

The Emergence of Generalizability and Semantic Low-Dim Subspaces in Diffusion Models

Speaker

Qing Qu

Assistant Professor

EECS Department – University
of Michigan

Abstract

Recent empirical studies have shown that diffusion models possess a unique reproducibility property, transiting from memorization to generalization as the number of training samples increases. This demonstrates that diffusion models can effectively learn image distributions and generate new samples. Remarkably, these models achieve this even with a small number of training samples, despite the challenge of large image dimensions, effectively circumventing the curse of dimensionality. In this work, we provide theoretical insights into this phenomenon by leveraging two key empirical observations: (i) the low intrinsic dimensionality of image datasets and (ii) the low-rank property of the denoising autoencoder in trained diffusion models. With these setups, we rigorously demonstrate that optimizing the training loss of diffusion models is equivalent to solving the canonical subspace clustering problem across the training samples. This insight has practical implications for training and controlling diffusion models. Specifically, it enables us to precisely characterize the minimal number of samples necessary for accurately learning the low-rank data support, shedding light on the phase transition from memorization to generalization. Additionally, we empirically establish a correspondence between the subspaces and the semantic representations of image data, which enables one-step, transferrable, efficient image editing. Moreover, our results have profound practical implications for training efficiency and model safety, and they also open up numerous intriguing theoretical questions for future research.

