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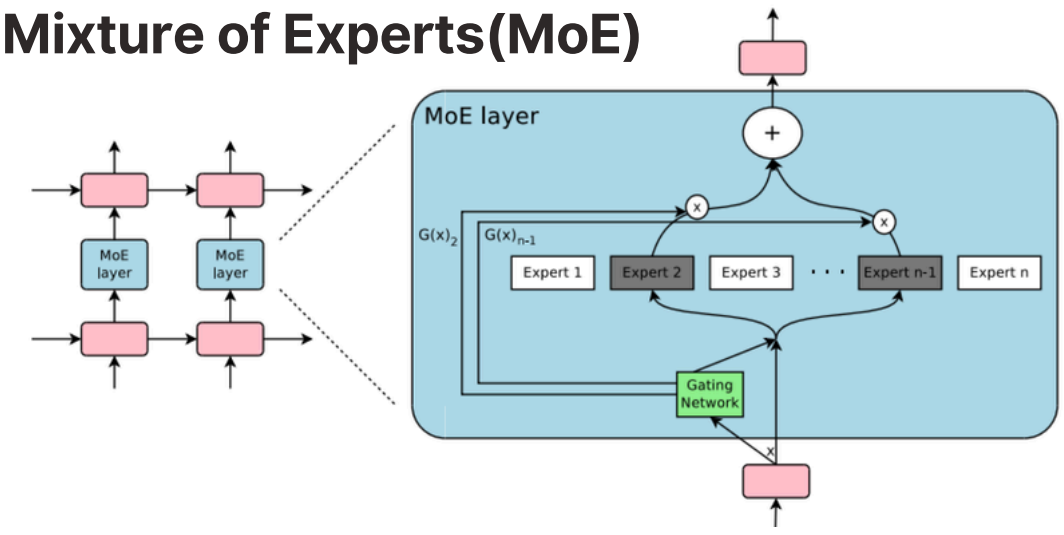
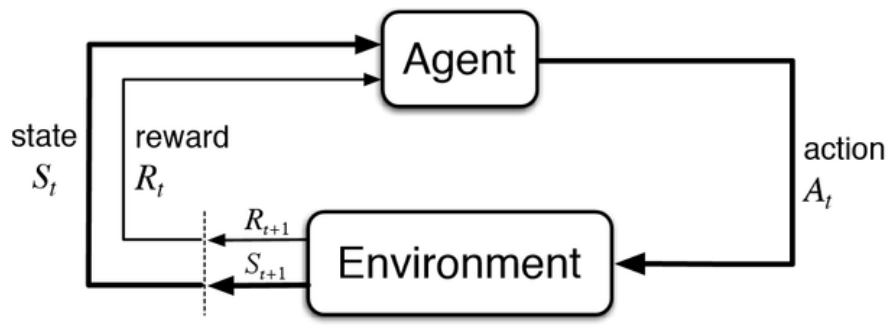
Top 5 Frameworks Used in deepseek

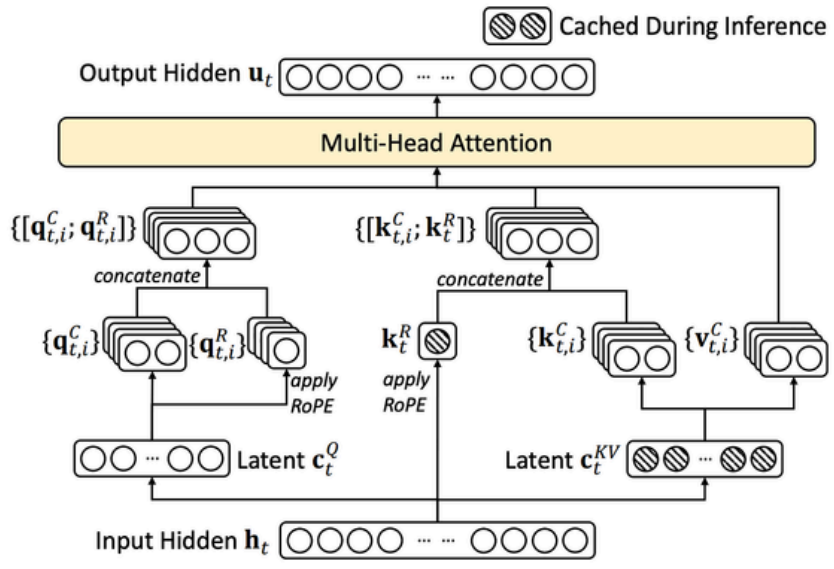
Mixture of Experts(MoE)



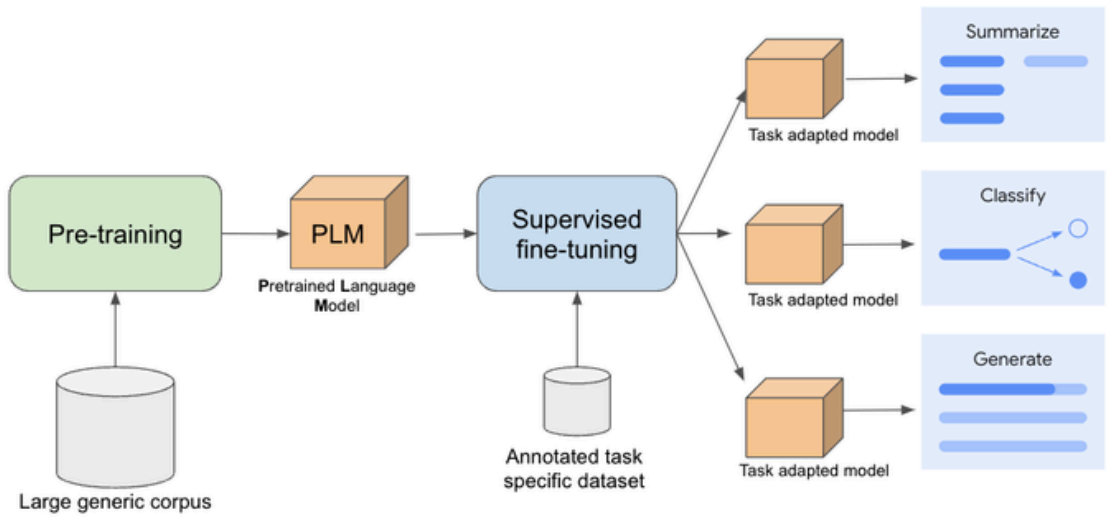
Reinforcement Learning Training



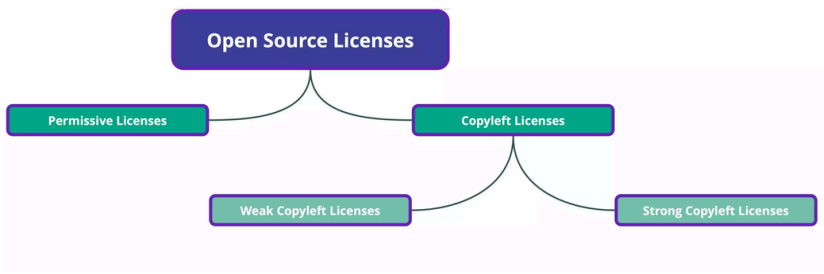
Multi-Head Latent Attention



Supervised Fine-Tuning (SFT)



Open-Source Framework



Here are the top five **frameworks** and **principles** that underpin DeepSeek R1's design: →

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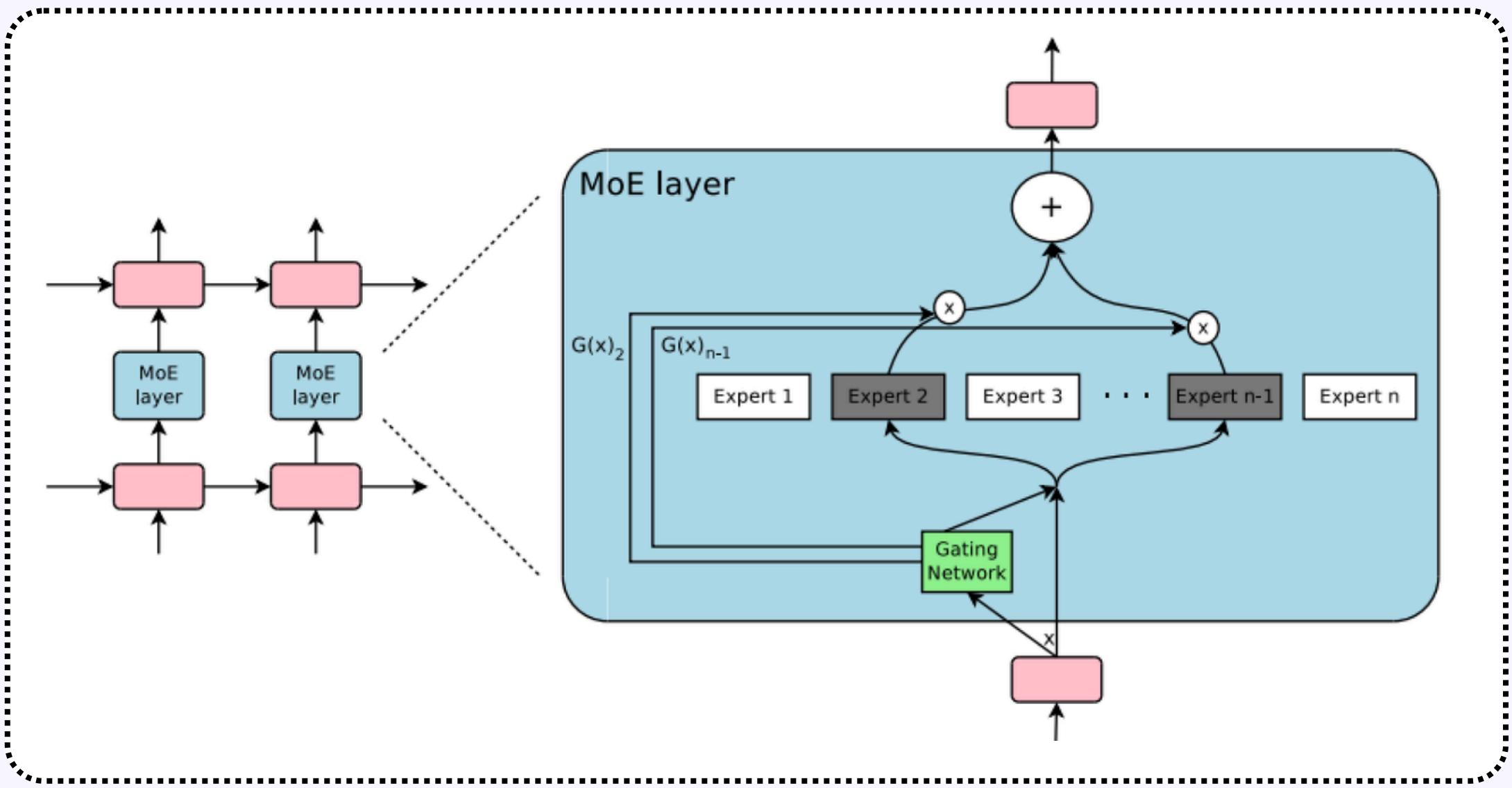
MoE Architecture

DeepSeek R1 employs the Mixture-of-Experts (MoE) architecture, a highly scalable model design that improves both computational efficiency and performance.

- Total Parameters: **671 billion**
- Active Parameters: **37 billion per forward pass**
- Number of Layers: **61**
- Context Window: **Up to 128,000 tokens**



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Why MoE?

- Unlike traditional dense transformer models, where all parameters are active for every input, MoE selectively activates only a subset of experts for each computation.

- This approach reduces the overall computational cost while maintaining high model capacity, making it suitable for large-scale AI reasoning tasks.

- Each expert module specializes in different tasks, leading to better problem-solving abilities.

Performance Gains:

- MoE allows DeepSeek R1 to compete with larger models while using fewer active parameters, making it more efficient than dense architectures.

Real-World Applications:

- MoE is widely used in models like Google’s Switch Transformer and GPT-4 MoE, proving its effectiveness in handling complex NLP and AI-driven reasoning.

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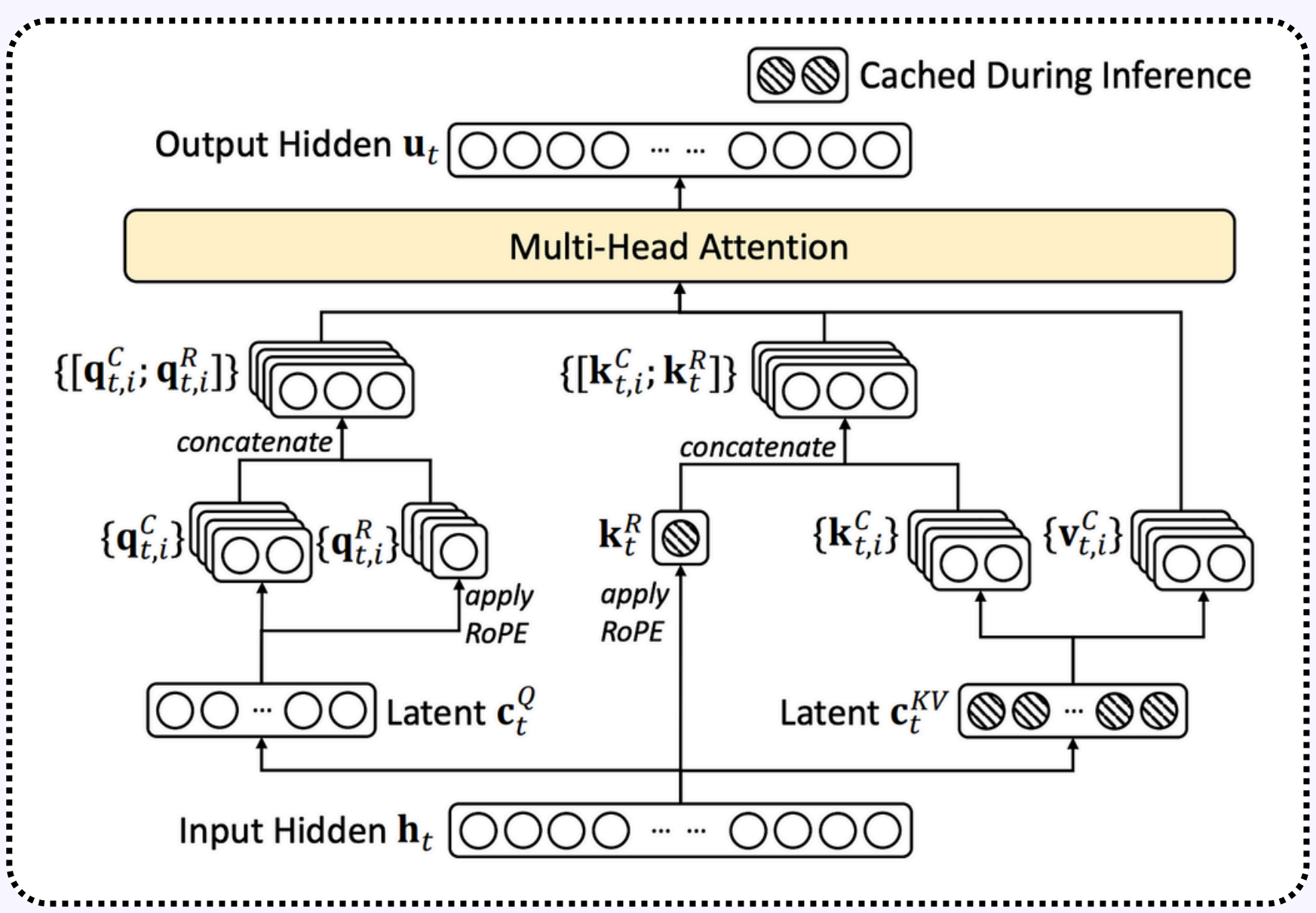
Multi-Head Latent Attention

DeepSeek R1 integrates Multi-Head Latent Attention (MLA) to refine its focus and processing power.

What is MLA?

- MLA enables the model to attend to multiple important regions in an input simultaneously, improving accuracy in long-context reasoning.

- This mechanism is a significant enhancement over traditional multi-head attention (MHA) by introducing latent variables that help optimize attention weight distribution.



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Benefits of MLA in DeepSeek R1

- Enhanced Long-Context Understanding: With a 128,000-token context window, MLA ensures better memory retention.

- Improved Code Generation: By attending to long-term dependencies in the input, MLA allows for more coherent and structured outputs in coding tasks.

- Faster Computation: Since MLA optimizes attention weight calculations, it reduces computational overhead.

Comparison with MHA

- Traditional Multi-Head Attention: Uses static attention heads.
- MLA: Introduces an adaptive, latent-based approach that enhances learning.

Practical Use Case

- Mathematical Reasoning & Code Generation: MLA improves DeepSeek R1’s ability to track complex equations and logic sequences over long-form text.

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Reinforcement Learning Training

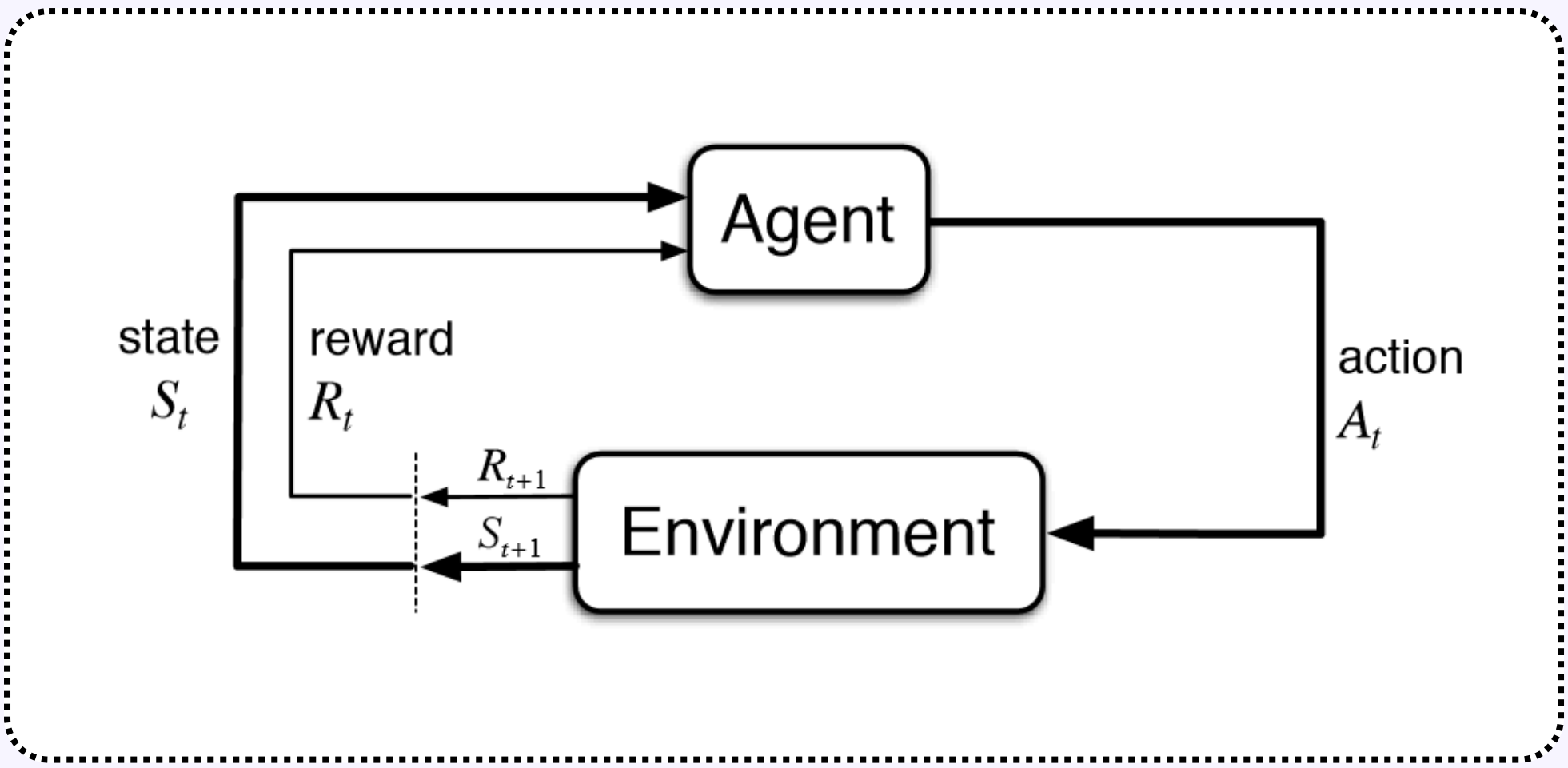
DeepSeek R1 incorporates Reinforcement Learning (RL) to optimize decision-making and self-improvement capabilities.

How is RL Used?

- The model was first fine-tuned using supervised learning (SFT) and then underwent a reinforcement learning process to enhance reasoning capabilities.

- Autonomous Self-Improvement: Unlike conventional training, RL allows the model to improve iteratively by rewarding better responses.

- Encourages the emergence of **Chain-of-Thought (CoT)** reasoning, self-verification, and error correction techniques.



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Key **RL Strategies** Used in DeepSeek R1:

- **Policy Optimization** – Adjusts model responses based on reward signals.
- **Reward Modeling** – Guides the model to prioritize correct and high-quality outputs.
- **Error Correction Mechanisms** – Helps the model recognize and fix mistakes autonomously.

Major Advantage

- Improves logical reasoning, problem-solving, and factual accuracy in real-world AI applications.

Example

DeepSeek R1, thanks to RL, outperforms other models in multi-step problem-solving, making it particularly strong in math, coding, and structured reasoning.

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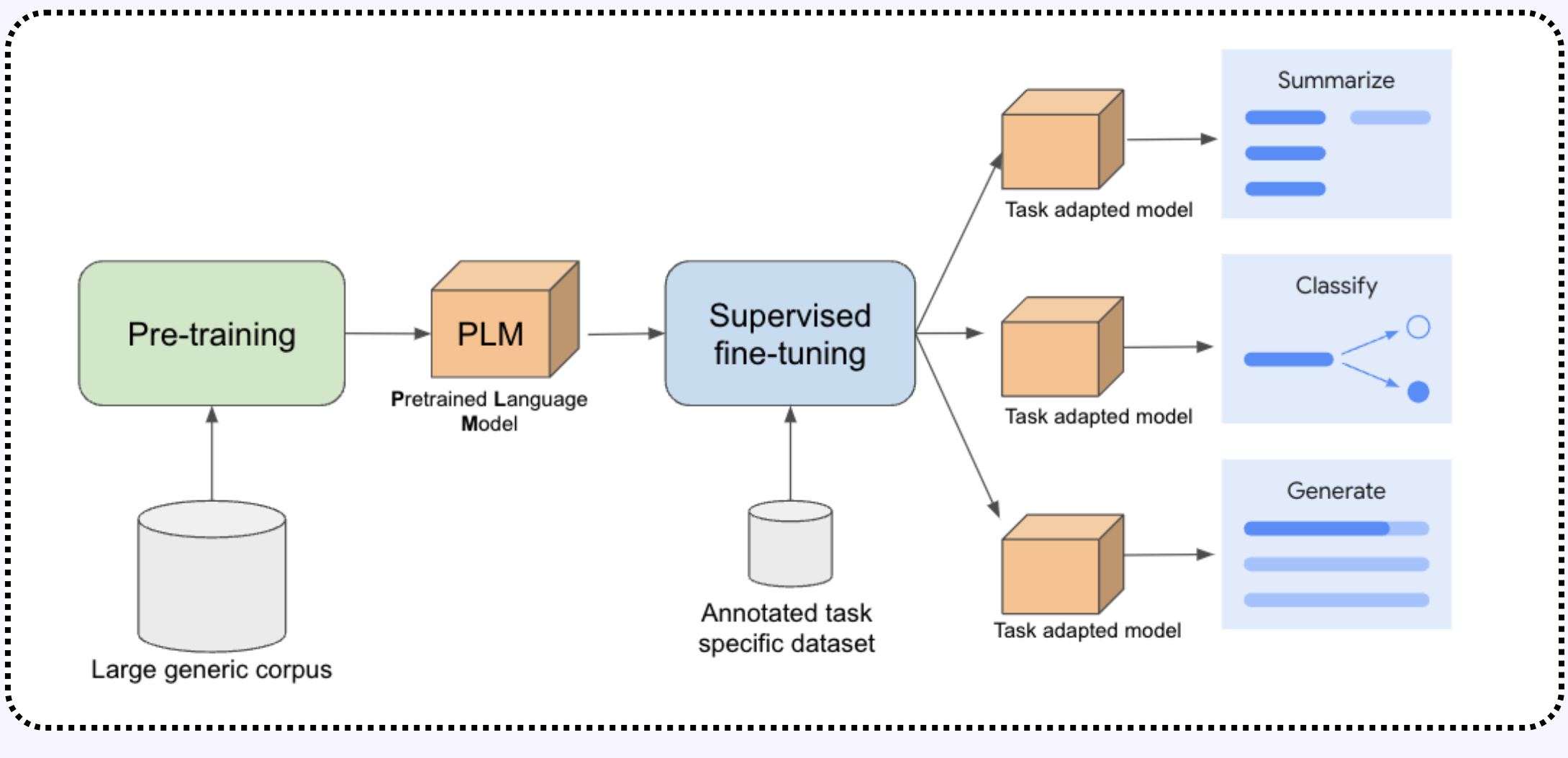
Supervised Fine-Tuning (SFT)

Before applying RL, DeepSeek R1 goes through a Supervised Fine-Tuning (SFT) phase.

Why SFT?

- Supervised Fine-Tuning ensures that the base model learns from high-quality, human-verified examples.
- DeepSeek R1's dataset includes:
    - **Chain-of-Thought (CoT) reasoning data**
    - **Mathematical proofs and code explanations**
    - **Real-world problem-solving demonstrations**
    - **Human-annotated long-form responses**



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Performance Impact

- Allows DeepSeek R1 to outperform models trained on purely unsupervised data.
- Increases model reliability in tasks requiring step-by-step logical thinking.

How It Differs from Standard Training

- Standard models learn from raw internet data.
- DeepSeek R1 refines its understanding using a guided curriculum to ensure higher accuracy and improved reasoning ability.

Open-Source Framework

DeepSeek R1 is an open-source model under the MIT license, making it highly accessible for research and development.

What Does Open-Source Mean?

- Developers and researchers can freely access, modify, and distribute DeepSeek R1.
- Unlike proprietary models like GPT-4 or Claude 2, DeepSeek R1 fosters a collaborative AI community.
- Allows users to customize the model for specific applications.

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Key Benefits of Open-Source AI Models

1. Transparency – Users can inspect how the model was built and trained.
2. Customization – Organizations can adapt the model for niche applications (e.g., finance, healthcare, legal AI).
3. Research Advancement – Helps the AI research community benchmark and improve AI models.

Comparison with Proprietary Models

- DeepSeek R1: Open-source, highly customizable.
- GPT-4, Claude 2: Closed-source, controlled access.

Real-World Use Case

- AI Research Labs: Can extend and retrain DeepSeek R1 for specialized domains (e.g., medical diagnosis, scientific discovery).

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Final Thoughts

DeepSeek R1 is a highly efficient AI model that integrates state-of-the-art architectures and training methodologies to optimize its performance in reasoning, mathematics, and structured problem-solving.

Key Takeaways

- Mixture-of-Experts (MoE) Architecture – Enables computational efficiency while maintaining high capacity.
- Multi-Head Latent Attention (MLA) – Enhances long-context understanding.
- Reinforcement Learning (RL) Training – Promotes logical self-improvement.
- Supervised Fine-Tuning (SFT) – Strengthens reasoning with curated data.
- Open-Source Framework (MIT License) – Enables collaboration and customization.

Moreover,
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