

Deep Generative Models

Lecture 2

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2026, Spring

Recap of Previous Lecture

We're given **finite** number of i.i.d. samples $\{\mathbf{x}_i\}_{i=1}^n \subset \mathbb{R}^m$ drawn from an **unknown** distribution $p_{\text{data}}(\mathbf{x})$.

Objective

Our aim is to learn a distribution $p_{\text{data}}(\mathbf{x})$ that allows us to:

- ▶ Generate new samples from $p_{\text{data}}(\mathbf{x})$ (sample $\mathbf{x} \sim p_{\text{data}}(\mathbf{x})$) — **generation**.
- ▶ Evaluate $p_{\text{data}}(\mathbf{x})$ on novel data (answering “How likely is an object \mathbf{x} ?”) — **density estimation**;

Divergence Minimization Task

- ▶ $D(\pi \| p) \geq 0$ for all $\pi, p \in \mathcal{P}$;
- ▶ $D(\pi \| p) = 0$ if and only if $\pi \equiv p$.

$$\min_{\theta} D(p_{\text{data}} \| p_{\theta})$$

Recap of Previous Lecture

Forward KL Divergence

$$\text{KL}(p_{\text{data}} \| p_{\theta}) = \int \pi(\mathbf{x}) \log \frac{p_{\text{data}}(\mathbf{x})}{p_{\theta}(\mathbf{x})} d\mathbf{x} \rightarrow \min_{\theta}$$

Reverse KL Divergence

$$\text{KL}(p_{\theta} \| p_{\text{data}}) = \int p_{\theta}(\mathbf{x}) \log \frac{p_{\theta}(\mathbf{x})}{p_{\text{data}}(\mathbf{x})} d\mathbf{x} \rightarrow \min_{\theta}$$

Maximum Likelihood Estimation (MLE)

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

Maximum likelihood estimation is equivalent to minimizing the Monte Carlo estimate of the forward KL divergence.

Recap of Previous Lecture

Likelihood as Product of Conditionals

Let $\mathbf{x} = (x_1, \dots, x_m)$, and define $\mathbf{x}_{1:j} = (x_1, \dots, x_j)$. Then,

$$p_{\theta}(\mathbf{x}) = \prod_{j=1}^m p_{\theta}(x_j | \mathbf{x}_{1:j-1}), \quad \log p_{\theta}(\mathbf{x}) = \sum_{j=1}^m \log p_{\theta}(x_j | \mathbf{x}_{1:j-1})$$

MLE for Autoregressive Models

$$\theta^* = \arg \max_{\theta} \sum_{i=1}^n \sum_{j=1}^m \log p_{\theta}(x_{ij} | \mathbf{x}_{i,1:j-1})$$

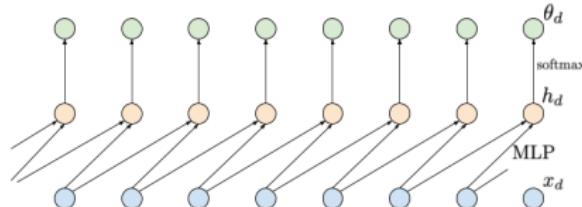
Sampling

$$\hat{x}_1 \sim p_{\theta}(x_1), \quad \hat{x}_2 \sim p_{\theta}(x_2 | \hat{\mathbf{x}}_1), \quad \dots, \quad \hat{x}_m \sim p_{\theta}(x_m | \hat{\mathbf{x}}_{1:m-1})$$

The generated sample is $\hat{\mathbf{x}} = (\hat{x}_1, \hat{x}_2, \dots, \hat{x}_m)$.

Recap of Previous Lecture

Autoregressive MLP



Autoregressive Transformer

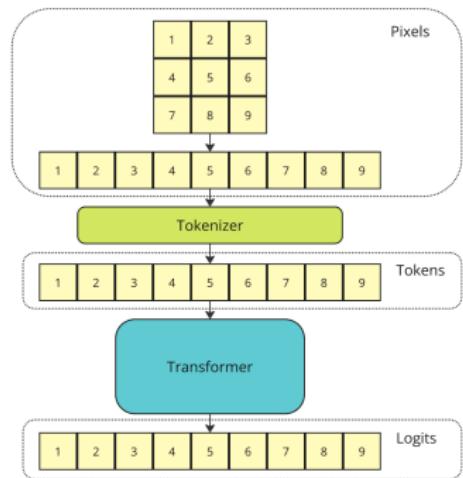
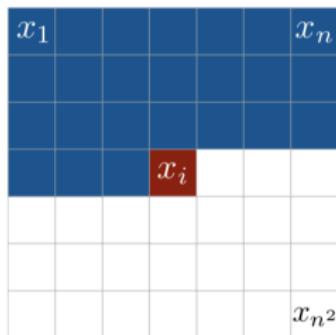


Image credit: https://jmtomczak.github.io/blog/2/2_ARM.html
Chen M. et al. Generative Pretraining from Pixels, 2020

Outline

1. Normalizing Flows (NF)

2. NF Examples

Linear Normalizing Flows

Gaussian Autoregressive NF

Coupling Layer (RealNVP)

3. Latent Variable Models (LVM)

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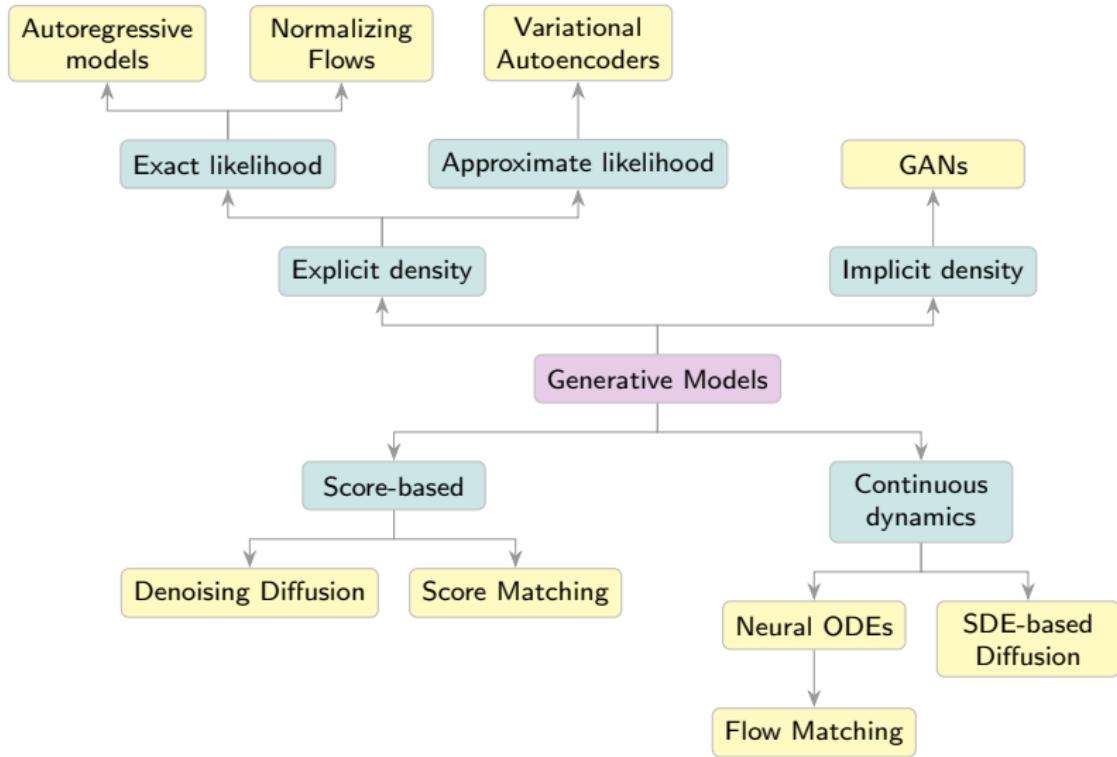
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Generative Models Taxonomy



Normalizing Flows: Prerequisites

Jacobian Matrix

Let $\mathbf{f} : \mathbb{R}^m \rightarrow \mathbb{R}^m$ be a differentiable function.

$$\mathbf{z} = \mathbf{f}(\mathbf{x}), \quad \mathbf{J} = \frac{\partial \mathbf{z}}{\partial \mathbf{x}} = \begin{pmatrix} \frac{\partial z_1}{\partial x_1} & \cdots & \frac{\partial z_1}{\partial x_m} \\ \vdots & \ddots & \vdots \\ \frac{\partial z_m}{\partial x_1} & \cdots & \frac{\partial z_m}{\partial x_m} \end{pmatrix} \in \mathbb{R}^{m \times m}$$

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Change of Variables Theorem (CoV)

Let $\mathbf{x} \in \mathbb{R}^m$ be a random vector with density $p(\mathbf{x})$, and let $\mathbf{f} : \mathbb{R}^m \rightarrow \mathbb{R}^m$ be a C^1 -diffeomorphism (\mathbf{f} and \mathbf{f}^{-1} are continuously differentiable mappings). If $\mathbf{z} = \mathbf{f}(\mathbf{x})$, then

$$p(\mathbf{x}) = p(\mathbf{z}) |\det(\mathbf{J}_f)| = p(\mathbf{z}) \left| \det \left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}} \right) \right|$$

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$$p(\mathbf{z}) = p(\mathbf{x}) |\det(\mathbf{J}_{f^{-1}})| = p(\mathbf{x}) \left| \det \left(\frac{\partial \mathbf{x}}{\partial \mathbf{z}} \right) \right| = p(\mathbf{f}^{-1}(\mathbf{z})) \left| \det \left(\frac{\partial \mathbf{f}^{-1}(\mathbf{z})}{\partial \mathbf{z}} \right) \right|$$

Jacobian Determinant

Inverse Function Theorem

If the function \mathbf{f} is invertible and its Jacobian is continuous and non-singular, then

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- ▶ $\mathbf{f}_\theta(\mathbf{x})$ is a parameterized transformation.

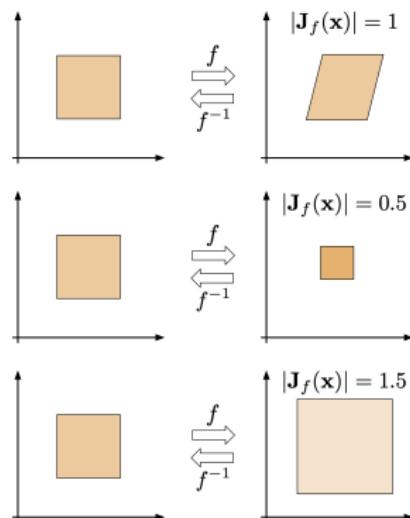
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- ▶ \mathbf{x} and \mathbf{z} reside in the same space (\mathbb{R}^m).
- ▶ $\mathbf{f}_\theta(\mathbf{x})$ is a parameterized transformation.
- ▶ The determinant of the Jacobian $\mathbf{J} = \frac{\partial \mathbf{f}_\theta(\mathbf{x})}{\partial \mathbf{x}}$ quantifies how the volume is changed by the transformation.



Fitting Normalizing Flows

MLE Problem

$$p_{\theta}(\mathbf{x}) = p(\mathbf{z}) \left| \det \left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}} \right) \right| = p(\mathbf{f}_{\theta}(\mathbf{x})) \left| \det \left(\frac{\partial \mathbf{f}_{\theta}(\mathbf{x})}{\partial \mathbf{x}} \right) \right|$$

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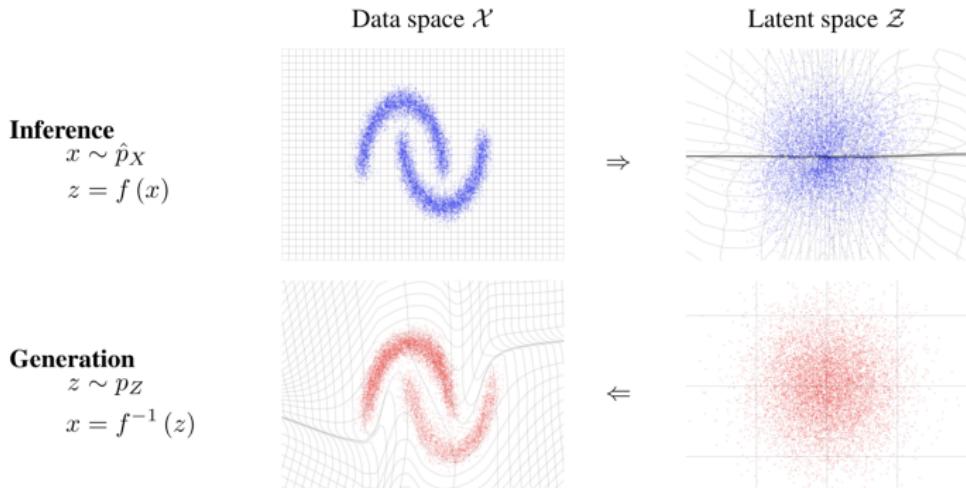
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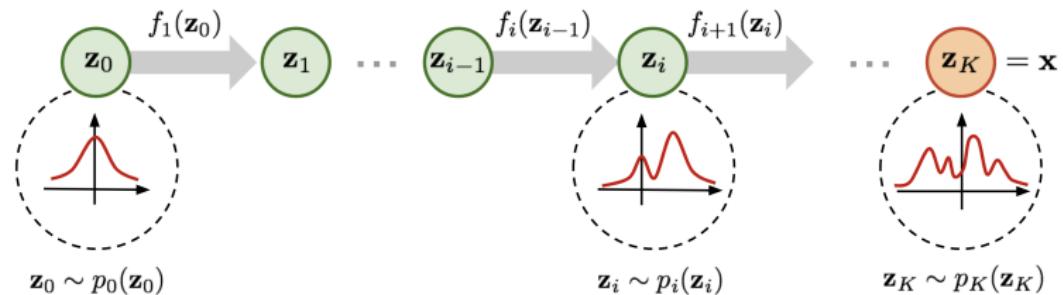
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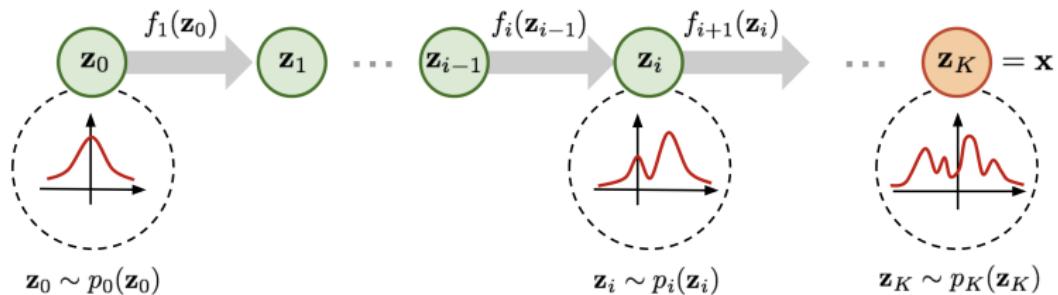
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Composition of Normalizing Flows



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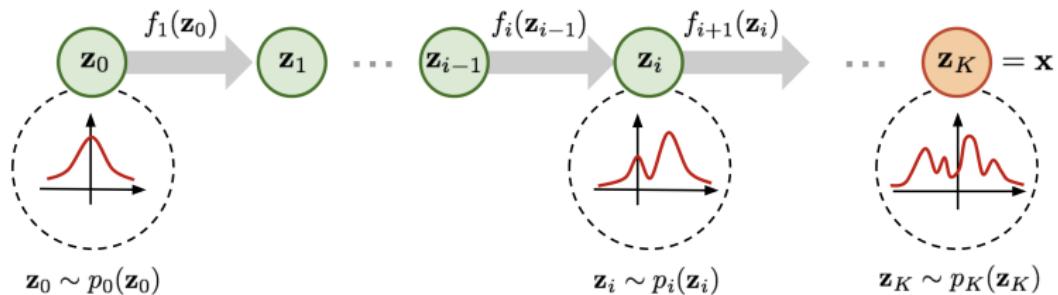


Theorem

If every $\{\mathbf{f}_k\}_{k=1}^K$ satisfies the conditions of the change-of-variables theorem, then the composition $\mathbf{f}(\mathbf{x}) = \mathbf{f}_K \circ \dots \circ \mathbf{f}_1(\mathbf{x})$ also satisfies them.

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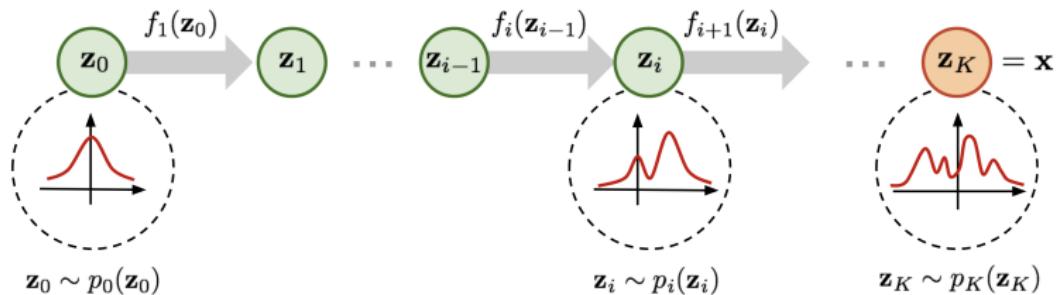


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Normalizing Flows (NF)

$$\log p_{\theta}(\mathbf{x}) = \log p(\mathbf{f}_{\theta}(\mathbf{x})) + \log |\det(\mathbf{J}_f)|$$

Definition

A normalizing flow is a C^1 -diffeomorphism that transforms data \mathbf{x} to noise \mathbf{z} .

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- ▶ **Normalizing** refers to mapping samples from $p_{\text{data}}(\mathbf{x})$ to a base distribution $p(\mathbf{z})$.
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Log-Likelihood

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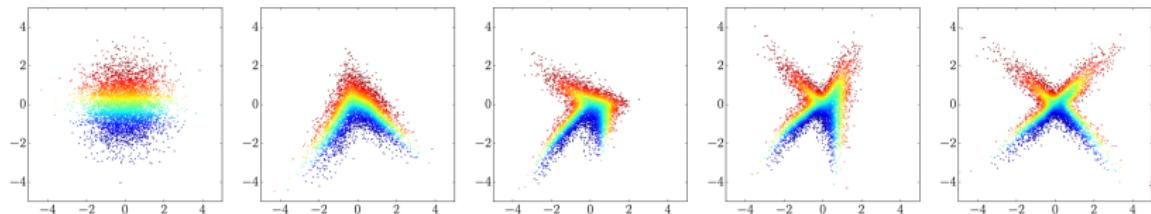
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where $\mathbf{J}_{\mathbf{f}_k} = \frac{\partial \mathbf{f}_k}{\partial \mathbf{f}_{k-1}}$.

Note: Here we consider only **continuous** random variables.

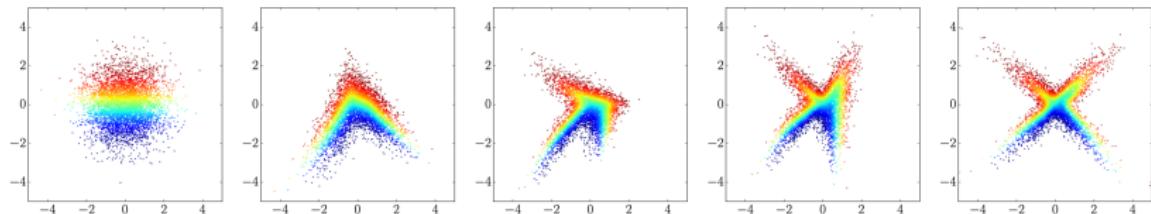
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Example: 4-Step NF



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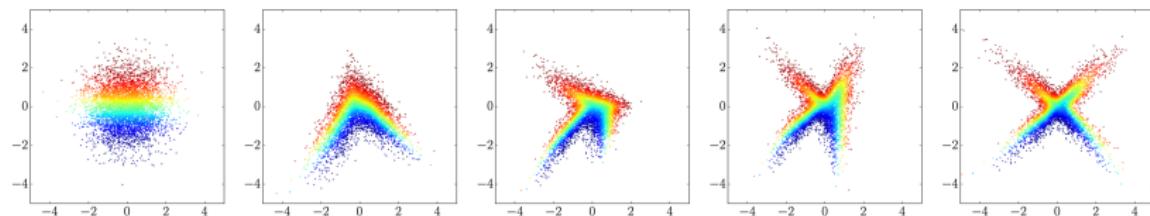
NF Log-Likelihood

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What's the computational complexity of evaluating this determinant?

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Requirements

- ▶ Efficient computation of the Jacobian $\mathbf{J}_f = \frac{\partial \mathbf{f}_{\theta}(\mathbf{x})}{\partial \mathbf{x}}$
- ▶ Efficient inversion of the transformation $\mathbf{f}_{\theta}(\mathbf{x})$

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Consider a linear layer $\mathbf{z} = \mathbf{W}\mathbf{x}$, $\mathbf{W} \in \mathbb{R}^{m \times m}$.

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$$\log \left| \det \left(\frac{\partial \mathbf{f}_{\theta}(\mathbf{x})}{\partial \mathbf{x}} \right) \right| = \log \left| \prod_{j=1}^m \frac{\partial f_{j,\theta}(x_j)}{\partial x_j} \right| = \sum_{j=1}^m \log \left| \frac{\partial f_{j,\theta}(x_j)}{\partial x_j} \right|$$

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3. z_j depends only on $\mathbf{x}_{1:j}$ (autoregressive dependency).

Linear Normalizing Flows

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In general, matrix inversion has computational complexity $O(m^3)$.

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Invertibility

- ▶ Diagonal matrix: $O(m)$.
- ▶ Triangular matrix: $O(m^2)$.
- ▶ Directly parameterizing all invertible matrices in a continuous way is infeasible
(there is not surjective function from \mathbb{R}^{m^2} to the set of all invertible matrices of size $m \times m$).

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Matrix Decompositions

- ▶ **LU Decomposition:**

$$\mathbf{W} = \mathbf{P}\mathbf{L}\mathbf{U},$$

where \mathbf{P} is a permutation matrix, \mathbf{L} is lower triangular with positive diagonal, and \mathbf{U} is upper triangular with positive diagonal.

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- ▶ **QR Decomposition:**

$$\mathbf{W} = \mathbf{Q}\mathbf{R},$$

where \mathbf{Q} is orthogonal, and \mathbf{R} is upper triangular with positive diagonal.

Linear Normalizing Flows

$$\mathbf{z} = \mathbf{f}_{\theta}(\mathbf{x}) = \mathbf{W}\mathbf{x}, \quad \mathbf{W} \in \mathbb{R}^{m \times m}, \quad \theta = \mathbf{W}, \quad \mathbf{J}_f = \mathbf{W}^T$$

Matrix Decompositions

- ▶ **LU Decomposition:**

$$\mathbf{W} = \mathbf{P}\mathbf{L}\mathbf{U},$$

where \mathbf{P} is a permutation matrix, \mathbf{L} is lower triangular with positive diagonal, and \mathbf{U} is upper triangular with positive diagonal.

- ▶ **QR Decomposition:**

$$\mathbf{W} = \mathbf{Q}\mathbf{R},$$

where \mathbf{Q} is orthogonal, and \mathbf{R} is upper triangular with positive diagonal.

Decomposition is performed only at initialization; the decomposed matrices ($\mathbf{P}, \mathbf{L}, \mathbf{U}$ or \mathbf{Q}, \mathbf{R}) are optimized during training.

Outline

1. Normalizing Flows (NF)

2. NF Examples

Linear Normalizing Flows

Gaussian Autoregressive NF

Coupling Layer (RealNVP)

3. Latent Variable Models (LVM)

Gaussian Autoregressive Model

Consider the autoregressive model:

$$p_{\theta}(\mathbf{x}) = \prod_{j=1}^m p_{\theta}(x_j | \mathbf{x}_{1:j-1}), \quad p_{\theta}(x_j | \mathbf{x}_{1:j-1}) = \mathcal{N}(\mu_{j,\theta}(\mathbf{x}_{1:j-1}), \sigma_{j,\theta}^2(\mathbf{x}_{1:j-1}))$$

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Sampling

$$x_j = \sigma_{j,\theta}(\mathbf{x}_{1:j-1}) \cdot z_j + \mu_{j,\theta}(\mathbf{x}_{1:j-1}), \quad z_j \sim \mathcal{N}(0, 1)$$

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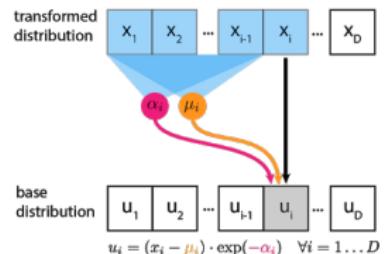
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- ▶ The Jacobian matrix of this transformation is triangular.

Gaussian Autoregressive NF

Forward Transformation: $\mathbf{f}_\theta(\mathbf{x})$

$$\mathbf{z} = \mathbf{f}_\theta(\mathbf{x})$$

$$z_j = \frac{x_j - \mu_{j,\theta}(\mathbf{x}_{1:j-1})}{\sigma_{j,\theta}(\mathbf{x}_{1:j-1})}$$



Gaussian Autoregressive NF

Forward Transformation: $\mathbf{f}_\theta(\mathbf{x})$

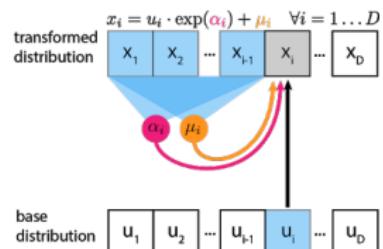
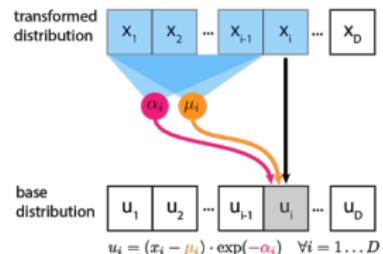
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Gaussian Autoregressive NF

Forward Transformation: $\mathbf{f}_\theta(\mathbf{x})$

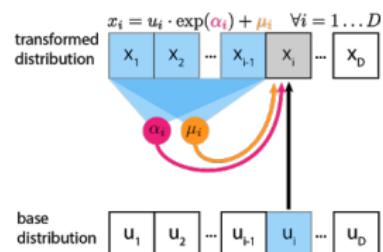
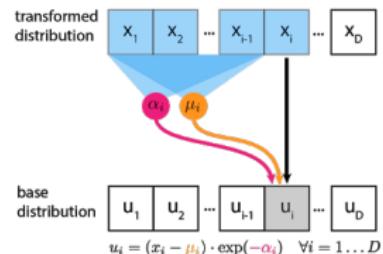
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- ▶ Sampling must be done sequentially, but density estimation can be parallelized.
- ▶ The forward KL divergence is a natural objective for training.

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RealNVP

Split \mathbf{x} and \mathbf{z} into two parts:

$$\mathbf{x} = [\mathbf{x}_1, \mathbf{x}_2] = [\mathbf{x}_{1:d}, \mathbf{x}_{d+1:m}]; \quad \mathbf{z} = [\mathbf{z}_1, \mathbf{z}_2] = [\mathbf{z}_{1:d}, \mathbf{z}_{d+1:m}]$$

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Coupling Layer

$$\begin{cases} \mathbf{x}_1 = \mathbf{z}_1 \\ \mathbf{x}_2 = \mathbf{z}_2 \odot \sigma_{\theta}(\mathbf{z}_1) + \mu_{\theta}(\mathbf{z}_1) \end{cases}$$

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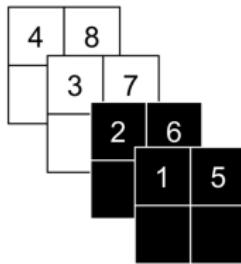
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Image Partitioning



- ▶ Checkerboard ordering corresponds to masking.
- ▶ Channelwise ordering relies on splitting.

RealNVP

Coupling Layer

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In both training and sampling, only a single forward pass is needed!

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Jacobian

$$\det \left(\frac{\partial \mathbf{z}}{\partial \mathbf{x}} \right) = \det \begin{pmatrix} \mathbf{I}_d & \mathbf{0}_{d \times m-d} \\ \frac{\partial \mathbf{z}_2}{\partial \mathbf{x}_1} & \frac{\partial \mathbf{z}_2}{\partial \mathbf{x}_2} \end{pmatrix}$$

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$$\mathbf{x} = \mathbf{f}_{\theta}^{-1}(\mathbf{z}) \quad \Rightarrow \quad \mathbf{x}_j = \sigma_{j,\theta}(\mathbf{x}_{1:j-1}) \cdot \mathbf{z}_j + \mu_{j,\theta}(\mathbf{x}_{1:j-1})$$

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How can the RealNVP layer be derived as a special instance of the
Gaussian autoregressive NF?

Outline

1. Normalizing Flows (NF)
2. NF Examples
 - Linear Normalizing Flows
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Bayesian Framework

Bayes' Theorem

$$p(\theta|x) = \frac{p(x|\theta)p(\theta)}{p(x)} = \frac{p(x|\theta)p(\theta)}{\int p(x|\theta)p(\theta)d\theta}$$

- ▶ x : observed variables;
- ▶ θ : unknown latent variables/parameters;
- ▶ $p_\theta(x) = p(x|\theta)$: likelihood;
- ▶ $p(x) = \int p(x|\theta)p(\theta)d\theta$: evidence;
- ▶ $p(\theta)$: prior distribution;
- ▶ $p(\theta|x)$: posterior distribution.

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Interpretation

- ▶ We begin with unknown variables θ and a prior belief $p(\theta)$.
- ▶ Once data x is observed, the posterior $p(\theta|x)$ incorporates both prior beliefs and evidence from the data.

Bayesian Framework

Consider the case where the unobserved variables θ are model parameters (i.e., θ are random variables).

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Posterior Distribution

$$p(\theta|\mathbf{X}) = \frac{p(\mathbf{X}|\theta)p(\theta)}{p(\mathbf{X})} = \frac{p(\mathbf{X}|\theta)p(\theta)}{\int p(\mathbf{X}|\theta)p(\theta)d\theta}$$

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Maximum a Posteriori (MAP) Estimation

$$\theta^* = \arg \max_{\theta} p(\theta|\mathbf{X}) = \arg \max_{\theta} (\log p(\mathbf{X}|\theta) + \log p(\theta))$$

Latent Variable Models (LVM)

Maximum Likelihood Estimation (MLE) Problem

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

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Extended Probabilistic Model

Introduce a latent variable \mathbf{z} for each observed sample \mathbf{x} :

$$p_{\theta}(\mathbf{x}, \mathbf{z}) = p_{\theta}(\mathbf{x}|\mathbf{z})p(\mathbf{z}); \quad \log p_{\theta}(\mathbf{x}, \mathbf{z}) = \log p_{\theta}(\mathbf{x}|\mathbf{z}) + \log p(\mathbf{z}).$$

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Motivation

Both $p_{\theta}(\mathbf{x}|\mathbf{z})$ and $p(\mathbf{z})$ are usually much simpler than $p_{\theta}(\mathbf{x})$.

Summary

- ▶ The CoV theorem provides a method for computing a random variable's density under an invertible transformation.
- ▶ Normalizing flows transform a simple base distribution into a complex one via a sequence of invertible mappings, each with efficient Jacobian determinants.
- ▶ Linear NFs capture invertible matrices by using matrix decompositions.
- ▶ Gaussian autoregressive NFs are AR models with triangular Jacobians.
- ▶ The RealNVP coupling layer provides an efficient normalizing flow (a special case of AR NF), supporting fast inference and sampling.
- ▶ The Bayesian framework generalizes nearly all standard machine learning methods.