Images as samples
Sample generation
Sample generation
Density estimation

\[ p(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right) \]

\[ q_\theta(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x - \mu)^2}{2\sigma^2}\right) \]
Training

\[ x^{(j)} \sim p_{\text{data}} \]
\[ j = 1, 2, \ldots, |\mathcal{D}| \]

Model family

\[ \theta \in \mathcal{M} \]
Domains

• Computer vision
• Computer graphics
• Text generation
• Medical imaging
• Audio synthesis
• Astrophysics
Deep generative modelling

Generative adversarial network

Variational autoencoder

Normalizing flow

Diffusion method
Inverse problems

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

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

$$p_\theta(x^{(i)}) = \int p_\theta(x^{(i)}|z)p_\theta(z)dz$$
Variational autoencoder

Variational autoencoder

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

Variational autoencoder

Generative adversarial network
Generative adversarial network

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

Cycle-GAN

Normalizing flows

$x'$  Bijective function  $z$

Normalizing flows

\[
f_1(z_0) \rightarrow z_1 \rightarrow \cdots \rightarrow f_{i-1}(z_{i-1}) \rightarrow z_i \rightarrow f_{i+1}(z_i) \rightarrow \cdots \rightarrow z_K = x
\]

\[
z_0 \sim p_0(z_0) \quad z_{i-1} \sim p_{i-1}(f_{i-1}^{-1}(z_i)) \quad z_i \sim p_i(z_i) \quad z_K \sim p_K(z_K)
\]

\[
p_i(z_i) = p_{i-1}(f_{i-1}^{-1}(z_i)) \left| \det \frac{df_i^{-1}}{dz_i} \right|
\]

Normalizing flows - coupling

Normalizing flows - coupling

(a) Forward

(b) Inverse

Flows - latent manipulation

Diffusion models

Use variational lower bound

$p_\theta(x_{t-1}|x_t)$

$q(x_t|x_{t-1})$

$q(x_{t-1}|x_t)$ is unknown
Score matching
Unified perspective

Deep generative modelling

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Summary

The Generative Learning Trilemma

- High Quality Samples
- Fast Sampling
- Mode Coverage / Diversity