



Exploring techniques to speed up the generation of high-dimensional objects in Diffusion Model



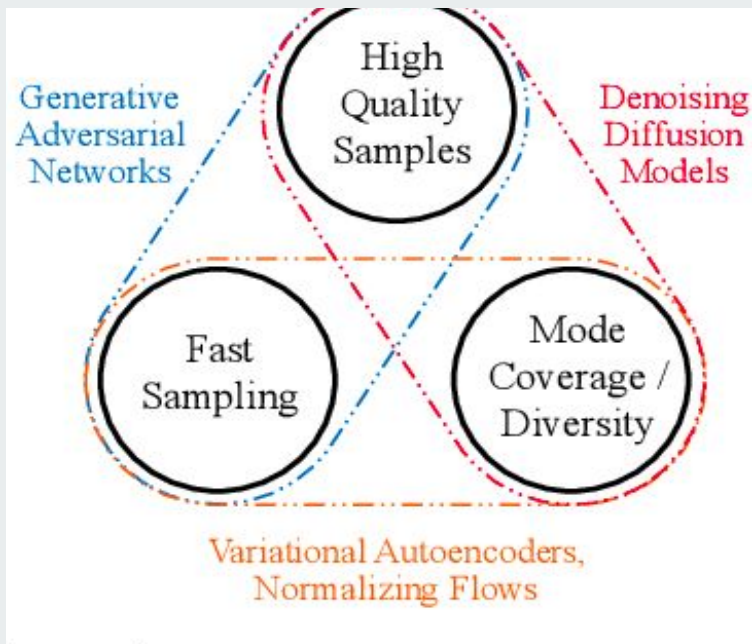
Team Members :

Meghana 200050135

Namitha 200050062

Ruthvika 200050018

Sindhuja 200050047



Tackle the trilemma by accelerating diffusion models



Variational diffusion models



<https://openreview.net/pdf?id=2LdBqxc1Yv>

Parametrization of Noise Schedule

SOTA likelihood



Denoising Diffusion GANs

Diffusion models are slow due to modelling the reverse process as a Gaussian distribution which only holds for small β_t requiring a large number of steps. DDGANs model the reverse process as a multi-modal distribution to produce samples in a small number of steps

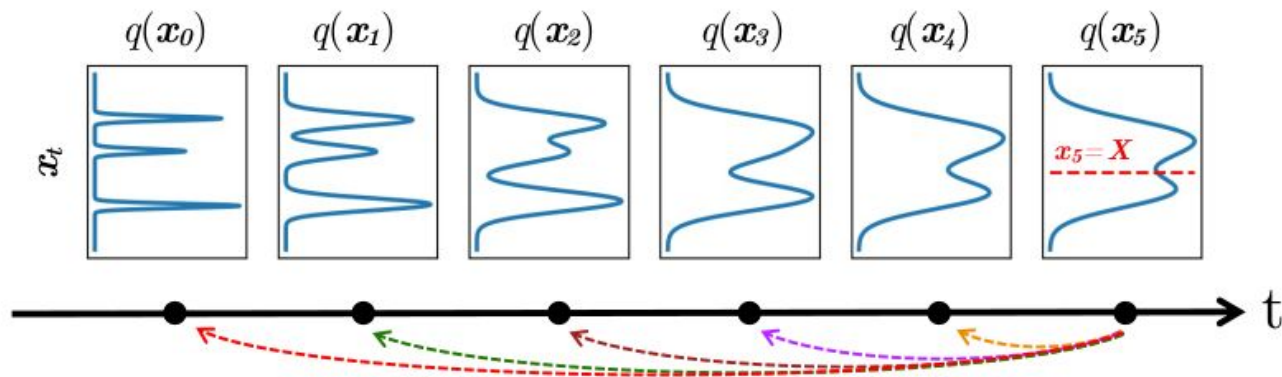
$$q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t \geq 1} q(\mathbf{x}_t|\mathbf{x}_{t-1}), \quad q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1 - \beta_t}\mathbf{x}_{t-1}, \beta_t \mathbf{I})$$

$$\min_{\phi} \sum_{t \geq 1} \mathbb{E}_{q(\mathbf{x}_t)} [\mathbb{E}_{q(\mathbf{x}_{t-1}|\mathbf{x}_t)} [-\log(D_{\phi}(\mathbf{x}_{t-1}, \mathbf{x}_t, t))] + \mathbb{E}_{p_{\theta}(\mathbf{x}_{t-1}|\mathbf{x}_t)} [-\log(1 - D_{\phi}(\mathbf{x}_{t-1}, \mathbf{x}_t, t))]]$$

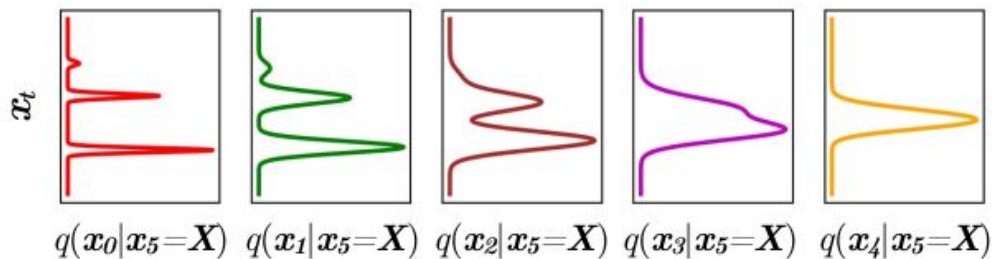
$$\max_{\theta} \sum_{t \geq 1} \mathbb{E}_{q(\mathbf{x}_t)} \mathbb{E}_{p_{\theta}(\mathbf{x}_{t-1}|\mathbf{x}_t)} [\log(D_{\phi}(\mathbf{x}_{t-1}, \mathbf{x}_t, t))],$$

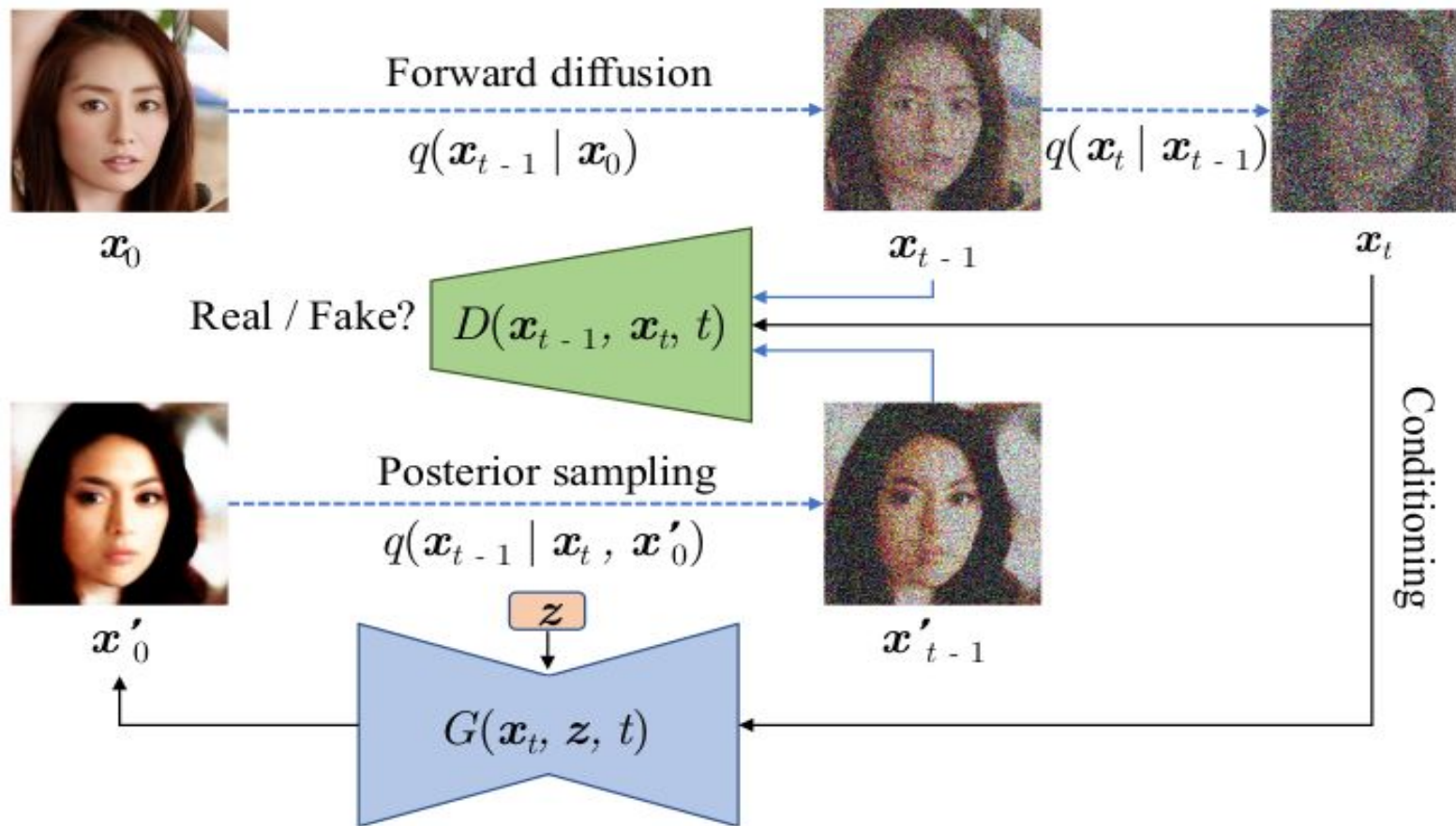
$$p_{\theta}(\mathbf{x}_{t-1}|\mathbf{x}_t) := \int p_{\theta}(\mathbf{x}_0|\mathbf{x}_t) q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0) d\mathbf{x}_0 = \int p(\mathbf{z}) q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0 = G_{\theta}(\mathbf{x}_t, \mathbf{z}, t)) d\mathbf{z}$$

Marginal Diffused Data Distributions



True Denoising Distributions







Denoising Diffusion Implicit models



Latent Space Diffusion Model