Deductive Synthesis and Verification for Robotics Systems

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Project Summary

Overview:

Decision-making in robotics domains often involves continuous state and action spaces, long horizons, and sparse reward feedback. Bi-level planning with state and action abstractions emerges as a promising solution where a high-level search for abstract control plans is used to guide low-level robot execution in the original state transition space. However, despite recent advances in bilevel planning, such techniques fail to generalize across multiple problems and to large tasks that are intractable for modern planners, depend on hand-crafted and hence possibly suboptimal state and action abstractions, and cannot formally guarantee that high-level abstract plans are correct and downward executable in low-level continuous space. This proposal aims to develop a novel bi-level robot learning paradigm based on program synthesis to address the aforementioned challenges. The project will explore (a) bi-level program synthesis techniques for learning robot execution programs that generalize in multi-task settings and are capable of operating in noisy, inconsistent environments, (b) automatically learning state and action abstractions from environment interaction to induce the desirable domain-specific language used for robot program synthesis, and (c) compositional verification frameworks for ensuring that synthesized robot execution programs obey desired correctness properties. Overall, the resulting algorithms will establish new methodologies and foundations to enable highly interpretable robotics control systems that are capable of making reliable decisions with provable guarantees.

Intellectual Merit:

The key intellectual merit of the proposal lies in the development of a programming-by-reward synthesis framework to learn robot execution programs in stochastic, goal-based, and multi-task settings with high-dimensional continuous state and action spaces where only partial observability is available. The programs conduct high-level planning to solve tasks with long horizons and sparse rewards, while integrating neural network-based components to scale to continuous spaces for low-level perception and control. First, this project will advance classical planning and deep reinforcement learning which are traditionally concerned with solving individual tasks. By synergistically combining execution-guided and deductive program synthesis, it will enable learning robot execution programs formed of state-conditioned loops, conditionals, and memory structures that warrant generalization across multiple tasks and uncertain environments. Second, this project will study domain-specific language (DSL) induction. It will automatically discover state and action abstractions of continuous spaces in an evolving DSL to form the discrete, factored spaces from which high-level programs are searched. Third, the bi-level structure of synthesized robot execution programs naturally leads to a scalable verification framework that supports formally reasoning about the correctness of high-level programs and their low-level components in a highly compositional manner.

Broader Impacts:

This project addresses important technical questions at the heart of an emerging paradigm for trustworthy robotics systems, focusing on building a new learning representation that facilitates generalizability and new learning algorithms that integrate formal methods for provable correctness guarantees. The results of this research will bring a significant impact on and demonstrate possible road-maps towards the next generation of learning-enabled robotics systems where trustworthiness must be a front-line consideration. The project will be accompanied by developing curriculum materials to instruct undergraduate and graduate students to build trustworthy controllers for robotics systems using technologies from this research.