# A Demonstration of Compositional, Hierarchical Interactive Task Learning

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## Abstract

We present a demonstration of the interactive task learning agent Rosie, where it learns the task of patrolling a simulated barracks environment through situated natural language instruction. In doing so, it builds a sizable task hierarchy composed of both innate and learned tasks, tasks formulated as achieving a goal or following a procedure, tasks with conditional branches and loops, and involving communicative and mental actions. Rosie is implemented in the Soar cognitive architecture, and represents tasks using a declarative task network which it compiles into procedural rules through chunking. This is key to allowing it to learn from a single training episode and generalize quickly.

## Introduction

As general-purpose, interactive learning robots become more capable and prevalent, it should be possible to direct, customize, and extend them without expert programming or hundreds of demonstrations. Research interactive task learning (ITL) (Gluck and Laird 2019) seeks to develop AI agents that learn new tasks through online interaction.

Rosie is an agent that learns new tasks and using one-shot Situated Interactive Instruction (SII). The instructor and the agent are *situated* in a shared environment, engaged in bidirectional *interaction*, and communication via natural language *instruction*. Language enables a skilled instructor to provide the agent with precise learning goals as well as curated, high quality situation-specific task instructions. In this demonstration, we show Rosie learning online a complex, embodied task, called interior guard, in a simulated barracks environment from a single training episode.

Rosie is developed within the Soar cognitive architecture (Laird 2012). Soar contains a symbolic working memory, a metric spatial memory, procedural and declarative long term memories, and several learning mechanisms, which support perception, communication, hierarchical planning and decision making, metacognition, and learning. Rosie uses SII to learn many different types of knowledge, including perceptual features and spatial relationships (Mohan et al. 2012), hierarchical state-based concepts (Kirk and Laird 2019), games and puzzles (Kirk and Laird 2016), hierarchical goal-
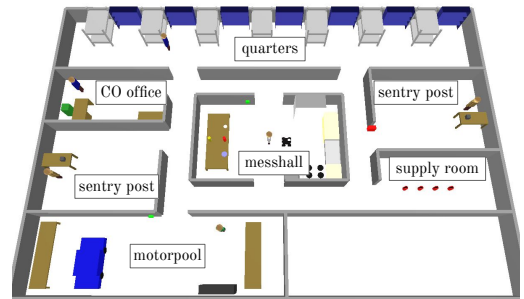
Figure 1: The simulated barracks environment.

based tasks (Mohan and Laird 2014), and hierarchical procedural tasks (Mininger and Laird 2018). Interior guard is the most complex and longest task Rosie has learned, including deep hierarchies of procedural and goal-based subtasks that include navigation, communication, and mental operations.

## Related Work

Learning from human instruction goes back to SHRDLU (Winograd 1972), and work by Crangle and Suppes (1994), who developed foundational ideas about the notion of an instructable robot that learns tasks from instruction. However, even today there are few examples of such agents.

Several approaches involve learning blocks-world style tasks in a tabletop setting, Frasca et al. (2018), Suddrey et al. (2016), She and Chai (2017), that do not involve the complexity of interior guard. Work by Mohseni-Kabir et al. (2019) combines learning a simple hierarchical task networks (HTN) with learning action primitives for a simulated tire rotation task. However, the language is limited and the HTN does not support reuse or generalization. ITL work has also been done with software agents, such as PLOW (Allen et al. 2007) and SUGILITE (Li, Mitchell, and Myers 2020).

There has been work involving learning tasks with a mobile robot. For example, Meriçli et al. (2013) teach a mobile robotic agent tasks such as getting coffee and following landmarks. However, the task learning is not compositional and has limited generalization. A similar agent from Gemignani, Bastianelli, and Nardi (2015) can learn parameterized procedures, but not hierarchical tasks.

| | | |
|---|---|---|
| Inspect the eastern SP. | Raise a fire-alarm. | Guard the barracks. |
| Go to the eastern SP. | Remember the current location | Ask "Who is my relieving officer?" |
| If the lightswitch is off, then turn the lightswitch on. | as the emergency location. | Remember the answer as the |
| If you are in a SP and an FE is not present, | Go to the eastern hallway. | relieving officer. |
| then fetch a FE from the supply room. | Turn on the alarm. | Repeat the following tasks until the |
| If you are in a SP, then ensure that a sentry is present. | Say "There is a fire." to the CO. | relieving officer is present. |
| If the current location is empty, | Describe the emergency location. | Inspect the messhall. |
| then turn off the lightswitch. | | Inspect the eastern SP. |
| | | Inspect the motorpool. |
| SP: Sentry Post | CO: Commanding Officer | Repeat. |
| FE: Fire Extinguisher | | |

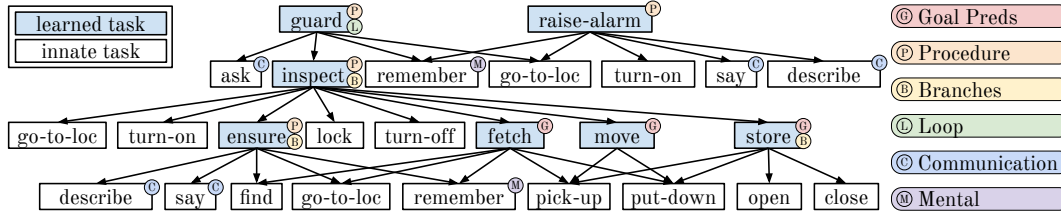Figure 2: Instructions used to teach the three main tasks, Rosie's dialog is omitted.



Figure 3: The hierarchy of tasks learned, with distinguishing features that are referenced in the discussion.

## Agent Overview

Rosie is a fully integrated end-to-end agent that performs perceptual processing and sends motor commands (Mininger and Laird 2019) in both real-world and simulated domains. Dialog is through a chat interface, with Rosie taking the initiative to ask questions. When it receives a response, it parses the language using the current context, grounding referents as appropriate (Lindes et al. 2017). The result is a precise, semantic structure, that Rosie then interprets within the current context. For new tasks, Rosie creates and stores a Task Concept Network (TCN) in semantic memory. It contains the task arguments, subtasks, and goal graph, as well as their connections. The goal graph is a directed graph consisting of subgoal nodes that include desired state predicates (e.g., the plate is in the sink) or a subtask to perform (e.g., inspect the messhall). Executing a task involves interpreting the nodes and control information in the TCN, which can involve following a procedure (including conditionals and loops), a learned policy, or planning.

As the agent processes the TCN knowledge, it learns rules that avoid interpretation and perform the processing directly. When a task or subtask is complete, the agent learns a state-based policy for future performance derived from a retrospective analysis of its behavior. As shown above, learned tasks in Rosie are truly compositional, so it can build up hierarchical tasks from previously learned subtasks.

## Interior Guard Demo

This demo occurs in a simulated, multi-room barracks environment (Figure 1) that supports realistic navigation. Actions involving objects are discrete and the perception involves error-free object detection and classification. The agent starts with knowledge of objects, people, locations, navigation, and simple actions. However, it has no specific knowledge related to guarding or patrolling.

The agent first learns three major tasks (Figure 2). It learns to inspect a room, with particular instructions given depending on the type of room. For a sentry post, it ensures that both a fire extinguisher and sentry are present. However, for the mess hall, it learns to store condiments and clean up plates, and for the motor pool, to lock vehicles. The agent also learns how to raise a fire alarm by pulling the alarm and reporting the location to the commanding officer (CO). Then it learns the overall guard task, where it asks the CO the name of the relieving officer, then repeats a patrol route until it sees that person. The full training scenario takes 17 minutes to teach and involves 224 individual tasks. After this instruction sequence, the agent is told to perform the guard task, with some variation. This final scenario takes 28 minutes and involves 389 individual tasks, which the agent accomplishes without asking any additional questions.

Figure 3 shows the full learned task hierarchy, with the learned tasks in the blue shaded rectangles. In addition to being a larger in scope than related work, it demonstrates several distinguishing capabilities, referenced by their letters in the figure. First, tasks can be represented as achieving a set of goal predicates (G) or following a procedure (P). For example, the goal of storing a condiment is that the condiment is in the fridge and the fridge is closed. Second, tasks can include branches (B) in the goal graph that represent conditional subtasks or goals, as well as loops (L). For example, the agent only fetches a fire extinguisher when inspecting a sentry post and if there is no fire extinguisher present. Third, tasks can involving communicative (C) and mental (M) actions. For example, the agent learns to ask who the relieving officer is, then remembers the answer for later use. A key contribution of this work is that the agent learns and uses a unified representation that enables it to compose all different types of tasks within the same hierarchy. Some limitations include restrictions on the language, and the amount of variation possible in a particular task; a focus of future work.

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