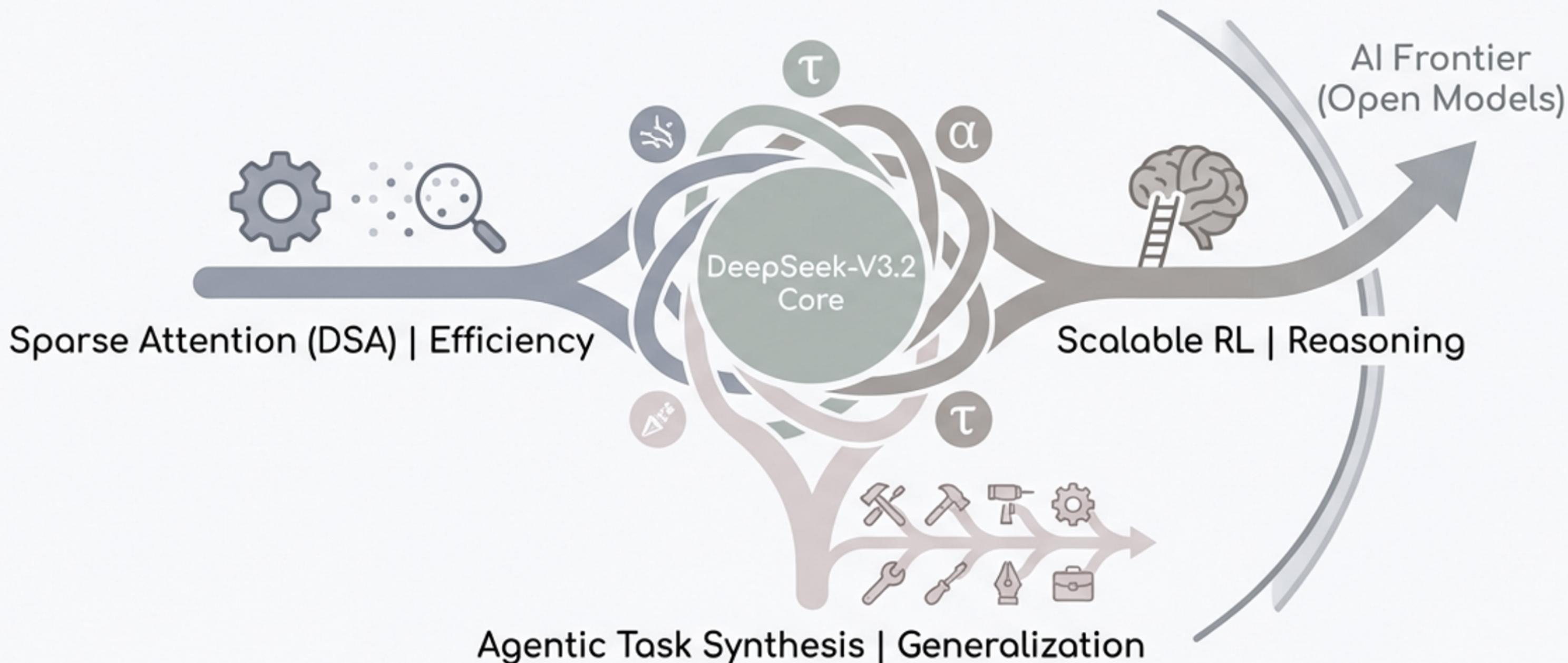


# DeepSeek-V3.2: Pushing the Frontier of Open Large Language Models



Authors: DeepSeek-AI

# Background and Problem Statement



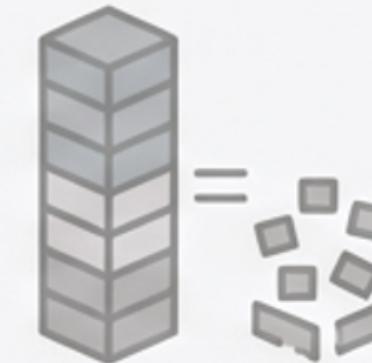
## Efficiency vs. Reasoning

The primary research problem of DeepSeek-V3.2 is to address the gap between high computational efficiency and superior reasoning and agentic performance in AI models.



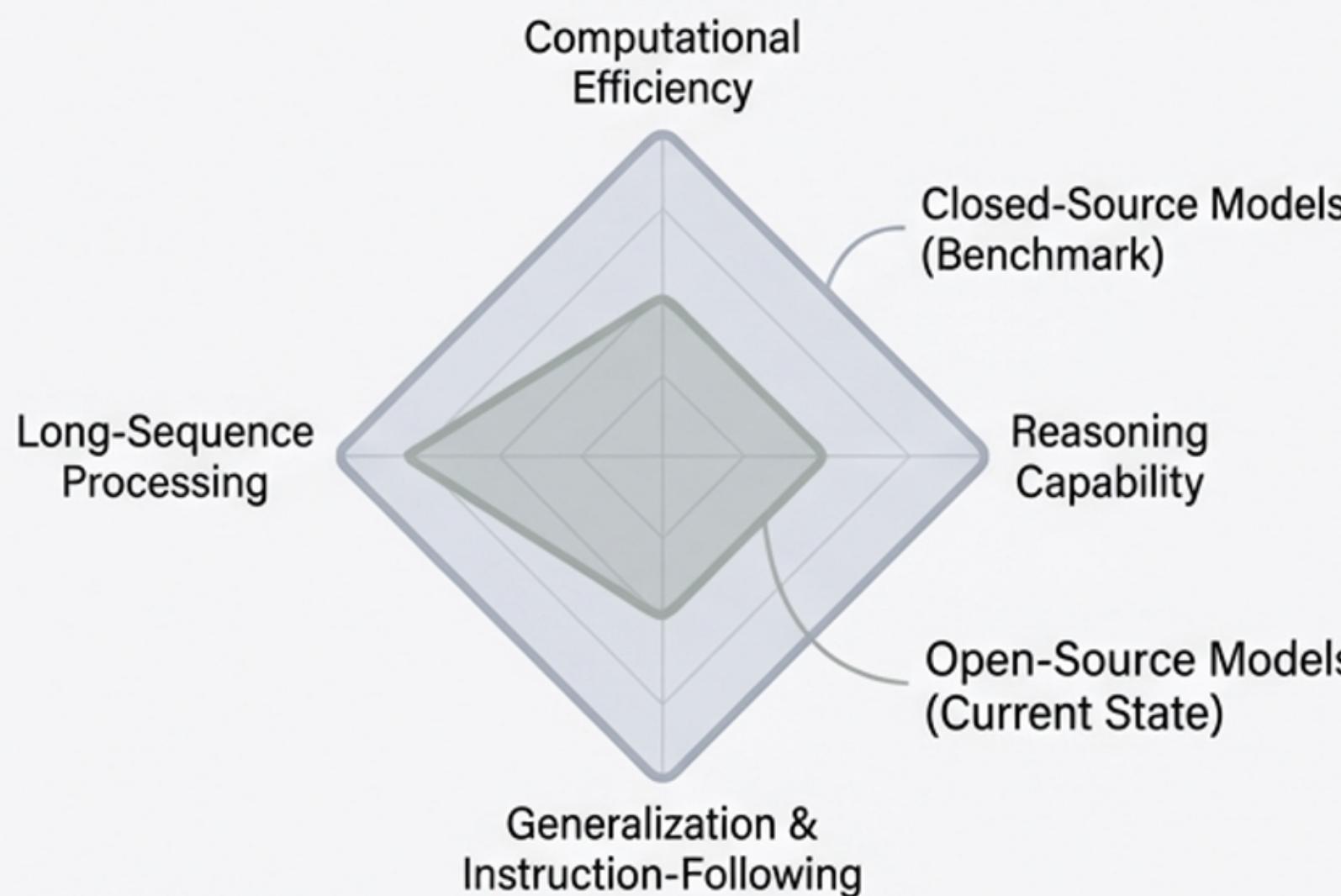
## Existing Limitations

Existing methods struggle with long-sequence processing due to their reliance on vanilla attention mechanisms, resulting in inefficiencies and scalability issues.

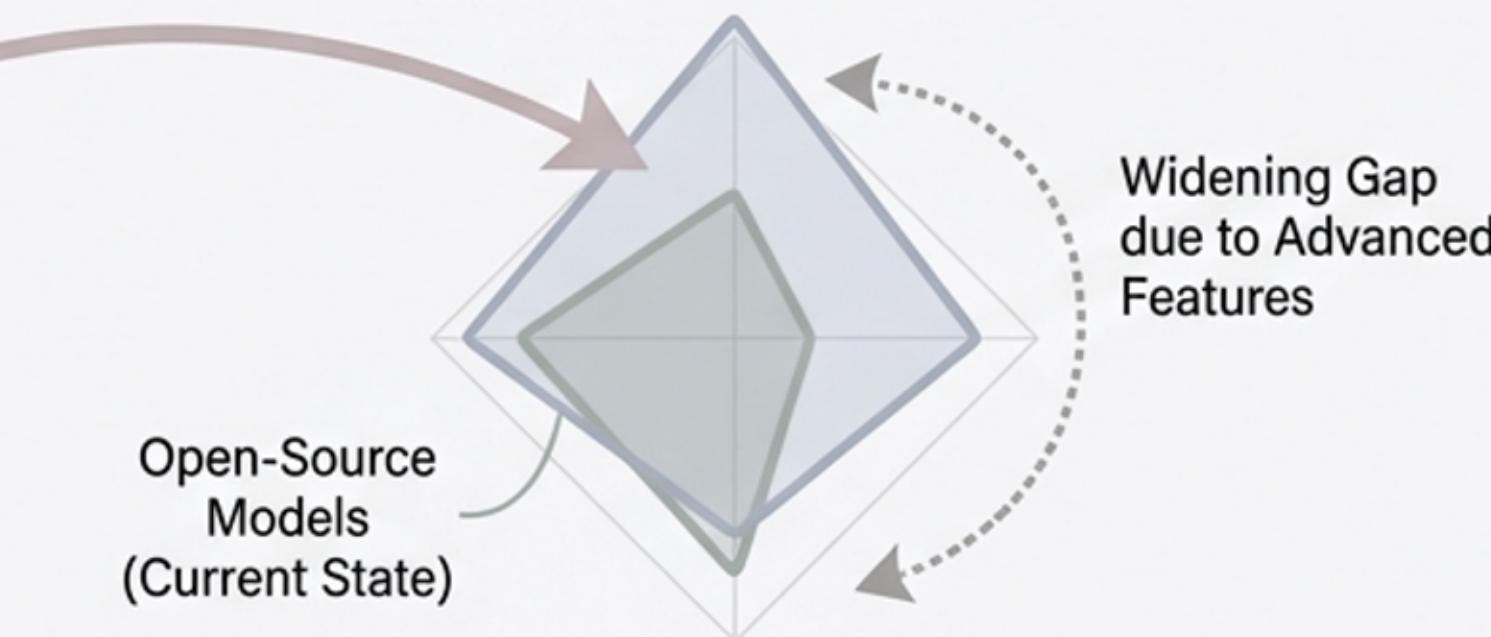


## Open-Source Gap

Open-source models suffer from insufficient computational resources and demonstrate poor generalization and instruction-following capabilities, creating a performance gap compared to closed-source models.



## Performance Gap and Current Challenges



→ This gap is further widened by a declining performance trajectory and integration challenges with advanced features.

# Methodology: Framework Overview



## DeepSeek Sparse Attention (DSA):

Reduces computational complexity while maintaining performance for long sequences. The lightning indexer computes relevance scores.



## Scalable RL Framework:

Expands computational resources during post-training, enhancing generalization capabilities.



## Agentic Task Synthesis Pipeline:

Enhances instruction-following by integrated reasoning and tool-use systematically.

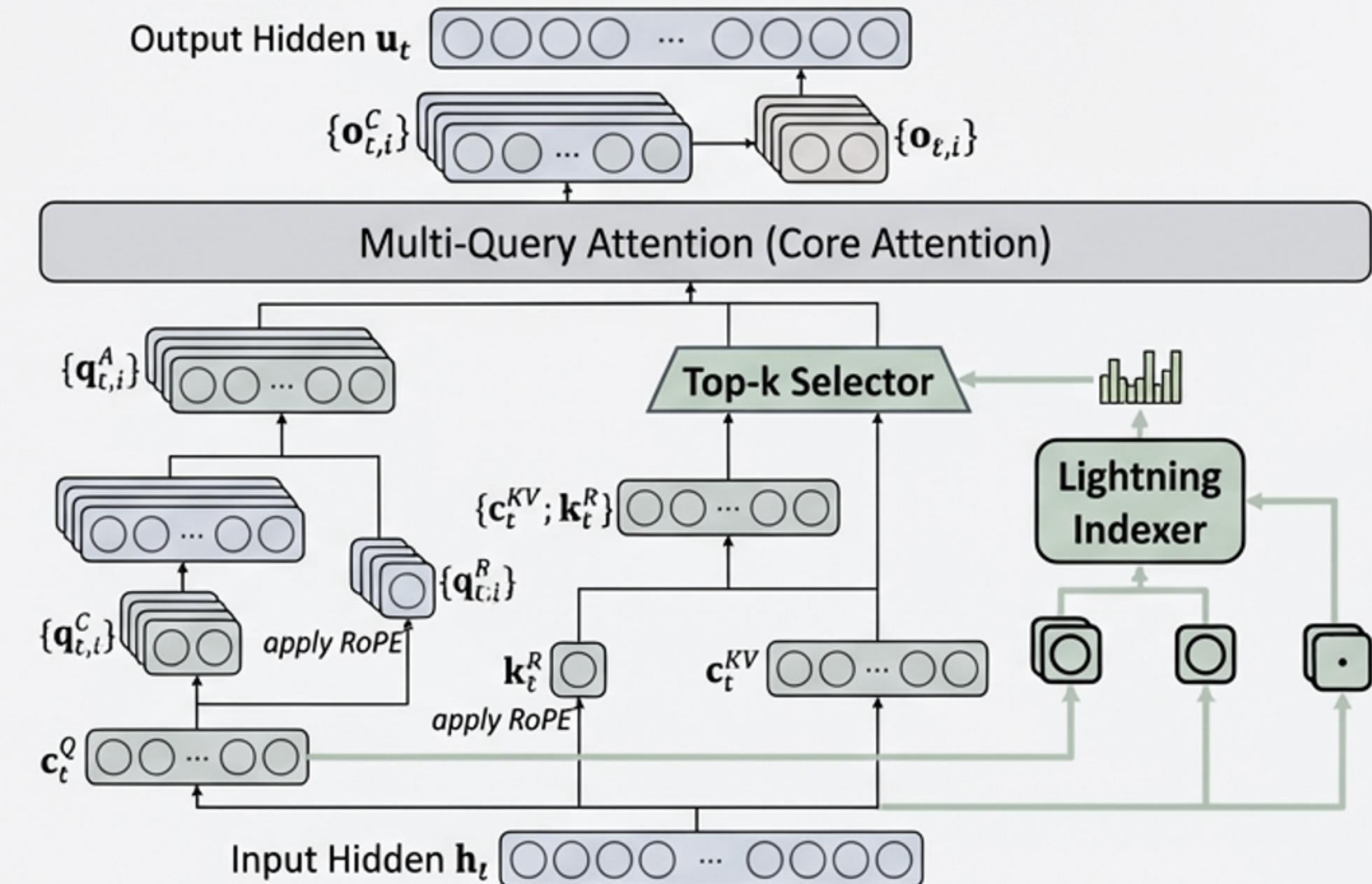
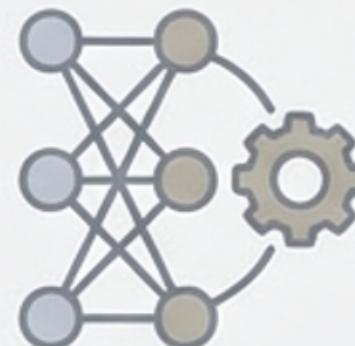


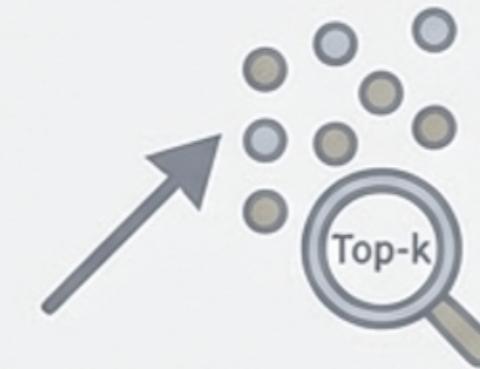
Figure 2: Attention architecture of DeepSeek-V3.2, where DSA is instantiated under MLA. The green part illustrates how DSA selects the top-k key-value entries according to the indexer.

# Mathematical Formulations and Key Components



DeepSeek-V3.2 employs several mathematical formulations to illustrate its attention mechanisms. One key equation, the Sparse Attention Output Equation, is:

$$\mathbf{u}_t = \text{Attn} \left( \mathbf{h}_t, \{\mathbf{c}_s \mid I_{t,s} \in \text{Top-}k(I_{t,:})\} \right)$$



Here,  $\mathbf{u}_t$  represents the attention output vector for the  $t^{th}$  query token,  $\mathbf{h}_t$  is the query token embedding, and  $\mathbf{c}_s$  the context vectors for the top  $k$  tokens. Additionally, an index score  $I_{t,s}$  is calculated by:

$$I_{t,s} = \sum_{j=1}^{H^I} w_{t,j}^I \cdot \text{ReLU} \left( \mathbf{q}_{t,j}^I \cdot \mathbf{k}_s^I \right)$$



These equations are crucial for processing complex reasoning tasks efficiently.

# Experimental Results



DeepSeek-V3.2 was evaluated across various benchmarks and achieved competitive performance compared to both open and closed-source models. It was tested on tasks including code and mathematical competitions, showing strong results in metrics such as Pass@1 and rating benchmarks. For instance, in LiveCodeBench and Codeforces, DeepSeek-V3.2 achieved Pass@1 rates and competitive ratings compared to proprietary models, demonstrating its robust reasoning and agentic task capabilities.



Table 2: DeepSeek-V3.2 Performance Metrics

Benchmark (Metric)	Pass@1 / Rating
LiveCodeBench	83.3
Codeforces	2386

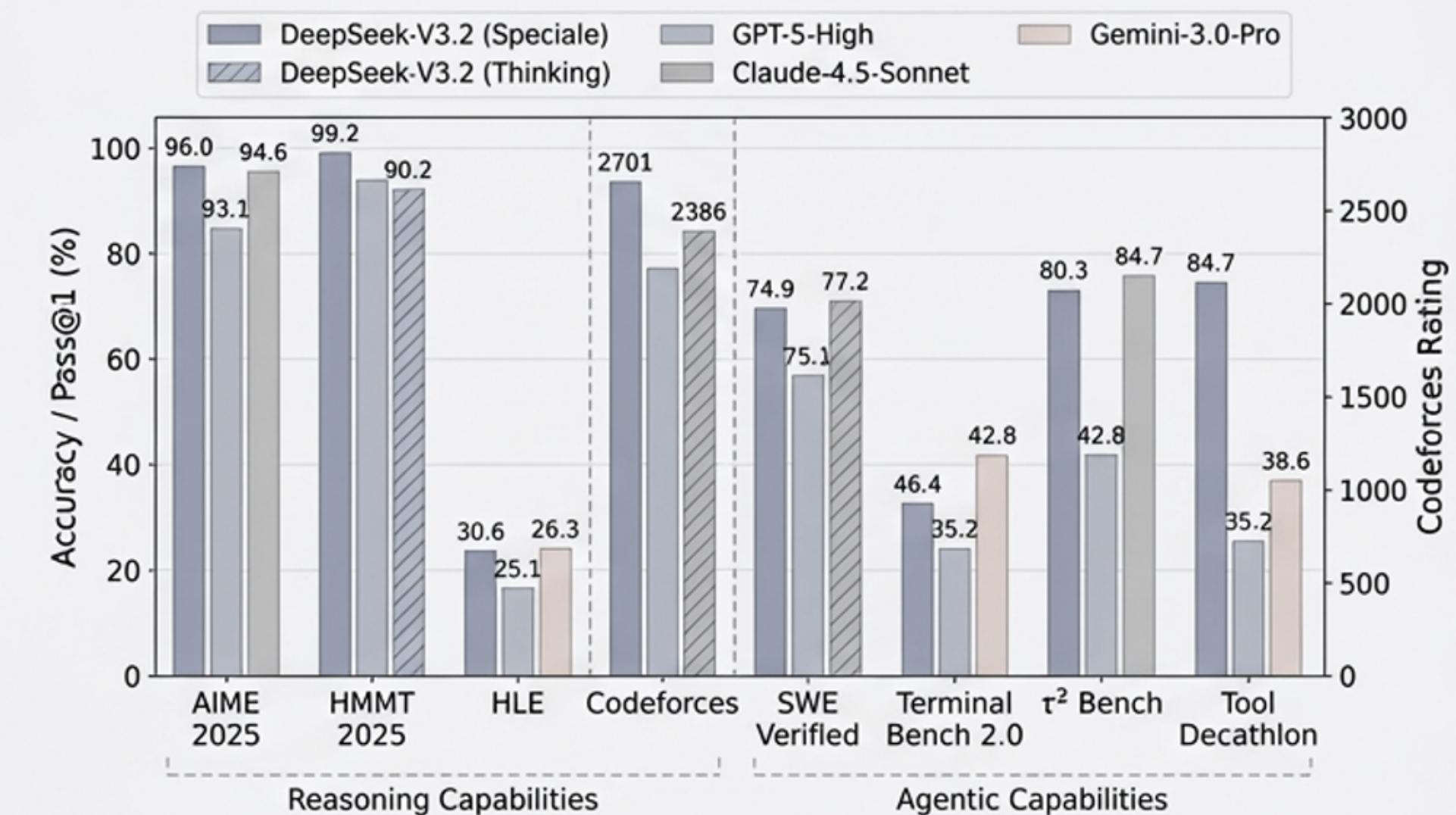
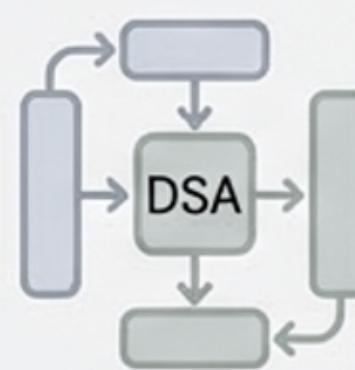


Figure 1: Benchmark Comparison

# Conclusion and Key Contributions



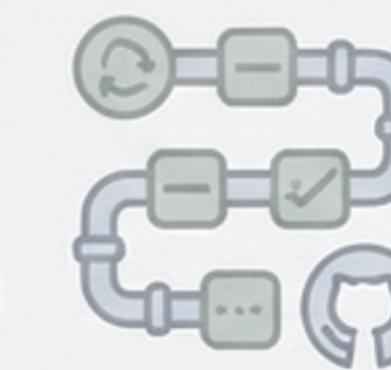
## Efficient DSA Mechanism

- Innovations in attention mechanisms, reducing complexity.



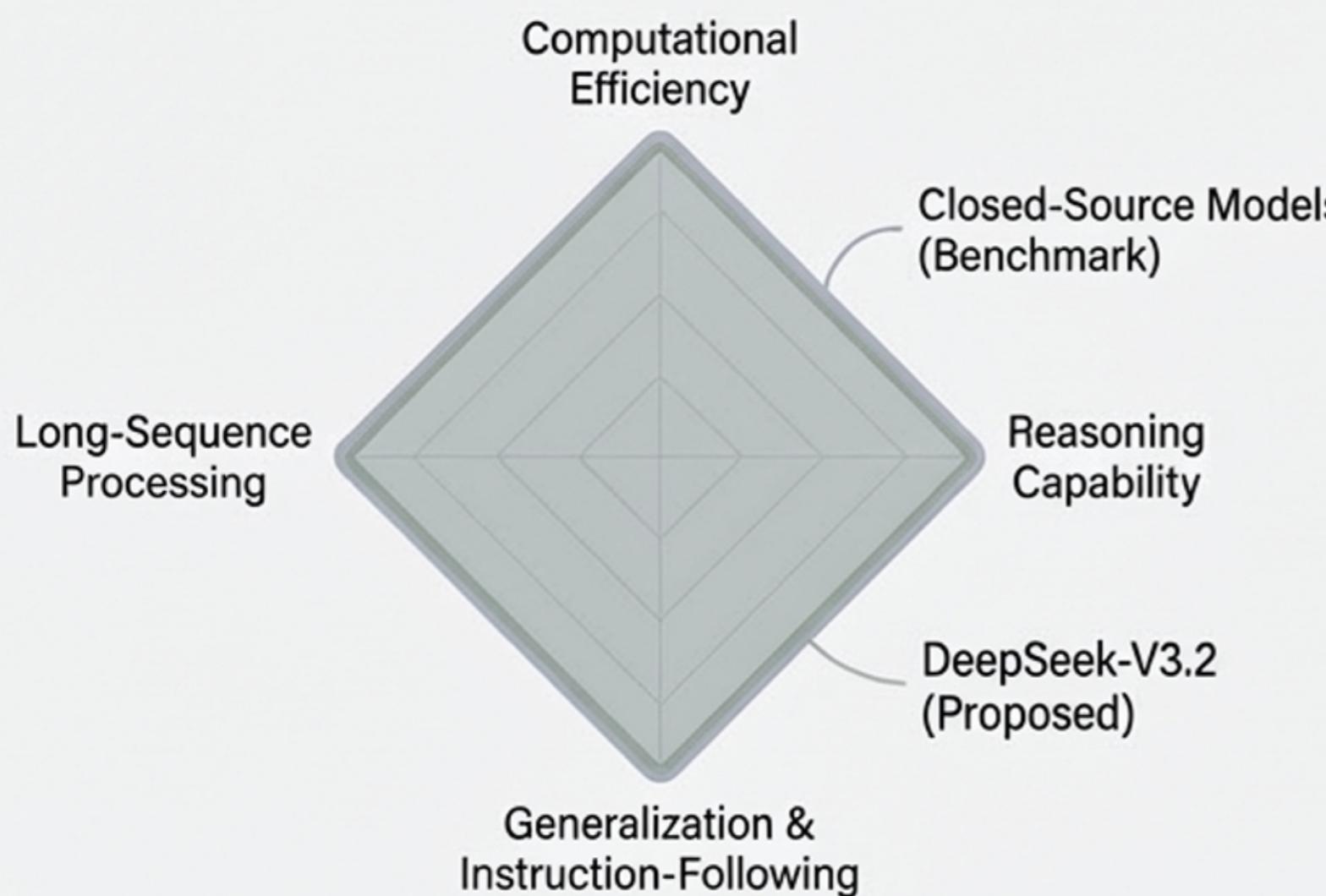
## Robust RL Framework

- Facilitating powerful computing resources and scalability.

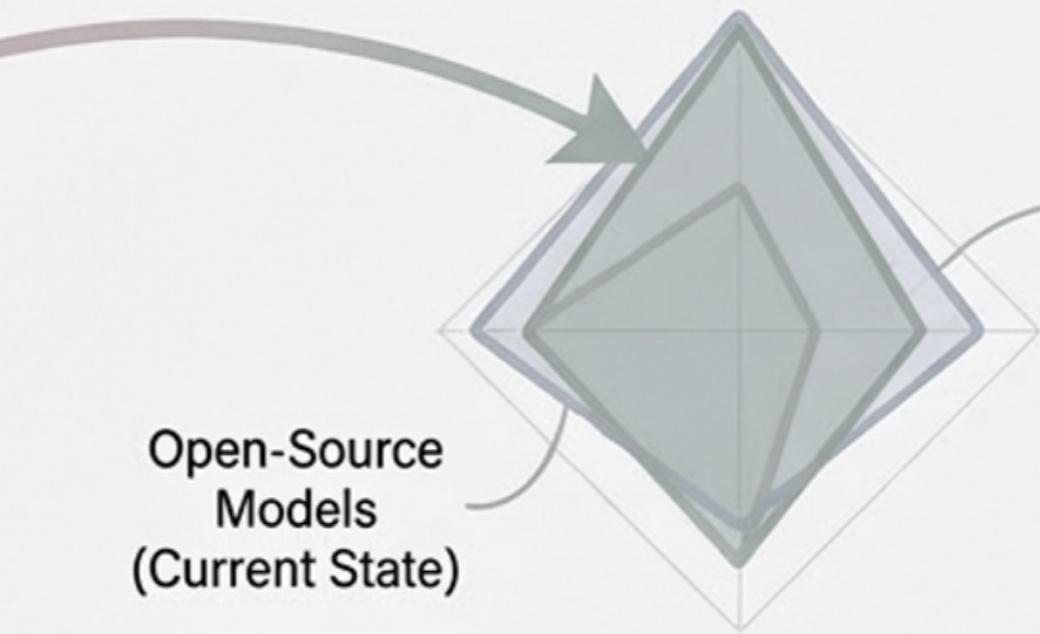


## Large-Scale Task Synthesis Pipeline

- Improving generalization across agentic tasks.



## Performance Gap Bridged & Enhanced Capabilities



→ Effective bridging of gaps; positioning DeepSeek-V3.2 as a competitive and efficient open-source model.