A holistic and critical look at language agents

Yu Su

The Ohio State University

Outline

Language Agents: Introduction

• The Power of Language: Memory, Planning, Grounding, Tool Use

Future Directions

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Language Agents: Introduction

• The Power of Language: Memory, Planning, Tool Use

Future Directions

The rise, and the divide

Bill Gates

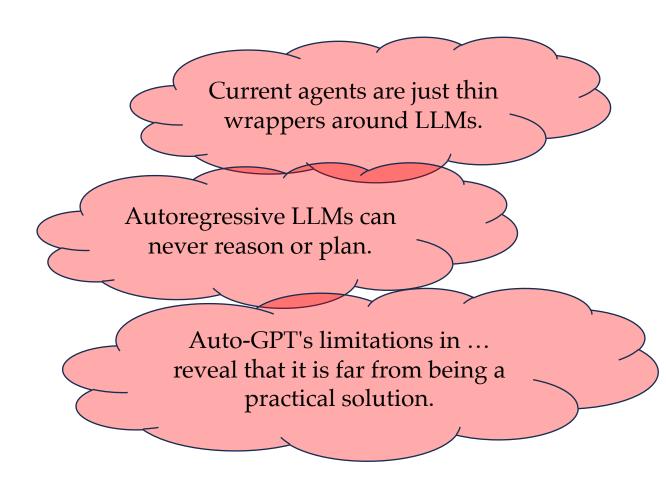
Agents are bringing about the **biggest revolution in computing** since we went from typing commands to tapping on icons.

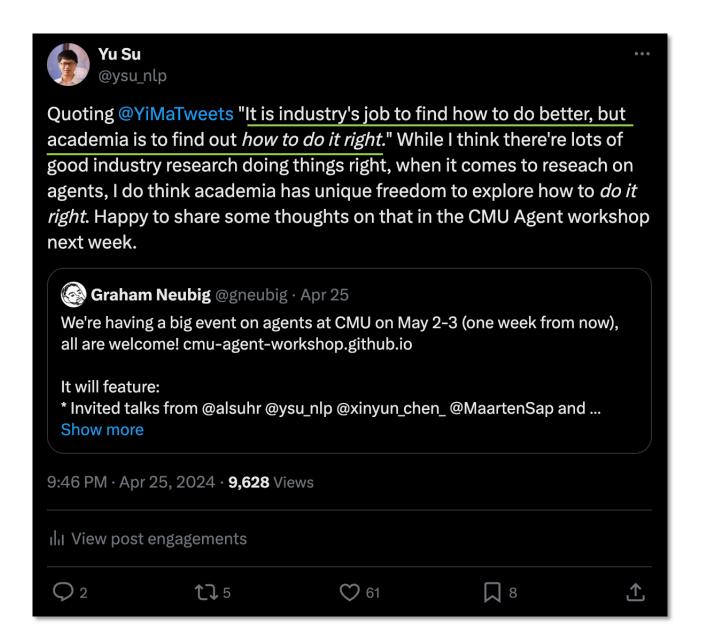
Andrew Ng

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

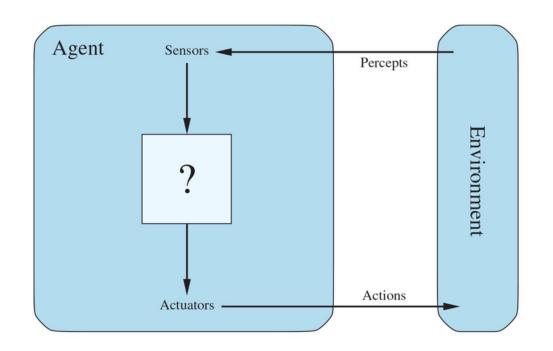
Sam Altman

2025 is when agents will work.





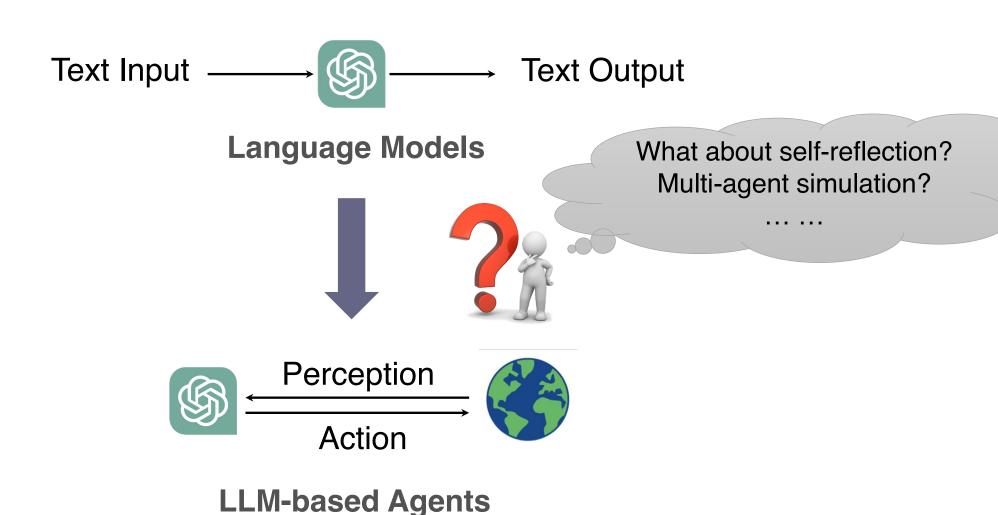
Why agents again?



"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

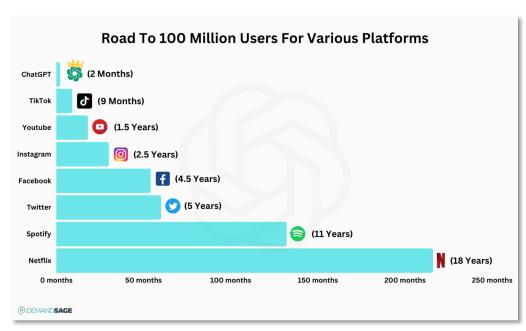
Agent-first view: An AI agent integrates LLMs so it can use language for reasoning and communication

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

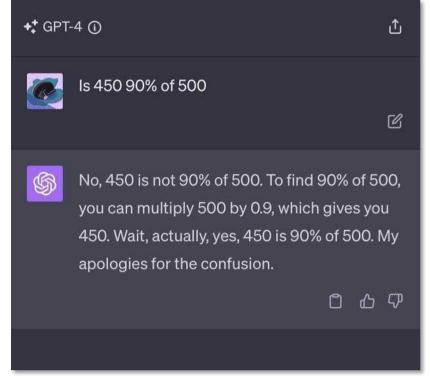
What's fundamentally different now?

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

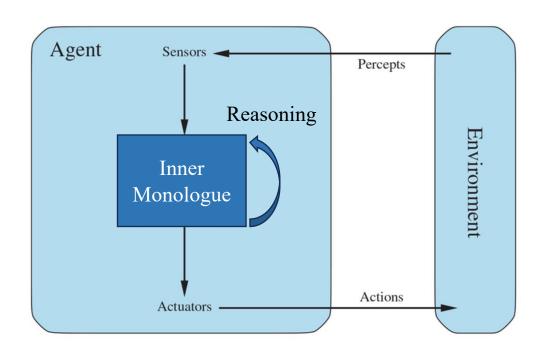
- 1 Instruction following, in-context learning, output customization
- A Reasoning (for better acting): state inferences, self-reflection, replanning, etc.



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

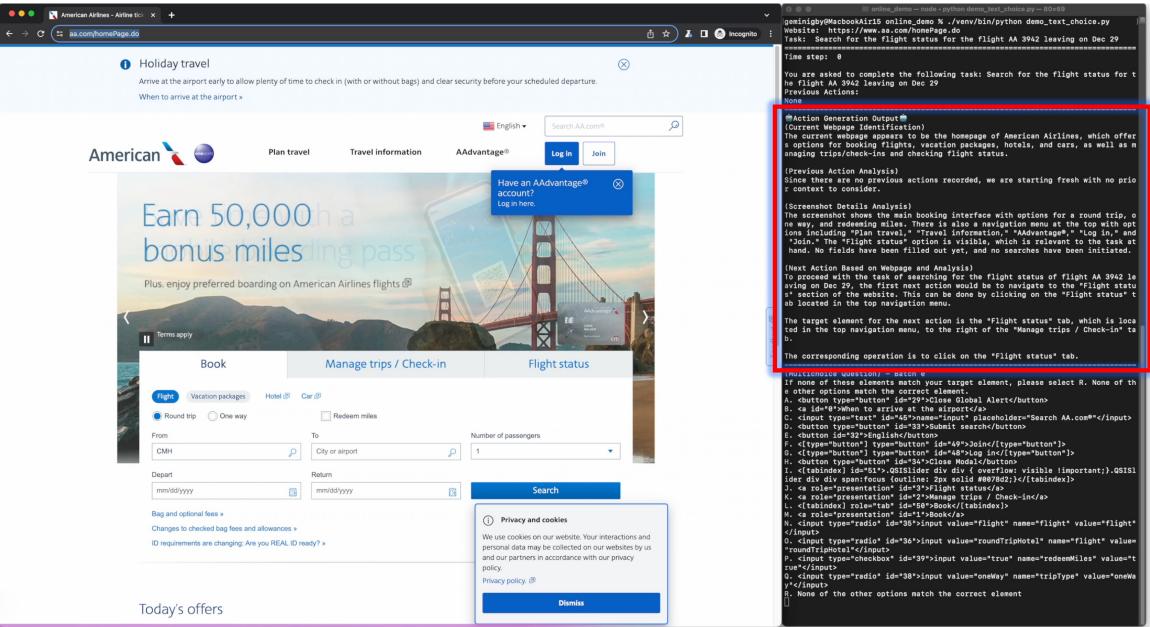


Schematic illustration: updated



- 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

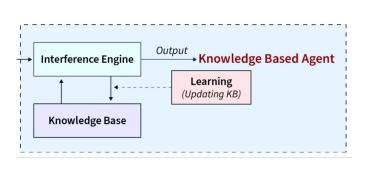
Web agent example

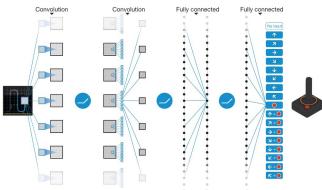


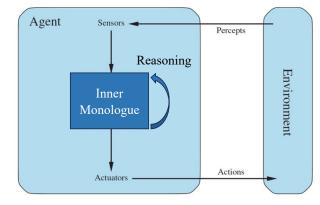
Let's call them language agents

 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 simply 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





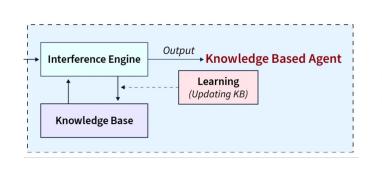


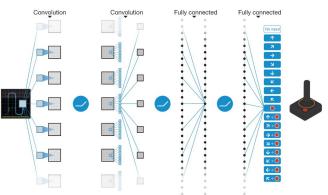
Logical Agent

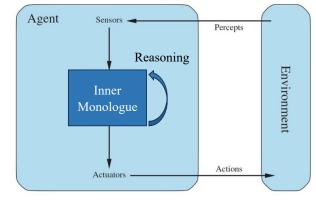
Neural Agent

Language Agent

Expressiveness		
Reasoning		
Adaptivity		





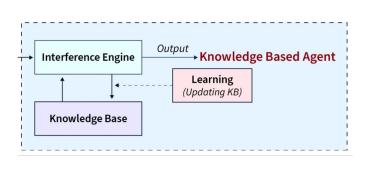


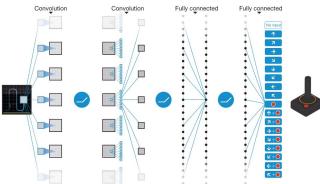
Logical Agent

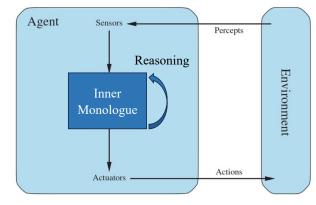
Neural Agent

Language Agent

Expressiveness	Low bounded by the logical language	
Reasoning	Logical inferences sound, explicit, rigid	
Adaptivity	Low bounded by knowledge curation	





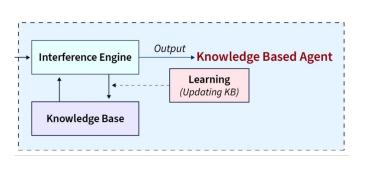


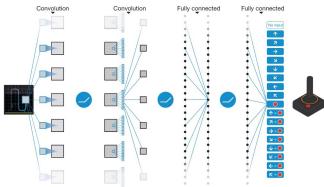
Logical Agent

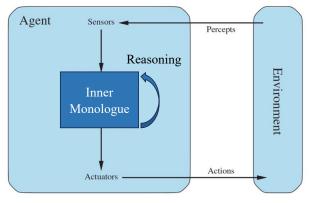
Neural Agent

Language Agent

Expressiveness	Low bounded by the logical language	Medium anything a (small-ish) NN can encode	
Reasoning	Logical inferences sound, explicit, rigid	Parametric inferences stochastic, implicit, rigid	
Adaptivity	Low bounded by knowledge curation	Medium data-driven but sample inefficient	







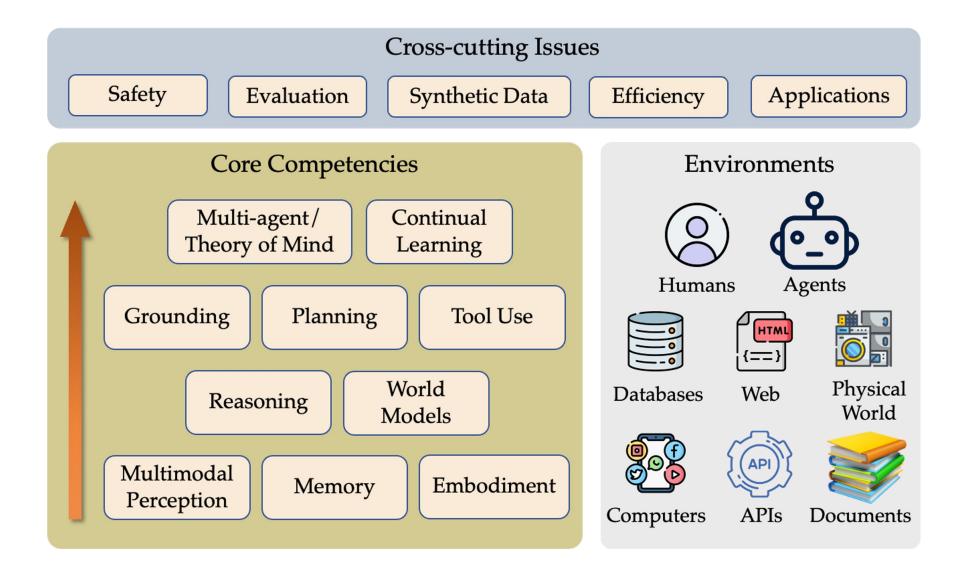
Logical Agent

Neural Agent

Language Agent

Expressiveness	Low bounded by the logical language	Medium anything a (small-ish) NN can encode	High almost anything, esp. those verbalizable
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



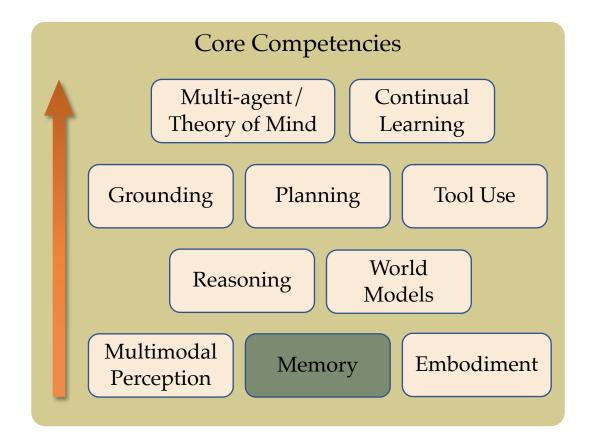
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Memory



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

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







Long-term memory in LLMs

LLMs still rely on RAG.

ChatGPT

- Who won the 2024 Super Bowl?

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

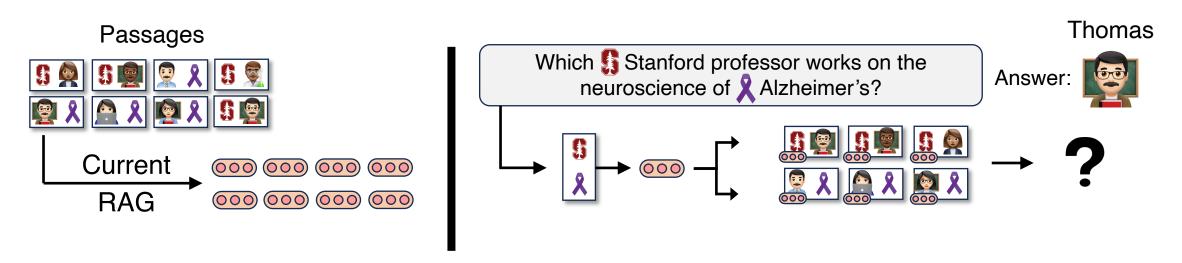


Which \subseteq Stanford professor works on the neuroscience of \textit{Alzheimer's?}

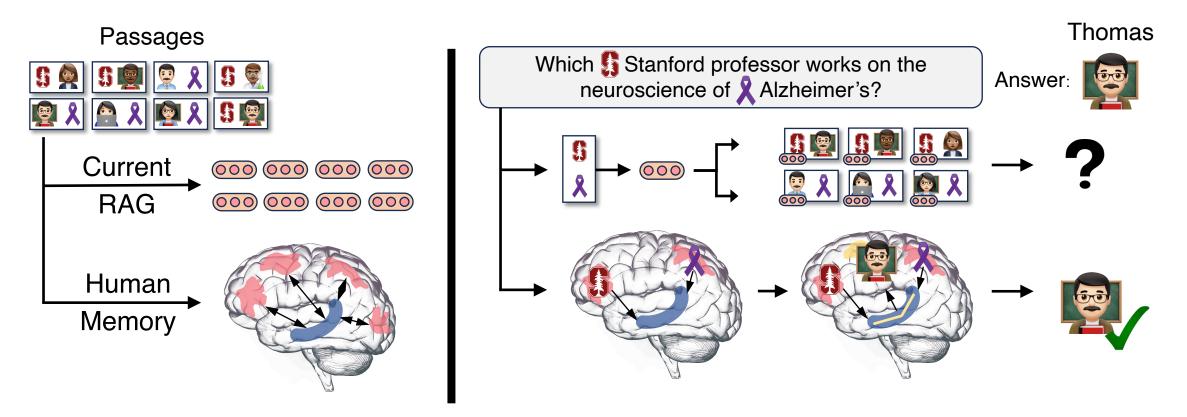
Thomas

Answer:

Current RAG does not always work

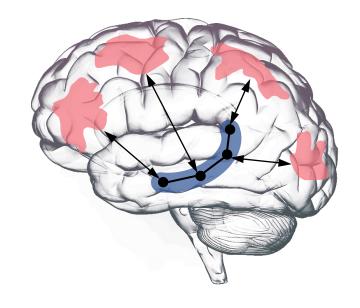


Current RAG does not always work



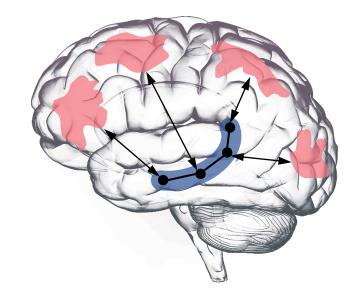
Long-term memory in humans

- 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.)

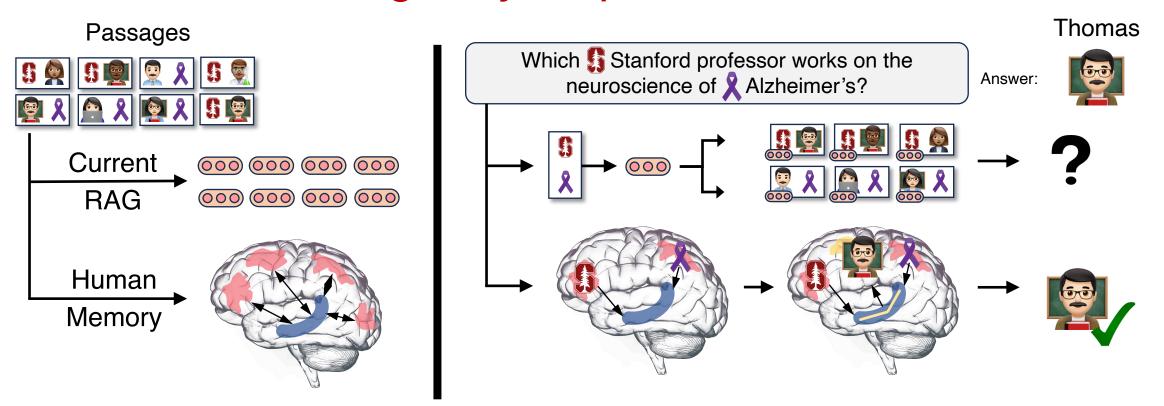


Long-term memory in humans

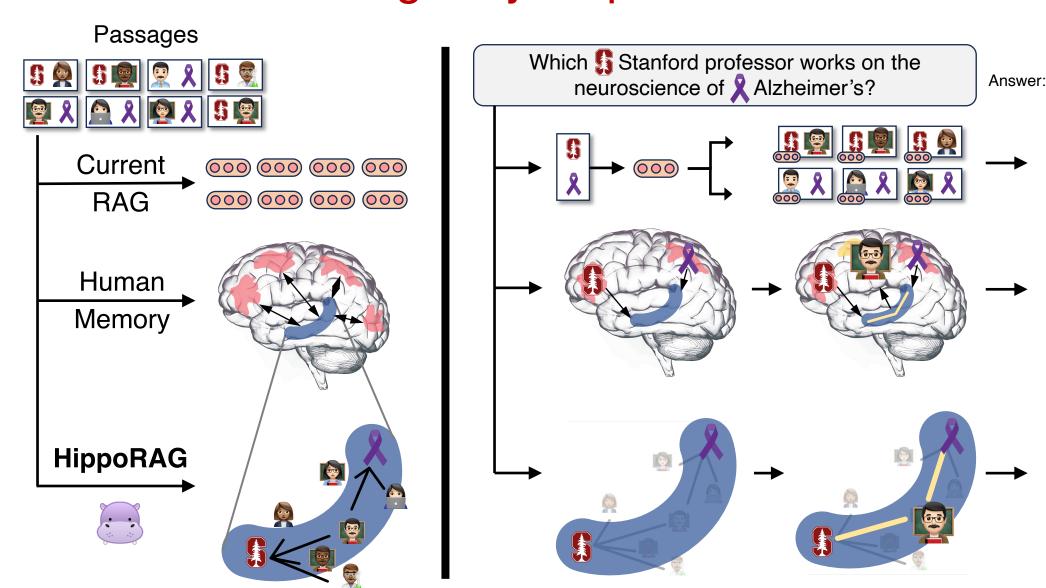
- Indexing procedure enables two fundamental faculties of human memory:
 - Pattern separation: process for differentiating memories (neocortex and parahippocampus)
 - Pattern completion: process for recovering complete memories from relevant associations (mostly hippocampus, specifically CA3)



HippoRAG: Neurobiologically-inspired LTM for LLMs



HippoRAG: Neurobiologically-inspired LTM for LLMs

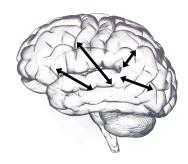


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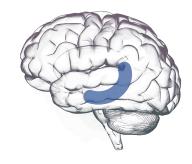
HippoRAG & the three components of LTM



Neocortex
Perception, linguistic abilities & reasoning

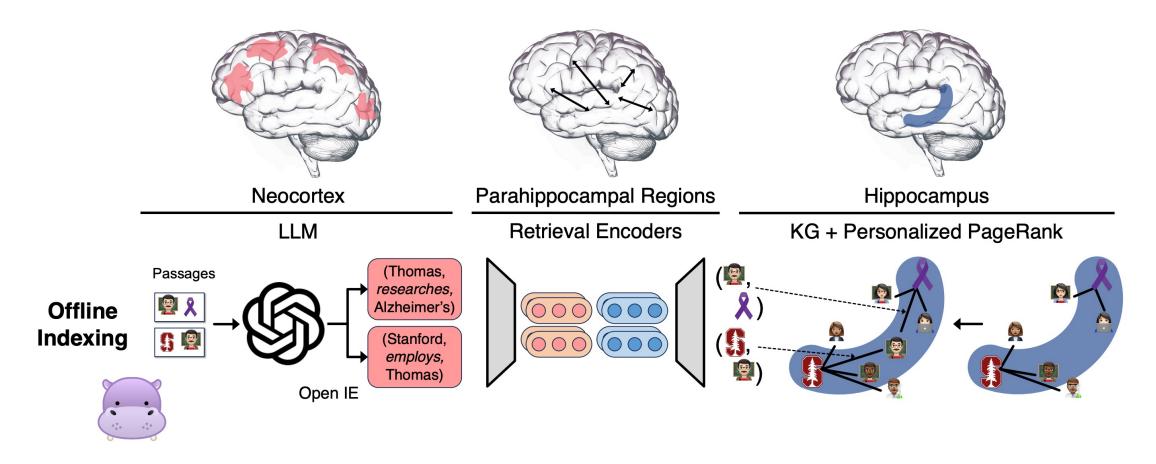


Parahippocampus
Bridge between areas;
working memory

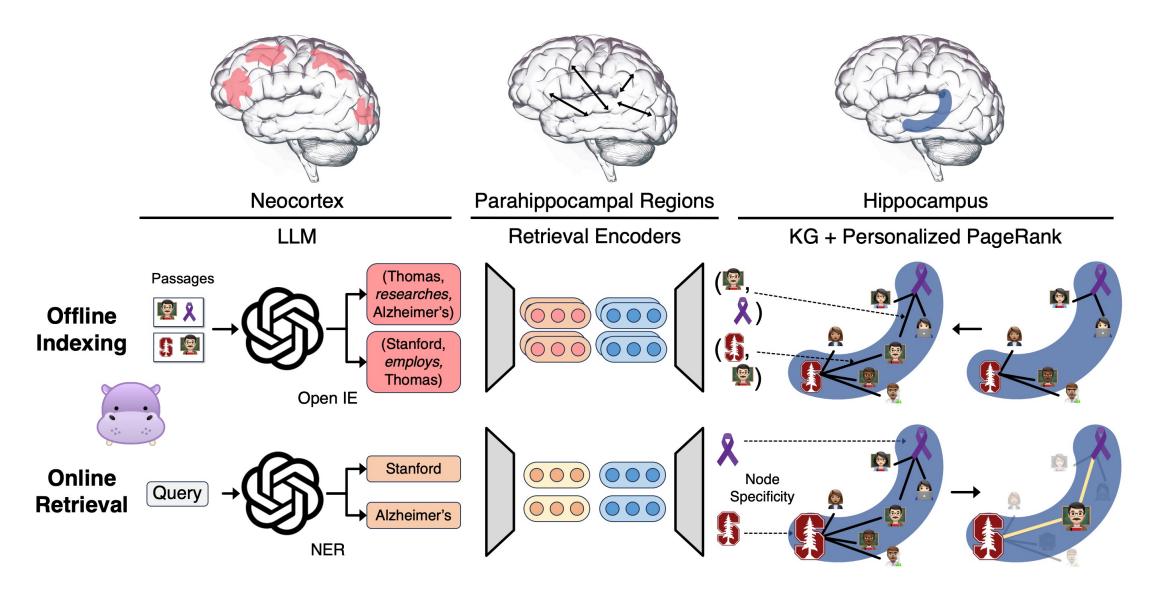


Hippocampus
Indexing & autoassociative memory

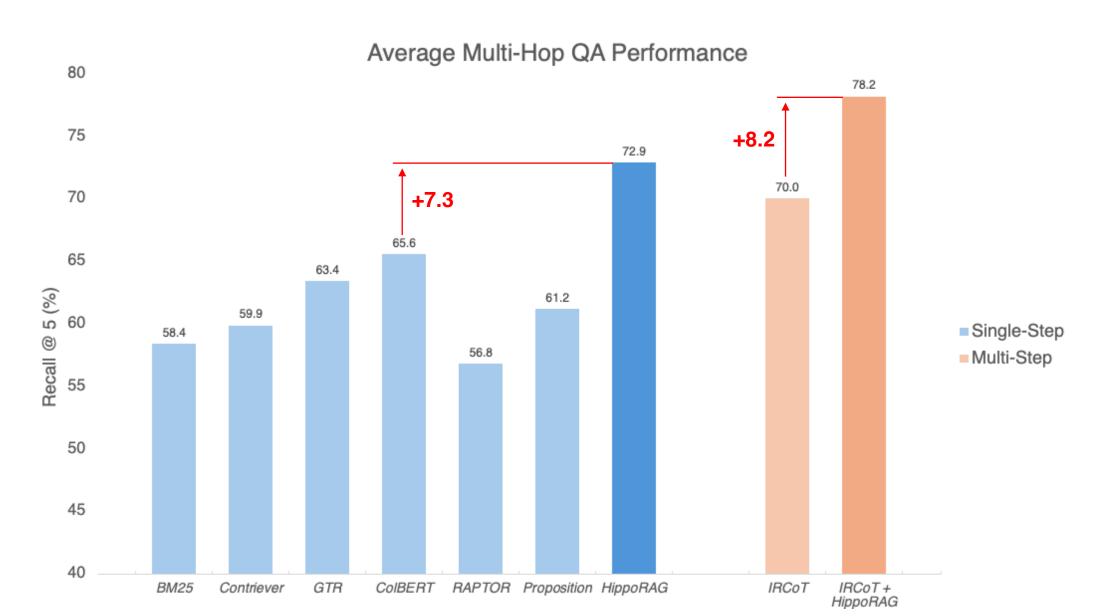
HippoRAG & the three components of LTM



HippoRAG & the three components of LTM



HippoRAG is a SoTA memory retriever

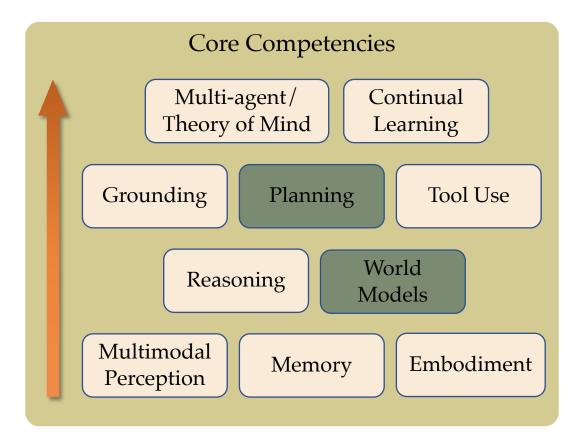


Practical aspects of HippoRAG

- Better retrieval directly translates to better QA (avg. 5% better)
- With single-step multi-hop retrieval, it's 10-30 times cheaper and 6-13 times faster than iterative RAG like IRCoT with similar or better recall

 Worried about indexing cost? Llama-3-8B achieves similar performance as GPT-3.5

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

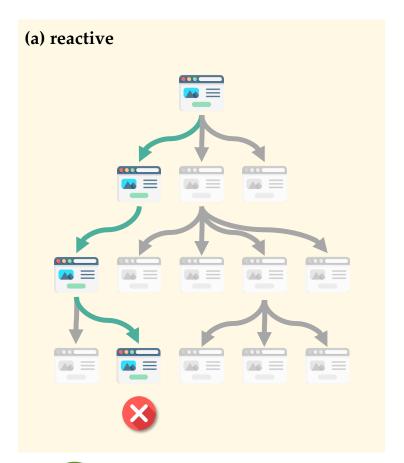






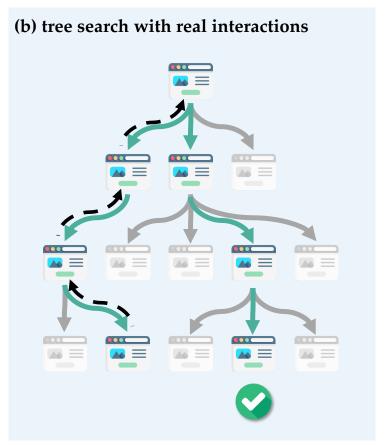


Planning paradigms for language agents



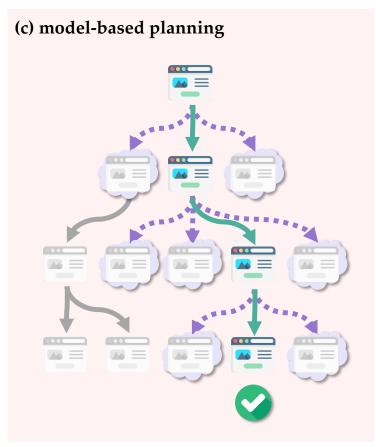
fast, easy to implement

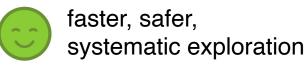
greedy, short-sighted

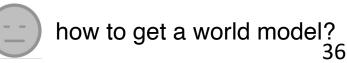




irreversible actions, unsafe, slow







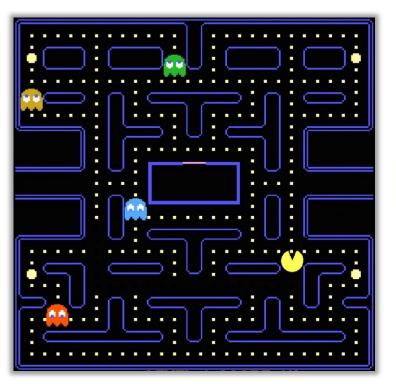
What's ... a world model?

A computational model of environment transition dynamics

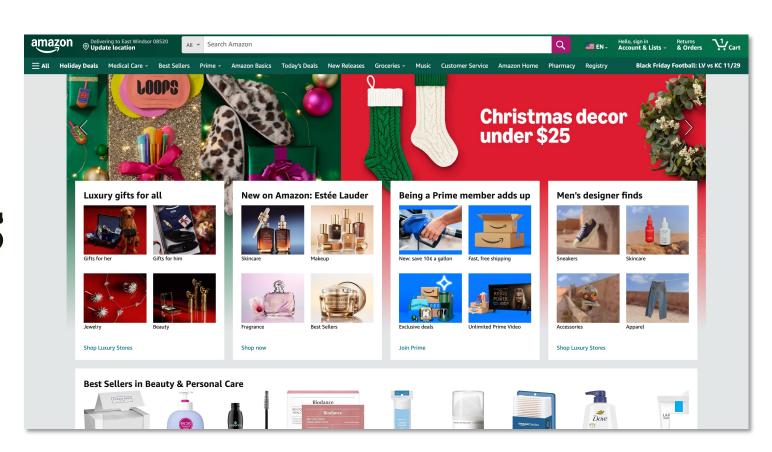
$$\widehat{T}: \mathcal{S} \times \mathcal{A} \to \mathcal{S}$$

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

Why hasn't it been done already?

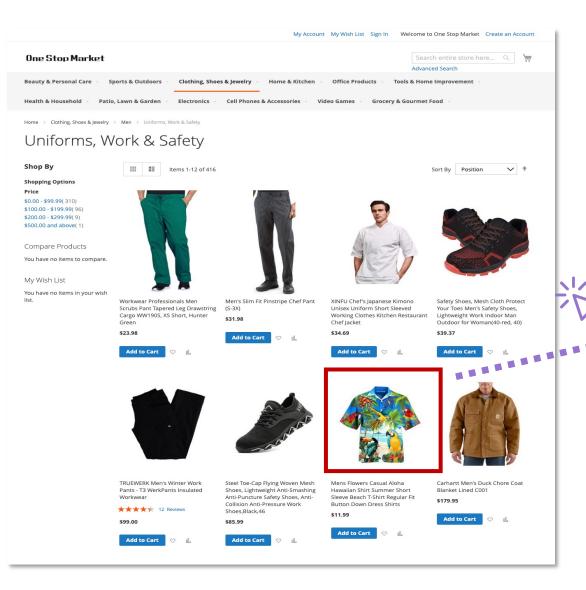




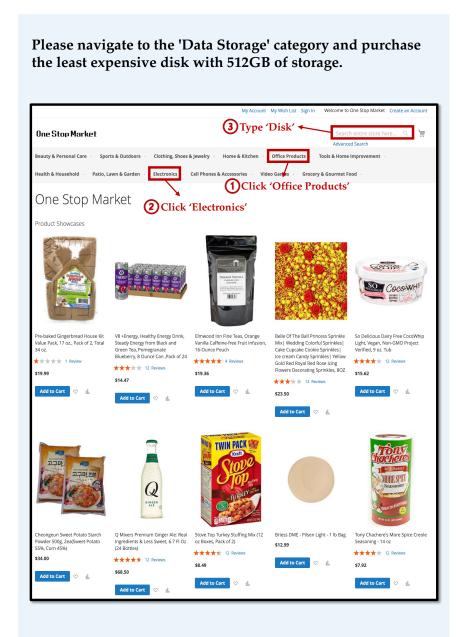


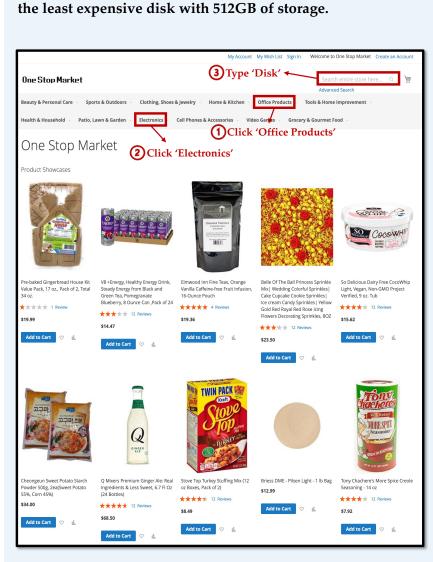
And billions of other websites on the Internet!

LLMs can predict state transitions

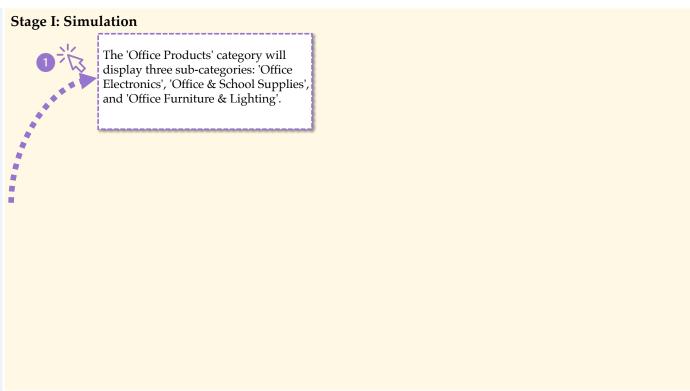


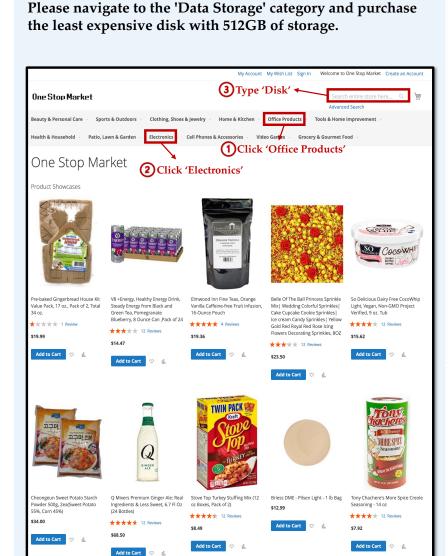
The page will navigate to a detailed product page for the "Mens Flowers Casual Aloha Hawaiian Shirt Summer Short Sleeve Beach T-Shirt Regular Fit Button Down Dress Shirts." This new page will likely contain additional information about the product including more detailed specifications, customer reviews, 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.

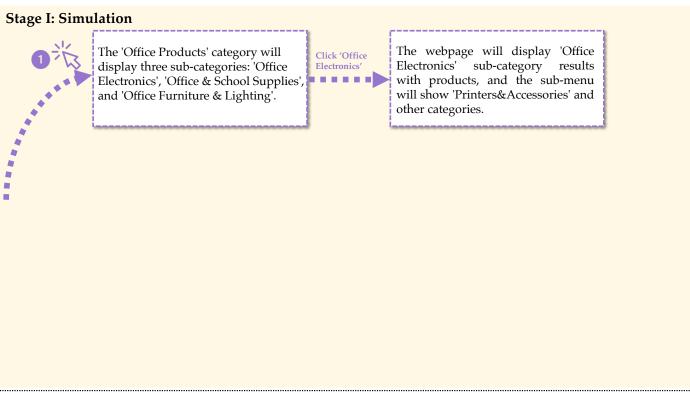


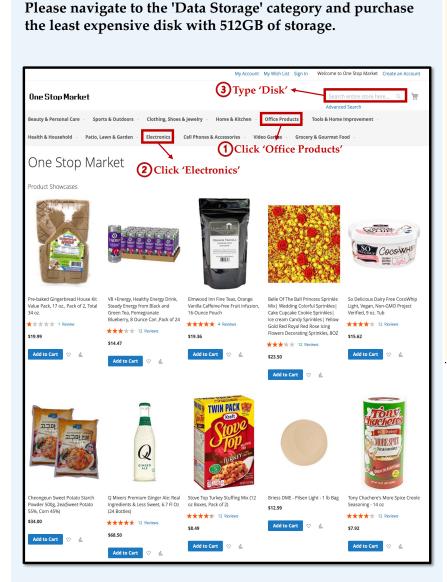


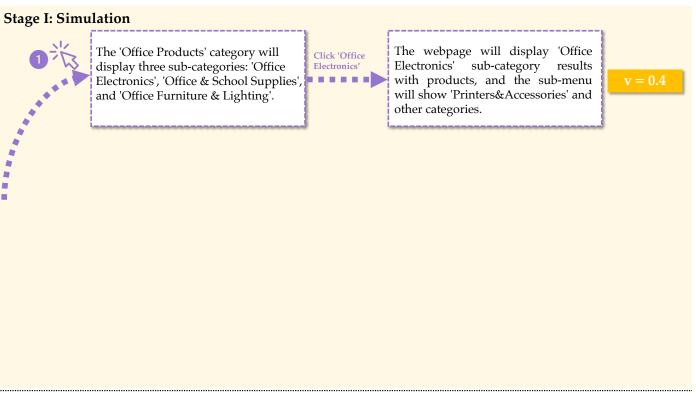
Please navigate to the 'Data Storage' category and purchase

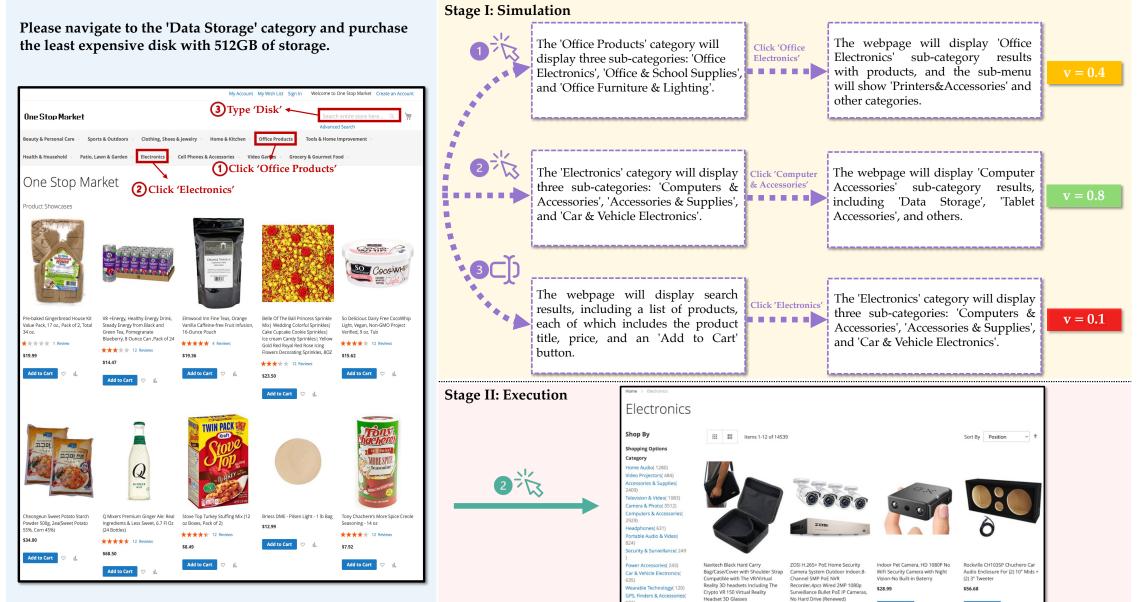






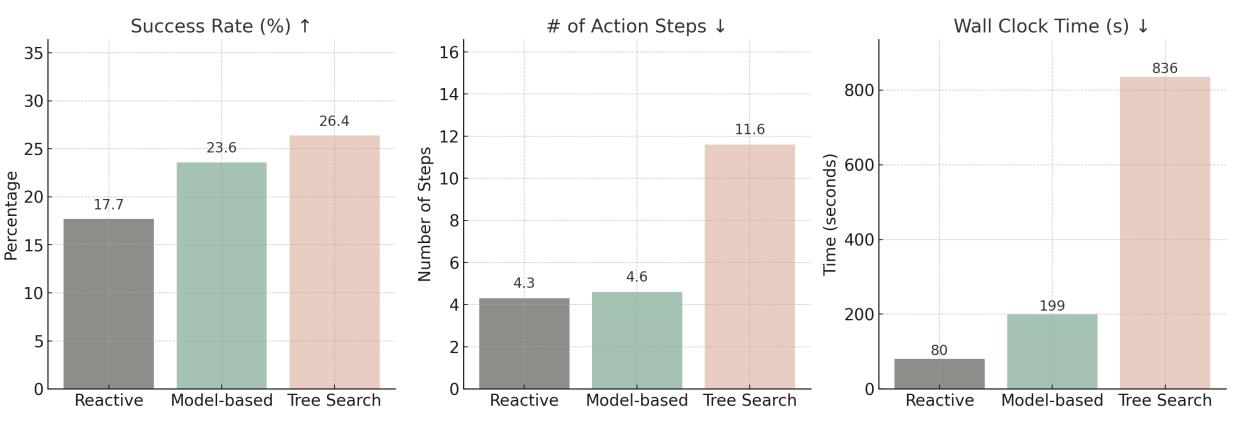






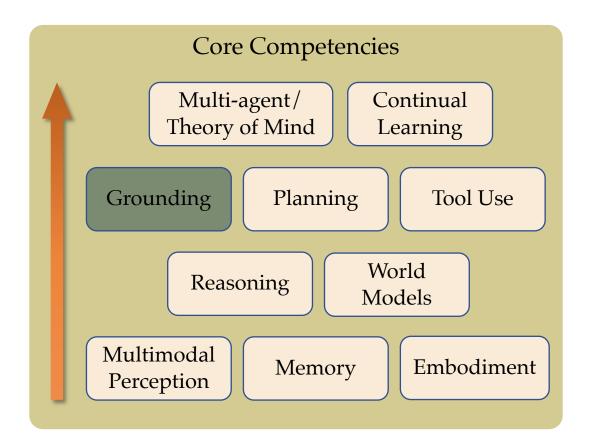
Results on VisualWebArena

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



Baselines are from Koh et al., (2024)

Grounding



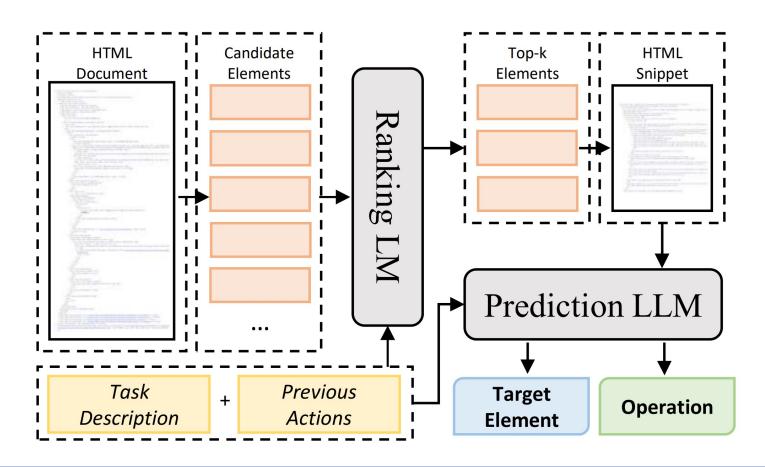
Navigating the Digital World as Humans Do: Universal Visual Grounding for GUI Agents

Boyu Gou, Ruohan Wang, Boyuan Zheng, Yanan Xie, Cheng Chang, Yiheng Shu, Huan Sun, Yu Su











Xiang Deng

Mind2Web (23' May)

Sensory Inputs

HTML/DOM

Effectors

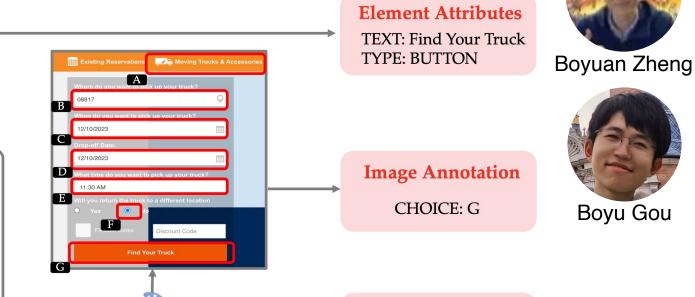
Multi-choice Selection

Action Description

Move the cursor over the "Find Your Truck" button located in the central portion of the webpage, just below the input fields for rental details, and perform a click action.



A: Moving Trucks & Accessories B: <input type="text" id="1">placeholder="US City,State or Zip Code"</input> F: <input type="radio" id="5">No name="one-wayradio"</input> G: <input type="button" id="6">value="Find Your Truck"</input> H: None

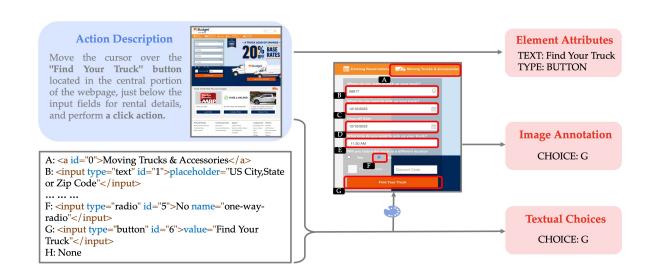


Textual Choices

CHOICE: G

Boyu Gou

Mind2Web (23' May) SeeAct (24' Jan) HTML/DOM **Sensory Inputs** Screenshot + DOM **Effectors** Multi-choice Selection Multi-choice Selection



Text-based Representations: Limitations

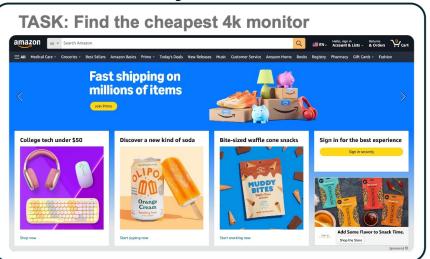
- Noisy and incomplete
 - 95.9% of home pages have accessibility conformance errors
 - Avg. 56.8 errors per page¹
- Additional input increases latency and inference costs
 - Consuming more tokens
 - Difficult and time-consuming to get
 - Compounding over long horizon

	Mind2Web (23' May)	SeeAct (24' Jan)	
Sensory Inputs	HTML/DOM	Screenshot + DOM	
Effectors	Multi-choice Selection	Multi-choice Selection	

SeeAct-V: Human-like, Vision-centric GUI Agent

Boyu Gou

Vision-Only Observation



Planning



Element Description:

The search bar at the top of the page

Action: Type Value: 4k monitor

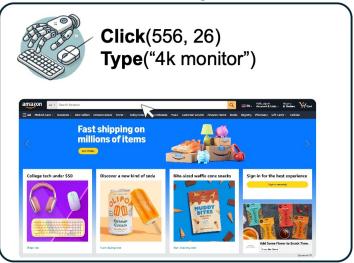
Grounding



What are the pixel coordinates of the element corresponding to "..."?

(556, 26)

Human-like Operation



	Mind2Web (23' May)	SeeAct (24' Jan)	SeeAct-V (24' Aug)
Sensory Inputs	HTML/DOM	Screenshot + DOM	Screenshot Only
Effectors	Multi-choice Selection	Multi-choice Selection	Pixel-level Operations

Visual Grounding is the Bottleneck

GPT-4V(ision) is a Generalist Web Agent, if Grounded

Boyuan Zheng ¹ Boyu Gou ¹ Jihyung Kil ¹ Huan Sun ¹ Yu Su ¹

https://osu-nlp-group.github.io/SeeAct

Abstract

The recent development on large multimodal models (LMMs), especially GPT-4V(ision) and Gemini, has been quickly expanding the capability boundaries of multimodal models beyond traditional tasks like image captioning and visual question answering. In this work, we explore the potential of LMMs like GPT-4V as a generalist web agent that can follow natural language instructions to complete tasks on any given website. We propose SEEACT, a generalist web agent that harnesses the power of LMMs for integrated visual understanding and acting on the web. We evaluate on the recent MIND2WEB benchmark. In addition to standard offline evaluation on cached websites, we enable a new online evaluation setting by developing a tool that allows running web agents on live websites. We show that GPT-4V presents a great potential for web agents—it can successfully complete 51.1% of the tasks on live websites if we manually ground its textual plans into

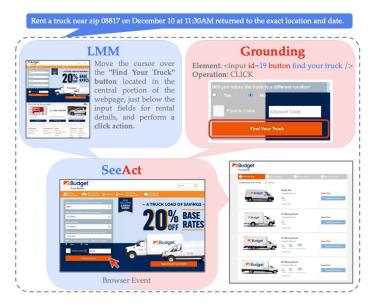
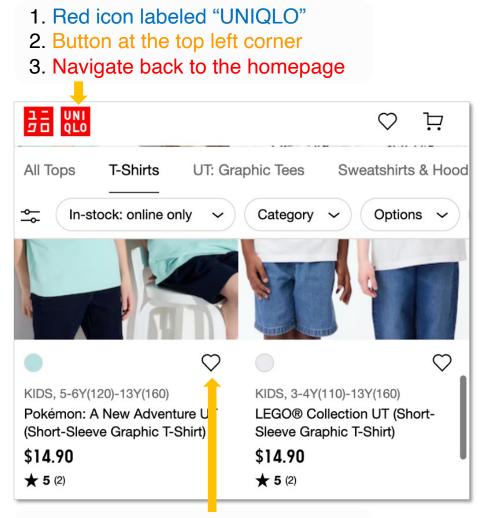


Figure 1: SEEACT leverages an LMM like GPT-4V to visually perceive websites and generate plans in textual forms. The textual plans are then grounded onto the HTML elements and operations to act on the website.

Referring Expressions for GUIs are Diverse

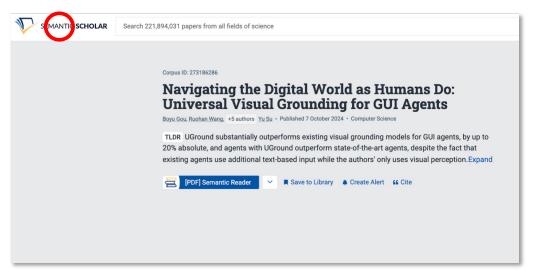


- 1. Hollow heart button
- 2. Button below the Pokémon shirt
- 3. Favor the Pokémon shirt

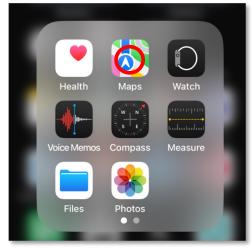
Visual Referring Expressions

- Salient visual features like textual content, element type (button, input field, checkbox, etc.), shape, color, ...
- Positional Referring Expressions
 - including absolute (e.g., "at the top left of the page") and relative positions (e.g., "to the right of element X")
- Functional Referring Expressions
 - Referring to elements by their functions
- Hybrid
 - "click the heart button under the Pokemon shirt to add it to favorite."

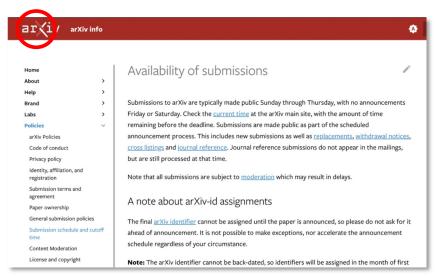
Shared Designs across GUIs



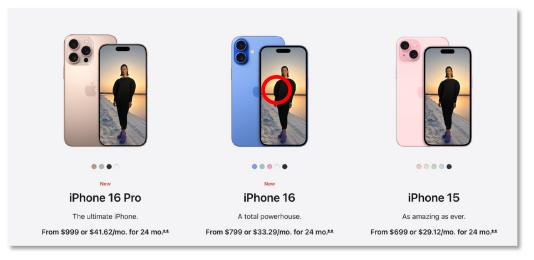
"Go to homepage"



"Open Maps"



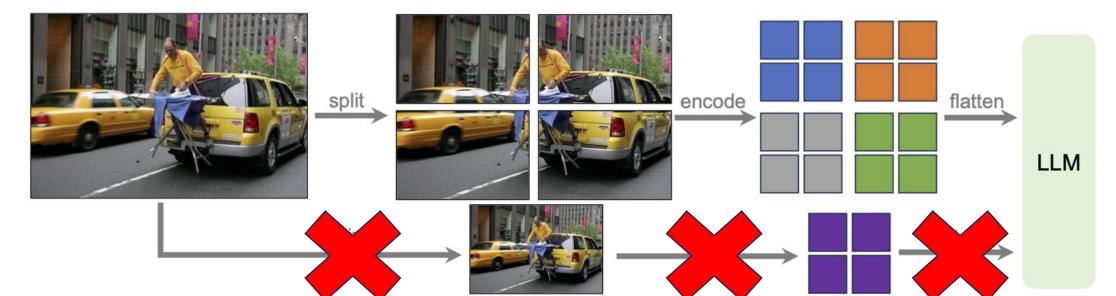
"Go to homepage"



"iPhone 16"

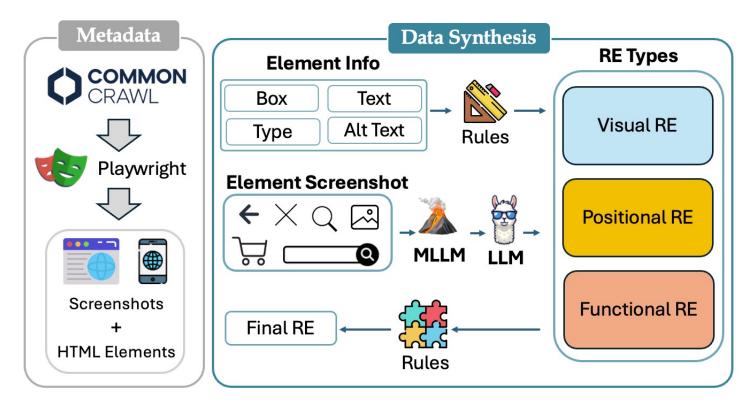
UGround: Universal Visual Grounding for GUI Agents

- What do we mean by universal?
 - o Generalize across different web, desktop, and mobile environments
 - Plug and play with different planners / LLMs
 - Handle input images of different resolutions
- Modeling
 - Input: Screenshot + RE; Output: Pixel Coordinates
 - LLaVA backbone: CLIP@224px, Vicuna-1.5-7B-16K, AnyRes

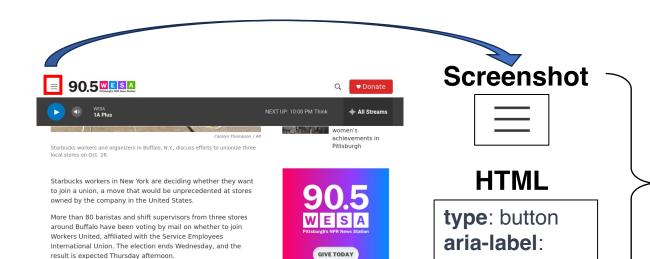


Synthetic Data is Key

- Collect all relevant information about an element
 - Visual (i.e., screenshot)
 - HTML attributes like inner-text,
 alt-text as additional visual cues
 - Accessibility labels like alt, arialabel as functionality cues
- Generate referring expressions using (multimodal) LLMs and rules



+ Positional information





Absolute Position: Top Left Corner

Relative Position: to the left of "Donate"

menu

. . .

No corporate-run Starbucks location in the U.S. has unionized so





MLLM Interpretation

The image shows a familiar "hamburger menu" icon, which consists of three horizontal, evenly spaced lines stacked vertically. This icon is often used in web and mobile interfaces to indicate a collapsible or expandable menu, commonly referred to as the "menu" or "navigation" icon. Its minimalistic design helps users quickly recognize it as a toggle for hidden menu items or additional navigation options. Given the context from the HTML information, it appears this icon is intended to open a menu when clicked.



LLM Rewrite

three-line menu icon





Final Referring Expression

three-line menu icon, at the top left corner of the page

Training Data Statistics

Dataset	Annotation	# of Elements	# of Screenshots	Platform
Web-Hybrid (Ours)	Rule + LLM	9 M	773K	Web
Web-Direct (Ours)	GPT	408K	408K	Web
GUIAct (Chen et al., 2024)	GPT + Human	140K	13 K	Web
AndroidControl (Li et al., 2024b)	Human	47K	47K	Android
Widget Caption (Li et al., 2020b)	Human	41 K	15 K	Android
UIBert (Bai et al., 2021)	Human	16 K	5K	Android
AITZ (Zhang et al., 2024b)	GPT + Human	8 K	8 K	Android
Total		10 M	1.3M	Web + Android

Human-like Vision-centric Embodiment is the Future for Web/GUI Agents

- Most comprehensive evaluation of GUI Agents to date
- SeeAct-V + UGround outperforms prior SoTA despite its minimalist design



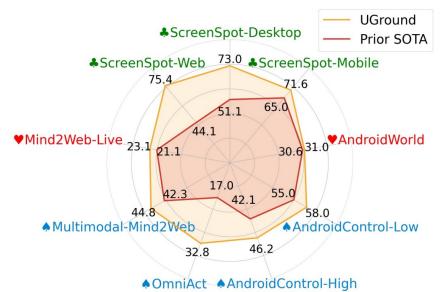
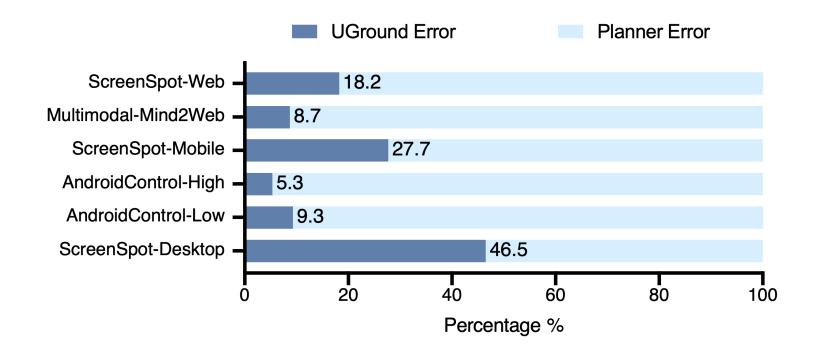


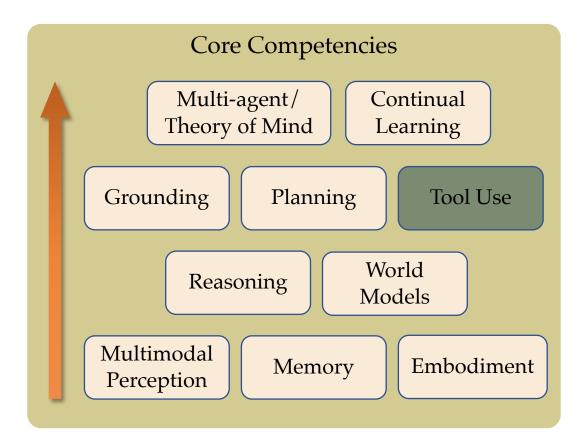
Figure 1: Examples of agent tasks across platforms and performance on **GUI grounding** (♣: ScreenSpot), **offline agent** (♠: Multimodal-Mind2Web, AndroidControl, and OmniAct), and **online agent benchmarks** (♥: Mind2Web-Live and AndroidWorld) when using GPT-4 as the planner.

Error Analysis

- Most remaining errors are due to planning rather than grounding
- Grounding errors on mobile and desktop are higher, but that doesn't necessarily manifest in the agent performance



Tool Use



LLMs in the Imaginarium: Tool Learning through Simulated Trial and Error

Boshi Wang, Hao Fang, Jason Eisner, Benjamin Van Durme, Yu Su







We don't master a tool by just reading the 'manual'



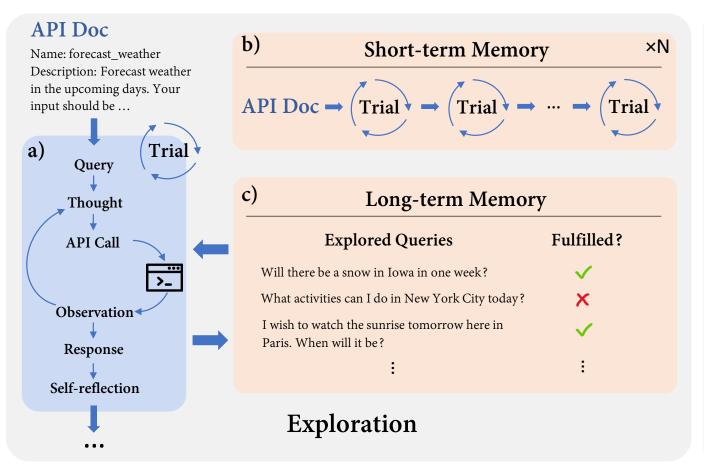
https://www.youtube.com/watch?v=s2IBayVsbz8

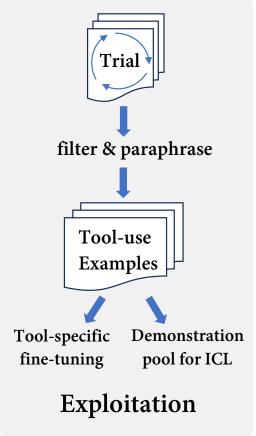
Trial and error

- Imagination
- Memory

Tool learning through simulated trial and error

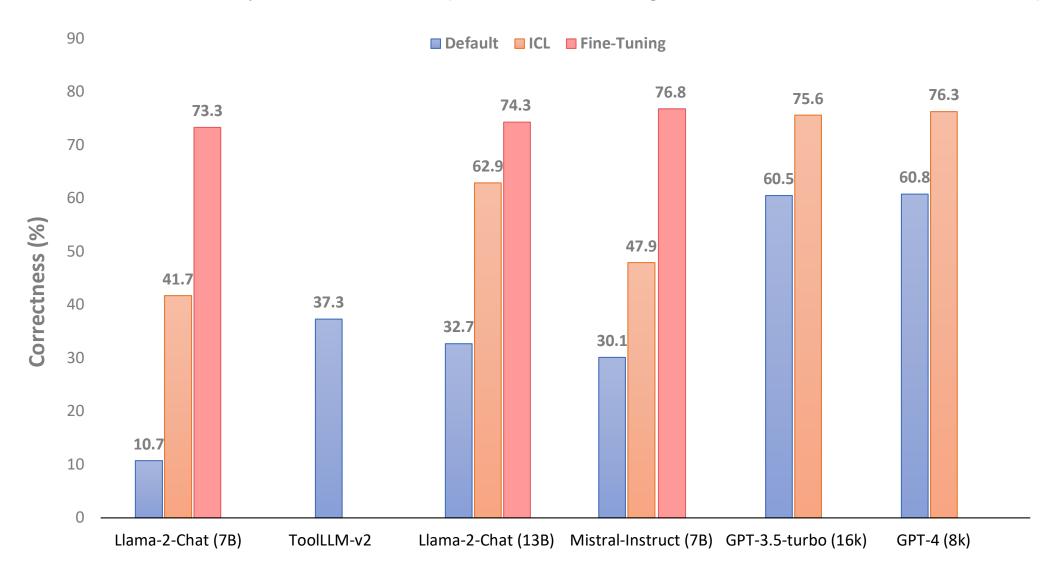
Synthesizing diverse perception-decision-execution data with LLMs





STE substantially improves tool use

ICL: Retrieve from STE synthesized examples. Fine-Tuning: Fine-tune LLM with STE examples



A few remarks

- Language agents are still Al agents. The same challenges remain. But the new capability of using language for reasoning and communication allows us to re-examine these challenges through a new, powerful lens.
- Natural selection is a real magical power. Over billions of years of evolution, natural selection has found numerous good designs ('local optima') that just make sense; we should take some inspirations!
- Tons of new venues for interesting research. We are barely scratching the surface...

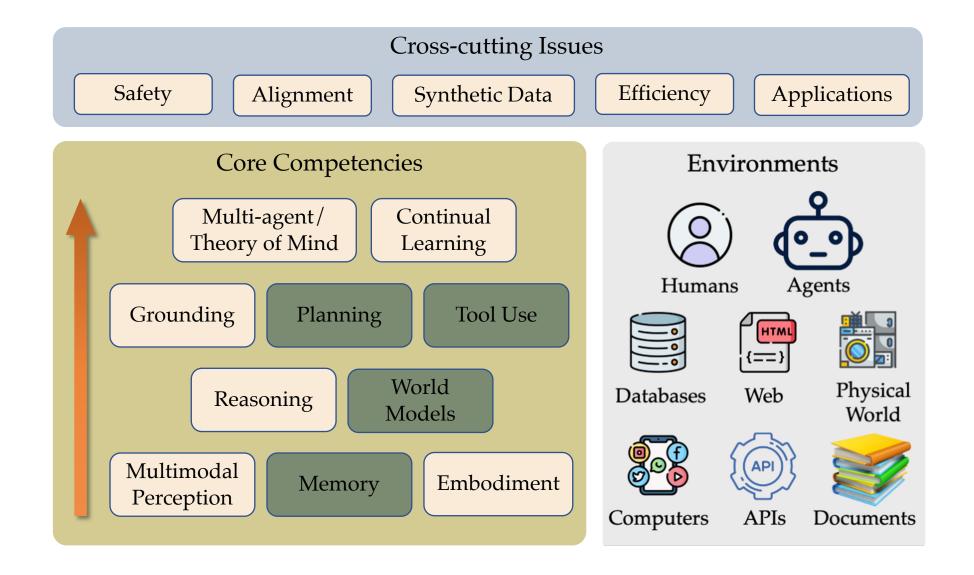
Outline

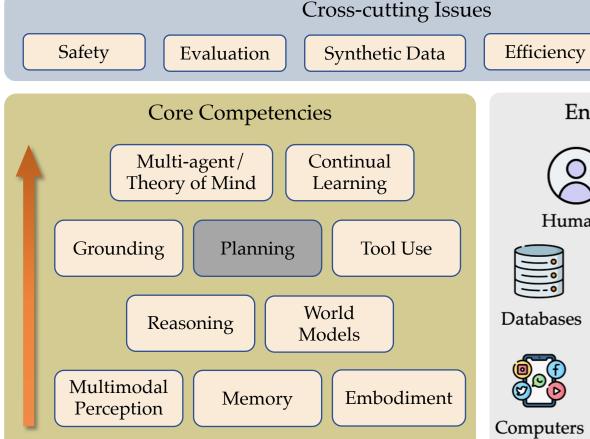
Language Agents: Introduction

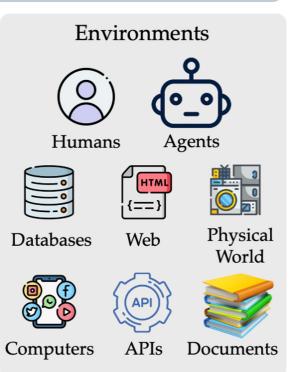
• The Power of Language: Memory, Planning, Grounding, Tool Use

Future Directions

We are just standing at the dawn of a long journey







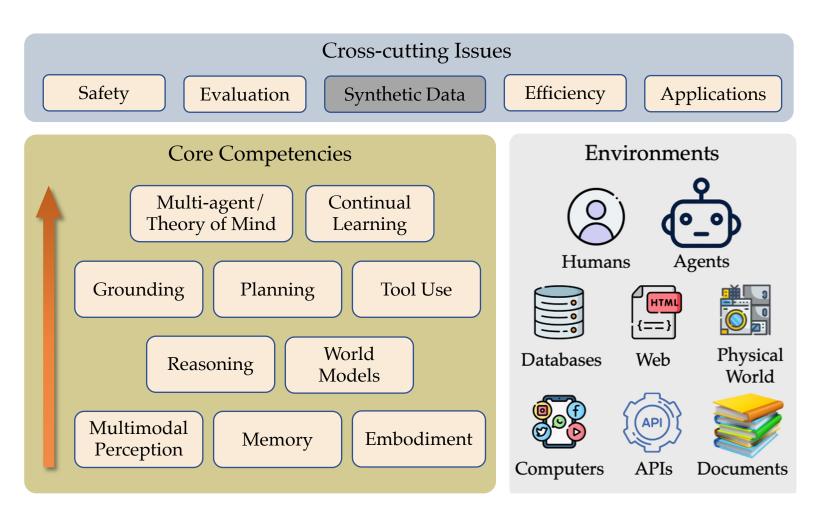
Applications

Hierarchical planning?

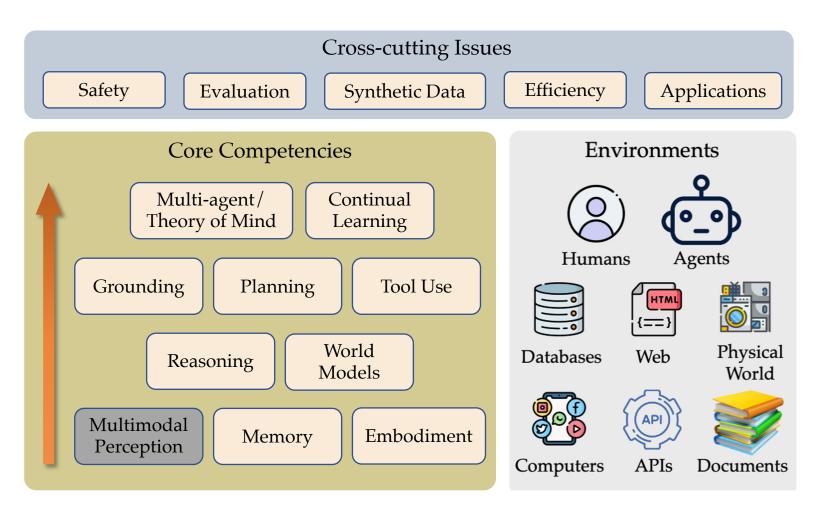
How far can (tree) search go?

 How to evaluate (partial) plans? Value functions? Reward models?

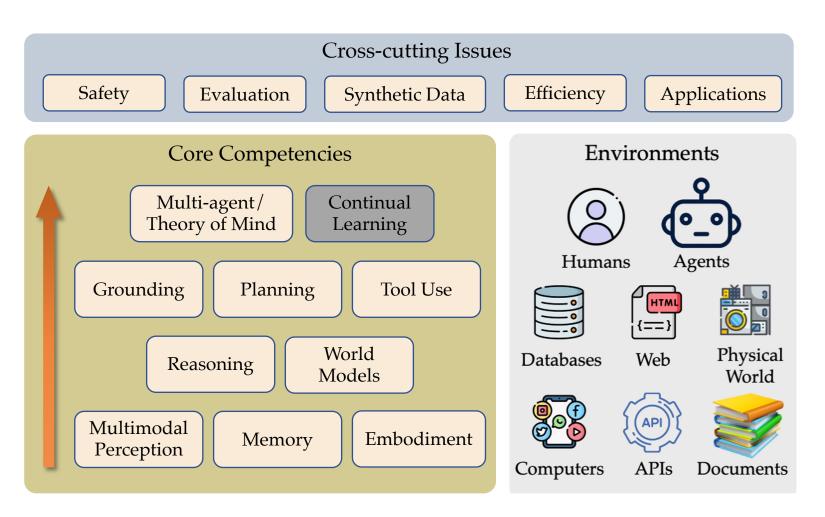
Speculative planning?



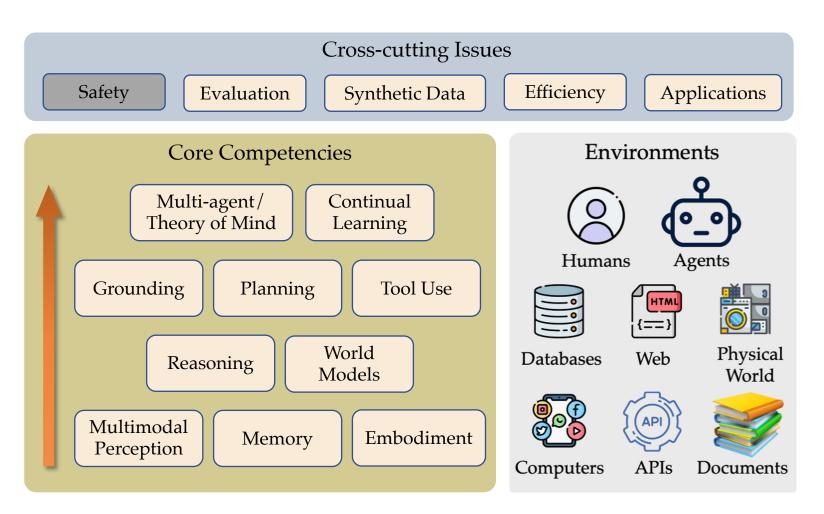
- Agents need to learn perception-decisionexecution capabilities
- Data on the Internet is mostly artifacts from such processes, not capturing the processes per se
- Synthesizing data with LLMs provides a possibility to uncover (some of) these hidden processes



- Existing MLLMs are not optimized for GUI understanding.
 - Resolution/grounding/finegrained understanding
- Current MLLMs do not seem to fuse visual and language well. New arch or training recipes are needed.



- Currently, the field is transitioning from prompting to behavior cloning / supervised fine-tuning
- Behavior cloning is unlikely to be sufficient for generalist agents; they need to explore the environments and trial and error
- Challenges from open action space, reward model, and safety



- Agent safety research is far behind agent development and deployment
- Language agents inherent all the safety risks of LLMs (e.g., bias, fairness, hallucination, privacy, transparency), amplify some of them (e.g., workforce displacement), and bring many new ones (e.g., irreversible actions)

Language Agents: Foundations, Prospects, and Risks

Yu Su, Diyi Yang, Shunyu Yao, Tao Yu

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











Acknowledgements























Thanks &

