# MIND2WEB: Towards a Generalist Agent for the Web

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`https://osu-nlp-group.github.io/Mind2Web`

## Abstract

We introduce MIND2WEB, the first dataset for developing and evaluating generalist agents for the web that can follow language instructions to complete complex tasks on any website. Existing datasets for web agents either use simulated websites or only cover a limited set of websites and tasks, thus not suitable for generalist web agents. With over 2,000 open-ended tasks collected from 137 websites spanning 31 domains and crowdsourced action sequences for the tasks, MIND2WEB provides three necessary ingredients for building generalist web agents: 1) diverse domains, websites, and tasks, 2) use of real-world websites instead of simulated and simplified ones, and 3) a broad spectrum of user interaction patterns. Based on MIND2WEB, we conduct an initial exploration of using large language models (LLMs) for building generalist web agents. While the raw HTML of real-world websites are often too large to be fed to LLMs, we show that first filtering it with a small LM significantly improves the effectiveness and efficiency of LLMs. Our solution demonstrates a decent level of performance, even on websites or entire domains the model has never seen before, but there is still a substantial room to improve towards truly generalizable agents. We open-source our dataset, model implementation, and trained models (`https://osu-nlp-group.github.io/Mind2Web`) to facilitate further research on building a generalist agent for the web.

## 1 Introduction

The web now hosts billions of websites [4] that cover virtually every aspect of the digital world. In this work, we seek to answer the question: *How can we build a generalist agent for the web that, given any website, can follow language instructions and carry out the corresponding tasks?* Some exemplar tasks for such an agent are shown in Figure 1. A generalist agent could make the web more accessible, which is becoming increasingly difficult as modern websites provide increasingly more functionalities that also increase their complexity and learning curve. On the other hand, such an agent may also turn the entire web into an unprecedentedly powerful and versatile tool [19, 23] that can enhance large language models (LLMs). For example, it may be used as a plugin for ChatGPT [20] to directly acquire information and carry out actions on HTML websites, instead of only retrieving web content through a retriever tool [5, 14] or relying on pre-defined APIs for each web service [30, 33].

A generalist agent for the web shall meet the following desiderata: First, **it shall work on any website on the Internet**. Since it is infeasible to collect sufficient training data that covers all websites, this requires the agent to be inherently generalizable to websites or even domains it has never seen before. Second, **it shall work on real-world websites, which can be dynamic, complex, and noisy**. Most modern websites are dynamic, generating and rendering different content in response to user actions. This necessitates the agent to model each website as a partially-observable environment instead of assuming full knowledge *a priori*. The agent should also not make strong simplifying assumptions

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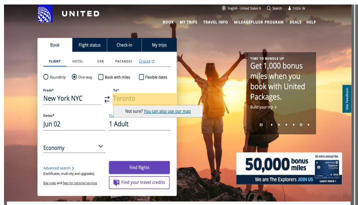
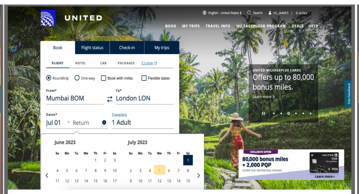
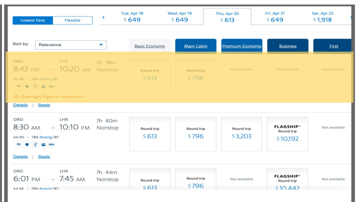
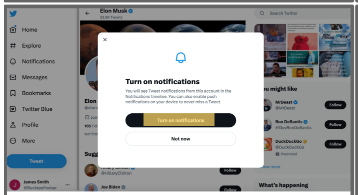
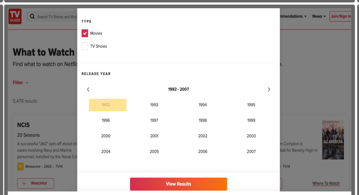
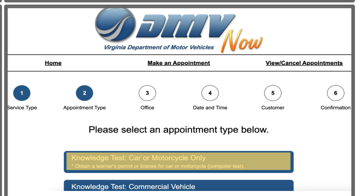

(a) Find one-way flights from New York to Toronto.


(b) Book a roundtrip on July 1 from Mumbai to London and vice versa on July 5 for two adults.


(c) Find a flight from Chicago to London on 20 April and return on 23 April.


(d) Find Elon Musk's profile and follow, start notifications and like the latest tweet.


(e) Browse comedy films streaming on Netflix that was released from 1992 to 2007.



(f) Open page to schedule an appointment for car knowledge test.

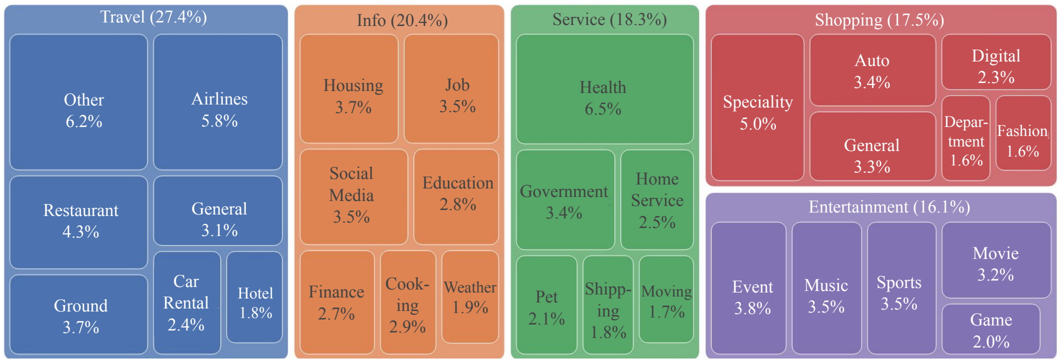


Figure 1: Sample tasks and all domains featured in MIND2WEB. The array of diversity allows for testing an agent's generalizability across tasks on the same website (a vs. b), similar tasks on different websites (a vs. c), and even to entirely disparate tasks, websites, and domains (d−f).

about the environments but must embrace the full complexity and sometimes noise, *e.g.*, due to sub-optimal website designs. Finally, **it shall support diverse and sophisticated interactions with websites.** Tasks from users can be highly diverse and take a large number of steps to complete (*e.g.*, the task in Figure 1(b) would take 14 actions). An agent that only supports simple tasks may provide limited value to users.

Building an agent for the web is not entirely new. There have been numerous prior efforts in varied forms. However, none of them meets all the requirements for a generalist agent listed above. Existing work falls short in one to all of the following aspects: 1) Only operating in a limited and pre-specified set of websites [3, 17, 18, 31, 36], 2) making strong simplifying assumptions about the websites [18, 36], and 3) only supporting specific types of tasks [17, 18, 36] and/or requiring tedious step-by-step instructions from users [3, 17, 18, 35]. Meanwhile, LLMs have been shown to excel at grounded language understanding in complex environments with good generalizability and sample efficiency [2, 9, 13, 29]. It is therefore promising to explore LLMs as a candidate solution towards generalist agents for the web. However, there lacks a good dataset that can support the development and evaluation of generalist web agents, which is the focus of this work.

In light of this, we present MIND2WEB, a new dataset with natural language tasks and manually annotated action sequences for developing and evaluating generalist agents for the web. It offers the following unique features:

**1. Diverse coverage of domains, websites, and tasks.** MIND2WEB boasts a collection of over 2,000 tasks curated from 137 websites that span 31 different domains. This extensive range of tasks and domains not only provides a vast landscape for exploration and learning but also opens up a new level of versatility and complexity, fostering a more comprehensive evaluation of generalist web agents.

**2. Use of real-world websites.** MIND2WEB replaces the oversimplified simulation environments commonly found in other datasets with an authentic, vibrant, and unpredictable realm of real-world websites. We provide full traces of user interactions, webpage snapshots, and network traffic, making it a rich source of raw, unfiltered, and dynamic data. By doing so, MIND2WEB equips models with the capacity to interact and cope with the complexities and uncertainties of real-world environments, thereby encouraging the development of more robust and adaptive models.

**3. A broad spectrum of user interaction patterns.** MIND2WEB enables users to engage in sophisticated ways with websites, as opposed to basic operations such as searching, following links, and reading content commonly found in existing work. Users can *click, select, and type in any elements* on the website, which significantly expands the space of possible tasks. This captures all the common actions users do on websites in real life and promotes the development of agents capable of handling complex tasks.

With the diverse domains and websites, we create challenging out-of-distribution evaluation settings where agents are tested on their generalizability to websites or even entire domains never seen during training. This presents a representative evaluation of generalist agents working on unseen websites.

MIND2WEB enables us to conduct an initial exploration in using LLMs for building generalist web agents. The HTML document of real-world webpages may contain thousands of elements, which makes it infeasible or too costly to be fed into an LLM's context. To address this issue, we propose MINDACT, a two-stage model that involves first using a fine-tuned small LM to filter the web elements and then using an LLM to select from the filtered elements in a multi-choice question answering fashion and predict the corresponding action with the selected element. We show that MINDACT significantly outperforms modeling strategies commonly adopted by prior work and achieves a decent level of generalization. It can also work well with both open-source LLMs like Flan-T5 [6] through fine-tuning and closed-source LLMs like GPT-3.5-turbo and GPT-4 through in-context learning. But there is still substantial room for further improvement towards generalist agents for the web. Promising future directions include integrating multi-modal information, reinforcement learning with feedback from real websites, and specialized LMs for web understanding and action taking.

## 2 MIND2WEB Dataset

Unlike existing datasets predominantly constructed within simulated environments [27, 36], our objective is to bridge the gap between simulation and reality so that agents trained on our dataset can work on real-world websites out of the box. To achieve this, our approach for data collection adheres to the following principles. Firstly, instead of recreating websites in simulation, which often leads to oversimplified environments, we engage directly with real-world websites and capture snapshots of these environments. Secondly, we collate a diverse set of websites from varied domains and crowd-source realistic tasks that cover a wide range of functionalities provided by these websites. Finally, acknowledging the challenge of perfectly replicating the complexity of real-world environments, we strive to capture a comprehensive snapshot of each website and the full interaction trace, to the extent that all the tasks can be seamlessly replayed offline. This supports rich modeling and evaluation approaches, ensuring a robust and practical dataset for research.

### 2.1 Task Definition

The primary objective of MIND2WEB is for the agent to complete a specific task on the target website through a series of actions. Each instance in our dataset contains three components:

**Task description,** which outlines the high-level goal of the task. We intentionally avoid low-level, step-by-step instructions, aiming to foster the development of agents that can comprehend and carry out tasks in a more autonomous fashion, rather than merely following prescriptive directives.

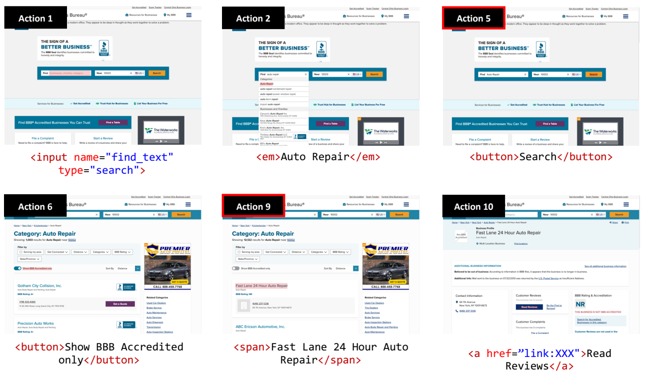
**Action sequence**, which is the sequence of actions required to accomplish the task on the website. Each action in the sequence comprises a `(Target Element, Operation)` pair. The `Target Element` is an interactable element on the current webpage, and the `Operation` refers to the action to be executed on that element. We support three common operations: `Click` (also including `Hover` and `Press Enter`), `Type`, and `Select Option`. For `Type` and `Select Option`, they also require an additional value as an argument. Actions in a sequence often span multiple webpages of a website.

**Task Description:**
***<u>Show me the reviews for the auto repair business closest to 10002.</u>***

**Action Sequence:**

| | Target Element | Operation |
|---|---|---|
| 1. | [searchbox] *Find* | TYPE: ***auto repair*** |
| 2. | [button] *Auto Repair* | CLICK |
| 3. | [textbox] *Near* | TYPE: ***10002*** |
| 4. | [button] *10002* | CLICK |
| **5.** | **[button] Search** | **CLICK** |
| 6. | [switch] *Show BBB Accredited only* | CLICK |
| 7. | [svg] | CLICK |
| 8. | [button] Sort By | CLICK |
| **9.** | **[link] *Fast Lane 24 Hour Auto Repair*** | **CLICK** |
| 10. | [link] *Read Reviews* | CLICK |

**Webpage Snapshots:**



```
<input name="find_text" type="search">
<em>Auto Repair</em>
<button>Search</button>
<button>Show BBB Accredited only</button>
<span>Fast Lane 24 Hour Auto Repair</span>
<a href="link:XXX">Read Reviews</a>
```

Figure 2: A sample data instance of our dataset with the three components. Actions marked in **red** will result in a transition to a new webpage.

**Webpage snapshots**, which constitute the environment within which the task is performed. We provide the snapshots in a variety of formats to accommodate different modeling approaches: self-contained MHTML file that includes the raw HTML code of the webpage, DOM snapshot containing the DOM tree along with the layout and style information of the screenshot of the rendered webpage, HAR file that includes all the network traffic for replaying the interaction if needed, and trace file that comprises the complete interaction trace during the task annotation process.

The agent receives the task description in the beginning. At each step, it also receives the current webpage and the history of previous actions. The objective is to accurately predict the subsequent action, which encompasses the target element for interaction and the operation.

## 2.2 Data Collection

Our data collection process consists of four stages: website selection, task proposal, task demonstration, and task verification. Website selection and task verification are done by the authors. For task proposal and demonstration, we develop a sophisticated annotation tool using Playwright [2] and hire annotators through Amazon Mechanical Turk. Refer to Supplementary for annotation tool details.

**Website Selection.** We start with 5 top-level domains: Travel, Shopping, Service, Entertainment, and Information, which are subsequently broken down into 31 (secondary) domains. We select websites within each domain based on their popularity in the US, as ranked by similarweb.com. We manually select 3-5 representative websites per domain, resulting in a collection of 137 websites in total.

**Task Proposal.** We present the annotators with a target website, a concise description of the website, and a few sample tasks associated with it. The annotators are then asked to propose *open-ended and realistic tasks* based on three criteria: the tasks should be of diverse types, require multiple rounds of interaction, and describe the high-level goal instead of step-by-step instructions. To further stimulate creativity and boost diversity, we use ChatGPT to generate seed tasks by prompting it to test different functionalities of a website. We generate 50 seed tasks per website, of which 10 are randomly sampled and presented to the annotator each time. These seed tasks are mainly for inspiration—annotators are explicitly instructed not to directly use them and we reject task proposals that are highly similar to the seed tasks. All the proposed tasks are further screened by the authors to ensure quality and diversity before entering the demonstration phase.

**Task Demonstration.** We develop a Playwright-based tool for demonstration (Figure 2). Workers will log into the tool and demonstrate how to perform the tasks they have proposed within a web browser. To ensure accuracy, each interaction round is split into two parts: *element selection* and *operation selection*. At each step, the worker first selects an element on the webpage by clicking within the browser. They are then asked to confirm the selection and choose the operation to execute on the selected element. Once the task is completed, the worker is given another opportunity to review and modify the task description.

[2]https://playwright.dev/

Table 1: Statistics of MIND2WEB compared with existing datasets.

| | # Dom. | # Env. | Env. Type | Avg. # Elements | # Tasks | Task Info. | Avg. # Actions |
|---|---|---|---|---|---|---|---|
| MiniWoB++ [18] | – | 100 | Simplified mobile websites | 28 | 100 | Low-level | 3.6 |
| WebShop [36] | 1 | 1 | Simplified shopping websites | 38 | 12,000 products | High-level | 11.3 |
| RUSS [35] | – | 22 | Real-world websites | 801 | 80 | High & low | 5.4 |
| PixelHelp [17] | 4 | 4 | Mobile apps | – | 187 | High & low | - |
| META-GUI [31] | 6 | 11 | Mobile apps | 79 | 1,125 dialogues | High-level | 4.3 |
| MoTIF [3] | 15 | 125 | Mobile apps | 188 | 756 | High & Low | 4.4 |
| MIND2WEB | 5 / 31 | 137 | Real-world websites | 1,135 | 2,350 | High-level | 7.3 |

**Task Verification.** Finally, all task demonstrations are verified by the authors to ensure the following. First, all actions are accurately reflected in the task description. The authors will modify the task description if needed to align it with the annotated actions; Second, the recorded actions are correct and clean, with extraneous steps discarded. Finally. the start and end points of tasks are consistent, such as excluding login steps unless specified in the task description, or ending the annotation at the search result page if the task was to find a certain item without clicking on specific items. After verification, we discarded 61 out of the total 2,411 tasks. Among the 2,350 retained tasks, the task description was refined in 390 instances to better correspond with the demonstrated actions, while some extraneous steps were discarded in 187 instances. Overall, the data collection pipeline has been proven effective and produces high-quality data.

### 2.3 Comparison with Existing Work and Research Challenges

MIND2WEB presents a unique ensemble of research challenges for the development of generalist agents for the web in real-world settings. As shown in Table 1, MIND2WEB distinguishes itself from existing literature in several ways. Firstly, MIND2WEB spans across 137 websites from 31 domains, allowing comprehensive testing of an agent's ability in generalizing across varied environments. Secondly, we utilize real-world websites without manual simplification. Consequently, the included environments exhibit complexity far surpassing that encountered in previous studies, yet better reflecting the intricacy of the modern web. With an average of over 1,000 elements per page embedded within complex DOM structures, how to effectively process such long and highly structured documents presents a significant challenge for modeling. Lastly, we direct the annotators to propose *open-ended tasks* that explore different functionalities of the website to mimic genuine web usage. Meanwhile, contrary to prior studies [3, 17, 18, 35] that provide step-by-step directives and primarily focus on testing the agent's ability to translate low-level instructions into actions, *e.g.*, "*Type New York in the location field, click the search button and choose the tomorrow tab*," we opted for the setting where only high-level goals are available, *e.g.*, "*What is the weather for New York tomorrow*?" This poses a much greater yet realistic planning and grounding challenge for the agent.

## 3 Method: MINDACT

Employing the data from MIND2WEB, we introduce an exploratory framework, MINDACT, for our task, leveraging the power of LLMs. Raw HTML documents, which could consist of thousands of elements, are either infeasible or cost-prohibitive to be directly fed into LLMs. We propose a two-stage process that synergizes the strength of small and large LMs, as shown in Figure 3. In the first stage, a fine-tuned small LM is used to rank the elements present on a webpage, yielding a small pool of promising candidates. In the second stage, these candidate elements are consolidated to form a representative snippet of the webpage, which is then processed by an LLM to predict the final action, including predicting both the element for interaction and the corresponding operation.

### 3.1 Candidate Generation with Small LMs

Given the task description, the snapshot of the webpage at step $t$, and the actions performed in the preceding $t-1$ steps, we treat candidate generation as a ranking task. The task is to select the top-$k$

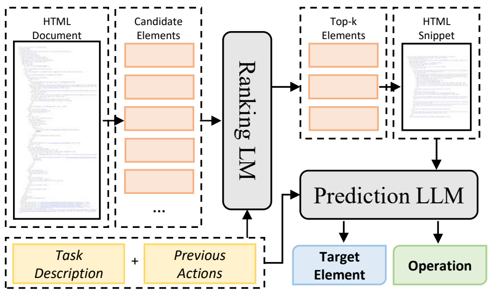
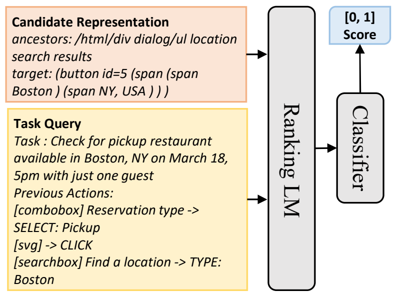


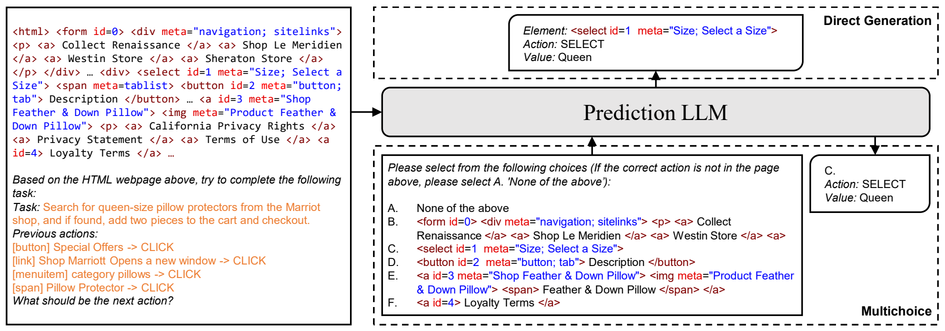
Figure 3: The overall pipeline for MindAct with a small ranking LM for candidate generation, and a large prediction LM for action prediction.



**Candidate Representation**
*ancestors: /html/div dialog/ul location search results*
*target: (button id=5 (span (span Boston ) (span NY, USA ) ) )*

**Task Query**
*Task : Check for pickup restaurant available in Boston, NY on March 18, 5pm with just one guest*
*Previous Actions:*
*[combobox] Reservation type -> SELECT: Pickup*
*[svg] -> CLICK*
*[searchbox] Find a location -> TYPE: Boston*

Figure 4: Illustration of the candidate generation module and the templates for constructing task query and candidate representation.



```
<html> <form id=0> <div meta="navigation; sitelinks">
<p> <a> Collect Renaissance </a> <a> Shop Le Meridien
</a> <a> Westin Store </a> <a> Sheraton Store </a>
</p> </div> … <div> <select id=1 meta="Size; Select a
Size"> <span meta=tablist> <button id=2 meta="button;
tab"> Description </button> … <a id=3 meta="Shop
Feather & Down Pillow"> <img meta="Product Feather &
Down Pillow"> <p> <a> California Privacy Rights </a>
<a> Privacy Statement </a> <a> Terms of Use </a> <a
id=4> Loyalty Terms </a> …
```

*Based on the HTML webpage above, try to complete the following task:*
*Task:* Search for queen-size pillow protectors from the Marriot shop, and if found, add two pieces to the cart and checkout.
*Previous actions:*
[button] Special Offers -> CLICK
[link] Shop Marriott Opens a new window -> CLICK
[menuitem] category pillows -> CLICK
[span] Pillow Protector -> CLICK
*What should be the next action?*

*Element:* <select id=1 meta="Size; Select a Size">
*Action:* SELECT
*Value:* Queen

*Please select from the following choices (If the correct action is not in the page above, please select A. 'None of the above'):*

A. None of the above
B. <form id=0> <div meta="navigation; sitelinks"> <p> <a> Collect Renaissance </a> <a> Shop Le Meridien </a> <a> Westin Store </a> <a>
C. <select id=1 meta="Size; Select a Size">
D. <button id=2 meta="button; tab"> Description </button>
E. <a id=3 meta="Shop Feather & Down Pillow"> <img meta="Product Feather & Down Pillow"> <span> Feather & Down Pillow </span> </a>
F. <a id=4> Loyalty Terms </a>

C.
*Action:* SELECT
*Value:* Queen

Figure 5: Illustration of action prediction with LLMs.

candidate DOM elements from the webpage that best align with both the task description and the current step. We formulate the task query by concatenating the task description with previous actions. The textual representation of each candidate DOM element is derived from a combination of the element's tag, its textual content, and salient attribute values, as well as the textual representation of its parent and child elements. As shown in Figure 4, we pair each DOM element with the task query and feed it to an encoder-only LM through the cross-encoder architecture [24], yielding a matching score. At training time, we randomly sample negative elements from the webpage, and use the target element as the positive example. The matching score is passed through a sigmoid activation function and optimized with a binary cross entropy loss. At inference time, we score all elements in the webpage and pick the top-$k$ elements with the largest logits as input to the second stage.

## 3.2 Action Prediction with LLMs

After obtaining the top-$k$ candidates, we utilize the candidate set to prune the webpage snapshot and construct snippets that only include the selected candidates and their neighbours as inputs to an LLM. Recent studies [6, 9] have suggested that training LMs for discrimination rather than generation is more generalizable and sample-efficient for other grounding tasks. Inspired by that, we convert the task of element selection into a *multi-choice question answering* (QA) problem. Instead of generating the complete target element, the LM is trained to instead select from a list of options. For comparison, we also include a baseline that directly generates the target element based on the provided webpage snippet. In both cases, we directly let the LLM generate the operation, along with the additional value needed for some operations. An example is shown in Figure 5. We incorporate up to 5 candidate elements within each input, together with a None option, and partition the candidate set into several groups. During training, we construct the target sequence using ground-truth actions and fine-tune the model using a left-to-right language modeling objective. During inference, we divide the top-$k$ candidates into multiple clusters of five options. If more than one option is selected after a round, we form new groups with the selected ones. This process repeats until a single element is selected, or all options are rejected by the model, i.e., the model chooses the None option for all groups.

Table 2: Main results. The classification baseline uses Deberta$_{\text{B}}$ and the generation baseline uses Flan-T5$_{\text{B}}$. * For GPT-4 we use 50 tasks for each setting with top-10 candidates due to limited budget.

| | **Cross-Task** | | | | **Cross-Website** | | | | **Cross-Domain** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Ele. Acc** | **Op. F1** | **Step SR** | **SR** | **Ele. Acc** | **Op. F1** | **Step SR** | **SR** | **Ele. Acc** | **Op. F1** | **Step SR** | **SR** |
| Classification | 26.8 | – | – | – | 21.6 | – | – | – | 24.5 | – | – | – |
| Generation | 20.2 | 52.0 | 17.5 | 0.0 | 13.9 | 44.7 | 11.0 | 0.0 | 14.2 | 44.7 | 11.9 | 0.4 |
| MINDACT | | | | | | | | | | | | |
| w/ Flan-T5$_{\text{B}}$ | 43.6 | 76.8 | 41.0 | 4.0 | 32.1 | **67.6** | 29.5 | 1.7 | 33.9 | **67.3** | 31.6 | 1.6 |
| w/ Flan-T5$_{\text{L}}$ | 53.4 | **75.7** | 50.3 | **7.1** | 39.2 | 67.1 | 35.3 | 1.1 | 39.7 | 67.2 | 37.3 | 2.7 |
| w/ Flan-T5$_{\text{XL}}$ | **55.1** | **75.7** | **52.0** | 5.2 | **42.0** | 65.2 | **38.9** | **5.1** | **42.1** | 66.5 | **39.6** | **2.9** |
| w/ GPT-3.5 | 20.3 | 56.6 | 17.4 | 0.8 | 19.3 | 48.8 | 16.2 | 0.6 | 21.6 | 52.8 | 18.6 | 1.0 |
| w/ GPT-4* | 41.6 | 60.6 | 36.2 | 2.0 | 35.8 | 51.1 | 30.1 | 2.0 | 37.1 | 46.5 | 26.4 | 2.0 |

## 4 Experiments

### 4.1 Experimental Setup

The diversity of MIND2WEB provides a unique opportunity to evaluate an agent's generalizability at different levels. We seek to understand how well an agent can generalize across domains, websites, and tasks: **Test$_{\text{Cross-Domain}}$**, for which we hold out two top-level domains, *Information* and *Service*, with 912 tasks from 73 websites. Here, the model is expected to generalize to an entirely new domain without having seen any websites or tasks associated with that domain during training. **Test$_{\text{Cross-Website}}$**, with 10 websites from each remaining top-level domain, containing 177 tasks. In this setting, the model is never exposed to the test websites during training. However, it has been trained on websites from the same domain and possibly with similar tasks. This setup allows us to assess an agent's ability to adapt to entirely new websites, yet within familiar domains and task contexts. **Test$_{\text{Cross-Task}}$**, where we randomly split 20% of the remaining data, regardless of domains and websites, resulting in 252 tasks from 69 websites. In this setting, the model has been exposed to webpages from the same website during training and has likely encountered similar tasks. The rest of data is used for training, which contains 1,009 tasks from 73 websites.

### 4.2 Data Preprocessing and Evaluation

We apply simple heuristics to clean the raw HTML documents, keeping only elements that are visible and carry substantial semantic meaning, as determined by their attributes, textual content, and neighboring elements. This effectively reduces the average number of elements from 1,135 to 580, while still maintaining an overall recall of 94.7% for the target element in the training data.

For evaluation, we first calculate **Element Accuracy** that compares the selected element with all acceptable elements, and **Operation F1** that calculates token-level F1 score for the predicted operation. This is the same as accuracy for `Click`, but considers the correctness of the input value for `Type` and `Select Option`. Each step of the task is evaluated independently with the ground truth action history provided. We then define **Step Success Rate** and **Success Rate** (for the whole task). A step is regarded as successful only if both the selected element and the predicted operation are correct. A task is regarded successful only if all steps have succeeded. It is therefore a stringent metric. For step-wise metrics, we report macro average across tasks.

### 4.3 Results

**Candidate Generation.** We fine-tune DeBERTa [12] as the small LM for candidate generation. As candidate generation requires high efficiency, we use the base version DeBERTa$_{\text{B}}$ with 86M parameters. Overall, it achieves 88.9% / 85.3% / 85.7% Recall@50 on Test$_{\text{Cross-Task}}$, Test$_{\text{Cross-Website}}$ and Test$_{\text{Cross-Domain}}$, respectively. We use its top-50 ranking results as the candidate pool for all subsequent experiments.

**Action Prediction.** We mainly compare against two baselines in Table 2. The first directly uses the candidate generation model (DeBERTa) for element selection, which is similar to existing work [10, 31] that combines an encoder with classification heads. However, such a design cannot benefit from many recent LMs that use an encoder-decoder or decoder-only architecture. It cannot predict actions and the element selection performance is also not competitive, as shown in Table 2. We

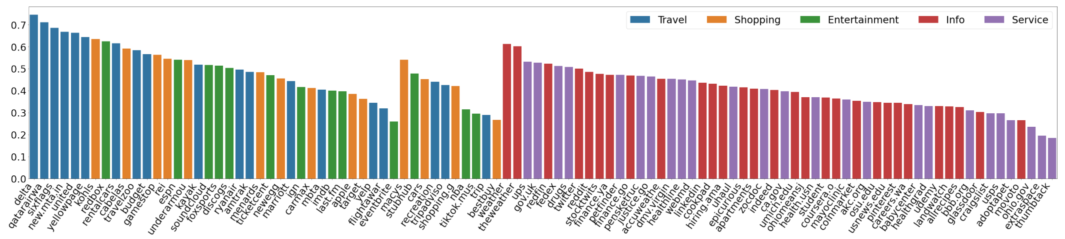


Figure 6: Step success rate per website grouped by the three splits: $\text{Test}_{\text{Cross-Task}}$, $\text{Test}_{\text{Cross-Website}}$ and $\text{Test}_{\text{Cross-Domain}}$ from left to right. Here we only show websites with more than three test tasks.

use Flan-T5 [6] as the backbone for the generation model. The autoregressive generation formulation (Figure 5 top) does not perform well, and even underperforms the classification baseline on element selection despite the larger model size (220M for Flan-$\text{T5}_{\text{B}}$). We observe a substantial gain with MINDACT using the multi-choice QA formulation. The best model achieves 52.0% step success rate under Cross-Task setting, and 38.9% / 39.6% when generalizing to unseen websites and domains. However, the overall task success rate remains low for all models, as the agent often commits at least one error step in most cases.

**Three Levels of Generalization.** All models perform best on the Cross-Task setting, with over 10% absolute gap (step SR) on average compared with Cross-Website and Cross-Domain settings, indicating that generalizing to unseen environments is still a major challenge. On the contrary, we note that the performance of Cross-Website and Cross-Domain settings are notably similar, which is also reinforced in Figure 6, where there is no clear distinction in performance across these settings. This suggests that the challenges primarily stem from the diversity in website designs and interaction logic rather than domain specifics. Tasks across domains tend to share common operations, and pretrained LMs may already have the capability to decompose complex tasks at a high level based on commonsense knowledge. Yet, grounding such knowledge into actionable steps in specific and varying environments remains a considerable challenge.

**In-context Learning with LLMs.** We also experiment with two popular LLMs, GPT-3.5-turbo and GPT-4 [21], through in-context learning. We use the same multiple-choice formulation as MINDACT, and include three demonstration examples for in-context learning. Note that this is not a fair comparison with the Flan-T5 models, which are fine-tuned on the full training data. We can see that both models are comparable to the two baselines with only three in-context examples. However, GPT-3.5 only has around 20% element selection accuracy, despite the superior performance people have observed on other datasets. Further analysis reveals that one possible problem is the model's propensity to select the None option, asserting that the task cannot be finished on the current webpage. This is somewhat accurate since tasks typically necessitate navigation through multiple webpages and performing a series of actions before reaching the final result. This aspect indeed represents the primary difficulty of our task. On the other hand, we observe highly promising outcomes with GPT-4. The performance is on par with the tuned Flan-T5 models under Cross-Website and Cross-Domain settings for element selection, indicating a great potential for developing generalist agents using LLMs. Nevertheless, GPT-4's high operational cost remains a concern. Developing smaller models specialized for the web is an interesting future avenue.

## 5 Related Work

**Autonomous Agents for Web and Mobile Applications.** Considerable initiatives have been invested in automating web navigation, driven by a vision of facilitating effortless human-web interaction. Yet, previous research has been limited by the types of tasks and websites it can handle, either confined to simplified simulation environments [18, 27, 36], or limited to a narrow set of domains and websites [35, 36]. Recent studies [3, 17, 31] have utilized similar techniques for mobile applications, however, these are often simpler and offer fewer functions compared with full-fledged websites. In contrast, MIND2WEB aims to adapt to a realistic web environment, characterized by its high diversity. Also related is the research on web automation systems [1, 15]. These technologies often demand programming skills, which can make them less accessible to general users. We aim to equip the web automation system with a natural language interface, thereby reducing the entry barrier significantly.

**Grounded Language Understanding.** Our work also aligns with the field of grounded language understanding, which aims to map natural language utterances onto executable plans in a target environment [9]. Many studies have centered around environments underpinned by a well-structured schema or ontology, including relational databases [32, 39] and knowledge bases [8, 38], which may not adequately reflect the more heterogeneous conditions in real-world situations. Our work instead grounds natural language in the noisy and schemaless web environment. Our setting is also connected to embodied AI, where an agent, guided by language instructions, carries out tasks in a physical environment [2, 28, 29]. Nonetheless, existing research primarily focuses on a specific setting (e.g., household environments), limiting their diversity. MIND2WEB provides a unique testbed for studying a broad range of grounding challenges in real-world environments.

**Tool Learning.** Recent developments have underscored LLMs' potential in using a myriad of tools (*i.e.*, taking actions) to augment their capacity [19, 23], including search engine, translator, calculator, etc. Example works include Toolformer [25], ReAct [37], and ToolkenGPT [11]. The creation of recent benchmarks on tool learning [16, 22] further highlights the growing interest in evaluating LLMs' proficiency in tool usage. However, existing research primarily concentrates on short-term tool invocation, neglecting long-term planning. MIND2WEB can bridge this lacuna by necessitating LLMs to take actions within realistic web-browsing environments that demand prolonged decision-making sequences. Furthermore, MIND2WEB may stimulate the development of more advanced tools based on LLMs that interface the web with natural language. These advanced tools could be subsequently employed by another LLM for more challenging problem-solving tasks [7, 26].

## 6 Conclusion

In this work, we introduced MIND2WEB, the first dataset for developing and evaluating generalist agents for the web. We also proposed MINDACT, an agent that leverages the power of (large) language models for effectively tackling this task. Our work opens up a wide range of promising future directions, including integrating multi-modal information, reinforcement learning with feedback from real websites, and specialized LMs for web understanding and action taking. We hope that MIND2WEB will serve as a valuable platform for the research community to advance towards generalist agents for the web.

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Table 3: Prompt for ChatGPT to generate seed tasks to inspire the annotators during task proposal.

| | |
|---|---|
| **Prompt** | We are testing the website<br><br>https://aa.com \| American Airlines - Airline tickets and low fares at aa.com<br>Book low fares to destinations around the world and find the latest deals on airline tickets, hotels, car rentals and vacations at aa.com. As an AAdantage member you earn miles on every trip and everyday spend.<br><br>We want to test practical daily tasks that a user would do on the website.<br>Come up with a list of 5 example tasks and try to cover different cases.<br>Requirements:<br><br>- Each example should be a single sentence and not just click one of the elements.<br>- Don't give step-by-step instructions or directly mention the element to interact.<br>- Describe the goal of the task and provide concrete information or constraints. Use mock-up information (identifier, number, personal information, name, date, attributes, constraints, etc.) to make the task more specific and realistic. |
| **Sample Responses** | Retrieve the confirmation number for a reservation made under the name jane smith departing from dallas (dfw) to miami (mia) on january 20th.<br><br>Find and book a round-trip flight from new york to london departing on december 15th and returning on december 22nd for under $800.<br><br>Find the lowest fare for a one-way flight from new york city (jfk) to los angeles (lax) leaving on august 15th and returning on august 20th, with no layovers exceeding 2 hours.<br><br>Rent a car in honolulu for one week starting on august 1st that can fit at least four passengers and has gps navigation included.<br><br>Cancel a car rental reservation for a compact car in orlando, florida that was scheduled to be picked up on may 25th at 5 pm without incurring any cancellation fees. |

## A Data Collection Details

### A.1 Crowd Sourcing Details

In this study, we employed annotators from the Amazon Mechanical Turk (mturk) platform. The annotators are required to have a minimum of 1,000 approved hits with an approval rate exceeding 98% on the platform. To prepare them for the task, we provided a comprehensive training document and a video tutorial, followed by a qualification assessment comprising a questionnaire and a series of test demonstrations using our tool. We designed the compensation to respect the minimum wage guidelines in Ohio, United States. Every worker passing our qualification received a bonus, and we paid $0.80 for each approved final task. It's noteworthy that the task was divided into two phases: task proposal and task demonstration. The proposal phase came with a nominal reward, with the majority of the compensation dispensed upon successful completion of the demonstration.

Quality and diversity were ensured through a two-stage review process. The first author reviewed all tasks after task proposal and manually select the tasks for demonstration. After task demonstration, a thorough final verification of all collected data was conducted by all authors to authenticate the tasks and recorded actions.

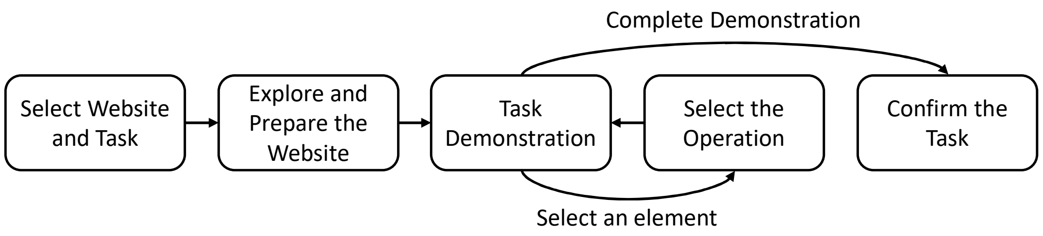
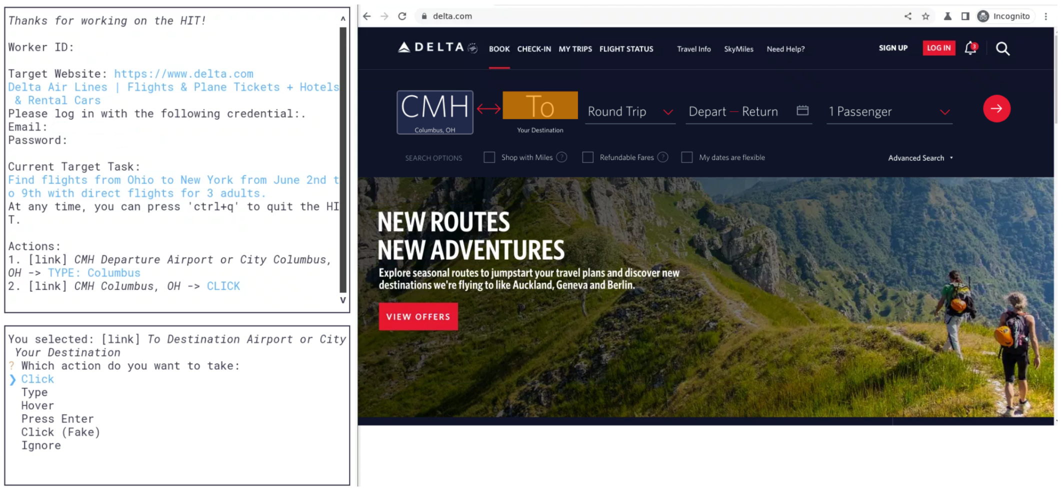


Figure 7: The overall procedure for task demonstration



```
Thanks for working on the HIT!

Worker ID:

Target Website: https://www.delta.com
Delta Air Lines | Flights & Plane Tickets + Hotels
 & Rental Cars
Please log in with the following credential:.
Email:
Password:

Current Target Task:
Find flights from Ohio to New York from June 2nd t
o 9th with direct flights for 3 adults.
At any time, you can press 'ctrl+q' to quit the HI
T.

Actions:
1. [link] CMH Departure Airport or City Columbus,
OH -> TYPE: Columbus
2. [link] CMH Columbus, OH -> CLICK
```

```
You selected: [link] To Destination Airport or City
 Your Destination
? Which action do you want to take:
❯ Click
  Type
  Hover
  Press Enter
  Click (Fake)
  Ignore
```

Figure 8: Illustration of our annotation tool composed of two windows. On the left we provide a dialogue window for the user to control the tool and select operations to take. On the right we provide the browser window for the user to interact with.

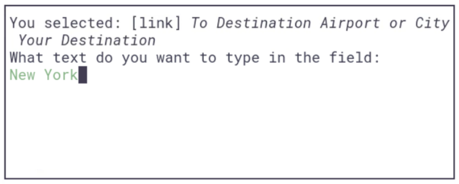
## A.2 Task Proposal

We use ChatGPT to generate sample tasks to provide inspiration to the annotators, the prompt used is shown in Table 3. For each HIT, we ask the annotator to select a website of their interest first. Following this, we present them with ten sample tasks produced by ChatGPT, and request them to propose a maximum of five additional tasks. The annotator is instructed not to directly copy the sample tasks. We manually evaluate all submitted tasks, rejecting those that demonstrate low quality or are too similar to previously accepted tasks. Once we have collected an approximate total of 20 tasks for a specific website, we desist from showing it to the user, aiming for a balanced distribution among websites and increased task diversity.

## A.3 Task Demonstration

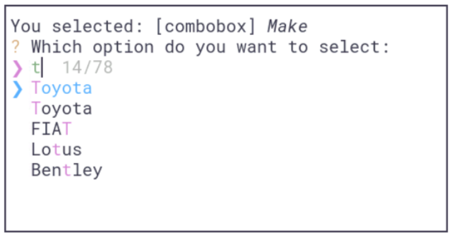
We develop a dedicated annotation tool for task demonstration using Playwright [3], which allows us to interact with the browser and record user actions. As shown in Figure 8. the tool is composed of two windows. The dialogue window on the left serves as the annotator's control panel for guiding the interaction flow and choosing operations. The browser window on the right is where the annotator navigate the website and selects elements for interaction. Figure 7 shows the overall procedure for task demonstration. The annotator starts by select the website and task to be demonstrated. Once selected, the tool will bring up the website in the browser. The annotator is then instructed to explore the website and practice the task. Along the way, they are also required to log in with the provided credentials, and close any pop-up windows. The exploration stage is not recorded and primarily serves to familiarize the annotator with the website and task, as well as to prepare the website to prevent future pop-ups, thereby ensuring a clean, streamlined set of final recorded actions. After exploration,

[3]https://playwright.dev/



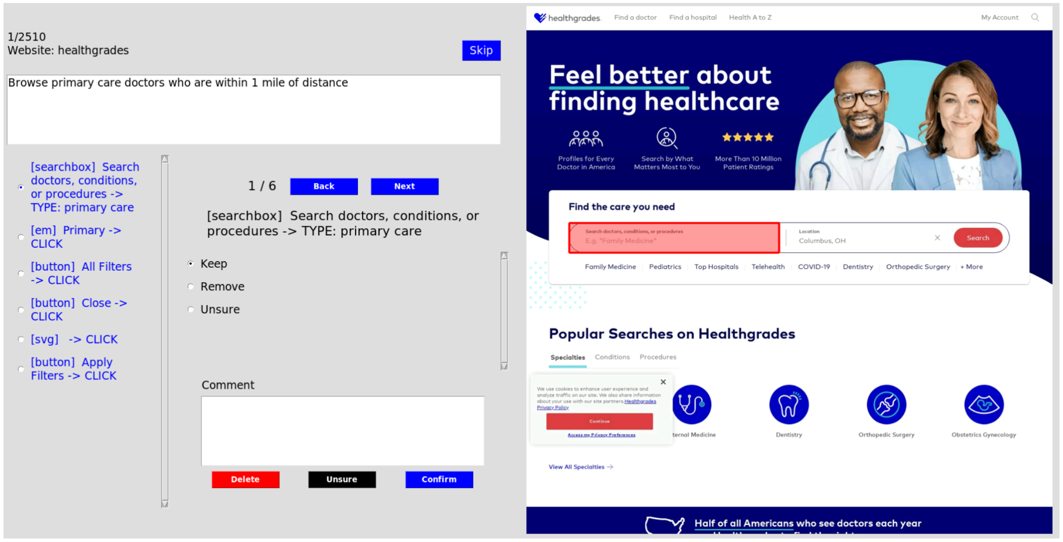
```
You selected: [link] To Destination Airport or City
 Your Destination
What text do you want to type in the field:
New York
```

Figure 9: Dialogue window for the Type operation.



```
You selected: [combobox] Make
? Which option do you want to select:
❯ t  14/78
❯ Toyota
  Toyota
  FIAT
  Lotus
  Bentley
```

Figure 10: Dialogue window for the Select Option operation.



1/2510
Website: healthgrades

Skip

Browse primary care doctors who are within 1 mile of distance

- [searchbox] Search doctors, conditions, or procedures -> TYPE: primary care
- [em] Primary -> CLICK
- [button] All Filters -> CLICK
- [button] Close -> CLICK
- [svg] -> CLICK
- [button] Apply Filters -> CLICK

1 / 6 Back Next

[searchbox] Search doctors, conditions, or procedures -> TYPE: primary care

[✓ Keep]
Remove
Unsure

Comment

Delete Unsure Confirm

Figure 11: Illustration of our verification tool.

the annotator is directed to return to the homepage and reset any altered values, allowing us to begin the demonstration in a fresh state. During the demonstration, the annotator will illustrate how to accomplish the task step-by-step using both the browser and the dialogue window. To ensure a clean set of annotated actions, annotators are restricted from directly engaging with the browser during the demonstration phase. Instead, we divide each action step into two stages: Element selection and operation selection. At each step, the annotator first selects the target element by clicking in the browser. We will highlight the selected element in the browser window but block the actual click event. The annotator is then prompted to select the operation to perform within the dialogue window, which the tool will then carry out in the browser. We provide 6 operations: `Click`, `Type`, `Hover`, `Press Enter`, `Click (Fake)` and `Ignore`. For the `Type` operation, the annotator is additionally required to supply the typing value as shown in Figure 9. If the chosen element is a `select` HTML element, and the annotator opts for `Click`, it translates to a `Select Option` operation and we will prompt the annotator to select one of the options as shown in Figure 10. To avoid ambiguity, the `Click`, `Hover` and `Press Enter` operations are all mapped to `Click` in the final dataset. `Click (Fake)` is a special operation. It will be recorded the same as a normal `Click` but not get executed in the browser. This is designed for cases that we don't want to execute the transaction, for example post a comment or schedule the appointment which might interfere with real users of the website. Finally, the annotator can also choose `Ignore` in case they select a wrong element. Once all actions have been annotated, the annotator can choose to complete the task. They will then be asked to confirm the task description again, and make any necessary modifications.

## A.4 Task Verification

All collected data undergoes an additional verification process conducted by the authors, as demonstrated in Figure 11. The verification interface is shown in Figure 11. This verification consists of

Table 4: Hyperparameters used in experiments.

| Experiment | Model | Hyperparamerters |
|---|---|---|
| Candidate Generation | `deberta-v3-base` | `batch_size:`32, `epoch:`5, `learning_rate:`3e−5 |
| Action Prediction Generation | `flan-t5-base` | `batch_size:`32, `epoch:`5, `learning_rate:`5e−5 |
| MINDACT | `flan-t5-base`, `flan-t5-large`, `flan-t5-xl` | `batch_size:`32, `epoch:`5, `learning_rate:`5e−5 |
|  | `gpt-3.5-turbo`, `gpt-4` | `temperature:`0, `# demonstrations:`3 |

three tasks. Firstly, we evaluate whether a task should be discarded due to its low quality. Secondly, we examine each step to determine if any action should be discarded, such as redundant actions. This includes a review of the initial and final actions of the task, and the exclusion of any additional actions, like logging into the account, that aren't outlined in the task description to ensure consistency across task annotations. Finally, we verify the task description to confirm that all actions are accurately represented and make modifications if necessary. If there is uncertainty regarding any action, the verifier can opt for the 'unsure' option, prompting a re-evaluation by the first author.

## B Experiment Details

### B.1 Evaluation

One complication that arises during evaluation on real-world websites is that multiple elements on a webpage may induce the same effect. For instance, a button might house a text span within it, both of which, when clicked, yield identical results. To enhance the robustness of our evaluation, we employ heuristics to detect elements equivalent to the ground truth. We first examine the ancestors of the labeled element to identify potential higher-level elements acceptable for the current action. We employ a straightforward heuristic that locates the nearest clickable element to the ground truth, including itself. After identifying the top-level acceptable element, we include all its visible descendants that are located within its post-rendering bounding box as acceptable as well. Manual checking on 100 instances where the heuristic identified a top-level element other than the ground truth confirmed its validity. For both training and evaluation stages, all acceptable elements are considered positive.

### B.2 Model Implementation Details

**Candidate Generation.** We use the Cross-Encoder implementation from Sentence-Transformers[4] and use DeBERTa as the backbone model. More specifically, we use `DeBERTa-v3-base` [5] for our experiments.

**Action Prediction.** We use the Seq2Seq model implementation from Transformers [34]. We experiment with the `base` [6], `large` [7] and `xl` [8] versions of Flan-T5 [6]

**LLM In-context Learning.** We use the OpenAI API for in-context learning with LLMs. We experiment with two versions of ChatGPT models: `gpt-3.5-turbo` and `gpt-4`. We include three demonstration examples for in-context learning. The complete prompt is shown in Table 5.

[4]`https://www.sbert.net/examples/applications/cross-encoder/README.html`

[5]`https://huggingface.co/microsoft/deberta-v3-base`

[6]`https://huggingface.co/google/flan-t5-base`

[7]`https://huggingface.co/google/flan-t5-large`

[8]`https://huggingface.co/google/flan-t5-xl`

**Training Details.** All experiments are run on servers with A6000 or A100 GPU cards. Please see Table 4 for all hyperparameters used in our experiments.

Table 5: Prompt for action prediction in MINDACT with ChatGPT models.
Only part of the HTML snippet is shown here to save space.

| Role | Content |
|---|---|
| system | You are a helpful assistant that is great at website design, navigation, and executing tasks for the user |
| user | ’’’<br><html> <div> <div> <a tock home page /> <button id=0 book a reservation. toggle open> <span> Book a reservation </span> </button> <button book a reservation. toggle open> </button> </div> <div> <select id=1 type> <option reservations true> Dine in </option> ... </html><br>’’’<br>Based on the HTML webpage above, try to complete the following task:<br>Task: Check for pickup restaurant available in Boston, NY on March 18, 5pm with just one guest<br>Previous actions:<br>None<br>What should be the next action? Please select from the following choices (If the correct action is not in the page above, please select A. ’None of the above’):<br><br>A. None of the above<br>B. <button id=0 book a reservation. toggle open> <span> Book a<br>C. <select id=1 type> <option reservations true> Dine in </option> <option<br>D. <div id=2> <p> Celebrating and supporting leading women shaking up |
| assistant | Answer: C.<br>Action: SELECT<br>Value: Pickup |
| user | ’’’<br><html> <div> <main main> <section tabpanel> <div> <ul tablist> <li tab heading level 3 search and> </li> <li id=0 tab heading level 3 search and> <span> Hotel </span> </li> <li tab heading level 3 search and> </li> <li tab heading level 3 search and> </li> </ul> <div tabpanel> <div id=1> <div> <span> Dates* </span> <button button clear dates /> </div> ... </html><br>’’’<br>Based on the HTML webpage above, try to complete the following task:<br>Task: Compare the fare types to book a 1-adult ticket from Springfiels, IL to Austin, TX for April 29th 2023<br>Previous actions:<br>[combobox] Enter your departing city, airport name, or airpor... -> TYPE: SPRINGFIELD<br>[button] Springfield, IL, US (SPI) -> CLICK<br>[combobox] Enter your destination city, airport name, or airp... -> TYPE: AUSTIN<br>[button] Austin, TX, US (AUS) -> CLICK<br>What should be the next action? Please select from the following choices (If the correct action is not in the page above, please select A. ’None of the above’):<br><br>A. None of the above<br>B. <li id=0 tab heading level 3 search and> <span> Hotel<br>C. <div id=1> <div> <span> Dates* </span> <button button clear dates<br>D. <ul id=2> <a mobile tools> </a> <a open united’s tiktok |
| assistant | Answer: A. |

Continued on next page

**Table 5 – continued from previous page**

| Role | Content |
|---|---|
| user | ’’’<br><html> <div> <nav main menu> <ul> <li> <div button> Car Sales </div> <div id=0> <div> <div> <div> Buy A Car </div> <div> Plan Your Purchase </div> </div> <div> <h4> Its Tax Refund Time. Treat Yourself to an Upgrade. </h4> <p> With a variety of options, invest your refund in what you really want - a quality, used vehicle from Enterprise. </p> ... </html><br>’’’<br><br>Based on the HTML webpage above, try to complete the following task:<br>Task: Find a mini van at Brooklyn City from April 5th to April 8th for a 22 year old renter.<br>Previous actions:<br>[searchbox] Pick-up & Return Location (ZIP, City or Airport) (... -> TYPE: Brooklyn<br>[option] Brooklyn, NY, US Select -> CLICK<br>What should be the next action? Please select from the following choices (If the correct action is not in the page above, please select A. ’None of the above’):<br><br>A. None of the above<br>B. <div id=0> <div> <div> <div> Buy A Car </div> <div><br>C. <div id=1> Enterprise Fleet Management </div><br>D. <button id=2 selected pick-up date 03/19/2023> <span> <span> 19 </span> |
| assistant | Answer: D.<br>Action: CLICK |