ARTIFICIAL INTELLIGENCE

Purposive learning: Robot reasoning about the meanings of human activities

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Reasoning about the meanings of human activities is a powerful way for robots to learn from humans.

Purely autonomous learning does not make sense without serving a final purpose; learning from humans is a powerful means to ensure a human-centric outcome. Early studies in robot imitation learning have revealed that behavioral imitation is a central aspect of human cognitive and social development. It has been pointed out that direct copying of body motions is fundamentally not useful because the model and the imitator often do not share the same body characteristics and surrounding object arrangements. Therefore, at the beginning of the whole imitation process, it is necessary to obtain meaningful features from the model's behavior and to reproduce them with the imitator's own behavior. One of the earliest seminal successes in robot imitation learning (*1*) classified different selections of the meaningful features with three cognitive strategies of imitation (*2*): (i) appearance-based strategy, focusing on the movements of the model; (ii) action-based strategy, focusing on an action only (i.e., the model's movement and its immediate result); and (iii) purposive-based strategy, focusing on the intention/goals of the entire observed task (i.e., a deeper understanding of the observation is needed; see Fig. 1, top).

Several approaches have taken an appearance-based strategy, in particular, by solving the sensorimotor coupling problem, which can be seen as close to early human development. First, a robot self-explores its own behaviors to learn sensorimotor maps. For example, in (*3*), a robotic hand was provided with some possible actions; the robot first generated these actions at random, then the robot observed the visual output of these actions, and thus, a sensorimotor pair can be learned. Such associations can be used to bootstrap the imitation of a person's hand motions by retrieving the memory of the self-observations. Another approach, which highlights the transformation of a single task into direct trajectory learning of motor skills, is via forward model(s) (*4*). For example, the motions of juggling three balls were observed via a motion capture system, and the trajectories were learned and refined via a reinforcement policy until the robot successfully juggled. Another well-established method is the dynamical movement primitives (DMPs), which has been accepted by the robotics community as a generalizable method to encode trajectory-level representations. The adaptive ability of DMPs makes it easy to teach and to execute adaptable trajectories (*5*). Recently, inverse reinforcement learning, whereby a reward function is inferred to explain the observed behaviors in a near-optimal manner (*6*), was used to extract goal(s) from observations.

An action-based strategy needs to develop learning approaches that focus on learning the correct mapping between the action and the learned primitive. Then, a policy is learned as to what and/or when to execute a particularly suitable action. Earlier works showed promising results with very dynamic situations, e.g., learning to play an air hockey game and a marble maze (*7*).

PURPOSIVE LEARNING

What are the key challenges involved in purposive learning from observations? Novel learning approaches that use artificial intelligence methods for inferring semantics to reason about observations have been proposed (*8*, *9*). The semantic-based techniques focus on two fundamental advances: (i) extracting meaningful intentions from human behaviors and (ii) the ability to transfer or reuse past experiences to new domains. Semantics mainly studies the construction of the meaning and knowledge representation because they play a crucial role in learning behaviors with partially observable information. Learning abstract concepts—such as action, space, and time—and physical objects can be achieved with an ontology representation. One recent advancement is KnowRob (*10*), a general upper ontology that covers a broad range of human manipulation knowledge. The KnowRob engine is used for loading, storing, and reasoning about the learned knowledge; this provides a promising abstraction tool for generalizable learning.

Recent successes in purposive learning have been realized by overcoming some key challenges (*8*, *9*): (i) learning object classifications and their relationships (knowledge is gathered on the objects and relation of all possible known actions in the form of ontology), (ii) activity classifications (identify known activities and reason about new activities), and (iii) a graph of possible transitions between activities leading to robotic plans (see Fig. 1, bottom).

Using ontology for purposive learning has shown great successes in learning complex scenarios with elaborate sequences, such as making pancakes, popcorn, and sandwiches; washing dishes; and setting a table. Furthermore, it has been shown that complex observations can extract rules valid for new situations even when observing multiple humans performing the same tasks with different styles (*8*). A virtual reality system (a fully equipped kitchen for cleaning dishes) was also developed to learn from realistic scenarios with multiple users (*9*), and more than 10 people performed the task in their own way. A generalized task graph was generated to cover all the situations; this level of generalization is very difficult for trajectory-based approaches.

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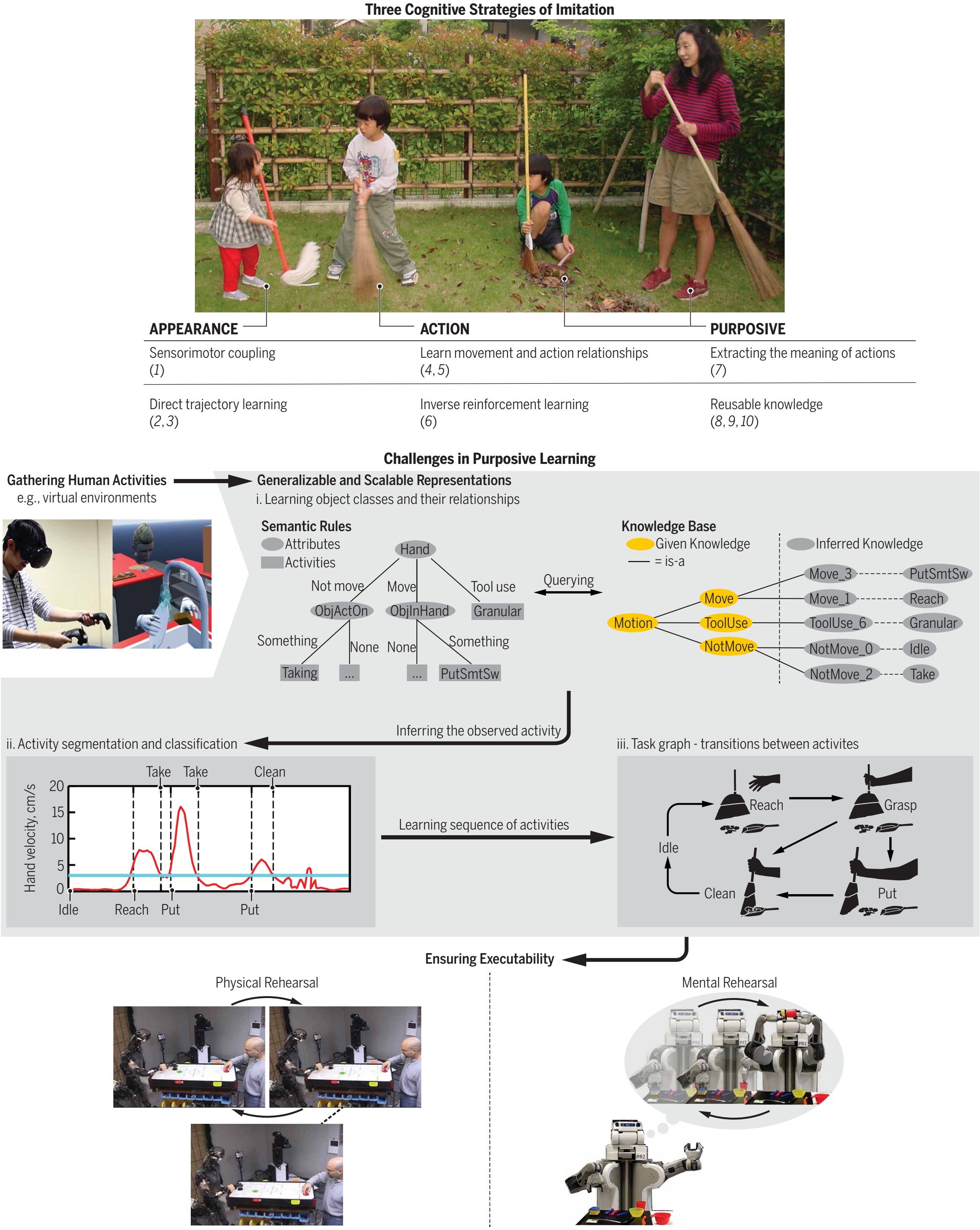

Fig. 1. Robots learning from humans: Past, current, and future purposive learning.

SELF-LEARNING TO ENSURE EXECUTABILITY

How can we ensure that tasks can be executed correctly and effectively, even across different robot bodies? To ensure success, we learn by mentally and physically rehearsing our own actions with our own body. This is a powerful means to enhance the performances of learned tasks, allowing the system to explore many or all possibilities (*7*). One key element of physical rehearsals is adapting the new tasks or skills to a different body with different dynamics—a general issue that is not considered in most learning methods. Allowing robots to mentally simulate the possible outcomes of a certain action will greatly ensure the success of the action executed in the real world. Going even further, rehearsing an action can help to predict the possible effects of the executed actions; this will guarantee correct parameterization of the robot plan (*6*).

Past approaches have focused on learning single tasks situated in a fairly fixed environment, that is, with small variances. Novel and flexible methods are needed to be able to deal with new and diverse situations. Recent advances in purposive learning have demonstrated its scalability in the sense of task complexity and its capability to generalize over multiple domains. The technique may provide a fundamental path to robots that successfully learn from humans.

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Acknowledgments: We are thankful for continuing support from members of the Institute for Cognitive Systems, Department of Electrical and Computer Engineering, Technical University of Munich. **Funding:** Research by G.C., K.R.-A., and M.B. reported in this paper has been (partially) supported by the German Research Foundation (DFG), as part of Collaborative Research Center (Sonderforschungsbereich) 1320 EASE-Everyday Activity Science and Engineering, University of Bremen. Y.K. is supported by the Next Generation Artificial Intelligence Research Center, University of Tokyo. The work of G.C. was also supported in part by Top Global University and Waseda University.

10.1126/scirobotics.aav1530

Citation: G. Cheng, K. Ramirez-Amaro, M. Beetz, Y. Kuniyoshi, Purposive learning: Robot reasoning about the meanings of human activities. *Sci. Robot.* **4**, eaav1530 (2019).

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Sci. Robotics **4**, eaav1530.
DOI: 10.1126/scirobotics.aav1530

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