

Clinical Text Summarization: Adapting Large Language Models Can Outperform Human Experts



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Abstract

Motivation

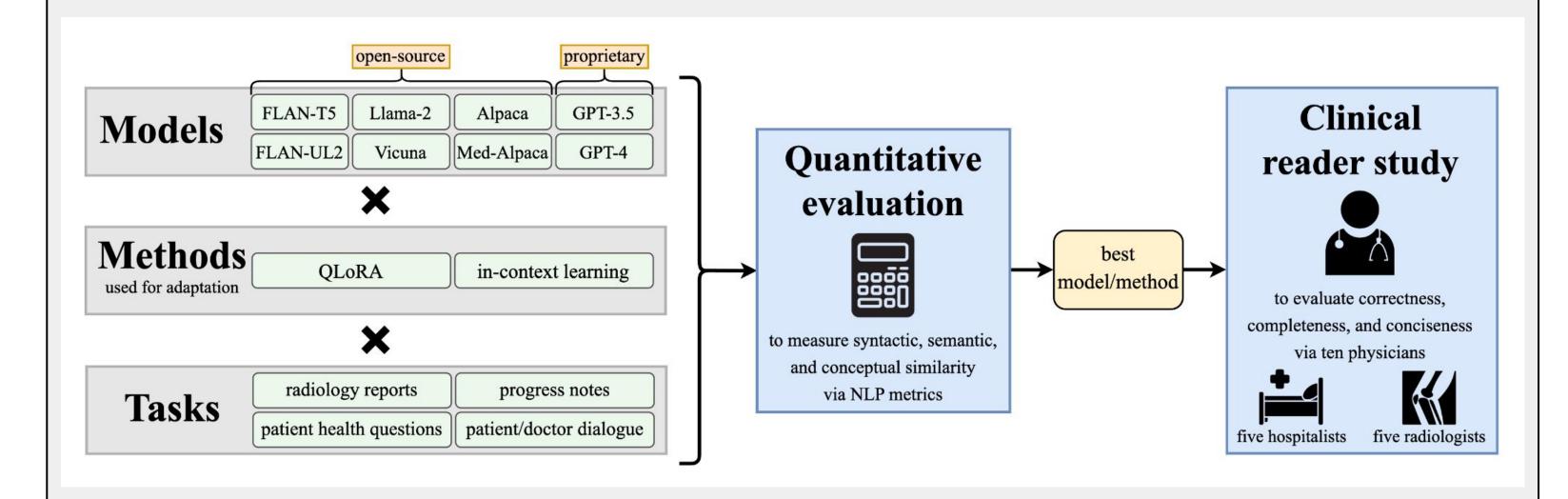
- Summarizing key information from electronic health records (EHR) imposes a substantial burden on how clinicians allocate their time.
- Large language models (LLMs) do well on general natural language processing (NLP) tasks, but their efficacy on summarizing clinical text has not been demonstrated.

<u>Outcome</u>

- Our research marks the first evidence of LLMs outperforming human experts for clinical text summarization.
- This implies that integrating LLMs into clinical workflows could alleviate documentation burden, enabling clinicians to focus more directly on patient care.

Overview 1

First, we quantitatively evaluate each valid combination (×) of LLM and adaptation method across four distinct summarization tasks comprising six datasets. We then conduct a clinical reader study in which ten physicians compare summaries of the best model/method against those of a human expert.

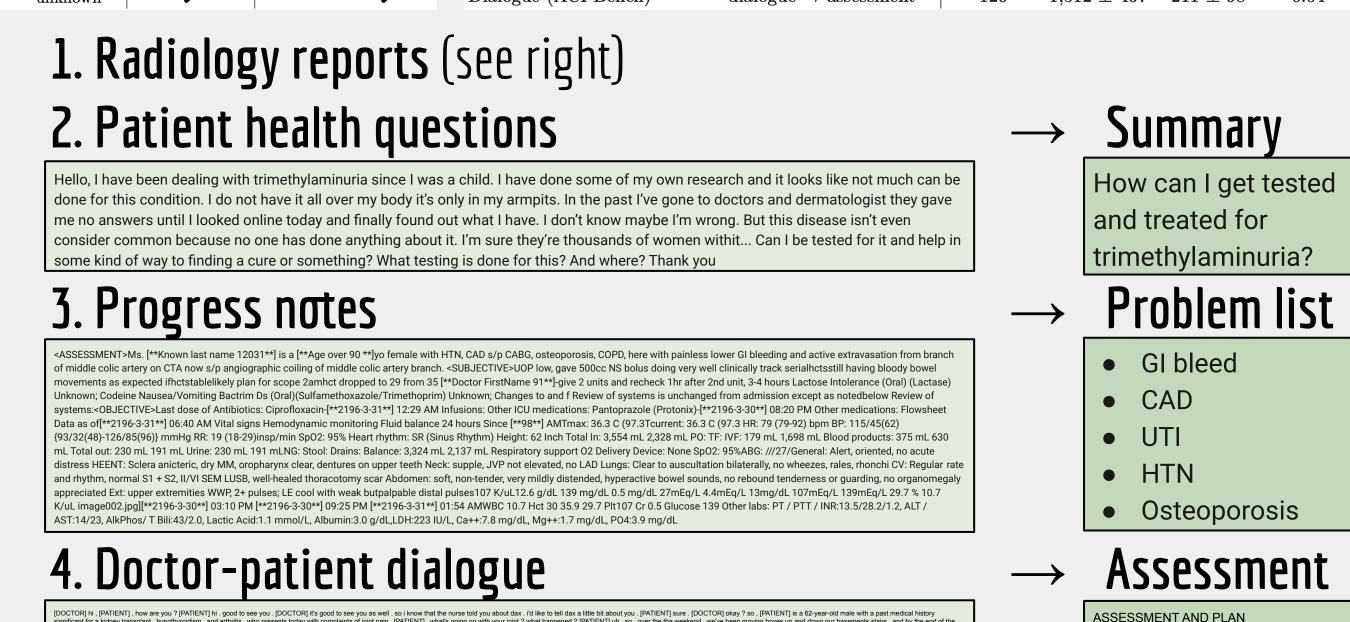


Approach

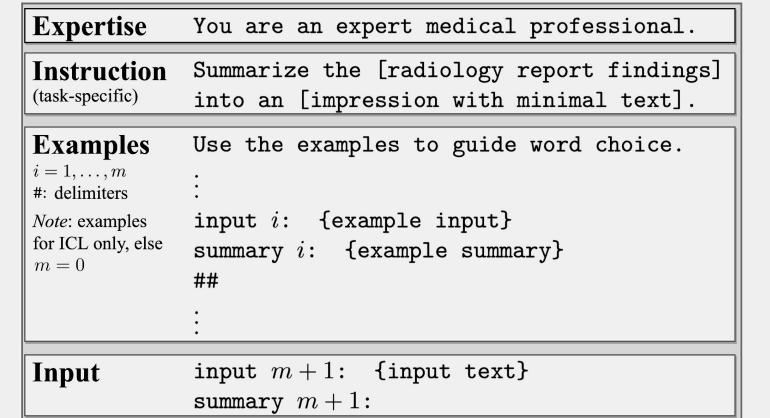
We compare two methods—quantized low-rank adaptation (QLoRA) and in-context learning (ICL)—for adapting eight models (**left**) to four summarization tasks (**right**).

Model	Context	Parameters	Proprietary?	Seq2seq	Autoreg.			Number	Avg. numbe	er of tokens	Lexica
FLAN-T5	512	2.7B	-	~		Task (Dataset)	Task description	of samples	Input	Target	variance
FLAN-UL2	2,048	20B	-	·		Radiol. reports (Open-i)	$\overline{\text{findings}} \rightarrow \overline{\text{impression}}$	3.4K	52 ± 22	14 ± 12	0.11
Alpaca	2,048	$7\mathrm{B}$	-	-	•	Radiol. reports (MIMIC-CXR)	0 1	128K	75 ± 31	22 ± 17	0.08
Med-Alpaca	2,048	$7\mathrm{B}$	-	-	•	Radiol. reports (MIMIC-III)	$findings \rightarrow impression$	67K	160 ± 83	61 ± 45	0.09
Vicuna	2,048	$7\mathrm{B}$	=	-	✓	- \	0	COUNTY ACCIONS			
Llama-2	4,096	7B, 13B	=	_	~	Patient questions (MeQSum)	$verbose \rightarrow short question$	1.2K	83 ± 67	14 ± 6	0.21
GPT-3.5	16,384	175B	✓	<u>,-</u>	~	Progress notes (ProbSum)	$notes \rightarrow problem list$	755	$1,013 \pm 299$	23 ± 16	0.15
GPT-4	32,768	unknown	/	_	✓	Dialogue (ACI-Bench)	$dialogue \rightarrow assessment$	126	1.512 ± 467	211 ± 98	0.04

Task examples



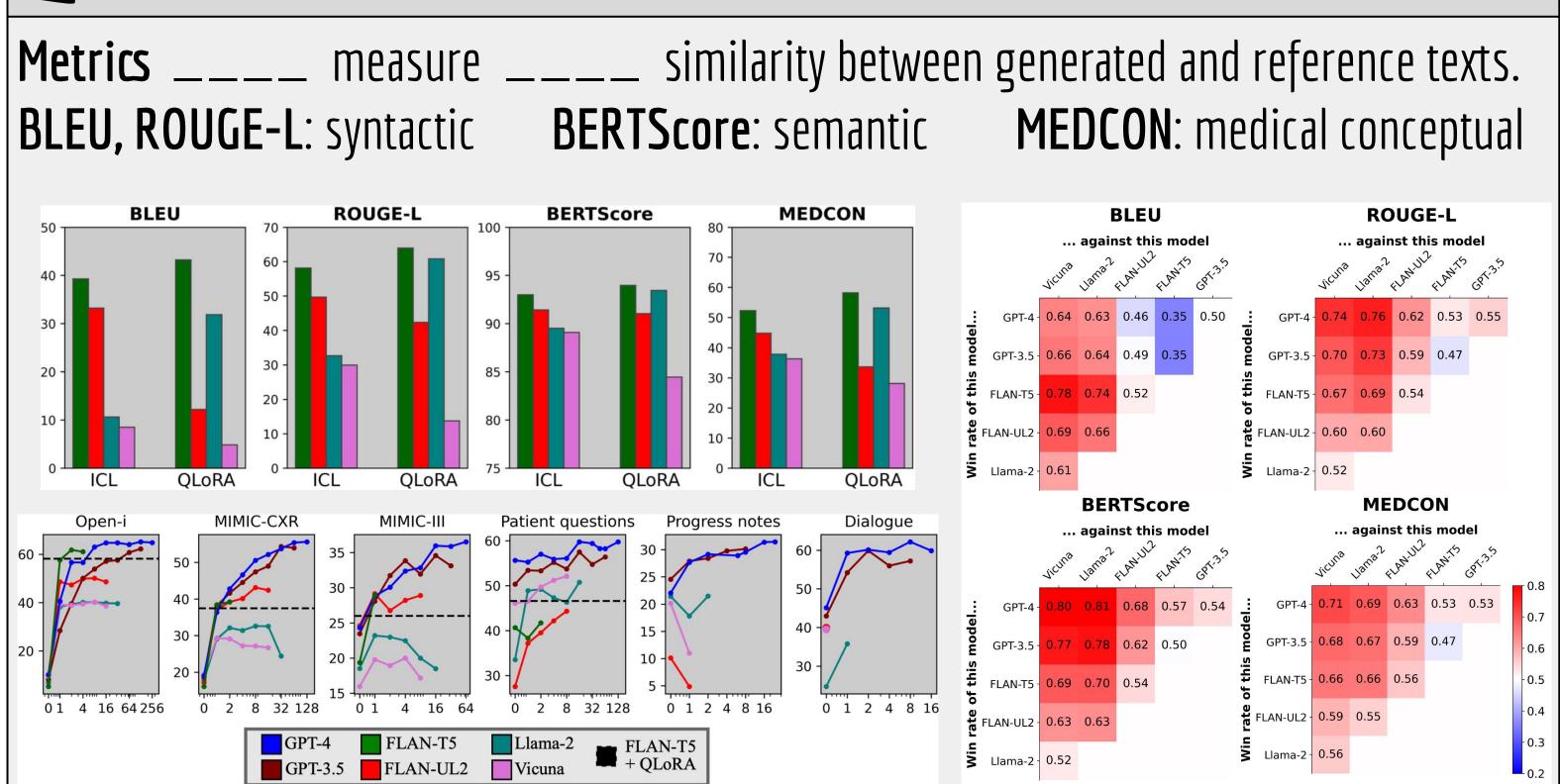
Prompt Anatomy



symby mises were job. Cort Ork of a vary. Is, so the was not extend to the past unit in the last of patients, in the was a petition and the weight of the boxes. [DOCTOR] okay, all right, and, and what have you taken for the pain ? [PATIENT] patients] petition and the weight of the boxes. [DOCTOR] okay, all right, and, and what have you taken for the pain ? [PATIENT] a little tylenol. i.iced them for a bit. nothing really seemed to help, though. [DOCTOR] okay, all right, um, and does it prevent you from doing, like, your activities of daily living, like alking and exercising and things like that? [PATIENT] no. [DOCTOR] okay, all right, and, in the was a perity of the pain? [PATIENT] no. [DOCTOR] okay, all right and you obtained the patients. [PATIENT] no. [DOCTOR] and thing like that? [PATIENT] no. [DOCTOR] was prevented to help, though a perity of the pain? [PATIENT] no. [DOCTOR] and thing like that? [PATIENT] no. [DOCTOR] was prevented and the patients of the patients. [PATIENT] no. [DOCTOR] was prevented and the patients of the patients of the patients of the patients. [PATIENT] no. [DOCTOR] was prevented and the patients of the patients of the patients of the patients. [PATIENT] no. [DOCTOR] okay, all right. and you're taking your immunosuppressive medications? [PATIENT] no. [DOCTOR] was prevented and the patients of the patients. [PATIENT] no. [DOCTOR] and patients. [PATIENT] no. [DOCTOR] okay. all right. and you're taking your immunosuppressive medications? [PATIENT] no. [DOCTOR] okay. all right. and you're taking your immunosuppressive medications? [PATIENT] no. [DOCTOR] okay. all right. and you're taking your immunosuppressive medications? [PATIENT] no. [DOCTOR] okay. all right. and you're taking your immunosuppressive medications? [PATIENT] no. [DOCTOR] okay. all right. and you're taking you immunosuppressive medications? [PATIENT] no. [DOCTOR] okay. all right. and you're taking you immunosuppressive medications? [PATIENT] no. [DOCTOR] okay. all right. and you're taking you immunosuppressive medications

ay? hey. dragon, order an autoimmune panel. and you know. i, i want, i want you to just take it easy for right now, and if your symptoms continue, we'll talk about further imaging and possibly referral to physical therapy, okay? [PATIENT] you got it. [DOCTOR] for your second problem, you prothyroidism, i wan na go ahead and continue you on this... on the synthroid, and I wan na go ahead and order some thyroid labs, okay? [PATIENT] sure. [DOCTOR] hey, dragon, order a thyroid panel. and then for your last problem, the antinitis, you know, we just kind talked about that. you know go no a be a struggle for you because again. you can't take some of those anti-inflammatory medications because of your kidney transplant, so ... [PATIENT] mm-hmm. [DOCTOR] you know, let's see how we do over the next couple weeks, and again, we'll refer you to physical therapy if we need to,

Quantitative evaluation

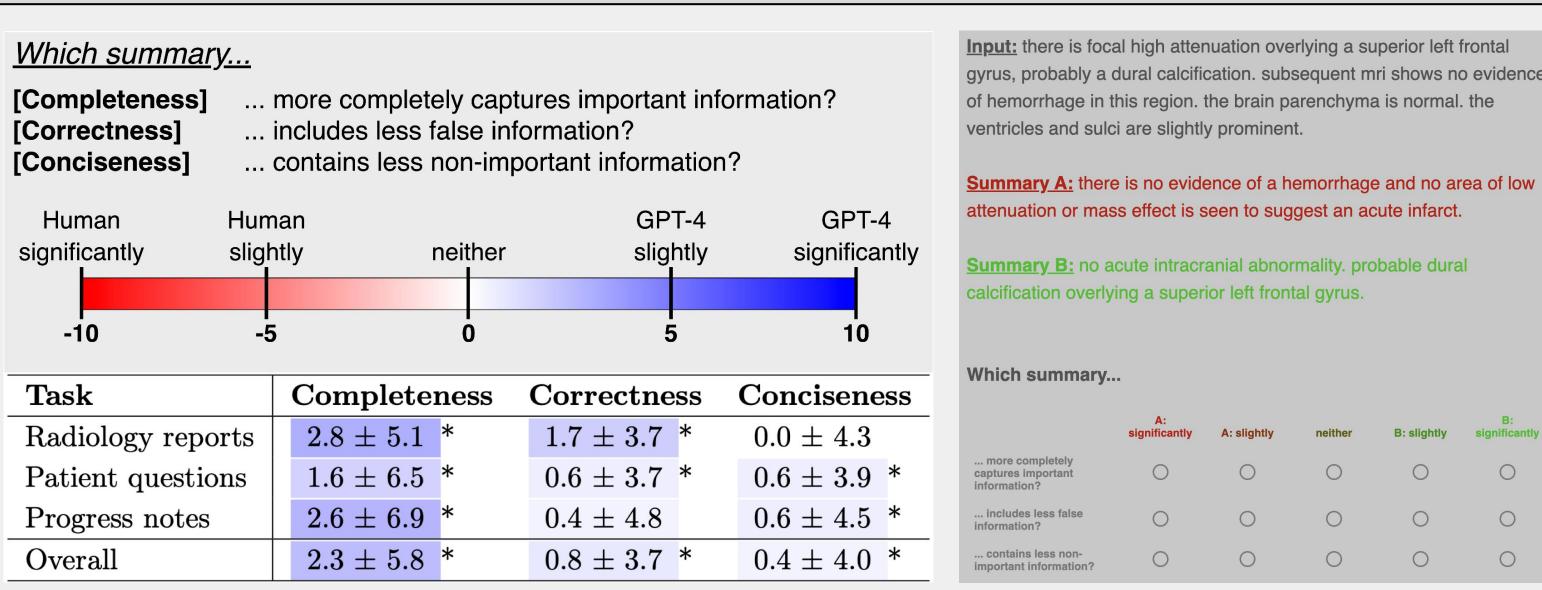


Top left: FLAN-T5 emerges as the best open-source model fine-tuned with QLoRA. **Bottom left:** Given enough examples, ICL surpasses QLoRA (dashed line). Including one example drastically improves performance compared to zero-shot prompting. **Right:** Head-to-head win rates of each model combination. GPT-4 generally performs best. Seq2seq models outperform open-source autoregressive models.

→ we conclude the best configuration is GPT-4 with maximal* in-context examples

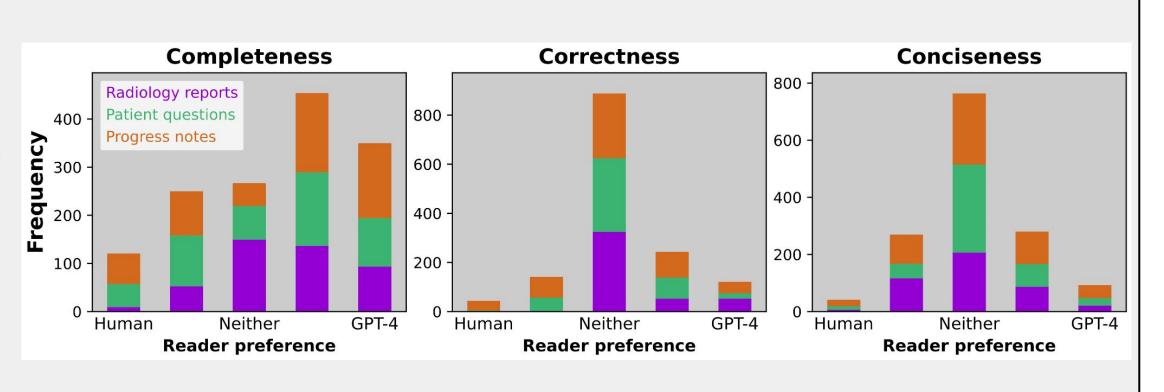
*determined by example size and model context length

Clinical Reader Study



<u>Left</u>: Summaries generated via GPT-4 with in-context examples are rated higher with statistical significance (*) on all three attributes. **<u>Right</u>**: Example of study user interface.

Distribution of reader scores across five-point Likert scale.



Radiology reports

Annotations of radiology report examples to illustrate the strengths and weaknesses of GPT-4 and humans.

[PATIENT] is a 62-year-old male with a past

transplant, hypothyroidism, and arthritis. He

presents today with complaints of joint pain.

• Medical Reasoning: The patient reports increased joint pain in his bilateral knees over

the past weekend. Given that his right knee

x-ray was unremarkable, I believe this is an

• Medical Treatment: Initiate Ultram 50 mg

advised the patient to rest his knees. If his

symptoms persist, we can consider further

maging and possibly a referral to physical

Medical Reasoning: The patient is doing

well on Synthroid and is asymptomatic at this

Additional Testing: We will order a thyroid

Medical Reasoning: He is doing well and

immunosuppressive medications. On recent labs, his white blood cell count was within a normal limits and his kidney function is

• Medical Treatment: Continue current

• Medical Treatment: Continue Synthroid.

Status post renal transplant.

has been compliant with his

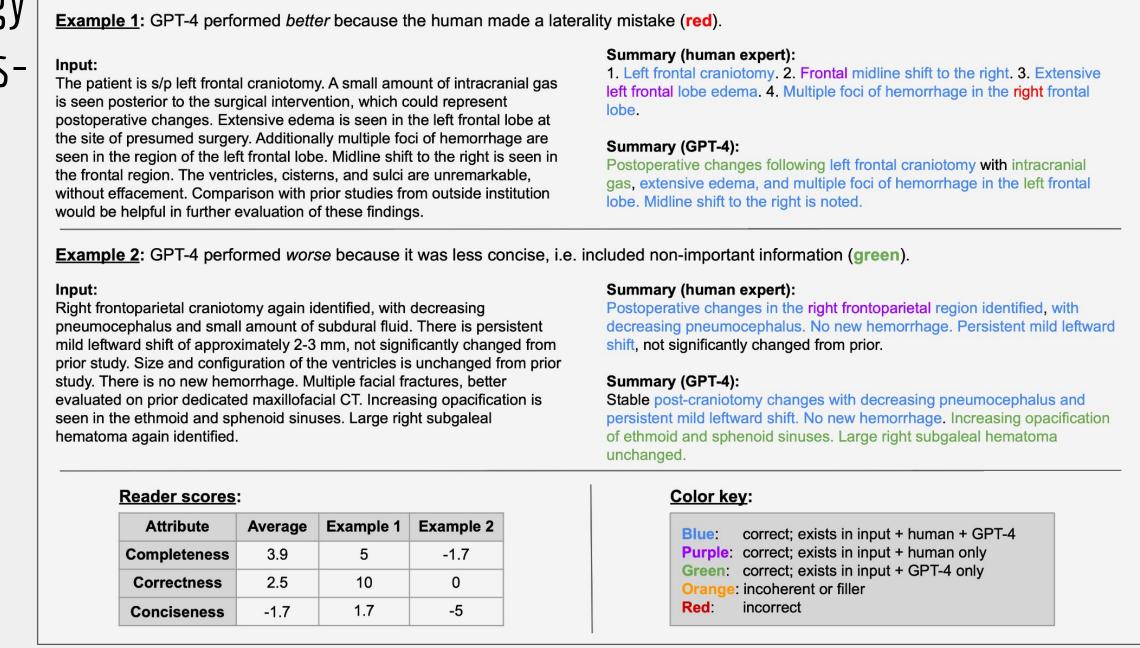
acute exacerbation of his arthritis.

every 6 hours as needed.

 Additional Testing: We will order an autoimmune panel for further evaluation.

Patient Education and Counseling: I

medical history significant for a kidney



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