Mapping Post-Training Forgetting in Language Models at Scale

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https://post-forget.github.io/

Abstract

Large-scale post-training now drives many of the largest capability gains in language models (LMs), yet its effect on pretrained knowledge remains poorly understood. Not all forgetting is equal: Forgetting one fact (e.g., a U.S. president or an API call) does not "average out" by recalling another. Hence, we propose a sample-wise paradigm to measure what is forgotten and when backward transfer occurs. Our metric counts 1→0 transitions (correct before post-training, incorrect after) to quantify forgetting and 0→1 transitions to quantify backward transfer. Traditional task averages conflate these effects and obscure large changes. For multiple-choice benchmarks, we add chance-adjusted variants that subtract the expected contribution of random guessing from pre- and post-training accuracies. We apply this framework across post-training stages, model sizes, and data scales. Our large-scale analysis shows that: (1) Domain-continual pre-training induces moderate forgetting with low-to-moderate backward transfer; (2) RL/SFT post-training applied to base models and Instruction tuning yields moderate-to-large backward transfer on math and logic with overall low-to-moderate forgetting; (3) Applying RL/SFT to instruction-tuned models is sensitive on data scale: at small scales, both forgetting and backward transfer are small; at larger scales, effects are mixed and warrant further study with better controls; (4) Model merging does not reliably mitigate forgetting. Overall, our framework offers a practical yardstick for mapping how post-training alters pre-trained knowledge at scale – enabling progress towards generally capable AI systems.

1 Introduction

Scaling post-training has become the dominant driver of capability gains in modern language models (LMs) [Jaech et al., 2024]. Practitioners now iterate through multi-step post-training pipelines often at data scales that rival early pre-training [Tie et al., 2025]. The implicit bet is that each step in the pipeline accumulates new capabilities, with dramatic improvements in areas like coding, math, tool use and safety, without sacrificing the broad world knowledge. In contrast, it is considered common knowledge in continual learning that this sequential training would lead to catastrophic forgetting (see Table 1). We test this assumption: as we scale post-training, do we erode the very breadth of world knowledge that pre-training painstakingly compresses into the weights? If the implicit assumption does not hold, we risk trading generalist competence for narrow specialization, undermining progress toward generally capable models.

Measuring forgetting in modern post-training pipelines is tricky. Classical evaluations compare aggregate test accuracy before and after training [Luo et al., 2025], implicitly treating a benchmark as a single task with fungible i.i.d. samples (e.g., classifying images of cats). Pre-trained knowledge

*Equal Supervision

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violates this assumption. Knowing one U.S. president does not compensate for forgetting another; recalling a NumPy broadcasting rule does not offset losing a specific cloud-API syntax. In short, knowledge samples are not fungible: Each carries unique value for quantifying pre-training knowledge. Aggregation can hide substantial losses. Hence, we measure forgetting and backward transfer in a sample-wise manner, rather than at the task level as proposed by Lopez-Paz and Ranzato [2017].

Specifically, we define *forgetting* as items that are answered correctly before a post-training stage but incorrectly afterward (the $1 \to 0$ transitions), and *backward transfer* as items that are answered incorrectly before but correctly after post-training (the $0 \to 1$ transitions). A further complication is that most knowledge-intensive LLM evaluation benchmarks are multiple-choice. Random guessing inflates accuracy, forgetting, and backward-transfer.

To account for these considerations we introduce chance-adjusted metrics for forgetting (F_{true}) and backward transfer ($\mathrm{BT}_{\text{true}}$), which correct for transitions expected under random chance. They do not require logits or repeated sampling and can be computed directly from the number of choices in the benchmark and the model's marginal accuracy before and after training, making them practical at scale. Intuitively, chance-adjusted forgetting asks: among items the model genuinely knew before, what fraction became wrong beyond chance? Conversely, chance-adjusted backward transfer asks: among items the model genuinely did not correctly solve, what fraction became correct beyond chance?

Our primary contribution is a large-scale study measuring forgetting caused by post-training across post-training pipelines. By evaluating the models on the same set of samples before and after each stage, we obtain a map of what was retained, what was forgotten, and where losses concentrate. We seek to answer three questions: (i) Where in the pipeline is forgetting most pronounced (e.g., instruction tuning vs. reasoning-focused training)?, (ii) What kinds of pre-training knowledge are most affected (culture vs. logic)?, and (iii) How much knowledge is forgotten or re-elicited?

2 When, What & How Much is Pre-Training Knowledge Forgotten?

This section examines knowledge forgetting in large language models through three questions: when, what, and how much is forgotten. We analyze nearly 30 model-training combinations across four common regimes on 12 benchmarks spanning about 100 subdomains. The extent of forgetting is quantified using chance-adjusted metrics for forgetting (F_{true}) and backward transfer ($\mathrm{BT}_{\text{true}}$).

2.1 Subarea 1: Domain-Continual Pre-Training

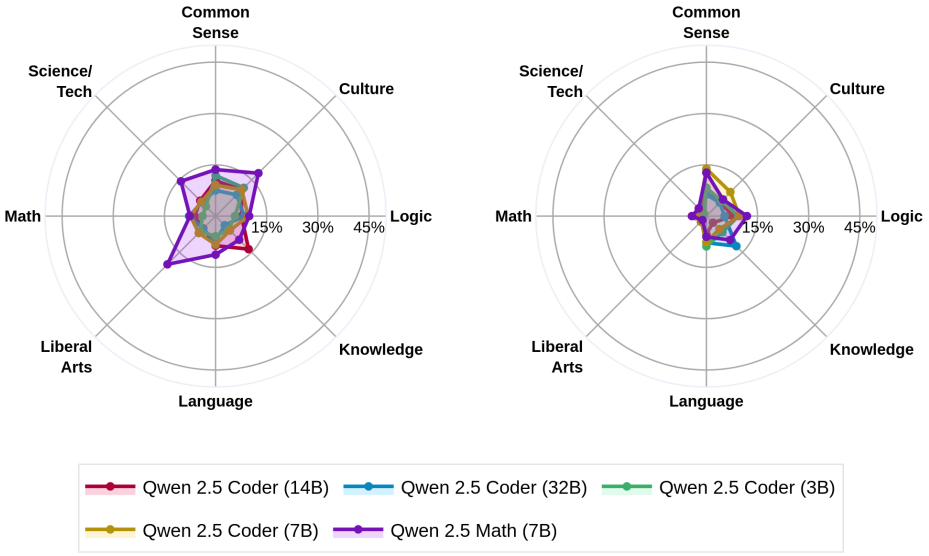

Figure 1: **Forgetting (left) and Backward Transfer (right) after domain-continual pretraining.** Forgetting is low-to-moderate and consistent across categories; backward transfer is low. Scaling model size reduces forgetting.

Motivation. A popular class of continual learning works adapt general LLMs at the application layer for domains such as coding, mathematics, search, and tool use. As generalist LLMs are increasingly wrapped with tools and domain-specific interfaces, specialization must not erode broad pre-training knowledge. Models still need to contextualize domain outputs, communicate with diverse users, respect cultural norms, and uphold safety and ethical standards. These needs motivate our study of forgetting and backward transfer under domain-continual pre-training.

Setup. We study continual pre-training that converts a general base model into a specialized one, exemplified by Qwen2.5-Coder [Hui et al., 2024] and Qwen2.5-Math [Yang et al., 2024b].[2] Unlike general instruction tuning or reasoning post-training, domain-continual pre-training shifts the underlying representation using large, relatively uncurated, web-scale domain corpora.

Results. Figure 1 summarizes our findings. Domain-continual pre-training induces little to moderate amounts of forgetting among all post-training methods we evaluate. Backward transfer to general abilities is weak: Gains in the specialized domain rarely improve non-target tasks. The effect spans categories of pre-training knowledge, with no single category driving it, although math-specialized models show significantly more forgetting. Lastly, larger models forget less and have marginally better backward transfer.

Qualitative analysis. We performed manual errors analysis, which indicates reduced instruction-following fidelity (e.g., weaker adherence to constraints, formats, and role-specific directives). Evidence of this is found in supplemental tests, where a zero-shot, chat-template evaluation is done. In this case, a coder model may, for example, answer “Who was the president of the US?” with a response followed by code, often with embedded answers, making extraction difficult of the "true answer". While few-shot prompting alleviates this, it demonstrates a weakened instruction-following ability and less easily elicited knowledge.

Takeaway

Domain-continual pre-training yields low-to-moderate forgetting across categories; backward transfer is limited. Scaling model size marginally reduces forgetting. This indicates current domain-continual pre-training pipelines appear to alleviate much of the large forgetting behavior seen in previous literature.

2.2 Subarea 2: Instruction Tuning

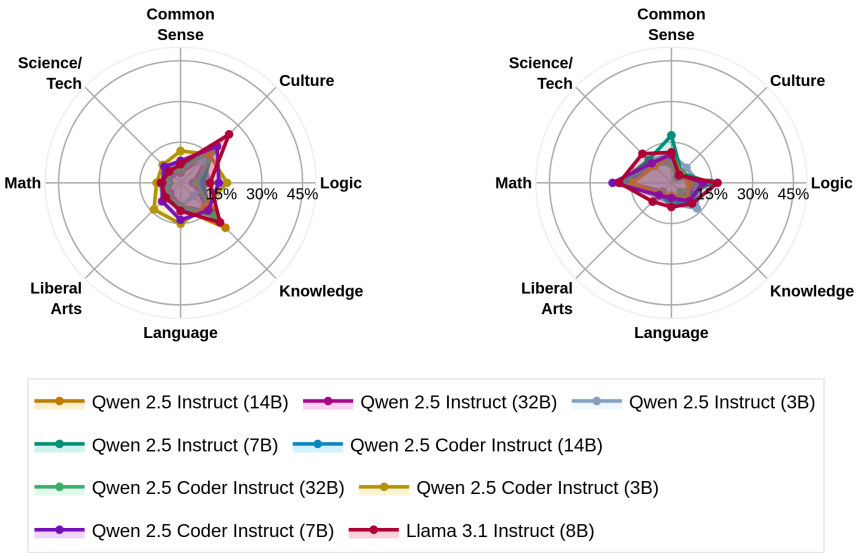

Figure 2: **Forgetting (left) and Backward Transfer (right) after instruction-tuning** yields moderate forgetting and backward transfer categories-wise. Scaling model size reduces forgetting and backward transfer.

[2]We treat domain-continual reasoning via SFT/RL separately in §2.3 and focus on domain-continual training here.

Motivation. Base models often require carefully engineered prompts to elicit pre-training knowledge, limiting usability. Modern post-training pipelines therefore add instruction tuning to enable natural user interaction with minimal prompting. Most continual-learning work we surveyed focuses on mitigating forgetting in this setting. We ask: To what extent does instruction following come at the expense of previously learned knowledge?

Setup. We measure forgetting and backward transfer from instruction tuning in generalist models (Qwen2.5 [Yang et al., 2024a], Llama 3.1 [Dubey et al., 2024]) and domain-continual pre-trained models (Qwen2.5-Coder).

Results. As shown in Figure 2, there is low-to-moderate forgetting across models, with spikes in the Culture and Knowledge categories. However, there is substantial backward transfer in the Math category. Furthermore, scaling model size reduces forgetting and backward transfer. This effect is consistent across domain-general and domain-specific base models. While most of the continual learning literature focuses on reducing forgetting in this area, we note the forgetting is low to moderate with current training practices.

Qualitative analysis. Transfer gains likely reflect better elicitation of pre-training knowledge: Instruction-tuned models use what they already know with straightforward prompts used in benchmarks, whereas base models often require carefully crafted prompts.

Takeaway

Instruction tuning produces low-to-moderate forgetting overall and moderate backward-transfer, particularly in the Math category, across model families; the forgetting and back-transfer tend to decrease with increasing model scale. Shifting focus to other subareas of post-training might spur interesting research directions, but there is still progress to be made in this area.

2.3 Subarea 3: Training with Reasoning Traces (SFT and RL)

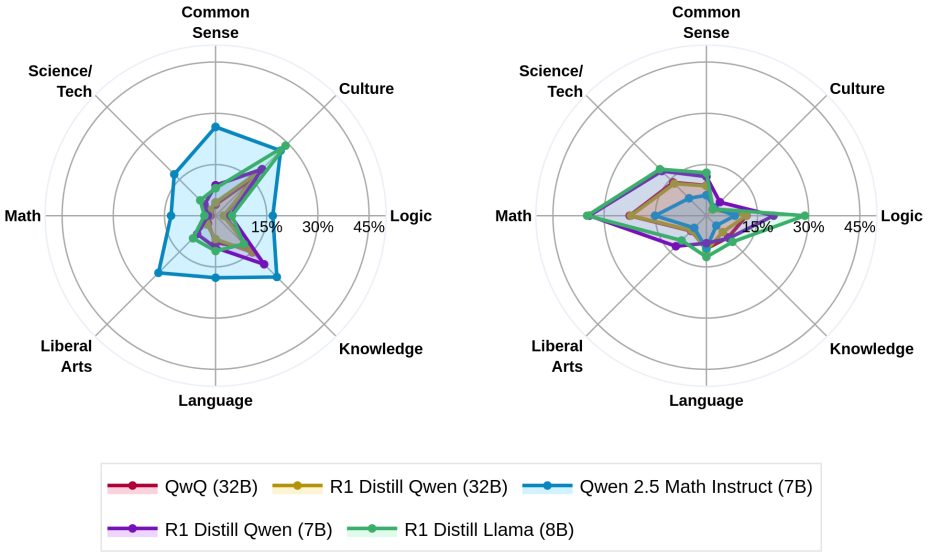

Figure 3: **Forgetting (left) and Backward Transfer (right) after reasoning training (SFT/RL) from base model.** It generally yields minimal forgetting, except in the Culture and Knowledge categories, and has moderate to high backward-transfer gains. Qwen2.5 Math Instruct (7B) is an exception to this trend, demonstrating forgetting across all categories.

Motivation. Recent methods encourage explicit reasoning by letting models *think* on a scratchpad before answering; which is now scaled in size and trace length with RL objectives. As training domains and data grow, we measure how much such reasoning training induces forgetting to guide continual-learning practice.

Setup. We consider two settings: (i) starting from a base model and (ii) starting from an instruction-tuned model. For the latter, we separate light-touch post-training (small datasets) from heavy post-training. We do not separate RL from SFT as the behavior across forgetting and backward transfer is similar between the two objectives.

2.3.1 Training with Reasoning Traces from Base Models

Models. We evaluate QwQ-32B (from Qwen2.5-32B Base) [Qwen Team, 2025], Qwen2.5-Math-7B-Instruct (RL post-trained with GRPO), and DeepSeek-R1-Distill models across different models (Qwen2.5 Base and Llama 8B base) [DeepSeek-AI, 2025].

Results. From Figure 3, we see that across scales, model families, and training types, we observe large gains, particularly in Math and Logic, in backward transfer with minimal forgetting. Forgetting is generally low, but is moderate for knowledge and large for Culture. The exception to this trend is the Qwen2.5 Math Instruct model which shows substantial forgetting across many categories. Sample-wise inspection shows this is primarily due to weak adherence to the prompt, sometimes outputting random multilingual text. Except for this case, when compared to instruction tuning on the same base model (Figure 2), we see similar forgetting and larger back-transfer [3].

We conclude that much of the backward transfer reflects improved instruction following. To isolate reasoning effects beyond elicitation, the next sections analyze reasoning training that starts from an instruction-tuned model, for better exploration of gains. However, models with light-touch reasoning training (i.e. low data) behave differently from those trained at scale (i.e. high data). We therefore present these two cases separately.

Takeaway

Training with SFT/RL for reasoning results in dynamics similar to instruction tuning, but to an even greater extent: We generally observe low to moderate forgetting overall and larger category-specific backward transfer gains. Forgetting mitigation in this domain should consider broad categories of knowledge/abilities when measuring forgetting and back transfer.

2.3.2 Reasoning Training from Instruction-Tuned Models: Low-Data Scenario

Models. We use the s1.1 family (7B, 14B, 32B) [Muennighoff et al., 2025] and LIMO (v1 and v2) [Ye et al., 2025] all tuned from corresponding sized Qwen instruct models.

Results. Figure 7 summarizes our findings. Across categories, models show minimal forgetting and low backward transfer. This makes sense, as training for a few passes on little data leaves pre-training knowledge largely intact. That is, the model does not forget much, but it also exhibits little backward transfer gains beyond the instruction-tuned baseline. Scaling model size marginally lowers forgetting, and the smaller teacher-student gap similarly tends to reduce backward transfer, with the exception of the Knowledge category.

Takeaway

In a low data regime, reasoning training from instruct models yields low forgetting and backward transfer. Forgetting decreases with model scale; backward transfer gains also tend to fall with a narrowing student-teacher gap. This suggests that future forgetting mitigation literature on reasoning models should focus on medium-to-large sized training datasets.

2.3.3 Reasoning Training from Instruction-Tuned Models: High-Data Scenario

Models. We evaluate OpenCodeReasoner and OpenMath2 [Bercovich et al., 2025], OpenThinker-7B, OpenThinker2-32B, and OpenThinker3-7B [Guha et al., 2025], and Intellect-2-32B [Prime Intellect Team et al., 2025]. This spans SFT (former) and RL (Intellect-2).

Results. Results vary by domain mix and model quality. The OpenThinker models shows low–to–moderate forgetting and moderate backward transfer, perhaps due to the breadth of the training datamix, whereas OpenCodeReasoner models show consistently high forgetting with low

[3] All corresponding tables are available in Appendix G.3 for detailed comparison.

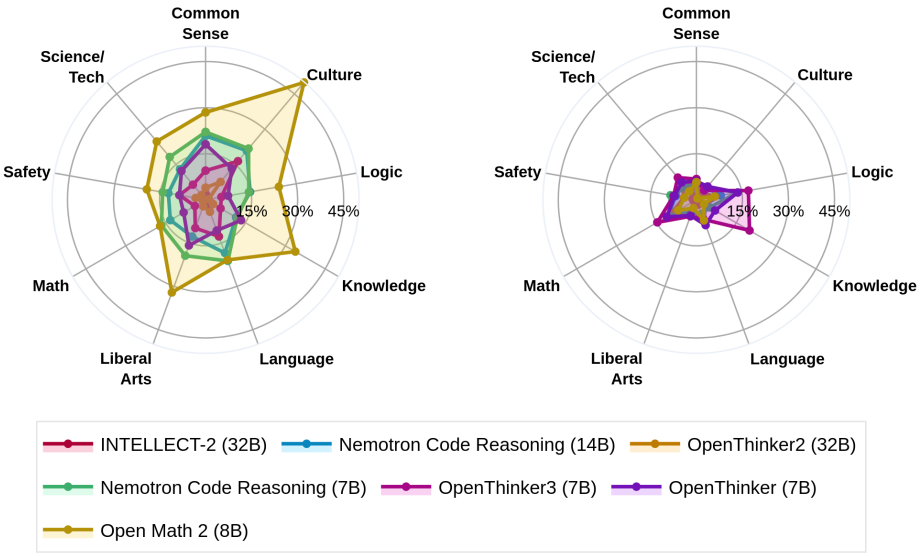

Figure 4: **Forgetting (left) and Backward Transfer (right) after reasoning training from instruct: high data scenario.** No single factor robustly explains the dynamics of forgetting and backward transfer.

backward transfer gains due to the narrower training data. Furthermore, we find this may be primarily due to weakened instruction-following capabilities, as sample outputs show the model will answer numerically that with the letter. Scaling model size, if compared in OpenThinker models, signals improvements in both forgetting and backward transfer, as seen in most previous sections. Decentralized training (as in Intellect-2), in contrast, showed minimal forgetting or backward transfer. We conjecture that the model largely remain unchanged compared to the original model as it shows negligible gains on the optimized math benchmarks Hochlehnert et al. [2025]. However, the results here remain preliminary. We do not find a single dominant factor, initialization, data regime, or scale that sufficiently explains forgetting and backward-transfer dynamics. We believe controlling the finer details which determine the quality of the trained model might lead to better conclusions.

Takeaway

No single factor robustly explains the dynamics of forgetting and backward transfer, but training on a mix of domains appears to improve both forgetting and backward transfer.

3 Does Model Merging Reduce Forgetting?

Motivation. Prior large-scale studies find these simple schemes effective for continual learning with foundation models [Roth et al., 2024]. Our experiments compare linear interpolations (e.g. LERP and SLERP) across OpenThinker-7B, OpenThinker3-7B, and Qwen2.5-Coder-7B, together with their base checkpoints.

Results. For OpenThinker3-7B and Qwen2.5-Coder-7B, even small mixes with the base checkpoint degrade performance, severely for the former case (Figures 9, 10). In contrast, OpenThinker-7B shows small overall gains, accompanied by moderate forgetting (Figure 13). In our setting, merging does not mitigate forgetting. This may reflect that we merge only two checkpoints, whereas prior work often merges eight or more [Yadav et al., 2023, 2024]. We further hypothesize that weight drift between our checkpoints is larger than is typical in the merging literature, which could explain these outcomes.

Takeaway

Model merging does not yet reliably mitigate forgetting in post-training pipelines.

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Part I
Appendix

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A Related Works

Post-training techniques. A broad set of post-training methods now underpins standard LLM pipelines. *Supervised fine-tuning (SFT)* [Ouyang et al., 2022] remains the core step, used for continued pre-training and instruction tuning. At later stages, *reinforcement learning from human feedback (RLHF)* [Ouyang et al., 2022] aligns model outputs with human preferences. To simplify preference learning, *direct preference optimization (DPO)* [Rafailov et al., 2023] provides a direct loss surrogate.

With the rise of test-time scaling (e.g. sampling depth or compute at inference), *group relative policy optimization (GRPO)* [Shao et al., 2024] has been proposed to elicit stronger intrinsic reasoning. Taken together, these methods introduce distinct objectives and optimizers, increasing the complexity of the post-training stack [Wang et al., 2025].

Measuring catastrophic forgetting. Catastrophic forgetting is the loss of previously acquired knowledge when a network learns new information. Early studies examined the effect in small models and simplified settings [McCloskey and Cohen, 1989, Ratcliff, 1990, French, 1999]. Lopez-Paz and Ranzato [2017] formalized forgetting via *backward transfer*, the effect of learning a new task on performance in earlier ones: positive values indicate improvement; negative values indicate forgetting. Recent work extends these analyses to deep networks trained on large-scale data, with growing attention to language models [Biesialska et al., 2020, Wu et al., 2022].

Benchmark paradigm. Task-incremental learning is the dominant paradigm for benchmarking forgetting [De Lange et al., 2022]. Models learn a sequence of tasks with clear boundaries, and task labels are available at train and test time. Class-incremental learning removes test-time task identifiers, making evaluation stricter [Wang et al., 2024]. Other views analyze continual learning through positive/negative transfer [Yıldız et al., 2025]. At the sample level, Toneva et al. [2019] introduced forgetting metrics that identify "unforgettable" examples (stable once learned) and "catastrophically forgotten" examples (highly plastic), and showed these patterns are consistent across architectures and random seeds.

Language-model forgetting. Recent studies focus on forgetting induced by instruction tuning. Luo et al. [2025] trained models up to 7B parameters with SFT and evaluated multiple knowledge categories. DeepSeek-AI [2024] reported instruction-tuning-related regressions on sentence completion even for 67B models. Fernando et al. [2025] examined forgetting across SFT followed by RLHF and proposed joint-training strategies to mitigate it. Lin et al. [2024] framed instruction-tuning degradation as an "alignment tax" (performance loss on pre-training skills due to alignment) and found model merging to be the most Pareto-efficient mitigation among tested techniques. Li and Lee [2024b] studied continual pre-training on aligned LMs and observed notable regressions in alignment-related behavior. We categorize the level of forgetting found in other works along the post-training pipeline of language models in Table 1.

Catastrophic forgetting in reasoning training pipelines. Work on reasoning-oriented LMs highlights new failure modes. Li et al. [2025] defined *temporal forgetting*: models lose the ability to solve problems they could solve at earlier training checkpoints. The effect appears in both RL-trained and instruction-tuned models. They proposed *temporal sampling*—round-robin sampling from recent checkpoints—as a mitigation. Pipatanakul et al. [2025] merged a language-fine-tuned model with DeepSeek R1 Distill (70B; both derived from Llama 3.3 70B [Dubey et al., 2024]) to adapt reasoning while preserving language competence. For multimodal models, Chen et al. [2025] found that later layers primarily support reasoning, whereas early layers concentrate perception, suggesting layer-wise interventions. We document forgetting extensively across post-training pipelines in our work.

Each new method introduces its own objective and optimization procedure, adding to the complexity of the post-training landscape [Wang et al., 2025].

Mitigation strategies. Sequential SFT to RLHF/DPO can exacerbate forgetting. To counteract this, researchers explore: (i) *model averaging*, interpolating between pre- and post-RLHF checkpoints to trade off alignment and retention [Lin et al., 2024]; (ii) *joint post-training*, optimizing supervised and preference objectives simultaneously with convergence guarantees [Fernando et al., 2024]; and (iii) *unified fine-tuning (UFT)*, which folds instruction tuning and alignment into a single implicit-reward objective [Wang et al., 2025]. Additional techniques—including advantage models and selective rehearsal—stabilize RLHF by shaping reward distributions and replaying curated data [Peng et al., 2023]. *Online Merging Optimizers (OMO)* combine gradients from SFT and RLHF models during training to maximize reward while preserving pre-trained skills [Lu et al., 2024]. Theory supports these interventions: up to permutation symmetries, weights of homologous models tend to lie in a shared low-loss basin [Ainsworth et al., 2023]. Surprisingly, model merging did not mitigate forgetting in our simple case of mitigating forgetting during post-training with only two deep networks.

Forgetting at scale. Pre-training mitigates forgetting relative to training from scratch [Mehta et al., 2023, McRae and Hetherington, 1993]. Ramasesh et al. [2022] further found that pretrained ResNets and Transformers (up to $\sim$100M parameters) are robust to forgetting at scale; language experiments showed similar trends. However, Luo et al. [2025] reported increased forgetting with scale in the 1–7B LM regime, suggesting modality- and regime-dependent behavior. In contrast to these works, we study forgetting during post-training of language models.

Table 1: **Catastrophic forgetting literature across LLM post-training stages.** Continual learning literature indicates extensive forgetting across the post-training pipeline. However, we find far less forgetting when testing widely used post-training pipelines, indicating an important gap existing between continual learning setups and how people post-train language models.

Stage	Name	Level	Summary
CPT (§2.1)	Investigating Continual Pretraining in LLMs: Insights and Implications [Yıldız et al., 2024]	Med	Most models show continual improvement; only Llama-2 models degrade.
	Examining Forgetting in Continual Pre-training of Aligned LLMs [Li and Lee, 2024a]	High	Continual pre-training degrades capabilities, alignment and alters output behavior.
SFT/DPO (§2.2)	Mitigating Forgetting in LLM Supervised Fine-Tuning and Preference Learning [Fernando et al., 2024]	Low	Combining SFT and DPO sequentially leads to forgetting and a poor balance between goals ($\sim 2\%$ on MMLU).
SFT (§2.3)	Interpretable Catastrophic Forgetting of LLM Fine-tuning via Instruction Vector [Jiang et al., 2024]	High	Fine-tuning on TRACE shows declines primarily from lost instruction-following ability.
	An Empirical Study of Catastrophic Forgetting in LLMs During Continual Fine-tuning [Luo et al., 2025]	High	Forgetting of domain knowledge, reasoning intensifies as model scale increases ($\sim 10\%$ MMLU drop).
	Catastrophic Forgetting in LLMs: A Comparative Analysis Across Language Tasks [Haque, 2025]	High	Severity varies by architecture and pre-training quality; some models degrade sharply while others barely change.
	Mitigating Catastrophic Forgetting in LLMs with Self-Synthesized Rehearsal [Huang et al., 2024]	High	Sequential fine-tuning causes major forgetting; synthetic rehearsal mitigates it.
RL (§2.2)	Mitigating the Alignment Tax of RLHF [Lin et al., 2024]	Med	RLHF induces forgetting ("alignment tax"); model averaging reduces it.
SFT/RL (§2.2)	Understanding Catastrophic Forgetting in LLMs via Implicit Inference [Kotha et al., 2024]	High	Fine-tuning skews the model's implicit task inference rather than erasing capabilities.
	Temporal Sampling for Forgotten Reasoning in LLMs [Li et al., 2025]	High	Fine-tuned LLMs often forget solutions they previously generated ("temporal forgetting") across sizes and methods (SFT, GRPO).

B Measuring Samplewise Forgetting and Backward Transfer

To formalize these metrics, first consider an evaluation set of N multiple-choice questions with k options. For each sample i, let $a_i^{\text{pre}}, a_i^{\text{post}} \in \{0, 1\}$ indicate correctness before and after post-training. As illustrated in Fig. 5, each sample falls into one of four quadrants based on effect of training on new task:

(i) Retention preserves knowledge $(1 \to 1)$,
(ii) Backward Transfer improves performance $(0 \to 1)$,
(iii) Forgetting reduces performance $(1 \to 0)$, and
(iv) non-acquisition has no effect $(0 \to 0)$.

We define sample-wise *forgetting* and *backward transfer* as the proportions of $1 \to 0$ and $0 \to 1$ flips, respectively:

$$\mathrm{F} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}\{a_i^{\text{pre}} = 1 \wedge a_i^{\text{post}} = 0\}$$

$$\mathrm{BT} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{1}\{a_i^{\text{pre}} = 0 \wedge a_i^{\text{post}} = 1\}$$

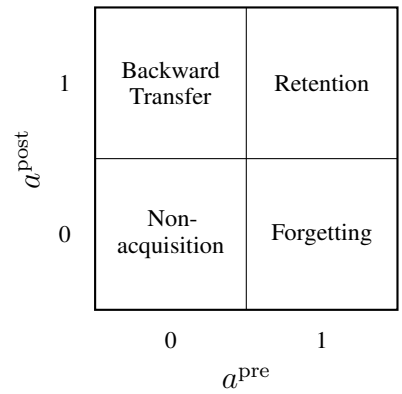

Figure 5: Each sample is assigned to one of four quadrants by correctness before and after.

However, these intuitive metrics confound genuine knowledge change with label flips caused by guessing, especially when k is small. For example, two independent random binary classifiers (k=2) yield $\mathrm{F} = 0.25$ because $0.5 \times 0.5 = 0.25$.

A chance baseline for flips. To account for guessing, we assume a simple response model: on each item the model either *knows* the answer or *guesses* uniformly among the k choices. Let $\bar{a}$ be mean accuracy on a set. Then $\bar{a} = \bar{a}_{\text{true}} + x$, where x is the fraction correct by chance. Since an incorrect guess occurs with probability $(k-1)/k$,

$$\frac{1 - \bar{a}}{x + (1 - \bar{a})} = \frac{k-1}{k} \quad \Longrightarrow \quad x = \frac{1 - \bar{a}}{k - 1}.$$

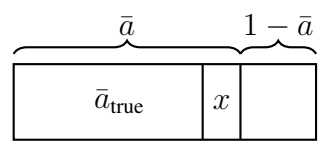

Figure 6: Accuracy $\bar{a}$ decomposes into true knowledge $\bar{a}_{\text{true}}$ and lucky guesses x.

A $1 \to 0$ flip due purely to chance requires (i) a pre-training correct guess and (ii) a post-training error (converse for backward transfer). Assuming independence between pre- and post-training guessing events,

$$\mathrm{F}_{\text{chance}} = \underbrace{\frac{1 - \bar{a}^{\text{pre}}}{k-1}}_{\text{correct by chance (pre)}} \cdot \underbrace{(1 - \bar{a}^{\text{post}})}_{\text{incorrect (post)}}, \qquad \mathrm{BT}_{\text{chance}} = \underbrace{(1 - \bar{a}^{\text{pre}})}_{\text{incorrect (pre)}} \cdot \underbrace{\frac{1 - \bar{a}^{\text{post}}}{k-1}}_{\text{correct by chance (post)}}.$$

These metrics depend only on aggregate accuracies and k; they require no logits or heavy computation.

Chance-adjusted forgetting and backward transfer. From these estimates we can isolate knowledge change beyond chance by subtracting the baselines from the respective forgetting/backward-transfer and clip at zero:

$$\mathrm{F}_{\text{true}} = \max\big(\mathrm{F} - \mathrm{F}_{\text{chance}},\, 0\big), \qquad \mathrm{BT}_{\text{true}} = \max\big(\mathrm{BT} - \mathrm{BT}_{\text{chance}},\, 0\big).$$

For example, if accuracy drops from 80% to 70% on a 4-option MCQ test, raw forgetting is 10%, but chance-adjusted forgetting is only about 6% – showing how the correction removes the effect of lucky guesses. Clipping ensures the metric remains valid even if models perform below chance.

Ceilings: how much could a model forget or improve? Observed forgetting can be small simply because little was truly correct to begin with. The *maximum possible* forgetting equals the fraction truly correct before post-training, which we adjust for guessing and clip at 0:

$$\mathrm{F}_{\max} = \bar{a}_{\text{true}}^{\text{pre}} = \max(\bar{a}^{\text{pre}} - x^{\text{pre}}, 0) = \max\left(\frac{k\,\bar{a}^{\text{pre}} - 1}{k-1},\, 0\right).$$

Similarly, the *maximum possible* backward transfer equals the fraction truly correct after post-training:

$$\mathrm{BT}_{\max} = \bar{a}^{\text{post}}_{\text{true}} = \max(\bar{a}^{\text{post}} - x^{\text{post}}, 0) = \max\left(\frac{k\,\bar{a}^{\text{post}} - 1}{k-1},\, 0\right).$$

where

$$x^{\text{pre}} = \frac{1-\bar{a}_{\text{pre}}}{k-1}, \qquad x^{\text{post}} = \frac{1-\bar{a}_{\text{post}}}{k-1}$$

By construction $\mathrm{F}_{\text{true}} \leq \mathrm{F}_{\max}$ and $\mathrm{BT}_{\text{true}} \leq \mathrm{BT}_{\max}$. Reporting the adjusted metrics alongside these ceilings separates true knowledge loss/acquisition from chance and contextualizes headroom for degradation or improvement.

Assumptions and scope. The correction uses two assumptions: (i) when the model does not know an answer, it guesses uniformly at random; and (ii) pre- and post-training guessing events are independent. These assumptions allow dataset-level adjustments from pre- and post-training accuracies alone. Note that F_{true} could quantify failure to elicit previously accessible knowledge and need not imply that the model has lost/unlearned the underlying information. Likewise, changes in $\mathrm{BT}_{\text{true}}$ often reflect improved elicitation rather than newly acquired knowledge.

C Experimental Setup

We standardize settings across models for fair comparison. All experiments use the `LightEval` framework [Habib et al., 2023] and log per-sample accuracy. We apply a zero-shot chain-of-thought prompt to all models and require answers in a fixed MCQ format (see Appendix); base models receive a few-shot prompt solely to teach the format. When available[4], we add chat-specific templates to be in line with best practices. We cap sequence length at 32K tokens, except for Qwen2.5-7B-Math and Qwen2.5-7B-Math-Instruct Yang et al. [2024a], which are limited to 4K[5]. Decoding uses temperature 0.6 with nucleus sampling (`top_p`) of 0.95. We provide additional details in the Appendix. To facilitate reproducibility and further inquiry, we release per-sample logs for every sub-benchmark alongside code.

C.1 Evaluation

To evaluate performance differences between models, we employ chain-of-thought (CoT) prompting Wei et al. [2022] on multiple-choice question answering (MCQA) datasets. In this setup, the model auto-regressively generates a reasoning chain prior to producing its final answer. The predicted choice is then extracted from the generated text and compared against the ground-truth label. When available, chat-specific templates are incorporated into the prompt to ensure consistent formatting.

Because some models, particularly base models, tend to continue generating responses for subsequent questions after completing the current one, we provide explicit stop sequences to terminate generation once a prediction has been produced.

To encourage answers in strict MCQA format (models sometimes output the option text instead of the letter), we prepend the following instruction prompt:

```
{Instruction}

On the very last line, write exactly "Answer: $LETTER" (e.g.
"Answer: B"), with no extra punctuation, no lowercase, no *,
and no trailing spaces.
Think step by step, showing your reasoning.
Question: "{Question}"
```

We find adding the additional instructions to not use extra punctuation, asterisks, lowercase letters, or trailing spaces necessary, as we find LightEval's letter extraction can fail in certain cases otherwise.

[4]This budget was sufficient in practice; we never required more tokens.

[5]Because base models sometimes continue into subsequent questions, we set explicit stop sequences to end generation once a prediction is produced.

We additionally tell the model to constrain its output to be of the form "Answer: $LETTER" as otherwise models will often provide the corresponding answer to a given letter or provide the answer in another format, making extraction more prone to error.

For the case of base models, where few-shot prompting yields a more accurate elicitation of their knowledge, we use few-shot prompting:

```
{Instruction}

Question: "{Few-Shot Question 1}"
Reasoning: {Few-shot Reasoning Trace 1}
Answer: {Few-shot Answer 1}

... <--- more examples

Question: "{Question}"
Reasoning:
```

Datasets where CoT reasoning traces are provided for few-shot prompting, we use those. In the cases where this is not provided (PIQA, MCTest, Social-IQa, ARC, MCTest, and Hellaswag) CoT few-shot examples were generated and then confirmed these are not included in the benchmarks[1].

All experiments are conducted using the Hugging Face `LightEval` framework, with results logged at the sample level. For generation, we allow up to 32,768 tokens, which we found sufficient for models to complete their chain of thought and provide an answer. In cases where the maximum trained context length is smaller, then the generation is reduced to that number, as is the case with Qwen2.5-7B-Math and Qwen2.5-7B-Math-Instruct Yang et al. [2024a]. The temperature is set to 0.6 and nucleus sampling with $p = 0.95$ is applied.

C.2 Datasets

To evaluate broad model knowledge and capabilities, we benchmark on twelve public datasets: MMLU Hendrycks et al. [2021b,a], BBH Suzgun et al. [2022], GPQA Rein et al. [2024], MuSR Sprague et al. [2024], ARC Clark et al. [2018], TruthfulQA Lin et al. [2022], HellaSwag Zellers et al. [2019], Social IQa Sap et al. [2019], MCTest Richardson et al. [2013], PIQA Bisk et al. [2020], CommonsenseQA Talmor et al. [2019], and SaladBench Li et al. [2024]. Several of these benchmarks, namely MMLU and BBH provide subject-level annotations, enabling fine-grained sub-benchmark analyses in addition to aggregate reporting. For the cases of MMLU and BBH, subcategory labels are provided which allow for splitting into further sub-benchmark evaluates by subjects. To enable easier understanding, we group these (sub-)benchmarks into high-level groups used to evaluate the capabilities of the models. They are grouped such that (sub-)benchmarks in the same group show similar trends in forgetting and improvement.

They are grouped as follows:

Commonsense:

- Commonsense QA
- PIQA

Culture:

- BBH (sports understanding and movie recommendation)

Logic

- BBH (navigate, causal judgment, penguins in a table, web of lies, tracking shuffled objects three objects, tracking shuffled objects seven objects, tracking shuffled objects five objects, temporal sequences, reasoning about colored objects, logical deduction three objects, logical deduction seven objects, logical deduction five objects, formal fallacies, and date understanding)
- ARC (easy and challenge)

- MuSR (murder mysteries, object placements, and team allocation)
- MMLU (logical fallacies)

Knowledge

- BBH (object counting)
- MMLU (miscellaneous and global facts)
- MCTest

Language

- BBH (snarks, disambiguation qa, ruin names, and hyperbaton)
- Social IQa
- Hellaswag
- BBH (salient translation error detection)

Liberal Arts

- MMLU (world religions, us foreign policy, sociology, security studies, public relations, professional psychology, professional law, prehistory, philosophy, management, international law, high school world history, high school us history, high school psychology, high school microeconomics, high school macroeconomics, high school government and politics, high school geography, and high school european history)

Math

- BBH (geometric shapes, and boolean expressions)
- MMLU (high school statistics, high school mathematics, formal logic, elementary mathematics, econometrics, college mathematics, and abstract algebra)

Safety [2]

- MMLU (moral scenarios, moral disputes, jurisprudence, and business ethics)
- TruthfulQA (mc1)
- SaladBench (mrq)

Science & Tech

- MMLU (marketing, virology, professional medicine, professional accounting, nutrition, medical genetics, machine learning, human sexuality, human aging, high school physics, high school computer science, high school chemistry, high school biology, electrical engineering, conceptual physics, computer security, college physics, college medicine, college computer science, college chemistry, college biology, clinical knowledge, astronomy, and anatomy)
- GPQA (diamond)

Unless otherwise noted, we follow the standard task formats and official evaluation splits; for TruthfulQA we report MC1, for GPQA the *Diamond* subset, and for SaladBench the MRQ configuration. This taxonomy serves as the backbone for our analyses of capability acquisition and retention across training and deployment.

[1] MMLU is evaluated with few-shot no CoT prompting for the base models

[2] These are only used in comparisons which do not include a base model because TruthfulQA and SaladBench are designed measure the default behavior of the model rather than knowledge, which few-shot prompting would bias.

D Additional Plots

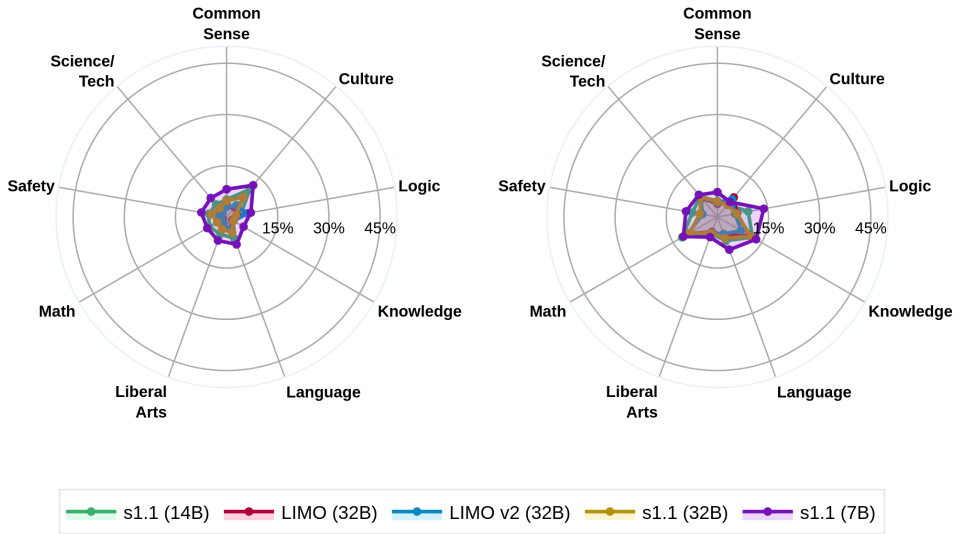

Figure 7: **Forgetting (left) and Backward Transfer (right) after reasoning training from instruct: low data scenario.** Yields little forgetting and backward transfer. Forgetting decreases with model scale.

E Model Merging

Recent work shows that offline model merging can combine capabilities from multiple models [Dziadzio et al., 2025]. Unlike classical continual learning [De Lange et al., 2022], it requires neither the original training data nor the ability to resume training, which is practical in resource-constrained settings.

Setup. We evaluate Exponential Moving Average (EMA) merging; in the two-checkpoint case this is linear interpolation,

$$\theta_{\text{EMA}}(\alpha) = \alpha\,\theta_{\text{pre}} + (1-\alpha)\,\theta_{\text{post}}.$$

E.1 Failure Case: OpenThinker3

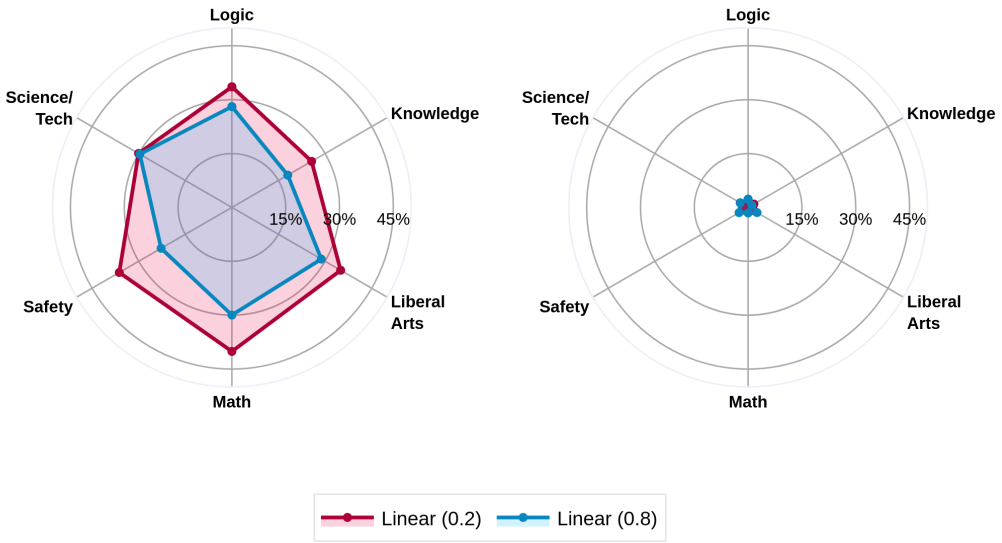

Figure 8: **Forgetting (left) and Backward Transfer (right) of Qwen 2.5 Instruct merged with OpenThinker3 (7B) relative to Qwen 2.5 Instruct on MMLU**. Large forgetting occurs. Sample-level analysis shows the model output degeneration, with the model often repeating words or phrases, typically without providing a final answer.

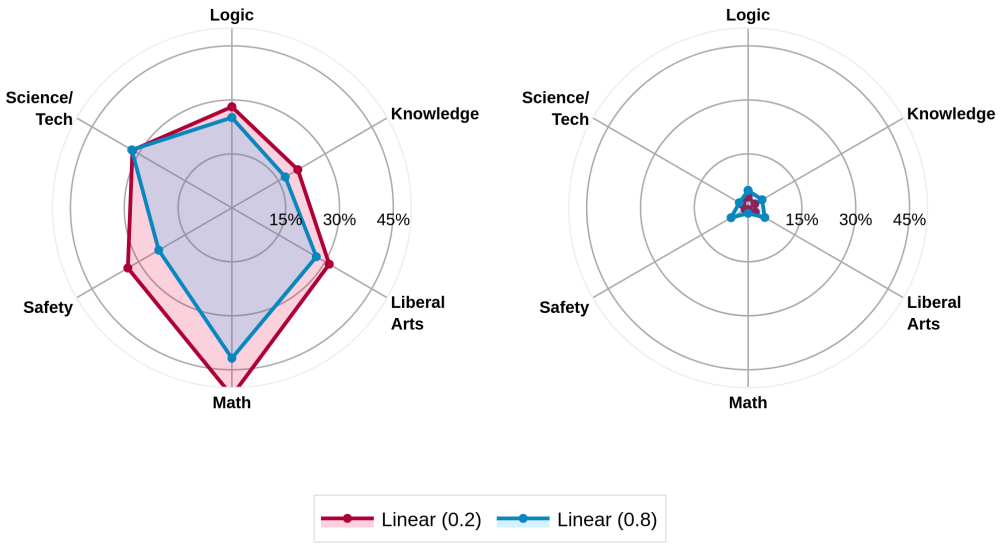

Figure 9: **Forgetting (left) and Backward Transfer (right) of Qwen 2.5 Instruct merged with OpenThinker3 (7B) relative to OpenThinker3 on MMLU**. Large forgetting occurs. Sample-level analysis shows the model output degeneration, with the model often repeating words or phrases, typically without providing a final answer.

E.2 Failure Case: Coder Models

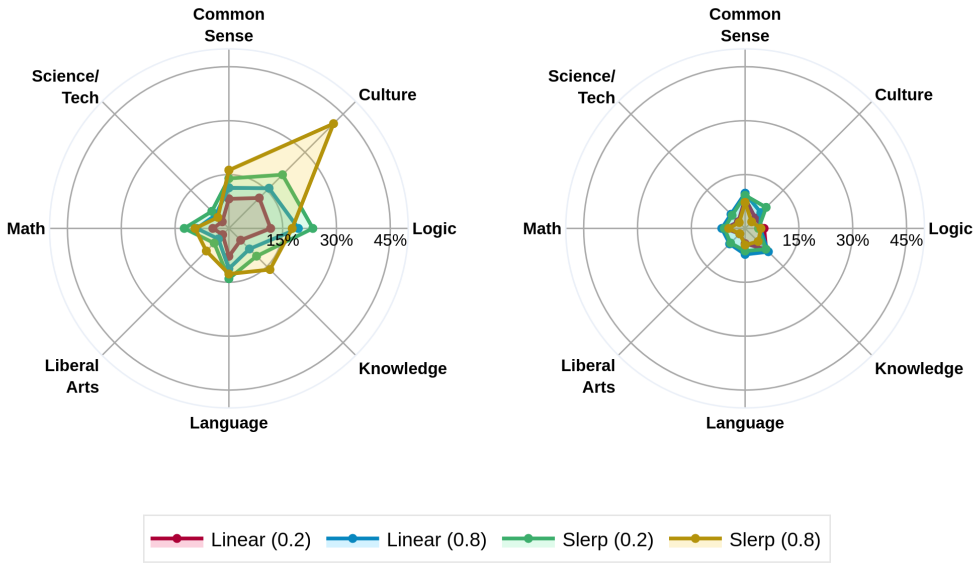

Figure 10: **Forgetting (left) and Backward Transfer (right) of Qwen 2.5 Base merged with Qwen 2.5 Coder (7B) relative to Qwen 2.5 Base on all Benchmarks**. Moderate-to-large forgetting occurs with low backward transfer.

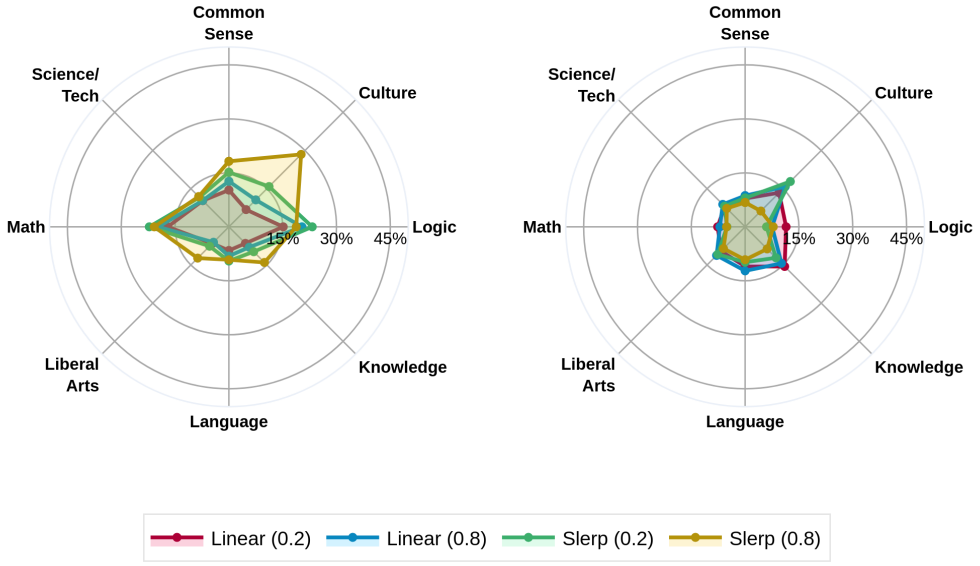

Figure 11: **Forgetting (left) and Backward Transfer (right) of Qwen 2.5 Base merged with Qwen 2.5 Coder (7B) relative to Qwen 2.5 Coder on all Benchmarks**. Moderate-to-large forgetting occurs with low-to-moderate backward transfer.

E.3 Moderate Case: OpenThinker

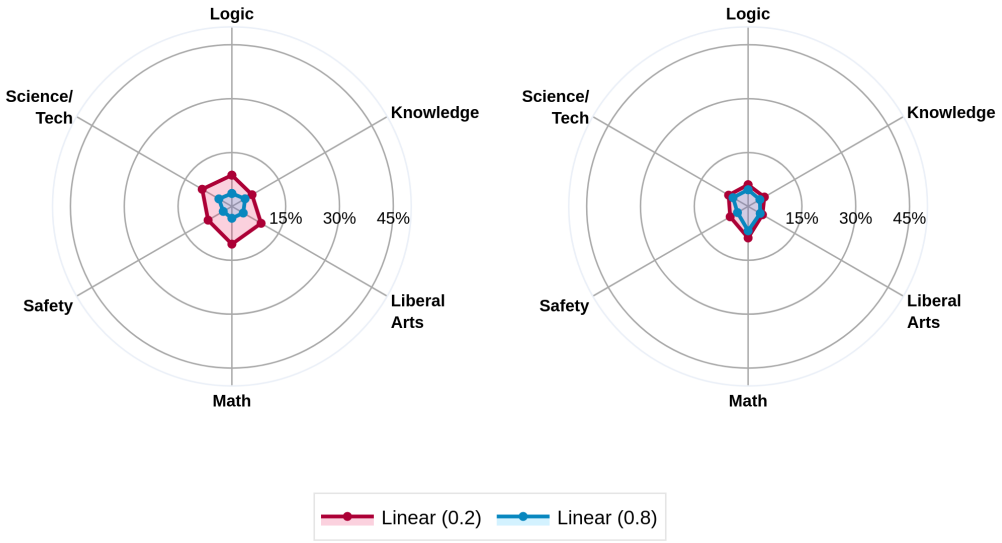

Figure 12: **Forgetting (left) and Backward Transfer (right) of Qwen 2.5 Instruct merged with OpenThinker Merge (7B) relative to Qwen 2.5 Instruct on MMLU**. We see a marginal overall performance improvement in the case of Linear (0.8).

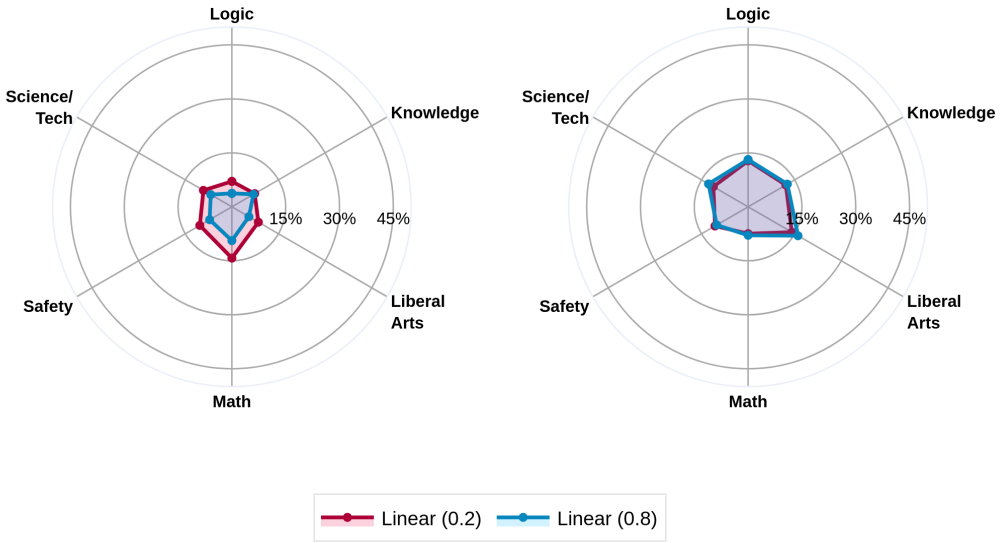

Figure 13: **Forgetting (left) and Backward Transfer (right) of Qwen 2.5 Instruct merged with OpenThinker (7B) relative to OpenThinker on MMLU**. We see a marginal overall performance improvement in both cases.

F Evaluation Methodology

F.1 Prompting

In additional tests, we measure the ability of base models using the same prompting as instruction-tuned models. Under these conditions we see ostensibly large forgetting in domain-continual pretrained models (Figure 15). Our qualitative analysis suggests that this is largely due to the models outputting code, wherein the location of the answer can be obscured. When this is contrasted with the few-shot prompting, where there is much less forgetting, we conclude that forgetting metrics can vary significantly depending on the way knowledge is elicited, especially when training on narrow tasks, which few-shot prompting alleviates.

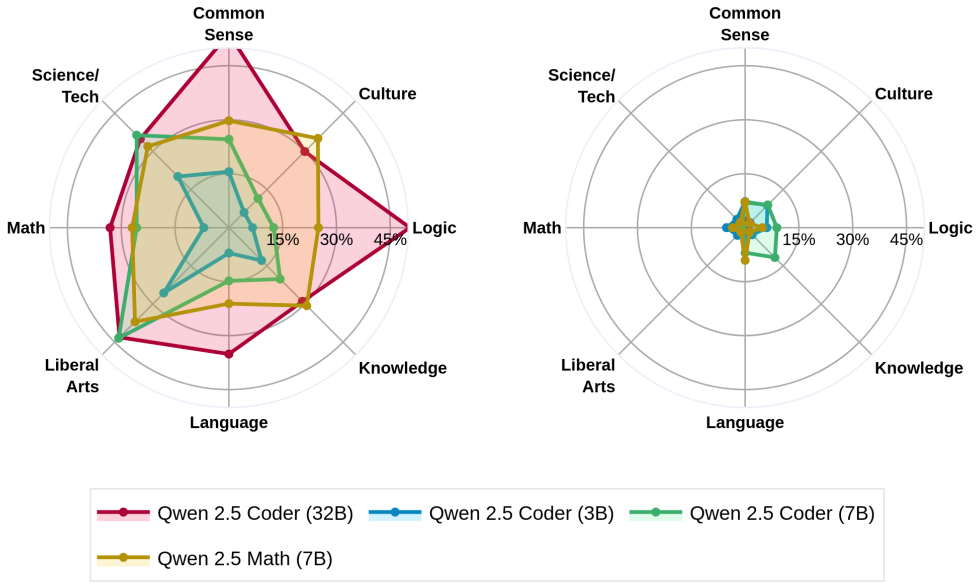

Figure 14: Domain-Adaptive Pretraining models using chat template prompting

For these reasons, measuring the performance of base models on behavioral evaluations can become nontrivial. While benchmarks measuring knowledge or capabilities may be elicited through few-shot prompting, others, such as truthfulness or safety become more difficult as prompting them with examples would bias their behavior. Further works should consider exploring the effect of providing no-knowledge few-shot prompting, where the format of the question and answer is provided without leaking examples to avoid biasing the base model's output.

F.2 Metric

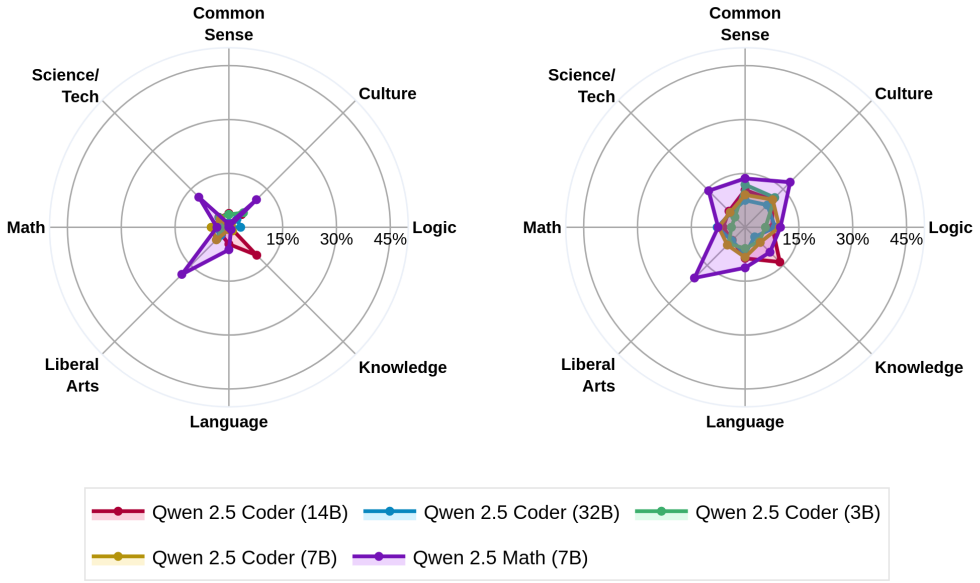

Figure 15: **Coder model comparing conventional forgetting (left) against our sample-wise forgetting (right).** More forgetting is uncovered when using the sample-wise forgetting metric.

The sample-wise nature of our introduced metric uncovers more forgetting than the standard metric, defined as

$$F_{\text{standard}} = \max(\bar{a}^{\text{pre}} - \bar{a}^{\text{post}}, 0)$$

Figure 15 illustrates this effect: our sample-based metric reveals substantially more forgetting relative to the standard formulation, in some cases finding what was originally low forgetting is actually moderate. This highlights sample-level degradation that is otherwise hidden when averaging over tasks.

G Quantifying Forgetting Accurately (Tables for referencing plots)[3]

Forgetting/backward transfer tables are listed with forgetting as the first number in each entry, standard deviation after the "±", and maximum possible forgetting/backward transfer respectively in brackets.

G.1 Instruction Tuning

Table 2: Instruction Tuning: Forgetting (Part 1 of 3)

Category	Q2.5 Inst. (3B)	Q2.5 Inst. (7B)	Q2.5 Inst. (14B)	Q2.5 Inst. (32B)
Common Sense	7.0 ±0.3 (64.2)	5.4 ±0.1 (60.8)	3.9 ±0.6 (75.8)	3.7 ±0.5 (79.5)
Culture	11.7 ±0.9 (55.8)	16.5 ±2.8 (64.8)	14.0 ±0.1 (76.4)	15.2 ±0.6 (78.9)
Logic	10.9 ±0.5 (36.2)	8.4 ±0.2 (52.5)	5.5 ±0.4 (65.3)	4.6 ±0.6 (74.4)
Knowledge/QA	6.8 ±1.3 (47.3)	15.0 ±1.0 (58.4)	23.4 ±0.3 (76.9)	15.3 ±1.9 (69.4)
Language	8.7 ±0.8 (31.0)	9.2 ±0.6 (45.1)	9.5 ±0.8 (59.2)	8.6 ±1.0 (60.2)
Liberal Arts	8.7 ±0.7 (65.3)	6.6 ±0.7 (74.2)	5.3 ±0.4 (78.6)	5.3 ±0.3 (81.9)
Math	7.7 ±0.4 (35.4)	4.2 ±0.4 (47.3)	6.2 ±0.7 (57.9)	4.5 ±1.5 (64.4)
Science/Tech	6.5 ±0.3 (45.6)	5.4 ±0.4 (56.5)	4.5 ±0.5 (65.2)	4.4 ±0.3 (69.7)
Total	8.5 ±0.1 (50.2)	8.2 ±0.3 (58.6)	8.0 ±0.3 (69.7)	6.7 ±0.5 (72.3)

Table 3: Instruction Tuning: Forgetting (Part 2 of 3)

Category	Q2.5 Coder Inst. (3B)	Q2.5 Coder Inst. (7B)	Q2.5 Coder Inst. (14B)	Q2.5 Coder Inst. (32B)
Common Sense	11.7 ±1.0 (59.5)	8.1 ±0.3 (67.2)	6.1 ±0.2 (70.7)	4.6 ±0.4 (77.9)
Culture	15.0 ±2.6 (45.7)	19.0 ±1.9 (60.8)	16.6 ±1.6 (66.9)	19.1 ±1.1 (73.8)
Logic	17.2 ±0.6 (41.2)	14.1 ±0.2 (51.9)	6.9 ±0.2 (64.0)	5.8 ±0.3 (69.8)
Knowledge/QA	12.6 ±0.1 (48.0)	14.4 ±0.3 (56.4)	14.3 ±0.3 (64.3)	17.6 ±1.0 (77.7)
Language	15.1 ±0.7 (36.4)	13.7 ±1.0 (43.2)	10.3 ±0.8 (52.7)	8.6 ±0.5 (59.2)
Liberal Arts	13.9 ±0.6 (59.2)	9.6 ±0.0 (67.6)	7.8 ±0.4 (74.6)	6.7 ±0.2 (77.7)
Math	8.9 ±0.9 (32.8)	6.8 ±0.2 (40.8)	6.2 ±0.4 (54.4)	4.9 ±0.6 (58.6)
Science/Tech	9.4 ±0.7 (40.5)	8.4 ±0.5 (52.0)	7.0 ±0.2 (59.9)	5.6 ±0.5 (65.1)
Total	13.0 ±0.2 (48.2)	10.9 ±0.3 (57.6)	8.9 ±0.3 (66.2)	8.4 ±0.1 (72.2)

Table 4: Instruction Tuning: Forgetting (Part 3 of 3)

Category	Llama 3.1 Inst. (8B)
Common Sense	6.9 ±0.4 (64.5)
Culture	25.3 ±2.2 (79.1)
Logic	10.9 ±0.5 (42.5)
Knowledge/QA	20.6 ±0.8 (60.8)
Language	10.4 ±0.7 (39.9)
Liberal Arts	7.6 ±0.6 (64.6)
Math	7.3 ±0.9 (30.5)
Science/Tech	5.9 ±0.9 (45.5)
Total	10.8 ±0.3 (54.5)

[3]For brevity we shorten Qwen 2.5 to Q2.5 as well as the associated models (e.g. Qwen 2.5 Instruct to Q2.5 Inst.)

Table 5: Instruction Tuning: Backward Transfer (Part 1 of 3)

Category	Q2.5 Inst. (3B)	Q2.5 Inst. (7B)	Q2.5 Inst. (14B)	Q2.5 Inst. (32B)
Common Sense	10.8 ±0.4 (69.2)	17.5 ±0.3 (76.9)	8.7 ±0.1 (82.1)	7.5 ±0.3 (84.6)
Culture	7.9 ±2.4 (49.2)	5.2 ±1.9 (45.3)	5.3 ±0.3 (63.7)	3.0 ±1.1 (62.1)
Logic	10.2 ±0.7 (33.6)	14.6 ±0.5 (60.4)	13.3 ±0.5 (75.6)	9.0 ±0.3 (80.4)
Knowledge/QA	13.3 ±2.8 (55.8)	7.5 ±2.0 (52.5)	5.1 ±1.0 (57.9)	7.7 ±1.7 (61.3)
Language	7.7 ±0.5 (29.8)	8.3 ±0.4 (41.4)	7.2 ±0.0 (54.0)	8.3 ±2.4 (57.0)
Liberal Arts	7.2 ±1.4 (63.3)	5.7 ±0.6 (73.0)	5.6 ±0.9 (78.9)	4.6 ±1.1 (80.9)
Math	18.9 ±0.9 (51.0)	19.0 ±0.8 (67.3)	17.8 ±1.4 (73.8)	15.9 ±1.9 (80.0)
Science/Tech	11.4 ±0.8 (52.1)	11.9 ±0.9 (65.2)	10.4 ±1.0 (73.0)	9.5 ±0.8 (76.5)
Total	10.5 ±0.5 (52.7)	11.0 ±0.5 (62.1)	8.9 ±0.4 (71.3)	8.2 ±0.7 (74.3)

Table 6: Instruction Tuning: Backward Transfer (Part 2 of 3)

Category	Q2.5 Coder Inst. (3B)	Q2.5 Coder Inst. (7B)	Q2.5 Coder Inst. (14B)	Q2.5 Coder Inst. (32B)
Common Sense	10.9 ±0.1 (58.3)	10.6 ±1.0 (70.5)	10.2 ±0.8 (76.2)	6.9 ±0.1 (80.9)
Culture	4.8 ±0.9 (31.0)	4.2 ±0.7 (37.8)	2.8 ±0.5 (47.0)	2.7 ±0.7 (50.0)
Logic	6.6 ±0.3 (25.3)	11.7 ±0.7 (47.2)	11.5 ±0.3 (70.6)	10.8 ±0.1 (76.4)
Knowledge/QA	8.3 ±1.2 (43.4)	9.4 ±1.9 (52.5)	10.2 ±1.3 (60.6)	4.8 ±1.5 (64.2)
Language	4.7 ±0.4 (19.2)	5.6 ±1.2 (29.4)	7.9 ±0.2 (48.0)	6.5 ±0.7 (55.2)
Liberal Arts	5.8 ±1.1 (48.4)	6.4 ±0.7 (63.3)	5.5 ±1.1 (71.6)	5.1 ±0.8 (75.6)
Math	14.4 ±1.8 (41.0)	21.7 ±1.4 (61.2)	17.5 ±1.9 (69.6)	19.1 ±1.5 (77.8)
Science/Tech	8.7 ±1.6 (39.5)	10.2 ±0.5 (54.3)	10.4 ±1.0 (64.4)	9.8 ±0.4 (70.6)
Total	7.4 ±0.2 (40.4)	9.3 ±0.6 (54.9)	8.6 ±0.3 (65.8)	7.6 ±0.4 (71.2)

Table 7: Instruction Tuning: Backward Transfer (Part 3 of 3)

Category	Llama 3.1 Inst. (8B)
Common Sense	11.2 ±0.3 (70.3)
Culture	3.9 ±0.2 (46.2)
Logic	17.0 ±0.9 (49.6)
Knowledge/QA	10.8 ±2.3 (52.9)
Language	8.9 ±1.4 (36.3)
Liberal Arts	9.8 ±1.7 (67.5)
Math	19.3 ±0.7 (46.9)
Science/Tech	15.1 ±1.3 (57.8)
Total	11.4 ±1.0 (55.1)

G.2 Domain-Continual Pretraining

Table 8: Domain-Continual Pretraining: Forgetting (Part 1 of 2)

Category	Q2.5 Coder (3B)	Q2.5 Coder (7B)	Q2.5 Coder (14B)	Q2.5 Coder (32B)
Common Sense	11.9 ±0.5 (64.2)	9.0 ±0.4 (60.8)	10.4 ±0.6 (75.8)	7.5 ±0.6 (79.5)
Culture	11.7 ±0.7 (55.8)	10.9 ±0.4 (64.8)	10.8 ±0.7 (76.4)	8.8 ±0.8 (78.9)
Logic	5.7 ±0.2 (36.2)	9.5 ±0.2 (52.5)	7.6 ±0.3 (65.3)	8.4 ±0.1 (74.4)
Knowledge/QA	5.6 ±0.5 (47.3)	6.0 ±0.8 (58.4)	13.7 ±0.2 (76.9)	3.8 ±0.5 (69.4)
Language	5.9 ±0.6 (31.0)	8.4 ±1.5 (45.1)	8.6 ±0.9 (59.2)	7.4 ±1.3 (60.2)
Liberal Arts	6.4 ±0.5 (65.3)	7.0 ±0.3 (74.2)	5.1 ±0.4 (78.6)	5.2 ±0.3 (81.9)
Math	3.8 ±0.9 (35.4)	7.4 ±1.0 (47.3)	6.2 ±0.2 (57.9)	7.8 ±0.5 (64.4)
Science/Tech	4.0 ±0.5 (45.6)	5.9 ±0.3 (56.5)	6.4 ±0.5 (65.2)	5.7 ±0.5 (69.7)
Total	6.8 ±0.0 (50.9)	7.6 ±0.2 (60.4)	8.0 ±0.1 (71.8)	6.4 ±0.2 (74.6)

Table 9: Domain-Continual Pretraining: Forgetting (Part 2 of 2)

Category	Q2.5 Math (7B)
Common Sense	13.6 ±0.8 (60.8)
Culture	17.8 ±0.3 (64.8)
Logic	9.8 ±0.4 (52.5)
Knowledge/QA	9.8 ±0.5 (58.4)
Language	11.3 ±0.9 (45.1)
Liberal Arts	20.0 ±1.3 (74.2)
Math	7.5 ±1.2 (47.3)
Science/Tech	14.4 ±0.5 (56.5)
Total	12.9 ±0.4 (60.4)

Table 10: Domain-Continual Pretraining: Backward Transfer (Part 1 of 2)

Category	Q2.5 Coder (3B)	Q2.5 Coder (7B)	Q2.5 Coder (14B)	Q2.5 Coder (32B)
Common Sense	8.3 ±0.4 (59.5)	13.8 ±0.3 (67.2)	6.6 ±0.3 (70.7)	6.3 ±0.5 (77.9)
Culture	6.3 ±2.1 (45.7)	10.0 ±1.3 (60.8)	5.8 ±0.4 (66.9)	5.6 ±0.2 (73.8)
Logic	9.4 ±0.5 (41.2)	9.7 ±0.2 (51.9)	7.7 ±0.8 (64.0)	5.3 ±0.4 (69.8)
Knowledge/QA	6.6 ±1.1 (48.0)	5.4 ±0.5 (56.4)	2.7 ±0.3 (64.3)	12.4 ±0.7 (77.7)
Language	8.9 ±0.9 (36.4)	7.6 ±0.8 (43.2)	5.3 ±0.5 (52.7)	7.8 ±2.2 (59.2)
Liberal Arts	2.0 ±0.2 (59.2)	2.2 ±0.3 (67.6)	2.3 ±0.3 (74.6)	2.1 ±0.1 (77.7)
Math	2.4 ±0.2 (32.8)	3.2 ±0.3 (40.8)	3.4 ±1.2 (54.4)	3.4 ±1.0 (58.6)
Science/Tech	1.0 ±0.3 (40.5)	2.8 ±0.0 (52.0)	2.6 ±0.1 (59.9)	2.4 ±0.2 (65.1)
Total	5.1 ±0.2 (48.2)	6.2 ±0.1 (57.6)	4.2 ±0.2 (66.2)	5.1 ±0.2 (72.2)

Table 11: Domain-Continual Pretraining: Backward Transfer (Part 2 of 2)

Category	Q2.5 Math (7B)
Common Sense	12.7 $\pm$0.5 (59.6)
Culture	6.9 $\pm$0.8 (46.3)
Logic	11.9 $\pm$0.2 (53.9)
Knowledge/QA	9.9 $\pm$1.8 (55.3)
Language	6.1 $\pm$0.2 (36.3)
Liberal Arts	1.6 $\pm$0.3 (49.5)
Math	4.3 $\pm$0.5 (43.1)
Science/Tech	3.2 $\pm$0.7 (40.7)
Total	6.3 $\pm$0.2 (50.1)

G.3 Trained from Base

Table 12: Trained from Base: Forgetting (Part 1 of 2)

Category	Q2.5 Math Inst. (7B)	QwQ (32B)	R1 Distill Qwen (7B)	R1 Distill Llama (8B)
Common Sense	26.0 ±0.3 (59.6)	3.2 ±0.4 (79.5)	8.9 ±0.3 (59.6)	8.1 ±0.2 (64.5)
Culture	27.0 ±2.4 (46.3)	15.7 ±0.6 (78.9)	19.3 ±2.1 (46.3)	29.0 ±1.0 (79.1)
Logic	16.8 ±0.4 (53.9)	2.8 ±0.2 (74.4)	4.4 ±0.4 (53.9)	4.8 ±0.2 (42.5)
Knowledge/QA	25.4 ±2.0 (55.3)	13.2 ±2.1 (69.4)	20.1 ±0.7 (55.3)	11.7 ±0.7 (60.8)
Language	18.2 ±0.9 (36.3)	7.9 ±1.2 (60.2)	9.4 ±0.8 (36.3)	10.4 ±0.4 (39.9)
Liberal Arts	23.7 ±0.7 (49.5)	3.1 ±0.2 (81.9)	7.6 ±0.4 (49.5)	9.4 ±0.9 (64.6)
Math	13.1 ±0.3 (43.1)	1.5 ±0.3 (64.4)	2.2 ±0.4 (43.1)	3.3 ±0.3 (30.5)
Science/Tech	17.1 ±0.9 (40.7)	2.2 ±0.2 (69.7)	4.6 ±0.2 (40.7)	6.4 ±0.4 (45.5)
Total	21.4 ±0.5 (50.1)	5.4 ±0.3 (72.3)	8.7 ±0.1 (50.1)	9.3 ±0.3 (54.5)

Table 13: Trained from Base: Forgetting (Part 2 of 2)

Category	R1 Distill Qwen (32B)
Common Sense	3.9 ±0.3 (79.5)
Culture	18.8 ±0.7 (78.9)
Logic	2.3 ±0.3 (74.4)
Knowledge/QA	15.3 ±1.3 (69.4)
Language	6.9 ±1.4 (60.2)
Liberal Arts	3.6 ±0.3 (81.9)
Math	1.8 ±0.5 (64.4)
Science/Tech	2.4 ±0.3 (69.7)
Total	6.0 ±0.2 (72.3)

Table 14: Trained from Base: Backward Transfer (Part 1 of 2)

Category	Q2.5 Math Inst. (7B)	QwQ (32B)	R1 Distill Qwen (7B)	R1 Distill Llama (8B)
Common Sense	6.0 ±0.6 (32.9)	8.9 ±0.5 (87.0)	11.4 ±0.1 (63.0)	12.6 ±0.8 (70.5)
Culture	3.4 ±1.3 (9.0)	2.9 ±1.0 (59.8)	5.6 ±1.4 (23.1)	2.8 ±0.4 (36.5)
Logic	8.4 ±0.4 (42.8)	11.8 ±0.5 (86.7)	19.7 ±0.1 (74.9)	28.9 ±0.1 (74.6)
Knowledge/QA	4.1 ±1.4 (31.2)	9.0 ±1.6 (65.2)	9.3 ±2.4 (45.6)	10.8 ±1.8 (61.8)
Language	9.6 ±0.6 (20.9)	9.7 ±2.8 (60.6)	8.1 ±0.8 (33.7)	12.1 ±1.0 (42.2)
Liberal Arts	5.0 ±0.4 (24.5)	6.3 ±1.0 (86.1)	12.7 ±1.6 (56.2)	10.3 ±1.5 (65.8)
Math	15.1 ±1.6 (46.5)	22.5 ±2.2 (92.2)	34.3 ±2.4 (85.8)	35.0 ±0.5 (72.8)
Science/Tech	7.2 ±0.2 (27.4)	13.8 ±1.0 (85.0)	18.5 ±1.5 (59.3)	19.3 ±1.2 (62.7)
Total	6.7 ±0.2 (30.1)	10.3 ±0.6 (78.6)	14.3 ±1.0 (57.4)	15.4 ±0.6 (62.1)

Table 15: Trained from Base: Backward Transfer (Part 2 of 2)

Category	R1 Distill Qwen (32B)
Common Sense	8.7 $\pm$0.3 (85.9)
Culture	2.5 $\pm$0.6 (55.4)
Logic	11.7 $\pm$0.4 (87.2)
Knowledge/QA	6.8 $\pm$1.3 (60.6)
Language	10.2 $\pm$2.7 (62.9)
Liberal Arts	6.1 $\pm$1.0 (85.2)
Math	22.1 $\pm$2.5 (91.4)
Science/Tech	13.3 $\pm$1.0 (84.2)
Total	10.0 $\pm$0.6 (77.5)

G.4 Trained from Instruct - High Data Scenario

Table 16: Trained from Instruct - High Data Scenario: Forgetting (Part 1 of 2)

Category	INTELLECT-2 (32B)	Open Math 2 (8B)	OpenThinker (7B)	OpenThinker2 (32B)
Common Sense	1.9 ±0.3 (87.0)	28.5 ±0.9 (64.5)	18.1 ±1.3 (76.9)	3.9 ±0.3 (84.6)
Culture	0.7 ±0.6 (60.2)	49.9 ±1.9 (79.1)	13.3 ±4.6 (45.3)	7.6 ±2.1 (62.1)
Logic	0.6 ±0.1 (87.4)	24.2 ±0.5 (42.5)	7.4 ±0.2 (60.4)	1.0 ±0.2 (80.4)
Knowledge/QA	2.5 ±0.6 (65.9)	33.8 ±1.4 (60.8)	13.4 ±1.1 (52.5)	2.8 ±0.5 (61.3)
Language	1.9 ±0.3 (62.7)	20.9 ±1.2 (39.9)	10.7 ±1.2 (41.4)	4.2 ±0.4 (57.0)
Liberal Arts	1.2 ±0.2 (86.1)	32.1 ±2.3 (64.6)	15.8 ±1.0 (73.0)	2.3 ±0.1 (80.9)
Math	0.9 ±0.1 (91.9)	17.1 ±1.4 (30.5)	8.3 ±0.8 (67.3)	1.0 ±0.3 (80.0)
Safety/Truth	0.9 ±0.2 (66.8)	19.5 ±0.7 (36.3)	8.6 ±0.5 (50.0)	3.3 ±0.2 (64.5)
Science/Tech	1.6 ±0.1 (85.0)	24.8 ±1.8 (45.5)	12.2 ±0.5 (65.2)	2.1 ±0.2 (76.5)
Total	1.3 ±0.1 (79.0)	28.8 ±0.8 (54.5)	12.6 ±1.5 (62.0)	2.9 ±0.2 (74.3)

Table 17: Trained from Instruct - High Data Scenario: Forgetting (Part 2 of 2)

Category	OpenThinker3 (7B)	Nemotron Code Reasoning (7B)	Nemotron Code Reasoning (14B)
Common Sense	9.5 ±0.4 (76.9)	22.1 ±0.1 (76.9)	20.9 ±2.4 (79.0)
Culture	16.4 ±4.5 (45.3)	21.8 ±3.1 (45.3)	20.9 ±0.7 (63.7)
Logic	5.2 ±0.2 (60.4)	14.3 ±0.4 (60.4)	14.7 ±0.3 (75.6)
Knowledge/QA	5.6 ±0.9 (52.5)	11.9 ±1.6 (52.5)	11.5 ±2.1 (57.9)
Language	12.7 ±0.8 (41.4)	21.2 ±1.4 (48.3)	18.4 ±1.2 (62.4)
Liberal Arts	9.8 ±0.6 (73.0)	19.4 ±0.7 (73.0)	12.8 ±1.0 (79.6)
Math	4.1 ±0.1 (67.3)	16.6 ±0.5 (67.3)	13.3 ±0.4 (73.8)
Safety/Truth	8.7 ±0.6 (50.0)	14.2 ±0.1 (50.0)	12.3 ±1.2 (63.0)
Science/Tech	6.4 ±0.3 (65.2)	18.2 ±0.4 (65.2)	13.0 ±0.2 (73.0)
Total	8.4 ±0.5 (62.1)	17.7 ±0.3 (62.4)	14.9 ±0.0 (72.1)

Table 18: Trained from Instruct - High Data Scenario: Backward Transfer (Part 1 of 2)

Category	INTELLECT-2 (32B)	Open Math 2 (8B)	OpenThinker (7B)	OpenThinker2 (32B)
Common Sense	1.7 ±0.1 (86.7)	5.7 ±0.4 (34.1)	6.1 ±0.8 (60.9)	4.2 ±0.5 (85.0)
Culture	1.1 ±0.3 (60.8)	0.5 ±0.4 (6.5)	5.7 ±1.6 (33.6)	2.9 ±0.3 (54.3)
Logic	0.7 ±0.1 (87.4)	6.0 ±0.4 (18.3)	13.7 ±0.6 (67.4)	6.2 ±0.4 (87.5)
Knowledge/QA	3.4 ±0.9 (67.5)	2.8 ±1.2 (25.3)	7.0 ±0.7 (43.0)	3.8 ±0.1 (62.3)
Language	1.7 ±0.2 (62.7)	7.2 ±0.8 (18.1)	8.8 ±1.6 (39.1)	6.4 ±0.7 (61.0)
Liberal Arts	1.2 ±0.1 (86.0)	2.9 ±0.2 (25.5)	5.5 ±0.5 (59.2)	5.6 ±0.3 (85.4)
Math	0.9 ±0.2 (92.1)	6.9 ±1.1 (15.0)	11.1 ±1.0 (71.3)	10.1 ±1.1 (91.7)
Safety/Truth	1.3 ±0.5 (67.2)	4.0 ±0.6 (15.9)	7.2 ±1.2 (48.1)	4.1 ±0.8 (65.5)
Science/Tech	1.5 ±0.1 (85.0)	3.6 ±0.9 (17.0)	7.4 ±0.4 (58.7)	7.6 ±0.3 (83.8)
Total	1.4 ±0.1 (79.2)	4.2 ±0.2 (21.1)	7.7 ±0.5 (55.1)	5.3 ±0.2 (77.3)

Table 19: Trained from Instruct - High Data Scenario: Backward Transfer (Part 2 of 2)

Category	OpenThinker3 (7B)	Nemotron Code Reasoning (7B)	Nemotron Code Reasoning (14B)
Common Sense	6.7 ±0.2 (73.2)	5.2 ±0.4 (54.3)	3.6 ±1.2 (56.0)
Culture	4.0 ±1.0 (23.3)	5.1 ±2.3 (19.2)	5.2 ±0.5 (37.8)
Logic	17.2 ±0.9 (76.3)	13.7 ±0.7 (57.4)	8.1 ±0.3 (65.4)
Knowledge/QA	20.0 ±0.3 (66.6)	5.0 ±0.5 (42.6)	3.2 ±0.2 (46.6)
Language	6.8 ±0.7 (33.6)	4.9 ±0.8 (23.3)	7.6 ±0.8 (46.3)
Liberal Arts	5.7 ±0.2 (67.5)	4.3 ±0.1 (52.8)	4.2 ±0.5 (68.3)
Math	14.7 ±0.3 (81.2)	10.4 ±0.0 (56.4)	10.7 ±0.8 (69.4)
Safety/Truth	7.5 ±0.9 (48.5)	8.6 ±1.2 (42.5)	6.8 ±0.6 (55.6)
Science/Tech	9.4 ±0.5 (69.2)	5.2 ±0.0 (47.7)	6.4 ±0.1 (64.3)
Total	9.7 ±0.2 (62.8)	6.7 ±0.4 (46.5)	5.8 ±0.1 (59.0)

G.5 Trained from Instruct - Low Data Scenario

Table 20: Trained from Instruct - Low Data Scenario: Forgetting (Part 1 of 2)

Category	s1.1 (7B)	s1.1 (14B)	s1.1 (32B)	LIMO (32B)
Common Sense	8.1 ±0.4 (76.9)	5.1 ±1.0 (82.1)	4.7 ±0.5 (84.6)	3.5 ±0.3 (84.6)
Culture	12.1 ±1.2 (45.3)	10.6 ±0.4 (63.7)	7.5 ±0.9 (62.1)	3.7 ±1.9 (62.1)
Logic	7.2 ±0.1 (60.4)	4.2 ±0.4 (75.6)	2.8 ±0.2 (80.4)	3.0 ±0.3 (80.4)
Knowledge/QA	5.7 ±1.1 (52.5)	2.3 ±0.1 (57.9)	2.3 ±1.2 (61.3)	2.0 ±0.4 (61.3)
Language	8.6 ±0.8 (41.4)	6.7 ±0.4 (54.0)	4.9 ±0.1 (57.0)	3.8 ±0.6 (57.0)
Liberal Arts	7.4 ±0.5 (73.0)	5.4 ±0.7 (78.9)	3.9 ±0.1 (80.9)	2.6 ±0.0 (80.9)
Math	6.6 ±0.8 (67.3)	5.8 ±0.9 (73.8)	3.2 ±0.4 (80.0)	1.3 ±0.1 (80.0)
Safety/Truth	7.5 ±0.9 (50.0)	5.3 ±0.3 (59.4)	4.5 ±0.4 (64.5)	2.9 ±0.3 (64.5)
Science/Tech	7.2 ±0.4 (65.2)	4.8 ±0.6 (73.0)	3.3 ±0.4 (76.5)	2.3 ±0.1 (76.5)
Total	7.7 ±0.2 (62.1)	5.3 ±0.2 (71.3)	3.9 ±0.1 (74.3)	2.6 ±0.1 (74.3)

Table 21: Trained from Instruct - Low Data Scenario: Forgetting (Part 2 of 2)

Category	LIMO v2 (32B)
Common Sense	3.0 ±0.3 (84.6)
Culture	4.4 ±0.9 (62.1)
Logic	6.1 ±0.4 (80.4)
Knowledge/QA	2.4 ±0.3 (61.3)
Language	4.2 ±0.6 (57.0)
Liberal Arts	2.3 ±0.3 (80.9)
Math	1.7 ±0.1 (80.0)
Safety/Truth	2.8 ±0.2 (64.5)
Science/Tech	1.9 ±0.2 (76.5)
Total	3.0 ±0.2 (74.3)

Table 22: Trained from Instruct - Low Data Scenario: Backward Transfer (Part 1 of 2)

Category	s1.1 (7B)	s1.1 (14B)	s1.1 (32B)	LIMO (32B)
Common Sense	7.3 ±0.5 (75.8)	4.6 ±0.3 (81.5)	4.5 ±0.2 (84.3)	3.9 ±0.4 (85.1)
Culture	5.7 ±0.5 (35.0)	4.6 ±0.4 (54.2)	4.6 ±0.4 (56.7)	7.5 ±0.8 (66.1)
Logic	13.8 ±0.6 (68.8)	9.2 ±0.5 (81.1)	5.7 ±0.4 (83.9)	5.8 ±0.3 (84.6)
Knowledge/QA	13.1 ±0.3 (59.3)	11.9 ±1.3 (69.0)	11.3 ±0.5 (71.2)	11.1 ±1.3 (71.2)
Language	10.2 ±0.7 (44.7)	7.4 ±1.2 (55.7)	6.6 ±0.5 (60.4)	5.6 ±0.7 (60.3)
Liberal Arts	6.3 ±0.7 (71.5)	5.3 ±0.6 (78.9)	5.0 ±0.1 (82.4)	4.7 ±0.2 (83.7)
Math	11.5 ±0.3 (74.2)	12.0 ±0.7 (81.9)	9.4 ±0.9 (87.8)	9.6 ±0.7 (90.7)
Safety/Truth	9.4 ±0.1 (52.5)	7.4 ±0.9 (62.2)	5.2 ±0.4 (65.4)	5.0 ±0.4 (67.1)
Science/Tech	8.5 ±0.1 (66.8)	7.9 ±0.3 (77.3)	7.6 ±0.5 (82.2)	7.2 ±0.3 (83.2)
Total	9.1 ±0.2 (63.5)	7.2 ±0.3 (73.5)	6.2 ±0.2 (76.9)	6.2 ±0.2 (78.8)

Table 23: Trained from Instruct - Low Data Scenario: Backward Transfer (Part 2 of 2)

Category	LIMO v2 (32B)
Common Sense	4.2 $\pm$0.2 (86.3)
Culture	6.7 $\pm$0.8 (64.6)
Logic	5.3 $\pm$0.6 (79.6)
Knowledge/QA	8.0 $\pm$0.7 (67.7)
Language	5.3 $\pm$0.3 (59.3)
Liberal Arts	4.9 $\pm$0.2 (84.4)
Math	10.1 $\pm$0.8 (90.8)
Safety/Truth	4.5 $\pm$0.7 (66.7)
Science/Tech	7.5 $\pm$0.2 (84.0)
Total	5.8 $\pm$0.3 (77.9)

G.6 Qwen2.5 Base and Coder Merge (Relative to Qwen2.5 Base)

Table 24: Qwen2.5 Base and Coder Merge: Forgetting

Category	Linear (0.2)	Linear (0.8)	Slerp (0.2)	Slerp (0.8)
Common Sense	8.2 ±0.6 (67.2)	11.3 ±0.7 (67.2)	13.9 ±2.2 (67.2)	16.2 ±6.4 (67.2)
Culture	12.0 ±2.0 (60.8)	15.8 ±1.8 (60.8)	21.1 ±3.4 (60.8)	41.3 ±3.3 (60.8)
Logic	11.6 ±0.4 (51.9)	19.4 ±1.0 (51.9)	23.4 ±1.1 (51.9)	17.7 ±0.9 (51.9)
Knowledge/QA	4.6 ±0.4 (56.4)	8.1 ±0.3 (56.4)	10.9 ±1.0 (56.4)	16.2 ±1.0 (56.4)
Language	7.8 ±0.4 (43.2)	11.2 ±0.2 (43.2)	14.0 ±0.5 (43.2)	12.7 ±0.4 (43.2)
Liberal Arts	2.5 ±0.5 (67.6)	4.1 ±0.9 (67.6)	5.8 ±1.6 (67.6)	8.9 ±0.5 (67.6)
Math	4.5 ±1.2 (44.9)	8.9 ±2.1 (44.9)	12.4 ±1.9 (44.9)	9.4 ±0.7 (44.9)
Safety/Truth	1.9 ±0.7 (49.9)	3.7 ±0.6 (49.9)	6.0 ±0.3 (49.9)	4.7 ±1.0 (60.4)
Science/Tech	2.6 ±0.6 (52.0)	5.2 ±0.7 (52.0)	6.7 ±1.3 (52.0)	4.4 ±0.9 (52.0)
Total	6.1 ±0.2 (58.0)	9.3 ±0.4 (58.0)	12.3 ±0.2 (58.0)	13.9 ±0.4 (59.0)

Table 25: Qwen2.5 Base and Coder Merge: Backward Transfer

Category	Linear (0.2)	Linear (0.8)	Slerp (0.2)	Slerp (0.8)
Common Sense	8.3 ±0.4 (67.4)	9.8 ±0.5 (65.2)	9.2 ±0.2 (61.0)	7.2 ±0.9 (55.3)
Culture	4.1 ±0.8 (46.8)	6.2 ±1.8 (46.1)	8.3 ±2.0 (44.0)	2.6 ±0.5 (15.1)
Logic	5.3 ±0.6 (43.7)	4.2 ±0.1 (31.0)	3.7 ±0.1 (24.6)	4.4 ±0.2 (33.3)
Knowledge/QA	8.3 ±0.4 (61.6)	9.2 ±0.4 (58.2)	8.2 ±0.8 (53.4)	5.1 ±0.6 (44.1)
Language	4.2 ±0.8 (39.1)	7.2 ±0.4 (37.4)	6.3 ±0.2 (32.1)	4.6 ±0.5 (30.7)
Liberal Arts	2.1 ±0.4 (67.3)	6.1 ±1.6 (70.2)	5.7 ±2.0 (67.6)	2.1 ±0.3 (58.7)
Math	5.5 ±1.0 (45.0)	6.5 ±1.6 (39.9)	5.8 ±2.9 (34.0)	4.6 ±1.4 (36.3)
Safety/Truth	2.4 ±0.7 (51.8)	5.0 ±1.9 (52.7)	6.8 ±3.0 (51.5)	3.0 ±1.0 (57.9)
Science/Tech	2.7 ±0.3 (51.4)	5.6 ±1.5 (52.3)	5.2 ±1.6 (49.7)	2.3 ±0.3 (48.1)
Total	4.8 ±0.1 (56.0)	6.5 ±0.7 (53.9)	6.4 ±0.9 (49.9)	4.0 ±0.1 (46.1)

G.7 Qwen2.5 Base and Coder Merge (Relative to Qwen2.5 Coder)

Table 26: Qwen2.5 Base and Coder Merge: Forgetting

Category	Linear (0.2)	Linear (0.8)	Slerp (0.2)	Slerp (0.8)
Common Sense	10.2 ±0.7 (70.5)	12.7 ±0.8 (70.5)	15.2 ±2.5 (70.5)	18.2 ±7.0 (70.5)
Culture	6.8 ±1.9 (37.8)	10.6 ±1.4 (37.8)	15.8 ±2.3 (37.8)	28.5 ±3.2 (37.8)
Logic	15.1 ±0.9 (47.2)	20.4 ±0.7 (47.2)	23.2 ±0.5 (47.2)	18.8 ±0.3 (47.2)
Knowledge/QA	6.5 ±0.8 (52.5)	8.0 ±0.6 (52.5)	9.8 ±0.3 (52.5)	14.0 ±1.9 (52.5)
Language	6.6 ±0.6 (29.4)	8.1 ±0.5 (29.4)	9.5 ±1.1 (29.4)	9.2 ±0.9 (29.4)
Liberal Arts	6.6 ±0.1 (63.3)	6.1 ±1.0 (63.3)	7.6 ±1.7 (63.3)	12.3 ±0.3 (63.3)
Math	17.1 ±0.5 (58.9)	19.6 ±1.2 (58.9)	22.2 ±2.1 (58.9)	20.8 ±0.3 (58.9)
Safety/Truth	10.9 ±1.7 (42.0)	10.0 ±1.4 (42.0)	10.6 ±1.3 (42.0)	11.2 ±1.2 (43.4)
Science/Tech	10.3 ±0.4 (54.3)	10.3 ±0.9 (54.3)	11.6 ±1.9 (54.3)	11.9 ±0.3 (54.3)
Total	9.5 ±0.3 (54.0)	11.1 ±0.4 (54.0)	13.4 ±0.3 (54.0)	15.3 ±0.9 (54.1)

Table 27: Qwen2.5 Base and Coder Merge: Backward Transfer

Category	Linear (0.2)	Linear (0.8)	Slerp (0.2)	Slerp (0.8)
Common Sense	7.9 ±0.4 (67.4)	8.7 ±0.5 (65.2)	8.0 ±1.3 (61.0)	6.8 ±1.6 (55.3)
Culture	13.4 ±1.7 (46.8)	15.8 ±3.2 (46.1)	17.8 ±3.6 (44.0)	6.2 ±1.9 (15.1)
Logic	11.4 ±0.2 (43.7)	7.5 ±0.3 (31.0)	6.0 ±0.2 (24.6)	7.8 ±0.0 (33.3)
Knowledge/QA	15.6 ±1.0 (61.6)	14.3 ±0.2 (58.2)	12.2 ±1.2 (53.4)	8.7 ±1.5 (44.1)
Language	11.0 ±0.5 (39.1)	12.2 ±0.3 (37.4)	9.9 ±0.6 (32.1)	9.1 ±0.2 (30.7)
Liberal Arts	9.6 ±0.4 (67.3)	11.2 ±0.9 (70.2)	10.8 ±1.3 (67.6)	8.5 ±0.2 (58.7)
Math	7.7 ±1.0 (45.0)	7.0 ±0.9 (39.9)	5.1 ±1.5 (34.0)	5.2 ±0.8 (36.3)
Safety/Truth	8.7 ±1.7 (39.1)	10.3 ±1.3 (42.4)	9.1 ±1.7 (39.9)	9.2 ±0.4 (41.0)
Science/Tech	8.1 ±0.2 (51.4)	8.8 ±0.6 (52.3)	8.1 ±0.6 (49.7)	7.2 ±0.2 (48.1)
Total	10.0 ±0.3 (54.8)	10.2 ±0.6 (52.9)	9.3 ±0.7 (48.8)	7.5 ±0.1 (44.4)

G.8 Qwen2.5 Instruct and OpenThinker 7B Merge (Relative to Qwen2.5 Instruct)

Table 28: Qwen2.5 Instruct and OpenThinker 7B Merge: Forgetting

Category	Linear (0.2)	Linear (0.8)
Logic	8.7 ±1.5 (75.2)	3.6 ±0.4 (75.2)
Knowledge/QA	6.5 ±0.4 (60.3)	4.2 ±2.8 (60.3)
Liberal Arts	9.4 ±0.8 (73.0)	3.7 ±0.1 (73.0)
Math	10.5 ±0.6 (65.3)	3.3 ±0.5 (65.3)
Safety/Truth	7.7 ±1.3 (55.1)	2.8 ±0.4 (55.1)
Science/Tech	9.6 ±0.3 (67.4)	4.2 ±0.2 (67.4)
Total	8.7 ±0.2 (66.1)	3.6 ±0.5 (66.1)

Table 29: Qwen2.5 Instruct and OpenThinker 7B Merge: Backward Transfer

Category	Linear (0.2)	Linear (0.8)
Logic	6.0 ±0.7 (71.6)	4.6 ±1.3 (76.6)
Knowledge/QA	5.2 ±1.8 (58.6)	3.8 ±0.9 (59.8)
Liberal Arts	4.6 ±0.5 (66.6)	3.9 ±0.6 (73.3)
Math	8.8 ±0.3 (63.1)	6.8 ±0.5 (70.1)
Safety/Truth	5.8 ±0.3 (52.7)	3.4 ±0.6 (56.1)
Science/Tech	6.3 ±0.3 (62.9)	4.9 ±0.3 (68.1)
Total	6.1 ±0.1 (62.6)	4.6 ±0.2 (67.3)

G.9 Qwen2.5 Instruct and OpenThinker 7B Merge (Relative to OpenThinker)

Table 30: Qwen2.5 Instruct and OpenThinker 7B Merge: Forgetting

Category	Linear (0.2)	Linear (0.8)
Logic	7.1 ±0.8 (64.0)	3.7 ±1.7 (64.0)
Knowledge/QA	7.3 ±1.6 (52.2)	7.0 ±1.2 (52.2)
Liberal Arts	8.5 ±0.2 (59.2)	5.5 ±0.4 (59.2)
Math	14.3 ±1.6 (72.1)	9.4 ±1.5 (72.1)
Safety/Truth	10.3 ±2.3 (52.2)	7.2 ±1.3 (52.2)
Science/Tech	9.2 ±0.2 (60.2)	6.8 ±0.6 (60.2)
Total	9.4 ±0.6 (60.0)	6.6 ±0.6 (60.0)

Table 31: Qwen2.5 Instruct and OpenThinker 7B Merge: Backward Transfer

Category	Linear (0.2)	Linear (0.8)
Logic	12.8 ±1.6 (71.6)	13.1 ±3.7 (76.6)
Knowledge/QA	12.1 ±2.5 (58.6)	12.6 ±2.0 (59.8)
Liberal Arts	14.1 ±0.2 (66.6)	16.1 ±0.6 (73.3)
Math	7.5 ±1.5 (63.1)	7.9 ±1.1 (70.1)
Safety/Truth	10.7 ±1.0 (52.7)	10.1 ±1.1 (56.1)
Science/Tech	11.2 ±0.8 (62.9)	12.7 ±0.4 (68.1)
Total	11.4 ±0.7 (62.6)	12.1 ±1.0 (67.3)

G.10 Qwen2.5 Instruct and OpenThinker3 7B Merge (Relative to Qwen2.5 Instruct)

Table 32: Qwen2.5 Instruct and OpenThinker3 7B Merge: Forgetting

Category	Linear (0.2)	Linear (0.8)
Logic	33.6 ±2.7 (75.2)	28.1 ±1.8 (74.2)
Knowledge/QA	25.7 ±8.0 (60.3)	18.0 ±5.2 (45.0)
Liberal Arts	35.0 ±2.9 (74.4)	28.8 ±1.7 (73.8)
Math	40.1 ±6.1 (65.3)	30.0 ±0.7 (65.3)
Safety/Truth	36.2 ±2.8 (64.1)	22.8 ±3.7 (61.0)
Science/Tech	30.1 ±3.2 (67.4)	29.6 ±0.9 (67.4)
Total	33.5 ±3.7 (67.8)	26.0 ±0.8 (63.8)

Table 33: Qwen2.5 Instruct and OpenThinker3 7B Merge: Backward Transfer

Category	Linear (0.2)	Linear (0.8)
Logic	1.3 ±2.0 (31.3)	2.3 ±1.0 (39.9)
Knowledge/QA	1.9 ±1.0 (28.8)	1.2 ±1.4 (21.7)
Liberal Arts	1.9 ±0.8 (30.2)	2.9 ±0.1 (39.2)
Math	0.7 ±0.8 (12.6)	1.6 ±0.8 (27.0)
Safety/Truth	0.9 ±1.1 (15.8)	2.9 ±0.6 (34.6)
Science/Tech	2.5 ±1.0 (30.4)	2.5 ±0.2 (30.9)
Total	1.5 ±1.1 (24.9)	2.2 ±0.3 (31.7)

G.11 Qwen2.5 Instruct and OpenThinker3 7B Merge (Relative to OpenThinker3)

Table 34: Qwen2.5 Instruct and OpenThinker3 7B Merge: Forgetting

Category	Linear (0.2)	Linear (0.8)
Logic	28.1 ±3.2 (65.4)	25.1 ±2.6 (66.9)
Knowledge/QA	21.2 ±6.4 (54.3)	17.2 ±7.3 (38.6)
Liberal Arts	31.3 ±2.9 (68.9)	27.2 ±1.7 (68.3)
Math	52.3 ±6.9 (81.1)	41.8 ±1.8 (81.1)
Safety/Truth	33.5 ±2.1 (59.8)	23.5 ±1.7 (58.6)
Science/Tech	32.0 ±3.5 (70.7)	32.2 ±1.4 (70.5)
Total	33.1 ±3.8 (66.7)	28.0 ±1.2 (63.8)

Table 35: Qwen2.5 Instruct and OpenThinker3 7B Merge: Backward Transfer

Category	Linear (0.2)	Linear (0.8)
Logic	3.0 ±5.0 (31.3)	4.9 ±0.9 (39.9)
Knowledge/QA	2.2 ±0.7 (28.8)	4.5 ±2.3 (21.7)
Liberal Arts	2.3 ±0.8 (30.2)	5.4 ±0.7 (39.2)
Math	0.5 ±0.6 (12.6)	1.5 ±0.2 (27.0)
Safety/Truth	1.0 ±0.8 (15.8)	5.5 ±0.4 (34.6)
Science/Tech	2.0 ±0.7 (30.4)	2.8 ±0.3 (30.9)
Total	1.8 ±1.3 (24.9)	4.0 ±0.4 (31.7)

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Disclaimer for use of LLMs

We primarily used LLMs in coding co-pilot applications to facilitate experimentation and help with plotting code for result presentation. LLMs were also used as writing tools to assist in refining the paper. However, the final version was carefully reviewed and finalized by the authors. No LLMs were used in ideation and experimental design.