

The CALLA Dataset: Probing LLMs’ Interactive Knowledge Acquisition from Chinese Medical Literature

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Abstract

The application of Large Language Models (LLMs) to the medical domain has stimulated the interest of researchers. Recent studies have focused on constructing Instruction Fine-Tuning (IFT) data through medical knowledge graphs to enrich the interactive medical knowledge of LLMs. However, the medical literature serving as a rich source of medical knowledge remains unexplored. Our work introduces the **CALLA** dataset to probe LLMs’ interactive knowledge acquisition from Chinese medical literature. It assesses the proficiency of LLMs in mastering medical knowledge through a free-dialogue fact-checking task. We identify a phenomenon called the “**fact-following response**”, where LLMs tend to affirm facts mentioned in questions and display a reluctance to challenge them. To eliminate the inaccurate evaluation caused by this phenomenon, for the golden fact, we artificially construct test data from two perspectives: one consistent with the fact and one inconsistent with the fact. Drawing from the probing experiment on the CALLA dataset, we conclude that IFT data highly correlated with the medical literature corpus serves as a potent catalyst for LLMs, enabling themselves to skillfully employ the medical knowledge acquired during the pre-training phase within interactive scenarios, enhancing accuracy. Furthermore, we design a framework for automatically constructing IFT data based on medical literature and discuss some real-world applications.

Introduction

The development of large language models (LLMs) (OpenAI 2023; Ouyang et al. 2022; Touvron et al. 2023; Chowdhery et al. 2022) has garnered significant attention due to their extensive knowledge and impressive capacity to interact with humans. Currently, LLMs (Scao et al. 2022; Taori et al. 2023; Du et al. 2022; Wang et al. 2018) have demonstrated commendable performance in general domains but have not yet established a solid foundation in specialized fields like medicine. Since the medical field demands a high level of professionalism and rigor, it is necessary to enrich the medical knowledge of LLMs. This endeavor is of utmost importance to ensure LLMs can provide accurate and reliable information to users seeking medical advice or information.

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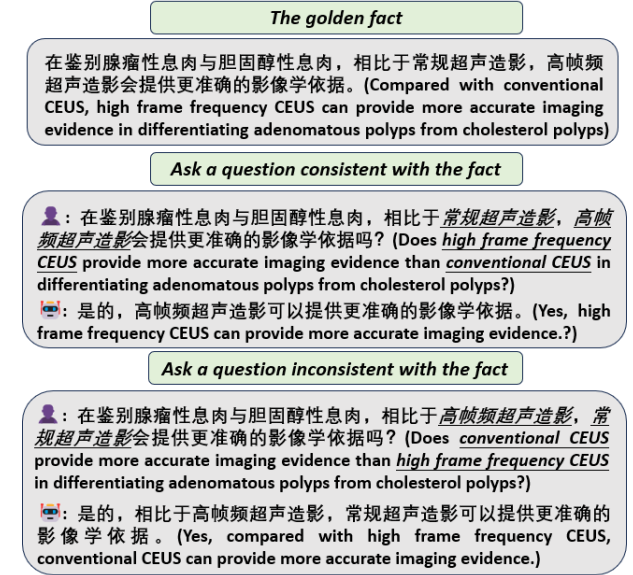


Figure 1: Illustration of “fact-following response” phenomenon. Whether questioned from the perspective of consistency or inconsistency with the golden fact, the LLMs tend to affirm the fact mentioned in the question.

Recent studies (Wu et al. 2023; Wang et al. 2022; Guo et al. 2023) have focused on integrating medical knowledge into IFT data, such as using ChatGPT¹ to construct IFT data through knowledge graphs, thereby enriching interactive medical knowledge of LLMs through Supervised Fine-Tuning (SFT). However, the medical literature, as a comprehensive repository of the latest medical knowledge, research findings, and clinical expertise, has not been widely probed. Previous work (Lee et al. 2020; raj Kanakarajan, Kundumani, and Sankarasubbu 2021; Rasmy et al. 2021; Jin et al. 2019) have revealed that pre-training Language Models (LMs) on medical literature can improve performance on various specialized medical tasks. Although pre-training LMs on medical literature undoubtedly enriches their medical knowledge, it doesn’t inherently mean that the LMs can utilize the knowledge to interact with humans. In the current

¹<https://openai.com/blog/chatgpt>

landscape dominated by LLMs, the spotlight is firmly on enabling effective interactions. Therefore, it is worth probing how to stimulate LLMs to obtain interactive knowledge from medical literature.

In our work, we introduce Chinese medical Literature-based multi-round dialogue (CALLA) dataset to probe the above problem. The CALLA dataset encompasses the medical literature corpus employed in the pre-training phase, the IFT data employed in the supervised fine-tuning phase, and artificially constructed test data. For the construction of IFT data, we design an automatic construction framework with the help of ChatGPT. Compared with directly prompting ChatGPT to construct IFT data, our framework can integrate more medical literature information into IFT data. Notably, for the construction of test data, we mainly consider the following two aspects.

- Previous work (Wei et al. 2022; Chowdhery et al. 2022) always use In-Context Learning (ICL) (Dong et al. 2022) to guide LLMs to do multiple-choice questions, but the LLMs’ response will be affected by many factors, such as the design of instructions or the choice of demonstrations. In contrast, we construct test data as the free-dialogue fact-checking task, which does not add any additional constraints, and can better mine the knowledge mastery of LLMs in the interactive scene.
- We identify the “fact-following response” phenomenon. As shown in Fig. 1, we ask a question consistent with the golden fact, and the LLMs respond correctly, which seems to indicate that it has mastered this knowledge. However, when we ask a question inconsistent with the golden fact, we expect the LLM to negate this fact but it still affirms it. To obtain a more accurate evaluation, based on the golden fact, we artificially construct test data from two perspectives: one consistent with the fact and one inconsistent with the fact.

In our experiments, due to the limitation of device memory, we adopt the LoRA (Hu et al. 2021) optimization under parameter-efficient fine-tuning (Mangrulkar et al. 2022). We conduct experiments under different base models and with different training parameters. Experimental results show that IFT data highly correlated with the medical literature corpus will serve as a powerful catalyst for LLMs, enabling them to more effectively apply the medical knowledge acquired during the pre-training phase in interactive scenarios. In contrast, the utilization of IFT data derived from other sources even compromises LLMs’ performance. Moreover, we discuss how LLMs based on medical literature can be better applied in real-world applications.

Overall, our work contributes in the following key ways:

- We introduce the CALLA dataset, aimed at probing LLMs’ interactive knowledge acquisition from medical literature, which lays the foundation for LLMs in medical literature research.
- We design an automatic construction framework for IFT Data based on medical literature, which helps to integrate more medical literature information into IFT data.
- Our experiment results reveal that it is extremely necessary to construct IFT data highly correlated with medical

literature, which serves as a potent catalyst for LLMs to acquire interactive knowledge from medical literature.

Related Work

LLMs have exhibited impressive capabilities in general domains, but there is still significant room for improvement when it comes to specialized domains like medicine. Ensuring the richness and professionalism of LLMs’ knowledge is crucial when users seek medical consultation or inquire about medical information. Currently, numerous efforts are underway to enhance the medical knowledge of LLMs. They almost follow a standardized technical approach, that parameter-efficient fine-tuning general domain LLMs with medical instruction fine-tuning data. For the collection of medical instruction fine-tuning data, they adopt different strategies as follows:

- HuatuoGPT (Zhang et al. 2023) and ChatDoctor (Li et al. 2023) have focused on collecting real-world question-answering data and distilling data from ChatGPT to create medical instruction fine-tuning data.
- BenTsao (Wang et al. 2023) and Shennong (Zhu and Wang 2023) have employed ChatGPT to construct question-answering data based on the existing medical knowledge map.
- MedicalGPT-zh (Liu et al. 2023) referred to BELLE (Ji et al. 2023), utilizing ChatGPT to generate dialogue data in various scenarios based on medical consensus and clinical guideline texts.
- ChatMed (Zhu and Wang 2023) first attempts to gather questions from online consultations and then utilizes ChatGPT to provide responses, thus obtaining question-and-answer datasets.

These endeavors have yielded varying degrees of improvement in the performance of LLMs within the medical domain, showcasing the potential of Medical LLMs. However, as far as we are aware, no studies have attempted to probe LLMs’ interactive knowledge acquisition from Chinese medical literature.

CALLA Dataset

Our CALLA dataset mainly consists of three parts: medical literature corpus, IFT data, and test data. Next, we will describe in detail how to collect or construct them.

Medical literature corpus. Since medical literature contains a large amount of information, we think that introducing too much information will make it difficult to distinguish the boundaries of knowledge, which is not conducive to our quantitative analysis. We consider that the abstract is the condensed essence of medical literature, including the purpose, method, experiment, conclusion, etc. Thus for the CALLA dataset, we collect Chinese medical literature abstracts from Chinese HowNet, and we select a main topic related to hepatobiliary and pancreatic diseases, which is an important and valuable medical field.

After the above steps, we will get high-quality IFT data. In the CALLA data, we focus on the integration of the conclusion information from the medical literature abstract into the IFT data. As shown in Fig. 2, the dialogue involves strict control over one dialogue round (covered by blue), which includes the conclusion information. The remaining dialogue rounds allow for more flexibility, incorporating contextual details (covered by green) such as experimental discussions, transitional content, and other relevant aspects.

Operation	Golden Fact	$Q_{consist}$	$Q_{inconsist}$
RA	相比于腹腔镜手术，超声引导下穿刺介入治疗肝囊肿患者对肝脏的损伤比较小 (Compared with laparoscopic surgery, ultrasound-guided puncture interventional therapy for patients with hepatic cysts has less damaging to the liver)	相比于腹腔镜手术，超声引导下穿刺介入治疗肝囊肿患者对肝脏的损伤较小吗？ (Compared with laparoscopic surgery, is ultrasound-guided puncture interventional therapy for patients with hepatic cysts less damaging to the liver?)	相比于腹腔镜手术，超声引导下穿刺介入治疗肝囊肿患者对肝脏的损伤较大吗？ (Compared with laparoscopic surgery, is ultrasound-guided puncture interventional therapy for patients with hepatic cysts more damaging to the liver?)
ANW	超声引导下TAP阻滞联合喉罩通气在原发性肝癌患者围手术期具备镇痛效果 (TAP block under ultrasound guidance combined with laryngeal mask ventilation has analgesic effect in perioperative period of primary liver cancer patients)	超声引导下TAP阻滞联合喉罩通气在原发性肝癌患者围手术期具备镇痛效果吗？ (Does ultrasound-guided TAP block combined with laryngeal mask ventilation have analgesic effects in perioperative patients with primary liver cancer?)	超声引导下TAP阻滞联合喉罩通气在原发性肝癌患者围手术期不具备镇痛效果吗？ (Does ultrasound-guided TAP block combined with laryngeal mask ventilation have no analgesic effects in perioperative patients with primary liver cancer?)
SPE	对于细微的肝脏占位病变，相较于螺旋CT增强，MRI的准确率相对更高 (For subtle liver lesions, MRI is more accurate than spiral CT enhancement)	对于细微的肝脏占位病变，相较于螺旋CT增强，MRI的准确率相对更高吗？ (Is MRI more accurate than spiral CT enhancement for subtle liver lesions?)	对于细微的肝脏占位病变，相较于MRI，螺旋CT增强的准确率相对更高吗？ (Is spiral CT enhancement more accurate than MRI for subtle liver lesions?)

Figure 3: RA, ANW, SPE represent replacing antonyms, adding negative words, and swapping the positions of entities to be compared respectively.

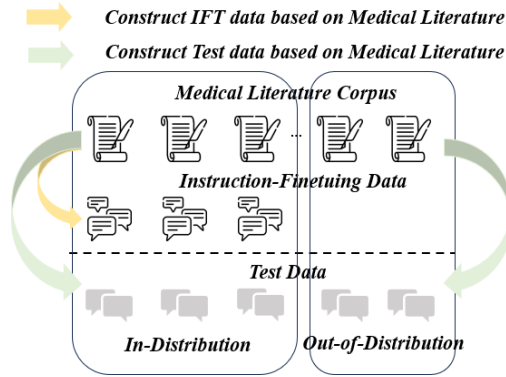


Figure 4: Display of the overall distribution of our CALLA dataset.

Test data. The CALLA dataset performs a free-dialogue fact-checking task to evaluate LLMs’ grasp of interactive medical knowledge. We take the conclusion information from the medical literature as the golden fact. For each golden fact, we first construct a question from a perspective consistent with the golden fact, and get the question $Q_{consist}$. Second, we ask the other question from a perspective inconsistent with the golden fact by modifying the $Q_{consist}$. As shown in Fig. 3, it mainly includes three aspects: **Replacing Antonyms (RA)**, **Adding Negative Words (ANW)**, and **Swapping the Positions of Entities to be compared (SPE)**, so as to obtain $Q_{inconsist}$.

Besides, since the medical literature corpus is endless in reality, it is unrealistic to construct IFT data for each medical literature. In order to better simulate the real situation, our CALLA dataset only constructs the IFT data for only 300 of the literature abstracts. Therefore, corresponding to the IFT data, as shown in Fig. 4, we can divide our test data into **In-Distribution (I.D.)** test data and **Out-Of-Distribution (O.O.D.)** test data. The knowledge contained in the I.D. test data has appeared in both the medical literature corpus and the IFT data, while the knowledge contained in the O.O.D.

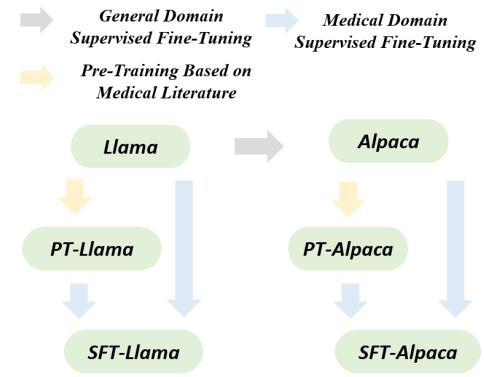


Figure 5: Technical routes of transforming the general domain LLMs into the medical domain.

test data has only appeared in the medical literature corpus. Overall, our CALLA dataset contains 10,000 medical literature abstracts, 1,212 multi-round dialogues (involving 4,288 single-round dialogues) as IFT data, 100 pairs of I.D. test data, and 100 pairs of O.O.D. test data.

Experiment

Training Details

In our experiments, we select Chinese Llama and Alpaca (Cui, Yang, and Yao 2023) as base LLMs respectively, where the former is just a pre-trained model and the latter is fine-tuned based on the general domain IFT data supervision on the basis of the former. As shown in Fig. 5, the transformation of the general domain into the medical domain LLMs is mainly divided into two technical routes: 1) Pre-training on medical literature, and then supervised fine-tuning on IFT data. 2) Supervised fine-tuning directly on IFT data. For the pre-training phase and the SFT phase, we both adapt the LoRA fine-tuning optimization technology, and the code and parameter settings can be found in the public repository ².

²<https://github.com/ymcui/Chinese-LLaMA-Alpaca>

Baseline	Llama						Alpaca					
	I.D.			O.O.D.			I.D.			O.O.D.		
	Q	$\neg Q$	$Q \wedge \neg Q$	Q	$\neg Q$	$Q \wedge \neg Q$	Q	$\neg Q$	$Q \wedge \neg Q$	Q	$\neg Q$	$Q \wedge \neg Q$
	-	-	-	-	-	-	87	31	26	82	26	21
76M												
General	78	31	26	72	23	17	72	21	14	75	25	20
Medicine	61	21	14	84	23	22	75	20	15	73	23	19
Our	91	33	30	81	42	36	87	35	31	84	31	27
w/o pt	93	34	31	82	25	22	82	35	30	82	24	20
16M												
General	63	23	16	64	20	14	76	32	25	79	21	17
Medicine	86	15	12	85	16	13	77	25	16	76	19	18
Our	86	37	32	81	26	21	81	33	27	79	26	21
w/o pt	87	36	32	82	22	18	77	32	23	69	15	12

Table 1: Experimental results on the CALLA dataset. Q represents the accuracy rate on $Q_{consist}$ test data, $\neg Q$ represents the accuracy rate on $Q_{inconsistent}$ test data, and $Q \wedge \neg Q$ represents the proportion that $Q_{consist}$ and $Q_{inconsistent}$ are simultaneously correct. General, Medicine, and Our respectively represent the utilization of IFT data from general domain, IFT data from other medical domains, and our constructed IFT data based on medical literature in the SFT stage. The w/o pt represents the abandonment of the pre-training stage.

Among them, for the pre-training stage, we update the parameters of 818MB, and for the supervised fine-tuning stage, we update the parameters of 16MB and 76MB respectively.

Evaluation Metric

In our evaluation, we invite ChatGPT³ as the judge. Given the question, golden fact, and LLM’s response, based on the designed prompt such as “For the answer to the question, is the LLM’s response semantically consistent with the golden fact? If it is consistent, return 1, and if inconsistent, return 0. Please return your answer.”, let ChatGPT judge whether the LLM’s response is correct. Considering the diversity of judgment given by ChatGPT, we let ChatGPT make three judgments and take the judgment with the highest number of occurrences as the final judgment. Besides, if the LLMs can give correct responses to the pairs of $Q_{consist}$ and $Q_{inconsistent}$ simultaneously, we believe that the LLMs have truly grasped the medical knowledge contained in the question. We separately report the proportion of models that are correct on $Q_{consist}$, the proportion that is correct on $Q_{inconsistent}$, and the proportion that both are correct.

Main Experiments

We explore from two aspects: 1) In the supervised fine-tuning stage after the pre-training stage, we separately apply the same scale of IFT data from general domain⁴, IFT data from other medical domains⁵, and our constructed IFT data based on medical literature to explore the impact of IFT data. 2) We try to abandon the pre-training stage to explore whether the pre-training stage is really helpful to bring interactive medical knowledge to LLMs.

Since Llama does not have good interactive capabilities, it always appears some strange responses on our free-dialogue fact-checking task. Therefore, we only report results on Alpaca as a baseline for comparison. As the experimental results are shown in Tab. 1, we observe that for each model, the accuracy on $Q_{consist}$ is much higher than that on $Q_{inconsistent}$, which indicates that LLMs tend to affirm the fact in $Q_{consist}$. To avoid the inaccurate evaluation brought by this tendency, we mainly observe **the accuracy of LLMs on $Q_{inconsistent}$ ($\neg Q$) and the proportion that both $Q_{consist}$ and $Q_{inconsistent}$ ($Q \wedge \neg Q$) are simultaneously correct.**

We observe that, firstly, compared to the baseline, our model achieves higher accuracy for both I.D. and O.O.D. test data. Such results reflect the effectiveness of integrating medical literature knowledge with the current technical route. Secondly, we observe that the utilization of the general domain and medical domain IFT data from other sources even damages the performance of LLMs to a certain extent. Such results show that the selection of IFT data needs to be cautious. Notably, for O.O.D. data that only contains knowledge in the pre-training stage, our model maintains a stable performance improvement. This shows that it is extremely necessary to construct IFT data highly correlated with medical literature, which will help the LLMs to skillfully use the medical knowledge accumulated in the pre-training stage in interactive scenarios.

Besides, we observe that after the abandonment of the pre-training stage, the performance of our model on the I.D. test data is basically unchanged, and still has a high level. On the O.O.D. test data, our model performance has a relatively large drop. We attribute this to the fact that the knowledge in the I.D. data is present not only in the medical literature corpus but also in the IFT data. Therefore, even if the pre-training stage is abandoned, our model can still maintain a high level with the help of IFT data. Such results reflect that

³In our work, we use the gpt-3.5-turbo API interface from August 1 to August 15, 2023.

⁴<https://github.com/LianjiaTech/BELLE>

⁵<https://github.com/SCIR-HI/Huatuo-Llama-Med-Chinese>

Golden Fact: 八宝丹胶囊联合哌拉西林他唑巴坦治疗急性胆囊炎会减轻肝脏的损伤程度 (Babaodan capsule combined with piperacillin and tazobactam in the treatment of acute cholecystitis can reduce the degree of liver injury)	
Q_{consist}: 八宝丹胶囊联合哌拉西林他唑巴坦治疗急性胆囊炎会减轻肝脏的损伤程度吗? (Does Babao Dan capsule combined with piperacillin and tazobactam in the treatment of acute cholecystitis reduce the degree of liver injury?)	Alpaca's Response: 相关信息表明, 八宝丹胶囊联合哌拉西林他唑巴坦治疗急性胆囊炎可以减轻肝脏的损伤程度。(The relevant information shows that Babaodan capsule combined with piperacillin and tazobactam in the treatment of acute cholecystitis can reduce the degree of liver injury.) Our Response: 是的, 根据研究结果, 使用八宝丹胶囊联合哌拉西林他唑巴坦治疗急性胆囊炎可以有效缓解症状, 降低体内炎症反应, 改善肝功能, 且安全性较高。(Yes, according to the study results, the use of Babaodan capsule combined with piperacillin and tazobactam in the treatment of acute cholecystitis can effectively relieve symptoms, reduce inflammation in the body, improve liver function, and have a high safety.)
Q_{inconsist}: 八宝丹胶囊联合哌拉西林他唑巴坦治疗急性胆囊炎会加重肝脏的损伤程度吗? (Does Babao Dan capsule combined with piperacillin and tazobactam in the treatment of acute cholecystitis aggravate the degree of liver damage?)	Alpaca's Response: 是的, 八宝丹胶囊联合哌拉西林他唑巴坦治疗急性胆囊炎可能会加重肝脏的损伤程度。(Yes, Babaodan capsule combined with piperacillin and tazobactam in the treatment of acute cholecystitis may aggravate the degree of liver injury.) Our Response: 根据研究结果, 临床疗效确切的八宝丹胶囊联合哌拉西林他唑巴坦治疗急性胆囊炎可使患者的症状得到显著改善, 同时能减轻肝脏的损伤程度。因此, 该疗法是安全有效的。(According to the results of the study, Babaodan capsule combined with piperacillin and tazobactam in the treatment of acute cholecystitis can significantly improve the symptoms of patients, and reduce the degree of liver damage. Therefore, the treatment is safe and effective.)

Figure 6: A real case. For the same question, responses of the Alpaca model and our model are compared.

if the knowledge can be fully integrated into the IFT data, the pre-training stage can be abandoned. However, it is extremely costly and difficult to fully integrate knowledge into IFT data. In contrast, since the knowledge in the O.O.D. test data has only appeared in the medical literature corpus, after the abandonment of the pre-training stage, it is reasonable to cause the performance of the model to decline on the O.O.D. test data. It is worth noting that such results reflect that LLMs can learn interactive medical knowledge from the pre-training stage.

Finally, we compare the effect of training with different parameter sizes in the SFT stage. Experimental results show that on the I.D. test set, the performance of LLMs trained with 16MB is close to that of LLMs trained with 76MB parameters. On the O.O.D. test set, the performance of LLMs trained with 16MB is completely behind, even just on par with the baseline Alpaca model. Such results indicate that the size of the training model parameters in the SFT stage is critical to the impact of LLMs' interactive knowledge acquisition from medical literature.

Overall, we summarize the main conclusions as follows:

- It is effective to integrate medical literature knowledge into LLMs with the current technical route.
- If medical literature knowledge can be fully integrated into IFT data, we believe that the pre-training stage may be abandoned.
- LLMs can acquire interactive medical knowledge from the pre-training stage, but it needs to construct IFT data

highly correlated with the medical literature as a catalyst.

Discussion

Case Study

We provide a real case to illustrate the success of LLMs' interactive knowledge acquisition from medical literature. As shown in Fig. 6, we compare the responses of the base Alpaca model with the response of our model. For the $Q_{consist}$ ("Does Babao Dan capsule combined with piperacillin and tazobactam in the treatment of acute cholecystitis reduce the degree of liver injury?"), both the Alpaca model and our model affirm the fact contained in the $Q_{consist}$. However, for the $Q_{inconsist}$ ("Does Babao Dan capsule combined with piperacillin and tazobactam in the treatment of acute cholecystitis aggravate the degree of liver damage?"), the Alpaca model still affirms the fact contained in the $Q_{inconsist}$. In contrast, our model can negate the fact contained in the $Q_{inconsist}$, thereby giving the correct response.

Automatic Construction Framework for SFT Data

Through guided experiments on our CALLA dataset, we have observed the importance of constructing IFT data highly correlated with medical literature. Therefore, we conduct further analysis and discussion on the automatic construction framework mentioned in the CALLA Dataset section. First, we analyze the extent to which our framework integrates medical literature information into IFT data. Specifically, we calculate the length of the Longest Common Sub-

<p>Question: 请问内引流手术和经皮肝穿刺胆道支架置入术对于不可切除胰腺癌所致黄疸的治疗效果有何区别？ (What is the difference between internal drainage and percutaneous hepatic puncture biliary stent in the treatment of jaundice caused by unresectable pancreatic cancer)</p>	<p>Alpaca's Response: 内引流手术通过将胆汁引流到外部，而经皮肝穿刺胆道支架置入术则在肝内放置支架来改善胆汁排泄功能。两种方法各有优缺点，具体选择应根据患者情况而定。 (Internal drainage works by draining bile externally, while percutaneous hepatic puncture biliary stenting works by placing a stent inside the liver to improve bile excretion function. Both methods have advantages and disadvantages, and the specific choice should be based on the patient's situation)</p> <p>Our Response: 内引流手术和经皮肝穿刺胆道支架置入术均能有效引流不可切除胰腺癌所致黄疸，研究表明，经皮肝穿刺胆道支架置入术较内引流手术并发症少，安全性更高。 (Both internal drainage and percutaneous hepatic aspiration biliary stenting can effectively drain jaundice caused by unresectable pancreatic cancer. Studies have shown that percutaneous hepatic aspiration biliary stenting has fewer complications and higher safety than internal drainage.)</p>
<p>Combined Response: 内引流手术和经皮肝穿刺胆道支架置入术均能有效引流不可切除胰腺癌所致黄疸。内引流手术通过将胆汁引流到外部，而经皮肝穿刺胆道支架置入术则在肝内放置支架来改善胆汁排泄功能。研究表明，经皮肝穿刺胆道支架置入术较内引流手术并发症少，安全性更高。 (Both internal drainage and percutaneous hepatic puncture with biliary stent can effectively drain unresectable pancreatic cancer induced jaundice. Internal drainage works by draining bile externally, while percutaneous hepatic puncture biliary stenting works by placing a stent inside the liver to improve bile excretion function. Studies have shown that percutaneous hepatic puncture biliary stenting has fewer complications and higher safety than internal drainage.)</p>	

Figure 7: The real-world application. Combining the response from our model and the response from the alpaca model.

string (LCS) between the response r and medical literature p . Based on this, we calculate the degree of integration of medical literature information, and the score is as follows.

$$Score = \frac{LCS(r, p)}{Len(r)} \quad (1)$$

If the score is greater than a certain threshold (we select 0.5 as a threshold), it is considered that the response r contains information from the medical literature. We regard the method of directly prompting LLMs as a comparison and count 100 samples. The method of directly prompting LLMs can generate an average of 3.4 rounds of dialogues, of which averaged 1.6 rounds contain literature information, with a ratio of 47.06%. The method of our framework can generate an average of 4.1 rounds of dialogues, of which averaged 2.7 rounds contain literature information, with a ratio of 65.86%. Therefore, our framework can help to integrate more literature information into IFT data.

Furthermore, we emphasize the importance of the “data cleaning” module in our framework. As mentioned in the CALLA Dataset section, the purpose of the data cleaning is to change some subjective expressions from IFT data into objective ones. We conduct an ablation experiment, selecting some subjective expression words and asking 100 random questions to observe the proportion of these words appearing in LLMs’ responses. Trained on IFT data without data cleaning, there is a 44% probability of subjective expression words in the LLMs’ responses. In contrast, trained on IFT data with data cleaning, there is only a 7% probability of subjective expression words in the LLMs’ responses. We believe that it is critical for real-world applications.

Real-world Application

In our practice, we observe that medical literature often represents a unique perspective, and the relationship between knowledge in medical literature and knowledge in existing

models is both intersecting and complementary. The existing technical route is more likely to cover the medical knowledge in the previous model with medical literature knowledge. However, compared to covering previous LLMs’ medical knowledge, we think it is more reasonable to integrate the previous LLMs’ medical knowledge and the medical knowledge of the literature. Therefore, we encourage the utilization of medical literature to train LLMs with the medical literature perspective. Then, through the controllable generation ability of the general domain LLMs, the response of the medical literature LLMs and the response of the general domain LLMs can be combined, so that a more comprehensive response will be obtained, which will be more conducive to practical application.

As shown in Fig. 7, we provide a case of the free-dialogue task in the real world. We observe that the response of the alpaca model focuses on explaining the specific implementation of the two treatment modalities involved in the question, while the response of our model focuses on how good or bad the two treatments are, drawn from conclusions from the medical literature. We observe that the information contained in both responses is helpful to users. Therefore, we use the general domain LLM to combine the two responses to get a more comprehensive response.

Conclusion

Our work introduces the CALLA dataset to probe LLMs’ interactive knowledge acquisition from medical literature. We observe that IFT data highly correlated with the medical literature corpus serves as a potent catalyst for LLMs, enabling them to skillfully employ the medical knowledge acquired during the pre-training phase within interactive scenarios. Furthermore, we design a framework for the automatic construction of IFT data and discuss some real-world applications. In the future, we will continue to explore some LLMs’ complex behavior on our CALLA dataset.

References

- Chowdhery, A.; Narang, S.; Devlin, J.; Bosma, M.; Mishra, G.; Roberts, A.; Barham, P.; Chung, H. W.; Sutton, C.; Gehrmann, S.; et al. 2022. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*.
- Cui, Y.; Yang, Z.; and Yao, X. 2023. Efficient and Effective Text Encoding for Chinese LLaMA and Alpaca. *arXiv preprint arXiv:2304.08177*.
- Dong, Q.; Li, L.; Dai, D.; Zheng, C.; Wu, Z.; Chang, B.; Sun, X.; Xu, J.; and Sui, Z. 2022. A survey for in-context learning. *arXiv preprint arXiv:2301.00234*.
- Du, Y.; Yan, J.; Chen, Y.; Liu, J.; Zhao, S.; She, Q.; Wu, H.; Wang, H.; and Qin, B. 2022. Less learn shortcut: Analyzing and mitigating learning of spurious feature-label correlation. *arXiv preprint arXiv:2205.12593*.
- Guo, Z.; Wang, P.; Wang, Y.; and Yu, S. 2023. Dr. LLaMA: Improving Small Language Models on PubMedQA via Generative Data Augmentation. *CoRR*.
- Hu, E. J.; Shen, Y.; Wallis, P.; Allen-Zhu, Z.; Li, Y.; Wang, S.; Wang, L.; and Chen, W. 2021. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*.
- Ji, Y.; Deng, Y.; Gong, Y.; Peng, Y.; Niu, Q.; Zhang, L.; Ma, B.; and Li, X. 2023. Exploring the Impact of Instruction Data Scaling on Large Language Models: An Empirical Study on Real-World Use Cases. *arXiv preprint arXiv:2303.14742*.
- Jin, Q.; Dhingra, B.; Liu, Z.; Cohen, W. W.; and Lu, X. 2019. Pubmedqa: A dataset for biomedical research question answering. *arXiv preprint arXiv:1909.06146*.
- Lee, J.; Yoon, W.; Kim, S.; Kim, D.; Kim, S.; So, C. H.; and Kang, J. 2020. BioBERT: a pre-trained biomedical language representation model for biomedical text mining. *Bioinformatics*, 36(4): 1234–1240.
- Li, Y.; Li, Z.; Zhang, K.; Dan, R.; Jiang, S.; and Zhang, Y. 2023. ChatDoctor: A Medical Chat Model Fine-Tuned on a Large Language Model Meta-AI (LLaMA) Using Medical Domain Knowledge. *Cureus*, 15(6).
- Liu, H.; Liao, Y.; Meng, Y.; Wang, Y.; and Wang, Y. 2023. <https://github.com/MediaBrain-SJTU/MedicalGPT-zh>.
- Mangrulkar, S.; Gugger, S.; Debut, L.; Belkada, Y.; and Paul, S. 2022. PEFT: State-of-the-art Parameter-Efficient Fine-Tuning methods. <https://github.com/huggingface/peft>.
- OpenAI. 2023. GPT-4 Technical Report. *arXiv:2303.08774*.
- Ouyang, L.; Wu, J.; Jiang, X.; Almeida, D.; Wainwright, C. L.; Mishkin, P.; Zhang, C.; Agarwal, S.; Slama, K.; Ray, A.; Schulman, J.; Hilton, J.; Kelton, F.; Miller, L.; Simens, M.; Askell, A.; Welinder, P.; Christiano, P.; Leike, J.; and Lowe, R. 2022. Training language models to follow instructions with human feedback. *arXiv:2203.02155*.
- raj Kanakarajan, K.; Kundumani, B.; and Sankarasubbu, M. 2021. BioELECTRA: pretrained biomedical text encoder using discriminators. In *Proceedings of the 20th Workshop on Biomedical Language Processing*, 143–154.
- Rasmy, L.; Xiang, Y.; Xie, Z.; Tao, C.; and Zhi, D. 2021. Med-BERT: pretrained contextualized embeddings on large-scale structured electronic health records for disease prediction. *NPJ digital medicine*, 4(1): 86.
- Scao, T. L.; Fan, A.; Akiki, C.; Pavlick, E.; Ilić, S.; Hesslow, D.; Castagné, R.; Luccioni, A. S.; Yvon, F.; Gallé, M.; et al. 2022. Bloom: A 176b-parameter open-access multilingual language model. *arXiv preprint arXiv:2211.05100*.
- Taori, R.; Gulrajani, I.; Zhang, T.; Dubois, Y.; Li, X.; Guestrin, C.; Liang, P.; and Hashimoto, T. B. 2023. Alpaca: A strong, replicable instruction-following model. *Stanford Center for Research on Foundation Models*. <https://crfm.stanford.edu/2023/03/13/alpaca.html>, 3(6): 7.
- Touvron, H.; Lavril, T.; Izacard, G.; Martinet, X.; Lachaux, M.-A.; Lacroix, T.; Rozière, B.; Goyal, N.; Hambro, E.; Azhar, F.; et al. 2023. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*.
- Wang, A.; Singh, A.; Michael, J.; Hill, F.; Levy, O.; and Bowman, S. R. 2018. GLUE: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461*.
- Wang, H.; Liu, C.; Xi, N.; Qiang, Z.; Zhao, S.; Qin, B.; and Liu, T. 2023. Huatuo: Tuning llama model with chinese medical knowledge. *arXiv preprint arXiv:2304.06975*.
- Wang, Y.; Kordi, Y.; Mishra, S.; Liu, A.; Smith, N. A.; Khashabi, D.; and Hajishirzi, H. 2022. Self-instruct: Aligning language model with self generated instructions. *arXiv preprint arXiv:2212.10560*.
- Wei, J.; Wang, X.; Schuurmans, D.; Bosma, M.; Xia, F.; Chi, E.; Le, Q. V.; Zhou, D.; et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems*, 35: 24824–24837.
- Wu, C.; Zhang, X.; Zhang, Y.; Wang, Y.; and Xie, W. 2023. Pmc-llama: Further finetuning llama on medical papers. *arXiv preprint arXiv:2304.14454*.
- Zhang, H.; Chen, J.; Jiang, F.; Yu, F.; Chen, Z.; Li, J.; Chen, G.; Wu, X.; Zhang, Z.; Xiao, Q.; Wan, X.; Wang, B.; and Li, H. 2023. HuatuoGPT, Towards Taming Language Models To Be a Doctor. *arXiv preprint arXiv:2305.15075*.
- Zhu, W.; and Wang, X. 2023. ChatMed: A Chinese Medical Large Language Model. <https://github.com/michael-wzhu/ChatMed>.