NAACL 2024

RST-LoRA: A Discourse-Aware Low-Rank Adaptation for Long Document Abstractive Summarization

Dongqi Pu, Vera Demberg

Department of Computer Science
Department of Language Science and Technology
Saarland Informatics Campus, Saarland University, Germany
dongqi.me@gmail.com

UNIVERSITÄT DES SAARLANDES

European Research Council
Established by the European Commission

TL;DR

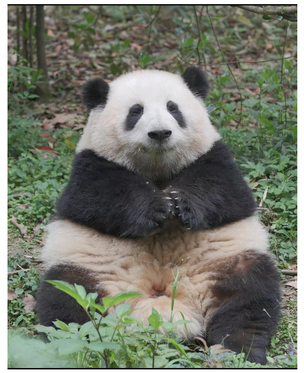
RST-LoRA improves long document summarization by integrating **rhetorical structure theory** into the LoRA model, outperforming previous methods.

Motivation

- Why do we need **low-rank** approximation?
- Why do we need **discourse** knowledge?

Motivation

- Why do we need low-rank approximation?
  - Model size ↑ 👉🏻 software and hardware ↑



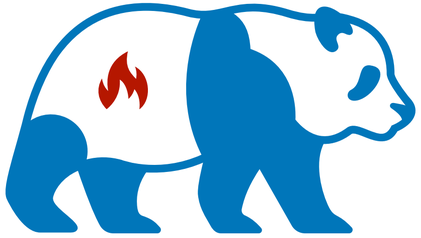
M

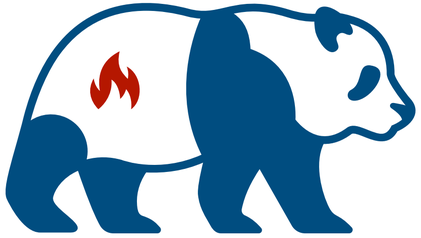
Pre-trained model

Fine-tuning

Fine-tuning

N Tasks





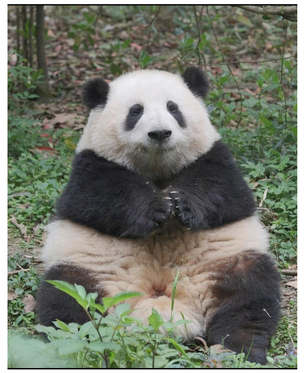
Fine-tuned model_1 ····· Fine-tuned model_n

Vanilla full-parameter fine-tuning (FFT)

$N \times M$

Motivation

- Why do we need low-rank approximation?
  - Model size ↑ 👉🏻 software and hardware ↑



M

Pre-trained model

Fine-tuning

Fine-tuning

N Tasks

m

m

Fine-tuned model_1 ····· Fine-tuned model_n

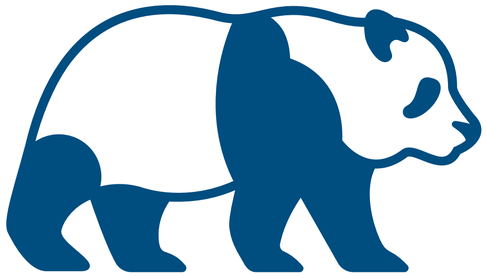
Parameter-efficient fine-tuning (PEFT)

$$N \times m + M$$

Motivation

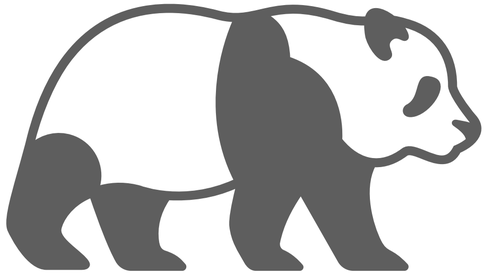
- Why do we need low-rank approximation?
  - Model size ↑ 👉🏻 software and hardware ↑
  - Only 0.01–1% of the parameters, PEFTs ≈ FFT

$N\times$



⩔

$N\times$ 🦋 $+$

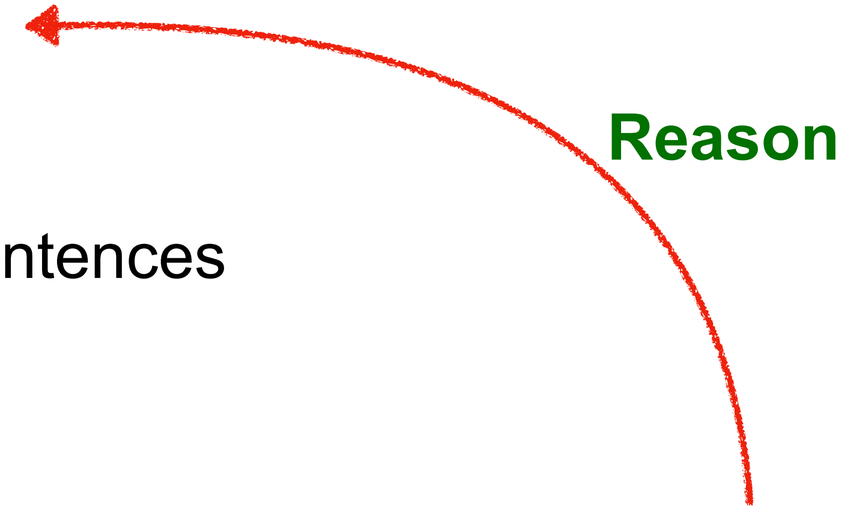


FFT vs PEFT

Motivation

- Why do we need discourse knowledge?
  - Challenges in PEFTs
    - Latent text relations
    - Importance level of different sentences

Ghazvininejad et al. (2022); Zhao et al. (2023)



EPFTs are not driven or guided by discourse knowledge during the training phase, as this is not explicitly present in the input data.

RST Prerequisite

- Rhetorical Structure Theory (RST) is helpful for determining:
  - Which sentences **should or should not** be included in the summary
    - Sentences relations
    - Discourse importance level

RST Prerequisite

- **EDU1** is the most pivotal component
- **EDU2** provides information for **EDU3**
  - It is not a problem to delete EDU2
  - It is still fine to delete both EDU2 and 3

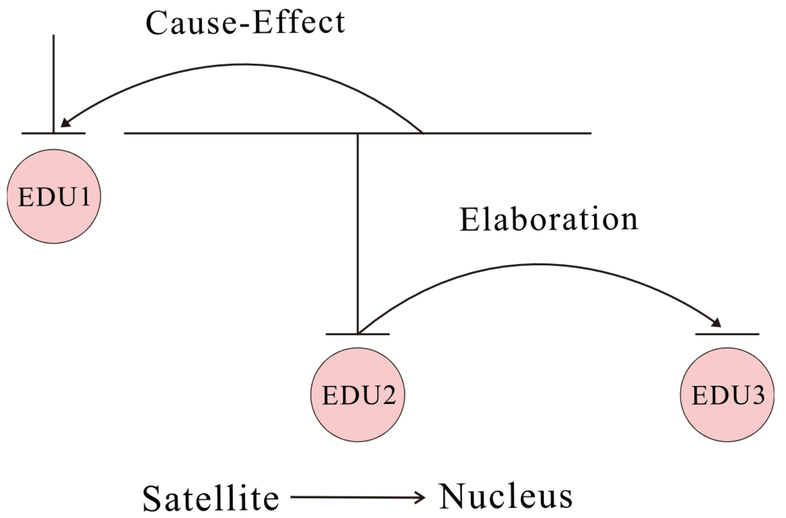


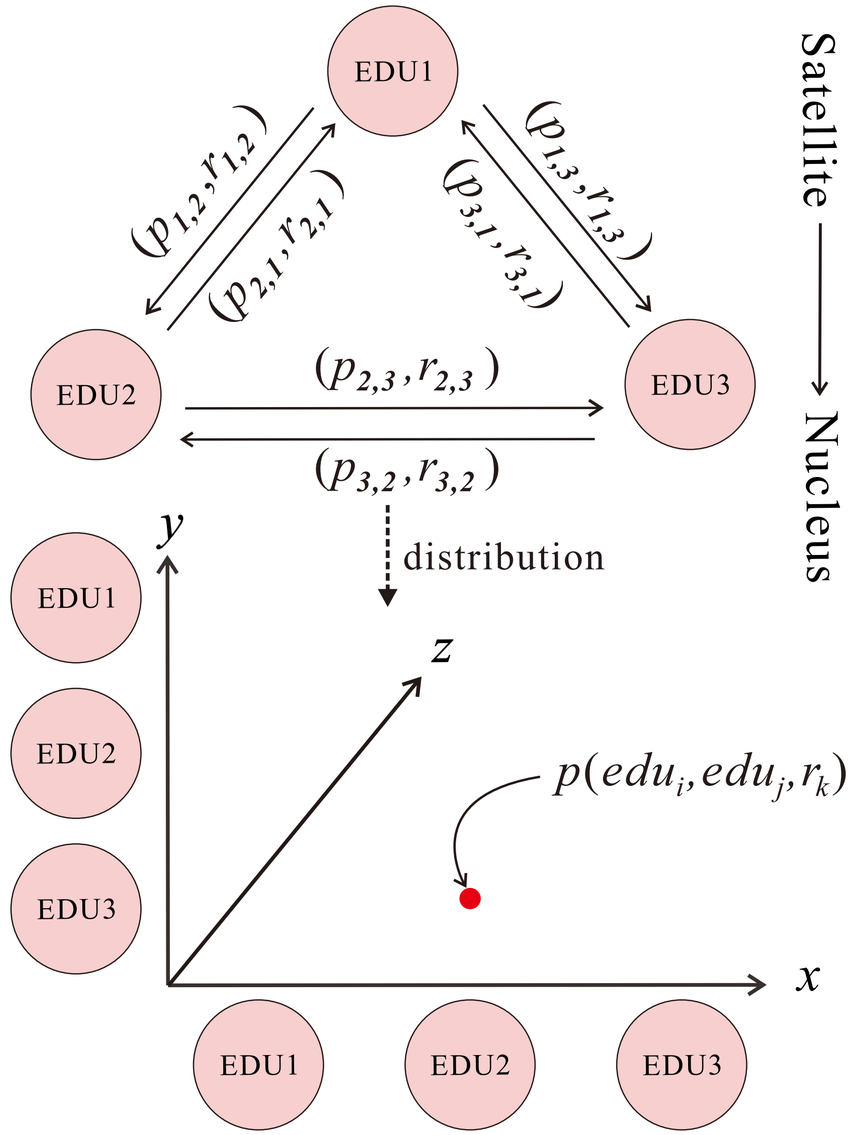
Figure 1: An example of RST tree: [*Utilizing discourse structure to enhance text summarization is beneficial.*]$^{\mathrm{EDU1}}$ [*This technique can be used to identify key ideas and capture often overlooked nuances.*]$^{\mathrm{EDU2}}$ [*Accurate capture of these complex structures facilitates the generation of good summaries.*]$^{\mathrm{EDU3}}$

Our Method

- RST Distribution
- RST-Aware Injection

Our Method

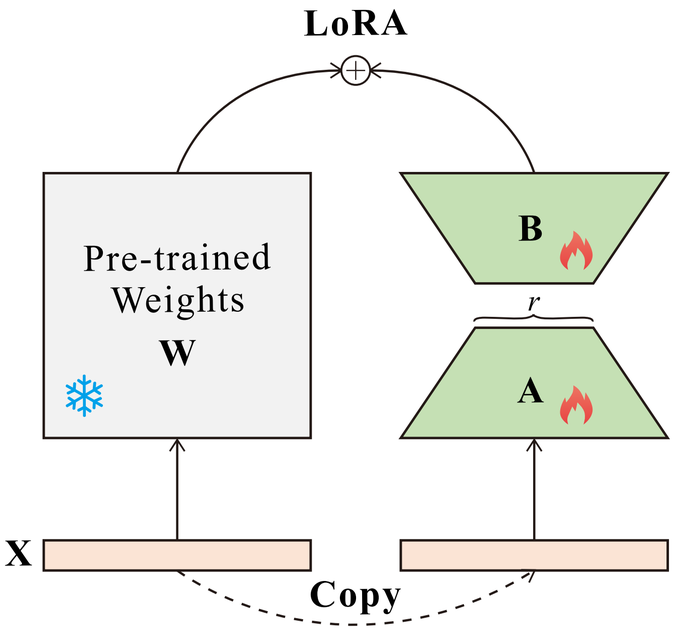
- RST Distribution
  - Each point indicates the probability value $p(edu_i, edu_j, r_k) \in [0,1] \subseteq \mathbb{R}$ that edu_i is the nucleus of edu_j with discourse relation r_k. (Pu et al., ACL 2023)
  - We average and merge the y-axis of the matrix, and the merged value $c(edu_i, \overline{edu_j}, r_k)$ is called the importance index of edu_i with relation r_k.

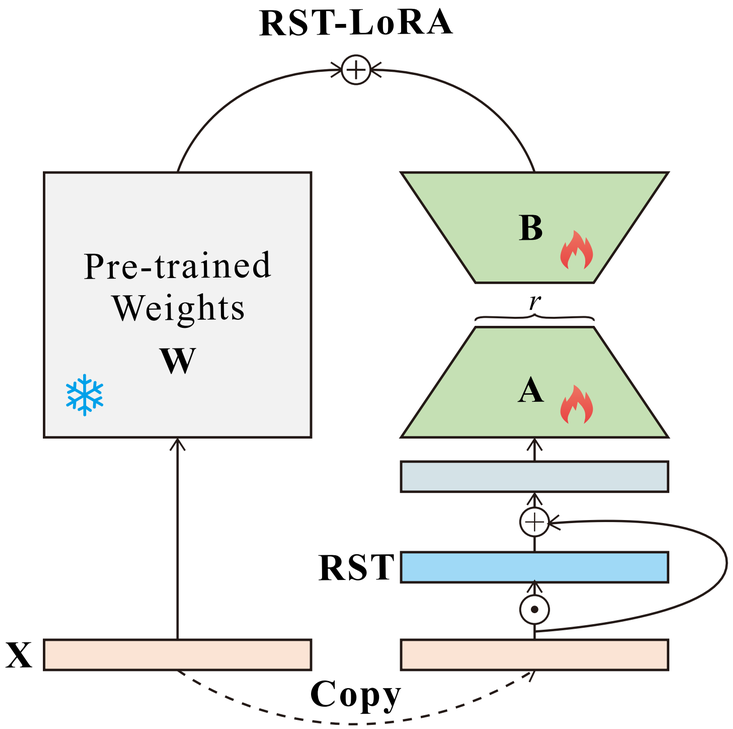


Our Method

- RST Distribution (4 variants)
  - RST^{b}_{wo}: Binary, label-agnostic representation (1 or 0)
  - RST^{b}_{w}: Binary distribution with relation labels
  - RST^{p}_{wo}: Label-omitted probabilistic representation
  - RST^{p}_{w}: Most fine-grained representation with relation types and probabilities

Our Method





RST

- RST-Aware Injection
  - $h \leftarrow h + X(W_{A\times r}^{down} W_{r\times B}^{up})$ (vanilla LoRA)
  - $h \leftarrow h + [(X \odot (1+\gamma))(W_{A\times r}^{down} W_{r\times B}^{up})$ (ours)

Experiments

- Experimental Settings
  - Datasets
  - Parser
  - Metrics
  - Training and Inference

Experiments

- **Datasets**
  - Multi-LexSum (ML, Shen et al., 2022)
  - eLife (Goldsack et al., 2022)
  - BookSum Chapter (BC, Kryscinski et al., 2022)

Experiments

- **Parser**
  - DMRST (Liu et al., 2020, 2021).
  - Extracting probabilities and type labels from final logits layer

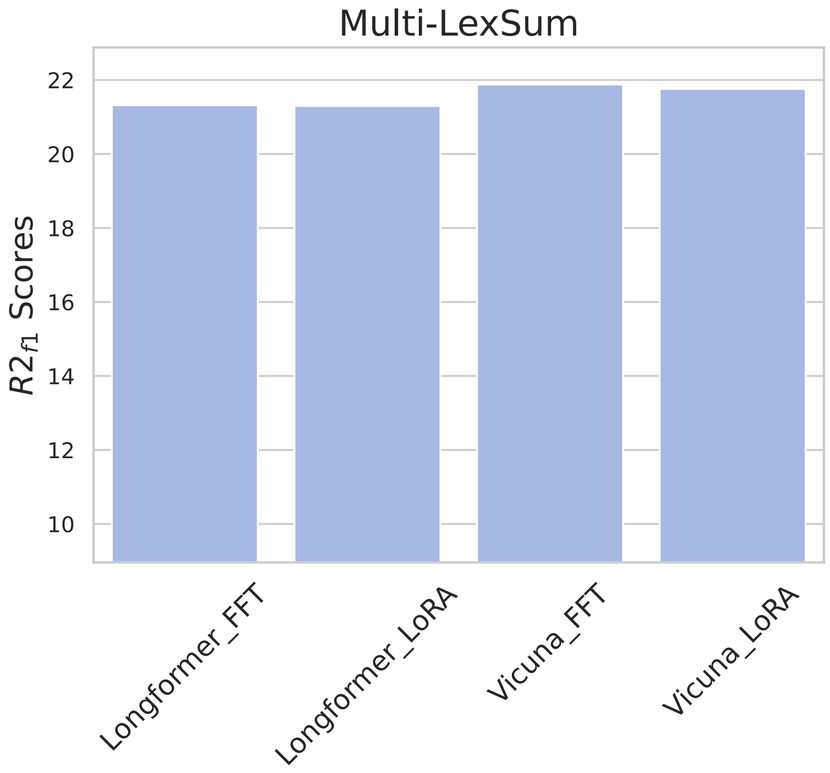
Experiments

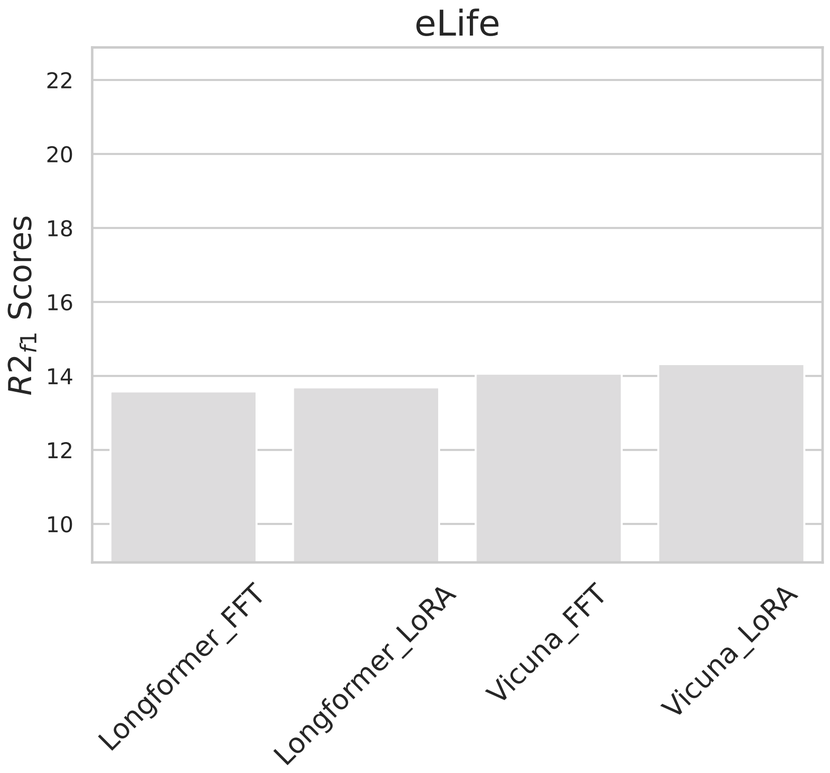
- **Metrics**
  - F1 scores of Rouge-1 (R1), Rouge-2 (R2), Rouge-L (RL), and Rouge-Lsum (RLsum) (Lin, 2004)
  - BERTScore (Zhang et al., 2020)
  - METEOR (Banerjee and Lavie, 2005)
  - sacreBLEU (Post, 2018)
  - NIST (Lin and Hovy, 2003)

Experiments

- **Training and Inference**
  - Backbones
    - Longformer (Beltagy et al., 2020) 👉🏻 Seq2Seq
    - Vicuna13B-16k (Zheng et al., 2023) 👉🏻 GPT
  - Baselines
    - Backbones w/ FFT
    - Backbones w/ LoRA
    - GPT-4 (in-context learning)
  - Other SOTAs

Main Results





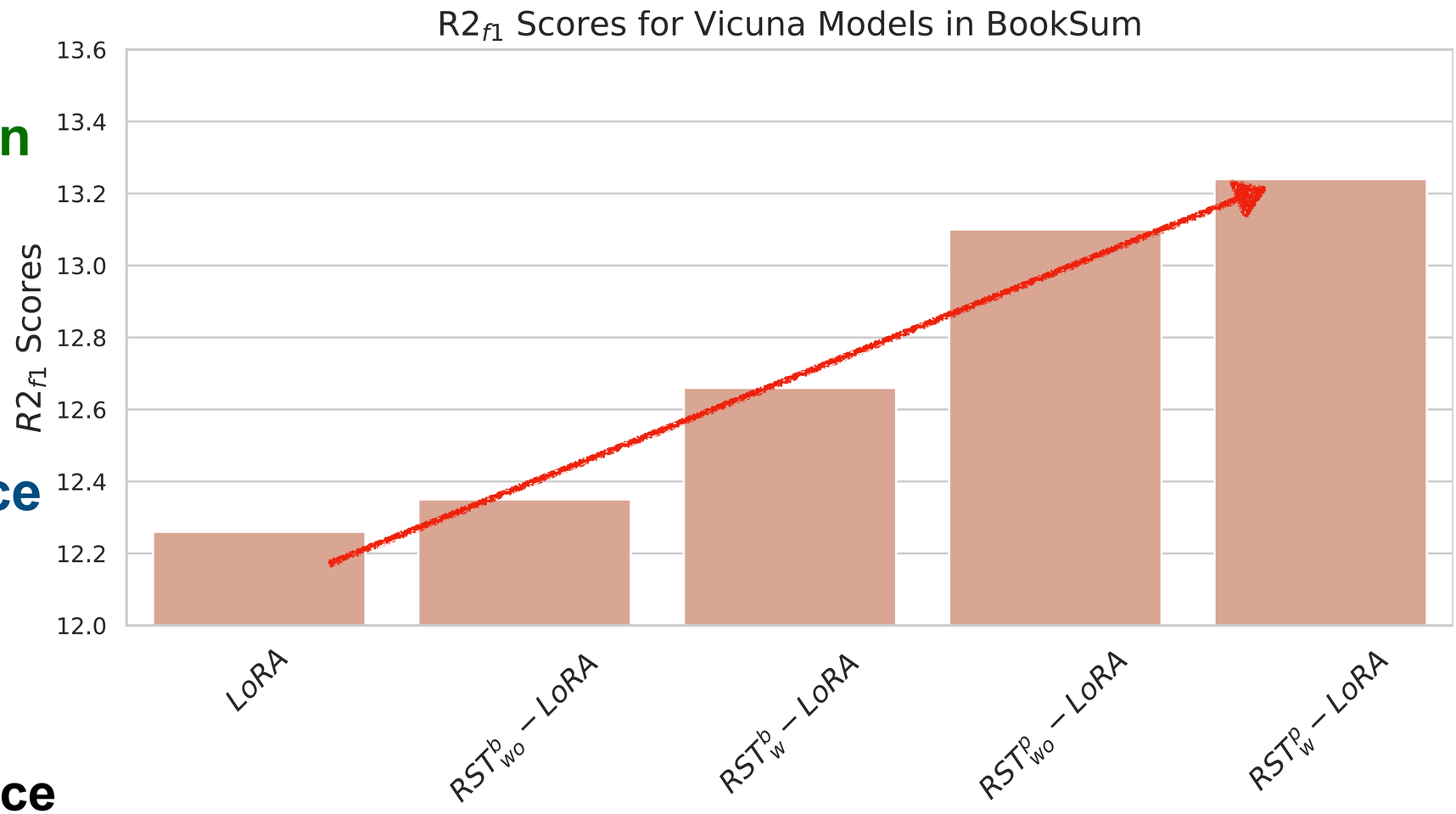
LoRA vs. FFT: Comparable, more efficient

RST variant performance

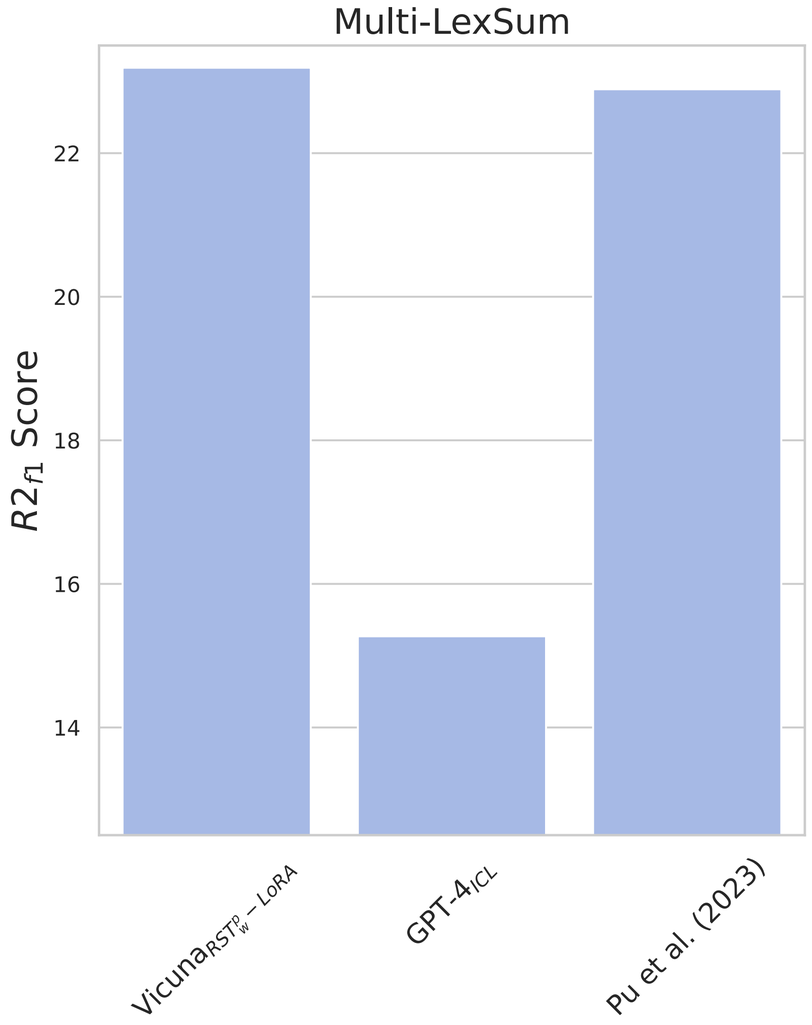
- **Label integration**
- **Uncertainty consideration**

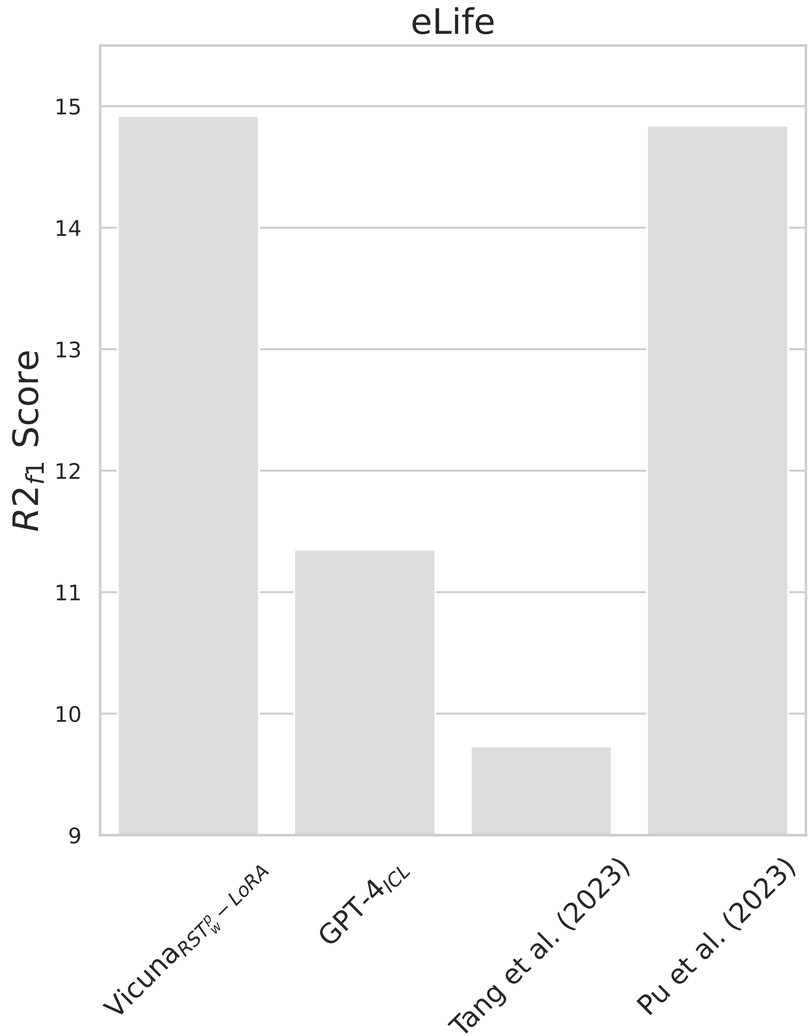
Both complementarily enhance model performance

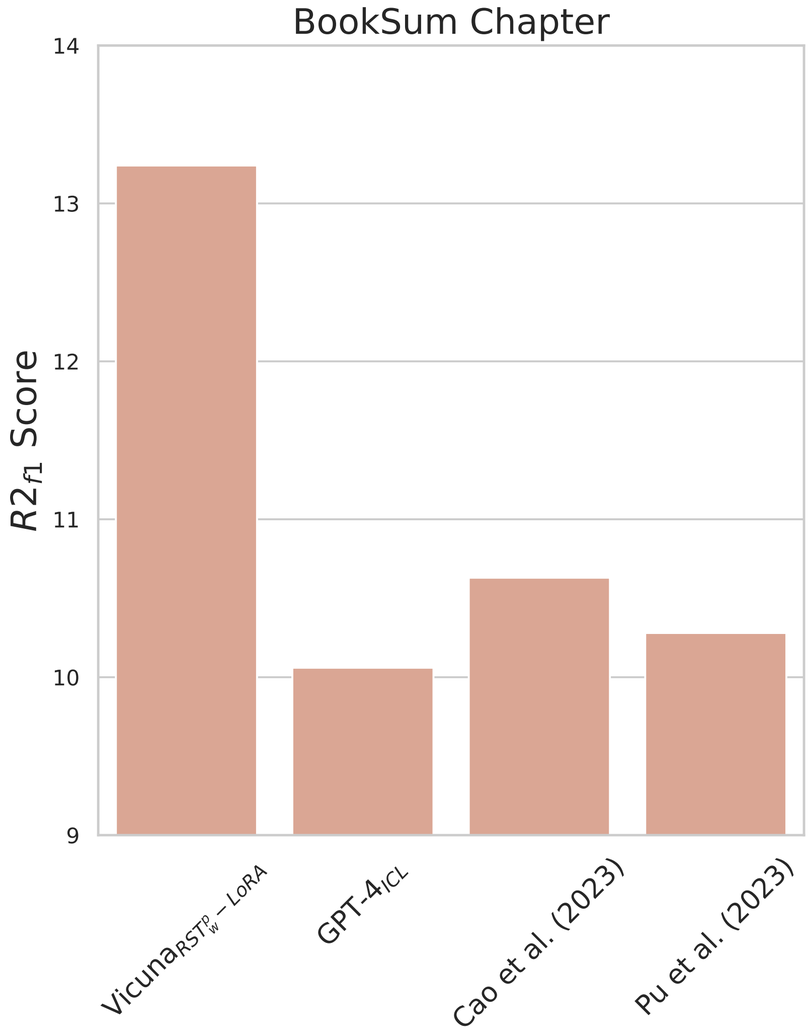
RST^{p}_{w}-LoRA: Best performance



Our best model vs GPT-4 and SOTAs



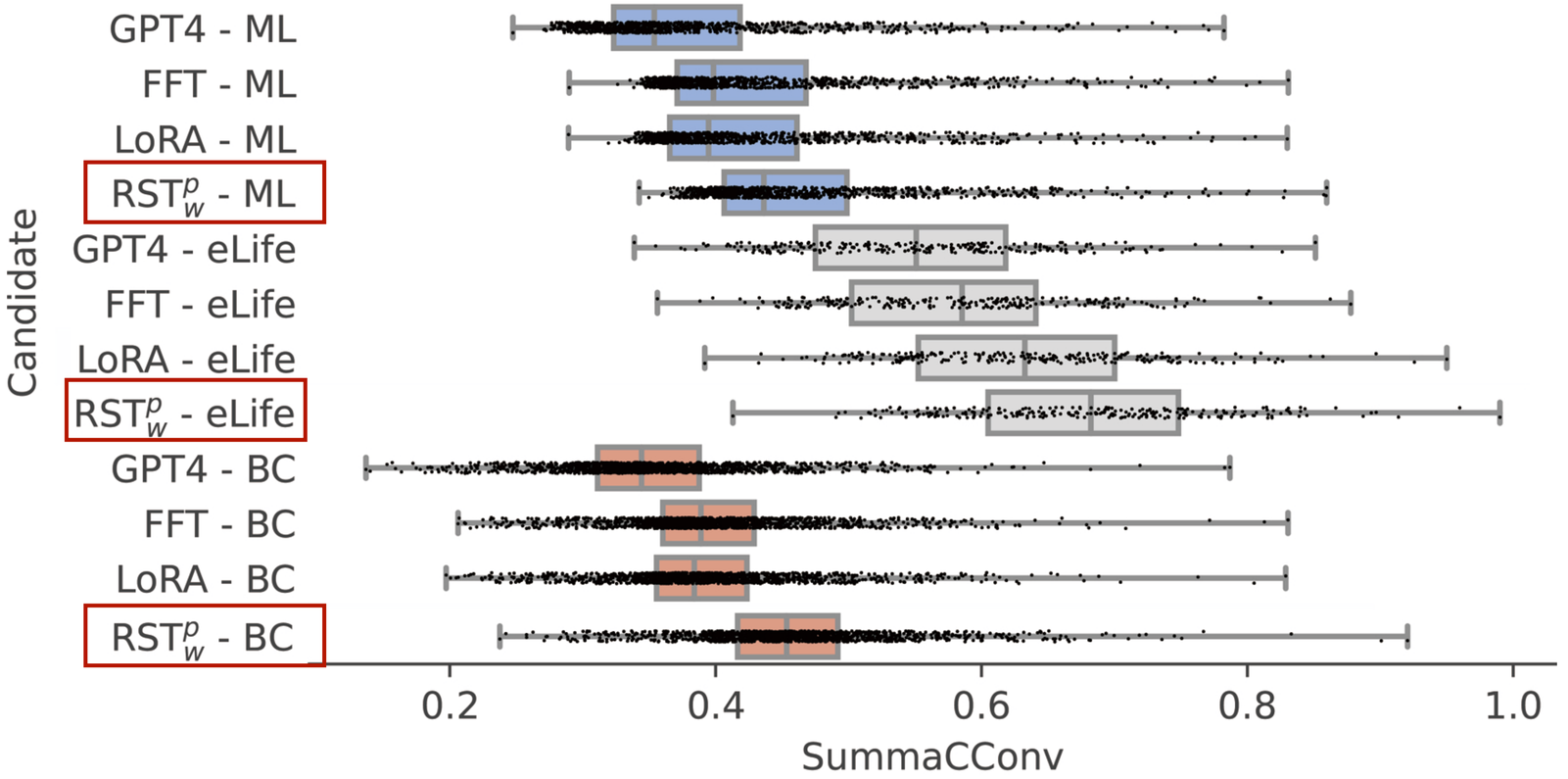




Hallucination Checking

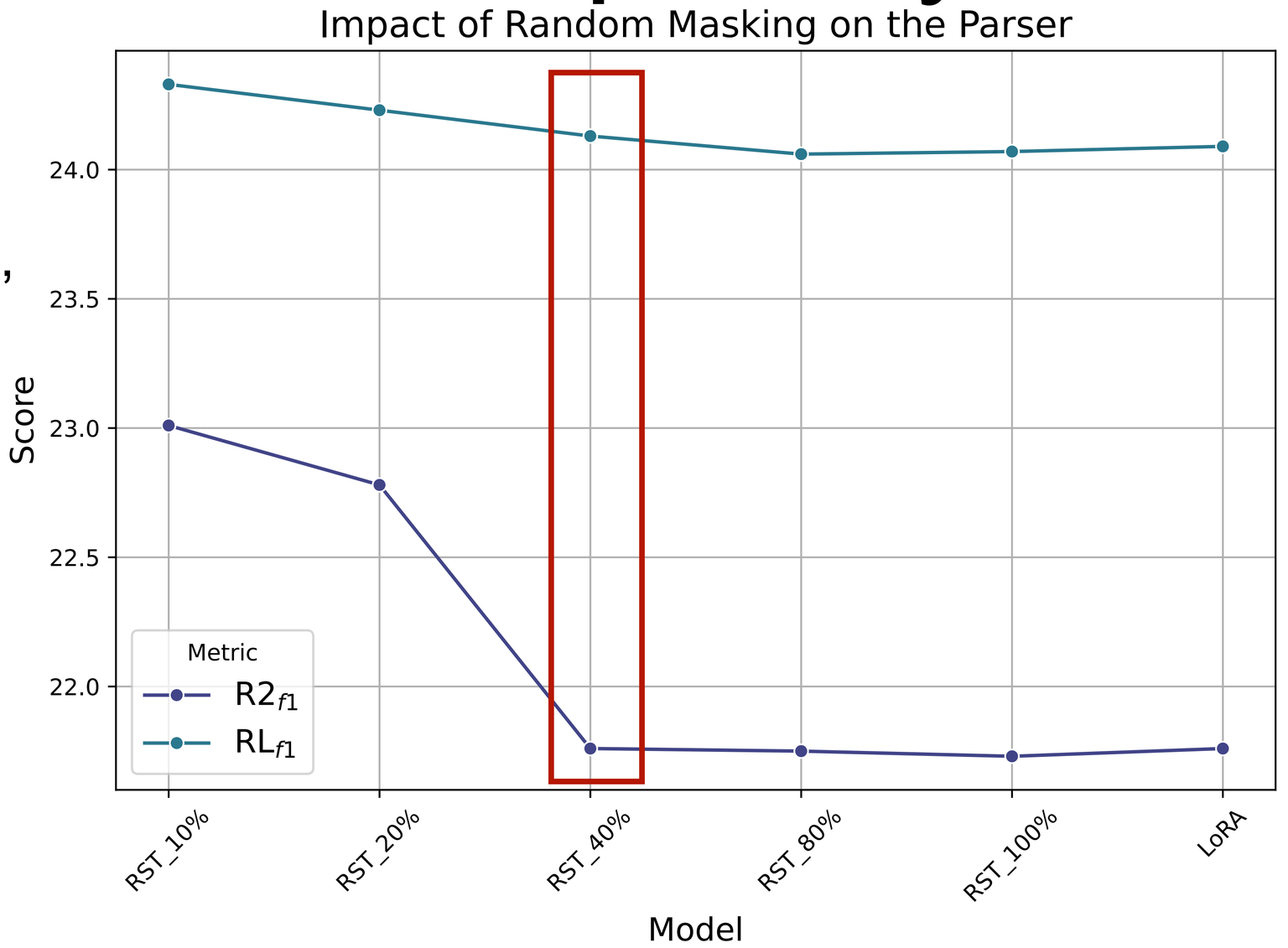
SummaC testing: 0-1 score range

- **GPT-4:** Weakest consistency
- **RST enhances LoRA:** Reduces hallucinations

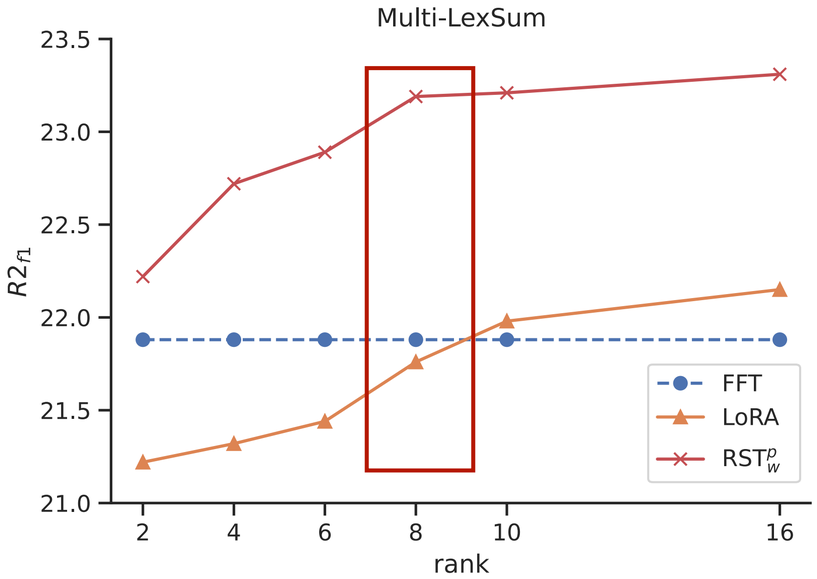


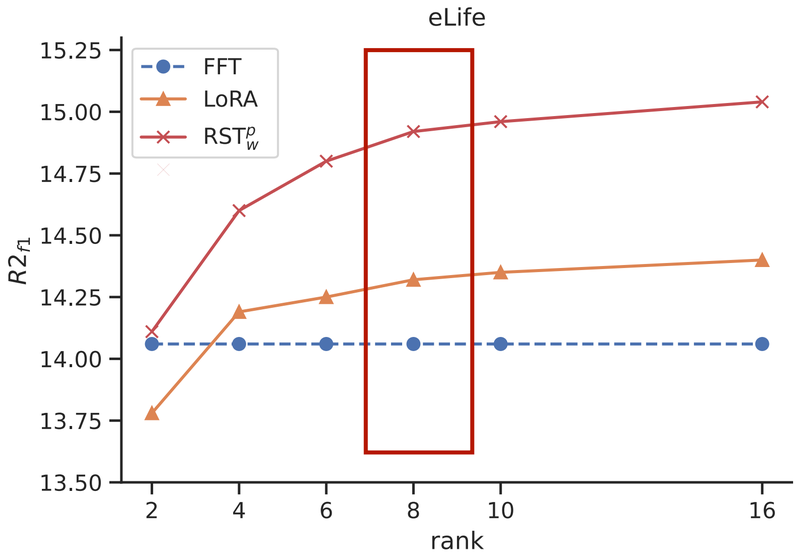
Impact of Parser Capability

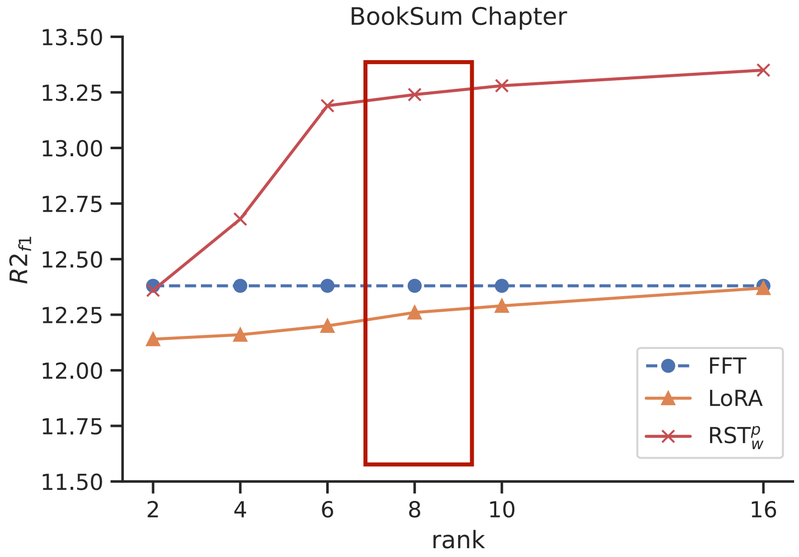
- **Parser impact test:** 10%, 20%, 40%, 80% masking
- **Vicuna backbone:** Multi-LexSum dataset
- **Performance declines:** >40% noise



Impact of Different Rank r



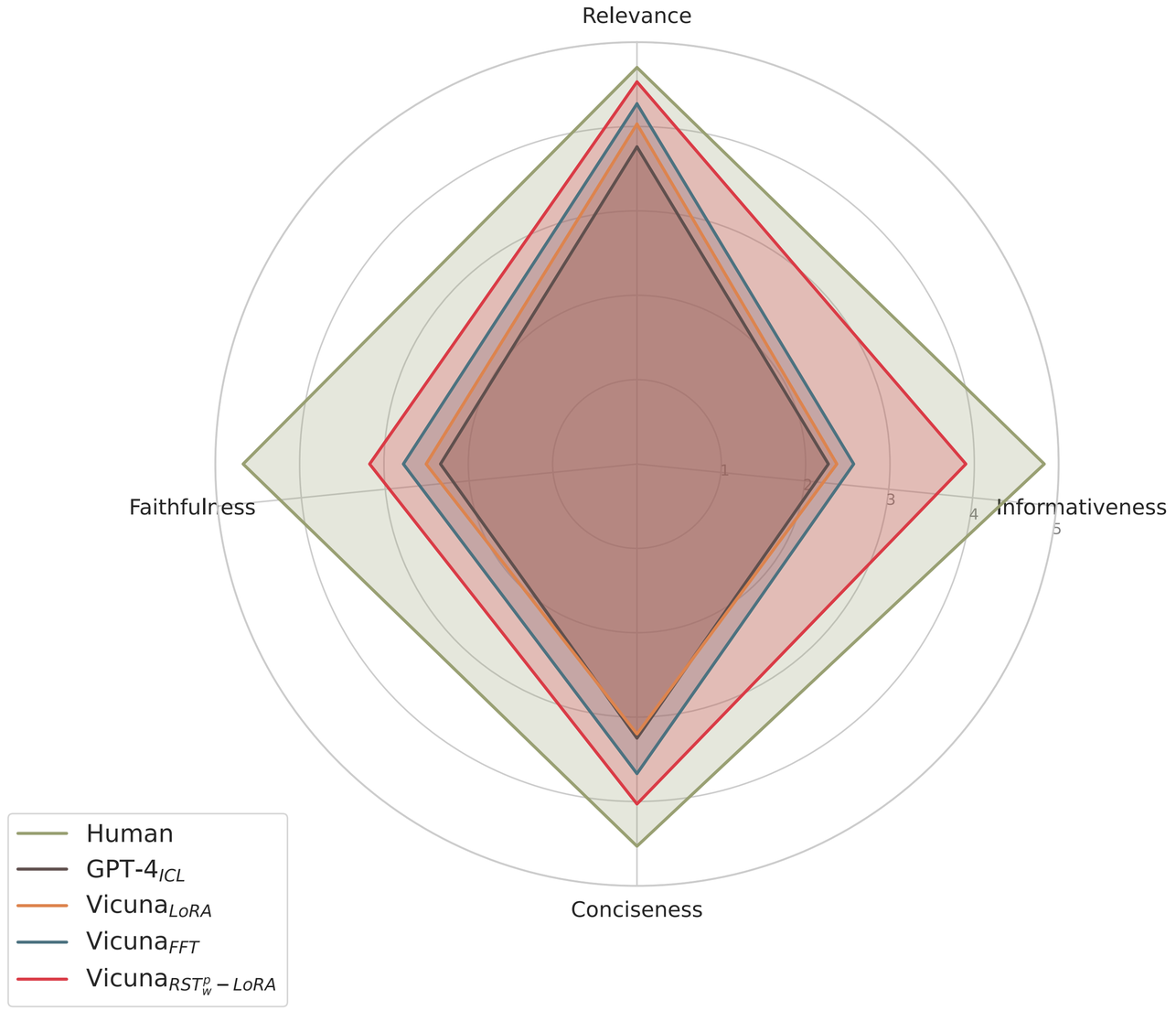




$r = 8$ is a trade-off point between performance gain and computational cost

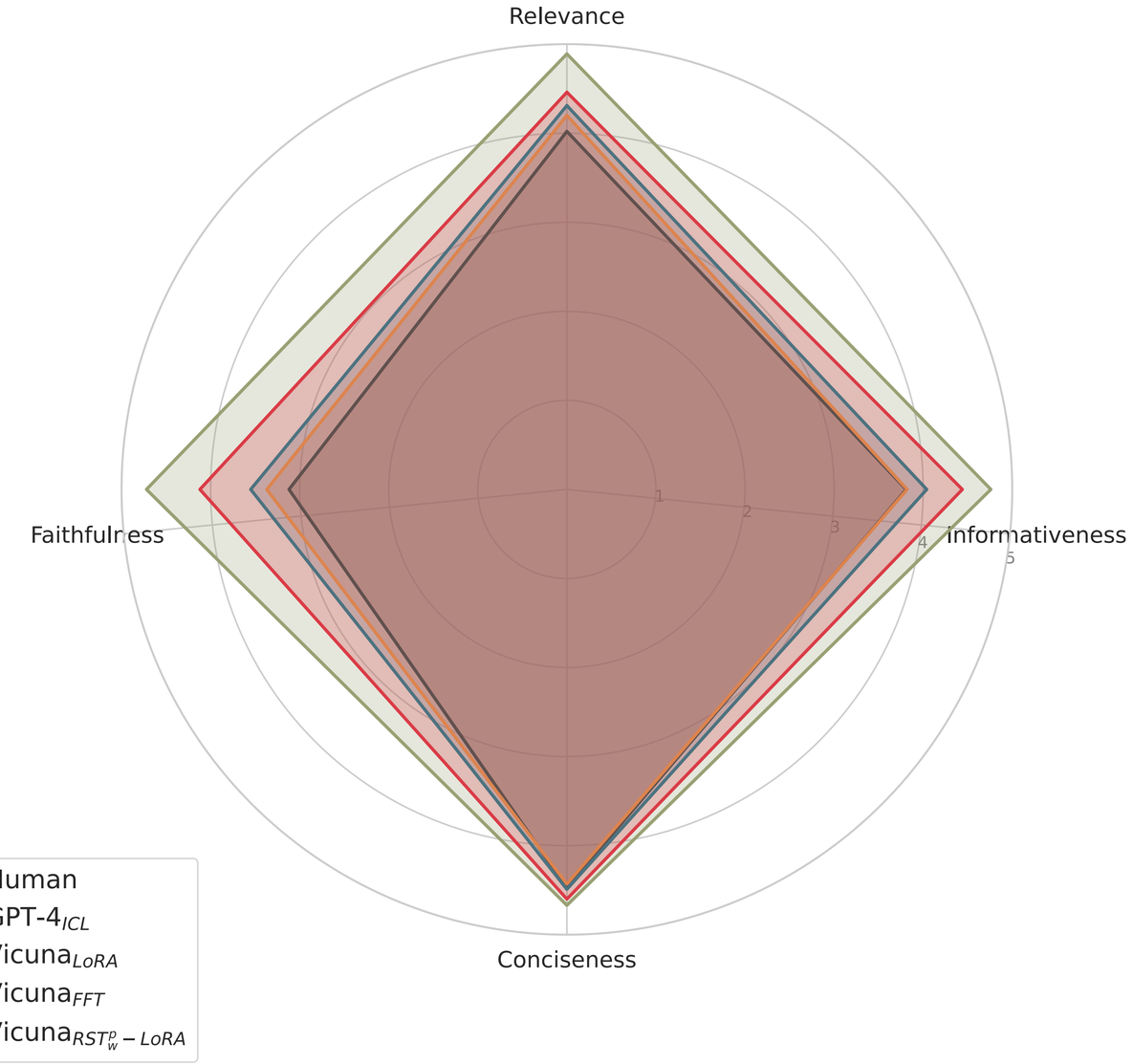
Human Evaluation

- **Human evaluation:** BookSum, 10 instances
- **Evaluators:** CL/CS Graduate candidates, blind test
- RST^{p}_{w}**-LoRA:** Highest neural model performance



GPT-4 Evaluation

- **GPT-4 self-evaluation:** Lowest scores to own answers
- RST_w^p**-LoRA:** more closer to the quality of human-generated summaries



Conclusion

- A method for injecting **discourse knowledge** into the training of LoRA model.
- Discourse uncertainty and relation labels are **complementarily**.
- Our model **outperforms** current SOTA models in specific evaluation metrics.

More Info

- **Data & Code:** https://donggi.me/projects/RST-LoRA
- **Questions:** donggi.me@gmail.com

Thanks for listening

Q&A

European Research Council

Established by the European Commission

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 Research and Innovation Programme (Grant Agreement No. 948878)