WebEvolver: Enhancing Web Agent Self-Improvement with Co-evolving World Model

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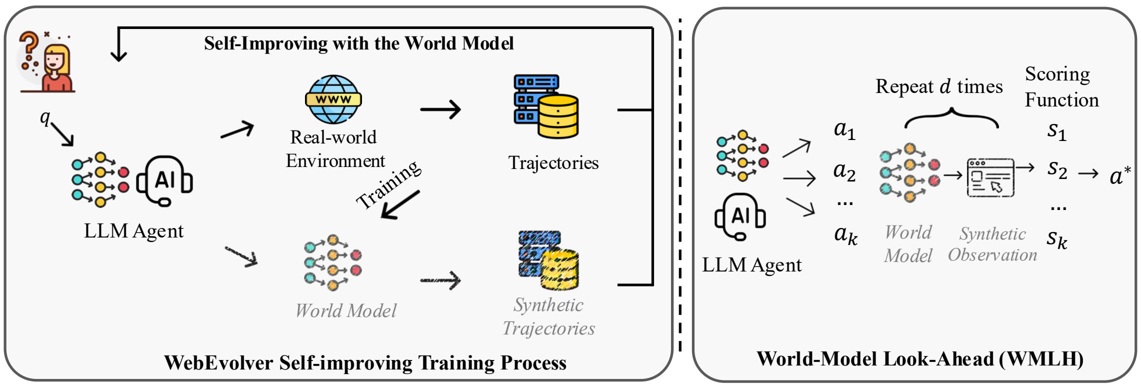

Figure 1: Overview of WebEvolver – A Self-Improving Framework with World-Model Look-Ahead. Our framework co-trains a world model alongside the agent by predicting next-step observations from current states and actions, using trajectory data collected during sampling. The world model then serves as a virtual web engine, enabling synthetic multi-step trajectories generation for training the policy. During inference, the world model performs look-ahead planning to help score and select optimal actions.

Abstract

Agent self-improvement, where the backbone Large Language Model (LLM) of the agent are trained on trajectories sampled autonomously based on their own policies, has emerged as a promising approach for enhancing performance. Recent advancements, particularly in web environments, face a critical limitation: their performance will reach a stagnation point during autonomous learning cycles, hindering further improvement. We argue that this stems from limited exploration of the web environment and insufficient exploitation of pre-trained web knowledge in LLMs. To improve the performance of self-improvement, we propose a novel framework that introduces a co-evolving World Model LLM. This world model predicts the next observation based on the current observation and action within the web environment. Leveraging LLMs' pretrained knowledge of abundant web content, the World Model serves dual roles: (1) as a virtual web server generating self-instructed training data to continuously refine the agent's policy, and (2) as an imagination engine during inference, enabling look-ahead simulation to guide action selection for the agent LLM. Experiments in real-world web environments (Mind2Web-Live, WebVoyager, and GAIA-web) show a 10% performance gain over existing self-evolving agents, demonstrating the efficacy and generalizability of our approach, without using any distillation from more powerful close-sourced models. Our work establishes the necessity of integrating world models into autonomous agent frameworks to unlock sustained adaptability.

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1 Introduction

Autonomous agents, especially Web agents operating in online environments, play a crucial role in automating complex tasks, advancing progress towards artificial general intelligence (OpenAI, 2025; Monica.Im, 2025; Qin et al., 2025; Liang et al., 2025). The capabilities of these agents stem from two key components, the design of the system, which facilitates accessing and processing abundant information from the web, and the agent foundation language model itself, which is typically a (Multimodal) Large Language Model (LLM) that generates actions based on the provide context.

Recent work in **agent self-improvement** focuses on refining these LLM-based agents through iterative cycles of autonomous interaction: the agent generates actions to interact with the environment, forming behavioral trajectories, and the backbone agent LLM is then fine-tuned on this self-collected data after rejection sampling (Yin et al., 2024; Murty et al., 2024; Patel et al., 2024; Aksitov et al., 2023; He et al., 2024b; Xi et al., 2024). Although this bootstrapping approach reduces the reliance on human-labeled trajectory data, it faces a critical limitation: performance eventually plateaus, preventing further improvement despite continued self-improvement (Zeng et al., 2024).

This stagnation stems from two critical bottlenecks. First, the agent's exploration diversity diminishes over time, as its policy becomes too specialized to familiar trajectories, failing to discover novel states or actions (He et al., 2024b). Second, despite the existence of inference-time exploration algorithms, such as variations of searching algorithms (Koh et al., 2024b; Zhang et al., 2024b; Zhou et al., 2024a; Putta et al., 2024; Yu et al., 2024), that can provide diversified action choices, they require significantly more real-world interactions that can be very costly, leading to marginal gains in useful information prohibitively expensive. Although there is work using simulations (Gu et al., 2024; Qiao et al., 2024) to perform action searching, they typically focus on one/two-step look-ahead, lacking the foresight needed for coherent multi-step rollouts.

To address these limitations, we propose integrating a **Co-evolving World Model** into the self-improvement loop, to support better multi-step trajectory synthesizing and look-ahead. The world model, in our context, is defined as a language model that predicts the next observation (a web page), conditioned on the current observation and an attempted action on the current web page. Our key insight is that LLMs, pretrained on vast web content (e.g., Llama-3; Dubey et al., 2024), inherently encode a structured understanding of website dynamics, user intents, and task workflows. The World Model LLM is trained via supervised fine-tuning (SFT) on trajectories collected during agent-environment interactions. Specifically, we fine-tune it to predict the next observation conditioned on the current observation and action, by extracting data from trajectories sampled during the self-improvement loop. This allows the World Model to evolve alongside the agent, improving its ability to simulate realistic web interactions.

The World Model serves two synergistic roles: (1) as a *virtual web server*, it generates diverse, self-instructed training trajectories by simulating interactions with unseen web environments. This mitigates exploration bottlenecks by exposing the agent to a broader range of scenarios than encountered in real interactions. Importantly, while the World Model may produce hallucinated (i.e., non-realistic) web states, this is not a critical issue during training, as the agent's objective is to learn flexible action prediction rather than perfect state prediction. and (2) as an *imagination engine* during inference, the World Model performs multi-step look-ahead simulations (Zhang et al., 2025a), enabling evaluating several possible actions generated by the agent policy model without costly real-world interactions. This dual mechanism of grounding self-improvement in both real interactions and model-based foresight ensures sustained adaptability while minimizing reliance on expensive environment interactions.

We validate our framework on real-world, open-domain web environments, including Mind2Web-Live (Pan et al., 2024), WebVoyager (He et al., 2024a), and GAIA-web (Mialon et al., 2024). Experiments demonstrate a 10% improvement in performance compared to self-evolving algorithm baseline, OpenWebVoyager (He et al., 2024b), with significant gains in handling complex and unseen tasks. Our contributions are twofold.

1. A novel idea of Co-evolving world model in self-improving web agents, for generating diverse training data and enabling action searching via low-cost multi-step imagination.
2. Empirical evidence that world-model-guided self-improvement improves the agent performance and unlocks sustained adaptability in open-domain settings, with minimal human supervision and without any distillation from more powerful LLMs.

This work underscores the necessity of integrating dynamic world models into agent frameworks to transcend the limitations of purely data-driven self-training.

2 Related Work

Web Agent Recent advances in web agents leverage (multimodal) large language models as their backbone (Dubey et al., 2024; Jia et al., 2024; OpenAI, 2023; Anthropic, 2025), enabling reasoning through frameworks like ReAct Yao et al. (2023), MCP (Anthropic, 2024), and cognitive kernel (Zhang et al., 2024a). These agents are evaluated on benchmarks such as WebShop (Yao et al., 2022), Mind2Web (Deng et al., 2023), WebArena (Zhou et al., 2024b), VisualWebArena (Koh et al., 2024a), WebVoyager (He et al., 2024a), WebWalker (Wu et al., 2025), and MMInA (Zhang et al., 2024c). Besides applying off-the-shelf LLMs, there are data scaling efforts like Explorer (Pahuja et al., 2025), NNetNav (Murty et al., 2025), and InSTA (Trabucco et al., 2025) enhance the training of LLMs. Inference-time optimization techniques, including AgentTreeSearch (Koh et al., 2024b), Monte-Carlo Tree Search (Putta et al., 2024; Yu et al., 2024; Zhou et al., 2024a; Zhang et al., 2024b), and Reflexion (Shinn et al., 2023), further improve decision-making.

Agent Self-Improvement In addition to simply applying off-the-shelf LLM as the policy model, or using imitation learning to fine-tune a policy model by distilling trajectories from powerful LLMs, there is another line of work focusing on bootstrapping agent LLM's ability using an open-source LLM (Aksitov et al., 2023; Patel et al., 2024), based on the success of self-improving LLM's reasoning ability (Wang et al., 2023; Zelikman et al., 2022; Zeng et al., 2024). BAGEL (Murty et al., 2024), OpenWebVoyager (He et al., 2024b), and Self-Improved Agents (Patel et al., 2024) explored iterative exploration-feedback-optimization cycles, where agents refine their policies by learning from high-quality trajectories in real-world or simulated web environments. Similarly, AgentQ (Putta et al., 2024) and ReST+ReAct (Aksitov et al., 2023) integrated reinforcement learning and preference optimization to enable agents to learn from both successful and failed trajectories, improving robustness in multi-step reasoning tasks. To improve the performance of such self-improvement cycle, Gödel Agent (Yin et al., 2024), push the boundaries of self-improvement by enabling agents to dynamically modify their own logic or accumulate skills across diverse computer tasks. Zhang et al. (2025b) explores bootstrapping the ability of backtracking in web agent tasks.

World Models World models have evolved from their reinforcement learning origins (Ha & Schmidhuber, 2018) to become powerful tools for agent reasoning Valevski et al. (2024); Alonso et al. (2024); Smith & Wellman (2023). Recent approaches leverage large language models (LLMs) as implicit world models, enabling agents to simulate and plan through complex tasks. For general reasoning, RAP (Hao et al., 2023) demonstrates how LLMs can serve dual roles as both world models and reasoning agents, using Monte Carlo Tree Search to explore future states. Similarly, WKM (Qiao et al., 2024) shows that structured world knowledge can be distilled from trajectories to guide agent planning. In web environments, methods like WebDreamer (Gu et al., 2024) and WMA (Chae et al., 2024) adapt this paradigm by using LLMs to predict action outcomes through natural language simulations. However, these approaches remain limited by their reliance on off-the-shelf LLMs, functioning more like sophisticated chain-of-thought reasoning than true multi-step simulation.

Our work advances beyond these limitations by co-learning a dedicated world model during agent self-improvement. This enables genuine multi-step trajectory synthesis and look-ahead planning, providing a more robust foundation for interactive decision-making than current prompt-based approaches.

3 Method

In this section, we introduce the WebEvolver, a co-learning framework of World Model and Agent Policy model. An overview illustration figure is presented in Figure 1.

3.1 Problem Formulation

The web agent task is formulated as a Partially Observable Markov Decision Process (POMDP) $(\mathcal{S}, \mathcal{A}, \mathcal{O}, \mathcal{T}, \mathcal{R})$, where the agent receives a natural language query q requiring multi-step web interaction under the environment. The state space $\mathcal{S}$ represents the complete web environment, while the observation space $\mathcal{O}$ is limited to visible elements. At each time step t: $o_t = \Omega(s_t)$, where Ω is a function extracting visible contents like $(\text{URL}, \text{Web Elements})$ from the current state s_t. $\mathcal{A}$ represents the whole action space, which, in our case we include `click`, `type`, `goback`, `scroll down/up`, and `stop`, as the atomic web operations. $\mathcal{T}$ represents the deterministic transition function that executes browser operations to advance the state. The agent's policy $\pi(o_t, q) \rightarrow a_t$ generates actions that produce trajectories $\tau = \{(o_1, a_1), \ldots, (o_t, a_t)\}$, with final rewards computed through self-assessment $\hat{r}(\tau, q) \in [0, 1]$.

Given a task query q and target website w, we initialize the web environment and get the first observation $o_1 \in \mathcal{O}$. We follow the settings in Cognitive Kernel (Zhang et al., 2024a) and use accessibility tree to represent the elements in o_t. Using an LLM as agent policy model parameterized by θ, we generate chain-of-thoughts h_t and actions a_t at time step t:

$$(h_t, a_t) \sim \pi_\theta(\cdot | I, q, o_{1:t}, h_{1:t-1}, a_{1:t-1}) \tag{1}$$

where I contains system instructions. The transition function $\mathcal{T}$ executes actions on the environment:

$$s_{t+1} = \mathcal{T}(s_t, a_t),\ o_{t+1} = \Omega(s_{t+1}) \tag{2}$$

The complete trajectory is $\tau = (o_1, h_1, a_1, \ldots, o_T, h_T, a_T)$, where T denotes the total number of navigation steps.

3.2 Agent Self-Improvement

In this subsection, we introduce the self-improvement of a backbone agent foundation model, denoted as $\mathcal{M}$, and the corresponding policy function is denoted as $\pi_{\mathcal{M}}$.

Trajectories Collection We employ $\mathcal{M}$ to sample actions based on an input query q, which are then used to collect web navigation trajectories. We use $\mathcal{M}$ as the agent foundation model to power Cognitive Kernel, which interacts with web environments. The agent observes the last k steps, represented as webpage accessibility trees, to inform its actions.

For each query $q \in \mathcal{Q}$, a trajectory τ_i is sampled from the policy $\pi_{\theta_M}(\tau \mid I, q)$. To prevent performance degradation from too long contexts, we clip the trajectory history c_t when $t - 1 > k$ by keeping only the latest observations. The thoughts and actions are kept as they contain some compressed information about the history.

$$c_t^{\text{clip}} = (h_1, a_1, h_2, a_2, \ldots, h_{t-k}, a_{t-k}, o_{t-k+1}, h_{t-k+1}, a_{t-k+1}, \ldots, o_{t-1}), \tag{3}$$

such that the new actions are generated with the following function:

$$(h_t, a_t) \sim \pi_{\theta_M}(\cdot \mid I, q, c_t^{\text{clip}}). \tag{4}$$

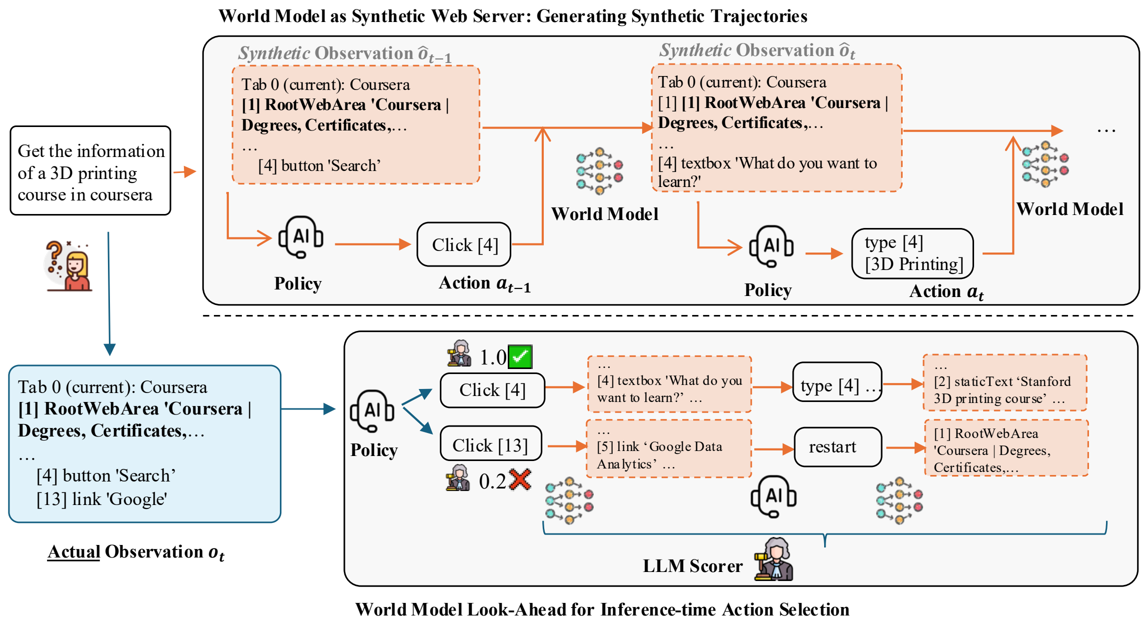


Figure 2: An illustration of the World Model trajectory synthesizing process and World Model Look-ahead for inference-time action selection.

Notably, we retain the **thought** and **action** at each step to preserve the full reasoning chain while avoiding context overload. Then, rejection sampling is conducted to keep those trajectories that are successfully finished, using an automatic evaluation method $\hat{r}(\tau, q)$.

Iterative Optimization At the i-th iteration of the self-improvement, we denote the collected trajectories after rejection sampling as D_i. We aim to maximize the following objective function:

$$\mathcal{J}(\theta) = \mathbb{E}_{(q,\tau)\sim D_{\mathrm{i}}} \sum_{t=1}^{T} \Big[\log \pi_\theta(a_t|q, c_t^{\mathrm{clip}'}, h_t) + \log \pi_\theta(h_t|q, c_t^{\mathrm{clip}'}) \Big], \tag{5}$$

After acquiring the new policy model $\mathcal{M}_i$, it is used to sample trajectories from the query set $\mathcal{Q}$ again. The newly successful trajectories are then appended to D_i to form a new training dataset D_{i+1} to perform the next round of optimization.

3.3 WebEvolver: Synergy between world model and self-improving agent.

In this subsection we introduce the co-learning world model, and how to use the world model for trajectory synthesizing and inference-time look-ahead. An illustration figure is presented in Figure 2.

Co-learning World Model The world model is a language model that simulates the next observation $\hat{o}_{t+1}$ conditioned on both the current webpage's accessibility tree (o_t) and a formatted action string (a_{t-1}), thereby predicting state transitions. We learn a world model LLM $\mathcal{M}_w$ using the collected trajectory during self-improvement.

From the a collected trajectory $\tau = \{(o_0, a_0), \ldots, (o_t, a_t)\}$, we can convert it to a world modeling trajectory $\tau_w = \{o_0, (a_0, o_1), \ldots, (a_{t-1}, o_t)\}$, such that the objective of world model is to predict the next observation o_t conditioned on the scheduled action a_{t-1} and previous observations. Similar with the trajectories in agent policy model, we truncate the history observations to avoid performance degrade on long contexts. Here, we simply use the latest observation as history. Besides, we distill some rationales using the original base LLM $\mathcal{M}$ about the logic of the transition function $\mathcal{T}$ to help the generation of the next webpage. Such chain-of-thoughts at step t is denoted as h_t^w. We do not omit the action and thoughts to make the world model aware of some of the previous information and the depth of the trajectory.

$$c_t^w = (a_1, h_1^w, \dots, a_{t-2}, h_{t-2}^w, o_{t-1}, a_{t-1}), \tag{6}$$

Such that the next webpage observation o_t is generated with the following function, where θ_w is the parameters of $\mathcal{M}_w$.

$$o_t \sim \pi_{\theta_w}(\cdot | I_w, c_t^w) \tag{7}$$

The world model is then optimized using the latest iteration of collected trajectories.

$$\mathcal{J}(\theta_w) = \mathbb{E}_{\tau_w \sim D_\mathrm{i}} \sum_{t=1}^{T} \Big[\log \pi_{\theta_w}(a_t | c_t^w, h_t^w) + \log \pi_{\theta_w}(h_t^w | c_t^w) \Big], \tag{8}$$

Trajectory Synthesize We can use an agent policy model M_i and a world model M_w to perform synthetic trajectory generation, enabling us to scale up the training data without interacting with the real web server, which can be very costly. Here, we directly replace the transition function $\mathcal{T}$ with the world model M_w. Specifically, the next synthetic observation is generated with:

$$\hat{o}^t \sim \pi_{\theta_w}(\cdot | I_w, c_t^w) \tag{9}$$

Then, in the next step, the policy model generates next action conditioned on the synthetic observation:

$$(\hat{h}_t, \hat{a}_t) \sim \pi_{\theta_M}(\cdot \mid I, q, \hat{c}_t^{\mathrm{clip}}). \tag{10}$$

Those collected trajectory is thus $\hat{\tau} = \{(o_0, a_0), (\hat{o}_1, \hat{a}_1), \dots, (\hat{o}_t, \hat{a}_t)\}$, which ultimately forms a trajectory dataset D_w after rejection sampling. By combining D_i from self-improvement and D_w, we can get an augmented new training dataset to train a new policy model, WebEvolver.

Inference-time Look-ahead To enhance decision-making during inference, we propose a look-ahead mechanism that simulates d-step trajectories using both the agent policy model M_i and the world model M_w. We call this method **W**orld **M**odel **L**ook-**A**head (WMLA). For each candidate action a_t at step t, we first simulate trajectories by generating d-step rollouts $\hat{\tau}_w$ through iterative application of:

$$\hat{o}_{t+j} \sim \pi_{\theta_w}(\cdot | I_w, c_{t+j}^w), \quad (\hat{h}_{t+j}, \hat{a}_{t+j}) \sim \pi_{\theta_M}(\cdot | I, q, \hat{c}_{t+j}^{\mathrm{clip}}), \tag{11}$$

where $j \in \{1, \dots, d\}$, c_{t+j}^w and $\hat{c}_{t+j}^{\mathrm{clip}}$ are truncated histories from the world model and policy model, respectively.

Next, we evaluate trajectories by employing an LLM-based evaluator to score each rollout $\hat{\tau}_w$. Following Koh et al. (2024b); Gu et al. (2024), the evaluator assigns a scalar from $\{0, 0.5, 1.0\}$ (incorrect, on track, or complete) based on the trajectory's alignment with task completion. Finally, we select the optimal action $a_t^* = \arg\max_{a_t} \mathrm{Score}(a_t)$ that maximizes expected progress.

4 Experiments

4.1 Setup

We use the Cognitive Kernel (Zhang et al., 2024a) as the foundation agent framework, specifically its Web Agent Module for autonomous Web interaction. Here, the state space $\mathcal{S}$ is the whole Internet, powered by Playwright[1] in the Web docker in Cognitive Kernel. The action space include `type`, `click`, `scroll`, `goback`, `stop`, and `restart`. At each time step t, the observation o_t is the accessibility tree of the visible components in the virtual browser, simulating what humans can perceive when browsing online. The transition function $\mathcal{T}$ executes atomic browser actions based on the current webpage state, updates the webpage, and thus the observation accordingly, and handles execution errors by feeding them back to the reasoning system until task completion or step limit is reached. Regarding the evaluation protocol $\mathcal{R}$, we address potential false negatives in human-annotated step-wise comparisons (Pan et al., 2024) by employing GPT-4o for end-to-end task completion assessment, following the methodology of He et al. (2024a). This method accommodates the existence of multiple distinct trajectories that can each successfully accomplish the same task objective, other than the human-annotated ones. GPT-4o will be provided the full trajectory of the task and asked to evaluate whether the original query q is completed or not, yielding a binary score of 0 or 1.

Regarding self-improvement, the backbone agent foundation model $\mathcal{M}$ we use is `Llama-3.3-70b`, and subsequently the self-improving experiments are also based on `Llama-3.3-70b`. During rejection sampling, `Llama-3.3-70b` is used to evaluate whether the task has successfully completed or not. More details regarding the agent system, including definitions of the atomic operations, system prompts, are detailed in Appendix A.

We select two live web navigation benchmarks for experiments, WebVoyager (He et al., 2024a) and Mind2Web-Live (Pan et al., 2024). Here, the web agent is expected to interact with the real-world web environment to complete the task. Since some websites are not accessible in our experimental web environment, either due to geographical locations or IP blocks, we filter out some websites for our experiments[2]. To ensure robustness, we conduct our experiments roughly at the same time window twice and report the average results.

4.2 Self-Improvement

We use `Llama3.3-70B` as the backbone LLM $\mathcal{M}$ for sampling and self-improving. For the training query, we follow OpenWebVoyager (He et al., 2024b)[3] to use the training set of Mind2web and self-instructed queries from both the websites in WebVoyager and Mind2web, in total 1,516 queries. We first use `Llama3.3-70B` as the backbone agent policy model for sampling queries, and conduct a round of rejection sampling using `Llama3.3-70B` itself as the backbone for evaluation function $\hat{r}$[4], using the evaluation prompt in Appendix A. The trajectories are then used to fine-tune `Llama3.3-70B` to acquire the model named *self-improve (iter 1)*. Then, we use the improved model to conduct another round of trajectory sampling, where the newly sampled finished trajectories are added to the training data in the first round, to train a new model named *self-improve (iter 2)*. In the meantime, we convert the trajectories to the form of training a world model, meaning predicting the next observation o_t based on the scheduled observation a_{t-1} and the histories of the observations.

World Model We adopt a `Llama3.3-70B` to fine-tune the world model, alongside the self-improving of policy model, to get *world model (iter 1)* and *world model (iter 2)*. For synthetic trajectory generation, we use the world model M_w (at iteration 2) and policy model M_1 (at iteration 1, which

[1] A Javascript version. More details in https://playwright.dev

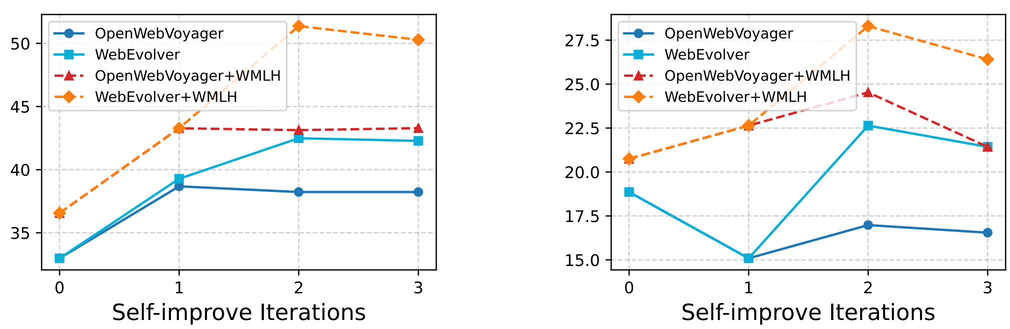
[2] Details about the websites are presented in Appendix B

[3] https://github.com/MinorJerry/OpenWebVoyager/tree/main/WebVoyager/data_for_training/IL

[4] In the original OpenWebVoyager paper, GPT-4o serves as the backbone for the scoring function. In this work, to ensure a purely self-improving process, we only employ `Llama3-70B` within the self-improvement loop.

	AllRe-cipes	Apple	ArXiv	BBC	Cam Dict	Cour-sera	ESPN	Git Hub	Google Map	HF	Wolfram Alpha	**WV All**	**M2W Live**
GPT-4o-mini	44.44	39.53	23.26	21.43	30.23	35.71	27.27	31.71	41.46	25.58	36.96	32.55	16.98
GPT-4o	31.11	41.86	27.91	32.56	41.86	47.62	27.27	36.59	36.58	46.51	56.52	38.83	20.75
Self-Improving													
Llama-3.3 70B	35.56	39.53	9.30	28.57	37.21	38.10	50.00	24.39	34.15	23.26	41.30	32.98	18.86
self-improve (1)	55.56	39.53	27.91	45.24	20.93	61.90	34.09	39.02	39.02	23.26	39.13	38.68	15.09
self-improve (2)	40.00	30.23	27.91	30.95	32.56	59.52	29.55	43.90	46.34	41.46	39.13	38.23	16.98
self-improve (3)	44.44	30.23	32.25	33.33	32.56	47.62	31.81	43.90	48.78	34.89	45.65	38.65	16.98
Synthetic Traj.	55.56	41.86	32.25	35.71	34.89	46.51	31.81	34.14	36.59	34.89	43.47	38.98	18.86
WebEvolver	62.22	30.23	37.21	47.62	53.49	59.52	34.09	26.83	46.34	23.26	45.65	42.49	22.64
Inference-time Look-ahead													
+ WebDreamer	64.44	41.86	44.19	57.14	30.23	59.52	20.45	41.46	46.34	41.86	43.48	44.61	22.64
+ **WMLH** (d=1)	66.67	46.51	39.53	42.86	32.56	69.05	22.73	43.90	68.29	37.21	41.46	46.24	**28.30**
+ **WMLH** (d=2)	64.44	41.86	46.51	42.86	62.79	66.67	40.91	46.34	43.90	53.49	54.34	**51.37**	24.53

Table 1: Task success rate on Text-only WebVoyager test set (WV; 473 queries) and Mind2Web-Live-filtered test set (M2W Live; 53 queries). **WebEvolver** and **WMLH** are our approaches. For *Inference-time Look-ahead*, the backbone policy model we use is WebEvolver. We leave more inference-time look-ahead results on different policy models in Figure 3.



(a) WebVoyager (b) Mind2web-Live

Figure 3: Visual illustration of overall success rate evolving on WebVoyager and Mind2Web-Live.

has a better performance). For each query q, beginning with an initial observation-action pair (o_0, a_0), we alternate between world model prediction and policy decisions: at each timestep t, the world model generates the next synthetic observation $\hat{o}_t$ according to Equation (9), which the policy model then uses to produce the subsequent action $\hat{a}_t$ via Equation (10). This interaction forms complete synthetic multi-step trajectories $\hat{\tau}$ of length $T = 7$ steps, with early termination if the world model generates a terminal state. An example if presented in Figure 4. To have a more diverse training set, we only use the queries that are not successfully executed in self-improving iterations to acquire synthetic trajectories. We apply another round of rejection sampling using the evaluation protocol $\mathcal{R}$, while using zero-shot `Llama3.3-70B` as the backbone language model to follow the setting of self-improving. In the end, the world-model-synthesized data are combined with the SFT data in self-improvement, to train `Llama3.3-70B` to acquire the final model of WebEvolver.

4.3 Inference-time World Model Look-ahead (WMLA)

To perform WMLA, we use the policy model $\mathcal{M}$ to sample up to 3 actions. At time step t, with observation o_t, we use the original policy model with temperature equal to 0 to generate the first

Model	All			Depth=1			Depth=2			Depth=3			Depth≥4		
	STR	Sim.	O/A	STR	Sim.	O/A	STR	Sim.	O/A	STR	Sim.	O/A	STR	Sim.	O/A
`gpt-4o`	40.62	33.26	37.85	41.24	35.73	40.21	38.20	32.58	36.70	36.99	31.96	37.44	42.41	32.91	37.45
`Llama-3.3-70b`	39.04	32.25	38.77	43.64	39.51	34.83	39.33	34.83	41.95	39.73	33.33	41.55	36.85	27.99	35.16
`iter-1`	49.23	37.83	43.15	55.44	44.91	50.52	53.03	39.77	46.59	53.70	40.28	46.30	43.76	33.33	37.73
`iter-2`	56.79	44.77	51.82	75.96	63.56	72.86	57.80	45.14	52.32	51.24	35.82	45.27	50.54	39.94	45.31

Table 2: Performance of intrinsic evaluation of world modeling. **Structural correctness (STR)** measures syntactic validity of the generated accessibility tree, **Similarity (Sim.)** assesses alignment with ground-truth webpage content, and **Overall assessment (O/A)** evaluates functional and semantic coherence. All values are percentages (range 0-100). Details of the evaluation metrics ae presented in Section 4.4.

action, $a_t^{(1)}$. Since the fine-tuned policy model will have a sharp output distribution, making it hard to directly sample different actions during decoding, besides setting the decoding temperature to 0.7, we add a sentence of additional prompt to guide the policy model to generate the k-th action: *Please generate actions different from* $\{a_t^{(j)}, j \in \{1, \ldots, k-1\}\}$. Then, we use the final world model *world model (iter 2)* and the policy agent model to iteratively sample future look-ahead trajectories based on Equation (11), with a look-ahead depth of 1, 2, and 3. Then, following WebDreamer, we use GPT-4o as the scoring function to rate each action based on the look-ahead results and choose the action with the highest score for execution.

4.4 Results and Analysis

In this subsection, we provide results of self-improvements, the effect of WMLA, the intrinsic evaluation of world models, and additional experiments on GAIA.

WebEvolver and WMLA Main Results Our key findings are presented in Table 1, with the progression of self-improvement across iterations visualized in Figure 3. The first two rows of the table establish reference performance using GPT-4o and GPT-4o-mini as foundation models. In terms of self-improvement, the initial self-improvement iteration yields a 6% success rate increase over the zero-shot baseline on WebVoyager, due to enhanced format compliance and task familiarity. Performance plateaus at iteration 2, suggesting limited gains from additional similar trajectories. However, incorporating world-model-synthesized data with iteration 1's supervised fine-tuning (SFT) data produces a further 4% improvement. This has better improvement compared to the baseline approach adapted from Patel et al. (2024) that generates synthetic trajectories without world modeling.

For inference-time action selection with WebEvolver, we benchmark against WebDreamer using GPT-4o for both outcome prediction and action evaluation. Our World Model-based Look-ahead (WMLH) demonstrates optimal performance at depth $d = 2$, balancing prediction accuracy against computational overhead. Notably, increasing to $d = 3$ provides diminishing returns, consistent with our world model's performance characteristics (see Table 2).

World Model Intrinsic Evaluation We evaluate our world model's ability to generate plausible next webpages through three metrics: **Structural correctness (STR)** measuring syntactic validity of the generated accessibility tree, **Similarity (Sim.)** assessing alignment with ground-truth webpage content, and **Overall assessment (O/A)** evaluating functional and semantic coherence. While real-time information (e.g., from BBC or Hugging Face) inevitably causes hallucinations during generation, we do not directly evaluate the degree of hallucination. Hallucinations are implicitly captured through Sim. and O/A scores, yet they pose minimal risk in our framework. In fact, they may enhance diversity and knowledge in synthesized trajectories, with benefits empirically validated by downstream performance gains. We use GPT-4o to perform an automatic evaluation of all three metrics and normalize the scores to 0$\sim$ 1. The prompt we used is presented in Appendix A.

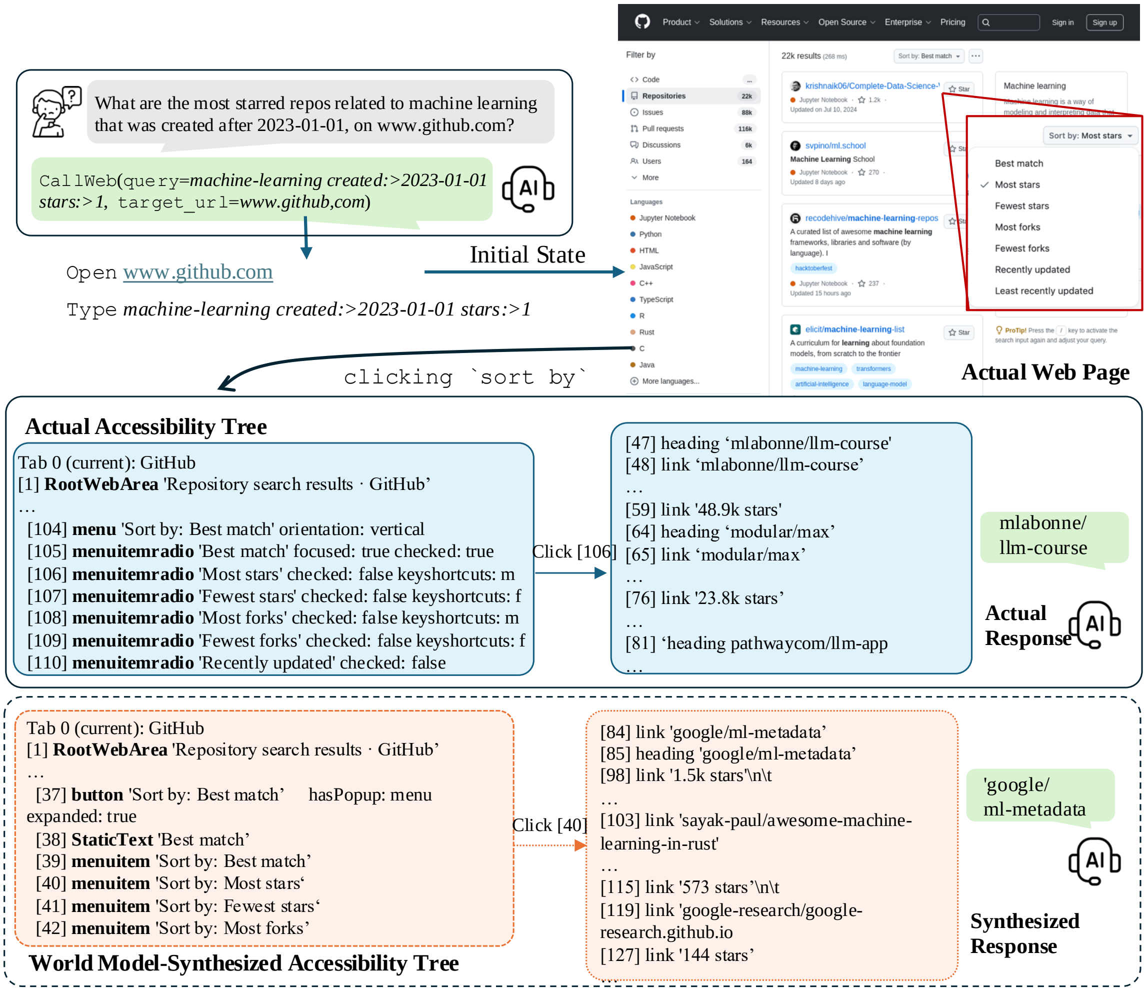


Figure 4: An example of world model-synthesized trajectory.

The results are presented in Table 2. We can see that the performance degrades sharply (scores < 0.50) for generation depths > 2, which is in line with the experiments in WMLH that the performance gain diminishes when WMLH depths ≥ 3.

Out-of-domain Generalization We evaluate our improved agent foundation model on GAIA (Mialon et al., 2024), focusing on the web-dependent query subset (GAIA-web)[5]. These tasks typically require multi-step web navigation combined with arithmetic/logical reasoning. Since the self-improved agent LLM focuses solely on action generation, we adopt a hybrid approach: we use GPT-4o to decompose queries into sub-tasks that web agents can address, and also leverage GPT-4o for result generation and calculation. The web agent component is based on Llama-based models including WebEvolver. We use bing.com instead of Google due to CAPTCHA challenges, which can also demonstrating our method's out-of-domain generalization since the training data does not contain trajectories in bing.com. Results on Table 3 show consistent

Model	Level 1	Level 2
Llama 3.3-70b	19.2	10.9
iter 1	26.9	15.6
iter 2	26.9	12.5
WebEvolver	**30.7**	**17.2**

Table 3: GAIA-web performance.

[5] https://github.com/MinorJerry/WebVoyager/blob/main/data/GAIA_web.jsonl

improvement on Level 1 queries through self-improvement and world model augmentation, mirroring trends observed in WebVoyager and Mind2web-live. However, Level 2 queries, which demand deeper reasoning and extended multi-step interactions, show limited gains, as these capabilities lie beyond our current training scope. This limitation highlights an important direction for future work in developing agents for complex, real-world web tasks.

Analysis of World-Model Synthesized Trajectories We provide two cases on the world-model synthesized trajectories, indicating that LLM itself contains useful knowledge about the common structures of the web and has the potential to provide diverse trajectories. It is provided in Figure 4. This case demonstrates an operation involving a click on the 'sort by' menu in the GitHub search console. Although the world model has not been further fine-tuned on trajectories that include clicking the 'sort by' button, it is still able to accurately generate the menu items for GitHub Search, such as sorting by best match, most stars, and so on. This capability arises from the commonsense knowledge inherently encoded in the LLM. We find that this feature is highly beneficial for improving the diversity of interactions with previously unseen websites.

5 Conclusion

In this paper, we present WebEvolver, a framework for agent foundation model self-improvement through co-learning with a world model, which enhances the effectiveness of the self-improvement cycle. The co-learned world model can also be utilized for inference-time look-ahead, aiding in the selection among different sampled actions. Experiments on WebVoyager, Mind2Web-Live, and GAIA-web demonstrate the effectiveness of boosting the performance of self-improving agent.

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A Details of Agent Implementation

In this section, we present additional details of the prompt we used for the web agent.

The system prompt for web agent action generation:

AGENT SYSTEM PROMPT

```
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 observation (web page's accessibility tree): This is a simplified representation of the webpage, providing key information. Optionally, you may be provided with a screenshot of the webpage. You should pay close attention to the screesnhot to make decisions.
- The open tabs: These are the tabs you have open.
- The previous actions: You can refer to the conversation history with the user to see the actions you have taken. It may be helpful to track your progress.

The actions you can perform are the following:

- 'click [id]': This action clicks on an element with a specific id on the webpage.
- 'type [id] [content] [press_enter_after=0|1]': Use this to type the content into the field with id. By default, the Ënterkey is pressed after typing unless press_enter_after is set to 0.
- 'wait': Wait for the page to load, with a duration of 5 seconds.
- 'goback': Navigate to the previously viewed page.
- 'restart': Navigate to the Google search homepage. When you can't find information in some websites, try starting over from Google search.
- '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. If you believe the task is impossible to complete, provide the answer as "N/A" in the bracket.

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. For
example, you should NOT type into buttons or click on statictext.

2. You should only issue one action at a time.

3. STRICTLY Avoid repeating the same action if the webpage remains unchanged. You
may have selected the wrong web element or numerical label. Continuous use of the
Wait is also NOT allowed.

4. Issue stop action when you think you have achieved the objective. Don't generate
anything after stop.

Your reply should strictly follow the format: Thought: {{Your brief thoughts
(briefly summarize the info that will help complete the task)}} Action: ```{{the
next action you choose to take}}```
```

The system prompt for using world model as a web server, by generating the next observation based on current observation and the scheduled action. We present two variation of world model objectives, the first one is to only predict an abstract short description of what the next observation is (denoted as **Abstract Description**), and the second one is to predict the structured accessibility tree of the next observation (denoted as **Accessibility Tree)**.

WORLD MODEL LOOK-AHEAD (ABSTRACT DESCRIPTION)

```
You are a web server. You are given the current observed accessibility tree of the
web page, and an action to perform.

The expected output is a short description on what the next observation is, in the
form of free text.
The definitions of the actions are as follows: The actions you can perform are the
following:
```

- `'click [id]'`: This action clicks on an element with a specific id on the webpage.
- `'type [id] [content] [press_enter_after=0|1]'`: 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.
- `'scroll [direction=down|up]'`: Scroll the page up or down.
- `'goback'`: Navigate to the previously viewed page.
- `'restart'`: Navigate to the original home page and restart the action.

WORLD MODEL LOOK-AHEAD (ACCESSIBILITY TREE)

```
You are an intelligent assistant designed to interact with web pages through an
accessibility tree. Your task is to predict the accessibility tree of the next web
page based on the given starting accessibility tree and a specified action. The
format of accessibility tree:

Tab 0 (current): Google \n \n[1] RootWebArea 'Google' focused: true\n[2] link
'Gmail '\n[3] link 'Search Image '\n[4] button 'Google Apps' expanded: false\n[5]
link 'Log in'\n[6] image '2024'\n[7] combobox 'Search' focused: true autocomplete:
both hasPopup: listbox required: false expanded: false\n[8] button 'Share'

The format of action:

type [7] [JQuery selector for elements with specific class] [1]

which indicates typing "JQuery selector for elements with specific class" into the
field with id 7, corresponding to the combobox (search box) on the Google homepage.

The definitions of the actions are as follows: The actions you can perform are the
following:
```

- `'click [id]'`: This action clicks on an element with a specific id on the webpage.
- `'type [id] [content] [press_enter_after=0|1]'`: 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.
- `'scroll [direction=down|up]'`: Scroll the page up or down.
- `'goback'`: Navigate to the previously viewed page.
- `'restart'`: Navigate to the Google search homepage. When you can't find information in some websites, try starting over from Google search.

The system prompt for automatic evaluation of a web agent task.

AUTOMATIC EVALUATION

```
As an evaluator, you will be presented with three primary components to assist you in
your role:

1. Web Task Instruction: This is a clear and specific directive provided in natural
language, detailing the online activity to be carried out. These requirements may
include conducting searches, verifying information, comparing prices, checking
availability, or any other action relevant to the specified web service (such as
Amazon, Apple, ArXiv, BBC News, Booking etc).

2. Result Webpage Accessibility Tree: This is a representation of the web page
showing the result or intermediate state of performing a web task. It serves as
proof of the actions taken in response to the instruction.

3. Result Response: This is a textual response obtained after the execution of the
web task. It serves as textual result in response to the instruction.
```

- You DO NOT NEED to interact with web pages or perform actions such as booking flights or conducting searches on websites.
- You SHOULD NOT make assumptions based on information not presented in the webpage when comparing it to the instructions.
- Your primary responsibility is to conduct a thorough assessment of the web task instruction against the outcome depicted in the screenshot and in the response, evaluating whether the actions taken align with the given instructions.
- NOTE that the instruction may involve more than one task, for example, locating the garage and summarizing the review. Failing to complete either task, such as not providing a summary, should be considered unsuccessful.
- NOTE that the screenshot is authentic, but the response provided by LLM is generated at the end of web browsing, and there may be discrepancies between the text and the screenshots.
- Note the difference: 1) Result response may contradict the screenshot, then the content of the screenshot prevails, 2) The content in the Result response is not mentioned on the screenshot, choose to believe the content.

You should elaborate on how you arrived at your final evaluation and then provide a definitive verdict on whether the task has been successfully accomplished, either as 'SUCCESS' or 'NOT SUCCESS'.

The system prompt for automatic evaluation of world modeling.

WORLD MODEL INTRINSIC EVALUATION

```
You are tasked with evaluating the accuracy of ntnerated accessibility tree against a
ground truth accessibility tree obtained from an actual web server. Your evaluation
should focus on three main criteria: structure correctness, element correctness, and
similarity. Follow the instructions below to perform a detailed comparison:

Criteria for Evaluation:
1. **Structure Correctness**:
```

- Ensure that the basic hierarchy and relationships between elements in the generated tree match the ground truth.
- Ensure that interactive elements (like buttons, links, forms) are correctly represented and maintain their intended functionality.

2. **Similarity (GPT-score)**:

- Assess how similar the generated content is compared to the ground truth.

```
• Provide a similarity score based on the overall content and structure comparison.
3. **Overall Functionality Assessment**:
• Compare the functional coherence of the generated tree to the ground truth tree,
  focusing on the representation and functionality of interactive elements.
• Evaluate the semantic coherence of the generated tree, ensuring that it conveys
  the same meaning and purpose as the ground truth.
For example, if if the webpage is on Allrecipe, as long as the generated tree contain
necessary recipe, no matter hallucination, it can be considered as success. For
example, if the webpage is on google, in searching for some information, then only
consider whether the generated tree contain roughly necessary information without the
need to check the factuality.

1. **Input Trees**:
• You will be provided with two accessibility trees: one generated by a language
  model simulating a web browser, and one obtained from an actual web server.
2. **Output Format**:
- Provide rationale of your findings, including:
• Structural discrepancies
• Similarity score with an explanation
• Scores should be selected from [0, 1, 2, 3]. 3 means exactly the same and 0 means
  a total failure of generation.
### Example Output
Structure Correctness: [THOUGHT]\n Score: [score]\n
Similarity: [THOUGHT]\n Score: [score]\n
Overall Functionality Assessment: [THOUGHT]\nScore: [score]\n
```

B Additional Details on Mind2web-live and WebVoyager Dataset

We conduct our evaluations using a subset of the testing portion of Mind2Web-Live[6] and WebVoyager[7]. Here is a list of the websites that are excluded:

EXCLUDED WEBSITES

```
EXCLUDED_WEBSITES_MIND2WEB = { 'exploretock', 'kohls', 'united', 'parking', 'viator',
'delta', 'redbox', 'soundcloud', 'gamestop', 'travelzoo', 'amctheatres', 'ryanair',
'cargurus', 'resy', 'rentalcars', 'kbb', 'cabelas', 'menards', 'yellowpages',
'tripadvisor', 'tiktok.music', 'stubhub', 'thumbtack', 'weather', 'uhaul',
'health.usnews', 'healthgrades', 'theweathernetwork', 'zocdoc', 'usnews.education',
'epicurious', 'osu.edu', 'ups', 'dmv.virginia.gov', 'extraspace', 'finance.yahoo',
'pinterest', 'sixflags', 'spothero', 'justice.gov', 'foxsports', 'ign', 'koa',
'tvguide', 'webmd', 'sports.yahoo', 'babycenter', 'tesla', }
EXCLUDED_WEBSITES_WEBVOYAGER = { 'booking', 'espn', 'amazon', 'google', 'googleflight'
}
```

[6] https://huggingface.co/datasets/iMeanAI/Mind2Web-Live/blob/main/mind2web-live_test_20241024.json

[7] https://github.com/MinorJerry/WebVoyager/blob/main/data/WebVoyager_data.jsonl