Establishing Common Ground for Learning Robots

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I. Introduction

Current robots have limited reasoning capabilities and language capabilities, making interacting with them an extremely challenging process. In the near future, we expect significant improvements in all of these areas as well as the ability to learn new tasks through natural language instruction, a capability we call Interactive Task Learning (ITL). Previous ITL research [6] has demonstrated that language instructions, coupled with demonstrations, are effective in teaching novel tasks by allowing the instructor to define the task problem space and guide the robot through the task. Our research is embodied in an ITL robot called Rosie (RObotic Soar Instructable Entity) that is implemented in the Soar cognitive architecture [7]. Rosie can learn over 50 games and puzzles [5], various procedural kitchen tasks [9] and mobile and navigation tasks [8] through situated interactive natural language instruction.

Robots that can learn new skills and tasks may solve some issues in human robot interaction, but we expect that new issues will arise exactly because of these new abilities. When our robots know more, can reason better, and especially can learn from their environment and other humans, a simple, static model of the robot's state and capabilities will be insufficient. In short, the human and robot will lack a common ground of understanding [3]. With ITL robots, establishing and maintaining common ground becomes even more difficult and crucial as the robot learns new tasks, concepts, and vocabulary from its own experience and interactions with human instructors. We thus characterized knowledge that constitutes this common ground and implemented question-answering mechanisms using which an instructor can build a mental model of the robot's current state and capabilities.

II. Related Work

Some previous research focuses on transparency mechanisms to improve a user's mental model of the robot either through question answering [4], visualization mechanisms [10] or estimates of uncertainty [2, 11]. There has also been work focusing on the robot providing specific information about its perception [1] and intentions [12, 13] taking into account the user's perspective, so that the user can assist with respect to a single task. Our research focuses on working towards common ground about not only knowledge of perception but also of those learned through instruction as well as instantiated task components. Secondly, we focus on robots that can learn different tasks across domains and our research is not restricted to a single type of task or environment.

III. Characterization of Common Ground

Here we characterize types of knowledge needed to establish and maintain common ground for a robot that can learn and use a variety of task knowledge, and we provide examples of Rosie that support achieving common ground.

A. Perception

During perception, an ITL robot builds an internal model of its environment, using both its innate and learned knowledge. Initially it may only have very simple, general ways of representing and characterizing the world, such as in terms of basic spatial primitives, colors, shapes, and sizes. As it learns new features, concepts, and relations, its internal understanding of the world will grow. A human attempting to instruct or command a robot needs to know which task components, features, concepts, and relations are available for communicating with and teaching the robot, and what distinctions the robot can make about its world.

Rosie has innate concepts for color, shape, and size, and can be taught, through instruction, specific colors ("The color of this block is blue."), shapes and sizes. It also has innate concepts of simple spatial relations, numbers, numeric comparators, functions, and nouns (objects, locations, ...). It can learn new concepts that are defined by compositions of innate and learned concepts. For example, Rosie can be taught *larger than* ("If the volume of a block is more than the volume of an object then the block is larger than the object."), or *surrounded* ("If the number of covered locations near a clear location is eight then the clear location is surrounded."), where "covered" and "clear" are previously learned concepts.

Rosie's perception and interpretation of its world can be accessed by asking questions about specific objects, or through more general questions such as: "What do you see?" From its answers, an instructor can learn which concepts Rosie has been taught, and confirm that Rosie's perception of the world is consistent with the instructor's model.

B. Task Knowledge

Rosie learns the definitional components of a task, including goal states, actions, failure conditions and task concepts from natural language interactions with an instructor. Internal representations are built up in Soar's working memory as relational graph structures, and then stored in long-term semantic memory [5] for later use. For example, the language used to describe the goal of Tower of Hanoi is "The goal is that a small block is on a medium block and the medium block is on a large block and the large block is on the blue location." The instructor can access any of its learned task knowledge through simple questions, such as, "What is the goal of Tower-of-Hanoi?" The robot dynamically constructs an answer from its internal representation: "The goal is that a small block is on a medium block and a large block is on a blue location and the medium block is on the large block."

C. Instantiation of Task Components

Possibly more important than accessing the robot's definitions of task knowledge, is determining if that knowledge applies to the current situation. That is, whether the knowledge is *instantiated* in the robot's current model of the environment. Through question asking, Rosie allows the instructor to query which innate and learned concepts (such as using *larger than* or *surrounded*) and task components (such as goal detection) are currently instantiated and which are not. This ability is critical for debugging instructions - determining why a concept or relation is not available, why a goal is not achieved when it should be, or why a failure condition is achieved when it shouldn't be.

For example, when the instructor asks "Do you see the goal of Tower-of-Hanoi?" in Figure 1, the robot needs to match its learned goal predicates to its perceptual world model. If it successfully instantiates all the necessary predicates, the robot responds "Yes." The instructor can use knowledge of successfully instantiated task components to evaluate whether the robot has learned relevant task knowledge correctly and can apply it to the world. However, in Figure 1, if the small block(ID: 4) was on location 2, instead of being on the medium block, then the *on* predicate (4,5) would not be satisfied. In that case, Rosie would answer, "No. A small block is not on a medium block." providing the exact unsatisfied precondition that led to this failure. This response contributes to understanding the cause of the robot's failure, and is especially useful when a non-expert instructor, someone who is unfamiliar with the internal working of the robot, is interacting with it. The robot can also tell the instructor which actions it can perform. For example, in the mobile domain, if the robot is in a room with a red box, blue box and trash bin, its response to "Which actions do you see?" is "I see the following actions: pick-up the blue box, pick-up the trash and pick-up the red box." When the robot learns new tasks, it incorporates those tasks into its answers. For example, after the instructor teaches Rosie the Deliver task, Rosie's response to the question is "I see the following actions: deliver the medium blue box, deliver the trash, deliver the medium red box, pick-up the medium red box, pick-up the trash and pick-up the medium blue box."

Having access to this knowledge also helps the instructor determine whether the robot correctly understands which actions it can perform in the current situation.
For example:

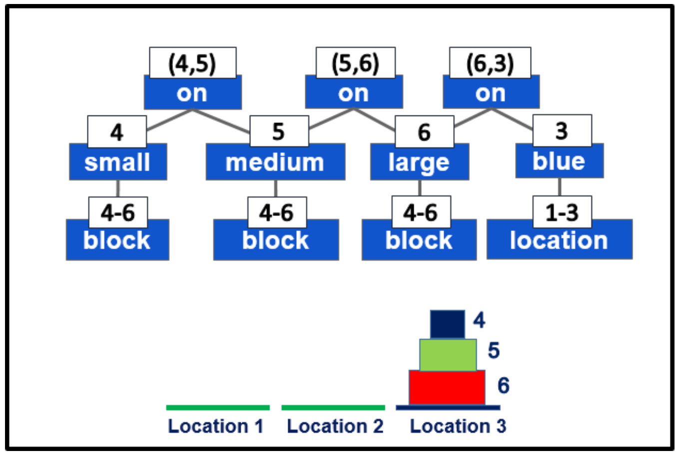

Fig. 1. At the bottom is a depiction of the Tower of Hanoi puzzle. On the top is a representation of the long-term task knowledge learned for its goal. The bold numbers uniquely identify the objects and show the instantiation of the task concepts in perception.

> **Instructor**: Pick up the red box.
> [Rosie picks up red box]
> **Instructor**: Which actions do you see?
> **Rosie**: I see the following actions: give the red box and put-down the red box.
> **Instructor**: Can you pick up the blue box?
> **Rosie**: No.

When the robot has picked up an object, it cannot pick up any other object until it has put the first object down. The instructor can use this knowledge to understand the robot's capabilities and limitations in different situations.

IV. Discussion and Future Work

The purpose of our research is to make it possible for an instructor to access a robot's knowledge through language, including what it learns through instructions and what it observes in its perception. The instructor can also access how the learned knowledge is *used* by the robot while performing a task, thus having access to the robot's internal state.

Initially, the instructor has more need to build up an accurate model of the robot's knowledge and capabilities, which led us to first implement instructor-driven explicit question-answering in the robot. We also plan to explore other modalities, so that the robot's state is more readily available, without explicit queries, such as via multi-modal transparency mechanisms where visual feedback continuously conveys the most important aspects of the robot's perceptual understanding and other internal reasoning during task learning and execution. We also plan to investigate ways for the robot to *anticipate* the needs and intentions of the instructor, proactively providing information that the instructor will need to maintain shared common ground.

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