

Given $g(X_{1:T}|X_0) = \prod_{t=1}^T g(X_t|X_{t-1})$

Show $g(X_{1:T}|X_0) = g(X_T|X_0) \prod_{t=T}^2 g(X_{t-1}|X_t, X_0)$

since X_1, X_2, \dots, X_T form a Markov chain when conditioned on X_0 :

$$\Rightarrow g(X_{1:T}|X_0) = \prod_{t=1}^T g(X_t|X_{t-1}, X_0)$$

$$\Rightarrow g(X_{1:T}|X_0) = \frac{g(X_T, X_{T-1}, X_0)}{g(X_{T-1}, X_0)} \times \frac{g(X_{T-1}, X_{T-2}, X_0)}{g(X_{T-2}, X_0)} \times \dots$$

$$\times \frac{g(X_2, X_1, X_0)}{g(X_1, X_0)} \times \frac{g(X_1, X_0)}{g(X_0)}$$

$$\Rightarrow g(X_{1:T}|X_0) = \frac{g(X_T, X_{T-1}, X_0)}{g(X_0)} \times \frac{g(X_{T-1}, X_{T-2}, X_0)}{g(X_{T-1}, X_0)} \times \dots \times \frac{g(X_2, X_1, X_0)}{g(X_2, X_0)}$$

$$= \frac{g(X_T, X_{T-1}, X_0)}{g(X_0)} \times \left[g(X_{T-2}|X_{T-1}, X_0) \times \dots \times g(X_1|X_2, X_0) \right]$$

$$= \frac{g(X_T, X_0)}{g(X_0)} \times \frac{g(X_T, X_{T-1}, X_0)}{g(X_T, X_0)} \times \prod_{t=T-1}^2 g(X_{t-1}|X_t, X_0)$$

$$= g(X_T|X_0) \times \left[g(X_{T-1}|X_T, X_0) \times \prod_{t=T-1}^2 g(X_{t-1}|X_t, X_0) \right]$$

$$= g(X_T|X_0) \prod_{t=T}^2 g(X_{t-1}|X_t, X_0)$$

eg(4). Define $\alpha_t = 1 - \beta_t$, $\bar{\alpha}_t = \prod_{i=1}^t \alpha_i$

Then $g(X_t|X_{t-1}) = \mathcal{N}(\sqrt{1 - \beta_t} X_{t-1}, \beta_t I)$

$$X_t = \sqrt{1 - \beta_t} X_{t-1} + \sqrt{\beta_t} \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, I)$$

$$= \sqrt{\alpha_t} X_{t-1} + \sqrt{1 - \alpha_t} \varepsilon$$

$$= \sqrt{\alpha_t \alpha_{t-1}} X_{t-2} + \sqrt{1 - \alpha_t \alpha_{t-1}} \varepsilon$$

$$= \dots$$

$$= \sqrt{\bar{\alpha}_t} X_0 + \sqrt{1 - \bar{\alpha}_t} \varepsilon$$

$$\therefore g(X_t|X_0) = \mathcal{N}(\sqrt{\bar{\alpha}_t} X_0, (1 - \bar{\alpha}_t) I)$$

eq(6). We know that $g(X_t|X_{t-1}, X_0) = g(X_t|X_{t-1})$ since Markov Chain.

$$g(X_t|X_{t-1}, X_0) = g(X_t|X_{t-1}) = N(\sqrt{1-\beta_t} X_{t-1}, \beta_t I)$$

And we also know that $g(X_t|X_0) = N(\sqrt{\alpha_t} X_0, (1-\alpha_t)I)$ from eq(4).

Thus, we get:

$$\begin{aligned} g(X_{t-1}|X_t, X_0) &= g(X_t|X_{t-1}, X_0) \cdot \frac{g(X_{t-1}|X_0)}{g(X_t|X_0)} \\ &\propto \exp\left[-\frac{1}{2}\left(\frac{(X_t - \sqrt{\alpha_t} X_{t-1})^2}{\beta_t} + \frac{(X_{t-1} - \sqrt{\alpha_{t-1}} X_0)^2}{1-\alpha_{t-1}} - \frac{(X_t - \sqrt{\alpha_t} X_0)^2}{1-\alpha_t}\right)\right] \\ &= \exp\left[-\frac{1}{2}\left(\frac{X_t^2 - 2\sqrt{\alpha_t} X_t X_{t-1} + \alpha_t X_{t-1}^2}{\beta_t} + \frac{X_{t-1}^2 - 2\sqrt{\alpha_{t-1}} X_0 X_{t-1} + \alpha_{t-1} X_0^2}{1-\alpha_{t-1}} - \frac{(X_t - \sqrt{\alpha_t} X_0)^2}{1-\alpha_t}\right)\right] \\ &= \exp\left[-\frac{1}{2}\left(\left(\frac{\alpha_t}{\beta_t} + \frac{1}{1-\alpha_{t-1}}\right) X_{t-1}^2 - \left(\frac{2\sqrt{\alpha_t}}{\beta_t} X_t + \frac{2\sqrt{\alpha_{t-1}}}{1-\alpha_{t-1}} X_0\right) X_{t-1} + C(X_t, X_0)\right)\right] \end{aligned}$$

$C(X_t, X_0)$ is an irrelevant part of X_{t-1} , so we can omit it.

Thus, $g(X_{t-1}|X_t, X_0)$ is Gaussian Distribution.

$$\text{And } \tilde{\beta}_t = \frac{1}{\left(\frac{\alpha_t}{\beta_t} + \frac{1}{1-\alpha_{t-1}}\right)} = \frac{1}{\left(\frac{\alpha_t - \alpha_t + \beta_t}{\beta_t(1-\alpha_{t-1})}\right)} = \frac{1-\alpha_{t-1}}{1-\alpha_t} \cdot \beta_t$$

$$\begin{aligned} \tilde{\mu}_t(X_t, X_0) &= \frac{\left(\frac{\sqrt{\alpha_t}}{\beta_t} X_t + \frac{\sqrt{\alpha_{t-1}}}{1-\alpha_{t-1}} X_0\right)}{\left(\frac{\alpha_t}{\beta_t} + \frac{1}{1-\alpha_{t-1}}\right)} = \left(\frac{\sqrt{\alpha_t}}{\beta_t} X_t + \frac{\sqrt{\alpha_{t-1}}}{1-\alpha_{t-1}} X_0\right) \cdot \frac{1-\alpha_{t-1}}{1-\alpha_t} \cdot \beta_t \\ &= \frac{\sqrt{\alpha_t}(1-\alpha_{t-1})}{1-\alpha_t} X_t + \frac{\sqrt{\alpha_{t-1}} \beta_t}{1-\alpha_t} X_0 \end{aligned}$$

$$\therefore g(X_{t-1}|X_t, X_0) = N(X_{t-1}; \tilde{\mu}_t(X_t, X_0), \tilde{\beta}_t I)$$

$$\text{where } \tilde{\mu}_t(X_t, X_0) := \frac{\sqrt{\alpha_{t-1}} \beta_t}{1-\alpha_t} X_0 + \frac{\sqrt{\alpha_t}(1-\alpha_{t-1})}{1-\alpha_t} X_t \quad \text{and} \quad \tilde{\beta}_t := \frac{1-\alpha_{t-1}}{1-\alpha_t} \beta_t$$

$$\begin{aligned} \text{eq (8.) } L &= E_q \left[-\log \frac{p_\theta(X_{0:T})}{q(X_{1:T}|X_0)} \right] \\ &= E_q \left[-\log p(X_T) - \sum_{t=1}^T \log \frac{p_\theta(X_{t-1}|X_t)}{q(X_t|X_{t-1})} \right] \\ &= E_q \left[-\log p(X_T) - \sum_{t=1}^T \log \frac{p_\theta(X_{t-1}|X_t)}{q(X_t|X_{t-1})} - \log \frac{p_\theta(X_0|X_1)}{q(X_1|X_0)} \right] \\ &= E_q \left[-\log p(X_T) - \sum_{t=1}^T \log \frac{p_\theta(X_{t-1}|X_t)}{q(X_{t-1}|X_t, X_0)} \cdot \frac{q(X_{t-1}|X_0)}{q(X_t|X_0)} - \log \frac{p_\theta(X_0|X_1)}{q(X_1|X_0)} \right] \\ &= E_q \left[-\log \frac{p(X_T)}{q(X_T|X_0)} - \sum_{t=1}^T \log \frac{p_\theta(X_{t-1}|X_t)}{q(X_{t-1}|X_t, X_0)} - \log p_\theta(X_0|X_1) \right] \\ &= E_q \left[\underbrace{D_{KL}(q(X_T|X_0) \| p(X_T))}_{L_T} + \sum_{t=1}^T \underbrace{D_{KL}(q(X_{t-1}|X_t, X_0) \| p_\theta(X_{t-1}|X_t))}_{L_{t-1}} - \underbrace{\log p_\theta(X_0|X_1)}_{L_0} \right] \end{aligned}$$

Then $D_{KL}(q(X_{t-1}|X_t, X_0) || p_\theta(X_{t-1}|X_t))$

$$= D_{KL}(N(X_{t+1}; \tilde{\mu}(X_t, X_0), \sigma_t^2 I) \| N(X_{t+1}; \mu_\theta(X_t, t), \sigma_t^2 I))$$

$$\left(\because D_{KL}(p_1 || p_2) = \frac{1}{2} (\text{tr}(\Sigma_2^{-1} \Sigma_1) + (\mu_2 - \mu_1)^T \Sigma_2^{-1} (\mu_2 - \mu_1) - n + \log \frac{\det(\Sigma_2)}{\det(\Sigma_1)}) \right)$$

$$= \frac{1}{2} \left(n + \frac{1}{\sigma_t^2} \left\| \tilde{\mu}_t(x_t, x_0) - \mu_\theta(x_t, t) \right\|^2 - n + \log | \right)$$

$$= \frac{1}{2\delta_t^2} \|\tilde{\mu}_t(X_t, X_0) - \mu_\theta(X_t, t)\|^2$$

$$\therefore L_{t-1} = E_g \left[\frac{1}{2\sigma_t^2} \left\| \tilde{\mu}_t(x_t, x_0) - \mu_0(x_t, t) \right\|^2 \right] + C.$$