Purposive learning: Robot reasoning about the meanings of human activities

Article *in* Science Robotics · January 2019

DOI: 10.1126/scirobotics.aav1530

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Science Robotics
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Manuscript Template

(Title) Purposive Learning: Robot Reasoning about the Meanings of Human Activities

(Short title) The renewed power of knowledge abstraction

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(Abstract) Reasoning about the meanings of human activities as 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, has revealed that behavioral imitation is a central aspect in cognitive and social development of humans. Fundamentally, it has been pointed out that direct copying of the body motions is 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 by 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*): 1) *Appearance-based*: focusing on the movements of the model; 2) *Action-based*: focusing on an action only, i.e. the model's movement and its immediate result; and 3) *Purposive-based*: focusing on the intention/goals of the entire observed task, i.e. a deeper understanding of the observation is needed (see Fig. 1 left).

Several approaches have taken an appearance-based strategy, noticeably, by solving the **sensorimotor** coupling problem, which can be seen as close to the early human development. First, a robot self-explores its own behaviors in order to learn sensorimotor maps. For example, in (*3*), a robotic hand is provided with some possible actions, the robot first generates these actions at random, then, the robot observes the visual output of these actions – thus, a sensorimotor pair can be learned. Such associations can be used to bootstrap the imitation of the hand motions of a person 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, the trajectories are learned and refined via a reinforcement policy until the success of the joggling. Another well-established method is the Dynamics Movements Primitives (DMP) which have been accepted by the robotics community as a generalizable method to encode trajectory level representations. The adaptive ability of DMP makes it easily used to teach and 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*), is used to extract goal(s) from observations. The 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/when to execute a particularly suitable action. Earlier works showed promising results to deal 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 have been proposed that utilizes Artificial Intelligence methods for inferring semantics to reason about observations(*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* since they play a crucial role in learning behaviors with partially observable information. Learning abstract concepts such as action, space, time, and physical objects can be achieved with an ontology representation. One recent advancement is KnowRob (*10*), it is 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 are 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 Figure 1 right).

Utilizing ontology for purposive learning have shown great successes in learning of complex scenarios with elaborated sequences such as: pancake making, popcorn making, sandwich making, washing dishes, and table setting. Furthermore, it has been shown that complex observations can deal even when observing multiple humans performing the same tasks with different styles (*8*), a Virtual Reality system was developed to learn from realistic scenarios with multiple users (*9*) e.g. a fully equipped kitchen was setup for cleaning dishes, more than 10 subjects 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.

Self-learning to ensure executability: *How can we ensure tasks can be executed correctly and effectively even across different robot bodies?* To ensure success, human learns by mentally and physically **reheard** our own actions with our own body. This is a powerful means to enhance the performances of learnt 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 certain action will greatly ensure the success of the action executed in the real world. Going even further, rehearsing an action can even help to predict the possible effects of the executed actions; this will guarantee with the correct parameterization of the robot plan (*6*).

While past approaches focused on learning single tasks situated in a fairly fixed environment, i.e. with small variances. In order to be able to deal with new and diverse situations, novel and flexible methods are needed. Recent advances in purposive learning demonstrated its scalability in the sense of task complexity and its capability to generalize over multiple domains serve as a fundamental path to future successes of robots learning from humans.

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Acknowledgments: We are thankful of the continuing supports of members of the Institute for Cognitive Systems, Department of Electrical and Computer Engineering, Technical University of Munich. **Funding:** GC, KR, and MB – The research 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. YK – is supported by the "Next Generation Artificial Intelligence Research Center", The University of Tokyo. GC – "This work was supported in part by Top Global University, Waseda University".

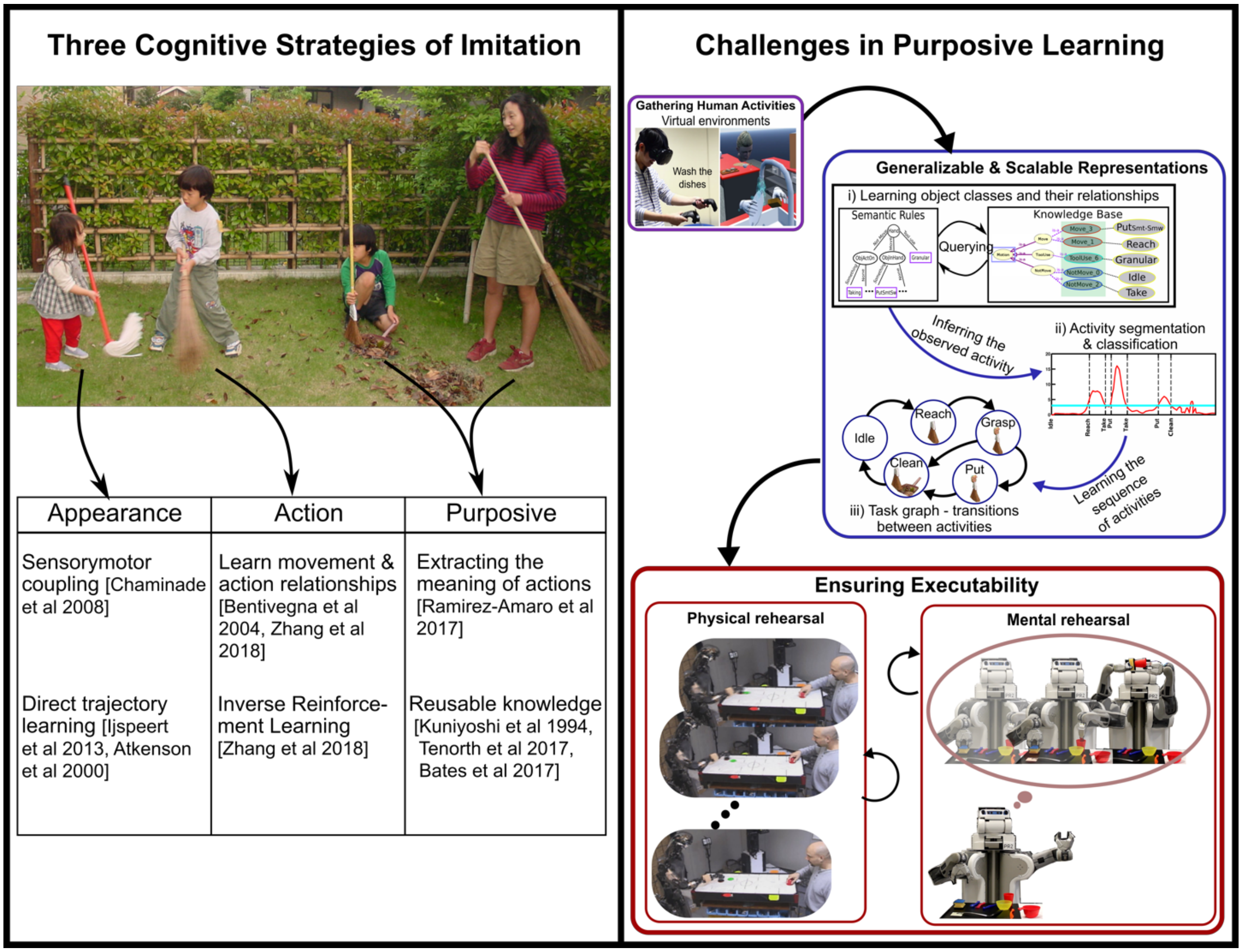

Figure 1: Robots Learning from Humans: Past, Current and Future to Purposive Learning