

Scaling Intelligence: From Pretrained Models to Agentic Systems

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Table of Contents

- 1 Evolutionary Pathways of Large Language Models
- 2 Improving Model Capabilities
- 3 The Rise of Agentic Intelligence
- 4 Next Frontiers in LLM and Agent Systems

Table of Contents

1 Evolutionary Pathways of Large Language Models

2 Improving Model Capabilities

3 The Rise of Agentic Intelligence

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Transformer Architecture

- “**Attention is All You Need**” (Vaswani et al., 2017)
- Self-attention mechanism: captures long-range dependencies
- Key components:
 - Multi-head attention
 - Positional encoding
 - Feed-forward networks
 - Layer normalization
- Technical evolution of transformer architectures:
 - From dense to sparse attention: MHA → GQA → MLA → DSA
 - From dense to sparse MLP: Dense FFN → MoE → fine-grained MoE

Probabilistic Modeling

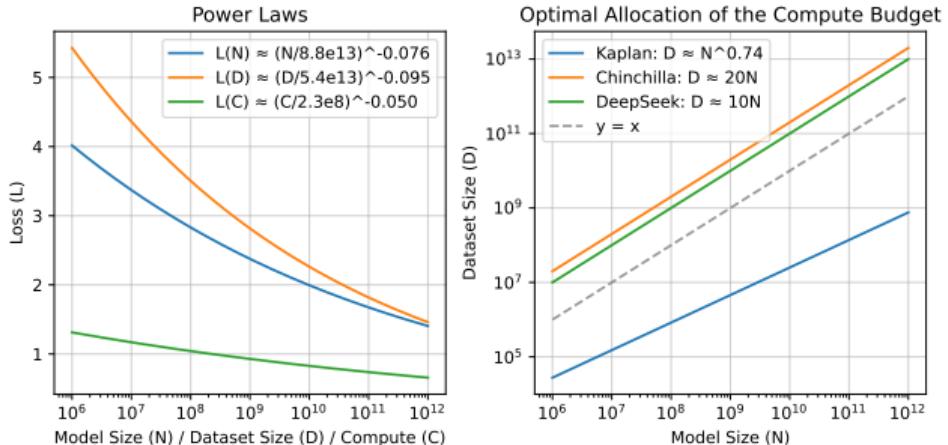
- Word-level probability prediction: $P(w_1, w_2, \dots, w_n)$
- Current training paradigms:
 - Autoregressive language modeling
 - Diffusion models
- Training methods: Pre-training, SFT, PPO, DPO, GRPO
- Trends:
 - From expert knowledge to autonomous exploration: RLHF → RLVR
 - From off-policy to on-policy learning: DPO → GRPO

Scaling Laws for LLMs

- Power law relationship:

$$L(N, D, C) \approx AN^{-\alpha} + BD^{-\beta} + E$$

- N : Model size (parameters)
- D : Dataset size (tokens)
- C : Compute budget (FLOPs)

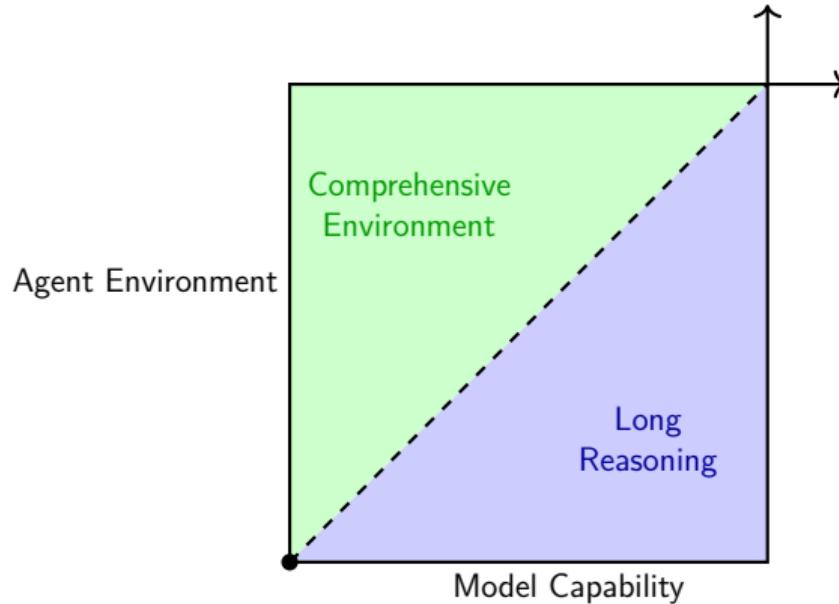


Model	Qwen1	Qwen2	Qwen2.5	Qwen3
Dataset Size	3T	7T	18T	36T

Emergent Abilities of LLMs

- Capabilities that appear at scale, absent in smaller models
- Key emergent behaviors:
 - Few-shot learning (Brown et al., 2020)
 - Zero-shot learning (Kojima et al., 2022)
 - Chain-of-thought reasoning (Wei et al., 2022)
 - Reasoning and acting (Yao et al., 2022)
 - Interleaved thinking (Unknown, 2025)

Evolution and Future Directions



Long divided, the world must unite. 天下大势，分久必合。

Table of Contents

1 Evolutionary Pathways of Large Language Models

2 Improving Model Capabilities

3 The Rise of Agentic Intelligence

4 Next Frontiers in LLM and Agent Systems

Pre-training on Large-Scale Corpora

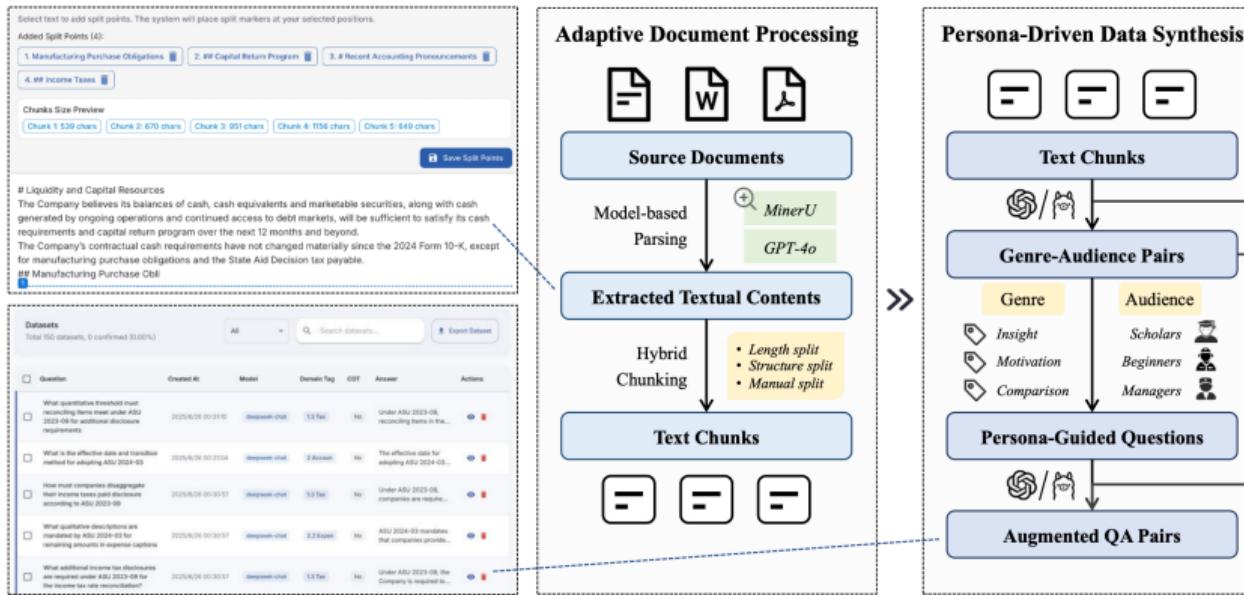
- Autoregressive pre-training objective:

$$\mathcal{L}_{\text{AR}} = - \sum_{t=1}^T \log P(x_t | x_{<t}; \theta)$$

- **High-quality data is the core of pre-training**
- Weak-to-strong generalization in data:
 - Natural web corpora → Large-scale synthetic data

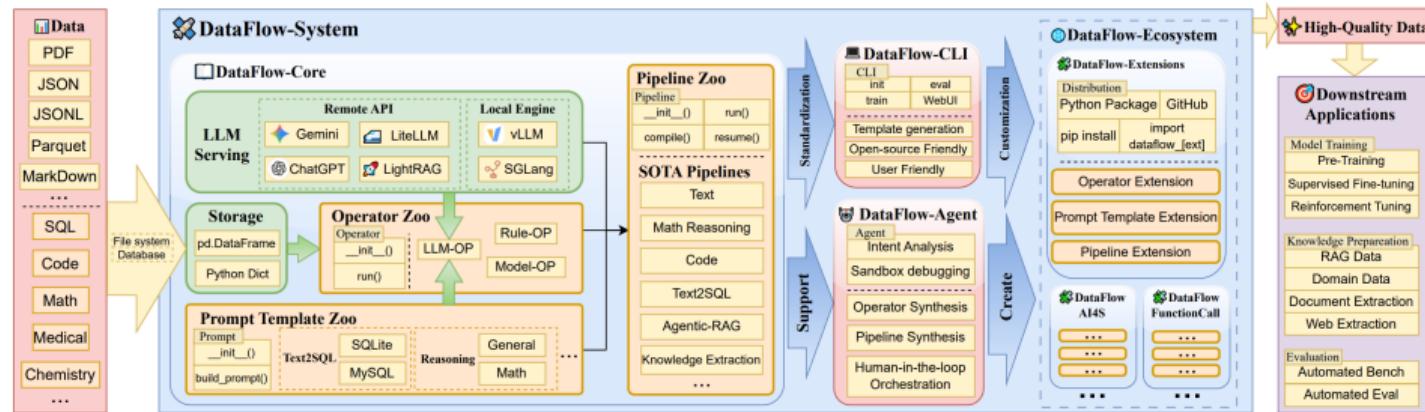
Our work: Easy Dataset (EMNLP'25, 13K GitHub Stars)

A software that uses LLMs to extract synthetic data from unstructured documents.



Our work: DataFlow (arXiv'25, 2.8K GitHub Stars)

A collection of reusable operators and pipelines for automated data processing.

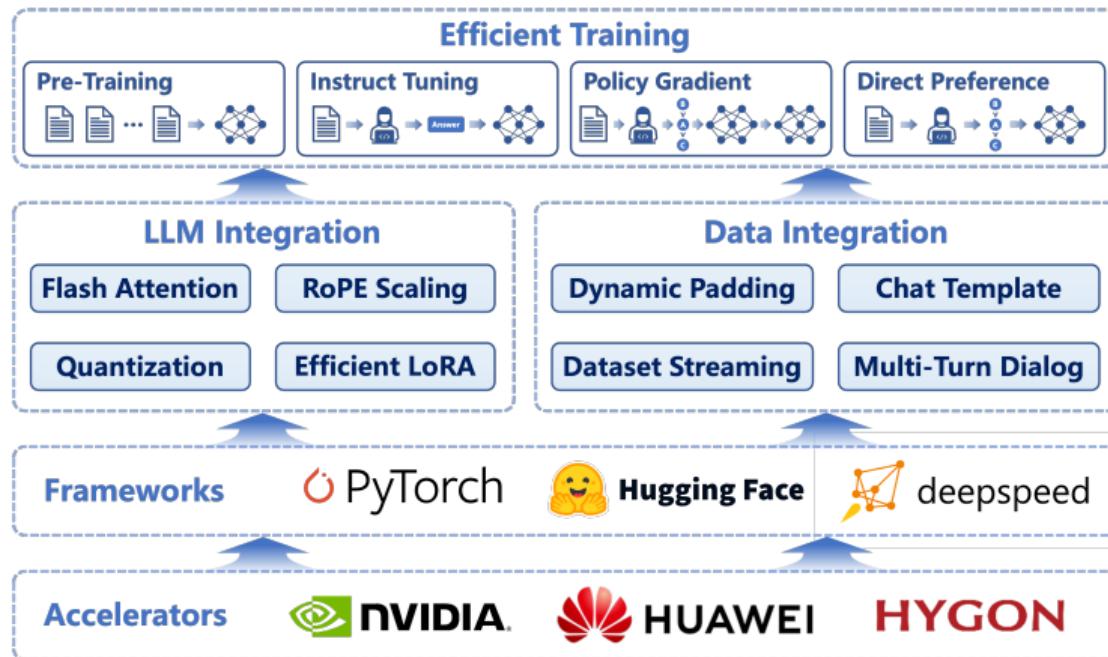


Post-training for Human Preference Alignment

- Traditional three-stage pipeline:
 - SFT → RM → RLHF
- Modern approaches:
 - Cold-start with knowledge distillation
 - RLVR (Reinforcement Learning with Verifiable Rewards)

Our work: LlamaFactory (ACL'24, 66K GitHub Stars)

Unified efficient training framework supporting over 500 LLMs.



Multimodal Alignment

- **Multimodal understanding**
 - Image-to-text (I2T)
 - Video-to-text (V2T)
 - Audio-to-text (A2T)
- **Multimodal generation**
 - Text-to-image (T2I)
 - Text-to-video (T2V)
 - Text-to-speech (TTS)
- **Unified multimodal understanding and generation**
 - Any-to-Any (X2X)

Our work: VeOmni (AAAI'26, 1.6K GitHub Stars)

A torch-native distributed training framework with decoupled 3D parallelism for omni-modal models.

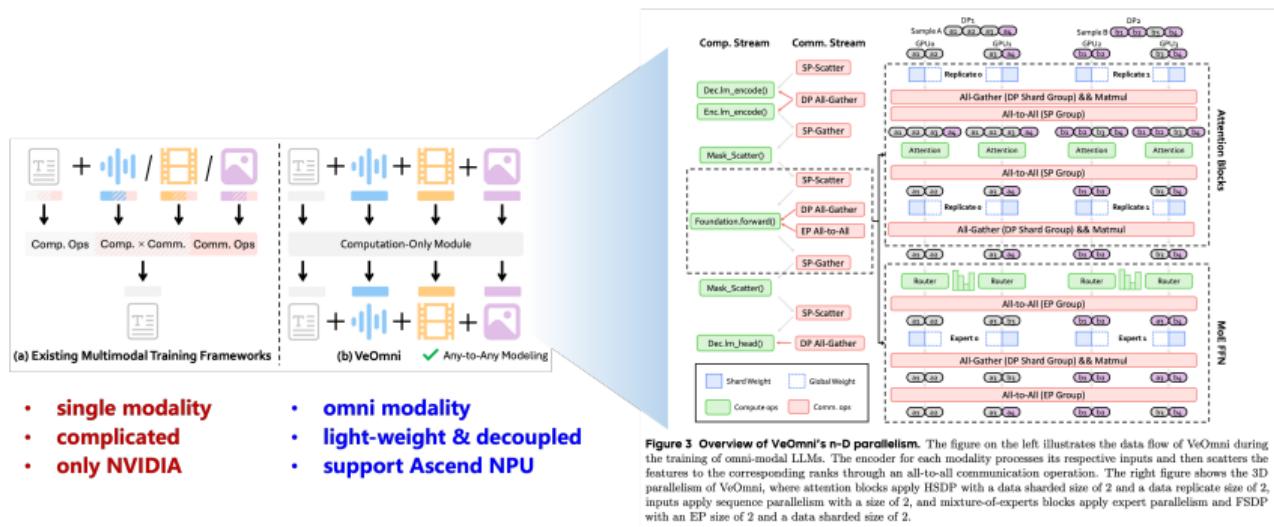


Figure 3: Overview of VeOmni's n-D parallelism. The figure on the left illustrates the data flow of VeOmni during the training of omni-modal LLMs. The encoder for each modality processes its respective inputs and then scatters the features to the corresponding ranks through an all-to-all communication operation. The right figure shows the 3D parallelism of VeOmni, where attention blocks apply HSDP with a data sharded size of 2 and a data replicate size of 2, inputs apply sequence parallelism with a size of 2, and mixture-of-experts blocks apply expert parallelism and FSDP with an EP size of 2 and a data sharded size of 2.

Training Infrastructure

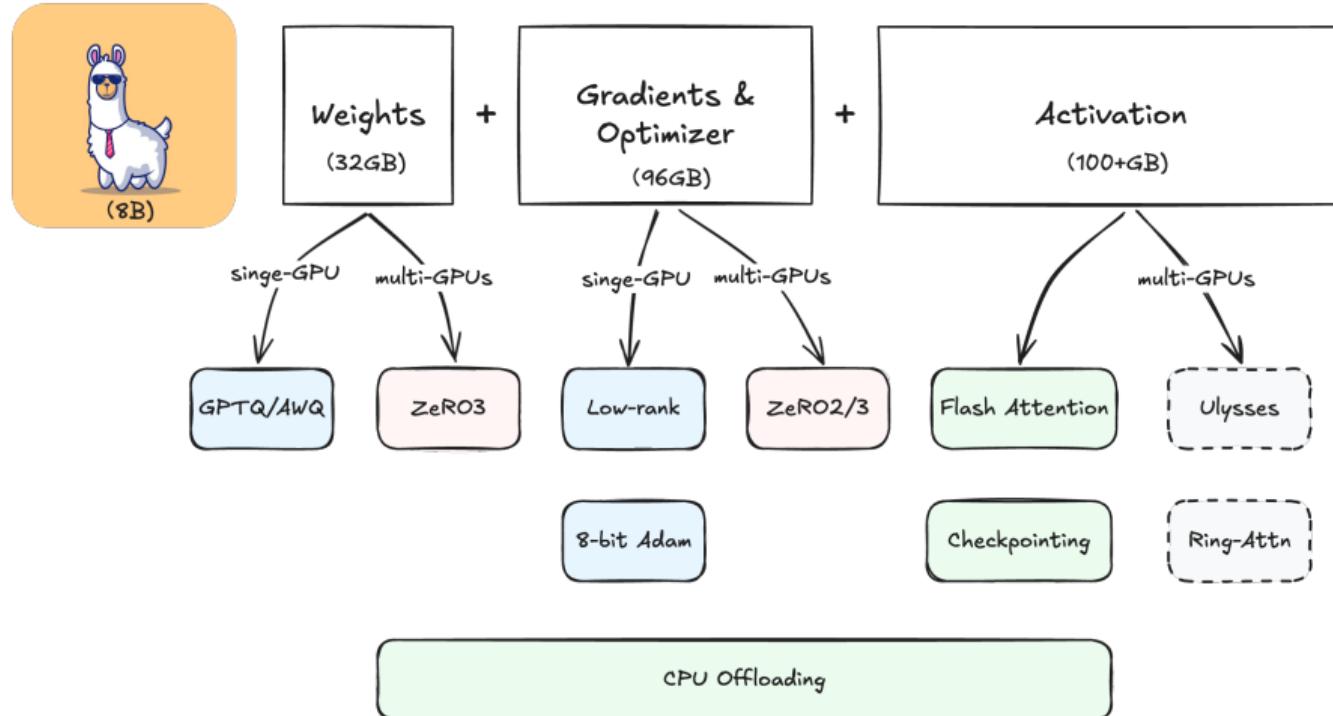
- **Distributed training::**

- Megatron: DP + TP + PP
- Torch-native: FSDP + SP + EP

- **Optimization techniques:**

- Mixed precision: FP16, BF16, FP8, FP4
- Gradient accumulation and activation recomputation
- GPU Kernels: FlashAttention, Triton, DeepEP, LinearAttention
- Distributed optimizers: DeepSpeed ZeRO

Model Training Anatomy



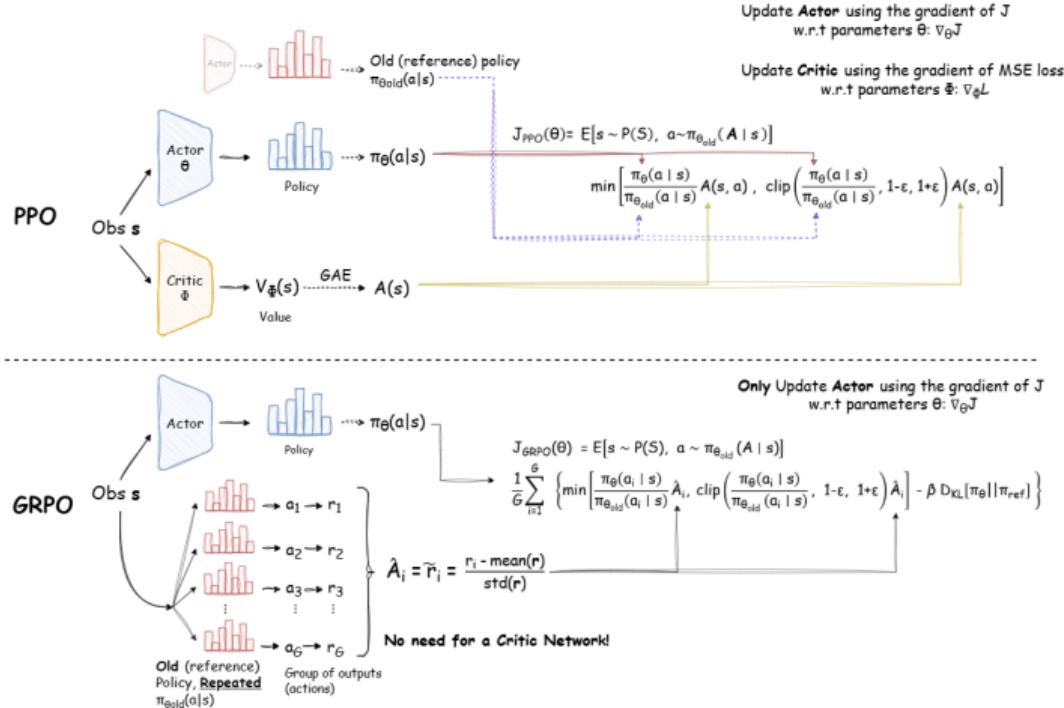
Inference Infrastructure

- **Popular frameworks:** vLLM, SGLang
- **Core technologies:**
 - PagedAttention
 - Continuous batching
 - Prefill-Decode disaggregation
 - Attention-FFN disaggregation
 - Model parallelism
 - Post Training Quantization (PTQ)
 - Speculative decoding
 - Multi-Token Prediction (MTP)

Reinforcement Learning for LLMs

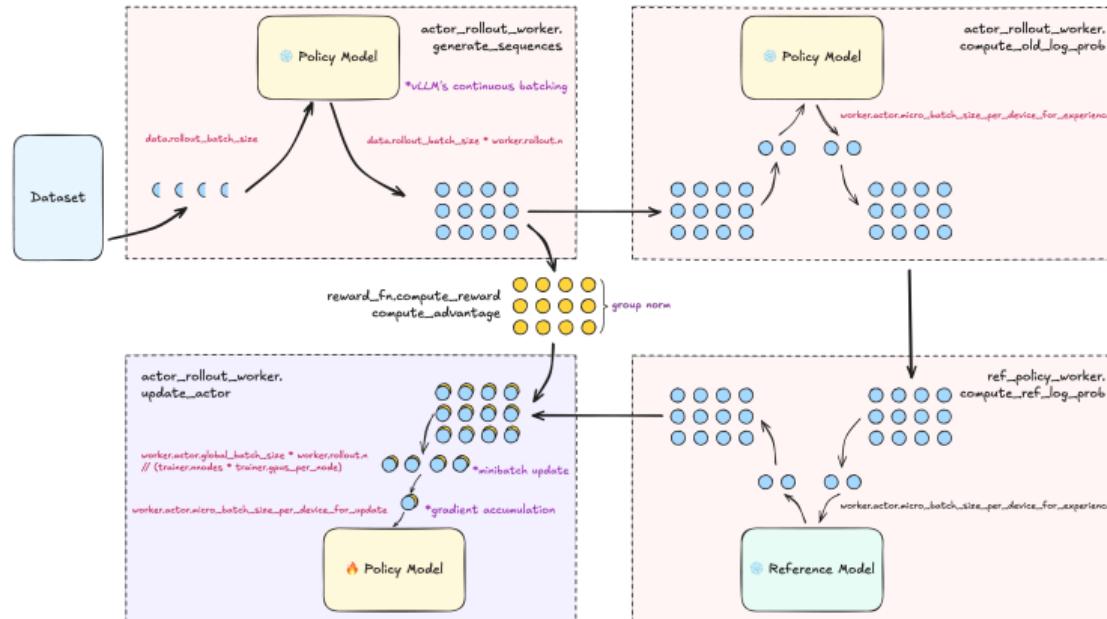
- **Example:** Playing card game
- **Trajectory sampling:** Play one complete game
- **Environment feedback:** Win or lose
- **Advantage function:** Game review and analysis
- **Policy update:** Adjust strategy for next game

RL Algorithms: PPO vs GRPO



Our work: EasyR1 (4.5K GitHub Stars)

An efficient, scalable and multimodality RL training framework for LLMs.



Reasoning Models Timeline

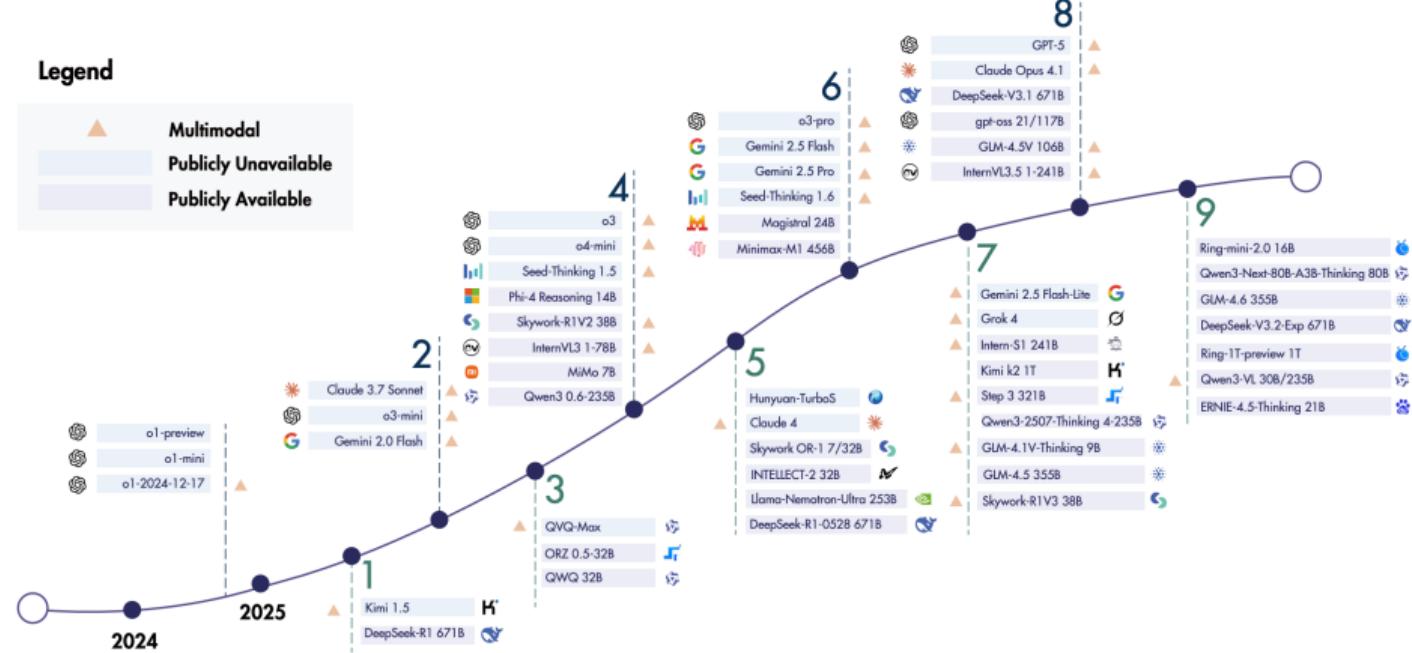


Table of Contents

1 Evolutionary Pathways of Large Language Models

2 Improving Model Capabilities

3 The Rise of Agentic Intelligence

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From Models to Agents

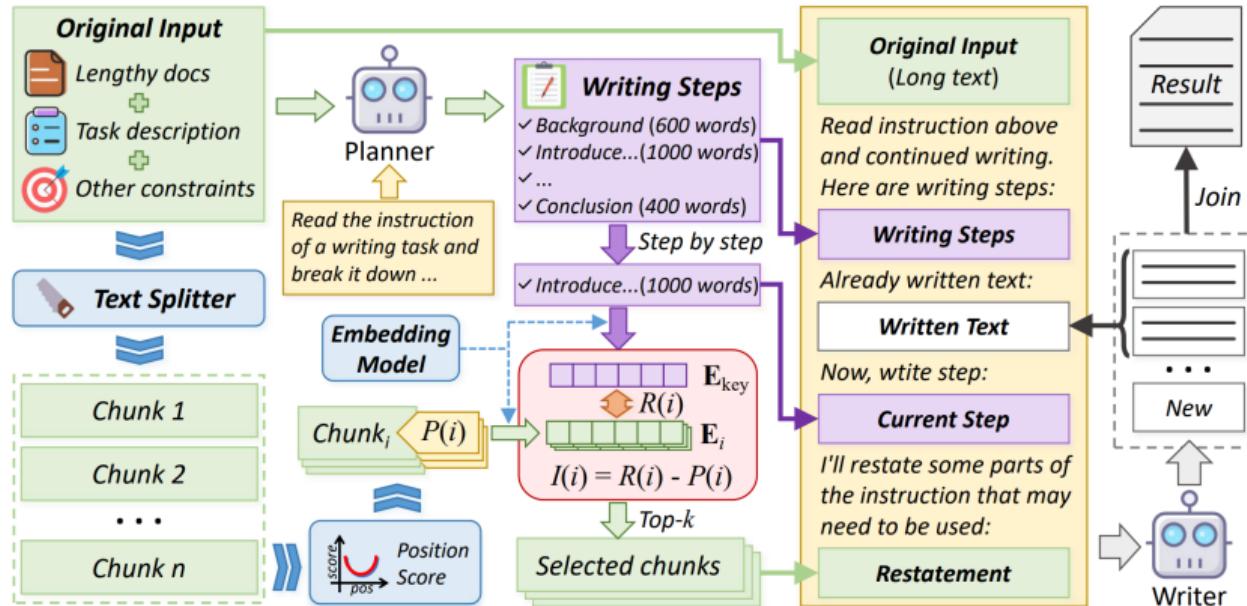
- **Traditional LLMs:** Passive text generators
- **LLM Agents:** Active problem solvers with:
 - Perception (understanding environment)
 - Planning (decomposing tasks)
 - Action (executing operations)
 - Memory (maintaining state)
- Evolution: Prompting → RAG → Web Search → Tools & MCP
- Goal: Autonomous task completion

Stage 1: Prompting Strategies

- **Few-shot prompting:** Few-shot exemplars
- **Zero-shot prompting:** Task instructions
- **Chain-of-Thought (CoT):**
 - “Let’s think step by step”
 - Improved complex problem solving
- **Advanced prompting techniques:**
 - Reflection: Self-evaluation and refinement
 - Planning: Task decomposition and strategy
 - Role playing: Adopting specific personas
 - Debating: Multi-perspective reasoning

Our work: RAL-Writer (arXiv'25)

Proposes a retrieval-augmented long-text writer, combines plan-and-write strategy and context retrieval for controllable long-text generation.



Stage 2: Retrieval-Augmented Generation (RAG)

- **Traditional RAG workflow:**

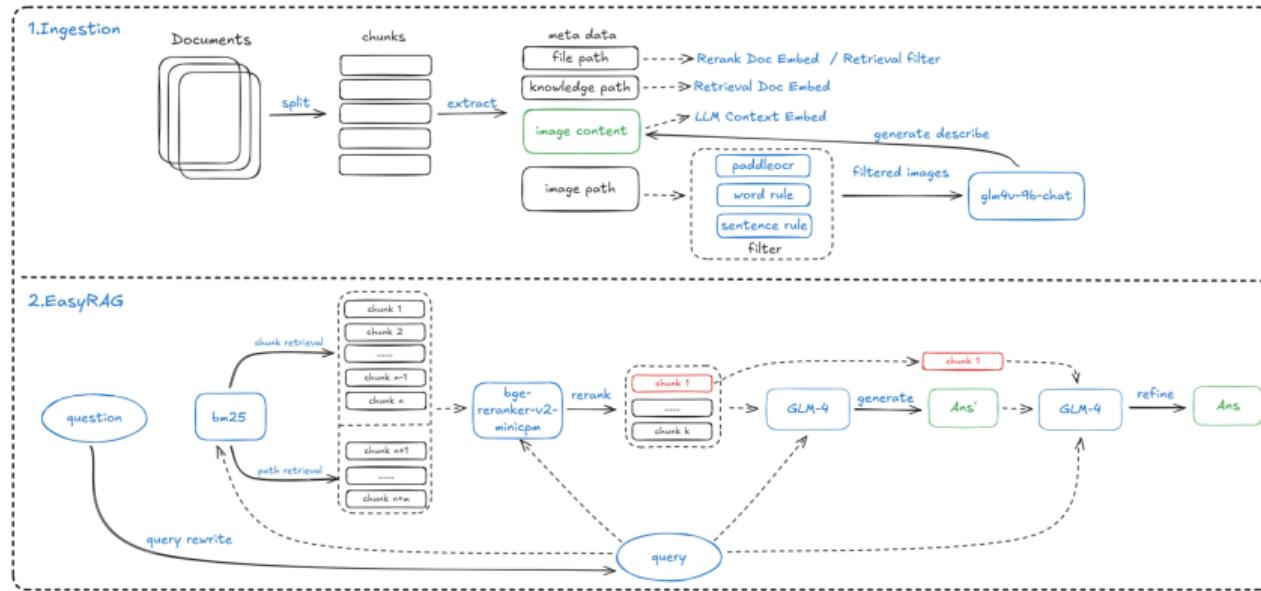
- 1 Document chunking
- 2 BM25 or vector-based retrieval
- 3 Prompt augmentation
- 4 LLM generates response

- **From traditional RAG to agentic RAG:**

- RAG as a tool that agents can invoke
- Active decision-making on when to retrieve
- Dynamic retrieval strategies

Our work: EasyRAG (KDD'25 Workshop, 600 GitHub Stars)

Enhanced Q&A accuracy through query expansion, dual-route retrieval, LLM re-ranking, and LLM answer refinement.

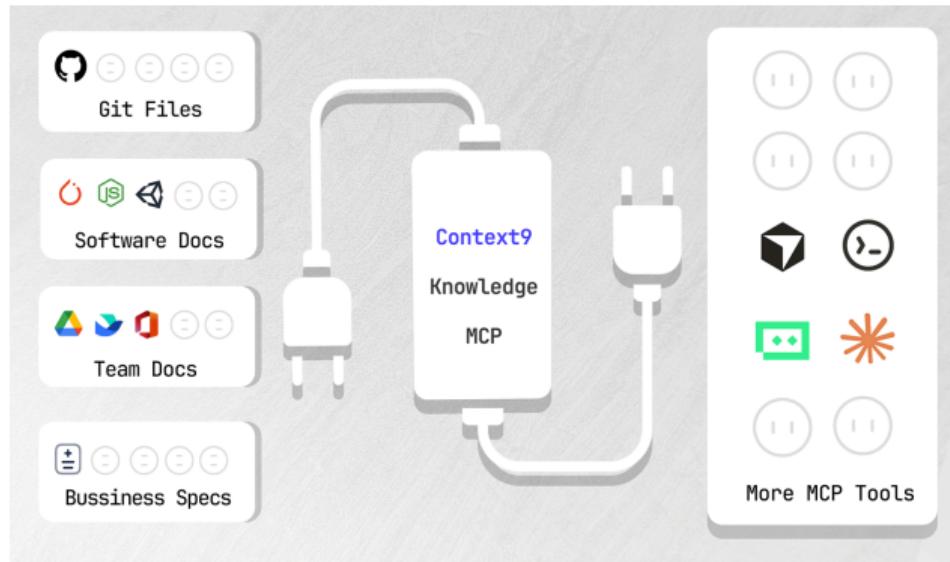


Stage 3: Web Search

- **Comparison with RAG:**
 - Web search: More proactive and dynamic
 - RAG: More passive with pre-indexed knowledge
 - Web search \approx Agentic RAG (both use tool-use capabilities)
- **Key insight:** Web search is essentially tool use
- **Advantages:**
 - Real-time information access
 - Broader knowledge coverage
 - Active query formulation

Our work: Context9 MCP Server

Transforming local knowledge into an LLM-ready second brain through MCP integration.



Stage 4: Tools and MCP

- **Evolution of tool use:**
 - Single tool call → Multi-turn tool calls
 - No reasoning → One-shot reasoning → Interleaved reasoning
- **Expanding tool scope:**
 - 1 Pre-defined functions
 - 2 Python interpreter
 - 3 GUI interactions (embodied AI)
 - 4 Full system shell access (Claude Code)
- **Model Context Protocol (MCP):**
 - Standard for connecting LLMs to data sources
 - Unified interface for tools and integrations
- **Skills is essentially an MCP layer for the bash tool.**

Our work: UI-TARS (arXiv'25, 9.1K GitHub Stars)

Breaking GUI agent benchmark records through carefully designed fine-tuning (SFT, DPO, and RL) and diverse agent environments.

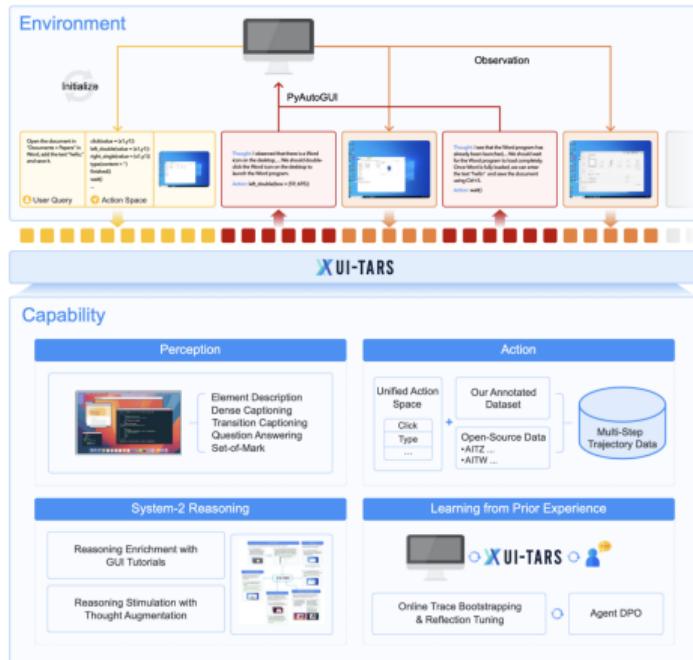


Table of Contents

1 Evolutionary Pathways of Large Language Models

2 Improving Model Capabilities

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Long-Horizon Reinforcement Learning

- **Longer reasoning traces**
 - Models will execute deeper multi-step thought processes to solve highly non-trivial problems.
- **Extended interaction rounds**
 - Agents will maintain coherence across much longer sequences of feedback and environment responses.
- **Complex agent environments**
 - Systems will evolve to navigate high-dimensional and unpredictable task spaces with minimal supervision.

Broader Agent Environments

- **Professional softwares**
 - Future agents will seamlessly interface with a vast array of specialized professional software tools.
- **Operating systems**
 - Agents will gain the capacity to operate directly on operating system interfaces and file systems.
- **Edge devices**
 - Agents will extend their operational environments to physical edge devices such as robotic systems.

- **Physical world modeling**

- Research will focus on teaching models to internalize the causal laws and constraints of the physical universe.

- **Advanced video generation**

- Generative models will move toward maintaining perfect temporal consistency and object permanence in video.

Continual Learning and Adaptation

- **Nested learning architecture**

- Google's nested learning framework utilizes varying parameter update frequencies to alleviate catastrophic forgetting.

- **Cross-scenario adaptation**

- Models will autonomously fine-tune their internal states to excel across rapidly changing task domains.

Thank You!

Questions?