Comparison of Deep Learning Methods for System Identification

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1 Introduction

There has been a recent interest in using deep learning techniques for data-driven modeling of dynamical systems in engineering and control due to the apparent function approximation capabilities of deep neural network models and due to the powerful computational methods developed within the deep learning framework. The introduction of these methods to data-driven modeling of engineering systems has been relatively ad hoc [1] and thus a more structured in-depth comparison study including the well-established methods [2] need to be performed. To this end, a unified framework should be established, including the newly developed deep learning approaches, to understand the practical and theoretical implications of choosing a particular model structure and an associated learning approach in the context of data-driven modelling.

2 Problem Statement

Developing such a unified framework can be split up in a theoretical and a practical part.

The theoretical part entail the analysis of these newly introduced methods using the already well-established frameworks known in system identification. This analysis should, for instance, consider the structure of these new models, discussing the noise model, model class generality, and dynamics representation. Furthermore, an analysis of the impact of the widely used regularization, normalization, and training techniques in machine learning would also be necessary.

The practical part of the framework would entail a direct comparison of the most impactful classical methods and most newly introduced methods evaluated on many kinds of practical (non-linear) system identification problems to determine the problem-dependent performance. Furthermore, the comparison would need to consider a large set of performance measures derived from: one-step-ahead prediction, simulation evaluation, extrapolation performance, computational cost, and problem-specific hyperparameter sensitivity i.e. ease of use.

3 Approach

Our first step in realizing this unified framework is providing a platform for the practical part as represented in Figure 1. We are developing an open-source python-based programming environment (i.e. module) which allows for the implementation of system identification methods with relative ease. Currently, we have implemented many well-established methods such as ARX, OE, linear state-space models, and feed-forward neural networks [2] and newly introduced methods such as LSTM, TCN (Temporal CNN), NL-LFR and auto-encoder based state-space methods [3]. Furthermore, our python module has incorporated a diverse set of system identification problems derived from real data sets (currently over 10) [4] and popular toy systems (currently over 20).

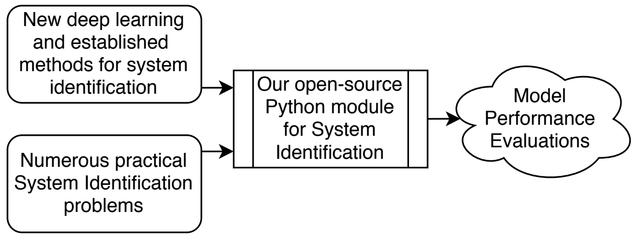

Figure 1: Our first step in creating a unified framework is the realization of a platform for evaluating system identification methods.

4 Conclusion

The development of a practical comparison framework is not only the first step towards a unified framework, for the analysis and comparison of (non-linear) system identification methods, but can also be seen as a tool for future system identification research as it provides an easy tool for comparing with known methods on numerous system identification problems.

References

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