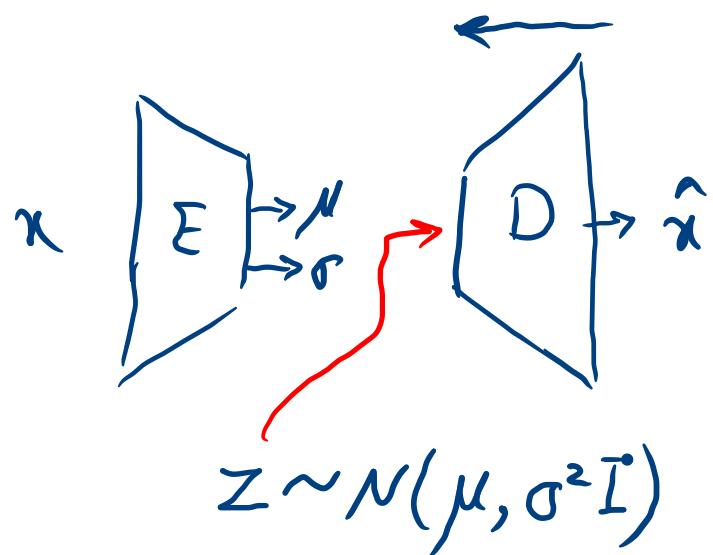
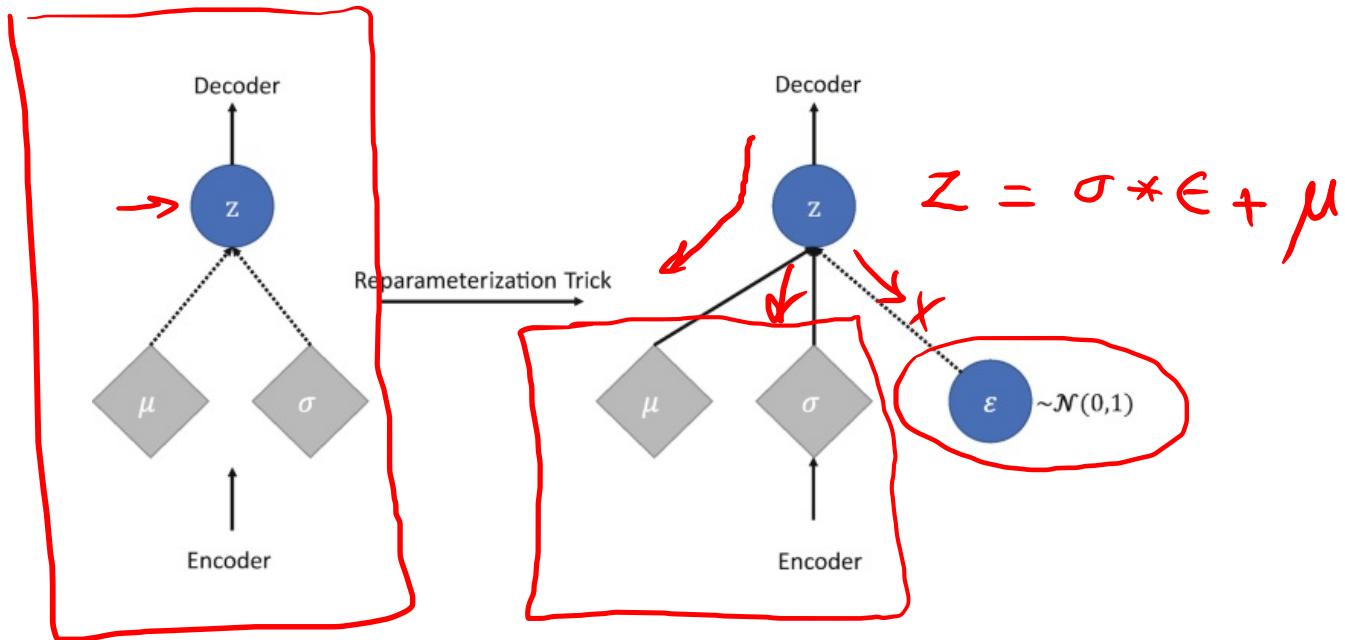


Reparametrization trick

VAE :



$$\|x - \hat{x}\|_2^2 + KL$$



DDPM

Denoising Diffusion Probabilistic Models

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$$x_t = \underline{a} \underline{x}_{t-1} + \underline{b} \epsilon \quad \epsilon \sim \mathcal{N}(0, I)$$

Denoising diffusion models

- Forward / noising process

- Sample data $p(x_0) \rightarrow$ turn to noise

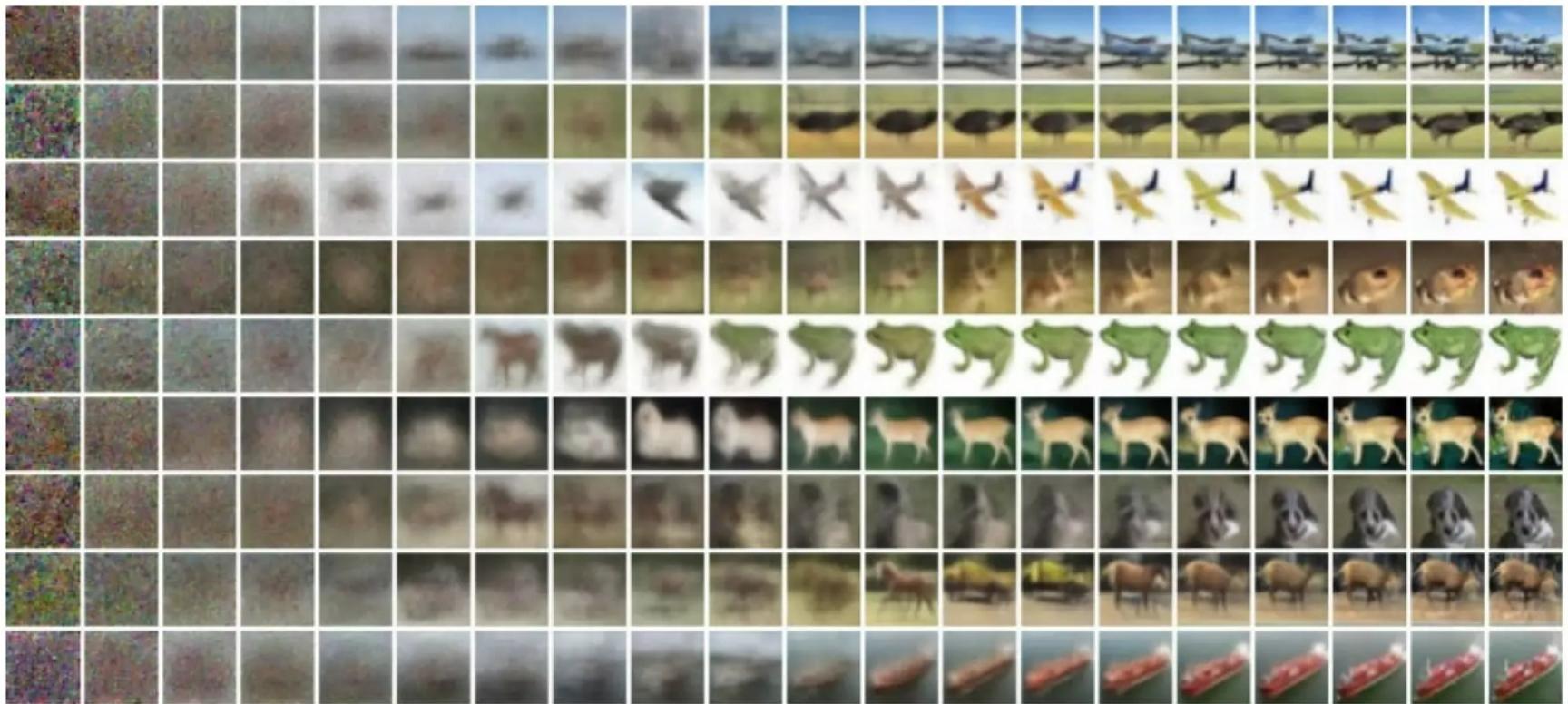


- Reverse / denoising process

- Sample noise $p_T(x_T) \rightarrow$ turn into data

Experiments

◆ Progressive Generation

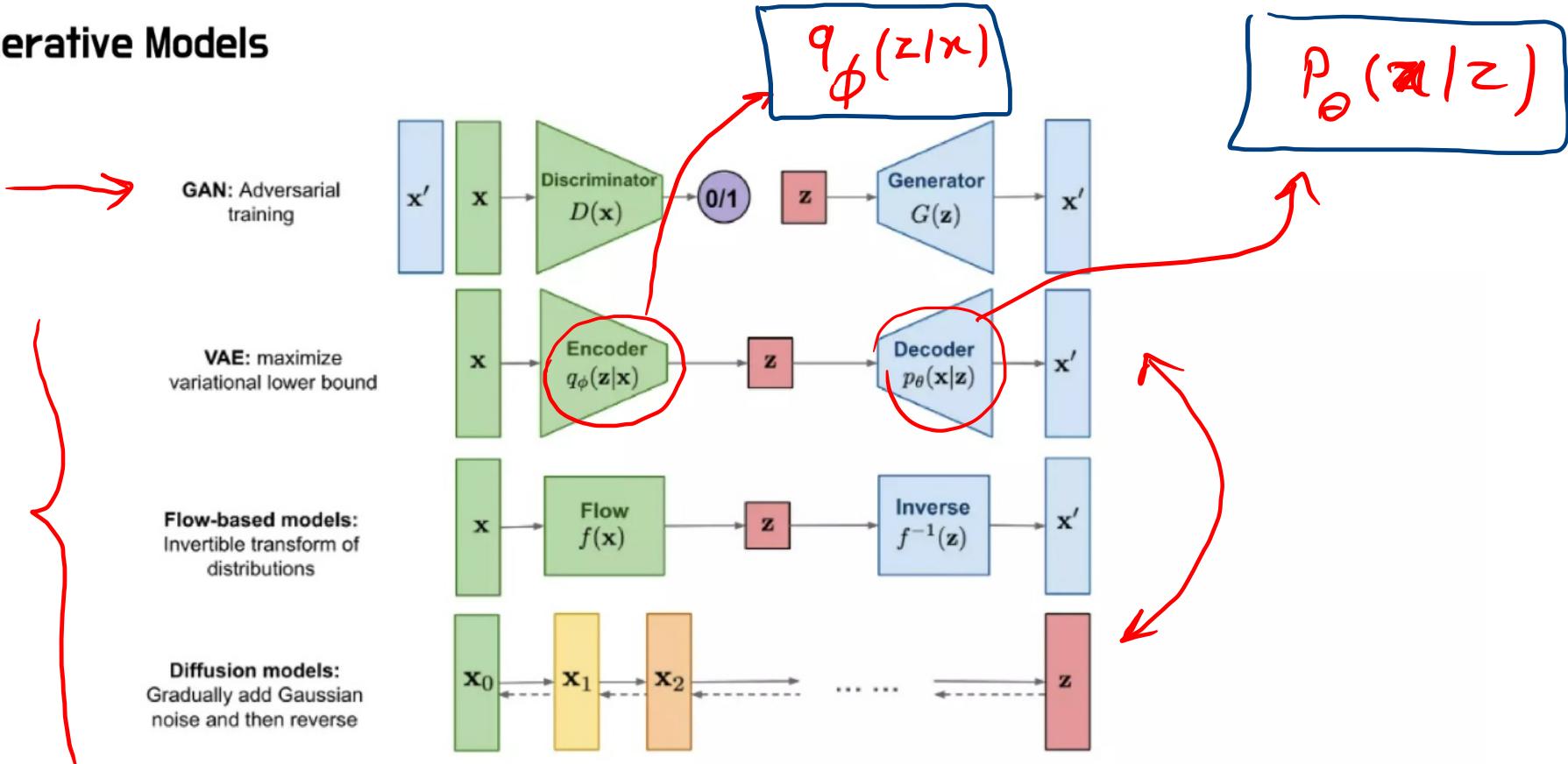


x_T

z_0

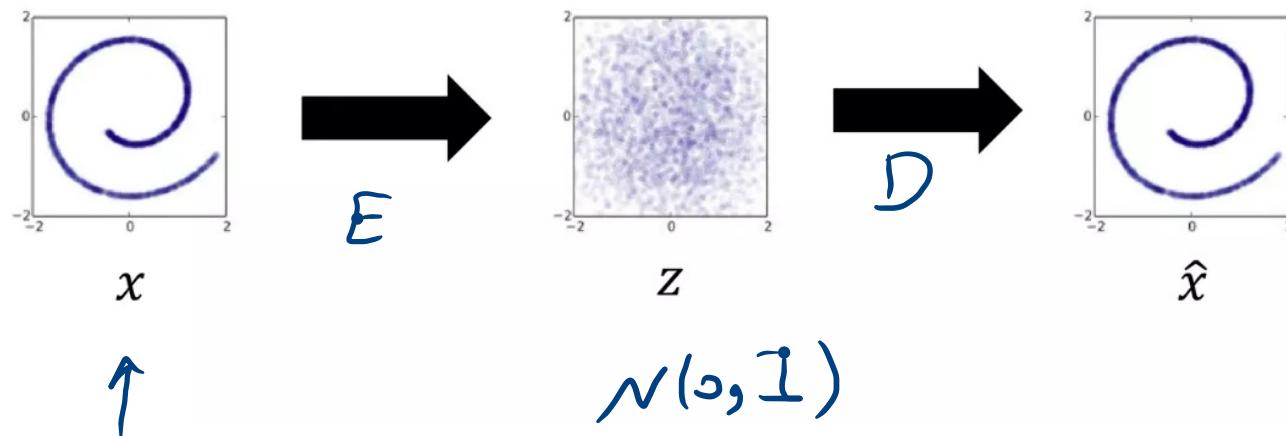
Generative Models

◆ Generative Models



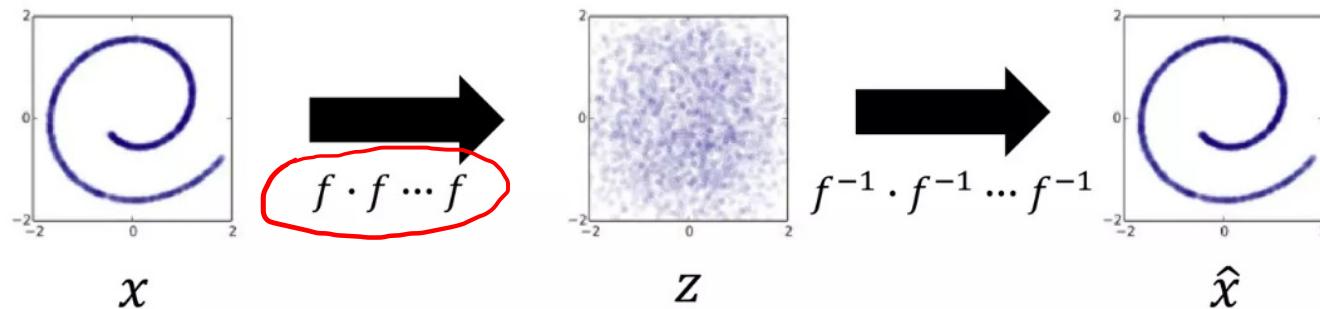
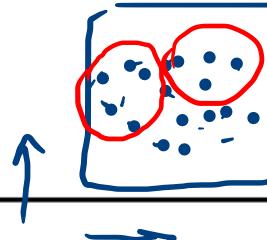
Generative Models

◆ Variational Auto Encoders



Generative Models

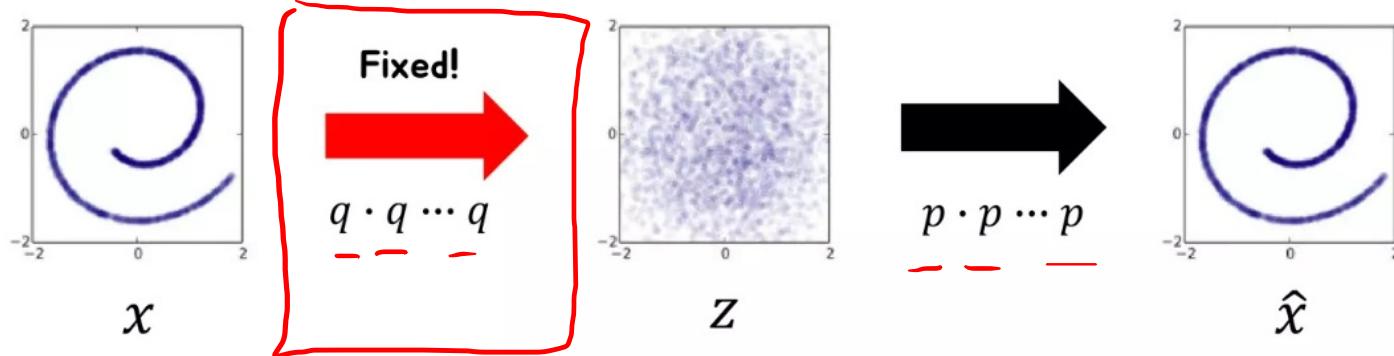
◆ Normalizing Flow Models



Generative Models

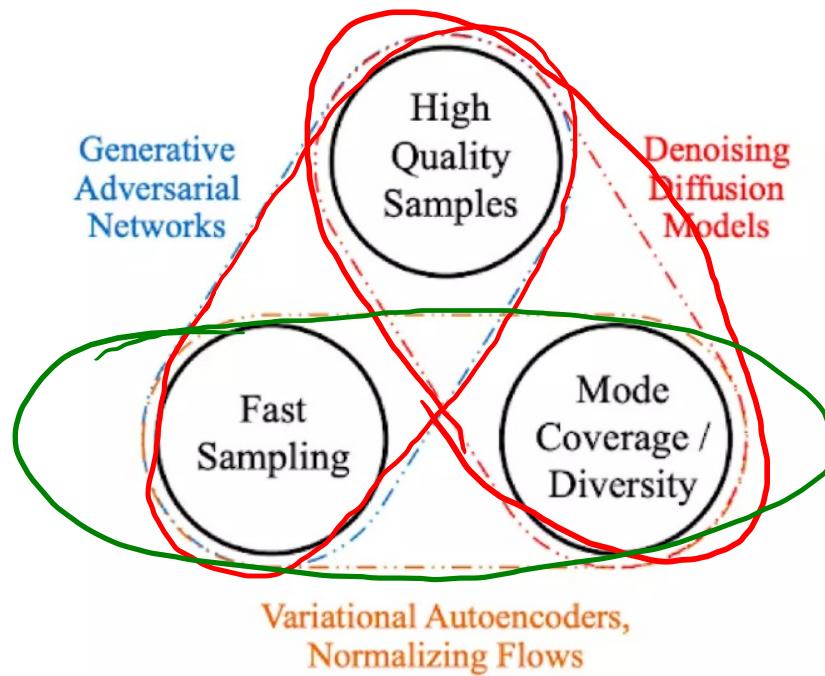
◆ Diffusion Models

DDPM



Generative Models

◆ Generative Models



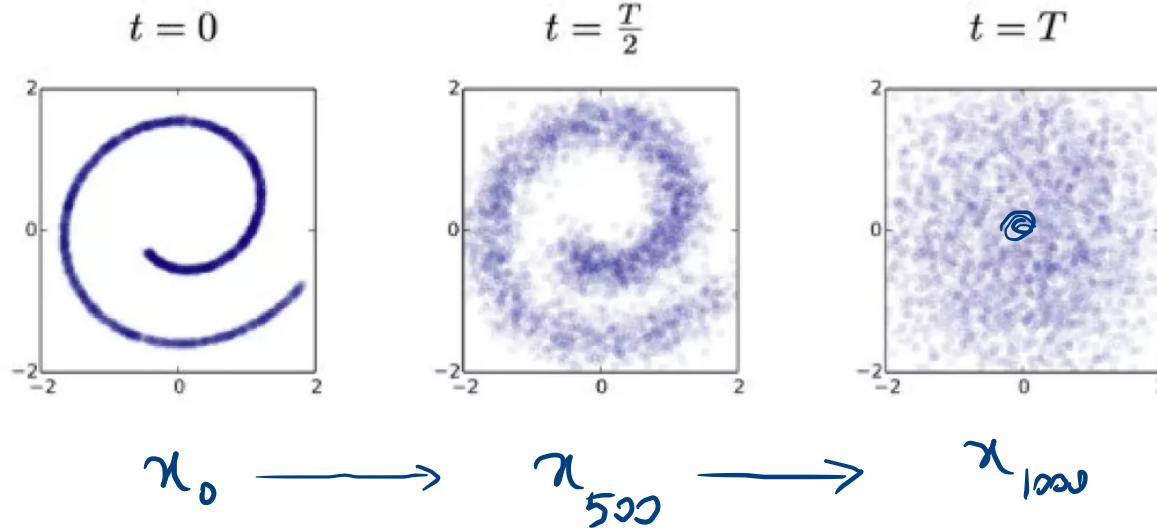
Mode
collapse

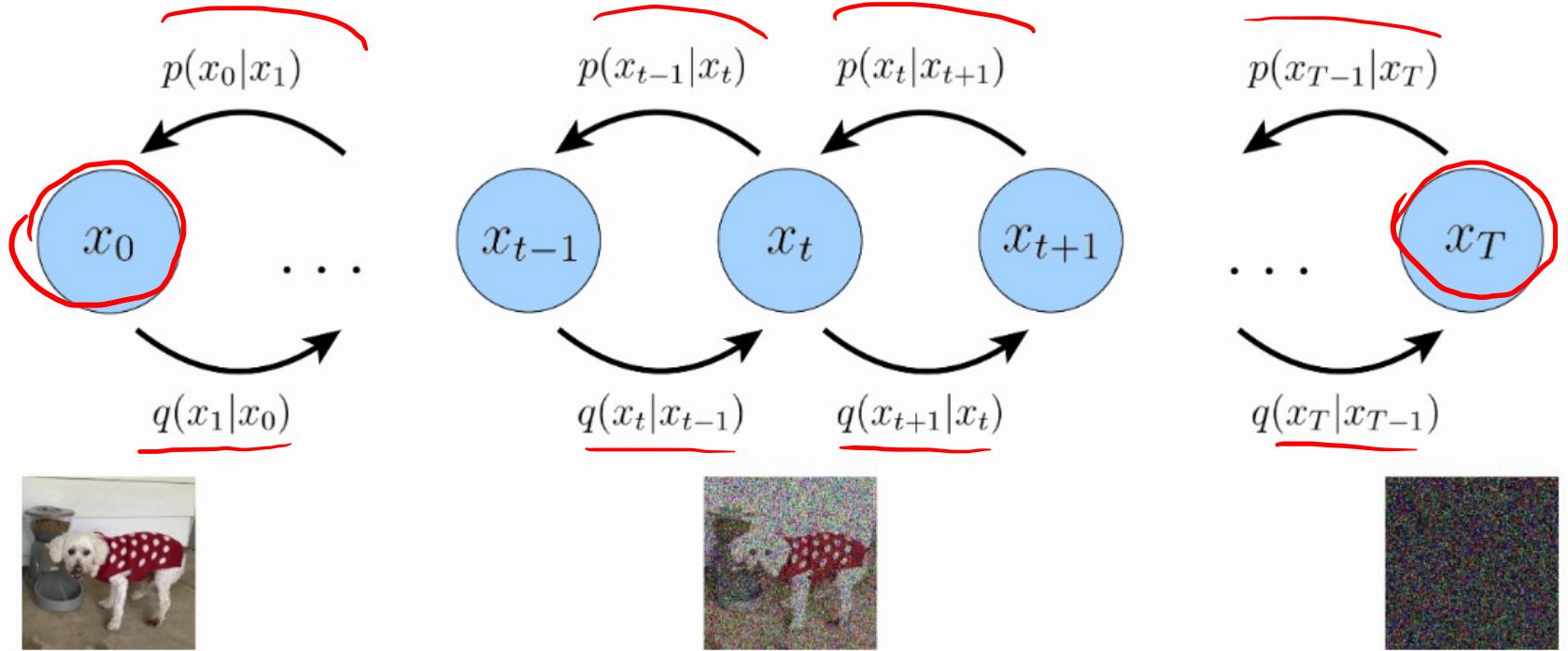
Diffusion Probabilistic Models

◆ Diffusion?

Backward

$T = 1000$



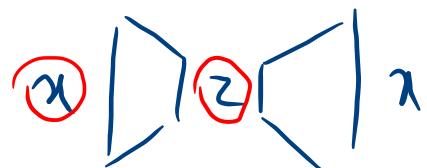


$$q(\mathbf{x}_{1:T}|\mathbf{x}_0) := \prod_{t=1}^T q(\mathbf{x}_t|\mathbf{x}_{t-1}), \quad q(\mathbf{x}_t|\mathbf{x}_{t-1}) := \mathcal{N}(\mathbf{x}_t; \sqrt{1 - \beta_t} \mathbf{x}_{t-1}, \beta_t \mathbf{I})$$

$$p_\theta(\mathbf{x}_{0:T}) := p(\mathbf{x}_T) \prod_{t=1}^T p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t), \quad p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) := \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

x
observed

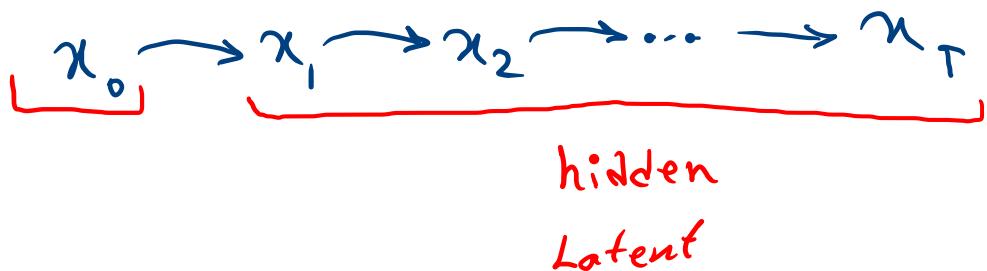
z
latent / hidden variables
space



VAE Diff

$x \rightarrow x_0$

$z \rightarrow x_1, x_2, \dots, x_T$

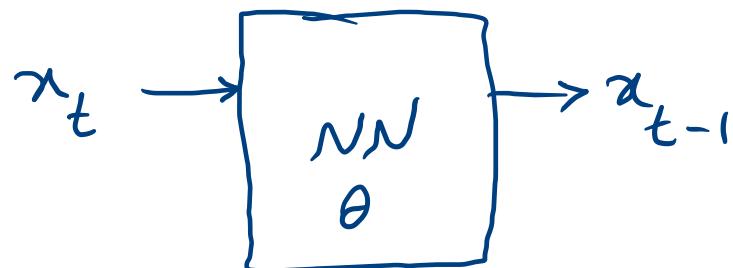


$$\log P_\theta(x) \geq -KL\left(q_\phi(z|x) \| P_\theta(x,z)\right)$$

$$z \rightarrow x_1, \dots, x_T$$
$$x \rightarrow x_0$$

$$\max_{\theta, \phi} -KL\left(q_\phi(z|x) \| P_\theta(x,z)\right)$$

$$\boxed{\max_{\theta} -KL\left(\underbrace{q(x_1, \dots, x_T | x_0)}_{\text{green}} \| \underbrace{P_\theta(x_0, x_1, \dots, x_T)}_{\text{blue}}\right)}$$



$$q(x_1, \dots, x_T | x_0) = q(x_1 | x_0) q(x_2 | x_1) \dots q(x_T | x_{T-1}) = \prod_{t=1}^T q(x_t | x_{t-1})$$

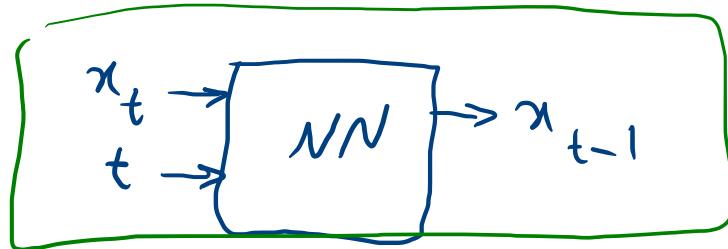


$$P_\theta(x_0, x_1, \dots, x_T) = P(x_T) \underbrace{P_\theta(x_{T-1} | x_T) P_\theta(x_{T-2} | x_{T-1}) \dots P_\theta(x_0 | x_1)}$$

A sequence of nodes labeled $x_T, x_{T-1}, x_{T-2}, \dots, x_1, x_0$ connected by directed arrows pointing from right to left, representing a sequence of states in reverse order. This sequence is equated to the forward sequence above.

$$= P(x_T) \prod_{t=1}^T P_\theta(x_{t-1} | x_t)$$

$$T = 1000$$



A diagram of a circle containing the letter x , with a tail extending to the right, representing a random variable $x_T \sim N(0, I)$.

$$x_T \sim N(0, I)$$

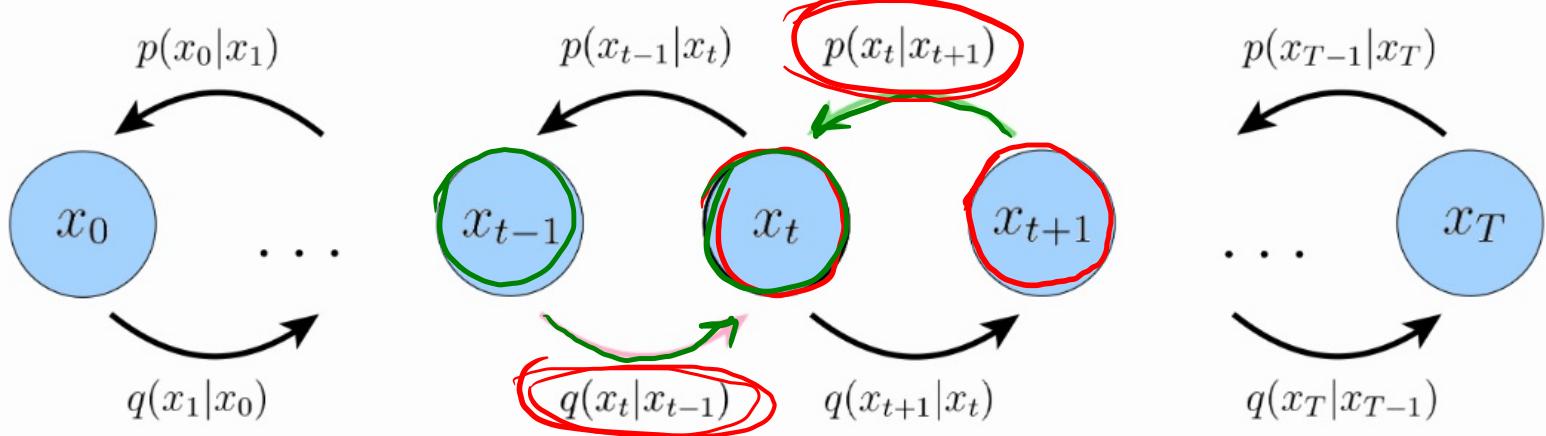
$$-KL\left(q(x_1, \dots, x_T | x_0) \| P_\theta(x_0, x_1, \dots, x_T)\right)$$

$$= -E_q \left[\log \frac{q(x_1, \dots, x_T | x_0)}{P_\theta(x_0, x_1, \dots, x_T)} \right] = -E \left[\log \frac{\prod_{t=1}^T q(x_t | x_{t-1})}{P(x_T) \prod_{t=1}^T P_\theta(x_{t-1} | x_t)} \right]$$

$$= -E \left[-\log P(x_T) + \sum_{t=1}^T \log \frac{q(x_t | x_{t-1})}{P_\theta(x_{t-1} | x_t)} \right]$$

$\max_{\theta} L(\theta) \quad L(\theta)$

$$\begin{aligned}
\underline{\log p(\mathbf{x})} &\geq \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_{0:T})}{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \right] \\
&= \underbrace{\mathbb{E}_{q(\mathbf{x}_1 | \mathbf{x}_0)} [\log p_\theta(\mathbf{x}_0 | \mathbf{x}_1)]}_{\text{reconstruction term}} - \underbrace{\mathbb{E}_{q(\mathbf{x}_{T-1} | \mathbf{x}_0)} [\mathcal{D}_{\text{KL}}(q(\mathbf{x}_T | \mathbf{x}_{T-1}) || p(\mathbf{x}_T))]}_{\text{prior matching term}} \\
&\quad - \sum_{t=1}^{T-1} \underbrace{\mathbb{E}_{q(\mathbf{x}_{t-1}, \mathbf{x}_{t+1} | \mathbf{x}_0)} [\mathcal{D}_{\text{KL}}(q(\mathbf{x}_t | \mathbf{x}_{t-1}) || p_\theta(\mathbf{x}_t | \mathbf{x}_{t+1}))]}_{\text{consistency term}}
\end{aligned}$$



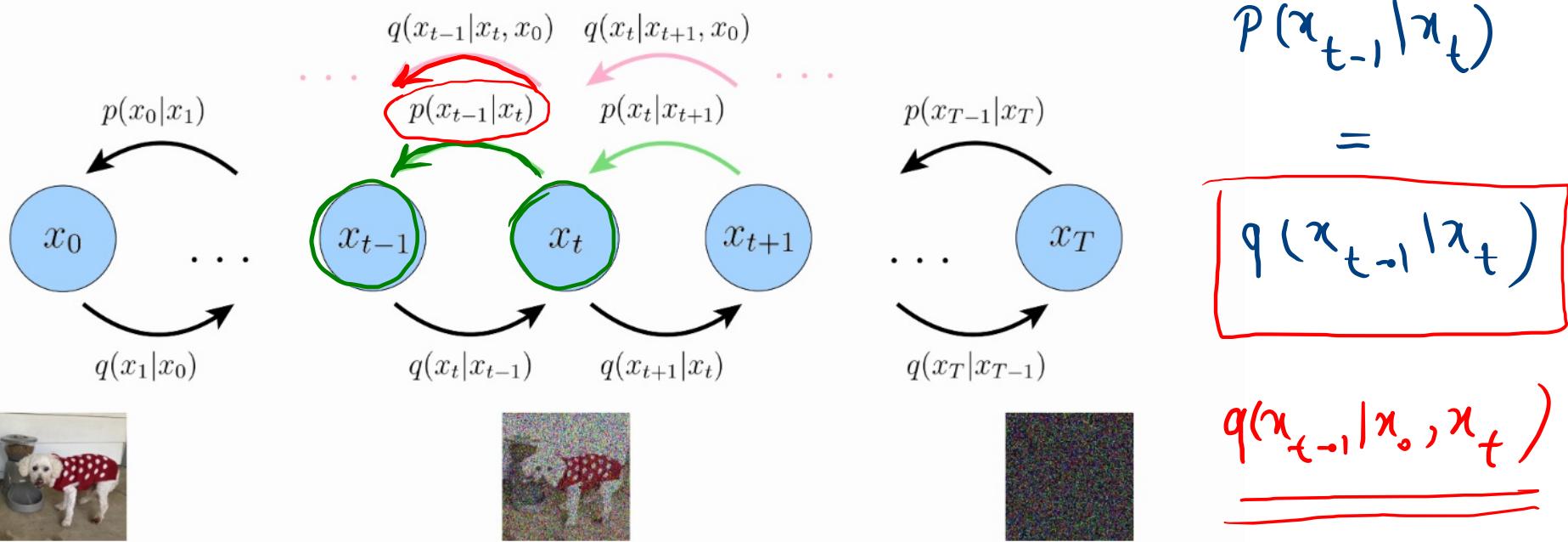
$$\begin{aligned}
\log p(\mathbf{x}) &= \log \int p(\mathbf{x}_{0:T}) d\mathbf{x}_{1:T} \\
&= \log \int \frac{p(\mathbf{x}_{0:T}) q(\mathbf{x}_{1:T} | \mathbf{x}_0)}{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} d\mathbf{x}_{1:T} \\
&= \log \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\frac{p(\mathbf{x}_{0:T})}{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \right] \\
&\geq \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_{0:T})}{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \right] \\
&= \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_T) \prod_{t=1}^T p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t)}{\prod_{t=1}^T q(\mathbf{x}_t | \mathbf{x}_{t-1})} \right] \\
&= \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_T) p_\theta(\mathbf{x}_0 | \mathbf{x}_1) \prod_{t=2}^T p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t)}{q(\mathbf{x}_T | \mathbf{x}_{T-1}) \prod_{t=1}^{T-1} q(\mathbf{x}_t | \mathbf{x}_{t-1})} \right] \\
&= \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_T) p_\theta(\mathbf{x}_0 | \mathbf{x}_1) \prod_{t=1}^{T-1} p_\theta(\mathbf{x}_t | \mathbf{x}_{t+1})}{q(\mathbf{x}_T | \mathbf{x}_{T-1}) \prod_{t=1}^{T-1} q(\mathbf{x}_t | \mathbf{x}_{t-1})} \right] \\
&= \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_T) p_\theta(\mathbf{x}_0 | \mathbf{x}_1)}{q(\mathbf{x}_T | \mathbf{x}_{T-1})} \right] + \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \prod_{t=1}^{T-1} \frac{p_\theta(\mathbf{x}_t | \mathbf{x}_{t+1})}{q(\mathbf{x}_t | \mathbf{x}_{t-1})} \right] \\
&= \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} [\log p_\theta(\mathbf{x}_0 | \mathbf{x}_1)] + \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_T)}{q(\mathbf{x}_T | \mathbf{x}_{T-1})} \right] + \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\sum_{t=1}^{T-1} \log \frac{p_\theta(\mathbf{x}_t | \mathbf{x}_{t+1})}{q(\mathbf{x}_t | \mathbf{x}_{t-1})} \right] \\
&= \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} [\log p_\theta(\mathbf{x}_0 | \mathbf{x}_1)] + \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_T)}{q(\mathbf{x}_T | \mathbf{x}_{T-1})} \right] + \sum_{t=1}^{T-1} \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p_\theta(\mathbf{x}_t | \mathbf{x}_{t+1})}{q(\mathbf{x}_t | \mathbf{x}_{t-1})} \right] \\
&= \mathbb{E}_{q(\mathbf{x}_1 | \mathbf{x}_0)} [\log p_\theta(\mathbf{x}_0 | \mathbf{x}_1)] + \mathbb{E}_{q(\mathbf{x}_{T-1}, \mathbf{x}_T | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_T)}{q(\mathbf{x}_T | \mathbf{x}_{T-1})} \right] + \sum_{t=1}^{T-1} \mathbb{E}_{q(\mathbf{x}_{t-1}, \mathbf{x}_t, \mathbf{x}_{t+1} | \mathbf{x}_0)} \left[\log \frac{p_\theta(\mathbf{x}_t | \mathbf{x}_{t+1})}{q(\mathbf{x}_t | \mathbf{x}_{t-1})} \right] \\
&= \underbrace{\mathbb{E}_{q(\mathbf{x}_1 | \mathbf{x}_0)} [\log p_\theta(\mathbf{x}_0 | \mathbf{x}_1)]}_{\text{reconstruction term}} - \underbrace{\mathbb{E}_{q(\mathbf{x}_{T-1} | \mathbf{x}_0)} [\mathcal{D}_{\text{KL}}(q(\mathbf{x}_T | \mathbf{x}_{T-1}) || p(\mathbf{x}_T))]}_{\text{prior matching term}} \\
&\quad - \sum_{t=1}^{T-1} \underbrace{\mathbb{E}_{q(\mathbf{x}_{t-1}, \mathbf{x}_{t+1} | \mathbf{x}_0)} [\mathcal{D}_{\text{KL}}(q(\mathbf{x}_t | \mathbf{x}_{t-1}) || p_\theta(\mathbf{x}_t | \mathbf{x}_{t+1}))]}_{\text{consistency term}}
\end{aligned}$$

$$\log p(\mathbf{x}) \geq \mathbb{E}_{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \left[\log \frac{p(\mathbf{x}_{0:T})}{q(\mathbf{x}_{1:T} | \mathbf{x}_0)} \right]$$

$$= \underbrace{\mathbb{E}_{q(\mathbf{x}_1 | \mathbf{x}_0)} [\log p_{\theta}(\mathbf{x}_0 | \mathbf{x}_1)]}_{\text{reconstruction term}} - \underbrace{\mathcal{D}_{\text{KL}}(q(\mathbf{x}_T | \mathbf{x}_0) || p(\mathbf{x}_T))}_{\text{prior matching term}}$$

$$- \sum_{t=2}^T \underbrace{\mathbb{E}_{q(\mathbf{x}_t | \mathbf{x}_0)} [\mathcal{D}_{\text{KL}}(q(\mathbf{x}_{t-1} | \mathbf{x}_t, \mathbf{x}_0) || p_{\theta}(\mathbf{x}_{t-1} | \mathbf{x}_t))] }_{\text{denoising matching term}}$$

$$q(\mathbf{x}_t | \mathbf{x}_{t-1})$$



$$q(\mathbf{x}_{t-1} | \mathbf{x}_0, \mathbf{x}_t)$$

$$q(x_t | x_{t-1})$$

$$q(x_{t-1} | x_t) =$$

$$\frac{q(x_t | x_{t-1}) q(x_{t-1})}{q(x_t)}$$

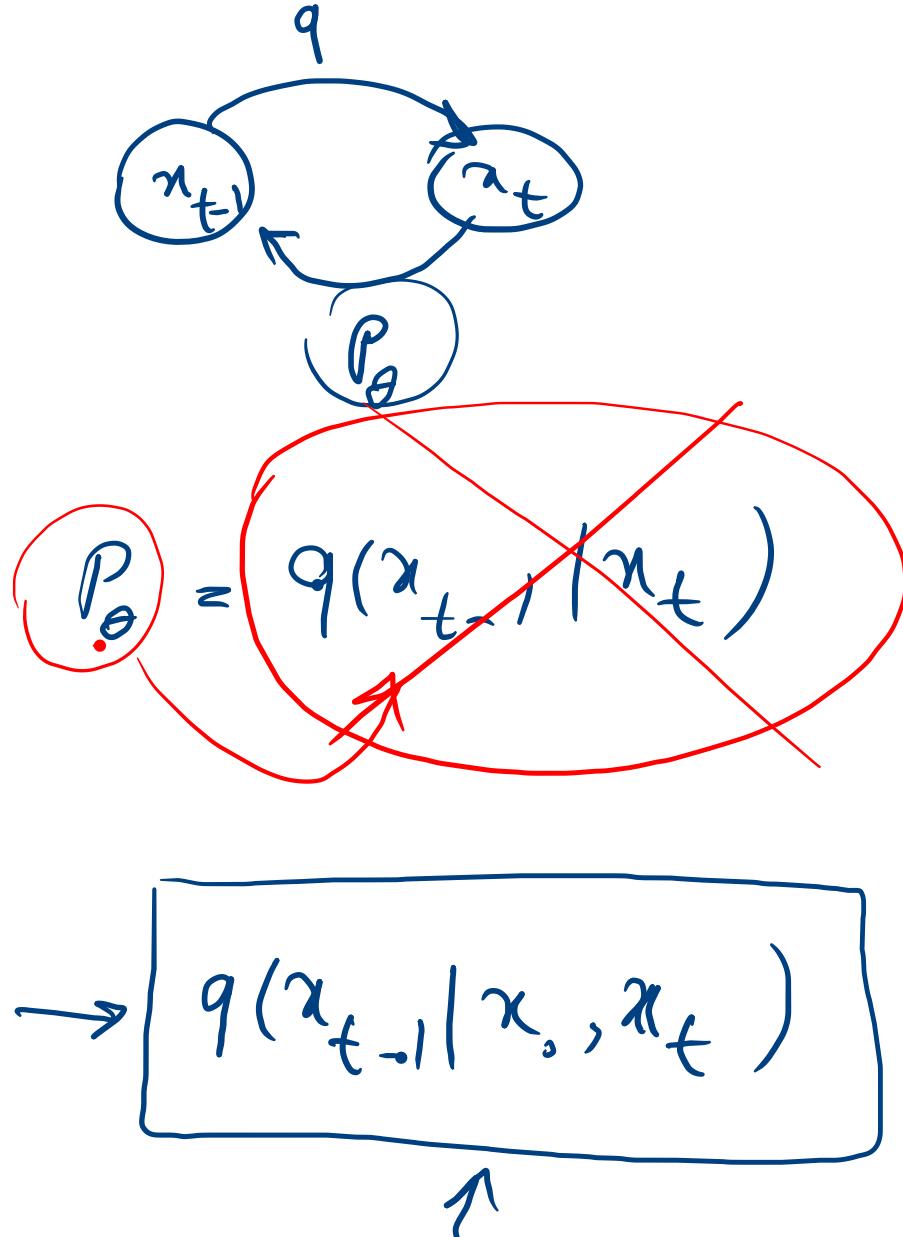
$$\boxed{x_t} = a \cancel{x_{t-1}} + b \cancel{\epsilon} \rightarrow$$

$$x_{t-1} = \frac{1}{a} x_t - \frac{b}{a} \epsilon$$

$$q(x_t | \underline{x_{t-1}}) = N(a \underline{x_{t-1}}, b^2 I)$$

$$\rightarrow q(x_{t-1} | x_t) \rightarrow$$

$$\therefore \text{جذر} \leftarrow q(x_{t-1} | x_t)$$



$$KL \left(q(x_{t-1} | x_0, x_t) || P_\theta(x_{t-1} | x_t) \right)$$

$N(\tilde{\mu}, \tilde{\Sigma})$

$N(\mu_\theta, \Sigma_\theta)$

Diffusion Probabilistic Models

◆ Diffusion Loss

$$\mathbb{E}_q \left[\underbrace{D_{KL}(q(\mathbf{x}_T|\mathbf{x}_0) \parallel p(\mathbf{x}_T))}_{L_T} + \sum_{t>1} \underbrace{D_{KL}(q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) \parallel p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t))}_{L_{t-1}} - \log \underbrace{p_\theta(\mathbf{x}_0|\mathbf{x}_1)}_{L_0} \right]$$

Regularization **Reconstruction**

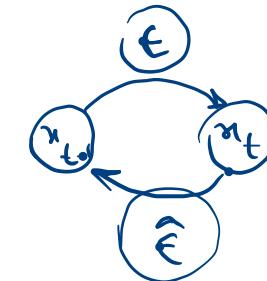
Learning β_t

Regularization **Reconstruction**

const

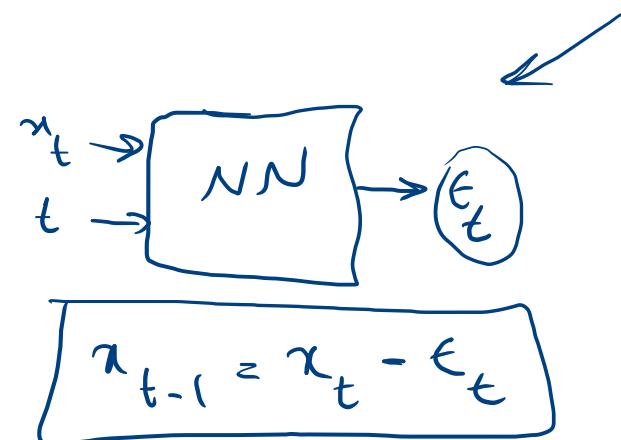
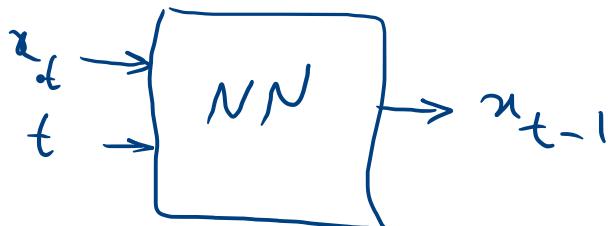
$$\mathbb{E}_q \left[\underbrace{D_{\text{KL}}(q(\mathbf{x}_T | \mathbf{x}_0) \| p(\mathbf{x}_T))}_{L_T} + \sum_{t>1} \underbrace{D_{\text{KL}}(q(\mathbf{x}_{t-1} | \mathbf{x}_t, \mathbf{x}_0) \| p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t))}_{L_{t-1}} - \underbrace{\log p_\theta(\mathbf{x}_0 | \mathbf{x}_1)}_{L_0} \right]$$

$$L_{t-1} = \mathbb{E}_q \left[\frac{1}{2\sigma_t^2} \|\tilde{\mu}_t(\mathbf{x}_t, \mathbf{x}_0) - \mu_\theta(\mathbf{x}_t, t)\|^2 \right] + C$$



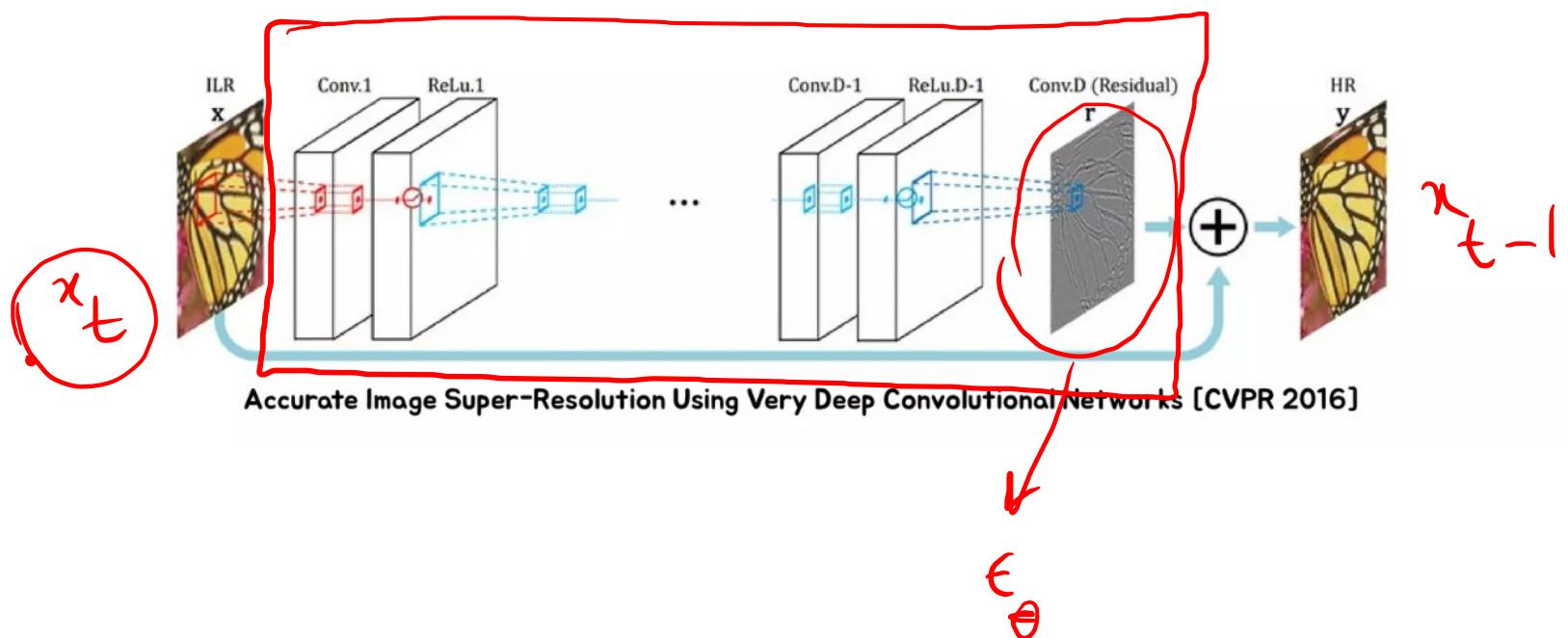
$$\rightarrow \mathbb{E}_{\mathbf{x}_0, \epsilon} \left[\frac{\beta_t^2}{2\sigma_t^2 \alpha_t (1 - \bar{\alpha}_t)} \|\epsilon - \epsilon_\theta(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, t)\|^2 \right]$$

$$L_{\text{simple}}(\theta) := \mathbb{E}_{t, \mathbf{x}_0, \epsilon} \left[\|\epsilon - \underline{\epsilon}_\theta(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon, t)\|^2 \right]$$



DDPM

◆ Residual Estimation



DDPM

◆ Loss Simplification

$$\mathbb{E}_q \left[\underbrace{D_{\text{KL}}(q(\mathbf{x}_T | \mathbf{x}_0) \| p(\mathbf{x}_T))}_{L_T} + \sum_{t>1} \underbrace{D_{\text{KL}}(q(\mathbf{x}_{t-1} | \mathbf{x}_t, \mathbf{x}_0) \| p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t))}_{L_{t-1}} - \underbrace{\log p_\theta(\mathbf{x}_0 | \mathbf{x}_1)}_{L_0} \right]$$



$$L_{\text{simple}}(\theta) := \mathbb{E}_{t, \mathbf{x}_0, \boldsymbol{\epsilon}} \left[\left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \boldsymbol{\epsilon}, t) \right\|^2 \right]$$