gaussian_diffusion.py

1. q_sample($\boldsymbol{x}_0, t, \boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I})$): $\quad //q(\boldsymbol{x}_t|\boldsymbol{x}_0)$

$$\text{return } \boldsymbol{x}_t = \underbrace{\sqrt{\bar{\alpha}_t}}_{\text{sqrt\_alphas\_cumprod}} \cdot \boldsymbol{x}_0 + \underbrace{\sqrt{1-\bar{\alpha}_t}}_{\text{sqrt\_one\_minus\_alphas\_cumprod}} \cdot \boldsymbol{\epsilon}$$

2. _predict_xstart_from_eps ($\boldsymbol{x}_t, t, \boldsymbol{\epsilon}_{\boldsymbol{\theta}}$):

$$\text{return } \boldsymbol{x}_0 = \frac{\boldsymbol{x}_t - \sqrt{1-\bar{\alpha}_t} \cdot \boldsymbol{\epsilon}_{\boldsymbol{\theta}}}{\sqrt{\bar{\alpha}_t}} = \underbrace{\sqrt{1/\bar{\alpha}_t}}_{\text{sqrt\_recip\_alphas\_cumprod}} \cdot \boldsymbol{x}_t - \underbrace{\sqrt{1/\bar{\alpha}_t - 1}}_{\text{sqrt\_recipm1\_alpha\_cumprod}} \cdot \boldsymbol{\epsilon}_{\boldsymbol{\theta}}$$

3. _predict_eps_from_xstart ($\boldsymbol{x}_t, t, \boldsymbol{x}_0$):

$$\text{return } \hat{\boldsymbol{\epsilon}}_t = (\underbrace{\sqrt{1/\bar{\alpha}_t}}_{\text{sqrt\_recip\_alphas\_cumprod}} \cdot \boldsymbol{x}_t - \boldsymbol{x}_0)/\underbrace{\sqrt{1/\bar{\alpha}_t - 1}}_{\text{sqrt\_recipm1\_alpha\_cumprod}}$$

4. q_posterior_mean_variance ($\boldsymbol{x}_0, \boldsymbol{x}_t, t$) : $\quad //q(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t, \boldsymbol{x}_0)$

$$\text{return } \boldsymbol{x}_{t-1} = \underbrace{\frac{\sqrt{\bar{\alpha}_{t-1}}\beta_t}{1-\bar{\alpha}_t}}_{\text{posterior\_mean\_coef1}} \boldsymbol{x}_0 + \underbrace{\frac{\sqrt{\alpha_t}(1-\bar{\alpha}_{t-1})}{1-\bar{\alpha}_t}}_{\text{posterior\_mean\_coef2}} \boldsymbol{x}_t$$

5. p_mean_variance ($\boldsymbol{\epsilon}_{\boldsymbol{\theta}}, \boldsymbol{x}_t, t$):

$$\text{return} \begin{cases} \boldsymbol{\epsilon}_t, \boldsymbol{v} = \boldsymbol{\epsilon}_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t) & \\ \Sigma_{\boldsymbol{\theta}}(\boldsymbol{x}_t, t) = \exp(\boldsymbol{v}\log\beta_t + (1-\boldsymbol{v})\log\tilde{\beta}_t) & //\text{model\_variance} \\ \boldsymbol{x}_0 = \text{\_predict\_xstart\_from\_eps}(\boldsymbol{x}_t,\text{t},\boldsymbol{\epsilon}_t) & //(\boldsymbol{x}_t - \sqrt{1-\bar{\alpha}_t}\cdot\boldsymbol{\epsilon}_{\boldsymbol{\theta}})/\sqrt{\bar{\alpha}_t} \\ \boldsymbol{x}_0 = \text{process\_xstart}(\boldsymbol{x}_0) & //\text{pred\_xstart:clamp}(\boldsymbol{x}_0, -1, 1) \\ \boldsymbol{x}_{t-1} = \text{q\_posterior\_mean\_variance}(\boldsymbol{x}_0,\boldsymbol{x}_t,\text{t}) & //\text{model\_mean: } q(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t, \boldsymbol{x}_0) \end{cases}$$

6. condition_score ($s_\phi, \boldsymbol{x}_{t-1}, \boldsymbol{x}_0, \boldsymbol{x}_t, t$): $\quad //s_\phi = \nabla_{\boldsymbol{x}_t}\log p_\phi(\boldsymbol{y}|\boldsymbol{x}_t)$: condition function

$$\text{return} \begin{cases} \hat{\boldsymbol{\epsilon}}_t = \boldsymbol{\epsilon}_{\boldsymbol{\theta}}(\boldsymbol{x}_t) - \sqrt{1-\bar{\alpha}_t}\cdot s_\phi & //\mathrm{s}_\phi = \nabla_{\boldsymbol{x}_\mathrm{t}}\log\mathrm{p}_\phi(\boldsymbol{y}|\boldsymbol{x}_\mathrm{t}) \\ \boldsymbol{x}_0 = \text{\_predict\_xstart\_from\_eps}(\boldsymbol{x}_t,\text{t},\hat{\boldsymbol{\epsilon}}_t) & //\text{pred\_xstart : } (\boldsymbol{x}_t - \sqrt{1-\bar{\alpha}_t}\cdot\boldsymbol{\epsilon}_{\boldsymbol{\theta}})/\sqrt{\bar{\alpha}_t} \\ \boldsymbol{x}_{t-1} = \text{q\_posterior\_mean\_variance}(\boldsymbol{x}_0,\boldsymbol{x}_t,\text{t}) & //\text{model\_mean: } q(\boldsymbol{x}_{t-1}|\boldsymbol{x}_t, \boldsymbol{x}_0) \end{cases}$$

7. condition_mean ($s, \boldsymbol{x}_{t-1}, \sigma_t, \boldsymbol{x}_t, t$): $\quad //$

$$\text{return } \boldsymbol{x}_{t-1} + \sigma_t \cdot s(\boldsymbol{x}_t, t)$$

7. ddim_sample ($\boldsymbol{\epsilon}_{\boldsymbol{\theta}}, \boldsymbol{x}_t, t$): $\quad //$sample $\boldsymbol{x}_{t-1}$

$\boldsymbol{x}_0, \boldsymbol{x}_{t-1}, \Sigma_{\boldsymbol{\theta}} =$ p_mean_variance$(\boldsymbol{\epsilon}_{\boldsymbol{\theta}}, \boldsymbol{x}_t, t)$ //mean:$\boldsymbol{x}_{t-1}$, pred_xstart: $\boldsymbol{x}_0$, variance: $\Sigma_{\boldsymbol{\theta}}$

$\boldsymbol{x}_0, \boldsymbol{x}_{t-1} =$ condition_score$(s_\phi, \boldsymbol{x}_{t-1}, \boldsymbol{x}_0, \boldsymbol{x}_t, t)$ //

$\hat{\boldsymbol{\epsilon}}_t =$ _predict_eps_from_xstart($\boldsymbol{x}_t$,t)

$\sigma = \eta \cdot \sqrt{(1-\bar{\alpha}_{t-1})/(1-\bar{\alpha}_t)} \cdot \sqrt{1-\bar{\alpha}_t/\bar{\alpha}_{t-1}}$

$\boldsymbol{x}_{t-1} = \sqrt{\bar{\alpha}_{t-1}} \cdot \boldsymbol{x}_0 + \sqrt{1-\bar{\alpha}_{t-1}-\sigma^2} \cdot \hat{\boldsymbol{\epsilon}}_t + \sigma \cdot \boldsymbol{\epsilon}$

$\sigma = \eta \cdot \sqrt{(1-\bar{\alpha}_{t-1})/(1-\bar{\alpha}_t)} \cdot \sqrt{1-\bar{\alpha}_t/\bar{\alpha}_{t-1}}$

8. p_sample $(\boldsymbol{\epsilon}_{\boldsymbol{\theta}}, \boldsymbol{x}_t, t)$: //sample $\boldsymbol{x}_{t-1}$

$\boldsymbol{x}_0, \boldsymbol{x}_{t-1}, \Sigma_{\boldsymbol{\theta}} =$ p_mean_variance$(\boldsymbol{\epsilon}_{\boldsymbol{\theta}}, \boldsymbol{x}_t, t)$ //mean:$\boldsymbol{x}_{t-1}$, pred_xstart: $\boldsymbol{x}_0$, variance: $\Sigma_{\boldsymbol{\theta}}$

$\hat{\boldsymbol{x}}_{t-1} =$ condition_mean$(s, \boldsymbol{x}_{t-1}, \sigma_t, \boldsymbol{x}_t, t)$ //

return $\boldsymbol{x}_{t-1} = \hat{\boldsymbol{x}}_{t-1} + \exp(0.5 \cdot \log \sigma_t) \cdot \boldsymbol{\epsilon}$