Natural language processing

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1 Text summarization with pretrained encoders

1.1 Some definitions

- **Good summary**: A good summary must be fluent and consistent, capture all the important topics, but not contain repetitions of the same information;

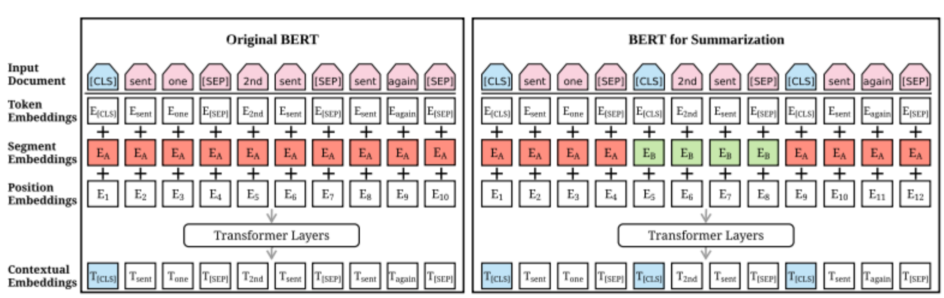
- **Abstractive modeling**: the task requires language generation capabilities in order to create summaries containing novel words and phrases not featured in the source text;

- **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.

2 Automatic Text Summarization: a State-of-the-art Review

2.1 Extractive methods

The main task is to determine which sentences are important and should be included in the summary.

- Cheng: data-driven approach for single-document summarization based on continuous a hierchical document encoder and an attention-based extractor. The model can be trained on large-scale datasets and learn informativeness features based on continuous representations without access to linguistic annotations. The labels are assigned to each sentence in the document individually based on their semantic correspondence with the gold summary;

- Nallapati: recurrent neural network based sequence model for extractive single-document summarization (SummaRuNNer). Identify the set of sentences which collectively collectively give the highest ROUGE with respect to the gold summary

- Narayan: similar approach but for sentence ranking there is a combination of maximum-likelihood cross-entropy with rewards from policy gradient reinforcement learning to direclty optimize the final evaluation metric (ROUGE), a sentence gets a high rank for summary selection if it often occurs in high scoring summaries.

- Yasunaga: GCN takes sentence embedding from RNN as input node feature and through multiple layers-wise propagation generates high-level hidden features for sentences. Sentence salience is then estimated through a regression on top and the important sentences are extracted in a greedy manner while avoiding redundancy.