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AUTOMATED NEWS SUMMARIZATION WITH BERT

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MOTIVATION

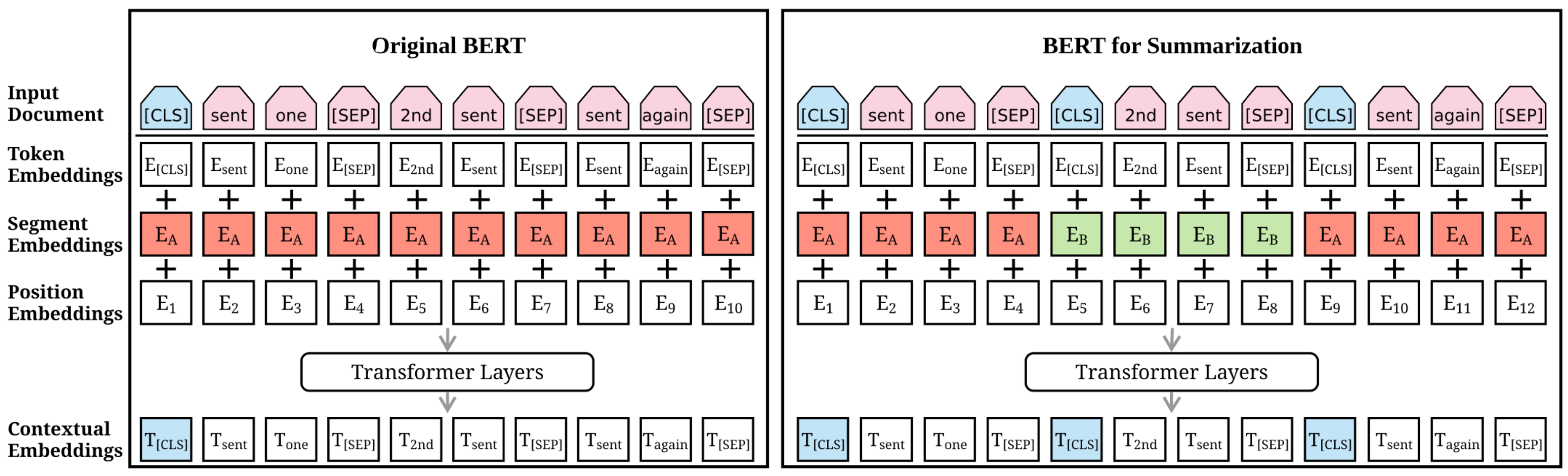
Automated text summarization is one of the central challenges of Natural Language Processing: helping to reduce complexity of documents, weeding out redundant information, decreasing the time to process large amounts of text, ultimately increasing productivity.

Our research adapts the BERTSUM model developed by Yang Liu and Mirella Lapata and apply it on the large and diverse Cornell Newsroom dataset and contribute to the literature on news summarization.

METHODOLOGY

BERTSUM utilizes a pre-trained neural network to create word embeddings as features for modeling with 3 approaches:

- **Extractive** (summary taken directly from source text): summarization-orientated layers are stacked and fine-tuned on top of BERT encoders.
- **Abstractive** (summary generated by the model): BERTSUM encodes input text and feed results to decoder to learn how to generate text.
- **Mixed**: weights of final extractive model are used for retraining model in abstractive setting.



CONCLUSION

Despite training only on a small subset of the training data BERTSUM achieves results quite close to the state-of-the-art. This shows that BERT powered models are a promising approach to text summarization that could - rival existing solutions.

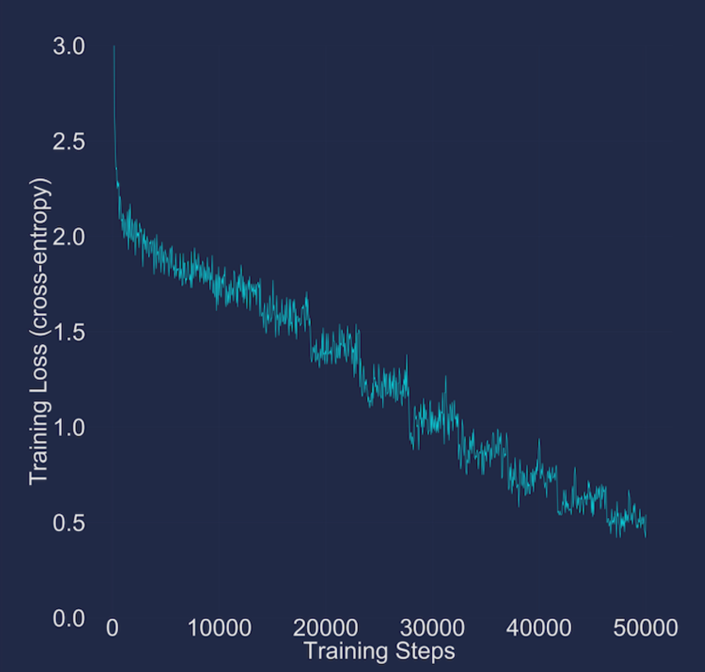
System	R-1	R-2	R-L
Extractive			
Lede-3 Baseline (by [3])	32.02	21.08	29.59
BERT (full testset)	28.74	17.76	26.15
Abstractive			
Seq2Seq + Attention (by [9])	5.99	0.37	5.41
BERT Model [4]	7.04	0.32	6.78
Mixed			
Modified P-G (by [10])	39.91	28.38	36.87
BERT Model	30.01	17.77	27

Model results in comparison to SOTA

RESULTS

Models are evaluated with ROUGE scores which calculate the overlap (n-grams or word sequences) between the automated summaries and the gold standard (often human-generated).

All three models achieve results that come fairly close to the state-of-the-art models implemented for the Cornell Newsroom dataset. Due to computational limits we trained only on a fraction (7%) of the full training set (60,000 articles out of 1.3 million) and tested on 12% of the full test set (20,000 articles out of 163477).



Cross-entropy loss over lifetime of training for extractive model

References

Y. Liu and M. Lapata. Text summarization with pretrainedencoders.arXiv preprint arXiv:1908.08345, 2019.