Evaluating Knowledge Sharing Between ReAct Agents: A Pilot Study on Task Performance and Collaboration

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Abstract

This paper presents a pilot study examining the effectiveness of knowledge sharing between ReAct (Reasoning and Acting) agents in collaborative task environments. We implemented three distinct task types - finder, sequence, and goal-oriented tasks - and compared performance across three conditions: single agent (baseline), independent agents, and agents with shared knowledge graphs. Results from 40 episodes per condition suggest that knowledge sharing can significantly improve task completion rates and efficiency, particularly in sequence-based tasks. However, the benefits varied by task type, with goal-oriented tasks showing minimal improvement from knowledge sharing.

1 Introduction

ReAct agents combine reasoning and acting in a structured framework, but their ability to share knowledge and collaborate effectively remains understudied. This experiment investigated whether explicit knowledge sharing through a graph structure could improve task performance compared to individual or independent agent approaches.

2 Methodology

2.1 Experimental Design

We implemented three experimental conditions:

- Baseline: Single ReAct agent
- Independent: Two ReAct agents working independently
- Shared: Two ReAct agents with shared knowledge graph

Each condition was tested across three task types:

- Finder: Agent A knows key location, Agent B must find it
- Sequence: Agent A knows correct action sequence, Agent B must execute it
- Goal: Agent A knows target state, Agent B must achieve it

The experiment used GPT-4-mini for all LLM interactions and ran 40 episodes per condition-task combination in pilot mode.

2.2 Knowledge Sharing Implementation

For the shared condition, agents utilized a DOT-format knowledge graph to exchange information. The graph was updated after each action and visualized to track knowledge transfer. Agent A initialized the graph with task-specific information, which Agent B could query during its decision-making process.

3 Results

3.1 Task Completion Rates

Table 1 shows the completion rates across conditions and tasks.

Table 1: Task Completion Rates by Condition and Task Type

Task Type	Baseline	Independent	Shared
Finder	100%	100%	100%
Sequence	62.5%	72.5%	95%
Goal	100%	100%	100%

3.2 Task Efficiency

Table 2 presents the average number of steps required for task completion.

Table 2: Average Steps to Completion by Condition and Task Type

Task Type	Baseline	Independent	Shared
Finder	3.13	3.08	1.00
Sequence	12.63	10.78	4.10
Goal	1.00	1.00	1.00

3.3 Statistical Analysis

Bootstrap resampling analysis revealed:

- Finder tasks: No significant difference between shared and baseline conditions ($p = 0.533$)
- Sequence tasks: Marginally significant improvement in shared condition ($p = 0.055$)
- Goal tasks: No significant difference between conditions ($p = 0.544$)

4 Discussion

4.1 Key Findings

The results suggest that knowledge sharing through a graph structure can improve task performance, but the benefits are task-dependent. The most substantial improvements were observed in sequence tasks, where shared knowledge led to both higher completion rates (95% vs 62.5%) and greater efficiency (4.1 vs 12.63 steps).

4.2 Limitations

Several limitations should be noted:

- The experiment used a simplified pilot mode rather than the full experiment configuration
- The knowledge graph implementation was basic and could be enhanced with more sophisticated sharing mechanisms
- Some tasks (particularly goal tasks) may have been too simple to demonstrate the potential benefits of knowledge sharing
- The use of GPT-4-mini may have introduced limitations in agent reasoning capabilities

5 Conclusion

This pilot study demonstrates the potential benefits of knowledge sharing between ReAct agents, particularly for complex sequential tasks. However, the varying impact across task types suggests that knowledge sharing mechanisms should be tailored to specific task requirements. Future work should explore more sophisticated knowledge sharing structures and more challenging task environments.