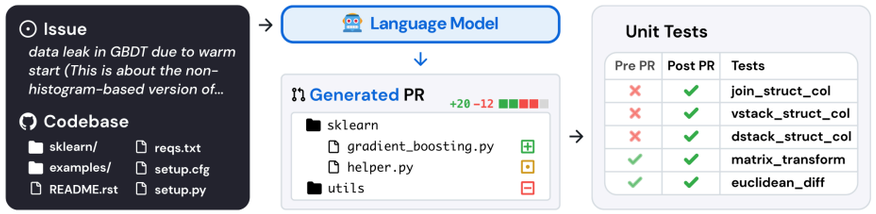
Scaling Long-Horizon LLM Agent via Context-Folding

https://context-folding.github.io

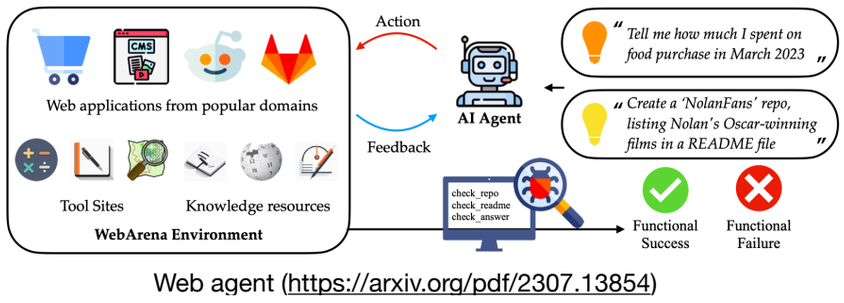
Joint work by Weiwei Sun*, Miao Lu*, Zhan Ling, Kang Liu, Xuesong Yao, Yiming Yang, Jiecao Chen

* Work down during internship at ByteDance Seed

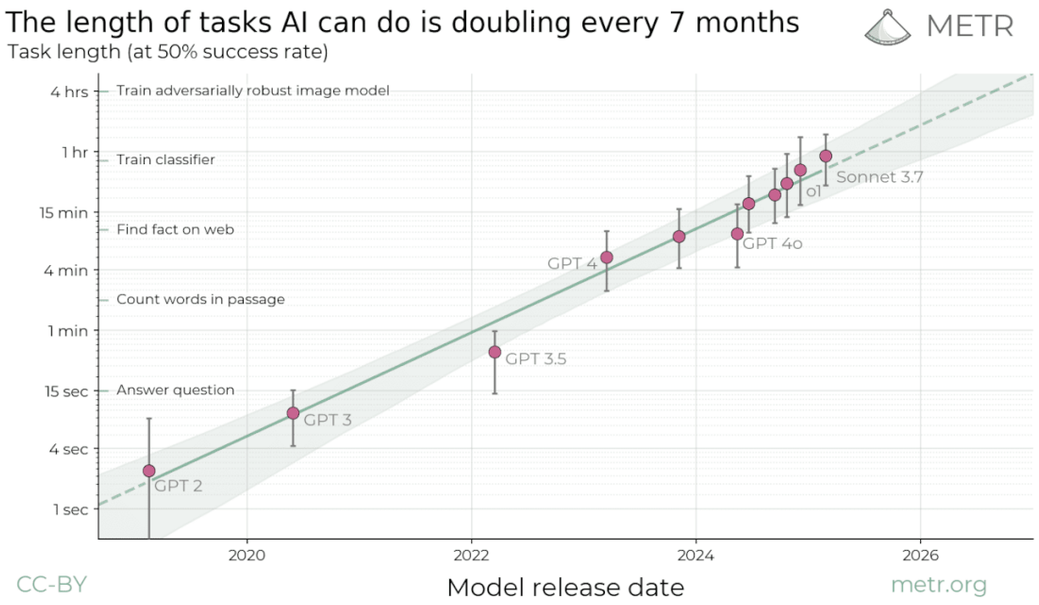
- LLM agents have shown remarkable capability in various complex tasks:
  - Deep research agent, Coding agent, Web agent, …
- A key bottleneck: Exploding context length
  - "Length of tasks AI can do is growing exponentially, with a doubling time of 7 months"



Coding agent (https://arxiv.org/pdf/2310.06770)



Web agent (https://arxiv.org/pdf/2307.13854)

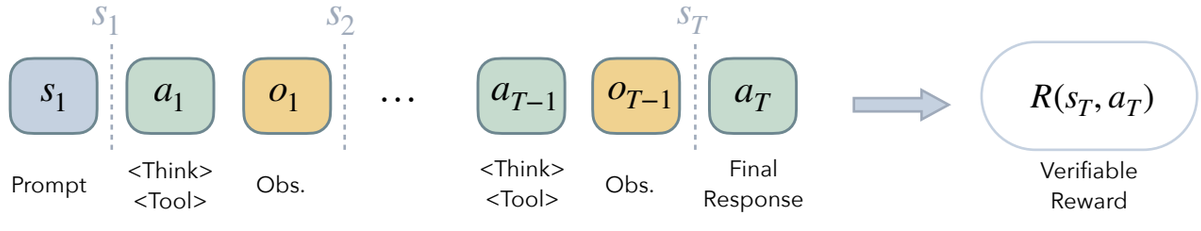


- Challenges in the long context length regime:
  - Context window limit by the backend LLM
  - Degrading instruction-following and reasoning capabilities
  - Quadratic attention cost, KV-cache overhead

- LLM agents have shown remarkable capability in various complex tasks:
  - Deep research agent, Coding agent, Web agent, …
- A key bottleneck: Exploding context length
  - "Length of tasks AI can do is growing exponentially, with a doubling time of 7 months"
- Existing approaches:
  - *Post-hoc context compression*: e.g., summarization, short-term memory
    - Cons: abrupt the agent's work flow; does not utilize the task structure
  - *Multi-agent systems*: split tasks among agents.
    - Cons: mostly the roles of agents are handcrafted; unknown how to optimize end2end
- Can we use RL to train long-horizon LLM agents that can actively manage their context?
  - This work: **Context-Folding** mechanism and **FoldGRPO**

Multi-Turn LLM Agent: ReAct Agent [Yao et al., 2022]

- Let's begin with the De facto modeling of LLM agents, known as ReAct agent [Yao et al., 2022]
- Formulation: at step/turn t
  - a_t: action (reasoning & tool call) at step t
  - o_t: observation at step t
  - s_t: agent state, the key quantity to formulate an MDP for doing RL
- ReAct agent:
  - s_t: the working context; $a_t \sim \pi_\theta(\cdot \mid s_t)$, where $s_t = (q, a_1, o_1, \cdots, a_{t-1}, o_{t-1})$
  - Appends entire history to the working context, i.e., $s_{t+1} = \delta\big(\cdot\,; (s_t, a_t, o_t)\big)$

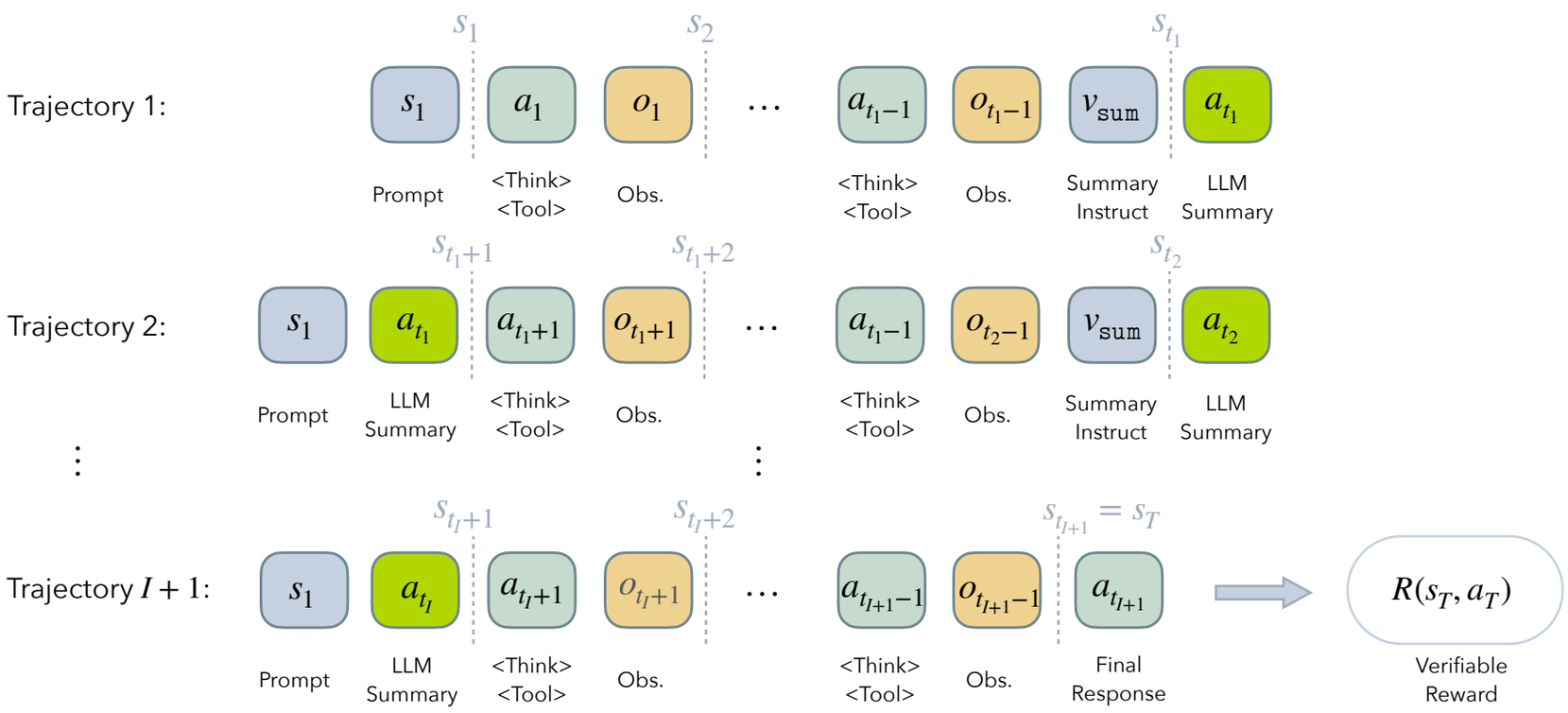


Yao, S., Zhao, J., Yu, D., Du, N., Shafran, I., Narasimhan, K. R., & Cao, Y. (2022, October). React: Synergizing reasoning and acting in language models. In *The eleventh international conference on learning representations*.

Multi-Turn LLM Agent: Summary Agent [Lu et al., 2025]

- Summary agent:
  - s_t: the working context; $a_t \sim \pi_\theta(\cdot \mid s_t)$; Summarize the working context upon context limit

$$s_{t+1} := \begin{cases} (s_t, a_t, o_t) & \text{if } v_{\texttt{sum}} \notin s_t \text{ and } |(s_t, a_t, o_t)| < L, \\ (s_t, a_t, o_t, v_{\texttt{sum}}) & \text{if } v_{\texttt{sum}} \notin s_t \text{ and } |(s_t, a_t, o_t)| \geq L, \\ (s_1, a_t) & \text{if } v_{\texttt{sum}} \subseteq s_t\,. \end{cases}$$



Lu, M., Sun, W., Du, W., Ling, Z., Yao, X., Liu, K., & Chen, J. (2025). Scaling LLM Multi-turn RL with End-to-end Summarization-based Context Management. *arXiv preprint arXiv:2510.06727*.

Multi-Turn LLM Agent: Context-Folding Agent [Sun et al., 2025]

- Context-Folding agent:
  - Idea: let the agent itself decide its context
  - Method: maintain two different types of agent state: planning state (P) and execution state (E)
  - Two special actions: Branch and Return, to switch between P and E

- Branch (description, prompt)
  - Branch from main thread (planning state) to use a separate working context to complete a sub-task (execution state), i.e., P to E

- Return (message)
  - Fold the context generated in the branch (execution state) and return to the main thread (planning state), i.e., E to P

- Planning state (P): high-level reasoning, decompose the task, decide when to Branch

- Execution state (E): complete assigned token-intensive sub-tasks, Return upon completion

- Mathematically, $a_t \sim \pi_\theta(\cdot \mid s_t)$, where $s_t = (q, \mathcal{F}(\tau_{<t}))$ and $\mathcal{F}(\cdot)$ folds the previous E state history.

$$\mathcal{F}\big(a_1, o_1, a_2, \underbrace{o_2, a_3, o_3, a_4}_{\text{branch 1}}, o_4, a_5, \underbrace{o_5, a_6, o_6, a_7, o_7, a_8}_{\text{branch 2}}, o_8, a_9, o_9, a_{10}, o_{10}\big)$$
$$\rightarrow \big(a_1, o_1, a_2, o_4, a_5, o_8, a_9, o_9, a_{10}, o_{10}\big)$$

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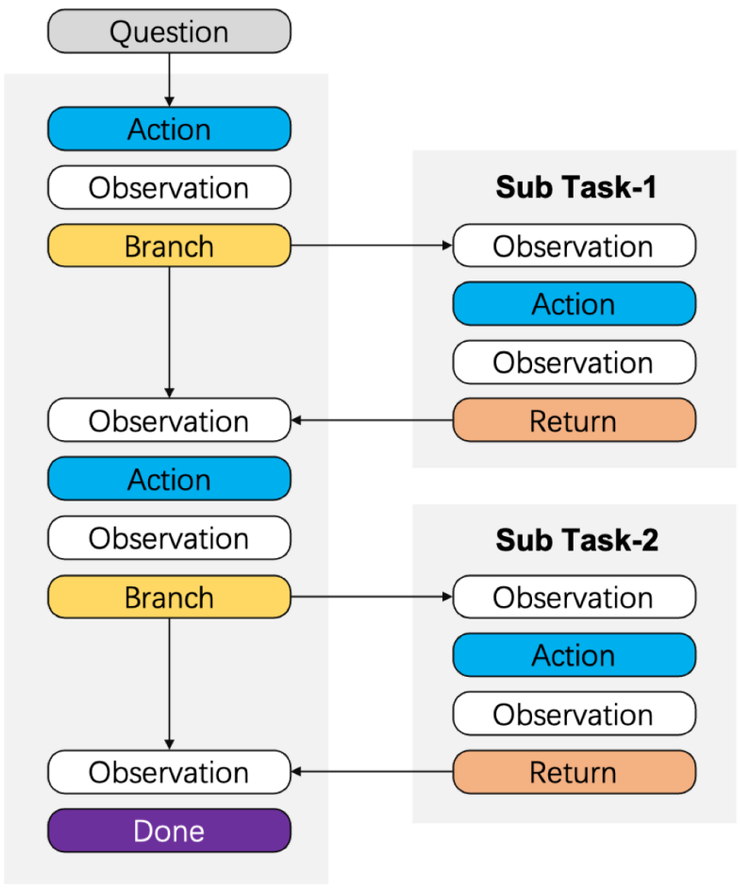

  - At state E, uses the same prefix as corresponding P state
    - The context length in state P is compact
    - KV-cache friendly
  - When is Return called, KV-cache rolls back to the corresponding Branch position
  - We disable creating new branches in an active E state

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  - Method: maintain two different types of agent state: planning state (P) and execution state (E)
  - Two special actions: Branch and Return, to switch between P and E
- Why context-folding?
  - Compact and efficient working context
  - Naturally preserves reasoning and task flow
  - Active management, ready for e2e RL to autonomously discover good agent state patterns

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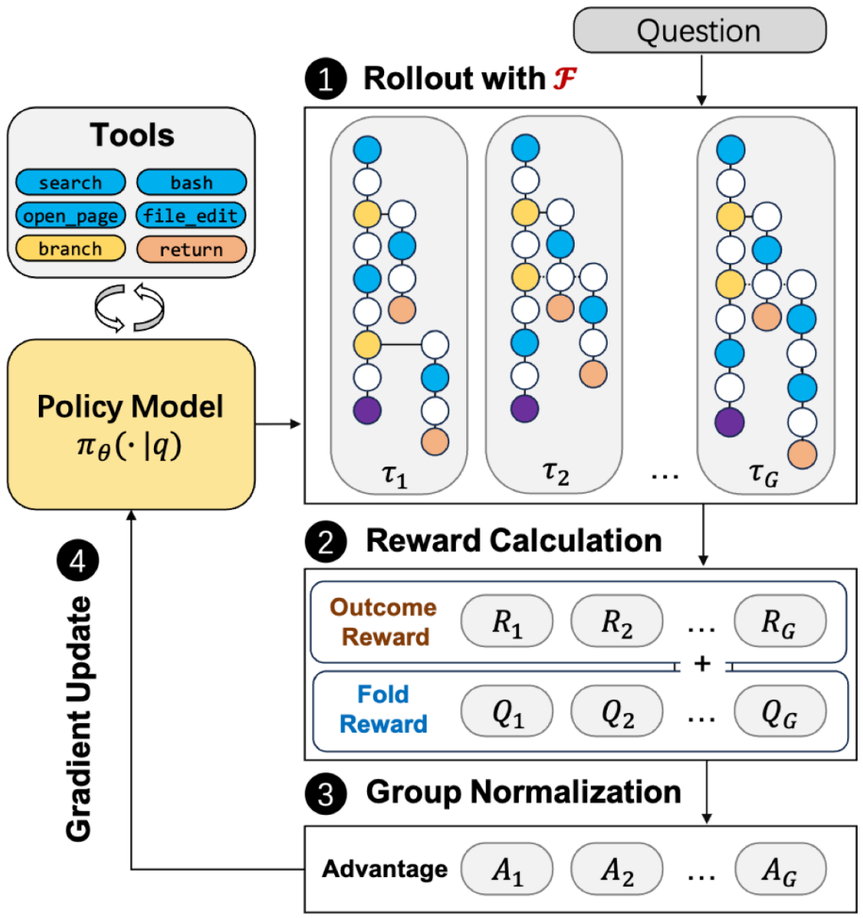
Scaling Long-horizon Agent with RL: FoldGRPO

- We aim to advance the context-folding agent via RL. An overview:



- Learning objective (FoldGRPO):

$$\mathbb{E}_{\substack{q\sim\mathcal{D},\\ \{\tau_i\}_{i=1}^{G}\sim\pi_{\text{old}}(\cdot\,|q)}}\left[\frac{1}{\sum_{i=1}^{G}|\tau_i|}\sum_{i=1}^{G}\sum_{t=1}^{|\tau_i|}\min\left\{r_{i,t}(\theta)\hat{A}_{i,t},\ \text{clip}\big(r_{i,t}(\theta),1-\epsilon_{\text{low}},1+\epsilon_{\text{high}}\big)\hat{A}_{i,t}\right\}\right],$$

- Importance sampling ratio & Group advantage estimator

$$r_{i,t}(\theta)=\frac{\pi_\theta(\tau_{i,t}\mid q,\mathcal{F}(\tau_{i,<t}))}{\pi_{\theta_{\text{old}}}(\tau_{i,t}\mid q,\mathcal{F}(\tau_{i,<t}))}\cdot\mathbf{1}^{\text{LLM}}_{\tau_{i,t}},\quad \hat{A}_{i,t}=\frac{\text{clip}(R_i+Q_{i,t},0,1)-\text{mean}(\{R_i\}_{i=1}^{G})}{\text{std}(\{R_i\}_{i=1}^{G})}.$$

- Two key components of FoldGRPO:
  - Context-folding $\mathcal{F}(\cdot)$ during rollout and optimization
  - Process reward signal $Q_{i,t}$ to efficiently guide c-f behavior

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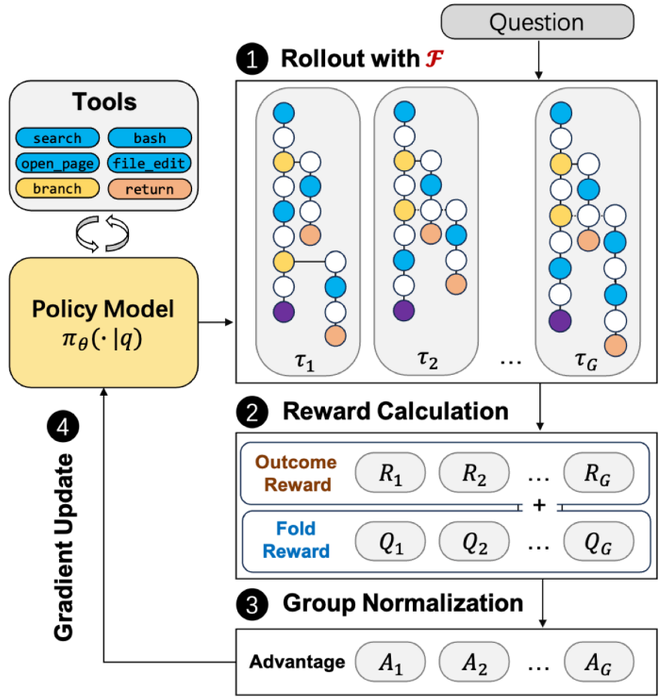
Key Component 1: Context-Folding

- The mechanism is as introduced previously. But how to implement and optimize in the RL pipeline?

- Rollout: each Branch action introduces a separate trajectory. Rollout i of task k results in $N_{k,i}$= 1+#Branch trajectories

  - The main thread (P states) is one trajectory with all the E states context folded

  - Each new E state is a separate trajectory with previous E states context folded



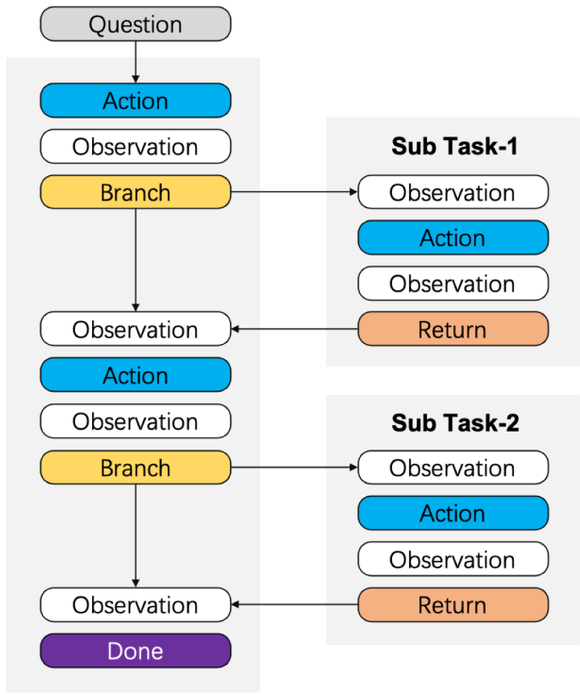
$$\mathbb{E}_{\substack{q\sim\mathcal{D},\\ \{\tau_i\}_{i=1}^{G}\sim\pi_{\text{old}}(\cdot|q)}}\left[\frac{1}{\sum_{i=1}^{G}|\tau_i|}\sum_{i=1}^{G}\sum_{t=1}^{|\tau_i|}\min\left\{r_{i,t}(\theta)\hat{A}_{i,t},\ \text{clip}\big(r_{i,t}(\theta),1-\epsilon_{\text{low}},1+\epsilon_{\text{high}}\big)\hat{A}_{i,t}\right\}\right],$$

$$r_{i,t}(\theta)=\frac{\pi_\theta(\tau_{i,t}\mid q,\mathcal{F}(\tau_{i,<t}))}{\pi_{\theta_{\text{old}}}(\tau_{i,t}\mid q,\mathcal{F}(\tau_{i,<t}))}\cdot\mathbf{1}^{\text{LLM}}_{\tau_{i,t}},\quad \hat{A}_{i,t}=\frac{\text{clip}(R_i+Q_{i,t},0,1)-\text{mean}(\{R_i\}_{i=1}^{G})}{\text{std}(\{R_i\}_{i=1}^{G})}.$$

- After rollout, the $N_{k,i}$ trajectory are returned to the training infra. Thus a rollout stage results in $N=\sum_{k=1}^{\text{batchsize}}\sum_{i=1}^{G}N_{k,i}$ trajectories

- The $N_{k,i}$ trajectory share the same reward $R_{k,i}$, and the group mean is averaged over G rollouts (instead of $\sum_{i=1}^{G}N_{k,i}$)

- We pad N with dummy samples to multipliers of mini_batchsize



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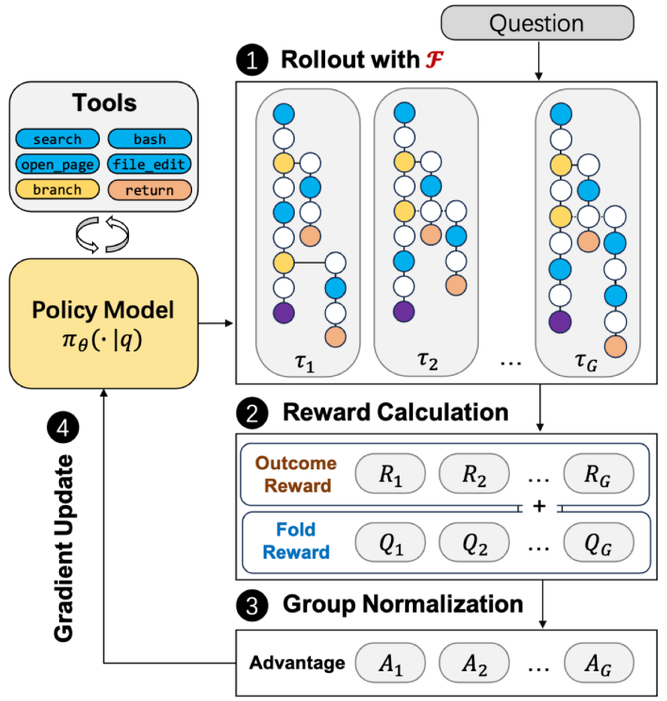
Key Component 2: Process Reward Signal

- At each token t of rollout i, we introduce signal $Q_{i,t}$
- Idea: $Q_{i,t}$ aims to penalize two bad behaviors: (i) unfolded token penalty; (ii) out-of-scope penalty.
  - Unfolded token penalty: $Q_{i,t} = -1$ to all the tokens in the main thread when len(main thread) > 0.5 * context limit
  - Out-of-scope penalty: $Q_{i,t} = -0.2$ to all the tokens in a branch to penalize out of scope behavior
  - We also apply $Q_{i,t} = -1$ to all the tokens in a failed tool call turn
  - In all other cases $Q_{i,t} = 0$



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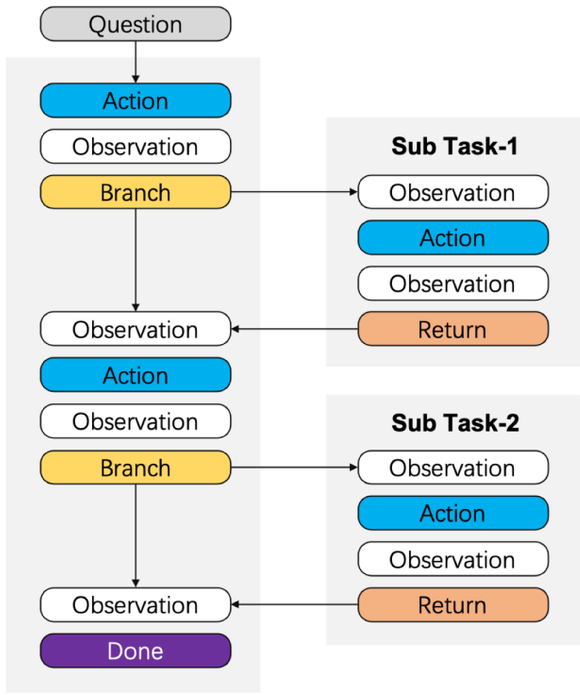

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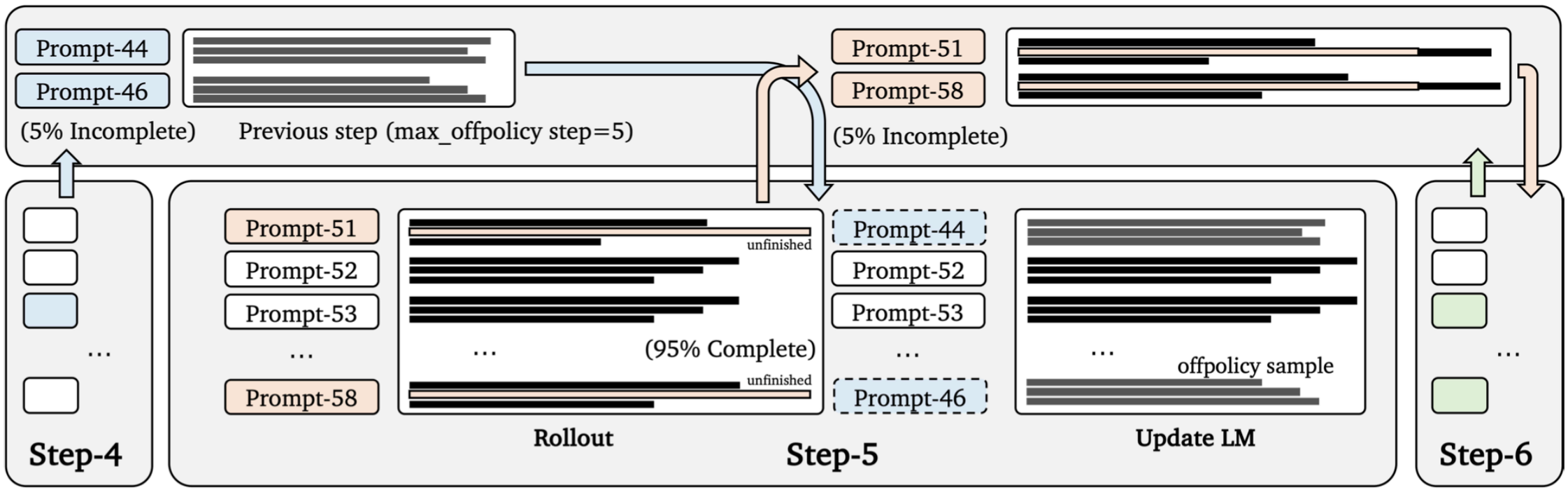
Other Components: Standalone Rollout Node



- The main rollout process stops once it completes 95% of the tasks in the batch
- Remaining jobs are handled by the standalone process
- At each optimization step, the data come from (i) 95% of current batch; (ii) completed rollout from previous step
- We setup a maximum off-policy step 5

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Experiments: Setups

- Base LLM: Seed-OSS-36B-Instruct
- Tasks: BrowseComp, SWE-Bench
  - Uses corpus from BrowseComp-Plus: 680 instances for training and 150 hold-out instances for val.
  - Use SWE-Bench Verified as evaluation set. Collected a subset of size 740 from SWE-Gym and SWE-Rebench as the training set.
- Methods compared:
  - ReAct Agent
  - Summary Agent
  - Context-Folding Agent

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Experiments: Main Results

Model	Peak Length	Max #Token	BrowseComp-Plus Pass@1	BrowseComp-Plus Tool Calls	SWE-Bench Verified Pass@1	SWE-Bench Verified Tool Calls
ReAct Agent with 100B+ LLM						
GPT-5	327K	327K	0.793	14.2	0.718	42.6
GPT-4.1	327K	327K	0.640	5.6	0.486	28.7
DeepSeek-V3.1	327K	327K	0.613	10.6	0.610	53.2
GLM-4.5-Air	327K	327K	0.566	11.1	0.576	51.2
Qwen3-235B-A22B	327K	327K	0.560	12.8	0.344	32.1
ReAct Agent						
Seed-OSS-36B	32K	32K	0.286 (-19.2)	3.8	0.436 (-11.6)	25.8
+ RL (GRPO)	32K	32K	0.446 (-3.2)	5.5	0.480 (-7.2)	27.8
Seed-OSS-36B$^{\psi}$	327K	327K	0.478 (+0.0)	10.8	0.552 (+0.0)	49.5
+ RL (GRPO)	327K	327K	0.540 (+6.2)	10.2	0.574 (+2.2)	55.4
Summary Agent						
Seed-OSS-36B	32K	32K × 10	0.386 (-9.2)	17.4	0.488 (-6.4)	77.0
+ RL (GRPO)	32K	32K × 10	0.527 (+4.9)	18.0	0.550 (-0.2)	74.9
Folding Agent (Ours)						
Seed-OSS-36B	32K	32K × 10	0.420 (-5.8)	12.9	0.492 (-6.0)	72.8
+ RL (GRPO)	32K	32K × 10	0.567 (+8.9)	16.0	0.564 (+1.2)	79.5
+ RL (FoldGRPO)	32K	32K × 10	**0.620** (+14.2)	19.2	**0.580** (+2.8)	96.5

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Experiments: Further Studies 1

	BrowseComp-Plus				SWE-Bench Verified			
	Finish	Main Len	Scope	# Branch	Finish	Main Len	Scope	# Branch
Folding Agent (Seed-OSS-36B)	0.806	12,195	0.774	3.51	0.781	47,475	0.473	3.05
+ RL (GRPO)	0.738	22,285	0.762	3.88	0.612	48,908	0.419	3.80
+ RL (FoldGRPO)	0.935	7,752	0.895	4.98	0.962	8,885	0.754	5.90

Table 2 Model behavior statistics of different optimization methods. FoldGRPO encourages focused branching and condensed main context, boosting both scope accuracy and finish rate.

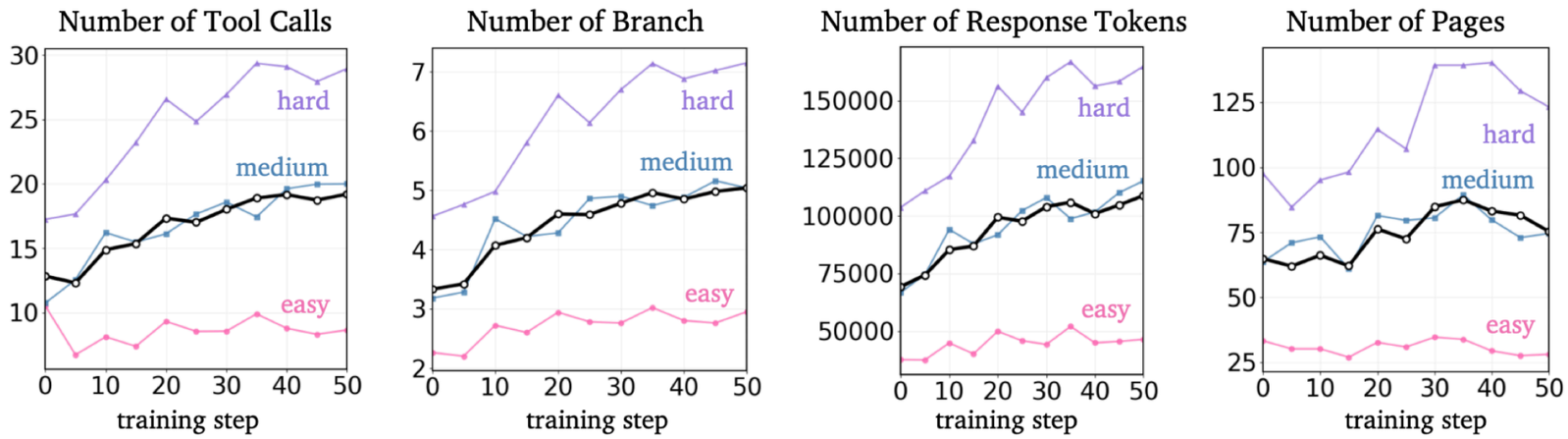

Figure 4 With RL training, we observe an increase in the number of tool calls, branching behavior, total number of tokens, and the number of searched pages.

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Experiments: Further Studies 2

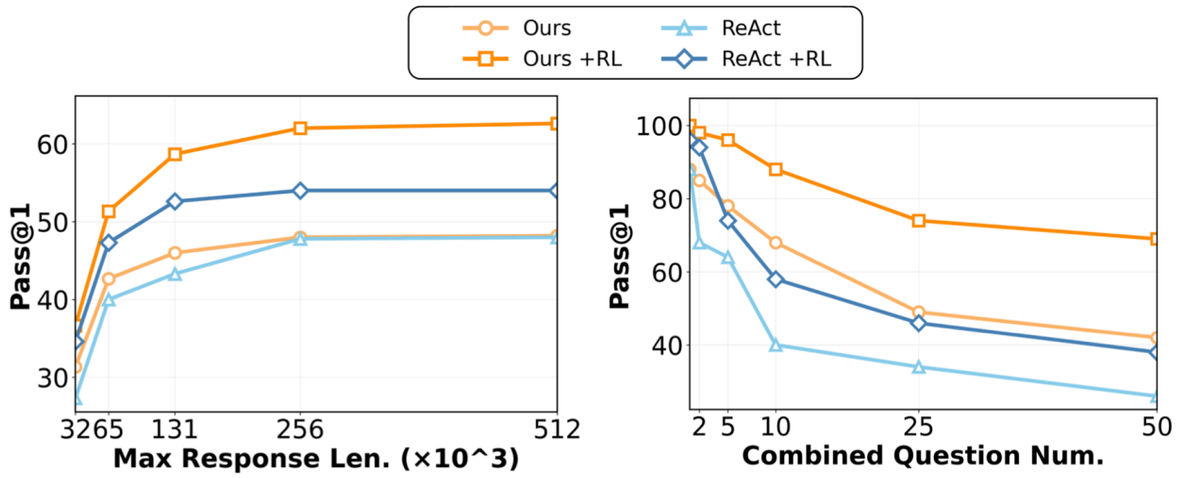

Figure 5 Left: Pass@1 vs. agent max context length. **Right:** Pass@1 vs. number of combined questions. Multiple easy questions are combined into a single harder question to increase problem complexity; a higher number of combined questions indicates more required actions and a longer context to answer them correctly. See Section 4.4.2 for details.

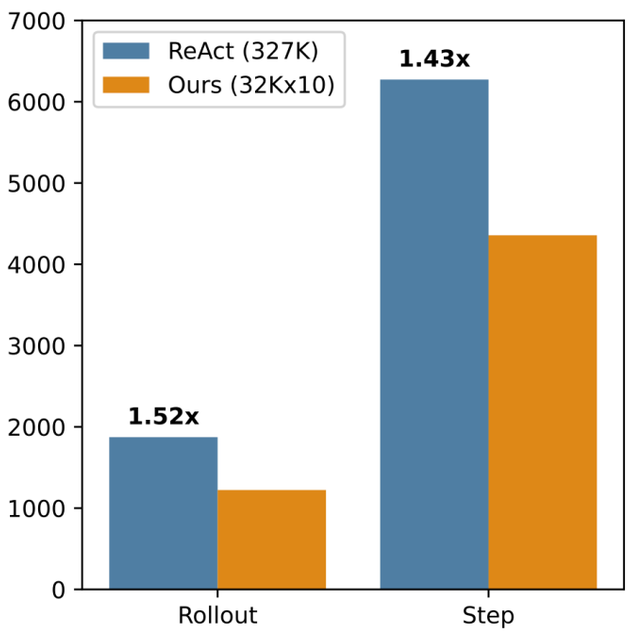

Figure 8 Training time cost. The figure shows the stepwise average time for rollout and for each training step.

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Experiments: Further Studies 3

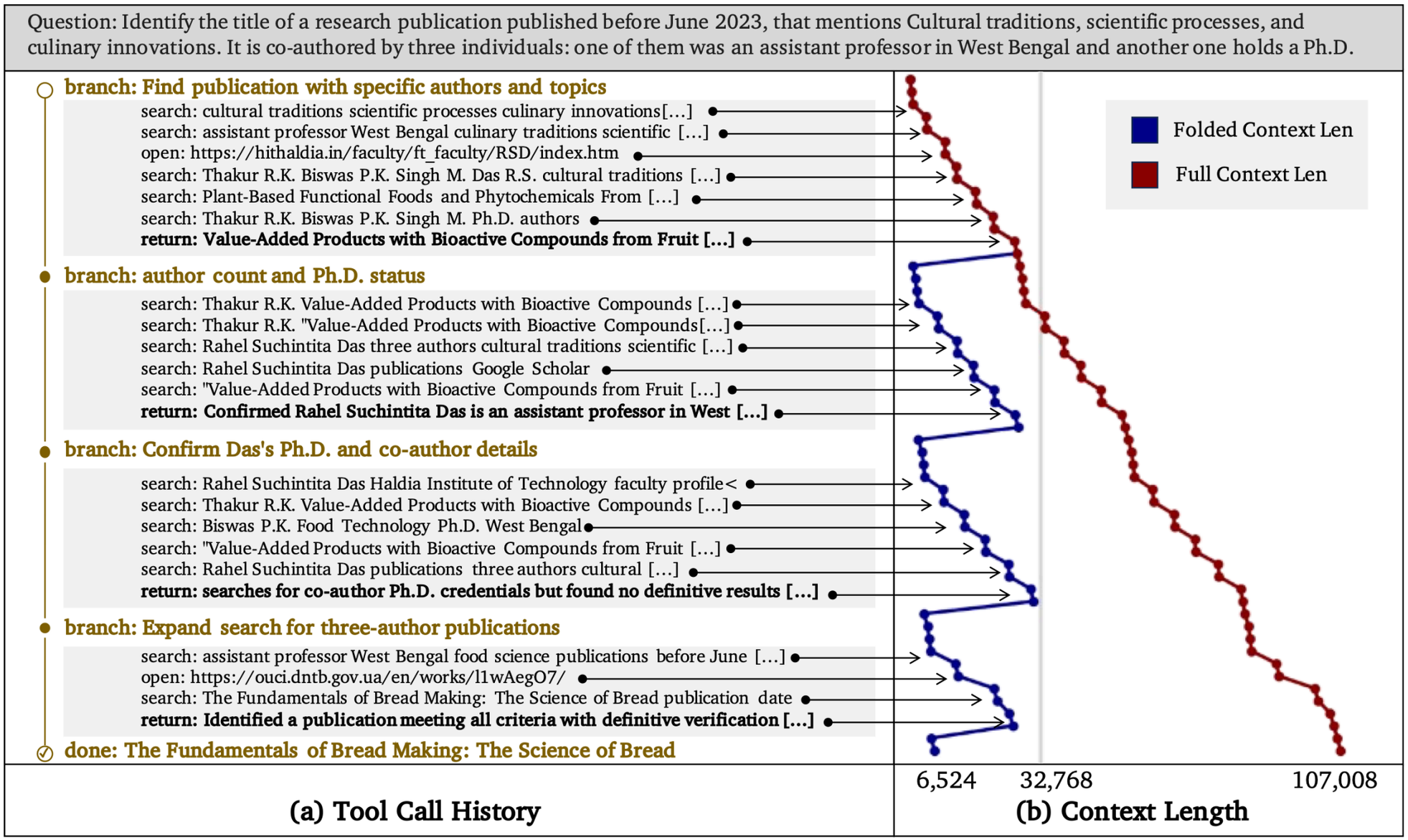

Figure 7 Example of an agent's tool call history and context length. on BrowseComp-Plus.

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Future Works

- Hierarchical Context-Folding Mechanisms
- Training with Proximal Policy Optimization (PPO)
- …

Thank you for your attention!