OPENCUA: Open Foundations for Computer-Use Agents

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Abstract

Vision-language models have demonstrated impressive capabilities as computer-use agents (CUAs) capable of automating diverse computer tasks. As their commercial potential grows, critical details of the most capable CUA systems remain closed and proprietary. As these agents will increasingly mediate digital interactions and execute consequential decisions on our behalf, the research community needs access to truly open CUA frameworks to study their capabilities, limitations, and risks. To bridge this gap, we propose OPENCUA, a comprehensive open-source framework for scaling CUA data and foundation models. Our framework consists of: (1) an annotation infrastructure that seamlessly captures human computer-use demonstrations; (2) AGENTNET, the first large-scale dataset of computer-use agent task spanning various operating systems, applications, and websites; (3) a pipeline that discretizes continuous actions into state-action pairs and synthesizes reflective long chain-of-thought (CoT) reasoning; (4) a training recipe for scalable CUA modeling; and (5) AGENTNETBENCH, a multi-dimensional offline benchmark for faster CUA evaluation. Our training recipe—especially its advanced reasoning mechanisms and strategic data mixture—enables robust performance scaling as data size increases. Our end-to-end agent models demonstrates strong grounding and planning performance across CUA benchmarks. Notably, OPENCUA-2.5-32B achieves state-of-the-art performance among open-source models on the OSWorld Public Evaluation Platform, reaching a success rate of **34.1%**. Further analysis confirms that our approach generalizes well across domains and benefits significantly from increased test-time computation. We will release the annotation tool, datasets, code, and models to build open foundations for further CUA research.

Website: https://opencua.xlang.ai
Code: https://github.com/xlang-ai/OpenCUA
Dataset: https://huggingface.co/xlang-ai/OpenCUA

1 Introduction

Computer-use agents (CUAs), powered by vision-language models (VLMs), aim to autonomously complete computer tasks and have great potential in facilitating daily and professional workflows.

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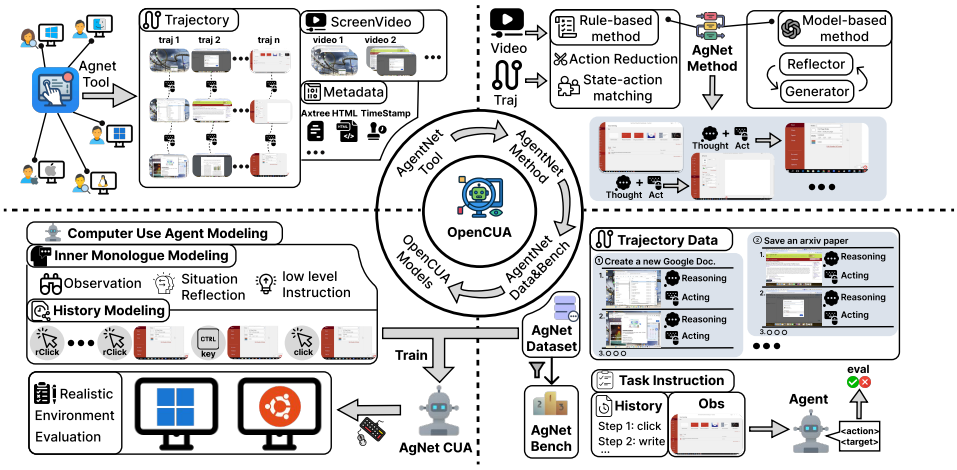

Figure 1: An overview of the OPENCUA framework, showing how user interaction videos and action flows (move, scroll, click, write) across various apps are captured and processed into trajectory and grounding data, then used to train and benchmark computer-use agents.

Despite their growing role in high-stakes decision-making, critical details including training data, architectures, and development processes about how state-of-the-art CUA systems are built remain closed and proprietary [1, 2, 26]. As the lack of transparency limits technical advancements and raises safety concerns [29, 34, 9], the research community needs *truly open* CUA frameworks to study their capabilities, limitations, and risks.

However, current open-source attempts in CUA face significant challenges that impede progress. Firstly, no open-sourced scalable infrastructure exists for collecting diverse, large-scale computer-use data — a complex requirement involving real-time capture of user interactions and state information, followed by transformation into agent-executable trajectories. Secondly, existing open-source graphical user interface (GUI) datasets remain limited in scope and scale due to the complexity and high cost of data collection; they either focus on specific domains (grounding [8, 37, 17], mobile [28, 22], or web [12, 10]) or lack sufficient diversity for general computer-use applications. Additionally, many CUA works provide insufficient details about their modeling strategies and training recipes, making replication difficult even with access to their collected data. These limitations collectively hinder advancements in general-purpose CUAs and restrict meaningful exploration of their scalability, generalizability, and potential learning approaches.

To address these challenges, we introduce OPENCUA, a fully open-source framework for scaling CUA data and foundation models (Figure 1). To resolve the infrastructure challenge, we first develop a user-friendly, cross-OS computer task annotation application – AGENTNET TOOL– that can be installed on personal computers to seamlessly record natural human demonstrations and corresponding computer states, without disrupting the user's workflow (Figure 1 top left). Using AGENTNET TOOL, we collect the AGENTNET, including more than 20K open-domain computer task trajectories spanning over 100 applications and 200 websites across Windows, macOS, and Ubuntu (Figure 1 top right). This dataset authentically captures the complexity of human behaviors and environmental dynamics from users' personal computing environments. Additionally, given that online CUA benchmarks like OSWorld [38] require substantial environment setup effort and runtime, we curated AGENTNETBENCH based on our collected human demonstrations (Figure 1 bottom right). This offline benchmark provides multiple gold-standard actions per step, efficiently approximating online metrics to dramatically accelerate agent evaluation and development.

Critical to our OPENCUA framework is our (1) data processing pipeline and (2) novel modeling and training recipe for constructing CUA training data from human demonstrations. We first introduce an action discretization pipeline that converts raw human demonstrations, which typically consist of videos and high-frequency, redundant keyboard/mouse actions, into state-action pairs feasible for vision language model training. Despite this, we observe that training on state-action pairs alone yields limited performance gains even as the dataset size scales (see Figure 7). Our first key insight is that scaling agent capabilities requires augmenting these trajectories with reflective long Chain-of-Thought (CoT) reasoning. We propose a reflective CoT synthesis method that explicitly injects planning, memory, and reflection into the per-step reasoning process via natural language "inner monologue" (Section 3.1). Different from previous work, our reasoning traces are notably more

detailed and contain refletion thoughts that help the agent detect and recover from errors. Moreover, we identify key modeling details that improves agent performance (Section 3.2), such as multi-image history. Finally, we show that carefully designing training data mixtures—including diverse reasoning and general text—is beneficial for computer-use agent training (Section 3.3).

Built upon our methodology, we developed strong computer-use agent models using supervised fine-tuning (SFT) (Figure 1 bottom left). Our results show that our approach enables robust performance scaling with increased data size (Section 4.2). Our model, OPENCUA-2.5-32B, achieves an average success rate of **27.7%** (50 step) in the OSWorld [38] and **28.0%** on 50-step tasks in the WindowsAgentArena [4]. On OSWorld Public Evaluation Platform, it achieves a success rate of 34.1%, establishing a new state-of-the-art among open-source models, even outperforming the closed-source OpenAICUA (GPT-4o based). We did extensive experiments and analysis on various model structures and data scales in Section 5. Thanks to the diversity and coverage of our training data, our models show strong cross-domain generalization. Our agent models also show promising scalability with increased test-time compute, such as increased number of steps and larger n in Pass@n evaluation. We also did additional experiments, including grounding and robustness analysis. Finally, we also provide detailed ablations to justify the important design choices in our method and training recipe (Section 5). We will open-source the complete suite of our OPENCUA framework, including the annotation tool, collected datasets, code, and models, providing open foundations for further CUA research.

2 AGENTNET Collection

OPENCUA aims to scale desktop computer-use data across diverse computer environments and user scenarios. We prioritize collecting demonstrations that follow natural user behavior, imposing the least additional constraints on how users interact with their computers to improve the scalability of data collection. To this end, we developed **AGENTNET TOOL** and collected **AGENTNET** dataset, the first large-scale desktop agent task dataset.

2.1 Task Definition

We model the agent's decision-making process – iterative observation of the computer state followed by action prediction – as a state-action transition trajectory: $(I, \langle s_0, a_0\rangle, \langle s_1, a_1\rangle, \ldots, \langle s_T, a_T\rangle)$. Given a task language instruction I and initial state s_0, the agent sequentially predicts a action a_i until goal state s_t and performs the termination action a_T: $P(a_i|I, s_0, a_0, \ldots, s_i)$.

An important design choice in building computer-use agent is to convert compute state s_i into model observation. In this work, we follow the recent trend of building pure vision-based computer agents [27, 43, 37] and use the screenshot of the computer as the observation for the agent. We use human computer-use actions, including keyboard and mouse movements, as the action space. To ensure the action space is applicable across various operating systems, we select a subset of PyAutoGUI actions and augment them with several necessary agent actions including the 'success' and 'fail' termination actions. The complete action space and its parameters are listed in Table 1.

Human Action	Action Description	Agent Action
Click	Click at a specific position	**click**(x, y, button)
Middle Click	Middle click at a specific position	**middleClick**(x, y)
Double Click	Double click at a specific position	**doubleClick**(x, y, button)
Triple Click	Triple click at a specific position	**tripleClick**(x, y, button)
Mouse Move	Move mouse to a specific position	**moveTo**(x, y)
Drag	Drag mouse to a position	**dragTo**(x, y)
Scroll	Scroll vertically or horizontally	**scroll**(dx, dy) / **hscroll**(dx, dy)
Type	Type a string of text	**write**(text)
Press	Press a specific key	**press**(key)
Hotkey	Perform a combination of keys	**hotkey**(key1, key2)
Terminate	End the task with success or failure	**terminate**('success' or 'fail')

Table 1: Overview of Human Actions and Corresponding Agent Action Functions

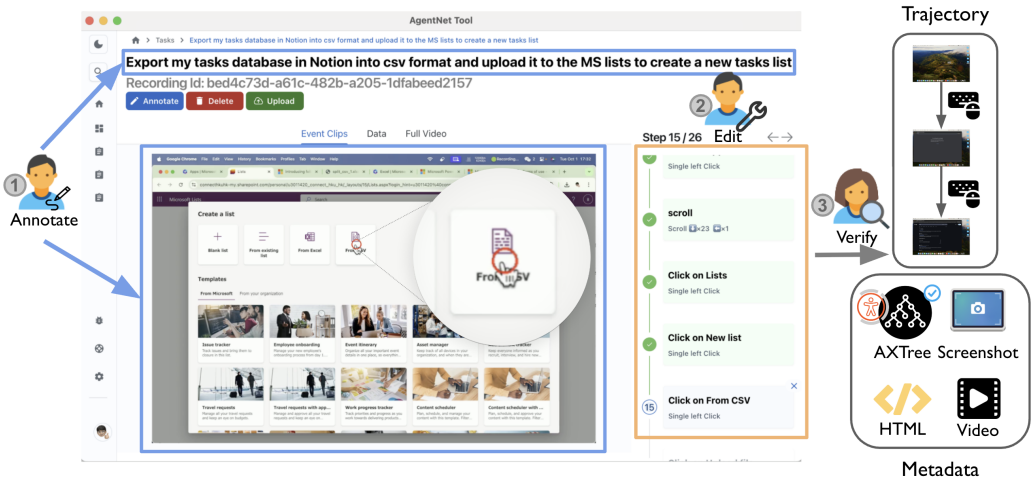

Figure 2: AGENTNET TOOL annotation and verification.

2.2 AGENTNET TOOL

Efficient and accurate annotation is essential for collecting high-quality computer-use agent data, yet no existing tools support natural, cross-platform task recording by non-technical users. To address this, we developed a user-friendly annotation tool that streamlines the collection and verification of computer-use demonstrations (Figure 2), runs on annotators' personal computers and records demonstrations in the background, capturing: (1) screen videos, (2) mouse and keyboard signals, and (3) accessibility trees (Axtree). These data are then processed into state-action trajectories (see details below in Section 2.2), allowing annotators to review, edit, and submit demonstrations along with task instructions describing the overall goal. Former works require the annotators to demonstrate "gold" trajectories with all-correct steps, but this actually limits model's capability to detect and recover from errors. We believe that annotation error is not all bad, as long as we can identify and utilize them (see Section 3.1), so we relax the requirement of all correct actions. Our implementation leverages several established tools: mouse and keyboard input tracking is based on DuckTrack [31] and OpenAdapt [25]; screen recording utilizes OBS Studio [24]; and accessibility tree (Axtree) parsing follows the OSWorld framework [38]. Additional implementation details can be found in Appendix E.2.

Annotation pipeline We designed our data collection with two key goals: **diversity** and **complexity**. Annotators were provided a curated list of around 200 applications and websites spanning various domains and were encouraged to demonstrate complex workflows involving professional features or multi-app interactions. Tasks were required to have more than 15 steps; those with <5 steps were rejected. To ensure wide coverage and real-world authenticity, we recruited annotators from both crowd-sourcing platforms and annotation companies. All annotators signed consent forms, and we use a multi-layer privacy protection mechanism to safeguard user data (Appendix E.3). To study model generalization, we split data into Windows/macOS and Ubuntu, ensuring no overlap with OSWorld tasks to prevent data leakage. All tasks were manually verified and labeled as *rejected*, *ok*, *good*, or *excellent* based on goal clarity, diversity, and complexity. Other annotation details are provided in Appendix E.1.

Constructing compact state-action trajectories Raw demonstrations consist of high-frequency screen recordings and fine-grained interaction signals (mouse movements, clicks, scrolls, key presses). A typical task can produce thousands of low-level actions that are too dense and inefficient for training. To address this challenge, we developed techniques including action reduction and state-action matching to construct compact state-action pairs $\langle s_i, a_i \rangle$. **Action reduction**: We developed a rule-based method to compress and reduce these dense action signals into a smaller set of meaningful actions while preserving essential action information. We first compress atomic signals into higher-level operations. Mouse move events are treated as preconditions for clicks or drags, and only their start and end positions are retained. Scrolls are merged into single-directional actions with accumulated wheel counts. Consecutive key presses are merged into text input strings, while modifier

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[20]	15283	5.5	Mobile	✗	✓	✓	✗	**Short**
AMEX[6]	2991	11.9	Mobile	✗	✓	✗	✗	✗
AitW[28]	2346	8.1	Mobile	✗	✓	✓	✗	✗
AitZ[47]	1987	6.0	Mobile	✗	✓	✗	✗	**Short**
GUI Odyssey[22]	7735	15.3	Mobile	✗	✓	✗	✗	✗
WonderBread[33]	598	8.4	Web	✗	✓	✓	✓	✗
AgentTrek[41]	10398	12.1	Web	✗	✗	✓	✓	**Short**
Mind2Web[10]	2350	7.3	Web	✗	✓	✓	✗	✗
GUIAct[7]	2482	6.7	Web	✗	✓	✓	✗	✗
AgentNet	**27804**	**17.2**	**Desktop**	✓	✓	✓	✓	**Long**

combinations (e.g., CTRL+C) are abstracted into hotkey actions. We also combine common multistep gestures such as drags or double-clicks. This process yields a streamlined action sequence aligned with the pyautogui action space, as shown in Table 1. **State-action matching**: To pair each action a_i with a representative state s_i, we extract keyframes from the screen recording that capture the system state *immediately before* the action occurs. However, naively aligning keyframes to action timestamps of mouse clicks risks leaking future information; e.g., the mouse may already be positioned over a button, making the prediction trivial. To address this challenge, for mouse clicks, we backtrack to the beginning of the mouse's pre-movement phase and search backward to find the last visually distinct frame.After the final action, we append a terminal frame along with a corresponding termination action.

2.3 AGENTNET Statistics

Our dataset consists of 27,804 human-annotated computer-use tasks, including 17K from Windows/-macOS and 10K from Ubuntu[2], with screen resolutions ranging from 720p to 4K. Each trajectory averages 17.2 steps, reflecting task complexity. As shown in Figure 3, the data spans over 140 applications and 190 websites, often involving multi-app workflows, professional tools, and uncommon features. Compared to prior GUI datasets (Table 2), OPENCUA is the first desktop trajectory-level dataset that is realistic, complex, diverse, and multimodal. Full statistics are provided in Appendix D.

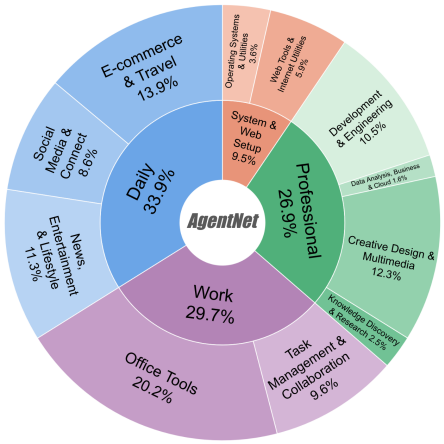

Figure 3: Domain distribution of tasks in AgentNet dataset

3 Training Computer-Use Agent Model

Our AGENTNET consist of task instructions I and state-action $\langle s_i, a_i \rangle$ trajectories. However, we find that directly finetuning vision-language action (VLA) models on our 27K trajectories leads to poor performance (4.4% success rate on OSWorld [38], shown in Figure 7). This section presents our modeling and training recipe to enable scalable training of computer-use agent models, including a novel reasoning augmentation, context encoding, and data mixtures techniques.

3.1 Synthesizing Reflective Long CoT Reasoning

Consistent with prior works [46, 43, 27], we find natural language reasoning crucial for generalizable computer-use foundation models, helping CUAs internalize cognitive capabilities. We propose a multi-stage CoT framework synthesizing structured reasoning per state-action pair $\langle s_i, a_i \rangle$. Inspired by Aguvis [43], our structured CoT includes three reasoning levels. The hierarchy begins with **L3**, contextual observation capturing salient visual and textual elements. Next, **L2** provides reflective reasoning analyzing state transitions, recalling previous steps, correcting errors, and planning subsequent

[2]This subset was annotated by MoonshotAI, and 3K high-quality demonstrations will be released for public research use.

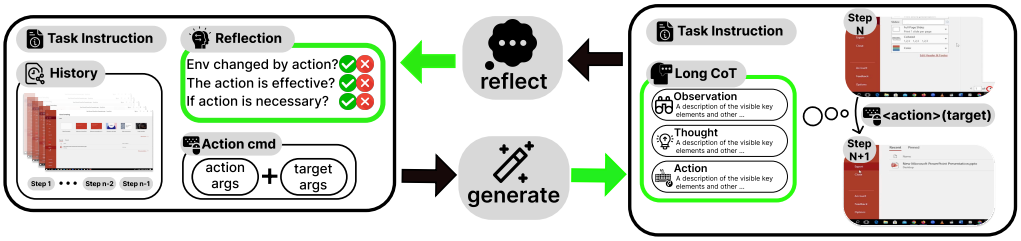

Figure 4: Reflective long CoT synthesis pipeline: generator and reflector iteratively generate and verify the reasoning components between the observation and ground-truth actions.

actions. Finally, the model predicts **L1**, a concise executable action grounded in prior perception and thought. This L3→L2→L1 structure mirrors perceptual-to-agentic decision flow, equipping the model with coherent, interpretable reasoning trajectories that enhance generalization and robustness.

Reflection augmentation for L2 reasoning Incorrect or redundant annotations in human demonstrations are not all bad, as long as we can identify and use them to teach the identification and correction of model errors. Therefore, we designed a `reflector` to identify errors and generate reflection reasoning for each step. Our CoT synthesis framework extends the pipeline of Aguvis [43] and ActRe [45] by equipping the "Thought" with more comprehensive agent components, especially state-transit perception and reflection, and minimizing hallucination. As shown in Figure 4, our CoT synthesis pipeline consists of three components: `reflector`, `generator`, and `summarizer`. The `reflector` inspects each step for correctness and redundancy by comparing screenshots before and after the action, examining the correctness of the action code itself and the generated CoT, expecially whether the "Action" aligns with the screenshot and code. When the step is incorrect or redundant, the `reflector` will ellaborate reason and this step will be ignored during training. If the step is correct, the `reflector` will explain the differences the actions brings to the before and after state. The `generator` conditions on the full agent context—previous reflections, action history, task goal, screenshots, and action code—to generate structured CoT. To help the model ground coordinate-related actions more accurately, we incorporate *visual cues*: a red marker on the mouse action coordinate and a zoomed-in image patch (inspired by V* [35]). Finally, the `summarizer` refines vague user-written goals into more precise and aligned task objectives, and scores each trajectory for alignment, efficiency, and difficulty. Our method produces rich and meaningful CoTs that significantly improve model reasoning and planning. We use `claude-3-7-sonnet-20250219` as the base model for synthesizing the three components. The reflection helps agent model identify former errors and adjust future plan to make the task back to the right track. An example of error identification and correction in evaluation can be seen in Section F. Ablations in Section 5 demonstrate that this module is a important driver of performance gains.

3.2 Context Encoding and Test-Time Reasoning

For end-to-end agent models, history encoding plays a critical role in reasoning and planning.

Context encoding: (1) Textual history: We propose a structured inner monologue framework for textual history representation. Specifically, we adopt a dialogue-style history format representing the model's responses and corresponding computer screenshots. Following Aguvis [43], we use L1 CoT (Action) to represent previous steps because it is more token-efficient and allows longer history windows without truncation. Moreover, our inner monologue includes memory components, further compensating for the absence of richer CoT in earlier steps. See Section 5 for ablations on history representation. (2) Visual history: Multi-image screenshot history is essential for agent model performance because screenshots are lossless visual representation of history, providing more grounded context than textual summaries. However, including more images also increases input length and reduces training efficiency. By default, we use three screenshots as visual representation, as our experiments show that this achieves a balance between performance and efficiency (see Figure 10).

Test-time reasoning format: While the model is trained with a mixture of CoT levels, we adopt the L2 CoT format at inference time due to its richer reasoning content, which enhances the model's

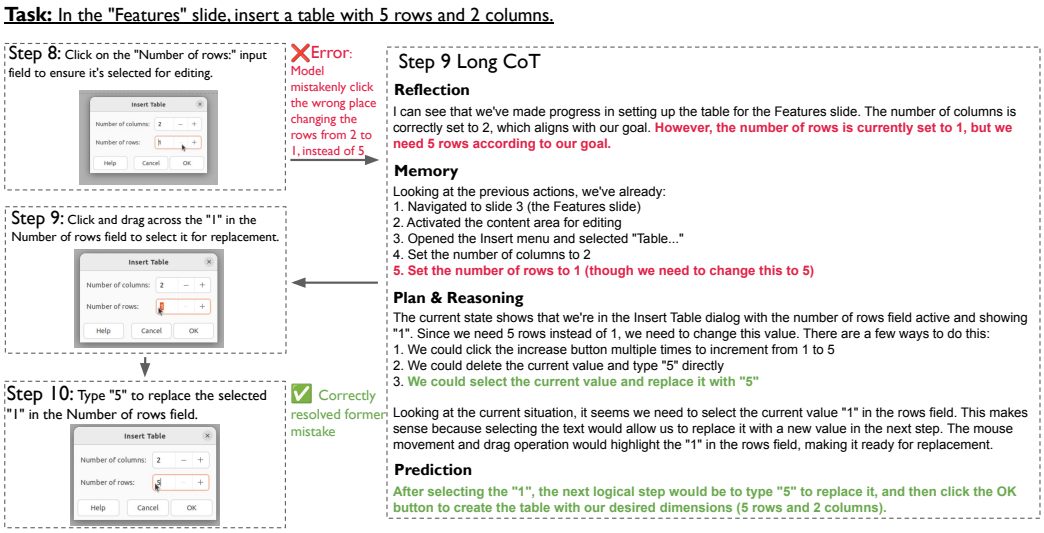

Figure 5: Reflective Long CoT Example: Before predicting the actual action, the model first reason according to the history and current action with reflection, memory, plan&reasoning and prediction in the CoT. The model identifies the former mistake and correct it in the later steps.

ability to reflect, plan, and reason. As shown in our ablation studies (Section 5), L2 CoT significantly improves test-time performance scalability—Pass@n success rates on OSWorld increase markedly over Pass@1. In contrast, models lacking this reasoning augmentation exhibit limited scalability, highlighting the importance of strong reasoning signals at inference time.

3.3 Training Data Mixtures

CoT data mixture: As we mentioned in the Section 3.1, our structured inner monologue contains three levels of CoT: L1 (Action), L2 (Thought + Action), and L3 (Observation + Thought + Action), each encoding complementary information for agent decision-making but has different conceptual information. L1 CoT has direct connection to the actual action; while there is helpful screenshot perception information in the L3 CoT, some irrelevant elements may also be described; L2 CoT contains planning and prediction that directly affect the predicted action in L1. Therefore, we propose to train the model with a mixture of all three levels of CoT to reinforce this different levels of connection. Data example of L1, L2, and L3 can be seen in Appendix G. We verify this design choice with ablations in Section 5.

Mixture of grounding, planning, and general SFT data: A general-purpose computer-use agent foundation model should be capable of both solving complex computer-use tasks and performing general reasoning grounded in world knowledge. To achieve this, we train on a mixture of data types that span both computer-use and general vision-language domains.

For grounding, we initialize the model using existing datasets such as ShowUI [21], UGround [13], and 189K bounding-box samples parsed from collected AXTree structures. For planning and reasoning, we include a diverse mix of Ubuntu and Windows/macOS demonstrations as well as task-instruction-augmented samples (Section 3.1). To enhance generalization and reasoning ability, we additionally incorporate general supervised fine-tuning (SFT) data from the Kimi Team [30]. The general text data covering domains such as instruction following, mathematical reasoning, and long-context understanding. The general vision data includes domains such as OCR and vision QA data. This mixture ensures both GUI grounding and high-level reasoning capabilities across domains. Although these general data are not directly related to GUI environments, we find that mixing them improves the model's overall agentic performance. We present ablation results on this effect in Section 5.

CUA Training Strategies Depending on computing budget, dataset availability, and the target model—e.g., building a specialized computer-use agent or a general-purpose VLM with agentic capabilities—different training strategies may be adopted. Following Aguvis [43], which proposes a two-stage curriculum training (Stage 1 for grounding and Stage 2 for planning and reasoning), we further explore three strategies:

- **(1) Stage 2 only:** When training resources are limited and the focus is on computer-use agent data, we aim to adapt a general open-source VLM into a specialized CUA. To preserve general instruction-following ability, we use a training mix of 70% CUA data (with a planning-to-grounding ratio of 4:1) and 30% general SFT data. We fine-tune Qwen2-VL with 30B tokens and Kimi-VL-A3B with 20B tokens. Both models exhibit strong improvements on CUA tasks (see Table 3).
- **(2) Stage 1 + Stage 2:** With more resources and diverse data, a staged approach yields better performance. In Stage 1, we enhance grounding and understanding using grounding trajectories, tutorial-style demonstrations, state-transition caption data, general vision language tasks, and general text SFT data. We trained Qwen2.5-VL-32B on this mixture for 40B tokens. In Stage 2, we shift focus to CUA planning, using 45% planning, 20% grounding, and the rest general data. This results in OPENCUA-2.5-32B, which achieves substantial gains in both grounding and planning benchmarks (Table 3, Figure 6).
- **(3) Joint training:** To build a general-purpose VLM with strong CUA abilities, we adopt joint training across domains with balanced data mixing. Given the complexity of multi-image trajectory data, we train these samples for 3 epochs to ensure sufficient learning. Based on Qwen2.5-VL-7B, we train a model on 200B tokens budget, maintaining a data ratio of 20% planning, 20% grounding, and 60% general. The resulting model, OPENCUA-2.5-7B, achieves state-of-the-art performance among 7B-scale open-source CUAs, achieving 27.3% success rate on OSWorld Online Evaluation Platform.

4 Experiments

4.1 Experimental Setup

Models Our experiments are conducted on multiple open-sourced vision-language models: Kimi-VL-A3B [30], Qwen2-VL-7B-Instruct [32], Qwen2.5-VL-7B-Instruct [3], and Qwen2.5-VL-32B-Instruct [3][3]. Kimi-VL-A3B adopts a Mixture-of-Experts (MoE) architecture with 16B total parameters and 3B active during training and inference. It demonstrates moderate capability as a computer-use agent, including grounding and planning. Qwen2-VL and Qwen2.5-VL are general-purpose vision-language models, with Qwen2.5-VL exhibiting enhanced digital agent capabilities and expertise in high-resolution understanding. We conduct supervised fine-tuning (SFT) on these models and obtain our OpenCUA model variants: OPENCUA-A3B, OPENCUA-7B, OPENCUA-2.5-7B, and OPENCUA-2.5-32B.

Evaluation We evaluated our models on online evaluation benchmarks, offline agent evaluation benchmark, and GUI grounding benchmarks.

- **Online agent evaluation:** (1) OSWorld [38] curated 369 human-crafted tasks on diverse applications, each with different environment setup and evaluation scripts; (2) We also submit our agent model to OSWorld Public Evaluation Platform, which is the official public evaluation benchmark of OSWorld [38]; (3) WindowsAgentArena [4] (WAA) focuses on 154 Windows tasks spanning Windows specific applications and several applications in OSWorld. We use the resolution of 1920×1080 during evaluation. 9 Google Drive tasks in OSWorld and 4 clock tasks in WAA are dropped due to API and system image limitation. During Online evaluation, we adopt the L2 CoT format (Thought + Action) for all models, following results of our ablation in Section 5. Temperature is set to 0 for deterministic decoding during evaluation. We use the average of 4 evaluations as our result.

[3]To align with the training infrastructure of the Kimi Team, we adopt the same chat template and tokenizer as Kimi-VL-A3B. M-RoPE in Qwen models is not implemented; we use 1D RoPE instead.

Table 3: Online evaluation results on OSWorld [38] and WindowsAgentArena (WAA) [4]. Reported OpenCUA scores are the mean of 4 independent runs.

Agent Model	OSWorld		WAA	
	15 steps	50 steps	15 steps	50 steps
GPT-4o [16]	5.0	–	–	–
Kimi-VL-A3B [30]	8.2	–	10.4	–
Qwen-2.5-VL-72B [3]	8.8	–	–	–
Aguvis-72B [43]	10.3	–	–	–
UI-TARS-7B-DPO [27]	18.7	–	–	–
UI-TARS-72B-DPO [27]	22.7	24.6	–	–
Claude 3.7 Sonnet [1]	15.5	26.0	–	–
OpenAI CUA [26]	19.7	32.6	–	–
OpenCUA-A3B	$15.5_{\pm 0.84}$	$17.3_{\pm 0.50}$	$16.0_{\pm 1.33}$	$17.5_{\pm 0.74}$
OpenCUA-7B	$18.5_{\pm 1.22}$	$20.1_{\pm 2.12}$	$16.1_{\pm 2.02}$	$21.1_{\pm 2.03}$
OpenCUA-2.5-7B	$21.8_{\pm 1.50}$	$25.3_{\pm 0.50}$	$22.5_{\pm 0.80}$	$27.1_{\pm 2.80}$
OpenCUA-2.5-32B	$\mathbf{24.4}_{\pm 0.40}$	$\mathbf{27.7}_{\pm 1.20}$	$\mathbf{23.8}_{\pm 1.50}$	$\mathbf{28.0}_{\pm 2.00}$

- **Offline agent evaluation:** AGENTNETBENCH includes 100 representative held-out tasks covering diverse domains. Introduction, details and its correlation with online metrics are in Appendix C.
- **GUI grounding evaluation:** We evaluate our model's GUI grounding ability, the ability to map natural language instructions to specific actions within graphical user interfaces on three benchmarks: OSWorld-G [40], Screenspot-V2 [36] and Screenspot-Pro [19]. OSWorld-G has 564 samples that systematically cover text matching, element recognition, layout understanding and fine-grained manipulation, with annotations for the element types required to solve each task. Screenspot-V2 includes screenshots from three platforms: mobile, desktop, and web. Screenspot-Pro focuses on high-resolution desktop environments, especially in professional settings.

Training settings: All models are trained on the Kimi Team's infrastructure using the Megatron framework and DeepSpeed with ZeRO-3 parallelism. We adopt different strategies depending on training objectives:

- **(1) Stage 2 only:** OPENCUA-7B and OPENCUA-A3B share a configuration of sequence length 32,768, learning rate 2e-5, weight decay 0.1, and batch size 384 (512 for ablations), trained on 96 A100 GPUs. The training set includes 18K Win&macOS and 10K Ubuntu trajectory data. OPENCUA-7B is trained for 3,400 steps (45 hours), with a 400-step warm-up on grounding data. OPENCUA-A3B is trained for 2,000 steps (10 hours).
- **(2) Stage 1 + Stage 2:** OPENCUA-2.5-32B is first trained for 35B tokens on general text, vision, and grounding data (batch size 3584, learning rate 3e-5, 224 A100 GPUs). We use the step 1200 checkpoint. In Stage 2, it is further trained for 60B tokens on trajectory, general, and grounding data (batch size 512, learning rate 2.5e-5 on 128 A100 GPUs). The training set includes 18K Win&macOS and 20K Ubuntu trajectory data. We select the last checkpoint - 4700 step.
- **(3) Joint training:** OPENCUA-2.5-7B is trained on the full data mixture for 200B tokens including 18K Win&macOS and 20K Ubuntu trajectory data with batch size 512, learning rate 2.5e-5 (min learning rate 3e-6), and decay tokens 200B. It runs on 128 A100 GPUs for 8 days. The final checkpoint is selected at step 14,600.

4.2 Main Results

Online agent evaluation The results are summarised in Table 3; each number is the mean success rate over four independent runs.

- (1) OSWorld. OPENCUA-2.5-32B reaches a success rate of **27.7 %**, surpassing most agent models, including the proprietary Claude 3.7 Sonnet, and outperforming the current best open-source baseline UI-TARS-72B-DPO. **WindowsAgentArena.** The same model attains **28.0 %**, greatly exceeding its base model and demonstrating strong cross-system generalisation (several tasks are judged incorrect due to environment or evaluation errors).

Table 4: OSWorld Public Evaluation Platform

Model	15 Steps	50 Steps	100 Steps
Close Sourced			
OpenAI CUA [26]	26.0	31.3	31.4
Seed1.5-VL [15]	27.9	-	34.1
Claude 3.7-Sonnet [1]	-	-	35.9
UI-TARS-0717 [27]	31.9	-	40.2
Claude 4-Sonnet [2]	-	-	41.5
Open Sourced			
OpenCUA-2.5-7B (Ours)	23.4	26.2	27.3
OpenCUA-2.5-32B (Ours)	27.4	**34.1**	32.5

Table 5: Computer-use agent performance on AGENTNETBENCH. "Finetuned" means the model has been finetuned on OPENCUA training data. Coord actions: *click, rightClick, doubleClick, moveTo, dragTo, scroll*; Content actions: *write, press, hotkey*; Function action: *terminate*.

Model	Size	Image Num.	Step SR	Coord. SR	Content SR	Func. SR
Zero-shot						
Qwen2.5-VL-7B [3]	7B	1	48.0	50.7	40.8	3.1
Aguvis-7B [43]	7B	1	52.4	56.7	43.3	0.0
Qwen2.5-VL-32B [3]	32B	1	64.8	66.6	47.2	41.5
Qwen2.5-VL-72B [3]	72B	1	67.0	67.2	52.6	50.5
OpenAI CUA [26]	—	1	73.1	71.7	57.3	80.0
Finetuned						
OpenCUA-2.5-7B	7B	3	71.0	75.4	46.4	53.6
OpenCUA-2.5-32B	32B	3	71.7	76.6	46.8	51.5

- (2) Experiments with differnt model size and strucutres, in cluding Kimi-VL-A3B, Qwen2-VL-7B, Qwen2.5-VL-7B, and Qwen2.5-VL-32B, show that our data and training methods transfer well across model architectures.
- (3) An OSWorld case study in Appendix F illustrates that our agent can recognise and correct earlier mistakes within a trajectory, leading to more reliable task completion.
- (4) **OSWorld Public Evaluation Platform.** On the public evalution, our agents perform even better than on our own infrastructure. OPENCUA-2.5-7B reaches **27.3 %** at 100 steps—the best result reported at the 7 B scale—while OPENCUA-2.5-32B achieves **34.1 %** at 50 steps, surpassing the closed-source OpenAI CUA (GPT-4o) [26] and approaching Seed1.5-VL [15] and Claude 3.7 Sonnet [1], which is the strongest open-source result to date.

Offline agent evaluation AGENTNETBENCH is constructed from representative tasks in the OPENCUA dataset. To account for domain overlap, we categorize models into "Zero-shot" (not trained on OPENCUA) and "Fine-tuned" (ours). As shown in Table 5:

- (1) In the Zero-shot group, performance scales with model size; the specialist model Aguvis outperforms the general-purpose Qwen2.5-VL-7B.
- (2) OpenAI CUA [25] surpasses all open-source models and approaches fine-tuned performance, especially excelling in terminate-state detection.
- (3) Among fine-tuned models, OPENCUA-2.5-32B slightly outperforms OPENCUA-2.5-7B on both Coordinate actions and Content actions. They are lower than OpenAI CUA, especially on Content actions, denoting the good generalizability of GPT-4o based model.

GUI grounding evaluation As illustrated in Figure 6, both OPENCUA-2.5-32B and OPENCUA-2.5-7B achieve the highest scores across all grounding benchmarks, OPENCUA-2.5-32B is better due to model scale. This advantage stems from the larger volume of grounding data used in Stage-1

training for OPENCUA-2.5-32B and the additional grounding data incorporated during the joint-training phase for OPENCUA-2.5-7B. The Qwen2.5-VL models also benefit from a larger pixel budget (12 845 056 versus 829 440 for Qwen2-VL and Kimi-VL-A3B), which improves perception in high-resolution scenarios and explains their strong results on ScreenSpot-Pro. Although Qwen2.5-VL-32B matches OPENCUA-7B and OPENCUA-A3B on OSWorld-G and ScreenSpot-V2—and surpasses them on ScreenSpot-Pro—the OpenCUA models obtain far higher success rates on the full OSWorld benchmark. These findings indicate that GUI grounding, while necessary, is only one component of real-world agent performance; superior high-level planning and reflective reasoning are ultimately more critical for reliable task completion.

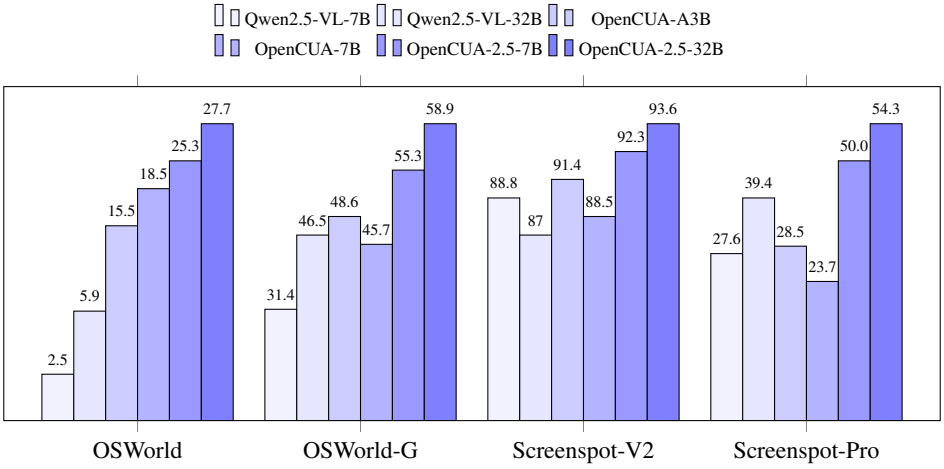

Figure 6: Grounding performance comparison among Qwen2.5-VL-7B Qwen2.5-VL-32B, OpenCUA-7B and OpenCUA-A3B.

Performance scaling with data scaling.

We explore the effect of data scale on Qwen2-VL from three perspectives: cross-domain data, in-domain data, and out-of-domain data. We first investigate cross-domain data in Figure 7. Specifically, we compare three training settings: (1) 7K Ubuntu data, (2) 7K Ubuntu + 14K Win&Mac data, and (3) 10K Ubuntu + 17K Win&Mac data. On OSWorld, performance improves significantly from **9.8%** to **18.5%**, despite the added Win&Mac data coming from a different platform. This indicates that even out-of-domain data can substantially enhance generalization and reasoning ability, rather than causing negative transfer. To further study the impact of in-domain and out-of-domain data scale, we randomly sampled 3K, 7K, 10K trajectories from Ubuntu data and 3K, 7K 14K from Win&Mac.

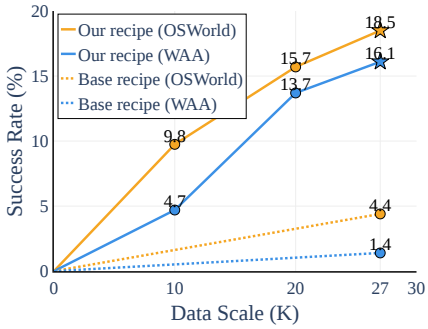

Figure 7: Our recipe enables performance to scaling effectively with increased AgentNet data, whereas the base recipe demonstrates poor scaling properties.

As shown in Figure 8, performance scales consistently across all benchmarks with both in-domain and out-of-domain data. When increasing the Ubuntu data from 3K to 10K, the average performance improves by 72%. Scaling the Win/Mac data from 3K to 14K yields a 125% improvement on average. These results demonstrate a strong positive correlation between data quantity and agent performance, highlighting the importance of large-scale, diverse CUA data for model generalization.

5 Analysis

Model performance upperbound analysis by scaling test-time compute We explore our model's performance upperbound by doing Pass@n evaluation on OSWorld. We set the temperature to 0.1

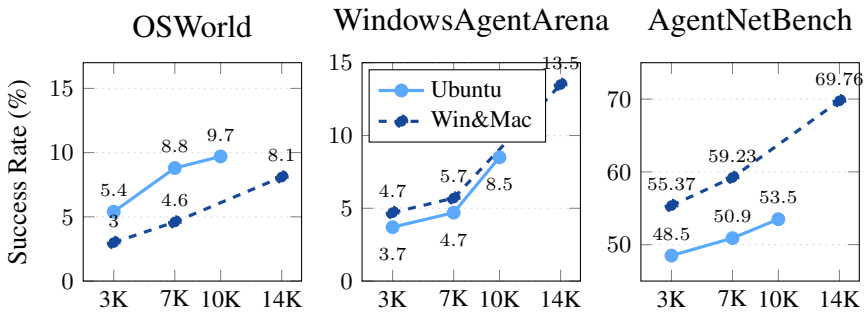

Figure 8: Scaling curves on three benchmarks as data volume from various OS domains increases.

and evaluate OPENCUA-7B for 16 times on the budget of 15, 30 and 50 steps and calculated the pass@1,4,8,16 success rate. In Table 9, we find: (1) There is a significant performance gap of our model between Pass@1 and Pass@16. On 15 step, the success rate increases from 16.9 to 34.6 (+104%), while on 50 step, the increacement is even large from 18.4 to 39.2 (+113%). (2) With larger n, the performance gains from increasing the step budget become more significant. (3) Online benchmarks have a large variance. To study model robustness, we did Pass@n evaluation when temperature is 0 in Appendix 5 and find higher temperature leads to higher Pass@n performance but lower Pass@1 performance.

Cross-platform training improves generalization, even with domain differences. As shown in Figure 8, there is a consistent performance gap between models trained on different domains. Models trained on Ubuntu data perform better on OSWorld, while those trained on Windows/macOS data perform better on WindowsAgentArena and AGENTNETBENCH. This domain gap reflects the underlying differences in GUI layouts, system styles, and application behavior across platforms. OSWorld primarily focuses on applications and websites aligned with Ubuntu environments, whereas WindowsAgentArena contains several OSWorld Windows-specific applications. Interestingly, the performance gap between training on Win&Mac data versus Ubuntu data is narrower on WAA than on OSWorld, suggesting that application-level knowledge can partially transfer across operating systems, even if interface styles differ.

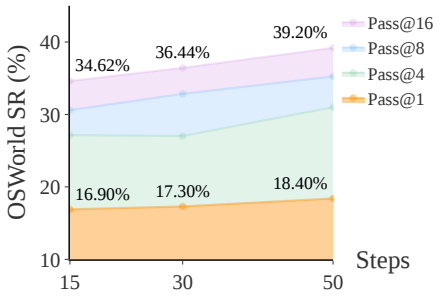

Figure 9: OSWorld Pass@N performance curves of OpenCUA-7B, temperature=0.1

L2 reasoning format achieves the best inference performance. Note that we trained the models with mixed reasoning format (L1, L2, L3, see Section 3.1). In this part, we explore which type of thinking format is the best at inference. We test OPENCUA-7B and OPENCUA-A3B on OSWorld in 15 steps. As in Table 6, using the L2 format, the performance is higher than L1 and L3. This result is actually different from the conclusion from previous work [43, 27] that L1 outperforms L2. We think this is because our L2 CoT has higher quality (e.g., planning and reflection), which can help the model make better decisions. On the other hand, L3 underperforms L2. By case study, we find that when model describes the information in the screenshot, there tend to be many elements irrelevant to the task or the next action, which may mislead the model. In summary, our results show that the right choice of high-quality, non-redundant reasoning can leverage VLM's language reasoning capability to improve the agent performance.

Using a moderate number of visual history images and concise textual history yields the best trade-off between performance and efficiency. We ablate history representation from both visual and textual perspectives. For vision, we vary the number of history screenshots (1, 3, 5) and fine-tune Qwen2-VL-7B on 7K trajectories. As the OSWorld results shown in Figure 10, using multiple screenshots substantially improves performance over single-image inputs, as GUI agents rely entirely

Table 6: Ablation results on OSWorld for different Chain-of-Thought (CoT) settings.

Ablation	CoT Variant	SR (%)
CoT Mixture	L2	13.1
	Mixture-CoT	18.5
Reflective Long CoT	Short-CoT	11.5
	Advanced-CoT	15.3
Test-time Reasoning Format	L1	16.9
	L2	18.5
	L3	17.6

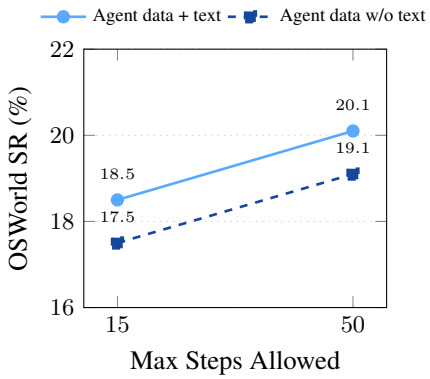

Figure 11: General text data ablation.

on vision for observing state changes. However, increasing from 3 to 5 images yields marginal gains while incurring 3K more context tokens and delayed convergence, suggesting diminishing returns.

On the textual side, we compare L1 and L2 history under the same 3-image setting. In Figure 10, L2 history offers no benefit and may introduce hallucinations that distract attention, while also reducing training efficiency. Hence, we adopt L1 CoT + 3 images as the default setting.

Training with a mixture of CoT formats outperforms using only L2 reasoning. Since our best performance is from L2 CoT inference, and L3 and L1 is lower than L2, we did an ablation of only training the L2 data instead of the mixture of L1, L2, and L3. We use the same recipe as our OPENCUA-7B, but only replace the mixture CoT data with L2 data. As the OSWorld result in Table 6, the model trained on L2 data using the same steps as OPENCUA-7B, but the performance drops to 13.1, which is aligned with the conclusion of Aguvis [43].

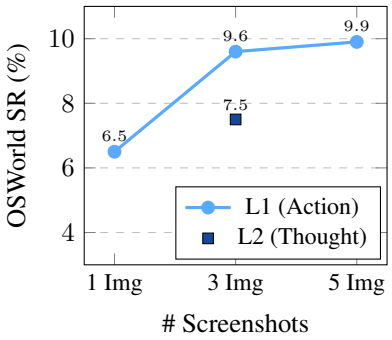

Figure 10: Effect of history representation: L1 (Action) benefits from more screenshots, while L2 (Thought) at 3 images lags behind.

General-domain text data provides a positive effect to agent performance. As we mentioned in Section 3.3, we used 35% general text data in our main experiment, so we also use the same agent data without the text data to fine-tune Qwen2-VL-7B with grounding warm-up stage for 2400 steps (approximately the same amount of agent data tokens) to ablate its influence. According to Figure 11, the general text data slightly improves model's agentic performance. Therefore, adding text data from totally different general domains doesn't impair the agent model's performance, on the contrary, helps improve the performance. We think the reason is that the general text data may help agent model's generalization and instruction understanding.

Reflective long CoT significantly boosts performance by improving error correction. To understand the effect of reflective long CoT (Secion 3.1), we do an ablation study on Qwen2-VL-7B with 14K Win&Mac and 3K Ubuntu trajectories. Without reflective long CoT, the CoT reduces to that used by Aguvis [43]. In Figure 5, we see that reflective long CoT improves the performance from 11.5 to 15.3. Since the reflective reasoning focuses on error correction, we conjecture that the improvement comes from improved self-correction capability.

Agent model is not robust: small variance in the environment affects the task result. As illustrated in Figure 12, AgentNet-7B's OSWorld performance (Pass@N) under temperature=0 exhibits significant outcome divergence despite nearly identical initial states—with only minor variations (e.g., system date). The curves for Pass@16 (38.60% SR at 50 steps) and Pass@1 (20.10% SR) demonstrate a >18% absolute gap, highlighting how minimal initial perturbations propagate into starkly different trajectories. This underscores the model's sensitivity to initial conditions even in deterministic (temp=0) settings, suggesting that seemingly trivial factors (e.g., temporal context) may critically influence multi-step reasoning.

6 Related Work

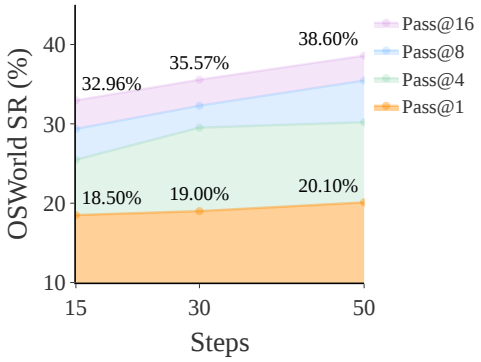

Figure 12: OSWorld Pass@N performance curves of OpenCUA-7B, temperature=0

CUA benchmarks and datasets Autonomous computer-use agents are now judged primarily through *execution-level* benchmarks that embed the agent inside genuine software environments rather than synthetic simulators. On the desktop side, suites such as [39, 5, 48] orchestrate multi-step workflows that span office productivity, source-code editing, file management, and operating-system configuration across Linux, Windows, and macOS. For the web domain, campaigns including [49, 18, 10, 44, 11] deploy agents on self-hosted or live sites with dynamic content, long navigation chains, and non-trivial information-retrieval subtasks. To support training at the necessary scale, several high-volume data pipelines have appeared: tutorial-to-trajectory conversion for browser tasks [41], cross-device grounding and action logs [17, 8, 14], plus our own collection of 27 K desktop demonstrations that pair screenshots, low-level mouse/keyboard events, and reflective chain-of-thought annotations.

CUA frameworks and models Approaches to building computer-use agents can be grouped into three broad categories. First, text-based language models operate on structured GUI metadata—such as DOM trees or accessibility labels—and issue symbolic commands; representative work ranges from early page-centric agents [23] to more recent language-only planners that still eschew raw pixels [42]. Second, vision-centric agents integrate screen imagery. Some focus on grounding—learning to associate natural-language references with bounding boxes or coordinate clicks [14, 36]—while others pursue end-to-end policies that translate full screenshots directly into action sequences [43, 27, 26, 1]. Third, modular agent frameworks wrap large language models with additional components—specialised vision encoders, hierarchical or search-based planners, episodic memory, and tool APIs—to tackle long-horizon tasks requiring perception, reasoning, and control [50].

7 Conclusion

We presented OPENCUA, a comprehensive open-source framework addressing critical gaps in computer-use agent development. By offering annotation infrastructure, data processing pipelines, diverse datasets, effective training recipes, and efficient evaluation benchmarks, we establish essential foundations for CUA research. Our models demonstrate strong performance across benchmarks while exhibiting clear data scaling laws and cross-domain generalization capabilities. By releasing all components—tools, datasets, code, and models—we aim to accelerate transparent CUA research, enabling the community to systematically investigate these agents' capabilities, limitations, and risks as they increasingly mediate our digital interactions and execute consequential decisions on our behalf.

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Table of Contents in Appendix

A Aknowledge

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B Limitations

The scalability of AGENTNET dataset is inherently limited by human annotation efforts. Although AGENTNET TOOL streamlines the data collection process, expanding the dataset beyond its current size would require additional human resources. Exploring alternative data sources or semi-automated annotation methods could help address this limitation. Additionally, though OPENCUA strives to collect authentic computer-use data from personal devices, our ethical requirement for explicit informed consent regarding data practices inevitably introduces selection bias. While our dataset maintains high diversity and authenticity, it necessarily excludes data from users who, upon understanding the potential risks, opt not to participate. This is a limitation we accept to uphold responsible data collection.

C AGENTNETBENCH

Figure 13: Illustration of the AgentNet Benchmark evaluation pipeline

There are several online benchmarks [38, 4] that evaluate agent performance in desktop environments. However, these online benchmarks typically require substantial computational resources for environment setup, making evaluations expensive, slow, and difficult to reproduce consistently through time due to their reliance on dynamic environments. Meanwhile, they only provide sparse, high-variance signals (i.e., trajectory-level accuracy). To address these limitations, we introduce an offline CUA evaluation benchmark, AGENTNETBENCH, comprising 100 representative tasks selected from the AGENTNET dataset. Tasks were strategically chosen from the center of sub-domain clusters (as detailed in Section D.1), ensuring diversity and representativeness across applications and websites on Windows and macOS platforms. Each task was manually reviewed to refine goals and remove redundant actions. Notably, we manually provide multiple valid action options at each step because of the inherent multiplicity of valid actions in computer-use tasks.

Benchmark statistics and evaluation dimensions The AGENTNETBENCH maintains a balanced domain distribution consisting of 38 Work tasks, 29 Daily tasks, 24 Professional tasks, and 9 System & Web Setup tasks. The tasks are split between two operating systems, with 61 tasks from Windows and 39 tasks from macOS. Screen resolutions are categorized into three levels (high, medium, and low) as detailed in Table 7 (note that, for practical purposes, all images in the benchmark are resized from their original resolutions). The distribution of actions within these tasks and additional benchmark statistics are also presented comprehensively in Table 7.

Multiple action choices for enhanced accuracy Previous offline benchmarks [28, 20] typically define a single ground-truth action at each step. This practice can negatively impact accuracy by disregarding alternative valid choices that an agent may reasonably make in real-world interactions.

Table 7: Comprehensive Statistics of AgentNetBench

Domain Distribution		**Operating System Distribution**	
Work	38	Windows	61
Daily	29	macOS (Darwin)	39
Professional	24		
System & Web Setup	9		
Resolution Distribution		**Overall Statistics**	
High	20	Total Tasks	100
Medium	33	Avg. Steps/Task	17.63
Low	47	Total Actions	2143

Action Distribution					
click	850	(67.0%)	doubleClick	19	(1.5%)
rightClick	17	(1.3%)	press	28	(2.2%)
dragTo	27	(2.1%)	write	137	(10.8%)
moveTo	45	(3.5%)	hotkey	30	(2.3%)
scroll	18	(1.4%)	terminate	100	(7.6%)

In contrast, in AGENTNETBENCH, we annotate multiple plausible action choices for each step to better reflect real-world decision-making variability.

Step success rate calculation and action matching criteria To calculate the Step Success Rate (Step SR), we evaluate the correctness of agent actions at each individual step using precise matching criteria tailored to different action types. For coordinate-based actions (*e.g.*, `click`, `doubleClick`, `moveTo`, `dragTo`, `rightClick`, and `hscroll`), we define bounding boxes around each action's target location; the agent earns the step success point if its predicted coordinates fall within these bounding boxes. For content- or keyboard-based actions, such as `write`, we measure correctness by computing the edit distance between the predicted and ground-truth text; actions like `hotkey` and `press` require perfect matches of the specified key combinations. For the `scroll` action, correctness depends on two key criteria: the agent's output coordinates must be within the designated bounding box, and the scrolling direction must exactly match the ground truth. Finally, the correctness of the `terminate` action depends on the agent appropriately terminating at precisely the correct step – neither prematurely nor delayed. Considering the distribution of actions (see Table 7), these fine-grained evaluation rules ensure accurate and fair evaluation of agent capabilities in diverse interaction scenarios.

AGENTNETBENCH strongly correlates with online benchmark performance The offline benchmark primarily assesses an agent's decision-making capability by evaluating its first-choice accuracy at each task step. While agents can leverage self-reflection to recover from errors made in earlier steps, offline and online SRs should correlate under a low step budget. Figure 14 and Table 5 indeed demonstrate a clear positive correlation, specifically following a power-law relation between the online task success rate (under a 15 step budget) and the offline step success rate. Therefore, metrics obtained from our offline benchmark provide a reliable indicator of an agent's foundational proficiency and its adaptability to realistic, resource-constrained online tasks.

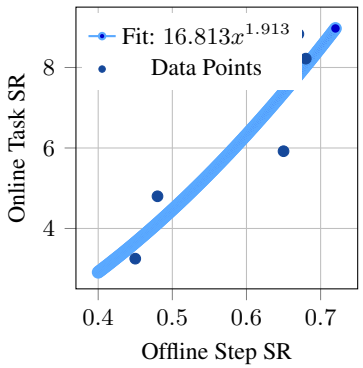


Figure 14: Offline vs. Online evaluation.

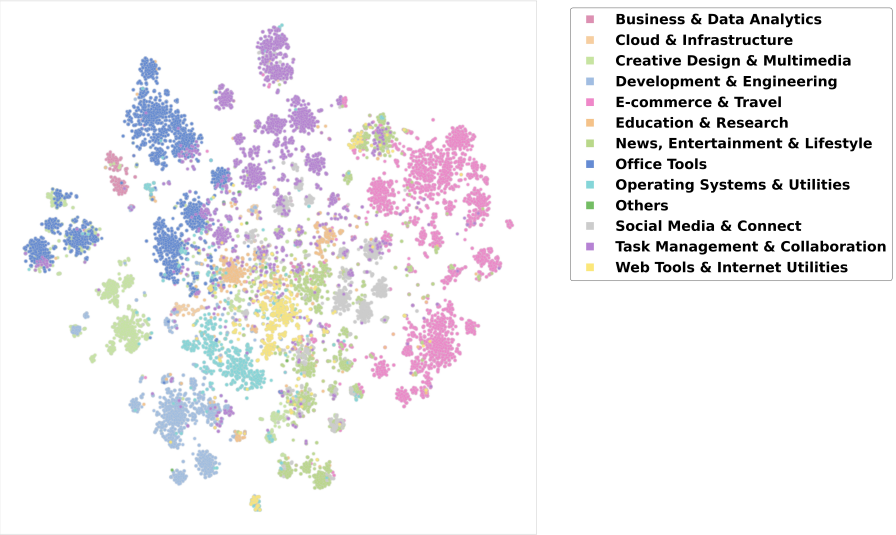


Figure 15: Clustering and t-SNE visualization of all task domains.

D AgentNet Dataset Annotation Details, Statistics and Analysis

D.1 Diversity

Task Domains We categorize the collected tasks into 4 main domains and 11 subdomains based on their topics, involved applications and actions in the tasks (Figure 3). Table 8 lists representative applications for each domain. To label each task trajectory, we leveraged `GPT-4o` to complete the classification by representing each task using the task instruction and L1-level CoT. We manually examined 200 tasks randomly and the classification accuracy is over 96%. We then embedded the task trajectories using OpenAI's `text-embedding-3-small` model and visualize them t-SNE visualization in Figure 15. Interestingly, the layout mirrors typical computer-usage patterns: for instance, Office Tools cluster near Business & Data-Analytics, while E-commerce & Travel sit close to Social-Media & Connect on the opposite side of the map. Finally, we chose 100 representative tasks around the cluster centroids to form our offline benchmark, AGENTNETBENCH.

Applications and Websites Applications and websites are tracked using the AgentNet Tool. Specifically, application names are captured by recording the process name when a user opens an application, while website URLs are recorded through our browser plugin. Discrepancies in process names across different operating systems and different versions are resolved using GPT, achieving an accuracy of up to 83% with this combined method. Based on these results, we analyzed the distribution of the dataset across applications and websites. Web browsers account for a significant portion of the dataset, as nearly half of the data involves web applications. The results indicate that the dataset encompasses over 140 applications and 190 mainstream websites.

D.2 Complexity

Our collected tasks average 17.2 steps per task. We evaluate task complexity across five dimensions: multi-application/website usage, professional knowledge requirement, uncommon feature usage, repetitive simple subtasks, and logically coherent long sequences. Based on GPT-4o analysis, 30.6% tasks require multiple applications/websites, 12.9% involve professional knowledge, and 12.9% use uncommon features in Figure 17. Then we asked GPT to rate the complexity of tasks on a 1-10 scale, where 1 represents basic operations like file opening, and 10 indicates complex tasks requiring multiple steps, domain knowledge, or sophisticated reasoning. The complexity distribution is shown in Figure 16. It can be seen that most of the tasks have a medium or high level of complexity.

Domain	App/Web
E-commerce & Travel	Amazon.com, Booking.com
News, Entertainment & Lifestyle	Spotify, Netflix
Social Media & Communication	WhatsApp, Instagram
Office Tools	Microsoft Office, Google Docs
Task Management & Collaboration	Zoom, Gmail, Slack
Creative Design & Multimedia	Photoshop
Development & Engineering	VSCode, PyCharm, Git
Knowledge Discovery & Research	Google Scholar, ResearchGate
Data Analysis, Business & Cloud	Tableau, Power BI, AWS
Web Tools & Internet Utilities	Chrome Extensions
Operating Systems & Utilities	Finder, Activity Monitor

Table 8: Example App/Web by Doman

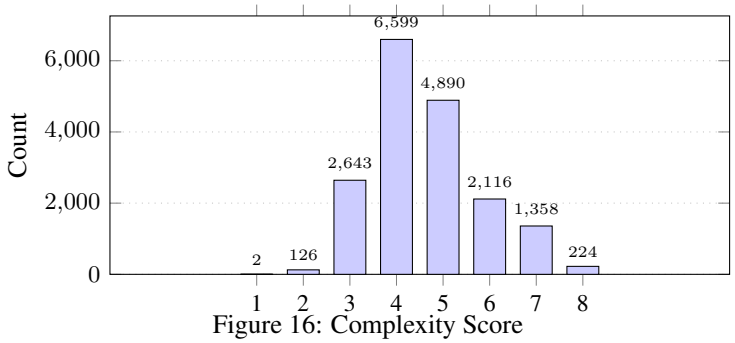


Figure 16: Complexity Score

E AgentNet Tool: System Design and Key Features

E.1 Annotator Sources

We recruited annotators from four sources: internal students, external university students, annotation companies, and crowd-sourcing platform - Prolific. Table 9 shows the distribution of annotators and tasks. While annotators from Prolific and Company1 were native English speakers, others were native Chinese speakers. All annotators were required to document task goals in English and try to use English system settings, applications and websites to ensure broader applicability.

Annotator Source	Accepted Uploads	Annotator Count
Internal Students	4943	38
External Students	5168	135
Prolific	1218	294
Company1	2235	72
Company2	3556	51
Company3	1975	14
Company4	8709	30
Total	**27804**	**634**

Table 9: User Source Statistics

E.2 Implementation and Features

1. **Action Reduction**: We use tools like `pynput` to capture users' atomic actions. These atomic actions are then reduced to semantically meaningful actions, such as 'click', 'key_press', 'key_release', 'type', 'drag', 'move', and 'scroll'. This reduction enables models to more effectively learn from human demonstrations and allows annotators and verifiers to understand trajectories more easily.

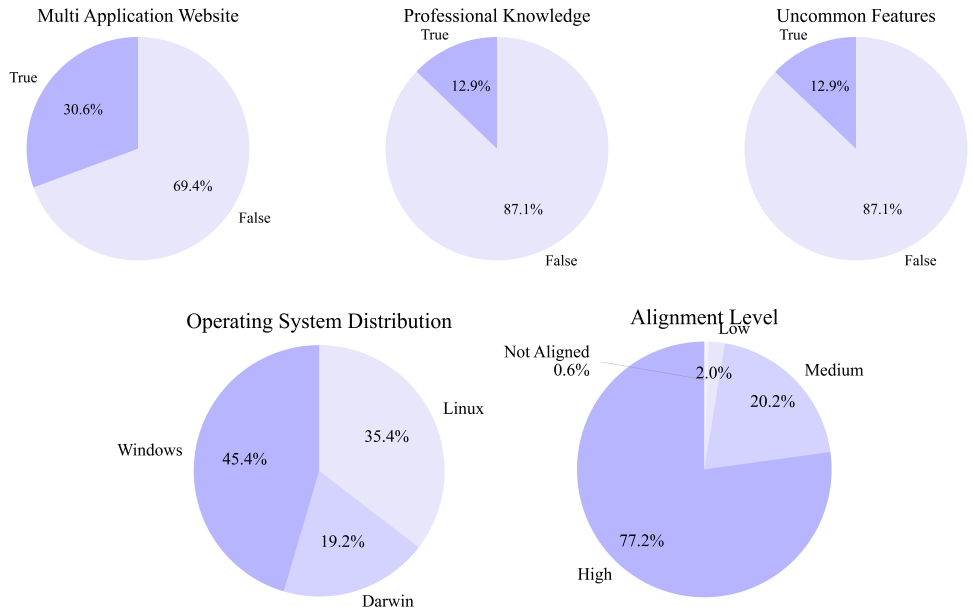


Figure 17: Distributions of data characteristics: presence of multi-application websites, inclusion of professional knowledge, presence of uncommon features, source operating systems and alignment levels.

2. **A11y Tree and HTML Processing**: To obtain textual representations of observations, we implement efficient fetching and processing mechanisms for accessibility (a11y) trees and HTML. For the a11y tree, we apply pruning rules to select only essential element attributes, ensuring the fetching process for each tree takes minimal time. For HTML, we develop a browser plugin that automatically captures the HTML structure of websites.

3. **Element Localization**: To help users verify the correctness of their actions, we extract text associated with click locations. Using the a11y tree or HTML, we fetch the bounding box most likely clicked and extract textual information from it. If the extracted text is insufficient, we leverage GPT to predict the semantic information of the clicked element.

4. **Trajectory Visualization**: We design a user-friendly interface to ensure a seamless annotation experience. For each action, we display its description, a corresponding video clip, and the a11y tree. Additionally, we provide the full video of the entire trajectory for better context.

5. **Verification and Administration Systems**: To ensure the quality of the collected data, we develop verification and administration systems that streamline the process of validating annotations and maintaining dataset integrity.

E.3 Privacy

We implemented a multi-layer privacy protection framework in our data collection process. First, annotators must agree to a consent form that clearly states the scope of data collection, including screen recordings, actions, and system information. The form explicitly prohibits recording private or sensitive information. The tool is designed with privacy-first principles: no data is transmitted to servers without manual upload by annotators, and annotators can review all collected data (including videos, actions, and accessibility tree structures) before submission. We further ensure privacy through a two-stage verification process: manual review by internal team members during task verification, and automated examination of the task trajectory using `GPT-4o` during post-processing. Tasks containing private information are rejected immediately. Detailed privacy protection protocols are provided in the Appendix E.3.

E.3.1 GPT-Based Privacy Analysis

Data Ingestion The system loads task descriptions and step-by-step user actions (*Observations*, *Thoughts*, *Action Descriptions*, etc.) from JSON. These records provide details of users' intent, the interface elements users interacted with, and any textual or visual cues relevant to the task.

GPT Inference The script calls OpenAI's API with a carefully structured prompt, requesting GPT to produce a privacy classification in one of four levels: *None*, *Low*, *Medium*, or *High*. By passing the user's detailed action steps and observations to GPT, the system gathers a structured output that includes an explicit `privacy_sensitivity` label.

GPT accelerates the classification process, effectively scanning large volumes of user trajectories with consistent logic. It can identify and label potentially sensitive fields or behaviors with minimal human oversight. However, GPT's inherent reliance on keywords sometimes causes it to mark a scenario as *High*, even if the user simply viewed (but did not fill) a password field. Such errors underscore the necessity of post-processing or additional contextual checks to distinguish between *potential* versus *actual* private data entry.

E.3.2 Human Verification

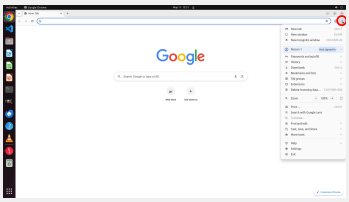
Human reviewers examine the same recordings or textual records to determine whether genuinely confidential information was entered. For example:

- If only an email address is mentioned, human reviewers might label it as *Low* or *None*.
- If a direct password or banking details appear, human reviewers assign *High*.

In "false alarm" cases (for example, a password field is displayed but left blank), humans typically label them as *None*. This nuanced reasoning often yields higher precision but comes at the cost of increased labor and time. Furthermore, variability in human judgments may occur if guidelines are not strictly enforced.

F OSWorld Case Example

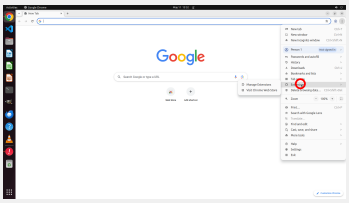
The trajectory outlines the process of installing a manually developed Chrome extension located in the Desktop directory into the Google Chrome browser for testing or usage purposes. Notably, the step labeled in red highlights the agent's capacity for reflection and error correction—it initially diverges into an incorrect path, subsequently recognizes the mistake, and successfully reorients itself to proceed with the correct course of action.



Step 1

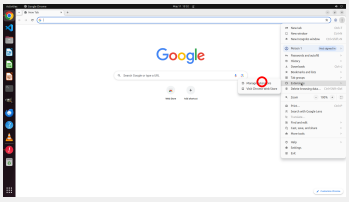
Thought: I need to install a Chrome extension that's located in the Desktop directory. Looking at the current state, I'm on the Google homepage in Chrome. To install an extension, I need to access the Chrome Web Store or use the extensions menu.
I can see that there's a "Web Store" shortcut on the Google homepage which could be useful. However, I also notice the Chrome menu button (three vertical dots) in the top-right corner of the browser. This menu would give me access to more Chrome settings and features, including extensions.
Since I need to install a local extension file, the most direct approach would be to: 1. Click on the Chrome menu (three dots) 2. Navigate to "More tools" > "Extensions" or directly to "Chrome Web Store" 3. Upload the extension file from the Desktop.
The Chrome menu button in the top-right corner is the logical next action because it provides access to all Chrome settings and features, including extensions management. Clicking this button will open a dropdown menu with various options, including those related to extensions.
I anticipate that after clicking the menu button, I'll see options that will allow me to navigate to the extensions page or Chrome Web Store, where I can then upload the extension file from the Desktop.
Action: Click on the three-dot menu button in the top-right corner of the Chrome browser window to open the Chrome menu.

Code: pyautogui.click(x=0.988, y=0.081)



Step 2

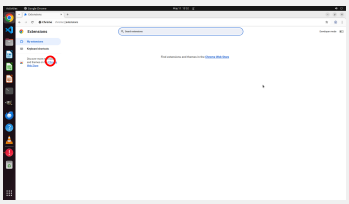
Thought: After clicking on the three-dot menu in the previous step, the Chrome menu has successfully opened, displaying various options. This is exactly what I expected to happen, so we're making good progress toward our goal of installing a Chrome extension from the Desktop.
Looking at the current state, I can see that the Chrome menu is now open with all its options. To install a Chrome extension, I need to access the Extensions page or use the Web Store. Based on the goal of installing an extension from the Desktop directory, I should look for the Extensions option in this menu.
I can see that there is an "Extensions" option in the menu, which is exactly what I need. Clicking on this option will take me to Chrome's Extensions page, where I can then load an unpacked extension from the Desktop directory.
The logical next action would be to click on the "Extensions" option in the Chrome menu. This will navigate to the Extensions management page where I can then find an option to load an unpacked extension. From there, I'll be able to browse to the Desktop directory and select the extension file for installation.
By clicking on the Extensions option, I expect to be taken to the Extensions management page where I'll see a list of currently installed extensions and options to manage them, including an option to "Load unpacked" which I'll need to use to install the extension from the Desktop.
Action: Click on the "Extensions" option in the Chrome menu to access the extensions management page.
Code: pyautogui.click(x=0.867, y=0.406)



Step 3

Thought: After clicking on the "Extensions" option in the Chrome menu, I can see that the menu has expanded to show more options related to extensions. This is the expected result of the previous action.
Looking at the current state, I can see that there are two main options related to extensions: 1. "Manage Extensions" - This would take me to the page where I can manage currently installed extensions 2. "Visit Chrome Web Store" - This would take me to the Chrome Web Store where I can download extensions from the official store
Since our goal is to install a Chrome extension that is located on the Desktop directory, I need to access the extensions management page first. From there, I would be able to access the "Load unpacked" button which allows installing extensions from local files rather than from the Chrome Web Store.
The logical next action would be to click on "Manage Extensions" since this is the option that will take me to the extensions management page where I can install the extension from the Desktop. This is the most direct path to achieving our goal of installing a locally developed extension.
By clicking on "Manage Extensions," I expect to be taken to a page that shows all currently installed extensions and provides options to add new extensions, including the "Load unpacked" option that I'll need to use to install the extension from the Desktop directory.
Action: Click on the "Manage Extensions" option in the Chrome menu to access the extensions management page.

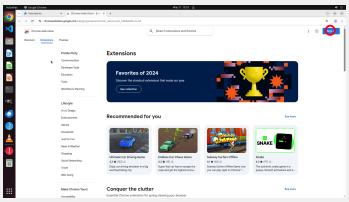
Code: pyautogui.click(x=0.755, y=0.403)



Step 4

Thought: After clicking on "Manage Extensions" in the previous step, I can see that I've successfully navigated to the Chrome extensions management page. This is exactly where I need to be to continue with the installation of the new Chrome extension.
Looking at the current state, I can see that I'm on the chrome://extensions page which shows the list of currently installed extensions. However, I don't see any extensions listed yet, which suggests either there are no extensions installed or the page needs to be refreshed to show them.
To install a new extension manually from a local file on the Desktop, I need to: 1. Access the Chrome Web Store or a similar interface where I can upload or load an extension from a file 2. Navigate to the extension file location (Desktop) 3. Install the extension
I notice there are a few options available to me: - I could click on "My extensions" to see if there are any installed extensions - I could click on "Keyboard shortcuts" to configure shortcuts - I could click on the "Chrome Web Store" link to browse the store - I could click on the "Chrome" link in "Discover more extensions and themes on the Chrome Web Store"
Since my goal is to install a locally developed extension, I need to find an option that would allow me to load an extension from a file. The "Chrome Web Store" link seems to be the most logical next step, as it would likely provide access to extension management functions including loading local extensions.
Clicking on the "Chrome" link in the text "Discover more extensions and themes on the Chrome Web Store" would take me to the Chrome Web Store, where I might find options to access developer tools or load extensions from local files. This seems like the most logical next action to progress toward my goal of installing the extension from the Desktop directory.
Action: Click on the "Chrome" link in the text "Discover more extensions and themes on the Chrome Web Store"

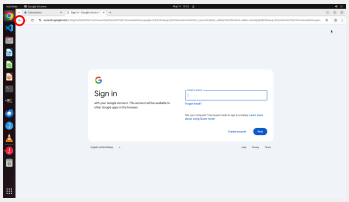
Code: pyautogui.click(x=0.138, y=0.284)



Step 5

Thought: After clicking on the "Chrome" link in the Extensions management page, I've been taken to the Chrome Web Store. This is a good start, but I notice that I'm currently in the Extensions category of the Chrome Web Store, which is for browsing and downloading extensions from the store, not for installing local extensions.
To install a Chrome extension from a local file (located in the Desktop directory as mentioned in the goal), I need to access the Chrome Web Store's developer page or use a different approach.
Looking at the current state, I need to navigate to a different section that allows for installing unpacked extensions.
I can see that there's a "Sign In" button in the top-right corner of the page. Signing in to Chrome is often necessary for extension development and installation. Additionally, there might be a way to access developer options or a special section for installing unpacked extensions after signing in.
Given the goal of installing a locally developed Chrome extension from the Desktop directory, the next logical step would be to sign in to Chrome. This would likely give me access to more advanced options for extension installation, including the ability to load an unpacked extension from a local directory.
After signing in, I expect to either find a direct option to load an unpacked extension or need to upload the extension file from the Desktop. Signing in is a necessary step in the process of manually installing a Chrome extension from a local directory.
Action: Click on the "Sign In" button in the top-right corner of the Chrome Web Store page.

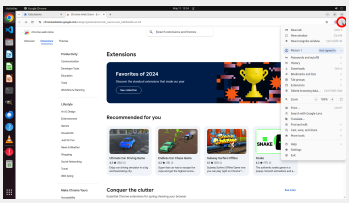
Code: pyautogui.click(x=0.954, y=0.131)



Step 6

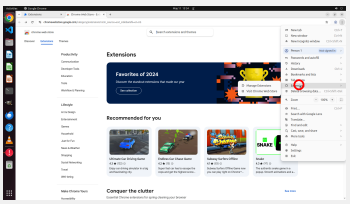
Thought: After clicking the "Sign In" button in the Chrome Web Store, I've been redirected to a Google sign-in page. This makes sense as many Chrome extensions require a signed-in profile to be installed properly. The sign-in page is asking for Google account credentials to proceed.
Looking at my progress toward the goal of installing a Chrome extension manually from the Desktop directory, I need to: 1. Access the Chrome Web Store (completed) 2. Sign in to Chrome (in progress) 3. Navigate to the extension file on the Desktop 4. Install the extension manually
I'm currently at step 2, where I need to sign in to a Google account to proceed. However, I notice that I might not need to complete the entire sign-in process. Since the goal is to install a locally downloaded extension, I might be able to go back and find an option to load an extension from a local file without fully signing in.
Looking at the browser interface, I see the back button in the top-left corner of the browser. Clicking this back button would allow me to return to the Chrome Web Store page where I might find alternative options for installing an extension from a local file, such as a "Load unpacked" button that's typically available when you're in the extensions management page.
The logical next action would be to click the back button to return to the Chrome Web Store. This would allow me to potentially find a more direct way to install the extension from the Desktop without completing the sign-in process. After clicking back, I expect to return to the Chrome Web Store page where I can look for options related to loading local extensions.
Action: Click the back button in the top-left corner of the Chrome browser window to return to the previous page.

Code: pyautogui.click(x=0.048, y=0.086)



Step 7

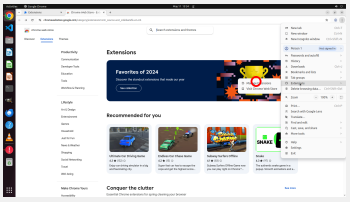
Thought: After clicking the back button, I've successfully returned to the Chrome Web Store page from the Google sign-in page. This was the right move since signing in wasn't necessary to install a local extension.
Now I need to find a way to install the extension from the Desktop directory. Looking at the current state of the Chrome Web Store page, I need to find an option that would allow me to load an extension from a local file. This functionality is typically available through an "More" menu or similar option on the Chrome Web Store page.
I can see that there's a three-dot menu button in the top-right corner of the Chrome browser window. This is likely where I'll find additional options for managing extensions, including the ability to load an extension from a local file. Clicking this button should reveal a dropdown menu with various options, potentially including "More Extensions" or "Load unpacked extension" which would allow me to navigate to the Desktop directory and select the extension file.
The logical next action is to click on this three-dot menu button in the top-right corner of the browser. This should open a menu with additional options related to extensions, which will help me progress toward manually installing the extension from the Desktop directory.
Action: Click on the three-dot menu button in the top-right corner of the Chrome browser window to access additional browser options.
Code:pyautogui.click(x=0.988, y=0.083)



Step 8

Thought: After clicking the three-dot menu in the top-right corner of the Chrome browser, a dropdown menu has appeared with various browser options. This is exactly what I was expecting to see, as this menu provides access to Chrome's core functionality including extensions management.
Looking at my progress toward the goal of installing a Chrome extension manually from the Desktop directory, I've successfully: 1. Opened the Chrome menu 2. Accessed the Extensions option 3. Navigated to the Chrome Web Store 4. Attempted to sign in (but determined it wasn't necessary) 5. Opened the Chrome menu again to access more options
Now I need to find the best way to install the extension from the Desktop. Since I already know the extension file is on the Desktop, I should look for an option that would allow me to load an unpacked extension or access the Desktop files.
Looking at the dropdown menu, I can see an "Extensions" option with a submenu indicator (>). This is exactly what I need to click next because: 1. It will take me to the Extensions management page or provide extension-related options 2. From there, I should be able to find an option to load an unpacked extension 3. This is the standard way in Chrome to manage extensions, including loading them from local files
Clicking on the "Extensions" menu item will likely show me additional options such as "Load unpacked" which would allow me to navigate to the Desktop and select the extension folder. This is the most direct path to manually installing the extension from the Desktop as required.
Action: Click on the "Extensions" option in the Chrome menu to access extension management functions.

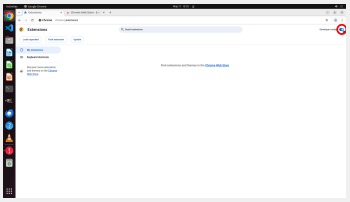
Code: pyautogui.click(x=0.863, y=0.406)



Step 9

Thought: After clicking on the "Extensions" option in the Chrome menu, a submenu has appeared with two options: "Manage Extensions" and "Visit Chrome Web Store". This is exactly what I need to continue with the installation process.
Looking at my progress toward installing the Chrome extension: 1. I opened the Chrome menu and accessed Extensions 2. I went to the Chrome Web Store's Extensions page 3. I attempted to sign in but decided to go back 4. I opened the Chrome menu again and clicked on Extensions 5. Now I'm seeing a submenu with extension-related options
To install a local extension from the Desktop directory, I need to access the extension management interface. The "Manage Extensions" option is exactly what I need, as it will allow me to access the extension installation functionality. This is where I'll be able to load an unpacked extension from a local directory.The "Manage Extensions" option is the first item in the submenu that has appeared. Clicking on this option will take me to the extensions management page where I can find the option to add an unpacked extension. From there, I'll be able to navigate to the Desktop directory and select the extension file to complete the installation.The logical next action is to click on "Manage Extensions" in the submenu. This will take me to the extensions management page where I can proceed with installing the extension from the Desktop directory.
Action: Click on the "Manage Extensions" option in the Chrome menu submenu.

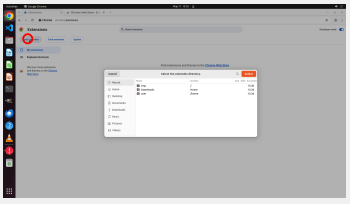
Code: pyautogui.click(x=0.738, y=0.401)



Step 10

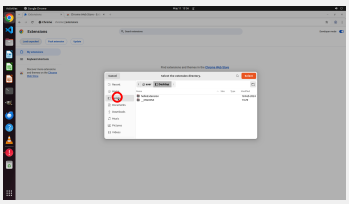
Thought: After clicking on "Manage Extensions" in the Chrome menu, I've been taken to the Chrome extensions management page. This is exactly where I need to be to continue with the installation of the new Chrome extension.
Looking at my progress toward the goal of installing a Chrome extension manually from the Desktop directory: 1. I've successfully accessed the Chrome browser 2. I've navigated to the extensions management page 3. I now need to find a way to load the extension from the Desktop
The extensions page shows several options, including "My extensions" and "Keyboard shortcuts," but I don't see a direct option to upload or add an extension from a file. However, I notice the "Developer mode" toggle in the top-right corner of the page. This is exactly what I need, as Developer mode typically provides additional options for developers, including the ability to load unpacked extensions.To install a manual extension, I need to enable Developer mode first. Once Developer mode is enabled, I should get additional options that will allow me to load an unpacked extension from a local directory like the Desktop.The logical next action is to click on the "Developer mode" toggle switch in the top-right corner of the page. This will enable developer options and should reveal additional controls that will allow me to load the extension from the Desktop directory. After clicking this toggle, I expect to see new buttons appear that will let me access the file system and select the extension file.
Action: Click on the "Developer mode" toggle switch in the top-right corner of the page to enable developer options.

Code: pyautogui.click(x=0.988, y=0.131)



Step 11

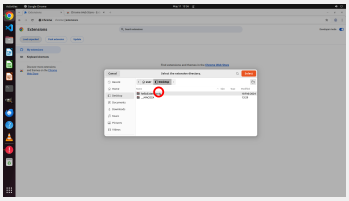
Thought: After clicking on the "Developer mode" toggle switch, it has successfully been enabled as shown by the blue toggle in the top-right corner of the page. This has revealed additional functionality that wasn't visible before, including the "Load unpacked" button which is exactly what we need to install our extension manually.Now that Developer mode is enabled, I can see the "Load unpacked" button which allows us to install extensions from local files rather than from the Chrome Web Store. This is perfect for our goal since we need to install an extension that's located in the Desktop directory.Looking at the available options, I can see: 1. "Load unpacked" button - This is what we need to install our local extension 2. "Pack extension" button - Used for creating a packaged version of an extension 3. "Update" button - For updating existing extensions 4. The sidebar navigation showing "My extensions" and "Keyboard shortcuts"To install the extension from the Desktop directory, the logical next action is to click on the "Load unpacked" button. This will open a file browser dialog that will allow us to navigate to the Desktop and select the extension folder. Once we select the folder, Chrome will install the extension from the unpacked files.Clicking the "Load unpacked" button is the most appropriate action because: 1. It directly addresses our goal of installing a locally developed extension 2. It's the standard way to install extensions from local files in Chrome 3. The Developer mode is already enabled, which is a prerequisite for using this feature
After clicking this button, I expect a file browser dialog to appear, allowing us to navigate to the Desktop and select the extension folder.
Action: Click on the "Load unpacked" button to open a file browser dialog for selecting the extension folder from the Desktop.
Code: pyautogui.click(x=0.072, y=0.179)



Step 12

Thought: After clicking the "Load unpacked" button, a file browser dialog has opened as expected. This dialog allows me to navigate to the location where the extension is stored, which according to our goal should be in the Desktop directory.
Looking at the current state, I can see that the file browser dialog is showing the contents of what appears to be the home directory, with folders like tmp, Downloads, and user visible. However, our goal is to install a Chrome extension that's located in the Desktop directory. Therefore, I need to navigate to the Desktop folder.
I notice that the Desktop folder is conveniently listed in the left navigation panel of the file browser. Since we need to access the Desktop to find the extension files, clicking on the Desktop folder in the left navigation panel is the logical next step. This will change the view to show the contents of the Desktop directory, where we should be able to find the extension files.
Once I click on Desktop, I expect the main panel to update and show all files and folders located on the Desktop. From there, I'll need to locate the specific extension folder and select it to complete the installation process.
The logical next action is to click on the "Desktop" option in the left navigation panel of the file browser dialog to navigate to the Desktop directory where our extension is located. **Action:** Click on the "Desktop" option in the left navigation panel of the file browser dialog.

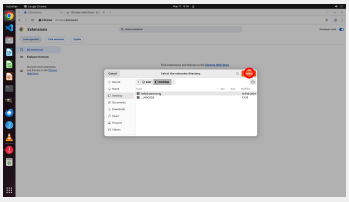
Code: pyautogui.click(x=0.333, y=0.470)



Step 13

Thought: After clicking on the "Desktop" option in the left navigation panel, the file browser dialog has now displayed the contents of the Desktop directory. This is exactly what we needed to proceed with installing the Chrome extension.
Looking at the current state, I can see that the Desktop directory contains two items: a folder named "helloExtension" and another folder named "_MACOSX". Since we're looking to install a Chrome extension, the "helloExtension" folder is most likely the extension we need to install. Chrome extensions typically follow a specific folder structure with an "manifest.json" file at the root, and "helloExtension" appears to be a properly named extension folder. Now that I've located what appears to be the extension folder, the next logical step would be to select this folder to proceed with the installation. According to the goal, we need to install a Chrome extension located in the Desktop directory, and we've now found what seems to be that extension.
I have several options at this point: 1. Click on the "helloExtension" folder to select it 2. Click the "Select" button (which would likely select the currently highlighted item) 3. Navigate into the folder to confirm its contents
Since the "helloExtension" folder is the most likely candidate for the extension we need to install, and it's already visible in the file browser, clicking on this folder to select it is the most logical next action. This will highlight the folder and prepare it for selection, after which I can click the "Select" button to complete the installation process.
I expect that after clicking on the "helloExtension" folder, it will become highlighted, indicating it's selected. Then I can proceed to click the "Select" button to load this unpacked extension into Chrome.
Action: Click on the "helloExtension" folder in the file browser dialog to select it for installation.

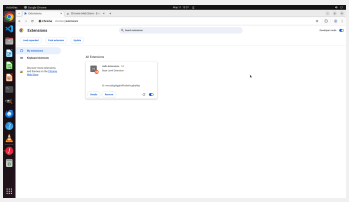
Code: pyautogui.click(x=0.454, y=0.456)



Step 14

Thought: After clicking on the "helloExtension" folder in the file browser dialog, I can see that the folder is now selected. This is exactly what we needed to do to identify the extension we want to install. The file browser dialog shows we're in the Desktop directory, and we can see the "helloExtension" folder that contains our newly developed Chrome extension.
Now that we've selected the "helloExtension" folder, the next logical step is to confirm this selection by clicking the "Select" button in the file browser dialog. This button is prominently displayed in orange in the top-right corner of the dialog. Clicking this button will finalize our selection and proceed with the installation process.
The installation workflow so far has been: 1. We enabled Developer mode in Chrome 2. We clicked "Load unpacked" to open the file browser 3. We navigated to the Desktop directory 4. We selected the "helloExtension" folder
The final step to complete the installation is to click the "Select" button, which will tell Chrome to load the unpacked extension from the selected folder. After clicking this button, Chrome should install the extension and possibly show a confirmation message or automatically add the extension to the browser.I expect that after clicking the "Select" button, the file browser dialog will close, and we'll return to the Extensions page in Chrome where we might see the newly installed extension appear in the list of installed extensions, or possibly see a notification about the successful installation.
Action: Click the "Select" button in the top-right corner of the file browser dialog to confirm the selection of the helloExtension folder and complete the installation process.

Code: pyautogui.click(x=0.718, y=0.358)



Step 15

Thought: After clicking the "Select" button in the file browser dialog, the extension installation process has completed successfully. The dialog has closed and we've been returned to the Extensions management page where we can now see that the "Hello Extensions" extension has been installed. The extension appears with its icon, version number (1.0), and description ("Base Level Extension").Looking at our progress toward the goal of installing the Chrome extension: 1. We enabled Developer mode in the Extensions page ✓2. We clicked the "Load unpacked" button which opened the file browser dialog ✓3. We navigated to the Desktop directory ✓4. We selected the "helloExtension" folder ✓5. We clicked the "Select" button to confirm the installation ✓6. The extension has now been successfully installed ✓The task has been completed successfully! The extension is now installed and appears in the Extensions management page. I can see that it's enabled (the toggle switch is turned on). If we wanted to configure any specific settings for this extension, we could click on the "Details" button which would likely show more options for the extension.Since our goal was to install the extension manually from the Desktop directory, and that has been accomplished, there's no further action needed for the basic installation task. The extension is now available for use in Chrome.
Action: Terminate the process with success status as the extension installation is complete.
Code: computer.terminate(status='success')

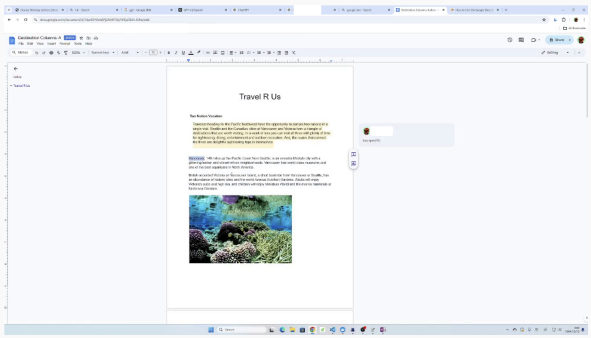
G AgentNet Data Example

G.1 L1 Data Example

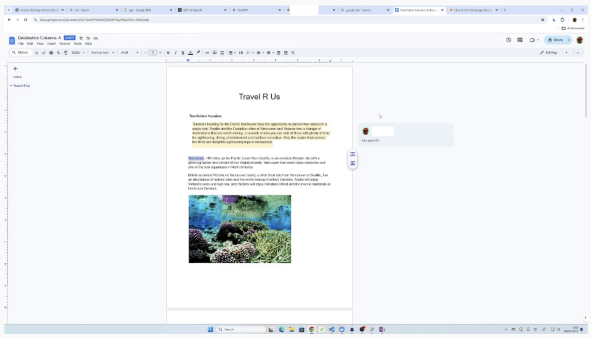
L1 data includes CoT-L1(Action) in its inner monologue. The assistant's final output will be included in the loss calculation (green color content).

L1 Data Example

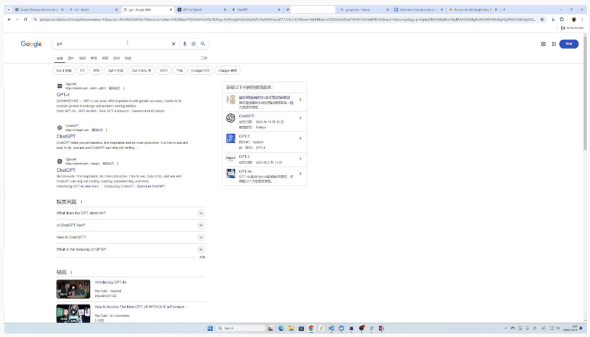
```
[
    {
        "role": "system",
        "content": "You are a GUI agent. You are given a task and a
        screenshot of the screen. You need to perform a series of pyautogui
        actions to complete the task.For each step, provide your response in
        this format:Action:  Provide clear, concise, and actionable
        instructions:  - If the action involves interacting with a specific
        target:    - Describe target explicitly without using coordinates    -
        Specify element names when possible (use original language if
        non-English)    - Describe features (shape, color, position) if name
        unavailable    - For window control buttons, identify correctly
        (minimize, maximize, close)  - if the action involves keyboard
        actions like 'press', 'write', 'hotkey':    - Consolidate repetitive
        keypresses with count    - Specify expected text outcome for typing
        actionsFinally, output the action as PyAutoGUI code or the following
        functions:- {"name": "computer.triple_click", "description": "Triple
        click on the screen", "parameters": {"type": "object", "properties":
        {"x": {"type": "number", "description": "The x coordinate of the
        triple click"}, "y": {"type": "number", "description": "The y
        coordinate of the triple click"}}, "required": ["x", "y"]}}- {"name":
        "computer.terminate", "description": "Terminate the current task and
        report its completion status", "parameters": {"type": "object",
        "properties": {"status": {"type": "string", "enum": ["success",
        "failure"], "description": "The status of the task"}}, "required":
        ["status"]}}"
    },
    {
        "role": "assistant",
        "content": "# Step 1:
        ## Action:Click on the "Destination Columns-A..." document thumbnail
        to open the document.

        # Step 2:
        ## Action:Select the word "Travelers" at the beginning of the second
        paragraph by clicking at the start of the word and dragging to the
        end of it."
    },
    {
        "role": "user",
        "image":
```




```
    ,
},
{
    "role": "assistant",
    "content": "# Step 3:
    ## Action:Press Ctrl+C to copy the selected word "Travelers""
},
{
    "role": "user",
    "image":
```




```
    ,
},
{
    "role": "assistant",
    "content": "# Step 4:
    ## Action:Click on the Google search tab near the top of the browser
    window."
},
{
    "role": "user",
    "image":
```



```
        ,
    },
    {
        "role": "user",
        "content": "# Task Instruction:
        Could you open the document 'Destination Columns-A', find the first
        word of the second paragraph, look up what that word means on
        Wikipedia, and then add that Wikipedia description as a footnote to
        that word in the document?
        Please generate the next move according to the screenshot, task
        instruction and previous steps (if provided)."
    },
    {
        "role": "assistant",
        "content": "# Step 5:
        ## Action:Click on the Google search box where "gpt" is currently
        displayed to prepare to enter a new search query.
        ## Code:'''pythonpyautogui.click(x=0.157, y=0.1229)'''"
    }
```

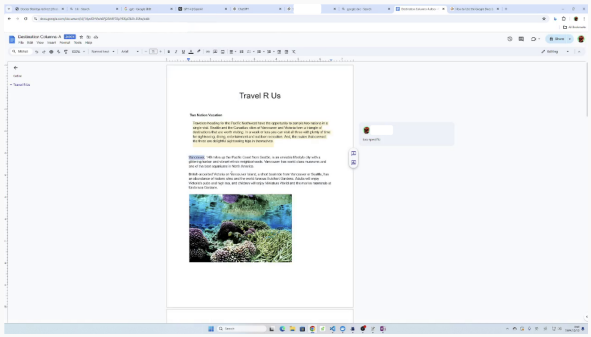
G.2 L2 Data Example

L2 data includes CoT-L2(Thought, Action) in its inner monologue. The assistant's final output will be included in the loss calculation.

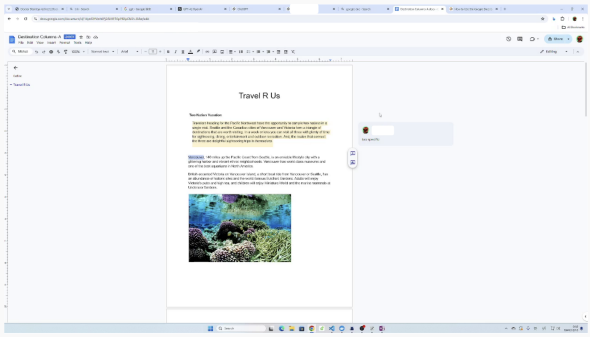
L2 Data Example

```
[
    {
        "role": "system",
```

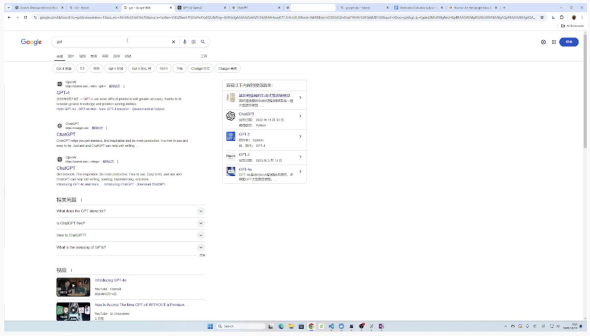
```
    "content": "You are a GUI agent. You are given a task and a
    screenshot of the screen. You need to perform a series of pyautogui
    actions to complete the task.For each step, provide your response in
    this format:Thought:  - Step by Step Progress Assessment:    -
    Analyze completed task parts and their contribution to the overall
    goal    - Reflect on potential errors, unexpected results, or
    obstacles    - If previous action was incorrect, predict a logical
    recovery step  - Next Action Analysis:    - List possible next
    actions based on current state    - Evaluate options considering
    current state and previous actions    - Propose most logical next
    action    - Anticipate consequences of the proposed action  - For
    Text Input Actions:    - Note current cursor position    -
    Consolidate repetitive actions (specify count for multiple
    keypresses)    - Describe expected final text outcome  - Use
    first-person perspective in reasoningAction:  Provide clear, concise,
    and actionable instructions:  - If the action involves interacting
    with a specific target:    - Describe target explicitly without using
    coordinates    - Specify element names when possible (use original
    language if non-English)    - Describe features (shape, color,
    position) if name unavailable    - For window control buttons,
    identify correctly (minimize, maximize, close)  - if the action
    involves keyboard actions like 'press', 'write', 'hotkey':    -
    Consolidate repetitive keypresses with count    - Specify expected
    text outcome for typing actionsFinally, output the action as
    PyAutoGUI code or the following functions:- {"name":
    "computer.triple_click", "description": "Triple click on the screen",
    "parameters": {"type": "object", "properties": {"x": {"type":
    "number", "description": "The x coordinate of the triple click"}, "y":
    {"type": "number", "description": "The y coordinate of the triple
    click"}}, "required": ["x", "y"]}}- {"name": "computer.terminate",
    "description": "Terminate the current task and report its completion
    status", "parameters": {"type": "object", "properties": {"status":
    {"type": "string", "enum": ["success", "failure"], "description":
    "The status of the task"}}, "required": ["status"]}}"
},
{
    "role": "assistant",
    "content": "# Step 1:
    ## Action:Click on the "Destination Columns-A..." document thumbnail
    to open the document.

    # Step 2:
    ## Action:Select the word "Travelers" at the beginning of the second
    paragraph by clicking at the start of the word and dragging to the
    end of it."
},
{
    "role": "user",
    "image":
```



```
    ,
},
{
    "role": "assistant",
    "content": "# Step 3:
    ## Action:Press Ctrl+C to copy the selected word "Travelers""
},
{
    "role": "user",
    "image":
```




```
    ,
},
{
    "role": "assistant",
    "content": "# Step 4:
    ## Action:Click on the Google search tab near the top of the browser
    window."
},
{
    "role": "user",
    "image":
```



```
    ,
},
{
    "role": "user",
    "content": "# Task Instruction:
    Could you open the document 'Destination Columns-A', find the first
    word of the second paragraph, look up what that word means on
    Wikipedia, and then add that Wikipedia description as a footnote to
    that word in the document?
    Please generate the next move according to the screenshot, task
    instruction and previous steps (if provided)."
```

```
    },
    {
        "role": "assistant",
        "content": "# Step 5:
        ## Thought:After clicking on the Google search tab, I can now see
        that the browser has successfully switched to a Google search page.
        This is a step forward in my task, as I need to search for the word
        "Travelers" on Wikipedia to complete the footnote insertion.Currently,
        I see that the search box contains "gpt" rather than the word
        "Travelers" that I copied from the document. To proceed with my task,
        I need to:1. Clear the current search term "gpt" from the search box2.
        Enter "Travelers Wikipedia" or navigate directly to Wikipedia and
        search there3. Find relevant information about "Travelers" on
        Wikipedia4. Return to the Google Docs document and insert this
        information as a footnoteMy progress on the overall task so far:1.
        I've opened the "Destination Columns-A" document v2. I've identified
        and selected the first word of the second paragraph ("Travelers") v3.
        I've copied this word to the clipboard v4. I've switched to a browser
        tab for searching v5. Now I need to clear the current search and look
        up "Travelers" on Wikipedia6. Then I need to insert the Wikipedia
        description as a footnoteLooking at the current state, I need to
        click directly on the search box where "gpt" is currently displayed.
        By clicking on the search box, I'll be able to select all the text,
        delete it, and replace it with "Travelers Wikipedia" to search for
        information about Travelers on Wikipedia. This is the most efficient
        next action as it allows me to directly modify the search query
        without any additional steps.After clicking on the search box, I
        expect the text cursor to be positioned within the box, allowing me
        to edit the current search term. I can then clear "gpt" and type
        "Travelers Wikipedia" to continue with my search. This will help me
        find the Wikipedia page for "Travelers" so I can obtain the
        description needed for the footnote.
        ## Action:Click on the Google search box where "gpt" is currently
        displayed to prepare to enter a new search query.
        ## Code:'''pythonpyautogui.click(x=0.157, y=0.1229)'''"
    }
]
```

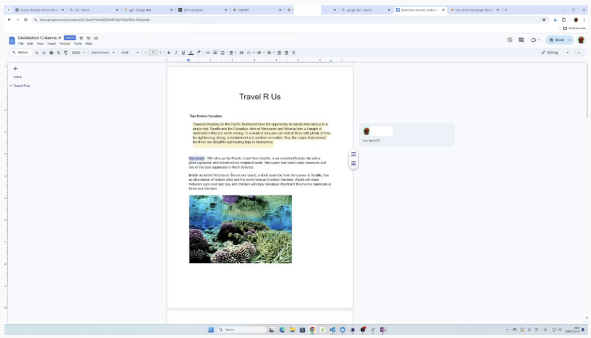
G.3 L3 Data Example

L3 data includes CoT-L3(Observation, Thought, Action) in its inner monologue. The assistant's final output will be included in the loss calculation.

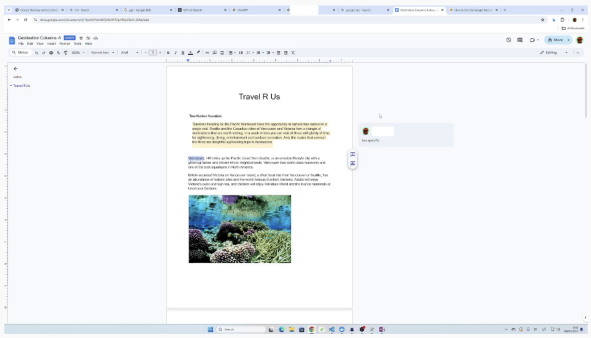
L3 Data Example

```
[
    {
        "role": "system",
```

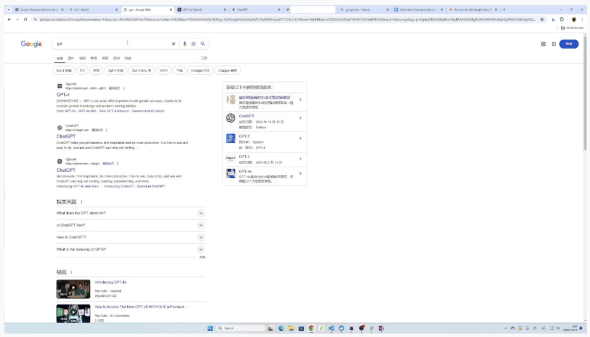
```
        "content": "You are a GUI agent. You are given a task and a
        screenshot of the screen. You need to perform a series of pyautogui
        actions to complete the task.For each step, provide your response in
        this format:Observation:  - Describe the current computer state based
        on the full screenshot in detail.   - Application Context:    - The
        active application    - The active window or page    - Overall layout
        and visible interface  - Key Elements:    - Menu items and toolbars
        - Buttons and controls    - Text fields and content    - Dialog boxes
        or popups    - Error messages or notifications    - Loading states
        - Other key elements  - Describe any content, elements, options,
        information or clues that are possibly relevant to achieving the task
        goal, including their name, content, or shape (if possible).Thought:
        - Step by Step Progress Assessment:    - Analyze completed task parts
        and their contribution to the overall goal    - Reflect on potential
        errors, unexpected results, or obstacles    - If previous action was
        incorrect, predict a logical recovery step  - Next Action Analysis:
        - List possible next actions based on current state    - Evaluate
        options considering current state and previous actions    - Propose
        most logical next action    - Anticipate consequences of the proposed
        action  - For Text Input Actions:    - Note current cursor position
        - Consolidate repetitive actions (specify count for multiple
        keypresses)    - Describe expected final text outcome  - Use
        first-person perspective in reasoningAction:  Provide clear, concise,
        and actionable instructions:  - If the action involves interacting
        with a specific target:    - Describe target explicitly without using
        coordinates    - Specify element names when possible (use original
        language if non-English)    - Describe features (shape, color,
        position) if name unavailable    - For window control buttons,
        identify correctly (minimize, maximize, close)  - if the action
        involves keyboard actions like 'press', 'write', 'hotkey':    -
        Consolidate repetitive keypresses with count    - Specify expected
        text outcome for typing actionsFinally, output the action as
        PyAutoGUI code or the following functions:- {"name":
        "computer.triple_click", "description": "Triple click on the screen",
        "parameters": {"type": "object", "properties": {"x": {"type":
        "number", "description": "The x coordinate of the triple click"}, "y":
        {"type": "number", "description": "The y coordinate of the triple
        click"}}, "required": ["x", "y"]}}- {"name": "computer.terminate",
        "description": "Terminate the current task and report its completion
        status", "parameters": {"type": "object", "properties": {"status":
        {"type": "string", "enum": ["success", "failure"], "description":
        "The status of the task"}}, "required": ["status"]}}"
    },
    {
        "role": "assistant",
        "content": "# Step 1:
        ## Action:Click on the "Destination Columns-A..." document thumbnail
        to open the document.

        # Step 2:
        ## Action:Select the word "Travelers" at the beginning of the second
        paragraph by clicking at the start of the word and dragging to the
        end of it."
    },
    {
        "role": "user",
        "image":
```




```
    ,
},
{
    "role": "assistant",
    "content": "# Step 3:
    ## Action:Press Ctrl+C to copy the selected word "Travelers""
},
{
    "role": "user",
    "image":
```




```
    ,
},
{
    "role": "assistant",
    "content": "# Step 4:
    ## Action:Click on the Google search tab near the top of the browser
    window."
},
{
    "role": "user",
    "image":
```



```
        ,
    },
    {
        "role": "user",
        "content": "# Task Instruction:
        Could you open the document 'Destination Columns-A', find the first
        word of the second paragraph, look up what that word means on
        Wikipedia, and then add that Wikipedia description as a footnote to
        that word in the document?
        Please generate the next move according to the screenshot, task
        instruction and previous steps (if provided)."
    },
    {
        "role": "assistant",
```

```
        "content": "# Step 5:
        ## Observation:I'm looking at a Google search page where "gpt" has
        been entered in the search box. The interface shows Google search
        results for "gpt" with various tabs available at the top (All, Images,
        Videos, Shopping, News, More). The search results show information
        about GPT and related technologies. Multiple search results are
        visible, including:- Information about GPT-4- ChatGPT (from
        https://chatgpt.com)- Multiple websites with GPT-related content The
        browser has multiple tabs open at the top, including a tab for
        "Destination Columns-A" document, which appears to be a Google Docs
        document that was previously being worked on. There's also a search
        bar at the top with the query "gpt" entered.Below the search results
        are some related questions in a FAQ section, such as "What does the
        GPT stand for?" and "Is ChatGPT free?" among others.The Google search
        interface includes various filters and options to refine the search,
        including some buttons like "Gpt-4 " (GPT-4 relevance) and several
        other filter options.
        ## Thought:After clicking on the Google search tab, I can now see
        that the browser has successfully switched to a Google search page.
        This is a step forward in my task, as I need to search for the word
        "Travelers" on Wikipedia to complete the footnote insertion.Currently,
        I see that the search box contains "gpt" rather than the word
        "Travelers" that I copied from the document. To proceed with my task,
        I need to:1. Clear the current search term "gpt" from the search box2.
        Enter "Travelers Wikipedia" or navigate directly to Wikipedia and
        search there3. Find relevant information about "Travelers" on
        Wikipedia4. Return to the Google Docs document and insert this
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        and selected the first word of the second paragraph ("Travelers") v3.
        I've copied this word to the clipboard v4. I've switched to a browser
        tab for searching v5. Now I need to clear the current search and look
        up "Travelers" on Wikipedia6. Then I need to insert the Wikipedia
        description as a footnoteLooking at the current state, I need to
        click directly on the search box where "gpt" is currently displayed.
        By clicking on the search box, I'll be able to select all the text,
        delete it, and replace it with "Travelers Wikipedia" to search for
        information about Travelers on Wikipedia. This is the most efficient
        next action as it allows me to directly modify the search query
        without any additional steps.After clicking on the search box, I
        expect the text cursor to be positioned within the box, allowing me
        to edit the current search term. I can then clear "gpt" and type
        "Travelers Wikipedia" to continue with my search. This will help me
        find the Wikipedia page for "Travelers" so I can obtain the
        description needed for the footnote.
        ## Action:Click on the Google search box where "gpt" is currently
        displayed to prepare to enter a new search query.
        ## Code:'''pythonpyautogui.click(x=0.157, y=0.1229)'''"
    }
```