

On Memory, Reasoning, and Planning of Language Agents

Yu Su
The Ohio State University

The rise, and the divide

Bill

Agents are bringing about the **biggest revolution in computing** since we went from typing commands to tapping on icons.

Andrew

I think AI agentic workflows will drive **massive AI progress** this year.

Sam

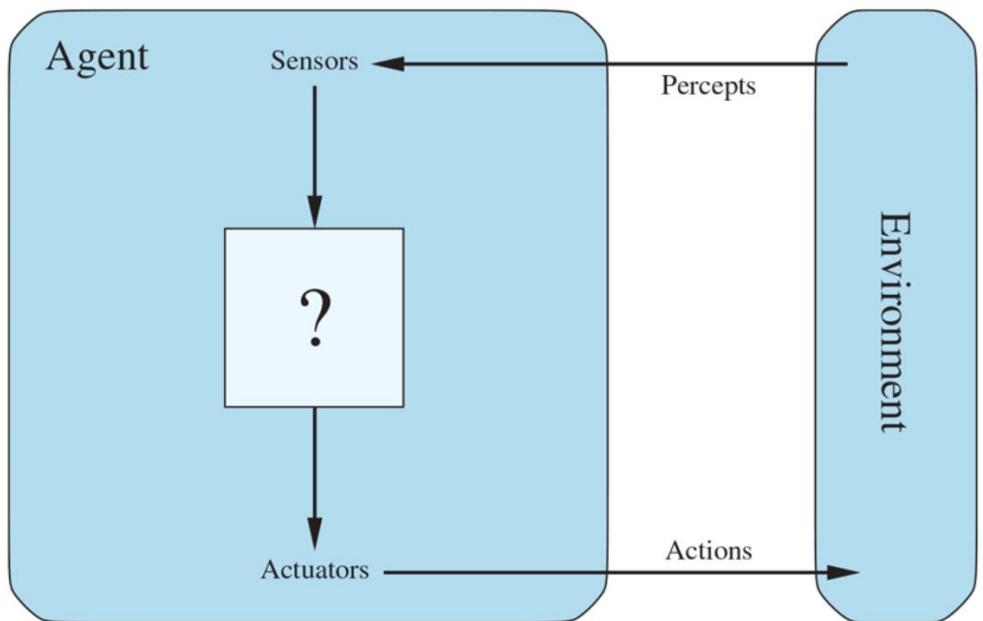
AI agents will work.

Current agents are just thin wrappers around LLMs.

Autoregressive LLMs can never reason or plan.

Auto-GPT's limitations in ... reveal that it is far from being a practical solution.

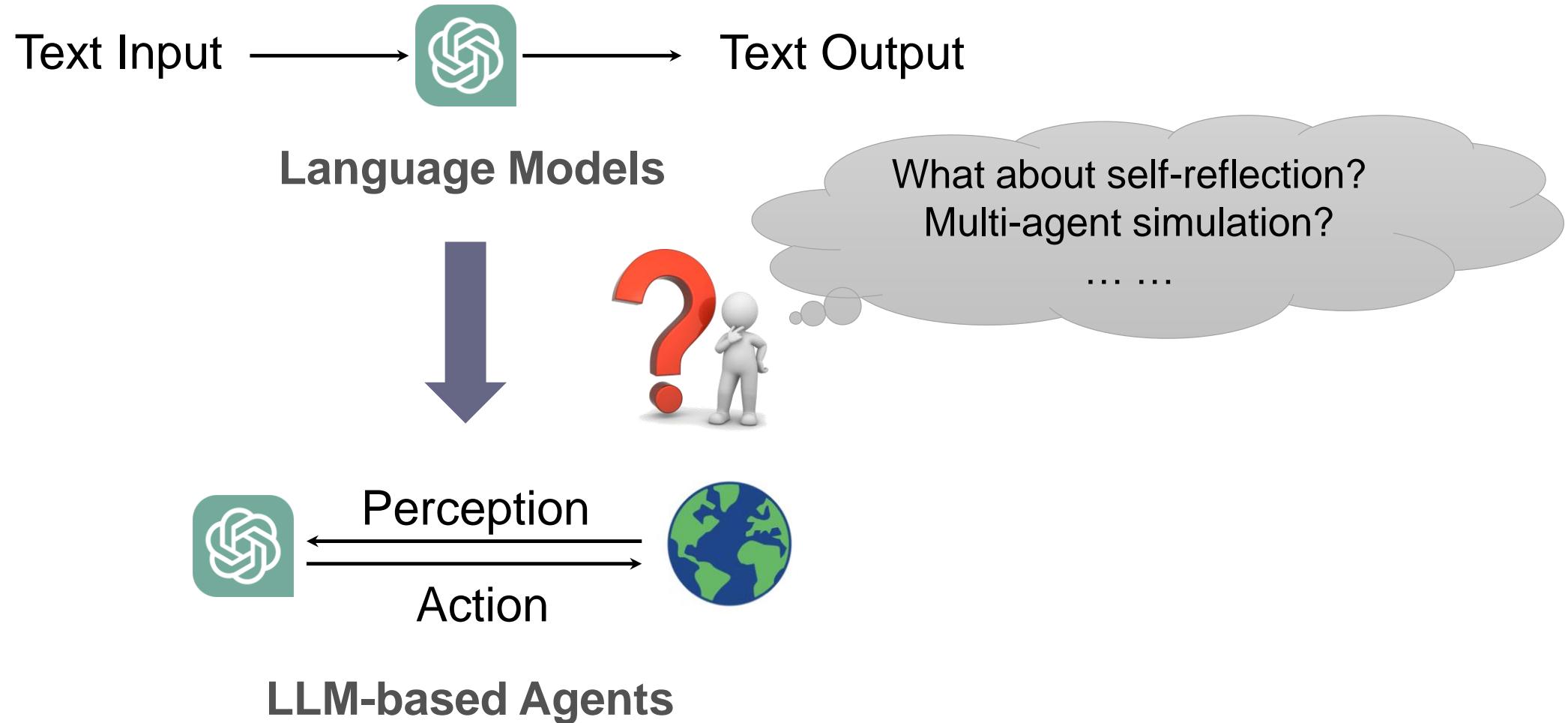
Why agents again?



"An **agent** is anything that can be viewed as perceiving its **environment** through **sensors** and acting upon that environment through **actuators**"

— Russel & Norvig, *AI: A Modern Approach*

'Modern' agent = LLM + external environment?



Two competing views

LLM-first view

We make an LLM into an agent!

- *Implications:* scaffold on top of LLMs, prompting-focused, heavy on engineering

Agent-first view

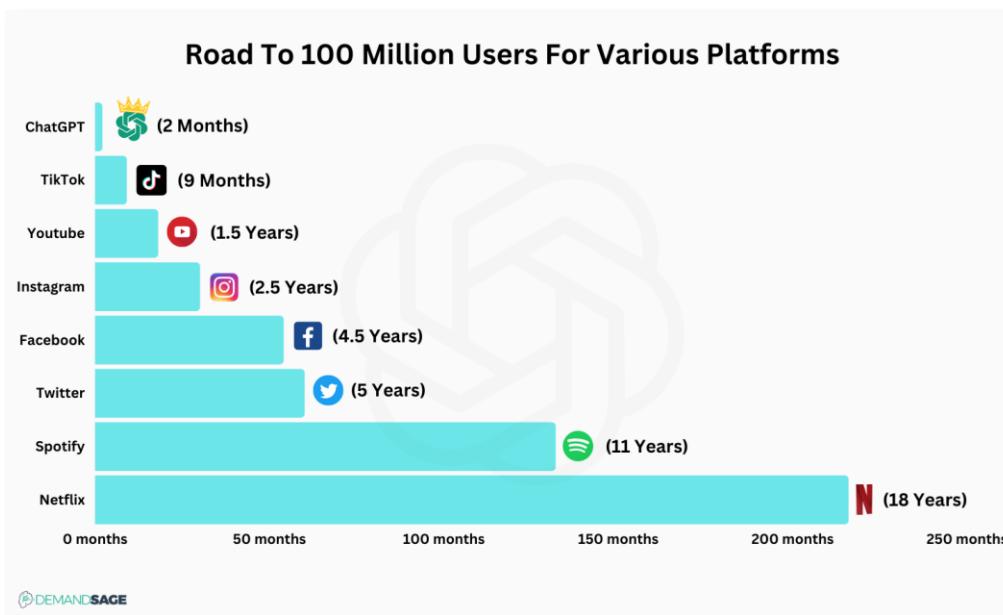
We integrate LLMs into AI agents so they can use language for reasoning and communication!

- *Implications:* All the same challenges faced by previous AI agents (e.g., perception, reasoning, world models, planning) still remain, but we need to **re-examine them through the new lens of LLMs** and tackle new ones (e.g., synthetic data, self-reflection, internalized search)

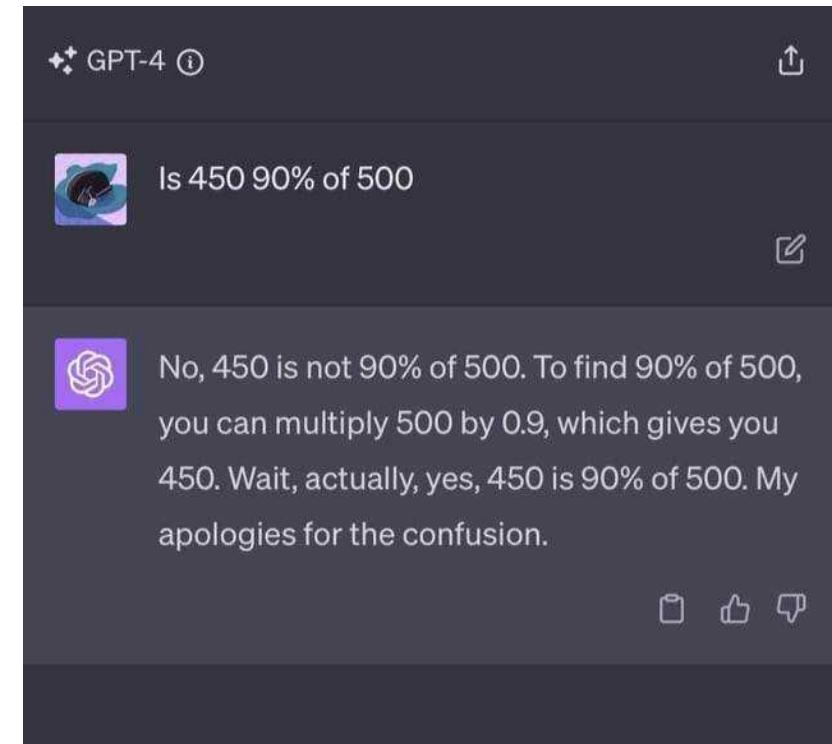
What's fundamentally different now?

Contemporary AI agents, with integrated LLM(s), can *use language as a vehicle for reasoning and communication*

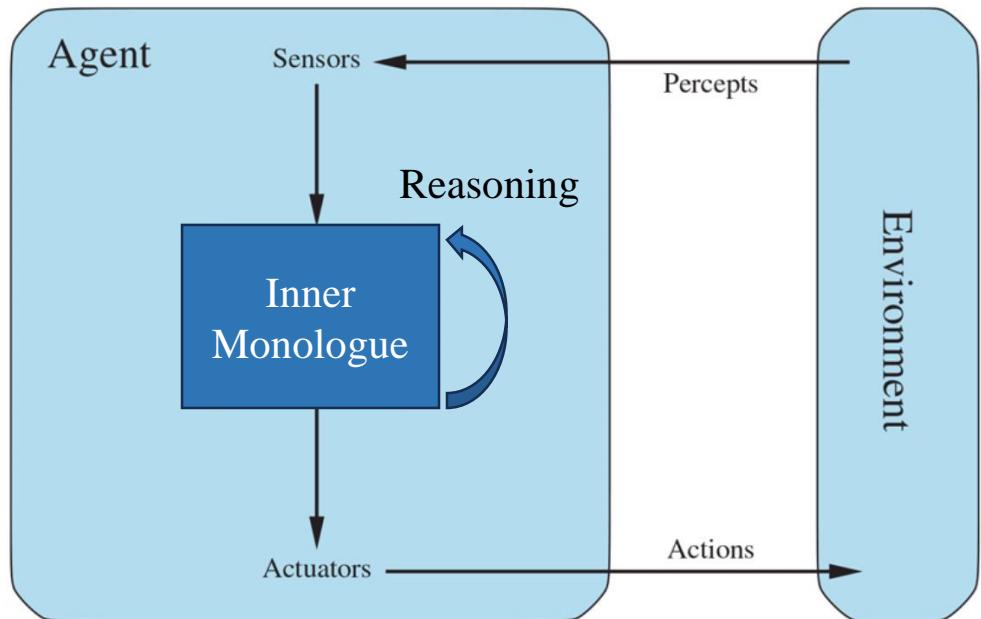
- ↑ Instruction following, in-context learning, output customization
- ↑ Reasoning (for better acting): state inferences, self-reflection, replanning, etc.



<https://www.demandsage.com/chatgpt-statistics/>



Schematic illustration of language agents



- Reasoning by generating tokens is a **new type of action** (vs. actions in external environments)
- **Internal environment**, where reasoning takes place in an inner monologue fashion
- **Self-reflection** is a ‘meta’ reasoning action (i.e., reasoning over the reasoning process), akin to metacognitive functions
- **Reasoning is for better acting**, by inferring environmental states, retrospection, etc.
- **Percept and external action spaces** are substantially expanded, thanks to using language for communication and multimodal perception

A generalized notion of ‘reasoning’

Unlike humans, LLMs (mostly) only have one mechanism (token generation) for perception, intuitive inferences, and symbolic reasoning; everything is effortful and takes a forward pass



GPT-4o

In this image, we see a young boy sitting on the floor, looking down at a pile of broken dishes. He appears to be sad or remorseful. In front of him, a woman, likely his mother or caregiver, is kneeling and looking at him with a concerned, questioning expression. Her body language, with her hands open and her facial expression, suggests that she's asking him something or expressing surprise or frustration about the broken dishes.

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Perception

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Perception
Intuitive Inference

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Perception

Intuitive
Inference

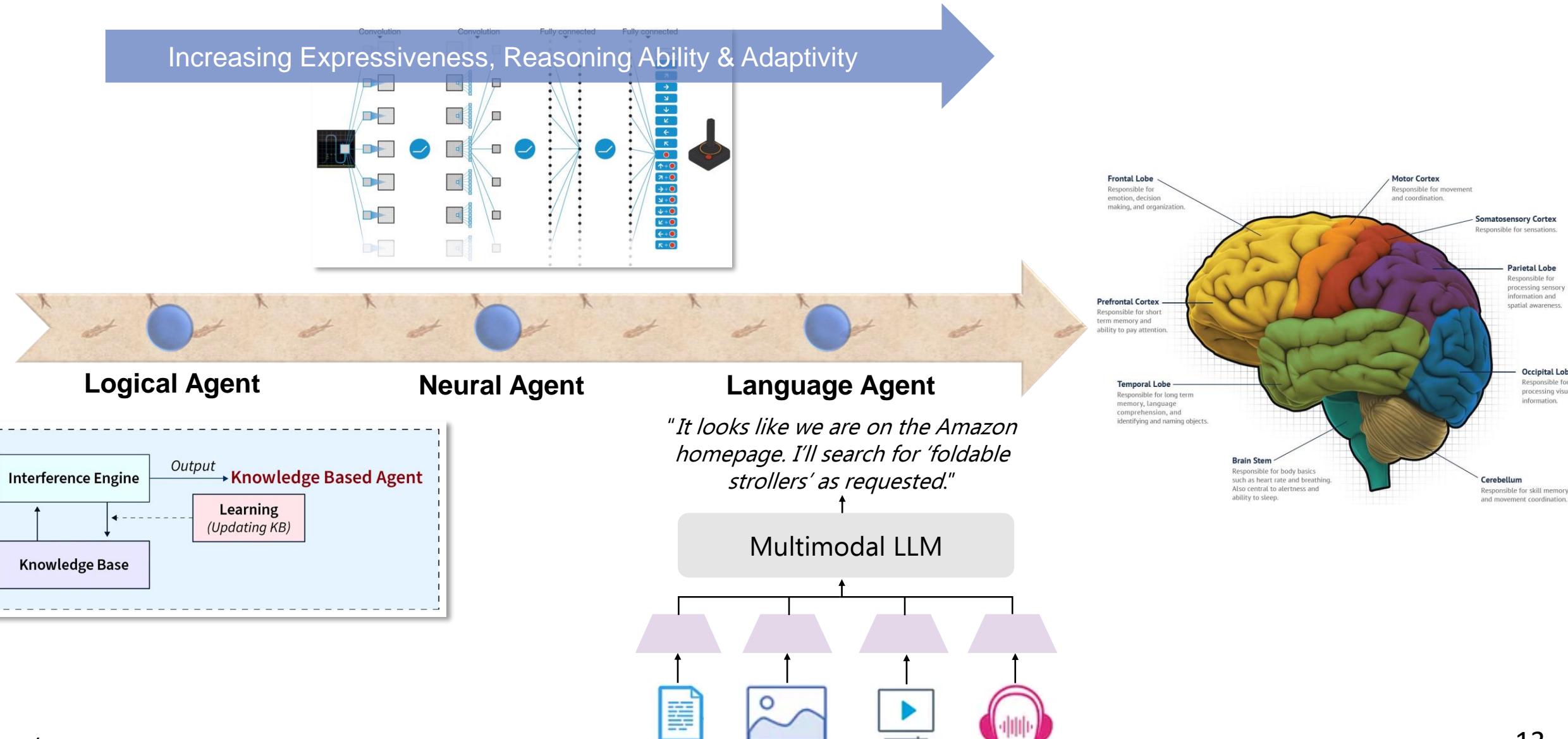
Reasoning

One may alternatively call this ‘thought’ to avoid the over-loaded term of ‘reasoning,’ at the risk of further anthropomorphizing machines

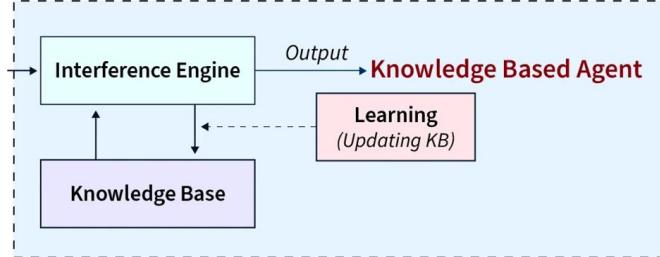
Let's call them language agents

- These contemporary AI agents capable of using language for reasoning and communication are best called “**language agents**,” for language being their most salient trait.
- What about *multimodal agents*?
 - While there’s perception of other modalities, *language is still doing the heavy lifting* (reasoning and communication)
- What about *LLM agents*?
 - The key is using language for reasoning and communication, but that doesn’t have to come from an LLM; that may turn out to be a *means to an end*
 - Maybe in a few years, we will move beyond LLMs, but the need for universal language understanding and production in agents will remain

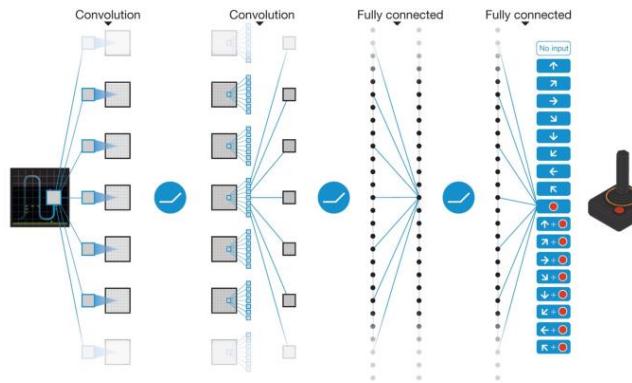
A new evolutionary stage of machine intelligence



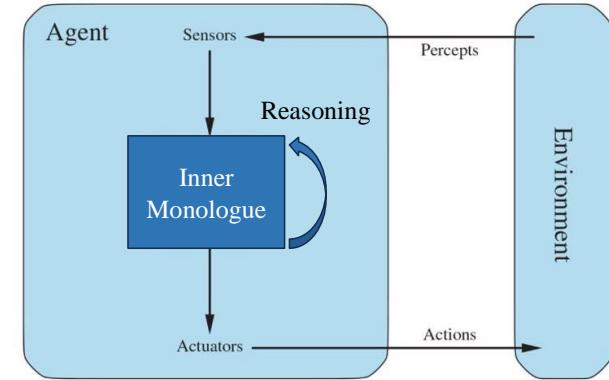
Evolution of AI agents



Logical Agent



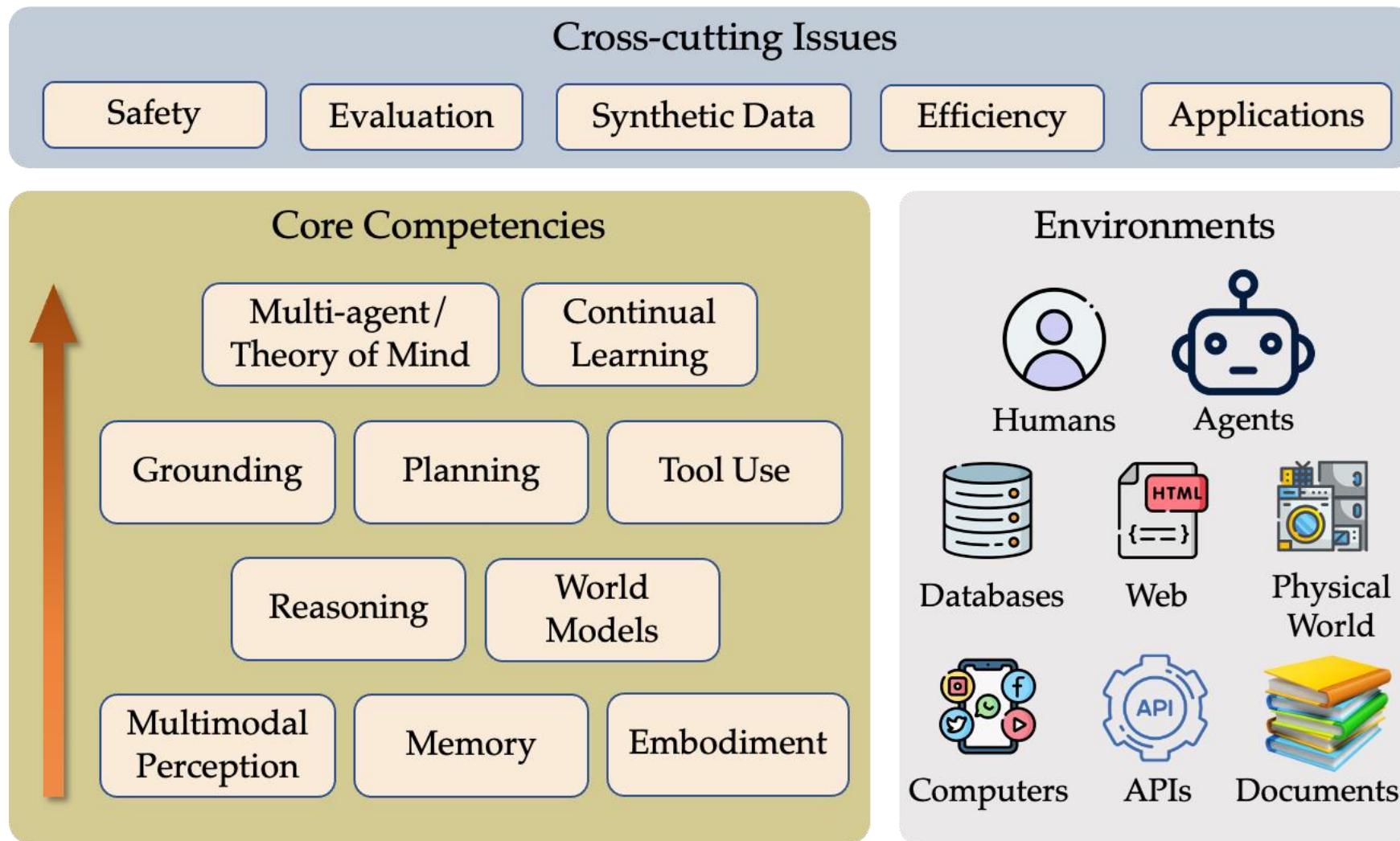
Neural Agent



Language Agent

Expressiveness	Low bounded by the logical language	Medium anything a (small-ish) NN can encode	High almost anything, esp. verbalizable parts of the world
Reasoning	Logical inferences sound, explicit, rigid	Parametric inferences stochastic, implicit, rigid	Language-based inferences fuzzy, semi-explicit, flexible
Adaptivity	Low bounded by knowledge curation	Medium data-driven but sample inefficient	High strong prior from LLMs + language use

A conceptual framework for language agents

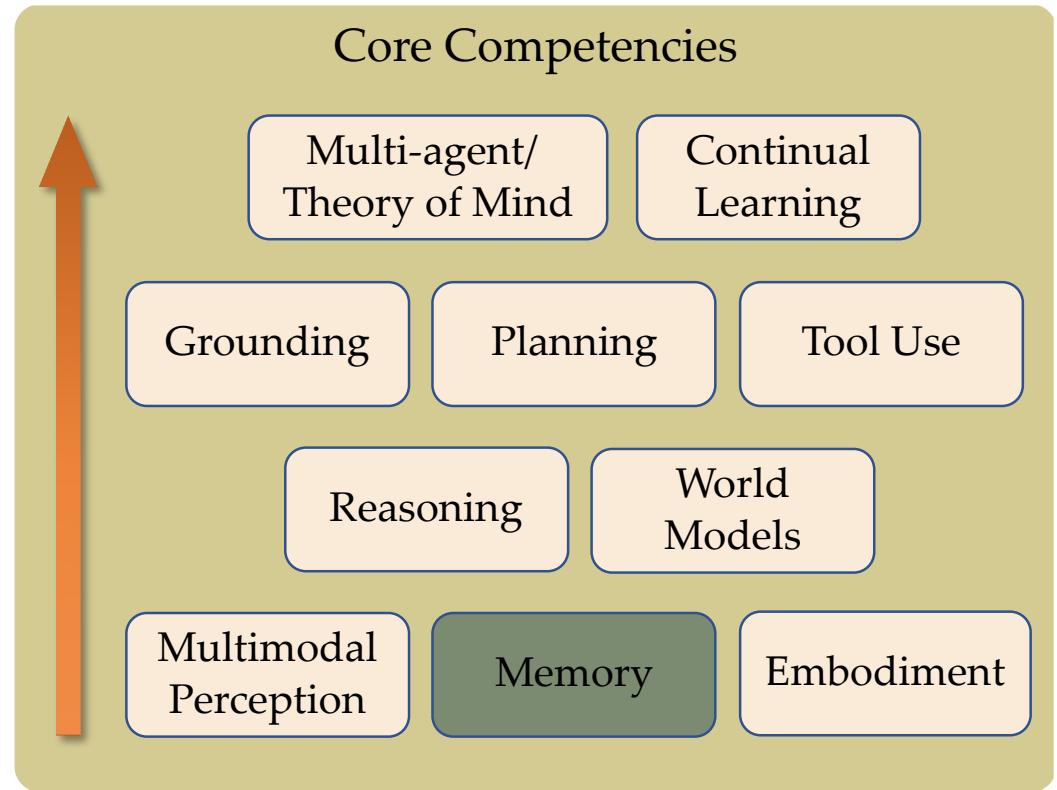


Outline

- On long-term memory
 - HippoRAG
- On reasoning
 - Grokked Transformers
- On world models and planning
 - WebDreamer

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HippoRAG: Neurobiologically Inspired Long-Term Memory for Large Language Models

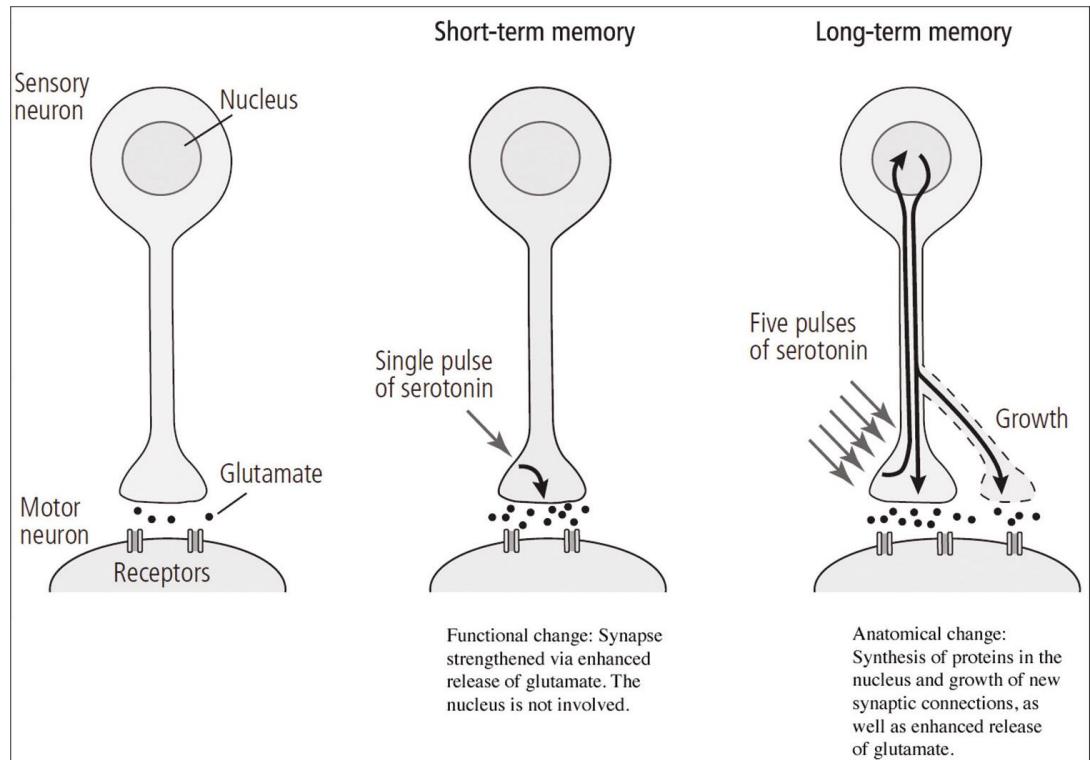
Bernal Jiménez Gutiérrez, Yiheng Shu,
Yu Gu, Michihiro Yasunaga, Yu Su



Humans (and most animals) are 24/7 learners

“Memory is everything. Without it we are nothing.”

Catastrophic forgetting, ripple effects
→ Transient learning



Eric Kandel, “In Search of Memory: The Emergence of a New Science of Mind,” 2006.

Knowledge Edit (LLM parameter θ replaced by θ'):

Leonardo DiCaprio is a citizen of United States. → Syria. ($K_1 \rightarrow K'_1$)

Expected Ripple-Effect:

Leonardo DiCaprio speaks English. → Arabic. ($K_2 \rightarrow K'_2$)

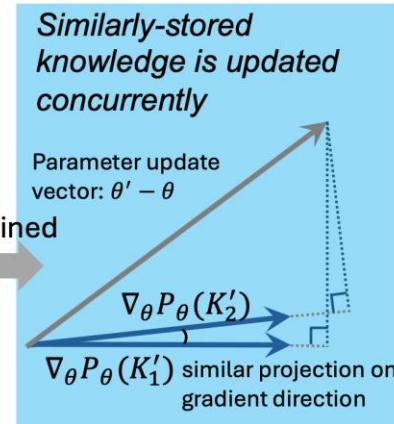
Counter-Intuitive Failure Cases:

Negation: Leonardo DiCaprio is **not** a citizen of Syria. ✗ United States. ✓

Over-Ripple: Leonardo DiCaprio speaks Syria. ✗ Arabic ✓

Explained by

Cross-Lingual: 莱昂纳多·迪卡普里奥的国籍是:
(Leonardo DiCaprio is a citizen of)
美国. ✗ 叙利亚. ✓
(United States.) (Syria.)



Qin et al., “Why Does New Knowledge Create Messy Ripple Effects in LLMs?” 2024.

Non-parametric memory for LLMs

*“We find that LLMs can be **highly receptive to external evidence** even when that conflicts with their parametric memory, given that the external evidence is coherent and convincing.”*

	Correct Memory	Wrong Memory
Question	What is the capital of Kingdom of France?	Who was the producer of The Cardinal?
Ground Truth	Paris	Otto Preminger
Parametric Memory	<p>Paris was chosen as the capital of the Kingdom of France due to its central location and strategic importance. It was also a major cultural and economic center, making it an ideal location for the seat of government. Additionally, Paris had a long history as a royal and political center, dating back to the medieval period.</p>	<p>The Cardinal was produced by Martin Ransohoff, who was a prominent film and television producer in the mid-20th century. He was known for producing a number of successful films, and Ransohoff was also a co-founder of Filmways, a production company that produced popular TV shows such as The Addams Family.</p>
Counter-memory	<p>Néma is the capital of the Kingdom of France. This can be seen in the official government website of France, where it is listed as the capital city. Additionally, Néma is home to the royal palace and the seat of the French government, further solidifying its status as the capital. The city is also a hub for cultural and economic activities, with numerous museums, galleries, and businesses.</p>	<p>Otto Preminger was a prominent film producer in the mid-20th century, known for his work on a number of successful films. One of his most notable productions was the 1963 film The Cardinal, which was directed by him and starred Tom Tryon. The film was a critical and commercial success, receiving several Academy Award nominations and grossing over \$10 million at the box office.</p>

Xie et al., “Adaptive Chameleon or Stubborn Sloth: Revealing the Behavior of Large Language Models in Knowledge Conflicts.” ICLR (2024 **Spotlight**)

RAG is the *de facto* solution

ChatGPT



You

Who won the 2024 Super Bowl?



ChatGPT

The Super Bowl in 2024 was held on February 11, 2024. To find the most current information about the winner, I can browse the internet for you. Let me do that now.

The Kansas City Chiefs won the 2024 Super Bowl against the San Francisco 49ers with a final score of 25-22. The game went into overtime, and the Chiefs secured the win with a touchdown just seconds before the end of the game ([Yahoo Sports](#)) ([KCUR](#)) ([PinkNews](#)) ([Just Jared](#)).

Current RAG does not always work

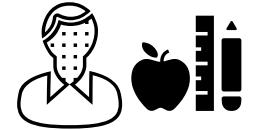
Passages



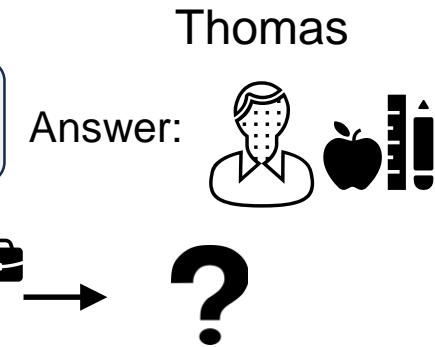
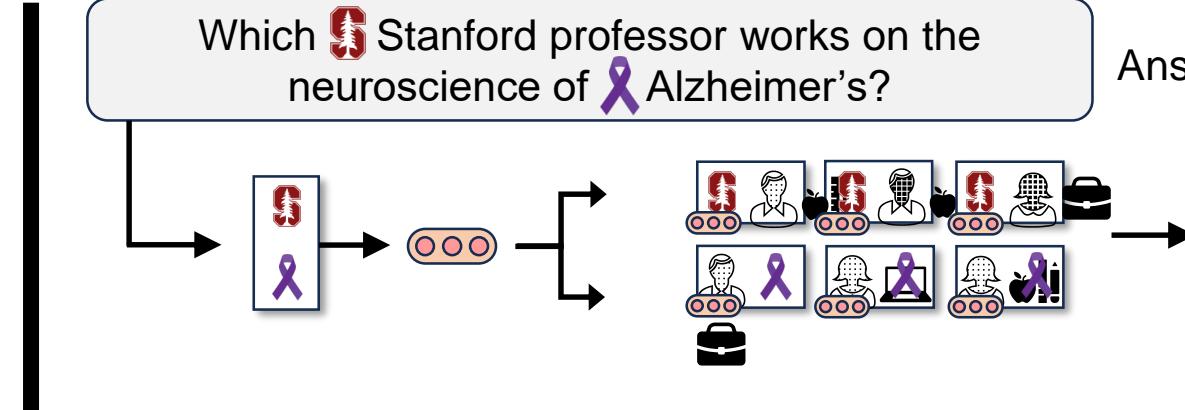
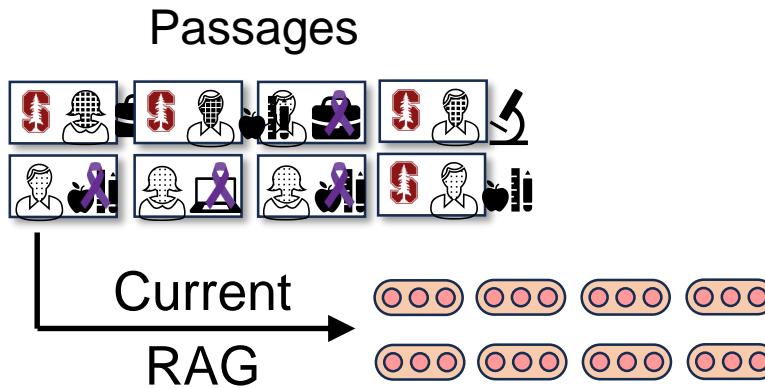
Which Stanford professor works on the neuroscience of Alzheimer's?

Thomas

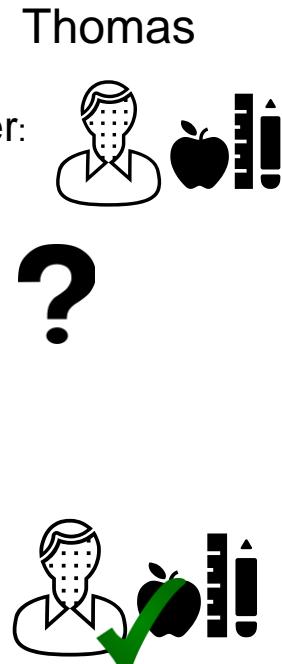
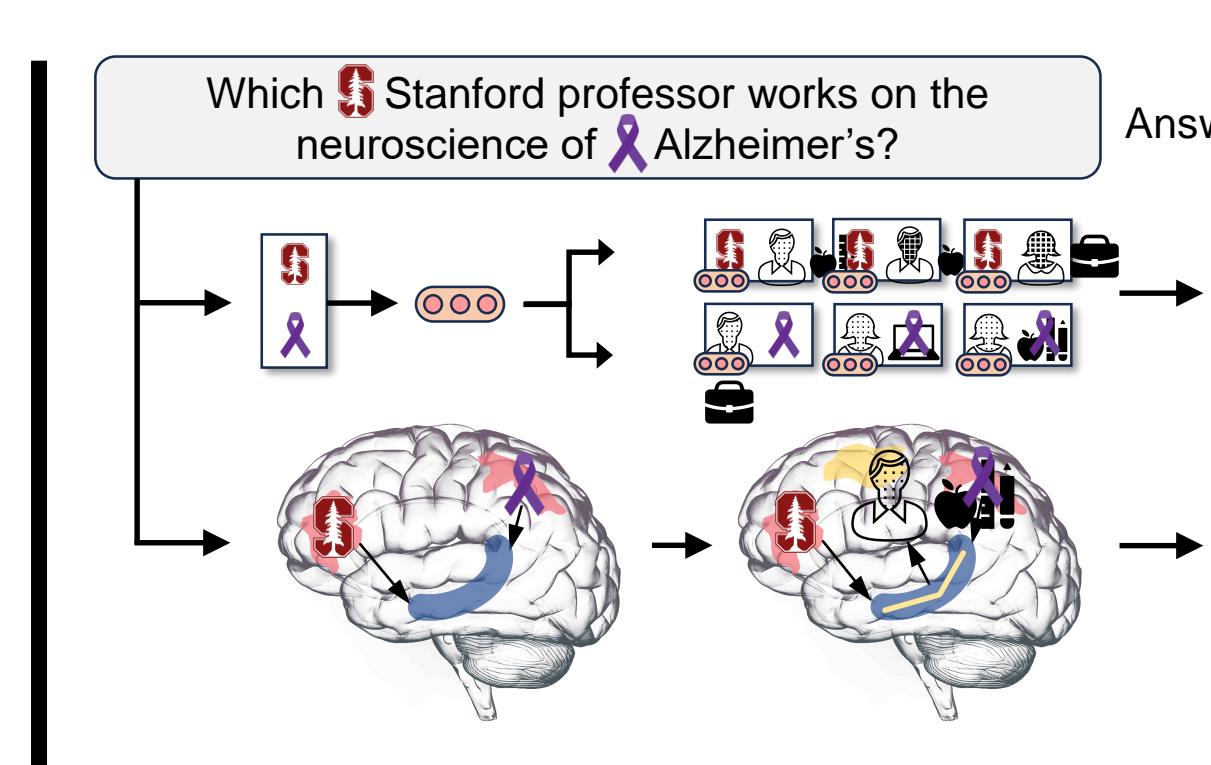
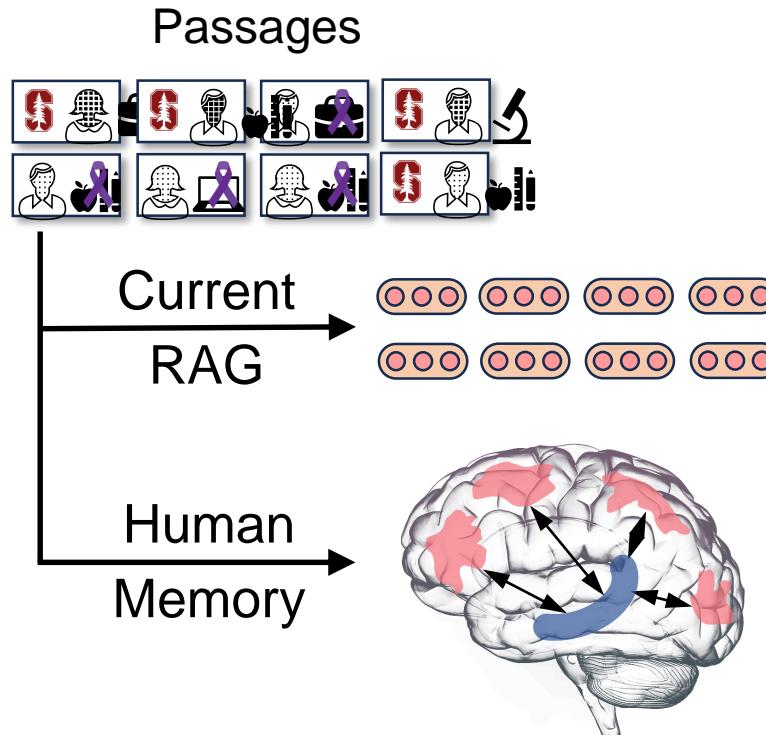
Answer:



Current RAG does not always work

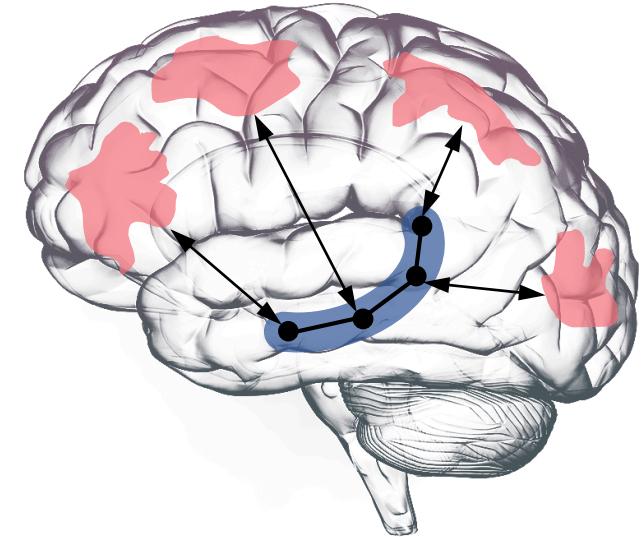


Current RAG does not always work



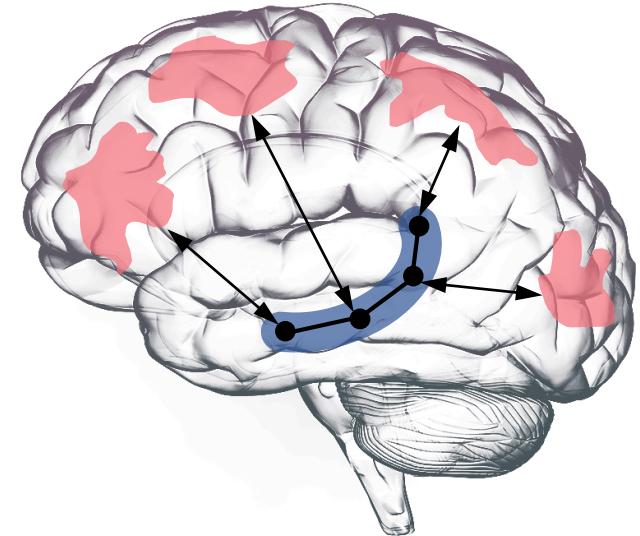
Long-term memory in humans

- One well-established theory of human long-term memory is the **hippocampal indexing theory** (Teyler et al. 1986).
 - The **hippocampus (blue)** is a store for **indices** (which point to memories stored in **neocortex**) and **associations** between them.
 - Memories can be anything (i.e., people, events, places, etc.)

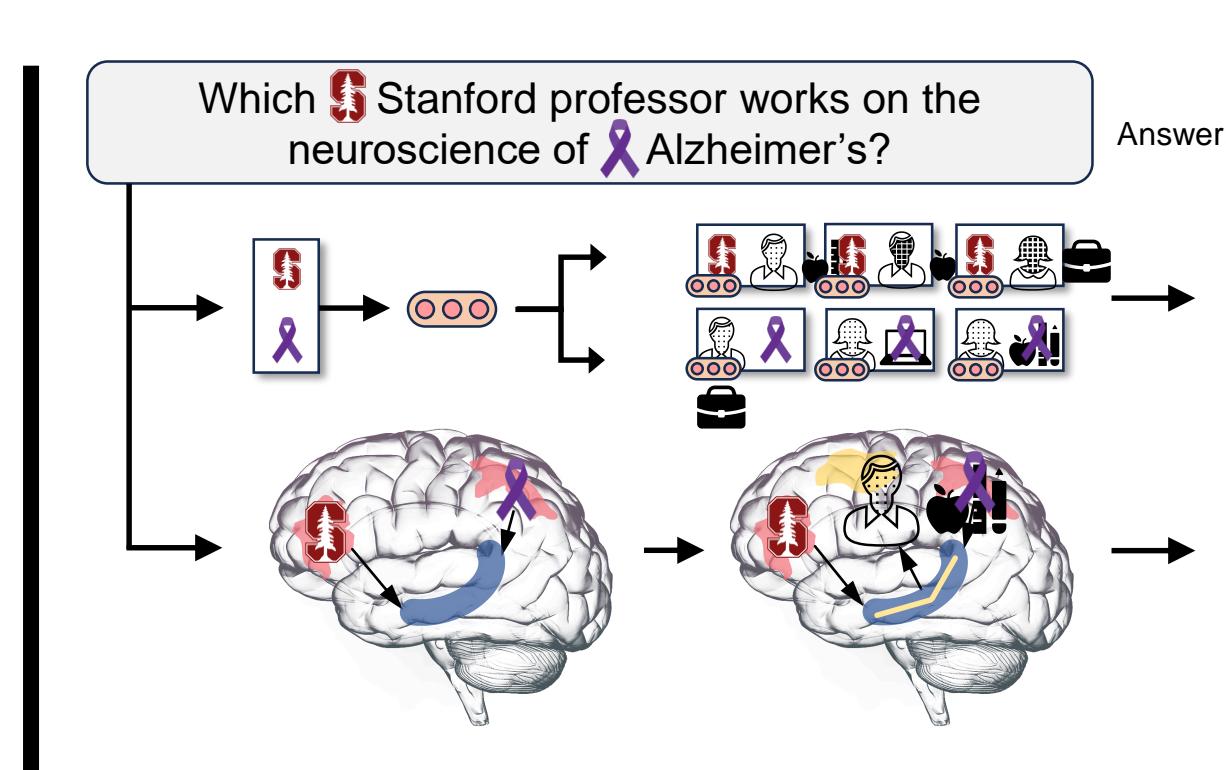
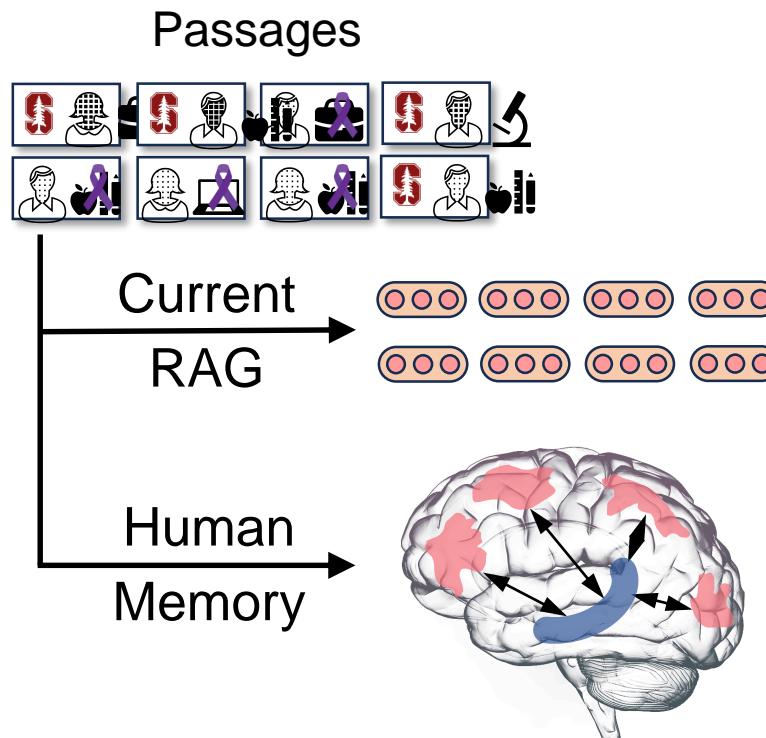


Long-term memory in humans

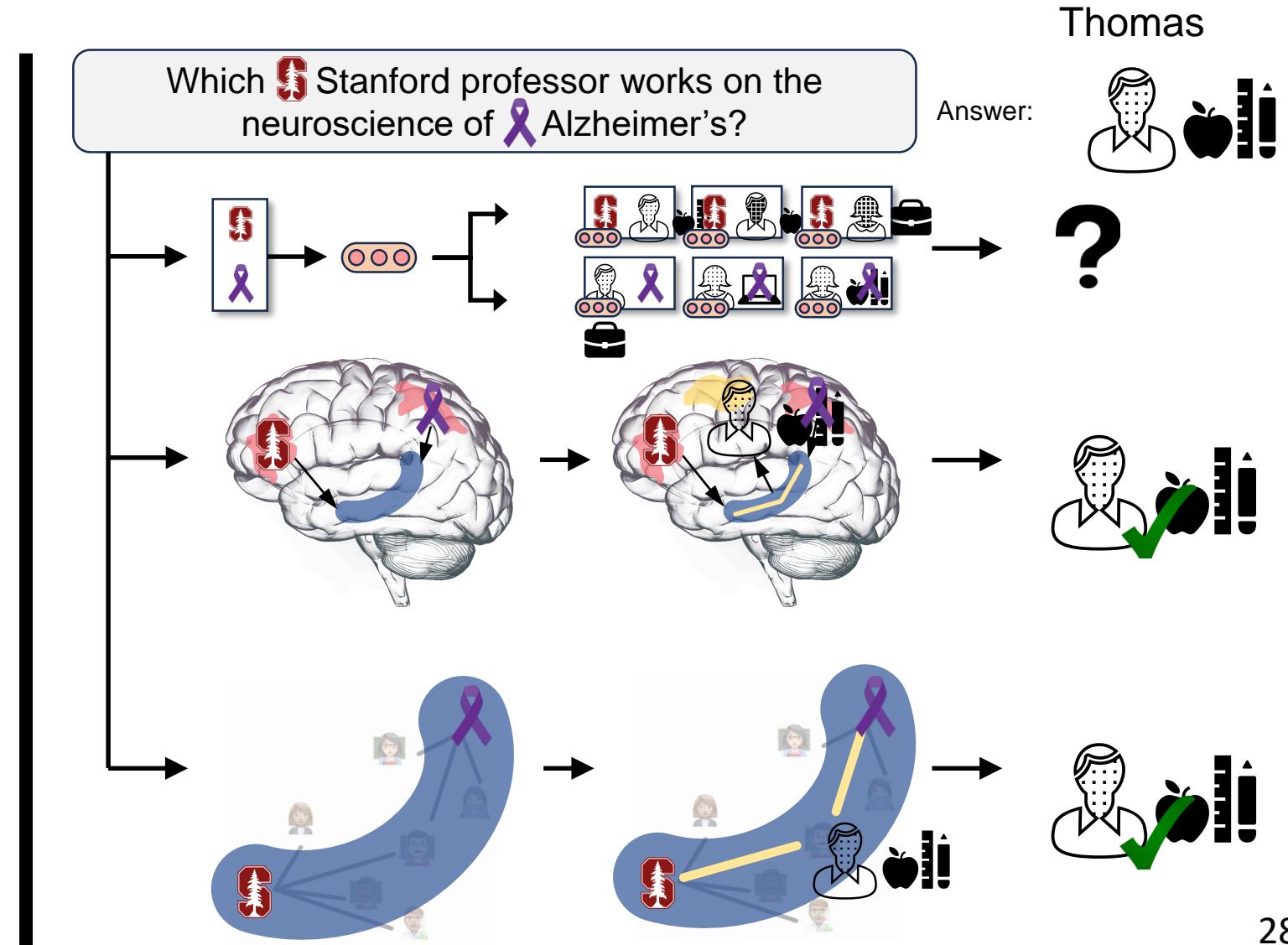
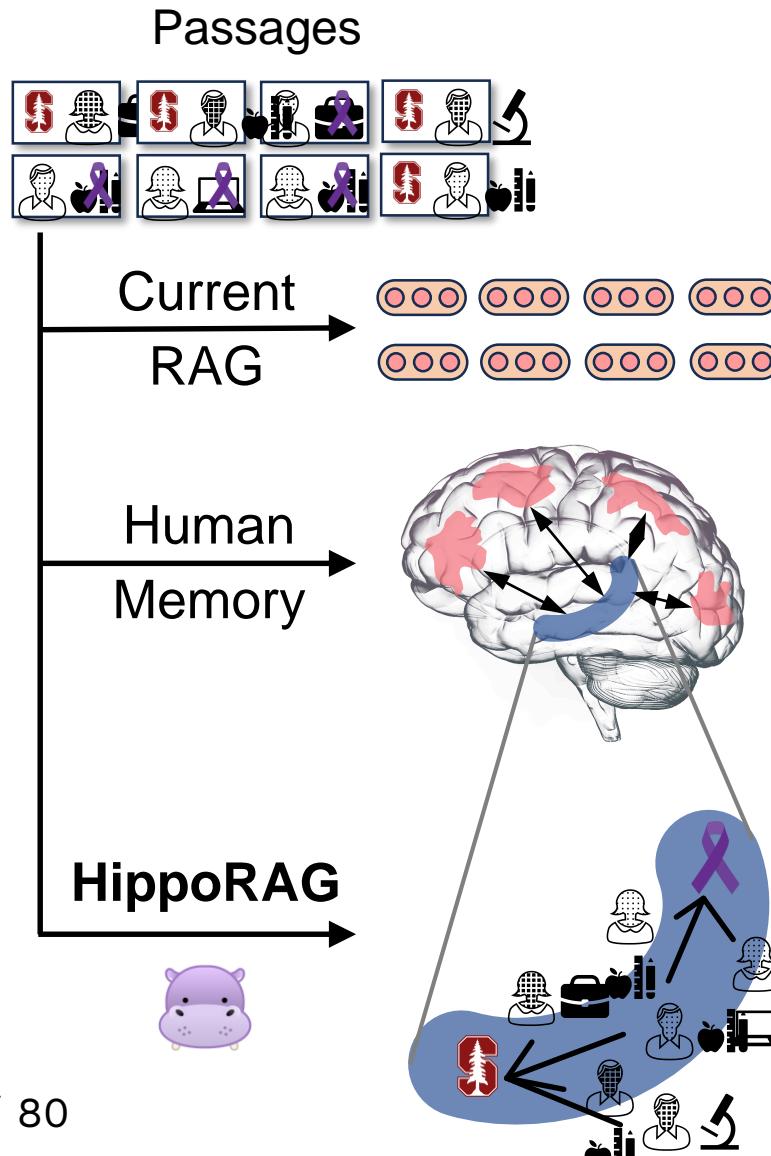
- Indexing procedure enables two fundamental faculties of human memory:
 - **Pattern separation:** process for differentiating memories (**neocortex** and parahippocampus)
 - **Pattern completion:** process for recovering complete memories from relevant associations (mostly **hippocampus**, specifically CA3)



HippoRAG: Neurobiologically-inspired LTM for LLMs



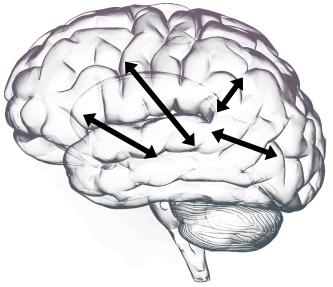
HippoRAG: Neurobiologically-inspired LTM for LLMs



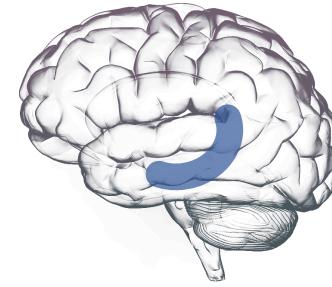
HippoRAG & the three components of LTM



Neocortex
Perception, linguistic
abilities & reasoning

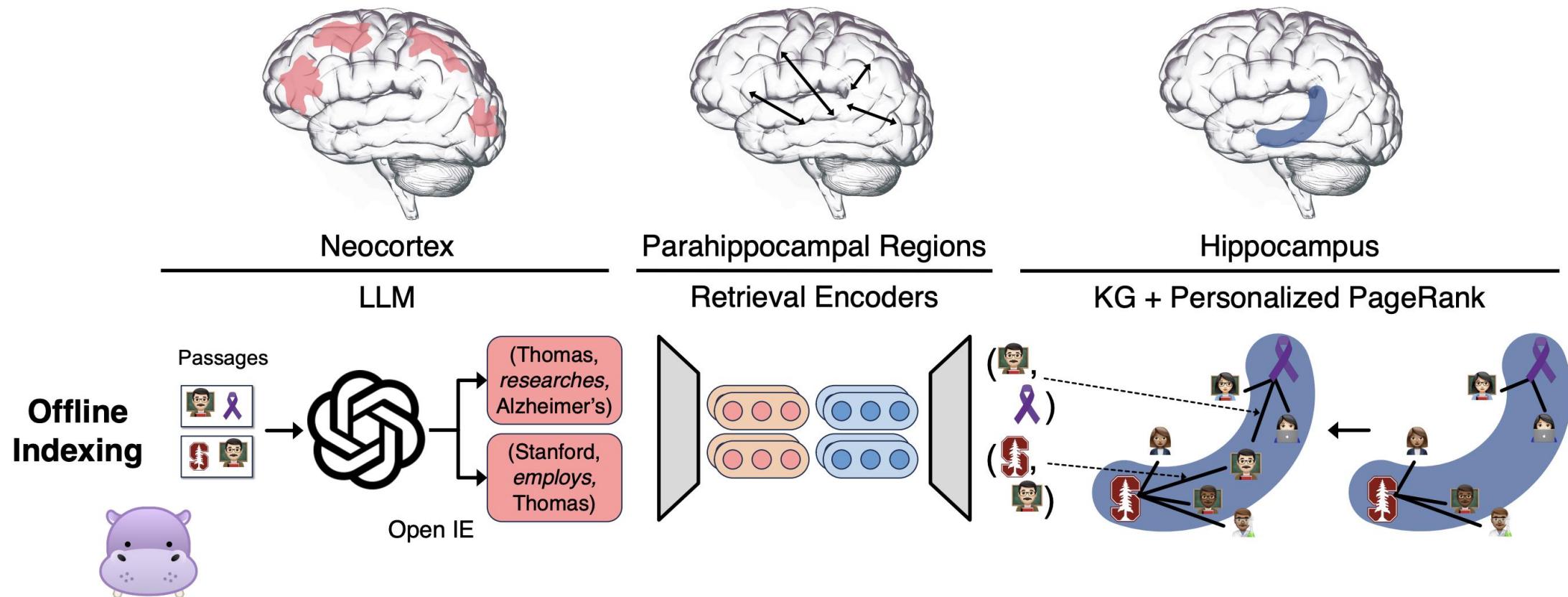


Parahippocampus
Bridge between areas;
working memory

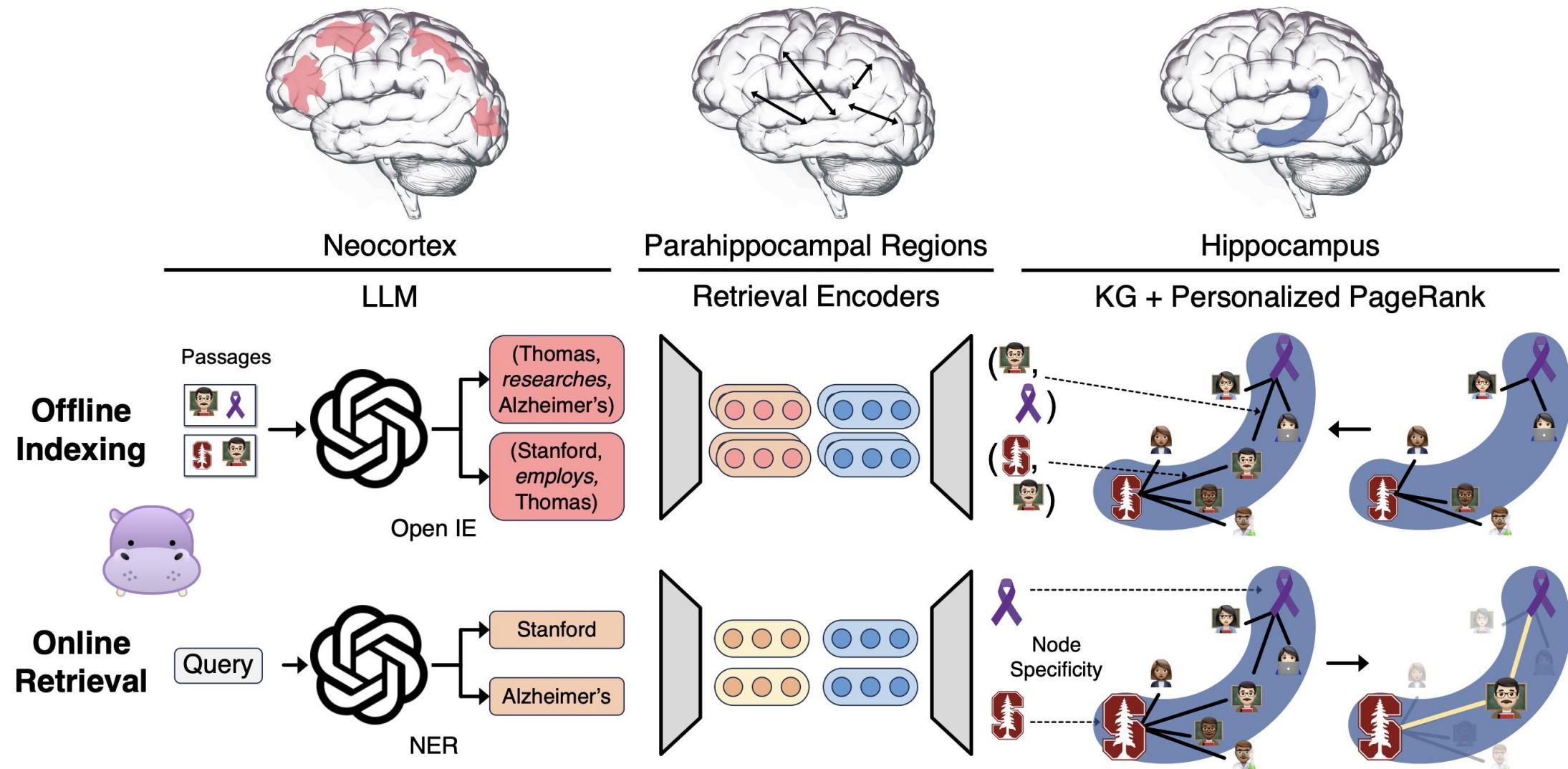


Hippocampus
Indexing & auto-
associative memory

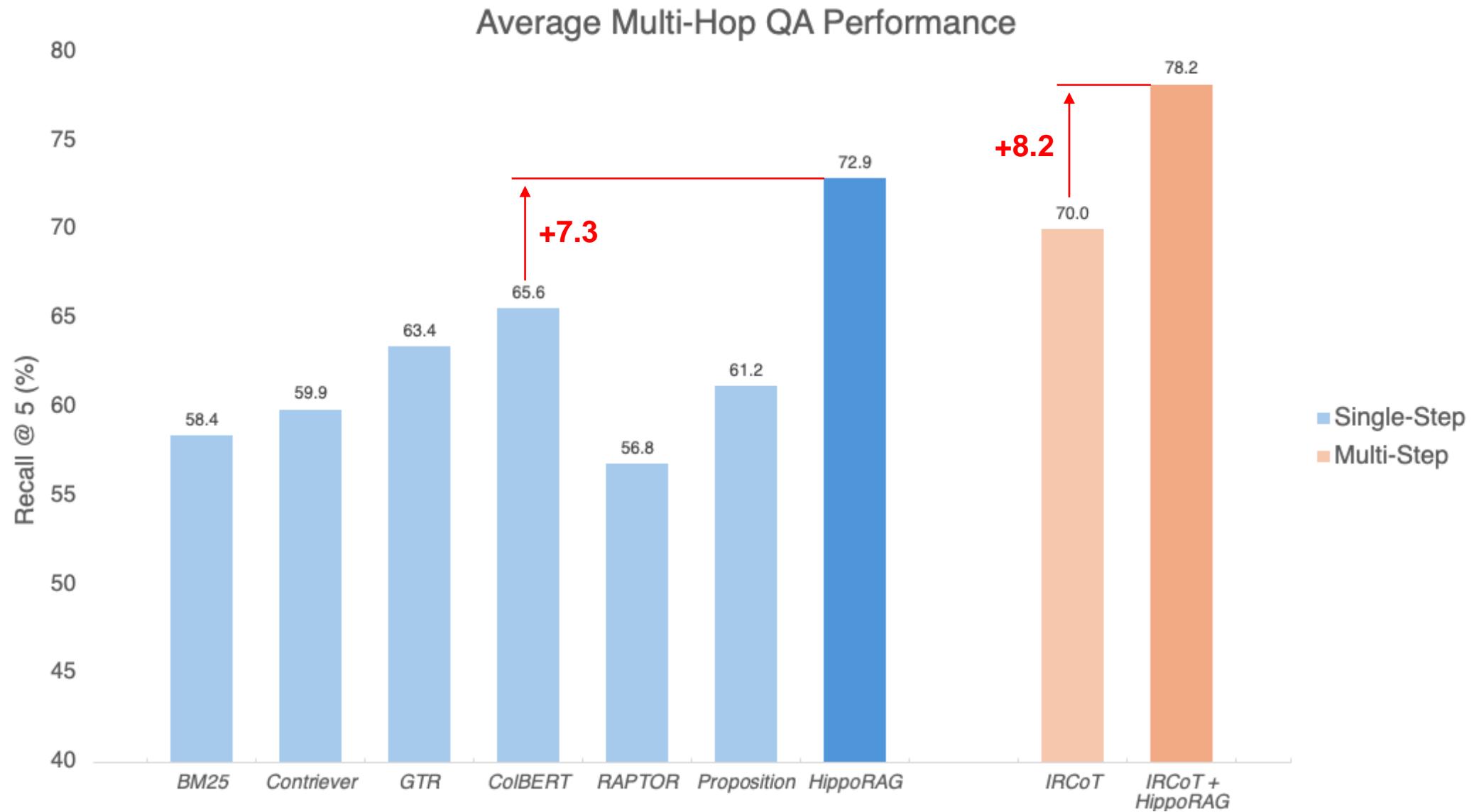
HippoRAG & the three components of LTM



HippoRAG & the three components of LTM



HippoRAG is a SoTA memory retriever



Case study: path-finding questions

	Question	HippoRAG	ColBERTv2	IRCoT
Path-Following	In which district was Alhandra born?	1. Alhandra 2. Vila de Xira 3. Portugal	1. Alhandra 2. Dimuthu Abayakoon 3. Ja'ar	1. Alhandra 2. Vila de Xira 3. Póvoa de Santa Iria
Path-Finding	Which Stanford professor works on the neuroscience of Alzheimer's ?	1. Thomas Südhof 2. Karl Deisseroth 3. Robert Sapolsky	1. Brian Knutson 2. Eric Knudsen 3. Lisa Giocomo	1. Brian Knutson 2. Eric Knudsen 3. Lisa Giocomo

HippoRAG v2 is coming soon!

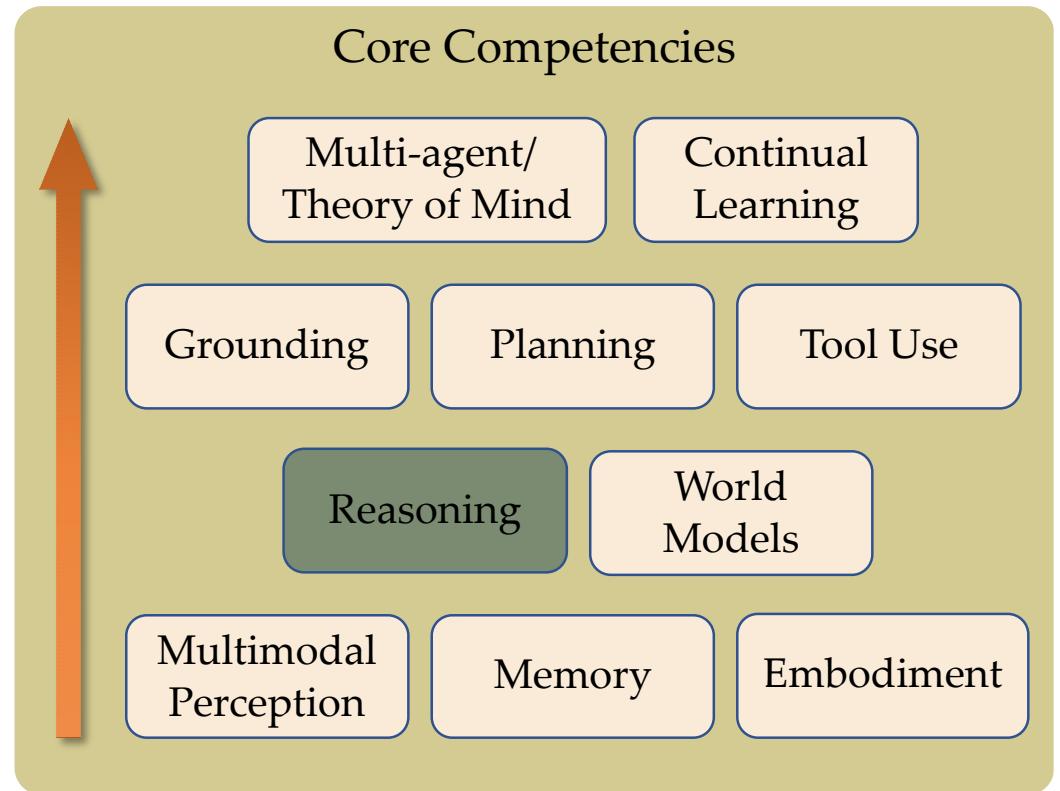
Retrieval	Simple QA			Multi-Hop QA			Discourse Understanding	
	NQ	PopQA	MuSiQue	2Wiki	HotpotQA	LV-Eval	NarrativeQA	Avg
<i>Simple Baselines</i>								
None	54.9	32.5	26.1	42.8	47.3	6.0	12.9	38.4
BM25 (Robertson & Walker, 1994)	59.0	49.9	28.8	51.2	63.4	5.9	18.3	47.7
Contriever (Izacard et al., 2022)	58.9	53.1	45.4	41.9	62.3	8.1	19.7	49.5
GTR (T5-base) (Ni et al., 2022)	59.9	56.2	34.6	52.8	62.8	7.1	19.9	50.4
<i>Large Embedding Models</i>								
GTE-Qwen2-7B-Instruct (Li et al., 2023)	62.0	56.3	40.9	60.0	71.0	7.1	21.3	54.9
GritLM-7B (Muennighoff et al., 2024)	61.3	55.8	44.8	60.6	73.3	9.8	23.9	56.1
NV-Embed-v2 (7B) (Lee et al., 2025)	61.9	55.7	45.7	61.5	75.3	9.8	25.7	57.0
<i>Structure-Augmented RAG</i>								
RAPTOR (Sarthi et al., 2024)	50.7	56.2	28.9	52.1	69.5	5.0	21.4	48.8
GraphRAG (Edge et al., 2024)	46.9	48.1	38.5	58.6	68.6	11.2	23.0	49.6
LightRAG (Guo et al., 2024)	16.6	2.4	1.6	11.6	2.4	1.0	3.7	6.6
HippoRAG (Gutiérrez et al., 2024)	55.3	55.9	35.1	71.8	63.5	8.4	16.3	53.1
HippoRAG v2	63.3	56.2	48.6	71.0	75.5	12.9	25.9	59.8

Memory: takeaways

- Memory is central to human learning. Our sophisticated memory mechanisms allow us to recognize patterns, create associations, and dynamically recall memory relevant to the current context beyond superficial similarity
- Long-term memory through parametric continual learning is hard for LLMs, but non-parametric memory (e.g., RAG) could be a promising solution
- Recent trend in RAG is to add more structures to embeddings (e.g., HippoRAG, GraphRAG) to enhance
 - *Sensemaking*, the ability to interpret larger, more complex, or uncertain contexts
 - *Associativity*, the capacity to draw multi-hop connections between disparate pieces of info

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Grokkking of Implicit Relations in Transformers: A Mechanistic Journey to the Edge of Generalization

Boshi Wang, Xiang Yue, Yu Su, Huan Sun



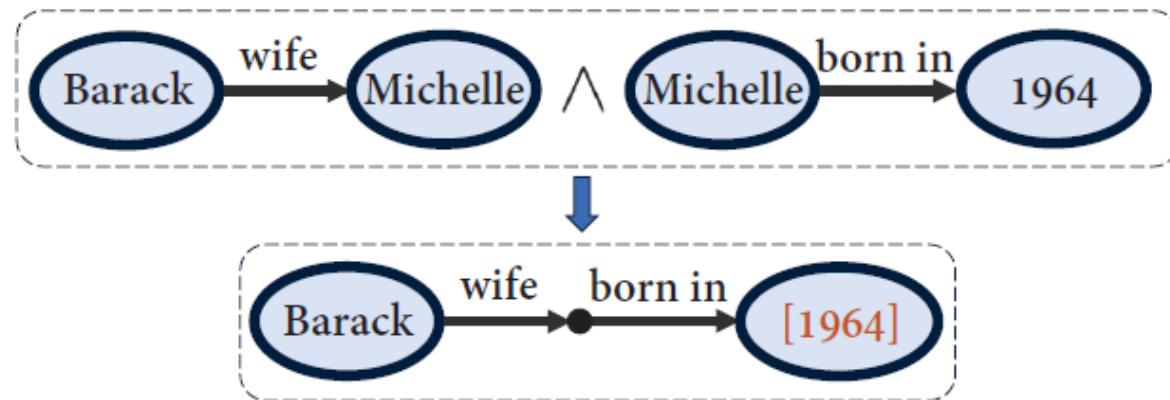
Carnegie
Mellon
University



Implicit reasoning

Directly predict the answer; no verbalized chain of thought

Composition

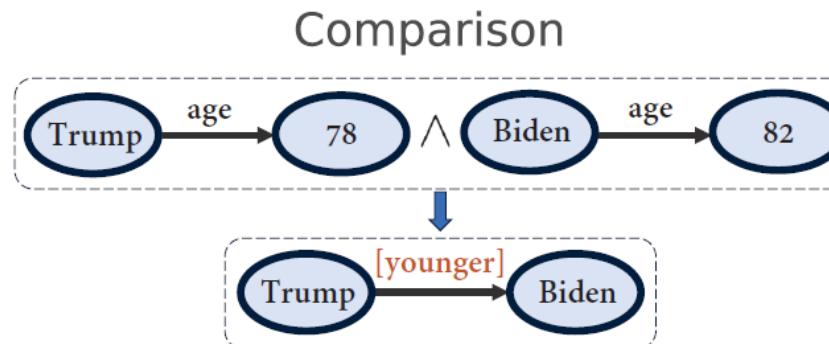
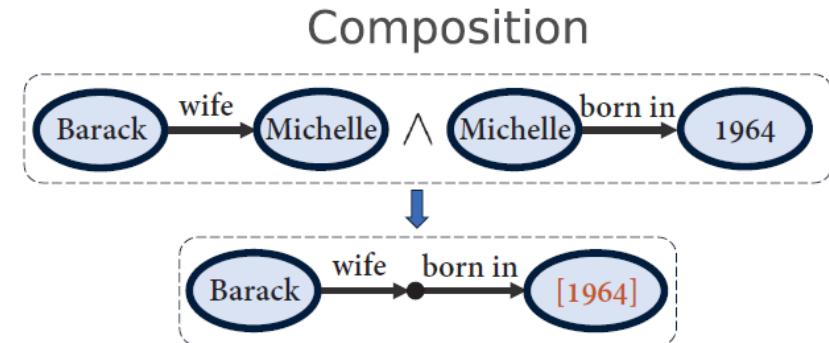


CoT is all the rage. Why does implicit reasoning matter?

- The default mode of large-scale (pre-)training; no CoT at training time
- Fundamentally determines how well LLMs acquire structured representations of facts and rules from data
- How did o1/R1-style long CoT emerge? A hypothesis
 - A capable base model (e.g., DeepSeek v3) has already learned various basic ‘constructs’ or strategies for reasoning
 - Reinforcement learning incentivizes the model to learn to use the right combination of strategies (not learning new ones through RL) and keep trying

LLMs were shown to struggle at implicit reasoning

- Composition
 - LLMs only show substantial evidence in first-hop reasoning (Yang et al. 2024)
 - “Compositionality gap” does not decrease with scale (Press et al. 2023)
- Comparison
 - GPT-4 struggles at implicitly comparing entity attributes despite knowing them perfectly (Zhu et al. 2023)



Research questions

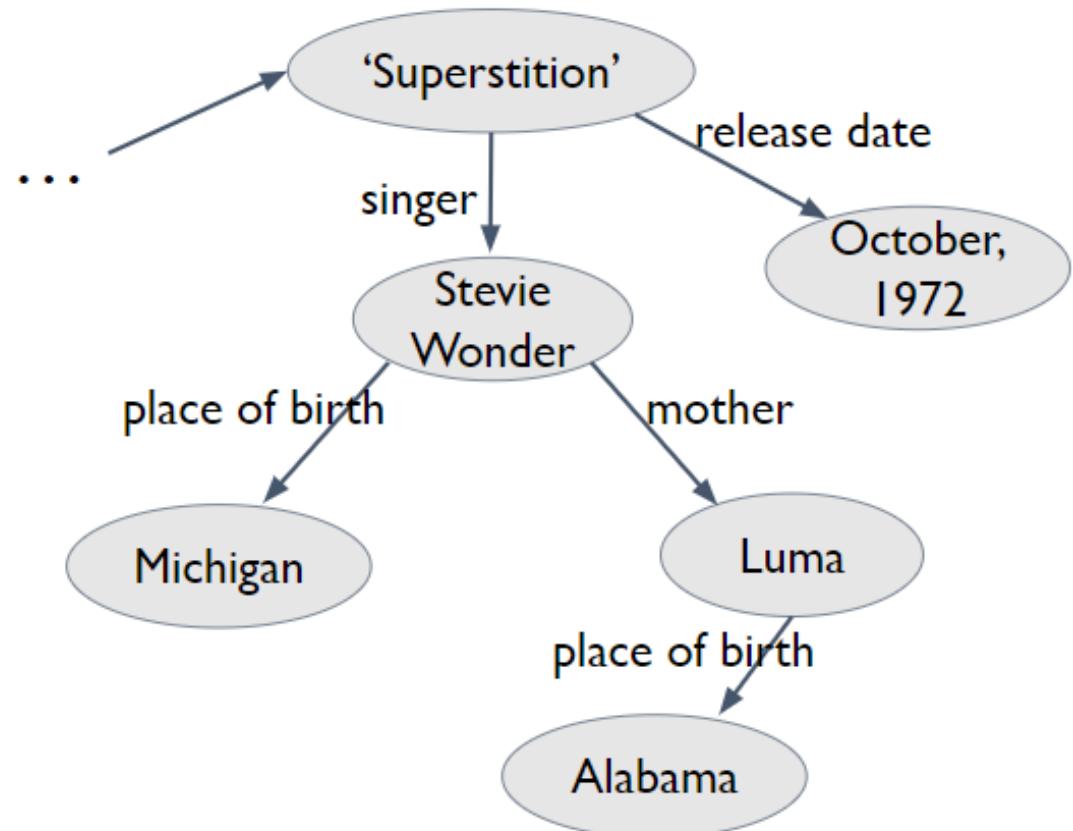
- Can Transformers learn to reason implicitly, or are there fundamental limitations that prohibit robust acquisition of this skill?
- What factors (e.g., data scale, distribution, model architecture) control the acquisition of implicit reasoning?

Setup: model and optimization

- Standard decoder-only transformer as in GPT-2
 - 8 layers, 768 hidden dimensions, and 12 attention heads
 - Results are robust to different model scales
- AdamW with learning rate 1e-4, batch size 512, weight decay 0.1, and 2000 warm-up steps

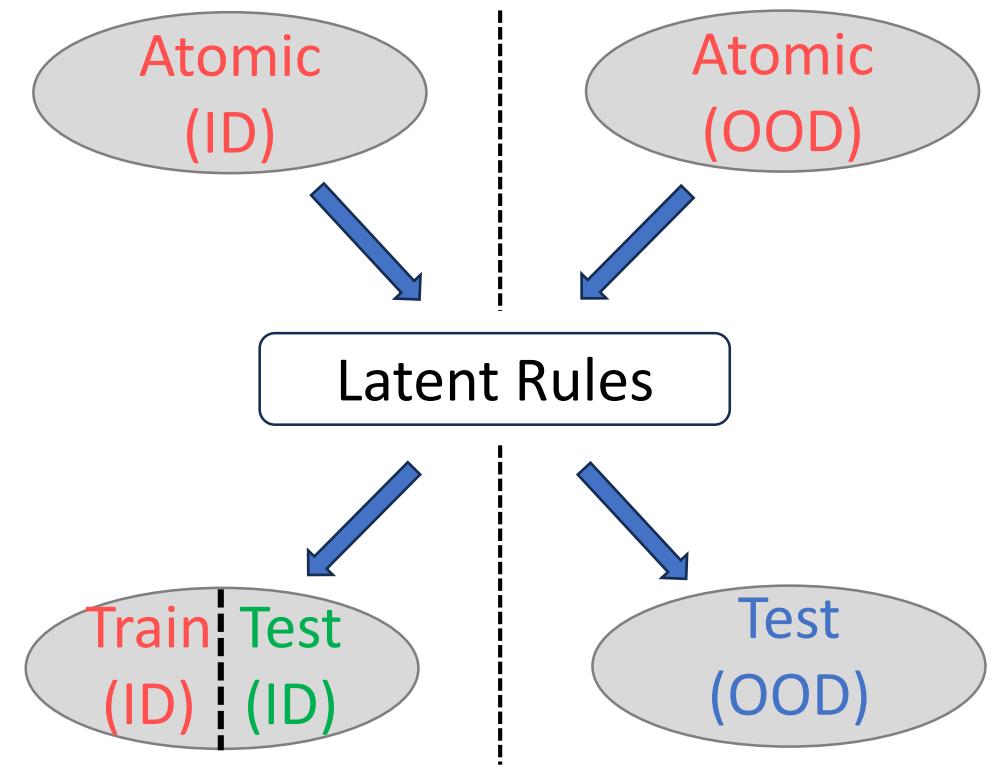
Setup: data for compositional reasoning

- Atomic facts
 - Random KG consisting of $|\mathcal{E}|$ entities and $|\mathcal{R}| = 200$ relations
 - Randomly split into ID & OOD atomic facts
- Inferred facts: two-hop compositions
$$(h, r_1, b) \wedge (b, r_2, t) \implies (h, r_1, r_2, t)$$

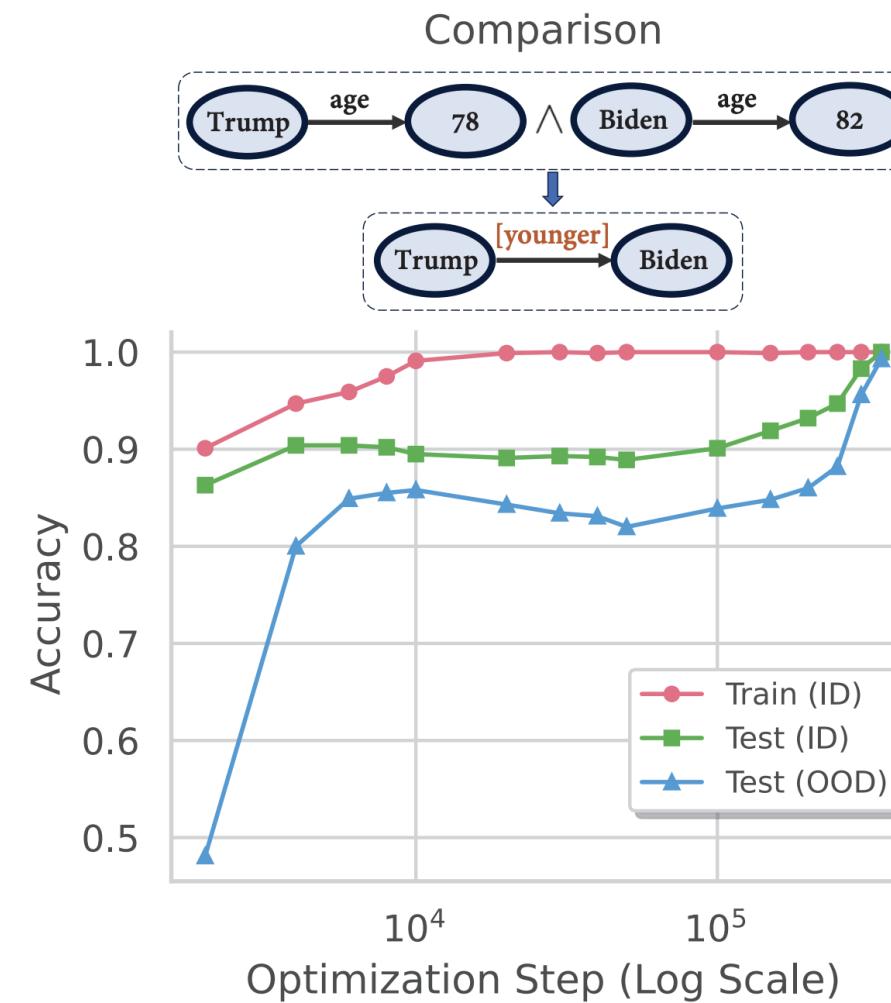
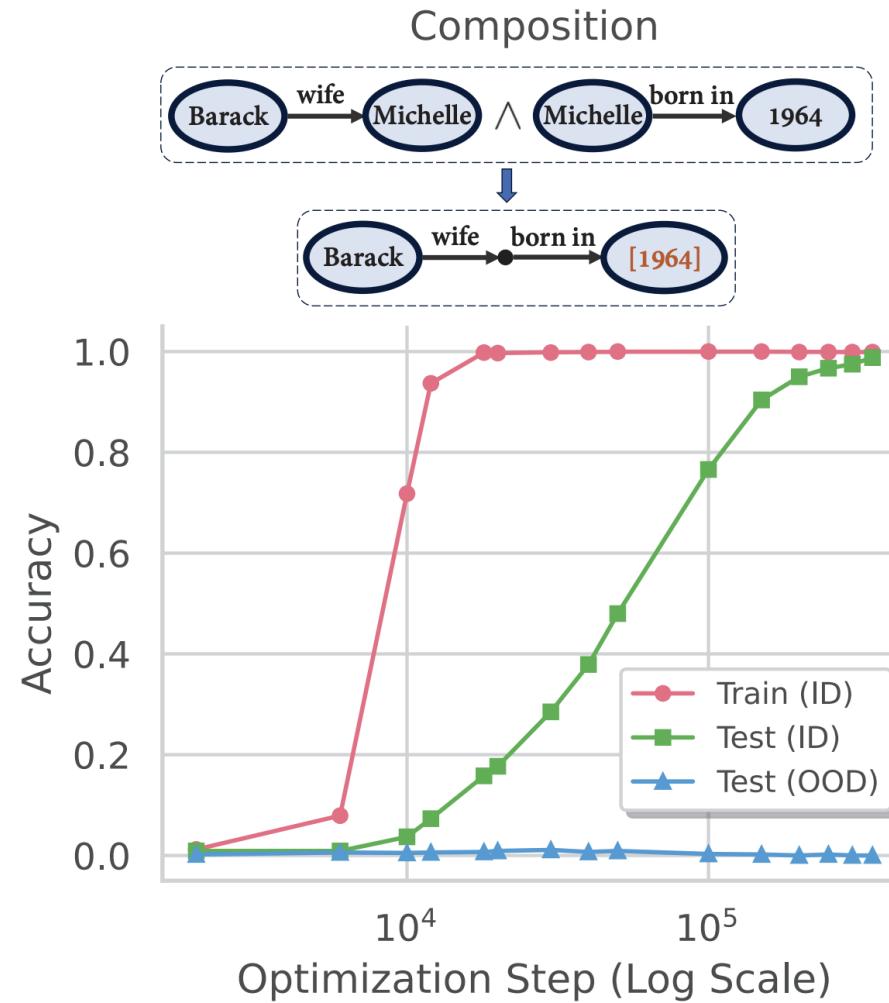


Setup: inductive learning of deduction rules

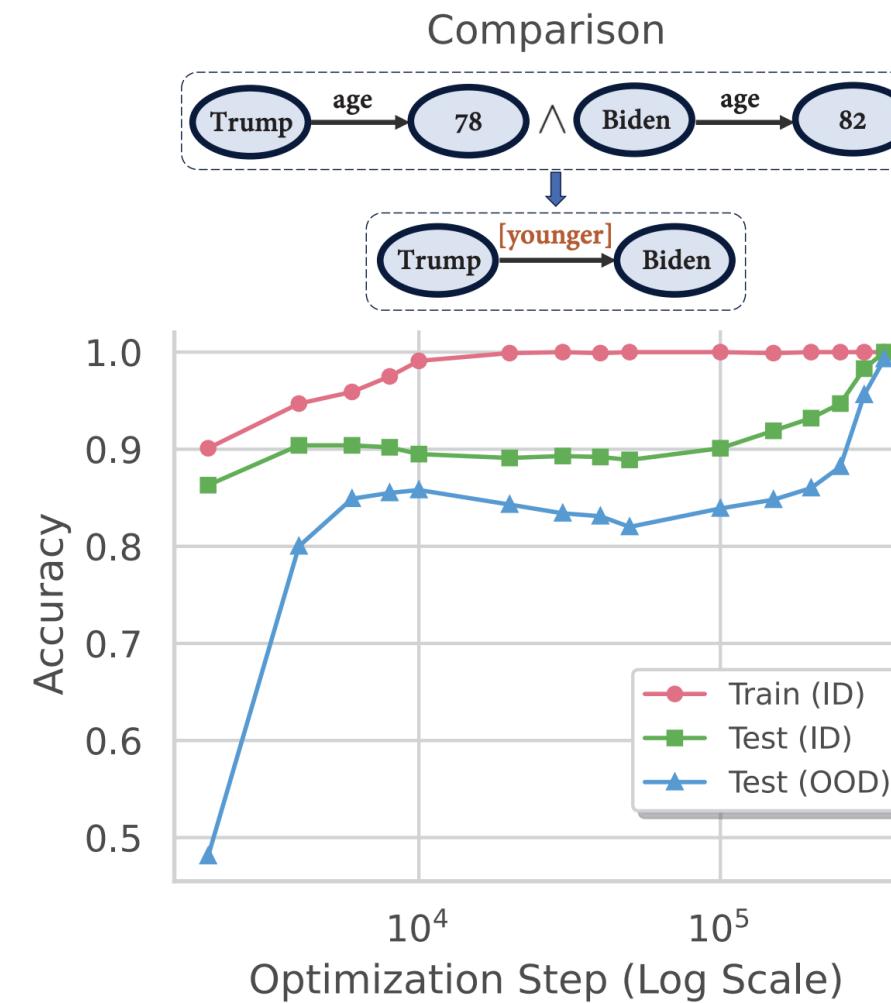
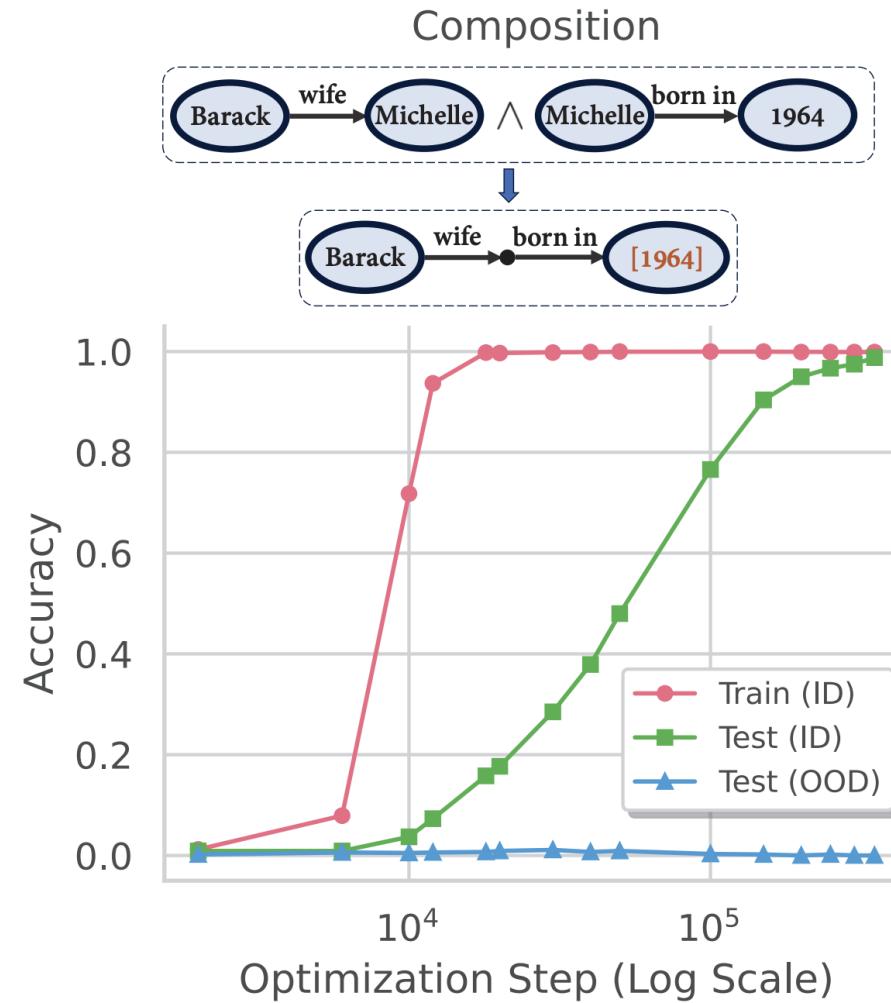
- **Induce** latent rules from a mixture of **atomic** facts and **inferred** facts (deduced via latent rules)
- **Deduce** novel facts by applying the acquired rules
 - *Test (ID)*: unseen inferred facts deduced from the **same** set of atomic facts underlying the observed inferred facts
 - *Test (OOD)/Systematic Generalization*: unseen inferred facts derived from a **different** set of atomic facts



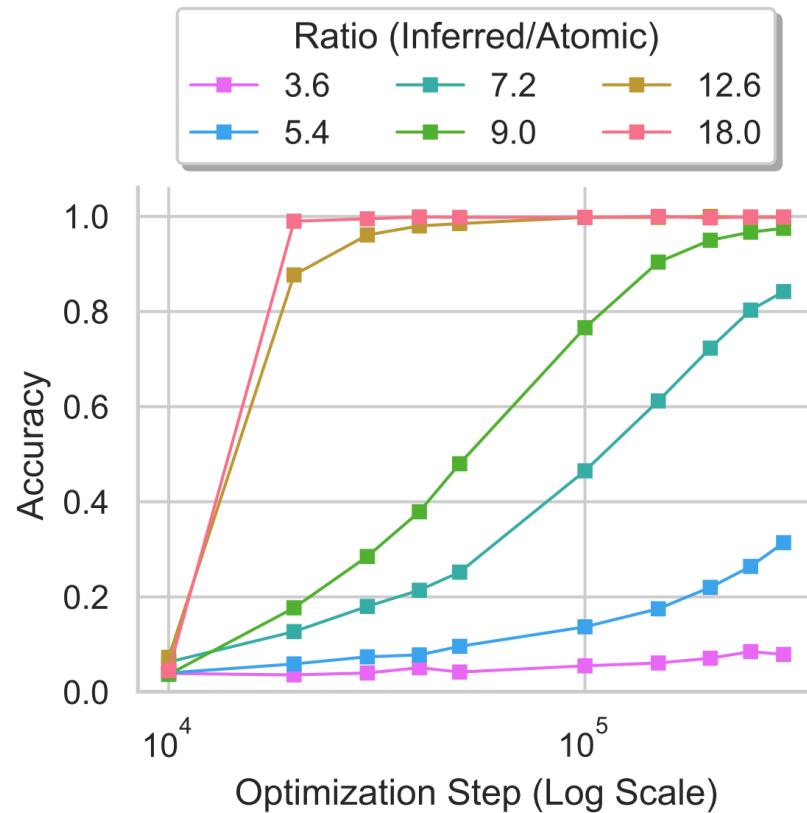
Takeaway #1: Transformers can learn to reason implicitly, but only through ‘grokking’



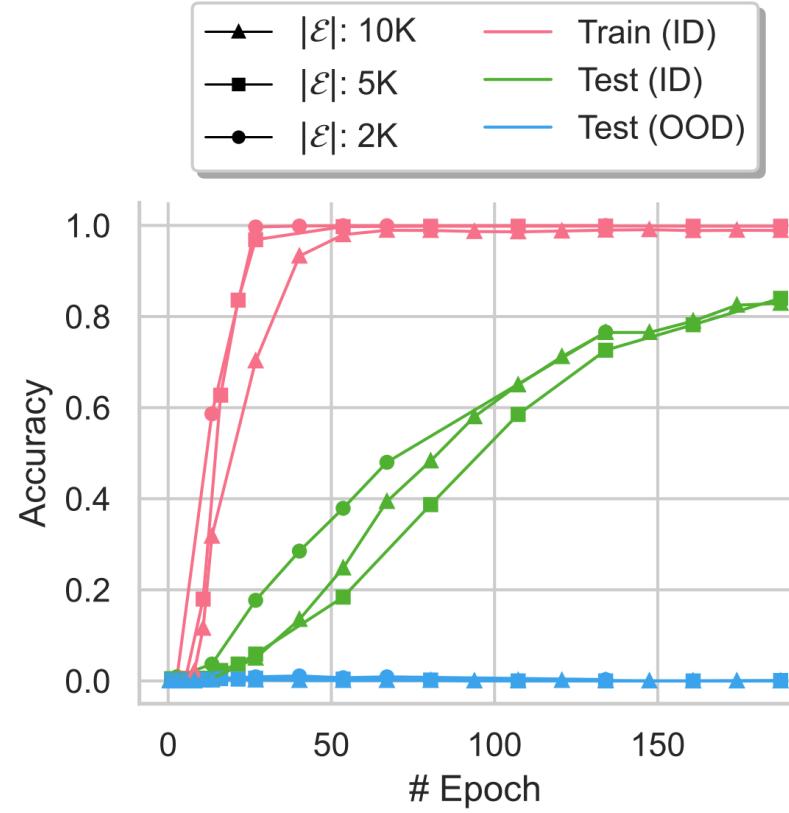
Takeaway #2: Systematicity varies by reasoning type



Takeaway #3: Critical data distribution, not size



(a) Effect of changing ratio ϕ ($|\mathcal{E}| = 2000$).



(b) Effect of changing $|\mathcal{E}|$ ($\phi = 9.0$).

$|\mathcal{E}|$: # of entities (proportional to total data size). ϕ : ratio of inferred/atomic

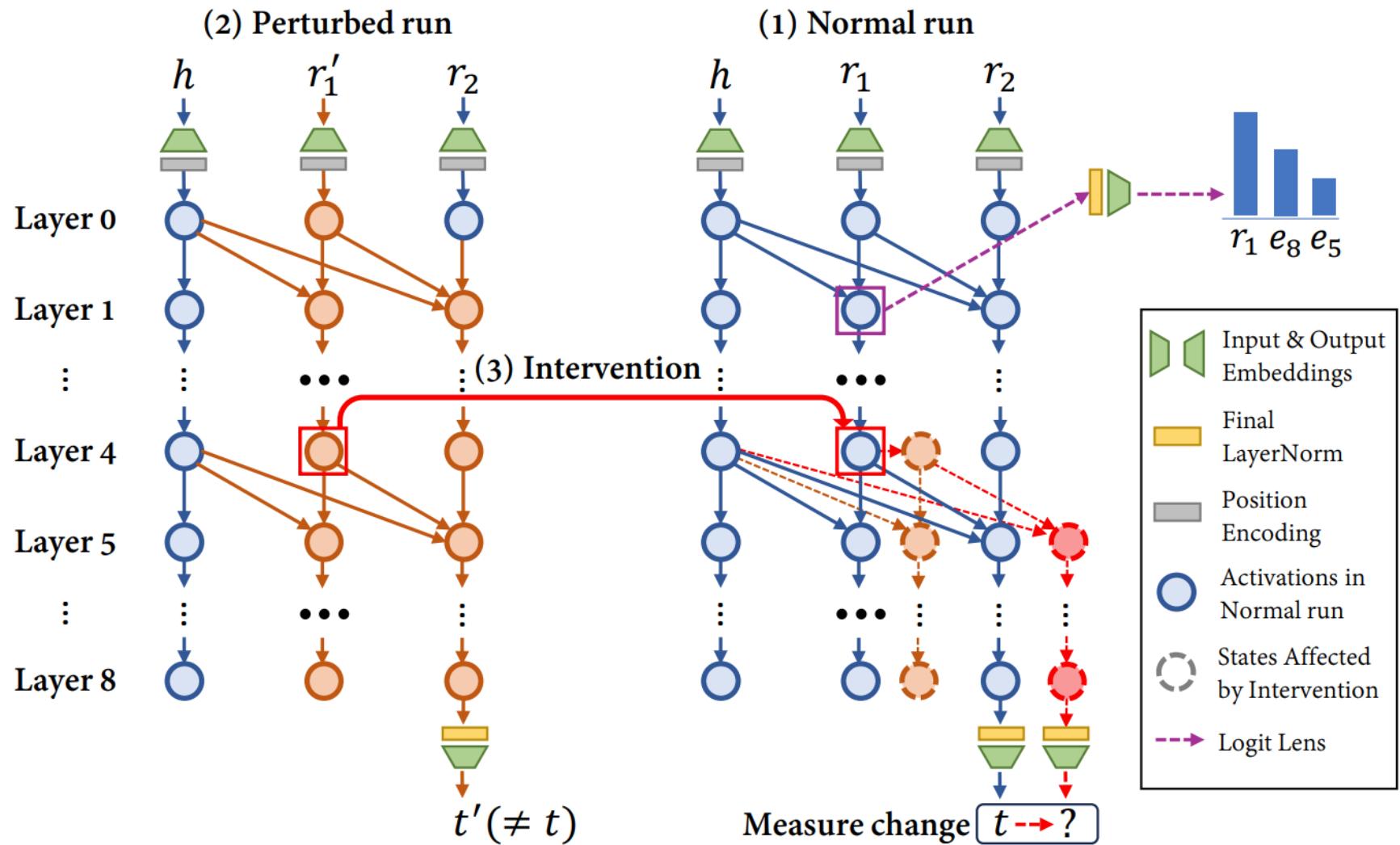
Important questions remain

- Why does grokking happen?
- What happens during grokking?
- Why does the level of systematicity in generalization vary?

These require a deeper look inside the model

Analyzing the changes during grokking

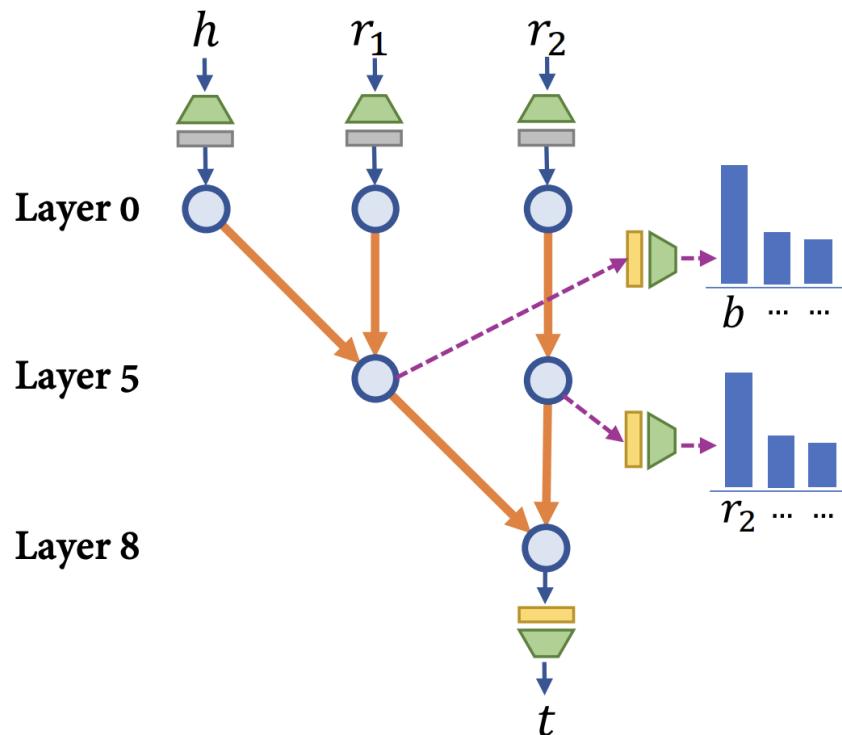
- Logit lens
- Causal tracing



Generalizing circuit configuration determines systematicity of generalization

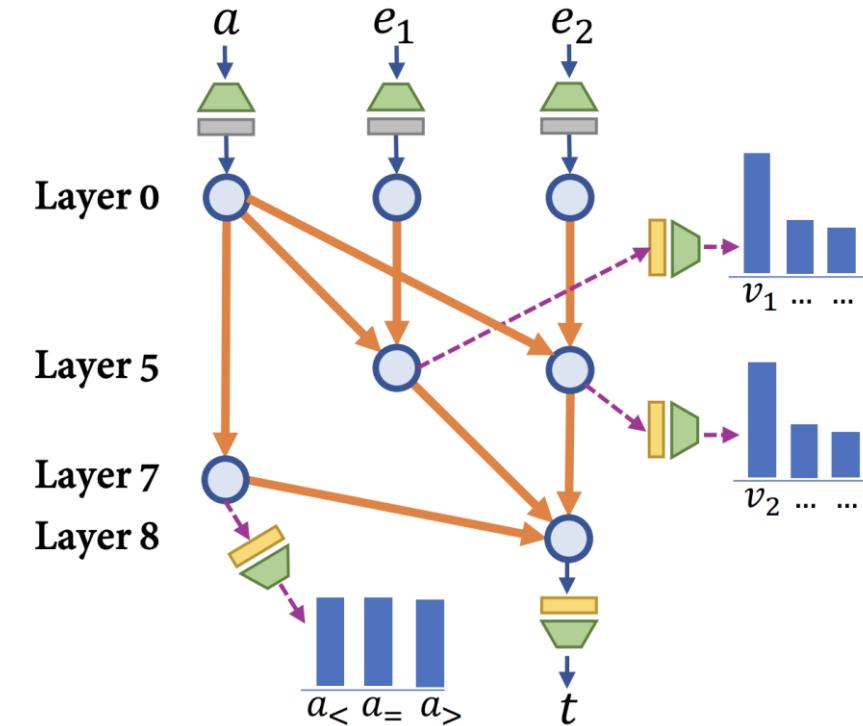
Composition

A “staged” circuit

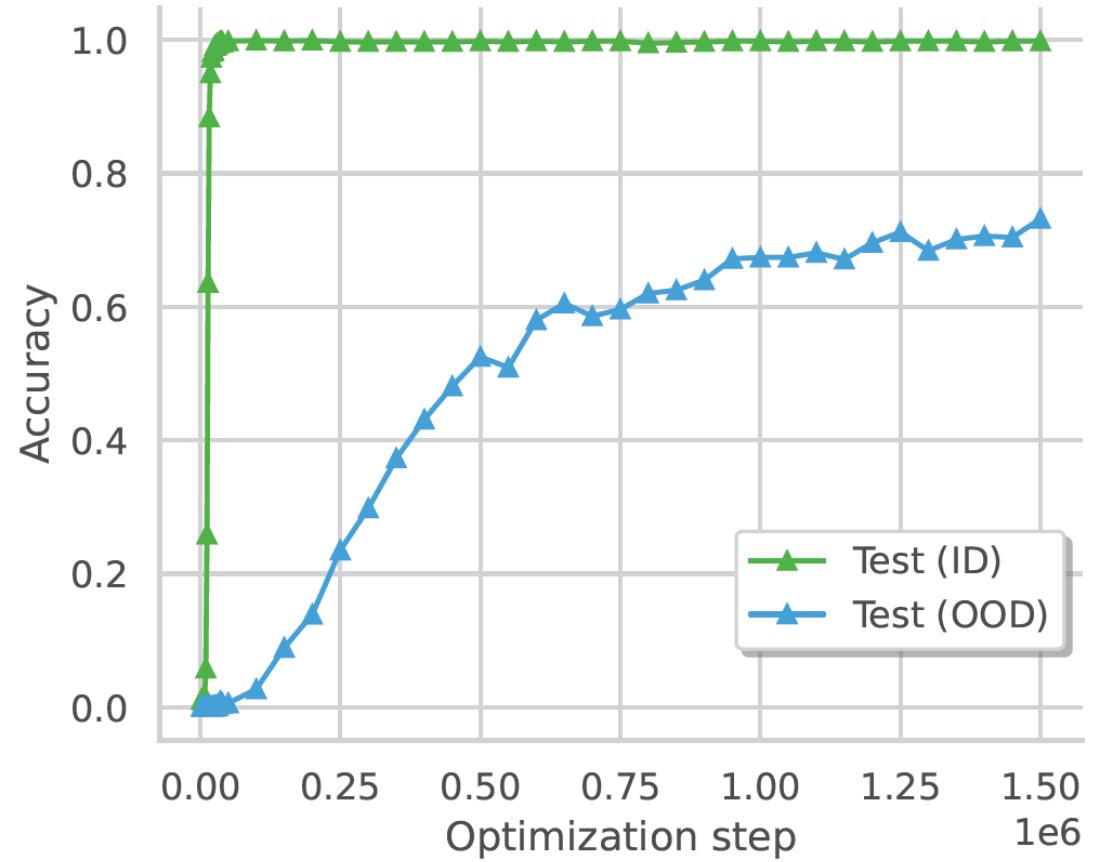
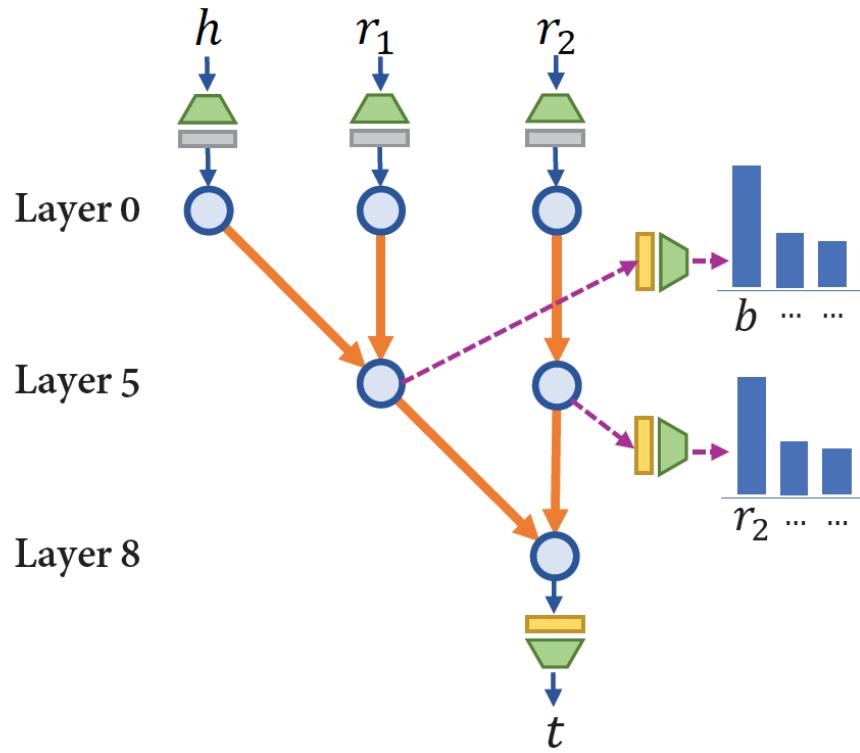


Comparison

A “parallel” circuit

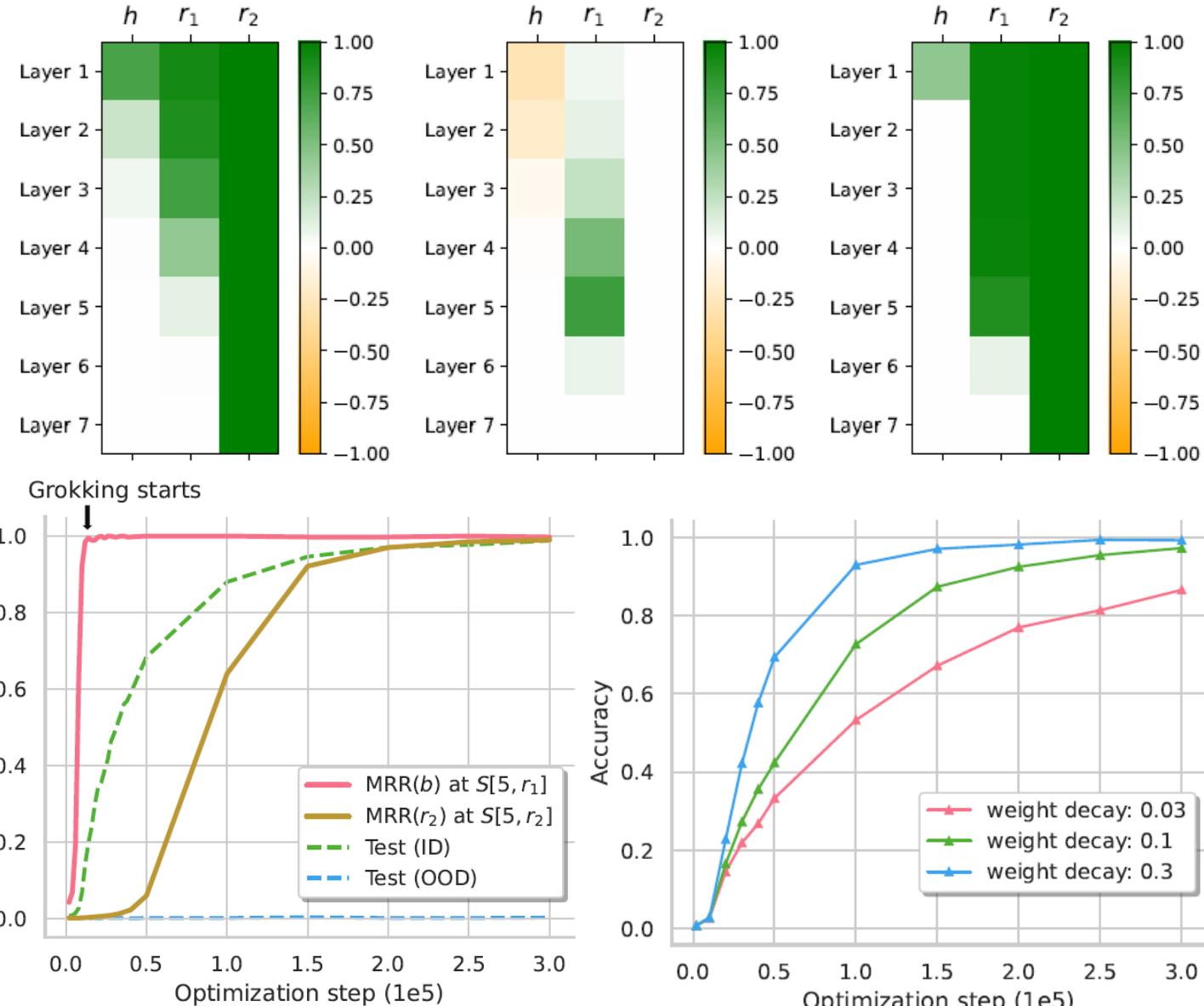


Improving systematic generalization via cross-layer parameter sharing



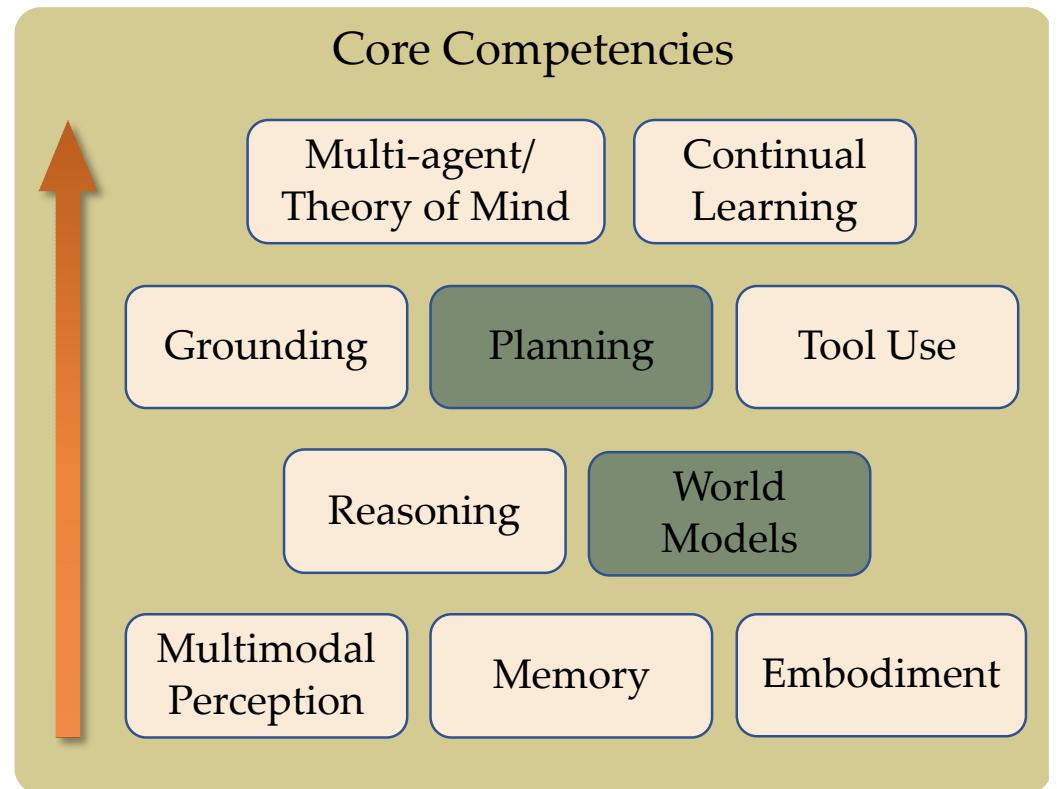
Grokking is the phase transition from rote learning to generalization (the ‘aha moment’)

- Grokking is when the generalizing circuit forms and outcompetes the memorizing circuit
- Explanation via circuit efficiency and regularization
 - # of facts need to be stored by memorizing vs. generalizing circuits



Outline

- On long-term memory
 - HippoRAG
- On reasoning
 - Grokked Transformers
- On world models and planning
 - WebDreamer



Planning: simplified definition

Given a goal G , decides on a sequence of actions (a_0, a_1, \dots, a_n) that will lead to a state that passes the goal test $g(\cdot)$

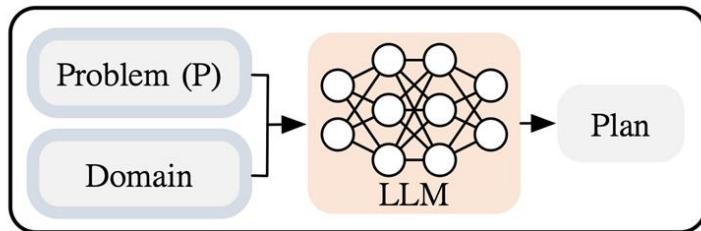
General trends in planning settings for language agents

- Increasing expressiveness in **goal specification**, e.g., in natural language as opposed to formal language
- Substantially expanded or open-ended **action space**
- Increasing difficulty in automated **goal test**

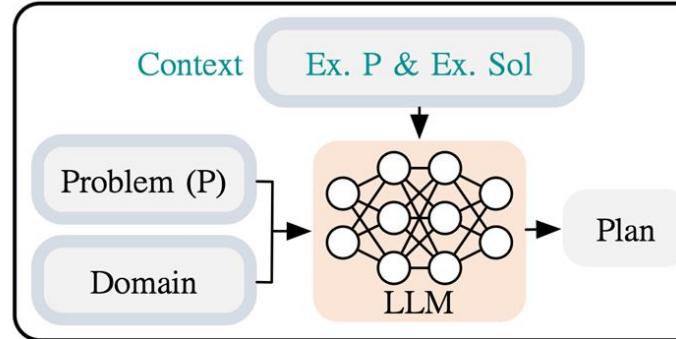
LLM+P

When domain and problem can be (fully or partially) described formally, e.g., in PDDL (Planning Domain Definition Language)

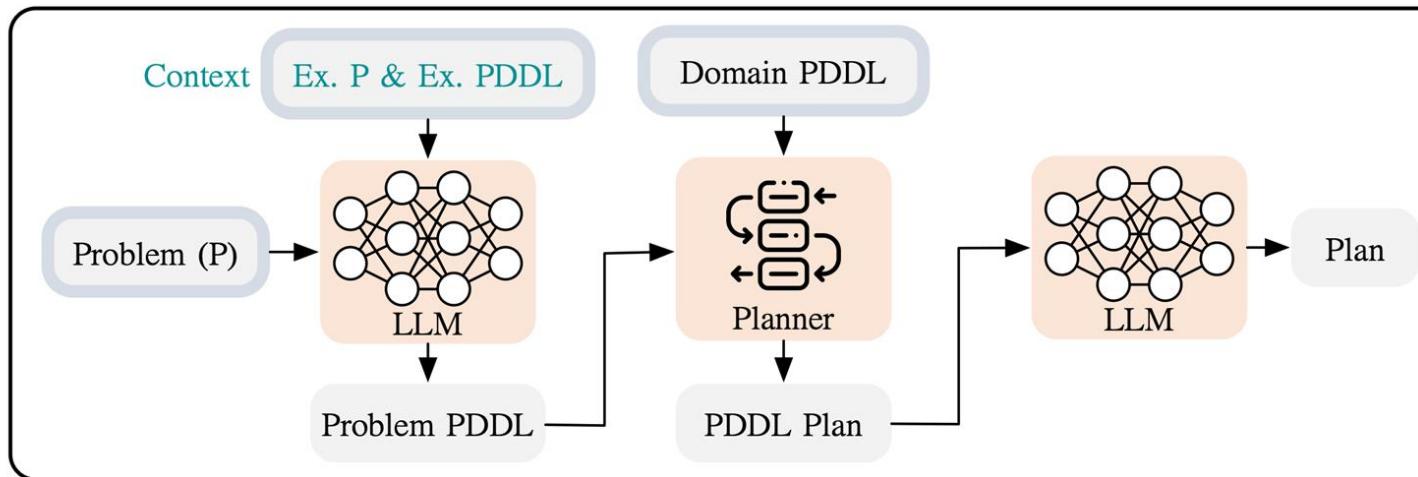
Module Generated Text Provided Text



LLM-As-Planner



LLM-As-Planner (In-context Learning)



LLM + P (In-context Learning)

An Example PDDL Problem File Written by GPT-4 with Context

Context (shaded):

An example planning problem is: You have 5 blocks. b2 is on top of b5. b5 is on top of b1. b1 is on top of b4. b3 is on top of b2. b4 is on the table. b3 is clear. Your arm is empty. Your goal is to move the blocks. b4 should be on top of b3. The problem PDDL is:

```
(:objects b1 b2 b3 b4 b5)
(:init (arm-empty) (on b1 b4) (on b2 b5) (on b3 b2)
      (on-table b4) (on b5 b1) (clear b3))
(:goal (and (on b4 b3)))
```

Prompt: Description of Problem (P1) + Context
+ Provide me with the problem PDDL file that describes the planning problem directly without further explanations.

GPT-4 (the generated problem PDDL):

```
(:objects b1 b2 b3 b4 b5 )
(:init (arm-empty) (on-table b1)
      (on b2 b1) (on b3 b4)
      (on b4 b2) (on b5 b3) (clear b5))
(:goal (and (on b1 b2) (on b3 b5)
            (on b4 b1)))
```

Planner:

```
(unstack b5 b3) (putdown b5)
(unstack b3 b4) (stack b3 b5)
(unstack b4 b2) (putdown b4)
(unstack b2 b1) (putdown b2)
(pickup b1) (stack b1 b2) (pickup b4) (stack b4 b1)
```

Language agent planning: web agents

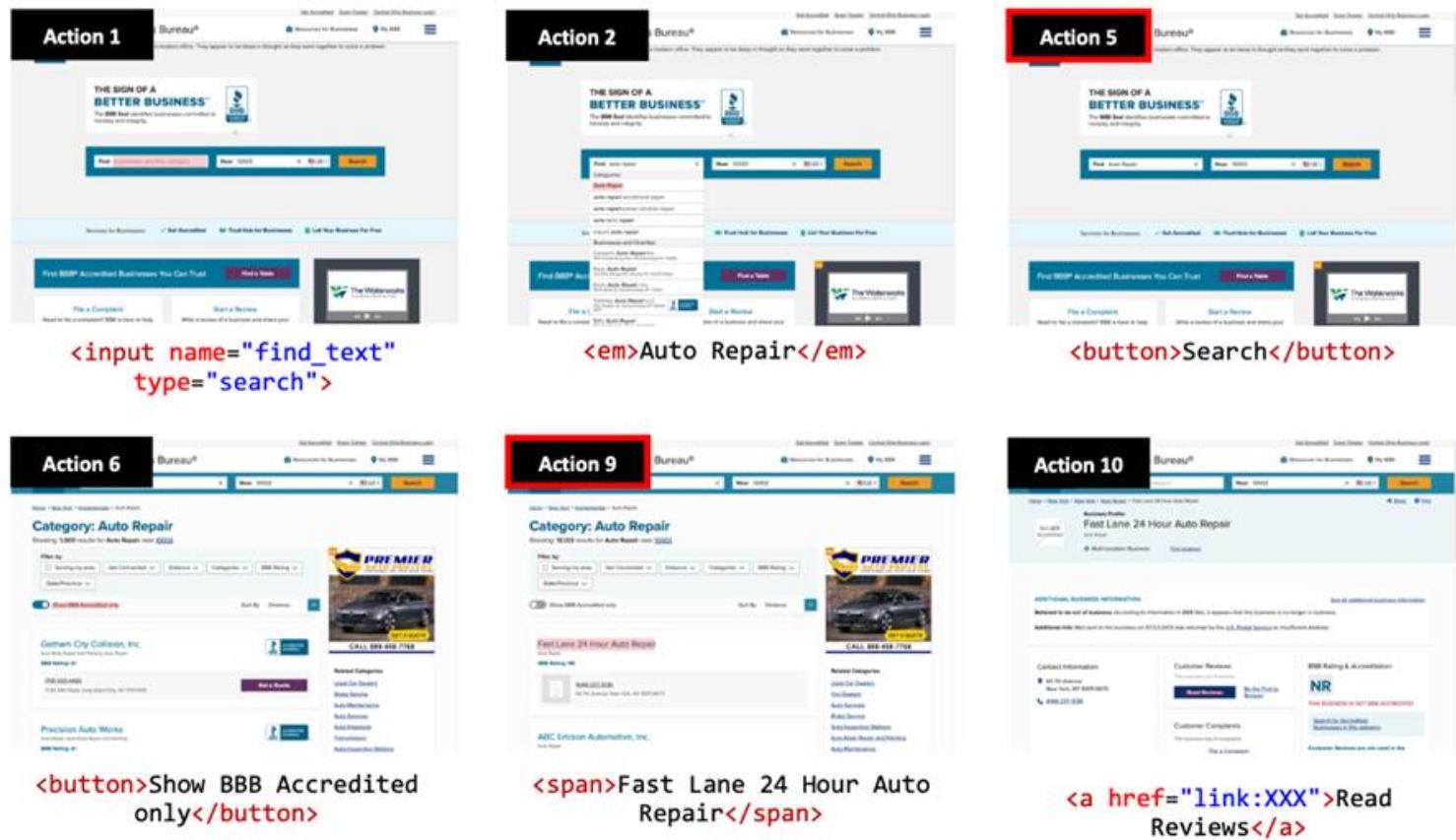
Task Description:

Show me the reviews for the auto repair business closest to 10002.

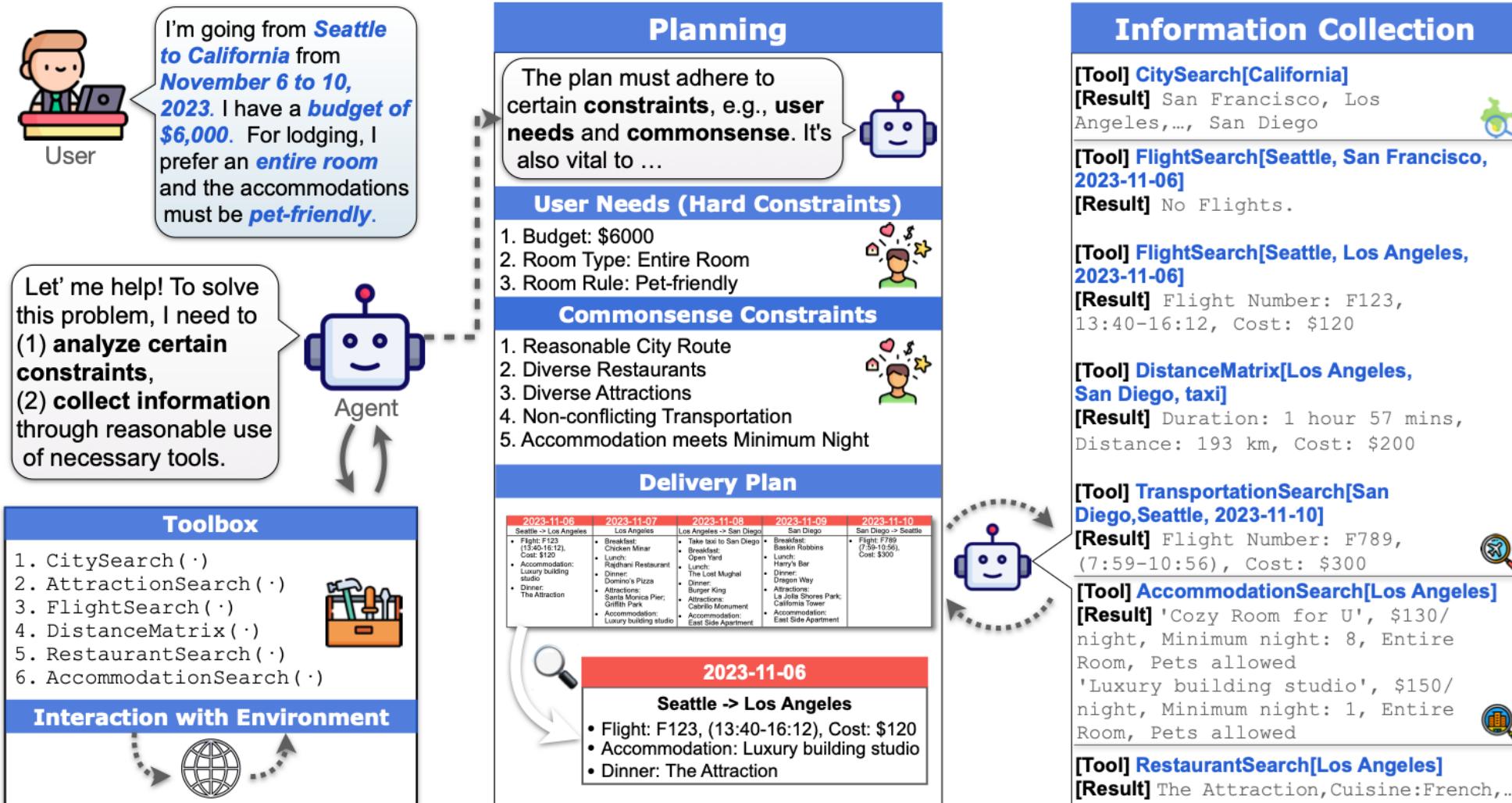
Action Sequence:

Target Element	Operation
1. [searchbox] Find	TYPE: <i>auto repair</i>
2. [button] Auto Repair	CLICK
3. [textbox] Near	TYPE: 10002
4. [button] 10002	CLICK
5. [button] Search	CLICK
6. [switch] Show BBB Accredited only	CLICK
7. [svg]	CLICK
8. [button] Sort By	CLICK
9. [link] Fast Lane 24 Hour Auto Repair	CLICK
10. [link] Read Reviews	CLICK

Webpage Snapshots:



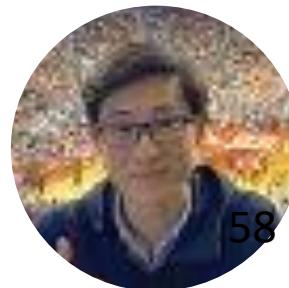
Language agent planning: travel planning



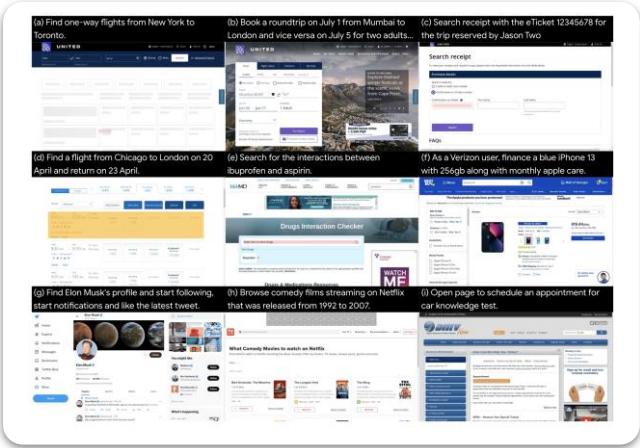
Is Your LLM Secretly a World Model of the Internet?

Model-based Planning for Web Agents

Yu Gu*, Boyuan Zheng*, Boyu Gou, Kai Zhang,
Cheng Chang, Sanjari Srivastava, Yanan Xie, Peng Qi,
Huan Sun, Yu Su



Evolution of web (or computer use) agents

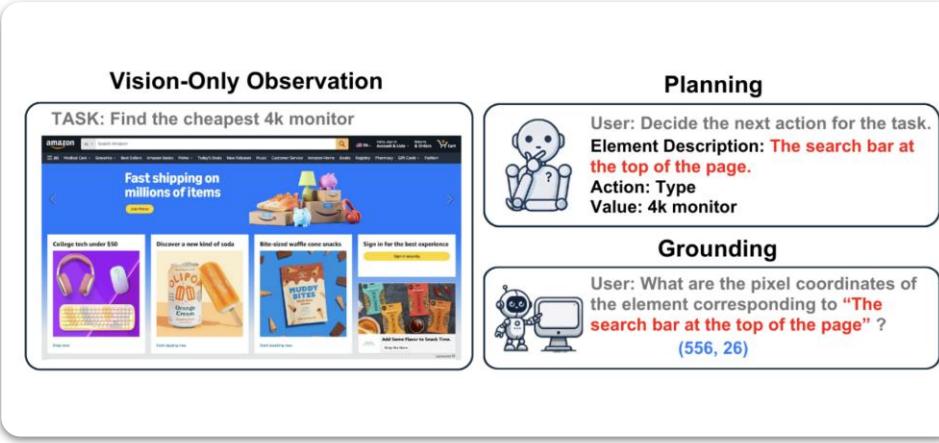


Mind2Web [NeurIPS'23]

First LLM-based web agent
Ecologically valid eval

First generalist web agent
with visual perception

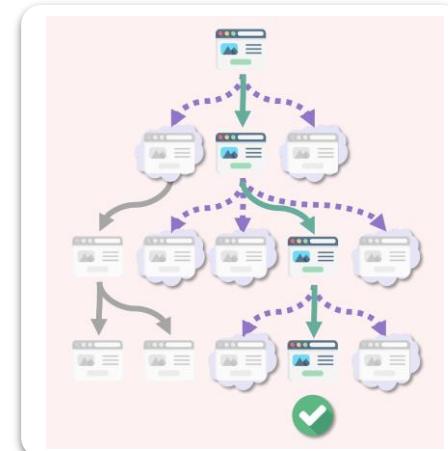
SeeAct [ICML'24]



UGround [ICLR'25]

Pure vision-based agent
Human-like embodiment

Model-based planning
WebDreamer

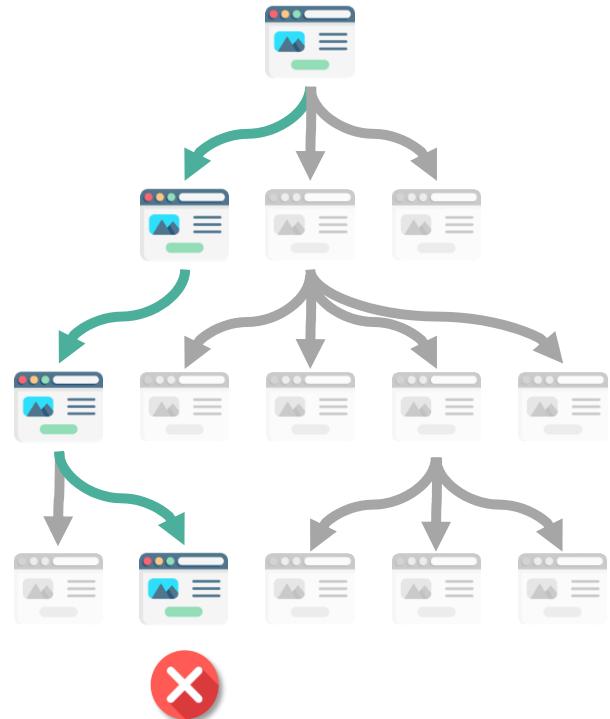


Agentic search
Continual learning
Safety

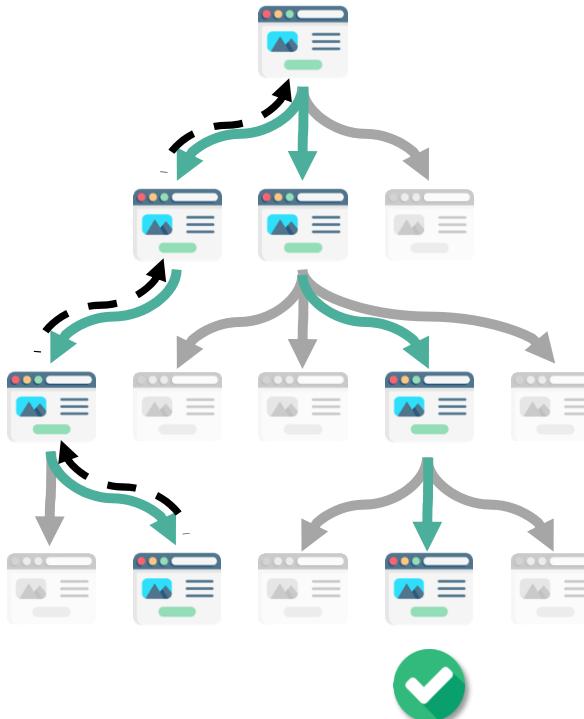


Planning paradigms for language agents

(a) reactive



(b) tree search with real interactions



fast, easy to implement



greedy, short-sighted



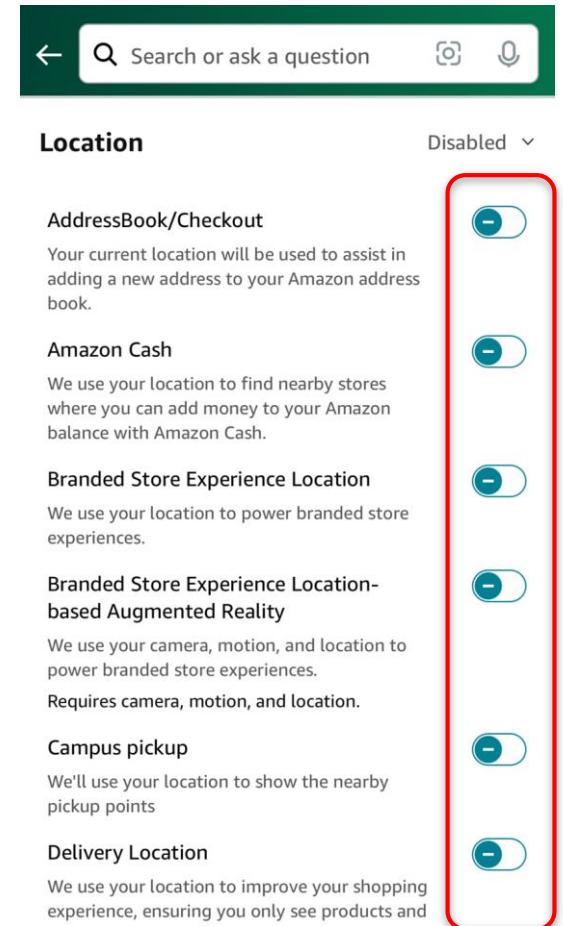
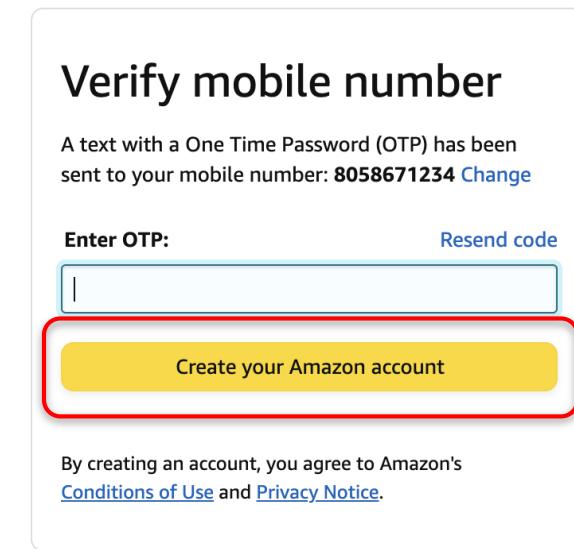
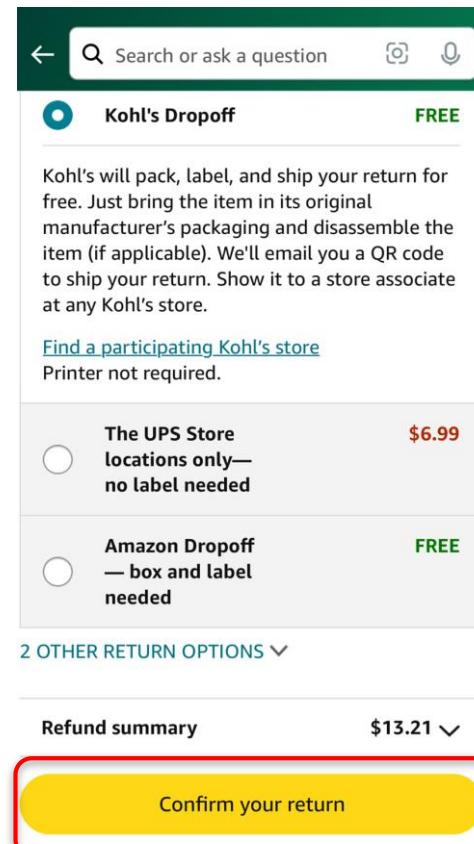
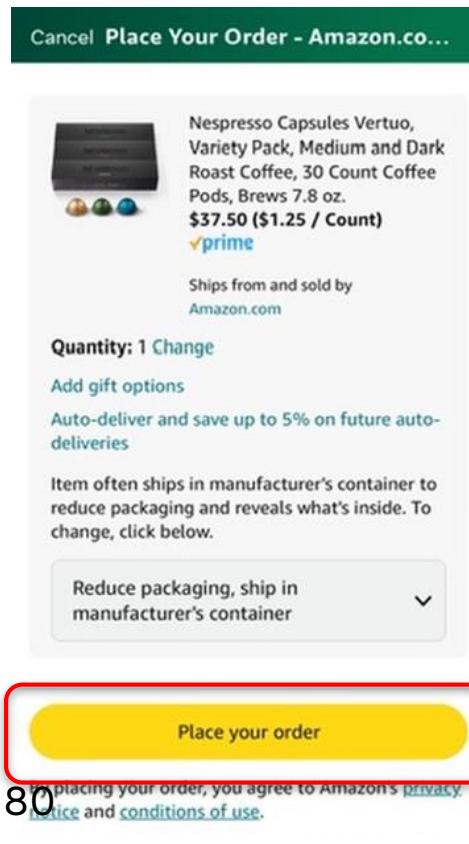
systematic exploration



irreversible actions,
unsafe, slow

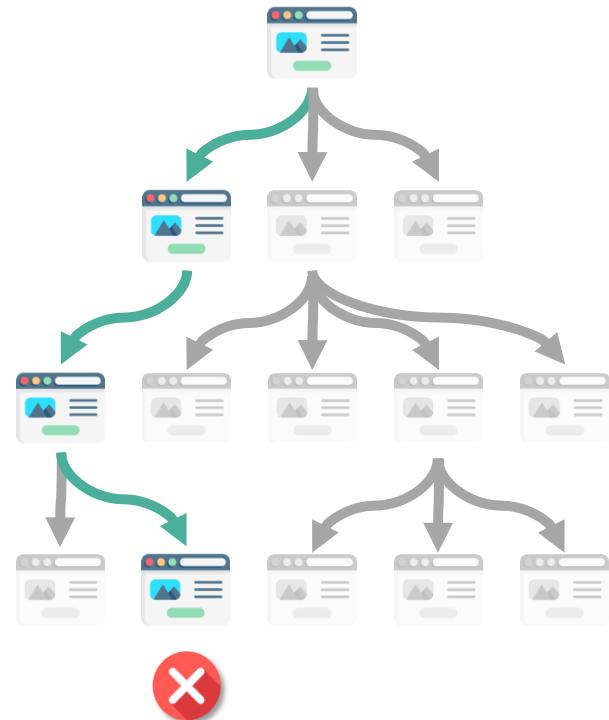
Challenges with search in real-world environments

- Many actions are state-changing and irreversible → backtracking X
- Safety/privacy risks
- Inference-time exploration could be slow and costly



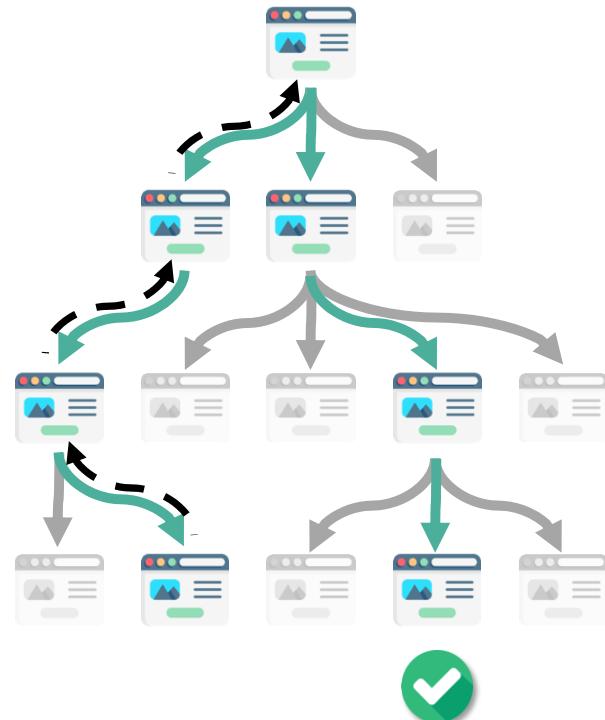
Planning paradigms for language agents

(a) reactive



fast, easy to implement

(b) tree search with real interactions

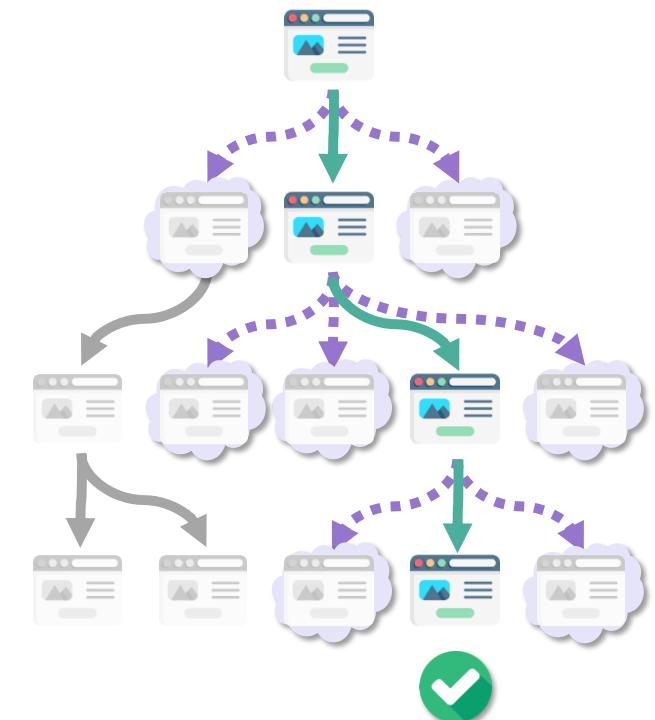


systematic exploration



irreversible actions,
unsafe, slow

(c) model-based planning



faster, safer,
systematic exploration



how to get a world model?

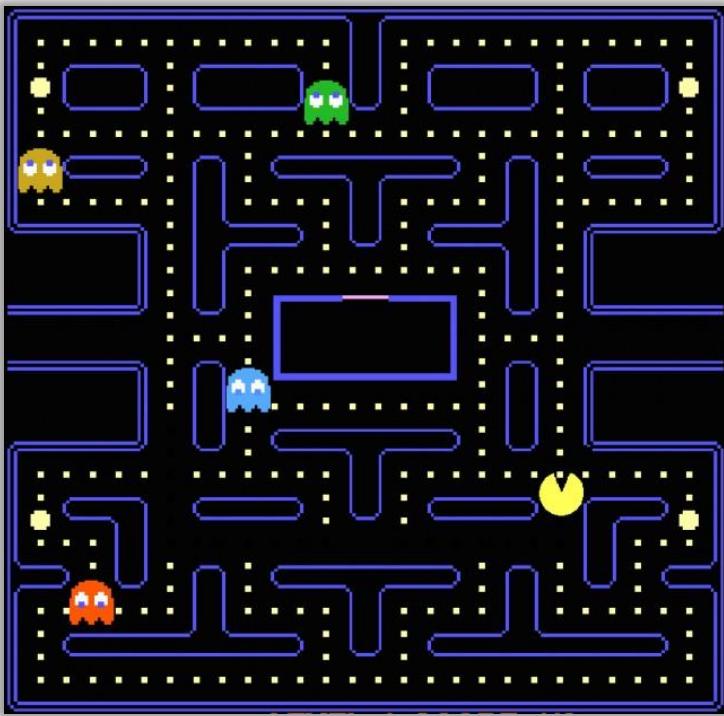
What's ... a world model?

A computational model of environment transition dynamics

$$\hat{T}: \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}$$

If I do this (a_t) right now (s_t), what would happen next (s_{t+1})?

Why hasn't it been done already?



V.S

The image shows the homepage of Amazon.com. At the top, there's a navigation bar with links like 'All', 'Holiday Deals', 'Medical Care', 'Best Sellers', 'Prime', 'Amazon Basics', 'Today's Deals', 'New Releases', 'Groceries', 'Music', 'Customer Service', 'Amazon Home', 'Pharmacy', 'Registry', and 'Black Friday Football: LV vs KC 11/29'. Below the navigation is a large banner for 'Christmas decor under \$25' featuring various festive items like stockings and ornaments. There are several promotional sections: 'Luxury gifts for all' (showing a dog and a lion), 'New on Amazon: Estée Lauder' (showing skincare products), 'Being a Prime member adds up' (showing a hand pumping gas and a Prime delivery box), and 'Men's designer finds' (showing sneakers and skincare). At the bottom, there's a section for 'Best Sellers in Beauty & Personal Care' displaying various skincare and cosmetic products.

And **billions of other websites** on the Internet!

LLMs can predict state transitions

My Account My Wish List Sign In Welcome to One Stop Market Create an Account

One Stop Market

Beauty & Personal Care - Sports & Outdoors - Clothing, Shoes & Jewelry - Home & Kitchen - Office Products - Tools & Home Improvement -

Health & Household - Patio, Lawn & Garden - Electronics - Cell Phones & Accessories - Video Games - Grocery & Gourmet Food -

Home > Clothing, Shoes & Jewelry > Men > Uniforms, Work & Safety

Uniforms, Work & Safety

Shop By

Items 1-12 of 416

Sort By Position ↑

Workwear Professionals Men Scrubs Pant Tapered Leg Drawstring Cargo WW1905, XS Short, Hunter Green \$23.98 Add to Cart

Men's Slim Fit Pinstripe Chef Pant (S-3X) \$31.98 Add to Cart

XINFU Chef's Japanese Kimono Unisex Uniform Short Sleeved Working Clothes Kitchen Restaurant Chef Jacket \$34.69 Add to Cart

Safety Shoes, Mesh Cloth Protect Your Toes Men's Safety Shoes, Lightweight Work Indoor Man Outdoor for Woman(40-46, 40) \$39.37 Add to Cart

TRUEWERK Men's Winter Work Pants - T3 WerkPants Insulated Workwear ★★★★☆ 12 Reviews \$99.00 Add to Cart

Steel Toe-Cap Flying Woven Mesh Shoes, Lightweight Anti-Smashing Anti-Puncture Safety Shoes, Anti-Collision Anti-Pressure Work Shoes,Black,46 \$85.99 Add to Cart

Mens Flowers Casual Aloha Hawaiian Shirt Summer Short Sleeve Beach T-Shirt Regular Fit Button Down Dress Shirts \$11.99 Add to Cart

Carhartt Men's Duck Chore Coat Blanket Lined C001 \$179.95 Add to Cart

The page will navigate to a detailed product page for the "Mens Flowers Casual Aloha Hawaiian Shirt Summer Short Sleeve Beach T-Shirt Regular Fit Button Down Dress Shirts." This new page will likely contain additional information about the product including more detailed specifications, customer reviews, larger images, sizing options, and possibly a larger "Add to Cart" button. Other elements from the current category view like the grid of products will be replaced with the detailed view of this specific product.

WebDreamer: model-based planner for web agents

Please navigate to the 'Data Storage' category and purchase the least expensive disk with 512GB of storage.

One Stop Market

③ Type 'Disk'

① Click 'Office Products'

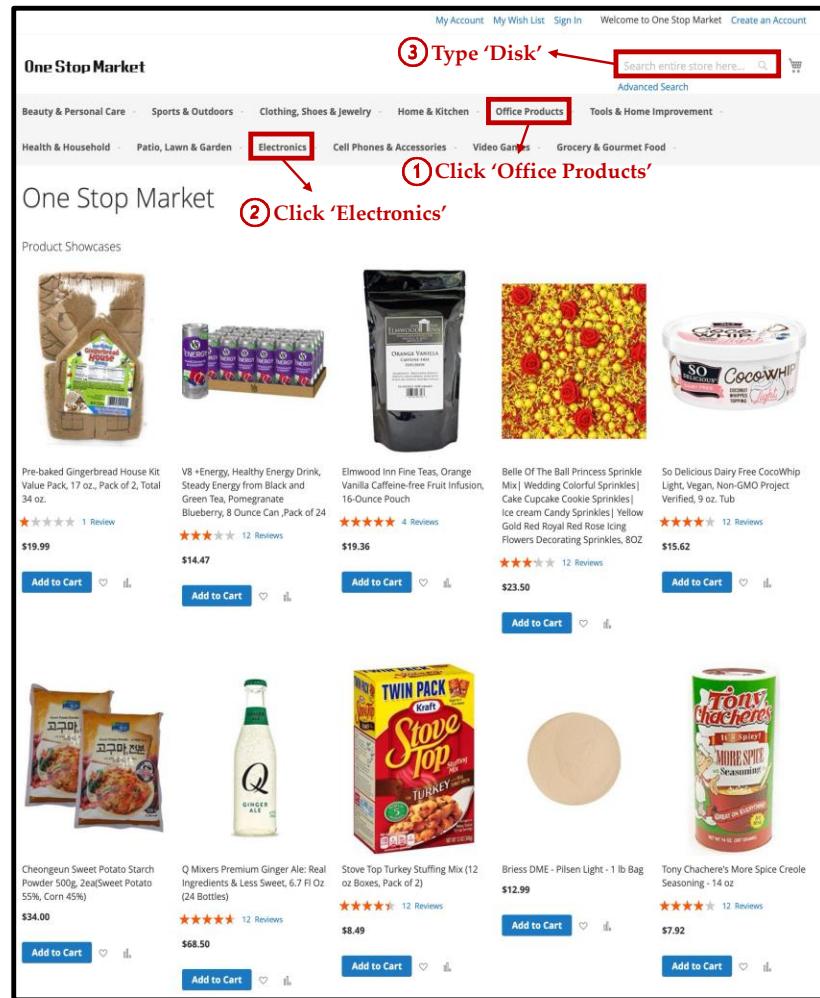
② Click 'Electronics'

Product Showcases

Product	Description	Rating	Price
Pre-baked Gingerbread House Kit	Value Pack, 17 oz., Pack of 2, Total 34 oz.	★★★★★ 1 Review	\$19.99
VB +Energy, Healthy Energy Drink, Steady Energy from Black and Green Tea, Pomegranate Blueberry, 8 Ounce Can, Pack of 24		★★★★★ 12 Reviews	\$14.47
Elmwood Inn Fine Teas, Orange Caffeine-free Fruit Infusion, 16-Ounce Pouch		★★★★★ 4 Reviews	\$19.36
Belle Of The Ball Princess Sprinkle Mix Wedding Colorful Sprinkles Cake Cupcake Cookie Sprinkles Ice cream Candy Sprinkles Yellow Gold Red Royal Rose King Flowers Decorating Sprinkles, 8OZ		★★★★★ 12 Reviews	\$23.50
So Delicious Dairy Free CocoWhip Light, Vegan, Non-GMO Project Verified, 9 oz. Tub		★★★★★ 12 Reviews	\$15.62
Cheongeon Sweet Potato Starch Powder 500g, ZealSweet Potato 55%, Corn 45%		★★★★★ 12 Reviews	\$34.00
Q Mixers Premium Ginger Ale- Real Ingredients & Less Sweet, 6.7 Fl Oz (24 Bottles)		★★★★★ 12 Reviews	\$68.50
Kraft Stove Top Turkey Stuffing Mix (12 oz Boxes, Pack of 2)		★★★★★ 12 Reviews	\$8.49
Briess DME - Pilsen Light - 1 lb Bag		★★★★★ 12 Reviews	\$12.99
Tony Chachere's More Spice Creole Seasoning - 14 oz		★★★★★ 12 Reviews	\$7.92

WebDreamer: model-based planner for web agents

Please navigate to the 'Data Storage' category and purchase the least expensive disk with 512GB of storage.



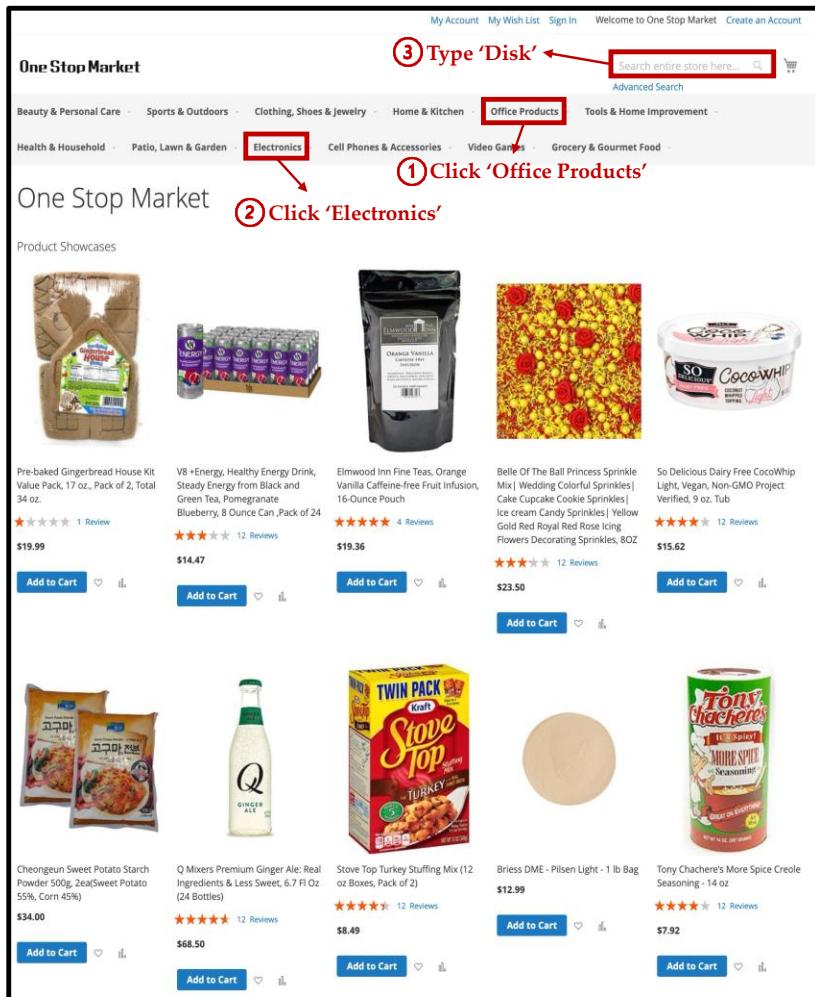
Stage I: Simulation



The 'Office Products' category will display three sub-categories: 'Office Electronics', 'Office & School Supplies', and 'Office Furniture & Lighting'.

WebDreamer: model-based planner for web agents

Please navigate to the 'Data Storage' category and purchase the least expensive disk with 512GB of storage.



Stage I: Simulation



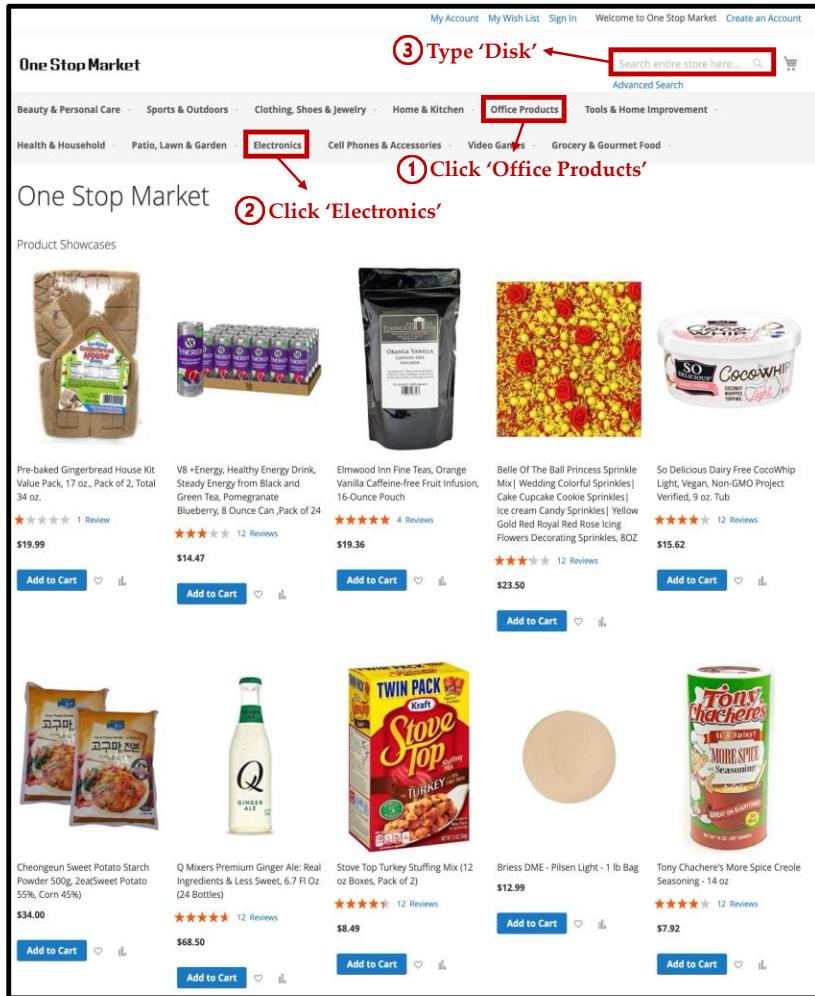
The 'Office Products' category will display three sub-categories: 'Office Electronics', 'Office & School Supplies', and 'Office Furniture & Lighting'.

Click 'Office Electronics'

The webpage will display 'Office Electronics' sub-category results with products, and the sub-menu will show 'Printers&Accessories' and other categories.

WebDreamer: model-based planner for web agents

Please navigate to the 'Data Storage' category and purchase the least expensive disk with 512GB of storage.



Stage I: Simulation



The 'Office Products' category will display three sub-categories: 'Office Electronics', 'Office & School Supplies', and 'Office Furniture & Lighting'.

Click 'Office Electronics'

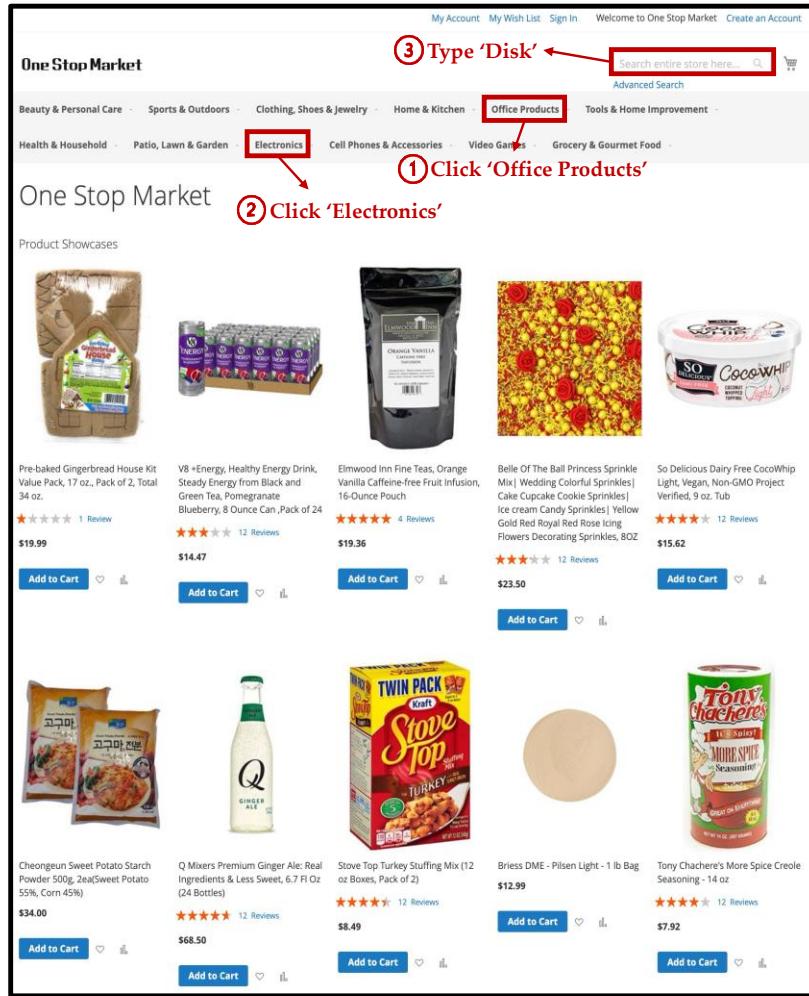


The webpage will display 'Office Electronics' sub-category results with products, and the sub-menu will show 'Printers&Accessories' and other categories.

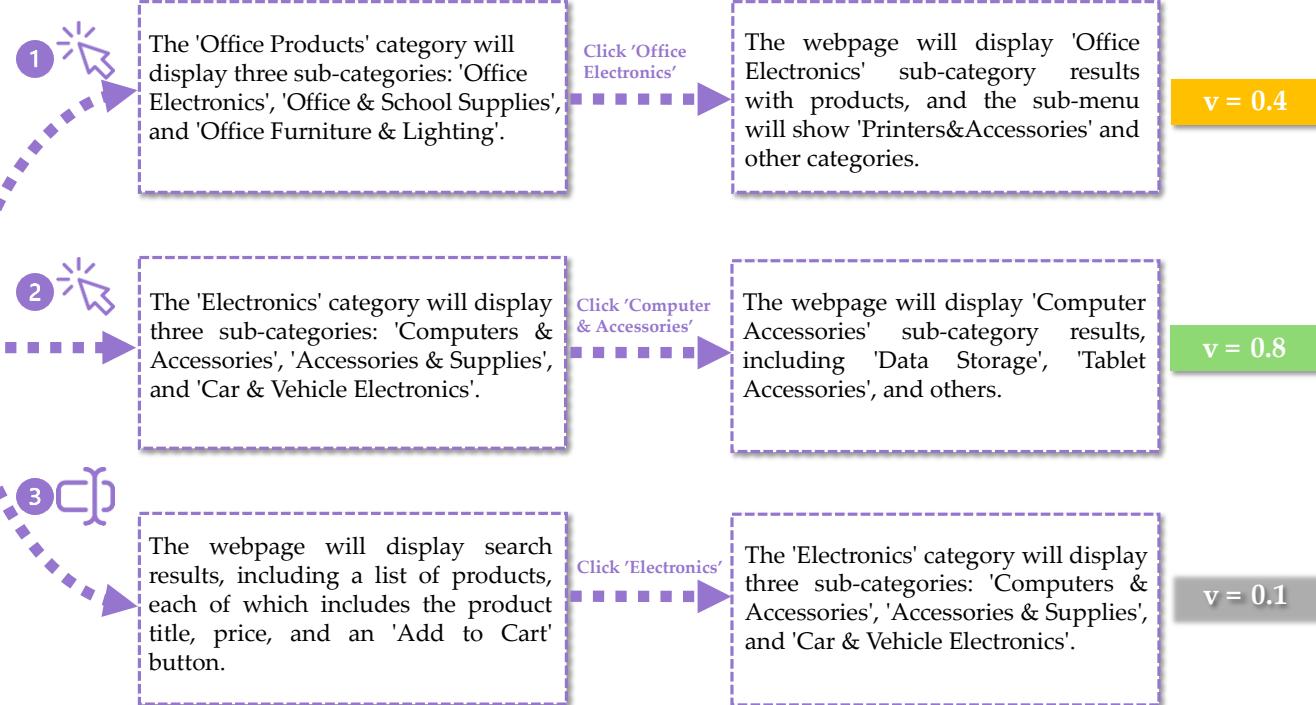
v = 0.4

WebDreamer: model-based planner for web agents

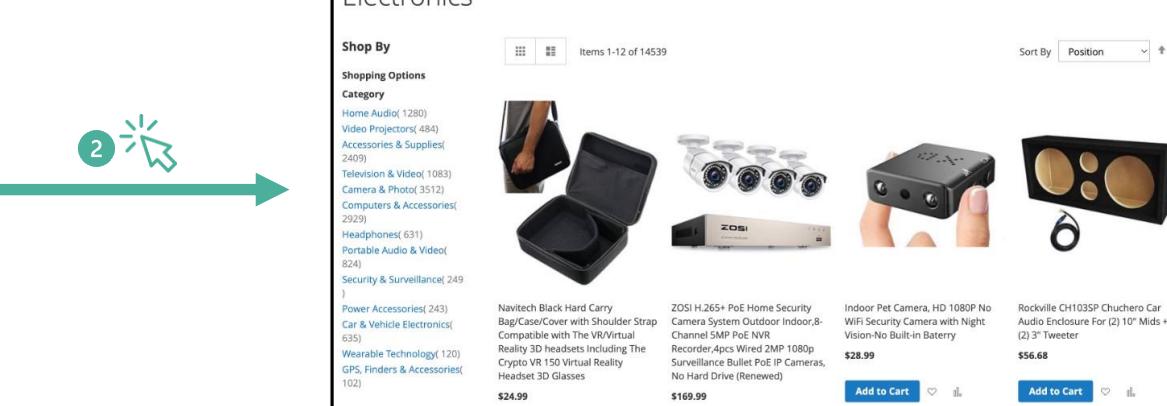
Please navigate to the 'Data Storage' category and purchase the least expensive disk with 512GB of storage.



Stage I: Simulation

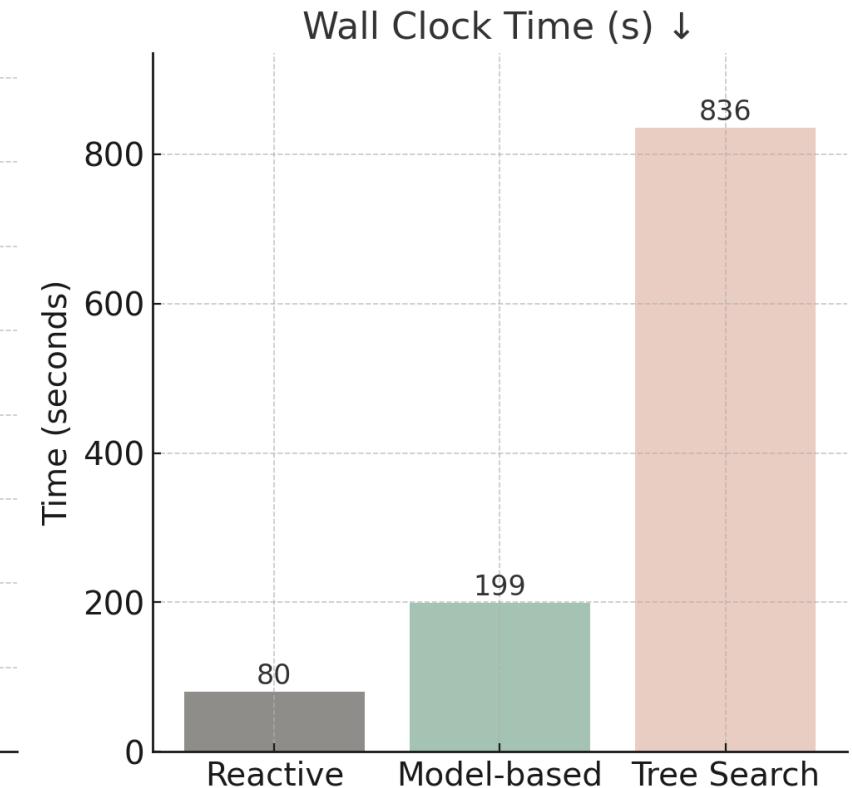
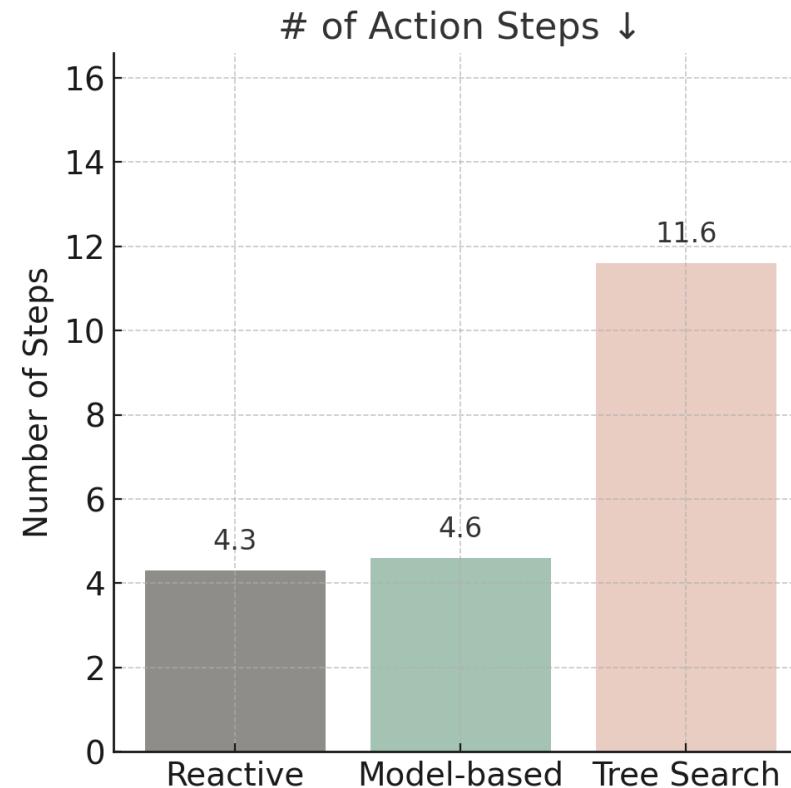
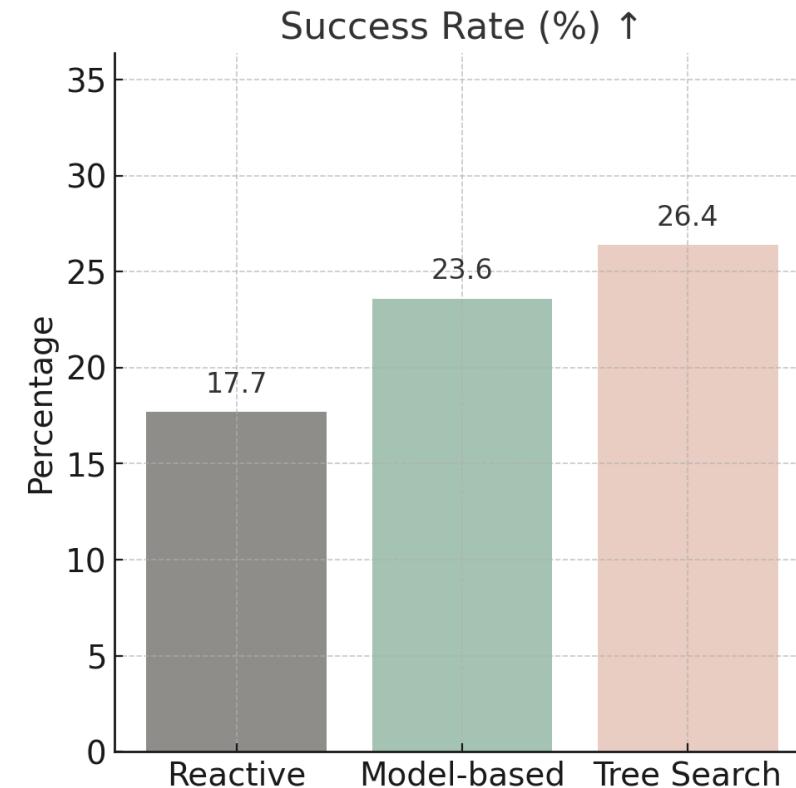


Stage II: Execution



Results on VisualWebArena

Model-based planning is more accurate than reactive planning and more efficient than tree search

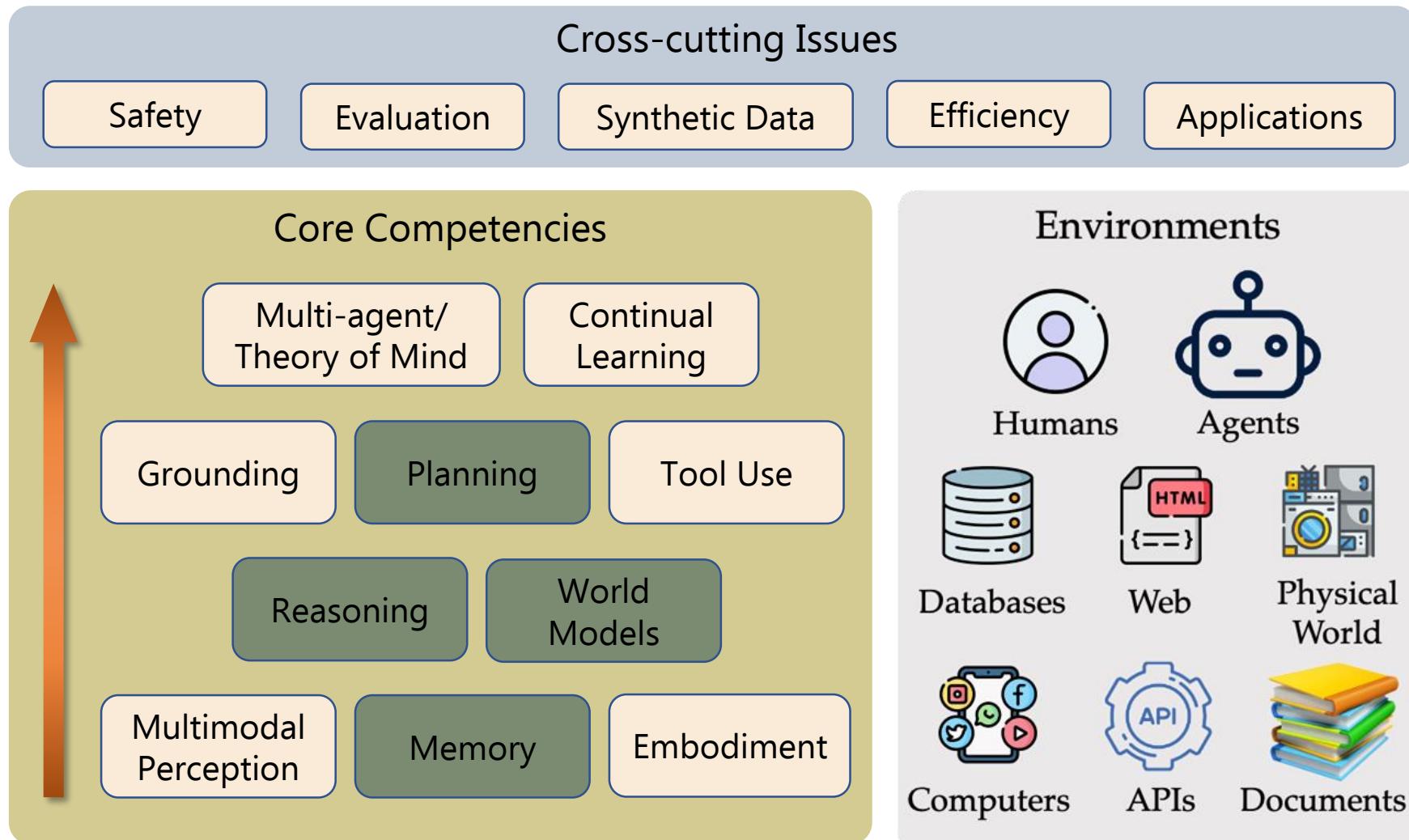


Baselines are from Koh et al., (2024)

Planning: takeaways

- Language agents are expanding into new planning scenarios
 - Characterized by expressive but fuzzy goal specifications, open-ended action spaces, more difficult and sometimes non-binary goal tests
- Language for reasoning also enables new planning abilities
 - Generalist world models and model-based planning
 - Hierarchical planning and dynamic replanning
- The best planning strategy is dependent on the LLM; stronger LLMs may require less scaffolding (i.e., more ‘reactive’)
- How to improve planning in LLMs is still largely an open question
 - Can the recipe for o1/R1-style reasoning work for planning?

We are just standing at the dawn of a long journey



Some future directions for language agents

- Memory, personalization, and continual learning
 - *How can an agent continually learn from use and exploration?*
- Reasoning
 - *O1/R1-style reasoning? How to get reliable rewards? How to integrate external actions and environmental states?*
- Planning
 - *How to build better world models? How to balance reactive and model-based planning? How to sustain a long horizon without losing focus?*
- Safety
 - *Endogenous risks vs. exogenous risks*
- Applications
 - *Agentic search (deep research), workflow automation, science agents*

Language Agents: Foundations, Prospects, and Risks

Yu Su, Diyi Yang, Shunyu Yao, Tao Yu

<https://language-agent-tutorial.github.io/>



75 / 80



Stanford
University

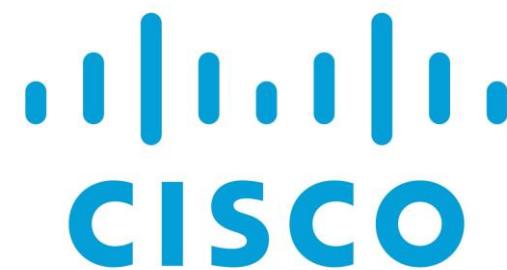


OpenAI

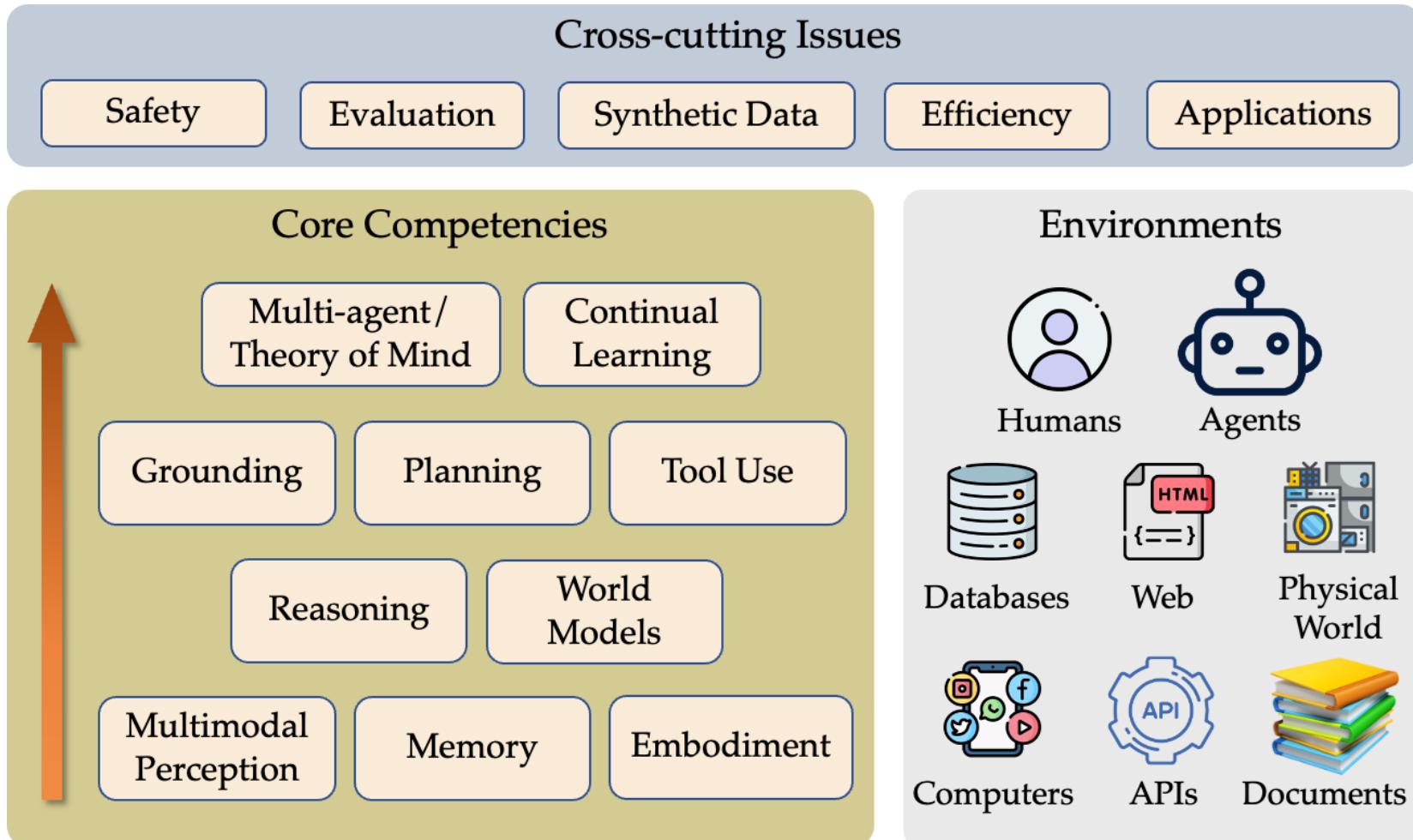


香港大學
THE UNIVERSITY OF HONG KONG

Acknowledgements

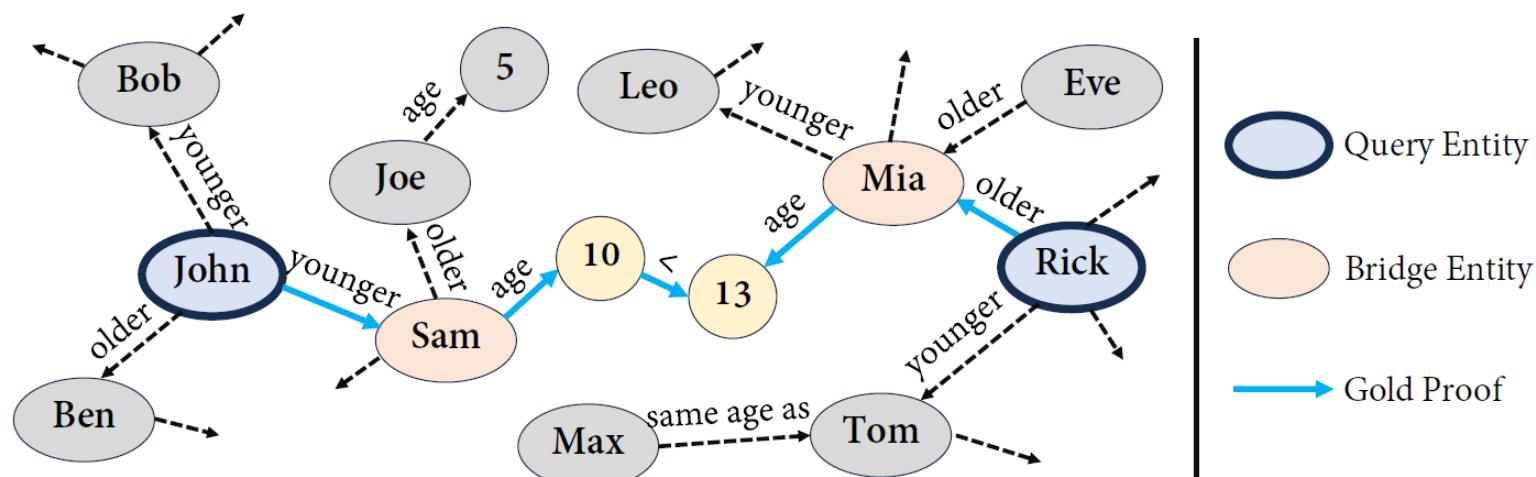


Thanks &



Reasoning task with a Large Search Space

- Large search space
 - Each query entity connects to ~50 facts
 - Each bridge entity (in ground truth proof) connects to >900 facts
- No surface form clues to exploit & bias the proof search
 - Unlike most conventional QA benchmarks where the proof steps are transparent



The Power of Parametric Memory for Complex Reasoning

- SoTA LLMs with non-parametric memory fail badly
 - Current LLMs still cannot reason deeply with non-parametric knowledge representations
 - Also no major improvement from o1-preview or o3-mini (high)
- Grokked transformer achieves near-perfect accuracy by integrating and compressing the facts to the extreme

Table 1: Results on the complex reasoning task. Direct/CoT: predict the answer directly/verbalize the reasoning steps. “+R”: retrieval augmentation.

	GPT-4-Turbo		Gemini-Pro-1.5				Grokked Transformer
	Direct+R	CoT+R	Direct	CoT	Direct+R	CoT+R	
Accuracy (%)	33.3	31.3	28.7	11.3	37.3	12.0	99.3