CRGPO: CONTEXT-GUIDED GRAPH REFINEMENT FOR GROUP-BASED AGENT REINFORCEMENT LEARNING

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ABSTRACT

Group-based reinforcement learning (RL) has improved the performance of large language models (LLMs) on agentic tasks. Despite these gains, it remains hampered by sparse and delayed rewards in long-horizon settings, where feedback often arrives only after dozens of interactions. Recent frameworks have shifted from trajectory-level to step-level training to enable finer-grained policy updates. Yet observation-based credit assignment still aggregates visits with the same local observation, overlooking contextual information from preceding interactions that is relevant to state values. Consequently, visits with different prospects of task success can fall into the same comparison group, distorting the credit assigned to their actions. To address this limitation, we propose CRGPO, a context-guided graph refinement method for agentic RL. CRGPO combines separately sampled linear trajectories into a state-transition graph by merging visits with the identical local observations, then refines its nodes through increasingly long context windows. At the first level that distinguishes two contexts, it attributes their estimated value difference to earlier actions at a shared decision branch. Policy updates combine these signals with suffix advantages from the final refined graph and episode-level feedback. Experiments on ALFWorld and WebShop with Qwen2.5-1.5B and Qwen2.5-7B show that CRGPO achieves the highest overall success rates among the challenge benchmarks.

1 INTRODUCTION

Large language models (LLMs) increasingly act as agents in complex environments, supporting embodied interaction (Ahn et al., 2022; Driess et al., 2023; Zitkovich et al., 2023), deep research (Li et al., 2025; Zheng et al., 2025b; Tongyi DeepResearch Team et al., 2026), and software development (Hong et al., 2024; Qian et al., 2024; Wang et al., 2025a). To strengthen their reasoning and decision-making capabilities, reinforcement learning (RL) has become an established part of post-training (Guo et al., 2025; Yang et al., 2025). Algorithms such as proximal policy optimization (PPO; Schulman et al., 2017), group relative policy optimization (GRPO; Shao et al., 2024), and decoupled clip and dynamic sampling policy optimization (DAPO; Yu et al., 2025) learn from reward feedback. Group-based methods obtain relative learning signals from sampled outcomes without a separately trained critic, making them attractive for agent training.

Long-horizon interaction makes this feedback difficult to use: agents may execute dozens of actions before receiving a task reward. Recent frameworks address the resulting training cost by treating individual observation–action pairs as separate samples (Feng et al., 2025; Chen et al., 2025b; Luo et al., 2025). Shared observations across trajectories provide a basis for finer credit assignment, often marking common intermediate stages or repeated, ineffective actions. GiGPO forms step-level comparison groups at matching observations (Feng et al., 2025), while G2PO organizes these groups into a state-transition graph and pools returns to estimate node values (Wang et al., 2026).

Our experiments reveal errors in tasks that depend on earlier prerequisites, such as placing an object before cleaning it. This raises a concern for step-level credit assignment: **observation-based grouping assigns a shared value to visits with the same observation but different task progress**. This grouping can distort the relative credit assigned to individual actions.

For example, in a GRPO rollout on the ALFWorld benchmark, the agent places an unwashed mug at a coffee machine twice without completing its cleaning task. After washing the mug, the same action

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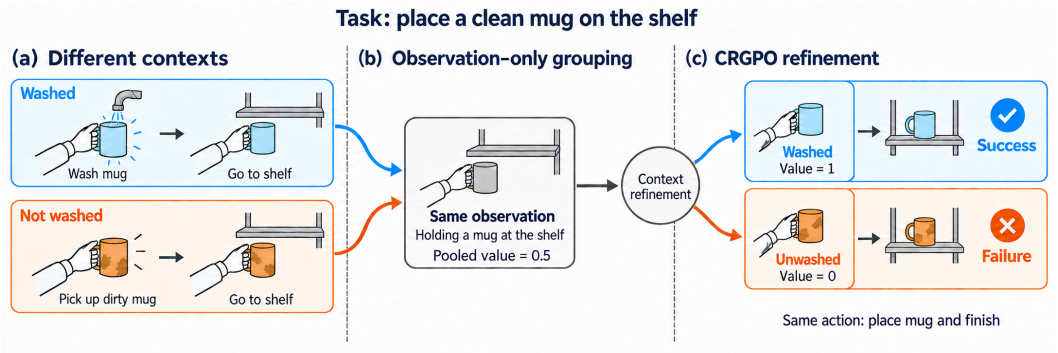

Figure 1: Value aliasing under observation-based grouping, illustrated by a schematic motivated by a GRPO rollout on ALFWorld. The shelf replaces the actual coffee machine; the two alternative contexts, outcomes 1 and 0, equal visit counts, and pooled value 0.5 are illustrative assumptions rather than measured rollout returns. Refinement separates the contexts when the distinguishing interactions fall within K.

under an identical local observation completes the task. Although the episode eventually succeeds, it contains both premature and successful placements. In GRPO, all actions within an episode share one advantage; observation-based step-level grouping would also assign these visits one node value.

Figure 1 gives a simplified illustration of this issue. Suppose the two contexts are followed by the same place-and-finish continuation: the washed mug satisfies the goal, whereas the unwashed mug does not. With equally many visits, normalized outcomes of one and zero, and $\gamma = 1$ for illustration, observation-based pooling assigns both contexts a value of 0.5. It therefore underestimates the return when the mug has been washed and overestimates it when the mug remains unwashed. The error arises because the grouping ignores the earlier cleaning history: the current observation is identical, but the preceding interactions establish different task progress and hence different expected returns. We call this conflation of context-dependent values *value aliasing*. The central question is: **how can we resolve value aliasing at shared observations and assign the resulting credit to the decisions that produced different contexts?** Longer contexts can distinguish these visits, but also leave fewer trajectories sharing each node. An effective solution must use those distinctions for credit assignment while retaining the comparisons available at shorter context lengths.

We propose CRGPO, a group-based RL method that redefines graph nodes using interaction context (Figure 2). Starting from a graph that merges matching observations, CRGPO successively requires agreement over longer windows of preceding observations and actions, up to a maximum length K. These nested partitions retain both the final graph and the intermediate groups through which its nodes were refined. For two visits from different trajectories to the same observation, we compare the values of their groups at the shortest context length that places the visits in separate groups.

Contextual advantages credit the earlier actions that produced different contexts. We compare trajectories that share a decision prefix, choose different actions there, and later reach the same observation. Their group values at the first separating level provide relative credit for the earlier branching actions; subsequent refinements do not repeat the comparison. Suffix advantages use generalized advantage estimation (GAE; Schulman et al., 2015b) to combine immediate rewards and changes in final-graph node values along each sampled continuation. We combine both advantages with episode-level GRPO feedback for policy optimization.

We evaluate CRGPO on ALFWorld and WebShop with Qwen2.5-1.5B and Qwen2.5-7B. It achieves the highest overall success rates across these challenging benchmarks among the evaluated prompt-based agents and RL methods.

Our contributions are as follows:

- We introduce a context-guided graph construction that organizes sampled trajectories into a hierarchy of state-transition graphs. Progressively longer interaction contexts refine

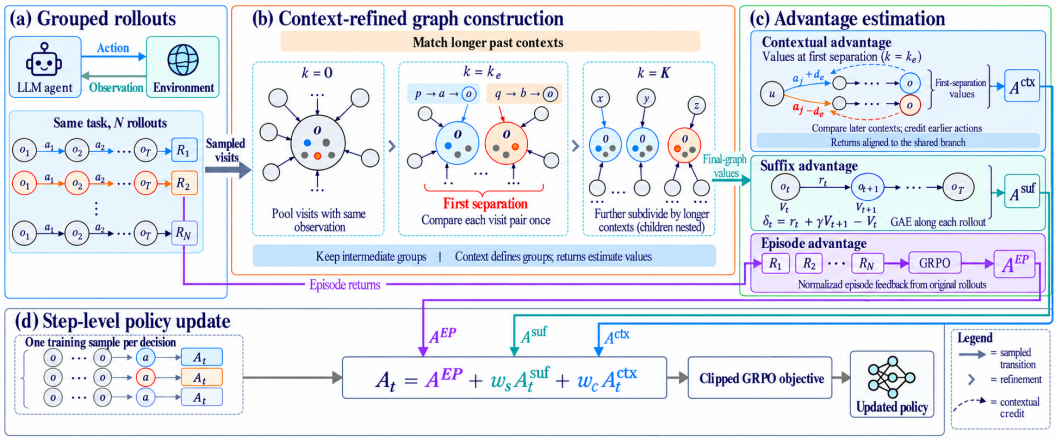

Figure 2: Overview of CRGPO. Sampled trajectories form a graph whose nodes are refined by progressively longer interaction contexts. Contextual advantages compare groups at the first level separating two visits and assign credit to earlier branching actions. Suffix GAE uses node values on the final graph, while episode-level GRPO uses trajectory returns. The three advantages are combined for step-level policy optimization.

observation-based nodes while preserving intermediate groups for value comparisons. We characterize the resulting reduction in value aliasing for expected node values.

- We introduce an advantage estimator that combines contextual credit for earlier branching actions with suffix credit on the refined graph. Contextual comparisons use group values at the first level separating two visits, while suffix GAE uses final-graph values to evaluate their continuations. Both terms complement episode-level GRPO feedback.
- Experiments on ALFWorld and WebShop show that CRGPO achieves the highest overall success rates among the evaluated baselines at both model scales. Ablations support the contributions of context refinement and both step-level advantage terms.

2 Related Work

Learning from interaction. LLMs have evolved from text generators into autonomous agents interacting with environments over multiple turns (Ahn et al., 2022; Yao et al., 2023; Wang et al., 2025a; Zheng et al., 2025b). Toolformer learns API use through self-supervision (Schick et al., 2023), ToolRL studies reward design for tool-use RL (Qian et al., 2025), and CodeAct represents actions as executable code (Wang et al., 2024). Self-consistency aggregates sampled reasoning paths (Wang et al., 2023) and ReAct interleaves reasoning and actions (Yao et al., 2023). Reflexion uses textual feedback (Shinn et al., 2023) and LATS incorporates feedback into tree search (Zhou et al., 2024a). For policy learning, ArCHer separates utterance- and token-level updates (Zhou et al., 2024b), RAGEN studies multi-turn trajectory optimization (Wang et al., 2025b), and LOOP learns without a value network (Chen et al., 2025a). Search-R1 and DeepResearcher extend RL to search-engine use and open-web research (Jin et al., 2025; Zheng et al., 2025b). Interaction histories can distinguish visits with the same observation but different task progress. CRGPO uses them to refine groups for value estimation and credit earlier branching actions and subsequent continuations.

Group-based credit assignment. Building on REINFORCE (Williams, 1992), leave-one-out estimators use other responses to the same input as a reward baseline (Kool et al., 2019; Ahmadian et al., 2024); GRPO standardizes rewards within the group (Shao et al., 2024). DAPO refines clipping and sampling (Yu et al., 2025), GSPO changes the importance ratio (Zheng et al., 2025a), and subsequent analyses address GRPO's response-length bias and entropy collapse during reasoning RL (Liu et al., 2025; Cui et al., 2025). iStar learns implicit step rewards (Liu et al., 2026), while TreeRL uses on-policy tree search for reasoning (Hou et al., 2025). For interactive tasks, GiGPO groups matching observations (Feng et al., 2025); G2PO connects these groups into a graph for value-based

credit assignment (Wang et al., 2026); and HGPO aggregates group advantages across context lengths for the current step (He et al., 2026). Our CRGPO compares child-node values at each pair's first separating level and credits differing actions at its last shared full prefix. Its suffix advantages use generalized advantage estimation (Schulman et al., 2015b) on the final refined graph.

3 PRELIMINARIES

3.1 PROBLEM SETUP

An LLM policy π_θ interacts with an environment to complete a given task x. At step t, it observes o_t, chooses a_t, and receives reward r_t and observation o_{t+1}. This observation–action step constitutes one interaction. A *rollout* is a sampled trajectory $\tau_i = (o_1^i, a_1^i, \ldots, o_{T_i}^i, a_{T_i}^i)$ with $T_i \leq T$ actions, where T is the step limit. Its prefix $h_t^i = (x, o_1^i, a_1^i, \ldots, o_t^i)$ contains the information available before a_t^i. Observations may reveal only part of the environment state; a *context* consists of preceding observation–action pairs.

For each task, π_θ samples N trajectories with episode returns $R_i = \sum_{t=1}^{T_i} r_t^i$; training seeks to maximize the expected return, by improving π_θ based on the obtained episode returns.

3.2 GROUP RELATIVE POLICY OPTIMIZATION

Group relative policy optimization (GRPO; Shao et al., 2024) computes $A_i^{\mathrm{GRPO}} = (R_i - \mu)/\sigma$ without a learned critic, where μ and σ are the within-task mean and standard deviation of episode returns. Every action in trajectory i shares $A_t^i = A_i^{\mathrm{GRPO}}$, leaving individual contributions undifferentiated.

Given A_t^i, we use PPO's clipped surrogate (Schulman et al., 2017), a first-order alternative to trust-region optimization (Schulman et al., 2015a), at the action level:

$$\mathcal{J}(\theta; A) = \mathbb{E}_{(i,t)\sim\nu}\left[\min\left(\rho_t^i A_t^i, \mathrm{clip}(\rho_t^i, 1-\varepsilon, 1+\varepsilon)A_t^i\right) - \beta D_{\mathrm{KL}}(\pi_\theta \| \pi_{\mathrm{ref}})\right]. \tag{1}$$

Here $\rho_t^i = \pi_\theta(a_t^i \mid h_t^i)/\pi_{\theta_{\mathrm{old}}}(a_t^i \mid h_t^i)$ is the probability ratio relative to the sampling policy $\pi_{\theta_{\mathrm{old}}}$, and ν denotes averaging over sampled decisions. The KL divergence compares action distributions conditioned on h_t^i; ε and β control clipping and KL regularization. The reference π_{ref} is the initial policy before RL training, held fixed as the target of KL regularization.

4 OUR METHOD

CRGPO constructs a hierarchy of context-refined state-transition graphs from sampled trajectories. For two visits to the same observation, it uses group values at their first separating level to estimate returns from an earlier shared decision point. The difference between these estimated returns provides credit for the actions taken there. Final-graph values evaluate each sampled continuation.

Section 4.1 defines the graph construction through context refinement. Section 4.2 introduces contextual and suffix advantages and combines them with episode-level GRPO feedback. Appendix D illustrates these operations with a worked example.

4.1 CONTEXT-REFINED GRAPH CONSTRUCTION

A graph node pools the returns from the sampled occurrences of the same decision context into one value estimate. Refinement starts with matching observations and progressively requires longer contexts to agree.

Consider the N trajectories sampled for task x (Section 3). In o_t^i and a_t^i, the superscript i identifies the trajectory and the subscript t its decision step. A *visit* (i,t) is the occurrence of observation o_t^i immediately before action a_t^i; repeated observations correspond to distinct visits. The set of sampled visits is $\mathcal{I}_x = \{(i,t) : 1 \leq i \leq N,\ 1 \leq t \leq T_i\}$. The full decision prefix of trajectory τ_i at this visit is $h_t^i = (x, o_1^i, a_1^i, \ldots, o_t^i)$.

Let K be the maximum context length. The context function c_k extracts the current observation and up to k preceding observation–action pairs from h_t^i: for $k = 0$, $c_0(h_t^i) = o_t^i$; for $1 \leq k \leq K$,

$$c_k(h_t^i) = (o_\ell^i, a_\ell^i, o_{\ell+1}^i, a_{\ell+1}^i, \ldots, o_{t-1}^i, a_{t-1}^i, o_t^i), \qquad \ell = \max(1, t-k). \tag{2}$$

This context window contains only information available before a_t^i.

At level k, a *node* is a set of visits with identical context windows. The node containing (i,t) is $C^{(k)}(i,t) = \{(j,n) \in \mathcal{I}_x : c_k(h_n^j) = c_k(h_t^i)\}$. The distinct nodes form a partition Φ_k of $\mathcal{I}_x$. Thus Φ_0 groups visits by their current observations, and increasing k can only split existing groups: $C^{(K)}(i,t) \subseteq \cdots \subseteq C^{(1)}(i,t) \subseteq C^{(0)}(i,t)$. We retain all levels: shorter contexts support comparisons among more visits, while longer contexts distinguish different routes to the same observation. Note that context equality determines node membership; sampled rewards are then used to estimate node values and advantages (see Section 4.2).

The graph $\mathcal{G}_k = (\Phi_k, \mathcal{E}_k)$ is a directed multigraph. Its edge multiset contains $(C^{(k)}(i,t), a_t^i, C^{(k)}(i,t+1))$ once per sampled transition with $t < T_i$. The label is the executed action; (i,t) identifies its occurrence. Transitions with identical source nodes, actions, and destinations retain separate occurrences, preserving rollout order through repeated transitions and cycles. Graph edges connect consecutive visits; node containment across levels records refinement.

The return from visit (i,t) is $g_t^i = \sum_{j=t}^{T_i} \gamma^{j-t} r_j^i$, where $\gamma \in (0,1]$ and r_j^i is the reward received after action a_j^i. With terminal rewards only, $g_t^i = \gamma^{T_i - t} R_i$. For any node C, we estimate its value as $\widehat{V}(C) = |C|^{-1} \sum_{(i,t)\in C} g_t^i$. The final graph $\mathcal{G}_K$ provides these values for suffix advantage estimation; intermediate partitions provide the groups used for contextual comparisons.

4.2 Advantage estimation and policy optimization

We introduce a *contextual advantage* for earlier actions that lead to different contexts and a *suffix advantage* for the continuation following each action. They supplement episode-level GRPO feedback.

Contextual advantage. When trajectories reach the same observation through different contexts, their subsequent returns can help evaluate the earlier decisions that led there. We compare these visits at the shortest context length that distinguishes them and assign credit to the preceding branch where the trajectories chose different actions.

Consider the prefix $u = h_s^r$ of a sampled trajectory τ_r, immediately before action a_s^r. All trajectories with this prefix have indices in $\mathcal{B}_u = \{i : 1 \le i \le N,\ s \le T_i,\ h_s^i = u\}$. We call u a *branch* if these trajectories choose at least two different actions at step s. For each sampled action a, let $\mathcal{B}_u(a) = \{i \in \mathcal{B}_u : a_s^i = a\}$. We process every distinct branch observed in the sampled trajectories, but only trajectories τ_i and τ_j with $i, j \in \mathcal{B}_u$ and $a_s^i \neq a_s^j$ are compared. Their interaction sequences agree through $h_s^i = h_s^j = u$ and first differ at these actions.

For a target observation o and $i \in \mathcal{B}_u$, the first arrival time after the branch is $t_i(u,o) = \min\{t : s < t \le T_i,\ o_t^i = o\}$, with $t_i(u,o) = +\infty$ if the target is not reached. Let $\mathcal{H}_{u,o} = \{i \in \mathcal{B}_u : t_i(u,o) < \infty\}$ contain the indices of trajectories that reach o. For each such trajectory, $(i, t_i(u,o))$ is its *first-arrival visit*. Using these visits permits at most one comparison per target observation and trajectory pair at u, even when a rollout returns to o in a loop.

Choose trajectories τ_i and τ_j with $i, j \in \mathcal{H}_{u,o}$, $i < j$, and $a_s^i \neq a_s^j$. Their first-arrival visits are (i,t) and (j,n), where $t = t_i(u,o)$ and $n = t_j(u,o)$. Write $e = ((i,t),(j,n))$ for this visit pair and define its first separating context length as

$$k_e = \min\{k \in \{1,\dots,K\} : c_k(h_t^i) \neq c_k(h_n^j)\}, \tag{3}$$

with $k_e = +\infty$ if the two contexts agree at every tested length. The pair is *eligible* for contextual comparison only if $k_e \le K$. For an eligible pair, (i,t) and (j,n) share a node at level $k_e - 1$ and belong to different children at level k_e. This visit pair contributes only at its first separating level, irrespective of further subdivisions at longer context lengths.

For comparison at branch u, we retain the following first-arrival visits in each node C with current observation o:

$$\mathcal{I}_{u,o}(C) = \{(j, t_j(u,o)) : j \in \mathcal{H}_{u,o},\ (j, t_j(u,o)) \in C\}. \tag{4}$$

When this set is nonempty, its mean return is $\widehat{V}_u(C) = |\mathcal{I}_{u,o}(C)|^{-1} \sum_{(j,n)\in\mathcal{I}_{u,o}(C)} g_n^j$. Every trajectory in $\mathcal{B}_u$ with a first-arrival visit in C contributes once, regardless of its action at u. Each compared child contains at least one such visit; the suffix value $\widehat{V}(C)$ averages all visits in the node.

For an eligible pair $e = ((i,t),(j,n))$, let $p_{s,t}^i = \sum_{q=s}^{t-1} \gamma^{q-s} r_q^i$ be the rewards between the branch and the arrival, discounted to step s. The estimated return difference is

$$d_e = \left[p_{s,t}^i + \gamma^{t-s} \widehat{V}_u(C^{(k_e)}(i,t))\right] - \left[p_{s,n}^j + \gamma^{n-s} \widehat{V}_u(C^{(k_e)}(j,n))\right]. \tag{5}$$

Both returns are evaluated from step s, allowing different arrival times. They give credits $+d_e$ and $-d_e$ to trajectories i and j at u. With terminal rewards only and $\gamma = 1$, it reduces to the difference between the two child-node means.

For $i < j$, let $\mathcal{P}_{ij}(u)$ be the set of eligible visit pairs $e = ((i,t),(j,n))$ obtained across target observations after branch u. We sum their contributions as

$$d_{ij}(u) = \sum_{e\in\mathcal{P}_{ij}(u)} d_e, \qquad d_{ji}(u) = -d_{ij}(u), \qquad d_{ii}(u) = 0. \tag{6}$$

An empty comparison set gives $d_{ij}(u) = 0$, including when the two trajectories select the same action at u.

The score for each trajectory at the branch is

$$b_i(u) = \frac{1}{|\mathcal{B}_u|} \sum_{j\in\mathcal{B}_u} d_{ij}(u). \tag{7}$$

The denominator includes all trajectories sharing u, including those without an eligible comparison. The scores have mean $\mu_u = |\mathcal{B}_u|^{-1} \sum_{i\in\mathcal{B}_u} b_i(u) = 0$ by antisymmetry, and standard deviation $\sigma_u = (|\mathcal{B}_u|^{-1} \sum_{i\in\mathcal{B}_u} (b_i(u) - \mu_u)^2)^{1/2}$. For each sampled action a at u, averaging the scores of trajectories that chose it gives

$$A^{\mathrm{ctx}}(u,a) = \frac{|\mathcal{B}_u(a)|^{-1} \sum_{i\in\mathcal{B}_u(a)} b_i(u) - \mu_u}{\sigma_u}. \tag{8}$$

We assign $A_t^{i,\mathrm{ctx}} = A^{\mathrm{ctx}}(h_t^i, a_t^i)$ to each sampled action. Prefixes with no eligible comparison receive zero contextual advantage; the same convention applies whenever $\sigma_u = 0$.

Suffix advantage. The suffix advantage evaluates the continuation following an action. Since its effect on task progress may become apparent only after several interactions, we accumulate rewards and changes in node values along the sampled continuation. The current node value provides a reference against which to evaluate those outcomes.

Write $\widehat{v}_t^i = \widehat{V}(C^{(K)}(i,t))$ for the value assigned to visit (i,t) by the final graph at level K, and set the terminal value $\widehat{v}_{T_i+1}^i = 0$. For the sampled action a_t^i, the observed reward r_t^i and next visit determine the temporal-difference residual δ_t^i. Its suffix advantage is

$$\delta_t^i = r_t^i + \gamma \widehat{v}_{t+1}^i - \widehat{v}_t^i, \qquad A_t^{i,\mathrm{suf}} = \sum_{\ell=0}^{T_i-t} (\gamma\lambda)^\ell \delta_{t+\ell}^i. \tag{9}$$

This is generalized advantage estimation (GAE; Schulman et al., 2015b), using graph values instead of a learned critic. The parameter $\lambda \in [0,1]$ controls how strongly later residuals affect the advantage: $\lambda = 0$ uses only δ_t^i, while larger values incorporate more of the sampled continuation. At $\lambda = 1$, the sum reduces to $g_t^i - \widehat{v}_t^i$, comparing the sampled return with its node mean. The computation follows the rollout's temporal order, so repeated visits and cycles require no change to the estimator.

Episode-Level Advantage Estimation. Following GRPO, we compute the episode-level advantage as $A_i^{\mathrm{EP}} = (R_i - \mu_x)/\sigma_x$, where μ_x and σ_x are the mean and standard deviation of the N trajectory returns for task x. If all returns are equal, we set $A_i^{\mathrm{EP}} = 0$.

Finally, we combine the episode-level and step-level advantages to obtain the overall advantage for each step:

$$A_t^i = w_{\mathrm{c}} A_t^{i,\mathrm{ctx}} + w_{\mathrm{s}} A_t^{i,\mathrm{suf}} + A_i^{\mathrm{EP}}, \tag{10}$$

where w_c and w_s control the contextual and suffix contributions. We set $w_c = w_s = 1$ for full CRGPO; ablations set the omitted term's weight to 0.

Following the GRPO framework, the overall objective function of CRGPO is formulated as:

$$\mathcal{J}(\theta) = \mathbb{E}_{\substack{x\sim\mathcal{D} \\ \{\tau_i\}_{i=1}^{N}\sim\pi_{\theta_{\text{old}}}(\cdot|x)}}\Bigg[\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\Big\{\min\Big(\rho_t^i A_t^i, \text{clip}\big(\rho_t^i, 1-\varepsilon, 1+\varepsilon\big)A_t^i\Big) - \beta D_{\text{KL}}\big(\pi_\theta(\cdot \mid h_t^i)\|\pi_{\text{ref}}(\cdot \mid h_t^i)\big)\Big\}\Bigg]. \tag{11}$$

Here $\rho_t^i = \pi_\theta(a_t^i \mid h_t^i)/\pi_{\theta_{\text{old}}}(a_t^i \mid h_t^i)$ is the importance sampling ratio. The parameters ε and β control the clipping range and the KL penalty, respectively. The pseudo code of CRGPO is given in Appendix A.

The following proposition describes how the hierarchy resolves value distinctions hidden by observation-based grouping.

Proposition 1 (Value aliasing under context refinement)**.** *Fix a task, a sampling policy, and a visit distribution. Let H be a visit's full decision prefix and Y its discounted remaining return, with $\mathbb{E}[Y^2] < \infty$. For the context functions $c_0, \ldots, c_K$ in Section 4.1, define the expected node value $V_k = \mathbb{E}[Y \mid c_k(H)]$ and the full-context value $m(H) = \mathbb{E}[Y \mid H]$. The value aliasing at level k is the mean squared discrepancy $\mathcal{A}_k = \mathbb{E}[(m(H) - V_k)^2]$. Then*

$$\mathcal{A}_0 = \mathcal{A}_K + \sum_{k=1}^{K}\mathbb{E}[(V_k - V_{k-1})^2]. \tag{12}$$

In particular, $\mathcal{A}_k \le \mathcal{A}_{k-1}$, with strict inequality if and only if $\Pr(V_k \neq V_{k-1}) > 0$.

Thus, each level removes the value differences that its additional context reveals, while $\mathcal{A}_K$ measures what remains unresolved at the maximum context length. The result concerns expected node values under a fixed distribution; the sample estimates $\widehat{V}$ can still be affected by the smaller number of visits in refined nodes. The proof and its connection to suffix advantages are given in Appendix B.

5 Experiments

We evaluate task performance, examine the two step-level advantages and graph refinement, compare maximum context lengths, and measure computational cost. Appendix E analyzes how interaction context changes node sharing and the comparisons available for credit assignment.

5.1 Experimental setup

Benchmarks. We evaluate on ALFWorld (Shridhar et al., 2021), which covers six household task types involving navigation and object manipulation, and WebShop (Yao et al., 2022), which requires product search and purchases under user-specified constraints.

Compared methods. Closed-model references are GPT-4o (OpenAI, 2024) and Gemini-2.5-Pro (Comanici et al., 2025). Open-model baselines comprise the initial policy, ReAct (Yao et al., 2023), Reflexion (Shinn et al., 2023), and five RL methods: PPO (Schulman et al., 2017), GRPO (Shao et al., 2024), GiGPO (Feng et al., 2025), G2PO (Wang et al., 2026), and HGPO (He et al., 2026).

Implementation details. We use Qwen2.5-1.5B-Instruct and Qwen2.5-7B-Instruct (Qwen et al., 2025). The policy receives the task instruction and two recent interactions. The maximum graph-context length defaults to $K = 2$, independently of this input window. Group-based methods use $N = 8$ rollouts per task. We follow the training settings of GiGPO and HGPO (Feng et al., 2025; He et al., 2026), with matched tasks, rewards, and rollout budgets. Appendix C details the baselines, environments, metrics, training settings, and prompts.

5.2 Test performance on ALFWorld and WebShop

We assess whether CRGPO improves task completion over prompting and RL baselines (Table 1). At $K = 2$, CRGPO with Qwen2.5-1.5B exceeds GRPO by 22.2 and 14.1 percentage points on ALFWorld and WebShop, respectively, and HGPO, the strongest baseline, by 6.2 and 2.1 points. At 7B, the gains over HGPO are 3.4 and 5.4 points. CRGPO also leads the baselines in WebShop score at both scales. At $K = 4$, it achieves the highest mean in every metric at each scale, including all six ALFWorld task categories.

Table 1: Test performance on ALFWorld and WebShop. ALFWorld columns give success rates (%); All is the success rate across test tasks. WebShop reports score and success rate (%). RL results are averaged over three independent training seeds; subscripts give standard deviations. For CRGPO, K denotes the maximum graph-context length.

Type	Method	ALFWorld							WebShop	
		Pick	Clean	Cool	Look	Heat	Pick2	All	Score	Succ.
Closed models										
Prompting	GPT-4o	75.3	31.2	21.6	60.8	56.7	49.8	48.0	31.8	23.7
Prompting	Gemini-2.5-Pro	92.8	62.1	26.6	63.3	69.0	58.7	60.3	42.5	35.9
Qwen2.5-1.5B-Instruct										
Prompting	Initial policy	5.9	3.3	4.2	5.5	9.7	0.0	4.1	23.1	5.2
Prompting	ReAct	17.4	15.7	7.7	20.5	6.2	2.0	12.8	40.1	11.3
Prompting	Reflexion	35.3	21.7	19.4	22.2	13.6	3.7	21.8	55.8	21.9
RL Training	PPO	$64.8_{\pm 3.5}$	$57.1_{\pm 4.9}$	$46.4_{\pm 4.0}$	$40.5_{\pm 6.9}$	$60.6_{\pm 6.6}$	$47.4_{\pm 1.9}$	$54.4_{\pm 3.1}$	$73.8_{\pm 3.0}$	$51.5_{\pm 2.9}$
RL Training	GRPO	$82.2_{\pm 2.1}$	$83.7_{\pm 5.6}$	$59.5_{\pm 3.9}$	$55.4_{\pm 8.5}$	$77.3_{\pm 4.3}$	$60.1_{\pm 6.2}$	$73.2_{\pm 1.8}$	$76.2_{\pm 4.4}$	$60.3_{\pm 5.1}$
RL Training	GiGPO	$93.5_{\pm 6.2}$	$95.0_{\pm 4.7}$	$79.9_{\pm 1.6}$	$73.1_{\pm 5.2}$	$94.4_{\pm 3.1}$	$82.4_{\pm 5.9}$	$84.7_{\pm 3.5}$	$82.5_{\pm 6.3}$	$70.2_{\pm 4.8}$
RL Training	G2PO	$88.3_{\pm 5.5}$	$84.6_{\pm 5.1}$	$89.1_{\pm 6.5}$	$\mathbf{86.8}_{\pm 3.9}$	$88.9_{\pm 2.0}$	$80.2_{\pm 3.8}$	$87.5_{\pm 4.3}$	$78.9_{\pm 2.6}$	$67.6_{\pm 4.2}$
RL Training	HGPO	$94.3_{\pm 1.1}$	$92.7_{\pm 2.8}$	$81.4_{\pm 3.9}$	$79.5_{\pm 0.9}$	$\mathbf{94.5}_{\pm 4.5}$	$84.9_{\pm 3.7}$	$89.2_{\pm 2.7}$	$84.6_{\pm 7.8}$	$72.3_{\pm 3.6}$
RL Training	**CRGPO**	$\mathbf{97.4}_{\pm 1.6}$	$\mathbf{97.2}_{\pm 0.8}$	$\mathbf{89.6}_{\pm 2.4}$	$86.6_{\pm 3.5}$	$94.4_{\pm 3.6}$	$\mathbf{86.6}_{\pm 1.2}$	$\mathbf{95.4}_{\pm 3.2}$	$\mathbf{85.3}_{\pm 1.5}$	$\mathbf{79.4}_{\pm 1.4}$
Qwen2.5-7B-Instruct										
Prompting	Initial policy	33.4	19.3	2.8	21.6	6.9	3.2	14.8	26.4	7.8
Prompting	ReAct	48.5	34.3	18.2	35.4	13.2	17.6	31.2	46.2	19.5
Prompting	Reflexion	62.0	44.9	36.3	41.6	30.9	23.8	42.7	58.1	28.8
RL Training	PPO	$92.3_{\pm 4.0}$	$92.5_{\pm 2.4}$	$80.3_{\pm 2.0}$	$64.0_{\pm 8.4}$	$89.5_{\pm 7.0}$	$68.8_{\pm 8.3}$	$80.4_{\pm 2.7}$	$81.4_{\pm 3.1}$	$68.7_{\pm 5.1}$
RL Training	GRPO	$89.9_{\pm 5.2}$	$89.7_{\pm 3.4}$	$68.1_{\pm 5.3}$	$69.1_{\pm 4.2}$	$80.9_{\pm 4.9}$	$69.0_{\pm 6.1}$	$79.9_{\pm 5.2}$	$81.5_{\pm 3.5}$	$71.1_{\pm 4.2}$
RL Training	GiGPO	$97.6_{\pm 1.7}$	$\mathbf{98.8}_{\pm 1.1}$	$88.1_{\pm 7.5}$	$82.9_{\pm 5.8}$	$86.2_{\pm 4.1}$	$86.2_{\pm 5.4}$	$92.3_{\pm 4.9}$	$86.5_{\pm 1.9}$	$75.8_{\pm 4.3}$
RL Training	G2PO	$86.9_{\pm 4.1}$	$88.2_{\pm 5.3}$	$85.1_{\pm 4.7}$	$79.4_{\pm 6.9}$	$92.4_{\pm 3.5}$	$80.9_{\pm 6.4}$	$87.6_{\pm 5.0}$	$82.5_{\pm 3.2}$	$74.8_{\pm 2.1}$
RL Training	HGPO	$97.7_{\pm 1.9}$	$97.9_{\pm 2.0}$	$90.2_{\pm 3.1}$	$82.3_{\pm 4.5}$	$88.9_{\pm 3.4}$	$87.1_{\pm 4.5}$	$93.1_{\pm 2.6}$	$86.7_{\pm 2.4}$	$77.1_{\pm 1.5}$
RL Training	**CRGPO**	$\mathbf{98.7}_{\pm 1.3}$	$\mathbf{98.8}_{\pm 0.5}$	$\mathbf{91.4}_{\pm 1.8}$	$\mathbf{89.4}_{\pm 3.1}$	$\mathbf{95.3}_{\pm 2.8}$	$\mathbf{89.7}_{\pm 3.6}$	$\mathbf{96.5}_{\pm 2.4}$	$\mathbf{90.6}_{\pm 0.7}$	$\mathbf{84.4}_{\pm 1.0}$

5.3 Ablation study

In this experiment, we measure the individual and combined contributions of contextual and suffix advantages beyond episode-level feedback. Using Qwen2.5-1.5B-Instruct, we compare episode feedback alone (EP), its two single-component extensions (EP + ctx and EP + suf), and full CRGPO. Removing a term sets its weight to zero while keeping the graph refinement procedure and training budget fixed.

Figure 3 shows that both single-component extensions improve over EP: contextual advantages raise ALFWorld and WebShop success by 9.9 and 10.9 percentage points, while suffix advantages raise them by 9.3 and 9.6 points. Full CRGPO reaches 95.4% and 74.4%. Removing contextual credit lowers these rates by 12.9 and 4.5 points; removing suffix credit lowers them by 12.3 and 3.2 points. The full estimator also has the highest mean success rate in each of the six ALFWorld categories.

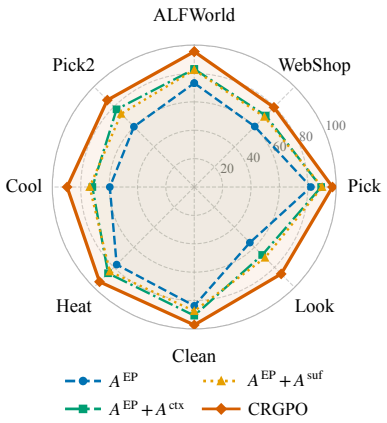

Figure 3: Advantage ablation with Qwen2.5-1.5B. Axes show success rates (%)

Graph refinement. This experiment isolates the effect of context-based graph partitioning on suffix credit assignment. Table 2 holds the advantage terms fixed at EP + suf ($w_c = 0$, $w_s = 1$) and changes the graph partition. Refinement raises mean success from 75.6% to 82.5% on ALFWorld and from 64.5% to 69.9% on WebShop, gains of 6.9 and 5.4 percentage points. This comparison supports using context-refined nodes for suffix credit assignment. The refined row reuses EP + suf from Figure 3; other training settings remain fixed.

Table 2: Graph refinement ablation with Qwen2.5-1.5B. Success rates (%, mean ± standard deviation); both variants use EP + suf.

Graph partition	ALFWorld	WebShop
Observation only	75.6 ± 3.1	64.5 ± 2.7
Context-refined	82.5 ± 2.2	69.9 ± 1.4

Maximum context length. This experiment examines how the maximum graph-context length affects task performance with a fixed policy input window. The CRGPO rows in Table 1 compare $K = 2$ and $K = 4$ at both model scales, with the policy input fixed at two interactions and matched advantage weights and training budgets. At 1.5B, extending the graph context raises mean success by 1.3 percentage points on ALFWorld and 1.1 on WebShop, and increases WebShop score by 1.4 points. At 7B, the corresponding gains are 0.7, 0.8, and 0.9 points. Longer contexts improve the reported means at both scales. Since context length changes both contextual comparisons and the final nodes used by suffix GAE, this comparison measures their combined effect.

5.4 Computational Budget

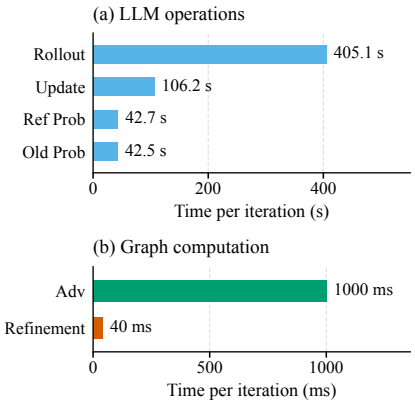

Figure 4: Per-iteration times on ALFWorld (Qwen2.5-1.5B). Separate linear scales show model operations in seconds (top) and graph computation in milliseconds (bottom).

In this experiment, we measure the cost of graph refinement and advantage estimation relative to the other training phases. Figure 4 reports six phase means for Qwen2.5-1.5B on ALFWorld. Rollout generation takes 405.1 seconds per iteration and policy updates take 106.2 seconds, accounting for 67.8% and 17.8% of the summed phase times. Reference- and sampling-policy probability evaluations take 42.7 and 42.5 seconds. Adv includes graph construction, value estimation, and both step-level advantages; Refinement covers context grouping, parent–child links, and graph reconstruction. The timers do not overlap.

Graph refinement takes 0.04 seconds per iteration and advantage computation takes 1 second. Together, they account for 0.17% of the summed time of the six measured phases. Appendix C.3 specifies the hardware and timing procedure.

6 Conclusion

We introduced CRGPO, a group-based RL method for context-sensitive credit assignment in long-horizon agentic tasks. CRGPO organizes sampled rollouts into a state-transition graph and progressively refines shared nodes using longer contexts. Contextual advantages use value differences revealed by refinement to credit the earlier actions that produced different contexts, while suffix advantages evaluate subsequent actions on the final refined graph. These complementary signals extend episode-level GRPO with step-level feedback. Experiments on ALFWorld and WebShop show that CRGPO achieves higher overall success rates than the evaluated baselines, with little additional graph computation. Ablations support the contribution of both advantage components and show that contextual refinement improves task success.

AI USE STATEMENT

AI assistance was used to draft and revise the text, identify relevant literature, and generate and revise an illustrative figure.

REPRODUCIBILITY STATEMENT

Section 4 defines the graph refinement rule and advantage estimator. Appendix A gives the training algorithm, and Appendix B proves Proposition 1. Appendix C specifies the training settings, evaluation metrics, and agent prompts. Appendix D gives a worked example of graph refinement and credit assignment.

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A PSEUDO CODE

Algorithm 1 CRGPO

Require: Initial policy π_{θ_0}, task distribution $\mathcal{D}$; $N, T, K, \gamma, \lambda, w_{\mathrm{c}}, w_{\mathrm{s}}, \varepsilon, \beta$
Initialize $\theta \leftarrow \theta_0$ and $\pi_{\mathrm{ref}} \leftarrow \pi_{\theta_0}$; keep the reference policy fixed
for each training iteration **do**
  Set $\theta_{\mathrm{old}} \leftarrow \theta$ and sample a task minibatch $\mathcal{X}$ from $\mathcal{D}$
  for each task $x \in \mathcal{X}$ **do**
    Sample N trajectories with $\pi_{\theta_{\mathrm{old}}}$, stopping by horizon T; retain all full prefixes, actions, and rewards
    Compute $g_t^i = \sum_{j=t}^{T_i} \gamma^{j-t} r_j^i$ and each episode return $R_i = \sum_{t=1}^{T_i} r_t^i$
    Group visits with equal current observations into Φ_0; retain each transition occurrence (i, t) with $t < T_i$ and its action label
    for $k = 1, \ldots, K$ **do**
      Split each node of Φ_{k-1} by exact equality of $c_k(h_t^i)$ to form Φ_k; retain all partitions and parent–child links
    end for
    Build $\mathcal{G}_K$ from the retained transitions; compute $\widehat{V}(C)$ from all visits in each $C \in \Phi_K$
    Initialize every contextual advantage to zero
    for each distinct sampled prefix $u = h_s^r$ with at least two different sampled next actions **do**
      Let $\mathcal{B}_u$ contain indices of all rollouts sharing u; initialize $d_{ij}(u) \leftarrow 0$ for all $i, j \in \mathcal{B}_u$
      for each distinct target observation o reached after step s by a rollout in $\mathcal{B}_u$ **do**
        For each $i \in \mathcal{B}_u$, set $t_i(u, o)$ to the first arrival time after s, or $+\infty$ if absent; let $\mathcal{H}_{u,o}$ contain indices with finite arrivals
        For every $C \in \Phi_k$, $k = 1, \ldots, K$, with nonempty $\mathcal{I}_{u,o}(C)$, estimate $\widehat{V}_u(C)$ from these first-arrival visits only (Equation 4)
        for each $i < j$ in $\mathcal{H}_{u,o}$ taking different actions at u **do**
          Let $t \leftarrow t_i(u, o)$, $n \leftarrow t_j(u, o)$, and $e \leftarrow ((i, t), (j, n))$
          if their arrival contexts first differ at some $k_e \leq K$ **then**
            Compute d_e at this first separating length, including intervening rewards and discounting both returns to s (Equation 5)
            Add d_e to $d_{ij}(u)$ and $-d_e$ to $d_{ji}(u)$ once for this (u, o, i, j)
          end if
        end for
      end for
      Compute $b_i(u)$, μ_u, and σ_u over all $\mathcal{B}_u$ (Equation 7)
      Average $b_i(u)$ over rollouts choosing each action, then standardize by μ_u, σ_u (Equation 8); assign the result to each occurrence of that action at u, or zero if $\sigma_u = 0$
    end for
    Compute suffix GAE along each sampled trajectory on Φ_K (Equation 9), with zero terminal value
    Set $A_i^{\mathrm{EP}} = (R_i - \mu_x)/\sigma_x$ over the N episode returns, or zero if $\sigma_x = 0$; combine all terms using Equation 10
  end for
  Update θ using Equation 11, holding graphs, values, and advantages fixed; mask policy and KL terms for $t > T_i$
end for
Return: Trained policy π_θ

B PROOF OF THE REFINEMENT PROPOSITION

Proof of Proposition 1. For each $k \geq 1$, the shorter context $c_{k-1}(H)$ is a deterministic truncation of $c_k(H)$, including prefixes shorter than k interactions. Hence the corresponding information sets are nested: $\sigma(c_{k-1}(H)) \subseteq \sigma(c_k(H)) \subseteq \sigma(H)$. The tower property gives $V_k = \mathbb{E}[m(H) \mid c_k(H)]$ and $\mathbb{E}[V_k \mid c_{k-1}(H)] = V_{k-1}$. All these variables have finite second moments because $\mathbb{E}[Y^2] < \infty$. Expanding the squared difference yields

$$(m(H) - V_{k-1})^2 = (m(H) - V_k)^2 + (V_k - V_{k-1})^2 + 2(m(H) - V_k)(V_k - V_{k-1}).$$

The factor $V_k - V_{k-1}$ is measurable with respect to $c_k(H)$, while $\mathbb{E}[m(H) - V_k \mid c_k(H)] = 0$. The cross term therefore has expectation zero, so

$$\mathcal{A}_{k-1} - \mathcal{A}_k = \mathbb{E}[(V_k - V_{k-1})^2] \geq 0.$$

Summing over $k = 1, \ldots, K$ gives Equation 12. The squared difference has positive expectation exactly when $V_k \neq V_{k-1}$ with positive probability, establishing the strict inequality condition. Structural separation alone need not lower the discrepancy: the child groups must differ in expected return. □

Connection to the advantage estimators. At $\lambda = 1$, replacing sample node means with their expected values gives the suffix score $Y - V_K$. Its mean squared difference from the full-context score $Y - m(H)$ is exactly $\mathcal{A}_K$. The proposition therefore characterizes the error introduced by the grouping used for this score, without implying a corresponding guarantee for finite-sample estimates or policy improvement. The same refinement argument also applies to the contextual-value groups when the visit distribution is fixed to first arrivals at a given target observation after a given branch. A pair's first separating level identifies where distinct group values become possible; it does not guarantee a nonzero value difference or that this level minimizes estimation error.

C Experiment Details

C.1 Compared Methods

We compare prompting agents and RL methods on ALFWorld and WebShop. Open-model comparisons use Qwen2.5-1.5B-Instruct and Qwen2.5-7B-Instruct, with the same initial checkpoint within each model block.

- **GPT-4o and Gemini-2.5-Pro.** These proprietary models provide prompting-based references for agent performance (OpenAI, 2024; Comanici et al., 2025).
- **Initial policy.** The instruction-tuned Qwen2.5 model interacts with the environment without task-specific RL training (Qwen et al., 2025).
- **ReAct.** The agent alternates reasoning with environment actions and uses the returned observations to guide subsequent decisions (Yao et al., 2023).
- **Reflexion.** Feedback from an attempted task is summarized into textual reflections that inform later attempts (Shinn et al., 2023).
- **PPO.** A learned critic supplies advantage estimates for clipped policy updates (Schulman et al., 2017).
- **GRPO.** Trajectory rewards are normalized within each task's rollout group, yielding an episode advantage shared by all actions in a trajectory (Shao et al., 2024).
- **GiGPO.** Steps with matching observations form additional comparison groups for step-level credit assignment (Feng et al., 2025).
- **G2PO.** Sampled trajectories form a state-transition graph, whose node values and transition value changes provide step-level advantages (Wang et al., 2026).
- **HGPO.** Steps with matching observations are grouped further by preceding state sequences of different lengths. It combines the normalized return comparisons from these nested groups, assigning greater weight to longer contexts (He et al., 2026).

C.2 Environment Details

ALFWorld. ALFWorld presents household tasks through a text interface (Shridhar et al., 2021). The agent navigates rooms, locates objects, and performs actions needed to satisfy an instruction. We evaluate six categories: Pick & Place, Clean & Place, Cool & Place, Examine in Light, Heat & Place, and Pick Two & Place. Success requires completing the environment's task conditions within the interaction limit. Table 1 reports each category's success rate and the overall rate across evaluated tasks.

WebShop. WebShop evaluates shopping agents on a simulated store containing over one million products and approximately 12,000 natural-language instructions (Yao et al., 2022). An agent searches, inspects product pages, selects options, and purchases an item that meets the requested constraints. We report the benchmark's graded task score and complete-task success rate, both on a

0–100 scale. The graded evaluation score is retained even though the training reward uses binary task completion.

C.3 Training details

We adopt the shared training settings of GiGPO and HGPO (Feng et al., 2025; He et al., 2026), summarized in Table 3. RL methods use the same training tasks, reward definitions, interaction limits, and rollout budgets within each environment and backbone. Group-based methods sample 16 tasks per iteration and eight trajectories per task, yielding 128 environment instances. PPO uses 128 environment instances without grouped advantage estimation.

Table 3: Training settings for ALFWorld and WebShop. The critic is used only by PPO. The policy input window is separate from the graph-context length K.

Setting	ALFWorld	WebShop
Maximum prompt length	4096 tokens	4096 tokens
Maximum response length	512 tokens	512 tokens
Maximum interaction steps	50	30
Policy input window	2 interactions	2 interactions
Maximum graph-context length K (CRGPO, default)	2	2
Actor learning rate	10^{-6}	10^{-6}
Critic learning rate (PPO)	10^{-5}	10^{-5}
Rollout group size N	8	8
Task groups per iteration	16	16
Rollout environment instances	128	128
Policy-update minibatch size	256	64
Rollout temperature	1.0	1.0
Evaluation temperature	0.4	0.4
Task reward: success / failure	$10/0$	$10/0$
Invalid-action penalty	-0.1	-0.1
KL coefficient β	0.01	0.01
Return discount γ	0.95	0.95
Contextual weight w_{c} (CRGPO)	1	1
Suffix weight w_{s} (CRGPO)	1	1
Training iterations	160	160
Validation episodes	512	512

Rewards and optimization. A completed task receives a terminal reward of 10; unsuccessful termination, including the interaction limit, receives zero task reward. An invalid action incurs a penalty of -0.1 at that step. Thus r_t^i includes the task reward and any action penalty, $R_i = \sum_t r_t^i$ is the episode return, and g_t^i is its discounted remaining return. Contextual comparisons include the discounted rewards between the action branch and the target arrival, as defined in Equation 5. The terminal boundary value is zero. We use the trainer's clipping parameter $\varepsilon = 0.2$. For CRGPO, suffix GAE uses $\lambda = 1$, and both advantage weights are fixed at $w_{\mathrm{c}} = w_{\mathrm{s}} = 1$ except when a term is removed in an ablation. In Equation 11, steps after termination ($t > T_i$) contribute zero to both the policy term and KL regularization.

Model and evaluation settings. The training configuration uses two NVIDIA A100 SXM4 80GB GPUs for Qwen2.5-1.5B-Instruct and four for Qwen2.5-7B-Instruct. Each run performs 160 training iterations, with validation over 512 episodes. We evaluate the final checkpoint and report test means and standard deviations over three independent training seeds. Repeated evaluations of a checkpoint are averaged within its training run before summarizing across runs. The same evaluation tasks and decoding settings are used for both context lengths and all matched-backbone RL comparisons.

Context length and ablations. The policy always receives the last two interactions. We use $K = 2$ by default for CRGPO and its component ablations. Table 1 compares full CRGPO at $K = 2$ and $K = 4$ with both Qwen2.5-1.5B and Qwen2.5-7B. Within each model scale, both context settings retain all three advantages, the same weights, and the same training budget, using the same set of

three training seeds on both benchmarks. HGPO uses a maximum grouping context of two steps, with weighting exponent $\alpha = 1$ and zero-advantage groups omitted from weight normalization, following its reported configuration (He et al., 2026). Advantage ablations set the removed term's weight to zero. The graph-refinement ablation fixes $w_c = 0$ and compares observation grouping with Φ_K under EP + suf; both graph configurations use the same remaining training settings, and the refined row reuses EP + suf from Figure 3.

Timing. Computational cost is measured with Qwen2.5-1.5B-Instruct on ALFWorld under the same training setup. Figure 4 reports mean time per iteration after warm-up, with GPU synchronization at timing boundaries. Rollout, Update, Ref Prob, Old Prob, Adv, and Refinement are timed separately without overlap. We report the mean duration of each phase, displaying Adv and Refinement in milliseconds to make their smaller costs visible. Any reported phase share uses the sum of these six measurements as its denominator.

C.4 Training metrics

We track task outcomes alongside the quantities that determine policy updates:

- **Episode return and success rate.** Return includes task rewards and action penalties; success records whether the task conditions are met.
- **Advantage statistics.** We record the mean and standard deviation of the episode, contextual, suffix, and combined advantages to monitor their relative scales.
- **Policy loss.** The clipped surrogate loss summarizes the policy update for the sampled actions.
- **KL divergence.** Divergence from the fixed reference policy measures policy drift under KL regularization.
- **Clip fraction.** We record the fraction of sampled likelihood ratios outside the clipping interval.

D Worked example of graph refinement and credit assignment

This example instantiates the construction in Section 4 with six sampled rollouts, terminal rewards only, $\gamma = 1$, and maximum context length $K = 2$. A rollout is one sampled episode: an ordered sequence of observations, actions, and rewards. The rewards below are hypothetical and serve only to illustrate the calculations.

Table 4: Six sampled rollouts in the worked example. The displayed paths end at the target observation C; each sampled continuation then ends with terminal reward R_i. The symbols u, v mark shared full decision prefixes, and each arrow is labeled by the sampled action.

Rollout	Sampled path to C	Visit to C	R_i
τ_1	$u \xrightarrow{A} v \xrightarrow{X} L \xrightarrow{\texttt{move}} P \xrightarrow{\texttt{enter}} C$	$(1, 5)$	0.9
τ_2	$u \xrightarrow{A} v \xrightarrow{X} L \xrightarrow{\texttt{move}} P \xrightarrow{\texttt{enter}} C$	$(2, 5)$	0.7
τ_3	$u \xrightarrow{A} v \xrightarrow{Y} M \xrightarrow{\texttt{move}} P \xrightarrow{\texttt{enter}} C$	$(3, 5)$	0.5
τ_4	$u \xrightarrow{A} v \xrightarrow{Y} M \xrightarrow{\texttt{move}} P \xrightarrow{\texttt{enter}} C$	$(4, 5)$	0.3
τ_5	$u \xrightarrow{B} W \xrightarrow{Z} N \xrightarrow{\texttt{move}} Q \xrightarrow{\texttt{enter}} C$	$(5, 5)$	0.2
τ_6	$u \xrightarrow{B} W \xrightarrow{Z} N \xrightarrow{\texttt{move}} Q \xrightarrow{\texttt{enter}} C$	$(6, 5)$	0.0

All rollouts share u at decision time $s = 1$. Rollouts 1–4 take A and share v at time 2, where $1, 2$ take X and $3, 4$ take Y. Rollouts $5, 6$ take B at u and then Z at W. Thus L, M, N occur at time 3, P, Q at time 4, and every displayed arrival at C at time 5. These are first arrivals at C after the relevant branches. Since $\gamma = 1$ and only the terminal action receives a reward, $g_5^i = R_i$.

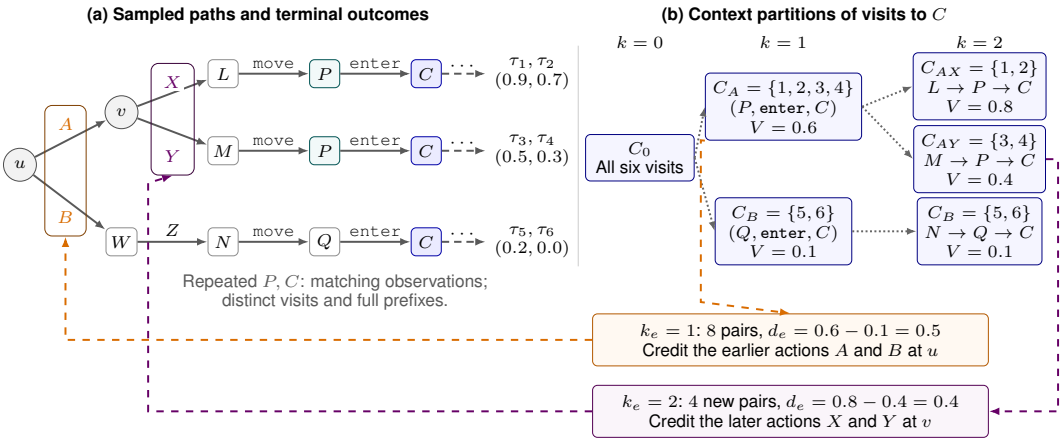

Figure 5: Context-guided refinement for six hypothetical rollouts (terminal rewards only, $\gamma = 1$). (a) Solid arrows show sampled interactions; circles u, v mark shared full prefixes. Repeated P, C boxes represent distinct visits with matching observations. (b) Dotted edges link nested context partitions for C; values average original returns. Colored dashed arrows route first-separation value differences to branching actions. Two-step labels omit the `move`/`enter` actions in (a).

AT: What does the following sentence actually mean? what shall the reader infer from it?

Comparisons for other shared observations are computed separately.

Partitions of visits to C. We show only the nodes for observation C; the complete partition Φ_k also contains the nodes for all other observations. At $k = 0$, the context $c_0(h_5^i) = C$ is identical for all six visits, giving the node

$$D^{(0)} = \{(1,5),(2,5),(3,5),(4,5),(5,5),(6,5)\}, \qquad \widehat{V}(D^{(0)}) = \frac{2.6}{6} = \frac{13}{30}. \tag{13}$$

At $k = 1$, $c_1(h_5^i) = (P, \texttt{enter}, C)$ for $i = 1,2,3,4$, whereas $c_1(h_5^i) = (Q, \texttt{enter}, C)$ for $i = 5,6$. The node therefore splits into

$$\begin{aligned} D_1^{(1)} &= \{(1,5),(2,5),(3,5),(4,5)\}, & \widehat{V}(D_1^{(1)}) &= 0.6, \\ D_2^{(1)} &= \{(5,5),(6,5)\}, & \widehat{V}(D_2^{(1)}) &= 0.1. \end{aligned} \tag{14}$$

At $k = 2$, the contexts are $(L, \texttt{move}, P, \texttt{enter}, C)$ for rollouts $1, 2$, $(M, \texttt{move}, P, \texttt{enter}, C)$ for $3, 4$, and $(N, \texttt{move}, Q, \texttt{enter}, C)$ for $5, 6$. They give

$$\begin{aligned} D_1^{(2)} &= \{(1,5),(2,5)\}, & \widehat{V}(D_1^{(2)}) &= 0.8, \\ D_2^{(2)} &= \{(3,5),(4,5)\}, & \widehat{V}(D_2^{(2)}) &= 0.4, \\ D_3^{(2)} &= \{(5,5),(6,5)\}, & \widehat{V}(D_3^{(2)}) &= 0.1. \end{aligned} \tag{15}$$

The superscript of each $D_r^{(k)}$ is its refinement level; r is a local node identifier with no action or observation meaning. For example, $C^{(1)}(1,5) = D_1^{(1)}$ and $C^{(2)}(1,5) = D_1^{(2)}$. Thus $D_1^{(1)}$ has two children, while $D_2^{(1)}$ is unchanged as a visit set at level 2. Context equality determines membership; returns determine the values after membership has been fixed.

First separation and the credited branch. Each comparison is between two visits, $e = ((i,5),(j,5))$, from distinct rollouts with $i < j$. Every pair with $i \in \{1,2,3,4\}$ and $j \in \{5,6\}$ first separates at $k_e = 1$. These rollouts take different actions A, B at their last shared full prefix u. There are $4 \times 2 = 8$ such visit pairs. Every pair with $i \in \{1,2\}$ and $j \in \{3,4\}$ first separates at $k_e = 2$. These rollouts share action A at u and take different actions X, Y at their last shared prefix v. There are $2 \times 2 = 4$ such visit pairs. The eight pairs already separated at level 1 receive no additional comparison at level 2. Visits within each final node have equal contexts through $K = 2$ and yield no contextual comparison for target C.

Numerical contextual advantages. We next evaluate Equations 5–8 on these visits, considering only target observation C. This restriction makes the numerical contribution of C explicit; the full method sums contributions from every eligible target observation before normalization. Here every rollout reaches C once, so each branch-local child mean $\widehat{V}_u$ or $\widehat{V}_v$ equals the corresponding mean listed above. The intervening returns are zero and $\gamma = 1$, so Equation 5 gives

$$\begin{aligned} d_{((1,5),(5,5))} &= 0.6 - 0.1 = 0.5 \quad \text{at } u, \\ d_{((1,5),(3,5))} &= 0.8 - 0.4 = 0.4 \quad \text{at } v. \end{aligned} \tag{16}$$

The first value applies to all eight comparisons at u; the second applies to all four at v. Each comparison contributes positively to its first rollout and negatively to its second.

At u, $\mathcal{B}_u = \{1, 2, 3, 4, 5, 6\}$. Each rollout taking A has two comparison partners taking B, whereas each rollout taking B has four partners taking A. Equation 7 therefore gives

$$b_i(u) = \begin{cases} 2(0.5)/6 = 1/6, & i \in \{1, 2, 3, 4\}, \\ -4(0.5)/6 = -1/3, & i \in \{5, 6\}. \end{cases} \qquad \mu_u = 0, \quad \sigma_u = \frac{1}{3\sqrt{2}}. \tag{17}$$

Consequently, the normalized action advantages are

$$A^{\mathrm{ctx}}(u, A) = \frac{1}{\sqrt{2}}, \qquad A^{\mathrm{ctx}}(u, B) = -\sqrt{2}. \tag{18}$$

At v, $\mathcal{B}_v = \{1, 2, 3, 4\}$, and every rollout has two partners taking the other action. Hence $b_1(v) = b_2(v) = 2(0.4)/4 = 0.2$, $b_3(v) = b_4(v) = -0.2$, $\mu_v = 0$, and $\sigma_v = 0.2$. The resulting advantages are

$$A^{\mathrm{ctx}}(v, X) = 1, \qquad A^{\mathrm{ctx}}(v, Y) = -1. \tag{19}$$

These credits are assigned to the sampled actions at u or v, respectively, even though the compared visits occur later at C.

Numerical suffix advantages. For $\lambda = 1$, Equation 9 reduces to the return minus the final node value. At the six visits to C, this gives

$$\begin{aligned} A_5^{1,\mathrm{suf}} &= 0.9 - 0.8 = 0.1, \quad A_5^{2,\mathrm{suf}} = 0.7 - 0.8 = -0.1, \\ A_5^{3,\mathrm{suf}} &= 0.5 - 0.4 = 0.1, \quad A_5^{4,\mathrm{suf}} = 0.3 - 0.4 = -0.1, \\ A_5^{5,\mathrm{suf}} &= 0.2 - 0.1 = 0.1, \quad A_5^{6,\mathrm{suf}} = 0.0 - 0.1 = -0.1. \end{aligned} \tag{20}$$

Each result uses $\widehat{V}(C^{(2)}(i, 5))$ as its baseline and is assigned to the action taken at that visit. Thus contextual advantages credit the earlier branches leading to different contexts, while suffix advantages distinguish sampled continuations within each final context node.

E Further analysis

In this analysis, we examine how interaction context changes node sharing and the comparisons available for credit assignment. Figure 6 uses Qwen2.5-1.5B-Instruct trained with CRGPO on ALFWorld, taking the checkpoint at training iteration 160. We sample from the training task pool with a fixed budget of 320 task groups and eight rollouts per group, giving 2,560 rollouts and 51,097 decision visits. Sampling performs inference only, with the policy receiving the two most recent interactions. The checkpoint was trained with maximum graph-context length $K = 2$; all five analysis levels are constructed offline from the same sampled trajectories. The statistics at context lengths three and four therefore describe additional partitions of these trajectories, not separately trained policies.

Context sharing. Each task group forms a separate graph. The sharing proportion counts visits whose nodes contain at least two distinct rollouts, using all decision visits as the denominator. Repeated visits within one rollout do not count as multiple rollout support. When nodes are defined by current observations alone, 93.50% of visits share a node with another rollout. Requiring two preceding interactions to match reduces this proportion to 53.52%, and four interactions reduce it to 33.25%. Thus, many visits grouped by the same observation have different interaction contexts. Finer refinement distinguishes these contexts, but fewer visits retain support from multiple rollouts within the same node.

First separating levels. Candidate comparisons follow Section 4.2: two rollouts share a full decision prefix, choose different actions there, and subsequently reach the same target observation, using only their first arrivals after that branch. The 43,998 candidate pairs are each assigned to their first separating level or to the unseparated category, which remains in the denominator. Two interactions suffice to distinguish 87.52% of candidate comparisons. The third and fourth interactions distinguish a further 9.80%, leaving 2.68% unseparated through length four. Most candidate comparisons therefore become available with short contexts, while longer contexts reveal additional distinctions. These observations motivate retaining the refinement hierarchy: different context lengths expose different comparisons, while finer nodes provide more specific contexts for suffix value estimation.

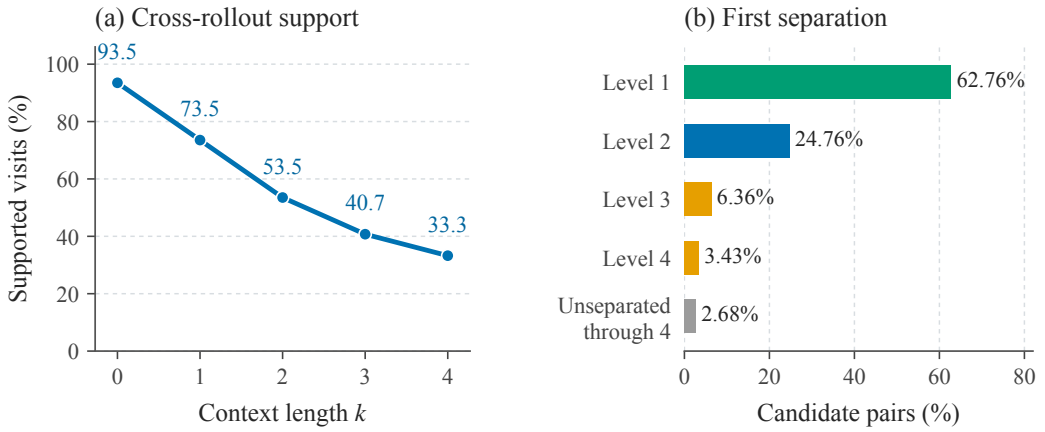

Figure 6: Context statistics for Qwen2.5-1.5B-Instruct on ALFWorld. (a) Visits sharing a node with another rollout. (b) Candidate comparisons grouped by the context length at which they first separate. Unseparated pairs have matching contexts through four interactions.

These statistics describe context sharing and comparison opportunities; they do not measure value-estimation error or establish a performance benefit from extending the context window.

F Case Study

Follow, we present a complete case study of an agent trained by CRGPO on ALFWorld and WebShop. Each trace includes the recorded prompt and response at every step. Prompts contain the task, current observation, admissible actions, and up to two recent observation–action pairs. Responses enclose the generated reasoning in `<think>` tags and the selected action in `<action>` tags. Gray boxes show prompts, blue boxes show responses, and gold text highlights the history and observations discussed below. Whitespace and hyphen typography are normalized for readability; the recorded wording is preserved, including occasional inaccuracies in the generated explanations.

ALFWorld, Step 1.

Prompt (ALFWorld, Step 1)

<lim_start|>system You are Qwen, created by Alibaba Cloud. You are a helpful assistant.<lim_end|>
<lim_start|>user
You are an expert agent operating in the ALFRED Embodied Environment. Your current observation is: -= Welcome to TextWorld, ALFRED! =-
You are in the middle of a room. Looking quickly around you, you see a cabinet 12, a cabinet 11, a cabinet 10, a cabinet 9, a cabinet 8, a cabinet 7, a cabinet 6, a cabinet 5, a cabinet 4, a cabinet 3, a cabinet 2, a cabinet 1, a coffeemachine 1, a countertop 2, a countertop 1, a diningtable 1, a drawer 3, a drawer 2, a drawer 1, a fridge 1, a garbagecan 1, a microwave 1, a sinkbasin 1, a stoveburner 4, a stoveburner 3, a stoveburner 2, a stoveburner 1, and a toaster 1.
Your task is to: put a clean ladle in drawer. Your admissible actions of the current situation are: [’go to cabinet 1’ ’go to cabinet 10’ ’go to cabinet 11’ ’go to cabinet 12’ ’go to cabinet 2’ ’go to cabinet 3’ ’go to

cabinet 4’ ’go to cabinet 5’ ’go to cabinet 6’ ’go to cabinet 7’ ’go to cabinet 8’ ’go to cabinet 9’ ’go to coffeemachine 1’ ’go to countertop 1’ ’go to countertop 2’ ’go to diningtable 1’ ’go to drawer 1’ ’go to drawer 2’ ’go to drawer 3’ ’go to fridge 1’ ’go to garbagecan 1’ ’go to microwave 1’ ’go to sinkbasin 1’ ’go to stoveburner 1’ ’go to stoveburner 2’ ’go to stoveburner 3’ ’go to stoveburner 4’ ’go to toaster 1’ ’inventory’ ’look’].
Now it’s your turn to take an action. You should first reason step-by-step about the current situation. This reasoning process MUST be enclosed within <think> </think> tags. Once you’ve finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags. <|im_end|> <|im_start|>assistant

Response (ALFWorld, Step 1)

<think> The task is to put a clean ladle in a drawer. First, I need to find a ladle. Let’s start by checking the dining table 1. </think>
<action>go to diningtable 1</action>

Environment feedback. You arrive at diningtable 1. On the diningtable 1, you see a bowl 3, a bread 1, a butterknife 3, a cup 2, a dishsponge 1, a fork 2, a ladle 1, a peppershaker 3, a peppershaker 2, a plate 2, a saltshaker 1, a soapbottle 3, a spatula 2, a spoon 3, and a tomato 3. Reward: 0.

ALFWorld, Step 2.

Prompt (ALFWorld, Step 2)

<|im_start|>system You are Qwen, created by Alibaba Cloud. You are a helpful assistant.<|im_end|>
<|im_start|>user
You are an expert agent operating in the ALFRED Embodied Environment. Your task is to: put a clean ladle in drawer. Prior to this step, you have already taken 1 step(s). Below are the most recent 1 observations and the corresponding actions you took: [Observation 1: ’-= Welcome to TextWorld, ALFRED! =-
You are in the middle of a room. Looking quickly around you, you see a cabinet 12, a cabinet 11, a cabinet 10, a cabinet 9, a cabinet 8, a cabinet 7, a cabinet 6, a cabinet 5, a cabinet 4, a cabinet 3, a cabinet 2, a cabinet 1, a coffeemachine 1, a countertop 2, a countertop 1, a diningtable 1, a drawer 3, a drawer 2, a drawer 1, a fridge 1, a garbagecan 1, a microwave 1, a sinkbasin 1, a stoveburner 4, a stoveburner 3, a stoveburner 2, a stoveburner 1, and a toaster 1.
Your task is to: put a clean ladle in drawer.’, Action 1: ’go to diningtable 1’] You are now at step 2 and your current observation is: You arrive at diningtable 1. On the diningtable 1, you see a bowl 3, a bread 1, a butterknife 3, a cup 2, a dishsponge 1, a fork 2, a ladle 1, a peppershaker 3, a peppershaker 2, a plate 2, a saltshaker 1, a soapbottle 3, a spatula 2, a spoon 3, and a tomato 3. Your admissible actions of the current situation are: [’examine diningtable 1’ ’go to cabinet 1’ ’go to cabinet 10’ ’go to cabinet 11’ ’go to cabinet 12’ ’go to cabinet 2’ ’go to cabinet 3’ ’go to cabinet 4’ ’go to cabinet 5’ ’go to cabinet 6’ ’go to cabinet 7’ ’go to cabinet 8’ ’go to cabinet 9’ ’go to coffeemachine 1’ ’go to countertop 1’ ’go to countertop 2’ ’go to drawer 1’ ’go to drawer 2’ ’go to drawer 3’ ’go to fridge 1’ ’go to garbagecan 1’ ’go to microwave 1’ ’go to sinkbasin 1’ ’go to stoveburner 1’ ’go to stoveburner 2’ ’go to stoveburner 3’ ’go to stoveburner 4’ ’go to toaster 1’ ’inventory’ ’look’ ’take bowl 3 from diningtable 1’ ’take bread 1 from diningtable 1’ ’take butterknife 3 from diningtable 1’ ’take cup 2 from diningtable 1’ ’take dishsponge 1 from diningtable 1’ ’take fork 2 from diningtable 1’ ’take ladle 1 from diningtable 1’ ’take peppershaker 2 from diningtable 1’ ’take peppershaker 3 from diningtable 1’ ’take plate 2 from diningtable 1’ ’take saltshaker 1 from diningtable 1’ ’take soapbottle 3 from diningtable 1’ ’take spatula 2 from diningtable 1’ ’take spoon 3 from diningtable 1’ ’take tomato 3 from diningtable 1’].
Now it’s your turn to take an action. You should first reason step-by-step about the current situation. This reasoning process MUST be enclosed within <think> </think> tags. Once you’ve finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags. <|im_end|> <|im_start|>assistant

Response (ALFWorld, Step 2)

<think> The diningtable 1 is currently empty. However, I have found that there is a ladle 1 on the diningtable 1 that needs to be cleaned before it can be put in the drawer. </think>
<action>take ladle 1 from diningtable 1</action>

Environment feedback. You pick up the ladle 1 from the diningtable 1. Reward: 0.

ALFWorld, Step 3.

Prompt (ALFWorld, Step 3)

<lim_start|>system You are Qwen, created by Alibaba Cloud. You are a helpful assistant.<lim_end|>
<lim_start|>user
You are an expert agent operating in the ALFRED Embodied Environment. Your task is to: put a clean ladle in drawer. Prior to this step, you have already taken 2 step(s). Below are the most recent 2 observations and the corresponding actions you took: [Observation 1: '-= Welcome to TextWorld, ALFRED! =-
You are in the middle of a room. Looking quickly around you, you see a cabinet 12, a cabinet 11, a cabinet 10, a cabinet 9, a cabinet 8, a cabinet 7, a cabinet 6, a cabinet 5, a cabinet 4, a cabinet 3, a cabinet 2, a cabinet 1, a coffeemachine 1, a countertop 2, a countertop 1, a diningtable 1, a drawer 3, a drawer 2, a drawer 1, a fridge 1, a garbagecan 1, a microwave 1, a sinkbasin 1, a stoveburner 4, a stoveburner 3, a stoveburner 2, a stoveburner 1, and a toaster 1.
Your task is to: put a clean ladle in drawer.', Action 1: 'go to diningtable 1'] [Observation 2: 'You arrive at diningtable 1. On the diningtable 1, you see a bowl 3, a bread 1, a butterknife 3, a cup 2, a dishsponge 1, a fork 2, a ladle 1, a peppershaker 3, a peppershaker 2, a plate 2, a saltshaker 1, a soapbottle 3, a spatula 2, a spoon 3, and a tomato 3.', Action 2: 'take ladle 1 from diningtable 1'] You are now at step 3 and your current observation is: You pick up the ladle 1 from the diningtable 1. Your admissible actions of the current situation are: ['examine diningtable 1' 'examine ladle 1' 'go to cabinet 1' 'go to cabinet 10' 'go to cabinet 11' 'go to cabinet 12' 'go to cabinet 2' 'go to cabinet 3' 'go to cabinet 4' 'go to cabinet 5' 'go to cabinet 6' 'go to cabinet 7' 'go to cabinet 8' 'go to cabinet 9' 'go to coffeemachine 1' 'go to countertop 1' 'go to countertop 2' 'go to drawer 1' 'go to drawer 2' 'go to drawer 3' 'go to fridge 1' 'go to garbagecan 1' 'go to microwave 1' 'go to sinkbasin 1' 'go to stoveburner 1' 'go to stoveburner 2' 'go to stoveburner 3' 'go to stoveburner 4' 'go to toaster 1' 'inventory' 'look' 'move ladle 1 to diningtable 1'].
Now it's your turn to take an action. You should first reason step-by-step about the current situation. This reasoning process MUST be enclosed within <think> </think> tags. Once you've finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags. <lim_end|> <lim_start|>assistant

Response (ALFWorld, Step 3)

<think> The current situation is that I have picked up the ladle 1 from the dining table 1. The ladle is now in my possession. </think>
<action>go to sinkbasin 1</action>

Environment feedback. You arrive at sinkbasin 1. On the sinkbasin 1, you see a apple 2, and a spatula 1. Reward: 0.

ALFWorld, Step 4.

Prompt (ALFWorld, Step 4)

<lim_start|>system You are Qwen, created by Alibaba Cloud. You are a helpful assistant.<lim_end|>
<lim_start|>user
You are an expert agent operating in the ALFRED Embodied Environment. Your task is to: put a clean ladle in drawer. Prior to this step, you have already taken 3 step(s). Below are the most recent 2 observations and the corresponding actions you took: [Observation 2: 'You arrive at diningtable 1. On the diningtable 1, you see a bowl 3, a bread 1, a butterknife 3, a cup 2, a dishsponge 1, a fork 2, a ladle 1, a peppershaker 3, a peppershaker 2, a plate 2, a saltshaker 1, a soapbottle 3, a spatula 2, a spoon 3, and a tomato 3.', Action 2: 'take ladle 1 from diningtable 1'] [Observation 3: 'You pick up the ladle 1 from the diningtable 1.', Action 3: 'go to sinkbasin 1'] You are now at step 4 and your current observation is: You arrive at sinkbasin 1. On the sinkbasin 1, you see a apple 2, and a spatula 1. Your admissible actions of the current situation are: ['clean ladle 1 with sinkbasin 1' 'examine ladle 1' 'examine sinkbasin 1' 'go to cabinet 1' 'go to cabinet 10' 'go to cabinet 11' 'go to cabinet 12' 'go to cabinet 2' 'go to cabinet 3' 'go to cabinet 4' 'go to cabinet 5' 'go to cabinet 6' 'go to cabinet 7' 'go to cabinet 8' 'go to cabinet 9' 'go to coffeemachine 1' 'go to countertop 1' 'go to countertop 2' 'go to diningtable 1' 'go to drawer 1' 'go to drawer 2' 'go to drawer 3' 'go to fridge 1' 'go to garbagecan 1' 'go to microwave 1' 'go to stoveburner 1' 'go to stoveburner 2' 'go to stoveburner 3' 'go to stoveburner 4' 'go to toaster 1' 'inventory' 'look' 'move ladle 1 to sinkbasin 1'].
Now it's your turn to take an action. You should first reason step-by-step about the current situation. This reasoning process MUST be enclosed within <think> </think> tags. Once you've finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags. <lim_end|> <lim_start|>assistant

Response (ALFWorld, Step 4)

<think> The current situation is that you are at sinkbasin 1, where you have taken the ladle 1 from diningtable 1. The ladle is now clean. </think>
<action>clean ladle 1 with sinkbasin 1</action>

Environment feedback. You clean the ladle 1 using the sinkbasin 1. Reward: 0.

ALFWorld, Step 5.

Prompt (ALFWorld, Step 5)

<|im_start|>system You are Qwen, created by Alibaba Cloud. You are a helpful assistant.<|im_end|>
<|im_start|>user
You are an expert agent operating in the ALFRED Embodied Environment. Your task is to: put a clean ladle in drawer. Prior to this step, you have already taken 4 step(s). Below are the most recent 2 observations and the corresponding actions you took: [Observation 3: 'You pick up the ladle 1 from the diningtable 1.', Action 3: 'go to sinkbasin 1'] [Observation 4: 'You arrive at sinkbasin 1. On the sinkbasin 1, you see a apple 2, and a spatula 1.', Action 4: 'clean ladle 1 with sinkbasin 1'] You are now at step 5 and your current observation is: You clean the ladle 1 using the sinkbasin 1. Your admissible actions of the current situation are: ['clean ladle 1 with sinkbasin 1' 'examine ladle 1' 'examine sinkbasin 1' 'go to cabinet 1' 'go to cabinet 10' 'go to cabinet 11' 'go to cabinet 12' 'go to cabinet 2' 'go to cabinet 3' 'go to cabinet 4' 'go to cabinet 5' 'go to cabinet 6' 'go to cabinet 7' 'go to cabinet 8' 'go to cabinet 9' 'go to coffeemachine 1' 'go to countertop 1' 'go to countertop 2' 'go to diningtable 1' 'go to drawer 1' 'go to drawer 2' 'go to drawer 3' 'go to fridge 1' 'go to garbagecan 1' 'go to microwave 1' 'go to stoveburner 1' 'go to stoveburner 2' 'go to stoveburner 3' 'go to stoveburner 4' 'go to toaster 1' 'inventory' 'look' 'move ladle 1 to sinkbasin 1'].
Now it's your turn to take an action. You should first reason step-by-step about the current situation. This reasoning process MUST be enclosed within <think> </think> tags. Once you've finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags. <|im_end|> <|im_start|>assistant

Response (ALFWorld, Step 5)

<think> The ladle has already been cleaned with the sinkbasin. The task is to put a clean ladle in a drawer. The ladle has been cleaned, but there is no specific drawer provided for cleaning. If the ladle needs to be put in a drawer, it should either be placed back on the dining table or put into a drawer as part of a final action, as the context does not suggest where it needs to be placed. </think>
<action>go to drawer 1</action>

Environment feedback. You arrive at drawer 1. The drawer 1 is closed. Reward: 0.

ALFWorld, Step 6.

Prompt (ALFWorld, Step 6)

<|im_start|>system You are Qwen, created by Alibaba Cloud. You are a helpful assistant.<|im_end|>
<|im_start|>user
You are an expert agent operating in the ALFRED Embodied Environment. Your task is to: put a clean ladle in drawer. Prior to this step, you have already taken 5 step(s). Below are the most recent 2 observations and the corresponding actions you took: [Observation 4: 'You arrive at sinkbasin 1. On the sinkbasin 1, you see a apple 2, and a spatula 1.', Action 4: 'clean ladle 1 with sinkbasin 1'] [Observation 5: 'You clean the ladle 1 using the sinkbasin 1.', Action 5: 'go to drawer 1'] You are now at step 6 and your current observation is: You arrive at drawer 1. The drawer 1 is closed. Your admissible actions of the current situation are: ['examine drawer 1' 'examine ladle 1' 'go to cabinet 1' 'go to cabinet 10' 'go to cabinet 11' 'go to cabinet 12' 'go to cabinet 2' 'go to cabinet 3' 'go to cabinet 4' 'go to cabinet 5' 'go to cabinet 6' 'go to cabinet 7' 'go to cabinet 8' 'go to cabinet 9' 'go to coffeemachine 1' 'go to countertop 1' 'go to countertop 2' 'go to diningtable 1' 'go to drawer 2' 'go to drawer 3' 'go to fridge 1' 'go to garbagecan 1' 'go to microwave 1' 'go to sinkbasin 1' 'go to stoveburner 1' 'go to stoveburner 2' 'go to stoveburner 3' 'go to stoveburner 4' 'go to toaster 1' 'inventory' 'look' 'open drawer 1'].
Now it's your turn to take an action. You should first reason step-by-step about the current situation. This reasoning process MUST be enclosed within <think> </think> tags. Once you've finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags. <|im_end|> <|im_start|>assistant

Response (ALFWorld, Step 6)

<think> You have already reached the drawer 1. The ladle is currently clean, but the drawer is closed, making it impossible to put the clean ladle inside. </think>
<action>open drawer 1</action>

Environment feedback. You open the drawer 1. The drawer 1 is open. In it, you see a knife 1. Reward: 0.

ALFWorld, Step 7.

Prompt (ALFWorld, Step 7)

<|im_start|>system You are Qwen, created by Alibaba Cloud. You are a helpful assistant.<|im_end|>
<|im_start|>user
You are an expert agent operating in the ALFRED Embodied Environment. Your task is to: put a clean ladle in drawer. Prior to this step, you have already taken 6 step(s). Below are the most recent 2 observations and the corresponding actions you took: [Observation 5: 'You clean the ladle 1 using the sinkbasin 1.', Action 5: 'go to drawer 1'] [Observation 6: 'You arrive at drawer 1. The drawer 1 is closed.', Action 6: 'open drawer 1'] You are now at step 7 and your current observation is: You open the drawer 1. The drawer 1 is open. In it, you see a knife 1. Your admissible actions of the current situation are: ['close drawer 1' 'examine drawer 1' 'examine ladle 1' 'go to cabinet 1' 'go to cabinet 10' 'go to cabinet 11' 'go to cabinet 12' 'go to cabinet 2' 'go to cabinet 3' 'go to cabinet 4' 'go to cabinet 5' 'go to cabinet 6' 'go to cabinet 7' 'go to cabinet 8' 'go to cabinet 9' 'go to coffeemachine 1' 'go to countertop 1' 'go to countertop 2' 'go to diningtable 1' 'go to drawer 2' 'go to drawer 3' 'go to fridge 1' 'go to garbagecan 1' 'go to microwave 1' 'go to sinkbasin 1' 'go to stoveburner 1' 'go to stoveburner 2' 'go to stoveburner 3' 'go to stoveburner 4' 'go to toaster 1' 'inventory' 'look' 'move ladle 1 to drawer 1'].
Now it's your turn to take an action. You should first reason step-by-step about the current situation. This reasoning process MUST be enclosed within <think> </think> tags. Once you've finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags. <|im_end|> <|im_start|>assistant

Response (ALFWorld, Step 7)

<think> The ladle is already clean in the sinkbasin, so there is no need to clean it again. The purpose of this task is to put the clean ladle in the drawer. </think> <action>move ladle 1 to drawer 1</action>

Environment feedback. You move the ladle 1 to the drawer 1. Reward: 10. The episode terminates successfully.

WebShop, Step 1.

Prompt (WebShop, Step 1)

system You are Qwen, created by Alibaba Cloud. You are a helpful assistant. user
You are an expert autonomous agent operating in the WebShop e-commerce environment. Your task is to: Find me wall mounted, white item, easy clean tv stands for living room with color: brown, and price lower than 130.00 dollars. Your current observation is: 'Search'. Your admissible actions of the current situation are: ['search[<your query>]', 'click[search]',].
Now it's your turn to take one action for the current step. You should first reason step-by-step about the current situation, then think carefully which admissible action best advances the shopping goal. This reasoning process MUST be enclosed within <think> </think> tags. Once you've finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags.
assistant

Response (WebShop, Step 1)

<think> To find the desired wall mounted, white item, easy clean tv stands for living room with color: brown, and price lower than 130.00 dollars, I need to search for the relevant keywords in the WebShop e-commerce environment. The available action options are 'search[<your query>]' or 'click[search]', which seem suitable for carrying out the search. </think>
<action>search[brown tv stands wall mounted white brown living room affordable]</action>

WebShop, Step 2.

Prompt (WebShop, Step 2)

system You are Qwen, created by Alibaba Cloud. You are a helpful assistant. user
You are an expert autonomous agent operating in the WebShop e-commerce environment. Your task is to: Find me wall mounted, white item, easy clean tv stands for living room with color: brown, and price lower than 130.00 dollars. Prior to this step, you have already taken 1 step(s). Below are the most recent 1 observations and the corresponding actions you took: [Observation 1: "Search", Action 1: 'search[brown tv stands wall mounted white brown living room affordable]'] You are now at step 2 and your current observation is: 'Back to Search' [SEP] 'Page 1 (Total results: 50)' [SEP] 'Next >' [SEP] 'B09F6SCW47' [SEP] 'hongxinq Floating TV Stand with Storage Shelves, Chipboard Wall Mounted Hanging Television Cabinet, Modern Storage Cabinet for Living Room, Bedroom, 12Inx11.8Inx35.4In, White' [SEP] '$90.79' [SEP] 'B09S6S7LG1' [SEP] 'TV Stand for 70 Inch TV Entertainment Center Stand TV Stand with Storage for TV Console Cabinet Media Cable Box Gaming 70 inch TV Stands for Bedroom Living Room' [SEP] '$169.99' [SEP] 'B0924PKLQ4' [SEP] 'V-MORO HomePod Mini Wall Mount Holder, Outlet Mount Stand Hidden Cable Management for Apple HomePod Mini Smart Speaker Shelf Without Messy Wires Excellent Space Saving Punch-Free 2-Pack White' [SEP] '$19.99' [SEP] 'B07ZYVWCZ7' [SEP] 'Universal TV Stand/ Base Tabletop TV Stand with Wall Mount for 40 to 86 inch 5 Level Height Adjustable, Heavy Duty Tempered Glass Base, Holds up to 132lbs Screens, HT03B-003' [SEP] '$73.95' [SEP] 'B09MNNBDTJ' [SEP] 'Woody BL-EF Electric Fireplace 77" TV Stand (White/Gray)' [SEP] '$100.0' [SEP] 'B09BKPV8LR' [SEP] 'Wood TV Stand for 65 Inch TV, TV Cabinet with Farmhouse Barn Doors, TV Console Table with Adjustable Shelves, Industrial, Rustic Brown' [SEP] '$317.58' [SEP] 'B07FKGQKZ1' [SEP] 'Home Dynamix Lyndhurst Rotana Modern Area Rug, Contemporary Blue/Gray/Ivory 5'2"x7'4"' [SEP] '$44.99 to $33.98' [SEP] 'B08K7LDM7Q' [SEP] '2 Pcs Cowhide Throw Pillow Covers Decorative Pillow Cases Farm Animal Brown Cow Hide Skin Print Pillow Case 18 X 18 Inch Velvet Square Cushion Cover for Sofa Bedroom' [SEP] '$17.99' [SEP] 'B09LHM4WQS' [SEP] 'Lift Top Coffee Tables for Living Room Coffee Table with Storage, Lift Cable Coffee Table, Dining Table with Hidden Storage Compartment Chestnut' [SEP] '$82.99' [SEP] 'B07GZLDJMC' [SEP] 'FITUEYES Universal TV Stand/Base Tabletop TV Stand with Swivel Mount for 32 to 65 inch Flat Screen TV Height Adjustable,Tempered Glass Base' [SEP] '$42.99'. Your admissible actions of the current situation are: ['click[back to search]', 'click[next >]', 'click[b09f6scw47]', 'click[b09s6s7lg1]', 'click[b0924pklq4]', 'click[b07zyvwcz7]', 'click[b09mnnbdtj]', 'click[b09bkpv8lr]', 'click[b07fkgqkz1]', 'click[b08k7ldm7q]', 'click[b09lhm4wqs]', 'click[b07gzldjmc]',].
Now it's your turn to take one action for the current step. You should first reason step-by-step about the current situation, then think carefully which admissible action best advances the shopping goal. This reasoning process MUST be enclosed within <think> </think> tags. Once you've finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags.

assistant

Response (WebShop, Step 2)

<think> To find the designated wall mounted, white item, easy clean tv stands for living room with color: brown, and price lower than 130.00 dollars, I should still find it by looking at the results returned from the search. It wasn't easy. It took a while to find white brown wall mounted TV stands on sales. </think>
<action>click[b09f6scw47]</action>

WebShop, Step 3.

Prompt (WebShop, Step 3)

system You are Qwen, created by Alibaba Cloud. You are a helpful assistant. user
You are an expert autonomous agent operating in the WebShop e-commerce environment. Your task is to: Find me wall mounted, white item, easy clean tv stands for living room with color: brown, and price lower than 130.00 dollars. Prior to this step, you have already taken 2 step(s). Below are the most recent 2 observations and the corresponding actions you took: [Observation 1: "Search", Action 1: 'search[brown tv stands wall mounted white brown living room affordable]'] [Observation 2: "Back to Search' [SEP] 'Page 1 (Total results: 50)' [SEP] 'Next >' [SEP] 'B09F6SCW47' [SEP] 'hongxinq Floating TV Stand with Storage Shelves, Chipboard Wall Mounted Hanging Television Cabinet, Modern Storage Cabinet for Living Room, Bedroom, 12Inx11.8Inx35.4In, White' [SEP] '$90.79' [SEP] 'B09S6S7LG1' [SEP] 'TV Stand for 70 Inch TV Entertainment Center Stand TV Stand with Storage for TV Console Cabinet Media Cable Box Gaming 70 inch TV Stands for Bedroom Living Room' [SEP] '$169.99' [SEP] 'B0924PKLQ4' [SEP] 'V-MORO HomePod Mini Wall Mount Holder, Outlet Mount Stand Hidden Cable Management for Apple HomePod Mini Smart Speaker Shelf Without Messy Wires Excellent Space Saving Punch-Free 2-Pack White' [SEP] '$19.99' [SEP] 'B07ZYVWCZ7' [SEP] 'Universal TV Stand/ Base Tabletop TV Stand with Wall Mount for 40 to 86 inch 5 Level Height Adjustable, Heavy Duty Tempered Glass Base, Holds up to 132lbs Screens, HT03B-003' [SEP] '$73.95' [SEP] 'B09MNNBDTJ' [SEP] 'Woody BL-EF Electric Fireplace 77" TV Stand (White/Gray)' [SEP] '$100.0' [SEP] 'B09BKPV8LR' [SEP] 'Wood TV Stand for 65 Inch TV, TV Cabinet with Farmhouse Barn Doors, TV Console Table with Adjustable Shelves, Industrial, Rustic Brown' [SEP] '$317.58' [SEP] 'B07FKGQKZ1' [SEP] 'Home Dynamix Lyndhurst Rotana Modern Area Rug, Contemporary Blue/Gray/Ivory 5'2"x7'4"' [SEP] '$44.99 to $33.98' [SEP] 'B08K7LDM7Q' [SEP] '2 Pcs Cowhide Throw Pillow Covers Decorative Pillow Cases Farm Animal Brown Cow Hide Skin Print Pillow Case 18 X 18 Inch Velvet Square Cushion Cover for Sofa Bedroom' [SEP] '$17.99' [SEP] 'B09LHM4WQS' [SEP] 'Lift Top Coffee Tables for Living Room Coffee Table with Storage, Lift Cable Coffee Table, Dining Table with Hidden Storage Compartment Chestnut' [SEP] '$82.99' [SEP] 'B07GZLDJMC' [SEP] 'FITUEYES Universal TV Stand/Base Tabletop TV Stand with Swivel Mount for 32 to 65 inch Flat Screen TV Height Adjustable,Tempered Glass Base' [SEP] '$42.99", Action 2: 'click[b09f6scw47]'] You are now at step 3 and your current observation is: 'Back to Search' [SEP] '< Prev' [SEP] 'color' [SEP] 'brown' [SEP] 'concrete gray' [SEP] 'grey' [SEP] 'white' [SEP] 'white+brown' [SEP] 'hongxinq Floating TV Stand with Storage Shelves, Chipboard Wall Mounted Hanging Television Cabinet, Modern Storage Cabinet for Living Room, Bedroom, 12Inx11.8Inx35.4In, White' [SEP] 'Price: $90.79' [SEP] 'Rating: N.A.' [SEP] 'Description' [SEP] 'Features' [SEP] 'Reviews' [SEP] 'Buy Now'. Your admissible actions of the current situation are: ['click[back to search]', 'click[< prev]', 'click[description]', 'click[features]', 'click[reviews]', 'click[buy now]', 'click[brown]', 'click[concrete gray]', 'click[grey]', 'click[white]', 'click[white+brown]',].
Now it's your turn to take one action for the current step. You should first reason step-by-step about the current situation, then think carefully which admissible action best advances the shopping goal. This reasoning process MUST be enclosed within <think> </think> tags. Once you've finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags.
assistant

Response (WebShop, Step 3)

<think> To find the desired wall-mounted, white item, easy clean white colored, brown colored TV stands for the living room with the best price lower than $130.00, let's search again by combining 'color', 'brown', 'white', and 'living room/TV stand' into a phrase. It seems a result would be found to this combination. </think>
<action>click[white+brown]</action>

WebShop, Step 4.

Prompt (WebShop, Step 4)

system You are Qwen, created by Alibaba Cloud. You are a helpful assistant. user
You are an expert autonomous agent operating in the WebShop e-commerce environment. Your task is to: Find me wall mounted, white item, easy clean tv stands for living room with color: brown, and price lower than 130.00 dollars. Prior to this step, you have already taken 3 step(s). Below are the most recent 2 observations and the corresponding actions you took: [Observation 2: "Back to Search' [SEP] 'Page 1 (Total results: 50)' [SEP] 'Next >' [SEP] 'B09F6SCW47' [SEP] 'hongxinq Floating TV Stand with Storage Shelves, Chipboard Wall Mounted Hanging Television Cabinet, Modern Storage Cabinet for Living Room, Bedroom, 12Inx11.8Inx35.4In, White' [SEP] '$90.79' [SEP] 'B09S6S7LG1' [SEP] 'TV Stand for 70 Inch TV Entertainment Center Stand TV Stand with Storage for TV Console Cabinet Media Cable Box Gaming 70 inch TV Stands for Bedroom Living Room' [SEP] '$169.99' [SEP] 'B0924PKLQ4' [SEP] 'V-MORO HomePod Mini Wall Mount Holder, Outlet Mount Stand Hidden Cable Management for Apple HomePod Mini Smart Speaker Shelf Without Messy Wires Excellent Space Saving Punch-Free 2-Pack White' [SEP] '$19.99' [SEP] 'B07ZYVWCZ7' [SEP] 'Universal TV Stand/ Base Tabletop TV Stand with Wall Mount for 40 to 86 inch 5 Level Height Adjustable, Heavy Duty Tempered Glass Base, Holds up to 132lbs Screens, HT03B-003' [SEP] '$73.95' [SEP] 'B09MNNBDTJ' [SEP] 'Woody BL-EF Electric Fireplace 77" TV Stand (White/Gray)' [SEP] '$100.0' [SEP] 'B09BKPV8LR' [SEP] 'Wood TV Stand for 65 Inch TV, TV Cabinet with Farmhouse Barn Doors, TV Console Table with Adjustable Shelves, Industrial, Rustic Brown' [SEP] '$317.58' [SEP] 'B07FKGQKZ1' [SEP] 'Home Dynamix Lyndhurst Rotana Modern Area Rug, Contemporary Blue/Gray/Ivory 5'2"x7'4"' [SEP] '$44.99 to $33.98' [SEP] 'B08K7LDM7Q' [SEP] '2 Pcs Cowhide Throw Pillow Covers Decorative Pillow Cases Farm Animal Brown Cow Hide Skin Print Pillow Case 18 X 18 Inch Velvet Square Cushion Cover for Sofa Bedroom' [SEP] '$17.99' [SEP] 'B09LHM4WQS' [SEP] 'Lift Top Coffee Tables for Living Room Coffee Table with Storage, Lift Cable Coffee Table, Dining Table with Hidden Storage Compartment Chestnut' [SEP] '$82.99' [SEP] 'B07GZLDJMC' [SEP] 'FITUEYES Universal TV Stand/Base Tabletop TV Stand with Swivel Mount for 32 to 65 inch Flat Screen TV Height Adjustable,Tempered Glass Base' [SEP] '$42.99", Action 2: 'click[b09f6scw47]'] [Observation 3: "Back to Search' [SEP] '< Prev' [SEP] 'color' [SEP] 'brown' [SEP] 'concrete gray' [SEP] 'grey' [SEP] 'white' [SEP] 'white+brown' [SEP] 'hongxinq Floating TV Stand with Storage Shelves, Chipboard Wall Mounted Hanging Television Cabinet, Modern Storage Cabinet for Living Room, Bedroom, 12Inx11.8Inx35.4In, White' [SEP] 'Price: $90.79' [SEP] 'Rating: N.A.' [SEP] 'Description' [SEP] 'Features' [SEP] 'Reviews' [SEP] 'Buy Now", Action 3: 'click[white+brown]'] You are now at step 4 and your current observation is: 'Back to Search' [SEP] '< Prev' [SEP] 'color' [SEP] 'brown' [SEP] 'concrete gray' [SEP] 'grey' [SEP] 'white' [SEP] 'white+brown' [SEP] 'hongxinq Floating TV Stand with Storage Shelves, Chipboard Wall Mounted Hanging Television Cabinet, Modern Storage Cabinet for Living Room, Bedroom, 12Inx11.8Inx35.4In, White' [SEP] 'Price: $90.79' [SEP] 'Rating: N.A.' [SEP] 'Description' [SEP] 'Features' [SEP] 'Reviews' [SEP] 'Buy Now'. Your admissible actions of the current situation are: ['click[back to search]', 'click[< prev]', 'click[description]', 'click[features]', 'click[reviews]', 'click[buy now]', 'click[brown]', 'click[concrete gray]', 'click[grey]', 'click[white]', 'click[white+brown]',].
Now it's your turn to take one action for the current step. You should first reason step-by-step about the current situation, then think carefully which admissible action best advances the shopping goal. This reasoning process MUST be enclosed within <think> </think> tags. Once you've finished your reasoning, you should choose an admissible action for current step and present it within <action> </action> tags.
assistant

Response (WebShop, Step 4)

<think> To find the wall mounted, white, easy clean tv stands for living room with color: brown, lower than price 130.00 US dollars, I need to carefully identify the options that best match the criteria. It's important to take up to three steps to gather enough information and review the options available in the search results. </think>
<action>click[buy now]</action>

Recorded outcome. Episode reward: 10 (benchmark success). This is the episode total broadcast to the decision records; no terminal page is available.