Master's Department of Engineering Sciences

MSc in Automation Engineering and Robotics

Name of the unit: Learning for Control

Lecturer: SIGAUD Olivier ()
Course code:
Student workload: 10 h of lectures, 20 h of labs
Credits: 3 ECTS
Specialization tracks: ☒ ROBOT (elective) ☐ SI ☐ MeDH
Semester offered: ☐ S1 ☐ S2 ☒ S3 ☐ S4
Language of instruction: ☐ French ☒ English
Targeted audience: ☒ Engineering Sciences students ☐ Other (specify): ENSAM
Localization : ☒ PMC Campus ☐ Other (specify):

Course Overview

Fundamental machine-learning tools for use in control applications, particularly robotics. Special emphasis is placed on supervised learning of robotic models from data and on reinforcement learning as a data-driven approach to optimal control.
Keywords: Machine learning, supervised learning, reinforcement learning

Prerequisites

Students should have previously acquired the following prerequisites to follow this course:

- programmation python
- Gradient calculation, statistics (expectation, variance, etc.)

Intended Learning Outcomes

By the end of this course, students will be able to:

1. Understanding regression algorithms
2. programmation pytorch
3. Understanding reinforcement-learning algorithms
4. Use of machine learning on practical simulated robotics cases

Indicative Teaching Sequence and Methods

Week	C/TD/TP*	Content	Preparation	Learn. outc.
S1	2 hours of lectures, 4 hours of practical work	Lecture: regression, from linear least squares to regression with neural networks in PyTorch. Practical: application of regression algorithms to synthetic data		
S2	2 hours of lectures, 4 hours of practical work	Lecture: regression for learning robotic models—geometric, kinematic and dynamic models; forward and inverse models; examples from the literature; hybrid models combining known and learned components. Practical: learning a model from simulated data in a model-based control loop.		
S3	2 hours of lectures, 4 hours of practical work	Lecture: model-free reinforcement learning for policy search (feedback controllers), policy-gradient theorem, REINFORCE algorithm and the bias-variance trade-off. Practical: application of REINFORCE to a simulated system.		
S4	2 hours of lectures, 4 hours of practical work	Lecture: proximal policy optimization (PPO) and related algorithms. Practical: application of PPO to a simulated system.		
S5	2 hours of lectures, 4 hours of practical work	Lecture: model-based reinforcement learning, data efficiency, and the use of MPC and variants including TD-MPC. Practical: application of TD-MPC to a simulated system.		

* C/TD/TP respectively corresponds to lectures, tutorials and lab sessions.

Indicative Assessment of Intended Learning Outcomes (1st session)

Week	Individ./group	In-person/remote	Type of exam	Evaluated outcomes	Scale %
1			TP		20 %
2			TP		20 %
3			TP		20 %
4			TP		20 %
5			TP		20 %

2nde session of exam

Session	Individ./group	In-person/remote	Type of exam	Evaluated outcomes	Scale %

Bibliographic references

- Sutton and Barto, Reinforcement learning, an introduction, MIT Press, 1998 / 2018
- Bishop, Pattern recognition and machine learning, Springer, 2006

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