

## Diffusion intro

# Image synthesis via denoiser.

Question  $\rightarrow$  given a denoiser  $D(y, \sigma)$ , how can one synthesise image with it effectively?

answer  $\rightarrow$  Use  $D(y, \sigma)$  as a Projector onto the image manifold.

Practical implication: iterated use of  $D(\cdot, \sigma)$  with varying  $\sigma$

## Core Idea

We know the problem of working with low dimensional manifolds in a very high dimensional embedding space.

We need 'some force' that will pull us toward the relevant manifold, even if we are in remote deserts of the embedding space in the cube  $[0, 1]^n \in \mathbb{R}^n$

The answer is Annealing  $\rightarrow$  instead of working with  $P(x)$ , work with a blurry version of it  $P(x) * N(0, \sigma^2 I)$  for a large value of  $\sigma \rightarrow \text{conv.}$

Blurred image manifold

☆ Sampling from  $P(x)$  is tough, Sampling from its gaussian-blurred could be much easier.

But we don't want noisy images.

Algorithm 1: Sampling from  $P(x)$  via Annealing

## Annealed Langevin Dynamics (ALD)

The idea of ALD is to use a sequence of  $L$  ( $\approx 500$ ) decreasing noise levels.

$$(\propto \infty) \sigma_0 > \sigma_1 > \sigma_2 > \sigma_3 \dots \rightarrow \sigma_L (\propto 0.01)$$

↳ we start from a very blurred manifold from which sampling is easy & reliable.  
and iterative we remove the noise and make it less noisier noisier.

