Denoising-Diffusion Models

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Dr. Mykhailo Vladymyrov

Introduction

- Denoising Diffusion Models (DDMs) are a class of generative models that have gained significant attention in recent years.
- They play a crucial role in the field of generative modeling, offering a unique approach to image generation and data synthesis.
- DDMs are composed of two fundamental components: the diffusion process and the generation process. These components work together to create high-quality and realistic samples.

Diffusion Process

- The diffusion process is a fundamental component of Denoising Diffusion Models (DDMs). It serves as the foundation for generating high-quality samples.
- In the diffusion process, noise is incrementally added to an input image. This step-by-step addition of noise gradually transforms the clean image into a noisy version.

Diffusion Process

$$x_{t+1} = \sqrt{\beta} x_t + \epsilon_t \,, \epsilon_t \in N(0, \beta)$$
$$x_t = \alpha_t \, x_0 + \epsilon, \epsilon \in N(0, \sigma_t)$$
$$\alpha_t = \sqrt{\prod_{i=1..t} (1 - \beta_i)}$$
$$\sigma_t = \sqrt{1 - \alpha_t^2}$$

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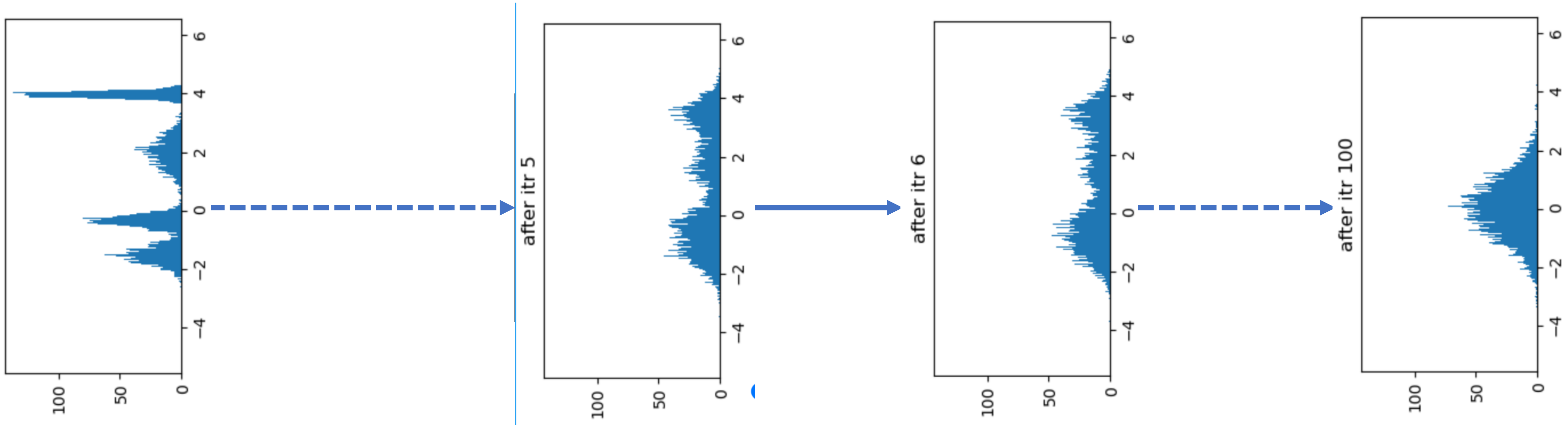

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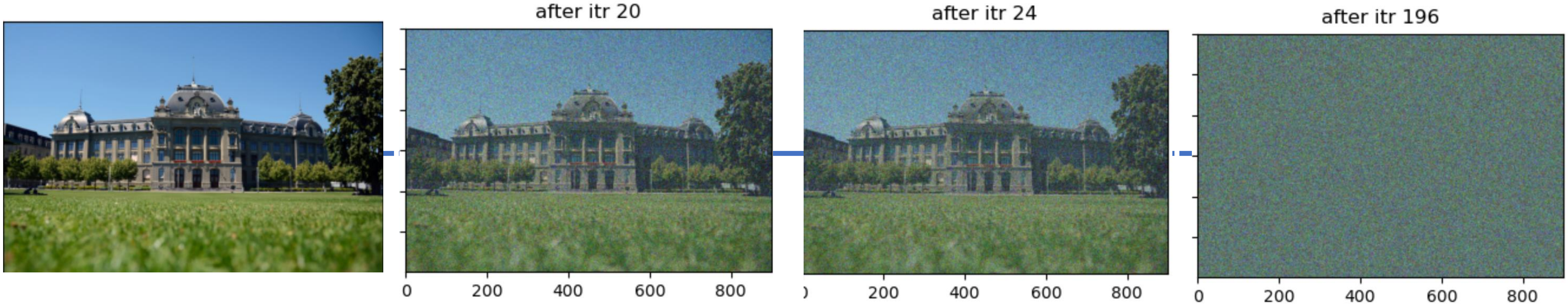

Denoising Model

The denoising model is then trained to predict the added noise on each step.

$$\min_{\boldsymbol{\theta}} \mathbb{E}_{t\sim U\{1,T\},\mathbf{x}_0\sim p(\mathbf{x}_0),\boldsymbol{\epsilon}\sim\mathcal{N}(\mathbf{0},\boldsymbol{I})} \left[w(t)||\boldsymbol{\epsilon} - \boldsymbol{\epsilon}_{\boldsymbol{\theta}}(\alpha_t\mathbf{x}_0 + \sigma_t\boldsymbol{\epsilon}, t)||_2^2\right], \quad w(t) = \frac{\beta_t^2}{2\rho_t^2(1-\beta_t)(1-\alpha_t^2)},$$

$$\mathbf{x}_{t-1} = \frac{1}{\sqrt{1-\beta_t}}\left(\mathbf{x}_t - \frac{\beta_t}{\sqrt{1-\alpha_t^2}}\boldsymbol{\epsilon}_{\boldsymbol{\theta}}(\mathbf{x}_t, t)\right) + \rho_t\boldsymbol{\eta},$$

Generation Process

- In DDMs, the generation process is where high-quality samples are created from noisy images generated during the diffusion process.
- The generation process involves a generative network that transforms noisy data into realistic samples.
- The processed is sequentially predicting the noise to be subtracted at each denoising iteration

Generation Process

- **Generative Network:** A neural network, often a deep neural network or a variational autoencoder (VAE), is employed to map noisy images to high-quality samples.
- **Gradual Improvement:** The generative network progressively refines the noisy images, reducing noise and enhancing details at each step.
- **Sampling:** During training, the generative network samples from a noise distribution to generate various versions of the same image.

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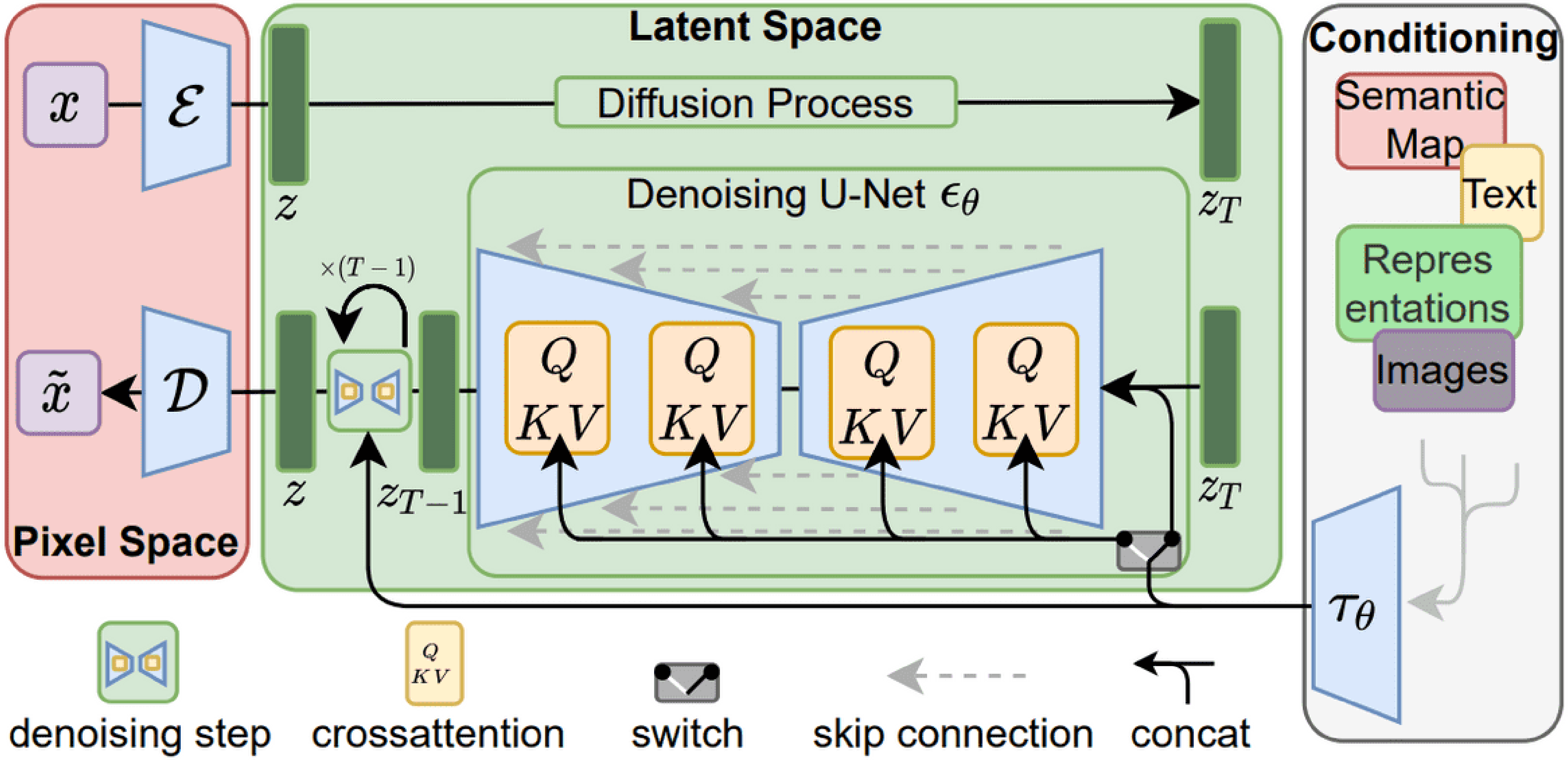

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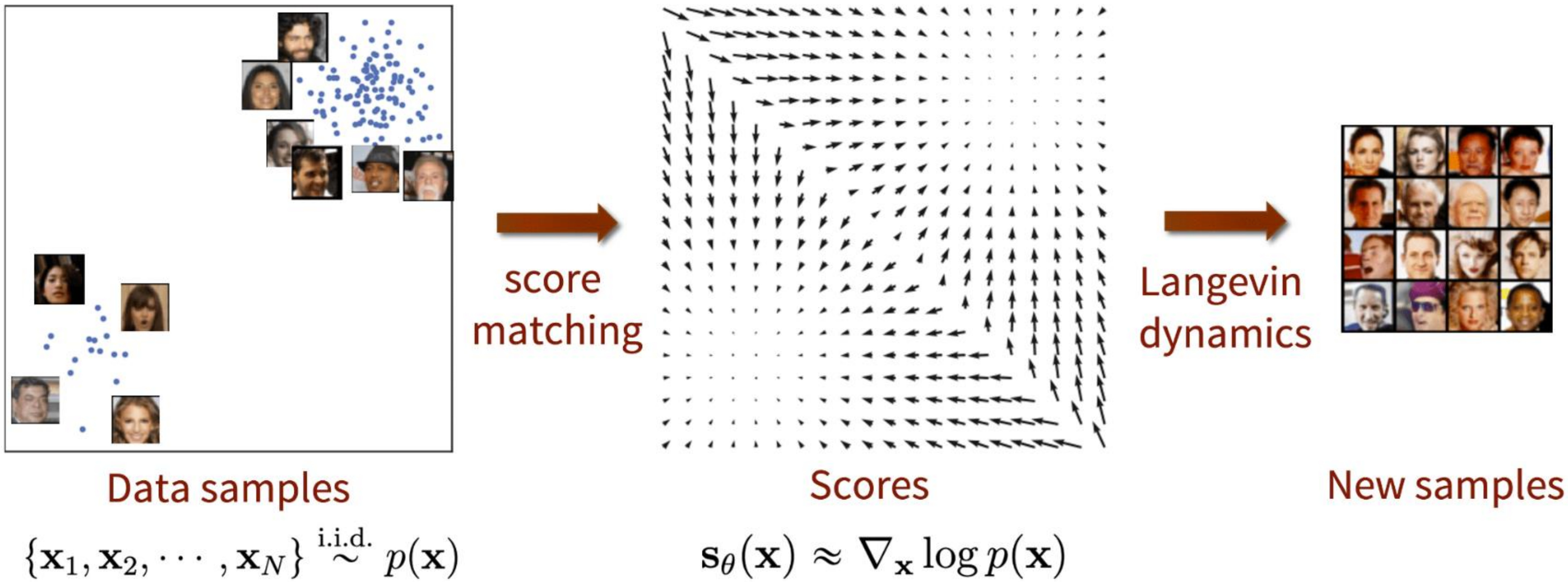
Challenges in Training DDMs

- **Computational Complexity:** DDMs can be computationally intensive, requiring substantial resources for training and inference.
- **Hyperparameter Tuning:** Properly configuring hyperparameters is crucial for DDMs, and finding the right settings can be challenging.
- **Data Size:** DDMs often require large datasets for effective training, which may not be readily available in some domains.

Advances in DDMs

- **Improved Sampling Methods:** Recent research has introduced more efficient sampling techniques, reducing the computational burden of DDMs.
- **Transfer Learning:** Applying pre-trained DDMs to new tasks or domains has become more accessible, thanks to advances in transfer learning.
- **Scalability:** Efforts to make DDMs more scalable have led to the development of smaller, more efficient models suitable for various applications.



Score-based generative modeling with score matching + Langevin dynamics. Source: [Generative Modeling by Estimating Gradients of the Data Distribution]