Natural language processing

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Contents

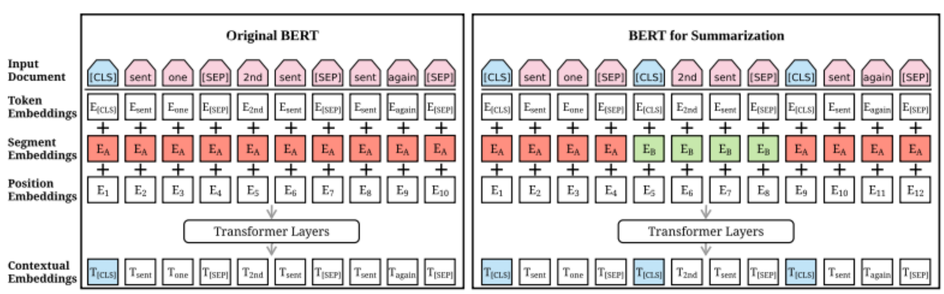
1 Text summarization with pretrained encoders

1.1 Some definitions

- **Abstractive modeling**: the task requires language generation capabilities in order to create summaries containing novel words and phrases not featured in the source text;
- **Extractive summarization**: is often defined as a binary classification task with labels indicating whether a text span (typically a sentence) should be included in the summary;
- **Pretrained language model**: extends the idea of word embeddings by learning representations from large-scale corpora using a language modeling objective.

1.2 Summary

Here they explore the potential of Bert under a general framework encompassing both extractive and abstractive summarization. They combine the Pretrained Bert with a randomly-initialized Transformer decoder. The difference here is that we eant to manipulate multi-sentential input w.r.t. the usual task of Bert. In Bert for summarization the document representations are learned hierarchically where lower transformer layers represent adjacent sentences, while higher layers (+self-attention) represent multi-sentence discourse.



1.2.1 Extractive summarization

With BertSum we have the vector v_i of the i-th [CLS] symbol from the top layer can be used as the representation of the i-th sentence. After this we have other inter-sentence transformer layers to capture document-level featurs for extracting summaries. The output layer is a sigmoid classifier.

1.2.2 Abstractive summarization

Standard encoder-decoder framework is used. The encoder is BertSum and the decoder is a 6-layered Transformer initialized randomly. To circumvent the fact that the decoder is not pretrained is designed a new fine-tuning method: Adam optimizer with $\beta_1 = 0.9$ and $\beta_2 = 0.999$ for the encoder and the decoder, each with different warmup-step and learning rates:

- $lr_\epsilon = \tilde{lr}_\epsilon \cdot min(step^{-0.5}, step \cdot warmup_\epsilon^{-1.5})$, where $\tilde{lr}_\epsilon = 2e^{-3}$, $warmup_\epsilon = 20000$ for the encoder;
- $lr_\mathcal{D} = \tilde{lr}_\mathcal{D} \cdot min(step^{-0.5}, step \cdot warmup_\mathcal{D}^{-1.5})$, where $\tilde{lr}_\mathcal{D} = 0.1$, $warmup_\mathcal{D} = 10000$ for the decoder;

The encoder can be trained with more accurate gradients when the decoder is becoming stable.

1.3 implementation

- PyTorch;
- OpenNMT;
- bert-based-uncased: https://git.io/fhbJQ;
- dropout for abstractive models;
- rouge-2 score for extractive models against gold summary (selct the top 3 sentences);
- Summarization quality using Rouge (1, 2, L)
- human evaluation.