Learning New Tasks with Situated Interactive Instruction

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1. INTRODUCTION

With the recent advances in robotics and AI research, we look forward to computational agents taking on new roles as intelligent assistants and autonomous collaborators. These agents are expected to perform diverse tasks in complex domains. The complete space of tasks that the agents are expected to perform cannot be predicted ahead of time. This limits what can be pre-programmed in the agents. Therefore, a key requirement of agent design is that they should be able to dynamically extend their knowledge and skills.

In a complex world, learning through self-directed experience alone can be slow, requiring repeated interactions with the environment. Human supervision can reduce the complexity of the learning task by reducing the need of exhaustive exploration by leading the learner through useful training experiences or by explicitly identifying the elements relevant to the task. There has been extensive work on learning action policies from *low-level* demonstration traces [1] that are obtained from the instructor either through teleoperation or shadowing. *LfD* approaches have been shown to be useful for learning control policies for various kinds of (*primitive*) actions such as manipulating objects and obstacle avoidance. Tasks such as *setting the table* can be characterized as instantiating primitive actions in accordance with the task goals and executing a policy defined over primitive policies that will achieve the goal. Learning such tasks from *LfD* is a challenging problem and may require a large number of long demonstrations for appropriate generality. Furthermore, the representations used in prior work are not amenable to transfer across structurally similar tasks.

We are exploring an alternative (and complimentary) approach to learn new tasks. Mixed-initiative, task-oriented dialog arises naturally in scenarios where an expert guides a novice to execute a novel task. This dialog is rich is useful information identifying task relevant features, decomposition structure, goals, and constituent actions. We are developing and studying mechanisms that can exploit task-oriented dialog to dynamically extend agent's knowledge and task behavior. This situated interactive instruction (*SII*)[5] approach focuses on learning from linguistic, *concept-level*, explicit interactions that do not directly encode the low-level details of behavior but exploit shared perceptions, domain knowledge, and experience between the human and the agent collaborators. Our agent is designed using the Soar cognitive architecture [4] that incorporates various learning, memory, and control mechanisms. The Soar architecture is committed to reactive behavior (50 ms perceive-decide-act cycle) and online learning that makes it a suitable AI architecture for use on robots and in interactive learning.

2. CHALLENGES AND APPROACHES

We assume a collaborative task execution scenario in which a human instructor and the learner robotic agent are simultaneously embedded in an environment (in Figure 1). Both participants have similar perceptions allowing them to situate their linguistic communication in the perceptible environmental state. Through a sequence of textual interactions, the instructor leads the agent through an example sequence of a task. The agent effectively combines information in interactions with its experience in the environment to extract generally applicable task knowledge and adds it to its repertoire. The agent also acquires linguistic and semantic knowledge of verbs corresponding to tasks that aid in further communication about the newly learned tasks. We are exploring the following two computational challenges that arise in designing an intelligent agent that not only communicates with its instructor but also learns from the communication and experience. Although we are not studying dialog management, it is key to designing communicative agents. Our dialog manager is adapted from COLLAGEN [8] and allows for mixed-initiative, flexible interactions.

2.1 Situated Comprehension

Language in collaborative dialog is used to identify and bring to the attention of the collaborator objects of interests, actions to be taken in the environment, useful relationships between objects, and feedback from the environment. For instance, *"You should be seeing a door in front of you"* [9]. The referential nature of language allows the hearer to *situate* the communication in the current task and create beliefs about the speakers intentions and act accordingly. Comprehending instructions requires the agent to translate the amodal symbols in the utterance to its modal beliefs about perceptual state, domain knowledge, and experiences. Human instructions can be linguistically complex and ambiguous and often require the use of non-linguistic context and domain knowledge for unambiguous interpretations.

We are developing a computational model of situated comprehension based on the Indexical Hypothesis [3]. The model [7] formulates linguistic comprehension as a search over the *common ground* - shared perceptions, common-sense knowledge, and shared experiences - between the speaker and the hearer. The information in instructions specifies the situation by identifying which components (objects, relationships, etc.) are relevant, and the semantic and experiential knowledge associated with these components augments the linguistic input with details that are required for reasoning and taking action. This approach has several interesting characteristics. First, the semantics are grounded in the agent's perception and experiences, allowing the use of

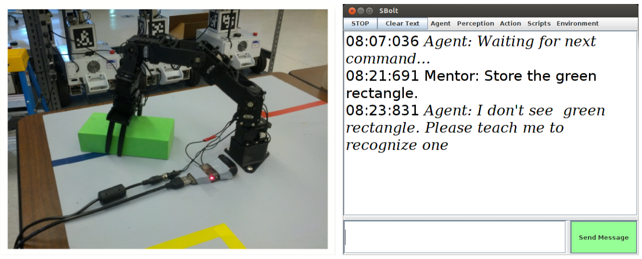

Figure 1: Table-top robot and interaction interface.

modality specific representations. For example, the semantics of nouns and adjectives are encoded as classifications in the perceptual space and those of verbs as goals and policies in task knowledge (Section 2.2). Second, it has been shown that these semantics can be learned through interactive instructions [6] and therefore, the model scales elegantly with knowledge acquisition. And third, the non-linguistic context derived from various sources including the ongoing discourse, reasoning, task knowledge, and attentional mechanisms has a natural role in such formulation. It provides constraints over the hypotheses space and guides search and can alleviate problems arising from linguistic ambiguities.

Our evaluations indicate that there are functional advantages to incorporating non-linguistic, grounded contexts for comprehension. When under-specific referring expressions (*it*, *that*) are used in instructions, our model can exploit information from non-linguistic contexts to constrain the reference hypotheses resulting in better performance than models that only use linguistic information. The model can also exploit the agent's task execution experience to complete under-specific task instruction. In future, we are interested in evaluating the model and its variations through user studies to identify the best variation and constrain the parameters to be ideal for communication with humans.

2.2 Task Learning

We are interested in learning *goal-oriented* tasks that can be hierarchically decomposed into constituent tasks/actions. To represent and execute such tasks, the agent must acquire diverse kinds of knowledge including task parameters, decomposition structure, goal definitions, policies defined over constituent subtasks, and availability and termination conditions. This knowledge not only is useful in reasoning about the tasks and executing them in the environment, but also provides grounding to verbs in instructions and contribute to non-linguistic contexts useful in comprehension.

We are looking at learning paradigms that have two desired properties. First, we are interested in active learning. Often in human controlled learning, the onus is on the instructor to provide good examples so that the agent can acquire general hypotheses. In contrast, with active learning, the instructor can rely on the agent to initiate an interaction when needed. This distributes the onus between the participants. The instructor takes initiative in structuring and decomposing the task. The learner guides its own learning by exploring its domain and asking relevant questions. Second, human time is costly and therefore numerous, repetitive interactions about the task are undesirable. Consequently, the data available to learn from is sparse. This motivates the use of knowledge-intensive explanation-based learning (EBL) mechanisms [2] that can exploit domain knowledge to deduce generally applicable knowledge from few examples.

We proposed an interactive variation of EBL that learns in two steps. When the agent is asked to execute an unknown task, it engages the instructor in task execution interactions. The instructor can guide the agent to execute the task by describing the goal and the sequence of actions or sub-tasks. This instructed task execution serves as an example in the second step. The agent retrospectively performs a causal analysis of why the particular action/subtask sequence taken in the example leads to goal achievement in the environment. This analysis yields a policy and availability and termination conditions of the task. Our evaluations establish that this approach can learn the entire task space from few examples. We have also shown that instructions can aid in transfer of execution policy between structurally similar tasks resulting in fewer learning interactions.

There are several avenues for future research. First, we are interested in expanding the diversity in goal-oriented tasks that can be acquired with our approach. Second, our assumption of no instructional errors does not hold for complex tasks in partially observable domains and novice instructors. We are interested in exploring corrective instructions so that the agent can recover from incorrectly acquired knowledge. Third, we want to evaluate SII in HRI contexts and study the mechanisms that make task teaching easier from the humans' perspective. Finally, we want to integrate our approach with primitive action learning from demonstration for a comprehensive account of task learning.

3. EXPECTED IMPACT

The overarching goal of our work is to design and develop robotic agents that can continually extend their task knowledge to adapt to new environments by interacting with their human collaborators. Efforts toward this goal will lead to the following contributions: (i) an SII framework that can learn diverse types of tasks, (ii) a grounded theory of task-oriented verb semantics, (iii) a novel model for situated language comprehension that elegantly incorporates information from non-linguistic sources alleviating ambiguities and under-specification, and (iv) an evaluation of SII that addresses the functional requirements such as fast, transferrable learning as well as its efficacy in HRI scenarios.

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