

Deep Generative Models

Lecture 5

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Recap of Previous Lecture

Assumptions

- ▶ Let $c \sim \text{Cat}(\boldsymbol{\pi})$, where

$$\boldsymbol{\pi} = (\pi_1, \dots, \pi_K), \quad \pi_k = P(c = k), \quad \sum_{k=1}^K \pi_k = 1.$$

- ▶ Suppose the VAE employs a discrete latent code c , with prior $p(c) = \text{Uniform}\{1, \dots, K\}$.

ELBO

$$\mathcal{L}_{\phi, \theta}(\mathbf{x}) = \mathbb{E}_{q_\phi(c|\mathbf{x})} \log p_\theta(\mathbf{x}|c) - \text{KL}(q_\phi(c|\mathbf{x}) \| p(c)) \rightarrow \max_{\phi, \theta} .$$

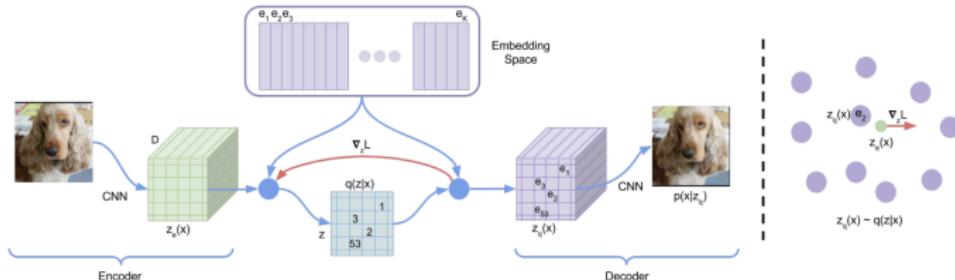
$$\text{KL}(q_\phi(c|\mathbf{x}) \| p(c)) = -H(q_\phi(c|\mathbf{x})) + \log K.$$

Vector Quantization

Define the codebook $\{\mathbf{e}_k\}_{k=1}^K$, where $\mathbf{e}_k \in \mathbb{R}^L$ and K is the size of the dictionary.

$$\mathbf{z}_q = \mathbf{q}(\mathbf{z}) = \mathbf{e}_{k^*}, \quad \text{where } k^* = \arg \min_k \|\mathbf{z} - \mathbf{e}_k\|.$$

Recap of Previous Lecture



Deterministic Variational Posterior

$$q_\phi(c_{ij} = k^* | \mathbf{x}) = \begin{cases} 1, & \text{if } k^* = \arg \min_k \|[\mathbf{z}_e]_{ij} - \mathbf{e}_k\|; \\ 0, & \text{otherwise.} \end{cases}$$

ELBO

$$\mathcal{L}_{\phi, \theta}(\mathbf{x}) = \mathbb{E}_{q_\phi(c|\mathbf{x})} \log p_\theta(\mathbf{x}|\mathbf{e}_c) - \log K = \log p_\theta(\mathbf{x}|\mathbf{z}_q) - \log K.$$

Straight-Through Gradient Estimation

$$\frac{\partial \log p(\mathbf{x}|\mathbf{z}_q, \theta)}{\partial \phi} = \frac{\partial \log p_\theta(\mathbf{x}|\mathbf{z}_q)}{\partial \mathbf{z}_q} \cdot \frac{\partial \mathbf{z}_q}{\partial \phi} \approx \frac{\partial \log p_\theta(\mathbf{x}|\mathbf{z}_q)}{\partial \mathbf{z}_q} \cdot \frac{\partial \mathbf{z}_e}{\partial \phi}$$

Recap of Previous Lecture

Theorem

$$\frac{1}{n} \sum_{i=1}^n \text{KL}(q_\phi(\mathbf{z}|\mathbf{x}_i) \| p(\mathbf{z})) = \text{KL}(q_{\text{agg},\phi}(\mathbf{z}) \| p(\mathbf{z})) + \mathbb{I}_q[\mathbf{x}, \mathbf{z}].$$

ELBO Surgery

$$\frac{1}{n} \sum_{i=1}^n \mathcal{L}_{\phi,\theta}(\mathbf{x}_i) = \underbrace{\frac{1}{n} \sum_{i=1}^n \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x}_i)} \log p_\theta(\mathbf{x}_i|\mathbf{z})}_{\text{Reconstruction Loss}} - \underbrace{\mathbb{I}_q[\mathbf{x}, \mathbf{z}]}_{\text{MI}} - \underbrace{\text{KL}(q_{\text{agg},\phi}(\mathbf{z}) \| p(\mathbf{z}))}_{\text{Marginal KL}}$$

Optimal Prior

$$\text{KL}(q_{\text{agg},\phi}(\mathbf{z}) \| p(\mathbf{z})) = 0 \Leftrightarrow p(\mathbf{z}) = q_{\text{agg}}(\mathbf{z}) = \frac{1}{n} \sum_{i=1}^n q_\phi(\mathbf{z}|\mathbf{x}_i).$$

Thus, the optimal prior distribution $p(\mathbf{z})$ is the aggregated variational posterior $q_{\text{agg},\phi}(\mathbf{z})$.

Recap of Previous Lecture

- ▶ Standard Gaussian $p(\mathbf{z}) = \mathcal{N}(0, \mathbf{I}) \Rightarrow$ over-regularization.
- ▶ $p(\mathbf{z}) = q_{\text{agg}, \phi}(\mathbf{z}) = \frac{1}{n} \sum_{i=1}^n q_\phi(\mathbf{z}|\mathbf{x}_i) \Rightarrow$ overfitting and extremely high computational cost.

Revisiting ELBO

$$\frac{1}{n} \sum_{i=1}^n \mathcal{L}_{\phi, \theta}(\mathbf{x}_i) = \text{RL} - \text{MI} - \text{KL}(q_{\text{agg}, \phi}(\mathbf{z}) \parallel p_{\lambda}(\mathbf{z}))$$

This is the forward KL divergence with respect to $p_{\lambda}(\mathbf{z})$.

ELBO with Learnable VAE Prior

$$\begin{aligned}\mathcal{L}_{\phi, \theta}(\mathbf{x}) &= \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} [\log p_{\theta}(\mathbf{x}|\mathbf{z}) + \log p_{\lambda}(\mathbf{z}) - \log q_{\phi}(\mathbf{z}|\mathbf{x})] \\ &= \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})} \left[\log p_{\theta}(\mathbf{x}|\mathbf{z}) + \underbrace{\left(\log p(f_{\lambda}(\mathbf{z})) + \log |\det(\mathbf{J}_f)| \right)}_{\text{flow-based prior}} - \log q_{\phi}(\mathbf{z}|\mathbf{x}) \right] \\ \mathbf{z} &= \mathbf{f}_{\lambda}^{-1}(\mathbf{z}^*) = \mathbf{g}_{\lambda}(\mathbf{z}^*), \quad \mathbf{z}^* \sim p(\mathbf{z}^*) = \mathcal{N}(0, \mathbf{I})\end{aligned}$$

Outline

1. Likelihood-Free Learning
2. Generative Adversarial Networks (GAN)
3. Wasserstein Distance
4. Wasserstein GAN

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Likelihood-Based Models

Poor Likelihood
High-Quality Samples

$$p_1(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^n \mathcal{N}(\mathbf{x} | \mathbf{x}_i, \epsilon \mathbf{I})$$

If ϵ is very small, this model produces excellent, sharp samples but achieves poor likelihoods on test data.

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High Likelihood
Poor Samples

$$p_2(\mathbf{x}) = 0.01p(\mathbf{x}) + 0.99p_{\text{noise}}(\mathbf{x})$$

$$\begin{aligned}\log [0.01p(\mathbf{x}) + 0.99p_{\text{noise}}(\mathbf{x})] &\geq \\ &\geq \log [0.01p(\mathbf{x})] = \log p(\mathbf{x}) - \log 100\end{aligned}$$

This model contains mostly noisy, irrelevant samples; for high dimensions, $\log p(\mathbf{x})$ scales linearly with m .

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This model contains mostly noisy, irrelevant samples; for high dimensions, $\log p(\mathbf{x})$ scales linearly with m .

- ▶ Likelihood isn't always a suitable metric for evaluating generative models.
- ▶ Sometimes, the likelihood function can't even be computed exactly.

Likelihood-Free Learning

Motivation

We're interested in approximating the true data distribution $p_{\text{data}}(\mathbf{x})$. Instead of searching over all distributions, let's learn a model $p_{\theta}(\mathbf{x}) \approx p_{\text{data}}(\mathbf{x})$.

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Suppose we have two sets of samples:

- ▶ $\{\mathbf{x}_i\}_{i=1}^{n_1} \sim p_{\text{data}}(\mathbf{x})$ — real data;
- ▶ $\{\mathbf{x}_i\}_{i=1}^{n_2} \sim p_{\theta}(\mathbf{x})$ — generated (fake) data.

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Define a discriminative model (classifier):

$$p(y = 1 | \mathbf{x}) = P(\mathbf{x} \sim p_{\text{data}}(\mathbf{x})); \quad p(y = 0 | \mathbf{x}) = P(\mathbf{x} \sim p_{\theta}(\mathbf{x}))$$

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Assumption

The generative model $p_{\theta}(\mathbf{x})$ matches $p_{\text{data}}(\mathbf{x})$ if a discriminative model $p(y|\mathbf{x})$ can't distinguish between them — that is, if $p(y = 1|\mathbf{x}) = 0.5$ for every \mathbf{x} .

Generative Adversarial Networks (GAN)

- ▶ The more expressive the discriminator, the closer we get to the optimal $p_\theta(\mathbf{x})$.
- ▶ Standard classifiers are trained by minimizing cross-entropy loss $-\mathbb{E}_{\hat{p}(\mathbf{x}, y)} \log p(y|\mathbf{x})$ with
$$\hat{p}(\mathbf{x}, y) = \frac{1}{2}[y = 1]p_{\text{data}}(\mathbf{x}) + \frac{1}{2}[y = 0]p_\theta(\mathbf{x}).$$

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Cross-Entropy for Discriminator

$$\min_{p(y|\mathbf{x})} \left[-\mathbb{E}_{p_{\text{data}}(\mathbf{x})} \log p(y=1|\mathbf{x}) - \mathbb{E}_{p_\theta(\mathbf{x})} \log p(y=0|\mathbf{x}) \right]$$
$$\max_{p(y|\mathbf{x})} \left[\mathbb{E}_{p_{\text{data}}(\mathbf{x})} \log p(y=1|\mathbf{x}) + \mathbb{E}_{p_\theta(\mathbf{x})} \log p(y=0|\mathbf{x}) \right]$$

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Cross-Entropy for Discriminator

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Generative Model

Suppose $p_\theta(\mathbf{x}, \mathbf{z}) = p_\theta(\mathbf{x}|\mathbf{z})p(\mathbf{z})$, where $p(\mathbf{z})$ is a base distribution, and $p_\theta(\mathbf{x}|\mathbf{z}) = \delta(\mathbf{x} - \mathbf{G}_\theta(\mathbf{z}))$ is deterministic.

Generative Adversarial Networks (GAN)

Cross-Entropy for Discriminative Model

$$\max_{p(y|x)} [\mathbb{E}_{p_{\text{data}}(x)} \log p(y=1|x) + \mathbb{E}_{p_{\theta}(x)} \log p(y=0|x)]$$

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- ▶ **Discriminator:** A classifier $p_{\phi}(y=1|x) = D_{\phi}(x) \in [0, 1]$, distinguishing real and generated samples. The discriminator aims to **maximize** cross-entropy.
- ▶ **Generator:** The generative model $x = \mathbf{G}_{\theta}(z)$, $z \sim p(z)$, seeks to fool the discriminator. The generator aims to **minimize** cross-entropy.

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GAN Objective

$$\min_G \max_D [\mathbb{E}_{p_{\text{data}}(x)} \log D(x) + \mathbb{E}_{p_{\theta}(x)} \log(1 - D(x))]$$

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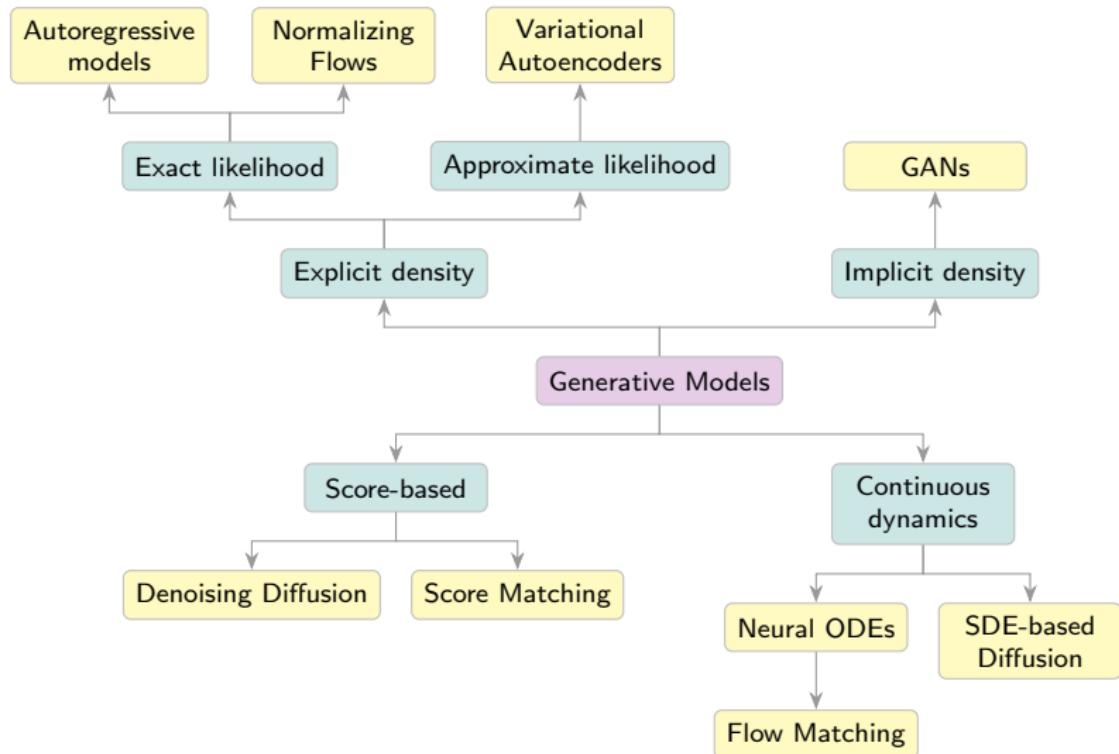
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1. Likelihood-Free Learning
2. Generative Adversarial Networks (GAN)
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Generative Models Taxonomy



GAN Optimality

Theorem

The minimax game

$$\min_G \max_D \underbrace{\left[\mathbb{E}_{p_{\text{data}}(\mathbf{x})} \log D(\mathbf{x}) + \mathbb{E}_{p(\mathbf{z})} \log(1 - D(\mathbf{G}(\mathbf{z}))) \right]}_{V(G,D)}$$

achieves its global optimum when $p_{\text{data}}(\mathbf{x}) = p_\theta(\mathbf{x})$, and $D^*(\mathbf{x}) = 0.5$.

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Proof (Fixed G)

$$V(G, D) = \mathbb{E}_{p_{\text{data}}(\mathbf{x})} \log D(\mathbf{x}) + \mathbb{E}_{p_\theta(\mathbf{x})} \log(1 - D(\mathbf{x}))$$

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$$\frac{dy(D)}{dD} = \frac{p_{\text{data}}(\mathbf{x})}{D(\mathbf{x})} - \frac{p_\theta(\mathbf{x})}{1 - D(\mathbf{x})} = 0 \quad \Rightarrow \quad D^*(\mathbf{x}) = \frac{p_{\text{data}}(\mathbf{x})}{p_{\text{data}}(\mathbf{x}) + p_\theta(\mathbf{x})}$$

GAN Optimality

Proof Continued (Fixed $D = D^*$)

$$V(G, D^*) = \mathbb{E}_{p_{\text{data}}(\mathbf{x})} \log \left(\frac{p_{\text{data}}(\mathbf{x})}{p_{\text{data}}(\mathbf{x}) + p_{\theta}(\mathbf{x})} \right) + \mathbb{E}_{p_{\theta}(\mathbf{x})} \log \left(\frac{p_{\theta}(\mathbf{x})}{p_{\text{data}}(\mathbf{x}) + p_{\theta}(\mathbf{x})} \right)$$

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Jensen-Shannon Divergence (Symmetric KL Divergence)

$$\text{JSD}(p_{\text{data}}(\mathbf{x}) \parallel p_{\theta}(\mathbf{x})) = \frac{1}{2} [\text{KL}(p_{\text{data}}(\mathbf{x}) \parallel \star) + \text{KL}(p_{\theta}(\mathbf{x}) \parallel \star)]$$

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This can be regarded as a proper distance metric!

$$V(G^*, D^*) = -2 \log 2, \quad p_{\text{data}}(\mathbf{x}) = p_{\theta}(\mathbf{x}), \quad D^*(\mathbf{x}) = 0.5.$$

GAN Optimality

Theorem

The following minimax game

$$\min_G \max_D \left[\mathbb{E}_{p_{\text{data}}(\mathbf{x})} \log D(\mathbf{x}) + \mathbb{E}_{p(\mathbf{z})} \log(1 - D(\mathbf{G}(\mathbf{z}))) \right]$$

achieves its global optimum precisely when $p_{\text{data}}(\mathbf{x}) = p_\theta(\mathbf{x})$, and $D^*(\mathbf{x}) = 0.5$.

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If the generator can express **any** function and the discriminator is **optimal** at every step, the generator **will converge** to the target distribution.

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Reality

- ▶ Generator updates are performed in parameter space, and the discriminator is often imperfectly optimized.
- ▶ Generator and discriminator losses typically oscillate during GAN training.

GAN Training

Assume both generator and discriminator are parametric models:
 $D_\phi(\mathbf{x})$ and $\mathbf{G}_\theta(\mathbf{z})$.

Objective

$$\min_{\theta} \max_{\phi} \left[\mathbb{E}_{p_{\text{data}}(\mathbf{x})} \log D_\phi(\mathbf{x}) + \mathbb{E}_{p(\mathbf{z})} \log(1 - D_\phi(\mathbf{G}_\theta(\mathbf{z}))) \right]$$

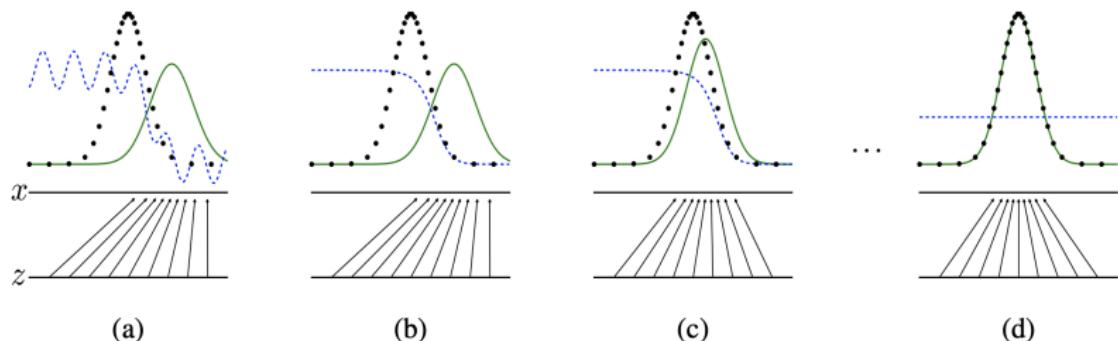
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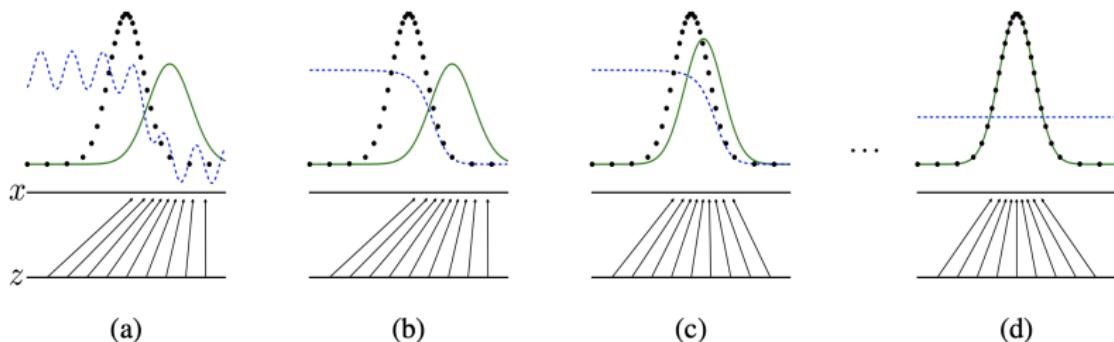


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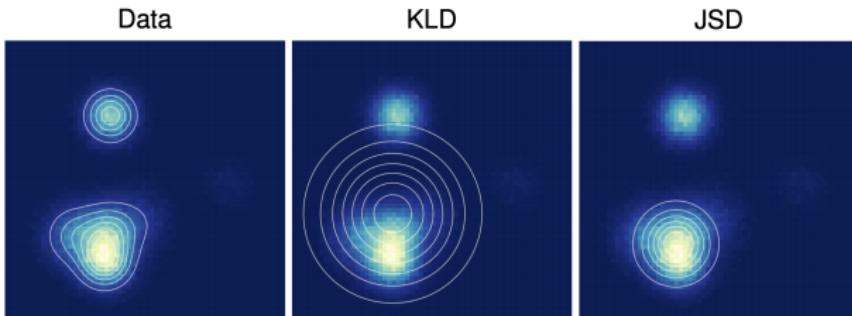
$$\min_{\theta} \max_{\phi} [\mathbb{E}_{p_{\text{data}}(\mathbf{x})} \log D_\phi(\mathbf{x}) + \mathbb{E}_{p(\mathbf{z})} \log(1 - D_\phi(\mathbf{G}_\theta(\mathbf{z})))]$$



- ▶ $\mathbf{z} \sim p(\mathbf{z})$ is a latent variable.
- ▶ $p_\theta(\mathbf{x}|\mathbf{z}) = \delta(\mathbf{x} - \mathbf{G}_\theta(\mathbf{z}))$ serves as a deterministic decoder (like normalizing flows).
- ▶ There is no encoder present.

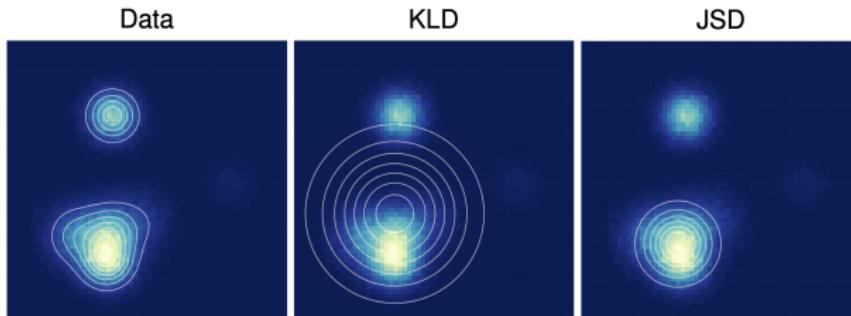
Mode Collapse

Mode collapse refers to the phenomenon where the generator in a GAN produces only one or a few different modes of the distribution.



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Numerous methods have been proposed to tackle mode collapse: changing architectures, adding regularization terms, injecting noise.

Goodfellow I. J. et al. Generative Adversarial Networks, 2014

Metz L. et al. Unrolled Generative Adversarial Networks, 2016

Jensen-Shannon vs Kullback-Leibler Divergences

- ▶ $p_{\text{data}}(\mathbf{x})$ is a fixed mixture of two Gaussians.
- ▶ $p(\mathbf{x}|\mu, \sigma) = \mathcal{N}(\mu, \sigma^2)$.

Mode Covering vs. Mode Seeking

$$\text{KL}(\pi \| p) = \int \pi(\mathbf{x}) \log \frac{\pi(\mathbf{x})}{p(\mathbf{x})} d\mathbf{x}, \quad \text{KL}(p \| \pi) = \int p(\mathbf{x}) \log \frac{p(\mathbf{x})}{\pi(\mathbf{x})} d\mathbf{x}$$

$$\text{JSD}(\pi \| p) = \frac{1}{2} \left[\text{KL}\left(\pi(\mathbf{x}) \| \frac{\pi(\mathbf{x}) + p(\mathbf{x})}{2}\right) + \text{KL}\left(p(\mathbf{x}) \| \frac{\pi(\mathbf{x}) + p(\mathbf{x})}{2}\right) \right]$$

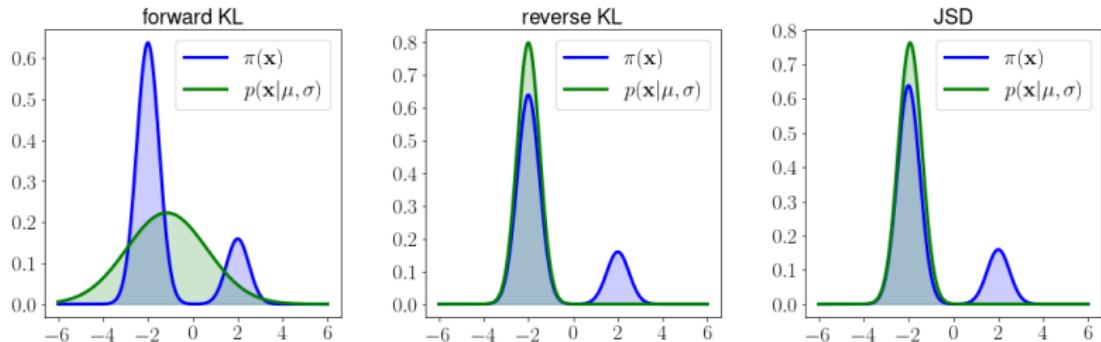
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Outline

1. Likelihood-Free Learning
2. Generative Adversarial Networks (GAN)
3. Wasserstein Distance
4. Wasserstein GAN

Theoretical Results

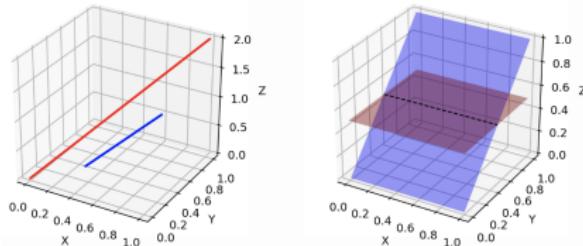
- ▶ The dimensionality of \mathbf{z} is less than that of \mathbf{x} , so $p_{\theta}(\mathbf{x})$ with $\mathbf{x} = \mathbf{G}_{\theta}(\mathbf{z})$ lives on a low-dimensional manifold.

Weng L. From GAN to WGAN, 2019

Arjovsky M., Bottou L. Towards Principled Methods for Training Generative Adversarial Networks, 2017

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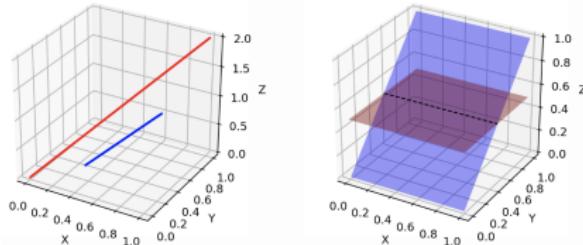


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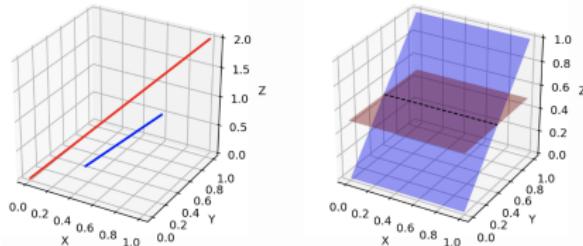
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- ▶ If $p_{\text{data}}(\mathbf{x})$ and $p_\theta(\mathbf{x})$ are disjoint, a smooth optimal discriminator can exist!
- ▶ For such low-dimensional, disjoint manifolds:

$$\text{KL}(p_{\text{data}} \parallel p_\theta) = \text{KL}(p_\theta \parallel p_{\text{data}}) = \infty, \quad \text{JSD}(p_{\text{data}} \parallel p_\theta) = \log 2$$

Weng L. From GAN to WGAN, 2019

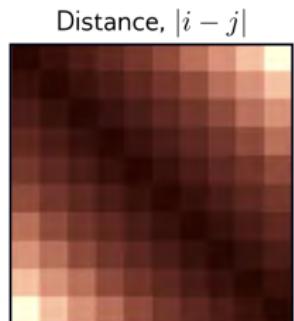
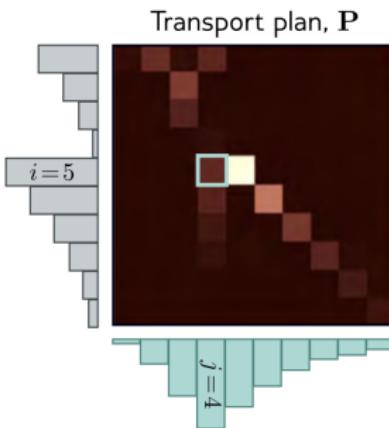
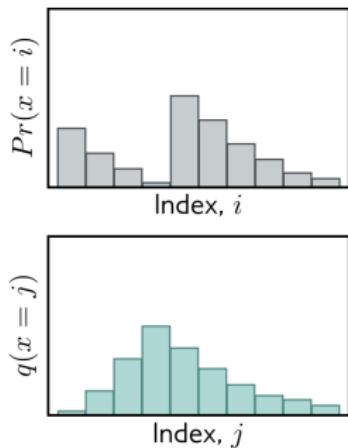
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Wasserstein Distance (Discrete)

Also known as the **Earth Mover's Distance**.

Optimal Transport Formulation

The minimum cost of moving and transforming a pile of "dirt" shaped like one probability distribution to match another.



$$\begin{aligned}\text{Wasserstein distance} \\ = \sum \mathbf{P} \cdot |i - j|\end{aligned}$$

Wasserstein Distance (Continuous)

$$W(\pi \| p) = \inf_{\gamma \in \Gamma(\pi, p)} \mathbb{E}_{(\mathbf{x}_1, \mathbf{x}_2) \sim \gamma} \|\mathbf{x}_1 - \mathbf{x}_2\| = \inf_{\gamma \in \Gamma(\pi, p)} \int \|\mathbf{x}_1 - \mathbf{x}_2\| \gamma(\mathbf{x}_1, \mathbf{x}_2) d\mathbf{x}_1 d\mathbf{x}_2$$

- ▶ $\gamma(\mathbf{x}_1, \mathbf{x}_2)$ is the transport plan: the amount of “dirt” assigned from \mathbf{x}_1 to \mathbf{x}_2 .

$$\int \gamma(\mathbf{x}_1, \mathbf{x}_2) d\mathbf{x} = p(\mathbf{x}_2); \quad \int \gamma(\mathbf{x}_1, \mathbf{x}_2) d\mathbf{x}_2 = \pi(\mathbf{x}_1).$$

- ▶ $\Gamma(\pi, p)$ denotes the set of all joint distributions $\gamma(\mathbf{x}_1, \mathbf{x}_2)$ with marginals π and p .
- ▶ $\gamma(\mathbf{x}_1, \mathbf{x}_2)$ is the mass, $\|\mathbf{x}_1 - \mathbf{x}_2\|$ is the distance.

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Wasserstein Metric

$$W_s(\pi, p) = \inf_{\gamma \in \Gamma(\pi, p)} \left(\mathbb{E}_{(\mathbf{x}_1, \mathbf{x}_2) \sim \gamma} \|\mathbf{x}_1 - \mathbf{x}_2\|^s \right)^{1/s}$$

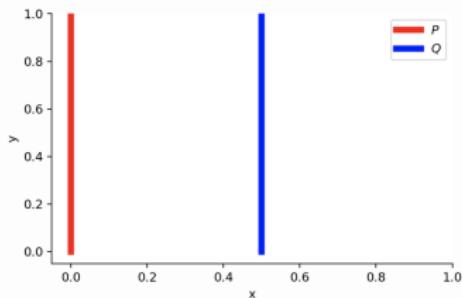
In our setting, $W(\pi \| p) = W_1(\pi, p)$, which is the transport cost formulation.

Wasserstein Distance vs KL vs JSD

Consider two-dimensional distributions:

$$p_{\text{data}}(x, y) = (0, U[0, 1])$$

$$p_{\theta}(x, y) = (\theta, U[0, 1])$$

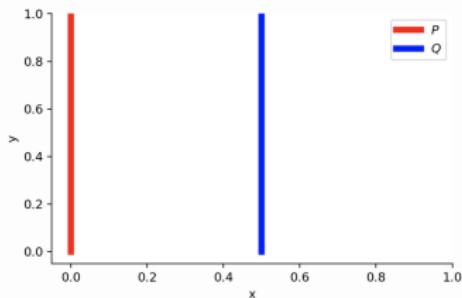


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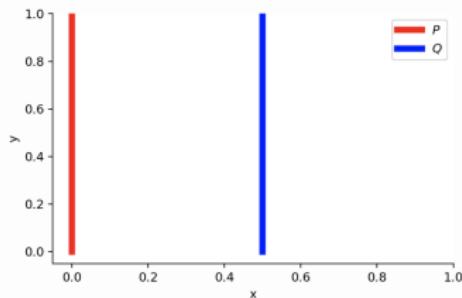
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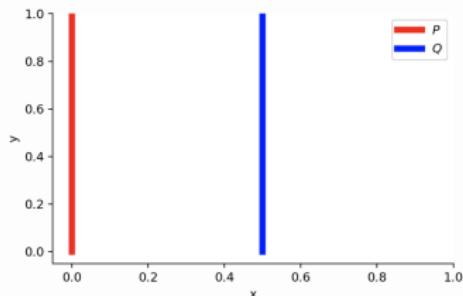
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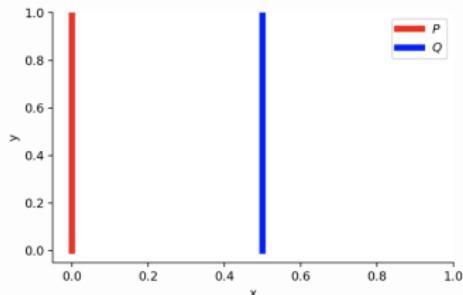
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Wasserstein Distance vs KL vs JSD

Theorem 1

Let $\mathbf{G}_\theta(\mathbf{z})$ be (almost) any feedforward neural network, and $p(\mathbf{z})$ a prior over \mathbf{z} such that $\mathbb{E}_{p(\mathbf{z})}\|\mathbf{z}\| < \infty$. Then $W(p_{\text{data}}\|p_\theta)$ is continuous everywhere and differentiable almost everywhere.

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Theorem 2

Let π be a distribution on a compact space \mathcal{X} and let $\{p_t\}_{t=1}^\infty$ be a sequence of distributions on \mathcal{X} .

$$\text{KL}(\pi \| p_t) \rightarrow 0 \quad (\text{or } \text{KL}(p_t \| \pi) \rightarrow 0) \tag{1}$$

$$\text{JSD}(\pi \| p_t) \rightarrow 0 \tag{2}$$

$$W(\pi \| p_t) \rightarrow 0 \tag{3}$$

In summary, as $t \rightarrow \infty$, (1) \Rightarrow (2), and (2) \Rightarrow (3).

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Wasserstein GAN

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Theorem (Kantorovich-Rubinstein Duality)

$$W(\pi \| p) = \frac{1}{K} \max_{\|f\|_L \leq K} \left[\mathbb{E}_{\pi(\mathbf{x})} f(\mathbf{x}) - \mathbb{E}_{p(\mathbf{x})} f(\mathbf{x}) \right]$$

where $f : \mathbb{R}^m \rightarrow \mathbb{R}$ is K -Lipschitz ($\|f\|_L \leq K$):

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Wasserstein GAN

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We can thus estimate $W(\pi \| p)$ using only samples and a function f .

Wasserstein GAN

Theorem (Kantorovich-Rubinstein Duality)

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- ▶ We must ensure that f is K -Lipschitz continuous.
- ▶ Let $f_{\phi}(\mathbf{x})$ be a feedforward neural network parameterized by ϕ .
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- ▶ If the weights ϕ are restricted to a compact set Φ , then f_{ϕ} is K -Lipschitz.
- ▶ Clamp weights within the box $\Phi = [-c, c]^d$ (e.g. $c = 0.01$) after each update.

$$\begin{aligned} K \cdot W(p_{\text{data}} \| p_{\theta}) &= \max_{\|f\|_L \leq K} \left[\mathbb{E}_{p_{\text{data}}(\mathbf{x})} f(\mathbf{x}) - \mathbb{E}_{p_{\theta}(\mathbf{x})} f(\mathbf{x}) \right] \geq \\ &\geq \max_{\phi \in \Phi} \left[\mathbb{E}_{p_{\text{data}}(\mathbf{x})} f_{\phi}(\mathbf{x}) - \mathbb{E}_{p_{\theta}(\mathbf{x})} f_{\phi}(\mathbf{x}) \right] \end{aligned}$$

Wasserstein GAN

Standard GAN Objective

$$\min_{\theta} \max_{\phi} \mathbb{E}_{p_{\text{data}}(\mathbf{x})} \log D_{\phi}(\mathbf{x}) + \mathbb{E}_{p(\mathbf{z})} \log(1 - D_{\phi}(\mathbf{G}_{\theta}(\mathbf{z})))$$

WGAN Objective

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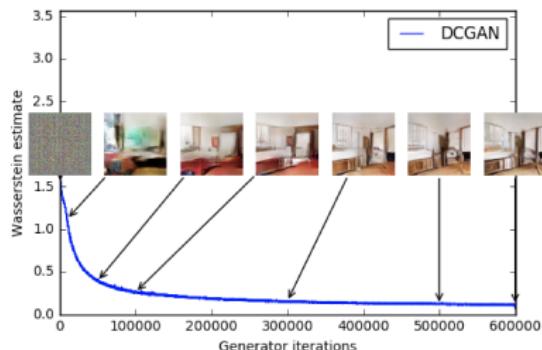
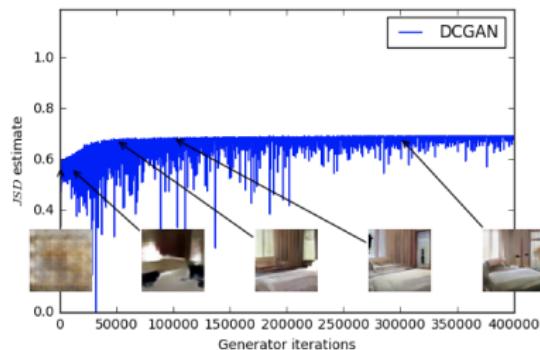
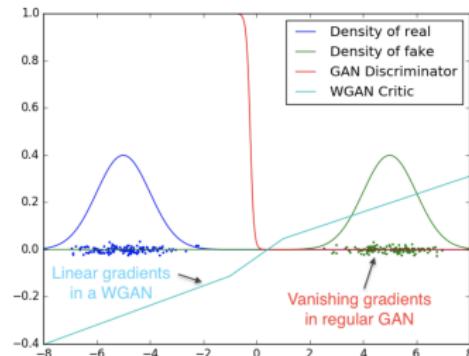
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- ▶ The discriminator D is replaced by function f : in WGAN, it is known as the **critic**, which is *not* a classifier.
- ▶ "*Weight clipping is a clearly terrible way to enforce a Lipschitz constraint.*"
 - ▶ If c is large, optimizing the critic is hard.
 - ▶ If c is small, gradients may vanish.

Wasserstein GAN

- ▶ WGAN provides nonzero gradients even if distributions' supports are disjoint.
- ▶ $JSD(p_{\text{data}} \| p_{\theta})$ is poorly correlated with sample quality and remains near its maximum value $\log 2 \approx 0.69$.
- ▶ $W(p_{\text{data}} \| p_{\theta})$ is tightly correlated with quality.



Summary

- ▶ Likelihood is not a reliable metric for generative model evaluation.
- ▶ Adversarial learning casts distribution matching as a minimax game.
- ▶ GANs, in theory, optimize the Jensen-Shannon divergence.
- ▶ KL and JS divergences fail as objectives when the model and data distributions are disjoint.
- ▶ The Earth Mover's (Wasserstein) distance provides a more meaningful loss for distribution matching.
- ▶ Kantorovich-Rubinstein duality allows us to compute the EM distance using only samples.
- ▶ Wasserstein GAN enforces the Lipschitz condition on the critic through weight clipping—although better alternatives exist.