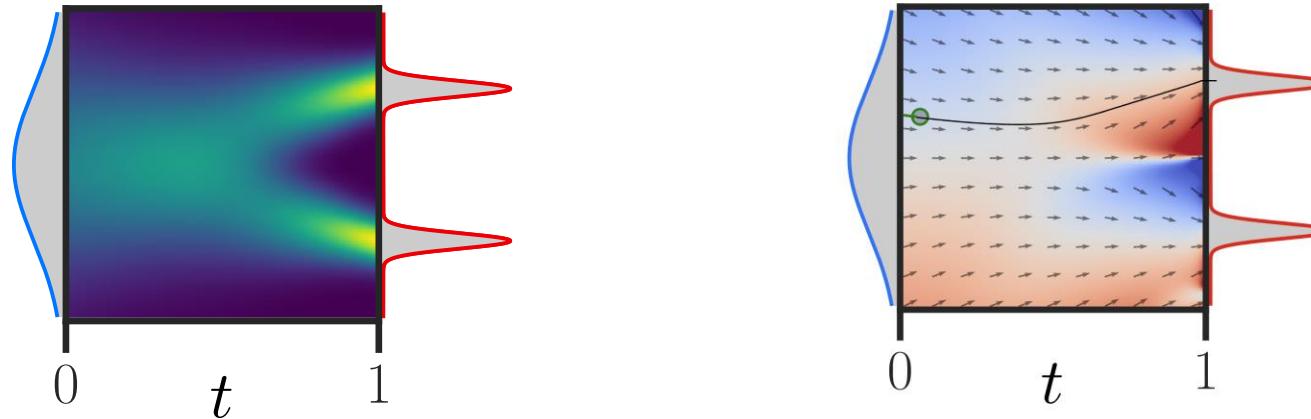


Flow Matching

Flow Matching

Learn the vector field to transport probability distribution



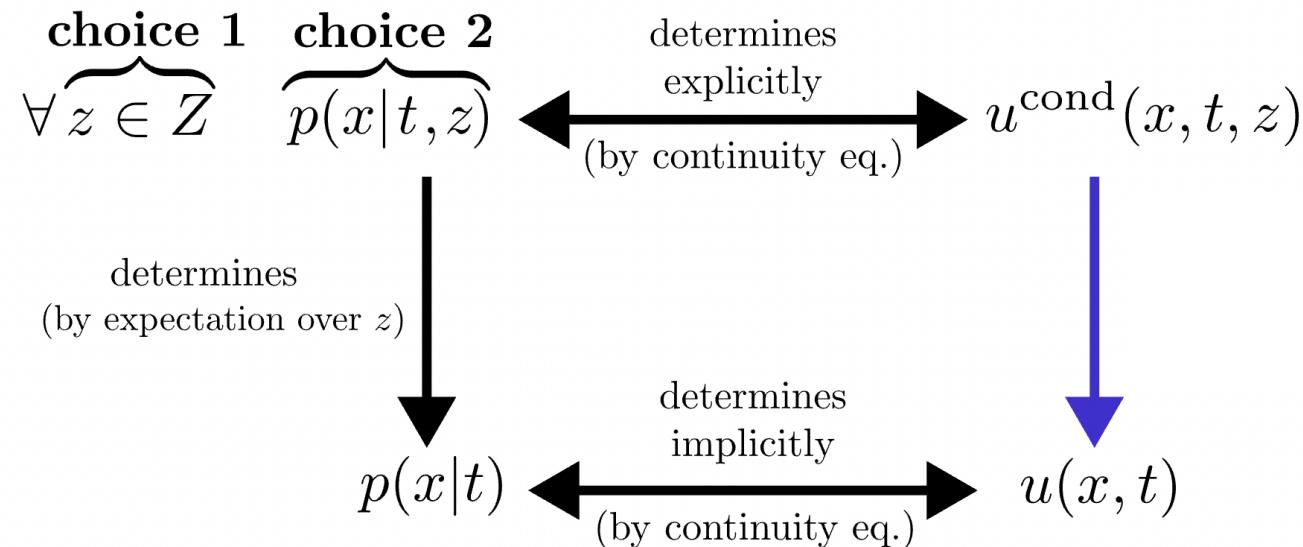
$$\partial_t p_t + \nabla \cdot u_t p_t = 0$$

$$x(0) = x^{(i)} + \int_1^0 u_\theta(x(t), t) dt$$

Ref: <https://dl.heeere.com/conditional-flow-matching/blog/conditional-flow-matching/>

Flow Matching

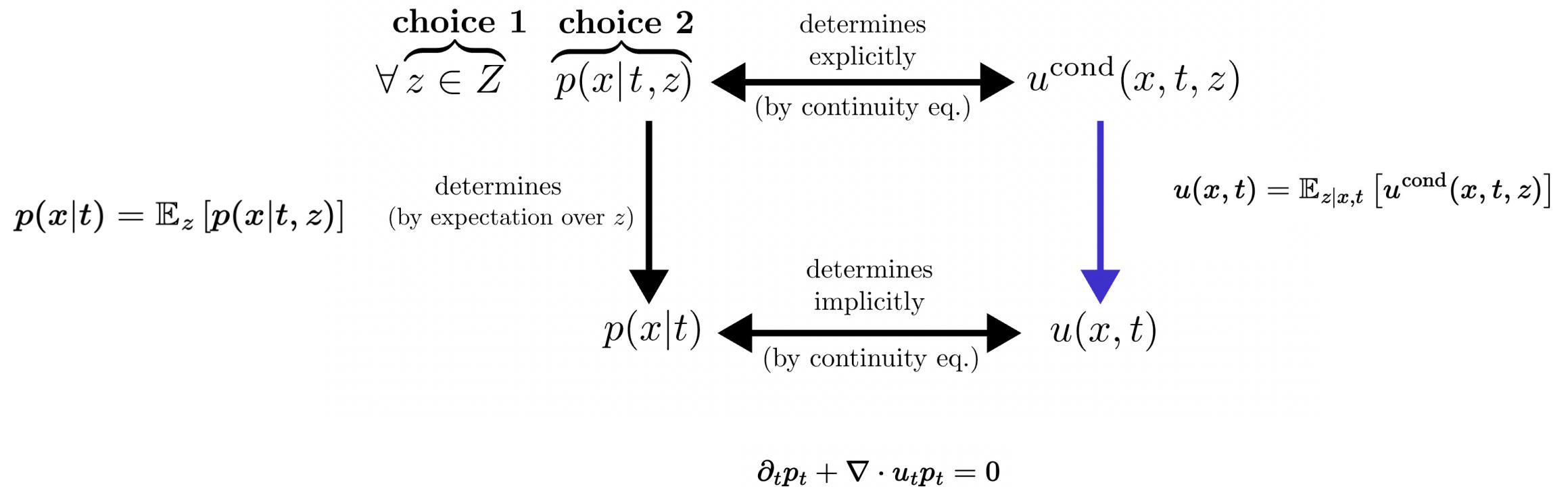
Central Idea: Learn the final flow from conditioned flows



Flow Matching

$$\begin{aligned}\forall x \quad \mathbb{E}_z [p(x|z, t=0)] &= p_0(x) , \\ \forall x \quad \mathbb{E}_z [p(x|z, t=1)] &= p_{\text{data}}(x) .\end{aligned}$$

$$\partial_t p_t + \nabla \cdot u_t p_t = 0$$



Flow Matching

Linear Paths

$$z \stackrel{\text{choice}}{=} (x_0, x_1) \sim p_0 \times p_{\text{data}}$$

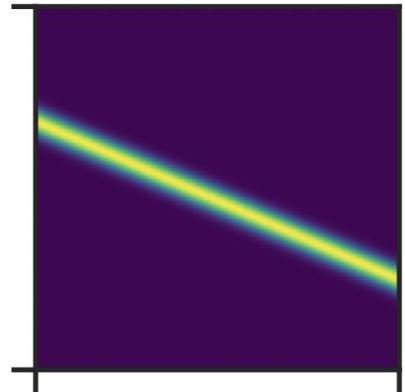
$$p(x|t, z = (x_0, x_1)) \stackrel{\text{choice}}{=} \mathcal{N}((1-t) \cdot x_0 + t \cdot x_1, \sigma^2 \text{Id})$$

$$p(x|t, z = (x_0, x_1)) \stackrel{\text{choice}}{=} \delta_{(1-t) \cdot x_0 + t \cdot x_1}(x)$$

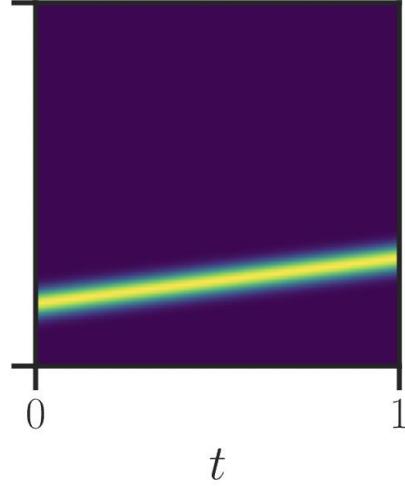
$$\begin{aligned} \forall x \quad & \mathbb{E}_z [p(x|z, t = 0)] = p_0(x) , \\ \forall x \quad & \mathbb{E}_z [p(x|z, t = 1)] = p_{\text{data}}(x) . \end{aligned}$$

$$u^{\text{cond}}(x, t, z = (x_0, x_1)) = x_1 - x_0$$

$$p(x, t | z = z^{(2)})$$



$$p(x, t | z = z^{(5)})$$



Flow Matching

Gaussian Paths

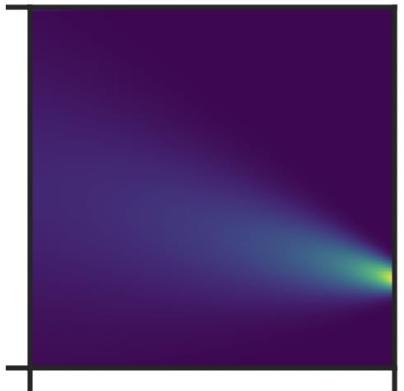
$$z \stackrel{\text{choice}}{=} x_1 \sim p_{\text{data}}$$

$$p(x|t, z = x_1) \stackrel{\text{choice}}{=} \mathcal{N}(tx_1, (1-t)^2 \text{Id})$$

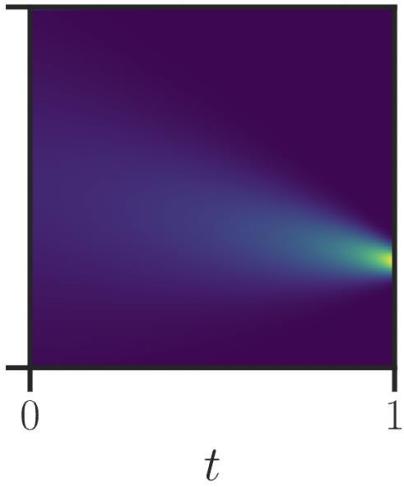
$$\begin{aligned} \forall x \quad & \mathbb{E}_z [p(x|z, t = 0)] = p_0(x) , \\ \forall x \quad & \mathbb{E}_z [p(x|z, t = 1)] = p_{\text{data}}(x) . \end{aligned}$$

$$u^{\text{cond}}(x, t, z = x_1) = \frac{x - x_1}{1 - t}$$

$$p(x, t | z = z^{(2)})$$



$$p(x, t | z = z^{(5)})$$



Flow Matching

Velocity flow from conditioned velocity flow

$$u(x, t) = \mathbb{E}_{z|x,t} [u^{\text{cond}}(x, t, z)]$$

To get the above result

$$\forall t, x, u(x, t) = \mathbb{E}_z \left[\frac{u^{\text{cond}}(x, t, z)p(x|t, z)}{p(x|t)} \right]$$

This gives us the loss function

$$\mathcal{L}^{\text{CFM}}(\theta) \stackrel{\text{def}}{=} \mathbb{E}_{\substack{t \sim \mathcal{U}([0,1]) \\ z \sim p_z \\ x \sim p(\cdot|t,z)}} \| u_{\theta}^{\text{CFM}}(x, t) - \underbrace{u^{\text{cond}}(x, t, z)}_{\substack{\text{chosen to be} \\ \text{explicitly defined,} \\ \text{cheap to compute,} \\ \text{e.g., } x_1 - x_0}} \|^2$$

Flow Matching

Proof:

$$\begin{aligned}\forall t, x, p(x|t) &= \int_z p(x, z|t) dz \\ \forall t, x, \frac{\partial p(x|t)}{\partial t} &= \frac{\partial}{\partial t} \mathbb{E}_z [p(x|t, z)] \\ &= \mathbb{E}_z \left[\frac{\partial}{\partial t} p(x|t, z) \right] \quad (\text{under technical conditions}) \\ &= -\mathbb{E}_z [\nabla \cdot (u^{\text{cond}}(x, t, z)p(x|t, z))] \quad \text{continuity equation for } p(x|t, z) \\ &= -\nabla \cdot \mathbb{E}_z [u^{\text{cond}}(x, t, z)p(x|t, z)] \quad (\text{under technical conditions}) \\ &= -\nabla \cdot \mathbb{E}_z \left[u^{\text{cond}}(x, t, z)p(x|t, z) \frac{p(x|t)}{p(x|t)} \right] \\ &= -\nabla \cdot \left(\mathbb{E}_z \left[\frac{u^{\text{cond}}(x, t, z)p(x|t, z)}{p(x|t)} \right] p(x|t) \right) \quad (p(x|t) \text{ is independent of } z)\end{aligned}$$

$$\text{Hence } \forall t, x, u(x, t) = \mathbb{E}_z \left[\frac{u^{\text{cond}}(x, t, z)p(x|t, z)}{p(x|t)} \right]$$

Flow Matching

Proof:

$$\begin{aligned}\forall t, x, u(x, t) &= \mathbb{E}_z \left[\frac{u^{\text{cond}}(x, t, z)p(x|t, z)}{p(x|t)} \right] \\ &= \int_z \frac{u^{\text{cond}}(x, t, z)p(x|t, z)}{p(x|t)} p(z) dz \\ &= \int_z u^{\text{cond}}(x, t, z) \underbrace{p(x|t, z)}_{\substack{= p(z|x, t) \cdot p(x, t) \\ p(t, z)}} \cdot p(z) \cdot \underbrace{\frac{1}{p(x|t)}}_{\substack{= \frac{p(t)}{p(x, t)}}} dz \\ &= \int_z u^{\text{cond}}(x, t, z) \frac{p(z|x, t) \cdot p(x, t)}{p(t, z)} \cdot p(z) \cdot \frac{p(t)}{p(x, t)} dz \\ &= \int_z u^{\text{cond}}(x, t, z) p(z|x, t) \underbrace{\frac{p(z) \cdot p(t)}{p(t, z)}}_{=1} dz \\ &= \int_z u^{\text{cond}}(x, t, z) p(z|x, t) dz \\ &= \mathbb{E}_{z|x, t} [u^{\text{cond}}(x, t, z)]\end{aligned}$$

Flow Matching

Flow Matching In Practice	Linear Interpolation	Conical Gaussian Paths
1. Define a variable z with some known distribution $p(z)$	$p(z = (x_0, x_1)) = p_0 \times p_{\text{data}}$	$p(z = x_1) = p_{\text{data}}$
2. Define a simple conditional distribution $p(x t, z)$	$\mathcal{N}((1 - t) \cdot x_0 + t \cdot x_1, \sigma^2 \cdot \text{Id})$	$\mathcal{N}(t \cdot x_1, (1 - t)^2 \cdot \text{Id})$
3. Compute an associated velocity field $u^{\text{cond}}(x, t, z)$	$x_1 - x_0$	$\frac{x_1 - x}{1 - t}$
4. Train model using the conditional loss \mathcal{L}^{CFM} Sample $t \sim \mathcal{U}_{[0,1]}$, $z \sim p_z$, $x \sim p(x t, z)$	Use data points $x^{(1)}, \dots, x^{(n)}$	
5. Sample from $p_1 \approx p_{\text{data}}$ Sample $x_0 \sim p_0$, Integration scheme on $t \in [0, 1]$	Numerical integration, e.g, Euler scheme: $x_{k+1} = x_k + \frac{1}{N} u_\theta(x_k, t)$	

Flow Matching

References:

1. [Flow Matching for Generative Modeling](#), Lipman et. al.
2. [Flow Matching Guide and Code](#), Lipman et. al.
3. [A Visual Dive into Conditional Flow Matching](#), Gagneux et. al.