



Building GUI Agent Data with OS-Genesis

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The Feasibility of Jarvis AI from Marvel in Real Life

Once out of reach, but we are turning it into reality.















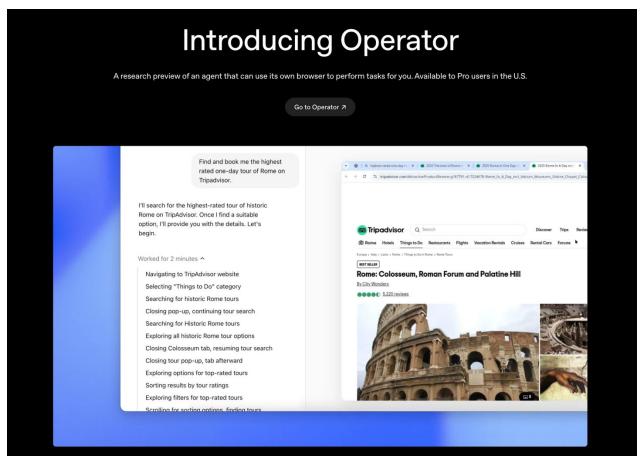


Both academia and industry are building computer use agents



Claude Computer Use

Both academia and industry are building computer use agents



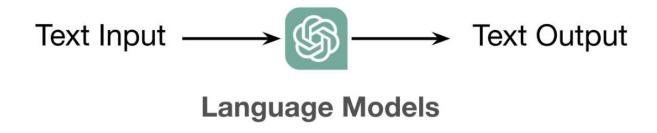
OpenAI Operator

They are quite promising for achieving Digital Automation.

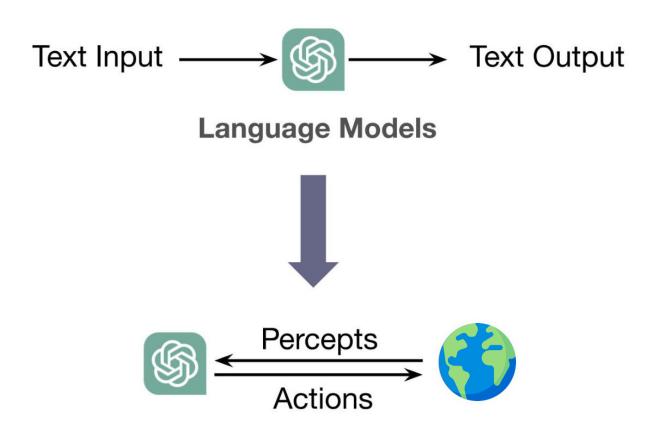
Can we transform a (V)LM into such computer / GUI agents?

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

Recap: Language Agents



Recap: Language Agents



LLM-based Agents

But this is not enough for Computer Use / GUI 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 Use Agents

Behavioral Cloning / Imitation Learning.



Sounds good, but where is our data?

Data Scarcity

Data curation is much more expensive than you think.

Take Scale AI as an example.

Not to mention scenario/domain - specific data.



Alexandr Wang 📀 🔳 @alexandr_wang · Jan 24

An interview today where I talk about how it relates to the US/China race and DeepSeek's score:



From cnbc.com

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Data Scarcity

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.

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

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













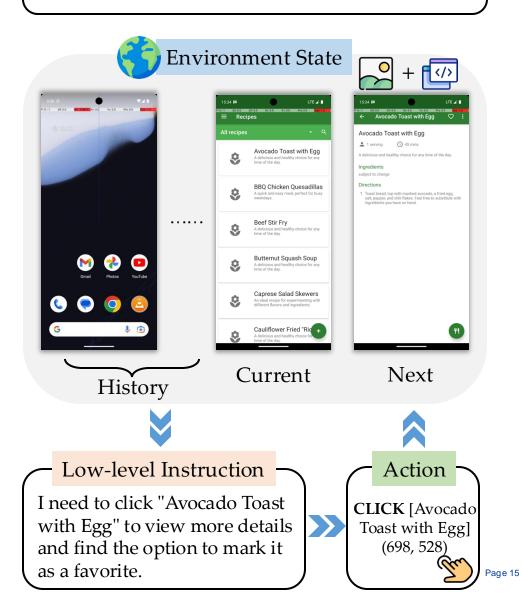
GUI Trajectory Data

The best data format of 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 allytree []

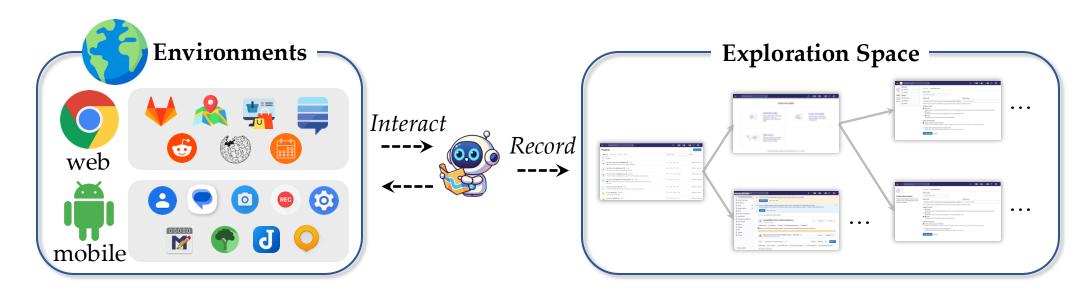
High-level Instruction

Mark the 'Avocado Toast with Egg' recipe as a favorite in the Broccoli app.



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

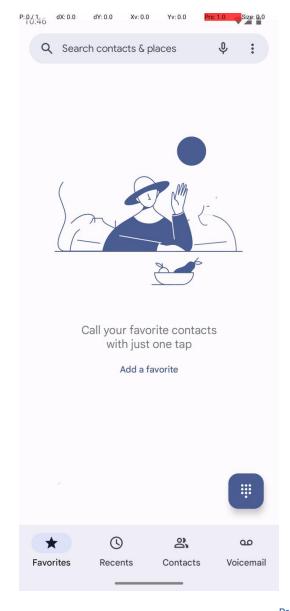
We collect: <Screen1, action, Screen2>



Dynamic Environments

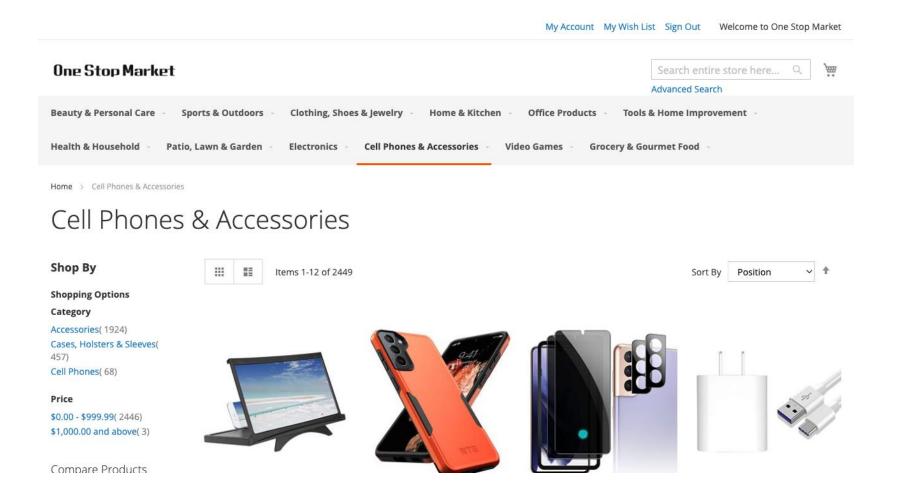






Dynamic Environments



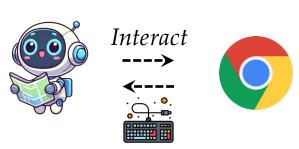


Retroactively interpreting changes in the GUI environment caused by actions.

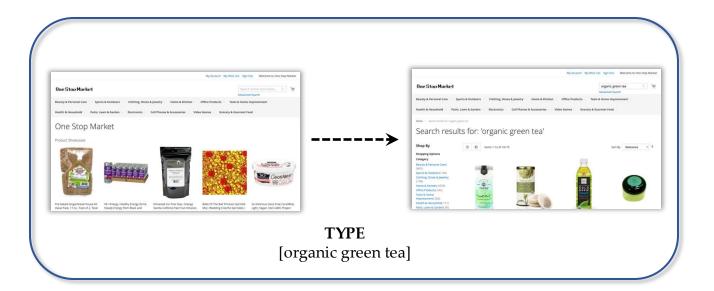


Screenshots & Actions

Retroactively interpreting changes in the GUI environment caused by actions.

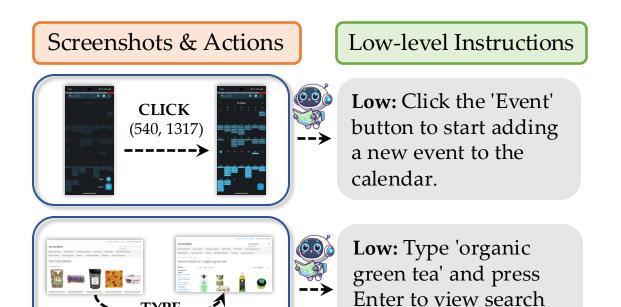


Screenshots & Actions



[organic green tea]

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



results.

The data we synthesized:

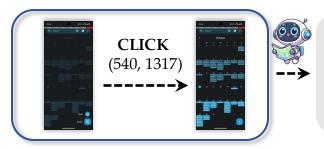
- 1. Grounded
- 2. Actionable

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

Screenshots & Actions

Low-level Instructions

High-level Instruction



Low: Click the 'Event' button to start adding a new event to the calendar.



High: In Simple Calendar Pro, create a new event titled 'Team Meeting' scheduled for October 15, 2023, at 10:00 AM. Save the event after filling in the details.

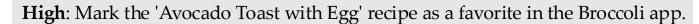


Low: Type 'organic green tea' and press Enter to view search results.



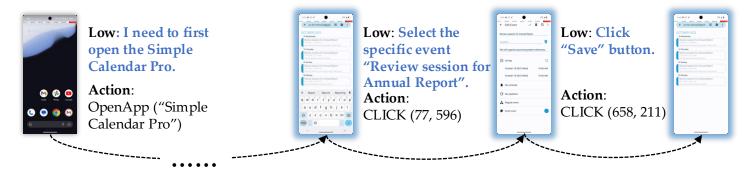
High: Search for 'organic green tea' and filter the results to show only products under the 'Health & Household' category, sorted by price from lowest to highest.

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





High: Set a reminder for the 'Review session for Annual Report' scheduled on October 18th in Simple Calendar Pro and save the changes.



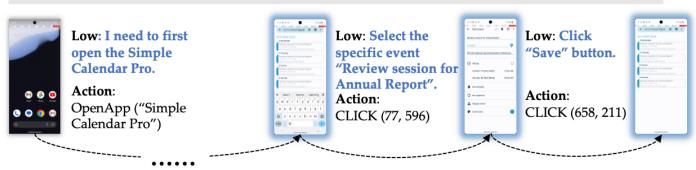
Trajectories collected! But is this all?

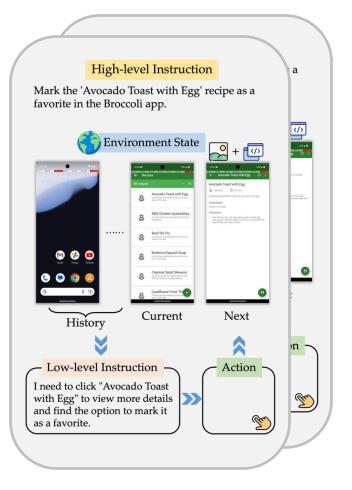
Let's consider data quality and synthesis efficiency.

High: Mark the 'Avocado Toast with Egg' recipe as a favorite in the Broccoli app.



High: Set a reminder for the 'Review session for Annual Report' scheduled on October 18th in Simple Calendar Pro and save the changes.





Data Quality Control

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

Previous approach:

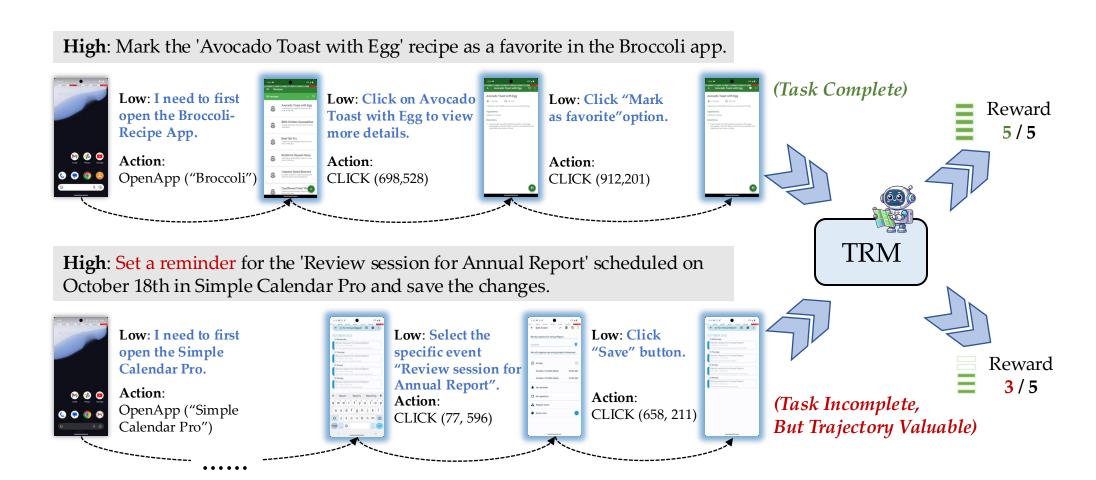
1. Training all data at once - what about the quality?

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-40



Qwen-VL Qwen2-VL-72B-Instruct

Backbones

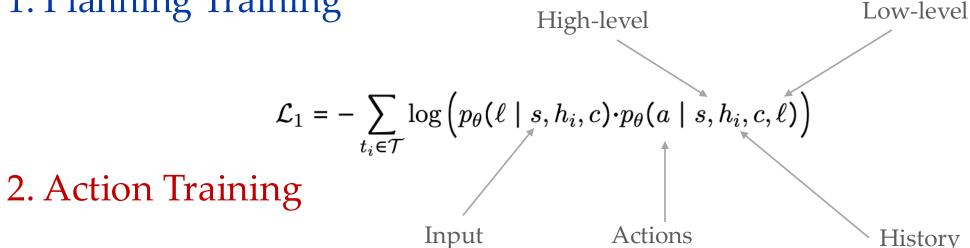




Training Strategies

Leverage trajectory characteristics to train GUI agents with complete capabilities

1. Planning 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.

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}
```

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

Experiments: Mobile

Base Model	Strategies	AndroidWorld	AndroidControl-High AndroidControl-Low				
			SR	Type	SR	Type	
GPT-40	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.

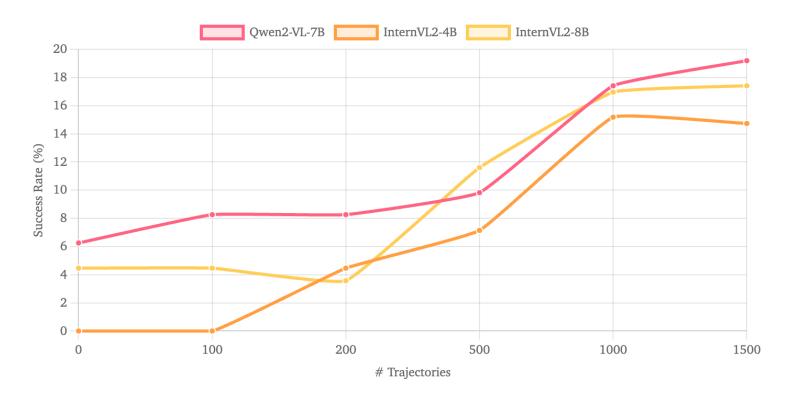
Findings: OS-Genesis + Opensource VLM > Propriety Models + Complex Prompting

Experiments: Web

Base Model	Strategies	Shopping	CMS	Reddit	Gitlab	Maps	Overall
GPT-40	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.

How Scaling Trajectory Data Improves Agentic Ability?



Insight: Generally improves, but will saturate.

How Far are we from Human Data?

Let's first take a look at high-level instructions.



Insight: Reverse Task Synthesis Elicits Better Executability.

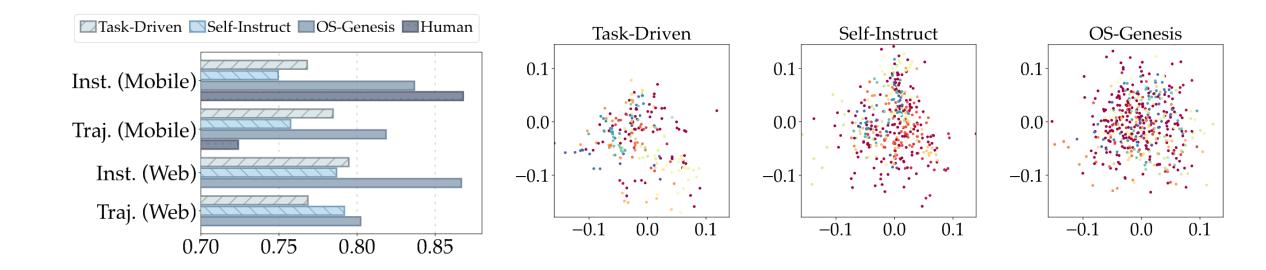
How Far are we from Human Data?

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



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

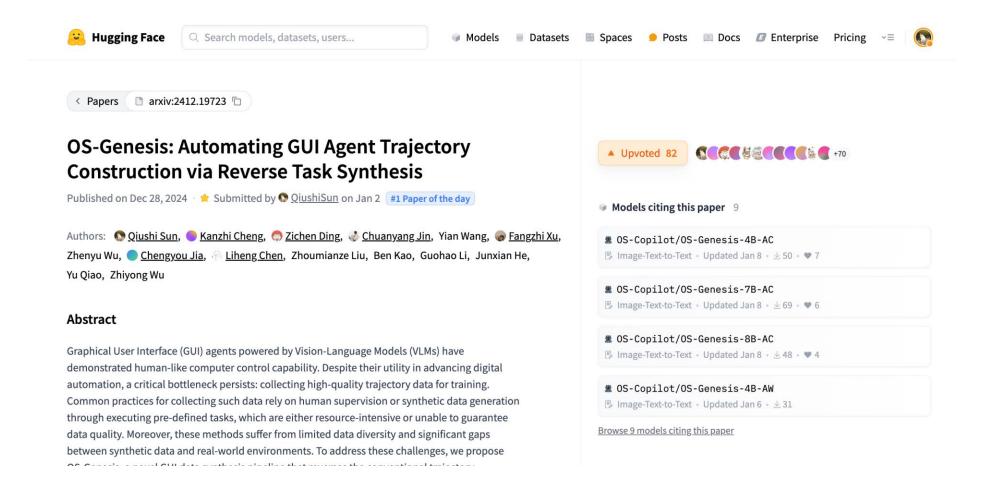
How about our data diversity?



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

Checkpoints & Data Access

Available on Hugging Face



Checkpoints & Data Access



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.
- X arXiv Code Checkpoints Oata







Thanks for listening

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