ARTIFICIAL INTELLIGENCE

Transfer learning in robotics: From promises to practice through the emerging role of foundation models

Foundation models offer a promising avenue to achieve transfer across robots, tasks, and environments.

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Humans' ability to transfer prior knowledge to novel tasks has made them the most innovative species on the planet. Drawing from this biological inspiration, we (and others) (*1*) previously argued that long-term progress of robotics will also depend on developing abilities to transfer knowledge across robots, tasks, and environments. This perspective positioned transfer learning as a central organizing principle for the field: a way to move beyond isolated demonstrations of task-specific competencies toward more general, adaptive, and reusable robotic capabilities. At the same time, the perspective (*1*) made clear that this promise would only be realized by unveiling the right transferable abstractions, by quantifying both transfer quality and transfer gap systematically, and by avoiding negative transfer in the absence of sufficient similarities between source and target spaces. The contributions gathered in the current special issue suggest that transfer learning in robotics is now entering a new phase. In particular, foundation models are emerging as a powerful mechanism for transfer, one that may help bring the early promises of transfer learning in robotics into practice.

Transfer learning in robotics revolves around three fundamental axes: the robot, the task, and the environment. From this perspective, transfer becomes the problem of identifying what knowledge can be reused when the robot embodiment changes, when the task parameters or goals are modified, when the environment varies, or when several of these dimensions shift simultaneously. Looking at the problem through this lens highlights that solutions need to evolve beyond narrow task success toward a more general question: What kinds of representations, policies, and priors allow robots to accumulate capabilities rather than relearn from scratch in every new setting? A key insight of (*1*) is that transfer is a question not only of whether and which knowledge can be reused but also of at what level of abstraction that reuse takes place. Drawing inspiration from biology, robotic transfer can be linked to different forms of social learning, from lower-level mimicry to imitation, emulation, and, last, causal understanding, showing that broader and robust transfer requires moving beyond copying motions or actions toward representing goals, constraints, and semantic task structure. As anticipated in (*1*), foundation models are especially relevant at the highest abstraction level because they open the door to enabling transfer through semantic planning, instruction following, and high-level task correspondences. At the same time, the perspective makes clear that high-level transfer is possible only when grounded in the full robotics capability stack, including perception, skills, planning, and control. In this sense, foundation models do not fully replace the original transfer learning framework but offer a promising direction for completing the capability stack.

Therefore, several challenges remain in focus. Transfer must occur at the right level of abstraction: rich enough to generalize yet grounded enough to remain useful in action. Its applicability and success must be assessed systematically, through quantitative measures that capture both transfer gap and transfer quality. At the same time, spurious similarities can be deceptive, making negative transfer a recurring risk. Moving forward therefore requires benchmarks, evaluation protocols, and training spaces that reflect realistic variation across robots, tasks, and environments, together with transfer mechanisms that remain interpretable, reliable, and robust as they scale.

The contributions in the current special issue revisit the agenda from (*1*) from complementary angles. Transfer across robots, specifically robot manipulators, was investigated by Gupta *et al.*, who show that structured kinematic abstractions can support effective cross-platform reuse. Transfer across tasks and object instances was further examined by Bilaloglu *et al.*, who propose a task representation designed to preserve transferable structure across geometric variations in objects, and by Chen *et al*., who adopt foundation model–based retrieval to ground manipulation in object-centric priors. The key challenge of measuring transfer systematically under realistic variation and distribution shift was investigated elegantly by Barreiros *et al*. In particular, through a carefully designed evaluation pipeline that combines large-scale simulation with blind, randomized real-world trials, this article offers a rigorous empirical view of robustness, multitask learning, and generalization while also emphasizing the substantial effort required to obtain statistically meaningful conclusions in robotics. Its central insight is that multitask pretraining improves robustness to distribution shift and substantially reduces the amount of task-specific data required to achieve strong performance, with gains becoming more pronounced as pretraining scale and diversity increase.

Several other contributions in this special issue also extend the transfer learning agenda into domains that became increasingly important with the rise of foundation models. The Viewpoint by Dey *et al*. complements the robot-task-environment space by adding social and collaborative dimensions, arguing that future robotic systems must also transfer knowledge among partners, roles, and interactions. On the other hand, the Viewpoint by Strobel *et al*. pushes the discussion toward multirobot and decentralized systems, where transfer must operate not only across robots and tasks but also across collective behaviors and scales of coordination. Last, the Focus by Robey *et al*. highlights the importance of safety during deployment, a concern that relates to the known issue of negative transfer. In the foundation model era, this concern becomes even stronger because broad priors can be powerful but also misleading unless they are grounded in context, constraints, and safety-aware deployment mechanisms.

Together, the contributions in this special issue reaffirm the central perspective that progress in robotics will depend on developing mechanisms that enable knowledge transfer across robots, tasks, environments, and, increasingly, social and multiagent settings. At the same time, they make equally clear that the foundational challenges identified in (*1*) have not been fully solved. The search for the right transferable abstraction level remains open, rigorous ways of quantifying transfer under realistic conditions are still costly and difficult to obtain, and the risk of negative transfer continues to grow as models become broader and more powerful. In this sense, foundation models mark not the end of the transfer learning agenda but rather its next phase.

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Acknowledgments: Authors who contributed equally to this work are listed in reverse alphabetical order.

10.1126/scirobotics.aeh4374

Science Robotics

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Sci. Robot. **11** (113), eaeh4374. DOI: 10.1126/scirobotics.aeh4374

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