BigBird and Clinical-BigBird

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Motivation

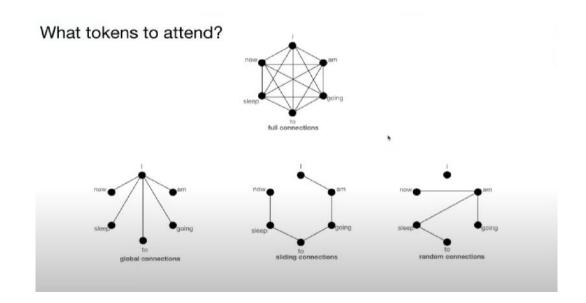
- Transformers-based models, such as BERT, have been one of the most successful deep learning models for NLP.
- One of their core limitations is the quadratic dependency (mainly in terms of memory) on the sequence length due to their full attention mechanism.
- To remedy this, BigBird model was proposed, that uses a sparse attention mechanism that reduces this quadratic dependency to linear.

Related Work

- There have been a number of attempts, that were aimed at alleviating the quadratic dependency of Transformers.
- SpanBERT, ORQA, REALM have achieved strong performance for different tasks. These models used mechanisms to select a smaller subset of relevant contexts to feed into the transformer. However, these methods often require significant engineering efforts and are hard to train.
- Several other models have been developed which used approaches that do not require full attention.

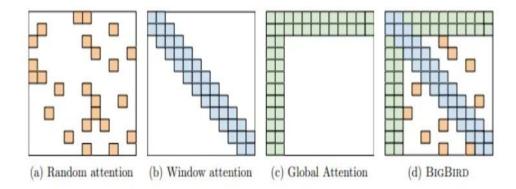
Architecture

- BigBird runs on sparse attention mechanism that allows it to overcome the quadratic dependency of BERT.
- In particular BigBird consists of three main parts:
- A set of g global tokens attending on all parts of the sequence.
- ii. All tokens attending to a set of w local neighboring tokens.
- iii. All tokens attending to a set of r random tokens.



Attention Mechanism:

- BigBird runs on sparse attention mechanism that makes it possible to have a linear complexity.. It's attention mechanism is a combination of:
- Random Attention
- ii. Window Attention
- iii. Global Attention



Maximum input size:

In BERT, the maximum input size is 512 tokens because of quadratic nature of it's complexity in terms of computation.

BigBird can process sequences of length 8x more than BERT(i.e. 4096 tokens)

Content Fragmentation:

In BERT, content fragmentation is present because longer sequences have to be broken into smaller segments.

BigBird overcomes the problem of content fragmentation.

Performance Comparison

- Question Answering Task(QA):
- BigBird was found to be performing better than models like RoBERTa, Longformer, SpanBERT on various QA datasets like HotpotQA, Natural Questions, TriviaQA, and WikiHop.

Classification:

 BigBird performs better in document classification and various GLUE tasks. It improves state-of-the-art for Arxiv dataset by about 5% points. On Patents dataset, there is improvement over using simple BERT/RoBERTa.

Performance on Clinical data

- The Pre-trained BigBird model was not found to be performing well on clinical dataset for sentiment analysis tasks.
- When used for a custom clinical dataset, it was observed that that BigBird was incorrectly labelling various samples.



Clinical-BigBird

- Inspired by the success of long sequence transformer models like Longformer and BigBird, domain enriched language models were introduced.
- One such model is the Clinical-BigBird, which is pre-trained from large-scale clinical corpora.
- It has achieved state-of-the-art results when performed on clinical named entity recognition and natural language inference tasks.

Related Work

- Transformer-based models, especially BERT, can be enriched with clinical and biomedical knowledge through pre-training on large-scale clinical and biomedical corpora.
- These domain-enriched models, e.g. BioBERT pretrained on biomedical publications and ClinicalBERT pre-trained on clinical narratives, set the state-of-the-arts when down-stream applied to clinical and biomedical NLP tasks.
- However, these models were built on the basic BERT architecture, which has a limitation of 512 tokens in the input sequence length.

Performance Comparison

- Clinical-BigBird has been found to outperform models like BERT, BioBERT and ClinicalBERT on various clinical Question Answering datasets.
- Similarly, it has better on various named entity recognition tasks and document classification datasets.

Performance on Custom dataset

 The Pre-trained Clinical-BigBird model was found to be performing well on clinical dataset for sentiment analysis tasks.

[]	Prediction
	array([0, 1, 0, 0, 1, 1, 0, 0])
[]	truth = df.iloc[:,1].values
[]	truth
	array([0., 1., 0., 1., 1., 0., 0.])
[]	from sklearn.metrics import accuracy_score , confusion_matrix,ConfusionMatrixDisplay
[]	acc-accuracy_score(Prediction,truth) acc
	0.875

THANK YOU