Simulation based transfer learning for complex dynamical systems

Background

A common approach to modeling dynamical systems is to construct models from first principles. These models offer physical insight, but perform poorly if the dynamics of a system are not properly understood.

Data-driven black-box modeling techniques offer accuracy without the need for in-depth physical insight, however, they require that the dynamics of interest are properly captured in the sample data.

Grey-box modeling is an umbrella term for a class of data-driven modeling techniques where prior information about a system is used to improve the quality of identified models. A variety of grey-box modeling techniques have been presented, but commonly they result in improved model performance, with reduced need for prior knowledge and sample data for training, outperforming both the aforementioned modeling techniques. For this reason, they have been widely used in complex industrial processing systems, where both quality data can be scarce and the dynamics are poorly understood.

Aim and Objectives

The aim of this project is on exploring the use of gray-box modelling techniques in modelling complex dynamical systems.

Specifically, the project will explore how *simulation based pre-training* on data from a first-principles model can be used to improve the quality of data-driven models.

The project will consider questions such as:

To what extent does simulation based pre-training reduce the need for real sample data?

Can the data-driven model be made physical interpretable?

Does the use of simulated data reduce the need for a wide variety of real data? (How well does the model extrapolate?)

The project will be focused on the analysis of a certain class of thermodynamical systems; a metal rod that is connected to an adjustable heat source. This system can be seen as an oversimplification of the much more complicated class of industrial metal processing furnaces, where the complexity of the system results in a poor understanding of the dynamics. Both a real implementation of the system and a first principles model has to be constructed.

The overall structure of the project is as follows:

1. Design and construction of hardware
2. Construction of an equation based first-principles model
3. Experiment design and data sampling from both systems
4. Construction, training and analysis of an appropriate machine learning model

Supervisors

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Prerequisites

The recommended prerequisites for this project are

- Knowledge of statistical learning methods
- Some knowledge of equation based modeling and Finite Element Analysis.

References

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