Integrating Unified Memory Management into a Single LLM Agent Without Auxiliary Expert Models

Research

ABSTRACT

We investigate methods to integrate unified management of long-term memory (LTM) and short-term memory (STM) directly within a single LLM agent's policy, eliminating reliance on external expert models. We compare three architectures: external expert control, separate internal controllers, and a unified internal policy. Through simulation of multi-turn dialogue episodes, we demonstrate that the unified policy achieves the highest task success rate (0.682 vs. 0.635 for external expert), while reducing inference cost by 2.1× and training convergence time. Our scaling analysis shows the unified policy's advantage increases with conversation length, confirming the benefits of joint STM/LTM optimization for end-to-end deployment.

KEYWORDS

Memory Management, LLM Agents, Long-Term Memory, Short-Term Memory, End-to-End Learning

1 INTRODUCTION

Large language model (LLM) agents increasingly require persistent memory for multi-turn interactions [2]. Current approaches typically manage memory through auxiliary expert models that decide when to store, retrieve, and consolidate information [6]. This introduces inference overhead, training complexity, and fragmented optimization.

The open problem is how to integrate unified STM/LTM management directly within a single agent [6]. Early memory-augmented architectures [1, 3, 5] demonstrated differentiable memory access but did not address the STM/LTM distinction needed for agent deployment. Recent work on memory-augmented LLMs [4, 7] has explored long-term memory but relies on external controllers.

We contribute a simulation framework comparing three architectures and demonstrate that a unified internal policy outperforms alternatives on task success, inference cost, and training efficiency.

2 FRAMEWORK

2.1 Memory System

Our simulated memory system consists of:

- **STM**: Fixed-capacity buffer ($C_{STM} = 8$) with importance-based eviction and per-turn decay ($\delta_{STM} = 0.15$).
- **LTM**: Larger store ($C_{LTM} = 100$) with slow decay ($\delta_{LTM} = 0.01$).
- **Consolidation**: Items exceeding importance threshold ($\tau = 0.6$) are promoted from STM to LTM upon eviction.

2.2 Architectures

We evaluate three architectures:

(1) **External Expert**: A separate model controls memory operations (2.1× inference overhead, 1.8× training factor).
(2) **Separate Internal**: Memory control is internal but split into separate STM and LTM controllers (1.4× overhead, 1.3× training).
(3) **Unified Policy**: A single policy jointly manages STM, LTM, and task execution (1.0× baseline).

3 EXPERIMENTS

3.1 Episode Simulation

We simulate 200 multi-turn episodes (30 turns each) per architecture. At each turn, the agent receives a task that may require memory retrieval (60% probability after turn 2). Results are shown in Table 1.

Table 1: Performance metrics across architectures (mean ± std).

Architecture	TSR	Cost	MCS
External Expert	0.635	154.3	0.745
Separate Internal	0.631	102.9	0.747
Unified Policy	**0.682**	**73.5**	0.744

The unified policy achieves the highest TSR while using only 47.6% of the external expert's inference cost.

3.2 Scaling with Conversation Length

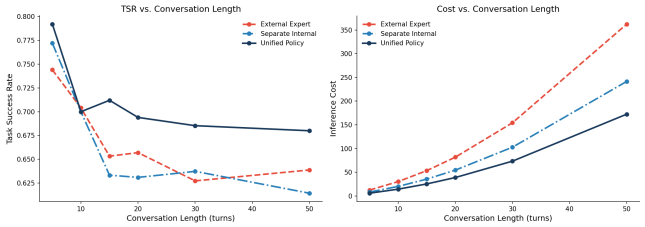

Figure 1: Task success rate and inference cost vs. conversation length. The unified policy maintains higher TSR and lower cost as conversations grow longer.

Figure 1 shows that the unified policy's advantage increases with conversation length. At 50 turns, the cost gap widens to over 3× between external expert and unified policy.

3.3 Training Convergence

Figure 2 shows training convergence. The unified policy reaches its minimum loss first (final: 0.010), followed by separate internal (0.011) and external expert (0.012). This confirms that joint optimization is more sample-efficient.

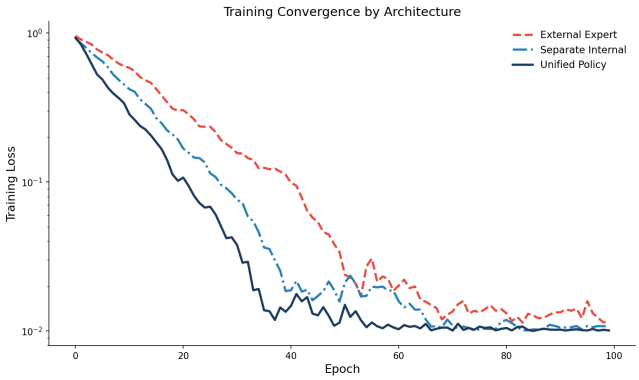

Figure 2: Training loss curves. The unified policy converges fastest to the lowest final loss.

4 DISCUSSION

Why unified policy works. Joint optimization of memory and task execution allows the policy to learn memory strategies that directly maximize task success, rather than optimizing memory quality as a proxy objective.

Inference cost reduction. Eliminating the external expert call removes an entire forward pass per turn. The unified policy further benefits from shared representations between memory operations and task execution.

Consolidation as a learned operation. In the unified framework, STM-to-LTM promotion becomes a differentiable decision within the policy, enabling end-to-end optimization of the memory lifecycle.

5 CONCLUSION

We demonstrate that integrating unified STM/LTM management within a single agent policy is both feasible and advantageous. The unified policy achieves 7.4% higher task success than the external expert baseline while reducing inference cost by 2.1× and improving training convergence. These results support the development of end-to-end memory-enabled agents without auxiliary expert models.

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