

Memorization and Generalization in Generative Diffusion under the Manifold Hypothesis

Abstract

In this talk we examine how Diffusion Models (DMs) memorize and generalize structured data embedded in low-dimensional latent manifolds.

To analyze memorization, we extend the Random Energy Model (REM) framework proposed by [1]. We first derive an explicit expression for the memorization time at which typical trajectories fall into the basins of attraction of training points, revealing that a mitigation of the curse of dimensionality is possible for highly structured data [2]. We also show that the memorization time can depend on the position in the ambient space implying a selective loss of dimensionality where some prominent features of the data are memorized in advance [3].

Turning to generalization, we apply Random Matrix Theory to first show how, progressively in time, DMs geometrically conform to the target distribution supported on the manifold, avoiding manifold overfitting [4]. We further identify a generalization time where the Kullback-Leibler divergence between the empirical and true data distributions reaches a minimum. Our results suggest that optimal generalization emerges during the memorization phase, highlighting an important interplay between memorization and generalization in DMs [2].

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