A Structured Transformer Neural Machine Translation on Abstractive Text Summarization for Bangla seq2seq Learning

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Abstract

To the best of our knowledge, there is no universal approach that is agnostic to language despite the fact that there has been a lot of study on text summarizing for many languages. Thereby, we propose a LSTM based solution that process text in Bangla input from valuable sources after training the model the pair of Bangla text-to-Bangla summaries visualize a momentous margin that will also employ next future work.

Introduction

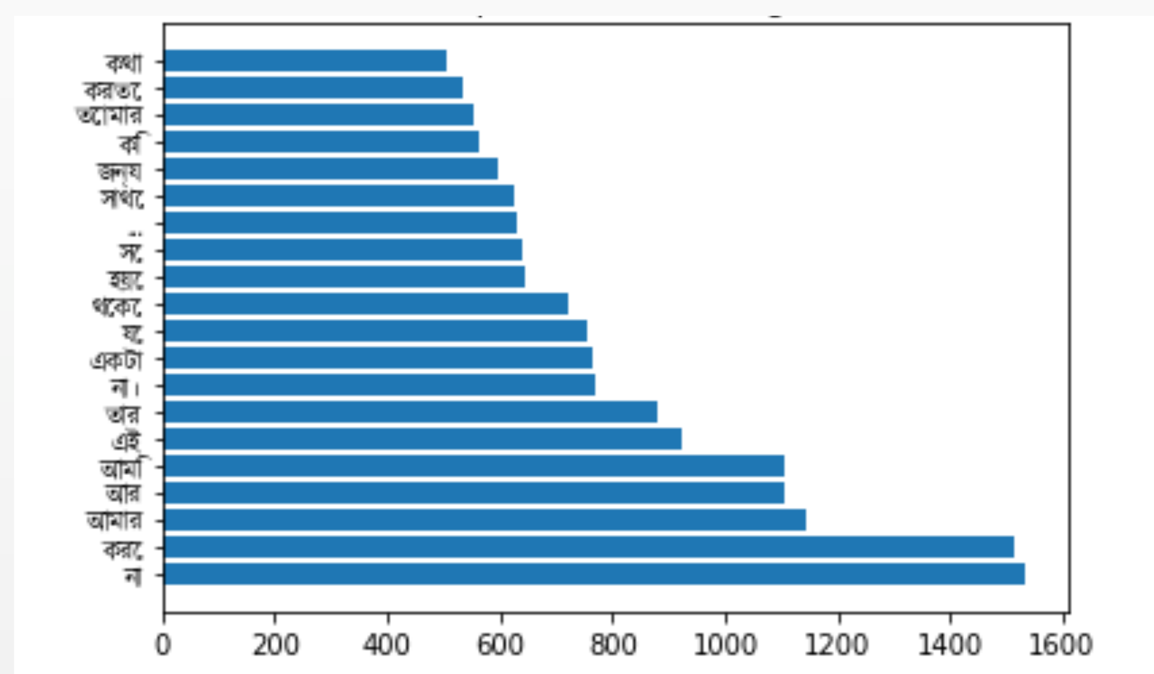
- The summary text refers to a process of language conversion in which languages are changed as a result of the efforts of neural networks.
- The ability of NMT to train a corpus into vector output in an end-to-end process allows it to translate the longest sequence of input in Bangla.
- The benefit of natural language processing's abstractive summarization of multiple languages comprises basic architecture updated by RNNs and Convolutional Neural Network encoding (CNN).

Challenge and Contribution

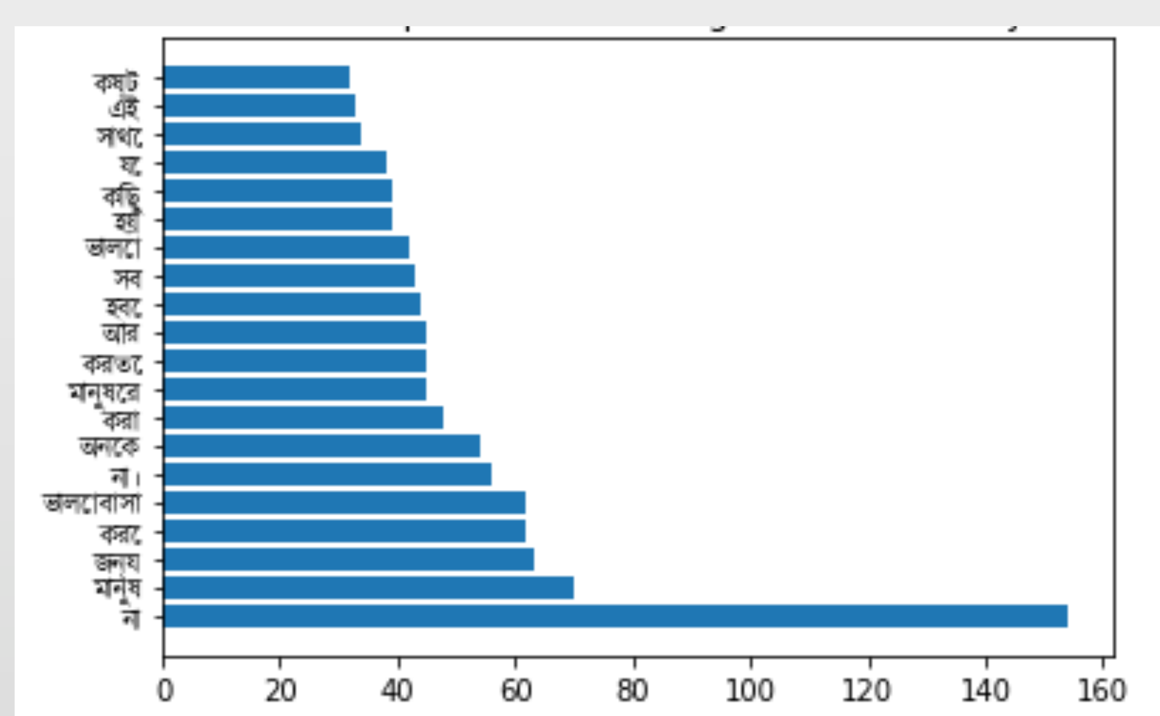
- Used self-attention which generates longer sequence translation for Bangla text input and tried best to decode the text summarization.
- To get a better enhancement and for solving difficulty in parallelization using the transformer model and getting a result of maximum length from the previous work.

Dataset properties & Statistics

- Construction in the description of the summary and text.
- Most Frequent Word in Bengali Text

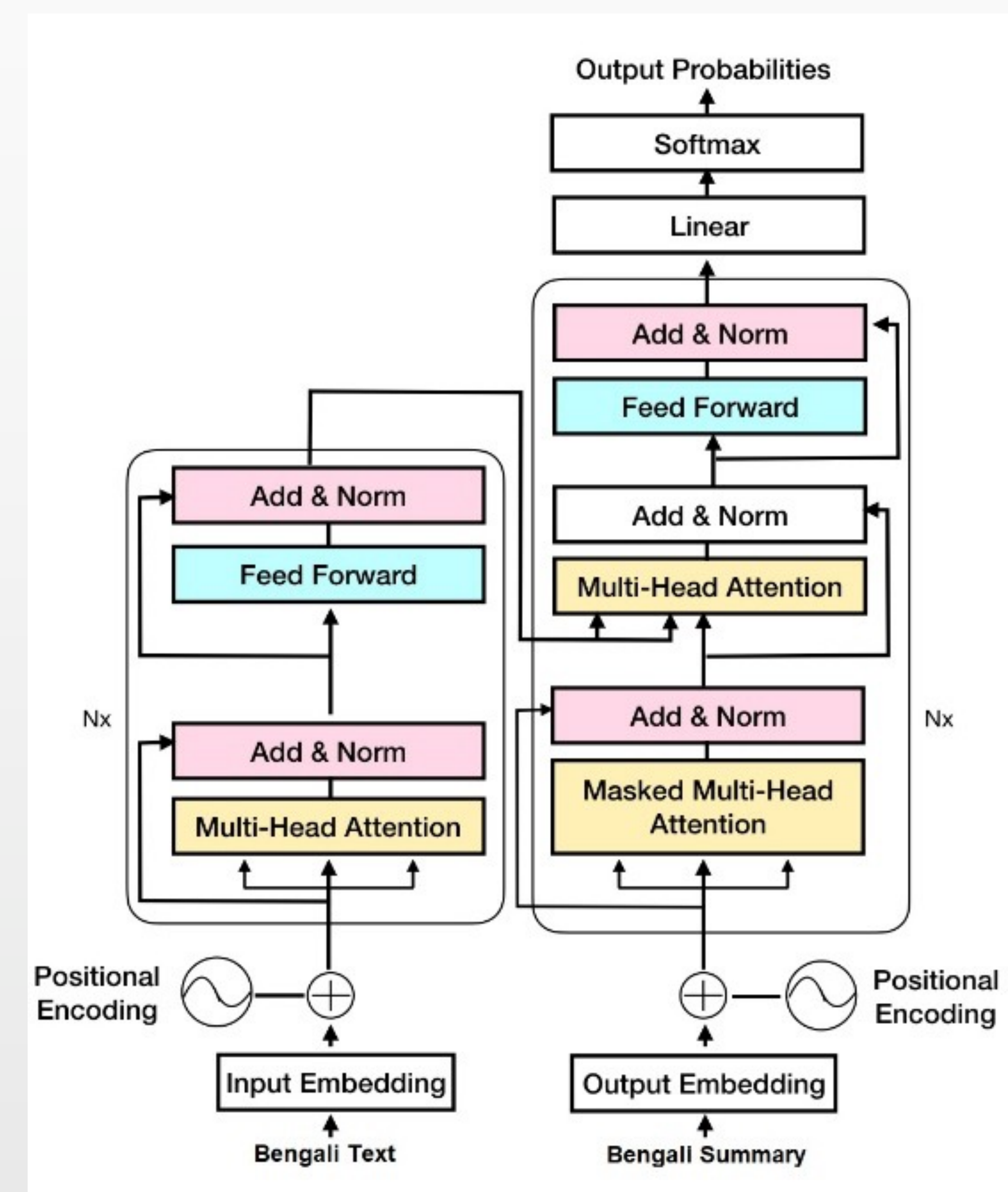


- Cleaning the texts, deleting the unwanted characters, encoding in the appropriate format, tokenized, PAD sequence, and removing the stop word.
- Most Frequent Word in Bengali Text Summary



Methodology

- Self-attention generates longer sequence translation where input Bangla text to decode the text summarization
- Neural Network Transformer defined with a model by encoding decoding with Layer.
- Multi-head attention used to 8 parallel attention levels.
- Feed-Forward Networks consist of a deeper transformation with the Relu activation function.
- Particularly encoder set up with two sub-layers of Multi head Attention for mapping the word head by the attention of SoftMax function



Results

- Attention-based transformers carry self-attention, and multi-head accomplishment and concatenate it simultaneously.
- The SoftMax function distributes the transpose function the weight of attention from the source location to the encoder and decoder.
- **Performance summary in terms of BLEU aggregate**

BLEU	
Score	0.82

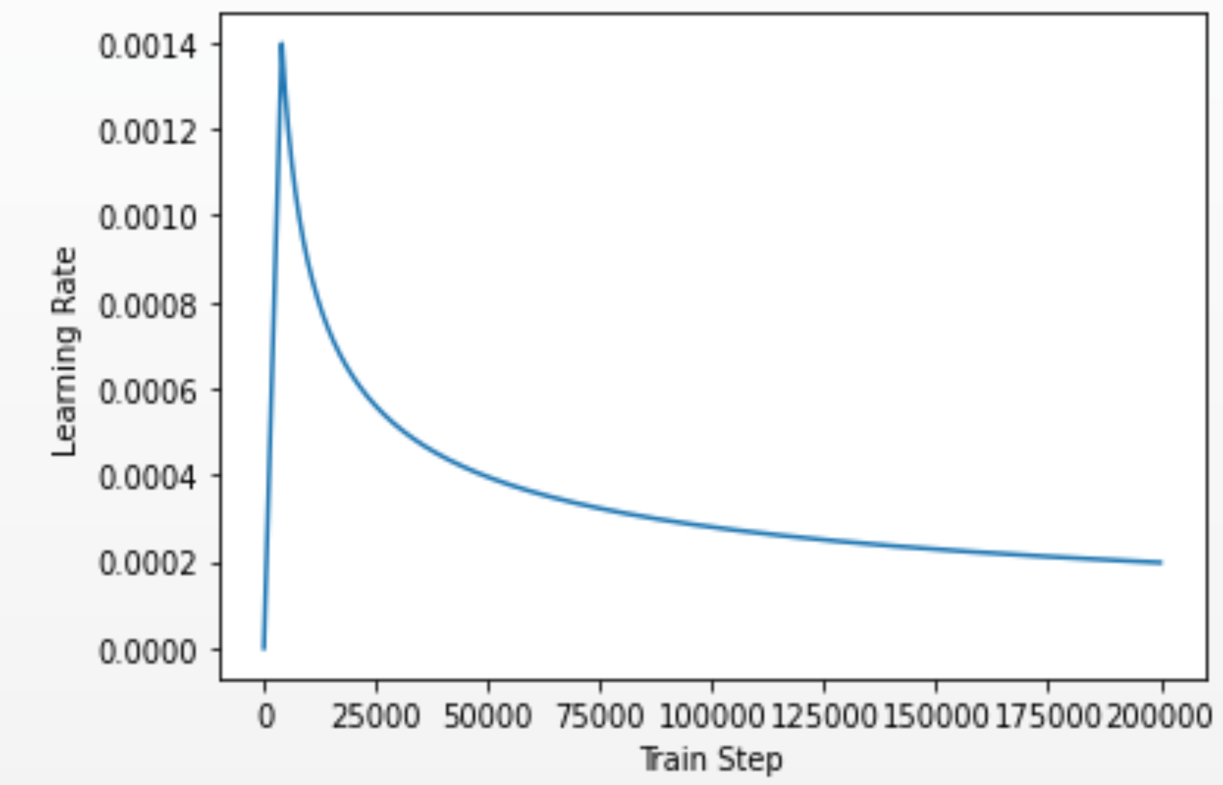
- **Rouge Score**

Rouge Score	
Score	F1-Score
Rouge 1	0.85
Rouge 2	0.83
Rouge 3	0.83

- **Transform model acceptance**

Batch Size	RNN Size	Probability	Learning Rate	EPOCHS
2	256	0.75	0.001	70
32	512	128	0.0014	100

- **Transformer model learning point scale.**



Conclusion

- Structured seq2seq process attention mechanism to explicit the Bangla language to Bangla text summarization.
- While input file analyzing the number of files was 1026 Bangla summary such as input as NMT.
- Will explore long document summarization by dynamically taking input into delivery as a response summary.

Acknowledgements

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