# Understanding Generalization In Conditional Flow Matching

**Rémi EMONET**, Laboratoire Hubert Curien - Saint-Étienne

Modern deep generative models can now generate high-quality synthetic samples that are often indistinguishable from real training data. A growing body of work seeks to understand why recent approaches, such as diffusion and flow matching techniques, generalize so well. Among the explanations proposed are the inductive biases of deep learning architectures and the noisy nature of the score matching or conditional flow matching loss. In this work, we clearly rule out the latter—the noisy nature of the loss—as a primary driver of generalization in flow matching. First, we empirically show that in high dimensions, the noisy and noise-free versions of the flow matching loss are nearly equivalent. Then, on state-of-the-art flow matching models and across a wide range of standard image datasets, we demonstrate that both versions lead to comparable statistical performance. Contrary to expectations of performance degradation, our experiments consistently show that using the closed-form, noise-free loss leads to speed improvements.

Contact :