

Diffusion models

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Diffusion



Idea: define forward noising process and try to reverse it.

$$q_{0..T}(x_0..x_T) = p_{\text{data}}(x_0) \prod_{t=1}^T q_{t|t-1}(x_t | x_{t-1})$$

$$q_{t|t-1}(x_t | x_{t-1}) = \mathcal{N}(x_t | \sqrt{1-\beta_t} x_{t-1}, \beta_t I)$$

$$q_{t|0}(x_t | x_0) = \mathcal{N}(x_t | \sqrt{d_t} x_0, (1-d_t)I)$$

$$\alpha_t = \prod_{s=1}^t (1-\beta_s) \rightarrow 0$$

$$p_{0..T}^\theta(x_0..x_T) = \mathcal{N}(x_T | 0, I) \underbrace{\prod_{t=1}^T p_{t-1|t}^\theta(x_{t-1} | x_t)}_{\mathcal{N}(x_{t-1} | A_t x_t + B_t \cdot D_t^\theta(x_t), C_t^2 I)}$$

$$KL(q_{0..T}(x_0..x_T) || p_{0..T}^\theta(x_0..x_T)) \rightarrow \min_\theta$$

$$\text{const} + \sum_{t=2}^T \mathbb{E}_{q_{0:t}(x_0, x_t)} \text{KL}(q_{t-1|t,0}(x_{t-1}|x_t, x_0) || P_{t-1|t}^{\theta}(x_{t-1}|x_t))$$

$$= \sum_{t=2}^T w_t \mathbb{E}_{q_{0:t}(x_0, x_t)} \| D_t^{\theta}(x_t) - x_0 \|^2 \rightarrow \min_{\theta}$$

$x_0^{(1)} \dots x_0^{(B)}$ ~ dataset

$t^{(1)} \dots t^{(B)}$ ~ pacup.ten } t ... T }

$\varepsilon^{(1)} \dots \varepsilon^{(B)}$ ~ $\mathcal{N}(0, I)$

$$x_{\text{noisy}}^{(i)} = \sqrt{d_{t^{(i)}}} x_0^{(i)} + \sqrt{1-d_{t^{(i)}}} \varepsilon^{(i)}$$

$$\frac{1}{B} \sum_{i=1}^B \| D_{t^{(i)}}^{\theta}(x_{\text{noisy}}^{(i)}) - x_0^{(i)} \|^2 . \text{backward}()$$

$$P_{t-1|t}^{\theta}(x_{t-1}|x_t) = \mathcal{N}(x_{t-1}|A_t x_t + B_t D_t^{\theta}(x_t), C_t^2)$$

Следиму: $X_T \sim \mathcal{N}(0, I)$

$$X_{t-1} = A_t X_t + B_t D_t^{\theta}(x_t) + C_t \varepsilon_t$$

Пуки: $\tau, \beta_1, \dots, \beta_T \rightarrow d_1, \dots, d_T$

$$\beta_1 \dots \beta_T \quad d_1 \dots d_T$$

$$\mathbb{E} \| P^{\theta}(\sqrt{d_t} x_0 + \sqrt{1-d_t} \varepsilon) - x_0 \|^2$$

$$\sqrt{d_t} x_0 + \sqrt{1-d_t} \varepsilon$$

$$x_0 + \sqrt{\frac{1-d_t}{d_t}} \varepsilon = 6$$

$$\hat{\beta}_1 \dots \hat{\beta}_T$$

$$\hat{d}_1 \dots \hat{d}_T$$

$$\mathbb{E} \| D^{\varphi}(\sqrt{d_s} x_0 + \sqrt{1-d_s} \varepsilon) - x_0 \|^2$$

$$-x_0 \|^2$$

$$x_0 + \sqrt{\frac{1-d_s}{d_s}} \varepsilon$$

Есть ли $s: \tau = 6$?

Yello: $\sim q_0(x_0) \rightarrow q_0(x_0|y)$

$$q_{0..T}(x_0..x_T|y) = q_0(x_0|y) \prod_t q_{t|t-1}(x_t|x_{t-1})$$

Observe give you pacup:

$$\sum_{t=2}^T w_t \left[\frac{q_{0,t}(x_0, x_t|y)}{q_0(x_0|y) q_{t|0}(x_t|x_0)} \right] \| D_t^\Theta(x_t|y) - x_0 \|^2$$

$x \sim \text{batch}$

$D_t(x_t)$

$x, y\text{-batch}$

$D_t(x_t|y)$

Cause: $x_t \sim N(0, I) \quad x_{t-1} = A_t x_t + B_t D_t^\Theta(x_t|y) + C_t \varepsilon_t$

Pacup:



Хотелось бы:

найти, как устроен

последовательность

$q_{t-1|t}$

$$q_{t|t} (x_t | x_{t-1}) = \frac{q_{t|t-1}(x_t | x_{t-1}) q_{t-1}(x_{t-1})}{q_t(x_t)} =$$

$$= q_{t|t-1}(x_t | x_{t-1}) \exp(\log q_{t-1}(x_{t-1}) - \log q_t(x_t))$$

$$\approx q_{t|t-1}(x_t | x_{t-1}) \exp(\log q_t(x_{t-1}) - \log q_t(x_t))$$

$$= q_{t|t-1}(x_t | x_{t-1}) \exp(\langle \nabla \log q_t(x_t), x_{t-1} - x_t \rangle + \tilde{o}(x_{t-1} - x_t))$$

Score суждение
расп. $q_t(x_t)$

$$q_t(x_t) = \int q_{0,t}(x_0, x_t) dx_0 = \int \cancel{q_{t|0}(x_t|x_0)} q_0(x_0) dx_0$$

hypoco

converse

$$\nabla_{x_t} \log q_t(x_t) =$$

$$= \frac{\nabla_{x_t} q_t(x_t)}{q_t(x_t)} = \frac{\nabla_{x_t} \int q_{t|0}(x_t|x_0) q_0(x_0) dx_0}{q_t(x_t)} =$$

$$= \frac{\int \nabla_{x_t} q_{t|0}(x_t|x_0) q_0(x_0) dx_0}{q_t(x_t)}$$

$$= \frac{\int \nabla_{x_t} \log q_{t|0}(x_t|x_0) q_{t|0}(x_t|x_0) q_0(x_0) dx_0}{q_t(x_t)} =$$

$$\int (\nabla_{x_t} \log q_{t|0}(x_t|x_0)) q_{0|t}(x_0|x_t) dx_0 = \mathbb{E}_{q_{0|t}(x_0|x_t)} \nabla \log q_{t|0}(x_t|x_0)$$

$$\nabla_{x_t} \log q_t(x_t) = \mathbb{E}_{q_0(x_0|x_t)} \nabla \log q_{t|0}(x_t|x_0)$$

$$q_0(x_0) = \frac{1}{3} \sum_{i=1}^3 \delta(x_0 = x^{(i)})$$

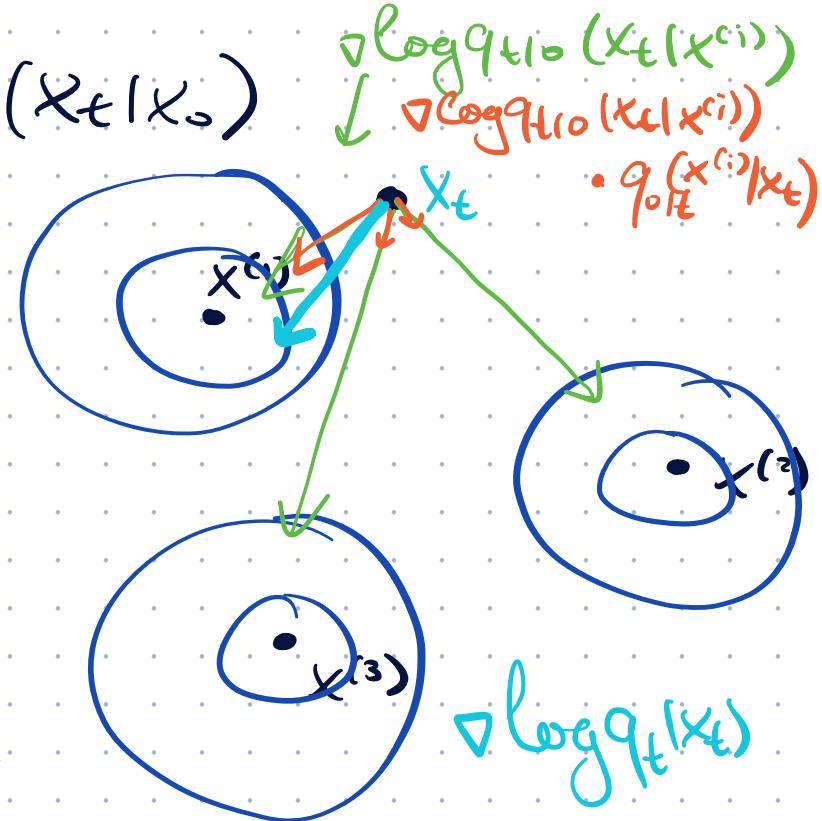
$$q_{t|0}(x_t|x_0) = \mathcal{N}(x_t|x_0, \sigma_t^2 I)$$

$$q_t(x_t) = \sum_{i=1}^3 q_{t|0}(x_t|x^{(i)}) q_0(x^{(i)}) =$$

$$= \sum_{i=1}^3 \frac{1}{3} \mathcal{N}(x_t|x^{(i)}, \sigma_t^2 I)$$

$$\nabla_{x_t} \log q_t(x_t) = \sum_{i=1}^3 q_{0|t}(x^{(i)}|x_t) \cdot \nabla \log q_{t|0}(x_t|x^{(i)})$$

$$q_{0|t}(x^{(i)}|x_t) \propto q_{t|0}(x_t|x^{(i)}) \cdot \frac{1}{3} \propto \frac{1}{3} \cdot \exp\left(-\frac{1}{2\sigma_t^2} \|x_t - x^{(i)}\|^2\right)$$



$$\nabla \log q_t(x_t) = \mathbb{E}_{q_{0|t}(x_0|x_t)} \nabla \log q_{t|0}(x_t|x_0)$$

$$q_{t|0}(x_t|x_0) = \mathcal{N}(x_t | \sqrt{\alpha_t} x_0, (1-\alpha_t) I)$$

$$= \text{const.} \cdot \exp\left(\frac{-1}{2(1-\alpha_t)} \|x_t - \sqrt{\alpha_t} x_0\|^2\right)$$

$$\nabla_{x_t} \log q_{t|0}(x_t|x_0) = \nabla_{x_t} \left(-\frac{1}{2(1-\alpha_t)} \|x_t - \sqrt{\alpha_t} x_0\|^2 \right) =$$

$$= -\frac{1}{2(1-\alpha_t)} 2(x_t - \sqrt{\alpha_t} x_0) = \frac{\sqrt{\alpha_t} x_0 - x_t}{1-\alpha_t}$$

$$\nabla_{x_t} \log q_t(x_t) = \mathbb{E}_{q_{0|t}(x_0|x_t)} \nabla \log q_{t|0}(x_t|x_0) =$$

$$= \frac{\mathbb{E} \frac{\sqrt{d_t} x_0 - x_t}{q_{0|t}(x_0|x_t)}}{1-d_t} = \frac{\sqrt{d_t} \mathbb{E}_{\substack{x_0 \\ q_{0|t}(x_0|x_t)}} x_0 - x_t}{1-d_t}$$

$$\begin{aligned} & \sum_t \left\| \mathbb{E}_{\substack{d_t^\varphi(x_t) \\ q_t(x_t)}} d_t^\varphi(x_t) - \mathbb{E}_{\substack{x_0 \\ q_{0|t}(x_0|x_t)}} x_0 \right\|^2 = \\ & = \sum_t \mathbb{E}_{\substack{d_t^\varphi(x_t) \\ q_t(x_t)}} \left(\|d_t^\varphi(x_t)\|^2 - 2 \langle d_t^\varphi(x_t), \mathbb{E}_{\substack{x_0 \\ q_{0|t}(x_0|x_t)}} x_0 \rangle \right) + \text{const} \\ & = \text{const} + \sum_t \mathbb{E}_{\substack{d_t^\varphi(x_t) \\ q_t(x_t)}} \|d_t^\varphi(x_t)\|^2 - 2 \sum_t \mathbb{E}_{\substack{d_t^\varphi(x_t) \\ q_t(x_t)}} \langle d_t^\varphi(x_t), \mathbb{E}_{\substack{x_0 \\ q_{0|t}(x_0|x_t)}} x_0 \rangle \end{aligned}$$

$$\mathbb{E}_{\substack{d_t^\varphi(x_t) \\ q_t(x_t)}} \langle d_t^\varphi(x_t), \mathbb{E}_{\substack{x_0 \\ q_{0|t}(x_0|x_t)}} x_0 \rangle = \mathbb{E}_{\substack{d_t^\varphi(x_t) \\ q_t(x_t)}} \mathbb{E}_{\substack{x_0 \\ q_{0|t}(x_0|x_t)}} \langle d_t^\varphi(x_t), x_0 \rangle =$$

$$= \mathbb{E}_{\substack{d_t^\varphi(x_t) \\ q_{0,t}(x_0, x_t)}} \langle d_t^\varphi(x_t), x_0 \rangle$$

$$\begin{aligned}
 & \stackrel{?}{=} \text{const} + \sum_t \left(\mathbb{E}_{q_{0,t}(x_0, x_t)} \left[\left\| d_t^\varphi(x_t) \right\|^2 \right] - 2 \mathbb{E}_{q_{0,t}(x_0, x_t)} \left[\langle d_t^\varphi(x_t), x_0 \rangle \right] \right) \\
 & = \text{const} + \sum_t \mathbb{E}_{q_{0,t}(x_0, x_t)} \left[\left\| d_t^\varphi(x_t) - x_0 \right\|^2 \right]
 \end{aligned}$$

\Leftrightarrow однозначное определение генерализатора $P_t^\Theta(x_t)$

$$\sum_t \mathbb{E}_{q_t(x_t)} \left[\left\| d_t^\varphi(x_t) - \mathbb{E}_{q_{0,t}(x_0|x_t)} x_0 \right\|^2 \right] = \text{const} + \sum_t \mathbb{E}_{q_{0,t}(x_0, x_t)} \left[\left\| d_t^\varphi(x_t) - x_0 \right\|^2 \right]$$

\Leftrightarrow близкое определение начального генерализатора $P_t^\Theta(x_t)$

$$P_t^*(x_t) = \mathbb{E}_{q_{0,t}(x_0|x_t)} x_0$$

$$q_{t+1|t} \Leftrightarrow \nabla \log q_t(x_t) \Leftrightarrow \underset{q_{0|t}(x_0|x_t)}{\mathbb{E}} x_0 \Leftrightarrow \sum_t \mathbb{E} \|P_t^\theta(x_t) - x_0\|^2 \hookrightarrow \min_\theta$$

$$q_t \rightarrow q_t^\alpha$$

$$\log q_t^\alpha = \alpha \log q_t + q$$



$$\sum_t \mathbb{E} \left[\frac{\| D_t^*(x_t) - x_0 \|^2}{q_{0,t}(x_0, x_t)} \right] \rightarrow D_t^*(x_t) = \mathbb{E}_{\substack{x_0 \\ q_{0,t}(x_0 | x_t)}} x_0$$

$$S_t^*(x_t) = \frac{-\varepsilon}{\sqrt{1-\alpha_t}} = \frac{\sqrt{\alpha_t} x_0 - x_t}{1-\alpha_t}$$

$$\nabla \log q_t(x_t) = \frac{\sqrt{\alpha_t} D_t^*(x_t) - x_t}{1-\alpha_t}$$

$$x_t = \sqrt{\alpha_t} x_0 + \sqrt{1-\alpha_t} \varepsilon \quad \sqrt{\alpha_t} x_0 - x_t = -\sqrt{1-\alpha_t} \varepsilon$$

$$S_t^*(x_t) = -\frac{\varepsilon_t^*(x_t)}{\sqrt{1-\alpha_t}}$$

$$\sum_t \mathbb{E} \left[\left\| \varepsilon_t^* \left(\sqrt{\alpha_t} x_0 + \sqrt{1-\alpha_t} \varepsilon \right) - \varepsilon \right\|^2 \right] \rightarrow \varepsilon_t^*(x_t) = \mathbb{E}_{\substack{\varepsilon \\ q(\varepsilon | x_t)}} \varepsilon$$

$$\nabla \log q_t(x_t) = \frac{\sqrt{d_t} P_t^*(x_t) - x_t}{1-d_t}$$

$$P_t^*(x_t) = \frac{(1-d_t)\nabla \log q_t(x_t) + x_t}{\sqrt{d_t}}$$

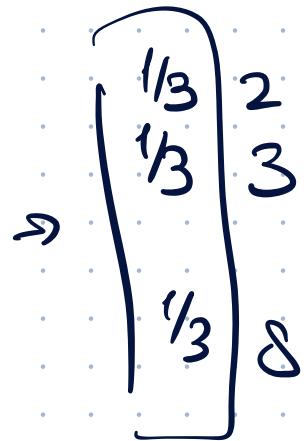
Как нонгруп) звесте $\nabla_{x_t} \log q_t(x_t)$?

$$\nabla_{x_t} \log q_t(x_t | y) = \nabla_{x_t} \log \frac{q_t(y|x_t)q_t(x_t)}{q(y)} =$$

$$= \nabla_{x_t} \log q_t(y|x_t) + \nabla_{x_t} \log q_t(x_t)$$

$$\approx \nabla_{x_t} C_t(y|x_t)$$

noisy classifier



$$(1+\gamma) \nabla_{x_t} \log q_t(y|x_t) + \nabla_{x_t} \log q_t(x_t)$$

$$\gamma \geq 0$$

Classifier guidance

$$\text{Deno: } \nabla_{x_t} \log q_t(x_t)$$

Yens:

$$\text{Deno: } \nabla_{x_t} \log q_t(x_t|y)$$

$$\begin{aligned}
 \text{Yens: } & \nabla_{x_t} \log q_t(x_t) + (1+\gamma) \nabla_{x_t} \log q_t(y|x_t) = \\
 &= (\nabla_{x_t} \log q_t(x_t) + \nabla_{x_t} \log q_t(y|x_t)) + \gamma \nabla_{x_t} \log q_t(y|x_t) \\
 &= \nabla_{x_t} \log q_t(x_t|y) + \gamma \cdot (\nabla_{x_t} \log q_t(x_t|y) - \nabla_{x_t} \log q_t(x_t)) \\
 &\approx S_t^0(x_t|y) + \gamma (S_t^0(x_t|y) - S_t^0(x_t|\emptyset))
 \end{aligned}$$

Было: $y \in \{1..c\}$ Где: $\hat{y} \in \{1..c, \emptyset\}$

$(x_i, y_i) \rightarrow (x_i, \hat{y}_i)$ $\hat{y}_i = \begin{cases} y_i, & \text{с вероят. } p \\ \emptyset, & \text{с вероят. } 1-p \end{cases}$

Целевая: $\mathbb{E} \sum_t \|D_t^\Theta(x_t | \hat{y}) - x_0\|^2$

classifier-free guidance

Effect of guidance



γ = Guidance scale

Summary

$$KL(q_{0-\tau} \parallel p_{0-\tau}^{\theta}) \rightarrow \min_{\theta}$$

$$\Leftrightarrow \sum_t \mathbb{E}_{q_{0,t}(x_0, \mathcal{R}_t)} \| D_t^{\theta}(x_t) - x_0 \|^2$$

\Rightarrow divergence score $q_{0-t} \nabla \log q_t(x_t)$

$$\nabla \log q_t(x_t) \rightarrow \nabla \log q_t(x_t | y)$$

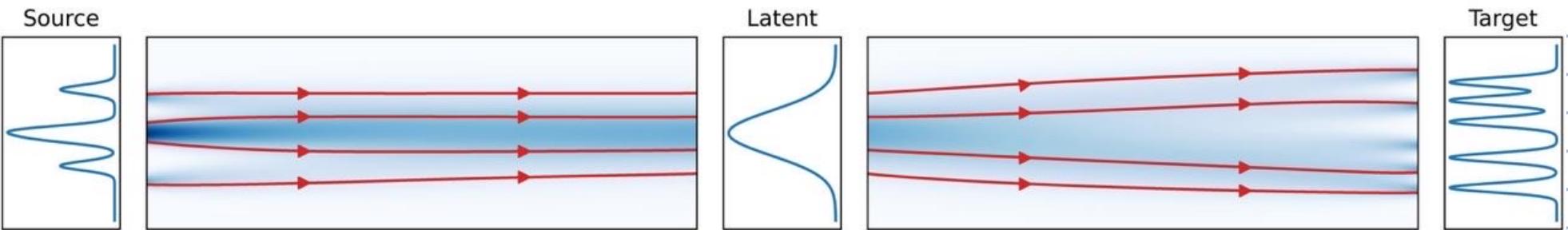
Knaccep.

$$\rightarrow \nabla \log q_t(x_t | y)$$

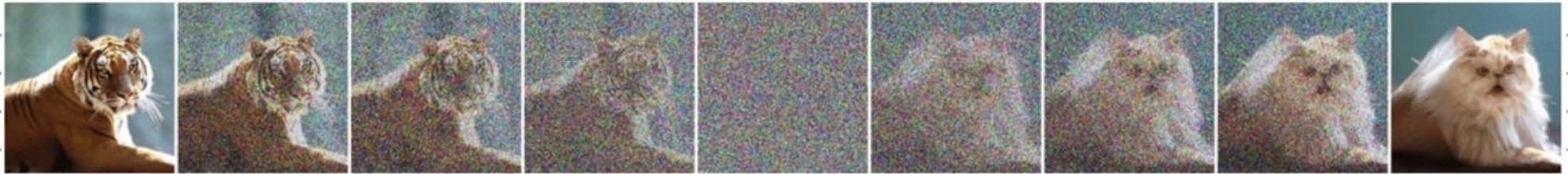
$$+ \gamma (\nabla \log q_t(x_t | y) - \nabla \log q_t(x_t))$$

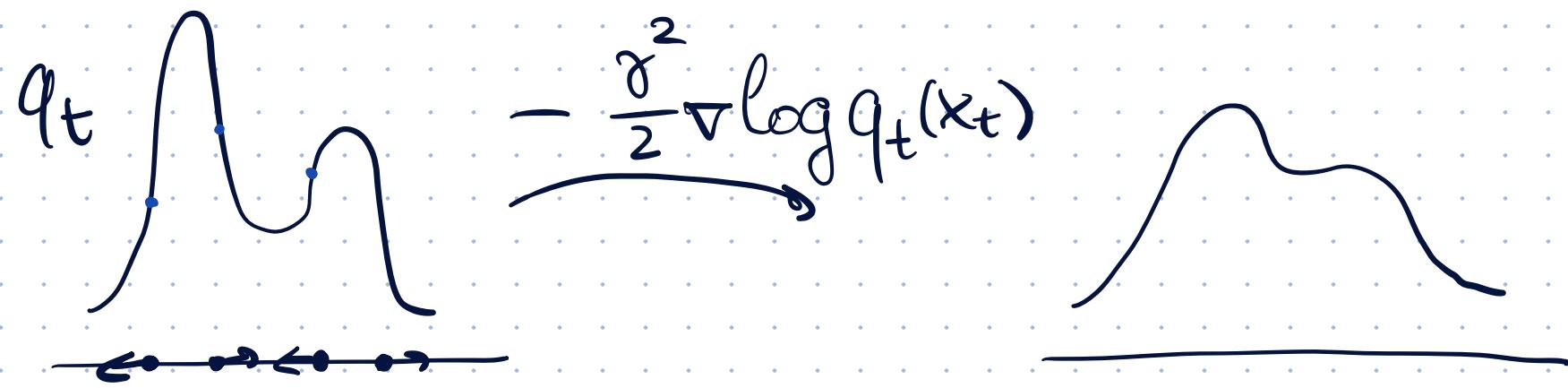
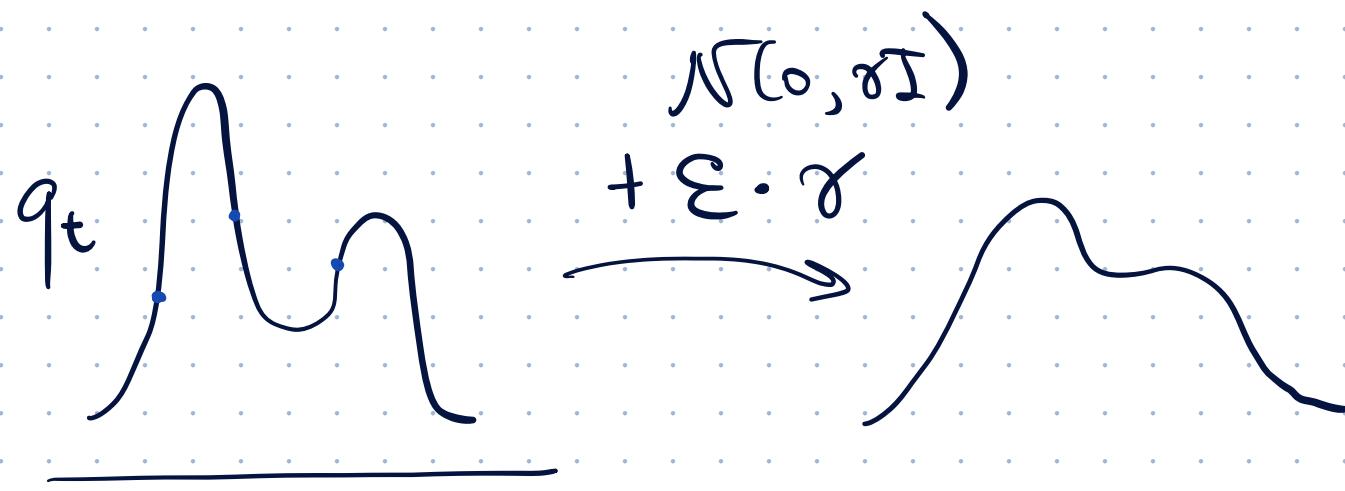
guidance scale

Deterministic sampling



$\mathbf{x}^{(s)}$ — Forward DDIM — $\mathbf{x}^{(l)}$ — Backward DDIM — $\mathbf{x}^{(t)}$





$$x_{t+1} = A_t x_t + B_t D_t^\Theta(x) + \boxed{C_t \varepsilon_t} - \frac{C_t^2}{2} \nabla \log q_t(x_t)$$

$$X \rightarrow X + \gamma \varepsilon = y \quad x \sim P$$

$$X \rightarrow X - \frac{\gamma^2}{2} \nabla \log p(x) = z$$

$$z = x - \dots$$

$$z = z(x)$$

$$x = x(z)$$

$$P_z(z) = P_x(x(z)) \left| \det \frac{\partial x(z)}{\partial z} \right|$$

$$P_y(y) = \int P_x(x) P_{\gamma\varepsilon}(y-x) dx$$

$$P_0, P_1, P_2, \dots$$

$$P_t, t \in [0, 1] \quad \frac{\partial}{\partial t} P_t(x) = \dots \frac{\partial}{\partial x} P_t(x) \dots$$

$$x_{t+1} = x_t + \frac{\sigma^2}{2} \nabla \log p(x_t) + \gamma \cdot \varepsilon_t$$

\uparrow

$$- \frac{\sigma^2}{2} \nabla \log p(x_t)$$

Jlycrn $x_t \sim p$

