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# Light-R1: Curriculum SFT, DPO and RL for Long COT from Scratch and Beyond

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## Abstract

This technical report introduces our Light-R1 line of work. All our models, data and code have been open-sourced<sup>1</sup>.

Firstly, we aimed to train long COT models *from scratch* - from models without long COT. We applied curriculum SFT and DPO to Qwen2.5-32B-Instruct and trained Light-R1-32B to surpass DeepSeek-R1-Distill-Qwen-32B in math. Curriculum SFT was divided into two stages with 76k and 3k data respectively, followed by one stage of DPO with semi-on-policy pairs. Model merging was performed in the end for further improvement. Although trained with pure math data, Light-R1-32B demonstrates strong generalization capabilities in other domains with estimated training cost of around only 1000 dollars.

Secondly, we show that the 3k data we constructed for SFT stage 2 are widely applicable to other models. Trained with only this 3k data from DeepSeek-R1-Distilled models, Light-R1-7B-DS, Light-R1-14B-DS and Light-R1-32B-DS have all significantly improved in math. Notably, Light-R1-7B-DS achieves SOTA (State-Of-The-Art) across 7B math models and Light-R1-32B-DS performs close to QwQ-32B and DeepSeek-R1.

Thirdly, we specifically introduce Light-R1-14B-DS, the first open-source successful RL attempt on already long-COT finetuned models of similar sizes under light budget. Light-R1-14B-DS is also the SOTA 14B math model with AIME24 & 25 scores 74.0 & 60.2, outperforming even many 32B models and DeepSeek-R1-Distill-Llama-70B. Light-R1-14B-DS marks one step further in reproducing and democratizing DeepSeek-R1. We have finally seen expected behavior during RL training: simultaneous increase in response length and reward score *on an already long-COT finetuned model*.

The Light-R1 line of work validates training long-COT models from scratch, demonstrates the art of SFT data construction and releases SOTA models from RL.

Table 1: Light-R1 models. “-DS” = from DeepSeek-R1-Distill, otherwise from Qwen-Instruct.

Model	AIME24	AIME25	GPQA Diamond
Light-R1-32B	76.6	64.6	61.8
Light-R1-7B-DS	59.1	44.3	49.4
Light-R1-14B-DS	74.0	60.2	61.7
Light-R1-32B-DS	78.1	65.9	68.0

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<sup>1</sup><https://github.com/Qihoo360/Light-R1>

# 1 Introduction

Since the release of DeepSeek-R1 [DeepSeek-AI, 2025], long chain-of-thought (long COT) reasoning has gained widespread popularity in both foundational AI models and various industrial AI applications. However, deploying full-capacity R1-level models (typically 70B+ parameters, DeepSeek-R1 with 671B parameters) incurs prohibitive computational costs [DeepSeek-AI, 2025, Qwen, 2025]. The resource barrier of training and deploying the giant models makes them impractical for edge devices and real-time applications. This limitation has sparked growing interest in developing compact yet capable models under a few 10B parameters that can perform extended long COT - a critical requirement for mathematical problem solving, algorithmic planning, and scientific analysis [Wei et al., 2022].

To this end, we conducted Light-R1 line of work. At the origin of everything, we established stable and trustworthy evaluation protocols that could precisely reproduce the evaluation results as reported in DeepSeek-AI [2025].

Based on trustworthy evaluation, our research addresses three fundamental challenges in this direction through systematic architectural and algorithmic innovations.

Firstly, we investigate how to train long-COT capabilities from scratch on initial models without prior reasoning skills (models who cannot perform long COT but have undergone basic instruction tuning). Conventional approaches [Fu et al., 2023] rely heavily on pre-existing COT annotations in initial models, which creates a paradoxical dependency. Through systematic experimentation with training progress monitoring, we develop a novel curriculum learning framework combining two-stage supervised fine-tuning (SFT) and further direct preference optimization (DPO). This methodology successfully implants COT capabilities into vanilla Qwen2.5-32B-Instruct and produces Light-R1-32B, surpassing DeepSeek-R1-Distill-Qwen-32B in math with little training cost of around 1000 dollars.

Secondly, we discover that the stage-2 SFT dataset (3k high-quality math data) we constructed when developing Light-R1-32B demonstrates remarkable transferability across different model series and sizes. Through cross-model validation on the 7B, 14B and 32B models in the DeepSeek-R1-Distill-Qwen family [DeepSeek-AI, 2025], we observe consistent performance gains ( $\Delta+2-5\%$  on AIME24) when training only on the 3k stage-2 SFT dataset. This suggests the existence of universal mathematical primitives in the stage-2 data that bear cross-model knowledge transfer and may be orthogonal to DeepSeek’s 800k SFT data in DeepSeek-R1. Notably, trained with only this 3k data, Light-R1-7B-DS achieves SOTA (State-Of-The-Art) across all public 7B math models.

Thirdly, we are excited to report our successful reinforcement learning (RL) training of Light-R1-14B-DS. Recent RL works have successfully trained RL on base or short-COT models (usually with *-zero* in their names) [Zeng et al., 2025, Hu et al., 2025], or on small models (with response length interestingly decreasing significantly then increasing) [Zeng et al., 2025, Luo et al., 2025], or on QwQ-32B with presumably prohibitively heavy compute. Among them, none except QwQ-32B could be regarded as full-scale RL reproduction of the *non-zero* RL of DeepSeek-R1, while QwQ-32B performed RL on 32B models with “scaling RL” [Qwen, 2025] - presumably prohibitively heavy compute. Our long-COT RL Post-Training is the first to show simultaneous increase in response length and reward score on long-COT 14B models with no length dropping in the beginning. This breakthrough demonstrates that careful curriculum design can overcome the known scalability limitations of RL in small models Gao et al. [2023].

The key contributions of this work include:

- A detailed, fully open-source Post-Training approach to train long-COT models from scratch. Curriculum SFT + DPO is validated on Qwen2.5-32B-Instruct and could be easily migrated to Qwen2.5-7B and 14B models. The total three-stage curriculum (SFT→SFT→DPO) incrementally builds reasoning capacity through difficulty-progressive data exposure, requiring only \$1000 training cost (6 hours on 12×H800 GPUs).
- A well established SFT stage 2 dataset of 3k mostly math questions that could significantly improve not only SFT stage 1 but also all DeepSeek-R1-Distill models, resulting in our SOTA 7B model Light-R1-7B-DS.

- First demonstration of RL effectiveness on 14B models for mathematical reasoning, achieving around 2% absolute improvement compared with before-RL, resulting in our SOTA 14B model Light-R1-14B-DS.

Our resulting Light-R1-32B model achieves 76.6% on AIME24 and 64.6% on AIME25, surpassing DeepSeek-R1-Distill-Qwen-32B by 4.0% and 9.7%. Light-R1-7B-DS and Light-R1-14B-DS are SOTA math models of equal sizes. Light-R1-14B-DS shows consistent and expected improvement during RL training.

The Light-R1 model series establishes new possibilities for deploying advanced reasoning capabilities in resource-constrained environments such as edge computing without sacrificing analytical depth.

## 2 The Origin of Everything: Stable and Trustworthy Evaluation of Long-COT Models

Following DeepSeek-AI [2025], long-COT models are commonly deployed with sampling temperature 0.6. While long-COT models generally perform better with sampling than with greedy decoding, it brings more burden for model evaluation as multiple samples for each question may be required, contrary to previous viable approaches of greedy decoding for evaluation [Song et al., 2024].

DeepSeek-AI [2025] generates 64 responses per query to estimate pass@1. We have verified this choice, witnessing large deviation of over 3 points using 16 responses or fewer across different runs of the same model. Such randomness is unacceptable to compare model performances.

For stable and trustworthy evaluation, we adapted Luo et al. [2025]’s evaluation code for all our evaluation runs. Our evaluation code and logs are all released.

We can reproduce all DeepSeek-R1-Distil models’ and QwQ’s scores as reported in DeepSeek-AI [2025], Qwen [2025] as shown in Tab. 2 with 64 samples per query, with deviation around 1 point. We could therefore train and evaluate our models in a trusted way using the same evaluation code and protocol.

Table 2: Reproduction of DeepSeek-AI [2025] evaluation results

Model	AIME24 pass@1, paper	AIME24 pass@1, ours
DeepSeek-R1-distill-Qwen-32B	72.6	72.3
DeepSeek-R1-distill-Qwen-14B	69.7	69.3
DeepSeek-R1-distill-Qwen-7B	55.5	54.0
QWQ-32B	79.5	78.5

## 3 Light-R1-32B: Long COT from Scratch with Curriculum SFT & DPO

While much work [Ye et al., 2025, Muennighoff et al., 2025, Team, 2025] has been open-sourced trying to reproduce DeepSeek-R1 on models of 72B or less, none achieves similar performance on the hard math competition AIME24 & 25 as DeepSeek-R1-Distill-Qwen-32B’s score 72.6 & 54.9.

Light-R1-32B starts from Qwen2.5-32B-Instruct without long COT (*from scratch* in terms of long-COT) and trains on decontaminated math data. It distills DeepSeek-R1 with curriculum SFT & DPO to surpass DeepSeek-R1-Distill-Qwen-32B on AIME24 & 25, and improved further with model merging, achieving 76.6 & 64.6.

More importantly, besides the state-of-the-art from-scratch model Light-R1-32B, we have also released all training datasets of our curriculum SFT & DPO and training code based on 360-LLaMA-Factory [Zou et al., 2024]. Estimated training time on 12 x H800 machines takes no more than 6 hours — around \$1000.

We believe Light-R1 represents a practical way of training strong long COT models from scratch (from models without long COT). While we have made RL work on 14B models (Sec. 5), curriculum SFT & DPO facilitates more control along the pipeline and is more cost-friendly.

We introduce our data processing and Post-Training pipeline in this section as illustrated by Fig. 1.

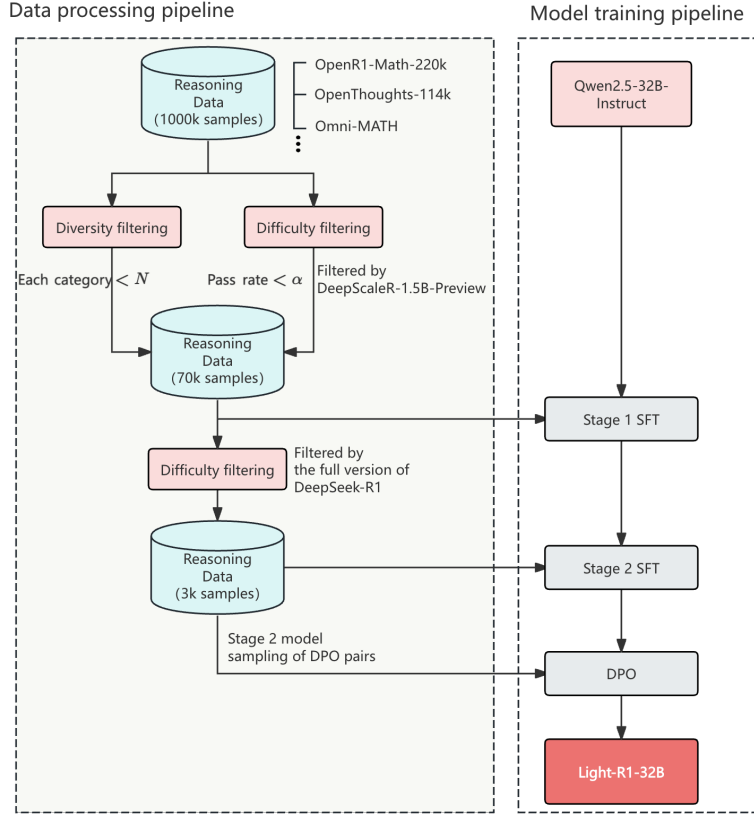


Figure 1: Overview of training pipeline of Light-R1-32B.

### 3.1 Data Preparation

The whole data preparation process spans data collection, data decontamination and data generation, detailed as follows.

#### 3.1.1 Data Collection

We began by collecting various sources of math questions with groundtruth answers. Iterating over all possible sources by the time, we collected around 1000k math questions as the seed set. Major data sources include:

- <https://huggingface.co/datasets/GAIR/LIMO>
- <https://huggingface.co/datasets/nvidia/OpenMathInstruct-2>
- <https://huggingface.co/datasets/open-r1/OpenR1-Math-220k>
- <https://huggingface.co/datasets/open-thoughts/OpenThoughts-114k>
- <https://huggingface.co/datasets/simplescaling/s1K-1.1>
- <https://huggingface.co/datasets/KbsdJames/Omni-MATH>
- [https://hf-mirror.com/datasets/baber/hendrycks\\_math](https://hf-mirror.com/datasets/baber/hendrycks_math)

All data are aggregated together to form around 1000k math questions as the seed set. Within this 1000k data, we kept only math questions with groundtruth answers. Questions without groundtruth answers could be used as synthetic data by letting multiple strong LLMs vote for groundtruths but we left it for future work.

The data is then filtered for diversity, where we tagged each question with an in-house tagging system and downsample categories with excessive data.

### 3.1.2 Data Decontamination

Table 3: Number of matched prompts in open-source datasets against benchmarks.

Dataset	AIME24+25	MATH-500	GPQA Diamond
OpenThoughts-114k	0	100	0
Open-R1-Math-220k	0	10	0
DeepScaleR-Preview-Dataset	0	196	0
LIMO	0	0	0
Bespoke-Stratos-17k	0	125	0
Open-Reasoner-Zero	0	325	0
simplescaling/data_ablation_full59K	0	244	1
simplescaling/s1K-1.1	0	3	1
ours	0	0	0

We carefully evaluated data contamination of several open-sourced datasets. While certain contamination may be inevitable during pre-training, it is unacceptable for post-training to compare on benchmarks. As can be seen in Tab. 3, we found that MATH-500 is somewhat compromised with tens of questions that are identical or only numbers changed. AIME 24 and 25 stay intact but we have to pay special attention when we incorporate AIME data up to 2023.

Light-R1 did thorough decontamination with exact matching (excluding digits, to filter out questions with only digits changed) and N-gram (N=32) matching against AIME24, AIME25, MATH-500 and GPQA.

### 3.1.3 Data Generation

With a diverse and clean dataset, we generate long-COT responses for SFT training. However, not all data are suitable and necessary to train on, and distilling DeepSeek-R1 could be expensive whether querying API or deploying locally. We therefore performed difficulty first on the dataset, to keep only questions that are not too easy.

We use Luo et al. [2025]’s DeepScaleR-1.5B-Preview model to sample responses for each question, as the model is small but strong enough. Only questions with pass rate  $< \alpha$  are kept to query DeepSeek-R1. This result in around 70k (76k to be precise) data. After querying DeepSeek-R1, only questions with correct long-COT answers are kept. If two or more sampled answers are correct, we randomly choose one of the long-COT answers for SFT.

This way, we constructed an over 70k SFT dataset, whose prompts are filtered by diversity and difficulty and long-COT responses are generated by DeepSeek-R1 and verified against the groundtruth.

However, directly training on this dataset cannot produce satisfactory results directly no matter how many epoches SFT is trained. After inspecting the trained model’ performance on different questions, we found that the model may need further training on more difficult questions. Therefore, instead of difficulty filtering with DeepScaleR-1.5B-Preview in the last stage, we performed another stage of difficulty filtering with DeepSeek-R1-Distill-Qwen-32B. Only questions with pass rate  $< \alpha$  and questions which DeepSeek-R1’s sampled responses cannot get all right or all wrong are kept in this stage, resulting in a SFT stage 2 dataset of size 3k. Interestingly, this dataset is of high quality that training merely on it could improve all DeepSeek-R1-Distill models, as will be discussed in Sec. 4.

## 3.2 Curriculum Post-Training

Our approach consists of three stages:

1. **SFT Stage 1:** Training on 76k filtered mathematical problems
2. **SFT Stage 2:** Fine-tuning on 3k high-difficulty problems
3. **DPO Optimization:** Preference-based optimization using verified response pairs

Both SFT stages are trained with the two-stage data as discussed in Sec. 3.1.3. Detailed hyperparameters could be found in our GitHub repo.

For DPO we adopted a semi-on-policy method with NCA loss [Chen et al., 2024]. Rejected responses are sampled from the SFT-stage-2 model with verified wrong answer. Specifically, responses too long, too short or think right but answer wrong are selected as rejected in DPO pairs. Chosen responses are verified correct answers from DeepSeek-R1. While we have been using fully on-policy DPO for a long time, we found that for hard math problems the chosen responses are better from much stronger models.

### 3.3 Results

Table 4: Stage-wise performance improvement

Stage	AIME24	AIME25	GPQA Diamond
Qwen2.5-32B-Instruct (base model)	16.6	13.6	48.8
Light-R1-32B-SFT-stage1	69.0	57.4	64.3
Light-R1-32B-SFT-stage2	73.0	64.3	60.6
Light-R1-32B-DPO	75.8	63.4	61.8
Light-R1-32B (merged model)	<b>76.6</b>	<b>64.6</b>	61.8

We have seen steady improvement in each stage of our curriculum SFT & DPO Post-Training, as shown in Tab. 4. Following DPO stage, we merged models of SFT-stage2, DPO and another DPO version with AIME24 score 74.7. The two DPO versions differ in that one of the data has special tokens skipped in rejected responses. Interestingly, the resulting version also exhibits improvement. On the GPQA evaluation of scientific questions we didn’t train on at all, math-specialized training has led to some degree of forgetting. However, Light-R1-32B still demonstrates strong generalization ability.

## 4 Light-R1-\*-DS: Universal Improvement with 3K Data of SFT Stage 2

Considering DeepSeek-R1-Distill-Qwen models as a stronger version of our SFT stage 1, we performed SFT stage 2 with the 3k stage 2 data on top of DeepSeek-R1-Distill-Qwen models.

Surprisingly as Tab. 5, we could achieve universal improvement on DeepSeek-R1-Distill-Qwen models with this 3k data alone, demonstrating the high quality of the stage 2 data. It may also be because this 3k data is to some extent orthogonal to DeepSeek-R1-Distill-Qwen models’ 800k SFT data, hence such easy improvement.

Light-R1-7B-DS and Light-R1-32B-DS are released as the directly SFT stage 2 version, while Light-R1-14B-DS has undergone additional RL training for further improvement.

GPQA is unexpectedly high for Light-R1-32B-DS, but in most of our experiments science and coding other than math should be further improved by specific training, which we haven’t done in this technical report.

## 5 Light-R1-14B-DS: Successful RL on Already Long-COT Finetuned Models

We conduct our reinforcement learning experiments on DeepSeek-R1-Distill-Qwen-14B. To the best of our knowledge, this is the first publicly documented work demonstrating significant improvements in performance through RL on 14B models. Previous studies by DeepSeek-AI [2025], Yuan et al. [2025], and Zhang et al. [2025] have shown that smaller models (with 32 billion parameters or fewer) can reach high performance levels through distillation from larger reasoning models. However,

Table 5: Improvement with 3k data.

Model	AIME24	AIME25	GPQA Diamond
DeepSeek-R1-Distill-Qwen-7B	55.5	39.2	49.1
Light-R1-7B-DS	<b>59.1</b>	<b>44.3</b>	49.4
DeepSeek-R1-Distill-Qwen-14B	69.7	50.2	59.1
Light-R1-14B-DS-SFT	<b>72.3</b>	<b>58.9</b>	N/A
DeepSeek-R1-Distill-Qwen-32B	72.6	54.9	62.1
Light-R1-32B-DS	<b>78.1</b>	<b>65.9</b>	<b>68.0</b>

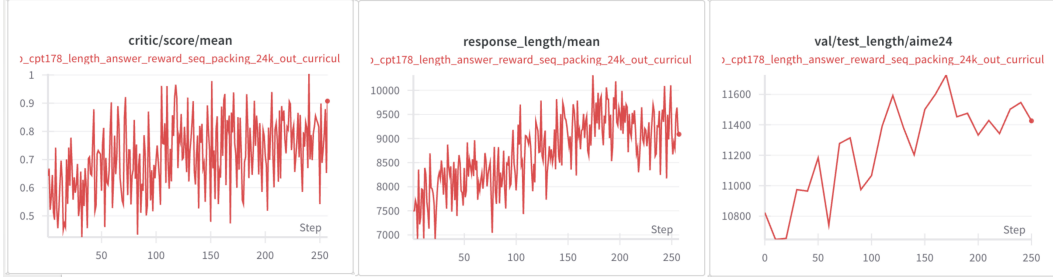


Figure 2: Learning curves of RL directly from verl wandb without smoothing. critic/score corresponds to training reward. Middle and right are training and test response lengths respectively.

attaining comparable performance via reinforcement learning from already long-COT finetuned models might require extensive training steps, and is not yet widely reached by the community. Our investigation focuses on determining whether RL can further enhance the performance of already-distilled models.

While Luo et al. [2025] successfully demonstrated promising reward improvements via RL on smaller models as DeepSeek-R1-Distill-Qwen-1.5B, we encountered challenges in replicating similar results with the larger DeepSeek-R1-Distill-Qwen-14B model use the same recipe.

Our final RL implementation employs a two-step process, drawing inspiration from our effective curriculum SFT attempt and Cui et al.. The process is as follows:

1. **Offline Data Selection:** Use Light-R1-7B-DS to sample results of RL training prompts. Keep only the prompts whose pass rates are not 0 or 1 and within a certain range.
2. **Online Reinforcement Learning:** Apply GRPO on the filtered dataset.

We choose GRPO ([Shao et al.]) as the optimization algorithm and implement it based on verl ([Sheng et al., 2024]). We also employ two techniques to stabilize the RL training process: length reward [Yeo et al.] and sampling weight clipping [MiniMax et al.].

We use a rule-based reward and the deduped version of the Big-Math dataset (Albalak et al. [2025]). The experiments are conducted on a cluster of 16 \* 8 A100 GPUs. The offline data selection process takes 4 hours, while the online reinforcement learning takes 26 hours to complete 140 steps and 42 hours to complete 220 steps.

As can be seen from Fig. 2, our RL training demonstrates expected behavior: simultaneous increase in response length and reward score. No interesting length dropping in the beginning. We evaluated RL epochs 1 and 2 after we finished training 3 epochs. As shown in Tab. 5, although first two epochs seem to bring not much improvement, the healthy RL training curves warrant much confidence to continue training. Light-R1-14B-DS is finally RL trained for around 3 epochs, or 220 steps.

Table 6: RL performance improvement of Light-R1-14B-DS.

Model	AIME24	AIME25	GPQA Diamond
DeepSeek-R1-Distill-Qwen-14B	69.7	50.2	59.1
Light-R1-14B-DS-SFT	72.3	58.9	N/A
Light-R1-14B-DS-SFT-GPRO epoch1	72.3	57.8	N/A
Light-R1-14B-DS-SFT-GPRO epoch2	73.4	60.5	N/A
Light-R1-14B-DS(-SFT-GPRO epoch3)	<b>74.0</b>	<b>60.2</b>	<b>61.7</b>

## 6 Conclusion

The Light-R1 line of work systematically addresses the challenge of training long-COT mathematical reasoning models under constrained resources, offering three key contributions. First, we establish a reproducible and cost-effective curriculum SFT+DPO pipeline that successfully trains long-COT capabilities from scratch on Qwen2.5-32B-Instruct, achieving SOTA performance with only \$1000 training cost. Second, our 3K stage-2 SFT dataset demonstrates universal transferability across model sizes and architectures, significantly improving DeepSeek-R1-Distill models and setting new benchmarks for 7B models. Third, we present the first successful RL training on a 14B long-COT model, Light-R1-14B-DS, which achieves SOTA performance while maintaining stable response length growth during training. These advancements not only democratize access to R1-level reasoning capabilities but also provide novel insights into curriculum design, data efficiency, and RL scalability. Our open-source models, datasets, and code (GitHub: Qihoo360/Light-R1) aim to accelerate research in compact yet powerful reasoning systems, particularly for resource-constrained applications. Future work will explore integrating multi-domain capabilities and further optimizing RL efficiency for smaller models.

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