WebVoyager: Building an End-to-End Web Agent with Large Multimodal Models

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Abstract

The advancement of large language models (LLMs) leads to a new era marked by the development of autonomous applications in the real world, which drives innovation in the creation of advanced web-based agents. Existing web agents typically only handle one input modality and are evaluated only in simplified web simulators or static web snapshots, greatly limiting their applicability in real-world scenarios. To bridge this gap, we introduce WebVoyager, an innovative Large Multimodal Model (LMM) powered web agent that can complete user instructions end-to-end by interacting with real-world websites. Moreover, we propose a new evaluation protocol for web agents to address the challenges of automatic evaluation of open-ended web agent tasks, leveraging the robust multimodal comprehension capabilities of GPT-4V. We create a new benchmark by gathering real-world tasks from 15 widely used websites to evaluate our agents. We show that WebVoyager achieves a 55.7% task success rate, significantly surpassing the performance of both GPT-4 (All Tools) and the WebVoyager (text-only) setups, underscoring the exceptional capability of WebVoyager in practical applications. We found that our proposed automatic evaluation achieves 85.3% agreement with human judgment, paving the way for further development of web agents in a real-world setting.[1]

1 Introduction

The recent advancement of large language models (LLMs), such as ChatGPT and GPT-4 (OpenAI, 2023), have sparked significant interest in developing LLM-based autonomous agents (AutoGPT, 2022) for complex task execution (Qin et al., 2023; Schick et al., 2023). Recent studies have explored the construction of text-based web browsing environments and how to instruct large language model agents to perform web navigation (Nakano et al., 2021; Gur et al., 2023; Zhou et al., 2023; Lu et al., 2023). The primary challenge in these works lies in managing complex and verbose HTML texts, and solutions include simplifying and structuring HTML (Nakano et al., 2021; Zhou et al., 2023; Gur et al., 2023; Deng et al., 2023).

However, existing approaches overlook a critical functionality of browsing: rendering HTML into visual webpages. Particularly, vision capability is crucial for utilizing tools like web browsers, as rendered web pages are inherently designed with user experience (UX), emphasizing intuitive information and structured presentation. This design principle of rendering makes visual analysis more effective than mere HTML representation. At present, large multimodal models (LMMs), particularly GPT-4V(ision) (OpenAI, 2023) and Gemini (Team et al., 2023), demonstrate a remarkable ability to integrate intricate visual cues with textual information. Existing studies such as Pix2Struct (Lee et al., 2023) and WebArena (Zhou et al., 2023), have initiated explorations into using screenshots as inputs for decision-making in web navigation, yet these are preliminary and do not represent a deep exploration. Therefore, building multimodal web agents to leverage the environment rendered by browsers through screenshots, thus mimicking human web browsing behavior, is now a viable approach to enhance web navigation efficiency.

We introduce WebVoyager, a multimodal web agent designed to handle web tasks online in an end-to-end manner, which denotes managing the process from start to finish autonomously without intermediate human intervention. We construct an online environment using Selenium for WebVoyager, feeding it with screenshots and textual content in interactive web elements. Inspired by Set-of-Mark Prompting (Yang et al., 2023a), we mark interactive web elements on screenshots (see Figure 2) to facilitate decision-making for Web-

*Work done during the internship at Tencent AI Lab.
[1]Our code and data will be released at https://github.com/MinorJerry/WebVoyager

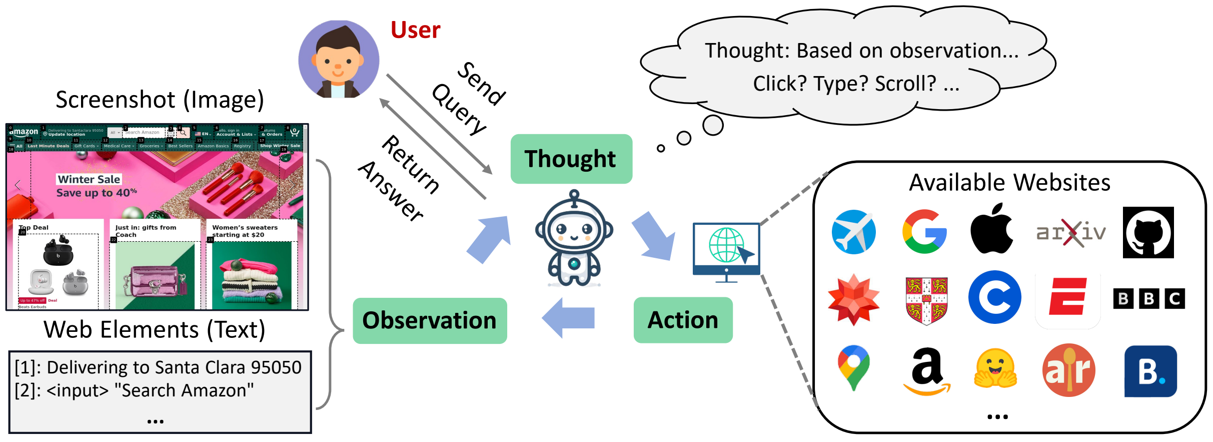

Figure 1: The overall workflow of WebVoyager. Humans assign web tasks to WebVoyager, which automatically browses the web online. At each step, WebVoyager selects actions based on screenshots and text (the 'type' of the web element and its contents). Once the task is completed, the answers will be returned to the user. For example, a user queries: "Find the cost of a 2-year protection for PS4 on Amazon." Agent interacts with Amazon online, locates the PS4, identifies the 2-year protection price, and returns "$30.99" to the user.

Voyager. As a pioneer in combining vision and text information during web navigation, we advocate that autonomous end-to-end task completion, multimodal capabilities and online navigation constitute the essential trajectory toward the genuine intelligence of web agents.

Another challenge arises when it comes to evaluating an end-to-end web agent with online navigation. Existing benchmarks, such as Mind2Web (Deng et al., 2023), primarily focus on stepwise and offline evaluation, where agents follow predefined "golden" trajectory for action selection. This approach, however, may not fully account for the variety of viable strategies to accomplish a task, as it only reflects one possible plan. This limitation could lead to a biased evaluation and difficulties in fairly comparing different methods. To more accurately gauge the capabilities of web agents in end-to-end task completion, we save screenshots throughout the online navigation process, and then use GPT-4V to evaluate these trajectories and the final results automatically. Human evaluations are also conducted to verify the results and confirm the reliability of GPT-4V as the evaluator.

We conduct evaluations on a collected dataset, which is semi-automatically generated using a self-instruct (Wang et al., 2022) method, comprising 300 web tasks from 15 commonly accessed websites. Additionally, we extract 90 web-related tasks of level 1 and level 2 from the GAIA (Mialon et al., 2023) to enrich our evaluation. We compare our WebVoyager with 1) GPT-4 (All Tools)[2], and 2) WebVoyager in a text-only setting, employing the accessibility tree proposed in WebArena (Zhou et al., 2023) to describe web pages. The results show that WebVoyager achieves a Task Success Rate of 55.7%, significantly outperforming GPT-4 (All Tools) with a rate of 32.7% and the text-only setting with a rate of 39.0%, demonstrating the effectiveness of our method. Furthermore, we report the consistency between human-human and human-GPT4V to ensure credibility. Our main contributions are as follows:

- We employ a multimodal web agent that integrates textual and visual information to address web tasks end-to-end and introduce a generalist planning approach for navigation.
- We build an online web browsing environment, offering a variety of tasks centered on widely used websites and introducing a method for expanding these tasks.
- We conduct manual evaluations of navigation trajectories and propose an automated evaluation protocol using GPT-4V. We present a comprehensive analysis of the evaluation results and show that GPT-4V can serve as a reliable evaluator for online agents.

2 Related Work

2.1 Web Agents

Autonomous web navigation (Shi et al., 2017; Yang et al., 2023b) requires an agent to follow instruc-

[2]GPT-4 (All Tools) is an integrated tool-based agent released by OpenAI in Oct. 2023. See https://chat.openai.com/

tions, construct plans, comprehend complex web structures, and decompose tasks into step-by-step decisions (Weng, 2023). To study web agents in a controlled environment, previous works constructed web simulators that contain simplified websites (Shi et al., 2017; Yao et al., 2022a). More recently, there has been a surge of interest in building more challenging and realistic benchmarks such as Mind2Web (Deng et al., 2023) and WebArena (Zhou et al., 2023).

Along with these new benchmarks, numerous efforts have been made to build autonomous web agents. WebGPT (Nakano et al., 2021) constructs a text-based web browsing environment and fine-tunes GPT-3 as a web agent. WebAgent (Gur et al., 2023) pretrains a T5 model to extract HTML snippets and leverages Flan-U-PaLM (Chowdhery et al., 2023) to generate Python code to interact with the environment. Besides fine-tuning, another line of work tries to build web agents by prompting LLMs (Yao et al., 2022b; Shinn et al., 2023; Ma et al., 2023). Multimodal web agents that integrate visual signals have also been explored, WebGUM (Furuta et al., 2023) combines T5 (Raffel et al., 2020) with a Vision Transformer (ViT) to navigate using both screenshots and HTML text. PIX2ACT (Shaw et al., 2023) instead solely relies on web screenshots as inputs to predict agent actions. Different from previous works that only consider a single modality or simplified web environments, in this work, we build a multimodal agent that can complete tasks on real-world websites. Concurrently with our work, SeeAct (Zheng et al., 2024) also leverages Large Multimodal Models (LMMs) for integrated visual understanding and actions on websites. This further highlights the significance of developing comprehensive end-to-end web agents and underscores the promising prospects in this field.

2.2 Large Multimodal Models

In recent years, significant strides have been made in unifying image and text representations within a single multimodal model through joint training with image and text (Li et al., 2019; Dosovitskiy et al., 2020; Wang et al., 2021; Dai et al., 2022; Aghajanyan et al., 2022). Large Multimodal Models (LMMs), following in the footsteps of Large Language Models (Brown et al., 2020; Chen et al., 2021; Chowdhery et al., 2023), attain the capability of instruction following (Ouyang et al., 2022) and exhibit robust multimodal comprehension. Represented by GPT-4V (OpenAI, 2023) and Gemini (Team et al., 2023), LMMs have demonstrated impressive performance on benchmarks (Goyal et al., 2017; Lu et al., 2022; Zellers et al., 2019; Hessel et al., 2022), establishing a foundation for the construction of multimodal agents in subsequent research.

3 WebVoyager

We aim to build an agent that can browse the open web autonomously without any human intervention to complete user instructions. Given an instruction, our WebVoyager first instantiates a web browser as the interface to the open web. Similar to humans, WebVoyager takes the visual signals from the web (e.g. screenshots) as the primary source of input at every step, and it considers text extracted from key HTML elements in addition. The agent produces an action based on the inputs at every step, which is then executed in the browser environment. The process continues until the agent decides to stop. Next, we describe the details of WebVoyager, including environment, interaction cycle, observation space, and action space.

3.1 Browsing Environment

We develop an automated web-browsing environment using Selenium, a powerful tool capable of emulating user browsing behaviors. Our environment provides the same level of website accessibility to the agent as a human user, i.e. a browser window, similar to WebArena (Zhou et al., 2023). Unlike WebArena, we do not host any websites locally and allow the agent to explore the open web instead. Unlike locally hosted websites, open web poses unique challenges, e.g. floating ads, pop-up windows, constant updates, etc.[3] Still, we opt for online interaction with real websites for our agent as we believe this setting truly reflects the real-world use cases (e.g. the agent needs access to real-time information from the web) and we hope to build the agent that can robustly adapt to these challenges and consistently solve the problem.

[3]Regarding CAPTCHAs (Completely Automated Public Turing test to tell Computers and Humans Apart) challenges, we believe it is important to respect the rules of these websites and prompt the agent to retrieve information from alternative sources.

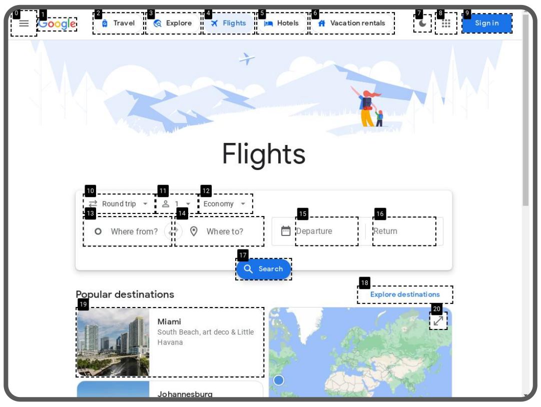

Figure 2: Examples of webpage screenshots provided to the agent. We add borders to most of the interactive elements on the web pages and label them with numerical tags in the top left corner.

3.2 Interaction Formulation

Formally, we denote the Environment as $\mathcal{E}$, the large Multimodal Model as $\mathcal{M}$, the Observation Space as $\mathcal{O}$, and the Action Space as $\mathcal{A}$. At time step t, the model receives the context c_t as inputs, which consists of historical actions a_t and observations o_t, defined as: $c_t = (o_1, a_1, ..., o_{t-1}, a_{t-1}, o_t, I)$ The the model produces the action a_t at time t, $a_t = \mathcal{M}(c_t)$, which is then executed in the environment. After execution, the environment sends back the observation at time $t+1$, $o_{t+1} = \mathcal{E}(o_t, a_t)$. Then the context will be updated and this interaction process continues until the model generates a terminating action or the maximum step is reached.

Inspired by the paradigm of ReAct Prompting (Yao et al., 2022b), we also prompt our agent to generate a thought process first before generating the action code. Hence (s_t, a_t) can be further composed into $\hat{a}_t$ where s_t and a_t represent the natural language thought and action code respectively. Figure 7 in Appendix A presents the System Prompt we designed for the action prediction step. Also, it's worth noting that excessive screenshots of web pages from longer episodes may confuse the agent. Therefore, we perform context clipping to remove outdated web page information and only keep the most recent 3 screenshots in the inputs and we keep the entire history of thoughts and actions to better guide the agent.

3.3 Observation Space

Similar to how humans browse the web, our agent also takes the visual information from the web (screenshots) as the primary source of input. Using screenshots allows us avoid the burden of processing HTML DOM tree or accessibility tree to portray the overall structure of webpages, which can lead to overly verbose texts and impact the decision-making process of the agent. Inspired by Set-of-Mark Prompting (Yang et al., 2023a), we overlay bounding boxes of the interactive elements on the websites to better guide the agent's action prediction. Unlike Yang et al. (2023a), we do not need any object detection module (Zou et al., 2023). Instead, we utilize GPT-4-ACT[4], a Javascript tool to extracts the interactive elements based on web element types and then overlays bounding boxes with numerical labels on the respective regions of the elements. As illustrated in Figure 2, the nature of webpages allows us to precisely locate and outline each interactive element using this tool. The numerical labels assigned to each element are also essential for the model to identify the elements requiring interaction, thereby facilitating accurate action determination. We empirically choose black as the color for the borders and the background of the labels to enhance clarity. We observe that using a single black color yields higher success rates in planning compared to using multiple colors. Additionally, we also provide the agent some auxiliary text as inputs, including the textual content embedded within the interactive element, the type of the element, and possibly some comment text in the aria-label attribute. To simplify the observation, we have disabled multiple tabs, i.e. all interactions occur within the current tab instead of opening new ones.

At every step, the agent receives current screenshot and auxiliary text along with history as inputs, as discussed in (§3.2). In case the agent's action raised an exception during execution, we additionally incorporated the error messages in the prompt and ask the model to regenerate the response. Note that each of the error correction attempts also consume one step from the total exploration budget.

3.4 Action Space

We define the action space of our agent similar to how human browse the web. To this end, we implement the most commonly used mouse and keyboard actions, sufficient for the agent to browse various web pages and locate the content required for the task. With the help of numerical labels in

[4]https://github.com/ddupont808/GPT-4V-Act

screenshots, we enable the agent to respond with a concise Action Format. This approach precisely locates the elements requiring interaction and executes the corresponding actions. The usage and format of actions are presented as follows:

- Click. This action involves clicking on an element within a webpage, typically a link or a button. If clicking a link results in the download of a PDF file, we automatically parse its content using the OpenAI Assistant API[5] and incorporate it into the Observation. Action Format: `Click [Numerical_Label]`.
- Input. This is a composite action that involves selecting a text box, deleting any existing content within it, and then inputting new content. To minimize interaction frequency, an automatic ENTER key press follows the input completion. Action Format: `Type [Numerical_Label]; [Content]`.
- Scroll. Scrolling is a common operation for browsing webpages, usually involving the vertical movement of the entire page. However, there are instances where only a specific section within the webpage is scrollable. In such cases, we expect the Agent to select an element within the scrollable area and navigate to that particular region for scrolling. Action Format: `Scroll [Numerical_Label or WINDOW]; [up or down]`.
- Wait. Action execution requires time, and this action is often used to wait for web pages to load. Action Format: `Wait`.
- Back. This action is used to return to the previous page. We consider the forward action unnecessary because it can be achieved by repeating previous actions. Action Format: `GoBack`.
- Jump to Search Engine. There are often situations where agents get stuck at a certain website, without finding an answer. This action enables the agent to jump to a search engine and start anew. In this work, we just adopt Google Search. Action Format: `Google`.
- Answer. Once all questions in the task are resolved, this action concludes the iteration and provides an answer in line with the task requirements. Action Format: `ANSWER; [Content]`.

[5] https://platform.openai.com/docs/assistants/overview

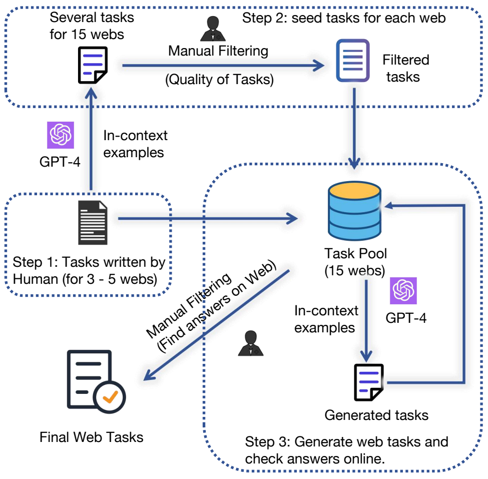
Several tasks for 15 webs
Step 2: seed tasks for each web
Manual Filtering
(Quality of Tasks)
Filtered tasks
GPT-4
In-context examples
Step 1: Tasks written by Human (for 3 - 5 webs)
Task Pool (15 webs)
Manual Filtering (Find answers on Web)
In-context examples
GPT-4
Generated tasks
Final Web Tasks
Step 3: Generate web tasks and check answers online.

Figure 3: Data creation process using self-instruct.

4 Benchmark for WebVoyager

4.1 Website Selection

In this paper, we select 15 popular and representative websites that cover different aspects in our daily life to ensure diversity in our evaluation, including Allrecipes, Amazon, Apple, ArXiv, BBC News, Booking, Cambridge Dictionary, Coursera, ESPN, GitHub, Google Flights, Google Map, Google Search, Huggingface and Wolfram Alpha. Due to technical limitations, we regretfully omit websites that necessitate login or CAPTCHA for accessing their content, but this does not impact the evaluation of effectiveness. Additionally, Google Search is a universal website that can serve as a starting point for any website, making our framework applicable to a wide array of scenarios.

4.2 Data Construction

We employ a combination of self-instruct (Wang et al., 2022) and human verification to construct our evaluation set. Figure 3 illustrates our data creation process. Initially, we draw inspiration from the web agent tasks in Mind2Web (Yin et al., 2023; Deng et al., 2023), and manually sample and rewrite some tasks for Google Flights, Google Map, Google Search, Booking, and Wolfram Alpha. We prioritize the diversify of tasks such that they can test various functionalities of these websites. This process yields initial seed tasks in the Task Pool for subsequent generation.

In step two, we sample tasks from Task Pool as in-context examples (Dong et al., 2022) and prompt

GPT-4 Turbo to generate approximately 100 new tasks (20 iterations). Then we manually verify each generated task and rewrite them if necessary to ensure its high quality and the answers can be found on the corresponding website, then we add them to the Task Pool as additional seed tasks. This step allows us to create human-validated seed tasks for each website.

Finally, the process of step three is very similar to step two, except that we sample more diverse in-context examples in Task Pool and directly add the generated tasks to Task Pool in each iteration. We manually verify that the generated tasks have low repetition and the answers to the generated tasks can be found on the websites. In total, we collected 20 tasks per website, resulting in a total of 300 tasks.

4.3 Annotation Process

After collecting the full task pool, we annotate answers for each task. Since some questions are open-ended and the web information may change, these questions may not have a fixed golden response. Thus we label each data entry with an answer, categorized as either 'Possible' or 'Golden'. For answers labeled as 'Golden', we provide a comprehensive listing of possible responses and consider them to be stable in a short term. The 'Possible' category covers the following scenarios: 1) Answers for open-ended tasks where it's hard to find a exact match answer, such as summarization. 2) There are multiple answers that satisfy the task, making it impractical to list all of them. Therefore, we provide a partial listing. 3) Tasks related to real-time information, where the answer may change frequently, e.g. flight ticket prices. Hence that the 'Possible' answers are also correct at the time of our experiments. In total, only 22.3% of questions in our benchmark are annotated with golden responses and the rest only has possible answers.

5 Experiment

5.1 Experimental Setup

Dataset and Metrics We evaluated our agent on the new benchmark introduced in Section 4. Additionally, we extract 90 web browsing tasks (Level 1 and Level 2) from the GAIA dataset (Mialon et al., 2023), which also come with golden responses. The tasks in GAIA are not annotated with specific websites, we instruct the agent to search for answers starting from Google Search. Following WebArena (Zhou et al., 2023), the primary evaluation metric we adopt is the **Task Success Rate**, measuring the successful completion of tasks, without considering whether the step-by-step execution is optimal. We set the maximum number of interactions for each task to be 15.

Experimental Details We employ GPT-4 Turbo with vision (gpt-4-vision-preview) as the backbone model of our agent, which showcases strong semantic and visual understanding capabilities equivalent to GPT-4V (OpenAI, 2023). For baselines, we include the GPT-4 (All Tools), which integrates vision, web browsing, code analysis, and various plugins in one model. Additionally, we consider an text-only baseline where the agent only receives the websites' accessibility tree as input to prediction actions. For our environment, we used a fixed browser window size of 1024 * 768 pixels, thereby ensuring a consistent size for the screenshots in our observations. We set the temperature to 1 during generation and allows the agent to explore at most 15 steps.

5.2 Evaluation Methods

We adopt human evaluation as our main evaluation metric since most of the questions in our benchmark have open-ended answers. In particular, we provide the human evaluators the complete trajectories of the agent's interaction with the web (all screenshots and all actions), and ask them to provide a binary judgement of whether the agent successfully completed the task. For each task, we ask three expert annotators to provide judgements. The final Task Success Rate reported is the consensus result after discussion, referred to as human labels. We observe that for most tasks, evaluators can determine the correctness of the task based on the final screenshot. For the remaining tasks, the evaluator may require the second-to-last, third-to-last, or even the entire trajectory to make an accurate judgment. On average, it takes an expert about 1 minute to evaluate one task.

Since it's very expensive to conduct human evaluation for the web agent tasks, we are interseted to see if it's feasible to leverage an LMM for automatic evalutaion. To this end, we propose to use GPT-4V as an auto evaluator that emulates the behavior of human evaluators to evaluate the navigation trajectories of WebVoyager. In particular, we provide the task, the responses from WebVoyager, and the last k screenshots to the evaluator and ask

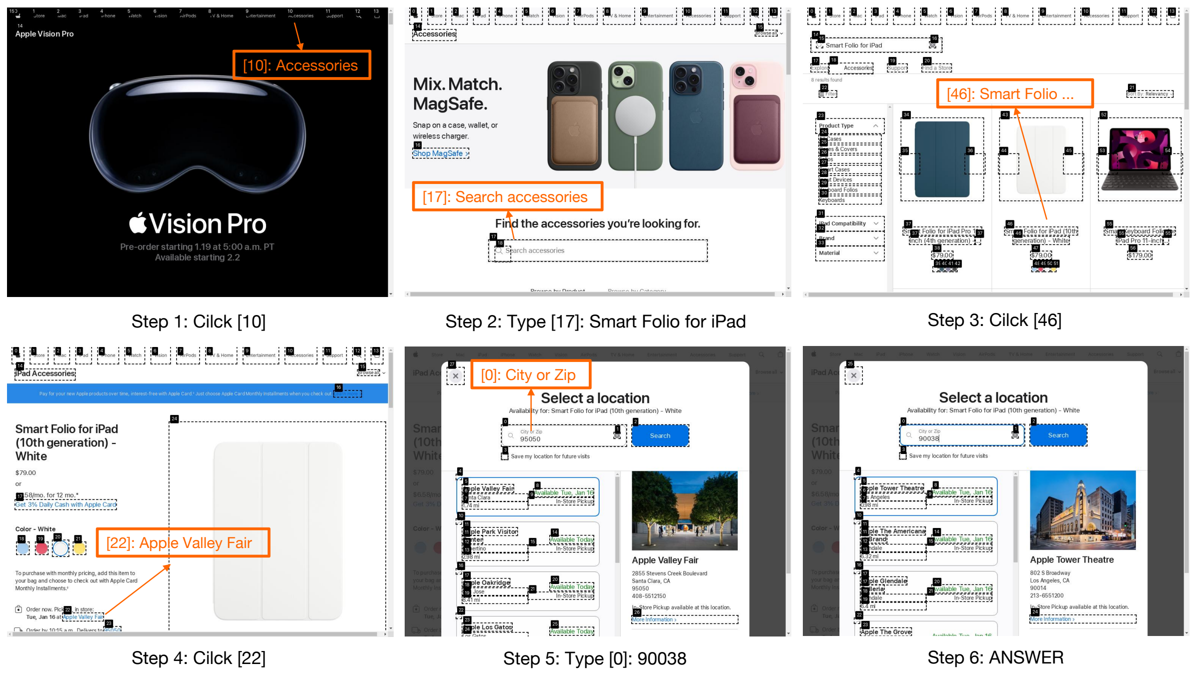

Figure 4: Screenshots of a complete trajectory of online web browsing. Given the task: ‘Search Apple for the accessory Smart Folio for iPad and check the closest pickup availability next to zip code 90038.’ The agent interacts with the Apple website and obtains the answer: ‘Apple Tower Theatre.’

it to judge whether the agent has successfully completed the task, where k is a hyper-parameter. The prompt of GPT-4V evaluator is shown in Appendix B. We hypothsize that the strong multimodal reasoning ability of GPT-4V allows it to act as a reliable evaluator, which could reduce the burden of human evaluators and significantly lower the cost of future experiments.

5.3 Result

In Figure 4, we present an example to demonstrate how the agent interacts with the Apple website step by step in an online fashion to complete a task. In the final screenshot, the Agent acquires the desired information, then selects the ‘ANSWER’ action to respond and conclude the navigation. This trajectory represents an optimal path without any redundant actions. However, in many cases, there may be some redundant actions in between. Additional examples are provided in the Appendix C to further demonstrate this.

We present the results for our dataset and the extracted GAIA web tasks in Table 1 and Figure 5. We see that WebVoyager outperforms text-only and GPT-4 (All Tools) baselines in the majority of website tasks, while it is slightly lower than Text-only on Cambridge Dictionary and Wolfram Alpha. This is primarily due to the fact that these two websites are more text-heavy than other websites. Since WebVoyager mostly relies on web screenshots for decision making, dense text might not be easy to fully recognize from the image. We think that extracting such text from the HTML to augment the input could be a potential solution to this problem, suggesting a potential direction for future work. In Figure 5, WebVoyager also achieves much stronger performance than both baselines, showing the efficacy of our proposed agent.

Next we delve into the consistency of our evaluations. First we compute the agreement score among our three human annotators before final discussion, we found the Fleiss’s Kappa (Fleiss, 1971) of human annotators to be 0.7, which is substantial agreement. We then report the Agreement (the ratio of overlap) and Kappa (κ; Cohen 1960) between consolidated human labels and GPT-4V’s judgements in Table 2. Here, k denotes the number of screenshots provided to GPT-4V, with ‘full’ implying the full trajectory. We see that GPT-4V’s agreement with human annotators gradually improves as it receives more information and its final Kappa score also reaches 0.7, which is on par with the agreement among human annotators. The annotation consistency between GPT-4V and humans suggests that using GPT-4V to automatically evaluate multi-modal web agent’s performance is

	Allrecipes	Amazon	Apple	ArXiv	GitHub	Booking	ESPN	Coursera
GPT-4 (All Tools)	5 (25%)	3 (15%)	8 (40%)	3 (15%)	9 (45%)	5 (25%)	8 (40%)	8 (40%)
WebVoyager$_{\text{Text-only}}$	10 (50%)	8 (40%)	7 (35%)	6 (30%)	11 (55%)	0 (0%)	7 (35%)	7 (35%)
WebVoyager	12 (60%)	9 (45%)	12 (60%)	9 (45%)	12 (60%)	8 (40%)	9 (45%)	15 (75%)
*WebVoyager**	11 (55%)	10 (50%)	12 (60%)	9 (45%)	12 (60%)	7 (35%)	11 (55%)	13 (65%)

	Cambridge Dictionary	BBC News	Google Flights	Google Map	Google Search	Huggingface	Wolfram Alpha	Overall
GPT-4 (All Tools)	6 (30%)	2 (10%)	2 (10%)	13 (65%)	11 (55%)	7 (35%)	8 (40%)	32.7%
WebVoyager$_{\text{Text-only}}$	13 (65%)	7 (35%)	1 (5%)	11 (55%)	14 (70%)	5 (25%)	10 (50%)	39.0%
WebVoyager	12 (60%)	12 (60%)	10 (50%)	13 (65%)	16 (80%)	9 (45%)	9 (45%)	55.7%
*WebVoyager**	16 (80%)	12 (60%)	11 (55%)	12 (60%)	17 (85%)	13 (65%)	9 (45%)	58.3%

Table 1: The main result for WebVoyager. Each website contains 20 tasks, and we report the Task Success Number (Task Success Rate) in the table. We provide the results for GPT-4 (All Tools), WebVoyager$_{\text{Text-only}}$ using the accessibility tree, and WebVoyager. Notice: the results of *WebVoyager** is given by GPT-4V based evaluator (full trajectory, kappa is equal to 0.70).

	Success Rate	Consistency	
		Agreement	κ
k=1	47.7%	75.3%	0.51
k=2	55.3%	79.7%	0.59
k=3	54.3%	81.3%	0.62
Full	58.3%	85.3%	0.70

Table 2: Consistency between GPT-4V and Human. Success Rate is the overall success rate of all tasks given by GPT-4V. Based on the annotations given by GPT-4V and Human (after alignment), we compute Agreement, i.e., the label overlap, and the Kappa values.

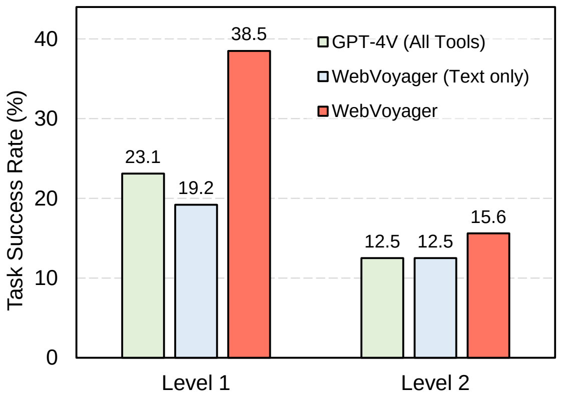

Figure 5: Task Success Rate for GAIA Level 1 and Level 2.

a promising approach and it has great potential for efficient and large-scale applications.

5.4 Discussions

Direct interaction with the websites is necessary From our experience of using GPT-4 (All Tools), the primary limitation of GPT-4 (All Tools)'s performance is rooted in its reliance on Bing search for web browsing, predominantly depending on web pages fetched by Bing. It lacks the capability to directly access certain websites (such as Apple, Amazon, BBC News, etc.) for searching, clicking, or utilizing their sorting functions. This greatly limits the agent's ability to complete certain types of tasks.

Both text and vision are necessary for generalist web agents. As discussed eariler, WebVoyager struggles with text-heavy websites. On the other hand, we observe that text-only agent demonstrates significantly poorer performance on websites with complex visual elements, such as Booking and Flights, which require interactions with calendars and other intricate components. In these scenarios, the textual input such as accessibility tree becomes highly complex and verbose, making it far less intuitive than using screenshots. Hence it's necessary to incorporate both modalities of inputs when building the general purpose agents.

Websites with more interact-able elements are more challenging for agents We also calculate the average trajectory length of tasks completed within the maximum number of iterations, as well as the average number of interactive web elements present on the webpage screenshots. Figure 6 illustrates their relationship with the Task Success Rate. We posit that the average trajectory length serves as a measure of a task's complexity to some extent, while the average number of numerical labels related to the decision-making process reflects the complexity of a webpage. Intuitively, websites depicted in the lower-left corner of Figure 6, characterized by relatively simple webpages and shorter

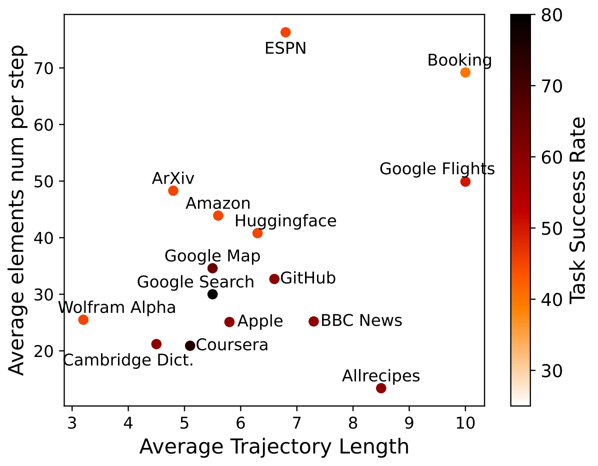

Figure 6: Factors related to Task success rate: Average number of labels per webpage and Average trajectory length. The color represents the Task success rate of WebVoyager, with darker colors indicating a higher Task success rate.

trajectory lengths, are expected to exhibit higher Task Success Rates. As observed in Figure 6, the results largely align with this intuition, though not entirely. It is important to note that our current measure of webpage complexity is somewhat rudimentary.

5.5 Error Analysis

In this section, we discuss and summarize the primary issues encountered by WebVoyager in the task completion process. These challenges will serve as critical entry points for future enhancements of the Task Success Rate and for devising strategies to obtain an Optimal Trajectory. We attribute the failure of the task to the following 4 issues, labeling each failed task with a major issue and showing the ratio in table 3. In Appendix D, we also provide specific examples for each issue.

Navigation Stuck The most common failure modes for our agent is running out of steps before completing the task. Upon inpsection, we found the following scenarios: 1) If the agent's search query is not precise and explicit enough, it be overwhelmed by the irrelevant search results. The agent may prefer to browse different results or wait on these incorrect outcomes rather than correct its previous action; 2) When the scroll-able area is only a small part of the screen, the agent might be unable to locate the correct scrolling area, and repeatedly request the execution of useless scrolling actions; 3) Sometimes in the middle of the page, the agent has trouble deciding whether to scroll up or down.

Main reasons for Failure	Ratio
Navigation Stuck	44.4%
Visual Grounding Issue	24.8%
Hallucination	21.8%
Prompt Misalignment	9.0%

Table 3: Main reasons for task failure. Each task is labeled with a primary issue and the ratio of occurrence for each issue is calculated.

Additionally, the agent also has tendency to repeat its previous mistakes due to the input clipping as mentioned in section 3.2. These meaningless or repetitive actions may hinder the completion of the task.

Visual Grounding Issue The visual grounding ability of our agent still has a large room for improvement. We have observed the following situations: 1) The agent cannot interpret less frequently observed patterns, such as misidentifying characters representing the pronunciations or math formulas; 2) The agent doesn't recognize the subtle difference between two observations and thinks the execution has failed; 3) The agent selected the wrong element for action execution due to proximity. For example, the confusion between adjacent elements and the misinterpretation of numbers on a calendar as numerical labels. Sometimes textual information plays a significant role, offering valuable cues and assisting in distinguishing between overly dense web elements. We find that incorporating the text content included in Web Elements can alleviate these problems to some extent. However, stronger visual encoder or additional text inputs might be needed to fully address the issue.

Hallucination Agents sometimes produce seemingly correct answers, which may require checking carefully to identify errors. We observed the following two scenarios: 1) The agent may overlook certain requirements of the task and settle for an answer that is only partially correct. For instance, when asked for the cheapest product, the agent might respond with a cheap product visible in a screenshot, neglecting the need to sort the options first. 2) The agent might execute an seemingly correct action without raising any errors, which actually deviate it from the correct reasoning path. For example, inputting content to the wrong textbox when there are many textboxes in the webpage is still a valid action, yet it would guide the agent to obtain a wrong answer.

Prompt Misalignment Understanding and following complex prompts, as illustrated in Figure 7, often poses significant challenges. Moreover, longer trajectories may result in excessively lengthy contexts, hindering effective instruction following. Although many of the errors in Navigation Stuck and Hallucination categories can also be attributed to prompt design, we use Prompt Misalignment to categorize the following situations: 1) the agent failed to generate outputs that can be parsed into executable actions, e.g. providing only the 'Thought' without the corresponding 'Action'; 2) Prematurely terminating the process using the ANSWER action, though agent knows that the task is not yet complete (explicitly mentioned in its answer).

6 Conclusion

In this paper, we introduce WebVoyager, an LMM-powered web agent designed for end-to-end web task resolution. To evaluate the performance of WebVoyager, we collect a variety of web tasks related to 15 websites. We propose Human Evaluation and GPT-4V based Automatic Evaluation, ensuring result reliability with consistent analyses. The results highlight WebVoyager's potential with a 55.7% Task Success Rate, yet there remains significant room for improvement. A comprehensive Error Analysis of the weaknesses of WebVoyager is provided after the experiments. For future work, we suggest the exploration of better integration methods for visual information and textual information. Additionally, it's worth investigating in building mutli-modal web agents similar to WebVoyager using open-sourced LMMs.

Limitations

We recognize the follow limitations of our work: firstly, we haven't support all possible actions in our environment compared to actions a human user might use when browsing the web. e.g. the Drag action on webpages. Supporting such an action is challenging since the degree of Drag is not a finite set. We may allow it to choose the pixel values to be dragged if the Visual Grounding capabilities of LMMs are further enhanced. Secondly, our agent can only analyze PDF files via OpenAI's Assistant API and doesn't support other file formats, especially videos. Supporting other file formats would also require non-trivial amount of effort and we consider it to be an important step towards building AGI-like agents.

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A Prompt for WebVoyager

The System Prompt for WebVoyager is shown in Figure 7. The Prompt's guidelines hold potential for optimization and should be generalist rather than website-specific in design. Incorporating specific issues from websites into the system prompt may compromise the agent's universality.

B Prompt for Auto Evaluation

Figure 8 demonstrates using GPT-4V as an evaluator for web tasks, involving web task instruction, screenshots in the trajectory, and WebVoyager responses. We require GPT-4V to mark success or not success. The temperature is set to 0 to reduce randomness during evaluation.

C Additional Trajectories

In our experiment, we present the complete trajectory of WebVoyager accessing the Apple website and addressing the task. In this section, we exhibit the trajectories for the remaining websites that complete web tasks successfully. We provide a screenshot for each step, accompanied by the action generated by WebVoyager. The specific navigation trajectories for each website are illustrated in Figures 9 to 22.

D Error Cases

In this section, we provide specific examples of the four types of errors mentioned in the Error Analysis section. Figure 23 illustrates a snippet of WebVoyager navigating on Google Flights and a Visual Grounding Issue appears. The task is to retrieve one-way flight information for January 22nd; however, it selects December 22nd on the Calendar and fails to make the necessary corrections. Although it attempts to modify the date in step 6, it ultimately fails to do so. Figure 24 illustrates a situation of WebVoyager navigating on Allrecipes, encountering the Navigation Stuck issue. The agent requires multiple downward scrolls to locate the correct ingredients. However, it experiences confusion during the process, uncertain whether to scroll up or down. Figure 25 depicts the Hallucination issue encountered by WebVoyager on the Coursera website. In the task, we query the number of quizzes in the "Artificial Intelligence for Healthcare" course. However, the agent only identifies the quiz in module 1 of the course, which is not the optimal answer and does not fulfill the task requirements. Figure 26 illustrates the issue of Prompt Misalignment encountered while browsing BBC News. WebVoyager fails to fulfill all the task requirements. Instead of completing the navigation, it provides partial answers and tells me how to find complete answers, which is not end-to-end.

Imagine you are a robot browsing the web, just like humans. Now you need to complete a task. In each iteration, you will receive an Observation that includes a screenshot of a webpage and some texts. This screenshot will feature Numerical Labels placed in the TOP LEFT corner of each Web Element. Carefully analyze the visual information to identify the Numerical Label corresponding to the Web Element that requires interaction, then follow the guidelines and choose one of the following actions:
1. Click a Web Element.
2. Delete existing content in a textbox and then type content.
3. Scroll up or down.
...

Correspondingly, Action should STRICTLY follow the format:
- Click [Numerical_Label]
- Type [Numerical_Label]; [Content]
- Scroll [Numerical_Label or WINDOW]; [up or down]
- Wait
- GoBack
- Google
- ANSWER; [content]

Key Guidelines You MUST follow:
* Action guidelines *
1) Execute only one action per iteration.
...
* Web Browsing Guidelines *
1) Don't interact with useless web elements like Login, Sign-in, donation that appear in Webpages.
...

Your reply should strictly follow the format:
Thought: {Your brief thoughts (briefly summarize the info that will help ANSWER)}
Action: {One Action format you choose}

Then the User will provide:
Observation: {A labeled screenshot Given by User}

Figure 7: System Prompt for WebVoyager. We instruct agents to perform web navigation, along with specific browsing actions and action formats. To enhance efficiency and accuracy, we can incorporate additional general into the prompts. These guidelines should be generic and not about a specific website to ensure generalizability.

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

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

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

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

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

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

Figure 8: System Prompt for Auto Evaluation by GPT-4V.

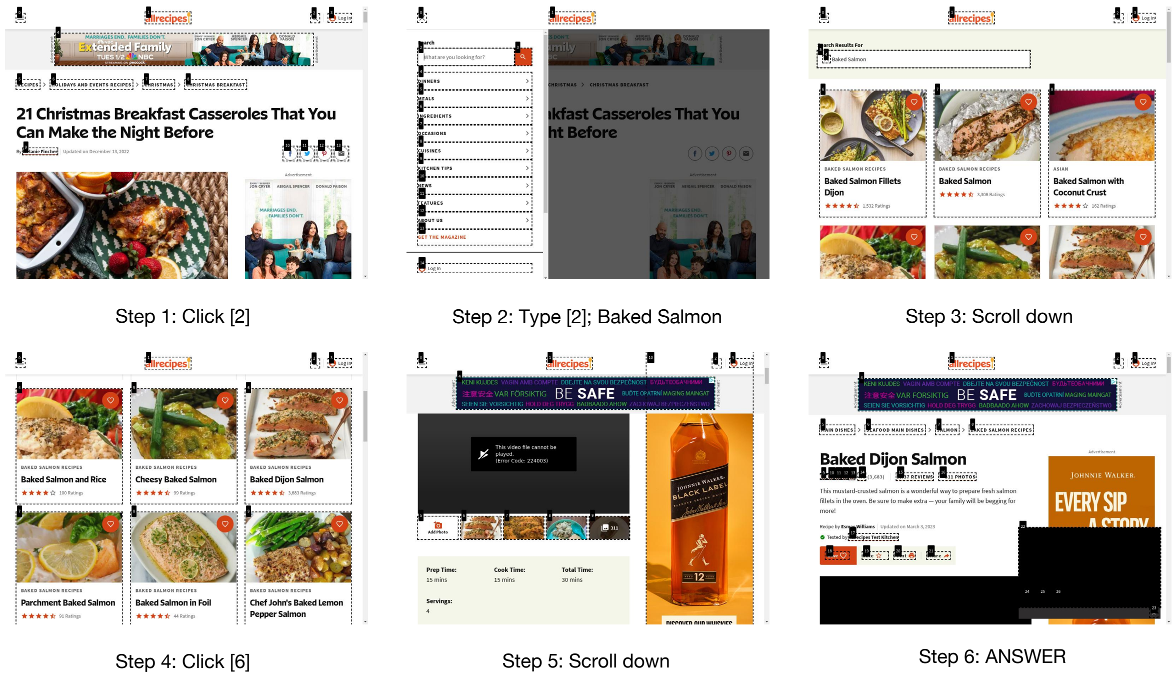


Figure 9: Screenshots of a complete trajectory of browsing Allrecipes. Given the task: “Find a recipe for Baked Salmon that takes less than 30 minutes to prepare and has at least a 4-star rating based on user reviews.” The agent interacts with the Allrecipes website and obtains the answer: “The "Baked Dijon Salmon" recipe meets the user’s criteria, with a 4.6-star rating and a preparation time of 15 minutes.”

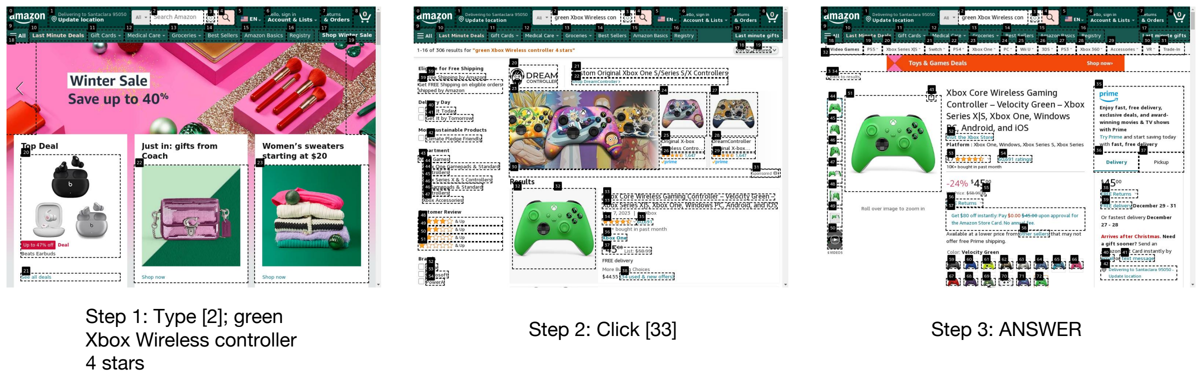


Figure 10: Screenshots of a complete trajectory of browsing Amazon. Given the task: “Search for an Xbox Wireless controller with green color and rated above 4 stars.” The agent interacts with the Amazon website and obtains the answer: “The green Xbox Wireless controller ("Xbox Core Wireless Gaming Controller – Velocity Green") rated above 4 stars has been found on Amazon with a rating of 4.7 out of 5 stars.”

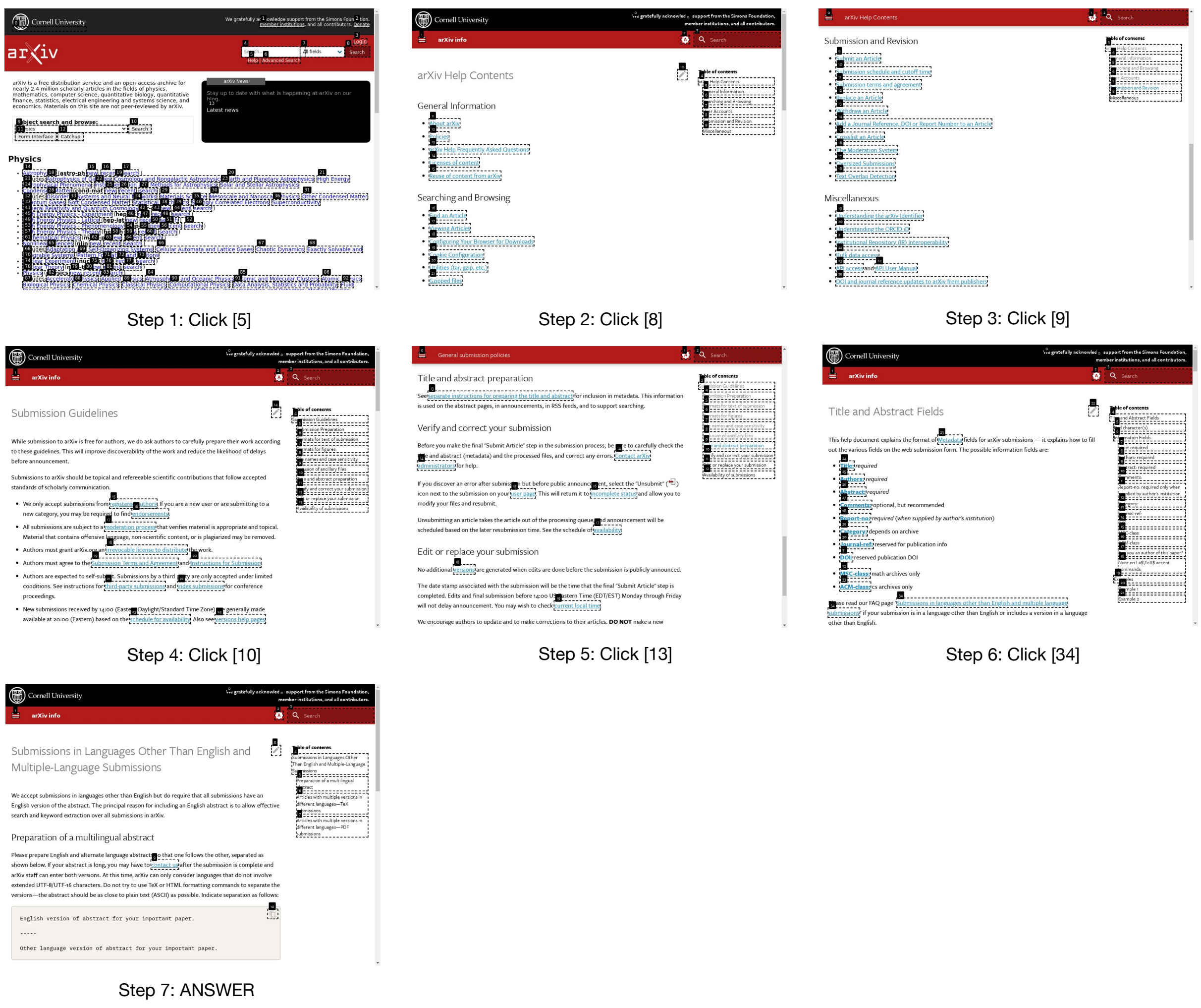


Figure 11: Screenshots of a complete trajectory of browsing ArXiv. Given the task: “For non-English submissions, do I need to provide a multi-language abstract, if need, answer the separator between the multiple abstracts.” The agent interacts with the ArXiv website and obtains the answer: “Line ("-----")”

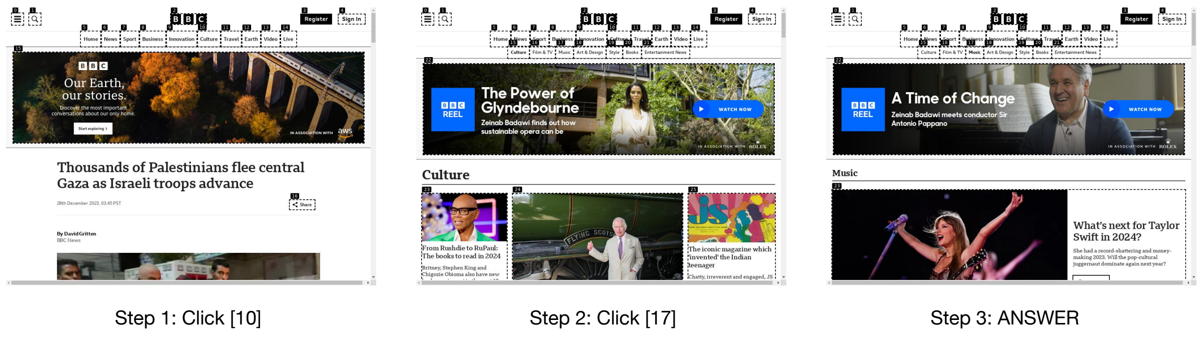


Figure 12: Screenshots of a complete trajectory of browsing BBC News. Given the task: “Find out which musician made the headlines in Music News.” The agent interacts with the BBC News website and obtains the answer: “The musician who made the headlines in Music News is Taylor Swift.”

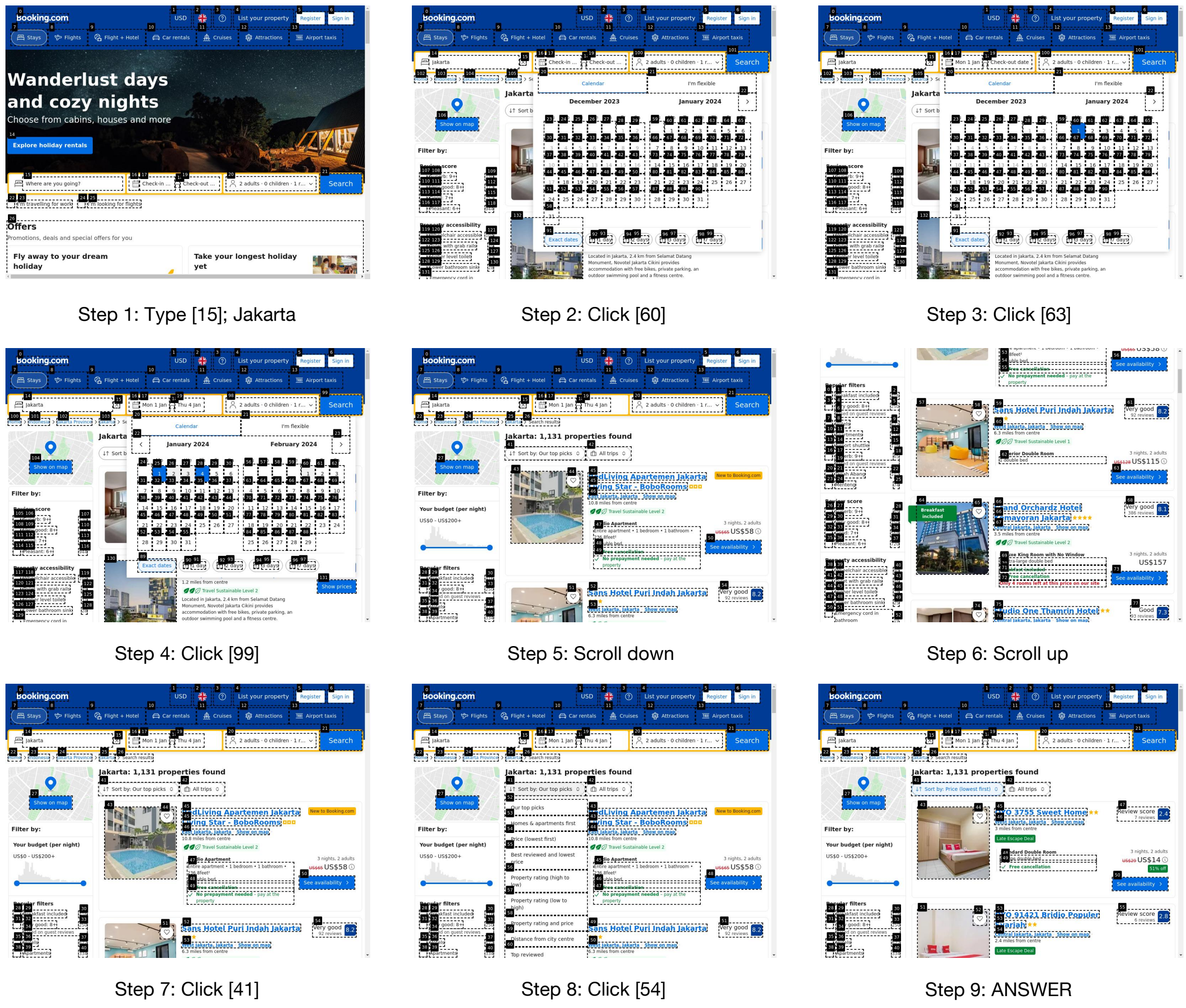


Figure 13: Screenshots of a complete trajectory of browsing Booking. Given the task: “Find the cheapest available hotel room for a three-night stay from 1st Jan in Jakarta. The room is for 2 adults, just answer the cheapest hotel room and the price.” The agent interacts with the Booking website and obtains the answer: “The cheapest hotel room is at OYO 3755 Sweet Home for US$14 for a three-night stay.”

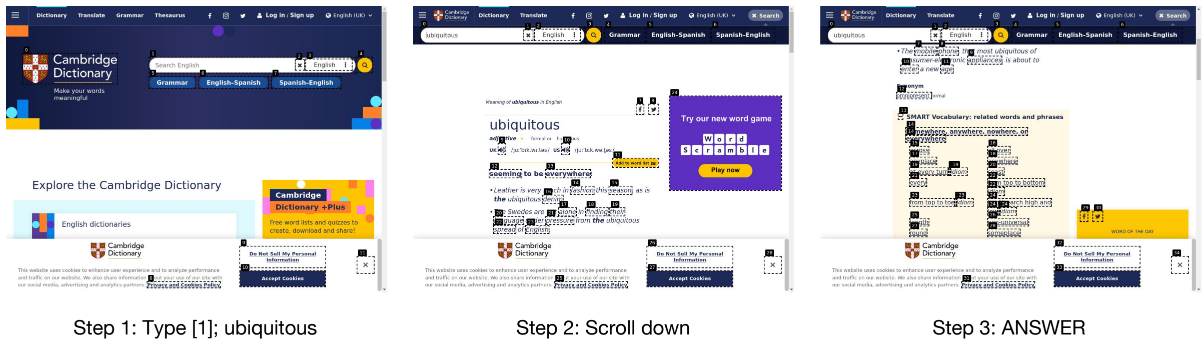
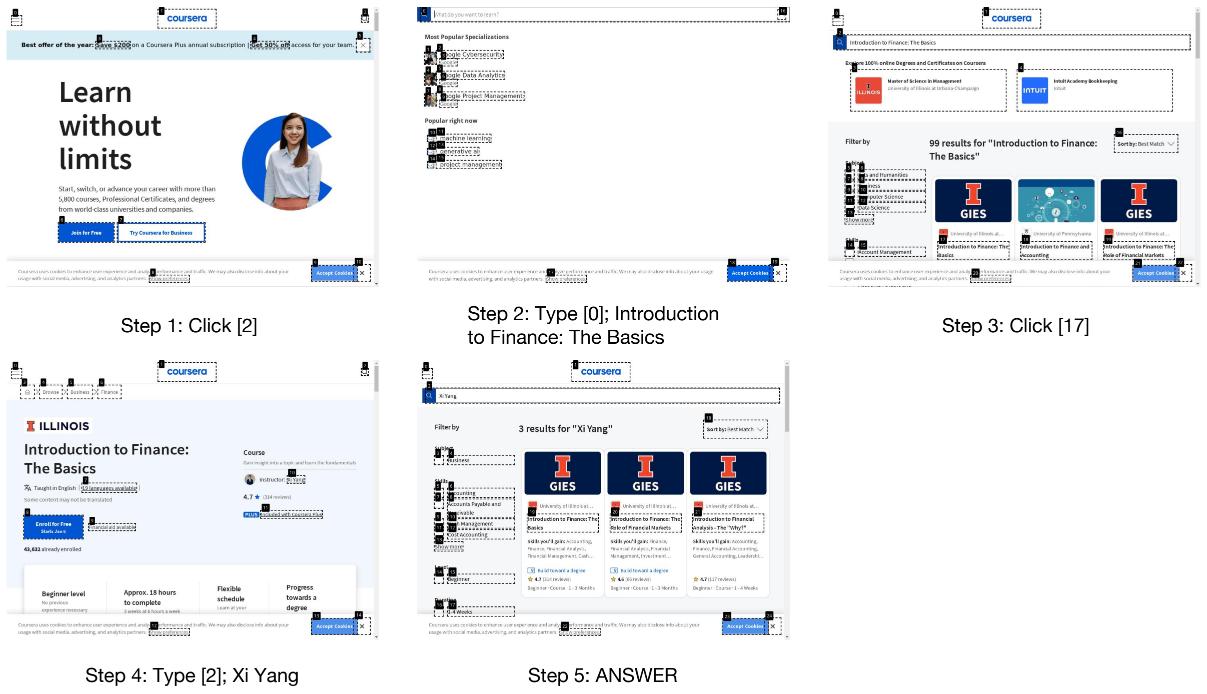


Figure 14: Screenshots of a complete trajectory of browsing Cambridge Dictionary. Given the task: “Look up the pronunciation, definition, and an example sentence for the word "ubiquitous" in UK and US English.” The agent interacts with the Cambridge Dictionary website and obtains the answer: “The UK English pronunciation of "ubiquitous" is /juːˈbɪk.wɪ.təs/ , and the US English pronunciation is /juːˈbɪk.wə.t̬əs/. The definition is "seeming to be everywhere", and an example sentence is "Leather is very much in fashion this season, as is the ubiquitous denim."”



Step 1: Click [2]
Step 2: Type [0]; Introduction to Finance: The Basics
Step 3: Click [17]
Step 4: Type [2]; Xi Yang
Step 5: ANSWER

Figure 15: Screenshots of a complete trajectory of browsing Coursera. Given the task: “Identify a course on Coursera named ’Introduction to Finance: The Basics’, who is the course instructor, and what other courses does he/she teach.” The agent interacts with the Coursera website and obtains the answer: The course instructor for ‘Introduction to Finance: The Basics’ is Xi Yang. Xi Yang also teaches ‘Introduction to Finance: The Role of Financial Markets’ and ‘Introduction to Financial Analysis - The "Why?"’

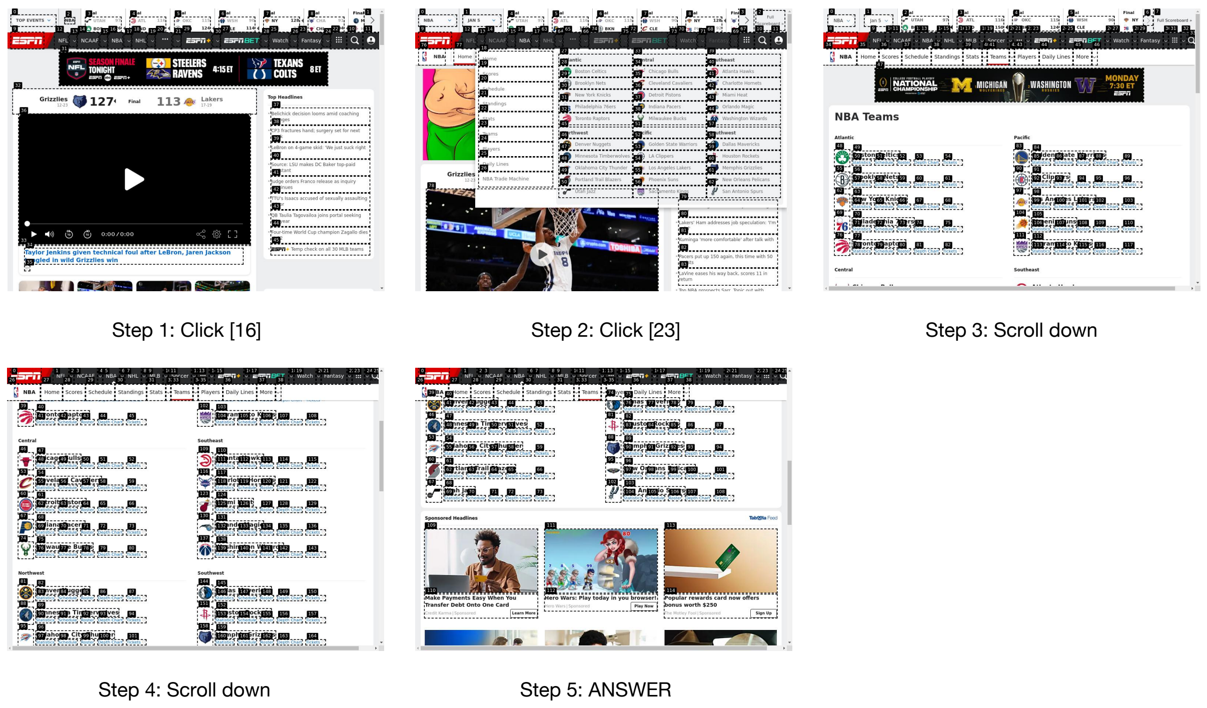


Figure 16: Screenshots of a complete trajectory of browsing ESPN. Given the task: “How many NBA teams are there and list all the teams with ‘New’ in their name.” The agent interacts with the ESPN website and obtains the answer: “There are 30 NBA teams. The teams with ‘New’ in their name are the New York Knicks and the New Orleans Pelicans.”

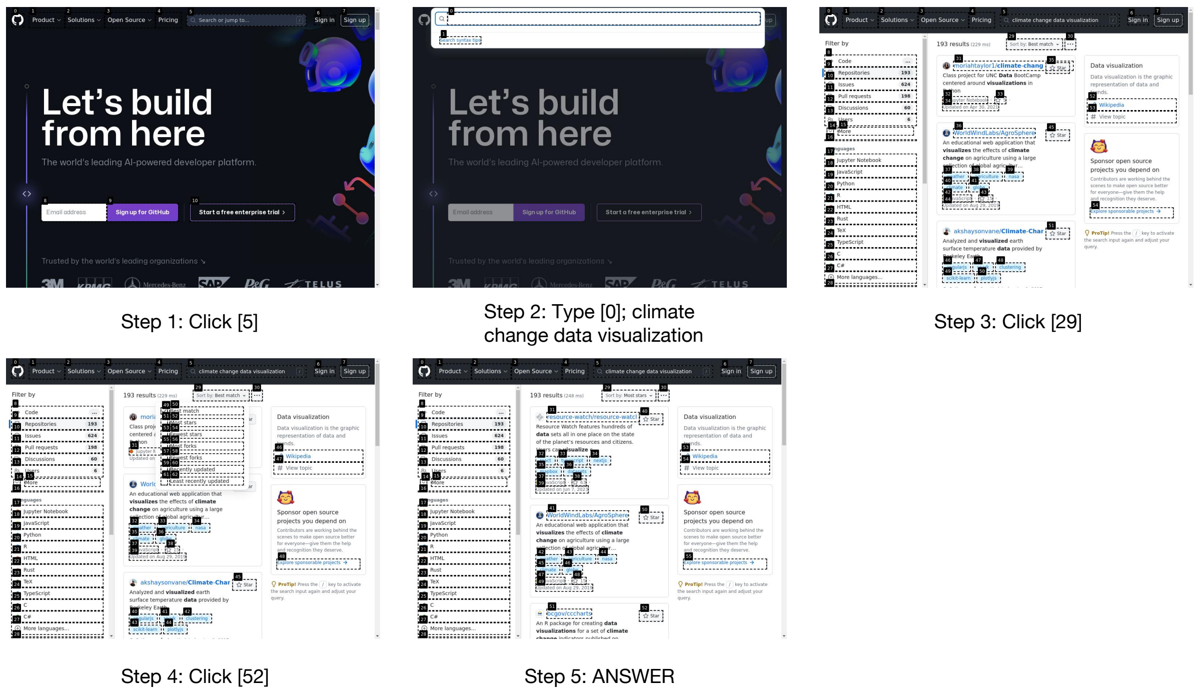


Figure 17: Screenshots of a complete trajectory of browsing GitHub. Given the task: “Search for an open-source project related to ‘climate change data visualization’ on GitHub and report the project with the most stars.” The agent interacts with the GitHub website and obtains the answer: “resource-watch/resource-watch with 63 stars”

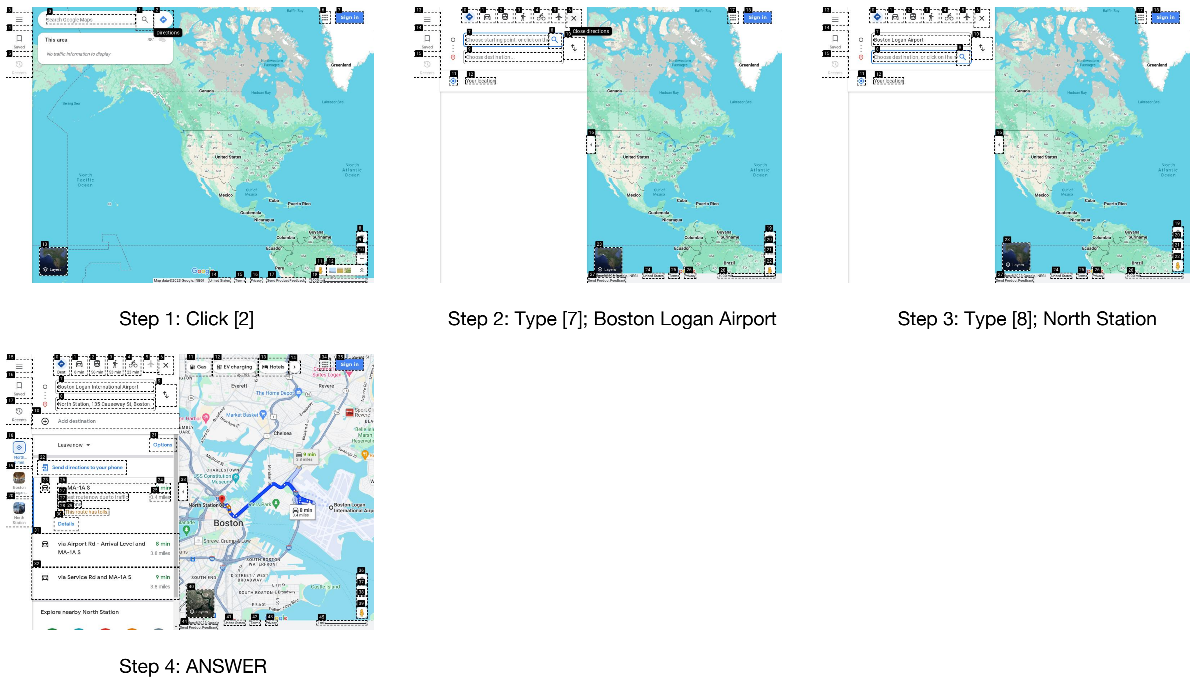

Step 1: Click [2]
Step 2: Type [7]; Boston Logan Airport
Step 3: Type [8]; North Station
Step 4: ANSWER

Figure 18: Screenshots of a complete trajectory of browsing Google Map. Given the task: “Plan a trip from Boston Logan Airport to North Station.” The agent interacts with the Google Map website and obtains the answer: “The fastest route from Boston Logan International Airport to North Station is via MA-1A S and takes approximately 8 minutes in current traffic conditions.”

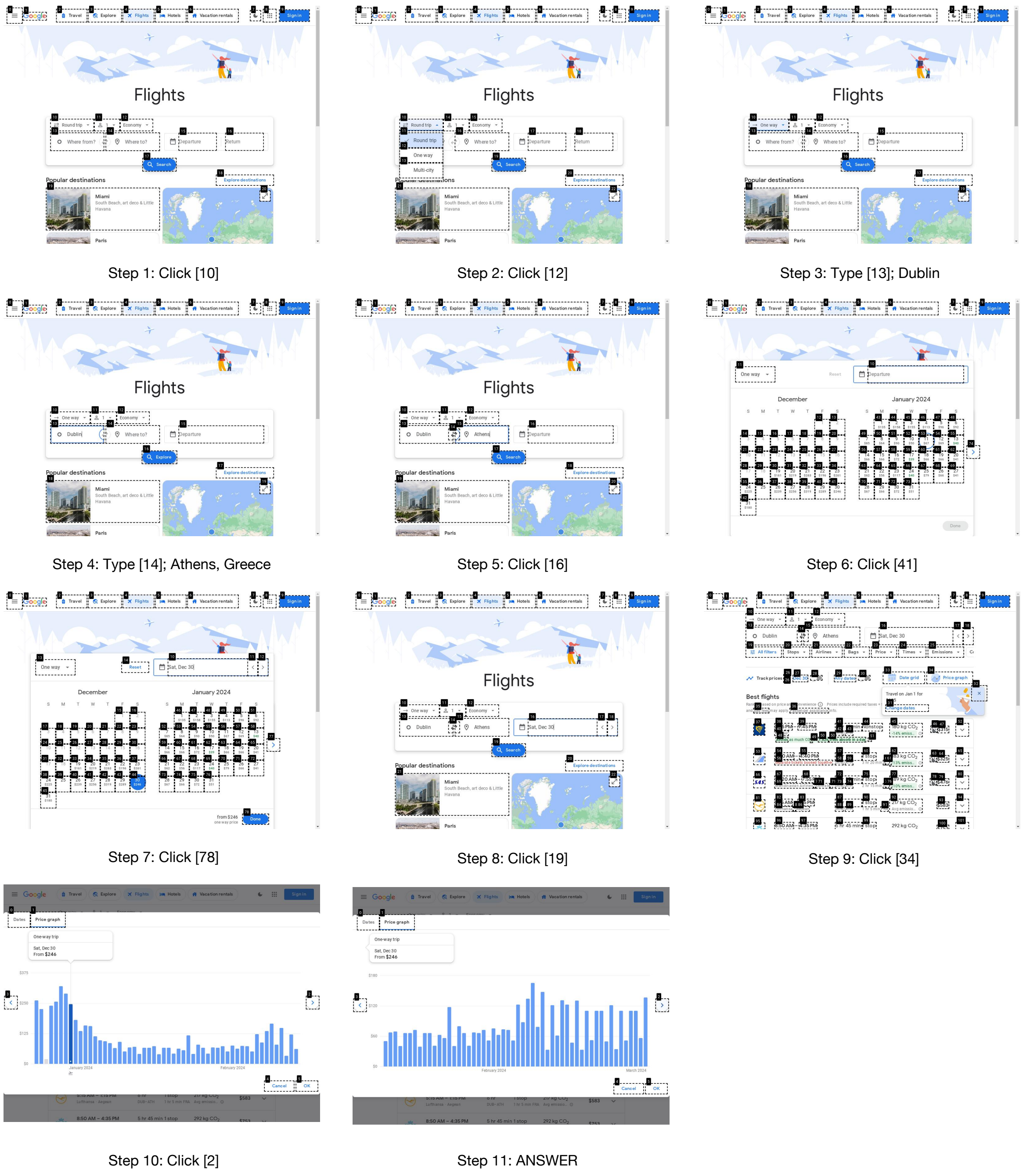


Figure 19: Screenshots of a complete trajectory of browsing Google Flights. Given the task: “Search a one-way flight from Dublin To Athens Greece for 1 Adult that leaves on December 30 and analyse the price graph for the next 2 months.” The agent interacts with the Google Flights website and obtains the answer: “The price graph has been analyzed, and it shows the trends for flight prices from Dublin to Athens over the next two months.”

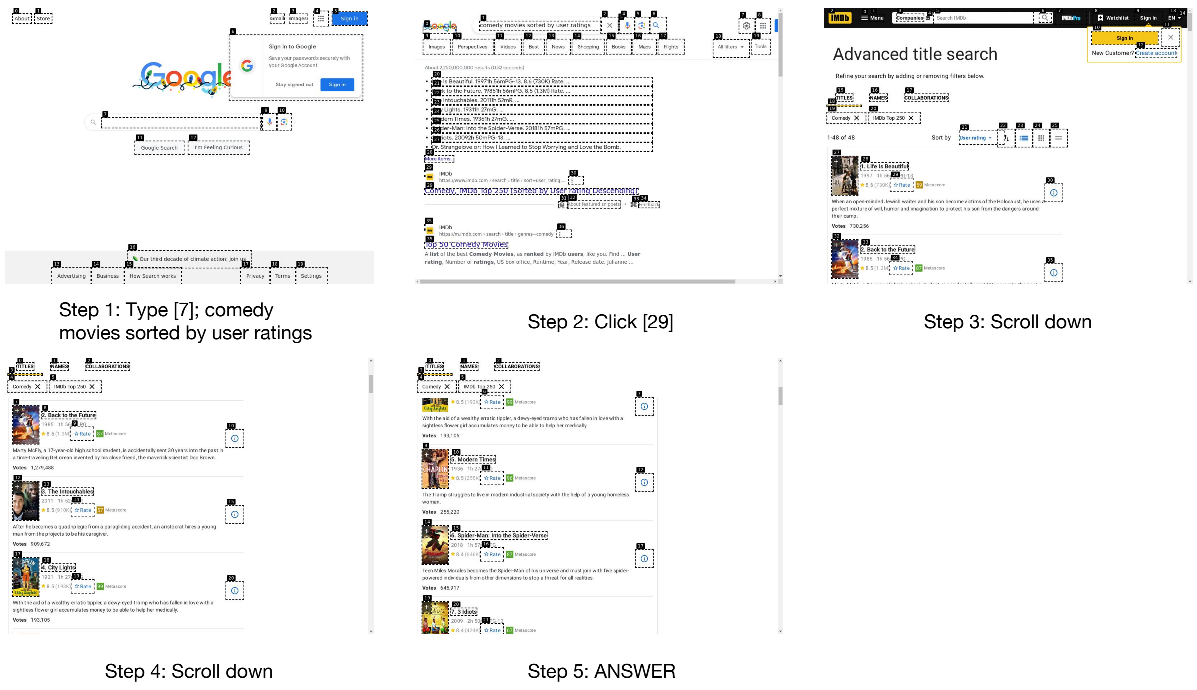


Figure 20: Screenshots of a complete trajectory of browsing Google Search. Given the task: “Show me a list of comedy movies, sorted by user ratings. Show me the Top 5 movies.” The agent interacts with the Google Search website and obtains the answer: “The Top 5 comedy movies sorted by user ratings are:Life Is Beautiful; Back to the Future; The Intouchables; City Lights; Modern Times”

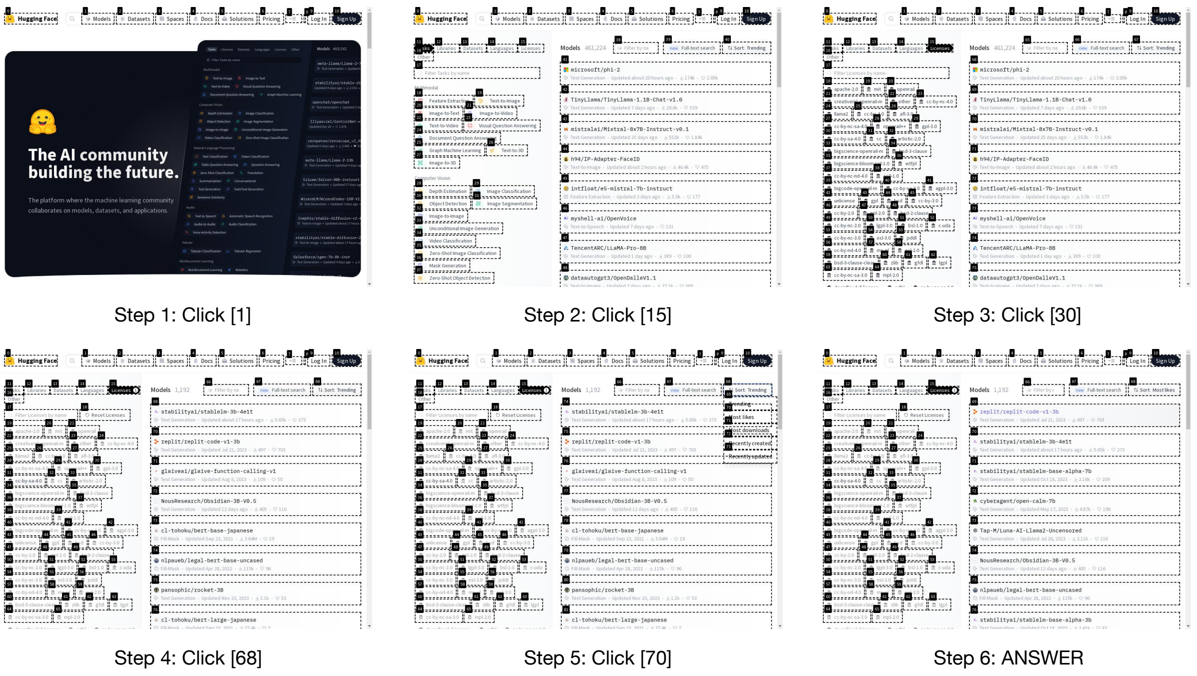
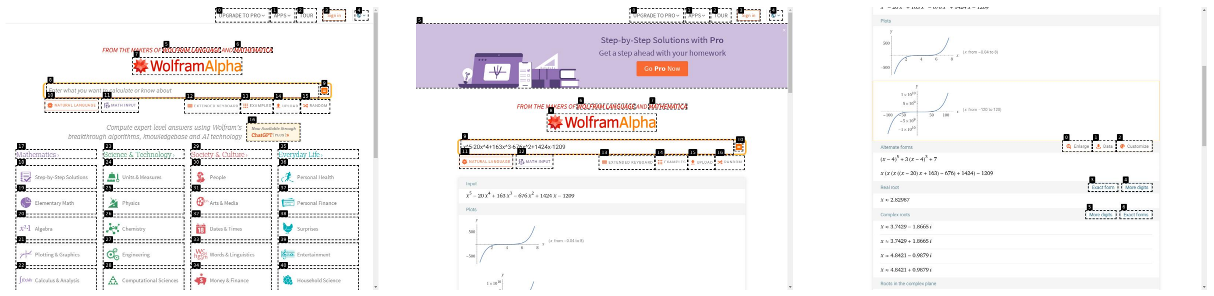


Figure 21: Screenshots of a complete trajectory of browsing Huggingface. Given the task: “Look up a model with a license of cc-by-sa-4.0 with the most likes on Huggingface.” The agent interacts with the Huggingface website and obtains the answer: “The model with a license of cc-by-sa-4.0 with the most likes on Hugging Face is "replit/replit-code-v1-3b" with 703 likes.”

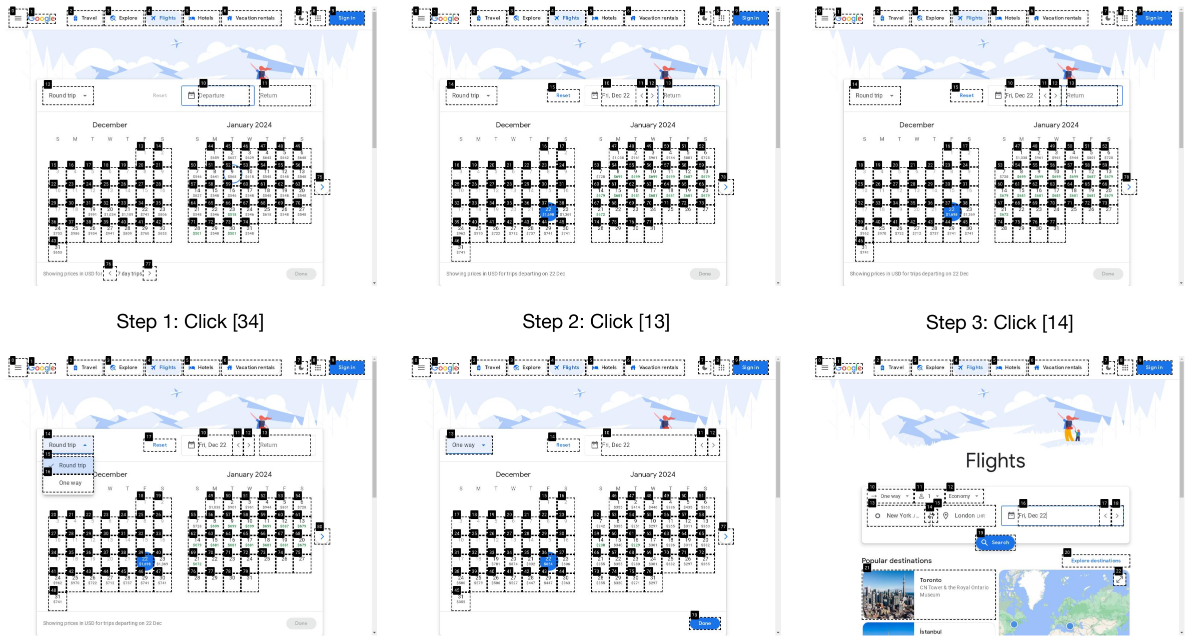


Step 1: Type [8]; x^5-20x^4 +163x^3-676x^2+1424x-1209

Step 2: Scroll down

Step 3: ANSWER

Figure 22: Screenshots of a complete trajectory of browsing Wolfram Alpha. Given the task: "Simplify x^5-20x^4+163x^3-676x^2+1424x-1209 so that it has fewer items." The agent interacts with the Wolfram Alpha website and obtains the answer: "(x - 4)^5 + 3(x - 4)^3 + 7"



Step 1: Click [34]

Step 2: Click [13]

Step 3: Click [14]

Step 4: Click [16]

Step 5: Click [78]

Step 6: Click [16]

Figure 23: An error case for Google Flights. Given the task:"Find the lowest fare from all eligible one-way flights for 1 adult from JFK to Heathrow on Jan. 22." Agent fails to select the correct numerical label though it really wants to select 22 January.

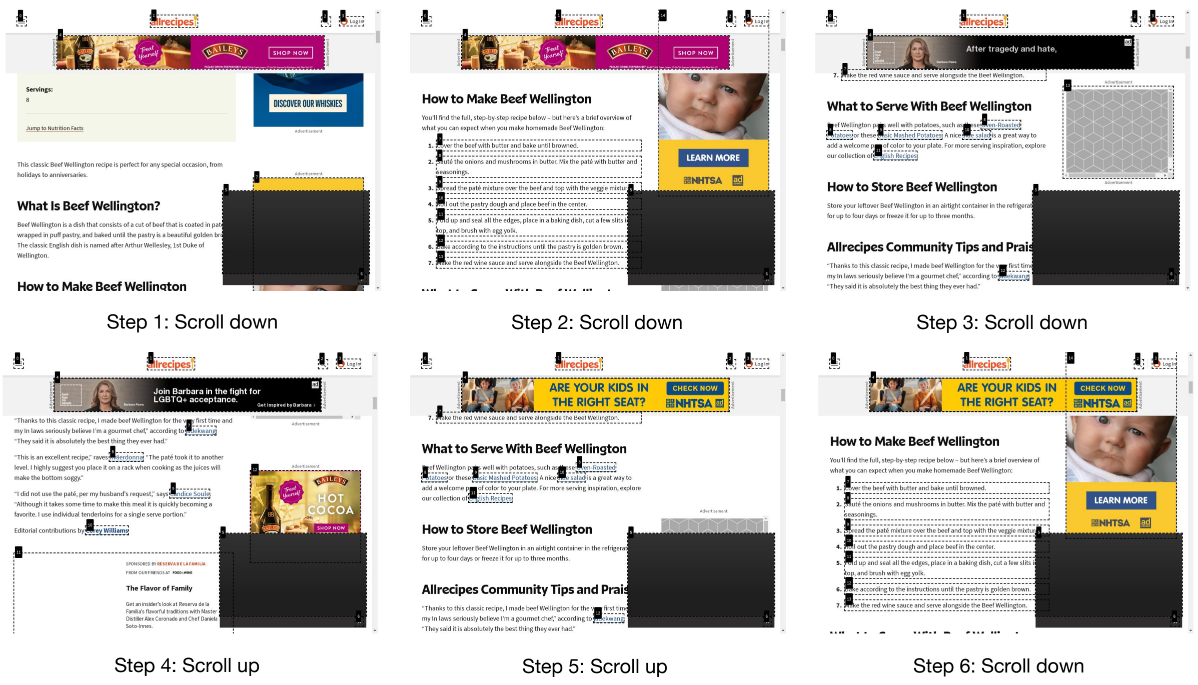


Figure 24: An error case for Allrecipes. Given the task:"Search for a recipe for Beef Wellington on Allrecipes that has at least 200 reviews and an average rating of 4.5 stars or higher. List the main ingredients required for the dish." Agent fails to scroll the page correctly and find ingredients.

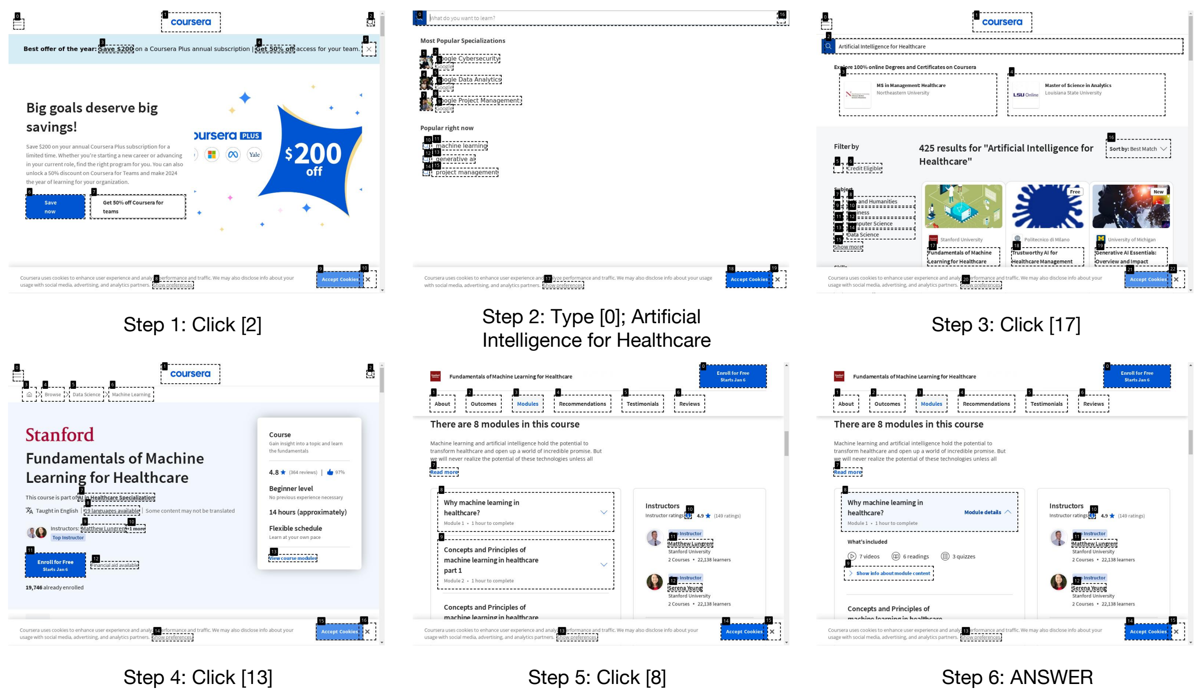
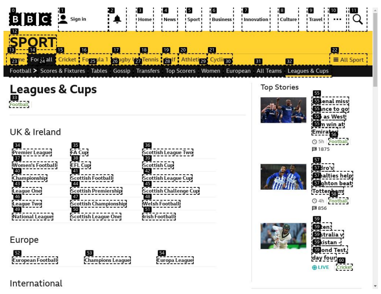
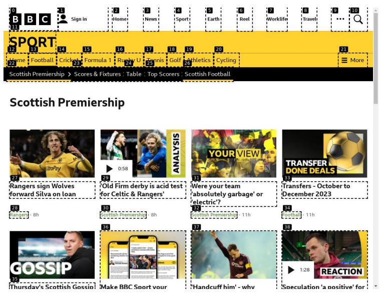


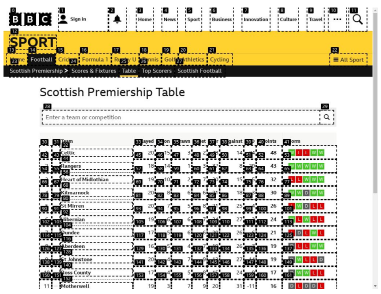
Figure 25: An error case for Coursera. Given the task: "Identify a course on Coursera related to 'Artificial Intelligence for Healthcare' and note the course duration along with the number of quizzes in Assessments." The agent provides the answer: "Module 1 includes 3 quizzes in the Assessments." However, we also require other Modules and agent fails to provide the results.



Step 1: Click [44]



Step 2: Click [24]



Step 3: ANSWER

Figure 26: An error case for BBC News. Given the task: “Find out how many teams are in the Scottish Premiership of the Football Tournament and when did the Hibernian team’s most recent match start?” The agent provides the answer: “There are 12 teams in the Scottish Premiership. To find out the exact start time of Hibernian’s most recent match, further interaction with the website would be required.” The Agent knows that the task is not yet complete, but it ends its navigation early, even though it can find the Hibernian team’s most recent match.