

VisualWebArena: EVALUATING MULTIMODAL AGENTS ON REALISTIC VISUAL WEB TASKS

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ABSTRACT

Autonomous agents capable of planning, reasoning, and executing actions on the web offer a promising avenue for automating computer tasks. However, the majority of existing benchmarks primarily focus on text-based agents, neglecting many natural tasks that require visual information to effectively solve. Given that most computer interfaces cater to human perception, visual information often augments textual data in ways that text-only models struggle to harness effectively. To bridge this gap, we introduce VisualWebArena, a benchmark designed to assess the performance of multimodal web agents on realistic *visually grounded tasks*. VisualWebArena comprises of a set of diverse and complex web-based tasks that evaluate various capabilities of autonomous multimodal agents. To perform on this benchmark, agents need to accurately process image-text inputs, interpret natural language instructions, and execute actions on websites to accomplish user-defined objectives. We conduct an extensive evaluation of state-of-the-art LLM-based autonomous agents, including several multimodal models. Through extensive quantitative and qualitative analysis, we identify several limitations of text-only LLM agents, and reveal gaps in the capabilities of state-of-the-art multimodal language agents. VisualWebArena provides a framework for evaluating multimodal autonomous language agents, and offers insights towards building stronger autonomous agents for the web. Our code, baseline models, and data is publicly available at <https://jykoh.com/vwa>.

1 INTRODUCTION

Automating routine computer tasks with autonomous agents is a long standing goal of artificial intelligence research (Franklin & Graesser, 1996; Jennings et al., 1998). To achieve this, we need agents that can navigate computers effectively, process visual and textual inputs, handle high-level natural language instructions, and execute actions to achieve desired goals. As digital interfaces today are primarily built for human eyes, effective visual understanding is necessary for many routine computer tasks. For example, humans frequently perform tasks on the web which involve visual references, such as “Help me order a green polo shirt from Amazon”. Many real world tasks also involve understanding image content: people frequently rely on pictures to communicate rather than text descriptions. Productive work done on the computer is also often explicitly visual, e.g., working with Microsoft Excel sheets, creating presentations in Google Slides, or performing creative work in Adobe Photoshop. However, many agent benchmarks today focus on text-based tasks, neglecting the evaluation (and consequently the development) of multimodal autonomous agents.

To address this gap, we propose VisualWebArena (Fig. 1), a benchmark suite designed to rigorously assess and advance the visual and textual capabilities of autonomous agents. VisualWebArena builds off the WebArena (Zhou et al., 2024) framework, which comes with reproducible self-hosted environments and execution-based evaluations. VisualWebArena introduces a set of unique visual tasks, and emphasizes integrating visual understanding with language processing, closely simulating human interaction with modern computing interfaces.

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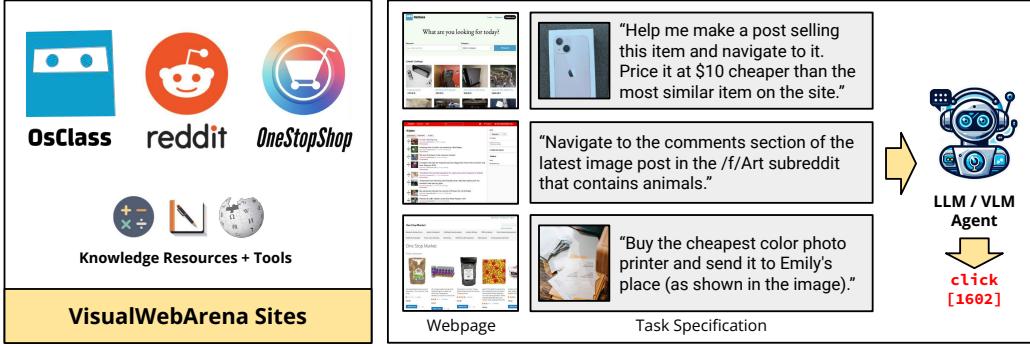


Figure 1: VisualWebArena is a benchmark suite of realistic classifieds, e-commerce, and Reddit sites. We benchmark state-of-the-art LLM and VLM agents on 910 diverse, natural, and visually grounded tasks that involve web navigation, action execution, and visual understanding.

By introducing VisualWebArena, we aim to bridge the existing gap in the evaluation of multimodal autonomous agents and to push the boundaries of AI-driven task automation. We envision a future where AI agents can not only process textual information but also effectively navigate and interact with visual settings (e.g., digital screens), truly augmenting human productivity and creativity. Our contributions are summarized as follows:

- We introduce VisualWebArena, a set of 910 realistic tasks over three diverse web environments: Classifieds, Shopping, and Reddit. The Classifieds environment is a new contribution with real world data, while the Shopping and Reddit environments are inherited from WebArena. All tasks we introduce are *visually grounded*, and require visual understanding of webpage content to effectively solve (while WebArena does not). 25.2% of our tasks also take images as input (Fig. 1), and require understanding of interleaved image-text inputs to correctly process and attempt. Our code, tasks, and baselines is publicly released.¹
- We extensively benchmark the autonomous capabilities of state-of-the-art (SOTA) large language models (LLM) and vision-language models (VLMs), demonstrating that strong VLMs outperform text-based LLMs. The best VLM agents achieve a success rate of only 16.4% on VisualWebArena tasks, significantly below human performance of 88.7%. Our results also highlight a large gap between API-based and open sourced VLM agents.
- We propose a new VLM agent inspired by Set-of-Marks prompting Yang et al. (2023a), simplifying the action space of the model. We show that this model substantially outperforms LLM agents, especially on sites that are more visually complex.

2 RELATED WORK

Language-Guided Web Agent Benchmarks The development of reproducible environments for autonomous agents has seen considerable progress in recent years. Earlier efforts introduced reinforcement learning environments (Brockman et al., 2016), but extended into the web (Shi et al., 2017; Liu et al., 2018), which laid the groundwork for reproducible web-based environments. Recent benchmarks in this domain introduced tasks involving actions on static internet pages (Deng et al., 2023) as well as interaction in simulated web environments (Yao et al., 2022; Zhou et al., 2024). AgentBench (Liu et al., 2023c) also extends the scope of agents for computer interaction beyond the web, exploring database management and operating system functionalities.

LLM Agents There has been significant recent interest in using Large Language Models (LLMs) for developing autonomous agents (Xi et al., 2023; Wang et al., 2023a). State-of-the-art LLMs (Google, 2023; OpenAI, 2023; Chowdhery et al., 2023; Rae et al., 2021; Zhang et al., 2022; Touvron et al., 2023a;b; Jiang et al., 2023; 2024) based on the Transformer (Vaswani et al., 2017) architecture have demonstrated impressive abilities in learning from in-context examples (Brown et al., 2020; Chan et al., 2022), reasoning (Wei et al., 2022; Yao et al., 2023; Wang et al., 2023c;

¹<https://jykh.com/vwa>

Besta et al., 2023), following instructions (Chung et al., 2022; Longpre et al., 2023; Ouyang et al., 2022), and operating over long-context sequences (Tay et al., 2021; Bertsch et al., 2023; Tworkowski et al., 2023). Several recent works leverage these compelling abilities for building autonomous web agents: Kim et al. (2023) propose a recursive prompting method to improve the performance of GPT-4 on the MiniWoB++ (Liu et al., 2018) benchmark. Liu et al. (2023d) propose a method of orchestrating multiple LLM agents to improve performance on web navigation in the WebShop (Yao et al., 2022) environment. Zeng et al. (2023) fine-tunes the LLaMA-2 (Touvron et al., 2023b) models on a set of interaction trajectories with instructions, improving over baseline agent models.

Vision-Language Models Finally, our work builds off advances in vision-language models (VLMs) which can process image-text inputs to generate text, used for many multimodal tasks such as image captioning (Vinyals et al., 2015), visual question answering (Antol et al., 2015), and other benchmarks (Mialon et al., 2023; Yue et al., 2023; Tong et al., 2024). Frozen (Tsimpoukelli et al., 2021) was one of the first approaches to demonstrate the effectiveness of finetuning a visual encoder to map images into the embedding space of a LLM, introducing compelling few-shot multimodal abilities. Alayrac et al. (2022) introduced cross-attention layers and scaled up models and training data to improve multimodal performance. Wang et al. (2023b) introduced trainable visual expert modules to improve the fusion between the vision and language models. Liu et al. (2023b) proposed fine-tuning on images paired with instructions to improve text generation performance on several multimodal tasks. GPT-4V (OpenAI, 2023) introduces visual processing abilities to the GPT-4 models, unlocking many compelling abilities (Yang et al., 2023c;a). Gemini (Google, 2023) is multimodal from the beginning (in contrast to post-hoc fine-tuned models), and can handle text input interleaved with visual and audio inputs. Several recent work have also explored the use of strong VLMs for building visual agents for mobile platforms (Zhan & Zhang, 2023; Chu et al., 2023; Yang et al., 2023b) as well as for the web (Gur et al., 2023; Hong et al., 2023). (Zheng et al., 2024) is contemporaneous work which performs action grounding to identify appropriate HTML elements for enabling VLM agents to execute actions on the web. In contrast, our proposed SoM agent directly leverages JavaScript to produce a Set-of-Marks (Yang et al., 2023a) for the VLM agent to directly use as both an action and observation space.

3 VisualWebArena ENVIRONMENT

In order to ensure reproducibility, realism, and determinism, we ensure that all websites in the VisualWebArena framework are available as standalone open-source web applications. The textual and visual content available in the websites are acquired from real world counterparts, while the code is based off open-source infrastructure commonly used in real world applications. We formally define the environment, observation space, and action space in the following sections, but encourage readers to refer to WebArena (Zhou et al., 2024) for more details.

The environment and agent can be modeled as a partially observable Markov decision process (POMDP): $\mathcal{E} = (S, A, \Omega, T)$, where S represents the set of states, A represents the set of actions (Sec. 3.2), and Ω represents the set of observations (Sec. 3.1). The transition function is defined as $T : S \times A \rightarrow S$, with deterministic transitions between states conditioned on actions. At each time step t , the environment is in some state s_t (e.g., a particular page), with a partial observation $o_t \in \Omega$. An agent issues an action $a_t \in A$ conditioned on o_t , which results in a new state $s_{t+1} \in S$ and a new partial observation $o_{t+1} \in \Omega$ of the resulting page. The action a_t may be an action to be executed on the webpage (Tab. 1), or it may simply be a string output for information seeking tasks (Sec. 3.3).

Finally, we define the reward function $R : S \times A \rightarrow \{0, 1\}$ (Sec. 3.3) to measure the success of a task execution. In VisualWebArena, the reward function returns 1 at the final step if the state transitions align with the expectations of the task objective (i.e., the goal is achieved), and 0 otherwise. For example, in the first task in Fig. 1, the reward function evaluates whether the order was correctly placed to the exact address provided in the input image, and contains the correct item.

3.1 OBSERVATION SPACE

The observation space Ω is modeled after a realistic web browsing experience. Observations include the webpage URLs, opened tabs (possibly multiple tabs of different websites), and the webpage content of the focused tab. In approximately 25% of tasks, the intent also involves one or more input

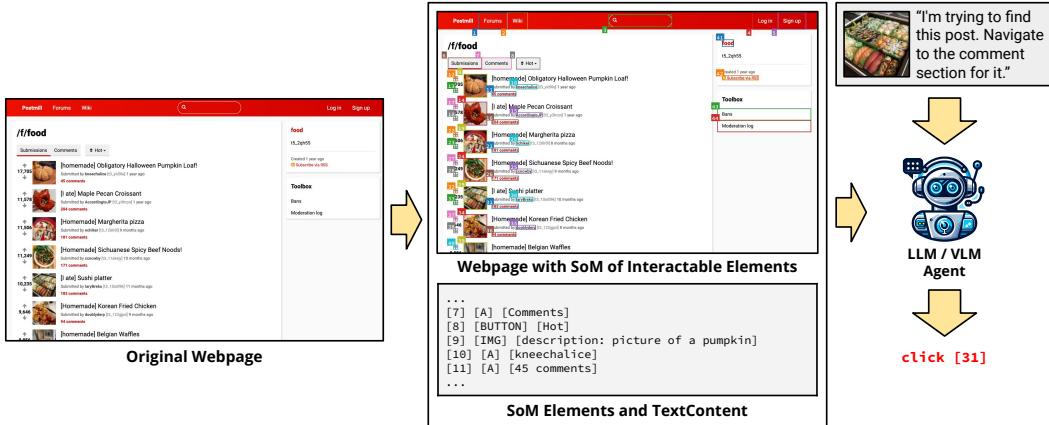


Figure 2: Set-of-Marks (Yang et al., 2023a) augmented webpage screenshot. Every interactable element is highlighted with a bounding box and a unique ID.

images which are provided as part of the observation (e.g., the first and third tasks in Fig. 1). The webpage content can be represented in several different ways:

1. Raw web page HTML as a Document Object Model (DOM) tree, commonly used in previous work on autonomous web agents (Shi et al., 2017; Liu et al., 2018; Deng et al., 2023).
2. Web page screenshots, represented as RGB arrays, which has demonstrated efficacy in prior work on visual agents (Gur et al., 2023; Hong et al., 2023; Yan et al., 2023).
3. The accessibility tree,² which provides a structured and simplified representation of the webpage content that is optimized for assistive technologies. This is the primary representation that WebArena (Zhou et al., 2024) uses for its baseline LLM agents.
4. We introduce a new visual representation inspired by Set-of-Marks (SoM) prompting (Yang et al., 2023a). For every interactable element on the webpage, we label it with a bounding box and an ID (Fig. 2), producing a screenshot that allows a visual agent to reference elements on the page by their unique ID. We provide more details and analysis in Sec. 5.3.

3.2 ACTION SPACE

The full set of actions A is summarized in Tab. 1. The arguments for action a_t is the unique element ID from the current observation o_t . An advantage of this representation (over predicting (x, y) coordinates) is that it allows us to focus on high level reasoning rather than low-level control, as many SOTA VLMs and LLMs were not explicitly trained for referencing elements at such fine granularity. For the agents with accessibility tree representations, the argument is the element ID in the tree. For the SoM representation, we use the unique IDs assigned in the current page (see Fig. 2).

3.3 EVALUATION

In order to evaluate performance on VisualWebArena, we introduce new visually grounded evaluation metrics to the functional evaluation paradigm of WebArena. These allow us to comprehensively evaluate the correctness of execution traces on open ended visually grounded tasks. The rewards for each task are hand designed functions using the primitives described below.

Action Type a	Description
click [elem]	Click on element elem.
hover [elem]	Hover over element elem.
type [elem] [text]	Type text on element elem.
press [key_comb]	Press a key combination.
new_tab	Open a new tab.
tab_focus [index]	Focus on the i-th tab.
tab_close	Close current tab.
goto [url]	Open url.
go_back	Click the back button.
go_forward	Click the forward button.
scroll [up down]	Scroll up or down the page.
stop [answer]	End the task with an optional output.

Table 1: Set of possible actions A .

²https://developer.mozilla.org/en-US/docs/Glossary/Accessibility_tree

Webpage / Input Image(s)	Example Intent	Reward Function $r(s, a)$ Implementation
	What is the ISIN of the company that occupies the largest portion in Warren Buffet's portfolio? Answer using the information from the Wikipedia site in the second tab.	<code>exact_match(\hat{a}, "US0378331005")</code>
	Add something like what the man is wearing to my wish list.	<code>url="/wishlist" locator(".wishlist .product-image-photo") eval_vqa(s, "Is this a polo shirt? (yes/no)", "yes") eval_vqa(s, "Is this shirt green? (yes/no)", "yes")</code>
	Create a post for each of the following images in the most related forums.	<code>eval_fuzzy_image_match(s, a^*)</code>
	Navigate to my listing of the white car and change the price to \$25000. Update the price in the description as well.	<code>url="/index.php?page=item&id=84144" must_include(\hat{a}, "\$25000 OR \$25,000") must_exclude(\hat{a}, "\$30000 OR \$30,000")</code>

Table 2: Various evaluation metrics to assign reward $r(s, a) \in R : S \times A \rightarrow \{0, 1\}$. Our execution-based reward primitives allow us to benchmark many diverse, realistic, and open-ended tasks.

Information Seeking Tasks Information seeking tasks (e.g., the first task in Tab. 2) expect a string output \hat{a} from the model. We mostly adopt similar reward functions introduced in WebArena for measuring text correctness against a groundtruth output a^* :

- **exact_match:** This can be defined as $\mathbf{1}_{\{\hat{a}=a^*\}}$ (where $\mathbf{1}$ represents the indicator function). Only outputs that are exactly equal to the groundtruth are given a score of 1. This is used in tasks where an exact response (e.g., a numerical answer) is expected.
- **must_include:** This reward function gives a score of 1 if all elements in a^* are contained in \hat{a} and 0 otherwise. For example, if $\hat{a} = "\$1.99, \$2.50, \$10.00"$ and $a^* = \{"1.99", "2.50", "10.00"\}$, the task is awarded a score of 1 as all expected elements are present in the output. This is primarily used in tasks where we expect an unordered list of outputs, or we expect text output to contain a particular keyword.
- **must_exclude:** This is a new function we introduce, which is the converse of **must_include**. A reward of 0 is assigned if any element from a specified set a^* is found in \hat{a} (and 1 otherwise). For instance, if $\hat{a} = "\$1.99, \$2.50, \$10.00"$ and $a^* = \{"1.50", "2.00"\}$, the reward is 1 as none of the prohibited elements are in the output.
- **fuzzy_match:** This function queries a LLM (in our implementation, gpt-4-1106-preview, to evaluate whether a^* and \hat{a} are semantically equivalent. The LLM is prompted to output either “correct”, “incorrect”, or “partially correct”, and we assign a reward of 1 if the output is “correct” and 0 otherwise.³

In addition, we also introduce several new visual functions for measuring open ended tasks:

- **eval_vqa:** Similar to **fuzzy_match**, this function queries a VLM capable of performing visual question answering (VQA) (Antol et al., 2015). We use BLIP-2-T5XL Li et al. (2023) in our implementation. We query the VLM with an image and a question. If the output of the VLM contains the groundtruth answer a^* , a reward of 1 is assigned (and 0 otherwise). This is useful for evaluating more open ended tasks, e.g., “Buy me a green hoodie under \$10.”. There are many possible products that satisfy this objective, and it would be infeasible to enumerate all their IDs.
- **eval_fuzzy_image_match:** This function checks whether a query image is similar to a groundtruth image according to the structural similarity index measure (SSIM) (Wang et al.,

³We do not consider non-binary rewards in this work, but it would be a useful direction to explore in the future towards more continuous scales of performance.

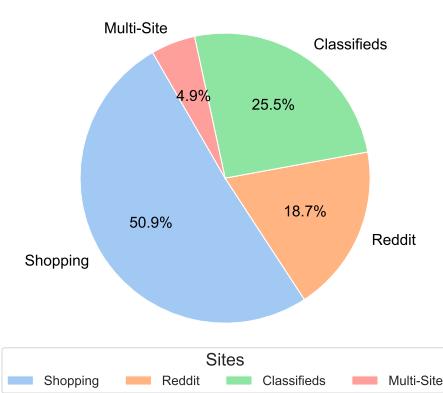
Distribution of Tasks Across Sites

Figure 3: Tasks proportion by sites.

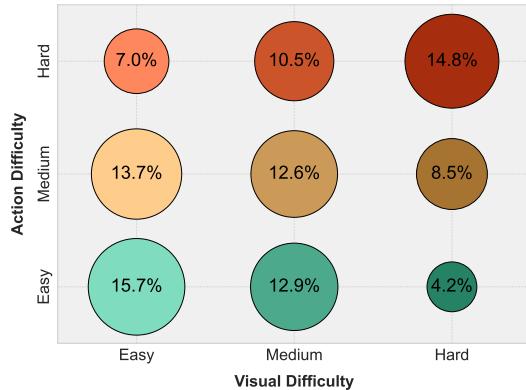
Distribution of Tasks by Difficulty

Figure 4: Tasks proportion by difficulty.

2004). If the SSIM between a query image and the groundtruth image is higher than a prespecified threshold $t \in [0, 1]$, a reward of 1 is assigned, and 0 otherwise.

Navigation and Actions Many tasks in VisualWebArena require navigating through multiple webpages, and executing actions to change the underlying state s of the environment. To accurately evaluate certain objectives, we require reward functions that examine the final webpage state to determine whether the task was successfully accomplished. These adopt the WebArena programmatic evaluation metrics, as well as the eval_vqa and eval_fuzzy_image_match metrics for measuring performance on visual or open-ended tasks.

Each evaluator consists of a locator as well as a URL. The URL can be a specific page, or a function (e.g., the last page that the agent navigated to). The locator describes the object on the page that should be examined (e.g., all img elements, or all elements with the .product-image-photo class). During evaluation, we use the locator to retrieve the corresponding image or text content, and reuse the functions from the information seeking tasks to check for correctness.

4 CURATING VISUALLY GROUNDED TASKS

4.1 WEB ENVIRONMENTS

VisualWebArena is designed around three realistic web environments that involve visually rich content. Several tasks also require referencing information from a self-hosted Wikipedia knowledge base, and others involve interaction across more than one of these websites (Fig. 3).

Classifieds We introduce a new Classifieds website in VisualWebArena, inspired by real world marketplaces such as Craigslist and Facebook Marketplace. This new site provides a distinct environment compared to existing ones in WebArena, introducing visually grounded tasks centered around user interactions typical in online classifieds websites (posting, searching, commenting). The site’s infrastructure uses OSClass,⁴ a robust open-source Content Management System (CMS) designed for classifieds websites, used in multiple real world sites. OSClass enables us to simulate functions such as search, posting new listings, commenting, and leaving reviews and ratings. The site contains 65,955 listings, each consisting of a title, a description, and a product image.

Shopping The Shopping site follows the e-commerce environment from WebArena (Zhou et al., 2024), with product information and content scraped from Amazon and released in WebShop (Yao et al., 2022). Visual understanding of product images is required for successfully navigating and completing tasks on e-commerce platforms, making this a natural choice for VisualWebArena. Most products on the site include at least one image, and the platform covers a diverse range of products.

⁴<https://osclass-classifieds.com/>

Reddit The Reddit site also follows the same environment from WebArena, and represents a social forum platform. The site contains 31,464 posts containing a diverse set of images across different subreddits and forums, such as natural images, memes, consumer electronics, and charts. The inclusion of the Reddit environment allows us to create a comprehensive benchmark that evaluates an agent’s ability to understand and operate with different types of visual information.

4.2 TASKS

We introduce a set of 910 new tasks, split across the three sites detailed earlier (Fig. 3). These tasks necessitate visual comprehension, and are designed to assess the visual and reasoning skills of autonomous agents in web-based environments.

Task Creation We focus on curating realistic visually grounded tasks, following a similar process as task creation in WebArena. We start by curating *intent templates* (e.g., “Find me the {{attribute}} {{item}}. It should be between {{range}}.”), which can be manually expanded by the annotator with different arguments to form multiple tasks (e.g., “Find me the cheapest red Toyota. It should be between \$3000 to \$6000.”). The tasks were curated by 6 graduate students (co-authors of this paper). We encouraged annotators to be creative, and make use of the visual layouts of the websites, input images, and cross-site functionalities to develop creative and realistic tasks. When tasks involved input images, these were sourced from royalty-free, attribution-free sources, and MS-COCO (Lin et al., 2014). Annotators also wrote the reward functions using the primitives described in Sec. 3.3. We collected a total of 314 templates (average of 2.9 tasks per template).

While the majority of tasks can be solved, we also included a small subset (46 tasks, or 5.1%) which are unachievable. This subset tests the ability of agents to terminate early in the event where a task cannot be solved, which is essential in many real world scenarios.

Visually Grounded Tasks A key aspect of VisualWebArena is the inherent visual grounding of all tasks. Each task demands visual understanding, requiring agents to process and interpret visual information rather than relying solely on textual or HTML-based cues. This aligns closely with modern human-computer interfaces, where visual information (e.g., icons, colors) is often critical. For instance, a typical task might involve selecting a visually specific item, such as a “green polo shirt” where the color is visually discernible but not explicitly mentioned in text.

Task Complexity We classify each task into three difficulty levels: **easy**, **medium**, and **hard**. This classification is particularly useful for assessing performance across a spectrum of agents, ranging from smaller models to state-of-the-art LLMs and VLMs. We find in our analysis (Sec. 5) that many open-source models (e.g., LLaMA-2-70B, IDEFICS-80B) achieve a success rate of close to 0 on medium or hard tasks, but non-zero performance on easy tasks. This suggests that running open-source models on the easy subset would provide useful signal during development as well as faster iteration cycles (assuming performance between weaker and stronger agents are correlated).

We annotate both the *action* and *visual* difficulty of each task (breakdown in Fig. 4). The action difficulty is determined by the estimated number of actions that a human would need to complete the task. **Easy** tasks are defined as those that require three or fewer actions, **Medium** tasks involve four to nine actions, and **Hard** tasks demand ten or more.

Visual difficulty is similarly segmented, with each difficulty level reflecting the complexity of visual processing required: **Easy** tasks involve basic visual identification such as colors, shapes, and high-level object detection (e.g., recognizing the existence of a cat). **Medium** tasks require discerning patterns, semantic understanding, and OCR on text of shorter lengths or large fonts. **Hard** tasks involve multiple image inputs, OCR on small or lengthy text, or detection of fine details.

4.3 HUMAN PERFORMANCE

We measure the success rate of 7 college students (who are familiar with commercial versions of the sites) on VisualWebArena tasks. Several of these students also assisted with task creation, and to avoid data leakage, we ensured that they were not assigned to the same tasks that they initially created. We sample one task per template, collecting a representative set of 230 tasks. We find that humans do well at this task, achieving an overall success rate of 88.7% (Tab. 3). The mistakes made

in the remaining 11.3% of tasks are usually minor, such as not reading the task correctly or missing a part of the objective. Another common failure mode was for tasks that required exhaustive search (e.g., ‘‘Navigate to the comments section of this exact image.’’). Users were often unable to find the appropriate post after searching for 5-10 mins and gave up, assuming that the task was unachievable. These types of laborious tasks represent problems that strong computer agents would be well poised to solve, possibly achieving above human performance (and speed).

5 BASELINES

We run several baselines on VisualWebArena to benchmark the performance of state-of-the-art LLM and VLM agents. We use a webpage viewport size of 1280×2048 , and truncate text observations to 3840 tokens (or 15360 characters for Gemini). For models with shorter context windows (e.g., LLaMA, IDEFICS, CogVLM), we instead use a viewport size of 1280×720 and truncate text observations to 640 tokens. For GPT-3.5 and GPT-4 models, we follow Zhou et al. (2024) in using a temperature of 1.0 and a top-p of 0.9. For Gemini models we use the suggested default temperature of 0.9 and top-p of 1.0. For the remaining models, we find that they benefit from sampling from lower temperatures, and use a temperature of 0.6 and top-p of 0.95. Nucleus sampling (Holtzman et al., 2020) is used in all experiments. All models are prompt-based and provided with 3 in-context examples (one from each environment), which share no overlap with the benchmark tasks. The prompts we use are provided in the appendix. We summarize the results in Tab. 3 and describe the baselines in detail in the following sections.

5.1 TEXT-BASED LLM AGENTS

Several prior works have developed strong autonomous agents through prompting text-only LLMs (Zhou et al., 2024; Kim et al., 2023; Liu et al., 2023d). We run several text-based LLM agents on the accessibility tree representations of the websites, by prompting them with Chain-of-Thought prompting (Wei et al., 2022), similar to Zhou et al. (2024). We leave more advanced prompting strategies for future work. Our baselines include several API-based LLM models, including GPT-4 Turbo (gpt-4-1106-preview), GPT-3.5 Turbo (gpt-3.5-turbo-1106), Gemini-Pro, as well as open sourced LLMs such as LLaMA-2-70B and Mixtral-8x7B.

5.2 IMAGE CAPTION AUGMENTED LLM AGENTS

VisualWebArena is a visually grounded benchmark, and we expect that leveraging complementary visual information would improve performance. Hence, we run pretrained image captioning models on every `img` element on the HTML page, and augment the accessibility tree with this information as the image alt-text before passing this as input to the LLM agents. If a task contains input images, we also caption them and include the captions as part of the prompt. We run experiments on GPT-3.5 with two recent image captioning models, BLIP-2-T5XL (Li et al., 2023) and LLaVA-v1.5-7B (Liu et al., 2023a). Our results with GPT-3.5 as the LLM backbone (“Caption-augmented” section of Tab. 3) suggest that the LLaVA and BLIP-2 captioning models achieve comparable performance. Since BLIP-2 achieves a slightly higher success rate, is a smaller model, and requires less GPU VRAM, we use it as the captioning backbone for the remaining experiments.

5.3 MULTIMODAL AGENTS

Finally, we benchmark the capabilities of strong closed-source and open-source vision language models. Unlike the previous text-based models, these multimodal models are trained on large datasets of paired text and images, allowing them to learn joint representations between vision and language. We evaluate several models capable of processing multiple interleaved image-and-text inputs: GPT-4V (OpenAI, 2023), Gemini-Pro (Google, 2023), IDEFICS-80B-Instruct⁵ (an open-source reproduction of Flamingo (Alayrac et al., 2022)), and CogVLM (Wang et al., 2023b). We experiment with two different input formats for these models:

⁵<https://huggingface.co/HuggingFaceM4/idefics-80b-instruct>

Model Type	LLM Backbone	Visual Backbone	Inputs	Success Rate (\uparrow)			
				Classifieds	Reddit	Shopping	Overall
Text-only	LLaMA-2-70B Mixtral-8x7B Gemini-Pro GPT-3.5 GPT-4	-	Acc. Tree	0.43%	1.43%	1.29%	1.10%
				1.71%	2.86%	1.29%	1.76%
				0.85%	0.95%	3.43%	2.20%
				0.43%	0.95%	3.65%	2.20%
				5.56%	4.76%	9.23%	7.25%
Caption-augmented	LLaMA-2-70B Mixtral-8x7B GPT-3.5 GPT-3.5 Gemini-Pro GPT-4	BLIP-2-T5XL BLIP-2-T5XL LLaVA-7B BLIP-2-T5XL BLIP-2-T5XL BLIP-2-T5XL	Acc. Tree + Caps	0.00%	0.95%	0.86%	0.66%
				1.28%	0.48%	2.79%	1.87%
				1.28%	1.43%	4.08%	2.75%
				0.85%	1.43%	4.72%	2.97%
				1.71%	1.43%	6.01%	3.85%
Multimodal	IDEFICS-80B-Instruct CogVLM Gemini-Pro GPT-4V	Image + Caps + Acc. Tree	Image + Caps + Acc. Tree	8.55%	8.57%	16.74%	12.75%
				0.43%	0.95%	0.86%	0.77%
				0.00%	0.48%	0.43%	0.33%
				3.42%	4.29%	8.15%	6.04%
Multimodal (SoM)	IDEFICS-80B-Instruct CogVLM Gemini-Pro GPT-4V	Image + Caps + SoM	Image + Caps + SoM	8.12%	12.38%	19.74%	15.05%
				0.85%	0.95%	1.07%	0.99%
				0.00%	0.48%	0.43%	0.33%
				3.42%	3.81%	7.73%	5.71%
Human Performance	-	-	Webpage	9.83%	17.14%	19.31%	16.37%
				91.07%	87.10%	88.39%	88.70%

Table 3: Success rates of baseline LLM and VLM agents on VisualWebArena.

Image Screenshot + Captions + Accessibility Tree: This approach provides the accessibility tree representation augmented with image captions as accessibility tree alt-text from BLIP-2-T5XL (similar to the caption-augmented agent), as well as the screenshot of the current webpage as inputs.

Image Screenshot + Captions + SoM: Inspired by Set-of-Marks prompting Yang et al. (2023a), we perform an initial preprocessing step by using JavaScript to automatically annotate every interactive element on the webpage with a bounding box and a unique ID. The annotated screenshot containing bounding boxes and IDs, are provided as input to the multimodal model along with a text representation of the SoM (see Fig. 2). Similar to the baselines above, we also provide the captions from BLIP-2-T5XL for all img elements on the page. There have been several projects⁶ that propose similar representations. Most have been proof-of-concept demos, and to the best of our knowledge, we are the first to systematically benchmark this on a realistic and interactive web environment.

5.4 RESULTS

Our main baseline results are summarized in Tab. 3. All existing models significantly underperform compared to humans, which indicate significant headroom in VisualWebArena for future work. We discuss some main findings below, with more detailed analysis in Sec. 6.

Text-based LLMs Perform Poorly State-of-the-art text-only LLMs generally achieve poor results, with the best model (GPT-4) achieving an overall success rate of 7.25%. When we augment the LLMs with caption information, this considerably improves success rate, from 7.25% to 12.75% for GPT-4. Other models also see a similar boost in success rate when provided caption information.

Multimodality Helps We achieve a substantial improvement in success rate when we use multimodal agents: GPT-4V (gpt-4-1106-vision-preview) achieves an overall success rate of 15.05%, substantially improving over the text-only GPT-4 model. Gemini-Pro also experiences a significant uplift in success rate, improving from 3.85% (caption-augmented) to 6.04% (multimodal). Text-only or caption-augmented models may be limited in their ability to process complex images (e.g., those that require OCR or recognition of non-salient objects), thus falling behind multimodal models.

SoM Improves Navigability We observe that the SoM representation (Sec. 5.3) further improves the performance of GPT-4V over using the accessibility tree observation and action space, boosting overall success rate (15.05% \rightarrow 16.37%). We observe particularly substantial improvements compared to the accessibility tree GPT-4V model on Classifieds and Reddit, from 12.38% \rightarrow 17.14%

⁶For example, GPT-4V-ACT and vimGPT propose similar interfaces.

Visual Difficulty (v)				
a \ v	Easy	Medium	Hard	Overall
Easy	18.9%	11.1%	10.5%	14.8%
Medium	1.6%	6.1%	7.8%	4.7%
hard	1.6%	4.2%	1.5%	2.4%
Overall	9.0%	7.3%	4.8%	7.3%

(a) Success rate of GPT-4 Text-only				
a \ v	Easy	Medium	Hard	Overall
Easy	23.1%	18.8%	13.2%	20.1%
Medium	14.4%	9.6%	5.2%	10.4%
Hard	7.8%	7.3%	8.1%	7.8%
Overall	16.9%	12.2%	8.0%	12.7%

(c) Success rate of GPT-4V + SoM				
a \ v	Easy	Medium	Hard	Overall
Easy	30.1%	20.5%	26.3%	25.8%
Medium	15.2%	11.3%	11.7%	12.9%
hard	14.1%	10.4%	8.9%	10.5%
Overall	21.4%	14.3%	12.4%	16.4%

(b) Success rate of GPT-4 + Captions				
a \ v	Easy	Medium	Hard	Overall
Easy	6.0	7.7	6.1	6.9
Medium	10.4	10.6	7.2	10.0
Hard	14.1	9.2	12.5	12.1
Overall	9.5	9.4	10.2	9.6

(d) Trajectory length of GPT-4V + SoM				
a \ v	Easy	Medium	Hard	Overall
Easy	6.0	7.7	6.1	6.9
Medium	10.4	10.6	7.2	10.0
Hard	14.1	9.2	12.5	12.1
Overall	9.5	9.4	10.2	9.6

Figure 5: Success rates (a, b, c) and trajectory lengths (d) across different difficulty levels.

and 8.12% → 9.83% respectively. We attribute this to the Classifieds and Reddit websites containing more dense visual content. For example, these websites often contain many smaller sized images that are arranged very closely (Fig. 2). In many of these cases, the accessibility tree does not always provide sufficient information to disentangle elements that are spatially close. We hypothesize that the SoM representation is superior in these cases, as a strong VLM model is able to more accurately disentangle and click on the desired content. For the other VLMs, SoM does not significantly improve success rates, which we attribute to the finding from Yang et al. (2023a) that only GPT-4V demonstrates this emergent grounding ability (perhaps due to scale or training data). This motivates future work in imbuing VLM agents with similar abilities.

6 ANALYSIS

6.1 PERFORMANCE BY TASK DIFFICULTY

We conduct an analysis of the GPT-4 models across different action and visual difficulty levels (Fig. 5). We observe that success rate generally decreases as action/vision difficulty increases, which makes intuitive sense based on the difficulty taxonomy described in Sec. 4.2. The findings also show that multimodal models perform better especially on hard visual tasks. On this subset, GPT-4V + SoM achieves an average success rate of 12.4%, which is significantly higher than that of the caption-augmented (8.0%) and the text-only agents (4.8%).

In addition to success rates, we also observed that the GPT-4V trajectory lengths increased with action difficulty, with harder tasks requiring more steps to complete.

6.2 PERFORMANCE BY TASK TYPE

We also analyze the success rate of the best VLM agent baseline (GPT-4V with SoM prompting) across several additional subsets of tasks. The results are summarized in Tab. 4 and discussed in the following paragraphs, with further analysis for other models provided in the appendix.

OCR Tasks 17.1% of VisualWebArena require optical character recognition (OCR), such as reading text from product images, or extracting text from an input image. We find that GPT-4V + SoM generally performs worse on tasks that require OCR (success rate of 13.4%) compared to tasks which do not (success rate of 16.9%), suggesting that OCR capabilities may be a bottleneck for completing certain tasks.

Exact Image Match 8.7% of tasks require exact image matching, which evaluates visual capabilities beyond semantic image recognition, and requires agents to identify precise visual matches. GPT-4V + SoM achieves a slightly improved success rate (18.9%) compared to tasks that do not require exact match (16.2%), suggesting that exact image matching is not a hurdle for the model.

Task Subset	% of Total	SR (\uparrow)
OCR required	17.1%	13.4%
No OCR required	82.9%	16.9%
Exact image match	8.7%	18.9%
No exact image match	91.3%	16.2%
Image inputs	25.2%	19.0%
No image inputs	74.8%	14.9%

Table 4: Success rate (SR) of GPT-4V (SoM) across different types of tasks.

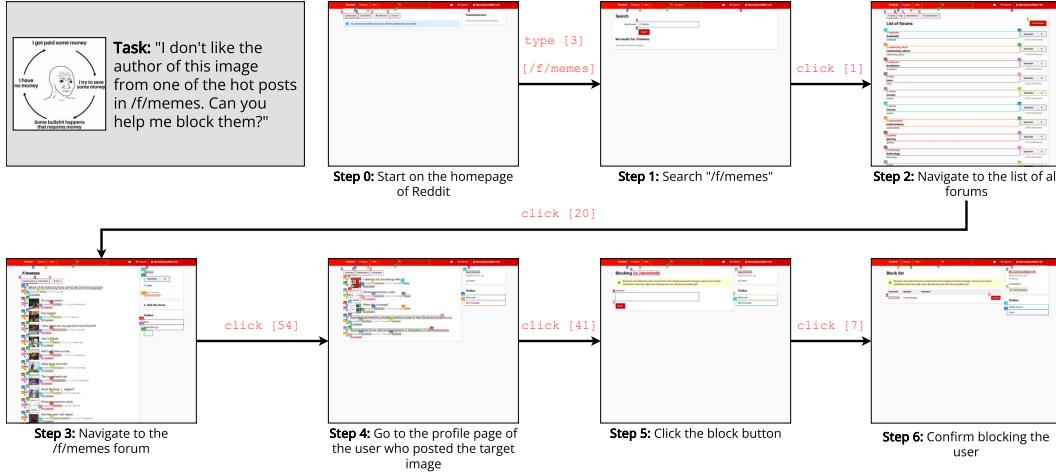


Figure 6: Successful execution trajectory of the GPT-4V + SoM agent on the task for blocking a user that posted a certain picture. The text in red represents the commands output by the agent.

Image Input Tasks 25.2% of VisualWebArena include one or more input images as part of the objective. These tasks generally appear more tractable for the GPT-4V + SoM agent, and it achieves a higher success rate (19.0%) compared to tasks without image inputs (14.9%).

6.3 QUALITATIVE RESULTS

Successful Execution We observed that the GPT-4V + SoM agent is able to complete several complex tasks efficiently. One example that we found particularly compelling was task 139 for Reddit, which requires exact image matching to find a post and block a user (Fig. 6). The model initially attempts to search for the correct forum, and when this fails it navigates to the list of forums. After navigating correctly to /f/memes, it identifies the offending image out of the many images on the page (Step 3 in Fig. 6) and blocks the author efficiently without any unnecessary actions.

Failure Modes We observed that in several examples, the agents would correctly perform a task but undo it, leading to failure. The GPT-4 captioning-only model on shopping task 54 (“Add the one [poster] with waves to my wish list.”) made an assumption that the product image with a caption about a lighthouse was the correct one, and added it to the wishlist. However, after going to the wish list page the agent removes the poster because “there is no explicit mention of waves in the current items listed on the Wish List page.” This issue is not unique to the text input agents; even the GPT-4 SoM agent faced a similar problem in shopping task 397 (“Buy the item on the page with a banana theme.”). The agent initially added the correct item to the shopping cart and proceeded to check out, but stopped in the middle stating in the reasoning trace output that it does not think the item fit the criteria (despite having added it to the cart just a few steps ago).

Failures on Easy Tasks We observed surprisingly poor performance on many tasks with easy action and easy visual difficulty levels, such as in shopping task 46, which tasks the agent to add the red product in the second row to the cart (starting on the page shown in Fig. 7). The multimodal and SoM GPT-4V agents clicked on a blue tablecloth in the first row and gave up when they couldn’t find an option to order it in red. Despite appearing to be a simple task (the correct product is the red cloth in the second row), none of the agents we benchmarked were able to successfully complete it.

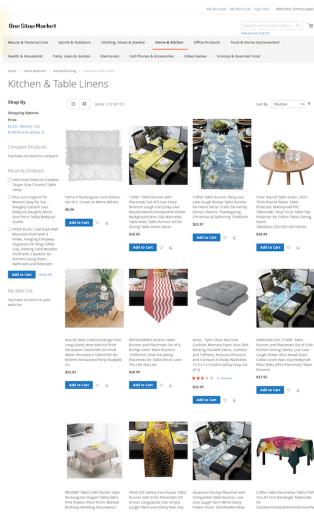


Figure 7: The starting page for the task “Add the red one in the second row of this page to my shopping cart.”

Spatial Reasoning Both the multimodal and SoM agents outperform the caption and text-only agents on tasks that require spatial reasoning. For shopping task 81 (“What is the price range for products in the first row.”), the caption-augmented GPT-4 model makes an assumption that there are three items to a row and provides the price range incorrectly. However, there are actually four products in each row, which the multimodal and SoM GPT-4V agents both correctly identify to succeed at this task.

SoM Benefits Longer Action Sequences The SoM representation generally performs better on tasks that require more navigation steps. For example, classifieds task 31 asks the agent to “Find the latest listing of a white Google Pixel phone and post a comment offering \$10 less than their asking price.” While the multimodal model was unable to search for the correct terms, the SoM model was able to leverage the simplified action space to traverse more efficiently throughout the environment. It succeeded at this task by filtering for cell phones after the initial search for more relevant results, and managed to fill out the necessary comment form fields. We believe that the SoM representation is superior to the multimodal representation (which only has access to the page screenshot and accessibility tree). With SoM, the agent does not have to implicitly perform visual co-referencing to match elements from the accessibility tree to the visual buttons and inputs that it wants to interact with.

7 CONCLUSION

In this work, we introduced VisualWebArena, a benchmark of realistic tasks designed to rigorously evaluate and advance the capabilities of autonomous multimodal web agents. VisualWebArena represents a significant step towards addressing the gap in the evaluation of multimodal agents on visually grounded tasks. We also introduce a visual agent inspired by Set-of-Marks prompting, and demonstrate the potential of this approach for simplifying action spaces and improving performance on visually complex websites. Our extensive evaluation of state-of-the-art LLM and VLM agents demonstrate that while VLMs show promise, there remains a considerable performance gap compared to humans, who achieve very high success rates on VisualWebArena. Our quantitative and qualitative analysis also highlights several common failure modes of existing LLM and VLM agents. We expect future work on improving the reasoning, visual understanding, and planning abilities of agents to be particularly exciting and promising areas.

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APPENDIX

We provide further analysis on model failure modes for Gemini and GPT-4 (Sec. A), more details on the new Classifieds environment (Sec. B), and on the task collection process (Sec. C).

A FURTHER ANALYSIS

A.1 FEW-SHOT PROMPTING

# Examples	Success Rate (\uparrow)			
	Classifieds	Reddit	Shopping	Overall
0	4.29%	2.38%	0.43%	2.86%
1	5.36%	1.43%	2.14%	3.63%
3	8.15%	4.29%	3.42%	6.04%

Table 5: Performance with different number of in-context examples.

In most of our main experimental results, we prompt the model with 3 in-context examples. We perform an analysis of the success rate against the number of in-context examples provided (Tab. 5). For 1-shot experiments, we provide the model with the single in-context example from its corresponding environment. All experiments are run with the multimodal Gemini-Pro model (as GPT-4V is prohibitively expensive) with the Image + Caption + Acc. Tree as the observation space.

We observe that overall success rate tends to increase with the number of examples provided, with a significant jump from 1 to 3 in-context examples. The improved results with a greater number of examples suggest that the performance of the VLM agents may improve significantly if we fine-tune the models on web trajectories, which will be an exciting direction for future work.

A.2 TASKS ANALYSIS

In this section, we provide more fine-grained analysis across different task subsets, similar to the one in Sec. 6.2 of the main paper. We examine both the GPT-4 text and multimodal agents, as well as the Gemini-Pro agents. This analysis may provide useful insights towards capabilities that future VLM models should have to perform well on web navigation tasks (specifically, OCR, exact image matching, and handling multiple interleaved image and text inputs).

OCR Tasks On OCR tasks, which take up 17.1% of the benchmark, we observe that the GPT-4 family of models achieve a lower success rate on tasks that require OCR compared to tasks that do not (Fig. 8). This is consistent with the findings for GPT-4V + SoM reported in Sec. 6.2 of the main paper. We also observe that introducing multimodality (over just captions) substantially improves performance on OCR tasks (from 6.4% to 12.2%), showcasing the importance of having multimodal models for text recognition capabilities, as captioning models generally do not capture such finegrained information.

For Gemini-Pro agents, we also observe similar trends, with the multimodal and SoM models achieving a higher than proportionate gain on the OCR subset (compared to the non-OCR subset). Interestingly, the multimodal Gemini-Pro agents achieve a higher success rate on tasks that require OCR compared to tasks that do not. These results may suggest that it has strong inherent OCR capabilities, which we believe will be useful to explore in future work (especially on the stronger Gemini-Ultra model once it is generally available).

Exact Image Match Of the tasks in VisualWebArena, 8.7% require exact image matching, which tests the ability of agents to identify images that have the exact same content (in contrast to those that are just semantically similar). From Fig. 9, we observe that the GPT-4V SoM model achieves a higher success rate on tasks that expect exact image match, while the other GPT-4 agents achieve a relatively lower success rate on the exact match subset. This suggests that the SoM representation may be more optimal for exact image match, due to its visual-centric observation and action space.

For the Gemini models, we observe that success rates on exact match tasks are substantially lower than success rates on non-exact match tasks. Interestingly, we also observe a similar trend as the

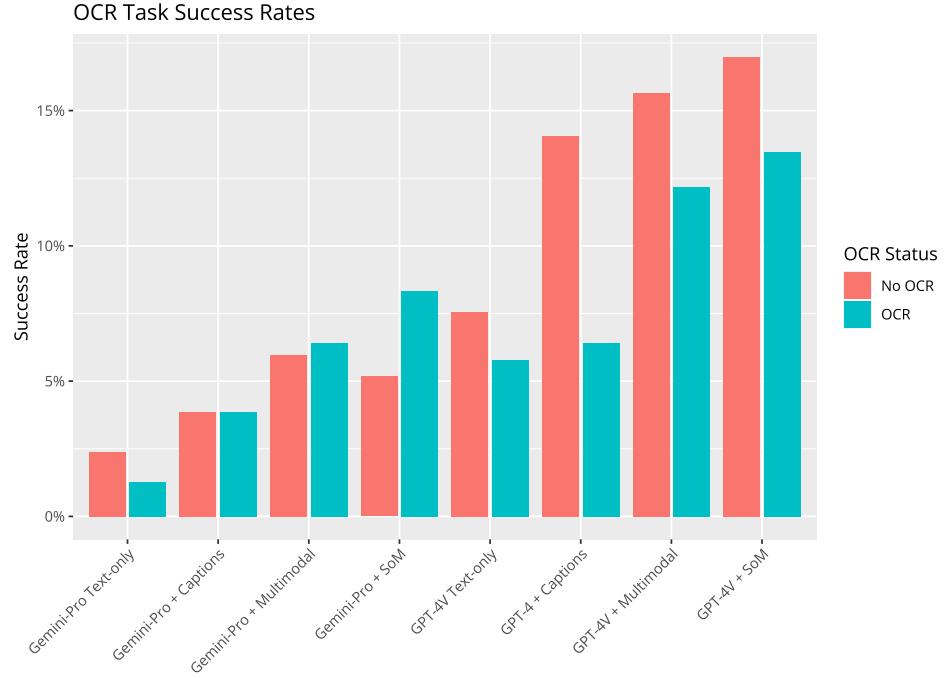


Figure 8: Success rate of GPT-4 and Gemini agents on tasks that do not require OCR vs. tasks that do.

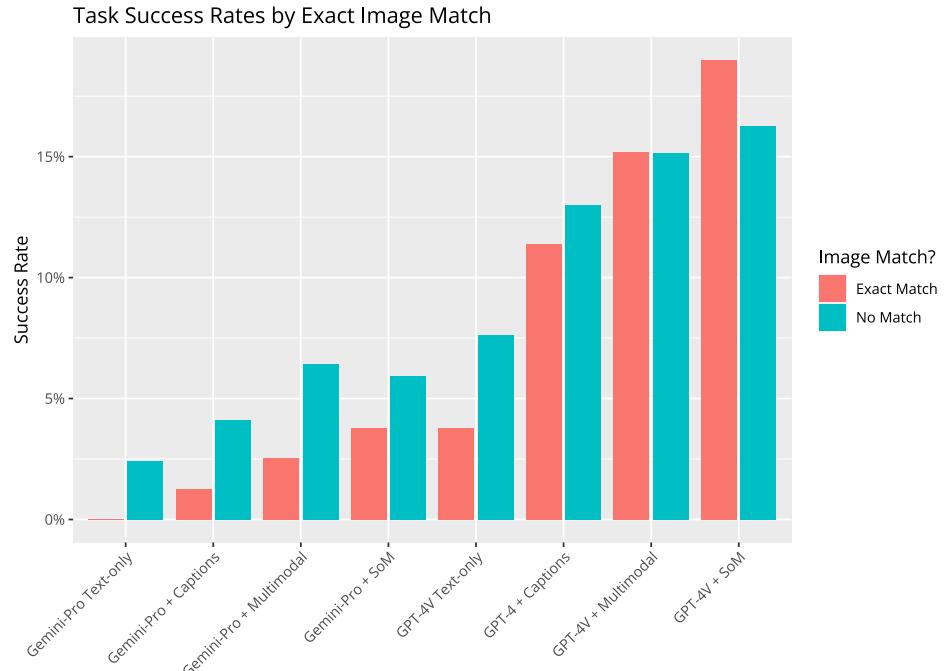


Figure 9: Success rates of agents on tasks that require exact image match vs. those that do not.

GPT-4 agents, where introducing multimodality improves success rates on exact match tasks, which is further bolstered with the SoM representation.

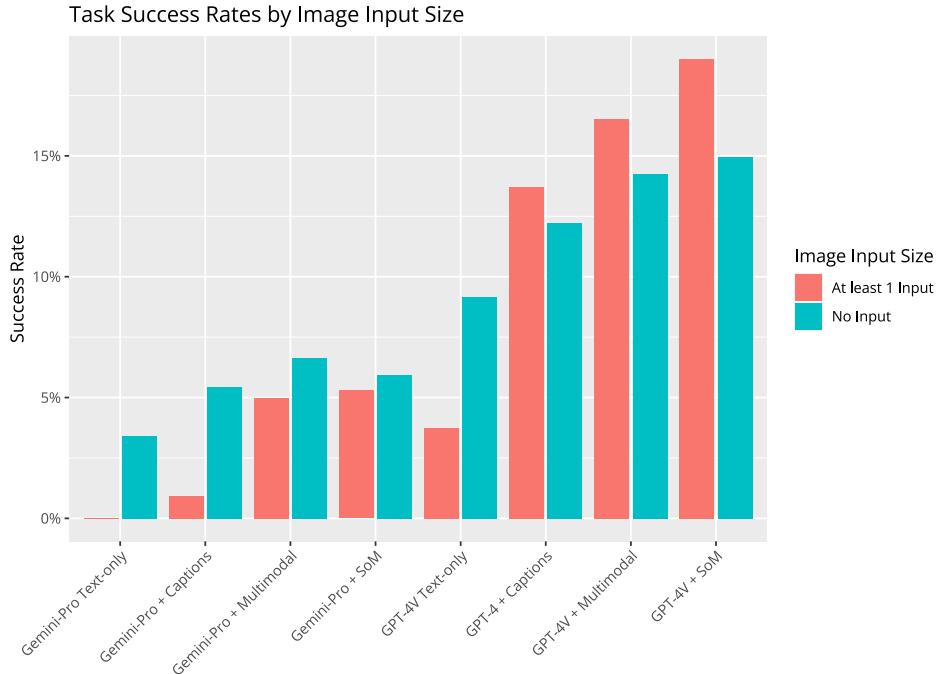


Figure 10: Success rates of agents on tasks that include input images as part of the specification vs. tasks that are specified with just written text.

Image Input Tasks 25.2% (229 tasks) in VisualWebArena are specified with image inputs (e.g., the task in Fig. 6, and the first and third tasks in Fig. 1). The results of the Gemini-Pro and GPT-4 agents are summarized in Fig. 10.

We observe that for the GPT-4 agent, success rates are generally higher on tasks that involve image inputs, with the exception of the text-only agent. This aligns with intuition, as agents that do not have access to visual information would not be able to understand the task correctly, and would perform worse at successfully accomplishing it. For the captioning, multimodal, and SoM GPT-4 agents, success rates are higher on the tasks involving image input, which we attribute to these tasks being more tractable once the visual content is correctly understood.

Interestingly, we see a contrast with the Gemini-Pro agents, where success rate is generally lower on tasks that involve input images. This may imply that the model may not be able to process multiple interleaved image-text inputs as well. This may be useful to revisit in the future with the stronger Gemini-Ultra model once it is released, or with stronger open sourced VLMs. We believe that being able to handle interleaved multimodal inputs will be a core requirement for strong web agents, and more comprehensive error analysis with stronger models may yield useful insights.

Trajectory Lengths vs. Success Rates Hard reasoning tasks, on average, require more steps to be successfully solved. We plot the trajectory length of the GPT-4V + SoM model in Fig. 11. The findings suggest that the model assumes a significant portion of tasks can be completed in a few steps, as it terminates a majority of tasks after less than 10 steps. However, this assumption doesn't imply that the model successfully solves the majority of tasks: the error rate remains relatively uniform across longer trajectory lengths.

A.3 OTHER FAILURE MODES

We described some failure modes in Sec. 6 of the main paper. In this section, we describe other common issues we observed.

Giving Up Too Early Another frequent issue we observed that occurred across all the agents was giving up too early. For example, GPT-4V + SoM fails on shopping task 248 (“Order a 6 pack of

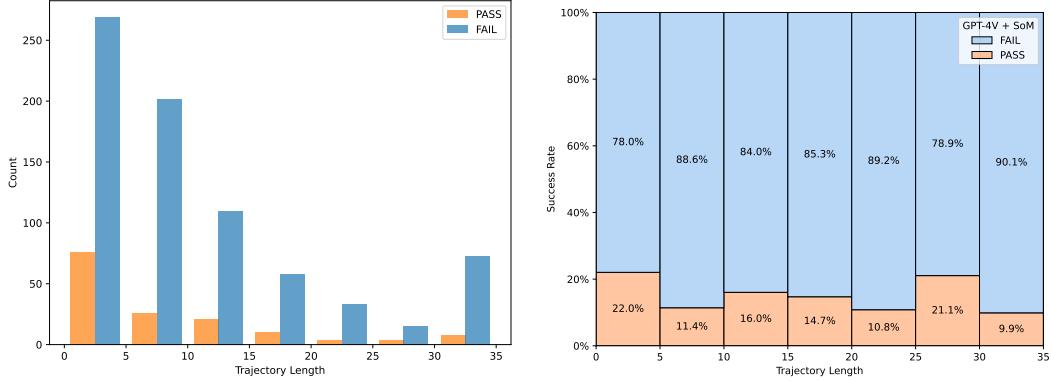


Figure 11: Performance of the GPT-4V + SoM agent across different trajectory lengths.

the green chocolate bars. If the shipping is more than 7% of the total price, leave a 3 star review mentioning it, otherwise 5.”). This task involves several steps which the model is able to correctly plan out, but the very first action needed is to slightly scroll down so the “add to cart” button is visible. However, even after identifying the correct product the model gives up on the first step instead of scrolling, because it does not immediately see the button. There are other instances of this occurring, such as in shopping task 175, where an agent will use the search bar to search for something, and then immediately give up because it does not see the target product instead of trying new ways to find the product.

Getting Stuck in Loops Another issue we observed was oscillating or looping between pages, where the agent would look something up or navigate to a page, unsuccessfully attempt to perform the next action (such as adding it to the cart), and on failure it goes back and repeats from the beginning. An example of this is in classifieds task 205 where the model is tasked to compare two makeup palettes in two tabs, and the GPT-4V agent spends most of the time switching between the tabs. We believe that these issues will likely be alleviated by introducing more sophisticated tracking of past states and execution history, which is a promising direction for future work.

Example of a Failure Case: Changing Account Phone Number One particular task for On-eStopShop and Wikipedia showcased several points of failure that we saw throughout the execution traces for many agents. Fig. 12 contains the execution trace of GPT-4V for the task “Prepend the country code of South Korea to the phone number of my account profile.” Below is a breakdown of the three major mistakes in this execution.

- **Useless actions** In step 3 of the trajectory, the agent creates a new blank tab and does not interact with it for the rest of the trajectory. While this does not impact the correctness of the final task, it does show that the agents sometimes take unnecessary steps.
- **Appending text instead of replacing** Many agents added text to input fields without deleting the previous text, which would often result in long, repeating search queries or addresses. An example of this occurs in step 7 of Fig. 12.
- **Repeating actions** Another frequent issue we saw across agents was repeating actions, like how the agent kept jumping between step 6 and step 7 of Fig. 12 until it hit the maximum trajectory length. In this case, we believe this looping effect stems from the issue mentioned above and each time the agent tries to correct the phone number, it keeps appending the correct number instead of replacing the incorrect number with the correct number.

B THE CLASSIFIEDS ENVIRONMENT

The Classifieds environment contains 65,955 listings, each with a title, text description, and a product image of the item being sold. To populate the site with realistic content, we scraped data across a variety of categories on Craigslist over 3 weeks, focusing on the Northeastern States of the US (similar to the geographic region in the Reddit site). This approach ensured a diverse and rich dataset,

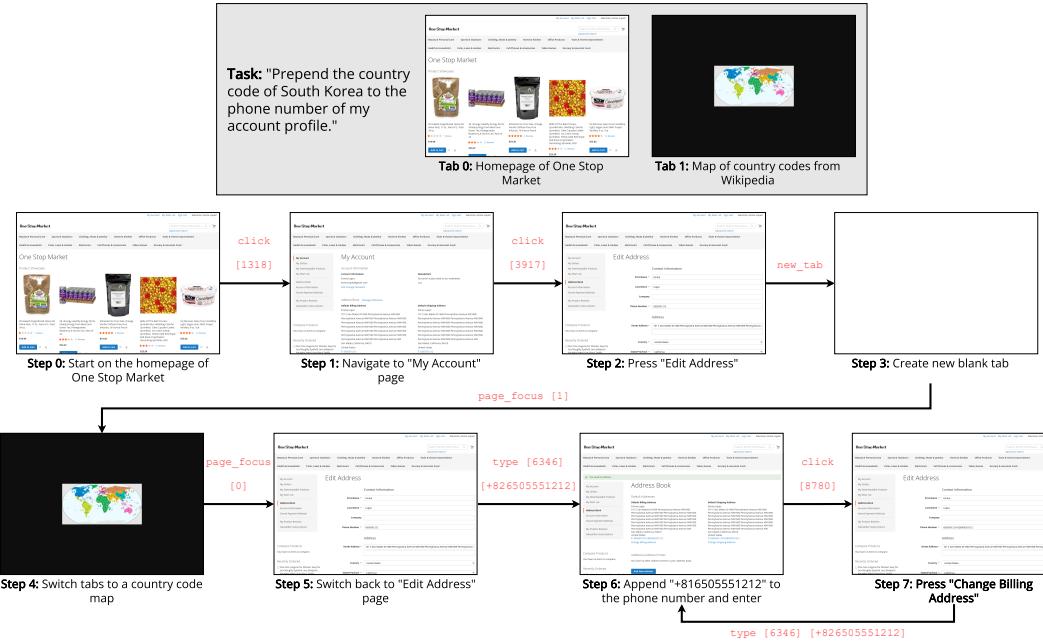


Figure 12: Unsuccessful execution trajectory of the GPT-4V agent on the task for adding the a country code to the user’s phone number. The text in red represents the commands output by the agent.

representative of real-world classifieds posts. We utilized the `scrubadub` Python package for redacting Personally Identifiable Information (PII), including addresses, phone numbers, and emails. We use generated placeholders for names (e.g., “Bill Smith”), emails with fictitious addresses (e.g., `bill_smith@example.com`), and phone numbers with the fictional 555-prefix numbers.

Fig. 13 and 14 show two pages within the Classifieds site, the homepage and the detail page of a particular listing. Users can also use the search function, or filter posts by category or location to find items.

C TASK COLLECTION PROCESS

Our main task collection process is described in Sec. 4.2. We collected the set of 910 tasks by recruiting 6 computer science graduate students (co-authors of this paper), who were all familiar with commercial versions of the Classifieds, Shopping, and Reddit sites, and have used them in their personal lives.

Annotators were first instructed to spend some time exploring the VisualWebArena websites, to familiarize themselves with their functionality and content (as this may differ slightly from real world implementations). During task creation, we encouraged annotators to be creative, and make use of the visual layouts of the websites, input images, and cross-site functionalities to develop creative and realistic tasks. We ensured that there were no repeated tasks, and that there were not too many tasks of the same type (by first producing templates, followed by instantiating them with different arguments to create multiple tasks, as described in Sec. 4.2).

D AGENT PROMPTS

We share the system message (Fig. 15) and the prompt with in-context examples (Fig. 16) for the baseline SoM agents. We prompt the model with 3 in-context examples for all baselines. For multimodal and SoM models, we include the screenshot of each in-context example as well as the screenshot of the current page. For text-only and caption augmented models, the examples consist of just the text and captions.

 OsClass
[My account](#)
[Logout](#)
[Publish Ad](#)

What are you looking for today?

Keyword

Category

[!\[\]\(1c230ae3e1bfef740ede90dde75d6544_img.jpg\) Search](#)

Latest Listings



Nintendo Switch
270.00 \$



JBL Powered PA Speaker ...
150.00 \$



xbox series x / with extras
350.00 \$



Canon EF 100-400mm f/4....
1645.00 \$



Engagement Ring
2200.00 \$



1997 FORD AIRSTREAM ...
28995.00 \$



Complete Guitar Rig Full S...
900.00 \$



Tennis bracelet
2000.00 \$



2021 Martin GPC 16e Ros...
1395.00 \$



KAIYO.COM | 646-844-8585
Century Furniture English ...
605.00 \$



2 Zebra Pillows
6.00 \$



KAIYO.COM | 646-844-8585
Highland House Furniture ...
220.00 \$

All categories

 Antiques	 Appliances	 Arts + crafts	 Auto parts	 Beauty + health
 Bikes	 Boats	 Books	 Cars + trucks	 Cell phones
 Items	 Furniture	 Electronics	 Power	 Plants

All locations

-  Virginia (31126)
-  Pennsylvania (22176)
-  Maryland (21674)
-  Ohio (5626)
-  Washington, D.C. (1567)
-  West Virginia (1109)
-  Delaware (870)
-  Alabama (1)

Figure 13: Homepage of the Classifieds site. Users can search for keywords, filter by category, or post location.

OsClass

My account Logout Publish Ad

Classifieds > Video gaming > Nintendo Switch

Nintendo Switch

Published date: 2024/01/03
Location: Adamsville, Alabama, United States

[Edit item](#)



Selling nintendo switch for \$270.

[Contact seller](#) [Share](#)

Contact publisher



Name: [Blake Sullivan](#) (online)

Useful information

- Avoid scams by acting locally or paying with PayPal
- Never pay with Western Union, Moneygram or other anonymous payment services
- Don't buy or sell outside of your country. Don't accept cashier cheques from outside your country
- This site is never involved in any transaction, and does not handle payments, shipping, guarantee transactions, provide escrow services, or offer "buyer protection" or "seller certification"

Related listings

 xbox series x / with ex... 350.00 \$	 gigabyte geforce rtx 4... 800.00 \$	 tom clancy R6 lockdo... 5.00 \$
--------------------------------------------------------------------------------------------------------------------------------	-------------------------------------------------------------------------------------------------------------------------------	---------------------------------------------------------------------------------------------------------------------------

Comments

Leave your comment (spam and offensive messages will be removed)

Rating 

Title

Comment

[Send](#)

Figure 14: Example post in the Classifieds website. Users can add comments and reviews to individual listings.

You are an autonomous intelligent agent tasked with navigating a web browser. You will be given web-based tasks. These tasks will be accomplished through the use of specific actions you can issue.

Here's the information you'll have:

The user's objective: This is the task you're trying to complete.

The current web page screenshot: This is a screenshot of the webpage, with each interactable element assigned a unique numerical id. Each bounding box and its respective id shares the same color.

The observation, which lists the IDs of all interactable elements on the current web page with their text content if any, in the format [id] [tagType] [text content]. tagType is the type of the element, such as button, link, or textbox. text content is the text content of the element. For example, [1234] [button] ['Add to Cart'] means that there is a button with id 1234 and text content 'Add to Cart' on the current web page. [] [StaticText] [text] means that the element is of some text that is not interactable.

The current web page's URL: This is the page you're currently navigating.

The open tabs: These are the tabs you have open.

The previous action: This is the action you just performed. It may be helpful to track your progress.

The actions you can perform fall into several categories:

Page Operation Actions:

```click [id]```: This action clicks on an element with a specific id on the webpage.

```type [id] [content]```: Use this to type the content into the field with id. By default, the "Enter" key is pressed after typing unless press\_enter\_after is set to 0, i.e., ```type [id] [content] [0]```.

```hover [id]```: Hover over an element with id.

```press [key\_comb]```: Simulates the pressing of a key combination on the keyboard (e.g., Ctrl+v).

```scroll [down]``` or ```scroll [up]```: Scroll the page up or down.

**Tab Management Actions:**

```new\_tab```: Open a new, empty browser tab.

```tab\_focus [tab\_index]```: Switch the browser's focus to a specific tab using its index.

```close\_tab```: Close the currently active tab.

URL Navigation Actions:

```goto [url]```: Navigate to a specific URL.

```go\_back```: Navigate to the previously viewed page.

```go\_forward```: Navigate to the next page (if a previous 'go\_back' action was performed).

**Completion Action:**

```stop [answer]```: Issue this action when you believe the task is complete. If the objective is to find a text-based answer, provide the answer in the bracket.

Homepage:

If you want to visit other websites, check out the homepage at <http://homepage.com>. It has a list of websites you can visit.

<http://homepage.com/password.html> lists all the account name and password for the websites. You can use them to log in to the websites.

To be successful, it is very important to follow the following rules:

1. You should only issue an action that is valid given the current observation
2. You should only issue one action at a time.
3. You should follow the examples to reason step by step and then issue the next action.
4. Generate the action in the correct format. Start with a "In summary, the next action I will perform is" phrase, followed by action inside ``````. For example, "In summary, the next action I will perform is ```click [1234]```".
5. Issue stop action when you think you have achieved the objective. Don't generate anything after stop.

Figure 15: System message used in our SoM agent.

example_user:
 IMAGES: (1) current page screenshot
 OBSERVATION:
 [31] [IMG] [Image, description: hp fx-7010dn fax machine, url: B08GKZ3ZKD.0.jpg]
 [32] [A] [HP CB782A#ABA 640 Inkjet Fax Machine (Renewed)]
 [] [StaticText] [\$279.49]
 [33] [BUTTON] [Add to Cart]
 [34] [A] [Add to Wish List]
 [35] [A] [Add to Compare]
 URL: <http://onestopmarket.com/office-products/office-electronics.html>
 OBJECTIVE: What is the price of HP Inkjet Fax Machine?
 PREVIOUS ACTION: None
example_assistant: Let's think step-by-step. This page lists the information of HP Inkjet Fax Machine, which is the product identified in the objective. Its price is \$279.49. I think I have achieved the objective. I will issue the stop action with the answer. In summary, the next action I will perform is 'stop [\$279.49]'

example_user:
 IMAGES: (1) current page screenshot
 OBSERVATION:
 [] [StaticText] [/f/food]
 [] [StaticText] [[homemade] Obligatory Halloween Pumpkin Loaf! Submitted by kneeChalice t3_yid9lu 1 year ago]
 [9] [IMG] []
 [] [StaticText] [Submitted by kneeChalice t3_yid9lu 1 year ago]
 [10] [A] [kneeChalice]
 [11] [A] [45 comments]
 [] [StaticText] [[I ate] Maple Pecan Croissant Submitted by AccordingtoJP t3_y3hrpn 1 year ago]
 [14] [IMG] []
 [] [StaticText] [Submitted by AccordingtoJP t3_y3hrpn 1 year ago]
 [15] [A] [AccordingtoJP]
 [16] [A] [204 comments]
 URL: <http://reddit.com>
 OBJECTIVE: Tell me what the top comment on the croissant post says.
 PREVIOUS ACTION: None
example_assistant: Let's think step-by-step. This page has a post titled '[I ate] Maple Pecan Croissant', which is the post mentioned in the objective. In order to find the top comment, I will navigate into the comments section of the post. In summary, the next action I will perform is 'click [11]'

example_user:
 IMAGES: (1) current page screenshot
 OBSERVATION:
 [] [StaticText] [What are you looking for today?]
 [5] [INPUT] []
 [6] [SELECT] [Select a category]
 [7] [BUTTON] [Search]
 [] [StaticText] [Latest Listings]
 [] [StaticText] [Atlas Powered Audio System w/ Tripod 150.00 \$ Music instruments Borough of Red Lion (Pennsylvania) 2023/11/16]
 [8] [IMG] [Atlas Powered Audio System w/ Tripod]
 [9] [A] [Atlas Powered Audio System w/ Tripod]
 [] [StaticText] [150.00 \$]
 [] [StaticText] [Neptune Gaming Console 350.00 \$ Video gaming Pennwyn (Pennsylvania) 2023/11/16]
 [10] [IMG] [Neptune Gaming Console]
 [11] [A] [Neptune Gaming Console]
 [] [StaticText] [350.00 \$]
 URL: <http://classifieds.com>
 OBJECTIVE: Help me find the cheapest dark colored guitar.
 PREVIOUS ACTION: None
example_assistant: Let's think step-by-step. The objective is to find the cheapest dark colored guitar on the site. The site has a search box whose ID is [5]. I can search for guitars by entering "guitar". I can submit this by pressing the Enter afterwards. In summary, the next action I will perform is 'type [5] [guitar] [1]'

Figure 16: In-context examples and prompt used for our SoM agents. The webpage screenshots with SoM are added to the end of each round of the **example_user** dialogue.