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Performance guarantees for deep Koopman autoencoders

From fluid flows to chaotic systems, the Koopman operator has emerged as a powerful tool to analyze dynamical systems and forecast data. Modern data-driven methods such as extended Dynamic Mode Decomposition provide a Galerkin approximation of the Koopman operator on a finite dictionary of user-defined functions. However since the quality of the approximation depends greatly upon the dictionary choice, a more recent approach to approximating the Koopman operator trains a deep autoencoder neural network to learn the basis functions from data. Universal approximation theorems justify the use of deep neural networks (DNNs) to learn the dictionary, but the network architecture, training plan, and amount of data required for high-quality approximations all merit further investigation. In this presentation, I will provide rigorous performance guarantees for learning the Koopman operator by DNNs via a sparsity-promoting training program. In particular, I will give insight into the accuracy and sample complexity of neural network Koopman approximations by providing generalization bounds based on recent function approximation techniques. Furthermore, I will highlight a DNN architecture and training routine that achieves these theoretical benchmarks in practice.