Guest Editorial
Introduction to the Special Issue of the IEEE L-CSS on Learning and Control

RECENT advances in machine learning and artificial intelligence have provided astounding performance gains in several domains, including computer vision, natural language processing and recommender systems, in particular when massive data is involved, and large computational power is needed. Similarly, modern control theory techniques have found very successful application in the analysis and control design of complex systems, for example in robotics and in the automotive industry. The connection between machine learning and control theory is more and more pertinent in view of the promise to surpass the potentialities of each discipline.

The design of control techniques for dynamical systems that are generally characterized by changing environments, uncertainty, unknown or unmodeled dynamics, and very large state dimension, continues to pose a challenging problem. The extension of control theoretic approaches to models that are unavailable or difficult to obtain, possibly exhibiting nonlinearities or built with large amount of data, by adding machine learning and deep learning elements in the loop, represents a very active research field. Therefore, the IEEE CONTROL SYSTEMS LETTERS has chosen to commit its second special issue to the subject of "Learning and Control."

One promising research direction in this field deals with the enhancement of model predictive control (MPC) schemes by the adoption of online model refinement using machine learning approaches, without relaxing closed-loop constraint satisfaction and performance. In this context, an alternative that does not require the large computational complexity of an online optimization to obtain MPC laws is offered by explicit MPC, which allows most of the computations to be performed offline. As an effective technique capable of dealing with the curse of dimensionality arising from a large state dimension, deep neural networks (DNNs) are being considered to approximate the expensive-to-evaluate closed-loop robust MPC laws.

A further research area that has the potential to significantly impact our society is reinforcement learning (RL). In the context of cyber-physical systems (CPS), RL techniques generate optimal policies in response to reward signals provided by sensors in real-time. Decision-making mechanisms, designed to enhance system performance with the help of artificial intelligence, hold the promise to enable cognitive control and autonomic operation of CPS, including robotics, smart grids, and self-driving vehicles. The biggest challenge, which will likely be faced by researchers in the years to come, lies in the autonomic system capability of learning online the correct policy in adversarial environments, and with partially known or unknown physical models.

An increasingly important research avenue considers neural networks for fast and efficient learning in uncertain systems. Sparse neural networks have been used to reduce computational complexity by decreasing the number of active neurons. Sparsification enables local learning through intelligent state segmentation without relying on a high adaptive learning rate. Moreover, it also allows local approximation across the segments, characterizing regions with fast-varying dynamics or non-negligible uncertainties. It is further envisaged that neural networks taking inspiration from the neuronal structure and operation principles of the brain will be able to effectively address the challenges of next-generation applications, as well as to provide a brain-inspired energy-efficient computation and control paradigm.

The trend towards a higher level of interaction between the fields of control theory and machine learning, targeting applications to dynamical systems, will continue, leading to further innovations. Hence, this Special Issue on Learning and Control highlights some of the advances made possible by such interactions, strengthening the Editors' vision that control methods will continue to play a fundamental role in conjunction with cognitive systems for the foreseeable future.

This Special Issue consists of 13 papers that deal with several topics in learning and control, and present new results on challenging theoretical as well as practical aspects. A brief overview is provided below, organized through five main topics.

Learning of Predictive Models: "Augmenting MPC Schemes With Active Learning: Intuitive Tuning and Guaranteed Performance": Soloperto, Köhler, and Allgöwer introduce a framework to augment an existing MPC implementation with a user defined active learning cost.

"Approximate Closed-Loop Robust Model Predictive Control With Guaranteed Stability and Constraint Satisfaction": Paulson and Mesbah address the real-time

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implementation of closed-loop robust MPC schemes by approximating MPC laws via deep learning.

"Torque Vectoring for High-Performance Electric Vehicles: An Efficient MPC Calibration": Lucchini, Formentin, Corno, Piga, and Savaresi present a Bayesian procedure for the efficient tuning of MPC parameters, with application to torque vectoring for high-performance electric vehicles with in-wheel motors.

"Learning Precisely Timed Feedforward Control of the Sensor-Denied Inverted Pendulum": Mohren, Daniel, and Brunton investigate biologically inspired strategies to learn predictive control laws for systems with time delays of similar order to their system dynamics.

"Learning Robustly Stabilizing Explicit Model Predictive Controllers: A Non-Regular Sampling Approach": Cervellera, Macciò, and Parisini deal with non-regular sampling techniques of the state space, which counter the curse of dimensionality for offline supervised learning from data of nonlinear explicit model predictive controllers.

Reinforcement Learning Techniques: "Sparse Learning-Based Approximate Dynamic Programming With Barrier Constraints": Greene, Deptula, Nivison, and Dixon provide an approximate online adaptive solution to the infinite-horizon optimal control problem for nonlinear systems with system safety using barrier certificates.

"On–Off Adversarially Robust Q-Learning": Sahoo and Vamvoudakis leverage Q-learning to learn optimal strategies with "on-off" actuation to achieve unpredictability of the learned behavior against physically plausible attacks, while maintaining system stability.

"Chance-Constrained Control With Lexicographic Deep Reinforcement Learning": Giuseppi and Pietrabissa introduce a lexicographic approach to deep reinforcement learning for chance-constrained control, where the evolution of the system is steered in such a way that its constraints are satisfied with at least a certain probability threshold.

"Reinforcement Learning of Control Policy for Linear Temporal Logic Specifications Using Limit-Deterministic Generalized Büchi Automata": Oura, Sakakibara, and Ushio propose a reinforcement learning method for the synthesis of a control policy that satisfies a control specification described by a linear temporal logic formula.

"Max-Plus Linear Approximations for Deterministic Continuous-State Markov Decision Processes": Berthier and Bach apply a max-plus linear method to approximate the value function with a specific dictionary of functions that leads to efficient state-discretization in continuous-state Markov decision processes.

Control of the Learning Rate in Deep Neural Networks: "Event-Based Control for Online Training of Neural Networks": Zhao, Cerf, Robu, and Marchand propose two event-based control strategies to dynamically adapt the learning rate of convolutional neural networks during the learning process.

Stochastic Big-Data Convex Optimization: "On the Linear Convergence Rate of the Distributed Block Proximal Method": Farina and Notarstefano analyze the convergence behaviour of the distributed block proximal method for solving stochastic big-data convex optimization problems.

Adaptive Control of Linear Quadratic Regulators: "Regret Lower Bounds for Unbiased Adaptive Control of Linear Quadratic Regulators": Ziemann and Sandberg present lower bounds for the regret of adaptive control of linear quadratic regulators, based on the insight that, under certain assumptions, the adaptive control problem can be reduced to a sequential estimation problem.

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