

forward

$$\text{step 1} \quad \begin{cases} X_t = \sqrt{\alpha_t} X_{t-1} + \sqrt{1-\alpha_t} \varepsilon \sim N(0, I) \\ f(x_t | x_{t-1}) = N(\sqrt{\alpha_t} x_{t-1}, (1-\alpha_t) I) \end{cases}$$

$$\text{step } t \quad \begin{cases} X_t = \sqrt{\tilde{\alpha}_t} X_0 + \sqrt{1-\tilde{\alpha}_t} \varepsilon \\ f(x_t | x_0) = N(\sqrt{\tilde{\alpha}_t} x_0, (1-\tilde{\alpha}_t) I) \end{cases}$$

backward

$$\textcircled{1} \quad p_\theta(x_{t-1} | x_t) \approx N(\mu_\theta(x_t, t), \beta_t I) \quad \beta \approx 0$$

$$\textcircled{2} \quad \begin{cases} \mu(x_t, t) = \frac{1}{\sqrt{1-\beta_t}} \cdot \left(x_t + \beta_t \nabla_{x_t} \log p_t(x_t) \right) \\ \mu_\theta(x_t, t) = \frac{1}{\sqrt{1-\beta_t}} \cdot \left(x_t + \beta_t \nabla_{x_t} \log p_\theta(x_t, t) \right) \end{cases}$$

$$(MSE) \quad \mathcal{L}(\theta) = \sum_{t=1}^T \lambda_t \mathbb{E}_{x_t} [\| \mu - \mu_\theta \|^2]$$

$$\text{learning} \quad \mathbb{E}[X_{t-1} | X_t]$$

$$\iff \text{learning} \quad \varepsilon$$

$$\mathbb{E}_{x_0 | x_t} \left\| \nabla_{x_t} \log p_{t|0}(x_t | x_0) - \nabla_{x_t} \log p_\theta(x_t, t) \right\|^2 = \sum_{t=1}^T \mathbb{E}_{x_0, \varepsilon, t} \left\| \varepsilon - \varepsilon_\theta(\sqrt{\tilde{\alpha}_t} x_0 + \sqrt{1-\tilde{\alpha}_t} \varepsilon, t) \right\|^2$$

∴

$$\log p_{t|0}(x_t | x_0) = \frac{-1}{2(1-\tilde{\alpha}_t)} \| x_t - \sqrt{\tilde{\alpha}_t} x_0 \|^2 + C$$

$$\nabla_{x_t} \log p_{t|0}(x_t | x_0) = - \frac{x_t - \sqrt{\tilde{\alpha}_t} x_0}{(1-\tilde{\alpha}_t)} = - \frac{\varepsilon}{\sqrt{1-\tilde{\alpha}_t}}$$

$$\nabla_{x_t} \log p_\theta(x_t, t) = \frac{-\varepsilon_\theta(x_t, t)}{\sqrt{1-\tilde{\alpha}_t}}$$

train ε_θ

① sample $x_0 \sim \text{data}$

② " $t \sim \text{Uniform}(\{1, \dots, T\})$

③ " $\varepsilon \sim N(0, I)$

④ G.D. $\nabla_{\theta} \| \varepsilon - \varepsilon_\theta(x_t, t) \|^2$

reverse

$$x_{t-1} = \frac{1}{\sqrt{1-\beta_t}} \left(x_t - \frac{\beta_t}{\sqrt{1-\tilde{\alpha}_t}} \varepsilon_\theta(x_t, t) \right) + \sqrt{\beta_t} \varepsilon_t$$

DDPM
forward

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

$$\approx \left(1 - \frac{\beta_t}{2}\right) X_t + \sqrt{\beta_t} \varepsilon$$

Note:

$$\sqrt{1-\alpha} \approx 1 - \frac{\alpha}{2}$$

SDE
forward

$$X_{t+\Delta t} - X_t = -\frac{1}{2} \beta(t) X_t \Delta t + \sqrt{\beta(t)} \sqrt{\Delta t} \varepsilon$$

$$dX_t = -\frac{1}{2} \beta(t) X_t dt + \sqrt{\beta(t)} dW_t$$

$$\bar{\alpha}_t = \prod (1-\beta_s) \approx \exp\left(-\int_0^t \beta(s) ds\right)$$

$$1-\alpha \approx e^{-\alpha}$$

$$\sum \beta(t) \Delta t \approx \int_0^T \beta(t) dt$$

Reverse SDE

$$d\bar{X}_t = \left[f(\bar{X}_t, t) - g(t)^2 \nabla_x \log p_t(\bar{X}_t) \right] dt + g(t) d\bar{W}_t$$

$$= \left[-\frac{\beta(t)}{2} \bar{X}_t - \beta(t) \nabla_x \log p_t(\bar{X}_t) \right] dt + \sqrt{\beta(t)} d\bar{W}_t$$