

Stochastic Interpolants

Based on “Stochastic Interpolations: A Unifying Framework for Flows and Diffusions”
(2025) by Albergo, Boffi, Vanden-Eijnden

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Continuity Equation Review

Continuity Equation

Continuity Equation

Let $(v_t, t \geq 0)$ be a time dependent velocity field, then

$$\partial_t \rho_t + \nabla \cdot (v_t \rho_t) = 0.$$

A **weak** solution means for all $f : \mathbb{R}^d \rightarrow \mathbb{R}$ smooth, compactly supported

$$\frac{d}{dt} \int_{\mathbb{R}^d} f d\rho_t = \int_{\mathbb{R}^d} \langle \nabla f, v_t \rangle d\rho_t$$

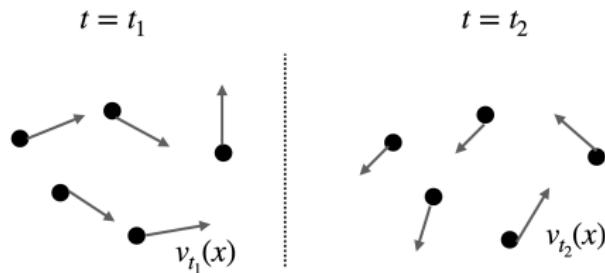


Figure: Eulerian picture

Continuity Equation

Let $\Phi(t, x)$ be such that $\frac{d}{dt}\Phi(t, x) = v_t(\Phi(t, x))$, then $\rho_t = (\Phi_t)_\#\rho_0$ [i.e., if $X_0 \sim \rho_0$, then $\Phi_t(X_0) \sim \rho_t$] is a weak solution of the continuity equation

$$\begin{aligned} \frac{d}{dt} \int_{\mathbb{R}^d} f d\rho_t &= \frac{d}{dt} \int_{\mathbb{R}^d} f(\Phi(t, x)) d\rho_0 \\ &= \int_{\mathbb{R}^d} \frac{d}{dt} f(\Phi(t, x)) d\rho_0 \\ &= \int_{\mathbb{R}^d} \langle \nabla f(\Phi(t, x)), \partial_t \Phi(t, x) \rangle d\rho_0 \\ &= \int_{\mathbb{R}^d} \langle \nabla f(\Phi(t, x)), v_t(\Phi(t, x)) \rangle d\rho_0 \\ &= \int_{\mathbb{R}^d} \langle \nabla f, v_t \rangle d\rho_t. \end{aligned}$$

Fokker Planck

Fokker Planck PDE

Let $(b_t, t \geq 0)$ be smoothly varying vector valued function, and recall $\Delta = \sum_{j=1}^d \partial_{x_j}^2$, then

$$\partial_t \rho_t + \nabla \cdot (b_t \rho_t) = \frac{\varepsilon}{2} \Delta \rho_t.$$

Key facts:

- $\Delta \rho_t = \nabla \cdot (\nabla \rho_t) = \nabla \cdot ((\nabla \log \rho_t) \rho_t)$, so get

$$\partial_t \rho_t + \nabla \cdot \left(\left(b_t - \frac{\varepsilon}{2} \nabla \log \rho_t \right) \rho_t \right) = 0.$$

- Gives time marginal evolution of **diffusion processes**

Stochastic Interpolations

Stochastic Interpolation

Stochastic Interpolation [ABVE25]

Let ρ_0, ρ_1 be two probability densities, a stochastic interpolant between ρ_0 and ρ_1 is the stochastic process defined as

$$x_t := I(t, x_0, x_1) + \gamma(t)z, \quad t \in [0, 1],$$

where

- $I(0, x_0, x_1) = x_0$, $I(1, x_0, x_1) = x_1$, $\gamma(0) = \gamma(1) = 0$,
- $(x_0, x_1) \sim \nu$ that is coupling of ρ_0, ρ_1
- $z \sim N(0, \text{Id})$ is independent of (x_0, x_1)

Common choice: linearly spaced interpolants [ABVE25, Section 4]

$$x_t^{\text{lin}} = \alpha(t)x_0 + \beta(t)x_1 + \gamma(t)z,$$

where $\alpha(0) = \beta(1) = 1$ and $\alpha(1) = \beta(0) = \gamma(0) = \gamma(1) = 0$

Stochastic Interpolation Examples

Introduces an element of **design choice**— what **theoretical basis** do we have for certain choices?

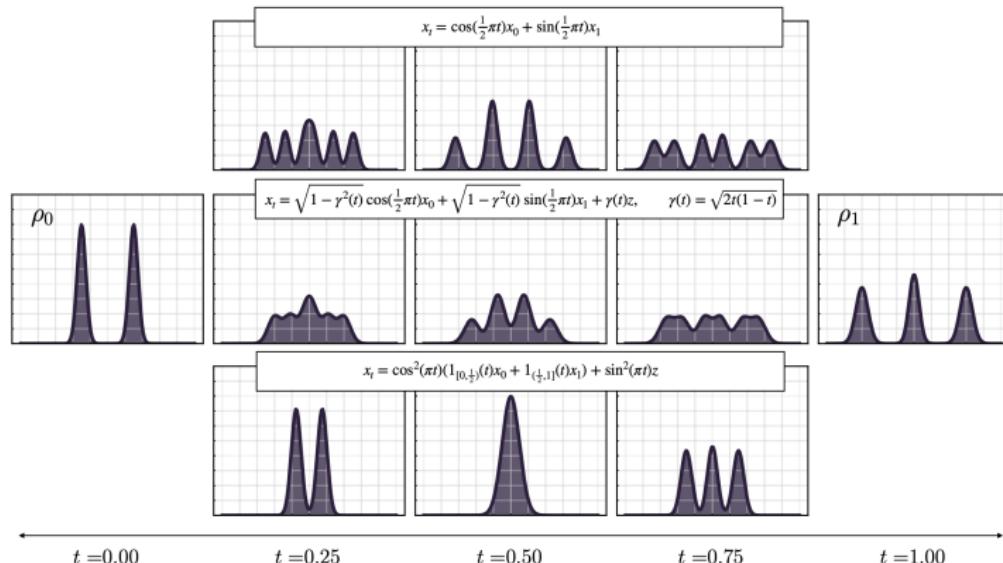


Figure: Different choices of stochastic interpolation [ABVE25, Figure 4]

Stochastic Interpolation

Given $x_t = I(t, x_0, x_1) + \gamma(t)z$, let $x_t \sim \rho_t$

Transport Equation

The PDE $\partial_t \rho_t + \nabla \cdot (b_t \rho_t) = 0$ is satisfied with

$$b(t, x) = \mathbb{E}[\dot{x}_t | x_t = x] = \mathbb{E}[\partial_t I(t, x_0, x_1) + \dot{\gamma}(t)z | x_t = x]$$

Fokker Planck Equation

The PDE $\partial_t \rho_t + \nabla \cdot (b_t^{FP} \rho_t) = \frac{\varepsilon}{2} \Delta \rho_t$ is satisfied with

$$s(t, x) = \nabla \log \rho(t, x) = -\gamma^{-1}(t) \mathbb{E}[z | x_t = x]$$

$$b^{FP} = b + \frac{\varepsilon}{2} s$$

Stochastic Interpolation

[ABVE25, Theorem 6]

Given $x_t = I(t, x_0, x_1) + \gamma(t)z$ and $\rho_t = \text{Law}(x_t)$, the PDE $\partial_t \rho_t + \nabla \cdot (b_t \rho_t) = 0$ is satisfied with

$$b(t, x) = \mathbb{E}[\dot{x}_t | x_t = x] = \mathbb{E}[\partial_t I(t, x_0, x_1) + \dot{\gamma}(t)z | x_t = x]$$

This derivation relies on computing the **characteristic function** (Fourier transform)

- Define $g(t, k)$ as the characteristic function of x_t (spatial variable)

$$g(t, k) = \mathbb{E}[\exp(i\langle k, x_t \rangle)] = \mathbb{E}[\exp(i\langle k, I(t, x_0, x_1) + \gamma(t)z \rangle)]$$

- We will compute $\partial_t g(t, k)$ and use identity

$$\int_{\mathbb{R}^d} \partial_{x_j} f(x) \exp(i\langle \xi, x \rangle) dx = -i\xi_j \int_{\mathbb{R}^d} f(x) \exp(i\langle \xi, x \rangle) dx$$

Stochastic Interpolation

Recall that $(x_0, x_1) \sim \nu$ and $z \sim N(0, \text{Id})$ is independent

$$\begin{aligned}
 \partial_t g(t, k) &= \frac{\partial}{\partial t} \mathbb{E} \left[\exp(i\langle k, I(t, x_0, x_1) + \gamma(t)z \rangle) \right] \\
 &= \mathbb{E} \left[i\langle k, \partial_t I(t, x_0, x_1) + \dot{\gamma}(t)z \rangle \exp(i\langle k, x_t \rangle) \right] \\
 &= i \left\langle k, \int_{\mathbb{R}^d} \mathbb{E} [\partial_t I(t, x_0, x_1) + \dot{\gamma}(t)z | x_t = x] \exp(i\langle k, x \rangle) \rho(t, x) dx \right\rangle \\
 &= i \left\langle k, \int_{\mathbb{R}^d} b(t, x) \rho(t, x) \exp(i\langle k, x \rangle) dx \right\rangle \\
 &= - \int_{\mathbb{R}^d} \nabla \cdot (b(t, x) \rho(t, x)) \exp(i\langle k, x \rangle) dx
 \end{aligned}$$

Apply Fourier inversion to then get

$$\partial_t \rho(t, x) + \nabla \cdot (b(t, x) \rho(t, x)) = 0.$$

Stochastic Interpolation

Recall $x_t = I(t, x_0, x_1) + \gamma(t)z$, why set $\gamma \neq 0$?

- [AVE23] considers $\gamma \equiv 0$
- Key point is **more regularity** in the interpolation

$$s(t, x) = \nabla \log \rho(t, x)$$

$$b(t, x) = \mathbb{E}[\partial_t I(t, x_0, x_1) | x_t = x]$$

- Example: encoder-decoder interpolation

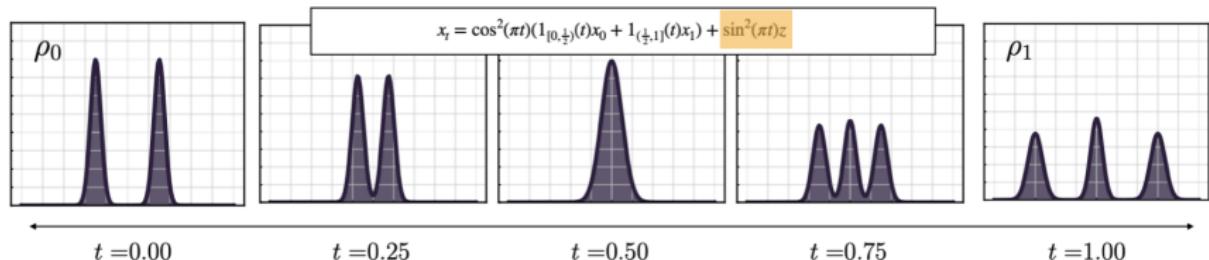


Figure: [ABVE25, Figure 4]

Stochastic Interpolation

What's the point of choosing $(X_0, X_1) \sim \nu$? Another **design choice**

- Diffusion models [SSDK⁺20], one marginal is noise and assume independent
- [AGB⁺24] analyzes theoretical and practical advantages of ν selection
- Another meaningful coupling is Schrödinger bridge [SDBCD23, DBKMD24]

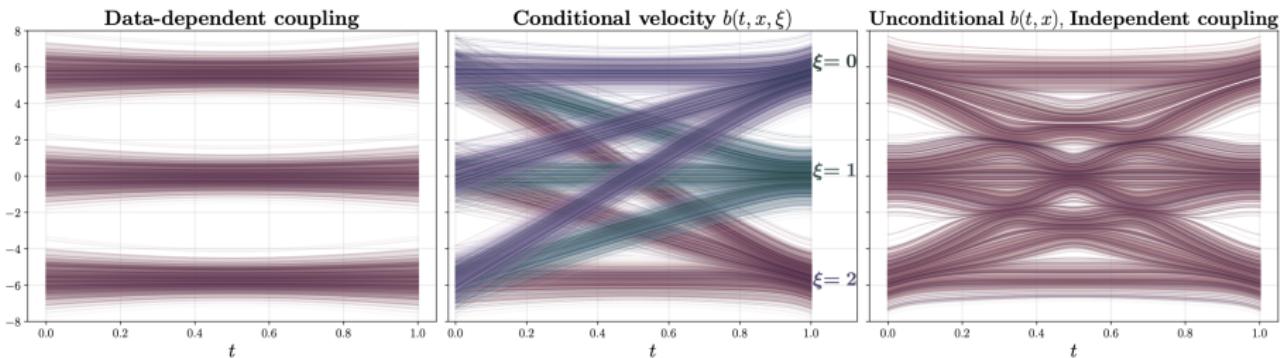


Figure: [AGB⁺24, Figure 3], Gaussian mixture with 3 modes, different couplings of endpoints

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