Augmented Large Language Models with Parametric Knowledge Guiding

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Abstract

Large Language Models (LLMs) have significantly advanced natural language processing (NLP) with their impressive language understanding and generation capabilities. However, their performance may be suboptimal for long-tail or domain-specific tasks due to limited exposure to domain-specific knowledge and vocabulary. Additionally, the lack of transparency of most state-of-the-art (SOTA) LLMs, which can only be accessed via APIs, impedes further fine-tuning with custom data. Moreover, data privacy is a significant concern. To address these challenges, we propose the novel **Parametric Knowledge Guiding (PKG)** framework, which equips LLMs with a knowledge-guiding module to access relevant knowledge at runtime without altering the LLMs' parameters. Our PKG is based on open-source "white-box" small language models, allowing offline storage of any knowledge that LLMs require. We demonstrate that our PKG framework can enhance the performance of "black-box" LLMs on a range of long-tail and domain-specific downstream tasks requiring factual, tabular, medical, and multimodal knowledge.

1 Introduction

Large Language Models (LLMs) such as GPT3 [Brown et al., 2020] have exhibited impressive proficiency across a diverse range of NLP tasks. These models are typically trained on extensive internet data, thereby enabling them to assimilate an immense amount of implicit world knowledge into their parameters. As a result, LLMs have emerged as versatile tools that find numerous applications in both NLP research and industrial applications. For instance, they can be used for machine translation [Jiao et al., 2023], passage summarization [Yang et al., 2023], and recommendation systems [Gao et al., 2023]. With their exceptional language understanding and generation capabilities, LLMs have opened up new opportunities for diverse industrial applications, such as the recently launched New Bing [Microsoft, 2023] and ChatGPT Plugins [OpenAI, 2023a].

Despite their impressive performance on general NLP tasks, LLMs may struggle to achieve optimal results on long-tail or domain-specific tasks [Chalkidis, 2023; Kasai et al., 2023; Nascimento et al., 2023] due to their limited exposure to relevant knowledge and vocabulary. While LLMs acquire implicit knowledge during pre-training, such knowledge may be lossy or inadequate for certain tasks, resulting in lower accuracy and less effective results. In addition, many SOTA LLMs are considered "black-box" models that can only be accessed through APIs. This lack of transparency makes fine-tuning these models difficult and costly for most researchers and companies. Moreover,

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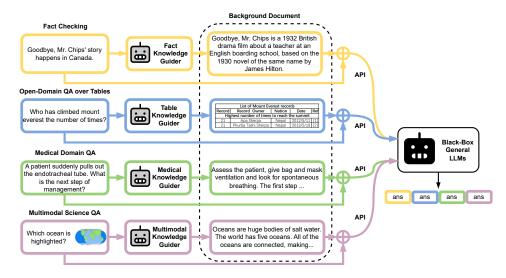


Figure 1: A brief introduction of our parametric knowledge guiding framework (PKG) for augmenting "black box" LLMs on long-tail or domain-specific tasks.

users who can afford to fine-tune must provide their private data to the LLM owner, exposing it to the risk of misuse, breaches, or other security threats [BBC, 2023]. These limitations impede the adaptability of LLMs to specific use cases or domains.

Recent research has mainly focused on improving LLMs' performance using retrieval-based methods to extract domain-specific knowledge from external knowledge bases [Liu, 2022; Shi et al., 2023; Peng et al., 2023a]. While this approach has shown promising results, it has some limitations. Firstly, it heavily relies on external knowledge sources, which may not always be easily accessible or available. Additionally, these methods may struggle with complex queries that require the integration of information from multiple sources or modalities. To overcome these limitations, we propose a novel framework called **Parametric Knowledge Guiding (PKG)**, which replaces retrieval with the generation, as illustrated in Figure 1. The PKG module is an extra background knowledge generation module that enables LLMs to access relevant information at runtime without updating their parameters. By providing the necessary knowledge, augmented LLMs can achieve better performance on long-tail or domain-specific tasks.

Our PKG framework is based on open-source and free-to-use "white-box" small language models, making it accessible to a wider range of users. To align with the specific knowledge required for a given task or domain, we introduce a two-step knowledge alignment method based on instruction fine-tuning [Ouyang et al., 2022]. The parametric module can store any knowledge required by the LLMs, and it can be updated efficiently offline. Our experiments demonstrate that the proposed PKG framework enhances the performance of "black-box" LLMs on various downstream tasks which require domain-specific background knowledge, including factual knowledge (FM2 [Eisenschlos et al., 2021], +7.9%), tabular knowledge (NQ-Table [Herzig et al., 2021], +11.9%), medical knowledge (MedMC-QA [Pal et al., 2022], +3.0%), and multimodal knowledge (ScienceQA [Lu et al., 2022], +8.1%). We summarize our contributions as follows:

- We propose a novel **Parametric Knowledge Guiding (PKG)** framework that enhances the capabilities of Language Models (LMs) by integrating an additional background knowledge generation module.
- We introduce a two-step knowledge alignment method to align the PKG module with the specific knowledge required for a given task or domain. This method is based on instruction fine-tuning and enables efficient offline updating of the parametric module.
- We conducted extensive experiments on various downstream tasks to evaluate the effectiveness of our proposed PKG framework. The results of these experiments demonstrate that our PKG framework can improve the capability of LLMs on these tasks.

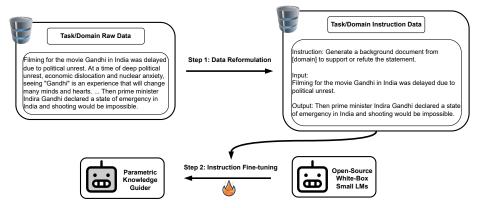


Figure 2: The two-step knowledge alignment of the parametric knowledge guider.

2 Related Work

Large language models. LLMs, such as GPT3 [Brown et al., 2020], Codex [Chen et al., 2021], PaLM [Chowdhery et al., 2022], and GPT4 [OpenAI, 2023b], have gained widespread attention due to their remarkable language understanding and generation capabilities. However, their performance can be limited when it comes to long-tail or domain-specific tasks, where they may lack exposure to specialized knowledge and vocabulary [Chalkidis, 2023; Kasai et al., 2023]. Moreover, while some SOTA LLMs such as InstructGPT3.5 and ChatGPT [Ouyang et al., 2022] exist, they are available only as "black box" APIs due to commercial considerations. This limits researchers and developers with limited resources, who may not be able to access or modify the models' parameters. While open-source LLMs such as OPT-175B [Zhang et al., 2022] and BLOOM-176B [Scao et al., 2022] are available, they lag significantly behind SOTA LLMs on most tasks. Additionally, running and fine-tuning these open LLMs locally requires significant computational resources.

Augmented Large Language Models. ALLMs are a recent popular topic in NLP that aim to enhance the context processing ability of LLMs by incorporating external modules [Mialon et al., 2023; Wu et al., 2023; Shen et al., 2023; Lu et al., 2023; Huang et al., 2023]. One approach to achieving this goal is through the use of retrieval-augmented large language models (RLLMs)[Guu et al., 2020; Izacard et al., 2022; Ram et al., 2023; Shi et al., 2023]. RLLMs leverage external knowledge by retrieving relevant documents or passages from knowledge sources using retrieval-based methods such as BM25[Robertson and Zaragoza, 2009] and DPR [Karpukhin et al., 2020]. These retrieved passages are then used as additional contexts to improve the LLMs' performance on the task at hand. Although RLLMs have shown promise in enhancing LLMs' performance, they have certain limitations. For instance, they rely heavily on external knowledge sources, which may not always be readily available or easily accessible. Furthermore, they may struggle with complex queries that require integrating information from multiple sources or modalities.

Instruction Fine-Tuning. IFT is a technique in NLP that aims to align language models with specific user intents [Ouyang et al., 2022]. While many LLMs are trained on large datasets of internet data to predict the next word, they may not be tailored to the specific language tasks that users require, meaning that these models are not inherently aligned with their users' needs. Recent research [Wei et al., 2022a; Sanh et al., 2022; Xu et al., 2022; Xie et al., 2022] has highlighted the potential of IFT as a key technique for improving the usability of LLMs. Our proposed approach, PKG, follows the same principle of aligning the basic module with task-specific knowledge to enhance its performance.

3 Parametric Knowledge Guiding

In this section, we present a novel framework named **Parametric Knowledge Guiding (PKG)** that aims to enhance "black-box" LLMs' performance on long-tail or domain-specific tasks. PKG leverages an offline parametric knowledge generation module, which is integrated with the LLM to provide relevant knowledge at runtime, guiding its reasoning. To achieve this, we first utilize a small, open-source language model to efficiently align with domain-specific knowledge, which is

often long-tail or not present in the LLM's training data. Then, given an input question or sentence, PKGs provide the corresponding background document, expanding the input context of LLMs, and enabling them to handle a broader range of tasks.

3.1 Knowledge Alignment of Guider

For a specific task or domain, we align the guider module with relevant knowledge through instruction fine-tuning [Ouyang et al., 2022]. As depicted in Figure 2, we divide this process into two steps. First, we collect raw data about the target task/domain, which serves as our knowledge sources. Then, we transform the data into a set of (instruction, input, output) triples. The instruction serves as a prompt for the input and guides the module to align with the expected output.

Next, this set of triples is adopted to tune our basic PKG module, optimizing its ability to provide relevant and effective guidance to the LLMs for the given task or domain. This process enables the PKG module to learn and generate domain-specific knowledge and provide it to the LLMs during runtime. An example of the instruction prompt is:

```
Below is an instruction that describes a task, paired with an input that provides
   further context.

Write a response that appropriately completes the request.

### Instruction:
{instruction}

### Input:
{input}

### Response:
{output}
```

The instruction serves as a prompt that guides the model to provide background knowledge related to a specific domain or task. The input is a prompt that prompts the model to generate a sentence or answer a question within the specified domain or task. The output is the relevant knowledge that the model generates based on the given instruction and input. To generate the output, we train the basic guiding module in an auto-regressive manner, where the model generates the output given the previous context. Once the training is complete, the basic model evolves into a parametric knowledge guider that can generate domain/task-specific background knowledge given the corresponding instruction.

3.2 Augmented LLMs with PKG

In many cases, the standard method for using "black-box" LLMs is to provide the input sentence/question as a prompt and request the LLMs to return the response/answer using APIs. However, this approach may not be effective for complex tasks that require knowledge beyond what is contained in the input alone. To overcome this limitation, a common approach is to provide additional context to the LLMs, enabling them to access more relevant information related to the task. In the case of PKG, we enhance the input with domain-specific background knowledge to expand the input context. This supplementary information serves as a guide for the LLMs, enabling them to access a richer understanding of the task context and potentially improving their accuracy in generating responses. An example of the augmented prompt is:

```
Refer to the passage below and answer the following question.

Passage: {background}

Question: {query}

The answer is
```

Models	FM2	NQ-Table	MedMC-QA
Direct generation without guiding. InstructGPT3.5 [Ouyang et al., 2022]	59.4	16.9	44.4
Generation with retrieval guiding. BM25 + InstructGPT3.5 [Karpukhin et al., 2020] ⋄REPLUG + InstructGPT3.5 [Shi et al., 2023]	65.2 65.9	17.1 24.3	-
Generation with parametric knowledge guiding. †CoT + InstructGPT3.5 [Kojima et al., 2022] ‡GenRead + InstructGPT3.5 [Yu et al., 2023] PKG + InstructGPT3.5 (Ours)	60.4 65.5 67.3	21.4 23.5 28.8	41.5 44.4 47.4

Table 1: Evaluating on three different tasks, requiring factual (FM2), tabular (NQ-Table), and medical (MedMC-QA) knowledge. \diamond : we fine-tune the dense retrieval models with the task data. †: we use instructGPT3.5 to generate the chain-of-thoughts as the background knowledge. ‡: we use instructGPT3.5 to generate the background documents.

4 Experiment

In this section, we evaluate the effectiveness of our proposed **PKG** framework on four distinct types of knowledge: factual, tabular, medical, and multimodal. We compare the performance of our approach with several baseline methods, and the results presented in Tables 1 and 2 show significant improvements achieved by our PKG over the "black box" LLMs. These findings provide compelling evidence of the generality and effectiveness of our approach.

4.1 Models Steup

Black-Box LLMs. We adopt the SOTA LLM InstructGPT3.5 [Ouyang et al., 2022] as our target "black box" general LLMs, using the text-davinic-002 version. With up to 175B parameters, this model is one of the largest LLMs and is pre-trained on a vast amount of internet data, which exhibits great language understanding and generation ability. However, it is important to note that, like other "black box" LLMs, this model can only be accessed through an API, which limits users' interaction.

Basic Knowledge Guider. Our knowledge guiding module employs the open-source and popular foundation model LLaMa-7B [Touvron et al., 2023]. Although LLaMa-7B has been pre-trained on massive amounts of text data and possesses extensive general world knowledge, it also may not contain domain-specific or long-tail knowledge, and its performance in many tasks may be inferior to the LLMs. Nevertheless, LLaMa-7B can be fine-tuned and customized [Taori et al., 2023; Xu et al., 2023; Peng et al., 2023b], making it an effective starting point for developing a task-specific parametric knowledge guider that can augment LLMs with task/domain-specific knowledge in an effective manner.

Baselines. Our work includes three different types of baselines for comparison: (1) Direct generation without guiding: In this approach, we do not provide any background knowledge for a given task and ask the LLMs to generate the answer or response directly in a zero-shot manner, following the approach of prior works [Brown et al., 2020; Ouyang et al., 2022]. (2) Generation with retrieval guiding: We follow the retrieve-then-read paradigm [Chen et al., 2017; Yang et al., 2019; Karpukhin et al., 2020] to retrieve related knowledge from external knowledge sources using retrieval models such as BM25 [Robertson and Zaragoza, 2009] and DPR [Karpukhin et al., 2020]. We fine-tune the DPR on specific tasks following the REPLUG [Shi et al., 2023] method. LLMs then generate responses based on the combination of the question and retrieved background documents. (3) Generation with parametric knowledge guiding: In this approach, LLMs themselves serve as the knowledge sources. First, the LLMs generate the related background knowledge themselves and then generate the responses based on the combination of the question and self-generated contexts. We include two different baseline methods. The first method, CoT Kojima et al. [2022], adopts the prompt "Let's think step-by-step" to generate the chain-of-thought, which will be considered as the background knowledge. The second method, GenRead Yu et al. [2023], directly requires the LLMs to provide task-specific knowledge with the prompt "Please provide the background document from [domain] to [task]."

Models	NAT	SOC	LAN	TXT	IMG	NO	G1-6	G7-12	Avg
Base on gpt-3.5-turbo.									
†ChatGPT	78.82	70.98	83.18	77.37	67.92	86.13	80.72	74.03	78.31
†Chameleon	81.62	70.64	84.00	79.77	70.80	86.62	81.86	76.53	79.93
Base on text-davinic-002.									
InstructGPT3.5	72.96	62.88	76.09	70.77	62.77	77.84	75.04	65.59	71.66
+CoT	71.94	61.19	74.00	69.50	61.18	75.75	72.61	65.92	70.22
+GenRead	72.91	64.68	76.36	72.14	63.31	76.66	74.96	66.91	72.08
+PKG (Ours)	79.35	82.90	81.91	79.86	74.32	83.41	80.80	80.69	80.76

Table 2: Evaluating on the ScienceQA, requiring multimodal science knowledge. †: results from Lu et al. [2023]. gpt-3.5-turbo is much more capable than text-davinic-002.

4.2 Factual Knowledge

Datasets and Implementation Details. We evaluate our approach on the FM2 dataset [Eisenschlos et al., 2021], which is a benchmark for fact-checking. In this task, given a factual claim, our models are required to determine whether it is true or false. We use the claim in the training set and the corresponding evidence as factual knowledge. Additionally, we sample 100k passages from English Wikipedia, each consisting of up to 256 tokens. We treat the first sentence as the input and the remaining sentences as background knowledge. To train our PKG, we transform this data into instruction data and use a batch size of 64 and train for 3 epochs. Accuracy is adopted as the evaluation metric.

Results. As shown in Table 1, our PKG outperforms all the baseline systems for fact-checking. In comparison to direct generation, the results reveal that it is necessary to provide extra background knowledge for LLMs with retrieval-based or generation-based methods. Specifically, our PKG outperforms InstructGPT3.5 by 7.9% (67.9% vs. 59.4%), and outperforms REPLUG, a retrieval-based method, by 1.4% (67.3% vs. 65.9%). It is noteworthy that our generation-based method does not necessitate an additional knowledge database as the retrieval-based methods. Additionally, our PKG performs better than the self-guiding method GenRead by 1.8% (67.3% vs. 65.5%), indicating that our PKG can provide more useful information than the LLMs themselves.

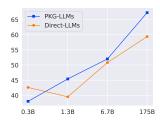
4.3 Tabular Knowledge

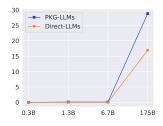
Datasets and Implementation Details. We evaluate the effectiveness of our approach on the NQ-Table dataset [Herzig et al., 2021], which serves as a benchmark for open-domain question answering over tables. The dataset consists of questions whose answers can be found in a Wikipedia table. We adopted the question in the training set as input and the corresponding table as background knowledge. Our PKG was trained to follow instructions and generate the relevant table. During training, the batch size is 32, and models are trained with 10 epochs. Exact matching is adopted as the evaluation metric.

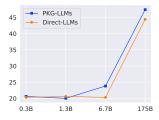
Results. Table 1 demonstrates the superior performance of our PKG framework over all the baseline systems on the tabular knowledge-related task. Notably, our PKG outperforms InstructGPT3.5 by a substantial margin of 11.9% (28.8% vs. 16.9%), and outperforms REPLUG, the retrieval-based method, by 4.5% (28.8% vs. 24.3%). Furthermore, our PKG significantly outperforms the self-guiding method GenRead by 5.3% (28.8% vs. 23.5%). These results demonstrate the efficacy and superiority of our approach in leveraging parametric knowledge to augment LLMs for tabular knowledge-related tasks.

4.4 Medical Knowledge

Datasets and Implementation Details. We evaluate the effectiveness of our approach on the MedMC-QA dataset [Pal et al., 2022], which serves as a benchmark for multi-subject multi-choice medical question answering. Each question requires the use of relevant medical information as background knowledge to provide the correct answer. We use the questions in the training set as input and the corresponding medical explanation as background knowledge. Our PKG is trained to follow the instruction and generate the relevant medical background. We tune our models with







- (a) Accuracy on FM2.
- (b) Exact Matching on NQ-Table.
- (c) Accuracy on MedMC-QA.

Figure 3: Comparing our PKGs framework with the direct generation on various types of LLMs. The number indicates the number of parameters in the LLMs. 0.3B: text-ada-001, 1.3B: text-babbage-001, 6.7B: text-curie-001, 175B: text-davinci-002.

a batch size of 32 and 3 epochs, with accuracy as the evaluation metric. Unlike the previous tasks with all Wikipedia passages as the knowledge database, we do not have access to an external medical knowledge database, and thus we do not evaluate the performance of retrieval-based methods on this task

Results. Our PKG framework also outperforms all the baseline systems on this medical knowledge-related task, as shown in Table 1. Specifically, our PKG outperforms InstructGPT3.5 by 3.0% (47.4% vs. 44.4%). It is worth noting that the baseline self-guiding methods, CoT and GenRead, do not improve the performance of LLMs. This may be due to the fact that LLMs lack sufficient medical information to effectively solve this task.

4.5 Multimodal Knowledge

Datasets and Implementation Details. Our approach is evaluated on the ScienceQA dataset [Lu et al., 2022], which presents a challenging multimodal multiple-choice question-answering task covering diverse science topics. Each question requires leveraging relevant scientific background knowledge to provide the correct answer. We use the training set's questions as input and their corresponding science lecture as background knowledge. To handle the multimodal aspect of the task, we augment our basic knowledge module, LLaMa, with the CLIP-ViT [Radford et al., 2021] model to extract visual features, which are then fused with text features using a simple one-head cross-attention mechanism in each layer of LLaMa:

$$H^{fuse} = H^{txt} + W^o \left(softmax \left((W^q H^{txt}) (W^k H^{img})^T \right) (W^v H^{img}) \right), \tag{1}$$

where $W^{o,q,k,v}$ are the linear projection, H^{txt} is the hidden state of texts and H^{img} is the hidden state of images. We train our PKG models with a batch size of 32 and 5 epochs, and adopt accuracy as the evaluation metric.

Since this task involves integrating multiple modes of information and it is difficult to obtain an external multimodal science knowledge database, retrieval-based methods are not considered. To facilitate a fair comparison of our methods, we include two additional baseline systems [Lu et al., 2023] based on the gpt-3.5-turbo model. The first baseline is ChatGPT direct generation, and the second is the Chameleon model, which utilizes several external tools, such as searching, OCR, and image captioning models. According to OpenAI, the gpt-3.5-turbo model is more capable than text-davinic-002.³

Results. Table 2 shows that our PKG framework achieves a significant improvement in the performance of LLMs on the multimodal scientific knowledge-related task. Specifically, the average accuracy is increased by 9.1% (80.76% vs. 71.66%), demonstrating the effectiveness of our approach. In contrast, other guiding methods, CoT (-1.44%) and GenRead (+0.42%), hard to improve the performance of LLMs. Moreover, our PKG framework outperforms the gpt-3.5-turbo based models on average by 2.45% (80.76% vs. 78.31%), despite using weaker LLMs.

³https://platform.openai.com/docs/models/overview

Basic PKG	FM2	NQ-Table	MedMC-QA	ScienceQA
LLaMa-7B [Touvron et al., 2023]	67.3	28.8	47.4	80.8
OPT-7B [Zhang et al., 2022]	60.0	21.5	36.8	79.8
OPT-2.7B	59.6	17.9	34.4	79.5
OPT-1.3B	58.2	16.5	33.9	77.0
OPT-0.3B	56.4	14.6	31.7	68.7

Table 3: Various types and sizes of small language models are used as the basic knowledge guider.

4.6 Analysis

Scale of LLMs. Figure 3 illustrates the impact of our PKG framework on different "black-box" LMs, including text-ada-001, text-babbage-001, text-curie-001, and text-davinci-002. The results suggest that the effectiveness of our approach is dependent on the size of the LMs, with larger LMs benefiting more from our PKGs than smaller ones. For example, in Figure 3b, the small LMs have almost zero exact matching scores on the tabular task with or without the background knowledge from our PKGs, while the LLMs exhibit significantly better performance. In Figure 3c, the 0.3B and 1.3B LMs have almost identical performance on the medical domain task. The 6.7B LM starts to benefit from the extra knowledge on the MedMC-QA task. This could be attributed to the weaker language understanding capabilities of smaller LMs, which struggle to reason over contexts and generate the correct responses even with relevant knowledge from our PKGs. These observations are consistent with the emergent abilities of LLMs, as discussed in Wei et al. [2022b]. Thus, the scale of LLMs is an important factor for great performance.

Comparison Different Basic PKGs. We conducted an investigation into the effectiveness of using various types and sizes of small language models as basic knowledge-guiding modules. Since LLaMa-7B is the smallest model in the LLaMa-family, we conducted experiments on the OPT-family [Zhang et al., 2022], another open-source large-scale language model with a similar structure to LLaMa. As shown in Table 3, we found that larger basic PKGs tend to achieve better performance. For example, increasing the number of parameters from 1.3B to 2.7B results in a performance increase of 1.4% on FM2, 1.4% on NQ_Table, 0.5% on MedMC-QA, and 2.5% on ScienceQA, which is consistent with the scaling law [Kaplan et al., 2020].

However, when compared to the performance in Table 1 and 2, we found that if the number of parameters is smaller than 2.7B, the OPT-based PKGs cannot improve the performance of the LLMs and may even have a negative impact. Furthermore, although OPT is of a similar size to LLaMa, LLaMa significantly outperforms OPT. These findings suggest that LLaMa is a better model for our framework.

5 Conclusion

In this work, we propose the novel **Parametric Knowledge Guiding (PKG)** framework to enhance the performance of "black-box" LLMs on domain-specific and long-tail tasks. PKG introduces a knowledge-guiding module that can provide relevant domain-specific knowledge at runtime without changing the LLMs' parameters. This enables LLMs to address various downstream tasks requiring specialized knowledge. The framework aligns the basic PKG modules with the domain-specific knowledge through a two-step process. Our experimental results demonstrate the effectiveness of our PKG framework over extensive tasks.

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