really proud of it and I think it can improve the relationship between my family and me.
- The place I would like to visit most is the outer space0the place where most of the physical laws on the earth do not apply. It is interesting to see everything floating in the air. And the term 201cin the air201d should also be modified simply because there is no air anyway. It is interesting to walk the distance in a whole new style. And it is interesting to see the mother planet from a whole new angle. This big blue crystal sphere0cfrom the pictures taken by those astronauts, the sight is marvelous. And I am dying to see this big blue ball in this style.
- I imagine my life ten years in the future to be free. My life will be different in one way from now that I don2019t have to be tied to a job. I can travel around the world, go anywhere, see different things, meet different people, broaden my horizon and thus feel the world. I don2019t have to confine myself to just one place. I can go to France, South Africa, South America and Islands in the Pacific. In addition, I can be a freelancer, live on my royalties. I will have plenty of time to write novels and read all the masterpieces. This is what I imagine my life will be in ten years.

A.2 TOEFL Essays polished by ChatGPT

- I favor preparing meals at home. Primarily, it's more cost-effective and secure than dining out, as I can purchase the necessary ingredients and ensure their cleanliness and freshness. Secondly, creating a delicious meal provides me with a sense of accomplishment. Every Spring festival, I always prepare dinner for my entire family, who consistently find the feast scrumptious and enjoy engaging in lively conversation around the table. I take great pride in this, and I believe it strengthens the bond between my family and me.
- The destination I'm most eager to explore is outer space, where many of Earth's physical laws cease to apply. It's fascinating to witness objects floating effortlessly, and the phrase in the airrequires adjustment since there's no air to speak of. It's intriguing to navigate in an entirely novel manner and observe our home planet from a fresh perspective. This vast blue globe, as captured in breathtaking photographs by astronauts, offers a truly awe-inspiring view. I'm eager to experience this magnificent sight firsthand.

- I envision my life ten years from now as one of unbounded freedom. In contrast to my current circumstances, I will no longer be tethered to a conventional job. Instead, I will embark on a journey to explore the globe, immersing myself in diverse cultures, witnessing stunning landscapes, and forging connections with unique individuals. This will inevitably expand my horizons and enable me to truly experience the world. Unshackled from a fixed location, I will traverse France, the African continent, South America, and the islands of the Pacific. As a freelancer thriving on royalties, I will have ample time to indulge my passions for writing novels and immersing myself in literary masterpieces. This is the life I foresee for myself in a decade's time.