Text Detoxification

Final Solution Report

Roman Makarov

Introduction

This report provides a comprehensive overview of my solution to the text-detoxification task. The following sections detail my processes of data analysis, model selection, training parameters, results, and potential improvements.

Data Analysis

Upon reviewing our primary dataset, I have identified some paraphrases that do not appear natural to me. To address this concern, I decided to incorporate an additional dataset comprising 20,000 human-translated sentences to improve the quality of my dataset.

For the original dataset, I selected only those entries with a reference toxicity score higher than 0.95 and a translation toxicity score lower than 0.01. This method allowed me to gather approximately 170,000 examples of sentences.

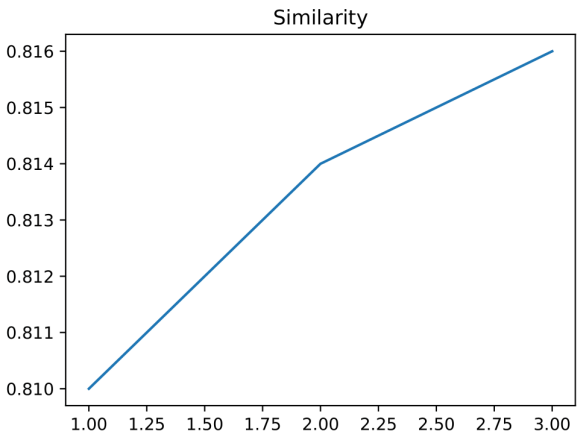
I merged the two acquired datasets to create a final dataset, which has been saved as "paradox.csv." In total, there are around 190,000 samples, with approximately 170,000 (about 90%) originating from the main dataset.

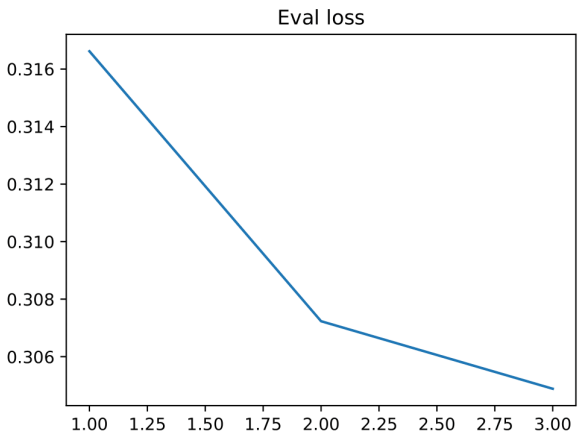
Model Specification

As my final model, I chose pre-trained T5 text-to-text transformer and fine-tuned it on the dataset that I described above.
I used AutoTokenizer from this model's checkpoint to tokenize sentences. I chose 70 to be the maximum length of the sentence, since all sentence examples are shorter than 70 words.

Training process

While training, I calculated the fundamental loss function from Hugging Face, which is the exponential of the cross-entropy loss. Furthermore, I computed BERT text similarity. In my 'Solution Process' report, I explain why I do not use toxicity as a metric during training.
I trained the model for 3 epochs for the reason I discussed in my *Hypothesis 2*.
Upon completing the training process, I achieved a loss value of 0.3 and a BERT similarity score of 0.82 for translations on the test dataset. Below, I present the graphs generated after training the model.





Results

Below, I present translation examples of the most toxic sentences from the main dataset, illustrating how the model successfully removes toxic language and maintains grammatical coherence:

Original: You have to send those idiots back in.
Paraphrase: you have to send them back.

Original: And don't let those idiots in radiology hold you up.
Paraphrase: and don't let those radiologists hold you up.

Original: It's coz of those two idiots. They escaped through a tunnel.
Paraphrase: they escaped through a tunnel.

Original: Audrey Cruz is an idiot. He's the boss.
Paraphrase: Audrey Cruz is a boss.

Original: Your shit is so tired, Justice.
Paraphrase: you're so tired, Justice.

As we can see, model learns to effectively eliminate toxic words and retain grammatical coherence in the translated versions.
What surprised me more, is that the model also learned to paraphrase a sentence in a way that it still makes sense from a grammatical point of view.
The only potential drawback is that, at times, it eliminates entire portions of the text, such as in the case of "*It's coz of those two idiots.*" Nevertheless, this does not significantly impact the overall meaning.

Potential improvements

If resources allow, the large t5 pretrained model can be fine-tuned, instead of a small one that I used due to computational limitations.