A study on quantifying effective training of DLDMD

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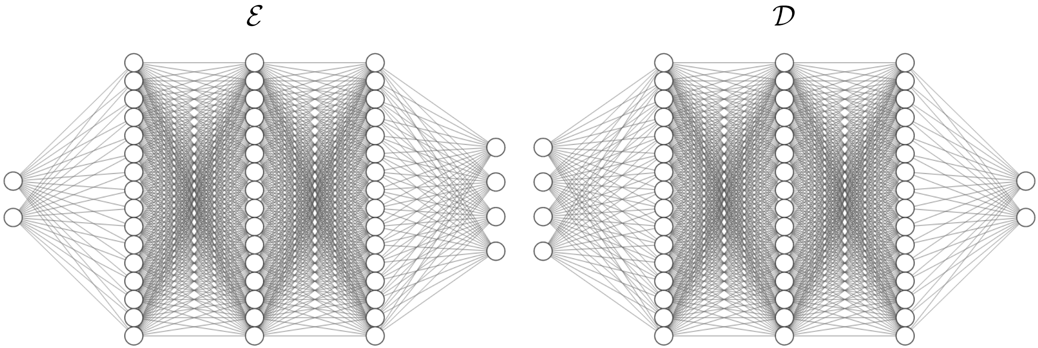
Introduction

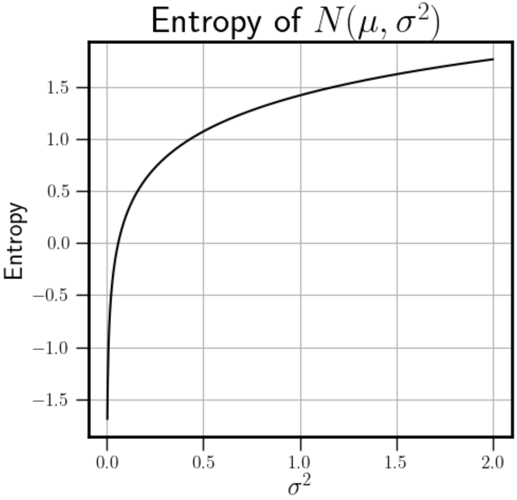
In the study of dynamical systems a central problem is how to derive models from measured data to facilitate the prediction of future states. The data-driven method Dynamic Mode Decomposition and it's extensions offer a compelling avenue in the problem of prediction from time-series data.
The marriage of these methods with Machine Learning and Neural Networks allows for the leveraging the power of these tools in the space.
If standard metrics of model training are unavailable,

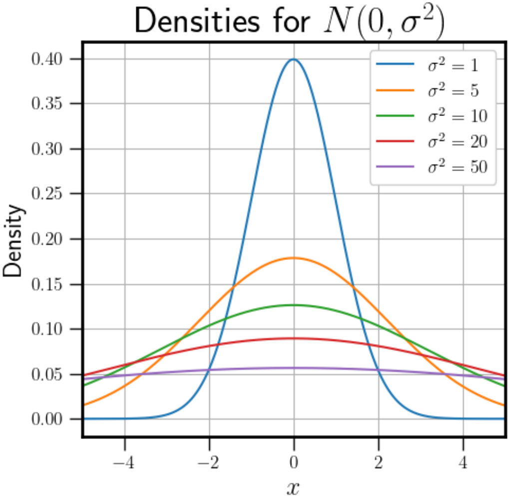
Introduction - The Network

Example of DLDMD newtork with $N_S = 2$, $N_O = 4$, and $N_L = 3$ where every hidden layer has 16 neurons.

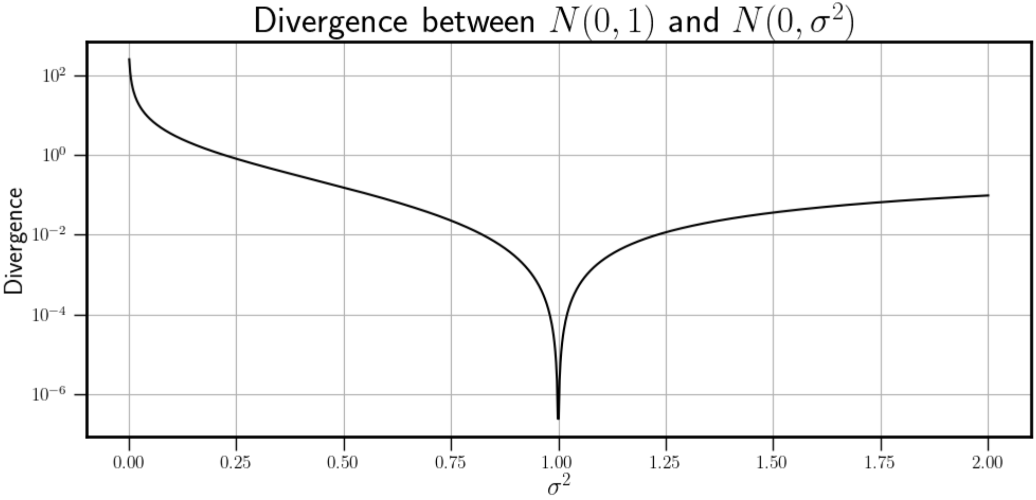


Kullback-Leibler Divergence - Entropy

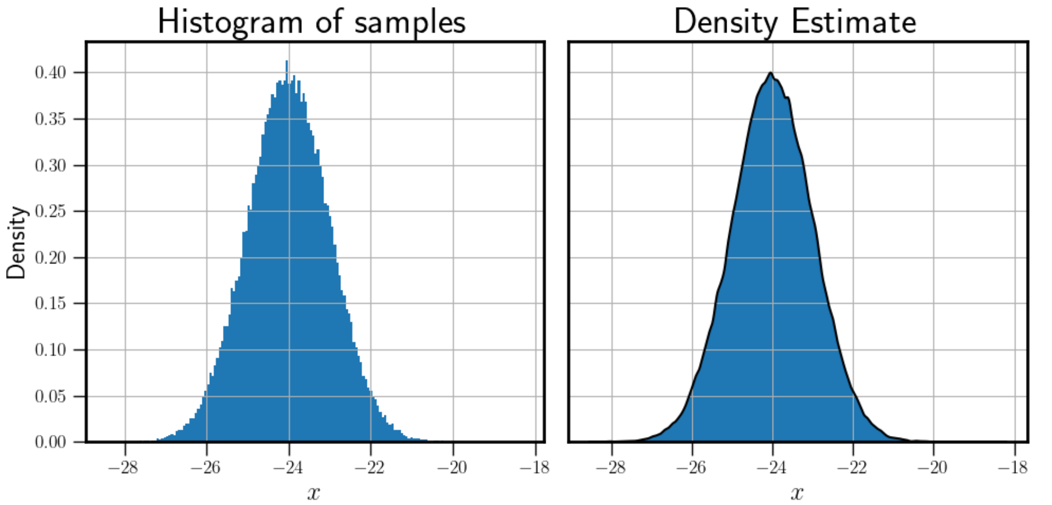




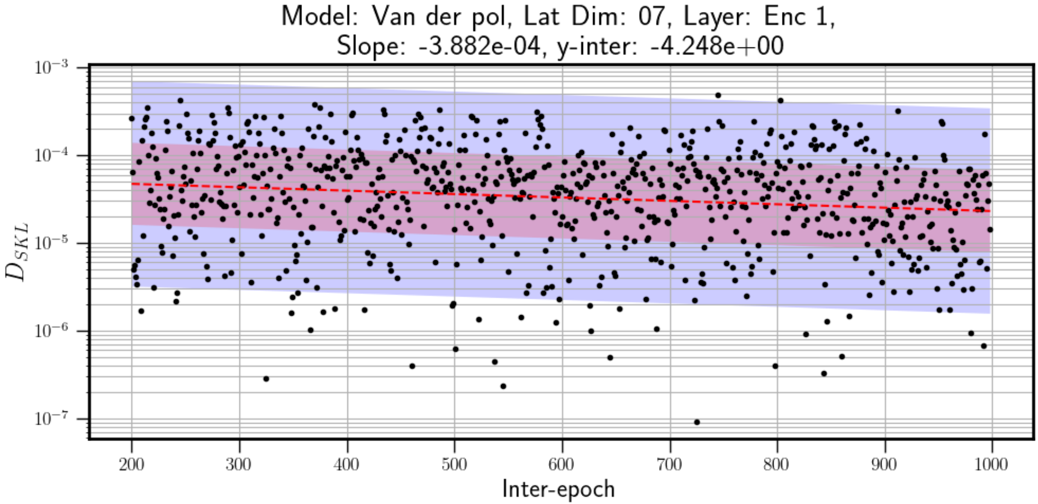
Kullback-Leibler Divergence - normal distribution example



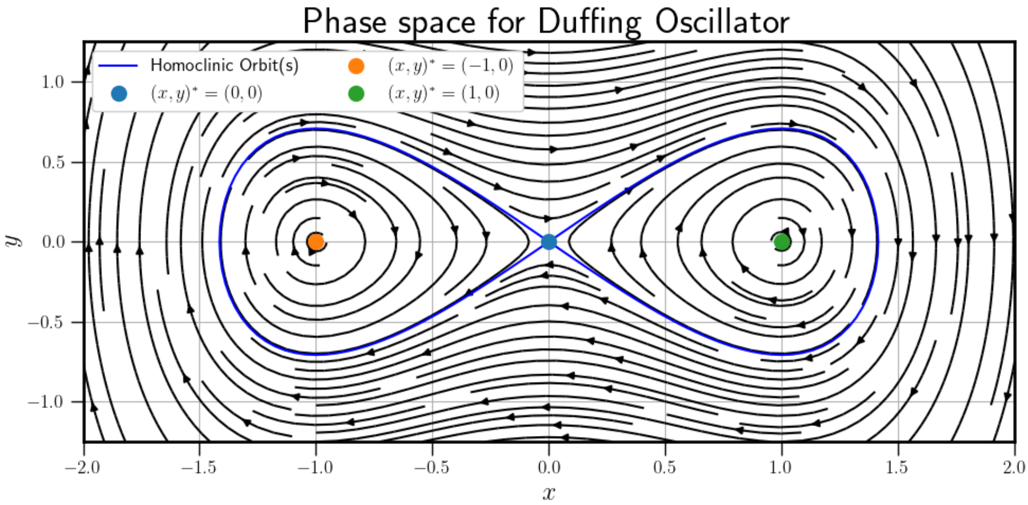
Kullback-Leibler Divergence - KDE example



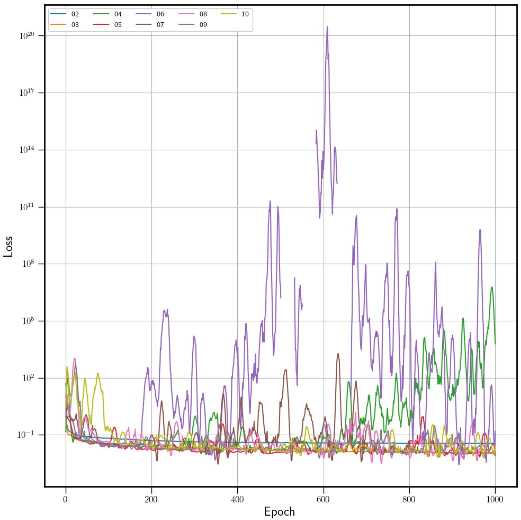
Kullback-Leibler Divergence - Example fitting

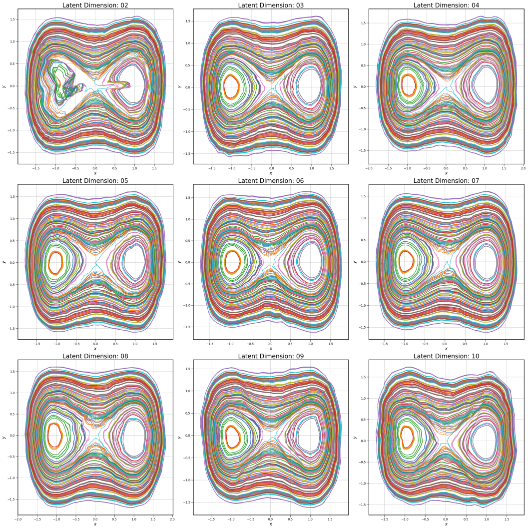


Results - Duffing

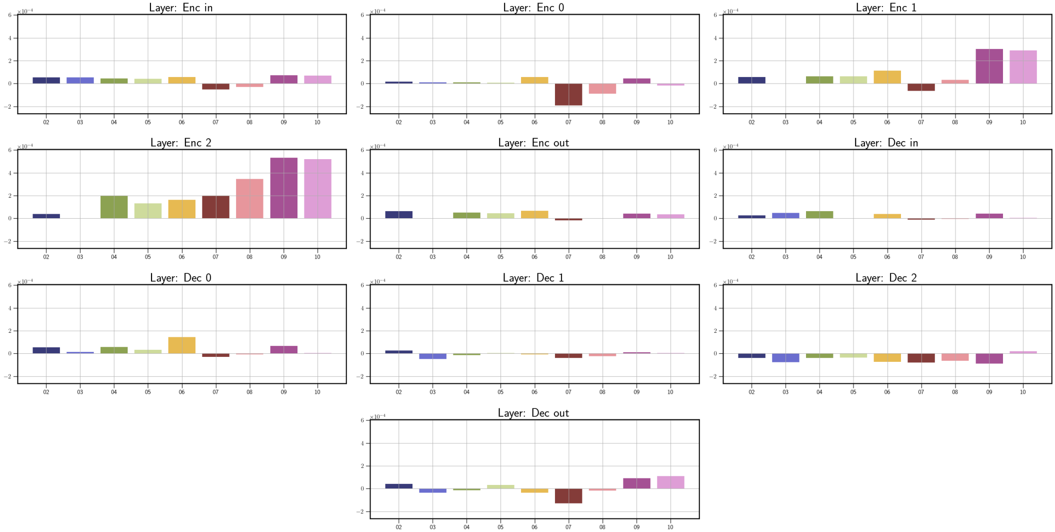


Results - Duffing loss curves and phase space

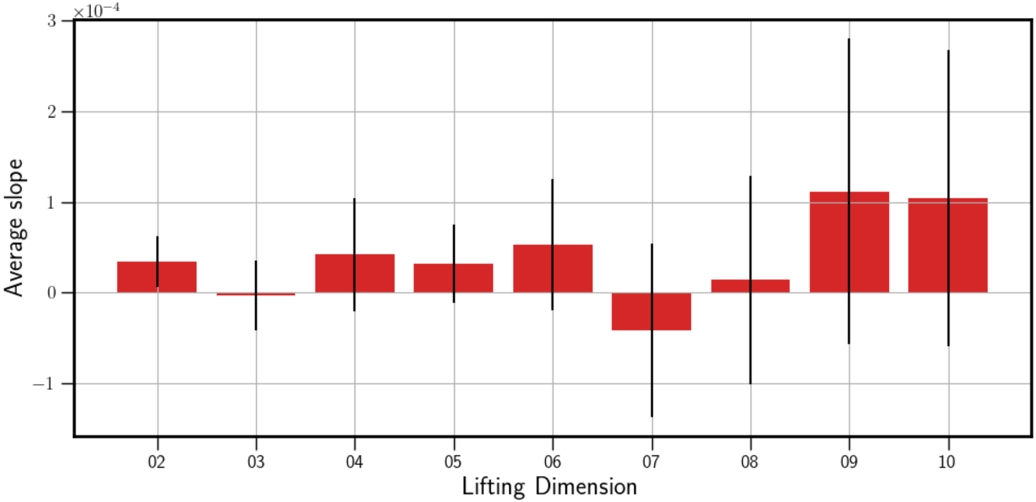




Results - Duffing linear fit slopes

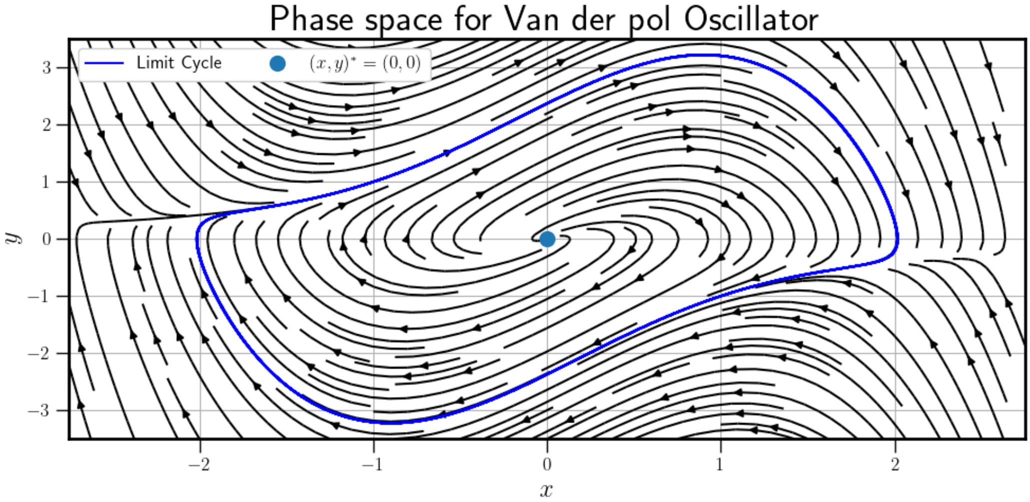


Results - Duffing linear fit slope averages and variances

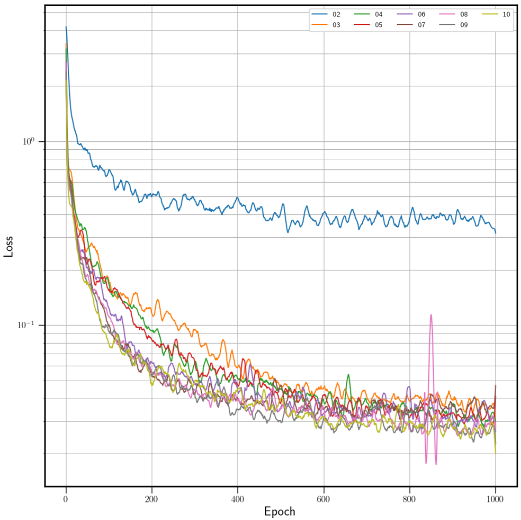


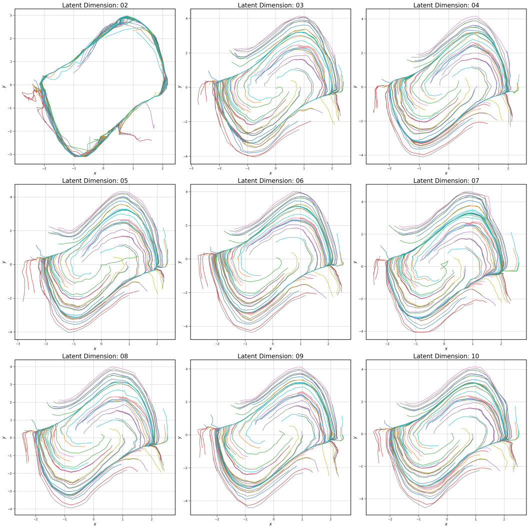
Results - Duffing notes

Results - Van der Pol

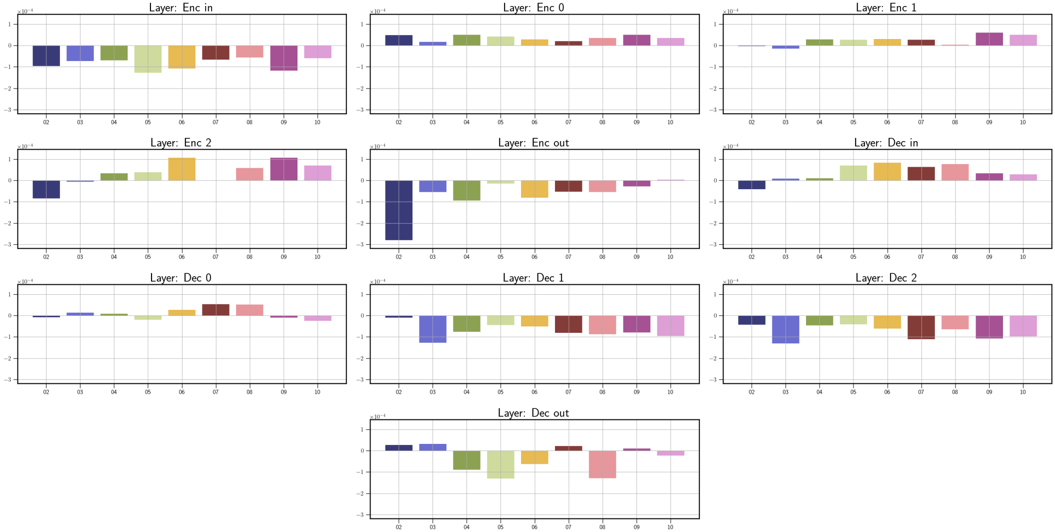


Results - Van der Pol loss curves and phase space

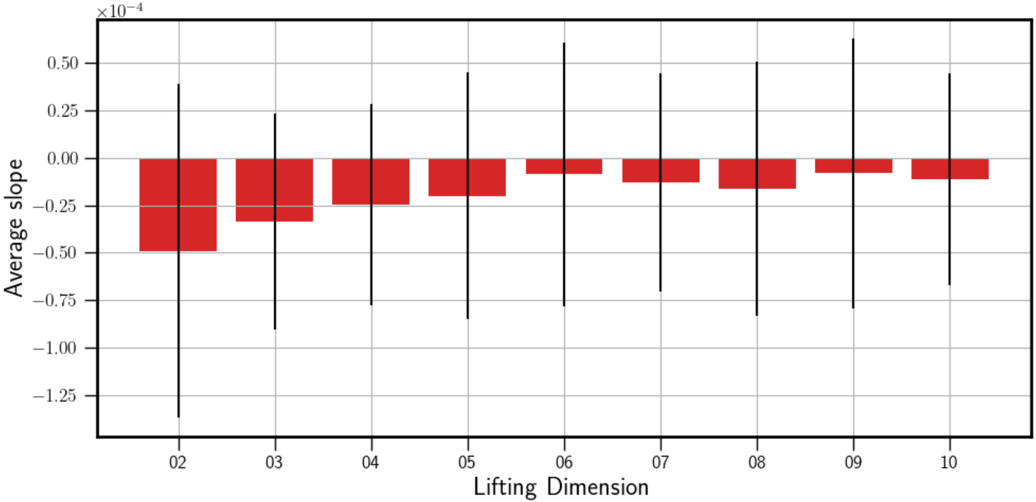




Results - Van der Pol linear fit slopes



Results - Van der Pol linear fit slope averages and variances



Results - Van der Pol notes