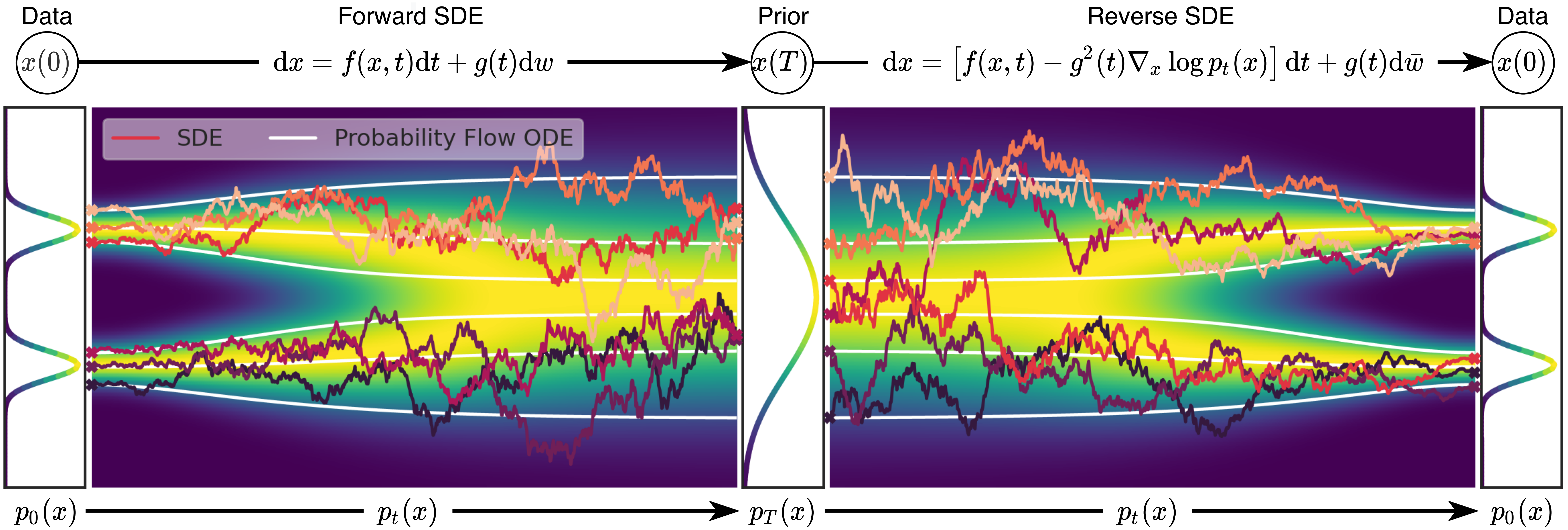
/70

Diffusion models are just normalizing flows trained in a "simulation-free" way by score/noise-matching!

68

Back to diffusion: the *probability flow ODE*

For any diffusion process, there exists a corresponding deterministic process whose trajectories share the same marginal probability densities $p(x_t)$ as the SDE [Song et al 2021]



Data
Forward SDE
Prior
Reverse SDE
Data
$x(0)$
$\mathrm{d}x = f(x,t)\mathrm{d}t + g(t)\mathrm{d}w$
$x(T)$
$\mathrm{d}x = \left[f(x,t) - g^2(t)\nabla_x \log p_t(x)\right]\mathrm{d}t + g(t)\mathrm{d}\bar{w}$
$x(0)$
SDE
Probability Flow ODE
$p_0(x)$
$p_t(x)$
$p_T(x)$
$p_t(x)$
$p_0(x)$

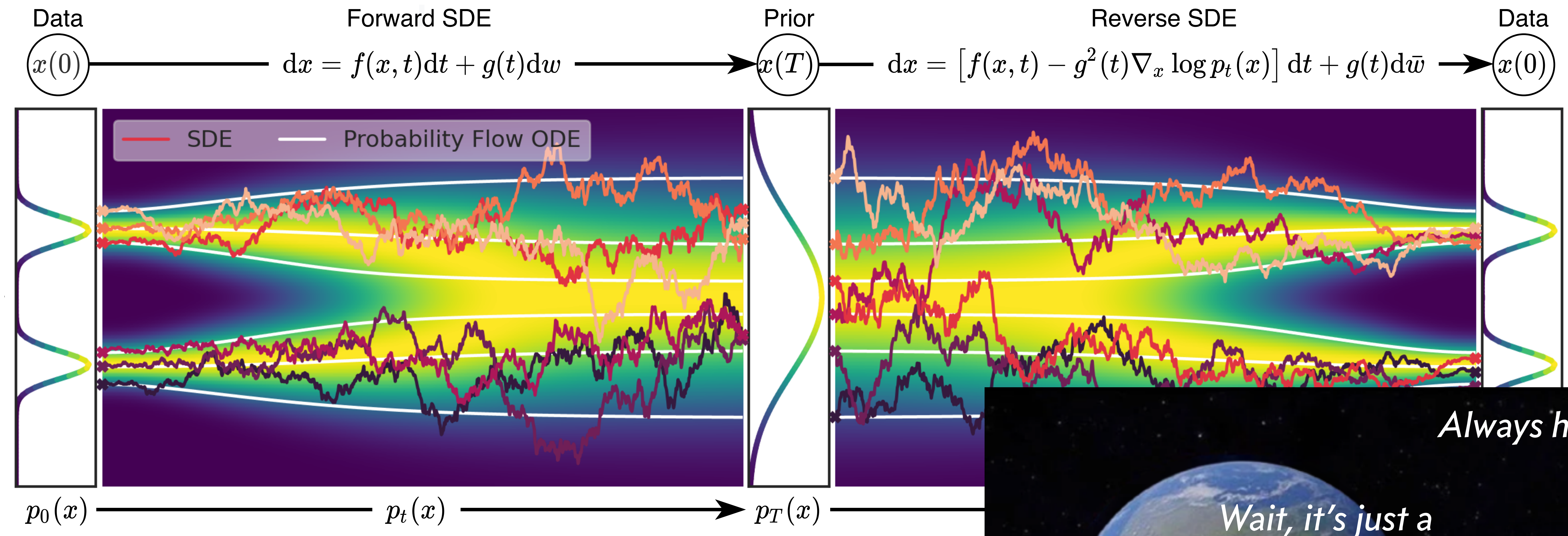
Probability flow ODE

$$\mathrm{d}x = \left[f(x, t) - \frac{1}{2} g^2(t) \nabla_x \log p_t(x) \right] \mathrm{d}t$$


Always has been
Wait, it's just a normalizing flow?

Back to diffusion: the *probability flow ODE*

For any diffusion process, there exists a corresponding deterministic process whose trajectories share the same marginal probability densities $p(x_t)$ as the SDE [Song et al 2021]



Probability flow ODE

$$dx = \left[f(x,t) - \frac{1}{2}g^2(t)\nabla_x \log p_t(x)\right] dt$$

Diffusion mo

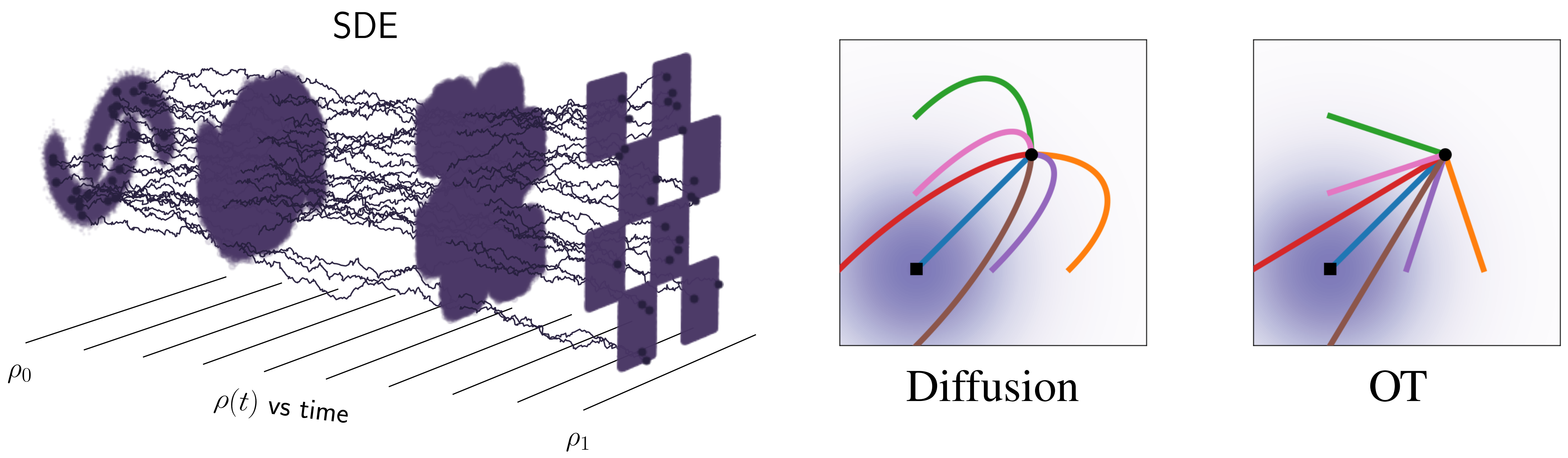
“simulation-f

Iterative refinement, interpolants, consistency, …

Empirical success of diffusion models has led to many new formulations and methods of training

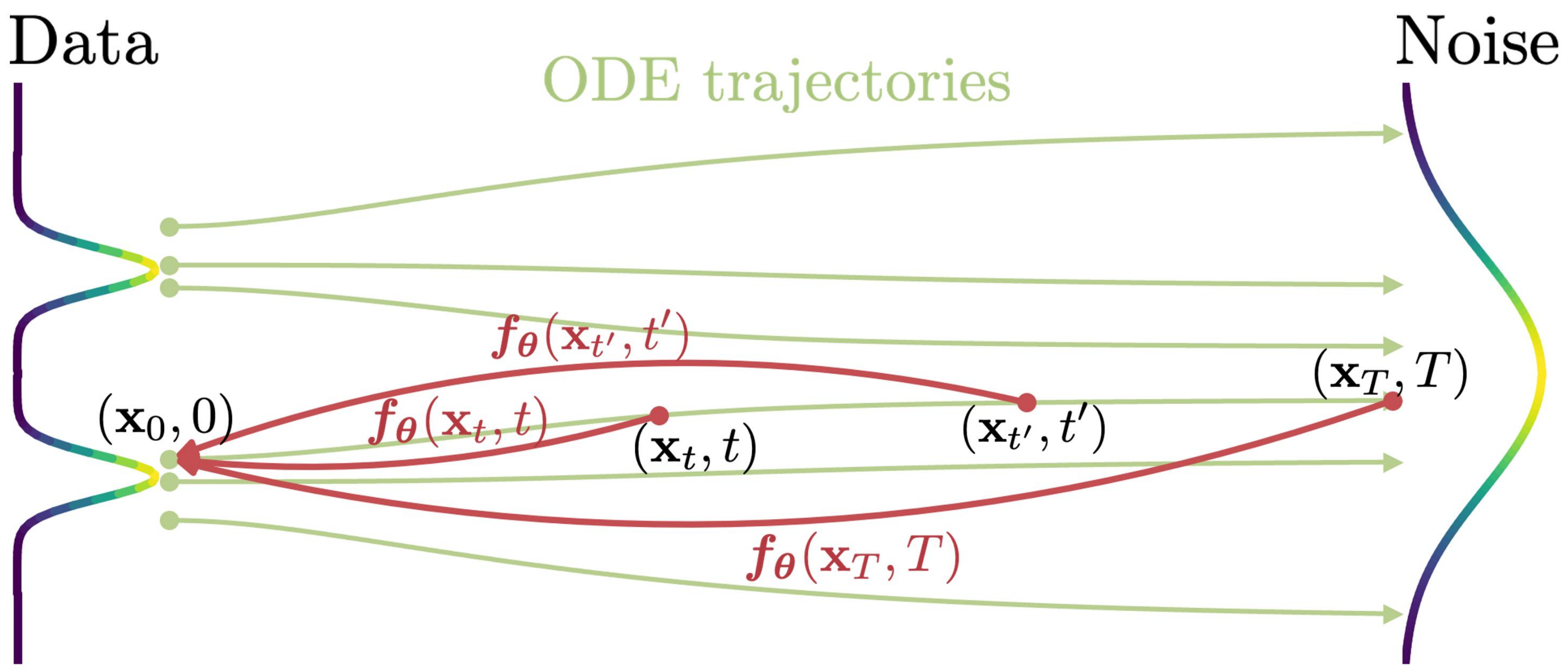
Stochastic interpolants and flow matching

[Albergo et al 2023, Lipman et al 2022, …]



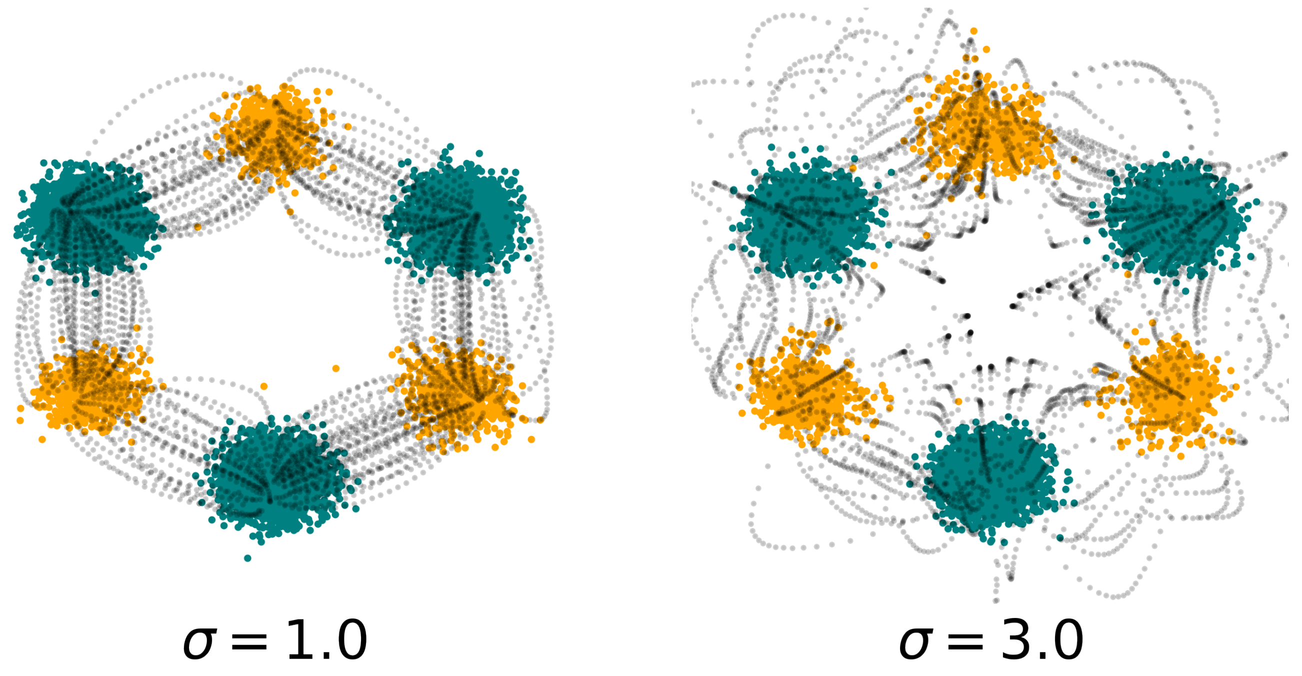
ODE trajectory consistency, Fokker-Planck regularization, …

[Song et al 2023, Lai et al 2023, …]



Diffusion Schrödinger's bridges

[Shi et al 2023, …]



Generative models inspired by other physical processes

[Xu et al 2022, Liu et al 2023, …]