

$$\mathcal{L}(\theta, \varphi) = \int q(z|x, \theta) \log \frac{p(x, z|\varphi)}{q(z|x, \theta)} dz =$$

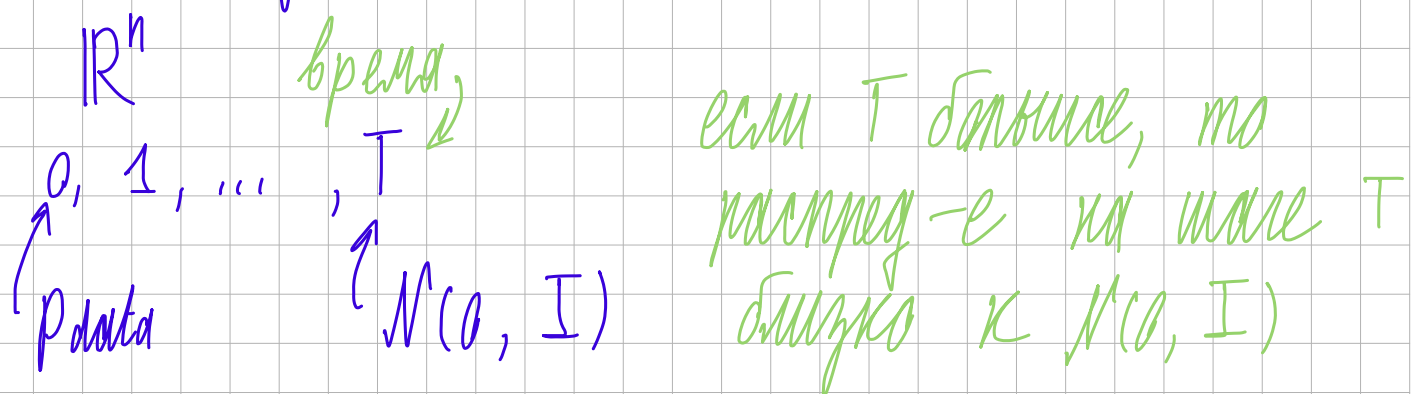
$$= \{ p(x, z|\varphi) = p(x|z, \varphi) p(z) \} = \int q(z) \log \frac{p(x|z, \varphi)}{q(z)} dz$$

богач ем крч....

лекция

Диффузионные модели

Denoising Diffusion Probabilistic Models (2020)



Forward process

$$q(x_t | x_{t-1}) = \mathcal{N}(x_t | \sqrt{1 - \beta_t} x_{t-1}, \beta_t I)$$

transition prob dist.

последовательно зашумляем картинку

$$q(x_{0:T} | x_0) = \prod_{t=1}^T q(x_t | x_{t-1})$$

Backward process

$$p_{\theta}(X_{t-1} | X_t) = \mathcal{N}(X_{t-1} | \mu_{\theta}(X_t, t), \Sigma_{\theta}(X_t, t))$$

↓
нормально нормально $\beta_t I$

$$p_{\theta}(X_{0:T}) := p(X_T) \cdot \prod_{t=T}^1 p_{\theta}(X_{t-1} | X_t)$$

$\mathcal{N}(0, I)$

как чиним?

1) $X_T \sim \mathcal{N}(0, I)$

2) for $t=T$ to 1:

$$X_{t-1} \sim p_{\theta}(X_{t-1} | X_t)$$

3) X_0 - final object

нормал: $X_0 \sim p_{data}$

правильно: $\log p_{\theta}(X_0) = \log \int p_{\theta}(X_{0:T}) dx_1 \dots dx_T =$

$$= \log \int q(X_{1:T} | X_0) \frac{p_{\theta}(X_{0:T})}{q(X_{1:T} | X_0)} dx_1 \dots dx_T =$$
$$= \log \mathbb{E}_{q(X_{1:T} | X_0)} \left[\frac{p_{\theta}(X_{0:T})}{q(X_{1:T} | X_0)} \right] \geq \{ \text{Jensen Ineq} \} \geq$$
$$\geq \mathbb{E}_{q(X_{1:T} | X_0)} \left[\log \frac{p_{\theta}(X_{0:T})}{q(X_{1:T} | X_0)} \right] \rightarrow \max_{\theta}$$

↑
находим

$$\mathbb{E}_{q(x_{1:T}|x_0)} \left[\log p(x_t) + \sum_{t=1}^T \log \frac{p_\theta(x_{t-1}|x_t)}{q(x_t|x_{t-1})} \right] = L$$

$$x_0 \rightarrow x_1 \rightarrow \dots x_T \rightarrow \nabla_\theta$$

Training:

$$1) \text{ Sample } x_1 \sim q(x_1|x_0) \dots x_T \sim q(x_T|x_{T-1})$$

$$2) \nabla_\theta \sum_t \log \frac{p_\theta(x_{t-1}|x_t)}{q(x_t|x_{t-1})}$$

$$L = \mathbb{E}_{q(x_{1:T}|x_0)} \left[-KL(q(x_T|x_1) \| p(x_T)) - \sum_{t=1}^T KL(q(x_{t-1}|x_t, x_0) \| p_\theta(x_{t-1}|x_t)) + \log p_\theta(x_0|x_1) \right]$$

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

$$q(x_t|x_0) = \mathcal{N}(x_t | \prod_{i=1}^t \sqrt{1-\beta_i} x_0, (1 - \prod_{i=1}^t (1-\beta_i)) \mathbb{I})$$

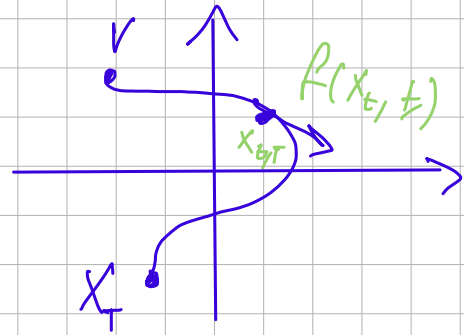
$$1) t \sim \mathcal{U}[1, \dots, T] \quad x_t \sim q(x_t|x_0)$$

$$2) \nabla_\theta KL(q(x_{t-1}|x_t, x_0) \| p_\theta(x_{t-1}|x_t))$$

Ordinary Differential Equation

$$X_t \in \mathbb{R}^n \quad t \in [0, T]$$

$$\begin{cases} dx_t = f(x_t, t) dt \\ X_0 = V \in \mathbb{R}^n \end{cases}$$



Euler scheme:

$$X_{t+h} = X_t + h \cdot f(X_t, t) + \bar{O}(h) \approx X_t + h f(X_t, t)$$

$X(t) - ?$

Stochastic Differential Equation (SDE)

$$t \in [0, T]$$

$$\begin{cases} dx_t = f(x_t, t) dt + g(t) dW_t \\ X_0 \sim p_0 \end{cases}$$

Wiener Process
стохастич., шум

Euler scheme:

$$X_{t+h} = X_t + h \cdot f(X_t, t) + \sqrt{h} g(t) \epsilon_t \quad \epsilon_t \sim N(0, I)$$

$X_t \sim p_t$ - solution

замыкание = стохастич. Dy!

$$t: 0 \rightarrow T$$

$$\begin{cases} dx_t = [f(x_t, t) - g^2(t) \nabla_x \log p_t(x_t)] dt + g(t) dW_t \\ X_T \sim p_T \end{cases}$$

$$t: T \rightarrow 0$$

$\nabla_x \log p_t(x_t)$ - score function

$$X_{t-h} = X_t - h f(x_t, t) + h g^2(t) \nabla_x \log p_t(x_t) + \sqrt{h} g(t) \varepsilon_t$$

SDE Forward:

$$\begin{cases} dx_t = -\frac{1}{2} \beta(t) x_t dt + \sqrt{\beta(t)} dW_t \\ X \sim p_{\text{data}} \end{cases}$$

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

SDE Backward:

$$\begin{cases} dx_t = (-\frac{1}{2} \beta(t) x_t dt - \beta(t) \nabla_x \log(p_t(x_t)) dt + \sqrt{\beta(t)} dW_t \\ X_T \sim \mathcal{N}(0, I) \end{cases}$$

но у нас нет $\nabla_x \log p_t(x_t)$! - можно грубо!

Denoising Score Matching

$$S_{\theta}(X, t) \approx \nabla_x \log p_t(X)$$

$$\int \int p_t(X) \|S_{\theta}(X, t) - \nabla_x \log p_t(X)\|^2 dx dt \rightarrow \min_{\theta}$$

\Updownarrow эквив. задача

$$\mathbb{E} \|S_{\theta}(X_t, t) - \nabla_x \log p_t(X_t | X_0)\|^2 \rightarrow \min_{\theta}$$

↑ *это время считаем!*

$$t \sim \mathcal{U}[0, T]$$

$$X_0 \sim p_{data}$$

$$X_t \sim p_t(X_t | X_0)$$

$h \rightarrow$ any real value