LEARNING GENERATIVE MODELS ACROSS INCOMPARABLE SPACES

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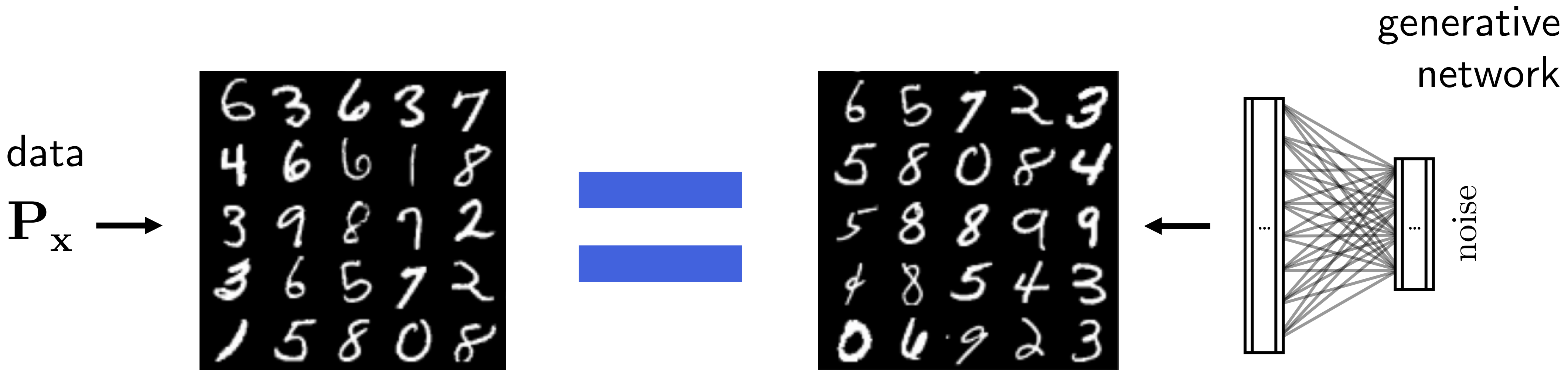
Poster #173

Generative Modeling



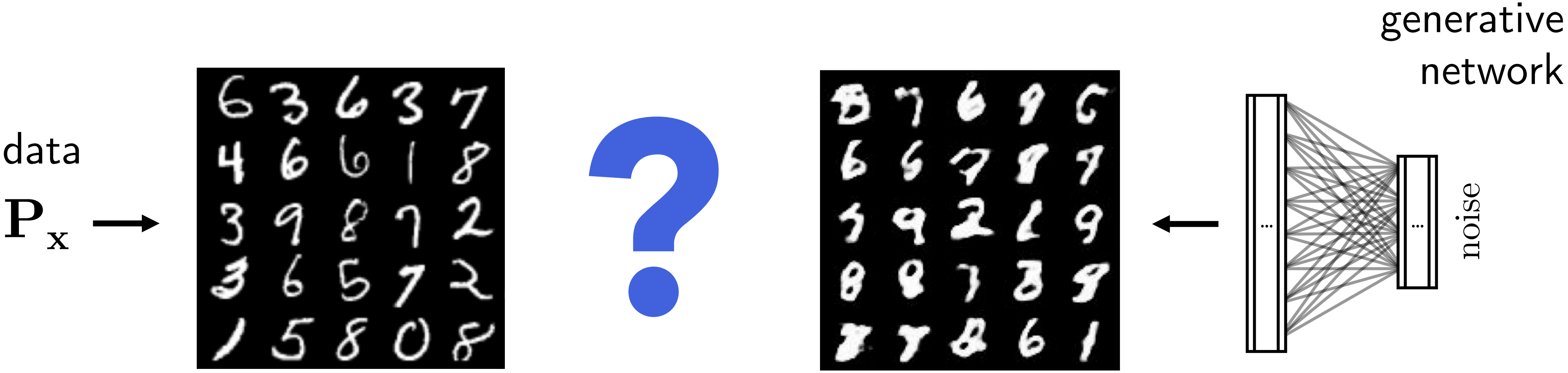
data

$\mathbf{P}_{\mathbf{x}}$

generative network

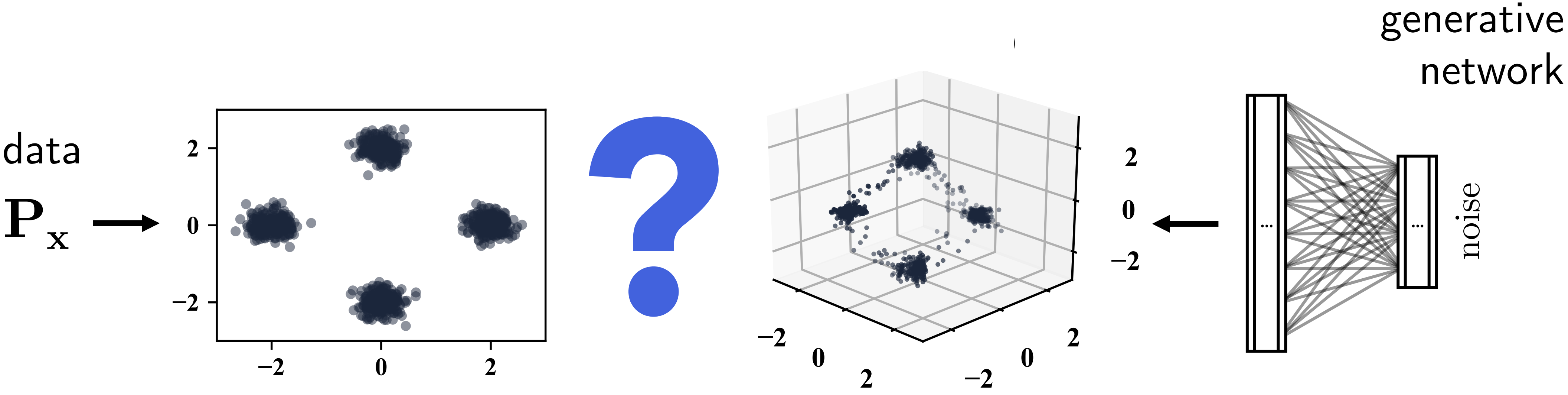
noise

Beyond Identical Generation ...



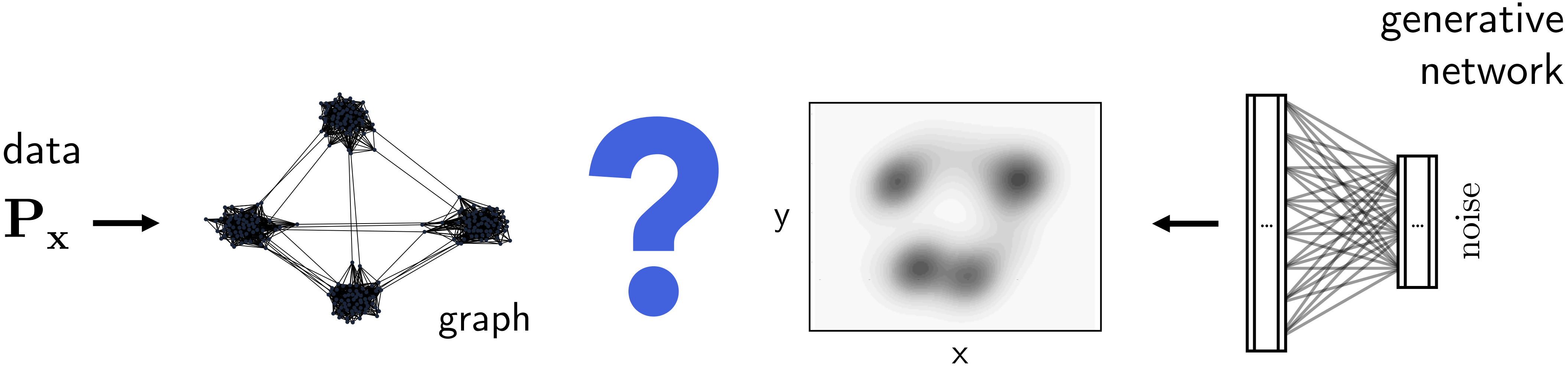
... enforce style.

Beyond Identical Generation ...



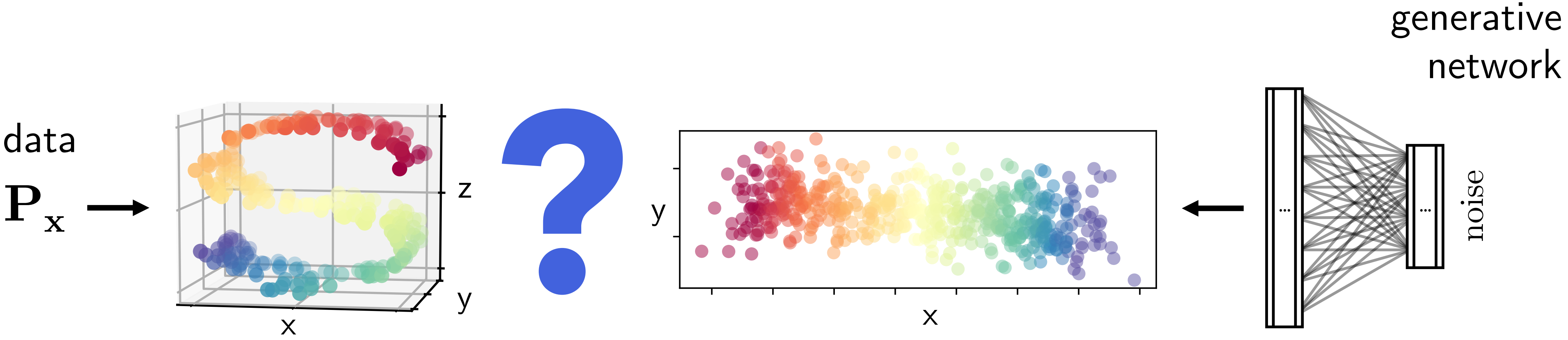
... learn across different dimensions.

Beyond Identical Generation ...



... translate between representation.

Beyond Identical Generation ...


data

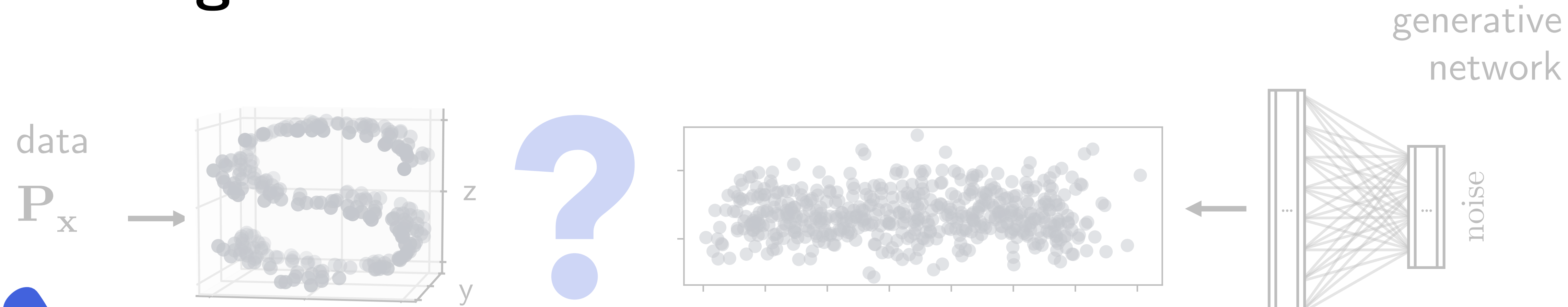
$\mathbf{P}_{\mathbf{x}}$

generative network

noise

... learn manifolds.

Challenges



1. How to compare samples from *incomparable* spaces?

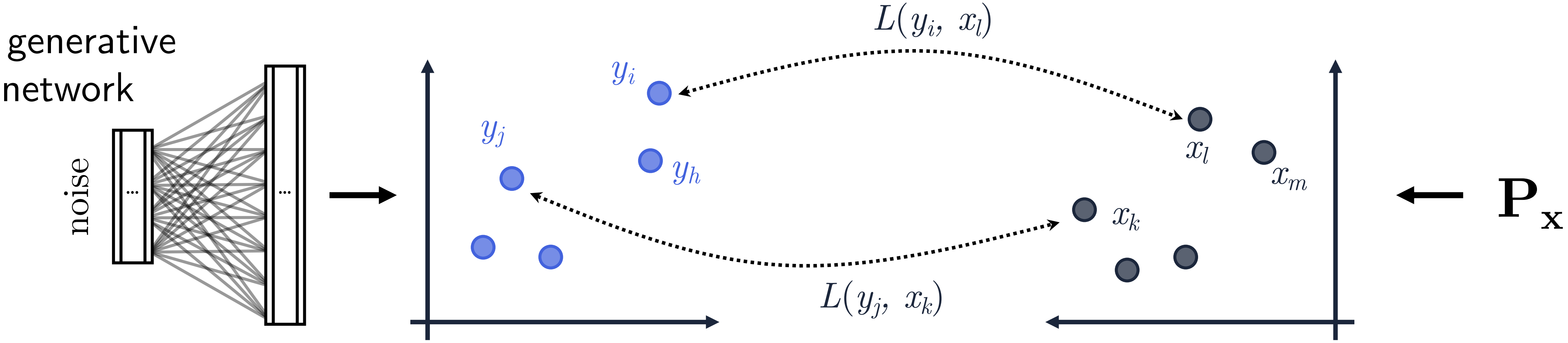
... learn manifolds.

2. What should be preserved? What can we modify?

3. How to stabilize learning despite additional freedom?

Learning Generative Models

Optimal Transport Distances



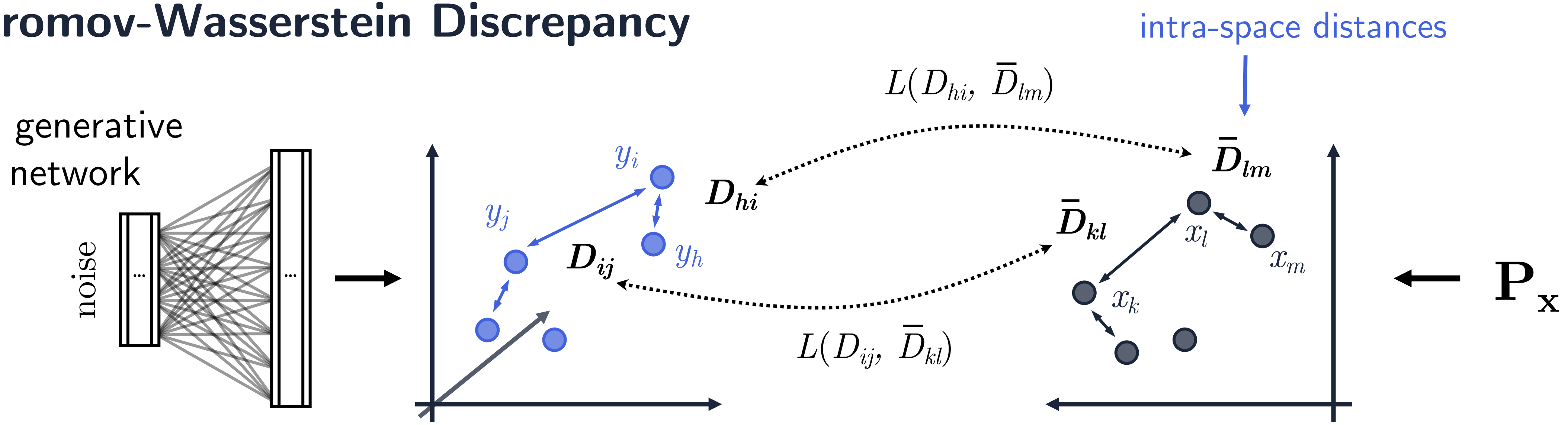
... distance between distributions: **minimal cost** of transporting mass between them.

... find an **optimal transport plan** T.

... classical Wasserstein distances assume that spaces are **comparable**!

Defining a Distance Across Different Spaces

Gromov-Wasserstein Discrepancy



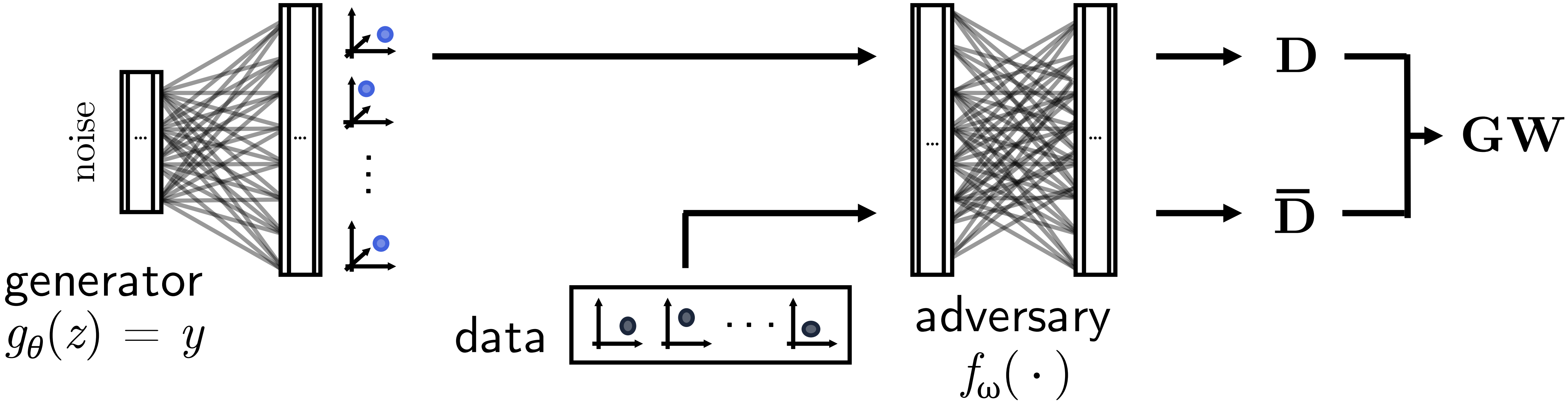
Definition:

$$GW(D, \bar{D}) := \min_{T} \sum_{ijkl} L(D_{ik}, \bar{D}_{jl}) T_{ij} T_{kl} := \left\{ \begin{array}{c} \text{total discrepancy} \\ \text{of pairwise distances} \\ \text{across domains} \end{array} \right\}$$

optimal transport plan

intra-space distances

Gromov-Wasserstein Generative Model (GW GAN)

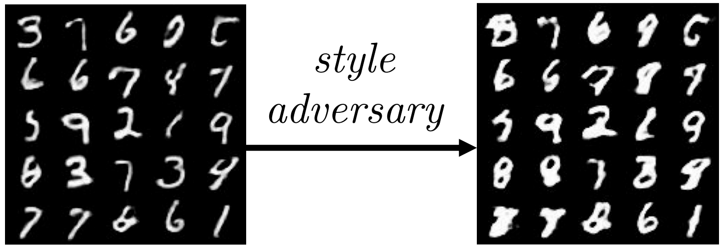


Flexibility of the Model

2

… recovers geometrical properties of the target distribution, but **global aspects** are undetermined

shape the generated distribution via design constraints



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GW GAN

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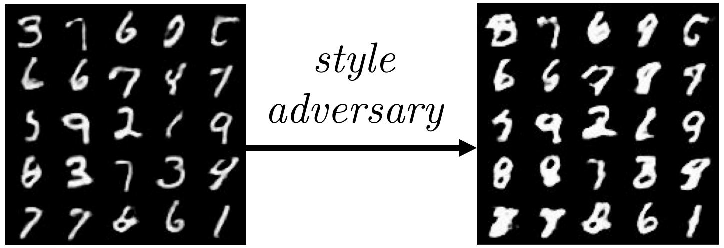
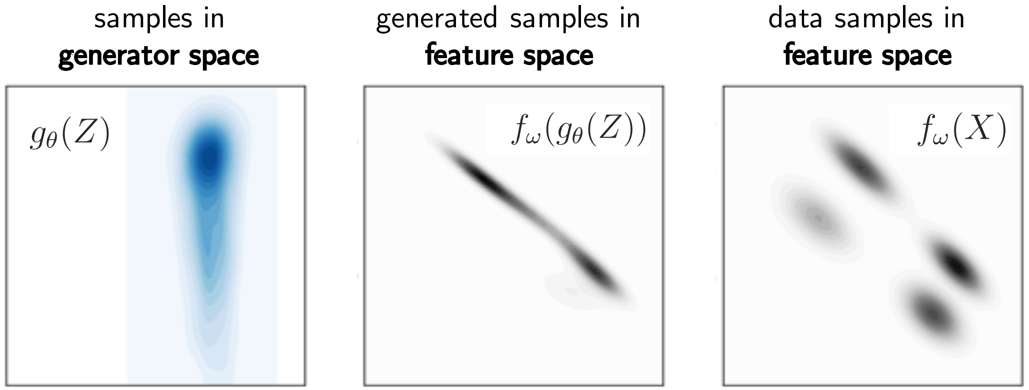


3

... adversary can arbitrarily distort the space

regularize adversary by enforcing it to define unitary transformations


samples in **generator space**

generated samples in **feature space**

data samples in **feature space**

Gromov-Wasserstein Generative Model

- By utilizing the **Gromov-Wasserstein** discrepancy we disentangle data and generator space.
- This enables us to **learn generative models across different data types and space dimensions** and **shape** the generated distributions with design constraints.

More details, **tonight** at Poster #173