



Problem & Background

- In society, proficiency in writing ability is a key skill for success. Despite this, less than one-third of high school seniors in the United States demonstrate writing proficiency.
- In this project, our group seeks to explore a successful autoregressive learning model that identifies argumentative components of written documents - such as claims, evidence, rebuttal, conclusions, etc.
- Identification of argumentative writing structure is a difficult natural language processing task that requires establishing abstract relationships between local and global textual context.
- This presents a potential solution to help students improve their writing abilities with little to no-cost.

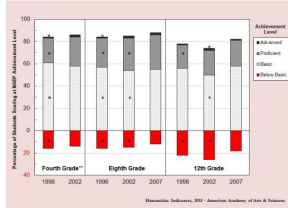


Fig 1. Writing proficiency of American students over time.

Conclusions

- With 3 days remaining in the competition, we placed 188 out of 1997 teams. The model performed with very high accuracy: the best models in the competition performed less than 5% better than our model and we performed less than 4% worse than human annotators.
- However, we had our fair share of issues. Despite having 16 GiB on our GPU we frequently ran out of memory when trying to train our models. This was a huge issue and led us to adapt our models with gradient accumulation and using small batch sizes. This also meant we could not use larger models with more parameters.

Methods

The Longformer

- The Long-Transformer (Longformer) is a state-of-the-art Transformer model designed for processing long sequences.
- Transformer attention scales quadratically with sequence length. Since our model will be reading and classifying long pieces of text (some over 4000 words) we require a faster attention computation. Therefore, we used a sliding window attention pattern.

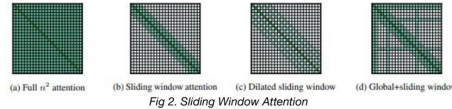


Fig 2. Sliding Window Attention

Gradient Accumulation

- Since our GPUs only have 16GB of memory and we are training very large transformer models, it became nearly impossible to use a batch size greater than 1.
- Gradient accumulation fixes this issue by effectively simulating a higher batch size by computing and storing the gradient for the last N forward passes, averaging them, and then doing a single backpropagation step with this mean gradient. This leads to more accurate weight updates and faster training.

Results

We were quite surprised to find that the Longformer that was pre-trained with additional data performed worse than when loading the original pretrained embeddings. The BigLongBirdformer also performed much worse than expected. The Longformer with Oversampling model surprisingly boosted our accuracy by over 6% a hefty improvement to the baseline Longformer. We attribute this to the additional feed-forward layer and extra training time on data that was better distributed because of the oversampling.

Evaluation accuracy on hidden testset

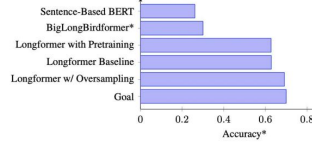


Fig 4. Results of all our models



Fig 5. Sample labeled output from the model

Notable Experiments

Sentence Based BERT

- Since argumentative components of essays are sentences, we thought a sentence-based classifier would naturally produce respectable results.
- This was not the case as the accuracy was only 26%.

Longformer + Big Bird

- The idea behind the model was that maybe using contextual embeddings from two different transformers would provide better contextual information to the feed-forward layers
- This did not seem to work as loss and accuracy stagnated very early.

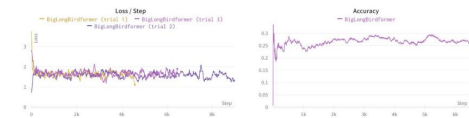


Fig 4. Loss and Accuracy of Longformer + Big Bird

Longformer with Oversampling

- After finalising the model architecture to be a single Transformer, we decided to oversample the data as some classes were severely under-represented.

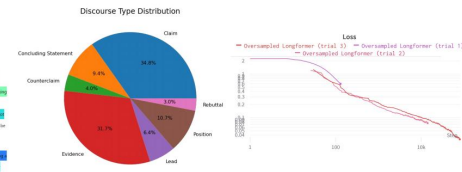


Fig 5. Class Distribution and Loss for Longformer w/ Oversampling

- This model had significantly better performance than our baseline and BigBird Model with the loss consistently dropping across epochs.