On the Latent Space of Deep Generative Models

Honors Thesis Presentation

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August 2018

Outline

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Deep Generative Models

- "[Generative Adversarial Networks], and the variations that are now being proposed is the most interesting idea in the last 10 years in ML, in my opinion." - Yann LeCun (courtesy of Quora post)

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- Sample noise from distribution (draw a latent vector), pass through a function (typically a neural net), and get meaningful output (some image)

Variational Autoencoders

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- *Encoder* mapping images to compressed representations (*latent vectors*)

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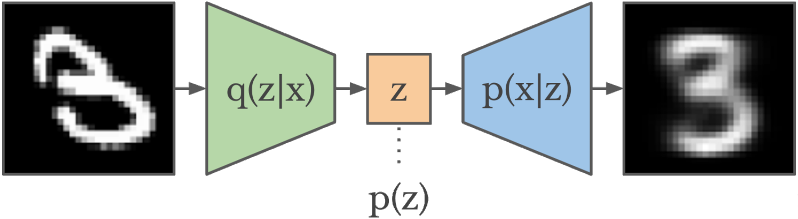
- Reconstruction error
  - On average, how lossy is the compression that the VAE is performing?
  - Use ℓ_2 distance between two images

VAE Architecture



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[1] Diagram courtesy of Danijar Hafner.

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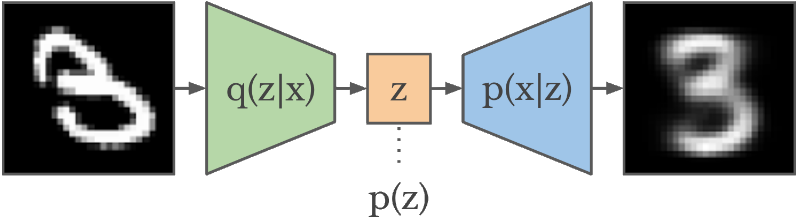

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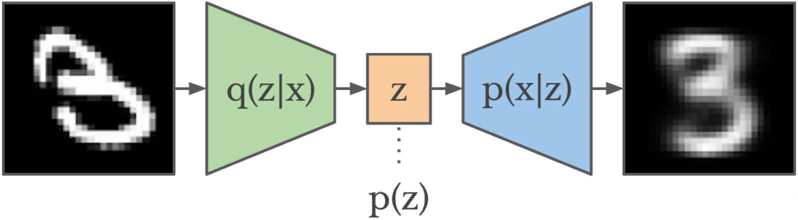

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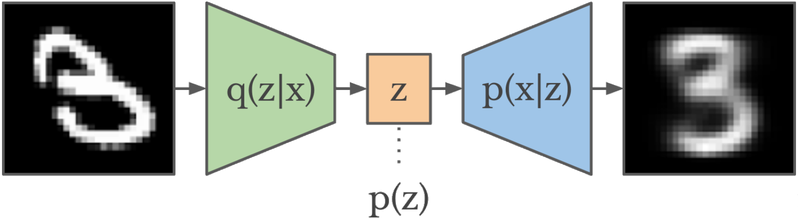

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- Formulated as min-max game

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Generally, theoretical understanding of deep generative models is still lacking.

Outline

Deep Generative Model

Definition (Deep Generative Model)

A *deep generative model* is a (possibly randomized) function, denoted g, that accepts some vector $z \in \mathbb{R}^d$ for some d as input and outputs some image $I \in \mathcal{I}$, where $\mathcal{I}$ represents the space of images.

Encoder

Definition (Encoder)

An *encoder* is a (possibly randomized) function, denoted f, that accepts some input image $I \in \mathcal{I}$ (where, again $\mathcal{I}$ is the space of images) and outputs some vector $z \in \mathbb{R}^d$.

Class

Definition (Class)

Suppose we are given a classifier into K classes $c : \mathcal{I} \to [K]$ that accepts as input an image and outputs a class label which is an integer index in $[K] := \{i\}_{i=1}^{K}$. Then, the *class* of an image I under c is given by:

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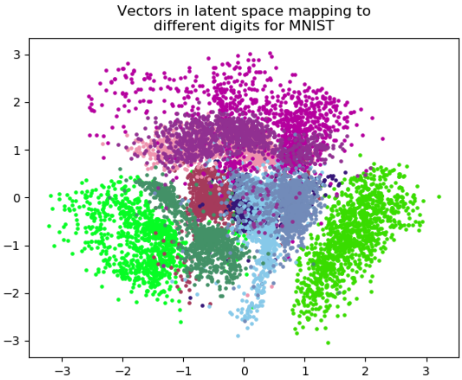
In words, K_i is the subset of the latent space that is classified into label i when a point $z \in K_i$ is passed through g and subsequently classified by c.

Latent Hole

Definition (Latent Hole)

A *hole* is a point $z \in \mathbb{R}^d$ such that there does not exist an image I in the data manifold for which $f(I) = z$.

Examples


Vectors in latent space mapping to
different digits for MNIST
3
2
1
0
−1
−2
−3
−3
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2
3

Class Radius

Definition (Class Radius)

Consider the probability vector $p \in \mathbb{R}^K$ such that:

$$p_i \propto \nu(K_i)$$

Then, the *class radius* is the expected distance from a random point $z \sim p$ in some class to the closest point in a different class. Specifically, define $r(z)$ below, and let $c(g(z)) = i$:

$$r(z) := \inf_{z' \in \bigcup_{j \neq i} K_j} \left\| z - z' \right\|$$

Then the class radius is simply:

$$\mathop{\mathbb{E}}_{z \sim p} [r(z)]$$

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  - Attempted resolution: bring classes closer to each other and cover more probability (our empirical contribution)

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Assumptions

Probability Decay

$$\|p\|_\infty \leq \min\left(\frac{1}{5}, h(K) \in \left[\Omega\left(\frac{1}{K}\right), o(1)\right]\right)$$

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Partition of Latent Space

$$\bigcup_{i=1}^{K} K_i = \mathbb{R}^d$$

- Every latent vector maps to some image in the data manifold

Outline

Class Radius to Diversity

Theorem

Under the aforementioned assumptions, we have the following regarding the expected class radius of each image in the latent space of our generative model:

$$\mathbb{E}\left[r(z)\right] \leq \frac{\log\left(4\pi \log\left(1/\left\|p\right\|_2^2\right)\right)}{\sqrt{2\log\left(1/\left\|p\right\|_2^2\right)}}$$

- Upper bound depends *only* on $\|p\|_2^2$

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$\|p\|_2^2$ as a Measure of Diversity

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I have a bunch of socks in a drawer distributed according to p. If I draw two socks, what is the probability that they are of the same type?

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- $\sum p_i^2 = \|p\|_2^2$

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Definition (α-order Rényi Entropy)

$$H_\alpha(p) = \frac{1}{1-\alpha} \log \left(\sum_{i=1}^{K} p_i^\alpha \right)$$

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Special Case: Collision Entropy

$$H_2(p) = -\log\left(\sum p_i^2\right) = \log\left(\frac{1}{\|p\|_2^2}\right)$$

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Fact (Maximum Entropy Distribution)

For all α, the distribution maximizing the α-order Rényi Entropy is the uniform distribution, yielding:

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$$\mathbb{E}[r(z)] \leq \frac{\log(4\pi \log(K))}{\sqrt{2\log(K)}}$$

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1. Introduction
   - Deep Generative Models Overview
   - Terms
   - Main Claim
2. Theory
   - Assumptions
   - Main Result
   - Relationship to Diversity
   - Proofs
   - Potential Implications
3. Experiments
   - VAE Modification
   - Experimental Setup
   - Results

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   - Our contribution

Some Details

(Slightly rewritten) Result from Fawzi et al. (2018)

$$\mathbb{E}\left[r(z)\right] \leq \sum_{i=1}^{K} \Phi^{-1}(p_i) \cdot p_i + \frac{e^{-\Phi^{-1}(p_i)^2/2}}{\sqrt{2\pi}}$$

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Then Jensen:

$$\mathbb{E}\left[r(z)\right] \leq g\left(\sum_{i=1}^{K} p_i \cdot p_i \right) = g\left(\|p\|_2^2 \right) = \boxed{\frac{\log\left(4\pi \log\left(1/\|p\|_2^2\right)\right)}{\sqrt{2\log\left(1/\|p\|_2^2\right)}}}$$

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Test for Diversity

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Solution

Compare $\mathbb{E}[r(z)]$ for g_1 and g_2; claim that the generator with higher class radius is less diverse.

Unfortunately, computing $\mathbb{E}[r(z)]$ might be more difficult than computing $\|p\|_2^2$ unless K is extremely large

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- "Find an adversarial example in z-space"
- If g is L-Lipschitz, then on average, you don't have to perturb too much in image space:

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- Under the probability decay assumption, above approaches 0 as the number of classes K grows arbitrarily large

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Regularize with $\omega(\cdot,\cdot)$ summed over many pairs of images. To force ω to be low, enforce Lipschitz constant via network weight clipping.

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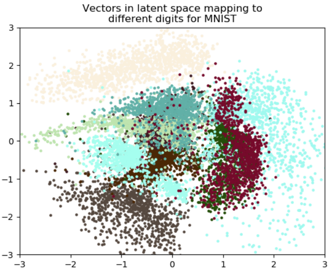
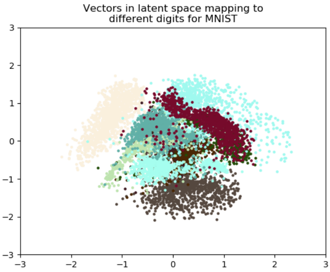
- Clip weights to $[-0.3, 0.3]$

Outline

Geometric Implications





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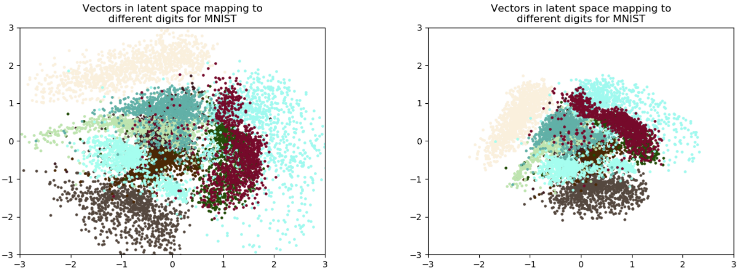

Conclusion: Modified VAE makes classes come closer to one another but decreases probability mass of space covered

Sample Quality

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Conclusion: Modified VAE does not change quality of generated samples noticeably

Interpretation of Results

Hyperparameter selection is tricky

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Problem

For future: Devise an optimization objective that favors both closer classes and better coverage of the latent space.

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Summary

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Future Work

We want to leverage these findings empirically.

- Develop optimization procedures to achieve these properties
- Test generative models for diversity
- Meta-Problem: Theoretically understand generative models better

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