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RESEARCH PROPOSAL

CONTEXT

The Transformers-based models prove their capability to outperform in a variety of Natural Language Processing (NLP) challenges—an enhanced version of Recurrent Neural Network. What makes this algorithm revolutionize is self-attention. This mechanism can tokenize each input without relying on sequence and compose multi-head attention with several layers to predict. However, the time complexity of self-attention is $O(n^2d)$ at worst and $O(rnd)$ at best (d represents dimension while r represents the size of the neighborhood) (Vaswani, et al., 2017). For that reason, the Big Bird algorithm reduces time complexity using block sparse attention type. The block sparse attention consists of three different types: global, random, and sliding attentions. The number of connections in block sparse attention is smaller than total of full connections in normal attention. Because the block sparse attention creates a vector of attentions, the mathematics behind this algorithm is unsurprisingly more complex. This algorithm is suggested to have ability to reduce this *quadratic dependency to linear* (in memory term), which is skeptical given the complex algorithm.

For example, the block sparse attention is in use for the encoder side while the full self-attention is on decoder side (Zaheer et al., 2020). For that reason, this algorithm is in use to evaluate, being compared to Transformers as a counterpart, using PubMed and ArXiv published journals. In this proposal, the objective is to determine what type of Big O notation is.

DATA SOURCES

As mentioned earlier, PubMed and ArXiv published journals are in use to train both Transformers and Big Bird algorithms. There are 6,440 ArXiv journals in testing set, 6,436 in validation set, and 203,037 in training set. Also, there are 6,658 PubMed journals in testing set, 6,633 in validation set, and 119,924 in testing set. Each journal contains article with no abstract as input and abstract as output.

PROBLEM IDENTIFICATION

What is a type of Big O notation for Big Bird? Unless time complexity of Big Bird equals $O(n)$, can this algorithm improve its efficiency without sacrificing performance? If so, how can the abstractive text summarization surpass the Recall-Oriented Understudy for Gisting Evaluation-1 (ROUGE-1) score of Big Bird? Can the data analytics be readily available on or before December 1, 2021? Does this analytics include the qualitative evaluation?

CRITERIA FOR SUCCESS

Relevant criteria for successes are:

- Type of Big O notation in Big Bird should successfully be identified.
- Efficiency in this algorithm should be improved without sacrificing performance.

- If Big O notation is *O(n)*, the different algorithm for abstractive text summarization should surpass the ROUGE-1 of Big Bird.
- The reproducible research and presentation including qualitative evaluation should be readily available on or before December 1, 2021.

SCOPE OF SOLUTION SPACE

This analysis focuses on abstractive text summarization using Big Bird and Transformers-based algorithms, and PubMed and ArXiv published journals. This analysis also focuses on model performance and scalability.

CONSTRAINTS

- Processing the PubMed and ArXiv datasets containing over 40,000 scientific publications may be time- consuming, which requires efficient computation.
- The qualitative analysis is difficult, if not impossible, to completely evaluate due to large number of abstracts that may easily be overlooked.
- This analysis is limited to PubMed and ArXiv scientific journals.

POTENTIAL STAKEHOLDERS

Program Manager
Lead Data Scientist

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