GenKnowSub: Improving Modularity and Reusability of LLMs through General Knowledge Subtraction

Anonymous ACL submission

Abstract

Large language models (LLMs) often struggle with zero-shot generalization, and several modular approaches have been proposed to address this challenge. Yet, we hypothesize that a key limitation remains: the entanglement of general knowledge and task-specific adaptations. To overcome this, we propose a modular framework that disentangles these components by constructing a library of task-specific LoRA modules alongside a general-domain LoRA. By subtracting this general knowledge component from each task-specific module, we obtain residual modules that focus more exclusively on task-relevant information—a method we call general knowledge subtraction (GenKnowSub). Leveraging the refined task-specific modules and the Arrow routing algorithm (Ostapenko et al., 2024), we dynamically select and combine modules for new inputs without additional training. Our studies on the Phi-3 model and standard Arrow as baselines reveal that using general knowledge LoRAs derived from diverse languages, including English, French, and German, yields consistent performance gains in both monolingual and cross-lingual settings across a wide set of benchmarks. Further experiments on Phi-2 demonstrate how GenKnowSub generalizes to weaker LLMs.

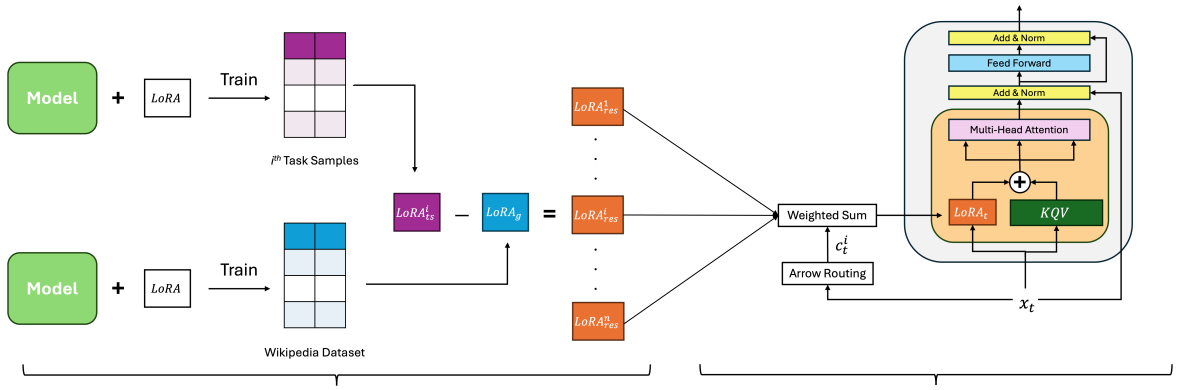
1 Introduction

The rapid advancement of large language models (LLMs) has led to their widespread adoption in various NLP tasks, ranging from text generation to machine translation and question-answering (Brown et al., 2020; Raffel et al., 2020). Despite their remarkable performance, a key challenge remains: ensuring effective generalization to unseen tasks without the need for extensive retraining (Bommasani et al., 2022; Wei et al., 2022).

In modular zero-shot transfer approaches (Pfeiffer et al., 2023), a two-stage process is typically followed: (i) task-specific modules are obtained via parameter-efficient fine-tuning (PEFT) methods, such as LoRA (Hu et al., 2021), Adapters (Houlsby et al., 2019), and $(IA)^3$ (Liu et al., 2022), on a multitask dataset (ii) a routing function is used to select and combine task-specific modules to address a new task. While some routing functions require joint training alongside task-specific modules (Fedus et al., 2022; Caccia et al., 2023; Ponti et al., 2023), recent approaches employ post-hoc routing methods that require no further training (Chronopoulou et al., 2023; Ostapenko et al., 2024). Hybrid approaches also exist, where the routing function is trained separately on a downstream dataset after freezing task-specific modules (Muqeeth et al., 2024; Huang et al., 2024).

In this paper, we adopt LoRA as the PEFT module and Arrow (Ostapenko et al., 2024) as the routing function. We choose Arrow for its ability to dynamically route each input token—rather than the entire input—to the most relevant task-specific modules in a post-hoc manner, without requiring additional training. We hypothesize that *redundant general knowledge within task-specific modules hampers generalization*. To mitigate that, we build a general knowledge LoRA using a general corpus, and then subtract it from each task LoRA. We call this process *GenKnowSub*, general knowledge subtraction. The Arrow algorithm then dynamically selects and integrates the most relevant LoRAs for each input token. An overview of the proposed method can be found in Figure 1.

The core intuition behind GenKnowSub is that reducing redundant general knowledge while preserving essential task-specific knowledge improves the model's effectiveness in zero-shot transfer learning. By disentangling task-specific and general-domain knowledge, we prevent redundancy and enable better adaptation. Additionally, removing redundant knowledge enhances the distinctiveness of residual modules, ensuring that routing mechanisms can more effectively select and com-



(a) *Training the Modules and General Knowledge Subtraction* (b) *Dynamic Task Adaptation via Arrow Routing*

Figure 1: Overview of our proposed approach. (a) illustrates the process of training task-specific and general modules, followed by performing general knowledge subtraction, or GenKnowSub. (b) represents the dynamic task adaptation stage in a model layer, where the Arrow algorithm selects and combines the most relevant task-specific modules for each input token.

pose appropriate modules for solving new tasks.

We evaluate our approach mainly on Phi-3 (Abdin et al., 2024) in a large set of benchmarks across English, German, and French. Experimental results demonstrate noticeable performance gains when compared to the base and Arrow models, underscoring the effectiveness of GenKnowSub in reducing redundancy and enhancing task-specific generalization. We further experiment with Phi-2 (Javaheripi et al., 2023) model and show how our findings extend to this model which is more English-focused with less general capabilities.

Here are our key contributions: (i) We propose GenKnowSub, a novel approach for general knowledge disentanglement by subtracting a general LoRA from task-specific LoRAs. GenKnowSub is simple, scalable, and seamlessly adaptable, making it applicable to broader modular LLM frameworks. (ii) We experimentally show that GenKnowSub improves the standard Arrow method and the Phi-3 baseline performance across multiple benchmarks and languages.

2 Method

In this work, we address zero-shot transfer learning problem, where the goal is to transfer knowledge from a multitask dataset to solve unseen tasks without requiring labeled data for further training. Modular approaches have emerged as promising solutions for this problem. These methods operate by first training task-specific modules and then combining them to solve unseen tasks. Here, we propose to use general knowledge modules to enhance modularity detailed in the following sections.

2.1 Training Modules and General Knowledge Subtraction

LoRA (Hu et al., 2021) is a PEFT method (Han et al., 2024) that updates only a small set of low-rank trainable parameters while keeping the pre-trained model weights frozen. By training LoRA modules on a diverse set of tasks, we enable the acquisition of distinct task-specific skills. To effectively isolate the task-specific knowledge within each LoRA module, we leverage the principle of *forgetting via negation* (Ilharco et al., 2023) in module-level (Zhang et al., 2023). Specifically, we define *Residual LoRA* as follows:

$$LoRA^i_{res} = LoRA^i_{ts} - LoRA_g \quad (1)$$

where $LoRA^i_{ts}$ denotes the module trained on task i and $LoRA_g$ represents the general knowledge module. We name this approach as **GenKnowSub** representing general knowledge subtraction.

We hypothesize that fine-tuning the model with LoRA on even a small Wikipedia-like dataset with a causal language modeling objective could act as a bridge or a flashback for the model, bringing forth the general knowledge it acquired during pre-training. This allows the LoRA module to represent broader linguistic and factual knowledge embedded in the base model. This knowledge is redundant since the base model already contains it. Further, we assume that task-specific modules include some of these redundant knowledge alongside their specific functionality. Consequently, GenKnowSub effectively removes unnecessary general knowledge

influence, isolating the unique task-specific characteristics essential for solving new unseen tasks.

2.2 Dynamic Task Adaptation

To enhance the adaptation to unseen tasks, we employ the Arrow routing algorithm introduced in Ostapenko et al. (2024), which dynamically selects the k best task-specific modules for each input token in each layer and integrates them to construct an optimal LoRA module for solving unseen tasks, based on the *learning via addition* principle (Ilharco et al., 2023). Arrow computes the SVD of each LoRA, extracts the top right singular vector as a prototype, and projects input tokens onto it. The top k coefficients are selected, softmax-normalized, and others set to zero.

Formally, we define the computed LoRA module in each layer of the model for each input token as:

$$LoRA_t^l = \sum_i^n c_t^{i,l} LoRA_{res}^{i,l} \quad (2)$$

where n is the number of trained task-specific modules, $LoRA_{res}^{i,l}$ represents the residual LoRA trained on task i within layer l of the model, and $c_t^{i,l}$ indicates the importance of $LoRA_{res}^{i,l}$ for the input token t, which is calculated using the Arrow algorithm based on the input in a zero-shot manner.

Given $LoRA_t^l$, the forward path for token t within layer l of the model is formulated as: $y_t^l = W_0^l x_t^l + B_t^l A_t^l x_t^l$ where $W_0^l \in \mathbb{R}^{d\times k}$ denotes the base model weights in layer l, $x_t^l \in \mathbb{R}^k$ is the input representation of token t entering layer l, $A_t^l \in \mathbb{R}^{r\times k}$, $B_t^l \in \mathbb{R}^{d\times r}$ are the corresponding LoRA parameter matrices associated with $LoRA_t^l$, and $r \ll \min(d, k)$ is the rank of low-rank decomposition. Figure 1 shows the overview of our proposed framework, including *Training the Modules*, *General Knowledge Subtraction (GenKnowSub)*, and *Dynamic Task Adaption* stages.

3 Experimental Setup and Results

Here, we first discuss some specifications of our experimental setup including how we build our LoRA modules, and then overview the results.

3.1 Constructing Task-Specific Modules

As stated earlier, the initial step for our proposed method, GenKnowSub, involves training modules, each tailored to a specific task or functionality. To avoid an excessive number of specialized modules, we utilize clustered Flan dataset (Longpre et al., 2023) proposed by (Ostapenko et al., 2024), which contains only English tasks. This dataset was constructed using a model-based clustering approach, where independent LoRAs were initially trained for each task and then clustered using the K-means algorithm. We assume that the clustering within this dataset effectively captures the relationships between tasks, regardless of the base model on which the LoRAs are trained. This assumption allows us to dedicate a single LoRA for each cluster of tasks, thereby reducing the number of experts required without compromising task-specific performance.

We select Phi-3-mini-4k-instruct (Abdin et al., 2024), a 3.8-billion-parameter model, for its strong instruction-following abilities and reasonable multilingual proficiency. To address hardware limitations, we use only 20% of each cluster's data ($\sim$2,000 samples) to improve training efficiency. The details regarding the setup and hyperparameters can be found in Appendix A.

3.2 Creating General Knowledge Modules

To obtain a module that effectively captures the general knowledge of a language, we train LoRAs on small Wikipedia corpora using causal language modeling. We select three higher-resource languages for Phi-3 model: English, French, and German. We assess their impact on GenKnowSub through various combinations across multilingual zero-shot benchmarks. For the Equation (1), we define $LoRA_g$ as follows: $LoRA_g = \{LoRA_{en}, LoRA_{de}, LoRA_{fr}, LoRA_{avg}\}$. Each LoRA is trained on 5,000 Wikipedia samples per language (details in Appendix A), with $LoRA_{avg}$ as their average.

3.3 Results

Table 1 presents the performance of the Phi-3 model, Arrow, and our method, on nine English reasoning benchmark datasets, including PIQA (Bisk et al., 2019), BoolQ (Clark et al., 2019), SWAG (Zellers et al., 2018), HellaSwag (Zellers et al., 2019), ARC-Easy and ARC-Challenge (Clark et al., 2018), WinoGrande (Sakaguchi et al., 2021), BIG-Bench Hard (Suzgun et al., 2023), and OpenBookQA (Mihaylov et al., 2018). We evaluate the impact of the different configurations of GenKnowSub on dynamic task adaptation.

As shown in Table 1, on average, Arrow enhances the performance of Phi-3 by more than 2%, confirming its effectiveness. Our contribution, GenKnowSub, further improves the result by around

Method	Setting	PIQA	BOOLQ	SWAG	HSWAG	ARC-E	ARC-C	WG	OQA	BBH	Avg
Phi-3		78.24	81.47	68.99	73.59	71.75	44.48	65.98	42.80	42.83	63.35
Arrow		80.20	80.00	68.95	71.89	80.53	53.85	65.98	47.40	41.23	65.56
GenKnowSub	*En*	80.20	81.96	70.00	73.36	82.11	53.85	64.72	48.40	43.30	66.43
	De	80.30	82.01	73.30	72.79	81.75	54.85	63.30	49.80	42.04	66.68
	Fr	78.78	82.11	71.64	74.02	81.75	57.19	64.40	49.00	44.40	67.03
	Avg	80.03	82.45	72.70	73.45	82.28	55.85	64.64	49.60	43.51	**67.17**

Table 1: Comparison of accuracy across different methods using Phi-3 as the base model on English datasets in a zero-shot setting. Various configurations of GenKnowSub are evaluated, with accuracy as the reported metric.

	Method	Setting	HSWAG	ARC-C	XNLI	MMLU	Avg
German	**Phi-3**		52.48	36.24	36.02	33.82	39.64
	Arrow		48.58	40.94	43.45	35.40	42.09
	GenKnowSub	*En*	51.16	40.60	50.14	36.85	44.69
		De	50.58	42.95	50.42	37.00	45.24
		Fr	50.58	42.62	49.17	37.17	44.88
		Avg	51.08	42.62	52.33	37.92	**45.99**
French	**Phi-3**		57.67	34.56	50.75	33.33	44.08
	Arrow		55.33	41.61	44.38	34.79	44.02
	GenKnowSub	*En*	56.08	41.95	50.66	36.69	46.34
		Fr	57.83	42.95	53.65	36.13	**47.64**
		De	56.42	42.28	46.33	35.58	45.15
		Avg	57.08	42.62	52.92	35.58	47.05

Table 2: Performance comparison of different methods with Phi-3 as the base model in a zero-shot setting for German and French lagnuages. Various configurations of GenKnowSub are evaluated, with accuracy as the reported metric.

1.5% when the average of LoRAs is subtracted. Such improvements are observed when we subtract LoRAs in individual languages as well, indicating that these modules share common knowledge despite incorporating language-specific information.

To evaluate GenKnowSub in other languages, we use XNLI (Conneau et al., 2018), the translated versions of the HellaSwag, MMLU (Hendrycks et al., 2021), and ARC-Challenge datasets provided by (Lai et al., 2023). Table 2 indicates that, on average, the Arrow method outperforms the base Phi-3 model only in German. GenKnowSub improves Arrow and Phi-3 by more than 2%, effectively enhancing zero-shot cross-lingual transfer learning. The improvement is observed when subtracting each separated general module, further suggesting that the foundation of this general knowledge is the most important factor, and it is largely shared across these languages.

A key factor in cross-lingual transfer learning is the base model's ability to encode at least a minimal level of multilinguality. To assess its impact more precisely, we run an additional experiment using **Phi-2**, which is weaker than Phi-3 in both multilingual and instruction-following capability. Following (Ostapenko et al., 2024), we use unquantized Phi-2 here, with task modules trained on the full task cluster data. As shown in Table 3 in Appendix, GenKnowSub, after subtracting the English general knowledge module, improves performance on English benchmark datasets in a zero-shot setting, increasing the average score by 1.1%. However, in German and French experiments (Table 4 in Appendix), both the base Phi-2 model and its combination with Arrow perform poorly—around 13% lower than Phi-3 in a similar setting—due to Phi-2's weak multilingual capabilities. Consequently, GenKnowSub achieves only comparable results, underperforming Arrow by 0.3%. These findings further confirm that our approach can enhance performance, provided the base model has at least a minimal level of multilinguality. Additional details and results are provided in Appendix B.

4 Conclusion

In this work, we propose a modular approach to zero-shot transfer learning, leveraging task-specific and general knowledge modules to enhance adaptability to unseen tasks. Our method first isolates task-relevant representations through GenKnowSub, then dynamically adapts these modules using the Arrow routing algorithm. By minimizing redundancy in task representations, our approach improves both efficiency and transferability. We demonstrate that GenKnowSub before task adaptation leads to better generalization in zero-shot settings for both Phi-3 and Phi-2. Our results show that this method not only enhances performance in monolingual tasks but also facilitates effective cross-lingual transfer when the language is highly present in the base model. Future work includes exploring alternative task adaptation methods, extending our approach to additional languages, especially low-resource ones, and testing it on other models. Furthermore, evaluating our method on broader benchmarks with open-ended tasks will further validate its effectiveness.

Limitations

One limitation of this study is the restricted task scope, as experiments were conducted exclusively on multiple-choice question-answering tasks and did not extend to open-ended tasks such as SNLI. Additionally, the evaluation was limited to a small number of large language models, primarily Phi-3 and Phi-2, due to hardware constraints, including limited GPU VRAM and slower processing speeds. These constraints prevented the testing of larger models and more extensive experimentation, thereby reducing the diversity of models evaluated and the number of tests performed. Moreover, while the study included multilingual settings, it was restricted to high-resource languages (e.g., English, French, German), leaving the effectiveness of the approach in lower-resource languages unexplored. Future work should address these limitations by expanding the range of tasks, models, and languages evaluated.

Ethics

Our research utilizes publicly available datasets and pre-trained models, ensuring compliance with ethical data usage practices and avoiding the use of private, proprietary, or personally identifiable information. All models and associated code will be made publicly available under permissive licenses, promoting accessibility, reproducibility, and unrestricted use for research and application development. However, we acknowledge that pre-trained language models (PLMs) and large language models (LLMs) have been shown to exhibit biases, as highlighted in prior work (Liang et al., 2021; He et al., 2023). Users should be mindful of these limitations when applying such models in practice. Our work does not introduce additional fairness or privacy concerns.

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A Implementation Details

A.1 Base Model

We utilize Phi-3-mini-4k-instruct (Abdin et al., 2024) with 4-bit quantization to reduce memory usage while maintaining strong performance. We selected this model due to its exceptional instruction-following capabilities and its acceptable multilingual proficiency. Additionally, with only 3.8 billion parameters, Phi-3-mini strikes an effective balance between model size and performance, allowing for efficient fine-tuning and deployment in resource-constrained environments while still demonstrating competitive reasoning and generalization abilities.

A.2 PEFT Structure

As the PEFT structure, we employ LoftQ (Li et al., 2024) with a rank of $r = 4$. LoftQ extends LoRA by integrating low-rank adaptation directly into the quantization process, thereby optimizing both fine-tuning and inference through rank-wise quantization, which minimizes precision loss while updating quantized model weights. We applied our PEFT modules to both the QKV components (concatenation of Query, Key, and Value matrices in the self-attention block) and the output projection layer of the multi-head attention.

A.3 Arrow Routing

To incorporate the Arrow routing algorithm, we implemented it from scratch using PyTorch (Paszke et al., 2019) and the PEFT library from HuggingFace (Wolf et al., 2020). We trained 10 task-specific modules, and selected the 3 best modules for each input token in each layer of the model to be combined.

A.4 Module Training

To train the LoRA modules representing general knowledge, we fine-tuned the model on a Wikipedia dataset using a causal language modeling objective on Quadro RTX 6000 GPUs. The dataset, sourced from Wikipedia articles, initially was downloaded from (WikimediaFoundation), then was formatted into prompt-completion pairs to ensure an effective learning structure. The prompt length varied by language while maintaining a total sequence length of 512 tokens. Specifically, English and German prompts consisted of 507 tokens followed by a 5-token completion, whereas French prompts contained 511 tokens with a 1-token completion.

For task-specific LoRA modules, we employed a supervised fine-tuning approach. Given the presence of relatively long examples in our dataset, we set the maximum sequence length to 4000 tokens to accommodate the full input structure.

Both the task-specific and general knowledge LoRA modules were trained for one epoch with a learning rate of $1e{-}4$, using cosine scheduling with a warmup start. To stabilize training, we applied gradient clipping. Additionally, to optimize memory efficiency, we utilized the Paged AdamW 8-bit optimizer (Dettmers et al., 2022), a quantized variant of AdamW (Loshchilov and Hutter, 2019), designed to reduce GPU memory consumption.

The batch size was set to 16 for training general knowledge modules and 1 for task-specific modules, due to the long input lengths. To further improve memory efficiency, we applied gradient checkpointing and gradient accumulation, enabling support for larger batch sizes when training task-specific modules.

B Experiments on Phi-2

B.1 Implementation Details

For conducting experiments using Phi-2, the baseline in Ostapenko et al. (2024), we used the LoRA modules they trained to evaluate their proposed routing algorithm, Arrow (the implementation details of Arrow are provided in Appendix A.3). Specifically, we used task LoRA modules trained by Ostapenko et al. (2024), available on Hugging Face.[1] These modules are obtained by fine-tuning Phi-2 on clustered Flan datasets (explained in Section 3.1) and are provided in PyTorch Lightning format.[2] Since our models are trained using the PEFT library,[3] we converted the existing LoRA weights into the PEFT format to ensure compatibility. Our implementation loads expert weights following the PEFT framework, and, consistent with their setup, the Phi-2 experiment weights remain unquantized.

[1] Library of LoRAs: https://huggingface.co/zhan1993/mbc_library_phi2_icml

[2] PyTorch Lightning: https://github.com/Lightning-AI/pytorch-lightning

[3] PEFT: https://github.com/huggingface/peft

Method	Setting	PIQA	BOOLQ	SWAG	HSWAG	ARC-E	ARC-C	WG	OQA	BBH	Avg
Phi-2		78.99	81.16	63.50	66.75	82.11	53.51	56.51	44.00	48.00	63.84
Arrow		79.65	81.13	65.75	66.41	83.38	54.84	60.85	48.60	54.75	65.15
GenKnowSub	*En*	79.97	80.12	65.58	66.75	84.38	54.51	61.24	49.80	54.00	**66.26**
	Avg	80.47	78.47	66.10	67.96	84.03	56.19	60.69	47.80	54.00	66.19

Table 3: Comparison of accuracy across different methods using Phi-2 as the base model on English datasets in a zero-shot setting, with Accuracy as the reported metric.

	Method	Setting	HSWAG	ARC-C	XNLI	MMLU	Avg
German	**Phi-2**		28.78	23.84	34.50	24.19	27.83
	Arrow		28.75	24.83	32.50	26.91	**28.25**
	GenKnowSub	*En*	28.33	24.55	33.33	24.91	27.78
		Avg	28.42	23.49	34.33	25.50	27.93
French	**Phi-2**		33.33	26.84	34.16	24.77	29.77
	Arrow		32.91	27.51	34.16	25.68	**30.06**
	GenKnowSub	*En*	33.50	25.50	31.83	26.11	29.23
		Avg	32.25	24.16	37.50	25.00	29.73

Table 4: Performance comparison of different methods using Phi-2 as the base model on multilingual datasets in a zero-shot setting for German and French, with Accuracy as the reported metric.

Additionally, we obtained general knowledge LoRA modules by fine-tuning Phi-2 in a setup aligned with the task-specific LoRA modules. The training process was similar to that of the Phi-3 version, as detailed in Appendix A.4.

B.2 Resutls

We demonstrated that with a sufficiently strong multilingual base model, we can effectively leverage its multilingual capabilities to generalize better to unseen tasks across different languages. The Phi-2 experiments further highlight the importance of base model strength and knowledge. As shown in Table 3, GenKnowSub, with subtracting the English general knowledge module, outperforms other settings, whereas averaging modules across different languages is less effective than using English alone. Additionally, Table 4 shows that all settings, including Phi-2 and Arrow, perform poorly in German and French. The improvement of our method on the English zero-shot dataset, along with its performance in the multilingual setting, demonstrates that our method can significantly enhance results—provided the base model exhibits at least a minimal level of cross-lingual capability.