NEURAL INFORMATION PROCESSING SYSTEMS

Workshop On
Topological Data Analysis and Beyond

TopoSampler: A Topology Constrained Noise Sampling for GANs

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Overview

- We study the disconnected manifold learning problem from a topological perspective, by posing the disconnectedness in terms of 0-dimensional holes.

- We propose a novel method for approaching this problem by breaking it down in two parts:

  - sample space topology optimization of uni-manifolded priors
  - Homeomorphic generation of the desired posterior

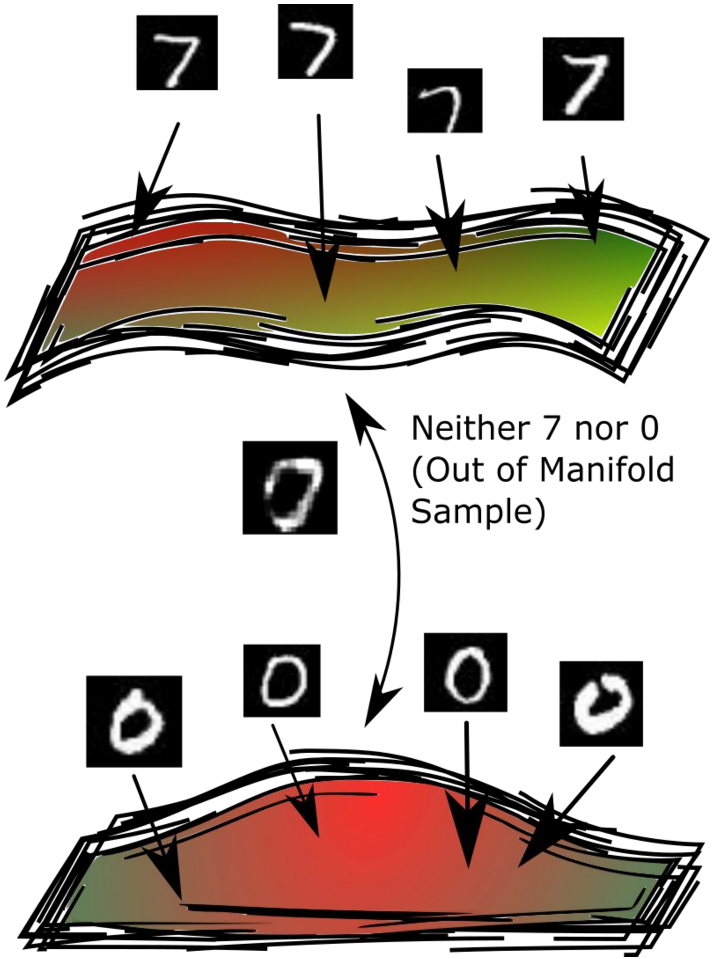
- We set up experiments for making initial assertions and present our findings

Motivation

Out of Manifold Sampling in GANs

- Multimodal real-world data, sometimes comes from distribution with disconnected support.(i.e., separate manifolds)

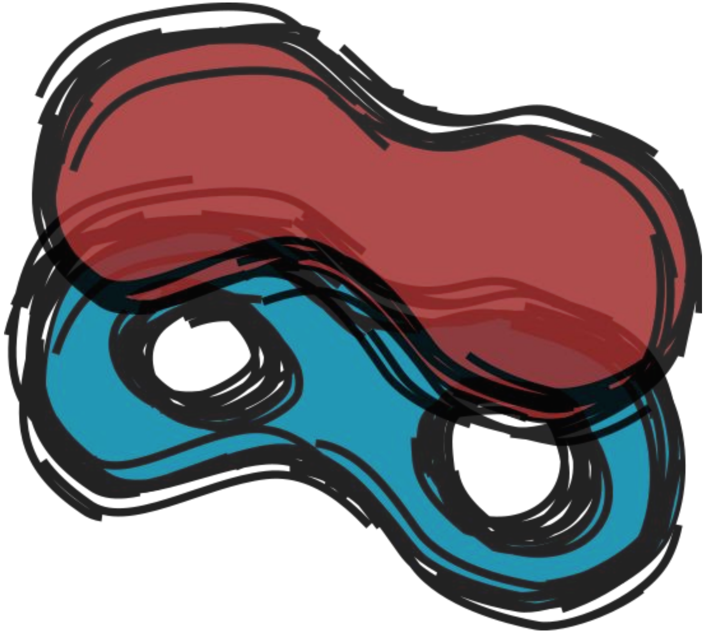
- GANs don't learn this separation, and thus tends to produce samples, which are unrealistic interpolation between two completely different sample classes.



Regular GAN with single-manifolded isotropic gaussian prior

Learned posterior space (in red) vs real data space (in blue)

(*Notice the inability to introduce d-dimensional holes*)



Related Work

- Multi-generator approach for learning each disconnected component.(Khayatkhoei, Elgammal and Singh, 2019)

- Rejection sampling in posterior space, for removing out of manifold samples.(Tanielian et al., 2020)

- Rejection sampling in prior space, for removing latent vectors that gives rise to out of manifold samples. (Anonymous, 2021)

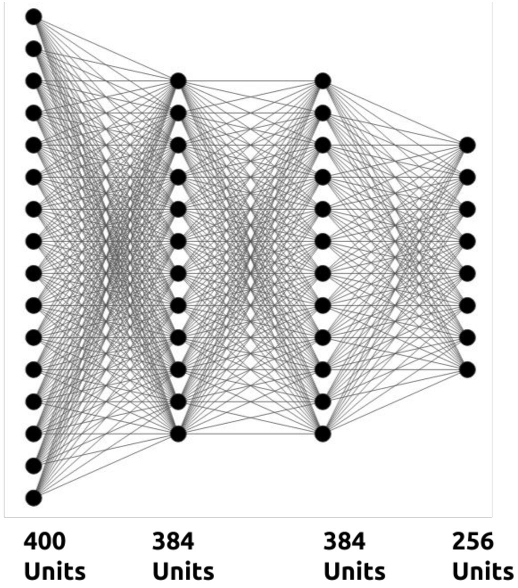
Proposed Method

Proposed Method

Topology Optimization for generating structured Noise

- Novel Noise Module for mapping the unimodal gaussian samples to a learned prior for the generator

- The learned prior is optimized to have persistent homology signatures similar to the persistent homology signatures of the original data samples. (Moor et al., 2020)



Proposed Method

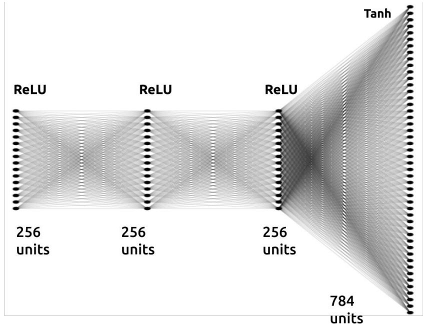
Homeomorphic posterior generation with Isometric Generator

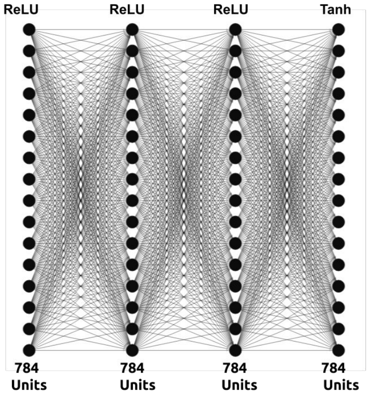
- Global isometric guarantees by making the generator, a composition of isometric functions.

- 1-lipschitz activation functions like (ELU,ReLU, LeakyReLU, Tanh, Sigmoid) for maintaining global isometry.

- Dimensionality jump to data space at the last layer

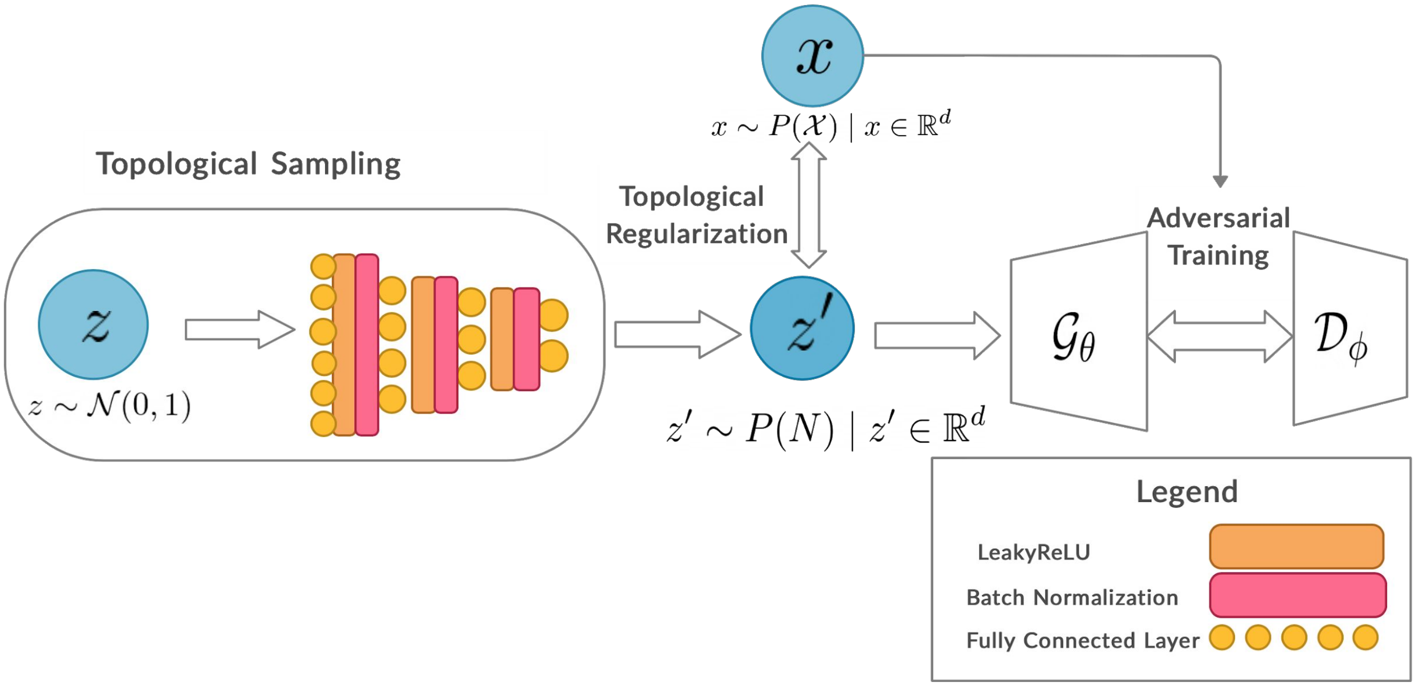
- Spectral normalized layers for generating 1-lipschitz maps, thus asserting isometry.(Miyato et al., 2018)





Proposed Method

Complete Architecture



Experiments

Sample Quality

- *Generator fails*: loses pretty soon in the two player game, with discriminator score going to 0

- *Mode collapse:* the generator keeps on mode collapsing to different classes.

- Label smoothing / Noisy labels doesn’t work and the same scenario persists.

- It has been observed that it happens mostly with spectral normalized generators, of any architectures.

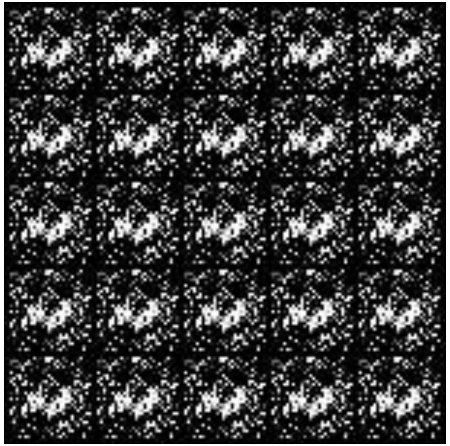


Figure: Training dynamics of spectral normed generator

Experiments

Topology (Noise Layer)

- Experimenting on learning two disconnected high dimensional spheres.

- Noise Layer, cannot tear a manifold, due to continuous nature of a Neural Network.

- (Right) disconnected sphere approximation with unimanifolded gaussian

- Has a stretching effect of manifold, but cannot tear.

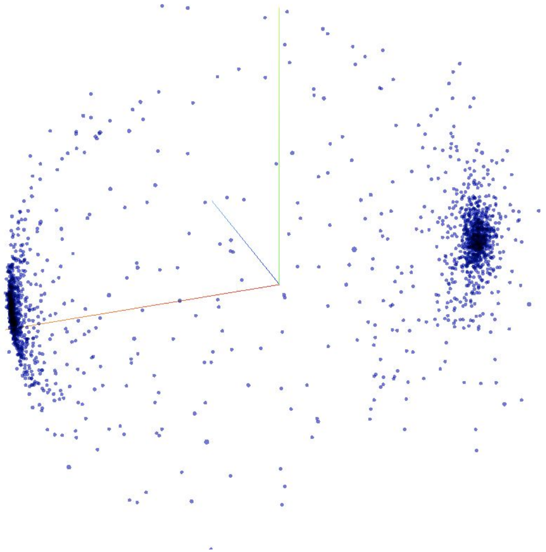


Figure: learned noise space topology

Experiments

Topology (GAN)

- (Right Top) Disconnected manifold, learned with disconnected gaussian distribution. Notice the lack of any out of manifold samples.

- (Right Bottom) Disconnected manifold learned with unimanifolded istropic gaussian. (notice the presence of out of manifold samples)

- Demonstrates the homeomorphic nature of the generator

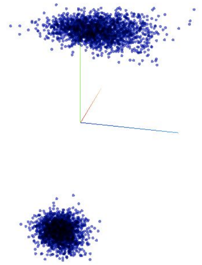


Figure: disconnected learning with disconnected prior

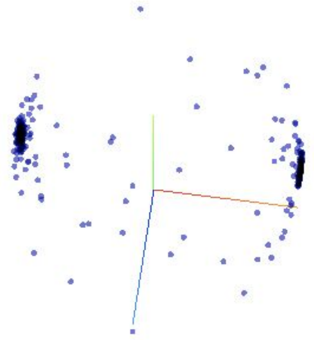


Figure: Disconnected learning with unimanifold prior

Conclusion

- We propose a topological perspective of viewing disconnected manifold learning in generative models, especially GANs.

- We demonstrate the effectiveness of prior space topology on disconnected manifold learning, by showing GANs with disconnected priors, learns the target distribution almost perfectly with little to no out of manifold samples.

- We find that, the spectral normed generator although produces poor quality sample, it does maintains a solid sense of homeomorphism between spaces.

Thank You!