Recurrent Neural Network Architecture based on Dynamic Systems Theory for Data Driven Modelling of Complex Physical Systems

Abstract

While dynamic systems can be modelled as sequence-to-sequence tasks by deep learning using different network architectures like DNN, CNN, RNNs or neural ODEs, the resulting models often provide poor understanding of the underlying system properties. We propose a new recurrent network architecture, the Dynamic Recurrent Network, where the computation function is based on the discrete difference equations of basic linear system transfer functions known from dynamic system identification. This results in a more explainable model, since the learnt weights can provide insight on a system's time dependent behaviour. It also introduces the sequences' sampling rate as an additional model parameter, which can be leveraged, for example, for time series data augmentation and model robustness checks. The network is trained using traditional gradient descent optimization and can be used in combination with other state of the art neural network layers. We show that our new layer type yields better results than other recurrent layer types on several system identification tasks.