

STEWARD: Natural Language Web Automation

Brian Tang
bjaytang@umich.edu
University of Michigan
Ann Arbor, MI, USA

ABSTRACT

Recently, large language models (LLMs) have demonstrated exceptional capabilities in serving as the foundation for AI assistants. One emerging application of LLMs, navigating through websites and interacting with UI elements across various web pages, remains somewhat underexplored. We introduce Steward, a novel LLM-powered web automation tool designed to serve as a cost-effective, scalable, end-to-end solution for automating web interactions. Traditional browser automation frameworks like Selenium, Puppeteer, and Playwright are not scalable for extensive web interaction tasks, such as studying recommendation algorithms on platforms like YouTube and Twitter. These frameworks require manual coding of interactions, limiting their utility in large-scale or dynamic contexts. Steward addresses these limitations by integrating LLM capabilities with browser automation, allowing for natural language-driven interaction with websites. Steward operates by receiving natural language instructions and reactively planning and executing a sequence of actions on websites, looping until completion, making it a practical tool for developers and researchers to use. It achieves high efficiency, completing actions in 8.52 to 10.14 seconds at a cost of \$0.028 per action or an average of \$0.18 per task, which is further reduced to 4.8 seconds and \$0.022 through a caching mechanism. It runs tasks on *real websites* with a 40% completion success rate. We discuss various design and implementation challenges, including state representation, action sequence selection, system responsiveness, detecting task completion, and caching implementation.

1 INTRODUCTION

Simulating user navigation and interactions on the web is required for a number of use-cases, including web measurement studies, UI testing and debugging, analyzing privacy practices, etc. The state-of-the-art (SOTA) approaches require the use of a browser automation framework like Selenium, Puppeteer, or Playwright to manually trace, record, and code interactions with HTML elements. This process is infeasible for conducting large-scale tests with many webpage contexts or multiple websites. Consider the task of studying recommendation algorithm behavior. With such content being dynamically generated and location/context-dependent, relying solely on a browser automation tool to record and playback actions would not scale.

Kang G. Shin
kgshin@umich.edu
University of Michigan
Ann Arbor, MI, USA

Website: <https://www.cabelas.com/shop/en>

Task: Add a dome tent to my shopping cart

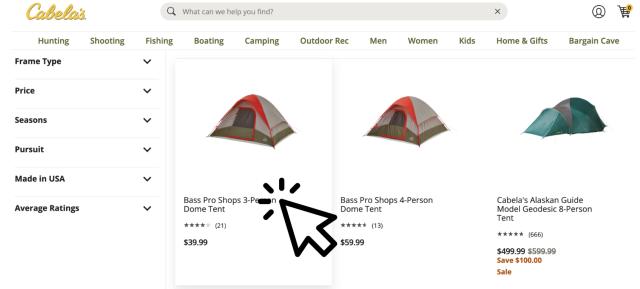


Figure 1: Given a natural language task, Steward iteratively selects UI elements to perform actions and interact with. Steward performs the actions in a browser automation tool.

Recently, large language models (LLMs) have demonstrated exceptional capabilities in serving as the foundation for AI assistants. They have been used widely for aiding users in a variety of applications, including text writing, task assistance, reasoning, information retrieval, Q&A, code interpretation, translation, and so on. Numerous assistant services built on LLMs have sprung up in the wake of ChatGPT [28], an instruction-tuned LLM created by OpenAI.

However, their (in)ability to interact with websites across various contexts and web pages remains under-explored despite its importance. LLMs are effective in predicting future states and tokens based on the currently provided context, a capability that naturally extends itself to performing activities on the web. So far, AI assistants have been limited to using search engine APIs, visiting URLs, and scraping site content for information retrieval. Very few systems have been created to enable these language models to *interact* with websites. Due to the complexity of content on the Internet, the SOTA approaches to AI services, such as ChatGPT, have focused on integrating developer-made APIs for popular online services and platforms [4]. These approaches, while more consistent and robust, are less scalable than the alternative — granting LLMs the ability to interface with a browser automation tool.

Augmenting LLMs with web capabilities is a challenging task that could reap numerous benefits by providing ad hoc intelligent crawling or API services to users, developers, and

researchers. This tool could provide flexible assistance vastly beyond the capabilities of current and prior assistants. With careful prompt engineering, fine-tuning, and system design, language models can perform complex sequences of actions and activities on the Internet on behalf of users.

1.1 Steward

We propose **Steward**, a fast, reliable, and cost-efficient LLM-powered web automation tool. It is an end-to-end system that takes a natural language instruction as input and performs operations on websites until the end state is detected/reached. Steward can simulate user behaviors on websites and even perform entire tasks to completion on real websites, for example, adding items to e-commerce site shopping carts, searching for and sharing YouTube videos, booking tickets, checking flight/lodging status or availability, etc. Using OpenAI’s language and vision model APIs, Steward intelligently and reactively performs actions on sites in only 8.52–10.14 seconds and at a cost of \$0.028 per action. Steward also uses a webpage interaction caching mechanism that reduces runtime to 4.8 seconds and \$0.013 per action.

Steward is also generalizable to handle previously unseen web contexts and perform correct action sequences even after sites update or remove their content. Rather than relying on fine-tuning or training on datasets, Steward uses purely zero/few-shot prompting. Thus, it is easily deployable, scalable, and relatively low-cost, allowing for plug-and-play integration with any LLM.¹.

1.2 Technical Challenges

Determining the correct action–element pair to perform on a website requires careful design of a state representation of the webpage’s current context. Selecting a correct action sequence on a site using minimal input/output tokens while maintaining accuracy poses another significant challenge. Finally, implementing a system design that runs in the order of seconds constitutes the last major challenge.

The SOTA systems have limitations, such as using proprietary models, lacking in reliability and scalability, cost more, or are not end-to-end systems. They mainly lack integration with browser automation tools and are impractical for larger intelligent web crawls or real-time operation.

1.3 Our Contributions

Our work consists of two main thrusts: (1) designing an automated framework for modeling the current website contexts and executing UI actions, and (2) the analysis of Steward’s performance with respect to various criteria.

We address each of the above technical challenges and make the following main contributions:

- (1) A unique LLM-powered web execution procedure that easily fits into browser automation frameworks. Steward was designed specifically for use with the Playwright framework. It is fully autonomous and only requires the user to type out a high-level goal/task to perform on a website in natural language.
- (2) A context-aware, site/app-agnostic UI exercising system capable of automating web interactions on a large scale. Steward can generalize its knowledge to navigate and interact with a variety of websites. For the top 5 elements, Steward is capable of achieving a top-1 action + element selection accuracy of 81.44% without any training or fine-tuning. It achieves a per-step accuracy of 46.70% on the Mind2Web benchmark and a 40% task completion rate, able to execute roughly 56% of the tasks’ actions until encountering an error.
- (3) An in-depth evaluation of Steward’s runtime and cost in various configurations. Its system design is optimized for runtime and cost efficiency, achieving a median runtime of 8.52 seconds or 10.14 seconds with text entry at a cost of \$0.028 per action. It also includes an implementation of a caching mechanism for storing and reusing website interactions, which reduces the runtime and cost of a step by 43.7% and 53.6%, respectively.

2 BACKGROUND

2.1 AI UI Exercising Tools

Earlier web UI automation tools have sought to use natural language inputs to perform complex user interaction sequences on websites. Earlier approaches were not as generalizable to unseen websites or interaction sequences, either. For example, some of the earlier works exploring advanced natural language UI exercising that leverage NLP and reinforcement learning resulted in lower success rates on websites and interactions outside of the training set distribution [22, 27]. By using LLMs and achieving a balance between a concise yet rich web page representation, Steward achieves accurate and broad coverage comparable to prior approaches.

Glider [22], an automated and scalable generation of web automation scripts (tasklets) from a natural language task query and a website URL, uses hierarchical reinforcement learning to navigate the website’s UI and maximize rewards based on task progress. It generates tasklets which are sequences of actions to perform on a particular site.

FLIN [27] proposes a natural language interface for web navigation that maps user commands to concept-level actions. The authors frame their approach as a ranking problem: scoring the most relevant navigation instruction given a user

¹<https://github.com/byron123t/Steward>

command and a webpage. By using semantic similarity, action keywords, and the BERT [13] model, FLIN is able to perform basic high-level tasks.

2.2 Natural Language UI Testing

Other earlier related works use natural language generation to augment UI testing frameworks by generating labels, comments, test inputs, test cases, and more.

CrawLabel [25] introduces techniques to compute natural-language labels for end-to-end UI test-cases in web applications by using information from the browser’s document object model (DOM).

The work of Wanwarang *et al.* [32] introduces an approach called *Link* for generating realistic test inputs for mobile apps. It leverages knowledge bases and uses label matching, NLP, and clustering, to cover more statements than randomly-generated text inputs for testing mobile apps.

Kirinuki *et al.* [21] propose script-free testing in web application development, using NLP and heuristic search algorithms to identify web elements and determine test procedures based on test-cases written in a domain-specific language, identifying the web elements to be operated.

Deng *et al.* propose creating a general natural language interface for the web to make the Internet more accessible to users with disabilities. They present their ongoing efforts of curating a benchmark dataset of websites and tasks [11].

Humanoid [23] is a deep learning-based approach to generating test inputs for mobile apps by learning from human interactions in the RICO [10] dataset, prioritizing inputs based on their perceived importance by users.

2.3 LLM Web Automation Systems

Since the advent of large language models, various open-source tools and datasets have been created to augment its capabilities. For example, AutoGPT [2] was created as an autonomous AI agent that continually loops until its high-level tasks are achieved. While accessing the Internet via BeautifulSoup for web scraping and information retrieval, it is unable to perform actions on sites. Another popular plugin, WebPilot [6], a ChatGPT plugin, grants access to a Bing search API and basic website information retrieval capabilities. Unlike these two approaches, Natbot [5] was created as an early-stage prototype exploring web interactions using OpenAI’s Davinci model and few-shot prompting.

Steward is not the first to explore the use of LLM’s potential for web automation; several researchers have achieved various levels of success in natural language web automation.

Mind2Web [12] is a dataset recently created by researchers. The dataset is a record of Amazon Mechanical Turk users’ actions on a web browser using the Playwright [1] automation framework. It serves as the primary data source for

evaluating the language models used in our design and our overall system (Section 3). The authors of [12] train their own language model using a derivative model of BERT.

Gur *et al.* performed an analysis of LLM HTML understanding using various transformers like T5 [30] and LaMDA [9]. They subsequently created WebAgent [17], another HTML-T5 type language model combined with a Flan-U-PaLM [8] program synthesis model trained on CommonCrawl [3] HTML and web interaction data. Their specially trained 540B parameter model achieves the best-known accuracy on the Mind2Web benchmark dataset.

Multimodalweb agents have also been a direction of interest as WebGUM [15] uses T5 [30] as an image and embedding encoder and a decoder that selects actions and elements. Another more general task automation framework leverages GPT-4 [37] using a combination of language and vision models to perform actions on websites and the user’s OS.

Sodhi *et al.* [31] proposed a contextual Markov decision process (MDP) in which the context is the web task objective expressed as an instruction, implicitly in a conversation, or as a set of structured parameters. The state of the MDP is the DOM of the current webpage, and the action and transition functions are based on clicking and typing to interact with an element (represented as an id and a value string). Their system uses hierarchical prompting to break down complex tasks into smaller policies. They note that there are several limitations, for example, when a dropdown menu does not appear in the DOM.

He *et al.* [18] implement their LLM tool by leveraging GPT-4-ACT [7], a GPT-4-Vision augmentation that uses *set of mark prompting* [36], to label and reference webpage elements on a screenshot. Their vast majority (as much as 91%) of errors result from navigation getting stuck, the language model hallucinating, or an issue with their visual grounding approach. They are specifically investigating GPT-4-Vision’s potential for parsing visual and textual information on webpages to use in website navigation.

Hong *et al.* [19] create models leveraging OCR and visual grounding with captioning datasets for representing GUIs via text. Their results appear to outperform smaller language models both prompted and fine-tuned for web navigation on the Mind2Web dataset for element selection from the top 10 elements, selecting the ground truth element up to 62.3% of the time.

2.4 LLM Web Automation Limitations and More

Given their limited performance, most of these autonomous agents are yet to be a practical solution for day-to-day usage [20]. Performing truncation on the HTML to feed into



Figure 2: High-level overview of Steward performing a task on a website (checking a flight’s status on united.com).

these language model agents was shown to significantly improve the performance over cases without truncation.

Furota *et al.* [14] extensively study the transferability of large multimodal agents(LMAs) to more realistic sequential task compositions. They design a new test bed, CompWoB, with 50 compositional tasks.

2.5 Design Comparison with Related Work

In the domain of natural language web automation, various methodologies have been employed to enhance web navigation accuracy. Many of these prior studies share similar design principles. A language model is given access to some state representation of a website and must select the appropriate HTML element and action given a natural language task specified by the user. These designs roughly fall into the following categories.

HTML Element Proposal and Selection: This methodology uses an element proposal followed by the selection of an appropriate action using a language model [12, 31]. It is simplistic, straightforward, and efficient, but yields over-reliance on the model’s performance and fine-tuning dataset.

Planning and Program Synthesis: The planning-based approach [17] focuses on generating correct subtasks or sub-instructions to automate a given task. However, this approach requires high accuracy in generating subtasks, i.e., the generator must have rich context/data (raw HTML) to make an informed prediction. It must also be consistent in generating browser automation code.

Multimodal Web Automation: In contrast to the other approaches, multimodal web automation emphasizes using screenshots of the webpage and identifying UI elements to interact with using semantic segmentation and/or element object detection [18, 19, 37].

Our Approach: Steward adopts an approach most similar to a combination of the 3 approaches. According to our preliminary investigations, this yielded fewer errors when used with off-the-shelf models. Our approach differs from prior work in its end-to-end system design with a reactive planning-based agent. This means our system plans and makes decisions on the fly after each step. It is built to

work with off-the-shelf language/vision models with just zero or few-shot prompting while operating as quickly and cost-efficiently as possible, without sacrificing reliability. It does this by filtering and cleaning the set of HTML elements to minimize the amount of noise and tokens the language models must process. Our system also integrates an action caching system to further improve runtime and cost-efficiency, reducing the already low 8 seconds per action step to just 4 seconds per step. Finally, our system also accounts for task completion by detecting the end state and terminating the program. We will discuss the advantages of our system and design philosophy in the following section.

3 DESIGN, IMPLEMENTATION, AND COMPARISON

We now detail Steward’s design and implementation. Steward consists of 3 main components: (1) a large language model (LLM) and prompting framework that can handle webpage state representation and navigation, (2) an HTML cleaner, a runtime/cost-optimized execution pipeline, an action caching system, and (3) an integration with the Playwright browser automation tool.

The design of Steward is inspired by how humans perceive, process, and interact with websites. The system is built to automate tasks that users (i.e., LLM users, website developers, and researchers) may want to conduct on websites. First, the system analyzes a website, providing a short high-level description of the page. In parallel with this analysis, the system considers its user-provided goal and a screenshot of the page to determine the next course of action. This contextual information is stored in a state representation that is used in every prompt and LLM query. It looks at the interactable elements from the DOM (in HTML) to select an element for the Playwright browser automation tool to interact with. Finally, the system records the actions taken and memorizes these prior action sequences when considering the next element to interact with. In addition, it caches previously seen contexts and action sequences to avoid repetitive calls to the LLMs.

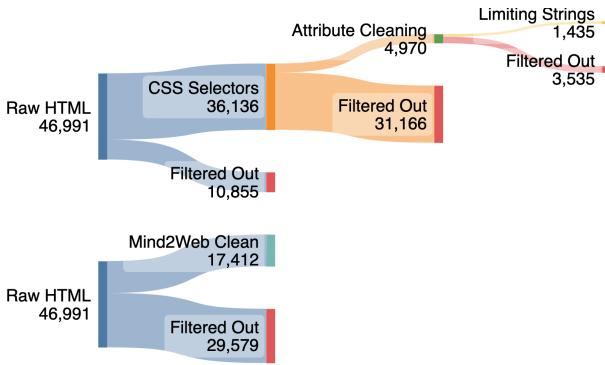


Figure 3: Token Counts for HTML Filtering Approaches. (Top) Our Approach, (Bottom) Deng *et al.*'s Approach [12].

Steward is built as a low-budget intelligent web automation tool that minimizes both the runtime and cost of operation.

3.1 Example: Adding Items to Shopping Cart

We take the following successfully executed example observed in our evaluations with Steward. For a website like cabelas.com, if Steward’s current user’s goal is to “Add a dome tent to my shopping cart”, and Steward has already performed the actions of clicking on “Camping”, clicking “Close” on a promotional popup window, and clicking “Dome Tents”, the system will “click on the first dome tent product displayed”. This is because the list of prior actions, the screenshot of the web page, and the generated page context have all been updated with the change in the web page’s state. Steward will proceed to filter the set of interactable web page elements down to a list of 15 elements and then select the best match:

“CLICK”

After executing this command, the web page will update to this 4-person dome tent’s product page. Steward’s internal state representation of the website will also update, causing it to select the best matching element after filtering again:

“CLICK” add to cart

Constructing Website State: After a web page initially loads, or after an action is selected and performed on that website, Steward first “perceives” the web page by taking a screenshot of the page. A vision transformer is prompted to identify the next best action to perform to achieve the user’s task, and the screenshot image is input along with relevant state information (website URL and prior actions performed),

Algorithm 1 Where string is the HTML element’s attribute value and threshold separates noisy strings from strings with information. Updating the dictionary of previously seen strings is excluded from the below pseudocode for simplicity.

```

1: function DETECTNOISYSTRING(string, threshold)
2:   if len(string) > 2 and len(string) < 100 then
3:     num_guesses = zxcvbn (string)
4:     log2 (num_guesses) /len(string)
5:     word = string contains dictionary words
6:     if not word and score > threshold then
7:       return True
8:     else if len(string) >= 100 then
9:       return True
10:    else
11:      return False

```

e.g., SCREENSHOT RESPONSE: “click the “Camping” category on the navigation bar”

In parallel, the page’s plaintext is retrieved from the HTML, and a language model is prompted to return a brief high-level summary of the current page context, e.g., PAGE CONTEXT: “Ecommerce website page for Cabela’s featuring a variety of tents for camping and outdoor activities, with filtering options by brand, type, size, and sleeping capacity.”

3.2 HTML Processing

The first major challenge with LLM web automation is enabling LLMs to parse large HTML representations of websites. These HTML snippets must fit within the context lengths of the language models while avoiding overcrowding the input. To minimize the amount of irrelevant information contained in HTML tags, we utilize a three-step approach to filtering and cleaning the list of HTML elements on a page.

Filtering for Interactable Elements: First, Steward filters the set of elements to interact with using CSS selectors. We are only concerned with interactable elements, which primarily include buttons, links, tabs, text fields, select options, and other related interactable UI elements. Certain attributes also help in identifying these elements, e.g., role=tab, onclick, aria-label, etc. This step will typically reduce the set of HTML elements on a page by an order of magnitude (e.g., from 4564 elements down to 371 elements on cabelas.com). Appendix A.2 contains the exhaustive list of CSS selectors.

Element String Matching: The next step involves limiting the HTML element search space by selecting only elements with strings relevant to the website’s current state. For example, if the screenshot response returns “click the “Camping” category on the navigation bar”, then:

[“explore”, “camping”, “outdoors”, “navigation”, “menu”]

will be the set of strings to search through the element list. Or, if the response is “click “Tents & Shelters” under the “Camping”

category”, then the list of search strings may be:

[“shelters”, “tents”, “camping”].

By limiting the element search space in this manner, the list of candidate elements is often reduced by another 10 \times (e.g., from 371 elements to 29 elements on [cabelas.com](http://www.cabelas.com)).

HTML Attribute Cleaning: Upon filtering for these elements, only a small set of HTML attributes are kept — those typically containing useful information relevant to the functionality of the element. These are attributes such as aria-label, role, type, placeholder, name, title, class, href, etc. We also preserve important data nested as child elements like plaintext or img tags, as these tags sometimes contain information relevant to the functionality of an element. Finally, we calculate the entropy of each HTML element’s attributes’ names and values, searching for and removing highly random strings in element attributes. This is accomplished using the *zxcvbn* password strength estimation tool [34] which uses a corpus of common English words and strings. Our system also removes very lengthy attribute values, resulting from long href or source URLs. By filtering out these strings, we can minimize input length and denoise our inputs. For example, sometimes the class attribute contains random hashes generated by frontend frameworks like Material or React. An example of the distillation of HTML content can be seen below. Further details like CSS selectors and HTML attributes, are available in Appendix A.2.

The HTML cleaning approach by Deng *et al.* [12] reduces these page representations down from a median of 47k characters to 17k tokens. Compared to their approach, we reduce the length of website HTML representations from 37k down to only 1.4k tokens. This 33 \times reduction of tokens strikes a balance between information retention and conciseness. (Figure 3) While this results in the ground truth element to select only presiding in 82.64% of the tested web pages, it is more than sufficient in handling most tasks and is a justifiable trade-off due to the increased accuracy from reducing the candidate list of HTML elements. This CSS selector list can also be updated to support additional elements.

3.3 Natural Language Component

Using a combination of HTML parsing and LLM prompting, we can construct a representation of the current page’s state. This state consists of a high-level user goal, the website’s base URL and current page context, a screenshot of the current page, a list of prior actions, a proposed candidate action, and a list of candidate HTML elements to interact with. These states are formatted as variables within prompts, and the prompts used by each component do not necessarily include all state variables. Thus, changes in the state of a web page can be measured with this state representation. For prompts that exceed a language model’s context window, the system

employs batching of the prompt variables. The following components use LLMs process the webpage state and serve as the execution flow required to perform an action on a site:

- (1) Summarize the current webpage’s context.
- (2) Process the page screenshot and suggest a candidate action to perform.
- (3) Propose the top 15 elements to interact with to achieve the user’s goal.
- (4) Select the next best action and element combination to perform from the proposed top-15 elements.
- (5) Determine the text to type in or the option(s) to select.
- (6) Determine whether the selected candidate action and element makes sense to perform.
- (7) Determine whether the current state has achieved the user’s goal, and thus the program should terminate.

HTML element filtering & cleaning example

Before Processing

```
1  <li class="hidden" role="menuitem">
2    <a id="
      departmentButton_3074457345616967"
      href="https://www.cabelas.com/
      shop/en/
      bargain-cave-sale-and-clearance"
      class="departmentButton navBC"
      aria-haspopup="true" data-toggle="
      departmentMenu_3074457345616967">
      Bargain Cave
4    </a>
5    <div ...>
6    </div>
7  </li>
```

After Processing

```
1  <li class="hidden" role="menuitem">
2    Bargain Cave
3  </li>
```

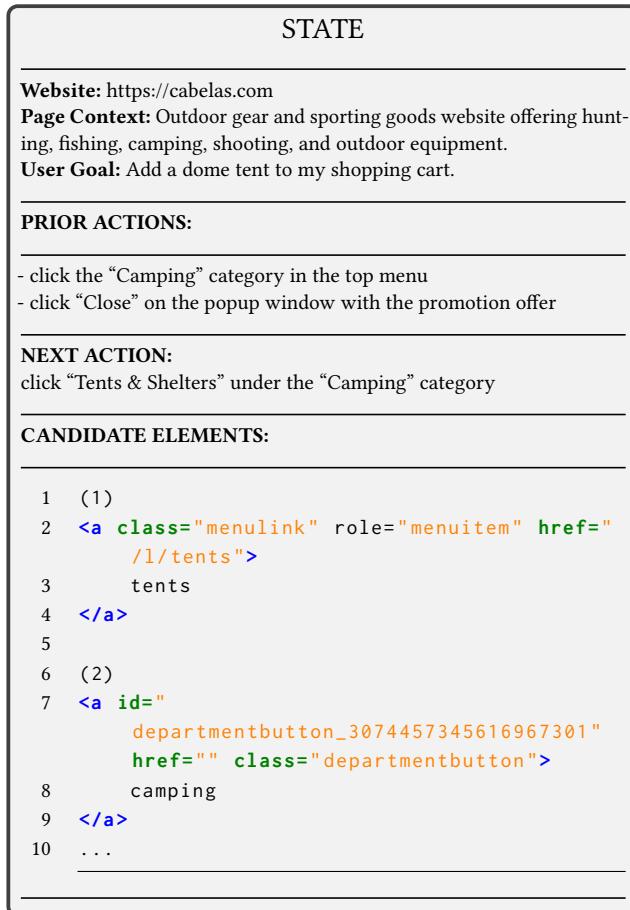
Figure 4 shows a diagram of each of these components and how they are integrated into Steward.

State Representation: Steward leverages basic prompting techniques like few-shot prompting [26, 29], chain of thought reasoning [33], and prompt optimization [35] to elicit better performance from the language models. In particular, the prompt contains only the minimum set of variables required for the language model to perform its task. The context inputs and response outputs are also kept minimal length to ensure quicker API response times. In the [cabelas.com](http://www.cabelas.com) example, our system represents a state in the text block shown

below. The state below contains information for the language model to cater its responses to the current context of the web page. Because of the embedded goal, prior actions, and candidate elements, the state also contains information for complex decision-making, e.g., selecting the next action and element to interact with, or determining if the state has completed the user’s goal. The full prompts used for each component of our system are available in Appendix A.3.

HTML Element Proposal (Top-15): Language models at lower temperature settings tend to produce outputs that are more deterministic, but simultaneously more simplified, conversely, higher temperature results in more random outputs. To address this, our system represents HTML elements in an indexed list as shown in the example state representation above. The approach of using indexes to select elements allows for more consistency in the outputs of the element proposal and selection steps, analogous to the set of marks prompting approach [36]. An example response looks like:

ELEMENTS[9, 1, 22, 109, 84, 31, 33, 77, 72, 81, 117, 4, 50, 54, 41]



These 15 elements are then used as the list of candidate elements to select from in the next step.

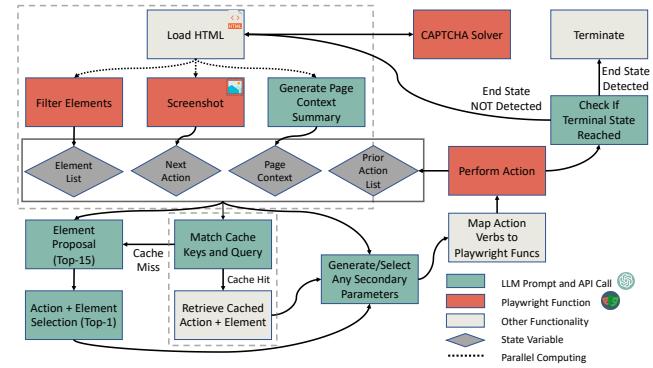


Figure 4: Execution loop for a website and high-level task.

Element Candidate Selection (Top-1): The top element and corresponding action verb are then selected from the top 15 elements. The response is returned in the format below, and mapped and performed via Playwright functions using the mapping defined in Table 1:

“ACTION_VERB” element_index

Double-Checking: After proposing the top 15 HTML elements, another prompt is used to determine whether the proposed candidates contain at least 1 element that makes sense given the next action state variable. This step is meant to sanity-check incorrectly hallucinated element indexes by double-checking the LLM response using the top 15 elements’ HTML.

Text Entry and Option Selection: If the selected element and action pair is a checkbox/dropdown option (select element) or requires typing, the system must generate these secondary parameters based on the user’s goal. This step is used to generate search queries, input fields, items to select, etc. The returned response is directly used as the text to type into the field, or in the case of a checkbox, the index of the option is used as the option to select.

Terminal State: Finally, after each action is selected and performed, the system must determine whether the context has reached the terminal state in which the user’s goal has been achieved. Only after this LLM responds with “yes” for the end state, does the program terminate.

3.4 Caching Action Sequences

Steward also supports caching previously performed actions to reduce runtime and costs. The cache is first keyed by the website URL. Subsequent key-value pairs map high-level descriptions of actions to the corresponding action verb and HTML element. A language model and prompt are used to determine the semantic similarity between the stored action description (key) and the new action description generated by the screenshot response of the current page. This step

is done such that the only LLM query required for each previously executed action is the screenshot response.

Cache Indexing: The cache is implemented as a dictionary that uses the stripped base URLs and the screenshot response containing the action descriptions as keys. The selected element and action/verb performed on Playwright are stored as the value to retrieve. Finally, the cache write/read timestamps are stored as metadata for the cache replacement policy. When storing new cached actions, another LLM component is used to ensure the action description matches the selected verb and element.

Cache Replacement Policy: The cache has a maximum number of action description keys of 100 to reduce issues resulting from language models having large input sizes. This is done to keep response times low while maintaining consistency and reducing overlap with the next action key, as LLMs are known to perform worse on reasoning benchmarks with longer inputs. The cache supports either LRU or LFU for its replacement policy.

4 IMPLEMENTATION

Steward was implemented with 1626 lines of code in Python and 20 prompts. Its main functionalities rely on OpenAI’s API, Playwright, BeautifulSoup4, lxml, zxvcvbn, NLTK’s corpus of words, and NopeCHA’s API. Depending on the component, the system utilizes 4 different models: GPT-3.5-Turbo, GPT-3.5-Turbo-16k, GPT-4-Turbo, and GPT-4-Vision. The system makes use primarily of Playwright’s Context, Page, and Locator classes and their respective functions. Table 1 contains a list of verbs used in the LLM prompts and their mapping to Playwright functions.

Browser Automation. As Steward needs to automatically perform tasks on websites, it uses the Playwright browser automation framework to interface with websites.

Playwright locators retrieve all visible interactable elements (e.g., <a>, <button>, <textarea>, <input>, [class*="ui-slider"], etc.), and extracts the outer HTML of each element. After the elements and interactions are chosen by the NLP component, Steward automatically performs the actions using Playwright selectors and locators and the click, type, select, goto, upload file, and enter functions. As these actions are implemented, each interaction and state is recorded. A screenshot is taken, and, optionally, a video recording begins to capture the browsing session. Finally, the browser state is stored. This includes data, such as network traffic, browser cookies, and local browser cache storage. The cached actions and elements performed in prior runs are retrieved and stored in a JSON file for simplicity.

Bypassing Bot Detection. To perform activities on behalf of the user, developer, or researcher, Steward must bypass bot detection techniques, such as Cloudflare. These

Table 1: Verb Mappings to Playwright Actions

LLM Verb	Playwright Function
click	Locator.click()
type_text	Locator.fill(text) and Locator.type(text)
select_option	Locator.select_option(options)
press_enter	Locator.press('Enter')
upload_file	Locator.set_input_files(file)
visit_url	Page.goto(url, wait_until='networkidle')
switch_tab	Page.bring_to_front()
close_tab	Page.close()

techniques typically first examine the browser’s user-agent header, IP address, browser configurations such as headless mode, and other information to determine whether the user is likely a bot. If these heuristics suggest so, or if the user is performing sensitive tasks such as signing into an account, these bot-detection services often prompt the user to click on a UI element or complete a visual reasoning task to prove that they are a human. We bypass bot detection by using browser configurations that mimic normal user configurations. In our evaluation, we use the Firefox Nightly browser with the UI configuration and a VPN.

5 EVALUATION OF STEWARD

We evaluate Steward’s efficacy, and describe the dataset details and model configurations in Section 5.1. The setup for each of evaluation criteria – accuracy, runtime, and cost – is discussed in Section 5.2. Accuracy is measured using component per-step accuracy, the system’s end-to-end correctness, and the system’s performance running tasks on live websites. Our evaluation results are provided in Section 6.

5.1 Dataset Configuration

To evaluate Steward’s efficacy as a web automation tool, we use the Mind2Web dataset [12], which consists of 2,350 natural language tasks to perform on real websites and over 10,000 recorded actions. This dataset was generated using Playwright, and includes the actions selected, elements selected, the raw HTML, and other metadata. Our system is built to run with off-the-shelf models and thus has not been fine-tuned *a priori* on any datasets. We use the Mind2Web test set solely to evaluate Steward’s performance on various tasks. In our experiments, we randomly sampled a subset totalling 122 tasks and 621 actions from the (test_domain, test_site, test_task) test sets.

Language Models Used. We utilize and report results with 3 different base models: GPT-3.5-Turbo, GPT-4-Turbo, and GPT-4-Vision. Table 6 in the Appendix provides more details on the components and their corresponding models.

5.2 Evaluation Methodology

Overall Evaluation (Correctness, Runtime, Cost): We evaluated each component in an end-to-end fashion on subsets of the Mind2Web test dataset which consists of 122 tasks and 621 actions. To ensure the correctness of the web automation sequences, we mapped the actions directly with the ground-truth actions and elements provided in the Mind2Web dataset. One limitation of this dataset is that it is annotated with only one correct ground-truth action sequence per task, an incorrect assumption. In reality, completing a task on a website could be accomplished in any number of alternative sequences. To address this limitation, we manually evaluated another subset of 30 tasks from our randomly sampled test set and reported the behavior correctness at each action step.

Component Per-Step Accuracy: Each of the components was evaluated in isolation on larger 200-sample subsets of from the Mind2Web dataset and the same samples were used for comparing different models. The element proposal samples typically contained 100–200 elements to select from, whereas the element + action selection samples contained 3–5 elements to select from. These components were evaluated in isolation to select the optimal models to use with each component.

System End-to-End Correctness: For the end-to-end evaluation, the best-performing models for each of the components were integrated into the designed system as depicted in Fig. 4, with the primary evaluation focused on the performance of the system: element proposal → action + element selection → secondary parameters. Thus, the performance of the element + action selection is dependent on the element proposal. In this evaluation, each sample consisted of a user-defined task that contained a set of action steps (typically 5–10 actions). The test subset contained 90 tasks across various websites.

System Manual Evaluation: Due to the limitations of the Mind2Web benchmark dataset, we conducted a manual evaluation of Steward using tasks from the Mind2Web dataset. The task dates and particular details were updated to reflect the date of testing. Using 30 tasks, we annotated each action the system selected, and the task success rate, as well as any points of failure.

Component Runtime: The computation time for each component was recorded in the prior end-to-end evaluation for measuring the system’s typical runtime. Steward’s LLM prompts are crafted to minimize response time and return only the information essential to continue operation. We do not include page load times nor Playwright interaction times due to (1) variability and dependence on network connection and (2) this runtime is experienced by a normal website user and/or browser automation tool user.

System Cost and Practicality: To evaluate the system’s cost, we measured the token count for each component’s inputs and outputs. Each component’s token usage was mapped to the API costs for their respective best-performing models shown in Section 6.1. Table 6 defines the mapping used for computing the cost of each component in the system for a single pass (element proposal $n = 1$), where n denotes the number of retries for the element proposal and selection steps.

6 EVALUATION RESULTS

We have conducted the experiments and evaluations described in Section 5, evaluating the following key metrics.

- **System Correctness, or Component Per-Step Accuracy:** We evaluated the performance of 5 of the 8 natural language processing components with various models. The action and element selection performs better than SOTA. For example, the element + action selection step in isolation achieves 81.44% top-1 accuracy using GPT-4. We perform an end-to-end evaluation of Steward’s performance in completing tasks with the system’s components working in tandem. The results indicate Mind2Web’s ground truth element and action are selected in 46.55–48.50% of the action steps. In our manual evaluation of Steward running live on websites, it achieved a 40% task completion rate and was able to get through an average of 56% step completion before encountering an error. Steward detected an end-state and terminated correctly in 71% of tasks. (Section 6.1)
- **System Runtime, Cost, Caching, Practicality:** To ensure Steward is practical for web automation, we measured the token counts and API costs at each action step and upon completing a task. Steward is shown to be cost-efficient for online tasks with an average cost of \$0.18 USD per task with a median runtime of 8.52 seconds / \$0.028 USD per action. Caching reduced this to a median of 4.8 seconds and \$0.013 USD per action. In a small evaluation of the caching system, a cache hit occurred on 49% of the actions when repeating tasks. (Section 6.2)

6.1 System Correctness

Component Per-Step Accuracy: Section 6.1 demonstrates the performance for each component of Steward. The action and element selection component performs consistently. In isolation, our prompting approach with GPT-4 achieves an 81.44% combined accuracy with element selection at 83.83% and action selection at 88.02% (for $n = 5$). The element proposal component picks the correct element in the top-5 proposals 50% of the samples, achieving a 0.5075 recall@5 score and a 0.7437 recall@25 (Fig. 5 portrays the recall up to $n = 50$). While a higher n yields an improved likelihood of the ground

Model	Element Proposal (Recall@5)	@25	Element + Action (Top-1)	Double Check (Prec)	End State Termination (F1)	Secondary Param (EM)
GPT 3.5 Turbo	0.5075	0.7437	0.5030	0.7525	0.4823	0.8300
GPT 3.5 FT	---	---	0.7305	0.9192	0.7980	0.8350
GPT 4	---	---	0.8144	0.7900	0.6452	0.8650

Table 2: Per-Step Component Results, In Isolation (Mind2Web)

Success Metric	Test Domain	Test Task	Test Website
GT Element in Filtered List	61.96%	63.98%	58.14%
Element + Action (Top-1)	46.55%	48.50%	46.70%
Text Field Match	85.71%	90.91%	92.59%

Table 3: End-to-End System Results (Mind2Web)

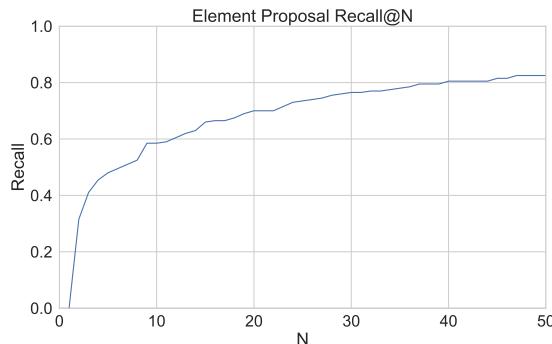


Figure 5: Recall@N score for the element candidate proposal component using the GPT 3.5 Turbo Model.

truth being in the proposal set, there is a trade-off between the number of elements proposed and the performance of the element + action selection component. The element proposal component was evaluated without reducing the set of candidate elements using string search. The fine-tuned GPT-3.5 models perform best for the double-checking (0.9192 precision) and end state termination (0.7980 F1 score) components, though we use the GPT-4 model instead of the fine-tuned models in later evaluations for simplicity. Finally, for selecting options and typing text, all models perform well in this task, with > 83.00% of samples matching the ground truth.

System End-to-End Step Correctness: The system’s end-to-end performance on the Mind2Web benchmark is lower than the evaluation of each component in isolation. This is primarily due to (1) errors propagating from the HTML filtering and top 15 candidate proposal and (2) the limitations of the dataset having only 1 ground truth element. After filtering for only the list of interactable HTML elements, Steward retains the ground truth element in 58.14–63.98% of steps. It only proposes the top-1 correctly labeled

ground truth element and action in 46.55–48.50% of samples (action steps). Text field input generation matches the ground truth text input 85.71–92.59% of the time. The components’ performance in this end-to-end setting are found in Section 6.1. However, this performance is not representative of the system’s actual performance. We observed fairly frequent occurrences of selected elements that were in line with the user’s task or elements that were parents/children of the ground truth, but were not considered correct according to the ground truth as shown in Appendix A.1. The search space of valid navigation sequences is practically infinite. For example, one could use either the search bar or the menu navbar to navigate to a product page. Thus, we also evaluate more representative system’s capabilities.

System End-to-End Task Correctness (Manual): Our tests found that Steward was able to perform many tasks, including tasks from the Mind2Web dataset, on real websites using Playwright. The system performs reliably and accurately, especially on popular websites or sites with fewer interactable HTML elements. For example, Steward was able to complete entire tasks, consistently perform searches, correctly click on links and buttons, and fill out forms. The exhaustive list of example tasks and the result of running them can be found in Section 6.1. Of the 30 tasks, 40% were successfully completed by our tool. 71% of the completed tasks were successfully terminated by Steward after reaching the end state. For the remaining tasks that failed, the most common failure reason was that an element required to progress in the task was not in the list of interactables or the list of limited elements after performing a string search. Following this, the next most common issues were that the LLM thought search icons were clickable, the end state was detected early, elements were hidden, or an issue occurred with the text field generation. A couple of failures were also due to the task not having account credentials set up and from a website error. Of the tasks that failed, the average number of steps completed before encountering issues was 2.33. Overall, 6 failures resulted from the LLM failing to return a valid sequence, 6 from HTML filtering, 2 from skipping a step, 2 from website errors, and 2 failures resulted from early termination. In general, Steward consistently completed search or e-commerce-related tasks, while it struggled to complete booking-related tasks.

Website	Natural Language Task Description	Completed	Progress	Termination	Failure Reason
macy's.com	find marriage registry with name JANE DOE	SUCCESS	5/5	SUCCESS	N/A
drugs.com	Show me the page with information about Adderall side effects.	SUCCESS	3/3	SUCCESS	N/A
drugs.com	Show me the latest FDA alerts.	SUCCESS	1/1	FAILURE	Late end state termination
tiktok.com	Show me the tik tok series playlist from brazil	SUCCESS	4/4	SUCCESS	N/A
tiktok.com	Browse the best Australian food songs.	SUCCESS	4/4	SUCCESS	N/A
google.com	Look for a White PlayStation 5 Console and save it	SUCCESS	3/3	SUCCESS	N/A
google.com	Identify Nike Air Women's size 6 cross training shoes that offer free return.	SUCCESS	3/3	SUCCESS	N/A
united.com	Open the baggage fee calculator	SUCCESS	6/6	SUCCESS	N/A
imdb.com	Browse the list of top 250 movies and add the first one to my watchlist.	SUCCESS	3/3	SUCCESS	N/A
budget.com	Find cars that can be picked up at SFO on April 20 and returned on April 27.	SUCCESS	6/6	SUCCESS	N/A
healthline.com	Browse a list of CDB product reviews.	SUCCESS	3/3	SUCCESS	N/A
healthline.com	Find an easy-to-follow evidence-based nutritious vegetarian diet to lose weight for a diabetic and heart patient, and sign-up to get the results by email buckeye.foodbar@gym.	SUCCESS	7/7	FAILURE	Late end state termination
nba.com	Find the current league leader in Assists Per Game.	FAILURE	3/4	N/A	Not in interactable elements list
adoptapet.com	Find an adult husky near zip code 10019.	FAILURE	2/6	N/A	Not in interactable elements
adoptapet.com	Find a shelter for rabbits and small animals within 100 miles of zip 77084.	FAILURE	3/6	N/A	Skipped a step
accuweather.com	find the Monthly forecast for Manchester, GB for May	FAILURE	3/5	FAILURE	Early end state termination
pinterest.com	Save on my pins a Halloween costume image.	FAILURE	4/9	N/A	No account, credentials invalid
ign.com	Find a walkthrough for the game The Legend of Zelda: Breath of the Wild.	FAILURE	3/5	FAILURE	Early end state termination
tvguide.com	Find more films from the director of Smile.	FAILURE	1/5	N/A	Search icon not clickable
mariott.com	Start the process of buying a gift card with a beach theme.	FAILURE	0/5	N/A	Failed to find hidden link
redfin.com	Find a real estate agent job in Atlanta Georgia and apply.	FAILURE	3/7	N/A	Failed to click hidden link
stubhub.com	Find \$100 egift card which has Happy Birthday on it for myself and add to cart.	FAILURE	2/3	N/A	Skipped a step
stubhub.com	Find a NOFX ticket for a show in Madrid, Spain on May 14 for 1 person.	FAILURE	1/7	N/A	Search icon not clickable
stubhub.com	Book 4 tickets in upper tier for any Trevor Noah show in Brisbane, Australia, before 30 November, view tickets prices with estimated fees.	FAILURE	3/7	N/A	Double checking failure
accuweather.com	Check the daily forecast in Madison, WI from April 21 - May 1.	FAILURE	1/3	N/A	Search icon not clickable
foxsports.com	add WWE superstar ALIYAH to your favorite by following her.	FAILURE	3/5	N/A	Website error: no search results
rentalcars.com	Find a large car with lowest price from Apr 28 to May 1 in Zurich.	FAILURE	2/6	N/A	Not in limited elements
ryanair.com	Show me tickets for food and drink attractions in Ireland from April 18 to April 19	FAILURE	6/8	N/A	Not in limited elements list
ryanair.com	Find a flight from Dresden to anywhere under \$100	FAILURE	2/8	N/A	Text field generation issue
trip.com	Find a Hotel in New York for the dates Wed, 17 Apr to Thu, 18 Apr	FAILURE	0/8	N/A	Text field generation issue
	1 room for 2 Adults providing 1 Bed with Breakfast and the rent payable at Hotel with Instant confirmation and Free cancellation				
Overall	Task Completion Rate: 12/30, 40%	Progress: 90/161, 56%		End State Success Rate: 10/14, 71%	

Table 4: End-to-End System Results (Manual Evaluation, Mind2Web Tasks). Tasks were completed successfully almost all on the first attempt and all within the second attempt. The system was not trained/validated/tuned on any Mind2Web test set.

6.2 System Runtime, Cost, Practicality

Figure 6 presents the distribution of API costs per LLM component, across the 122 tasks. Most of the incurred costs come from processing the page screenshot, checking the top 15 candidate elements, and selecting the top 1 element and action pair. Each step costs a median of \$0.028 to run. The system typically has a median runtime of 8.52 to 10.14 seconds per action step, depending on several variables: web page length, number of element proposals, number of encountered errors, and whether the action selected is to type or select. With a cache hit, the system will perform the action with a median runtime of 4.8 seconds and a median cost of \$0.013. As a reference, it took one of the authors an average of 6.64 seconds (median of 5.98 seconds) to identify each webpage element and interact with them by clicking or pasting text on a subset of the manually evaluated tasks.

Caching Performance: We evaluated caching performance by running on a set of the 5 manually evaluated tasks that successfully completed most consistently (macy's.com, google.com 2, united.com, imdb.com, and healthline.com 1). We ran Steward on each task 10 times after caching the initial set of actions and measured the frequency of cache hits. The number of cache hits for all actions was a median of 4/10 and an average of 4.9/10. Some of the stored actions were unnecessary for task completion, and after filtering these tasks out, the average and median cache hits were roughly 6/10. Only 2 out of 28 actions were duplicate keys in the cache, making most of the keys unique. All of the cache entries contained correctly mapped screenshot responses and corresponding action verbs and elements.

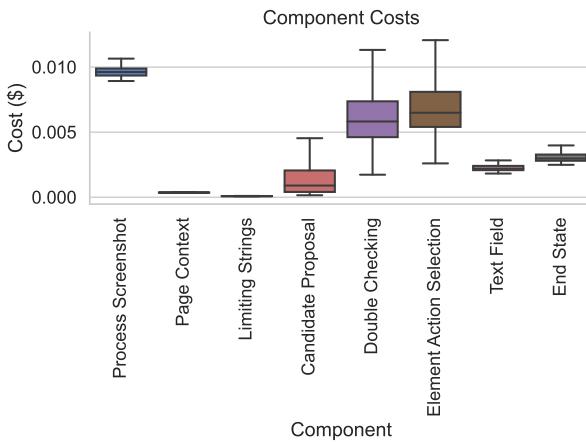


Figure 6: Per-Step API Costs Steward

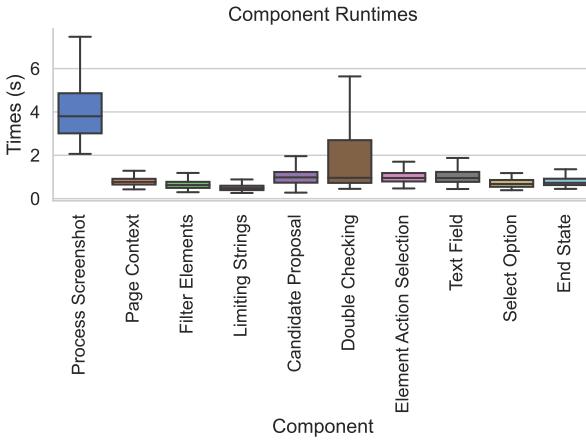


Figure 7: Per-Component Runtime Steward

6.3 Error Analysis

Much of the current limitations of Steward come from its first few procedures, the HTML filtering (via CSS selectors), the HTML string search limiting, and the element proposal step, likely in part due to the challenging nature of the task, distilling hundreds and thousands of web page elements and proposing the top 15 elements. For the more complex combinations of web pages and tasks with unintuitive elements to interact with, these earlier steps fail. Even with fine-tuning, preliminary experiments indicate performance is only improved by a few percentage points. Most of the other errors result from the selection of alternative navigation paths different from the ground truth. To address this, we can further expand the list of CSS selectors and regenerate the string search limiters in the event of a failure to find an element.

The other most common source of issues, the end state detection and termination, can also be improved by adding it as a component of the screenshot response generation. Alternatively, checking the page screenshot state after an end state is detected may reduce false positives (early termination). Finally, adding a screenshot component for detecting form field errors would allow the system to update its state with information from website error messages, preventing failures resulting from skipping task steps.

7 DISCUSSION

7.1 Design Philosophy

Steward is designed to be easy and practical to use. Other related works focus on augmenting AI assistants with web browser automation, but end-users will unlikely feel comfortable using LLM web automation systems due to the numerous safety/security/privacy concerns. We targeted Steward’s design for developers and researchers so that it can be easily integrated with any LLM, used to automatically generate UI-exercising sequences, or used to conduct dynamic analyses of websites. Rather than using program synthesis via browser automation code generation, Steward is more robust and deterministic using an element list filtering and indexing approach. Finally, it is designed to be practical without sacrificing accuracy. It is cheaper and more efficient than other existing solutions.

7.2 Ethical Concerns

Although the datasets do not explicitly include account creation, malicious actors may re-purpose the approach of Steward to automate the creation of fake or bot accounts to impersonate people, spread disinformation, drive traffic, scalp products, perform DoS attacks, create disingenuous reviews, or artificially up-vote content on social media. These malicious actors may make the Internet an unfair and untrustworthy environment. One option to mitigate these threats is to reduce misuse by training the model to disallow registration, sign-up, and account creation contexts, although this may negatively impact the efficacy of Steward.

Additionally, people who use Steward as a web assistant may provide it with sensitive/authentication credentials. This may be risky as sensitive data such as user names, passwords, PII, etc., could be unintentionally divulged by the language model, inputting them into incorrect fields. Thus, these types of web automation and assistant tools should be limited to experimental developer and research use only to mitigate user-end security/privacy risks.

Security/Privacy Concerns: We do not recommend using Steward or similar LLM web automation tools for tasks that require sensitive personal information or account access. While Steward offers advantages like flexibility and

runtime/cost-efficiency, granting web automation tools access to account and settings pages can create security/privacy vulnerabilities. An attacker may attempt to hijack web automation tools by placing prompt injections [16, 24] or adversarial examples [38] on websites, social media feeds, or comments sections. These attacks may be capable of altering the system’s original task. Such an attack may redirect the tool to change account passwords/2FA, or redirect the tool to visit a malicious website.

7.3 Limitations and Future Work

Steward is composed of many components, and although the HTML cleaning approach significantly reduces the token count, there are other ways to improve its cost-effectiveness. For example, substituting the element proposal component with a fine-tuned T5 or larger language model may make significant improvements in the performance and cost of **Steward**. We only conducted low-budget instruction tuning on open-source LLMs, so there may be more successful model configurations we have not yet explored. An ideal approach would be training a foundation model on the HTML of web pages and fine-tuning the model for the specialized components described in this paper, although this method is prohibitively expensive.

While our system supports additional browser actions when integrated with Playwright, we have not yet evaluated this due to the unavailability of relevant datasets.

We consider two main approaches that may improve results: (1) retraining the validity checking component to detect and suggest solutions that can be used in re-generating a component’s outputs, targeting the exact error source; (2) training a language model to predict a high-level representation of the next action and element using the context state. This prediction would be used to aid the element proposal and element + action selection components.

8 CONCLUSION

LLMs have shown a significant promise for automating intelligent web navigation and interactions. We have proposed, **Steward**, that enables LLMs to truly interact with websites on behalf of users. It is a *practical* natural language web automation framework augmented with optimizations like HTML filtering, caching, and branch prediction. It is capable of exercising UIs in a context-aware manner and is reliable and accurate, usually selecting an optimal action and element sequence for a given user’s goal. This application of LLMs could enable more complex UI exercising and website analyses tools. **Steward** can serve as a first step for re-defining how we interact with the web.

REFERENCES

- [1] 2022. Fast and reliable end-to-end testing for modern web apps | Playwright. <https://playwright.dev> [Online; accessed 13. Sep. 2022].
- [2] 2023. AutoGPT. <https://github.com/Significant-Gravitas/AutoGPT> [Online; accessed 25. Sep. 2023].
- [3] 2023. Common Crawl - Open Repository of Web Crawl Data. <https://commoncrawl.org> [Online; accessed 25. Sep. 2023].
- [4] 2023. Introducing ChatGPT and Whisper APIs. <https://openai.com/blog/introducing-chatgpt-and-whisper-apis> [Online; accessed 8. Oct. 2023].
- [5] 2023. natbot. <https://github.com/nat/natbot> [Online; accessed 25. Sep. 2023].
- [6] 2023. WebPilot - Copilot for All. <https://www.webpilot.ai/signin> [Online; accessed 25. Sep. 2023].
- [7] 2024. GPT-4V-Act. <https://github.com/ddupont808/GPT-4V-Act> [Online; accessed 12. Apr. 2024].
- [8] Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2022. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416* (2022).
- [9] Eli Collins. 2021. LaMDA: our breakthrough conversation technology. *Google* (May 2021). <https://blog.google/technology/ai/lamda>
- [10] Biplob Deka, Zifeng Huang, Chad Franzen, Joshua Hirschman, Daniel Afergan, Yang Li, Jeffrey Nichols, and Ranjitha Kumar. 2017. Rico: A mobile app dataset for building data-driven design applications. In *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology*. 845–854.
- [11] Xiang Deng. 2023. A More Accessible Web with Natural Language Interface. In *Proceedings of the 20th International Web for All Conference*. 153–155.
- [12] Xiang Deng, Yu Gu, Boyuan Zheng, Shijie Chen, Samuel Stevens, Boshi Wang, Huan Sun, and Yu Su. 2023. Mind2Web: Towards a Generalist Agent for the Web. *arXiv preprint arXiv:2306.06070* (2023).
- [13] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).
- [14] Hiroki Furuta, Yutaka Matsuo, Aleksandra Faust, and Izzeddin Gur. [n. d.]. Exposing Limitations of Language Model Agents in Sequential-Task Compositions on the Web. In *ICLR 2024 Workshop on Large Language Model (LLM) Agents*.
- [15] Hiroki Furuta, Ofir Nachum, Kuang-Huei Lee, Yutaka Matsuo, Shixiang Shane Gu, and Izzeddin Gur. 2023. Multimodal Web Navigation with Instruction-Finetuned Foundation Models. *arXiv preprint arXiv:2305.11854* (2023).
- [16] Kai Greshake, Sahar Abdelnabi, Shailesh Mishra, Christoph Endres, Thorsten Holz, and Mario Fritz. 2023. Not what you’ve signed up for: Compromising real-world llm-integrated applications with indirect prompt injection. In *Proceedings of the 16th ACM Workshop on Artificial Intelligence and Security*. 79–90.
- [17] Izzeddin Gur, Hiroki Furuta, Austin Huang, Mustafa Safdari, Yutaka Matsuo, Douglas Eck, and Aleksandra Faust. 2023. A real-world webagent with planning, long context understanding, and program synthesis. *arXiv preprint arXiv:2307.12856* (2023).
- [18] Hongliang He, Wenlin Yao, Kaixin Ma, Wenhao Yu, Yong Dai, Hongming Zhang, Zhenzhong Lan, and Dong Yu. 2024. WebVoyager: Building an End-to-End Web Agent with Large Multimodal Models. *arXiv preprint arXiv:2401.13919* (2024).
- [19] Wenyi Hong, Weihan Wang, Qingsong Lv, Jiazheng Xu, Wenmeng Yu, Junhui Ji, Yan Wang, Zihan Wang, Yuxiao Dong, Ming Ding, et al. 2023. Cogagent: A visual language model for gui agents. *arXiv preprint arXiv:2312.08914* (2023).

- [20] Faria Huq, Jeffrey P Bigham, and Nikolas Martelaro. 2023. "What's important here?": Opportunities and Challenges of Using LLMs in Retrieving Information from Web Interfaces. *arXiv preprint arXiv:2312.06147* (2023).
- [21] Hiroyuki Kirinuki, Shinsuke Matsumoto, Yoshiki Higo, and Shinji Kusumoto. 2021. NLP-assisted web element identification toward script-free testing. In *2021 IEEE International Conference on Software Maintenance and Evolution (ICSME)*. IEEE, 639–643.
- [22] Yuanchun Li and Oriana Riva. 2021. Glider: A reinforcement learning approach to extract UI scripts from websites. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1420–1430.
- [23] Yuanchun Li, Ziyue Yang, Yao Guo, and Xiangqun Chen. 2019. Humanoid: A deep learning-based approach to automated black-box android app testing. In *2019 34th IEEE/ACM International Conference on Automated Software Engineering (ASE)*. IEEE, 1070–1073.
- [24] Yi Liu, Gelei Deng, Yuekang Li, Kailong Wang, Tianwei Zhang, Yeping Liu, Haoyu Wang, Yan Zheng, and Yang Liu. 2023. Prompt Injection attack against LLM-integrated Applications. *arXiv preprint arXiv:2306.05499* (2023).
- [25] Yu Liu, Rahulkrishna Yandrapally, Anup K Kalia, Saurabh Sinha, Rachel Tzoref-Brill, and Ali Mesbah. 2022. CrawLabel: computing natural-language labels for UI test cases. In *Proceedings of the 3rd ACM/IEEE International Conference on Automation of Software Test*. 103–114.
- [26] Robert L Logan IV, Ivana Balažević, Eric Wallace, Fabio Petroni, Sameer Singh, and Sebastian Riedel. 2021. Cutting down on prompts and parameters: Simple few-shot learning with language models. *arXiv preprint arXiv:2106.13353* (2021).
- [27] Sahisnu Mazumder and Oriana Riva. 2020. Flin: A flexible natural language interface for web navigation. *arXiv preprint arXiv:2010.12844* (2020).
- [28] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems* 35 (2022), 27730–27744.
- [29] Laria Reynolds and Kyle McDonell. 2021. Prompt programming for large language models: Beyond the few-shot paradigm. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–7.
- [30] Adam Roberts, Colin Raffel, Katherine Lee, Michael Matena, Noam Shazeer, Peter J Liu, Sharan Narang, Wei Li, and Yanqi Zhou. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. (2019).
- [31] Paloma Sodhi, SRK Branavan, and Ryan McDonald. 2023. HeaP: Hierarchical Policies for Web Actions using LLMs. *arXiv preprint arXiv:2310.03720* (2023).
- [32] Tanapuch Wanwarang, Nataniel P Borges Jr, Leon Bettscheider, and Andreas Zeller. 2020. Testing apps with real-world inputs. In *Proceedings of the IEEE/ACM 1st International Conference on Automation of Software Test*. 1–10.
- [33] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems* 35 (2022), 24824–24837.
- [34] Daniel Lowe Wheeler. 2016. zxcvbn: {Low-Budget} Password Strength Estimation. In *25th USENIX Security Symposium (USENIX Security 16)*. 157–173.
- [35] Chengrun Yang, Xuezhi Wang, Yifeng Lu, Hanxiao Liu, Quoc V Le, Denny Zhou, and Xinyun Chen. 2023. Large language models as optimizers. *arXiv preprint arXiv:2309.03409* (2023).
- [36] Jianwei Yang, Hao Zhang, Feng Li, Xueyan Zou, Chunyuan Li, and Jianfeng Gao. 2023. Set-of-mark prompting unleashes extraordinary visual grounding in gpt-4v. *arXiv preprint arXiv:2310.11441* (2023).
- [37] Zhizheng Zhang, Xiaoyi Zhang, Wenxuan Xie, and Yan Lu. 2023. Responsible Task Automation: Empowering Large Language Models as Responsible Task Automators. *arXiv preprint arXiv:2306.01242* (2023).
- [38] Andy Zou, Zifan Wang, J Zico Kolter, and Matt Fredrikson. 2023. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043* (2023).

A APPENDIX

A.1 Examples of Close/Valid Action and Element Selections Labeled as Incorrect

Example “Incorrect” Selections

Task: Add a set of wireless headphones with active noise-cancelling feature.

Ground Truth

```
1 click <div role="button">wireless headphones</div>
```

Predicted Selection

```
1 click <div role="button">wireless headphones noise cancelling</div>
```

Task: Find a Hotel in New York City with lowest price ... (April 1st and 2nd).

Ground Truth

```
1 click <a>Hotels</a>
```

Predicted Selection

```
1 click <a>Hotels in New York City </a>
```

Table 5: Average Action Steps per Subdomain Task

Subdomain	Airlines	Auto	Car Rental	Department	Digital	Event	Fashion	Game	General	Ground	Hotel	Movie	Music	Other	Restaurant	Speciality	Sports
Actions per Task	9.49	9.11	9.21	5.23	6.93	5.40	7.68	3.80	9.06	7.42	7.73	4.78	5.49	6.04	5.89	6.79	3.59

Table 6: Component Model Costs

Component	Best Model	Input \$/1M tok	Output \$/1M tok
Screenshot	GPT 4 Vision	\$10.00	\$30.00
Element Proposal Top-15	GPT 3.5 Turbo	\$0.50	\$1.50
Cache Matching	GPT 3.5 Turbo	\$0.50	\$1.50
Tab Management	GPT 3.5 Turbo	\$0.50	\$1.50
Search Key Generation	GPT 3.5 Turbo	\$0.50	\$1.50
Page Context	GPT 3.5 Turbo	\$0.50	\$1.50
Element + Action Top-1	GPT-4 Turbo	\$10.00	\$30.00
Secondary Parameter	GPT-4 Turbo	\$10.00	\$30.00
Cache Key Check	GPT-4 Turbo	\$10.00	\$30.00
Double Check	GPT-4 Turbo	\$10.00	\$30.00
End State	GPT-4 Turbo	\$10.00	\$30.00

A.2 CSS Selectors

CSS Selectors for Interactable Elements

```
button:visible
a:visible
input:visible
select:visible
textarea:visible
[role*="radio"]:visible
[role*="option"]:visible
[role*="checkbox"]:visible
[role*="button"]:visible
[role*="tab"]:visible
[role*="textbox"]:visible
[role*="link"]:visible
[role*="menuitem"]:visible
[role*="menu"]:visible
[role*="tabpanel"]:visible
[role*="combobox"]:visible
[role*="select"]:visible
[class*="radio"]:visible
[class*="option"]:visible
[class*="checkbox"]:visible
[class*="button"]:visible
[class*="textbox"]:visible
[class*="menuitem"]:visible
[class*="menu"]:visible
[class*="tabpanel"]:visible
[class*="combobox"]:visible
[class*="select"]:visible
[class*="suggestion"]:visible
[class*="search-bar"]:visible
[class*="search-result"]:visible
[class*="toggle"]:visible
[onclick]:visible
[href]:visible
[aria-controls]:visible
[aria-label]:visible
[aria-labelledby]:visible
[aria-haspopup]:visible
[aria-owns]:visible
[aria-selected]:visible
```

A.3 Prompts

This section contains sample prompts used in each of the 7 components of Steward. These prompts contain both the instruction portion and the input portion of the prompts. The instructions contain high-level instructions for the language model to follow, whereas the inputs contain the current web page state. “...” is used to maintain brevity and typically

Table 7: Dataset Details

	Element Proposal	Element + Action	Secondary Param	High Level	Page Context	Validity Check	End State
Num Samples	7351	1650	700	1500	1500	1500	1700

contains either additional elements to select from, example states used in few-shot prompting, or are self-explanatory.

Webpage Context Summary

Take a deep breath. You are an AI assistant made for browsing the web. You will get the text found on a web page. Provide a 1-sentence high level description that summarizes the primary purpose and context of the page. E.g., "Search engine landing page for duckduckgo of the search result for software jobs", "Facebook post creation interface and homepage", "Ecommerce shopping search results page for bubbly soda", "Sign in page with email or phone input for youtube", "Video player home feed with recommendations", "Social media forum detailing todays events, news, community posts", etc.

STATE:

Website visited: united.com
Page text: ...

HTML Element Proposal

Take a deep breath. You are an AI assistant made for browsing the web. You will get a state containing information on a web page, a goal, a list of previously performed actions, and a list of candidate elements. Considering the last actions you took, return the index of the next HTML element to interact with next to achieve your goal followed by a reasoning. Return the single best candidate element. E.g., "ELEMENT (1)

STATE:

Website visited: united.com

Page context: Airline booking and travel information website for United Airlines.

Goal: Search the status of flight from Columbus, number 1234 on April 5th, 2023.

Goal: Select a high speed train ticket with a departure time before 23:00 from Shanghai to Beijing.

ACTIONS PERFORMED:

- None

CANDIDATE ELEMENTS:

(1) <button class="atm-c-btn--bare" type="button">Close Panel </button>
(2) <button type="button">+</button>
(3) <button class="app-components-SearchModal-styles__searchTrigger--ttVhr" type="button">Search for a topic</button>
...

Based on this state, ELEMENT (9) clicking on the Flight status tab is the best option.

HTML Element+Action Ranking

Take a deep breath. You are an AI assistant made for browsing the web. You will get a state containing information on a web page, a goal, a list of previously performed actions and a list of candidate elements. Considering the last actions you took, format your response with the best action and element pair to perform next. Return the word "click", "type_text", "select_option", "press_enter", "upload_file" followed by the index of the element to perform the next action on.

E.g., "click (1)"

or

"type_and_enter (4)"

If none of the candidate elements are appropriate, return just the word "None".

STATE:

Website visited: tiktok.com

Page context: This is the homepage of TikTok.com, which offers various tools, showcases, and insights that help marketers and businesses create successful TikTok advertising campaigns by leveraging trends, hashtags, songs, and creators.

Goal: Find and show me the analytics for the top trending educational hashtag in egypt in the last 120 days that is new to top 10

ACTIONS PERFORMED:

- click Content navigation with tags and categories.
- click Hashtag Navigation Dropdown.
- type_text egypt in Advertising keyword search bar.
- click Location option in a dropdown list.
- click Timeframe label - "Last 7 days".
- click Timeframe selection.
- click Checkbox for "new to top 100" songs.

CANDIDATE ELEMENTS:

- (1)
Top Products

- (2) See analytics
- ...

Screenshot Response

You are an AI assistant made for browsing the web. You will get a state containing the desired task to perform on a website, a list of previously performed actions, and a screenshot of the website. Respond with a verb (click, type_text, select_option, press_enter, upload_file) to perform on an element and a description of the element to interact with next to achieve the task. E.g., "click search button with magnifying glass icon"

Generative Text Inputs

Take a deep breath. You are an AI assistant made for browsing the web. You will get a state containing a goal, a page context, and a high level action. What text would make the most sense to type into the input field? Only return this text. E.g., "New York", "4/5! I thought the restaurant was a great experience", "how to find a job in my neighborhood", "That's awesome, bring me a souvenir!", "french fries", etc.

STATE:

Website visited: thumbtack.com

Page context: This is the website for Thumbtack, a platform that connects customers with professionals for various services such as home improvement, cleaning, repairs, and more.

Goal: find electricians near 10203

CANDIDATE ACTION:

type_text in Task input field.

Select Option

Take a deep breath. You are an AI assistant made for browsing the web. You will get a state containing a goal, a page context, a high level action, and a list of options. Return the index of the option to select. E.g., "1", "2", "3", etc.

STATE:

Website visited: newegg.com

Page context: The page is a product listing page for an online retailer specializing in computer components, electronics, and other tech products. Goal: Build an entry-level pc with an windows 11 64 bit intel i7 CPU with a256gb ssd drive + 4gb ram and adding cheapest component and accessories available.

CANDIDATE ACTION:

select_option in Featured Items Selector

SELECT OPTIONS:

- (1) <option value="0">
Featured Items
</option>
- (2) <option value="1">
Lowest Price
</option>
- (3) <option value="2">
Highest Price
</option>
- ...

Double Checking

Take a deep breath. You are an AI assistant made for browsing the web. You will get a state containing information on a web page, a goal, and a list of candidate elements. If none of the proposed elements make any sense to interact with given the context and state, respond "No". Otherwise, if even one of the elements makes sense, respond "Yes".

STATE:

Website visited: apartments.com

Page context: A web page for finding apartments and homes for rent in various cities, along with tools for managing rentals and advertising properties.

Goal: calculate and search rent for a \$6000 monthly income with 30% rent budget near 90012 area.

ACTIONS PERFORMED:

None

CANDIDATE ELEMENTS:

click Menu toggle button.

...

Check For End State

Take a deep breath. You are an AI assistant made for browsing the web. You will get a state containing the desired task to perform on a website and a list of performed actions. Do the performed actions seem to finish the task? Respond with "Yes" or "No" followed by an explanation.

E.g., for this state: ...

...

STATE:

Website visited: recreation.gov

Page context: Recreation.gov is a website that provides tools and tips for discovering outdoor and cultural destinations, offering trip planning, information sharing, and reservations for incredible experiences.

Goal: Find campgrounds from April 1st to 4th 2023 that are available at Illinois for 2 adults and 2 kids.

ACTIONS PERFORMED:

- type_text Illinois in Search bar.
- click Search suggestion: Illinois.
- click Accommodation selector.
- click Accommodation search dropdown.
- click Apply button.
- click Check-in date picker.
- click Reservation button.
- click Date picker input field.
- click Selected date on calendar.
- click End date input field.
- click Calendar day.
- click "Search button"
- select_option Price in Search sorting dropdown.
- select_option Available in Search Sorting Dropdown.