MEDIATOR: MEMORY-EFFICIENT LLM MERGING WITH LESS PARAMETER CONFLICTS AND UNCERTAINTY BASED ROUTING

Anonymous authors
Paper under double-blind review

ABSTRACT

Model merging aggregates Large Language Models (LLMs) finetuned on different tasks into a stronger one. However, parameter conflicts between models leads to performance degradation in averaging. While model routing addresses this issue by selecting individual models during inference, it imposes excessive storage and compute costs, and fails to leverage the common knowledge from different models. In this work, we observe that different layers exhibit varying levels of parameter conflicts. Building on this insight, we average layers with minimal parameter conflicts and use a novel task-level expert routing for layers with significant conflicts. To further reduce storage costs, inspired by task arithmetic sparsity, we decouple multiple fine-tuned experts into a dense expert and several sparse experts. Then, we select and merge appropriate experts based on the task uncertainty of the input data. We conduct extensive experiments on both LLaMA and Qwen with varying parameter scales, and evaluate on real-world reasoning tasks. Results demonstrate that our method consistently achieves significant performance improvements while requiring less system cost.

1 INTRODUCTION

Finetuning Large Language Models (LLMs) enables them to adapt to downstream applications including sentiment analysis (Sun et al., 2023), text summarization (Fang et al., 2024), mathematical reasoning (Ruis et al., 2024), code writing (Jiang et al., 2024a), roleplay chatting (Chen et al., 2025) so on. Open-source platforms such as Huggingface (Wolf et al., 2019) facilitate access to a diverse array of highly trained expert models with varying capabilities. Because the computational resources are scarce and implementing green computing (Stojkovic et al., 2024), the community is increasingly interested in how to merge these models to create a superior LLM that retains the strengths of finetuned ones without retraining (Yang et al., 2024a).

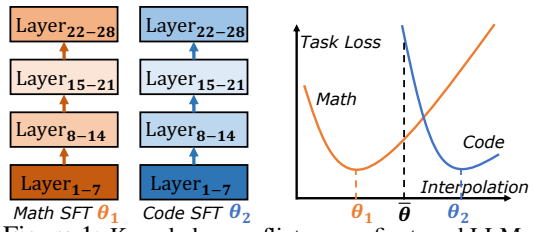


Figure 1: Knowledge conflict across finetuned LLMs and math and code dataset. Deeper color means larger parameter conflicts. And it is difficult for the linear averaged model to achieve low loss of both tasks.

Current merging strategies generally fall into two categories, each with distinct limitations. The first is model averaging (Yang et al., 2024a; Thennal et al., 2024), which computes weighted averages of parameters to synthesize collective knowledge. However, this approach suffers from parameter conflicts arising from diverse finetuning tasks, leading to performance degradation as shown in Figure 1. The second direction is model routing (Lu et al., 2024a; He et al., 2024a; Wei et al., 2024a), which maintains multiple models and selects the best one during inference. While this avoids parameter conflicts, it incurs significant computing and storage costs due to the necessity of maintaining all finetuned models in memory, and loses aggregating shared knowledge into one model. This dichotomy motivates us to rethink the following question:

How to merge common and unique knowledge from various finetuned models while simultaneously avoiding parameter conflicts and minimizing system costs?

To address this, we first investigate the nature of parameter conflicts. By employing sign consistency between different task arithmetics to measure conflict levels, we discover that conflicts are not uniform: front and last layers tend to exhibit the highest levels of conflict (noise), while central layers demonstrate comparatively lower levels (Section 3). This insight drives our proposed framework, Mediator, which employs an adaptive merging strategy. We average layers with lower conflict levels to capture common knowledge (He et al., 2024b), while layers with significant conflicts are treated as distinct experts to be routed during inference (Section 4.1). This hybrid approach effectively preserves unique task-specific knowledge without dilution.

However, the "adaptive merging" strategy introduces a new challenge: maintaining multiple expert layers for the high-conflict regions remains memory-intensive. To resolve this storage bottleneck, we introduce expert decomposition. Leveraging the high sparsity of task arithmetics (Yadav et al., 2023a), we decouple finetuned models into a shared dense base and lightweight, sparse task-specific components (Δ_τ) (Ilharco et al., 2023; Tang et al., 2024a) (Section 4.2). By storing only one dense model and N sparse experts, we reduce storage requirements from 50% to 7%, making the system highly efficient.

With these sparse experts available, the challenge shifts to efficient selection. Existing token-level routing (Sukhbaatar et al., 2024a; Jiang et al., 2024b) often fragments the context, which is suboptimal given that LLMs are finetuned on complete sentences. Therefore, we propose a task-level expert router (Section 4.3). This mechanism selects the appropriate sparse experts based on the input prompt, better preserving the integrity of task-specific knowledge.

Furthermore, a static task-level router may struggle with complex or out-of-distribution (OOD) samples. To address this, we incorporate uncertainty-based routing. Mediator estimates task uncertainty for input data. For ambiguous or OOD inputs, it intelligently merges multiple sparse experts to create a composite expert on the fly (Section 4.3). This allows the unified model to adapt dynamically to the characteristics of the input data.

Finally, to validate that our system preserves high-level capabilities, we evaluate Mediator using Chain-of-Thought (CoT) enhanced datasets (Wei et al., 2022; Guo et al., 2025) (Section 5). Our evaluations show that Mediator achieves minimal performance degradation ($0.06\% \sim 0.3\%$) while enabling a model comparable to a 7B $\times$ 4 LLM ensemble to run effectively on a single consumer-grade RTX 4090 GPU (Appendix I.4).

Our main contributions can be summarized as follows:

- We quantify layer-wise parameter conflicts (Section 3) and propose Mediator, an adaptive merging framework that averages low-conflict layers to share common knowledge while routing high-conflict layers to avoid interference (Section 4.1).
- To solve the storage overhead of routing, we introduce expert decomposition (Section 4.2), separating models into one dense base and multiple sparse experts. This achieves a high compression ratio while maintaining accuracy.
- We develop an uncertainty-based routing mechanism (Section 4.3) that performs task-level selection for standard inputs and dynamic expert merging for OOD data. Experiments on LLaMA and Qwen with CoT datasets demonstrate that Mediator outperforms existing methods in both accuracy and system efficiency (Section 5).

2 Preliminary and Related Works

2.1 Language Modeling and LLM Finetuning

Task Data Distribution. Given a set of different downstream tasks $\mathcal{T}$, based on the sampling task $\tau \in \mathcal{T}$, the pretraining data sample is a sequence $x_{1:T}$ of tokens with the maximum length T generated from a distribution $p_\tau = p(x_{1:T}|\tau) = p(o_1, \ldots, o_T|\tau)$ (Xie et al., 2022; Wies et al., 2023; Hahn and Goyal, 2023; Li et al., 2024a). We define the pretraining data is sampled from

$p(x|\mathcal{T}^\star) = \int_{\tau^\star \in \mathcal{T}^\star} p(o_1, \ldots, o_T|\tau)p(\tau^\star)d\tau^\star$. Each token o is sampled from a vocabulary $\mathbb{O}$. And both ($\mathcal{T}$ and $\mathcal{T}^\star$ belong to a large task family Ω, i.e. $\mathcal{T}, \mathcal{T}^\star \subset \Omega$.

Language Modeling. Current LLMs (Brown et al., 2020; Touvron et al., 2023; Xie et al., 2022) usually utilize the next word prediction as the language modelling, which predicts the next token x_t given the previous tokens $x_{1:t-1}$ for all $t = 1, \ldots, T$. Formally, a LLM parameterized by θ is a distribution $f_\theta(x_t|x_{1:t-1})$. And it is pretrained on a huge corpus sampled from the pretraining distribution $p(x|\mathcal{T}^\star)$ (Xie et al., 2022).

Finetuning LLM. Normally, for each downstream task $\tau \in \mathcal{T}$, finetuning LLM is to minimize the cross-entropy loss function as $L_{\text{CE}}(\theta, \tau) = -\sum_{t=1}^{T} \mathbb{E}[p_\tau(x_t|x_{1:t-1}) \cdot \log f_\theta(x_t|x_{1:t-1})]$. After finetuning, the model parameters θ are updated to θ_τ.

2.2 Model Merging

Given finetuned task-specific LLMs $\{\theta_1, \theta_2, \ldots, \theta_{n_\tau}\}$ finetuned on task set $\mathcal{T}$, where $n_\tau = |\mathcal{T}|$, model merge aims to find a unified model parameterized by ϕ that can achieve the low loss on all tasks $\mathcal{T}$ as following

$$\min_{\phi} L_{\text{CE}}(\phi, \mathcal{T}) = \frac{1}{n_\tau} \sum_{\tau \in \mathcal{T}} L_{\text{CE}}(\phi, \tau). \tag{1}$$

Different from training ϕ that can be optimized towards any direction, model merging aims to exploit combining $\{\theta, \theta_1, \theta_2, \ldots, \theta_{n_\tau}\}$ to obtain the ϕ. The current model merging methods include following two categories.

Model Averaging. Averaging parameters to fuse the knowledge from different finetuned models is straightforward. Mathematically, averaged model is $\phi = \sum_{\tau \in \mathcal{T}} w_\tau \theta_\tau$, in which w_τ is the averaging weight and $\sum_{\tau \in \mathcal{T}} w_\tau = 1$. Because different model parameters have different importance on downstream tasks, some works (Kirkpatrick et al., 2017; Sun et al., 2024; Dong et al.) assign larger weights to more important parameters. Current methods usually utilize Taylor expansion (Lee et al., 2019; Matena and Raffel, 2022) to measure the importance of the parameters. However, the knowledge conflicts still exist for parameters that have high importance simultaneously.

Model Routing. To completely avoid conflicts, another way is to select the most relevant model for each task. This approach typically employs a selection mechanism to activate the most relevant model based on the input task τ (Yang et al., 2024b) or sequence $x_{1:t}$ at t-th token like the Mixture of Experts (MoE) (Tang et al., 2024b). Current methods propose different routing and re-training mechanisms to improve the performance (He et al., 2024a; Wei et al., 2024a; Sukhbaatar et al., 2024b). However, these methods fail to consider merging parameters to find the common knowledge that can be shared across different tasks, and cause large memory and computational costs. We leave detailed discussions about related works in Appendix C).

Out-of-distribution Data. In real-world deployment, the test data x may come from other distributions instead of the $p(x|\tau)_{\tau \in \mathcal{T}}$. To this end, we need to consider how to handle OOD data x within merging LLMs. In this work, we mainly consider two OOD cases and tackle them in Section 4.

3 Understanding Conflict between LLMs

Preliminary Experiments. Before introducing our framework, we first investigate the nature of parameter conflicts in model merging. We conduct preliminary experiments to quantify how conflicts arise and distribute across layers. We finetune Llama-3.2-3B on three datasets and evaluate them on corresponding tasks (experimental details in Section 5). Let $P(\theta, \tau)$ denote the performance of model θ on task τ. We define three baselines: the original pretrained model (P_{ORI}), the simply averaged model (P_{AVG}), and an oracle selection model (P_{SEL}) that selects the optimal finetuned expert θ_τ for each task. As shown in Table 1, we observe the performance hierarchy $P_{\text{ORI}} < P_{\text{AVG}} < P_{\text{SEL}}$. This inequality implies two key insights. First, merging knowledge via

Table 1: Accuracy of finetuning Llama 3.2 3B.

Model	GSM8K Math	TriviaQA	H.Eval Code	All tasks
θ (Pretrained)	27.52	57.71	22.56	35.93
θ_1 (Math SFT)	**46.47**	54.59	25.00	42.02
θ_2 (QA SFT)	32.75	**61.45**	28.05	40.75
θ_3 (Coding SFT)	33.13	57.71	**40.85**	43.90
ϕ_{AVG}	42.61	60.99	31.30	44.97
ϕ_{SEL}	**46.47**	**61.45**	**40.85**	**49.59**

averaging (P_{AVG}) improves upon the base model (P_{ORI}). Second, simple averaging fails to fully recover the specialized capabilities of individual experts (P_{SEL}). This gap suggests that indiscriminate averaging dilutes task-specific knowledge due to parameter conflicts.

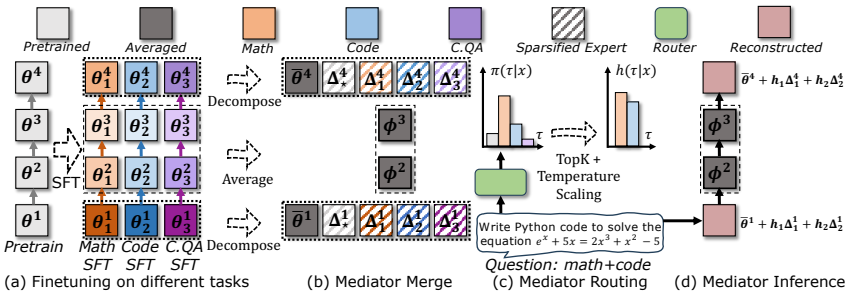


Figure 2: The framework of Mediator.

To close the gap between P_{AVG} and P_{SEL}, we must identify where conflicts occur. We utilize Task Arithmetic to isolate task-specific updates.

Definition 3.1 (Task Arithmetic)**.** A task arithmetic on task τ is the parameter difference between the finetuned LLM θ_τ and the pre-trained LLM θ, i.e., $\Delta_\tau = \theta_\tau - \theta$.

Parameter Denoising. A critical challenge in measuring conflicts is the presence of stochastic noise. Finetuning is an optimization process where non-essential parameters often undergo random fluctuations (Yadav et al., 2023a; He et al., 2024b). For instance, a parameter might shift by $+10^{-5}$ in Task A and -10^{-5} in Task B purely by chance. Although these shifts are negligible for performance, a raw sign-based metric would incorrectly flag them as a "conflict" ($+$ vs $-$).

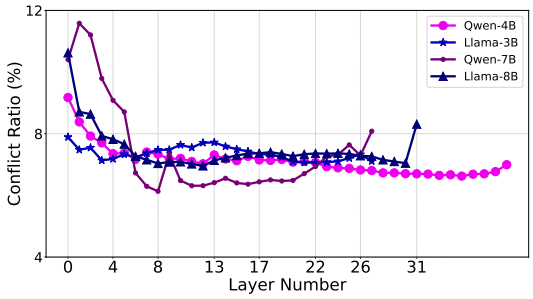


Figure 3: Parameter conflict distribution across different layers of finetuned models (Qwen 2.5 7B).

To prevent such false positives, we denoise the task arithmetic before measurement. We model the update elements of Δ_τ as a Gaussian distribution $\mathcal{N}_{\text{UPD}}(\mu_{\text{UPD}}, \sigma^2_{\text{UPD}})$. We identify parameters within the range $(\mu_{\text{UPD}} - \sigma_{\text{UPD}}, \mu_{\text{UPD}} + \sigma_{\text{UPD}})$ as noise and prune them to zero. We then obtain the denoised arithmetic $\hat{\Delta}_\tau$ and the corresponding denoised model $\hat{\theta}_\tau = \theta + \hat{\Delta}_\tau$ (further details in Appendix F.1).

Measuring Parameter Conflict. Using the denoised parameters, we measure conflicts using sign consistency (Yadav et al., 2023a). For a layer l, given parameters $w_i^l \in \hat{\theta}^l_{\tau_i}$ and $w_j^l \in \hat{\theta}^l_{\tau_j}$, a conflict exists if $sgn(w_i^l w_j^l) = -1$. The conflict ratio d_l is the proportion of conflicting parameters:

$$d_l = \frac{\sum_{i,j} \mathbb{I}(sgn(w_i^l w_j^l) = -1)}{|\theta^l|} \tag{2}$$

Observation. Figure 3 illustrates the distribution of d_l across layers. We observe that conflict levels are non-uniform. Specifically, front layers consistently exhibit high conflict ratios, likely due to the divergence in shallow feature extraction for different tasks. In contrast, central layers demonstrate significantly lower conflict, suggesting a region of shared, common knowledge.

It is worth noting that while the final layers often show high conflict (as seen in Llama-3), this is not universal; for example, Qwen-4B exhibits relatively lower conflict in its final layers. This variability in conflict distribution—where the "safe-to-merge" zones differ by model architecture—underscores the necessity for an adaptive merging strategy rather than fixed layer selection.

4 The Design of Mediator

This section introduces Mediator, a unified framework designed to efficiently merge multiple finetuned LLMs. Our approach begins with **Adaptive Merging** (Section 4.1), which leverages our finding that parameter conflicts are concentrated in the front and last layers. By averaging low-conflict central layers and routing the high-conflict ones, we preserve task-specific capabilities without noise. To address the storage overhead of maintaining these multiple experts, we introduce **Expert Decomposition** (Section 4.2), which utilizes sparsity to decouple experts into lightweight task arithmetics. Finally, we implement **uncertainty-aware Expert Routing** (Section 4.3), a mechanism that dynamically selects or mixes these sparse experts to handle ambiguous or out-of-distribution inputs effectively.

Algorithm 1 Adaptive Merging and Routing with Sparsified Expert Decomposition in Mediator

Input: Different finetuned models $\theta_1, \theta_2, \ldots, \theta_{n_\tau}$.
Output: The merged layers Φ.

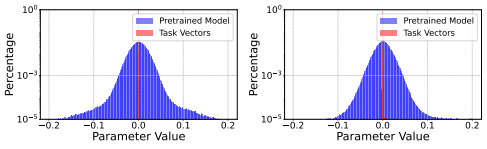
Calculate the conflict distribution $\{d_l\}_{l=1,\cdots,|\mathcal{L}|}$;
Estimate μ, σ based on $\{d_l\}_{l=1,\cdots,|\mathcal{L}|}$;
for layer $l = 1, \cdots, |\mathcal{L}|$ **do**
  if $d_l < \mu + \sigma$ **then**
    $\phi^l_{\text{AVG}} = \mathcal{M}(\theta^l_1, \theta^l_2, \ldots, \theta^l_{n_\tau})$;
  else
    $\bar{\theta}^l = 1/n_\tau \sum_{\tau \in \mathcal{T}} \theta^l_\tau$;
    $\Delta^l_\tau = \theta^l_\tau - \bar{\theta}^l$, $\Delta^l_\star = \theta^l - \bar{\theta}^l$;
    $\hat{\Delta}^l_\tau = \text{Denoise}(\Delta^l_\tau)$;
    $\phi^l_{\text{UP}} = \left\{\bar{\theta}^l, \hat{\Delta}^l_1, \hat{\Delta}^l_2, \ldots, \hat{\Delta}^l_{n_\tau}, \hat{\Delta}^l_\star\right\}$;
  end if
  Insert ϕ^l_{AVG} or ϕ^l_{UP} into Φ_{AVG} and Φ_{UP};
end for
Return $\Phi = \{\Phi_{\text{AVG}}, \Phi_{\text{UP}}\}$. =0

4.1 Adaptive Layer-wise Model Averaging and Routing

The core challenge in model merging is that parameter conflicts are not uniformly distributed across the model. As analyzed in Section 3, averaging on high-conflict layers destroys task-specific information, while routing every layer is computationally prohibitive. Mediator solves this via an adaptive merging strategy: we average layers with shared knowledge (low conflict) and route layers with distinct task requirements (high conflict) as shown in Figure 2.

Dynamic Thresholding. Instead of manually designating "front" or "back" layers, Mediator dynamically identifies conflict zones. We first calculate the conflict score d_l for each layer l (as defined in Eq. 2). We model the distribution of these layer-wise conflicts as a Gaussian distribution $d_l \sim \mathcal{N}(\mu, \sigma)$. We apply the *Route operation* to layers falling above the adaptive threshold ($\mu + \sigma$) and *Average* those falling below it. Empirically, we observe that layers satisfying $d_l \geq \mu + \sigma$ (high conflict) are primarily located in the front and last layers of the model, corresponding to shallow feature processing and final output formatting as shown in Figure 3. Conversely, central layers typically satisfy $d_l < \mu + \sigma$, indicating they store common knowledge suitable for averaging. Additionally, following findings that attention mechanisms largely store non-specific domain knowledge (Sukhbaatar et al., 2024a), we default to averaging all attention layers.

Merging Operations. For layers designated for averaging (ϕ^l_{AVG}), we employ TIES-Merging (Yadav et al., 2023a) to compute a unified parameter set. For layers designated for routing (ϕ^l_{UP}), we maintain the distinct parameters for each task, which we address in the following subsection.



(a) Qwen 1.5 4B (b) Qwen 2.5 7B

Figure 4: Comparing magnitudes of task arithmetic and pretrained model parameters.

4.2 Expert Decomposition

The adaptive merging strategy creates a new challenge: maintaining N distinct experts for the routed layers (ϕ^l_{UP}) requires memory $N \times M_l$, where M_l is the layer size. This linear scaling with the number of tasks (N) is inefficient.

To resolve this, we introduce Expert Decomposition. We leverage the observation that while the base weights are dense, the task-specific updates (task arithmetics) are highly sparse and distinguishable

from noise. As shown in Figure 4, the magnitude of task updates is significantly smaller than the pretrained parameters.

We decompose each routed expert θ_τ into a shared base θ and a sparse task arithmetic Δ_τ:

$$\theta_\tau = \theta + \Delta_\tau \tag{3}$$

We then sparsify Δ_τ into $\hat{\Delta}_\tau$ by pruning parameters below a noise threshold (derived from Section 3). This reduces the storage cost from $N \times M_l$ to roughly $N \times M_l \times c$, where c is the sparsity ratio (typically $< 10\%$).

Preserving Pretraining Knowledge (OOD-I). (OOD to $\mathcal{T}$ but in-distribution to pretraining data $p(x|\mathcal{T}^\star)$) Finetuning often induces catastrophic forgetting of the pretraining distribution. To ensure Mediator retains general capabilities for inputs that are Out-Of-Distribution (OOD) to the specific tasks but In-Distribution to the pretraining data ($x \sim p(x|\mathcal{T}^\star)$), we explicitly store the "pretraining arithmetic" $\Delta_\star = \theta - \bar{\theta}$, where $\bar{\theta}$ is the average of the finetuned models. This allows us to revert to the generalist capability when necessary.

4.3 Expert Routing

With the experts decomposed into sparse components $\hat{\Delta}_\tau$, the next challenge is selecting the correct expert during inference like the token-level expert routing in MoE (Sukhbaatar et al., 2024a).

Task-level vs. Token-level Routing. Standard MoE models use token-level routing. However, finetuned LLMs are trained on complete sequences $x_{1:T} \sim p_\tau$. Therefore, a subsequence $x_{1:t} \subset x_{1:T}$ might be OOD to the another model $\theta_{\hat{\tau}}$. Switching experts mid-sentence (token-level) fragments the semantic context and degrades performance (theoretical analysis provided in Appendix D). Therefore, Mediator employs *Task-level Routing*, selecting experts once per input sequence. Besides, task-level routing is more system friendly than token-level routing because there is no expert reloading during decoding process.

Algorithm 2 Uncertainty based Expert Routing in Mediator

Input: The question prompt $x_{1:t}$, router π_κ, Φ_{UP}, k, β.
Output: Reconstructed routing layers $\Phi_{\text{UP},x}$.

```
T_k^x = Indexes of TopK({π_κ(τ|x)}, k);
Calculate and cache {h(τ|x)} (Equation 4);
for φ^l_UP ∈ Φ_UP do
    φ^l_{UP,x} = θ̄^l + Σ_{τ∈T_k^x} h(τ|x) Δ̂^l_{n_τ};
    Insert φ^l_{UP,x} into Φ_{UP,x};
end for
Return Φ_{UP,x}. =0
```

Handling Compositional Tasks (OOD-II). (OOD but close to $\mathcal{T}$ and Ω) A rigid selector fails on inputs x that do not belong strictly to a single training task τ (e.g., a query requiring both coding and reasoning). To handle such OOD samples, we propose **Uncertainty-based Expert Selection**. We treat the selection as a probabilistic merging problem.

Specifically, we train a lightweight classifier κ to predict the task likelihood. During inference, we apply temperature scaling to the logits to estimate the posterior distribution (uncertainty) $h(\tau|x)$:

$$h(\tau|x) = \frac{e^{\pi_\kappa(\tau|x)/\beta}}{\sum_{\tau \in \mathcal{T} \cup \star} e^{\pi_\kappa(\tau|x)/\beta}} \tag{4}$$

For clear task inputs, this distribution is sharp (selecting a single $\hat{\Delta}_\tau$). For ambiguous or OOD inputs, the distribution flattens, effectively computing a weighted average of relevant experts. The final parameters for the routed layer are constructed dynamically as $\theta_{\text{routed}} = \theta_{\text{base}} + \sum_\tau h(\tau|x)\hat{\Delta}_\tau$. This process is summarized in Algorithm 2.

4.4 System-level Optimization

The dynamic construction of θ_{routed} introduces latency due to memory loading. We implement two system-level optimizations to mitigate this overhead:

Asynchronous Prefetching. The bottleneck lies in loading sparse experts from CPU/disk to GPU. We implement asynchronous prefetching: while the GPU computes layer l, the CPU prepares and

transfers the sparse experts for layer $l + 1$ (i.e., Algorithm 2). This effectively masks the loading latency behind the computation time.

Fused Sparse Integration. To accelerate the summation $\theta + \sum h\hat{\Delta}$, we utilize a custom CUDA kernel based on atomicAdd. This allows us to parallelize the addition of sparse matrices directly into the dense backbone without materializing intermediate dense tensors.

For non-sparse components stored on disk, we utilize ZipNN (Hershcovitch et al., 2024) for rapid decompression. As detailed in Appendix G, these optimizations result in an inference latency only $0.2\text{s} \sim 0.4\text{s}$ higher than a standard single model, despite the dynamic routing capabilities.

5 EXPERIMENTS

Models and Evaluation Tasks. We conduct comprehensive experiments on cutting-edge LLMs including Qwen-1.5-4B, Qwen-2.5-7B (Yang et al., 2024c), LLaMA-3.1-3B, and LLaMA-3.2-8B (Dubey et al., 2024). We select different evaluation tasks to effectively demonstrate model capability in resolving parameter conflicts during model merging, including GSM8K of mathematical question-answering (Cobbe et al., 2021), TriviaQA (Joshi et al., 2017) of a large-scale Wikipedia-based question answering dataset, HumanEval (Chen et al., 2021) of Python programming tasks, WinoGrande (Sakaguchi et al., 2019) of logical reasoning, MMLU (Hendrycks et al., 2021) of vertical domain knowledge (as OOD to the finetuned models).

Finetuning Settings. The finetuning datasets are constructed by augmenting some publicly datasets (task related but without overlap) with GPT-4o (Gilardi et al., 2023) and Chain-of-Thoughts (Wei et al., 2022). For each finetuning process, we use at least 180K training samples to ensure sufficient performance improvement on the corresponding task, which helps validate the effectiveness of our experiments (Details of constructing finetuning datasets in Appendix H and hyperparameters in Appendix E). *To the best of our knowledge, this is the first LLM merging study with CoT enhanced finetuning and evaluated with generative tasks.*

Table 2: Comparing performance of model merging methods on Llama 3.1 3B and Llama-3.2 8B.

Model	Llama 3.1 3B						Llama-3.2 8B					
Alg./Tasks	GSM.	TrA.	Wino.	H.Eval	MMLU	AVG.	GSM.	TrA.	Wino.	H.Eval	MMLU	AVG.
Base	27.52	57.71	**69.69**	22.56	**54.08**	46.31	56.33	72.39	73.64	27.44	**67.99**	59.56
Math	**46.47**	54.59	69.06	25.00	52.73	49.57	**77.18**	73.99	74.98	20.12	62.10	61.67
QA	32.75	**61.45**	**69.69**	28.05	54.17	49.22	69.60	**74.14**	**75.45**	31.71	62.21	62.43
Code	33.13	57.71	68.59	**40.85**	53.09	**50.67**	61.41	73.94	74.59	**62.80**	62.73	**67.09**
All data	44.12	47.74	69.21	34.76	53.75	49.92	70.89	69.77	75.06	48.17	62.94	65.37
TIES	42.61	60.99	71.11	31.30	54.32	51.27	76.04	76.78	74.19	53.05	62.36	68.48
PCB	46.02	60.39	71.27	29.88	54.21	52.35	76.04	76.89	74.35	53.66	62.42	68.67
Twin	39.04	52.45	69.27	29.94	53.91	48.11	76.80	72.71	74.49	59.14	64.43	69.51
BTX	45.19	**62.05**	71.87	28.05	54.44	52.33	76.72	73.99	75.22	60.98	65.68	70.52
Mediator	**46.47**	61.02	**72.03**	**40.42**	**54.91**	**54.97**	**76.95**	**76.70**	**75.69**	**62.80**	**67.87**	**71.80**

Table 3: Comparing performance of model merging methods on Qwen 1.5 4B and Qwen 2.5 7B.

Models	Qwen 1.5 4B						Qwen 2.5 7B					
Alg./Tasks	GSM.	TrA.	Wino.	H.Eval	MMLU	AVG.	GSM.	TrA.	Wino.	H.Eval	MMLU	AVG.
base	47.16	44.54	56.75	**41.46**	54.45	48.87	83.41	51.67	67.68	67.68	67.70	**67.63**
Math	**51.00**	46.95	54.62	26.83	53.54	46.79	**85.14**	51.67	65.75	61.59	67.27	66.27
Code	43.29	46.39	54.14	43.29	**54.82**	48.39	52.31	49.47	64.64	**71.95**	**72.30**	62.13
QA	45.56	**48.02**	**57.93**	39.02	52.32	48.57	84.62	**55.58**	62.83	43.29	71.51	63.57
all-sft	48.52	47.73	55.88	39.14	53.93	**49.04**	64.90	52.98	**69.30**	65.85	69.66	64.59
TIES	47.76	46.59	54.14	44.51	54.58	49.5	84.76	54.46	66.46	65.85	71.55	68.62
PCB-merging	47.83	47.60	56.75	43.90	54.58	49.93	73.46	53.90	69.53	60.98	71.41	65.86
Twin-merging	47.99	44.63	57.54	40.85	52.98	48.80	83.46	54.64	66.37	69.51	70.56	68.91
BTX	48.44	46.94	57.77	42.68	53.88	49.94	84.46	55.89	67.72	67.68	72.30	69.61
Mediator	**50.94**	**48.20**	**57.85**	**45.12**	**54.87**	**51.40**	**85.14**	**56.06**	**69.30**	**71.95**	**72.56**	**71.00**

Baselines. We compare pretrained, finetuned models, and the state-of-the-art static and dynamic merging methods with Mediator. The *static merging methods* include TIES (Yadav et al., 2023b) and PCB-merging (Du et al., 2024) achieve the best performance in weighted average method and do not require calibration data, and also partly consider OOD evaluation tasks. The dynamic merging methods include BTX (Sukhbaatar et al., 2024b) with token-level routing and the twin-merge

with task-level routing and SVD decomposition (Lu et al., 2024b) (Details of hyperparameters and optimization of these baselines in Appendix E).

5.1 Main Results

Fine-grained Comparison on All Tasks. Table 2 and 3 show the fine-grained performance on each tasks and their overall averaged one of different methods and algorithms. In most of time, the finetuned LLM can achieve the best performance across all single and merged models on its specialized domain, like Math finetuned models on GSM8K and Code finetuned models on HumanEval. While merged LLMs can generally outperform single models on the averaged performance, their specialized domain performance is weaker. However, Mediator can catch up the domain performance of specialized models, and almost always outperform other merged models. Also, the overall performance on all tasks of Mediator is consistently better than other methods. Expert routing methods includes BTX and Mediator generally improve performance. This aligns with findings in TIES (Yadav et al., 2023b) and Twin-merging (Lu et al., 2024a). As model scale increases, the improvement of all merging algorithms decrease, which may be attributed to enhanced comprehensive capabilities of individual finetuned models.

Overall Comparison. As shown in Table 4, the advantages of PCB over TIES become less pronounced at larger model scales, and even shows performance degradation on Qwen-7B, which demonstrates PCB's instability. Dynamic routing approaches include BTX and Mediator show stable performance improvements. Our method demonstrates consistent improvements across different models.

Table 4: Overall Performance on all tasks.

Model/Algo.	Qwen-4B	Llama-3B	Qwen-7B	Llama-8B
base model	48.87	46.31	67.63	59.56
all data sft	49.04	49.92	64.59	65.37
TIES	49.50	51.27	68.62	68.48
Twin	48.80	48.11	68.91	69.51
PCB	49.93	52.35	65.86	68.67
BTX	49.94	52.33	69.61	70.52
Mediator	**51.40** (↑2.9%)	**54.97**(↑5.0%)	**71.00** (↑2.0%)	**71.80** (↑1.8%)

Post-Training Time After Merging. As many model merging methods like Twin, PCB and BTX require post-training, it is critical to compare the extra training time. Table 5 shows the post-training time of different methods. PCB merging require weight exploration thus leads to higher time. The BTX with token-level routing needs to completely train the layer-wise routers for each token, thus, the post-training time of them is significantly high. In contrast, for task-level routing approaches like Twin-merging and Mediator, taking the lowest time.

Table 5: Post Training Time (Hours).

Model/Algo	LlaMA-3B	LlaMA-8B	Qwen-4B	Qwen-7B
Twin	1.33	1.87	1.60	1.80
PCB	3.42	5.75	5.73	5.80
BTX	7.55	12.52	8.83	12.18
Mediator	1.35	2.03	1.57	1.78

Inference Time. Table 6 shows the inference time of different methods. As the token-level routing methods need to load and compute the layer-wise routers for each token, the inference time of them is significantly higher (more than 2x) than our method. We have detailed our inference acceleration process in Section 4.4 and Appendix G.

Table 6: Inference time per sample (seconds).

Model/Algo	LlaMA-3B 32 layers	LlaMA-8B 32 layers	Qwen-4B 40 layers	Qwen-7B 28 layers
Base model	1.452	3.600	3.112	3.057
Twin	1.725	4.151	3.792	3.648
BTX	3.237	8.68	7.082	7.153
Mediator	1.609	4.053	3.674	3.489

Table 7: Comparing memory costs.

Model/Algo	LLaMA-3B	LLaMA-8B	Qwen-4B	Qwen-7B
Base model	9G	33G	11G	31G
Twin-merging	10G	35G	13G	32G
BTX (MOE)	37G	80G	40G	78G
Mediator	10G	35G	13G	33G

Memory Cost. Table 7 shows the memory costs of different methods. Our method significantly reduces the memory costs compared to saving all finetuned models because there is only one router for all experts, and the sparsified experts saving, and the layer-wise merging strategy (Details of formally comparing memory costs of merging methods in Appendix C).

5.2 Ablation Studies

Scalability of Finetuned Models. To verify the scalability of Mediator, we finetune another 4 LLMs according to the following 4 extra evaluation tasks including: (1) *Instruction Following* with IFEval. (Zhou et al., 2023) which assess models ability to accurately interpret and execute natural language instructions; (2-4) *Medicine, College Economics and Law* from CEval which assess

knowledge and capabilities across various academic and professional domains (Huang et al., 2023a). We utilize four accordingly domain datasets for finetuning including Magpie (Xu et al., 2024), IndustryInstruction (Ind), DISC-Med (Bao et al., 2023), DISC-Law (Yue et al., 2023a) without overlap with IFEval and CEval (Details in Appendix H).

Table 8 demonstrates several key findings: 1) Static merging methods like PCB and TIES show diminished performance improvements after task expansion, performing even worse than instruction-following finetuned models in overall scores. The similar performance between PCB merging and TIES aligns with findings from the TIES paper, which noted degraded model capabilities when merging more than three tasks; 2) Dynamic merging approaches like BTX, Twin and Mediator maintain relatively stable performance after task expansion; 3) Mediator consistently outperforms BTX by a margin of 2.09% and achieves the best scores across all individual tasks, showing its good scalability.

Table 8: Performance of scaling up finetuned models.

Alg./Tasks	GSM.	TrA.	Wino.	H.Eval	MMLU	I.Eval	C.Eco	C.Med	C.law	AVG.
Base	47.16	44.54	56.75	41.46	54.45	30.70	49.09	55.10	41.67	46.77
Math	**50.95**	46.95	54.62	26.83	53.54	34.05	45.45	55.10	45.83	45.92
QA	45.56	**48.02**	**57.93**	39.02	52.32	31.65	43.64	59.18	45.83	47.02
code	43.29	46.39	54.14	**43.29**	54.82	31.65	43.64	59.18	45.83	46.91
Instruct.	47.54	40.96	55.09	37.80	**54.88**	**38.37**	52.73	59.18	50.00	48.51
Economy	45.56	46.24	57.93	28.86	54.21	32.13	**56.36**	55.10	45.83	46.78
medicine	39.12	44.50	56.67	1.83	54.63	28.30	50.09	**61.22**	41.66	42.00
Law	40.64	46.64	56.59	0.61	54.61	27.94	41.82	57.14	**58.33**	**47.15**
All Data	43.75	46.25	56.43	40.85	54.60	35.37	49.09	55.10	41.67	46.90
TIES	47.38	47.19	55.80	36.59	55.38	34.17	40.00	57.14	50.00	47.07
PCB	47.38	47.19	55.80	36.59	55.45	34.29	41.82	57.14	50.80	47.38
Twin	47.91	44.78	57.54	40.85	53.01	37.53	53.32	59.56	50.00	49.38
BTX	48.44	46.94	57.85	42.68	54.93	36.93	54.40	60.36	58.33	51.18
Mediator	**50.64**	**48.04**	**57.93**	**44.51**	**55.12**	**38.50**	**56.01**	**61.17**	**58.33**	**52.25**

Layer-wise Merging. Layers with low conflicts are averaged thus reducing $n_\tau\times$ memory occupation. Table 9 averaging or not on Qwen-1.5 with 4 and 8 experts show almost no performance loss of the parameter averaging. Given the significant compression ratios achieved (3.5x for 4 experts, 7x for 8 experts), this minor performance trade-off is acceptable.

Table 9: Model Performance w/o layer-wise merging.

Model scale	with averaging	w/o averaging	perf. gap
Qwen-1.5	51.40	51.43	-0.06%
Qwen-2.5	71.00	71.29	-0.27%

Comparison between Task-level routing and Token-level routing. Fig. 7 in Appendix demonstrates the expert selection probabilities of the BTX model across different tasks (MMLU, math, coding, and QA). The results indicate that 1) bottom and upper layers show obvious task preference; 2) middle layers suggesting some shared logical processing across tasks in these layers, which explains why averaging middle layers that have less conflicts in Mediator results in small performance loss.

Different Temperatures. In the routing process, the hyperparameter temperature β is a key factor. Table 10 shows performance change of Mediator with different temperatures. Results show that only around 2.2% score variation, the $\beta = 1.5$ achieves the highest performance, $\beta = 0.1$ almost equals to the Top-1 routing, results in the lowest performance.

Table 10: Performance under Different Temperature β.

Temperature	0.1	0.5	1.0	1.25	1.50	1.75	2.0
Mediator	50.31	50.35	50.64	51.02	51.40	50.84	50.92

6 CONCLUSION

We propose Mediator, a framework for merging LLMs that addresses parameter conflicts through adaptive layer-wise strategies, which average low-conflict layers and routing high-conflict ones via task-specific experts. This preserves individual model strengths while integrating shared knowledge, improving performance and reducing system costs.

By decomposing experts into a dense core and sparse components, Mediator minimizes storage without sacrificing efficacy. Dynamic expert selection via task uncertainty enhances adaptability across diverse inputs. Experiments on LLaMA and Qwen demonstrate significant performance gains over existing methods, with CoT enhanced datasets further enhancing reasoning capabilities.

Mediator advances efficient LLM merging methods, balancing resource constraints with practical versatility. Future work should explore theoretical foundations of parameter conflicts, large-scale deployment optimizations, and faster expert loading mechanisms.

ETHICS STATEMENT

We declare no conflicts of interest that could inappropriately influence our work. All experiments were conducted using publicly available resources. Our study does not involve human subjects, data collection from individuals, or experiments on protected groups. The models and basic datasets used in this work are publicly available and widely used in the research community. We have made efforts to ensure our experimental design and reporting of results are fair, unbiased, and do not misrepresent the capabilities or limitations of the methods presented.

REPRODUCIBILITY STATEMENT

For openness of LLM research, we declare our code and the CoT enhanced crafted finetuning datsets will be made available to ensure reproducibility. We will provide detailed documents of code implemnetation. And we have provided the details of all hyper-parameters of implementing Mediator and optimizing baselines.

REFERENCES

Xiaofei Sun, Xiaoya Li, Shengyu Zhang, Shuhe Wang, Fei Wu, Jiwei Li, Tianwei Zhang, and Guoyin Wang. Sentiment analysis through llm negotiations, 2023. URL https://arxiv.org/abs/2311.01876.

Jiangnan Fang, Cheng-Tse Liu, Jieun Kim, Yash Bhedaru, Ethan Liu, Nikhil Singh, Nedim Lipka, Puneet Mathur, Nesreen K. Ahmed, Franck Dernoncourt, Ryan A. Rossi, and Hanieh Deilamsalehy. Multi-llm text summarization, 2024. URL https://arxiv.org/abs/2412.15487.

Laura Ruis, Maximilian Mozes, Juhan Bae, Siddhartha Rao Kamalakara, Dwarak Talupuru, Acyr Locatelli, Robert Kirk, Tim Rocktäschel, Edward Grefenstette, and Max Bartolo. Procedural knowledge in pretraining drives reasoning in large language models, 2024. URL https://arxiv.org/abs/2411.12580.

Juyong Jiang, Fan Wang, Jiasi Shen, Sungju Kim, and Sunghun Kim. A survey on large language models for code generation, 2024a. URL https://arxiv.org/abs/2406.00515.

Nuo Chen, Yan Wang, Yang Deng, and Jia Li. The oscars of ai theater: A survey on role-playing with language models, 2025. URL https://arxiv.org/abs/2407.11484.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. Huggingface's transformers: State-of-the-art natural language processing. *arXiv preprint arXiv:1910.03771*, 2019.

Jovan Stojkovic, Esha Choukse, Chaojie Zhang, Inigo Goiri, and Josep Torrellas. Towards greener llms: Bringing energy-efficiency to the forefront of llm inference, 2024. URL https://arxiv.org/abs/2403.20306.

Enneng Yang, Li Shen, Guibing Guo, Xingwei Wang, Xiaochun Cao, Jie Zhang, and Dacheng Tao. Model merging in llms, mllms, and beyond: Methods, theories, applications and opportunities. *arXiv preprint arXiv:2408.07666*, 2024a.

DK Thennal, Ganesh Nathan, and MS Suchithra. Fisher mask nodes for language model merging. In *LREC-COLING*, pages 7349–7355, 2024.

Zhenyi Lu, Chenghao Fan, Wei Wei, Xiaoye Qu, Dangyang Chen, and Yu Cheng. Twin-merging: Dynamic integration of modular expertise in model merging. *arXiv preprint arXiv:2406.15479*, 2024a.

Ethan He, Abhinav Khattar, Ryan Prenger, Vijay Korthikanti, Zijie Yan, Tong Liu, Shiqing Fan, Ashwath Aithal, Mohammad Shoeybi, and Bryan Catanzaro. Upcycling large language models into mixture of experts. 10 2024a. URL https://arxiv.org/pdf/2410.07524.pdf.

Tianwen Wei, Bo Zhu, Liang Zhao, Cheng Cheng, Biye Li, Weiwei Lü, Peng Cheng, Jianhao Zhang, Xiaoyu Zhang, Liang Zeng, Xiaokun Wang, Yutuan Ma, Rui Hu, Shuicheng Yan, Han Fang, and Yahui Zhou. Skywork-moe: A deep dive into training techniques for mixture-of-experts language models. 06 2024a. URL https://arxiv.org/pdf/2406.06563.pdf.

Yifei He, Yuzheng Hu, Yong Lin, Tong Zhang, and Han Zhao. Localize-and-stitch: Efficient model merging via sparse task arithmetic. *arXiv preprint arXiv:2408.13656*, 2024b.

Prateek Yadav, Derek Tam, Leshem Choshen, Colin Raffel, and Mohit Bansal. Ties-merging: Resolving interference when merging models. 06 2023a. URL https://arxiv.org/pdf/2306.01708.pdf.

Gabriel Ilharco, Marco Tulio Ribeiro, Mitchell Wortsman, Ludwig Schmidt, Hannaneh Hajishirzi, and Ali Farhadi. Editing models with task arithmetic. In *ICLR*, 2023.

Anke Tang, Li Shen, Yong Luo, Nan Yin, Lefei Zhang, and Dacheng Tao. Merging multi-task models via weight-ensembling mixture of experts. *ICML*, 02 2024a. URL https://arxiv.org/pdf/2402.00433.pdf.

Sainbayar Sukhbaatar, Olga Golovneva, Vasu Sharma, Hu Xu, Xi Victoria Lin, Baptiste Rozière, Jacob Kahn, Daniel Li, Wen tau Yih, Jason Weston, and Xian Li. Branch-train-mix: Mixing expert llms into a mixture-of-experts llm. 03 2024a. URL https://arxiv.org/pdf/2403.07816.pdf.

Albert Q. Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, Gianna Lengyel, Guillaume Bour, Guillaume Lample, Lélio Renard Lavaud, Lucile Saulnier, Marie-Anne Lachaux, Pierre Stock, Sandeep Subramanian, Sophia Yang, Szymon Antoniak, Teven Le Scao, Théophile Gervet, Thibaut Lavril, Thomas Wang, Timothée Lacroix, and William El Sayed. Mixtral of experts. 01 2024b. URL https://arxiv.org/pdf/2401.04088.pdf.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.

Sang Michael Xie, Aditi Raghunathan, Percy Liang, and Tengyu Ma. An explanation of in-context learning as implicit Bayesian inference. In *International Conference on Learning Representations*, 2022.

Noam Wies, Yoav Levine, and Amnon Shashua. The learnability of in-context learning. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023.

Michael Hahn and Navin Goyal. A theory of emergent in-context learning as implicit structure induction. *arxiv*, arXiv:2303.07971, 2023. URL https://arxiv.org/abs/2303.07971.

Jiaoda Li, Yifan Hou, Mrinmaya Sachan, and Ryan Cotterell. What do language models learn in context? the structured task hypothesis. *arXiv preprint arXiv:2406.04216*, 2024a.

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

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

James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, et al. Overcoming catastrophic forgetting in neural networks. *Proceedings of the national academy of sciences*, 114 (13):3521–3526, 2017.

Mingjie Sun, Zhuang Liu, Anna Bair, and J Zico Kolter. A simple and effective pruning approach for large language models. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=PxoFut3dWW.

Peijie Dong, Lujun Li, Zhenheng Tang, Xiang Liu, Xinglin Pan, Qiang Wang, and Xiaowen Chu. Pruner-zero: Evolving symbolic pruning metric from scratch for large language models. In *Forty-first International Conference on Machine Learning*.

Namhoon Lee, Thalaiyasingam Ajanthan, and Philip Torr. SNIP: SINGLE-SHOT NETWORK PRUNING BASED ON CONNECTION SENSITIVITY. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=B1VZqjAcYX.

Michael S Matena and Colin A Raffel. Merging models with fisher-weighted averaging. *NeurIPS*, 35:17703–17716, 2022.

Enneng Yang, Zhenyi Wang, Li Shen, Shiwei Liu, Guibing Guo, Xingwei Wang, and Dacheng Tao. Adamerging: Adaptive model merging for multi-task learning. *ICLR*, 10 2024b. URL https://arxiv.org/pdf/2310.02575.pdf.

Anke Tang, Li Shen, Yong Luo, Nan Yin, Lefei Zhang, and Dacheng Tao. Merging multi-task models via weight-ensembling mixture of experts. *ICML*, 2024b.

Sainbayar Sukhbaatar, Olga Golovneva, Vasu Sharma, Hu Xu, Xi Victoria Lin, Baptiste Roziere, Jacob Kahn, Shang-Wen Li, Wen tau Yih, Jason E Weston, and Xian Li. Branch-train-mix: Mixing expert LLMs into a mixture-of-experts LLM. In *First Conference on Language Modeling*, 2024b. URL https://openreview.net/forum?id=nqLAuMOF6n.

Moshik Hershcovitch, Andrew Wood, Leshem Choshen, Guy Girmonsky, Roy Leibovitz, Ilias Ennmouri, Michal Malka, Peter Chin, Swaminathan Sundararaman, and Danny Harnik. Zipnn: Lossless compression for ai models. *arXiv preprint arXiv:2411.05239*, 2024.

An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, et al. Qwen2. 5 technical report. *arXiv preprint arXiv:2412.15115*, 2024c.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. Training verifiers to solve math word problems, 2021. URL https://arxiv.org/abs/2110.14168.

Mandar Joshi, Eunsol Choi, Daniel S. Weld, and Luke Zettlemoyer. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension, 2017. URL https://arxiv.org/abs/1705.03551.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, and etc. Evaluating large language models trained on code, 2021. URL https://arxiv.org/abs/2107.03374.

Keisuke Sakaguchi, Ronan Le Bras, Chandra Bhagavatula, and Yejin Choi. Winogrande: An adversarial winograd schema challenge at scale, 2019. URL https://arxiv.org/abs/1907.10641.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding, 2021. URL https://arxiv.org/abs/2009.03300.

Fabrizio Gilardi, Meysam Alizadeh, and Maël Kubli. Chatgpt outperforms crowd workers for text-annotation tasks. *Proceedings of the National Academy of Sciences*, 120(30):e2305016120, 2023.

Prateek Yadav, Derek Tam, Leshem Choshen, Colin Raffel, and Mohit Bansal. Resolving interference when merging models. *NeurIPS*, 2023b.

Guodong Du, Junlin Lee, Jing Li, Runhua Jiang, Yifei Guo, Shuyang Yu, Hanting Liu, Sim Kuan Goh, Ho-Kin Tang, Daojing He, and Min Zhang. Parameter competition balancing for model merging. *NIIPS*, 10 2024. URL https://arxiv.org/pdf/2410.02396.pdf.

Zhenyi Lu, Chenghao Fan, Wei Wei, Xiaoye Qu, Dangyang Chen, and Yu Cheng. Twin-merging: Dynamic integration of modular expertise in model merging. *NIPS*, 06 2024b. URL https://arxiv.org/pdf/2406.15479v2.pdf.

Jeffrey Zhou, Tianjian Lu, Swaroop Mishra, Siddhartha Brahma, Sujoy Basu, Yi Luan, Denny Zhou, and Le Hou. Instruction-following evaluation for large language models, 2023. URL https://arxiv.org/abs/2311.07911.

Yuzhen Huang, Yuzhuo Bai, Zhihao Zhu, Junlei Zhang, Jinghan Zhang, Tangjun Su, Junteng Liu, Chuancheng Lv, Yikai Zhang, Jiayi Lei, Yao Fu, Maosong Sun, and Junxian He. C-eval: A multi-level multi-discipline chinese evaluation suite for foundation models, 2023a. URL https://arxiv.org/abs/2305.08322.

Zhangchen Xu, Fengqing Jiang, Luyao Niu, Yuntian Deng, Radha Poovendran, Yejin Choi, and Bill Yuchen Lin. Magpie: Alignment data synthesis from scratch by prompting aligned llms with nothing. *arXiv preprint arXiv:2406.08464*, 2024.

Baai/industryinstruction - finance - economics. URL https://huggingface.co/datasets/BAAI/IndustryInstruction_Finance-Economics.

Zhijie Bao, Wei Chen, Shengze Xiao, Kuang Ren, Jiaao Wu, Cheng Zhong, Jiajie Peng, Xuanjing Huang, and Zhongyu Wei. Disc-MedLLM: Bridging General Large Language Models and Real-World Medical Consultation. *arXiv*, abs/2308.14346, 2023.

Shengbin Yue, Wei Chen, Siyuan Wang, Bingxuan Li, Chenchen Shen, Shujun Liu, Yuxuan Zhou, Yao Xiao, Song Yun, Xuanjing Huang, and Zhongyu Wei. Disc-LawLLM: Fine-tuning Large Language Models for Intelligent Legal Services. *arXiv*, abs/2309.11325, 2023a.

Yuanchun Li, Hao Wen, Weijun Wang, Xiangyu Li, Yizhen Yuan, Guohong Liu, Jiacheng Liu, Wenxing Xu, Xiang Wang, Yi Sun, Rui Kong, Yile Wang, Hanfei Geng, Jian Luan, Xuefeng Jin, Zilong Ye, Guanjing Xiong, Fan Zhang, Xiang Li, Mengwei Xu, Zhijun Li, Peng Li, Yang Liu, Ya-Qin Zhang, and Yunxin Liu. Personal llm agents: Insights and survey about the capability, efficiency and security, 2024b. URL https://arxiv.org/abs/2401.05459.

Xin Chan, Xiaoyang Wang, Dian Yu, Haitao Mi, and Dong Yu. Scaling synthetic data creation with 1,000,000,000 personas. *arXiv preprint arXiv:2406.20094*, 2024.

Le Yu, Bowen Yu, Haiyang Yu, Fei Huang, and Yongbin Li. Extend model merging from fine-tuned to pre-trained large language models via weight disentanglement. *arXiv preprint arXiv:2408.03092*, 2024a.

Carlos Gómez-Rodríguez and Paul Williams. A confederacy of models: a comprehensive evaluation of llms on creative writing, 2023. URL https://arxiv.org/abs/2310.08433.

Joachim Utans. Weight averaging for neural networks and local resampling schemes. In *AAAI Workshop*, pages 133–138. Citeseer, 1996.

Ken Shoemake. Animating rotation with quaternion curves. In *Proceedings of the 12th annual conference on Computer graphics and interactive techniques*, pages 245–254, 1985.

Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. Communication-efficient learning of deep networks from decentralized data. In *AISTATS*, pages 1273–1282. PMLR, 2017.

Zhenheng Tang, Shaohuai Shi, Xiaowen Chu, Wei Wang, and Bo Li. Communication-efficient distributed deep learning: A comprehensive survey. *arXiv preprint arXiv:2003.06307*, 2020.

Jianyu Wang, Qinghua Liu, Hao Liang, Gauri Joshi, and H Vincent Poor. Tackling the objective inconsistency problem in heterogeneous federated optimization. *NeurIPS*, 33:7611–7623, 2020a.

Divyansh Jhunjhunwala, Shiqiang Wang, and Gauri Joshi. Fedfisher: Leveraging fisher information for one-shot federated learning. In *AISTATS*, pages 1612–1620. PMLR, 2024a.

Mikhail Yurochkin, Mayank Agarwal, Soumya Ghosh, Kristjan Greenewald, Nghia Hoang, and Yasaman Khazaeni. Bayesian nonparametric federated learning of neural networks. In *ICML*, pages 7252–7261. PMLR, 2019a.

Sidak Pal Singh and Martin Jaggi. Model fusion via optimal transport. *NeurIPS*, 33:22045–22055, 2020.

Hongyi Wang, Mikhail Yurochkin, Yuekai Sun, Dimitris Papailiopoulos, and Yasaman Khazaeni. Federated learning with matched averaging. In *ICLR*, 2020b.

Zhenheng Tang, Yonggang Zhang, Shaohuai Shi, Xinmei Tian, Tongliang Liu, Bo Han, and Xiaowen Chu. Fedimpro: Measuring and improving client update in federated learning. In *The Twelfth International Conference on Learning Representations*, 2024c. URL https://openreview.net/forum?id=giU9fYGTND.

Zhenheng Tang, Yonggang Zhang, Shaohuai Shi, Xin He, Bo Han, and Xiaowen Chu. Virtual homogeneity learning: Defending against data heterogeneity in federated learning. In *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*, pages 21111–21132. PMLR, 17–23 Jul 2022.

Neel Guha, Ameet Talwalkar, and Virginia Smith. One-shot federated learning. *arXiv preprint arXiv:1902.11175*, 2019.

Zhenheng Tang, Yonggang Zhang, Peijie Dong, Yiu ming Cheung, Amelie Chi Zhou, Bo Han, and Xiaowen Chu. Fusefl: One-shot federated learning through the lens of causality with progressive model fusion. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024d. URL https://openreview.net/forum?id=E7fZOoiEKl.

Peijie Dong, Lujun Li, Yuedong Zhong, Dayou Du, Ruibo Fan, Yuhan Chen, Zhenheng Tang, Qiang Wang, Wei Xue, Yike Guo, and Xiaowen Chu. Stbllm: Breaking the 1-bit barrier with structured binary llms, 2024. URL https://arxiv.org/abs/2408.01803.

Anthony Robins. Catastrophic forgetting, rehearsal and pseudorehearsal. *Connection Science*, 1995.

Didi Zhu, Zhongyi Sun, Zexi Li, Tao Shen, Ke Yan, Shouhong Ding, Kun Kuang, and Chao Wu. Model tailor: Mitigating catastrophic forgetting in multi-modal large language models. *ICML*, 2024.

Daniel Marczak, Bartłomiej Twardowski, Tomasz Trzciński, and Sebastian Cygert. Magmax: Leveraging model merging for seamless continual learning. In *ECCV*, 2024.

Divyansh Jhunjhunwala, Shiqiang Wang, and Gauri Joshi. Towards a theoretical and practical understanding of one-shot federated learning with fisher information. In *Federated Learning and Analytics in Practice: Algorithms, Systems, Applications, and Opportunities*, 2023.

Zhe Qu, Xingyu Li, Rui Duan, Yao Liu, Bo Tang, and Zhuo Lu. Generalized federated learning via sharpness aware minimization. In *International Conference on Machine Learning*, pages 18250–18280. PMLR, 2022.

Yuyan Zhou, Liang Song, Bingning Wang, and Weipeng Chen. Metagpt: Merging large language models using model exclusive task arithmetic. *arXiv preprint arXiv:2406.11385*, 2024.

Divyansh Jhunjhunwala, Neharika Jali, Gauri Joshi, and Shiqiang Wang. Erasure coded neural network inference via fisher averaging. In *ISIT*, pages 13–18. IEEE, 2024b.

Nico Daheim, Thomas Möllenhoff, Edoardo Ponti, Iryna Gurevych, and Mohammad Emtiyaz Khan. Model merging by uncertainty-based gradient matching. In *ICLR*, 2024.

Yang He and Lingao Xiao. Structured pruning for deep convolutional neural networks: A survey. *TPAMI*, 2023.

Tejalal Choudhary, Vipul Mishra, Anurag Goswami, and Jagannathan Sarangapani. A comprehensive survey on model compression and acceleration. *Artificial Intelligence Review*, 53:5113–5155, 2020.

Pala Tej Deep, Rishabh Bhardwaj, and Soujanya Poria. Della-merging: Reducing interference in model merging through magnitude-based sampling. *arXiv preprint arXiv:2406.11617*, 2024.

Le Yu, Bowen Yu, Haiyang Yu, Fei Huang, and Yongbin Li. Language models are super mario: Absorbing abilities from homologous models as a free lunch. *ICML*, 11 2024b. URL https://arxiv.org/pdf/2311.03099.pdf.

Le Yu, Bowen Yu, Haiyang Yu, Fei Huang, and Yongbin Li. Language models are super mario: Absorbing abilities from homologous models as a free lunch. *ICML*, 2024c.

MohammadReza Davari and Eugene Belilovsky. Model breadcrumbs: Scaling multi-task model merging with sparse masks. *arXiv preprint arXiv:2312.06795*, 2023.

Ke Wang, Nikolaos Dimitriadis, Guillermo Ortiz-Jimenez, François Fleuret, and Pascal Frossard. Localizing task information for improved model merging and compression. *ICML*, 2024.

Fanshuang Kong, Richong Zhang, and Ziqiao Wang. Activated parameter locating via causal intervention for model merging. *arXiv preprint arXiv:2408.09485*, 2024.

Chenyu Huang, Peng Ye, Tao Chen, Tong He, Xiangyu Yue, and Wanli Ouyang. Emr-merging: Tuning-free high-performance model merging. *arXiv preprint arXiv:2405.17461*, 2024.

Anke Tang, Li Shen, Yong Luo, Liang Ding, Han Hu, Bo Du, and Dacheng Tao. Concrete subspace learning based interference elimination for multi-task model fusion. *arXiv preprint arXiv:2312.06173*, 2023.

Gabriel Ilharco, Marco Tulio Ribeiro, Mitchell Wortsman, Suchin Gururangan, Ludwig Schmidt, Hannaneh Hajishirzi, and Ali Farhadi. Editing models with task arithmetic. 12 2022. URL https://arxiv.org/pdf/2212.04089.pdf.

Donato Crisostomi, Marco Fumero, Daniele Baieri, Florian Bernard, and Emanuele Rodolà. Cycle-consistent multi-model merging. 05 2024. URL https://arxiv.org/pdf/2405.17897.pdf.

Pingzhi Li, Zhenyu Zhang, Prateek Yadav, Yi-Lin Sung, Yu Cheng, Mohit Bansal, and Tianlong Chen. Merge, then compress: Demystify efficient smoe with hints from its routing policy. *ICLR*, 2024c.

Mohammed Muqeeth, Haokun Liu, and Colin Raffel. Soft merging of experts with adaptive routing. *TMLR*, 2024.

Junmo Kang, Leonid Karlinsky, Hongyin Luo, Zhen Wang, Jacob Hansen, James Glass, David Cox, Rameswar Panda, Rogerio Feris, and Alan Ritter. Self-moe: Towards compositional large language models with self-specialized experts. *arXiv preprint arXiv:2406.12034*, 2024.

Lei Shen, Zhenheng Tang, Lijun Wu, Yonggang Zhang, Xiaowen Chu, Tao Qin, and Bo Han. Hot pluggable federated learning. In *International Workshop on Federated Foundation Models in Conjunction with NeurIPS 2024*, 2024. URL https://openreview.net/forum?id=FazIrAXoM6.

Anke Tang, Li Shen, Yong Luo, Shiwei Liu, Han Hu, and Bo Du. Towards efficient pareto set approximation via mixture of experts based model fusion. *arXiv preprint arXiv:2406.09770*, 2024e.

R. A. Jacobs, M. I. Jordan, S. J. Nowlan, and G. E. Hinton. Adaptive mixtures of local experts. *Neural computation,*, 3(1):79–87, 1991.

M. I. Jordan and R. A. Jacobs. Hierarchical mixtures of experts and the em algorithm. *Neural computation*, 6(2):181– 214, 1994.

Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc Le, Geoffrey Hinton, and Jeff Dean. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. 01 2017. URL https://arxiv.org/pdf/1701.06538.pdf.

Dmitry Lepikhin, HyoukJoong Lee, Yuanzhong Xu, Dehao Chen, Orhan Firat, Yanping Huang, Maxim Krikun, Noam Shazeer, and Zhifeng Chen. Gshard: Scaling giant models with conditional computation and automatic sharding. 06 2020. URL https://arxiv.org/pdf/2006.16668.pdf.

Yanqi Zhou, Tao Lei, Hanxiao Liu, Nan Du, Yanping Huang, Vincent Zhao, Andrew Dai, Zhifeng Chen, Quoc Le, and James Laudon. Mixture-of-experts with expert choice routing. 02 2022. URL https://arxiv.org/pdf/2202.09368.pdf.

Damai Dai, Chengqi Deng, Chenggang Zhao, R. X. Xu, Huazuo Gao, Deli Chen, Jiashi Li, Wangding Zeng, Xingkai Yu, Y. Wu, Zhenda Xie, Y. K. Li, Panpan Huang, Fuli Luo, Chong Ruan, Zhifang Sui, and Wenfeng Liang. Deepseekmoe: Towards ultimate expert specialization in mixture-of-experts language models. 01 2024. URL https://arxiv.org/pdf/2401.06066.pdf.

Zewen Chi, Li Dong, Shaohan Huang, Damai Dai, Shuming Ma, Barun Patra, Saksham Singhal, Payal Bajaj, Xia Song, Xian-Ling Mao, Heyan Huang, and Furu Wei. On the representation collapse of sparse mixture of experts. 04 2022. URL https://arxiv.org/pdf/2204.09179.pdf.

Jianan Chen, Qin Hu, Fangtian Zhong, Yan Zhuang, and Minghui Xu. Upcycling noise for federated unlearning. 12 2024. URL https://arxiv.org/pdf/2412.05529.pdf.

Anonymous. Drop-upcycling: Training sparse mixture of experts with partial re-initialization. In *Submitted to The Thirteenth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=gx1wHnf5Vp. under review.

Margaret Li, Suchin Gururangan, Tim Dettmers, Mike Lewis, Tim Althoff, Noah A Smith, and Luke Zettlemoyer. Branch-train-merge: Embarrassingly parallel training of expert language models. *arXiv preprint arXiv:2208.03306*, 2022.

Chengsong Huang, Qian Liu, Bill Yuchen Lin, Tianyu Pang, Chao Du, and Min Lin. Lorahub: Efficient cross-task generalization via dynamic lora composition. 07 2023b. URL https://arxiv.org/pdf/2307.13269.pdf.

Sara Babakniya, Ahmed Roushdy Elkordy, Yahya H. Ezzeldin, Qingfeng Liu, Kee-Bong Song, Mostafa El-Khamy, and Salman Avestimehr. Slora: Federated parameter efficient fine-tuning of language models. 08 2023. URL https://arxiv.org/pdf/2308.06522.pdf.

Geoffrey E Hinton, Simon Osindero, and Yee-Whye Teh. A fast learning algorithm for deep belief nets. *Neural computation*, 18(7):1527–1554, 2006.

Yoshua Bengio, Pascal Lamblin, Dan Popovici, and Hugo Larochelle. Greedy layer-wise training of deep networks. *Advances in neural information processing systems*, 19, 2006.

Naftali Tishby, Fernando C Pereira, and William Bialek. The information bottleneck method. *arXiv preprint physics/0004057*, 2000.

Rabeeh Karimi Mahabadi, Yonatan Belinkov, and James Henderson. Variational information bottleneck for effective low-resource fine-tuning. *arXiv preprint arXiv:2106.05469*, 2021.

Naftali Tishby and Noga Zaslavsky. Deep learning and the information bottleneck principle. In *2015 ieee information theory workshop (itw)*, pages 1–5. IEEE, 2015.

Yuwen Xiong, Mengye Ren, and Raquel Urtasun. Loco: Local contrastive representation learning. *Advances in neural information processing systems*, 33:11142–11153, 2020.

Aidan N Gomez, Oscar Key, Kuba Perlin, Stephen Gou, Nick Frosst, Jeff Dean, and Yarin Gal. Interlocking backpropagation: Improving depthwise model-parallelism. *The Journal of Machine Learning Research*, 23(1):7714–7741, 2022.

Hesham Mostafa, Vishwajith Ramesh, and Gert Cauwenberghs. Deep supervised learning using local errors. *Frontiers in neuroscience*, 12:608, 2018.

Eugene Belilovsky, Michael Eickenberg, and Edouard Oyallon. Greedy layerwise learning can scale to imagenet. In *International conference on machine learning*, pages 583–593. PMLR, 2019.

Eugene Belilovsky, Michael Eickenberg, and Edouard Oyallon. Decoupled greedy learning of cnns. In *International Conference on Machine Learning*, pages 736–745. PMLR, 2020.

Mandar Kulkarni and Shirish Karande. Layer-wise training of deep networks using kernel similarity. *arXiv preprint arXiv:1703.07115*, 2017.

Arild Nøkland and Lars Hiller Eidnes. Training neural networks with local error signals. In *International conference on machine learning*, pages 4839–4850. PMLR, 2019.

Shoaib Ahmed Siddiqui, David Krueger, Yann LeCun, and Stéphane Deny. Blockwise self-supervised learning at scale. *arXiv preprint arXiv:2302.01647*, 2023.

Yulin Wang, Zanlin Ni, Shiji Song, Le Yang, and Gao Huang. Revisiting locally supervised learning: an alternative to end-to-end training. In *International Conference on Learning Representations*, 2020c.

Maithra Raghu, Justin Gilmer, Jason Yosinski, and Jascha Sohl-Dickstein. Svcca: Singular vector canonical correlation analysis for deep learning dynamics and interpretability, 2017. URL https://arxiv.org/abs/1706.05806.

Chaoyang He, Shen Li, Mahdi Soltanolkotabi, and Salman Avestimehr. Pipetransformer: Automated elastic pipelining for distributed training of large-scale models. In Marina Meila and Tong Zhang, editors, *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pages 4150–4159. PMLR, 18–24 Jul 2021.

Rui Pan, Xiang Liu, Shizhe Diao, Renjie Pi, Jipeng Zhang, Chi Han, and Tong Zhang. Lisa: Layerwise importance sampling for memory-efficient large language model fine-tuning. 03 2024. URL https://arxiv.org/pdf/2403.17919.pdf.

Pengxiang Li, Lu Yin, and Shiwei Liu. Mix-ln: Unleashing the power of deeper layers by combining pre-ln and post-ln. 12 2024d. URL https://arxiv.org/pdf/2412.13795.pdf.

Balaji Lakshminarayanan, A. Pritzel, and C. Blundell. Simple and scalable predictive uncertainty estimation using deep ensembles. In *Neural Information Processing Systems*, 2016.

C. Blundell, Julien Cornebise, K. Kavukcuoglu, and D. Wierstra. Weight uncertainty in neural networks. *arXiv.org*, 2015.

Dan Hendrycks and Kevin Gimpel. A baseline for detecting misclassified and out-of-distribution examples in neural networks. *International Conference on Learning Representations*, 2016.

Chuan Guo, Geoff Pleiss, Yu Sun, and Kilian Q. Weinberger. On calibration of modern neural networks. In *International Conference on Machine Learning*, 2017.

Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*, 2014.

P Izmailov, AG Wilson, D Podoprikhin, D Vetrov, and T Garipov. Averaging weights leads to wider optima and better generalization. In *UAI*, pages 876–885, 2018.

Wesley J Maddox, Pavel Izmailov, Timur Garipov, Dmitry P Vetrov, and Andrew Gordon Wilson. A simple baseline for bayesian uncertainty in deep learning. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

A. Wilson and Pavel Izmailov. Bayesian deep learning and a probabilistic perspective of generalization. *Neural Information Processing Systems*, 2020.

Xiang Liu, Liangxi Liu, Feiyang Ye, Yunheng Shen, Xia Li, Linshan Jiang, and Jialin Li. Fedlpa: One-shot federated learning with layer-wise posterior aggregation. *Neural Information Processing Systems*, 2024a.

Liang Liu, Xi Jiang, Feng Zheng, Hong Chen, Guo-Jun Qi, Heng Huang, and Ling Shao. A bayesian federated learning framework with online laplace approximation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2021.

Maruan Al-Shedivat, Jennifer Gillenwater, E. Xing, and Afshin Rostamizadeh. Federated learning via posterior averaging: A new perspective and practical algorithms. *International Conference on Learning Representations*, 2020.

Mikhail Yurochkin, Mayank Agarwal, Soumya Ghosh, Kristjan Greenewald, Nghia Hoang, and Yasaman Khazaeni. Bayesian nonparametric federated learning of neural networks. In Kamalika Chaudhuri and Ruslan Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 7252–7261. PMLR, 09–15 Jun 2019b. URL https://proceedings.mlr.press/v97/yurochkin19a.html.

Hongyi Wang, Mikhail Yurochkin, Yuekai Sun, Dimitris Papailiopoulos, and Yasaman Khazaeni. Federated learning with matched averaging. In *International Conference on Learning Representations*, 2020d.

Deyuan Liu, Zecheng Wang, Bingning Wang, Weipeng Chen, Chunshan Li, Zhiying Tu, Dianhui Chu, Bo Li, and Dianbo Sui. Checkpoint merging via bayesian optimization in llm pretraining. *arXiv preprint arXiv:2403.19390*, 2024b.

Weitang Liu, Xiaoyun Wang, John Douglas Owens, and Yixuan Li. Energy-based out-of-distribution detection. *Neural Information Processing Systems*, 2020.

Yaniv Ovadia, Emily Fertig, Jie Jessie Ren, Zachary Nado, D. Sculley, Sebastian Nowozin, Joshua V. Dillon, Balaji Lakshminarayanan, and Jasper Snoek. Can you trust your model's uncertainty? evaluating predictive uncertainty under dataset shift. *Neural Information Processing Systems*, 2019.

Alex Kendall and Yarin Gal. What uncertainties do we need in bayesian deep learning for computer vision? In I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc., 2017.

John Duchi and Hongseok Namkoong. Learning models with uniform performance via distributionally robust optimization. *arXiv preprint arXiv:1810.08750*, 2018.

Martin Arjovsky, Léon Bottou, Ishaan Gulrajani, and David Lopez-Paz. Invariant risk minimization. *arXiv preprint arXiv:1907.02893*, 2019.

Elliot Creager, Jörn-Henrik Jacobsen, and Richard Zemel. Environment inference for invariant learning. In *ICML*, pages 2189–2200. PMLR, 2021.

Yoshua Bengio, Aaron Courville, and Pascal Vincent. Representation learning: A review and new perspectives. *IEEE TPAMI*, 35(8):1798–1828, 2013.

Francesco Locatello, Stefan Bauer, Mario Lucic, Gunnar Raetsch, Sylvain Gelly, Bernhard Schölkopf, and Olivier Bachem. Challenging common assumptions in the unsupervised learning of disentangled representations. In *ICML*, pages 4114–4124. PMLR, 2019.

Mengyue Yang, Furui Liu, Zhitang Chen, Xinwei Shen, Jianye Hao, and Jun Wang. Causalvae: disentangled representation learning via neural structural causal models. In *CVPR*, pages 9593–9602, 2021.

Peter Bühlmann. Invariance, causality and robustness. *arXiv preprint arXiv:1812.08233*, 2018.

Krikamol Muandet, David Balduzzi, and Bernhard Schölkopf. Domain generalization via invariant feature representation. In *ICML*, 2013.

Isabela Albuquerque, João Monteiro, Mohammad Darvishi, Tiago H Falk, and Ioannis Mitliagkas. Adversarial target-invariant representation learning for domain generalization. 2020.

Haoliang Li, Sinno Jialin Pan, Shiqi Wang, and Alex C Kot. Domain generalization with adversarial feature learning. In *CVPR*, pages 5400–5409, 2018.

Rui Gong, Wen Li, Yuhua Chen, and Luc Van Gool. Dlow: Domain flow for adaptation and generalization. In *CVPR*, pages 2477–2486, 2019.

Anthony Sicilia, Xingchen Zhao, and Seong Jae Hwang. Domain adversarial neural networks for domain generalization: When it works and how to improve. *arXiv preprint arXiv:2102.03924*, 2021.

Geli Fei and Bing Liu. Breaking the closed world assumption in text classification. In *NAACL*, 2016.

Stefan Larson, Anish Mahendran, Joseph J Peper, Christopher Clarke, Andrew Lee, Parker Hill, Jonathan K Kummerfeld, Kevin Leach, Michael A Laurenzano, Lingjia Tang, et al. An evaluation dataset for intent classification and out-of-scope prediction. In *EMNLP-IJCNLP*, 2019.

Amita Kamath, Robin Jia, and Percy Liang. Selective question answering under domain shift. In *ACL*, 2020.

Joo-Kyung Kim and Young-Bum Kim. Joint learning of domain classification and out-of-domain detection with dynamic class weighting for satisficing false acceptance rates. *arXiv preprint arXiv:1807.00072*, 2018.

Dan Hendrycks, Mantas Mazeika, and Thomas Dietterich. Deep anomaly detection with outlier exposure. In *ICLR*, 2019.

Kimin Lee, Honglak Lee, Kibok Lee, and Jinwoo Shin. Training confidence-calibrated classifiers for detecting out-of-distribution samples. In *ICLR*, 2018.

Zhiyuan Zeng, Hong Xu, Keqing He, Yuanmeng Yan, Sihong Liu, Zijun Liu, and Weiran Xu. Adversarial generative distance-based classifier for robust out-of-domain detection. In *ICASSP*, 2021a.

Zhiyuan Zeng, Keqing He, Yuanmeng Yan, Zijun Liu, Yanan Wu, Hong Xu, Huixing Jiang, and Weiran Xu. Modeling discriminative representations for out-of-domain detection with supervised contrastive learning. In *ACL*, 2021b.

Wenxuan Zhou, Fangyu Liu, and Muhao Chen. Contrastive out-of-distribution detection for pretrained transformers. In *EMNLP*, 2021.

Hyunsoo Cho, Choonghyun Park, Jaewook Kang, Kang Min Yoo, Taeuk Kim, and Sang-goo Lee. Enhancing out-of-distribution detection in natural language understanding via implicit layer ensemble. In *EMNLP*, 2022.

Yutao Mou, Pei Wang, Keqing He, Yanan Wu, Jingang Wang, Wei Wu, and Weiran Xu. Uninl: Aligning representation learning with scoring function for ood detection via unified neighborhood learning. In *EMNLP*, 2022.

Geoffrey E. Hinton, O. Vinyals, and J. Dean. Distilling the knowledge in a neural network. *arXiv.org*, 2015.

Shiyu Liang, Yixuan Li, and R. Srikant. Enhancing the reliability of out-of-distribution image detection in neural networks. *International Conference on Learning Representations*, 2017.

Elias Frantar and Dan Alistarh. Sparsegpt: Massive language models can be accurately pruned in one-shot. In Andreas Krause, Emma Brunskill, Kyunghyun Cho, Barbara Engelhardt, Sivan Sabato, and Jonathan Scarlett, editors, *International Conference on Machine Learning, ICML 2023, 23-29 July 2023, Honolulu, Hawaii, USA*, volume 202 of *Proceedings of Machine Learning Research*, pages 10323–10337. PMLR, 2023. URL https://proceedings.mlr.press/v202/frantar23a.html.

Hang Shao, Bei Liu, and Yanmin Qian. One-shot sensitivity-aware mixed sparsity pruning for large language models. In *ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 11296–11300, 2024.

Yuxin Zhang, Lirui Zhao, Mingbao Lin, Sun Yunyun, Yiwu Yao, Xingjia Han, Jared Tanner, Shiwei Liu, and Rongrong Ji. Dynamic sparse no training: Training-free fine-tuning for sparse LLMs. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=1ndDmZdT4g.

Pavlo Molchanov, Arun Mallya, Stephen Tyree, Iuri Frosio, and Jan Kautz. Importance estimation for neural network pruning. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019*, pages 11264–11272. Computer Vision Foundation / IEEE, 2019. doi: 10.1109/CVPR.2019.01152.

Xinyin Ma, Gongfan Fang, and Xinchao Wang. LLM-pruner: On the structural pruning of large language models. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023. URL https://openreview.net/forum?id=J8Ajf9WfXP.

Bo-Kyeong Kim, Geonmin Kim, Tae-Ho Kim, Thibault Castells, Shinkook Choi, Junho Shin, and Hyoung-Kyu Song. Shortened llama: A simple depth pruning for large language models. *ICLR Workshop on Mathematical and Empirical Understanding of Foundation Models (ME-FoMo)*, 2024.

Song Han, Jeff Pool, John Tran, and William Dally. Learning both weights and connections for efficient neural network. In C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc., 2015.

Wei Wen, Chunpeng Wu, Yandan Wang, Yiran Chen, and Hai Li. Learning structured sparsity in deep neural networks. In D. Lee, M. Sugiyama, U. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 29. Curran Associates, Inc., 2016.

Yifei He, Yuzheng Hu, Yong Lin, Tong Zhang, and Han Zhao. Localize-and-stitch: Efficient model merging via sparse task arithmetic. *Transactions on Machine Learning Research*, 2025. ISSN 2835-8856. URL https://openreview.net/forum?id=9CWU8Oi86d.

Gunho Park, Baeseong park, Minsub Kim, Sungjae Lee, Jeonghoon Kim, Beomseok Kwon, Se Jung Kwon, Byeongwook Kim, Youngjoo Lee, and Dongsoo Lee. LUT-GEMM: Quantized matrix multiplication based on LUTs for efficient inference in large-scale generative language models. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=gLARhFLE0F.

Mohammad Rastegari, Vicente Ordonez, Joseph Redmon, and Ali Farhadi. Xnor-net: Imagenet classification using binary convolutional neural networks. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, *Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part IV*, volume 9908 of *Lecture Notes in Computer Science*, pages 525–542. Springer, 2016. doi: 10.1007/978-3-319-46493-0_32. URL https://doi.org/10.1007/978-3-319-46493-0_32.

Elias Frantar, Saleh Ashkboos, Torsten Hoefler, and Dan Alistarh. OPTQ: Accurate quantization for generative pre-trained transformers. In *The Eleventh International Conference on Learning Representations*, 2023. URL https://openreview.net/forum?id=tcbBPnfwxS.

Elias Frantar and Dan Alistarh. Optimal brain compression: A framework for accurate post-training quantization and pruning. In Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho, editors, *Advances in Neural Information Processing Systems*, 2022.

Jerry Chee, Yaohui Cai, Volodymyr Kuleshov, and Christopher De Sa. QuIP: 2-bit quantization of large language models with guarantees. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023. URL https://openreview.net/forum?id=xrk9g5vcXR.

Ji Lin, Jiaming Tang, Haotian Tang, Shang Yang, Xingyu Dang, and Song Han. AWQ: activation-aware weight quantization for LLM compression and acceleration. *CoRR*, abs/2306.00978, 2023. doi: 10.48550/arXiv.2306.00978. URL https://doi.org/10.48550/arXiv.2306.00978.

Changhun Lee, Jungyu Jin, Taesu Kim, Hyungjun Kim, and Eunhyeok Park. OWQ: outlier-aware weight quantization for efficient fine-tuning and inference of large language models. In Michael J. Wooldridge, Jennifer G. Dy, and Sriraam Natarajan, editors, *Thirty-Eighth AAAI Conference on Artificial Intelligence*, pages 13355–13364. AAAI Press, 2024. doi: 10.1609/AAAI.V38I12.29237. URL https://doi.org/10.1609/aaai.v38i12.29237.

Tim Dettmers, Ruslan A. Svirschevski, Vage Egiazarian, Denis Kuznedelev, Elias Frantar, Saleh Ashkboos, Alexander Borzunov, Torsten Hoefler, and Dan Alistarh. SpQR: A sparse-quantized representation for near-lossless LLM weight compression. In *The Twelfth International Conference on Learning Representations*, 2024. URL https://openreview.net/forum?id=Q1u25ahSuy.

Sehoon Kim, Coleman Hooper, Amir Gholami, Zhen Dong, Xiuyu Li, Sheng Shen, Michael W. Mahoney, and Kurt Keutzer. Squeezellm: Dense-and-sparse quantization. *CoRR*, abs/2306.07629, 2023. doi: 10.48550/ARXIV.2306.07629. URL https://doi.org/10.48550/arXiv.2306.07629.

Yiming Zhu, Peixian Zhang, Ehsan-Ul Haq, Pan Hui, and Gareth Tyson. Can chatgpt reproduce human-generated labels? a study of social computing tasks. *arXiv preprint arXiv:2304.10145*, 2023.

Meysam Alizadeh, Maël Kubli, Zeynab Samei, Shirin Dehghani, Juan Diego Bermeo, Maria Korobeynikova, and Fabrizio Gilardi. Open-source large language models outperform crowd workers and approach chatgpt in text-annotation tasks. *arXiv preprint arXiv:2307.02179*, 101, 2023.

Petter Törnberg. Chatgpt-4 outperforms experts and crowd workers in annotating political twitter messages with zero-shot learning. *arXiv preprint arXiv:2304.06588*, 2023.

Weihao Zeng, Can Xu, Yingxiu Zhao, Jian-Guang Lou, and Weizhu Chen. Automatic instruction evolving for large language models. *arXiv preprint arXiv:2406.00770*, 2024.

Lifan Yuan, Ganqu Cui, Hanbin Wang, Ning Ding, Xingyao Wang, Jia Deng, Boji Shan, Huimin Chen, Ruobing Xie, Yankai Lin, et al. Advancing llm reasoning generalists with preference trees. *arXiv preprint arXiv:2404.02078*, 2024.

Tanay Dixit, Bhargavi Paranjape, Hannaneh Hajishirzi, and Luke Zettlemoyer. Core: A retrieve-then-edit framework for counterfactual data generation. *arXiv preprint arXiv:2210.04873*, 2022.

Lisa Dunlap, Alyssa Umino, Han Zhang, Jiezhi Yang, Joseph E Gonzalez, and Trevor Darrell. Diversify your vision datasets with automatic diffusion-based augmentation. *Advances in neural information processing systems*, 36:79024–79034, 2023.

Zeming Chen, Qiyue Gao, Antoine Bosselut, Ashish Sabharwal, and Kyle Richardson. Disco: Distilling counterfactuals with large language models. *arXiv preprint arXiv:2212.10534*, 2022.

Qingxiu Dong, Lei Li, Damai Dai, Ce Zheng, Zhiyong Wu, Baobao Chang, Xu Sun, Jingjing Xu, and Zhifang Sui. A survey on in-context learning. *arXiv preprint arXiv:2301.00234*, 2022.

Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language models with self-generated instructions. In *The 61st Annual Meeting Of The Association For Computational Linguistics*, 2023.

Or Honovich, Thomas Scialom, Omer Levy, and Timo Schick. Unnatural instructions: Tuning language models with (almost) no human labor. *arXiv preprint arXiv:2212.09689*, 2022.

Minghao Wu, Abdul Waheed, Chiyu Zhang, Muhammad Abdul-Mageed, and Alham Fikri Aji. Lamini-lm: A diverse herd of distilled models from large-scale instructions. *arXiv preprint arXiv:2304.14402*, 2023.

Xian Li, Ping Yu, Chunting Zhou, Timo Schick, Luke Zettlemoyer, Omer Levy, Jason Weston, and Mike Lewis. Self-alignment with instruction backtranslation. *arXiv preprint arXiv:2308.06259*, 2023a.

Ronen Eldan and Yuanzhi Li. Tinystories: How small can language models be and still speak coherent english? *arXiv preprint arXiv:2305.07759*, 2023.

Suriya Gunasekar, Yi Zhang, Jyoti Aneja, Caio César Teodoro Mendes, Allie Del Giorno, Sivakanth Gopi, Mojan Javaheripi, Piero Kauffmann, Gustavo de Rosa, Olli Saarikivi, et al. Textbooks are all you need. *arXiv preprint arXiv:2306.11644*, 2023.

Yuanzhi Li, Sébastien Bubeck, Ronen Eldan, Allie Del Giorno, Suriya Gunasekar, and Yin Tat Lee. Textbooks are all you need ii: phi-1.5 technical report. *arXiv preprint arXiv:2309.05463*, 2023b.

Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model, March 2023a. URL https://github.com/tatsu-lab/stanford_alpaca.

Lichang Chen, Shiyang Li, Jun Yan, Hai Wang, Kalpa Gunaratna, Vikas Yadav, Zheng Tang, Vijay Srinivasan, Tianyi Zhou, Heng Huang, et al. Alpagasus: Training a better alpaca with fewer data. *arXiv preprint arXiv:2307.08701*, 2023.

Yuxiang Wei, Zhe Wang, Jiawei Liu, Yifeng Ding, and LINGMING ZHANG. Magicoder: Empowering Code Generation with OSS-Instruct. In *Forty-first International Conference on Machine Learning*, 2024b.

Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. Wizardcoder: Empowering Code Large Language Models with Evol-Instruct. In *International Conference on Learning Representations (ICLR)*, 2024.

Aitor Lewkowycz, Anders Andreassen, David Dohan, Ethan Dyer, Henryk Michalewski, Vinay Ramasesh, Ambrose Slone, Cem Anil, Imanol Schlag, Theo Gutman-Solo, et al. Solving quantitative reasoning problems with language models. *Advances in Neural Information Processing Systems*, 35:3843–3857, 2022.

Huajian Xin, Daya Guo, Zhihong Shao, Zhizhou Ren, Qihao Zhu, Bo Liu, Chong Ruan, Wenda Li, and Xiaodan Liang. Deepseek-Prover: Advancing Theorem Proving in LLMs through Large-Scale Synthetic Data. *arXiv*, abs/2405.14333, 2024.

Haoxiong Liu, Yifan Zhang, Yifan Luo, and Andrew C Yao. Augmenting Math Word Problems via Iterative Question Composing. In *ICLR 2024 Workshop on Navigating and Addressing Data Problems for Foundation Models*, 2024c.

Chen Li, Weiqi Wang, Jingcheng Hu, Yixuan Wei, Nanning Zheng, Han Hu, Zheng Zhang, and Houwen Peng. Common 7b language models already possess strong math capabilities. *arXiv preprint arXiv:2403.04706*, 2024e.

Xiang Yue, Xingwei Qu, Ge Zhang, Yao Fu, Wenhao Huang, Huan Sun, Yu Su, and Wenhu Chen. Mammoth: Building math generalist models through hybrid instruction tuning. *arXiv preprint arXiv:2309.05653*, 2023b.

Yichao Fu, Peter Bailis, Ion Stoica, and Hao Zhang. Break the sequential dependency of llm inference using lookahead decoding. In *Forty-first International Conference on Machine Learning*.

Ingo Steinwart. How to compare different loss functions and their risks. *Constructive Approximation*, 26:225–287, 2007. URL https://api.semanticscholar.org/CorpusID:16660598.

Bernardo Ávila Pires and Csaba Szepesvári. Multiclass classification calibration functions. *arXiv preprint arXiv:1609.06385*, 2016.

Kleijn and Van der Vaart. The bernstein-von-mises theorem under misspecification. *Electronic Journal of Statistics*, 6:354–381, 2012. URL https://api.semanticscholar.org/CorpusID:85548207.

Yuze Zhao, Jintao Huang, Jinghan Hu, Xingjun Wang, Yunlin Mao, Daoze Zhang, Zeyinzi Jiang, Zhikai Wu, Baole Ai, Ang Wang, Wenmeng Zhou, and Yingda Chen. Swift:a scalable lightweight infrastructure for fine-tuning, 2024. URL https://arxiv.org/abs/2408.05517.

Xisen Jin, Xiang Ren, Daniel Preotiuc-Pietro, and Pengxiang Cheng. Dataless knowledge fusion by merging weights of language models. *ICLR*, 12 2023. URL https://arxiv.org/pdf/2212.09849.pdf.

Sainbayar Sukhbaatar, Olga Golovneva, Vasu Sharma, Hu Xu, Xi Victoria Lin, Baptiste Rozière, Jacob Kahn, Daniel Li, Wen-tau Yih, Jason Weston, et al. Branch-train-mix: Mixing expert llms into a mixture-of-experts llm. *arXiv preprint arXiv:2403.07816*, 2024c.

Arindam Mitra, Hamed Khanpour, Corby Rosset, and Ahmed Awadallah. Orca-math: Unlocking the potential of slms in grade school math, 2024. URL https://arxiv.org/abs/2402.14830.

Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. https://github.com/tatsu-lab/stanford_alpaca, 2023b.

Antoine Bordes, Sumit Chopra, and Jason Weston. Question answering with subgraph embeddings, 2014. URL https://arxiv.org/abs/1406.3676.

Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text, 2016. URL https://arxiv.org/abs/1606.05250.

Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, and Charles Sutton. Program synthesis with large language models, 2021. URL https://arxiv.org/abs/2108.07732.

Tristan Coignion, Clément Quinton, and Romain Rouvoy. A performance study of llm-generated code on leetcode. In *Proceedings of the 28th International Conference on Evaluation and Assessment in Software Engineering*, EASE 2024, page 79–89. ACM, June 2024. doi: 10.1145/3661167.3661221. URL http://dx.doi.org/10.1145/3661167.3661221.

Pengcheng Yin, Bowen Deng, Edgar Chen, Bogdan Vasilescu, and Graham Neubig. Learning to mine aligned code and natural language pairs from stack overflow. In *International Conference on Mining Software Repositories*, MSR, pages 476–486. ACM, 2018. doi: https://doi.org/10.1145/3196398.3196408.

APPENDIX

A THE USE OF LARGE LANGUAGE MODELS

We used LLMs solely for grammar and wording improvements. It did not generate ideas, analyses, or results. No additional or undisclosed LLM use occurred.

B BROADER IMPACT

Societal Impacts. Our approach demonstrates significant effectiveness by enabling the deployment of merging 7B x 4 LLMs with only 24GB VRAM. Compared to ensemble learning with these models, our method not only maintains better accuracy but also requires significantly less computational resources and demonstrates superior performance. This breakthrough in resource efficiency makes advanced language models more accessible and cost-effective.

Potential Applications. The technology may have significant potential across specialized vertical domains. Considering that many vertical domains, personalized LLM agents (Li et al., 2024b), LLM applications like roleplay chatting (Chan et al., 2024; Yu et al., 2024a) and professional domain-specific writing (Gómez-Rodríguez and Williams, 2023), an LLM service provider may need to simultaneously deploy different finetuned LLMs. Our technology enables efficient and effective serving multiple popular LLM applications, and merging knowledge from different LLMs together.

C MORE RELATED WORKS

We introduce more related works about model merging and routing in this section. Current common methods include: (1) **Averaging based merging.** This direction combines multiple models into a single model while preserving their capabilities with minimal or no additional training; (2) **Routing based merging.** It considers to route inputs to specialized expert modules like mixture-of-experts (MoE) approaches but completely different.

Table 11 provides an overview of comparing different model merging methods and our framework. Given n_τ different finetuned models, averaging based methods do not completely address the parameter conflicts, thus having higher parameter conficts than routing based merging. The weighted averaging requires calibration data to compute the importance metrics. The token-level routing requires routing for each layer, thus having totally $n_{\mathcal{L}}$ routers. Our framework Mediator exploits layer-wise characteristics to both reduce parameter conflict and improve common knowledge fusion. And Mediator utilizes compression to further reduce the memory costs. To the best of our knowledge, the most of previous model merging works focus on experiments on traditional CV and NLP tasks (Matena and Raffel, 2022), while Mediator conducts experiments on modern LLMs and real-world experiments.

Table 12 provides the system performance comparison. Because token-level routing like MoE requires to route each token towards different (possibly) experts, its inference cost is significantly large as more than $T \times n_{\mathcal{L}}$ times than task-level routing, where T is the sequence length. Besides, the token-level routing requires more than $n_{\mathcal{L}}$ times routers in memory costs. With the layer-wise adaptive averaging and Routing, Mediator significantly reduce the memory costs of from $M_\theta \times n_\tau$ to $M_\theta \times (c_{\text{avg}} + c_{\text{route}} \times n_\tau \times c)$ [1]. The experimental memory reduction and the system performance comparisons are shown in the Section 5.1. We also provide system optimization to accelerate the inference during the deployment of Mediator in Section 4.4 and Appendix H. And the hyper-parameters c_{avg} and c_{route} are adaptively decided by the parameter conflict estimation.

Besideds, we also review some highly related works include following directions that are closely related to our framework. Insights from these directions have provided valuable guidance for our framework.

1. **Layer-wise training dynamics and optimization.** This direction discusses the layer-wise training dynamics to help shed some light on the paramter conflicts and the layer-wise adaptivity.

[1] Normally, each transformer layer occupies the same memory.

Table 11: Demystifying different merging methods. The n_τ represents the number of finetuning tasks, $n_\mathcal{L}$ the number of layers in the model.

Method Type	Parameter Conlict Level	Merging Common Knowledge	Require Calibration Data	Routing Type	Considering Layer-wise Characteristics	Considering Compression	Considering OOD Samples	Experimental Scenario
Basic Averaging	High	✓	✗	NA	✗	✗	✗	Traditional CV, NLP
Weighted Averaging	Middle	✓	✓	NA	✗	✗	✗	Traditional CV, NLP
Subspace Averaging	Middle	✓	✗	NA	✗	✗	✗	Traditional CV, NLP
Token-Level Routing	**Low**	✗	✗	Token-level	✗	✗	✗	Traditional CV, NLP
Task-Level Routing	**Low**	✗	✗	Task-level	✗	✗	✗	Traditional CV, NLP
Mediator	**Low**	✓	✗	Task-level	✓	✓	✓	Generative LLMs

Table 12: Demystifying different merging methods in system performance costs. Considering the memory costs of the base model and one router are M_θ and M_h, each layer occupies the same memory M_l, compression ratio c, the ratio of selected layers for averaging is c_{avg}, for routing is c_{route}, FP_θ and BP_θ are the forward time and backward time of the model. FP_h and BP_h are the forward time and backward time of the router.

Method Type	Requiring # of routers	Costs of Trainig Routers	Memory Costs After Merging	Inference Cost
Basic Averaging	NA	NA	M_θ	FP_θ
Weighted Averaging	NA	NA	M_θ	FP_θ
Subspace Averaging	NA	NA	M_θ	FP_θ
Token-Level Routing	$n_\mathcal{L} \times n_\tau$	High	$M_\theta \times n_\tau + M_h \times n_\mathcal{L}$	$FP_\theta + FP_h \times T \times n_\mathcal{L} \times n_\tau$
Task-Level Routing	n_τ	Middle	$M_\theta \times n_\tau + M_h$	$FP_\theta + FP_h \times n_\tau$
Mediator	n_τ	Low	$M_\theta \times (c_{\text{avg}} + c_{\text{route}} \times n_\tau \times c) + M_h$	$FP_\theta + FP_h \times n_\tau$

2. **Bayesian deep learning.** This direction reviews some works of the Bayesian deep learning, discussing the uncertainty and Bayesian model averaging.
3. **OOD Detection & Generalization.** This direction reviews some works of the OOD Detection and Generalization, shedding light on deployment of the model merging on the out-of-distribution data.
4. **Model compression.** This direction shortly review some works about the model compression, in which many methods can be directly applied into our framework to further reduce the memory costs. Note that in our paper we propose a general framework instead of a new model compression method. Different model compression methods can be combined into our framework.
5. **Data Synthesis.** This direction reviews some works about how to generate new synthetic data to improve the model merging performance. In our framework, we exploit the CoT to generate new synthetic data to improve the finetuning performance on downstream tasks, which is a real-world downstream task instead of traditional model fine-tuning using the in-domain training and testing data.

C.1 Averaging-based Model Merging

Model merging, also known as model fusion, combines the parameters of multiple separate models with different capabilities to create a universal model. In this paper, we temporarily focus on models that have the same architecture but different parameters that are finetuned on different downstream tasks.

Basic Averaging. The traditional approach to merge different trained or finetuned models is to evenly average the parameters of different models (Utans, 1996; Shoemake, 1985). This process does not require access to the original training data and allows for enhanced performance without the need for expensive computation. However, the performance of these simply weight averaging is generally unsatisfactory.

Some related directions of model averaging also include Federated learning (FL) (McMahan et al., 2017; Tang et al., 2020). In FL, the model averaging is performed on the server side to reduce the communication costs after the local training. Many methods have been proposed to stable and smooth the model averaging process (Wang et al., 2020a; Jhunjhunwala et al., 2024a; Yurochkin et al., 2019a; Singh and Jaggi, 2020; Wang et al., 2020b; Tang et al., 2024c; 2022) to enhance the averaging performance. Different from the multi-rounds FL, the model merging is performed in a single round, which is more similar to the one-shot FL (Guha et al., 2019; Tang et al., 2024d).

Weighted Averaging. Rethinking the cause of the poor performance of the basic averaging method, many works propose to use the weighted averaging method to improve the merging performance.

Intuitively, different model parameters have different importance on downstream tasks. Such a heterogeneity of the parameter importance motivates other research directions including model sparsification (Sun et al., 2024; Dong et al.; 2024; Tang et al., 2020), continual learning (Robins, 1995; Kirkpatrick et al., 2017; Zhu et al., 2024; Marczak et al., 2024) and FL (Jhunjhunwala et al., 2024a; Yurochkin et al., 2019a; Singh and Jaggi, 2020). Thus, to avoid the important parameters being overwhelmed by the unimportant parameters, during averaging, we can assign large weights to those important parameters. To this end, the importance measurement is crucial. Many works propose to use *fisrt or second orders of Taylor expansion* to measure the importance of the parameters (Lee et al., 2019; Jhunjhunwala et al., 2023; Qu et al., 2022). Some works employ *local linearization and task vectors* to measure the importance of the parameters (Zhou et al., 2024). The *fisher information* also a kind of importance measurement (Matena and Raffel, 2022; Jhunjhunwala et al., 2024b; Thennal et al., 2024; Jhunjhunwala et al., 2024a; Thennal et al., 2024; Daheim et al., 2024).

While these importance measurement methods can improve the merging performance than the basic averaging method, they still face some typical challenges.

1. *Require Calibration Dataset.* The importance measurement is based on the calibration dataset. In the LLM era, the pretrained dataset is significantly large, it is difficult to collect the complete pretrained dataset and measure the importance of the parameters on it.
2. *Computation Costs.* Because that the importance measurement is based on the calibration dataset, the computation costs is almost similar to conduct the complete forward process of the different models. In traditional small models, such a computaton cost is acceptable. However, in the LLM era, the model size is significantly large, such a computation cost is unbearable.
3. *Unaddressed Parameter Conflicts.* While methods in these importance based weighted averaging methods can improve the merging performance, they still face the parameter conflicts between different models. Because of the highly non-convex structure of the LLMs, it is difficult to find a optimal merging method based on averaging the parameters of different models.

Subspace Averaging. Considering that the neural networks are over-parameterized, removing most of the parameters from the model barely affects its accuracy (He and Xiao, 2023; Choudhary et al., 2020). Besides, during the training or finetuning, some parameters might be optimized towards a random direction which has small impact on the model performance (Yadav et al., 2023b). Thus, works propose to firstly process different models in a subspace manner. Then, the parameter conflicts can be mitigated by the subspace averaging methods (Deep et al., 2024; He et al., 2024b).

DARE (Drop and Rescale) (Yu et al., 2024b;c) introduces a parameter pruning and rescaling strategy that significantly reduces the number of parameters in SFT models while preserving their performance, thereby serving as an effective preprocessing step for model merging. Similarly, Model Breadcrumbs (Davari and Belilovsky, 2023) enhances sparsification by eliminating both low-magnitude parameters and outlier parameters with exceptionally high weights, thereby reducing noise and improving the generalization of hyperparameters during model merging.

TALL-masks (Wang et al., 2024) creates task-specific mask matrices based on predefined thresholds tailored to individual models, while Model Tailor (Zhu et al., 2024) further refines this approach by masking parameters according to their sensitivity to loss changes and deviations from pre-trained values. APL (Kong et al., 2024) advances parameter importance estimation through causal interventions, providing a robust metric for selective parameter retention.

EMR-Merging (Huang et al., 2024) departs from traditional model merging by maintaining a shared model across multiple tasks alongside sparse task-specific models, where each shared parameter is determined by the maximum value among corresponding parameters from all models. Concrete (Tang et al., 2023) further innovates by framing mask construction and model merging as a learnable bi-level optimization problem, with the outer level optimizing the mask matrix and the inner level performing model merging and optimization utilizing unlabeled test samples.

Task Arithmetic (Ilharco et al., 2022) exploits parameter-space arithmetic operations, treating model parameters as vectors and employing addition and subtraction to synthesize new model capabilities. However, many of these approaches, including DARE and Task Arithmetic, heavily rely on hyper-parameters for parameter fusion, which can negatively impact the performance of model merging. Additionally, as highlighted in studies such as TIES (Yadav et al., 2023a) and Crisostomi (Crisostomi

et al., 2024), model merging often encounters parameter conflicts that degrade performance when integrating multiple models.

Addressing these challenges, TIES (Trim, Elect, and Disjoint Merge) (Yadav et al., 2023a) implements a comprehensive approach by trimming parameters based on magnitude, selecting relevant weights, and disjointly merging weights using outcomes from task arithmetic operations. This methodology mitigates parameter conflicts and enhances the overall performance of the merged model, positioning TIES as a robust solution in the domain of model merging.

C.2 Routing-based Model Merging.

Average-based methods primarily aim to enhance the averaging process of client models. However, the inherently non-linear architecture of deep neural networks complicates the derivation of a globally comparable model through simple averaging.

The basic, weighted-based, and subspace-based merging methods are *static* merging techniques. This implies that the merged model remains consistent across all samples or tasks. Given the variability among input samples and tasks, the model's performance can fluctuate when processing diverse inputs. To this end, certain studies advocate for the *dynamic* merging of models (or subsets of layers) tailored to specific samples or tasks (Li et al., 2024c; Muqeeth et al., 2024; Tang et al., 2024b; Lu et al., 2024a; Kang et al., 2024; Tang et al., 2024d; Shen et al., 2024) during the inference phase.

For each input instance, SMEAR (Muqeeth et al., 2024) initially computes a weighted average of the parameters from each expert by leveraging the distribution of router inputs to the expert modules. This approach maintains a computational cost comparable to that of a single expert. Similarly, Twin-Merging (Lu et al., 2024a) adaptively integrates task-shared and task-specific knowledge based on routing mechanisms during inference. In the same vein, Weight-Ensembling MoE (Tang et al., 2024b) introduces a dynamic merging Transformer architecture. This method identifies that the parameters of the linear layer in the fine-tuned model undergo more significant changes compared to the nonlinear layers, which adversely affects merging performance. Consequently, Weight-Ensembling MoE employs a standard weighted average for all modules except the linear layer, which is dynamically weighted and merged based on the routing network (utilizing sample features as input and merging coefficients as output) during inference. PWE MoE (Tang et al., 2024e) extends Weight-Ensembling MoE to a multi-objective optimization framework, incorporating the preference vector as an input for routing.

AdaMerging (Yang et al., 2024b) adaptively learns merging coefficients in a task-aware or layer-wise manner, offering an automated and unsupervised approach to task arithmetic. While this method significantly enhances performance, it incurs high computational costs. *PCB Merge* (Du et al., 2024) introduces a parameter importance detection mechanism that accounts for parameter conflicts and employs heuristic algorithms to explore model fusion parameters, thereby achieving superior results. *TwinMerge* (Lu et al., 2024b) utilizes LoRA or SVD techniques in conjunction with supervised training for parameter fusion, resulting in improved performance.

Nevertheless, these methods encounter inherent limitations. Both AdaMerging and PCB Merge utilize static fusion approaches, which can lead to performance degradation when the actual sample distribution varies during runtime. Meanwhile, TwinMerge performs parameter fusion at the task level; however, the application of LoRA and SVD matrix decomposition markedly reduces model accuracy and introduces substantial online computational overhead. Besides, the code implementation of the TwinMerge actually exploits the LoRA finetuning to replace SVD decomposition. Using SVD decomposition in compressing model parameters leads to disturbed LLMs and significantly degraded model performance.

Mixture-of-Experts (MoE) (Jacobs et al., 1991; Jordan and Jacobs, 1994) is a foundational model concatenation and routing strategy comprising multiple expert networks and a router that dynamically selects relevant experts based on the input. This methodology has been extensively adopted in large language models, offering significant reductions in computational costs while preserving model performance. Recent studies, particularly sparse gated MoE (Shazeer et al., 2017) in transformer-based large language models (Lepikhin et al., 2020), have concentrated on maintaining load balancing among experts during training (Zhou et al., 2022; Jiang et al., 2024b), reducing training costs (Dai

et al., 2024), and mitigating performance degradation due to uncoordinated expert training (Chi et al., 2022).

Upcycling Methods have been developed to alleviate the high computational demands of training MoE models from scratch by initializing experts from existing dense models. These methods encompass copying existing dense models as experts (He et al., 2024a; Wei et al., 2024a), introducing noise to the MLP layers of dense models to create experts (Noise upcycling) (Chen et al., 2024), and drop upcycling (Anonymous, 2024), which combines parameter dropout with expert copying during training to enhance model robustness, reduce overfitting, and improve performance.

Branch-Train-Merge (BTM) (Li et al., 2022) and *Branch-Train-Mix (BTX)* (Sukhbaatar et al., 2024b) are methodologies aimed at further optimizing model training efficiency. These approaches employ different SFT-trained dense models derived from the same base LLM as MoE experts. The experts are interconnected via a router without necessitating additional training, while non-expert components are amalgamated through model merging techniques such as parameter averaging. Only the router undergoes training, thereby substantially reducing overall training costs. Although these methods achieve lower training expenses and marginally outperform traditional model merging approaches, our research indicates that token-level routing can partially degrade model performance. Additionally, maintaining all experts in GPU memory leads to significant parameter redundancy and escalates inference costs, which motivates our ongoing research endeavors.

However, the token-level routing methods are not suitable for model merging. We have provided detailed discussions in the main text Section 4.1 and Appendix D. The token-level routing methods after merging normally require re-training based on all training datasets to obtian a better token-level router, which significantly increases the computational costs, which is discussed in the main text Section 4.4 and Appendix G.

LoRA based Routing. Routing samples to different LoRA experts is a promising direction to dynamically route the input to different LoRA experts. This direction includes the *LoraHub* (Huang et al., 2023b) and *sLora* (Babakniya et al., 2023), which explore serving multiple LoRA adapters through techniques like unified paging and tensor parallelism. However, these methods do not consider the better dynamic expert merging method to further improve the model merging performance. In real-world applications, the input distribution is dynamic and the input samples are diverse, which motivates our ongoing research endeavors. Besides, their reliance on LoRA matrix decomposition significantly degrades model serving performance. Additionally, they do not consider model compression opportunities or the potential to average similar layers between models, which could further optimize storage and computation costs while maintaining model capabilities.

C.3 Layer-wise Training Dynamics and Optimization

Layer-wise training was initially explored to achieve effective initialization (Hinton et al., 2006; Bengio et al., 2006). From the perspective of the information propagation (Tishby et al., 2000; Mahabadi et al., 2021; Tishby and Zaslavsky, 2015), the fundamental issue with layer-wise training is that each layer is unable to access information from the layers that precede it. Some works (Xiong et al., 2020) proposed a method that permits backpropagation within a local block, allowing information from subsequent layers to progressively influence earlier layers by training them sequentially. Furthermore, (Gomez et al., 2022) builds upon the concept of "overlapping local updates", introducing a learning strategy that harmonizes the high parallelism characteristic of layer-wise training with the superior predictive accuracy associated with end-to-end (E2E) learning. Besides, classification-based loss functions are employed at each layer (Mostafa et al., 2018; Belilovsky et al., 2019; 2020), whereas similarity-based loss functions are utilized in other scenarios (Kulkarni and Karande, 2017; Nøkland and Eidnes, 2019; Siddiqui et al., 2023). Additionally, (Wang et al., 2020c) incorporates a reconstruction error term into the local objective function, drawing from an information-theoretic perspective.

Some works find that different layers have different convergence rates during the whole training process (Raghu et al., 2017). This property can be used to freeze front layers and only train the later layers, thus reducing the training costs. The PipeTransformer (He et al., 2021) utlizes this property to reduce the training costs of transformer models.

LISA (Pan et al., 2024) discovered that the weight norm distributions across layers in LoRA and full parameter fine-tuning are skewed, indicating varying layer importance in large-scale LLM training. Based on this observation, LISA applies importance sampling to different layers in LLMs, randomly freezing most intermediate layers during optimization. It periodically samples Transformer layers from the model, randomly selecting r layers for fine-tuning while keeping others frozen. The initial word/position embeddings (wte/wpe) and final language modeling head (lm_head) are consistently fine-tuned. This aligns with our observations regarding layer merging.

Layer-wise model training and merging approaches have also provided inspiration for our research direction. (Li et al., 2024d) discovered that in the field of large language models, the effectiveness of deeper layers gradually diminishes, with many studies showing that deeper layers can be pruned without significantly affecting model performance - a phenomenon often viewed as an opportunity for model compression. To address this, they proposed a novel normalization technique called Mix-LN, which combines pre-LN and post-LN within the same model. Specifically, Mix-LN applies post-LN to earlier layers and pre-LN to deeper layers, ensuring more uniform gradients across all layers.

Different from these methods that focus on improving the layer-wise training and optimization, we focus on improving merging LLMs inspired from the layer-wise training dynamics.

C.4 Bayesian Deep Learning

Bayesian Neural Networks. Considering the uncertainty of the model parameters, sampling bias in the training datasets, predictive uncertainty to domain shift (also referred to as out-of-distribution examples) (Lakshminarayanan et al., 2016; Blundell et al., 2015; Hendrycks and Gimpel, 2016), Bayesian Neural Networks (BNNs) view the model parameters as a random variable. Then, optimizing the model parameters is equivalent to optimizing the posterior distribution of the model parameters conditioned on the training datasets) (Blundell et al., 2015). However, the training costs of BNNs are significantly higher than the non-Bayesian neural networks (Lakshminarayanan et al., 2016). A proper scoring creterion for training non-Bayesian NN (Lakshminarayanan et al., 2016), model ensemble (Guo et al., 2017) and adversarial training (Goodfellow et al., 2014) are found to be a good way to improve the robustness of neural networks as an alternative to BNNs.

Bayesian Model Averaging (BMA). Except for the static importance measurement mentioned in previous section, Bayesian model averaging is another promising direction to improve the model merging performance based on the Bayesian inference. The deep model ensemble and Stochastic Weight Averaging (Izmailov et al., 2018; Maddox et al., 2019) are actually a compelling approach to BMA (Wilson and Izmailov, 2020). The Bayesian marginalization can particularly improve the accuracy and calibration of modern deep neural networks (Wilson and Izmailov, 2020).

However, the previous works in BNN and BMA consider the model parameters trained with the same datasets. How to merge models trained with different datasets is a new open problem which also emerges in FL (Tang et al., 2024d; Liu et al., 2024a; 2021; Al-Shedivat et al., 2020; Yurochkin et al., 2019b; Wang et al., 2020d) and merging LLM models in pretraining (Liu et al., 2024b).

C.5 OOD Detection and Generalization

The input test samples in the real-world deployment are usually diverse and the distribution of the input test samples is dynamic. Normally, these samples are not shown in the training datasets, and their distribution might be different from the training distribution, which is call out-of-distribution (OOD) data. It is important to detect the OOD data (**OOD Detection**) (Liu et al., 2020; Hendrycks and Gimpel, 2016) and improve the model generalization on the OOD data (**OOD Generalization**) (Ovadia et al., 2019; Kendall and Gal, 2017; Lakshminarayanan et al., 2016). When confronted with distributional shifts, models optimized purely based on average training errors lead to poor performance (Duchi and Namkoong, 2018; Arjovsky et al., 2019; Creager et al., 2021).

OOD Generalization. Some methods seek to find better invariant representations in neural networks (Bengio et al., 2013; Locatello et al., 2019), which means the representations are invariant to the distribution shift. From the causal perspective, the invariant representations are the representations that are invariant to the causal factors (Yang et al., 2021). Causal learning methods aim to learn the underlying causal structure of the data and to predict the outcome variable based on the identified causal variables. By correctly identifying the cause-effect relationships, these methods are expected

to perform well even when the data distribution changes, as the underlying causal structure is often assumed to remain invariant across different environments or domains (Bühlmann, 2018). The invariant learning is to learn an invariant representation or model across environments leveraging contextual information such as domain labels (Muandet et al., 2013; Arjovsky et al., 2019; Albuquerque et al., 2020), where methods can be mainly divided into invariant risk minimization (Arjovsky et al., 2019) and domain-irrelevant representation learning (Li et al., 2018; Gong et al., 2019; Sicilia et al., 2021).

OOD Detection. Some methods assume access to extensive OOD data alongside in-distribution (ID) data during training, formulating OOD detection as a discriminative classification task by allocating a special label for OOD samples (Fei and Liu, 2016; Larson et al., 2019; Kamath et al., 2020; Kim and Kim, 2018). Another approach optimizes outlier exposure regularization terms on OOD samples to refine the representations and OOD scores, such as the generalized outlier exposure (OE) loss introduced by (Hendrycks et al., 2019), which pushes the predicted distribution of OOD samples toward uniformity (Hendrycks et al., 2019; Lee et al., 2018), and entropy regularization objectives employed by (Zeng et al., 2021a) to enforce high entropy predictions for OOD samples. Additionally, leveraging contrastive learning techniques (Zeng et al., 2021b; Zhou et al., 2021; Cho et al., 2022; Mou et al., 2022) to increase inter-class discrepancies and enhance discriminative features for ID and OOD samples has been demonstrated to improve OOD detection performance.

Previous works have found that the softmax outputs from models can be used as a measurement of the uncertainty of model predictions (Guo et al., 2017; Hinton et al., 2015). And the early work in model distillation utilizes the softmax outputs as a kind of soft labels to guide the model training (Hinton et al., 2015). Some works propose to scale the logits with the temperature scaling (Liang et al., 2017), thus the ID and OOD samples are more distinguishable based on the scaled softmax scores.

Our work proposes dynamically merging task arithmetics from the Bayesian perspective to improve the OOD generalization. Inspired by the temperature scaling and the uncertainty measurement, we propose to scale the logits with the temperature scaling and to use the softmax outputs as an adjustment factor to estimating the likelihood of the task arithmetics conditioned on the input.

C.6 Model Compression

Pruning. *Unstructured pruning* (Frantar and Alistarh, 2023; Sun et al., 2024; Shao et al., 2024; Zhang et al., 2024; Dong et al.; Tang et al., 2020) effectively maintains LLM performance without requiring retraining, but leads to irregular structures that necessitate specialized optimizations for inference. SparseGPT (Frantar and Alistarh, 2023) offers a novel one-shot pruning strategy by framing it as a sparse regression problem, achieving over 50% sparsity with minimal perplexity increase. Wanda (Sun et al., 2024) reduces weight update costs by pruning low-magnitude weights scaled by input activations, while SAMSP (Shao et al., 2024) adjusts sparsity based on weight sensitivity using the Hessian matrix. DSnoT (Zhang et al., 2024) iteratively prunes and grows weights to minimize reconstruction error in sparse models.

Structured pruning is hardware-agnostic, facilitating accelerated inference but may degrade performance due to the removal of critical components, often necessitating fine-tuning. Loss-based Pruning (Molchanov et al., 2019) measures the impact of unit removal on loss. LLM-Pruner (Ma et al., 2023) uses gradient information to identify dependent structures for optimal pruning. In contrast, Shortened LLaMA (Kim et al., 2024) focuses on depth pruning of Transformer blocks based on loss derivatives, employing LoRA to quickly recover performance post-pruning. Magnitude-based Pruning (Han et al., 2015) assesses pruning unit importance based on their magnitudes, pruning those below a set threshold. Regularization-based Pruning (Wen et al., 2016) incorporates regularization terms to induce sparsity.

Different from these pruning methods which focus on the weight pruning, our method is inspired from the sparse property of the task arithmetics to reduce the expert memory occupation (He et al., 2025; Tang et al., 2020). We sparsity the task arithmetics based on denoising and the magnitudes in our work. Note that our framework is a general framework, any other sparsity method can be combined with our framework.

Quantization. Weight-only quantization is the most conventional and widespread method. For example, LUT-GEMM (Park et al., 2024) uses binary-coding quantization (BCQ) (Rastegari et al., 2016) format, which factorizes the parameters of LLMs into binary parameters and a set of scaling

factors, to accelerate quantized matrix multiplications in weight-only quantization. GPTQ (Frantar et al., 2023) proposes a layer-wise quantization method based on Optimal Brain Quantization (OBQ) (Frantar and Alistarh, 2022), which updates weights with inverse Hessian information, and quantizes LLMs into 3/4-bit. QuIP (Chee et al., 2023) optimally adjusts weights by utilizing the LDL decomposition of the Hessian matrix derived from vectors drawn uniformly at random from a calibration set, and multiplies weight and Hessian matrices with a Kronecker product of random orthogonal matrices to ensure incoherence between weight and Hessian matrices. Combining these two steps, QuIP successfully quantizes LLMs into 2-bits with minimal performance loss.

To further minimize quantization errors in the weight-only quantization of LLMs, lots of works identify sensitive weights, which have an important effect on LLMs' quantization performance, and store these sensitive weights in high precision. For example, AWQ (Lin et al., 2023) stores the top 1% of weights that have the most significant impact on LLM performance in high-precision, and integrates a per-channel scaling method to identify optimal scaling factors. Here, "channel" denotes individual dimensions or feature maps within the model. Similar with AWQ, OWQ (Lee et al., 2024) store weights sensitive to activation outliers in high-precision, and quantizes other non-sensitive weights. Different from OWQ, SpQR (Dettmers et al., 2024) employs the L2 error between the original and quantized predictions as a weight sensitivity metric. Furthermore, SqueezeLLM (Kim et al., 2023) introduces a weights clusters algorithm based on sensitivity, using k-means centroids as quantized weight values, to identify sensitive weights.

C.7 Data Synthesis

Data Labeling. The data labeling process utilizes the advanced language comprehension capabilities of large language models (LLMs) to annotate extensive unlabeled datasets, proving particularly beneficial in areas like cross-lingual processing and multimodal learning (Zhu et al., 2023; Gilardi et al., 2023; Alizadeh et al., 2023). Automating this process enhances data preparation efficiency. Recent studies have investigated the zero-shot potential of models like GPT-4 for annotating political discourse on platforms like Twitter (Törnberg, 2023). Some works consider constructing a preference tree (Zeng et al., 2024; Yuan et al., 2024) from LLM responses to refine incorrect responses based on feedback from models like GPT-4, creating more diverse and robust preference data.

Data Reformation. Data reformation aims to transform existing datasets into diverse variations to improve data augmentation (Dixit et al., 2022; Dunlap et al., 2023). This enriches the training set with varied examples, enhancing model robustness and generalization. Novel approaches leveraging LLMs have emerged, such as Disco by Chen et al. (Chen et al., 2022), which generates large-scale, high-quality counterfactual datasets. A prominent method in this area is in-context learning (Dong et al., 2022), where examples embedded in prompts guide LLMs to generate responses that reflect the provided patterns. Early works, such as Self-Instruct (Wang et al., 2023) and Unnatural Instructions (Honovich et al., 2022), utilized task pools with hand-crafted seed examples. In contrast, LaMini-LM (Wu et al., 2023) built on this foundation by leveraging extensive data from Wikipedia to generate a wider range of instructions. Auto Evol-Instruct (Zeng et al., 2024), originally designed to evolve instructions, automates the optimization of evolution rules through an Optimizer LLM that iteratively refines these rules based on evolving feedback data. Furthermore, Instruction Backtranslation (Li et al., 2023a) enhances instruction-following capabilities by creating instruction-response pairs from unannotated data, thus minimizing the need for manual annotation. This ongoing refinement of data reformation is essential for enhancing performance across various tasks.

Generation from LLMs. Model generation utilizes powerful models—such as ChatGPT, StableVicuna, and GPT-4—to create datasets that enhance the performance of weaker models. Techniques include generating concise narratives through templates (Eldan and Li, 2023) and assessing dataset quality with LLMs. Research by Phi-1 and its subsequent studies (Gunasekar et al., 2023; Li et al., 2023b) indicates that even a small volume of high-quality data can effectively train models via generated textbooks and exercises using GPT-3.5. Additionally, performance has been improved by developing instructional datasets and fine-tuning models to enhance dataset quality (Honovich et al., 2022; Taori et al., 2023a; Chen et al., 2023). Domain model generation concentrates on the use of specialized models to produce domain-specific data. For example, domain generation can provide instructional materials for specific programming tasks in coding (Wei et al., 2024b; Luo et al., 2024).

In mathematics, initiatives like Minerva (Lewkowycz et al., 2022) and DeepSeekMath (Xin et al., 2024) focus on generating accurate solutions.

Synthetic Multi-step Reasoning. To enhance reasoning in LLMs, additional reasoning steps are incorporated into data synthesis. The MMIQC framework (Liu et al., 2024c) iteratively creates synthetic question-response pairs by expanding problems and integrating reasoning steps while preserving logical structure. A complementary strategy involves generating chain-of-thought (CoT) answers based on questions (Li et al., 2024e). Building on question-CoT pairs through Self-Instruct, MathInstruct (Yue et al., 2023b) introduces the Program-of-Thought (PoT) rationale to streamline mathematical problem-solving.

In this work, we utilize the stronger LLM to generate CoT based domain training data to enhance the reasoning performance of the downstream tasks. As far as we know, *this work is the first to explore whether the model merging influences the CoT based reasoning performance.*

D THEORETICAL UNDERSTANDING

In this section, we provide the theoretical interpretation from the perspective from the In-context learning (ICL) to further understand why routing *finetuned models* with task-level router instead of token-level ones might be better. Note that here the *different finetuned models have been trained on individual tasks and never see other tasks*. We re-write the preliminary in Section 2 here for convenience of reading.

Task Data Distribution. Given a set of different downstream tasks $\mathcal{T}$, based on the sampling task $\tau \in \mathcal{T}$, the pretraining document (data sample) is a sequence $o_{1:T}$ of tokens with the maximum length T generated from a distribution $p_\tau = p(x_{1:T}|\tau) = p(o_1, \ldots, o_T|\tau)$ (Xie et al., 2022; Wies et al., 2023; Hahn and Goyal, 2023; Li et al., 2024a).

Pretraining Data Distribution. And we define the pretraining data is sampled from $p(o|\mathcal{T}^\star) = \int_{\tau^\star \in \mathcal{T}^\star} p(o_1, \ldots, o_T|\tau) p(\tau^\star) d\tau^\star$. Each token o is sampled from a vocabulary $\mathbb{O}$. $p(\tau^\star)$ is a prior distribution about $\tau^\star$. And both ($\mathcal{T}$ and $\mathcal{T}^\star$ belong to a large task family Ω, i.e. $\mathcal{T}, \mathcal{T}^\star \subset \Omega$.

Language Modeling. Current LLMs (Brown et al., 2020; Touvron et al., 2023; Xie et al., 2022) usually utilize the next word prediction as the language modelling, which predicts the next token o_t given the previous tokens $o_{1:t-1}$ for all $t = 1, \ldots, T$. Formally, a LLM parameterized by θ is a distribution $f_\theta(o_t|o_{1:t-1})$. And it is pretrained on a huge corpus sampled from the pretraining distribution $p(o_{1:T}|\mathcal{T}^\star)$ (Xie et al., 2022).

Finetuning LLM. Normally, for each downstream task $\tau \in \mathcal{T}$, finetuning LLM is to minimize the cross-entropy loss function as below:

$$L_{\text{CE}}(\theta, \tau) = -\sum_{t=1}^{T} \mathbb{E}[p_\tau(x_t|x_{1:t-1}) \cdot \log f_\theta(x_t|x_{1:t-1})].$$

After finetuning, the model parameters θ are updated to θ_τ for each task τ.

Prompt distribution in Pretraining & Finetuing. Following (Xie et al., 2022), a prompt is composed of an input token sequence $o_{1:T}$ followed by an output token y. Then, the i-th training example [2] that can appear in any place in the whole prompt $o_{1:T}$ is defined as O_i consisting of an input $s_i = O_i\,[1 : k-1]$ (the first $k-1$ tokens) followed by the output $y_i = O_i\,[k]$ at the end, where the length k is fixed for simplicity.

The i-th training example is independently generated as follows: 1) Generate a start hidden state h_i^{start} from a *prompt start distribution* p_{prompt}; 2) Given h_i^{start}, generate the example sequence $O_i = [s_i, y_i]$ from $p(O_i|h_i^{\text{start}}, \tau^\perp)$. The test input $x_{\text{test}} = s_{n+1}$ is sampled similarly. Between each example, a special delimiter token o^{delim} "reset" the transition between examples (Xie et al., 2022). Then, the prompt consists of a sequence of training examples (S_n) followed by the example x_{test}:

$$[S_n, x_{\text{test}}] = [s_1, y_1, o^{\text{delim}}, s_2, y_2, o^{\text{delim}}, \ldots, s_n, y_n, o^{\text{delim}}, x_{\text{test}}] \sim p_{\text{prompt}}. \tag{5}$$

[2] Here, training example in prompts means happens during the prompt learning, instead of the pretraining or the finetuning.

Different from (Xie et al., 2022), here we distinguish the pretraining tasks (concepts) $\mathcal{T}^\star$ and the finetuning tasks (concepts) $\mathcal{T} = \{\tau_1, \tau_2, ..., \tau_{n_\tau}\}$, from which the prompts might be sampled. We mainly consider $\tau^\perp \in \mathcal{T}$.

In-context learning setups and Assumptions. We follow other settings and assumptions in (Xie et al., 2022). With the greedy decoding (Fu et al.), sampling the next token from the language modeling $f_\theta(o_t|o_{1:t-1})$ becomes the predictor as $y = \arg\max_{o_t} f_\theta(o_t|o_{1:t-1})$. For simplicity, following (Xie et al., 2022), we consider that the finetuned LLMs have been aligned with its pretraining and finetuning data distribution, i.e. $p_{\mathcal{T}^\star \cup \tau} = p(o_{1:T}|\mathcal{T}^\star \cup \tau)$ for any task $\tau \in \mathcal{T}$. For convenience, we write $p_{A\tau} = p_{\mathcal{T}^\star \cup \tau}$ which means that the $\mathcal{T}^\star$ is augmented with τ.

Thus, for $[S_n, x_{\text{test}}]$, the in-context learning predictor can be written as $f^n_{\theta_\tau}(x_{\text{test}}) := \arg\max_y p_{A\tau}(y|S_n, x_{\text{test}})$, which outputs the most likely prediction over the *pretraining distribution* conditioned on the *prompt distribution*. Its expected 0-1 error with n examples is $L_{0\text{-}1}(f^n_{\theta_\tau}) = \mathbb{E}_{x_{\text{test}}, y_{\text{test}} \sim p_{\text{prompt}}}[\mathbf{1}[f^n_{\theta_\tau}(x_{\text{test}}) \neq y_{\text{test}}]]$.

We define $p^i_\tau(o) := p(O[i] = o|O[1:i-1], \tau)$ of the i-th token with previous tokens and the analogous distribution $p^i_{prompt} := p_{prompt}(O[i] = o|O[1:i-1])$ under the prompt distribution. Following (Xie et al., 2022), there is a distinguishability condition formalizes when in-context learning occurs giving the downstream task τ.

The distinguishability condition is dependent on a KL divergence between the previous two distributions and the error terms ϵ_τ resulting from the distribution mismatch between the prompt and the pertaining distributions for each example. Letting $p^i_\tau(o)$ and p^i_{prompt} correspond to the task τ and and $\tau^\perp$.

Condition D.1 (distinguishability (Xie et al., 2022))**.** The $\tau^\perp$ is distinguishable if for all $\tau \in \Omega$, $\tau \neq \tau^\perp$,

$$\sum_{i=1}^{k} \text{KL}_i(\tau^\perp||\tau) > \epsilon_\tau, \tag{6}$$

where the $\text{KL}_i(\tau^\perp||\tau) := \mathbb{E}_{O[1:i-1] \sim p_{prompt}}[\text{KL}(p^i_{prompt}||p^i_\tau)]$.

Lemma D.2. *(Xie et al., 2022) let $\mathcal{B}$ denotes the set of τ which does not satisfy Condition D.1. We assume that KL$(p_{prompt}(y_{test}|x_{test}))||p(y_{test}|x_{test}, \tau)$ is bounded for all τ and that $\tau^\perp$ minimizes the multi-class logistic risk as,*

$$L_{CE}(\tau) = -\mathbb{E}_{x_{test} \sim p_{prompt}}[p_{prompt}(y_{test}|x_{test}) \cdot \log p(y_{test}|x_{test}, \tau)]. \tag{7}$$

If

$$\mathbb{E}_{x_{test} \sim p_{prompt}}[KL(p_{prompt}(y_{test}|x_{test})||p(y_{test}|x_{test}, \tau))] \leq \epsilon_\tau, \quad \forall \quad \tau \in \mathcal{B}, \tag{8}$$

then

$$\lim_{n \to \infty} L_{0-1}(f^n_{\theta_\tau}) \leq \inf_f L_{0-1}(f) + g^{-1}\left(\sup_{\tau \in \mathcal{B}}(\epsilon_\tau)\right), \tag{9}$$

where $g(\nu) = \frac{1}{2}\big((1-\nu)\log(1-\nu) + (1+\nu)\log(1+\nu)\big)$ is the calibration function (Steinwart, 2007; Pires and Szepesvári, 2016) for the multiclass logistic loss for $\nu \in [0, 1]$.

Following (Kleijn and der Vaart, 2012; Xie et al., 2022), the task parameter τ is assumed to have the continuity, where the KL divergence is assumed to haver the 2nd-order Taylor expansion. Then, we have the following theorem and proof.

Theorem D.3. *(Xie et al., 2022) Let the set of τ which does not satisfy Equation 6 in Condition D.1 to be $\mathcal{B}$. Assume that KL divergences have a 2nd-order Taylor expansion around $\tau^\perp$:*

$$\forall j > 1, \;\; KL_i(\tau^\perp||\tau) = \frac{1}{2}(\tau - \tau^\perp)^\top I_{j,\tau^\perp}(\tau - \tau^\perp) + O(\|\tau - \tau^\perp\|^3) \tag{10}$$

where $I_{j,\tau^\perp}$ is the Fisher information matrix of the j-th token distribution with respect to $\tau^\perp$. Let $\gamma_{\tau^\perp} = \frac{\max_j \lambda_{max}(I_{j,\tau^\perp})}{\min j \lambda_{min}(I_{j,\tau^\perp})}$ where $\lambda_{max}, \lambda_{min}$ return the largest and smallest eigenvalues. Then for $k \geq 2$ and as $n \to \infty$, the 0-1 risk of the in-context learning predictor $f^n_{\theta_\tau}$ is bounded as

$$\lim_{n \to \infty} L_{0\text{-}1}(f^n_{\theta_\tau}) \leq \inf_f L_{0\text{-}1}(f) + g^{-1}\left(O\left(\frac{\gamma_{\tau^\perp} \sup_{\tau \in \mathbb{B}}(\epsilon^\theta_{start} + \epsilon^\theta_{delim})}{k-1}\right)\right) \tag{11}$$

Proof. (Xie et al., 2022) By the continuity assumption, we have for any τ in $\mathcal{B}$ that

$$\sum_{j=2}^{k} \mathrm{KL}_i(\tau^\perp||\tau) \geq \frac{1}{2}\sum_{j=2}^{k}(\tau-\tau^\perp)^\top I_{j,\tau^\perp}(\tau-\tau^\perp) + (k-1)O(\|\tau-\tau^\perp\|^3) \tag{12}$$

$$\geq \frac{1}{2}(k-1)\lambda_{\text{min}}(I_{j,\tau^\perp})\|\tau-\tau^\perp\|^2 \tag{13}$$

$$\implies \|\tau-\tau^\perp\|^2 \leq \frac{\epsilon^\theta_{\text{start}}+\epsilon^\theta_{\text{delim}}}{\frac{1}{2}(k-1)(\min_j\ \lambda_{\text{min}}(I_{j,\tau^\perp}))}. \tag{14}$$

Using the above term to bound the last KL term (k-th token), we have:

$$\mathrm{KL}_k(\tau^\perp||\tau) = \frac{1}{2}(\tau-\tau^\perp)^\top I_{k,\tau^\perp}(\tau-\tau^\perp) + O(\|\tau-\tau^\perp\|^3) \tag{15}$$

$$\leq \frac{1}{2}(\max_j\ \lambda_{\text{max}}(I_{j,\tau^\perp}))\|\tau-\tau^\perp\|^2 + O(\|\tau-\tau^\perp\|^2) \tag{16}$$

$$\leq \frac{(\epsilon^\theta_{\text{start}}+\epsilon^\theta_{\text{delim}})(\max_j\ \lambda_{\text{max}}(I_{j,\tau^\perp})+O(1))}{(k-1)\min_j\ \lambda_{\text{min}}(I_{j,\tau^\perp})}. \tag{17}$$

Rearranging above equation, and with the defintion that $\mathrm{KL}_k(\tau^\perp||\tau) = \mathbb{E}_{x_{\text{test}}\sim p_{\text{prompt}}}[KL(p_{\text{prompt}}(y_{\text{test}}|x_{\text{test}})\|p(y_{\text{test}}|x_{\text{test}},\tau))]$, we have

$$\mathbb{E}_{x_{\text{test}}\sim p_{\text{prompt}}}[KL(p_{\text{prompt}}(y_{\text{test}}|x_{\text{test}})\|p(y_{\text{test}}|x_{\text{test}},\tau))] \leq \frac{(\epsilon^\theta_{\text{start}}+\epsilon^\theta_{\text{delim}})(\max_j\ \lambda_{\text{max}}(I_{j,\tau^\perp})+O(1))}{(k-1)\min_j\ \lambda_{\text{min}}(I_{j,\tau^\perp})} \tag{18}$$

Combining Equation 18 with Equation 8 into Lemma D.2 completes the proof. □

Task-level Routing. Observing the Equation 7 in Lemma D.2, the $L_{\text{CE}}(\tau^\perp)$ is the optimal risk over $\tau \in \Omega$. The $\tau \in \mathcal{B}$ which does not satisfy Condition D.1 means that the $\tau \in \mathcal{B}$ should be close to $\tau^\perp$ enough. Thus, we can have $L_{0-1}(f^n_{\theta_\tau})$ converges with $n \to \infty$ as in Lemma D.2. The task-level routing means to route $\tau^\perp$ to the finetuned LLM that has been trained on $p(o_{1:T}|\tau^\perp)$. Thus, the task-level routing can satisfy the requirement of $\tau \in \mathcal{B}$.

Token-level Routing. The core motivation of using token-level routing is that different tokens prefer different routers. Here, inspired by the distinguishability condition D.1, we can interpret the token-level router which dynamically finds the expert model $i^\star$ for i-th token that satistifies:

$$\sum_{i}^{k} \arg\min_{i^\star} \mathrm{KL}_i(\tau^\perp||\tau_{i^\star}). \tag{19}$$

However, there is distribution shift between the $\tau^\perp$ and different $\tau_{i^\star}$. Revisiting the prompt sequence sampled as $[S_n, x_{\text{test}}] = [s_1, y_1, o^{\text{delim}}, s_2, y_2, o^{\text{delim}}, \ldots, s_n, y_n, o^{\text{delim}}, x_{\text{test}}] \sim p_{\text{prompt}}$, each pair $O_i = [s_i, y_i]$ is sampled from $p(O_i|h^{\text{start}}_i, \tau^\perp)$. If the $\tau_{i^\star}$ is choosed as different from $\tau^\perp$, the distribution shift implies that the KL_i cannot be minimized.

Out-of-distribution Cases. While the above intuition illustrates that the task-level routing might be more suitable for the in-distribution test data $x_{\text{test}} \sim p_{\text{prompt}}$, we illustrate that two cases of new prompt sampling might need need combination of different LLM experts.

- **OOD task.** Considering that the $\tau^\perp$ is different from all $\tau \in \mathcal{T}$, there might be needs to process different tokens with different experts following equation 19.
- **Compositional task.** Considering that $O_i = [s_i, y_i]$ might be sampled from $p(O_i|h^{\text{start}}_i, \tau_i)$, and each τ_i is different from others, the Equation 19 may helps to find the suitable experts.

However, the theoretical analysis of how Equation 19 benefits ICL is difficult and we left it as the future work, which might also be beneficial to analyse the MoE models (Dai et al., 2024). Currently, we utilize the uncertainty-based model task-level routing and merging to address the OOD problem.

E Detailed Experiment Settigns

E.1 Detailed Experimental Setup

Hardware. All experiments were conducted on an A800 GPU with 80GB VRAM, Intel Xeon 6348 CPU, and 100GB RAM.

Models and Datasets. We conduct comprehensive experiments on two cutting-edge large language model families: Qwen and LLaMA. Table 13 shows the number of parameters, memory occupation and release data of these models. These models represent the latest advancements in language model development. *To the best of our knowledge, this is the first model merging study focusing primarily on generative tasks, finetuning with CoT based data and cutting-edge LLM tasks.*

Table 13: Backbone Models Overview

Model	Number of Parameters	Release Date	Memory Occupation (GB)
Qwen-1.5-4B	4 Billion	February 2024	15.26
Qwen-2.5-7B	7 Billion	September 2024	26.00
LLaMA-3.1-3B	3 Billion	April 2024	11.31
LLaMA-3.2-8B	8 Billion	September 2024	30.52

Generative and Reasoning Tasks in Evaluation. In designing our evaluation tasks, we strategically selected orthogonal benchmarks to effectively demonstrate our method's capability in resolving parameter conflicts during model merging. Our task selection follows these principles:

- *(1) The mathematical reasoning and code generation tasks represent fundamentally different parameter spaces*. Specifically, mathematical computation requires numerical reasoning parameters, while code generation relies on syntax and programming logic parameters, allowing us to evaluate how well our merging approach handles potentially conflicting parameter updates.
- (2) *Knowledge-based QA (TriviaQA) and concept understanding tasks (MMLU) evaluate distinct knowledge representations*. TriviaQA focusing on factual retrieval parameters and MMLU covering broader conceptual understanding parameters across domains. This helps assess our method's ability to preserve different types of knowledge without interference.
- (3) The logical reasoning task (WinoGrande) may prefer to yet another independent parameter space focused on *abstract reasoning*, providing insights into how well our merging technique maintains reasoning capabilities while optimizing for other tasks.

Based on above principle, we utilize the following cutting-edge LLm evaluation tasks about math reasoning, code generation, common sense QA, common sense logical reasoning, multi-domain knowledge.

- **Mathematical Reasoning**: We evaluate mathematical question-answering capabilities using the GSM8K dataset (Cobbe et al., 2021), which contains 8,500 high-quality elementary school math word problems (about 7,500 training, about 1,000 test) designed to evaluate mathematical reasoning capabilities. The problems feature diverse language styles and formats while avoiding templated designs. They use basic arithmetic operations with natural language solutions.
- **Knowledge-based QA**: We utilize TriviaQA (Joshi et al., 2017), a large-scale Wikipedia-based question answering dataset, where models are required to generate direct answers without multiple-choice options. It contains complex questions requiring cross-sentence inference, with significant syntactic and lexical variations between questions and answer sentences. The dataset provides challenging evaluation scenarios that better approximate human-like question answering.
- **Code Generation**: The HumanEval (Chen et al., 2021) consists of human-written programming tasks where models must complete missing Python code snippets based on provided inputs. The problems simulate real-world programming challenges requiring context understanding, reasoning, and multi-step operations across varying difficulty levels and abstraction layers.
- **Logical Reasoning**: WinoGrande (Sakaguchi et al., 2019) is a large-scale commonsense reasoning dataset of approximately 2800 questions developed by University of Washington researchers.

Questions are presented as fill-in-the-blank tasks with two options and correct answers, with dataset bias reduced through the AfLite algorithm. The benchmark evaluates models' commonsense reasoning abilities in understanding and generating relevant text.

- **Multi-domain Knowledge**: We employ MMLU (Hendrycks et al., 2021) to assess knowledge retention across diverse 57 subjects ranging from basic mathematics to US history, computer science, law, and ethics. Using multiple-choice questions of varying difficulty levels. Notably, we exploit the generation-based approach for multiple-choice evaluation, analyzing knowledge preservation across base models, fine-tuned variants, and merged models. The generation-based evaluation is better to measure the generative abilities of LLMs than choice-based evaluation.

In the experiments of evaluating the scalability of Mediator, we also finetune another 4 LLMs according to the following 4 extra evaluation tasks.

IFEval. (Zhou et al., 2023) A comprehensive benchmark dataset designed to evaluate instruction-following capabilities of language models. It contains carefully curated instruction-response pairs across diverse task categories including text generation, analysis, and reasoning. The dataset aims to assess models' ability to accurately interpret and execute natural language instructions while maintaining coherence and relevance in responses. The evaluation spans multiple dimensions including instruction comprehension, output quality, and adherence to specified constraints.

CEval. (Huang et al., 2023a) A comprehensive Chinese evaluation suite designed to assess language models' knowledge and capabilities across various academic and professional domains. It consists of multiple-choice questions drawn from professional qualification exams and academic tests in China. For our evaluation, we specifically focus on three key subjects: (1) *Medicine:* testing clinical knowledge, diagnosis, and treatment principles from medical licensing exams; (2) *College Economics:* evaluating understanding of micro/macroeconomics concepts, market principles, and economic theories; (3) *Law:* assessing comprehension of Chinese legal principles, regulations, and judicial procedures. These subjects were chosen to evaluate models' domain-specific expertise in technically demanding professional fields.

Finetuning Settings. We adopt the ms-swift (Zhao et al., 2024) to finetune the given pretrained LLM. The finetuning datasets are constructed by augmenting some publicly datasets (task related but without overlap) with GPT-4o (Gilardi et al., 2023) and Chain-of-Thoughts (Wei et al., 2022). For each finetuning process, we use at least 180K training samples to ensure sufficient performance improvement on the corresponding task, which helps validate the effectiveness of our experiments. We provide the details of how we construct the finetuning datasets in Section H.

Baselines. Following the summary of the related works in Section C, we compare methods in following four categories:

- **Pretrained model.** The pretrained models are directly downloaded from its open-source repository. These models are pretrained on the large corpus and have included enormous knowledge about the evaluation tasks.
- **Finetuned Models**: We finetune the pretrained models on datasets that we construct for each domain. Then, each finetuned model is evaluated on all tasks. The results help to show wheter finetuning on task A enhance or decrease model performance on task B.
- **Static merging methods.** These methods use fixed weights to merge multiple finetuned models. The advanced static merging methods like Fisher merging (Matena and Raffel, 2022) and RegMean (Jin et al., 2023) require extra dataset and forward process to estimate some information like gradients, hessian, features to estimate parameter importance, which causes significant computational costs. Furthermore, considering that LLMs need to be deployed on various tasks, the utilized dataset actually cannot reflect the real-world data distribution. Therefore, these methods are shown empirically to perform worse than some calibration-less methods (Du et al., 2024). Recently, TIES (Yadav et al., 2023b) and PCB-merging (Du et al., 2024) achieve the best performance in weighted average method and do not require calibration data. Thus, we choose it for comparison.
- **Dynamic Advanced Methods**: We compare with state-of-the-art dynamic merging techniques that adapt model fusion parameters based on the input data. For example, Branch-train-mix dynamically routes different tokens to corresponding experts for generation

through token-level routing. Similarly, the twin-merge (Lu et al., 2024b) computes merging weights through task-level routing mechanisms and dynamically fuses SVD-decomposed task vectors into the pretrained model in real-time.

E.2 Hyperparameters of Finetuning and Implementing Baselines

Hyperparameters for Single-task Finetuning. For single-task finetuning, we utilize a set of hyperparameters that remain consistent across all models and tasks. The learning rate is set at 1.2e-5, applying a cosine decay schedule. The batch size varies, with one sequence per batch for both the 7B and 8B models, while the 3B and 4B models use two sequences per batch considering the GPU memory limitation. The maximum sequence length is confined to 4096 tokens for both math and QA tasks and extends to 7000 tokens for coding tasks. The training consists of two epochs, and we employ the AdamW optimizer with parameters $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 1e - 8$. Additionally, warmup steps constitute 5% of the total steps.

For all model merging baselines, the finetuned LLMs are the same. And all finetuned LLMs have shown that they can successfully improve the performance of the pretrained model on various tasks. The following is the details of how we tune and implement baseline methods.

Hyperparameters for PCB-merging. We follow the original paper of PCB merging and have searched its hyperparameters. The weight clipping ratio is established at 0.1, which means weights with magnitudes in the bottom 10% are clipped to zero, following recommendations from the original paper concerning LLM generalization tasks. For model merging exploration, we perform 200 random exploration steps. The initial weights for random exploration are set to (0.4, 0.4, 0.4, 0.4) for the 3B, 4B, 7B, and 8B models with four experts, while for all models with eight experts, they are set to a repeated value of 0.2 across eight instances. The validation batch size is configured to handle 8 samples per task, and we implement early stopping with a patience of 10 steps without improvement. The weight clipping ratio and exploration parameters are uniform across all model sizes and tasks to facilitate fair comparison. It's worth noting that for the 7B and 8B models, the validation batch size is reduced to 4 due to memory limitations.

Optimizing PCB-merging. To enhance the computational speed of PCB-merging, several optimizations were introduced based on the original framework, which do not influence its task performance. Instead of merging entire models simultaneously, we adopt a layer-wise model merging strategy. This layer-by-layer merging approach has multiple benefits: it decreases memory overhead during the merging process, facilitates parallel processing of different layers, and allows for the assignment of layer-specific merging weights. Moreover, we implemented asynchronous model input/output operations which enable overlapping of I/O with computational processes. This adjustment is instrumental in reducing the total merging time by as much as 40%, enabling the seamless streaming of large models. These optimizations have significantly boosted both the efficiency and effectiveness of PCB-merging, particularly the layer-wise method, which has lowered peak memory usage by approximately 60% while maintaining or enhancing final model performance. And other hyper-parameters and settings are completely followed as the original paper.

Hyperparameters for Twin-merging finetuning. For Twin-merging, we leverage LoRA finetuning in lieu of SVD to attain greater precision following the original paper. The rank is set as 32, and both the alpha and dropout parameters are also set at 32 and 0.1, respectively. The target modules involved in this finetuning process include the query and value matrices within the attention layers. And we also have conducted grid search for the hyper-parameters. Each task involves training over two epochs, with a batch size set at 16; this batch size is reduced to 8 for the 7B and 8B models. The learning rate is specified at 1.5e-4, utilizing a cosine decay schedule, and the optimizer employed is AdamW.

Hyperparameters for Branch-train Mix (BTX). For the training of the BTX router, we follow the original implementation of it within ms-swift and its original paper to implement it. The relevant hyperparameters for this setup include a training duration of 2 epochs, with a batch size of 2; this is adjusted to 1 for the 7B and 8B models. The learning rate is established at 1.5e-6, utilizing a linear decay schedule, alongside the AdamW optimizer, which is configured with a weight decay of 0.001. The router's architecture consists of an input dimension derived from 2 layers of an FFN, with a hidden dimension of 256, an output dimension corresponding to the number of experts, and a dropout rate of 0.1. Warmup steps account for 5% of the total steps, and evaluations are conducted at every

1000 steps. To ensure balanced representation, the router is trained on a dataset that equally samples from all tasks, employing early stopping with a patience of 2 epochs based on validation accuracy.

Hyperparameters for Mediator. For Mediator training, we utilize the same single-task finetuned experts as delineated in Appendix E.2. The task-level router is constructed from the first 9 layers of the pretrained LLM (with gradients stopped) and includes 2 additional FFN layers. The router is trained on a balanced dataset with equal samples from each task domain to ensure unbiased task routing. We evaluate the router performance every 1000 steps and use early stopping with patience of 2 epochs based on validation accuracy. The training process for the router involves sampling 2000 examples from each task domain, specifically in mathematics, coding, question answering, law, economics, instruction following, and medicine. The specific hyperparameters applicable to router training encompass a duration of 2 epochs, and a batch size of 256, which is decreased to 128 for the 7B and 8B models. The learning rate is set to 3e-4, accompanied by a cosine decay schedule, and the optimizer remains as AdamW. The warmup ratio is defined as 10% of the total steps. The router's architecture features a frozen backbone comprising the initial 9 layers from the pretrained LLM, along with 2 trainable FFN layers. These layers have a hidden dimension of 1280, with the output dimension reflecting the number of experts, and a dropout rate fixed at 0.05.

For router based selection, we use the temperature parameter β in Equation 4 as 1.5 to convert the prediction rates into concrete merging parameters for each expert, which achieves the best experimental results. This temperature scaling helps balance between being decisive in expert selection while maintaining some degree of smoothness in the merging weights. A temperature of 1.5 empirically provides the optimal trade-off, where lower temperatures lead to more concentrated weights but potentially miss useful signals from secondary experts, while higher temperatures result in overly diffuse weights that don't sufficiently leverage expert specialization.

F THE VARIATIONS AND DETAILS OF DIFFERENT PARTS OF MEDIATOR

In this section, we provide the detailed variations and implementation details of different parts of Mediator. Some definitions and operations that appear in the main text may be re-defined in this section for better clarity of reading.

F.1 MEASURING PARAMETER CONFLICTS

Task Arithmetics. We define the task arithmetics as the parameter difference between the finetuned LLM θ_τ based on task τ and the pre-trained LLM θ, i.e., $\Delta_\tau = \theta_\tau - \theta$. Such a task arithmetics can represent the update on the finetuned LLM θ_τ based on task τ. Given a pretrained LLM θ, one can recover the finetuned LLM $\theta_\tau = \theta + \Delta_\tau$.

Denoising Parameters. Because the finetuing directions on different tasks are various and stochastic, there exist some elements in Δ_τ that do not influence the performance on task τ. Before measuring the parameter conflicts (Yadav et al., 2023a; He et al., 2024b), we firstly denoise the parameters by removing the elements in Δ_τ that do not influence the performance on task τ. We also model the update directions of different elements as the Gaussian distribution $\mathcal{N}_{\text{UPD}}(\mu_{\text{UPD}}, \sigma^2_{\text{UPD}})$, where μ_{UPD} is the mean of the update direction and σ^2_{UPD} is the variance.

Based on the estimated μ_{UPD} and σ_{UPD}, we can regard the elements within range ($\mu_{\text{UPD}} - \sigma_{\text{UPD}}$, $\mu_{\text{UPD}} + \sigma_{\text{UPD}}$) as the elements that do not influence the performance on task τ. Thus, we can denoise the parameters by removing the elements within range ($\mu_{\text{UPD}} - \sigma_{\text{UPD}}$, $\mu_{\text{UPD}} + \sigma_{\text{UPD}}$) (set as 0) and obtain the new parameter arithmetic $\hat{\theta}_\tau = \theta + \hat{\Delta}_\tau$. In the deployment, these elements are saved with their indexes and values for realistic sparsification thus saving memory.

F.2 ADAPTIVE MERGING

Inspired by the empirical observation in Figure 3 in Section 3, we propose to leverage the parameter conflict distribution across different finetuned LLMs to adaptively merge the finetuned models.

Practically, before merging, Mediator automatically calculates the conflicts d_l across different finetuned LLMs. Then, Mediator models the conflicts as a Gaussian distribution $\mathcal{N}(\mu, \sigma)$. Then,

for each layer index l, Mediator average layer parameters if the conflict d_l is less than the $\mu + \sigma$, otherwise, Mediator Routing this layer. We denote the averaged layer parameters as ϕ^l_{AVG} and the Routing layer parameters as ϕ^l_{UP}. Algorithm 1 shows this detailed process.

F.3 Averaging Operations

Naive Average Operation. The naive average operation $\mathcal{M}_{\text{AVG}}$ is defined as:

$$\mathcal{M}_{\text{AVG}}(\theta_1, \theta_2, \ldots, \theta_{|\mathcal{T}|}) = \frac{1}{|\mathcal{T}|} \sum_{\tau=1}^{|\mathcal{T}|} \theta_\tau, \tag{20}$$

which regards all finetuned LLMs equally and utilizes the same weight for each finetuned LLM. Such a simple average operation is easy to implement, without fabricated procedures, thus having low computational overhead. However, different parameters may have different sensitivities to the final merged model, which may lead to suboptimal performance.

Taylor Expansion. The Taylor expansion is a powerful tool for approximating a function around a specific point, and it is widely used in various fields, including model compression (Lee et al., 2019) and previous works on model merging (Jhunjhunwala et al., 2023; Qu et al., 2022). We can utilize the Taylor expansion to measure the sensitivity of each parameter that influences the model performance on the downstream task τ as follows:

$$L_{\text{CE}}(\theta + \delta_\theta, \tau) = L_\tau(\theta) + \frac{\partial L_\tau(\theta)}{\partial \theta} \theta \delta_\theta + O(\delta_\theta^2). \tag{21}$$

The first-order derivative $\frac{\partial L_{\text{CE}}(\theta,\tau)}{\partial \theta}$ measures the sensitivity of the loss function L_τ to the parameter θ. Thus, we can see that utilizing the same averaging operation for all parameters may not be the optimal choice for merging different finetuned LLMs, as it does not take into account the different contributions of each finetuned LLM to the final merged model.

Parameter-level Importance based Model Merging. To this end, one can utilize the first-order derivative or higher-order derivative to measure the sensitivity of the loss function L_τ to the parameter θ, based on which, the parameter-level importance can be measured as $w_\tau = \frac{\partial L_\tau(\theta)}{\partial \theta}\theta$. Then, the parameter-level importance can be used as the averaging weight for each finetuned LLM like the following:

$$\mathcal{M}_{\text{FO-Taylor}}(\theta_1, \theta_2, \ldots, \theta_{|\mathcal{T}|}) = \sum_{\tau=1}^{|\mathcal{T}|} w_\tau \theta_\tau. \tag{22}$$

Preprocessing Parameters. Considering that the finetuing directions on different tasks are various and stochastic, some elements in θ_τ that are optimized stochastically and may not influence the performance on task τ. Thus, before averaging, we can denoise the parameters by removing the elements in θ_τ that do not influence the performance on task τ. Like the preprocessing the task arithmetics and the denoising, we recover the finetuned LLM $\hat{\theta}_\tau = \theta + \hat{\Delta}_\tau$ by removing the elements in Δ_τ that do not influence the performance on task τ. Then, the averaged models can be obtained by the following equation:

$$\mathcal{M}_{\text{de-noise}}(\theta_1, \theta_2, \ldots, \theta_{|\mathcal{T}|}) = \sum_{\tau=1}^{|\mathcal{T}|} w_\tau \hat{\theta}_\tau. \tag{23}$$

F.4 Details of Expert Routing

For an input $x_{1:t}$ sampled from the training dataset p_τ, the intuitive routing mechanism is to directly use the finetuned LLM θ_τ that is trained on the training dataset p_τ to generate the output $x_{t+1:T}$. However, the real-world deployment is usually different from the training distribution, which may lead to suboptimal performance. Especially for an LLM deployment scenario, the input distribution is various.

Modeling the likelihood $\pi_\kappa(\tau|x)$. We build a task-level deep neural network as the router. In designing the router structure, we carefully balance model accuracy with additional memory requirements. While LLMs inherently demonstrate excellent classification capabilities, we need an efficient solution that wouldn't significantly impact performance. After extensive experimentation, we opt to utilize the embeddings from the first 9 layers of the base LLM combined with 2 FFN layers as our router architecture. This design choice eliminates the need for a separate complex router structure while maintaining high classification accuracy with minimal memory overhead and fast execution speed. The router leverages the rich semantic understanding already present in the base model's lower layers, making it both resource-efficient and effective for expert selection.

Constructing training datasets for learning $\pi_\kappa(\tau|x)$. For training the router, we randomly sample 2000 examples from each domain rather than using the entire finetuned dataset for efficiency. For each task, we only extract the question part (other than the question and answer pairs) to better simulate real-world deployment scenarios. We do not explicitly construct a training dataset for the "others" category to consider the OOD category and the sample will be regarded as prefering the original pretrained model. Instead, during inference, if the predicted probabilities for math, coding, and QA tasks are all below 0.5, the input is classified as "others" and processed this question by the base model. The training dataset can be represented as $\{(x,\tau)|x \sim p_\tau\}_{\tau\in\{\text{math,coding,QA}\}}$.

G System Optimization

The inference latency and memory consumption are critically important for the real-world LLM applications. Thus, we consider to optimize the inference latency and memory consumption of Mediator. The overall latency of Mediator is mainly affected by the routing, loading experts between CPUs and GPUs (if required offloading), inference of the models itself.

Routing Latency. We run expert routing only once per sample because we use task-level routing. The classifier κ consists of two FFN layers, and its input is the hidden state of the first through ninth layers of the LLM. The total execution time of the classifier κ is between 0.2s and 0.4s.

Loading Experts. After obtaining $\pi_\kappa(\tau|x)$, we compute $h(\tau|x)$ according to Equation 4. We also load expert parameters only once. To optimize this process, we explore two methods. For sparse expert parameters, we store all of them in the CPU and prefetch the parameters for the next layer while performing computations in the current layer. For non-sparse expert parameters, we store them on disk and use ZipNN (Hershcovitch et al., 2024) to accelerate loading from disk to CPU.

Inference Timeline. We present the optimized inference timeline of Mediator, as shown in Figure 5. The additional time incurred by Mediator is fixed and relatively small(approximately 0.2s to 0.4s). This portion of the time overhead will decrease as the model size increases or the decoding length becomes longer.

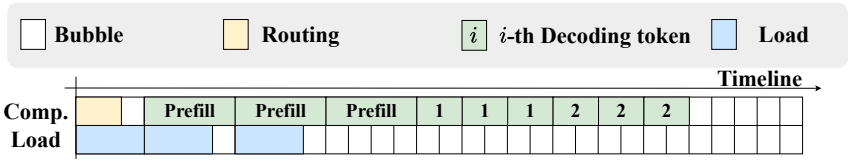


Figure 5: The inference timeline of Mediator, assuming that the number of layers is three.

G.1 CUDA Kernal Merging

We accelerate the integration or disintegration of sparse experts into the dense backbone by using CUDA's atomicAdd, which enables parallel merging of multiple experts while maintaining accuracy. Through this approach, we can split the weights into individual elements, allowing each element to be processed in parallel. However, we have observed that parallel merging alone is sufficient to mask the associated costs.

G.2 Serving with Batched requests

The traditional LLM serving usually accepts different requests asynchronously. Then, different requests are allocated to different batches with a predifined batch size and feed into the model. A batch-style inference usually is faster than the single-request inference, because the computation matrix is more dense and become GPU friendly.

However, the Mediator and many routing based merging works (Sukhbaatar et al., 2024c; Lu et al., 2024b) require to select different experts for different requests. Thus, a batch of various requests may lead to various experts being selected, which would disturb the regularity of the computation matrix. To implement the batch-style serving, we implement following two new system optimization schemes to improve Mediator.

- Clustering Serving: Since each task arithmetic expert has been compressed to a small capacity, we can merge task arithmetics with different parameter fusions into several merged experts. When multiple tasks begin serving, we select the merged experts with the closest overall distance. While this batch inference approach may introduce some errors, the key research focus lies in how to effectively cluster and construct merged experts;
- Batch arithmetic inference: This is our lossless solution for batch inference. Similarly, due to the small size of compressed task arithmetics, we propose the following approach: Let Θ_o be the parameters of the original large model, $ta_1, ta_2, ...ta_n$ be the weighted Task arithmetics for tasks 1,2,3...n respectively, and $x_1, x_2, ...x_n$ be the input parameters for different tasks. We decompose the ideal case $(\Theta_o + ta_j)(x_j)$ into $\Theta_o(x_j) + ta_j(x_j)$ to achieve efficient batch inference.

H Finetuning Data Generation

H.1 Task-related Training Datasets

Following benchmark datasets are used for evaluating model performance across different domains. The datasets used for finetuning are introduced

Math Training Data for GSM8K. For mathematical reasoning tasks, we constructed our training dataset by combining several high-quality math-focused datasets:

- GSM8K Socratic Training Set: A subset of GSM8K training data augmented with Socratic-style step-by-step reasoning, which helps models develop systematic problem-solving approaches. Note that this dataset does not have overlapped question answer pairs same with the GSM8K.
- Orca-Math (Mitra et al., 2024): A comprehensive mathematics dataset that covers various mathematical concepts and problem types, designed to enhance mathematical reasoning capabilities.

Example 1
Question: Natalia sold clips to 48 of her friends in April, and then she sold half as many clips in May. How many clips did Natalia sell altogether in April and May? **Answer:** Natalia sold $48 \div 2 = 24$ clips in May. Natalia sold $48 + 24 = 72$ clips altogether in April and May. #### 72
Example 2
Question: Weng earns $12 an hour for babysitting. Yesterday, she just did 50 minutes of babysitting. How much did she earn? **Rationale:** One rotates a Rubik's Cube in 0.2 second, only needing to know how many steps it takes to solve one. Someone solve a Rubik's Cube requires a minimum of 50 steps. It takes 4 seconds to solve the Rubik's Cube at the fastest. **Answer:** Weng earns $12 an hour for babysitting. Yesterday, she just did 50 minutes of babysitting. How much did she earn? #### 10

Table 14: Examples of GSM8K Socratic Training Set. The red color represents the CoT sequences.

By combining these datasets, we created a rich and diverse training corpus that exposes models to different mathematical reasoning patterns, problem-solving strategies, and difficulty levels. Furthermore, with the help of CoT based answers generated by the GPT-4o, this comprehensive approach helps ensure robust mathematical reasoning capabilities across various scenarios. We assembled approximately 200,000 training samples.

Example 1
Question:A number divided by 10 is 6. Yoongi got the result by subtracting 15 from a certain number. What is the result he got? **Answer:** Let's call the certain number "x". According to the information given: A number divided by 10 is 6: x / 10 = 6 Yoongi got the result by subtracting 15 from x: Result = x - 15 First, we need to find the value of x. We can do this by solving the first equation: x / 10 = 6 x = 6 * 10 x = 60 Now that we know x is 60, we can find the result Yoongi got by subtracting 15 from x: Result = x - 15 Result = 60 - 15 Result = 45. So, the result Yoongi got is 45.
Example 2
Question: For the natural number A, the quotient of A divided by 9 is 6 and the remainder is 5. What is the value of A? **Answer:** To find the value of A, we can use the formula for division with remainder: A = (quotient × divisor) + remainder In this case, the quotient is 6, the divisor is 9, and the remainder is 5. Plugging these values into the formula, we get: A = (6 × 9) + 5 A = 54 + 5 A = 59. Therefore, the value of A is 59.

Table 15: Examples of orca-math Training Set. The red color represents the CoT sequences.

Example 1
Question: Who was the first person to reach the South Pole? **Answer:** Norwegian explorer Roald Amundsen led the first expedition to successfully reach the South Pole on December 14, 1911. His team beat British explorer Robert Falcon Scott's expedition by about a month. Amundsen's careful planning and use of dog sleds proved crucial to his success in reaching the pole first. Roald Amundsen was the first person to reach the South Pole.
Example 2
Question: What is the capital city of Australia? **Answer:** While many people think Sydney or Melbourne is Australia's capital, Canberra is actually the capital city. It was purpose-built as a compromise between these two rival cities and became the capital in 1927. The city is home to Parliament House and many important government institutions. The capital city of Australia is Canberra.

Table 16: Examples of TriviaQA Training Set. The red color represents the CoT sequences.

QA Training Data for TriviaQA and WinoGrande. For question answering tasks, we constructed our training dataset by combining and filtering several QA datasets:

- TriviaQA-Wikipedia subsets: A dataset derived from Wikipedia articles containing trivia questions and answers, which helps train models on factual knowledge and reading comprehension.
- Alpaca QA Pairs(Taori et al., 2023b): We filtered the Alpaca dataset to extract QA pairs, specifically excluding math and programming related questions to maintain domain focus. This dataset provides diverse general knowledge questions and answers for training conversational capabilities.
- WebQuestions (Bordes et al., 2014): A dataset of natural language questions paired with answers, derived from web queries.
- SQuAD v1 & v2(Rajpurkar et al., 2016): The Stanford Question Answering Dataset, both versions 1 and 2, from which we sampled question-answer pairs where explicit answers were provided.

This combined dataset provides diverse question answer pairs across different domains and formats while maintaining high quality through careful filtering and sampling. The exclusion of math and programming questions helps maintain clear task boundaries for our specialized models. Through careful combination and sampling of these datasets, we assembled approximately 200,000 training samples.

Code Training Data for HumanEval. For programming-related tasks, we constructed our training dataset by combining several programming-focused datasets:

- MBPP (Mostly Basic Python Programming)(Austin et al., 2021): A dataset containing Python programming problems ranging from basic to intermediate difficulty levels.
- Magicoder-Evol-Instruct(Wei et al., 2024b): A dataset of 110K high-quality programming instructions and solutions from the ise-uiuc project, covering diverse programming tasks and patterns.
- LeetCode dataset (Coignion et al., 2024): A comprehensive collection of coding problems with varying difficulty levels, commonly used for programming practice and assessment.
- ConalaMineded (Yin et al., 2018): A curated subset of the CoNaLa dataset containing high-quality Python programming snippets with natural language annotations, which helps models understand

Example 1
Question: What is the primary purpose of the United Nations Security Council? **Answer:** The United Nations Security Council's primary purpose is to maintain international peace and security. It has the power to establish peacekeeping operations, implement international sanctions, and authorize military action. The Security Council is the only UN body that can issue binding resolutions to member states. The Security Council is responsible for maintaining international peace and security.
Example 2
Question: How does photosynthesis work in plants? **Answer:** Photosynthesis is the process by which plants convert light energy into chemical energy. Plants use sunlight, water, and carbon dioxide to produce glucose and oxygen. The process takes place in the chloroplasts, specifically using the green pigment chlorophyll. The glucose provides energy for the plant, while the oxygen is released into the atmosphere as a byproduct. Plants use sunlight to convert carbon dioxide and water into glucose and oxygen.

Table 17: Examples of Alpaca QA Training Set. The red color represents the CoT sequences.

Example 1
Question: What company did Warren Buffett start his career at? **Answer:** Warren Buffett began his career at Buffett-Falk & Co., an investment firm in Omaha, Nebraska. He worked there from 1951 to 1954 after graduating from Columbia Business School. This was before he went on to form Buffett Partnership Ltd. in 1956 and later acquire Berkshire Hathaway in 1965. Warren Buffett started his career at Buffett-Falk & Co.
Example 2
Question: What is the longest river in Europe? **Answer:** The Volga River is the longest river in Europe, flowing entirely within Russia. It stretches for approximately 3,530 kilometers (2,193 miles) and drains into the Caspian Sea. The river has played a crucial role in Russian history, culture, and economic development. The Volga River is the longest river in Europe.

Table 18: Examples of WebQuestions Training Set. The red color represents the CoT sequences.

implementation details of specific functions and how to implement micro-level functionality, thereby improving overall chain-of-thought capabilities.

This comprehensive dataset covers various programming concepts, difficulty levels, and coding patterns, enabling robust evaluation of models' programming capabilities.

In the scalability experiments, we utilize the following 4 datasets to finetune extra 4 models according to another 4 evaluation tasks. Note that these datasets have no overlap with the evaluation tasks.

- **Instruction Following.** For instruction following tasks, we utilize the Magpie dataset (Xu et al., 2024), which contains 200K high-quality English instruction-following samples. The dataset covers diverse instruction types including writing, analysis, and problem-solving. We evaluate the model's instruction following capabilities on IFEval, a comprehensive benchmark containing 1,000 carefully curated instructions across multiple categories like reasoning, writing, and task completion.
- **Economics:** We use the IndustryInstruction (Ind) dataset for training, which contains instruction-response pairs focused on finance and economics concepts, analysis, and problem-solving. The model is evaluated on CEval economics benchmark, which tests understanding of economic principles, market analysis, and financial concepts.
- **Medicine:** We utilize the DISC-Med (Bao et al., 2023) Chinese medical dataset for training, which covers various aspects of medical knowledge including diagnosis, treatment, and healthcare concepts. Evaluation is performed on CEval physician tasks that assess medical domain knowledge and reasoning.
- **Law:** Training data comes from the DISC-Law Chinese legal dataset (Yue et al., 2023a), containing legal concepts, case analysis, and regulatory knowledge. The model's legal capabilities are evaluated using CEval law tasks, which test understanding of legal principles and reasoning.

H.2 CoT based Data Augmentation

High-quality task-related training datasets are crucial for evaluating model merging algorithms effectively. When a pretrained model achieves strong performance through single-task fine-tuning, it creates greater headroom for different model merging approaches to demonstrate their capabilities

Example 1
Question: Who wrote the play "Romeo and Juliet"? **Answer:** William Shakespeare
Example 2
Question: What is the capital city of Japan? **Answer:** Tokyo

Table 19: Examples of SQuAD Training Set.

Example 1

Question:Write a python function to find the first repeated character in a given string.
Answer:

```
def first_repeated_char(str1):
    for index,c in enumerate(str1):
        if str1[:index+1].count(c) > 1:
            return c
    return "None"
```

Example 2

Question: Write a function to reverse words in a given string..
Answer:

```
    def reverse_words(s):
        return ' '.join(reversed(s.split()))
```

Table 20: Examples of MBPP Training Set.

and differentiate themselves. The quality of task-specific datasets thus becomes a key prerequisite for meaningful experimental comparisons.

Therefore, we carefully curated high-quality training datasets for each specialized domain to ensure our experimental results meaningfully reflect the relative strengths of different merging strategies. The following sections detail the specific datasets used for each task domain.

To enhance model performance through single-task fine-tuning, we constructed three Chain-of-Thought (CoT) datasets, as CoT has been shown to significantly improve model capabilities:

H.3 CoT based Data Augmentation

High-quality task-related training datasets are crucial for evaluating model merging algorithms effectively. When a pretrained model achieves strong performance through single-task fine-tuning, it creates greater headroom for different model merging approaches to demonstrate their capabilities and differentiate themselves. The quality of task-specific datasets thus becomes a key prerequisite for meaningful experimental comparisons.

Therefore, we carefully curated high-quality training datasets for each specialized domain to ensure our experimental results meaningfully reflect the relative strengths of different merging strategies. The following sections detail the specific datasets used for each task domain.

To enhance model performance through single-task fine-tuning, we constructed three Chain-of-Thought (CoT) datasets, as CoT has been shown to significantly improve model capabilities:

Math CoT. We utilized GSM8K Socratic and Orca-Math datasets for our mathematical Chain-of-Thought training. The GSM8K Socratic dataset, containing approximately 7,500 samples, fully exhibits step-by-step CoT reasoning characteristics. While Orca-Math does not consistently maintain CoT patterns across all examples, the combined datasets provide about 30% of samples with clear CoT reasoning, which we used for training. This mixed dataset approach helps balance between high-quality CoT examples and broader mathematical coverage.

Code CoT. For coding training data, we combined multiple data sources. The MBPP dataset provides non-CoT examples, while Magicoder-Evol-Instruct and LeetCode datasets mostly contain CoT programming examples. Additionally, although ConalaMineded is a CoT dataset, it uniquely

Example 1

Question: Please amend the subsequent Python script so that it includes a 'while' loop rather than the existing 'for' loop, which iterates through the items of an integer list. The script currently has a bug where it attempts to print an object that is outside the bounds of the list. Fix this error and modify the script to use 'while' instead of 'for' loop. Ensure your script correctly handles empty lists.

```
python
# Establish an integer list
arr = [1, 2, 3, 4]
# Determine the length of the list
n = len(arr)
# Traverse the list and output each individual element
for i in range(n+1):
    print(arr[i])
```

Answer: python

```
# Establish an integer list
arr = [1, 2, 3, 4]
# Determine the length of the list
n = len(arr)
# Initialize index at 0
i = 0
# Traverse the list and output each individual element
while i < n:
    print(arr[i]) i += 1
```

In the given code, it tries to access arr[n] which is out of bounds as python list indexing starts from 0 and ends at n-1 for a list of length n. Also, I used while loop as per your request. By initializing i=0 before the loop and i += 1 within the loop, we can iterate over the list. This iteration continues until i is less than n, the length of the list. The while loop will not proceed if the list is empty so it correctly handles empty lists.

Example 2

Question: Create a function to search for a word in an array. The word should be searched in the lowercase version of the array and it should return the index location of its first occurrence. word = "test" words_array = ["Hello", "World", "Test", "Test", "me"]

Answer: Here's how you can create the function in Python:

```
python
def search_word(word, words_array):
    word = word.lower()
    words_array = [w.lower() for w in words_array]
    if word in words_array:
        return words_array.index(word)
    else:
        return "Word not found"
word = "test"
words_array = ["Hello", "World", "Test", "Test", "me"]
print(search_word(word, words_array))
```

This script turns both the search term and the words in the array to lower-case to ensure the search is case-insensitive. It checks if the word is within the array. If it is, it returns the index of the first occurrence of the word. If not, it returns a Ẅord not foundm̈essage.

Table 21: Examples of Magicoder-Evol-Instruct Training Set. The red color represents the CoT sequences.

explains the meaning of each small programming snippet, which helps models better understand micro-level programming components. We sampled and integrated examples from all these sources to create a comprehensive training set.

QA CoT. For question answering tasks, we integrated multiple data sources with varying levels of content. We used Claude 3.5 Sonnet to augment TriviaQA-Wikipedia and WebQuestions datasets with CoT reasoning by prompting it to "expand the QA pair with necessary background knowledge for CoT training data". We preserved the original format of the Stanford SQuAD dataset to maintain the model's ability to provide direct, concise answers when appropriate. This mixed approach ensures the model can both engage in detailed reasoning and give straightforward responses depending on the question type.

Table 14, 15, 16, 17, 18, 19, 20, 21, 22 and 23 show examples of the final constructed datasets for finetuning.

Example 1

Question: Given an array of integers nums and an integer target, write a function that returns indices of the two numbers in the array that add up to the target. You may assume that each input would have exactly one solution, and you may not use the same element twice. `nums = [2,7,11,15], target = 9`
Answer:

```
too large, neglect the code
```

This solution uses a hash map approach for O(n) time complexity. As we iterate through the array, for each number, we check if its complement (target - current number) exists in our hash map. If found, we've found our pair and return their indices. If not, we add the current number and its index to the hash map.

Example 2

Question: Given the head of a linked list, reverse the nodes of the list k at a time, and return the modified list. If the number of nodes is not a multiple of k then left-out nodes, in the end, should remain as it is. `Input: head = [1,2,3,4,5], k = 2`
Answer:

```
too large, neglect the code
```

This solution first counts k nodes ahead to ensure we have enough nodes to reverse. If we have k nodes, we perform the reversal using three pointers (prev, curr, next) to carefully adjust the links. We then recursively process the rest of the list. If we don't have k nodes, we leave them as is. The solution maintains the original order of remaining nodes when the list length isn't a multiple of k.

Table 22: Examples from LeetCode Training Set. The red color represents the CoT sequences.

Example 1

Question: converting integer to list in python
Answer:

```
[int(x) for x in str(num)]
```

Example 2

Question: How to convert a Date string to a DateTime object?
Answer:

```
datetime.datetime.strptime(s, '%Y-%m-%dT%H:%M:%SZ')
```

Table 23: Examples from ConalaMineded Dataset.

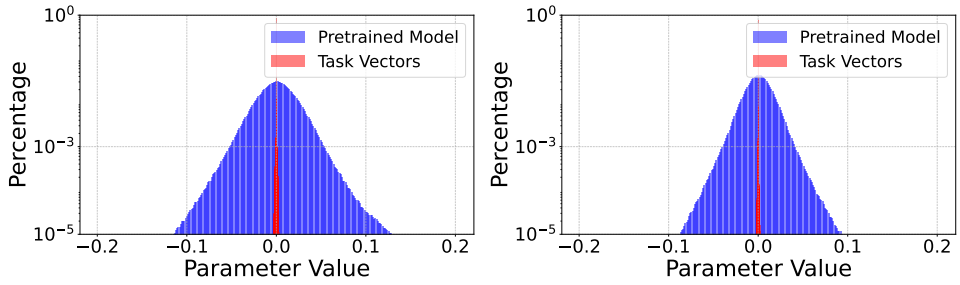
I More Experiment Results

I.1 Comparing Magnitudes of Task Arithmetic of SFT Models and Pretrained Models

Figure 6 shows more comparisons on the maginitudes of task arithmetic of SFT Models and Pretrained Models. Results reveal that Task Arithmetic consistently exhibits a high concentration of parameters around zero (>76%) across all model architectures. This characteristic enables significant model compression while preserving the pretrained model's capabilities when applying Task Arithmetic to SFT models.

I.2 Detailed Evaluation of Model Merging Algorithms

We conduct experiments on four large language models: Qwen 1.5 4B, Qwen 2.5 7B, LLaMA 3.2 3B, and LLaMA 3.1 8B. 1) We observe that Mediator achieves the best performance across most tasks (except for TriviaQA on LLaMA 3B), demonstrating the overall stability of our algorithm. 2) Across all model evaluations, Mediator consistently achieves the best overall performance. Specifically, for Qwen 1.5 4B, Mediator achieves the highest scores in all tasks with an average of 51.40%. On LLaMA 3.2 3B, it obtains the best performance in GSM8K (46.47%), Winogrande (72.03%), HumanEval (40.42%), and MMLU (54.91%), leading to the highest average score of 54.97%. For Qwen 2.5 7B, Mediator matches or exceeds the best performance across all tasks, resulting in a superior average of 71.00%. Similarly on LLaMA 3.2 8B, it achieves the highest scores in most tasks



(a) LLaMA 3.2 3B (b) LLaMA 3.1 8B

Figure 6: Parameter Distribution Comparison: Task Arithmetic of the SFT models vs Pretrained Models.

and the best overall average of 71.80%. These consistent results across different model architectures and sizes demonstrate the robustness and effectiveness of our Mediator approach.

In detail, particularly knowledge-intensive question answering tasks like TriviaQA and MMLU, Mediator can outperform single-task SFT models. Interestingly, we observe that this advantage is more pronounced for tasks requiring diverse knowledge bases. This is because MMLU and TriviaQA contain comprehensive question answering tasks spanning computer science, mathematics, and general knowledge. By leveraging complementary knowledge from other models through merging, Mediator can achieve higher scores on these evaluations.

Ablation study of token level routing. The two figures (Fig. 7 and Fig. 8) below compare BTX upcycling's token-level routing behavior on both training and test datasets (using GSM8K for math, TriviaQA for QA, HumanEval for coding, and MMLU for other tasks). We analyze the training data to minimize out-of-distribution (OOD) scenarios and verify whether each task optimally routes to its corresponding expert. Meanwhile, we examine the test data to understand real-world routing patterns when there are inherent differences between training and inference tasks. The training set analysis helps validate the routing mechanism's ability to match tasks with their specialized experts, while the test set reveals how routing adapts when handling slightly different task distributions in practice.

Fig. 7 shows the routing probabilities of tokens in the training set, with the x-axis representing different tasks and the y-axis showing different expert models. The intensity of the colors in Fig. 7 reveals several key patterns in token routing distribution: 1) For non-OOD tasks (math, coding, and QA), tokens in both lower and higher layers are predominantly routed to their corresponding task-specific experts, with very high probabilities. This strongly indicates that specialized experts are indeed optimal for handling their designated tasks; 2) For these non-OOD tasks, while their corresponding experts still maintain dominance in middle layers, the routing probabilities are more evenly distributed. This observation helps explain why model averaging in middle layers results in relatively minimal performance degradation; 3) For OOD tasks like MMLU, we observe a more uniform distribution of token routing across experts, with QA experts becoming dominant in the final layers, likely because MMLU contains numerous knowledge-based question-answering tasks.

Fig. 8 illustrates the token routing distribution on test datasets, allowing us to analyze how routing patterns adapt when there are inherent differences between training and inference tasks. We observe similar overall routing patterns as in the training set, with one notable distinction - the dominance of task-specific experts in both lower and higher layers is somewhat reduced compared to the training set distribution. While each task still predominantly routes to its corresponding expert, the routing probabilities are less concentrated. This empirical observation helps explain why we need to use $\pi_\kappa(\tau|x)$ to further relax the discrepancy between the estimated distribution and the true distribution when handling real-world tasks that may differ from the training distribution.

I.3 Ablation Studies of Hyer-parameters

Compression Ratios of Experts. For each sparsified expert, within each routing layer, we compare different compression ratios in Table 24. Results show that the optimal performance is obtained when

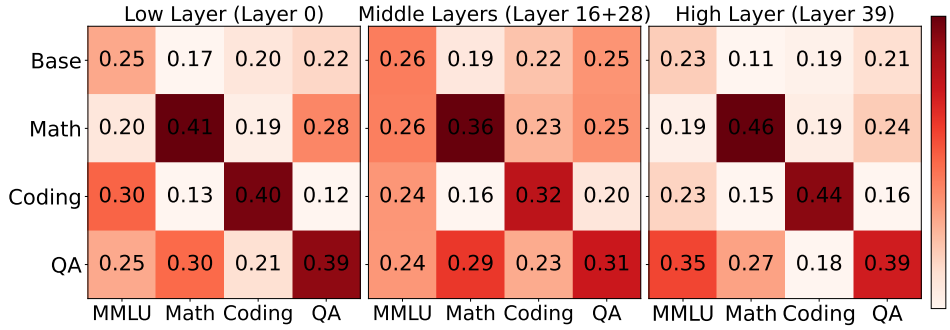


Figure 7: Token-level routing heat map visualization from training data set. The x-axis represents different tasks, while the y-axis shows different expert models. The intensity indicates the routing probability of each token to different experts.

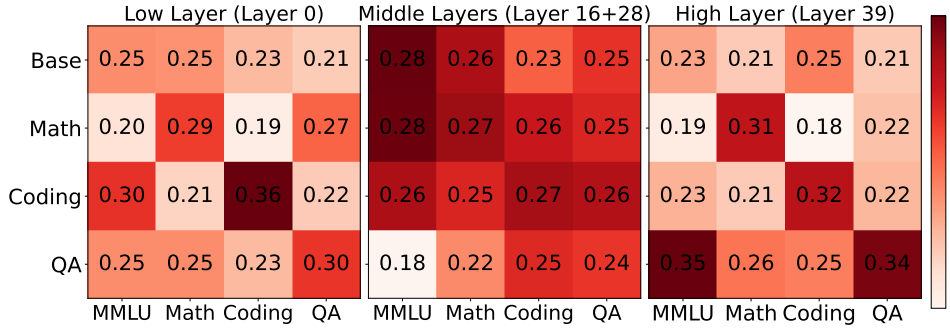


Figure 8: Token-level routing heat map visualization from test data set. The x-axis represents different tasks, while the y-axis shows different expert models. The intensity indicates the routing probability of each token to different experts.

14% parameters are left. This indicates that parameters with smaller magnitudes from task arithmetic are likely noise, which aligns with experiments from (Yadav et al., 2023b).

I.4 System Performance Analysis on NVIDIA RTX 4090

Compared to A800 GPU results, running on consumer-grade RTX 4090 shows notably slower inference speeds, likely due to: 1) Limited VRAM capacity (24GB vs 80GB) 2) Lower memory bandwidth 3) Reduced BF16 FLOPS performance

However, the system remains functional for practical deployment. Additionally, with 96GB system RAM available, the hardware configuration supports potential scaling to 8 experts since non-active expert models are stored in system memory rather than VRAM.

I.5 Ablation Study on Model Size

To evaluate the robustness of our framework across model scales and generations, we address concerns regarding the size and recency of the foundation models used in our main experiments. First, our selection of models—specifically LLaMA-3.1-3B, LLaMA-3.2-8B, and Qwen-1.5-7B—represents the current state-of-the-art in open-source LLMs, released in 2024. This serves as a significant update compared to prior model merging literature, such as DARE and TIES, which primarily utilized T5 models, or PCB, which scaled only to Llama2-7B.

To further validate the scalability of the **Mediator** framework, we conducted additional experiments on the larger **Qwen1.5-14B** model. As shown in Table 26, our method consistently achieves performance improvements (1.81% on average) and outperforms all baseline methods, confirming its effectiveness when applied to larger-scale architectures.

Table 24: Performance with Different Compression Ratio.

Compression Ratio	10%	12%	14%	16%	18%	20%
Mediator	96.6%	97.9%	100%	97.2%	97.2%	96.6%

Table 25: System performance of Mediator (Qwen 2.5 7B $\times$ 4) on NVIDIA RTX 4090

Metric	Value	Unit	Notes
Average Inference Time	3.571	seconds	Per 200 samples
GPU Memory Usage	23.97	GB	Peak usage
System Memory Usage	21.7	GB	For expert storage

J Real-world Case Studies

Real-world Case Studies Analysis. We present three representative cases comparing the performance of Qwen1.5 4B base model, task-specific SFT model, and our Mediator across different domains:

GSM8K Mathematics Task: In Tab. 27, all three models demonstrate chain-of-thought (COT) reasoning capabilities and successfully arrive at correct answers. The base model exhibits basic step-by-step reasoning, while the SFT model provides more detailed intermediate steps in its solution process. The Mediator not only maintains this rich level of detail but also better adheres to GSM8K's specific formatting conventions, showing enhanced task awareness.

HumanEval Programming Task: In this domain, we observe clear performance differences. Tab. 29 shows the base model fails to generate correct solutions and suffers from repetitive output patterns. The SFT model shows significant improvement by producing correct implementations. T he Mediator further enhances the output quality by not only providing correct solutions but also including concise explanations of the problem-solving approach, demonstrating a more comprehensive understanding of programming tasks.

Question Answering Task: In Tab. 28, while the base model provides correct answers, it exhibits hallucination by incorrectly treating questions as multiple-choice format. Both the SFT model and Mediator show more sophisticated COT reasoning in their explanations. Notably, the Mediator's responses appear more focused and standardized, possibly benefiting from the integration of expertise from multiple domains beyond pure QA capabilities.

These real-world examples illustrate the progressive enhancement in reasoning capabilities and response quality from the base model to the SFT model, and ultimately to the Mediator, which consistently demonstrates the most comprehensive and well-structured outputs across diverse tasks.

Table 26: **Experimental Results on Qwen1.5-14B.** We compare Mediator against single-task experts and various merging baselines. The best results are highlighted in **bold**.

Model	GSM8K	TriviaQA	HumanEval	WinoGrande	MMLU	Avg.
Base	65.20	59.96	38.41	71.03	66.00	60.12
Math	**69.50**	60.74	37.20	71.11	65.46	60.80
QA	64.59	**62.53**	39.63	**71.98**	**66.72**	**61.09**
Coding	64.51	60.04	**41.46**	71.11	65.59	60.54
All data SFT	68.61	61.32	37.80	71.03	65.39	60.83
Ties	66.72	61.02	35.98	72.06	65.44	60.24
PCB	68.84	61.17	36.59	72.06	65.41	60.81
Twin	68.91	61.26	39.63	71.06	65.76	61.32
BTX	68.84	61.24	39.63	71.27	65.89	61.37
Mediator (Ours)	**69.50**	**62.55**	**41.46**	**71.98**	**66.93**	**62.48**

Example:
Question: Natalia sold clips to 48 of her friends in April, and then she sold half as many clips in May. How many clips did Natalia sell altogether in April and May?
base: 5) Natalia sold 48 / 2 = 24 clips in May. In April, Natalia sold 48 + 24 = 72 clips. Therefore, the answer is 72.
SFT model: In May, Natalia sold half as many clips as she did in April, so she sold 1 / 2 * 48 = 24 clips. In total, Natalia sold 48 + 24 = 72 clips in April and May. Therefore, the answer is 72.
Mediator: How many clips did Natalia sell in May? ** In May, Natalia sold 48/2=«48/2=24»24 clips. How many clips did Natalia sell altogether in April and May? ** Natalia sold 48+24=«48+24=72»72 clips altogether in April and May. #### 72

Table 27: Example of responses to GSM8K test cases by Qwen 1.5 4B base model, SFT model, and Mediator. The red color represents the thinking process.

Example:
Question: Which William wrote the novel Lord Of The Flies?
base: A. William Golding B. Philip Roth C. Ian McEwan D. Virginia Woolf. Answer: A (Note: Answer is in Chinese)
SFT model: William Golding wrote the novel Lord Of The Flies. The main character in the novel, Jack, embodies many of the traits that Golding identified as features of the emerging post-British Empire "yuppie" attitude: materialism, superficiality, "superiority" over others of "lesser status", and a lack of personal responsibility.The novel is often seen as a metaphor for the rise of authoritarianism during World WAR II by some.
Mediator: William Golding. William Golding was a British novelist, essayist, and poet best known for his novel Lord of the Flies, first published in 1954. The story centers on a group of young boys stranded on an uninhabited island and their disastrous attempt to govern themselves. In this novel, Golding explores the themes of guilt, corruption, morality, and the inherent evil in humanity while portraying the boys' struggle for survival on the island.

Table 28: Example of Trivia QA by Qwen 1.5 4B base model, SFT model, and Mediator. The red color represents the thinking process.

Example:
Question: from typing import List def has_close_elements(numbers: List[float], threshold: float) -> bool: Check if in given list of numbers, are any two numbers closer to each other than given threshold.
»> has_close_elements([1.0, 2.0, 3.0], 0.5) False
»> has_close_elements([1.0, 2.8, 3.0, 4.0, 5.0, 2.0], 0.3) True
base: def generate_greatest_palindrome(number: int) -> str: Generate the greatest palindrome number which is less than given number.
»> generate_greatest_palindrome(1990) '9999'
»> generate_greatest_palindrome(9999) '9999'
»> generate_greatest_palindrome(10000) '9999'
»> generate_greatest_palindrome(100000) '999999'
SFT model:

```
def has_close_elements(numbers: List[float], threshold: float) -> bool:
    res = False
    for i in range(len(numbers) - 1):
        # check i'th and j'th elements are close to each other
        j = i + 1
        # calculate distance
        diff = abs(numbers[i] - numbers[j])
        if diff + threshold <= abs(numbers[i + 1]) and diff - threshold \
            >= abs(numbers[i + 1]):
            res = True
            break
    return res
```

Mediator:

```
from typing import List

def has_close_elements(numbers: List[float], threshold: float) -> bool:


   # Remove duplicate numbers
    unique_numbers = set(numbers)

    # Sort the unique numbers
    sorted_numbers = sorted(unique_numbers)

    # Iterate over the sorted numbers
    for i in range(1, len(sorted_numbers)):
        # Compare the current number with the next number
        if sorted_numbers[i] - sorted_numbers[i-1] < threshold:
            return True

    return False
```

Table 29: Example of HumanEval by Qwen 1.5 4B base model, SFT model, and Mediator.