Non-Adversarial Image Synthesis with Generative Latent Nearest Neighbors[1]

February 12, 2020

[1] "Non-Adversarial Image Synthesis With Generative Latent Nearest Neighbors" by Hoshen, Li, and Malik

Overview

Overview

- Authors built a “non-orthodox” generative model (by merging GLO and IMLE)

Overview

- Authors built a “non-orthodox” generative model (by merging GLO and IMLE)
- They achieved competitive FID/PRD scores and good interpolation properties.

Generative Latent Optimization (GLO)

- For each image x_i define (randomly) a latent vector z_i, s.t. $\|z_i\| = 1$
- Define a decoder $G_\theta(z_i) = x_i$.
- Optimize both G_θ and $z_1, ..., z_n$ to minimize

$$\min_{\theta, z_1, \ldots, z_n} \sum_{i=1}^{n} \| G_\theta(z_i) - x_i \|_2^2$$

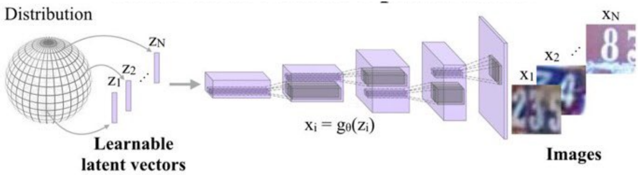


Figure: Generative Latent Optimization (GLO) [2]

[2] The picture by Shao-Hua Sun @shaohua0116

GLO pros and cons

Pros:

GLO pros and cons

Pros:

- Optimization is simple

GLO pros and cons

Pros:

- Optimization is simple
- Optimization is stable

GLO pros and cons

Pros:

- Optimization is simple
- Optimization is stable
- No mode collapse

Cons:

GLO pros and cons

Pros:

- Optimization is simple
- Optimization is stable
- No mode collapse

Cons:

- Novel samples are bad

GLO pros and cons

Pros:

- Optimization is simple
- Optimization is stable
- No mode collapse

Cons:

- Novel samples are bad
- We have to store $O(n)$ training latent vectors z_i

Implicit Maximum Likelihood Estimation (IMLE)

Implicit Maximum Likelihood Estimation (IMLE)

- Define a Generator $G_\theta(e) = x$

Implicit Maximum Likelihood Estimation (IMLE)

- Define a Generator $G_\theta(e) = x$
- On each iteration, sample $e \sim \mathcal{N}(0, I)$ and compute $G(e) = \tilde{x}$

Implicit Maximum Likelihood Estimation (IMLE)

- Define a Generator $G_\theta(e) = x$
- On each iteration, sample $e \sim \mathcal{N}(0, I)$ and compute $G(e) = \tilde{x}$
- Find the closest image x from your dataset and optimize $\|G(e) - x\|_2^2$.

Implicit Maximum Likelihood Estimation (IMLE)

- Define a Generator $G_\theta(e) = x$
- On each iteration, sample $e \sim \mathcal{N}(0, I)$ and compute $G(e) = \tilde{x}$
- Find the closest image x from your dataset and optimize $\|G(e) - x\|_2^2$.
- This procedure was shown to be equivalent to MLE.

IMLE pros and cons

Pros:

IMLE pros and cons

Pros:

- Idea is simple

IMLE pros and cons

Pros:

- Idea is simple
- Has a theoretical justification

IMLE pros and cons

Pros:

- Idea is simple
- Has a theoretical justification
- Sampling is easy at test time

Cons:

IMLE pros and cons

Pros:

- Idea is simple
- Has a theoretical justification
- Sampling is easy at test time

Cons:

- l_2-nearest neighbour in an image space is costly and not very sensible.

IMLE pros and cons

Pros:

- Idea is simple
- Has a theoretical justification
- Sampling is easy at test time

Cons:

- l_2-nearest neighbour in an image space is costly and not very sensible.
- Samples are blurry

Generative Latent Nearest Neighbors (GLANN)

Generative Latent Nearest Neighbors (GLANN)

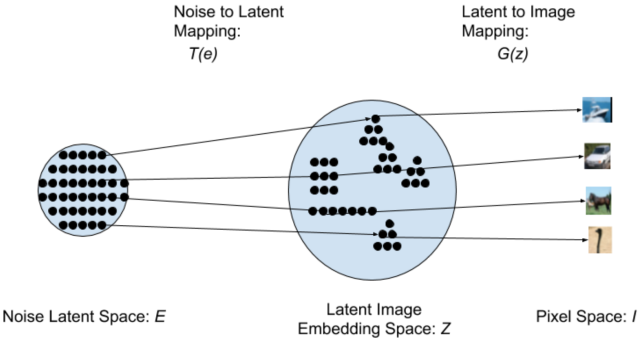
- Stage 1. Train a GLO model $G : z \to x$ on top of images.

Generative Latent Nearest Neighbors (GLANN)

- Stage 1. Train a GLO model $G : z \rightarrow x$ on top of images.
- Some details: use perceptual loss instead of Laplacian pyramid to train it.

Generative Latent Nearest Neighbors (GLANN)

- Stage 1. Train a GLO model $G : z \to x$ on top of images.
- Some details: use perceptual loss instead of Laplacian pyramid to train it.
- Stage 2. Train an IMLE model $T : e \to z$ on top of latent vectors.



Results

Table 1. Quality of Generation (FID)

	Adversarial					Non-Adversarial		
Dataset	MM GAN	NS GAN	LSGAN	WGAN	BEGAN	VAE	GLO	Ours
MNIST	9.8 ± 0.9	6.8 ± 0.5	7.8 ± 0.6	$\mathbf{6.7} \pm 0.4$	13.1 ± 1.0	23.8 ± 0.6	49.6 ± 0.3	8.6 ± 0.1
Fashion	29.6 ± 1.6	26.5 ± 1.6	30.7 ± 2.2	21.5 ± 1.6	22.9 ± 0.9	58.7 ± 1.2	57.7 ± 0.4	$\mathbf{13.0} \pm 0.1$
Cifar10	72.7 ± 3.6	58.5 ± 1.9	87.1 ± 47.5	55.2 ± 2.3	71.4 ± 1.6	155.7 ± 11.6	65.4 ± 0.2	$\mathbf{46.5} \pm 0.2$
CelebA	65.6 ± 4.2	55.0 ± 3.3	53.9 ± 2.8	41.3 ± 2.0	$\mathbf{38.9} \pm 0.9$	85.7 ± 3.8	52.4 ± 0.5	46.3 ± 0.1

Figure: GLANN FID scores

Figure: GLANN interpolations properties