Investigating Cross-Modal Skill Injection: Scenarios, Methods, and Hyperparameters

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Abstract

Vision-Language Models (VLMs) have demonstrated remarkable proficiency in general multimodal understanding; yet they struggle to efficiently acquire continually evolving domain-specific skills. Conventional approaches to enhancing VLM capabilities, such as Supervised Fine-Tuning (SFT), require extensive dataset curation and substantial computational resources. Model merging has emerged as an efficient alternative that enables the transfer of domain-specific expertise from Large Language Models (LLMs) to VLMs without incurring additional training data requirements or significant computational overhead. Unlike conventional merging of homogeneous LLMs, which aims to integrate independent skills, cross-modal skill injection seeks to elicit emergent combinational capabilities by integrating a domain-expert LLM with a VLM backbone. However, existing research lacks a systematic analysis of the applicability and methodology of cross-modal skill injection. In this study, we investigate cross-modal skill injection across three main aspects: scenarios, methods, and hyperparameters. For scenarios, we find that cross-modal skill injection generally performs well in instruction-following and cross-lingual settings, yet struggles with mathematical reasoning. For methods, we find that classic approaches such as TA and DARE consistently achieve superior performance over alternative merging methods. We also provide a systematic and quantitative analysis of the hyperparameter tuning that these classic methods critically depend on.

1 Introduction

Vision-Language Models (VLMs) have garnered increasing attention for their capacity to jointly process and comprehend visual and textual information (Alayrac et al., 2022; Li et al., 2023b; Liu et al., 2024a). Despite strong general performance, VLMs remain limited in specialized domains such as visual mathematical reasoning and multilingual understanding (Lu et al., 2024a; Zhang et al., 2024a).

Fine-tuning on specialized multimodal datasets faces significant challenges despite being a prevalent strategy to enhance domain-specific capabilities (Guo et al., 2025; Srinivasan et al., 2021). First, fine-tuning VLMs requires substantial computational resources. Although Parameter-Efficient Fine-Tuning (PEFT) methods, such as LoRA and QLoRA (Hu et al., 2022; Dettmers et al., 2023), have effectively mitigated computational costs, acquiring sufficient high-quality training data remains a persistent bottleneck. High-quality vision datasets for specialized tasks are scarce, necessitating labor-intensive construction of balanced datasets that carefully account for factors such as data mixing ratios and domain coverage (Li et al., 2025b).

Model merging offers a promising alternative for integrating expert capabilities into VLMs without extensive dataset construction or additional retraining (Ilharco et al., 2023; Yadav et al., 2023; Yu et al., 2024). However, merging guidelines developed for homogeneous models may not apply to cross-modal skill injection. First, cross-modal skill injection is asymmetric: rather than combining peer models symmetrically, it integrates a domain-expert LLM into a VLM backbone. Second, while homogeneous merging typically aims to aggregate existing expertise, cross-modal skill injection focuses on enabling new cross-modal capabilities to emerge. For example, merging a mathematics expert into a VLM aims to enable visual mathematical reasoning—such as solving geometry problems—that neither model exhibits in isolation.

Despite its potential, cross-modal skill injection remains underexplored. To establish comprehensive guidelines for cross-modal skill injection, we systematically investigate the transfer of expert LLM capabilities to VLMs from three main as-

pects: scenarios, methods, and hyperparameters.

For scenarios, we examine three distinct settings: multilingual understanding, mathematical reasoning, and instruction following. Our extensive experiments across six benchmarks demonstrate that VLMs can successfully inherit specialized capabilities from expert LLMs in multilingual and instruction-following scenarios. However, we observe that transferring mathematical reasoning proves more challenging than transferring linguistic or instruction-following abilities.

For methods, we evaluate three categories of model merging approaches. Our results show that classic merging methods consistently yield superior performance. Notably, certain tuning-free methods also demonstrate competitive performance; for instance, NaN (Si et al., 2025) achieves the second-best overall results.

For hyperparameters, since hyperparameter tuning is essential for classic methods and constitutes their primary practical cost, we conduct a thorough analysis of the hyperparameter landscape. The search space is low-dimensional but exhibits slight multimodality. Our analysis identifies GP-BO (Jones et al., 1998) as the most effective optimizer, while local directional search methods, though yielding competitive results, are more susceptible to entrapment in local maxima.

Our main contributions are as follows:

- **Scenario Analysis.** We systematically investigate three representative scenarios for cross-modal skill injection: language ability, mathematical reasoning, and instruction following, providing empirical insights into which scenarios are more suited for cross-modal skill transfer.

- **Method Comparison.** We conduct a comprehensive evaluation of eight merging methods across three categories (classic, data-aware, and tuning-free) on six benchmarks, offering practical guidelines for method selection based on available resources.

- **Hyperparameter Analysis.** We provide a quantitative analysis of the hyperparameter optimization landscape for classic merging methods, comparing the effectiveness of different optimization strategies.

2 Preliminary

2.1 Model Merging Methods

Model merging is inspired by the concept of task vectors(Ilharco et al., 2023), which suggests that specific abilities are encoded as vectors in parameter space. Formally, the task vector τ is defined as the difference between the parameters of a fine-tuned expert LLM ($\theta_{\text{finetuned}}$) and the base model ($\theta_{\text{base}}$):

$$\tau = \theta_{\text{finetuned}} - \theta_{\text{base}} \tag{1}$$

Task Arithmetic constructs the merged model by adding a linear combination of these task vectors to the base model:

$$\theta_{\text{merged}} = \theta_{\text{base}} + \sum_{i=1}^{n} \lambda_i \tau_i \tag{2}$$

where n represents the number of models being merged, and λ_i denotes the merging coefficient for the i-th task vector.

Classic Merging. This approach of linearly combining task vectors to yield a multi-skilled model is known as Task Arithmetic (TA) (Ilharco et al., 2023). In this paper, we refer to such method and its variants, such as TIES (Yadav et al., 2023) and DARE (Yu et al., 2024), as *classic merging*, characterized by combining **task vectors** (or their variants) with tunable **merging coefficients**. In addition to model coefficients, some variants (Davari and Belilovsky, 2024; Deep et al., 2024; Goddard et al., 2024) introduce a *density* hyperparameter to control the sparsity of task vectors. For instance, TIES-Merging (Yadav et al., 2023) prunes low-magnitude updates and resolves sign conflicts, while DARE (Yu et al., 2024) employs random sparsification followed by rescaling. Since these methods rely on hyperparameter tuning over in-domain validation data, they typically incur higher computational costs compared to vanilla TA.

Recent works have improved upon *classic merging* in two directions.

Data-Aware Merging. This line of work leverages training data from each model's capability domain to refine the merging process. For instance, Fisher Merging weights parameters according to their task-specific importance via empirical Fisher information, while RegMean minimizes layer-wise representation discrepancies through closed-form

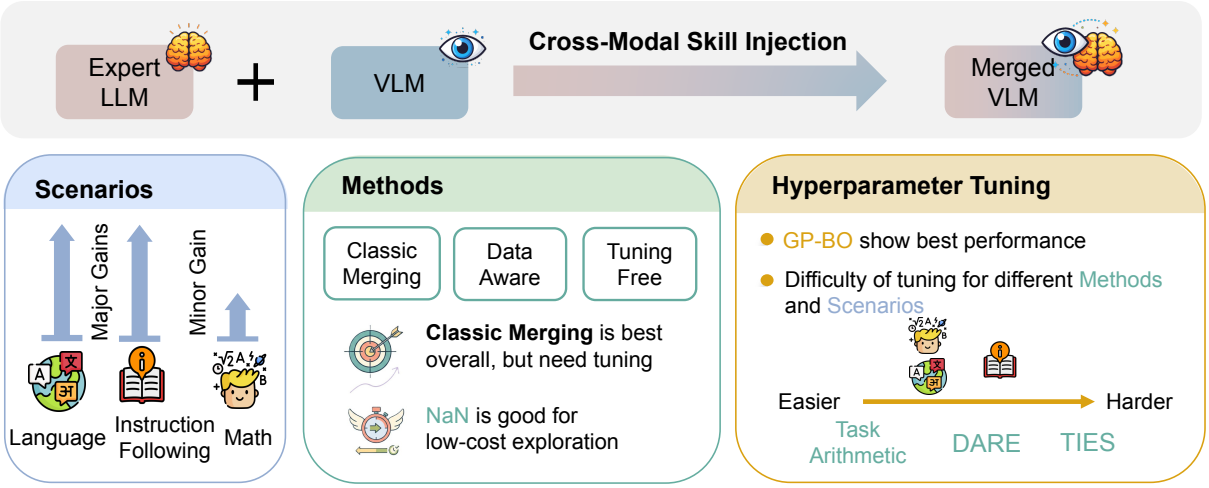

Figure 1: Overview of our work investigating cross-modal skill injection across three dimensions: **scenarios** (language ability, mathematical, instruction-following), **methods** (classic, data-aware, and tuning-free merging), and **hyperparameters**. Our findings reveal that classic methods consistently outperform alternatives, language and instruction-following capabilities transfer more readily than mathematical reasoning, and we further provide quantitative analysis of the hyperparameter optimization landscape.

linear regression solutions. Intuitively, by incorporating auxiliary training data, these approaches exploit richer information and should yield better performance. However, as we will show in Section 3, for cross-modal skill injection, the empirical gains from data-aware methods are often marginal, suggesting that, in cross-modal scenarios, practitioners can safely forgo the overhead of data collection without sacrificing much performance.

Tuning-Free Merging. Instead of exhaustive hyperparameter tuning, these methods estimate optimal coefficients directly from expert parameters under certain assumptions. Representative examples include MetaGPT (Zhou et al., 2024), which provides a closed-form, data-agnostic solution to task arithmetic by leveraging local linearity and approximate task-vector orthogonality; NAN (Si et al., 2025), which estimates per-model coefficients via inverse parameter-norm weighting without any training; and WUDI (Cheng et al., 2025), which suppresses cross-task interference by operating in the task-vector subspace, eliminating the need for rescaling or additional data. These approaches are plug-and-play and particularly attractive when data acquisition is constrained or tuning budgets are limited.

2.2 Cross-Modal Skill Injection

Similar to LLM merging, expert LLMs can be merged into the language encoder backbone of a VLM to transfer specialized capabilities, which we refer to as cross-modal skill injection.

Formally, we define cross-modal skill injection as follows: Given a VLM, denoted as $\mathcal{M}_{vlm} = (\mathcal{E}_v, \mathcal{L}_{base})$, where $\mathcal{E}_v$ is the vision encoder, and $\mathcal{L}_{base}$ is the LLM backbone, our goal is to endow $\mathcal{M}_{vlm}$ with domain-specific expert capabilities by integrating a domain expert LLM $\mathcal{L}_{exp}$, without modifying $\mathcal{E}_v$ or requiring full finetuning of $\mathcal{M}_{vlm}$. Specifically, we aim to construct a merged model

$$\mathcal{M}_{merged} = (\mathcal{E}_v, f(\mathcal{L}_{base}, \mathcal{L}_{exp}))$$

where $f(\cdot)$ denotes a merging algorithm that fuses the parameters of the backbone and expert LLMs.

cross-modal skill injection inherits the core advantages of LLM merging: minimal training overhead, rapid domain specialization, and independence from large-scale multimodal datasets. Though most LLM merging methods are conceptually compatible with cross-modal skill injection, several notable differences remain between the two settings.

Unlike symmetric LLM merging among peer models, cross-modal skill injection typically involves only two models and operates under an inherently asymmetric setting: the VLM provides perceptual grounding, while the expert LLM contributes specialized capabilities or knowledge. Traditional LLM merging combines multiple models with identical architectures and comparable contributions, aiming to preserve diverse capabilities across all participants. In contrast, cross-modal

skill injection integrates a domain-expert LLM into the backbone of a VLM, where the two components serve functionally distinct purposes. This asymmetry implies that methods designed for reconciling conflicts among multiple peer models may be less effective in this context.

Cross-modal skill injection focuses on enabling the emergence of novel cross-modal capabilities that neither model possesses independently. By integrating the complementary strengths of text-only LLMs and VLMs, the merged model may acquire enhanced abilities to jointly reason over visual and textual information in ways that go beyond the original models. However, for specialized visual domains such as medical imaging, legal document analysis, or scientific figure understanding, paired image-text data for validation is often scarce or expensive to collect, imposing tighter constraints on hyperparameter tuning than in typical LLM merging scenarios.

3 Scenario and Methods for Cross-Modal Skill Injection

In this section, we derive practical guidelines regarding which scenarios and merging strategies are more suitable for VLM and LLM merging. Specifically, we focus on three representative visual capability scenarios: language ability, mathematical reasoning ability, and instruction-following ability. These are among the most commonly evaluated and practically relevant abilities in prior work (Chen et al., 2025b; Yang et al., 2025).

Model Settings. We conduct experiments using publicly available models from Hugging Face. Our selection of vision–language models (VLMs) covers a diverse range of architectures, including Idefics2 (Laurencon et al., 2024), LLaVA (with both Mistral and LLaMA backbones) (Liu et al., 2023b,a, 2024b), and Qwen2-VL (Wang et al., 2024). For each experimental scenario, we pair the VLM with a corresponding expert large language model (LLM). See Appendix A for the details of the checkpoints used.

Evaluation Settings. We employ six benchmarks to evaluate the merged VLMs under different scenarios. For visual mathematical reasoning, we use MathVista (math subset) (Lu et al., 2024a) and MathVerse (Zhang et al., 2024c); for language understanding with visual inputs, CMMMU (Chinese) (Zhang et al., 2024a) and JMMMU (Japanese) (Onohara et al., 2025); and for visual instruction following, MIA-Bench (Qian et al., 2025) and WildVision (Lu et al., 2024b). For each benchmark, 20% of the samples are randomly held out for hyperparameter tuning, while the remaining 80% are used exclusively for testing.

To estimate the cost of merging and hyperparameter tuning, we conduct experiments on a single A800 GPU, utilizing the Python package MergeKit (Goddard et al., 2024) for merging and lmms-eval (Zhang et al., 2024b; Li et al., 2024) for evaluation. The total cost is computed by summing the GPU cost and the OpenAI API cost for evaluating the merged models. The reported total duration includes both merging and evaluation time.

Methods Settings. We employ the three categories of merging methods introduced in Section 2.1; further details on hyperparameter settings and calibration data are provided in the Appendix C. (1) *classic merging methods* (Task Arithmetic, DARE, TIES-Merging): We perform grid search over VLM and LLM coefficients in $\{0.1, 0.3, 0.5, 0.7, 0.9\}$; for methods requiring a density parameter, we additionally search over $\{0.2, 0.4, 0.6, 0.8\}$. (2) *Data-aware methods* (Fisher, RegMean): We use 500 calibration samples drawn from corresponding domain-specific datasets; see Appendix C for details. (3) *Data-free methods* (MetaGPT, NaN, WUDI): These methods require neither hyperparameter tuning nor external data.

Finding 1: cross-modal skill injection is more effective for transferring linguistic and instruction-following abilities than for transferring reasoning and mathematical abilities. As shown in Table 1, the most substantial improvements are observed in language and instruction-following benchmarks, with average gains of 3.4 and 28.1 absolute points, respectively. Instruction following is particularly favorable for merging, as such capabilities are largely modality-agnostic, enabling effective transfer to base VLMs. Notably, merging Idefics2-base with an instruction-following LLM expert achieves over 70 on MIA-Bench, surpassing the fine-tuned Idefics2 (56.4).

In contrast, mathematical ability transfer yields considerably smaller and less consistent gains. On the MathVista dataset, no significant overall improvement is observed (see Appendix D); only on the math-specific subset is a modest average improvement of 1.05 absolute points achieved. For

Method	CMMMU	JMMMU	MathVista (math)		MathVerse		MIA-Bench		WildVision		Avg
	Mistral	LLaMA	Mistral	LLaMA	Mistral	LLaMA	Qwen2	Idefics2	Qwen2	Idefics2	
TA	25.0↑2.4	**42.1**↑5.7	26.7↑1.4	29.2↑3.4	17.1↑1.9	15.0↓1.1	**76.1**↑43.1	75.9↑66.1	**50.1**↑34.0	22.8↑19.0	**38.0**
DARE	**28.5**↑5.9	39.0↑2.6	**29.0**↑3.7	30.6↑4.8	16.1↑0.9	**17.0**↑0.9	75.4↑42.4	74.3↑64.5	47.5↑31.4	19.9↑16.1	37.7
TIES	27.4↑4.8	40.9↑4.5	23.7↓1.6	27.1↑1.3	14.5↓0.7	15.3↓0.8	74.7↑41.7	76.3↑66.5	45.1↑29.0	**23.3**↑19.5	36.8
Fisher	25.3↑2.7	36.0↓0.4	22.3↓3.0	**32.4**↑6.6	15.9↑0.7	13.9↓2.2	68.6↑35.6	**78.3**↑68.5	23.1↑7.0	**23.3**↑19.5	33.9
RegMean	28.1↑5.5	40.5↑4.1	27.1↑1.8	26.0↑0.2	**17.9**↑2.7	16.0↓0.1	69.1↑36.1	4.9↓4.9	26.4↑10.3	2.3↓1.5	25.8
WUDI	25.4↑2.8	35.6↓0.8	24.8↓0.5	29.4↑3.6	11.3↓3.9	16.2↑0.1	66.8↑33.8	5.3↓4.5	25.4↑9.3	3.1↓0.7	24.3
MetaGPT	28.1↑5.5	37.1↑0.7	18.4↓6.9	25.3↓0.5	12.3↓2.9	15.4↓0.7	60.6↑27.6	76.1↑66.3	36.3↑20.2	22.9↑19.1	33.3
NaN	26.5↑3.9	40.5↑4.1	23.7↓1.6	29.4↑3.6	17.3↑2.1	**17.0**↑0.9	73.8↑40.8	73.0↑63.2	47.8↑31.7	21.5↑17.7	37.1
Base VLM	22.6	36.4	25.3	25.8	15.2	16.1	33.0	9.8	16.1	3.8	20.4

Table 1: Performance comparison across merging methods, datasets, and models, with average scores computed for each method. Key observations: (1) language and instruction-following abilities show substantial improvements, while mathematical reasoning remains challenging; (2) classic methods (TA, DARE) achieve the best overall performance, and NaN offers a competitive tuning-free alternative. Colored deltas indicate improvement (green) or degradation (red) relative to the base VLM. **Bold**: best; underline: second best.

MathVerse, more than half of the merging configurations proved detrimental to performance. Overall, only DARE demonstrates consistent improvement in mathematical scenarios. More than 40% of the merged models fail to achieve any improvement over the original VLM, with some even proving counterproductive. While some overall improvement is observed in mathematical tasks, it is far less consistent compared to the linguistic and instruction-following scenarios.

Finding 2: Classic merging methods consistently outperform other approaches with superior stability. NaN offers a viable low-cost option for preliminary exploration, though with modest performance trade-offs. Among all merging methods, classic approaches yield the most consistently strong and stable results (Table 1). Task Arithmetic outperforms TIES on average, whereas DARE demonstrates the best consistency, being the only method that yields consistent improvements across all scenarios. These methods do require domain-specific visual-text data and hyperparameter tuning (Table 2), yet this investment consistently translates into superior performance.

For data-aware merging methods, RegMean achieves better results than Fisher while also being more efficient, as it requires only activation information without gradient computation. RegMean even achieves the highest accuracy among all methods on the MathVerse benchmark, though its overall average still falls short of classic merging methods and NaN.

Among tuning-free methods, which require neither additional data nor hyperparameter tuning, NaN stands out as the most effective. While its performance is slightly inferior and less stable compared to classic methods, NaN serves as a practical low-barrier entry point—enabling practitioners to quickly gauge whether model merging is promising for a new scenario before committing to more resource-intensive hyperparameter search. Moreover, NaN is among the most efficient approaches: along with MetaGPT, it is the least time-intensive and consumes only a fraction of WUDI's total computing time while surpassing its accuracy (see Appendix E). This combination of minimal overhead and reasonable performance makes NaN particularly suitable for rapid feasibility assessment in unfamiliar domains.

In summary, classic merging methods remain the gold standard when accuracy and stability are paramount, provided that domain visual data is available and hyperparameter tuning is feasible. For scenarios requiring quick preliminary exploration with minimal overhead, NaN offers a reasonable first-pass solution to assess merging potential before deeper investment. When domain text data is accessible, RegMean is preferable to Fisher, though its results may not match classic methods or NaN despite the additional cost.

4 Analysis of Hyperparameter Optimization Landscape and Strategies

As discussed in Section 3, hyperparameter-tuning merging methods achieve consistently strong results, but they can be time-consuming and resource-

Dataset	Total cost (dollars)	Total Duration
CMMMU	2040.21	29h 36m 17s
JMMMU	1976.88	29h 43m 15s
MathVista	1644.35	24h 13m 26s
MathVerse	3599.98	45h 49m 2s
Miabench	2008.87	19h 14m 30s
Wildvision	8044.11	45h 0m 22s

Table 2: Average cost and duration of hyperparameter tuning for DARE on each dataset using an A800 GPU, highlighting the substantial computational overhead of the optimization process.

Scenario	TA		DARE		TIES	
	S=1	S≈1	S=1	S≈1	S=1	S≈1
CMMMU	0	0	0	0	0	0
JMMMU	3.6	0	3.6	0	0.9	0.9
MVis-L	0	0	0	0	0	0
MVis-M	0	0	2.6	2.6	0	0
MV-L3	5.3	0	7.8	2.6	1.5	0
MV-M	2.7	0	13	0	4.5	4.5
MIA-I2	1.5	1.5	3.3	1.3	0	0
MIA-Q2	1.2	0	0	0	1.9	0
WV-I2	25	0	19	8.1	13	13
WV-Q2	0	0	5.7	0	13	0

Table 3: Relative regret (%) under constrained search spaces. Restricting the coefficient sum S to approximately 1 leads to substantial performance degradation in certain scenarios (e.g., WildVision). S≈1: $S \in [0.8, 1.2]$. Abbreviations—MV: MathVerse, MVis: MathVista, MIA: MIA-Bench, WV: WildVision; L3: LLaMA3, M: Mistral, I2: Idefics2, Q2: Qwen2.

intensive. Therefore, it is essential to provide guidelines for effective hyperparameter tuning.

4.1 Revisiting the Sum-to-One Constraint

Existing approaches often constrain the sum of merging coefficients to 1 (Chen et al., 2025a). However, this constraint is largely intuitive and lacks empirical validation. Our experiments reveal that while the sum-to-one constraint proves effective in most scenarios, it can lead to substantial performance degradation in others.

Let $S := \lambda_{\text{VLM}} + \lambda_{\text{LLM}}$ denote the sum of merging coefficients. To investigate whether restricting the search space around $S = 1$ suffices to identify the optimal hyperparameters, we introduce the notion of *relative regret*. Specifically, we first identify the global optimum over the full coefficient grid obtained in Section 3, then compute the best achievable performance when the search is restricted to $S = 1$ or $S \in [0.8, 1.2]$. The relative regret is defined as the percentage of performance degradation relative to the global optimum caused by the restricted search space.

As shown in Table 3, restricting the search to $S \approx 1$ can be suboptimal. In certain scenarios such as WildVision and MathVerse, the $S = 1$ constraint leads to substantial performance degradation, with relative regret as high as 25%, and relaxing S to $[0.8, 1.2]$ provides only limited mitigation. While most other cases exhibit regret within 5% under the $S = 1$ constraint, and often drop to zero when the search space is relaxed to $S \in [0.8, 1.2]$, the existence of high-regret cases demonstrates the necessity of allowing greater flexibility in the search space.

4.2 Benchmarking Hyperparameter Optimization Algorithms

The demand for comprehensive hyperparameter search is significant, particularly when the optimal merging coefficients do not adhere to the $S = 1$ constraint. Given that the evaluation cost of merged models is substantial, employing a sample-efficient hyperparameter optimization algorithm is crucial to minimize the number of trials. In this section, we evaluate the performance of various hyperparameter optimization algorithms in the context of cross-modal skill injection.

Optimization Algorithms. To ensure a comprehensive evaluation of the optimization landscape, we consider a diverse spectrum of derivative-free algorithms. We include *Random Search* and *Sobol Sequences* (Sobol, 1967), the latter providing low-discrepancy quasi-random coverage, as reference methods. Beyond these, we evaluate *CMA-ES* (Hansen and Ostermeier, 2001), which adapts its sampling covariance during evolution, and *GP-BO* (Jones et al., 1998), which fits a Gaussian process surrogate to guide the search. We also examine **direct-search methods** (Kolda et al., 2003), including *Pattern Search* (Torczon, 1997), a coordinate-descent variant, and *Powell's Method* (Powell, 1964), which proceeds via sequential line searches. Comparing these local direct-search methods against global optimizers (e.g., GP-BO) allows us to probe the presence of multiple local optima in the hyperparameter landscape: a large performance gap between them would indicate that greedy searches are trapped by suboptimal local maxima.

Evaluation Metric. We measure search performance using the *normalized regret* after k evalua-

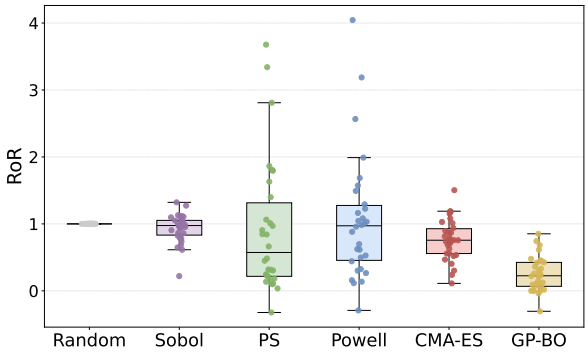

Figure 2: Distribution of regret-over-random (RoR) across optimization algorithms. Values below 1 indicate better performance than random search. GP-BO achieves the lowest median RoR, demonstrating superior sample efficiency. Pattern Search shows competitive mean performance but high variance due to sensitivity to initialization.

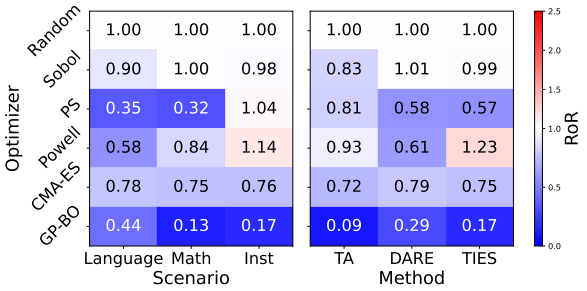

Figure 3: Regret-over-random (RoR) heatmap across optimization algorithms, scenarios and merging methods. Lower values (blue) indicate better performance. Instruction-following tasks show larger gaps between local and global methods, while Task Arithmetic and DARE are more amenable to local optimization than TIES.

tions, defined as

$$r_k = \frac{f_{\max} - f^\star(k)}{f_{\max} - f_{\min}},$$

where $f_{\max}$ and $f_{\min}$ denote the global maximum and minimum, respectively, and $f^\star(k)$ is the best function value observed within the first k evaluations. The normalized regret satisfies $r_k \in [0, 1]$, with $r_k = 0$ indicating that the global optimum has been found.

To compare the effectiveness of different optimization algorithms, we report the *regret-over-random* (RoR), defined as

$$\mathrm{RoR}_k = \frac{r_k^{\text{method}}}{r_k^{\text{random}}},$$

which normalizes each method's regret by that of Random Search. This ratio eliminates the influence of varying optimization difficulty across datasets, allowing for direct comparison: $\mathrm{RoR}_k < 1$ indicates the method outperforms Random Search, while $\mathrm{RoR}_k > 1$ indicates underperformance.

Experimental Setup. We set the evaluation budget k to balance computational cost and search effectiveness: $k = 40$ for Task Arithmetic, which involves two hyperparameters, and $k = 60$ for TIES and DARE, which involve three. All optimizers employ a multi-start strategy, restarting from a new random initial point upon convergence or local budget exhaustion until the total budget is depleted. To ensure fair comparison and reduce variance from random initialization, we conduct 10 independent runs per optimizer with different random seeds and report averaged results.

All hyperparameter searches are conducted on the validation set. The optimization trajectories on the validation and test sets exhibit strong agreement, with normalized regret decreasing consistently on both as the search progresses. (See Appendix F) This close correspondence justifies our use of the validation set as a low-cost proxy, avoiding the prohibitive expense of repeated test-set evaluations while preserving the reliability of our conclusions.

4.2.1 Comparison of Optimization Algorithms

Among all methods evaluated, Gaussian Process Bayesian Optimization (GP-BO) consistently achieves the lowest median regret-over-random (Figure 2), demonstrating its superior efficiency in navigating the hyperparameter space for model merging.

Pattern Search attains competitive mean performance but exhibits high variance across runs. As a local search method that greedily descends along coordinate directions, it is prone to converging to local optima, and its sensitivity to initialization reflects the presence of multiple local optima in the hyperparameter landscape. Nevertheless, its strong average performance suggests that while the objective surface is non-convex, the number of local optima remains limited and their quality is relatively high, rendering the space reasonably tractable despite lacking a unique global optimum.

CMA-ES shows limited effectiveness in our experiments, as it is designed for higher-dimensional problems with larger evaluation budgets. In our

low-dimensional setting with only 2–3 hyperparameters and 40–60 evaluations, CMA-ES cannot complete enough generations for its covariance matrix adaptation to converge, and its population-based sampling is less efficient than the sequential, model-guided acquisition of GP-BO. Powell's method, another gradient-free local optimizer, performs similarly to Pattern Search but with slightly worse results.

4.2.2 Optimization Landscape Across Tasks and Merging Methods

We analyze how both the choice of merging method and the target task affect optimization difficulty (Figure 3).

Across Task Domains. Instruction-following tasks are harder to optimize with local methods than mathematical and language tasks. For mathematical and language tasks, local methods (Pattern Search, Powell) achieve performance comparable to global optimizers (GP-BO, CMA-ES). In contrast, for instruction-following tasks, local methods suffer significant degradation while global methods remain unaffected, suggesting the presence of local optima that trap greedy searches.

Across Merging Methods. Among the three merging methods, Task Arithmetic is the easiest to optimize, followed by DARE, with TIES being slightly more challenging. Task Arithmetic benefits from a two-dimensional search space that requires fewer optimization rounds, making it straightforward to optimize in absolute terms, despite some degradation observed with local methods. DARE, although involving three hyperparameters, exhibits a smooth optimization landscape where local methods still achieve competitive performance. TIES presents somewhat more difficulty, as Powell's method suffers notable performance degradation.

5 Related Work

VLM Domain Adaptation While supervised fine-tuning (SFT) can adapt VLMs to specific domains such as medicine and mathematics (Li et al., 2023a; Shi et al., 2024), it remains resource-intensive and time-consuming. Parameter-efficient fine-tuning (PEFT) offers an economical alternative by training only a small subset of parameters—such as adapters, LoRA, or prompt tuning—while keeping pretrained weights frozen (Hu et al., 2022; Dettmers et al., 2023; Sung et al., 2022). However, PEFT still requires substantial curated image–text pairs, which can be expensive to obtain or scarce in specialized domains. In contrast, cross-modal skill injection (discussed in this paper) offers a promising alternative that efficiently transfers specialized capabilities without requiring additional vision data or incurring extra training overhead.

VLM Merging With the growing prominence of VLMs, model merging has been extended from purely language-based settings to multimodal contexts. Most existing work focuses on VLM-to-VLM merging, whether under homogeneous or heterogeneous backbones, exploring techniques such as uncertainty-guided selection, module-level recipes, fine-grained parameter splicing, and cross-architecture alignment (Qu et al., 2025; Zhu et al., 2025; Dai et al., 2025; Du et al., 2025).

More closely related to our work is the VLM-LLM merging paradigm, where a domain-specialized LLM is merged into a VLM backbone to induce cross-modal capabilities. Chen et al. (2025a) inject reasoning abilities into VLMs and investigate how perception and reasoning are distributed across layers. Anonymous (2025) integrate a code-specialized LLM with a VLM to enable multimodal code generation. Li et al. (2025a) merge text-based reward models into VLMs to construct vision-language reward models that preserve the original preferences.

However, these prior efforts remain task-specific (targeting reasoning, code, or reward modeling) and do not systematically examine when cross-modal skill injection succeeds, which merging methods are most effective, or how sensitive performance is to hyperparameter choices. In contrast, we present a comprehensive study spanning diverse scenarios, merging methods, and hyperparameter configurations.

6 Conclusion

We systematically investigate cross-modal skill injection for transferring expert LLM capabilities to VLMs. Our experiments reveal that language and instruction-following abilities transfer effectively, while mathematical reasoning remains challenging. Among merging methods, classic merging (i.e., TA, DARE) achieves the best performance, and NaN offers low-cost tuning-free exploration. GP-BO proves most effective for hyperparameter optimization. Our findings provide practical guidelines for efficient cross-modal model merging.

Limitations

Due to computational resource constraints, our study focuses exclusively on visual-language modalities and does not extend to other modalities such as audio or video. Additionally, our experiments are conducted on 7B-8B parameter models; scaling behaviors on larger architectures remain to be explored. We leave the investigation of cross-modal skill injection across a broader range of modalities and model sizes to future work.

Risks and Ethical Considerations

This work is primarily methodological and does not involve user data or deployment in high-stakes decision-making. We do not identify significant direct risks. We encourage future work to assess downstream fairness, privacy, and safety impacts in application-specific settings.

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Appendix

A The models used in experiments

Table 4 summarizes the models used in our experiments across different scenarios. For each scenario, we pair a VLM with a domain-expert LLM that shares the same base architecture. Specifically, for language understanding tasks, we select Chinese (Mistral-7B-v0.3-Chinese-Chat) and Japanese (Llama-3-ELYZA-JP-8B). For mathematical reasoning, we use the DART-Math series, which are LLaMA and Mistral models fine-tuned on mathematical problem-solving data. For instruction following, we pair Qwen2-VL with Qwen2-Instruct, and Idefics2-base with Mistral-7B-Instruct. All models are publicly available on Hugging Face.

B Hyperparameters Used

Table 5 details the hyperparameter configurations in Section 3 for each merging method. Classic merging methods (Task Arithmetic, DARE, TIES) require tuning merging coefficients for both the VLM and expert LLM components. We perform grid search over coefficient values in $\{0.1, 0.3, 0.5, 0.7, 0.9\}$. For DARE and TIES, which incorporate sparsification, we additionally search over density values in $\{0.2, 0.4, 0.6, 0.8\}$. This results in 25 configurations for Task Arithmetic and 100 configurations for DARE and TIES.

Data-aware methods (Fisher and RegMean) and tuning-free methods (WUDI, MetaGPT, NaN) do not require hyperparameter search, as they either derive merging weights from data statistics or compute them directly from model parameters.

C Calibration Data for Data-Aware Methods

For data-aware merging methods (Fisher and RegMean), we use 500 calibration samples randomly drawn from the corresponding dataset (i.e., for merging between base VLMs and math expert LLMs, we calibrate the VLM on a vision dataset and the math expert LLM on a mathematical reasoning dataset, respectively). The specific data sources for each scenario are as follows (all datasets can be downloaded from HuggingFace):

- **Vision Perception:** `liuhaotian/LLaVA-Instruct-150K`, a large-scale visual instruction tuning dataset. (Liu et al., 2023b,a, 2024b)
- **Language (Chinese):** `hfl/alpaca_zh_51k`, a Chinese instruction-following dataset translated and adapted from the original Alpaca dataset. (Cui et al., 2024)
- **Language (Japanese):** `fujiki/japanese_alpaca_data`, a Japanese version of the Alpaca dataset for instruction tuning. (fujiki, 2023)
- **Mathematical Reasoning:** `qwedsacf/competition_math`, a subset of challenging mathematical problems requiring multi-step reasoning, combined with `openai/gsm8k`. We mix the two datasets in a 50/50 ratio and shuffle the samples. (Lightman et al., 2023; Cobbe et al., 2021)
- **Instruction Following:** `databricks/databricks-dolly-15k`, a high-quality instruction following dataset created by Databricks. (Conover et al., 2023)

D Full Results on MathVista

Table 6 presents the complete results on the MathVista benchmark, including both the full dataset and the math-specific subset. While the math-specific subset shows modest improvements after merging, the full dataset results are less conclusive, with several merging configurations yielding negligible or even negative gains. This discrepancy arises because the full MathVista benchmark includes questions that rely more heavily on visual perception than mathematical reasoning, where transferring mathematical expertise from LLMs provides limited benefit.

E Efficiency Comparison of Merging Methods

Table 7 compares the computational efficiency of different merging methods in terms of merging time. Note that the time shown is only a single merging pass. In practice, tuning-free methods (NaN, MetaGPT, WUDI) require only a single merging and evaluation pass, while classic merging methods require multiple iterations.

Among tuning-free methods, NaN and MetaGPT are the most efficient, completing the entire merging process in under 5 minutes. In contrast, WUDI requires approximately 16 minutes due to its subspace computation overhead. Despite this additional cost, WUDI's accuracy remains inferior to NaN, making NaN the preferred choice for rapid feasibility assessment.

Scenario	Expert LLM	VLM
Language	shenzhi-wang/Mistral-7B-v0.3-Chinese-Chat elyza/Llama-3-ELYZA-JP-8B	llava-hf/llava-v1.6-mistral-7b-hf lmms-lab/llama3-llava-next-8b
Math	hkust-nlp/dart-math-llama3-8b-prop2diff hkust-nlp/dart-math-mistral-7b-prop2diff	lmms-lab/llama3-llava-next-8b llava-hf/llava-v1.6-mistral-7b-hf
Instruction Following	Qwen/Qwen2-7B-Instruct mistralai/Mistral-7B-Instruct-v0.1	Qwen/Qwen2-VL-7B HuggingFaceM4/idefics2-8b-base

Table 4: Expert LLMs and VLMs used in our experiments across different scenarios. Each VLM is paired with a domain-expert LLM that shares the same base architecture.

Category	Algorithm	Hyperparameters
Classic merging	Task Arithmetic	`vl_weight` $\in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ `exp_weight` $\in \{0.1, 0.3, 0.5, 0.7, 0.9\}$
	DARE	`vl_weight` $\in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ `exp_weight` $\in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ `density` $\in \{0.2, 0.4, 0.6, 0.8\}$
	TIES	`vl_weight` $\in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ `exp_weight` $\in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ `density` $\in \{0.2, 0.4, 0.6, 0.8\}$
Data-aware	Fisher Merging	n/a
	RegMean	n/a
Tuning-free	WUDI	n/a
	MetaGPT	n/a
	NaN	n/a

Table 5: Overview of merging algorithms and their hyperparameter search spaces. Classic merging methods require tuning merging coefficients, while data-aware and tuning-free methods operate without hyperparameter search.

Method	Overall	General	Math
TA	34.75	44.38	26.67
DARE	**36.12**	**48.22**	25.98
TIES	32.25	41.10	24.83
Fisher	29.88	38.90	22.30
RegMean	30.88	35.34	**27.13**
WUDI	30.38	36.99	24.83
MetaGPT	20.88	23.84	18.39
NaN	29.62	36.71	23.68
Base VLM	36.00	48.77	25.29

Table 6: Performance on MathVista across different subsets. Best results among merging methods are in **bold**.

Method	Merge Time
Classic	
TA	3 min
DARE	3 min
TIES	3 min
Data-aware	
Fisher	101 min
RegMean	48 min
Tuning-free	
WUDI	16 min
MetaGPT	3 min
NaN	3 min

Table 7: Merge time per configuration on a single A800 GPU for 7B-parameter models (LLaVA and Mistral-Chinese). For classic models, we use MergeKit (Goddard et al., 2024), for other methods, we use our own implementation. Note that actual merge times may vary depending on implementation details and, for data-aware methods, the size of the calibration dataset.

F Validation-Test Consistency Analysis

To validate the reliability of using validation sets for hyperparameter optimization, we analyze the correlation between optimization trajectories on the validation and test sets (based on the grid described in Appendix B). Figure 4 illustrates the normalized regret curves for DARE across CMMMU dataset.

The optimization trajectories exhibit strong agreement between validation and test sets across all scenarios. As the number of evaluations increases, normalized regret decreases consistently on both sets, with the validation set serving as a faithful proxy for test performance.

This close correspondence justifies our experimental design: by conducting hyperparameter search exclusively on the 20% validation split, we avoid the prohibitive expense of repeated test-set evaluations while maintaining the reliability of our conclusions.

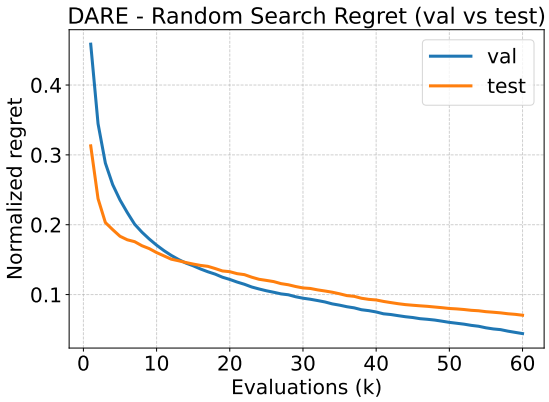

Figure 4: Normalized regret curves for validation and test sets across hyperparameter configurations. The closely aligned trajectories indicate that validation-based optimization effectively generalizes to unseen test data.

G Surrogate Model Fidelity Analysis

Conducting a comprehensive Hyperparameter Optimization (HPO) benchmark across multiple algorithms (e.g., repeating each optimizer 50 times to ensure statistical significance and searching across all datasets for every merging method) is computationally prohibitive and incurs substantial API costs if metrics are evaluated directly for every trial. To address this challenge, we employ a surrogate model based on Radial Basis Function (RBF) interpolation to approximate the hyperparameter landscape. This surrogate serves as a continuous, query-efficient proxy for the resource-intensive evaluation process.

To validate the fidelity of this approximation, we performed a Leave-One-Out Cross-Validation (LOOCV) experiment. For each dataset and method, we randomly withheld one sample point from the interior of the hyperparameter grid (excluding boundary points), fitted the RBF model on the remaining points, and calculated the prediction error for the withheld point. This process was repeated 20 times with different random seeds. We report the Root Mean Square Error (RMSE) normalized by the range of the metric values (RMSE %).

According to Table 8, for the majority of scenarios (e.g., Miabench and Wildvision), the RMSE is low ($< 10\%$), indicating that the surrogate accurately captures the nuances of the merging land-

scape.

In cases where RMSE is higher (10–20%), the surrogate essentially acts as a low-pass filter. The "real" landscape of model merging can exhibit high-frequency noise or sharp local fluctuations that may be artifacts of the evaluation set. The RBF smooths these out while preserving the global convexity and major trends (e.g., the location of the optimal basin).

This trade-off is reasonable for our HPO study: we aim to evaluate an optimizer's ability to find the global optimum based on the landscape's macro-structure, rather than its sensitivity to micro-level noise. Therefore, the surrogate provides a reliable environment for comparing the relative performance of different search algorithms.

Dataset	**DARE**	**TA**	**TIES**
CMMMU	9.27	7.77	15.99
JMMMU	6.96	18.79	8.72
MV-L3	17.42	14.75	9.24
MV-M	9.55	17.53	14.06
MVis-L	10.25	20.35	11.36
MVis-M	11.15	16.69	11.91
MIA-I2	4.58	5.63	7.65
MIA-Q2	4.60	11.37	4.45
WV-I2	7.62	11.47	12.22
WV-Q2	8.26	13.16	4.58

Table 8: Interpolation RMSE (%) for the surrogate model, averaged over 20 runs using a leave-one-out protocol. DARE refers to DARE-Linear. Lower values indicate higher fidelity. Even higher values ($\sim$15%) are acceptable as they reflect a smoothing of local noise while preserving global landscape structure. Abbreviations—MV: MathVerse, MVis: MathVista, MIA: MIA-Bench, WV: WildVision; L3: LLaMA3, M: Mistral, L: LLaMA, I2: Idefics2, Q2: Qwen2.