Extractive Summarization of Terms of Service

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Outline

I. Motivation and Task
II. Reference Model and Our Methods
III. Dataset
IV. Experiments
V. Conclusion

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Motivation

- Terms of Service (**ToS**) are the legal agreements between a service provider and a person who wants to use that service.
- The person must agree to abide by the ToS in order the use the offered service.

Motivation

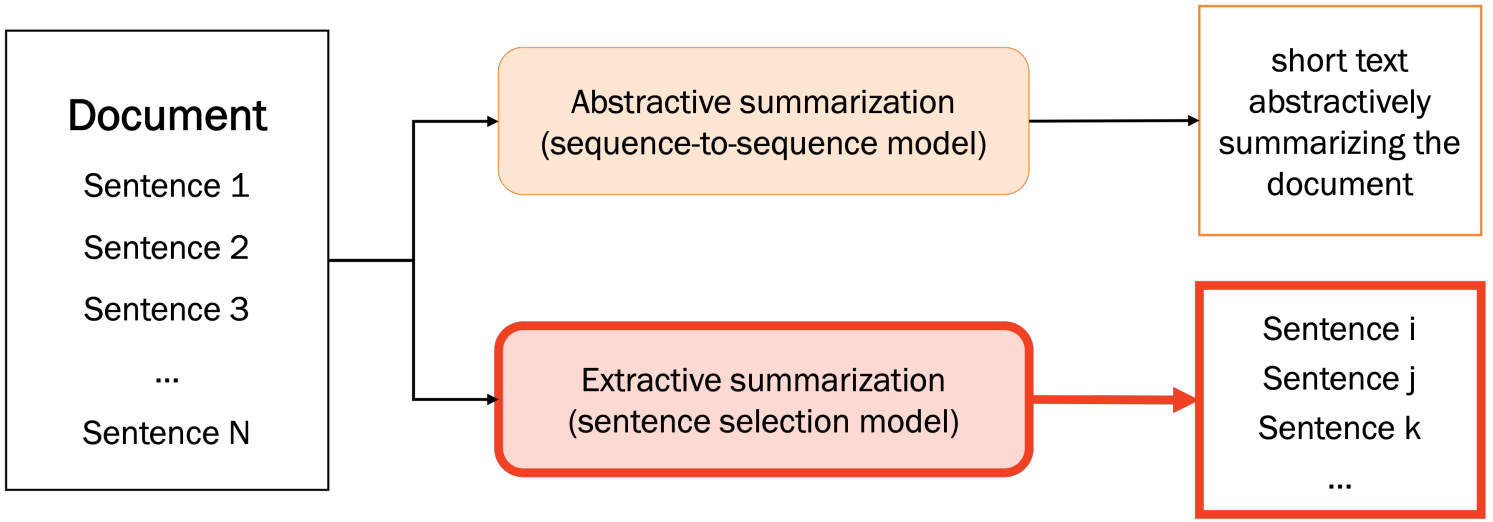
- But ToS are too long.
  - 98% of users do not fully read the terms of service before accepting them.[1)]
- If we can summarize ToS, we can help people quickly understand the consequences of the agreement.

[1)] paper : [Information, Communication & Society 2018] Obar et al., The biggest lie on the internet: Ignoring the privacy policies and terms of service policies of social networking services

Target Task

Summarize ToS extractively

- Why extractive summarization?
  - ToS are legal documents that requires stringent faithfulness.
  - We believe that extractive summarization is more faithful in general than abstractive summarization.



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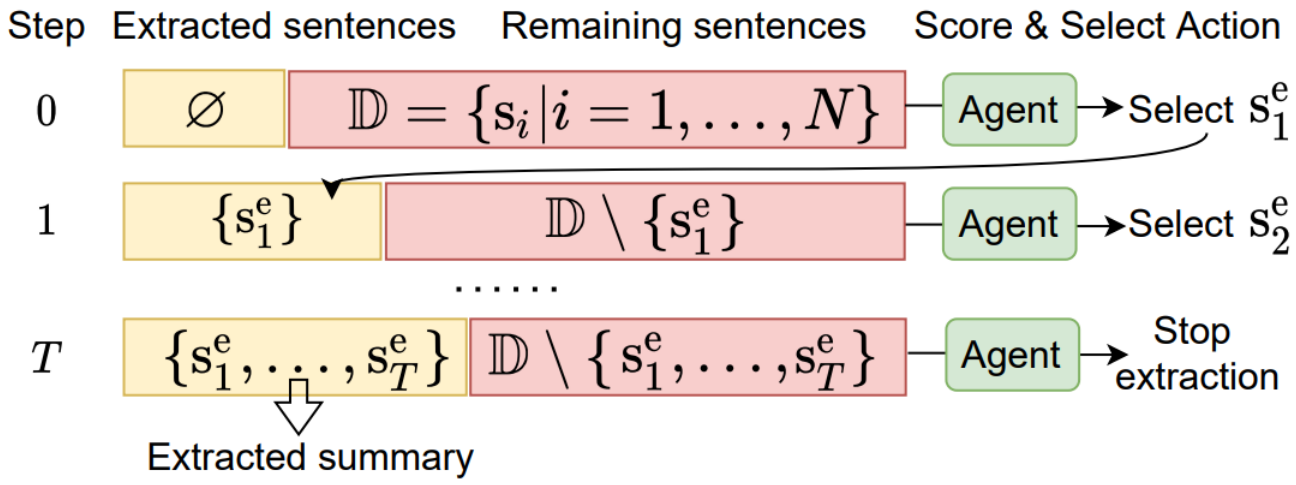
Reference Model: MemSum

- models extractive summarization as a multi-step episodic Markov decision process

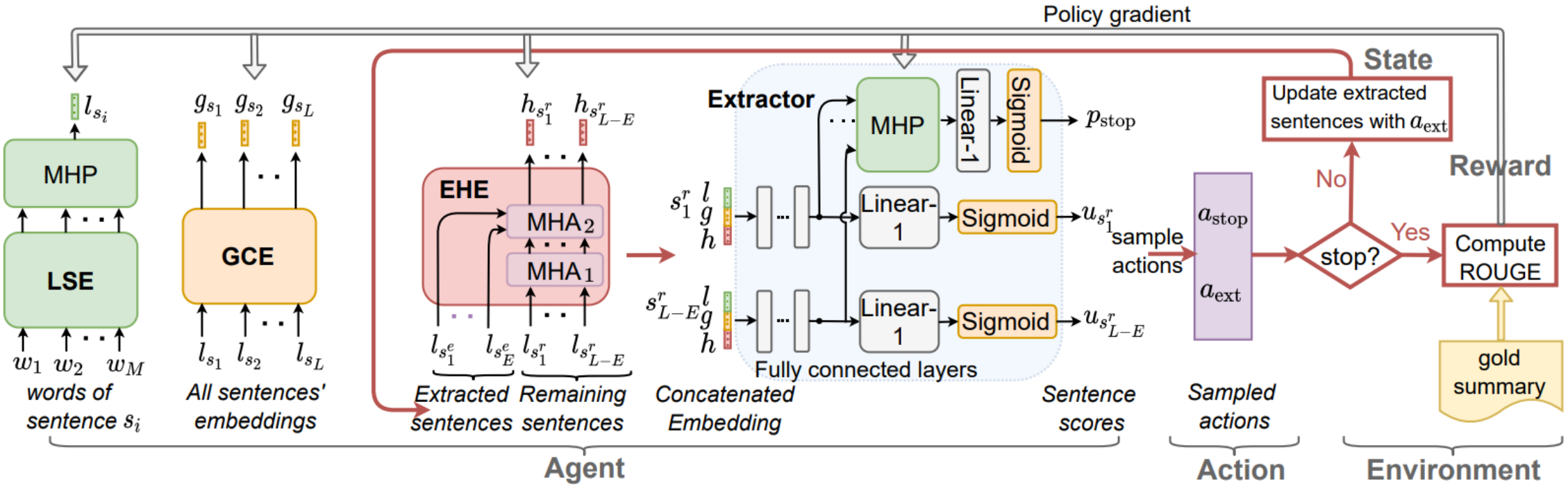
- Why MemSum?
  - MemSum reaches SotA on long, jargon-intensive documents: arXiv, PubMed, and GovReport



paper : [ACL 2022] Gu et al., MemSum: Extractive Summarization of Long Documents Using Multi-Step Episodic Markov Decision Processes
github : https://github.com/nianlonggu/MemSum

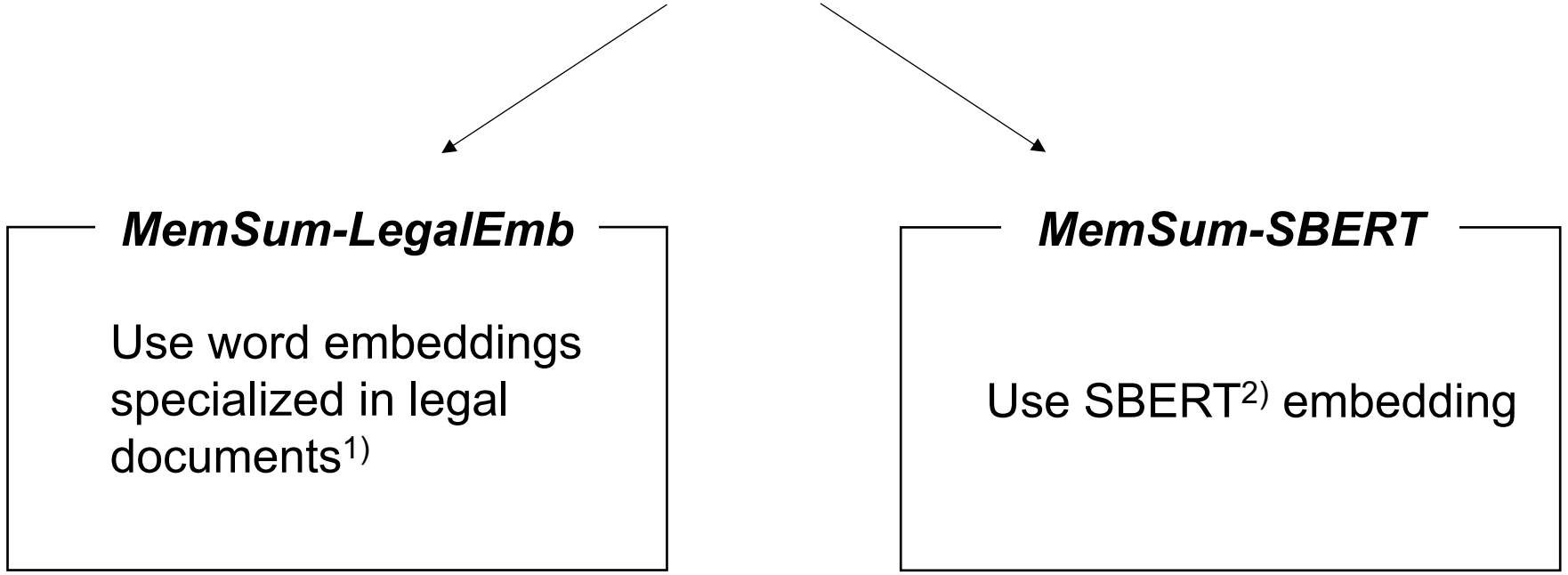
Reference Model: MemSum

Architecture



Our Method

- Improve Local Sentence Encoder (LSE)
  - MemSum originally uses Glove embeddings to represent words



[1)] paper : [2017] Sugathadasa et el., Synergistic Union of Word2Vec and Lexicon for Domain Specific Semantic Similarity
[2)] paper : [EMNLP 2019] Reimers et al., Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks

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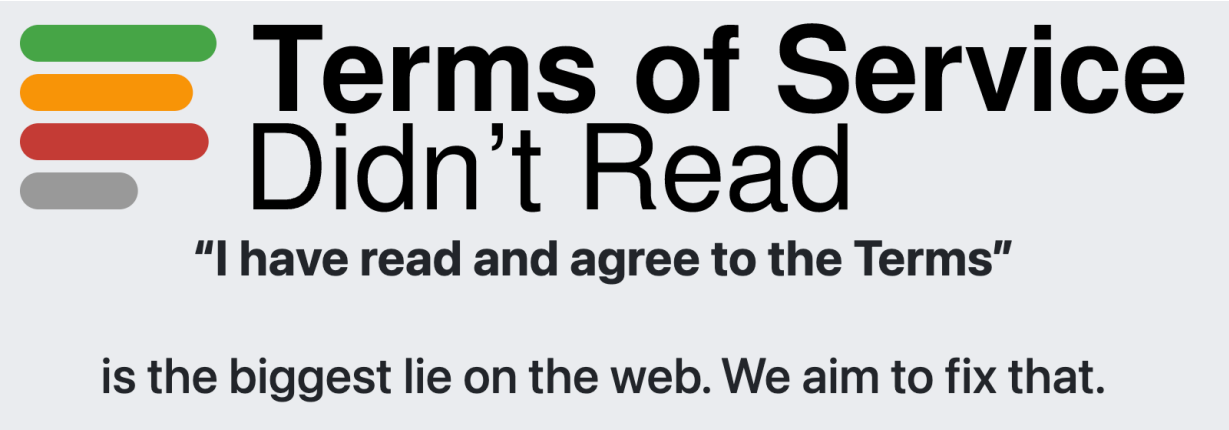
Source of Data: ToS;DR

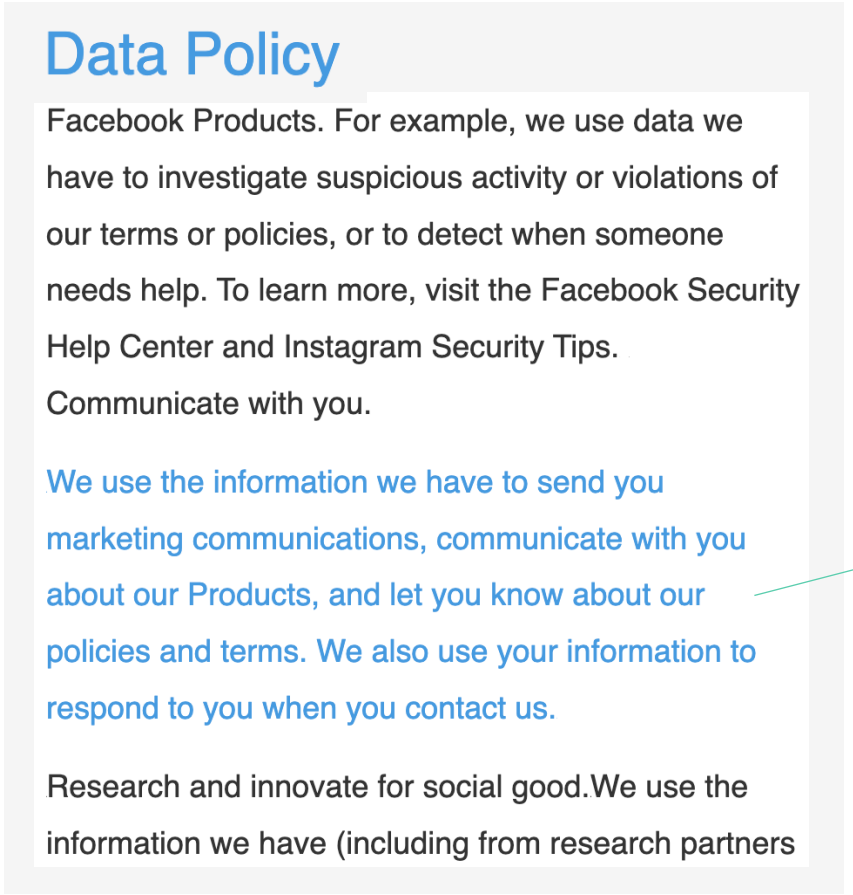


- Large online community that rates fairness and transparency of various services' ToS documents
- A contributor reviews a ToS document, marks sentences that indicate important points, and a curator approves the remark.

https://tosdr.org/en/frontpage

Annotation Example

Highlighted sentences in ToS are linked to important cases and are approved via peer review.



APPROVED

Your personal data may be used for marketing purposes.

https://edit.tosdr.org/

Dataset Construction

Reference summaries in a single ToS document:

- Gold summary
  - Sentences highlighted by ToS;DR reviewers
- Oracle summaries
  - Candidate summaries, by sequentially selecting the optimal sentence that maximally improves the average ROUGE-1/2/L score once added to the current subset of selected sentences

Avg # of sentences		Avg # of words in a sentence		Avg # of summaries	# of samples		
Original doc.	Gold summary	Original doc.	Gold summary	Oracle summary	Train	Valid	Test
222	13	17	20	4	1,611	202	201

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Experiment Design

- Traditional approaches for ToS as baseline: not reproducible
  - LDA topic modeling + TextRank[1)], LSA[2)]
  - method and experiment results are not reported (code unavailable)

- Original MemSum as baseline (***MemSum***)
  - Does our improved MemSum work for a **verified dataset (GovReport)**?
  - Does our improved MemSum work for **ToS;DR**?

- Ablation studies
  - Does **fine-tuning** from a pre-trained model work better?
  - Does using only **gold summaries as reference** during training work better?

[1)] https://github.com/cagaray/tos-summarization
[2)] https://huggingface.co/spaces/ml6team/distilbart-tos-summarizer-tosdr

Evaluation on GovReport

Model	Best Epoch	GovReport		
		ROUGE-1	ROUGE-2	ROUGE-L
MemSum	50	**0.5945**	**0.2851**	**0.5668**
MemSum-LegalEmb	40	0.5935	0.2823	0.5658
MemSum-SBERT	**5**	0.5827	0.2465	0.5507

- *MemSum* is the best.
- *MemSum-LegalEmb* shows comparable performance.
- *MemSum-SBERT* approaches the baseline performance **even after training for only 5 epochs**.

Evaluation on ToS;DR

Model	ToS;DR		
	ROUGE-1	ROUGE-2	ROUGE-L
MemSum	0.4075	0.2598	0.3937
MemSum-LegalEmb	0.4141	0.2705	0.4001
MemSum-SBERT	**0.4244**	**0.2732**	**0.4111**

Both of our models **outperform** the baseline!

Transferability from GovReport to ToS;DR

Model	Train	Best Epoch	ToS;DR		
			ROUGE-1	ROUGE-2	ROUGE-L
MemSum	ToS;DR	10	0.4075	0.2598	0.3937
	GovReport → ToS;DR	5	0.4076	0.2617	0.3941
MemSum-LegalEmb	ToS;DR	10	0.4141	0.2705	0.4001
	GovReport → ToS;DR	4	0.4088	0.2662	0.3952
MemSum-SBERT	ToS;DR	5	0.4244	0.2732	0.4111
	GovReport → ToS;DR	4	0.4178	0.2631	0.4034

After fine-tuning,

- All models have reached peak performance in earlier training epochs.
- Both of our models show lower scores than before.

Fine-tuned models may converge to the local optimum rather than the global optimum.

Choice of Reference Summaries for Training

Model	Reference Summaries	ToS;DR		
		ROUGE-1	ROUGE-2	ROUGE-L
MemSum-SBERT	Gold	0.4168	0.2597	0.4026
MemSum-SBERT	**Gold + Oracle**	**0.4244**	**0.2732**	**0.4111**

Using both gold and oracle summaries as reference summaries are better than just using gold summaries

- because of improved robustness
- (… or just by chance)

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Conclusion

- To ease the difficulty of reading long terms of service documents, we propose a task of extractively summarizing ToS and construct a ToS;DR dataset for it.
- We improve the reference model, MemSum, by utilizing 1) legal-specific word embeddings and 2) a Transformer-based architecture to encode sentences.
- Both of our methods beat the original MemSum model on the ToS;DR dataset.