Navigating the Digital World as Humans Do: UNIVERSAL VISUAL GROUNDING FOR GUI AGENTS

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ABSTRACT

Multimodal large language models (MLLMs) are transforming the capabilities of graphical user interface (GUI) agents, facilitating their transition from controlled simulations to complex, real-world applications across various platforms. However, the effectiveness of these agents hinges on the robustness of their grounding capability. Current GUI agents predominantly utilize text-based representations such as HTML or accessibility trees, which, despite their utility, often introduce noise, incompleteness, and increased computational overhead. In this paper, we advocate a human-like embodiment for GUI agents that perceive the environment entirely visually and directly take pixel-level operations on the GUI. The key is visual grounding models that can accurately map diverse referring expressions of GUI elements to their coordinates on the GUI across different platforms. We show that a simple recipe, which includes web-based synthetic data and slight adaptation of the LLaVA architecture, is surprisingly effective for training such visual grounding models. We collect the largest dataset for GUI visual grounding so far, containing 19M GUI elements and their referring expressions over 1.3M screenshots, and use it to train UGround, a strong universal visual grounding model for GUI agents. Empirical results on six benchmarks spanning three categories (grounding, offline agent, and online agent) show that 1) UGround substantially outperforms existing visual grounding models for GUI agents, by up to 20% absolute, and 2) agents with UGround outperform state-of-the-art agents, despite the fact that existing agents use additional text-based input while ours only uses visual perception. These results provide strong support for the feasibility and promises of GUI agents that navigate the digital world as humans do.

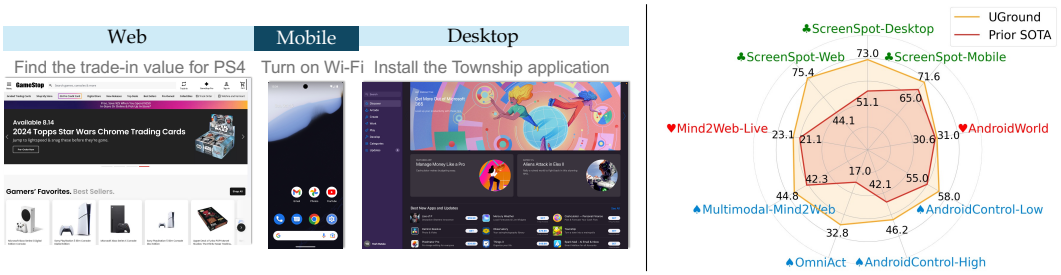

Figure 1: Examples of agent tasks across platforms and performance on **GUI grounding** (♣: ScreenSpot), **offline agent** (♠: Multimodal-Mind2Web, AndroidControl, and OmniAct), and **online agent benchmarks** (♥: Mind2Web-Live and AndroidWorld) when using GPT-4 as the planner.

1 INTRODUCTION

GUI (graphical user interface) agents, which are autonomous agents acting in the digital world via operating on GUIs, have been rapidly co-evolving with large language models (LLMs). On the one hand, the general multimedia understanding and generation capability of (multimodal) LLMs empower GUI agents to generalize beyond simple simulated settings (Shi et al., 2017; Humphreys et al., 2022) to diverse and complex real-world environments, including the web (Deng et al., 2023;

Zhou et al., 2024; Yao et al., 2022), desktop (Xie et al., 2024; Wu et al., 2024) and mobile operating systems (Rawles et al., 2023; Yan et al., 2023; Rawles et al., 2024). On the other hand, GUI agents have become an important testbed for LLMs, providing both the necessary breadth and depth for driving continued development as well as a pathway to many commercially viable automation applications.

Most humans perceive the digital world visually and act via keyboards, mice, or touchscreens. In principle, the embodiment of a GUI agent should already be *complete* if it can 1) visually perceive the GUI renderings, and 2) have effectors equivalent to a keyboard for typing and equivalent to a mouse or touchscreen for pixel-level operations like clicking and hovering.[1] However, current GUI agents assume more than that. For perception, most current agents rely on reading the underlying text-based representations such as HTML or accessibility (a11y) trees (Deng et al., 2023; Gur et al., 2024; Zhou et al., 2024).[2] Only with the recent advances in multimodal LLMs (MLLMs) does visual perception become broadly viable, but text-based representations are still used jointly (Zheng et al., 2024; Koh et al., 2024; Zhang et al., 2024a). For effectors, most current agents act via selecting from a list of options, e.g., HTML elements (Deng et al., 2023; Zheng et al., 2024) or labeled bounding boxes (He et al., 2024; Zhang et al., 2024a), instead of pixel-level operations directly on the GUI. Obtaining those options in turn often requires access to text-based representations and/or separate models for detecting objects and text (Wang et al., 2024a; Kapoor et al., 2024).

However, there is no free lunch, and those additional requirements come with their limitations. On the one hand, *text-based representations are noisy and incomplete*. Full HTMLs contain a considerable amount of irrelevant information. A11y trees are more compact and mainly contain semantic information, but similar to other semantic annotations that rely on voluntary participation, they widely suffer from incomplete and incorrect annotations.[3] In contrast, visual renderings, by design, are information-complete and only contain information relevant to users. On the other hand, *the additional input increases latency and inference costs*. Zheng et al. (2024) found that HTML can consume up to 10 times more tokens to encode than the corresponding visual. Meanwhile, obtaining the a11y tree can be time-consuming in itself, especially in desktop or mobile environments. The added latency and cost at every step are further compounded in the long-horizon agent tasks, compromising user experience and practicality.

In this work, we are interested in *how far GUI agents with a human-like embodiment, i.e., only visual observation of environments and pixel-level operations, can go*. There have been a few attempts (Shaw et al., 2023; Hong et al., 2024; Cheng et al., 2024), but they are rarely adopted in state-of-the-art solutions. We find that a major bottleneck is *grounding*, i.e., mapping textual plans generated by an (M)LLM to the precise locations on the GUI. There are three desiderata for a GUI agent grounding model: 1) *High accuracy*. A single grounding error can get an agent stuck and fail the whole task. 2) *Strong generalization*. It should work on different GUIs: desktop (Windows, Linux, macOS), mobile (Android, iOS), different websites, etc. 3) *Flexibility*. It should plug and play in different MLLMs instead of being tightly coupled with a certain model. Existing visual grounding methods for GUI agents (Shaw et al., 2023; Hong et al., 2024; Cheng et al., 2024) fail to meet these desiderata, hindering the advances towards GUI agents with human-like embodiment.

The main contributions of this work are three-fold:

1. We make careful arguments and a strong case for GUI agents with human-like embodiment that perceive the digital world entirely visually and take pixel-level operations on GUIs, and propose a generic framework, **SeeAct-V**, for building such agents by adapting from the popular SeeAct framework (Zheng et al., 2024).

2. We show that a simple recipe, which includes web-based synthetic data and slight adaptation of the LLaVA architecture (Liu et al., 2024c), is surprisingly effective for GUI visual grounding. Using this recipe, we construct and release the **largest GUI visual grounding dataset** to date, covering

[1] Except for auditory perception, which is out of scope of this study.

[2] The a11y tree is a compact yet informative representation intended for assistive technologies to facilitate people with disabilities, e.g., visual impairment.

[3] A 2024 survey over the top one million websites found that 95.9% of the home pages had accessibility conformance errors such as missing alternative text for images or missing form input labels, with an average of 56.8 errors per page (WebAIM, 2024).

19M GUI elements and their referring expressions over 1.3M GUI screenshots. We also train and release a universal visual grounding model, **UGround**, on the dataset.

3. We conduct the most comprehensive evaluation for GUI agents to date, covering six benchmarks spanning three categories (Figure 1): **grounding** (desktop, mobile, and web), **offline agent evaluation** (desktop, mobile, and web), and **online agent evaluation** (mobile and web). The results demonstrate: 1) UGround substantially outperforms existing visual grounding models for GUI agents across the board, by up to 20% absolute. 2) SeeAct-V agents with UGround can achieve at least comparable and often much better performance than state-of-the-art agents that use additional text-based input. These results provide strong support for the feasibility and promises of GUI agents that navigate the digital world as humans do.

2 METHOD

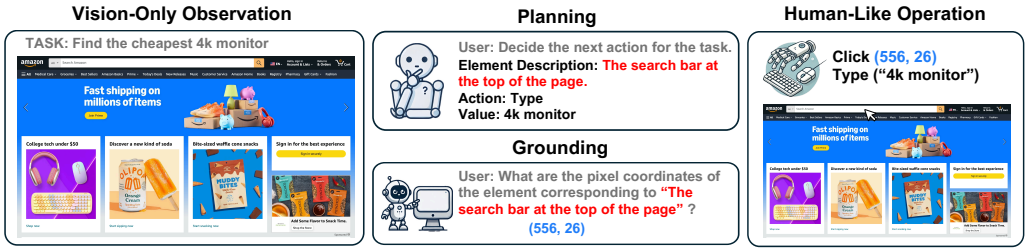

Figure 2: **SeeAct-V**, which uses screenshots as the only environmental observation (task instructions are input as text), without relying on HTML or a11y trees. It includes an MLLM that generates textual plans and a visual grounding model to map textual plans into coordinates on the screenshot. *Note: "Click" is always automatically inserted before "Type".*

2.1 OVERVIEW

We adapt the popular SeeAct framework (Zheng et al., 2024) to one in which agents only take visual observation of the environment and directly conduct pixel-level operations, denoted as *SeeAct-V* (Figure 2). The original SeeAct has two stages, planning and grounding. An MLLM is used for both planning and grounding. At each step, an MLLM first generates a textual plan, and grounding is then done by asking the MLLM to select from a short list of grounding candidates. The grounding candidates are either filtered HTML elements or labels of Set-of-Mark (SoM; Yang et al. (2023)) annotations on the screenshot, both of which require HTMLs or a11y trees as additional input. In contrast, SeeAct-V only uses screenshots for environmental observation. For grounding, SeeAct-V uses a separate model specialized for visual grounding that directly produces the coordinates on the current screen where the agent should act. We provide our philosophy behind the modular design of SeeAct-V in Appendix C.

A strong visual grounding model therefore becomes the key for making SeeAct-V a compelling framework. Ideally, it should generalize across platforms (e.g., web, desktop, and mobile) and handle diverse ways of referring to GUI elements. Considering the rapid evolution of MLLMs, this grounding model should be easily pluggable into different MLLMs to help ground their plans into different GUI environments. Finally, GUI screenshots can vary drastically in resolution and orientation, therefore the grounding model should handle a wide range of input resolutions. *The main technical contribution of this work is a surprisingly simple recipe (incl. data and modeling) for training such universal visual grounding models.* We introduce our simple data synthesis strategy in §2.2, followed by modeling considerations in §2.3. With this simple recipe, we construct the largest training data for GUI grounding to date and train *UGround*, a strong universal visual grounding model for GUI agents.

2.2 DATA CONSTRUCTION

We synthesize a large, high-quality, and diverse set of ⟨*screenshot*, *referring expression*, *coordinates*⟩ triplets as training data for visual grounding, where we use the center point coordinates of an element as the expected output. Our data synthesis will be based on webpages. Webpages are ideal for grounding data synthesis because their *dual* representation—we can easily get the full HTML, the visual rendering, and fine-grained correspondences between the two (e.g., HTML elements to precise bounding boxes). HTML elements also contain rich metadata such as CSS or accessibility attributes, opening numerous opportunities for synthesizing diverse referring expressions (REs). Finally, since GUI designs share many similarities across platforms, we hypothesize that visual grounding models trained only on web data may still generalize to other platforms like desktop and mobile UIs.

Common RE Types for GUIs. People use diverse ways to refer to GUI elements (Figure 3). Previous visual grounding works (Hong et al., 2024; Cheng et al., 2024) have not sufficiently considered this dimension of diversity. We categorize common REs for GUI elements into three types: 1) **Visual REs**, i.e., salient visual features like text or image content, element types (e.g., buttons or input fields), shapes, colors, etc. 2) **Positional REs**, including both absolute (e.g., "*at the top left of the page*") and relative positions (e.g., "*to the right of element X*") to other elements. Besides straightforward positional information, *contextual references* (e.g., "*for Item A*," "*under the section X*") are more challenging for grounding because they require understanding both positional relationships and semantic relationships between elements (e.g., a like button is associated with a product). 3) **Functional REs**, i.e., referring to elements by their main functions (e.g., "*Navigate to Home*," "*Go to My Cart*"). Composite types that combine two or more of these types are also common, especially when stronger disambiguation is needed, e.g., "*click the heart button under the Pokémon shirt to add to favorite*."

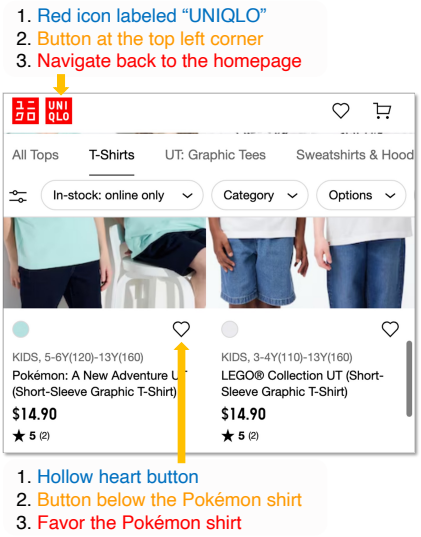

Figure 3: Examples of visual, positional, and functional REs.

Hybrid RE Synthesis from Web. We propose a novel hybrid synthesis pipeline, orchestrating both carefully curated rules as well as LLMs to generate diverse REs for HTML elements: 1) **Primary Descriptors:** We extract abundant visual and functional information that are embedded in the attributes of HTML elements. For example, HTML attributes like `inner-text` and `alt` provide visual clues (including text content), while accessibility attributes like `aria-label` reveal more functional aspects of an HTML element. However, HTML attributes are often incomplete. To harvest visual and functional signals beyond HTML attributes, we use an open MLLM, LLaVA-NeXT-13B (Liu et al., 2024b). We input the visual rendering of an HTML element along with its available attributes to the MLLM and prompt it to generate diverse REs. This process often yields composite REs that combine some HTML attributes with visual features (e.g., "*hollow heart*") or new knowledge from the MLLM (e.g., a blue bird icon represents Twitter). Similar to Lai et al. (2023), we also employ an LLM (Llama-3-8B-Instruct; AI@Meta (2024)) to make these generated REs more concise. We randomly select one of the following as the *primary descriptor* of an element: a visual HTML attribute, a functional HTML attribute, or the synthesized description by LLMs. 2) **Positional Expressions:** We curate rules to generate positional REs according to the absolute position of an element in the screenshot as well as its spatial relationship to neighboring elements (e.g., "*at the top of the page*," "*between element A and B*"). We also create multiple rules to generate contextual references. For example, we identify elements of certain types in the screenshot (e.g., radio buttons, checkboxes, input fields), and generate REs for them based on their spatial and structural relationship (e.g., hierarchical structure of the DOM tree) to others (e.g., "*the input field labeled Birthday*").

We collect screenshots (mix of portrait and landscape views in various resolutions) and metadata of web elements (salient HTML attributes, bounding box coordinates) from Common Crawl,[4] and then

[4]https://commoncrawl.org/

Table 1: Overview of training datasets used for UGround.

Dataset	Annotation	# of Elements	# of Screenshots	Platform
Web-Hybrid (Ours)	Rule + LLM	18M	773K	Web
Web-Direct (Ours)	GPT	408K	408K	Web
GUIAct (Chen et al., 2024)	GPT + Human	140K	13K	Web
AndroidControl (Li et al., 2024b)	Human	47K	47K	Android
Widget Caption (Li et al., 2020b)	Human	41K	15K	Android
UIBert (Bai et al., 2021)	Human	16K	5K	Android
AITZ (Zhang et al., 2024c)	GPT + Human	8K	8K	Android
Total		19M	1.3M	Web + Android

apply our data synthesis pipeline to get our main training dataset (**Web-Hybrid**). We leave more details to Appendix F.1.

Supplementary Data. There have been multiple prior efforts on constructing grounding data for Android, so we incorporate the existing datasets as well. We also use GPT-4o to directly synthesize a small set of REs for web elements, with a focus on more open-ended REs (no constraints on the type) and functional REs (**Web-Direct**). These additions help provide more diverse REs and cover elements in Android, especially those not commonly found on the web (e.g., toggle buttons).

In total, we compile a dataset totaling 19M UI elements, with the majority (95%) from our hybrid synthesis pipeline (Table 1). Elements on the same screenshot are batched to accelerate training.

2.3 Model Design

We adopt a widely used open-source model architecture, 7B LLaVA-NeXT (Liu et al., 2024b), as our backbone model for visual grounding. We make a few adaptations to tailor it for GUI grounding.

Input-Output Formulation. We always instruct the model to answer "*In the screenshot, what are the pixel element coordinates corresponding to* {*Description*}*?*" Following recent work in visual grounding (Cheng et al., 2024), we represent the answer in natural language so we can directly use autoregressive decoding. Specifically, we opt for coordinates in the numerical form (e.g., "*(1344, 1344)*") to precisely point to an element without any normalization.

Image Resolution. GUI screenshots are much larger than typical natural images, often requiring a resolution above 1,000px for legibility. LLaVA (Liu et al., 2024c;a) was initially built for 336px images, and was later scaled up to at most 772px via the `AnyRes` technique (Cheng et al., 2023; Gao et al., 2024; Liu et al., 2024b; Xu et al., 2024; Dong et al., 2024). It resizes and splits a large image into small slices, encodes each slice independently with the vision encoder, and adds a special token at the end of each row to help the language model keep track of the image shape. `AnyRes` allows easy scaling up of input resolution. However, it is always a trade-off between the diversity of supported resolutions and the speed of training and inference. To strike a balance and avoid meaningless excessive resolutions, we enlarge the allowed input sizes to 36 ViT (Dosovitskiy et al., 2021) slices, and use CLIP@224px (Radford et al., 2021) as the image encoder for more flexible splitting, pushing the maximum supported resolution to $1{,}344 \times 1{,}344$ (landscape) and $896 \times 2{,}016$ (portrait). Additionally, we use Vicuna-1.5-7b-16k (Zheng et al., 2023) with 16K context length to handle long visual contexts. Finally, there is a low-resolution image fusion module commonly used in `AnyRes`. However, we find it ineffective for GUI grounding, as 224px is too small to provide informative global context, so we leave it out from our model. More details are in Appendix G.

3 Experiments

Most existing studies on GUI agents typically evaluate on one or two benchmarks. In contrast, we conduct a much more comprehensive evaluation on GUI agents to show the universality of our method. Our evaluation employs six benchmarks that span all three major platforms (i.e., web, desktop, and mobile) and cover three settings: *visual grounding* (§3.1), *offline agent evaluation* on cached environment states (§3.2), and *online agent evaluation* in live environments (§3.3). The visual grounding setting focuses on the grounding performance of UGround, while the agent settings test the end-to-end effectiveness of the SeeAct-V framework with UGround integrated. On the agent

Table 2: Grounding accuracy on ScreenSpot (Standard Setting). Results for GPT-4, CogAgent, and SeeClick are from Cheng et al. (2024).

Grounding Model	Mobile		Desktop		Web		Average
	Text	Icon/Widget	Text	Icon/Widget	Text	Icon/Widget	
GPT-4	22.6	24.5	20.2	11.8	9.2	8.8	16.2
GPT-4o	20.2	24.9	21.1	23.6	12.2	7.8	18.3
CogAgent (Hong et al., 2024)	67.0	24.0	74.2	20.0	70.4	28.6	47.4
SeeClick (Cheng et al., 2024)	78.0	52.0	72.2	30.0	55.7	32.5	53.4
UGround (Ours)	**82.8**	**60.3**	**82.5**	**63.6**	**80.4**	**70.4**	**73.3**

Table 3: Grounding accuracy on ScreenSpot (Agent Setting) with planner-generated REs.

Planner	Grounding	Mobile		Desktop		Web		Avg.
		Text	Icon/Widget	Text	Icon/Widget	Text	Icon/Widget	
GPT-4	SeeClick	76.6	55.5	68.0	28.6	40.9	23.3	48.8
	UGround	90.1	70.3	87.1	55.7	85.7	64.6	75.6
GPT-4o	SeeClick	81.0	59.8	69.6	33.6	43.9	26.2	52.3
	UGround	**93.4**	**76.9**	**92.8**	**67.9**	**88.7**	**68.9**	**81.4**

benchmarks, we compare the vision-only SeeAct-V framework with prior SOTA methods that usually require additional text-based representations (HTML or a11y tree) as input. Within SeeAct-V, we also compare UGround with existing visual grounding models whenever possible.

3.1 GUI Visual Grounding

We first evaluate UGround on the ScreenSpot benchmark (Cheng et al., 2024), which is specifically designed for visual grounding on GUIs. The benchmark consists of 1,272 single-step instructions and the corresponding bounding box of the target elements across mobile (e.g., iOS and Android), desktop (e.g., macOS and Windows), and web environments. These elements vary between text-based elements, icons (e.g., the trash can icon) and widgets (e.g., to-do lists), representing diverse GUI element types.

We evaluate under two settings: 1) **Standard Setting**. In the standard setting of ScreenSpot, the instructions are written by human annotators with a primary focus on *functional description* of the target elements, e.g., simply "*close*" to refer to the 'X' button that closes a window or "*set an alarm for 7:40*" when the input image shows the iPhone clock app with a list of inactive alarms. 2) **Agent Setting**. For GUI agents, a grounding model needs to work with a planning model (e.g., an MLLM) and ground the REs it generates, which includes not only functional REs but also visual and positional REs (see §2.2). To provide a more comprehensive evaluation on visual grounding for GUI agents, we input each ScreenSpot example to an MLLM, which acts as a planning model, and asks it to generate diverse REs for the target element. This setting is therefore more representative of the grounding challenges in GUI agents. We mainly compare UGround with SeeClick (Cheng et al., 2024), the state-of-the-art visual grounding model on ScreenSpot, and another visual grounding model CogAgent (Hong et al., 2024). To show the challenge of visual grounding for general-purpose models, we also compare with GPT-4 and GPT-4o.

Results. As shown in Table 2 and Table 3, UGround outperforms all existing models across all the settings and platforms by a substantial margin, about an absolute improvement of **20%** on average under the standard setting and **29%** under the agent setting. Interestingly, UGround performs remarkably well on desktop UIs, despite the fact that it is never trained on desktop screenshots (Table 1). Compared with existing models, UGround performs especially well on icons and widgets, which are generally more challenging for grounding because that requires deeper understanding of the contextual (e.g., positional) and semantic (e.g., functional) information. Overall, the strong results on ScreenSpot clearly demonstrates UGround's universal grounding capability across platforms and planners as well as the remarkable effectiveness of our simple data synthesis and modeling recipe.

Table 4: Element accuracy on Multimodal-Mind2Web. Results by Choice and SoM are from Zheng et al. (2024). The SoM results are on subsets of 30 tasks for each split.

Input	Planner	Grounding	Cross-Task	Cross-Website	Cross-Domain	Avg.
Image + Text	GPT-4	Choice	46.4	38.0	42.4	42.3
		SoM	29.6	20.1	27.0	25.6
Image (SeeAct-V)	GPT-4	SeeClick	29.7	28.5	30.7	29.6
		UGround	45.1	44.7	44.6	44.8
	GPT-4o	SeeClick	32.1	33.1	33.5	32.9
		UGround	**47.7**	**46.0**	**46.6**	**46.8**

3.2 Offline Agent Evaluation

We discuss the experimental setup for three offline agent evaluation benchmarks followed by result discussion. Concrete examples from each benchmark are given in Appendix E.

Web: Multimodal-Mind2Web. We use Multimodal-Mind2Web (Zheng et al., 2024), the multimodal extension of Mind2Web (Deng et al., 2023), for our evaluation on realistic web tasks. The test split consists of 1,013 tasks spanning over 100 different websites. Each task contains a high-level task instruction and a sequence of actions, with a screenshot of the webpage before each action, as the golden trajectory. All the webpages along the golden trajectory are cached to support offline evaluation. The tasks are crowdsourced with a focus on ensuring real-world meaningfulness (i.e., what real users would need on those websites).

Zheng et al. (2024) have clearly demonstrated the necessity of visual perception for web agents, so we mainly compare with zero-shot methods that use MLLMs as planners and omit text-only LLMs. Zheng et al. (2024) have also identified grounding as the main challenge and proposed several grounding strategies, including 1) **Choice**, where the planner is asked to choose from a short list of filtered HTML elements, and 2) **SoM**, where the input screenshot is superposed with set-of-mark (Yang et al., 2023) labels and the planner is asked to select from the labels. Both strategies require additional text-based representations (i.e., HTML) to obtain the candidates and/or locate the elements in the screenshot to label. We report *element accuracy*, i.e., accuracy of selecting the correct element, and omit operation scores because they are orthogonal to grounding comparisons.

Mobile: AndroidControl. We use AndroidControl (Li et al., 2024b), a large-scale Android dataset comprising 15K unique tasks over 833 Apps. Screenshots, action sequences, and a11y trees are cached from human demonstrations as golden trajectories for training and evaluation purposes. Each action is also labeled by a corresponding low-level instruction (e.g., "*set the hours to 6*"). Following Li et al. (2024b), we use 500 random steps from the test set. We compare with the SOTA zero-shot method, the text-only version of M3A (Rawles et al., 2024), which instructs GPT-4 to generate textual actions as well as select elements from the a11y tree (**Choice**). We adopt the two task settings in Li et al. (2024b): high-level tasks, where only the high-level intent is provided, and low-level tasks, where both the high-level intent and the corresponding low-level instruction for each step are available. We use the standard metric, *step-wise accuracy*, where a step is considered successful only if all the predicted actions, elements, and arguments (if applicable) are correct.

Desktop: OmniACT. We use OmniACT (Kapoor et al., 2024) to evaluate the accuracy of UGround on desktop tasks. The dataset consists of 9,802 tasks covering 38 desktop applications and 27 websites across different desktop platforms (macOS, Windows, and Linux). Each task requires the generation of a PyAutoGUI script, which is a sequence of actions to complete the task on a single screenshot. The SOTA method, DetACT (Kapoor et al., 2024), extracts UI elements and their coordinates through a combination of OCR (optical character recognition), icon matching, and color detection modules. These elements are filtered by task relevance and then passed to LLMs or MLLMs to generate the PyAutoGUI script with the appropriate coordinates for interaction.

For SeeAct-V, we replace the input of the DetACT pipeline with only screenshots and instruct MLLMs to generate element descriptions rather than directly generate coordinates. We then employ UGround to obtain the coordinates of the elements, which are subsequently integrated into the PyAutoGUI scripts. To ensure a fair comparison, we strictly follow the approach in Kapoor et al. (2024), including the same prompt and retrieval strategy that selects five in-context examples from the training set based on task similarity. We report the *action score*, which measures the accuracy of the action sequences while penalizing errors in generated arguments.

Table 5: Step accuracy on AndroidControl over 500 random actions from the test split. Baseline results are from Li et al. (2024b).

Input	Planner	Grounding	Step Accuracy	
			High	Low
Text	GPT-4	Choice	42.1	55.0
Image (SeeAct-V)	GPT-4	SeeClick	39.4	47.2
		UGround	46.2	58.0
	GPT-4o	SeeClick	41.8	52.8
		UGround	**48.4**	**62.4**

Table 6: Action scores (AS) on OmniACT. Baseline reults are from Kapoor et al. (2024).

Inputs	Planner	Grounding	AS
Text	GPT-4	DetACT	11.6
Image + Text		DetACT	17.0
Image (SeeAct-V)	GPT-4	SeeClick	28.9
		UGround	31.1
	GPT-4o	SeeClick	29.6
		UGround	**32.8**

Table 7: Completion rate (CR) and task success rate (SR) on Mind2Web-Live. Baseline results are from Pan et al. (2024).

Inputs	Planner	Grounding	CR	SR
Text	GPT-4	Choice	44.3	21.1
	GPT-4o		47.6	22.1
Image (SeeAct-V)	GPT-4	UGround	50.7	**23.1**
	GPT-4o		**50.8**	19.2

Table 8: Task success rate (SR) on Android-World. Baseline results are from Rawles et al. (2024)

Input	Planner	Grounding	SR
Text	GPT-4	Choice	30.6
Image + Text		SoM	25.4
Image (SeeAct-V)	GPT-4	UGround	31.0
	GPT-4o		**32.8**

Results. As shown in Table 4, Table 5, and Table 6, SeeAct-V with UGround outperforms all the baselines across the board, despite only using raw screenshots as input while baselines use additional input. UGround also consistently outperforms a strong GUI grounding model, SeeClick. These results provide solid support for human-like vision-only embodiment for GUI agents, a position this work aims to make a case for. The results also further validate UGround's efficacy as a universal grounding model for GUI agents.

3.3 Online Agent Evaluation

We further evaluate our approach in an end-to-end manner on two online agent benchmarks that closely resemble the offline web and Android benchmarks in §3.2, but involve interactions with live websites and mobile applications. Due to the high cost of online evaluation, we only use UGround for grounding.

Web: Mind2Web-Live. We use the test set from Mind2Web-Live (Pan et al., 2024). The benchmark is built on Mind2Web (Deng et al., 2023) by adding functional evaluation to the tasks that makes automated evaluation possible on live websites. Specifically, it defines and annotates *key nodes* for each task, which are critical steps that must be completed for a task to be considered successful, regardless of which trajectory an agent takes. The baseline agent from Pan et al. (2024) is text-only, perceives and interacts with webpages by hundreds of HTML elements at a time. For SeeAct-V, we change the observation to be screenshots only, and make necessary changes to the original action space to fully eliminate the dependency on HTML during planning, grounding, and execution (details in Appendix H.5). We use standard metrics: *micro completion rate*, which measures the proportion of completed key nodes across all the tasks, and *task success rate*, which measures the proportion of fully completed tasks.

Mobile: AndroidWorld. We use AndroidWorld (Rawles et al., 2024), an online mobile agent benchmark running in Android emulators. It includes 116 tasks across 20 Apps, with evaluation based on the final states of the device. We compare with the SOTA agent M3A and its text-only variant from Rawles et al. (2024). They receives both raw and SoM images, together with textual UI elements, or only the textual UI elements as the observation respectively. Both variants employ a ReAct-style reasoning process (Yao et al., 2023) to select the next target element from a list of UI elements. Additionally, they integrate self-reflection (Shinn et al., 2024) for the agent to summarize its current action and improve decision-making in subsequent steps. We report *task success rate*, which measure the percentage of fully completed tasks.

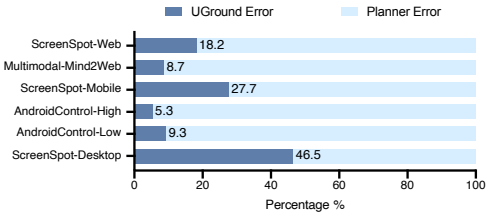

Figure 4: Error distribution from manual analysis.

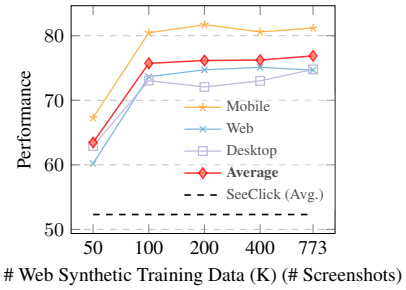

Figure 5: Scaling curve of UGround on ScreenSpot w.r.t. Web-Hybrid data size.

Results. SeeAct-V with UGround gets comparable or higher performance in online agent evaluation, as shown in Table 7 and Table 8. Particularly, it achieves a much higher success rate compared with the SoM variant of M3A, even though Android environments have less dense UI layouts and are generally more suitable for SoM (i.e., less obstruction by the SoM labels). These results again provide solid support for the feasibility and promises of human-like vision-only embodiment for GUI agents and the effectiveness of UGround.

3.4 Error Analysis

We conduct a manual error analysis of the best performing method, SeeAct-V with UGround, to understand the bottleneck for further improvement. We randomly sample 60 failure cases from each split of ScreenSpot (agent setting with GPT-4o), AndroidControl, and Multimodal-Mind2Web. Except for data annotation errors, errors from the models can be categorized into *planning errors*, i.e., generating plans with incorrect element descriptions, and *grounding errors*, i.e., predicting incorrect coordinates for a correct element description from the planner.

As shown in Figure 4, planning errors are the dominant cause of failures across all benchmarks, further confirming the strong grounding capability of UGround. The most frequent error is that the planner generates (otherwise correct) description of an incorrect element on the screen, indicating a lack of correct understanding of either the task and/or the elements. Other common planning errors include hallucinating non-existent elements or producing overly generic descriptions that are too vague to uniquely locate the target element, even for human evaluators.

On the other hand, on ScreenSpot-Mobile and ScreenSpot-Desktop, a considerable portion of the failures do stem from grounding errors. Both desktop and mobile UIs feature a pervasive use of icons with idiosyncratic meaning. For example, a stylized dollar sign represents the Zelle App, or an icon with two cartoon people represents one's contact list in Miscorosft Outlook. We find that pretrained MLLMs and our web-centric grounding training are effective in capturing the semantics of popular icons (e.g., icons representing Google) or commonsense meaning (e.g., clock icons usually represent time-related functions like alarms). However, it is challenging to capture the idiosyncratic semantics of icons in the long tail, which arguably requires either additional documentation or more targeted exploration to learn. This is a major cause of the grounding errors. Interestingly, when tested on more realistic agent tasks, e.g., in AndroidControl, AndroidWorld, and OmniACT, UGround still proves to be relatively robust. This is because most of the agent tasks concern things in the head of the distribution; things in the long tail are naturally rare (though still important). This explains the strong performance of UGround on mobile and desktop agent benchmarks. Nonetheless, how to capture idiosyncratic semantics in the long tail is still an open challenge for grounding.

3.5 Training Data Analysis: Scaling and Ablations

We conduct scaling analysis and ablation studies on our training data to better understand the contribution of different data for UGround's strong performance, and use the agent setting of ScreenSpot for the evaluation (with GPT-4o as the planner). Further ablations around data, model design, and RE types are provided in Appendix D.

Table 9: Training data ablations for UGround on ScreenSpot (Agent Setting).

Training Data	Mobile		Desktop		Web		Average
	Text	Icon/Widget	Text	Icon/Widget	Text	Icon/Widget	
Web-Hybrid	89.0	**73.4**	**88.1**	**61.4**	84.8	**64.6**	**76.9**
Others	**92.3**	71.2	84.5	46.4	**87.0**	59.2	73.4
All	93.4	76.9	92.8	67.9	88.7	68.9	81.4

Scaling Curve on Web-Hybrid. We investigate the scaling of our primary synthetic dataset, Web-Hybrid, which consists of 18M data instances over 773K web screenshots in total. The scaling results in Figure 5 show that the average performance consistently improves as the data scales up, though the return starts diminishing after 100K screenshots. Notably, with just 50K screenshots (about 1M elements) as training data, UGround surpasses SeeClick by more than 10%, which is trained on about 3M web and Android elements from about 400K screenshots. The results clearly show the high data quality and the effectiveness for grounding training of our data synthesis pipeline. Upon manual inspection, we observe that additional data after 100K screenshots primarily enhances understanding of less frequent elements such as radio buttons, checkboxes, or very small text elements. As data increases, the model can point to the center of element bounding boxes more accurately and better handle tiny hyperlinks.

Training Data Ablations. To further investigate the impact of training data sources, we compare the performance of UGround trained on only Web-Hybrid, only the supplementary data, or both (see Table 1). Results in Table 9 further validate the necessity of Web-Hybrid. Training on other data without Web-Hybrid often underperforms training on Web-Hybrid alone. This is most evident on icons and widgets, which require understanding more diverse aspects, such as visual features and functions, than text-based elements. Finally, these two data sources are complementary and their combination yield the best performance across the board.

4 Conclusions and Limitations

We introduce UGround, a universal GUI visual grounding model developed with large-scale web-based synthetic data. UGround shows strong cross-platform generalization and significantly outperforms the prior SOTA model SeeClick on ScreenSpot. We propose a vision-only framework SeeAct-V that allows pixel-level interactions based solely on visual input. Our evaluations on both offline and online benchmarks demonstrate that SeeAct-V agents with UGround can achieve comparable and often better performance than prior SOTA agents that rely on additional textual inputs like HTML or a11y trees for observation or grounding.

Nevertheless, there are still some limitations that can be addressed in future work to advance visual grounding in GUI and visually grounded GUI agents. First, UGround is trained on very large-scale synthetic data. Considering the similarity and repetition of elements between web pages, there is room to improve on data efficiency during training, for example by better data grouping and deduplication. On the other hand, despite the cross-platform generalization shown in our experiment results, the issue of long-tail elements remains unaddressed in this work. Mobile UIs and desktop UIs often feature specific icons, where it can be impractical to account for every long-tail element in the training set. Additionally, no desktop UI data is incorporated in the training of this work, which limits the performance on desktop UIs. Given the scarcity of training datasets for desktop UIs, we anticipate the development of more comprehensive datasets in this domain. Lastly, UGround depends on an external planner, and without training on downstream tasks, it cannot function independently as a GUI agent. Nonetheless, we hope that our datasets, model, and framework can contribute to future studies of vision-only agents, as well as contribute to advancing the grounding capabilities of end-to-end models, as strong grounding data has been shown to improve end-to-end models (Cheng et al., 2024; Hong et al., 2024; Chen et al., 2024).

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I Prompts **28**

A Related Work

GUI Agents. LLMs and MLLMs have demonstrated great capabilities and potentials in GUI automation, working as digital agents in various GUI environments (Yan et al., 2023; Kim et al., 2024; Wang et al., 2024a; Zheng et al., 2024; Xie et al., 2024). Despite the growing number of studies focused on building multimodal agents (Koh et al., 2024; Zhou et al., 2024; Cao et al., 2024), most work still relies on HTML or a11y trees for grounding, even when they are not used for observation. In this work, we advance an alternative line of research: pixel-level visually grounded GUI agents (Shaw et al., 2023; Zhan & Zhang, 2023; Hong et al., 2024; Cheng et al., 2024; Niu et al., 2024). Unlike nearly all previous work of this line, we propose a generic two-stage approach that separates planning and visual grounding to build vision-only GUI agents, which perform remarkably well on realistic agent benchmarks with vision-only inputs, and offers the flexibility to the choices of planning and grounding models.

Visual Grounding. Visual grounding has been long studied on natural images (Karpathy et al., 2014; Mao et al., 2016; Yu et al., 2016). More recently, with the advancements of MLLMs, their visual grounding capabilities on natural images have attracted significant attention (Bai et al., 2023; Chen et al., 2023a;b; Peng et al., 2023; Wang et al., 2024b;c; Ma et al., 2024). However, due to significant gaps in image resolution and GUI understanding, these models trained on natural contexts work poorly on GUI visual grounding (Cheng et al., 2024). One of the most popular approaches, SoM (Yang et al., 2023), proposes a visual prompting method that adds marks such as boxes and numbers to images and instructs MLLM to identify the referred objects by the labels. It is widely adopted in GUI scenarios (Yan et al., 2023; He et al., 2024; Koh et al., 2024), but still suffers from problems including reliance on complete object information or object segmentation. Only few studies have been conducted for visual grounding on GUI screenshots. Based on Rico (Deka et al., 2017), Bai et al. (2021) annotates referring expressions by humans; RicoSCA (Li et al., 2020a) generate a larger synthetic referring expression dataset; and Li et al. (2020b) collect human-labeled captions of UI elements. They have been primary resources for GUI grounding for a long time (Li & Li, 2022; Banerjee et al., 2022). Later on, Qian et al. (2024) synthesize referring expressions from Rico by heuristic rules and train a vision language model by a new layout-aware contrastive learning technique. CogAgent (Hong et al., 2024) compiles HTML documents and screenshots from real websites to GUI grounding data for the pretraining stage, and finetunes on open-source and in-house human-labeled data, to build a 18B MLLM with strong pixel-level GUI grounding capabilities. Ferret-UI (You et al., 2024) develop a UI generalist MLLM trained on a series of UI-related tasks including grounding. The most similar effort to ours is SeeClick (Cheng et al., 2024), which enhances Qwen-VL (Bai et al., 2023) by finetuning on GUI grounding data, including simplistic synthetic data compiled from real websites. It still falls shorts of the small image resolution of Qwen-VL, as well as the simplistic nature of the training data. Cheng et al. (2024) also create a new grounding benchmark for GUIs, which benefits our evaluation and analysis.

B Ethical Statement

Our data collection follows the prior works in the field of GUI visual grounding (Hong et al., 2024; Cheng et al., 2024).

The webpages we use are sourced from the Common Crawl dataset[1], which is a publicly available Internet archive designed for research and non-commercial use. We utilize only a small subset of it (773K webpages out of 3.35B) and strictly adhere to Common Crawl's Terms of Use[2] throughout our work.

Our use of the data is strictly for academic research purposes and is fully compliant with Section 107 of the U.S. Copyright Law: *Limitations on exclusive rights: Fair use*.

[1] https://commoncrawl.org/

[2] https://commoncrawl.org/terms-of-use

C PHILOSOPHY BEHIND SEEACT-V AND UGROUND

When it comes to agent designs, the current wisdom, by and large, is to train a monolithic LLM (e.g., CogAgent (Hong et al., 2024), SeeClick (Cheng et al., 2024), many ongoing supervised fine-tuning efforts for enhancing *"agentic behaviors"*). At a philosophical level, part of the goal of SeeAct-V is to challenge that status quo and advocate a modular design for language agents instead.

A fundamental challenge of language agents comes from the complex, dynamic, and often idiosyncratic environments where they operate. Just take web agents as an example. There are over a billion websites out there. Each website could have an infinite number of states and be constantly changing (driven by updates in the backend databases). There is also a considerable amount of highly idiosyncratic semantics in each environment, e.g., uncommon icons, jargon, and counter-intuitive designs.

As a result, although we are still at the early stage of agent research, we hold a strong belief that a monolithic model, no matter how large and strong it will become, is unlikely to capture all the complexity and idiosyncrasy of all the environments. In order to develop a generalist agent that can generalize reliably across environments, we need to adopt a modular system design and synergistically orchestrate a foundation model (e.g., GPT-4o) with multiple specialized modules that serve different functionalities.

Grounding is one of such capabilities for which a specialized module makes a lot of sense. Fundamentally, grounding is about understanding domain-specific semantics and creating a map between that and natural language (that LLMs know about). A dedicated module makes it much easier to capture idiosyncratic semantics and easily adapt to different domains (e.g., imagine fine-tuning the grounding model instead of the foundation model for a domain). The grounding model can then supply domain-specific semantics to the foundation model and lead to a $1 + 1 > 2$ kind of system efficacy. That's a fundamental motivation for the design of SeeAct-V and this whole work.

Our design also offers several practical advantages:

Modularity: It allows us to study and enhance UGround as a standalone grounding model, independent of specific planners.

Flexibility: It supports diverse MLLMs and grounding models, without specific finetuning on downstream benchmarks.

Comparative Consistency: By standardizing the planning stage, we can remove the confounding factor and study the impact of various grounding models and methods on the agent performance.

As demonstrated in our experiments, SeeAct-V with UGround surpasses the performance of end-to-end MLLMs (whether they are using textual or SoM grounding), while training end-to-end models requires a large amount of quality data on agent trajectories (essentially combining planning and grounding) for downstream tasks, which is very challenging to obtain in general.

D FURTHER ABLATION STUDIES

In addition to the studies in §3.5, we provide a series of further ablation studies to extend our ablations on model design and effectiveness of our web-based synthetic data. We report grounding accuracy on ScreenSpot (Agent Setting), with GPT-4o as the planner.

D.1 CONTROLLED COMPARISON TO BASELINE MODELS

In general, both model design and training data are essential for UGround's good performance. To isolate and study the contributions of them independently, we introduce a new model variant, UGround-Qwen, fine-tuned from Qwen-VL-Chat (the same backbone used in SeeClick), using only our web-based synthetic dataset Web-Hybrid (processed into the data format of SeeClick[3]). The results are shown in Table 1.

[3]Given the maximum sequence length used in the training of Qwen-VL and SeeClick, we reduce the elements to a maximum of 30 for each page.

Table 1: Ablations of data and base models for UGround on ScreenSpot (Agent Setting).

Model	Model Design	Continual SFT Data	Mobile		Desktop		Web		Avg
			Text	Icon/Widget	Text	Icon/Widget	Text	Icon/Widget	
Qwen-VL-Chat	Qwen-VL	None	21.3	21.4	18.6	10.7	9.1	5.8	14.5
SeeClick	Qwen-VL	Full SeeClick	**81.0**	**59.8**	69.6	33.6	43.9	26.2	52.3
UGround-Qwen	Qwen-VL	Web-Hybrid	80.2	57.2	**76.3**	**39.3**	**74.4**	**47.1**	**62.4**
UGround	Ours	Web-Hybrid	**89.0**	**73.4**	**88.1**	**61.4**	**84.8**	**64.6**	**76.9**

Table 2: Ablations of image resolution for UGround on ScreenSpot (Agent Setting).

Continual SFT Data	Image Resolution	Mobile		Desktop		Web		Avg.
		Text	Icon/Widget	Text	Icon/Widget	Text	Icon/Widget	
Web-Hybrid	Fixed 448 x 448	**89.4**	65.1	83.5	56.4	77.0	61.7	72.2
	Fixed 896 x 896	86.8	69.0	85.1	**62.9**	81.4	57.8	73.8
	Fixed 1,344 x 1,344	79.9	68.6	86.1	62.1	79.1	63.6	73.2
	Dynamic (Ours)	89.0	**73.4**	**88.1**	61.4	**84.8**	**64.6**	**76.9**

Training Data: With the same backbone (Qwen-VL-Chat), UGround-Qwen trained on Web-Hybrid substantially outperforms SeeClick and the base model, with an average absolute improvement of 10.1% over SeeClick, despite SeeClick leveraging additional open-source mobile data. It further confirms the quality of our web-based synthetic data and the cross-platform generalization.

Model Design: With the same training data (Web-Hybrid), UGround achieves a 14.5% absolute improvement over UGround-Qwen, demonstrating the effectiveness of our model design.

We are not comparing with CogAgent here because of its lower performance compared with SeeClick despite its significantly larger model size (18B parameters) and data size (140M grounding data).

D.2 Model Design

We focus on the model design around image resolution here, mainly examining the following two aspects: 1) larger image resolution (scaled-up large `AnyRes` grid settings) 2) dynamic resolution and aspect ratio (compared to fixed squares).

Scaling of Image Resolution. We scale up image resolution with fixed square sizes for convenience (448 x 448 $\rightarrow$ 896 x 896$\rightarrow$ 1,344 x 1,344).

As shown in Table 2, larger image resolution generally improves the model performance, except for the mobile UIs, where the UIs are less dense. Notably, web and desktop UIs often contain tiny links/icons. Therefore, larger image resolution is more suitable for developing a universal model for GUIs that can handle the challenging cases.

Dynamic Image Resolution and Aspect Ratio. As shown in Table 2, UGround benefits from dynamic image resolution supported by AnyRes, effectively adapting to varied resolutions and aspect ratios (for example, to mobile UIs or desktop UIs). This flexibility leads to improved performance across all platforms. Notably, on Desktop and Web UIs, UGround achieves comparable or better results with fewer tokens compared to the 1,344 x 1,344 fixed-resolution model, requiring only about 2/3 of the tokens in 16:9 scenarios.

Similar findings around these two aspects are also discussed in general domains (Li et al., 2024a; Zhang et al., 2024b), as well as some concurrent GUI works (Chen et al., 2024; Li et al., 2024c).

D.3 RE Types

The taxonomy for REs is an innovation in this work and was not considered in prior work (Li et al., 2020b; Hong et al., 2024; Cheng et al., 2024). Here we conduct an ablation study around positional REs. Visual REs and functional REs are skipped because 1) they are more or less interleaved in HTML DOMs and are hard to entirely separate 2) they have been largely visited by prior works. For example, an HTML attribute (e.g., `aria-label`) can provide both visual and functional cues depending on the element and context; the MLLM can pick up different aspects of the input when generating the RE.

Table 3: RE ablations for UGround on ScreenSpot (Agent Setting).

Training Data	Mobile		Desktop		Web		Average
	Text	Icon/Widget	Text	Icon/Widget	Text	Icon/Widget	
Web-Hybrid (w/o Pos REs)	86.5	73.4	87.1	61.4	82.2	**65.5**	76.0
Web-Hybrid	**89.0**	73.4	**88.1**	61.4	**84.8**	64.6	**76.9**

Table 4: RE ablations for UGround on ScreenSpot (Standard Setting).

Training Data	Mobile		Desktop		Web		Average
	Text	Icon/Widget	Text	Icon/Widget	Text	Icon/Widget	
Web-Hybrid (w/o Pos REs)	72.2	52.0	72.7	**55.0**	76.5	61.2	64.9
Web-Hybrid	**75.5**	**54.2**	**79.9**	**58.6**	**77.0**	**68.0**	**68.8**

We train a new checkpoint with Web-Hybrid, where all of the positional REs are removed (but the total number of web elements remains the same). As shown in Table 3 and Table 4, the model trained with positional REs is generally stronger than the model trained without them.

We hypothesize that, with positional and contextual data, the model is better trained to learn and pay attention to the context of elements. This is generally beneficial for UI understanding, and is crucial for tasks requiring contextual understanding. In other words, training with positional RE somehow prevents models from degenerating to object detectors, which are not enough for grounding diverse referring expressions in GUIs, especially the challenging cases where visual/functional REs are not sufficient enough to help locate.

E EXAMPLES

E.1 MULTIMODAL-MIND2WEB

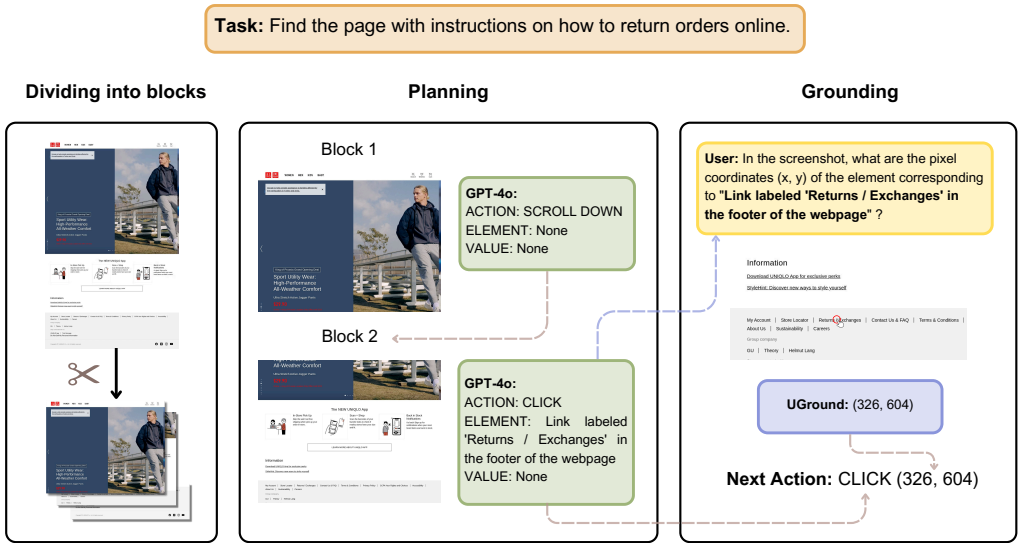

Figure 1: Example of the Mind2Web evaluation pipeline.

E.2 ANDROIDCONTROL

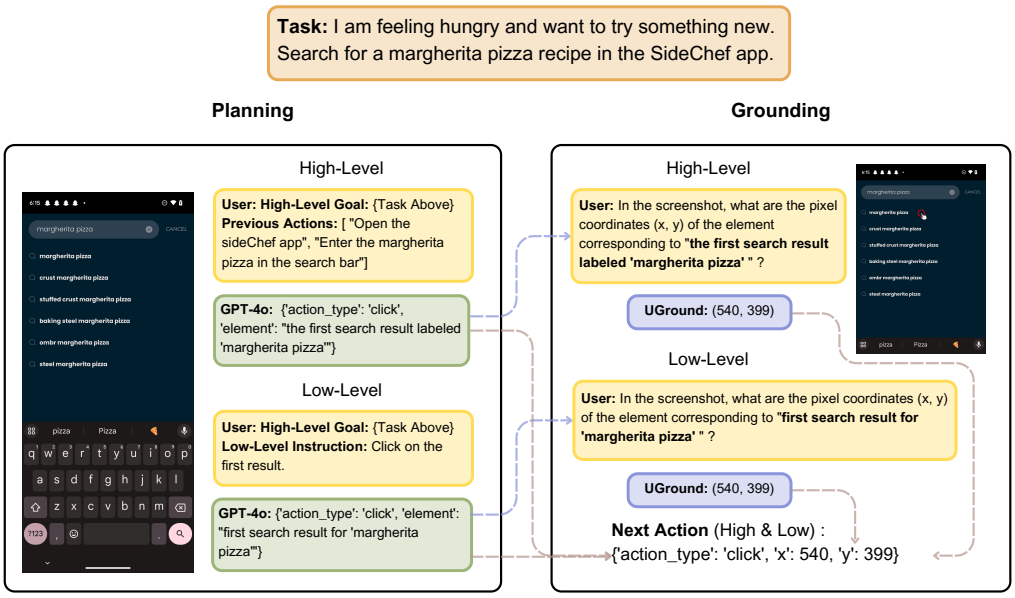

Figure 2: Example of the AndroidControl evaluation pipeline.

E.3 OMNIACT

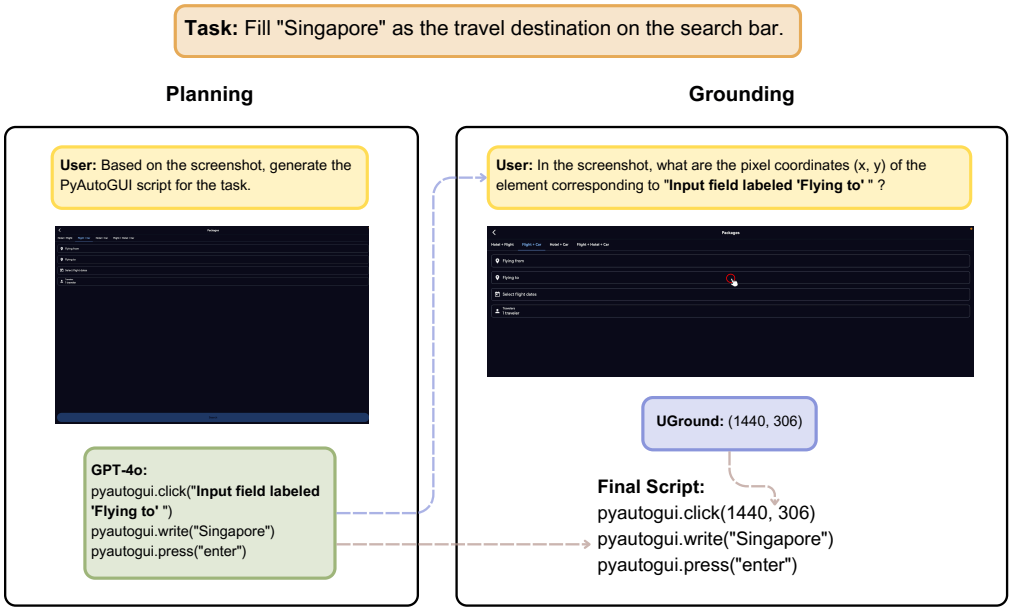

Figure 3: Example of the OmniACT evaluation pipeline.

E.4 TRAINING DATA

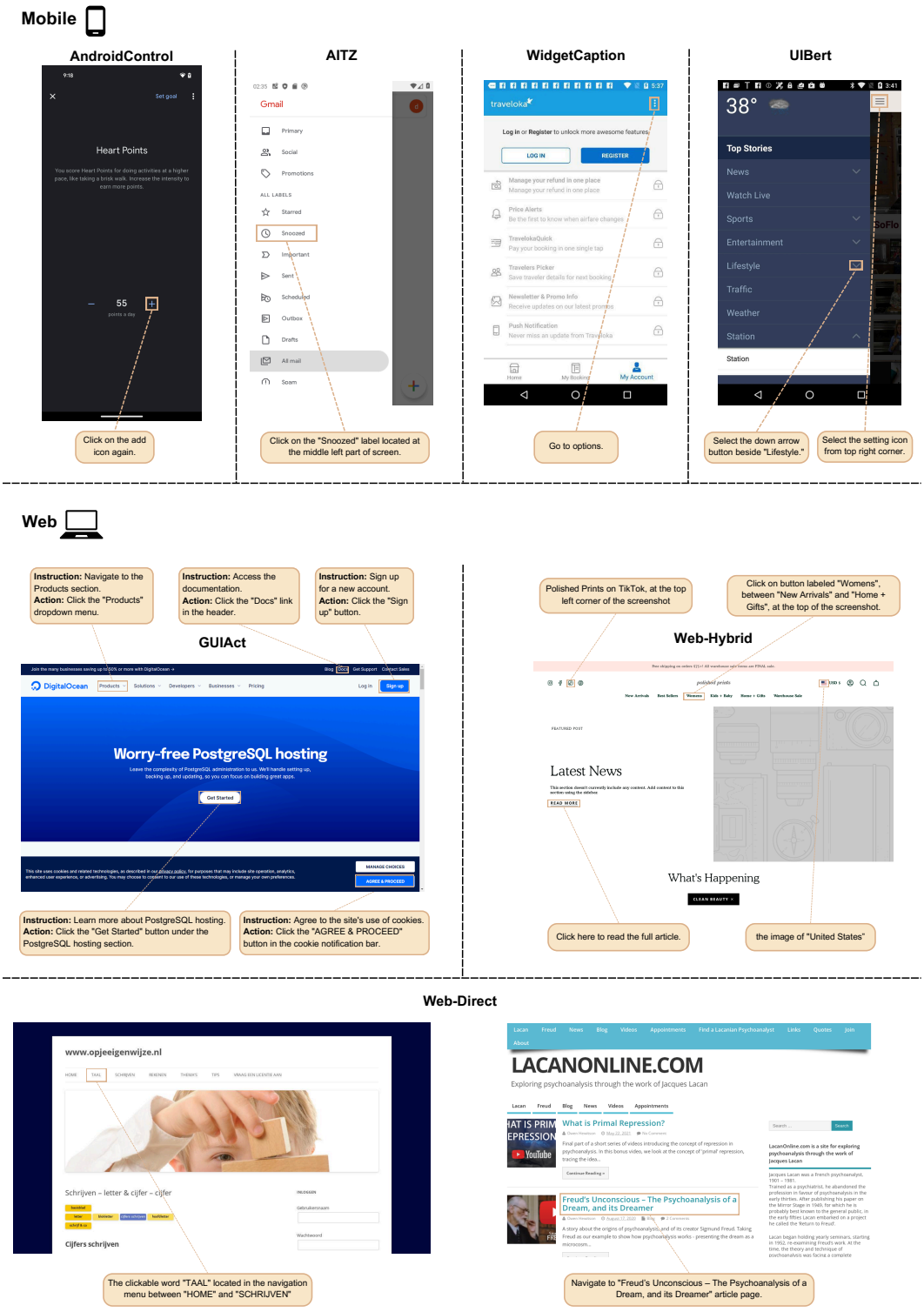

Figure 4: Examples of training data from different sources.

F DATA CONSTRUCTION

We describe the details of our data construction in this section. Illustrative examples of all our training data are given in Figure 4.

F.1 WEB-HYBRID

Following prior work (Hong et al., 2024; Cheng et al., 2024), we download and randomly sample from the latest Common Crawl[4]. We apply a few filtering methods, excluding non-webpage files based on URLs, and removing non-English pages based on labels of language provided by Common Crawl. We use Playwright to load and render the webpages, capturing screenshots and collecting metadata for web elements. We simulate scrolling down to capture screenshots and elements at different heights. The element metadata includes bounding box coordinates and potentially useful HTML attributes, such as the element's tag, text (`inner_text`), and alternative text (e.g., `alt`).

During the rendering process with Playwright, we randomly apply different image sizes to cover a wide range of resolutions and aspect ratios. Specifically, approximately one-third of the data uses mobile-friendly aspect ratios, where the webpages are rendered in mobile web mode. By doing this, some of the websites automatically switch to their mobile versions, which helps improve the coverage of mobile UI environments. For each long webpage, we randomly sample at most 3 blocks of content within a viewport-sized area to ensure diversity in the captured content.

As detailed in §2.2, we employ a hybrid strategy to generate referring expressions (REs) for webpage elements. Below, we firstly describe how we leverage MLLMs (LLaVA-NeXT-13B) and LLMs (Llama-3-8B) to generate concise, element-level descriptions without positional or contextual information.

We extract the bounding box regions from the webpage screenshots corresponding to the elements and pass these smaller cropped element images along with their main HTML attributes into LLaVA. Using the prompts outlined below, we prompt LLaVA to generate an element description based on its internal knowledge, the element's image, and relevant HTML attributes:

> Based on the attached image of a web element, please provide a short description of the web element displayed. The goal is to capture the intuitive and visual appearance of the element. Use the accompanying HTML information as context but focus more on describing what is visually observable. Avoid directly referencing HTML attributes; instead, interpret their possible visual implications if they can be inferred from the image. Be cautious of potential inaccuracies in the HTML attributes and use them to enhance understanding only when they align reasonably with what can be inferred visually.
>
> HTML: {A list of salient HTML attributes}

We observe that since the input to LLaVA is a small cropped image, the model tends to have less hallucinations compared to directly caption an element with a bounding box overlaid in the image. However, due to the limited language capabilities of 13B LLaVA, it often generates lengthy interpretations rather than concise referring expressions.

To address this, we then pass the generated description to Llama-3-8B, using the following prompt to instruct it to condense the interpretation into a brief referring expression:

> Here is a description to an element in an webpage. Using the detailed description provided, create a concise phrase that captures the essential visual and functional characteristics of the web element. The rephrased description should be straightforward, simple and precise enough to allow humans quickly spot this element in a webpage screenshot. Focus on the most prominent visual features and any critical function indicated by the text.
>
> Description: {}
>
> Leave only your final description in the answer, without any explanation.

Next, we describe the generation process for each crawled element.

[4]CC-MAIN-2023-50

Table 5: Statistics of element types (by HTML tags) in Web-Hybrid (%).

a	img	button	input	svg	select	textarea	video
68.99	15.41	6.81	5.32	2.25	0.99	0.18	0.04

Table 6: Statistics of element HTML attributes and MLLM-based synthetic REs used in Web-Hybrid (%). Calculated as the number of elements using an attribute/RE divided by the total number of elements.

MLLM-based RE	inner-text	title	alt	aria-label	aria-describedby	placeholder	value
11.19	43.58	20.01	12.25	11.32	0.21	0.06	0.02

We begin by categorizing the webpage elements based on their `tags` into two groups: interactive elements (e.g., `a`, `input`, `select`, etc.) and pure text elements (e.g., `p`, `h1`, `h2`, etc.). Referring expressions are only generated for interactive elements, while pure text elements are used as potential sources for generating referring expressions. The primary reason is that interactive elements are the main targets in GUI grounding tasks. Additionally, the bounding boxes of certain pure text elements, as crawled, tend to have a few mismatches, which can introduce noise into the dataset.

For each interactive element, we first apply an OCR model (EasyOCR[5]) to extract text from the element's bounding box. If the similarity between the OCR-extracted text and the element's `inner-text` exceeds a threshold of 0.7, we treat the element as a textual element and skip the MLLM-based synthesis pipeline. This helps us avoid generating trivial data, such as "Gray links labeled by *link text*". Furthermore, for textual elements, we filter out those that share identical text with other elements on the same page to prevent grounding ambiguities, which could arise when multiple elements share the same label within a single screenshot.

Based on handwritten rules, we label each element's neighboring elements in various directions (multiple neighbors are allowed), mark the nearest upper `h1`, `h2`, or `h3` elements (titles), and determine its absolute position (e.g., center of the screenshot, top, top-left corner) to generate absolute position-based referring expressions. We randomly select 0-2 relative elements in different directions and randomly pick elements whose distance from the target is within 500 pixels (empirically, always selecting the closest element does not yield the best performance). These are used to generate relative position descriptions. Some of the relative descriptions are further randomly modified to common terms such as "next to" or "between". For contextual references, we create the following rules: If an element is detected as a checkbox or radio button based on its HTML properties, we assume it has a corresponding label (e.g., "radio button for Yes"). If such labels are provided in the HTML attributes, we use them directly; otherwise, we select the nearest element on the same row as the label (or the nearest element in the same column if none exist in the same row). Similarly, we add potential labels for `input` fields and `select` boxes. We then generate expressions like "under", "in", or "under section A" based on the hierarchical structure of the titles (primarily `h1`, `h2`, and `h3`). If an element has `title`, `alt`, or `aria-label` attributes, they are always utilized as potential descriptors, typically covering both visual and functional REs, with most being functional REs.

Finally, for each element, we randomly combine any descriptors (from accessibility labels, the element's own text, or MLLM-based descriptions) with absolute position descriptions (randomly included, not always) and randomly add 0-2 relative or contextual descriptions (for radio buttons or similar elements, the label is always included; in other cases, 0-2 descriptors are randomly added) to generate the final referring expression. For each webpage, we use up to 100 elements. When randomly selecting elements, we prioritize those with accessibility labels or those annotated by MLLMs. We limit the total number of pure text elements to no more than three times the sum of elements with accessibility labels and MLLM-annotated elements (with a minimum of 10, or the actual number of available elements, whichever is lower) to reduce the number of pure text elements. We also count the occurrences of all unique accessibility labels and their respective frequencies. In total, our training set contains approximately 1.9M unique accessibility labels. For labels appearing more than 1,000 times, we downsample them to appear only 1,000 times in the training set. For example, the label "Next" appears 13K times, but is downsampled to 1K occurrences in our training data.

To illustrate the primary data distribution, we provide the statistics for the HTML element types, as well as attributes and types of positional REs used for the final REs in Web-Hybrid. The statistics are shown in Table 5, Table 6, and Table 7. We do not provide exact percentages of visual and functional REs because they are often interleaved in HTML DOMs and MLLM-based synthetic REs, and generally are hard to distinguish.

[5]https://github.com/JaidedAI/EasyOCR/

Table 7: Statistics of relative positional REs, absolute Positional REs, and contextual REs used in Web-Hybrid (%). Contextual References are also counted as relative positional REs. Calculated as the number of elements using an RE divided by the total number of elements.

Relative Positional RE	Contextual RE	Absolute Positional RE
23.49	8.43	3.05

F.2 WEB-DIRECT

For the Web-Direct dataset, we directly employ GPT-4o to generate referring expressions. We observed that, due to its limited grounded understanding capabilities, simply enclosing an element in the image with a bounding box often leads to notable hallucinations, even with GPT-4o. This is especially prevalent when it provides descriptions of nearby elements. However, we aim to avoid the high cost of manual post-verification. Through empirical studies, we found that highlighting an element with an arrow, in addition to a bounding box, helps mitigate hallucinations. Therefore, for each webpage and any arbitrary element on the page, we annotate the element with a red bounding box and a red arrow pointing to it. Additionally, we explicitly ask GPT whether it can identify the element, which further reduces potential hallucinations and helps filter out a small number of crawling errors or occluded elements.

Figure 5: Example of the image annotations of a bounding box and an arrow

We use the following prompt to generate free-form referring expressions:

> Here is supposed to be an interactive element (button, link, dropdown, text box etc) in the red box pointed by an arrow in the screenshot. Can you find int? Is it visible from the screenshot? Can you write a concise description that is sufficient for humans to locate it from the screenshot? Your response should be a json. For example, "visible": true, "description": "your description here".

Furthermore, we use the following prompt to generate more functionally oriented referring expressions:

> Here is supposed to be an interactive element (button, link, dropdown, text box etc) in the red box pointed by an arrow in the screenshot. Can you find int? Is it visible from the screenshot? What unique function does this element enable? Your response should be a json. For example, "visible": true, "action": "subscribe the latest updates".

F.3 OPEN-SOURCE DATA

We leverage several high-quality open-source referring expression datasets in Android, as well as GUIAct, as an additional source of web data. Specifically:

1. **GUIAct**: We use the annotated data from GUIAct (web-single). Any steps that do not involve coordinates or are marked as multi-step operations (for example, "click ... then type") are filtered out. We use both the *Instruction* and *Action* annotations for grounding (i.e., each element is seen in training twice with different expressions).

2. **AndroidControl**: Similarly, we use the human-annotated actions from the training set. We filter out any actions that do not have associated coordinate data, ensuring that only steps with specific visual grounding targets are included in the dataset.

3. **Widget Caption**: For each element in the training set, multiple functional captions are provided. To enhance data variety, we randomly select two captions per element from the available set of functional captions during data construction.

4. **UIBert**: We use the training set elements from UIBert without any additional special processing, directly utilizing the referring expressions provided by this dataset.

5. **AITZ**: We incorporate the annotated actions (`Thought`) from AITZ, using each step's action annotation for grounding in the dataset. These annotations contribute to a more diverse set of referring expressions, particularly for action-oriented grounding tasks.

G MODEL AND TRAINING DETAILS

G.1 OVERVIEW

For flexible investigation about the model architecture, we build the architecture based on LLaVA-NeXT (Liu et al., 2024b), and train from scratch using opensource data from Liu et al. (2024a). We use CLIP-ViT-L-14 (224px) as our base image encoder for more flexible splitting of `AnyRes` , and freeze it during training. We use Vicuna-1.5-7b-16k (Zheng et al., 2023) as the language backbone as a long-context LM backbone for handling long visual contexts.

G.2 ANYRES

As described in §2.3, `AnyRes` allows convenient scaling up of image resolutions, although it's not always beneficial to enlarge image resolutions (Li et al., 2024a). We keep the main pipeline of `AnyRes`, splitting images into 224px grids. However, to keep identical image aspect ratios, we resize only by width and pad to the bottoms if needed, and use pixel-level coordinates in numbers that are compatible with this design. We allow at most 36 grids, for a maximum resolution of 1,344 x 1,344 and 896 x 2,016. We empirically find `AnyRes` does not generalize to unseen image resolutions for visual grounding. Therefore, we resize images by width to keep them within the training resolution ranges when needed. We remove the low-resolution image for providing global context, because it intuitively does not providing informative contexts when images are larger than 1,000px, and we empirically find it slightly hurt the performance.

G.3 TRAINING

Our training primarily consists of two stages:

1. **LLaVA-1.5 Pretraining and Finetuning**: We follow the exact pretraining in Liu et al. (2024a). Then, in the instruction finetuning stage, we change the grounding data from normalized coordinates to absolute coordinates as we wish, and start to use our modified `AnyRes` setting.

2. **GUI Visual Grounding**: Then we train UGround on our training datasets.

Due to the huge computation cost of handling high resolution images, we use LoRA (Hu et al., 2022) for instruction finetuning in the two stages, with a device batch size of 4.

The first stage takes about 50 hours on a single 4x NVIDIA A100 machine (global batch size 128 with gradient accumulation). And for the large scale GUI data training, we use 112 NVIDIA H100 GPUs and finish the training in about 6 hours (global batch size 448).

H EVALUATION DETAILS

H.1 MODEL ENDPOINTS

As studied in (Pan et al., 2024), different GPT endpoints could lead to slight differences to the performance of GUI tasks. Hence, we provide the specific endpoint names we use in our evaluation, as well as those of the baselines we use (if available).

- Ours (across every benchmark): `gpt-4-turbo-2024-04-09` and `gpt-4o-2024-05-13`
- Multimodal-Mind2Web: `gpt-4-1106-vision-preview`
- OmniACT: `gpt-4-0613` and `gpt-4-1106-vision-preview`
- Mind2Web-Live: `gpt-4-0125-preview` and `gpt-4o-2024-05-13`
- AndroidWorld: `gpt-4-turbo-2024-04-09`

H.2 MULTIMODAL-MIND2WEB

Many screenshots in Multimodal-Mind2Web have giant vertical heights (e.g., $1{,}280 \times 10{,}000$ pixels). Similar to Zheng et al. (2024), to avoid the overly long screenshots, we divide whole webpage screenshots into viewport-sized blocks, and simulate scrolling down to the next block when agents either determine that no valid action can be taken or explicitly choose to scroll. Specifically, we divide each full-page screenshot into $1{,}280 \times 1{,}000$ pixel blocks, except for the final block, which may be shorter depending on the page's total height. Most of the target elements are within the first block (about 80%). See Figure 1 for an illustrative example of the pipeline.

We report element accuracy on the benchmark, and an element grounding is considered to be correct if the output coordinates fall in the box coordinates of the ground truth element.

H.3 ANDROIDCONTROL

We adopt the M3A (Multimodal Autonomous Agent for Android) prompt (Rawles et al., 2024), the state-of-the-art zero-shot method in Li et al. (2024b). We make minor modifications to integrate UGround to M3A.

We follow the standard data processing steps outlined in Li et al. (2024b). During evaluation, coordinates generated by grounding models are translated to the smallest visible element that includes the coordinates.

H.4 OMNIACT

We follow the method in Kapoor et al. (2024) for prompt design and the selection of five in-context examples. The prompt is slightly modified to generate element descriptions as function parameters for PyAutoGUI scripts, instead of directly outputting coordinates. The examples are selected based on task similarity using MiniLM (Wang et al., 2020) (MiniLM-L12-H384) embeddings. After generating the PyAutoGUI script with element descriptions, we use grounding models to predict the corresponding coordinates and substitute them back into the original script. See Figure 3 for an illustrative example of the pipeline.

The evaluation metrics in OmniACT include Sequence Score and Action Score. The Sequence Score measures whether the predicted action sequence exactly matches the ground truth. If the sequence is correct, the Action Score is calculated by penalizing inaccuracies in how the script performs the task, including: *Click Penalty* (M_p), applied when predicted coordinates fall outside the target element's bounding box; *Key Penalty* (K_p), triggered when the predicted key set differs from the ground truth for `press` and `hotkey` actions; and *Write Penalty* (W_p), which measures discrepancies between the predicted and actual typed text using the BLEU score.

We compare our method with DetACT (Kapoor et al., 2024), the state-of-the-art method in Kapoor et al. (2024), which extracts UI elements and their coordinates through a combination of OCR, icon matching, and color detection. These elements are filtered by task relevance and passed to LLMs or MLLMs to generate the PyAutoGUI script. In contrast, our method does not use a pre-generated elements list. The planner model focuses on generating precise element descriptions based solely on the screenshot. Additionally, we corrected basic errors in the public evaluation scripts (for example, wrong file paths and wrong calculation of distances).

H.5 MIND2WEB-LIVE

The baseline agent in Pan et al. (2024) is text-only, perceives and interacts with webpages by hundreds of textual HTML elements at a time. To study vision-only agents, we change the observation to pure screenshots. We also make necessary changes to the standard action space to entirely isolate HTML from the planning, grounding, and execution: 1) We add `Scroll_Up` and `Scroll_Down` to the action space to better support vision-only agents with viewport-sized observation. 2) We remove `Fill_Form` and `Fill_Search` from the action space, which use an additional judgment model to determine whether to press enter after typing through HTML information. Instead, we use `Type` and `Press_Enter` to let the agent make its own decisions autonomously. 3) We disable API-based `Select`, and force agents to select options merely through clicking and makes the action more challenging. We admit some select buttons cannot be easily operated with only `Click`. We compromise this point to fulfill the motivation of this vision-only study.

H.6 ANDROIDWORLD

We build SeeAct-V agents based on the M3A agent in Rawles et al. (2024), which receives both raw and SoM images, and reason about the next action in a ReAct style (Yao et al., 2023) and choose the next target element from the element list. It also adopts self-reflection (Shinn et al., 2024) in the agent pipeline to instruct agents to summarize the current move and facilitate the following steps.

We mainly remove SoM images and textual list of elements from a11y tree in the observation (in both planning and reflection phases), and change element-based actions to pixel-level actions.

I PROMPTS

Table 8: Prompt used for the planning model in **Multimodal-Mind2Web**, modified from the prompt in (Zheng et al., 2024)

System Role You are imitating humans doing web navigation for a task step by step. At each stage, you can see the webpage like humans by a screenshot and know the previous actions before the current step through recorded history. You need to decide on the first following action to take. You can click an element with the mouse, select an option, type text with the keyboard, or scroll down.
Task Description You are asked to complete the following task: {Task description} Previous Actions: {List of previous actions, if any} The screenshot below shows the webpage you see.
Useful Guidelines First, observe the current webpage and think through your next step based on the task and previous actions. To be successful, it is important to follow the following rules: 1. Make sure you understand the task goal to avoid wrong actions. 2. Ensure you carefully examine the current screenshot and issue a valid action based on the observation. 3. You should only issue one action at a time. 4. The element you want to operate with must be fully visible in the screenshot. If it is only partially visible, you need to SCROLL DOWN to see the entire element. 5. The necessary element to achieve the task goal may be located further down the page. If you don't want to interact with any elements, simply select SCROLL DOWN to move to the section below.
Reasoning Explain the action you want to perform and the element you want to operate with (if applicable). Describe your thought process and reason in 3 sentences.
Output Format Finally, conclude your answer using the format below. Ensure your answer strictly follows the format and requirements provided below, and is clear and precise. The action, element, and value should each be on three separate lines. ACTION: Choose an action from CLICK, TYPE, SELECT, SCROLL DOWN. You must choose one of these four, instead of choosing None. ELEMENT: Provide a description of the element you want to operate. (If ACTION == SCROLL DOWN, this field should be none.) It should include the element's identity, type (button, input field, dropdown menu, tab, etc.), and text on it (if applicable). Ensure your description is both concise and complete, covering all the necessary information and less than 30 words. If you find identical elements, specify its location and details to differentiate it from others. VALUE: Provide additional input based on ACTION. The VALUE means: If ACTION == TYPE, specify the text to be typed. If ACTION == SELECT, specify the option to be chosen. Otherwise, write 'None'.

Table 9: Prompts used for the planning model in **AndroidControl**, modified from the prompt in (Li et al., 2024b) and (Rawles et al., 2024)

General Instruction

You are an agent who can operate an Android phone on behalf of a user.
Based on user's goal/request, you may complete some tasks described in the requests/goals by performing actions (step by step) on the phone.

When given a user request, you will try to complete it step by step. At each step, you will be given the current screenshot and a history of what you have done (in text). Based on these pieces of information and the goal, you must choose to perform one of the action in the following list (action description followed by the JSON format) by outputting the action in the correct JSON format.
- If you think the task has been completed, finish the task by using the status action with complete as goal_status: {"action_type":"status","goal_status":"successful"}
- If you think the task is not feasible (including cases like you don't have enough information or cannot perform some necessary actions), finish by using the 'status'action with infeasible as goal_status: {"action_type": "status", "goal_status": "infeasible"}
- Click/tap on an element on the screen, describe the element you want to operate with: {"action_type": "click", "element": ⟨target_element_description⟩}
- Long press on an element on the screen, similar with the click action above: {"action_type": "long_press", "description": ⟨target_element_description⟩}
- Type text into a text field: {"action_type": "type_text", "text": ⟨text_input⟩, "element": ⟨target_element_description⟩}
- Scroll the screen in one of the four directions: {"action_type": "scroll", "direction": ⟨up, down, left, right⟩}
- Navigate to the home screen: {"action_type": "navigate_home"}
- Navigate back: {"action_type": "navigate_back"}
- Open an app (nothing will happen if the app is not installed): {"action_type": "open_app", "app_name": ⟨name⟩}
- Wait for the screen to update: {"action_type": "wait"}

Useful Guidelines

Here are some useful guidelines you need to follow:
General:
- Usually there will be multiple ways to complete a task, pick the easiest one. Also when something does not work as expected (due to various reasons), sometimes a simple retry can solve the problem, but if it doesn't (you can see that from the history), SWITCH to other solutions.
- If the desired state is already achieved (e.g., enabling Wi-Fi when it's already on), you can just complete the task.

Action Related:
- Use the 'open_app' action whenever you want to open an app (nothing will happen if the app is not installed), do not use the app drawer to open an app unless all other ways have failed.
- Use the 'type_text' action whenever you want to type something (including password) instead of clicking characters on the keyboard one by one. Sometimes there is some default text in the text field you want to type in, remember to delete them before typing.
- For 'click', 'long_press' and 'type_text', the element you pick must be VISIBLE in the screenshot to interact with it.
- The 'element' field requires a concise yet comprehensive description of the target element in a single sentence, not exceeding 30 words. Include all essential information to uniquely identify the element. If you find identical elements, specify their location and details to differentiate them from others.
- Consider exploring the screen by using the 'scroll' action with different directions to reveal additional content.
- The direction parameter for the 'scroll' action specifies the direction in which the content moves and opposites to swipe; for example, to view content at the bottom, the 'scroll' direction should be set to 'down'.

Text Related Operations:

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- Normally to select certain text on the screen: ⟨i⟩ Enter text selection mode by long pressing the area where the text is, then some of the words near the long press point will be selected (highlighted with two pointers indicating the range) and usually a text selection bar will also appear with options like 'copy', 'paste', 'select all', etc. ⟨ii⟩ Select the exact text you need. Usually the text selected from the previous step is NOT the one you want, you need to adjust the range by dragging the two pointers. If you want to select all text in the text field, simply click the 'select all' button in the bar. - At this point, you don't have the ability to drag something around the screen, so in general you cannot select arbitrary text. - To delete some text: the most traditional way is to place the cursor at the right place and use the backspace button in the keyboard to delete the characters one by one (can long press the backspace to accelerate if there are many to delete). Another approach is to first select the text you want to delete, then click the backspace button in the keyboard. - To copy some text: first select the exact text you want to copy, which usually also brings up the text selection bar, then click the 'copy' button in bar. - To paste text into a text box, first long press the text box, then usually the text selection bar will appear with a 'paste' button in it. - When typing into a text field, sometimes an auto-complete dropdown list will appear. This usually indicates this is a enum field and you should try to select the best match by clicking the corresponding one in the list.
High-Level Prompt {General Instruction} The current user goal/request is: {High-level goal} Here is a history of what you have done so far: {History} The current raw screenshot is given to you. {Useful Guidelines} Now output an action from the above list in the correct JSON format, following the reason why you do that. Your answer should look like: Reason: ... Action: {"action_type": ...} Your Answer:
Low-Level Prompt {General Instruction} The user's high-level goal/request is: {High-level goal} The current next step's low-level goal is: {Low-level goal} The current raw screenshot is given to you. {Useful Guidelines} Now output an action from the above list in the correct JSON format, following the reason why you do that. Your answer should look like: Reason: ... Action: {"action_type": ...} Your Answer:

Table 10: Prompt used for the planning model in **OmniACT**, modified from the prompt in (Kapoor et al., 2024)

General Instruction
You are an excellent robotic process automation agent who needs to generate a PyAutoGUI script for the tasks given to you.
You will receive some examples to help with the format of the script that needs to be generated.

There are some actions that require you to provide an element description for the elements you want to operate on. For the description, follow the requirements below:
Element Description Requirements:
Provide a concise description of the element you want to operate.
It should include the element's identity, type (button, input field, dropdown menu, tab, etc.), and text on it (if have).
If you find identical elements, specify their location and details to differentiate them from others.
Ensure your description is both concise and complete, covering all the necessary information and less than 30 words, and organize it into one sentence.

[IMPORTANT!!] Stick to the format of the output scripts in the example.
[IMPORTANT!!] Use only the functions from the API docs.
[IMPORTANT!!] Follow the output format strictly. Only write the script and nothing else.

API Reference
Here is the API reference for generating the script:

```
def click(element=description):
'''Moves the mouse to the element corresponding to the description and performs a left click.
Example:
High Level Goal: Click at the rectangular red button labeled "Next".
Python script:
import pyautogui
pyautogui.click("Rectangular red button labeled "Next" ")
'''
pass

def rightClick(element=description):
'''Moves the mouse to the element corresponding to the description and performs a right click.
Example:
High Level Goal: Right-click at link labeled "vacation rentals"under the "housing"section.
Python script:
import pyautogui
pyautogui.rightClick("Link labeled "vacation rentals"under the "housing"section")
'''
pass

def doubleClick(element=description):
'''Moves the mouse to the element corresponding to the description and performs a double click.
Example:
High Level Goal: Double-click at folder named "courses".
Python script:
import pyautogui
pyautogui.doubleClick("Folder named "courses" ")
'''
pass

def scroll(clicks=amount_to_scroll):
'''Scrolls the window that has the mouse pointer by float value (amount_to_scroll).
Example:
High Level Goal: Scroll screen by 30.
Python script:
import pyautogui
pyautogui.scroll(30)
'''
pass
```

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Table 10 – Continued from the previous page

```
def hscroll(clicks=amount_to_scroll):
'''Scrolls the window that has the mouse pointer horizontally by float value (amount to scroll).
Example:
High Level Goal: Scroll screen horizontally by 30.
Python script:
import pyautogui
pyautogui.hscroll(30)
'''
pass

def dragTo(element=description, button=holdButton):
'''Drags the mouse to the element corresponding to the description with (holdButton) pressed. holdButton can be 'left', 'middle', or 'right'.
Example:
High Level Goal: Drag the screen from the current position to recycle bin with the left click of the mouse.
Python script:
import pyautogui
pyautogui.dragTo("Recycle bin with trash can shape", "left")
'''
pass

def moveTo(element = description):
'''Takes the mouse pointer to the element corresponding to the description.
Example:
High Level Goal: Hover the mouse pointer to search button.
Python script:
import pyautogui
pyautogui.moveTo("Request appointment button")
'''
pass

def write(str=stringType, interval=secs_between_keys):
'''Writes the string wherever the keyboard cursor is at the function calling time with (secs_between_keys) seconds between characters.
Example:
High Level Goal: Write "Hello world"with 0.1 seconds rate.
Python script:
import pyautogui
pyautogui.write("Hello world", 0.1)
'''
pass

def press(str=string_to_type):
'''Simulates pressing a key down and then releasing it up. Sample keys include 'enter', 'shift', arrow keys, 'f1'.
Example:
High Level Goal: Press the enter key now.
Python script:
import pyautogui
pyautogui.press("enter")
'''
pass

def hotkey(*args = list_of_hotkey):
'''Keyboard hotkeys like Ctrl-S or Ctrl-Shift-1 can be done by passing a list of key names to hotkey(). Multiple keys can be pressed together with a hotkey.
Example:
High Level Goal: Use Ctrl and V to paste from clipboard.
Python script:
import pyautogui
```

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pyautogui.hotkey("ctrl", "v") ''' pass
Examples Here are some examples similar to the tasks you need to complete. However, these examples use coordinate format for actions like click, rightClick, doubleClick, moveTo, dragTo, instead of element description. You should only refer to the actions in these examples, and for the output format, stick to the content in the API reference. For example, do not output "pyautogui.click(100,200)", instead output "pyautogui.click("Gray Tools menu button with a downward arrow in the top right corner") ". Omit "import pyautogui", do not include any comments or thoughts. Your output should only contain the script itself. {Example list}
Task Description Based on the screenshot, generate the PyAutoGUI script for the following task: {Task description} You should list all the necessary steps to finish the task, which could involve multiple steps. Also, ensure simplifying your steps as much as possible, avoid dividing a single task into multiple steps if it can be completed in one.

Table 11: Prompt used for the planning model in **ScreenSpot (Agent Setting)**.

Task Description You are an excellent agent for mobile, web, and desktop navigation tasks. Describe the target element for this task based on the provided screenshot: Task: {Task description}
Element Description Requirements Provide a concise description of the element you want to operate. Ensure your description is both concise and complete, covering all the necessary information in less than 30 words, and organized into one sentence. If you find identical elements, specify their location and details to differentiate them from others.
Output Format Your output should only include the element description itself and follow the requirements. Do not start with “the target element” or “the element”.