On the Effectiveness of Trainable Steering Vectors in Supervised Fine-Tuning

Anonymous ACL submission

Abstract

Prior work showed that trainable steering vectors can match full-model reinforcement learning fine-tuning on mathematical reasoning benchmarks while updating only a tiny fraction of parameters. We test whether this equivalence extends to supervised fine-tuning and identify the factors that control it. Using Qwen2.5-Math-7B and LLaMa3.1-8B-Instruct trained on OpenThoughts-114k-math and evaluated on six math benchmarks, we find a consistent gap under SFT: steering vectors underperform full-model fine-tuning, unlike in the RL setting. We show that SFT-trained steering models deviate more from their base models, and that closing the gap by increasing adapter capacity requires full-rank updates (e.g., $\approx 27\%$ of parameters for Qwen2.5-Math-7B when scaling `MLP.down_proj` LoRA). Finally, we show that changing the data removes the gap: when we distill from RL-trained teachers by training on selected positive generations, low-parameter steering vectors match full-tuning, without simply reproducing RL steering directions.

1 Introduction

Prior work by Sinii et al. (2025b) showed that applying Reinforcement Learning (RL) to trainable steering vectors can achieve the same accuracy on math reasoning tasks as full-model RL fine-tuning, despite using extremely few trainable parameters. This raises the question of whether Supervised Fine-Tuning (SFT) adheres to the same equivalence, and more generally, what determines when a small representational subspace is sufficient for reasoning-relevant tuning.

SFT and RL provide qualitatively different training signals. SFT supplies token-level supervision from curated reasoning traces, whereas RL with verifiable rewards can optimize from outcome-level feedback. Motivated by recent analyses (Schulman and Lab, 2025) suggesting that such differences matter most under constrained adaptation capacity, we compare steering-vector training and full-model fine-tuning under both objectives in a matched experimental setup.

We find that the RL equivalence does not carry over to SFT: steering vectors consistently underperform full-model fine-tuning across several model families on six math-reasoning benchmarks. We then probe two potential explanations. First, we measure deviation from the base model and observe that SFT-trained steering models produce lower-probability generations under the base distribution. Second, we extend the adaptation capacity from steering vectors to LoRA (Hu et al., 2022) on `MLP.down_proj` module and find that the SFT gap closes only at full LoRA rank. Finally, we show that the gap is not inevitable: training on generations produced by RL-trained teachers (distillation) closes the steering/full-tuning gap, and the resulting steering vectors are not aligned with the RL-trained steering vectors, suggesting that distillation induces a different mechanism within the same constrained parameterization.

2 Related Work

Reinforcement Learning and Supervised Fine-Tuning for Reasoning. Both supervised fine-tuning (SFT) and reinforcement learning with verifiable rewards (RLVR) have been shown to improve reasoning performance in large language models. SFT-based approaches leverage curated reasoning traces or chain-of-thought annotations and can yield substantial gains when sufficient high-quality data is available (Li et al., 2024; Ye et al., 2025; Yao et al., 2023). More recently, RLVR has emerged as a dominant paradigm for reasoning-centric training, underpinning systems such as OpenAI *o1* (Jaech et al., 2024), DeepSeek-R1 (Guo et al., 2025), and several open reproductions (Zeng et al., 2025; Hu et al., 2025), and demonstrating that outcome-based rewards alone can induce long reasoning trajectories and strong benchmark performance. Prior work has also highlighted that the two training paradigms can lead to systematically different behaviors and capabilities (Matsutani et al., 2025; Chu et al., 2025).

Parameter-Efficient Adaptation and Steering. A large body of work has explored parameter-efficient fine-tuning (PEFT) as an alternative to full-model adaptation. Low-Rank Adaptation (LoRA) (Hu et al., 2022) introduced the idea of constraining updates to low-dimensional subspaces, initially applied to attention projections. Subsequent work demonstrated that apply-

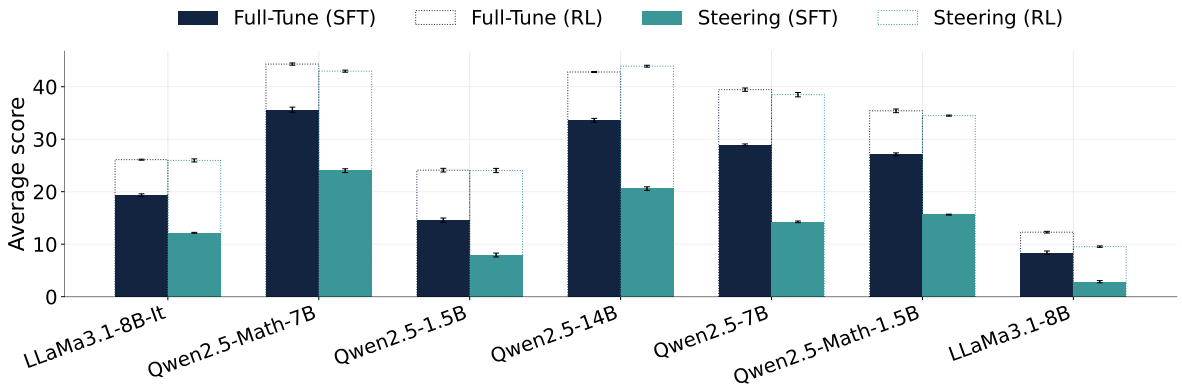


Figure 1: **Steering vectors vs full-model fine-tuning.** Mean accuracy across six mathematical reasoning benchmarks for multiple model architectures. Filled bars show results after supervised fine-tuning (SFT), while dotted outlines indicate performance after reinforcement learning (RL). For each configuration, we report the checkpoint with the best validation performance. Steering vectors approach the performance of full-model fine-tuning in the RL setting but consistently underperform it under SFT.

ing LoRA more broadly, including to MLP layers, can further improve performance, highlighting the importance of where adaptation capacity is allocated within the model (Zaken et al., 2022). In parallel, bias-only fine-tuning methods such as BitFit showed that even extremely restricted update regimes can be effective across a range of NLP tasks (Zaken et al., 2022).

Steering vectors build on these ideas by operating directly at the level of hidden representations, inducing behavioral changes through low-dimensional directions rather than widespread parameter updates. Prior work on activation engineering and contrastive steering demonstrated that such directions can reliably elicit target behaviors at inference time (Turner et al., 2023; Panickssery and Bowman, 2023). More recent studies have shown that steering vectors trained with reinforcement learning can match full-model RL fine-tuning on reasoning benchmarks despite modifying only a tiny fraction of parameters (Sinii et al., 2025b,a). Together, these results suggest that reasoning-relevant adaptations may be concentrated in small representational subspaces, making adaptation capacity a critical factor independent of the training objective.

3 Steering Vectors Fail to Match Full Fine-Tuning under SFT

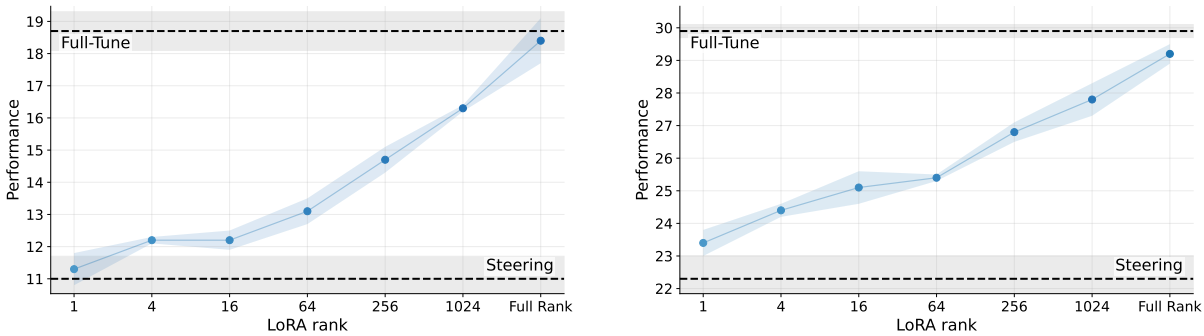
Setup To enable a direct comparison with the RL results of Sinii et al. (2025b), we adopted the same set of benchmarks, training setup, and steering vector implementation. We used the OpenThoughts-114k dataset (Open Thoughts Team, 2025) since it allowed both SFT and RL training. For the SFT dataset, we extracted tasks within the math domain and constructed each example by combining the original problem statement with the corresponding DeepSeek-R1 solution. We selected a random 10% of this dataset as a validation split and trained on the remaining 90% of the problems.

We considered two primary base models in our study: Qwen2.5-Math-7B (Yang et al., 2024) and LLaMA3.1-8B-Instruct (Grattafiori et al., 2024). Most of our experiments were also replicated on additional models, including Qwen2.5-Math-1.5B, Qwen2.5-{1.5,7,14}B, and LLaMA3.1-8B.

We ran SFT for seven epochs. After each epoch, we evaluated the model on the validation set and selected the best-performing checkpoint for evaluation on the benchmarks. Validation results for all checkpoints are reported in the appendix in Table 5.

Our evaluation covered six math reasoning benchmarks: AIME24/25, AMC23, MATH500 (Hendrycks et al., 2021), MinervaMath (Lewkowycz et al., 2022), and OlympiadBench (He et al., 2024). We report the mean score across these benchmarks in the main text and provide the raw scores in Table 2. For MATH500, MinervaMath, and OlympiadBench, we report PASS@1; for AIME24/25 and AMC23, we report AVG@32 due to their smaller sizes. We additionally evaluated SFT- and RL-trained models on out-of-distribution benchmarks such as GPQA (Rein et al., 2024), SynLogic (Liu et al., 2025), and IFEval (Zhou et al., 2023). We calculated the mean and standard deviation over three random evaluation seeds in all our experiments. For the reinforcement learning setup, we closely followed Sinii et al. (2025b): online sampling with a binary correctness reward and optimization via the RLOO objective. We implemented steering vectors by activating the bias terms in the `MLP.down_proj` blocks of all transformer layers, thereby adding the newly trained vectors directly to the inter-layer residual stream. Full details and additional experimental details are given in Section A.

Results The results for RL and SFT models evaluated on the math benchmarks are shown in Figure 1. In line with Sinii et al. (2025b), training the steering vectors



LLaMa3.1-8B-It

Qwen2.5-Math-7B

Figure 2: **Capacity scaling of MLP down-projection adapters under SFT.** Mean accuracy across all evaluation benchmarks as a function of LoRA rank when applied exclusively to the MLP down-projection. Performance increases monotonically with adapter rank, eventually almost matching the performance of full-tuning. This demonstrates that, under supervised fine-tuning, improvements in reasoning accuracy depend critically on adaptation capacity even when restricted to a fixed representational subspace.

with the RL objective achieved results that almost always matched full-model fine-tuning. In contrast, this equivalence did not extend to the SFT setup: steering vectors consistently underperformed full-model fine-tuning across all evaluated models. Results on out-of-distribution benchmarks follow the same pattern; these additional evaluations are reported in Section C.

4 Capacity Scaling in Supervised Fine-Tuning

To pinpoint the source of this discrepancy, we asked whether simply increasing the number of trainable parameters would close the gap – and, if so, how much capacity would be required. Rank-1 LoRA applied to the `MLP.down_proj` layer can be viewed as a gradual increase in the complexity of a steering vector, since it allows a token-specific magnitude. We therefore swept the LoRA rank at this location from 1 up to full rank, searching for the capacity threshold at which the gap disappears. Figure 2 shows that the gap closes only under full-rank training, which corresponds to training $\approx 27\%$ of parameters for Qwen2.5-Math-7B.

This result aligns with the analysis of Schulman and Lab (2025), who argue that SFT requires substantially more information (bits) to be learned, which can limit the effectiveness of small-parameter methods such as low-rank LoRA (Hu et al., 2022). They motivate the success of rank-1 LoRA in RL by contrasting trainable capacity with the amount of learning signal available: in RL, each generation produces a single scalar reward, so the signal scales as (dataset_size $\times$ num_generations), whereas in SFT it is spread across all tokens that contribute to the loss. In the next section, however, we show that with an appropriate data source, low-parameter steering vectors can still match full-tuning.

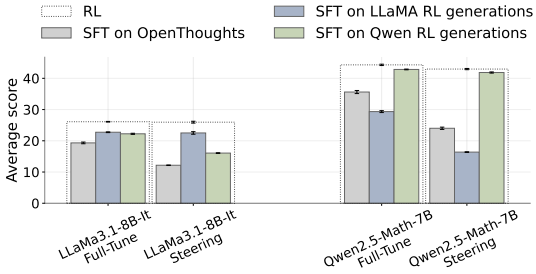


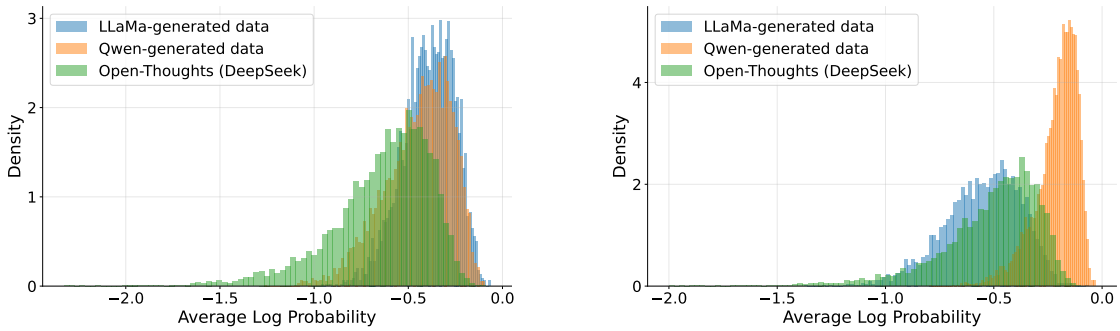
Figure 3: **Steering with Distillation.** When models are trained on generations produced by their respective RL-trained teachers, the performance gap between steering and full-model fine-tuning largely disappears. With an appropriate data source, low-parameter steering vectors have sufficient capacity to match full-tuning. The values are normalized between the base and RL models.

5 Changing Data Removes the Gap

In previous sections, we showed that trainable steering vectors fail to match full-model fine-tuning when trained with SFT. We also found that increasing training capacity can reduce this gap, but only at the cost of training an impractically large number of parameters. Here we show that, with appropriately chosen data, the capacity of steering vectors is in fact sufficient for SFT.

For Qwen2.5-Math-7B and Llama3.1-8B-It, we construct a distillation dataset using its RL-trained counterpart by sampling solutions for OpenThoughts tasks. We then train SFT on generations with positive reward, distilling the knowledge encoded by RL into the student models.

Figure 3 shows that under this distillation setup the gap between steering and full-tuning closes. This indicates that steering vectors are not fundamentally capacity-limited; rather, their effectiveness depends on the training data. Importantly, distillation does not sim-



LLaMa3.1-8B-It Qwen2.5-Math-7B

Figure 4: Generations under steering vectors are lower-probability under the base model, when trained in SFT setup. Since SFT weights all tokens equally, the training constrains low-parameter steering vector from fine-grained updates and prohibits high accuracy. In contrast, full-tuning stays closer to the base model and does not disrupt generations.

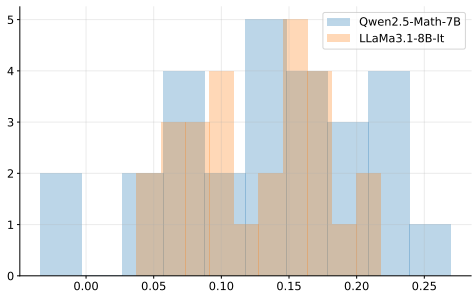


Figure 5: **Cosine similarity between steering vectors in RL and distilled models.** The steering vectors learned under RL and under distillation are poorly aligned, indicating that distillation does not simply copy the donor model's steering directions. Instead, it learns a different mechanism.

ply reproduce the RL-trained steering vectors. Figure 5 reports cosine similarities between steering vectors from the RL-trained and distilled models: across all layers, the vectors are poorly aligned, suggesting that distillation learns a different mechanism.

To further characterize the data difference, we compare the distributions of sequence log-probabilities assigned by the corresponding base models to OpenThoughts examples and to the two distillation datasets (Figure 6). We find that the distillation datasets differ substantially in how likely they are under the base model, and that these differences correlate with downstream SFT performance: datasets with lower base-model log-probabilities tend to produce weaker final results. We emphasize that this is a correlational observation rather than evidence of causality. Still, it points to data likelihood under the base model as one factor that changes across datasets and tracks the resulting performance differences. This interpretation is consistent with recent findings Sun et al. (2025) that more surprising, lower-probability training data can have disproportionately strong and potentially undesirable effects during SFT. Representative generations from the distillation datasets are shown in Section E.

6 Limitations

Our experiments cover a narrow slice of online-training settings. Broader sweeps – across settings, tasks, and model families – would test generality of our observations.

7 Conclusion

We studied when trainable steering vectors can serve as a parameter-efficient alternative to full-model fine-tuning for reasoning. Our results show that their effectiveness depends strongly on the training signal and the data: in some settings, constrained steering updates are sufficient to reach full-tuning performance, while in others they fall short unless substantially more capacity is introduced. Overall, this work clarifies the conditions under which steering vectors are a viable substitute for full-model adaptation and highlights the central role of supervision quality and objective choice in making low-parameter training competitive.

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A SFT and RL Setups; Steering Vectors implementation

In RL training setup, for each prompt, we sample multiple candidate solutions from the current policy and assign a binary reward based on whether the generated answer is correct and enclosed in a `\boxed{...}` template. Optimization is performed using the RLOO objective.

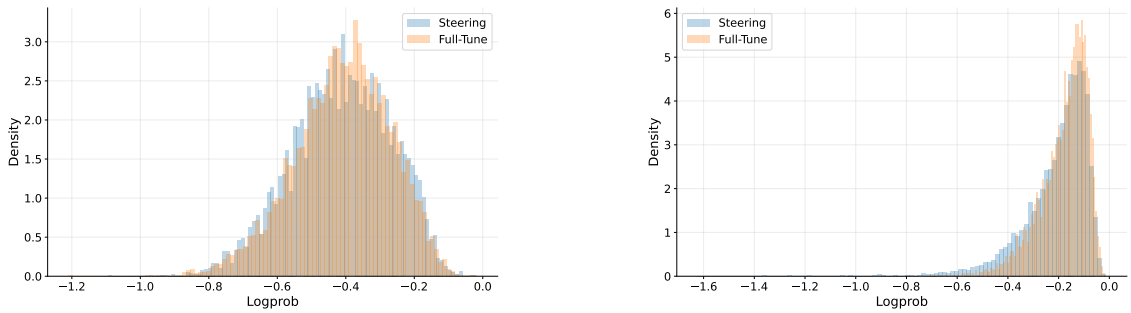
$$\nabla_\theta J = \mathbb{E}_{x\sim\mathcal{D},\, y\sim\pi_\theta(\cdot|x)}\big[\, a(x,y)\, \nabla_\theta \log \pi_\theta(y \mid x)\,\big],$$

All hyperparameters and evaluation procedures are identical to those used in the referenced work.

Steering vectors are implemented by enabling a learnable bias term in the MLP down-projection linear layer in every transformer block. Concretely, this corresponds to setting `bias=True` for the down-projection module and training only this bias parameter. All other model parameters are frozen throughout training. This parameterization exactly matches the steering vector setup of Sinii et al. (2025b) and ensures that all observed effects arise from additive directions in the residual stream.

During both training and evaluation in both RL and SFT setups, model generations were truncated to a maximum length of 4096 tokens for Qwen-based models and 8192 tokens for LLaMA-based models, respectively.

B Deviation from Base for RL-Trained Models



LLaMa3.1-8B-It

Qwen2.5-Math-7B

Figure 6: RL-trained models exhibit similar deviation from their respective base models.

C Out-of-Distribution Evaluation

We evaluate the trained models on three out-of-distribution (OOD) benchmarks: GPQA (Rein et al., 2024), Syn-Logic (Liu et al., 2025), and IFEval (Zhou et al., 2023). All results are reported as AVG@8 scores averaged over three evaluation seeds.

Figure 7 summarizes the results for the primary models. Full-model fine-tuning largely preserves its OOD performance under both RL and SFT. In contrast, steering vectors exhibit a substantial drop in performance across all benchmarks.

These results mirror our in-distribution findings: while steering vectors match full fine-tuning under RL, they underperform it under SFT and generalize worse under distribution shifts. Per-benchmark results are reported in Table 1.

D Full Evaluation Results

In this section we provide all unnormalized accuracies for all evaluated models on each benchmark. All numbers are averaged over three evaluation seeds.

Table 3 reports SFT results on the OpenThoughts dataset, comparing steering vectors, LoRA adaptations, and full-model fine-tuning across all benchmarks.

Table 2 reports RL results on the OpenThoughts and DeepScaleR (Luo et al., 2025) datasets, as well as base-model results that serve as the reference for scaling and analyzing SFT performance.

Tables 4 and 5 report validation performance on OpenThoughts together with the average score across the math benchmarks for each checkpoint during RL and SFT training, respectively. The best validation checkpoint within each configuration is underlined.

Table 1: Evaluation results across IFEval, GPQA, and SynLogic.

Model	Method	Setup	IFEval	GPQA	Synlogic	Avg.
Qwen2.5-Math-7B	RL	Full-Tune	16.2 ± 0.04	25.0 ± 0.01	7.3 ± 0.02	16.2 ± 0.02
Qwen2.5-Math-7B	RL	Steering	17.1 ± 0.02	21.4 ± 0.08	8.2 ± 0.03	15.6 ± 0.04
LLaMa3.1-8B-It	RL	Full-Tune	59.9 ± 0.05	23.5 ± 0.10	8.3 ± 0.03	30.6 ± 0.06
LLaMa3.1-8B-It	RL	Steering	60.3 ± 0.04	19.8 ± 0.10	7.7 ± 0.02	29.2 ± 0.05
Qwen2.5-Math-7B	SFT	Full-Tune	11.7 ± 0.02	26.7 ± 0.05	4.2 ± 0.02	14.2 ± 0.03
Qwen2.5-Math-7B	SFT	Steering	10.6 ± 0.02	10.8 ± 0.10	2.9 ± 0.01	8.1 ± 0.04
LLaMa3.1-8B-It	SFT	Full-Tune	54.4 ± 0.03	30.3 ± 0.06	4.0 ± 0.03	29.6 ± 0.04
LLaMa3.1-8B-It	SFT	Steering	48.8 ± 0.05	21.7 ± 0.11	2.6 ± 0.03	24.3 ± 0.06
Qwen2.5-Math-7B	-	Base, $\tau = 1$	11.5 ± 0.02	7.2 ± 0.07	2.5 ± 0.03	7.1 ± 0.04
LLaMa3.1-8B-It	-	Base, $\tau = 1$	59.1 ± 0.10	4.8 ± 0.03	4.7 ± 0.02	22.9 ± 0.05
Qwen2.5-Math-7B	-	Base, $\tau = 0$	17.2 ± 0.00	9.1 ± 0.00	4.4 ± 0.00	10.3 ± 0.00
LLaMa3.1-8B-It	-	Base, $\tau = 0$	66.7 ± 0.00	7.8 ± 0.00	6.0 ± 0.00	26.8 ± 0.00

Table 2: Full RL OpenThoughts-114k and DeepScaler per-benchmark results. AVG@32 denotes accuracy averaged over 32 sampled generations. All values are mean $\pm$ standard deviation across three seeds.

Model	Dataset	Setup	AIME25@32	AIME24@32	AMC@32	MATH500	MinervaMath	Olympiad-Bench	Avg.
LLaMa3.1-8B-It	DeepScaler	Steering	1.5 ± 0.2	10.3 ± 0.2	32.4 ± 0.7	58.7 ± 0.8	29.3 ± 1.5	24.6 ± 1.3	26.1 ± 0.6
	DeepScaler	Full-Tune	1.6 ± 0.2	10.8 ± 0.2	35.3 ± 0.4	58.0 ± 0.7	29.4 ± 0.6	21.8 ± 0.8	26.1 ± 0.1
	OpenThoughts	Steering	1.5 ± 0.0	8.6 ± 0.2	31.0 ± 0.4	56.8 ± 1.6	27.9 ± 1.1	23.6 ± 0.4	26.0 ± 0.3
	OpenThoughts	Full-Tune	3.3 ± 0.1	6.2 ± 0.2	34.8 ± 0.3	58.1 ± 0.7	29.8 ± 1.1	24.2 ± 0.5	26.1 ± 0.3
		Base, $\tau = 1$	0.0 ± 0.0	0.0 ± 0.0	11.7 ± 2.4	34.6 ± 0.7	12.3 ± 1.5	9.6 ± 0.6	11.7 ± 0.5
Qwen2.5-Math-7B	DeepScaler	Steering	12.6 ± 0.2	24.4 ± 0.2	62.5 ± 0.2	79.9 ± 1.2	36.0 ± 2.8	44.1 ± 0.8	43.3 ± 0.3
	DeepScaler	Full-Tune	14.0 ± 0.1	25.7 ± 0.1	64.2 ± 0.1	79.3 ± 0.6	36.9 ± 2.0	41.1 ± 0.9	43.5 ± 0.4
	OpenThoughts	Steering	15.0 ± 0.2	23.9 ± 0.0	60.4 ± 0.3	77.6 ± 1.9	34.2 ± 0.6	41.1 ± 0.4	43.0 ± 0.2
	OpenThoughts	Full-Tune	12.3 ± 0.1	25.0 ± 0.2	63.4 ± 0.1	80.3 ± 0.7	36.3 ± 0.9	42.0 ± 0.9	44.3 ± 0.2
		Base, $\tau = 1$	2.2 ± 1.6	10.0 ± 4.7	25.0 ± 8.2	37.7 ± 6.1	8.3 ± 1.5	10.2 ± 2.9	14.3 ± 1.7
Qwen2.5-1.5B	OpenThoughts	Steering	1.1 ± 0.0	2.7 ± 0.0	31.2 ± 0.1	57.3 ± 1.0	20.3 ± 0.3	23.1 ± 1.6	24.0 ± 0.4
	OpenThoughts	Full-Tune	1.4 ± 0.0	4.4 ± 0.1	30.1 ± 0.2	59.0 ± 0.7	17.0 ± 1.7	23.2 ± 1.2	24.1 ± 0.4
Qwen2.5-14B	OpenThoughts	Steering	14.5 ± 0.1	14.5 ± 0.6	65.0 ± 0.5	81.1 ± 0.6	37.5 ± 0.3	46.0 ± 0.4	43.9 ± 0.2
	OpenThoughts	Full-Tune	12.1 ± 0.6	15.9 ± 0.4	59.2 ± 0.2	80.5 ± 0.1	38.6 ± 0.3	41.3 ± 1.4	41.3 ± 0.1
Qwen2.5-7B	OpenThoughts	Steering	10.2 ± 0.1	12.7 ± 0.1	53.2 ± 0.1	75.1 ± 1.5	32.5 ± 1.1	40.4 ± 0.3	38.5 ± 0.4
	OpenThoughts	Full-Tune	7.4 ± 0.1	13.1 ± 0.0	57.5 ± 0.4	76.9 ± 0.7	32.7 ± 2.0	41.7 ± 1.2	39.4 ± 0.3
Qwen2.5-Math-1.5B	OpenThoughts	Steering	8.7 ± 0.1	10.1 ± 0.2	48.1 ± 0.2	69.2 ± 0.4	27.7 ± 1.1	36.6 ± 0.4	34.5 ± 0.1
	OpenThoughts	Full-Tune	8.1 ± 0.2	11.9 ± 0.1	49.7 ± 0.1	71.5 ± 1.9	29.7 ± 0.5	35.0 ± 0.7	35.4 ± 0.3
LLaMa3.1-8B	OpenThoughts	Steering	0.3 ± 0.0	0.2 ± 0.0	7.4 ± 0.2	19.1 ± 1.0	13.0 ± 0.8	5.6 ± 0.7	9.5 ± 0.1
	OpenThoughts	Full-Tune	0.2 ± 0.0	1.1 ± 0.0	11.7 ± 0.0	25.6 ± 0.3	16.7 ± 0.8	7.3 ± 0.2	12.3 ± 0.2

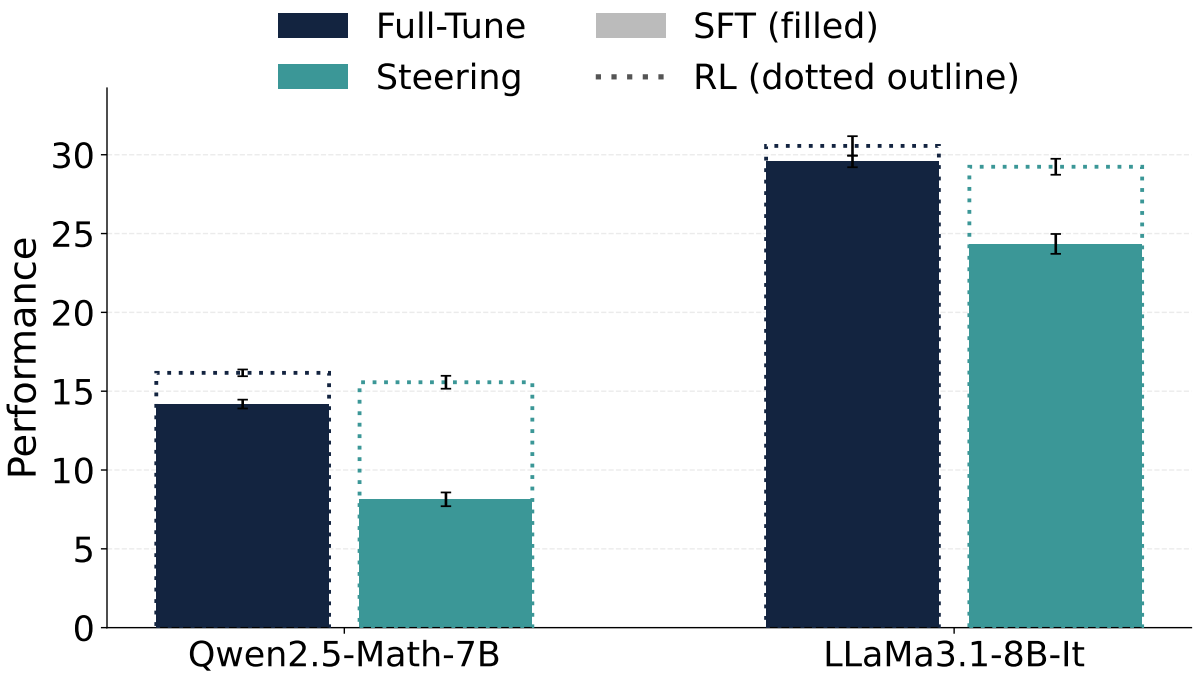


Figure 7: **Out-of-Distribution Evaluation.** Mean accuracy across three OOD benchmarks comparing trainable steering vectors with full-model fine-tuning. Under SFT, steering vectors exhibit a larger performance drop, indicating weaker generalization than full-model fine-tuning.

E Qualitative Comparison of Training Text

To further illustrate the differences between the datasets, we present representative examples of training text and analyze them using log-probabilities assigned by the corresponding base models (Figures 8 and 9).

In RL-generated outputs, the lowest-probability tokens typically correspond to special response-format markers, such as `<|im_end|>` or `\boxed{}`. The content tokens themselves generally remain relatively high-probability under the base model.

In contrast, examples from the OpenThoughts dataset contain many ordinary content words that also receive low probability under the base model. This indicates a broader shift in the text distribution, rather than differences arising purely from formatting conventions.

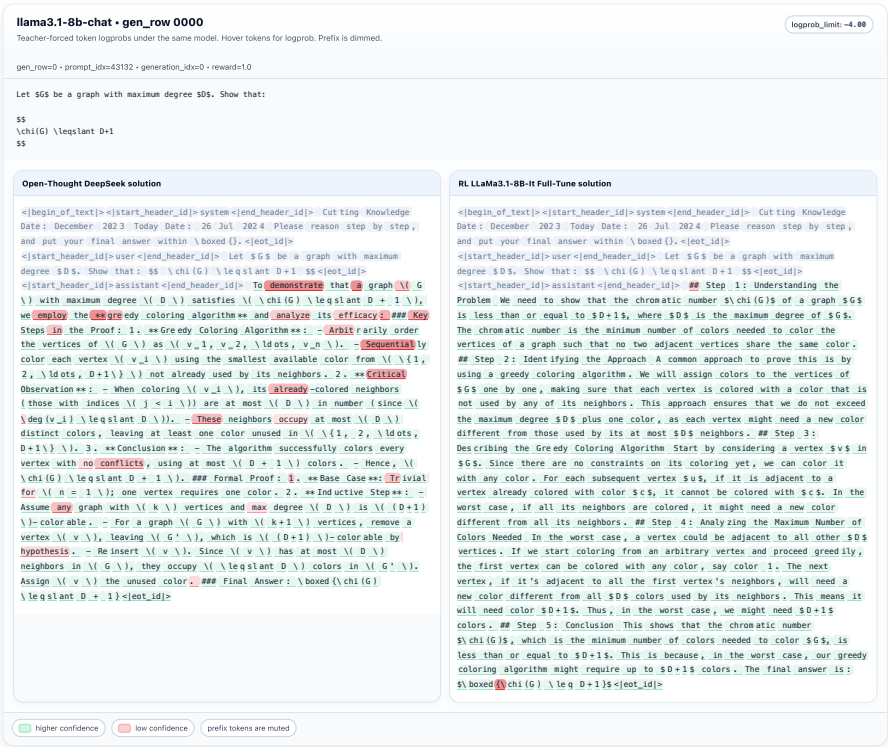


Figure 8: **Example generations from the LLaMa3.1-8B-Instruct RL distillation dataset.** In RL-generated outputs, low-probability tokens are primarily associated with formatting markers such as `\boxed{}`. The content tokens themselves generally remain relatively high-probability under the base model. In contrast, OpenThoughts examples contain many ordinary content words that also receive low probability, indicating a broader shift in the text distribution rather than differences driven solely by formatting.

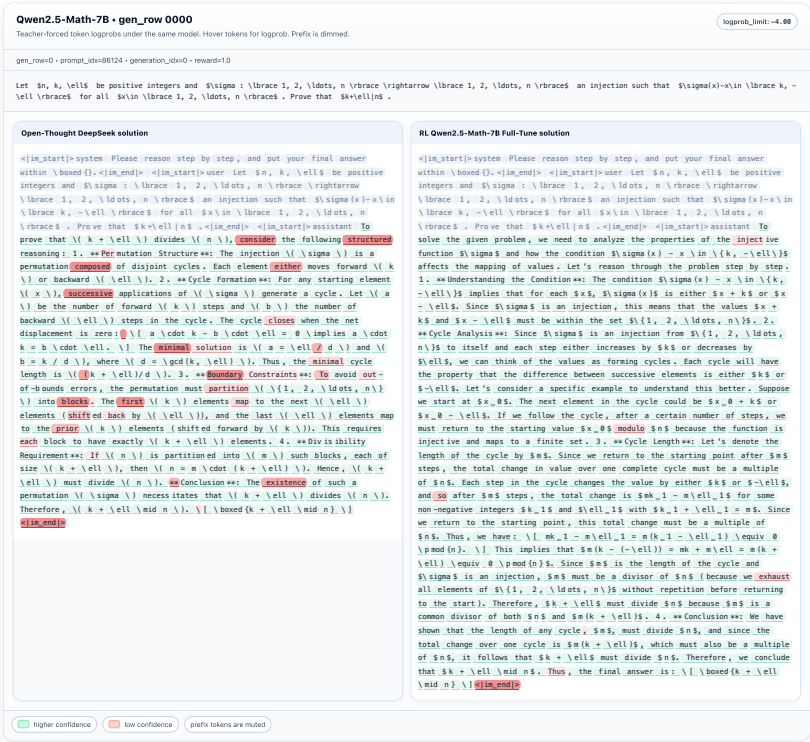


Figure 9: **Example generations from the Qwen2.5-Math-7B RL distillation dataset.** In RL-generated outputs, the lowest-probability tokens are mostly formatting-related, including markers such as `<|im_end|>` and `\boxed{}`, while the content tokens remain relatively high-probability under the base model. In contrast, OpenThoughts examples include many regular content words with low probability, suggesting a broader distributional shift beyond formatting differences.

Table 3: Full SFT OpenThoughts-114k per-benchmark results. AVG@32 denotes accuracy averaged over 32 sampled generations. All values are mean ± standard deviation across three seeds.

Model	Setup	AIME25@32	AIME24@32	AMC@32	MATH500	MinervaMath	Olympiad-Bench	Avg.
LLaMa3.1-8B-It	Full-Tune	0.5 ± 0.0	3.7 ± 0.0	22.9 ± 0.2	48.1 ± 2.8	21.7 ± 1.5	15.5 ± 0.5	18.7 ± 0.6
	Steering	0.3 ± 0.0	0.9 ± 0.0	12.6 ± 0.1	32.1 ± 2.5	12.0 ± 1.4	8.3 ± 0.8	11.0 ± 0.7
	MLP	0.6 ± 0.0	2.4 ± 0.1	25.2 ± 0.3	47.2 ± 2.3	20.6 ± 1.0	16.4 ± 0.7	18.7 ± 0.5
	MLP.down_proj	1.1 ± 0.0	3.1 ± 0.1	22.4 ± 0.1	46.5 ± 2.0	21.8 ± 1.4	15.2 ± 0.9	18.4 ± 0.7
	LoRA-1	0.3 ± 0.0	1.1 ± 0.1	11.3 ± 0.1	32.6 ± 1.9	14.7 ± 0.6	8.0 ± 1.2	11.3 ± 0.5
	LoRA-4	0.8 ± 0.0	1.3 ± 0.0	14.8 ± 0.0	32.7 ± 0.7	14.2 ± 1.4	9.1 ± 0.3	12.2 ± 0.1
	LoRA-16	0.3 ± 0.0	1.2 ± 0.0	15.3 ± 0.1	35.1 ± 1.1	12.7 ± 0.5	8.8 ± 0.3	12.2 ± 0.3
	LoRA-64	0.4 ± 0.1	1.6 ± 0.0	15.5 ± 0.4	37.0 ± 2.0	15.2 ± 0.2	8.9 ± 0.2	13.1 ± 0.4
	LoRA-256	0.6 ± 0.0	1.8 ± 0.0	17.8 ± 0.1	41.3 ± 0.6	16.2 ± 1.3	10.5 ± 1.0	14.7 ± 0.4
	LoRA-1024	0.6 ± 0.0	2.6 ± 0.1	19.4 ± 0.5	43.5 ± 1.6	17.9 ± 1.5	13.8 ± 0.5	16.3 ± 0.1
Qwen2.5-Math-7B	Full-Tune	3.5 ± 0.0	6.2 ± 0.1	44.5 ± 0.2	67.1 ± 1.0	30.4 ± 1.0	27.7 ± 1.7	29.9 ± 0.2
	Steering	2.5 ± 0.0	3.8 ± 0.0	32.9 ± 0.4	52.8 ± 1.5	21.3 ± 0.8	20.3 ± 2.1	22.3 ± 0.7
	MLP	5.5 ± 0.2	7.2 ± 0.2	43.9 ± 0.1	66.6 ± 0.7	29.4 ± 2.4	27.8 ± 0.9	30.1 ± 0.7
	MLP.down_proj	4.5 ± 0.1	5.7 ± 0.0	39.8 ± 0.3	55.5 ± 2.2	25.0 ± 0.8	25.7 ± 0.8	26.0 ± 0.2
	LoRA-1	3.7 ± 0.1	4.3 ± 0.1	31.1 ± 0.2	57.1 ± 1.5	21.3 ± 1.4	22.7 ± 0.7	23.4 ± 0.4
	LoRA-4	3.6 ± 0.0	6.8 ± 0.1	33.7 ± 0.2	56.9 ± 2.1	21.9 ± 0.8	23.5 ± 1.6	24.4 ± 0.2
	LoRA-16	4.1 ± 0.1	4.3 ± 0.1	34.8 ± 0.3	58.7 ± 1.6	26.8 ± 0.9	22.0 ± 0.9	25.1 ± 0.5
	LoRA-64	3.8 ± 0.2	5.0 ± 0.2	36.1 ± 0.3	59.2 ± 1.2	25.1 ± 1.5	23.3 ± 0.7	25.4 ± 0.1
	LoRA-256	4.3 ± 0.1	5.6 ± 0.1	37.8 ± 0.2	61.3 ± 0.5	27.1 ± 0.8	24.5 ± 1.2	26.8 ± 0.3
	LoRA-1024	5.4 ± 0.0	5.9 ± 0.1	40.6 ± 0.2	60.8 ± 1.1	28.6 ± 0.5	25.6 ± 2.0	27.8 ± 0.5
LLaMa3.1-8B	Full-Tune	0.4 ± 0.0	0.6 ± 0.0	9.2 ± 0.2	20.5 ± 1.0	7.1 ± 2.2	7.5 ± 0.6	8.4 ± 0.3
	Steering	0.1 ± 0.0	0.0 ± 0.0	2.9 ± 0.1	5.6 ± 0.3	2.9 ± 0.8	1.4 ± 0.1	2.9 ± 0.2
Qwen2.5-1.5B	Full-Tune	0.2 ± 0.0	0.4 ± 0.1	15.7 ± 0.2	40.2 ± 1.3	9.9 ± 1.7	11.2 ± 0.9	14.5 ± 0.4
	Steering	0.5 ± 0.0	0.6 ± 0.0	6.2 ± 0.0	20.8 ± 2.0	4.7 ± 0.7	4.8 ± 0.4	7.4 ± 0.4
Qwen2.5-14B	Full-Tune	4.8 ± 0.1	8.9 ± 0.3	44.8 ± 0.6	70.4 ± 1.3	34.4 ± 0.2	33.0 ± 1.7	33.6 ± 0.4
	Steering	2.5 ± 0.0	2.6 ± 0.1	27.5 ± 0.3	46.2 ± 0.7	21.4 ± 2.4	18.5 ± 0.3	20.6 ± 0.3
Qwen2.5-7B	Full-Tune	2.3 ± 0.1	6.4 ± 0.2	38.6 ± 0.1	65.4 ± 1.2	27.5 ± 0.5	26.8 ± 0.6	28.9 ± 0.2
	Steering	0.5 ± 0.0	1.7 ± 0.0	16.8 ± 0.1	29.1 ± 0.4	10.4 ± 1.7	11.2 ± 0.7	12.5 ± 0.2
Qwen2.5-Math-1.5B	Full-Tune	3.4 ± 0.0	3.6 ± 0.1	36.9 ± 0.5	60.5 ± 0.9	23.5 ± 1.3	21.7 ± 0.9	25.9 ± 0.3
	Steering	1.2 ± 0.1	1.8 ± 0.0	19.3 ± 0.1	39.5 ± 1.0	13.0 ± 1.1	13.6 ± 0.6	15.6 ± 0.1

Table 4: RL checkpoints on OpenThoughts. Each cell reports validation / benchmark average, where validation corresponds to OpenThoughts and average is the mean across evaluation benchmarks. The best validation checkpoint within each row is underlined; the best average checkpoint is shown in bold.

Model	Setup	ckpt-104	ckpt-156	ckpt-208	ckpt-260	ckpt-312
Qwen2.5-1.5B	Full-Tune	29.8 / 20.1	31.1 / 22.0	32.2 / 23.0	32.7 / 23.7	33.6 / **24.1**
Qwen2.5-1.5B	Steering	31.4 / 22.5	31.9 / 23.4	32.2 / 23.8	32.4 / 23.2	32.6 / **24.0**
Qwen2.5-7B	Full-Tune	43.7 / 36.6	44.6 / 37.8	45.9 / 38.9	46.7 / **39.4**	46.3 / 38.7
Qwen2.5-7B	Steering	43.0 / 37.1	43.8 / 37.4	44.5 / 37.8	45.3 / 38.5	44.9 / **38.6**
Qwen2.5-14B	Full-Tune	44.7 / 37.8	46.9 / 40.4	49.2 / 43.1	48.9 / 43.7	49.1 / **43.8**
Qwen2.5-14B	Steering	43.9 / 38.1	46.2 / 39.8	47.6 / 41.9	48.6 / 43.0	48.8 / **43.9**
Qwen2.5-Math-1.5B	Full-Tune	36.2 / 30.5	38.5 / 31.8	39.8 / 32.8	41.1 / 34.9	42.0 / **35.4**
Qwen2.5-Math-1.5B	Steering	37.1 / 31.1	38.3 / 32.3	39.4 / 33.1	40.0 / 34.0	41.0 / **34.5**
Qwen2.5-Math-7B	Full-Tune	44.9 / 39.6	46.9 / 40.7	49.0 / 42.6	49.5 / 42.9	51.0 / **44.3**
Qwen2.5-Math-7B	Steering	45.5 / 39.4	46.3 / 40.5	47.6 / 42.2	48.5 / **43.0**	48.3 / 41.7
LLaMa3.1-8B	Full-Tune	21.6 / 11.7	22.5 / 11.7	23.0 / 11.8	23.3 / 11.8	23.4 / **12.3**
LLaMa3.1-8B	Steering	19.0 / 7.7	19.8 / 8.4	21.1 / **9.5**	20.7 / 9.4	20.4 / 8.6
LLaMa3.1-8B-It	Full-Tune	28.7 / 25.4	31.0 / 26.3	32.1 / 26.2	32.0 / **26.6**	32.2 / 26.3
LLaMa3.1-8B-It	Steering	29.9 / 24.1	31.1 / 25.7	31.9 / 25.4	31.9 / **26.1**	32.3 / 26.0

Table 5: SFT checkpoints on OpenThoughts. Each cell reports validation / average, where validation corresponds to OpenThoughts and average is the mean across evaluation benchmarks. The best validation checkpoint within each model–setup pair is underlined; the best average checkpoint is shown in bold.

Model	Setup	LR	ckpt-582	ckpt-1164	ckpt-1746	ckpt-2328	ckpt-2910	ckpt-3492	ckpt-4074
LLaMa3.1-8B-It	Full-Tune	5e-06	22.0 / 13.7	24.0 / 15.7	25.7 / 17.6	26.4 / 18.6	27.5 / 19.0	27.8 / 19.1	28.4 / **19.3**
LLaMa3.1-8B-It	Full-Tune	1e-05	21.1 / 12.8	23.2 / 14.3	25.0 / 16.3	25.8 / 17.0	27.0 / 16.9	27.3 / 17.1	27.6 / 17.0
LLaMa3.1-8B-It	Full-Tune	5e-05	17.3 / 6.7	19.4 / 9.0	20.7 / 9.4	21.7 / 10.3	22.7 / 10.9	22.9 / 10.3	23.3 / 11.0
LLaMa3.1-8B-It	Steering	0.0005	19.2 / 12.3	19.7 / 12.3	19.3 / 11.9	19.3 / 11.5	19.6 / 11.7	19.9 / 12.2	19.1 / 11.4
LLaMa3.1-8B-It	Steering	0.001	19.2 / **12.4**	19.5 / 11.4	19.4 / 11.3	19.2 / 11.1	19.1 / 11.3	19.6 / 11.8	19.0 / 11.1
LLaMa3.1-8B-It	Steering	0.01	17.3 / 9.3	17.1 / 8.8	17.4 / 9.0	17.9 / 9.4	17.2 / 8.5	1.6 / 0.6	17.4 / 10.1
LLaMa3.1-8B	Full-Tune	5e-06	9.7 / 4.6	10.3 / 5.9	11.6 / 7.0	12.6 / 7.5	12.5 / 7.6	12.6 / **8.6**	13.4 / 8.4
LLaMa3.1-8B	Full-Tune	1e-05	8.7 / 4.3	7.8 / –	8.8 / –	8.8 / 5.8	9.9 / 7.1	12.4 / 7.7	9.6 / 5.9
LLaMa3.1-8B	Full-Tune	5e-05	1.7 / 0.9	0.3 / 0.2	0.1 / 0.1	0.0 / 0.1	0.1 / 0.1	0.0 / 0.0	0.0 / 0.0
LLaMa3.1-8B	Steering	0.0005	6.4 / 2.8	6.6 / 3.0	5.8 / 2.7	5.4 / 2.5	6.1 / 2.9	6.0 / 3.0	6.6 / 2.9
LLaMa3.1-8B	Steering	0.001	4.5 / 2.0	5.6 / 2.6	5.8 / 2.7	5.8 / 2.8	6.6 / 2.9	6.9 / 3.1	6.5 / **3.3**
LLaMa3.1-8B	Steering	0.01	5.8 / 1.9	0.0 / 0.0	5.5 / 2.5	0.0 / 0.0	7.1 / 2.9	5.2 / 2.1	4.6 / 2.3
Qwen2.5-1.5B	Full-Tune	5e-06	20.1 / 10.9	21.3 / 12.0	21.6 / 12.4	22.5 / 13.0	22.8 / 13.7	23.1 / 14.0	23.7 / 14.5
Qwen2.5-1.5B	Full-Tune	1e-05	20.0 / 11.3	21.4 / 11.7	22.0 / 12.6	22.9 / 13.9	23.6 / 14.4	23.7 / 14.4	24.1 / **14.6**
Qwen2.5-1.5B	Full-Tune	5e-05	18.8 / 8.3	19.6 / 10.0	21.3 / 11.1	21.8 / 11.3	22.6 / 12.2	22.7 / 12.0	22.8 / 12.0
Qwen2.5-1.5B	Steering	0.0005	12.3 / 6.8	13.5 / 7.7	14.1 / 7.9	14.5 / 7.7	14.9 / 7.9	14.6 / 7.9	14.8 / 7.6
Qwen2.5-1.5B	Steering	0.001	13.0 / 7.3	14.4 / 7.6	14.4 / 7.9	14.7 / **8.1**	15.2 / 7.9	14.9 / 8.1	15.2 / 8.1
Qwen2.5-1.5B	Steering	0.01	13.0 / 6.9	13.6 / 7.6	14.3 / 7.4	12.2 / 6.2	10.8 / 5.5	13.0 / 7.1	12.4 / 6.1
Qwen2.5-7B	Full-Tune	5e-06	29.2 / 22.4	31.7 / 24.8	33.3 / 26.5	34.1 / 28.1	34.8 / 28.1	35.4 / 28.4	35.7 / **28.9**
Qwen2.5-7B	Full-Tune	1e-05	29.2 / 22.4	31.4 / 24.9	33.2 / 26.3	34.3 / 27.5	35.4 / 28.3	35.4 / 28.6	35.6 / 28.7
Qwen2.5-7B	Full-Tune	5e-05	23.3 / 14.7	26.2 / 17.6	27.7 / 18.8	27.7 / 18.5	28.8 / 19.2	28.6 / 18.7	29.0 / 18.2
Qwen2.5-7B	Steering	0.0005	13.0 / 9.7	14.3 / 11.1	16.2 / 11.8	16.0 / 11.3	18.6 / 13.7	18.1 / 13.4	18.0 / 12.8
Qwen2.5-7B	Steering	0.001	14.0 / 10.0	16.2 / 11.5	17.4 / 13.1	17.2 / 12.5	19.4 / **14.3**	14.4 / 10.5	17.0 / 12.0
Qwen2.5-7B	Steering	0.01	18.0 / 12.5	9.5 / 6.1	8.4 / 6.4	11.5 / 8.1	7.3 / 5.3	13.1 / 9.8	7.5 / 5.7
Qwen2.5-14B	Full-Tune	5e-06	33.0 / 27.9	35.0 / 30.1	36.0 / 30.6	37.8 / 32.5	38.2 / 33.0	38.6 / 33.4	38.8 / **33.6**
Qwen2.5-14B	Full-Tune	1e-05	32.6 / 27.4	35.0 / 29.8	36.4 / 31.6	37.9 / 32.2	38.4 / 32.6	38.6 / 32.8	38.8 / 33.4
Qwen2.5-14B	Full-Tune	5e-05	26.6 / 19.5	29.5 / 21.4	31.1 / 23.7	31.5 / 23.8	32.3 / 24.2	33.3 / 22.7	32.6 / 23.4
Qwen2.5-14B	Steering	0.0005	16.0 / 12.4	12.2 / 9.7	10.5 / 8.6	9.9 / 8.2	11.4 / 8.7	10.8 / 8.8	11.6 / 9.2
Qwen2.5-14B	Steering	0.001	15.5 / 11.7	13.8 / 11.1	12.2 / 9.2	12.6 / 9.8	14.8 / 11.1	16.9 / 12.7	12.8 / 10.6
Qwen2.5-14B	Steering	0.01	20.1 / 16.3	14.6 / 11.5	21.9 / 18.4	22.3 / 18.1	25.2 / **20.6**	24.3 / 19.2	23.7 / 18.6
Qwen2.5-Math-1.5B	Full-Tune	5e-06	27.2 / 20.8	28.5 / 22.5	29.1 / 23.5	30.5 / 24.5	30.8 / 24.5	31.5 / 25.7	31.8 / 25.9
Qwen2.5-Math-1.5B	Full-Tune	1e-05	28.0 / 22.0	29.4 / 22.8	29.9 / 23.6	31.5 / 25.4	32.4 / 26.7	32.8 / 26.7	33.7 / **27.7**
Qwen2.5-Math-1.5B	Full-Tune	5e-05	28.1 / 21.4	30.4 / 24.1	31.7 / 26.1	32.7 / 26.7	33.4 / 27.2	33.9 / 27.1	33.9 / 26.6
Qwen2.5-Math-1.5B	Steering	0.0005	13.6 / 11.8	16.2 / 13.1	17.0 / 13.4	17.1 / 12.9	17.2 / 13.2	17.2 / 13.2	17.2 / 13.0
Qwen2.5-Math-1.5B	Steering	0.001	15.3 / 13.2	16.7 / 13.3	17.3 / 12.9	17.7 / 13.1	17.8 / 14.0	17.6 / 13.6	17.3 / 13.4
Qwen2.5-Math-1.5B	Steering	0.01	17.6 / 13.5	18.6 / 14.5	19.2 / 14.8	20.5 / 15.4	21.0 / 15.6	20.6 / 15.8	20.9 / **16.1**
Qwen2.5-Math-7B	Full-Tune	5e-06	33.8 / 28.8	35.7 / 30.7	37.6 / 32.3	38.7 / 33.8	39.8 / 34.7	39.8 / 34.7	39.7 / 35.1
Qwen2.5-Math-7B	Full-Tune	1e-05	34.2 / 28.8	36.6 / 31.7	38.3 / 33.3	39.8 / 34.4	40.5 / 35.0	40.7 / 35.3	41.4 / **35.6**
Qwen2.5-Math-7B	Full-Tune	5e-05	32.9 / 27.6	35.6 / 29.9	36.6 / 30.4	37.4 / 31.4	38.3 / 31.7	38.6 / 31.7	37.8 / 31.1
Qwen2.5-Math-7B	Steering	0.0005	23.7 / 19.7	24.3 / 19.7	23.7 / 18.7	23.5 / 19.1	24.2 / 19.9	25.6 / 21.6	24.9 / 20.8
Qwen2.5-Math-7B	Steering	0.001	23.7 / 19.3	23.6 / 19.7	23.9 / 19.9	24.3 / 19.8	26.4 / 22.3	25.9 / 21.9	27.0 / 22.0
Qwen2.5-Math-7B	Steering	0.01	20.2 / 16.6	26.2 / 21.5	22.4 / 17.8	26.1 / 21.7	28.0 / **24.0**	17.4 / 13.3	25.0 / 20.5