UNDERSTANDING HTML WITH LARGE LANGUAGE MODELS

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ABSTRACT

Large language models (LLM) have shown exceptional performance on a variety of natural language tasks. Yet, their capabilities for HTML understanding – i.e., parsing the raw HTML of a webpage, with applications to automation of web-based tasks, crawling, and browser-assisted retrieval – have not been fully explored. We contribute HTML understanding models (fine-tuned LLMs) and an in-depth analysis of their capabilities under three tasks: (i) *Semantic Classification* of HTML elements, (ii) *Description Generation* for HTML inputs, and (iii) *Autonomous Web Navigation* of HTML pages. While previous work has developed dedicated architectures and training procedures for HTML understanding, we show that LLMs pretrained on standard natural language corpora transfer remarkably well to HTML understanding tasks. For instance, fine-tuned LLMs are 12% more accurate at semantic classification compared to models trained exclusively on the task dataset. Moreover, when fine-tuned on data from the MiniWoB benchmark, LLMs successfully complete 50% more tasks using 192x less data compared to the previous best supervised model. To promote further research on LLMs for HTML understanding, we create and open-source a large-scale HTML dataset distilled and auto-labeled from CommonCrawl. We show evidence that T5-based models due to the bidirectional encoder-decoder architecture are the best choice and that for practitioners larger models are not necessarily better.

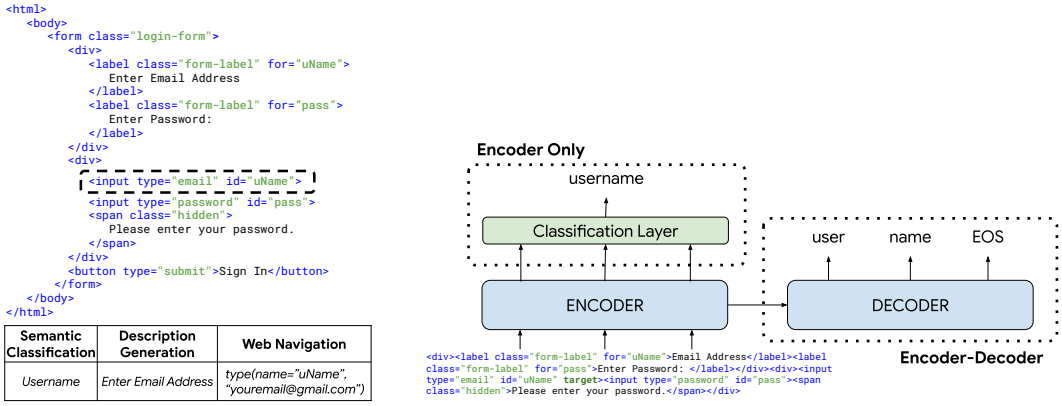
1 INTRODUCTION

Web crawling (Olston et al., 2010), form-filling (Diaz et al., 2013; Gur et al., 2021), or information retrieving web agents (Nogueira & Cho, 2016) are important for both automating and assisting users in web-based tasks. These and similar applications rely on models that can search for specific content or controls on a web page as well as navigate a website autonomously. Since a web page in its raw form is represented as an HTML-based text sequence, the success of models for web-based tasks relies on their ability to understand HTML semantics, structure and embedded interactions.

The predominant approach to web automation and HTML understanding is to train specialized models, i.e., gathering application-specific datasets and designing neural network (NN) architectures to leverage inductive biases of the HTML's structure; see, e.g., Liu et al. (2018); Toyama et al. (2021); Gur et al. (2021); Humphreys et al. (2022). However, both dataset collection and neural architecture design are expensive, time-consuming, and require highly-specialized, domain-specific knowledge.

Meanwhile, in the natural language processing (NLP) literature, large language models (LLMs) have emerged as a solution to the difficulties of dataset collection and specialized NN design (Kaplan et al., 2020; Bommasani et al., 2021). A popular paradigm in NLP is to take an off-the-shelf LLM – pretrained on a large text corpus via an unsupervised and task-agnostic learning objective – and either fine-tune or prompt the LLM on a small task-specific dataset. This paradigm has shown exceptional performance on a variety of NLP tasks (Xue et al., 2020; Brown et al., 2020; Austin et al., 2021). Whether LLMs can be applied to HTML understanding – especially given the much larger context and sequence lengths – remains an under-explored question.

In this paper, we investigate whether LLMs can be applied to HTML understanding to produce better-performing, more sample-efficient HTML understanding models and without the need for custom NN architecture design. To that end, we present a suite of three benchmarking tasks for HTML understanding that capture the essence of these applications and require understanding both



(a) (b)

Figure 1: a) HTML example page with a highlighted salient element, an element of interest (dashed box). All canonical tasks evaluate a distinct interaction with this element, either by classifying it as one of given categories, generating text description of its purpose, or applying an action as part of a sequential navigation of a multi-page website. b) LLM architectures overview. Dashed boxes denote sub-modules that are specific to either encoder-only or encoder-decoder models. For encoder-only models, we add an extra classification layer. Decoder-only models (not in the diagram) are similar to encoder-decoder models, the main difference is that HTML snippet is fed to the decoder and processed from left-to-right.

structure and content. First, we devise *Semantic Classification* as a task that requires a model to classify a given HTML element into one of the set of categories, such as address, email, password etc., with application to automated form-filling. Second, we present *Description Generation*, a label-extraction task where a model is given an HTML snippet and is asked to produce a natural language description. For instance for an email field, the description might be "Please enter your email address." Note that in the majority of web pages, this connection between input elements and description content is only implicit in the raw HTML code and inferring such links is a prerequisite for higher-level navigation objectives. The third task is *Autonomous Web Navigation* (Shi et al., 2017). A model is presented with an HTML page paired with a natural language command and must apply appropriate actions on a sequence of HTML pages to satisfy the command. See Figure 1a for a simplified example of these tasks.

With these benchmark tasks in hand, we evaluate the transfer capabilities of a variety of pretrained LLMs (Table 1), varying in architecture (encoder-only, encoder-decoder, or decoder-only), model size (from 24.6M to 62B parameters), and training data corpora (both including and excluding pre-training NLP and HTML corpus). While prior work universally pre-parses the HTML as input to the model (Gur et al., 2021; Liu et al., 2018; Nakano et al., 2021), ours – to the best of our knowledge – is the first work that uses raw, unprocessed HTML. Our results show that LLMs demonstrate a remarkable level of HTML understanding across all tasks, with up to $192\times$ more sample-efficiency than models trained from scratch, and achieving a new SoTA for supervised learning on the MiniWoB benchmark suite (Shi et al., 2017). The encoder-decoder architectures with bi-directional attention show the best performance across the board even when the pre-training does not include HTML. In addition, we show that the performance scales sub-linearly with the model size.

In summary, our paper provides a new perspective on machine learning for HTML understanding and web automation, showing that pretrained LLMs can achieve significant performance on such tasks, eschewing the need for specialized architectures and training protocols. To encourage further research in this direction, we plan to open-source our dataset for description generation. The further details are available at `https://sites.google.com/view/llm4html/home`

2 Related Work

HTML Understanding Autonomous web navigation has been a popular application for neural network models, and a variety of works propose simulated websites for training web-based agents, with application to task fulfillment (Yao et al., 2022; Gur et al., 2021; Burns et al., 2022; Mazumder &

Riva, 2020; Shi et al., 2017; Liu et al., 2018) as well as information retrieval or question-answering (Adolphs et al., 2021; Nogueira & Cho, 2016). Simulated websites provide an easy way to evaluate models online, and for this reason we use the existing MiniWoB benchmark (Shi et al., 2017) for our web navigation setting. However, it is still important to have a mechanism for evaluating models on a wide variety of real-world websites. This was the key motivation for generating our own dataset for the description generation task, which distilled and auto-labeled from CommonCrawl and is a key contribution of our paper.

Alongside these benchmarks, many works have developed models for web navigation and related subtasks (Pasupat et al., 2018; Bommasani et al., 2021; He et al., 2021; Gur et al., 2021; Humphreys et al., 2022; Liu et al., 2018; Jia et al., 2019). These works often rely on specialized neural network architectures that leverage inductive biases of HTML structure, or on preprocessing of HTML to make it easier to input to a model. In contrast, our work takes a minimalist approach, providing HTML in raw text form and using widely-adopted transformer networks.

LLMs and HTML Works that explore the intersection of LLMs and HTML generally fall into two categories. First category uses LLMs to assist web navigation (Nakano et al., 2021; Yao et al., 2022), and typically relies on a custom preprocessing to map the context and structure of a web page to natural language, thus severely restricting what HTML pages the model can parse. The second category pretrains LLMs on a large corpora of HTML text (Aghajanyan et al., 2021). However, these works typically restrict the model evaluation to standard NLP tasks, e.g., summarization and question/answering as opposed to tasks more relevant to HTML understanding and web automation. Our work can be thought of as the reverse: We keep the pretraining of LLMs unchanged and focus on the mechanisms for transferring the pretrained LLMs on HTML-relevant tasks.

3 Brief Background on HTML as Semi-structured Text Data

HTML is a markup language, used to organize web page **structure** and **content**. Consider the example HTML page in Figure 1a. This web page includes two adjacent `input` elements, one for e-mail and another for password, with their corresponding `labels` on a separate branch of the page. These `inputs` and `labels` are one of many possible *elements* that serve as HTML building blocks. Each element has a set of attributes – key and value pair – that describe the element's content, such as style and human-readable text. When rendered in a browser, these attributes will be responsible for how the element is shown and where it is positioned. In the example in Figure 1a, the first `input` has three attributes, `tag="input"`, `type="email"`, and `id="uName"`, that identify the element as an email input with an identifier ("uName") that can be accessed programmatically.

4 Canonical Tasks for HTML Understanding

Autonomous Web Navigation task evaluates how well a model navigates multi-page websites, as a sequential decision-making problem Shi et al. (2017); Liu et al. (2018). At the beginning of an episode, the agent is given a natural language instruction, e.g. *Enter the username "lyda" and the password "N22t" into the text fields and press login*. The agent applies actions to a sequence of HTML pages. The action have the form: `function(selector, text)`. `function` is one of *click* or *type*, `selector` is an integer pointer that uniquely identifies an element, and `text` is a text to input if the *type* functionality is activated. An episode terminates when either the page reaches a terminal state (e.g., the 'sign in' button is clicked) or the maximum number of steps is reached.

Semantic Classification. Many HTML understanding applications require a model that can classify HTML elements into standardized categories. In automated form-filling (Diaz et al., 2013; Gur et al., 2021), it is useful to identify a 'submit button' across many websites (e.g., shopping, flight booking, utility application) with various button representations (e.g., position, color, or text). Thus, we formulate *Semantic Classification* as classifying elements into *role* categories. Take the example HTML in Figure 1a which includes two `input` elements and a submit `button`. Let's pick the first `input` as an element of interest to be classified by the system, also called a *salient element*. The system should classify this element as *username*, since it appears on a login page and it has a `label` with *Email Address* which is typically associated with the username in form-filling applications. To solve this, the system can aggregate information from multiple sources in the page – the label that says *Enter Email Address*, the `input` attributes (*type="email"* and *id="uName"*), or even the

Task	Dataset	Size	Model Input	Model Architecture	Model Output	Task Output
Autonomous Web Navigation	MiniWoB Demos (Shi et al., 2017)	12K	Page	Enc-Dec Dec	Text	Dictionary
Semantic Classification	Annotated Shopping Webpages (Gur et al., 2021)	38K	Snippet	All	Text	Category
Description Generation	CommonCrawl (new)	85K	Snippet	Enc-Dec Dec	Text	Text

Table 1: Task, dataset, and model summary. All models receive raw HTML. *Autonomous Web Navigation* receives the entire HTML, while the other tasks receive HTML snippets extracted given salient element.

ordering of other elements in the page such as 'password' and 'sign in'. To properly solve this task, a model must build an understanding of the structure and content of the page and use this understanding to make an accurate prediction.

Description Generation. Motivated by applications in accessibility-minded web browser control (Jorgensen & Binsted, 2005), we formulate description generation as an extractive problem where the goal is to locate the textual description of an element in the HTML and generate it as output. For instance, the description of the salient element in Figure 1a is *Enter Email Address*; when rendered, this `label` will appear above the 'email' `input` field. HTML provides a large amount of flexibility, and so in general a descriptive text that appears alongside a specific element when rendered can be very far from that element when looking at the HTML plaintext. Thus, this task evaluates a model's ability to understand the structure of HTML as it would appear to a user, despite not having access to the rendered web page directly.

5 DATASETS

Autonomous Web Navigation. We use the 12K demonstrations included in the publicly available MiniWoB benchmark (Shi et al., 2017), which encompass 62 website applications ranging from email forwarding to social media interactions. Every element in a MiniWoB demonstration is accompanied by a reference number unique within its respective pages. This number can be used as an element selector, making the action space unified across all tasks and time steps.

Semantic Classification. We use a dataset of 28K labelled examples, containing 66 different categories, of the form **(HTML, element, category)**, previously used in the context of environment generation (Gur et al., 2021). The dataset consists of URLs from the real shopping websites.

Description Generation. We derive a dataset from CommonCrawl.[1] CommonCrawl does not include renderings or annotations that would reveal what text in the HTML is associated with the elements. Instead, we infer descriptions of various elements by exploiting a special attribute in the HTML schema known as `for`.As an example in Figure 1a, the first `label` in the HTML has a `for` attribute with value *uName*, which is the `id` of the element described by `label`; in this case, it is the first `input` in the page. While this annotation procedure is typically used for accessibility purposes, we utilize it to create a large-scale dataset to study description generation. A small sample is available in the supplemental material, while the entire dataset will be available upon publication.

We randomly collected 100 WARC (from April 2019) files from the CommonCrawl project and extracted all HTML `labels` that have a `for` attribute. Removing non-Unicode and alphanumeric text in HTML `labels`, results in 400K example datset. Balancing the labels downsamples the dataset to $85K$ samples. Each example is represented as **(HTML, element, description)**, where **HTML** is the HTML plaintext of the page, **element** is the element whose `id` attribute matches that appearing in the `label`'s `for` attribute, and **description** is the text inside the `label` element (see example in Figure 1a). More details of the dataset can be found in Appendix A.1.

6 PRE-PROCESSING

In treating HTML as token sequences, we minimize any HTML tree pre-processing prior to model input. We thus provide HTML as raw text (i.e., sequences of text tokens) and only apply a snippet extraction pre-processing for pages which are too large to fit into the typical LLMs context windows.

[1] `http://commoncrawl.org`

Snippet Extraction. Real HTML pages can grow extremely large, reaching thousands of elements, far beyond the context window of the largest LLM that we studied (1920 tokens in PaLM (Chowdhery et al., 2022)). LLMs typically truncate such long sequences, which can be detrimental to HTML understanding as HTMLs are not linearly structured. We take an element-centric approach and extract HTML snippets (a small portion of HTML code) surrounding a salient element (Figure 5). A simple heuristic, which controls the tree's width and depth, guides the process – start with a salient element and traverse its ancestors in the HTML tree until a stopping condition is satisfied. As we traverse up, we estimate the height of the tree and the increased number of descendants of the new root. We stop when either violates a pre-defined limit and take the current sub-tree as the snippet. We mark the salient element using a special attribute, called *target*, to distinguish it from other elements .We perform the snippet extraction for the semantic classification and description generation datasets, and keep the full HTML pages in MiniWoB because these pages are typically much smaller than real-world HTML.

HTML un-Parsing. We provide the models with the unparsed plaintext HTML in the form of a sequence of tokens. This canonical representation does not require specific model architectures such as hierarchical networks (Liu et al., 2018; Gur et al., 2021) and can be fed into any LLM. We transform all datasets by converting every HTML page or snippet into a sequence. For MiniWoB, we additionally concatenate (action history, instruction, HTML) tuples into a single sequence.

7 Model Training

We study a variety of Transformer-based LLMs with different sizes and architectures for HTML understanding tasks (Table 1). In the rest of the text, we prefix models fine-tuned for *Autonomous Web Navigation*, *Description Generation*, and *Semantic Classification* with WebN-, WebD-, WebC- respectively. For instance, WebD–T5-3B is the three billion parameter T5 model (Raffel et al., 2020) fine-tuned for the *Description Generation* task. The rest of this section introduces training details.

Encoder-Decoder and Decoder-only Models. We train encoder-decoder, T5 (Raffel et al., 2020) and decoder-only models, LaMDA (Thoppilan et al., 2022) and PaLM (Chowdhery et al., 2022), with text input and text output (Figure 1b). Inputs are raw HTML pages or snippet texts; similarly, outputs are categories, natural language descriptions, or actions represented as text. While descriptions are already represented in natural language, we use names of categories for *Semantic Classification* similar to previous classification problems in NLP (Raffel et al., 2020). Actions are converted into text by first converting them into key and value pairs and then concatenating the pairs.

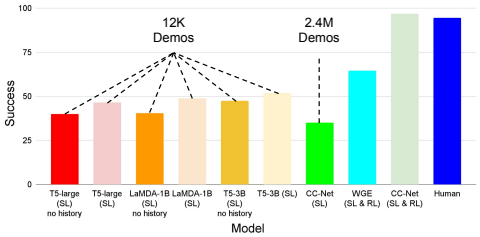
Many websites in MiniWoB require multiple interaction, such as *click-button-sequence* or *click-checkboxes*, where each interaction might cause a subtle change in the website state. For instance, after clicking on a checkbox in the *click-checkboxes* website, its value flips from positive to negative or the other way around, which is not always reflected in LLMs' predictions and leads to action repetitions. We solve this issue by augmenting tuples in the dataset with a sequence of past actions, **(action history, instruction, HTML, action)**, and allowing LLMs to learn from past experience.

Encoder-only Models. We train encoder-only models, BERT style (Devlin et al., 2018), with text input and categorical output. We keep semantic categories as discrete one-hot classes. To train encoder-only models, we add a new classification layer after the final encoder layer to produce a distribution over semantic categories. In addition to the typical BERT models, we study MobileBERT (Sun et al., 2020), distilled from BERT-large with inverted bottlenecks, and Albert-XL (Lan et al., 2020), with parameter sharing and embedding split.

8 Results

This Section evaluates the performance of the HTML pre-trained encoder-decoder architectures (Web-T5 class of LLMs) on the three HTML Understanding tasks. (Web-T5 class of LLMs). We compare the models' performance with the existing baselines where possible (N), and against other LLM architectures and training regimes (all tasks). Subsections 8.1, 8.2, and 8.3 evaluate task-specific performance, while the Section 8.4 assesses the performance across all the tasks.

Metrics: Autonomous Web Navigation *Success Rate* evaluates the model performance, averaged over 100 episodes per task. Episodes end with either 1.0 for success and 0.0 for failure. *Accuracy*



(a) Baseline comparison.

Model Name	Success (%)	Model Size
T5-large	18.1	800M
LaMDA-1B	15.6	1B
T5-3B	11.1	3B
WebN-T5-large	46.4	800M
WebN-LaMDA-1B	48.8	1B
WebN-T5-3B	51.8	3B

(b) Pre-training effect.

Figure 2: a) WebN–T5* performance compared to the previous SOTA models on MiniWoB benchmark. WebN-T5-3B improves the task success 16% while using 192 times less data, over to the best SL model, CC-Net (SL). LLMs performance is only surpassed by works utilizing RL, requiring orders of magnitude more online experience interaction with websites. b) LLMs with and without pretraining on *Autonomous Web Navigation* task. 2.5-4.5x performance improvement with pretraining.

measures exact match between prediction and ground truth in semantic classification and description generation tasks. In the description generation task, we additionally use typical text evaluation metrics, *BLEU* and *ROUGE-1*, to understand if a model fails to locate or to generate the description.

8.1 Autonomous Web Navigation Results

For *Autonomous Web Navigation* we fine-tune two WebN- encoder-decoder architectures (WebN-T5-large and WebN-T5-3B) on 12k demonstrations from human-annotated real websites. We evaluate the models on MiniWob (Liu et al., 2018) benchmark, and compare with specialized architectures trained using supervised learning (SL) on 2.4 million human expert demonstrations *CC-Net (SL)* (Humphreys et al., 2022), and two RL models bootstrapped with SL, CC-Net (SL) (CC-Net (SL & RL) (Humphreys et al., 2022), and WGE (SL & RL) (Liu et al., 2018)). We provide human expert data as well. Additionally, we compare with the decoder-only architecture (WebN-Lambda-1B) and perform an ablation study on the impact of including the action history in the input.

Comparison to SoTA. Since previous works report success on only a subset of websites in MiniWoB, we evaluate on 48 out of 62 websites that are common across all models (Figure 2a). Table 8 in the Appendix reports all results. Compared to CC-Net (SL) which is trained on all 2.4M demonstrations, WebN-T5-3B improves the success 16% while significantly sample efficient. It yields 192x training data reduction, being trained only on the 12K publicly-available demonstrations. All LLMs outperform SL models. Specifically, WebN-T5-3B significantly improves on websites requiring multiple-action sequences such as *click_checkboxes* or websites requiring entering text such as *login_user* (Table 8).

Action history ablation. Across all LLMs we consistently observe a decrease in success, on average 6.4%, when past actions are excluded from the inputs (Figure 2a). Action history helps with websites that require entering multiple texts, as well as understanding minor changes that could be difficult to detect (e.g. *click_checkboxes* and *multi_layout*). *multi_layout* requires entering 3 different texts in the website where the layout is randomized at each episode, yet, surprisingly, even the (relatively smaller) WebN-T5-large model without action history outperforms the CC-Net (SL) model; illustrating that incorporating action history is not the only contributing factor for the better success.

8.2 Semantic Classification Task Results

To evaluate the *Semantic Classification* we compare the T5 encoder-decoder architecture's three size variants (WebC-T5-base, WebC-T5-large, and WebC-T5-3B) fine-tuned on 38K real, human-labeled websites. We compare with a fine-tuned encoder only architectures (WebC-*BERT*), three fine-tuned decoder-only architectures (WebC-LaMDA and PaLM), and both encoder-decoder and decoder-only models trained on 38K human labeled websites from scratch (Table-2) All WebC-LLMs perform well, having accuracy over 75%.

Accuracy per category. The fine-tuned encoder-decoder model performs strongly on majority of the categories (Figure 3), even on those with very few samples. For instance, the model is 100%

Model Name	Test (%)	Dev (%)	Model Size	Code in training Corpus
WebC-MobileBERT	78.1	77.7	24.6 M	0%
WebC-Albert-XL	83.5	83.1	58.9 M	
WebC-BERT-smallest	84.4	83.6	38.7 M	
WebC-BERT-small	84.4	85.2	52.8 M	
WebC-BERT-medium	85.2	84.5	67 M	
WebC-BERT-base	83.9	84.8	109.5 M	
WebC-BERT-large	84.1	85.8	335.2 M	
WebC-T5-base	86.8	89.9	250 M	
WebC-T5-large	87.0	89.3	800 M	
WebC-T5-3B	87.7	90.3	3 B	
WebC-LaMDA-1B	87.4	87.1	1 B	12.5% Code
WebC-PaLM-8B	86.6	89.9	8 B	5% Code (0.875% HTML)
WebC-PaLM-62B	**88.7**	**90.5**	62 B	5% Code (0.875% HTML)
T5-large	76.4	75.2	800 M	0%
T5-3B	77.2	73.8	3 B	
PaLM-8B	73.3	70.1	8 B	

Table 2: LLMs performance on the *Semantic Classification* task. Pre-training helps LLMs transfer better, improving the accuracy of PaLM-8B more than 12% when compared to the same architecture trained only on HTML data (no pretraining). While WebC-PaLM-62B clearly performed better than all other models, we found WebC-T5-large to be competitive with much larger models such as WebC-LaMDA-1B or WebC-PaLM-8B.

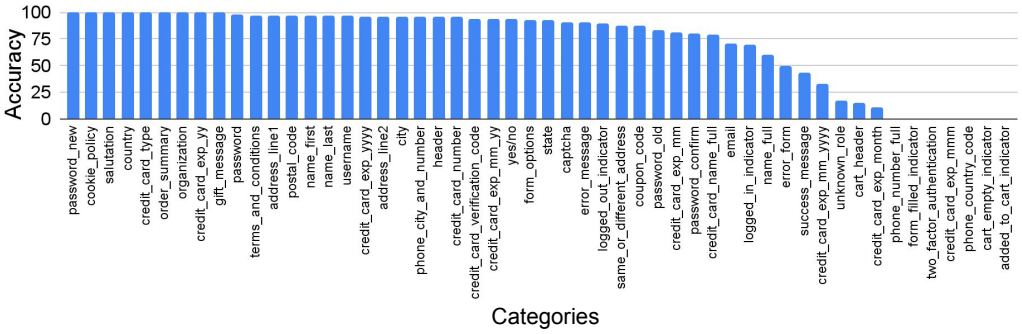
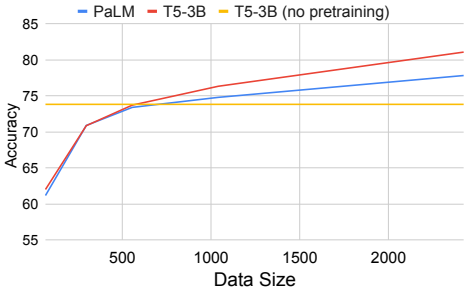


Figure 3: Accuracy per classification category of the WebC-T5-3B model on the development dataset.

New descendants (%)	Height	Test (%)	Dev (%)
25	3	87.7	90.3
25	4	88.6	89.2
50	3	88.4	90.0
50	4	89.3	89.2
300	5	87.8	88.8
500	7	75.8	74.5

(a)



(b)

Figure 4: a) Effect of snippet extraction parameters on WebC-T5-3B. Increases above 50% in new descendants and height of 4. Large increases in both parameters lead to large snippets and decrease in accuracy. b)Accuracy over training data size. WebC-T5-3B outperforms T5-3B (no pretraining) using only 1000 labeled examples (3.4% of all training dataset), and outperforms WebC-PaLM-8B which is an order of magnitude larger.

	Test			Dev		
Model Name	**Accuracy**(%)	**BLEU**	**ROUGE-1**	**Accuracy**(%)	**BLEU**	**ROUGE-1**
WebD-T5-large	90.1	94.1	94.7	76.9	87.4	87
WebD-LaMDA-1B	89.7	92.3	94.6	77.5	83.2	86.5
WebD-T5-3B	90.8	94.7	95	78.1	87.8	87.5
Closest Description	61.2	35.8	62.7	56.8	17.1	58.4

Table 3: Description generation accuracy of LLMs.

accurate on *password_new* which has only 56 training examples, because the class is unambiguous. On the other hand, unsurprisingly, the performance drops when the category is ambiguous, such as in the *email* category which is frequently mistaken as *username*.

Snippet generation ablation. Two hyper-parameters govern snippet generation: percentage of new descendants and height of the new root. While small variations of both parameters don't change the performance, increasing both degrades the performance significantly (Table 4a). With new descendants up to 500% and height up to 7, the performance drops by more than 15%. Note that snippet generation returns the full-page HTML when both parameters increase indefinitely.

Data size impact. When varying the fine-tuning training data sizes (1, 5, 10, 20, or 50 samples per class) in Figure 4b, WebC-T5-3B slightly outperforms WebC-PaLM-8B which is an order of magnitude larger. Compared to T5-3B that is trained on all available HTML data without pretraining, WebC-T5-3B achieves better performance while using only 3.4% of labeled data (1000 samples); showing outstanding sample efficiency.

8.3 Description Generation Task Results

For *Description Generation* we split the CommonCrawl dataset based on URL top-level domains to test LLMs' capabilities to generalize to unseen HTML. We fine-tune encoder-decoder architectures (WebD–T5*), decoder-only models (Table 3). We also present a strong intuitive baseline, finding the description closest to the salient element in the HTML text (Closest Description).

Accuracy and Similarity Performance All pre-trained models achieve scores across all metrics (90% on the accuracy) and higher BLEU and ROUGE-1 scores (Table 3). The difference indicates that the models are capable of locating the descriptions, but not generating the exact output. It is interesting that WebD–T5-large and WebD–LaMDA-1B with similar accuracy and ROUGE-1 scores, WebD–T5-large has substantially higher (3%) BLEU score.

8.4 HTML Understanding LLMs Performance Analysis Across Tasks

8.4.1 Pre-training effect: Pre-training on large text corpora matters.

Fine-tuned pretrained LLMs outperform LLMs trained on HTML-only data, improving the performance by more than 34.1% on the *Autonomous Web Navigation* (Table 2b), and 10% to 12.7% on the *Semantic Classification* task (Table 2).

Since *Autonomous Web Navigation* is the most difficult task, the improved performance is an encouraging evidence of the value of LLMs in HTML understanding tasks. Specifically, we observe that LLMs without pretraining were comparable to fine-tuned pretrained models only on websites that require simple text matching. However, in websites such as *click_checkboxes*, text matching is harder and pretraining helps. We also found that without pretraining, model outputs were frequently in an incorrect format such as invalid dictionaries or invalid refs with non-integer values. This suggests the large corpora used for pretraining helps models to learn the general HTML structure.

8.4.2 Architecture Effect: T5 based models perform best across all tasks

Encoder-decoder T5 based models perform better across all three tasks. On the *Autonomous Web Navigation* task, encoder-decoder (WebN-T5) architectures are better or comparable to WebN-LaMDA-1B (Figure 2a). On the *Semantic Classification*, the smallest encoder-decoder model (WebC-T5-base) performs comparably to much larger decoder-only models (WebC-LaMDA-1B or

WebC-PaLM-8B) and the largest encoder-only model (WebC-BERT-large) which has 85M more parameters (Table 2). We also observe that decoder-only PaLM-8B performs worse than much-smaller encoder-decoder T5-large when trained only on HTML data. Finally, on the *Description Generation* encoder-decoder architecture has higher BLEU score which approximately measures precision.

One particular explanation is that encoder-decoder T5 models utilize an encoder with a bidirectional attention mechanism, not present in the LaMDA and PaLM decoders. The bidirectional attention mechanism can process HTML pages from both ends, potentially overcoming the loss of information when tree-structured HTML pages are converted into a fixed linear text sequences. This hypothesis would explain the strong performance of T5 models on all three tasks.

8.4.3 MODEL SIZE EFFECT: SIZE (SUB-LINEARLY) MATTERS.

Across the tasks it appears that the architecture plays an important role in the model performance. Model size and performance are also positively correlated, although they reach diminishing returns. For instance, the model performance is $O(\log \log n)$ if n is model size on the *Semantic Classification*(Figure 4b in Appendix). On the *Autonomous Web Navigation* task performance grows slowly with the model size (Table 8, while on the *Description Generation* it plateaus 3.

8.5 DISCUSSION

Bi-directional attention vs training corpora: Pretraining on large corpora matters, yielding $\leq$4.5x performance improvements. Larger models tend to be better and we credit the bi-directional attention for T5's best overall performance across the tasks. PaLM And LaMDA included HTML and other code in the pre-training corpora, but BERT and T5 architectures did not. This strengthens the hypothesis behind the role of the bi-directional attention, and opens up a possibility to improving the performance on T5 architectures by training them on the corpora with HTML.

Practical impact on labeling: When available, the pretrained LLMs need very little new expert data (200x and 30x reduction on the web navigation and classification tasks). This has a big potential impact on practical applications, reducing the data collection time and cost by orders of magnitude.

Bigger is not always better: When choosing the model size, the expected performance gains (sub-linear at best and asymptotic at worst) should be considered alongside the model's training and inference time and cost. For instance, on the classification task, the largest model WebC-PaLM-62B takes several days to fine-tune, and infers at 30 Hz, while WebC-T5-large fine-tunes in several hours and infers at 700 Hz – an order of magnitude more expensive for a single percent uplift in accuracy. BERT models on the other hand train in minutes. If the application does not require high precision, they might be a good choice.

Context window is a bottleneck: The major bottleneck for the HTML understanding tasks seems to be the context window length that the current LLMs support, even with models that accept 1000+ tokens. It remains prohibitive to evaluate web navigation tasks on the real websites that are orders of magnitude larger than pages in MiniWob. Similarly, we observed that increasing the snippet size leads to major performance degradation. This makes HTML Understanding an interesting benchmark for future LLM development. For instance, new methods may need to be developed to compress the state representation of web content for use in LLM context windows.

9 CONCLUSION

We presented canonical tasks and fine-tuned LLMs for HTML understanding. The comprehensive evaluations and analyses over a range of architectures, dataset sizes, and baselines yields practical findings and highlights current limitations of these models. We find that a) pretraining is critical for the performance and can reduce labeled data requirements / improve sample efficiency up to 200x; b) model architecture is the second most important factor and T5 models with bi-directional attention and encoder-decoder architecture performs the best across the board; c) given a choice, model size should be evaluated in the context of the models training and inference performance, as the model size sub-linearly predicts its performance. Finally, the proposed HTML understanding tasks highlight the relatively short context window that limits current LLMs, suggesting possibilities for future research that incorporate or eliminate this constraint.

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A APPENDIX

A.1 DATASET DETAIL

Examining the description distribution, we found the original $400K$ dataset to be very skewed; only 20 descriptions (such as *Email* and *Password*) were covering 50% of the dataset. We sub-sampled the

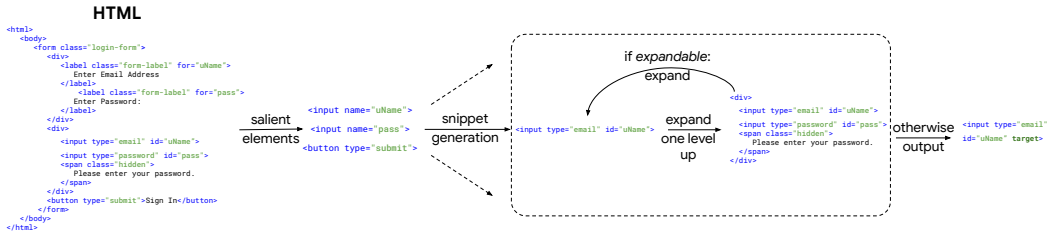


Figure 5: High-level overview of our pre-processing pipeline for generating snippets from a full HTML webpage. Given the page, we detect salient elements and for each one of them we extract snippets by recursively moving up in the HTML tree until a validation heuristic fails.

dataset so that each unique description has at most 10 data points. We also found that `for` attributes are almost always defined for HTML `labels`. This could cause a model to overfit and just find the `label` element in the HTML and ignore everything else. To avoid this sort of 'cheating' we replace the tags of HTML `labels` by randomly sampling from {`div, span, a, label`}. These tags are also frequently used to inject text in HTML but they are very rarely used with `for` attributes. Finally, we removed examples where there are only a single text in the HTML since models can trivially generate descriptions by finding the only text in the HTML, which biases model weights and evaluation metrics. After this final step, we have a total of $85K$ labeled examples.

A.1.1 Snippet Generation

In Figure 5, we give a high-level overview of our snippet generation procedure.

A.2 Additional Results

A.2.1 Semantic Classification

Error Analysis. We manually examined 50 errors of T5-3B model over the development set (Table 4) and assigned them into one of the 9 error types that we devised. We found that 32% of the errors are due to lack of information in the HTML snippets, which is mainly the result of lost information during snippet extraction process. Annotation errors or email/username ambiguity make up 30% of the errors. These can't be improved without revising the annotated data or adding extra information to resolve the ambiguity. We also found that the model sometimes picks a more general category, or a nearby text misleads the model; the latter usually happens when the HTML snippet is long where majority of the elements are noise.

Error Type	Percentage of Examples
Not enough information in the HTML snippet	30
Incorrect annotation (ex: "unknown_role" instead of "organization")	12
Annotation tool translates user selection incorrectly	8
Email/Username ambiguity	10
More general category (ex: "header" instead of "cart_header")	8
Immediate neighboring text misleads	8
Incorrect date formatting (ex: "mm" instead of "mmm")	4
No information in the HTML snippet	2
Others	18

Table 4: Types of errors over 50 manually examined examples. 32% of errors are due to lack of information in HTML snippets, 30% of errors are related to annotations or can't be improved due to ambiguity (email/username), and the remaining errors are incorrect predictions by the model.

Few-Shot Prompting In Table 5, we present few-shot prompting performance of a 540B PaLM model. We probe the model using a prompt template `<html> Role: <category>` with 1 example per category and generate categories using greedy-decoding. In our preliminary experiments, we found that few-shot prompting achieves only 45.6 accuracy, much lower than a model fine-tuned

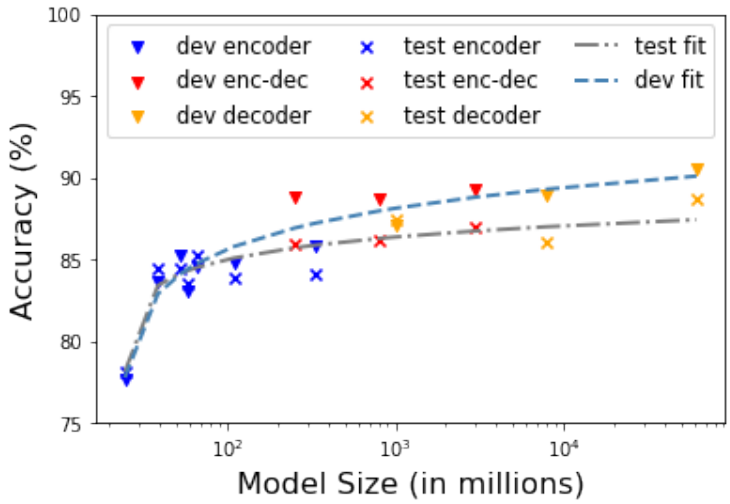
on the same data (Figure 6). We found two common problems – the model is not able to canonicalize predictions into categories and many of the examples are dropped due to context length.

We developed post-processing methods to alleviate the canonicalization problem and pre-processing methods to reduce lengths of examples. Adding a dictionary-based mapping on predictions – a manually curated paraphrase dictionary – improves the performance to 52.1. We also tried rewriting predictions by changing the order of tokens around "_" such as *name_first* to *first_name* which further improved the performance to 57.9. Finally, we cleaned examples in the prompt by removing certain elements such as *"svg", "path", "img"*, and *"iframe"* and also removing *class* attribute from every element; this pre-processing step gives 64.2.

Model Name	Test	Dev
PaLM-540B	64.2	60.3
- w/o Example Cleaning	57.9	57.2
- w/o Category Rewriting	52.1	50.7
- w/o Dictionary Mapping	45.6	45.1

Table 5: Few-shot prompting performance with different pre- and post-processing steps.

Figure 6: Performance comparison w.r.t. increasing model size. As the model size increases, we observe an increase in overall accuracy with PaLM-62B model achieving the highest accuracy while being 7x larger than PaLM-8B.



A.3 Sample Episodes from MiniWoB

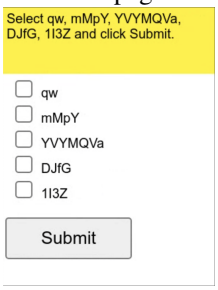
A.4 Detailed MiniWoB Results

Realistic Alaska Airlines Websites. While evaluating on simulated websites is useful to compare performance of models in a controllable setup, it is important to understand the sim-to-real gap for web navigation systems to be useful in practice. We split publicly available demonstrations into training and development set. We have 291 demonstrations for evaluation. We report numbers using offline demonstration replay experiment, mainly, percentage of actions that overlap with ground truth (offline accuracy) and percentage of episodes where all actions are same as ground truth (offline success). We achieve 10.3 offline task success and 73.7 offline accuracy. The accuracy indicates that the model takes the correct action 73.7% of the time but it finishes an episode correctly only 10.3% of the time.

A.5 Resource Requirements

Table 6: A sample web page and corresponding episode using the T5-3B model. At each time step, previous actions, instruction, and HTML are concatenated into a single HTML text. Note that at the beginning of episode, there is no past actions and we simply concatenate instruction and HTML. Action is generated as a sequence of tokens which is later parsed into a dictionary. The *ref* in the action points to an element that has a *ref* attribute with the same value. For instance, at the beginning of episode, *ref: 6* corresponds to an input with *ref=6*. At the end of the episode, the model clicks on the submit button and the episode terminates.

Web page



HTML Text	Action Text
Select qw, mMpY, YVYMQVa, DJfG, lI3Z and click Submit. <body ref="1"> <label ref="5"><input type="checkbox" id="ch0" ref="6" value="False"></input><t class="TEXT_CLASS" ref="None">qw</t></label><label ref="7"><input type="checkbox" id="ch1" ref="8" value="False"></input><t class="TEXT_CLASS" ref="None">hHfDn8</t></label><label ref="9"><input type="checkbox" id="ch2" ref="10" value="False"></input><t class="TEXT_CLASS" ref="None">mMpY</t></label><label ref="11"><input type="checkbox" id="ch3" ref="12" value="False"></input><t class="TEXT_CLASS" ref="None">YVYMQVa</t></label><label ref="13"><input type="checkbox" id="ch4" ref="14" value="False"></input><t class="TEXT_CLASS" ref="None">DJfG</t></label><label ref="15"><input type="checkbox" id="ch5" ref="16" value="False"></input><t class="TEXT_CLASS" ref="None">lI3Z</t></label> <button id="subbtn" class="secondary-action" ref="17">Submit</button> </body>	{action: click, ref: 6}
{action: click, ref: 6} Select qw, mMpY, YVYMQVa, DJfG, lI3Z and click Submit. <body ref="1"> <label ref="5"><input type="checkbox" id="ch0" ref="6" value="True">/input><t class="TEXT_CLASS" ref="None">qw</t></label><label ref="7"><input type="checkbox" id="ch1" ref="8" value="False"></input><t class="TEXT_CLASS" ref="None">hHfDn8</t></label><label ref="9"><input type="checkbox" id="ch2" ref="10" value="False"></input><t class="TEXT_CLASS" ref="None">mMpY</t></label><label ref="11"><input type="checkbox" id="ch3" ref="12" value="False">/input><t class="TEXT_CLASS" ref="None">YVYMQVa</t></label><label ref="13">input type="checkbox" id="ch4" ref="14" value="False"></input><t class="TEXT_CLASS" ref="None">DJfG</t></label><label ref="15"><input type="checkbox" id="ch5" ref="16" value="False"></input><t class="TEXT_CLASS" ref="None">lI3Z</t></label> <button id="subbtn" class="secondary-action" ref="17">Submit</button> </body>	{action: click, ref: 10}
{action: click, ref: 6},{action: click, ref: 10} Select qw, mMpY, YVYMQVa, DJfG, lI3Z and click Submit. <body ref="1"> <label ref="5"><input type="checkbox" id="ch0" ref="6" value="True"></input><t class="TEXT_CLASS" ref="None">qw</t></label><label ref="7"><input type="checkbox" id="ch1" ref="8" value="False"></input><t class="TEXT_CLASS" ref="None">hHfDn8</t></label><label ref="9"><input type="checkbox" id="ch2" ref="10" value="True"></input><t class="TEXT_CLASS" ref="None">mMpY</t></label><label ref="11"><input type="checkbox" id="ch3" ref="12" value="False"></input><t class="TEXT_CLASS" ref="None">YVYMQVa</t></label><label ref="13"><input type="checkbox" id="ch4" ref="14" value="False"></input><t class="TEXT_CLASS" ref="None">DJfG</t></label><label ref="15"><input type="checkbox" id="ch5" ref="16" value="False"></input><t class="TEXT_CLASS" ref="None">lI3Z</t></label> <button id="subbtn" class="secondary-action" ref="17">Submit</button> </body>	{action: click, ref: 12}
{action: click, ref: 6},{action: click, ref: 10},{action: click, ref: 12} Select qw, mMpY, YVYMQVa, DJfG, lI3Z and click Submit. <body ref="1"> <label ref="5"><input type="checkbox" id="ch0" ref="6" value="True"></input><t class="TEXT_CLASS" ref="None">qw</t></label><label ref="7"><input type="checkbox" id="ch1" ref="8" value="False"></input><t class="TEXT_CLASS" ref="None">hHfDn8</t></label><label ref="9"><input type="checkbox" id="ch2" ref="10" value="True"></input><t class="TEXT_CLASS" ref="None">mMpY</t></label><label ref="11"><input type="checkbox" id="ch3" ref="12" value="True"></input><t class="TEXT_CLASS" ref="None">YVYMQVa</t></label><label ref="13"><input type="checkbox" id="ch4" ref="14" value="False"></input><t class="TEXT_CLASS" ref="None">DJfG</t></label><label ref="15"><input type="checkbox" id="ch5" ref="16" value="False"></input><t class="TEXT_CLASS" ref="None">lI3Z</t></label> <button id="subbtn" class="secondary-action" ref="17">Submit</button> </body>	{action: click, ref: 14}

```
{action: click, ref: 6},{action: click, ref: 10},{action: click, ref: 12},
{action: click, ref: 14} Select qw, mMpY, YVYMQVa, DJfG, lI3Z and click Submit.
<body ref="1"><div id="wrap" ref="2"><div id="area" ref="3"><div id="boxes"
ref="4"><label ref="5"><input type="checkbox" id="ch0" ref="6" value="True">
</input><t class="TEXT\_CLASS" ref="None">qw</t></label><label ref="7"><input
type="checkbox" id="ch1" ref="8" value="False"></input><t class="TEXT\_CLASS"
ref="None">hHfDn8</t></label><label ref="9"><input type="checkbox" id="ch2"
ref="10" value="True"></input><t class="TEXT\_CLASS" ref="None">mMpY</t></label>
<label ref="11"><input type="checkbox" id="ch3" ref="12" value="True"></input>
<t class="TEXT\_CLASS" ref="None">YVYMQVa</t></label><label ref="13"><input
type="checkbox" id="ch4" ref="14" value="True"></input><t class="TEXT\_CLASS"
ref="None">DJfG</t></label><label ref="15"><input type="checkbox" id="ch5"
ref="16" value="False"></input><t class="TEXT\_CLASS" ref="None">lI3Z</t>
</label></div><button id="subbtn" class="secondary-action" ref="17">Submit
</button></div></div></body>
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{action: click, ref: 16}

```
{action: click, ref: 6},{action: click, ref: 10},{action: click, ref: 12},
{action: click, ref: 14},{action: click, ref: 16} Select qw, mMpY, YVYMQVa,
DJfG, lI3Z and click Submit. <body ref="1"><div id="wrap" ref="2"><div id="area"
ref="3"><div id="boxes" ref="4"><label ref="5"><input type="checkbox" id="ch0"
ref="6" value="True"></input><t class="TEXT\_CLASS" ref="None">qw</t></label>
<label ref="7"><input type="checkbox" id="ch1" ref="8" value="False"></input><t
class="TEXT\_CLASS" ref="None">hHfDn8</t></label><label ref="9"><input
type="checkbox" id="ch2" ref="10" value="True"></input><t class="TEXT\_CLASS"
ref="None">mMpY</t></label><label ref="11"><input type="checkbox" id="ch3"
ref="12" value="True"></input><t class="TEXT\_CLASS" ref="None">YVYMQVa</t>
</label><label ref="13"><input type="checkbox" id="ch4" ref="14" value="True">
</input><t class="TEXT\_CLASS" ref="None">DJfG</t></label><label ref="15"><input
type="checkbox" id="ch5" ref="16" value="True"></input><t class="TEXT\_CLASS"
ref="None">lI3Z</t></label></div><button id="subbtn" class="secondary-action"
ref="17">Submit</button></div></div></body>
```

{action: click, ref: 17}

Table 7: Success rate comparison of various models in MiniWoB tasks. Baseline results are borrowed from (Humphreys et al., 2022). Note that these are normalized between 0 and 1.

TASK	Human	WebC-T5-3B	WebC-T5-3B (no history)	CC-Net (SL & RL)	CC-Net (SL)	World of bits (SL & RL)	Workflow guided exploration (SL & RL)	Learning to navigate the web (RL)	DOM-Q-Net (RL)	Workflow guided exploration (Augmented)	Learning to navigate the web (Augmented)	Aggregated SOTA (SL & RL)	Aggregated SOTA (Augmented)
bisect-angle	0.92	n/a	n/a	0.97	0.29	0.8	n/a	n/a	n/a	n/a	n/a	0.8	0.8
book-flight	0.87	0	0	0.87	0	0	0	n/a	n/a	0	1	0	1
chase-circle	0.82	n/a	n/a	0.93	0.8	1	n/a	n/a	n/a	n/a	n/a	1	1
choose-date-easy	0.99	0.03	0.05	0.99	0.42	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
choose-date-medium	0.98	0	0	0.99	0.26	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
choose-date	0.97	0	0	0.97	0.12	0	0	n/a	1	0	n/a	1	1
choose-list	0.98	0.26	0.14	0.99	0.19	0.25	0.16	0.26	n/a	0.16	0.26	0.26	0.26
circle-center	0.96	n/a	n/a	0.97	0.36	0.98	n/a	n/a	n/a	n/a	n/a	0.98	0.98
click-button-sequence	0.94	1	1	1	0.47	0.22	0.99	n/a	1	1	n/a	1	1
click-button	0.98	1	0.96	1	0.78	0.62	1	1	1	1	1	1	1
click-checkboxes-large	0.87	0.22	0	0.71	0	n/a	0.68	n/a	n/a	0.84	n/a	0.68	0.84
click-checkboxes-soft	0.73	0.54	0.43	0.95	0.04	n/a	0.51	n/a	n/a	0.94	n/a	0.51	0.94
click-checkboxes-transfer	0.98	0.63	0.34	0.99	0.36	n/a	0.64	n/a	n/a	0.64	n/a	0.64	0.64
click-checkboxes	0.97	0.96	0.84	0.98	0.32	0.48	0.98	n/a	1	1	n/a	1	1
click-collapsible-2	0.97	0	0.01	0.98	0.17	0.11	0.65	n/a	n/a	0.99	n/a	0.65	0.99
click-collapsible	0.99	0	0.01	1	0.81	0.98	1	1	n/a	1	1	1	1
click-color	0.97	0.27	0.23	1	0.82	0.23	1	n/a	n/a	1	n/a	1	1
click-dialog-2	0.99	0.24	0.35	1	0.88	0.53	1	n/a	n/a	1	n/a	1	1
click-dialog	1	1	1	1	0.95	1	1	1	1	1	1	1	1
click-link	0.99	1	0.96	0.99	0.59	0.31	1	1	1	1	1	1	1
click-menu-2	0.98	n/a	n/a	0.83	0.52	0.16	n/a	n/a	n/a	n/a	n/a	0.16	0.16
click-menu	0.97	0.37	0.38	0.94	0.22	0.13	n/a	n/a	n/a	n/a	n/a	0.13	0.13
click-option	0.99	0.87	0.78	0.99	0.21	0.28	1	n/a	1	1	n/a	1	1
click-pie	0.98	0.51	0.14	0.97	0.15	0.15	0.32	1	n/a	0.32	1	1	1
click-scroll-list	0.91	0	0	0.6	0.01	0.07	n/a	n/a	n/a	n/a	n/a	0.07	0.07
click-shades	0.91	0	0	1	0.04	0.27	0.22	n/a	n/a	0.99	n/a	0.27	0.99
click-shape	0.88	0.53	0.54	0.95	0.11	0.11	0.64	n/a	n/a	0.64	n/a	0.64	0.64
click-tab-2-easy	0.99	n/a	n/a	0.99	0.61	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
click-tab-2-hard	0.96	0.12	0.13	0.98	0.19	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
click-tab-2-medium	0.97	n/a	n/a	0.99	0.54	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
click-tab-2	0.97	0.18	0.09	0.98	0.27	0.08	0.64	n/a	1	0.98	n/a	1	1
click-tab	0.99	0.74	1	1	0.95	0.97	0.55	1	1	1	1	1	1
click-test-2	0.99	1	1	1	0.95	0.83	1	n/a	1	1	n/a	1	1
click-test-transfer	0.99	n/a	n/a	1	0.94	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
click-test	1	1	1	1	1	1	1	n/a	1	1	n/a	1	1
click-widget	0.83	1	0.97	1	0.56	0.34	0.93	n/a	1	0.93	n/a	1	1
copy-paste-2	0.94	n/a	n/a	0.63	0.01	0	n/a	n/a	n/a	n/a	n/a	0	0
copy-paste	0.94	n/a	n/a	0.79	0.04	0	n/a	n/a	n/a	n/a	n/a	0	0
count-shape	0.82	0.41	0.43	0.85	0.21	0.18	0.59	n/a	n/a	0.76	n/a	0.59	0.76
count-sides	0.98	n/a	n/a	1	0.74	0.3	n/a	n/a	n/a	n/a	n/a	0.3	0.3
drag-box	0.99	n/a	n/a	1	0.61	0.31	n/a	n/a	n/a	n/a	n/a	0.31	0.31
drag-cube	0.99	n/a	n/a	0.79	0.23	0.18	n/a	n/a	n/a	n/a	n/a	0.18	0.18
drag-item	0.98	n/a	n/a	1	0.61	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
drag-items-grid	0.87	n/a	n/a	0.98	0.05	0.01	n/a	n/a	n/a	n/a	n/a	0.01	0.01
drag-items	0.93	n/a	n/a	0.99	0.13	0.41	n/a	n/a	n/a	n/a	n/a	0.41	0.41
drag-shapes	0.96	n/a	n/a	0.99	0.26	0.92	n/a	n/a	n/a	n/a	n/a	0.92	0.92
drag-sort-numbers	0.92	n/a	n/a	0.97	0.11	0.66	n/a	n/a	n/a	n/a	n/a	0.66	0.66
email-inbox-delete	0.99	n/a	n/a	1	0.22	n/a	n/a	n/a	1	n/a	n/a	1	1
email-inbox-forward-nl-turk	0.88	0.33	0.09	1	0	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
email-inbox-forward-nl	0.91	0.60	0.09	1	0	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
email-inbox-forward	0.96	n/a	n/a	1	0.01	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
email-inbox-important	0.99	n/a	n/a	1	0.3	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
email-inbox-nl-turk	0.93	0.23	0.26	1	0.05	n/a	0.77	n/a	n/a	0.93	n/a	0.77	0.93
email-inbox-noscroll	0.96	n/a	n/a	1	0.13	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
email-inbox-reply	0.91	n/a	n/a	1	0	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
email-inbox-star-reply	0.95	n/a	n/a	1	0.11	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
email-inbox	0.96	0.38	0.21	1	0.09	0.03	0.43	n/a	0.54	0.99	n/a	0.54	0.99
enter-date	0.97	0	0	1	0.02	0.61	0	1	n/a	0.96	1	1	1
enter-password	0.96	0.97	0.92	1	0.02	0	0.99	1	1	1	1	1	1
enter-text-2	0.91	n/a	n/a	0.98	0.04	0	n/a	n/a	n/a	n/a	n/a	0	0
enter-text-dynamic	0.97	0.98	0.92	1	0.39	1	1	1	1	1	1	1	1
enter-text	0.98	0.89	0.99	1	0.35	0	1	n/a	1	1	n/a	1	1
enter-time	0.98	0	0.01	0.97	0.04	0.08	0.52	n/a	n/a	0.9	n/a	0.52	0.9
find-midpoint	0.94	n/a	n/a	0.97	0.35	0.31	n/a	n/a	n/a	n/a	n/a	0.31	0.31
find-word	0.96	n/a	n/a	0.88	0.05	0	n/a	n/a	n/a	n/a	n/a	0	0
focus-text-2	0.99	1	1	1	0.96	0.83	1	n/a	1	1	n/a	1	1
focus-text	1	1	1	1	0.99	0.95	1	n/a	1	1	n/a	1	1
grid-coordinate	0.87	0.49	0.42	1	0.66	0.26	1	n/a	n/a	1	n/a	1	1
guess-number	0.99	0	0	1	0.21	0.2	0	n/a	n/a	0	n/a	0.2	0.2
highlight-text-2	0.97	n/a	n/a	1	0.4	0.13	n/a	n/a	n/a	n/a	n/a	0.13	0.13
highlight-text	0.97	n/a	n/a	1	0.51	0.9	n/a	n/a	n/a	n/a	n/a	0.9	0.9
identify-shape	0.98	0.88	0.89	1	0.68	0.36	0.9	n/a	n/a	1	n/a	0.9	1
login-user-popup	0.94	0.72	0.40	1	0.02	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
login-user	0.96	0.82	0.64	1	0	0	0.99	1	1	1	1	1	1
moving-items	0.18	n/a	n/a	0.88	0.13	0.78	n/a	n/a	n/a	n/a	n/a	0.78	0.78
multi-layouts	0.95	0.83	0.48	1	0	n/a	0.99	n/a	n/a	1	n/a	0.99	1
multi-orderings	0.96	0.88	0.64	1	0	n/a	0.05	n/a	n/a	1	n/a	0.05	1
navigate-tree	0.98	0.91	0.99	0.99	0.32	0.2	0.99	1	1	0.99	1	1	1
number-checkboxes	0.96	n/a	n/a	0.99	0	0.16	n/a	n/a	n/a	n/a	n/a	0.16	0.16
read-table-2	0.95	n/a	n/a	0.94	0	0	n/a	n/a	n/a	n/a	n/a	0	0
read-table	0.97	n/a	n/a	0.97	0.01	0	n/a	n/a	n/a	n/a	n/a	0	0
resize-textarea	0.94	n/a	n/a	1	0.27	0.11	n/a	n/a	n/a	n/a	n/a	0.11	0.11
right-angle	0.87	n/a	n/a	0.98	0.26	0.38	n/a	n/a	n/a	n/a	n/a	0.38	0.38
scroll-text-2	0.97	n/a	n/a	1	0.88	0.96	n/a	n/a	n/a	n/a	n/a	0.96	0.96
scroll-text	0.97	n/a	n/a	0.96	0.04	0	n/a	n/a	n/a	n/a	n/a	0	0
search-engine	0.97	0.34	0.34	1	0.15	0	0.26	n/a	1	0.99	n/a	1	1
simon-says	0.62	n/a	n/a	0	0.02	0.28	n/a	n/a	n/a	n/a	n/a	0.28	0.28
simple-algebra	0.86	n/a	n/a	0.75	0.03	0.04	n/a	n/a	n/a	n/a	n/a	0.04	0.04
simple-arithmetic	0.96	n/a	n/a	0.86	0.38	0.07	n/a	n/a	n/a	n/a	n/a	0.07	0.07
social-media-all	0.89	0	0	0.75	0	n/a	0.01	n/a	n/a	0.01	1	0.01	1
social-media-some	0.91	0.02	0	0.85	0.01	n/a	0.01	n/a	n/a	0.42	n/a	0.01	0.42
social-media	0.96	0.21	0.24	0.9	0.03	0.23	0.39	n/a	1	1	n/a	1	1
terminal	0.88	n/a	n/a	-0.01	0	0	n/a	n/a	n/a	n/a	n/a	0	0
text-editor	0.88	n/a	n/a	0.98	0.11	0.01	n/a	n/a	n/a	n/a	n/a	0.01	0.01
text-transform	0.86	n/a	n/a	0.6	0.19	0	n/a	n/a	n/a	n/a	n/a	0	0
tic-tac-toe	0.71	0.48	0.40	0.83	0.32	0.34	0.37	n/a	n/a	0.47	n/a	0.37	0.47
unicode-test	0.99	n/a	n/a	1	0.86	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
use-autocomplete	0.98	0.22	0.15	1	0.07	0	0.78	n/a	n/a	0.98	n/a	0.78	0.98
use-colorwheel-2	0.94	n/a	n/a	0.95	0.38	1	n/a	n/a	n/a	n/a	n/a	1	1
use-colorwheel	0.9	n/a	n/a	0.98	0.68	1	n/a	n/a	n/a	n/a	n/a	1	1
use-slider-2	0.97	n/a	n/a	0.95	0.03	0.15	n/a	n/a	n/a	n/a	n/a	0.15	0.15
use-slider	0.98	n/a	n/a	0.91	0.18	0.51	n/a	n/a	n/a	n/a	n/a	0.51	0.51
use-spinner	0.98	0.07	0.05	1	0.47	0.17	0.04	n/a	n/a	0.04	n/a	0.17	0.17
visual-addition	0.97	n/a	n/a	0.99	0.36	0.01	n/a	n/a	n/a	n/a	n/a	0.01	0.01

Table 8: Resource requirements and running time of LLMs.

Model Name	Model Size	TPU version	Batch size	Input sequence length	Examples per sec (training)	Examples per sec (inference)
PaLM	62B	TPU v4	8	1920	9.313	30.51
PaLM	8B	TPU v4	32	1920	64.4	184.3
T5	3B	TPU v4	128	512	163.8	734.5
LaMDA	1B	TPU v2	128	512	363.1	1416