Breaking Barriers: Do Reinforcement Post Training Gains Transfer To Unseen Domains?

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Abstract

Reinforcement post training (RPT) has recently shown promise in improving the reasoning abilities of large language models (LLMs). However, it remains unclear how well these improvements generalize to new domains, as prior work evaluates RPT models on data from the same domains used for fine-tuning. To understand the generalizability of RPT, we conduct two studies. (1) Observational: We compare a wide range of open-weight RPT models against their corresponding base models across multiple domains, including both seen and unseen domains in their fine-tuning data. (2) Interventional: we fine-tune LLMs with RPT on single domains and evaluate their performance across multiple domains. Both studies converge on the same conclusion that, although RPT brings substantial gains on tasks similar to the fine-tuning data, the gains generalize inconsistently and can vanish on domains with different reasoning patterns.

1 Introduction

Large language models (LLMs) have achieved remarkable performance across a wide range of tasks, from structured reasoning domains such as math [15, 30, 39, 73] and code [4, 7, 11, 29, 46, 64, 93], to general reasoning domains including legal [24], finance [90], and medical [23, 33]. Recent advances in reinforcement post training (RPT) [61] have produced dramatic improvements, rivaling top human performers in programming competitions and mathematics contests [6, 16, 21, 22, 25, 40, 42, 43, 54, 60, 67, 69, 78, 79, 87, 91]. This raises an important question: does RPT provide generalizable improvements, as broadly as those achieved through pretraining?

Existing evaluation frameworks and RPT setups provide limited evidence to answer this question. To address it systematically, we design a two-stage investigation pipeline (Figure 1a).

First, prior work evaluates RPT models within their fine-tuning domains [42, 43]. To overcome this limitation, we conduct an *observational study* in which we evaluate 14 recent open-weight RPT models with publicly disclosed fine-tuning data alongside their corresponding base models across a wide range of domains, including legal, financial, and medical benchmarks, spanning their seen and unseen domains. This study is designed to provide an initial view into the generalizability of RPT.

Additionally, we notice that these RPT models, as a representative selection of existing open-weight models such as DeepSeek R1 [18] and RLVR [66], are fine-tuned on mixed domain data. The presence of such confounding factors makes it difficult to isolate and interpret the generalizability of RPT at a finer granularity. To strengthen our findings, we conduct an *interventional study* in which we fine-tune LLMs via RPT on math, coding, and general reasoning data and evaluate their performance on both in-domain and out-of-domain tasks. We illustrate our methodology in detail in Section 3.

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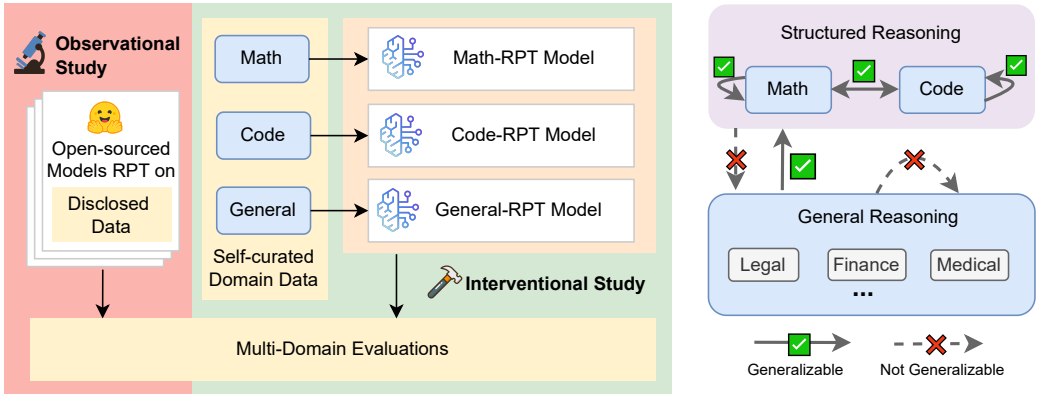


(a) Overview of our two-stage investigation pipeline. (b) Summary of RPT generalizability.

Figure 1: The method (a) and key findings (b) of our work. Through a unified multi-domain evaluation framework combining observational and interventional studies, we find that RPT exhibits limited generalizability across domains.

As we summarize in Figure 1b, our findings show that gains from RPT on domains involving structured reasoning patterns (e.g., math, code) generalize well within and across structured domains, but fails to generalize to unstructured domains. In contrast, gains from RPT on unstructured domains (e.g., legal, finance) do not generalize well within unstructured domains, but show transferability to structured domains. We analyze these results comprehensively in Section 4.

Our findings suggest that RPT models are most effective when the target task shares reasoning patterns with the RPT data. Consequently, while RPT remains a powerful method for improving LLMs' performance, its benefits are largely limited to the domains represented in the fine-tuning data and do not generalize to a wide range of new, unseen domains.

2 Background

In this section, we introduce the motivation behind our study. We begin by demonstrating the strong performance of LLMs fine-tuned via RPT across various reasoning tasks, particularly in mathematics and coding. We then discuss the limitations of existing work in understanding the mechanisms and boundaries of RPT. We close by introducing the data-domain taxonomy grounds our investigations.

RPT models demonstrate promising performance across a wide range of tasks. RPT models have achieved remarkable improvements on complex reasoning benchmarks. For example, Gemini 2.5 Pro [21] achieves over 90% accuracy on AIME 2024 [30], a math competition benchmark. Grok 3 Beta [78] solves roughly 80% of the tasks in LiveCodeBench v5 [29], a coding benchmark, while Claude 3.7 Sonnet [6] reaches around 85% accuracy on GPQA Diamond [57], a benchmark for graduate-level scientific reasoning.

Out-of-domain generalizability of RPT models remains understudied. Despite impressive results, recent work has examined the limitations of RPT models and the opaque nature of their underlying reasoning capabilities [45, 70, 85, 88]. In particular, there is growing interest in the role of RPT data, especially the extent to which RPT algorithms rely on large, diverse corpora to achieve generalization [91].

While RPT models benefit from training on diverse, mixed-domain data, this diversity makes it difficult to directly assess their generalizability to unseen domains. As a result, prior work evaluates RPT models on tasks within the same domains as their training data [45, 70, 85, 88]. However, many reasoning tasks remain underrepresented or entirely absent from existing training corpora. Exploring the generalizability of LLMs trained with RPT to such tasks is therefore essential for identifying the boundaries of their applicability in real-world, complex scenarios.

Understanding RPT generalizability requires a systematic view of reasoning domains. Following the task suites defined in prior work [66], we focus on three major *domains* of interest: code, math, and general reasoning (Figure 1b). These domains are chosen to capture a broad spectrum of reasoning challenges commonly seen in language model evaluations. The general reasoning domain can be further divided into application-specific subdomains such as legal, finance, medical, etc. In this paper, we not only examine performance across the high-level domains, but also evaluate how reasoning patterns and generalization behaviors vary across subdomains.

Among the three, we consider math and code domain tasks to follow structured reasoning patterns, where solutions follow deterministic logical steps and require precise syntax and formal semantics [66]. In contrast, tasks within the general reasoning domain require more flexible and context-sensitive reasoning, referred to here as *unstructured* reasoning. We define unstructured reasoning as problem-solving processes that do not adhere to a fixed sequence of logical operations and often lack a well-defined intermediate representation or symbolic grounding. Such tasks typically demand broader world knowledge, interpretive judgment, and the ability to handle ambiguity or incomplete information. For instance, legal and financial question answering may involve interpreting lengthy documents, extracting relevant information from loosely connected statements, or evaluating conflicting evidence.

3 Study Design

We present our study design that aims to investigate the generalizability of RPT. We propose the following research questions (RQs) that have not been systematically examined in prior work.

- ***(RQ1)*** *Cross-domain generalization.* To what extent do the capabilities acquired through RPT transfer to tasks from domains not included in the training data?
- ***(RQ2)*** *Role of reasoning structure.* How does the structure of reasoning required by a task affect generalization? Do skills learned from highly structured domains (e.g., mathematics, code generation) transfer to less-structured domains (e.g., medical or legal reasoning), and vice versa?
- ***(RQ3)*** *Intra-domain generalization.* How effectively do RPT gains generalize across subdomains within the same domain?

To address these research questions, we design a two-stage pipeline. First, we perform an observational study by evaluating 14 RPT models, each compared against its corresponding base model across a diverse set of benchmarks, spanning their seen and unseen domains. Because existing RPT models are typically trained with different configurations (e.g., different RL algorithms and hyperparameters) on multi-domain data, it is challenging to isolate the effect of RPT itself from the advantages brought by specific configuration or data.

To mitigate confounding factors, we further conduct an interventional study, where we fine-tunedd three RPT models from the same base model with the same configuration, each on a disjoint single-domain dataset. We then evaluate these trained models using the same benchmarks as in the observational analysis. In the rest of this section, we describe the evaluation settings and experimental setup for both studies.

Benchmarks. For evaluation, we use 16 popular benchmarks, covering a wide range of domains and difficulty levels. We categorize these benchmarks into the following three representative domains:

- *Math*: For easier questions, we use GSM8K [15] and MATH-500 [39], while for more challenging problems, we select AIME 2024 [30] and AMC 2023 [73].
- *Code*: We use easy coding problems, including MBPP [7] and HumanEval [11], and relatively challenging problems, including BigCodeBench [93], LiveCodeBench [29], USACO [64], and Codeforces [46]. To test programming language generalization, we also include the multi-language benchmark Polyglot [4].
- *General reasoning*: We use high-quality benchmarks that are not mathematics nor programming problems for general reasoning, including PubMedQA [33] and MedQA [23] for medical reasoning, TabFact [13] for fact verification, LegalBench [24] for legal reasoning, and FinBench [90] for financial problem solving.

Table 1: Selected RFT models for observational analysis. The `RFT Domain(s)` refers to the domain(s) covered in the RFT training data.

***(Model ID)* Reasoning Model**	**Base Model**	**RPT Domain(s)**
(1) DeepScaleR-1.5B-Preview [43]	DeepSeek-R1-Distill-Qwen-1.5B [18]	Math
(2) DeepCoder-1.5B-Preview [42]	DeepSeek-R1-Distill-Qwen-1.5B [18]	Code
(3) Skywork-o1-Open-Llama-3.1-8B [51]	Llama-3.1-8B-Instruct [47]	Code, Math
(4) Eurus-2-7B-PRIME [16, 87]	Qwen2.5-Math-7B [84]	Code, Math
(5) Absolute_Zero_Reasoner-Coder-3b [91]	Qwen2.5-Coder-3B [28, 83]	Code
(6) Absolute_Zero_Reasoner-Coder-7b [91]	Qwen2.5-Coder-7B [28, 83]	Code
(7) ZR1-1.5B [94]	DeepSeek-R1-Distill-Qwen-1.5B [18]	Code, Math
(8) Llama-3.1-Nemotron-Nano-8B-v1 [9]	Llama-3.1-8B-Instruct [47]	Instruction Following
(9) Thespis-Llama-3.1-8B [41]	Meta-Llama-3.1-8B-Instruct-abliterated [49]	Chat
(10) STILL-3-1.5B-preview [31, 48, 71]	DeepSeek-R1-Distill-Qwen-1.5B [18]	Math
(11) Arcee-Maestro-7B-Preview [3]	DeepSeek-R1-Distill-Qwen-7B [18]	Code, Math
(12) Fino1-8B [56]	Llama-3.1-8B-Instruct [47]	Finance
(13) OREAL-7B [44]	OREAL-7B-SFT [44]	Math
(14) Open-RS3 [17]	DeepSeek-R1-Distill-Qwen-1.5B [18]	Math

Evaluation Configurations. For all benchmarks, we use a consistent sets of generation hyperparameters across all models. The maximum response length is set to $\min\{16192,\, C\}$, where C denotes the model's context window. For each model, we run the small benchmarks (i.e., AMC 2023 and AIME 2024) 16 times, while executing all other benchmarks once.

For prompting, we apply each model's default chat template and system prompt. For model pairs whose base models are pretrained-only (i.e., not instruction-tuned), we evaluate under two prompting strategies: (1) the default prompt, and (2) the official CoT+few-shot template used for evaluating Qwen2.5-Math [84], using $\min\{4,\, N\}$ shots, where N is the maximum number of few-shot exemplars that can fit within the model's context window. For each model (the reasoning model and its corresponding base model), we report the higher score across the two prompting strategies, ensuring that both models are evaluated under their most favorable prompting conditions. We evaluate each model on each benchmark on a single 24 GB RTX A5000.

Metrics. To assess whether RPT improves the accuracy performance within or across domains, we report the aggregated accuracy improvement $\Delta_{i,j}^{(\mathcal{D})}$ of an RPT model i over its base model j for a given domain $\mathcal{D}$:

$$\Delta_{i,j}^{(\mathcal{D})} = \frac{\sum_{t\in\mathcal{D}} N_t R_t (A_{i,t} - A_{j,t})}{\sum_{t\in\mathcal{D}} N_t R_t},$$

where N_t is the number of problems in t, R_t is the number of repetitions we executed for t, $A_{i,t}$ is the accuracy of model i on benchmark t, and $A_{j,t}$ is the accuracy of model j on benchmark t.

In addition, to ensure statistical significance in our findings, we applied the Cochran–Mantel–Haenszel (CMH) test [1], a statistical test for analyzing stratified categorical data. We treat each benchmark as an independent stratum—that is, a random sample of distinct downstream tasks. Given an RPT model i, a base model j, and a domain $\mathcal{D}$ of benchmarks, we calculate the common odds ratio estimate ($\theta_{i,j,\mathcal{D}}$) that estimates the correlation between the RPT process and the accuracy improvement on $\mathcal{D}$:

$$\hat{\theta}_{i,j}^{(\mathcal{D})} = \frac{\sum_{t\in\mathcal{D}} N_t R_t A_{i,t}(1 - A_{j,t})}{\sum_{t\in\mathcal{D}} N_t R_t A_{j,t}(1 - A_{i,t})}$$

An odds ratio greater than 1 indicates improvement due to RPT; a value less than 1 indicates a decrease in accuracy due to RPT. We evaluate the statistical significance under the null hypothesis $H_0 : \theta_{i,j}^{(\mathcal{D})} = 1$ against the alternative hypothesis $H_1 : \theta_{i,j}^{(\mathcal{D})} \neq 1$, using the standard CHM test statistics,

$$\xi = \frac{\left(\sum_{t\in\mathcal{D}} N_t R_t (A_{i,t} - A_{j,t})\right)^2}{\sum_{t\in\mathcal{D}} N_t^2 R_t^2 A_{i,t} A_{j,t} (1 - A_{i,t})(1 - A_{j,t})(2N_t - 1)^{-1}}$$

which follows a chi-squared distribution asymptotically with 1 degree of freedom.

Observational Study. To ensure a comprehensive and representative evaluation of RPT model generalizability, we adopt a systematic approach to selecting models for our observational study:

- *Stage 1.* We collect the 466 models from Hugging Face applying the following filtering criteria: as of April 23rd, 2025: (1) the model supports `Text Generation` tasks, (2) its model card description contains the keyword `reasoning`, `chain-of-thought`, and/or `chain of thought` and (3) the model has received at least 10 likes.
- *Stage 2.* We use `o4-mini` [53] to prefilter models potentially trained with RPT, based on their model card descriptions. This automatic filtering is followed by manual verification, resulting in 31 models that we confirm to be RPT models.
- *Stage 3.* From the 31 RPT models, we manually select 12 that meet the following criteria: (1) the RPT datasets are publicly disclosed, (2) the model sizes range from 1.5B to 8B parameters, and (3) the base models are not purely pretrained models, ensuring they can generate coherent responses and follow basic instructions for evaluating reasoning capabilities.

Additionally, we include 2 recently released models, `Absolute_Zero_Reasoner-Coder-3B` and `Absolute_Zero_Reasoner-Coder-7B` [91], both fine-tunedd with limited RPT data and released on May 6th, 2025. These models demonstrate strong performance on math and code reasoning tasks and serve as representative cases for examining RPT generalizability.

We finalize our selection of 14 RPT models, with the details, including base models and RPT domains, presented in Table 1. For each RPT model and its corresponding base model, we compare performance across 16 benchmarks.

Interventional Analysis. To isolate the effect of RPT from other training configurations, including datasets, algorithms, and hyperparameters, we trained three RPT models based on `DeepSeek-R1-Distill-Qwen-1.5B` [18] on three disjoint datasets—math, code, and general reasoning—respectively. We curated these datasets based on existing datasets that leads to performant RPT models. Specifically,

- *Math*: we uniformly sampled 40,000 problems from a combination of the math split of Eurus-2-RL [16], which originates from the NuminaMath-CoT dataset [36].
- *Code*: we uniformly sampled 40,000 deduplicated problems from a combination of KodCode [82], DeepCoder-Preview [42], Apps [26], TACO [37], and the code split of Eurus-2-RL [16].
- *General Reasoning*: we selected 40,000 high-quality, non-math, and non-code data from the multi-subject RLVR dataset [67]. To achieve that, we applied o3-mini [53] to exclude math-related, code-related, or fact-recall questions.

To ensure fair evaluation, we clean this data to ensure that it does not overlap with our evaluation set.

We applied consistent settings for all three RPT training processes. In terms of the RL algorithm, we applied Group Relative Policy Optimization (GRPO) with the same setting as DeepCoder [42]. In terms of hyperparameters, we trained each of the dataset for one epoch with a batch size of 64 and a context length of 8,192. To stabilize the training process, we used a learning rate of 10^{-6} and an entropy coefficient of 0. We fine-tuned the models on 8 80GB H100 GPUs.

4 Findings

In this section, we present the findings of our study based on results from observational and interventional studies. We summarize our findings as follows:

- ***(RQ1)*** RPT does not exhibit generalizability in arbitrary unseen domains (Section 4.1).
- ***(RQ2)*** RPT demonstrates cross-domain generalizability when reasoning patterns are similar, such as mutual transfer between math and code, but fails to generalize across distinct reasoning patterns, such as from math or code to general reasoning (Section 4.2).
- ***(RQ3)*** Intra-domain generalizability of RPT strongly depends on the structural similarity between subdomain tasks (Section 4.3).

4.1 RPT Gains Do Not Generalize to Arbitrary Unseen Domains

Existing RPT models fail to transfer beyond their training domains. We begin by analyzing our observational study, which evaluates a diverse set of existing RPT models using multi-domain

Table 2: Existing Open-sourced RPT models achieve significantly larger accuracy gains Δ (%) and odds ratios $\hat{\theta}$ on in-domain (*ID*) tasks compared to out-of-domain (*OOD*) tasks. An asterisk (*) denotes statistical significance at $p < 0.05$.

Metric	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	**Avg.**
$\Delta^{(ID)} \uparrow$	5.40	4.61	6.96	30.03	-6.27	30.12	2.82	7.07	-26.01	4.31	-4.27	-3.84	-0.41	-0.59	**3.57**
$\Delta^{(OOD)} \uparrow$	1.67	4.01	-2.64	46.32	2.55	-23.31	-5.47	13.22	-4.73	-1.33	-7.39	-27.89	-8.44	-0.34	**-1.48**
$\Delta^{(ID)} - \Delta^{(OOD)}$	3.73	0.60	33.37	-16.29	-8.82	53.43	8.30	-6.15	-2.13	5.64	3.12	24.05	-8.85	-0.25	**5.04**
$\hat{\theta}^{(ID)} \uparrow$	1.36*	1.45*	1.59*	7.13*	0.52*	22.47*	1.22*	1.34*	0.34*	1.28*	0.72*	0.83*	0.97	0.97	**3.01**
$\hat{\theta}^{(OOD)} \uparrow$	1.07*	1.18*	0.31*	14.09*	1.15*	0.41*	0.80*	1.98*	0.68*	0.95*	0.69*	0.30*	1.47*	0.99	**1.86**
$\hat{\theta}^{(ID)}/\hat{\theta}^{(OOD)}$	1.27	1.22	5.15	0.51	0.45	54.61	1.53	0.68	0.50	1.35	1.03	2.74	0.66	0.98	**5.19**

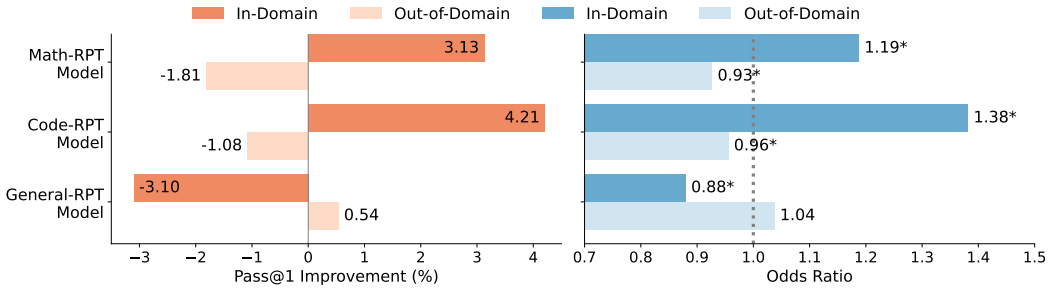


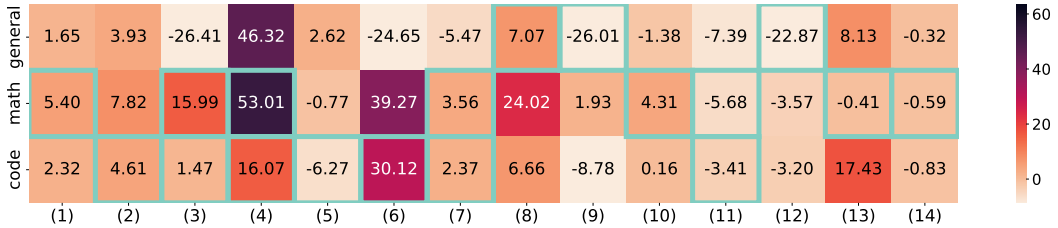
Figure 2: RPT models on single domains show significant pass@1 improvements over base models and higher odds ratios on in-domain tasks, but not on out-of-domain tasks. No single-domain model achieves statistically significant gains in out-of-domain tasks (* denotes $p < 0.05$).

tasks. Specifically, we compare the performance improvements of each model in tasks from the same domain as their training data (ID), and tasks that are out-of-domain with their training data (OOD). For instance, *(1)* `DeepScaleR-1.5B-Preview` is trained exclusively on math-related data. Therefore, ID tasks for this model include GSM8K, MATH500, AIME 2024, and AMC 2023, while all other tasks (e.g., legal, medical, coding) are OOD.

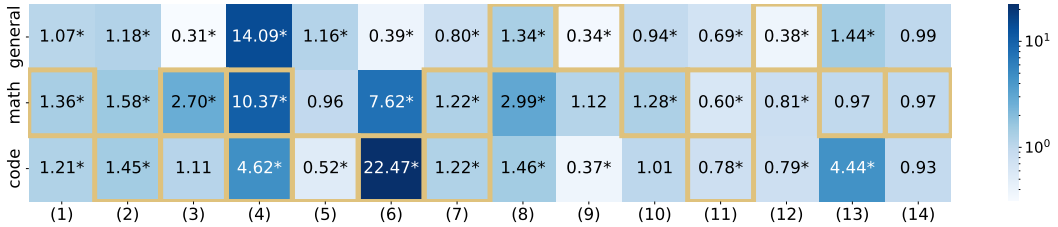
We present the results in Table 2. Across the table, RPT models exhibit considerably higher improvements on *ID* tasks compared to *OOD* tasks, with a 3.57% increase in pass@1 for ID tasks, but a 1.48% decrease for OOD tasks. For example, *(1)* DeepScaleR-1.5B-Preview shows a 5.1% gain in pass@1 on math domain tasks, but only 1.7% in others, representing a 3× drop. This lack of generalizability stems from the RPT algorithm itself rather than simply from overfitting to large-scale training data: notably, a similar trend is observed in *(6)* `Absolute_Zero_Reasoner-Coder-7B`, which was fine-tunedd on a near-zero amount of data. Despite its minimal training data exposure, this model experiences a 23.31% decrease in pass@1 accuracy on unseen domains, while achieving a 30.12% improvement within its RPT domain. We also observe that the generalizability of RPT algorithms is sensitive to the training data, implementation details, and finetuning strategy. For example, although all trained on math data, *(1)* `DeepScaleR-1.5B-Preview` demonstrates improvements in both ID and OOD tasks, whereas *(7)* `ZR1-1.5B` and *(10)* `STILL-3-1.5B-Preview` show statistically significant performance gains in ID tasks as well as statistically significant performance drops on OOD tasks. These findings suggest that the gains from RPT are largely domain-specific: models significantly improve on tasks similar to their training data, but fail to generalize robustly to other unseen domains.

Single-domain finetuning reinforces evidence of RPT's limited generalizability. To further dissect the generalizability limitations identified in our observational study, we conduct a more controlled investigation by isolating models fine-tuned exclusively on single domains. To do so, we analyze our interventional study results, where ID corresponds to the training domain, while OOD include all tasks from the remaining two domains in our evaluation.

As shown in Figure 2, none of the models fine-tunedd on a single domain exhibit statistically significant improvement on OOD tasks. Both the Math-RPT model and the Code-RPT model show performance drops on OOD tasks with statistical significance, in contrast to the statistically

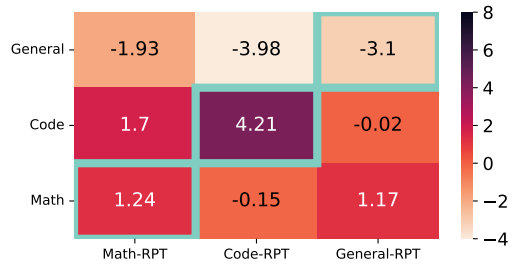


(a) Pass@1 improvement $\Delta^{(\mathcal{D})}$ in percentage across domains.

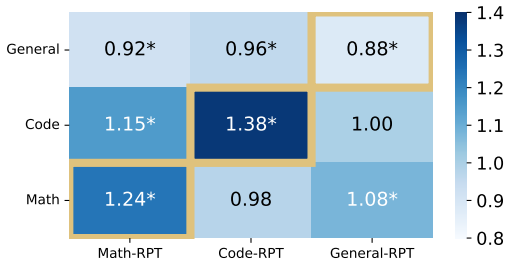


(b) Odds ratio $\hat{\theta}^{(\mathcal{D})}$ across domains. An asterisk $(*)$ denotes statistical significance at $p < 0.05$.

Figure 3: Multi-domain evaluation results of existing RPT models. We highlight in-domain results with frames. RPT shows mutual generalizability between math and code, one-way transfer from general reasoning to math and code, but no generalization from math or code to general reasoning.



(a) Pass@1 improvement $\Delta^{(\mathcal{D})}$ (%) across domains.



(b) Odds ratio $\hat{\theta}^{(\mathcal{D})}$ across domains.

Figure 4: Multi-domain evaluation results of RPT models on single domains. An asterisk $(*)$ denotes statistical significance at $p < 0.05$. We highlight in-domain results with frames. RPT demonstrates generalizability from math to code and from general reasoning to math, but shows no generalizability from math or code to general reasoning.

significant gains they achieve in-domain. The General-RPT model also demonstrates no statistically significant gains on its OOD tasks.

4.2 RPT Gains Generalize Across Domains with Similar Reasoning Patterns

Structured-to-structured generalization is effective. We observe that models fine-tuned on math and code data exhibit strong mutual generalizability. In our observational analysis (Figure 3), models fine-tuned exclusively on math or code demonstrate transferable performance gains across these two domains. For example, models fine-tuned on math domain data achieve an average improvement of 2.18% in pass@1 on math domain tasks and 4.77% on code domain tasks. Similarly, models fine-tuned on code domain data improve by 9.49% in pass@1 on code domain tasks and 15.44% on math domain tasks. In both cases, the improvement is even greater on the non-finetuned domain, suggesting that math and code tasks share common structured reasoning patterns that enable RPT to generalize effectively across these domains.

Structured reasoning patterns that are more foundational tend to exhibit stronger cross-domain transfer. Building on the findings from our observational study, we further examine the generalizability across structured reasoning domains using interventional study results from models fine-tuned on single domains (Figure 4). We observe that the generalizability from math to code is notably stronger and more consistent than the reverse. This aligns with the intuition that mathematical reasoning is a more fundamental form of structured thinking, serving as the backbone for coding tasks, and thus enables better cross-domain transfer when used as RPT data.

Structured-to-unstructured generalization is limited. Models trained on structured reasoning domains—such as math and code—exhibit substantially reduced improvements when evaluated on general-domain tasks. In our observational study (Figure 3), models fine-tuned on structured reasoning domains (i.e., math, code, or both) achieve an average improvement of -0.27% in pass@1 on general-domain tasks, compared to significant gains of 11.08% on math and 5.82% on code tasks. While the improvements in math and code domain tasks are statistically significant, the performance drops on general reasoning tasks, indicating a lack of generalizability to unstructured domains. For instance, in the *(1)* `DeepScaleR-1.5B-Preview` and *(2)* `DeepCoder-1.5B-Preview` pair, the observed gains in math and code domain tasks are both significantly higher than those in general-domain tasks. Our interventional study results further confirm this trend (Figure 4): while the Math-RPT model shows improvements in both math and code domain tasks, its performance drops notably on general-domain tasks. Similarly, the Code-RPT model shows a statistically significant drop in performance on general reasoning tasks. These results suggest that although structured reasoning skills generalize well across similarly structured domains, they fail to transfer effectively to domains that require less structured, more heterogeneous reasoning patterns.

Unstructured-to-structured generalization is promising. RPT models trained on unstructured general-domain data still exhibit measurable gains in structured tasks. In our observational study (Figure 3), general-domain RPT models show substantially higher pass@1 improvements on math (21.40%) and code (12.16%) tasks compared to tasks within the general reasoning domain. Similarly, in our interventional analysis (Figure 4), the General-RPT model achieves statistically significant gains on math domain tasks and shows no noticeable degradation on code domain tasks, while underperforming on tasks within its own domain. This suggests that unstructured reasoning patterns encompass broader representational complexity and implicitly subsume the essential components of structured reasoning, functioning as a conceptual superset.

4.3 Intra-domain RPT Gains Depend on Structural Similarity among Subdomains

Structured reasoning patterns generalize effectively within domain. Consistent with prior work on math and code reasoning, our observational study shows that models fine-tunedd on structured domains generalize well across tasks within the same domain (Figure 3). On average, models trained on math data achieve a pass@1 improvement of 2.18% on math tasks, while models trained on code data show an average improvement of 9.49% on code tasks. Our interventional analysis further confirms this trend where structured-domain models (i.e., the Code-RPT model and the Math-RPT model) exhibit the largest gains on tasks from their corresponding training domain (Figure 4). These results suggest that data following consistent and structured reasoning templates facilitates reliable generalization within the same domain, as downstream tasks can leverage similar inductive patterns.

Unstructured reasoning patterns lack intra-domain consistency. In contrast, models trained on general-domain (unstructured) data demonstrate limited or negative transfer to other unstructured tasks from different domains in our observational study (Figure 3). For instance, `Fino1-8B` (model *(12)*), fine-tunedd on financial data, exhibits notable performance drops when evaluated on all unrelated general-domain tasks. Its pass@1 on `PubMedQA` (medical domain) declines from 3.26% to 1.28%, on `LegalBench` (legal domain) from 6.42% to 4.84%, and on `TabFact` declines from 64.18% to 48.39% (general tabular knowledge). Our interventional results reinforce this observation: the General-RPT model underperforms the base model on general-domain tasks, with the degradation in accuracy being statistically significant (Figure 4). This suggests that, unlike structured domains, unstructured reasoning tasks are highly diverse and domain-specific. They lack a shared logical template, making it difficult for RPT to generalize even within what is nominally the same domain.

5 Related Work

In this section, we review RPT from the following four aspects.

RPT algorithms. The dominant approach for RPT is Proximal Policy Optimization (PPO) [58, 59], which builds on classical policy-gradient methods such as REINFORCE [76] and Trust Region Policy Optimization (TRPO) [58] and has been widely used in the post-training of OpenAI's ChatGPT [52], Google's Gemini [68], and Anthropic's Claude [5]. However, PPO is an actor-critic-based algorithm, which requires an additional critic network that is typically also initialized from the same pretrained LLM. This introduces both computational overhead and algorithmic complexity compared to the vanilla REINFORCE algorithm [77]. In recognition of this, recent work has attempted to design simplified alternative approaches to PPO for LLM post-training. A line of work studies arguably simplest rejection sampling fine-tuning [20, 72], which iteratively generates multiple completions per prompt, filters out low-quality responses, and fine-tunes on the selected outputs. Another direction revisits Reinforce-style methods, such as GRPO [61], DAPO [86], VAPO [89], ReMax [38], RLOO [2, 34], Reinforce++ [27], and Reinforce-rej [80]. These algorithms discard the critic network and instead rely on Monte Carlo estimates from on-policy samples to update the policy. These methods primarily differ in how they estimate the advantage function. Among them, GRPO has garnered particular attention for its strong empirical performance in the post-training of DeepSeek-R1 [60].

RPT frameworks. RPT was first widely applied under the reinforcement learning from human feedback (RLHF) framework in the context of LLM post-training [8, 55]. In RLHF, a proxy reward is learned from human-annotated preference dataset and Bradley-Terry model [10], and the models are trained to optimize a KL-regularized reward objective to prevent overfitting the imperfect learned reward. RLHF has since become a standard technique in LLM training pipelines [5, 52, 68, 72]. More recently, RPT with verifiable reward has received significant attention in building powerful reasoning models, following the release of OpenAI o1 [54] and DeepSeek-R1 [18]. In this framework, a verifier is employed to check the correctness of the final answer for reasoning-related tasks, and serves as the reward signal for the RPT training. The major advantage is that this verifier score is much more reliable than the learned reward in RLHF, thus enabling large-scale RPT training in the post-training stage. This has also led to the development of increasingly capable and open-source RPT frameworks [42, 43, 63].

Limitations of RPT. Despite the recent successes of RPT in improving language model reasoning capabilities, the limitations of RPT in general have been widely studied. At the training phase, SFT with LLM reasoning traces, without RL, has been shown to be effective enough [70, 88]. At the inference phase, the quality of reasoning models depends crucially on their ability to scale under test-time compute constraints [50, 92]. Moreover, the effectiveness of LLMs' lengthy "thinking" processes has also been challenged: recent findings suggest that bypassing explicit multi-step reasoning through simpler prompting or parallelized sampling can achieve comparable or even superior results [45, 85]. Building on these observations, our work aims to examine the limitations of RPT at a finer granularity, specifically its data generalizability across the training and inference phases.

Applications of RPT across tasks. RPT has proven effective for a broad range of tasks with well-defined correctness, where LLMs are finetuned using reward feedback. These range from structured tasks such as math [16, 81] and coding [35, 62, 65, 75], to unstructured tasks like search engine use [32] and open-ended question answering [66]. However, all these models are trained and evaluated on tasks within a single domain or task type. Even works on general knowledge [66] remain confined to open-ended question answering tasks, without testing transfer across fundamentally different task types. In contrast, our work directly addresses this cross-domain generalization gap.

6 Conclusion

In this paper, we identify important limitations in the generalizability of RPT across domains. Through both observational and interventional studies, we consistently find that while RPT produces substantial improvements within training domains, its generalization to unseen domains is limited. In particular, while there is evidence of cross-domain transfer between structured domains like math and code, there is little evidence of transfer to unstructured domains. Our work emphasizes the need for a more nuanced understanding of cross-domain knowledge transfer in LLMs.

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A Limitations

Our work has several important limitations:

- **Use of RL algorithms:** The RPT techniques we experiment with (e.g., PPO, reward-modulated finetuning) may differ from those used in frontier models such as o3 [53] and Gemini [21]. As such, our findings may not directly apply to LLMs with proprietary optimization strategies.
- **Scale limitations:** Emergent behaviors often arise at larger model or dataset scales [74]. While our experiments are conducted on widely used open-weight models, it is possible that scaling effects in models with more parameters or trained on larger datasets could lead to different generalization dynamics or failure modes.

- **Synthetic data design:** Our use of structured or domain-specific data for reward-based finetuning is necessarily limited in scope. Other forms of synthetic data, such as instruction-augmented samples [14], adversarial examples [12], or data curated through human-AI collaboration [19], may lead to improved generalization that we do not capture in this study.

B Broader Impacts

This paper encourages the development of more robust evaluation suites and transparent training paradigms for reasoning-capable language models. By analyzing how reasoning finetuning (RPT) affects model generalization across structured and unstructured domains, our work contributes to understanding the risks of narrow overfitting and domain brittleness.

We also highlight the importance of open-weight baselines and reproducible experimental pipelines, which are essential for aligning model behavior with desirable generalization properties. However, as with any finetuning method, RPT may unintentionally amplify domain-specific biases or incentivize brittle heuristics if not evaluated rigorously. We urge future work to incorporate fairness, calibration, and robustness criteria into such assessments.

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    Justification: We used o3-mini and o4-mini to select models and filter data. We illustrated the process in detail in Section 3.