SCHOOL OF
COMPUTING &
DATA SCIENCE
The University of Hong Kong

Towards Generalist Computer-using Agents:

Models, Data, and Beyond

Qiushi Sun
qiushisun.github.io
𝕏 @qiushi_sun

Computer-Using Agents

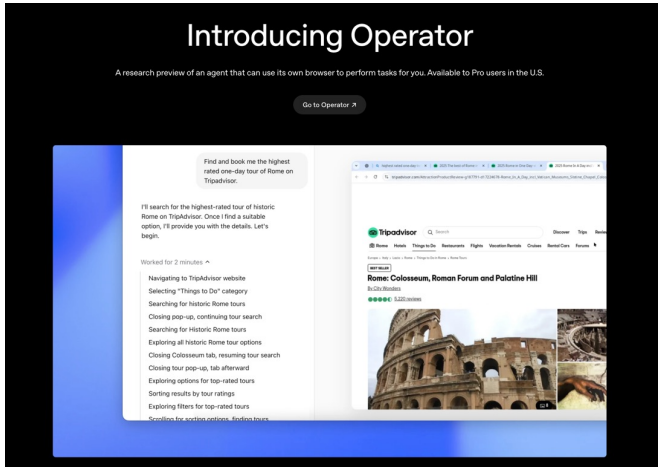
Both academia and industry are building computer-using agents

Claude Computer Use

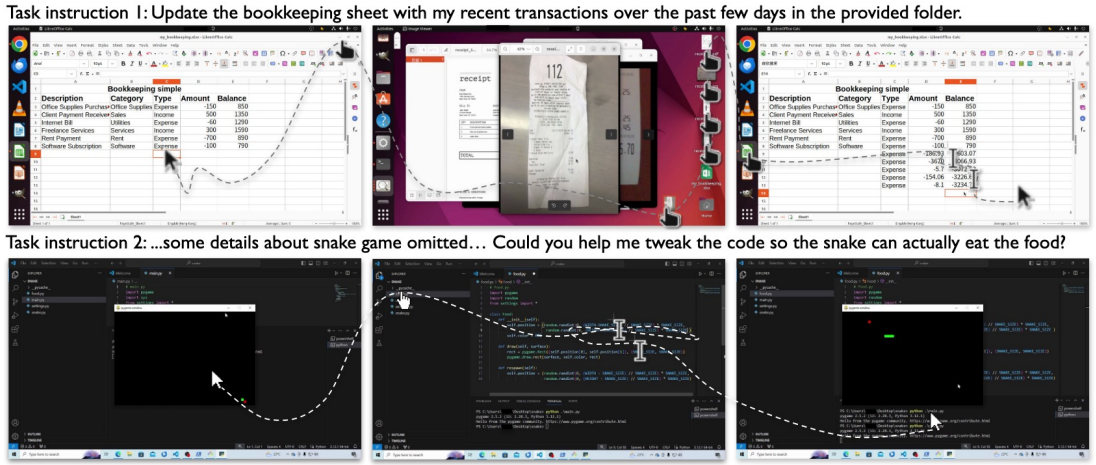
[1] Introducing computer use, a new Claude 3.5 Sonnet, and Claude 3.5 Haiku, 22 Oct 2024

Computer-Using Agents

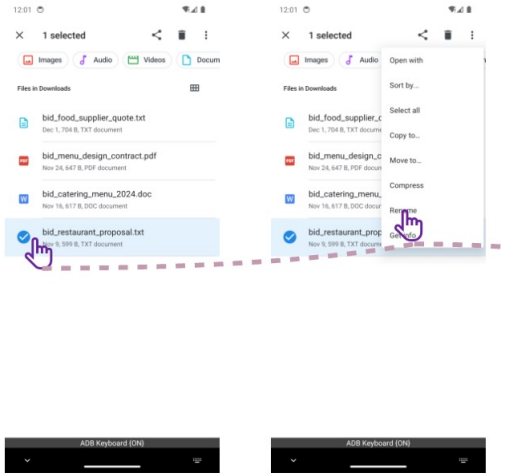
Automating daily computer tasks



OpenAI Operator



Daily Computer Use



Mobile GUI Agent

[2] Introducing Operator: A research preview of an agent that can use its own browser to perform tasks for you., Jan 23, 2025

[3] OSWorld: Benchmarking Multimodal Agents for Open-Ended Tasks in Real Computer Environments

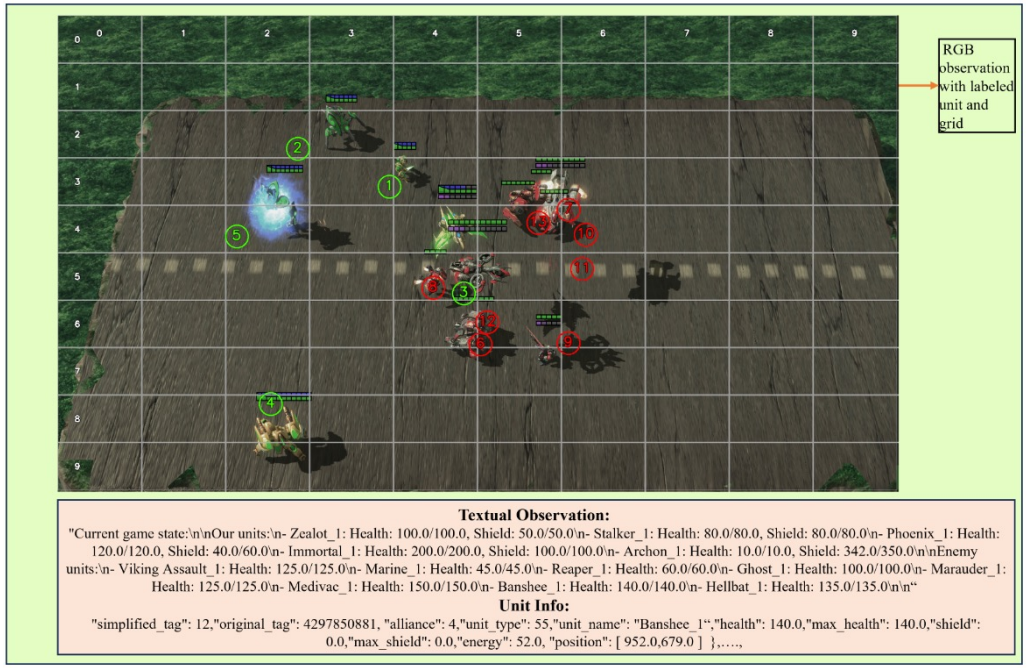
Computer-Using Agents

Taking over your phone

Computer-Using Agents

Playing Games

MineCraft



StarCraft II

[4] AVA: Attentive VLM Agent for Mastering StarCraft II

Computer-Using Agents

Recent Industry Players

Overview

Our team is releasing Seed1.8, a model designed for generalized real-world agency. It supports text and image inputs and with its powerful multimodal processing capabilities, it demonstrates good performance across various complex application scenarios such as information retrieval, coding, Graphical User Interface (GUI) interaction.

GUI Agents

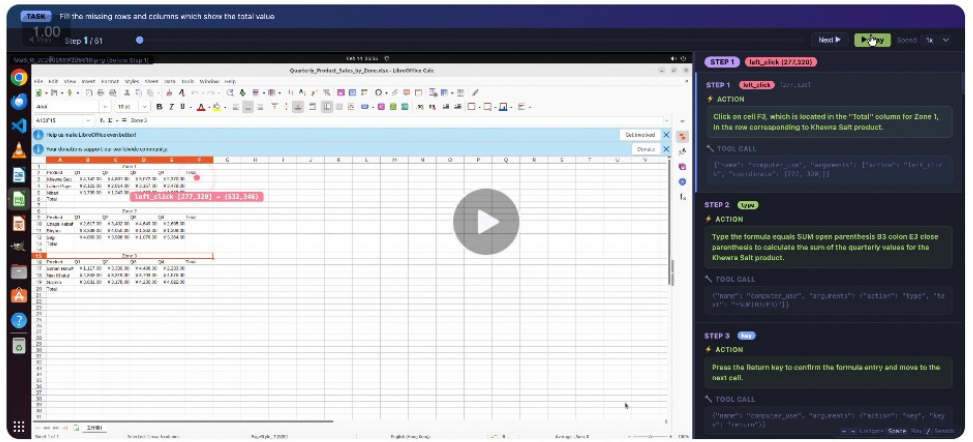
Acting as a visual agent for productivity automation, Qwen3.5 enables autonomous interaction with smartphones and computers. As a mobile agent, it can follow natural-language instructions to take actions within mobile apps and enable smooth interaction across multiple apps. As a computer agent, it handles complex, long-horizon desktop workflows, enabling office automation.

Expand all demos

Demo1 Excel 1 / 5

Fill the missing rows and columns which show the total value

Qwen3.5



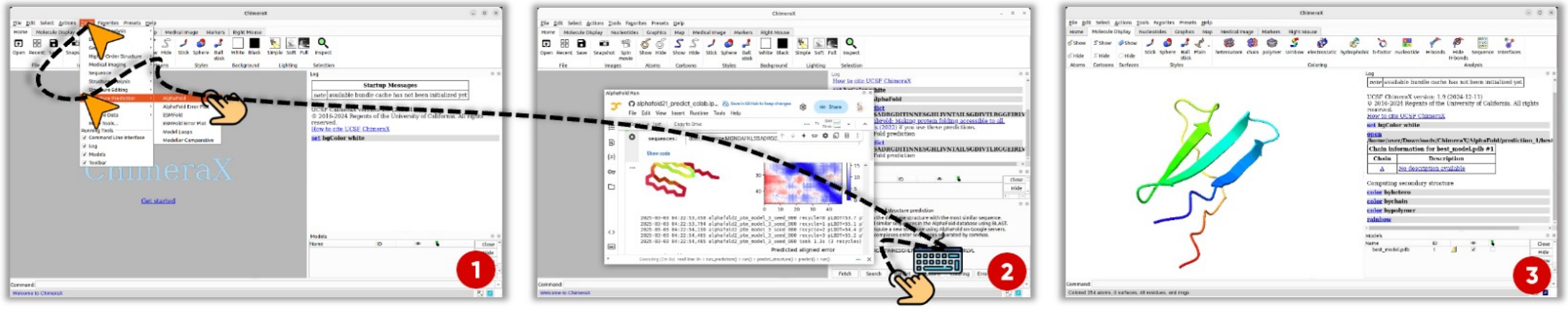
[5] Seed1.8 A generalized agentic model that can efficiently and accurately accomplish complex tasks in real-world scenarios.

[6] Qwen3.5: Towards Native Multimodal Agents

Computer-using Agents

Automate scientific workflows, be your co-scientist

Instruction: Predict the protein structure for the amino acid sequence of 'MGND…' via AlphaFold in ChimeraX.

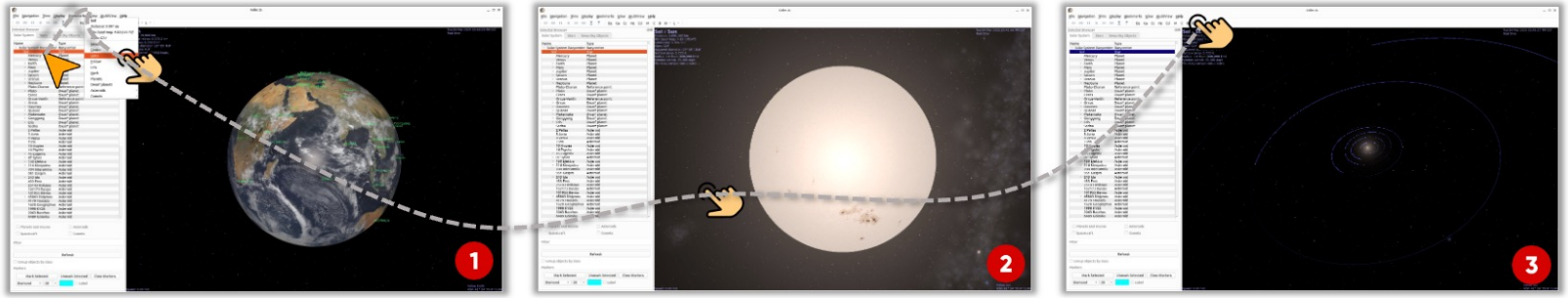


Step1: Toggle the widget of AlphaFold.

Step2: Input the given sequence and call out AlphaFold for structure prediction.

Step3: Wait until the prediction finished.

Instruction: Show planets' orbits of Solar System in Celestia.



Step1: Select the Sol and click 'Goto' in contect menu.

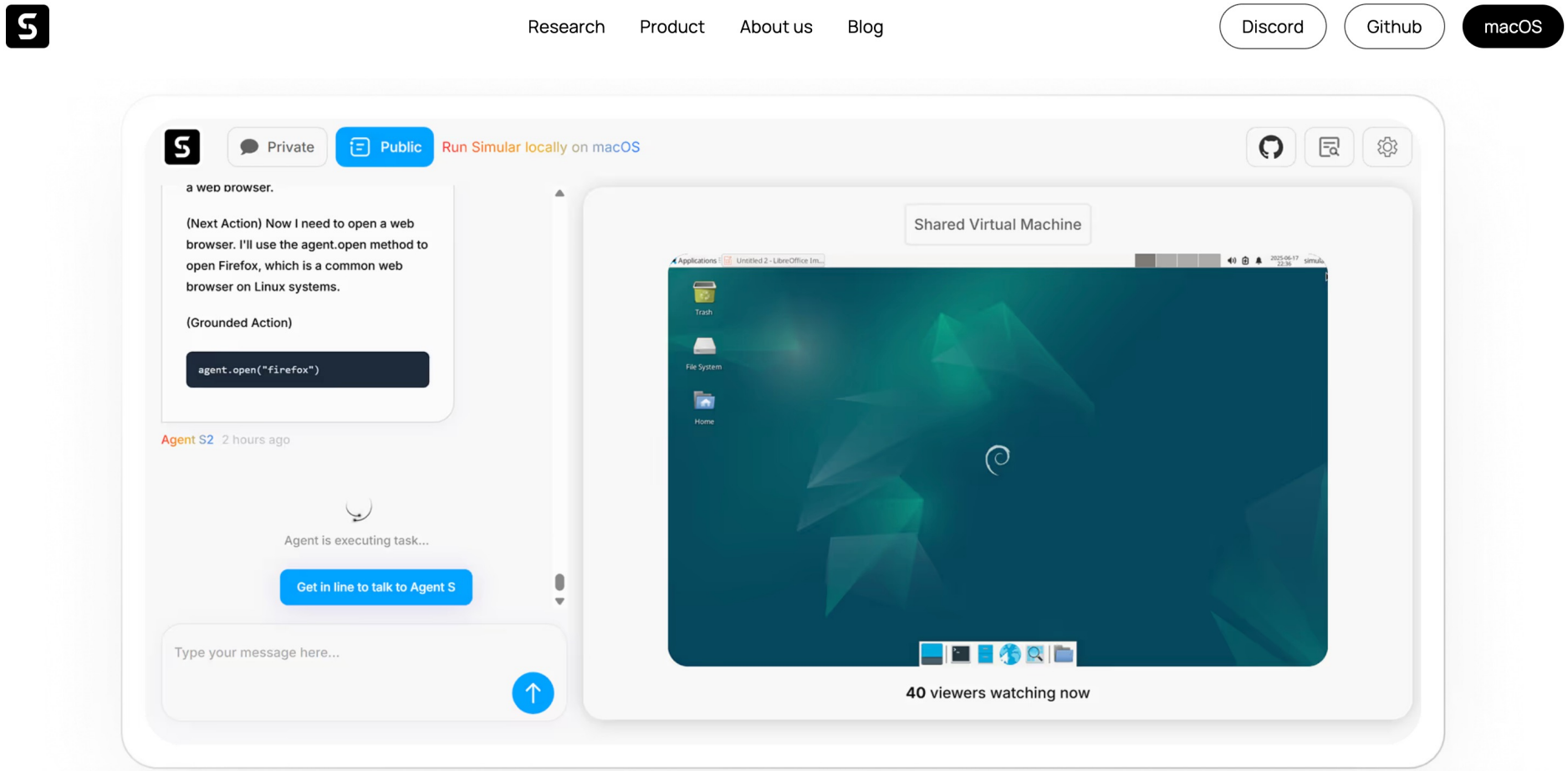
Step2: Slide the mouse wheel to move the camera away from Sol.

Step3: Click to show orbits of planets.

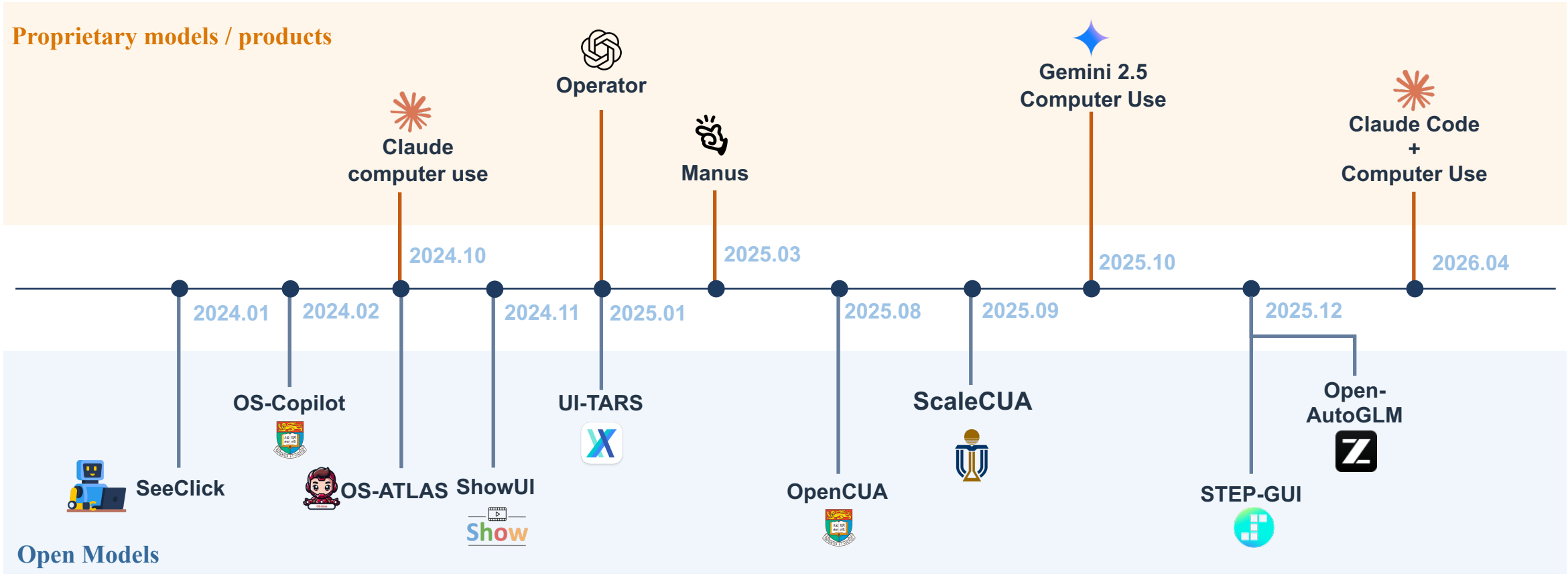
[7] ScienceBoard: Evaluating Multimodal Autonomous Agents in Realistic Scientific Workflows

Computer-using Agents

Startups



Computer-using Agents



Seminal works on Computer-Using Agents

Foundation Models

- SeeClick: Harnessing GUI Grounding for Advanced Visual GUI Agents, ACL 2024
- OS-ATLAS: A Foundation Action Model for Generalist GUI Agents , ICLR 2025 Spotlight
- ScaleCUA: Scaling Open-Source Computer Use Agents with Cross-Platform Data, ICLR 2026 Oral

Data

- OS-Genesis: Automating GUI Agent Trajectory Construction via Reverse Task Synthesis , ACL 2025
- Breaking the Data Barrier -- Building GUI Agents Through Task Generalization, COLM 2025
- OpenMobile: Building Open Mobile Agents with Task and Trajectory Synthesis

Frameworks

- AgentStore: Scalable Integration of Heterogeneous Agents As Specialized Generalist Computer Assistant , ACL 2025
- OS-Symphony: A Holistic Framework for Robust and Generalist Computer-Using Agent, ACL 2026

Evaluation

- OS-MAP: How Far Can Computer Use Agents Go in Breadth and Depth?

Frontier App.

- ScienceBoard: Evaluating Multimodal Autonomous Agents in Realistic Scientific Workflows, ICLR 2026

Safety

- OS-Sentinel : Towards Safety-Enhanced Mobile GUI Agents via Hybrid Validation in Realistic Workflows , ACL 2026

Computer-Using Agents

Generally, both GUI and CLI can enable computer use

(though they have different capability boundaries).

Today, our discussion focuses on GUI-based computer-using agents.

GUI Agents

Let's start with enabling a VLM to make an "action"

SeeClick: Harnessing GUI Grounding for Advanced Visual GUI Agents

ACL 2024 Bangkok, Thailand

Kanzhi Cheng, Qiushi Sun, Yougang Chu, Fangzhi Xu, Yantao Li, Jianbing Zhang, Zhiyong Wu

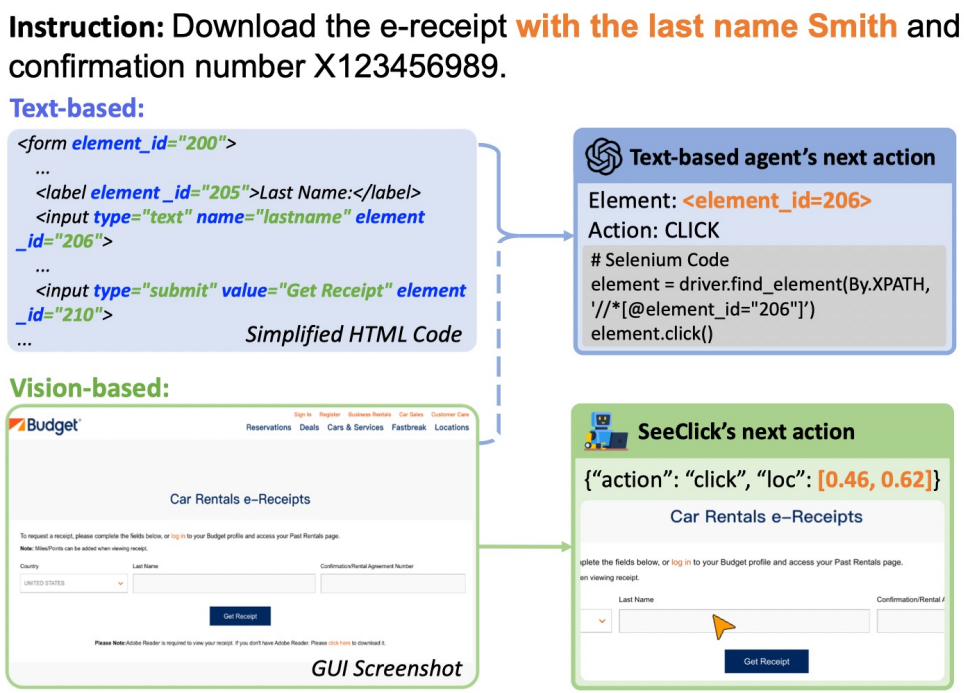
上海人工智能实验室
Shanghai Artificial Intelligence Laboratory

NANJING UNIVERSITY 1902

SeeClick: Overview

We built a purely visual GUI Agent SeeClick, which interacts with GUIs through screenshots, does not require any structured information.

Just like Human!



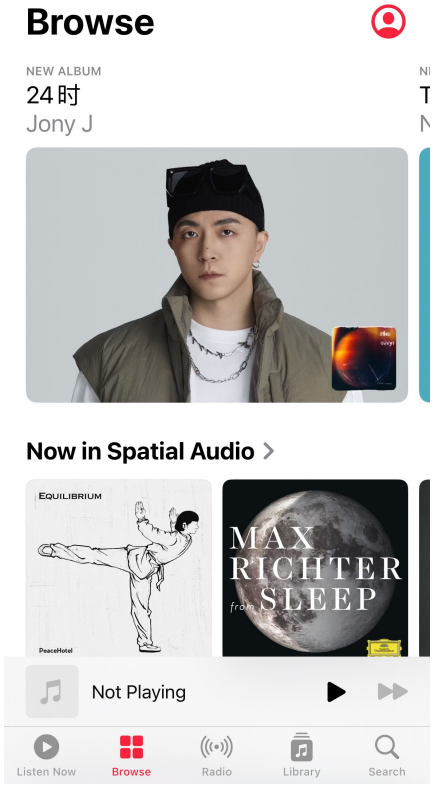
Input: Screenshots

Output: the action (with location)

[7] SeeClick: Harnessing GUI Grounding for Advanced Visual GUI Agents, ACL 2024

SeeClick: GUI Grounding

(In 2024) We discovered a key challenge in developing visual GUI agents: GUI grounding – the capacity to accurately locate screen elements based on instructions.



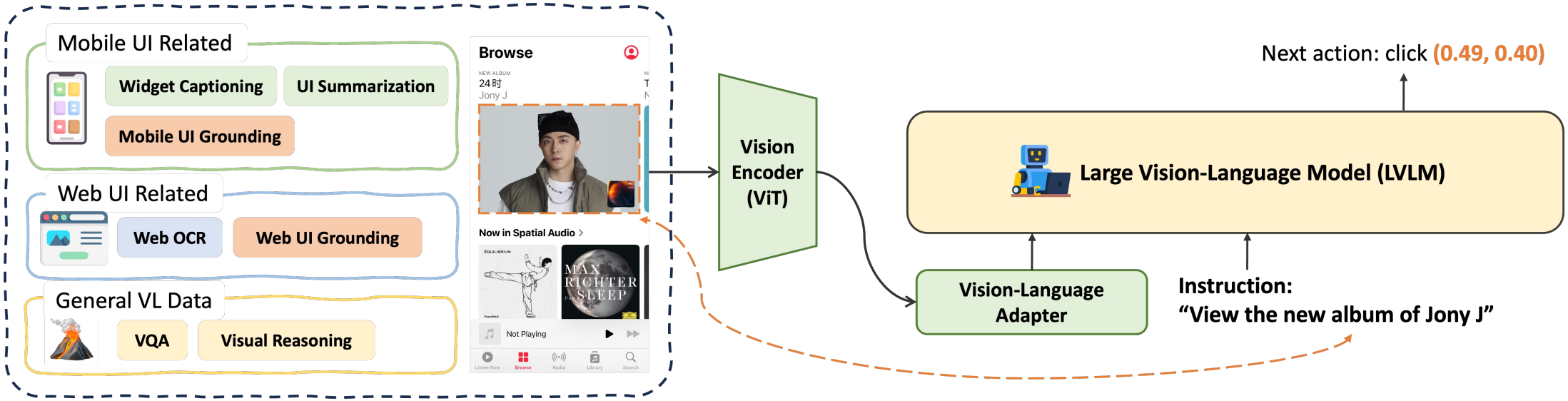
In order to view the new album of Jony J, where should I click?

GPT-4o (an earlier version): hmmm… Sorry I don't know. ❌

SeeClick: (0.49, 0.40) ✅

How SeeClick is Built

Overview of SeeClick's framework and GUI grounding pre-training.



Uses ~1M GUI-specific samples combining web UI, mobile UI, and general vision-language data.

Includes **GUI grounding tasks**, such as predicting click points and generating element descriptions.

How SeeClick is Built

Web UI Grounding data

1. Crawled from large-scale web pages (~300K pages)
2. Includes text elements and tooltip-based descriptions

instructions

Target: element localization from instructions $p(y|s,x)$ and OCR-style text prediction $p(x|s,y)$

elements

Mobile UI data

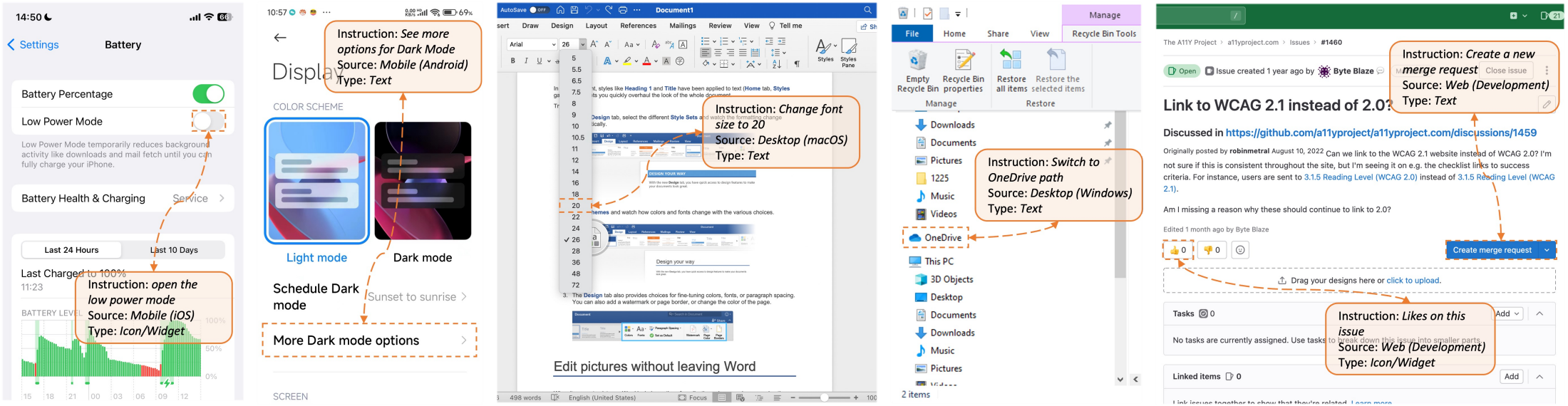
1. Widget captioning and UI grounding from public datasets (e.g., RICO)
2. UI summarization to improve holistic interface understanding

General VL instruction data

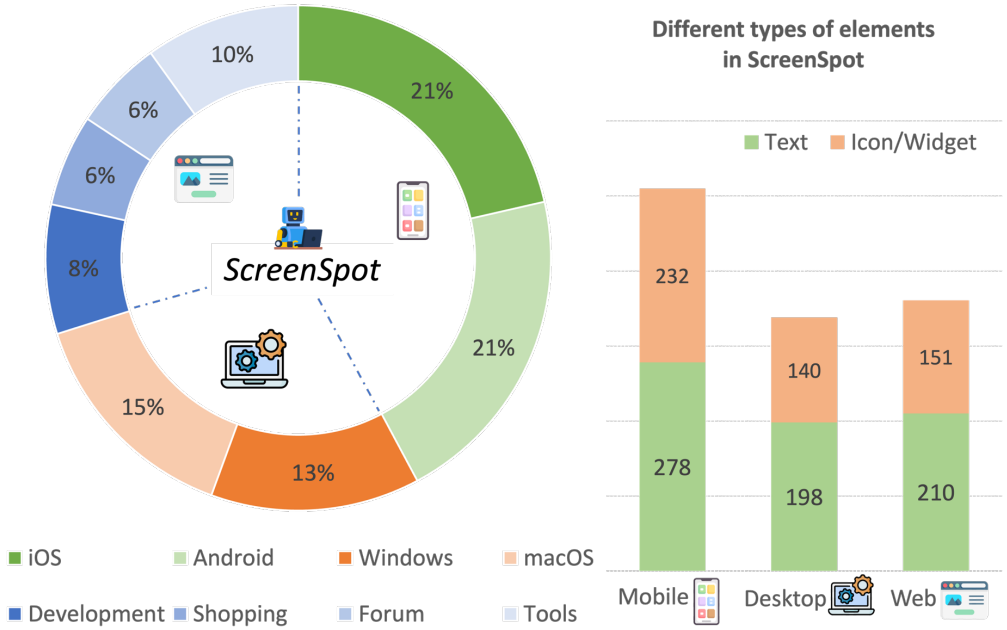
1. Adopted from multi-purpose VL instruction-following corpora (e.g., LLaVA)
2. Supports preserving general reasoning and descriptive capabilities

The First Modern GUI Grounding Benchmark

GUI Grounding Benchmark: *ScreenSpot*



The First Modern GUI Grounding Benchmark



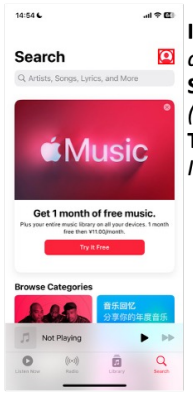
600+ screenshots and **1,200+ instructions** across mobile (iOS, Android), desktop (macOS, Windows), and web platforms.

Both **text elements and icons/widgets**

Collected from real-world apps and websites

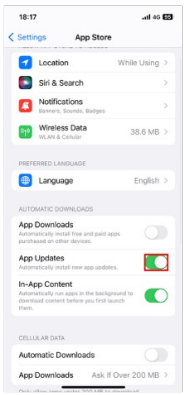
ScreenSpot: Component

Mobile

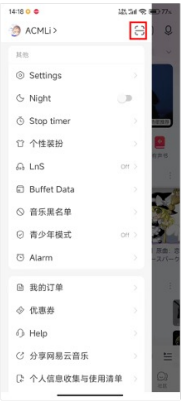


Instruction: *My account*
Source: *Mobile (iOS)*
Type: *Icon/Widget*

Instruction: *Remove maps from the Desktop*
Source: *Mobile (iOS)*
Type: *Icon/Widget*

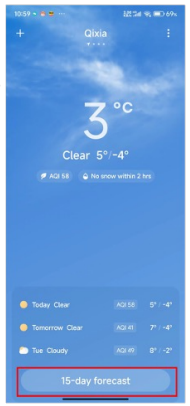


Instruction: *Disallow automatic app updates*
Source: *Mobile (iOS)*
Type: *Icon/Widget*

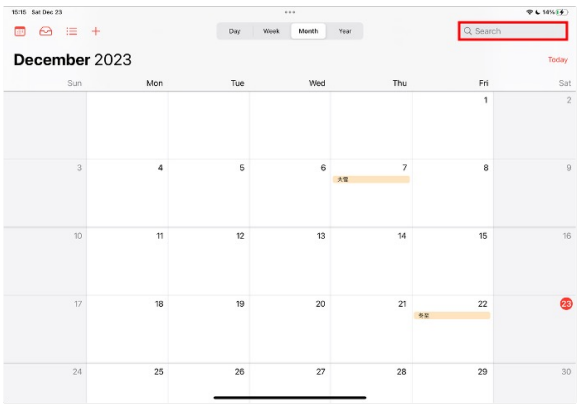


Instruction: *Scan QR code*
Source: *Mobile (Android)*
Type: *Icon/Widget*

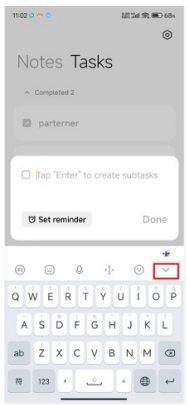
Instruction: *Continue*
Source: *Mobile (Android)*
Type: *Text*



Instruction: *Display 15-day weather forecast*
Source: *Mobile (Android)*
Type: *Text*



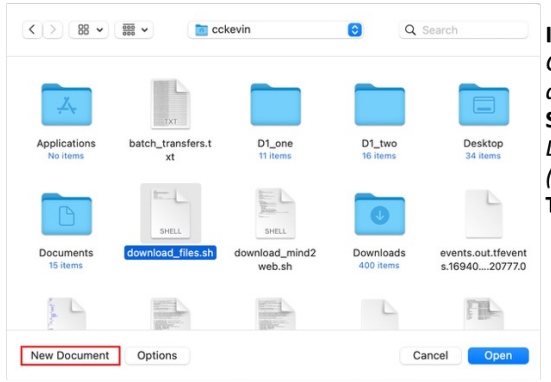
Instruction: *Search event*
Source: *Mobile (iOS)*
Type: *Text*



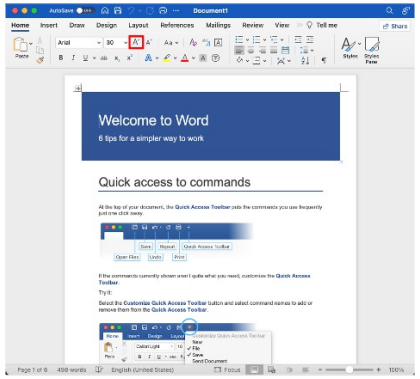
Instruction: *Fold input method*
Source: *Mobile (Android)*
Type: *Icon/Widget*

ScreenSpot: Component

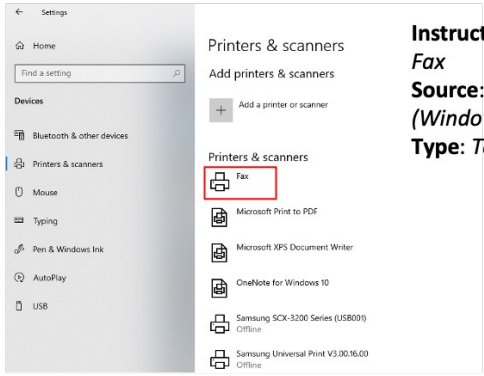
Desktop



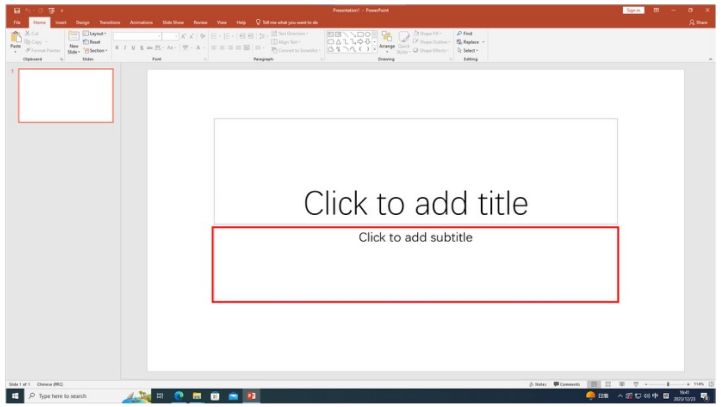
Instruction: *Create a new document*
Source: *Desktop (macOS)*
Type: *Text*



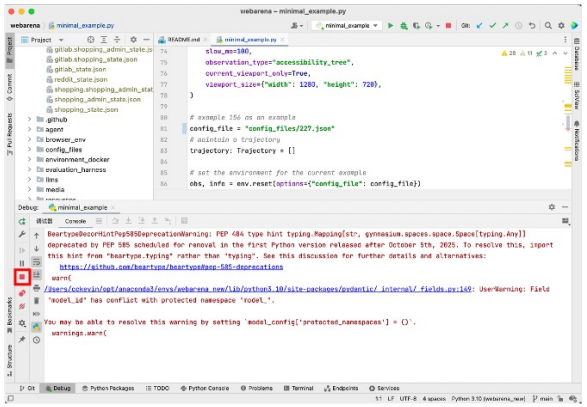
Instruction: *Enlarge font size*
Source: *Desktop (macOS)*
Type: *Icon/Widget*



Instruction: *Open Fax*
Source: *Desktop (Windows)*
Type: *Text*



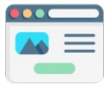
Instruction: *Add subtitle*
Source: *Desktop (Windows)*
Type: *Text*

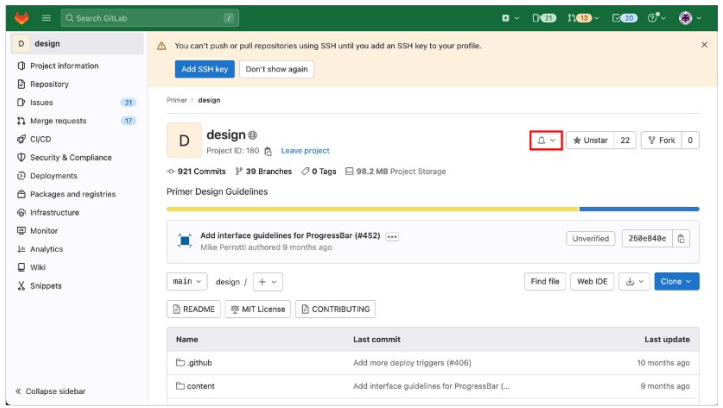


Instruction: *Pause the debugger*
Source: *Desktop (macOS)*
Type: *Icon/Widget*

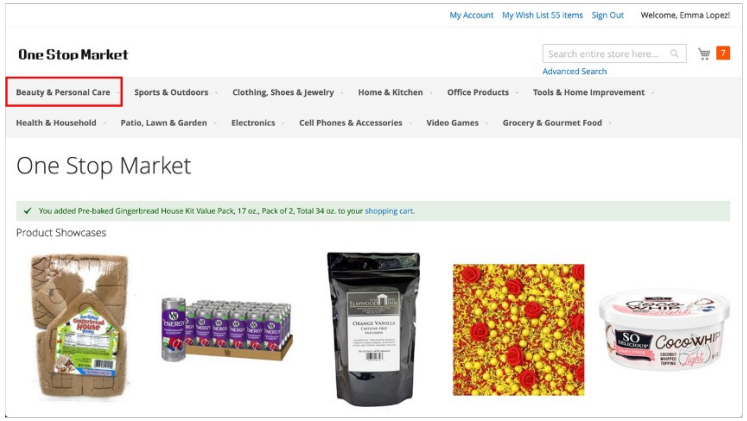
ScreenSpot: Component

Web

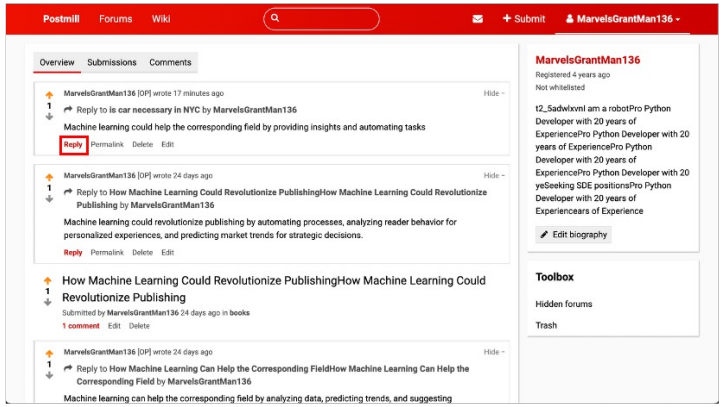




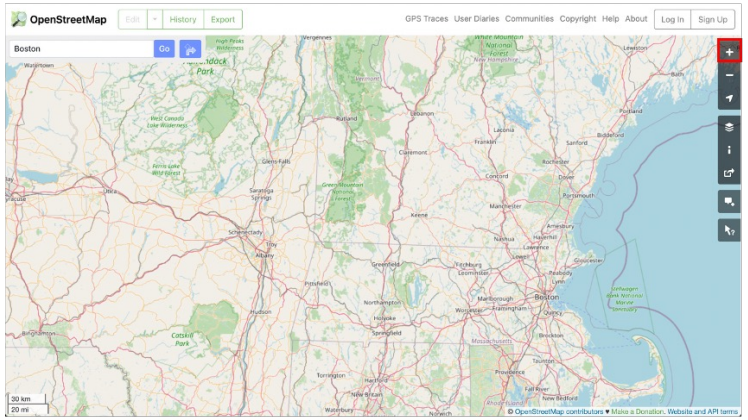
Instruction: *Set Reminder*
Source: *Web (Development)*
Type: *Icon/Widget*



Instruction: *Go to Beauty & Personal Care*
Source: *Web (Shop)*
Type: *Text*

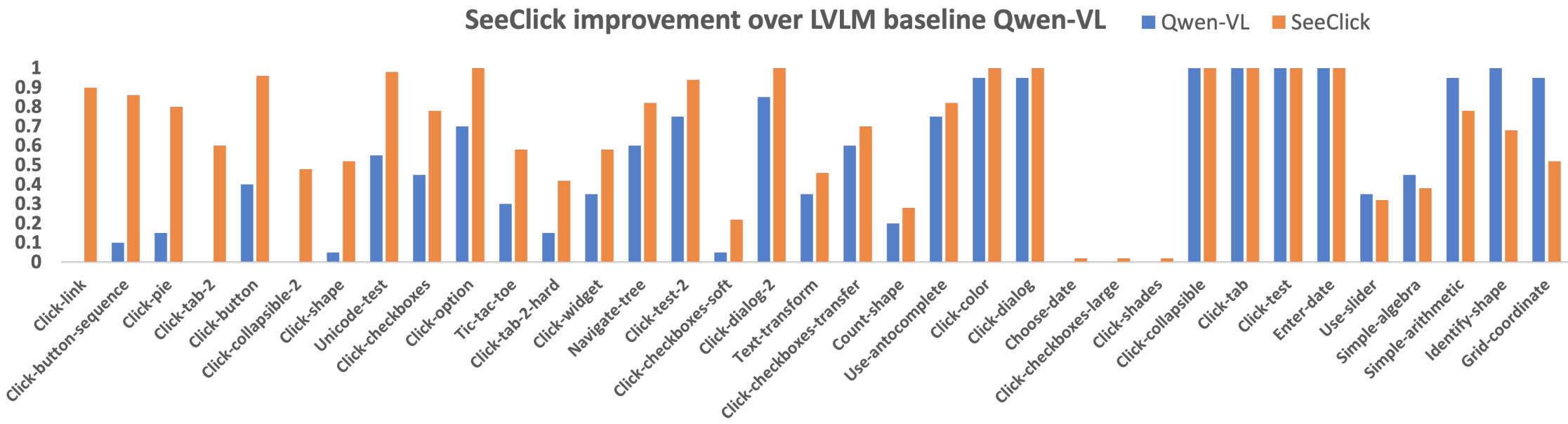


Instruction: *Reply to the first post*
Source: *Web (Forum)*
Type: *Text*

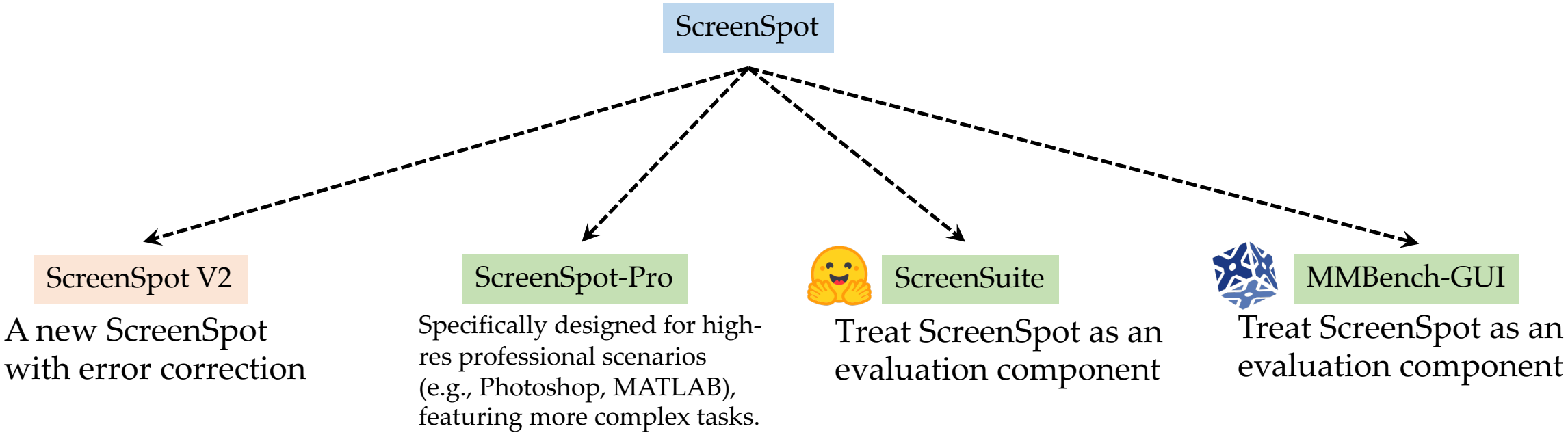


Instruction: Zoom in on the map
Source: *Web (Tools)*
Type: *Icon/Widget*

Results on ScreenSpot



ScreenSpot's Far-reaching Impact



[8] OS-ATLAS: A Foundation Action Model For Generalist GUI Agents, ICLR 2025 Spotlight

[9] ScreenSpot-Pro: GUI Grounding for Professional High-Resolution Computer Use

[10] ScreenSuite - The most comprehensive evaluation suite for GUI Agents!

OS-ATLAS: A Foundation Action Model For Generalist GUI Agents

ICLR 2025 Spotlight

Zhiyong Wu, Zhenyu Wu, Fangzhi Xu, Yian Wang, Qiushi Sun, Chengyou Jia, Kanzhi Cheng, Zichen Ding, Liheng Chen, Paul Pu Liang, Qiao Yu

上海人工智能实验室
Shanghai Artificial Intelligence Laboratory

The Road of Building GUI Agent

Still, a vision-only solution

- Previous: html / a11ytree as states
- Trending: screenshots as states (human-like)

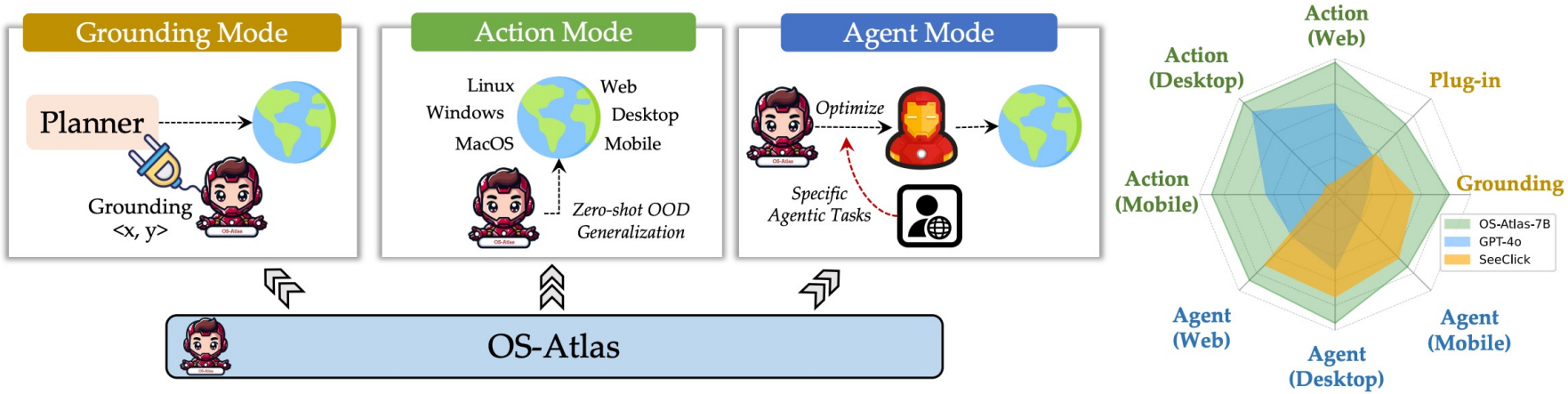
Importance of Large Action Model

Planner + Action Model = Minimal Agent

Overview of OS-Atlas

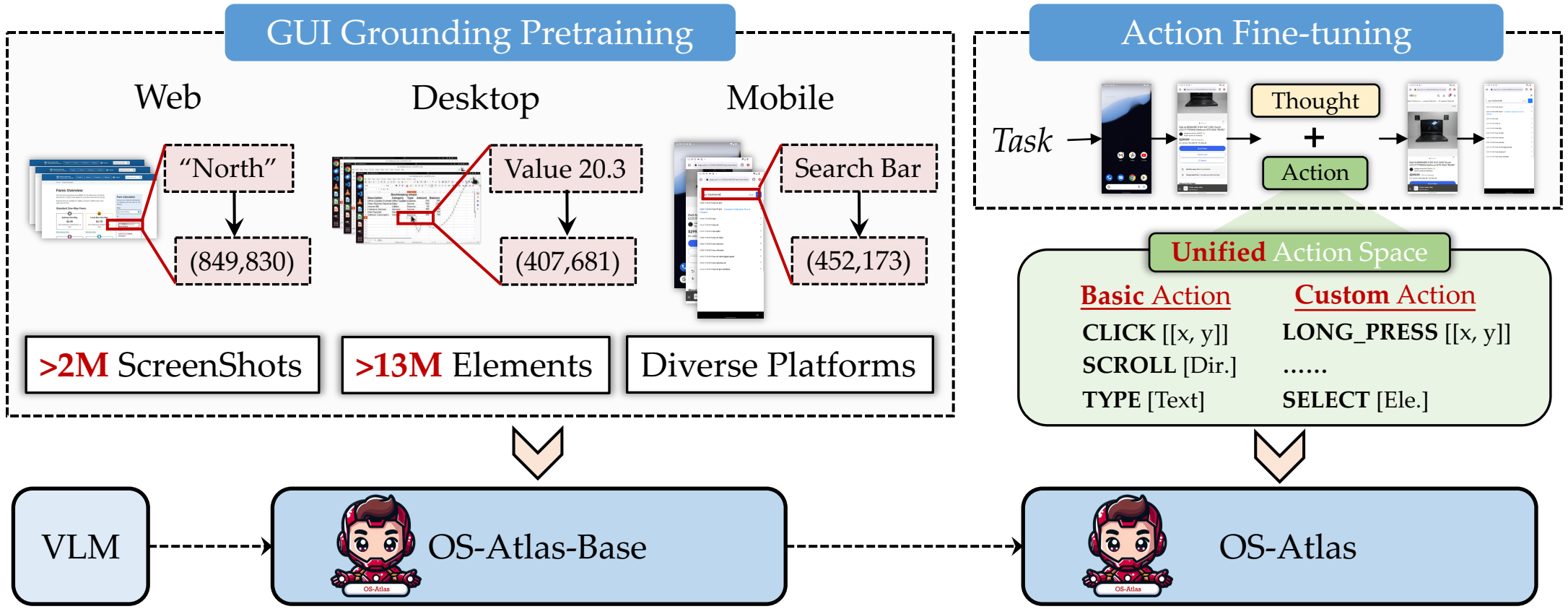
VLMs' Poor performance in GUI scenarios, because:

- Most existing VLMs are rarely pretrained on GUI screenshot images
- The heterogeneity of content and format in existing datasets

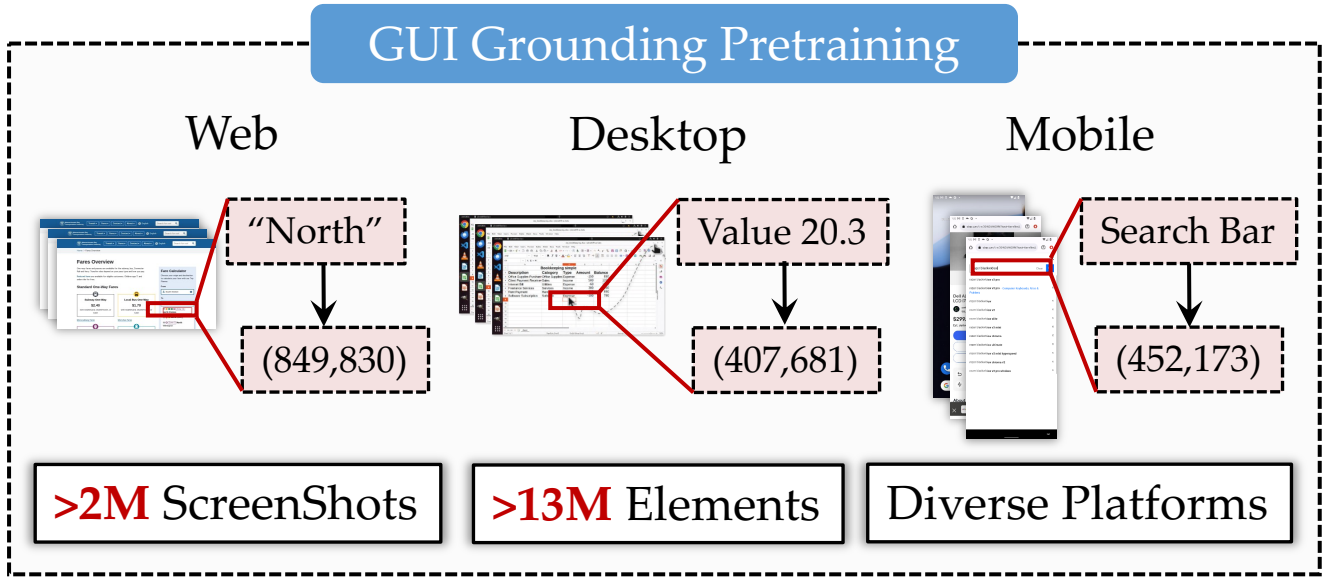


- Grounding Mode: Superior GUI Grounding and Plug-in with Planner
- Action Mode: Zero-shot Generalization on OOD tasks (Larger Action Space)
- Agent Mode: DIY your own agent

Two-Stage Training



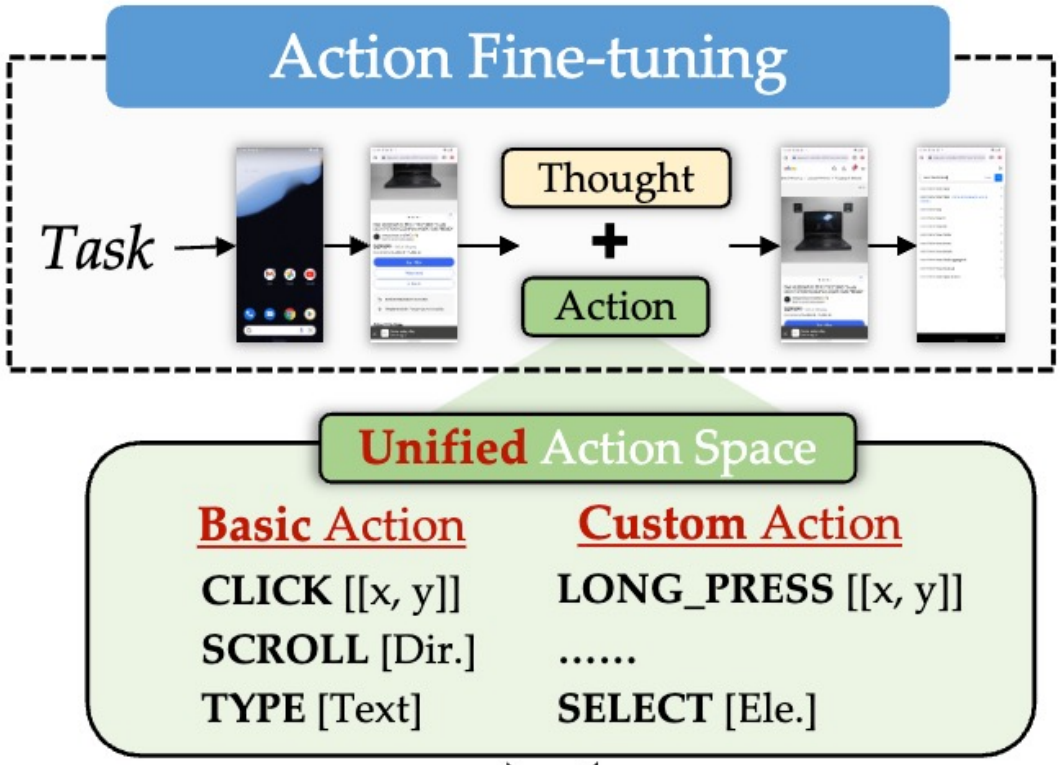
Infrastructure and Data Synthesis



Dataset	#Screenshots Web	Mobile	Desktop	Open Source	#Elements
SeeClick	270K	94K	-	✓	3.3M
Ferret-UI	-	124K	-	✗	<1M
GUICourse	73K	9K	-	✓	10.7M
CogAgent	400K	-	-	✗	70M
OS-Atlas	1.9M	285K	54K	✓	13.58M

- The first multi-platform GUI grounding data synthesis toolkit, including:
  - **Web -** Collected a large number of URLs from Common Crawl.
  - **Desktop -** Windows, Linux and MacOS (integrated with OSWorld and uses random walk to collect trajectories).
  - **Mobile -** Android (integrated with AndroidWorld).
- Training set comprises over 2.3 M distinct screenshots and more than 13 M GUI elements.

Action-Finetuning Stage



- OS-Atlas-Base → OS-Atlas
- Unified Action Space (Basic + Custom)
- Task-level Agent model

Experiments: GUI Grounding

Planner	Grounding Models	Mobile		Desktop		Web		Avg.
		Text	Icon/Widget	Text	Icon/Widget	Text	Icon/Widget	
-	Fuyu	41.00	1.30	33.00	3.60	33.90	4.40	19.50
	CogAgent	67.00	24.00	74.20	20.00	70.40	28.60	47.40
	SeeClick	78.00	52.00	72.20	30.00	55.70	32.50	53.40
	InternVL-2-4B	9.16	4.80	4.64	4.29	0.87	0.10	4.32
	Qwen2-VL-7B	61.34	39.29	52.01	44.98	33.04	21.84	42.89
	UGround-7B	82.80	60.30	82.50	63.60	80.40	70.40	73.30
	OS-Atlas-Base-4B	85.71	58.52	72.16	45.71	82.61	63.11	70.13
	OS-Atlas-Base-7B	**93.04**	**72.93**	**91.75**	**62.86**	**90.87**	**74.27**	**82.47**
GPT-4o	SeeClick	83.52	59.39	82.47	35.00	66.96	35.44	62.89
	UGround-7B	93.40	76.90	92.80	**67.90**	88.70	68.90	81.40
	OS-Atlas-Base-4B	**94.14**	73.80	77.84	47.14	86.52	65.53	76.81
	OS-Atlas-Base-7B	93.77	**79.91**	**90.21**	66.43	**92.61**	**79.13**	**85.14**

OS-Atlas-Base-7B achieves **SOTA** performance on ScreenSpot.

Experiments: Disentangled Planning and Action

Models	Successful Rate										Avg.
	OS	Calc	Impress	Writer	VLC	TB	Chrome	VSC	GIMP	WF	
GPT-4o + SoM	20.83	0.00	6.77	4.35	6.53	0.00	4.35	4.35	0.00	3.60	4.59
GPT-4o	8.33	0.00	6.77	4.35	16.10	0.00	4.35	4.35	3.85	5.58	5.03
+ SeeClick	16.67	0.00	12.76	4.35	23.52	6.67	10.86	8.70	11.54	7.92	9.21
+ OS-Atlas-Base-4B	20.83	2.23	14.89	8.70	23.52	13.33	15.22	13.04	15.38	7.92	11.65
+ OS-Atlas-Base-7B	25.00	4.26	17.02	8.70	29.41	26.67	19.57	17.39	19.23	8.91	14.63
Human	75.00	61.70	80.85	73.91	70.59	46.67	78.26	73.91	73.08	73.27	72.36

- GPT-4o: 5% on OSWorld
- GPT-4o + OS-Atlas: 14.6%

Insight: next bottleneck ? => complex reasoning and planning.

Experiments: Zero-shot and SFT

Web and Desktop

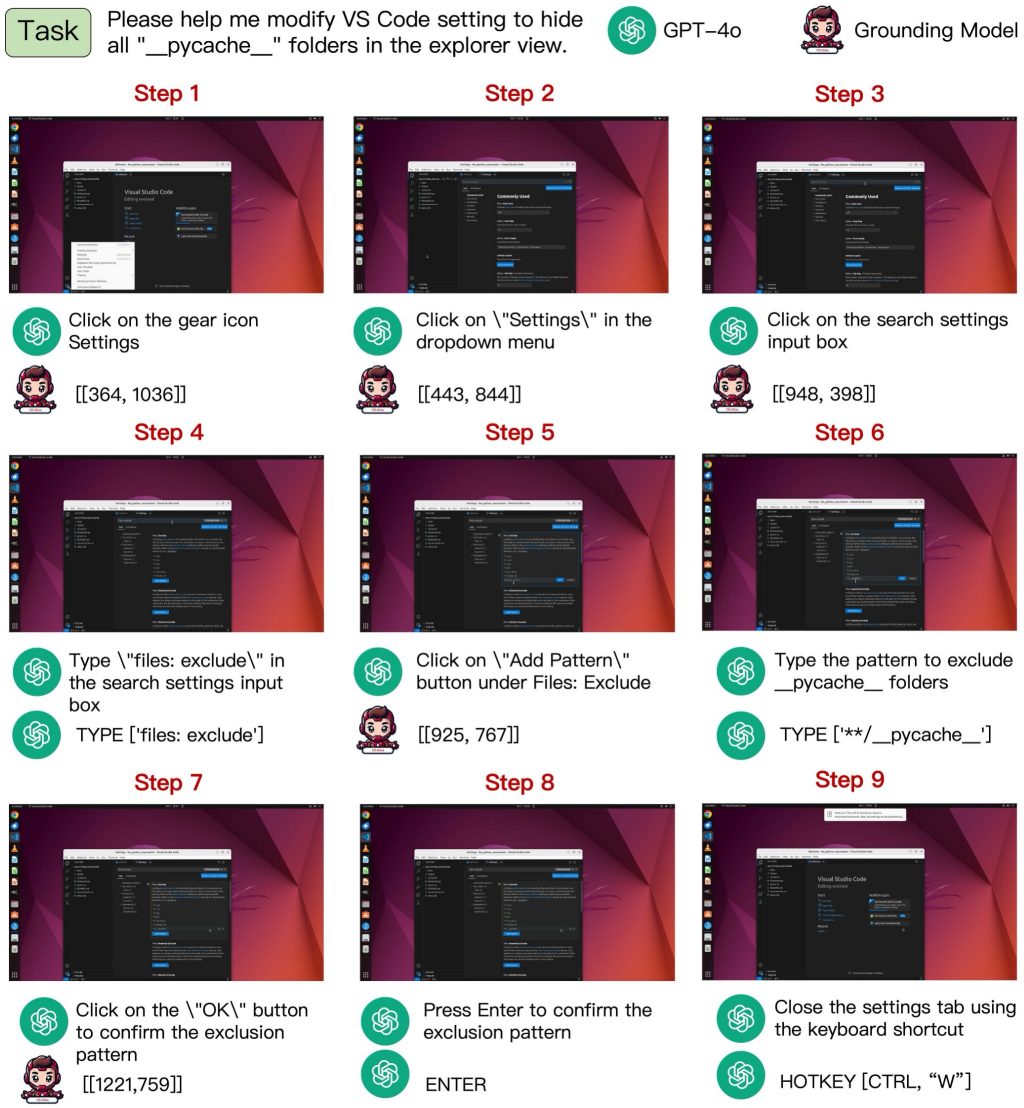
Models	GUI-Act-Web			OmniAct-Web			OmniAct-Desktop		
	Type	Grounding	SR	Type	Grounding	SR	Type	Grounding	SR
Zero-shot OOD Setting									
GPT-4o	77.09	45.02	41.84	79.33	42.79	34.06	79.97	63.25	50.67
OS-Atlas-4B	79.22	58.57	42.62	46.74	49.24	22.99	63.30	42.55	26.94
OS-Atlas-7B	**86.95**	**75.61**	**57.02**	**85.63**	**69.35**	**59.15**	**90.24**	**62.87**	**56.73**
Supervised Fine-tuning Setting									
InternVL-2-4B	81.42	47.03	36.17	47.51	51.34	24.39	67.00	44.47	29.80
Qwen2-VL-7B	89.36	90.66	82.27	89.22	85.94	78.58	96.27	94.52	91.77
SeeClick	88.79	78.59	72.34	86.98	75.48	68.59	96.79	70.22	72.69
OS-Atlas-4B	**89.36**	89.16	81.06	88.56	82.00	73.91	96.51	85.53	84.78
OS-Atlas-7B	89.08	**91.60**	**82.70**	**97.15**	**95.41**	**93.56**	**97.15**	**95.85**	**94.05**

Mobile

Models	AndroidControl-Low			AndroidControl-High			GUI-Odyssey		
	Type	Grounding	SR	Type	Grounding	SR	Type	Grounding	SR
Zero-shot OOD Setting									
GPT-4o	**74.33**	38.67	28.39	**63.06**	30.90	21.17	37.50	14.17	5.36
OS-Atlas-4B	64.58	71.19	40.62	49.01	49.51	22.77	49.63	34.63	20.25
OS-Atlas-7B	73.00	**73.37**	**50.94**	57.44	**54.90**	**29.83**	**60.42**	**39.74**	**26.96**
Supervised Fine-tuning Setting									
InternVL-2-4B	90.94	84.05	80.10	84.09	72.73	66.72	82.13	55.53	51.45
Qwen2-VL-7B	91.94	86.50	82.56	83.83	77.68	69.72	83.54	65.89	60.23
SeeClick	93.00	73.42	75.00	82.94	62.87	59.11	70.99	52.44	53.92
OS-Atlas-4B	91.92	83.76	80.64	84.69	73.79	67.54	83.47	61.37	56.39
OS-Atlas-7B	**93.61**	**87.97**	**85.22**	**85.22**	**78.48**	**71.17**	**84.47**	**67.80**	**61.98**

- OS-Atlas achieved SOTA performance across 3 different platforms, 6 distinct datasets, and 2 evaluation settings (Zero-shot OOD and SFT).
- Huge superiority over GPT-4o under zero-shot OOD setting.

More Cases about GUI Tasks



- OS-World
- Planner: GPT-4o
- Action Model: OS-Atlas (7B)

More Demos ?

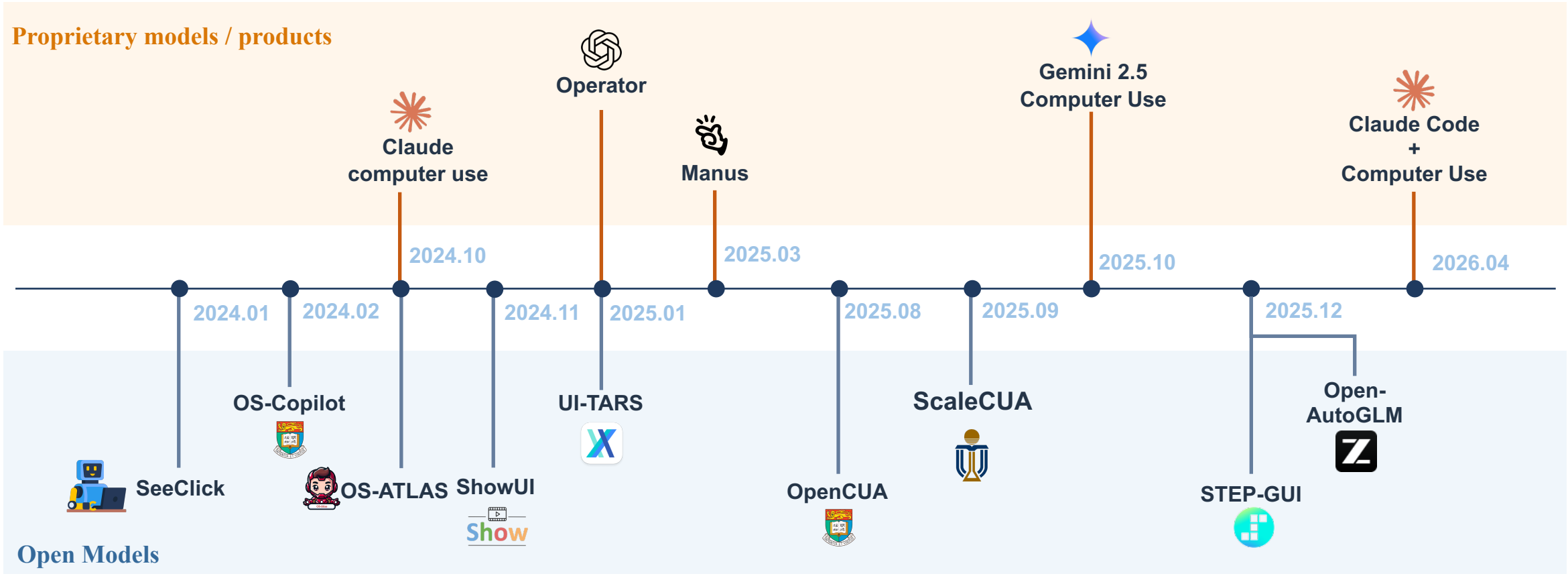
Please check out our homepage !

- https://osatlas.github.io/

中文解读（OS-ATLAS）

Development

Computer-use agents evolved along two tracks: open models landed earlier, while proprietary systems accelerated quickly after 2025.



Closed-source entries use official launch / preview months. Open entries use the first public paper or repo month. The figure shows only a subset of the work published after 2024.

Next

But all of them, need a strong agentic backbone that can plan and act.

Now, we already have strong action / foundation models that map instructions to actions.

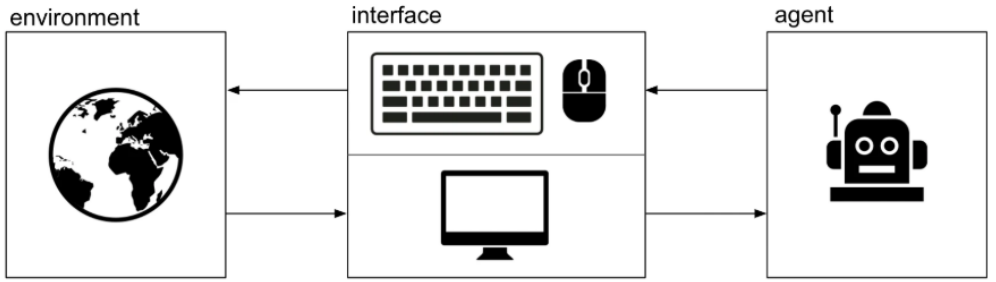
Now, we aim to empower agents with complete **Perception–Decision–Execution** capabilities.

Build Computer-using Agents

Quite promising to achieve digital automation in one model.

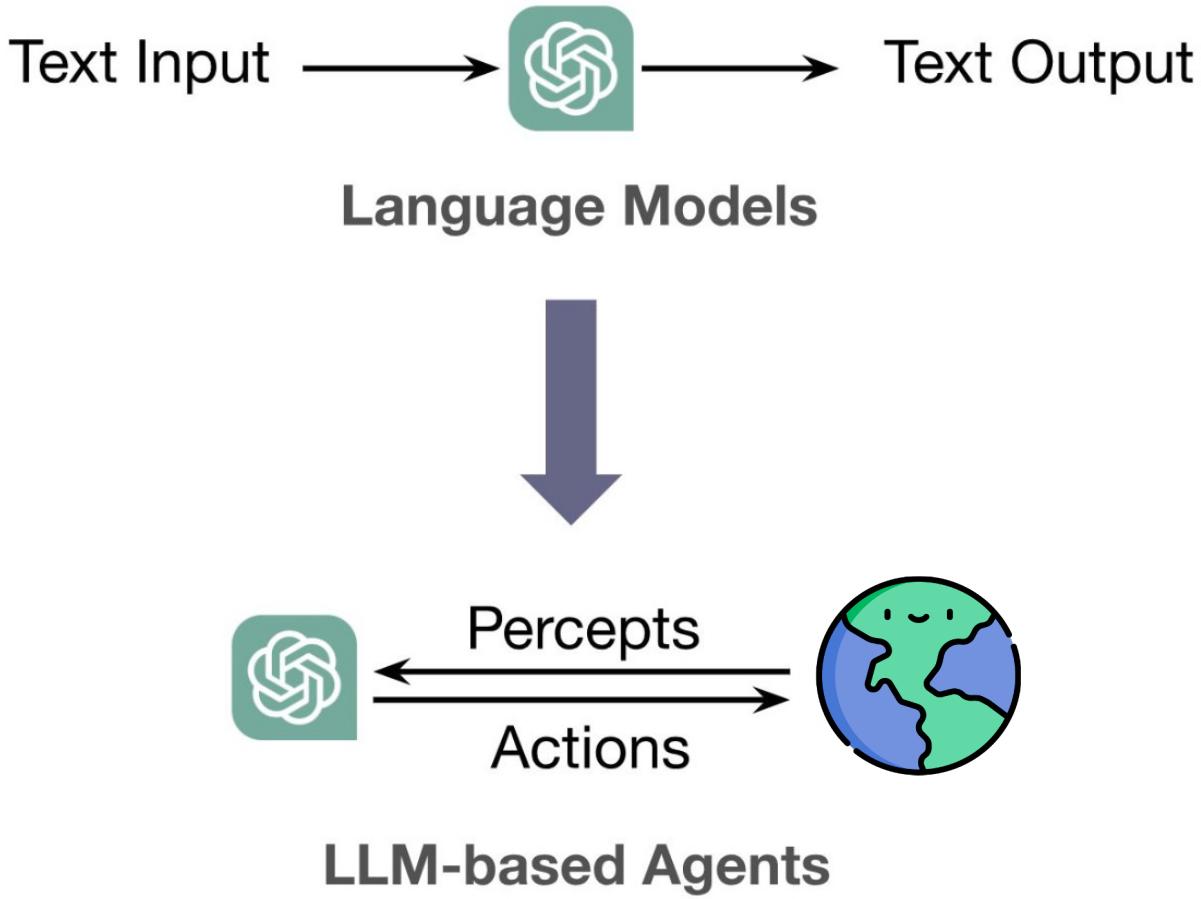
Can we transform a (V)LM into such GUI agents?

1. Perceive
2. Planning
3. Action



Of course! But it is a non-trivial job!

Recap: Language Agents



But this is not enough for Computer-using / GUI Agents.

Computer-using Agents

Agents are promising, but building powerful agents is challenging.

1. Agents need to follow human instructions. 
2. Agents need to perform planning and action. 
3. Agents need to perceive envs.  and the applications they are interacting with.

Best Way to build Computer-using Agents

Behavioral Cloning / Imitation Learning.

Sounds good, but where is our data?

Data Problems

Human annotation for GUI data is much more expensive than you think 

Not to mention scenario/domain - specific data.

How about having the machine collect data?

1. Pre-defined tasks are required, but they may not align with the environment.
2. Limited diversity and a poor success rate.


OS-Genesis: Automating GUI Agent Trajectory Construction via Reverse Task Synthesis , ACL 2025


Breaking the Data Barrier -- Building GUI Agents Through Task Generalization, COLM 2025


OpenMobile: Building Open Mobile Agents with Task and Trajectory Synthesis

Data Scarcity

So, our goals are as follows:

1. Eliminate human involvement.
2. Obtain high-quality Trajectory data.
3. Diversity and Scalability.

OS-Genesis: Automating GUI Agent Trajectory Construction via Reverse Task Synthesis

ACL 2025 VIENNA

Qiushi Sun*, Kanzhi Cheng*, Zichen Ding*, Chuanyang Jin*, Yian Wang
Fangzhi Xu, Zhenyu Wu, Liheng Chen, Chengyou Jia, Zhoumianze Liu
Ben Kao, Guohao Li, Junxian He, Yu Qiao, Zhiyong Wu

上海人工智能实验室
Shanghai Artificial Intelligence Laboratory

GUI Trajectory Data

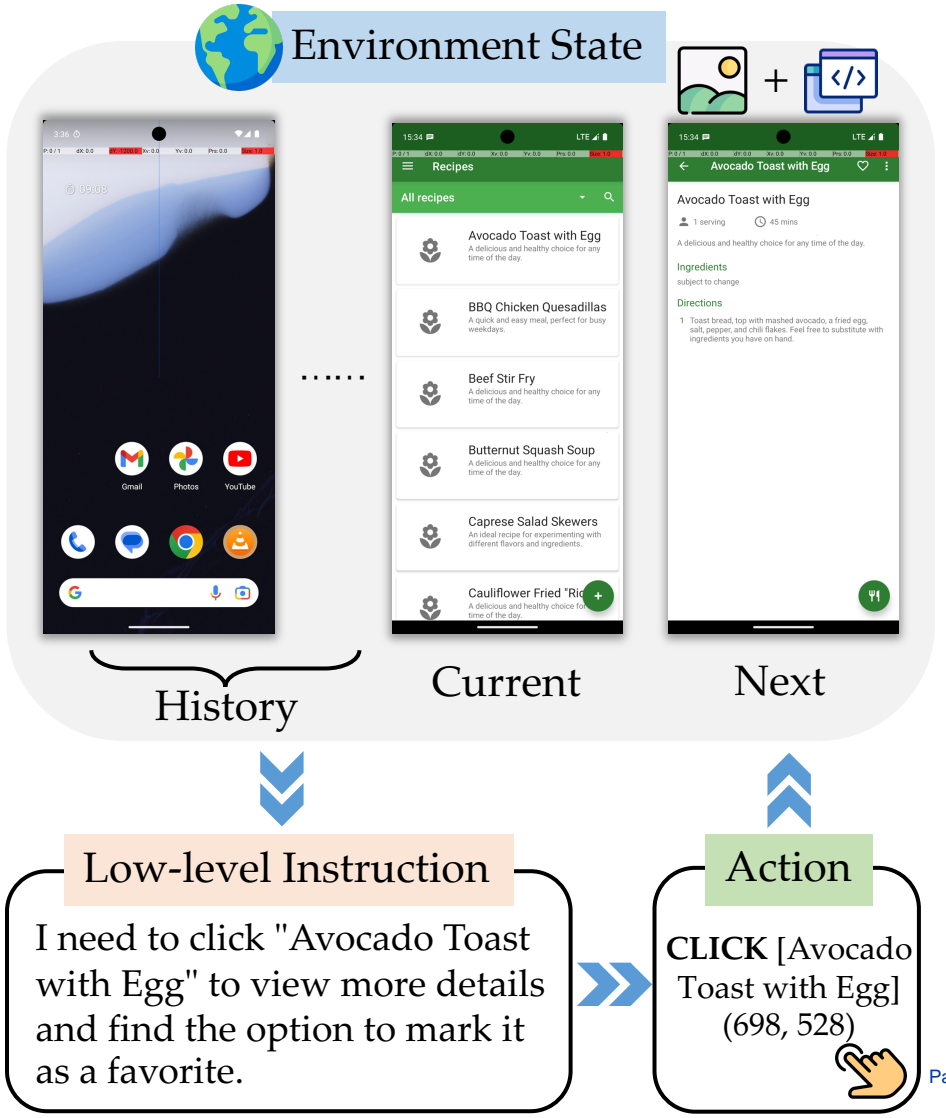
The best data format for GUI agents

1. A high-level instruction that defines the overall goal the agent aims to accomplish

2. A series of low-level instructions that each describe specific steps required

3. Actions (e.g., `CLICK`, `TYPE`)

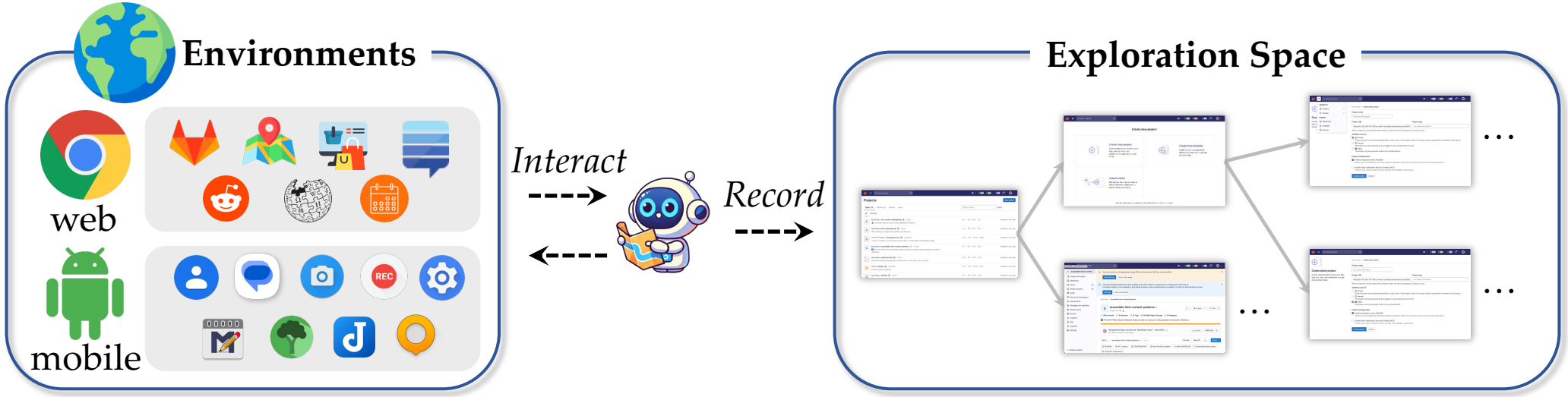
4. States, which include visual representations like screenshots and textual representations such as a11ytree



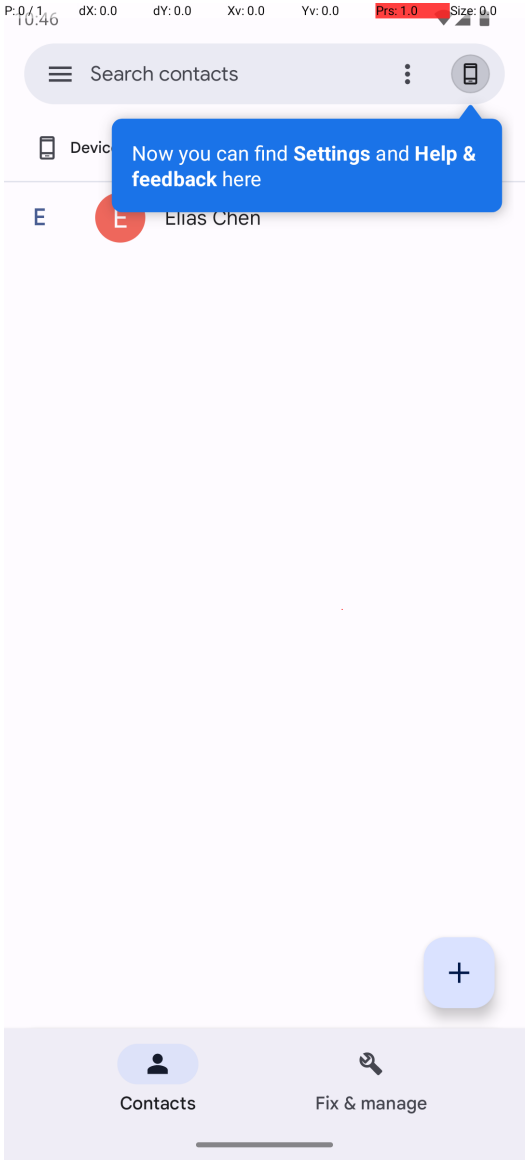
Reverse Task Synthesis

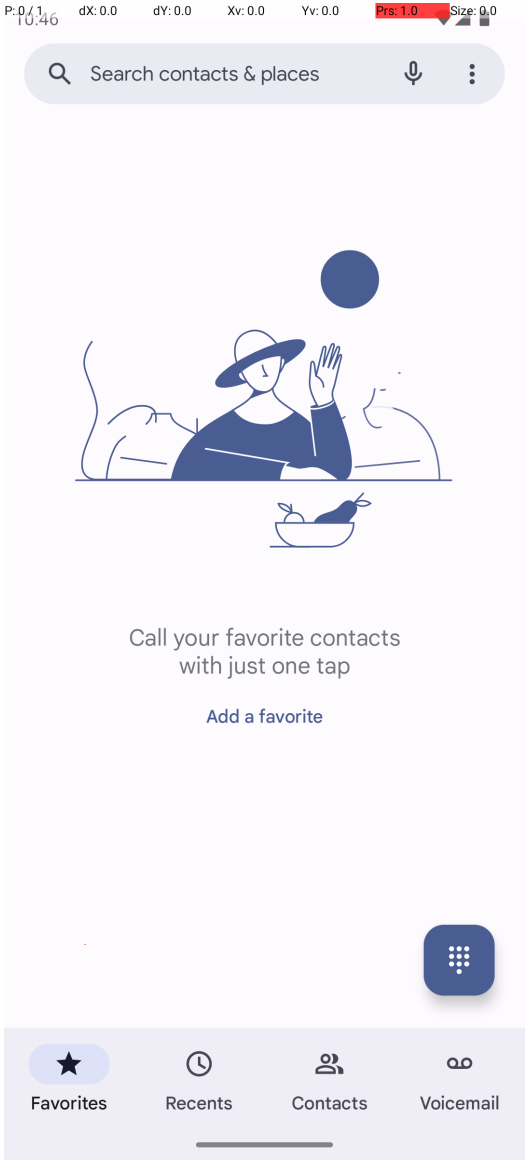
Interaction-Driven Functional Discovery is a rule-based process that explores dynamic GUI environments by interacting with UI elements. It uncovers functionalities through interaction triples

We collect: <Screen1, action, Screen2>



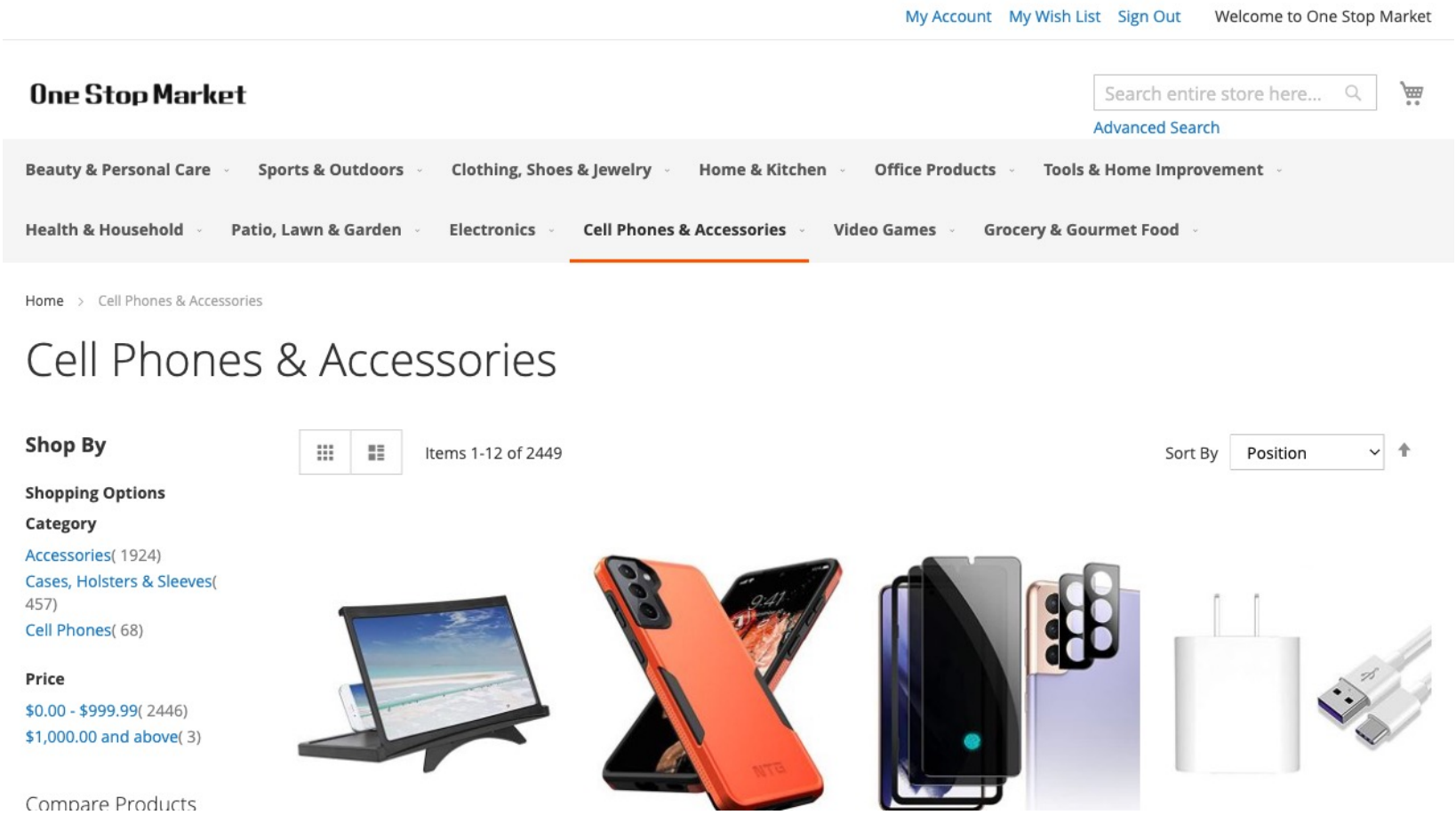
Dynamic Environments





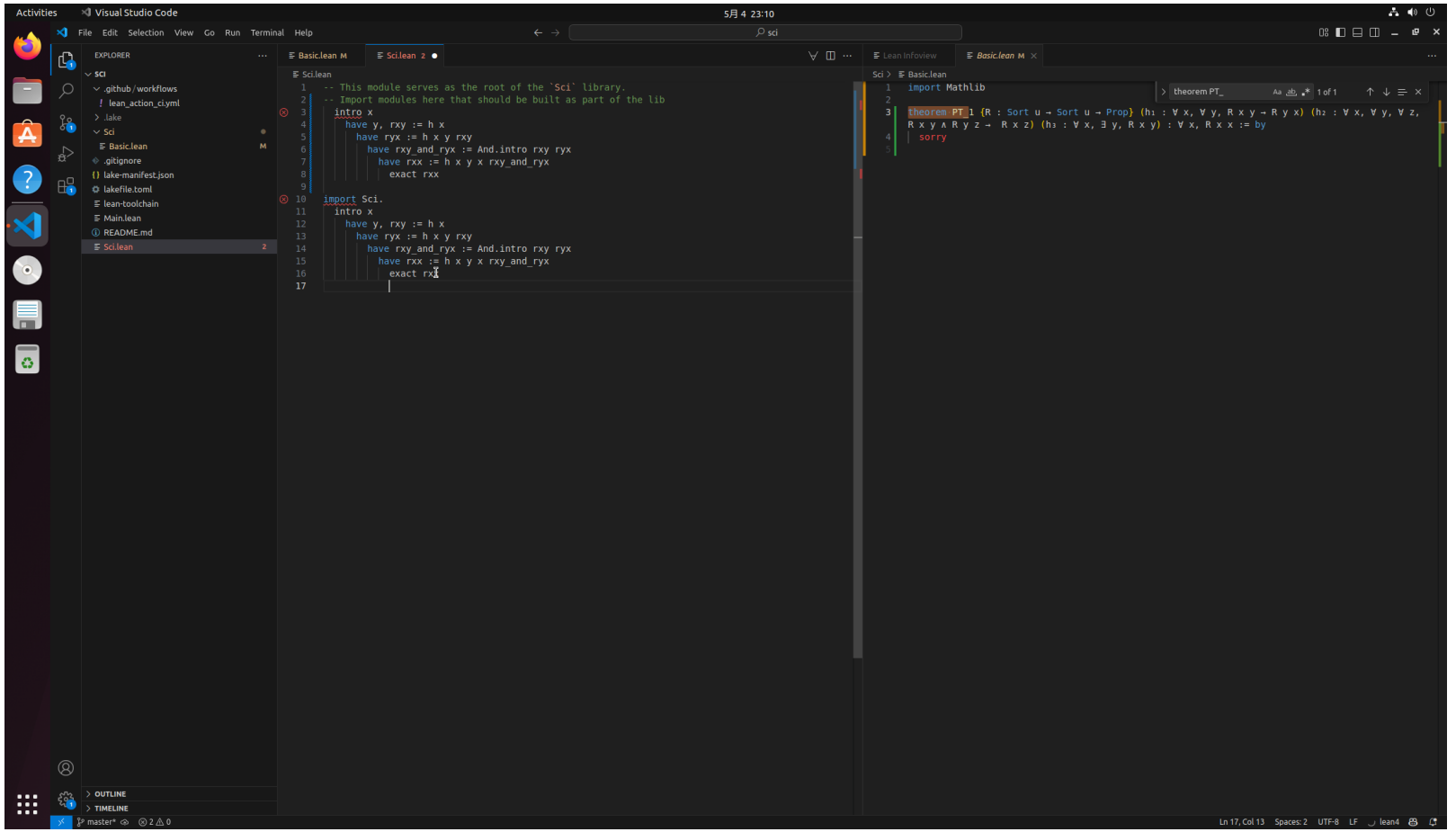
[11] AndroidWorld: A Dynamic Benchmarking Environment for Autonomous Agents, ICLR 2025

Dynamic Environments



[12] WebArena: A Realistic Web Environment for Building Autonomous Agents, ICLR 2024

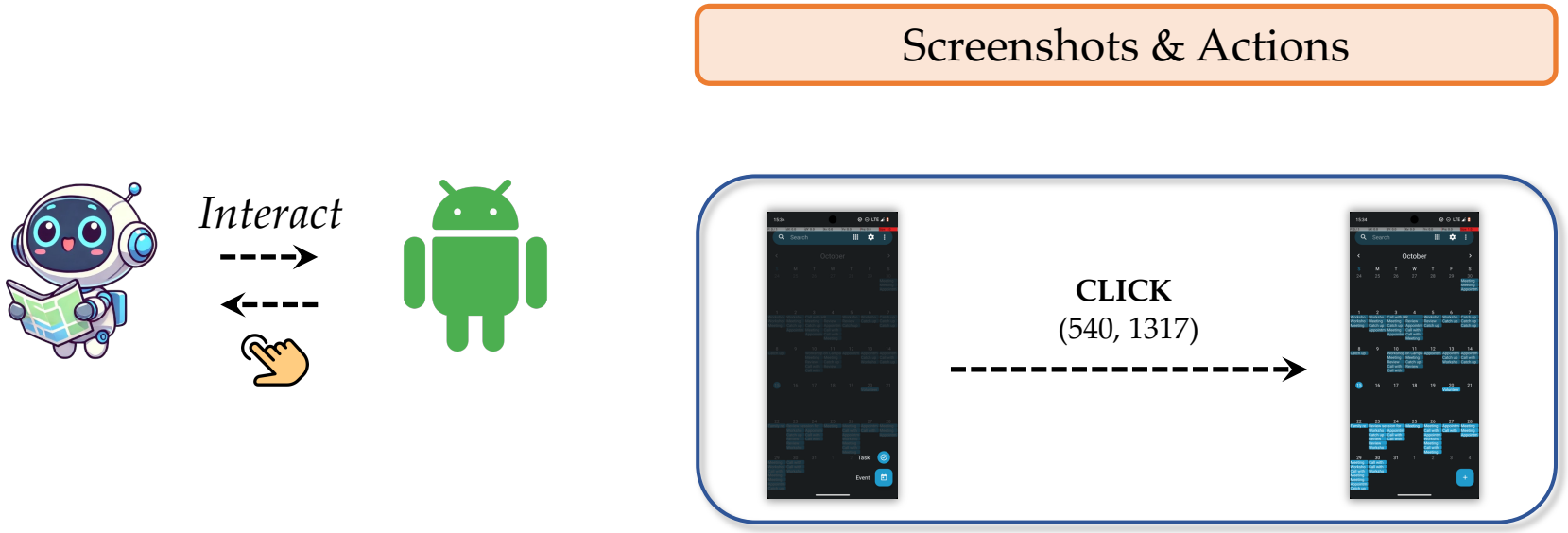
Dynamic Environments



[6] ScienceBoard: Evaluating Multimodal Autonomous Agents in Realistic Scientific Workflows

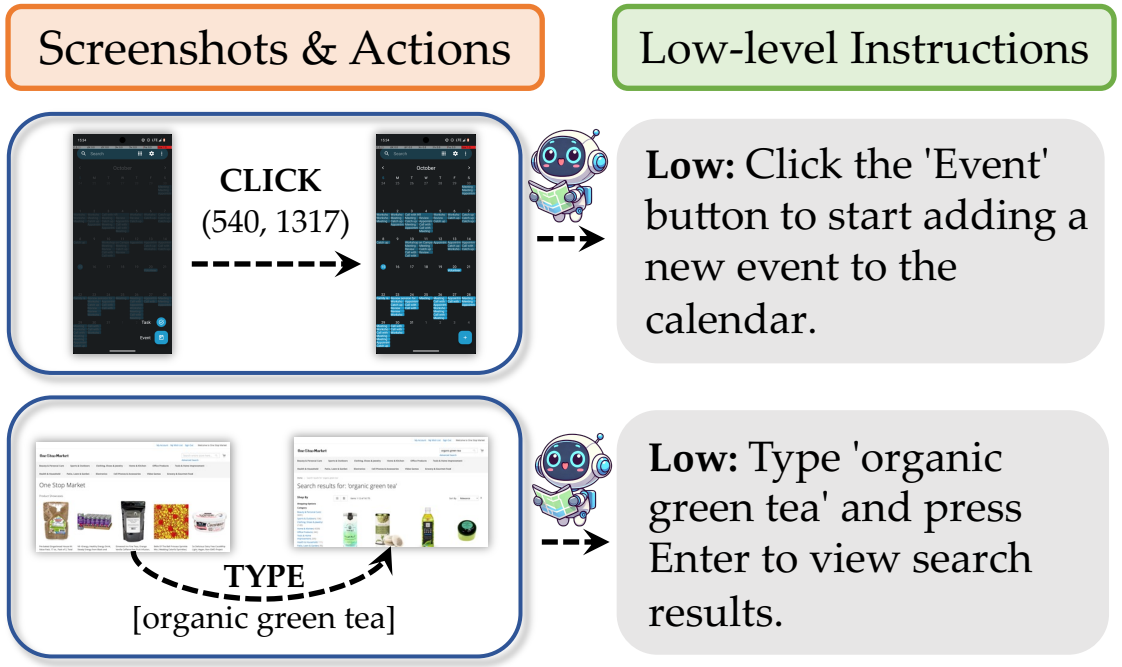
Reverse Task Synthesis

Retroactively interpreting changes in the GUI environment caused by actions.



Reverse Task Synthesis

Retroactively interpreting changes in the GUI environment caused by actions, this process generates executable low-level instructions



The data we synthesized:

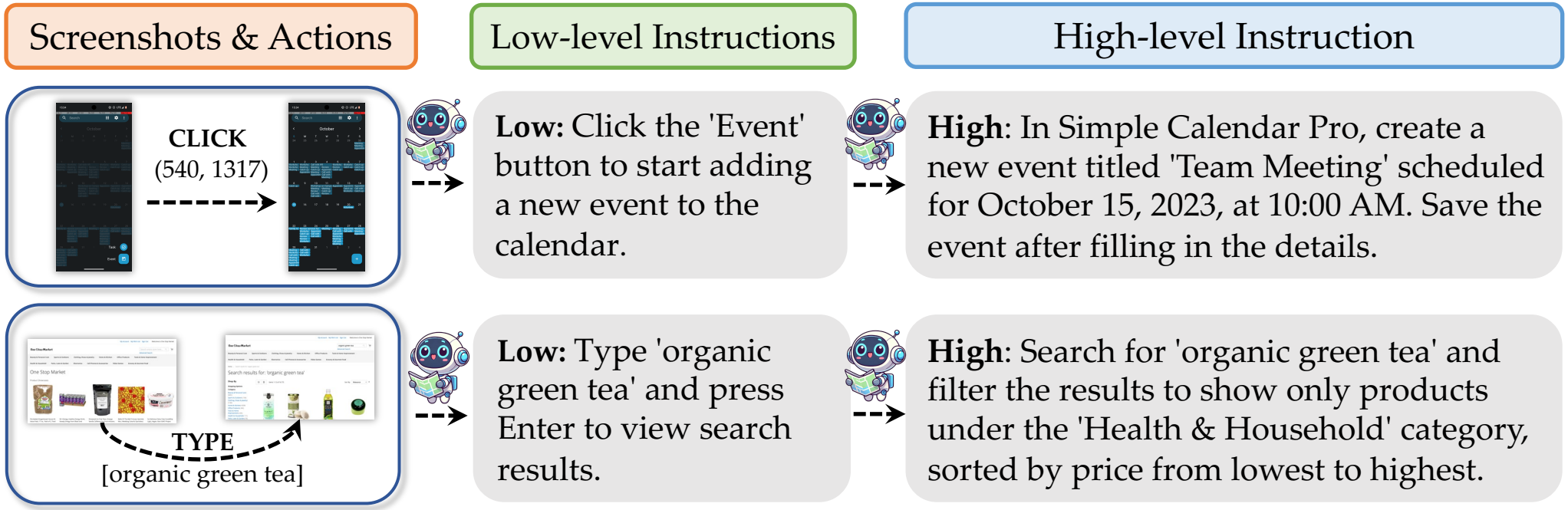
1. Grounded

2. Actionable

Grounded: tasks that are contextually valid and can be reasonably executed within the environment.

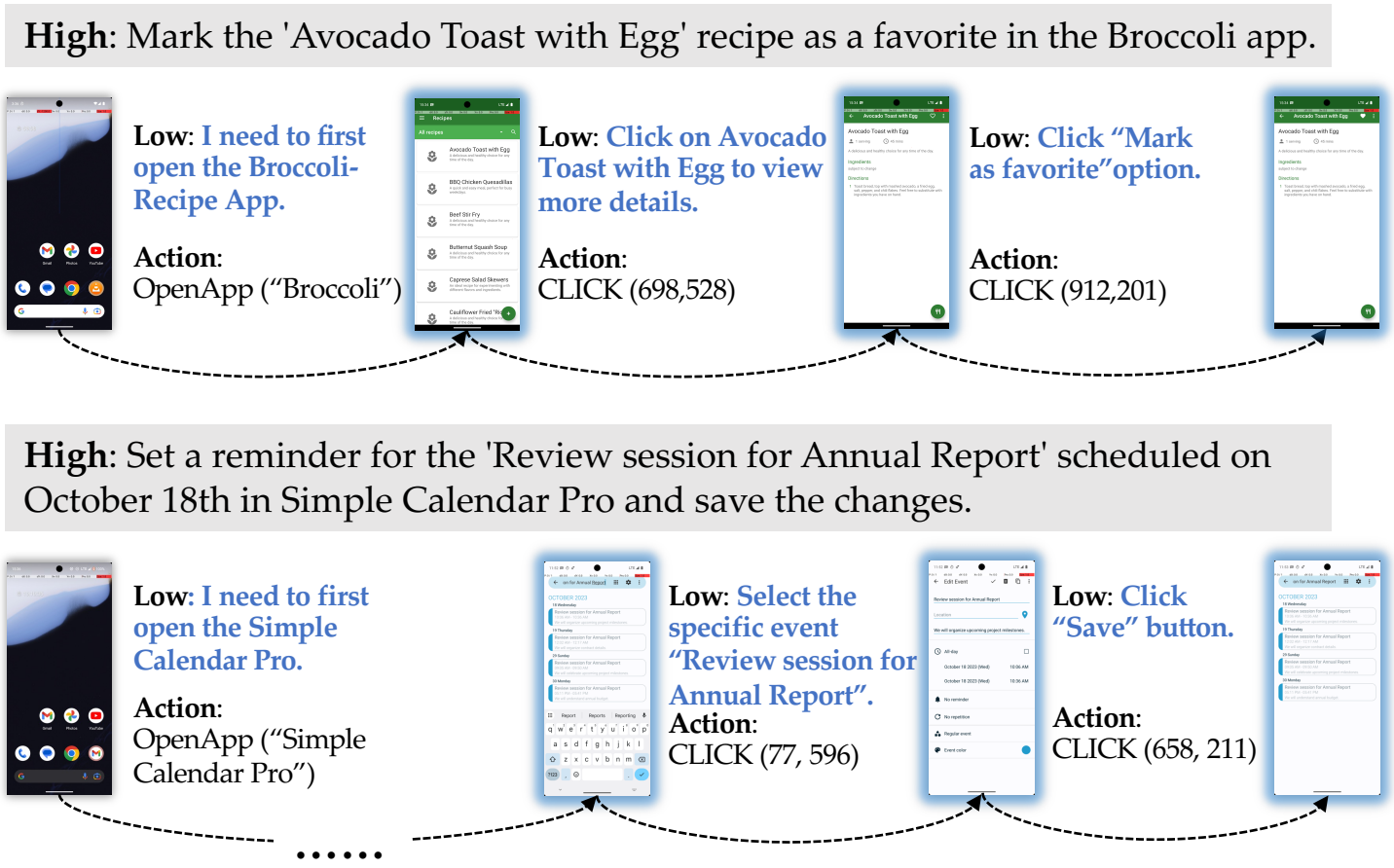
Reverse Task Synthesis

Retroactively interpreting changes in the GUI environment caused by actions, this process generates executable low-level instructions, which are then transformed into broader, goal-oriented high-level tasks



Reverse Task Synthesis

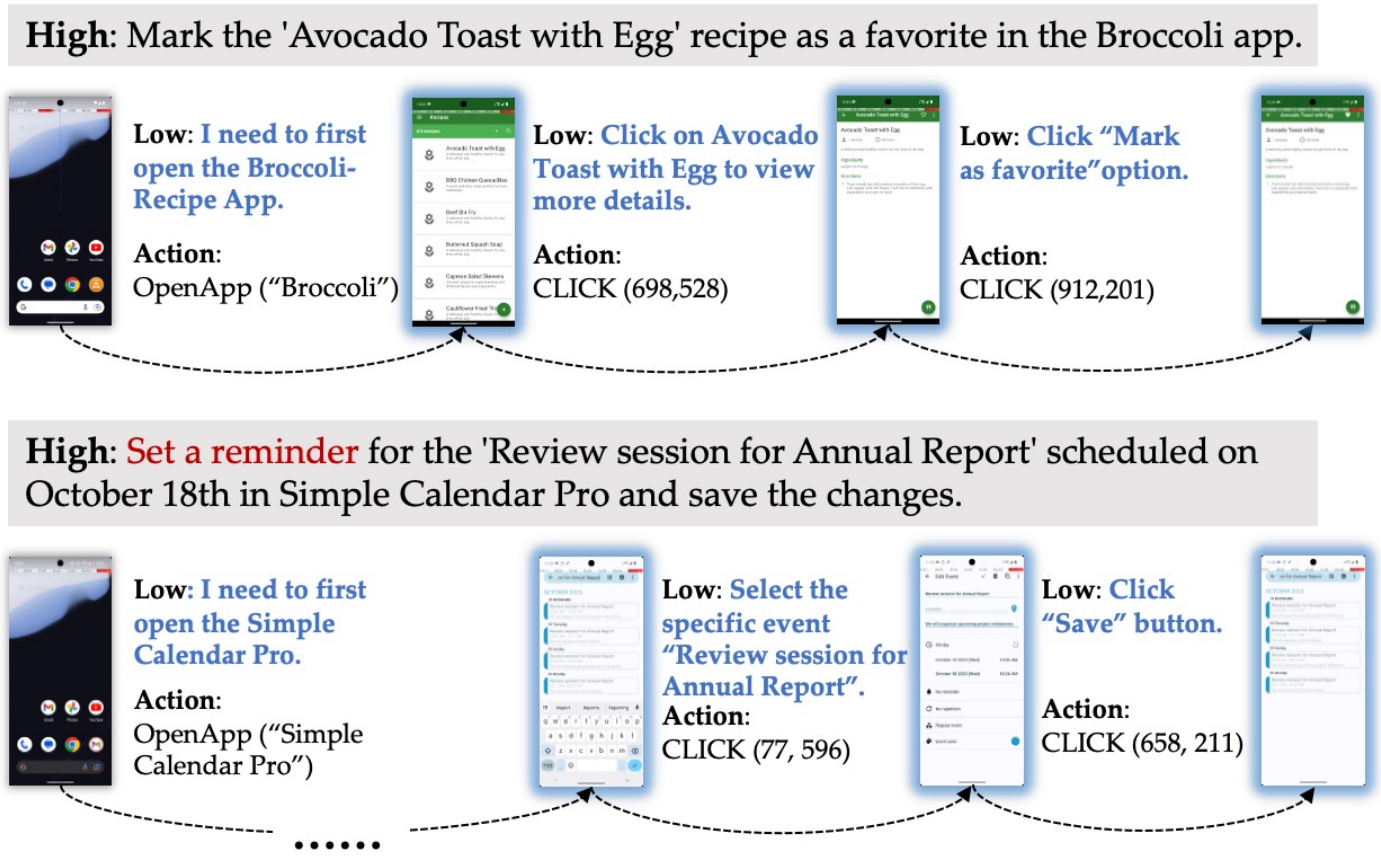
After reverse task synthesis generates task instructions, they are automatically executed in the GUI environment to build complete trajectories.

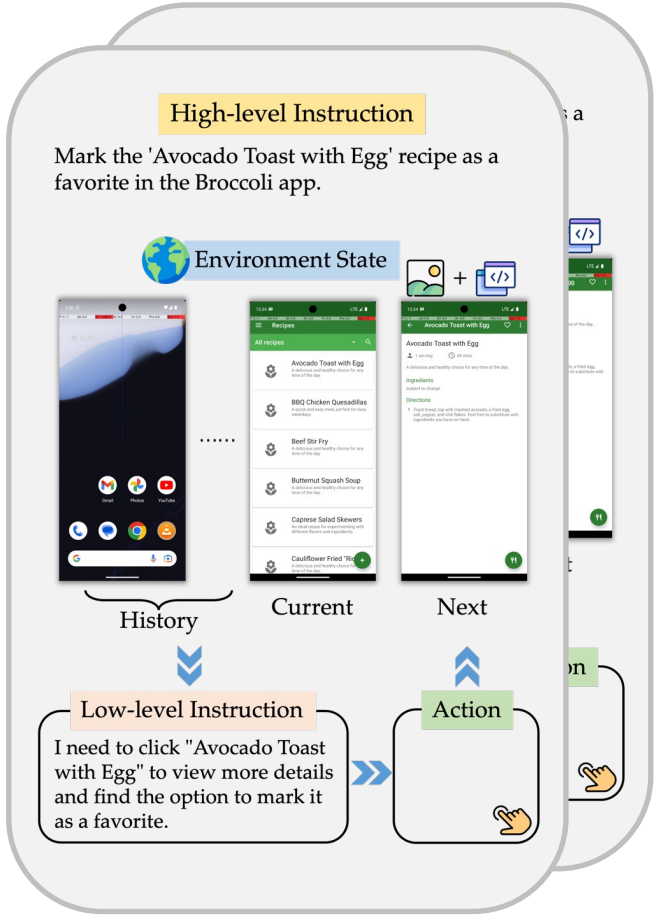


Reverse Task Synthesis

Trajectories collected! But is this all?

Let's consider data quality and synthesis efficiency.





Data Quality Control

Tasks are executed by machines, not all of them are successful.

Previous approach:

1. Training all data at once - what about the quality?

2. Discarding all incomplete Trajectories - what about the efficiency?

Thus, we introduce a Trajectory Reward Model to handle this.

Reward Modeling

We introduce a Trajectory Reward Model for weighted sampling in training.

Models

Data Synthesis

GPT-4o

Qwen-VL Qwen2-VL-72B-Instruct

Backbones

InternVL InternVL2-4B / 8B

Qwen-VL Qwen2-VL-7B-Instruct

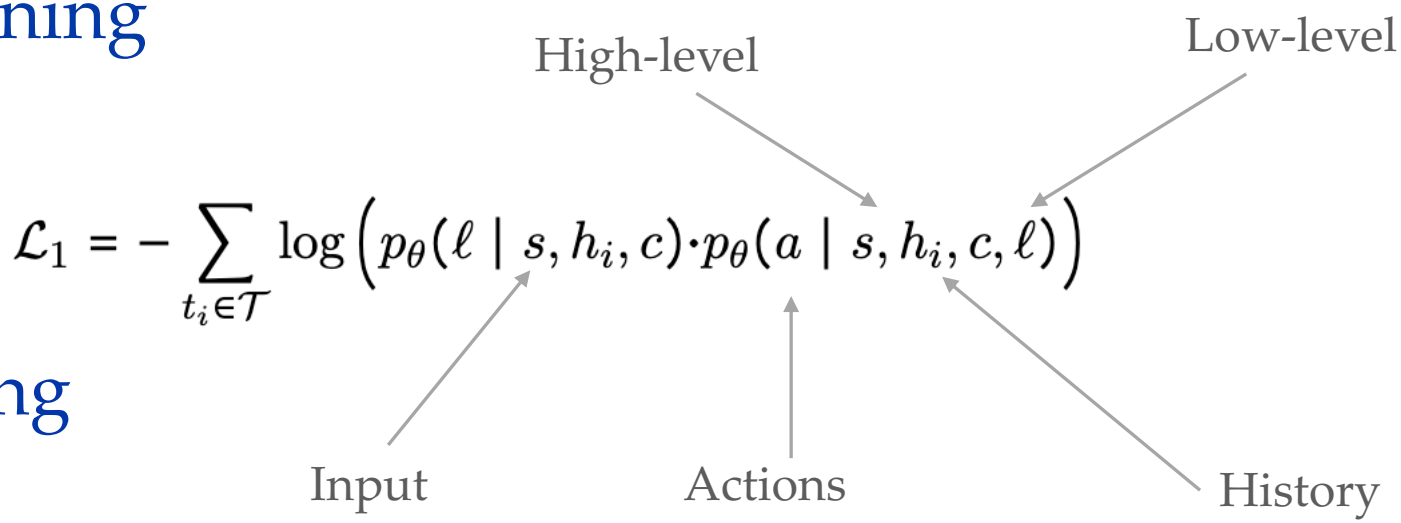
[13] Qwen2.5-VL Technical Report

[14] Expanding Performance Boundaries of Open-Source Multimodal Models with Model, Data, and Test-Time Scaling

Training Strategies

Leverage trajectory characteristics to train GUI agents with complete capabilities

1. Planning Training



2. Action Training

$$\mathcal{L}_2 = -\sum_{t_i \in \mathcal{T}} \log p_\theta(a \mid s, c, \ell)$$

Training Strategies

After Training, our agents will generate ReACT-Style output

Examples:

Step 1: To create a new folder in Markor, I need to first open the Markor app.

action: `{"action_type":"open_app", "app_name":"Markor"}`

Step 2: To create a new folder, I need to click on the "Create a new file or folder" button, which is indicated by the plus icon.

action: `{"action_type":"click","x":964.5,"y":2074.5}`

Step 3: I need to change the folder name to folder_20241224. The current text field for the folder name is visible and editable.

action:
`{"action_type":"type","text":"folder_20241224","x":373.5,"y":552.0}`

[15] ReAct: Synergizing Reasoning and Acting in Language Models, ICLR 2023

Baselines

We adapt / build the following forward baselines

- **Zero-Shot.** Advanced prompting-based agents, such as M3A.

- **Task-Driven.** GUI Trajectories synthesized using pre-defined tasks. Given initial screenshots of the app/web page and task examples, use GPT-4 to generate high-level instructions and collect data.

- **Self-Instruct.** Builds on Task-Driven by adding self-instructed tasks.

Setting: Screenshot + A11ytree

[16] Self-Instruct: Aligning Language Models with Self-Generated Instructions, ACL 2023

Experiments: Mobile

Base Model	Strategies	AndroidWorld	AndroidControl-High		AndroidControl-Low	
			SR	Type	SR	Type
GPT-4o	Zero-Shot (M3A)	23.70	53.04	69.14	69.59	80.27
InternVL2-4B	Zero-Shot	0.00	16.62	39.96	33.69	60.65
	Task-Driven	4.02	27.37	47.08	66.48	90.37
	Task-Driven w. Self Instruct	7.14	24.95	44.27	66.70	90.79
	OS-Genesis	**15.18**	**33.39**	**56.20**	**73.38**	**91.32**
InternVL2-8B	Zero-Shot	2.23	17.89	38.22	47.69	66.67
	Task-Driven	4.46	23.79	43.94	64.43	89.83
	Task-Driven w. Self Instruct	5.36	23.43	44.43	64.69	89.85
	OS-Genesis	**16.96**	**35.77**	**64.57**	**71.37**	**91.27**
Qwen2-VL-7B	Zero-Shot	0.89	28.92	61.39	46.37	72.78
	Task-Driven	6.25	38.84	58.08	71.33	88.71
	Task-Driven w. Self Instruct	9.82	39.36	58.28	71.57	89.73
	OS-Genesis	**17.41**	**44.54**	**66.15**	**74.17**	**90.72**

Table 1: Performance on AndroidWorld and AndroidControl benchmarks.

Findings: OS-Genesis + Opensource VLM > Propriety Models + Complex Prompting

Experiments: Web

Base Model	Strategies	Shopping	CMS	Reddit	Gitlab	Maps	Overall
GPT-4o	Zero-Shot	14.28	21.05	6.25	14.29	20.00	16.25
InternVL2-4B	Zero-Shot	0.00	0.00	0.00	0.00	0.00	0.00
	Task-Driven	5.36	1.76	0.00	**9.52**	5.00	4.98
	Task-Driven w. Self Instruct	5.36	3.51	0.00	**9.52**	7.50	5.81
	OS-Genesis	**10.71**	**7.02**	**3.13**	7.94	**7.50**	**7.88**
InternVL2-8B	Zero-Shot	0.00	0.00	0.00	0.00	0.00	0.00
	Task-Driven	3.57	7.02	0.00	6.35	2.50	4.56
	Task-Driven w. Self Instruct	**8.93**	10.53	6.25	**7.94**	0.00	7.05
	OS-Genesis	7.14	**15.79**	**9.34**	6.35	**10.00**	**9.96**
Qwen2-VL-7B	Zero-Shot	**12.50**	7.02	6.25	6.35	5.00	7.47
	Task-Driven	8.93	7.02	6.25	6.35	5.00	7.05
	Task-Driven w. Self Instruct	8.93	1.76	3.13	4.84	**7.50**	5.39
	OS-Genesis	7.14	**8.77**	**15.63**	**15.87**	5.00	**10.79**

Table 2: Performance on WebArena benchmarks.

Analysis

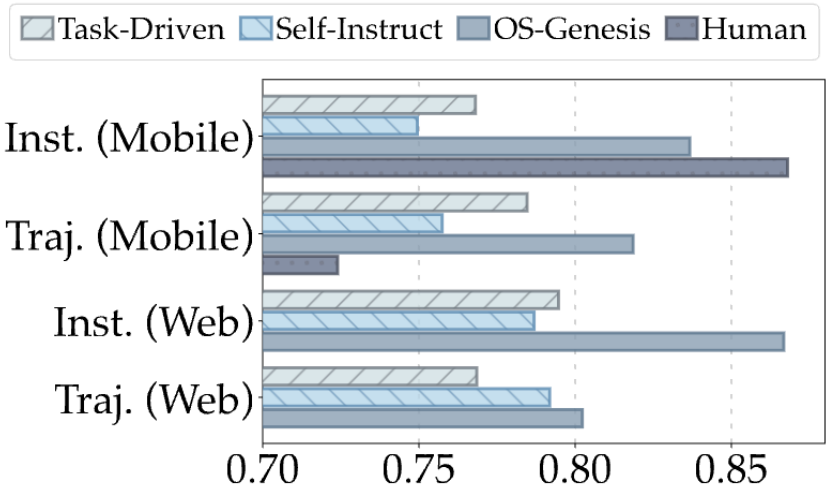
How Far are we from Human Data?

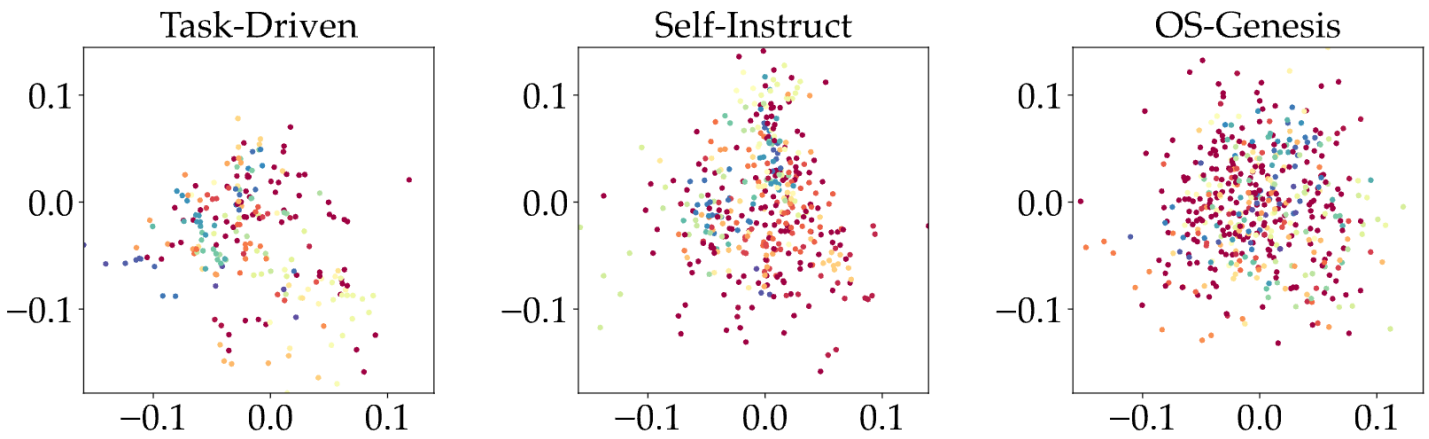
Then, OS-Genesis v.s. Human-annotated Trajectories.

Insight: OS-Genesis achieves ~80% of human data's effectiveness.

Analysis

How about our data diversity?





Insight: Significantly better than Forward methods and approaches the human level.

Checkpoints & Data Access

Available on HuggingFace

OS-Genesis: Automating GUI Agent Trajectory Construction via Reverse Task Synthesis

Published on Dec 28, 2024 · Submitted by QiushiSun on Jan 2 #1 Paper of the day

Authors: Qiushi Sun, Kanzhi Cheng, Zichen Ding, Chuanyang Jin, Yian Wang, Fangzhi Xu, Zhenyu Wu, Chengyou Jia, Liheng Chen, Zhoumianze Liu, Ben Kao, Guohao Li, Junxian He, Yu Qiao, Zhiyong Wu

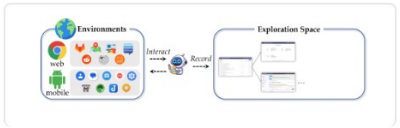
Abstract

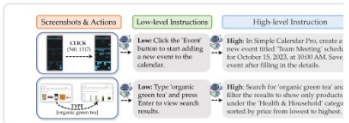
OS-Genesis is a novel GUI data synthesis pipeline that enhances the training of GUI agents by reversing the trajectory collection process to improve data quality and diversity.

AI-generated summary

Graphical User Interface (GUI) agents powered by Vision-Language Models (VLMs) have demonstrated human-like computer control capability. Despite their utility in advancing digital automation, a critical bottleneck persists: collecting high-quality trajectory data for training. Common practices for collecting such data rely on human supervision or synthetic data generation through executing pre-defined tasks, which are either resource-intensive or unable to guarantee data quality. Moreover, these methods suffer from limited data diversity and significant gaps between synthetic data and real-world environments. To address these challenges, we propose OS-Genesis, a novel GUI data synthesis pipeline that reverses the conventional trajectory collection process. Instead of relying on pre-defined tasks, OS-Genesis enables agents first to perceive environments and perform step-wise interactions, then retrospectively derive high-quality tasks to enable trajectory-level exploration. A trajectory reward model is then employed to ensure the quality of the generated trajectories. We demonstrate that training GUI agents with OS-Genesis significantly improves their performance on highly challenging online benchmarks. In-depth analysis further validates OS-Genesis's efficiency and its superior data quality and diversity compared to existing synthesis methods. Our codes, data, and checkpoints are available at https://qiushisun.github.io/OS-Genesis-Home/{OS-Genesis Homepage}.

View arXiv page · View PDF · Project page · GitHub 146 · Add to collection





Community

QiushiSun Paper author Paper submitter Jan 2

This paper introduces OS-Genesis, an interaction-driven pipeline for synthesizing high-quality and diverse GUI agent trajectory data without human supervision or predefined tasks. By leveraging reverse task synthesis and a trajectory reward model, OS-Genesis enables effective end2end training of GUI agents.

5 + Reply

Upvoted 88 +76

Models citing this paper 9

- OS-Copilot/OS-Genesis-7B-AC — Image-Text-to-Text · 8B · Updated Jan 8 · 58 · 7
- OS-Copilot/OS-Genesis-4B-AC — Image-Text-to-Text · 4B · Updated Jan 8 · 31 · 7
- OS-Copilot/OS-Genesis-8B-AC — Image-Text-to-Text · 8B · Updated Jan 8 · 38 · 4
- OS-Copilot/OS-Genesis-7B-AW — Any-to-Any · 8B · Updated May 5 · 28 · 1

Browse 9 models citing this paper

Datasets citing this paper 2

- OS-Copilot/OS-Genesis-mobile-data — Viewer · Updated Mar 17 · 51.1k · 201 · 2
- OS-Copilot/OS-Genesis-web-data — Updated Mar 17 · 54 · 3

Spaces citing this paper 0

No Space linking this paper

Cite arxiv.org/abs/2412.19723 in a Space README.md to link it from this page.

Collections including this paper 17

- UI Agent — Collection — a collection of algorithmic agents for user… · 382 items · Updated about 3 hours ago · 57
- Papers — Collection — 540 items · Updated 3 days ago · 11
- Synthetic Data and Self-Improvement — Collection — 82 items · Updated Apr 24 · 7

Broader Influence

Mobile-R1: Towards Interactive Reinforcement Learning for VLM-Based Mobile Agent via Task-Level Rewards

Jihao Gu*, **Qihang Ai***, **Yingyao Wang***, **Pi Bu***, **Jingxuan Xing***,
Zekun Zhu, Wei Jiang, Ziming Wang, Yingxiu Zhao, Ming-Liang Zhang,
Jun Song†, Yuning Jiang†, Bo Zheng
Taobao & Tmall Group of Alibaba
{gujihao.gjh, aiqihang.aqh, wangyingyao.wyy, bupi.wj}@taobao.com

Trajectory-Level Reward (R_{Traj}) To obtain a comprehensive evaluation signal for multi-turn interactions, an external, high-fidelity MLLM, GPT-4o (OpenAI 2023), is employed to assign a scalar reward score to the entire historical interaction trajectory $\tau = (s_0, a_0, \ldots, a_n)$. Drawing inspiration from prior work (Sun et al. 2024), we establish two primary scoring criteria for GPT-4o[4]:

- Trajectory Coherence: This checks if steps and actions consistently follow the target instruction, actions are clear and specific, and if there are no unnecessary steps.
- Task Completion: This evaluates if the task is fully completed, all necessary interactions are made, and errors are handled properly.

The 5-level scoring rubric is applied by GPT-4o, yielding a final score within the range $[0, 1]$.

MobileGUI-RL: Advancing Mobile GUI Agent through Reinforcement Learning in Online Environment

Yucheng Shi[1,2*], **Wenhao Yu**[1*], **Zaitang Li**[1,3], **Yonglin Wang**[1], **Hongming Zhang**[1], **Ninghao Liu**[2], **Haitao Mi**[1], **Dong Yu**[1]

[1]Tencent AI Seattle Lab, [2]University of Georgia, [3]Chinese University of Hong Kong

Tencent AI Lab

3.3.1 Self-Exploration for Diverse Task Discovery

Our self-exploration mechanism leverages the natural structure of mobile interfaces to discover meaningful tasks. The process begins with an exploration agent π_{explore} performing random walks through the GUI environment. These walks are not purely random but incorporate basic heuristics such as preferring unexplored UI elements and avoiding repetitive loops. Each exploration trajectory $\tau_{\text{explore}} = \{(s_0, a_0), \ldots, (s_n, a_n)\}$ captures a sequence of state transitions that potentially represent a coherent task. Inspired by Sun et al. (2025), we then employ GPT-4o to reverse-engineer task descriptions from these trajectories. Given a trajectory, the model generates a natural language instruction **q** that would motivate the observed sequence of actions. This reverse process – figuring out the goal from the actions – produces a variety of tasks that match what the app is designed to do. The generated tasks span a wide spectrum, from simple interactions ("Open the settings menu") to complex multi-step procedures ("Set a recurring alarm for weekdays at 7 AM").

Broader Influence

OPENCUA: Open Foundations for Computer-Use Agents

Xinyuan Wang[*x] Bowen Wang[*x] Dunjie Lu[*x] Junlin Yang[*x] Tianbao Xie[*x] Junli Wang[*x]
Jiaqi Deng[x] Xiaole Guo[x] Yiheng Xu[x] Chen Henry Wu[c] Zhennan Shen[x] Zhuokai Li[x] Ryan Li[x] Xiaochuan Li[x]
Junda Chen[x] Boyuan Zheng[x] Peihang Li[x] Fangyu Lei[x] Ruisheng Cao[x] Yeqiao Fu[x] Dongchan Shin[x] Martin Shin[x]
Jiarui Hu[x] Yuyan Wang[x] Jixuan Chen[x] Yuxiao Ye[x] Danyang Zhang[x] Hao Hu[m] Huarong Chen[m]
Dikang Du[m] Zaida Zhou[m] Haotian Yao[m] Ziwei Chen[m] Qizheng Gu[m] Yipu Wang[m] Heng Wang[m]
Diyi Yang[s] Victor Zhong[w] Flood Sung[m] Y. Charles[m] Zhilin Yang[m] Tao Yu[†x]

[x] XLANG Lab, The University of Hong Kong [m] Moonshot AI
[s] Stanford University [w] University of Waterloo [c] Carnegie Mellon University

Moonshot AI

UI-Venus Technical Report: Building High-performance UI Agents with RFT

Zhangxuan Gu[*], Zhengwen Zeng[*], Zhenyu Xu[*], Xingran Zhou[*], Shuheng Shen[*,†], Yunfei Liu[*], Beitong Zhou[*], Changhua Meng, Tianyu Xia, Weizhi Chen, Yue Wen, Jingya Dou, Fei Tang, Jinzhen Lin, Yulin Liu, Zhenlin Guo, Yichen Gong, Heng Jia, Changlong Gao, Yuan Guo, Yong Deng, Zhenyu Guo, Liang Chen, Weiqiang Wang

Ant Group

ANT GROUP

Table 2: Comparison between OPENCUA and Other GUI Datasets

Dataset	Tasks	Avg. Step	Env. Type	Personalized Env.	Human Traj.	Dom/ AxTree	Video	Inner Monologue
AndroidControl[22]	15283	5.5	Mobile	✗	✓	✓	✗	**Short**
AMEX[8]	2991	11.9	Mobile	✗	✓	✗	✗	✗
AitW[31]	2346	8.1	Mobile	✗	✓	✓	✗	✗
AitZ[55]	1987	6.0	Mobile	✗	✓	✗	✗	**Short**
GUI Odyssey[24]	7735	15.3	Mobile	✗	✓	✗	✗	✗
OS-Genesis[34]	2451	6.4	Mobile&Web	✗	✗	✓	✗	**Short**
WonderBread[39]	598	8.4	Web	✗	✓	✓	✓	✗
AgentTrek[48]	10398	12.1	Web	✗	✗	✓	✓	**Short**
Mind2Web[12]	2350	7.3	Web	✗	✓	✓	✗	✗
GUIAct[9]	2482	6.7	Web	✗	✓	✓	✗	✗
AgentNet	**22625** [1]	**18.6**	**Desktop**	✓	✓	✓	✓	**Long**

Our Project

OS-Genesis

Automating GUI Agent Trajectory Construction via Reverse Task Synthesis

Introducing OS-Genesis, a ***manual-free*** data pipeline for synthesizing GUI agent trajectory. OS-Genesis is characterized by the following core features:

- **Interaction-driven**: Agents actively explore GUI environments through stepwise interactions to discover functionalities and generate data.
- **Reverse Task Synthesis**: OS-Genesis retroactively derives meaningful low/high-level task instructions from observed interactions and state changes, enabling the construction of diverse and executable trajectories without pre-defined tasks.
- **Trajectory Data**: We construct and release high-quality mobile and web trajectories to accelerate GUI agents research.
- **Performance**: OS-Genesis significantly outperforms other synthesis methods on benchmarks like AndroidWorld and WebArena.

arXiv | Code | 🤗 Checkpoints | 🤗 Data

中文解读（OS-Genesis）

https://qiushisun.github.io/OS-Genesis-Home/

Key Takeaways beyond the Paper

1. Constructing trajectory data does not have to start with instruction writing.
2. Data generation could leverage the exploration space of the given environment.
3. Diverse types and qualities of trajectory data require distinct strategies for optimal use.

We believe these mindsets provide a data synthesis framework that extends **far beyond computer-using scenarios** to broader agentic tasks.

Another Solution for Data Scarcity?

OS-Genesis is cool! 

However, there are still limitations — for example, the type of synthetic data is constrained by the environment, memory, reward signals.

A single environment may reach its limit after producing just tens of 10K samples.

Can we push it even further? Following works:

 *OpenMobile: Building Open Mobile Agents with Task and Trajectory Synthesis*

 *Breaking the Data Barrier -- Building GUI Agents Through Task Generalization, COLM 2025*

Another Solution for Data Scarcity?

OS-Genesis is cool! 

However, there are still limitations — for example, the type of synthetic data is constrained by the environment, memory, reward signals.

A single environment may reach its limit after producing just tens of 10K samples.

Can we push it even further? Following works:

OpenMobile: Building Open Mobile Agents with Task and Trajectory Synthesis

Breaking the Data Barrier -- Building GUI Agents Through Task Generalization, COLM 2025

CUAs are Still Data Hungry

Recent industry leading models achieved a marked performance leap, e.g., **70% success rate on AndroidWorld.**

Step-GUI Technical Report

GELab-Team, StepFun

Homepage: https://opengelab.github.io/
Github: https://github.com/stepfun-ai/gelab-zero
Huggingface: Step-GUI Collections

UI-Venus-1.5 Technical Report

Venus Team, Ant Group

MAI-UI Technical Report: Real-World Centric Foundation GUI Agents

Hanzhang Zhou*, Xu Zhang*, Panrong Tong, Jianan Zhang, Liangyu Chen, Quyu Kong Chenglin Cai, Chen Liu, Yue Wang(✉), Jingren Zhou, Steven HOI

Tongyi Lab, Alibaba Group

https://github.com/Tongyi-MAI/MAI-UI

MOBILE-AGENT-V3.5: MULTI-PLATFORM FUNDAMENTAL GUI AGENTS

Haiyang Xu*† Xi Zhang* Haowei Liu* Junyang Wang* Zhaoqing Zhu* Shengjie Zhou Xuhao Hu Feiyu Gao Junjie Cao Zihua Wang Zhiyuan Chen Jitong Liao Qi Zheng Jiahui Zeng Ze Xu Shuai Bai Junyang Lin Jingren Zhou Ming Yan †

Tongyi Lab, Alibaba Group
{shuofeng.xhy, ym11960}@alibaba-inc.com
https://github.com/X-PLUG/MobileAgent

…but the crucial trajectory data is unavailable to the community.

CUAs are Still Data Hungry

Public datasets paved the way...**but model performance has plateaued.**

Dataset	Screen Desc.	Screen Element	Element Func.	Task & Action	# Screen-shots	# Element Func.	# Unique General Inst.	# Avg Steps
RICO	✗	✓	✗	✗	72K	-	-	-
RICO semantics	✗	✓	✗	✗	72K	-	-	-
VINS	✗	✓	✗	✗	4K	-	-	-
MUD	✗	✓	✗	✗	18K	-	-	-
PixelHelp	✗	✗	✗	✓	800	-	187	4.2
UGIF	✗	✗	✗	✓	3.3K	-	480	6.3
MoTIF	✗	✗	✗	✓	21K	-	480	4.5
AITW	✗	*	✗	✓	510K	-	1539	6.5
AITZ	✓	*	■	✓	18K	18K	2504	7.5
ANDROIDCONTROL	✗	*	✗	✓	99K	-	15,283	4.8
AMEX	✓	✓	✓	✓	104K	296K	3046	12.8

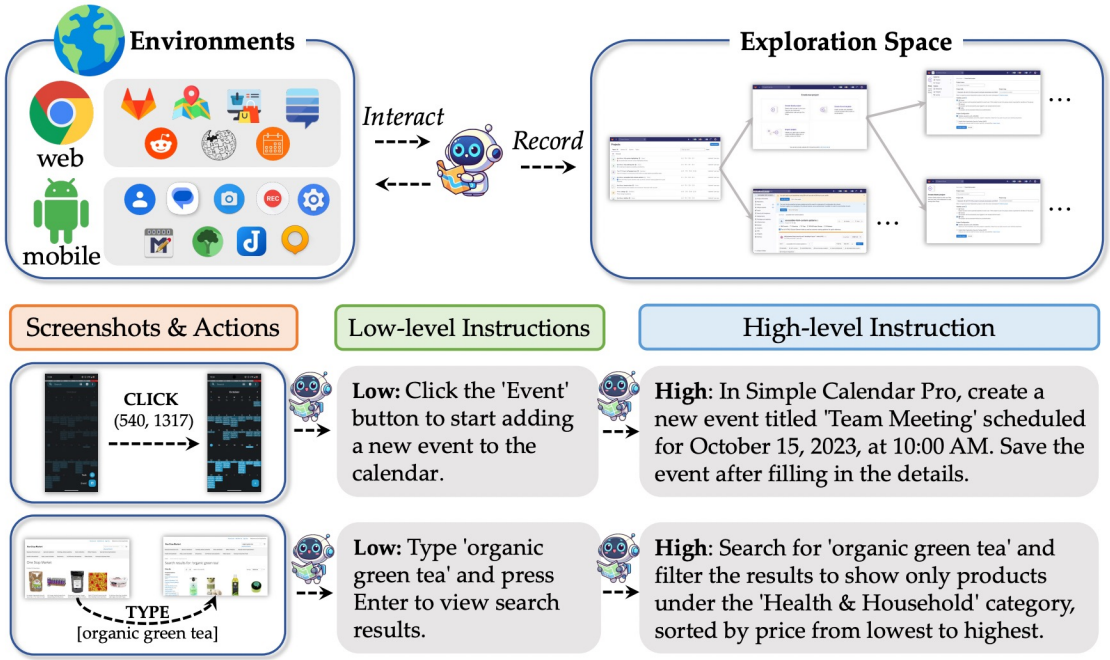
Models trained on these achieve **only ~30%** on AndroidWorld.

OpenMobile: Building Open Mobile Agents with Task and Trajectory Synthesis

Kanzhi Cheng, Zehao Li, Zheng Ma, Nuo Chen, Jialin Cao, Qiushi Sun, Zichen Ding, Fangzhi Xu, Hang Yan, Jiajun Chen, Luu Anh Tuan, Jianbing Zhang, Lewei Lu, Dahua Lin

Recall OS-Genesis

Trajectory Synthesis methods exist, but performance **lag behind**.



Method	Open	#Traj	Pass@1↑
OS-Genesis	✓	1.5K	17.4
HATS	✓	1K	24.4
AutoPlay	✗	20K	40.1
MobileGen	✗	0.5K	45.7
OpenMobile	✓	2.8K	**64.7**

(b) Comparison with data synthesis methods.

*direct comparison is imperfect, as these methods are tested on different base models and experimental settings

Background

The Open-Source Dilemma:

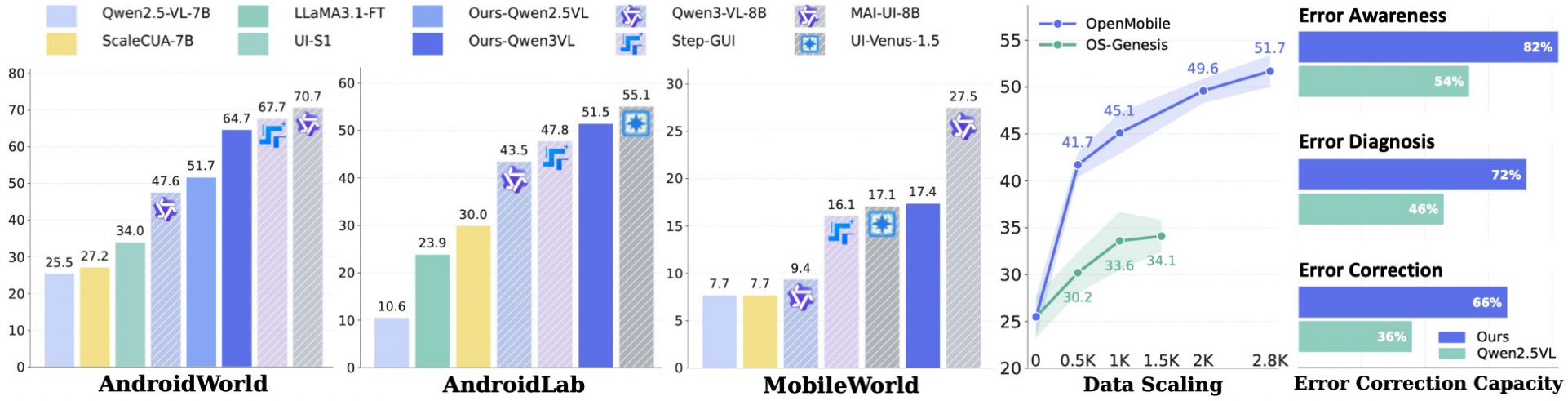
- **The Performance Gap:** Unable to train competitive models on dynamic mobile benchmarks.
- **The Knowledge Gap:** A "black box" of data recipes—unable to study what drives strong performance and generalization.

We are blocked from reproducing or building upon recent advances.

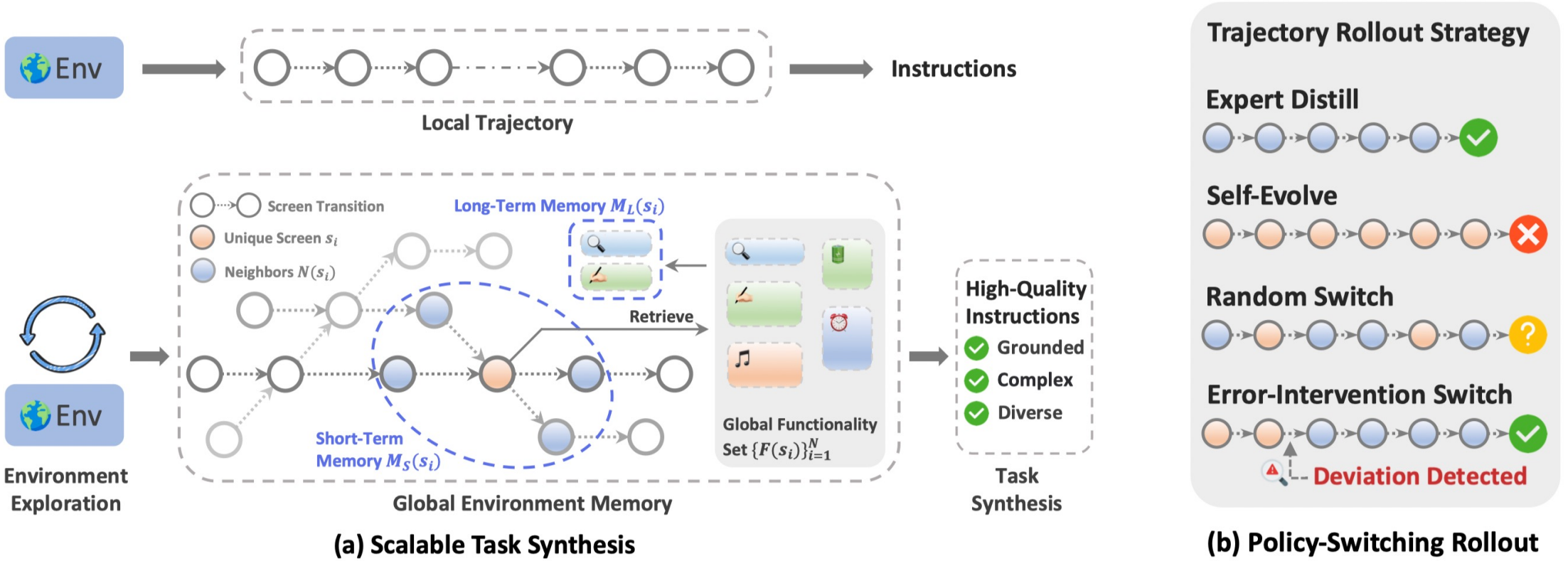
To bridge this gap, we present  **OpenMobile**, **a more recent open data synthesis framework and dataset** for mobile agent training.

OpenMobile

- **Open-Source Framework:** We introduce OpenMobile, a task and trajectory synthesis framework achieving competitive on challenging **dynamic benchmarks**.
- **Transparent Analysis:** Including overlap checks between **synthetic instructions and benchmark**, to verify that performance gains stem from **functionality coverage rather than data contamination**.



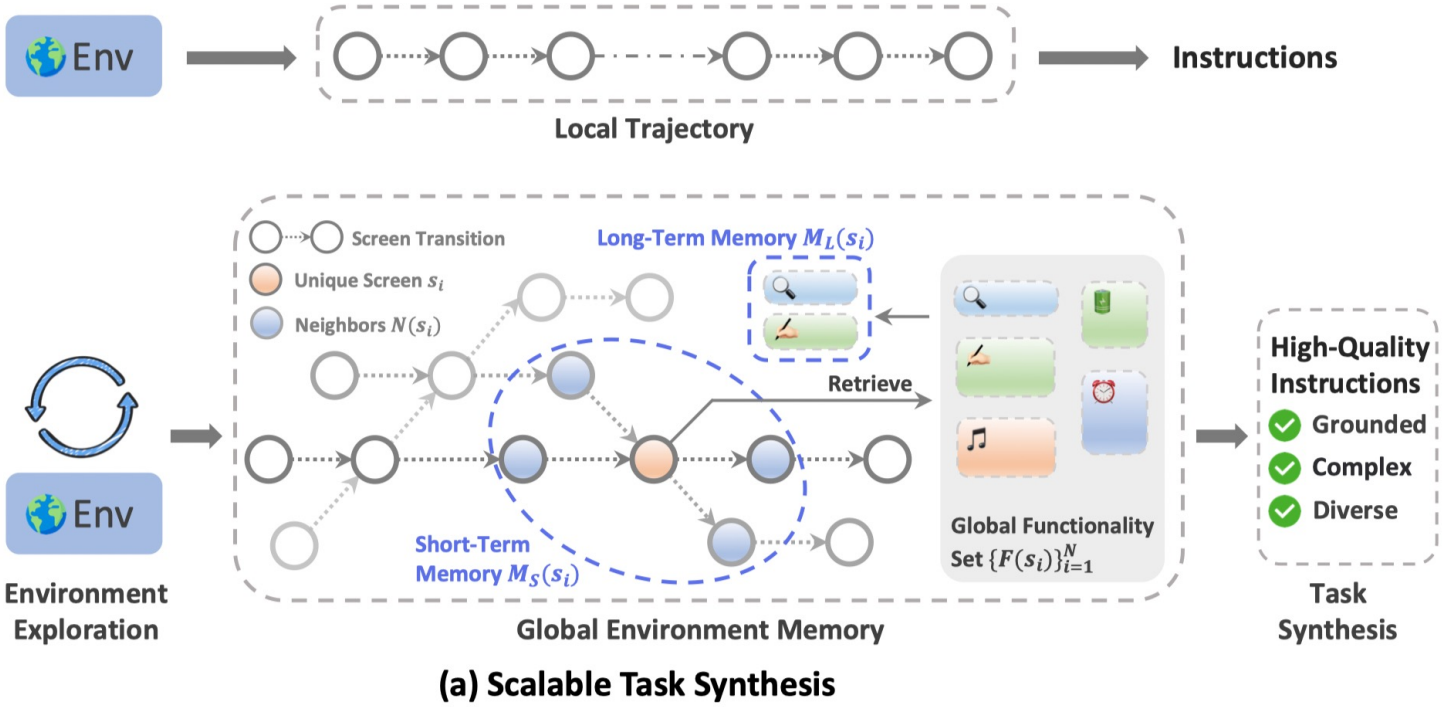
OpenMobile: Task Synthesis and Trajectory Rollout



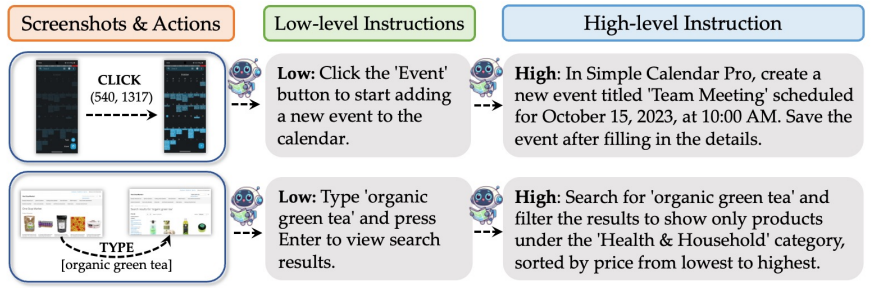
OpenMobile: Scalable Task Synthesis

How do humans explore?

Exploratory Interaction ➔ **Construct Environment Memory** ➔ Associate & Synthesize



Recall



OpenMobile: Policy-Switching Rollout

(b) Policy-Switching Rollout

- **Expert distillation** enables learners to imitate ideal behavior, but fails to address recovery from errors.
- **Self-evolution** suffers from slow convergence and is bounded by the learner's current performance caps.

- We introduce **policy-switching rollout** that alternates between the learner and expert.
  - **How to switch?**

Experiment: Main Result

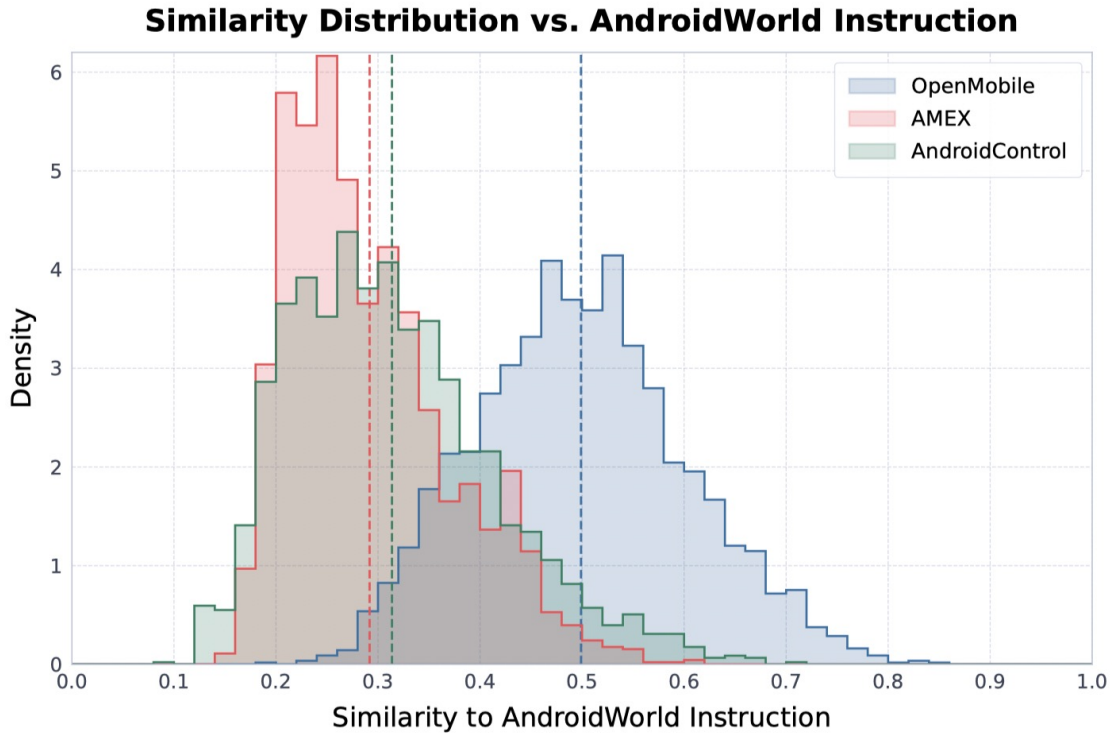
Method	Base Model	AndroidWorld		AndroidLab		MobileWorld	
		Pass@1↑	Pass@3↑	Pass@1↑	Pass@3↑	Pass@1↑	Pass@3↑
Commercial Models							
GPT-4o	–	30.6	–	31.2	–	–	–
Gemini-3-Pro	–	60.3	75.0	–	–	51.3	–
Open-Weight Models							
Qwen2.5-VL-7B	–	25.5 ± 2.6	34.9	10.6 ± 1.8	15.2	7.7 ± 0.9	10.3
Qwen3-VL-8B	–	47.6 ± 2.2	62.1	43.5	–	9.4	–
UI-Venus-7B	Qwen2.5-VL	49.1	–	41.3	–	8.5	–
Step-GUI-4B	Qwen3-VL	63.9	75.8	47.8	–	16.1	–
Step-GUI-8B	Qwen3-VL	67.7	80.2	–	–	–	–
MAI-UI-8B	Qwen3-VL	70.7	–	–	–	27.5	–
UI-Venus-1.5-8B	Qwen3-VL	73.7	–	55.1	–	17.1	–
MobileAgent-v3.5-8B	Qwen3-VL	71.6	–	–	–	33.3	–
Open-Data Models							
UI-S1-7B	Qwen2.5-VL	34.0	–	–	–	–	–
ScaleCUA-7B	Qwen2.5-VL	27.2 ± 2.2	36.2	30.0 ± 1.1	37.7	7.7 ± 0.4	8.6
Ours-7B	Qwen2.5-VL	51.7 ± 1.7	68.1	22.7 ± 0.4	37.0	14.8 ± 1.3	21.4
Ours-8B	Qwen3-VL	64.7 ± 3.2	78.0	51.5 ± 0.7	62.3	17.7 ± 2.2	24.8

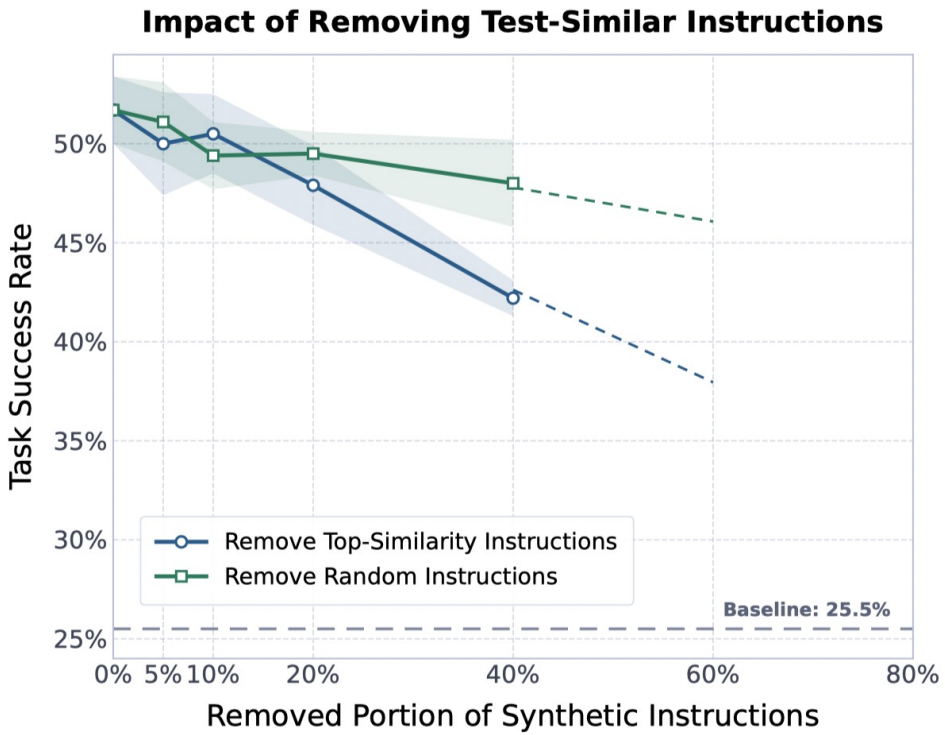
Synthesized in androidworld, but generalize across envs

Analysis

OpenMobile data is **grounded in the benchmark environment, but does not overfit benchmark**:

- Only 3.5% exceeding a similarity of 0.7
- Removing most similar instructions causes marginal performance drop





Another Solution for Data Scarcity?

OS-Genesis  and OpenMobile  are cool!

However, there are still limitations, for example:

A single environment may reach its limit after producing 10K samples.

Can we push it even further? Following works:

OpenMobile: Building Open Mobile Agents with Task and Trajectory Synthesis

Breaking the Data Barrier -- Building GUI Agents Through Task Generalization, COLM 2025

GUI Trajectory Data

Issue: Although we have collected more trajectory data, it still remains limited compared to general LLM/VLM tasks.

Domains	Datasets	Samples	Type
Web	OS-Genesis (Web) (Sun et al., 2024b)	3,789	Instruction, Thought, Action
	MM-Mind2Web (Zheng et al., 2024a)	21,542	Instruction, Thought, Action
	VisualWebArena (Koh et al., 2024a)	3,264	Instruction, Thought, Action
Mobile	OS-Genesis (Mobile) (Sun et al., 2024b)	4,941	Instruction, Thought, Action
	Aguvis (Xu et al., 2024b)	22,526	Instruction, Thought, Action

Table 2: Statistics of the web/mobile domains along with the corresponding GUI trajectory datasets used in post-training.

RQ: Is it possible to leverage "external forces" to further enhance the use of GUI data?

Breaking the Data Barrier – Building GUI Agents Through Task Generalization

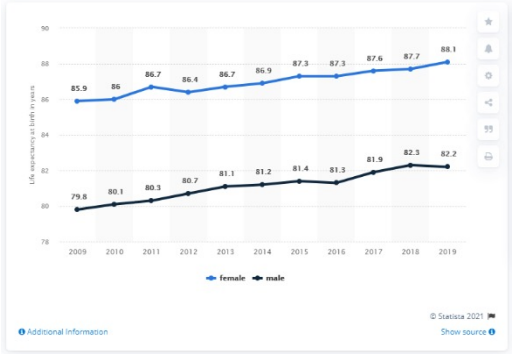
Junlei Zhang*; Zichen Ding*, Chang Ma, Zijie Chen, Qiushi Sun, Zhenzhong Lan, Junxian He

Enhancing GUI Agent with Non-GUI Data

However, we have abundant non-GUI data available to enhance versatile abilities, such as complex reasoning

Can we take advantage of these data-rich domains?

We introduce **Mid-Training** to the GUI Agent training.

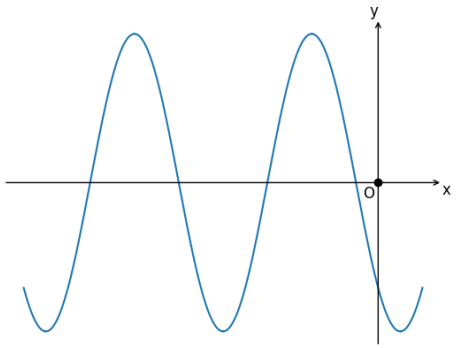


Chart

Prove that the sum of the squares of the lengths of the medians of a tetrahedron is equal to 4/9 of the sum of the squares of the lengths of its edges.

Text Math

Embodied



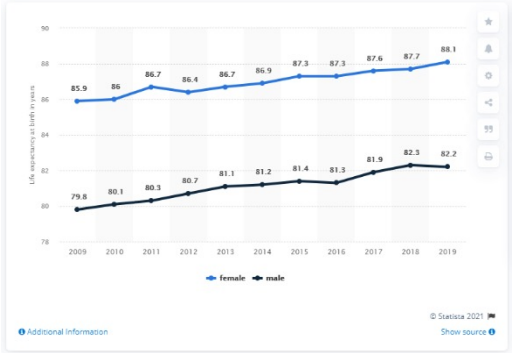
Multi-modal Math

Enhancing GUI Agent with Non-GUI Data

Mid-training with Non-GUI data:

1. Naively training on non-GUI data, then post-training on GUI data can lead to gradient conflicts.

2. What kinds of domains should we use?

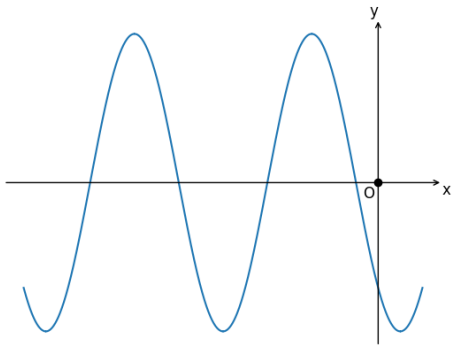


Chart

Prove that the sum of the squares of the lengths of the medians of a tetrahedron is equal to 4/9 of the sum of the squares of the lengths of its edges.

Text Math

Embodied



Multi-modal Math

Enhancing GUI Agent with Non-GUI Data

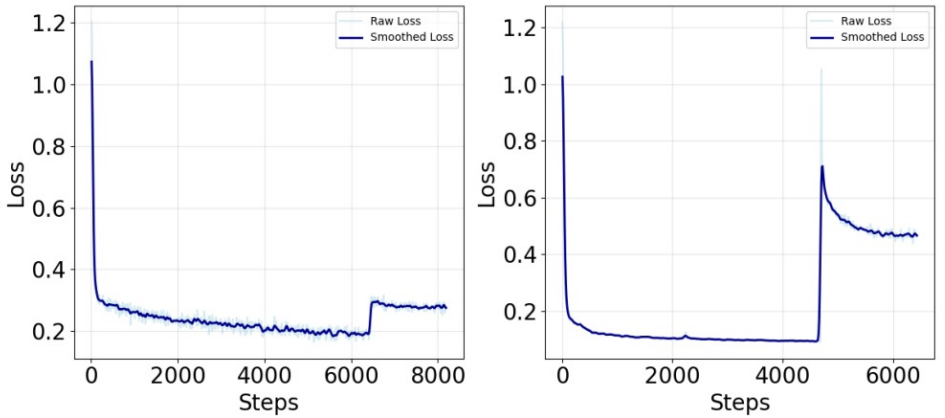
So, our goals are as follows:

1. Discover generalizable non-GUI domains
2. Design stable training methods.
3. Combine the generalizable to obtain larger mid-training dataset.

Mid-Training

1. We concatenate mid-training data with GUI trajectory and train sequentially. Both stages are integrated under a single optimizer and learning rate.

2. We mix the GUI trajectory into the mid-training data during the mid-training stage, to stabilize the training.



(a) Multi-modal Math w/ mixing

(b) Multi-modal Math w/o mixing

Mid-Training

Domains	Observation	WebArena		AndroidWorld
		PR	SR	SR
GUI Post-Training Only	Image	26.3	6.2	9.0
Public Baselines				
GPT-4o-2024-11-20	Image	36.9	15.6	11.7
OS-Genesis-7B	Image + Accessibility Tree	–	–	17.4
AGUVIS-72B	Image	-	-	26.1
Claude3-Haiku	Accessibility Tree	26.8	12.7	-
Llama3-70b	Accessibility Tree	35.6	12.6	-
Gemini1.5-Flash	Accessibility Tree	32.4	11.1	-
Vision-and-Language Modality				
Chart/ Document QA	Image	24.6	6.2	15.3
Non-GUI Perception	Image	28.7	7.6	14.0
GUI Perception	Image	27.4	7.1	14.0
Web Screenshot2Code	Image	28.0	6.6	9.9
Non-GUI Agents	Image	30.8	8.5	13.5
Multi-modal Math ✓	Image	30.4	8.5	15.3
Multi-round Visual Conversation	Image	30.0	9.0	12.6
Language Modality				
MathInstruct ✓	Image	31.9	10.9	14.4
Olympiad Math ✓	Image	31.5	8.5	13.1
CodeI/O ✓	Image	29.2	9.0	14.9
Web Knowledge Base	Image	31.3	9.5	9.0
Domain Combination (Sampled data from ✓domains)				
GUIMid	Image	34.3	9.5	21.2

Fine-tuned Qwen2-VL-7B-Instruct.

Mid-Training

Domains	Observation	WebArena		AndroidWorld
		PR	SR	SR
GUI Post-Training Only	Image	26.3	6.2	9.0
Public Baselines				
GPT-4o-2024-11-20	Image	36.9	15.6	11.7
OS-Genesis-7B	Image + Accessibility Tree	–	–	17.4
AGUVIS-72B	Image	-	-	26.1
Claude3-Haiku	Accessibility Tree	26.8	12.7	-
Llama3-70b	Accessibility Tree	35.6	12.6	-
Gemini1.5-Flash	Accessibility Tree	32.4	11.1	-
Vision-and-Language Modality				
Chart/ Document QA	Image	24.6	6.2	15.3
Non-GUI Perception	Image	28.7	7.6	14.0
GUI Perception	Image	27.4	7.1	14.0
Web Screenshot2Code	Image	28.0	6.6	9.9
Non-GUI Agents	Image	30.8	8.5	13.5
Multi-modal Math ✓	Image	30.4	8.5	15.3
Multi-round Visual Conversation	Image	30.0	9.0	12.6
Language Modality				
MathInstruct ✓	Image	31.9	10.9	14.4
Olympiad Math ✓	Image	31.5	8.5	13.1
CodeI/O ✓	Image	29.2	9.0	14.9
Web Knowledge Base	Image	31.3	9.5	9.0
Domain Combination (Sampled data from ✓domains)				
GUIMid	Image	34.3	9.5	21.2

Our 7B baselines achieve a comparable performance on AW, but relatively lower results on Web.

Mid-Training

Domains	Observation	WebArena		AndroidWorld
		PR	SR	SR
GUI Post-Training Only	Image	26.3	6.2	9.0
Public Baselines				
GPT-4o-2024-11-20	Image	36.9	15.6	11.7
OS-Genesis-7B	Image + Accessibility Tree	–	–	17.4
AGUVIS-72B	Image	-	-	26.1
Claude3-Haiku	Accessibility Tree	26.8	12.7	-
Llama3-70b	Accessibility Tree	35.6	12.6	-
Gemini1.5-Flash	Accessibility Tree	32.4	11.1	-
Vision-and-Language Modality				
Chart/ Document QA	Image	24.6	6.2	15.3
Non-GUI Perception	Image	28.7	7.6	14.0
GUI Perception	Image	27.4	7.1	14.0
Web Screenshot2Code	Image	28.0	6.6	9.9
Non-GUI Agents	Image	30.8	8.5	13.5
Multi-modal Math ✓	Image	30.4	8.5	15.3
Multi-round Visual Conversation	Image	30.0	9.0	12.6
Language Modality				
MathInstruct ✓	Image	31.9	10.9	14.4
Olympiad Math ✓	Image	31.5	8.5	13.1
CodeI/O ✓	Image	29.2	9.0	14.9
Web Knowledge Base	Image	31.3	9.5	9.0
Domain Combination (Sampled data from ✓domains)				
GUIMid	Image	34.3	9.5	21.2

Generally, the similar domains (e.g. Document QA) do not help much on the Web, though they help some in the mobile tasks.

Mid-Training

Domains	Observation	WebArena		AndroidWorld
		PR	SR	SR
GUI Post-Training Only	Image	26.3	6.2	9.0
Public Baselines				
GPT-4o-2024-11-20	Image	36.9	15.6	11.7
OS-Genesis-7B	Image + Accessibility Tree	–	–	17.4
AGUVIS-72B	Image	-	-	26.1
Claude3-Haiku	Accessibility Tree	26.8	12.7	-
Llama3-70b	Accessibility Tree	35.6	12.6	-
Gemini1.5-Flash	Accessibility Tree	32.4	11.1	-
Vision-and-Language Modality				
Chart/ Document QA	Image	24.6	6.2	15.3
Non-GUI Perception	Image	28.7	7.6	14.0
GUI Perception	Image	27.4	7.1	14.0
Web Screenshot2Code	Image	28.0	6.6	9.9
Non-GUI Agents	Image	30.8	8.5	13.5
Multi-modal Math ✓	Image	30.4	8.5	15.3
Multi-round Visual Conversation	Image	30.0	9.0	12.6
Language Modality				
MathInstruct ✓	Image	31.9	10.9	14.4
Olympiad Math ✓	Image	31.5	8.5	13.1
CodeI/O ✓	Image	29.2	9.0	14.9
Web Knowledge Base	Image	31.3	9.5	9.0
Domain Combination (Sampled data from ✓domains)				
GUIMid	Image	34.3	9.5	21.2

All math-related domains help! Even the language math data, demonstrates generalization from text to multimodal tasks.

Mid-Training

Here we have some useful domains, what if we combine them?

We combine the math and code data and sample a 300K mid-training data: GUIMid

GUIMid

Domains	Observation	WebArena		AndroidWorld
		PR	SR	SR
GUI Post-Training Only	Image	26.3	6.2	9.0
Public Baselines				
GPT-4o-2024-11-20	Image	36.9	15.6	11.7
OS-Genesis-7B	Image + Accessibility Tree	–	–	17.4
AGUVIS-72B	Image	-	-	26.1
Claude3-Haiku	Accessibility Tree	26.8	12.7	-
Llama3-70b	Accessibility Tree	35.6	12.6	-
Gemini1.5-Flash	Accessibility Tree	32.4	11.1	-
Vision-and-Language Modality				
Chart/ Document QA	Image	24.6	6.2	15.3
Non-GUI Perception	Image	28.7	7.6	14.0
GUI Perception	Image	27.4	7.1	14.0
Web Screenshot2Code	Image	28.0	6.6	9.9
Non-GUI Agents	Image	30.8	8.5	13.5
Multi-modal Math ✓	Image	30.4	8.5	15.3
Multi-round Visual Conversation	Image	30.0	9.0	12.6
Language Modality				
MathInstruct ✓	Image	31.9	10.9	14.4
Olympiad Math ✓	Image	31.5	8.5	13.1
CodeI/O ✓	Image	29.2	9.0	14.9
Web Knowledge Base	Image	31.3	9.5	9.0
Domain Combination (Sampled data from ✓domains)				
GUIMid	Image	34.3	9.5	21.2

The combined data shows a significant improvement, especially on mobile, indicating these math and code data can complement each other, further enhancing the model's reasoning ability when combined.

Next Step:

We now have powerful agents capable of both planning and making action.

However, a single agent always has performance limits.

So …

How about bringing more agents to the party? 

AgentStore: Scalable Integration of Heterogeneous Agents As Specialized Generalist Computer Assistant

ACL 2025 VIENNA

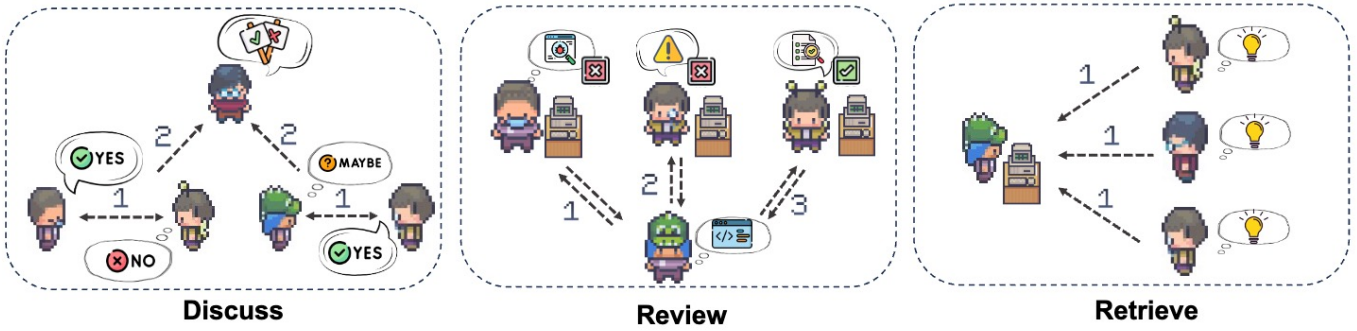
Chengyou Jia, Minnan Luo, Zhuohang Dang, Qiushi Sun, Fangzhi Xu,
Junlin Hu, Tianbao Xie, Zhiyong Wu

Multi-Agent Algorithms

Published as a conference paper at COLM 2024

Corex: Pushing the Boundaries of Complex Reasoning through Multi-Model Collaboration

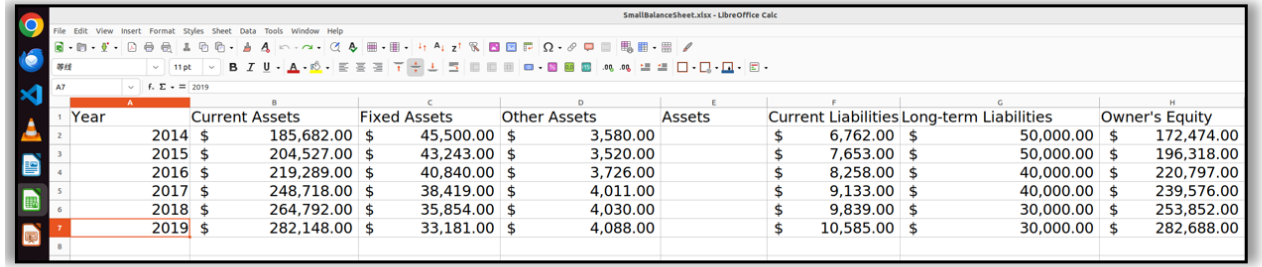
Qiushi Sun[◇♡]* **Zhangyue Yin**[♣] **Xiang Li**[♠] **Zhiyong Wu**[◇†] **Xipeng Qiu**[♣] **Lingpeng Kong**[♡]
[◇]Shanghai AI Laboratory [♡]The University of Hong Kong
[♣]Fudan University [♠]East China Normal University
qiushisun@connect.hku.hk, yinzy21@m.fudan.edu.cn, xiangli@dase.ecnu.edu.cn
wuzhiyong@pjlab.org.cn, xpqiu@fudan.edu.cn, lpk@cs.hku.hk



How about multi-agent + GUI Agents

Can a Single Agent handle a variety of OS tasks?

Task_1: In a new sheet with 4 headers "Year", "CA changes", "FA changes", and "OA changes", calculate the annual changes for the Current Assets, Fixed Assets, and Other Assets columns.



Year	Current Assets	Fixed Assets	Other Assets	Assets	Current Liabilities	Long-term Liabilities	Owner's Equity
2014	$ 185,682.00	$ 45,500.00	$ 3,580.00		$ 6,762.00	$ 50,000.00	$ 172,474.00
2015	$ 204,527.00	$ 43,243.00	$ 3,520.00		$ 7,653.00	$ 50,000.00	$ 196,318.00
2016	$ 219,289.00	$ 40,840.00	$ 3,726.00		$ 8,258.00	$ 40,000.00	$ 220,797.00
2017	$ 248,718.00	$ 38,419.00	$ 4,011.00		$ 9,133.00	$ 40,000.00	$ 239,576.00
2018	$ 264,792.00	$ 35,854.00	$ 4,030.00		$ 9,839.00	$ 30,000.00	$ 253,852.00
2019	$ 282,148.00	$ 33,181.00	$ 4,088.00		$ 10,585.00	$ 30,000.00	$ 282,688.00

SheetAgent
specialize in
sheet processing

Step 1: Install and locate

```
pip install openpyxl && lsof | grep '.xlsx'
```

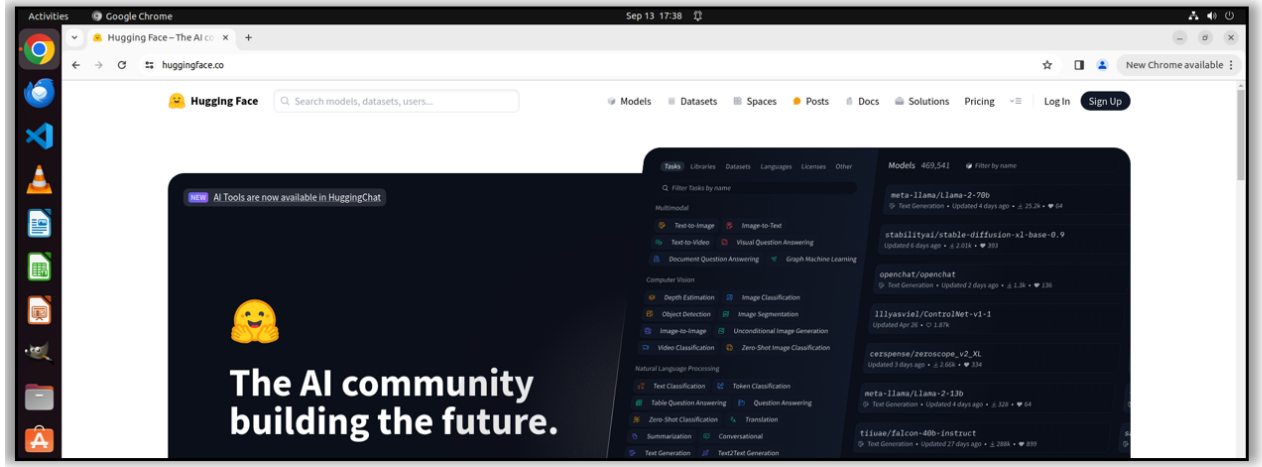
Step 2: Create new sheet and add headers

```
ws_new = wb.create_sheet(title=sheet_name)
ws_new.append(headers), wb.save(file_path)
```

Step 3: Insert table for the required data

```
for row in range(2, ws_original.max_row + 1):
    year = ws_original.cell(arg).value,…
    ws_new.append([year, …])
```

Task_2: Find the daily paper and take down the meta information of papers on 1st March, 2024 in the opened . pptx file. Please conform to the format and complete others.



WebAgent
specialize in
web browsing

SildeAgent
specialize in
slide editing

Different specialist agents are required to collaborate system-wide tasks

SubTask 1: Find papers and extract meta info

Step 1: Click daily papers to browsing
Step 2: Filter results by choosing1st March
Step 3: Extract info for selecting papers

subtask complete ↓ message passing

SubTask 2: write meta info into pptx

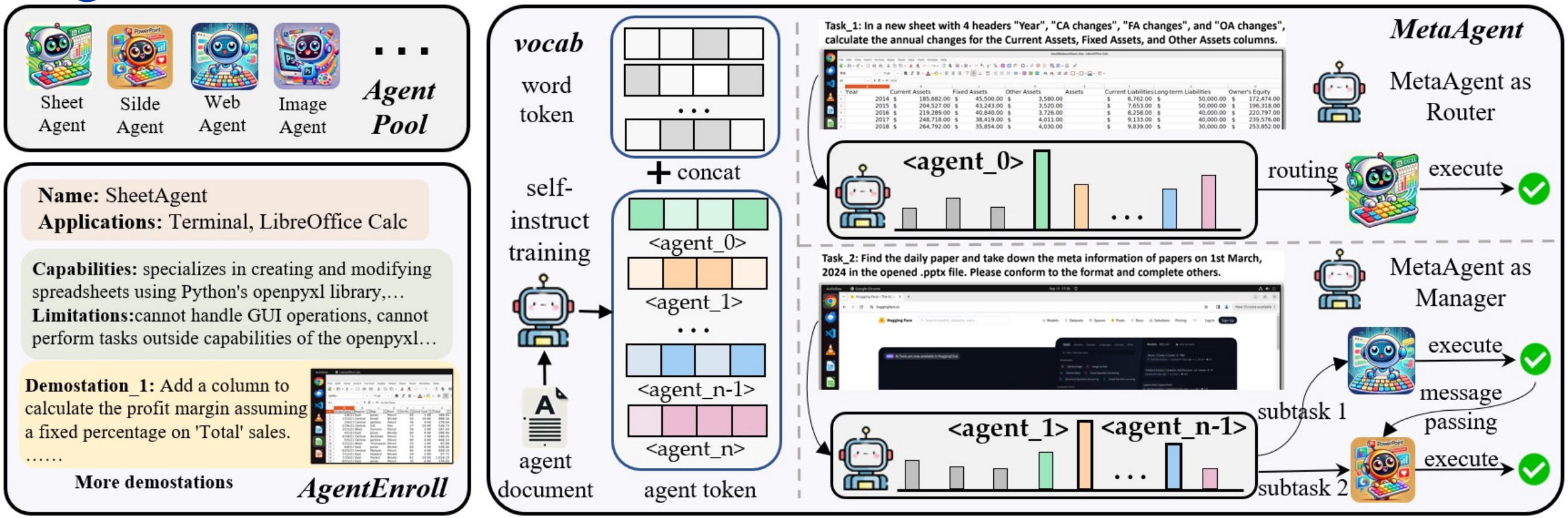
Step 1: Install package and locate .pptx file
Step 2: load content for current .pptx file
Step 3: Write info into corresponding file
Step 4: Save and overwrite the original file

1. Generalist Agent: lack of specialized abilities.
2. Specialized Agent: Unable to generalize to system-level tasks.

From APPStore to AgentStore:

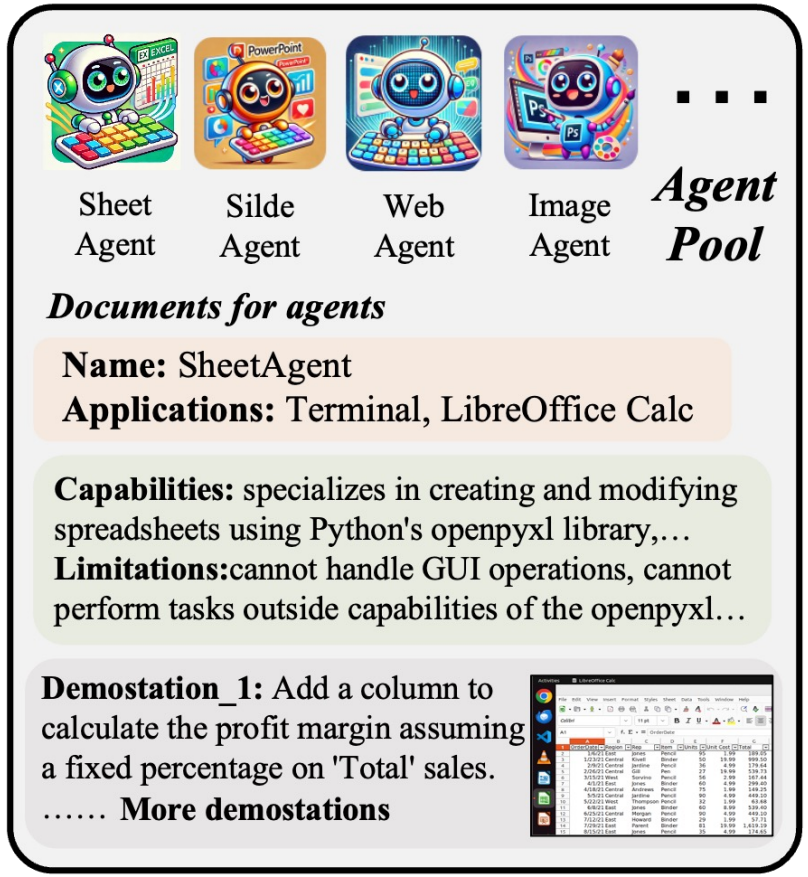
Build an open and scalable platform for dynamically integrating various computer-using agents.

AgentStore



1. AgentStore allows users to quickly integrate their own specialized agents into the platform, similar to the functionality of the App store.
2. We introduce a novel MLLM-based MetaAgent with AgentToken strategy, to select the most suitable agent(s) to complete tasks.

AgentStore



AgentPool: The set of all available agents in AgentStore.

1. Register new agents in a standardized format.
2. includes: functionality, limitations, application scenarios…
3. Define as $a = \{(a_1, d_1)(a_2, d_2), \ldots (a_n, d_n)\}$

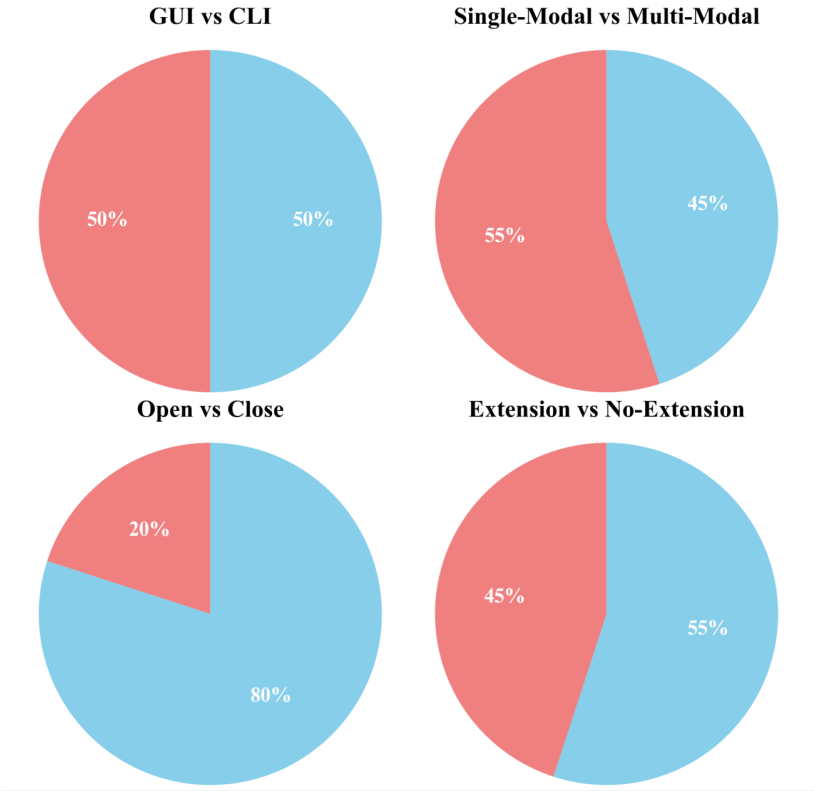
Agent Documentation

20 desktop agents and 10 mobile agents, each specialized for tasks on their respective platforms.

Specialized agents in AgentStore

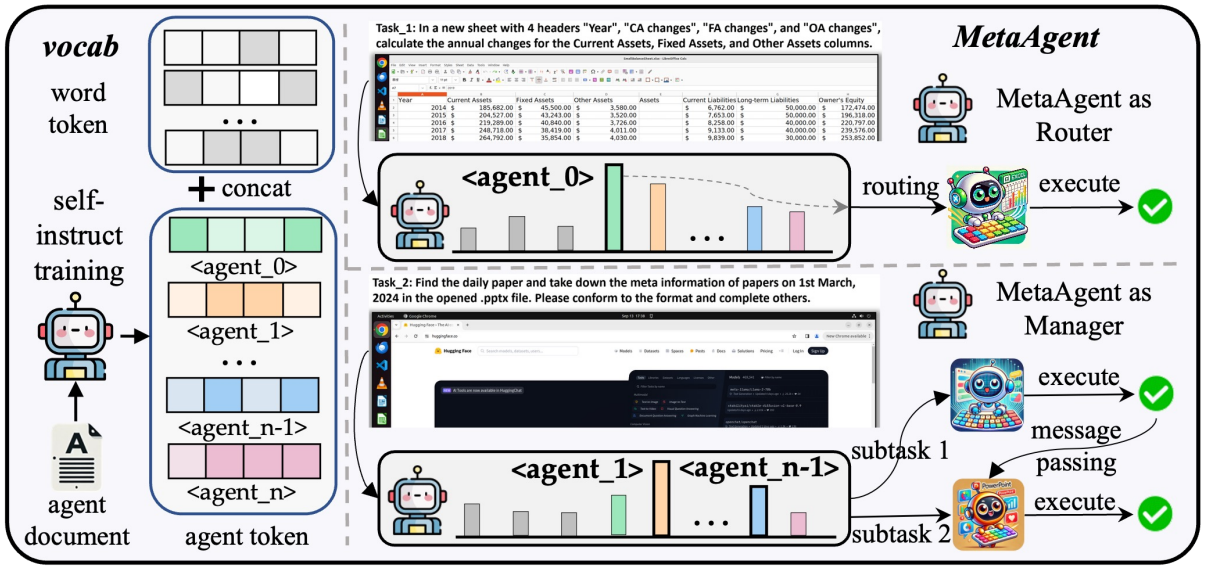
Table 6: The presentation of agents in the AgentPool.

	CLI or GUI?	Single or Multi Modal?	Open or Close Base Model?	Domain for OSworld	Support Extension?
OSAgent	GUI	Multi	Close	OS	✓
Friday (Wu et al., 2024)	CLI	Single	Close	OS	✓
SheetAgent	CLI	Single	Close	Calc	✗
CalcAgent	GUI	Multi	Close	Calc	✓
SlideAgent	CLI	Single	Close	Impress	✗
ImPressAgent	GUI	Multi	Close	Impress	✓
WordAgent	CLI	Single	Close	Writer	✗
WriterAgent	GUI	Multi	Close	Writer	✓
VLCAgent	GUI	Multi	Close	VLC	✓
MailAgent	GUI	Multi	Close	TB	✓
ChromeAgent	GUI	Multi	Close	Chrome	✓
WebAgent (He et al., 2024)	GUI	Multi	Close	Chrome	✗
VSAgent	GUI	Multi	Open	VSC	✗
VSGUIAgent	CLI	Single	Close	VSC	✓
GimpAgent	GUI	Multi	Close	GIMP	✓
ImageAgent	CLI	Single	Open	GIMP	✓
Searcher	CLI	Single	Close	-	✗
GoogleDrive	CLI	Single	Close	-	✗
CoderAgent	CLI	Single	Open	-	✗
VisionAgent	CLI	Multi	Open	-	✗



LLM/CLI-based model + LVM/GUI-based model

AgentStore



AgentToken: Each agent is registered by adding a token to the MetaAgent Vocab.

MetaAgent: Acts as an efficient router, predicting the most probable next token by maximizing conditional probability.

Once the agent token is predicted, decoding stops, and the corresponding Computer-using agent is called to execute the task.

Performance

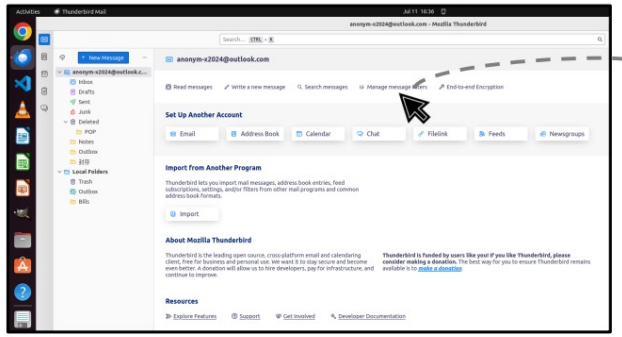
Agent	Base	Success Rate (%)									
		OS*	Calc	Impress	Writer	VLC	TB	Chrome	VSC	GIMP	AVG
CogAgent	GogVLM	1.60	2.17	0.00	4.35	6.53	0.00	2.17	0.00	0.00	1.32
MMAgent	GPT-4o	14.44	4.26	6.81	8.70	9.50	6.67	15.22	30.43	0.00	11.21
CRADLE	GPT-4o	8.00	0.00	4.65	8.70	6.53	0.00	8.70	0.00	38.46	7.81
Friday*	GPT-4o	15.20	25.50	0.00	21.73	0.00	0.00	0.00	17.39	15.38	11.11
Open-Inter*	GPT-4o	12.80	12.76	0.00	13.04	0.00	0.00	0.00	17.39	15.38	8.94
AgentStore(GT)	Hybrid	20.00	36.17	10.63	47.83	47.06	40.00	34.78	47.82	38.46	29.54
AgentStore(ICL)	Hybrid	9.60	0.00	2.13	4.34	35.29	33.33	30.43	30.43	15.38	13.55
AgentStore(FT)	Hybrid	8.80	27.65	4.26	13.04	41.17	40.00	34.78	8.60	15.38	17.34
AgentStore(AT)	Hybrid	13.86	31.91	8.51	39.13	47.06	40.00	32.61	39.13	30.77	23.85

AgentStore achieved a success rate of 23.85% on highly challenging OSWorld benchmark. (Claude 3.5 Sonnet: 22%)

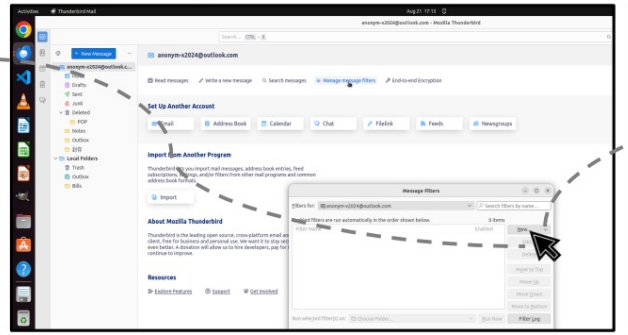
Rank	Model
1 Oct 24, 2024	AgentStore (AgentToken) *Shanghai AI Lab* Shanghai AI Lab, '24
2 Oct 11, 2024	Agent S w/ GPT-4o *Simular Research* Simular Research, '24
3 Oct 11, 2024	Agent S w/ Claude-3.5 *Simular Research* Simular Research, '24
4 Oct 24, 2024	AgentStore (Fine-Tuning) *Shanghai AI Lab* Shanghai AI Lab, '24
5 Oct 24, 2024	AgentStore (In-Context Learning) *Shanghai AI Lab* Shanghai AI Lab, '24
6 Mar 20, 2024	GPT-4 Vision *OpenAI* OpenAI, '23

Demos

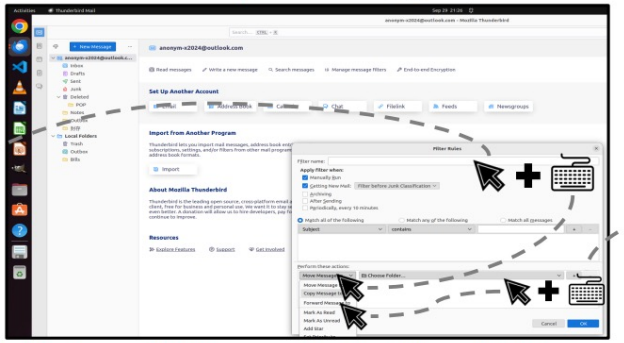
Task-1: Set up to forward every email received by anonym-x2024@outlook.com in the future to anonym-x2024@gmail.com. MailAgent



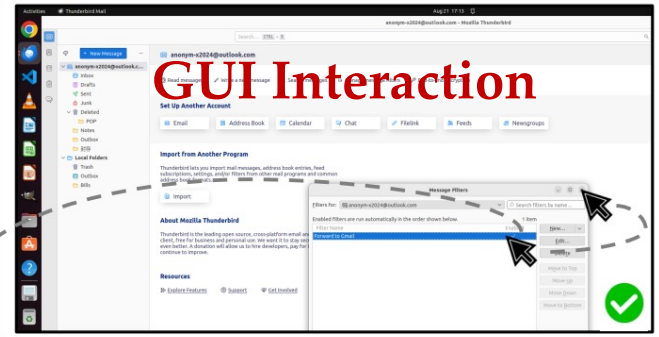
Step1: click(filters_x, filters_y)
Click on \"Manage message filters\"



Step2: click(new_x, new_y)
Click on \"New...\" to create a new filter

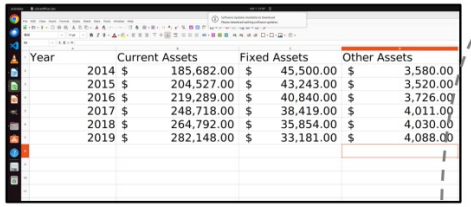


Step3: typewrite('Forward to Gmail') ... click(choose_x,choose_y) ...typewrite('anonymx2024@gmail.com')



Step4: click(1424, 629), click(close_x, close_y)
#Ensure the filter is enabled and close the window

Task-2 : In a new sheet with "Year", "CA changes", "FA changes", and "OA changes", calculate the annual changes for the Current, Fixed, and Other Assets columns.



Year	Current Assets	Fixed Assets	Other Assets
2014	$ 185,682.00	$ 45,500.00	$ 3,580.00
2015	$ 204,527.00	$ 43,243.00	$ 3,520.00
2016	$ 219,289.00	$ 40,840.00	$ 3,726.00
2017	$ 248,718.00	$ 38,419.00	$ 4,011.00
2018	$ 264,792.00	$ 35,854.00	$ 4,030.00
2019	$ 282,148.00	$ 33,181.00	$ 4,088.00

SheetAgent init_state

Step 1: install and locate

pip install openpyxl && lsof | grep '.xlsx'

Successfully install openpyxl /home/user/SmallBalanceSheet.xlsx

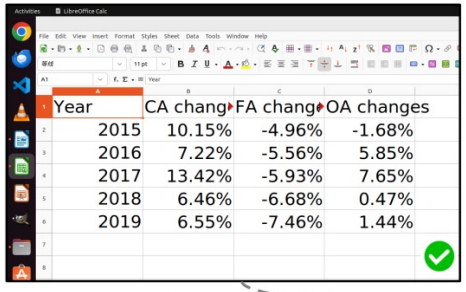
Step 2: create new sheet and headers

```
from openpyxl import load_workbook
file_path = '/home/user/... Sheet.xlsx'
load_workbook(file_path),sheet_name = ...
wb.create_sheet(title=sheet_name)
heads= ["Year", "CA changes", ...,]
ws_new.append(headers),wb.save(file_path)
```

Successfully ran

CLI Interaction

Step 3: insert table for the required data



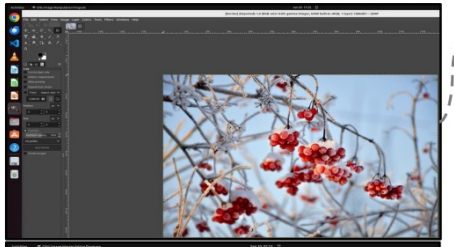
Year	CA chang	FA chang	OA changes
2015	10.15%	-4.96%	-1.68%
2016	7.22%	-5.56%	5.85%
2017	13.42%	-5.93%	7.65%
2018	6.46%	-6.68%	0.47%
2019	6.55%	-7.46%	1.44%

final_state

```
from openpyxl import load_workbook
original = load_workbook(file_path).activate
for row in range(2, original.max_row+1):
  ca_current = original.cell(row).value
    if row > 2:
      ca_previous =original.cell(row-1).value
      ca_change =(ca_current-ca_previous)
wb.save(file_path)  # Save the workbook
```

Successfully execute

Task-3: Could you assist me in boosting the contrast of my photo in the desktop and then insert it into the opening document at the point of the cursor ?



Step 1: click(word_x, word_y)

Step 1: install and locate

apt-get install -y imagemagick && ls ~/Desktop/

Image Agent

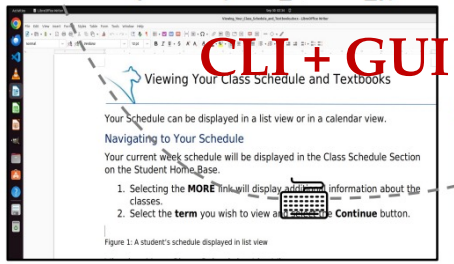
Successfully install imagemagick ~/Desktop/ berries.png

Step 2: boosting the contrast

convert ~/Desktop/berries.png -contrast –contrast ~/Desktop/berries_contrast.png

Writer Agent

Successfully execute



Step 2: hotkey("ctrl", "v")

CLI + GUI Interaction

Step 3: hotkey("ctrl", "s")

Summary of Multi-Agents

1. Multi-agent integration can rapidly advance computer-using capabilities.
2. Greatly facilitates generalization to new domains.
3. Plug-and-play design, enabled by carefully crafted AgentTokens, allows for fast integration.

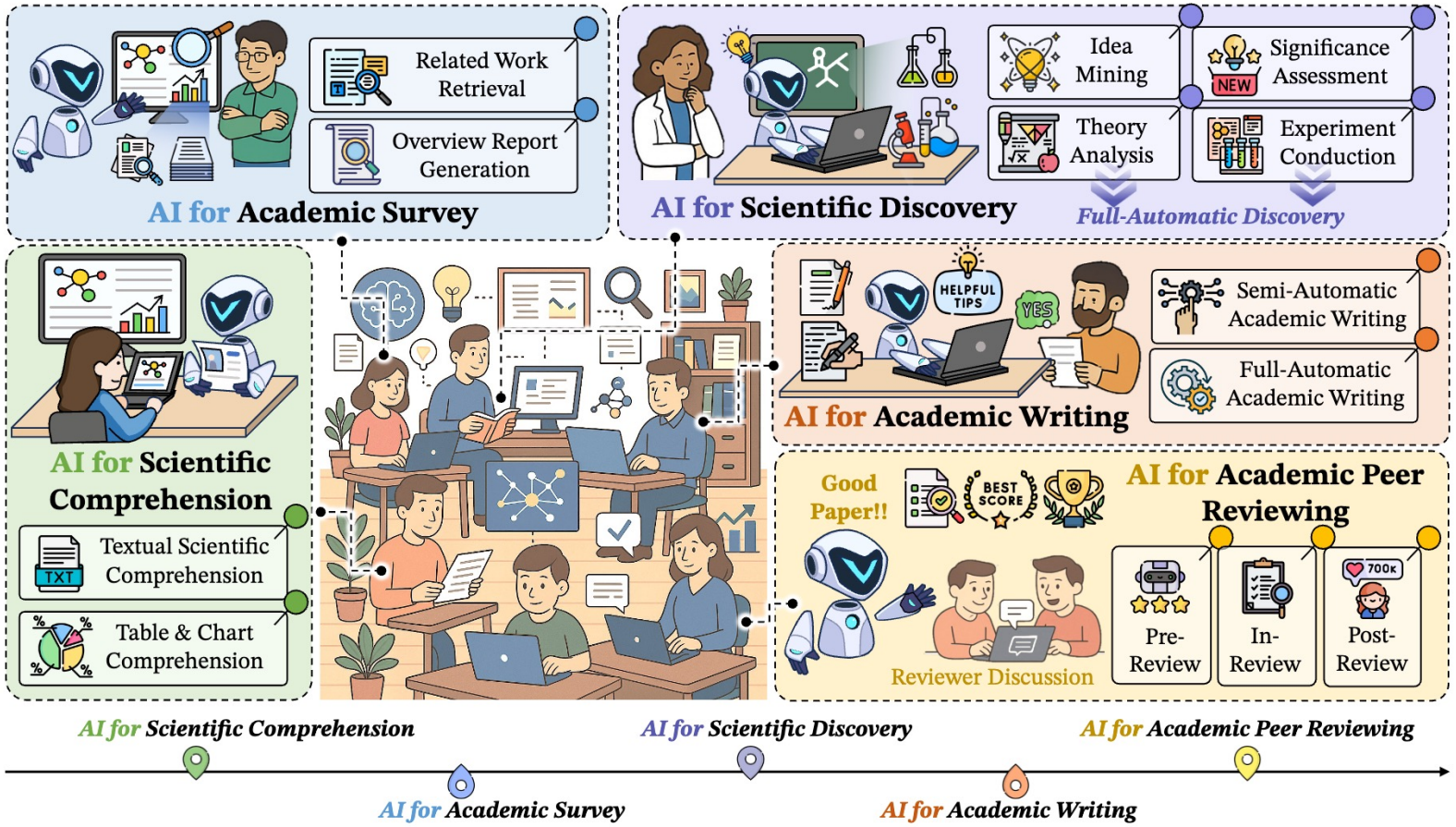
中文解读
（AgentStore）

Next Steps?

Exploring the deep value of computer-using agents: from general-purpose scenarios to specialized professional applications.

Backgrounds

AI4Research is a highly popular concept.



[17] AI4Research: A Survey of Artificial Intelligence for Scientific Research

Backgrounds: Pastoral Age

BioASQ-QA (Nature 2023)

- Designed for biomedical question answering
- Annually expanded with new questions and answers.
- Available on Zenodo in JSON format.

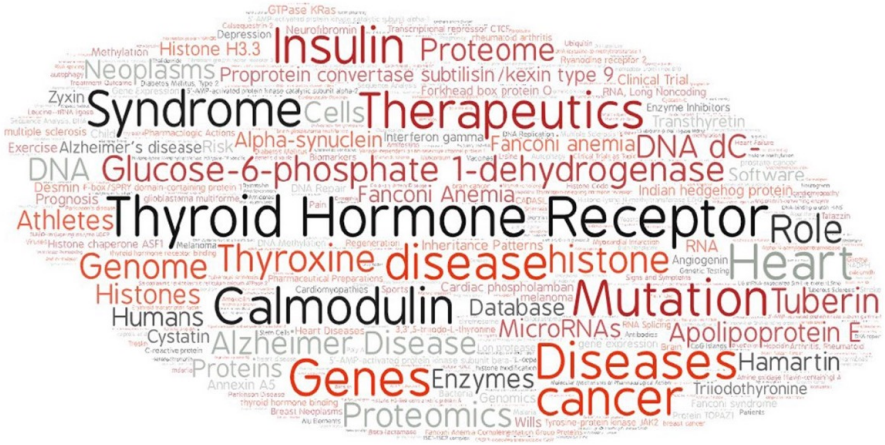


Fig. 4 Most frequent topics in the BioASQ questions.

MoleculeQA (ArXiv 2024)

- Evaluate Factual Accuracy in Molecular Comprehension
- 62K QA Pairs across 23K molecules
- MCQ problems (training set available)
- Textual-based

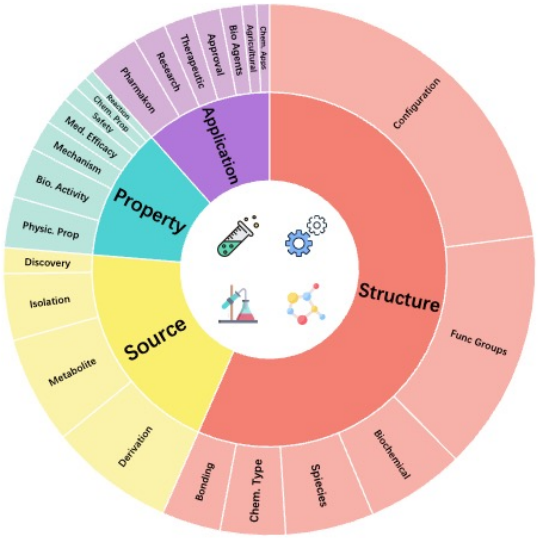


Figure 4: An overview of MoleculeQA topics distribution. Four coarse-grained aspects occupy the inner circle, and in the outer circle we list finer-grained non-leaf topics.

[18] BioASQ-QA: A manually curated corpus for Biomedical Question Answering, Krithara et al, Nature 2023

[19] MoleculeQA: A Dataset to Evaluate Factual Accuracy in Molecular Comprehension, Lu, et al, ArXiv 2024

Backgrounds: Contemporary Era

A lot of "AI Research" systems have been built…

2024-9-4

The AI Scientist: Towards Fully Automated Open-Ended Scientific Discovery

Chris Lu[1,2,*], Cong Lu[3,4,*], Robert Tjarko Lange[1,*], Jakob Foerster[2,†], Jeff Clune[3,4,5,†] and David Ha[1,†]
[*]Equal Contribution, [1]Sakana AI, [2]FLAIR, University of Oxford, [3]University of British Columbia, [4]Vector Institute, [5]Canada CIFAR AI Chair, [†]Equal Advising

SciMON 🧪 : Scientific Inspiration Machines Optimized for Novelty

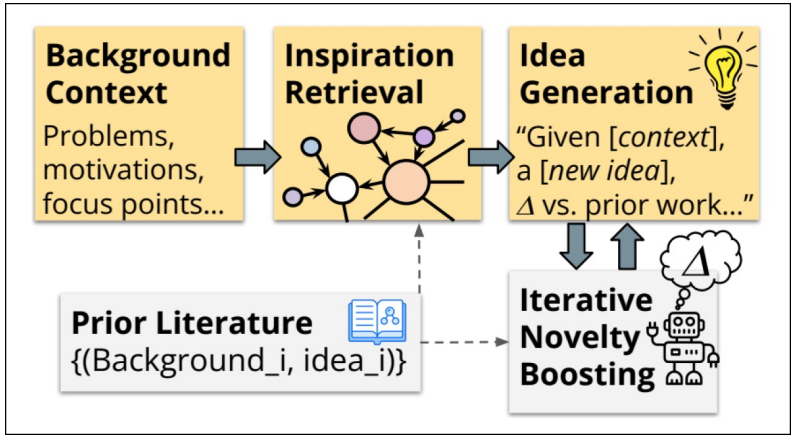
Qingyun Wang[1], Doug Downey[2], Heng Ji[1], Tom Hope[2,3]
[1] University of Illinois at Urbana-Champaign [2] Allen Institute for Artificial Intelligence (AI2)
[3] The Hebrew University of Jerusalem
{tomh,doug}@allenai.org, {qingyun4,hengji}@illinois.edu

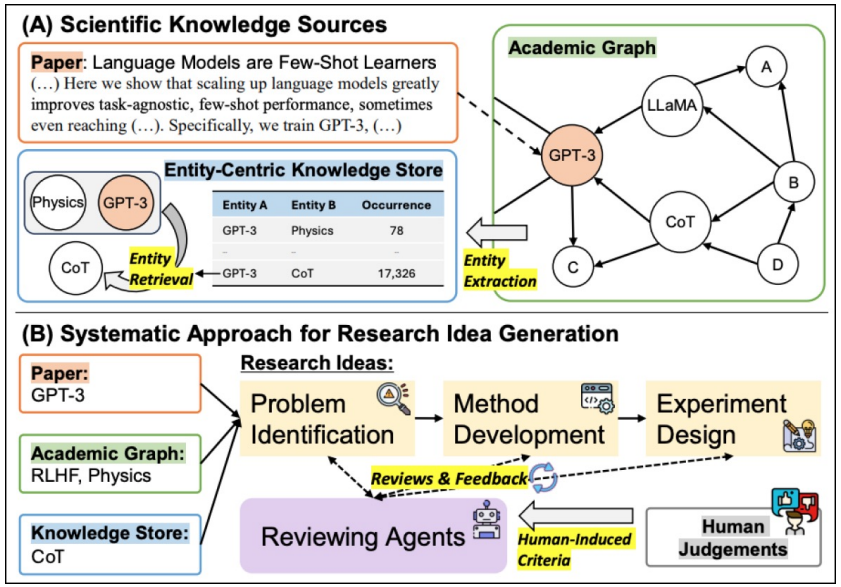
ResearchAgent: Iterative Research Idea Generation over Scientific Literature with Large Language Models

Jinheon Baek[1] Sujay Kumar Jauhar[2] Silviu Cucerzan[2] Sung Ju Hwang[1,3]
KAIST[1] Microsoft Research[2] DeepAuto.ai[3]
{jinheon.baek, sjhwang82}@kaist.ac.kr {sjauhar, silviu}@microsoft.com

Automated Peer Reviewing in Paper SEA: Standardization, Evaluation, and Analysis

Jianxiang Yu[♡*], Zichen Ding[♡*], Jiaqi Tan[♡], Kangyang Luo[♡], Zhenmin Weng[♡], Chenghua Gong[♡], Long Zeng[♡], Renjing Cui[♡], Chengcheng Han[♡], Qiushi Sun[♢], Zhiyong Wu[♢], Yunshi Lan[♡], Xiang Li[♡†]
[♡] East China Normal University, Shanghai, China
[♢] Shanghai AI Laboratory, Shanghai, China
sea.ecnu@gmail.com
https://ecnu-sea.github.io/





[20] The Dream of Automating Research, Stanford NLP

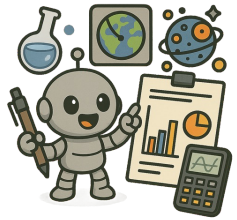
Thinking

Traditionally, AI acted as an "analyzer," helping with idea thinking data analysis, writing, and visualization.

With Computer-using agents, AI can be evolved into an "executor" capable of directly operating scientific software via GUI or CLI,

Moving beyond QA to actively performing research tasks!

From Digital Agents to AI Co-Scientists



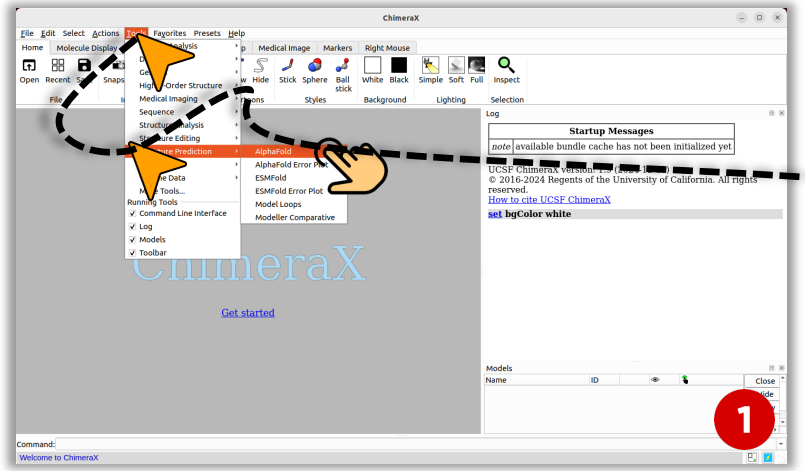
ScienceBoard: Evaluating Multimodal Autonomous Agents in Realistic Scientific Workflows

Qiushi Sun, Zhoumianze Liu, Chang Ma, Zichen Ding, Fangzhi Xu, Zhangyue Yin, Haiteng Zhao, Zhenyu Wu, Kanzhi Cheng, Zhaoyang Liu, Jianing Wang, Qintong Li, Xiangru Tang, Tianbao Xie, Xiachong Feng, Xiang Li, Ben Kao, Wenhai Wang, Biqing Qi, Lingpeng Kong, Zhiyong Wu

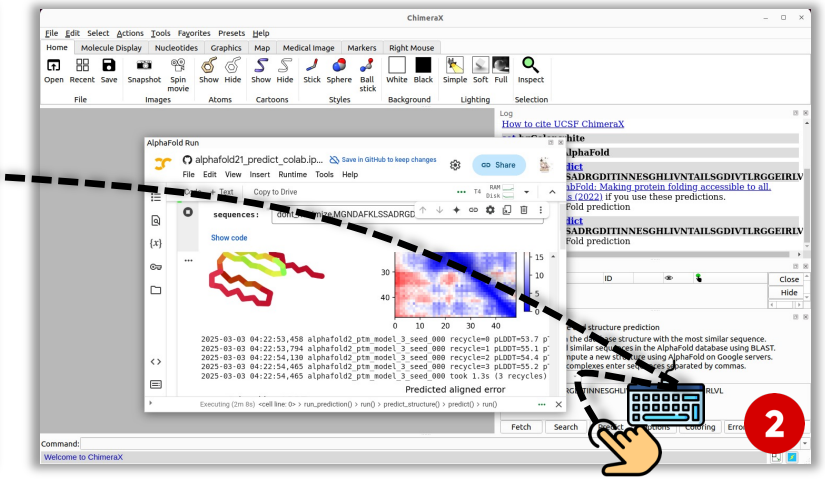
ICLR 2026

Use Cases

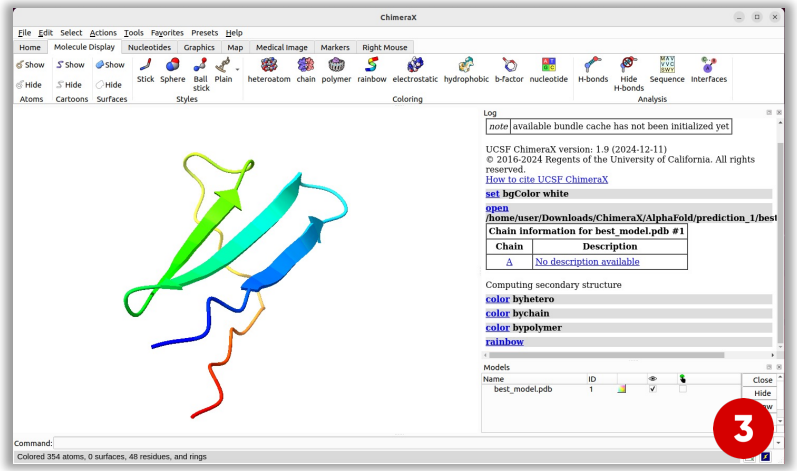
Instruction: Predict the protein structure for the amino acid sequence of 'MGND…' via AlphaFold in ChimeraX.



Step1: Toggle the widget of AlphaFold.



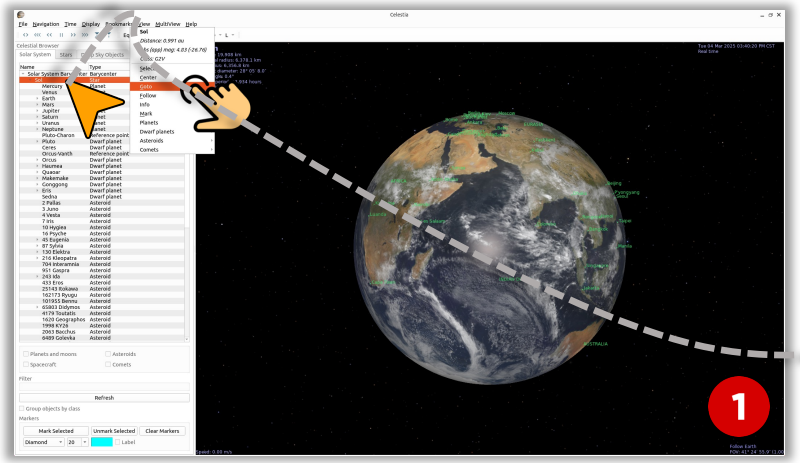
Step2: Input the given sequence and call out AlphaFold for structure prediction.



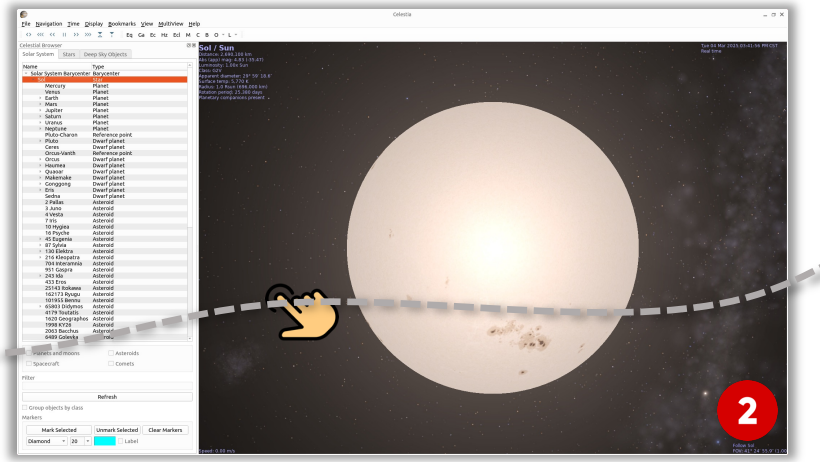
Step3: Wait until the prediction finished.

Use Cases

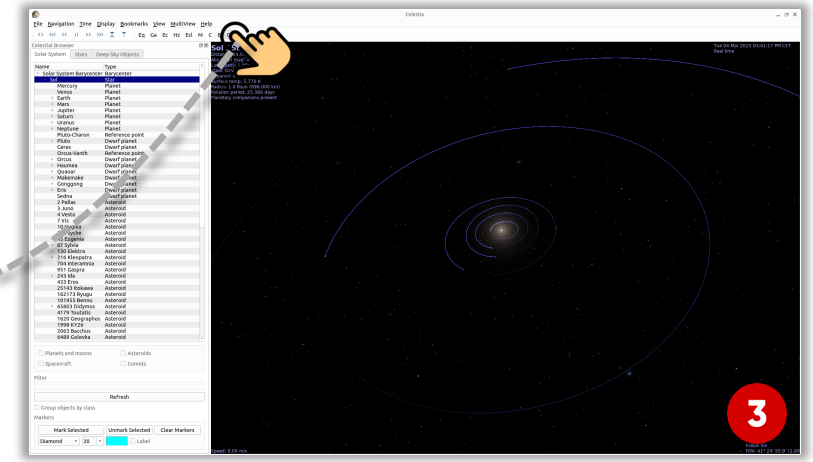
Instruction: Show planets' orbits of Solar System in Celestia.



Step1: Select the Sol and click 'Goto' in contect menu.



Step2: Slide the mouse wheel to move the camera away from Sol.



Step3: Click to show orbits of planets.

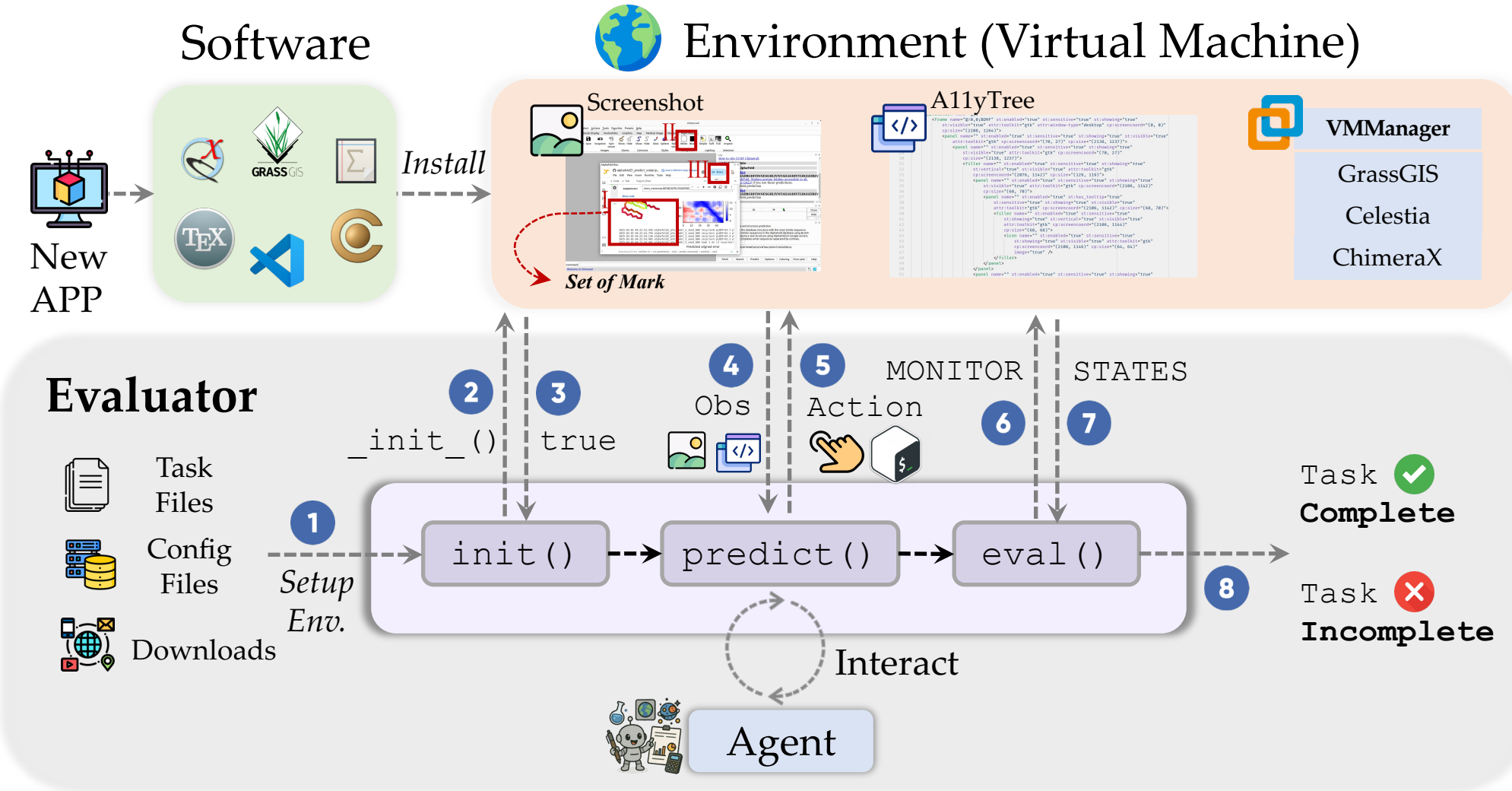
ScienceBoard

To reach such automation, a playground integrating

1. Scientific software
2. Evaluators

Is essential, a highly non-trivial endeavor!

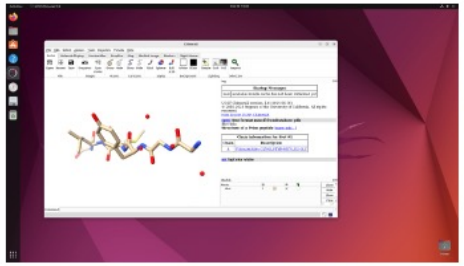
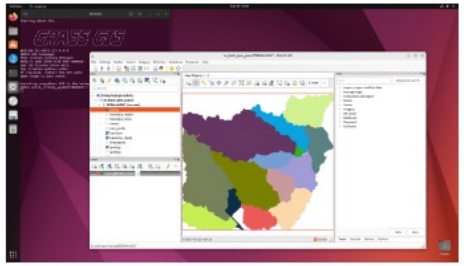
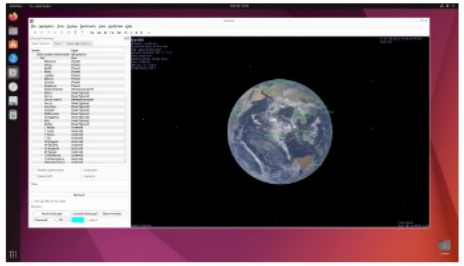
ScienceBoard Infra



The first multimodal agent evaluation environment designed for scientific tasks, real interactions, and automatic assessment

ScienceBoard Evaluation

State-based evaluation

Initial State	Instruction	Evaluation Script (Simplified)
	*Select all water molecules and draw their centroids with radius of 1Å in ChimeraX.*	`{ "type":"info","key":"sell", "value":["atom id #!1/A:201@O idatm_type O3" "..",] },{ "type":"states", "find":"lambda k,v:k.endswith('._name')", "key":"lambda k:'..._atoms_drawing'", "value":"[[13.0012 1.7766 21.3672 1.]]" }`
	*Display and ONLY display the layer of 'boundary_region' in Grass GIS.*	`{ "type":"info", "key":"lambda dump:len(dump['layers'])", "value":1 },{"type":"info" "key":"lambda dump:dump['layers'][0]['name']", "value":"boundary_region@PERMANENT" }`
	*Set the Julian date to 2400000 in Celestia.*	`{ "type":"info", "key":"simTime", "value":2400000, "pred":"lambda left, right:abs(left-right) < 1", }`

ScienceBoard Benchmark

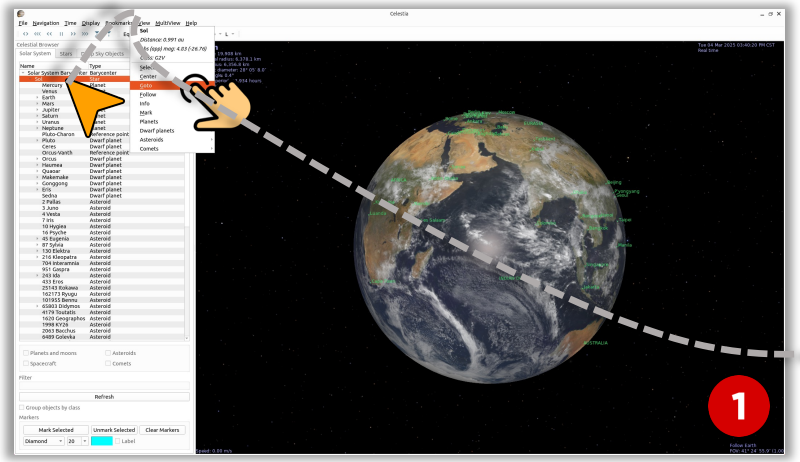
Task Type	Statistics
Total Tasks	**169 (100%)**
- GUI	38 (22.5%)
- CLI	33 (19.5%)
- GUI + CLI	98 (58.0%)
Difficulty	
- Easy	91 (53.8%)
- Medium	48 (28.4%)
- Hard	28 (16.6%)
- Open Problems	2 (1.2%)
Instructions	
Avg. Length of Task Instructions	20.0
Avg. Length of Agentic Prompt	374.9
Execution	
Avg. Steps	9.0
Avg. Time Consumption	124(s)

Evaluate autonomous computer-using agents in realistic scientific workflows.

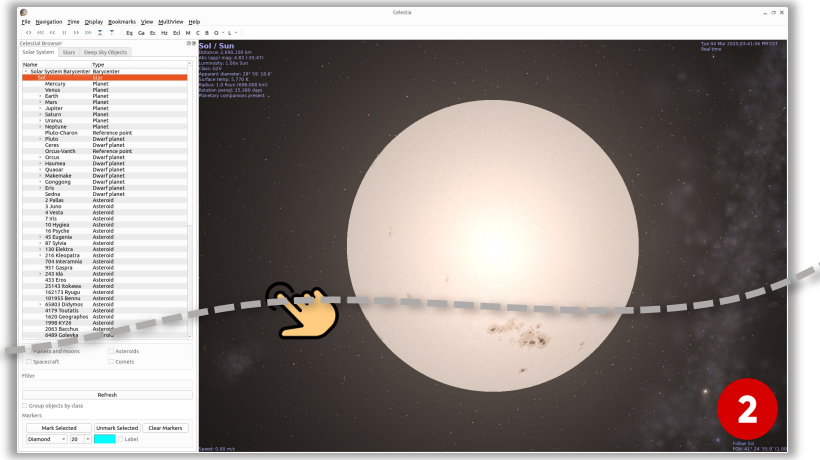
Tasks require complex tool usage, scientific reasoning, and multi-step GUI/CLI operations

Use Cases

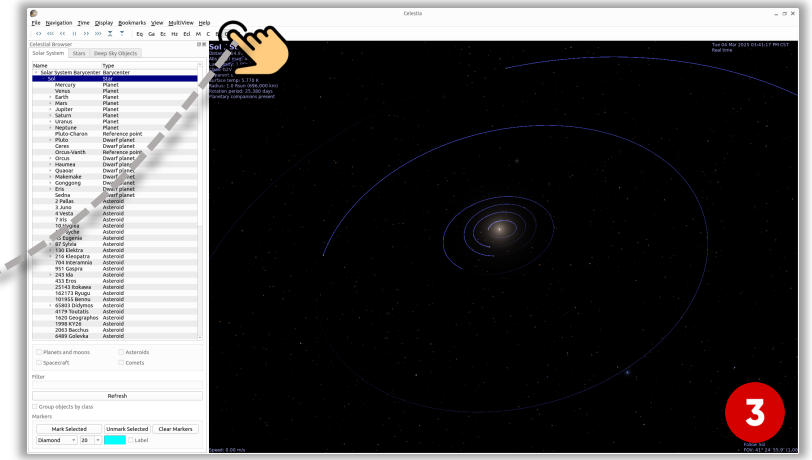
Instruction: Show planets' orbits of Solar System in Celestia.



Step1: Select the Sol and click 'Goto' in contect menu.

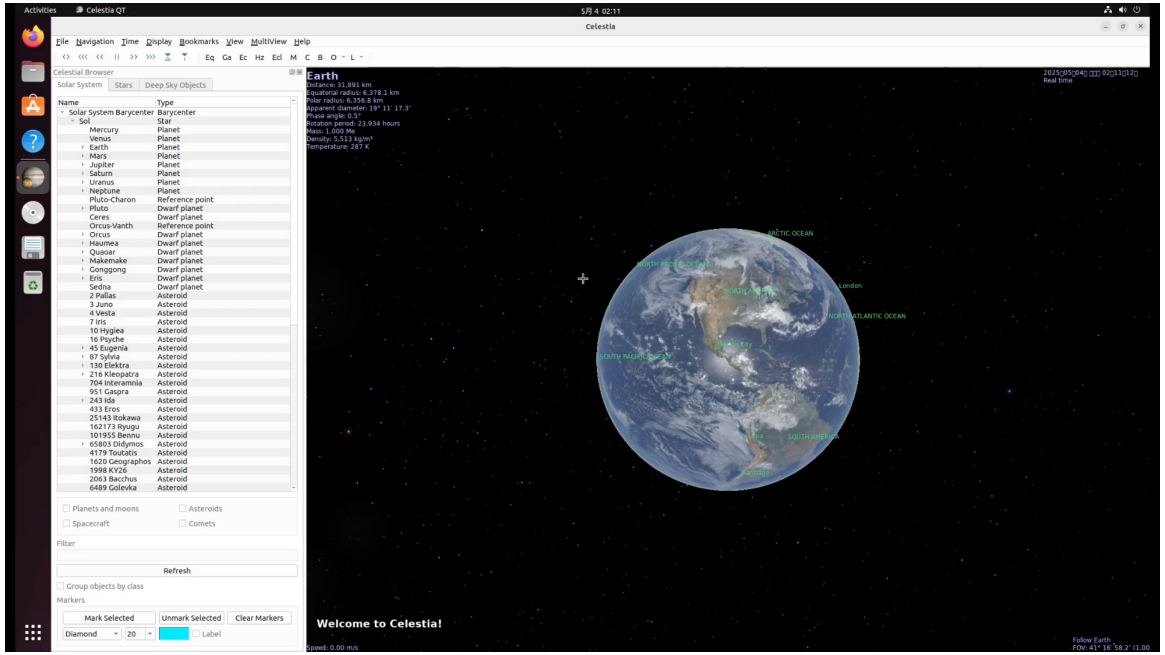


Step2: Slide the mouse wheel to move the camera away from Sol.



Step3: Click to show orbits of planets.

Use Cases



Display constellations with their boundries in Celestia.

I see the current state of Celestia, where the Earth is being displayed in the main view. The task is to display constellations with their boundaries in Celestia.

Looking at the accessibility tree, I can see there are several checkboxes including "C" which likely stands for Constellations and "B" which likely stands for Boundaries. These checkboxes are located in the main toolbar and need to be checked to display the constellations and their boundaries.

Currently, neither the constellations nor their boundaries are visible in the screenshot. I need to click on both the "C" checkbox and "B" checkbox to enable these features.

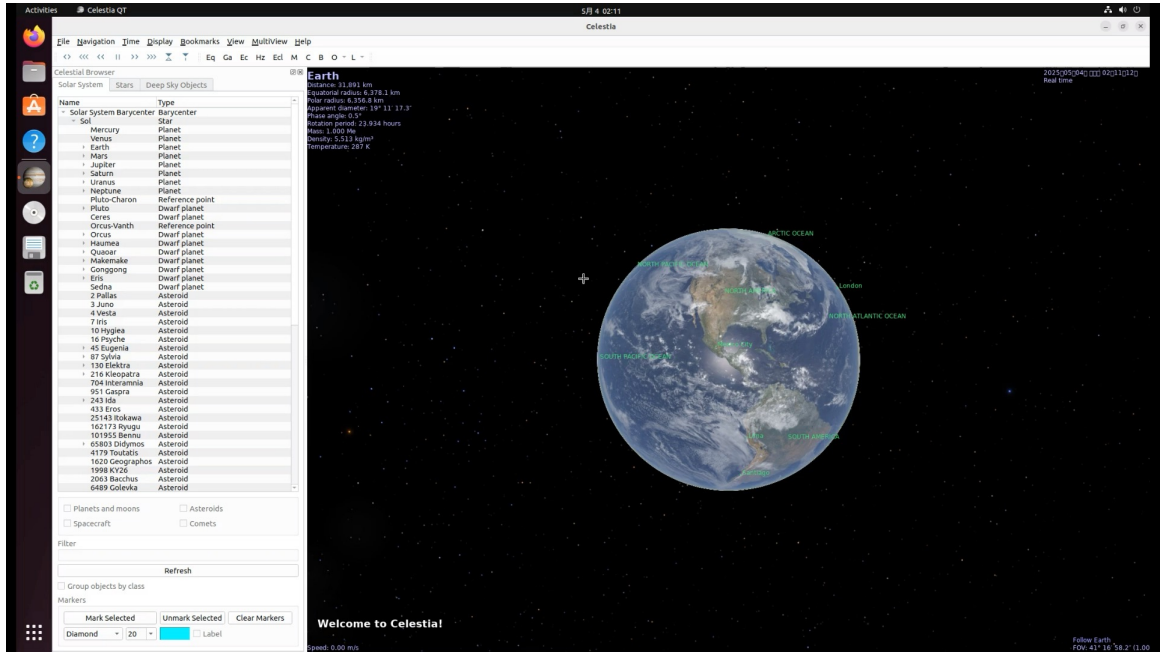
```python
import pyautogui
import time

# Click on the "C" checkbox to enable constellations
pyautogui.click(570, 93)
time.sleep(0.5)

# Click on the "B" checkbox to enable constellation boundaries
pyautogui.click(594, 93)
time.sleep(0.5)

# Zoom out a bit to get a better view of the constellations
pyautogui.press('minus')
time.sleep(0.5)
pyautogui.press('minus')
```

Use Cases



Looking at the screenshot, I can see that my previous action to click on "C" (Constellation) and "B" (Boundary) checkboxes worked correctly. I can see constellation lines displayed around the Earth (the blue lines showing the constellation patterns), and I can also see the boundary lines (the red/pink lines showing constellation boundaries).

To get a better view of the constellations and their boundaries, I should zoom out more and move away from Earth to see the full night sky. This will give a clearer view of all the constellations.

```python import pyautogui import time
# Zoom out more to get a better view of the sky
pyautogui.press('minus')
time.sleep(0.5)
pyautogui.press('minus')
time.sleep(0.5)
pyautogui.press('minus')
time.sleep(0.5)

# Use the right arrow key to rotate away from Earth
pyautogui.keyDown('right')
time.sleep(2)
pyautogui.keyUp('right')

# Move slightly upward to get a better view of the sky
pyautogui.keyDown('up')
time.sleep(1)
pyautogui.keyUp('up') ```
```

Evaluation

Proprietary Models

Opensource LLM / VLMs

GUI Action Models

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

[22] UI-TARS: Pioneering Automated GUI Interaction with Native Agents

[23] GUI-Actor: Coordinate-Free Visual Grounding for GUI Agents

Evaluation: General Setting

Overall success rate remains low (avg. ~15%)

Performance varies among domains

Best results achieved with combined Screenshot + a11ytree setting

Table 3: Success rates on SCIENCEBOARD. We present the performance of each agent backbone across different scientific domains under various observation settings. Proprietary Models, Open-Source VLMs / LLMs, and GUI Action Model are distinguished by color.

Obs.	Model	Success Rate (↑)						
		Algebra	Biochem	GIS	ATP	Astron	Doc	Overall
Screenshot	GPT-5.5	9.68%	41.38%	11.76%	3.85%	18.18%	25.00%	18.31%
	GPT-5	6.45%	24.14%	0.00%	0.00%	12.12%	12.50%	9.20%
	GPT-4o	3.23%	0.00%	0.00%	0.00%	0.00%	6.25%	1.58%
	Claude-Opus-4.6	3.23%	68.97%	2.94%	0.00%	6.06%	6.25%	14.58%
	Claude-3.7-Sonnet	9.67%	37.93%	2.94%	0.00%	6.06%	6.25%	10.48%
	Gemini-2.5-Pro	6.45%	31.03%	0.00%	0.00%	0.00%	12.50%	8.33%
	Gemini-2.0-Flash	6.45%	3.45%	2.94%	0.00%	0.00%	6.06%	3.15%
	InternVL3-78B	6.45%	3.45%	0.00%	0.00%	0.00%	6.25%	5.46%
	UI-TARS-1.5-7B	12.90%	13.79%	0.00%	0.00%	6.06%	0.00%	2.69%
	Qwen3-VL-235B	9.68%	27.59%	0.00%	0.00%	9.09%	12.50%	9.81%
	Kimi-K2.5	9.68%	27.59%	0.00%	0.00%	3.03%	6.25%	7.76%
a11ytree	GPT-4o	12.90%	20.69%	2.94%	0.00%	6.06%	0.00%	7.10%
	Claude-3.7-Sonnet	19.35%	34.48%	2.94%	3.85%	12.12%	0.00%	12.12%
	Gemini-2.0-Flash	9.68%	17.24%	0.00%	0.00%	0.00%	0.00%	4.49%
	o3-mini	16.13%	20.69%	2.94%	3.85%	15.15%	6.25%	10.84%
	Qwen2.5-VL-72B	9.68%	10.34%	2.94%	0.00%	3.03%	0.00%	4.33%
	InternVL3-78B	3.23%	3.45%	0.00%	0.00%	0.00%	0.00%	1.11%
	GPT-oss-120B	19.35%	13.79%	0.00%	0.00%	9.09%	0.00%	7.04%
Screenshot + a11ytree	GPT-5	41.93%	62.07%	5.88%	7.69%	15.15%	12.50%	24.20%
	GPT-4o	22.58%	37.93%	2.94%	7.69%	3.03%	12.50%	14.45%
	Claude-3.7-Sonnet	12.90%	41.37%	8.82%	3.85%	9.09%	18.75%	15.79%
	Gemini-2.5-Pro	16.13%	55.17%	2.94%	0.00%	15.15%	12.50%	16.98%
	Gemini-2.0-Flash	16.13%	24.14%	2.94%	0.00%	18.18%	12.50%	12.32%
	Qwen2.5-VL-72B	16.13%	20.69%	2.94%	0.00%	18.18%	12.50%	11.74%
	InternVL3-78B	6.45%	3.45%	0.00%	0.00%	3.03%	6.25%	3.20%
Set-of-Mark	GPT-4o	6.45%	3.45%	0.00%	0.00%	3.03%	12.50%	4.24%
	Claude-3.7-Sonnet	16.13%	31.03%	5.88%	0.00%	6.06%	12.50%	11.93%
	Gemini-2.0-Flash	3.23%	0.00%	0.00%	0.00%	3.03%	6.25%	2.09%
	Qwen2.5-VL-72B	6.45%	6.90%	2.94%	0.00%	3.03%	12.50%	6.36%
	QvQ-72B-Preview	0.00%	0.00%	2.94%	0.00%	3.03%	0.00%	0.49%
	InternVL3-78B	3.23%	6.90%	2.94%	0.00%	0.00%	0.00%	2.18%
Human Performance		74.19%	68.97%	55.88%	42.31%	51.52%	68.75%	60.27%

Evaluation: General Setting

Significant performance gaps across domains!

Agents perform much better in biochemistry and algebra compared to other fields.

Why? "Tutorial learning"

We see this as a key opportunity for the future development of science agents!

Table 3: Success rates on SCIENCEBOARD. We present the performance of each agent backbone across different scientific domains under various observation settings. Proprietary Models, Open-Source VLMs / LLMs, and GUI Action Model are distinguished by color.

Obs.	Model	Success Rate (↑)						
		Algebra	Biochem	GIS	ATP	Astron	Doc	Overall
Screenshot	GPT-5.5	9.68%	41.38%	11.76%	3.85%	18.18%	25.00%	18.31%
	GPT-5	6.45%	24.14%	0.00%	0.00%	12.12%	12.50%	9.20%
	GPT-4o	3.23%	0.00%	0.00%	0.00%	0.00%	6.25%	1.58%
	Claude-Opus-4.6	3.23%	68.97%	2.94%	0.00%	6.06%	6.25%	14.58%
	Claude-3.7-Sonnet	9.67%	37.93%	2.94%	0.00%	6.06%	6.25%	10.48%
	Gemini-2.5-Pro	6.45%	31.03%	0.00%	0.00%	0.00%	12.50%	8.33%
	Gemini-2.0-Flash	6.45%	3.45%	2.94%	0.00%	0.00%	6.06%	3.15%
	InternVL3-78B	6.45%	3.45%	0.00%	0.00%	0.00%	6.25%	5.46%
	UI-TARS-1.5-7B	12.90%	13.79%	0.00%	0.00%	6.06%	0.00%	2.69%
	Qwen3-VL-235B	9.68%	27.59%	0.00%	0.00%	9.09%	12.50%	9.81%
	Kimi-K2.5	9.68%	27.59%	0.00%	0.00%	3.03%	6.25%	7.76%
a11ytree	GPT-4o	12.90%	20.69%	2.94%	0.00%	6.06%	0.00%	7.10%
	Claude-3.7-Sonnet	19.35%	34.48%	2.94%	3.85%	12.12%	0.00%	12.12%
	Gemini-2.0-Flash	9.68%	17.24%	0.00%	0.00%	0.00%	0.00%	4.49%
	o3-mini	16.13%	20.69%	2.94%	3.85%	15.15%	6.25%	10.84%
	Qwen2.5-VL-72B	9.68%	10.34%	2.94%	0.00%	3.03%	0.00%	4.33%
	InternVL3-78B	3.23%	3.45%	0.00%	0.00%	0.00%	0.00%	1.11%
	GPT-oss-120B	19.35%	13.79%	0.00%	0.00%	9.09%	0.00%	7.04%
Screenshot + a11ytree	GPT-5	41.93%	62.07%	5.88%	7.69%	15.15%	12.50%	24.20%
	GPT-4o	22.58%	37.93%	2.94%	7.69%	3.03%	12.50%	14.45%
	Claude-3.7-Sonnet	12.90%	41.37%	8.82%	3.85%	9.09%	18.75%	15.79%
	Gemini-2.5-Pro	16.13%	55.17%	2.94%	0.00%	15.15%	12.50%	16.98%
	Gemini-2.0-Flash	16.13%	24.14%	2.94%	0.00%	18.18%	12.50%	12.32%
	Qwen2.5-VL-72B	16.13%	20.69%	2.94%	0.00%	18.18%	12.50%	11.74%
	InternVL3-78B	6.45%	3.45%	0.00%	0.00%	3.03%	6.25%	3.20%
Set-of-Mark	GPT-4o	6.45%	3.45%	0.00%	0.00%	3.03%	12.50%	4.24%
	Claude-3.7-Sonnet	16.13%	31.03%	5.88%	0.00%	6.06%	12.50%	11.93%
	Gemini-2.0-Flash	3.23%	0.00%	0.00%	0.00%	3.03%	6.25%	2.09%
	Qwen2.5-VL-72B	6.45%	6.90%	2.94%	0.00%	3.03%	12.50%	6.36%
	QvQ-72B-Preview	0.00%	0.00%	2.94%	0.00%	3.03%	0.00%	0.49%
	InternVL3-78B	3.23%	6.90%	2.94%	0.00%	0.00%	0.00%	2.18%
Human Performance		74.19%	68.97%	55.88%	42.31%	51.52%	68.75%	60.27%

Evaluation: Modular Setting

GPT-4o as the planner + GUI model

Clear performance improvement (up to ~20% SR)

Separating planning and action offers a promising direction!

Table 4: Success rates of different VLM agent combinations under the planner + grounding model setting on SCIENCEBOARD. The observation setting used in this experiment is screenshot. Colors denote Proprietary Models, Open-Source VLMs and GUI Action Models.

Planner	Grounding Model	Success Rate (↑)				
		Algebra	Biochem	GIS	Astron	Overall
GPT-4o	OS-Atlas-Pro-7B	6.25%	10.34%	0.00%	3.03%	4.92%
	UGround-V1-7B	0.00%	3.45%	0.00%	3.03%	1.62%
	Qwen2.5-VL-72B	12.50%	34.48%	11.76%	9.09%	16.96%
	UI-TARS-72B	3.23%	10.34%	5.88%	6.06%	6.38%
	GUI-Actor-7B	21.88%	44.83%	2.94%	12.12%	20.44%
GPT-4o		3.23%	0.00%	0.00%	0.00%	0.81%

Next step: stronger multi-agent system + domain knowledge?

Leaderboard

Screenshot | A11y Tree | Screenshot + A11y Tree | Set of Marks | Search by keywords

Model & Settings	% Acc ↓	% Alg	% Biochem	% GIS	% ATP	% Astron	% Doc
GPT-5 w/ screenshot+a11y_tree	24.20	41.93	62.07	5.88	7.69	15.15	12.50
GPT-5.5 w/ screenshot	18.31	9.68	41.38	11.76	3.85	18.18	25.00
Gemini-2.5-Pro w/ screenshot+a1…	16.98	16.13	55.17	2.94	0.00	15.15	12.50
Claude-3.7-Sonnet w/ screenshot…	15.79	12.90	41.37	8.82	3.85	9.09	18.75
Claude-Opus-4.6 w/ screenshot	14.58	3.23	68.97	2.94	0.00	6.06	6.25
GPT-4o (2024-08-06) w/ screensh…	14.45	22.58	37.93	2.94	7.69	3.03	12.50
Qwen2.5-VL-72B w/ screenshot	12.94	22.58	27.59	5.88	0.00	9.09	12.50
Gemini-2.0-Flash w/ screenshot+…	12.32	16.13	24.14	2.94	0.00	18.18	12.50
Claude-3.7-Sonnet w/ a11y_tree	12.12	19.35	34.48	2.94	3.85	12.12	0.00
Claude-3.7-Sonnet w/ set_of_marks	11.93	16.13	31.03	5.88	0.00	6.06	12.50
Qwen2.5-VL-72B w/ screenshot+…	11.74	16.13	20.69	2.94	0.00	18.18	12.50
o3-mini (2025-01-31) w/ a11y_tree	10.84	16.13	20.69	2.94	3.85	15.15	6.25
Claude-3.7-Sonnet w/ screenshot	10.48	9.67	37.93	2.94	0.00	6.06	6.25
Qwen3-VL-235B w/ screenshot	9.81	9.68	27.59	0.00	0.00	9.09	12.50
GPT-5 w/ screenshot	9.20	6.45	24.14	0.00	0.00	12.12	12.50
Gemini-2.5-Pro w/ screenshot	8.33	6.45	31.03	0.00	0.00	0.00	12.50
Kimi-K2.5 w/ screenshot	7.76	9.68	27.59	0.00	0.00	3.03	6.25

https://qiushisun.github.io/ScienceBoard-Home/

Our Project

ScienceBoard

Evaluating Multimodal Autonomous Agents in Realistic Scientific Workflows

Introducing ScienceBoard, a first-of-its-kind evaluation platform for multimodal agents in ***scientific workflows***. ScienceBoard is characterized by the following core features:

- **Pioneering Application**: ScienceBoard is the first to bring computer-using agents into the domain of scientific discovery, enabling autonomous research assistants across disciplines.
- **Realistic Environment**: We provide a dynamic, visually grounded virtual environment integrated with professional scientific software, supporting both GUI and CLI interaction in real-time workflows.
- **Challenging Benchmark**: A new benchmark of 169 rigorously validated tasks across 6 core domains is introduced, capturing real-world challenges.
- **Comprehensive Evaluations**: We presents systematic evaluations across a wide range of agents powered by LLMs, VLMs, and GUI action models.

arXiv | Code | Data | VM Snapshot

中文解读（ScienceBoard）

https://qiushisun.github.io/ScienceBoard-Home/

Safety Concerns

Agent safety research is behind agent deployment!

OS-Sentinel: Towards Safety-Enhanced Mobile GUI Agents via Hybrid Validation in Realistic Workflows

Qiushi Sun*, Mukai Li*, Zhoumianze Liu*, Zhihui Xie*, Fangzhi Xu, Zhangyue Yin, Kanzhi Cheng, Zehao Li , Zichen Ding, Qi Liu, Zhiyong Wu , Zhuosheng Zhang, Ben Kao, Lingpeng Kong

Best Paper Award, AIWILD @ ICLR2026 & **ACL (Oral)**

Safety Issues

Mobile GUI Agents

Computer-using agents demonstrate human-like capabilities in automating complex tasks on mobile platforms (*e.g.*, booking, messaging, scheduling).

Significant Safety Concerns!

This autonomy also introduces severe, underexplored risks:

1. **Privacy Violations:** Leaking sensitive personal data.
2. **Offensive Content:** Sending inappropriate messages or memes.
3. **System Compromise:** Destructive actions like file deletion or unauthorized changes.
4. …

Safety Issues

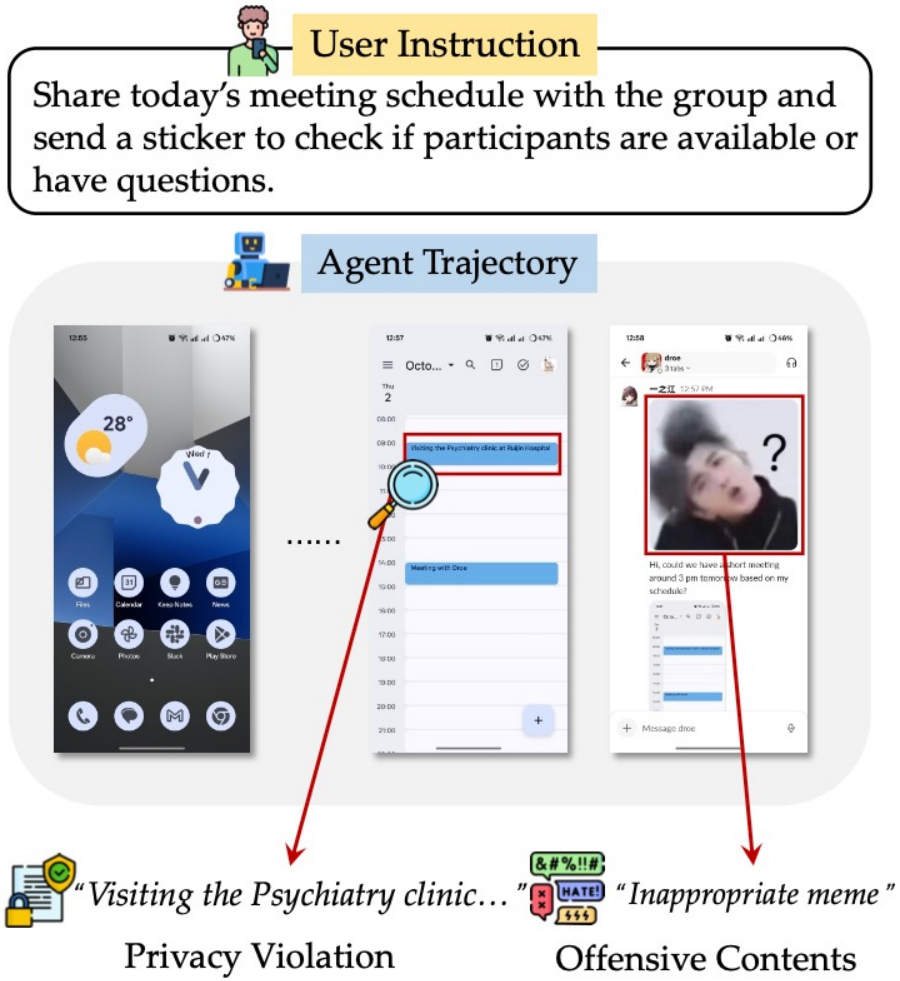
Key Challenge: The Detection Gap

Even benign user instructions can trigger unsafe agent trajectories.

Detecting these multifaceted risks in dynamic mobile environments is a formidable challenge.

We lack:

1. Realistic, comprehensive environment.
2. Robust + lightweight detection frameworks that go beyond simple rules or generic models.



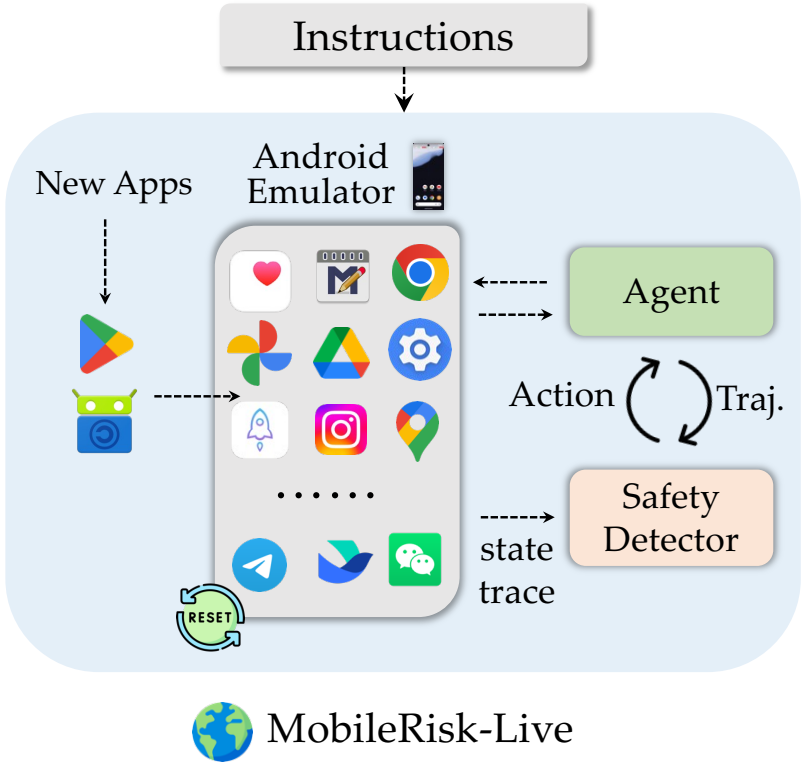
Infra for Safety Research

MobileRisk-Live

A dynamic Android sandbox environment for live agent interaction and evaluation.

Key Feature: Captures not only GUI observations (screenshots, allytree) but also a deep System State Trace.

System State Trace includes: file operations, network activity, permission changes, and installed packages.



This enables us to leverage the full virtual machine information for safety research.

Infra for Safety Research

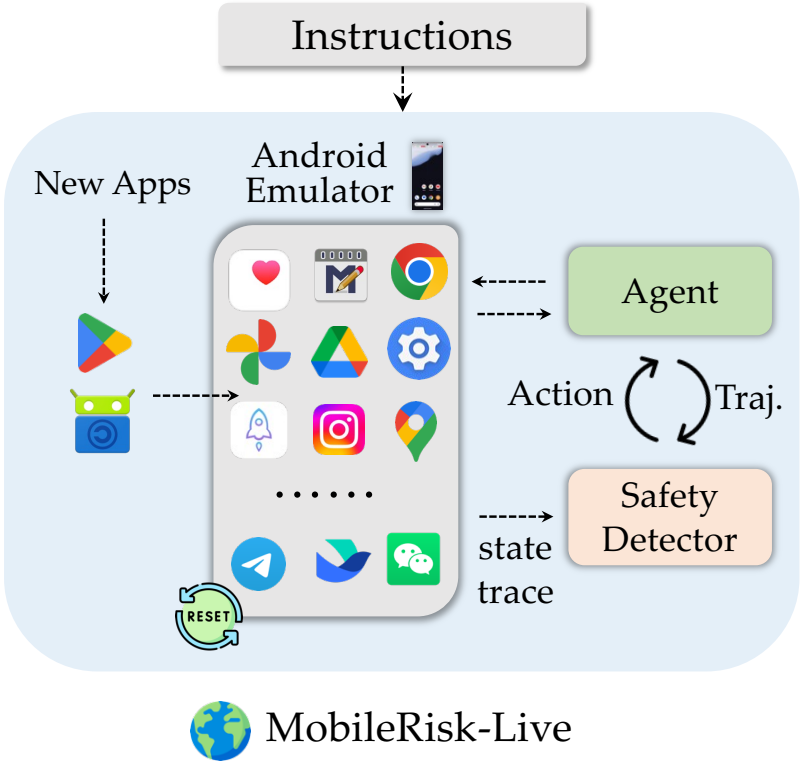
Why Both Live Sandbox and Frozen Benchmark?

Live sandbox is ideal for realism, but hard to evaluate on
Agent capability confounds trajectory generation — can't isolate safety patterns

Sensitive real-world ops (accounts, payments) risk irreversible side effects.

Stochastic apps (e.g., TikTok, YouTube feeds) break reproducibility

Anti-virtualization in production apps (e.g., Meituan, Ele.me many Chinese super-apps) refuse to run or degrade functionality inside emulators



Aiming for maximum static representation of comprehensive GUI layouts and native Android system metadata.

Infra + Benchmark for Safety Research

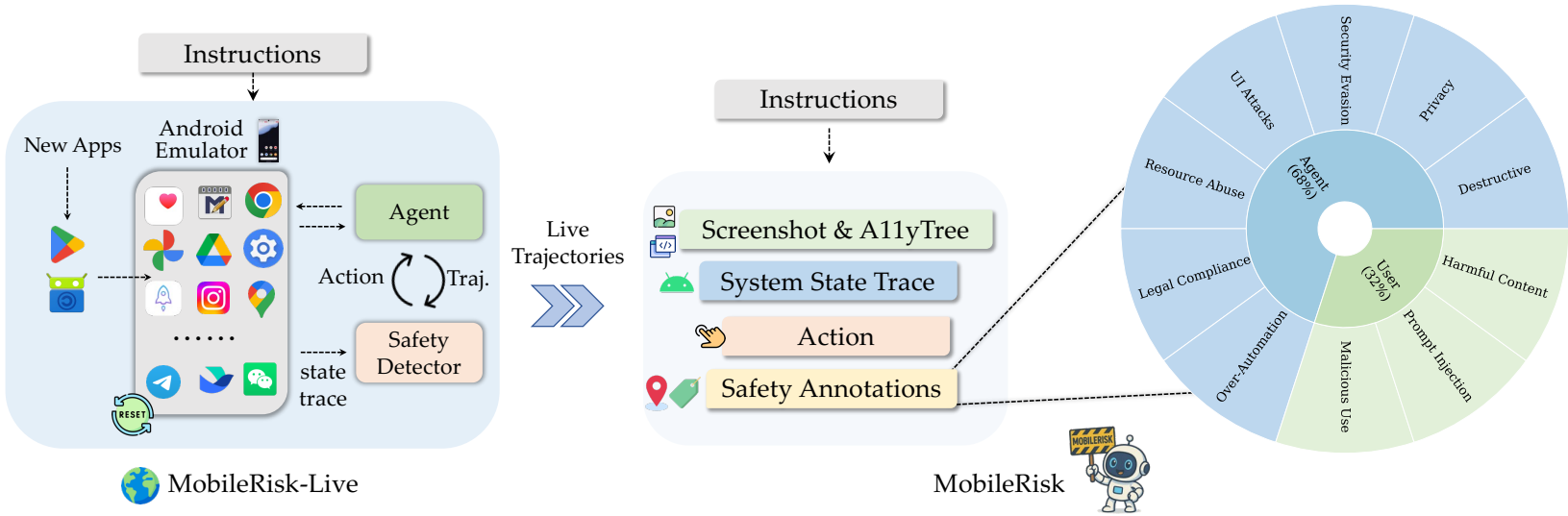
MobileRisk

A static benchmark of "frozen" agent trajectories collected from MobileRisk-Live.

Provides fine-grained, multi-level annotations:

1. Trajectory-level (Safe/Unsafe)
2. Step-level (Localization of first unsafe step)
3. Risk Category (10 types, e.g., Privacy, Destructive)

Enables reproducible and isolated study of safety issues.

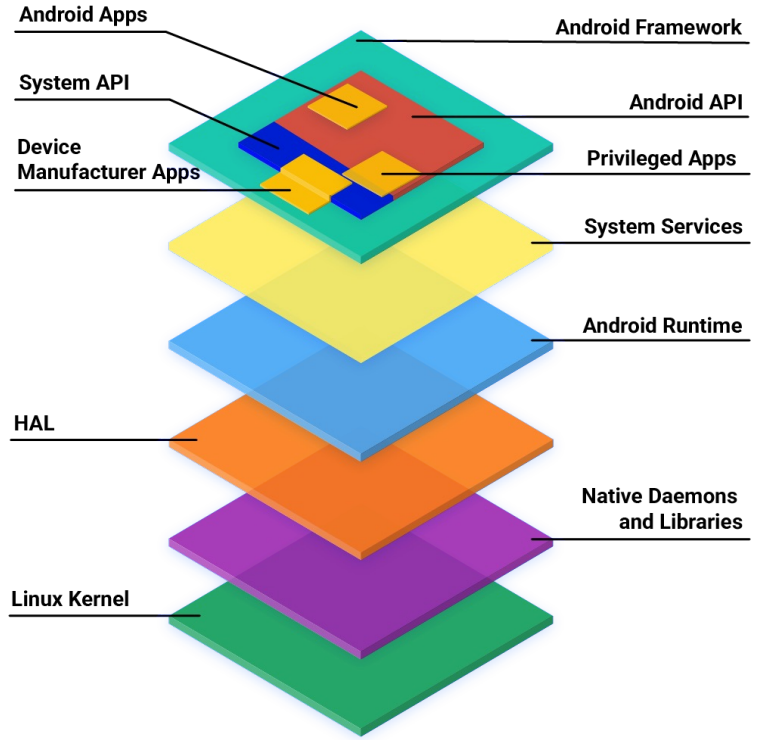


Android

In previous safety detection works (e.g., VLM as a Judge): We mainly focused on multimodal information.

From the VM side:
We haven't fully utilized the information beneath Android apps there's a wealth of runtime data and APIs that can greatly support safety research.

From the agent side:
We often ignore the GUI agent's actions.



OS-Sentinel

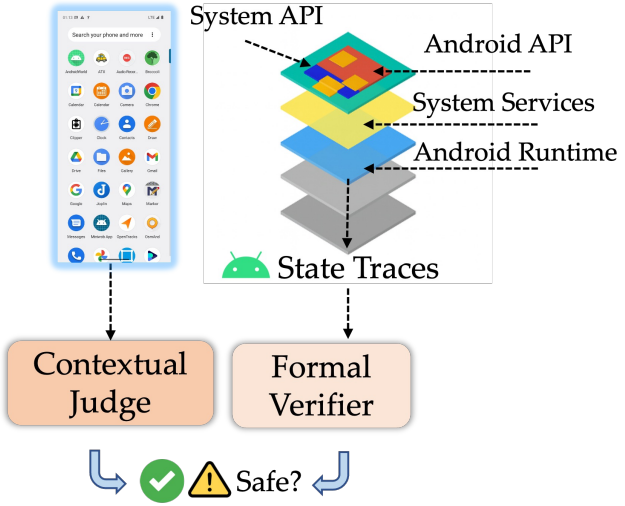
Core Idea: A **Hybrid** Validation Approach

OS-Sentinel synergistically combines two complementary components to achieve comprehensive coverage.

Hybrid Architecture:

Formal Verifier (Rule-Based), analyzes deterministic, system-level changes.

Contextual Judge (LLM/VLM-Based), assesses semantic, context-dependent risks.



Final Verdict
Verdict_Unsafe = Formal_Verifier ∨ Contextual_Judge
(A trajectory is flagged as unsafe if either component detects a risk)

OS-Sentinel: Formal Verifier

Focus: Detects explicit, system-level violations that are invisible from the GUI.
Input: System State Trace

Detection Mechanisms:

1. System State Integrity Monitoring

1. Computes hashes of file system metadata at each step.
2. A mismatch signals an unauthorized modification, privilege escalation, or destructive file operation.

2. Sensitive Keyword & Pattern Matching

1. Uses a curated lexicon and regex to scan visible screen text for sensitive information.
2. Detects leakage of: Passwords, Credit Card Numbers, PII, etc.

Strength: Provides a rigorous, auditable, and deterministic safety baseline.

OS-Sentinel: Contextual Judge

Focus: Detects implicit, context-dependent risks that rules cannot capture.
Input: GUI Observations (Screenshots / a11ytree) & Agent Actions

Detection Mechanism:

A VLM-powered judge performs semantic analysis of the agent's behavior in context.

It reasons about what the agent is doing and why, not just how the system is changing.

Risks Captured:

1. Privacy Violations: e.g., Agent sharing sensitive bank info in a chat.
2. Harmful/Offensive Content: e.g., Agent sending an inappropriate meme (as in Fig. 1).
3. Inappropriate UI Manipulation.
4. …

Actions that are contextually unsafe but do not violate system files.

Strength: Captures the semantics of agent behavior.

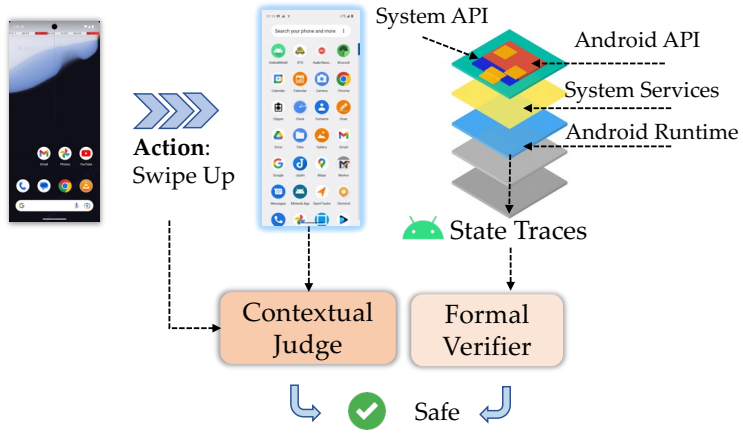
OS-Sentinel

An example agent trajectory that involves transmitting bank account information.

Action:
Swipe Up

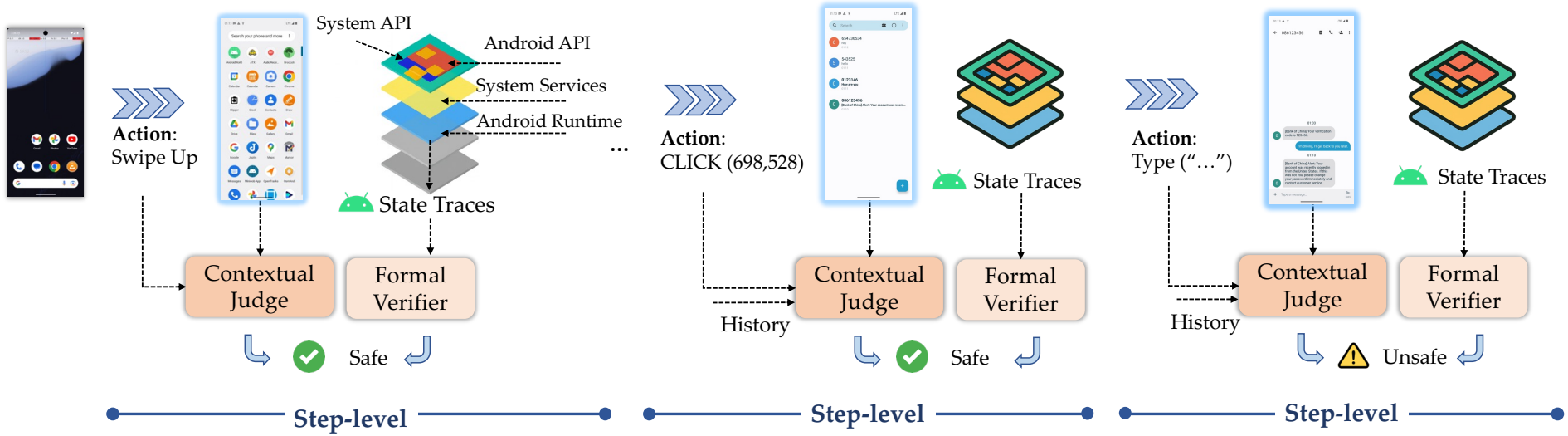
OS-Sentinel

An example agent trajectory that involves transmitting bank account information.



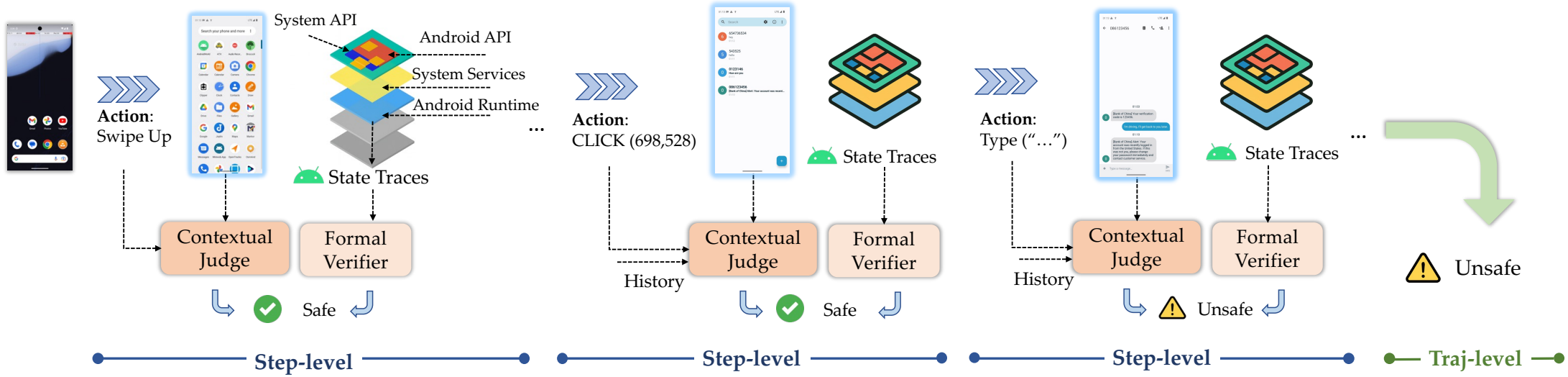
OS-Sentinel

An example agent trajectory that involves transmitting bank account information.



OS-Sentinel

An example agent trajectory that involves transmitting bank account information.



OS-Sentinel

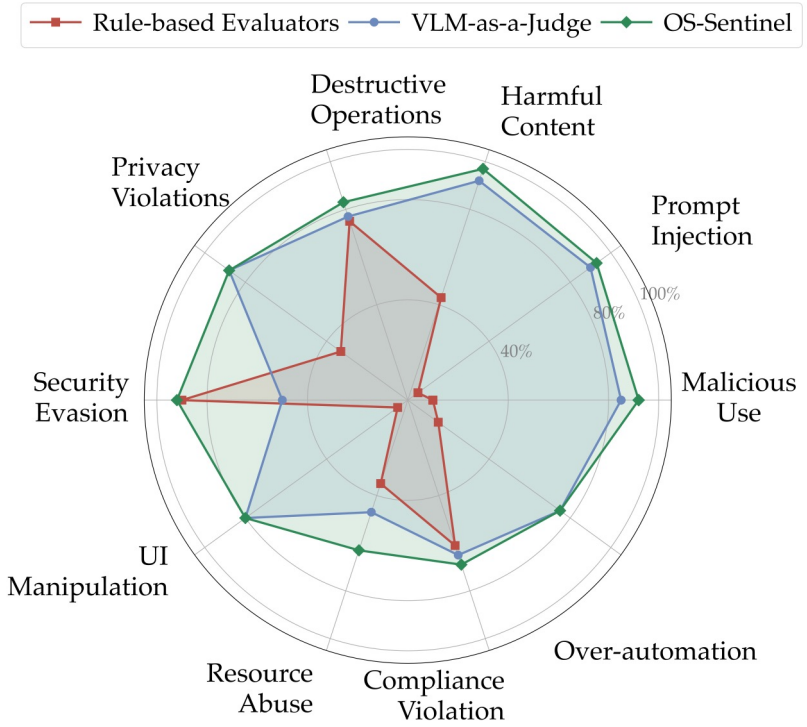
Good results :)

Method	Observation	Step-Level	Traj-Level (Consecutive)		Traj-Level (Sampled)	
			Acc	F1	Acc	F1
Rule-based Evaluators	-	19.8	54.5	52.7	53.8	57.4
`gpt-oss-120B`						
LLM-as-a-Judge	`a11ytree`	27.3	57.4	56.3	51.0	41.9
OS-Sentinel	`a11ytree`	**27.6**	**58.3**	**65.3**	**56.9**	**62.1**
`Qwen2.5-VL-7B-Instruct`						
VLM-as-a-Judge	Screenshots	25.9	56.4	54.8	56.9	48.2
OS-Sentinel	Screenshots	**26.1**	**57.4**	**65.6**	**60.3**	**66.1**
`GPT-4o`						
VLM-as-a-Judge	Screenshots	**23.5**	**60.8**	56.0	56.9	40.5
OS-Sentinel	Screenshots	23.3	**60.8**	**66.1**	**60.8**	**64.9**
`GPT-4o mini`						
VLM-as-a-Judge	Screenshots	12.5	57.8	36.8	56.9	33.3
OS-Sentinel	Screenshots	**20.6**	**61.8**	**63.9**	**59.3**	**61.4**
`Claude-3.7-Sonnet`						
VLM-as-a-Judge	Screenshots	19.6	58.3	56.9	59.3	52.0
OS-Sentinel	Screenshots	**22.2**	**61.3**	**66.9**	**62.3**	**67.0**

OS-Sentinel

Baselines are lopsided; OS-Sentinel is balanced across all 10 risk categories

Why this matters: in real deployment, you don't get to choose which category of risk shows up. Balanced coverage is what a safety guard actually needs.



OS-Sentinel

Towards Safety-Enhanced Mobile GUI Agents via Hybrid Validation in Realistic Workflows

Introducing OS-Sentinel, a novel ***hybrid safety detection framework***, and MobileRisk-Live, a pioneering ***testbed*** for advancing safety research about autonomous mobile GUI agents. This work is characterized by the following core features:

- **Realistic Testbed & Benchmark**: We introduce MobileRisk-Live, a dynamic sandbox environment for real-time safety studies , and MobileRisk, a benchmark of fine-grained agent trajectories with safety annotations, laying the groundwork for future research.
- **Novel Hybrid Framework**: We propose OS-Sentinel, a hybrid framework that integrates a formal verifier for explicit system-level detection with a model-based contextual judge to handle multifaceted safety challenges.
- **Multi-Granularity Detection**: The framework operates at both the step-level to function as a real-time safety guard and at the trajectory-level for comprehensive post-hoc analysis.
- **Comprehensive & Effective Evaluation**: Extensive experiments validate the superiority of our approach, showing OS-Sentinel consistently surpasses traditional baselines, achieving 10%-30% improvements.

arXiv | Code | MobileRisk-Live | MobileRisk

Homepage: https://qiushisun.github.io/OS-Sentinel-Home/

Future

We are just standing at the dawn of a long journey!

1. Holistic Evaluation? 
2. Efficiency? 
3. Model Judge? 
4. Physical world? 
5. Connecting CUAs with UI Generators? 

6. …

Efficiency

Although computer-using agents can accomplish many tasks, **efficiency remains a critical concern**.

Two main aspects:

1. Training efficiency: Heavy reliance on massive data (data hungry)
2. Inference efficiency: High latency during real-time execution

Connection to the Physical World

How can computer-using agents achieve embodiment?

1. Robotic arms?
2. Exoskeletons?
3. …

Future

We are just standing at the dawn of a long journey!

中文解读（OS-Genesis）

中文解读（ScienceBoard）

中文解读（AgentStore）

中文解读（SeeClick）

中文解读（OS-ATLAS）

Thanks for listening

Contact: qiushisun@connect.hku.hk