Resolving the Alignment-Calibration Trade-off: A Pareto-Superior Frontier via Model Merging

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Abstract

The "alignment tax" of post-training is typically framed as a drop in task accuracy. We show it also involves a severe loss of calibration, making models overconfident, less reliable, and model outputs less diverse. We show that this trade-off can be navigated effectively via a simple post-hoc intervention: interpolating between a model's weights before and after alignment. Crucially, this is not a strict trade-off. We find that the process consistently reveals Pareto-optimal interpolations—models that improve accuracy beyond both parents while substantially recovering the calibration lost during alignment. Our work demonstrates that simple model merging provides a computationally efficient method for mitigating the full scope of the alignment tax, yielding models that are more capable and more reliable.

1 Introduction

Post-training is a double-edged sword. While it makes Large Language Models (LLMs) more helpful and safe, it also imposes a well-documented "alignment tax" by degrading performance on some benchmarks (Ouyang et al., 2022). This tax, however, is often viewed narrowly through the lens of accuracy metrics. We argue this perspective overlooks a concurrent and equally critical problem: a severe degradation of model calibration. Alignment techniques are known to induce mode collapse leading to overconfident, low-diversity outputs that signal a loss of the model's ability to represent uncertainty and produce diverse outputs (Achiam et al., 2023; Kirk et al., 2024; Xiong et al., 2024; Wu et al., 2025a), even though being calibrated is key to user trust and actual usability of the model (Xiong et al., 2024; Steyvers et al., 2025).

This paper connects these two phenomena. We propose a more holistic view of the alignment tax, framing it not just as a drop in accuracy, but as a broader degradation of model quality that encompasses both performance and calibration. By considering these issues in unison, we can devise more effective solutions.

We show that post-hoc model merging is a simple, powerful, and computationally cheap remedy for this expanded alignment tax. By blending a well-calibrated pre-trained (PT) model with its aligned instruction-tuned (IT)[1] counterpart, we can navigate the trade-off between alignment and calibration. Our central discovery is that this is not a necessarily zero-sum game: we consistently identify "sweet spot" merges that **Pareto-dominate both parent models**, simultaneously improving accuracy while restoring calibration. Our work provides a practical path toward mitigating the alignment tax in its entirety, leading to models that are more capable, reliable, and diverse.

2 Related Work

Mitigating Alignment Tax A growing body of work seeks to mitigate the alignment tax (Lu et al., 2024; Fu et al., 2024; Lin et al., 2024; Li et al., 2025), proposing novel regularization schemes or data curation techniques. However, these studies almost universally diagnose and address the tax through the lens of task performance and accuracy. They do not consider the concurrent degradation of calibration or output diversity—dimensions which are no less critical than accuracy for trustworthy AI, especially as models become increasingly capable. Our work introduces these critical dimensions into the analysis of the alignment tax.

Model Merging Merging has been shown to be very effective at combining the capabilities of multiple specialized fine-tunes while largely retaining the constituent model's strengths (Utans, 1996;

[1] We use the term instruction tuning to refer to any alignment related post-training, including by not limited to the narrowly defined instruction tuning

Wortsman et al., 2022; Ilharco et al., 2023). While the vast majority of merging research focuses on merging different fine-tunes, some prior work aims to merge pre-trained and instruction-tuned models to enhance performance on specialized tasks (Yu et al., 2024a; Wu et al., 2025b) or treating skills like instruction-following as transferable modules (Cao et al., 2025); we discuss these strands of research in detail in Appendix D. In contrast, our goal is mitigating the alignment tax to restore the model's fundamental calibration.

3 Experimental Setup

We consider the Gemma-3 (Team et al., 2025a) and Qwen2.5 (Team et al., 2025b) model families, analyzing both their pre-trained (PT) base versions and officially released instruction-tuned (IT) counterparts. To explore the continuous space between a base model and its aligned version, we employ model merging to generate a series of interpolated models. We combine the weights of the PT model (θ_{PT}) and IT model (θ_{IT}) using a coefficient $\lambda \in [0, 1]$, where $\lambda = 0$ recovers the pure PT model and $\lambda = 1$ yields the pure IT model. Our primary results use Spherical Linear Interpolation (SLERP) (Shoemake, 1985), with linear interpolation and DARE-TIES (Wortsman et al., 2022; Yu et al., 2024b) used to confirm robustness. All merging operations are performed using MergeKit (Goddard et al., 2024). Crucially, this is a post-hoc procedure that requires no additional training or gradient-based optimization and can be done without GPUs.

We evaluate models along two axes: **task performance**, measured by accuracy on a suite of challenging benchmarks (MMLU-Pro, GPQA, BBH, MATH, and IFEval), and **calibration**, measured by Expected Calibration Error (ECE; Naeini et al., 2015; Guo et al., 2017). This defines our *alignment-calibration frontier*. All evaluations are conducted using the LM Evaluation Harness (Gao et al., 2021). We continue our discussion of related work in Appendix A. Our code and data will be made publicly available.

4 Results and Analysis

The Calibration Cost of Instruction Tuning. While instruction tuning is a cornerstone of modern LLM development, it is not a panacea. We observe a consistent and significant trade-off between a model's capabilities and its calibration. Table 1 quantifies this effect on the MMLU-Pro benchmark across a diverse set of models. The results reveal two patterns. First, accuracy on benchmarks like MMLU-Pro yields mixed results, with some models improving while others degrade—a known facet of the alignment tax. Second, calibration is universally degraded. ECE values consistently increase by an order of magnitude, signifying a severe rise in model overconfidence that undermines reliability. This "calibration cost" appears to be an inherent side effect of current instruction tuning methods. We see similar trends in the other datasets (Table 2).

Model	Base		Instruct	
	Acc. (%)	ECE ↓	Acc. (%)	ECE ↓
Gemma-3-1B	11.2	0.07	14.2	0.66
Gemma-3-4B	27.9	0.02	29.8	0.64
Gemma-3-12B	42.4	0.02	39.8	0.53
Gemma-3-27B	49.4	0.04	47.8	0.48
Qwen2.5-1.5B	28.7	0.06	28.1	0.33
Qwen2.5-3B	32.1	0.04	32.8	0.47
Qwen2.5-7B	43.6	0.06	43.1	0.45

Table 1: The Calibration Cost of Instruction Tuning on MMLU-Pro. Accuracy sees mixed results, while calibration is universally degraded.

Navigating the Frontier with Model Merging. Given this stark trade-off, we investigate model merging as a principled method to navigate the space between a base model's high calibration and an instruction-tuned model's alignment. Rather than treating the base and instruct models as discrete endpoints, merging allows us to trace the continuous frontier between them by varying a merge coefficient, λ. We found $\lambda > 1$ to catastrophically degrade performance (Appendix E) so we constrain $\lambda \in [0, 1]$.

Figure 1 illustrates this process for several models. The left panel visualizes the "cost of alignment." As the weight of the instruct model (λ) increases, alignment improves, but at a direct cost to calibration. This confirms that merging provides fine-grained control over this fundamental trade-off. The right panel reveals that model merging could create a Pareto-superior capability frontier: The path traced by the merged models (solid lines) strictly dominates the naïve linear interpolation between the base and instruct models (dotted lines). Crucially, this process uncovers an optimal merge coefficient (λ^*, marked by a star) that yields a model with higher accuracy than either of its par-

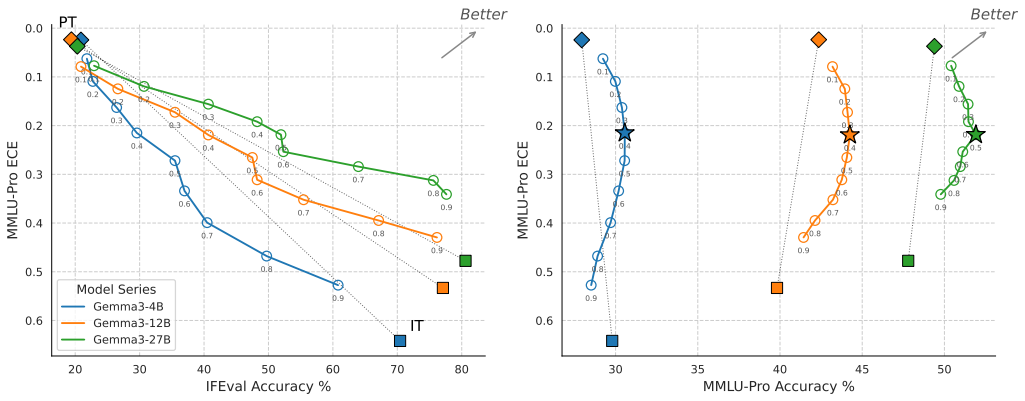

Figure 1: The alignment-calibration frontier for Gemma-3 models. (**Left**) IFEval Accuracy vs. MMLU-Pro ECE. (**Right**) MMLU-Pro Accuracy vs. ECE. Solid lines trace the performance of the PT and IT merges.

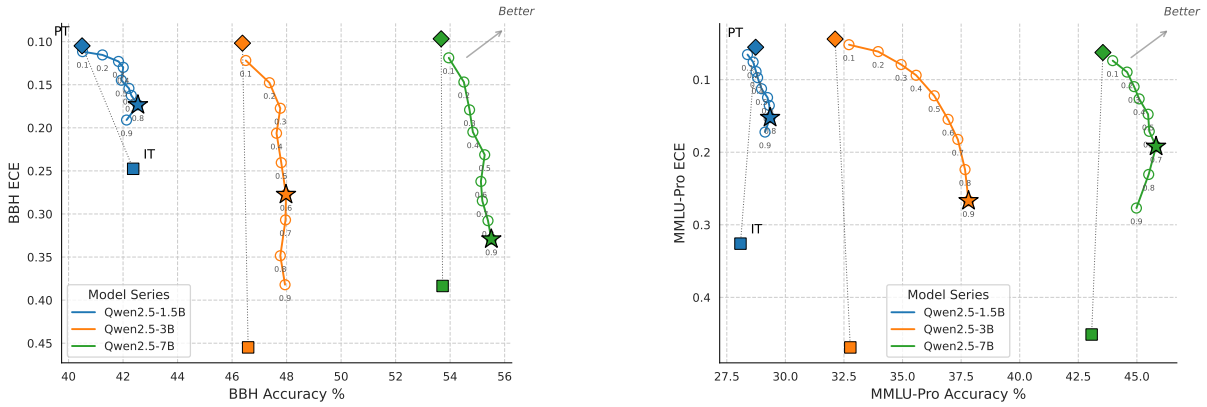

Figure 2: Performance vs. calibration for the Qwen2.5 model series on (**Left**) BBH and (**Right**) MMLU-Pro.

ents, while simultaneously recovering a substantial portion of the calibration lost during instruction tuning.

General Trend Across Models, Datasets and Merge Methods. To demonstrate the generality of our findings, we present the model merging analysis on the Qwen2.5 model series on MMLU-Pro and BBH. As illustrated in Figure 2, the results are similar. For both benchmarks, model merging creates a Pareto-superior frontier, revealing an optimal "sweet spot" that improves upon both the base and instruction-tuned models in accuracy and calibration simultaneously. We additionally show the results on other datasets across model families,sizes and merging methods in Table 2.

We further investigate whether this phenomenon is robust across merging algorithms. Figure 6 extends the analysis by comparing three popular techniques—Linear, SLERP, and DARE-TIES (density 0.9) — on the Gemma-3-12B model. The three methods have very similar trend - each method traces a distinct trajectory, yet all three consistently create a frontier that dominates the naïve linear trade-off between the PT and IT parents.

Merging Becomes More Effective and Robust at Scale. Beyond improving individual model performance, we find that the benefits and robustness of merging increase dramatically with model scale. Figure 3 illustrates this across the Gemma3 family on the MMLU-Pro benchmark. The peak accuracy gain from merging over the instruction-tuned parent grows substantially with model size (Panel a); while the gain is marginal for smaller models, it exceeds 4 percentage points for the 12B and 27B models. Furthermore, the process of finding an optimal merge becomes more robust. The performance landscape for larger models is a smooth, concave curve, indicating that performance is not highly sensitive to the exact merge coefficient (Panel b). In contrast, smaller models can exhibit more volatile behavior, making the choice of λ more critical. Finally, the optimal merge strategy becomes more predictable at scale (Panel c). The optimal coefficient (λ^*) for tasks like MMLU-Pro and GPQA

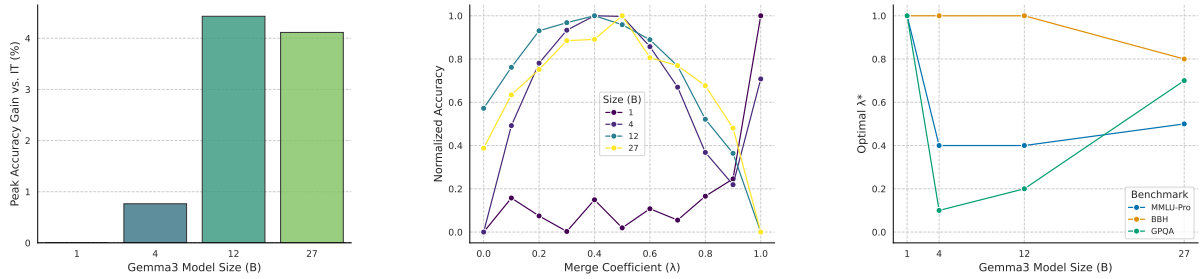

Figure 3: Scaling trends for model merging with the Gemma3 family. (a) Peak accuracy gain vs. model size. (b) Normalized accuracy vs. merge coefficient (λ). (c) Optimal merge coefficient (λ^*) vs. model size.

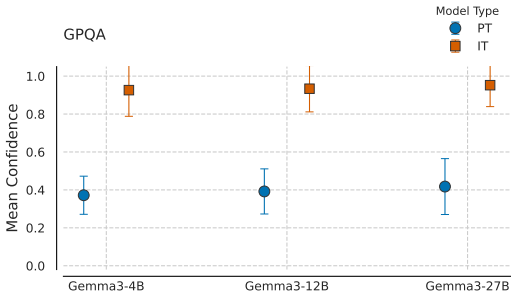

Figure 4: Mean prediction confidence of PT and IT Gemma3 models of varying sizes on GPQA.

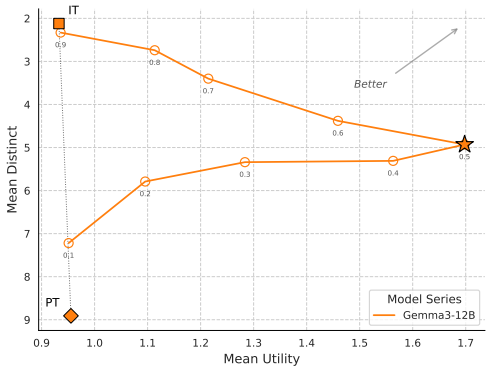

Figure 5: The trade-off between generation utility and distinctness on NoveltyBench for Gemma3-12B merges. The path traces merges from the PT to the IT parent.

converges towards a stable value (around 0.4-0.5).

Alignment Induces Calibration Error via Confidence Inflation. To understand the root cause of this calibration degradation, we investigate the underlying changes in model predictions. While accuracy on knowledge-intensive tasks often changes only marginally after instruction tuning (Table 1), we observe a dramatic shift in model confidence. As illustrated for the challenging GPQA benchmark in Figure 4, the mean prediction confidence of instruction-tuned models surges from around 40% to over 90%. This sharp inflation of confidence, without a commensurate improvement in accuracy, is the direct driver of the observed catastrophic miscalibration.

Restoring Calibration via Merging Improves Generative Diversity and Fidelity. The benefits of our merging approach extend beyond discriminative tasks. On NoveltyBench for generative diversity (Figure 5), merging again reveals a Pareto-superior frontier. It resolves the trade-off between the over-confident IT model's low diversity (mode collapse) and the PT model's diffuse outputs, yielding a "sweet spot" model with both high utility and creative diversity. This trend holds on SimBench for distributional prediction, where the optimal merged model (score: 20.4) substantially outperforms both PT (7.7) and IT (18.2) parents. These findings demonstrate that restoring calibration unlocks tangible performance improvements across diverse applications.

5 Conclusion

We demonstrate that the "alignment tax" extends beyond accuracy degradation to a severe loss of model calibration. By framing this as a fundamental trade-off, we show that simple model merging is a computationally cheap and highly effective method for navigating the alignment-calibration frontier. Our central finding is that this is not a zero-sum game: we consistently identify merged "sweet spot" models that Pareto-dominate their parents, simultaneously improving task performance (up to >4 percentage points accuracy) while partially restoring calibration. We have further shown that these improvements scale favorably with model size, and are due to instructing-tuning causing over-confident predictions. This work provides a practical path toward developing LLMs that are both more capable and more reliable.

Limitations

A key prerequisite for our approach is full access to the model weights. Consequently, our findings are most directly relevant to the open-source ecosystem, as the merging techniques we explore cannot be applied to proprietary, closed-source models that are accessible only through APIs.

Furthermore, our work focuses on demonstrating the alignment-calibration trade-off and its navigability using simple, computationally inexpensive merging techniques like linear interpolation and SLERP. We did not perform an exhaustive hyperparameter search for more complex methods (e.g., varying densities in DARE-TIES) nor did we explore more sophisticated merging strategies. For instance, hierarchical merging, where different merge coefficients are applied to different layers or modules, could offer finer-grained control over the trade-off and potentially unlock even better performance.

However, the primary goal of this work was to establish the existence of a Pareto-superior frontier using the most straightforward methods possible. The remarkable effectiveness of these simple approaches underscores the fundamental nature of our findings and highlights these more complex techniques as promising and important avenues for future research.

Ethical Considerations

The primary goal of this research is to improve the reliability of LLMs by restoring the calibration lost during alignment, leading to more trustworthy systems. A well-calibrated model is less likely to be confidently wrong, which is a positive contribution to AI safety.

However, merging an instruction-tuned (IT) model with its base pre-trained (PT) counterpart inherently re-introduces weights from a model that has not undergone full safety fine-tuning. This process could potentially dilute or compromise the safety guardrails, such as refusal to generate harmful content, that were instilled during the alignment process.

Our experiments are designed to illustrate the fundamental trade-off between alignment and calibration, not to prescribe a universally safe deployment strategy. We strongly caution practitioners that applying this technique requires careful evaluation. Any "sweet spot" model identified through merging must not only be assessed for accuracy and calibration but must also undergo rigorous and comprehensive safety testing to ensure it does not regress on critical safety benchmarks. The ultimate goal is to find a balance that enhances reliability without undermining the essential safety alignment of the model.

AI assistants were used for coding assistance and for copy-editing the paper.

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A Task Description and Implementation Details

We run all model inference in BF16. We adopt the standard configurations of the Open LLM Leaderboard (Fourrier et al., 2024) for few-shot counts and prompting, but do not perform accuracy normalization, as raw accuracy is required for calibration calculations.

MMLU-Pro (Wang et al., 2024) An enhanced version of MMLU, MMLU-Pro increases difficulty by incorporating more reasoning-focused questions and expanding the choice set from four to ten, significantly reducing the chance of correct guesses. It spans 14 diverse domains, offering a more robust and discriminative evaluation of language understanding. We measure accuracy using a 5-shot setup.

GPQA (Rein et al., 2024) GPQA is a graduate-level, "Google-proof" question-answering benchmark with questions authored by domain experts in biology, physics, and chemistry. It is designed to be extremely difficult for non-experts to solve, even with web access, providing a rigorous test of advanced reasoning. We measure accuracy using a 0-shot setup.

Big-Bench Hard (BBH) (Suzgun et al., 2023) A curated subset of 23 challenging tasks from the BIG-Bench suite where prior models performed below the average human-rater baseline. BBH focuses on tasks requiring complex, multi-step reasoning, such as logical deduction and multi-step arithmetic. We measure accuracy using a 3-shot setup.

MATH (Hendrycks et al., 2021) The MATH dataset evaluates mathematical problem-solving with problems from high school competitions. These problems require sophisticated reasoning beyond simple calculation. For our experiments, we focus exclusively on the most challenging problems, designated as Level 5. We measure exact match accuracy in a 4-shot setting.

IFEval (Zhou et al., 2023) IFEval (Instruction-Following Evaluation) assesses an LLM's ability to adhere to explicit, verifiable instructions within a prompt. It automatically checks compliance with constraints on format (e.g., "end your response with..."), length (e.g., "write at least 400 words"), and content (e.g., "mention 'AI' 3 times"). We measure strict accuracy in a 0-shot setting.

NoveltyBench (Zhang et al., 2025) NoveltyBench evaluates a model's ability to generate diverse and novel outputs, counteracting the "mode collapse" phenomenon where models produce repetitive answers. It uses open-ended prompts and measures performance with metrics for distinctness (number of unique ideas) and utility (a combined score of novelty and quality).

SimBench (Hu et al., 2025) SimBench is a large-scale, standardized benchmark for evaluating how well LLMs simulate human behavior. It unifies 20 diverse social and behavioral science datasets to test a model's ability to predict group-level response distributions across various human populations and tasks, from moral dilemmas to economic choices.

B Full Merging Results

This section provides the comprehensive empirical data that underpins the analyses and conclusions presented in the main body of the paper. Table 2 offers a detailed breakdown of performance and calibration metrics across our entire suite of experiments, demonstrating the generality and robustness of our findings.

The table is organized by model family (Gemma-3 and Qwen2.5), model scale, and merging algorithm (SLERP, Linear, and DARE-TIES). For each configuration, we report results for the base Pre-Trained (PT) and Instruction-Tuned (IT) models, which serve as the endpoints ($\lambda = 0$ and $\lambda = 1$, respectively), alongside the series of merged models with the interpolation coefficient λ varying from 0.1 to 0.9.

C Full Results for Scaling Analysis

This appendix (Figures 7 to 11) provides the full set of figures supporting our scaling analysis in the main text. We demonstrate that the core trends observed for the Gemma3 family on MMLU-Pro - namely that the peak accuracy gain, performance landscape smoothness, and optimal λ^* convergence of merging all increase with scale - are broadly consistent across the Qwen2.5 model family and other challenging benchmarks (BBH and GPQA). While the magnitude of the effects varies by task and model family, the overarching conclusion remains robust: model merging is an increasingly effective, stable, and practical technique for larger models.

D Additional Related Work and Background

Model merging is the process of combining model parameters $\theta_1, .., \theta_n$ into a single set of parameters θ_{merge}, where $\theta_1, .., \theta_n$ are typically fine-tunes of the same base model. There exists a wide variety of model merging methods, ranging from simple (spherical) linear interpolation between the constituent model parameters (Ilharco et al., 2023; Goddard et al., 2024) to sophisticated methods aiming to minimize interference between the merge constituents (Yu et al., 2024b; Yadav et al., 2023; Deep et al., 2024).[2]

While the vast majority of merging research focuses on merging different fine-tuned models, some prior research investigates merging pre-trained and instruction-tuned models.

Shadow-FT (Wu et al., 2025b) proposes that additional fine-tuning of an instruction-tuned model (e.g., to specialize to a particular domain) can be improved by conducting the additional training on the base model, then merging this additionally trained model and the original instruction-tuned model.

Param Δ (Cao et al., 2025) suggests that an instruction-tuned model can be transferred to an updated base model (i.e., a newer base model version) by adding the instruction-tuning task vector $\theta_{\text{IT}} - \theta_{\text{PT}}$ to the new backbone weights $\theta_{\text{PT}'}$ analogous to Task Arithmetic (Ilharco et al., 2023).[3]

WIDEN (Yu et al., 2024a) introduces a method to merge a fine-tuned model with a base model which has undergone additional training. This is in some sense comparable to Param Δ, however, in the case of WIDEN, the base model with additional training has undergone heavy specialization to a particular set of languages.

In contrast, we investigate merging as a way to mitigate the alignment tax. We are the first to show that merging an instruction-tuned model with the base model consistently reveals models that achieve higher accuracy than both parent models and improve calibration compared to the IT model.

[2] See Yang et al. (2024) for a detailed overview.

[3] Interestingly, this suggests that our method could also be used to interpolate between an instruction-tuned model and a *newer version* of its base model. However, we do not investigate this further here.

E Amplifying Task Vectors Leads to Performance Collapse

While merging offers a tunable knob to navigate the alignment-calibration frontier, we also investigated the effect of amplifying a task vector by setting its coefficient $\lambda > 1$. This experiment tests whether one can "supercharge" a model's capabilities by pushing its weights further along a specific skill direction. Our findings, detailed in Table 3, reveal that this approach is fundamentally destructive. We observe a performance cliff: as λ increases beyond 1, model performance enters a sharp and monotonic decline across all evaluation axes. The degradation is particularly catastrophic on benchmarks measuring Helpfulness and complex reasoning. For instance, performance on `IFEval` plummets from 75.4% at $\lambda = 1.1$ to just 10.3% at $\lambda = 2.0$, and accuracy on `MATH Lvl 5` collapses from 55.1% to a near-total failure of 0.6%. Concurrently, the model's calibration degrades severely; ECE scores on BBH, GPQA, and MMLU-PRO consistently worsen, indicating that the model becomes progressively more miscalibrated and overconfident as its accuracy falls. This demonstrates that amplifying task vectors is not a viable strategy for capability enhancement; instead, it systematically dismantles the model's general capabilities and its grasp on probabilistic uncertainty.

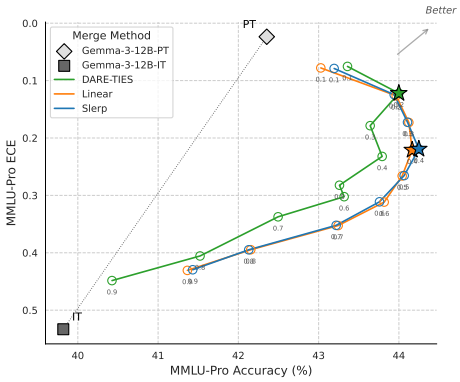


Figure 6: Different merging methods (SLERP, Linear, DARE-TIES) trace distinct but similar Pareto-superior paths.

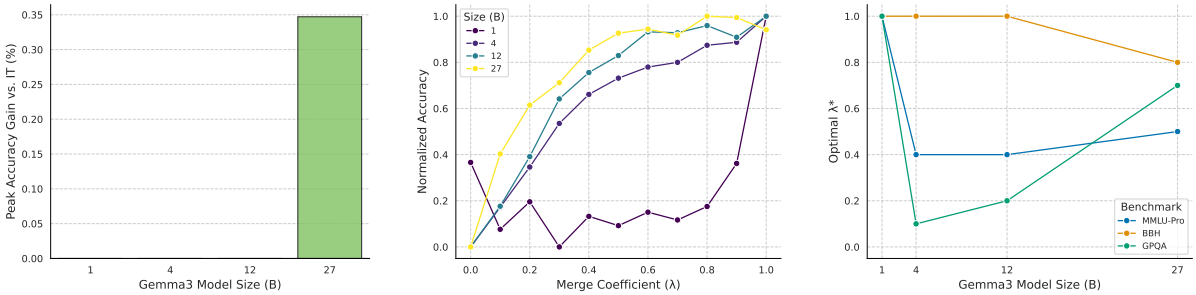


Figure 7: Scaling trends for the Gemma3 family on the **BBH** benchmark.

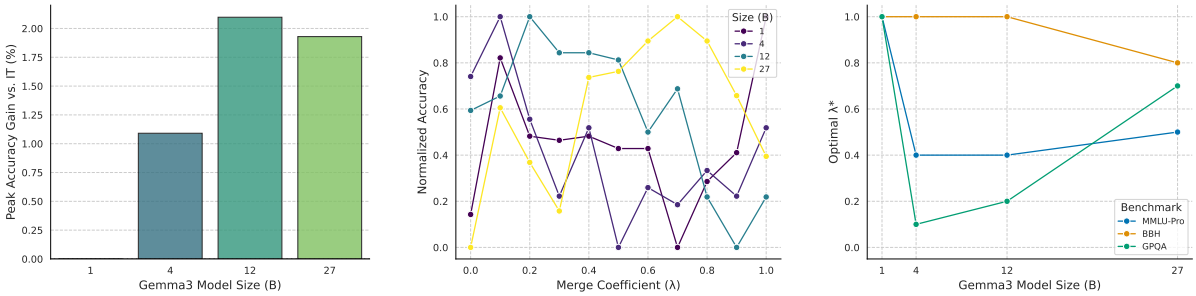


Figure 8: Scaling trends for the Gemma3 family on the **GPQA** benchmark.

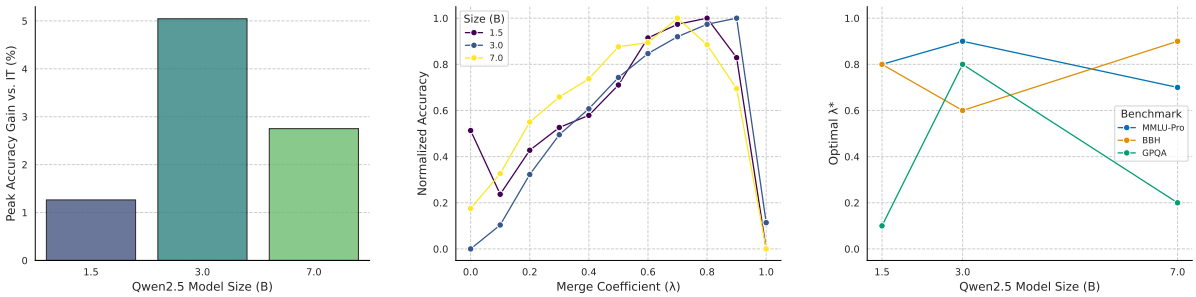


Figure 9: Scaling trends for the Qwen2.5 family on the **MMLU-Pro** benchmark.

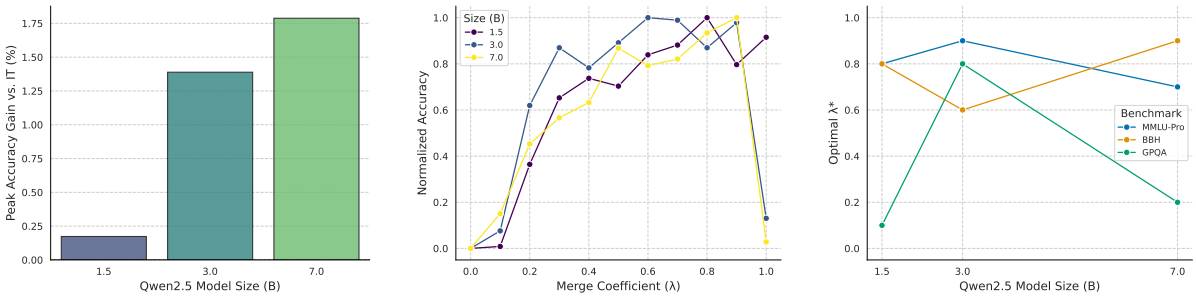
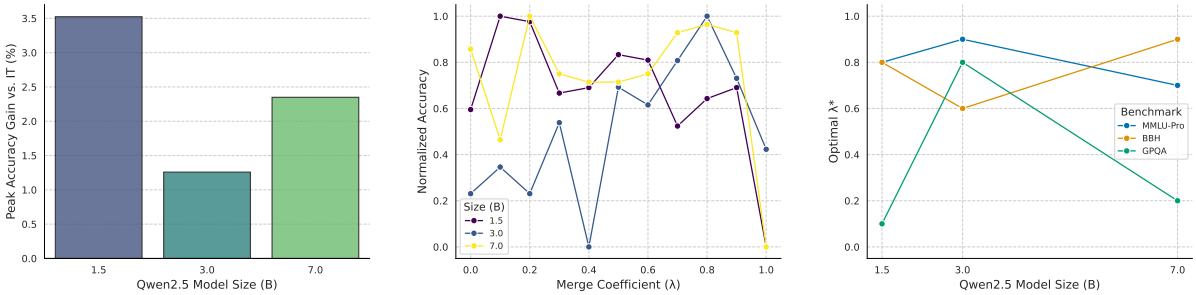


Figure 10: Scaling trends for the Qwen2.5 family on the **BBH** benchmark.



(a) Payoff vs. Scale (b) Robustness vs. Scale (c) Predictability vs. Scale

Figure 11: Scaling trends for the Qwen2.5 family on the **GPQA** benchmark.

Table 2: Full Performance and Calibration Comparison of Merged Models

Model	Type / λ	BBH		GPQA		MMLU-PRO		Additional Benchmarks (Accuracy %)	
		Acc (%)	ECE	Acc (%)	ECE	Acc (%)	ECE	IFEval	MATH L5
Gemma-3 12B									
gemma-3-12b-pt	*Base PT*	54.31	0.022	34.65	0.046	42.35	0.024	19.41	16.31
gemma-3-12b-it	*Base IT*	63.27	0.325	33.64	0.597	39.82	0.533	77.08	55.82
Gemma-3 12B SLERP Merges									
gemma3-12b-slerp	0.1	55.89	0.034	34.82	0.087	43.19	0.079	20.89	23.79
gemma3-12b-slerp	0.2	57.82	0.059	35.74	0.123	43.94	0.125	26.62	26.59
gemma3-12b-slerp	0.3	60.06	0.083	35.32	0.175	44.11	0.173	35.49	32.40
gemma3-12b-slerp	0.4	61.08	0.112	35.32	0.224	44.25	0.219	40.67	38.75
gemma3-12b-slerp	0.5	61.74	0.146	35.23	0.272	44.07	0.265	47.50	42.98
gemma3-12b-slerp	0.6	62.66	0.172	34.40	0.329	43.76	0.311	48.24	46.75
gemma3-12b-slerp	0.7	62.63	0.202	34.90	0.368	43.22	0.352	55.45	48.49
gemma3-12b-slerp	0.8	62.91	0.229	33.64	0.423	42.13	0.395	67.10	52.87
gemma3-12b-slerp	0.9	62.45	0.260	33.05	0.471	41.43	0.430	76.16	55.06
Gemma-3 12B Linear Merges									
gemma3-12b-linear	0.1	55.84	0.032	35.57	0.093	43.03	0.078	22.00	23.26
gemma3-12b-linear	0.2	57.75	0.064	35.82	0.121	43.97	0.126	26.43	26.21
gemma3-12b-linear	0.3	59.76	0.085	35.07	0.178	44.12	0.173	34.75	32.55
gemma3-12b-linear	0.4	60.81	0.116	35.32	0.224	44.17	0.221	41.40	39.12
gemma3-12b-linear	0.5	61.66	0.147	35.15	0.274	44.04	0.266	46.40	43.28
gemma3-12b-linear	0.6	62.85	0.170	34.82	0.326	43.82	0.312	49.17	47.21
gemma3-12b-linear	0.7	62.59	0.203	34.56	0.371	43.24	0.353	55.45	48.72
gemma3-12b-linear	0.8	63.20	0.228	34.06	0.419	42.15	0.395	67.65	51.89
gemma3-12b-linear	0.9	62.49	0.259	32.80	0.476	41.36	0.431	75.05	55.89
Gemma-3 12B DARE-TIES Merges									
gemma3-12b-dare_ties	0.1	55.89	0.035	35.32	0.084	43.36	0.075	20.52	24.47
gemma3-12b-dare_ties	0.2	57.79	0.059	34.90	0.126	44.00	0.122	25.88	26.21
gemma3-12b-dare_ties	0.3	59.16	0.089	35.32	0.174	43.64	0.179	35.30	32.25
gemma3-12b-dare_ties	0.4	60.39	0.118	35.65	0.229	43.79	0.232	48.98	37.84
gemma3-12b-dare_ties	0.5	62.02	0.135	35.15	0.279	43.26	0.282	45.66	41.99
gemma3-12b-dare_ties	0.6	62.51	0.172	33.81	0.327	43.32	0.302	50.09	44.86
gemma3-12b-dare_ties	0.7	62.47	0.203	33.81	0.371	42.50	0.337	56.19	49.17
gemma3-12b-dare_ties	0.8	61.88	0.236	34.14	0.424	41.52	0.406	65.99	51.59
gemma3-12b-dare_ties	0.9	61.34	0.291	33.56	0.463	40.43	0.448	73.75	50.60
Gemma-3 27B Family									
gemma-3-27b-pt	*Base PT*	61.66	0.049	34.98	0.068	49.39	0.037	20.33	24.92
gemma-3-27b-it	*Base IT*	67.21	0.302	36.24	0.590	47.80	0.478	80.59	63.14
Gemma-3 27B SLERP Merges									
gemma3-27b-slerp	0.1	64.03	0.015	36.91	0.088	50.41	0.077	22.92	33.08
gemma3-27b-slerp	0.2	65.28	0.037	36.16	0.140	50.89	0.119	30.68	36.71
gemma3-27b-slerp	0.3	65.86	0.075	35.49	0.192	51.44	0.156	40.67	43.81
gemma3-27b-slerp	0.4	66.69	0.104	37.33	0.219	51.46	0.192	48.24	48.87
gemma3-27b-slerp	0.5	67.12	0.133	37.42	0.266	51.91	0.219	51.94	52.64
gemma3-27b-slerp	0.6	67.23	0.161	37.84	0.305	51.11	0.254	52.31	56.50
gemma3-27b-slerp	0.7	67.07	0.189	38.17	0.350	50.96	0.284	63.96	58.61
gemma3-27b-slerp	0.8	67.56	0.209	37.84	0.403	50.58	0.312	75.60	62.16
gemma3-27b-slerp	0.9	67.52	0.232	37.08	0.455	49.78	0.341	77.63	63.14
Gemma-3 27B Linear Merges									
gemma3-27b-linear	0.1	63.79	0.017	36.74	0.088	50.23	0.078	24.58	33.16
gemma3-27b-linear	0.2	65.18	0.038	36.49	0.135	50.84	0.122	30.50	37.39
gemma3-27b-linear	0.3	66.06	0.073	35.57	0.190	51.44	0.156	39.19	43.96
gemma3-27b-linear	0.4	66.55	0.106	36.74	0.224	51.55	0.192	49.91	48.34
gemma3-27b-linear	0.5	67.19	0.133	36.91	0.269	51.59	0.222	51.76	52.49
gemma3-27b-linear	0.6	67.38	0.161	38.00	0.305	51.16	0.255	53.97	55.59
gemma3-27b-linear	0.7	67.28	0.188	38.17	0.349	50.82	0.285	63.03	59.14
gemma3-27b-linear	0.8	67.70	0.207	37.33	0.407	50.54	0.314	77.63	62.08
gemma3-27b-linear	0.9	67.35	0.234	36.91	0.455	49.69	0.342	78.37	61.93
Gemma-3 27B DARE-TIES Merges									
gemma3-27b-dare_ties	0.1	63.95	0.015	36.41	0.094	50.28	0.078	23.48	32.63
gemma3-27b-dare_ties	0.2	65.32	0.035	36.16	0.141	50.83	0.121	31.42	37.76
gemma3-27b-dare_ties	0.3	66.17	0.071	35.91	0.183	51.41	0.154	39.74	43.28
gemma3-27b-dare_ties	0.4	66.38	0.108	36.83	0.227	51.48	0.193	51.57	48.94
gemma3-27b-dare_ties	0.5	67.25	0.130	37.25	0.267	51.21	0.227	49.35	53.02
gemma3-27b-dare_ties	0.6	67.58	0.158	37.84	0.302	50.96	0.260	58.04	55.74
gemma3-27b-dare_ties	0.7	67.16	0.192	36.74	0.368	50.39	0.286	65.99	58.76
gemma3-27b-dare_ties	0.8	67.44	0.211	36.07	0.424	49.73	0.322	76.89	60.50
gemma3-27b-dare_ties	0.9	66.72	0.238	38.17	0.434	48.55	0.347	78.19	63.14
Gemma-3 4B Family									
gemma-3-4b-pt	*PT*	40.58	0.048	29.53	0.077	27.94	0.024	20.89	7.33

Table 2 – continued from previous page

Model	Type / λ	BBH		GPQA		MMLU-PRO		Additional Benchmarks (Accuracy %)	
		Acc (%)	ECE	Acc (%)	ECE	Acc (%)	ECE	IFEval	MATH L5
gemma-3-4b-it	*IT*	49.96	0.476	29.03	0.637	29.80	0.642	70.43	38.07
Gemma-3 4B SLERP Merges									
gemma3-4b-slerp	0.1	42.20	0.038	30.12	0.109	29.23	0.063	21.81	8.91
gemma3-4b-slerp	0.2	43.83	0.045	29.11	0.166	29.99	0.109	22.74	11.25
gemma3-4b-slerp	0.3	45.60	0.082	28.36	0.224	30.39	0.163	26.43	13.29
gemma3-4b-slerp	0.4	46.78	0.128	29.03	0.275	30.56	0.215	29.57	17.67
gemma3-4b-slerp	0.5	47.44	0.186	27.85	0.345	30.55	0.272	35.49	21.90
gemma3-4b-slerp	0.6	47.89	0.243	28.44	0.393	30.19	0.334	36.97	27.57
gemma3-4b-slerp	0.7	48.08	0.298	28.27	0.446	29.70	0.399	40.48	31.19
gemma3-4b-slerp	0.8	48.78	0.339	28.61	0.496	28.91	0.468	49.72	37.16
gemma3-4b-slerp	0.9	48.90	0.380	28.36	0.550	28.52	0.527	60.81	37.16
Gemma-3 4B Linear Merges									
gemma3-4b-linear	0.1	42.15	0.040	28.94	0.119	28.95	0.065	22.37	9.06
gemma3-4b-linear	0.2	44.11	0.043	28.78	0.166	30.05	0.109	22.55	11.63
gemma3-4b-linear	0.3	45.50	0.083	28.27	0.226	30.44	0.161	27.36	13.60
gemma3-4b-linear	0.4	46.26	0.133	28.27	0.282	30.67	0.212	30.31	17.98
gemma3-4b-linear	0.5	47.34	0.186	28.02	0.346	30.41	0.274	34.01	21.75
gemma3-4b-linear	0.6	48.00	0.242	27.60	0.401	30.15	0.333	38.08	27.27
gemma3-4b-linear	0.7	47.77	0.299	28.52	0.449	29.72	0.401	42.14	31.19
gemma3-4b-linear	0.8	48.53	0.341	27.94	0.504	28.97	0.465	49.54	36.33
gemma3-4b-linear	0.9	48.76	0.381	28.69	0.546	28.38	0.527	63.77	38.67
Gemma-3 4B DARE-TIES Merges									
gemma3-4b-dare_ties	0.1	42.25	0.042	29.78	0.110	29.28	0.064	21.81	8.76
gemma3-4b-dare_ties	0.2	43.57	0.043	30.29	0.142	29.85	0.103	24.40	10.95
gemma3-4b-dare_ties	0.3	44.92	0.085	28.86	0.227	30.11	0.169	28.10	13.97
gemma3-4b-dare_ties	0.4	45.93	0.134	27.94	0.286	30.65	0.197	32.53	16.47
gemma3-4b-dare_ties	0.5	46.52	0.202	27.94	0.345	29.72	0.293	33.09	21.07
gemma3-4b-dare_ties	0.6	46.83	0.256	27.52	0.430	29.60	0.360	35.86	24.55
gemma3-4b-dare_ties	0.7	47.46	0.303	26.85	0.461	28.61	0.412	41.59	29.08
gemma3-4b-dare_ties	0.8	48.88	0.339	28.10	0.511	28.77	0.412	46.58	32.93
gemma3-4b-dare_ties	0.9	47.65	0.370	26.26	0.561	26.97	0.503	61.92	33.16
Qwen 2.5 1.5B									
Qwen2.5-1.5B	*PT*	40.50	0.105	28.27	0.114	28.73	0.055	22.74	8.91
Qwen2.5-1.5B-Instruct	*IT*	42.37	0.248	26.17	0.244	28.08	0.326	41.22	21.75
Qwen 2.5 1.5B SLERP Merges									
qwen2.5-1.5b-slerp	0.1	40.51	0.112	29.70	0.107	28.38	0.065	22.00	8.99
qwen2.5-1.5b-slerp	0.2	41.24	0.115	29.61	0.122	28.62	0.076	22.74	10.05
qwen2.5-1.5b-slerp	0.3	41.83	0.123	28.52	0.150	28.75	0.089	22.37	9.89
qwen2.5-1.5b-slerp	0.4	42.01	0.130	28.61	0.162	28.81	0.097	24.77	10.73
qwen2.5-1.5b-slerp	0.5	41.94	0.145	29.11	0.183	28.98	0.113	24.77	10.57
qwen2.5-1.5b-slerp	0.6	42.21	0.154	29.03	0.191	29.24	0.125	26.25	10.35
qwen2.5-1.5b-slerp	0.7	42.30	0.162	28.02	0.211	29.31	0.136	25.88	10.20
qwen2.5-1.5b-slerp	0.8	42.54	0.173	28.44	0.222	29.35	0.152	26.80	10.57
qwen2.5-1.5b-slerp	0.9	42.13	0.191	28.61	0.235	29.13	0.172	26.62	10.27
Qwen 2.5 1.5B Linear Merges									
qwen2.5-1.5b-linear	0.1	40.83	0.112	29.45	0.113	28.72	0.064	22.37	10.05
qwen2.5-1.5b-linear	0.2	41.52	0.115	29.78	0.123	28.73	0.075	19.04	9.29
qwen2.5-1.5b-linear	0.3	41.61	0.124	28.86	0.146	28.64	0.089	21.63	9.82
qwen2.5-1.5b-linear	0.4	42.32	0.128	29.11	0.159	28.81	0.101	24.40	9.37
qwen2.5-1.5b-linear	0.5	41.94	0.145	29.11	0.183	28.98	0.113	19.96	10.73
qwen2.5-1.5b-linear	0.6	42.15	0.154	28.36	0.196	29.23	0.123	26.06	10.12
qwen2.5-1.5b-linear	0.7	42.09	0.166	28.69	0.205	29.30	0.134	27.36	10.88
qwen2.5-1.5b-linear	0.8	42.46	0.173	28.94	0.218	29.32	0.150	23.11	10.27
qwen2.5-1.5b-linear	0.9	42.27	0.188	28.10	0.236	29.26	0.163	24.95	10.50
Qwen 2.5 1.5B DARE-TIES Merges									
qwen2.5-1.5b-dare_ties	0.1	40.86	0.108	29.53	0.110	28.56	0.064	22.55	10.05
qwen2.5-1.5b-dare_ties	0.2	41.05	0.117	29.53	0.122	28.57	0.076	23.48	9.29
qwen2.5-1.5b-dare_ties	0.3	41.75	0.123	29.36	0.146	28.73	0.087	22.74	10.57
qwen2.5-1.5b-dare_ties	0.4	42.02	0.129	29.19	0.159	28.80	0.096	24.21	10.57
qwen2.5-1.5b-dare_ties	0.5	42.21	0.144	28.86	0.181	29.01	0.115	26.06	10.50
qwen2.5-1.5b-dare_ties	0.6	42.13	0.155	28.44	0.193	29.25	0.122	26.80	10.65
qwen2.5-1.5b-dare_ties	0.7	42.11	0.166	28.36	0.211	29.45	0.137	24.21	9.97
qwen2.5-1.5b-dare_ties	0.8	42.11	0.178	28.86	0.221	29.29	0.155	27.36	9.37
qwen2.5-1.5b-dare_ties	0.9	42.08	0.187	28.52	0.233	29.44	0.164	26.62	9.29
Qwen 2.5 3B									
Qwen2.5-3B	*PT*	46.38	0.102	28.36	0.183	32.12	0.044	20.89	15.94
Qwen2.5-3B-Instruct	*IT*	46.59	0.455	28.78	0.347	32.77	0.469	58.04	37.54
Qwen 2.5 3B SLERP Merges									
qwen2.5-3b-slerp	0.1	46.50	0.122	28.61	0.188	32.71	0.052	23.11	15.26

Table 2 – continued from previous page

Model	Type / λ	BBH		GPQA		MMLU-PRO		Additional Benchmarks (Accuracy %)	
		Acc (%)	ECE	Acc (%)	ECE	Acc (%)	ECE	IFEval	MATH L5
qwen2.5-3b-slerp	0.2	47.37	0.148	28.36	0.213	33.96	0.061	28.10	16.62
qwen2.5-3b-slerp	0.3	47.77	0.177	29.03	0.232	34.94	0.079	36.04	18.20
qwen2.5-3b-slerp	0.4	47.63	0.206	27.85	0.265	35.58	0.094	36.97	18.20
qwen2.5-3b-slerp	0.5	47.80	0.240	29.36	0.275	36.35	0.122	39.37	20.47
qwen2.5-3b-slerp	0.6	47.98	0.277	29.19	0.302	36.94	0.155	42.51	19.11
qwen2.5-3b-slerp	0.7	47.96	0.307	29.61	0.319	37.36	0.182	48.43	20.39
qwen2.5-3b-slerp	0.8	47.77	0.348	30.03	0.344	37.67	0.224	45.29	21.15
qwen2.5-3b-slerp	0.9	47.94	0.382	29.45	0.379	37.82	0.267	48.24	25.30
Qwen 2.5 3B Linear Merges									
qwen2.5-3b-linear	0.1	46.83	0.125	28.19	0.196	33.04	0.054	19.59	15.63
qwen2.5-3b-linear	0.2	47.02	0.155	28.27	0.217	33.80	0.066	28.84	16.47
qwen2.5-3b-linear	0.3	47.56	0.180	27.60	0.247	35.06	0.079	34.94	17.82
qwen2.5-3b-linear	0.4	47.68	0.211	28.27	0.265	35.67	0.098	38.82	18.20
qwen2.5-3b-linear	0.5	47.80	0.240	29.36	0.275	36.35	0.122	39.37	20.47
qwen2.5-3b-linear	0.6	47.79	0.274	28.86	0.303	36.76	0.149	29.02	18.43
qwen2.5-3b-linear	0.7	47.91	0.309	29.11	0.326	37.18	0.186	30.31	17.22
qwen2.5-3b-linear	0.8	47.53	0.348	29.61	0.347	37.52	0.218	46.95	21.45
qwen2.5-3b-linear	0.9	47.84	0.375	29.70	0.372	37.67	0.260	50.09	21.15
Qwen 2.5 3B DARE-TIES Merges									
qwen2.5-3b-dare_ties	0.1	46.57	0.122	28.36	0.190	32.78	0.051	24.77	17.07
qwen2.5-3b-dare_ties	0.2	47.16	0.147	27.85	0.217	33.68	0.064	28.47	17.60
qwen2.5-3b-dare_ties	0.3	47.58	0.178	28.36	0.237	34.83	0.079	35.12	17.82
qwen2.5-3b-dare_ties	0.4	47.56	0.202	28.19	0.258	35.38	0.094	36.97	18.35
qwen2.5-3b-dare_ties	0.5	47.86	0.246	29.36	0.279	36.49	0.127	41.77	19.11
qwen2.5-3b-dare_ties	0.6	47.93	0.274	29.45	0.297	37.02	0.148	42.70	19.41
qwen2.5-3b-dare_ties	0.7	47.72	0.316	29.28	0.329	37.21	0.192	47.69	18.43
qwen2.5-3b-dare_ties	0.8	47.87	0.350	30.03	0.346	37.71	0.226	45.66	22.05
qwen2.5-3b-dare_ties	0.9	47.75	0.375	29.19	0.373	37.81	0.254	50.09	21.45
Qwen 2.5 7B									
Qwen2.5-7B	*PT*	53.67	0.097	32.30	0.133	43.55	0.063	29.39	22.58
Qwen2.5-7B-Instruct	*IT*	53.72	0.384	30.29	0.484	43.07	0.451	71.35	49.02
Qwen 2.5 7B SLERP Merges									
qwen2.5-7b-slerp	0.1	53.95	0.119	31.38	0.167	43.97	0.074	31.61	23.64
qwen2.5-7b-slerp	0.2	54.50	0.147	32.63	0.174	44.58	0.090	35.49	25.30
qwen2.5-7b-slerp	0.3	54.71	0.179	32.05	0.201	44.88	0.110	40.67	26.28
qwen2.5-7b-slerp	0.4	54.83	0.205	31.96	0.225	45.10	0.126	44.92	26.96
qwen2.5-7b-slerp	0.5	55.27	0.231	31.96	0.252	45.48	0.148	51.39	28.70
qwen2.5-7b-slerp	0.6	55.13	0.262	32.05	0.277	45.53	0.171	53.42	29.98
qwen2.5-7b-slerp	0.7	55.18	0.285	32.47	0.298	45.82	0.192	55.82	32.25
qwen2.5-7b-slerp	0.8	55.39	0.308	32.55	0.324	45.50	0.231	58.04	35.50
qwen2.5-7b-slerp	0.9	55.51	0.329	32.47	0.356	44.98	0.277	56.75	35.80
Qwen 2.5 7B Linear Merges									
qwen2.5-7b-linear	0.1	54.02	0.123	32.38	0.156	44.00	0.076	31.05	23.94
qwen2.5-7b-linear	0.2	54.43	0.150	31.71	0.178	44.77	0.089	23.11	25.60
qwen2.5-7b-linear	0.3	55.04	0.175	32.55	0.194	45.01	0.107	43.25	25.91
qwen2.5-7b-linear	0.4	55.01	0.204	31.54	0.231	45.20	0.127	26.99	28.40
qwen2.5-7b-linear	0.5	55.16	0.232	32.13	0.248	45.53	0.147	50.09	29.00
qwen2.5-7b-linear	0.6	55.32	0.257	32.30	0.276	45.63	0.169	32.72	30.51
qwen2.5-7b-linear	0.7	55.39	0.282	32.13	0.300	45.76	0.192	34.01	31.95
qwen2.5-7b-linear	0.8	55.13	0.309	31.96	0.333	45.67	0.225	36.41	33.46
qwen2.5-7b-linear	0.9	55.13	0.330	32.21	0.352	45.19	0.266	56.93	34.59
Qwen 2.5 7B DARE-TIES Merges									
qwen2.5-7b-dare_ties	0.2	54.42	0.147	31.54	0.177	44.56	0.089	35.30	25.15
qwen2.5-7b-dare_ties	0.3	54.87	0.177	32.80	0.191	45.05	0.106	41.77	26.96
qwen2.5-7b-dare_ties	0.4	54.97	0.202	31.80	0.229	45.02	0.125	42.88	27.95
qwen2.5-7b-dare_ties	0.5	55.08	0.236	31.96	0.256	45.47	0.149	51.39	29.08
qwen2.5-7b-dare_ties	0.6	55.25	0.260	32.30	0.272	45.56	0.171	51.39	29.38
qwen2.5-7b-dare_ties	0.7	55.41	0.284	32.05	0.303	45.57	0.199	56.38	31.87
qwen2.5-7b-dare_ties	0.8	55.22	0.311	32.13	0.330	45.57	0.233	56.38	33.61
qwen2.5-7b-dare_ties	0.9	55.23	0.329	32.30	0.355	45.20	0.265	56.38	34.89

Model	λ	BBH		GPQA		MMLU-PRO		Other Benchmarks	
		Acc (%)	ECE	Acc (%)	ECE	Acc (%)	ECE	IFEval (%)	MATH L5 (%)
Reference Models									
gemma-3-12b-pt	*Base PT*	54.31	0.022	34.65	0.046	42.35	0.024	19.41	16.31
gemma-3-12b-it	*Base IT*	63.27	0.325	33.64	0.597	39.82	0.533	77.08	55.82
Arithmetic Task Vector Applied to PT Model									
task arithmetic	1.1	62.77	0.339	32.55	0.622	38.36	0.548	75.42	55.06
task arithmetic	1.2	61.73	0.354	32.30	0.635	36.69	0.565	71.35	52.79
task arithmetic	1.4	59.02	0.386	30.29	0.661	32.45	0.591	64.51	42.22
task arithmetic	1.5	57.15	0.401	29.78	0.664	29.46	0.608	58.78	33.91
task arithmetic	1.6	53.72	0.433	29.19	0.674	26.02	0.624	50.46	21.37
task arithmetic	1.7	48.98	0.478	28.44	0.683	22.17	0.655	43.62	10.35
task arithmetic	1.8	43.62	0.529	27.85	0.678	17.84	0.670	32.53	2.42
task arithmetic	1.9	38.26	0.573	23.99	0.697	13.83	0.659	19.78	1.44
task arithmetic	2.0	31.66	0.612	24.66	0.669	11.64	0.672	10.35	0.60

Note: PT refers to the Pre-trained base model; IT refers to the post-instruction-tuned model. ECE (Expected Calibration Error) is a measure of miscalibration where higher values are worse.

Table 3: Performance and Calibration Degradation when amplifying an arithmetic task vector ($\lambda > 1$) applied to the Gemma-3-12B-PT model. Extrapolating beyond the instruction-tuned model leads to a catastrophic and monotonic decline in performance and calibration across all benchmarks.