NATURALREASONING: Reasoning in the Wild with 2.8M Challenging Questions

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Abstract

Scaling reasoning capabilities beyond traditional domains such as math and coding is hindered by the lack of diverse and high-quality questions. To overcome this limitation, we introduce a scalable approach for generating diverse and challenging reasoning questions, accompanied by reference answers. We present NATURALREASONING, a comprehensive dataset comprising 2.8 million questions that span multiple domains, including STEM fields (e.g., Physics, Computer Science), Economics, Social Sciences, and more. We demonstrate the utility of the questions in NATURALREASONING through knowledge distillation experiments which show that NATURALREASONING can effectively elicit and transfer reasoning capabilities from a strong teacher model. Furthermore, we demonstrate that NATURALREASONING is also effective for unsupervised self-training using external reward models or self-rewarding. To foster future work, we publicly release NATURALREASONING at `https://huggingface.co/datasets/facebook/natural_reasoning`.

1 Introduction

Large language models (LLMs) have demonstrated increased reasoning capabilities [OpenAI et al., 2024, Guo et al., 2025]. These models are designed to devote more time to deliberation before responding, enabling them to tackle intricate tasks and solve more complex problems in science, coding, and mathematics. Such reasoning models are trained via large-scale reinforcement learning on tasks where the reward can be derived using rule-based verification. Existing reasoning datasets are often limited to narrow domains where the solutions are short and easy to verify, while the majority of reasoning problems across broader domains are open-ended reasoning. To bridge this gap, we introduce NATURALREASONING, a comprehensive dataset curated from pretraining corpora, comprising 2.8 million reasoning questions spanning various topics, including Mathematics, Physics, Computer Science, Economics & Business, etc. NATURALREASONING is compared to a wide range of reasoning datasets, showcasing its advantageous properties, in particular its diversity and difficulty.

NATURALREASONING possesses several desirable attributes as a dataset, serving multiple research purposes. Firstly, the questions are backtranslated from the pretraining corpora, ensuring that it represents **diverse** reasoning problems in the real world, as opposed to synthetic datasets derived from benchmark datasets like MetaMathQA [Yu et al.] and OpenMathInstruct-2 [Toshniwal et al.]. Secondly, it consists of both questions with **easy-to-verify** answers and those with **open-ended** solutions (e.g., theorem proving), providing a rich resource for developing learning algorithms to enhance LLMs' reasoning abilities across broader domains.Thirdly, we show that NATURALREASONING

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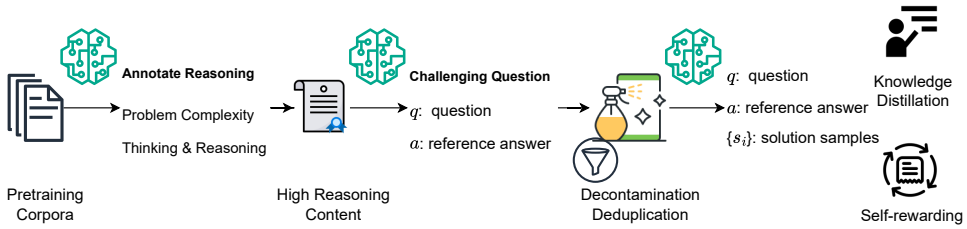

Figure 1: An overview of the data creation approach of NATURALREASONING.

poses more **difficult** reasoning problems than existing datasets. Its questions therefore provide an effective testbed for improving LLM reasoning—whether through knowledge distillation from a stronger teacher model or reinforcement learning with external and self-generated reward signals [Yuan et al.]. Lastly, the NATURALREASONING dataset complements existing reasoning datasets in terms of both **quality** and **quantity**.

Our contributions are threefold:

- We create a large-scale and high-quality reasoning dataset by using pretraining data and LLMs alone without extra human annotation. The dataset contains challenging questions which require deliberate thinking accompanied with reference answers. We release the NATURALREASONING dataset to the research community at `https://huggingface.co/datasets/facebook/natural_reasoning`.
- We show that NATURALREASONING is a highly performant dataset to enhance reasoning capabilities in post-training. Specifically, using questions from NATURALREASONING in distillation is more sample efficient than existing datasets.
- We investigate how NATURALREASONING supports self-training methods. Our results show that the questions in our dataset effectively enable self-learning, where self-rewarding techniques can yield performance comparable to some strong external reward models.

2 Data Collection

Backtranslating questions based on pretraining corpora has been shown to be a scalable approach to create instruction-following datasets [Li et al., 2023, Yue et al., 2024]. We take a similar approach to extract diverse and realistic reasoning questions grounded in pretraining data, i.e. we generate *grounded synthetic data*. An overview of the data creation approach is illustrated in Figure 1. A key differentiator of our approach is its emphasis on simplicity; we use LLMs throughout the entire cycle of synthetic data generation and curation, without any human annotation nor manual steps such as preprocessing to detect relevant documents and extracting questions with rule-based filtering.

2.1 Annotate Reasoning

Inspired by the meta-cognitive capabilities of state-of-the-art LLMs [Didolkar et al., 2024], we use an LLM to perform detailed annotation of pretraining documents to detect documents which contain sophisticated reasoning traces. We use the public pretraining corpora DCLM-baseline [Li et al., 2024b] and FineMath [Allal et al., 2025] as sources, which have demonstrated steeper scaling laws than alternative corpora. More specifically, given a document d from the pretraining corpus, we prompt an LLM to rate the content in d along multiple axes: Problem Completeness, Problem Complexity and Technical Depth, Technical Correctness and Accuracy, Thinking and Reasoning. The detailed prompt is provided in Appendix I. Empirically, we found that the model could analyze the document well and is able to follow the format requirement in the instruction.

2.2 Synthesize Questions and Answers

For documents which are identified with a high degree of reasoning (e.g., scored full points on axes of Problem Complexity and Technical Depth, Thinking and Reasoning), we further prompt an LLM to

Table 1: Comparison of four large publicly available reasoning datasets with NATURALREASONING. "Q" denotes "question", and question length is measured by the number of words.

Dataset	Domain	Q. #	Q. Len.	Question source	Response model
MetaMathQA	Math	395K	41±24	Rephrased by GPT-3.5-Turbo from GSM8K+MATH	GPT-3.5-Turbo
NuminaMath	Math	860K	48±32	Grade-level and competition-level math datasets	GPT-4o
OpenMath2	Math	607K	46±44	Synthesized by Llama3-405B-Inst from GSM8K+MATH	Llama3-405B-Inst
WebInstruct	Multi	13M	34±28	Recalled and Extracted from the Web	Mixtral-22B×8, Qwen-72B
NaturalReasoning	Multi	2.8M	55±21	Synthesized by Llama-3.3-70B-Inst grounded in the Web	Llama-3.3-70B-Inst

compose a self-contained and challenging reasoning question q based on the content in d. Different from existing work, which extracts questions appearing in the document [Yue et al., 2024], our approach allows us to synthesize more novel questions not directly contained in pretraining corpora. Then, we prompt the LLM to verify whether a correct reference answer a to the synthesized question q can be derived from d and, if possible, include it as a reference answer. Finally, for every question we generate an additional response with a relatively strong open-source model (Llama-3-70B-Instruct), which we later use as a teacher signal for knowledge distillation (see Section 5).

2.3 Question Deduplication and Decontamination

Deduplication Our deduplication process focuses on identifying and removing near-duplicate questions using locality-sensitive min-hashing at the word level. We apply a similarity threshold of 0.55 to filter out closely related variations, ensuring that questions with the same core reasoning task but different prompts are not redundantly included.

Decontamination We filter out questions that are similar to popular reasoning benchmarks including MATH [Hendrycks et al., 2021b], GPQA, MMLU-Pro [Wang et al., 2024] and MMLU-Stem [Hendrycks et al., 2021a]. The standard 13-gram decontamination method from EleutherAI's llm-eval-harness [Gao et al., 2024] is used to identify and remove 0.026% items from the dataset.

3 Data Analysis

We compare NATURALREASONING to the following representative existing datasets which were curated to boost reasoning capabilities.

MetaMathQA is created by bootstrapping mathematical questions from GSM8K and MATH, rewriting them from multiple perspectives to form a new dataset [Yu et al., 2024]. The responses are generated using GPT-3.5-Turbo.

NuminaMath is a comprehensive collection of 860K pairs of math problems and solutions [Li et al., 2024c]. The questions cover multiple sources including grade-level questions and competition problems. The solutions in NuminaMath dataset are generated or rewritten by GPT-4o.

OpenMathInstruct-2 is a collection of 14M synthesized math questions and solutions, based on GSM8K and MATH [Toshniwal et al., 2024]. The solutions are generated by Llama3.1-405B-Instruct [Grattafiori et al., 2024] and curated through majority vote on the final answer.

WebInstruct recalls relevant documents from Common Crawl using a fastText model trained on a diverse seed dataset of quiz websites. It then extracts question-answer pairs contained in recalled web pages and uses LLMs (Qwen-72B [Bai et al., 2023], Mixtral-8×7B [Jiang et al., 2024]) to refine the answer [Yue et al., 2024].

In addition, we compare models trained on NATURALREASONING with those trained on the OpenThoughts dataset [Guha et al., 2025], a recent open-source collection designed for reasoning in math, code, and science. As shown in Appendix G, models trained on NATURALREASONING

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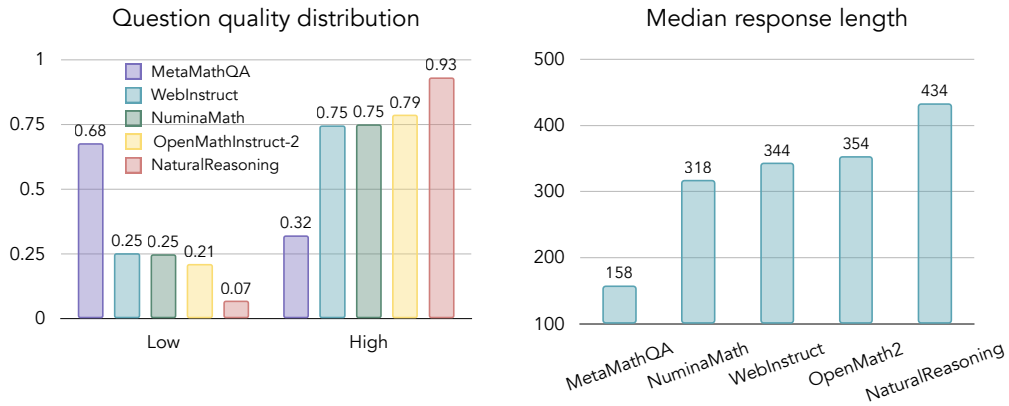

Figure 2: **Left**: Question quality distribution based on LLM annotations: Low (0-6), High (7-10). **Right**: Median response length (in words) of Llama3.3-70B-Instruct responses across all datasets.

achieve better performance across general reasoning benchmarks, demonstrating its broader coverage and stronger generalization compared to OpenThoughts.

3.1 Basic Statistics

We present a comparison of key dataset statistics in Table 1. Most large open reasoning datasets primarily focus on the math domain, with datasets such as OpenMathInstruct-2, NuminaMath, and MetaMathQA containing only math-related questions. In contrast, NATURALREASONING covers reasoning problems from more diverse domains. Additionally, NATURALREASONING consists of 2.8M **unique** questions, significantly larger than OpenMathInstruct-2 (607K), NuminaMath (860K), and MetaMathQA (395K), though smaller than WebInstruct (13M).

With an average length of 55 words, questions in NATURALREASONING are notably longer than those in OpenMathInstruct-2 (46), WebInstruct (34), NuminaMath (48), and MetaMathQA (41). Longer questions embed richer context and multi-step requirements, demanding deeper reasoning. Coupled with our varied, web-grounded sources, this added complexity sets NATURALREASONING apart as a uniquely challenging dataset.

3.2 Question Quality and Difficulty

Quality We evaluate question quality in NATURALREASONING with both automatic and human judgments. Three strong LLMs (DeepSeek-R1-Distill-Qwen-32B, Qwen2.5-72B-Instruct, Llama-3-70B-Instruct) independently score every question on a 0–10 scale reflecting solvability and completeness. For each comparison dataset, we randomly sample 10% of its questions and apply the same prompt. Scores of 0–6 are labeled low quality and 7–10 high quality; a question is deemed high quality when at least two models assign a high score. As shown in Figure 2, NATURALREASONING contains the highest fraction of high-quality questions (93%), surpassing the next-best dataset (79%). To corroborate these results, we conduct a small human study: two expert annotators independently score 100 randomly selected questions from each dataset, and we average their ratings. The pattern holds—NATURALREASONING achieves the top mean score (6.45) versus 5.92 for the second best. Full details are provided in Appendix D.

Difficulty To estimate question difficulty, we leverage a strong LLM to generate responses and use response length as a proxy, as longer chain-of-thoughts typically correspond to more complex questions. Specifically, we randomly selected 10% of questions from each dataset, and employ Llama3.3-70B-Instruct to generate responses for each question. As is shown in Figure 2, NATURALREASONING exhibits the longest median response length (434 words), significantly surpassing all other datasets. This suggests that our dataset contains more intricate and reasoning-demanding questions compared to existing open reasoning datasets.

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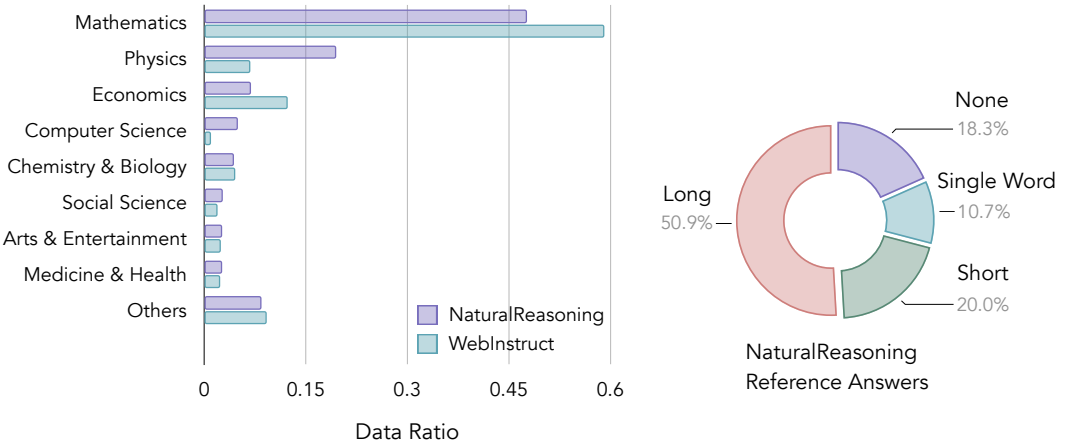

(a) Question topic distributions.

(b) Reference answer lengths in NATURALREASONING.

Figure 3: **Left**: Topic distributions of NATURALREASONING and WebInstruct. NATURALREASONING generally shows equivalent or even greater coverage on non-Math topics like Computer Science and Physics. **Right**: Distribution of reference answer lengths in NATURALREASONING, showing that the majority of questions have long reference answers ($\geq$10 words).

3.3 Question Diversity

In addition to being difficult, questions in NATURALREASONING are also diverse. We analyze diversity of the questions in terms of question similarity and the topics, and compare to WebInstruct, an existing dataset covering multiple domains.

Embedding Clustering We use an off-the-shell sentence encoder[3] to generate embeddings for questions in WebInstruct and NATURALREASONING. We then apply UMAP [McInnes et al., 2018] to project the high-dimensional embeddings into a 2D space, followed by K-means clustering [Wu, 2012] to identify distinct groups. We use Mixtral-8B to assign high-level labels to these clusters, which is prompted with a few examples from each cluster. As Figure 5 shows, NATURALREASONING contains a more diverse and dense representation of non-mathematical topics, including Physics, Chemistry, Computer Science, and Law, besides Math. In contrast, WebInstruct is primarily skewed toward mathematical content, highlighting the broader topic coverage of NATURALREASONING.

Classifier Categorization To estimate the topic distribution, a multi-class topic classifier is used to classify each question into 16 knowledge classes. The class labels are motivated by Wikipedia academic disciplines[4]. Figure 3a shows that NATURALREASONING is complementary to WebInstruct, where NATURALREASONING has better coverage on non-Math topics especially Physics, Computer Science, Social Science, etc.

3.4 Reference Answer Analysis

Among the 2.8 million questions we synthesized, 81.68% have reference answers which could be derived from pretraining data. The distribution of reference answer lengths is illustrated in Figure 3b, with single-word answers accounting for 10.7%, short answers (2–9 words) making up 20.0%, and long answers ($\geq$10 words) constituting the majority at 50.9%.

We provide examples of questions with single-word, short, and long answers in Appendix B. In general, we found that questions with single word answers typically involve numerical, factual, or definitional queries, while questions with long answers demand more free-form in-depth analysis. For questions with a long answer, the extracted reference answer is typically a short summary content

[3] https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2

[4] https://en.wikipedia.org/wiki/Outline_of_academic_disciplines

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from the original documents or useful clues to answer the question. While reference answers may contain some noise, we demonstrate their utility in Appendix F for both filtering training data in knowledge distillation and enabling reinforcement learning with verifiable rewards (RLVR) [Lambert et al., 2025].

4 Experimental Setup

We highlight the efficacy of NATURALREASONING in two settings: (1) **Knowledge distillation**, and (2) **Unsupervised Self-Training**. For (1), we evaluate whether NATURALREASONING enables steeper scaling than existing datasets when distilling reasoning capabilities to a student model via supervised finetuning (Section 5). We experiment with different model families such as Llama3.1-8B and Qwen2.5-7B. Specifically we show that questions from NATURALREASONING are very effective at distilling long chain-of-thoughts from reasoning models and compare it to manually curated questions such as LIMO [Ye et al., 2025] and S1K [Muennighoff et al., 2025] (Section 6). To demonstrate (2), we evaluate how well NATURALREASONING supports self-training either through a strong external reward model or self-rewarding mechanisms [Yuan et al., 2024] (Section 7).

Evaluation We evaluate our models on a diverse set of benchmarks that encompass both math and science reasoning: MATH, GPQA, GPQA-Diamond [Rein et al., 2024], and MMLU-Pro. In Appendix H, We also show NATURALREASONING's utility for broader NLP tasks (e.g., writing). To ensure a fair and consistent comparison, we adopt a zero-shot evaluation setting across all trained models. For inference we use vllm [Kwon et al., 2023] and employ greedy decoding to maintain determinism and eliminate variability introduced by stochastic generation. Unless mentioned otherwise, we report accuracy averaged over the last three saved model checkpoints during training.

5 Steeper Scaling with Challenging and Diverse questions

Our hypothesis is that challenging and diverse questions which require thinking and reasoning are more sample efficient for post-training. To verify this, we run supervised finetuning (SFT) starting from a base model, and evaluate overall performance across MATH, GPQA, and MMLU-Pro.

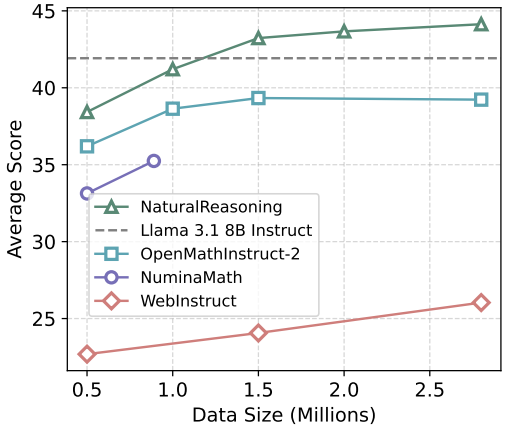
We fine-tuned the Llama3.1-8B-Base model and Qwen2.5-7B using fairseq2 training recipes [Balioglu, 2023], exploring the impact of varying dataset sizes. Specifically, we trained models on our dataset and the comparison datasets introduced in Table 1, and evaluated their average performance across three benchmarks: MATH, GPQA, and MMLU-Pro. For all datasets, we train 3 epochs for each data size, using batch size 128, learning rate $5e^{-6}$, with cosine learning rate schedule where final learning rate is 1% of peak learning rate.

5.1 Results

The scaling trends for Llama3.1-8B-Base model plotted by averaging performance on the three benchmarks are shown in Figure 4a, and Figure 4b provides a detailed breakdown of model performance across different dataset sizes and benchmarks. The scaling trends for Qwen2.5-7B model also show the superiority of NATURALREASONING and we put the results in Appendix E.

NATURALREASONING is significantly more sample-efficient than existing reasoning datasets. As shown in Figure 4a, models trained on NATURALREASONING require fewer training examples to achieve superior performance. With just 1.5 million training examples, the model trained on NATURALREASONING already outperforms Llama3.1-8B-Instruct, which was extensively tuned for instruction-following with more data [Grattafiori et al., 2024]. In contrast, other datasets, including OpenMathInstruct-2 and WebInstruct, fail to surpass Llama3.1-8B-Instruct even when trained on 2.8 million data. Each NATURALREASONING sample therefore provides denser, more effective reasoning supervision, making it the most data-efficient choice for boosting model reasoning performance.

Math-specific datasets like OpenMathInstruct-2 excel at math reasoning but fail to generalize beyond math. A closer look at Figure 4b reveals that OpenMathInstruct-2 consistently achieves the highest scores on the MATH benchmark, with performance increasing from 50.83 (500K) to 59.25 (2.8M). This confirms that OpenMathInstruct-2 is well-optimized for pure math reasoning. However,



(a) Average performance across MATH, GPQA, and MMLU-Pro when using varying sizes of data for training Llama3.1-8B-Base. SFT with 1.5 million examples from NATURALREASONING is able to surpass Llama3.1-8B-Instruct.

(b) Performance breakdown by benchmark, where the highest accuracy per data size is bolded.

SFT Dataset	500K	1M	1.5M	2.8M
		MATH		
WebInstruct	9.60	–	11.65	14.46
NuminaMath	49.53	–	–	–
OpenMathInstruct-2	**50.83**	**54.58**	**56.47**	**59.25**
NaturalReasoning	45.17	48.55	52.49	55.55
		GPQA		
WebInstruct	**29.02**	–	25.37	26.12
NuminaMath	13.84	–	–	–
OpenMathInstruct-2	25.60	27.31	27.23	26.45
NaturalReasoning	26.64	**29.91**	**31.77**	**30.13**
		MMLU-Pro		
WebInstruct	29.44	–	35.17	37.54
NuminaMath	42.36	–	–	–
OpenMathInstruct-2	32.16	34.03	34.30	31.99
NaturalReasoning	**43.47**	**45.16**	**45.43**	**46.71**

Figure 4: Scaling results for Llama3.1-8B-Base model.

its performance on GPQA and MMLU-Pro is significantly weaker, where GPQA accuracy plateaus around 27–26 as dataset size increases, and MMLU-Pro accuracy fluctuates without significant improvement. This suggests that while OpenMathInstruct-2 provides strong supervision in math reasoning, it lacks the diversity required to generalize to broader scientific reasoning tasks.

Some datasets show diminishing returns as training data increases, highlighting potential inefficiencies in data composition. While scaling up dataset size generally improves performance, datasets like WebInstruct and OpenMathInstruct-2 exhibit inconsistent or plateauing performance trends. For example, WebInstruct's GPQA performance peaks at 500K (29.02) but drops at 1.5M (25.37) and only marginally improves at 2.8M (26.12). Similarly, OpenMathInstruct-2's GPQA accuracy fluctuates with increased training data, suggesting that simply adding more data does not always lead to better reasoning abilities. These observations imply that data quality and diversity matter more than data volume when training models for complex reasoning.

6 Eliciting Long Chain-of-Thought

In addition to the emergence of OpenAI-o1 and DeepSeek-R1, several studies suggest that simpler tasks require fewer steps while complex tasks benefit significantly from longer CoTs [Jin et al., 2024]. When encouraging the model to think for longer, they are able to solve questions that they previously could not. Motivated by this, we investigate whether the questions in NATURALREASONING are complex enough to benefit from longer CoTs from a stronger reasoning model. We do so by distilling Deepseek-R1 responses to Llama3.3-70B-Instruct.

We randomly sampled 1K questions from NATURALREASONING and used SGLang [Zheng et al., 2023] to prompt DeepSeek-R1, generating one response per question. Resulting response lengths range from 745 to 14.6K tokens with an average length of 4430 tokens. We then supervised finetune Llama-3.3-70B-Instruct on this set and compare its performance against training on two strong, heavily curated datasets: s1K-1.1 [Muennighoff et al., 2025] and LIMO [Ye et al., 2025]. Both datasets underwent multiple filtering stages to ensure that their questions are high-quality, diverse, and challenging; for consistency, all responses were generated with DeepSeek-R1. To keep the evaluation consistent with the setting used in Guo et al. [2025], we report pass@1 averaged across $n = 24$ samples. Each sample is generated using temperature=0.6, top_p=0.95.

The results in Table 2 show that a randomly selected subset of 1k questions from NATURALREASONING matches—even slightly exceeds—the performance obtained on datasets that underwent several

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Table 2: Pass@1 of Llama-3.3-70B-Instruct after distilling DeepSeek-R1 responses. We compare the performance of random selection from NATURALREASONING with curated datasets such as s1K-1.1[Muennighoff et al., 2025] and LIMO[Ye et al., 2025], as well as the scaling effect of NATURALREASONING.

	Training size	GPQA-Diamond	MMLU-Pro	MATH-500	Average
Llama3.3-70B-Instruct	0	50.5	70.5	77.0	66.0
LIMO	817	56.5	76.8	86.6	73.3
s1K-1.1	1,000	62.7	77.4	86.6	75.6
NATURALREASONING	1,000	63.5	78.0	86.2	75.9
NATURALREASONING	10,000	65.6	78.4	87.4	77.1
NATURALREASONING	100,000	**67.3**	**79.5**	89.8	78.9
DeepSeek-R1-Distill-Llama-70B	800,000	65.2	78.5	**94.5**	79.4

rounds of meticulous filtering and curation. This parity underscores that NATURALREASONING contains questions that are diverse, challenging, and of consistently high quality.

To examine the impact of scale, we expanded the random sample size from 1K to 10K and finally to 100K NATURALREASONING questions; the corresponding results are also presented in Table 2. Performance increases monotonically across every benchmark, providing further evidence that enlarging the slice of NATURALREASONING delivers substantial gains precisely because the added questions maintain the same high standard of quality. Moreover, fine-tuning Llama-3.3-70B-Instruct on just 100K randomly sampled questions from NATURALREASONING brings the model close to DeepSeek-R1-Distill-Llama-70B, which was trained on 800K examples. Despite using only one-eighth the data, our model outperforms DeepSeek-R1-Distill-Llama-70B on GPQA-Diamond and MMLU-Pro, and falls only slightly behind on MATH-500. This further attests to both the scalability and the intrinsic quality of NATURALREASONING.

7 Unsupervised Self-Training

Since open-ended reasoning questions are difficult to evaluate using exact match with reference answers, we explore whether our dataset can facilitate self-training through either strong external reward models or self-reward mechanisms [Yuan et al.]

To test the effectiveness of self-training without confounding factors from distribution shift, we evaluate on GPQA-Diamond as test set, and use the remaining questions from GPQA as seeds to retrieve similar questions from NATURALREASONING. We curated 15,000 questions in total, which we refer to as `SelfTrain-15k`. More details are in Section C.2. Models trained on this subset can still be evaluated on the GPQA-Diamond test set as those questions are not used for data selection.

We verify unsupervised self-training under two different training method: Rejection-based sampling Fine-Tuning (RFT) and Direct Preference Optimization (DPO) [Rafailov et al., 2023], focusing on the effectiveness of different reward scoring strategies. Each approach relies on sampling 32 candidate responses per question, followed by selecting responses based on reward scores. RFT employs rejection sampling, selecting the highest-scoring response for SFT training, while DPO constructs training pairs using both the highest and lowest-scoring responses. For external reward models, we consider `Qwen2.5-Math-RM-72B` [Yang et al., 2024] and `INF-ORM-Llama3.1-70B`[5]. In addition, we explore a self-rewarding framework where the model evaluates and assigns rewards to its own generated responses. Specifically, we consider the following self-rewarding strategies:

Self-consistency: Inspired by prior work such as Prasad et al. [2024], the best response is selected based on response frequency, while the worst response is chosen randomly. To determine frequencies, we extract final answers formatted as `\boxed{X}` and compute their occurrence counts. Responses without a clearly extractable final answer are filtered out.

Self-scoring: The model receives the question and candidate response in a single prompt and is asked to assess whether the response is valid. We define the reward as the log-probability difference between the judgements "yes" and "no". The full prompt is in Figure 11.

[5]https://huggingface.co/infly/INF-ORM-Llama3.1-70B

Table 3: Unsupervised self-training results. We employ RFT and DPO training of Llama3.1-8B-Instruct, using various reward scoring strategies.

Model	GPQA-Diamond	MMLU-Pro	Average
Llama3.1-8B-Instruct	31.82	49.79	40.81
RFT training using external reward model & self-reward			
INF-ORM-Llama3.1-70B	32.66	50.95	41.81
Qwen2.5-Math-RM-72B	34.18	49.84	42.01
Self-consistency	34.18	49.83	41.91
Self-score	34.34	50.36	42.35
Self-score-filtered	**35.02**	50.06	42.54
DPO training using external reward model & self-reward			
INF-ORM-Llama3.1-70B	33.50	**52.74**	43.12
Qwen2.5-Math-RM-72B	30.13	49.17	39.65
Self-consistency	30.81	48.60	39.71
Self-score	34.34	52.11	43.22
Self-score-filtered	**35.02**	52.31	**43.67**

Self-scoring with filtering: on top of self-scoring, when applying RFT or DPO, we introduce an additional filtering mechanism. Specifically, for RFT, if the highest-ranked response has a self-score below zero, it is discarded. For DPO, if the preferred response in a pair has a self-score below zero, the pair is removed from training.

We train Llama3.1-8B-Instruct using RFT data and DPO data constructed through these methods. We use learning rate of $1e^{-6}$, batch size of 64, and train for three epochs, with checkpoints saved every 50 steps. We report test performance on GPQA-Diamond and MMLU-Pro in Table 3.

7.1 Results

Self-training improves performance over the baseline. Llama3.1-8B-Instruct, serving as the baseline, achieves an average score of 40.81 across GPQA-Diamond and MMLU-Pro. Almost all self-training methods lead to improvements, demonstrating the effectiveness of fine-tuning on high-quality model-generated responses.

Self-reward methods are highly competitive, often surpassing external reward models. While using external reward models, such as INF-ORM-Llama3.1-70B, could outperform the baseline, self-reward methods achieve comparable or even superior results. Notably, self-score-filtered SFT and self-score-filtered DPO deliver the best performance on GPQA-Diamond (35.02), with self-score-filtered DPO achieving the highest overall score (43.67). These results highlight that self-reward mechanisms can effectively guide self-training without relying on external reward models.

Self-score filtering further enhances performance by improving training data quality. Among self-reward methods, applying simple filtering improves results across both RFT and DPO. In RFT, self-score-filtered (42.54 AVG) outperforms unfiltered self-scoring (42.35 AVG), while in DPO, self-score-filtered (43.67 AVG) surpasses unfiltered self-scoring (43.22 AVG). This suggests that filtering out low-confidence responses strengthens self-training by reducing noise in the training data.

8 Related Work

Synthetic Reasoning Data. Synthetic data has emerged as a promising solution for improving performance. Some approaches bootstrap new data from existing data (e.g., STaR [Zelikman et al., 2022] augments with new CoT rationales and MetaMath [Yu et al.] rewrites the questions in MATH and GSM8K in several ways), but these techniques rely on the existence of a high-quality dataset. Other techniques such as that of OpenMathInstruct-2 [Toshniwal et al.], Xwin-Math [Li et al., 2024a], and Self-Instruct [Wang et al., 2023] generate new data from only a few seed examples using an LLM but scaling to new domains remains a significant challenge. MMIQC [Liu et al.] parses QA pairs

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from Mathematics Stack Exchange, using the highest-ranked answer, but few measures are taken to curate for quality and the resulting dataset is also specific to the math domain. Similar to our work, WebInstruct [Yue et al., 2024] harvests question-answer pairs from pre-training corpora and spans multiple domains, but is dependent on carefully crafted rule-based filters.

Unsupervised Self-training Most prior works typically depend on human-annotated (gold) final answers [Zelikman et al., 2022, Chen et al., 2024, Pang et al., 2024] or the use of an external reward model [Singh et al., 2024, Dong et al., 2023]. However, manually annotating or verifying final answers is particularly resource-intensive for complex, multi-step problems and training effective reward models for reasoning often requires human evaluation of LLM outputs [Cobbe et al., 2021, Uesato et al., 2022, Lightman et al., 2023], making it similarly costly. Like works such as She et al. [2024], Yuan et al. [2024], Rosset et al. [2024], Tran et al. [2023], our work explores self-training in the absence of gold labels and does not limit itself to questions with short, easily verifiable targets.

9 Conclusion

We present NATURALREASONING, a dataset of 2.8 million questions for enhancing LLM reasoning capabilities. Our questions are challenging, requiring more deliberate thinking than existing datasets. The dataset covers diverse reasoning problems across multiple domains including math, physics, computer science, economics, social sciences, etc. Using questions from NATURALREASONING in distillation experiments, we observe consistent improvement on reasoning benchmarks when scaling the data size. We also demonstrate that NATURALREASONING is effective for enabling LLM unsupervised self-training using external reward models or self-rewarding.

Limitation & Impact Statement

Although our study already validates NATURALREASONING 's value for large-scale offline training—covering supervised distillation and preference-based self-training (RFT, DPO)—we also conduct preliminary experiments using online RL with verifiable rewards with General Verifier, which show promising gains even with limited training. A more systematic exploration of reinforcement learning paradigms, including alternative reward models and scaling strategies remains natural extensions for future work. This paper seeks to improve reasoning capabilities of large language models through leveraging pretraining corpora. While our efforts are focused on curating high-quality, diverse data, models trained using this data may exhibit undesirable behavior not examined in our work. Therefore, comprehensive evaluation would be needed to evaluate and address any potential pre-existing or existing biases in LLMs which leverage this data.

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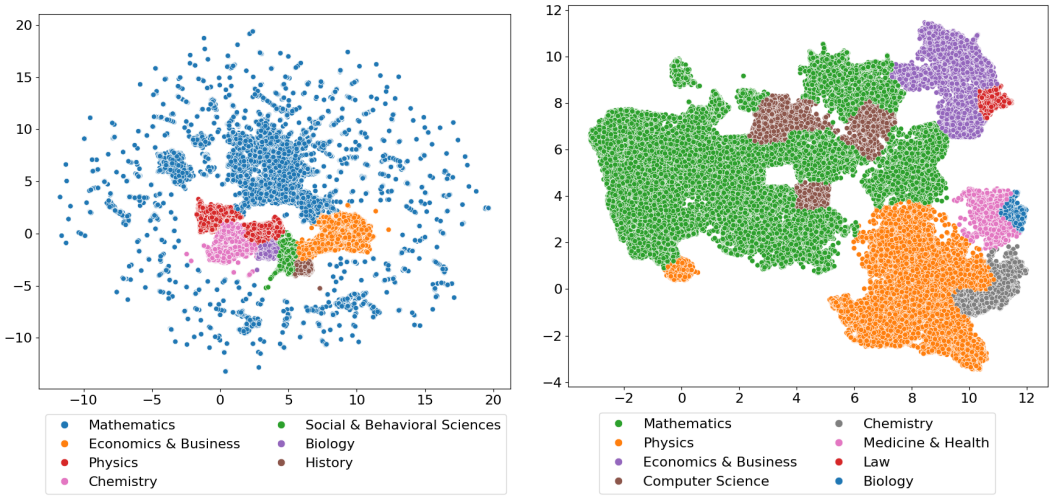
A Clustering Results

We present the results of our clustering in Figure 5. The procedure for producing this clustering is described in Section 3.3.



(a) WebInstruct (b) NATURALREASONING

Figure 5: Topic clustering of WebInstruct and NATURALREASONING.

B Example questions

Example questions with single word answer, short answer, long answer are shown in Table 4.

C Data Creation Details

C.1 Generation

We use vllm for all generations. For annotating documents and synthesizing questions, we use greedy decoding (i.e. temperature=0). For response generation for each question in NATURALREASONING, we use temperature=0.7 top_p=0.9. Responses used in unsupervised self-training experiments are sampled using temperature={0, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.2} to encourage response diversity.

C.2 SelfTrain-15k Curation

Specifically, for each question in the non-Diamond subset of GPQA, we retrieve the 1,000 most similar questions from NATURALREASONING, which were already decontaminated against the entire GPQA datset. Similarity is computed using cosine similarity between two question embeddings. After obtaining this candidate set, we apply deduplication and perform clustering, grouping the questions into 15,000 clusters. From each cluster, we select the questions closest to the cluster center, ensuring a diverse and representative dataset for downstream science reasoning tasks. This process resulted in a pool of 15,000 questions, which we refer to as `SelfTrain-15k`.

D Human Evaluation of Question Quality

To assess question quality reliably, we also conducted a human evaluation by randomly sampling 100 questions from each dataset. Two expert annotators independently rated each question, and we used the average of their scores as the final quality measure. The results, shown in Table 5, confirm that the NATURALREASONING dataset consistently produces higher-quality questions.

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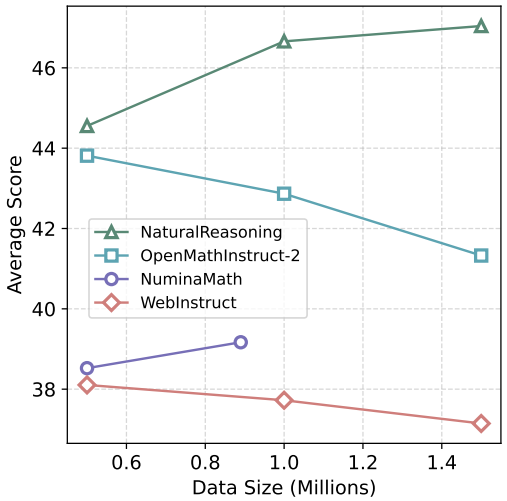
Table 4: Example questions with single word, short, and long reference answers.

Example questions with single word answer
(1) You have 5 cards with letters and numbers on either side. The rule is: If the letter on one side of a card is a vowel, the number on the other side is odd. What is the minimum number of cards you need to turn over to prove or disprove this rule? (2) What is the approximate number of grapes required to produce one bottle of wine, considering the conversion factors and variability in grape yields, and how does this relate to the overall wine production process? (3) A company is facing financial difficulties and is in danger of not meeting its obligations. In an effort to secure a bridge loan, the company's management decides to manipulate its financial statements by not reversing cancelled orders, thereby overstating its accounts receivable. This action allows the company to collateralize the loan and secure the necessary funding. However, this practice is in direct violation of revenue recognition rules. Analyze this situation and determine whether the company's actions constitute blatant fraud. Be sure to discuss the technical and ethical implications of such actions. (4) Evaluate the definite integral $\int_0^{\pi} \cos^2(x) \sin^7(x) dx$ using an appropriate substitution method and provide a step-by-step solution. (5) Speed of boat in still water is 10kmph. If it travels 24km downstream, 16km upstream in the same amount of time, what is the speed of the stream?
Example questions with short answer
(1) What are the parameters that need to be estimated in the general equation of an ellipse, and how do the variables x and y differ from the constants a and b in this context? Provide a detailed explanation of your answer, including the roles of a, b, x, and y in defining the ellipse. (2) Given a company's historical data on revenues, working capital, and net capital expenditures, is it acceptable to forecast change in working capital / net capex by regressing (linear) historical data on revenues? What are the limitations of this approach, and what alternative methods could be used to improve the accuracy of the forecast? (3) Solve the inequality 4(3w+4) $\geq$ 4(2w+12) using interval notation, and express the solution in set-builder notation. (4) Given an image with shape [1,28,28], what will be the shape of the output of a convolution layer with 10 5x5 kernels (filters) without padding? Assume the image dimensions follow the CHW (Channel, Height, Width) format. (5) A gas bubble, from an explosion under water, oscillates with a period T proportional to $P^a * d^b * E^c$. Where 'P' is the static pressure, 'd' is the density of water, and 'E' is the total energy of the explosion. Find the values of a, b, and c, and explain the physical reasoning behind your answer.
Example questions with long answer
(1) Analyze the impact of errors in data analysis on the validity of research findings, using the example of Reinhart and Rogoff's research on the relationship between debt and economic growth. How do such errors affect the development of economic policies, and what are the implications for the field of economics? (2) Prove that the relation $R = \{(1,2),(1,3),(1,4),(2,1),(2,3),(2,4),(3,1),(3,2),(3,4),(4,1),(4,1),(4,3)\}$ is not transitive. Use the definition of transitivity to show that there exist elements x_0, y_0, z_0 such that $(x_0, y_0) \in R$ and $(y_0, z_0) \in R$ but $(x_0, z_0) \notin R$. (3) Astronomers use a new method to detect asteroids and measure their velocity. The method involves detecting energized electromagnetic waves at two different Earth times and using the relative motion of Earth with respect to the asteroid to calculate the velocity. Suppose the Earth spins about 360 degrees within 24 hours, and the asteroid moves in a straight path with respect to other stellar objects. If the angle between the flat Earth surface at point A0 and the direction of asteroid observable is ?, and the angle between the flat Earth surface at point A and the direction of asteroid observable is ?, derive an expression for the relative velocity of Earth with respect to the asteroid at position A0 and A. Use the relativistic Doppler formula to relate the frequencies of the electromagnetic waves detected at points A0 and A. Assume the velocity of the asteroid does not change within the time interval of two detections, and estimate the value of the asteroid's velocity. (4) Bob, a resident outside the US, has purchased a mobile app subscription from a California-based business for under $200. However, due to a showstopper bug, the app is unusable for its main purpose. Bob has attempted to report the issue to the business's support team without success. Discuss the practicalities of Bob suing the California-based business from abroad, considering the requirements of Small Claims court in California and the potential application of consumer protection laws from Bob's home country. How might Bob's approach differ if he were to pursue litigation in a 'normal' court versus Small Claims court, and what are the implications of using an online store like Apple for the purchase? (5) Describe the differences in flow resistance between laminar and turbulent flows in a tube, and explain how the velocity profile changes in the transition from laminar to turbulent flow. Be sure to include the role of viscosity, density, and eddy viscosity in your answer.

Table 5: Human evaluation of question quality across five datasets.

Dataset	MetaMathQA	OpenMathInstruct-2	NuminaMath	WebInstruct	NaturalReasoning
Quality score	5.09	5.37	5.61	5.92	6.46



(a) Average performance across MATH, GPQA, and MMLU-Pro when using varying sizes of data for training Qwen2.5-7B.

(b) Performance breakdown by benchmark, where the highest accuracy per data size is bolded.

SFT Dataset	500K	1M	1.5M
MATH			
WebInstruct	38.82	40.12	38.49
NuminaMath	62.68	–	–
OpenMathInstruct-2	64.25	65.51	65.55
NaturalReasoning	**65.85**	**66.26**	**66.67**
GPQA			
WebInstruct	**31.85**	**30.28**	**29.76**
NuminaMath	1.71	–	–
OpenMathInstruct-2	18.23	14.21	9.08
NaturalReasoning	16.44	20.76	21.35
MMLU-Pro			
WebInstruct	43.65	42.77	43.18
NuminaMath	51.18	–	–
OpenMathInstruct-2	48.96	48.88	49.36
NaturalReasoning	**51.37**	**52.96**	**53.10**

Figure 6: Scaling results for Qwen2.5-7B model.

E Qwen2.5-7B Scaling Results

The scaling trends for the Qwen2.5-7B model plotted by averaging performance on the three benchmarks are shown in Figure 6a. Figure 6b provides a detailed breakdown of model performance across different dataset sizes and benchmarks. It is clear that NATURALREASONING shows superior scaling trends than other datasets.

F Reference Answer Usefulness

F.1 Data Filtering In Knowledge Distillation

We demonstrate the potential usefulness of reference answers using questions from `SelfTrain-15k`. We remove the questions that we are not able to extract a reference answer for and conduct a comparison to understand the utility of reference answers. We fine-tune the Llama3.1-8B-Instruct model using data filtered by final answer verification against a model trained on the unfiltered data.

For final answer verification, we use the prompt in Appendix Figure 10 that prompts the model to judge whether the generated response using Llama3.3-70B-Instruct is in line with the reference final answer, using CoT reasoning. For training data filtering, we only keep the responses that have received a "Yes" final judgement. The training setup includes a learning rate of $1e^{-6}$, a batch size of 64, and training for three epochs, with checkpoints saved every 100 steps for the unfiltered experiment and 50 steps for the filtered experiment due to much smaller data size.

The results are shown in Table 6. Filtering training data using reference answers leads to better performance despite a smaller training set. The filtered dataset contains 7,646 examples, significantly fewer than the 12,349 examples in the unfiltered dataset, yet achieves a higher score on both GPQA-Diamond (32.15 vs. 31.82) and MMLU-Pro (50.06 vs. 49.92). This suggests that higher-quality training data outweighs raw data quantity.

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Table 6: SFT results using reference answer filtering. We fine-tune Llama3.1-8B-Instruct on both an unfiltered subsample of NATURALREASONING and a filtered version, where questions are excluded if Llama3.3-70B-Instruct's response disagrees with the reference answer. Despite its smaller size, the filtered set performs better, highlighting the quality of our reference answers.

	Training size	GPQA-Diamond	MMLU-Pro	Average
Llama3.1-8B-Instuct	–	31.82	49.79	40.81
Unfiltered SFT	12,349	31.82	49.92	40.87
Filtered SFT	7,646	**32.15**	**50.06**	**41.11**

Table 7: Online RL results using verifiable rewards on NATURALREASONING. We apply GRPO to Llama3.1-8B-Instruct using the General Verifier as the reward model.

Model	MATH	MMLU-Pro	GPQA	Average
Llama3.1-8B-Instuct	48.74	**49.79**	29.24	42.59
GRPO (Step 50)	**52.20**	49.48	**31.47**	**44.39**

F.2 Reinforcement Learning With Verifiable Rewards

We conduct preliminary experiments applying reinforcement learning with verifiable rewards (RLVR) on the NATURALREASONING dataset. Specifically, we sample a subset of questions whose reference answers are shorter than 10 words and train Llama3.1-8B-Instuct using GRPO [Shao et al., 2024] with the General Verifier [Ma et al., 2025] as the reward model. Training is performed with a batch size of 768. Despite only 50 optimization steps, the model already exhibit noticeable performance gains over the untrained baseline across multiple reasoning benchmarks as shown in Table 7.

These early results suggest that reference answers in NATURALREASONING can be used in RLVR to further enhance reasoning performance, even with limited training. Due to current constraints in computational resources, we leave a more comprehensive exploration of RL-based fine-tuning methods for future work.

G Evaluating NaturalReasoning Against OpenThoughts

To ensure a fair comparison, we adopt a similar knowledge distillation setup, using a stronger reasoning model (i.e., DeepSeek-R1) as the teacher and Llama-3.1-8B-Instruct as the student. Following the procedure in the OpenThoughts paper [Guha et al., 2025], we apply length filtering and then sample 100K questions from each dataset. As shown in Table 8, the model trained on NATURALREASONING outperforms the one trained on OpenThoughts-114k on three out of four benchmarks.

These results show that NATURALREASONING achieves stronger performance on general reasoning and science benchmarks such as GPQA-Diamond, MMLU-Pro, and SuperGPQA [Team et al., 2025], indicating that it complements existing reasoning datasets like OpenThoughts by providing broader coverage and better generalization.

H Cross-Domain Generalization of NaturalReasoning

While our main experiments focus on reasoning benchmarks, we also conduct preliminary studies to examine NATURALREASONING 's applicability to broader knowledge domains. Specifically, we train Llama-3.1-8B-Instruct on 100K randomly sampled NATURALREASONING examples, using DeepSeek-R1 as the teacher model for knowledge distillation. The resulting model is then evaluated on SuperGPQA [Team et al., 2025], which includes diverse subjects beyond mathematics and science—such as philosophy, law, history, economics, literature, and sociology. The results on non-reasoning categories are shown in Table 9.

Despite its focus on reasoning-centric tasks, NATURALREASONING improves performance across a wide range of non-reasoning domains. These results highlight its potential as a versatile foundation for training models with broad domain generalization.

Table 8: Knowledge distillation results comparing training on NATURALREASONING and OpenThoughts. We distill from DeepSeek-R1 into Llama3.1-8B-Instruct using 100K samples from each dataset after applying length filtering following Guha et al. [2025].

Train Set	GPQA-Diamond	MATH-500	MMLU-Pro	SuperGPQA
OpenThoughts-114k (100K)	37.8	**82.2**	59.0	30.0
NaturalReasoning (100K)	**43.1**	69.0	**61.2**	**32.2**

Table 9: Cross-domain evaluation results after training on NATURALREASONING. We fine-tune Llama3.1-8B-Instruct on 100K NATURALREASONING examples with DeepSeek-R1 as the teacher model and evaluate on SuperGPQA's non-reasoning subjects.

Model	Philosophy	Economics	History	Education	Law	Management	Literature	Sociology
Baseline	29.36	23.17	17.24	26.03	**29.63**	29.54	23.37	23.78
Train on NR	**32.56**	**34.86**	**27.49**	**30.17**	**29.63**	**31.14**	**27.08**	**33.57**

I Prompts

The prompt we used for annotating reasoning from the document is shown in Figure 7, Figure 8. We additionally provide the prompt for annotating question validity and difficulty (Figure 9), the prompt used to check if a generated response matches the reference (Figure 10), and the prompt for self scoring (Figure 11).

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```
Evaluate the text below according to the scoring instruction and criteria. If the scores are
     high on each axis, derive an exam question following the instructions.

## Scoring Instruction
1. Evaluate the text on each criteria step by step. Provide your honest answer to each sub-
     question. If the answer to a sub-question is a confident Yes, add or subtract the points
     corresponding to the criteria.
2. Keep track of the running points from each criteria to get the total score.
3. Summarize your final evaluation results in a valid JSON object following the instruction
     below.

### Scoring Criteria

**Criteria 1: Problem Completeness**
* The content does not have clear main question, or enough clues to derive the correct answer.
     (0 point)
* The content includes a main question, and enough clues to derive the correct answer. (+1
     point)
* The text shows evidence of engagement and discussion among multiple authors, including
     proposing answers, evaluating and reflecting on answers, responding to critiques, revising
      and editing answers. (+1 point)

**Criteria 2: Problem Complexity and Technical Depth**

* The difficulty of the content is college-level or below. (0 point)
* The difficulty of the content is graduate-level or above, and only domain experts can
     understand. (+1 point)
* The question being discussed is so challenging that even highly skilled non-experts would not
      be able to fully understand the question or provide a correct answer, even after spending
      30 minutes searching the internet or reading up literature. (+1 point)

**Criteria 3: Technical Correctness and Accuracy**

* The text contains significant technical errors or inaccuracies. (-1 point)
* The text demonstrates some technical correctness, but with notable flaws or omissions (e.g.,
     incorrect units, incomplete derivations). (0 point)
* The text demonstrates technical correctness, with some minor flaws or omissions (e.g., minor
     algebraic errors, incomplete explanations). (+0.5 point)
* The text demonstrates high technical correctness, with clear and accurate explanations (e.g.,
      precise definitions, complete derivations). (+0.5 point)
* The text exemplifies exceptional technical correctness, with rigorous and precise
     explanations (e.g., formal proofs, precise calculations). (+1 point)

**Criteria 4: Thinking and Reasoning**

* The text lacks any evidence of thinking or reasoning. (-1 point)
* The text demonstrates some basic thinking and reasoning (+0.5 point), such as:
        + A straightforward application of a known technique.
        + A simple analysis of a problem.
* The text demonstrates some thinking and reasoning (+0.5 point), such as:
        + A consideration of multiple approaches to a problem.
        + A discussion of the trade-offs between different solutions.
* The text demonstrates significant thinking and reasoning (+1 points), such as:
        + Multi-step reasoning chains to solve a complex problem.
        + Advanced reasoning patterns often used in specialized science domains.
* The text exemplifies exceptional thinking and reasoning (+1 points), such as:
        + A highly innovative and creative approach to solving a complex problem in specialized
              domains.
        + Combining multiple reasoning and thinking techniques, with novel abstraction of the
             problem.

## Instruction on Exam Question and Final Report
* Step 1. If BOTH Criteria 1 and Criteria 2 scores above zero, transform the original question
     being discussed to an exam question. The question should focus on problem-solving and
     there should exist a correct answer to the question. The question should be descriptive, i
     .e. use the details and notations from the original text as much as possible. The question
      must be self-contained, concrete, well-defined, i.e. it should NOT contain any missing
     information nor should it contain any ambiguity or subjectiveness.
* Step 2. If BOTH Criteria 1 and Criteria 3 scores above zero, determine whether the text
     contains a correct solution to the question or not. If the discussion DOES contain a
     correct solution, try to extract the gists and important details from the correct answer.
     Then use those key information to derive a correct answer to the question. If there is a
     single final answer, conclude the correct answer with: "Therefore, the final answer is: \\
     boxed{{answer}}.", where [answer] is the number or expression that is the final answer.
* Step 3. If BOTH Criteria 2 and Criteria 4 have non-zero scores, write down a list of critical
      knowledge and reasoning steps which are required to derive a correct answer to the exam
     question. Each item in the list must be descriptive, specific and concrete.
* Step 4. Label the question difficulty with Easy, Medium, Hard, and Extra Hard.
```

Figure 7: Prompt for annotating reasoning from the document, generating a question and reference answer. (Part 1)

```
Finally, copy all your analysis from above into a JSON object at the end of the final report.
     The JSON object should contain the following attributes:
- ‘"scores"‘: a list of dictionary entries, where each entry contains the criteria name and
     corresponding score on that criteria.
- ‘"exam\_question"‘: a string recording the full exam question derived from Step 1 analysis.
     DO NOT omit any details. If the scores for Criteria 1 and Criteria 2 are low and no exam
     question can be made out of the text, return an empty string.
- ‘"correct\_answer"‘: a string recording the correct answer derived from Step 2. If the
     discussion does not contain a correct answer, return an empty string.
- ‘"knowledge\_and\_reasoning\_steps"‘: a list of strings, where each entry copying the
     critical piece of knowledge or important reasoning steps derived from Step 3. If either
     Criteria 2 or Criteria 4 has score zero, return an empty list.
- ‘"question\_difficulty"‘: a string recording the difficulty of the question derived from Step
      4.

### Text
{text}
```

Figure 8: Prompt for annotating reasoning from the document, generating a question and reference answer. (Part 2)

```
Your task is to verify and improve the quality of a question.

A valid question must meet the following criteria:
* The question should contain a problem to be solved, instead of
     only presenting statements.
* The question should be well-defined and self-contained, i.e.
    have all the necessary information to derive an answer.
* The question should be specific and clear. There should be one
     correct answer to the question.
* The question should not refer to external resources, such as
    figures, videos, etc.
* To derive an answer, multi-step reasoning and recalling
    relevant knowledge is required.
* The difficulty should be graduate-level or above.
* The question can contain LaTex but it should be correct.
If a question does not meet any of the criterion above, revise
    it till it meets all the criteria.

IMPORTANT: Put your final answer in a JSON object with two
    fields:
- "question_quality_score": rate how well the question meets all
     the criteria, on a scale of 1 to 10.
- "improved_question": revised question which will meet the
    criteria better and thus has a higher question quality score.

Question:
{question}
```

Figure 9: Prompt for annotating quality scores.

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```
You are an expert evaluator tasked with deciding whether a
    response meets the standards of quality and correctness for
    general reasoning tasks. Your evaluation must consider both
    the quality of the reasoning process (chain of thought, CoT)
     and the correctness or appropriateness of the final answer.

### Evaluation Criteria:
1. **Correctness of the Final Answer**:
   - Does the final answer align with the reference answer or
       the expected outcome?
2. **Quality of the Thinking Process (CoT)**:
   - Is the reasoning logical, coherent, and free from
       significant errors?
   - Does the reasoning support the final answer in a clear and
        step-by-step manner?
3. **Completeness**:
   - Does the response adequately address all aspects of the
       instruction or problem?

### Input Details:
- **Instruction**: {Describe the task, problem, or instruction
    here.}
- **Reference Answer**: {Provide the expected or ideal outcome
    here.}
- **Response**: {Include the response to be evaluated,
    containing both the CoT and the final answer.}

### Task:
Analyze the response provided and decide if it is a "Yes" or "
    No" based on the following:
- **"Yes"**: The response meets the required standards for
    correctness, reasoning, and completeness.
- **"No"**: The response fails to meet one or more of the
    standards.

Provide a brief explanation of your decision, highlighting
    specific strengths or weaknesses in the reasoning process (
    CoT), the final answer, or completeness.

**Response Format**:
1. **Explanation**:
   - **Final Answer Evaluation**: (Discuss correctness and
       consistency.)
   - **Chain of Thought Evaluation**: (Discuss logic and
       coherence.)
   - **Completeness**: (Assess whether the response fully
       addresses the instruction.)
2. **Judgment**: Yes/No
---

[FEW-SHOT EXAMPLES HERE]
---

### Current Input:
**Instruction**: <INSTRUCTION>
**Reference Answer**: <ANSWER>
**Response**:
<RESPONSE>

**Evaluation**:
```

Figure 10: Prompt used to check if a response matches the reference answer.

```
You are an expert evaluator tasked with analyzing a response to
    a general reasoning problem. Your goal is to determine if the
     response demonstrates good reasoning (CoT) and whether the
    reasoning makes sense overall.

### **Evaluation Criteria**:
1. **Reasoning Quality (CoT)**:
   - Does the reasoning follow a logical and coherent sequence?
   - Are the steps valid and free of major errors?
   - Does the reasoning align with standard problem-solving
       practices?

2. **Accuracy**:
   - Does the reasoning lead to the correct or valid conclusion
       based on the instruction?

3. **Clarity**:
   - Is the response clear and easy to understand?

### Input Details:
- **Instruction**: {Describe the task, problem, or instruction
    here.}
- **Response**: {Include the response to be evaluated,
    containing the chain of thought (CoT).}

### **Task**:
Analyze the response and decide if it meets the standards for
    correctness, reasoning quality, and clarity. Provide your
    judgment as either **"Yes"** (the response is good) or **"No
    "** (the response is not good). Then, briefly explain your
    decision.

**Response Format**:
1. **Judgment**: Yes/No
2. **Explanation**:
   - **Reasoning Quality (CoT)**: (Assess the reasoning process
       in detail.)
   - **Accuracy**: (Evaluate whether the reasoning leads to the
       correct conclusion.)
   - **Clarity**: (Comment on the clarity of the response.)

---
[FEW-SHOT EXAMPLES]

---

### Current Input:
**Instruction**: <INSTRUCTION>
**Response**:
<RESPONSE>

**Evaluation**:
1. **Judgment**:
```

Figure 11: Prompt for self scoring.

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The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and follow the (optional) supplemental material. The checklist does NOT count towards the page limit.

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   Answer: [Yes]

   Justification: We present a new dataset containing 2.8M challenging reasoning questions and demonstrate its effectiveness in training reasoning models through knowledge distillation and self-training experiments.

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