Notes for Diffusion Model

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1 DDPM

We first introduce the basic theory of Denoising Diffusion Probabilistic Models (DDPM) [1]. Overall, the DDPM consists of two processes: a forward diffusion process that gradually adds noise to the data, and a reverse denoising process that learns to remove the noise and recover the original data.

1.1 Forward Diffusion Process

The forward diffusion process is defined as a Markov chain that progressively adds Gaussian noise to the data over T time steps. Given a data point $\mathbf{x}_0$ sampled from the data distribution $q(\mathbf{x}_0)$, the forward process produces a sequence of noisy samples $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T$ according to the following transition probabilities:

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1-\beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I}), \tag{1}$$

where β_t is a variance schedule that controls the amount of noise added at each time step. The cumulative effect of this process can be expressed as:

$$q(\mathbf{x}_t|\mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t}\mathbf{x}_0, (1-\bar{\alpha}_t)\mathbf{I}), \tag{2}$$

where $\bar{\alpha}_t = \prod_{s=1}^{t}(1-\beta_s)$.

References

[1] J. Ho, A. Jain, and P. Abbeel, “Denoising diffusion probabilistic models,” in *NeurIPS*, 2020, pp. 6840–6851.