Physics-based neural networks for nonlinear system identification enabled reinforcement learning

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Résumé

In contrast to classical model-based optimal control methods, reinforcement learning (RL) offers the ability to learn optimal control laws without requiring prior knowledge of the system dynamics. However, these methods are heavily data-dependent, posing practical challenges. Model-based reinforcement learning (MBRL), which uses a prior system model (e.g. first-principles model) to learn control laws in simulation, addresses some of these data limitations but remains constrained by the accuracy and quality of the model.
In this context, the mature field of system identification provides a dataefficient approach to modeling dynamical systems from measurements, which can improve the control law learning process. This talk will explore the interaction between model learning and control learning, emphasizing how system identification techniques can bridge the gap between data-driven and model-based control approaches.
Finally, recent advances in multilayer perceptron (MLP)-based nonlinear system identification will be presented. These methods leverage the classical gray-box modeling paradigm to find a balance between descriptive capability and sample efficiency.

Mots-Clés: System Identification, Reinforcement Learning

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