Training-free LLM Merging for Multilingual Multi-task Learning

Anonymous ACL submission

Abstract

Large Language Models (LLMs) have demonstrated exceptional capabilities across diverse natural language processing (NLP) tasks. The release of open-source LLMs like LLaMA and Qwen has triggered the development of numerous fine-tuned models tailored for various tasks and languages. In this paper, we explore an important question: is it possible to combine these specialized models to create a unified model with multi-task and multi-lingual capabilities. We introduces **H**ierarchical **I**terative **Merging** (Hi-Merging), a training-free method for unifying multiple specialized LLMs into a single model. Specifically, Hi-Merging employs model-wise and layer-wise pruning and scaling, guided by contribution analysis, to mitigate parameter conflicts. Extensive experiments on English and Chinese datasets, covering multiple-choice and question-answering tasks, validate Hi-Merging across three paradigms: multilingual merging, multi-task merging, and multilingual multi-task merging. The results demonstrate that Hi-Merging consistently outperforms existing merging techniques and surpasses the performance of models fine-tuned on combined datasets in most scenarios. Code is available at this anonymous link[1].

1 Introduction

Large Language Models (LLMs) have revolutionized Natural Language Processing (NLP) by demonstrating unprecedented capabilities in capturing and utilizing world knowledge (Zhao et al., 2024). Recent advances in architecture design and training methodologies have enabled models like GPT-4 (OpenAI, 2023) to engage in human-like dialogue and solve real-world problems, enabling breakthroughs in healthcare, education, and scientific research.

With the advent of open-source large language models (LLMs) like LLaMA-3 (Dubey et al., 2024) and Qwen (Yang et al., 2024a), significant research efforts have been dedicated to fine-tuning these models for specific tasks, domains, and languages. As a result, Hugging Face[2] now hosts over one million specialized LLMs across various languages and tasks, and this number continues to grow rapidly. These models represent a vast repository of task-specific and language-specific expertise, ranging from Chinese medical applications (Chen et al., 2023) to English financial question and answering (Cheng et al., 2024). A natural question arises: is it possible to combine these language-specific and task-specific fine-tuned LLMs into a single unified model with broad capabilities, including multi-lingual and multi-task functionalities? If achievable, the deployment of such a unified model could perform multiple tasks that currently require multiple LLMs, thereby significantly enhancing the application of LLMs. One potential solution is to gather all fine-tuning data and retrain the LLMs from scratch. However, this approach has three significant disadvantages: 1) the availability of fine-tuning data, as the models are often public but the data is not; 2) retraining large LLMs requires substantial computational resources; and 3) balancing the training data from different tasks and languages to achieve overall optimal performance is a non-trivial challenge.

Based on the above considerations, model merging (Yang et al., 2024b) emerges as a promising solution for unifying multiple specialized models while preserving their individual capabilities. However, current model merging methods face two fundamental challenges. First, interference between merged models can arise from noise introduced by data bias (Tsuchiya, 2018) or the training process, such as overfitting, impairs the merged model's generalization. Second, models trained independently follow distinct optimization trajectories, leading

[1] https://anonymous.4open.science/r/hi-merging

[2] https://huggingface.co/

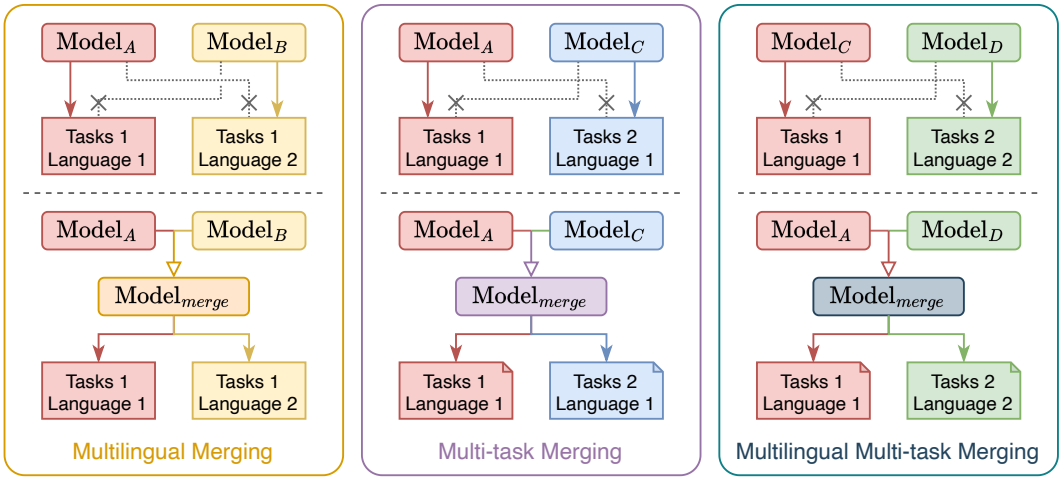

Figure 1: Illustration of three paradigms for our LLM merging: merging models that specialize in different languages (left), merging models that excel at different tasks (middle), and merging models that exhibit expertise in both different languages and different tasks (left). Through such merging, a single model can inherit the combined capabilities of both original models, enabling broader applicability and enhanced performance.

to different knowledge alignments in their parameter spaces (Ilharco et al., 2023). These misaligned parameters become incompatible for direct combination without additional training.

To address these challenges, we propose Hi-Merging, a **H**ierarchical **I**terative **Merging** method. It first applies model-wise pruning and scaling to the delta vectors (parameter differences between fine-tuned models and the foundation model) to eliminate noisy parameters introduced during fine-tuning. Then, we apply layer-wise pruning and scaling iteratively for the knowledge misalignment, starting from the most conflicted layers. To identify the severity of layer-wise conflicts, we develop contribution analysis - a method that quantifies each layer's contribution by measuring how adding or removing specific layers affects model capabilities. By analyzing how our contribution metrics change before and after a pre-merging process, we can identify potential conflicts, thereby guiding our iterative optimization process to resolve parameter incompatibilities without additional training systematically.

Our contributions can be summarized as follows:

- We pioneer the use of model merging to enhance LLMs' multilingual and multi-task capabilities without additional training.
- We propose Hi-Merging, a hierarchical iterative approach that effectively reduces the interference of noise and knowledge alignment conflicts during model merging.
- Extensive experiments on four datasets demonstrate the effectiveness of Hi-Merging under three merging paradigms: multilingual merging, multi-task merging, and multilingual multi-task merging, consistently achieving superior performance across all settings.

2 Preliminary for LLM Merging

In this section, we detail notations and introduce existing model (LLM) merging solutions as the preliminary.

Model merging aims to combine multiple models with distinct capabilities as a single model, which has all the strengths of these models. In this paper, we user two-model merging for illustration: Given models $\mathcal{M}_A$ and $\mathcal{M}_B$ with parameters $\boldsymbol{\theta}_A$ and $\boldsymbol{\theta}_B$, both fine-tuned from a foundation model $\mathcal{M}_F$ with parameters $\boldsymbol{\theta}_F$ for tasks t_A and t_B respectively, model merging aims to combine them into a single model $\mathcal{M}_{\text{merge}}$ with parameters $\boldsymbol{\theta}_{\text{merge}}$ that preserves capabilities for both tasks.

Typical model merging strategies include weighted averaging and delta vector-based merging. The former combines model parameters through a weighted sum (Wortsman et al., 2022):

$$\boldsymbol{\theta}_{\text{merge}} = \sum_{m \in \{A,B\}} \omega_m \boldsymbol{\theta}_m \tag{1}$$

where ω_m is the weight to balance different capabilities constrained to $\sum_{m\in\{A,B\}} \omega_m = 1, \omega_m > 0$. And $m \in \{A, B\}$ is the model identifier.

The second strategy merges models based on delta vectors, the parameter differences between fine-tuned models and their foundation model,

which can be mathematically defined as:

$$\boldsymbol{\delta}_m = \boldsymbol{\theta}_m - \boldsymbol{\theta}_F \tag{2}$$

Delta vectors $\boldsymbol{\delta}_m$ defined in Equation (2) reveal model-specific updates from the foundation model, enabling a delta-weighted merging strategy (Ilharco et al., 2023):

$$\boldsymbol{\theta}_{\text{merge}} = \boldsymbol{\theta}_F + \sum_{m \in \{A,B\}} \omega_m \boldsymbol{\delta}_m \tag{3}$$

where $\omega_m > 0$. Note that both strategies, illustrated in Equation (1) and Equation (3), can be easily extended to multiple model merging scenarios by expanding the model list $\{A, B\}$.

3 Method

In this section, we introduce the proposed method, which consists of two major components: (1) model-wise pruning and scaling that removes noisy and redundant parameters and moderate excessive ones and (2) layer-wise pruning and scaling iterating on conflicted layers to address knowledge misalignment issues.

3.1 Model-wise Pruning and Scaling

This section introduces two operations to process delta vectors: pruning and scaling.

During the fine-tuning, models can accumulate noisy parameters and learn sharp parameters for the specific fine-tuning task. We introduce the pruning and scaling operations to tackle these two problems, respectively, which are controlled by the following hyperparameters:

- **Pruning Threshold** (p): This parameter specifies the proportion of the delta vector that should be preserved. By retaining the largest p percentage of the vector's components and rendering the remaining $(1 - p)$ to zero, the pruning operation can eliminates trivial parameter updates (data-specific noise) while preserving meaningful task-specific knowledge.
- **Scaling Factor** (s): This factor controls the magnitude of the delta vector. With this parameter, the scaling operation contributes to addressing over-aggressive parameters by scaling down sharp updates, which may result from the overfitting during fine-tuning. The pruning does not apply to large parameter changes as they likely encode essential knowledge. The scaling provides a way to moderate their excessive influence.

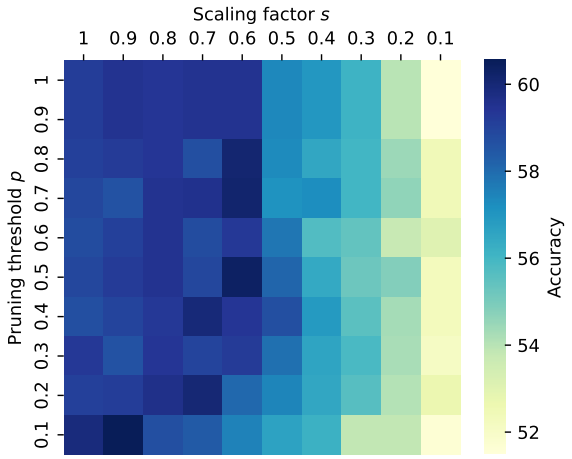

Figure 2: The accuracy of the fine-tuned Qwen2-7B-Instruct on the MedQA dataset after the model-wise pruning and scaling process with different combinations of the pruning threshold p and the scaling factor s.

With these hyperparameters, the pruning and scaling cooperatively process the delta vectors in a complementary manner: pruning eliminates negligible parameter changes while scaling moderates the significant ones. Note that both p and s constrained to $[0, 1]$.

We empirically validate the effectiveness of the pruning and scaling operations by iterating p and s from $[0.1, 1]$. The result is visualized in Figure 2. We can find that the individual model can maintain or even improve performance with appropriate pruning and scaling. For example, $p = 0.1, s = 0.9$ (preserving 10% of parameters and scaling all delta values with 0.9) can defeat the original model ($p = 1, s = 1$). This finding supports our idea of conducting model-wise pruning and scaling to overcome noisy and radical parameter updates.

Next, we introduce the model-wise pruning and scaling details. Specifically, the delta vector (defined in Equation (2)) for a given LLM $\mathcal{M}_m$ can be defined as $\boldsymbol{\delta}_m = [\delta_{m,1}, \delta_{m,2}, \ldots, \delta_{m,N}]$, where $m \in \{A, B\}$ is the model identifier and N indicates the size of trainable parameters.

The **pruning** operation Top_p retains the $\lceil p \cdot N \rceil$ elements of $\boldsymbol{\delta}_m$ with the largest absolute value and zeros out the rest, resulting in $\tilde{\boldsymbol{\delta}}_m$:

$$\tilde{\boldsymbol{\delta}}_m = \text{Top}_p(\boldsymbol{\delta}_m) \tag{4}$$

In detail, the n-th component of $\tilde{\boldsymbol{\delta}}_m$ is:

$$\tilde{\delta}_{m,n} = \begin{cases} \delta_{m,n}, & \text{if } n \in \{\pi(1), \pi(2), \ldots, \pi(\lceil p \cdot N \rceil)\} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where $\pi(n)$ represents the index of the n-th largest component of $\boldsymbol{\delta}_m$ in absolute value, such that:

$$\left|\delta_{m,\pi(1)}\right| \geq \left|\delta_{m,\pi(2)}\right| \geq \cdots \geq \left|\delta_{m,\pi(N)}\right| \quad (6)$$

The **scaling** operation adjusts the magnitude of the pruned delta vector $\tilde{\boldsymbol{\delta}}_m$ by multiplying it with the scaling factor $s \in [0, 1]$ as $s\tilde{\boldsymbol{\delta}}_m$.

Regarding the different setting of p and s for each model, the model-wise pruning and scaling can be compactly expressed as:

$$\hat{\tilde{\boldsymbol{\delta}}}_m = s_m \cdot \mathrm{Top}_{p_m}(\boldsymbol{\delta}_m) = s_m \tilde{\boldsymbol{\delta}}_m \quad (7)$$

where $\hat{\tilde{\boldsymbol{\delta}}}_m$ represents the delta vector after the model-wise pruning and scaling.

Through model-wise processing with pruning and scaling, we effectively identify noisy and excessive parameter updates from the fine-tuning, maintaining and moderating the key knowledge about the fine-tuning task for the subsequent merging.

3.2 Layer-wise Pruning and Scaling

In this section, we conduct the layer-wise model merging with pruning and scaling operations with a novel contribution analysis method to measure the parameter conflict.

3.2.1 Contribution Analysis

Directly merging the model-wise processed delta vectors $\{\hat{\tilde{\boldsymbol{\delta}}}_m\}_{m\in\{A,B\}}$ as in Equation 1 or Equation 3 will encounter the weight misalignment problem, which is overlooked by existing methods.

To investigate potential conflicts when merging a specific layer, we measure its contribution by calculating the performance difference before and after the merge. Precisely, we assess the merging contribution from two directions:

- **Deletion Impact** (α): To estimate this impact, we first construct a merged model $\mathcal{M}_G$ that merges all layers using the merging process mentioned in Equation (1) or Equation (3). Then, we calculate the performance degradation caused by removing the delta vector for a specific layer.
- **Addition Impact** (β): This impact is measured by the performance improvement of adding the delta vector for a specific layer to the pre-trained foundation model $\mathcal{M}_F$.

These impacts can be mathematically represented as:

$$\alpha^l_{m1,m2} = \mathrm{P}_{t_{m1}}(\boldsymbol{\theta}_{m2} - \hat{\tilde{\boldsymbol{\delta}}}^l_{m2}) - \mathrm{P}_{t_{m1}}(\boldsymbol{\theta}_{m2}) \quad (8)$$

$$\beta^l_{m1,m2} = \mathrm{P}_{t_{m1}}(\hat{\boldsymbol{\theta}}_F + \boldsymbol{\delta}^l_{m2}) - \mathrm{P}_{t_{m1}}(\boldsymbol{\theta}_F) \quad (9)$$

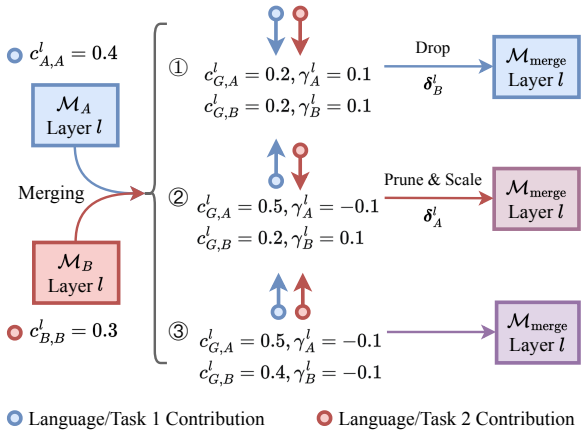

Figure 3: The demonstration of different conflict elimination strategies for three pre-merging conditions.

where $m1 \in \{A, B\}$ is the task capability identifier and $m_2 \in \{A, B, G\}$ is the model identifier. We investigate the layer-wise contribution so that l is the layer index. $\hat{\tilde{\boldsymbol{\delta}}}^l_{m2}$ is the delta vector for $\mathcal{M}_{m2}$ at layer l. $\mathrm{P}_{t_{m1}}(\cdot)$ represents the performance metric on the task t_{m1}. For example, BLEU-4 (Papineni et al., 2002) score for the QA task.

We sum up two impacts as the overall contribution:

$$c^l_{m1,m2} = \alpha^l_{m1,m2} + \beta^l_{m1,m2} \quad (10)$$

3.2.2 Iterative Conflict Elimination

The contribution analysis method defined in Equation (8)-(10) provides a solution to measure the importance of merging specific layers. We can then define the conflict resulted by model $\mathcal{M}_m (m \in \{A, B\})$ within the layer l of the merged model as:

$$\gamma^l_m = c^l_{m,m} - c^l_{m,G} \quad (11)$$

In this formula, we set the capability identifier $m1 = m$ as we expect the merged model can maintain the performance of $\mathcal{M}_m$ on t_m. We can then identify the most severe conflicting layers that impair the fine-tuned performance by sorting $\Gamma^l = \sum_{m\in\{A,B\}} \gamma^l_m$.

To mitigate the parameter misalignment, we iteratively merge the most conflicting layers (with the largest Γ^l). Specifically, to process a specific layer, there are three types of conflict as illustrated in Figure 3:

1. **Severe Conflict:** $\gamma^l_A > 0$ and $\gamma^l_B > 0$, indicating both capabilities are impaired by the merging. In such cases, only the delta vector with a larger contribution is retained, e.g., dropping $\hat{\tilde{\boldsymbol{\delta}}}^l_B$ in the figure. Namely, $\hat{\tilde{\boldsymbol{\delta}}}^l_B$ is set to zero.

2. **Partial Conflict:** $\gamma_A^l * \gamma_B^l < 0$, i.e., one of the delta vectors leads to the parameter misalignment. The solution for this case is to prune and scale the conflict delta vector again, as we defined in Section 3.1. For example, in Figure 3, the overfitting on t_A ($\gamma_A^l < 0$ and $\gamma_B^l > 0$) leads to the degradation of the ability for t_B. As a result, we prune and scale $\hat{\boldsymbol{\delta}}_A^l$ again as[3]:

$$\hat{\hat{\boldsymbol{\delta}}}_A^l = s_A \cdot \mathrm{Top}_{p_A}(\hat{\boldsymbol{\delta}}_A^l), \tag{12}$$

3. **Mutual Enhancement:** If $\gamma_A^l \leq 0$ and $\gamma_B^l \leq 0$, the merging process improves for both capabilities. In this case, no further adjustment is necessary for this layer.

After resolving the conflicts of all layers, the parameters of the final merged model $\mathcal{M}_{merge}$ is:

$$\boldsymbol{\theta}_{\text{merge}} = \boldsymbol{\theta}_{\text{F}} + \hat{\boldsymbol{\delta}}_A + \hat{\boldsymbol{\delta}}_B \tag{13}$$

4 Experiments

In this section, we conduct comprehensive experiments to evaluate the effectiveness of Hi-Merging on multilingual multi-task merging problems by answering following research questions (RQ):

- **RQ1:** How does Hi-Merging compare with baselines on merging LLMs for different languages?
- **RQ2:** How do these methods perform for merging LLMs for different tasks?
- **RQ3:** Are these methods applicable to combine LLMs on different taks and languages?
- **RQ4:** Is Hi-Merging able to merge open-source models from the Hugging Face?

4.1 Experimental Settings

4.1.1 Datasets

We select four datasets listed in Table 1 that cover multilingual multi-task capabilities, including English and Chinese languages, with multiple-choice question answering (MCQA) and open-domain question answering (QA) tasks.

4.1.2 Baselines

In our experiments, we compare Hi-Merging with weighted averaging (Model Soups (Wortsman et al., 2022)) and delta vector-based methods (Arithmetic (Ilharco et al., 2023), TIES-Merging (Yadav et al., 2023), DARE (Yu et al., 2024), DELLA (Deep et al., 2024), and Model Breadcrumbs (Davari and Belilovsky, 2024)), as well as the multilingual and multi-task models fine-tuned on combined datasets. Details of these baselines are in Appendix A.1.1.

[3]We use the same notation $\hat{\boldsymbol{\delta}}_A^l$ for clarity.

Table 1: The brief description and statistics of the four datasets (MedQA (Jin et al., 2020), CMExam (Liu et al., 2023), HealthCareMagic (Li et al., 2023), and cMedQA2) (Zhang et al., 2018) used for fine-tuning.

Name	Task	Language	Train	Validation	Test
MedQA	MCQA	English	10,000	400	400
CMExam	MCQA	Chinese	50,000	4,000	4,000
HealthCareMagic	QA	English	30,000	1,000	1,000
cMedQA2	QA	Chinese	30,000	1,000	1,000

4.1.3 Implementation Details

We use Qwen2-7B-Instruct as foundation model-swith results for other foundation models presented in Appendix A.2. For fine-tuning, we employ LLaMA-Factory [4] with LoRA (rank=8, alpha=16, dropout=0.01) and a batch size of 64. The learning rate is 1.0^{-4} with cosine decay and warm-up. LLM merging is performed using mergekit [5]. For hyperparameter tuning, both p and s in model-wise processing range from 0.1 to 1.0 with a step of 0.1. In layer-wise processing, the pruning threshold p and scaling factor s are successively set to half of their model-wise values.

4.1.4 Evaluation Metrics

For the MCQA task, accuracy is employed to measure the proportion of correct answers (Devlin et al., 2019).For the QA task, we use BLEU-4 (Papineni et al., 2002) to evaluate the precision of the generation, and ROUGE-1,2,L (Lin, 2004) to assess the overlap and coherence with the ground truth. The averaged performance across all metrics is reported as "Avg.". Additionally, we report the relative improvement over the foundation model.

4.2 Multilingual Merging (RQ1)

We first verify the effectiveness of Hi-Merging on multilingual LLM merging. Here, we merge models trained on datasets in different languages (English and Chinese) but for the same task type (QA in Table 2 and MCQA results in Table 3).

With the foundation model Qwen2-7B-Instruct (Yang et al., 2024a), we observe more moderate performance degradation with our method, while Llama3-8B-Instruct (Dubey et al., 2024) exhibits persistent conflicts (results in

[4]https://github.com/hiyouga/LLaMA-Factory
[5]https://github.com/arcee-ai/mergekit

Table 2: Performance comparison of merging methods for multilingual QA using Qwen2-7B-Instruct.

Types	Methods	L1 (HealthCareMagic)				L2 (cMedQA2)				Avg.	Impr.
		BLEU-4	ROUGE-1	ROUGE-2	ROUGE-l	BLEU-4	ROUGE-1	ROUGE-2	ROUGE-l		
Pre-trained	Qwen2-7B-Instruct	30.1209	26.3524	5.3280	15.7451	1.7090	14.1527	1.7822	9.0934	13.0355	-
Fine-tuned	Model A (L1)	35.5717	30.2512	8.9044	20.3625	3.7609	19.1370	3.1364	15.1441	17.0335	+30.66%
	Model B (L2)	24.8587	24.9841	4.1492	15.1967	4.4159	21.2210	4.0680	17.4600	14.5442	+11.57%
	Multilingual	35.7637	29.9781	8.6687	20.1184	3.7660	20.9869	3.7784	16.8850	17.4932	+34.19%
Merged	Model Soups	33.2627	28.8258	7.5487	18.9459	4.6801	**21.5564**	4.0502	17.5380	17.0510	+30.80%
	Task Arithmetic	33.0398	28.7169	7.5726	18.9600	4.7181	21.4108	4.0503	17.6772	17.0182	+30.55%
	TIES	33.6571	29.0496	7.7769	19.1503	4.3751	20.8551	3.7518	17.1978	16.9767	+30.23%
	DARE	33.3031	28.9575	7.8222	19.1702	**4.7578**	21.0865	3.8996	17.2488	17.0307	+30.64%
	DARE+TIES	26.8091	26.0330	5.2307	16.5201	4.2456	20.6276	3.7531	17.1445	15.0455	+15.41%
	Model Breadcrumbs	34.3247	29.4403	8.1518	19.6443	4.4092	20.9365	3.8138	17.1378	17.2323	+32.19%
	DELLA	33.4207	28.9234	7.6728	18.9674	4.6827	21.1596	4.0709	17.4775	17.0469	+30.77%
	DELLA+TIES	27.2331	26.1723	5.4339	16.6009	4.7130	21.2275	**4.2944**	**17.7694**	15.4306	+18.37%
	Hi-Merging (Ours)	**35.9500**	**29.9826**	**8.8738**	**20.3844**	4.7009	21.1752	3.9704	17.2361	**17.78**	**+36.42%**

Note: (1) Model A is fine-tuned on HealthCareMagic (L1: English), Model B is fine-tuned on cMedQA2 (L2: Chinese), Multilingual model is fine-tuned on both datasets; (2) Merged models are obtained by merging Model A and B; (3) The overall best result is marked in bold and the best merging result is underlined.

Table 3: Performance comparison of merging methods for multilingual MCQA using Qwen2-7B-Instruct.

Types	Methods	L1 (MedQA)	L2 (CMExam)	Avg.	Impr.
Pre-trained	Qwen2-7B-Instruct	51.4062	74.6217	63.0140	-
	Yi-1.5-9B	46.8185	58.6499	52.7342	-16.31%
	Baichuan2-7B	6.4415	7.1439	6.7927	-89.22%
Fine-tuned	Model A (L1)	59.1406	83.7771	71.4589	+13.40%
	Model B (L2)	54.4531	88.6171	71.5351	+13.52%
	Multilingual	60.0781	88.2246	74.1514	+17.67%
Merged	Model Soups	59.6094	88.6926	74.1510	+17.67%
	Task Arithmetic	59.5312	88.7681	74.1497	+17.67%
	TIES	59.0625	**88.7832**	73.9229	+17.31%
	DARE	58.6719	88.6926	73.6823	+16.93%
	DARE + TIES	58.9063	88.6021	73.7542	+17.04%
	Model Breadcrumbs	58.8281	88.6322	73.7302	+17.00%
	DELLA	58.9844	88.7681	73.8763	+17.24%
	DELLA + TIES	58.2812	88.7530	73.5171	+16.67%
	Hi-Merging (Ours)	**61.0156**	88.6501	**74.8329**	**+18.76%**

Note: (1) Model A is fine-tuned on MedQA (L1: English). Model B is fine-tuned on CMExam (L2: Chinese), Multilingual model is fine-tuned on both datasets. (2) Merged models are obtained by merging Model A and B. (3) The overall best result is in bold and the best merging result is underlined.

Appendix A.2). This difference stems from the capability gap of foundation models. Qwen2's stronger language ability enables more structured parameter updates, where new knowledge aligns better. In contrast, weaker foundation models lead to dispersed parameter updates and knowledge misalignment. In addition, we investigate the impact of different training sample sizes on LLM merging in Appendix A.3.

Baselines like Model Soups and Task Arithmetic that combine models without considering noises and conflicts achieve relatively stable average performance. Methods that reduce conflicts, such as TIES and DARE, occasionally achieve the best results on individual metrics by discarding delta vectors. However, their average performance needs more systematic processing strategies. In contrast, our Hi-Merging method, with hierarchical pruning and scaling approach, not only achieves the best average performance but attains optimal results in about half of the individual metrics.

4.3 Multi-task Merging (RQ2)

For multi-task merging, we combine models trained on the same task but in different languages (e.g., English MCQA with Chinese MCQA), as shown in Table 4. The results show that merged models consistently outperform their individual fine-tuned counterparts, with many merging methods even surpassing multi-task fine-tuned models. Notably, our Hi-Merging approach achieves a 1.84% relative improvement over the multi-task fine-tuned model. We attribute this success to three factors. 1) During multi-task fine-tuning with limited data (compared to pre-training), tasks can interfere with each other due to the "seesaw effect". In contrast, model merging allows parameters to be optimized independently before integration, avoiding such interference. 2) Since both models are fine-tuned from the same foundation model, their parameter updates tend to follow similar optimization trajectories, making successful merging more likely. 3) The inherent sparsity of large language models provides sufficient parameter space to accommodate multi-task knowledge from both models without significant conflicts.

4.4 Multilingual Multi-task Merging (RQ3)

For multilingual multi-task merging, we combine models trained on completely different tasks and languages. Specifically, we merge a model

Table 4: Performance comparison of merging methods for multi-task learning.

Types	Methods	L1 (English)					L2 (Chinese)					Avg.	Impr.
		T1 (MedQA)	T2 (HealthCareMagic)				T1 (CMExam)	T2 (cMedQA2)					
		Accuracy	BLEU-4	ROUGE-1	ROUGE-2	ROUGE-l	Accuracy	BLEU-4	ROUGE-1	ROUGE-2	ROUGE-l		
Pre-trained	Qwen2-7B-Instruct	51.4062	30.1209	26.3524	5.3280	15.7451	74.6217	1.7090	14.1527	1.7822	9.0934	23.0312	-
Fine-tuned	Model A (T1)	59.1406	34.6533	28.7482	6.9168	17.9525	88.6171	2.8064	16.8617	2.5603	12.0561	27.0313	+17.36%
	Model B (T2)	53.0469	35.5717	30.2512	8.9044	20.3625	81.5670	4.4159	21.2210	4.0680	17.4600	27.6869	+20.21%
	Multi-task	59.2188	35.6009	30.2101	9.1375	20.4645	88.6926	3.7790	20.5919	3.8096	16.9265	28.8431	+25.23%
Merged	Model Soups	58.5156	36.4411	30.5654	9.1754	20.4259	88.8285	4.3912	21.0216	4.0040	17.2843	29.0653	+26.19%
	Task Arithmetic	58.5938	36.3290	**30.6624**	**9.1945**	**20.5406**	88.7983	4.3018	20.6467	3.7496	16.9995	29.0493	+26.13%
	TIES	60.4688	35.7851	30.3243	9.0310	20.3723	88.6171	4.5434	21.5629	4.1910	17.4909	29.1996	+26.78%
	DARE	58.4375	**36.5802**	30.5488	9.0818	20.3945	88.7681	4.5487	21.3255	3.8403	17.4471	29.0865	+26.29%
	DARE+TIES	59.3750	35.7062	30.1950	8.7840	20.0878	88.8285	4.1587	21.1291	3.8124	17.2868	28.9361	+25.63%
	Model Breadcrumbs	57.8906	36.4620	30.2173	8.7845	20.0169	88.8889	4.4472	21.2492	3.8931	17.2846	28.9128	+25.53%
	DELLA	58.5938	36.3494	30.1715	8.8125	20.1879	88.8134	4.3718	21.0226	3.9300	17.3403	28.9818	+25.83%
	DELLA+TIES	59.5312	36.0774	30.4743	9.1151	20.4599	88.6021	4.3202	21.2269	4.0164	17.3779	29.0115	+25.96%
	Hi-Merging (Ours)	**60.5469**	36.4926	30.5467	9.1231	20.3523	**88.9795**	**4.6781**	**21.5367**	**4.2165**	**17.5038**	**29.2673**	**+27.07%**

Note: (1) Model A is fine-tuned on English datasets (T1: MedQA or HealthCareMagic), Model B is fine-tuned on Chinese datasets (T2: CMExam or cMedQA2), Multi-task models are fine-tuned on datasets with the same language; (2) Merged models are obtained by merging Model A and B; (3) The overall best result is marked in bold and the best merging result is underlined.

Table 5: Performance comparison of merging methods for multilingual multi-task learning.

Types	Methods	T1, L1 (MedQA)	T2, L2 (cMedQA2)				T1, L2 (CMExam)	T2, L1 (HealthCareMagic)				Avg.	Impr.
		Accuracy	BLEU-4	ROUGE-1	ROUGE-2	ROUGE-l	Accuracy	BLEU-4	ROUGE-1	ROUGE-2	ROUGE-l		
Pre-trained	Qwen2-7B-Instruct	51.4062	1.709	14.1527	1.7822	9.0934	74.6217	30.1209	26.3524	5.328	15.7451	23.0312	-
Fine-tuned	Model A (T1)	59.1406	2.8064	16.8617	2.5603	12.0561	88.6171	34.6713	28.4279	6.6122	18.1117	26.9865	+17.17%
	Model B (T2)	54.4922	4.4159	21.221	4.068	17.46	79.6875	35.5717	30.2512	8.9044	20.3625	27.6434	+20.03%
	Multilingual Multi-task	**60.7812**	3.8473	20.8741	4.0434	16.9525	**88.9795**	35.7429	30.1735	8.9153	20.3902	29.0700	+26.22%
Merged	Model Soups	58.3584	4.6592	21.2316	4.0559	17.3805	88.6322	36.1765	**30.7169**	**9.2702**	**20.5227**	29.1004	+26.35%
	Task Arithmetic	58.0469	4.6682	21.2618	4.0984	17.4231	88.7379	36.1222	30.2256	8.757	20.1357	28.9477	+25.69%
	TIES	59.6094	4.3764	21.0083	3.9002	17.4194	88.7228	35.7708	30.5143	8.8994	20.3487	29.0570	+26.16%
	DARE	57.8906	4.5671	21.1856	3.9549	17.2328	88.6322	35.8639	30.1489	8.815	20.1025	28.8394	+25.22%
	DARE+TIES	58.75	4.4929	21.3194	4.0824	17.4826	88.5568	34.8223	29.7597	8.3004	19.7624	28.7329	+24.76%
	Model Breadcrumbs	57.1094	4.7217	21.4192	4.1477	17.4182	88.6021	36.4961	30.3911	9.0696	20.4108	28.9786	+25.82%
	DELLA	58.0469	**4.8065**	**21.5135**	4.1356	17.4962	88.6167	36.0159	30.3747	9.0414	20.3929	29.0440	+26.11%
	DELLA+TIES	59.0625	4.4854	20.9954	4.0491	**17.563**	88.6624	35.0176	29.9666	8.658	20.1406	28.8601	+25.31%
	Hi-Merging (Ours)	60.2344	4.7743	21.1954	**4.1749**	17.3991	88.7983	**36.5223**	30.3932	8.7882	20.1619	**29.2442**	**+27.02%**

Note: (1) Model A is fine-tuned on MCQA datasets (T1: MedQA or CMExam), Model B is fine-tuned on QA datasets (T2: cMedQA2 or HealthCareMagic); (2) Merged models are obtained by merging Model A and B; (3) The overall best result is marked in bold and the best merging result is underlined.

trained for MCQA in one language (Model A: MedQA in English or CMExam in Chinese) with another model trained for QA in the opposite language (Model B: cMedQA2 in Chinese or HealthCareMagic in English), as illustrated in Table 5.

An intriguing phenomenon observed in our experiments is that multilingual multi-task fine-tuning tends to predominantly affect QA task performance, while model merging methods typically significantly impact MCQA task performance. We attribute this to two key factors. First, the QA task requires free-form text generation, demanding a more complex representation space than the relatively constrained choice selection in the MCQA task. Therefore, this complexity makes QA performance more vulnerable to degradation during joint fine-tuning. Second, model merging directly combines model parameters. Since MCQA tasks need exact boundaries for classification, these boundaries are more easily disrupted during the merging process, making MCQA performance more vulnerable to merging operations.

4.5 Open-source LLM Merging (RQ4)

To validate the generality of our merging approach, we conduct experiments using two open-source medical models from Hugging Face: Echelon-AI/Med-Qwen2-7B [6], fine-tuned on English datasets for tasks such as medical QA and information retrieval (IR), and shtdbb/qwen2-7b-med [7], fine-tuned on Chinese datasets for dialogue generation. Both models are derived from Qwen2-7B-Instruct. Figure 4 illustrates the performance comparison across 12 medical datasets, with metrics normalized for better visualization.

Our approach demonstrates robust performance across the task spectrum. In 7 out of 12 datasets, Hi-Merging achieves the best performance among all models, with only two datasets showing apparent degradation compared to the better-performing individual model. These results demonstrate Hi-

[6] https://huggingface.co/Echelon-AI/Med-Qwen2-7B

[7] https://huggingface.co/shtdbb/qwen2-7b-med

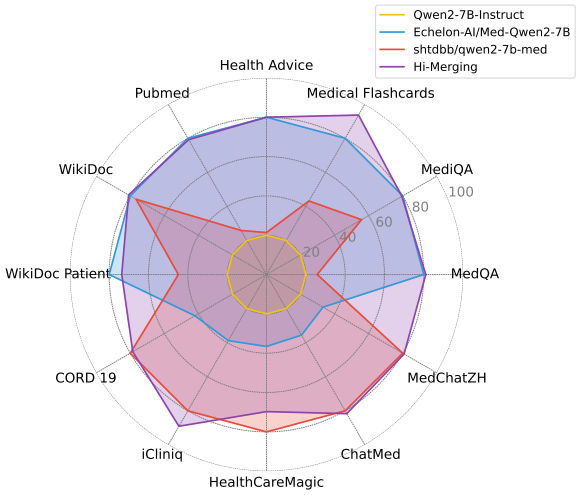

Figure 4: Performance of Hi-Merging on two open-source medical models, Echelon-AI/Med-Qwen2-7B and shtdbb/qwen2-7b-med, which are fine-tuned from the foundation model Qwen/Qwen2-7B-Instruct.

Merging's ability to effectively fuse medical knowledge while maintaining or enhancing performance across diverse languages and tasks. Detailed implementation setup and unprocessed numerical results can be found in Appendix A.1.2 and A.4.

5 Related Works

5.1 Multilingual Task-Oriented LLMs

Multilingual tasks in NLP encompass a broad range of challenges, including machine translation (Wang et al., 2022), multilingual text summarization (Gambhir and Gupta, 2017), and sentiment analysis (Dashtipour et al., 2016) etc. Recently, LLMs have greatly contributed to advancing multilingual tasks by leveraging massive amounts of multilingual data (Brown et al., 2020; Devlin et al., 2019; Xue et al., 2021). Despite their success, LLMs struggle with multilingual limitations due to imbalanced pre-training data, resulting in better performance for high-resource languages over low-resource ones.

To enhance multilingual capabilities, LLMs employ continual training on specific languages, as seen in models like Chinese-LLaMA (Cui et al., 2023) and EuroLLM (Martins et al., 2024). Additionally, supervised fine-tuning techniques, such as LoRA in Chinese-Alpaca (Cui et al., 2023) and incorporating translation tasks in XGLM-7B (Li et al., 2024), further improve multilingual understanding. However, LLMs are usually enhanced for one language at a time, resulting in multiple isolated models.

5.2 Model Merging

Model merging aims to integrate knowledge from multiple fine-tuned models into a single one. These methods are categorized into two types: weighted-based merging and interference mitigation.

Weighted-based merging focuses on combining model parameters effectively. This includes simple techniques like parameter averaging, such as Model Soups (Wortsman et al., 2022), Fisher-weighted merging (Matena and Raffel, 2022) and RegMean (Jin et al., 2023). While computationally efficient, these methods often miss conflicting parameter updates, leading to performance degradation. Therefore, Task Arithmetic (Ilharco et al., 2023) proposes manipulating delta vectors. AdaMerging (Yang et al., 2024c) and evolutionary algorithms (Akiba et al., 2024) optimize merging coefficients and blend diverse models, respectively.

Interference mitigation techniques aim to reduce parameter conflicts based on the over-parameterization and sparsity of LLM. DARE (Yu et al., 2024) and SparseGPT (Frantar and Alistarh, 2023) show high LLM performance despite significant parameter pruning. DELLA (Deep et al., 2024) introduces MAGPRUNE for selective pruning and parameter rescaling. TALL-masks (Wang et al., 2024) isolate task-specific parameters to minimize interference. However, these techniques focus mainly on individual parameter-level operations without considering the structural relationships and knowledge dependencies across model layers.

6 Conclusion

In this paper, we proposed Hi-Merging, a novel approach for merging LLMs for multilingual multi-task learning. Hi-Merging leverages model-wise and layer-wise pruning and scaling strategy to minimize the conflict between fine-tuned models' delta vectors. The model-wise process eliminates the fine-tuning noise and overfitting parameters of the original models. Then, the layer-wise process analyzes the contribution of each layer's delta vector to the fine-tuning performance, reducing the interference of conflicts in several key layers. Extensive experiments on the MCQA and QA datasets demonstrated that Hi-Merging outperforms traditional merging techniques and even surpasses models trained on multiple datasets. Future work will explore finer-grained conflict analysis strategies.

7 Limitations

While our proposed Hi-Merging method demonstrates promising results, several limitations should be acknowledged. First, our evaluation is currently limited to two task types (MCQA and QA) and two languages (English and Chinese). The effectiveness of Hi-Merging on a broader range of NLP tasks and language families remains to be investigated.

Second, our method focuses on merging models fine-tuned from the same foundation model. The applicability and performance of Hi-Merging when merging models from different architectural families or pre-training approaches is yet to be explored. This limitation becomes particularly relevant as the field continues to see diverse model architectures and training paradigms.

Finally, our current implementation assumes relatively balanced task importance. The method might need adaptation for scenarios where certain tasks or languages should be prioritized over others, potentially requiring a more flexible weighting mechanism in the merging process.

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A Appendix

A.1 Experimental Settings

A.1.1 Baselines

In our experiments, we compare it against a comprehensive set of baseline methods, including traditional weighted averaging techniques and state-of-the-art approaches specifically developed for fine-tuned models.

- **Multilingual Multi-task Training** This approach trains a single model on the combined datasets of multiple languages simultaneously, without distinguishing between tasks.
- **Model Soups** (Wortsman et al., 2022) Uniform Soup is a simple merging method where the parameters of the fine-tuned models are averaged based on their importance.
- **Task Arithmetic** (Ilharco et al., 2023) This method performs arithmetic operations on the parameter differences between the pre-trained and fine-tuned models.
- **TIES** (Yadav et al., 2023) The Task Interference Elimination Strategy (TIES) minimize negative transfer and task interference by pruning redundant parameters and using a chosen sign to determine parameter update directions.
- **DARE** (Yu et al., 2024) Delta Alignment for Robust Ensemble (DARE) reduces the interference across tasks by randomly drop the delta vectors.
- **Model Breadcrumbs** (Davari and Belilovsky, 2024) This approach tracks and prunes maxima and minima in delta vectors to retain critical task-specific features.
- **DELLA** (Deep et al., 2024) DELLA follows DARE and assign drop rates to delta vectors according to their absolute values, improving performance stability.

A.1.2 Implementation Details

Our experimental environment consisted of a CentOS Linux 7 operation system with Python 3.12.4 and CUDA 12.2. All model training and inference operations were implemented using PyTorch 2.4.0. The hardware setup included 8 Tesla V100 GPUs, each equipped with 32GB of memory, enabling efficient parallel processing of large-scale models.

For model adaptation, we applied LoRA to all linear networks in the model. The learning rate schedule was carefully designed with a 100-step warm-up phase followed by cosine decay, which helped achieve stable convergence while maintaining optimal model performance. This configuration proved effective in balancing training efficiency and model quality across both multilingual and multi-task scenarios.

In addition to Qwen2-7B-Instruct, we also experimented with other foundation models including Llama-3-8B-Instruct (results shown in A.2). However, Qwen2-7B-Instruct demonstrated more consistent performance, particularly in handling both English and Chinese tasks, making it the preferred choice for our main experiments.

For visualization in Figure 4, we normalized the performance metrics to facilitate clear comparisons. The performance values of the models on each dataset represent the average of the QA task metrics (BLEU-4, ROUGE-1, ROUGE-2, and ROUGE-L). We scaled the pre-trained Qwen2-7B-Instruct's performance to 20 and the better-performing fine-tuned model's performance to 80 for each task. The performance values of the other fine-tuned model and our merged model were then proportionally adjusted within this range to maintain their relative differences.

A.2 Multilingual Merging

We further conduct experiments on Llama-3-8B-Instruct, as presented in Table 6 and 7. The results in Table 7 show that the performance of merged models based on Llama-3-8B-Instruct is generally inferior to that of the pre-merged fine-tuned models. This indicates that the effectiveness of the merging process is strongly influenced by the quality of the foundation models.

The observed degradation in performance can

Table 6: Performance comparison of merging methods for multilingual MCQA using Llama-3-8B-Instruct.

Types	Methods	L1 (MedQA)	L2 (CMExam)	Avg.
Pre-trained	Llama-3-8B-Instruct	57.9733	17.2821	37.6277
	GLM-4-9B	54.7656	69.5194	62.1425
	Gemma-2-9B	14.2583	2.7698	8.5141
Fine-tuned	Model A (L1)	60.4688	52.2706	56.3697
	Model B (L2)	60.3906	60.5525	61.0575
	Multilingual	**62.8906**	61.0356	**61.9631**
Merged	Model Soups	61.2500	61.0507	61.1504
	Task Arithmetic	61.2500	**61.8750**	61.5625
	TIES	61.7188	61.3225	61.5207
	DARE	61.5625	61.3678	61.4652
	DARE + TIES	60.9375	59.4656	60.2016
	Model Breadcrumbs	61.0156	60.4318	60.7237
	DELLA	60.8594	60.7186	60.7890
	DELLA + TIES	61.9531	61.3527	61.6529
	Hi-Merging (Ours)	62.2656	61.0757	61.6707

Note: (1) Model A is fine-tuned on MedQA (L1: English). Model B is fine-tuned on CMExam (L2: Chinese), Multilingual model is fine-tuned on both datasets. (2) Merged models are obtained by merging Model A and B. (3) The overall best result is in bold and the best merging result is underlined.

be attributed to several factors. First, weaker foundation models, such as Llama-3-8B-Instruct, tend to produce delta vectors with more dispersed and less coherent parameter distributions during fine-tuning. These delta vectors often carry noisy or conflicting information, which makes the merging process prone to parameter conflicts. Second, the weaker representational capacity of these models limits their ability to encode robust and semantically aligned knowledge, further exacerbating the challenges of merging.

In contrast, stronger foundation models, such as Qwen2-7B-Instruct, exhibit fewer conflicts during merging and demonstrate consistent performance improvements across tasks and languages. This is because their fine-tuned delta vectors are more compact and carry knowledge that is better aligned with the foundation model's semantic space, making the integration process more effective.

A.3 Number of training samples

We examine the impact of varying the number of training samples on the conflict during model merging, as shown in Figure 5. In the experiment, we use two QA datasets, HealthCareMagic (English) and cMedQA2 (Chinese), sampling 10k, 20k, 30k, 40k, and 50k training examples from each to produce a series of fine-tuned models, five per dataset. This setup evaluates how the number of training samples influences both individual model performance and compatibility during merging. The x-axis of Figure 5 represents the number of training samples, while the y-axis denotes the average performance metrics, including BLEU-4, ROUGE-1, ROUGE-2, and ROUGE-L.

However, Figures 5b and 5c show that merged models through either Model Soups or Task Arithmetic suffer from performance drops driven by the increasing size of training sample as further training leads to conflicting highly specialized models. Figure 5d shows the opposite: our method retains performance trends in line with fine-tuned models and addresses conflicts to retain improving performance through larger training sets.

These results highlight the robustness of our method in resolving merging conflicts, ensuring that the merged models retain the strengths of individual models while achieving stable and superior performance across training sample sizes.

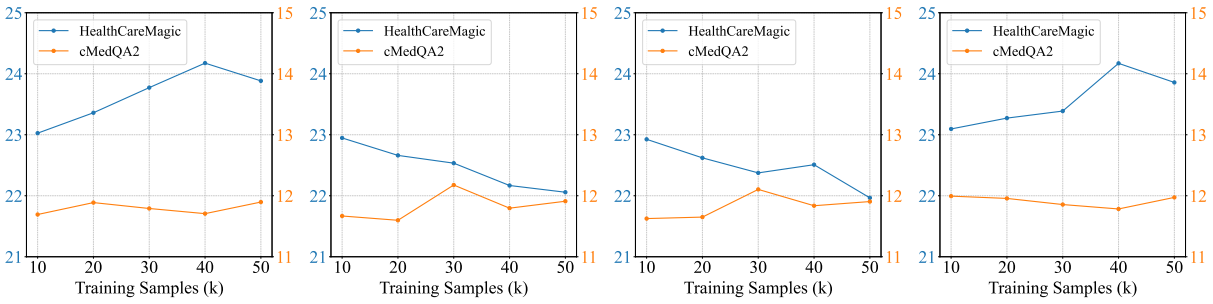
A.4 Open Source LLM Merging

Table 8 presents the detailed numerical results for all models across the 12 medical datasets. The datasets cover a wide range of medical tasks and languages, allowing us to comprehensively evaluate the models' capabilities and the effectiveness of our merging approach.

Table 7: Performance comparison of merging methods for multilingual QA using Llama-3-8B-Instruct.

Types	Methods	L1 (HealthCareMagic)				L2 (cMedQA2)				Avg.	Impr.
		BLEU-4	ROUGE-1	ROUGE-2	ROUGE-L	BLEU-4	ROUGE-1	ROUGE-2	ROUGE-L		
Pre-trained	Llama-3-8B-Instruct	16.3118	21.6011	3.1389	10.8666	0.0225	0.4710	0.0211	0.2343	6.5834	-
Fine-tuned	Model A (L1)	**36.0325**	30.4111	**9.2743**	**20.7236**	0.0185	0.1288	0.0025	0.0841	12.0844	+83.5%
	Model B (L2)	3.9950	7.7673	0.9267	4.6358	3.0638	20.4016	3.4178	16.3067	7.5643	+14.9%
	Multilingual	35.6154	**30.5447**	9.2156	20.4271	3.0250	20.3136	**3.4964**	16.0911	**17.3411**	**+163.5%**
Merged	Model Soups	32.1199	28.2278	6.3715	18.2456	3.3256	19.5499	2.8670	15.4688	15.7720	+139.5%
	Task Arithmetic	31.6679	27.7646	6.0354	18.0448	3.3805	19.6475	2.9507	15.4806	15.6215	+137.2%
	TIES	32.1494	28.0527	6.7440	18.2913	3.2238	19.5369	2.8854	15.2112	15.7618	+139.4%
	DARE	25.9679	25.6716	4.5173	16.3803	3.5337	20.8586	3.1736	16.6716	14.5968	+121.7%
	DARE+TIES	26.6707	25.9106	5.2031	16.5525	3.2236	19.8564	2.9963	15.5967	14.5012	+120.2%
	Model Breadcrumbs	26.9844	26.1004	4.7037	16.3247	3.3307	20.7442	3.3069	16.2874	14.7228	+123.6%
	DELLA	25.6313	25.6792	4.5522	16.1313	**3.6612**	**20.9176**	3.3286	**16.7355**	14.5796	+121.4%
	DELLA+TIES	27.1246	26.0186	5.3163	16.6170	3.3433	19.9122	3.0848	15.9942	14.6764	+122.9%
	Hi-Merging (Ours)	33.5960	28.4141	7.2167	18.8804	3.1967	19.8207	2.9509	15.7833	16.2324	+146.5%

Note: (1) Model A is fine-tuned on HealthCareMagic (L1: English), Model B is fine-tuned on cMedQA2 (L2: Chinese), Multilingual model is fine-tuned on both datasets; (2) Merged models are obtained by merging Model A and B; (3) The overall best result is marked in bold and the best merging result is underlined.



(a) Fine-tuned models (b) Model Soups (c) Task Arithmetic (d) Our method

Figure 5: Impact of training sample size on model merging conflicts. Blue and orange lines represent the average performance metrics for HealthCareMagic and cMedQA2, respectively.

Table 8: Numerical performance of Hi-Merging on two open-source models, Echelon-AI/Med-Qwen2-7B and shtdbb/qwen2-7b-med.

Models	MedQA	MediQA	Medical Flashcards	Health Advice	Pubmed	WikiDoc	WikiDoc Patient	CORD 19	iCliniq	HealthCareMagic	ChatMed	MedChatZH
Qwen2-7B-Instruct	37.3868	17.3595	22.7668	2.8205	5.7994	17.6217	18.785	39.1748	19.3292	28.7051	9.9138	8.0654
Echelon-AI/Med-Qwen2-7B	64.2862	**32.052**	41.1081	97.7523	**92.9898**	20.7237	**26.9203**	40.7167	26.5593	30.3212	15.1218	9.2714
shtdbb/qwen2-7b-med	40.1598	27.1442	29.85	4.096	11.5017	20.5808	21.1528	**41.2026**	27.332	**33.3678**	19.4513	11.2665
Hi-Merging (Ours)	**64.9011**	31.9421	**45.1714**	**97.755**	92.1692	**21.0211**	26.3293	40.9803	**28.7816**	31.6779	**19.8074**	**11.2958**