

Q1. 給定 $q(x_{1:T} | x_0) = \prod_{t=1}^T q(x_t | x_{t-1})$

根據 Markov 的定理可以得到: $\prod_{t=1}^T q(x_t | x_{t-1}, x_0) \quad -①$

對於 diffusion 來說, 是從 x_T 一路消除 noise 以得到與 x_0 相似的圖片.

由 ① $\Rightarrow q(x_1 | x_0) \prod_{t=2}^T q(x_t | x_{t-1}, x_0)$

$$= q(x_1 | x_0) \prod_{t=2}^T \frac{q(x_{t-1} | x_t, x_0) q(x_t | x_0) \cancel{q(x_0)}}{q(x_{t-1} | x_0) \cdot \cancel{q(x_0)}}$$

$$= q(x_1 | x_0) \prod_{t=2}^T \frac{q(x_t | x_0)}{q(x_{t-1} | x_0)} \prod_{t=2}^T q(x_{t-1} | x_t, x_0)$$

$$= q(x_1 | x_0) \left(\frac{\cancel{q(x_2 | x_0)}}{\cancel{q(x_1 | x_0)}} \cdot \frac{\cancel{q(x_3 | x_0)}}{\cancel{q(x_2 | x_0)}} \cdot \frac{\cancel{q(x_4 | x_0)}}{\cancel{q(x_3 | x_0)}} \cdots \frac{q(x_T | x_0)}{\cancel{q(x_{T-1} | x_0)}} \right) \prod_{t=2}^T q(x_{t-1} | x_t, x_0)$$

$$= q(x_T | x_0) \cdot \prod_{t=2}^T q(x_{t-1} | x_t, x_0)$$

Q2,

$$q(\mathbf{x}_t | \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t} \mathbf{x}_0, (1 - \bar{\alpha}_t) \mathbf{I})$$

proof 4

$$x_t = \sqrt{\alpha_t} \underline{x_{t-1}} + \sqrt{1 - \alpha_t} \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, 1)$$

$$\Rightarrow \sqrt{\alpha_t} \left(\sqrt{\alpha_{t-1}} \underline{x_{t-2}} + \sqrt{1 - \alpha_{t-1}} \epsilon_{t-1} \right) + \sqrt{1 - \alpha_t} \epsilon_t$$

$$\Rightarrow \sqrt{\alpha_t \cdot \alpha_{t-1}} x_{t-2} + \sqrt{\alpha_t (1 - \alpha_{t-1})} \epsilon_{t-1} + \sqrt{1 - \alpha_t} \epsilon_t$$

$$\Rightarrow \sqrt{\alpha_t \cdot \alpha_{t-1}} \left(\sqrt{\alpha_{t-2}} x_{t-3} + \sqrt{1 - \alpha_{t-2}} \epsilon_{t-2} \right) + \sqrt{\alpha_t (1 - \alpha_{t-1})} \epsilon_{t-1} + \sqrt{1 - \alpha_t} \epsilon_t$$

$$\Rightarrow \sqrt{\alpha_t \cdot \alpha_{t-1} \cdot \alpha_{t-2}} x_{t-3} + \sqrt{\alpha_t \cdot \alpha_{t-1} (1 - \alpha_{t-2})} \epsilon_{t-2} + \sqrt{\alpha_t (1 - \alpha_{t-1})} \epsilon_{t-1} + \sqrt{1 - \alpha_t} \epsilon_t$$

:

$$\Rightarrow \sqrt{\alpha_t \cdot \alpha_{t-1} \cdots \alpha_1} x_0 + \left(\sqrt{\alpha_t \cdots \alpha_2 (1 - \alpha_1)} \epsilon_1 + \cdots + \sqrt{\alpha_t (1 - \alpha_{t-1})} \epsilon_{t-1} + \sqrt{1 - \alpha_t} \epsilon_t \right)$$

獨立的 Gaussian noise $\sim \mathcal{N}(0, \bar{\alpha}_t)$. 其中 $\bar{\alpha}_t = 1 - (\alpha_t \cdots \alpha_1)$

持續項的, total variance. 設 $\alpha = 1 - \beta$

$$\begin{aligned} & \alpha_t \alpha_{t-1} \dots \alpha_1 + \alpha_t \alpha_{t-1} \dots \alpha_2 \beta_1 + \alpha_t \alpha_{t-1} \dots \alpha_3 \beta_2 + \dots + \alpha_t \beta_{t-1} + \beta_t \\ &= (\alpha_t \alpha_{t-1} \dots \alpha_2) (\alpha_1 + \beta_1) + \alpha_t \alpha_{t-1} \dots \alpha_3 \beta_2 + \dots + \alpha_t \beta_{t-1} + \beta_t \\ &= (\alpha_t \alpha_{t-1} \dots \alpha_2) \cdot 1 + \alpha_t \alpha_{t-1} \dots \alpha_3 \beta_2 + \dots + \alpha_t \beta_{t-1} + \beta_t \\ &= (\alpha_t \alpha_{t-1} \dots \alpha_3) (\alpha_2 + \beta_2) + \dots + \alpha_t \beta_{t-1} + \beta_t \\ &= (\alpha_t \alpha_{t-1} \dots \alpha_3) \cdot 1 + \dots + \alpha_t \beta_{t-1} + \beta_t \end{aligned}$$

$$\vdots$$

$$= \alpha_t + \beta_t = 1$$

\therefore noise variance

$$= 1 - \alpha_t \alpha_{t-1} \dots \alpha_1$$

$$= 1 - \bar{\alpha}_t$$

$$\therefore q(x_t | x_0) = \mathcal{N}(x_t; \sqrt{\bar{\alpha}_t} x_0, (1 - \bar{\alpha}_t) \mathbf{I})$$

proof b $q(\mathbf{x}_{t-1} | \mathbf{x}_t, \mathbf{x}_0) = \mathcal{N}(\mathbf{x}_{t-1}; \tilde{\boldsymbol{\mu}}_t(\mathbf{x}_t, \mathbf{x}_0), \tilde{\boldsymbol{\beta}}_t \mathbf{I}),$

從方程式中, 可得 x_t :

$$x_t = x_0 \sqrt{\bar{\alpha}_t} + \sqrt{1 - \bar{\alpha}_t} \epsilon_t$$

$$\Rightarrow x_0 = \frac{1}{\sqrt{\bar{\alpha}_t}} (x_t - \sqrt{1 - \bar{\alpha}_t} \epsilon_t)$$

$$\text{if } q(x_t | x_{t-1}) \sim \mathcal{N} \text{ 且 } \beta_t = (1 - \alpha_t) \text{ 可知, 則 } q(x_{t-1} | x_t) \sim \mathcal{N}$$

$$\therefore q(x_{t-1} | x_t) = q(x_{t-1} | x_t, x_0)$$

$$= \mathcal{N}(x_{t-1}, \tilde{\boldsymbol{\mu}}_t(x_t, x_0), \tilde{\boldsymbol{\beta}}_t \mathbf{I})$$

proof 8 $L_{t-1} = \mathbb{E}_q \left[\frac{1}{2\sigma_t^2} \|\tilde{\boldsymbol{\mu}}_t(\mathbf{x}_t, \mathbf{x}_0) - \boldsymbol{\mu}_\theta(\mathbf{x}_t, t)\|^2 \right] + C$

跟據 DDPM 中的方程式 5

$$\mathbb{E}_q \left[\underbrace{D_{\text{KL}}(q(\mathbf{x}_T | \mathbf{x}_0) \| p(\mathbf{x}_T))}_{L_T} + \sum_{t>1} \underbrace{D_{\text{KL}}(q(\mathbf{x}_{t-1} | \mathbf{x}_t, \mathbf{x}_0) \| p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t))}_{L_{t-1}} - \underbrace{\log p_\theta(\mathbf{x}_0 | \mathbf{x}_1)}_{L_0} \right] \quad (5)$$

L_T 是 forward process 可忽略, L_0 是固定

\therefore 只須看 L_{t-1} 項, 已知 $q(x_{t-1} | x_t, x_0) \sim \mathcal{N}$, $p_\theta(x_{t-1} | x_t) \sim \mathcal{N}$

可知 $D_{\text{KL}}(\mathcal{N}(M_1, \sigma_1^2) \| \mathcal{N}(M_2, \sigma_2^2))$

$$= \int \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(x-M_1)^2}{2\sigma_1^2}} \cdot \log \frac{\frac{1}{\sqrt{2\pi}\sigma_1} \cdot e^{-\frac{(x-M_1)^2}{2\sigma_1^2}}}{\frac{1}{\sqrt{2\pi}\sigma_2} \cdot e^{-\frac{(x-M_2)^2}{2\sigma_2^2}}} dx$$

$$\begin{aligned}
&= \int \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} \cdot \left(\log \frac{\sigma_2}{\sigma_1} - \frac{(x-\mu_1)^2}{2\sigma_1^2} + \frac{(x-\mu_2)^2}{2\sigma_2^2} \right) \\
&= \int \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} \cdot \log \frac{\sigma_2}{\sigma_1} - \int \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} \cdot \frac{(x-\mu_1)^2}{2\sigma_1^2} + \int \frac{1}{\sqrt{2\pi}\sigma_1} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} \cdot \frac{(x-\mu_2)^2}{2\sigma_2^2} \\
&= \log \frac{\sigma_2}{\sigma_1} - \frac{1}{2} + \frac{\sigma_1^2 + (\mu_1 - \mu_2)^2}{2\sigma_2^2}
\end{aligned}$$

$$\therefore L_{t-1} = D_{KL} \left(q(x_{t-1} | x_t, x_0) \parallel p_\theta(x_{t-1} | x_t) \right)$$

$$= D_{KL} \left(N(x_{t-1}; \tilde{\mu}_t(x_t, x_0), \sigma_t^2 I) \parallel N(x_{t-1}; \mu_\theta(x_t, t), \sigma_t^2 I) \right)$$

$$= \mathbb{E}_q \left[\frac{1}{2\sigma_t^2} \parallel \tilde{\mu}_t(x_t, x_0) - \mu_\theta(x_t, t) \parallel^2 \right] + C$$