

February 19, 2020

MASTER'S THESIS

for

Student's name

Student ID 0815, Degree EI

Data-driven linear prediction methods for nonlinear dynamical systems

Problem description:

On the ever more important quest of efficient and efficacious solutions to non-convex problems, obtaining locally optimal results is challenging let alone obtaining globally optimal ones. One idea to tackle the aforementioned involves the utilization of the theory that non-linearly evolving system states can be represented as an infinite dimensional collection of linearly evolving variables. It predicated on the fact that one can "lift" nonlinear system's states into a new set of linearly behaved *observables* [1] (via the Koopman operator). Identifying such a mapping, in the lifted space of *observables*, results in a linear method for nonlinear system state prediction. Such a method can possibly tackle many today's challenges such as non-convex optimization offering better accuracy and considerable speed-ups. Furthermore, it could offer tractable solutions to, at their core, infinite dimensional problems i.e. fluid flow reconstruction, Hamilton-Jacobi PDE for nonlinear optimal control, dynamics of soft universal grippers etc.

However, one of the biggest challenges lies in identifying a good finite collection (as infinite states are intractable) of variables for an approximate Koopman mapping. Some recent attempts at identifying the mapping can be found in [3] as well as determining the number of feature maps found in [2]. Furthermore, for deployment in safety-critical scenarios, a need for a systematic error quantification of the Koopman mapping arises and has not been addressed in the literature before.

Tasks:

- Literature research
- Evaluation of prediction efficacy for test-bed systems
- Quantifying the Koopman projection error
- Test on non-convex optimization problems and/or nonlinear system controller design

Bibliography:

- [1] Milan Korda and Igor Mezić. Linear predictors for nonlinear dynamical systems: Koopman operator meets model predictive control. *Automatica*, 93:149–160, 2018.
- [2] Yingzhao Lian and Colin N Jones. Learning Feature Maps of the Koopman Operator : A Subspace Viewpoint. *Proceedings of the 2019 IEEE Conference on Decision and Control*, pages 1–7, 2019.
- [3] Alexandre Mauroy and Jorge Goncalves. Koopman-Based Lifting Techniques for Nonlinear Systems Identification. *IEEE Transactions on Automatic Control*, pages 1–16, 2019.

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