SHRED: SHallow REcurrent Decoder for Model Discovery

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Sensing is a universal task in science and engineering. Downstream tasks from sensing include learning dynamical models, inferring full state estimates of a system (system identification), control decisions, and forecasting. These tasks are exceptionally challenging to achieve with limited sensors, noisy measurements, and corrupt or missing data. Existing techniques typically use current (static) sensor measurements to perform such tasks and require principled sensor placement or an abundance of randomly placed sensors. In contrast, we propose a SHallow REcurrent Decoder (SHRED) neural network structure which incorporates (i) a recurrent neural network (LSTM) to learn a latent representation of the temporal dynamics of the sensors, and (ii) a shallow decoder that learns a mapping between this latent representation and the high-dimensional state space. By explicitly accounting for the time-history, or trajectory, of the sensor measurements, SHRED enables accurate reconstructions with far fewer sensors, outperforms existing techniques when more measurements are available, and is agnostic towards sensor placement. In addition, a compressed representation of the high-dimensional state is directly obtained from sensor measurements, which provides an on-the-fly compression for modeling physical and engineering systems. Forecasting is also achieved from the sensor time-series data alone, producing an efficient paradigm for predicting temporal evolution with an exceptionally limited number of sensors. In the example cases explored, including turbulent flows, complex spatio-temporal dynamics can be characterized with exceedingly limited sensors that can be randomly placed with minimal loss of performance.

Bio: Nathan Kutz is the Yasuko Endo and Robert Bolles Professor of Applied Mathematics and Electrical and Computer Engineering and Director of the AI Institute in Dynamic Systems at the University of Washington, having served as chair of applied mathematics from 2007-2015. He received the BS degree in physics and mathematics from the University of Washington in 1990 and the Phd in applied mathematics from Northwestern University in 1994. He was a postdoc in the applied and computational mathematics program at Princeton University before taking his faculty position. He has a wide range of interests, including neuroscience to fluid dynamics where he integrates machine learning with dynamical systems and control.