

# Deep Generative Models

## Lecture 11

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## Recap of Previous Lecture

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{f}_\theta(\mathbf{x}(t), t); \quad \text{with initial condition } \mathbf{x}(t_0) = \mathbf{x}_0$$

### Theorem (Continuity Equation)

If  $\mathbf{f}$  is uniformly Lipschitz continuous in  $\mathbf{x}$  and continuous in  $t$ , then

$$\frac{d \log p_t(\mathbf{x}(t))}{dt} = -\text{tr} \left( \frac{\partial \mathbf{f}(\mathbf{x}(t), t)}{\partial \mathbf{x}(t)} \right)$$

### Solution of the Continuity Equation

$$\log p_1(\mathbf{x}(1)) = \log p_0(\mathbf{x}(0)) - \int_0^1 \text{tr} \left( \frac{\partial \mathbf{f}(\mathbf{x}(t), t)}{\partial \mathbf{x}(t)} \right) dt.$$

- ▶ This solution gives us the density along the trajectory (not the total probability path).
- ▶ However, it's difficult to efficiently estimate **the last term**.

# Recap of Previous Lecture

## SDE Basics

Let's define a stochastic process  $\mathbf{x}(t)$  with initial condition  $\mathbf{x}(0) \sim p_0(\mathbf{x})$ :

$$d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt + g(t)d\mathbf{w},$$

where  $\mathbf{w}(t)$  is the standard Wiener process (Brownian motion):

$$\mathbf{w}(t) - \mathbf{w}(s) \sim \mathcal{N}(0, (t-s)\mathbf{I}), \quad d\mathbf{w} = \epsilon \cdot \sqrt{dt}, \text{ where } \epsilon \sim \mathcal{N}(0, \mathbf{I}).$$

## Discretization of SDE (Euler Method) - SDEsolve

$$\mathbf{x}(t + dt) = \mathbf{x}(t) + \mathbf{f}(\mathbf{x}(t), t) \cdot dt + g(t) \cdot \epsilon \cdot \sqrt{dt}$$

- ▶ At each time  $t$ , we have the density  $p_t(\mathbf{x}) = p(\mathbf{x}, t)$ .
- ▶  $p : \mathbb{R}^m \times [0, 1] \rightarrow \mathbb{R}_+$  is a **probability path** between  $p_0(\mathbf{x})$  and  $p_1(\mathbf{x})$ .

# Recap of Previous Lecture

## Theorem (Kolmogorov-Fokker-Planck)

The evolution of the distribution  $p_t(\mathbf{x})$  is given by:

$$\frac{\partial p_t(\mathbf{x})}{\partial t} = -\text{div}(\mathbf{f}(\mathbf{x}, t)p_t(\mathbf{x})) + \frac{1}{2}g^2(t)\Delta_{\mathbf{x}}p_t(\mathbf{x})$$

## Langevin SDE (Special Case)

$$d\mathbf{x} = \frac{1}{2} \frac{\partial}{\partial \mathbf{x}} \log p_t(\mathbf{x}) dt + \mathbf{1} \cdot d\mathbf{w}$$

The density  $p_{\theta}(\mathbf{x})$  is a **stationary** distribution for the SDE.

## Langevin Dynamics

Samples from the following dynamics will come from  $p_{\theta}(\mathbf{x})$  under mild regularity conditions for a small enough  $\eta$ :

$$\mathbf{x}_{t+1} = \mathbf{x}_t + \frac{\eta}{2} \nabla_{\mathbf{x}_t} \log p_{\theta}(\mathbf{x}_t) + \sqrt{\eta} \cdot \epsilon, \quad \epsilon \sim \mathcal{N}(0, \mathbf{I}).$$

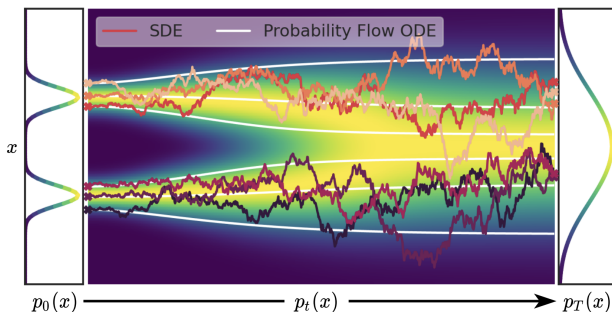
# Recap of Previous Lecture

$$d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt + g(t)d\mathbf{w} \quad (\text{SDE with the probability path } p_t(\mathbf{x}))$$

## Probability Flow ODE

There exists an ODE with the identical probability path  $p_t(\mathbf{x})$  of the form:

$$d\mathbf{x} = \left( \mathbf{f}(\mathbf{x}, t) - \frac{1}{2}g^2(t)\frac{\partial}{\partial \mathbf{x}} \log p_t(\mathbf{x}) \right) dt$$



Song Y., et al. *Score-Based Generative Modeling through Stochastic Differential Equations*, 2020

# Recap of Previous Lecture

$$d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt, \quad \mathbf{x}(t + dt) = \mathbf{x}(t) + \mathbf{f}(\mathbf{x}, t)dt$$

## Reverse ODE

Let  $\tau = 1 - t$  ( $d\tau = -dt$ ):

$$d\mathbf{x} = -\mathbf{f}(\mathbf{x}, 1 - \tau)d\tau$$

## Reverse SDE

There's a reverse SDE for  $d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt + g(t)d\mathbf{w}$  in the following form:

$$d\mathbf{x} = \left( \mathbf{f}(\mathbf{x}, t) - g^2(t) \frac{\partial}{\partial \mathbf{x}} \log p_t(\mathbf{x}) \right) dt + g(t)d\mathbf{w}, \quad dt < 0$$

## Sketch of the Proof

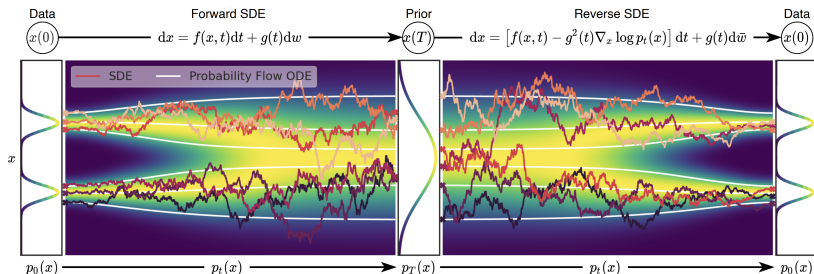
- ▶ Convert the initial SDE to the probability flow ODE.
- ▶ Reverse the probability flow ODE.
- ▶ Convert the reverse probability flow ODE to the reverse SDE.

# Recap of Previous Lecture

$$d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt + g(t)d\mathbf{w} \quad (\text{SDE})$$

$$d\mathbf{x} = \left( \mathbf{f}(\mathbf{x}, t) - \frac{1}{2}g^2(t)\frac{\partial}{\partial \mathbf{x}} \log p_t(\mathbf{x}) \right) dt \quad (\text{probability flow ODE})$$

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# Outline

1. Diffusion and Score Matching SDEs
2. Score-Based Generative Models Through SDEs
3. Flow Matching
4. Conditional Flow Matching



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# Score Matching SDE

## Denoising Score Matching

$$\mathbf{x}_t = \mathbf{x} + \sigma_t \cdot \boldsymbol{\epsilon}_t,$$

$$q(\mathbf{x}_t|\mathbf{x}) = \mathcal{N}(\mathbf{x}, \sigma_t^2 \cdot \mathbf{I})$$

$$\mathbf{x}_{t-1} = \mathbf{x} + \sigma_{t-1} \cdot \boldsymbol{\epsilon}_{t-1},$$

$$q(\mathbf{x}_{t-1}|\mathbf{x}) = \mathcal{N}(\mathbf{x}, \sigma_{t-1}^2 \cdot \mathbf{I})$$

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$$\mathbf{x}_t = \mathbf{x}_{t-1} + \sqrt{\sigma_t^2 - \sigma_{t-1}^2} \cdot \boldsymbol{\epsilon}, \quad q(\mathbf{x}_t | \mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_{t-1}, (\sigma_t^2 - \sigma_{t-1}^2) \cdot \mathbf{I})$$

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Let's transform this Markov chain into the continuous stochastic process  $\mathbf{x}(t)$  by letting  $T \rightarrow \infty$ :

$$\mathbf{x}(t) = \mathbf{x}(t - dt) + \sqrt{\sigma^2(t) - \sigma^2(t - dt)} \cdot \epsilon$$

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# Score Matching SDE

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## Variance Exploding SDE

$$d\mathbf{x} = \sqrt{\frac{d[\sigma^2(t)]}{dt}} \cdot d\mathbf{w}$$

$\sigma(t)$  is a monotonically increasing function.



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$$d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt + g(t)d\mathbf{w}, \quad \mathbf{f}(\mathbf{x}, t) = 0, \quad g(t) = \sqrt{\frac{d[\sigma^2(t)]}{dt}}$$

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# Diffusion SDE

## Denoising Diffusion

$$\mathbf{x}_t = \sqrt{1 - \beta_t} \mathbf{x}_{t-1} + \sqrt{\beta_t} \epsilon, \quad q(\mathbf{x}_t | \mathbf{x}_{t-1}) = \mathcal{N}(\sqrt{1 - \beta_t} \mathbf{x}_{t-1}, \beta_t \mathbf{I})$$

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Let's turn this Markov chain into a continuous stochastic process by letting  $T \rightarrow \infty$  and setting  $\beta_t = \beta(\frac{t}{T}) \cdot \frac{1}{T}$  (where  $dt = \frac{1}{T}$ ):

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## Variance Preserving SDE

$$d\mathbf{x} = -\frac{1}{2}\beta(t)\mathbf{x}(t)dt + \sqrt{\beta(t)} \cdot d\mathbf{w}$$

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Variance is preserved as long as  $\mathbf{x}(0)$  has unit variance.



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## Variance Exploding SDE (NCSN)

$$d\mathbf{x} = \sqrt{\frac{d[\sigma^2(t)]}{dt}} \cdot d\mathbf{w}$$

## Variance Preserving SDE (DDPM)

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## Efficient Solvers

- ▶ Converting SDEs to PF-ODEs yields more efficient inference.
- ▶ We can apply any ODEsolve procedure to reduce the number of inference steps.
- ▶ In practice, this reduces the number of steps from 100–1000 to 20–50.

# Outline

1. Diffusion and Score Matching SDEs
2. Score-Based Generative Models Through SDEs
3. Flow Matching
4. Conditional Flow Matching

# Score-Based Generative Models Through SDEs

## Discrete-Time Objective

$$\mathbb{E}_{p_{\text{data}}(\mathbf{x}_0)} \mathbb{E}_{t \sim U\{1, T\}} \mathbb{E}_{q(\mathbf{x}_t | \mathbf{x}_0)} \left\| \mathbf{s}_{\theta, t}(\mathbf{x}_t) - \nabla_{\mathbf{x}_t} \log q(\mathbf{x}_t | \mathbf{x}_0) \right\|_2^2$$

Is it possible to train score-based diffusion models in continuous time?

# Score-Based Generative Models Through SDEs

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## Continuous-Time Objective

$$\mathbb{E}_{p_{\text{data}}(\mathbf{x}(0))} \mathbb{E}_{t \sim U[0, 1]} \mathbb{E}_{q(\mathbf{x}(t) | \mathbf{x}(0))} \left\| \mathbf{s}_{\theta}(\mathbf{x}(t), t) - \nabla_{\mathbf{x}(t)} \log q(\mathbf{x}(t) | \mathbf{x}(0)) \right\|_2^2$$

# Score-Based Generative Models Through SDEs

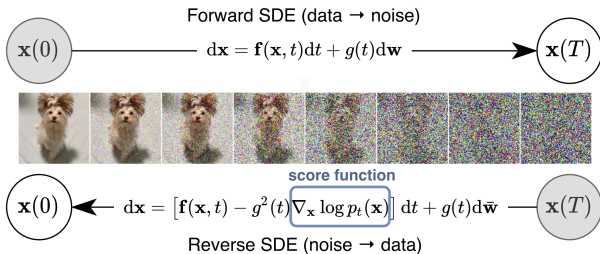
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Song Y., et al. *Score-Based Generative Modeling through Stochastic Differential Equations*, 2020



# Score-Based Generative Models Through SDEs

## Continuous-Time Objective

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## Continuous-Time Objective

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$$q(\mathbf{x}(t)|\mathbf{x}(0)) = \mathcal{N}\left(\boldsymbol{\mu}(t, \mathbf{x}(0)), \boldsymbol{\sigma}^2(t, \mathbf{x}(0)) \cdot \mathbf{I}\right)$$

$$\nabla_{\mathbf{x}(t)} \log q(\mathbf{x}(t)|\mathbf{x}(0)) = -\frac{1}{\boldsymbol{\sigma}} \odot (\mathbf{x}(t) - \boldsymbol{\mu})$$

**Note:** Normality holds for  $\mathbf{f}(\mathbf{x}, t)$  affine in  $\mathbf{x}$ .

# Score-Based Generative Models Through SDEs

## Continuous-Time Objective

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$$d\mathbf{x} = \sqrt{\frac{d[\sigma^2(t)]}{dt}} \cdot d\mathbf{w} \quad (\text{Variance Exploding SDE})$$

$$d\mathbf{x} = -\frac{1}{2}\beta(t)\mathbf{x}(t)dt + \sqrt{\beta(t)} \cdot d\mathbf{w} \quad (\text{Variance Preserving SDE})$$

Is it possible to explicitly derive  $\boldsymbol{\mu}(t, \mathbf{x}(0))$  and  $\boldsymbol{\Sigma}(t, \mathbf{x}(0))$  for VE-SDE and VP-SDE?

# Score-Based Generative Models Through SDEs

$$q(\mathbf{x}(t)|\mathbf{x}(0)) = \mathcal{N}\left(\boldsymbol{\mu}(t, \mathbf{x}(0)), \boldsymbol{\Sigma}(t, \mathbf{x}(0))\right)$$

## Theorem

The moments of the SDE  $d\mathbf{x} = \mathbf{f}(\mathbf{x}, t)dt + g(t)d\mathbf{w}$  satisfy:

$$\frac{d\boldsymbol{\mu}(t, \mathbf{x}(0))}{dt} = \mathbb{E}[\mathbf{f}(\mathbf{x}(t), t)|\mathbf{x}(0)]$$

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# Score-Based Generative Models Through SDEs

$$q(\mathbf{x}(t)|\mathbf{x}(0)) = \mathcal{N}\left(\boldsymbol{\mu}(t, \mathbf{x}(0)), \boldsymbol{\Sigma}(t, \mathbf{x}(0))\right)$$

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## Proof

$$\mathbb{E}[d\mathbf{x}|\mathbf{x}(0)] = \mathbb{E}[\mathbf{f}(\mathbf{x}, t)dt|\mathbf{x}(0)] + \mathbb{E}[g(t)d\mathbf{w}|\mathbf{x}(0)]$$

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# Score-Based Generative Models Through SDEs

## Theorem

$$\frac{d\mu(t, \mathbf{x}(0))}{dt} = \mathbb{E} [\mathbf{f}(\mathbf{x}(t), t) | \mathbf{x}(0)]$$



# Score-Based Generative Models Through SDEs

## Theorem

$$\frac{d\mu(t, \mathbf{x}(0))}{dt} = \mathbb{E} [\mathbf{f}(\mathbf{x}(t), t) | \mathbf{x}(0)]$$

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$$\mathbb{E} [d\mathbf{x} | \mathbf{x}(0)] = \mathbb{E} [\mathbf{f}(\mathbf{x}, t) | \mathbf{x}(0)] dt$$

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## Examples

$$\text{NCSN: } \mathbf{f}(\mathbf{x}, t) = 0 \quad \Rightarrow \quad \mu = \mathbf{x}(0)$$

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# Score-Based Generative Models Through SDEs

## Theorem

$$\frac{d\boldsymbol{\mu}(t, \mathbf{x}(0))}{dt} = \mathbb{E} [\mathbf{f}(\mathbf{x}(t), t) | \mathbf{x}(0)]$$

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$$\mathbb{E} [d\mathbf{x} | \mathbf{x}(0)] = \mathbb{E} [\mathbf{f}(\mathbf{x}, t) | \mathbf{x}(0)] dt$$

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$$\boldsymbol{\mu} = \mathbf{x}(0) \exp \left( -\frac{1}{2} \int_0^t \beta(s) ds \right)$$

# Score-Based Generative Models Through SDEs

## Training

$$\mathbb{E}_{p_{\text{data}}(\mathbf{x}(0))} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{q(\mathbf{x}(t)|\mathbf{x}(0))} \left\| \mathbf{s}_{\theta}(\mathbf{x}(t), t) - \nabla_{\mathbf{x}(t)} \log q(\mathbf{x}(t)|\mathbf{x}(0)) \right\|_2^2$$

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## NCSN

$$q(\mathbf{x}(t)|\mathbf{x}(0)) = \mathcal{N}\left(\mathbf{x}(0), [\sigma^2(t) - \sigma^2(0)] \cdot \mathbf{I}\right)$$

# Score-Based Generative Models Through SDEs

## Training

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Here we omit the derivations of the variance.

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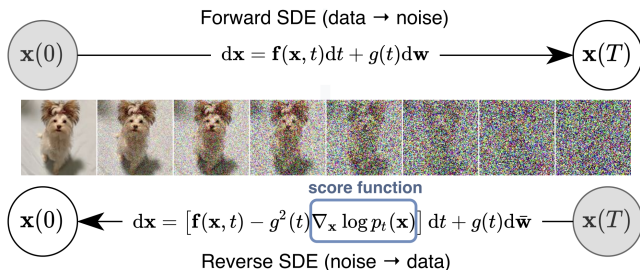
*Song Y., et al. Score-Based Generative Modeling through Stochastic Differential Equations, 2020*



# Score-Based Generative Models Through SDEs

## Sampling

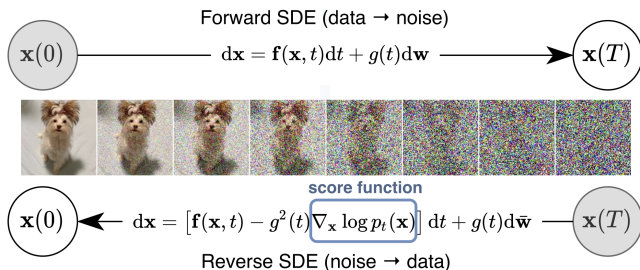
Solve the reverse SDE using numerical solvers (SDEsolve).



# Score-Based Generative Models Through SDEs

## Sampling

Solve the reverse SDE using numerical solvers (SDEsolve).



- ▶ Discretizing the reverse SDE provides ancestral sampling.
- ▶ Discretizing the probability flow ODE yields deterministic sampling.

# Outline

1. Diffusion and Score Matching SDEs
2. Score-Based Generative Models Through SDEs
3. Flow Matching
4. Conditional Flow Matching

# Continuous-Time Normalizing Flows

Let's return to ODE dynamics  $\mathbf{x}(t)$  in the interval  $t \in [0, 1]$ :

- ▶  $\mathbf{x}_0 \sim p_0(\mathbf{x}) = p(\mathbf{x})$ ,  $\mathbf{x}_1 \sim p_1(\mathbf{x}) = p_{\text{data}}(\mathbf{x})$ ;
- ▶  $p(\mathbf{x})$  is a base distribution (e.g.,  $\mathcal{N}(0, \mathbf{I})$ ), and  $p_{\text{data}}(\mathbf{x})$  is the true data distribution.

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}, t), \quad \text{with initial condition } \mathbf{x}(0) = \mathbf{x}_0.$$

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$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}, t), \quad \text{with initial condition } \mathbf{x}(0) = \mathbf{x}_0.$$

## KFP Theorem (Continuity Equation)

$$\frac{\partial p_t(\mathbf{x})}{\partial t} = -\text{div}(\mathbf{f}(\mathbf{x}, t)p_t(\mathbf{x})) \Leftrightarrow \frac{d \log p_t(\mathbf{x}(t))}{dt} = -\text{tr} \left( \frac{\partial \mathbf{f}(\mathbf{x}(t), t)}{\partial \mathbf{x}(t)} \right)$$

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- ▶ It's hard to solve the continuity equation directly due to the trace term.
- ▶ There's a method (the adjoint method) that solves this equation directly, but it's unstable and unscalable.

# Continuous-Time Normalizing Flows

## KFP Theorem (Continuity Equation)

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- ▶ Knowing the vector field  $\mathbf{f}(\mathbf{x}, t)$ , the KFP (or continuity) equation allows us to compute the density  $p_t(\mathbf{x})$ .
- ▶ Flow matching provides an alternative approach to Neural ODEs.

# Continuous-Time Normalizing Flows

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## Flow Matching

$$\mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_\theta(\mathbf{x}, t)\|^2 \rightarrow \min_{\theta}$$



# Continuous-Time Normalizing Flows

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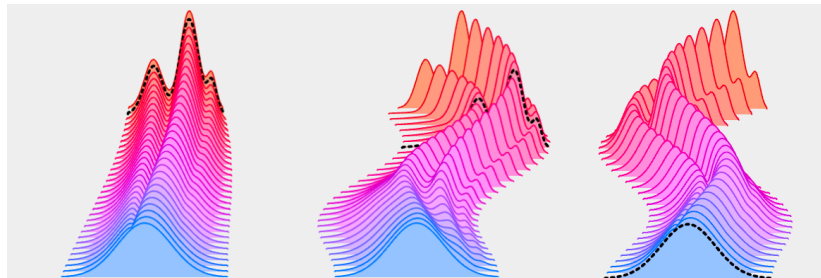
$$\mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_\theta(\mathbf{x}, t)\|^2 \rightarrow \min_{\theta}$$

- ▶ Approximate the true vector field  $\mathbf{f}(\mathbf{x}, t)$  using  $\mathbf{f}_\theta(\mathbf{x}, t)$ .
- ▶ Use  $\mathbf{f}_\theta(\mathbf{x}, t)$  for deterministic sampling from the ODE.

# Flow Matching

$$\mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_\theta(\mathbf{x}, t)\|^2 \rightarrow \min_{\theta}$$

- ▶ There are infinitely many possible  $\mathbf{f}(\mathbf{x}, t)$  between  $p_{\text{data}}(\mathbf{x})$  and  $p(\mathbf{x})$ .
- ▶ The true vector field  $\mathbf{f}(\mathbf{x}, t)$  is **unknown**.
- ▶ We need to select the "best"  $\mathbf{f}(\mathbf{x}, t)$  and make the objective tractable.



# Outline

1. Diffusion and Score Matching SDEs
2. Score-Based Generative Models Through SDEs
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# Flow Matching

## Latent Variable Model

Let's introduce the latent variable  $\mathbf{z}$ :

$$p_t(\mathbf{x}) = \int p_t(\mathbf{x}|\mathbf{z})p(\mathbf{z})d\mathbf{z}$$

Here,  $p_t(\mathbf{x}|\mathbf{z})$  is a **conditional probability path**.

# Flow Matching

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where  $\mathbf{f}(\mathbf{x}, \mathbf{z}, t)$  is a **conditional vector field**:

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where  $\mathbf{f}(\mathbf{x}, \mathbf{z}, t)$  is a **conditional vector field**:

$$\frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}, t) \quad \Rightarrow \quad \frac{d\mathbf{x}}{dt} = \mathbf{f}(\mathbf{x}, \mathbf{z}, t)$$

What's the relationship between  $\mathbf{f}(\mathbf{x}, t)$  and  $\mathbf{f}(\mathbf{x}, \mathbf{z}, t)$ ?

---

*Tong A., et al. Improving and Generalizing Flow-Based Generative Models with Minibatch Optimal Transport, 2023*

# Flow Matching

$$\frac{\partial p_t(\mathbf{x}|\mathbf{z})}{\partial t} = -\text{div}(\mathbf{f}(\mathbf{x}, \mathbf{z}, t)p_t(\mathbf{x}|\mathbf{z})),$$

## Theorem

The following vector field generates the probability path  $p_t(\mathbf{x})$ :

$$\mathbf{f}(\mathbf{x}, t) = \mathbb{E}_{p_t(\mathbf{z}|\mathbf{x})} \mathbf{f}(\mathbf{x}, \mathbf{z}, t) = \int \mathbf{f}(\mathbf{x}, \mathbf{z}, t) \frac{p_t(\mathbf{x}|\mathbf{z})p(\mathbf{z})}{p_t(\mathbf{x})} d\mathbf{z}$$

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## Proof

$$\frac{\partial p_t(\mathbf{x})}{\partial t} = \frac{\partial}{\partial t} \int p_t(\mathbf{x}|\mathbf{z})p(\mathbf{z})d\mathbf{z}$$



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$$\mathbf{f}(\mathbf{x}, t) = \mathbb{E}_{p_t(\mathbf{z}|\mathbf{x})} \mathbf{f}(\mathbf{x}, \mathbf{z}, t) = \int \mathbf{f}(\mathbf{x}, \mathbf{z}, t) \frac{p_t(\mathbf{x}|\mathbf{z})p(\mathbf{z})}{p_t(\mathbf{x})} d\mathbf{z}$$

## Proof

$$\begin{aligned} \frac{\partial p_t(\mathbf{x})}{\partial t} &= \frac{\partial}{\partial t} \int p_t(\mathbf{x}|\mathbf{z})p(\mathbf{z})d\mathbf{z} = \int \left( \frac{\partial p_t(\mathbf{x}|\mathbf{z})}{\partial t} \right) p(\mathbf{z})d\mathbf{z} = \\ &= \int (-\text{div}(\mathbf{f}(\mathbf{x}, \mathbf{z}, t)p_t(\mathbf{x}|\mathbf{z}))) p(\mathbf{z})d\mathbf{z} = \\ &= -\text{div} \left( \int \mathbf{f}(\mathbf{x}, \mathbf{z}, t)p_t(\mathbf{x}|\mathbf{z})p(\mathbf{z})d\mathbf{z} \right) = -\text{div}(\mathbf{f}(\mathbf{x}, t)p_t(\mathbf{x})) \end{aligned}$$

# Flow Matching

## Flow Matching (FM)

$$\mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_\theta(\mathbf{x}, t)\|^2 \rightarrow \min_{\theta}$$

## Conditional Flow Matching (CFM)

$$\mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} \|\mathbf{f}(\mathbf{x}, \mathbf{z}, t) - \mathbf{f}_\theta(\mathbf{x}, t)\|^2 \rightarrow \min_{\theta}$$

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## Theorem

If  $\text{supp}(p_t(\mathbf{x})) = \mathbb{R}^m$ , then the optimal value of the FM objective equals the optimal value of the CFM objective.

# Flow Matching

## Flow Matching (FM)

$$\mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_\theta(\mathbf{x}, t)\|^2 \rightarrow \min_{\theta}$$

## Conditional Flow Matching (CFM)

$$\mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} \|\mathbf{f}(\mathbf{x}, \mathbf{z}, t) - \mathbf{f}_\theta(\mathbf{x}, t)\|^2 \rightarrow \min_{\theta}$$

## Theorem

If  $\text{supp}(p_t(\mathbf{x})) = \mathbb{R}^m$ , then the optimal value of the FM objective equals the optimal value of the CFM objective.

## Proof

This can be proved in a similar way as in the denoising score matching theorem.

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*Tong A., et al. Improving and Generalizing Flow-Based Generative Models with Minibatch Optimal Transport, 2023*

# Conditional Flow Matching

## Theorem

$$\begin{aligned} \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 &= \\ = \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} \|\mathbf{f}(\mathbf{x}, \mathbf{z}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 \end{aligned}$$



# Conditional Flow Matching

## Theorem

$$\begin{aligned} \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 &= \\ = \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} \|\mathbf{f}(\mathbf{x}, \mathbf{z}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 \end{aligned}$$

## Proof

$$\begin{aligned} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 &= \\ = \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} [\|\mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 - 2\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t)\mathbf{f}(\mathbf{x}, t)] + \text{const}(\theta) \end{aligned}$$

# Conditional Flow Matching

## Theorem

$$\begin{aligned} \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 &= \\ &= \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} \|\mathbf{f}(\mathbf{x}, \mathbf{z}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 \end{aligned}$$

## Proof

$$\begin{aligned} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 &= \\ &= \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} [\|\mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 - 2\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t)\mathbf{f}(\mathbf{x}, t)] + \text{const}(\theta) \\ \mathbb{E}_{p_t(\mathbf{x})} [\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t)\mathbf{f}(\mathbf{x}, t)] &= \int p_t(\mathbf{x}) \left[ \mathbf{f}_{\theta}^{\top}(\mathbf{x}, t) \left( \int p_t(\mathbf{z}|\mathbf{x}) \mathbf{f}(\mathbf{x}, \mathbf{z}, t) d\mathbf{z} \right) \right] d\mathbf{x} \end{aligned}$$

# Conditional Flow Matching

## Theorem

$$\begin{aligned} \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 &= \\ &= \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} \|\mathbf{f}(\mathbf{x}, \mathbf{z}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 \end{aligned}$$

## Proof

$$\begin{aligned} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 &= \\ &= \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} [\|\mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 - 2\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t)\mathbf{f}(\mathbf{x}, t)] + \text{const}(\theta) \\ \mathbb{E}_{p_t(\mathbf{x})} [\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t)\mathbf{f}(\mathbf{x}, t)] &= \int p_t(\mathbf{x}) \left[ \mathbf{f}_{\theta}^{\top}(\mathbf{x}, t) \left( \int p_t(\mathbf{z}|\mathbf{x}) \mathbf{f}(\mathbf{x}, \mathbf{z}, t) d\mathbf{z} \right) \right] d\mathbf{x} = \\ &= \int \int p_t(\mathbf{x}) p_t(\mathbf{z}|\mathbf{x}) [\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t) \mathbf{f}(\mathbf{x}, \mathbf{z}, t)] d\mathbf{z} d\mathbf{x} \end{aligned}$$

# Conditional Flow Matching

## Theorem

$$\begin{aligned} \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 &= \\ &= \arg \min_{\theta} \mathbb{E}_{t \sim U[0,1]} \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} \|\mathbf{f}(\mathbf{x}, \mathbf{z}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 \end{aligned}$$

## Proof

$$\begin{aligned} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x})} \|\mathbf{f}(\mathbf{x}, t) - \mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 &= \\ &= \mathbb{E}_{\mathbf{z} \sim p(\mathbf{z})} \mathbb{E}_{\mathbf{x} \sim p_t(\mathbf{x}|\mathbf{z})} [\|\mathbf{f}_{\theta}(\mathbf{x}, t)\|^2 - 2\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t)\mathbf{f}(\mathbf{x}, t)] + \text{const}(\theta) \\ \mathbb{E}_{p_t(\mathbf{x})} [\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t)\mathbf{f}(\mathbf{x}, t)] &= \int p_t(\mathbf{x}) \left[ \mathbf{f}_{\theta}^{\top}(\mathbf{x}, t) \left( \int p_t(\mathbf{z}|\mathbf{x}) \mathbf{f}(\mathbf{x}, \mathbf{z}, t) d\mathbf{z} \right) \right] d\mathbf{x} = \\ &= \int \int p_t(\mathbf{x}) p_t(\mathbf{z}|\mathbf{x}) [\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t) \mathbf{f}(\mathbf{x}, \mathbf{z}, t)] d\mathbf{z} d\mathbf{x} = \\ &= \mathbb{E}_{p(\mathbf{z})} \mathbb{E}_{p_t(\mathbf{x}|\mathbf{z})} [\mathbf{f}_{\theta}^{\top}(\mathbf{x}, t) \mathbf{f}(\mathbf{x}, \mathbf{z}, t)] \end{aligned}$$

# Summary

- ▶ Score matching (NCSN) and diffusion models (DDPM) are discretizations of SDEs (variance exploding and variance preserving).
- ▶ It's possible to train continuous-in-time score-based generative models using forward and reverse SDEs.
- ▶ Discretizing the reverse SDE yields ancestral sampling of the DDPM.
- ▶ Flow matching suggests fitting the vector field directly.
- ▶ Conditional flow matching introduces the latent variable  $\mathbf{z}$ , reformulating the initial task in terms of conditional dynamics.