AdaMergeX: Cross-Lingual Transfer with Large Language Models via Adaptive Adapter Merging

Anonymous ACL submission

Abstract

As an effective alternative to the direct fine-tuning on target tasks in specific languages, cross-lingual transfer addresses the challenges of limited training data by decoupling "task ability" and "language ability", achieved by fine-tuning on the target task in the source language and another selected task in the target language, respectively. However, they fail to fully separate the task ability from the source language or the language ability from the chosen task. In this paper, we acknowledge the mutual reliance between task ability and language ability and direct our attention toward the gap between the target language and the source language on tasks. As the gap removes the impact of tasks, we assume that it remains consistent across tasks. Based on this assumption, we propose a new cross-lingual transfer method called `AdaMergeX` that utilizes adaptive adapter merging. By introducing a reference task, we can determine that the divergence of adapters fine-tuned on the reference task in both languages follows the same distribution as the divergence of adapters fine-tuned on the target task in both languages. Hence, we can obtain target adapters by combining the other three adapters. Furthermore, we propose a structure-adaptive adapter merging method. Our empirical results demonstrate that our approach yields new and effective cross-lingual transfer, outperforming existing methods across all settings.[1]

1 Introduction

Recent advancements in multilingual large language models (LLMs) (OpenAI, 2022, 2023; Gemini Team et al., 2023; AI@Meta, 2024) have gained significant attention given the growing need for multilingual requirements. To further enhance the model's multilingual capability, particularly in cases where training data of certain tasks for low-resource languages is scarce and fine-tuning becomes impractical (Ma et al., 2023), cross-lingual transfer is introduced to extend the task-solving ability from a source language to various target languages (Lin et al., 2019; Chen et al., 2022).

Essentially, cross-lingual transfer aims to transfer the ability to solve a certain task ("task-ability") from a source language to a particular target language ("language ability"). However, some cross-lingual transfer techniques fail to directly improve the language ability in specific languages. As a compromise, they reply on the language ability in English for multilingual tasks, employing methods like translation (Liang et al., 2023; Huang et al., 2023b), representation alignment (Nguyen et al., 2023; Gao et al., 2023), or prompting method specifically developed for LLMs (Tanwar et al., 2023; Zhang et al., 2023b). On the contrary, some studies aim to enhance the language abilities in target languages, so they endeavor to decouple task ability and language ability, enhance them separately, and subsequently merge them (Pfeiffer et al., 2020; Ansell et al., 2022; Ponti et al., 2023). However, this approach overlooks the intrinsic interdependence between task ability and language ability. Given that any specific task would be expressed in a particular language, these two abilities cannot be distinctly isolated from one another.

In this work, we argue that language ability and task ability are inherently interconnected. Instead of separating one from another, they should follow that task ability is affiliated with the source language while language ability refers to the capacity gap between the target language and the source language. In line with the famous equation "$king - queen = man - woman$" in the word embedding space (Mikolov et al., 2013), we assume that the divergences between LLMs fine-tuned in different languages on a particular task follow the same distribution across diverse tasks. In the case of parameter-efficient fine-tuning, the equation becomes $read^{fr} - read^{en} = math^{fr} - math^{en}$ in the adapter space, where $read$ and $math$ refers to

[1] Code will be publicly available.

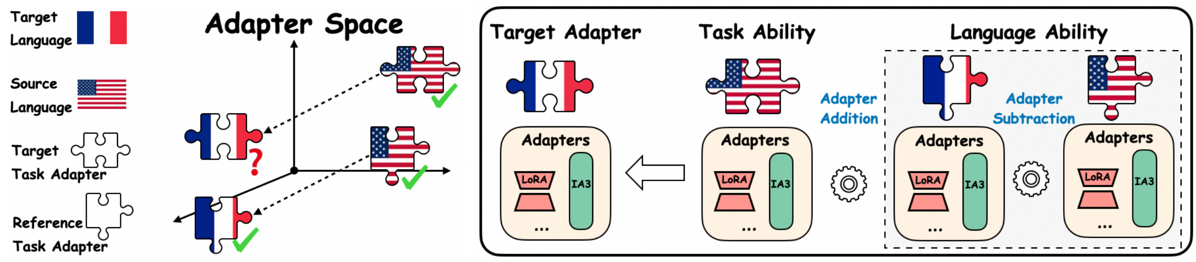

Figure 1: An overview of invariants of the language ability gap among different tasks in the adapter space, where by employing any three we can get the remaining one. In light of this observation, we propose `AdaMergeX`.

two tasks, and fr and en indicates two languages of the corresponding tasks. As shown in the left side of Figure 1, in the adapter space, the divergence between the target language and source language on the target task follows the same distribution as the divergence on the reference task.

Therefore, we propose to accomplish the cross-lingual transfer through adapter merging with such a relation as shown in the right side of Figure 1. Specifically, we introduce a reference task from which we obtain the divergence between the target language and source language, thereby capturing "language ability". It is worth noting that the reference task can be an easily accessible task for both high-resource and low-resource languages, such as causal language modeling. In addition, we fine-tune LLMs on the target task in the source language, from which we obtain "task ability". Finally, by merging these two abilities, we can obtain the adapter for the target task in the target language.

Furthermore, in contrast to previous studies that combine models or adapters through a linear combination (Ilharco et al., 2022; Zhang et al., 2023a; Ponti et al., 2023), we argue that the adapter merging method should consider the manner in which adapters are integrated with language models, specifically the structure of adapters. Therefore, we design a structure-adaptive adapter merging method, which can adaptively select merging methods for LoRA (Hu et al., 2021), $(IA)^3$ (Liu et al., 2022), Adapter (Houlsby et al., 2019), Prefix-Tuning (Li and Liang, 2021) etc. Combined with the cross-lingual transfer method proposed in Figure 1, we propose an Adaptive Adapter Merging approach for cross-lingual transfer (`AdaMergeX`).

We evaluate the proposed `AdaMergeX` method on a wide range of multilingual tasks spanning 12 languages, covering a broad resource spectrum from high-resource to low-resource languages. Our evaluation demonstrates that `AdaMergeX` consistently outperforms other state-of-the-art methods including model merging, prompting, and general adapter merging methods. Notably, compared to MAD-X (Pfeiffer et al., 2020) which separates the task and language ability with two adapters, `AdaMergeX` achieves 8.0% and 15.9% absolute improvement on XCOPA and XQuAD respectively with XLM-R. In the case of state-of-the-art adapter merging method Arimerge (Zhang et al., 2023a), `AdaMergeX` achieves 31.1% relative improvement on average in all languages and all tasks with Llama2. Moreover, the ablation analysis shows that `AdaMergeX` performs consistently well with different backbone models, source languages, and reference tasks.

2 Background

Given a pre-trained model, fine-tuning is often employed to improve the performance on specific tasks. Specifically, for a layer $h = W_0 x$, where $x \in \mathbb{R}^k$ is input, $h \in \mathbb{R}^d$ is output and $W_0 \in \mathbb{R}^{d \times k}$ is pre-trained parameters, fine-tuning updates parameters from W_0 to W' and the layer becomes $h = W'x$. However, full fine-tuning requires many training data points and computing resources, which inspires the design of adapters (Houlsby et al., 2019). With adapters, the layer is changed to $h = (W_0 \circ W_A)x$, where W_A denotes the parameters of adapters and $\circ$ denotes the combination operation of pre-trained parameters and adapter parameters. During such parameter-efficient fine-tuning, pre-trained parameters W_0 are fixed and only adapter parameters W_A are updated. With the number of parameters growing much bigger for LLMs, adapters become more widely used in the current practice of fine-tuning LLMs (Hu et al., 2021; Li and Liang, 2021; Liu et al., 2022)

Various combination methods $\circ$ have been designed for different adapters. In this paper, we focus on two main widely used combination methods: addition and multiplication, corresponding to

LoRA (Hu et al., 2021) and $(IA)^3$ (Liu et al., 2022), respectively. We also involve Adapter (Houlsby et al., 2019) and Prefix-Tuning (Li and Liang, 2021) in to guarantee the generaliability.

LoRA Specializing the combination method "$\circ$" to element-wise addition denoted as "$\oplus$", LoRA employs low-rank decomposition to reduce training complexity. The layer is thus changed to

$$h = (W_0 \oplus W_A)x = (W_0 \oplus BA)x, \quad (1)$$

where $B \in \mathbb{R}^{d\times r}$ and $A \in \mathbb{R}^{r\times k}$ are low-rank decomposed matrices, and the rank $r \ll \min(d, k)$. Specifically, the LoRA can be implemented in any layer of the Transformer (Vaswani et al., 2017) architecture, including the attention layer and the feed-forward layer.

$(IA)^3$ $(IA)^3$ specializes the combination method to element-wise multiplication "$\odot$":

$$h = (W_0 \odot W_A)x, \quad (2)$$

where $W_A \in \mathbb{R}^k$ is element-wise multiplied to each row of W_0. Furthermore, $(IA)^3$ can only be implemented to the key and value neuron in the attention layer and dimension reduction neuron in the feed-forward layer of the Transformer architecture.

Adapter & Prefix-Tuning By inserting layers and prefix tokens into the model, combination methods of Adapter and Prefix-Tuning can be formulated as

$$h = ([W_0, W_A])x, \quad (3)$$

where $[\cdot, \cdot]$ represents concatenation to original layer or original pre-trained parameters.

3 AdaMergeX: Adaptive Adapter Merging for Cross-lingual Transfer

3.1 Cross-Lingual Transfer via Adapter Merging

Generally, the ability of a model in a particular task and language can be seen as a composite of two abilities, namely, "task ability" and "language ability". The former denotes the model's competence in performing a certain task (e.g., text classification, sentence completion), whereas the latter signifies their general proficiency in the given language (e.g., English, Chinese, German). Built on the premise that language ability and task proficiency are inherently intertwined, it is advocated that rather than isolating one from the other, the inference should be drawn that task ability is associated with the source language, whereas language ability refers to the capacity difference between the target language and the source language. In line with the famous equation "$king - queen = man - woman$" in the word embedding space, we assume that the divergences between LLMs fine-tuned in different languages on a particular task follow the same distribution across diverse tasks.

Formally speaking, $A_{l_i t_j}$ denotes the adapter of task t_j in language l_i, then for any two languages l_1, l_2 and two NLP tasks t_1, t_2, we have

$$A_{l_1 t_1} \| A_{l_2 t_1} \sim A_{l_1 t_2} \| A_{l_2 t_2}, \quad (4)$$

where $\|$ denotes the divergence among two adapters. For example, let's consider l_1 and l_2 as English and German, respectively, and t_1 and t_2 as the text classification task and question answering task, respectively. Assuming we have training data for each task in both languages, we can fine-tune LLMs to obtain four adapters: text classification in English, text classification in German, question answering in English, and question answering in German. We assume that the divergence between adapters for the text classification task in English and German, as well as the divergence between adapters for the question answering task in English and German, follows the same distribution. This divergence represents the "language ability" that is independent of specific tasks.

In the context of cross-lingual transfer, we aim to solve the task t_1 for the target language l_1, with the knowledge transferred from a source language l_2, which is often a high-resource language such as English. By imposing the condition of cross-lingual transfer, where labeled data is available only for the target task in the source language and there is unlabeled data in both the source and target languages, we can introduce another "reference task" t_2. This task can be easily constructed using unlabeled data, and language ability can be obtained by $A_{l_1 t_2} \| A_{l_2 t_2}$. Moreover, to obtain the ability of performing target task t_1 in the target language l_1, we can further transform Equation (4) as:

$$A_{l_1 t_1} = A_{l_2 t_1} \|^R (A_{l_1 t_2} \| A_{l_2 t_2}), \quad (5)$$

where $\|^R$ is the reverse function of $\|$. Intuitively, $A_{l_2 t_1}$ represents the "task ability" in the source language, while $A_{l_1 t_2} \| A_{l_2 t_2}$ represents the "language ability". Through merging these two terms, we can transfer the "task ability" of t_1 from l_2 to l_1.

To transfer the knowledge from labeled data in the high-resource language (i.e., given $A_{l_2 t_1}$), the next step is to specify the reference task t_2. We observe that there are many easily obtained corpora of low-resource languages, such as Wikipedia, online blogs, etc. These corpora can be used to construct intuitive tasks such as causal language modeling, which can serve as the reference task t_2. Simultaneously, we can also construct such tasks for the high-resource language l_2. Therefore, adapters can be fine-tuned on such easily accessible reference tasks in different languages to obtain $A_{l_1 t_2}$ and $A_{l_2 t_2}$. Cross-lingual transfer thus can be achieved by merging these three adapters.

3.2 Structure-Adaptive Adapter Merging

As introduced in Section 2, adapters have different structures, which inspires us to devise different adapter merging methods. We propose that the adapter merging approach must align with the way that the adapter combined with the original model, as illustrated in Figure 2.

LoRA In the fine-tuning process of LoRA, where the method involves element-wise addition to the original parameters, the merging method used to combine task ability and language ability should also employ element-wise addition. Additionally, since the divergence calculation approach $\|$ is intended to be the inverse function of the merging method, it should be carried out through element-wise subtraction in this scenario. Therefore, Equation (4) is equivalently transferred to

$$A_{l_1 t_1} \ominus A_{l_2 t_1} \sim A_{l_1 t_2} \ominus A_{l_2 t_2}, \qquad (6)$$

where $\ominus$ denotes element-wise subtraction, and Equation (5) is equivalently transferred to

$$A_{l_1 t_1} = A_{l_2 t_1} \oplus t \cdot (A_{l_1 t_2} \ominus A_{l_2 t_2}), \qquad (7)$$

where $\oplus$ denotes element-wise addition and t is the hyper-parameter that adapts the scale of two distributions in the same family of distributions.

(IA)^3 Similarly, the fine-tuning method of (IA)^3 is element-wise multiplication to the original parameters, and the merging method should also be element-wise multiplication. Furthermore, we need to employ element-wise division to obtain the divergence between $A_{l_1 t_2}$ and $A_{l_2 t_2}$. Therefore, Equation (4) is equivalently transferred to

$$A_{l_1 t_1} \oslash A_{l_2 t_1} \sim A_{l_1 t_2} \oslash A_{l_2 t_2}, \qquad (8)$$

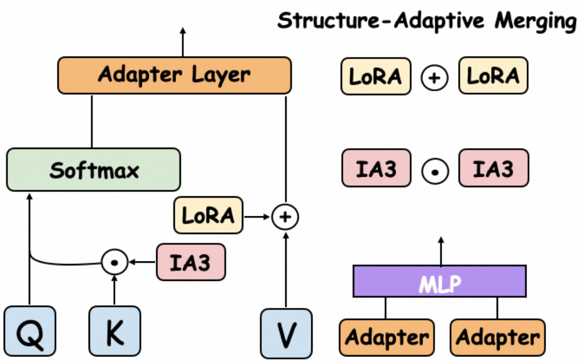

Figure 2: Structure-adaptive adapter merging method aligns with the manner in which adapters are integrated with language models. For example, "addition" for LoRA, "multiplication" for (IA)^3, and "MLP" for Adapter and Prefix-Tuning.

where $\oslash$ denotes element-wise devision, and Equation (5) is equivalently transferred to

$$A_{l_1 t_1} = A_{l_2 t_1} \odot \Big((t \cdot (A_{l_1 t_2} \oslash A_{l_2 t_2}) - \mathbb{1}) + \mathbb{1} \Big), \qquad (9)$$

where $\odot$ denotes element-wise multiplication and t is the hyper-parameter determining the scale of two distributions in the same family of distributions.

Adapter & Prefix-Tuning In the case of other adapter structures such as Adapter and Prefix-Tuning, which involve the insertion of layers and prefix tokens into the model, the merging process necessitates transferring adapters within the same space, such as MLP. Formally, the adaptive merging method is

$$A_{l_1 t_1} = t \cdot (A_{l_1 t_2} * A_{l_2 t_2}^{-1}) * A_{l_2 t_1}, \qquad (10)$$

where $*$ represents matrix multiplication and $A_{l_2 t_2}^{-1}$ represents Moore-Penrose pseudo-inverse of the matrix. For Prefix-Tuning, A_{lt} represents the prefix tokens, while for Adapter A_{lt} represents corresponding layers. In this paper, we mainly focus on LoRA and (IA)^3 when Llama2 is the backbone model due to the lack of training data in the target language for the Adapter and the subpar performance of prefix-tuning on fine-tuning (He et al., 2021). On the contrary, in the case of smaller language models such as mT5 (Xue et al., 2021), we implement `AdaMergeX` on it with prefix-tuning. The experiment results are shown in Appendix A.1.

3.3 `AdaMergeX`

Following notations in Section 3.1, to solve a target task t_1 in a target language l_1, i.e., obtain the

Task	Zero-Shot Prompt
MGSM	Let's think step by step. Question: {question}
XCOPA	Here is a premise and a question. Help me pick the more plausible option. Premise: {premise} Question: What is the {question}? (A) {choice1} (B) {choice2}
XNLI	You should judge whether the hypothesis is true (entailment), false (contradiction), or undetermined (neutral) given the premise. Premise: {premise} Hypothesis: {hypothesis}
XQuAD	{context} Question: {question}
XLSum	Summarize the context in one sentence. Title: {title} Context: {article}

Table 1: Zero-shot prompts for each dataset.

adapter $A_{l_1t_1}$, we need to fine-tune another three adapters: adapters on the target task in the source language ($A_{l_2t_1}$), adapters on the reference task in the target language ($A_{l_1t_2}$), and adapters on the reference task in the source language ($A_{l_2t_2}$). Note that $A_{l_1t_2}$ and $A_{l_2t_2}$ are easily obtainable, as we can choose any task in the target and source language. As mentioned earlier, the task can even be causal language modeling, which only requires unlabeled text corpora. Therefore, with only unlabeled data in both source and target language, our proposed `AdaMergeX` effectively transfers the target task proficiency from the source language to the target language. Moreover, given that the reference task remains constant, fine-tuning LLMs in the source language on the target task is the sole requirement for each new target task. This efficiency characterizes `AdaMergeX`.

In the case of LoRA, which fine-tunes LLMs by tuning $\{B, A\}$ in tuned layers of LLMs as introduced in Equation (1), adapters are merged following Equation (7) by element-wise addition and subtraction on $\{B, A\}$ in the corresponding layers of $A_{l_2t_1}$, $A_{l_1t_2}$, and $A_{l_2t_2}$. On the other hand, in the case of (IA)^3, the fine-tuning parameters are W_A in tuned layers as depicted in Equation (2). Thus the merging method follows Equation (9), which involves performing element-wise multiplication and division of the corresponding layers of $A_{l_2t_1}$, $A_{l_1t_2}$, and $A_{l_2t_2}$.

4 Experiments

4.1 Experimental Setup

Datasets and Language To evaluate the effectiveness of our method, we conduct experiments on a wide variety of multilingual tasks in three main categories: reasoning tasks, natural language understanding (NLU) tasks, and natural language generation (NLG) tasks. For reasoning tasks, we test on multilingual arithmetic reasoning dataset XGSM (Shi et al., 2022) and multilingual commonsense reasoning dataset XCOPA (Ponti et al., 2020). For NLU tasks, we test on the multilingual natural language inference dataset XNLI (Conneau et al., 2018), and question-answering dataset XQuAD (Artetxe et al., 2020). For NLG tasks, we test on multilingual summarization dataset XL-Sum (Hasan et al., 2021). We choose 12 languages that appear in more than once in the above datasets, including German (de), Russian (ru), French (fr), Spanish (es), Chinese (zh), Vietnamese (vi), Turkish (tr), Arabic (ar), Greek (el), Thai (th), Hindi (hi), and Swahili (sw). Detailed settings of zero-shot prompts are shown in Table 1. We utilize intuitive prompting methods for all tasks except for XCOPA and XNLI, where we employ prompts from Huang et al. (2023b). Detailed examples of the prompting approach can be found in Appendix A.2. For MGSM, XCOPA and XQuAD, we adopt the whole testset, while for XNLI and XLSum we randomly sample 1000 and 500 data points from the whole testset respectively.

Baselines We conduct comparisons between our proposed method, which utilizes model merging for achieving cross-lingual transfer, and seven competing techniques: (i) Vanilla zero-shot prompting ("Vanilla"), which directly assesses target languages using the pre-trained LLM. (ii) English Tuning ("Eng-FT"), which involves fine-tuning the model in English for target tasks and subsequently transferring it directly to target languages. (iii) Cross-Lingual-Thought Prompting ("XLT (Vanilla)") (Huang et al., 2023b) achieves state-of-the-art results on cross-lingual transfer with LLMs through carefully designed prompt template, which involves explicit translation from the target to the source language, reasoning in the source language, and translating back to the target language. (iv) "XLT (Eng-FT)", where XLT approach is applied to the Eng-FT model. (v)

Arithmetic Merging ("AriMerge") (Zhang et al., 2023a), which is the state-of-the-art adapter merging method by arithmetic addition. (vi) MAD-X (Pfeiffer et al., 2020) decomposes language and task via independent invertible adapters. (vii) LF-SFT (Ansell et al., 2022) adopts sparse fine-tuning on language and task respectively and directly merging via addition.

Evaluation Metrics For reasoning and NLU tasks, we use accuracy scores as our evaluation metric. For the summarization task, we evaluate the performance by ROUGE-L score (Lin, 2004).

Experiment Details The backbone model that we use to test `AdaMergeX` is Llama2-7b (Touvron et al., 2023) for LoRA and $(IA)^3$, and XLM-R for Prefix-Tuning. To fine-tune Llama2 using LoRA and $(IA)^3$, we configure the target modules to include all available layers. We employ conventional causal language modeling as the reference task, where the prediction of the subsequent token is based on preceding inputs. Specifically, we generate the training set from the corpora provided by Wikimedia Foundation[2] by dividing them into segments with a length of 512. There is only one hyperparameter in our method, which is t in Equation (7), (9), and (10). When tuning this hyperparameter, for each task, we select the validation set from French and then extend it to encompass all other languages, for those tasks that do not contain French validation set, we adopt Vietnamese instead. For XLT method (Huang et al., 2023b), we adopt the same zero-shot prompts as in the original paper.

4.2 Main Results

Table 2 presents our main experimental results on 5 representative cross-lingual tasks with LlaMa2, where we report the average scores across all languages. Detailed results of each language are shown in Table 8 and 9 in Appendix A.3 for LoRA and $(IA)^3$ respectively. Table 3 presents the results on XLM-R, where we compare with MAD-X and LF-SFT on XCOPA and XQuAD[3].

`AdaMergeX` outperforms direct transfer and prompting methods When comparing to fine-tuning on the task in English and direct transfer to the target language, `AdaMergX` outperforms it on all settings and achieves 1.4% absolute improvement with LoRA and 1.5% absolute improvement with $(IA)^3$. When comparing to the state-of-the-art method for cross-lingual transfer in LLMs via prompting, XLT with Vanilla Llama2 model ("XLT (Vanilla)") and model fine-tuned on target task in English ("XLT (Eng-FT)"), `AdaMergeX` outperforms it on all settings and achieves 3.4% absolute improvement with LoRA and 7.3% absolute improvement with $(IA)^3$. This achievement proves that the introduction of adapter merging to achieve cross-lingual transfer is effective, especially in the circumstance of LLMs.

`AdaMergeX` outperforms decoupling task ability and language ability method As shown in Table 3, compared to MAD-X and LF-SFT, which struggle to fully separate task ability from language ability, AdaMergeX demonstrates remarkable enhancements. In particular, AdaMergeX showcases an impressive absolute improvement of 8.0% and 15.9% on XCOPA and XQuAD, respectively, in comparison to MAD-X. Additionally, it achieves a significant 4.6% absolute improvement on XQuAD when compared to LF-SFT. Therefore, our proposed new decoupling method is much more effective than others.

`AdaMergeX` outperforms general adapter merging methods Compared with the state-of-the-art method for adapter merging namely Arimerge, `AdaMergeX` outperforms it on all settings and achieves 6.9% absolute improvement with LoRA and 2.3% absolute improvement with $(IA)^3$. Therefore, `AdaMergeX`, which adaptively considers the structure of adapters, outperforms all previous general adapter merging methods that adopt arithmetic addition for all kinds of adapters.

`AdaMergeX` performances consistently well with LoRA and $(IA)^3$ LoRA achieves higher absolute performance than $(IA)^3$, which shows the effectiveness of LoRA on fine-tuning. However, compared to the absolute improvement of `AdaMergeX` on LoRA and $(IA)^3$, they are comparable. For example, for MGSM, LoRA and $(IA)^3$ get the same absolute improvement 1.1%, and for XNLI, on which LoRA and $(IA)^3$ both achieve the highest absolute improvement, their performance are comparable. This proves that `AdaMergeX` performs consistently well on different adapters.

[2] https://dumps.wikimedia.org/

[3] We only test XCOPA and XQuAD because encoder-only models can only be applied to classification tasks.

Adapters	Method	Reasoning		NLU		NLG	Avg.
		MGSM	XCOPA	XNLI	XQuAD	XLSum	
LoRA	Vanilla	2.7	52.3	28.8	0.0	20.9	20.9
	Eng-FT	17.4	58.1	39.6	31.0	22.9	33.8
	XLT(Vanilla)	2.8	52.6	30.7	19.3	1.3	21.3
	XLT(Eng-FT)	18.1	58.2	39.4	26.4	19.1	32.2
	AriMerge	6.0	57.9	42.7	30.1	19.5	31.2
	AdaMergeX	**19.2**	**61.5**	**46.2**	**33.8**	**23.3**	**36.8**
$(IA)^3$	Vanilla	2.7	52.3	28.8	0.0	20.9	18.1
	Eng-FT	2.3	55.7	36.4	34.0	17.4	29.2
	XLT(Vanilla)	2.8	52.6	30.7	19.3	1.3	21.3
	XLT(Eng-FT)	2.8	56.2	38.3	21.3	1.4	24.0
	AriMerge	0.7	51.5	27.1	32.4	15.5	25.4
	AdaMergeX	**3.9**	**59.2**	**43.9**	**35.5**	**21.4**	**32.8**

Table 2: Main experimental results on 5 representative cross-lingual tasks. Details of the selected zero-shot prompt, the baselines, and hyperparameters are described in Section 4.1.

Task	Method	tr	vi	th	sw	el	ru	Avg.
XCOPA	MAD-X	60.3	66.1	61.8	56.3	-	-	59.5
	AdaMergeX	69.4	70.5	66.9	63.2	-	-	**67.5**
XQuAD	MAD-X	-	-	54.3	57.8	55.7	51.1	54.7
	LF-SFT	-	-	65.5	64.6	75.2	58.6	66.0
	AdaMergeX	-	-	70.2	70.4	77.9	63.8	**70.6**

Table 3: Results on XCOPA and XQuAD with XLM-R, where AdaMergeX is implemented on LoRA.

	Method	Reasoning		NLU		NLG	Avg.
		MGSM	XCOPA	XNLI	XQuAD	XLSum	
LoRA	De-Tune	20.9	–	48.3	44.4	–	37.9
	AdaMergeX	22.3	–	50.9	46.5	–	**39.9**
	Fr-Tune	19.9	–	52.9	–	24.1	32.3
	AdaMergeX	22.2	–	57.1	–	24.8	**34.7**
	Es-Tune	19.2	–	33.9	45.4	22.1	30.2
	AdaMergeX	18.7	–	35.1	49.1	23.7	**31.7**
	Th-Tune	3.2	49.3	1.9	39.8	20.3	22.9
	AdaMergeX	4.5	48.9	6.2	44.2	20.1	**24.8**
	Vi-Tune	–	63.8	49.1	36.2	21.7	42.7
	AdaMergeX	–	64.2	53.2	38.9	22.3	**44.7**
$(IA)^3$	De-Tune	2.9	–	43.5	45.6	–	30.7
	AdaMergeX	6.3	–	44.0	47.1	–	**32.5**
	Fr-Tune	2.5	–	48.7	–	19.8	23.7
	AdaMergeX	4.1	–	47.9	–	21.6	**24.5**
	Es-Tune	3.5	–	49.2	45.9	18.2	29.2
	AdaMergeX	5.3	–	50.9	44.6	20.1	**30.2**
	Th-Tune	1.2	49.8	0.0	27.7	20.2	19.8
	AdaMergeX	1.9	50.4	0.0	28.9	24.1	**21.1**
	Vi-Tune	–	49.8	45.5	33.2	20.1	37.2
	AdaMergeX	–	48.7	50.2	36.1	22.5	**39.4**

Table 4: Ablation study on source language.

4.3 Detailed Analysis

In this section, we validate the generalizability of our proposed method across various aspects including the source language, reference task, backbone model, and target modules. Furthermore, we perform an ablation analysis to assess the essentiality of the adaptive merging method.

Source Language To prove the generalizability of AdaMergeX on the source language, we explore its performance with different source languages in Table 4. We test on five source languages including German, French, Spanish, Thai, and Vietnamese. We find that the performance is highly related to the source language, which depends on the language ability of the corresponding language. However, the improvements are consistent across languages. For example, the improvement was most significant with Vietnamese as the source language, with an absolute improvement of 3.4% with LoRA and 3.8% with $(IA)^3$. Therefore, AdaMergeX consistently performs well with different source languages.

Reference Task To prove the generalizability of AdaMergeX on the reference task, we explore its performance with different reference task in Table 5. We test on three different reference tasks, including XCOPA, XNLI, XQuAD, while the source language is English. The dataset was tested on the corresponding available languages among German, French, Spanish, Thai, and Vietnamese. Specifically, the improvement was most significant with XQuAD as the reference task, with an absolute improvement of 1.3% with LoRA and 1.7% with $(IA)^3$. Thus, it verifies that AdaMergeX is general to any reference task.

Backbone Models Not limited to Decode-only Models such as Llama2, we do further analysis on Encoder-Decoder model T5-base (Raffel et al., 2020) to prove its universal effectiveness.

	Ref. Task	Method	MGSM	XCOPA	XNLI	XQuAD	XLSum	Avg.
LoRA	–	Eng-Tune	14.4	59.9	44.6	42.3	16.1	35.1
LoRA	XCOPA	AdaMergeX	15.2	60.2	45.1	43.8	18.2	36.5
LoRA	XNLI	AdaMergeX	14.5	60.9	46.7	44.1	18.4	**36.9**
LoRA	XQuAD	AdaMergeX	14.9	61.8	45.4	44.4	18.1	**36.9**
$(IA)^3$	–	Eng-Tune	2.6	52.7	40.0	39.2	10.8	29.1
$(IA)^3$	XCOPA	AdaMergeX	4.9	54.3	40.5	40.4	12.4	30.5
$(IA)^3$	XNLI	AdaMergeX	3.6	54.6	41.2	39.9	13.1	30.5
$(IA)^3$	XQuAD	AdaMergeX	4.1	53.9	42.1	41.0	12.9	**30.8**

Table 5: Ablation study on reference Task.

AdaMergeX achieves consistently the best performance compared to fine-tuning on English and AriMerge as shown in Table 10 of Appendix A.4. Furthermore, we also implement our method on Encoder-only model XLM-R and compare with MAD-X and LF-SFT as shown in Table 3. This shows the flexibility of choosing the backbone model when implementing AdaMergeX.

Merging Method We conduct an ablation analysis on merging method to ascertain the indispensability and the effectiveness of adaptive merging in AdaMergeX. Table 11 in Appendix A.5 shows the detailed results, where AdaMergeX (adaptive) represents AdaMergeX with adaptive merging methods, while AdaMergeX (cross) represents AdaMergeX with cross merging methods, i.e., LoRA with merging method of $(IA)^3$ and vice versa. We find that when applying the merging method of $(IA)^3$ to LoRA, the performance is reduced much, and vice versa. As a result, the adaptive merging method is crucial for adapter merging.

5 Related Work

Cross-Lingual Transfer The emergence of multilingual systems (Kenton and Toutanova, 2019; Conneau and Lample, 2019; Conneau et al., 2020; OpenAI, 2022; Anil et al., 2023; Touvron et al., 2023) has sparked interest in cross-lingual transfer (Kim et al., 2017; Lin et al., 2019; Schuster et al., 2019; Pfeiffer et al., 2020). Fine-tuning on the target language and target task is an intuitive way to make models obtain the ability of this task, but it is too costly in the era of LLMs as we always lack enough training data (Ma et al., 2023). Alternatively, some researchers explore realigning representations among languages (Nguyen et al., 2023; Salesky et al., 2023; Gao et al., 2023). However, Gaschi et al. (2023) demonstrates that aligned representations do not significantly benefit cross-lingual transfer. To address this issue, some works adopt explicit translation to achieve cross-lingual transfer (Liang et al., 2023; Huang et al., 2023b). However, they rely on translation ability which is not guaranteed. In addition, Pfeiffer et al. (2020) and Ansell et al. (2022) decouple language ability and task ability, but they ignore the interconnection of these two abilities. Furthermore, in the era of in-context learning (Brown et al., 2020; Chowdhery et al., 2022; Touvron et al., 2023; OpenAI, 2023), Li et al. (2023) and Tanwar et al. (2023) utilize prompt tuning to achieve cross-lingual transfer. Nevertheless, the performance remains limited for low-resource languages, which is often not carefully considered in the pre-training of LLMs.

Model Merging Model merging has been widely used in image identification (Wortsman et al., 2022; Matena and Raffel, 2022), knowledge editing (Mitchell et al., 2022; Meng et al., 2022) and task combination (Ilharco et al., 2022). In the era of PEFT, researchers have started exploring different approaches to merging adapters (Zhang et al., 2023a; Yadav et al., 2023; Huang et al., 2023a; Chronopoulou et al., 2023; Ponti et al., 2023). These studies, however, have primarily focused on task transfer and have solely utilized linear combinations of different adapters, which may not be applicable to all types of adapters. Moreover, the utilization of model merging for cross-lingual transfer is under-studied.

6 Conclusion

In this work, we propose a new cross-lingual transfer method AdaMergeX. We split target task ability in the target language into two parts: "task ability" and "language ability". In the context of PEFT, task ability can be obtained by tuning on the target task in the source language. To achieve cross-lingual transfer, which aims to transfer task ability from the source language to the target language, we introduce a reference task from which we obtain language ability and further merge it to task ability by adapter merging. Different from all previous adapter merging methods, we propose a structure adaptive adapter merging method that aligns the adapter merging method with the way adapters combined to LLMs. Experiment results show that AdaMergeX performs well among all settings. Moreover, ablation analysis proves that AdaMergeX is robust to backbone models, source languages, and source tasks.

Limitations

Our research primarily utilizes models with around 7 billion parameters, specifically Llama2-7b, due to limitations in computational resources. Exploring our methodologies on larger-scale models may offer further valuable perspectives. Furthermore, although the training set for the reference task is easily accessible, fine-tuning the parameters of the entire model necessitates a certain investment of time. However, this training time can be significantly reduced by integrating language-specific adapters or employing language-specific Mixture of Experts (MoE) techniques, which ultimately lowers the overall training cost.

References

AI@Meta. 2024. Llama 3 model card.

Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, et al. 2023. Palm 2 technical report. *arXiv preprint arXiv:2305.10403*.

Alan Ansell, Edoardo Ponti, Anna Korhonen, and Ivan Vulić. 2022. Composable sparse fine-tuning for cross-lingual transfer. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1778–1796.

Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. 2020. On the cross-lingual transferability of monolingual representations. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4623–4637.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901.

Guanhua Chen, Shuming Ma, Yun Chen, Dongdong Zhang, Jia Pan, Wenping Wang, and Furu Wei. 2022. Towards making the most of cross-lingual transfer for zero-shot neural machine translation. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 142–157.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. 2022. Palm: Scaling language modeling with pathways. *arXiv preprint arXiv:2204.02311*.

Alexandra Chronopoulou, Matthew E Peters, Alexander Fraser, and Jesse Dodge. 2023. Adaptersoup: Weight averaging to improve generalization of pretrained language models. In *Findings of the Association for Computational Linguistics: EACL 2023*, pages 2009–2018.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Édouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451.

Alexis Conneau and Guillaume Lample. 2019. Cross-lingual language model pretraining. *Advances in neural information processing systems*, 32.

Alexis Conneau, Guillaume Lample, Ruty Rinott, Adina Williams, Samuel R Bowman, Holger Schwenk, and Veselin Stoyanov. 2018. Xnli: Evaluating cross-lingual sentence representations. *arXiv preprint arXiv:1809.05053*.

Pengzhi Gao, Liwen Zhang, Zhongjun He, Hua Wu, and Haifeng Wang. 2023. Improving zero-shot multilingual neural machine translation by leveraging cross-lingual consistency regularization. *arXiv preprint arXiv:2305.07310*.

Félix Gaschi, Patricio Cerda, Parisa Rastin, and Yannick Toussaint. 2023. Exploring the relationship between alignment and cross-lingual transfer in multilingual transformers. *arXiv preprint arXiv:2306.02790*.

Gemini Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al. 2023. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*.

Tahmid Hasan, Abhik Bhattacharjee, Md Saiful Islam, Kazi Mubasshir, Yuan-Fang Li, Yong-Bin Kang, M Sohel Rahman, and Rifat Shahriyar. 2021. Xl-sum: Large-scale multilingual abstractive summarization for 44 languages. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 4693–4703.

Junxian He, Chunting Zhou, Xuezhe Ma, Taylor Berg-Kirkpatrick, and Graham Neubig. 2021. Towards a unified view of parameter-efficient transfer learning. In *International Conference on Learning Representations*.

Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for nlp. In *International Conference on Machine Learning*, pages 2790–2799. PMLR.

Edward J Hu, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. 2021. Lora: Low-rank adaptation of large language models. In *International Conference on Learning Representations*.

Chengsong Huang, Qian Liu, Bill Yuchen Lin, Tianyu Pang, Chao Du, and Min Lin. 2023a. Lorahub: Efficient cross-task generalization via dynamic lora composition. *arXiv preprint arXiv:2307.13269*.

Haoyang Huang, Tianyi Tang, Dongdong Zhang, Wayne Xin Zhao, Ting Song, Yan Xia, and Furu Wei. 2023b. Not all languages are created equal in llms: Improving multilingual capability by cross-lingual-thought prompting. *arXiv preprint arXiv:2305.07004*.

Gabriel Ilharco, Marco Tulio Ribeiro, Mitchell Wortsman, Ludwig Schmidt, Hannaneh Hajishirzi, and Ali Farhadi. 2022. Editing models with task arithmetic. In *The Eleventh International Conference on Learning Representations*.

Jacob Devlin Ming-Wei Chang Kenton and Lee Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of naacL-HLT*, volume 1, page 2.

Joo-Kyung Kim, Young-Bum Kim, Ruhi Sarikaya, and Eric Fosler-Lussier. 2017. Cross-lingual transfer learning for pos tagging without cross-lingual resources. In *Proceedings of the 2017 conference on empirical methods in natural language processing*, pages 2832–2838.

Shuang Li, Xuming Hu, Aiwei Liu, Yawen Yang, Fukun Ma, Philip S Yu, and Lijie Wen. 2023. Enhancing cross-lingual natural language inference by soft prompting with multilingual verbalizer. *arXiv preprint arXiv:2305.12761*.

Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4582–4597, Online. Association for Computational Linguistics.

Yaobo Liang, Quanzhi Zhu, Junhe Zhao, and Nan Duan. 2023. Machine-created universal language for cross-lingual transfer. *arXiv preprint arXiv:2305.13071*.

Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pages 74–81.

Yu-Hsiang Lin, Chian-Yu Chen, Jean Lee, Zirui Li, Yuyan Zhang, Mengzhou Xia, Shruti Rijhwani, Junxian He, Zhisong Zhang, Xuezhe Ma, et al. 2019. Choosing transfer languages for cross-lingual learning. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, volume 57.

Haokun Liu, Derek Tam, Mohammed Muqeeth, Jay Mohta, Tenghao Huang, Mohit Bansal, and Colin A Raffel. 2022. Few-shot parameter-efficient fine-tuning is better and cheaper than in-context learning. *Advances in Neural Information Processing Systems*, 35:1950–1965.

Bolei Ma, Ercong Nie, Helmut Schmid, and Hinrich Schütze. 2023. Is prompt-based finetuning always better than vanilla finetuning? insights from cross-lingual language understanding. *arXiv preprint arXiv:2307.07880*.

Michael S Matena and Colin A Raffel. 2022. Merging models with fisher-weighted averaging. *Advances in Neural Information Processing Systems*, 35:17703–17716.

Kevin Meng, Arnab Sen Sharma, Alex J Andonian, Yonatan Belinkov, and David Bau. 2022. Mass-editing memory in a transformer. In *The Eleventh International Conference on Learning Representations*.

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781*.

Eric Mitchell, Charles Lin, Antoine Bosselut, Christopher D Manning, and Chelsea Finn. 2022. Memory-based model editing at scale. In *International Conference on Machine Learning*, pages 15817–15831. PMLR.

Hoang H Nguyen, Chenwei Zhang, Tao Zhang, Eugene Rohrbaugh, and Philip S Yu. 2023. Enhancing cross-lingual transfer via phonemic transcription integration. *arXiv preprint arXiv:2307.04361*.

OpenAI. 2022. Chatgpt: Optimizing language models for dialogue. *OpenAI Blog*.

OpenAI. 2023. Gpt-4 technical report.

Jonas Pfeiffer, Ivan Vulić, Iryna Gurevych, and Sebastian Ruder. 2020. Mad-x: An adapter-based framework for multi-task cross-lingual transfer. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 7654–7673.

Edoardo Maria Ponti, Goran Glavaš, Olga Majewska, Qianchu Liu, Ivan Vulić, and Anna Korhonen. 2020. Xcopa: A multilingual dataset for causal commonsense reasoning. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 2362–2376.

Edoardo Maria Ponti, Alessandro Sordoni, Yoshua Bengio, and Siva Reddy. 2023. Combining parameter-efficient modules for task-level generalisation. In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pages 687–702.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *The Journal of Machine Learning Research*, 21(1):5485–5551.

Elizabeth Salesky, Neha Verma, Philipp Koehn, and Matt Post. 2023. Pixel representations for multilingual translation and data-efficient cross-lingual transfer. *arXiv preprint arXiv:2305.14280*.

Sebastian Schuster, Sonal Gupta, Rushin Shah, and Mike Lewis. 2019. Cross-lingual transfer learning for multilingual task oriented dialog. In *Proceedings of NAACL-HLT*, pages 3795–3805.

Freda Shi, Mirac Suzgun, Markus Freitag, Xuezhi Wang, Suraj Srivats, Soroush Vosoughi, Hyung Won Chung, Yi Tay, Sebastian Ruder, Denny Zhou, et al. 2022. Language models are multilingual chain-of-thought reasoners. In *The Eleventh International Conference on Learning Representations*.

Eshaan Tanwar, Manish Borthakur, Subhabrata Dutta, and Tanmoy Chakraborty. 2023. Multilingual llms are better cross-lingual in-context learners with alignment. *arXiv preprint arXiv:2305.05940*.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. *Advances in neural information processing systems*, 30.

Mitchell Wortsman, Gabriel Ilharco, Samir Ya Gadre, Rebecca Roelofs, Raphael Gontijo-Lopes, Ari S Morcos, Hongseok Namkoong, Ali Farhadi, Yair Carmon, Simon Kornblith, et al. 2022. Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time. In *International Conference on Machine Learning*, pages 23965–23998. PMLR.

Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2021. mt5: A massively multilingual pre-trained text-to-text transformer. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 483–498.

Prateek Yadav, Derek Tam, Leshem Choshen, Colin Raffel, and Mohit Bansal. 2023. Resolving interference when merging models. *arXiv preprint arXiv:2306.01708*.

Jinghan Zhang, Shiqi Chen, Junteng Liu, and Junxian He. 2023a. Composing parameter-efficient modules with arithmetic operations. *arXiv preprint arXiv:2306.14870*.

Wenxuan Zhang, Sharifah Mahani Aljunied, Chang Gao, Yew Ken Chia, and Lidong Bing. 2023b. M3Exam: A multilingual, multimodal, multilevel benchmark for examining large language models. *arXiv preprint arXiv:2306.05179*.

A Appendix

A.1 `AdaMergeX` on Prefic-Tuning

The results demonstrate that `AdaMergeX` excels remarkably within the realm of prefix-tuning, a distinct and separate approach to fine-tuning. Results on XNLI task with mT5 (Xue et al., 2021) are shown as follows in Table 6.

A.2 Prompts

Detailed prompts of tasks in each language are listed in Table 7.

A.3 Detailed Results

We present detailed results in Table 8 and Table 9.

A.4 `AdaMergeX` on T5-base

Because T5-base only supports Spanish and French in chosen languages, we only test these two languages. In the case of LoRA on XNLI, `AdaMergeX` obtains 4.2% absolute improvements in Spanish and 2.8% absolute improvements in French. For $(IA)^3$, the improvements are 1.1% and 4.0% respectively.

A.5 Ablation on Adaptive Merging

We find that when applying the merging method of $(IA)^3$ to LoRA, the performance is reduced much. Specifically, on XNLI the performance gets 39.5% absolute reduction, while for XQuAD the reduction is 45.9% absolute value. When applying the merging method of LoRA to $(IA)^3$, the performance also decreases compared to that of the adaptive merging method. For XNLI the reduction is 2.4%, while for XQuAD the reduction is 0.7%. The reduction is smaller than that for LoRA. This can be attributed to the fact that the fine-tuning of $(IA)^3$ is not as effective as that of LoRA and has a relatively minor impact on the overall model performance.

A.6 Ablation on Merging Modules

We present ablation on merging methods in Table 12 and Table 13.

Task	Method	es	fr	ru	tr	vi	th	sw	el	Avg.
XCOPA	Eng-FT	–	–	–	–	69.5	57.4	62.8	–	65.2
	AriMerge	–	–	–	–	65.4	59.7	64.1	–	63.1
	AdaMergeX	–	–	–	–	71.3	63.2	65.6	–	**66.7**
XNLI	Eng-FT	31.2	29.7	30.4	19.8	43.1	11.6	13.2	16.3	24.4
	AriMerge	29.8	28.3	33.2	21.4	42.9	11.8	14.6	21.8	25.5
	AdaMergeX	34.1	31.4	34.2	20.9	44.8	20.3	16.7	25.3	**28.5**
XLSum	Eng-FT	13.4	14.2	12.7	14.1	18.9	14.9	7.8	–	13.7
	AriMerge	14.5	15.2	15.6	13.9	20.2	15.6	8.6	–	14.8
	AdaMergeX	14.9	16.1	17.4	16.1	19.8	17.1	10.3	–	**16.0**

Table 6: Results of AdaMergeX on Prefix-tuning with mT5.

MGSM (French)

Let's think step by step.

Question: Les canes de Janet pondent 16 œufs par jour. Chaque matin, elle en mange trois au petit déjeuner et en utilise quatre autres pour préparer des muffins pour ses amis. Ce qui reste, elle le vend quotidiennement au marché fermier, au prix de 2 $ l'œuf de cane frais. Combien (en dollars) gagne-t-elle chaque jour au marché fermier ?
Answer:

XCOPA (Vietnamese)

Here is a premise and a question. Help me pick the more plausible option. Answer with (A) or (B).

Premise: Các mt hàng đã đc đóng gói trong bc bong bóng.
Question: What is the cause?
(A) Nó d v.
(B) Nó nh.
Answer:

XNLI (French)

You should judge whether the hypothesis is true (entailment), false (contradiction), or undetermined (neutral) given the premise. The relationship can be chosen from entailment, contradiction, and neutral.

Premise: Cela fait 17 ans que je suis affilié à l'IRT.
Hypothesis: Je n'ai rien à voir avec l'IRT.
Relationship:

XLSum (Vietnamese)

Summarize the context in one sentence.

Title: Côte d'Ivoire : le groupe Magic System fête ses 20 ans
Context: Formé en 1997, le groupe a connu la consécration deux ans plus tard avec son tube Ÿremier Gaou.. Le groupe ivoirien fête ses 20 ans avec une tournée africaine et une autobiographie. N̈ous célébrons 20 ans d'amitiés, de collaboration, de moments de joies et de tristesses,, raconte A'Salfo, le leader du groupe qui a su ouvrir les portes du marché africain et international au genre zouglou mais aussi aux autres genres ivoiriens, dont le coupé-décalé. A'Salfo, Manadja, Tino et Goudé, les quatre boys d'Anoumabo, quartier déshérités d'Abidjan, aux ruelles boueuses et sablonneuses, ont joué partout, des stades africains aux salles mythiques comme l'Apollo à New York ou l'Olympia à Paris et jusqu'au Louvre, le 7 mai, pour le concert célébrant la victoire du président français Emmanuel Macron. Magic System a bénéficié de conseils avisés d'Alpha Blondy. Formé en 1997, le groupe a connu la consécration deux ans plus tard avec son tube P̈remier Gaou,, fable sur les déboires sentimentaux d'un jeune homme naïf - le gaou est un homme crédule en nouchi, l'argot abidjanais. Le tube va propulser les quatre amis sur la scène mondiale. Magic System a multiplié les succès, enchaînant les albums, sans oublier l'amitié. M̈agic System est aussi un groupe qui a toujours voulu relever les défis, après Premier Gaou, nos détracteurs ont parlé de coup de chance! On a donc relevé ce défi,, explique Manadja, le g̈rosdu groupe. Le groupe reconnaît avoir bénéficié de conseils avisés, dont ceux de la star ivoirienne du reggae, Alpha Blondy.
Summary:

XQuAD (French)

Ni mà din tích mt ct ngang liên quan đn khi lng mà ten-x ng sut đc tính toán. Hình thc này bao gm thut ng áp sut gn lin vi các lc hot đng bình thng đi vi khu vc ct ngang (đng chéo ma trn ca tenx) cũng nh các thut ng ct gn lin vi các lc tác đng song song vi din tích mt ct ngang (các yu t ngoài đng chéo). Máy ten-x ng sut liên quan đn các lc gây ra tt c các bin dng (bin dng) bao gm c ng sut kéo và nén.:133–134:38-1–38-11

Question: Điu gì đc s dng đ tính din tích mt ct trong th tích ca mt vt th?
Answer:

Table 7: One-shot prompting examples of tested datasets.

Models	**Method**	de	ru	fr	es	zh	vi	tr	ar	el	th	hi	sw
MGSM	Vanilla	2.4	3.6	3.6	3.2	2.4	–	–	–	–	2.0	–	2.0
	Eng-FT	22.4	24.8	20.4	22.4	22.8	–	–	–	–	6.8	–	2.4
	XLT(Vanilla)	2.0	2.8	2.8	3.2	2.8	–	–	–	–	2.0	–	3.2
	XLT(Eng-FT)	22.0	24.0	22.8	24.4	24.2	–	–	–	–	5.2	–	4.4
	AriMerge	6.4	8.0	2.4	10.4	3.2	–	–	–	–	11.6	–	0.0
	AdaMergeX	24.8	26.2	23.6	22.4	22.0	–	–	–	–	8.0	–	7.2
XCOPA	Vanilla	–	–	–	–	54.4	54.0	–	–	–	51.8	–	49.0
	Eng-FT	–	–	–	–	61.8	67.2	–	–	–	52.6	–	50.6
	XLT(Vanilla)	–	–	–	–	56.8	52.4	–	–	–	51.0	–	50.0
	XLT(Eng-FT)	–	–	–	–	60.6	70.0	–	–	–	51.6	–	50.4
	AriMerge	–	–	–	–	61.0	69.8	–	–	–	50.6	–	50.0
	AdaMergeX	–	–	–	–	65.6	72.3	–	–	–	54.3	–	53.9
XNLI	Vanilla	43.1	43.9	35.8	39.6	21.8	39.6	29.5	16.3	18.1	10.9	14.3	33.0
	Eng-FT	54.0	54.0	58.2	60.5	33.5	47.0	29.6	23.6	35.4	21.8	25.8	31.8
	XLT(Vanilla)	44.7	44.4	39	36.9	25.7	36.3	20.6	27.4	20.8	13.9	15.7	42.6
	XLT(Eng-FT)	54.1	44.3	44.6	58.6	34.0	43.0	34.6	28.9	36.3	23.7	36.7	33.9
	AriMerge	58.6	57.4	51.3	51.7	40.6	47.2	35.8	34.3	32.9	29.8	30.5	42.8
	AdaMergeX	62.3	63.7	63.1	62.8	36.7	49.2	31.6	40.3	38.5	23.4	39.1	43.1
XLSum	Vanilla	–	13.4	12.5	11.4	56.0	22.1	15.7	23.5	–	14.8	31.6	8.1
	Eng-FT	–	21.7	16.1	11.3	58.4	21.2	16.4	25.8	–	15.6	32.9	9.9
	XLT(Vanilla)	–	0.6	2.3	1.8	0.5	1.3	2.5	0.8	–	0.2	0.8	2.1
	XLT(Eng-FT)	–	17.8	5.0	6.6	56.8	13.5	10.8	28.9	–	13.5	33.9	3.9
	AriMerge	–	14.5	8.7	9.8	49.8	12.6	11.7	29.8	–	17.2	34.2	6.5
	AdaMergeX	–	21.6	16.2	11.9	58.4	21.6	16.7	25.6	–	15.5	33.9	11.4
XQuAD	Vanilla	0.0	0.0	–	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	–
	Eng-FT	49.0	34.1	–	48.2	53.5	40.9	17.3	10.2	13.9	31.0	11.8	–
	XLT(Vanilla)	34.8	14.0	–	29.8	33.1	21.8	20.2	12.0	8.6	7.1	12.1	–
	XLT(Eng-FT)	39.1	26.3	–	40.7	41.2	33.9	19.0	13.8	13.0	23.8	13.2	–
	AriMerge	50.7	31.8	–	49.1	50.2	42.3	15.9	10.4	12.6	28.7	9.7	–
	AdaMergeX	53.4	34.1	–	54.2	59.3	43.9	20.6	12.4	14.6	31.8	13.1	–

Table 8: Comprehensive experimental results for both baselines and AdaMergeX are obtained across all datasets in corresponding available languages. The fine-tuning method employed was LoRA, with Llama2-7b serving as the backbone model.

Models	Method	de	ru	fr	es	zh	vi	tr	ar	el	th	hi	sw
MGSM	Vanilla	2.4	3.6	3.6	3.2	2.4	–	–	–	–	2.0	–	2.0
	Eng-FT	2.0	2.0	3.6	2.4	1.6	–	–	–	–	2.4	–	2.0
	XLT(Vanilla)	2.0	2.8	2.8	3.2	2.8	–	–	–	–	2.0	–	3.2
	XLT(Eng-FT)	0.8	1.6	4.8	4.0	3.2	–	–	–	–	2.8	–	2.4
	AriMerge	0.0	0.4	0.4	0.0	1.6	–	–	–	–	2.0	–	0.4
	AdaMergeX	4.4	3.6	4.8	6.0	3.6	–	–	–	–	2.8	–	2.0
XCOPA	Vanilla	–	–	–	–	54.4	54.0	–	–	–	51.8	–	49.0
	Eng-FT	–	–	–	–	59.3	58.6	–	–	–	54.9	–	49.8
	XLT(Vanilla)	–	–	–	–	56.8	52.4	–	–	–	51.0	–	50.0
	XLT(Eng-FT)	–	–	–	–	60.4	59.2	–	–	–	55.4	–	49.8
	AriMerge	–	–	–	–	53.0	50.6	–	–	–	52.2	–	50.2
	AdaMergeX	–	–	–	–	64.2	59.4	–	–	–	60.2	–	53.1
XNLI	Vanilla	43.1	43.9	35.8	39.6	21.8	39.6	29.5	16.3	18.1	10.9	14.3	33.0
	Eng-FT	46.4	45.3	51.9	50.7	24.6	51.0	31.4	22.1	34.6	20.8	23.9	34.3
	XLT(Vanilla)	44.7	44.4	39	36.9	25.7	36.3	20.6	27.4	20.8	13.9	15.7	42.6
	XLT(Eng-FT)	49.8	46.3	51.8	52.4	27.8	50.8	33.4	24.1	36.6	20.9	27.2	38.9
	AriMerge	42.4	47.2	48.6	49.3	40.6	46.3	32.4	29.1	31.8	21.2	20.8	35.6
	AdaMergeX	59.7	58.6	56.8	58.3	32.3	52.7	31.6	37.6	37.9	23.2	34.1	43.4
XLSum	Vanilla	–	13.4	12.5	11.4	56.0	22.1	15.7	23.5	–	14.8	31.6	8.1
	Eng-FT	–	4.2	9.0	6.8	56.6	14.7	13.6	16.6	–	12.5	32.3	7.6
	XLT(Vanilla)	–	0.6	2.3	1.8	0.5	1.3	2.5	0.8	–	0.2	0.8	2.1
	XLT(Eng-FT)	–	0.6	3.1	1.8	0.4	1.3	2.5	1.1	–	0.3	0.8	2.1
	AriMerge	–	4.8	6.3	7.6	44.1	9.9	11.8	15.4	–	13.1	32.3	9.4
	AdaMergeX	–	14.5	13.1	11.5	55.2	24.4	15.3	23.5	–	13.6	33.4	9.2
XQuAD	Vanilla	0.0	0.0	–	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	–
	Eng-FT	47.3	32.8	–	47.6	53.7	35.1	28.9	22.8	21.9	26.9	23.2	–
	XLT(Vanilla)	34.8	14.0	–	29.8	33.1	21.8	20.2	12.0	8.6	7.1	12.1	–
	XLT(Eng-FT)	37.1	16.8	–	32.4	37.6	25.1	19.3	14.0	10.0	7.0	14.1	–
	AriMerge	46.0	32.2	–	44.5	51.2	35.4	28.2	23.4	20.6	21.6	20.7	–
	AdaMergeX	48.6	33.0	–	48.2	56.0	35.7	29.3	25.4	24.5	29.2	24.6	–

Table 9: Comprehensive experimental results for both baselines and AdaMergeX are obtained across all datasets in corresponding available languages. The fine-tuning method employed was $(IA)^3$, with Llama2-7b serving as the backbone model.

Table 10: Ablation study on backbone models. Results are evaluated on T5-base.

Adapters	Task	Method	es	fr	Avg.
LoRA	XNLI	Eng-FT	33.0	32.9	33.0
		AriMerge	34.1	30.1	32.1
		AdaMergeX	37.2	35.7	36.5
	XLSum	Eng-FT	12.4	15.3	13.9
		AriMerge	13.1	16.5	14.8
		AdaMergeX	14.9	16.6	15.8
$(IA)^3$	XNLI	Eng-FT	38.2	38.4	38.3
		AriMerge	35.6	36.1	35.9
		AdaMergeX	39.3	42.4	40.8
	XLSum	Eng-FT	13.2	14.7	14.0
		AriMerge	14.3	15.1	14.7
		AdaMergeX	14.2	16.7	15.5

Table 11: Ablation study on adaptive merging method. AdaMergeX (adaptive) represents AdaMergeX with adaptive merging methods, while AdaMergeX (cross) represents AdaMergeX with cross merging methods, i.e., LoRA with merging method of $(IA)^3$ and vice versa. Increase ↑ and decrease ↓ are both compared to the baseline method Eng-Tune.

Adapters	**Tasks**	**Method**	es	vi	Avg.
LoRA	XNLI	Eng-Tune	60.5	47.0	53.8
		AdaMergeX (adaptive)	**62.8** ↑ 2.3	**49.2** ↑ 2.2	**56.0** ↑ 2.2
		AdaMergeX (cross)	17.6 ↓ 42.9	15.4 ↓ 31.6	16.5 ↓ 37.3
	XQUAD	Eng-Tune	48.2	40.9	44.6
		AdaMergeX (adaptive)	**50.0** ↑ 1.8	**41.7** ↑ 0.8	**45.9** ↑ 1.3
		AdaMergeX (cross)	0.0 ↓ 48.2	0.0 ↓ 40.9	0.0 ↓ 44.6
$(IA)^3$	XNLI	Eng-Tune	50.7	51.0	50.9
		AdaMergeX (adaptive)	**54.3** ↑ 3.6	**58.8** ↑ 7.8	**56.4** ↑ 5.5
		AdaMergeX (cross)	50.9 ↑ 0.2	57.4 ↑ 6.4	54.2 ↑ 3.1
	XQUAD	Eng-Tune	47.6	35.1	41.4
		AdaMergeX (adaptive)	**48.2** ↑ 0.6	**35.7** ↑ 0.6	**42.0** ↑ 0.6
		AdaMergeX (cross)	47.5 ↓ 0.1	34.9 ↓ 0.2	41.3 ↓ 0.1

Models	**Method**	de	ru	fr	es	th	sw	Avg.
XNLI	Eng-Tune	63.3	56.4	56.6	58.6	4.1	41.5	46.8
	AdaMergeX	63.8	57.2	58.2	58.9	3.7	41.8	**47.3**↑ 0.5
XQuAD	Eng-Tune	9.8	8.7	–	15.2	4.4	–	9.5
	AdaMergeX	10.4	7.8	–	21.4	5.4	–	**11.2**↑ 1.7

Table 12: Llama2-7b on LoRA with fine-tuning target modules as W^Q, W^V and merging target modules as W^Q, W^V.

Models	**Method**	de	ru	fr	es	th	sw	Avg.
XNLI	Eng-Tune	54.0	54.0	58.2	60.5	3.3	31.8	43.6
	AdaMergeX	53.7	55.6	60.5	62.7	4.9	33.6	**45.2**↑ 1.6
XQuAD	Eng-Tune	49.0	34.1	–	48.2	31.0	–	40.6
	AdaMergeX	50.2	32.9	–	48.9	31.3	–	**40.8** ↑ 0.2

Table 13: Llama2-7b on LoRA with fine-tuning target modules as W^Q, W^K, W^V, W^O, W_1, W_2 and merging target modules as W^Q, W^K, W^V, W^O, W_1, W_2.