Sample-Efficient Reinforcement Learning for Real-World Robot Control

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Robotic support and assistance are growing social need due to demographic trends such as the aging population combined with a diminishing number of children. In this regard, promising motion planning and control methods are key ingredients to implement robots for helping our daily activities, while there is *uncertainty* in surrounding environment or humans to interact.

Recent advances in machine learning and artificial intelligence may provide a lot of beneficial technologies to potentially overcome the difficulty. One promising approach is reinforcement learning that allows robots to learn complex behaviors by own experiences (samples) collected through trial and error without requiring explicit mathematical models of the environment. Its direct application for real-world robots is, however, often infeasible since collecting sufficient sample quantity is generally difficult due to high sample cost (cost of executing real robot experiments and the risk of robot failure). Therefore, sample-efficient reinforcement learning algorithms are crucial to be developed.

In this talk, we introduce two reinforcement learning algorithms, Kernel Dynamic Policy Programming (KDPP) and Deep DPP (DDDP), which are designed to alleviate the issue of insufficient sample quantity by regulating information loss in policy update. We then share our recent application results of sample-efficient reinforcement learning for such practical robot control scenarios, as cloth manipulation, exoskeleton robot control for user-motion assistance, and so on.

Keyword: Reinforcement learning, Robot Control, Robot learning