



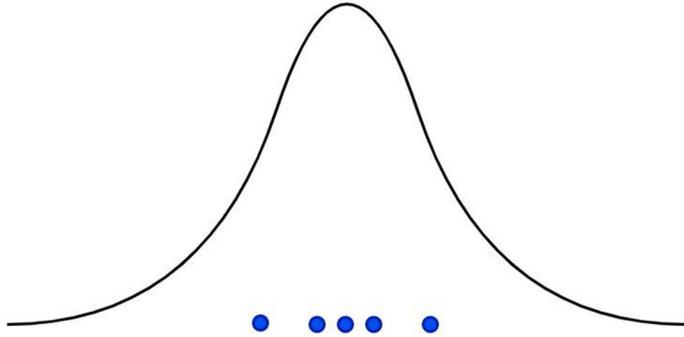
GENERATIVE MODELLING

Param Hanji • Nov 2022

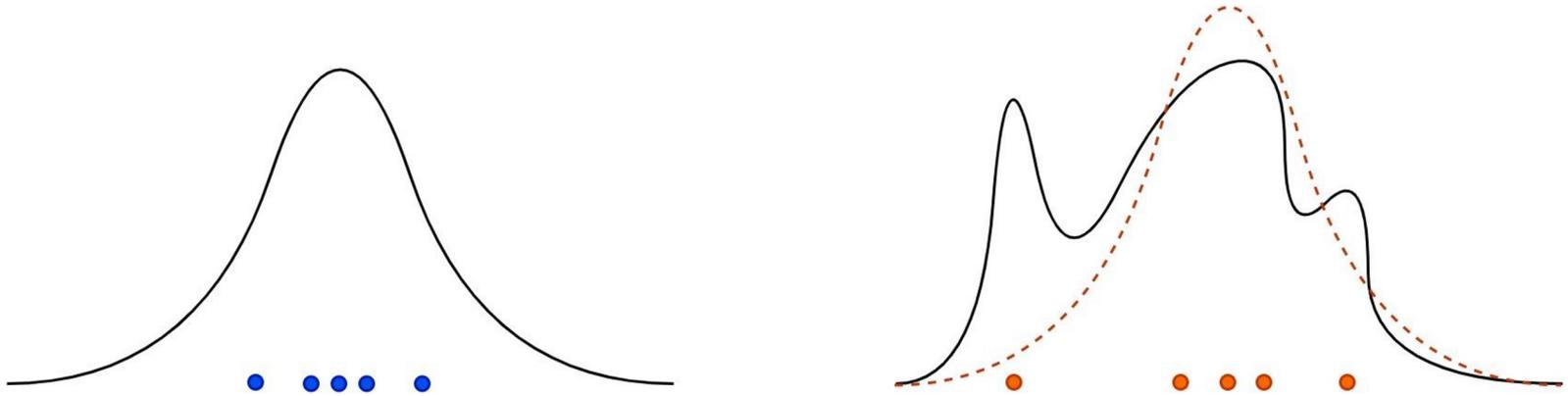
Images as samples



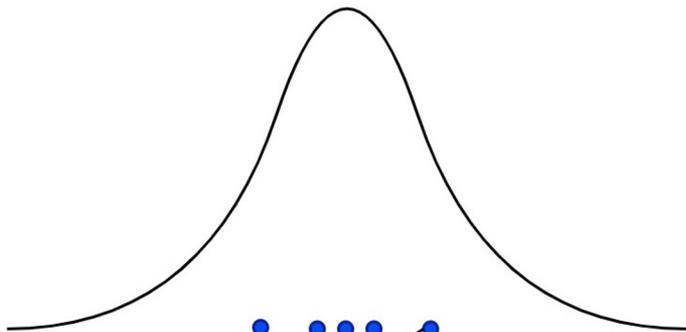
Sample generation



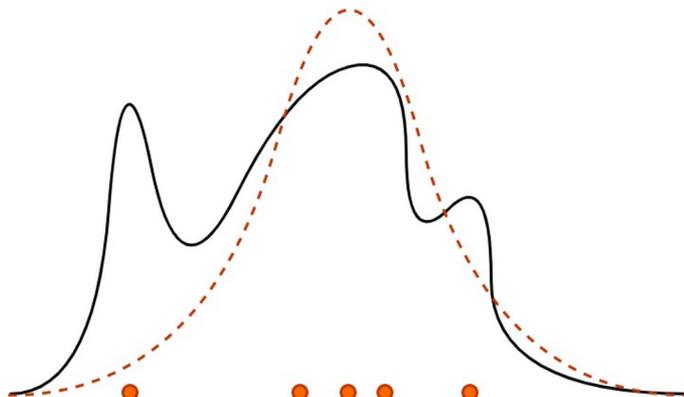
Sample generation



Density estimation



$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp - \frac{(x - \mu)^2}{2\sigma^2}$$



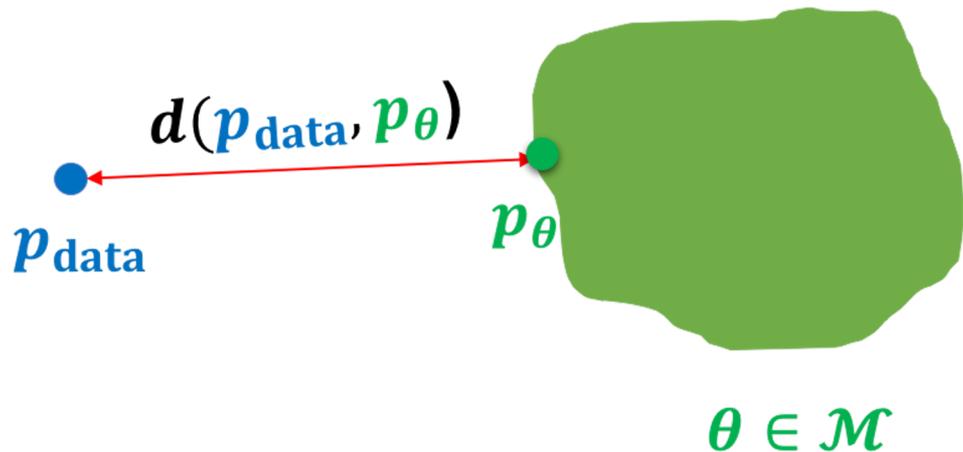
$$p(x) = ?$$

$$q_{\theta}(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp - \frac{(x - \mu)^2}{2\sigma^2}$$

Training



$$\mathbf{x}^{(j)} \sim p_{\text{data}}$$
$$j = 1, 2, \dots, |\mathcal{D}|$$

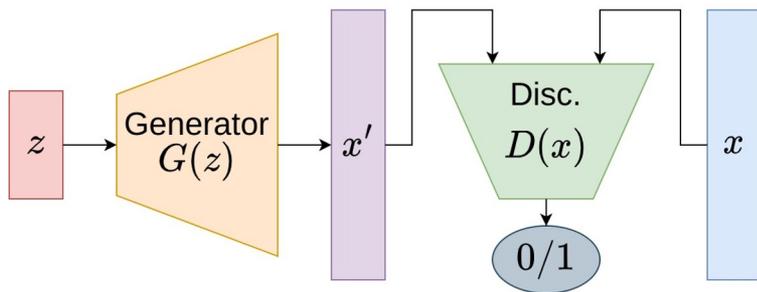


Model family

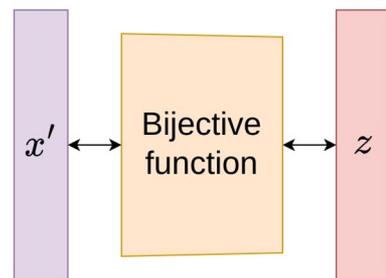
Domains

- Computer vision
- Computer graphics
- Text generation
- Medical imaging
- Audio synthesis
- Astrophysics

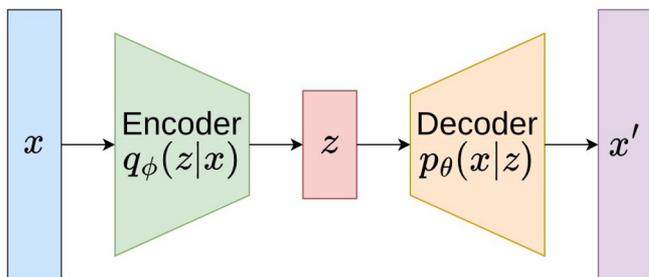
Deep generative modelling



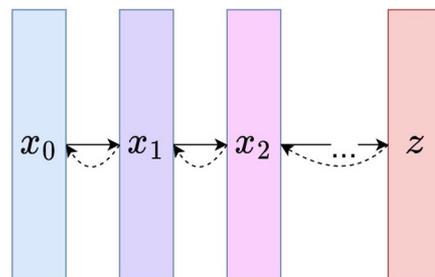
Generative adversarial network



Normalizing flow

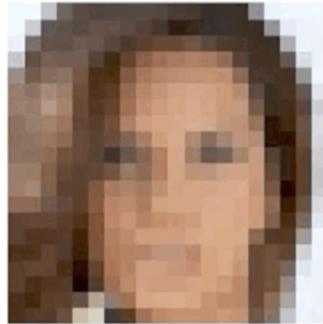


Variational autoencoder



Diffusion method

Inverse problems



Input

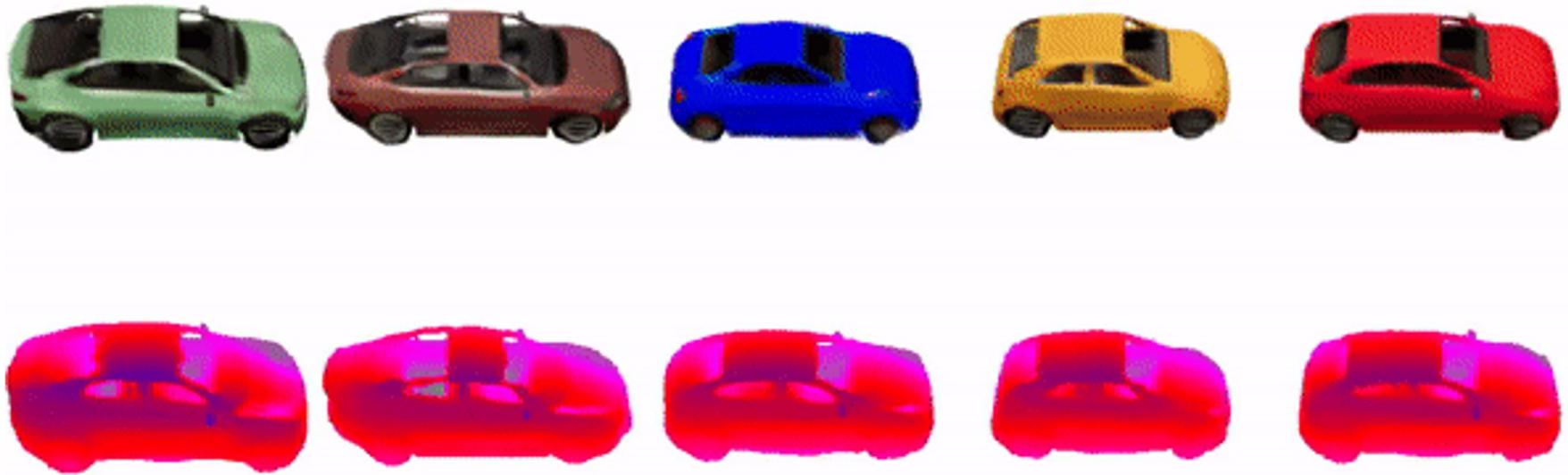


Super-Resolution

Inverse imaging

- Colorization
- Inpainting
- Uncropping
- Deblurring
- Single-image HDR

Inverse graphics



Conditional generation



A dragon fruit wearing karate belt in the snow.



Android Mascot made from bamboo.



A bald eagle made of chocolate powder, mango, and whipped cream.

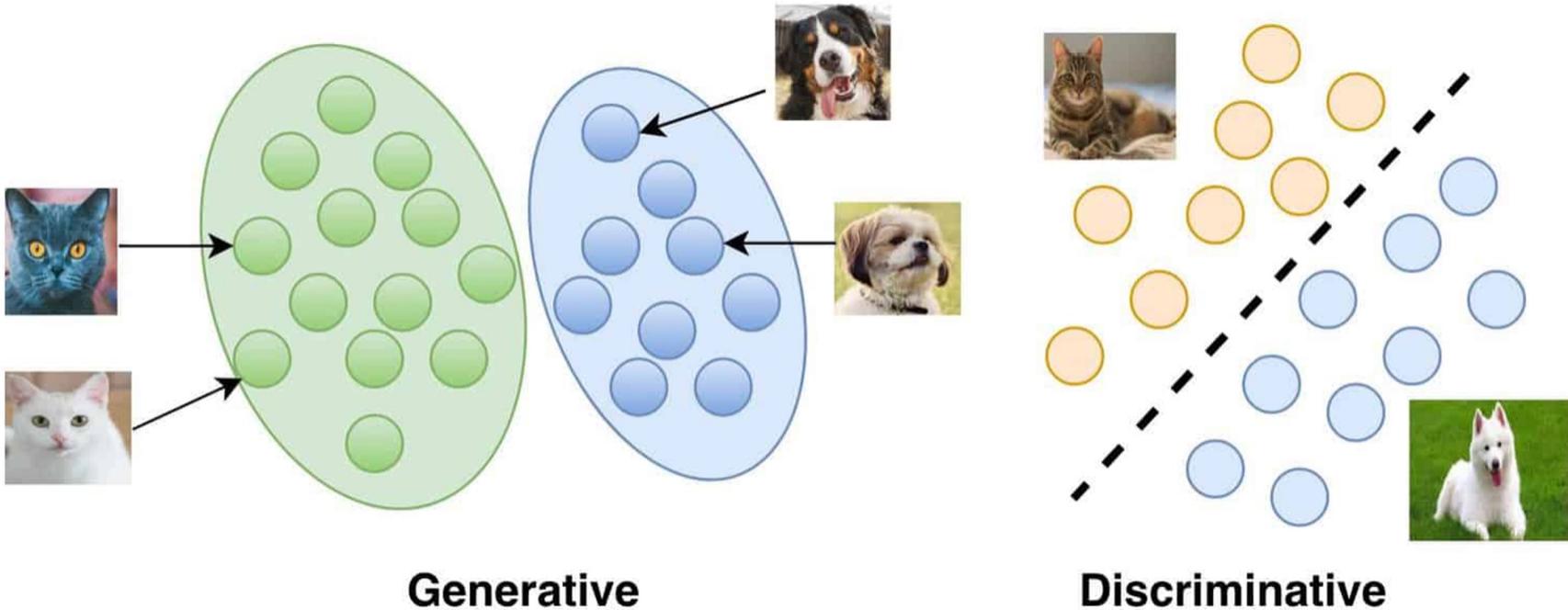


A strawberry mug filled with white sesame seeds. The mug is floating in a dark chocolate sea.

Image-to-image translation



Classification



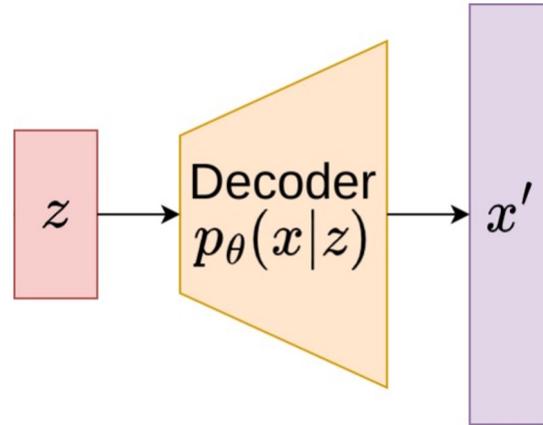
Requirements

- Handle high dimensional data
- Fast, efficient sampling
- High sample quality
- Diverse samples
- [Optional] Density evaluation
- Low dimensional latent

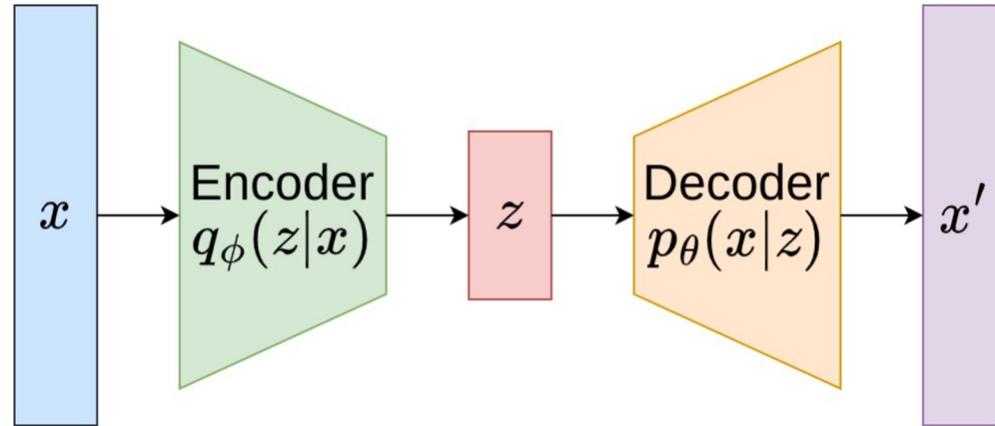
Variational autoencoder

$$\theta^* = \arg \max_{\theta} \sum_{i=1}^n \log p_{\theta}(\mathbf{x}^{(i)})$$

$$p_{\theta}(\mathbf{x}^{(i)}) = \int p_{\theta}(\mathbf{x}^{(i)} | \mathbf{z}) p_{\theta}(\mathbf{z}) d\mathbf{z}$$

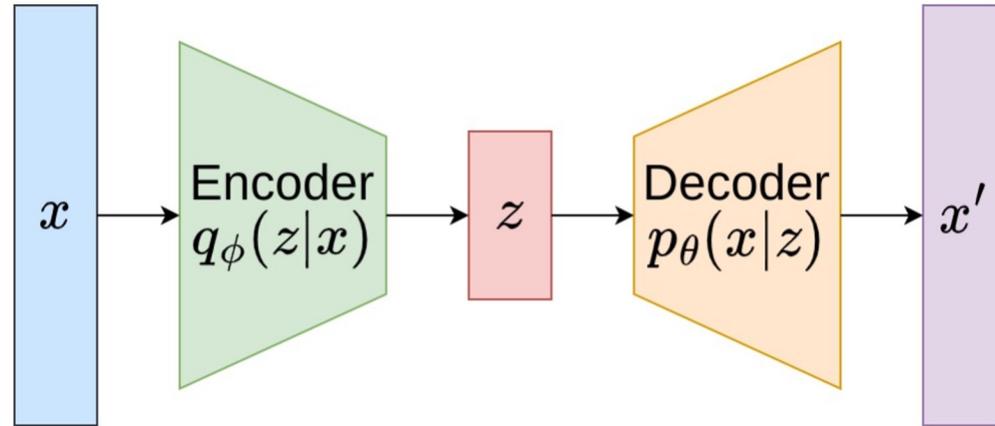


Variational autoencoder



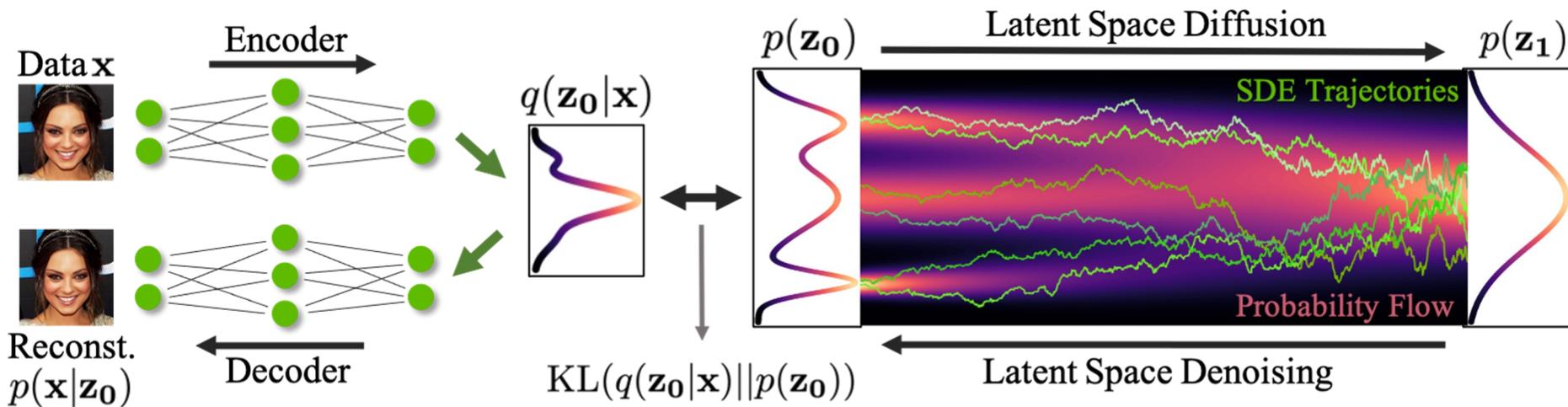
$$D_{\text{KL}}(P \parallel Q) = \int_{-\infty}^{\infty} p(x) \log \left(\frac{p(x)}{q(x)} \right) dx$$

Variational autoencoder

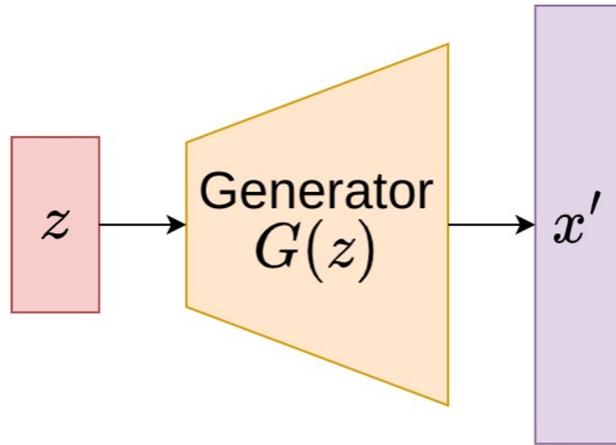


$$-L_{\text{VAE}} = \log p_{\theta}(\mathbf{x}) - D_{\text{KL}}(q_{\phi}(\mathbf{z}|\mathbf{x}) || p_{\theta}(\mathbf{z}|\mathbf{x})) \leq \log p_{\theta}(\mathbf{x})$$

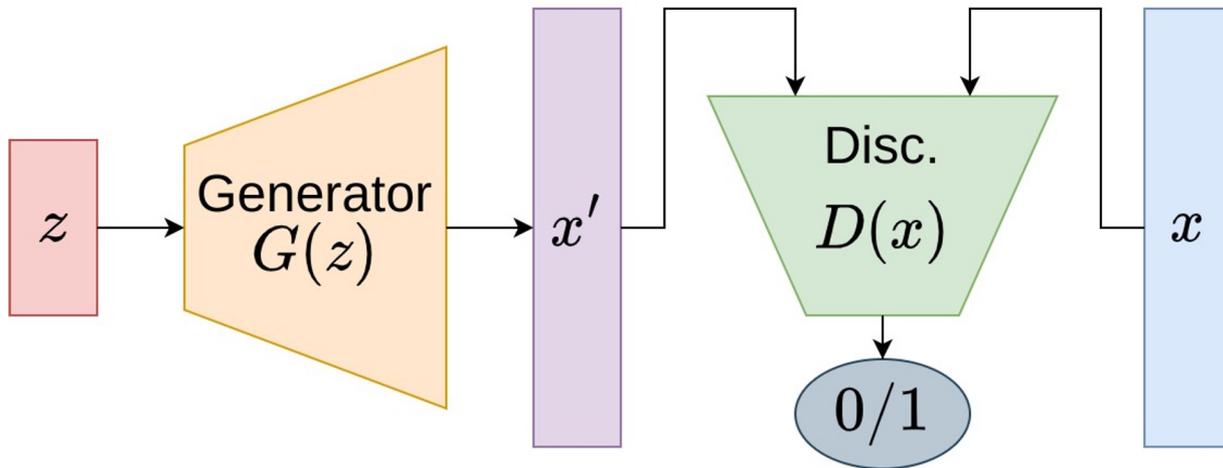
Variational autoencoder



Generative adversarial network

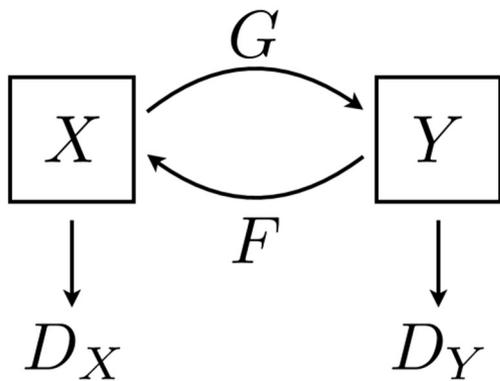


Generative adversarial network



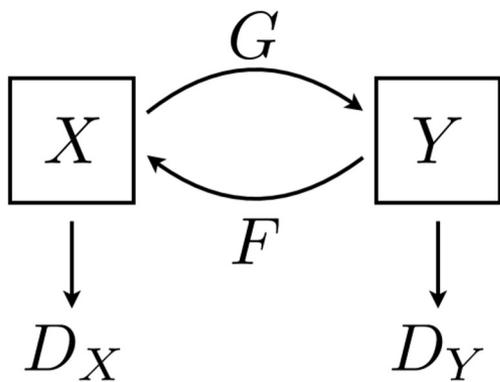
$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_z(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]$$

Cycle-GAN

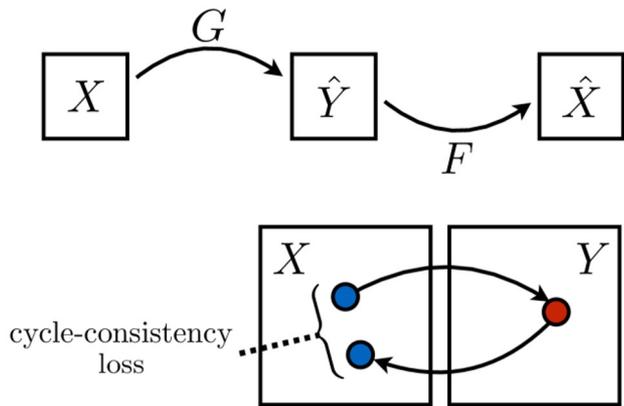


(a)

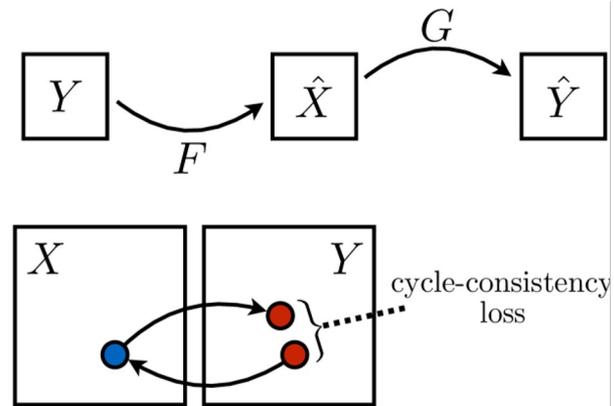
Cycle-GAN



(a)

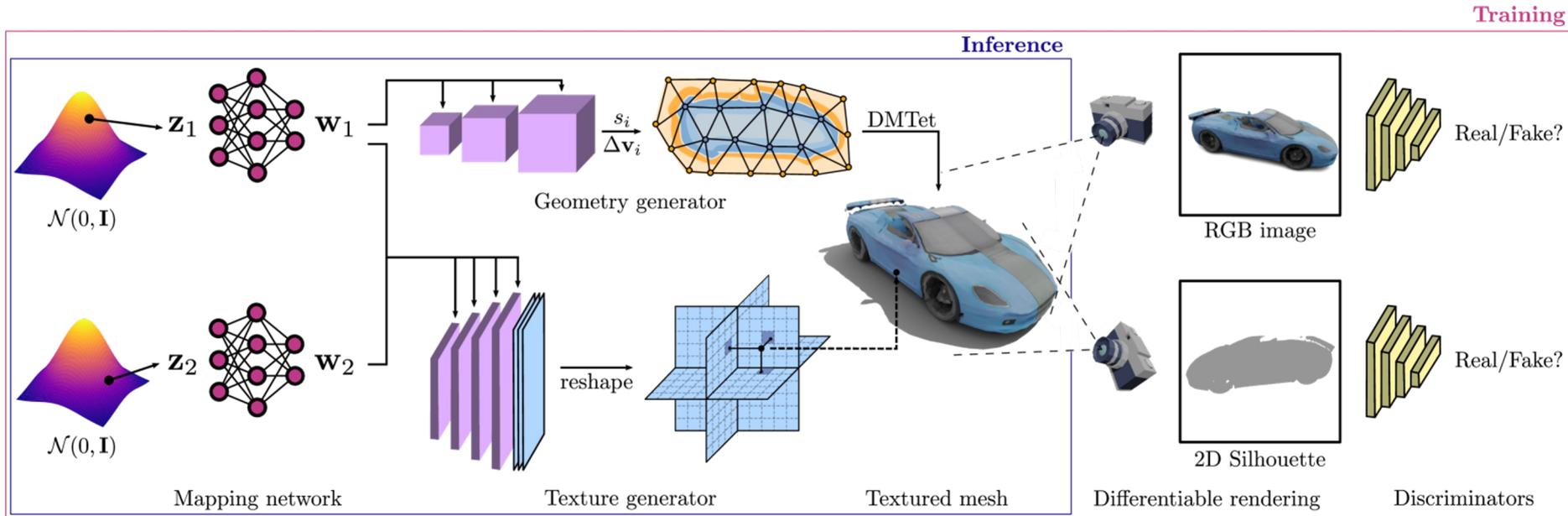


(b)

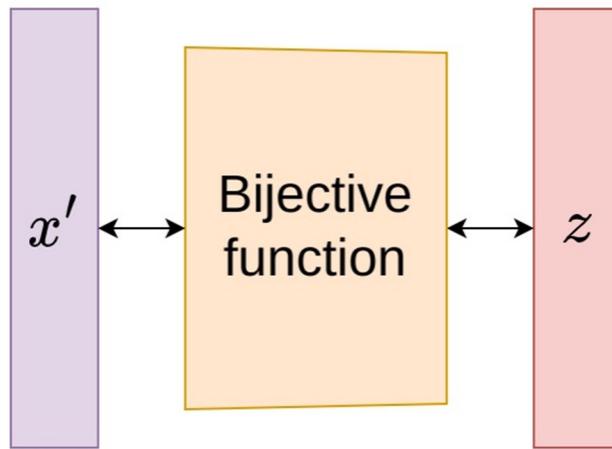


(c)

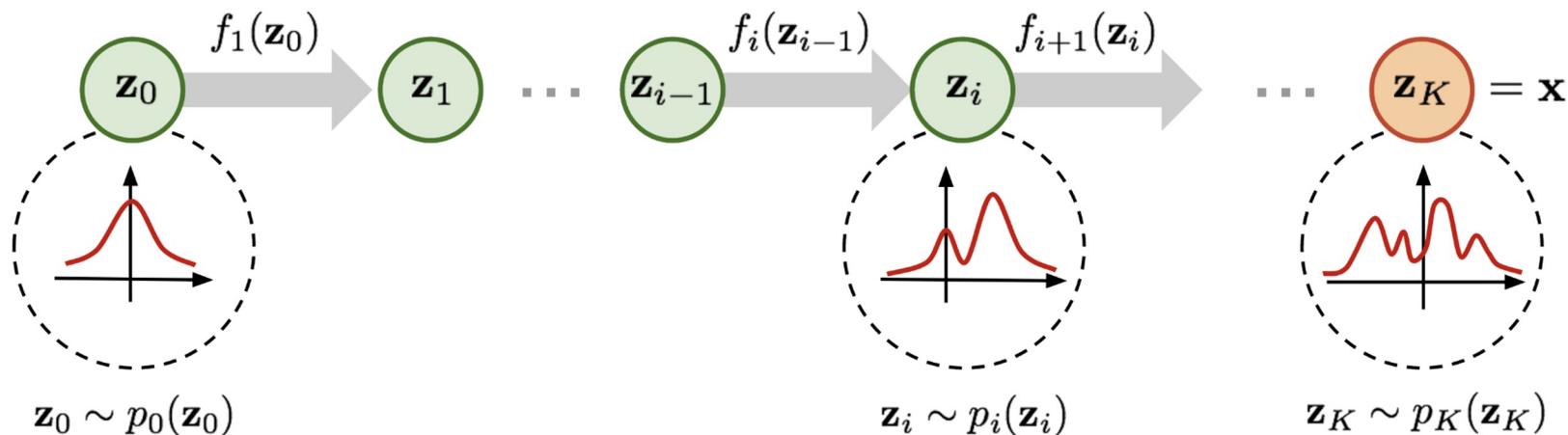
GAN - complex models



Normalizing flows

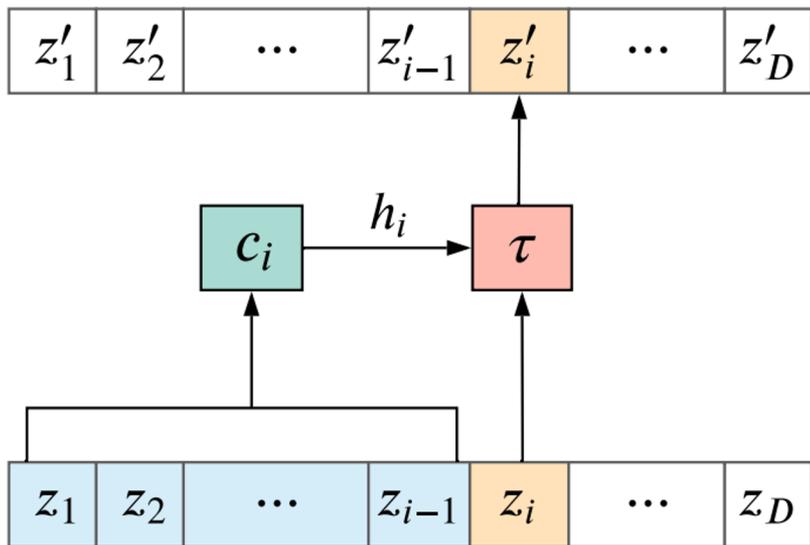


Normalizing flows



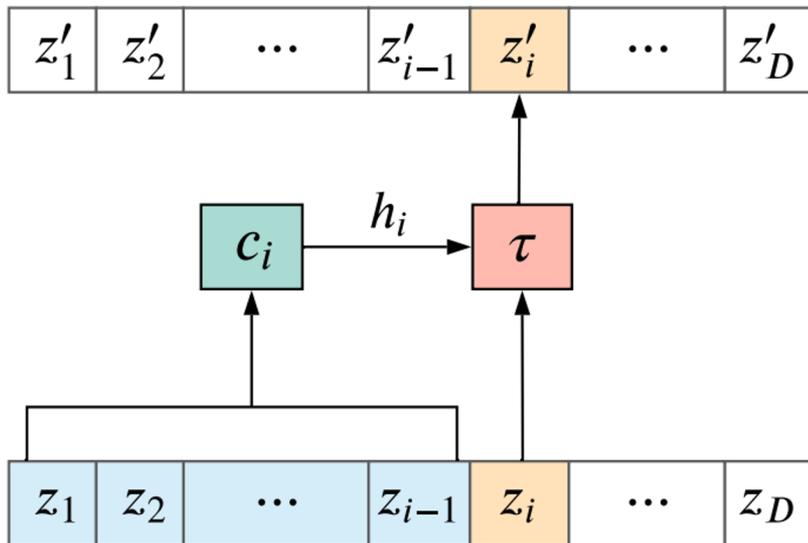
$$p_i(\mathbf{z}_i) = p_{i-1}(f_i^{-1}(\mathbf{z}_i)) \left| \det \frac{df_i^{-1}}{d\mathbf{z}_i} \right|$$

Normalizing flows - coupling

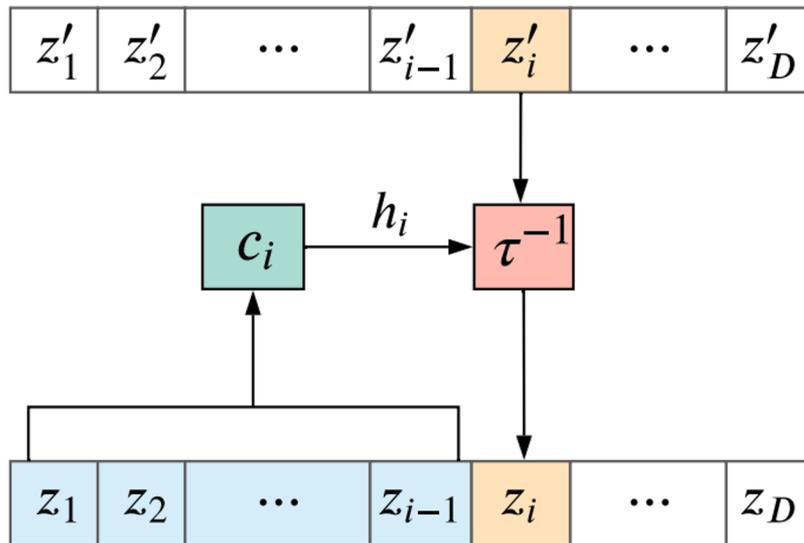


(a) Forward

Normalizing flows - coupling

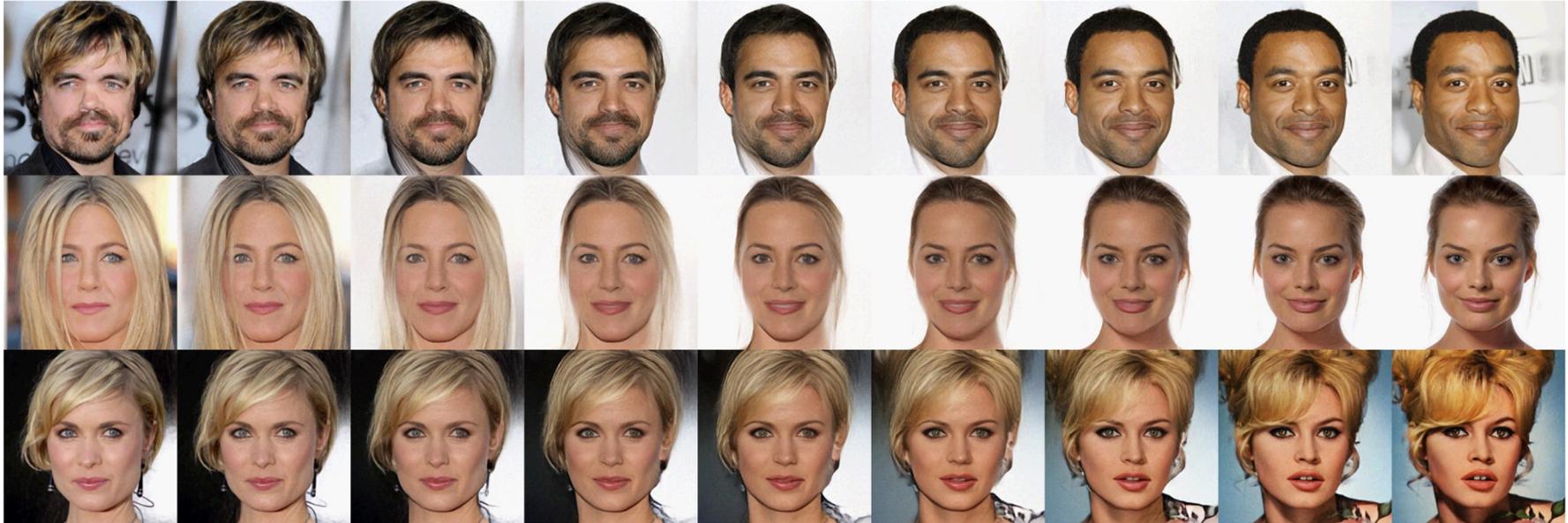


(a) Forward

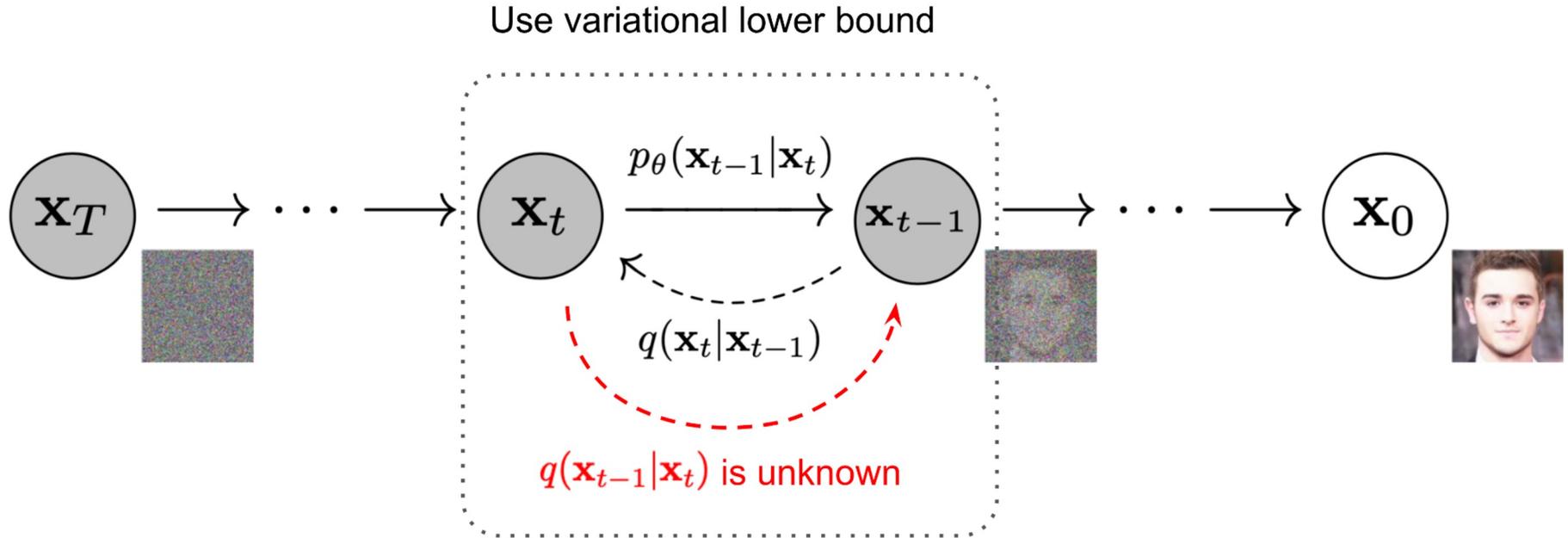


(b) Inverse

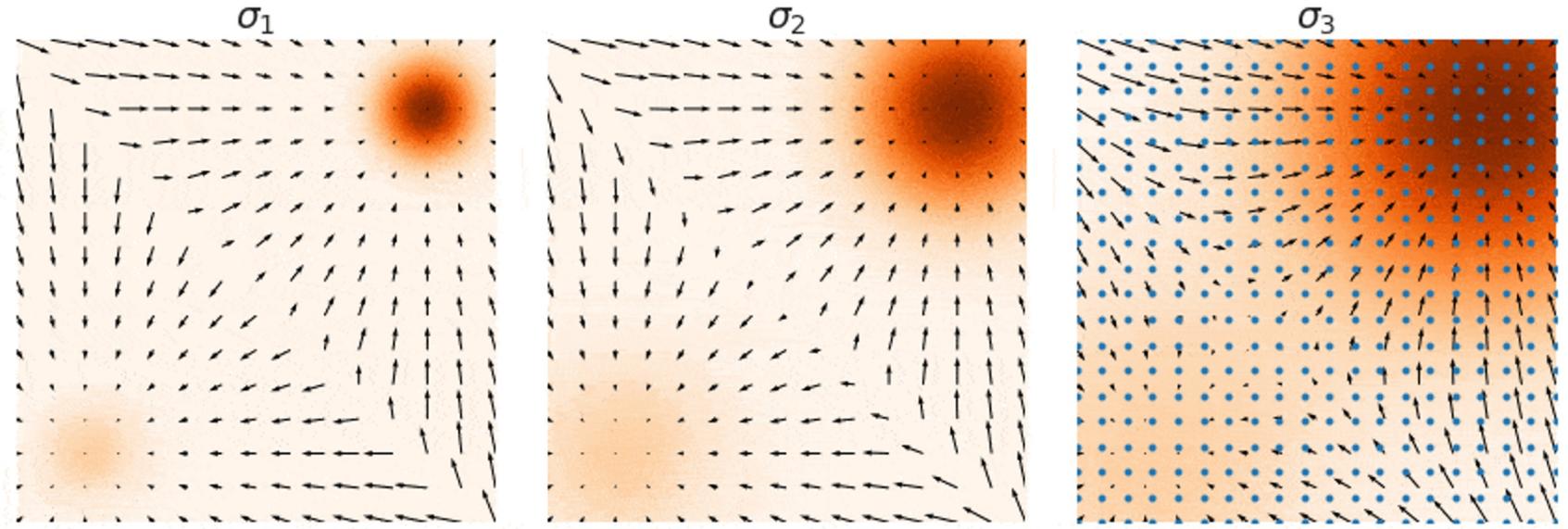
Flows - latent manipulation



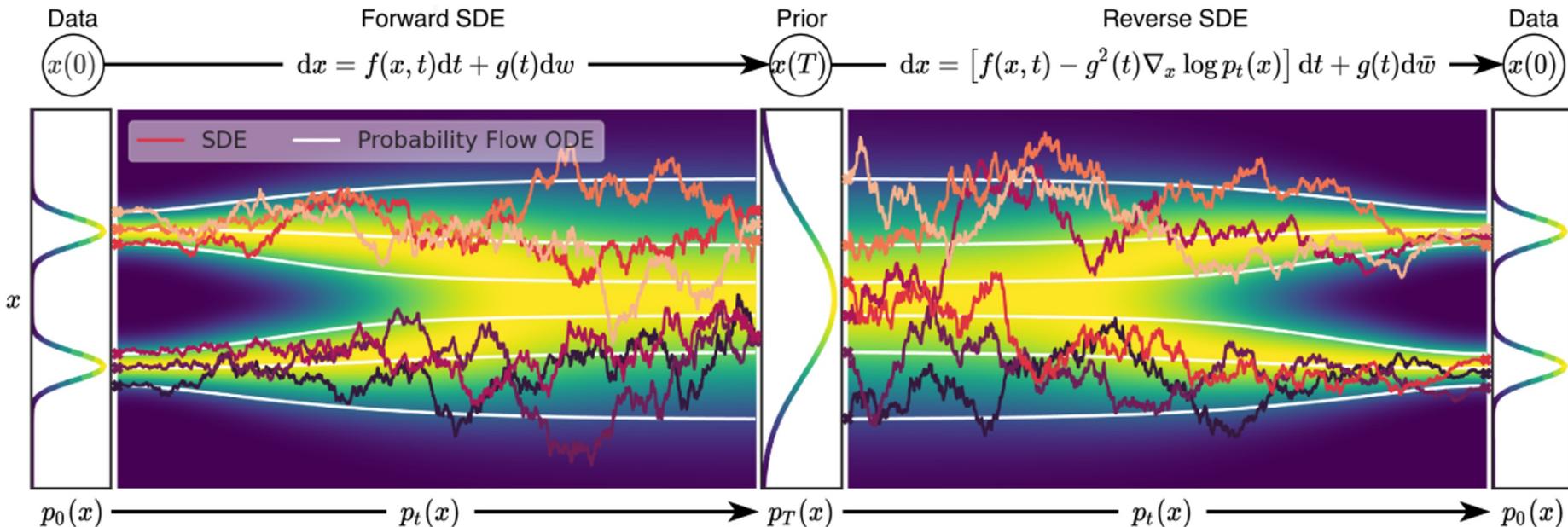
Diffusion models



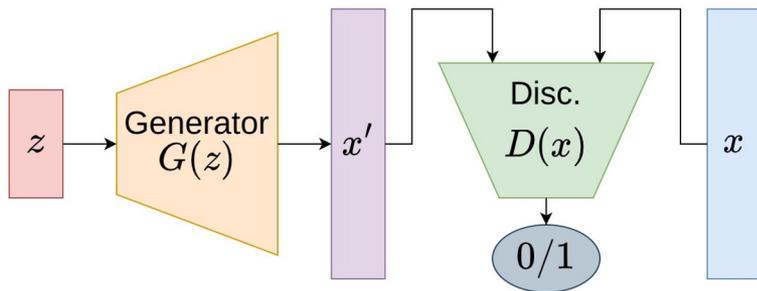
Score matching



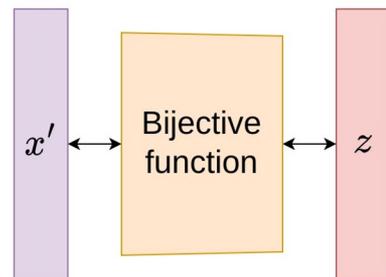
Unified perspective



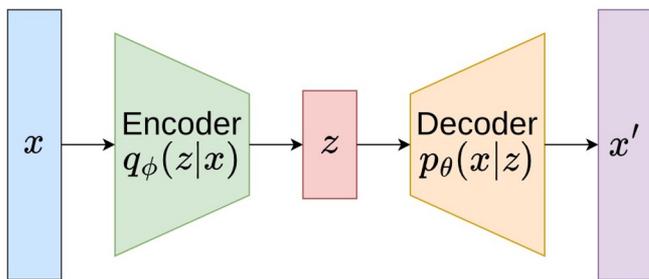
Deep generative modelling



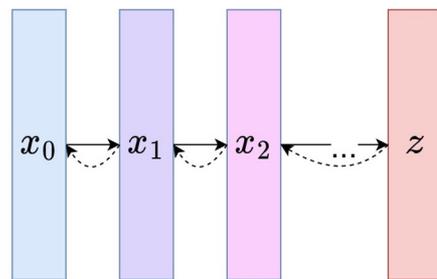
Generative adversarial network



Normalizing flow



Variational autoencoder



Diffusion method

Summary

The Generative Learning Trilemma

