ETH zürich

Human Feedback for Query-Focused Abstractive Summarization

Tuan Pham Huu
Annina Stahl
Gabriel Gavrilas
Rik de Graaff

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Outline

Introduction

OurBERT

Query-focused abstractive summarization (QFAS) with human feedback-based reward modeling

- Extend existing text summarization system to train with human feedback data
- First implementation of query-focused abstractive summarization with human feedback

Background
Text Summarization

Text Summarization

- Extractive – Abstractive
- Generic – Query-focused

BERT-based Summarization Systems

- QAbsBert[1]: Query-focused abstractive text summarization
- Based on BertSum[2], which is based on BERT[3]

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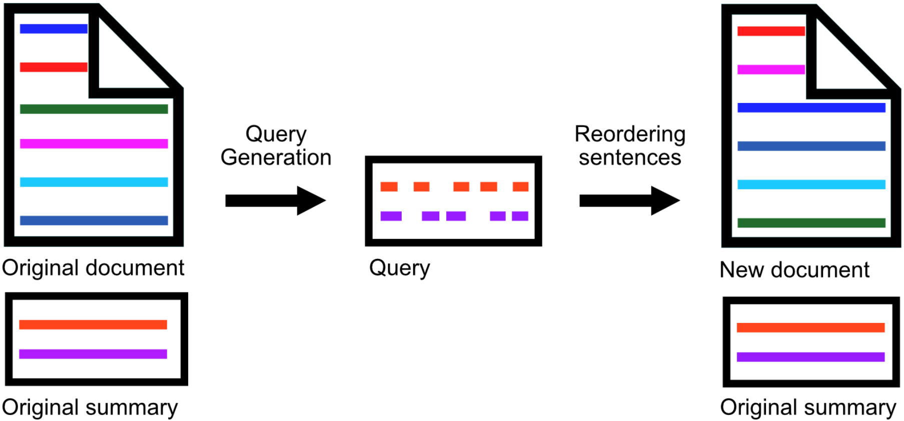
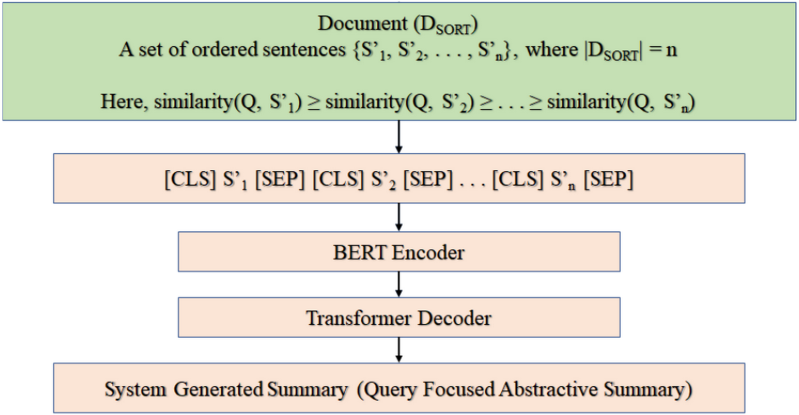
[1] (Abdullah and Chali 2020)
[2] (Liu and Lapata 2019)
[3] (Devlin et al. 2019)

Background
QAbsBert



Background
QAbsBert



Source: (Abdullah and Chali 2020)

Summary Evaluation

- ROUGE scores
- Human preference

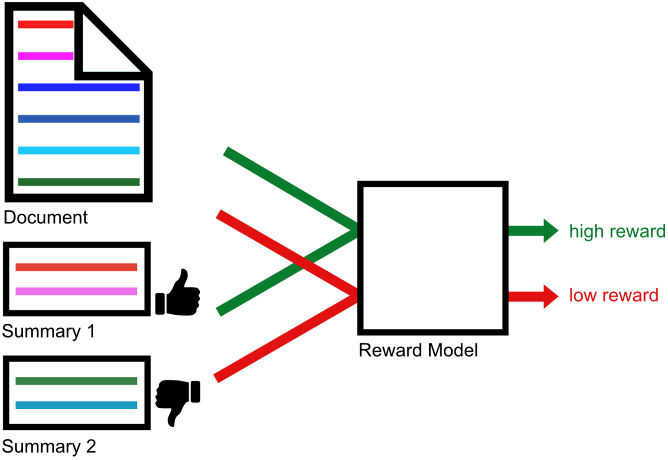
Reward Modeling

- Incorporate human feedback into summarization[4]
- Learn what humans consider a good summary

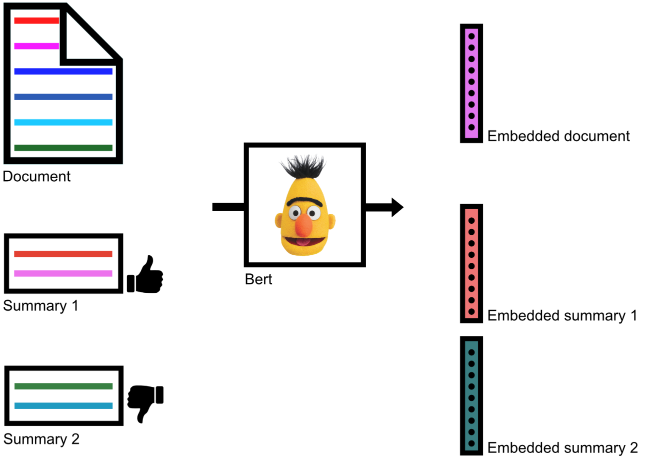
[4] (Stiennon et al. 2020; Böhm et al. 2019)

Method

OurBert – Reward Model – Idea

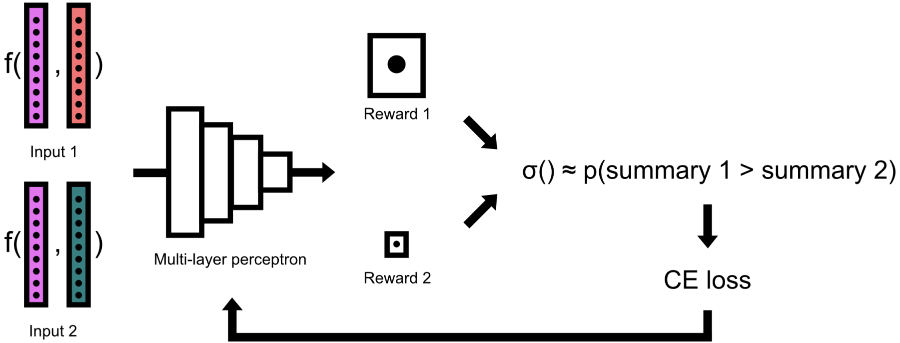


Method
OurBert – Reward Model – Embedding



Method

OurBert – Reward Model – Training



Method

OurBert – Incorporation of Reward

Loss weighting

Let $x = x_1, ..., x_n$ be the source documents
Let $y = y_1, ..., y_n$ be the target summaries
Let $\hat{y} = \hat{y}_1, ..., \hat{y}_n$ be the generated summaries

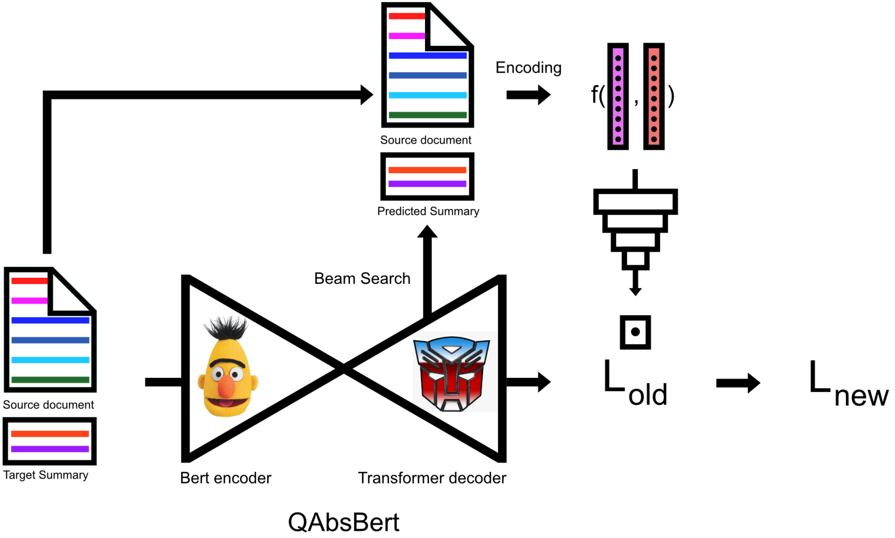
$$\mathcal{L}_{\text{new}}(x, y) = \sum_{i}^{n} \mathcal{L}_{old}(x_i, y_i) * \frac{1}{\max(1, \text{reward}(x_i, \hat{y}_i))}$$

Add reward as a loss term

$$\mathcal{L}_{\text{new}}(x, y) = \sum_{i}^{n} \mathcal{L}_{old}(x_i, y_i) - \text{reward}(x_i, \hat{y}_i)$$

Methods

OurBert – Full model



Results
Replication

Model	R1	R2	RL
BertSum			
Original	42.13	19.60	39.18
Replication	40.95	18.61	38.09[5]
QAbsBert			
Original	44.91	21.81	41.70
Replication	40.32	17.94	37.40

ROUGE F1 scores on CNN/DailyMail data.

[5] There was a typo in the final write-up.

Results
OurBert

Reward Model	
Validation Score	72%

Evaluation on human feedback data.

Model	R1	R2	RL
OurBERT			
with RM loss term	39.68	17.33	36.78
with RM loss weighting	39.80	17.44	36.94
QAbsBert (Baseline)	40.02	17.57	37.07

ROUGE F1 scores on CNN/DailyMail data.

Discussion

OurBERT

- Performance like QAbsBert
- High cost of using human feedback, long training time
- Evaluation of quality to humans and integration of queries not possible

Summary Samples

Target summary

david healy is head of psychiatry at the hergest psychiatry unit in bangor. claims the idea low levels of serotonin causes depression is a fallacy. marketing of ssri drugs like prozac has been ’ based on a myth ’ , he claims. experts refute his claims saying ’ ssris work in the real world of the clinic ’

QABSBERT 170k summary

psychiatrists warn controversy could harm depressed patients if they were deterred from taking the drugs , which had been proved to work in trials and the ‘ real world ’. they warn the controversy might harm depressed people if they are deterred of taking the drug they have fewer troublesome side - effects than their predecessors , and are safer in overdose

QABSBERT 160k + 10k with RM loss weighting

psychiatrists warn controversy might harm depressed patients if they were deterred from taking the drugs , which had been proved to work in trials and the ‘ real world ’. professor david sanctions the idea that the most popular antidepressants raise serotonin levels in the brain is nothing more than a myth

QABSBERT 160k + 10k with RM loss term

psychiatrists warn the controversy might harm depressed patients if they were deterred from taking the drugs , which had been proved to work in trials and the ‘ real world ’. other psychiatrists warned that the controversy may harm depressed people if they are deterred

References

Abdullah, Deen Mohammad and Yllias Chali (Dec. 2020). "Towards Generating Query to Perform Query Focused Abstractive Summarization using Pre-trained Model". In: *Proceedings of the 13th International Conference on Natural Language Generation*. Association for Computational Linguistics, pp. 80–85.

Böhm, Florian et al. (Nov. 2019). "Better Rewards Yield Better Summaries: Learning to Summarise Without References". In: *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*. Association for Computational Linguistics, pp. 3110–3120.

Devlin, Jacob et al. (2019). *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*. arXiv: 1810.04805 [cs.CL].

Liu, Yang and Mirella Lapata (2019). "Text Summarization with Pretrained Encoders". In: *CoRR* abs/1908.08345. arXiv: 1908.08345.

Stiennon, Nisan et al. (2020). "Learning to summarize from human feedback". In: *CoRR* abs/2009.01325. arXiv: 2009.01325.