DeepSeek vs Open ai

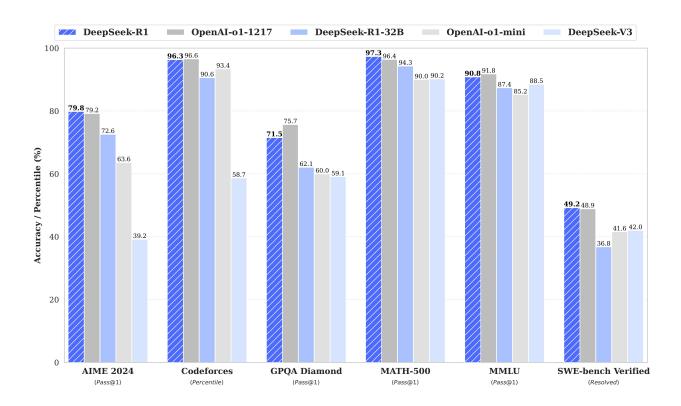
DeepSeek R1 vs. OpenAl o1: Which One is Faster, Cheaper, and Smarter, Popular?

Feature	DeepSeek R1	OpenAl o1
License	Open-source (MIT License)	Proprietary (Closed-source)
Commercial Use	✓ Free for commercial use	➤ Restricted by OpenAI's policies
Cost (1M Tokens Input)	\$0.55	\$15
Cost (1M Tokens Output)	\$2.19	\$60
Training Cost	~\$6M (Highly optimized)	~\$6B+ (Expensive)
GPU Hours Used	2.78M	Unknown (Much higher)
Distilled Models	Available (Efficient versions)	✗ Not available
API Availability	Yes (Public API & Free Chat)	✓ Yes (Paid API)
Performance Benchmarks	✓ Excels in reasoning & math	✓ Strong general NLP capabilities
Sparse Attention	Yes (Efficient for long contexts)	X No
Mixture of Experts (MoE)	✓ Uses selective activation	X Not used
Reasoning Power (AIME 2024 Score)	79.8%	Unknown
Math Benchmark (MATH-500 Score)	97.3%	Unknown
General Knowledge (MMLU Score)	90.8%	Unknown
Code Performance (Codeforces Rank)	Top 3.7%	Unknown
Fine-Tuning Approach	Self-evolution & RLHF	Heavily fine-tuned

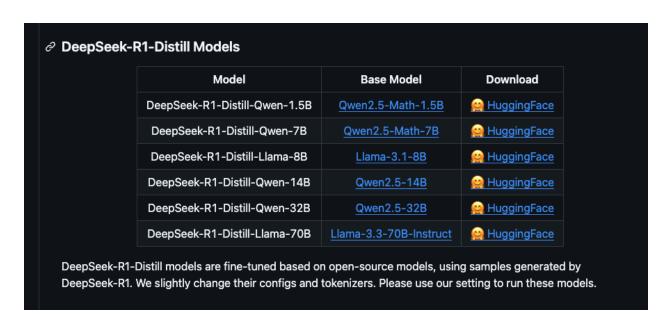
Key Takeaways

- **✓** DeepSeek R1 is much cheaper (96.4% cost savings) than OpenAl o1.
- **✓** It provides open-source flexibility, while OpenAl o1 remains closed.
- **✓** Better in reasoning, math, and structured benchmarks.
- **✓** Uses innovative training methods (RLHF, distillation, sparse attention).

BenchMark:



Models:

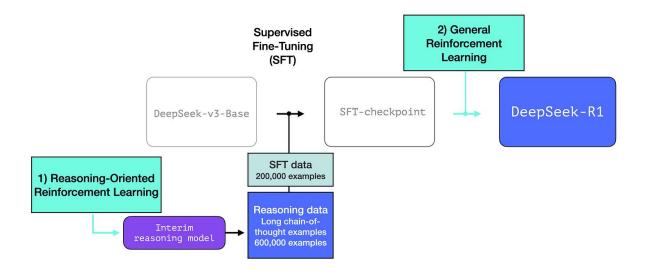


Innovations in Training

How DeepSeek R1 Achieves Efficiency

- 1. **Reinforcement Learning First** Utilized self-evolution to enhance reasoning, reducing dependency on human-labeled data and cutting annotation costs.
- 2. **Smart Distillation** Transferred complex reasoning abilities from large models to smaller ones (e.g., 14B parameters) while maintaining high performance.
- 3. **Benchmark Excellence** Achieved top-tier scores in key areas like:
 - AIME (Math & Reasoning): 79.8%
 - MMLU (General Knowledge): 90.8%

4. **Efficient Architecture** – Utilizes **Sparse Attention** and **Mixture** of **Experts** (MoE) for fast and cost-effective processing.



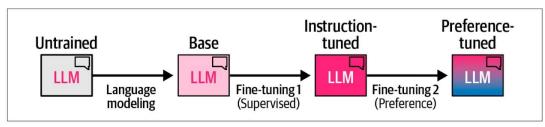
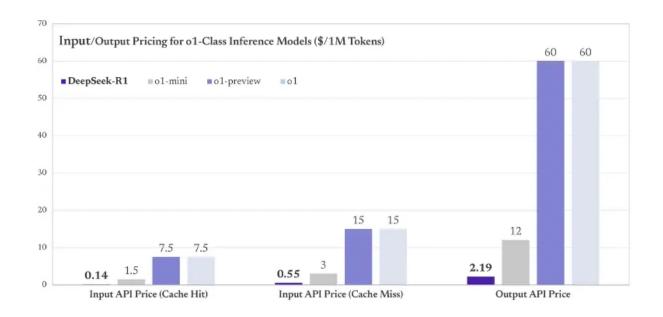


Figure 12-3. The three steps of creating a high-quality LLM.

Price comparison:



Cost & Performance Comparison

DeepSeek R1 provides exceptional performance at a **96.4% lower cost** than OpenAI o1.

Feature	DeepSeek R1	OpenAl o1
Cost (1M Tokens - Input)	\$0.55	\$15
Cost (1M Tokens - Output)	\$2.19	\$60
Reinforcement Learning	✓ Yes	X No
Sparse Attention	✓ Yes	X No
Distilled Models	✓ Yes	X No
General Knowledge (MMLU Score)	90.8%	Unknown
Math & Reasoning (AIME Score)	79.8%	Unknown
Code Performance (Codeforces Rank)	Top 3.7%	Unknown

API is 96.4% cheaper than chatgpt.

DeepSeek R1's lower costs and free chat platform access make it an

attractive option for budget-conscious developers and enterprises looking for scalable AI solutions.

Steps to use:

Groq API to interact with the **DeepSeek-R1-Distill-LLaMA-70B** model:

Step 1: Install the Groq SDK

pip install groq

Step 2: Import the Required Library

from groq import Groq

Step 3: Initialize the Groq Client

client = Groq(api_key="your_api_key_here")

Step 4: Create a Chat Completion Request

Step 5: Process and Print the Response

```
for chunk in completion:
print(chunk.choices[0].delta.content or "", end="")
```

This implementation follows a **stepwise approach** to using **Groq's API** to get responses from the DeepSeek model.

How DeepSeek Trained AI 30 Times Cheaper?

1.

Selective Training with Load Balancing

Trained only relevant model parts (

"experts") instead of updating the entire model.

Used

auxiliary-loss-free load balancing to distribute tasks dynamically, reducing computational waste.

5% model parameter

95% GPU requirements reduce

2.

Efficient Resource Utilization

- Minimized hardware requirements by optimizing model efficiency.
- Achieved high performance without excessive hardware investments.

3.

Innovative Architectural Techniques

Used

Multi-head Latent Attention and Mixture of Experts (MoE).

Improved processing efficiency, reducing training and operational costs.

low value key parr joint compression techniques

4

Smart Distillation Process

- Transferred knowledge from large models to smaller, efficient versions.
- Maintained high accuracy while lowering computational needs.

5.

Reinforcement Learning (RL) First Approach

Relied on

self-evolution instead of expensive human-labeled data.

Used a

small supervised dataset for a cost-effective "cold start."

R1 -Zero: no use of supervised fine tuning

6.

Optimized Model Scaling

Activated only

37 billion parameters out of 671 billion in most operations.

Reduced

energy consumption while maintaining strong reasoning capabilities.

7.

Leveraging Open-Source Tools & Alternative Resources

Used

open-source AI tools to cut licensing and infrastructure costs.

Overcame hardware limitations due to e

xport restrictions by finding alternative computing resources