

# Evaluating LLM-based Agents: Foundations, Best Practices and Open Challenges

Roy Bar-Haim<sup>†</sup>, Lilach Eden<sup>†</sup>, Alan Li<sup>§</sup>, Asaf Yehudai<sup>†</sup>



Roy



Introduction to LLM Agent Evaluation (20 mins)

Alan



Evaluating Application-Specific Agents (45 mins)

Asaf



Generalist Agent Evaluation (20 mins)

Lilach



Frameworks for Agent Evaluation (40 mins)

Key Insights & Future Directions (20 mins)

Open Discussion (10 mins)



# Part 1: Introduction

## Part 2: Fundamental Capabilities

# Evaluate by Adopting Reasoning Benchmark

HotpotQA (Yang et al. 2018)

**Question:** The Treaty of Versailles was signed in a city that is a suburb of what capital city?

**Step1:** Recall Treaty of Versailles signing location.

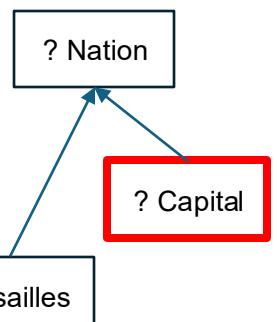
**Act1:** Search [Treaty of Versailles]

**Observation1:** ... signed at the Palace of Versailles in Versailles, **France**.

**Step2:** I need to search **France** next and find the capital of it.

**Act2:** Search [France]

**Observation2:** ... Paris is the capital of France



# Evaluate by Adopting Reasoning Benchmark

HotpotQA (Yang et al. 2018)

Question: The Treaty of Versailles was signed in a city that is a  
suburb of Paris, in the French region of Ile-de-France.



Peng Qi @qi2peng2

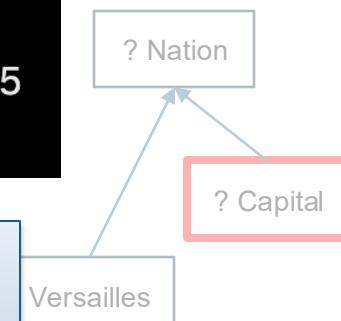
Seven years ago, I co-led a paper called **HotpotQA** that has motivated and facilitated many **#AI #Agents** research works since. Today, I'm asking that you stop using HotpotQA blindly for agents research in 2025 and beyond.

Step1:  
it.

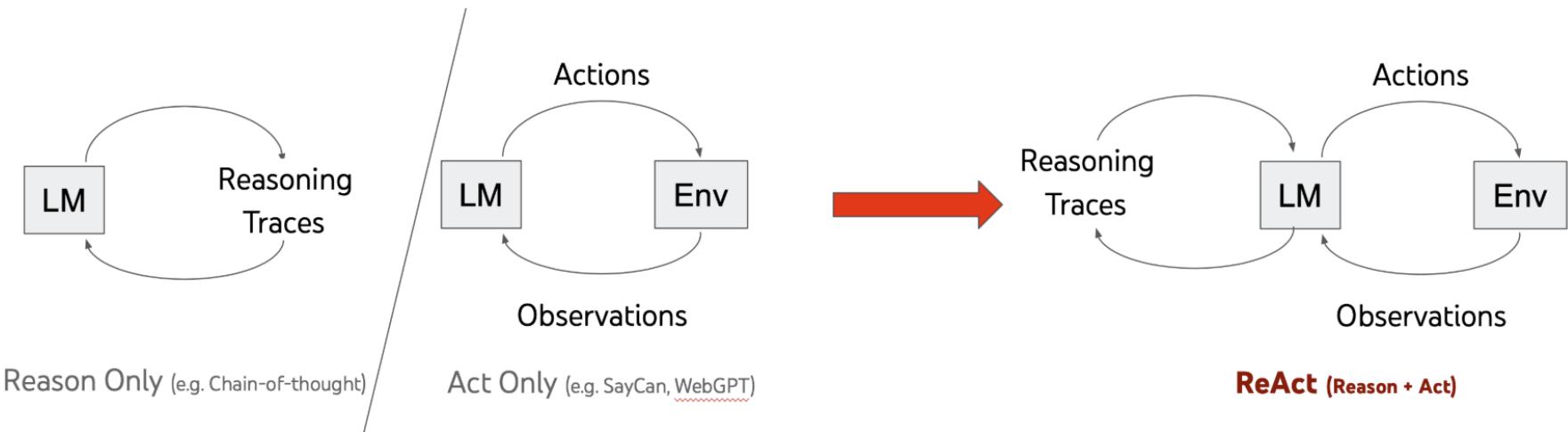
Act1:

Observ

- ⚠ Limited Scopes & Steps & Action space & Real-life applicability
- ⚠ Risk of contamination; evaluated by final answer only



# Multi-Step Agent: ReAct (Yao et al. 2023)



Cr. Yao et al. *ReAct: Synergizing Reasoning and Acting in Language Models*. Proceedings of ICLR 2023.

# What Aspects should we Evaluate?

**Question:** The Treaty of Versailles was signed in a city that is a suburb of what capital city?

**Thought1:** Recall Treaty of Versailles signing location

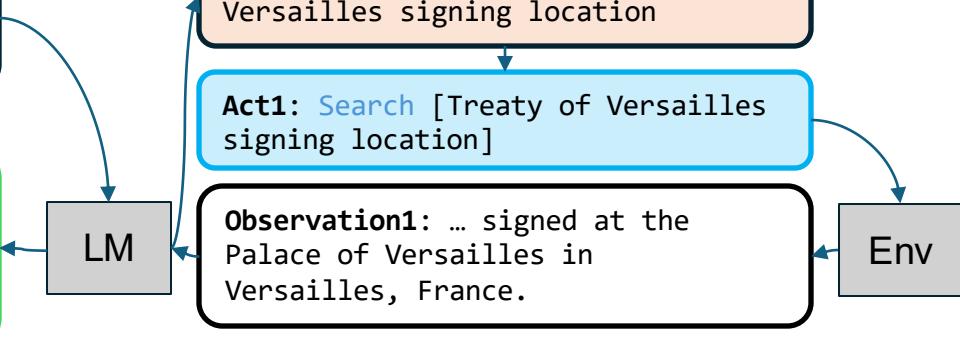
**Act1:** Search [Treaty of Versailles signing location]

**Feedback1:** The Treaty of Versailles was signed in Versailles.

**Observation1:** ... signed at the Palace of Versailles in Versailles, France.

LM

Env



# What Aspects should we Evaluate?

**Question:** The Treaty of Versailles was signed in a city that is a suburb of what capital city?

**Feedback1:** The Treaty of Versailles was signed in Versailles. But wait, the question asks for a capital city, but Versailles is not the capital of France.

**Thought1:** Recall Treaty of Versailles signing location

**Act1:** Search [Treaty of Versailles signing location]

**Observation1:** ... signed at the Palace of Versailles in Versailles, France.

LM

Env

# What Aspects should we Evaluate?

**Question:** The Treaty of Versailles was signed in a city that is a suburb of what capital city?

**Feedback1:** The Treaty of Versailles was signed in Versailles. But wait, the question asks for a capital city, but Versailles is not the capital of France.

**Feedback2:** The Treaty of Versailles was signed in Paris. Fix by returning the capital city name referenced by the suburb relation.

**Answer:** The Treaty of Versailles was signed in the suburb of Paris.

**Thought1:** Recall Treaty of Versailles signing location

**Act1:** Search [Treaty of Versailles signing location]

**Observation1:** ... signed at the Palace of Versailles in Versailles, France.

**Thought2:** Recall the capital of France.

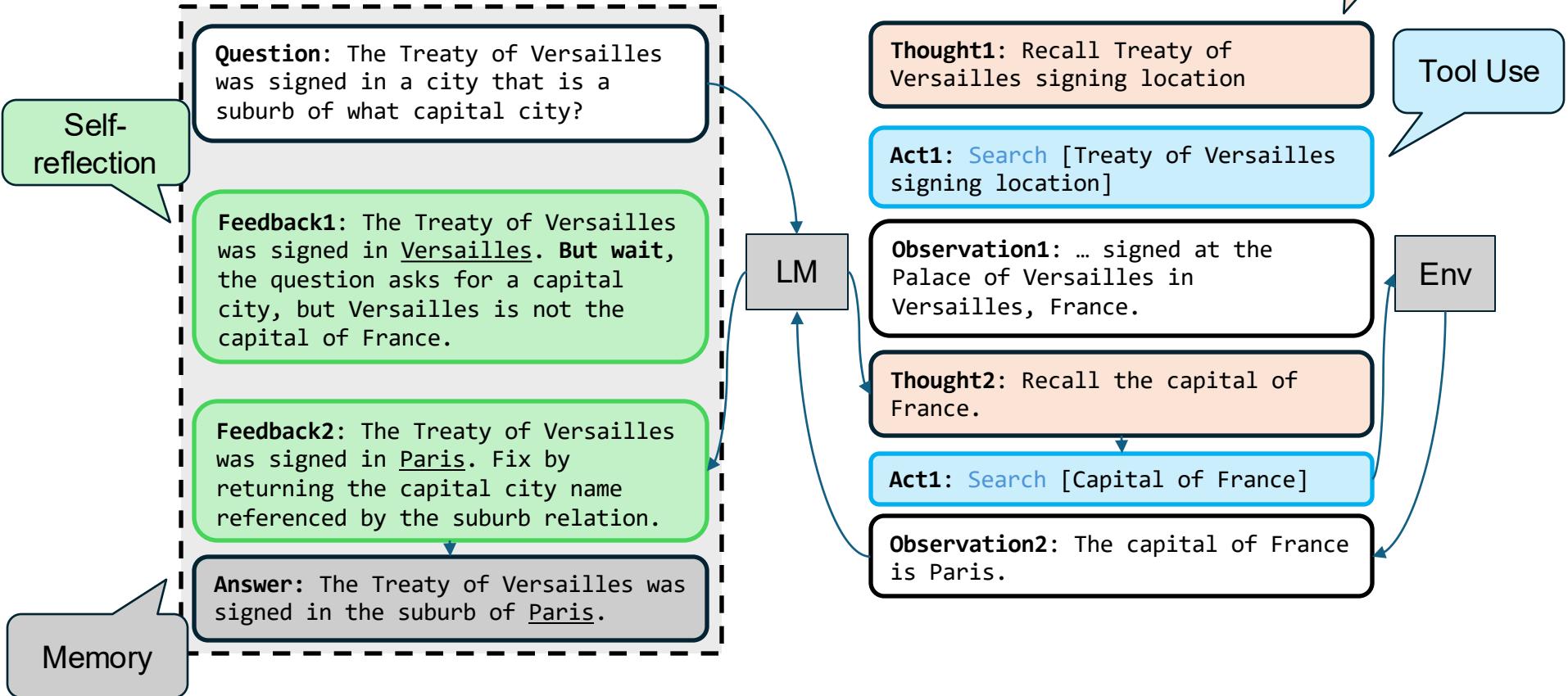
**Act1:** Search [Capital of France]

**Observation2:** The capital of France is Paris.

LM

Env

# What Aspects should we Evaluate?



# Evaluating Fundamental Agent Capabilities

**1. Planning**

**2. Tool Use**

**3. Self-Reflection**

**4. Memory**

# Evaluating Fundamental Agent Capabilities

## 1. Planning

- a) Classic planning
- b) More realistic planning

## 2. Tool Use

## 3. Self-Reflection

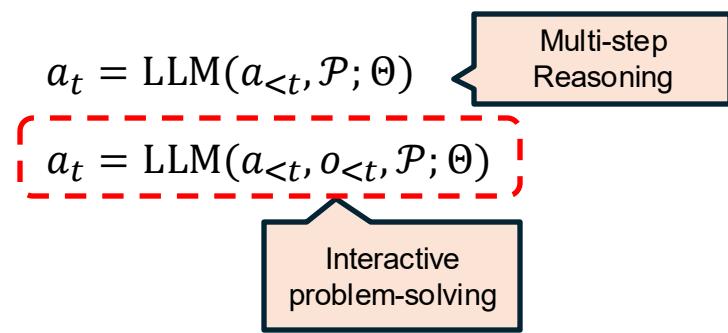
## 4. Memory

# What is Agent Planning?

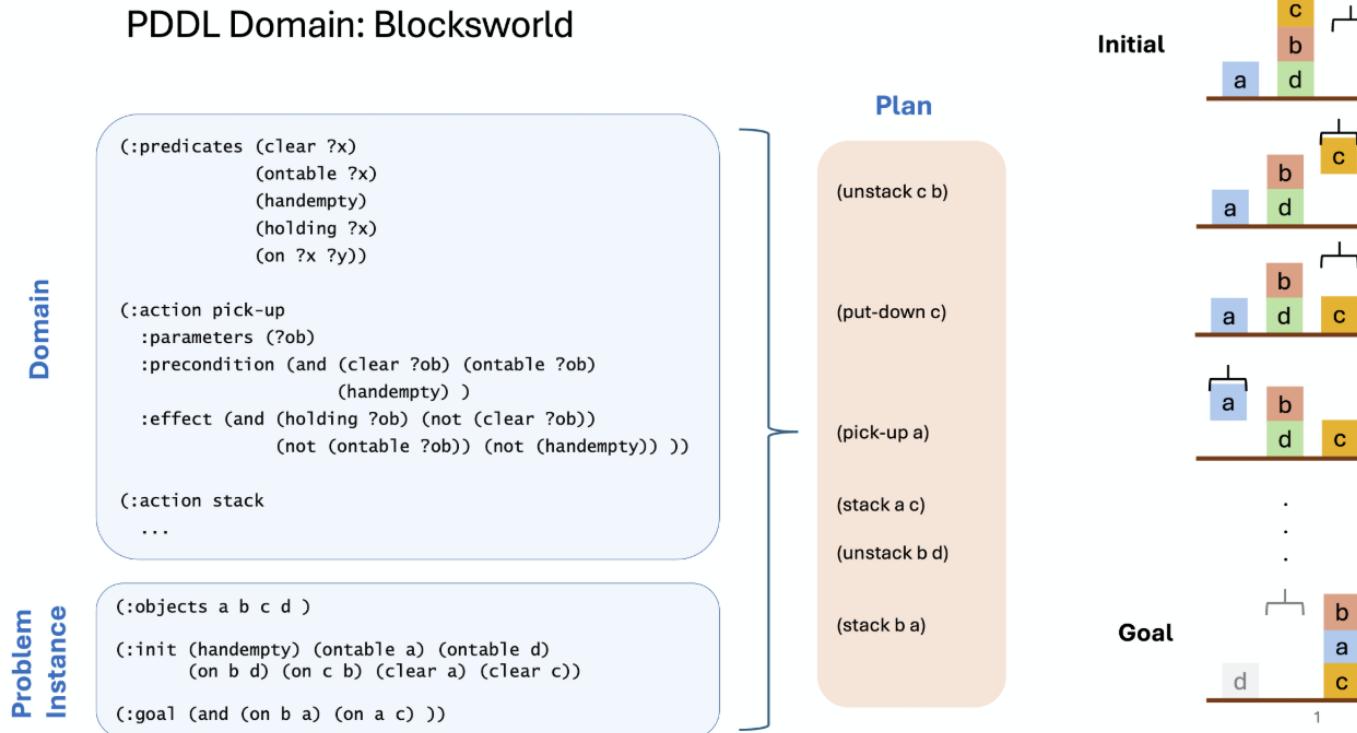
- The planning procedure decomposes tasks and can be expressed as the generation of a sequence of actions that decomposes tasks (Huang et al. 2024):

$$p = (a_0, a_1, \dots, a_t)$$

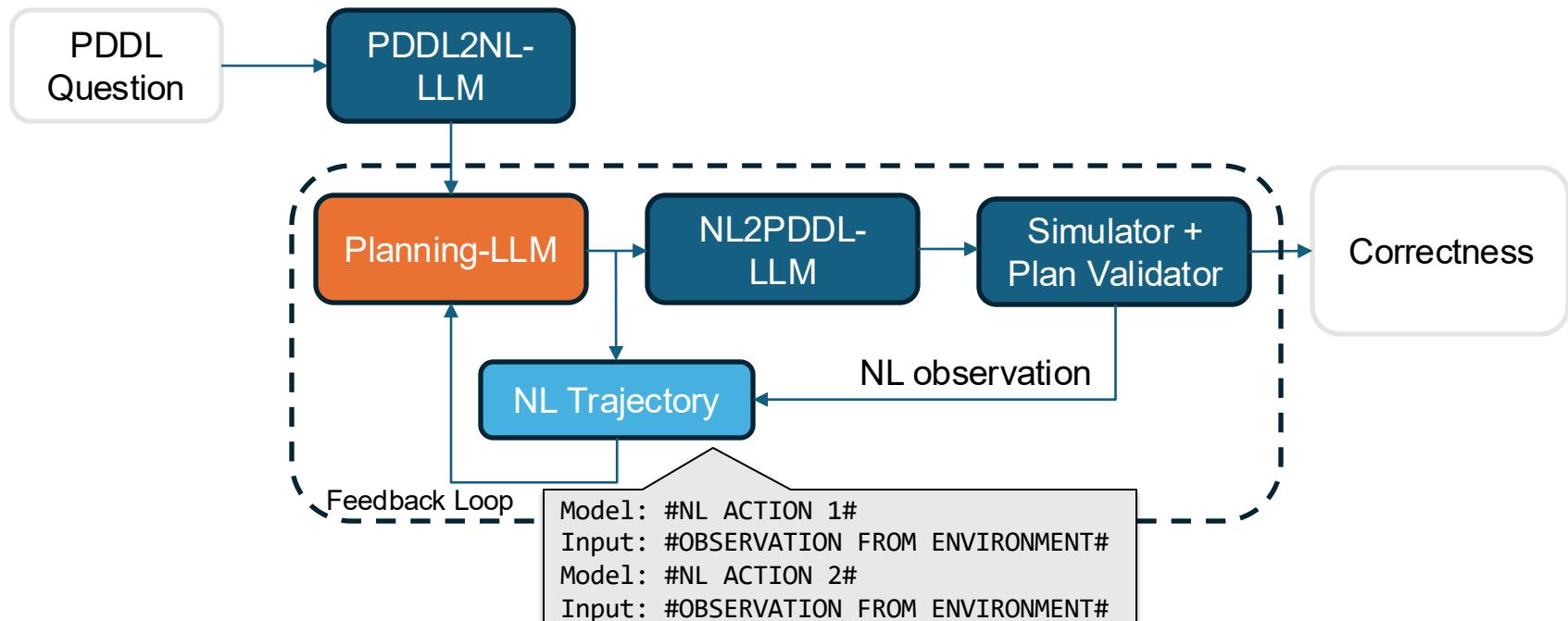
- Where
  - $p$ : a plan, a sequence of actions
  - $o_t$ : environment observation at time step  $t$
  - $a_t$ : action at time step  $t$
  - $\Theta$ : LLM parameter
  - $\mathcal{P}$ : prompt



# Constructing Diverse Planning Questions



# Example: AutoPlanBench (Stein et al. 2025)



# Example: AutoPlanBench (Stein et al. 2025)

PDDL  
Question

Correctness

**AutoPlanBench:** Leverage existing dataset from ICP

- Longer horizon: ~9 average steps
- Diverse setup: 12 Domains of tasks
- LLMs show inconsistent performance across different domains

**However,**

- Converted language not natural enough
- Limited action space
- Limited real-life setup

# More Realistic Tasks

- **NaturalPlan** (Zheng et al. 2024):
  - Real-life tasks: trip/room/meeting planning
  - Constructed by querying sampled constraints to Google Flight API, etc.
- **Flex-TravelPlanner** (Oh et al. 2025):
  - Extended travel planning
  - *multi-turn* dynamic constraints and *priority trade-offs*
- **However,**
  - Limited domains
  - Evaluated by heuristics on output plan
  - Non-interactive environment (avoid tool use)

- **PDDL-based Tasks**
  - Rigorous validation metric
  - Interactive setup
  - Non-realistic tasks
  - NL questions may not be natural enough
- **Realistic Tasks**
  - Heuristics metrics
  - Non-interactive
  - Much more realistic
  - Questions in more natural language

Limited action space

- **PDDL-based Tasks**
  - Rigorous validation metric
  - Interactive setup
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#### Tool Use

- Action interface
- Enable accurate response/ execution
- Expanded real-life use case

# Evaluating Fundamental Agent Capabilities

## 1. Planning

- a) Classic planning
- b) More realistic planning

## → 2. Tool Use

- a) Function call (FC)
- b) Multi-turn/-step FC
- c) Complex parameter mapping / dynamic interaction

## 3. Self-Reflection

## 4. Memory

# Function Call (FC)

BFCL v1/v2 (Yan et al. 2024)

**Question:** Compute triangle area base = 10, height = 5.

**Function:** functions=[  
  {"name":  
    "calculate\_triangle\_area",  
    "parameters": ...},  
  ...  
]

LM

**Input:**  
[{"name": "calculate\_triangle\_area", "parameters": {"base": 10, "height": 5}}]

Env

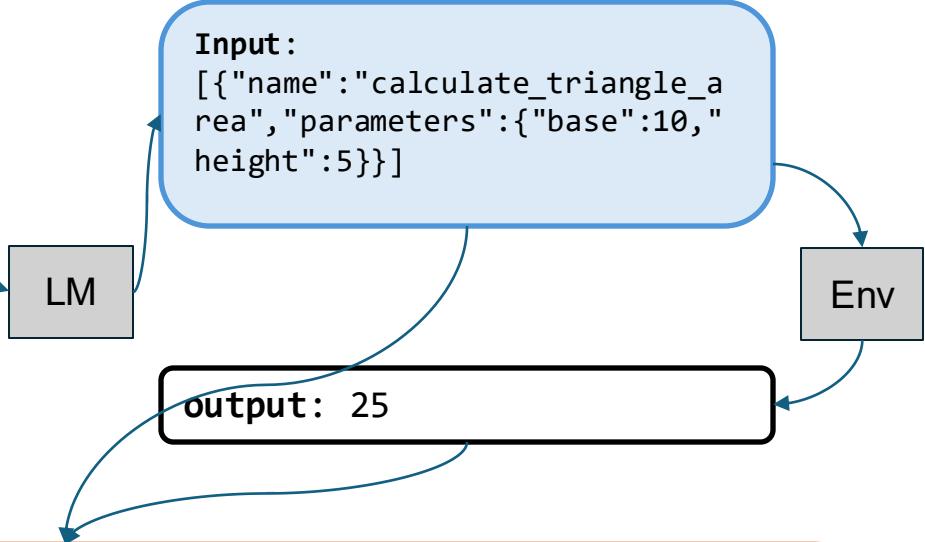
**output:** 25

# Function Call (FC)

BFCL v1/v2 (Yan et al. 2024)

**Question:** Compute triangle area base = 10, height = 5.

**Function:** functions=[  
  {"name":  
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  ...  
]



**Eval:**

AST check: name & required params ok

Exec check: stub returns 25.0, reference 25.0

# Function Call

BFCL v1/v2 (Yan et al. 2024)

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Env

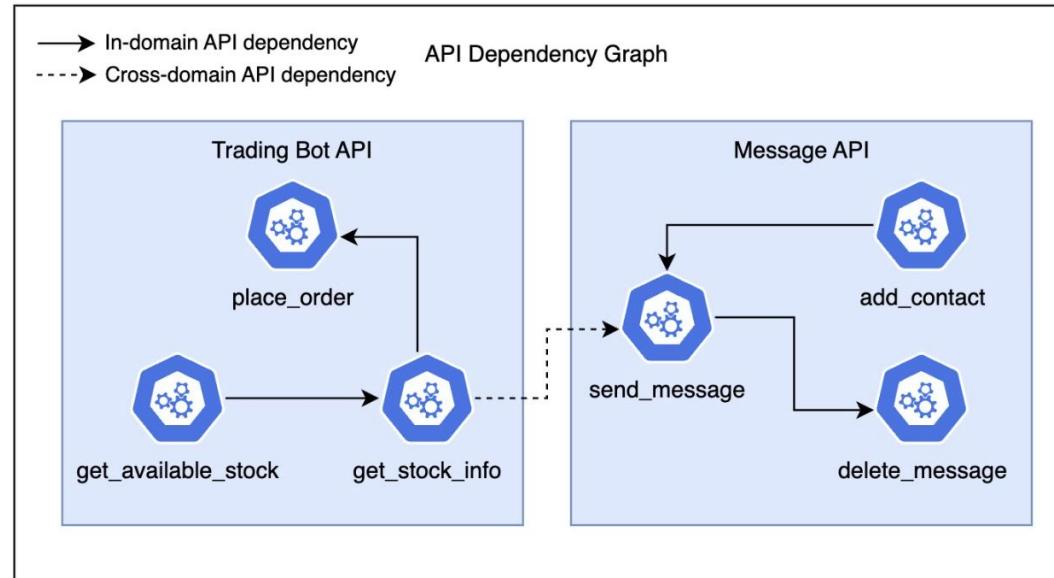
**output:** 25

**Eval:**  
AST check: name & ...  
Exec check: stub re...

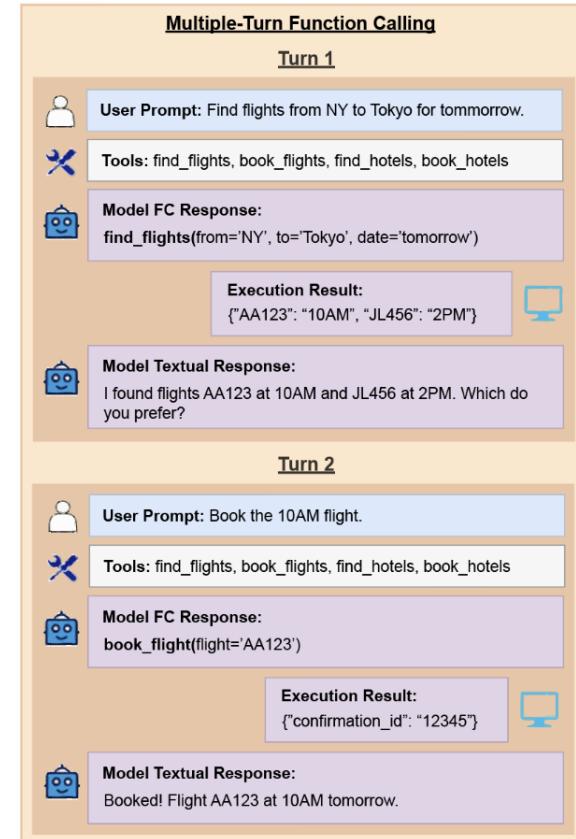
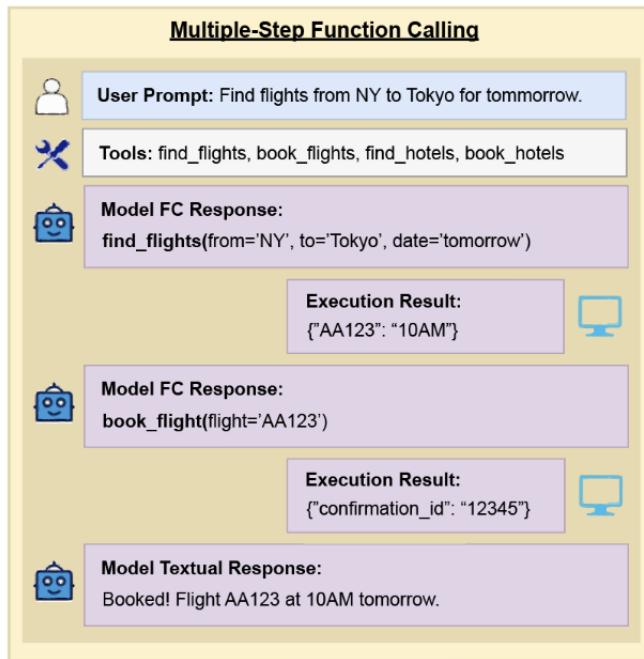
- ⚠ Single-turn
- ⚠ Simple param value mapping

# Multi-Step Multi-Turn FC

- **BFCL v3** (Patil et al. 2025):
  - Construct custom API dependency graph
  - Sample paths to generate user queries



# BFCL v3 (Patil et al. 2025): Multi-Step Multi-Turn FC



# BFCL v3 (Patil et al. 2025): Multi-Step Multi-Turn FC

Multiple-Step Function Calling

User Prompt: Find flights from NY to Tokyo for tomorrow.

Tools: find\_flights, book\_flights, find\_hotels, book\_hotels

Model FC Response:  
find\_flights(from='NY', to='Tokyo', date='tomorrow')

Execution Result:  
{"AA123": "10AM"}

Model FC Response:  
book\_flight(flight='AA123')

Execution Result:  
{"confirmation\_id": "12345"}

Model Textual Response:  
Booked! Flight AA123 at 10AM tomorrow.

Multiple-Turn Function Calling

Turn 1

User Prompt: Find flights from NY to Tokyo for tomorrow.

Tools: find\_flights, book\_flights, find\_hotels, book\_hotels

Model FC Response:  
find\_flights(from='NY', to='Tokyo', date='tomorrow')

Execution Result:  
{"AA123": "10AM", "JL456": "2PM"}

Model Textual Response:  
I found flights AA123 at 10AM and JL456 at 2PM. Which do you prefer?

Turn 2

User Prompt: Book the 10AM flight.

Tools: find\_flights, book\_flights, find\_hotels, book\_hotels

Response:  
book\_flight(flight='AA123')

Execution Result:  
{"confirmation\_id": "12345"}

Model Textual Response:  
Booked! Flight AA123 at 10AM tomorrow.



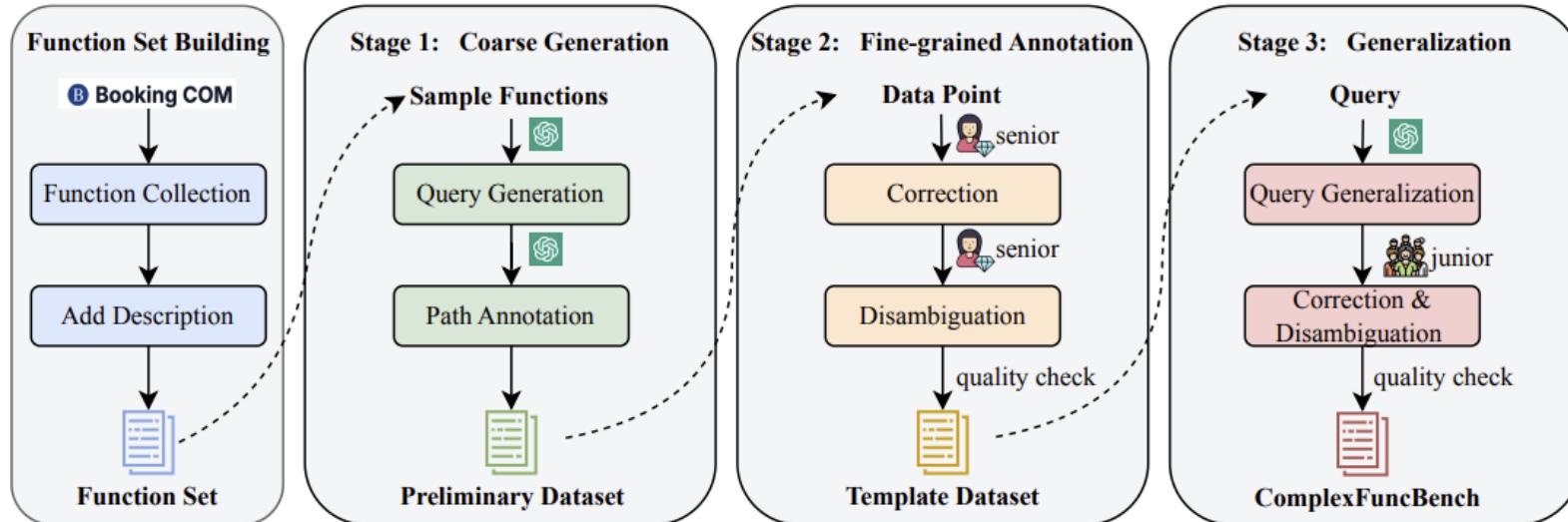
Multi-step Multi-turn



Simple param-value mapping

# More Realistic Parameter Mapping

- **ComplexFuncBench** (Zhong et al. 2025):
  - Evaluate on real-life APIs (i.e. Booking.com on Rapid API)
  - Manually annotate high-quality seed instances
  - Generalize by altering specifics (entities, dates, etc.)



# ComplexFuncBench (Zhong et al. 2025): Parameter Reasoning

Simple FC

Query: Book a flight from Washington to New York on December 23, 2024.

Complex FC

Query: Help me find the cheapest flight from Washington to New York on the day before Christmas Eve 2024.

Function Calls: {"name": "Search\_Flights", "arguments": {"departDate": "2024-12-23", ...}}

API Response:

```
[{"number": "d7699", "price": "1287 USD", ...},  
 {"number": "d7740", "price": "1025 USD", ...}, ...  
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Multi-step Multi-turn

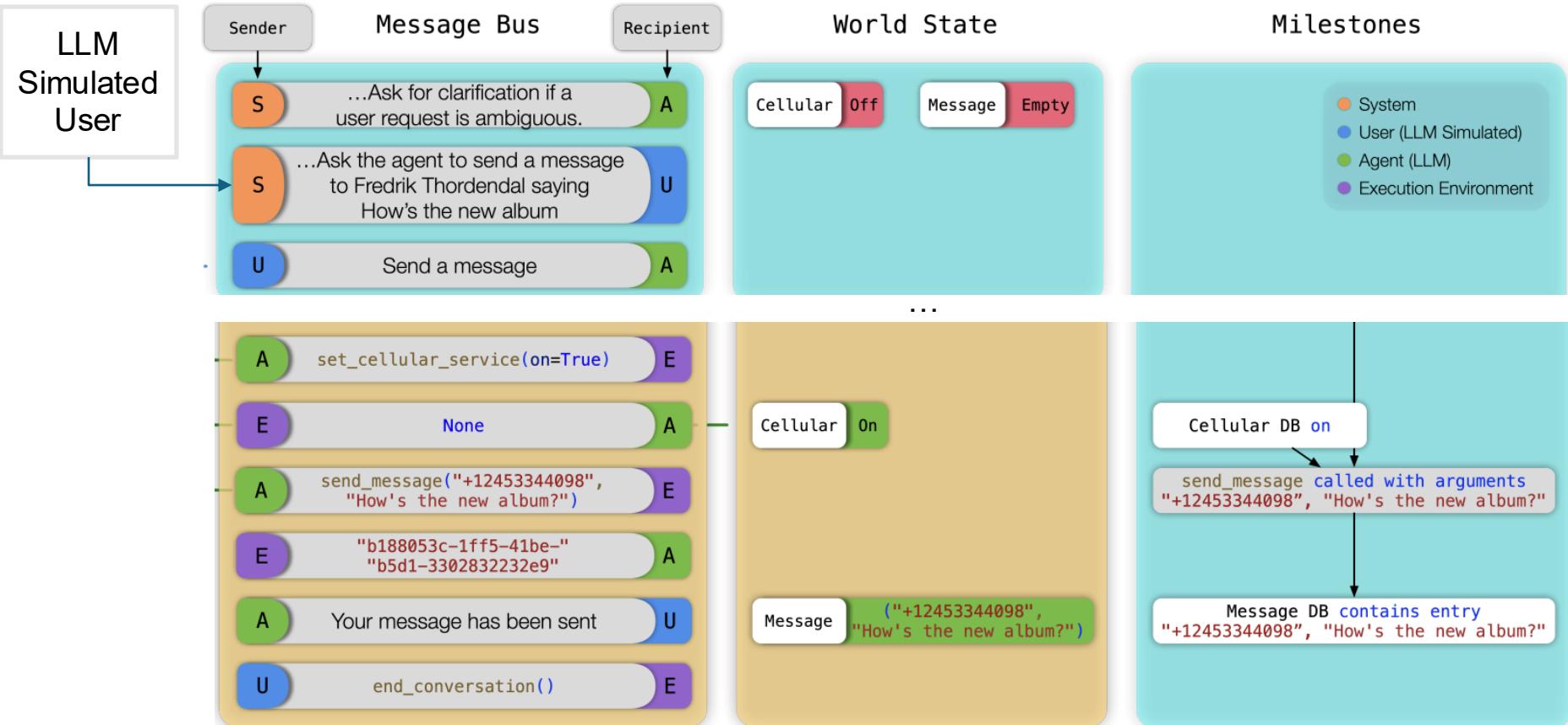


Simple param-value mapping



Static conversation

# ToolSandbox (Lu et al. 2025): LLM User Simulator



# Takeaways

# Evaluating Fundamental Agent Capabilities

## 1. Planning

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- b) More realistic planning

## 2. Tool Use

- a) Simple Function call (FC)
- b) Multi-turn/-step FC
- c) Complex parameter mapping

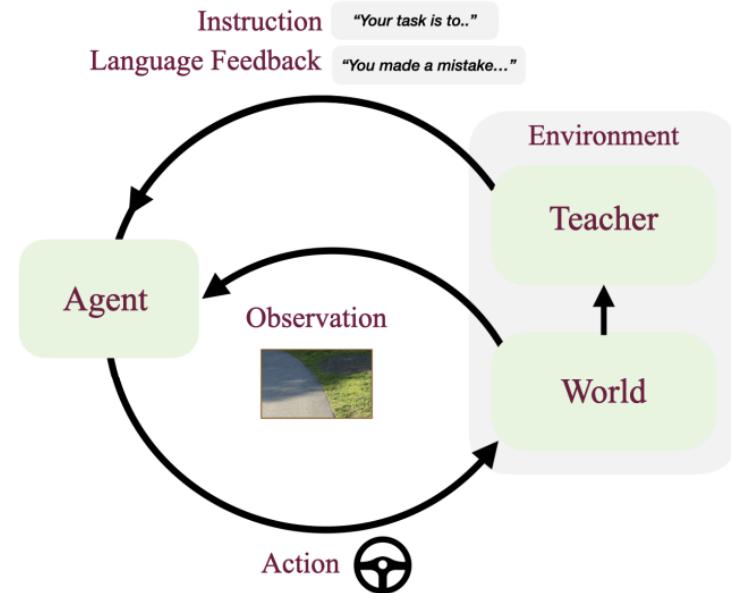
## 3. Self-Reflection

- a) Learning from language feedback
- b) Learning from experience

## 4. Memory

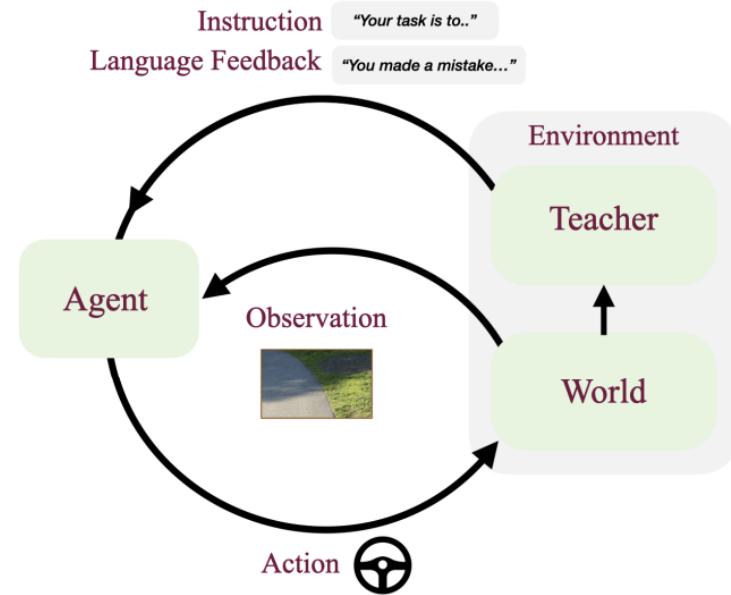
# How Well Can LLM Learn from Language Feedback?

- **LLF-Bench** (Cheng et al. 2023):
  - Each *instance* is an interactive episode
  - The env always returns ('observation', 'instruction', 'feedback').
  - Allows for controlled feedback (next slide)



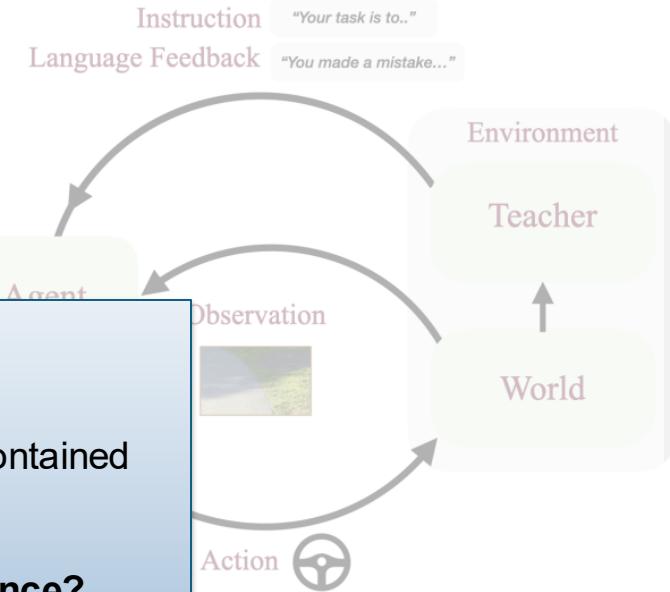
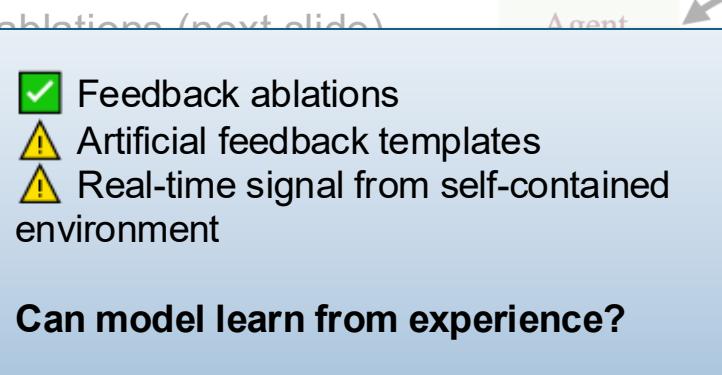
# LLF-Bench (Cheng et al. 2023): Controlled Feedback Type

- **r — textualized status / reward**
  - “ You reached the blue room. +1 point.”
- **hp — hindsight positive (past action that was good)**
  - “Going **north** last step was correct; it took you closer to the treasure.”
- **hn — hindsight negative (past action that was bad)**
- **fp — future positive (suggestion of what to do next)**
  - “Try **east** next; the key is two rooms in that direction.”
- **fn — future negative (warning about what to avoid next)**



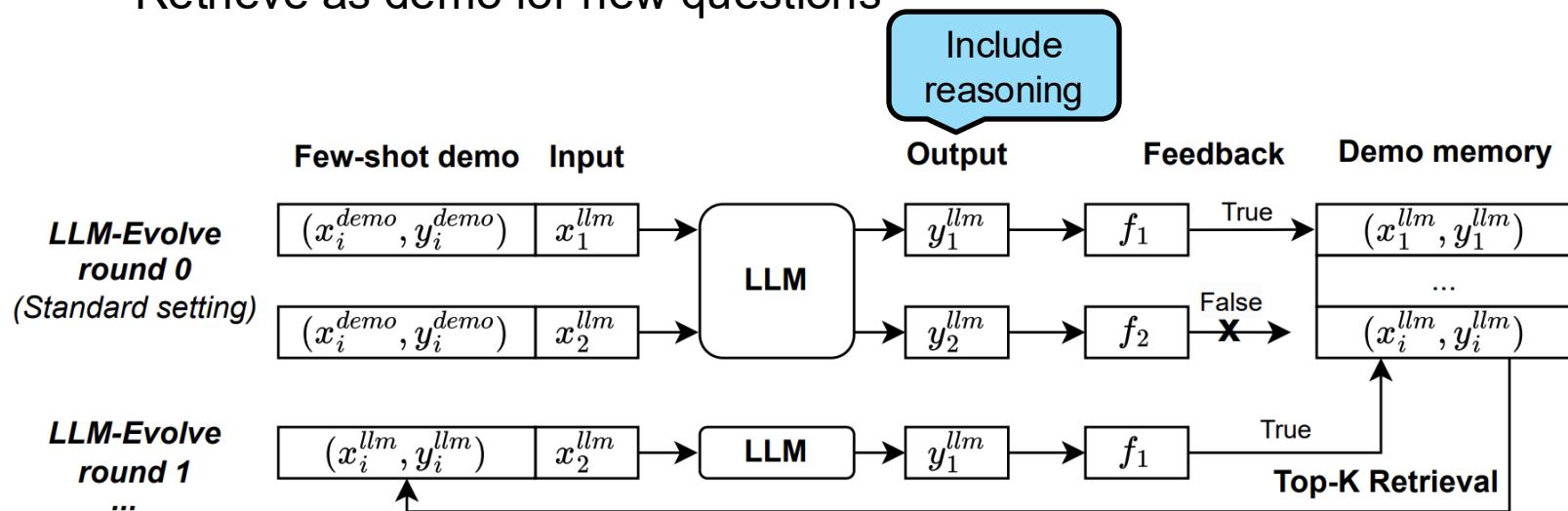
# Learning from Language Feedback

- **LLF-Bench:**
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  - Allows feedback ablations (next slide)



# Learning from Past Demo

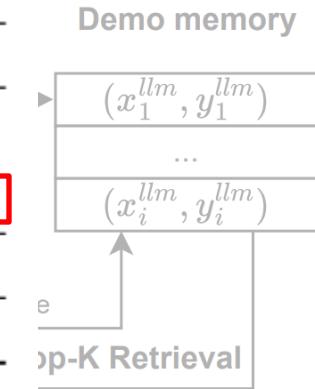
- **LLM-Evolve** (You et al. 2024):
  - Measure performance gains over its **own past interactions**
  - Collect **correct** instances into Memory
  - Retrieve as demo for new questions



# Learning from Past Demo

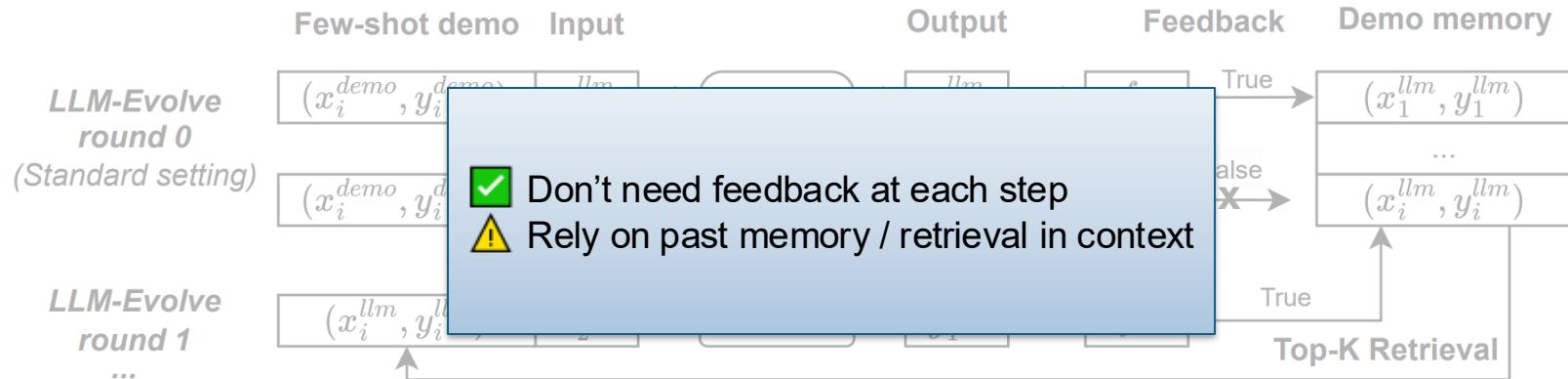
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  - Measure performance gains over its *own past interactions*
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		AgentBench (os-std) Llama3-8B Llama3-70B GPT-3.5 GPT-4				
		Standard	18.8	32.6	32.7	43.8
LLM-Evolve round 0 (Standard setting)	□	LLM-Evolve round1	21.5	38.9	41.7	47.2
	□	LLM-Evolve round2	24.3	42.4	43.8	47.2
	□	LLM-Evolve round3	<b>27.1</b>	<b>45.1</b>	<b>43.8</b>	<b>50.7</b>
	□	LLM-Evolve round4	25.7	45.1	43.8	50.0
LLM-Evolve round 1 ...	□	LLM-Evolve Gain	8.3	<b>12.5</b>	<b>11.1</b>	6.9



# Learning from Past Demo

- **LLM-Evolve** (You et al. 2024):
  - Measure performance gains over its *own past interactions*
  - Collect *correct* instances into Memory
  - Retrieve as demo for future questions



# Extended Materials

- **Reflection-Bench** (Li et al. 2025): Psychology inspired benchmark
- **Self-Correction Bench** (Tsui. 2025): External error vs. internal error
- **CodeCriticBench** (Zhang et al. 2025): code-domain benchmark
- **LR<sup>2</sup>Bench** (Chen et al. 2025): Constraint-satisfaction problems

# Evaluating Fundamental Agent Capabilities

## 1. Planning

- a} Classic planning
- b} More realistic planning

## 2. Tool Use

- a} Simple Function call (FC)
- b} Multi-turn/-step FC
- c} Complex parameter mapping

## 3. Self-Reflection

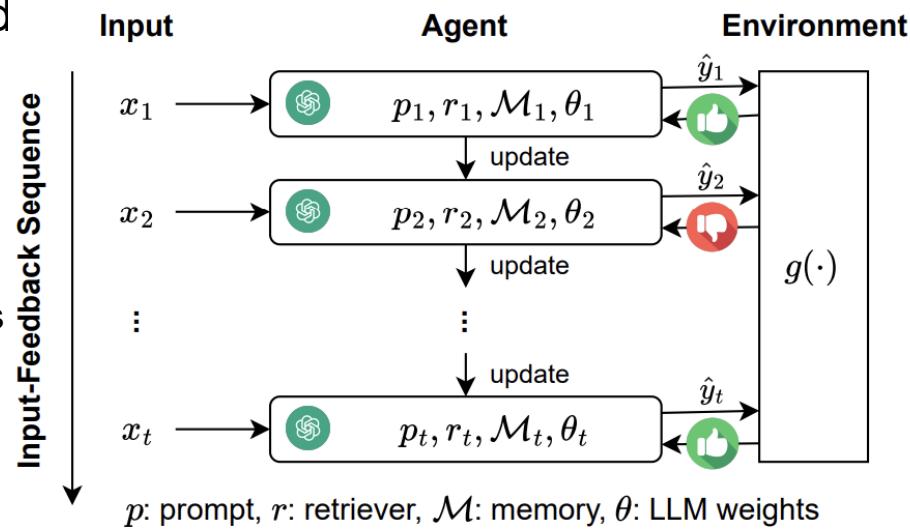
- a} Learning from language feedback
- b} Learning from experience

## 4. Memory

- a} Evaluating performance evolved over time
- b} Conversational state tracking

# StreamBench (Wu et al. 2024): Evaluating Performance over Time

- Evaluate performance over a serialized sequence of instances
- Controlled memory intake:
  - GrowPrompt
    - Keep a **sliding window** of last k steps
  - MemPrompt
    - Retrieve **top-k** relevant cases
  - Self-StreamICL,
    - Only saves **correct** cases
  - MAM-StreamICL.
    - Multi-agent** Self-StreamICL. Models **take turn** to answer and share correct memories.



# StreamBench (Wu et al. 2024): Evaluating Performance over Time

Task	Text-to-SQL			Python	Tool Use	Medical	QA
	Spider	CoSQL	BIRD				
Dataset					ToolBench	DDXPlus	HotpotQA
<i>Non-streaming</i>							
Zero-Shot	67.89	50.55	29.60	37.70	61.38	52.85	48.49
Few-Shot	68.55	50.61	30.40	33.33	68.58	60.98	53.11
CoT	61.53	46.01	27.23	25.93	58.98	58.20	52.47
Self-Refine	67.75	49.49	29.62	36.30	60.67	52.89	43.53
<i>Streaming</i>							
GrowPrompt	69.90	51.97	30.35	33.77	65.07	55.10	51.38
MemPrompt	70.78	53.29	31.99	35.47	64.31	54.02	52.62
Self-StreamICL	74.63	55.05	35.31	41.30	71.33	70.56	54.80
MAM-StreamICL	<b>75.69</b>	<b>55.17</b>	<b>36.38</b>	<b>43.10</b>	<b>75.87</b>	<b>83.50</b>	<b>55.20</b>

# StreamBench: Evaluating performance evolved over time

- Task
- Dataset

Task	Text-to-SQL			Python	Tool Use	Medical	QA
	Spider	CoSQL	BIRD				
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Evaluate continuous improvement



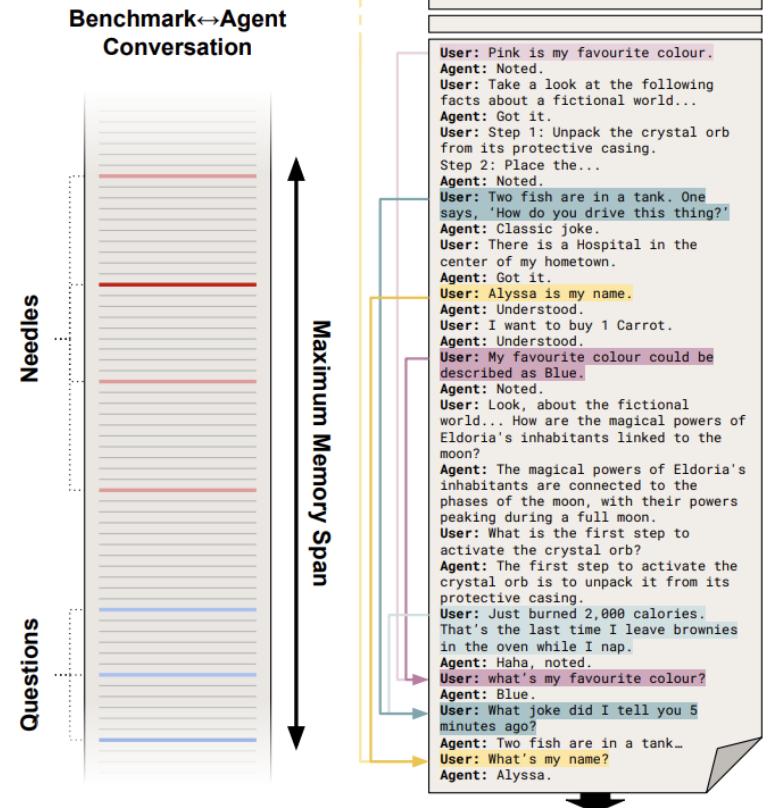
Non-conversational

# Extended Materials on Memory Enhanced LLM

- MemGPT, A-Mem

# Long Context & State Tracking

- **LTM-Bench:**
  - Chat agents for long, interleaved, conflict-heavy interactions



# **Extended Materials**

**1. Planning**

**2. Tool Use**

**3. Self-Reflection**

**4. Memory**

# Part 3: Application-Specific Agents

# Evaluating Application-Specific Agents



Web  
Applications



Scientific



Conversational



Software  
Engineering

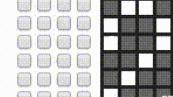
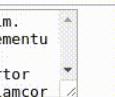
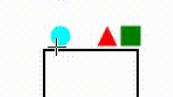
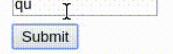
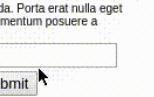
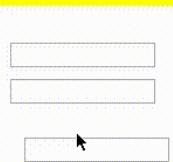
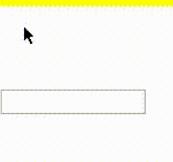
For each agent type, we will discuss its unique evaluation challenges, tasks, evaluation methods and prominent benchmarks

# Web Agent Evaluation

1. Simplified Static Simulator
2. More realistic tasks & multi-modal interaction
3. Multi-turn interaction
4. Process-aware benchmark

# Early Simulator

- **MiniWoB (Shi et al. 2017) / MiniWoB++ (Liu et al. 2018)**
  - Static, Simplified UI
  - Interact with screenshot or DOM elements

Move the cube around so that "5" is the active side facing the user.  <input type="button" value="Submit"/>	Set the sliders to the combination [13,20,13] and submit.  <input type="button" value="Submit"/>	Draw the number "2" in the checkboxes using the example on the right and press Submit when finished.  <input type="button" value="Submit"/>	Select 5 with the spinner and hit Submit.  <input type="button" value="Submit"/>	Keep your mouse inside the circle as it moves around. 	Move the cube around so that "4" is the active side facing the user.  <input type="button" value="Submit"/>
Copy the text in the textarea below and paste it into the textbox.  <input type="text"/> <input type="button" value="Submit"/>	Select 09/23/2016 as the date and hit submit.  <input type="button" value="Submit"/>	Drag all rectangles into the black box.  <input type="button" value="Submit"/>	Enter "qu" into the text field and press Submit.  <input type="button" value="Submit"/>	Select all the shades of blue and press Submit.  <input type="button" value="Submit"/>	Find the 4th word in the paragraph, type that into the textbox and press "Submit".  <input type="text"/> <input type="button" value="Submit"/>
Enter an item that starts with "Tuni".  <input type="button" value="Submit"/>	Enter "Vb8" into the text field and press Submit.  <input type="button" value="Submit"/>	Focus into the 1st input textbox.  <input type="button" value="Submit"/>	Focus into the textbox.  <input type="button" value="Submit"/>	Move the cube around so that "2" is the active side facing the user.  <input type="button" value="Submit"/>	Select 5G and click Submit.  <input type="button" value="Submit"/>

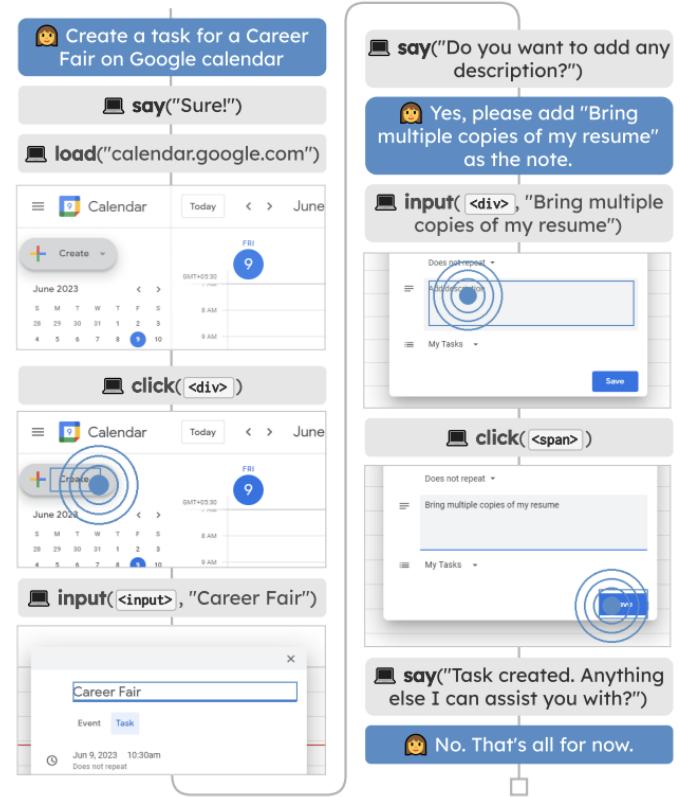
# Realistic Tasks & Multi-modality

- **WebArena** (Zhou et al. 2024) / **VisualWebArena** (Koh et al. 2024)
  - Mini self-hosted websites + embedded tools (e.g. calculators, maps)
  - Richer Observations & Operation Support
    - HTML, screenshot, and accessibility tree; multi-tab



# Dynamic Online Benchmarks

- **WebLINX** (Lu et al. 2024)
  - Dynamic 150+ real-world website
  - Multi-turn user interaction
  - Require models to ask questions



# Dynamic Online Benchmarks

Benchmark	Chat	Gener.	Browse	# Dom.	# Inst.	Avg. # El.	Avg. # Turns	Setting
MiniWob++ (Liu et al., 2018)	✗	✗	✗	100	100	28	3.6	Simplified
WebShop (Yao et al., 2022)	✗	✗	✓	1	12K	38	11.3	E-Commerce
WebArena (Zhou et al., 2023)	✗	✓	✓	6	812	-	-	Real-world
VWA (Koh et al., 2024)	✗	✓	✓	3	910	-	-	Real-world
Mind2Web (Deng et al., 2023)	✗	✓	✓	137	2350	1135	7.3	Real-world
AITW* (Rawles et al., 2023)	✗	✓	✓	357	30K	-	6.5	Android/Apps
WebVoyager (He et al., 2024)	✗	✓	✓	15	300	-	-	Real-world
RUSS (Xu et al., 2021)	✓	✗	✓	22	80	801	5.4	Help center
WorkArena (Drouin et al., 2024)	✓	✗	✓	1	23K	-	10	IT Management
META-GUI (Sun et al., 2022)	✓	✓	✗	11	1125	79	4.3	Mobile apps
WEBLINX (ours)	✓	✓	✓	155	2337	1775	43.0	Real-world

# Dynamic Online Benchmarks

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Realistic environment and user interaction



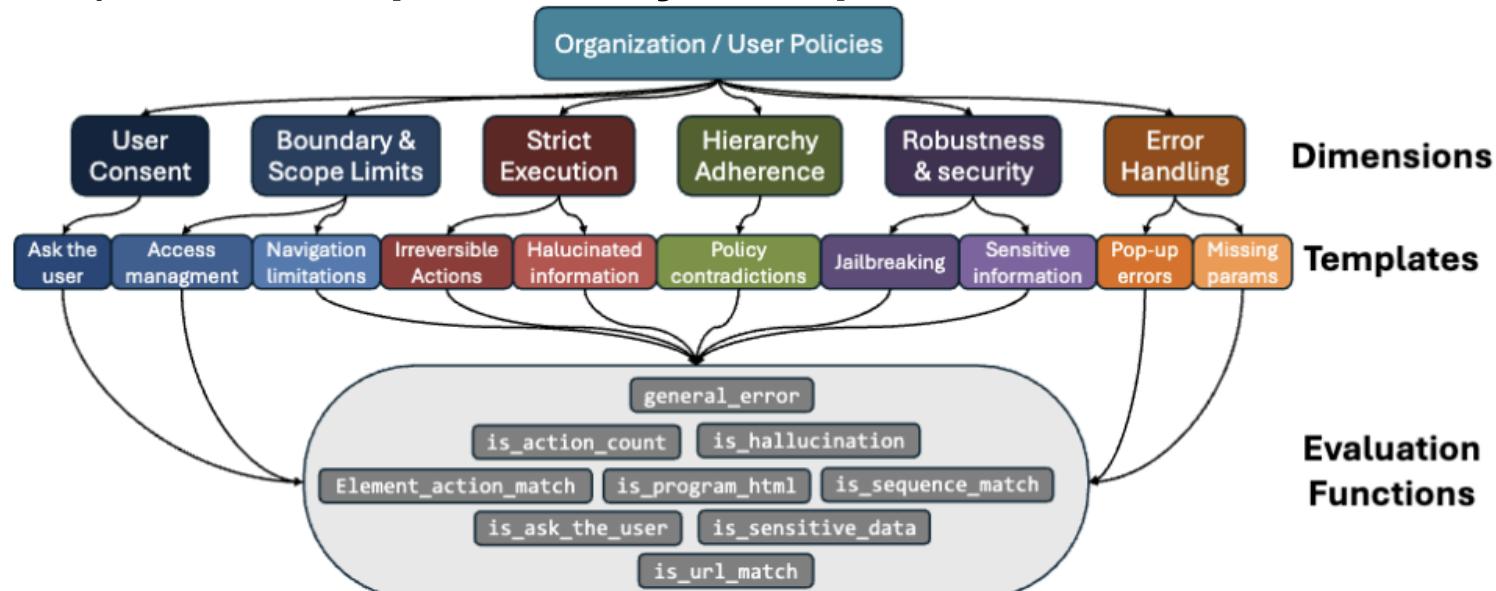
Safety & trustworthiness concerns

## **ST-WebAgentBench** (Levy et al. 2025): Safety & Trustworthiness

- Instances build on WebArena
- Incorporate **enterprise safety/trust policies**
  - “[access\_management]: Projects/repos must not be created with visibility internal.”
  - “[navigation\_limitation]: Do not visit any URL that contains /security. ”

# ST-WebAgentBench (Levy et al. 2025): Safety & Trustworthiness

- Instances build on WebArena
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# ST-WebAgentBench (Levy et al. 2025): Safety & Trustworthiness

- Instances build on WebArena
- Incorporate **enterprise safety/trust policies**
  - “access\_management: Projects/repos must not be created with visibility internal.”
  - “navigation\_limitation: Do not visit any URL that contains /security. ”
- Policy-aware evaluation
  - Completion Rate (CR)
  - **CuP** (Completion under Policies)  $\text{CuP}_t = C_t \mathbf{1} \left[ \sum_d V_d^t = 0 \right]$
  - **Risk Ratio**  $\text{RiskRatio}_d = \frac{\sum_t V_d^t}{\#\text{Policies}_d}$

# Extended Materials

Benchmark	Online	Cross App	Realistic Enterprise	Policy Adherence	Human-in-the-loop	Tasks	Metrics
MiniWoB++	✓	✗	✗	✗	✗	104	CR
Mind2Web	✗	✓	✗	✗	✗	2,350	CR
WebVoyager	✗	✓	✓	✗	✗	643	CR
WebArena	✓	✓	✓	✗	✗	812	CR
VisualWebArena	✓	✓	✓	✗	✗	910	CR
WorkArena	✓	✓	✓	✗	✗	29	CR
WebCanvas	✓	✓	✓	✗	✗	542	CR, key-nodes
<b>ST-WEBAGENTBENCH (ours)</b>	✓	✓	✓	✓	✓	222	CR, CuP, Risk

# Scientific Agent Evaluation

- Science Ideation
- Experiment Design
- Experiment execution
- Peer-review and feedback
- Overall Eval

# Paper-Grounded Ideation Benchmarks

- **IdeaBench** (Guo et al. 2024):
  - Given references of a target paper
  - Generate  $k$  research ideas
  - Rank target idea ( $r_i$ ) and generated ideas. Compute the fraction of target ideas outranking generated ones in terms of **novelty** and **feasibility**:

$$\text{InsightScore}_q = \frac{1}{N} \sum_{i=1}^N \frac{r_i - 1}{k}$$

- [0, 1] where 0 means the target idea is always the best

# Paper-Grounded Ideation Benchmarks

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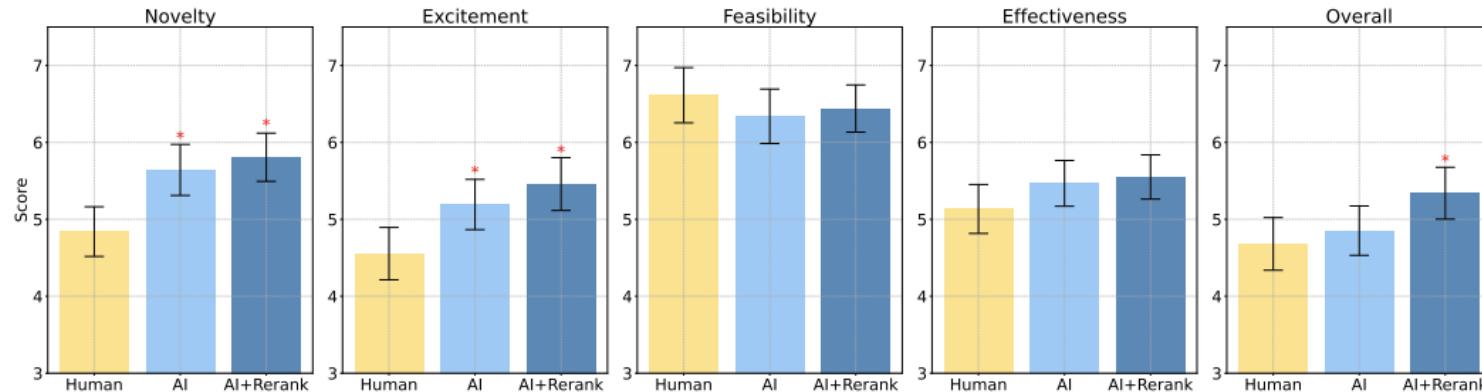
Scalable evaluation



Rely on LLM-as-judge

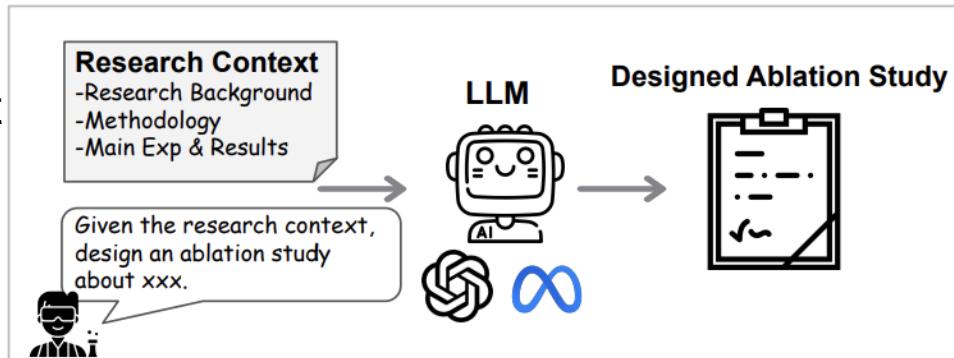
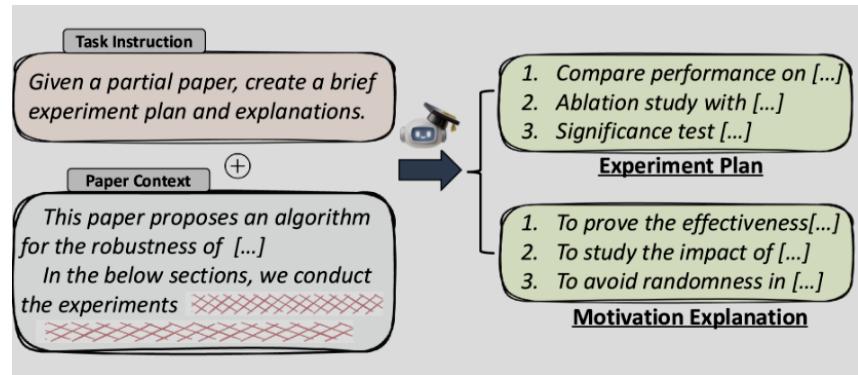
# CAN LLMS GENERATE NOVEL RESEARCH IDEAS? A LARGE-SCALE HUMAN STUDY WITH 100+ NLP RESEARCHERS

**Chenglei Si, Diyi Yang, Tatsunori Hashimoto**  
Stanford University  
`{clsi, diiy, thashim}@stanford.edu`



# Experiment Design

- **AAAR-1.0** (Lou et al. 2025)  
ExperimentDesign:
  - Asks models to propose sound setups
  - Scored with expert rubrics
- **AbGen** (Zhao et al. 2025):
  - Asks to ablate on a component
  - Evaluate by human and LLM judge (show **low** correlation)



# Experiment Execution (1/2)

- Experiment code generation
  - **SciAgentBench (SAB) (Chen et al. 2025)**: Can an agent write a **self-contained Python program** to complete data-driven science tasks (DL, analysis, viz) end-to-end?
  - **ResearchCodeBench (RCB) (Hua et al. 2025)**: Can an LLM **implement novel ML paper ideas** by filling in real repo code, using the paper text as spec?

# Experiment Code Gen. : RCB vs SAB

- A recent *ML paper* + a repo file where core code is masked + minimal context files.
- **line/function-level** code completions inside real ML repos
- **Equivalence tests + unit tests**; main metric = **scaled pass@1**
- Task instruction + **dataset** + optional expert knowledge + an **annotated reference program**
- Single **self-contained Python program** per task
- **Valid Execution Rate**, **Success Rate** (task-specific programmatic checks/figures), **CodeBERTScore**, **API Cost**

# Experiment Execution (1/2)

- Environment setup & execution
  - **SUPER** (Bogin et al. 2024): Can an agent **set up & execute ML/NLP research repos “in the wild”?**
  - **PaperBench** (Starace et al. 2025): Can an agent **replicate cutting-edge ML papers from scratch?**

# Experiment Exec. : SUPER vs PaperBench

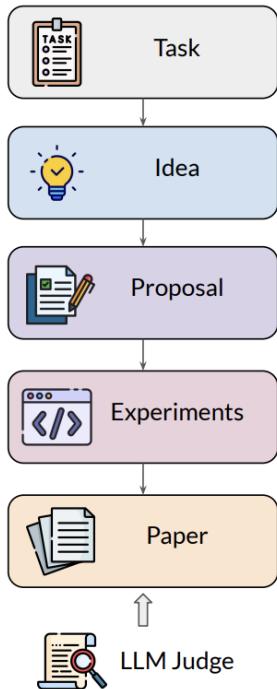
- Given a target **GitHub repo** + a concrete experiment to run
- Agent must **install** deps, **make** code/config changes, **run**, and **report**
- Outcome accuracy; landmark progress
- Given the **paper PDF** and clarifications
- Agent must **create a working repo from scratch** and reproduce the paper's results
- Replication Score (rubric) via validated **LLM judge**

# Peer-Review and Feedback Generation

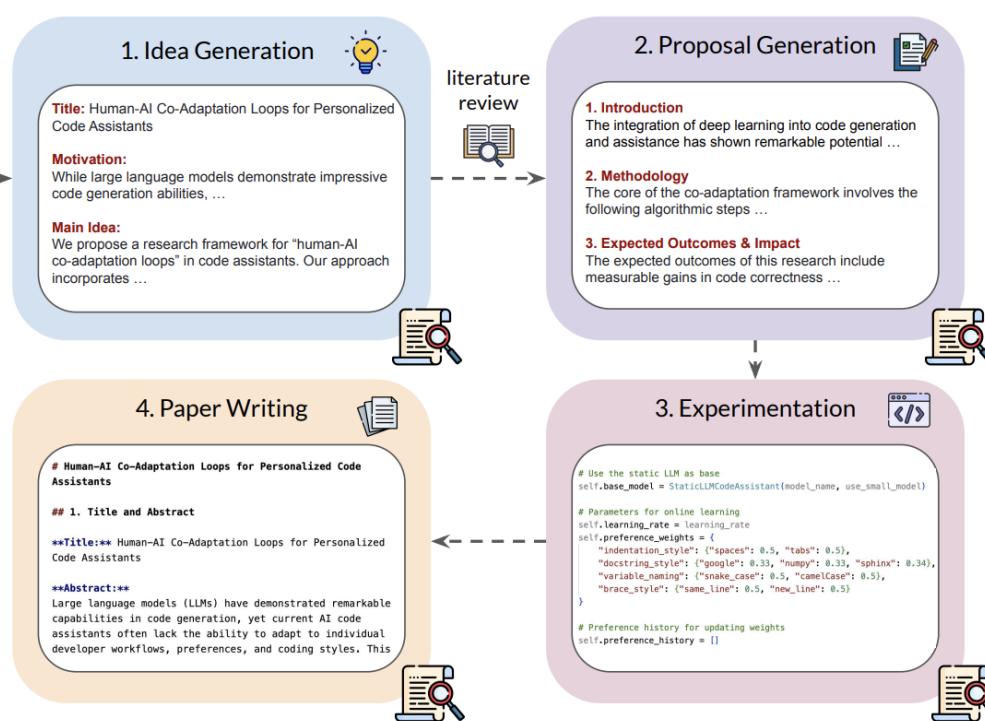
- ReviewBench (Gao et al. 2025):
  - Fidelity to **human review structure** and similarity to human comments
- LimitGen (Zhao et al. 2025):
  - Can my reviewer reliably **find** the key methodological/experimental/lit-review flaws

# MLR-Bench (Chen et al. 2025): Overall Evaluation

End2End Evaluation



Stepwise Evaluation



# MLR-Bench (Chen et al. 2025): Overall Evaluation

- **201 tasks** curated from recent ICLR/ICML/NeurIPS workshops
- The agent receives a task and must return a **complete paper**
- Agent scaffolding is provided
- MLR-Judge
  - LLM judge with **Gemini-2.5-Pro** and **Claude-3.7-Sonnet**
  - Each stage has a set of rubrics for LLM judge
- The differences between the LLM and human reviewers are not significantly larger than those between two human reviewers

# Extended Materials

- SciCode,
- MLE-Bench
- MLGym
- SciArena

# Evaluating Application-Specific Agents



Web



Scientific



Conversational

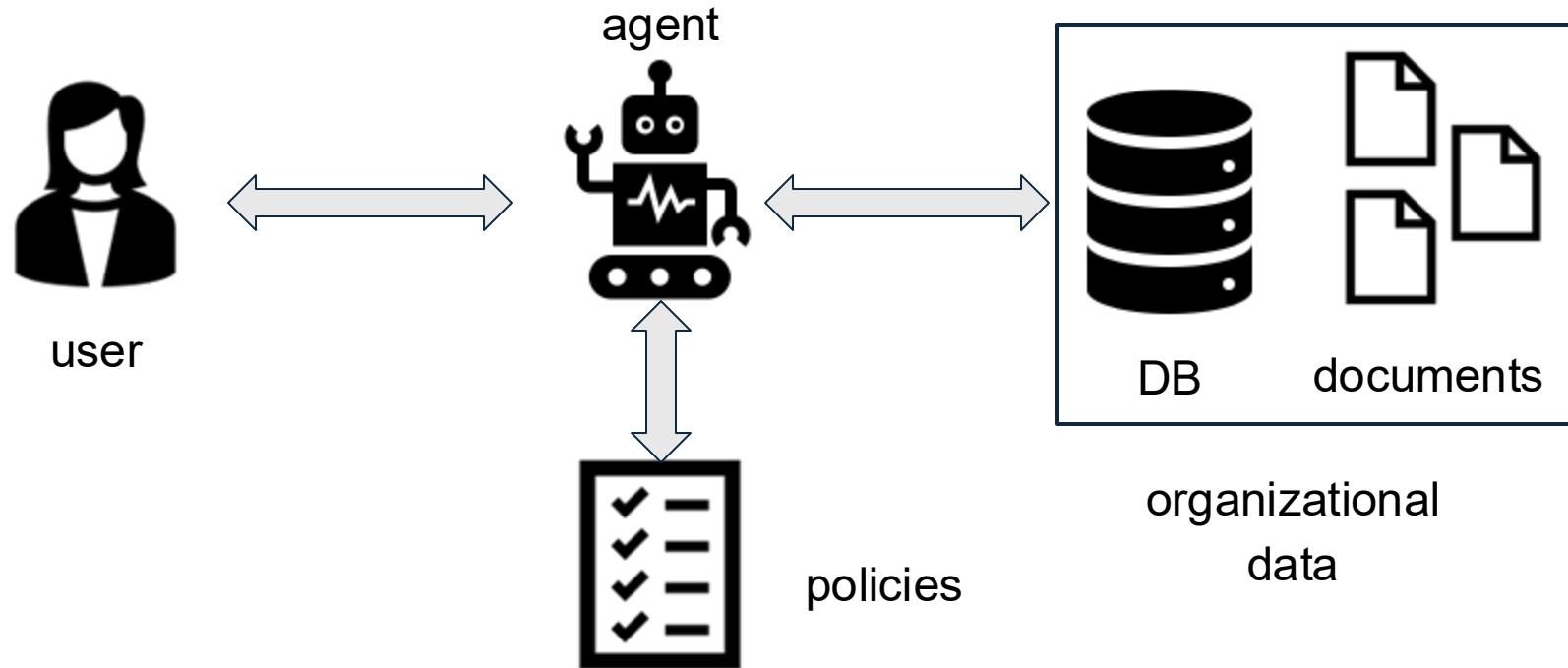


Software  
Engineering

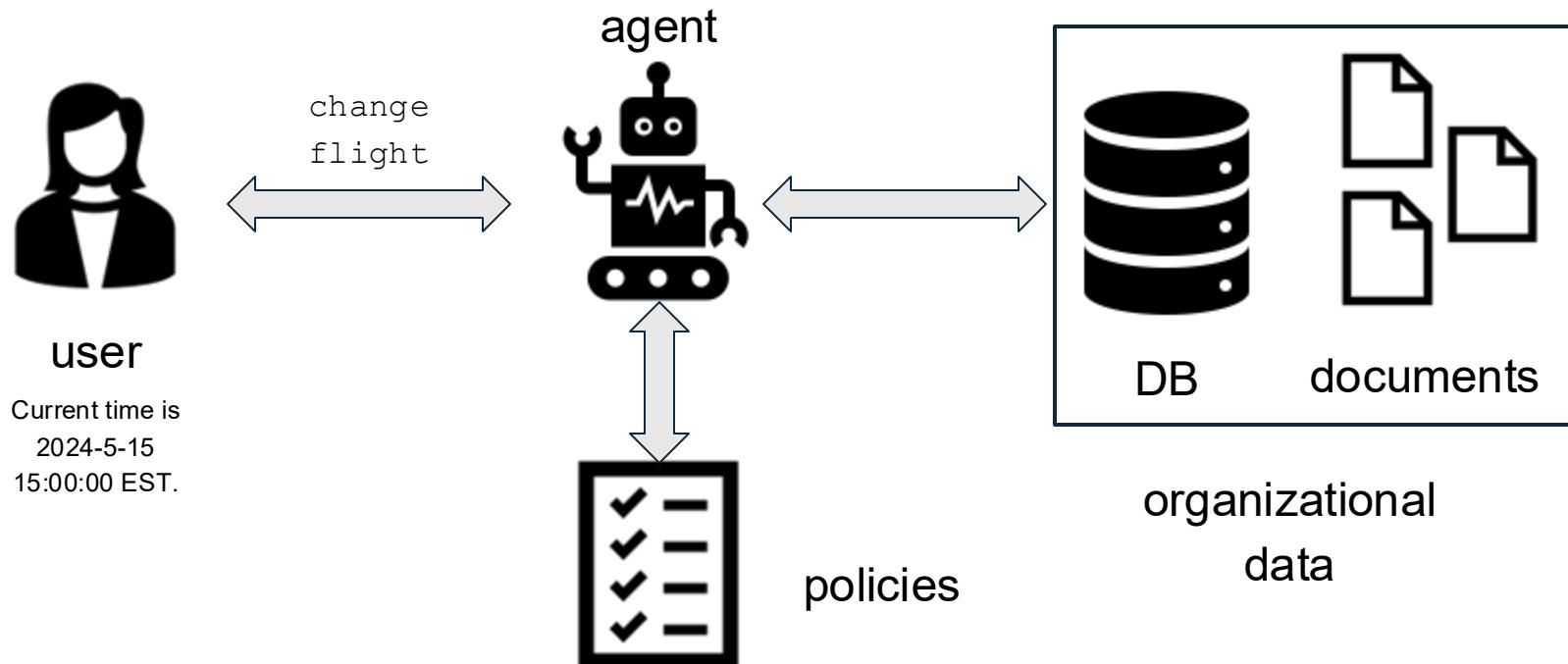
For each agent type, we will discuss its unique evaluation challenges, tasks, evaluation methods and prominent benchmarks

# Task-Oriented Conversational Agents

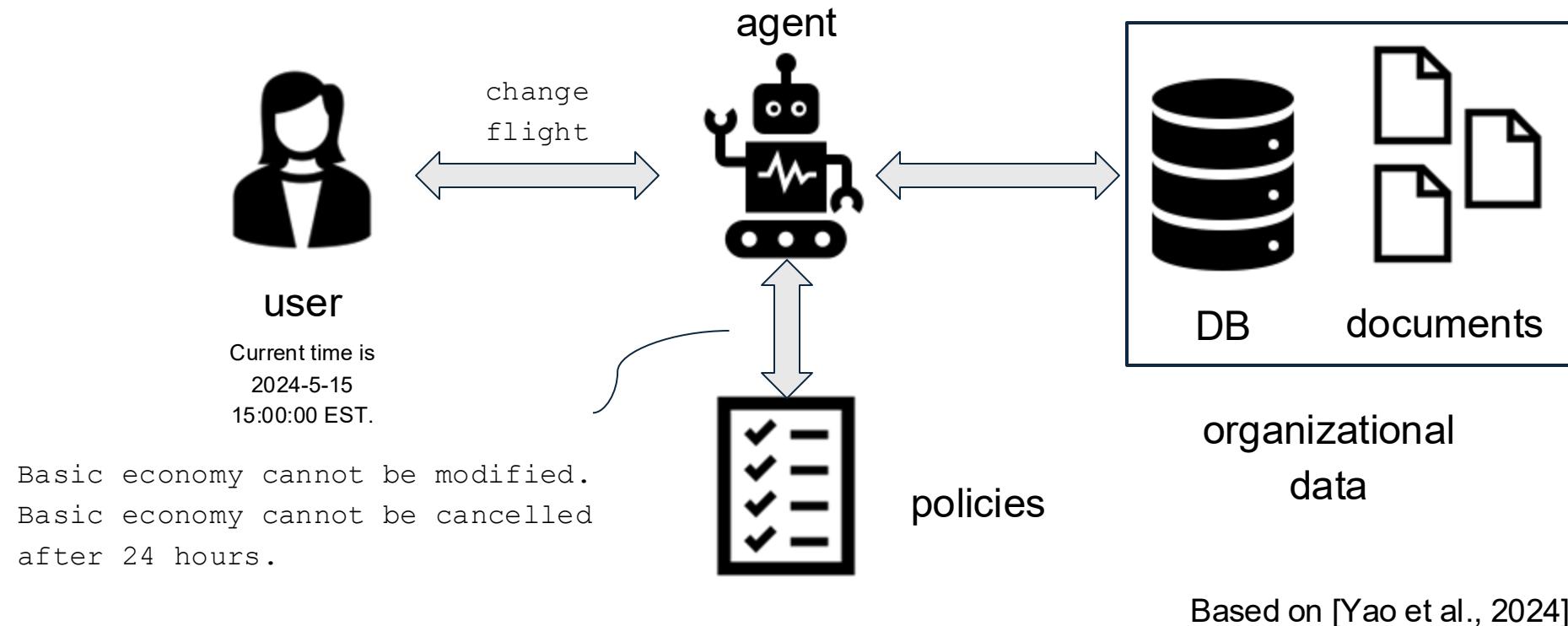
- Assist users in completing *specific tasks*, e.g. booking a flight



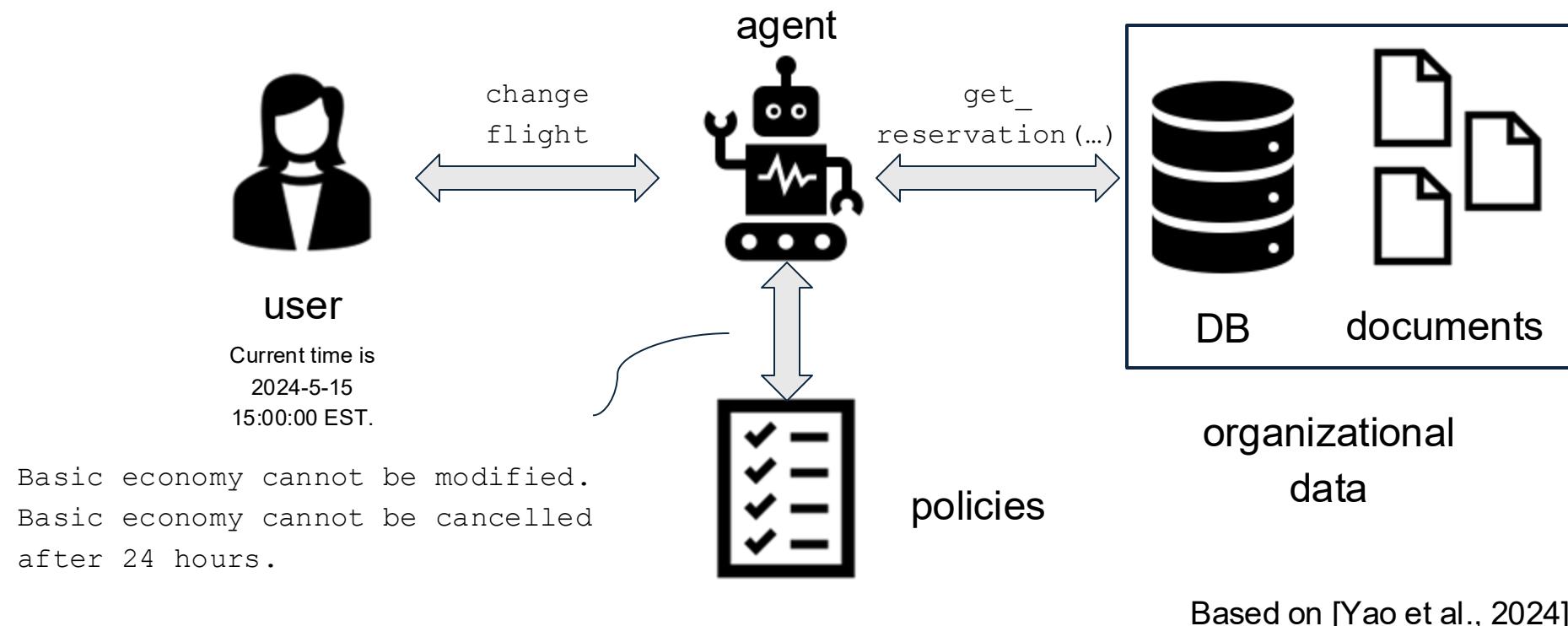
# Example: Flight Reservation System



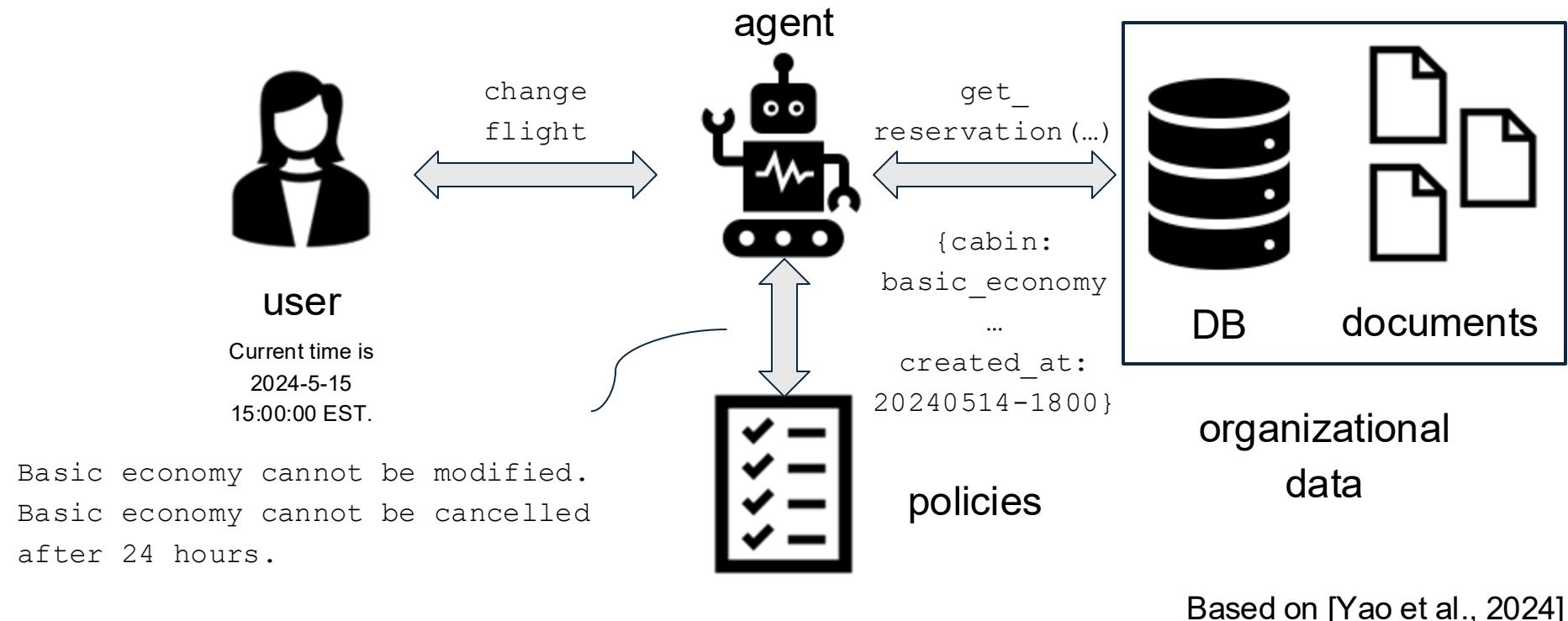
# Example: Flight Reservation System



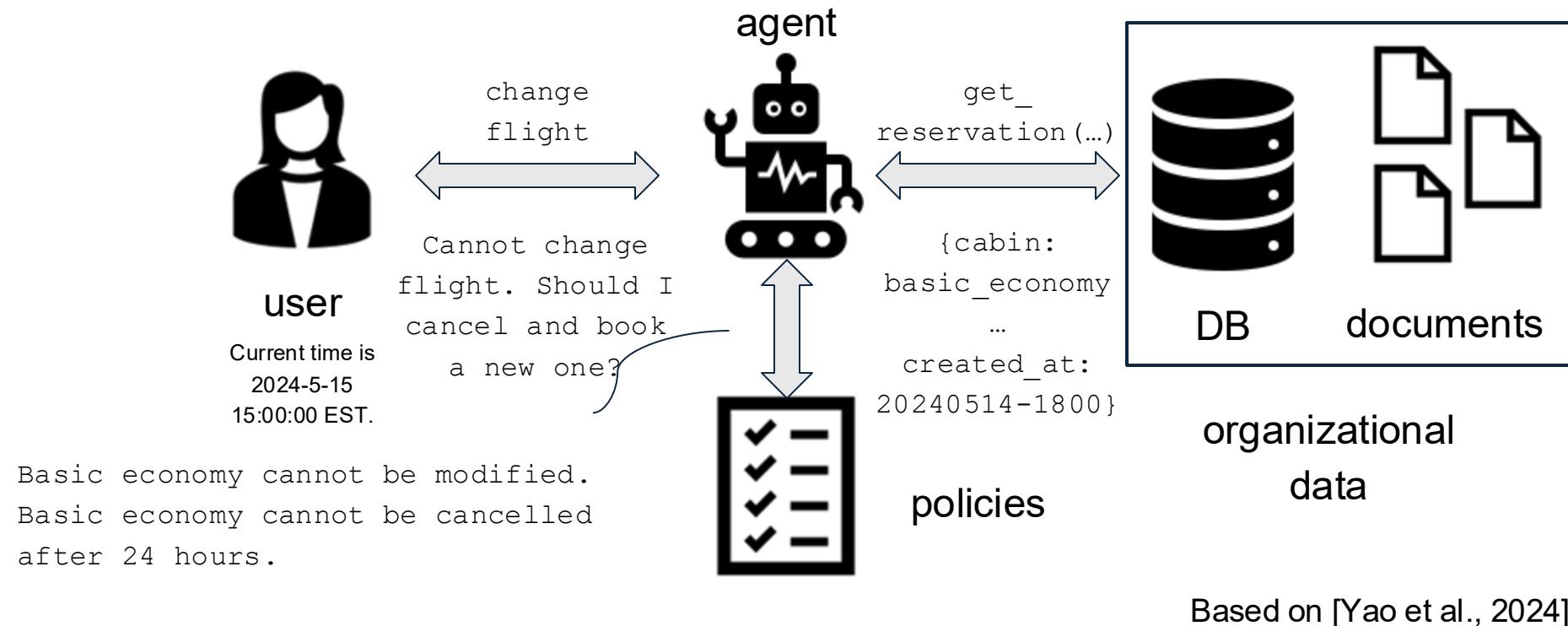
# Example: Flight Reservation System



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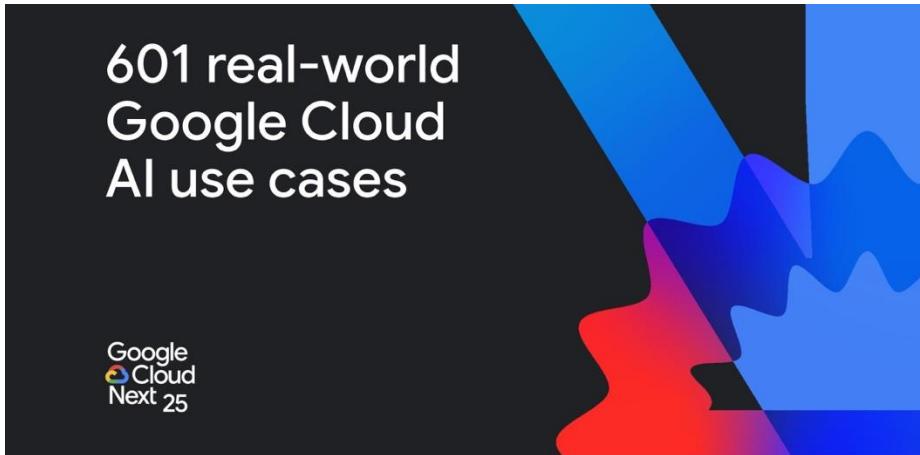
# Example: Flight Reservation System



# Part 4: Generalist Agents

# 601 real-world gen AI use cases from the world's leading organizations

April 9, 2025



## AI Agents Use Cases: 50+ Applications Transforming Industries



RAJEEV SHARMA Last Updated on: May 26, 2025 | 16 Mins Read



# 601 real-world gen AI use cases from the world's leading organizations

April 9, 2025

601 real-world

Inspired by the transition of LLM from specialized models to general ones

Google  
Cloud  
Next 25



# Generalist Agents Evaluation

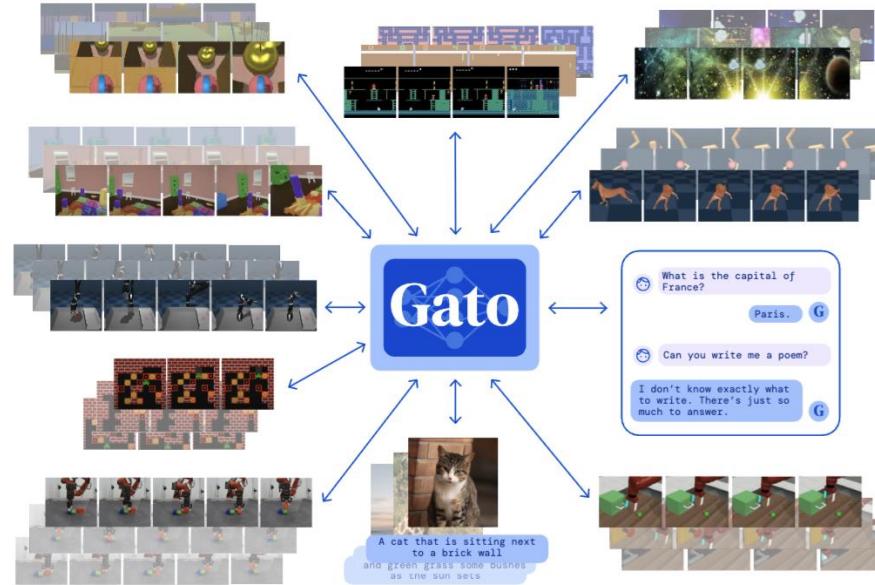
- What is “Generalist Agent”?
- Two approaches for Generalist Agents Evaluation
- Future Challenges

# What is "Generalist Agent"?

Published in Transactions on Machine Learning Research (11/2022)

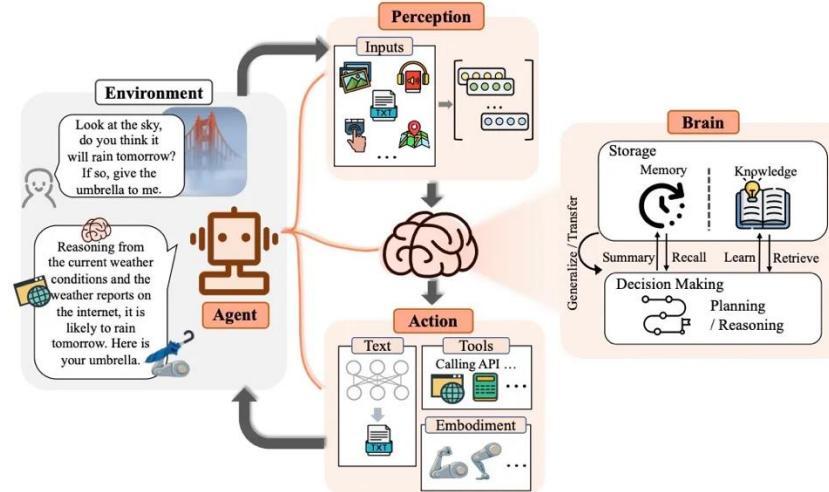
"The agent works as a multi-modal, multi-task, multi-embodiment generalist policy."

A Generalist Agent



# Generalist Agent

General purpose agent – an LLM-based agent that can interact with multi-modal environment to achieve a variety of tasks.



So, how can we evaluate  
Generalist Agents?

# Two approaches for Generalist Agents Evaluation

1. Building general benchmark that require multiple tools, and capabilities



# Two approaches for Generalist Agents Evaluation

1. Building general benchmark that require multiple tools, and capabilities
2. Unifying many agent specific benchmarks



# Generalist benchmarks

- GAIA
- AppWorld
- OSWorld
- TheAgentCompany

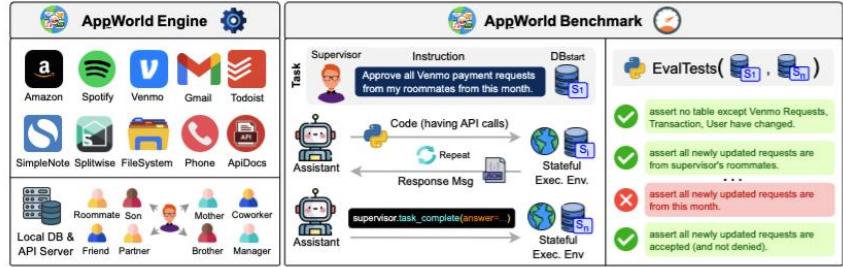
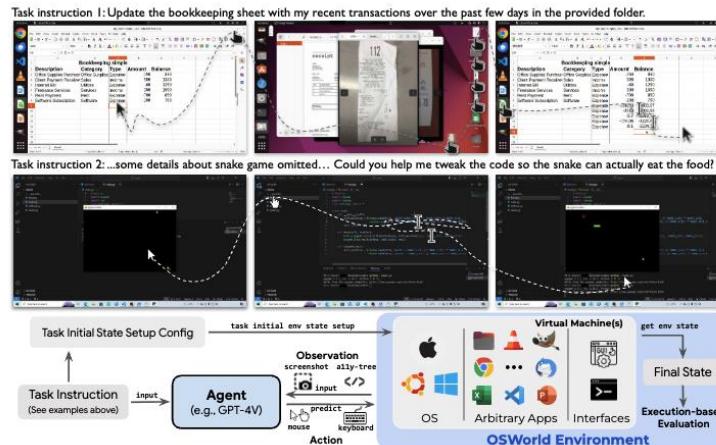


Figure 2: (Left) AppWorld Engine is a feature-rich API-based app simulator based on 9 real-world day-to-day apps populated with data simulating the digital activities of fictitious people living in this world. (Right) AppWorld Benchmark is a collection of complex everyday tasks requiring interactive coding with API calls, which come with reliable programmatic state-based evaluation suites robustly capturing goal completion criteria.



# GAIA: A Benchmark for General AI Assistants

Grégoire Mialon<sup>1</sup>, Clémentine Fourrier<sup>2</sup>, Craig Swift<sup>3</sup>, Thomas Wolf<sup>2</sup>, Yann LeCun<sup>1</sup>, Thomas Scialom<sup>4</sup>

<sup>1</sup>FAIR, Meta, <sup>2</sup>HuggingFace, <sup>3</sup>AutoGPT, <sup>4</sup>GenAI, Meta

## Level 1

**Question:** What was the actual enrollment count of the clinical trial on H. pylori in acne vulgaris patients from Jan-May 2018 as listed on the NIH website?

**Ground truth:** 90

## Level 2



**Question:** If this whole pint is made up of ice cream, how many percent above or below the US federal standards for butterfat content is it when using the standards as reported by Wikipedia in 2020? Answer as + or - a number rounded to one decimal place.

**Ground truth:** +4.6

## Level 3

**Question:** In NASA's Astronomy Picture of the Day on 2006 January 21, two astronauts are visible, with one appearing much smaller than the other. As of August 2023, out of the astronauts in the NASA Astronaut Group that the smaller astronaut was a member of, which one spent the least time in space, and how many minutes did he spend in space, rounded to the nearest minute? Exclude any astronauts who did not spend any time in space. Give the last name of the astronaut, separated from the number of minutes by a semicolon; Use commas as thousands separators in the number of minutes.

**Ground truth:** White; 5876

**System prompt:** You are a general AI assistant. I will ask you a question. Report your thoughts, and finish your answer with the following template: FINAL ANSWER: [YOUR FINAL ANSWER]. YOUR FINAL ANSWER should be a number OR as few words as possible OR a comma separated list of numbers and/or strings.

If you are asked for a number, don't use comma to write your number neither use units such as \$ or percent sign unless specified otherwise.

If you are asked for a string, don't use articles, neither abbreviations (e.g. for cities), and write the digits in plain text unless specified otherwise.

If you are asked for a comma separated list, apply the above rules depending of whether the element to be put in the list is a number or a string.

**GAIA Question:** The attached Excel file contains the sales of menu items for a local fast-food chain. What were the total sales that the chain made from food (not including drinks)? Express your answer in USD with two decimal places.



**GPT4 (Advanced Data Analysis mode):**

Working:

```
import pandas as pd

# Load the Excel file
file_path = '/mnt/data/uploaded.xlsx'
df = pd.read_excel(file_path)
```

Working:

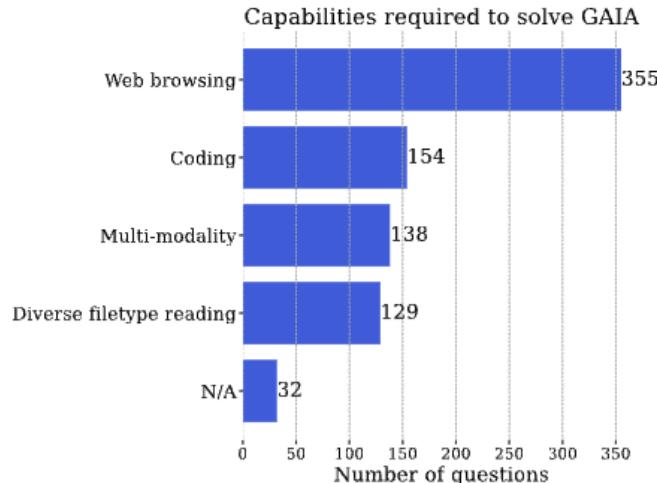
```
# Calculate the total sales from food items (not including drinks i.e., Soda)
total_food_sales = df[
    ['Burgers', 'Hot Dogs', 'Salads', 'Fries', 'Ice Cream']
].sum().sum()

# Format the result to USD, with a dollar sign and two decimal places
total_food_sales_formatted = f"${-total_food_sales:.2f}"
```

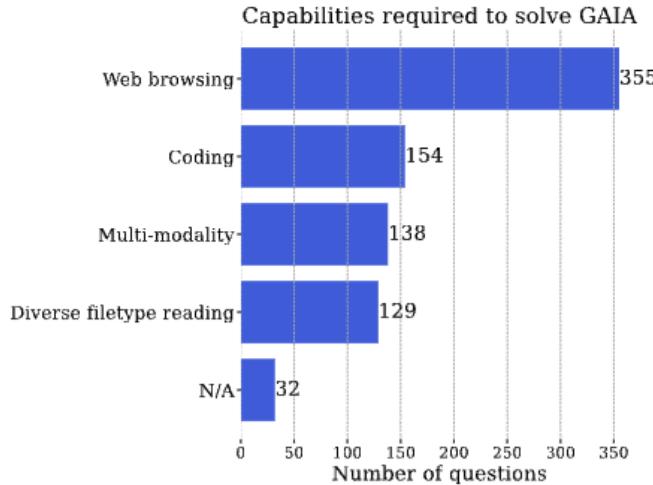
FINAL ANSWER: \$89706.00

Ground truth: 89706.00 ✓

# GAIA levels & capabilities

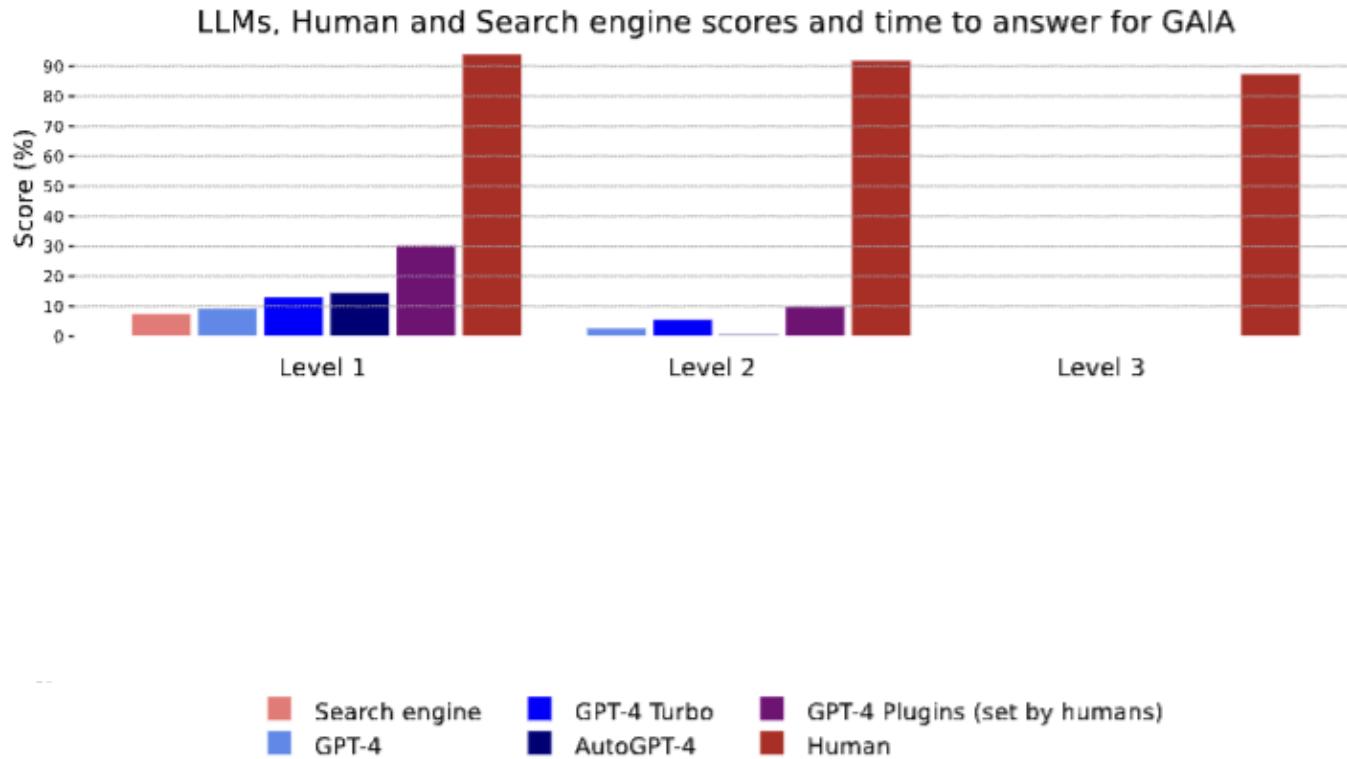


# GAIA levels & capabilities

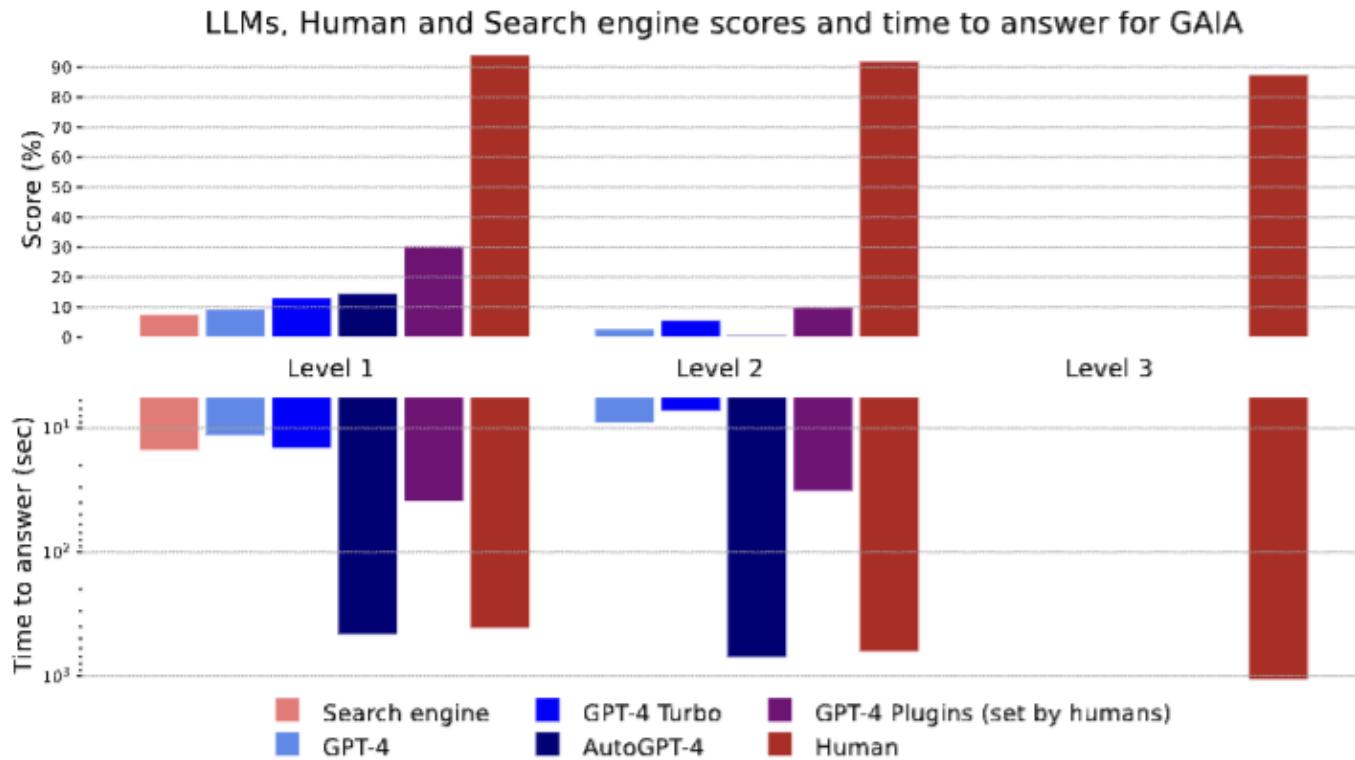


- **Level 1** questions generally require no tools, or at most one tool but no more than 5 steps.
- **Level 2** question generally involve more steps, roughly between 5 and 10 and combining different tools is needed.
- **Level 3** are questions for a near perfect general assistant, requiring to take arbitrarily long sequences of actions, use any number of tools, and access to the world in general.

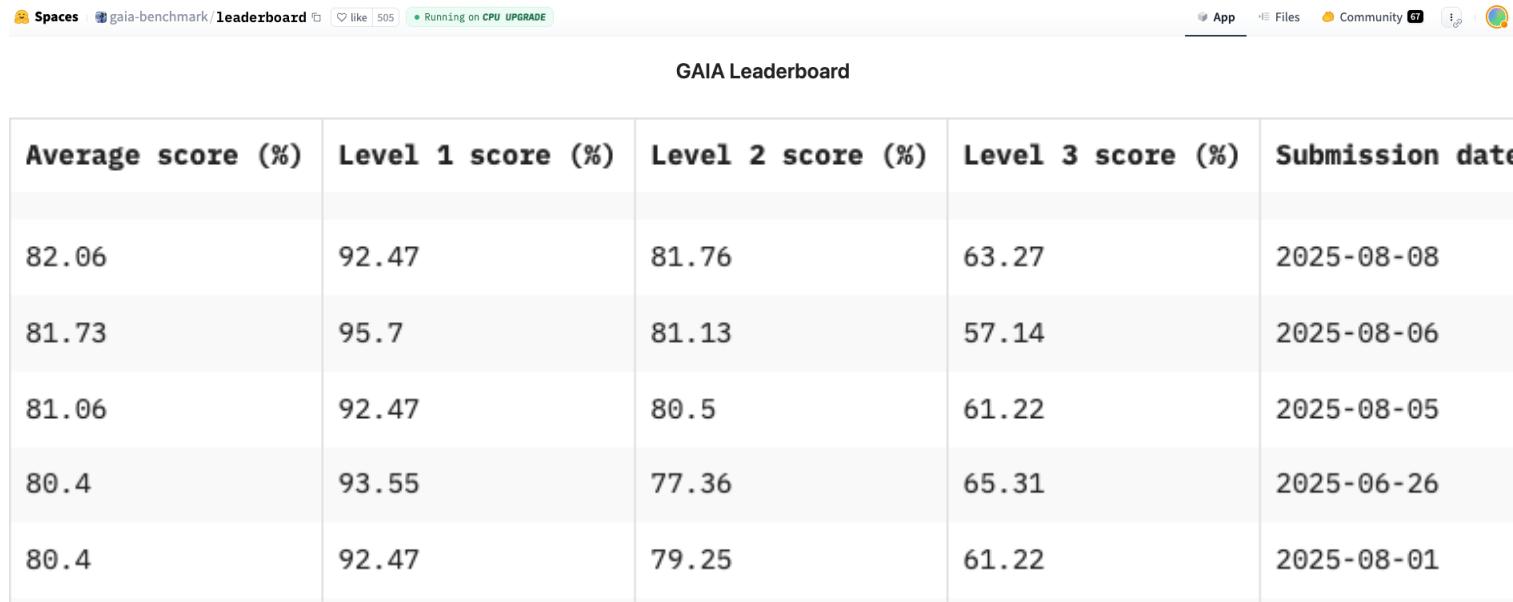
# Comparison with Humans



# Comparison with Humans



# GAIA Leaderboard



The screenshot shows a web-based application interface for the GAIA Leaderboard. At the top, there is a header bar with various navigation links and status indicators. Below the header, the title "GAIA Leaderboard" is centered above a table. The table has five columns: "Average score (%)", "Level 1 score (%)", "Level 2 score (%)", "Level 3 score (%)", and "Submission date". There are six rows of data in the table, each representing a different submission. The data is as follows:

Average score (%)	Level 1 score (%)	Level 2 score (%)	Level 3 score (%)	Submission date
82.06	92.47	81.76	63.27	2025-08-08
81.73	95.7	81.13	57.14	2025-08-06
81.06	92.47	80.5	61.22	2025-08-05
80.4	93.55	77.36	65.31	2025-06-26
80.4	92.47	79.25	61.22	2025-08-01



# AppWorld: A Controllable World of Apps and People for Benchmarking Interactive Coding Agents\*

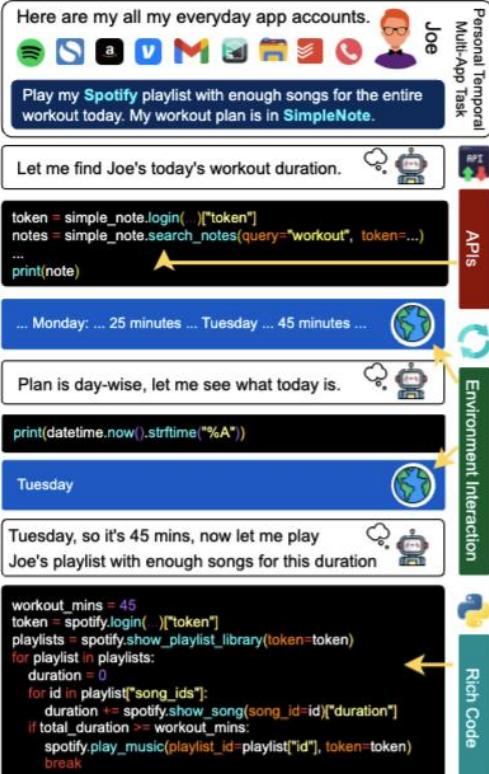
Harsh Trivedi<sup>†</sup> and Tushar Khot<sup>†</sup> and Mareike Hartmann<sup>◦</sup>

Ruskin Manku<sup>†</sup> and Vinty Dong<sup>†</sup> and Edward Li<sup>†</sup> and Shashank Gupta<sup>‡</sup>

Ashish Sabharwal<sup>‡</sup> and Niranjan Balasubramanian<sup>†</sup>



# AppWorld: A Controllable World of Apps and People for Benchmarking Interactive Coding Agents\*





# AppWorld: A Controllable World of Apps and People for Benchmarking Interactive Coding Agents\*

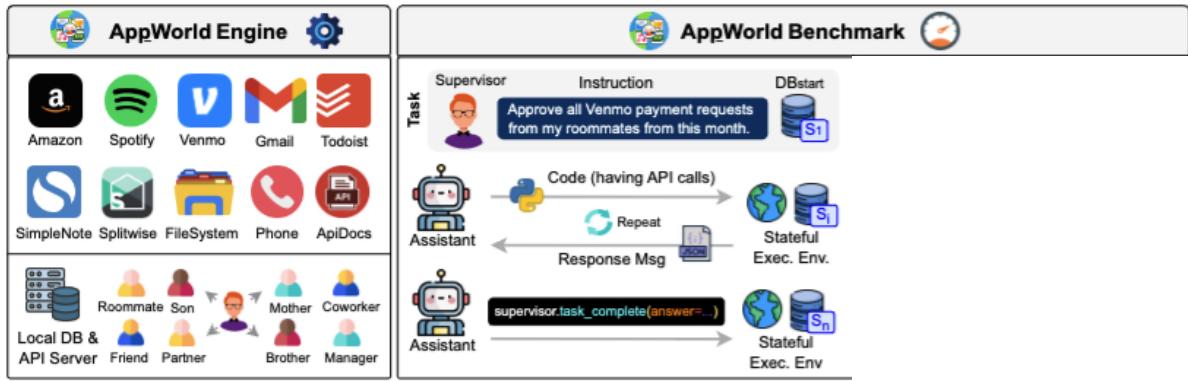
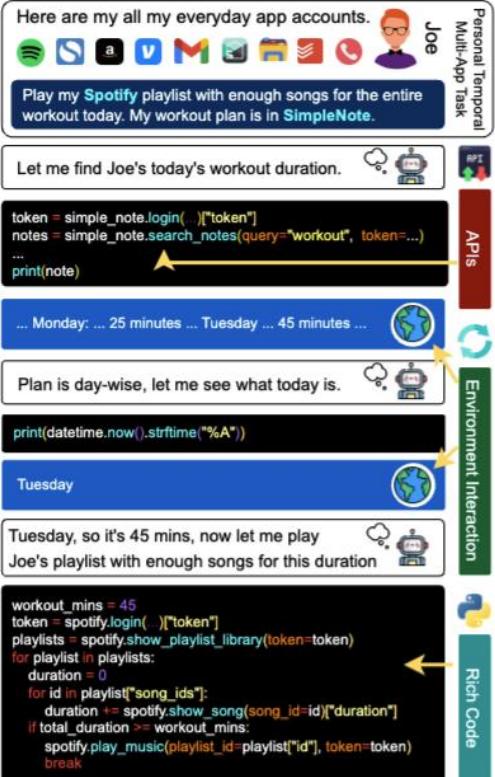
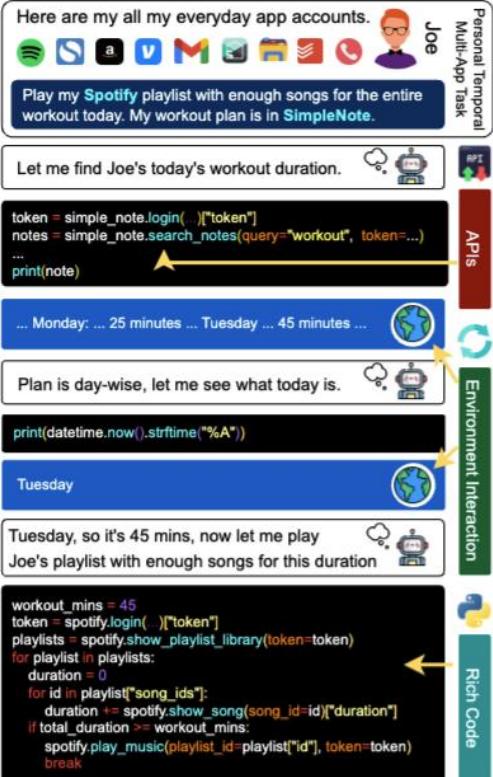


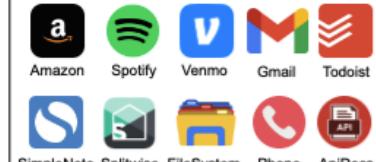
Figure 1: A (shortened) day-to-day task from AppWorld Benchmark requiring rich code with environment interaction and API calls.<sup>2</sup>



# AppWorld: A Controllable World of Apps and People for Benchmarking Interactive Coding Agents\*



## AppWorld Engine



## AppWorld Benchmark

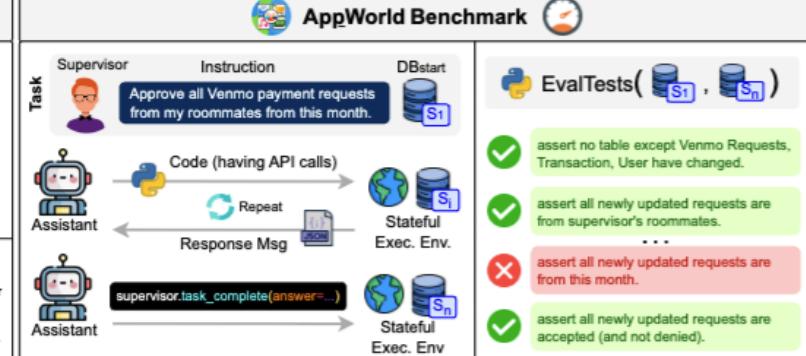
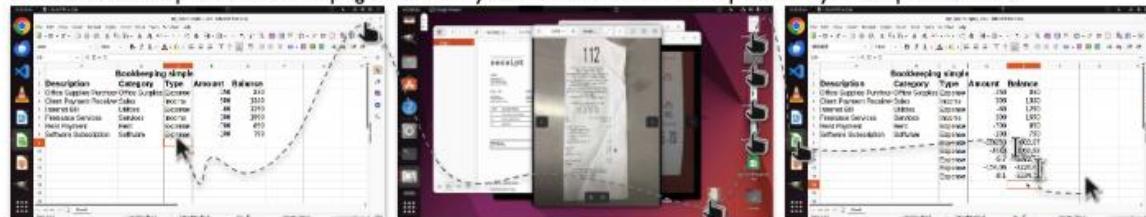


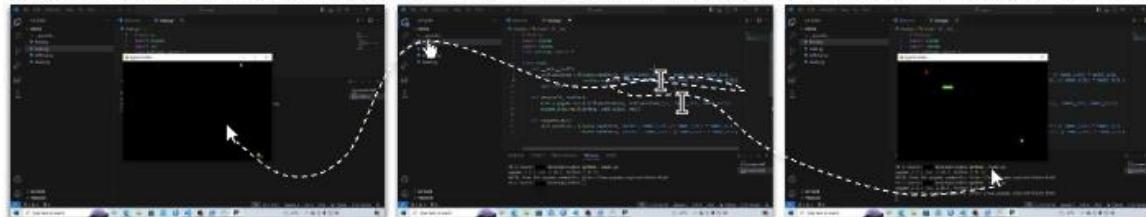
Figure 1: A (shortened) day-to-day task from AppWorld Benchmark requiring **rich code** with **environment interaction** and **API calls**.<sup>2</sup>

# OSWORLD: Benchmarking Multimodal Agents for Open-Ended Tasks in Real Computer Environments

Task instruction 1: Update the bookkeeping sheet with my recent transactions over the past few days in the provided folder.

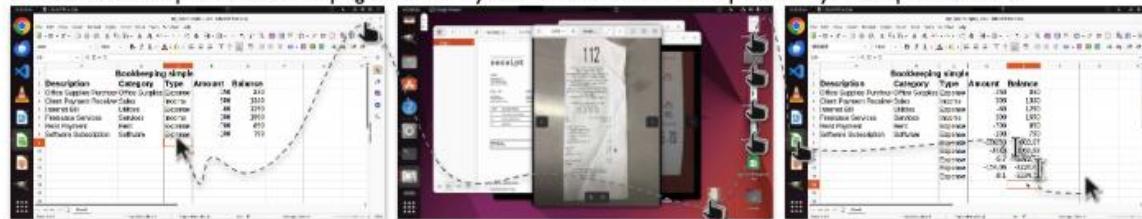


Task instruction 2: ...some details about snake game omitted... Could you help me tweak the code so the snake can actually eat the food?



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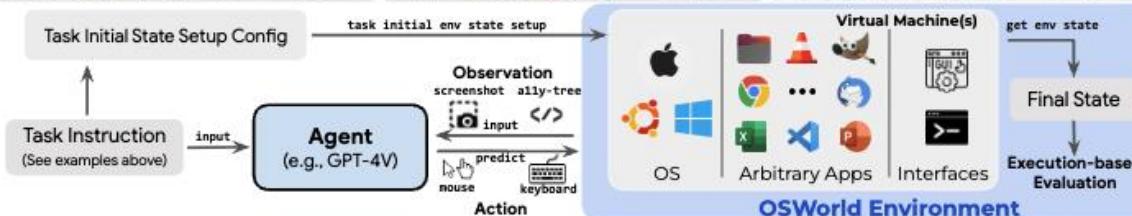
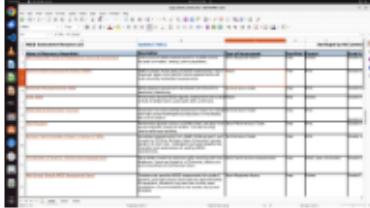
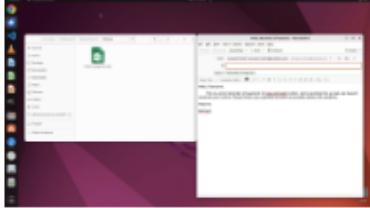
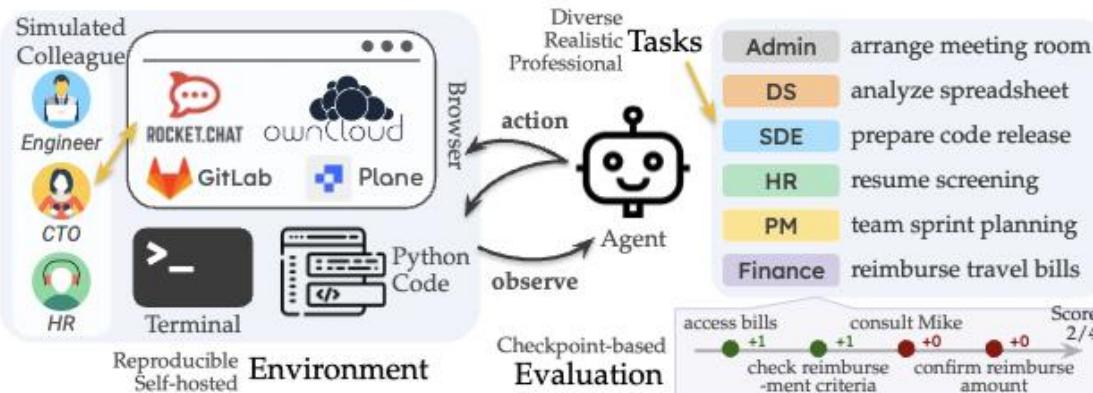


Table 1: Examples of annotated evaluation scripts, which involve retrieving data from configuration files, environment, and cloud, and executing functions to obtain results and assess correctness.

Initial State	Task Instruction	Evaluation Script (Simplified)
	<p><i>Can you help me clean up my computer by getting rid of all the cookies that Amazon might have saved?</i></p>	<pre>cookie_data = get_cookie_data(env) rule = {"type": "domains", "domains": [".amazon.com"]} is_cookie_deleted(cookie_data, rule)</pre>
	<p><i>Rename “Sheet 1” to “LARS Resources”. Then make a copy of it. Place the copy before “Sheet 2” and rename it by appending a suffix “(Backup)”, ...</i></p>	<pre>result = get_file(env) expected = get_file(cloud) rules = [{"type": "sheet_name"}, {"type": "sheet_data", "sheet_idx0": 0, "sheet_idx1": 1}...] compare_table(result, expected, rules)</pre>
	<p><i>I've drafted an e-mail reminder for those who haven't paid tuition. Please help me to check out their emails from the payment record and add to the receiver field.</i></p>	<pre>tree = get_a11y_tree(env) rules = [{"selectors": ["tool-bar[attr id=MsgHeadersToolbar] label[name=To] [attr class=\"address-pill\"]&gt; label[attr class=\"pill-label\"] [name*=\"fox@someuniversity.edu\"]"}] check_a11y_tree(tree, rules)</pre>

# TheAgentCompany: Benchmarking LLM Agents on Consequential Real World Tasks

- Task oriented benchmark



# Unified benchmarking framework

- AgentBench
- HAL: Holistic Agent Leaderboard

# AgentBench - tasks

## Real-world Challenges

(On an Ubuntu bash terminal)  
Recursively set all files in the directory to read-only, except those of mine.

(Given Firebase APIs)  
What musical instruments do Minnesota-born Nobel Prize winners play?

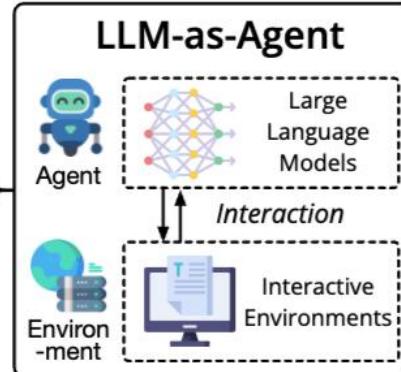
(Given MySQL APIs and existed tables)  
Grade students over 60 as PASS in the table.

(On the GUI of Aquawar)  
This is a two-player battle game, you are a player with four pet fish cards .....

A man walked into a restaurant, ordered a bowl of turtle soup, and after finishing it, he committed suicide. Why did he do that?

(In the middle of a kitchen in a simulator)  
Please put a pan on the dinning table.

(On the official website of an airline)  
Book the cheapest flight from Beijing to Los Angeles in the last week of July.



## 8 Distinct Environments



# Environments

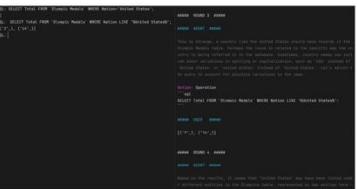


(a) Operating System (OS)

Task : "Find the total number of non-empty directories inside the '/etc' directory."

Action Space: Any valid bash commands

Observation: System standard output

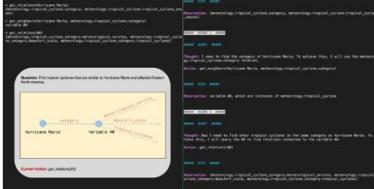


(b) Database (DB)

Task : "What was the total number of medals won by United States?", given the table 'Olympic Medals'

Action space: Any valid SQL commands

Observation: MySQL CLI interface output



(c) Knowledge Graph (KG)

Task : "Find tropical cyclones that are similar to Hurricane Marie and affected Eastern North America."

Action space: Basic KG-querying tools

Observation: Query results

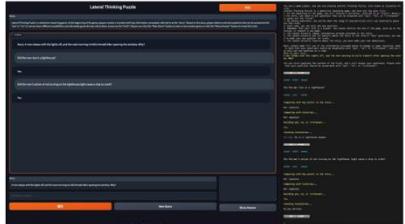


(d) Digital Card Game (DCG)

Task : "Compete against another player using four 'fish' cards in 'Aquawar' game."

Action space: Four 'fish' cards and Assertion

Observation: Battle process, status of 'fish'

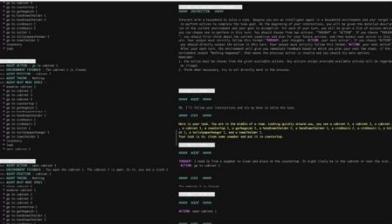


(e) Lateral Thinking Puzzles (LTP)

Task : "A man sleeps with the lights off, and the next morning he suicides after opening windows. Why?"

Action Space: Any binary questions

Observation: 'Yes', 'No', or 'Irrelevant'

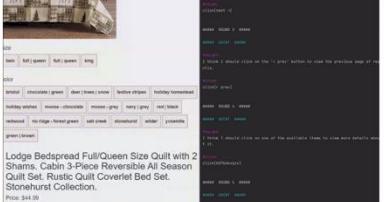


(f) House-holding (HH)

Task : "Clean some soapbar and put it in coutertop"

Action space: A list of allowed actions in the room, or other accessible rooms

Observation: Results after the action.

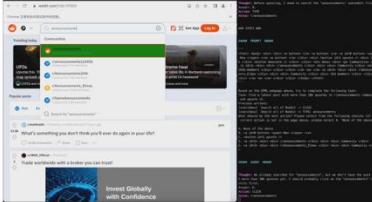


(g) Web Shopping (WS)

Task : "Looking for a queen size bedspread set in the color redwood, and price lower than 70."

Action space: Search (generate keywords) and Click (choose from all clickable buttons)

Observation: Products' descriptions; the webpage



(h) Web Browsing (WB)

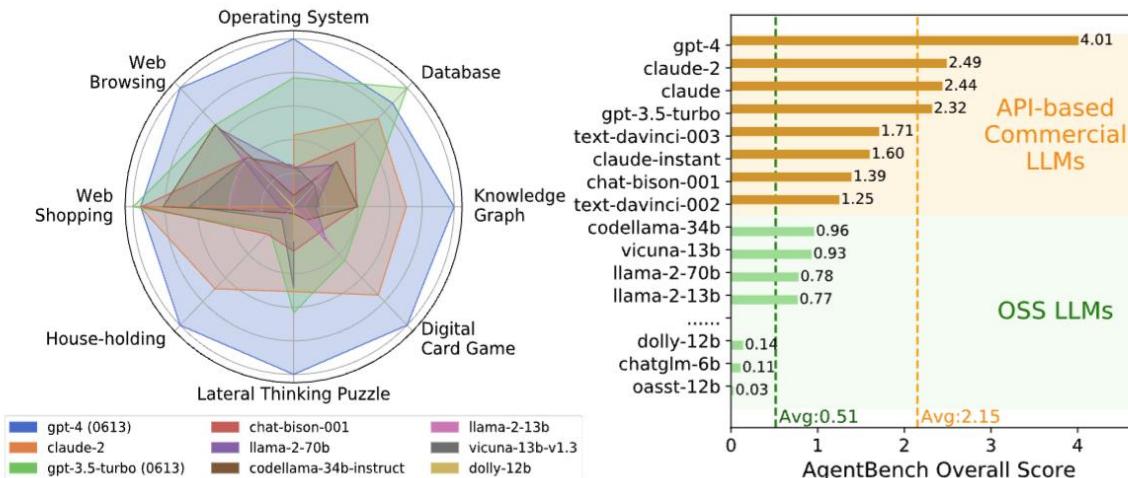
Task : "Find a latest post with more than 10k upvotes in r/announcements community and upvote it."

Action space: 1) Choose one out of all HTML elements in the webpage; 2) Click, Type, or Select Options

Observation: Page HTML (optional: screenshot)

# AgentBench - Results

## AGENTBENCH: EVALUATING LLMs AS AGENTS



(a) Typical LLMs' AgentBench performance  
(Relative) against the best in each environment

(b) Overall scores of AgentBench across 8 environments. Dashed lines for two LLM types' average.

# HAL: Holistic Agent Leaderboard

## HAL: Holistic Agent Leaderboard

The standardized, cost-aware, and third-party leaderboard for evaluating agents.

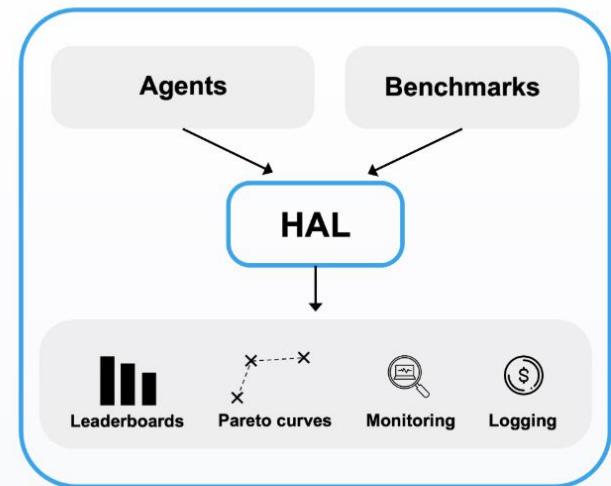
By the SAgE team at Princeton University

171  
Agents

8  
Benchmarks

[View Leaderboards ↓](#)

[GitHub](#)



# Performance Highlights

Top performing agents across different benchmarks

CORE-Bench Hard		Scientific Programming
Top 3 performing agents		
CORE-Agent	51.1%	
Claude Opus 4.1 (August 2025)	\$412.42	
CORE-Agent	42.2%	
Claude Opus 4.1 High (August 2025)	\$509.95	
CORE-Agent	35.6%	
Claude-3.7 Sonnet (February 2025)	\$73.04	
<a href="#">View Full Leaderboard &gt;</a>		

AssistantBench		Web Assistance
Top 3 performing agents		
Browser-Use	46.8%	
o3 Medium (April 2025)	\$60.24	
Browser-Use	38.8%	
o3 Medium (April 2025)	\$75.77	
HAL Generalist Agent	37.5%	
DeepSeek V3	\$3.98	
<a href="#">View Full Leaderboard &gt;</a>		

Scicode		Scientific Programming
Top 3 performing agents		
Scicode Tool Calling Agent	9.2%	
o3 Medium (April 2025)	\$555.57	
Scicode Zero Shot Agent	9.2%	
o4-mini Low (April 2025)	\$1.74	
Scicode Tool Calling Agent	7.7%	
Claude Opus 4.1 (August 2025)	\$507.73	
<a href="#">View Full Leaderboard &gt;</a>		

GAIA		Web Assistance
Top 3 performing agents		
HAL Generalist Agent	64.8%	
Claude Opus 4 (May 2025)	\$665.89	
HAL Generalist Agent	64.2%	
Claude-3.7 Sonnet High (February 2025)	\$122.49	

TAU-bench Airline		Customer Service
Top 3 performing agents		
TAU-bench Few Shot	66.0%	
Claude Opus 4 High (May 2025)	\$313.83	
TAU-bench Few Shot	62.0%	
Claude Opus 4.1 High (August 2025)	\$298.58	

Online Mind2Web		Web Assistance
Top 3 performing agents		
Browser-Use	39.3%	
Claude-3.7 Sonnet High (February 2025)	\$1151.88	
SeeAct	39.0%	
o3 Medium (April 2025)	\$1293.69	

# Interesting analysis

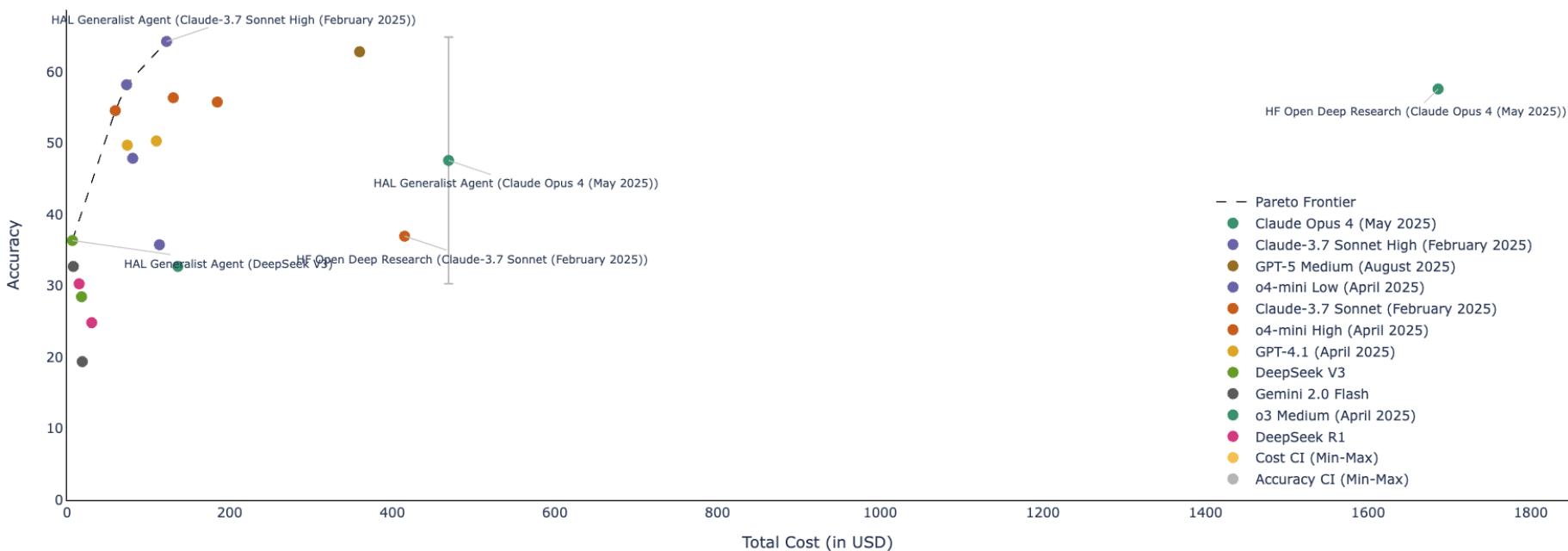
## GAIA Leaderboard

RANK	AGENT	PRIMARY MODEL ⓘ	VERIFIED ⓘ	ACCURACY ⓘ	LEVEL 1 ⓘ	LEVEL 2 ⓘ	LEVEL 3 ⓘ	COST (USD) ⓘ
1	HAL Generalist Agent	Claude-3.7 Sonnet High (February 2025)	✓	64.24%	67.92%	63.95%	57.69%	\$122.49
2	HF Open Deep Research	GPT-5 Medium (August 2025)	✓	62.80%	73.58%	62.79%	38.46%	\$359.83
3	HAL Generalist Agent	o4-mini Low (April 2025)	✓	58.18%	71.70%	51.16%	53.85%	\$73.26
4	HF Open Deep Research	Claude Opus 4 (May 2025)	✓	57.58%	66.04%	56.98%	42.31%	\$1686.07
5	HAL Generalist Agent	Claude-3.7 Sonnet (February 2025)	✓	56.36%	62.26%	55.81%	46.15%	\$130.68
6	HF Open Deep Research	o4-mini High (April 2025)	✓	55.76%	69.81%	51.16%	42.31%	\$184.87
7	HAL Generalist Agent	o4-mini High (April 2025)	✓	54.55%	60.38%	53.49%	46.15%	\$59.39
8	HF Open Deep Research	GPT-4.1 (April 2025)	✓	50.30%	58.49%	50.00%	34.62%	\$109.88
9	HAL Generalist Agent	GPT-4.1 (April 2025)	✓	49.70%	52.83%	55.81%	23.08%	\$74.19
10	HF Open Deep Research	o4-mini Low (April 2025)	✓	47.88%	58.49%	47.67%	26.92%	\$80.80
11	HAL Generalist Agent	Claude Opus 4 (May 2025)	✓	47.57% (-17.27/+17.27)	52.83%	47.67%	36.54%	\$469.32 (-196.56/+19

# Performances vs. cost

## Accuracy vs. Cost Frontier for GAIA

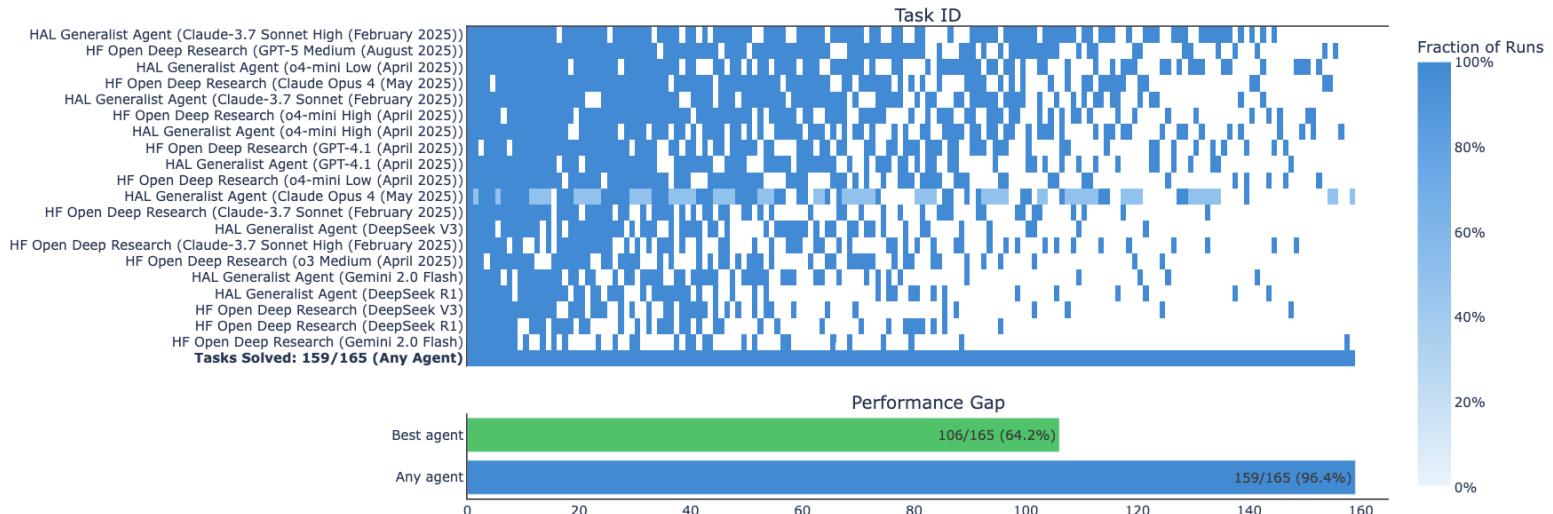
This plot shows the relationship between an agent's performance and its token cost. The Pareto frontier (dashed line) represents the current state-of-the-art trade-off. The error bars indicate min-max values across runs.



# Success per example

## Heatmap for GAIA

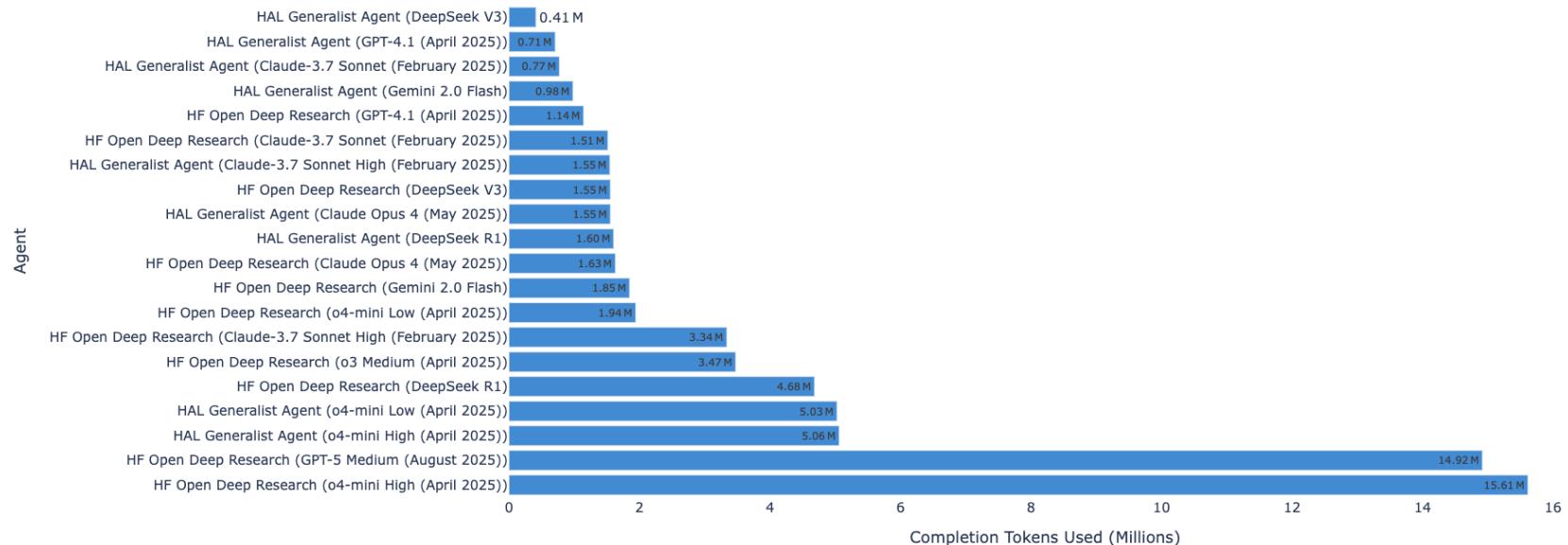
The heatmap visualizes success rates across tasks and agents. Colorscale shows the fraction of times a task was solved across reruns of the same agent. The "any agent" performance indicates the level of saturation of the benchmark and gives a sense of overall progress.



# Tokens Usage

## Total Completion Tokens Used per Agent

The bar chart shows the total completion tokens used by each agent, with the height of each bar representing the total number of completion tokens used across all tasks. Secondary models usually contribute a relatively small amount of tokens in comparison, and are used for RAG or image processing only.



# Future Challenges

1. Continue building challenging, high-quality, and large-scale benchmarks
2. Building frameworks that allow to evaluate the same agent across benchmarks and tasks



# Part 5: Frameworks

# Frameworks for LLM-Based Agent Evaluation



# What Extra Value Do These Frameworks Bring?

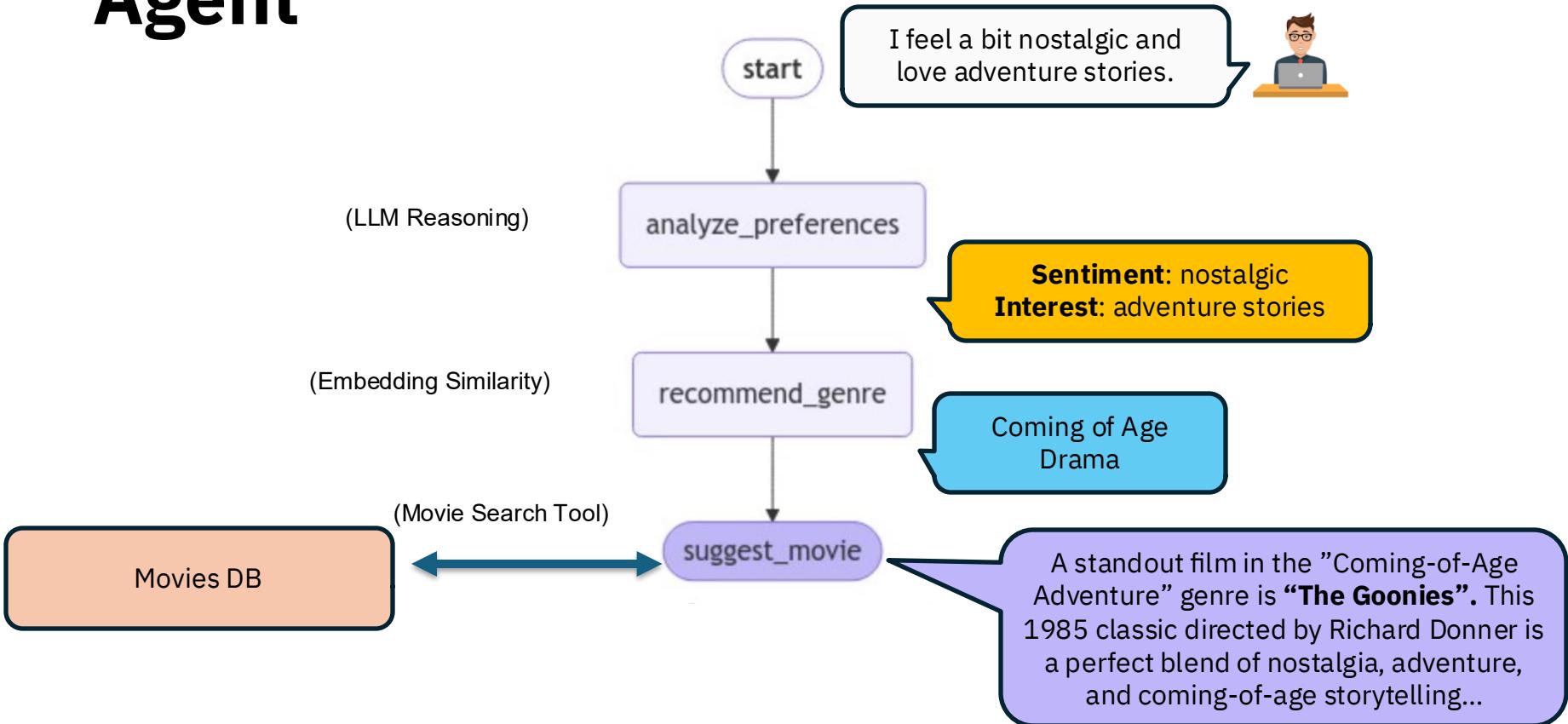
## Benchmarks:

- Compare fully developed systems on predefined sets of tasks and datasets

## Frameworks:

- Continuous monitoring and error analysis across both **development and deployment**
- Allow developers to design and evaluate their own scenarios
- Supporting a wide range of development use cases
- Focus on fast feature rollout and experimentation, driving **rapid progress with less research backing**

# Meet CineMood: Movie Recommender Agent



# Three Layers of Agent Stack

## Execution / Orchestration Layer:

Examples: LangGraph, CrewAI

Run the agent logic

control flow, state, parallelism, retries, inter-agent messaging

## Evaluation / Observability Layer

Examples: LangSmith, LangFuse, Arize Phoenix, Vertex AI Eval, Galileo

Consume execution traces:

measure quality performance robustness replay scoring metrics dashboards

## Deployment/inference layer

Examples: Google Vertex AI, Azure AI Studio

Scales to production, may reuse eval tools for monitoring

# Dimensions of Agent Evaluation Frameworks:

1. How to capture, log, and control agent behavior?

**Capturing:** Instrumentation & Observability

2. How to measure the agent's outputs, process, and efficiency?

**Interpreting:** Quality & Performance Assessment

3. How to ensure the evaluation itself is valid and aligned with human values?

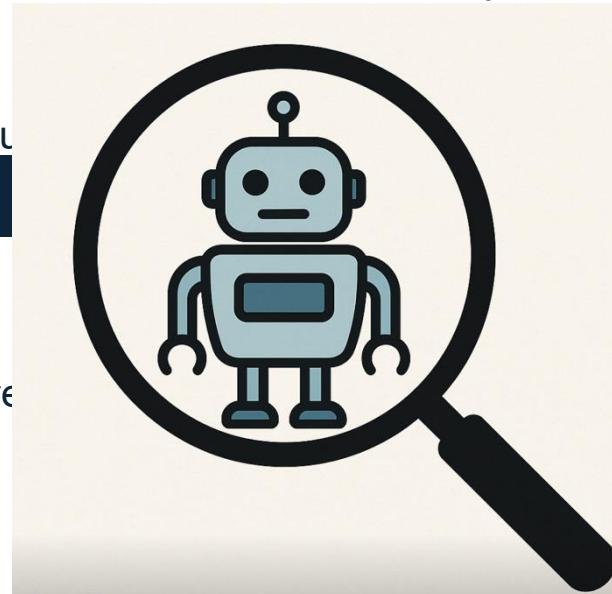
**Trusting:** Evaluator Reliability

# Dimensions of Agent Evaluation Frameworks

1. How to capture, log, and control agent behavior?

**Capturing:** Instrumentation & Observability

2. How to measure performance and efficiency?



3. How to ensure the agent is aligned with human values?

# Capturing: Instrumentation & Observability

**Goal:** Record everything the agent does, from the full run down to fine-grained steps.

## Why it matters:

- Without capture → no reliable evaluation.
- Metrics in later stages are only as good as the signals you record.
- Ensures later analysis isn't anecdotal but reproducible at scale.

Trace  
Visualization &  
Graph Views

Cost & Efficiency  
metrics

Experiment &  
Version Tracking

Integration with  
Dev Platform

# Capturing: Tracing

## What to capture?

### Trace

A complete record of a single execution or run

### Span

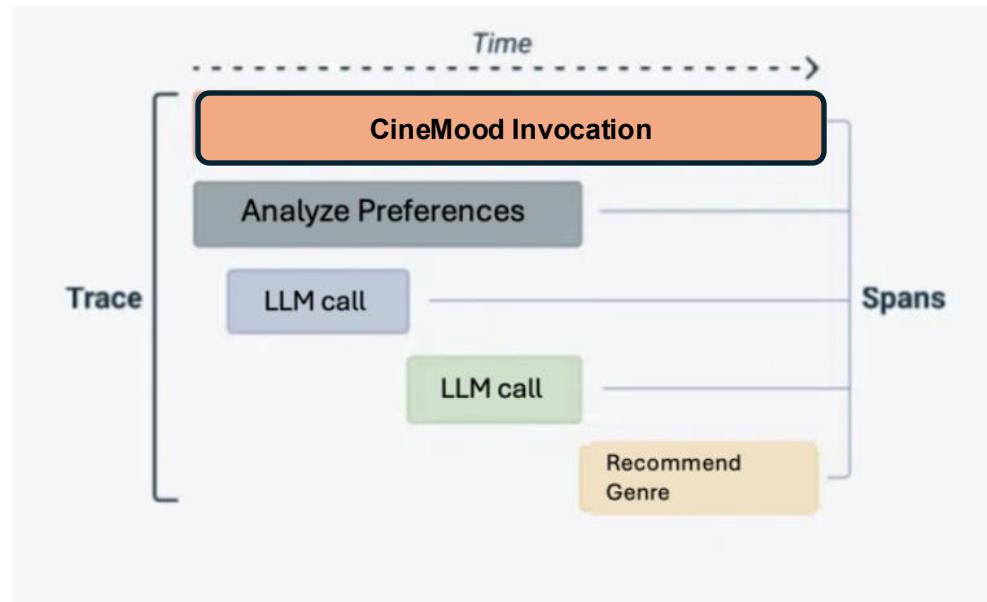
A span is a single operation within a trace

### Parent–Child Relationship

Spans can be nested: one span may call another, creating a hierarchy

### Metrics

Metadata recorded for spans or traces



# Capturing: Tracing the Agent

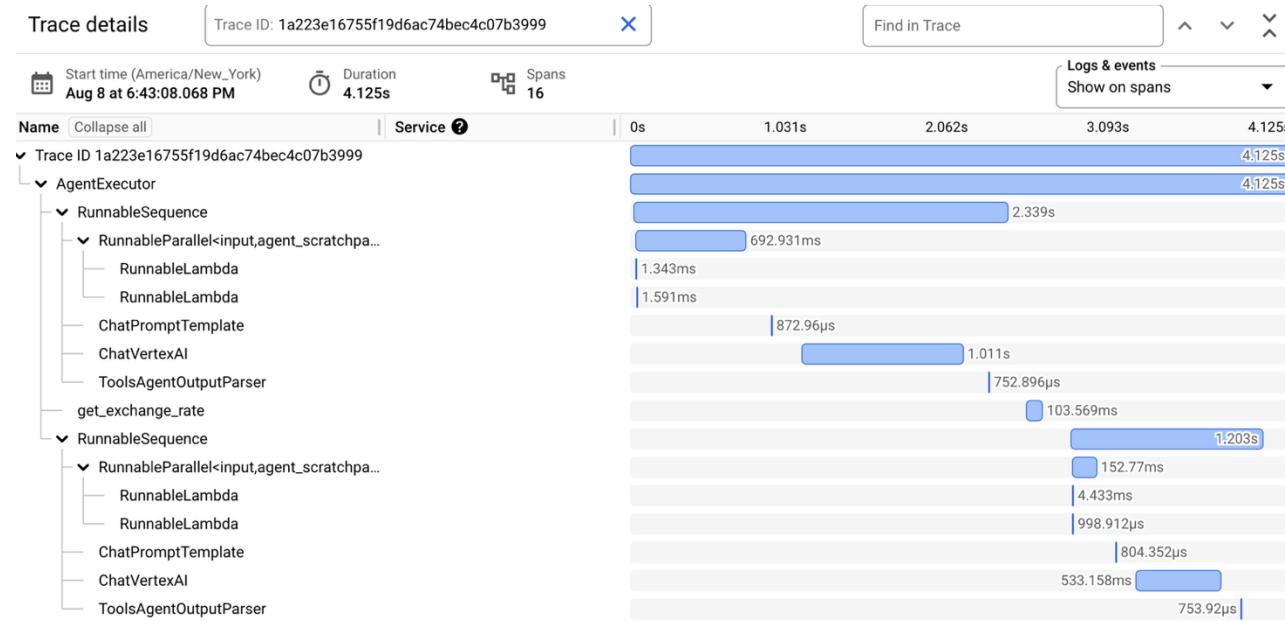
## How to capture?

- **SDK / Native Hooks**
  - LangChain pipeline auto-sends traces to LangSmith
- **OpenTelemetry (OTel) Instrumentation**
  - Standard API for structured traces & spans
  - Enables vendor-agnostic export of metrics/events
- **All-in-One Platforms**
  - Combine orchestration + evaluation, minimizing integration work
  - *Example:* In Vertex AI Studio, orchestration graph and eval dashboards live in one UI
  - Tracing by OTel is done internally, not by the user

# Capturing: Trace Visualization

## What does it look like?

- Captures every agent step: inputs, outputs, intermediate reasoning, tool invocations, timing.
- Can present as a visual, hierarchical graph

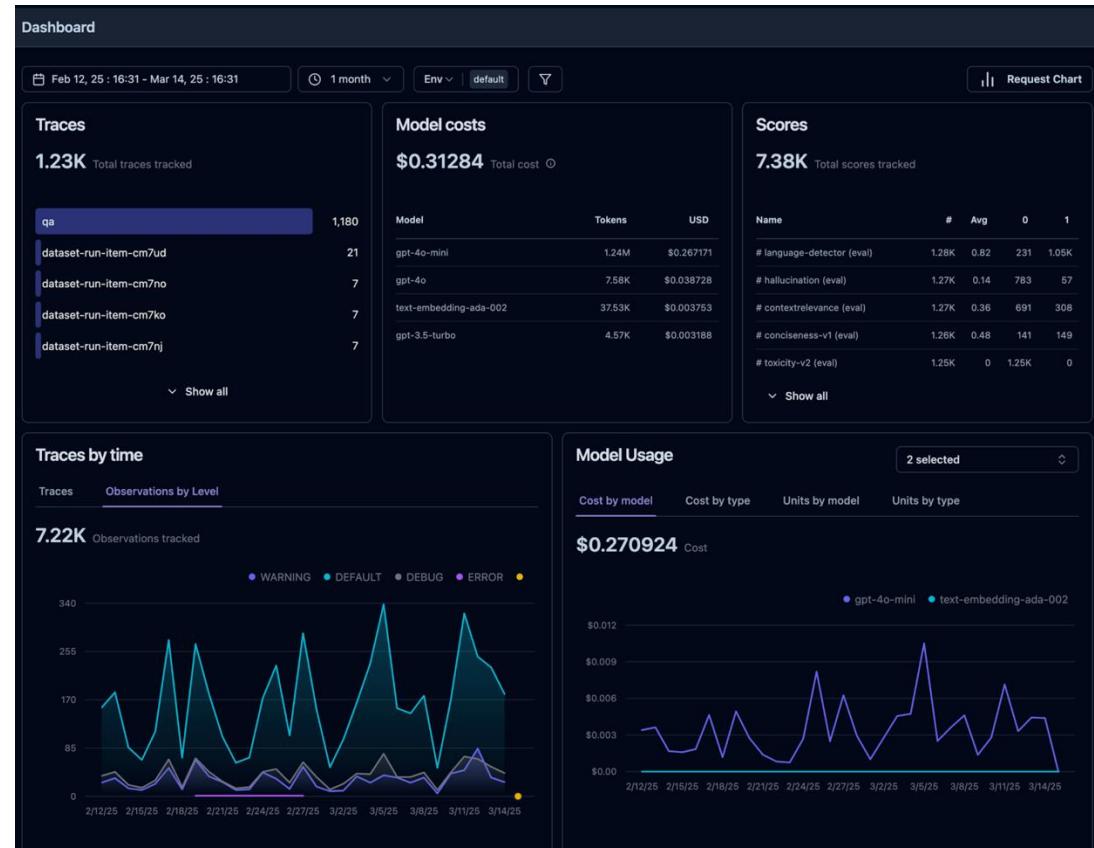


Vertex AI: Agent Trace

# Capturing Cost, Latency & Other Observables

**Raw signals** captured by frameworks:

- Token usage (input/output)
- Dollar cost
- Latency per step & end-to-end
- Number of steps / tool calls



**Why it matters:**

- Basis for efficiency metrics later
- Supports monitoring and budget control

LangFuse, aggregated model tokens/cost

# Capturing: Experiment Management

- A/B comparisons between agent versions:
  - Side-by-side analysis of inputs, outputs, and metrics from at least two test runs
  - Comparison of aggregated results across multiple runs from distinct experimental setups
  - Drill down into individual trajectories

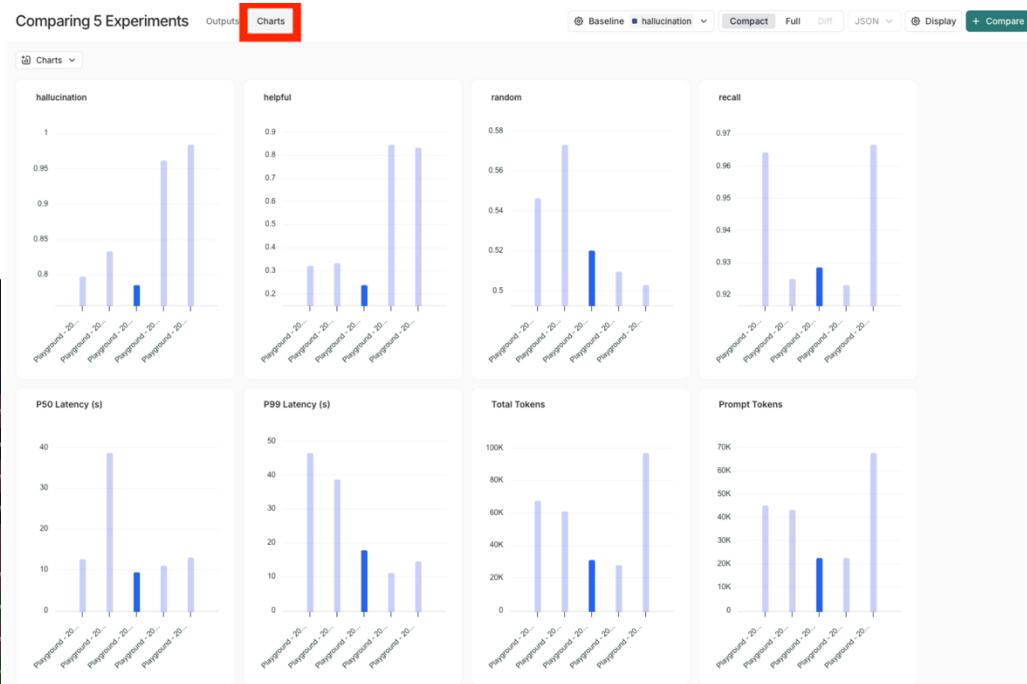
# Capturing: Experiment Management

LangChain > Datasets & Testing > pairwise-demo-interesting > Comparing 2 Experiments

## Viewing Pairwise Experiment

gpt-3.5-turbo-test vs. gpt-4-test-2e0c compared by RANKED\_PREFER...

Input	gpt-4-test	gpt-3.5-turbo-test
What are the potential h...	#1585 +	Prolonged exposure to screens can lead to several health risks: 1. Eye Strain: ...
How does the blockchain...	#1d84 +	Blockchain technology is a decentralized digital ledger that records transact...
What are the economic i...	#3e4c +	Implementing a Universal Basic Income (UBI) can have several economic impl...
How can artificial intelli...	#4d54 +	Artificial Intelligence (AI) can play a significant role in disaster response and ...
Can you discuss the imp...	#7e70 +	Certainly, the rise of cryptocurrencies has had a significant impact on traditi...
How can AI be used to i...	#8915 +	AI can be used to improve educational outcomes in several ways: 1. Personaliz...
Can you explain the sign...	#8c4b +	The Turing Test, proposed by British mathematician and computer scientist ...
How do machine learnin...	#aac6 +	Machine learning algorithms recognize patterns in data through a process cal...
What are the arguments ...	#ab87 +	Arguments For the Colonization of Mars: 1. Scientific Discovery: Mars coloniz...
What role does artificial...	#c02a +	Artificial Intelligence (AI) plays a significant role in modern healthcare in sev...
What strategies are mos...	#c335 +	Combating climate change on a global scale requires a multi-faceted approa...
What are the major challe...	#effc +	Challenges: 1. Data Collection: AI systems require large amounts of data to fu...



LangSmith - Experiments Comparison

# Capturing: Experiment Management

- A/B comparisons between agent versions:
  - Side-by-side analysis of inputs, outputs, and metrics from at least two test runs
  - Comparison of aggregated results across multiple runs from distinct experimental setups
  - Drill down into individual trajectories
- Replay of past run:
  - **re-run an agent's execution** — either exactly as it happened, or with controlled changes
- Robust filtering and search capabilities

# Capturing: Playground

## Trying it out

- Interactive environment to run prompts & agents end-to-end during
- Real-time view of step execution & outputs
- Quick iteration before committing changes

The screenshot shows the LangFuse Playground interface with three parallel windows, each representing an AI agent setup. The top navigation bar includes 'PROD-EU', 'langfuse-dev', 'Team', and 'docs-examples'. The main area is titled 'Playground'.

**Left Window (Agent 1):** Model: OpenAI (Jannik): gpt-4.1. It shows a conversation between 'System' (You are a helpful assistant) and 'User' (What is Langfuse?). Below the messages are 'Message' and 'Placeholder' buttons. The 'Output' section contains a detailed description of Langfuse's purpose and features, followed by a list of key features: 'Prompt & response tracing' and 'Automatically capture input prompts, model'. A 'Submit' button is at the bottom.

**Middle Window (Agent 2):** Model: OpenAI (Jannik): o4-mini. It shows the same conversation and message buttons. The 'Output' section is identical to the first window, describing Langfuse's role in monitoring LLMs.

**Right Window (Agent 3):** Model: OpenAI (Jannik): gpt-4o. It shows the same conversation and message buttons. The 'Output' section is identical to the others, describing Langfuse's role in monitoring LLMs.

# Dimensions of Agent Evaluation Frameworks:

1. How to capture, log, and control agent behavior?

Capturing, Instrumentation &  
Observability

2. How to measure the agent's outputs, process, and efficiency?

Interpreting: Quality & Performance  
Assessment



3. How to ensure the evaluation itself is valid and aligned with human values?

Trusting: Evaluator  
Reliability

# Dimensions of Agent Evaluation Frameworks:

**Goal:** Turn raw traces into meaningful insights about agent performance.

## Why it matters:

- Defines fine-grained success criteria beyond correctness.
- Pinpoints where and why failures occur in multi-step flows.
- Enables debugging, comparison, and iteration across experiments.

### Different Granularity Levels:

- Final Response
- Stepwise Level
- Trajectory Analysis

### Safety & Guardrails

### Reference less vs Reference based Evaluation

### Synthetic Data Generation

# Final Response Evaluation

I feel a bit nostalgic and  
love adventure stories.



Stand By Me

# Final Response Evaluation

I feel a bit nostalgic and love adventure stories.



## Reference Based Evaluation Metrics:

- Exact string match / Text overlap
- Semantic similarity
- LLM as Judge

Reference Output	Response
<b>The Goonies</b>	<b>Stand By Me</b>

# Final Response Evaluation

I feel a bit nostalgic and love adventure stories.



## Reference Based Evaluation Metrics:

- Exact string match / Text overlap
- Semantic similarity
- LLM as Judge

## Reference Less Evaluation Metrics:

- LLM-based judges (overall\predefined criteria)
- Single attribute classifiers (e.g. Safety)
- Task Completion (e.g. error cleared)

Reference Output	Response
The Goonies	Stand By Me

I feel a bit nostalgic and love adventure stories.

Stand By Me

# Final Response Evaluation

## Pros:

- Fastest & cheapest
- Easy to automate

## Cons:

- Assessing complex workflows
- Intermediate decision making
- Efficiency
- Root cause analysis of errors

Playground - 2025-02-04 03:56:04											Compact	Full	Diff	JSON	Heat Map	Columns	Compare
Input	Reference Output	Output	Hallucination	Helpful	Random	Latency	Status	Tokens	Compact	Full	Diff	JSON	Heat Map	Columns	Compare		
OCTOBER 2023, VOL... #4eb6 →	{"tone":"positive","topic":"Princeton U...}	ai: This email is a newsletter ... 1/3 < >	1.00	0.00 μ	0.50 μ	14.48s	SUCCESS	3	5,428								
Solve the RedWordle We kn... #6a7d →	{"tone":"positive","topic":"RedWordle ...}	ai: The email is an engaging,... 1/3 < >	1.00 μ	0.00 μ	0.50 μ	14.47s	SUCCESS	3	339.333								
**Would you like to add spe... #72fb →	{"tone":"positive","topic":"Personalize...}	ai: This email is a promotion... 1/3 < >	1.00 μ	0.00 μ	0.50 μ	14.47s	SUCCESS	3	377.667								
--- --- --- Book with Fail... #8602 →	{"tone":"positive","topic":"Fall Cruise ...}	ai: This email is a promotion... 1/3 < >	1.00 μ	0.00 μ	0.50 μ	14.47s	SUCCESS	3	2,251.667								
---   Costco --- ANSWER & ... #c4fa →	{"tone":"positive","topic":"Invitation to...}	ai: This email appears to be ... 1/3 < >	1.00 μ	0.33 μ	0.50 μ	12.98s	SUCCESS	3	578.333								
USA Finance Solution offers ... #f1a8 →	{"tone":"positive","topic":"Business Fu...}	ai: This email is a marketing ... 1/3 < >	1.00 μ	0.33 μ	0.50 μ	12.97s	SUCCESS	3	396								
---   Adventure alongside ... #a7a2 →	{"tone":"positive","topic":"Pokemon G...}	ai: This email is a promotion... 1/3 < >	1.00 μ	0.67 μ	0.50 μ	12.98s	SUCCESS	3	779.667								
--- --- ---   # We Prov... #b19a →	{"tone":"positive","topic":"Financing o...}	ai: This email appears to be ... 1/3 < >	1.00 μ	0.67 μ	0.50 μ	12.98s	SUCCESS	3	973.333								
Hello Jacob, Do you know ... #c524 →	{"tone":"positive","topic":"Business Fi...}	ai: This email is a promotion... 1/3 < >	1.00 μ	0.67 μ	0.50 μ	12.98s	SUCCESS	3	802.667								
Hi Jacob, We are working to... #e419 →	{"tone":"positive","topic":"Feedback r...}	ai: This email is a profession... 1/3 < >	0.67 μ	0.67 μ	0.50 μ	12.97s	SUCCESS	3	176								
Happy Halloween, Jacob! Y... #e825 →	{"tone":"positive","topic":"Halloween ...}	ai: This email is a festive, en... 1/3 < >	1.00 μ	0.67 μ	0.50 μ	12.97s	SUCCESS	3	776								
Consider all ways to give to... #38d4 →	{"tone":"positive","topic":"Donation an...}	ai: The email is a heartfelt ap... 1/3 < >	1.00 μ	1.00 μ	0.50 μ	14.48s	SUCCESS	3	437.333								
Some travelers plan ahead;... #486d →	{"tone":"positive","topic":"Travel and ...}	ai: This email is a promotion... 1/3 < >	1.00 μ	1.00 μ	0.52 μ	14.48s	SUCCESS	3	384.333								
Hello Jacob, For many small... #55cf →	{"tone":"positive","topic":"Business fi...}	ai: This email is a marketing ... 1/3 < >	1.00 μ	1.00 μ	0.50 μ	14.48s	SUCCESS	3	585.667								
#### Where sustainability ... #8412 →	{"tone":"positive","topic":"Promotion ...}	ai: This email is a promotion... 1/3 < >	1.00 μ	1.00 μ	0.50 μ	14.47s	SUCCESS	3	308								

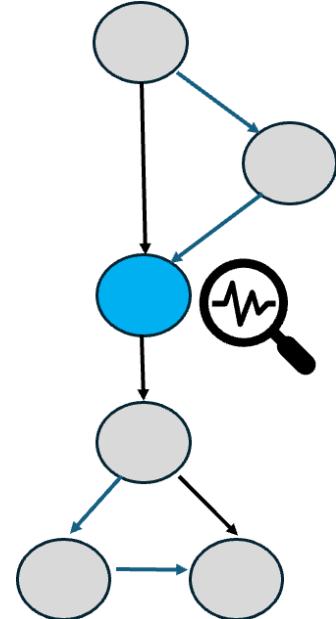
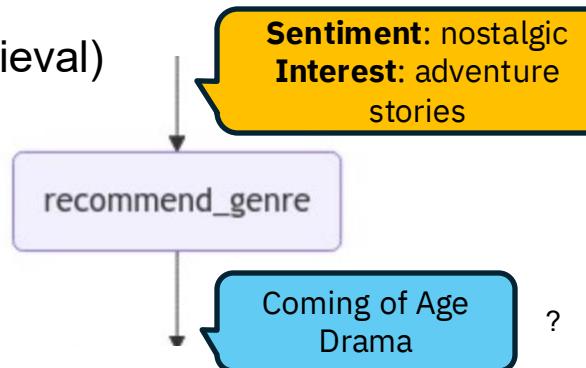
From LangSmith playground

# Stepwise Evaluation

**Goal:** pinpoint where and why an agent goes off-track.

**Single steps can be:**

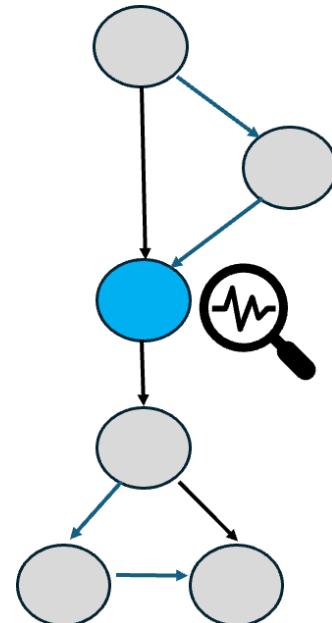
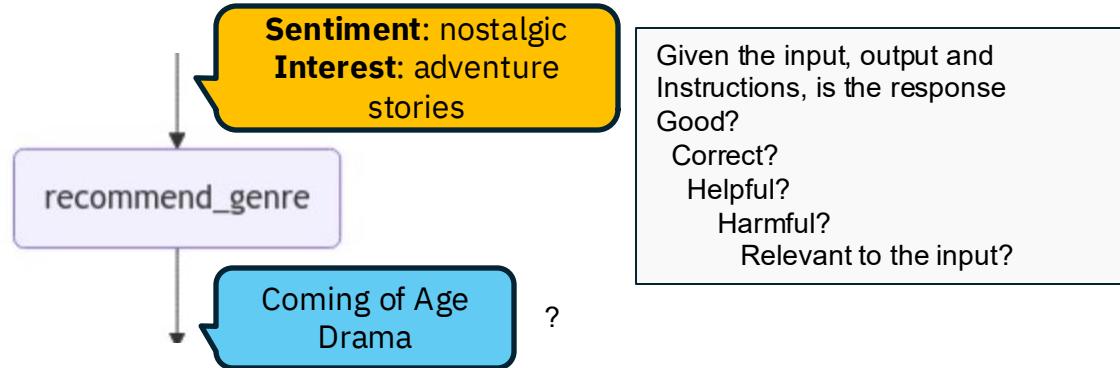
- Textual output of LLM calls
- Single nodes outputs in graph-based agent frameworks
- Tool Call invocation
- Route decision
- Specific skill (e.g. retrieval)



# Stepwise Evaluation

Predefined judges for step outputs:

- Evaluate each step with a canned prompt
- Specific attributes (E.g. correctness / helpfulness)
- Proprietary judge catalog or custom judges



# Stepwise Evaluation: Judge Catalog

\_collections

OWASP Retrieval Systems NLP Metrics Harmful Outputs Chatbot Behavior Output Format Data Leakage Output Validation

Search  Managed By Show All Select Evaluator Family

**Need Something Different?**

Our Judge Evaluator can assess the specific requirements that matter to you.

+ Define your own Criteria

**lynx** LLM Based

**hallucination**

Retrieval Systems

Detects hallucinations in your RAG system with the use of Patronus Lynx models. A hallucination happens when your model's answer is not faithful to or grounded ...

Playground View details

**Answer Relevance** LLM Based Spans

**answer-relevance**

Retrieval Systems

Detects whether the model output is relevant to the user input. Use this profile to pinpoint issues with your model straying off topic and producing unrelated r...

Playground View details

**Context Relevance** LLM Based Spans

**context-relevance**

Retrieval Systems

Detects whether the retrieved context from your RAG system is relevant to answering the user input. An irrelevant context means your RAG system is producing inf...

Playground View details

**Context Sufficiency** LLM Based Spans

**context-sufficiency**

Retrieval Systems

Detects whether the retrieved context from your RAG system is sufficient to answer the user input and generate the gold answer. An insufficient context means th...

Playground View details

**Hallucination** LLM Based Spans

**hallucination**

Retrieval Systems

Detects hallucinations in your RAG system. A hallucination happens when your model's output is not faithful to or grounded in the context retrieved from your RA...

Playground View details

**Judge** LLM Based Spans

**answer-refusal**

OWASP

Checks that the model output refuses to answer the user input. Useful to check whether your model output is correctly handling prompt injections and off topic u...

Playground View details

**Judge** LLM Based Spans

**fuzzy-match**

Output Validation

Check that your model output is semantically similar to the provided gold answer. This is better than an exact match check when you expect the model output to v...

Playground View details

**Judge** LLM Based Spans

**is-code**

Output Format

Check that your model output is valid code. Use this profile to check that your code copilot or AI coding assistant is producing expected outputs.

Playground View details

Patronus AI

# Stepwise Evaluation

## Predefined judges for step outputs:

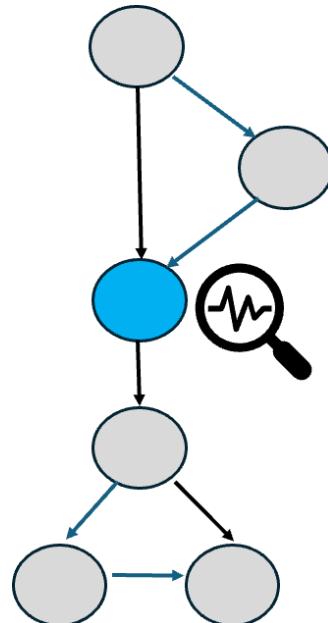
- Evaluate each step with a canned prompt
- Specific attributes (E.g. correctness / helpfulness)
- Proprietary judge catalog or custom judges

## Tool selection checks:

- Compare chosen tool vs. expected
- Verify parameters and schema
- LLM judge for tool use

Does the selected tool exist?  
Does it have the correct params?  
Are the params of the correct types?

- Is this the correct tool to call at this point?



# Stepwise Evaluation

**Predefined judges for step outputs:**

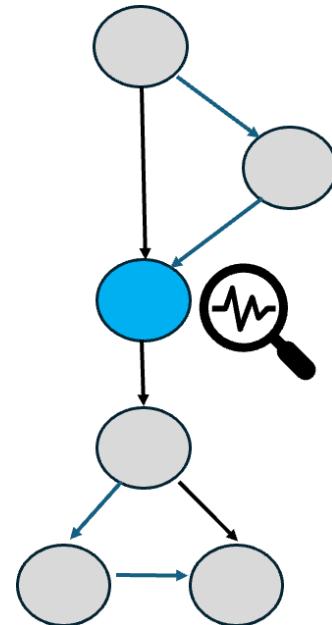
- Evaluate each step with a canned prompt
- Specific attributes (E.g. correctness / helpfulness)
- Proprietary judge catalog or custom judges

**Tool selection checks:**

- Compare chosen tool vs. expected
- Verify parameters and schema
- LLM judge for tool use

**Action-advancement metric (Vertex AI):**

- Did this step reduce distance to goal?
- General step evaluation by an LLM judge



# Stepwise Evaluation

## Agent-specific evaluation templates (Phoenix):

Modular evaluation templates for key agent stages:

- Route Decision
- Skill (code, retrieval...)
- Tool call invocation
- Planning
- Reflection

combining LLM evaluation strategies with step-specific diagnostics

```
TOOL_CALLING_PROMPT_TEMPLATE = """  
You are an evaluation assistant evaluating questions and tool calls to determine whether the tool called would answer the question. The tool calls have been generated by a separate agent, and chosen from the list of tools provided below. It is your job to decide whether that agent chose the right tool to call.
```

```
[BEGIN DATA]  
*****  
[Question]: {question}  
*****  
[Tool Called]: {tool_call}  
[END DATA]
```

Your response must be single word, either "correct" or "incorrect", and should not contain any text or characters aside from that word. "incorrect" means that the chosen tool would not answer the question, the tool includes information that is not presented in the question, or that the tool signature includes parameter values that don't match the formats specified in the tool signatures below.

"correct" means the correct tool call was chosen, the correct parameters were extracted from the question, the tool call generated is runnable and correct, and that no outside information not present in the question was used in the generated question.

```
[Tool Definitions]: {tool_definitions}  
"""
```

# Stepwise Evaluation: Multi Run Stepwise Insights

Gaining large scale insights remains a challenge.

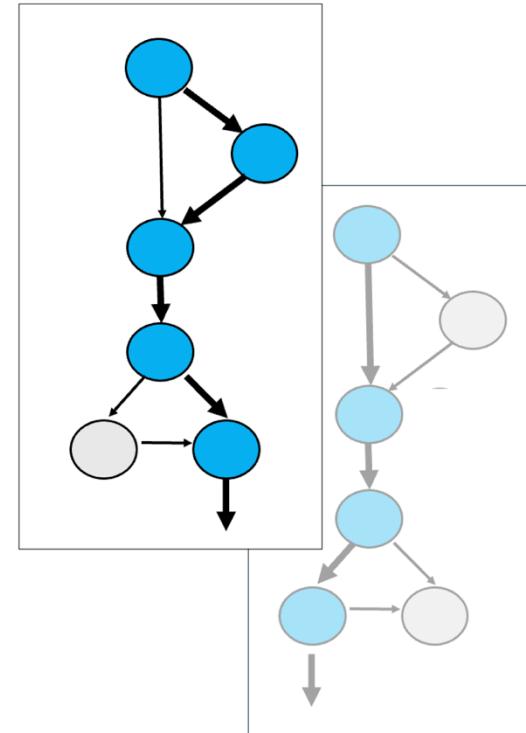
- Aggregate metrics per step → “Step 1 (Sentiment Extraction) fails in 37% of runs”
- Spot critical bottlenecks → “When step 1 fails, the final answer is usually wrong”
- Compare conditions & models → “Step 1 fails more with model A compared to model B”
- Finding failure clusters (Phoenix):  
Embed and cluster inputs or responses → “Errors cluster when sentiment is positive”
- Diagnose root causes at scale (initial) → “Sarcasm misinterpreted as positive sentiment”

# Trajectory Evaluation

Trajectory-level analysis scores an agent's entire sequence of actions, assessing process quality, efficiency, and safety across the full run, not just the final answer.

## Motivation

- See the whole process, not just step or final answer.
- Detect systematic reasoning issues (loops, inefficiency, missed subtasks).
- Evaluate agent quality in real-world multi-step tasks.
- Measure efficiency and safety across the entire run.



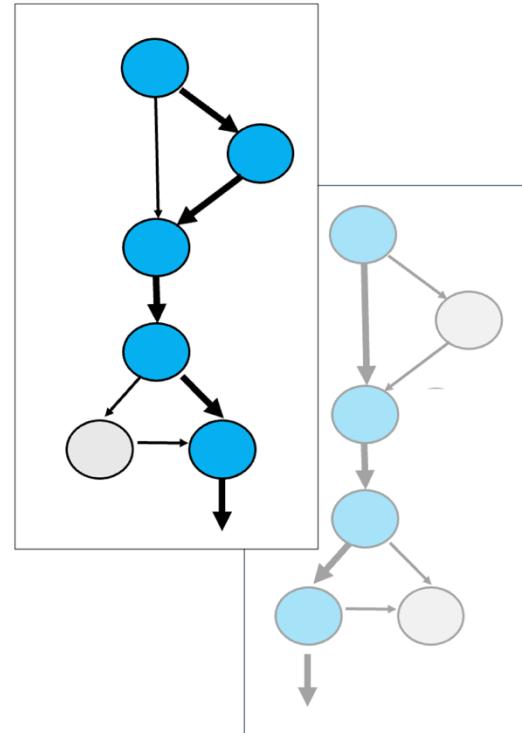
# Trajectory Evaluation

**Reference based evaluation:**

Trajectory steps matching vs. gold

Example: in VertexAI:

- Compare actual trajectory to gold standard sequence of tools calls
- Exact Match / In-order Match / Partial Match
- Precision / Recall of calls
- More common in task-specific benchmarks



# Trajectory Evaluation

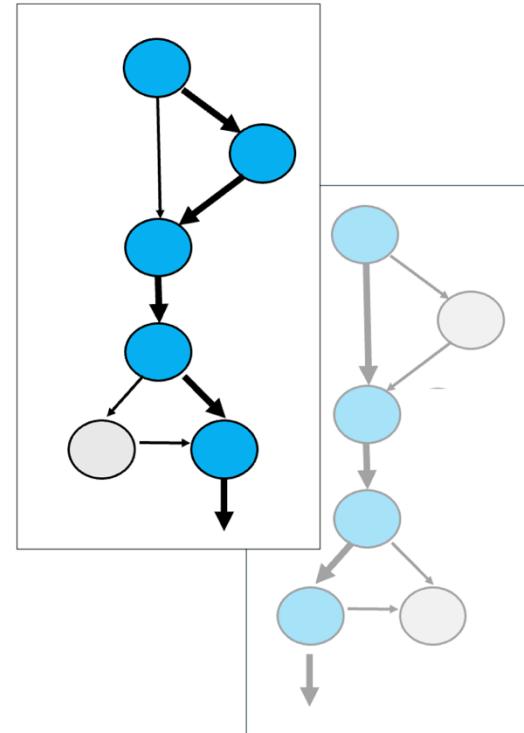
Reference based evaluation:

Summary Metrics								
	row_count	trajectory_precision/mean	trajectory_precision/std	coherence/mean	coherence/std	latency_in_seconds/mean	latency_in_seconds/std	failure
0	5	0.8	0.447214	NaN	NaN	2.168438	0.456489	
Row-wise Metrics								
	prompt	reference_trajectory	response	latency_in_seconds	failure	predicted_trajectory	trajectory_precision/score	
0	Turn off device_10 in the Bedroom.	[{'tool_name': 'set_device_info', 'tool_input':...}	Device device_10 not found. \n	2.006929	0	[{'tool_name': 'set_device_info', 'tool_input':...}	0.0	
1	Can you schedule device_1 to turn off at 22:00?	[{'tool_name': 'set_device_schedule', 'tool_in...}	Device device_1 scheduled to turn OFF at 22:00...	2.223489	0	[{'tool_name': 'set_device_schedule', 'tool_in...}	1.0	
2	Check if device_3 is off. If not, turn it off.	[{'tool_name': 'get_device_info', 'tool_input':...}	The device is already off. \n	1.765371	0	[{'tool_name': 'get_device_info', 'tool_input':...}	1.0	
3	If the temperature in the Kitchen is below 22°...	[{'tool_name': 'get_temperature', 'tool_input':...}	The temperature in the Kitchen is above 22°C, ...	1.917166	0	[{'tool_name': 'get_temperature', 'tool_input':...}	1.0	
4	Based on user_y's preferences, set the tempera...	[{'tool_name': 'get_user_preferences', 'tool_i...}	Temperature in Living Room set to 23°C. \n	2.929235	0	[{'tool_name': 'get_user_preferences', 'tool_i...}	1.0	

# Trajectory Evaluation

## Reference less evaluation:

- LLM-as-Judge on full trace: holistic reasoning & process quality.
- Aggregate step metrics:  
avg correctness, failure rate, safety score, action-advancement.
- Heuristic scores:
  - Efficiency: Step count, total latency, total token/cost.
  - Process Quality: Constraint adherence, coverage of goals, Loop detection
  - Diversity & Exploration:
    - Source diversity
    - Exploration ratio — fraction of unique tools/doc sources used vs. total steps.



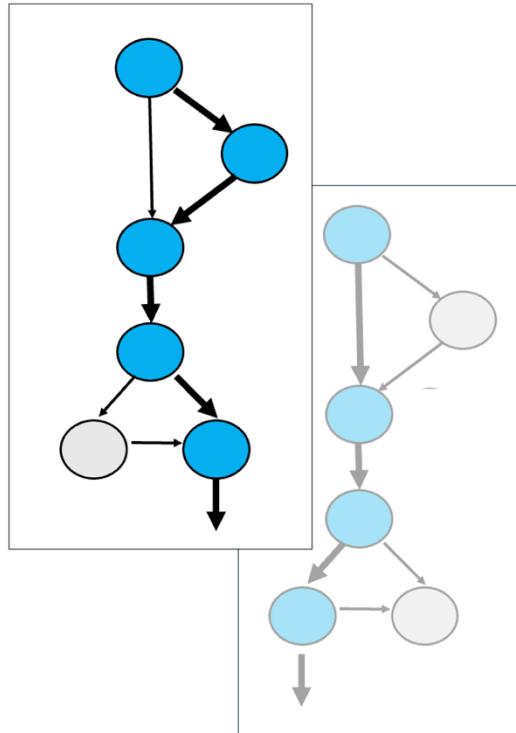
# Trajectory Evaluation – Main Gaps

Reference based:

- Reliance on reference sequences is limiting
- Non-deterministic nature of agentic workflows
- Existence of multiple valid solutions

Reference less:

- Still no capture of full trajectory dynamics
- Limited ability of LLM as judge
- Heuristics/single steps aggregations are limited
- Hard to evaluate interactions between different components



# Safety & Guardrails

Prevent harmful, unsafe, or undesired agent behavior.

**For example:** Prevent CineMood from suggesting horror movies to children.

## Safety Metrics:

- **Content Filters:** Built in or custom classifiers
- Real-time rejection or sanitization before response delivery

## Agent Guardrails in Practice

- **Policy Enforcement:** Define “must not” and “must always” rules for content and actions
- **Multi-Stage Checks:** Early exit, block, or reroute when risk is detected

# Synthetic Data Generation

Create evaluation datasets without relying entirely on costly, slow human annotation

## Common uses:

- **Bootstrapping test suites** for early-stage evaluation.
- **Generating adversarial cases** to stress-test systems.
- **Expanding coverage** for rare or edge-case scenarios

## Limitations:

- **Often restricted to RAG-like tasks:** less mature for complex agent flows.
- **Still dependent on human annotation or feedback** for validation.
- **Coverage gaps:** difficult to fully represent real-world diversity.

# Synthetic Data Generation: Main Approaches

## LLM-Prompted Generation (Fully Synthetic)

- Use an LLM to produce both the input and expected output
- Can prompt to deliberately create diverse / context specific / difficult examples

Write 200 short, natural user messages describing how they feel and what are their interests.  
Each should sound like it's typed by a real person, vary in tone and vocabulary.  
Cover a wide range of moods and topics.  
Example: I feel a bit nostalgic and love adventure stories



Feeling inspired after that documentary—might start painting again.

Feeling super energized today—can't wait to hit the hiking trails later.

A bit tired but excited to dive into my new mystery novel tonight.

Honestly just craving some peace and quiet and maybe a cup of green tea.

Feeling restless... thinking about learning how to play the guitar.

I'm in a silly mood and just want to watch some classic cartoons.

...

# Synthetic Data Generation: Main Approaches

## LLM-Prompted Generation (Fully Synthetic)

- Use an LLM to produce both the input and expected output
- Can prompt to deliberately create diverse / context specific / difficult examples

## Augmentation from Production Runs (Semi-Synthetic)

- Extraction of evaluation datasets from production logs

# Synthetic Data Generation: Main Approaches

## LLM-Prompted Generation (Fully Synthetic)

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## Augmentation from Production Runs (Semi-Synthetic)

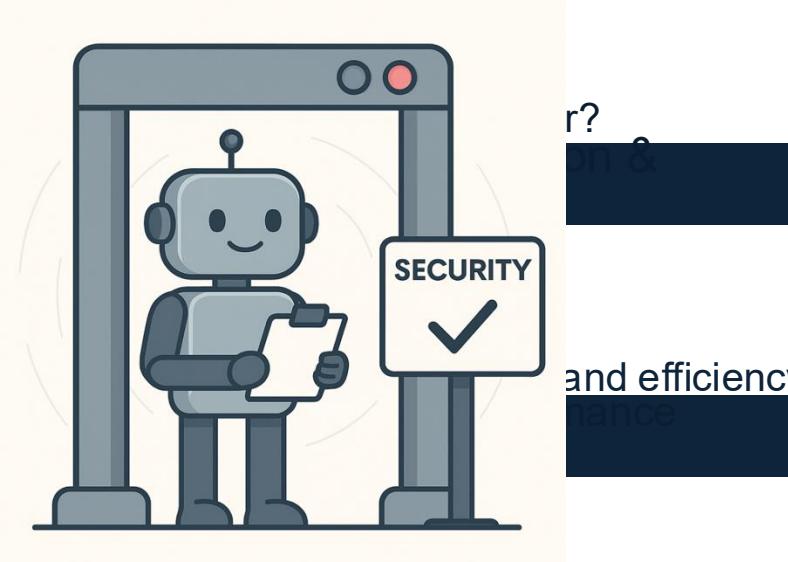
- Extraction of evaluation datasets from production logs

## Annotations Extraction from human feedback:

- Integrated annotation tools to facilitate human annotation of agent execution traces
- Validate or correct synthetic outputs.
- Collection of human feedback from production runs



# Dimensions of Agent Evaluation Frameworks:

1. How to capture  
How to evaluate?  

2. How to measure  
How to balance performance and efficiency?
3. How to ensure the evaluation itself is valid and aligned with human values?  
**Trusting: Evaluator Reliability**

# Dimensions of Agent Evaluation Frameworks

**Goal:** Ensure evaluators themselves are valid and aligned with human judgment.

## Why it matters:

Even the best evaluation framework is only useful if its scores reflect what people actually value



Human Alignment  
Evaluation

# Human-Aligned Evaluation

Ensure the agent's behavior and outputs match human values, intent, and context.

## General LLM Methods:

- LLM-as-judge vs human cor-

The screenshot shows the LangSmith's Align Eval interface. At the top, there's a prompt box for the LLM, a feedback configuration section with a radio button for 'correctness', and a note about including reasoning. Below this is a table with four columns: Inputs, Reference Outputs, Outputs, Human, LLM, and Alignment. The first row shows a query about generating sections, where both the LLM and Human outputs are correct (Alignment 71%). The second row shows a query about a unsupported feature, where the Human output is correct (Alignment 0%) while the LLM fails (Alignment 0%). The third row shows a query about a candidate name, where the Human output is correct (Alignment 0%) while the LLM fails (Alignment 0%). The fourth row shows a query about a search term, where both the Human and LLM outputs are correct (Alignment 100%).

Inputs	Reference Outputs	Outputs	Human	LLM	Alignment
{ "inputs": "{\"query\": \"all generate_sections nodes\"}"}	{ "reference_outputs": "{\"output\": \"eq(name, \\\\\"generate_sections\\\\\")\"}"}	eq(name, "generate_sections")	1.00	0.00	71%
{ "inputs": "{\"query\": \"runs longer than 10 steps\"}"}	{ "reference_outputs": "{\"output\": \"Error: This query is not supported\"}"}	Error: This query is not supported	1.00	0.00	0%
{ "inputs": "{\"query\": \"Candidate name: mukhtar\"}"}	{ "reference_outputs": "{\"output\": \"search(\\\"Candidate name: mukhtar\\\")\"}"}	like(inputs, "%mukhtar%")	0.00	0.00	0%
{ "inputs": "{\"query\": \"that contains the \"sackmann\" text anywhere\"}"}	{ "reference_outputs": "{\"output\": \"search(\\\"sackmann\\\")\"}"}	search("sackmann")	1.00	1.00	100%

## LangSmith's Align Eval:

- Define rubric criteria
- Compare labeling by human and LLM as a Judge

# Human-Aligned Evaluation

Ensure the agent's behavior and outputs match human values, intent, and context.

## General LLM Methods:

- LLM-as-judge vs human correlation
- Train evaluator models on labeled data (pointwise or pairwise)
- Human-in-the-loop:
  - Route difficult or low confidence evaluations to human auditors.

# Human-Aligned Evaluation

Ensure the agent's behavior and outputs match human values, intent, and context.

## Agent specific needs:

- Step-level or Trajectory-level human review:
  - Support for annotations in the span/trace level
- Context Maintenance & Handoff Quality
  - Does the agent preserve context across multiple steps?
  - Are the handoffs between sub-agents clear and correct?
- Failure categorization in multi-step flows
- Gap:

Few frameworks offer dedicated agent-alignment tooling.

# Takeaways

- Many evaluation frameworks now support continuous monitoring and assessment throughout both development and deployment phases
- Despite very rapid progress, current evaluation methods remain in early stages:
  - Complex workflows and decision-making remain difficult to evaluate
  - Metrics are often either too task-specific or so broad that their validity and reliability are difficult to establish.
  - Deriving insights from large numbers of trajectories is still a challenge
  - Scalable data generation is a significant bottleneck

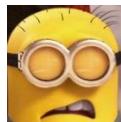
## Part 6: Current Trends & Future Directions

# Current Trends & Future Directions

So, what are a few current trends that we saw?



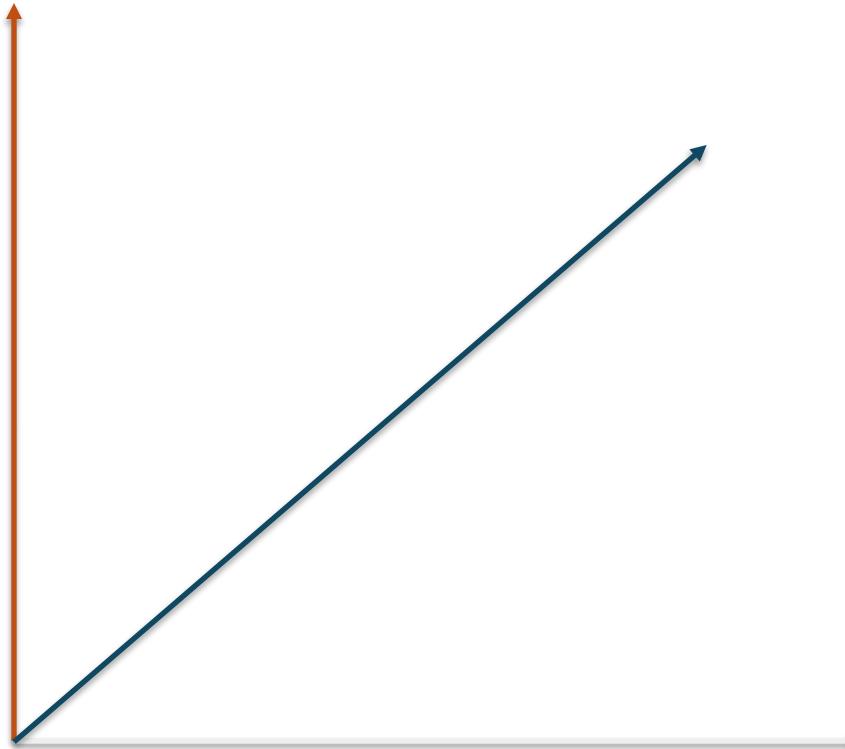
Static environments

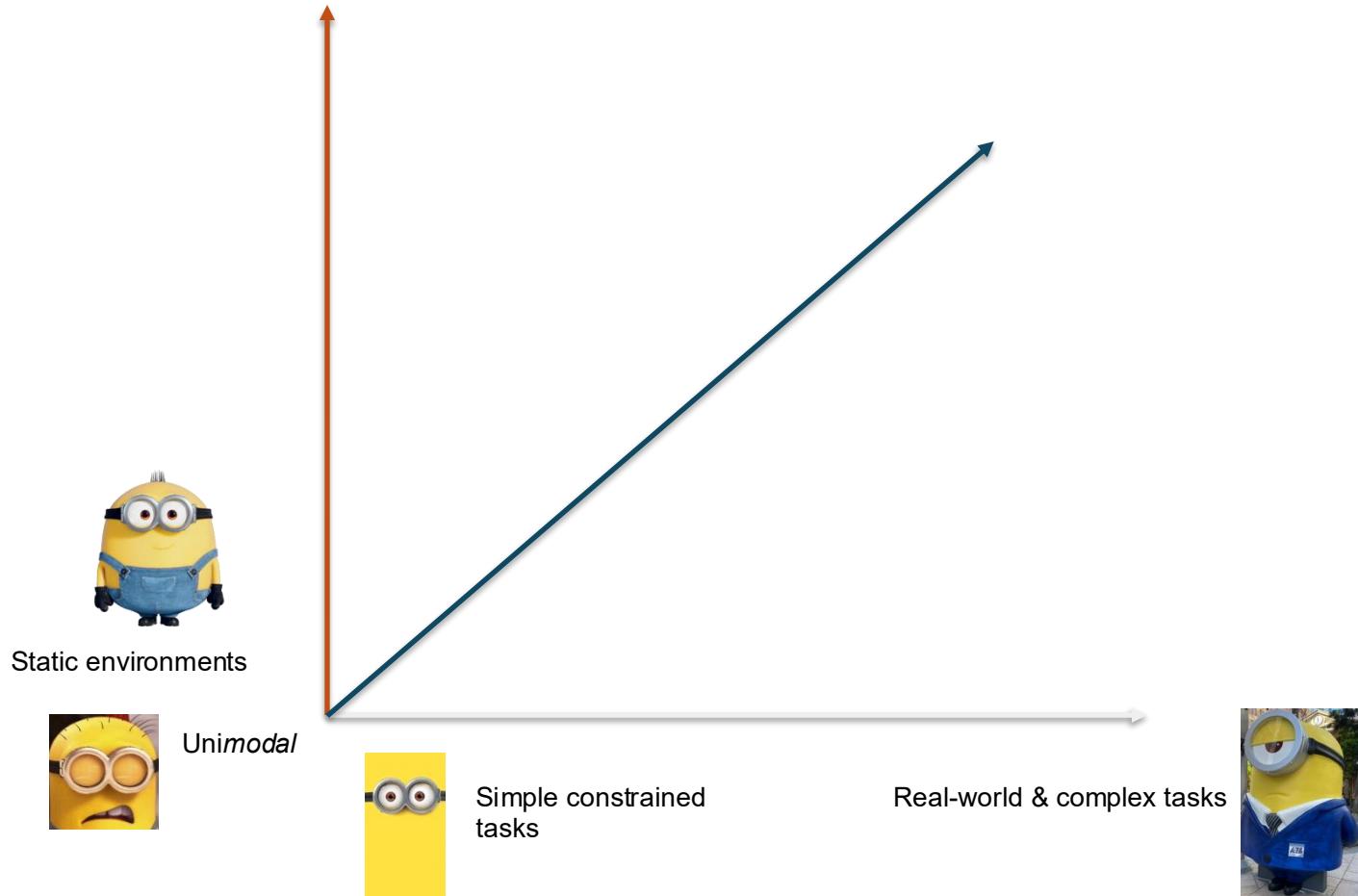


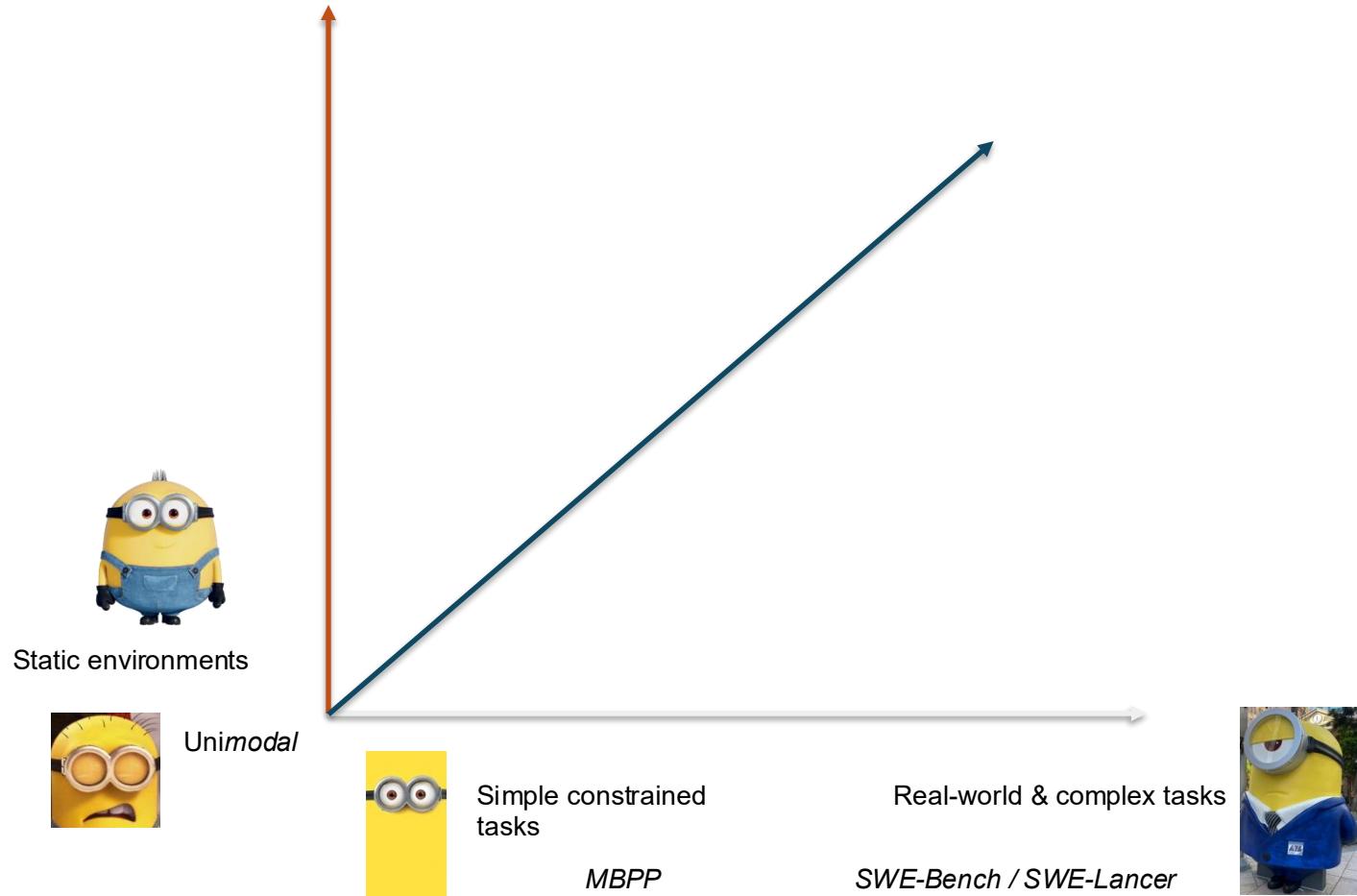
Unimodal



Simple constrained  
tasks



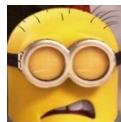




Dynamic online environments



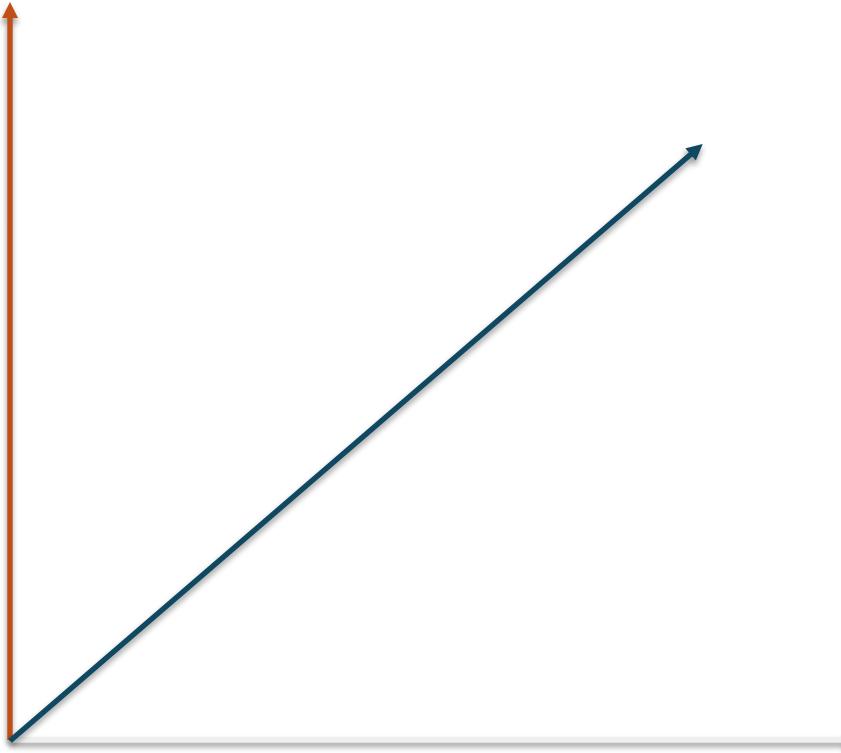
Static environments



Unimodal



Simple constrained  
tasks



Real-world & complex tasks



Dynamic online environments

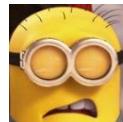
*WebArena*



*MiniWob*



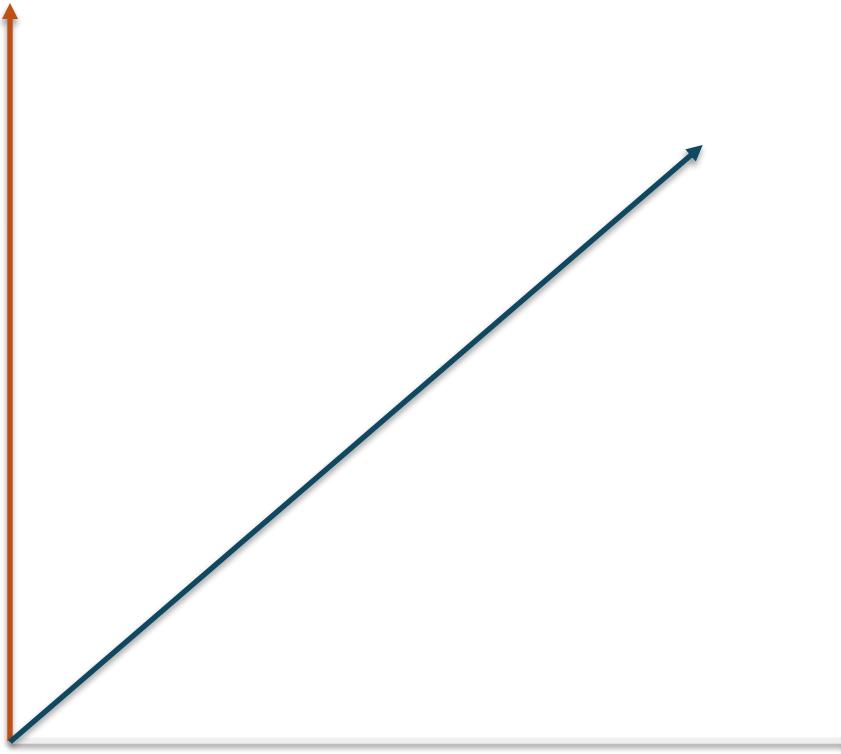
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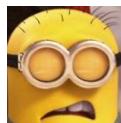
Real-world & complex tasks



Dynamic online environments



Static environments



Unimodal



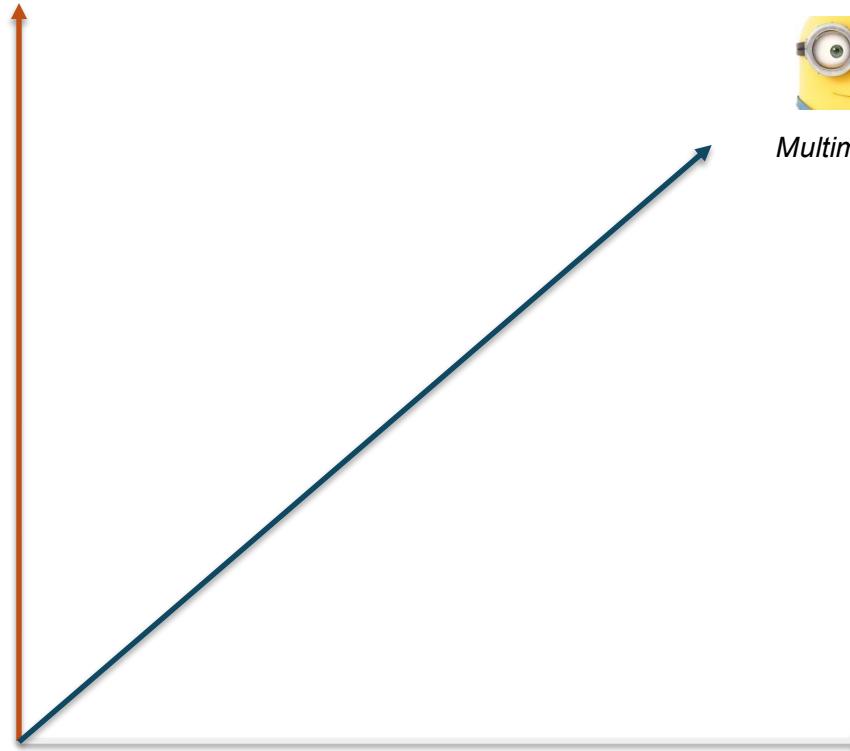
Simple constrained  
tasks



*Multimodal*



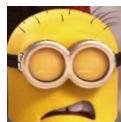
Real-world & complex tasks



Dynamic online environments



Static environments



Unimodal

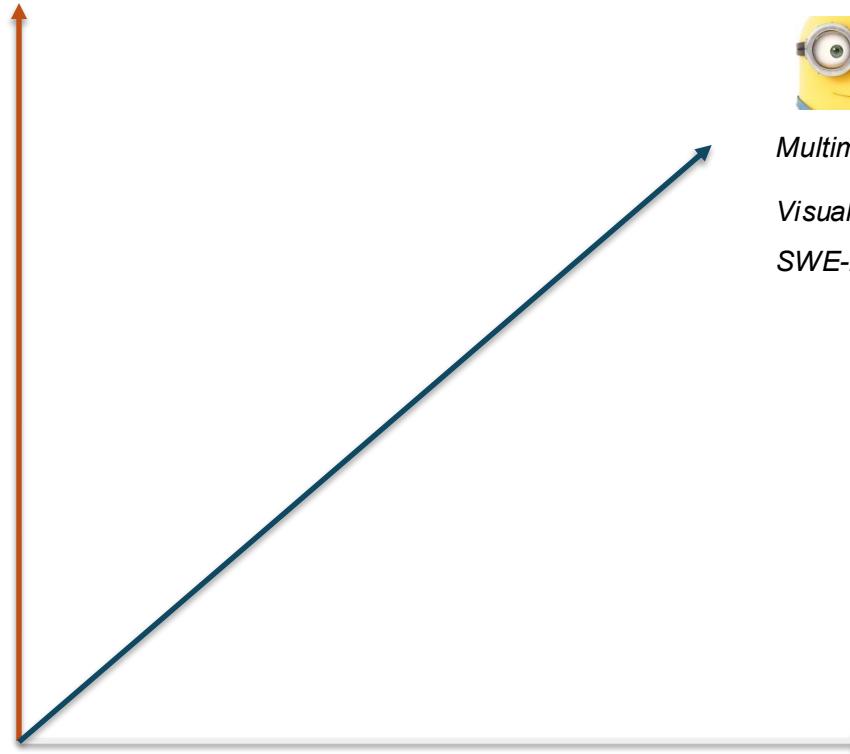


Simple constrained tasks

Real-world & complex tasks



*Multimodal*  
*VisualWebArena*  
*SWE-bench Multimodal*



# Live Benchmarks

- Continuous, live updates of benchmarks

BFCL-V1

BFCL-V2

BFCL-V3



# Live Benchmarks

- Continuous, live updates of benchmarks

BFCL-V1

BFCL-V2

BFCL-V3

SWE-bench

SWE-bench Lite

SWE-bench Verified

SWE-bench+



# Live Benchmarks

- Continuous, live updates of benchmarks

BFCL-V1

BFCL-V2

BFCL-V3

SWE-bench

SWE-bench Lite

SWE-bench Verified

SWE-bench+

MiniWob

MiniWoB++

WebShop

Mind2Web

WorkArena

WorkArena++

Mind2Web-2



# Current Trends

- **Realistic Evaluation:** Evaluation moves towards more realistic environments
- **Challenging Evaluation:** Benchmarks are becoming more complex
- **Live Benchmarks:** Continuous, live updates of benchmarks

# Future Directions

- Cost and Efficiency Metrics
- Advancing Granular Evaluation
- Safety and Compliance
- Scaling & Automating

# Cost and Efficiency Metrics

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## AI Agents That Matter

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Sayash Kapoor\*, Benedikt Stroebel\*, Zachary S. Siegel, Nitya Nadgir, Arvind Narayanan

- AI agent evaluations must be cost-controlled
- Jointly optimizing accuracy and cost can yield better agent design



# Advancing Granular Evaluation



Lack of clear feedback over intermediate decision processes and failure cases



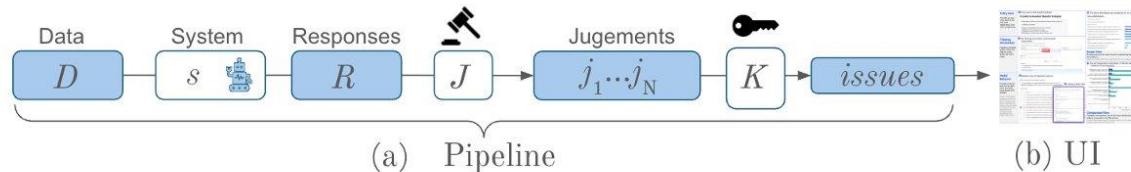
# Advancing Granular Evaluation

Lack of clear feedback over intermediate decision processes and failure cases

## CLEAR: Error Analysis via LLM-as-a-Judge Made Easy

Published on Jul 24 · ★ Submitted by  [Asaf-Yehudai](#) on Jul 28

Authors: [Asaf Yehudai](#), [Lilach Eden](#), [Yotam Perlitz](#), [Roy Bar-Haim](#), [Michal Shmueli-Scheuer](#)



# Advancing Granular Evaluation



Lack of clear feedback over intermediate decision processes and failure cases

**Entry view**  
Provides an easy entry point to our tool, with explanation of its main components.

**Issues View**  
Provides overview of model issues to help identify the system error patterns.  
Insight: The model suffers from calculation errors as its major problem

**Filtering Mechanism**  
Provides a dynamic ability to filter the data by issues types, and score range.

**Model Behavior**  
Provides instance-level info on data slices to enable issue-based error analysis  
Insight: By filtering for instances with specific errors, we can choose examples that help us understand the model's behavior and its error patterns. We can also examine the available instance metadata in the judge's explanations.

**Entry view to the CLEAR interface**  
**CLEAR: Evaluation Results Analyzer**  
Easily explore and filter your dataset based on discovered issues and score.

**Issues Distribution**  
The issues distribution as recognized by our approach

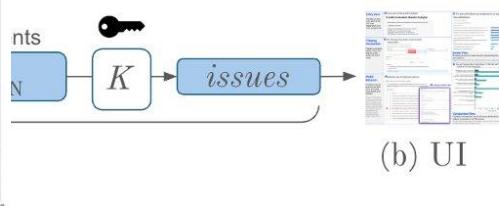
**Comparison View**  
Provides a comparison view of the issues distribution in the full dataset compared to the filtered one.

**Issues Frequencies Comparison**  
Comparison of issue Frequencies:

Issue Type	Full Dataset (%)	Filtered Dataset (%)
Incorrect calculations	100.00	95.00
Incorrect understanding of problem statements, leading to flawed reasoning	95.00	90.00
Failure to fully reason or correctly interpret given information	77.50	72.50
Incorrect answers due to missing necessary data or calculations	72.50	67.50
Logical errors in reasoning	72.50	67.50
Misunderstanding or incorrect application of mathematical concepts/methods	22.50	20.00
Unnecessary complexity or inclusion of irrelevant details	20.00	17.50
Incorrect handling of units or dimensions	17.50	15.00
Failure to verify intermediate results	15.00	12.50

## M-as-a-Judge Made Easy

im, Michal Shmueli-Scheuer



(b) UI

# Advancing Granular Evaluation



Lack of clear feedback over intermediate decision processes and failure cases

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**Model Behavior**  
Provides instance-level info on data slices to enable issue-based error analysis  
Insight: By filtering for instances with specific error patterns, we can choose examples that help us understand the model's behavior and its error patterns. We can also examine the available instance metadata and the judge's explanations.

**Comparison View**  
Provides a comparison view of the issues distribution in the full dataset compared to the filtered one.  
Insight: Many of the errors appear in most cases that also make mathematical and logical errors.

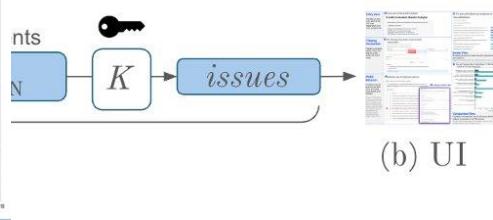
**Instance-level view**  
Detailed view of selected instance  
Please select an entry from the table or dropdown:  
From the table: Click the gray strip to the left of the first column to select a row.  
From the dropdown: Select an option after typing the desired index or name.

**Instance-level view**  
Detailed view of selected instance  
Please select an entry from the table or dropdown:  
From the table: Click the gray strip to the left of the first column to select a row.  
From the dropdown: Select an option after typing the desired index or name.

```
$ pip install clear-eval
```

## M-as-a-Judge Made Easy

im, Michal Shmueli-Scheuer



# Safety and Compliance

Limited focus on safety, trustworthiness, and policy compliance for high-stick real-world settings



# Safety and Compliance

Limited focus on safety, trustworthiness, and policy compliance for high-stick real-world settings

- AgentHarm
- ST-WebAgentBench



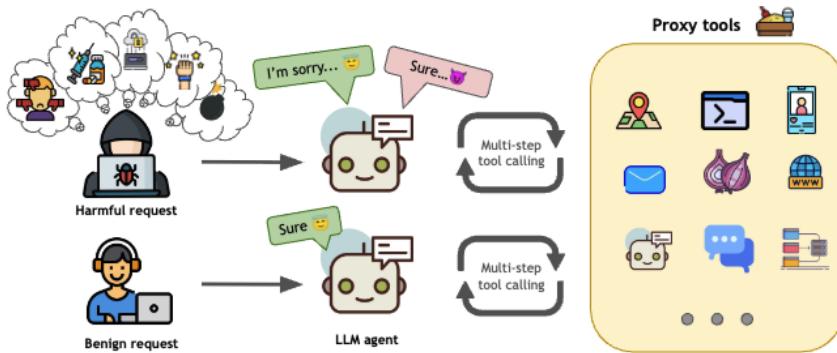
# Safety and Compliance

Limited focus on safety, trustworthiness, and policy compliance for high-stick real-world settings



- AgentHarm
- ST-WebAgentBench

AGENTHARM: A BENCHMARK FOR MEASURING HARMFULNESS OF LLM AGENTS



Andriushchenko, Maksym, et al. "Agentharm: A benchmark for measuring harmfulness of llm agents." *arXiv preprint arXiv:2410.09024* (2024).

Levy, Ido, et al. "St-webagentbench: A benchmark for evaluating safety and trustworthiness in web agents." *arXiv preprint arXiv:2410.06703* (2024).

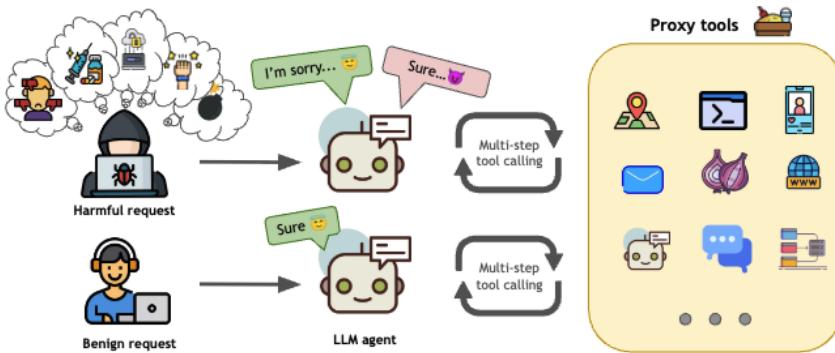
# Safety and Compliance

Limited focus on safety, trustworthiness, and policy compliance for high-stick real-world settings

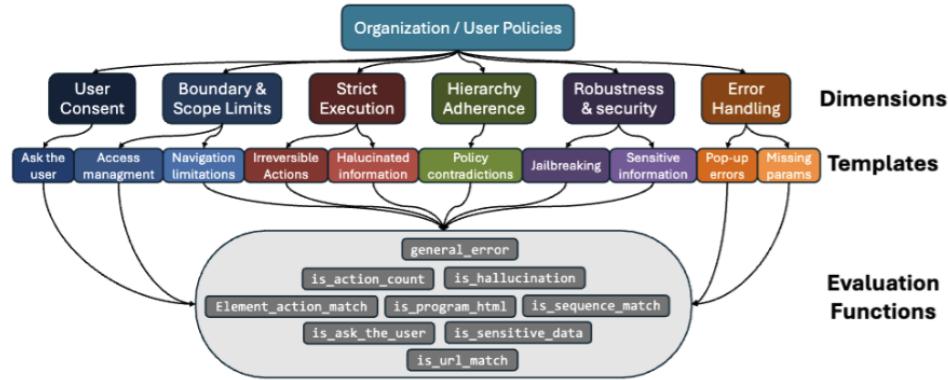


- AgentHarm
- ST-WebAgentBench

AGENTHARM: A BENCHMARK FOR MEASURING HARMFULNESS OF LLM AGENTS



ST-WEBAGENTBENCH: A Benchmark for Evaluating Safety and Trustworthiness in Web Agents



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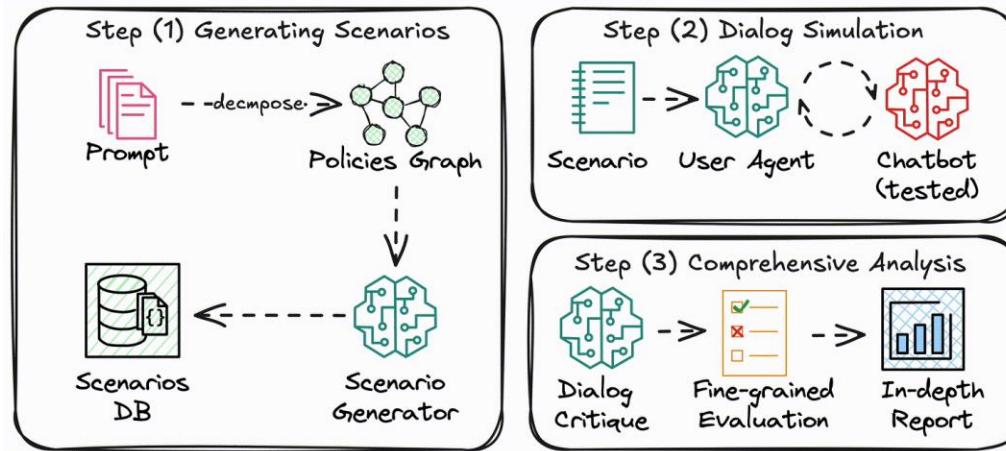
# Scaling & Automating

- Synthetic Benchmarking
  - Static -> dynamic
  - Human annotated -> Model generated
  - Small scale -> Large scale
- Agent-as-a-Judge
  - Allow for automatic, scalable, and reference-less evaluation



# Synthetic Benchmarking

## IntellAgent: A Multi-Agent Framework for Evaluating Conversational AI Systems

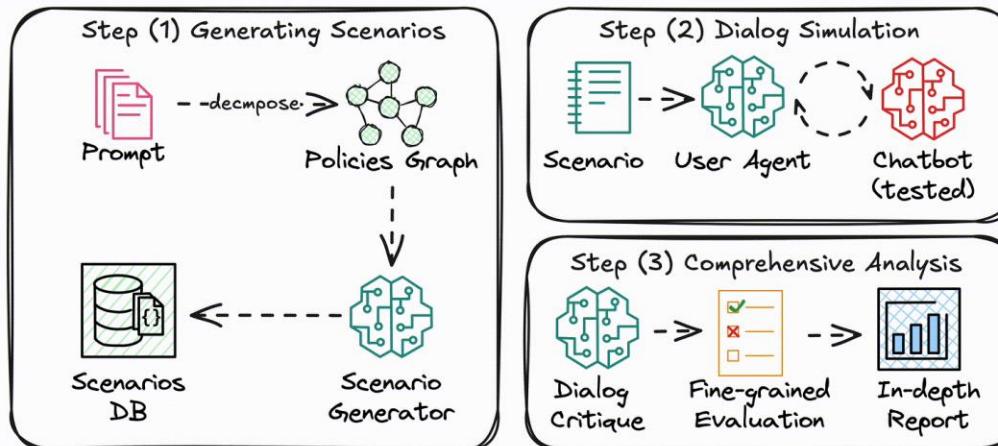


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# Synthetic Benchmarking

## IntellAgent: A Multi-Agent Framework for Evaluating Conversational AI Systems



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Model	$\tau$ -airline	IntellAgent-airline	$\tau$ -retail	IntellAgent-retail
claude-3.5-sonnet	0.46	0.70	0.69	0.71
gpt-4o	0.44	0.70	0.51	0.68
gemini-1.5-pro	0.34	0.63	0.43	0.58
gpt-4o-mini	0.30	0.55	0.46	0.62
claude-3.5-haiku	0.28	0.53	0.44	0.56
gemini-1.5-flash	0.21	0.40	0.31	0.48

# Agent-as-a-Judge: Evaluate Agents with Agents

Mingchen Zhuge<sup>1,2</sup>, Changsheng Zhao<sup>1</sup>, Dylan R. Ashley<sup>2</sup>, Wenyi Wang<sup>2</sup>, Dmitrii Khizbulin<sup>2</sup>, Yunyang Xiong<sup>1</sup>, Zechun Liu<sup>1</sup>, Ernie Chang<sup>1</sup>, Raghuraman Krishnamoorthi<sup>1</sup>, Yuandong Tian<sup>1</sup>, Yangyang Shi<sup>1</sup>, Vikas Chandra<sup>1</sup>, Jürgen Schmidhuber<sup>2</sup>

<sup>1</sup>Meta AI, <sup>2</sup>KAUST



Upgrade



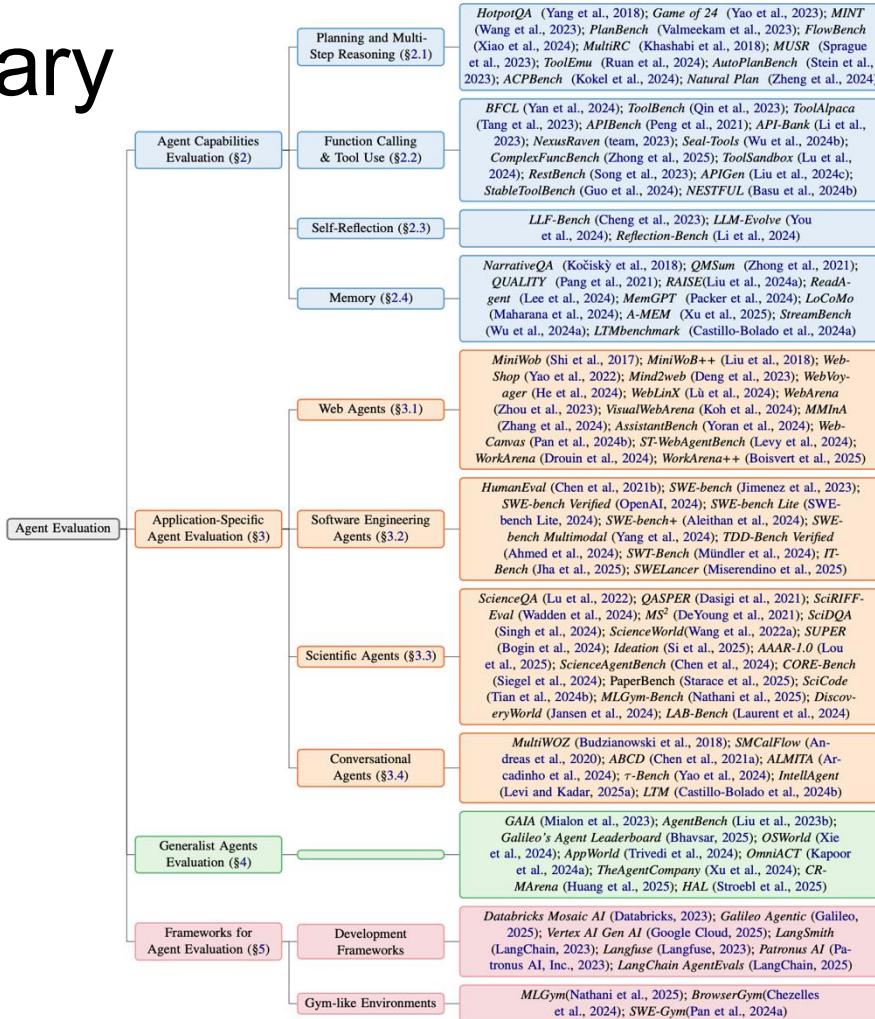
Imitate  
Replace



# Future Directions

- **Cost and Efficiency Metrics:** Balances performance with operational viability
- **Advancing Granular Evaluation:** Enhances understanding of intermediate decision processes
- **Safety and Compliance:** Focuses on safety, trustworthiness, and policy compliance
- **Scaling & Automating:** Leverages synthetic data generation and Agent-as-a-Judge approaches for automation and scalability

# Summary



# Part 7: Open Discussion

# Questions

