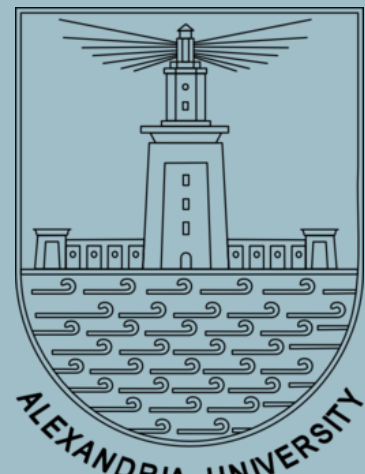


AUTOMATIC TEXT SUMMARIZATION



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Predicting

- Text summarization is the process of generating a concise and logical version of a larger original document.
- In our problem, we followed the single-document generic abstractive approach.
- Our model is seq2seq model; an encoder-decoder network with attention.
- For the evaluation, we use the ROUGE metric.

Data

- Preprocessed Gigaword dataset:
 - lowercase conversion
 - number replacement
- A total of 3,803,957 training samples and 189,651 test samples.
- Data samples are articles, supplemented with single-sentence ground truth summaries.

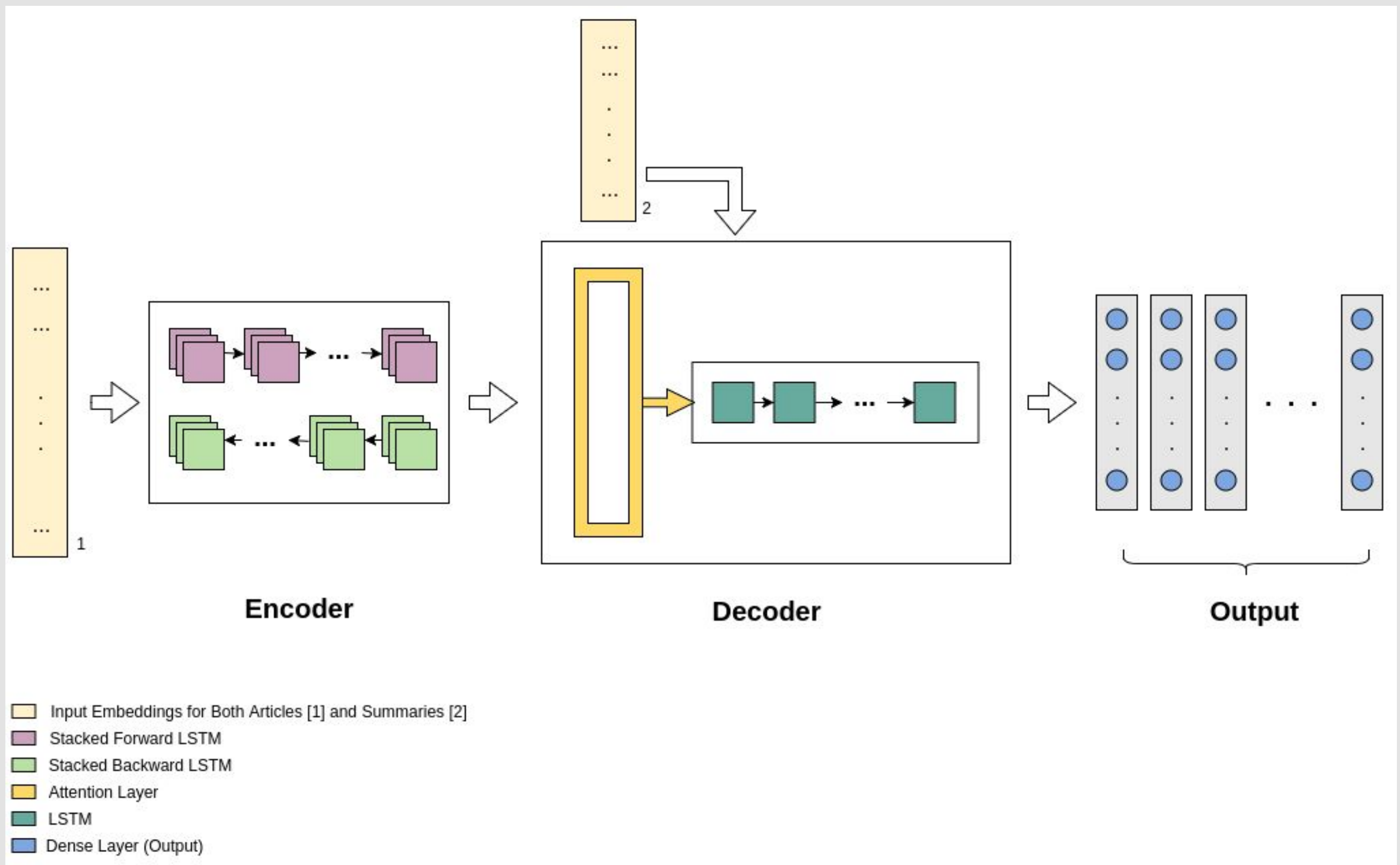
Features

- d-feature vector of each input word, where (d) is a user-configured dimension.
- Either pretrained GloVe embeddings, or self-learned by the model network.

Model

Encoder-Decoder network; where:

- Encoder: stacked bidirectional LSTM with dropout
- Decoder: LSTM network with attention



Discussion

- Better results are achieved when using pretrained embeddings, unlike self-learned embeddings that performed very poorly.
- As stacked LSTM gets deeper, the model output becomes less acceptable

Future Work

- Apply “Beam Search” technique for better sequence generation.
- Support “Pointer-Generator” method to tackle factual errors, OOV (out-of-vocab) words and repeating.
- Generalize decoder network to work on CNN and other datasets with multi-sentence summaries.

References

[1] Haoyu Zhang, Yeyun Gong, Yu Yan, Nan Duan, Jianjun Xu, Ji Wang, Ming Gong and Ming Zhou. Pretraining-Based Natural Language Generation for Text Summarization. arXiv preprint arXiv:1902.09243, 2019.

[2] Linqing Liu, Yao Lu, Min Yang, Qiang Qu, Jia Zhu, and Hongyan Li, “Generative adversarial network for abstractive text summarization,” AAAI, 2018.

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Hyperparameters and Evaluation

stacked LSTM layers	LSTM hidden units	embedding type	embedding size	batch size	learning rate	dropout keep prob.	ROUGE-1	ROUGE-2	ROUGE-L
2	150	GloVe	300	512	0.01	0.8	31	12.53	27.27
2	100	self-learned	200	64	0.01	0.8	19.77	6.02	16.7
4	150	GloVe	300	512	0.01	0.8	19.37	5.55	17.02