Machine learning to efficiently linearize systems for control

Department: Artificial Intelligence. Size: 45 EC.
Supervision: Aditya Gilra (CWI, Amsterdam) and Sander Keemink (Donders, Nijmegen)
(aditya.gilra@cwi.nl, sander.keemink@donders.ru.nl)

Background

Most real-world systems are nonlinear. We can transform the state and control variables of a non-linear dynamical system into those of a linear dynamical system, albeit in a higher number of dimensions, using Koopman operator theory [1]. Such a transformation can be learned using machine learning architectures [2,3]. This transformed linear system can be used to analyse and control the non-linear system using techniques which are analytically solvable or work better for linear systems. In this project, you will develop neural network architectures to learn these transformations efficiently from less data and investigate how to minimize the number of dimensions needed for the transformed linear dynamical system. Then you can use standard libraries for control on the linearized system.

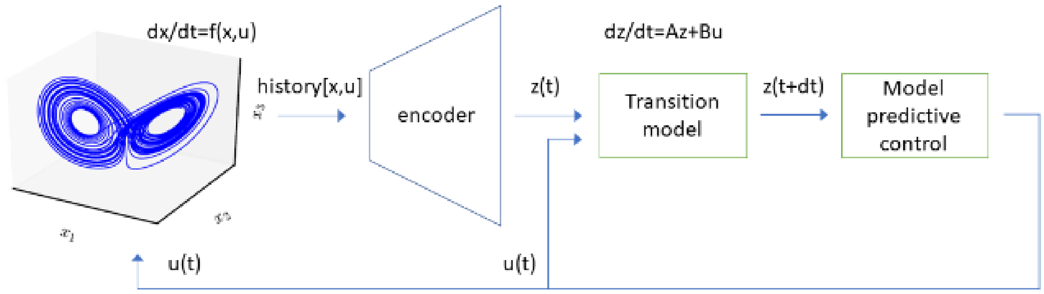

Figure: State and control variables x(t) and u(t) of a nonlinear system (here Lorenz oscillator) can be transformed using a learned encoder to high-dimensional variables z(t) which follow linear dynamics learned by the transition model. Model predictive control can use the learned linear transition model to plan and produce u(t) that controls the original non-linear system. Encoder and transition model are to be learned via machine learning from data.

Goals and scope

The student will learn to apply: a) control theory, Koopman operators and dynamic mode decomposition, and b) machine learning techniques like autoencoders and contrastive learning, to enable global linearization and control of nonlinear systems. The project consists of three tasks:

1. Learn encoder and transition model of an autonomous system (no control input u(t)) like Lorenz oscillator from data using contrastive learning techniques. Analyze how this can be made more efficient.
2. Extend to a controlled system like a 2-link pendulum and implement linear quadratic regulator and / or model predictive control to control the system.
3. Apply the architecture to a neuroscience / climate / economics system with simulated or real data.

Student profile

Background in machine learning and/or dynamical systems.

References

[1] Korda, M., & Mezić, I. (2018). Linear predictors for nonlinear dynamical systems: Koopman operator meets model predictive control. Automatica, 93, 149–160.

[2] van der Heijden, B., Ferranti, L., Kober, J., & Babuška, R. (2021). DeepKoCo: Efficient latent planning with a task-relevant Koopman representation. 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).

[3] Song, L., Wang, J., & Xu, J. (2021). A Data-Efficient Reinforcement Learning Method Based on Local Koopman Operators. 2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA), 515–520.