Domain-Adaptive Robust Training and Deployment in Real-World Noisy Data-Driven Robotics Applications

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Abstract:
The integration of robotics and machine learning (ML) represents a transformative shift, empowering robots to evolve from traditionally programmed machines into data-driven learners operating in the real world. This transition brings forth a new set of challenges, chiefly revolving around the robot’s ability to learn from imperfect, real-world data and its capacity to adapt to challenging and dynamic environments. In the realm of machine learning, robotics projects invariably encompass three critical phases: training, evaluation, and deployment. The training phase’s efficacy is heavily contingent on the quality of the dataset, which frequently includes noisy and suboptimal data. Similarly, the deployed robot’s performance hinges on its adaptability to the target environment, which may significantly differ from the environments encountered during training and evaluation. In this work, we propose new algorithms capable of addressing these challenges. In particular, to tackle the training phase’s challenges, we propose a new stochastic gradient descent algorithm with adaptive robustness that can detect and reduce the effect of corrupted gradients during the learning process, allowing robots to enjoy machine learning advantages and be able to train on heavy-tailed datasets. And similarly, for the deployment phase, we propose a new reinforcement learning framework under which we present various algorithms capable of generating policies with domain uncertainty awareness that can adapt to different target environments and system identification uncertainties, allowing for efficient sim-to-real transfers.