Mobile-Env: An Evaluation Platform and Benchmark for Interactive Agents in LLM Era

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Abstract

Diverse evaluation benchmarks play a crucial role to assess a wide range of capabilities of large language models (LLM). Although plenty of endeavors have been dedicated to building valuable benchmarks, there is still little work aiming at evaluating the capability of LLM in multistep interactive environments. Noticing that LLM requires a text representation of the environment observations for interaction, we choose to fill such a blank by building a novel benchmark based on the information user interface (InfoUI). InfoUI consists of rich text contents and can be represented in some text formats, thus is suitable for the assessment of interaction ability of LLM. Additionally, the complex structures of InfoUI can further raise a challenge for LLM to understand structured texts rather than plain texts. An interaction platform is always used to evaluate an agent, however, there is still a lack of a satisfactory interaction platform dedicated to InfoUI. Consequently, we propose to build a novel easily-extendable, adaptable, and close-to-reality interaction platform, Mobile-Env, to provide a base for an appropriate benchmark. Based on Mobile-Env, an InfoUI task set WikiHow is then built to establish a benchmark for the multistep interaction capability of LLM in structured text-based environments. Agents based on a series of LLMs are tested on the task set to obtain an insight into the potential and challenge of LLM for InfoUI interaction. It is sincerely welcome that the community contribute new environments and new task sets for Mobile-Env to provide better test benchmarks and facilitate the development of the corresponding domains.

1 Introduction

Along with the remarkable advancement of large language models (LLM) [Brown et al., 2020, Chowdhery et al., 2022, Du et al., 2022, Scao et al., 2022, Ouyang et al., 2022, Bai et al., 2022, Touvron et al., 2023], LLM evaluation benchmark is emerging as an important topic to assess the incredible capability and intelligence of LLM. Numbers of benchmarks have been proposed to assess the capacity of LLM for reasoning [Fu et al., 2023], mathematics [Cobbe et al., 2021, Hendrycks et al., 2021c, Frieder et al., 2023, Yuan et al., 2023], and coding [Chen et al., 2021, Austin et al., 2021, Hendrycks et al., 2021a, Li et al., 2022, Tony et al., 2023]. Moreover, some work [Hendrycks et al., 2021b, Srivastava et al., 2022, Liang et al., 2022, OpenAI, 2023, Nunes et al., 2023, Huang et al., 2023] combines a wide range of natural language processing (NLP) tasks and even human exams to conduct a comprehensive evaluation. Nevertheless, there is still a shortage of benchmarks to assess the capability of LLM to interact with RL (Reinforcement Learning) environments. Different from the conventional interaction models, LLM requires a text representation of the environment observations. Thus, the existing interaction benchmarks based on embodied or visual-based environments [Bellemare et al., 2013, Brockman et al., 2016] are inapplicable to



- (a) Embodied simulation environment
- (b) Visual game UI (c) Text-based game (d) Information UI interface

Figure 1: Comparison of different types of interaction environments. Compared to the environments consisting of pure visual-based or text-based information, InfoUI comprises both rich texts and complex spatial structures, and constitutes an appropriate challenge to LLM-based agents. Fig. 1a, Fig. 1b, and Fig. 1c are extracted from Foundation [2022], Toyama et al. [2021], and Shridhar et al. [2021] respectively.

LLM assessment. Aiming at filling in such a blank, we choose to build a benchmark based on the information user interfaces (InfoUI). InfoUI comprises rich text information and can be conveyed in some text formats, thus is highly suitable for the assessment of interaction ability of LLM. Besides, compared to pure text-based environments like ALFWorld [Shridhar et al., 2021], InfoUI consists of complex structures as well. Hence, two challenges can be highlighted for LLM on InfoUI: (1) multistep interaction (2) in structured text-based environments. (See the comparison in Fig. 1.)

An interaction platform is always adopted to evaluate the interaction capability of an agent. However, there is still a lack of a satisfactory interaction platform dedicated to InfoUI to assess the capability of LLM or other agents. Existing work like World of Bits [Shi et al., 2017] and WebShop [Yao et al., 2022a] suffers from the difficulty of extending to new environments or new tasks, as well as the synthetic simulated pages that are far different from real-world UIs. A comparison can be referred to in Tab. 1. A satisfactory interaction platform is expected to have the following features: (1) can be easily extended with new task goals, (2) is adaptable to a variety of environments (*i.e.*, different apps or websites) to help to evaluate an agent comprehensively, (3) is close to real-world scenarios to assess the most practical capability. To achieve task extensibility, the task definitions should be decoupled from the program internals. A universal interaction interface and multi-class event sources should be enabled to achieve environment adaptability and build environments close to real problems.

In order to offer a suitable benchmark for assessment of the InfoUI interaction capability of LLM. we design an InfoUI interaction platform Mobile-Env with the aforementioned features in this paper. To be specific, we separate the task definition from the program internals into an external task definition file, and build our platform upon Android TM operating system (OS), which offers millions of apps that can serve as diverse environments. Multiple types of OS feedback are exploited to parse the episode signals (i.e., step instructions, rewards, and the episode end) to further improve the adaptability of the platform to in-the-wild apps. Thus, large amounts of real-world apps can be exploited beyond the customized dedicated apps to provide the closest-to-reality environments. In this way, Mobile-Env offers a universal interface for interaction with different Android app environments, enabling an opportunity for comprehensive evaluation of LLM-based agents. Training and evaluating conventional RL agents are supported as well. Furthermore, an InfoUI task set based on WikiHow app is crafted to demonstrate the usage of Mobile-Env and constitute a preliminary benchmark for the InfoUI interaction capability of LLM. Finally, we tested the agents based on a series of LLMs (i.e., ChatGLM-6B [Du et al., 2022], LLaMA-13B [Touvron et al., 2023], GPT-3.5 [Brown et al., 2020], and ChatGPT [Ouyang et al., 2022]) on WikiHow task set to evaluate the potential and challenge of LLM for multistep interaction in structured text-based environments.

Our contributions are summarized as follows: (1) A novel InfoUI interaction platform Mobile-Env is designed. Mobile-Env is designed to be easily-extendable, highly adaptable, and close to real-world scenarios to provide a universal and flexible evaluation for the interaction capability of LLMs or other

Table 1: Comparison of Mobile-Env with existing UI-based interaction platforms. The table tells about whether the platform is designed for InfoUI interaction, whether a new task can be added through an external definition file, the mechanism of triggering episode signals, and whether the environments are based on real pages or apps.

Platform	InfoUI	Task via Def.	Episode Signal*	Real Page/App
World of Bits [Shi et al., 2017]	✓	X	Internal	×
WebShop [Yao et al., 2022a]	✓	✓	Internal	X
AndroidEnv [Toyama et al., 2021]	×	✓	Log	X
Mobile-Env (Ours)	✓	✓	Multi	√

^{* &}quot;Internal" indicates that the episode signals are generated by the hard-coded internal mechanism of the platform. "Log" indicates parsing episode signals from the OS runtime log (one type of available OS feedback). "Multi" means that the platform can take advantage of multiple types of OS feedback.

agents. (2) A novel InfoUI task set WikiHow is built upon Mobile-Env to establish a benchmark for assessment of InfoUI interaction capability of LLMs. (3) A series of LLMs are tested on the proposed WikiHow task set to obtain an insight into the potential and challenge of LLM for multistep interaction in structured text-based environments. ¹

2 Related work

LLM evaluation benchmark As LLM has demonstrated remarkable performance in a wide range of NLP tasks, various benchmarks are proposed to assess the ability and intelligence of LLM comprehensively and deeply. Reasoning is considered to be a pivotal mark of the intelligence and constitutes one of the most outstanding features of LLM compared to the conventional models. Thus, Most work focuses on the assessment of LLM's reasoning ability. Fu et al. [2023] proposes CoTHub to evaluate the capacity of LLM for free-form reasoning with chains-of-thought (CoT). Other work [Cobbe et al., 2021, Hendrycks et al., 2021c, Frieder et al., 2023, Yuan et al., 2023] chooses to assess reasoning ability through mathematic problems. Some work [Chen et al., 2021, Austin et al., 2021, Hendrycks et al., 2021a, Li et al., 2022] offers a benchmark for the capacity of LLM for coding, which is always regarded as a typical logical activity. Further work [Hendrycks et al., 2021b, Srivastava et al., 2022, Liang et al., 2022, OpenAI, 2023, Nunes et al., 2023, Huang et al., 2023] attempts to combine multiple tasks and even human exams like the admission tests and bar exams to establish a comprehensive benchmark. Nevertheless, little existing work investigates the assessment of the interaction capability of LLM. We argue that multistep interaction in structured text-based environments still constitutes a challenge to LLM. Consequently, to fill such a blank, this work aims at establishing an interactive platform for the assessment of LLM based on InfoUI interaction. Based on our platform, WikiHow task set is crafted as an evaluation benchmark, and several insights are drawn through a series of experiments.

Interaction platform for InfoUI There is already a little work for the InfoUI interaction platform. Some typical platforms are compared in Tab. 1. Existing work usually suffers from simplified simulated pages and is difficult to add a new task owing to the coupling of task definitions with the program internals. World of Bits (WoB) [Shi et al., 2017] is an early interaction platform for UI interaction comprising numbers of single-page tasks, which are built on synthetic simulated mobile web pages. WebShop [Yao et al., 2022a] designs multipage tasks in a scene of a shopping website with handcrafted simulated pages. Information of new products can be appended to extend new task goals. However, the action space designed by WebShop is dedicated to the shopping website and will cause extra efforts to migrate it to other domains. AndroidEnv [Toyama et al., 2021] is capable of importing a new task through an external definition file. However, AndroidEnv parses the episode signals through the system log, which requires the app to print several characteristic lines into the log just at the time an episode signal is triggered. This feature prevents most real-world apps from being used in AndroidEnv, and seriously harms its adaptability. The proposed Mobile-Env is built based on AndroidEnv and preserves the extensibility brought by the external task definition file. Multiple

¹Mobile-Env code repository: https://github.com/X-LANCE/Mobile-Env. Task set repository: https://huggingface.co/datasets/zdy023/WikiHow-taskset.

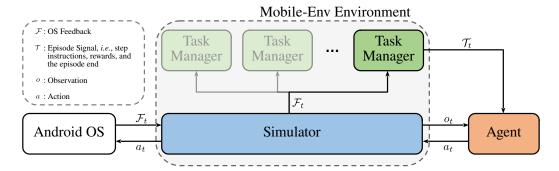


Figure 2: Main components of Mobile-Env environment. The simulator serves as a proxy to the Android OS, offers observations and accepts actions from the agent. Task managers manage the episode signals according to the loaded task definition files. Multiple task managers can be loaded during launch, however, only one can be active for interaction at one time.

types of operating system feedback are further adopted to parse the episode signals to seize better adaptability and take advantage of voluminous real-world apps.

LLM for UI understanding & interaction Prior work has investigated the potential of LLM for UI understanding and interaction. Wang et al. [2022] applies LLM to four conversational mobile screen understanding tasks and depicts both the potential and room for improvement of the LLM on the screen tasks. ReAct [Yao et al., 2022b] injects reasoning into the interaction trajectory and achieves a promising performance. Kim et al. [2023] combines LLM with iterative self-improvement to complete WoB tasks. This work aims at InfoUI interaction and evaluated a series of LLM-based agents on Mobile-Env to acquire perspectives on the potential and challenge of LLMs.

3 Platform features

3.1 Overview

Mobile-Env is designed as a universal interaction *platform* supporting various environments and different tasks to support the evaluation of LLM-based or conventional InfoUI agents. An *environment* is usually referred to as a specific app running on Mobile-Env, enabling agents to interact with it and accomplish the task goal. A *task* corresponds to a specific goal and several configurations, which will be detailed later in § 3.3. Based on Mobile-Env, agent designers can train and evaluate their agents with various environments and tasks, meanwhile, environment and task designers are welcome to build new environments and tasks as well.

A runtime instance of Mobile-Env consists of two types of components: *simulator* and *task manager*, as shown in Fig. 2. The simulator wraps Android Emulator TM² and provides the agent with a suite of interaction interface with the Android OS. The simulator predefines basic observation space and action space and supports multiple kinds of wrappers to customize the interaction interface, which will be elaborated on in § 3.2. A task manager is corresponding to a specific task goal. During the launch of Mobile-Env instance, the task manager will be loaded by reading and parsing a task definition file. Then, during the episode, the task manager will control the triggering of the episode signals according to the loaded task definition. The task definition file will be detailed in § 3.3. Multiple task managers can be loaded during launch to support multiple task goals that can be switched at runtime. But there will be only one task manager active for the current episode at one time.

During interaction, the agent will receive the observation from the simulator and the episode signals (*i.e.*, step instructions, rewards, and the episode end) from the active task manager. The action decision will then be made accordingly and sent to the OS through the simulator. Both continuous control and discrete control agents can be evaluated on Mobile-Env with the help of different wrappers. And both image-based and text-based agents (*e.g.*, LLM-based agents) are supported, as the screenshots and the view hierarchy XMLs are enabled as the observation simultaneously.

²https://developer.android.com/about

3.2 Observation & action spaces

Observation space The observation space of Mobile-Env comprises four components: a screenshot, the screen orientation, a time delta, and an XML-format view hierarchy (VH). The screenshot is an RGB image captured from the gRPC³ interface of the emulator. It conveys exactly the same information as the human perceives. The time delta is the amount of time passed since the last fetch of observation. Both screen orientation and time delta are proposed originally in Toyama et al. [2021] to offer the agent some extra hints at the environment state. The view hierarchy is a tree description of the Android screen, just like the HTML DOM (Document Object Model) of the web page. The properties of a VH element can provide helpful information like the content, name, and purpose of the element in many cases. Meanwhile, the text format of VH enables the text-based agents (*e.g.*, LLM-based agents) to interact with Mobile-Env environments.

Action space The action space of Mobile-Env comprises three types of actions: TOUCH, LIFT, and TEXT. TOUCH indicates to touch a specific point on the screen, and LIFT means to lift the "finger" off from the screen. The coordinates of the touchpoint are measured from the top-left of the screen and are normalized to [0,1]. TEXT action will input a token from a predefined vocabulary. Sub-word tokens are supported as well. It is proposed by the previous work [Shi et al., 2017] that it is too challenging for the agent to learn to type texts through the screen keyboard character by character. Consequently, TEXT is implemented to reduce the difficulty.

Wrappers for observation & action spaces Besides the basic observation and action spaces, a suite of wrappers is supported to customize the observation and action spaces the agent deals with. For example, a discretization wrapper will discretize the screen into grids to enable agents with discrete action space, or a VH wrapper can be used to convert the VH-element-wise interaction to the combination of the basic actions so that the text-based agents (*e.g.*, LLM-based agents) can interact with Android OS through Mobile-Env.

3.3 Task definition

A task corresponds to a particular task goal and several configurations defined in a definition file. The task definition file is supposed to contain the following information:

- How the environment should be set up and reset, *e.g.*, to install and launch a particular app on the device.
- A *task description* describing the task goal, *e.g.*, "find me an article about how to use ChatGPT".
- Step instructions and how the step instructions are triggered.
- Rewards and how the rewards are triggered.
- *Episode end* and how the episode end is triggered.

The step instructions, rewards, and episode end constitute the episode signals the agent will have a perception to. These episode signals will be

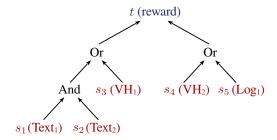


Figure 3: Demonstration of event triggering logic f with diverse operating system feedback. The triggering state t of the event slot depends on a combinatorial boolean logic of the matching states s_i of multiple event sources. Text, VH, and Log indicate different types of OS feedback.

triggered during interaction after some crucial steps in accordance with the task definition file. A so-called crucial step may be opening a target page, scrolling to the correct area, *etc*. The step instruction is proposed to provide some auxiliary information during the episode, *e.g.*, the detailed tour information for a ticket booking task. Intermediate rewards can be defined to mitigate the sparsity of the single reward at the episode end during training conventional RL agents.

³https://grpc.io/

The timing of the episode signals are defined in the task definition file. To be specific, the step instruction, reward, and episode end are referred to as predefined *event slots* in the task definition file. The triggering state of an event slot depends on the *event sources* defined in the task definition file. An event source indicates a specific pattern for the OS feedback. Given a triggering state of an event slot t, matching states of a group of event sources $S = \{s_1, s_2, \dots, s_n\}$, the triggering logic can be formalized as

$$t = f(s_1, s_2, \dots, s_n), \tag{1}$$

where f is a boolean function defined in the task definition file. Fig. 3 offers an intuitive illustration. Among all the types of available OS feedback, the VH and the system log are supported internally, while the screen texts and icons should be enabled with an external OCR system and icon recognition system.

4 WikiHow task set

To establish a preliminary benchmark for the multistep interaction capability of LLM in structured text-based environments, a navigation task set based on WikiHow app is built. This section will elaborate on the construction of WikiHow task set, including app data collection in § 4.1 and task definition generation in § 4.2.

4.1 App data collection for WikiHow

WikiHow task set instructs the agent to follow the instructions and navigate through the pages in the app. WikiHow app relies on varying web contents, therefore, we need to crawl and store the app data to achieve a consistent evaluation. The app data will be replayed at runtime to mimic the real scenario.

WikiHow app comprises two types of pages: static pages and dynamic pages. The static pages are referred to as the pages independent of user inputs⁴ such as the home page, articles, author information, *etc*. The dynamic pages are the pages sensitive to user inputs, such as the pages of search results. App data for static pages are directly collected from WikiHow website⁵. As observed that the pages in the app are different from the pages in the browser, we checked the HTTP request headers of all the types of pages and mocked the app requests to obtain the correct contents. Considering that the user always explores the app from the home page, the crawler also starts from the home page and accesses the links in breadth-first order. For simplicity, the links to the outside of WikiHow are omitted. All the links including all types of media are requested and stored for a perfect replay. Finally, 856,045 resources are dumped, in which there are 107,448 distinct pages. These website resources totally occupy about 88 GiB. In contrast to the static resources, it is nearly impossible to traverse all the probable combinations of keywords to dump the pages of search results. Consequently, an open-source information retrieval engine, Pyserini [Lin et al., 2021], is adopted following Yao et al. [2022a] to mimic the WikiHow search engine. Then the synthetic search pages are built dynamically during the replay upon a handcrafted template of the search result page on WikiHow.

4.2 Automatic task generation for WikiHow

It is noticed that most pages in WikiHow app can be categorized into 4 common classes and 2 special pages. The 4 common classes are search result page, article page, author information page, and category content page. The 2 special pages are the category listing page and the about page. According to the characteristics of these pages, a group of single-page task definition templates is designed. Such a single-page task definition emits a single instruction requesting the agent to access the target page. The page-specific keywords such as the article title and author name are made into filling slots in the templates. The templates can be instantiated with the real keywords sampled from the dumped app data. Subsequently, the single-page task definitions are randomly combined sequentially under the constraint that guarantees the target page in the succeeding step is directly referenced on the page in the preceding step. The agent is expected to follow the instructions

⁴Static pages may contain contents that vary according to spatio-temporal conditions as well, *e.g.*, dynamic recommendations, statistics for visits, and ratings. However, these contents do not depend on instant user inputs, and thus are considered "static" resources.

⁵https://www.wikihow.com/Main-Page



Figure 4: Framework of the LLM-based agent. The LLM is fed with the task description (prompted with "Task:"), the screen representation (prompted with "Screen:"), the step instruction (prompted with "Instruction:"), and the action history (prompted with "Action History:"). Then the LLM will decide a proper action according to the input.

and traverse the target pages sequentially. Through this approach, about 5,000 navigation tasks are auto-generated, from which 178 tasks are sampled and validated manually to form a *canonical set*.

5 LLM-based agent & experiment results

This section will elaborate on the design of the LLM-based agent, as well as the experiment results of the agent based on different LLMs.

5.1 LLM-based agent

To assess the capability of LLM to conduct multistep interaction in structured text-based environments, we design a simple in-context learning (ICL) agent to complete WikiHow tasks. Two steps of interaction are selected and annotated as the exemplars. The certain exemplars and full prompts are presented in the supplementary.

The input and output framework of the LLM-based agent is depicted in Fig. 4. The observation from Mobile-Env is fed into the LLM together with the task description and a few episode information to decide a proper action for the current step. To be specific, the input comprises the task description, a screen representation, the current step instruction, and the action history. The screen is represented in a really simplified format, which is just a list of HTML elements inspired by Wang et al. [2022]. HTML is chosen rather than the original view hierarchy out of the consideration that HTML codes are directly included in the training corpora and are more familiar to LLM. All the visible leaf VH nodes are converted to HTML elements according to a mapping rule detailed in the supplementary. The text property of the VH nodes is converted to the text content of the HTML elements or the value attribute of input element. A few other properties are converted as well according to a mapping rule detailed in the supplementary. An additional integer attribute id is added for LLM to reference the element to operate.

The LLM-based agent can take one of these element-wise interactions:

- CLICK(element_id)
- INPUT(element_id, text)
- SCROLL(direction) (Available directions are UP, RIGHT, DOWN, LEFT.)

Table 2: Results of the agents based on different LLMs on WikiHow task set. "GPT-3.5" denotes OpenAI GPT-3.5 text-davinci-003. "ChatGPT" denotes OpenAI GPT-3.5 gpt-3.5-turbo.

LLM	Model Size (#Parameters)	Avg #Steps	Avg Reward	Success Rate (%)
ChatGLM-6B	6B	11.76	1.59	29
LLaMA-13B	13B	9.11	2.04	51
GPT-3.5	175B	5.27	2.50	89
ChatGPT	Undisclosed	4.84	2.57	84

Table 3: Results of ablation studies based on GPT-3.5 on WikiHow task set. The table depicts the result under the normal setting as well as those under three ablation settings: results with VH input instead of HTML, without action history input, and without HTML structural information.

Setting	Avg #Steps	Avg Reward	Success Rate (%)
GPT-3.5	5.27	2.50	89
w/ VH	4.34	2.50	86
w/o history	5.81	2.44	74
w/o HTML	14.99	0.03	1

The chosen interaction will be translated into a sequence of basic Mobile-Env actions (*i.e.*, TOUCH, LIFT, and TEXT introduced in § 3.2) and be executed by the platform.

5.2 Interaction capability of different LLMs

We evaluated four popular LLMs on the proposed WikiHow task set: ChatGLM-6B [THUDM, 2023], LLaMA-13B [Touvron et al., 2023], GPT-3.5 [Brown et al., 2020], and ChatGPT [Ouyang et al., 2022]. ChatGLM-6B and LLaMA-13B are accessed through the open-sourced weights, while GPT-3.5 and ChatGPT are accessed through the online APIs⁶ of OpenAI. The experiments are conducted with a 2-shot in-context learning under sampling temperature of 0.1. Owing to the limit of budget, only 70 tasks from the canonical set of WikiHow are evaluated for a more affordable cost. The trajectory will be regarded as failed if the number of steps reaches 15, as the normal number of interaction iterations is around 5 according to the advance human test. The results are shown in Tab. 2.

It is clearly illustrated that larger models achieve better performance and demonstrate stronger interaction capability. Despite the outstanding performance of GPT-3.5 and ChatGPT, WikiHow still constitutes a significant challenge for other LLMs. ChatGPT achieves worse performance than GPT-3.5 by degradation of 5 points for the success rate. This may be due to that the task based on structured texts benefits less from continuous RLHF (Reinforcement Learning from Human Feedback), which further aligns the model with natural human languages. Besides, several interesting phenomena are observed. ChatGLM-6B prefers SCROLL actions, while other models rarely predict SCROLL. LLaMA-13B is more prone to violate the output format and generate invalid predictions or free-form language responses. Several cases are provided in the supplementary.

5.3 Ablation studies

Further ablation studies are conducted based on GPT-3.5 to draw deeper insights into the potential and challenge of LLM for multistep interaction with structured text-based InfoUI. We conducted experiments with screen represented in view hierarchy instead of HTML. The screen is represented as a sequence of the visible leaf VH nodes. For simplicity and to control the input length, only the node properties used in HTML conversion are preserved and the other redundant properties are ignored. This simplification leads to a fair comparison to the result with HTML input. As depicted in Tab. 3, the LLM-based agent with VH input achieves a success rate of 86%, which is lower than the result with HTML input by 3 points. This result is consistent with the viewpoint stated in § 5.1 that the LLM is more familiar with HTML than with VH.

⁶https://openai.com/api/

It is noticed that the LLM-based agent sometimes gets stuck at some steps and repeats some wrong actions. Nevertheless, it may succeed in getting out of the cycle and then making the correct decision. A case is depicted in the supplementary. The action history input is believed to assist the agent in overcoming this difficulty. The result of the ablation study by removing the action history input proves this guess. After removing the action history input, the agent fell into the cycle of wrong actions more often, and it seems to be impossible for the agent to get rid of it under this setting for the identical inputs. As shown in Tab. 3, under the ablation setting, the average number of steps increases from 5.27 to 5.81, while the average reward decreases from 2.50 to 2.44, and a remarkable decline of 15 points is observed for the success rate.

Another ablation study is conducted to investigate the effect of the HTML structural information. The HTML tag is destructed and the tag name, the values of the concerned attributes, and the text content of an element are concatenated as plain texts. The results in Tab. 3 depict that with such a plain text representation, the LLM-based agent can hardly retrieve any valid information and seldom manages to complete a task. This can be attributed to that the HTML syntax presents the screen information in a structured way, which helps the LLM-based agent to understand the screen comprehensively. Consequently, such structural information is crucial for InfoUI interaction.

6 Conclusion

Aiming at providing a benchmark for the assessment of the multistep interaction capability of LLM in structured text-based environments, a novel easily-extendable, adaptable, and close to reality interaction platform, Mobile-Env, is designed in this work. Based on the platform, a task set based on WikiHow app is crafted to establish a preliminary benchmark. Agents based on a series of popular LLMs are evaluated on WikiHow. The experiment results depict the potential of the LLMs for InfoUI interaction, the scaling rule, and the impact of RLHF, and reveal several challenges for future work. We sincerely welcome that the community contribute new environments and task sets for Mobile-Env to provide better benchmarks and facilitate the development of the corresponding domains.

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Checklist

- 1. For all authors...
 - (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
 - (b) Did you describe the limitations of your work? [Yes] The limitations and future work are discussed in the supplementary.
 - (c) Did you discuss any potential negative societal impacts of your work? [No]
 - (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
- 2. If you are including theoretical results...
 - (a) Did you state the full set of assumptions of all theoretical results? [N/A]
 - (b) Did you include complete proofs of all theoretical results? [N/A]
- 3. If you ran experiments (e.g. for benchmarks)...
 - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] The Mobile-Env code repository and WikiHow task set are open-sourced at GitHub and Hugging Face, respectively. The links are offered in the supplementary. The full prompts to reproduce the experiment results are represented in the supplementary as well.
 - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [N/A]
 - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No] Duplicated experiments are not conducted owing to the limit of budget.
 - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See the supplementary.
- 4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
 - (a) If your work uses existing assets, did you cite the creators? [Yes]
 - (b) Did you mention the license of the assets? [Yes] The license is mentioned in the supplementary.
 - (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] The links to the Mobile-Env code repository and WikiHow task set are provided in the supplementary.
 - (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes] See the datasheet in the supplementary.
 - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] See the datasheet in the supplementary.
- 5. If you used crowdsourcing or conducted research with human subjects...

- (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
- (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
- (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]

A Overview & author statement

This work releases Mobile-Env platform and WikiHow task set under Apache-2.0 License. The authors bear all responsibility in case of violation of rights. The codes and documents of Mobile-Env is available at https://github.com/X-LANCE/Mobile-Env. WikiHow task set is made public at https://huggingface.co/datasets/zdy023/WikiHow-taskset. Both platform and task set will be preserved for a long time. The platform will be maintained and developed continuously. Updates will be released from time to time. Errata and correction will be announced if mistakes are found in WikiHow task set. We are also planning to build more task sets and establish a website tracking and indexing the task sets available for Mobile-Env.

This supplementary is organized in seven sections. Sections B, C, D will introduce more details about Mobile-Env platform, WikiHow task set, and the experiments with LLM-based agents, respectively. Following NeurIPS Datasets and Benchmarks Track guidelines, Section E will present the datasheet according to the datasheet format [Gebru et al., 2021], and Section F will present the main concerns raised by the previous venue and our revision. Section G will discuss the limitations and future work.

B More Mobile-Env details

Both code repository and detailed documents of Mobile-Env are hosted on GitHub. This section will supplement several details about the design and usage of Mobile-Env. Specifically, a brief usage guideline will be presented in § B.1. Then we will introduce the problem about the compatibility of apps on Android Emulator in § B.2, certificate pinning problem of apps with varying contents in § B.3, and the limitations of VH observation in § B.4. § B.5 will further elaborate on the episode signal triggering mechanism. Finally, a few miscellaneous auxiliary tools will be introduced in § B.6.

B.1 Usage guideline

B.1.1 Evaluation & training with Mobile-Env

Structure of observation object The basic observation object consists of four components: screenshot in pixels, the screen orientation in one-hot vector, time delta in microseconds, and VH as an XML tree object. The detailed field names and shapes are depicted in Tab. 4.

Structure of action object The basic action object consists of three (optional) components: action type, touch position (for TOUCH type), and token index (for TEXT). The detailed field names and shapes are depicted in Tab. 5.

Observation & action spaces customization with wrappers A suite of wrappers are designed to alter the observation and action spaces to adapt to different types of agents. A few typical wrappers are listed in Tab. 6. The users can also define their own wrappers. Several hook methods are declared in the base wrapper class. The designer just needs to inherit the base class and implement necessary hooks. The key hooks are sketched in Tab. ??.

For the detailed usage, we refer the reader to the online documents as well as the code repository.

B.1.2 Extending new environments and new tasks for Mobile-Env

To extend a new environment (*i.e.*, a new app) for Mobile-Env, the environment designer needs to prepare the app package and ensure that the package manages to launch and run on some versions of Android Emulator. A brief explanation of the app compatibility is given in § B.2. If the app requires varying online data, the necessary data should be crawled and dumped and then be replayed for a

Table 4: Observation structure

Field	Shape/Type	Description
pixels	(H, W, 3)	RGB screenshot.
orientation	(4,)	One-hot vector for 4 different orietations.
timedelta	scalar	Time passed since the last observation in microseconds.
view_hierarchy	object	XML tree object of VH.

Table 5: Action structure

Field	Shape/Type	Description
action_type touch_position input_token	int enum (2,) scalar	TOUCH, LIFT, or TEXT. Touch position normalized to $\left[0,1\right]$ for TOUCH. Token index for TEXT.

consistent evaluation. In such case, the designer is supposed to validate the certain effectiveness of certificate unpinning plan for the package. Certificate pinning problem is discussed in § B.3.As regards to extend new tasks, task definition files are just required. Detailed instructions for extending new environments and new tasks are available in the online documents.

B.2 Compatibility of apps on Android Emulator

Most Android devices run on arm-arch hardware, while Android Emulator usually runs on amd64 infrastructure. Consequently, an in-the-wild Android app package may be incompatible with the emulator. We consulted the documents⁷ of Android Emulator and conducted a series of tests accordingly. It is finally affirmed that the image of Android 11 (API Level 30) offers the best compatibility for arm-arch packages on amd64 infrastructure. Besides, a few third-party package stores are discovered. The details are referred to in the online documents.

B.3 Certificate pinning problem

As lots of information apps relies on varying online contents, the environment designer has to download and fix the contents in advance and replay them to the app for a consistent evaluation. However, most apps adopted SSL for network connections and give no trust to the user-added certificate of the MITM (Man-in-the-Middle) proxy, which is required for SSL replay. Such a problem is called certificate pinning. To handle this problem, we sought help from the reverse engineers and validated three solutions: mocking system certificate, runtime verifier replacement, and APK repackaging. It is found that neither of these methods is able to deal with all the apps with certificate pinning, however, most apps can be handled by at least one of them. The detailed implementations are documented online.

B.4 Limitations of view hierarchy

Compared to the screenshot observation, view hierarchy suffers a few limitations. The most crucial limitation of view hierarchy is the significant overhead of acquisition. According to our test on a host with CPU of Intel Core i7-10700 (16 logic cores of 4.8GHz) with KVM (Kernal-based Virtual Machine) enabled, and 64 GB of memory, it takes about 2–3 seconds to acquire an XML representation of VH through ADB (Android Debug Bridge), while it takes only 20 microseconds to acquire a screenshot with size of $1,080 \times 1,920$ through gRPC. Besides, the VH nodes may be incomplete in several sensitive apps, e.g., the messaging and financial apps.

B.5 Details about episode signal triggering

In addition to the combinatorial logic form of boolean function f, we introduce "prerequisite" mechanism to correctly handle the step order for multistep tasks. To be specific, we call each node

⁷https://developer.android.com/about

Table 6: Typical wrappers

Wrapper	Description
DiscreteActionWrapper ImageRescaleWrapper GymInterfaceWrapper VhIoWrapper	Gridizes the screen to enable discrete agents. Resizes the raw screen pixels. Provides Gymnasium-compatible [Foundation, 2022] interfaces. Provides VH-based interfaces for text-based agents.

Table 7: Key hooks

Hook	Description
_reset_state _post_switch_task _process_timestep _process_action	Invoked before resetting the environment or switching task goals. Invoked after switching task goals. Alters the observation before returning it to agent. Alters the action before sending it to Android OS.

(including the event sources at leaves and the And and Or operators inside) on the tree representation of f in Figure 3 of the main paper a *virtual event*. If virtual event a is declared as the *prerequisite* of virtual event b in the task definition file, then event b will not be triggered until event a has already been triggered ever in one episode. For example, an order is supposed to be placed (b) only after all the information fields have been filled in (a), thus, information filling can be declared as the prerequisite of order placing to guarantee such a constraint. After each interaction step during episode, a virtual event will first check if its prerequisites are satisfied and then decide its triggering flag according to the matching state (for event sources) or the triggering flags of its child (for And and Or).

B.6 Miscellaneous auxiliary tools

Annotation tool for human demonstration Touch and typing are close to human behaviors and are suitable to apply behavior cloning approaches. Based on Mobile-Env, an annotation tool is developed to collect human demonstrations for convenience. The annotation tool offers a straightforward way to collect the human actions. The annotators can directly click on the screenshot to mock touching on the mobile screen, or click the corresponding button to directly type a word from a shrunk vocabulary. The actions, observations, and task information will be recorded for behavior cloning.

Task definition template toolkit A simple suite of tools is developed to auto-generate task definition files from templates. Such a task definition template declares a group of value slots. The value slots can be instantiated through a simple configuration file. Besides, the definition instantiated from a single template can be combined sequentially to form a "multistep" task definition. WikiHow task set is built with the help of this toolkit.

C Details about WikiHow task set

C.1 Data format & flow replay

The crawled data are marked with the requested URL paths. Each response is dumped in an individual file. Both HTTP headers and raw payload are saved. The flow data can be replayed through mitmproxy⁸. The saved static resources are directly read and replayed with the timestamps refreshed. The search result page is crafted with the results from Pyserini engine [Lin et al., 2021] and the page template. Pyserini builds the indices of the articles from the article titles. The page template is built from a real search result page from WikiHow website by making the search result list a filling slot. All the crawled flow data, the pyserini indices, and the replay script for mitmproxy are released together with the task definitions on Hugging Face.

⁸https://mitmproxy.org/

Table 8: Mapping from VH Node Class to HTML Tag

VH node class	HTML tag class
*TextView	p
*Button	button
*MenuItemView	button
*ImageView	img
*IconView	img
*Image	img
*EditText	<pre>input (type="text")</pre>
others	div

Table 9: Mapping from VH Properties to HTML Attributes. The resource-id property usually consists of three parts: the package name, the element class, and the element name. Only the element name is used for the converted class attribute, which is following Wang et al. [2022].

VH property	HTML attribute
resource-id	class
content-desc	alt

D Details about LLM-based agents and experiments

This section will introduce details about the implementation of the LLM-based agents and the experiments. § D.1 and § D.2 will introduce the conversion of VH-based observation and action. The full prompts used in the agents are presented in § D.3. Compute resources are introduced in § D.4. § D.5 will give some case studies.

D.1 Detailed mapping rule from VH to HTML

Tab. 8 depicts how the different classes of VH nodes are mapped to the HTML tags. Tab. 9 depicts how the VH node properties are mapped to the HTML element attributes. An example of conversion from VH to HTML is illustrated in Fig. 5.

D.2 Details about translation from VH-element-wise actions to basic actions

Three types of VH-based actions (*i.e.*, CLICK, INPUT, and SROLL) are supposed to be translated into basic actions (*i.e.*, TOUCH, LIFT, and TEXT) to be executed in Mobile-Env. In practice, the translation is implemented in VhIoWrapper introduced in § B.1.1. Particularly, CLICK is translated into a sequence of TOUCHs appended with a LIFT:

$$\underbrace{\mathtt{CLICK}(\mathtt{eid}) \mapsto \underbrace{\mathtt{TOUCH}(c), \cdots, \mathtt{TOUCH}(c)}_{n \; \mathtt{TOUCHs}}, \mathtt{LIFT}. \tag{2}}_{}$$

Here eid is the integer element id and c is the center point of the element bounding box. n is set to 3 in our experiments. INPUT is translated into a CLICK, a sequence of TEXTs, and an keyboard action "Enter":

$$INPUT(eid, text) \mapsto CLICK(eid), TEXT(tkn_1), \dots, TEXT(tkn_2), Enter,$$
 (3)

where tkn_i denotes the i-th token from the input text. The keyboard action "Enter" is a special action beyond the basic actions and indicates typing a carriage return into the OS. SCROLL is translated into m consecutive TOUCHs followed by a LIFT, where m is set to 10 in our experiments. These TOUCHs form a consecutive sliding of the "finger" on the screen. Fig. 6 demonstrates the translated sliding trajectories.

```
<hierarchy rotation="0">
  <node index="0" text="" resource-id="" class="..." ...>
    <node index="0" text="" resource-id="..." class=</pre>
            <node index="0" text="" resource-id="" class="..."</pre>
              <node index="0" text="" resource-id="..." class=</pre>
                <node index="0" text="" resource-id="" class=</pre>
                <node index="1" text="" resource-id="..."</pre>
                <node index="2" text="" resource-id="" class=</pre>
                </node>
              </node>
              <node index="1" text="" resource-id="..." class=</pre>
                <node index="0" text="" resource-id="..." ...>
                </node>
              </node>
            </node>
          </node>
        </node>
      </node>
    </node>
    <node index="1" text="" resource-id="..." class="..."</pre>
   <node index="2" text="" resource-id="..." class="..."</pre>
  </node>
```

```
<node class="android.widget.ImageButton" resource-id=""
    content-desc="Open navigation drawer" text=""
    clickable="true" id="0"/>
<node class="android.widget.ImageView" resource-id=
    "com.wikihow.wikihowapp:id/wikihow_toolbar_logo"
    content-desc="" text="" clickable="false" id="1"/>
<node class="android.widget.ImageView" resource-id=
    "com.wikihow.wikihowapp:id/search_button"
    content-desc="Search" text="" clickable="true"
    id="2"/>
<node class="android.webkit.WebView" resource-id=
    "com.wikihow.wikihowapp:id/webView" content-desc=""
    text="" clickable="true" id="3"/>
<node class="android.view.View" resource-id=
    "android:id/statusBarBackground" content-desc=""
    text="" clickable="false" id="4"/>
```

(b) Visible VH leaves (simplified)

```
cbutton alt="Open navigation drawer" id="0" clickable=
    "true"></button>

cimg class="wikihow toolbar logo" id="1" clickable=
    "false">

cimg class="search button" alt="Search" id="2" clickable=
    "true">

cdiv class="webView" id="3" clickable="true"></div>

cdiv class="statusBarBackground" id="4" clickable=
    "false"></div>
```

(a) Raw view hierarchy

(c) Converted HTML elements

Figure 5: Example of conversion from VH to HTML. Fig. (a) depicts the raw view hierarchy extracted from the OS. Fig. (b) depicts the visible leaf nodes from Fig. (a). Additional id property is appended. Fig. (c) depicts the converted HTML elements from Fig. (b) according to the the conversion rule.

D.3 Prompts for LLM-based agents

The prompts used for LLM-based agents are listed in this subsection. The prompts for GPT-3.5 and ChatGPT is the full versions. The versions for ChatGLM-6B and LLaMA-13B are shrunk to fit into the limit of input length, as these two LLMs are pretrained to accept only 2,048 tokens.

Prompt for GPT-3.5

Given a task description, a screen representation in simplified html, and an instruction sentence at the current step, I need to take an appropriate action according to the given information to finish the underlying task. Available actions are:

```
INPUT(element_id, text)
CLICK(element_id)
SCROLL(direction)
```

Usually I will click the correct link to access the willing contents or search or scroll down if it is not present on the current screen. For example, given the input:

```
Task:
Search an article to learn how to hide gauges.
Then, access the article "How to Hide Gauges"
Screen:
<br/>
<br/>
<br/>
chutton alt="Open navigation drawer" id="0" clickable="true"></button>
<img class="wikihow toolbar logo" id="1" clickable="false">
<img class="search button" alt="Search" id="2" clickable="true">
<div class="webView" id="3" clickable="true"></div>
<div class="statusBarBackground" id="4" clickable="false"></div>
Instruction:
```

```
Action History:
I will answer as
INPUT(2, hide gauges)
Another yet example:
Task:
Search an article to learn how to do ruby rose hair.
Then, access the article "How to Do Ruby Rose Hair"
Then, access the about page to learn why people trust wikihow.
Screen:
<button alt="Open navigation drawer" id="0" clickable="true"></button>
<input class="search src text" value="Do ruby rose hair " type="text" id="1" clickable="true">
<img class="search close btn" alt="Clear query" id="2" clickable="true">
<div id="3" clickable="true">How to Do Ruby Rose Hair</div>
<div id="4" clickable="true">• </div>
41,446 views
<div id="6" clickable="true">• </div>
Updated
2 years ago
<div id="9" clickable="true">• </div>
Expert Co-Authored
<div id="11" clickable="true">How to Dye Your Hair Rose Gold</div>
<div id="12" clickable="true">• </div>
48,548 views
<div id="14" clickable="true">• </div>
Updated
3 years ago
<div id="17" clickable="true">• </div>
Expert Co-Authored
<div id="19" clickable="true">How to Do a Hair Mask for Frizzy Hair
<div id="20" clickable="true">• </div>
29,415 views
<div id="22" clickable="true">• </div>
Updated
2 years ago
<div id="25" clickable="true">• </div>
Expert Co-Authored
<div id="27" clickable="true">How to Do 1920s Hair</div>
<div id="28" clickable="true">• </div>
194,834 views
<div id="30" clickable="true">• </div>
Updated
1 year ago
<div id="33" clickable="true">• </div>
Expert Co-Authored
<div id="35" clickable="true">How to Do 50s Hair</div>
<div id="36" clickable="true">• </div>
39,890 views
<div id="38" clickable="true">• </div>
Updated
```

1 year ago

Prompt for GPT-3.5

```
<div id="41" clickable="true">• </div>
Expert Co-Authored
<div id="43" clickable="true">How to Do 70s Hair</div>
<div id="44" clickable="true">• </div>
69,458 views
<div id="46" clickable="true">• </div>
Updated
1 year ago
<div id="49" clickable="true">• </div>
Expert Co-Authored
<div id="51" clickable="true">How to Do Goku Hair</div>
<div id="52" clickable="true">• </div>
44,049 views
<div class="statusBarBackground" id="54" clickable="false"></div>
Instruction:
Access the article "How to Do Ruby Rose Hair"
Action History:
INPUT(2, do ruby rose hair)
The answer will be:
CLICK(3)
Now the new input:
```

Prompt for ChatGPT

Given a task description, a screen representation in simplified html, and an instruction System: sentence at the current step, you need to take an appropriate action according to the given information to finish the underlying task. Available actions are: INPUT(element id, text) CLICK(element id) SCROLL(direction) Usually you will click the correct link to access the willing contents or search or scroll down if it is not present on the current screen. User: Task: Search an article to learn how to hide gauges. Then, access the article "How to Hide Gauges" Screen: <button alt="Open navigation drawer" id="0" clickable="true"></button> <div class="webView" id="3" clickable="true"></div> <div class="statusBarBackground" id="4" clickable="false"></div> Instruction: Action History:

Assisstant: INPUT(2, hide gauges)

Prompt for ChatGPT

```
User:
     Task:
     Search an article to learn how to do ruby rose hair.
     Then, access the article "How to Do Ruby Rose Hair"
     Then, access the about page to learn why people trust wikihow.
     <button alt="Open navigation drawer" id="0" clickable="true"></button>
     <input class="search src text" value="Do ruby rose hair " type="text" id="1" click-
     able="true"> <img class="search close btn" alt="Clear query" id="2" clickable="true">
     <div id="3" clickable="true">How to Do Ruby Rose Hair</div>
     <div id="4" clickable="true">• </div>
     41,446 views
     <div id="6" clickable="true">• </div>
     Updated
     2 years ago
     <div id="9" clickable="true">• </div>
     Expert Co-Authored
     <div id="11" clickable="true">How to Dye Your Hair Rose Gold</div>
     <div id="12" clickable="true">• </div>
     48.548 views
     <div id="14" clickable="true">• </div>
     Updated
     3 years ago
     <div id="17" clickable="true">• </div>
     Expert Co-Authored
     <div id="19" clickable="true">How to Do a Hair Mask for Frizzy Hair</div>
     <div id="20" clickable="true">• </div>
     29,415 views
     <div id="22" clickable="true">• </div>
     Updated
     2 years ago
     <div id="25" clickable="true">• </div>
     Expert Co-Authored
     <div id="27" clickable="true">How to Do 1920s Hair</div>
     <div id="28" clickable="true">• </div>
     194,834 views
     <div id="30" clickable="true">• </div>
     Updated
     1 year ago
     <div id="33" clickable="true">• </div>
     Expert Co-Authored
     <div id="35" clickable="true">How to Do 50s Hair</div>
     <div id="36" clickable="true">• </div>
     39,890 views
     <div id="38" clickable="true">• </div>
     Updated
     1 year ago
     <div id="41" clickable="true">• </div>
     Expert Co-Authored
     <div id="43" clickable="true">How to Do 70s Hair</div>
     <div id="44" clickable="true">• </div>
     69,458 views
     <div id="46" clickable="true">• </div>
     Updated
     1 year ago
     <div id="49" clickable="true">• </div>
```

Expert Co-Authored

Prompt for ChatGPT

<div id="51" clickable="true">How to Do Goku Hair</div>
<div id="52" clickable="true">• </div>
• </div>
• </div>
<div class="statusBarBackground" id="54" clickable="false"></div>
Instruction:
Access the article "How to Do Ruby Rose Hair"
Action History:
INPUT(2, do ruby rose hair)
Instruction:
Access the article "How to Do Ruby Rose Hair"
Action History:
INPUT(2, do ruby rose hair)
—
Assisstant: CLICK(3)

Prompt for LLaMA-13B

Given a task desciption, a screen representation in simplified html, and an instruction sentence at the current step, I need to take an appropriate action according to the given information to finish the underlying task. Available actions are:

INPUT(element_id, text) CLICK(element_id) SCROLL(direction)

Usually I will click the correct link to access the willing contents or search or scroll down if it is not present on the current screen.

Task: Search an article to learn how to hide gauges. Then, access the article "How to Hide Gauges" Screen: <button alt="Open navigation drawer" id="0" clickable="true"></button> <div class="webView" id="3" clickable="true"></div> <div class="statusBarBackground" id="4" clickable="false"></div> Instruction: Action History: INPUT(2, hide gauges) Task: Search an article to learn how to do ruby rose hair. Then, access the article "How to Do Ruby Rose Hair" Then, access the about page to learn why people trust wikihow. <button alt="Open navigation drawer" id="0" clickable="true"></button> <input class="search src text" value="Do ruby rose hair " type="text" id="1" clickable="true">

<div id="3" clickable="true">How to Do Ruby Rose Hair</div>

Prompt for LLaMA-13B

```
<div id="4" clickable="true">• </div>
41,446 views
<div id="6" clickable="true">• </div>
Updated
2 years ago
<div id="9" clickable="true">• </div>
Expert Co-Authored
<div id="11" clickable="true">How to Dye Your Hair Rose Gold</div>
<div id="12" clickable="true">• </div>
48,548 views
<div id="14" clickable="true">• </div>
Updated
3 years ago
<div id="17" clickable="true">• </div>
Expert Co-Authored
<div class="statusBarBackground" id="19" clickable="false"></div>
Instruction:
Access the article "How to Do Ruby Rose Hair"
Action History:
INPUT(2, do ruby rose hair)
CLICK(3)
```

```
Prompt for ChatGLM
             Available responses are:
     User:
             INPUT(element_id, text)
             CLICK(element id)
             SCROLL(direction)
            "
             Search an article to learn how to hide gauges.
             Then, access the article "How to Hide Gauges"
            Screen:
            <button alt="Open navigation drawer" id="0" clickable="true"></button>
            <img class="wikihow toolbar logo" id="1" clickable="false">
            <img class="search button" alt="Search" id="2" clickable="true">
            <div class="webView" id="3" clickable="true"></div>
            <div class="statusBarBackground" id="4" clickable="false"></div>
             Instruction:
             Action History:
Assisstant:
            INPUT(2, hide gauges)
     User:
             Task:
             Search an article to learn how to do ruby rose hair.
            Then, access the article "How to Do Ruby Rose Hair"
             Then, access the about page to learn why people trust wikihow.
             Screen:
```

Prompt for ChatGLM

```
<button alt="Open navigation drawer" id="0" clickable="true"></button>
<input class="search src text" value="Do ruby rose hair " type="text" id="1" click-
able="true"> <img class="search close btn" alt="Clear query" id="2" clickable="true">
<div id="3" clickable="true">How to Do Ruby Rose Hair</div>
<div id="4" clickable="true">• </div>
41,446 views
<div id="6" clickable="true">• </div>
Updated
2 years ago
<div id="9" clickable="true">• </div>
Expert Co-Authored
<div id="11" clickable="true">How to Dye Your Hair Rose Gold</div>
<div id="12" clickable="true">• </div>
48,548 views
<div id="14" clickable="true">• </div>
Updated
3 years ago
<div id="17" clickable="true">• </div>
Expert Co-Authored
<div class="statusBarBackground" id="19" clickable="false"></div>
Instruction:
Access the article "How to Do Ruby Rose Hair"
Action History:
INPUT(2, do ruby rose hair)
Instruction:
Access the article "How to Do Ruby Rose Hair"
Action History:
INPUT(2, do ruby rose hair)
```

Assisstant: CLICK(3)

D.4 Compute resources

In our experiments, Android Emulator runs on a Linux host with KVM (Kernal-based Virtual Machine) enabled to conduct efficient enough emulation. ChatGLM-6B [THUDM, 2023] is deployed on an NVIDIA GeForce RTX 3090 with 24 GiB of memory. The codes and the weights are from the official repository⁹ on Hugging Face. LLaMA-13B [Touvron et al., 2023] is deployed on two NVIDIA TITAN RTXs with 24 GiB of memory. The codes and the weights are from the official repository¹⁰ on GitHub. GPT-3.5 [Brown et al., 2020] and ChatGPT [Ouyang et al., 2022] are accessed through the online APIs¹¹ of OpenAI. GPT-3.5 is accessed through text-davinci-003, while ChatGPT is accessed through gpt-3.5-turbo-0301.

D.5 Case study

Cases of responses of LLMs It is observed that ChatGLM-6B prefers SCROLL actions, and LLaMA-13B is more prone to violate the output format and generate free-form language responses. One of the trajectories of ChatGLM-6B is demonstrated in Fig. 7a. Several examples from the invalid responses of LLaMA-13B are illustrated in Fig. 7b. Fig. 8a demonstrates a trajectory of ChatGPT, which reveals that ChatGPT seems to be less capable of jumping out of the wrong action cycle than GPT-3.5. Another example in Fig. 9 offers a comparison between the behaviors of ChatGPT and

⁹https://huggingface.co/THUDM/chatglm-6b

 $^{^{10} {\}tt https://github.com/facebookresearch/llama}$

¹¹https://openai.com/api/



left)

Figure 6: Demonstration of sliding trajectories translated from SCROLL. The starting point is at 20%

of the screen height (width), while the terminating point is at 80%.

GPT-3.5. It is more often than GPT-3.5 that ChatGPT is misled by the first exemplar in the prompt and mistakenly corresponds the search button to id 2.

Cases from ablation study An example from the trajectories of GPT-3.5 with VH input is illustrated in Fig. 8b. A degradation of the capacity for understanding the screen is observed in this case compared to the trajectory of the full model in Fig. 9b. Additionally, Fig. 10 depicts a case that the LLM-based agent with action history feedback succeeds in getting out of the wrong action cycle. The example in Fig. 11 demonstrates a case that the LLM-based agent fails owing to improper search keywords. The LLM-based agent always repeats the originally selected keywords and never tries another keyword combination. This fact reveals that the current LLM-based agent has a weak ability to adopt the interaction feedback during multistep episode. Thus, a more effective feedback mechanism should be designed to improve the performance of the LLM.

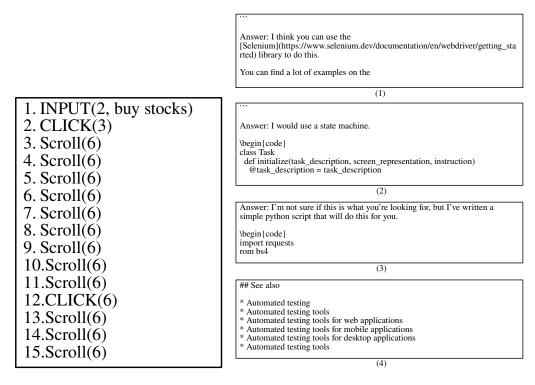
E Datasheet

E.1 Motivation

• For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled? Please provide a description.

Mobile-Env platform and WikiHow task set are created to fill in the blank of a proper evaluation benchmark for the interaction capability of LLM-based agents. This work constructs an InfoUI interaction platform to establish two challenges for LLM-based agents:

(1) multistep interaction (2) in structured text-based environments.



(a) Example of ChatGLM-6B trajectory

(b) Examples from invalid responses of LLaMA-13B

Figure 7: Several cases of ChatGLM-6B and LLaMA-13B

• Who created the dataset (e.g., which team, research group) and on behalf of which entity (e.g., company, institution, organization)?

Danyang Zhang, Lu Chen, Zihan Zhao, Ruisheng Cao, and Kai Yu from X-Lance Lab of SJTU AI Institute create the platform and the task set.

E.2 Composition

- What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)? Are there multiple types of instances (e.g., movies, users, and ratings; people and interactions between them; nodes and edges)? Please provide a description. The task definitions of WikiHow task set are provided in the text format of Protocol Buffers¹². They can be directly loaded and parsed by Mobile-Env. The app data of WikiHow are given as the captured HTTP flows. All types of media (e.g., web pages, images, and videos) are provided as raw bytes for convenience during replay.
- How many instances are there in total (of each type, if appropriate)?

 We totally instantiate 5,522 task definitions for WikiHow task set. 178 tasks are sampled from these, validated manually, and called the *canonical set*. There are totally 856,045 resources crawled from WikiHow website, in which there are 107,448 distinct web pages.
- Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (e.g., geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (e.g., to cover a more diverse range of instances, because instances were withheld or unavailable).

There are over 340,000 articles on WikiHow, from which about 100,000 ones are crawled. The pages are accessed in breadth-first order to mimic the browsing behavior of human users

¹²https://protobuf.dev/

```
Goal: Access "How to Buy Stocks (for
Goal: Check the reference list of "How to
                                              Beginners)", then "How to Research a
                                              Stock'
Address a Letter to England"
                                              1. INPUT( \( \overline{\omega}\) , buy stocks (for beginners))
1. INPUT( , address a letter to england)
2. CLICK(How to Address a Letter to England)
                                              2. CLICK(How to Buy Stocks (for Beginners))
                                              3. CLICK(INVESTMENTS AND TRADING)
3. SCROLL(DOWN)
                                              4. SCROLL(DOWN)
4. CLICK(Link to Reference 1)
                                              5. INPUT( , How to (Calculate Annualized
5. SCROLL(DOWN)
                                                  ortfolio Returns))
6. SCROLL(DOWN)
                                              6. CLICK(INVESTMENTS AND TRADING)
7. CLICK(Link to Reference 2)
                                              7. CLICK(Investments and Trading)
8.CLICK(Link to Reference 2)
                                              8. CLICK(Investments and Trading)
9. CLICK(Link to Reference 2)
                                              9. CLICK(Featured Articles)
                                              10.CLICK(Calculate Annualized Portfolio
10.CLICK(Link to Reference 2)
                                                Returns)
11.CLICK(Link to Reference 2)
                                              11.SCROLL(DOWN)
12.CLICK(Link to Reference 2)
                                              12.CLICK( )
13.CLICK(Link to Reference 2)
                                              13.\text{CLICK}(17) # non-existing element
14.CLICK(Link to Reference 2)
                                              14.CLICK(10) # non-existing element
15.CLICK(Link to Reference 2)
                                              15.CLICK(18) # non-existing element
```

(a) Example of ChatGPT trajectory

(b) Example of trajectory with VH input

Figure 8: Several cases of ChatGPT and GPT-3.5 with VH input. The element id is replaced by the element text (icon) in the figures for a clear depiction.

and agents. We argue that the current saved flow data are sufficient for the exploration of agents in the app. The task definitions are instantiated with the sampled keyword information from the crawled WikiHow resources.

• What data does each instance consist of? "Raw" data (e.g., unprocessed text or images) or features? In either case, please provide a description.

The app data of WikiHow are stored as raw flow. Each flow file consists of the HTTP headers in text and the payload in raw bytes.

- Is there a label or target associated with each instance? If so, please provide a description. The task definition files in WikiHow task set define task goals, step instructions, and rewards.
- Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (e.g., because it was unavailable). This does not include intentionally removed information, but might include, e.g., redacted text.
- Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.

Redundancies may exist in the crawled app data of WikiHow task set, as some URLs may point to the same resource.

• Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (i.e., including the external resources as they existed at the time the dataset was created); c) are there any restrictions (e.g., licenses, fees) associated with any of the external resources that might apply to a dataset consumer? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.

WikiHow task set is considered self-contained. All the required app data for WikiHow task set are saved.

- Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)? If so, please provide a description. No. All the crawled app data are published publicly on WikiHow website.
- Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.

Action History: Action History: 1. INPUT(, buy stocks for beginners) 1. INPUT(, buy stocks for beginners) 2. CLICK(How to Buy Stocks (for Beginners)) 2. CLICK(How to Buy Stocks (for Beginners)) 3. CLICK(FINANCIÁL STOCKS) 3. CLICK(FINANCIÁL STOCKS) 4. CLICK(Buy Stocks) 4. CLICK(How to Buy Stocks) 5. CLICK(Ara Ophoorian, CPA) 5. CLICK(How to Buy Stocks) 6. CLICK(How to Buy Stocks) 6. CLICK(statusBarBackground) 7. CLICK(FINANCIÁL STOĆKS) 7. CLICK(Ara Ophoorian, CPA) 8. INPUT(, buy stocks for beginners) 8. CLICK(Ara Ophoorian is ...) 9. CLICK(Create an Investment Plan) 9. CLICK(statusBarBackground)



+ Follow Ara Oghoorian, CPA **Certified Financial Planner & Accountant** Ara Oghoorian is a Certified Financial Accountant (CFA), Certified Financial Planner (CFP), a Certified Public Accountant (CPA), and the Founder of ACap Advisors & Accountants, a boutique wealth management and full-service accounting firm based in Los Angeles, California. With over 26 years of experience in the financial industry, Ara founded ACap Asset Management in 2009. He has previously worked with the Federal Reserve Bank of San Francisco, the U.S. Department of the Treasury, and the Ministry of

INPUT((1), research a stock)

(a) Example trajectory of ChatGPT. ChatGPT is (b) Example trajectory of GPT-3.5. GPT-3.5 is not misled by the exemplar and mistakenly regards el- misled in this case and correctly locates the search ement 2 as the search button. However, the search button. button is actually element 1 on this page.

INPUT((2), research a stock)

Figure 9: Comparison between behaviors of ChatGPT and GPT-3.5. The element id is replaced by the element text (icon) in the figures for a clear depiction.

No. All the crawled app data have already been published according to the content policy of WikiHow website.

• Does the dataset identify any subpopulations (e.g., by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.

No.

• Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset? If so, please describe

The article authors may be identified through the pages of article and author information, which are publicly available on WikiHow website.

Instruction:

Access the article "How to Research a Stock"

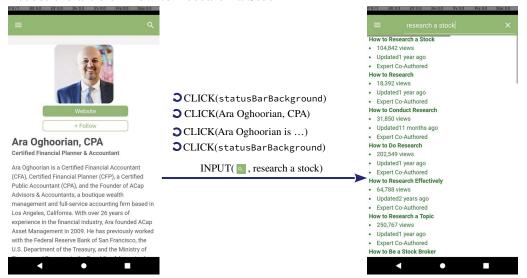


Figure 10: A Case that the LLM-based agent gets out of the cycle of wrong actions. After repeating some wrong CLICKs for several steps, the agent manages to get out of the cycle and perform the proper action to reach the next page from the current one.

Instruction:

Access the article "How to Get a Loan Without Private Mortgage Insurance (PMI)"

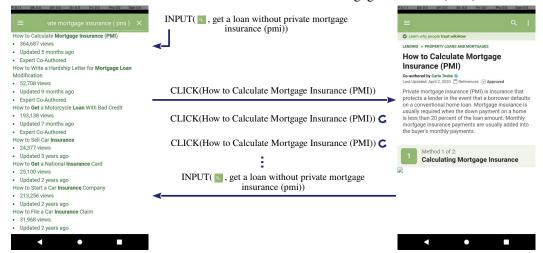


Figure 11: A Case that the LLM-based agent failed because of improper search keywords. The agent refuses to try some different keywords after failing to reach the target.

• Does the dataset contain data that might be considered sensitive in any way (e.g., data that reveals race or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.

No. All the crawled app data have already been published according to the content policy of WikiHow website.

E.3 Collection Process

• How was the data associated with each instance acquired? Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data (e.g., part-of-speech tags, model-based guesses for age or language)? If the data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.

All the crawled app data and information used in the task definitions of WikiHow task set are directly observable on WikiHow website.

• What mechanisms or procedures were used to collect the data (e.g., hardware apparatuses or sensors, manual human curation, software programs, software APIs)? How were these mechanisms or procedures validated?

Mobile-Env platform is developed with Python based on Androin Emulator. Several auxiliary tools and scripts are created with Tcl, JavaScript, *etc*. The task definitions of WikiHow task set are generated with the template toolkit (introduced in § B.6) of Mobile-Env. The app data of WikiHow task set are crawled with a Python crawler on a host with 8 CPU threads and 15GiB of memory.

• If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?

The task definitions of WikiHow task set are combined from the single-page task definitions randomly under the constraint that guarantees the target page in the succeeding step is directly referenced on the page in the preceding step. The app data are crawled in breadth-first order starting from the home page to mimic the browsing behavior of agents and offer the largest coverage of the agents' exploration.

- Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?
 - All the development of platform, app data collection, and task definition creation are completed by the authors.
- Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.

The app data of WikiHow task set are collected from WikiHow website from Jul. 6th, 2022 to Aug. 18th, 2022. Wiki articles published on the website before the date may be included.

• Did you collect the data from the individuals in question directly, or obtain it via third parties or other sources (e.g., websites)?

The app data including the published wiki articles and public author information are crawled from WikiHow website.

- Were the individuals in question notified about the data collection? If so, please describe (or show with screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself. The individuals as the wiki article authors are not notified.
- Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented.

Only the publicly available data on WikiHow website are crawled. We obey the terms of use and robots.txt of WikiHow website. Thus, it is considered that the individuals as the wiki article authors consent to the collection and usage of their works.

• If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate).

The crawled app data are regared as a snapshot of WikiHow website. Currently, no mechanism for revocation is designed. However, if there is really a need to revoke the particular resources, the indidual can contact the paper authors directly.

E.4 Uses

- Has the dataset been used for any tasks already? If so, please provide a description.

 Agents based on different LLMs have been evaluated on WikiHow task set in this paper.
- Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point.
 - Currently, no. We plan to develop a website tracking and indexing the available task sets for Mobile-Env.
- Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a dataset consumer might need to know to avoid uses that could result in unfair treatment of individuals or groups (e.g., stereotyping, quality of service issues) or other risks or harms (e.g., legal risks, financial harms)? If so, please provide a description. Is there anything a dataset consumer could do to mitigate these risks or harms?

 No.

E.5 Distribution

• Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created? If so, please provide a description.

Yes. Both Mobile-Env platform and WikiHow task set are open-sourced.

• How will the dataset will be distributed (e.g., tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?

The platform is open-sourced at GitHub. The task set is released at Hugging Face. We do not apply for a DOI.

· When will the dataset be distributed?

Both the platform and the task set have already been made public.

- Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? If so, please describe this license and/or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.
 - Both Mobile-Env platform and WikiHow task set are open-sourced under Apached-2.0 license.
- Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.
 - The copyright of the app data in WikiHow task set are owned by the original wiki authors and WikiHow website. No other third parties own the copyright of Mobile-Env platform and the task definitions of WikiHow task set.
- Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.

 No.

E.6 Maintenance

- · Who will be supporting/hosting/maintaining the dataset?
 - The authors will support, host, and maintain both Mobile-Env platform and WikiHow task set.
- How can the owner/curator/manager of the dataset be contacted (e.g., email address)? Issues and discussions on GitHub and Hugging Face are welcome. One can also seek help from Danyang Zhang (zhang-dy20@sjtu.edu.cn), Lu Chen (chenlusz@sjtu.edu.cn), and Kai Yu (kai.yu@sjtu.edu.cn).

- **Is there an erratum?** If so, please provide a link or other access point. Currently, no. Errata will be anounced if there is any in future.
- Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to dataset consumers (e.g., mailing list, GitHub)?
 - Mobile-Env platform will be continuously developed and maintained. Updates will be released on GitHub from time to time. Currently, there is no remarkable updating plan for WikiHow task set. Errata may be released to correct errors if there is any in future.
- If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were the individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced.

 No.
- Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to dataset consumers.
 - Old versions of Mobile-Env and WikiHow task set can be accessed through GitHub and Hugging Face, respectively.
- If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to dataset consumers? If so, please provide a description.

We sincerely welcome that one can contribute features or report bugs for Mobile-Env through the mechanisms like pull request, issues, *etc.* on GitHub. If new environments or task sets are crafted, it will be welcome that the creators notify the authors through e-mail or GitHub, so that we can update the indices of available task sets.

F Review from previous venue & revision

This work is previously submitted to ACL Demo 2023. The main concerns of the reviewers are (1) the particular motivation of this work, (2) how the platform is used, (3) and the structure of the task definition file. Accepted these suggestions, we first highlight two challenges for LLM-based agents: (1) multistep interaction (2) in structured text-based environments. Then we further clarify our motivation: to fill in a blank and build an evaluation platform for interactive agents in the LLM era. Moreover, in the main paper, we supplement clear descriptions of a few terms in Mobile-Env and the structure of the task definition file. Meanwhile, a brief usage guideline (§ B.1) involving the structure of observation and action objects and usage of wrappers is supplemented in the supplementary.

G Limitations & future work

There are still several limitations of this work. More LLMs are expected to be evaluated to draw deeper insights into the interaction capability of LLM in structured text-based environments. Meanwhile, more environments and task sets are supposed to be constructed to establish more challenging and comprehensive benchmarks. It is also sincerely welcome that the community contribute diverse environments and task sets based on Mobile-Env. We will continue maintaining and developing Mobile-Env platform in future work as well. We plan to develop a distributed version of Mobile-Env, so that the host with hardware virtualization (*e.g.*, KVM) for launching Android Emulator can be separated from the GPU host for deploying agents, on which hardware virtualization is usually turned off by default. Other new functions are going to be developed, aiming at supporting more diverse tasks and agents.