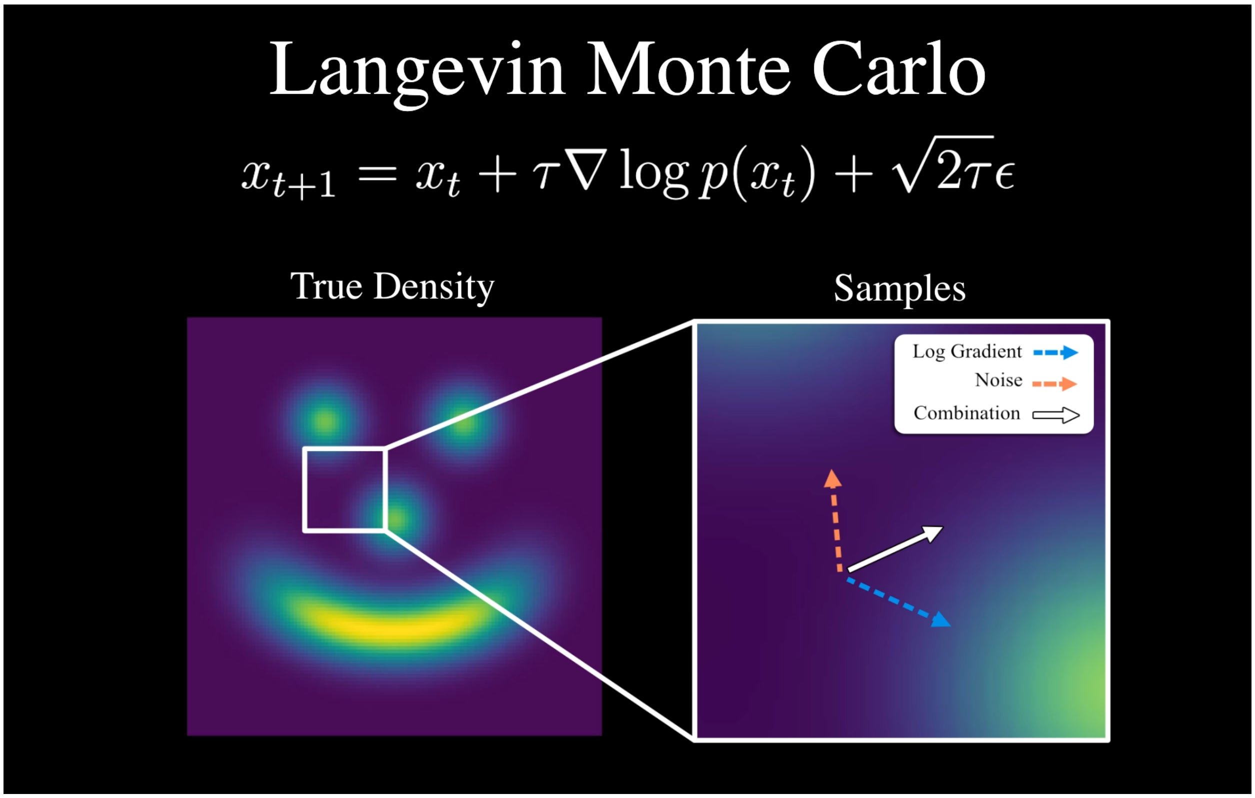
Diffusion Visualizations

For my special problems course, I designed and implemented visualizations of diffusion models, a popular generative modeling framework for generating images. I implemented these algorithms from scratch and made faithful videos depicting how the underlying algorithms work.

Langevin Monte Carlo



Langevin Monte Carlo allows you to sample from a probability distribution using its log gradient ∇ log p(x). This is very useful when a distribution is difficult to sample from directly, but you have information about it's gradient (as is true in many deep learning based techniques).

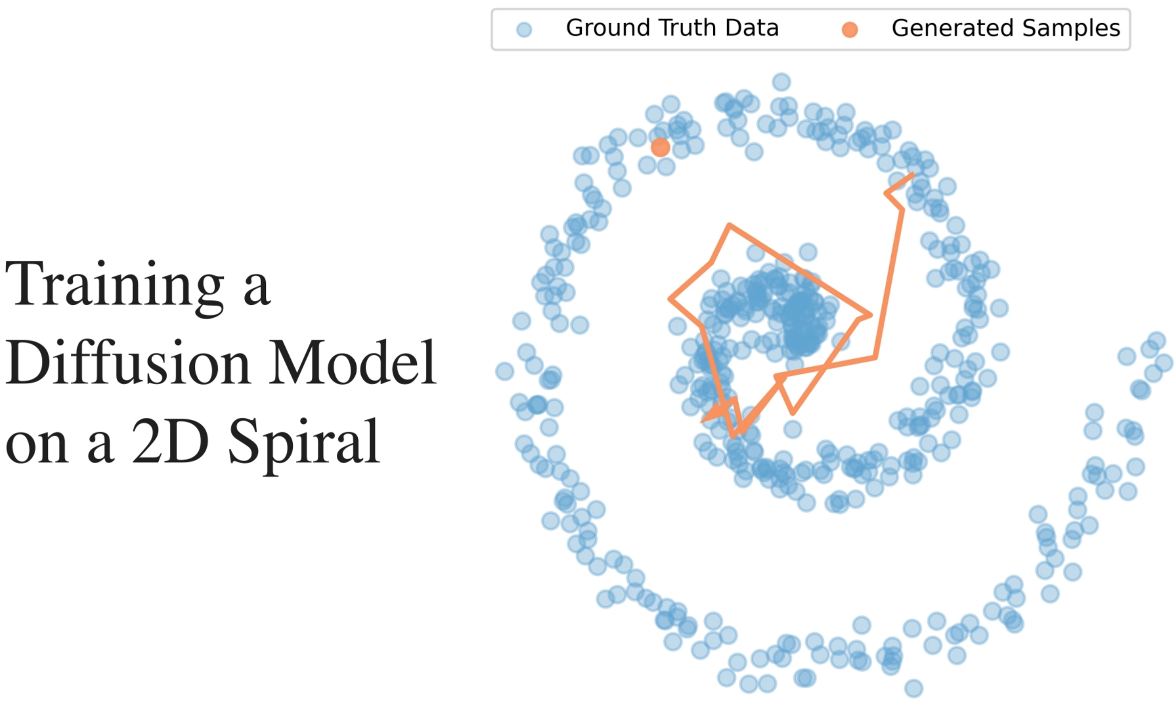
By performing a sort of gradient ascent with noise you can navigate around the distribution. Adding noise intuitively prevents the gradient ascent process from converging to one of the modes of the distribution.

Langevin MC draws on methods from statistical physics and is heavily related to modern diffusion models. Diffusion models approximate this log gradient (also called the score) using a neural network.

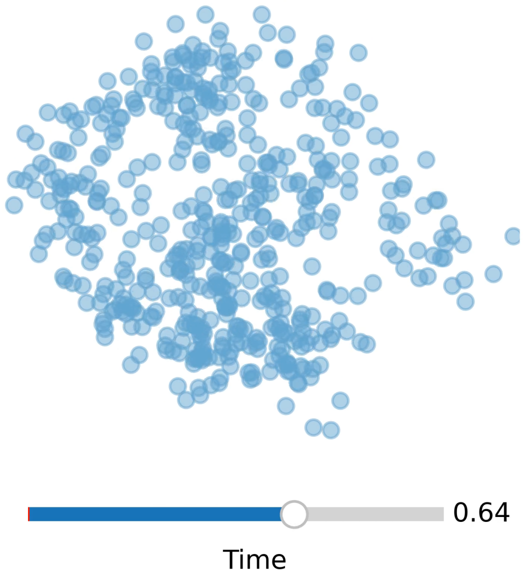
Abdul Fatir has a great blog post that goes much more in depth on this topic here.

Denoising Diffusion Probabilistic Models

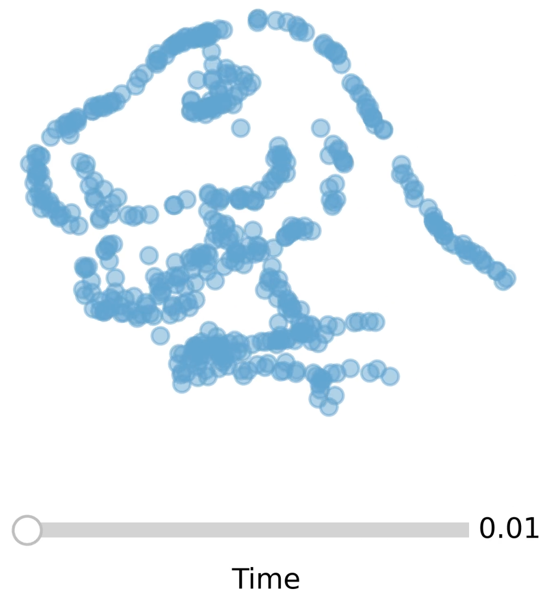
Diffusion models allow a user to sample from a distribution. Unlike Langevin Dynamics, we don't need to actually know the true log gradient of a distribution, but can instead approximate it with a neural network.



Here are two screenshots showing another demonstration of how the distributions of points sampled by a diffusion model evolve over time. The points slowly transform from a standard multivariate Gaussian to one revealing a dinosaur like structure.



0.64
Time



0.01
Time