

From Search to Research: Training Agents and Retrievers for Deep Research

Akari Asai

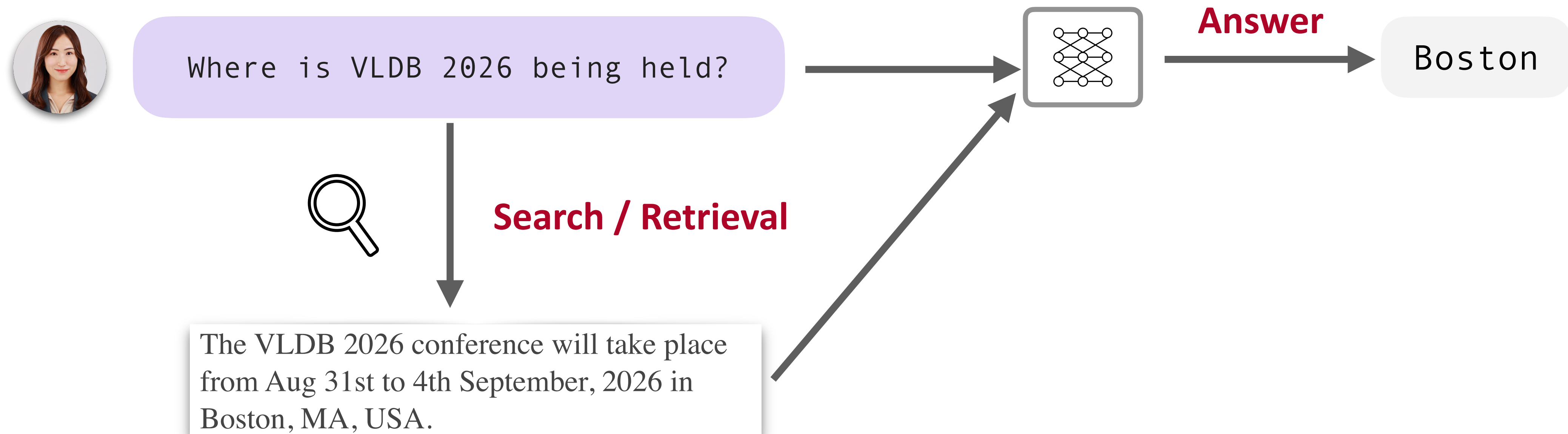
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Traditional Systems Handle a Single Information Need



Retrieve-then-Generate (RAG) works well for simple questions

Complex Questions Require Research, Not a Single Search



Find all workshops held from 2020–2026 on RAG, deep research, and vector databases. Compile their accepted papers and analyze how the research themes have evolved.



The First Workshop on Multilingual Report Generation via Retrieval Augmented Generation (RAG4Reports)

Organizers: Dawn Lawrie, Sean MacAvaney, James Mayfield, Eugene Yang, Andrew Yates

Half-day workshop (morning)

Room: Harbor A&B

Description: RAG4Reports focuses on developing systems for the Multilingual Report Generation, which is a multilingual task with complex information need.



Full Day Workshops



Aug. 10 Afternoon Workshops



ICML 2025 Workshop

ICML 2025 Workshop PRAL

ICML 2025 Workshop PUT

Sixth Workshop on Inclusion (LTEDI-2026)

Organizers: Blanca Martínez, María Jiménez

Full-day workshop

Room: Virtual-only on Underline

Description: LTEDI-2026 invites theoretical, empirical, and applied research in Natural Language Processing (NLP), Artificial Intelligence (AI), and communities particularly those focusing on bias in language technology.

The Second Workshop on Multimodal Augmented Generation (MAGMaR)

Organizers: Reno Kriz; Kenton Murray; Andrew Yates; Des Ferraro; Xiang Xiang; William Walden; Jeremy Gwinnup; J Alexander Martin

Adaptation and Evidence-grounding of Generative Interventional Systems (AEGIS)

Mattia Prosperi (University of Florida) · Yi Guo (University of Florida) · Aprinda I Queen (University of Florida), et al.

RelSciFM 2026: The workshop on Reliable Scientific Foundation Models: Design, Training, Grounding, and Verification

Qiankun Li (NTU) · Wei Wang (UCLA) · Carl Yang (Emory), et al.

The 5th Workshop on AI Agent for Information Retrieval: Generating and Ranking (Agent4IR)

Qingsongwen (Squirrel AI) · Yongfeng Zhang (Rutgers) · Zhiwei Liu (Salesforce AI), et al.

ICML 2025 Workshop TAIG

ICML 2025 Workshop TerraBytes

ICML 2025 Workshop TokShop

ICML 2025 Workshop TTODLer-FM

ICML 2025 Workshop VecDB

ICML 2025 Workshop WCUA

ICML 2025 Workshop WM

ICML 2025 Workshop World Models

No single document contains the complete answer

Deep Research Agents Autonomously Plan, Search, and Synthesize



Find all workshops held from 2020–2026 on RAG, deep research, and vector databases. Compile their accepted papers and analyze how the research themes have evolved.

I need to identify relevant workshops across seven years, verify their dates and topics, collect accepted-paper lists, and then compare themes over time.

Plan:

1. Define workshop inclusion criteria.
2. Search conference programs and proceedings by year. Extract accepted papers and metadata.
3. Verify missing years and duplicate workshops.
4. Group papers by topic and analyze trends.

Plan



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Web search: “workshop retrieval augmented generation vector databases deep research accepted papers”



Search

1. Workshop on Retrieval-Augmented Generation — Program
Topics: retrieval, grounding, knowledge-intensive NLP
2. Vector Database Workshop — Proceedings
Topics: indexing, approximate nearest-neighbor search, vector database systems
-
3. Workshop on Deep Research Agents — Accepted Papers
Topics: search agents, long-horizon reasoning, citation-grounded synthesis

Deep Research Agents Autonomously Plan, Search, and Synthesize



Find all workshops held from 2020–2026 on RAG, deep research, and vector databases. Compile their accepted papers and analyze how the research themes have evolved.

These results identify several recent workshops, but they do not cover the entire 2020–2026 period. “Deep research” may also have appeared under earlier terms such as open-domain QA, knowledge-intensive NLP, or multi-hop retrieval.

Reflect

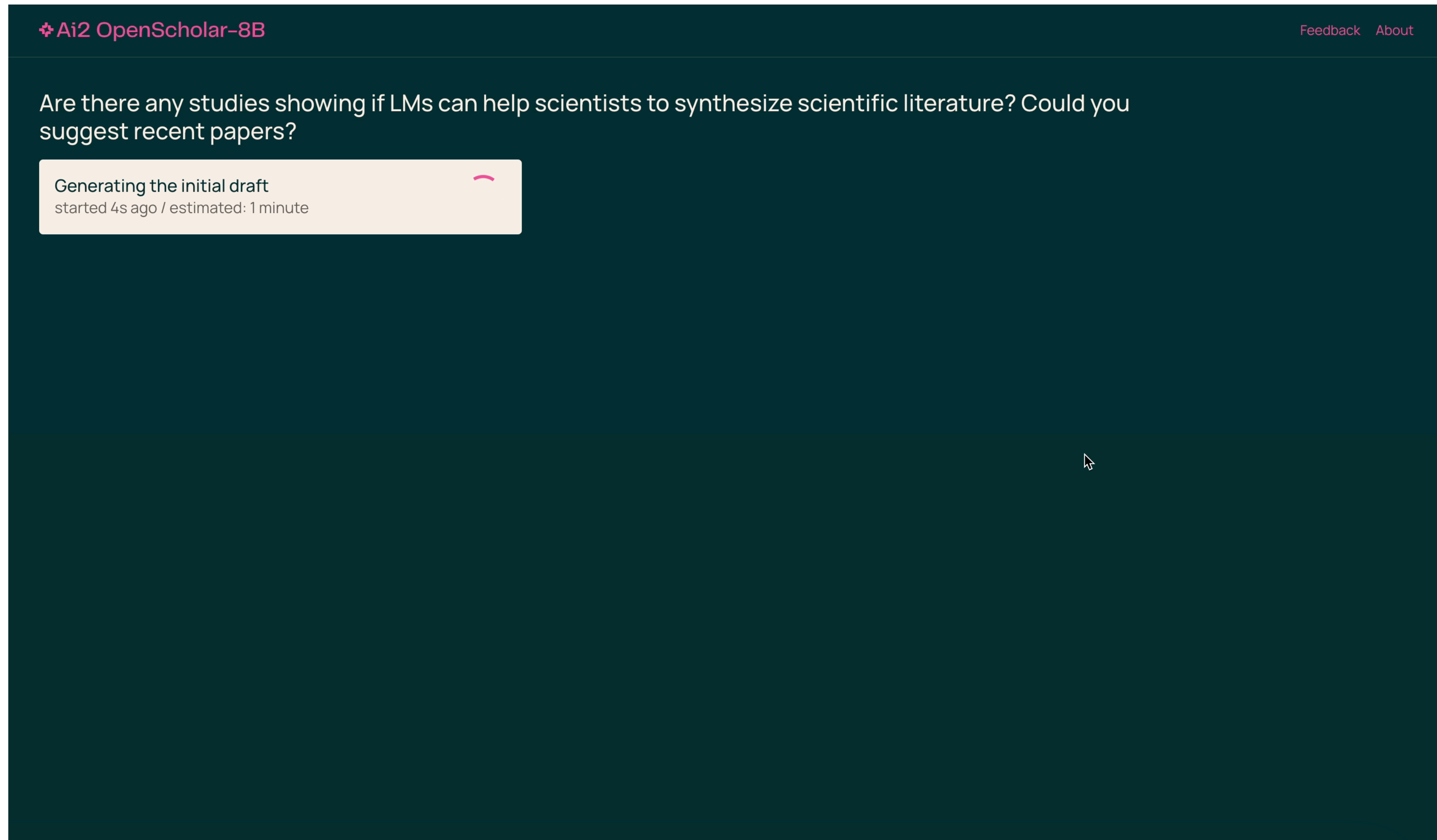


2020 2021 2022 workshop knowledge-intensive NLP multi-hop retrieval
open-domain QA proceedings

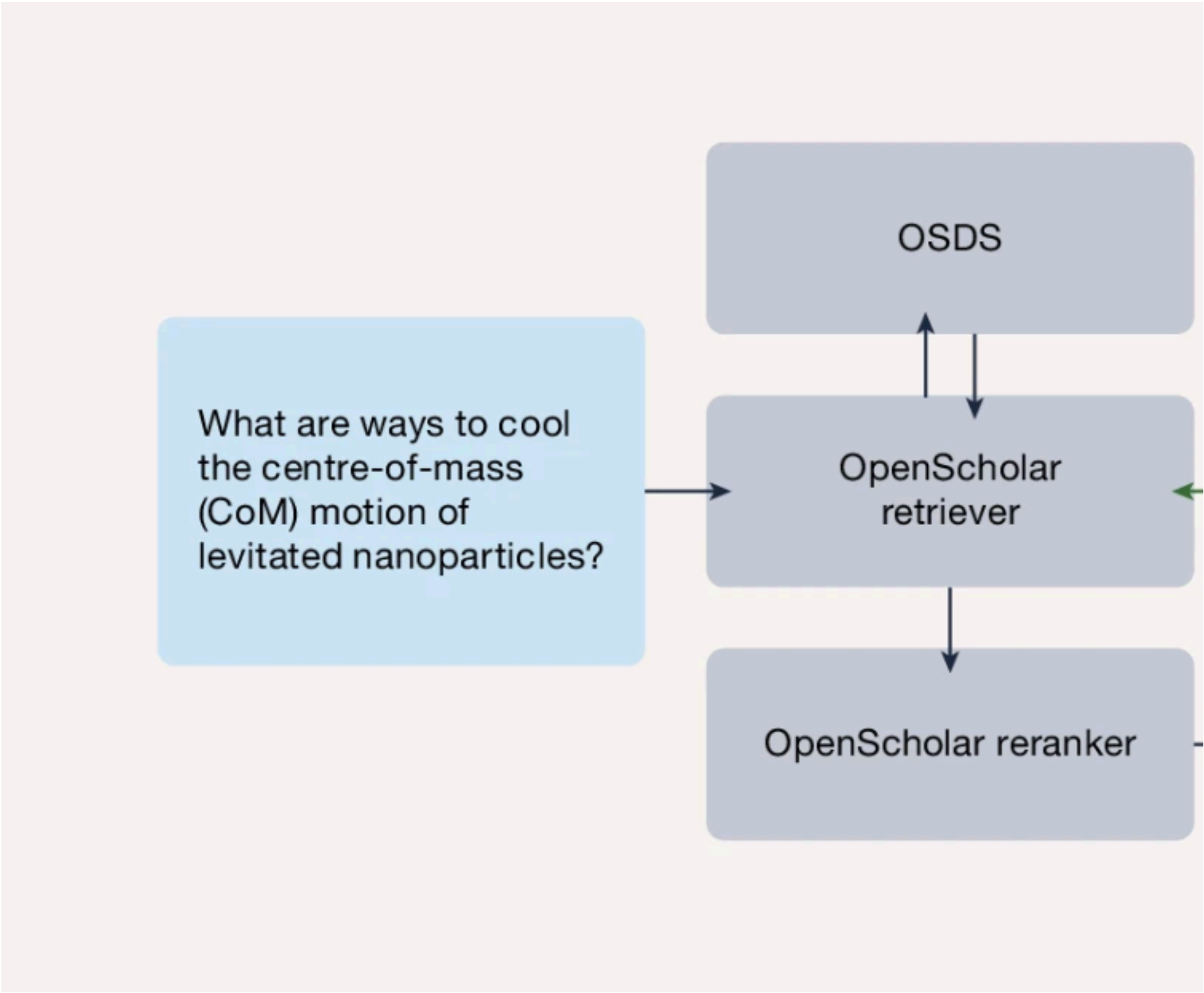
Search



OpenScholar Turns Scientific Search into Literature Synthesis



What Enables OpenScholar to Conduct Deep Research?



Letter | Published: 20 March 2011

Millikelvin cooling of an optically trapped microsphere in vacuum

[Tongcang Li](#), [Simon Kheifets](#) & [Mark G. Raizen](#)

[Nature Physics](#) **7**, 527–530 (2011) | [Cite this article](#)

[Save article](#)

10k Accesses | 514 Citations | 10 Altmetric | [Metrics](#)

Abstract

Cooling of micromechanical resonators towards the quantum mechanical ground state in their centre-of-mass motion has advanced rapidly in recent years^{1,2,3,4,5,6,7,8}. This work is an important step towards the creation of ‘Schrödinger cats’, quantum superpositions of macroscopic observables, and the study of their destruction by decoherence. Here we report optical trapping of glass microspheres in vacuum with high oscillation frequencies, and cooling of the centre-of-mass motion from room temperature to a minimum temperature of about 1.5 mK. This new system eliminates the physical contact inherent to clamped cantilevers, and can allow ground-state cooling from room temperature^{9,10,11,12,13,14,15}. More importantly, the optical trap can be switched off, allowing a microsphere to undergo free-fall in vacuum after cooling¹⁵. This is ideal for studying the gravitational state reduction^{16,17,18,19}, a manifestation of the apparent conflict between general relativity and quantum mechanics^{16,20}. A cooled optically trapped object in vacuum can also be used to search for non-Newtonian gravity forces at small scales²¹, measure the impact of a single air molecule¹⁴ and even produce Schrödinger cats of living organisms⁹.

PHYSICAL REVIEW LETTERS **122**, 123602 (2019)

Editors' Suggestion Featured in Physics

Cavity Cooling of a Levitated Nanosphere by Coherent Scattering

Uroš Delić,^{1,2,*} Manuel Reisenbauer,¹ David Grass,^{1,†} Nikolai Kiesel,¹ Vladan Vuletić,³ and Markus Aspelmeyer^{1,2}

¹*Vienna Center for Quantum Science and Technology (VCQ), Faculty of Physics, University of Vienna, Boltzmannngasse 5, A-1090 Vienna, Austria*

²*Institute for Quantum Optics and Quantum Information (IQOQI), Boltzmannngasse 3, A-1090 Vienna, Austria*

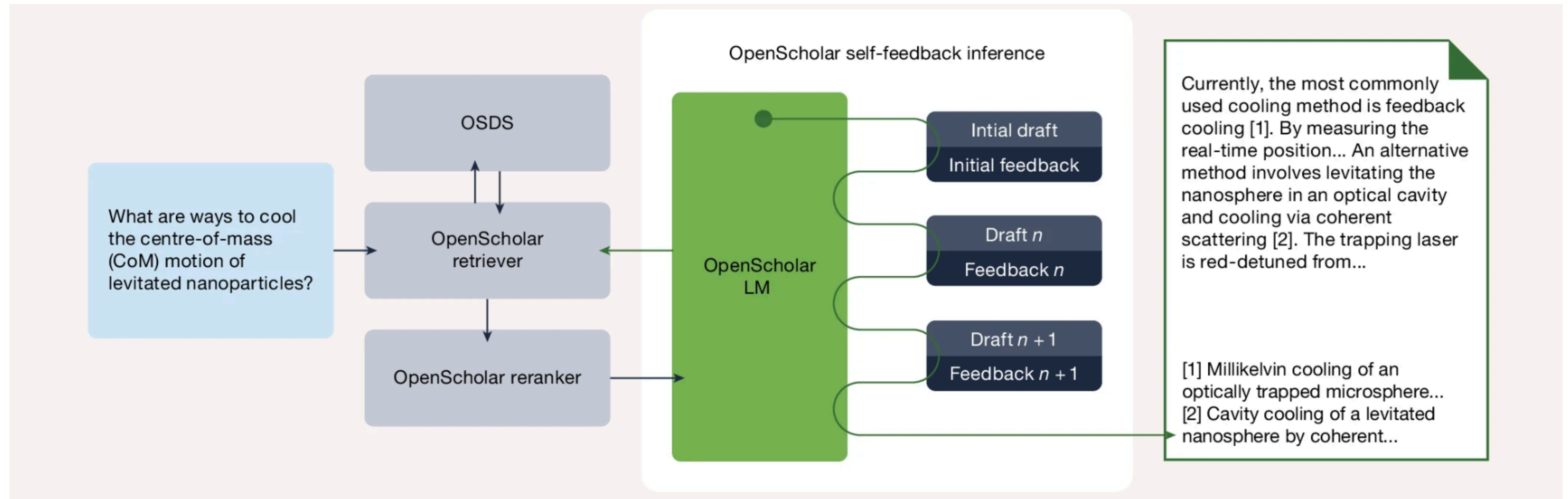
³*Department of Physics and Research Laboratory of Electronics, Massachusetts Institute of Technology, Cambridge, Massachusetts 02139, USA*

(Received 21 December 2018; published 27 March 2019)

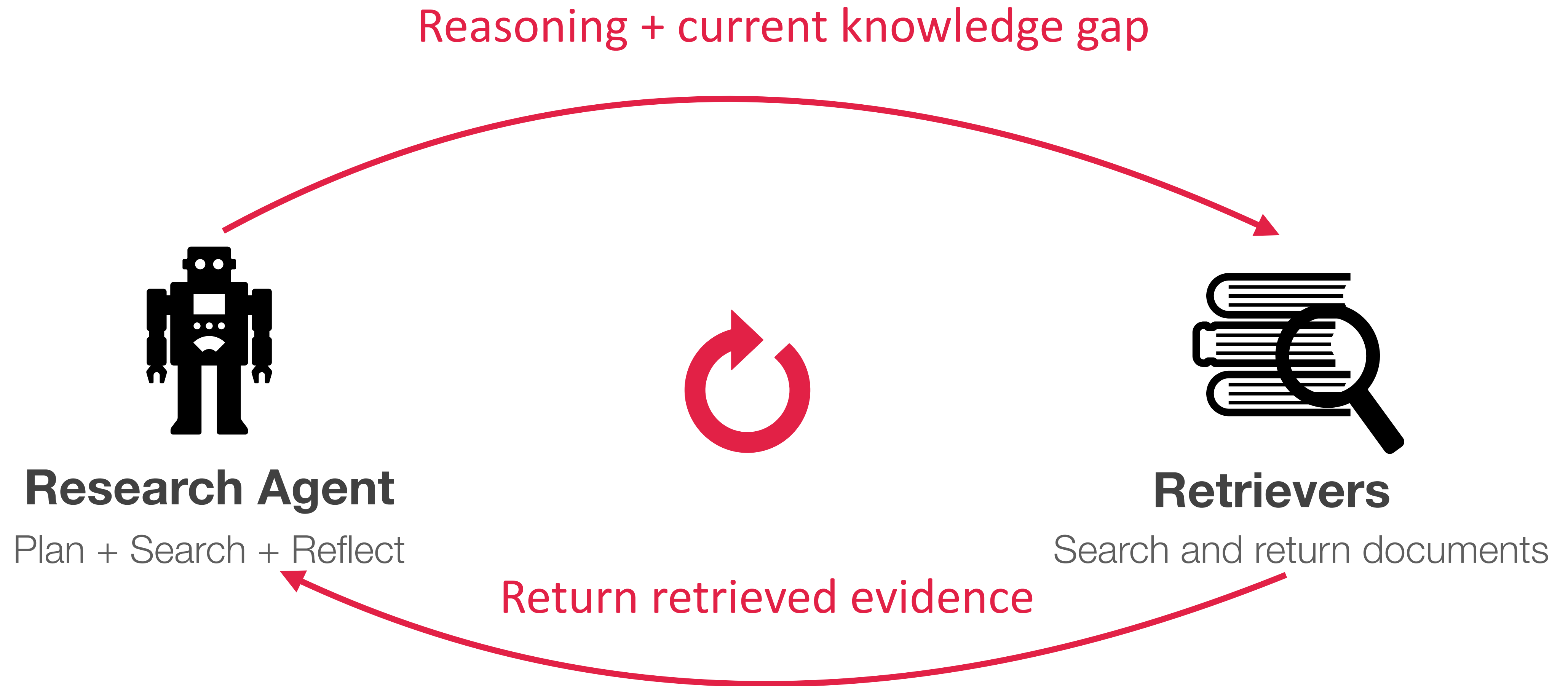
We report three-dimensional (3D) cooling of a levitated nanoparticle inside an optical cavity. The cooling mechanism is provided by cavity-enhanced coherent scattering off an optical tweezer. The observed 3D dynamics and cooling rates are as theoretically expected from the presence of both linear and quadratic terms in the interaction between the particle motion and the cavity field. By achieving nanometer-level control over the particle location we optimize the position-dependent coupling and demonstrate axial cooling by two orders of magnitude at background pressures of 6×10^{-2} mbar. We also estimate a significant (> 40 dB) suppression of laser phase noise heating, which is a specific feature of the coherent scattering scheme. The observed performance implies that quantum ground state cavity cooling of levitated nanoparticles can be achieved for background pressures below 1×10^{-7} mbar.

DOI: 10.1103/PhysRevLett.122.123602

What Enables OpenScholar to Conduct Deep Research?

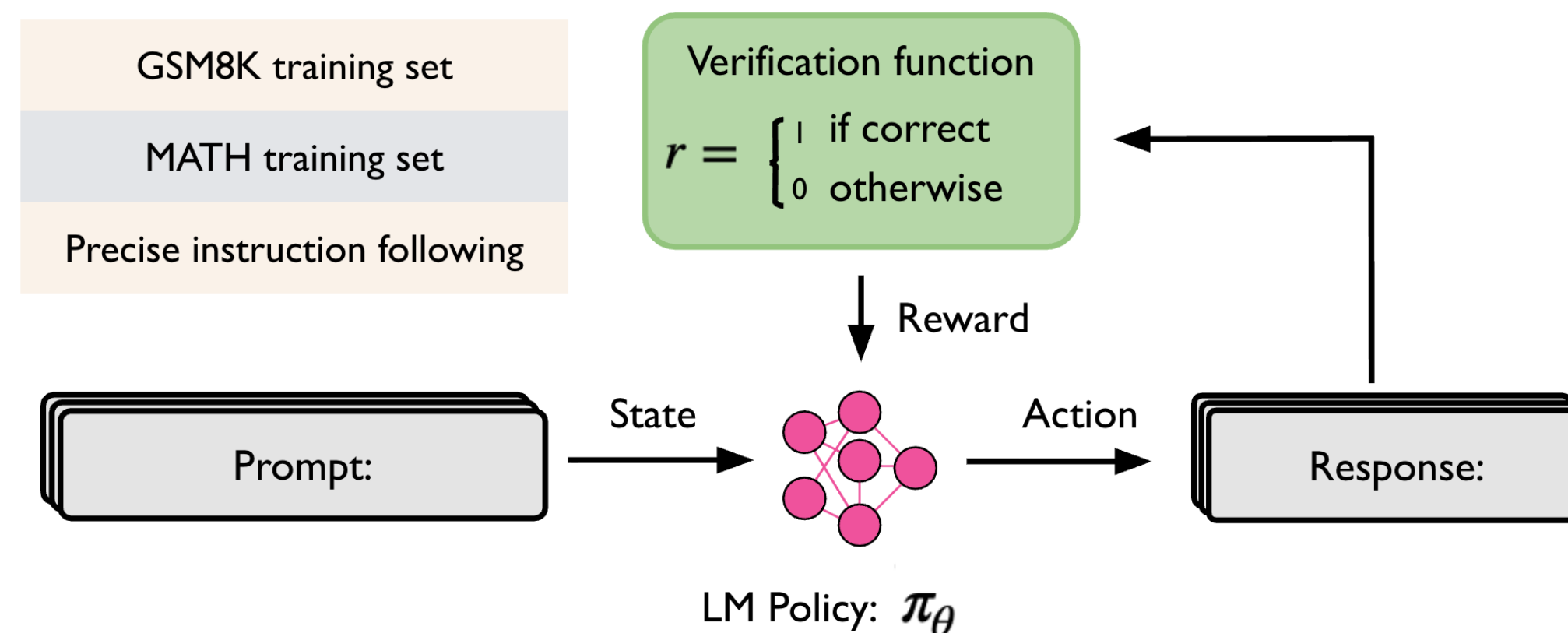


Deep Research Requires Co-Designing Agents and Retrievers



Two Challenges in Co-Designing Deep Research Systems

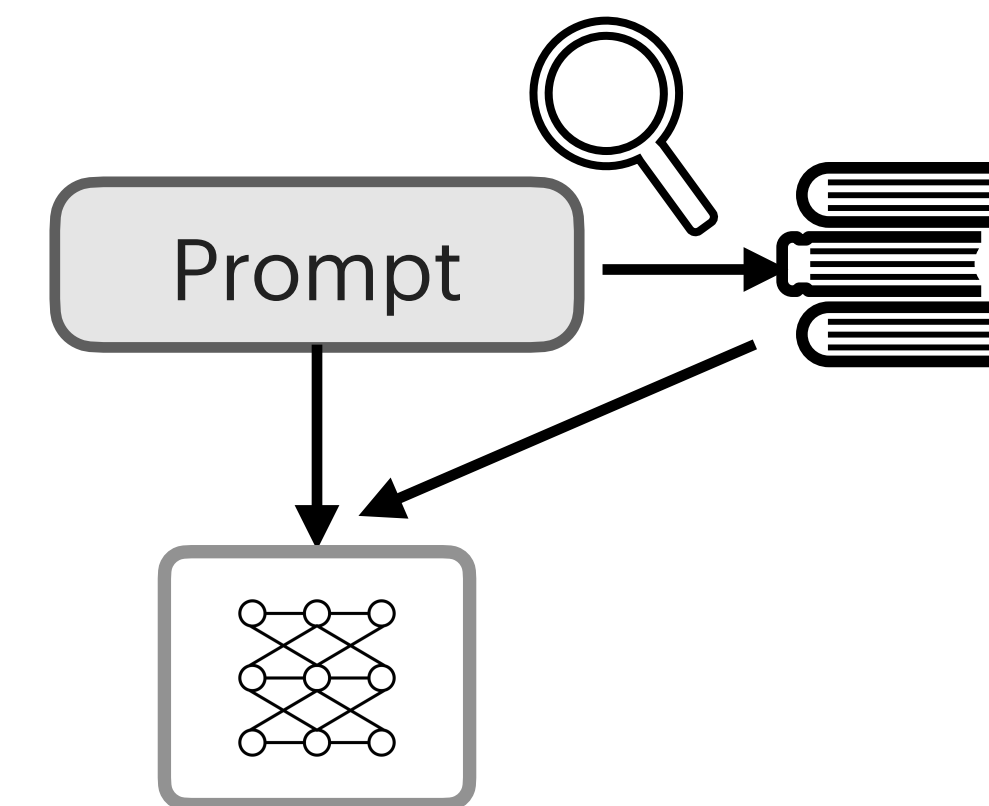
Agent Learning



Relies on **RL with Verifiable Rewards (RLVR)**

How can agents learn from open-ended, hard-to-verify research outcomes?

Retrieval

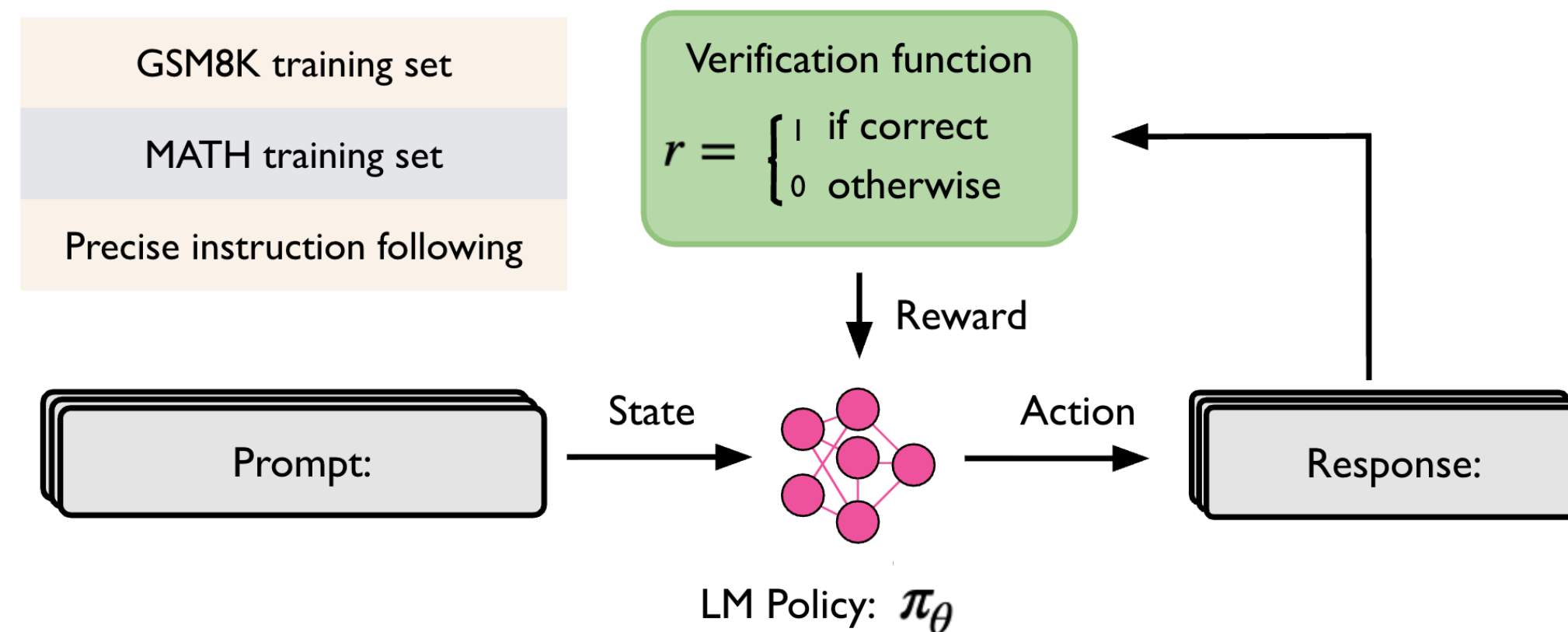


Relies on **retrievers optimized for human queries or static RAG**

How should agents search as their reasoning evolves?

Two Challenges in Co-Designing Deep Research Systems

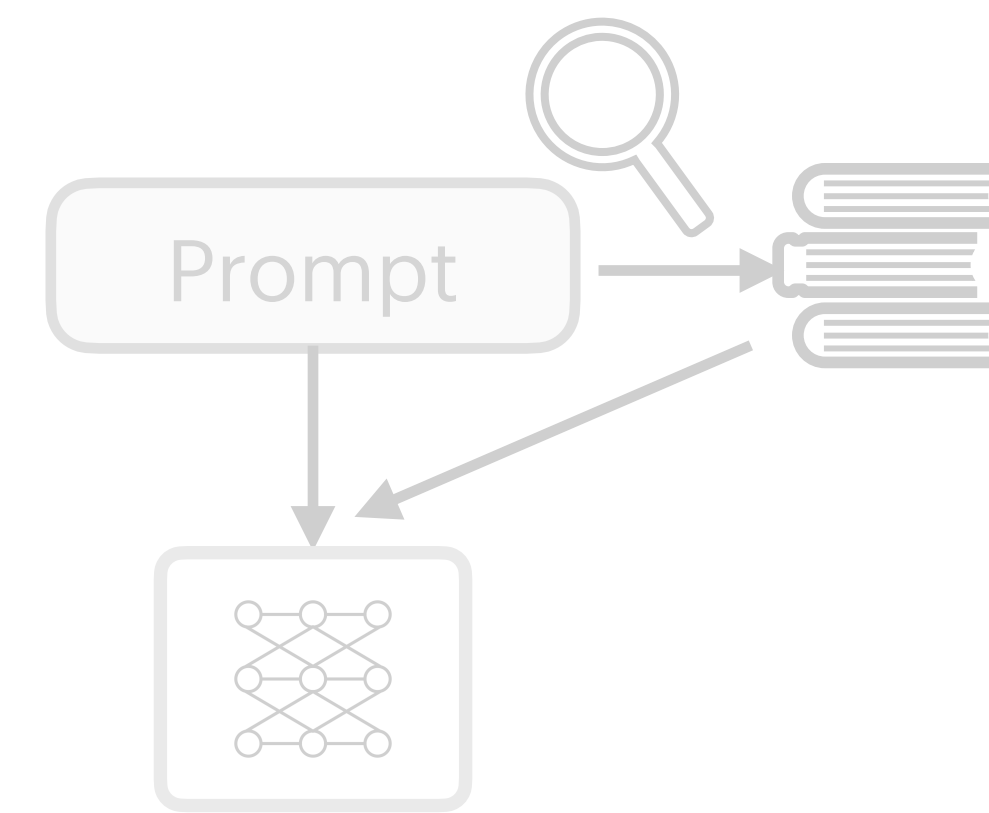
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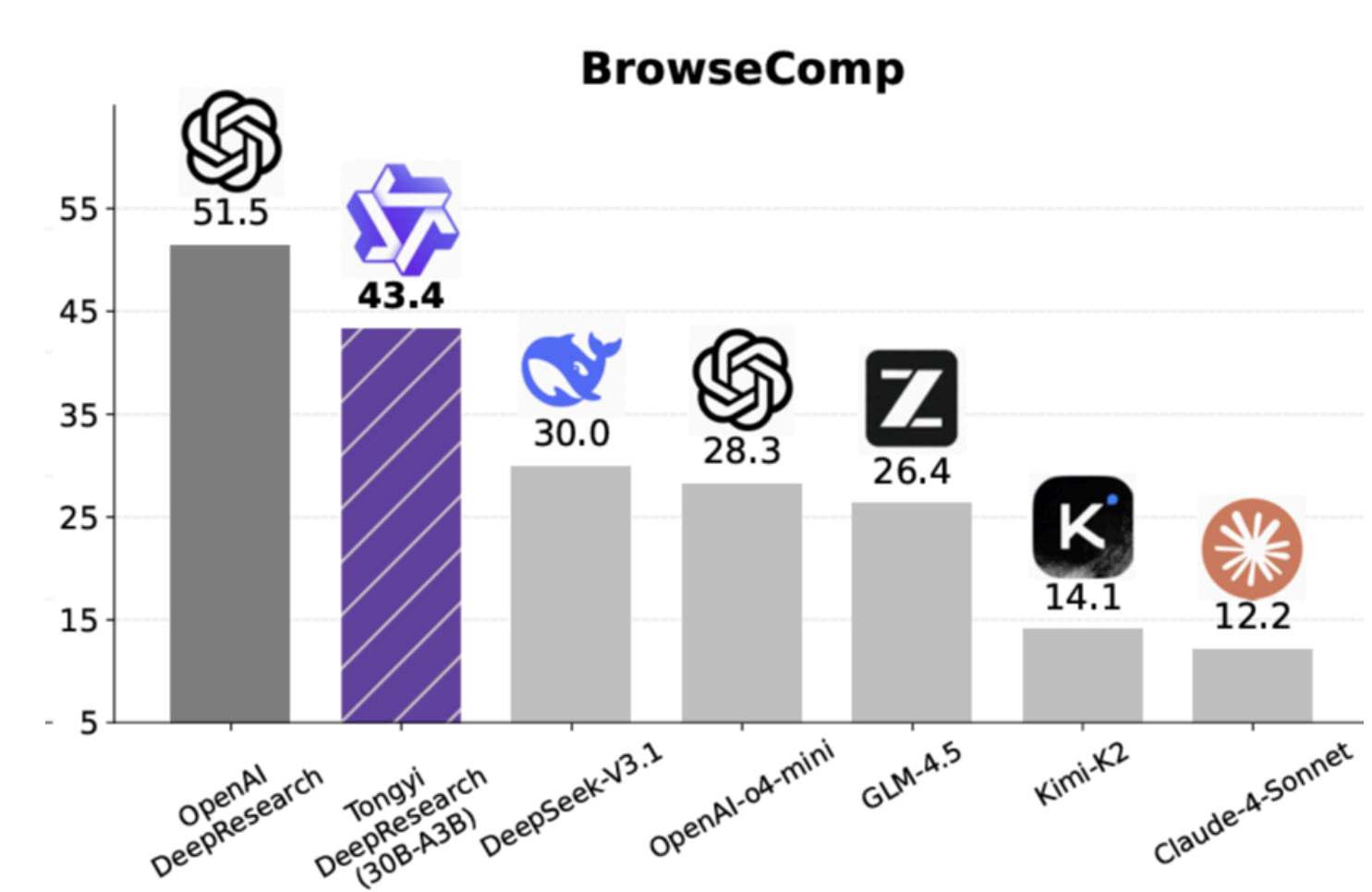
Retrieval



Relies on **retrievers optimized for human queries or static RAG**

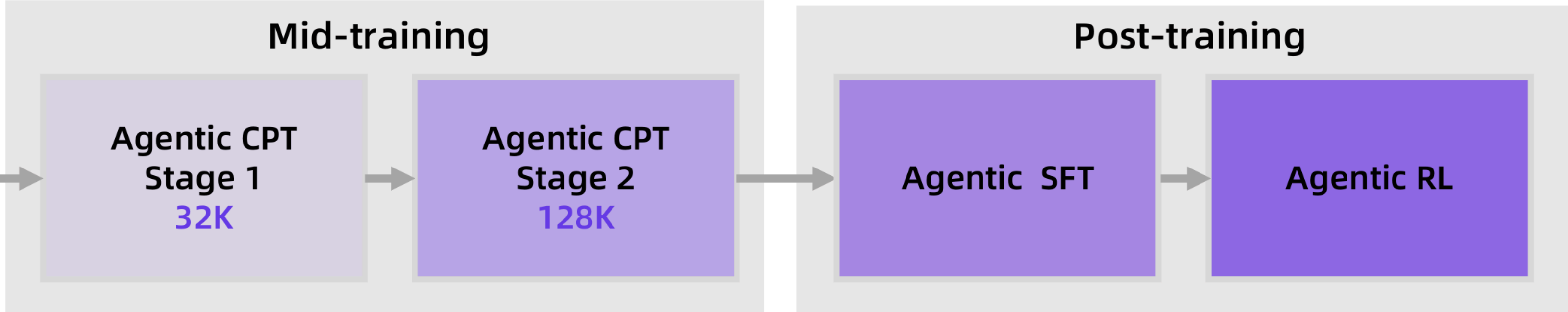
How should agents search as their reasoning evolves?

Most DR Training Still Focuses on Short-Answer Tasks

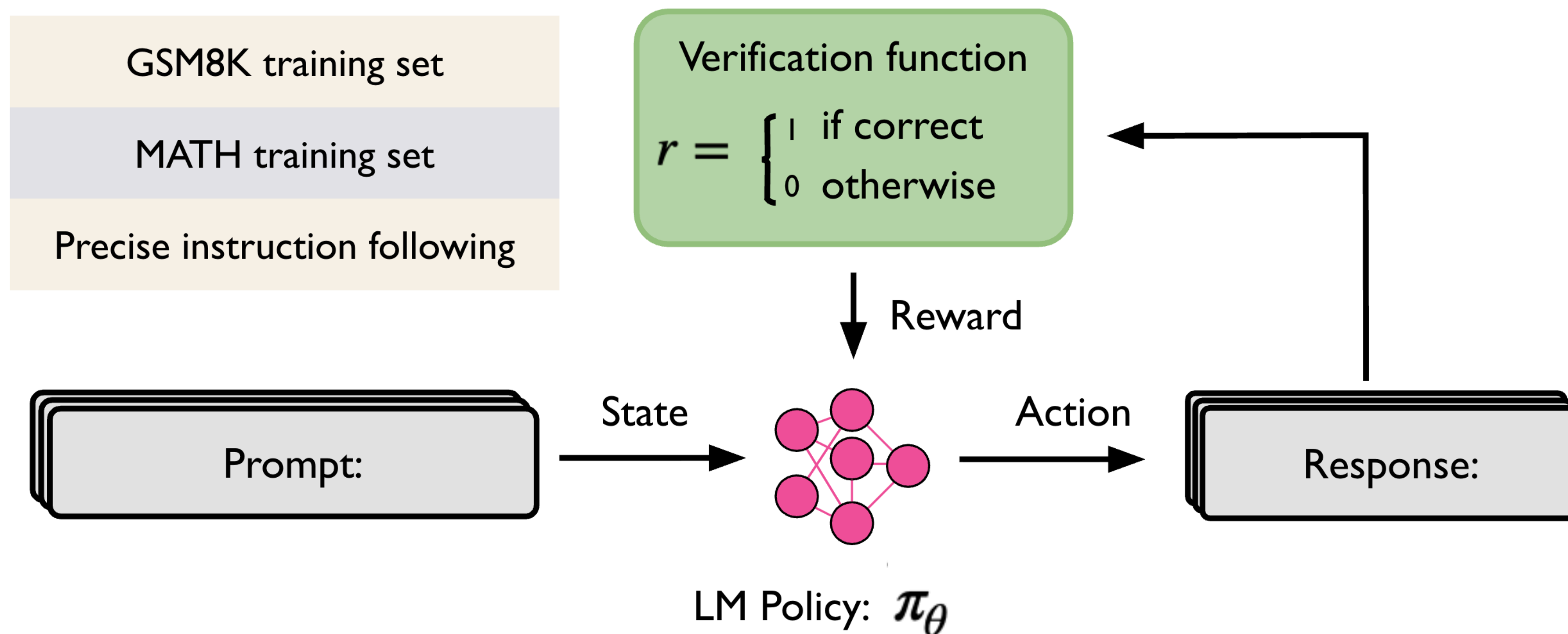


Q: Please identify the fictional character who occasionally breaks the fourth wall with the audience, has a backstory involving help from selfless ascetics, is known for his humor, and had a TV show that aired between the 1960s and 1980s with fewer than 50 episodes.

A: Plastic Man



Short Answers Enable Verifiable Rewards



Long-Form Research Has No Single Correct Answer



Find all workshops held from 2020–2026 on RAG, deep research, and vector databases. Compile their accepted papers and analyze how the research themes have evolved.

I found 18 relevant workshops and 426 accepted papers across ACL, SIGIR, KDD, NeurIPS, and VLDB [1–18]. The complete list appears below.



The focus shifted from dense retrieval and QA to RAG and vector infrastructure, and more recently to agentic search and long-horizon research [3, 7, 11].



There are many valid answers; quality is not binary

DR Tulu Trains Open Agents for Long-Form Research



User

How did Netflix manage to successfully adapt One Hundred Years of Solitude, a notoriously difficult book to bring to the screen?



DR Tulu

Agentic Workflow

Think Tool 1 Think Tool 2 ... Answer

Long-form Report with Citations

Netflix's adaptation **avoided a literal replica of Macondo and instead fused real locations with meticulously built sets**^[1] to honor the novel's essence while giving the show contemporary visual grammar. **The production grounded magical realism in front-of-camera practical craft, relying on makeup, special effects,**^[2]
The location strategy and production design...

Sources

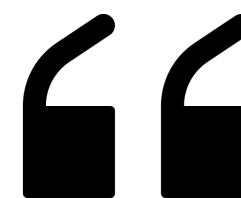
- [1] The production team behind Netflix's adaptation of "One Hundred Years of Solitude," LA Times
- [2] The article discusses Netflix's adaptation of Gabriel García Márquez's celebrated novel, NY Times



Fully open 8B deep research agent

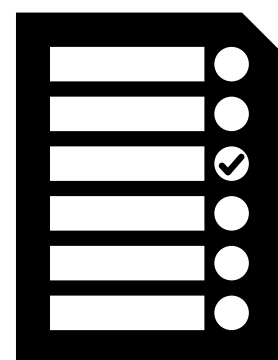
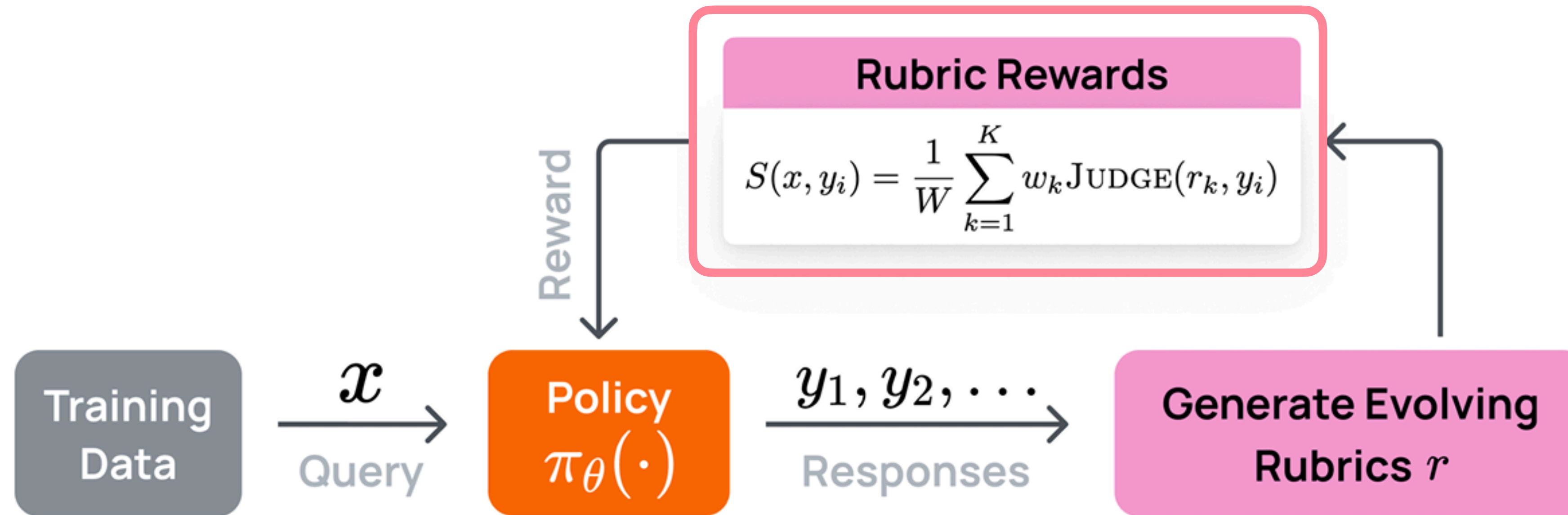


Selects and uses appropriate search tools



Produces claim-level citations from credible sources

Evolving Rubrics Turn Research Criteria into Rewards



Rubrics specify the criteria that a strong answer should satisfy

Rubrics Evolve as the Agent Discovers Better Answers

User query

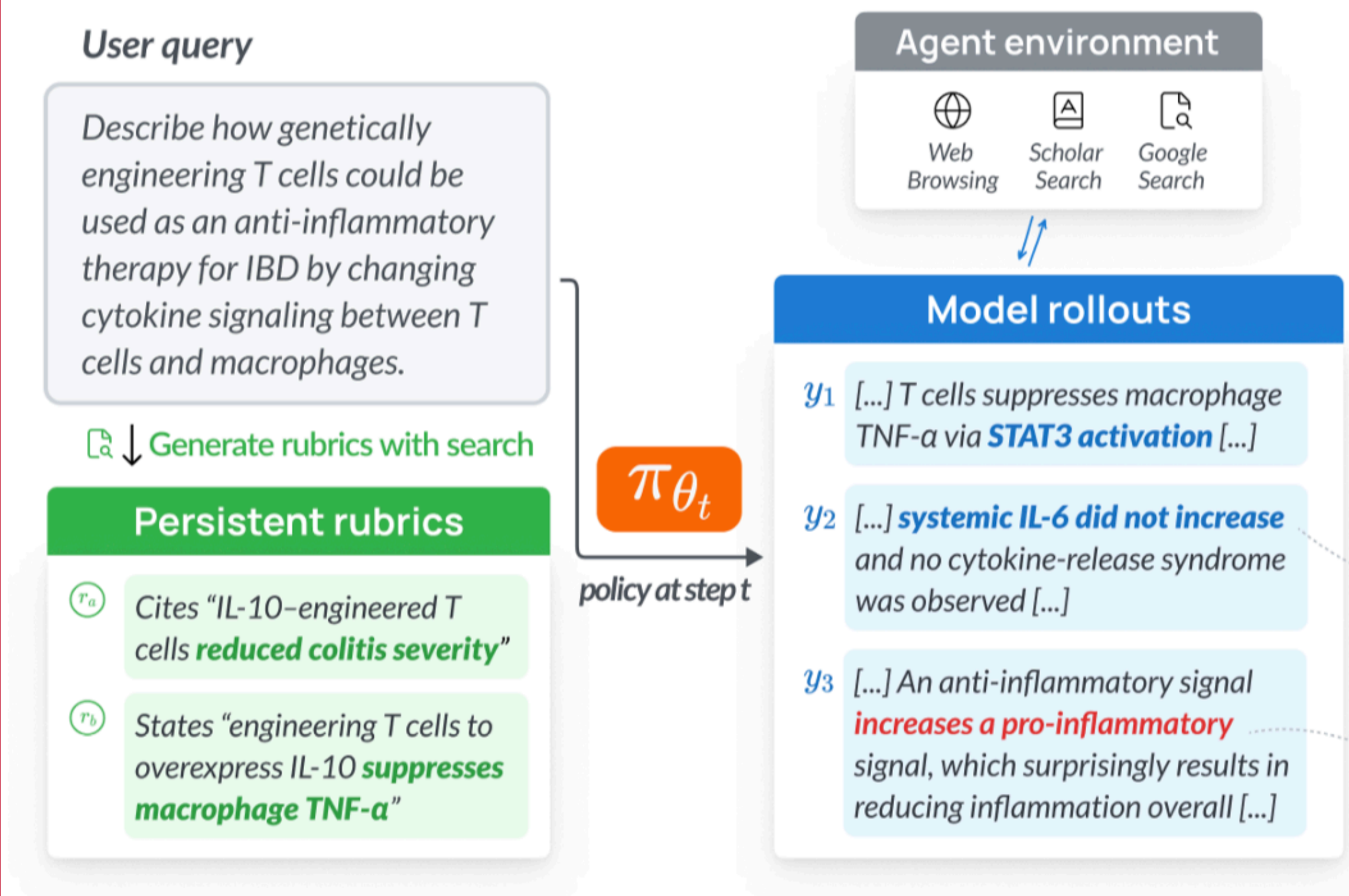
Describe how genetically engineering T cells could be used as an anti-inflammatory therapy for IBD by changing cytokine signaling between T cells and macrophages.

🔍 ↓ Generate rubrics with search

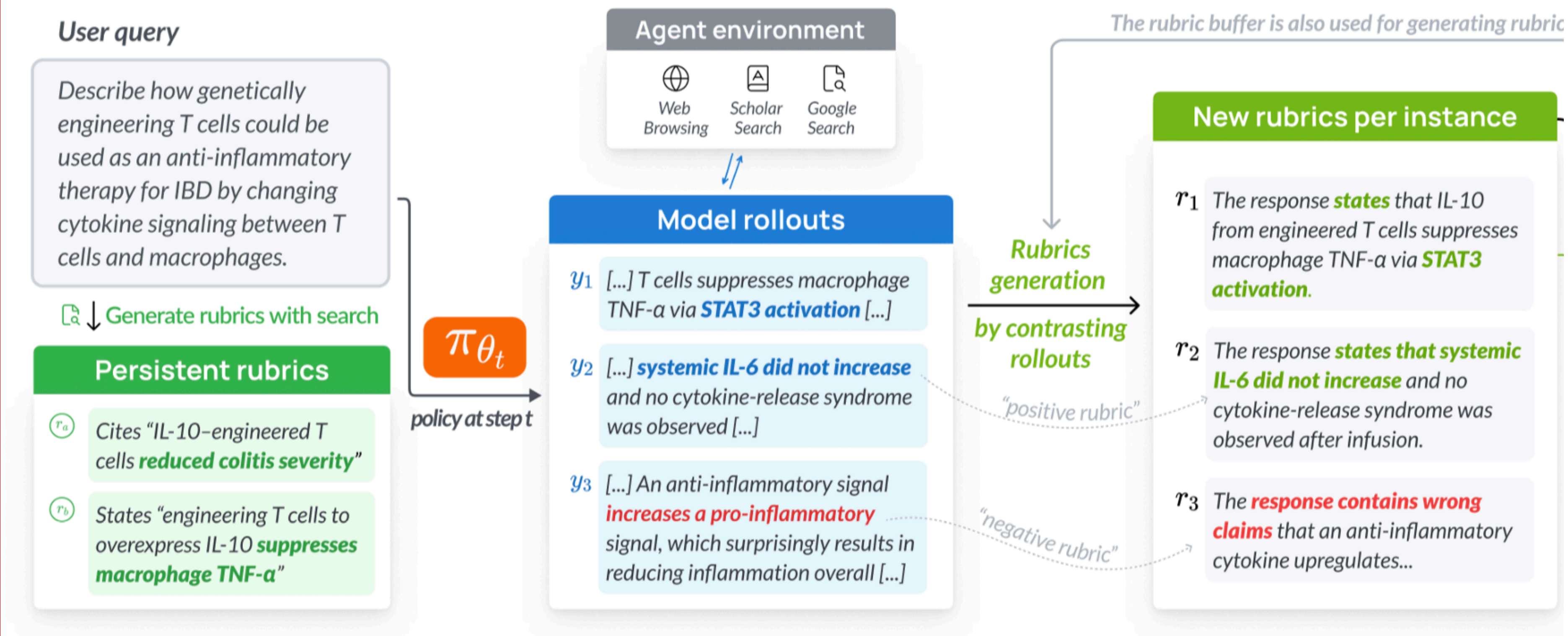
Persistent rubrics

- r_a Cites "IL-10-engineered T cells **reduced colitis severity**"
- r_b States "engineering T cells to overexpress IL-10 **suppresses macrophage TNF- α** "

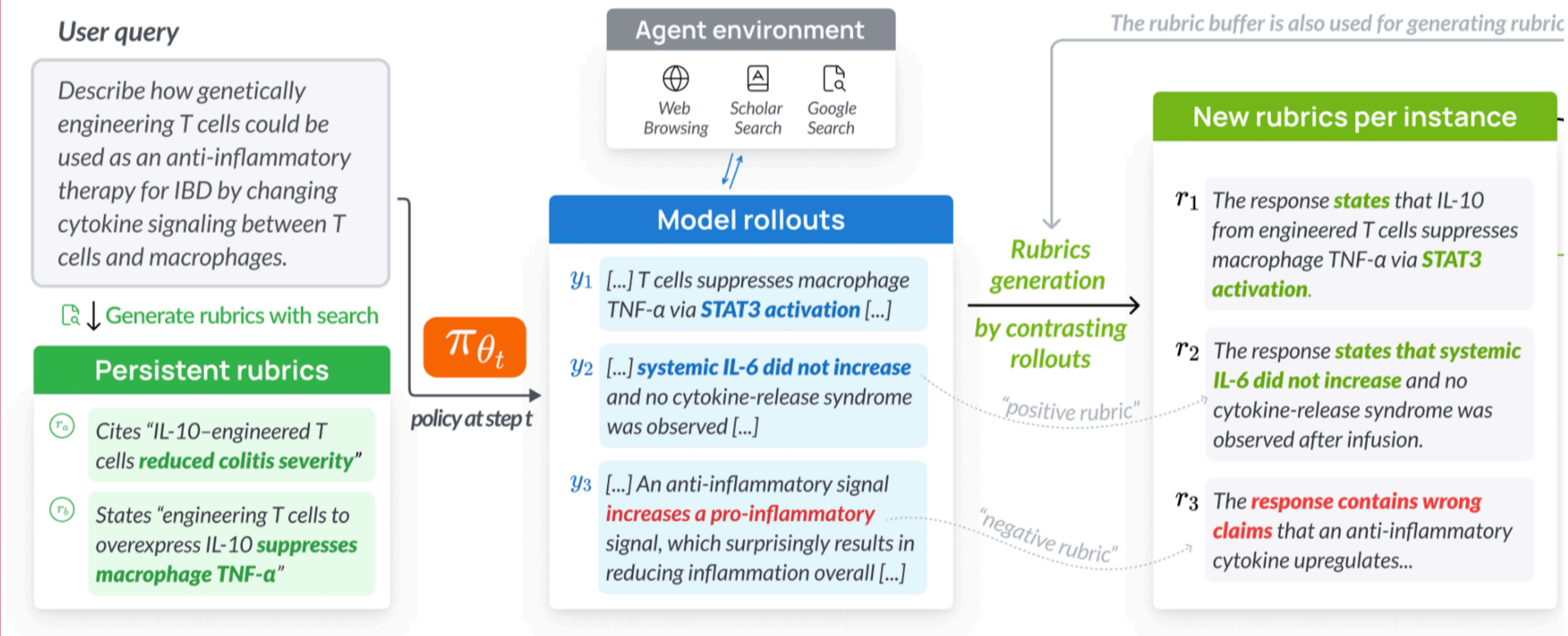
Rubrics Evolve as the Agent Discovers Better Answers



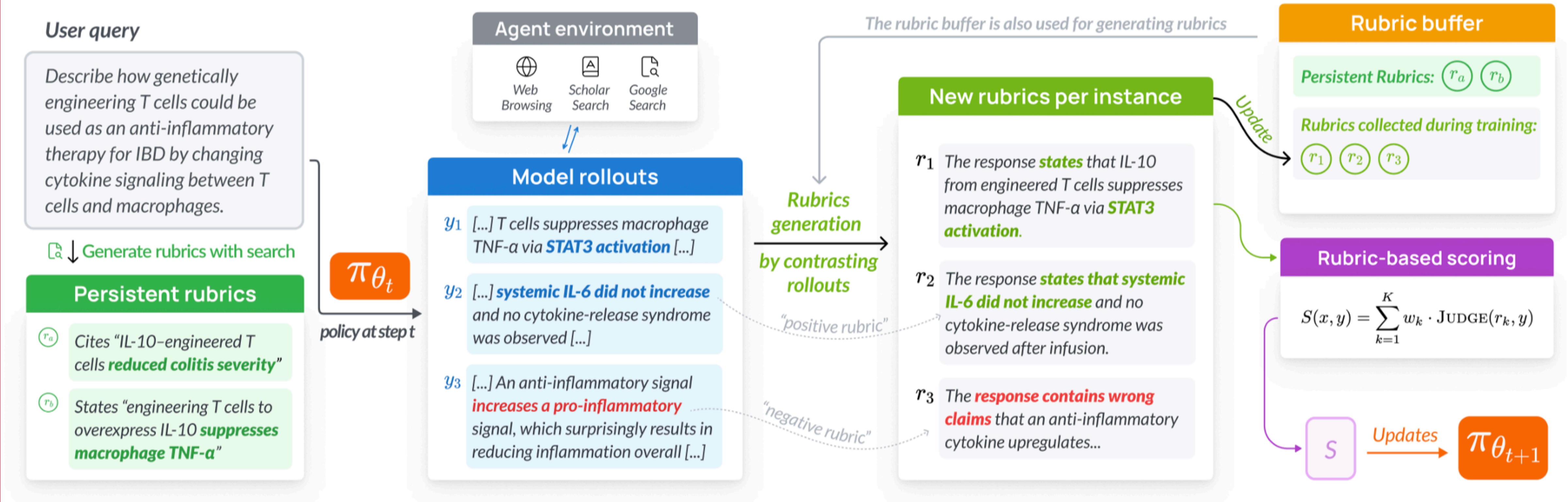
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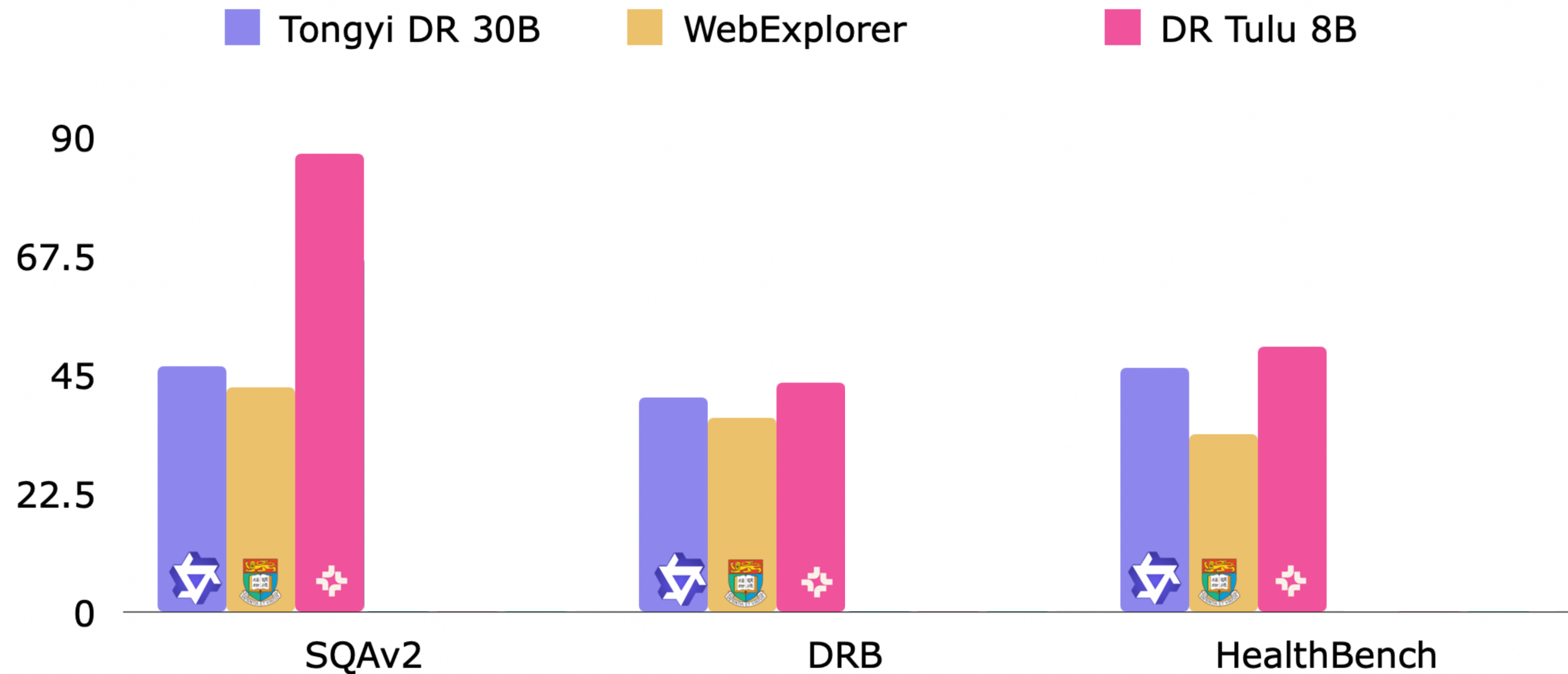
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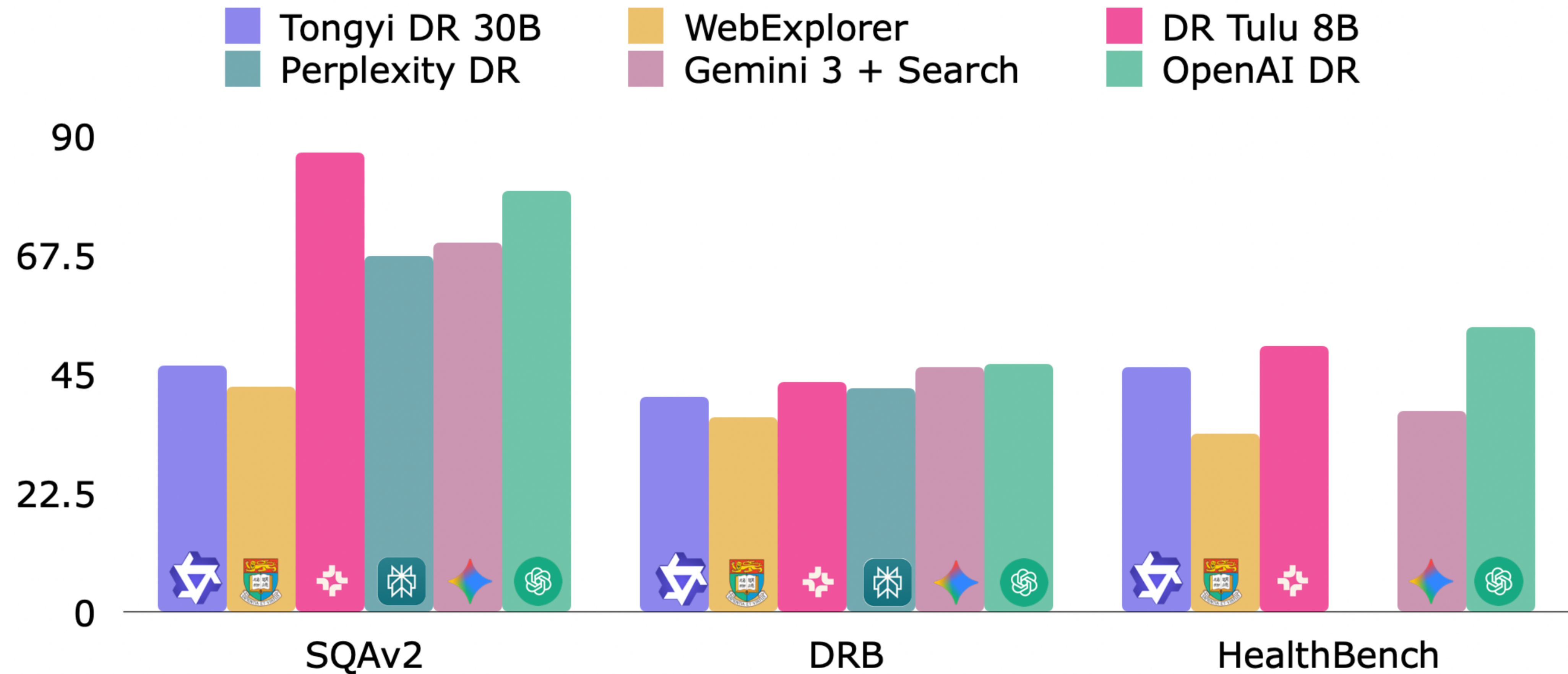
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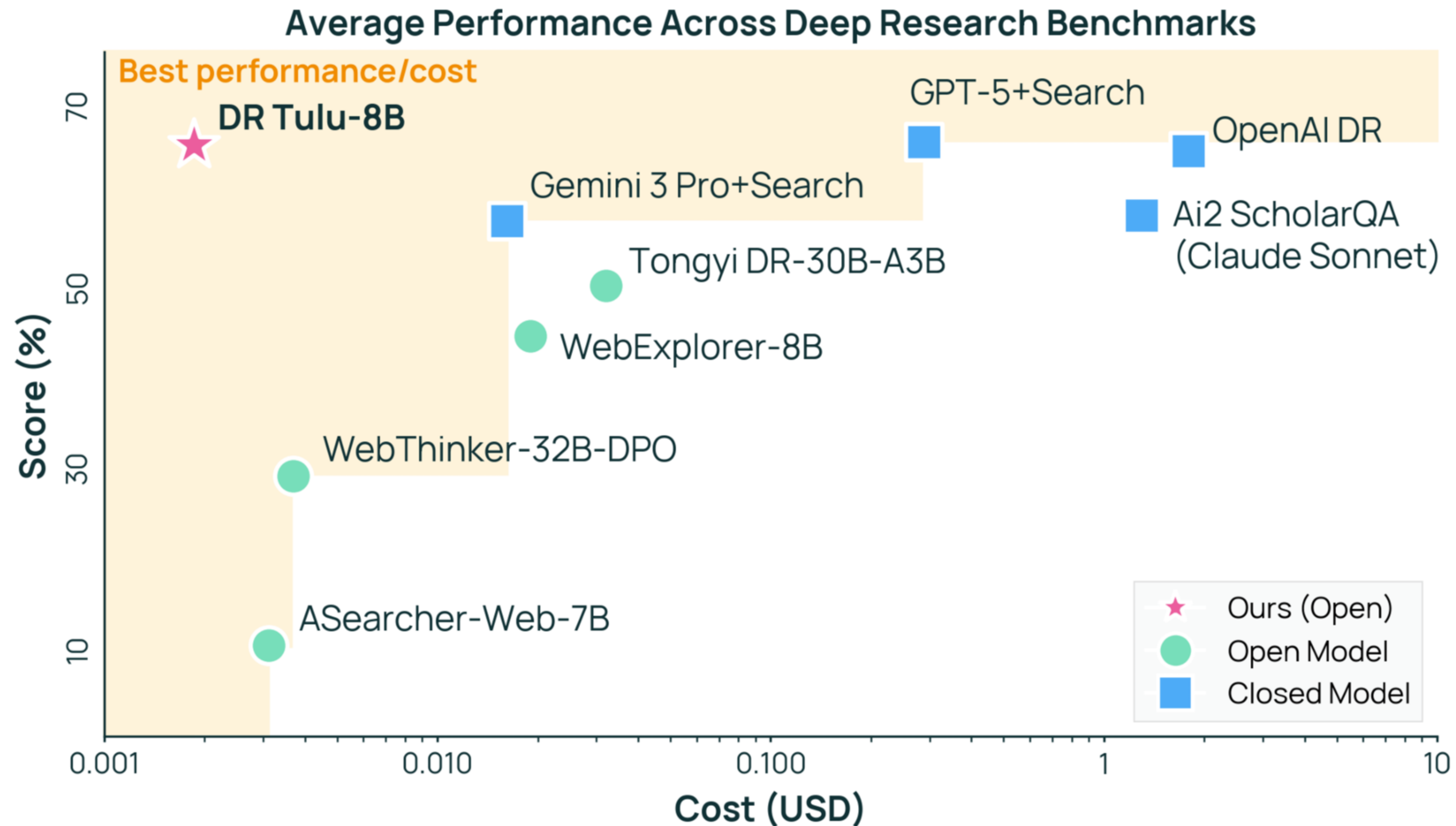
DR Tulu Achieves SOTA on Long-Form DR Benchmarks



Open Deep-Research Agents Can Compete with Frontier Systems

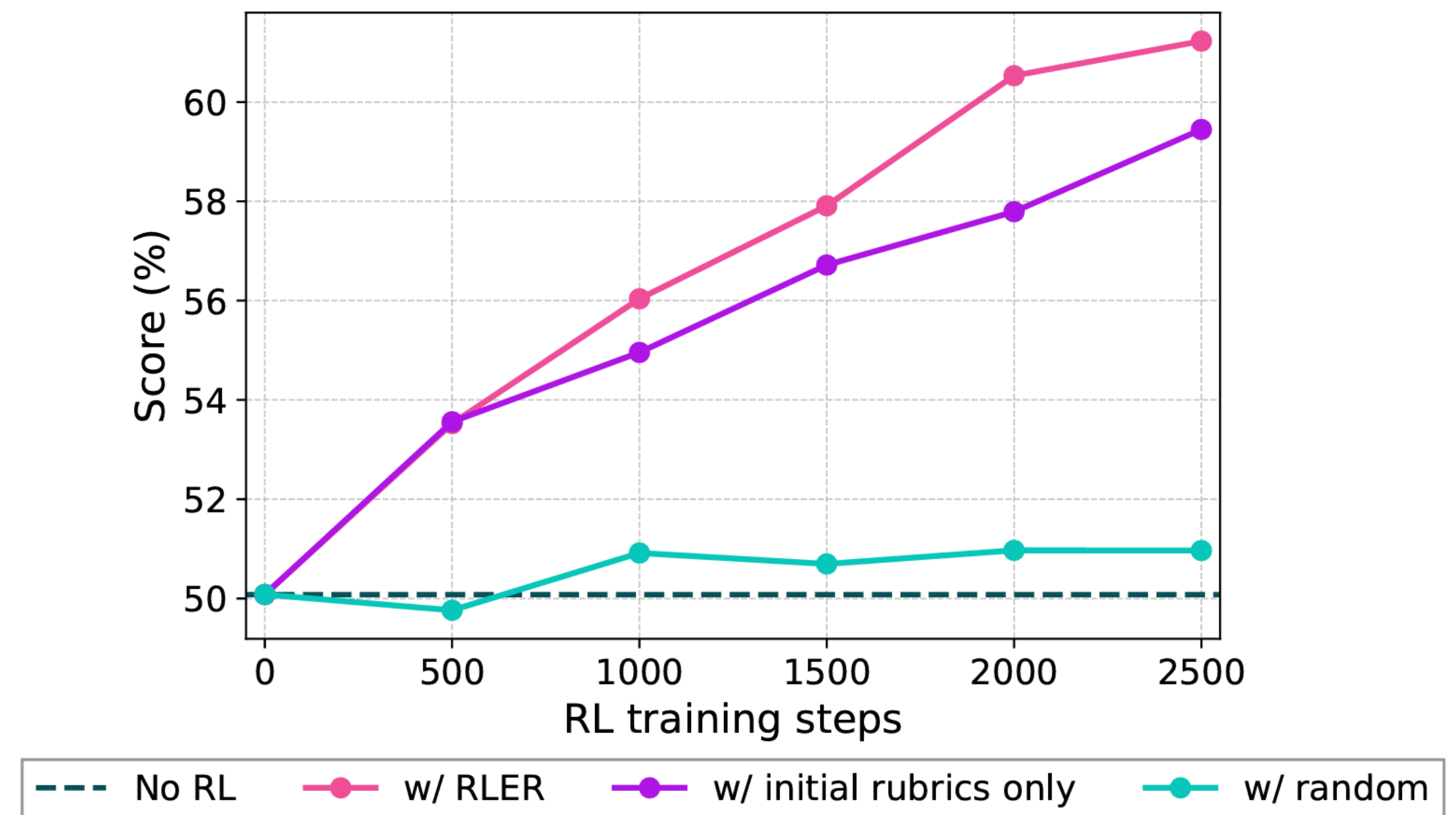
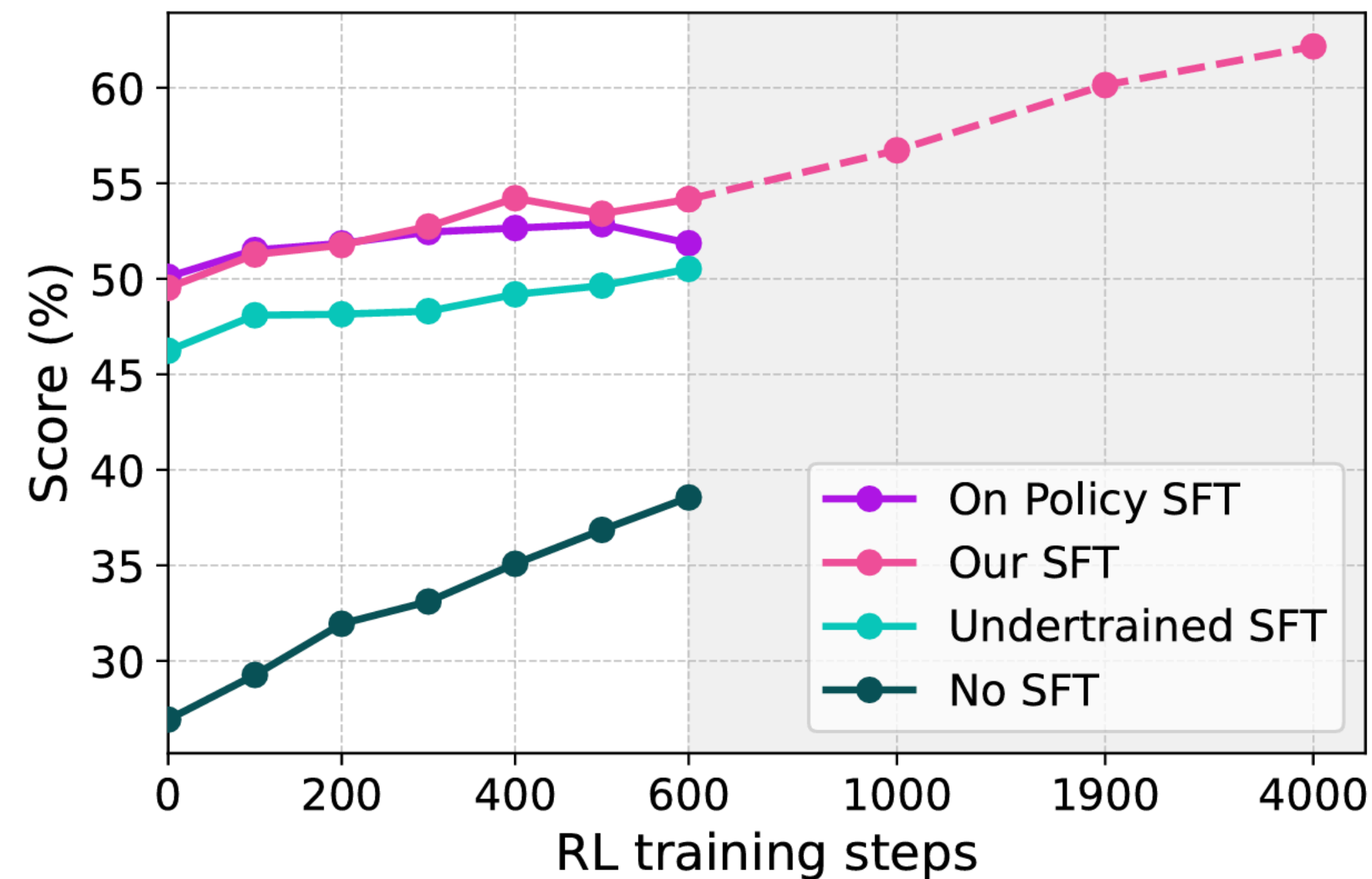


Open Deep-Research Agents Can Compete with Frontier Systems



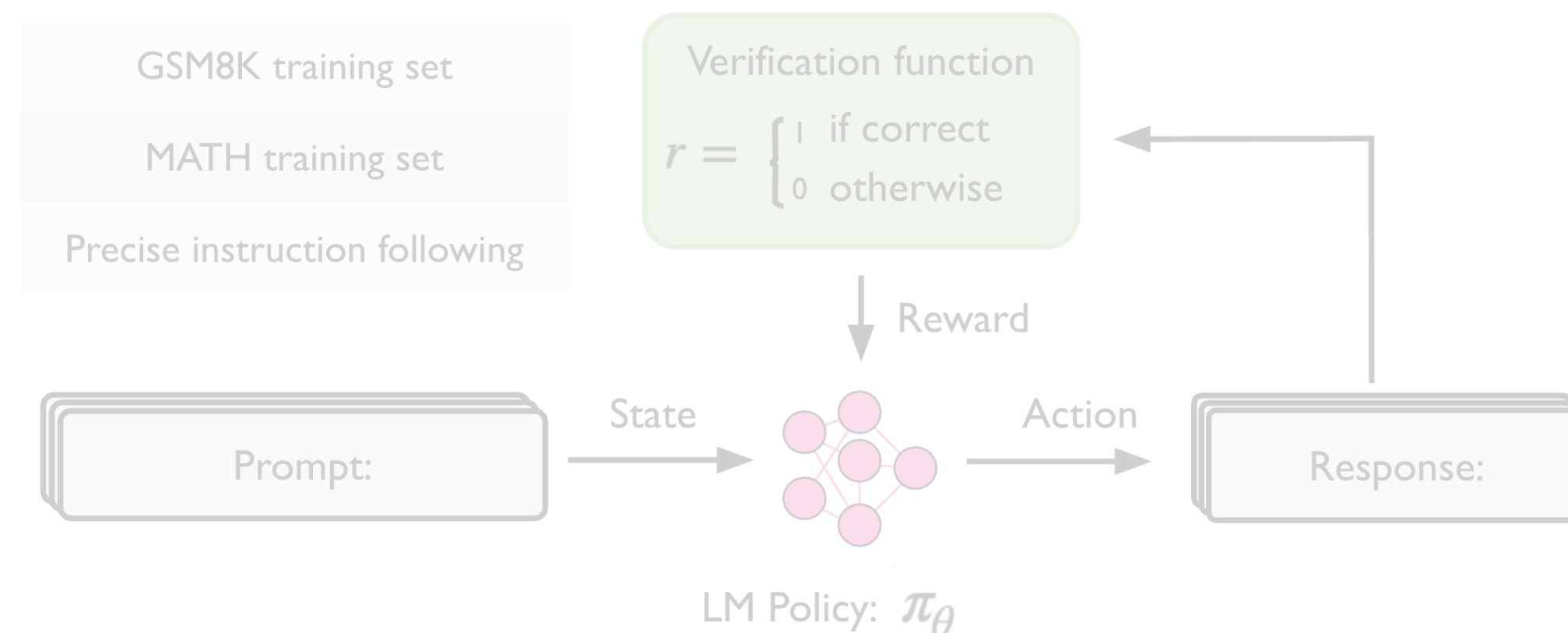
Longer RL Continues to Improve Research Performance

Performance continues to improve beyond 3k RL steps



Two Challenges in Co-Designing Deep Research Systems

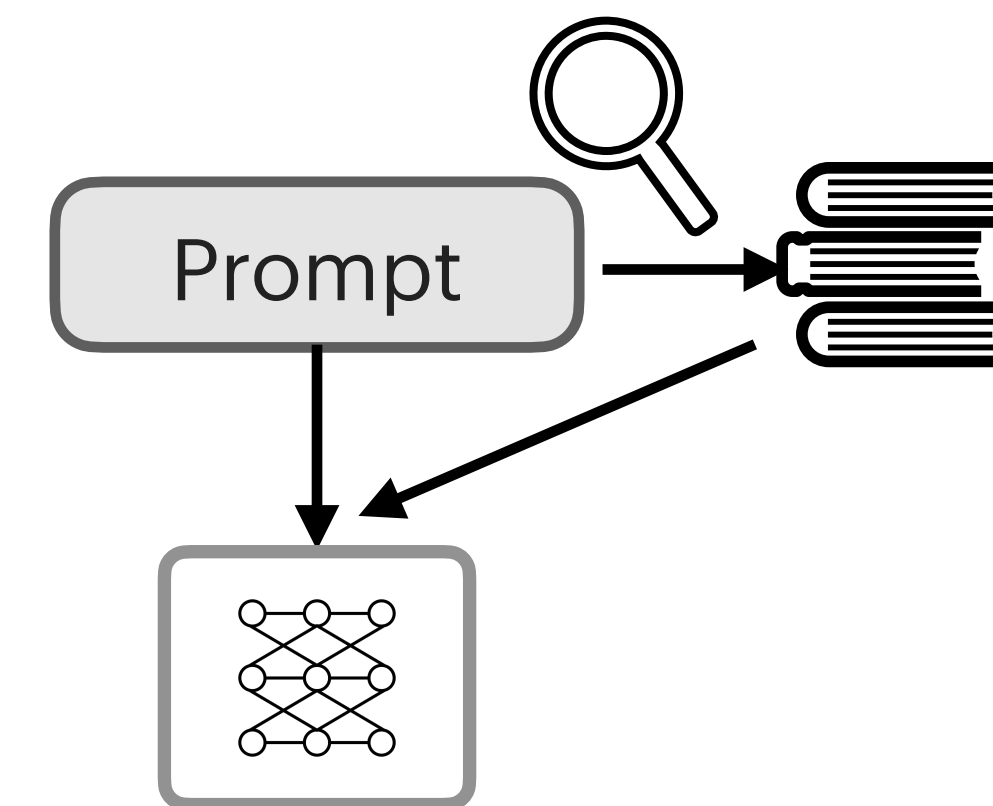
Agent Learning



Relies on **RL with Verifiable Rewards (RLVR)**

How can agents learn from open-ended, hard-to-verify research outcomes?

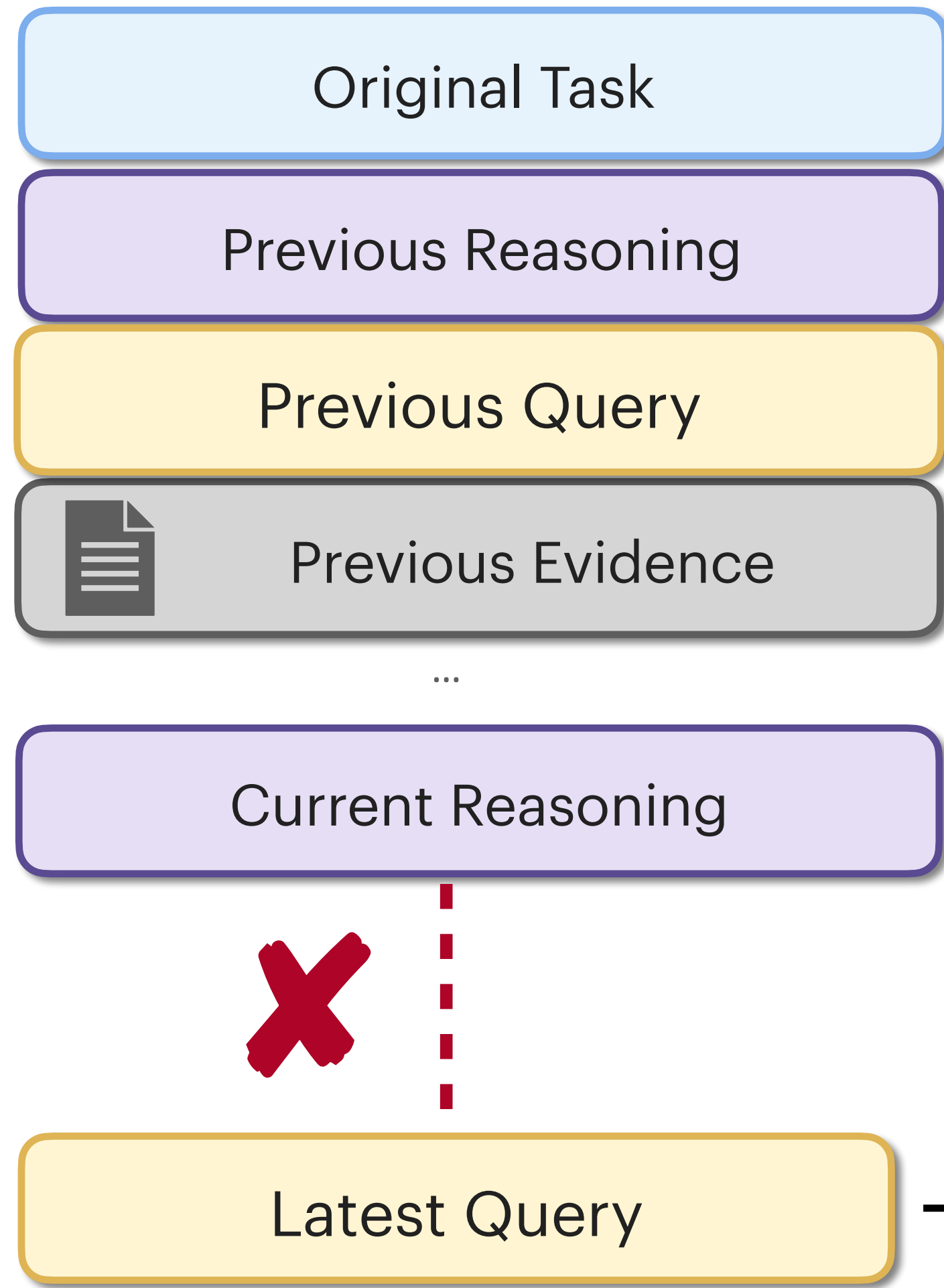
Retrieval



Relies on **retrievers optimized for human queries or static RAG**

How should agents search as their reasoning evolves?

Existing Retrievers See Only the Query



What is the overall goal?

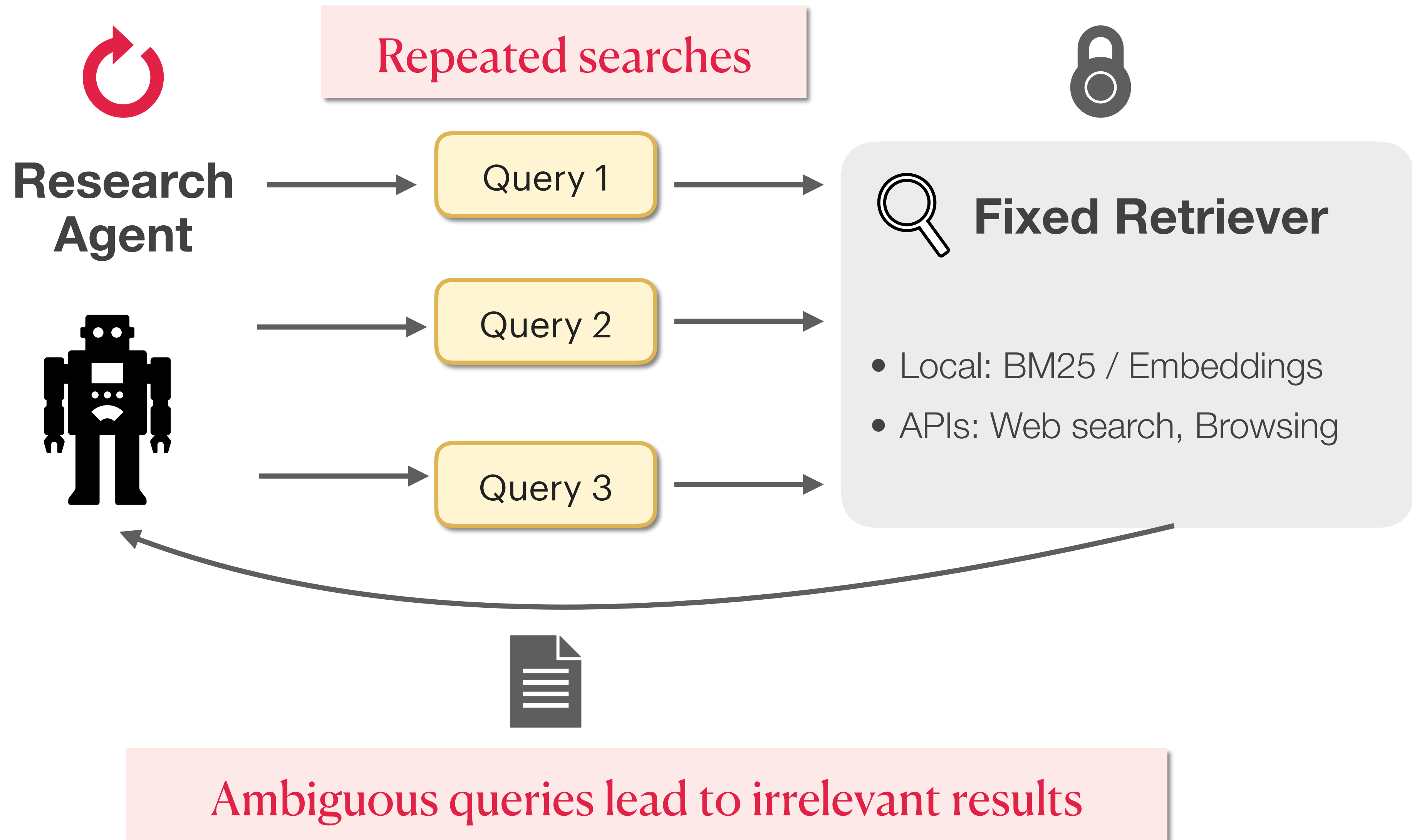
What's already been found?

What evidence is missing?

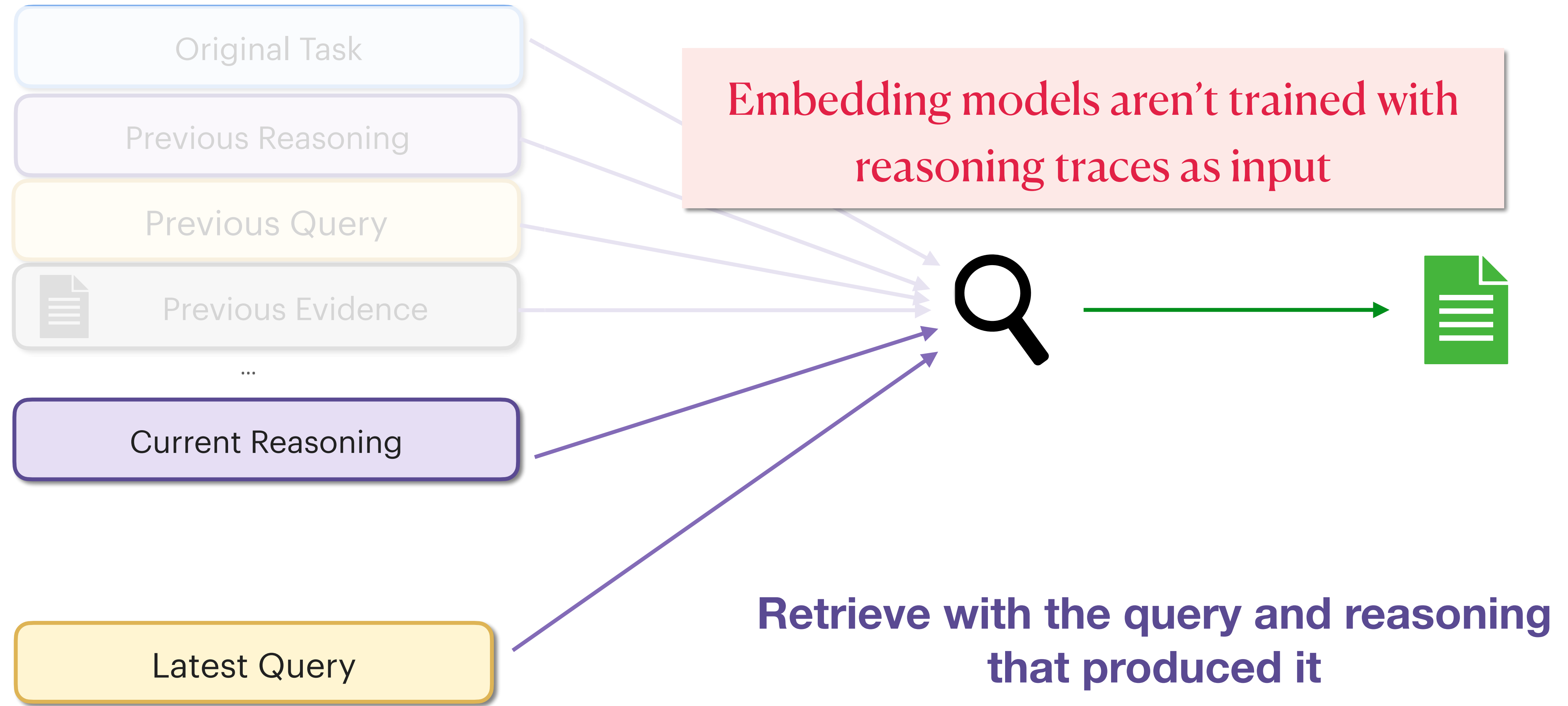
We use only the latest query and
discard all prior context



Deep Research Agents Often Work around Fixed Retrievers

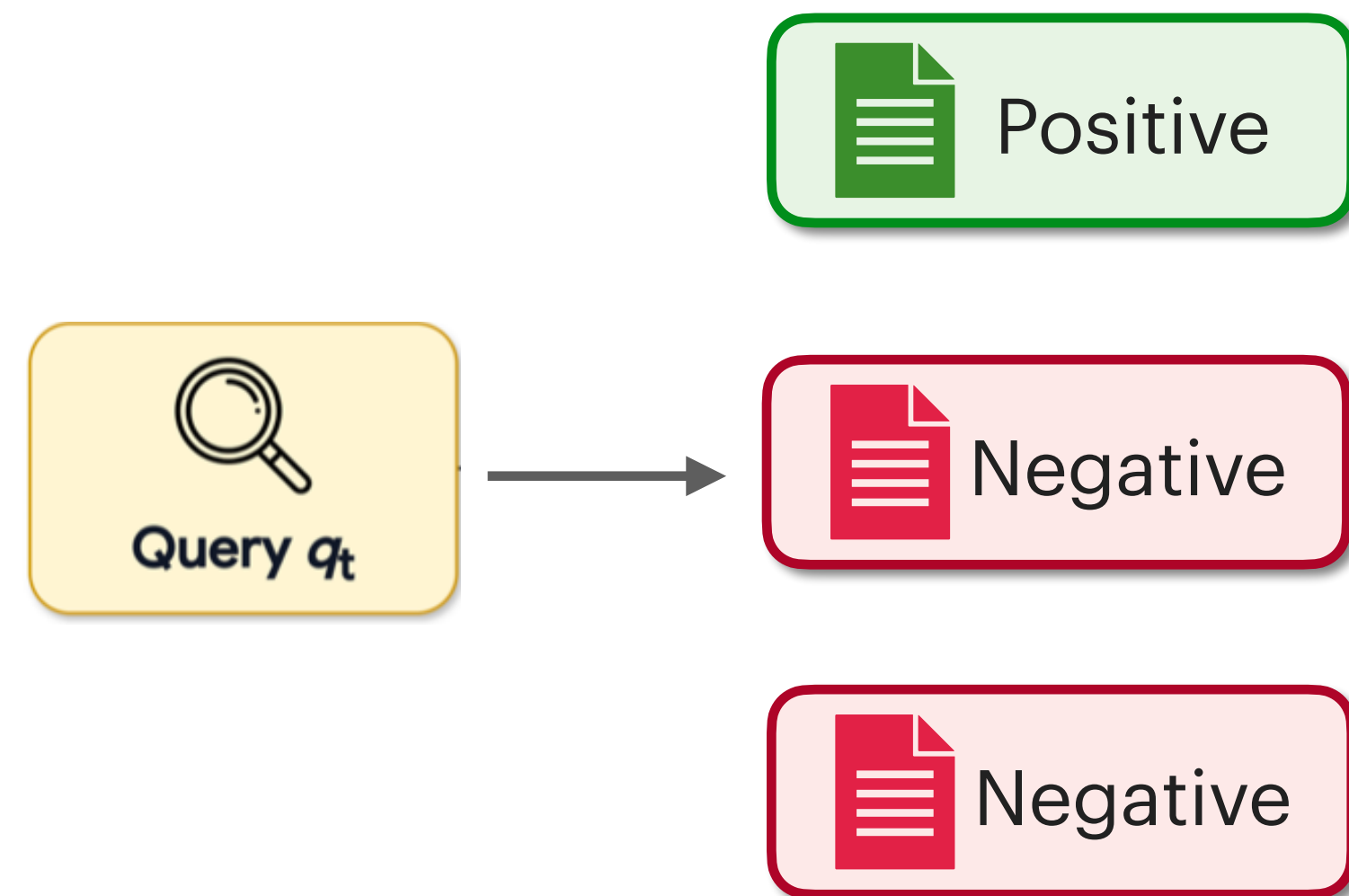


Reasoning-Aware Retrieval Leverages the Agent's History



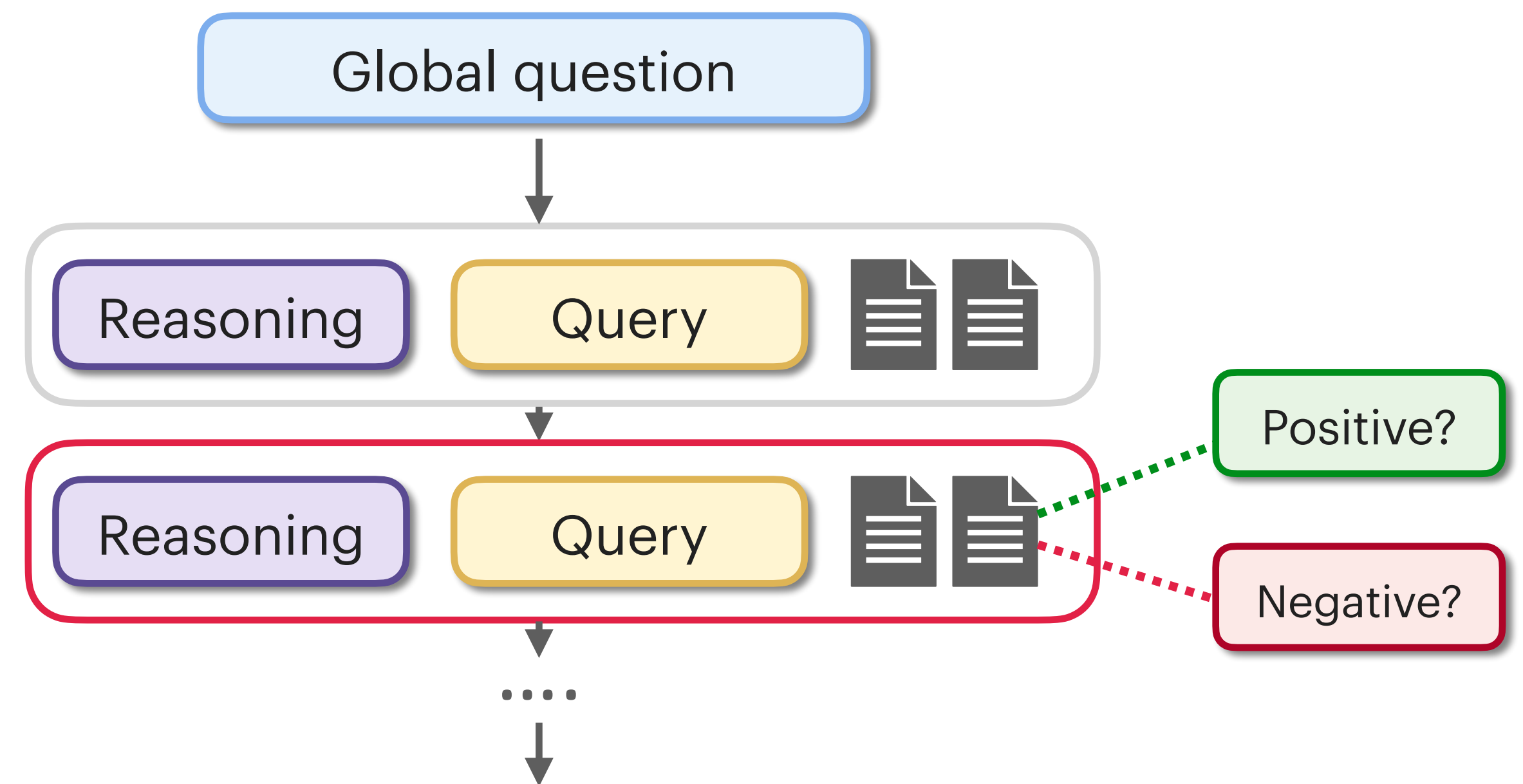
Deep Research Has No Labels for Intermediate Searches

Standard Retriever Training



Relevance labels are provided or easily inferred (e.g., including answer strings)

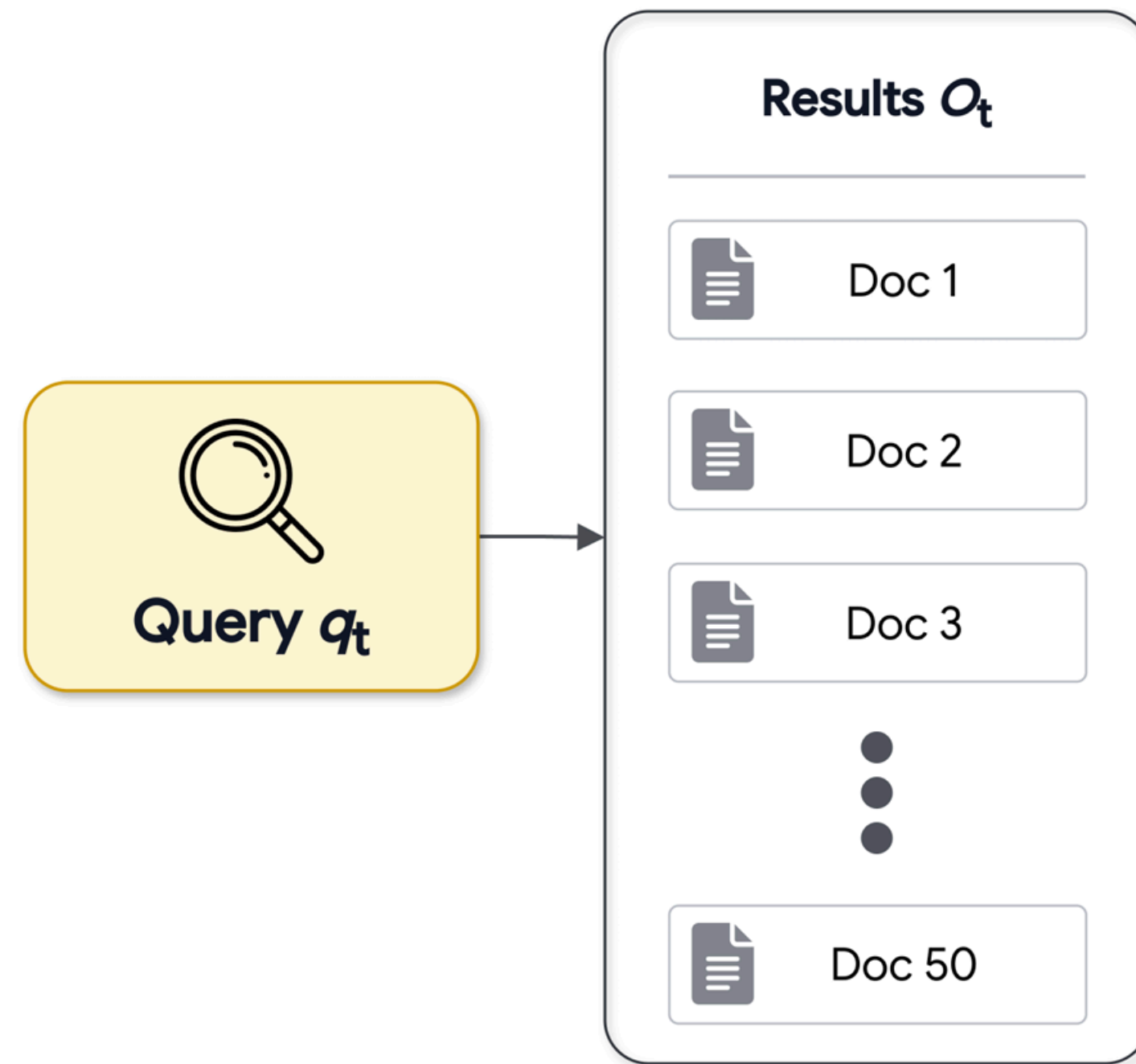
Deep Research Trajectory



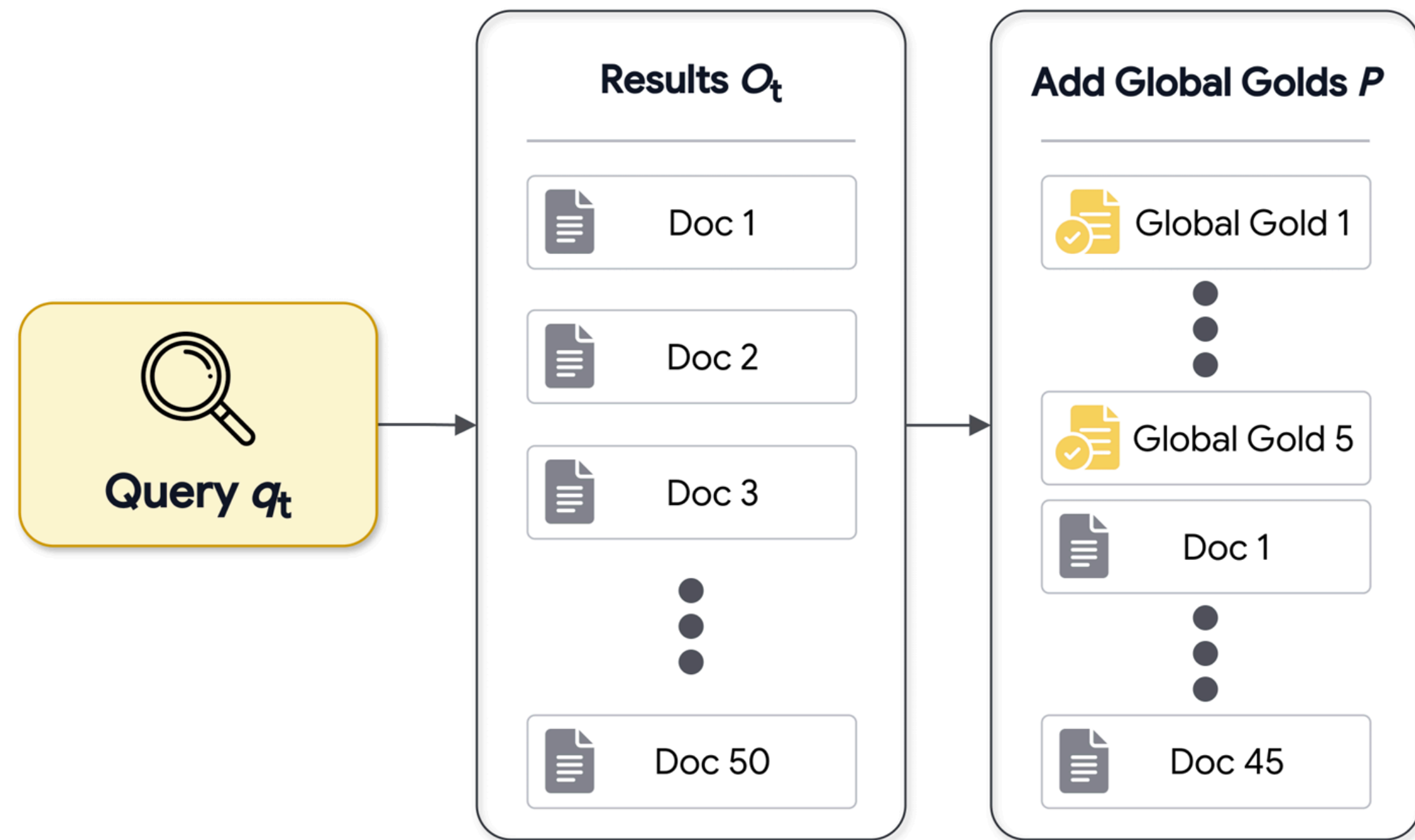
Intermediate searches have no local labels

The trajectory gives us queries but not the supervision to train a retriever

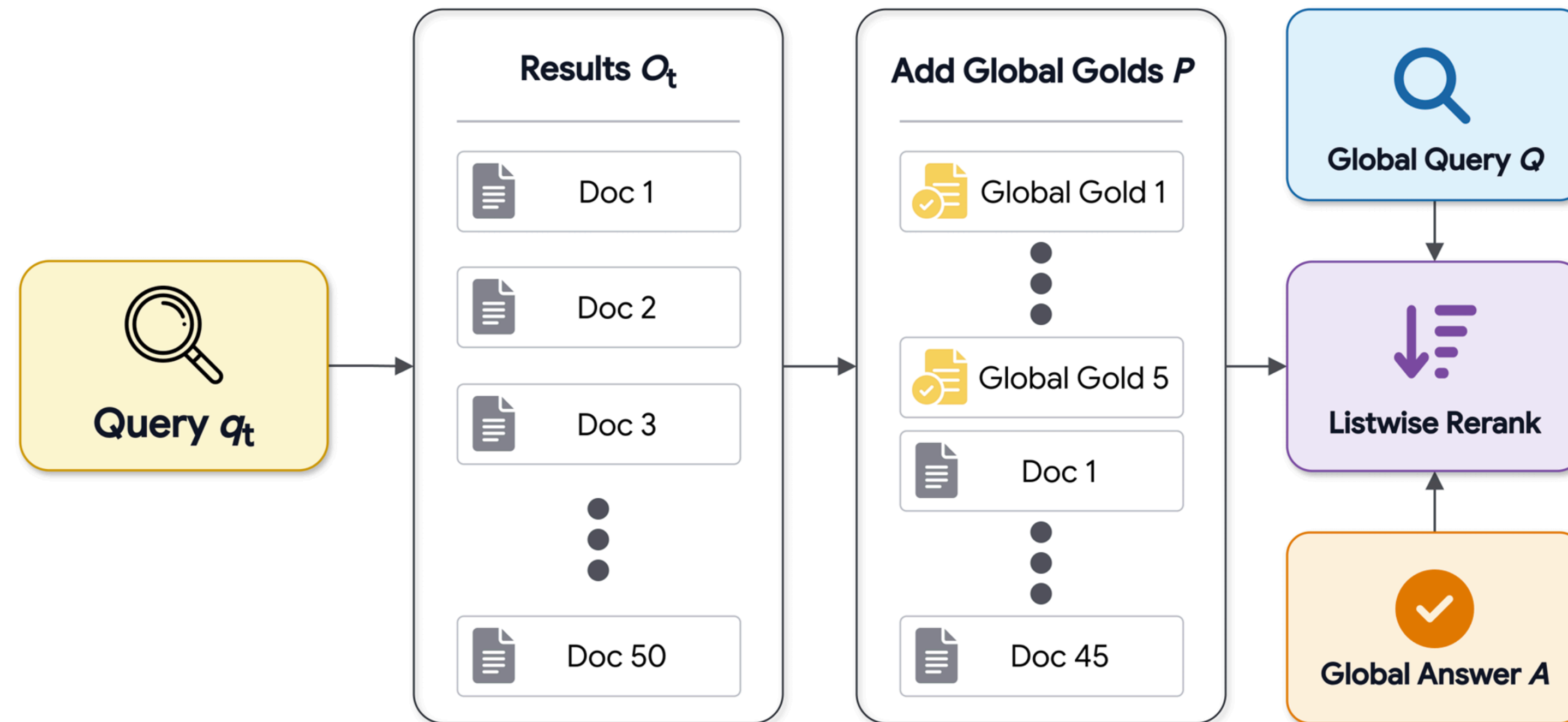
DR-Synth Trains Retrievers on Agent-Generated Information Needs



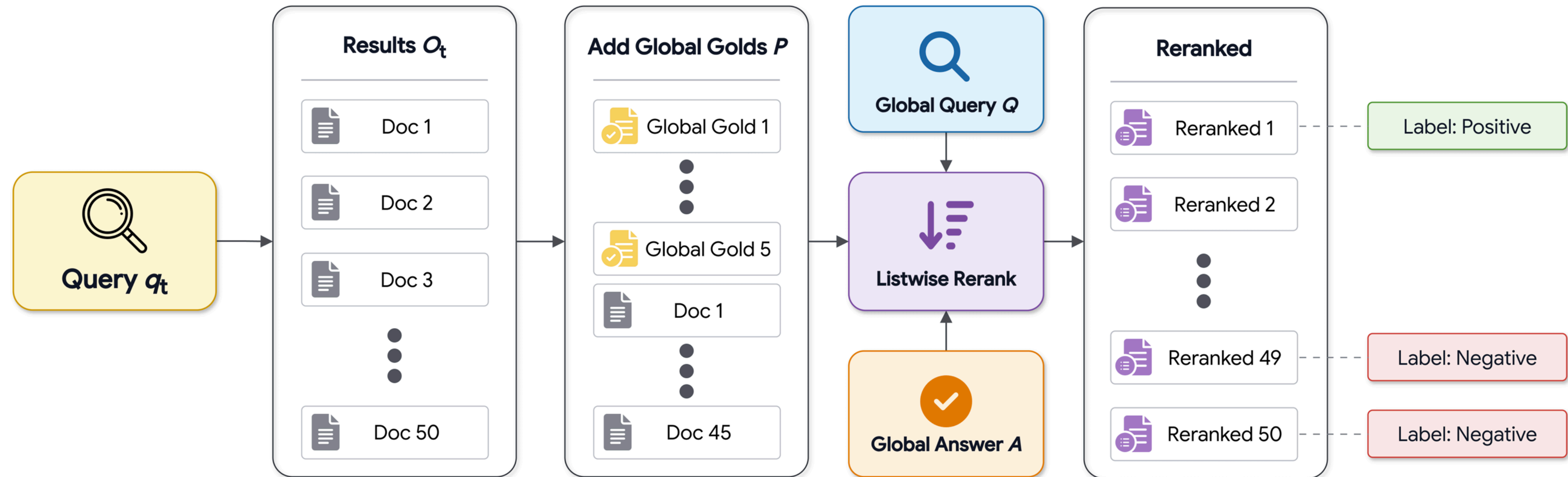
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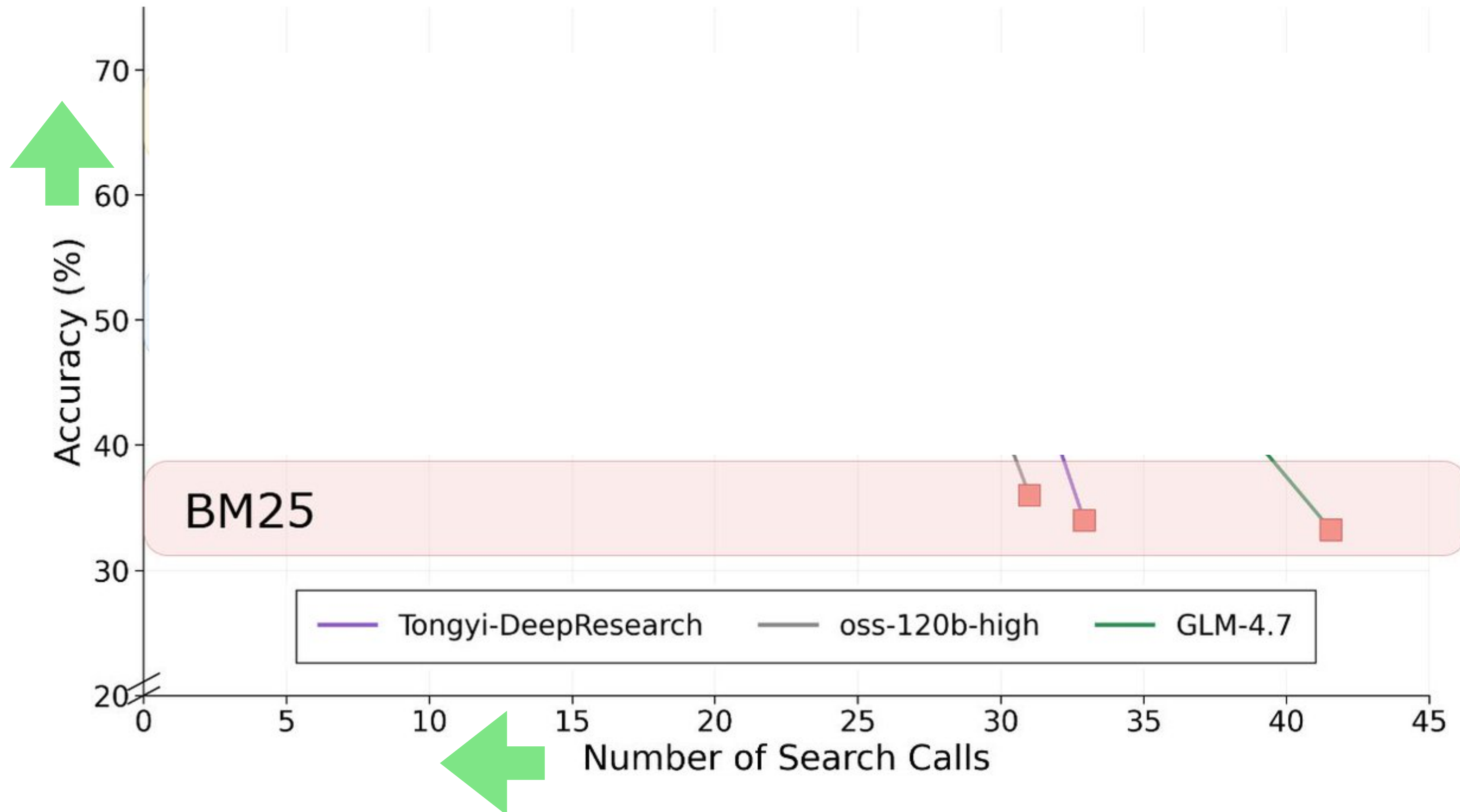
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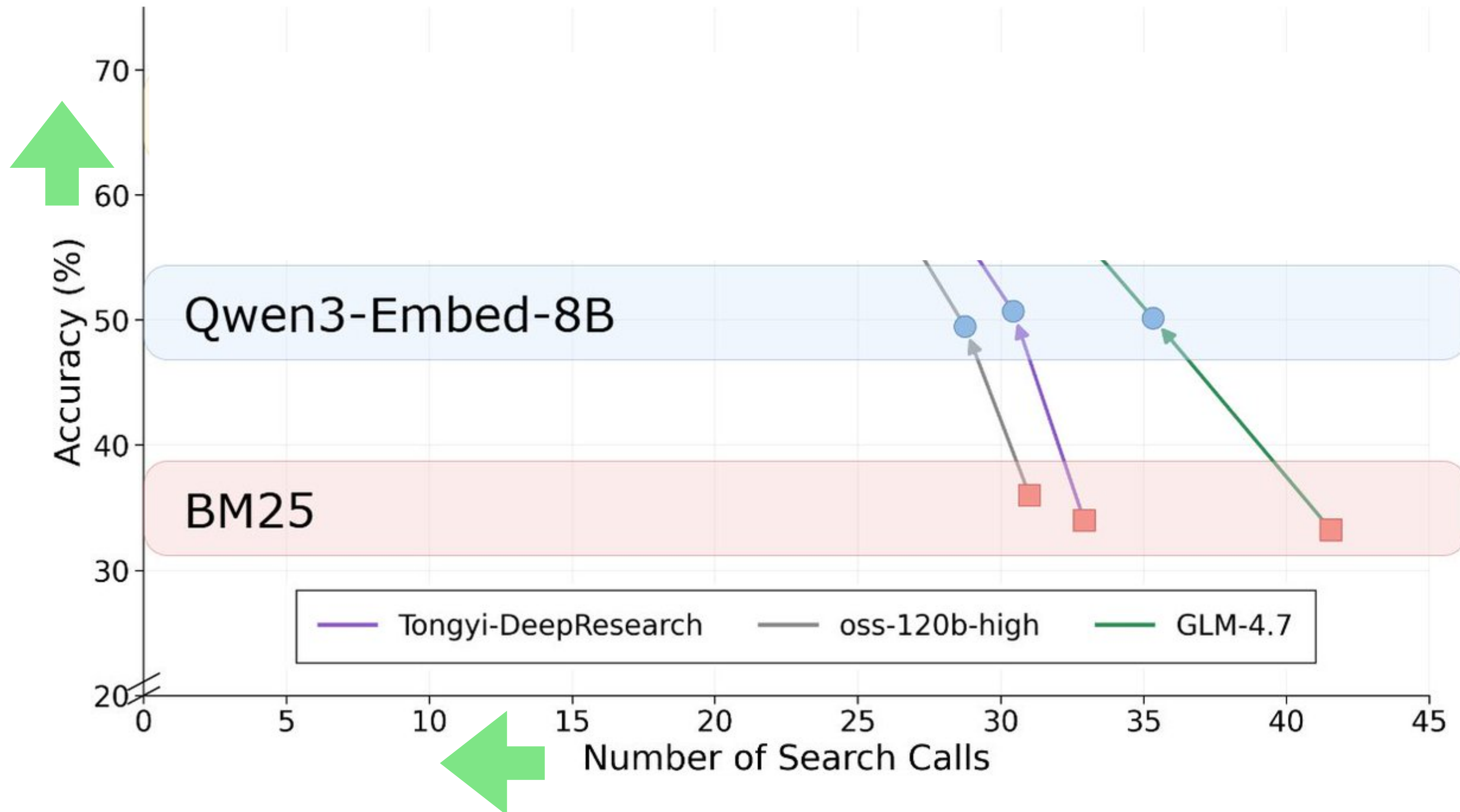
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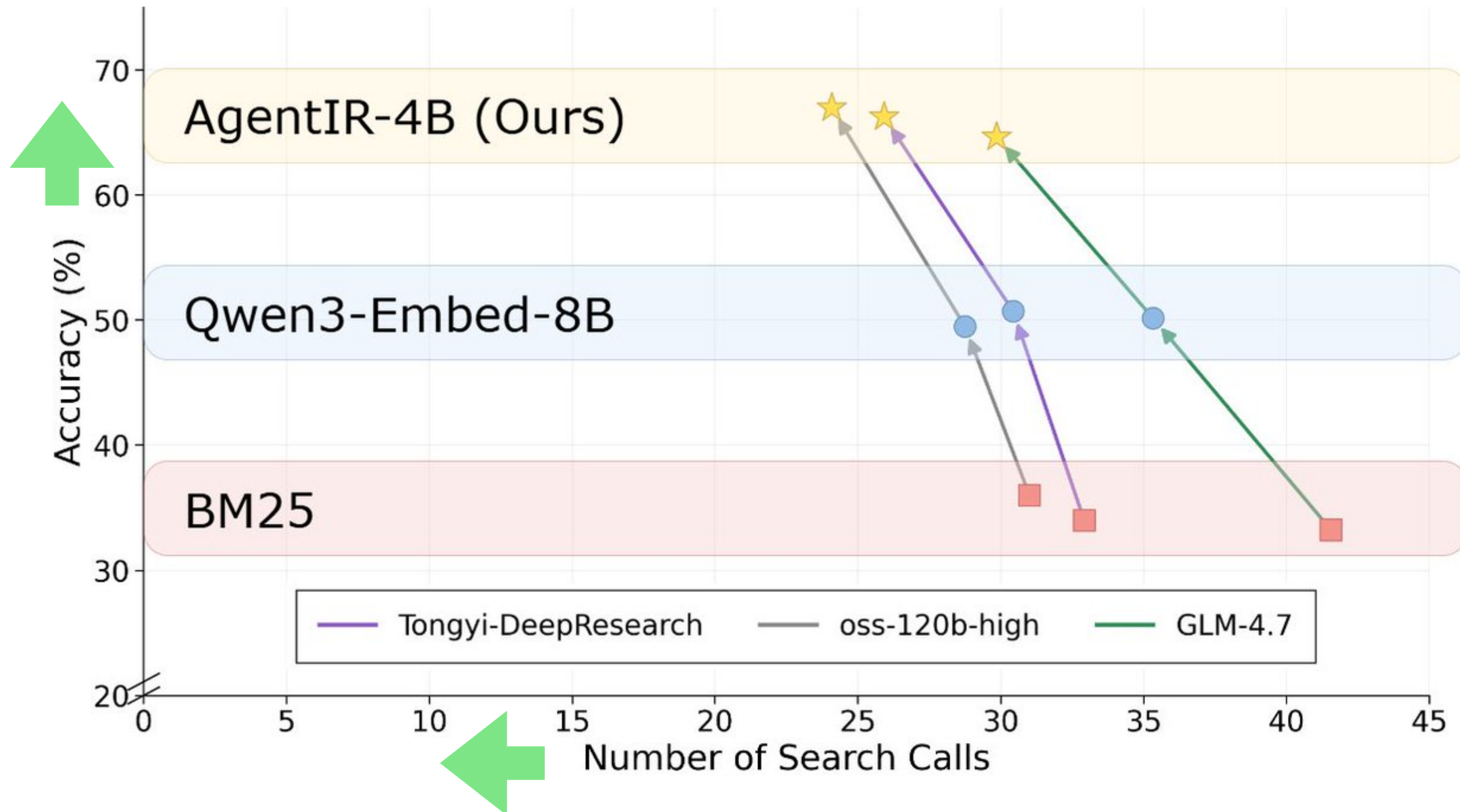
AgentIR Finds More Evidence with Fewer Searches



AgentIR Finds More Evidence with Fewer Searches

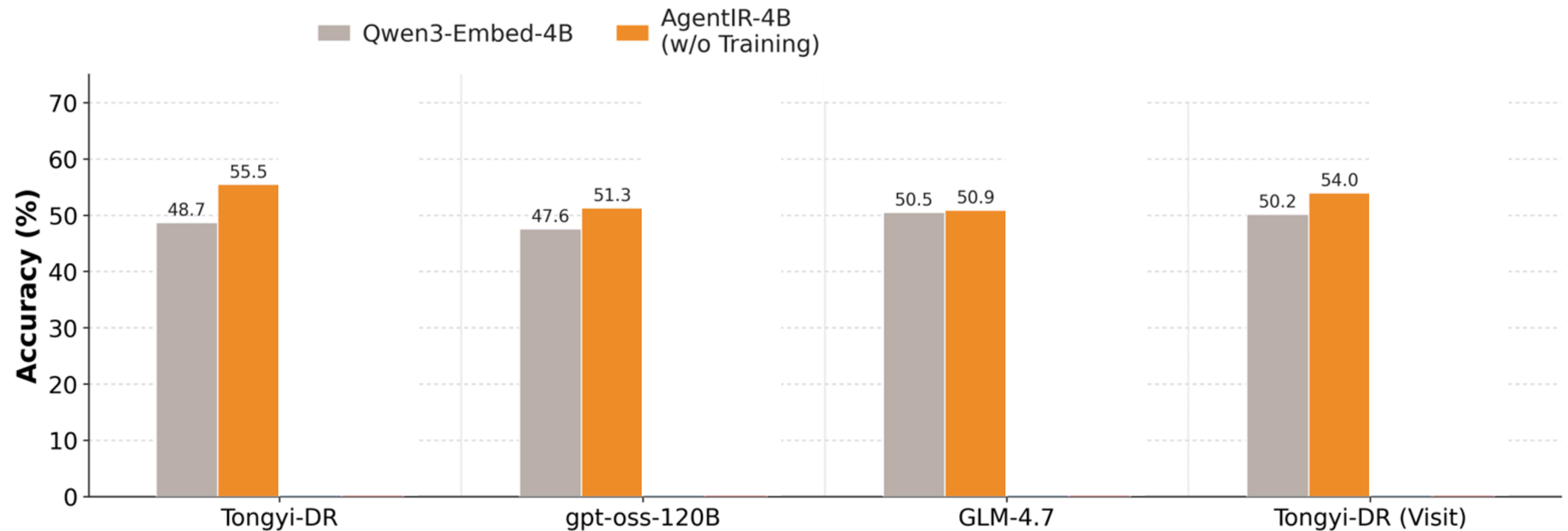


AgentIR Finds More Evidence with Fewer Searches



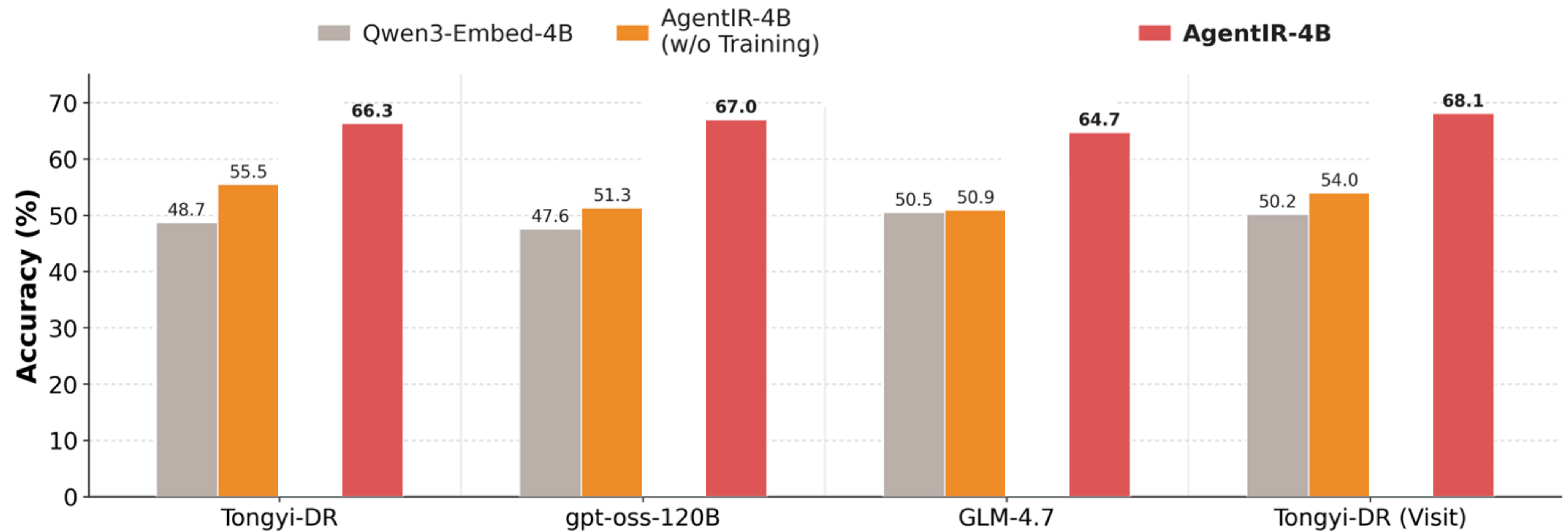
Ablation: Effectiveness of Reasoning-Aware Retrieval

Simply augmenting queries with reasoning traces during inference helps



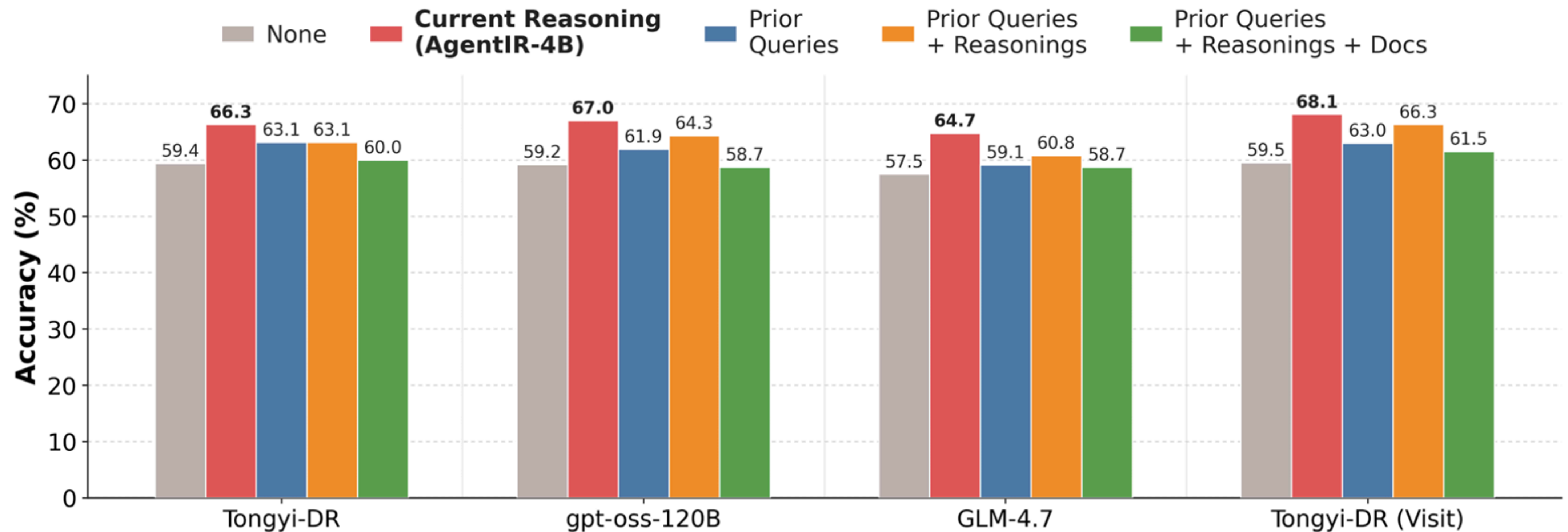
Ablation: Effectiveness of DR-Synth

DR-Synth training + reasoning-aware retrieval provides the largest gain



Ablation: Alternative Source of Retrieval Signals

Current reasoning provides the strongest retrieval signal



Deep Research Requires Co-Designing Agents and Retrievers

DR Tulu:
Train research agents

Learn from open-ended research
outcomes

AgentIR:
Redesign retrieval for agents

Retrieve for evolving information needs



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