Learning to Contextualize Web Pages for Enhanced Decision Making of LLM agents

Dongjun Lee*[1], Juyong Lee*[1], Kyuyoung Kim[1], Jihoon Tack[1], Jinwoo Shin[1], Yee Whye Teh[2], Kimin Lee[1]
KAIST[1], University of Oxford[2]

Introduction

Web page observations (e.g., HTML, AxTree) are often too long and full of unfamiliar UI elements, hindering decision-making of the LLM agents.

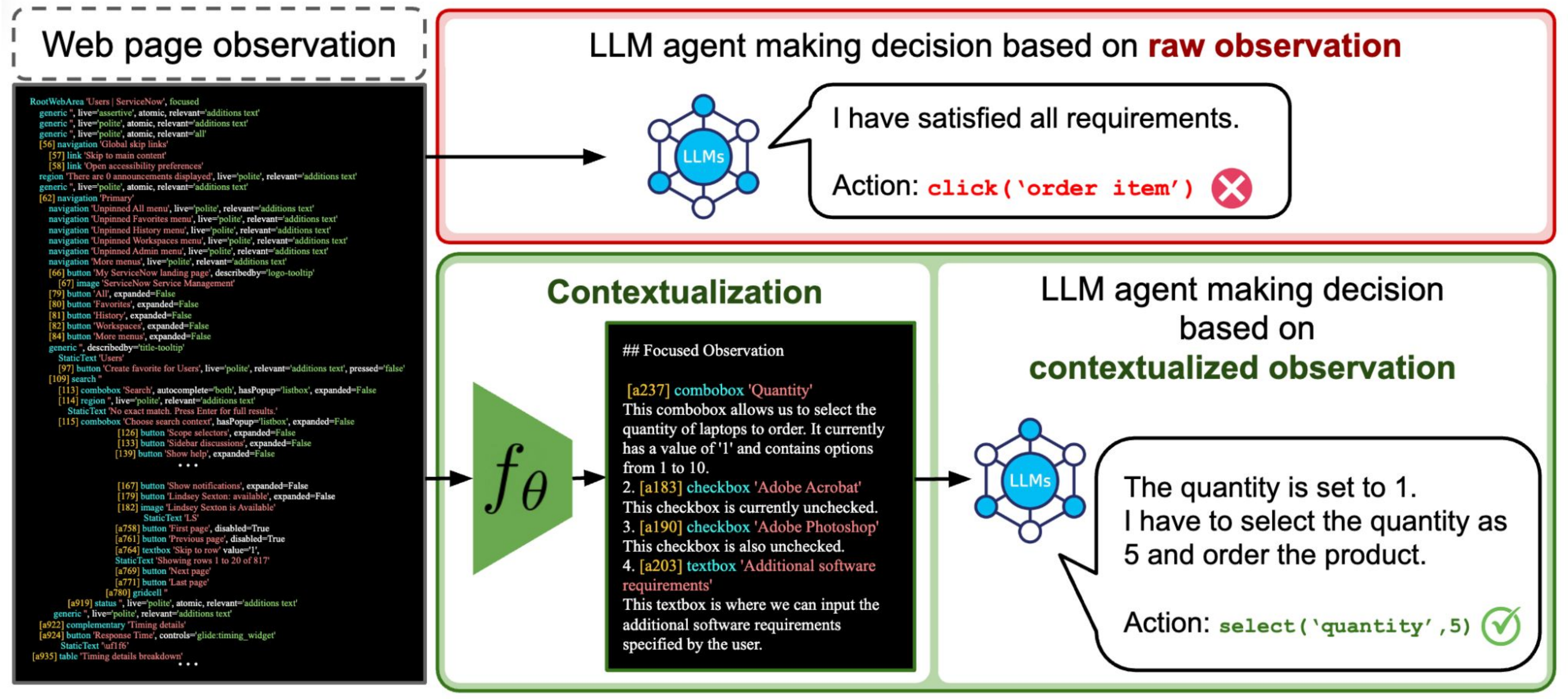


Figure 1. Contextualization module transforms complex web pages into a comprehensible format.

We introduce **LCoW**, a framework for **L**earning language models to **Co**ntextualize complex **W**eb pages into a more comprehensible form, thereby enhancing decision making by LLM agents

Method

Training algorithm for contextualization module in LCoW

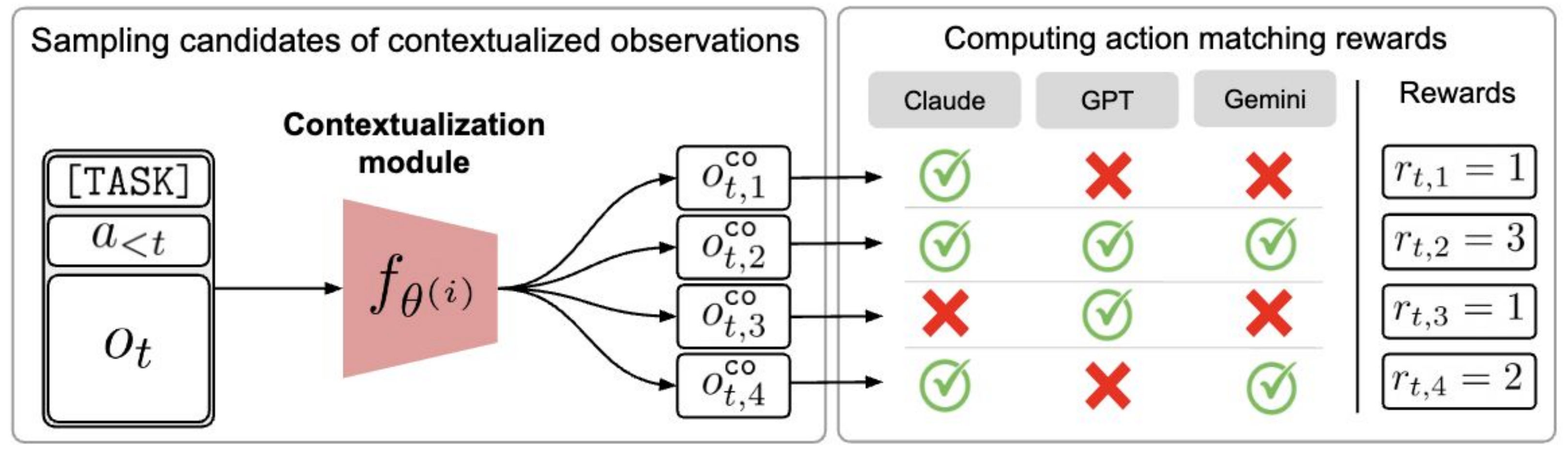


Figure 2. Illustration of action matching reward computation process.

- Step 1 - **Trajectory collection** (optionally, utilize demonstration)
  : Collect trajectories that successfully accomplish the instruction from environment.
- Step 2 - **Sampling optimal contextualization**
  - (a) Sample K contextualizations (temperature = 1.0).
  - (b) Measure how many LLM agents output correct action (action matching reward).
  - (c) Choose the contextualization with maximum action matching reward.
  - (d) If action matching rewards are zeros across every K contextualizations, we re-sample better contextualizations by prompting ground-truth action a_t as a hint.
- Step 3 - **Model update**
  : Train contextualization module with collected $([\texttt{TASK}, o_t, a_{<t}], o^{\text{co}}_{t,*})$ pairs via SFT.

Experiments

WebShop Experiment

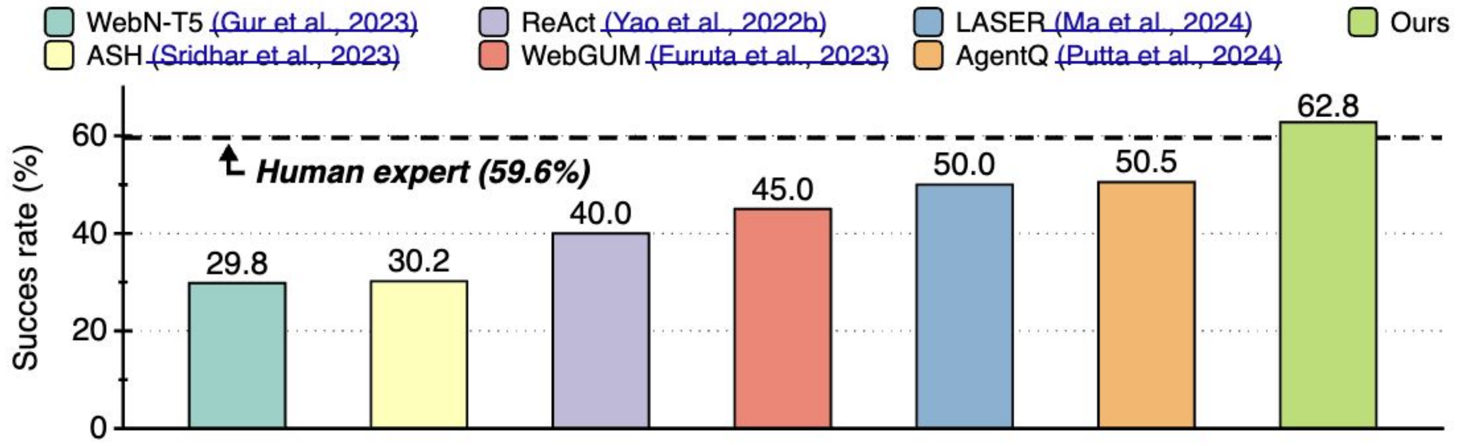


Figure 3. Comparison to baselines in WebShop benchmark.

	GPT-4o		Gemini-1.5-flash		Claude-3.5-Sonnet		Llama-3.1-70B (Unseen)	
	Success	Reward	Success	Reward	Success	Reward	Success	Reward
Raw observation	34.8%	0.496	43.6%	0.693	26.6%	0.336	34.2%	0.590
Self-ctx	26.2%	0.459	46.4%	0.608	12.4%	0.146	40.2%	0.547
LCoW (iter 1)	27.8%	0.545	46.4%	0.705	39.4%	0.600	39.2%	0.666
LCoW (iter 2)	46.0%	0.647	58.2%	0.796	58.8%	**0.780**	55.0%	0.781
LCoW (iter 3)	**50.6%**	**0.666**	**62.8%**	**0.803**	**59.8%**	0.771	**59.6%**	**0.803**

Table 1. Experimental result in WebShop benchmark.

- LCoW (contextualization module as fine-tuned Phi-3-mini-Instruct combined with an LLM agent using Gemini-1.5-flash) achieves **state-of-the-art results on the WebShop benchmark,** outperforming human expert.
- LCoW shows **consistent improvement** in performance over the iterations.
- Contextualization module is also effective when combined with LLM agent did not used for action matching reward computation (i.e., Llama-3.1-70B)

WorkArena Experiment

	GPT-4o	Gemini-1.5-flash	Claude-3.5-Sonnet	Llama-3.1-70B (Unseen)	Llama-3.1-8B (Unseen)
Raw observation	38.2%	11.5%	44.8%	26.1%	1.2%
Self-ctx	43.0%	12.7%	50.3%	29.1%	7.3%
LCoW	**44.2%**	**41.2%**	**55.8%**	**40.0%**	**37.0%**

Table 2. Experimental result in WorkArena benchmark.

- LCoW improves the success rates of closed-source LLMs by an average of 15.6%, and demonstrates 23.7% average improvement in success rates for open-source LMs on the WorkArena benchmark.
- **LCoW + Llama-3.1-8B agent** shows better performance compared to **Llama-3.1-8B agent trained via BC.**

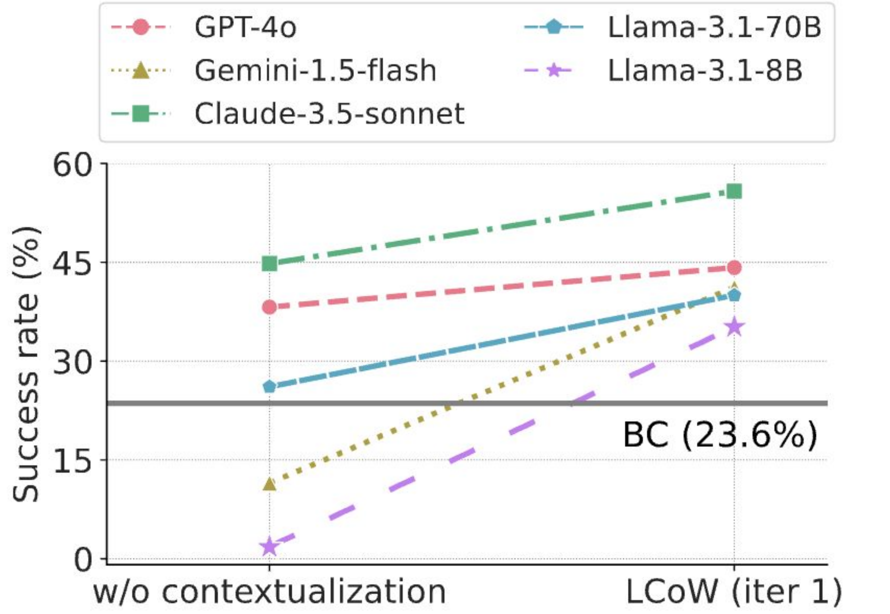


Figure 3. Comparison to Llama-3.1-8B agent trained via Behavior cloning (BC)

Analysis

Generalization capability

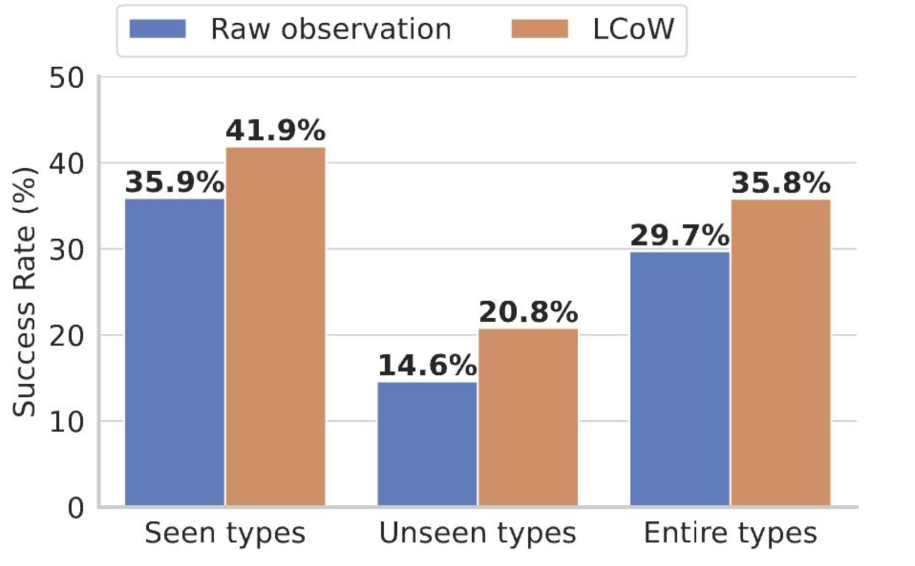
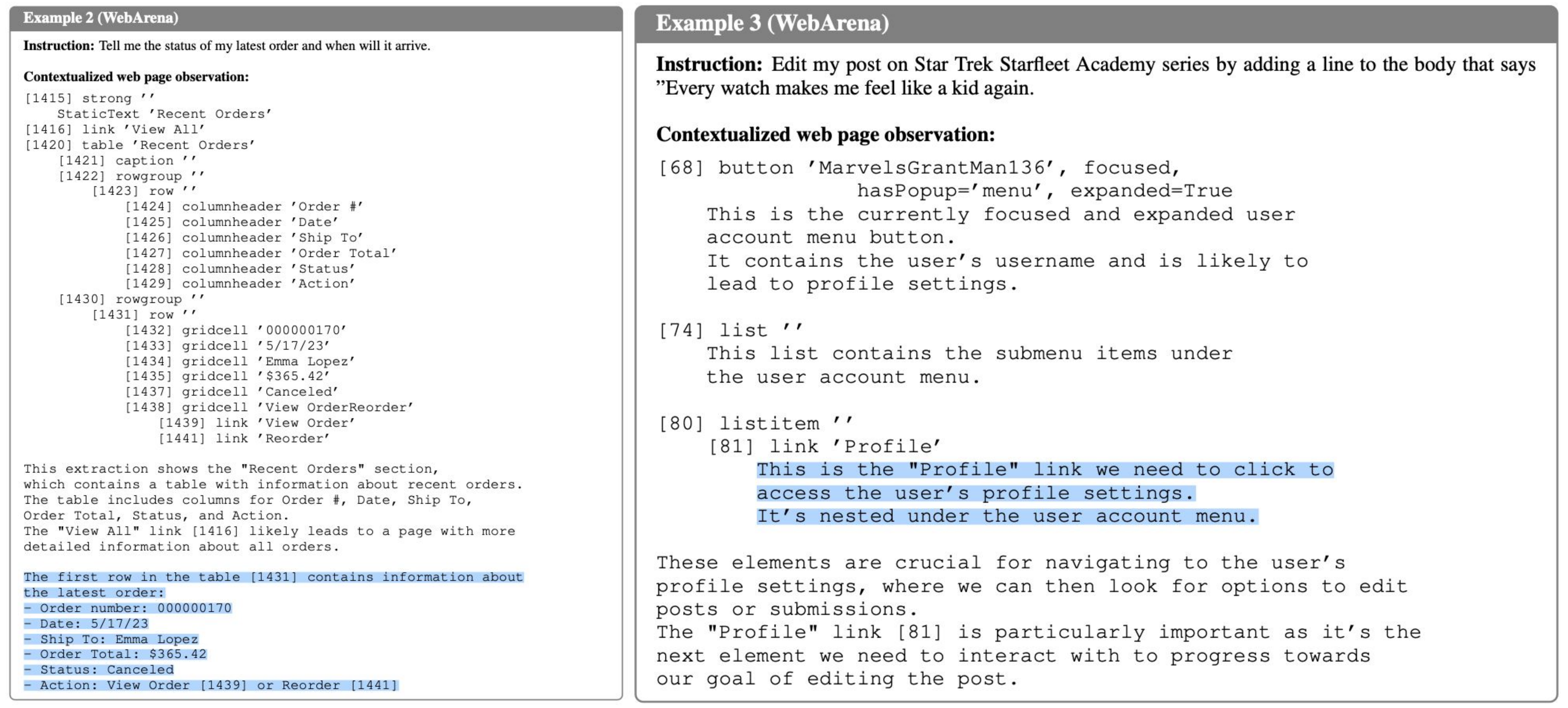


Figure 4. Effectiveness of LCoW in WebArena-Lite, and generalization to unseen task types.

- LCoW demonstrates 6% success rate improvement in both seen-type and unseen-type tasks*, **indicating generalization capability**.

*Given a task "What is the top-3 best-selling product in 2023" used in training, we test with tasks:
- seen-type: sharing similar task templates (e.g., "What is the top-1 best-selling product in 2022")
- unseen-type: not sharing task templates (e.g., "Tell me the email address, name, phone number of the customer who has the most cancellations in the history")

Qualitative analysis



- (Left) Contextualization module **extracts information of UI element**, providing better context to the LLM agent (the latest order from lengthy table).
- (Right) Contextualization module **explains the effect of manipulating UI** element (explanation on the `Profile` element).

Conclusion

- We propose a novel framework for enhancing LLM agents performances, by decoupling perception from decisions.
- With contextualization, LCoW demonstrates significant improvement on the web agents of varying scales.

Check out for more details in this QR code →