LEARNING GENERATIVE MODELS ACROSS INCOMPARABLE SPACES

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Poster #173
Generative Modeling

\[ P_x \rightarrow \text{data} \]

\[ \text{generative network} \rightarrow \text{noise} \]
Beyond Identical Generation ...

\[ \text{data} \xrightarrow{P_x} \text{?} \xrightarrow{\text{enforce style.}} \]

- Generative network
- Noise
Beyond Identical Generation ... 

\[ P_x \rightarrow \text{data} \]

... learn across different dimensions.
Beyond Identical Generation ...

data

\( P_x \rightarrow \) graph

\( y \rightarrow \) generative network

... translate between representation.
Beyond Identical Generation ...

\[ P_x \rightarrow \text{data} \]

\[ ? \]

... learn manifolds.

generative network
Challenges

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

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: \( GW(D, \bar{D}) := \min_T \sum_{ijkl} L(D_{ik}, \bar{D}_{jl}) T_{ij} T_{kl} := \) total discrepancy of pairwise distances across domains

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Gromov-Wasserstein Generative Model (GW GAN)

\[
g_\theta(z) = y
\]

data

adversary

\[
f_\omega(\cdot)
\]

noise

generator

\[
g_\theta(z) = y
\]

D

\[\overline{D}\]

GW

\[
g_\theta(z) = y
\]
Flexibility of the Model

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

shape the generated distribution via design constraints
Flexibility of the Model

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

shape the generated distribution via design constraints

... adversary can arbitrarily distort the space

regularize adversary by enforcing it to define unitary transformations

GW GAN

samples in generator space

$g_\theta(Z)$

samples in feature space

$f_\omega(g_\theta(Z))$

data samples in feature space

$f_\omega(X)$
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