Title: Learning Methods for Safe-against-Uncertainty Control

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Subject description

I. Context

From energy networks to space systems: complex Autonomous Systems (AS) have become pervasive in our society [1]. In this context, the design of increasingly sophisticated methods for the modeling of AS is of utmost relevance, given that they regularly operate in uncertain and dynamic circumstances.

Specifically, to mitigate hazardous and possibly catastrophic uncertain perturbations during the decision-making process, one is led to reliably infuse Learning-based Models (LM) in the control pipeline [2]. LM offer numerous advantages, including accurate representations of sophisticated systems which accomplish complex tasks [3, 4]. Nevertheless, due to the high degree of uncertainty in which AS operate, one must devise LM capable of offering *guarantees of reliability*. For instance, robotic surgeons must reliably be aware of uncertain disturbances caused by human surgeons which accidentally perturbs the robot, so that safe evasive maneuvers can be planned accordingly.

Postdoc goal: Develop novel learning techniques to design LM which offer guarantees of reliability for efficient and safe-against-uncertainty control and deployment of AS in complex settings.

II. Scientific approach

The candidate will pursue the aforementioned goal by extending and combining recent promising advances respectively in Reproducing Kernel Hilbert Spaces (RKHS) [5] and in Model-Based Reinforcement Learning (MBRL) [2], which have been so far developed independently. On the one hand, RKHS have been leveraged to learn probability densities from samples with sharp theoretical guarantees of representability [6]. In particular, promising results through the use of this technique have been recently obtained for reliable modeling of Stochastic Differential Equations (SDE) [7].

On the other hand, recent techniques in infinite-dimensional linear matrix inequalities and control contraction metrics have allowed the design of deterministic control LM which capture inherent control-theoretic properties of the control system to learn, e.g., controllability and stability (under appropriate controls) [8]. Upon these results, the main research direction the candidate will investigate consists of extending and combining provable RKHS-based methods with control theoretic-based LM to learn controlled SDE which capture inherent control-theoretic properties of the dynamics of the complex AS to learn, which can then be leveraged to improve control strategies.

III. References

[1] J. A. Starek et al. Spacecraft Autonomy Challenges for Next-Generation Space Missions. In E. Feron, editor, *Adv. in Control System Technology for Aerospace Applications*, pages 1–48. Springer, 2016.

[2] B. Recht. A Tour of Reinforcement Learning: The View from Continuous Control. *Annual Review of Control, Robotics, and Autonomous Systems*, 2:253–279, 2019.

[3] R. S. Sutton, A. G. Barto, and R. J. Williams. Reinforcement Learning is Direct Adaptive Optimal Control. *IEEE Control Systems Magazine*, 12(2):19–22, 1992.

[4] Assessment, Standards Division Office of Transportation, and Air Quality U.S. Environmental Protection Agency. Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources. Final Report and Peer Review Report, 2016.

[5] U. Marteau-Ferey, F. Bach, and A. Rudi. Non-parametric Models for Non-negative Functions. *arXiv preprint arXiv:2007.03926*, 2020.

[6] A. Rudi and C. Ciliberto. PSD Representations for Effective Probability Models. In *Advances in Neural Information Processing Systems*, pages 19411–19422, 2021.

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[7] R. Bonalli and A. Rudi. Non-Parametric Learning of Stochastic Differential Equations with Fast Rates of Convergence. Sumbitted.

[8] S. Singh et al. Learning Stabilizable Nonlinear Dynamics with Contraction-Based Regularization. *The Int. Journal of Robotics Research*, 40(10–11):1123–1150, 2021.

Job information, required skills, and application procedure

The offered position consists of a 18-month postdoc, funded by Dr. Riccardo BONALLI's ANR JCJC project ROCH. The candidate will work at L2S (Laboratoire des Signaux et Systèmes) in Gif-sur-Yvette, one of the leading laboratory in systems and control at Université Paris-Saclay. (S)he will be jointly supervised by Dr. Brandon AMOS (New York), Dr. Riccardo BONALLI (L2S, Gif-sur-Yvette), and Dr. Alessandro RUDI (SIERRA, Paris). In addition, a visiting period in Prof. Marco PAVONE's laboratory at Stanford University can be envisioned to flight test the algorithms on realistic free-flyers. In the latter case, Prof. Marco PAVONE will offer supervision as an external collaborator.

The topic mainly requires skills which often come with a PhD in statistical machine learning and/or mathematics (candidates which are going to obtain their PhD before the starting date of the position will be considered as well). Expertise in the topics related to control and stochastic differential equations, as well as coding skills in Julia, Matlab, or Python will constitute valuable perks. The proposed subject shall lead to the acquisition of strong theoretical and numerical skills in learning-based modelization of control systems described by stochastic differential equations.

The starting date coincides with the candidate's earliest convenience starting from September 1, 2023. Salary and benefits are in accordance with the French ANR Agreement (salary indication: 3100–3300 € per month gross). A candidate's background check, in accordance to the French HFDS, see this website (in French), is part of the recruiting process. To apply, please send the following documents to Dr. Riccardo Bonalli (email: `riccardo.bonalli@centralesupelec.fr`):

- curriculum vitae, motivation letter, and research statement,
- transcripts of courses with grades and obtained degrees, and list of publications,
- contact information for three academic references,
- up to 3 research-oriented documents (e.g., PhD thesis, conference/journal publication).

Supervisors' Biographies

Brandon AMOS. He holds a PhD in Computer Science from Carnegie Mellon University supported by the USA National Science Foundation Graduate Research Fellowship (NSF GRFP), and has worked at Adobe Research, DeepMind, and Intel Labs prior to joining Meta as research scientist in 2019. His research interests are in machine learning and optimization, with a focus on reinforcement learning, control, and recently on optimal transport, and geometry. He has developed foundations for controlling and optimizing unknown and latent systems in research on differentiable and amortized optimization.

Riccardo BONALLI (CNRS Researcher at L2S and Université Paris-Saclay, France). He received his PhD degree in control theory and applied mathematics from Sorbonne Université in 2018, in collaboration with ONERA-The French Aerospace Lab. He is recipient of the ONERA DTIS Best PhD Student Award 2018. He was a postdoctoral researcher with the Department of Aeronautics and Astronautics, Stanford University. Since October 2021, he is tenured CNRS Researcher at L2S and Université Paris-Saclay. He is PI of the ANR JCJC project ROCH–Risk-averse Optimal Control via Homotopy (230k €, 2023–2025). His research interests concern theoretical and numerical robust optimal control with techniques from differential geometry, statistical analysis, and machine learning, and applications in aerospace systems, energy, and robotics.

Alessandro RUDI (INRIA Researcher at SIERRA and École Normale Supérieure, France). His research interests span machine learning from an applied mathematics viewpoint. He is PI of the ERC starting grant REAL–Reliable and cost-effective large scale machine learning (1.5 millions €, 2021–2026). The goal of REAL is to lay the foundations of a solid theoretical and algorithmic framework for reliable and cost-effective large-scale machine learning on modern computational architectures, extending the classical supervised learning framework to provide algorithms with two additional guarantees in terms of the reliability of the predictions and the cost-effectiveness of the computation.