

Diffusion process

$\alpha_t = \sqrt{\alpha_t} x_{t-1} + \sqrt{1-\alpha_t} z_t$
 $= \sqrt{\alpha_t} (\sqrt{\alpha_{t-1}} x_{t-2} + \sqrt{1-\alpha_{t-1}} z'_1) + \sqrt{1-\alpha_t} z_t$
 $= \sqrt{\alpha_t \alpha_{t-1}} x_{t-2} + \sqrt{1-\alpha_t \alpha_{t-1}} z'_1 + \sqrt{1-\alpha_t} z_t$
 \vdots
 $= \sqrt{\prod_{i=1}^t \alpha_i} x_0 + \sqrt{1-\prod_{i=1}^t \alpha_i} z_t = \sqrt{\alpha_t} x_0 + \sqrt{1-\alpha_t} z_t$

$z_1 := \sqrt{1-\alpha_1} z_1 \sim \mathcal{N}(0, (1-\alpha_1)I)$
 $z'_1 := \sqrt{\alpha_1(1-\alpha_{t-1})} z'_1 \sim \mathcal{N}(0, \alpha_1(1-\alpha_{t-1})I)$
 $z_t + z'_1 \sim \mathcal{N}(0, (1-\alpha_t \alpha_{t-1})I)$

$(= \text{keep adding noise})$
 $z_1, z'_1, z_t \sim \mathcal{N}(0, I)$
 $(\Rightarrow \{\alpha_i\}_{i=1}^T \text{ are hyperparameters})$

Forward

$q(x_t | x_{t-1}) = \mathcal{N}(\sqrt{\alpha_t} x_{t-1}, \sqrt{1-\alpha_t} I)$ $q(x_t | x_0) = \mathcal{N}(\sqrt{\alpha_t} x_0, \sqrt{1-\alpha_t} I)$ $x_0 = \frac{1}{\sqrt{\alpha_t}} (x_t - \sqrt{1-\alpha_t} z_t)$

Backward

$① q(x_{t-1} | x_t, x_0) = q(x_t | x_{t-1}, x_0) \cdot \frac{q(x_{t-1} | x_0)}{q(x_t | x_0)}$
 $= \mathcal{N}(\sqrt{\alpha_t} x_{t-1}, \sqrt{1-\alpha_t} I) \times \frac{\mathcal{N}(\sqrt{\alpha_{t-1}} x_0, \sqrt{1-\alpha_{t-1}} I)}{\mathcal{N}(\sqrt{\alpha_t} x_0, \sqrt{1-\alpha_t} I)} = \mathcal{N}(\tilde{\mu}_t(x_t, x_0), \tilde{\Sigma}_t(x_t, x_0))$
 $\Rightarrow \tilde{\mu}_t(x_t, x_0) = \frac{1}{\sqrt{\alpha_t}} \left(x_t - \frac{1-\alpha_t}{\sqrt{1-\alpha_t}} z_t \right)$
 $\Rightarrow \tilde{\Sigma}_t(x_t, x_0) = \frac{1-\alpha_{t-1}}{1-\alpha_t} (1-\alpha_t) I$
 $② p_\theta(x_{t-1} | x_t) = \mathcal{N}(\mu_\theta(x_t, t), \Sigma_\theta(x_t, t))$
 $\Rightarrow \mu_\theta(x_t, t) = \frac{1}{\sqrt{\alpha_t}} \left(x_t - \frac{1-\alpha_t}{\sqrt{1-\alpha_t}} z_\theta(x_t, t) \right)$
 $\Rightarrow \Sigma_\theta(x_t, t) = \tilde{\Sigma}_t(x_t, x_0)$

correspondingly

Training objective

Step 1: Set T and $\{\alpha_t\}_{t=1}^T$ in advance

Step 2: Update θ to maximize the lower bound of $\log p_\theta(x_0)$

$\Rightarrow \log p_\theta(x_0) = \log \int p_\theta(x_{0:T}) \cdot dx_{1:T} = \log \int q(x_{1:T} | x_0) \cdot \frac{p_\theta(x_{0:T})}{q(x_{1:T} | x_0)} dx_{1:T}$
 $\geq \int q(x_{1:T} | x_0) \log \frac{p_\theta(x_{0:T})}{q(x_{1:T} | x_0)} dx_{1:T} = \mathbb{E}_q \left[\log \frac{p_\theta(x_0)}{q(x_0 | x_0)} \prod_{t=1}^T \frac{p_\theta(x_{t-1} | x_t)}{q(x_{t-1} | x_t)} \right]$
 $= \mathbb{E}_q \left[\log p_\theta(x_0) + \log \frac{p_\theta(x_0 | x_1)}{q(x_0 | x_1)} + \sum_{t=2}^T \left(\log \frac{p_\theta(x_{t-1} | x_t)}{q(x_{t-1} | x_t, x_0)} + \log \frac{q(x_{t-1} | x_0)}{q(x_{t-1} | x_t)} \right) \right]$
 $= \mathbb{E}_q \left[\log \frac{p_\theta(x_0)}{q(x_0 | x_1)} + \log p_\theta(x_1) + \sum_{t=2}^T \log \frac{p_\theta(x_{t-1} | x_t)}{q(x_{t-1} | x_t, x_0)} \right]$
 $= \mathbb{E}_q \left[\log p_\theta(x_0 | x_1) - \text{KL}(q(x_0 | x_1) \| p_\theta(x_0)) - \sum_{t=2}^T \text{KL}(q(x_{t-1} | x_t, x_0) \| p_\theta(x_{t-1} | x_t)) \right]$
 $\quad \mathcal{N}(\mu_\theta(x_1, 1), \Sigma_\theta(x_1, 1)) \quad \text{both} \approx \mathcal{N}(0, I)$
 $\quad \Rightarrow \text{maximize likelihood} \quad \Rightarrow \text{may remove for simplicity}$
 $\Rightarrow \text{KL}(q(x_{t-1} | x_t, x_0) \| p_\theta(x_{t-1} | x_t)) \approx \mathbb{E} \left[\frac{1}{2 \|\Sigma_\theta(x_t, t)\|_2} \|\tilde{\mu}_t(x_t, x_0) - \mu_\theta(x_t, t)\|_2^2 \right]$
 $= \mathbb{E} \left[\frac{(1-\alpha_t)^2}{2 \alpha_t (1-\alpha_t) \|\Sigma_\theta(x_t, t)\|_2} \|z_t - z_\theta(x_t, t)\|_2^2 \right]$
 $= \mathbb{E} \left[\frac{(1-\alpha_t)^2}{2 \alpha_t (1-\alpha_t) \|\Sigma_\theta(x_t, t)\|_2} \|z_t - z_\theta(\sqrt{\alpha_t} x_0 + \sqrt{1-\alpha_t} z_t, t)\|_2^2 \right]$

may remove for simplicity

Inference process

Step 1: $x_T \sim \mathcal{N}(0, I)$

Step 2: for $t = T, \dots, 1$, $x_{t-1} \sim p_\theta(x_{t-1} | x_t)$

i) $z_t \sim \mathcal{N}(0, I)$

ii) $x_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left(x_t - \frac{1-\alpha_t}{\sqrt{1-\alpha_t}} z_\theta(x_t, t) \right) + \frac{1-\alpha_{t-1}}{1-\alpha_t} (1-\alpha_t) z_t$