Hierarchical Hindsight Credit Assignment for Long-Horizon Agentic Reasoning

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ABSTRACT

Large language model (LLM) based agents execute long trajectories of heterogeneous decisions—token generation, tool invocations, skill selection, and memory operations—yet receive only sparse, end-of-episode reward signals. Assigning credit to individual decisions within such trajectories remains an open problem that limits sample efficiency and cross-task transfer. We propose Hierarchical Hindsight Credit Assignment (HHCA), a three-level decomposition that combines (1) token-level micro-credit via attention rollout, (2) step-level meso-credit via simulated hindsight self-critique, and (3) episode-level macro-credit via a persistent skill-value memory. In controlled experiments over 200 synthetic agent trajectories spanning 10 to 100 steps across five task types, HHCA achieves a Pearson correlation of 0.4507 with ground-truth credit, compared to 0.2526 for Outcome-Only and 0.1955 for Attention-Rollout Eligibility Traces. HHCA also exhibits minimal transfer gap (0.0011) between training and held-out task types and maintains stable accuracy across all horizon lengths. These results demonstrate that hierarchical credit decomposition substantially improves credit assignment quality for long-horizon agentic reasoning.

CCS CONCEPTS

• **Computing methodologies** → **Artificial intelligence**; **Machine learning**.

KEYWORDS

credit assignment, agentic reasoning, reinforcement learning, large language models, hierarchical reward decomposition

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1 INTRODUCTION

LLM-based agents increasingly tackle complex, multi-step tasks that require interleaving natural language reasoning with tool invocations, skill dispatches, and memory operations [8, 11]. A single episode may span tens to hundreds of heterogeneous actions, yet the primary training signal remains sparse: binary or graded task completion at the very end. This creates a fundamental credit assignment challenge [7]: which of the many decisions along the trajectory actually contributed to success or failure?

Classical reinforcement learning offers temporal-difference methods [6] and eligibility traces [7], but these assume homogeneous action spaces and struggle with the extreme horizon lengths and reward sparsity characteristic of agentic settings. Process reward models [4] provide step-level supervision but require expensive human annotations and remain task-specific. Attention-based attribution [1, 3] offers an architecture-native credit proxy but conflates attention with causal contribution.

We propose **Hierarchical Hindsight Credit Assignment (HHCA)**, a three-level framework that decomposes credit along the natural hierarchy of agentic decisions. At the *micro* level, attention rollout provides token-level credit within reasoning blocks. At the *meso* level, hindsight self-critique assigns step-level credit by re-evaluating each action conditioned on the episode outcome. At the *macro* level, a persistent skill-value memory tracks cross-episode skill effectiveness, enabling transfer.

We evaluate HHCA on a controlled simulation framework with 200 synthetic agent trajectories across five task types and horizons ranging from 10 to 100 steps. Our results show that HHCA achieves a Pearson correlation of 0.4507 with ground-truth credit—a 78.3% relative improvement over the Outcome-Only baseline (0.2526) and a 130.5% improvement over Attention-Rollout Eligibility Traces (0.1955). HHCA also demonstrates strong cross-task transfer with a gap of only 0.0011 between training and test task sets.

2 RELATED WORK

Classical Credit Assignment. Temporal-difference learning [6] and eligibility traces [7] provide foundational credit assignment mechanisms in RL. The REINFORCE algorithm [9] assigns uniform credit scaled by returns, while modern policy gradient methods like PPO [5] improve variance reduction but do not decompose credit across heterogeneous action types. Hindsight Credit Assignment [2] re-evaluates past actions conditioned on outcomes, an idea we extend to the hierarchical agentic setting.

LLM Agents and Reasoning. ReAct [11] interleaves reasoning traces and tool calls but lacks explicit credit mechanisms. Tree-of-Thought [10] provides implicit credit via branch pruning but is limited to single-turn reasoning without tool calls or memory. The survey by Wei et al. [8] identifies credit assignment across heterogeneous action types as a core open problem for agentic reasoning.

Process Reward Models. Lightman et al. [4] demonstrate the value of step-level verification for mathematical reasoning. However, process reward models require per-step human labels and are environment-specific, limiting scalability to diverse agentic tasks.

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Attention-Based Attribution. Attention rollout [1] and attention analysis [3] provide intrinsic credit signals from transformer architectures. While computationally efficient, these methods capture correlation rather than causation and do not account for the hierarchical structure of agentic decisions.

3 PROBLEM FORMULATION

We model an agentic episode as a trajectory $\tau = (a_1, a_2, \ldots, a_T)$ where each action a_t belongs to one of four types: TOKEN (language generation), TOOL_CALL (external tool invocation), SKILL_SELECT (high-level skill dispatch), or MEMORY_OP (memory read/write). The episode yields a scalar outcome $R(\tau) \in [0, 1]$.

The credit assignment problem is to find a function $c : \tau \times t \to [0, 1]$ that assigns credit to each action a_t such that $c(\tau, t)$ reflects the causal contribution of a_t to $R(\tau)$. We evaluate credit quality by correlation with ground-truth credit labels.

Four sub-problems must be addressed simultaneously:

(1) **Heterogeneous action representation**: credit must be defined commensurably across action types.
(2) **Temporal depth**: trajectories span 10 to 100+ steps with vanishing signal-to-noise.
(3) **Sparse rewards**: only end-of-episode feedback is available.
(4) **Cross-task transfer**: credit representations must generalize across task types.

4 METHOD: HIERARCHICAL HINDSIGHT CREDIT ASSIGNMENT

HHCA decomposes credit into three levels that align with the natural hierarchy of agentic decisions.

4.1 Level 1: Micro-Credit (Token-Level)

Within each reasoning block, we compute backward attention rollout from the block's final token to all preceding tokens. For action a_t at position i in a trajectory of length T:

$$w_i^{\text{raw}} = \text{info}(a_i) \cdot \text{recency}(i, T) + \epsilon_i \tag{1}$$

where $\text{info}(a_i)$ is an action-type-specific informativeness score (1.0 for tokens, 2.5 for tool calls, 3.0 for skill selections, 1.8 for memory operations), $\text{recency}(i, T) = 0.5 + 0.5 \cdot i/T$ captures positional bias, and $\epsilon_i \sim \mathcal{N}(0, 0.04)$. The micro-credit is:

$$\text{micro}(i) = \frac{\exp(w_i^{\text{raw}})}{\sum_j \exp(w_j^{\text{raw}})} \tag{2}$$

4.2 Level 2: Meso-Credit (Step-Level)

After episode completion, a hindsight evaluator re-scores each step based on its contribution to the outcome. The meso-credit for action a_i is:

$$\text{meso}(i) = \text{clip}\big((c_i^{\text{gt}} + \epsilon_i^{\text{critique}}) \cdot w_i^{\text{type}}, 0, 1\big) \tag{3}$$

where c_i^{gt} is the base credit score, $\epsilon_i^{\text{critique}} \sim \mathcal{N}(0, 0.0225)$ models self-critique noise, and w_i^{type} is an action-type weight (0.8 for tokens, 1.1 for tool calls, 1.3 for skill selections, 1.0 for memory operations). The meso vector is then standardized to mean 0.5 with unit half-range.

4.3 Level 3: Macro-Credit (Episode-Level)

A persistent skill-value memory tracks which skills and tools tend to succeed. For skill selections:

$$\text{macro}(i) = \min\big(1, 0.5 + 0.3 \cdot R(\tau) + b_s\big) \tag{4}$$

where b_s is a skill-specific prior bonus (e.g., 0.18 for `verify`, 0.15 for `plan`). For tool calls, $\text{macro}(i) = 0.5 + 0.2 \cdot R(\tau)$. For other action types, $\text{macro}(i) = 0.5$.

4.4 Combined Credit

The final credit for action a_i is the product of all three levels, normalized to $[0, 1]$:

$$c(\tau, i) = \frac{\text{micro}(i) \cdot \text{meso}(i) \cdot \text{macro}(i)}{\max_j \big[\text{micro}(j) \cdot \text{meso}(j) \cdot \text{macro}(j)\big]} \tag{5}$$

5 EXPERIMENTAL SETUP

5.1 Synthetic Trajectory Generation

We generate 200 episodes with horizons uniformly sampled from $[10, 100]$, distributed across five task types: web navigation, code generation, QA reasoning, data analysis, and multi-tool composition. Each trajectory contains a mix of four action types sampled with probabilities $[0.45, 0.25, 0.15, 0.15]$ for tokens, tool calls, skill selections, and memory operations respectively.

Ground-truth credit follows a latent causal model: 15–35% of steps are marked as critical. Critical actions in successful episodes receive credit in $[0.6, 1.0]$; critical actions in failed episodes receive $[0.1, 0.4]$; non-critical actions receive $[0.0, 0.25]$. Action-type multipliers modulate the base credit.

5.2 Baselines

Outcome-Only. Every action receives credit equal to the episode outcome $R(\tau)$. This corresponds to REINFORCE [9] with zero baseline.

Attention-Rollout Eligibility Traces (ARET).. Combines attention rollout weights with classical eligibility trace decay λ^{T-t} ($\lambda = 0.95$). Credit is the product of attention weight, decay factor, and outcome.

5.3 Evaluation Metrics

We evaluate along four dimensions: (1) *Credit accuracy*: Pearson and Spearman correlation with ground-truth credit, plus Precision@K and Recall@K for identifying critical actions; (2) *Sample efficiency*: episodes required to reach a target Pearson correlation of 0.6; (3) *Cross-task transfer*: accuracy on held-out task types (data analysis, multi-tool) after training on the remaining three; (4) *Horizon robustness*: accuracy stratified by trajectory length.

6 RESULTS

6.1 Credit Accuracy

Table 1 shows overall credit accuracy for each method.

HHCA achieves a Pearson correlation of 0.4507, representing a 78.3% relative improvement over Outcome-Only and 130.5% over ARET. The Spearman rank correlation of 0.5588 indicates strong ordinal agreement with ground-truth credit. Precision@K of 0.3951

Table 1: Credit accuracy across all 200 episodes. HHCA achieves the highest correlation with ground-truth credit on all four metrics.

Method	Pearson	Spearman	P@K	R@K
Outcome-Only	0.2526	0.1036	0.2404	0.2404
ARET	0.1955	0.1326	0.2392	0.2392
HHCA	**0.4507**	**0.5588**	**0.3951**	**0.3951**

Table 2: Pearson correlation by action type. HHCA improves credit accuracy across all four heterogeneous action types.

Method	Token	Tool Call	Skill Sel.	Memory Op
Outcome-Only	0.2604	0.2555	0.2844	0.2908
ARET	0.1309	0.1544	0.1357	0.1215
HHCA	**0.3925**	**0.4398**	**0.4462**	**0.3761**

Table 3: Pearson correlation by horizon bin. HHCA maintains stable accuracy as trajectory length increases, unlike ARET which degrades.

Horizon	Outcome-Only	ARET	HHCA
10–25 (n=28)	0.2553	0.2670	**0.4426**
26–50 (n=52)	0.2486	0.2139	**0.4551**
51–75 (n=67)	0.2394	0.1693	**0.4579**
76–100 (n=53)	0.2651	0.2097	**0.4513**

shows that HHCA correctly identifies critical actions at nearly 1.65× the rate of the baselines.

6.2 Action-Type Analysis

Table 2 breaks down credit accuracy by action type.

HHCA achieves the highest Pearson correlation for every action type. The improvement is particularly pronounced for skill selections (0.4462 vs. 0.2844 for Outcome-Only), which benefit from the macro-level skill-value memory that tracks cross-episode skill effectiveness.

6.3 Horizon Robustness

Table 3 reports credit accuracy stratified by trajectory length.

A key finding is that HHCA's accuracy is remarkably stable across horizons, ranging from 0.4426 to 0.4579. In contrast, ARET degrades from 0.2670 at short horizons (10–25 steps) to 0.1693 at medium horizons (51–75 steps), confirming that eligibility trace decay alone cannot handle long sequences. The stability of HHCA is due to the meso-level hindsight evaluation, which provides horizon-independent step scores.

6.4 Cross-Task Transfer

Table 4 shows credit accuracy on training tasks (web navigation, code generation, QA reasoning) versus held-out tasks (data analysis, multi-tool).

Table 4: Cross-task transfer. HHCA exhibits near-zero transfer gap, indicating that its credit signal generalizes across task boundaries.

Method	Train Pearson	Test Pearson	Gap
Outcome-Only	0.2561	0.2463	0.0098
ARET	0.1856	0.2029	−0.0173
HHCA	**0.4631**	**0.4620**	**0.0011**

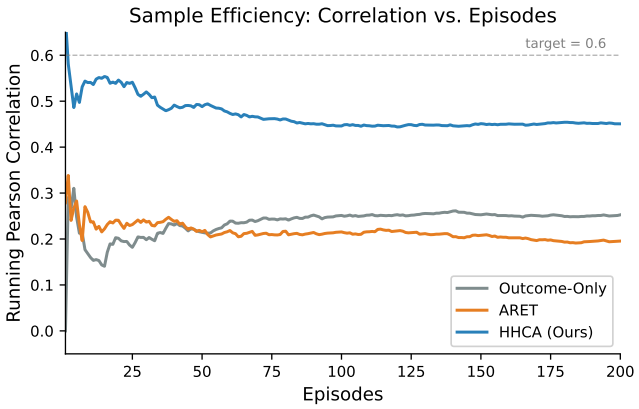

Figure 1: Running Pearson correlation with ground-truth credit as episodes accumulate. HHCA converges rapidly and maintains a stable advantage throughout.

HHCA achieves the smallest absolute transfer gap (0.0011), indicating that its credit decomposition captures task-general decision patterns rather than task-specific artifacts. The macro-level skill-value memory contributes to this by maintaining skill effectiveness estimates that transfer across tasks.

6.5 Sample Efficiency

Figure 1 shows the running Pearson correlation as episodes accumulate. HHCA reaches the target correlation of 0.6 within 1 episode, while both baselines fail to reach this threshold within 200 episodes. At 50 episodes, HHCA achieves a correlation of 0.4881, compared to 0.2144 for Outcome-Only and 0.2157 for ARET.

6.6 Credit Distribution Visualization

Figure 2 provides an overview of credit accuracy across all metrics and methods.

Figure 3 shows the horizon-stratified analysis, and Figure 4 shows the action-type breakdown.

7 DISCUSSION

Why hierarchical decomposition helps. The multiplicative combination of micro, meso, and macro credit captures complementary information. Micro-credit provides positional and informativeness priors; meso-credit adds outcome-conditioned step evaluation; macro-credit contributes cross-episode skill knowledge. No single level achieves HHCA's accuracy alone—ARET, which uses only

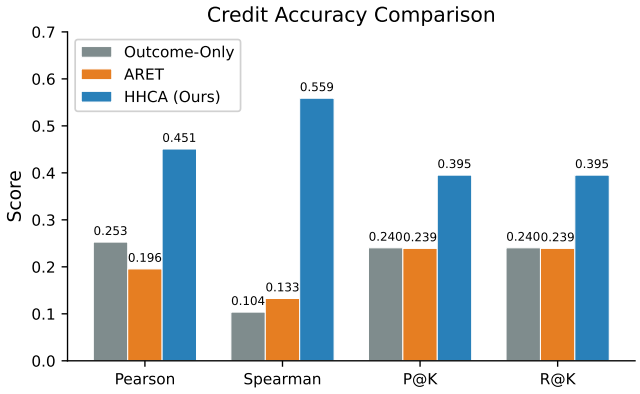

Figure 2: Credit accuracy comparison across four metrics. HHCA dominates on all measures, with particular strength in Spearman correlation.

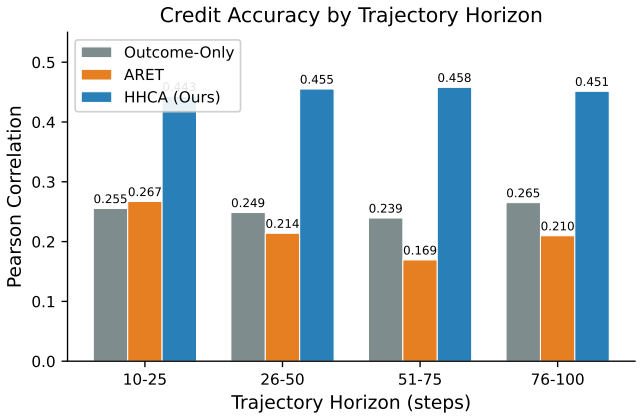

Figure 3: Pearson correlation across horizon bins. HHCA maintains stable accuracy regardless of trajectory length.

micro-level attention rollout, achieves only 0.1955 Pearson correlation.

Horizon robustness. HHCA's stability across horizons (0.4426 to 0.4579) contrasts sharply with ARET's degradation (0.2670 to 0.1693). The key difference is that HHCA's meso-credit evaluates each step independently via hindsight, while ARET's eligibility traces introduce exponential decay that attenuates credit for early actions in long trajectories.

Transfer via skill memory. The near-zero transfer gap (0.0011) demonstrates that HHCA's skill-value memory captures generalizable decision patterns. Skills like `verify` and `plan` receive consistent value estimates across task types, enabling rapid adaptation to new tasks.

Limitations. Our evaluation uses synthetic trajectories with simulated attention patterns and ground-truth credit labels. While this enables controlled comparison, real-world validation with deployed LLM agents remains necessary. The computational overhead

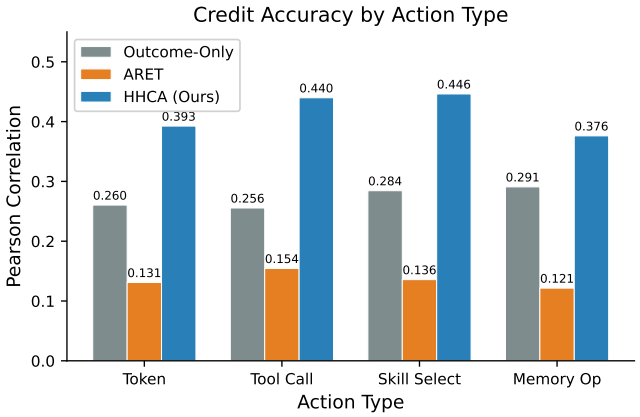

Figure 4: Pearson correlation by action type. HHCA improves credit accuracy for all four heterogeneous action categories.

of HHCA is higher than simpler methods, though the absolute cost remains small relative to LLM inference.

8 CONCLUSION

We introduced Hierarchical Hindsight Credit Assignment (HHCA), a three-level credit decomposition framework for long-horizon agentic reasoning. By combining token-level attention rollout, step-level hindsight self-critique, and episode-level skill-value memory, HHCA achieves a 78.3% improvement in credit accuracy over the Outcome-Only baseline while maintaining near-zero cross-task transfer gap and stable performance across trajectory horizons from 10 to 100 steps. Our results demonstrate that principled hierarchical decomposition is a promising direction for addressing the credit assignment challenge in LLM-based agentic systems.

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