

# Llama-Nemotron: Efficient Reasoning Models

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## 1. Llama-Nemotron-V1 family

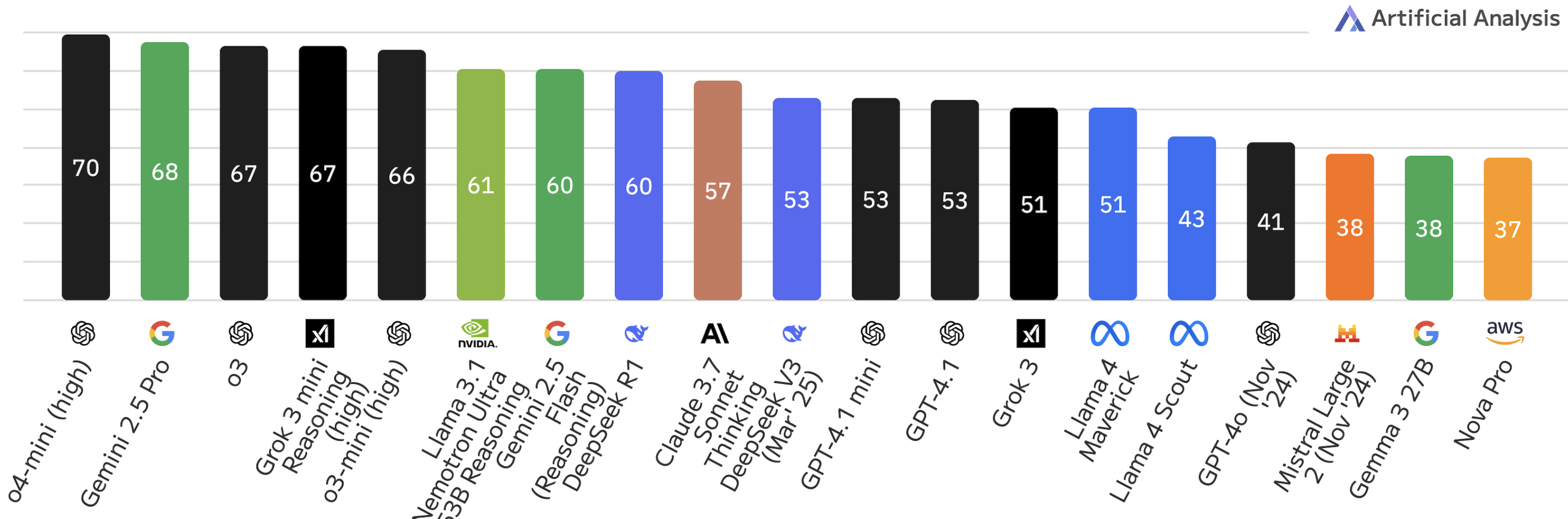
Open-weights, open source post-training SW, open post-training & RLHF data. First open-weights with reasoning control On/Off.  
3 model sizes:

- **LN-Nano** (8B and 4B)
- **LN-Super** (49B)
- **LN-Ultra** (253B)

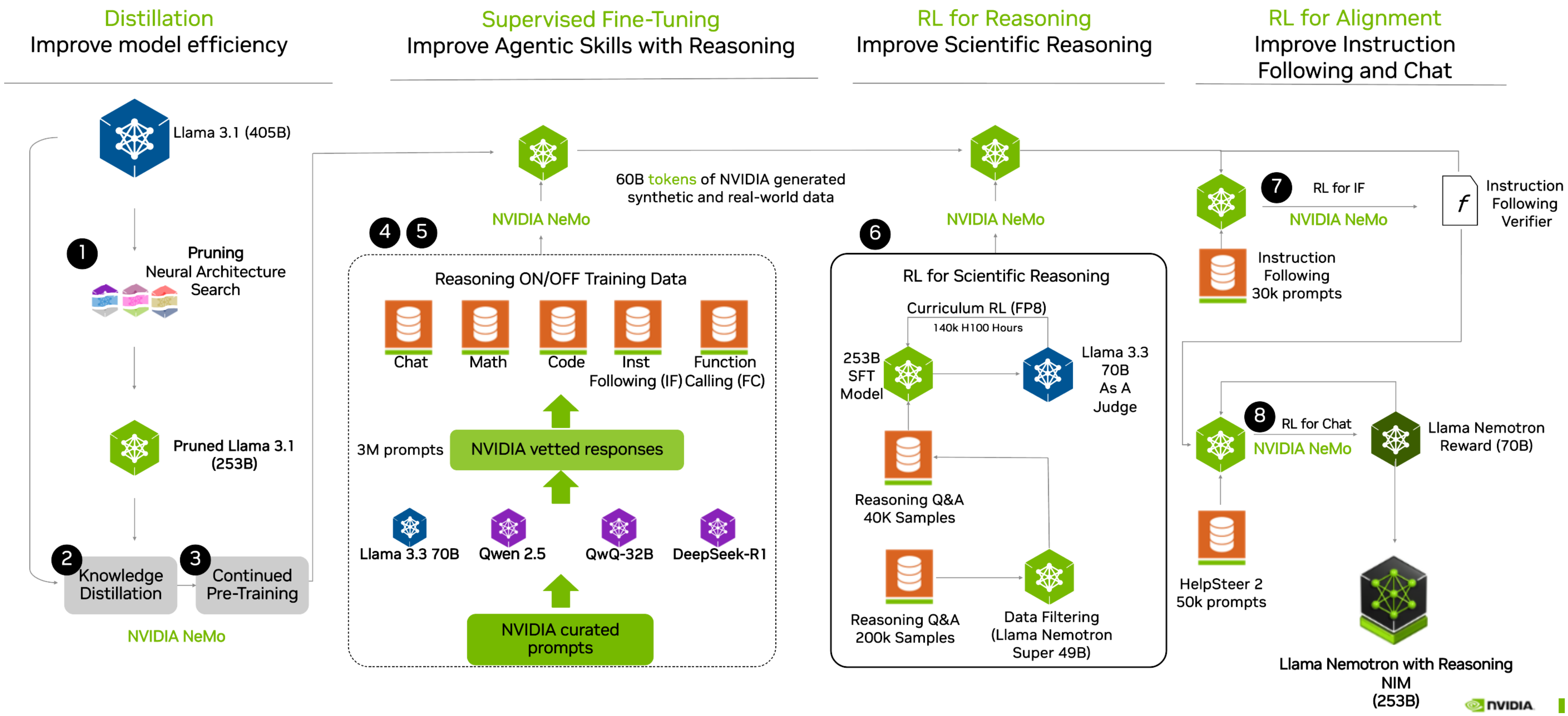
Smartest open-weights model as of April 2025. The highest ranking llama variant on lmarena.ai

### Artificial Analysis Intelligence Index

Intelligence Index incorporates 7 evaluations: MMLU-Pro, GPQA Diamond, Humanity's Last Exam, LiveCodeBench, SciCode, AIME, MATH-500



## 2. Post-training pipeline



## 3. RLVR for Scientific Reasoning

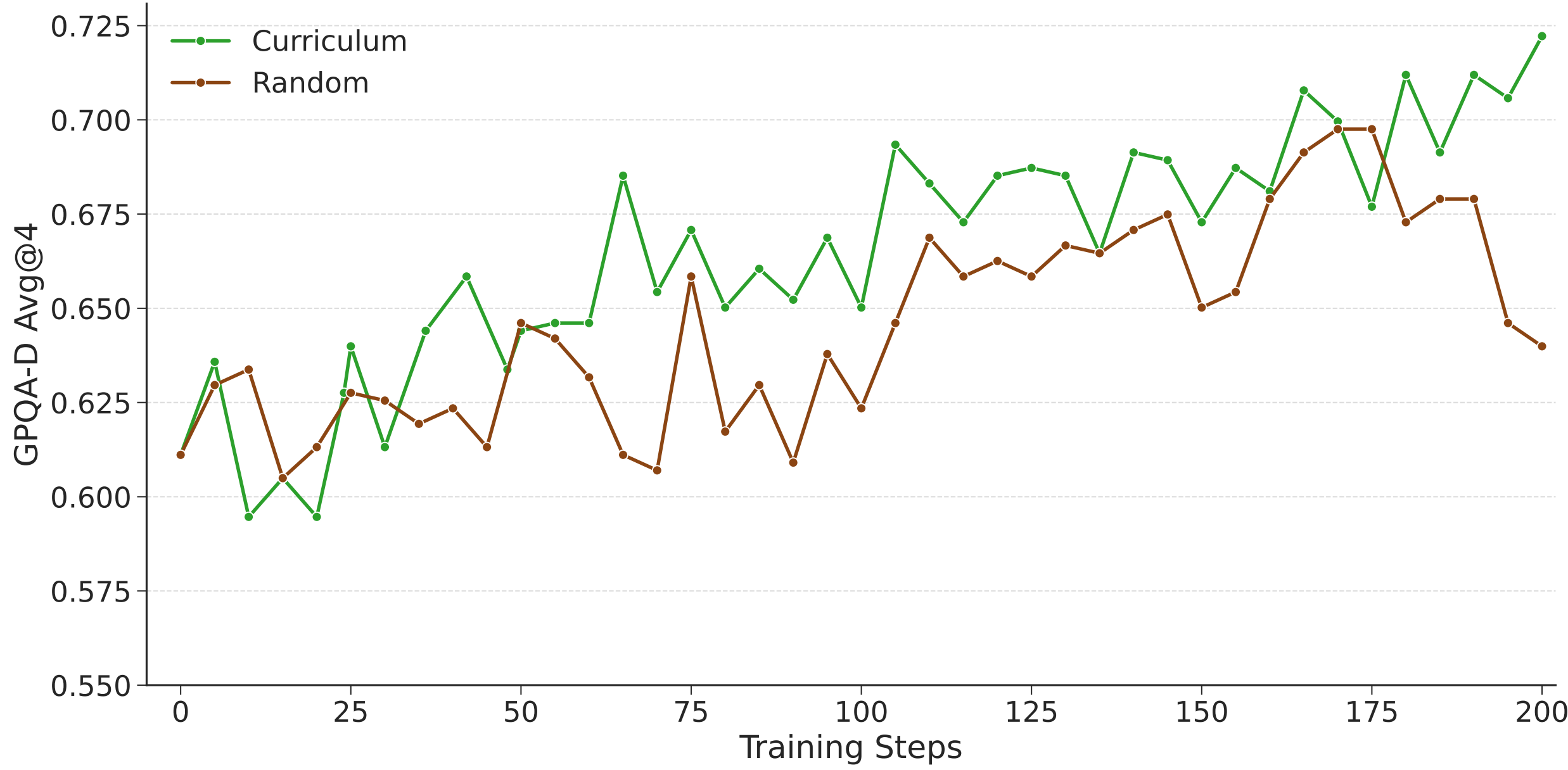
While SFT enables strong capabilities through teacher distillation, it limits performance to the teacher's level. Large-scale RL with verifiable rewards empowers LN-Ultra to explore beyond imitation and surpass the teacher.

### Key RL Features:

- GRPO training for 140k H100 hours with FP8 inference for rollouts
- Prompt size of 72, 16 responses per prompt with  $\tau = 1$  and  $top\_p = 1$
- Global batch size of 576 with 2 gradient updates per rollout
- Accuracy rewards using Llama-3.3-70B-Instruct as judge
- Format rewards ensuring proper thinking tag usage

## 4. Curriculum Learning

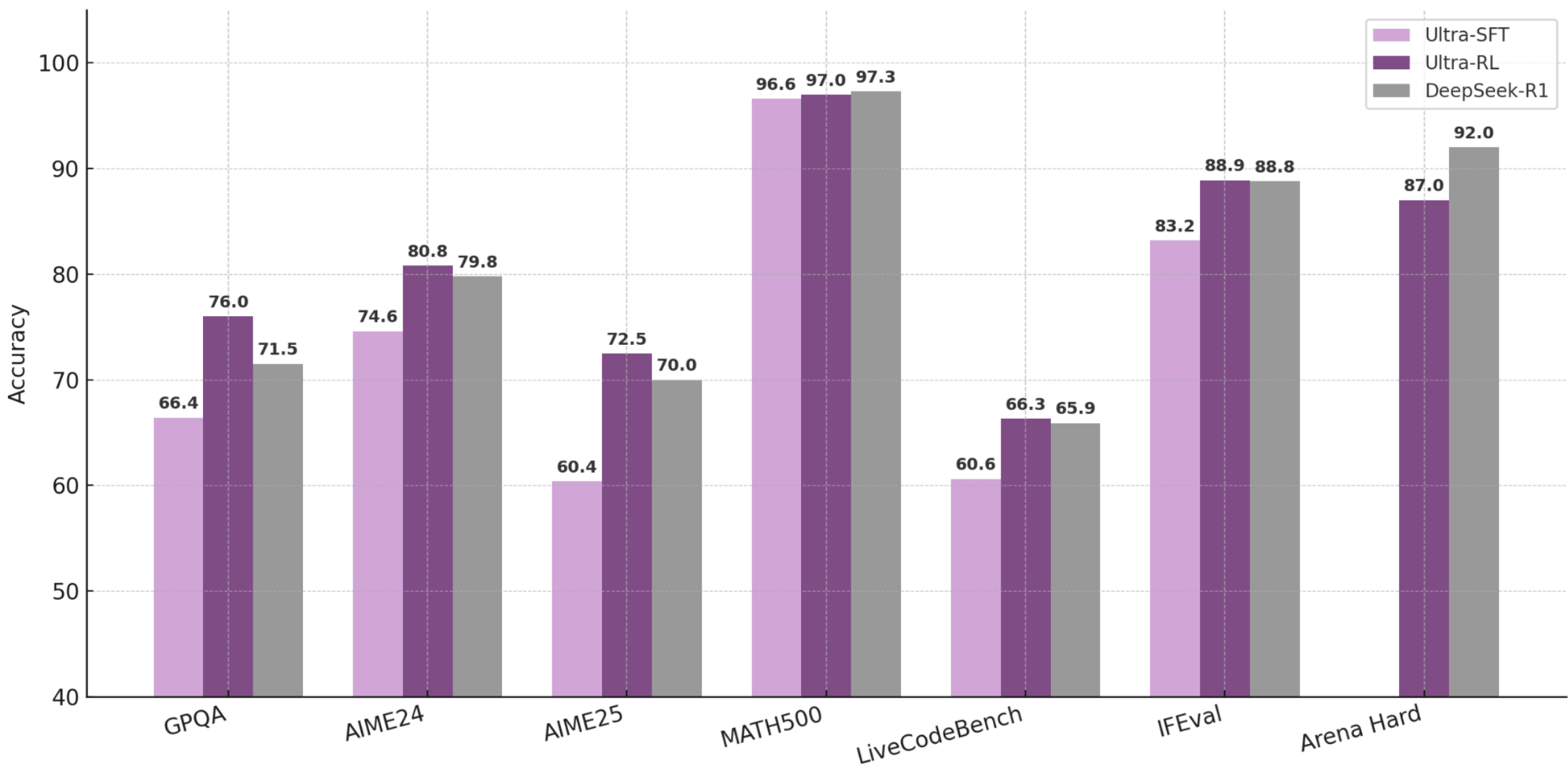
We implement an exploration-driven progressive batching strategy to systematically challenge LN-Ultra during RL training. Data is preprocessed by generating 8 responses per question using LN-Super, calculating pass rates, and discarding easy prompts (pass rate  $\geq 75\%$ ).



### Progressive Batching:

- Gaussian distribution targeting difficulty progression across batches
- Early batches: high pass rates (easier examples)
- Later batches: low pass rates (harder examples)
- Forces exploration beyond teacher capabilities

## 5. LN-Ultra Results



The RL stage is critical for surpassing teacher performance, particularly on GPQA where LN-Ultra achieves 76.0% vs DeepSeek-R1's 71.5%.

## 6. Links and Resources



HF Collection



Technical Report



NeMo-RL



Post-Training Dataset



HelpSteer3