Having access to a powerful generative model allows for a wide range of downstream applications, such as probabilistic inference, sampling, data completion, density evaluation, outlier detection, etc. Diffusion models (DMs) are an emerging class of deep generative models that have demonstrated remarkable synthesis quality. DMs rely on a diffusion process that gradually perturbs the data towards white noise, while the generative model learns to denoise. A major drawback of DMs, compared to, for example, Generative Adversarial Networks, is that sampling can be relatively slow.

In this seminar, I will give an accessible introduction to DMs and present our work on critically-damped Langevin DMs (CLD) which is based on ideas from statistical mechanics. CLD can be interpreted as running a joint diffusion in an extended space, where the auxiliary variables can be considered “velocities” that are coupled to the data variables as in Hamiltonian dynamics. CLD significantly accelerates sampling compared to the original DM formulation, however, many further improvements can be made by borrowing ideas from the ODE solver literature.