Generative Adversial Network

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Introduction

- We want to generate handwritten digits thanks to a **GAN** (Generative Adversarial Network).
- A GAN consists on training a **Generator** and a **Discriminator**, that compete with each other to generate new instances of data that are indistinguishable from real data.

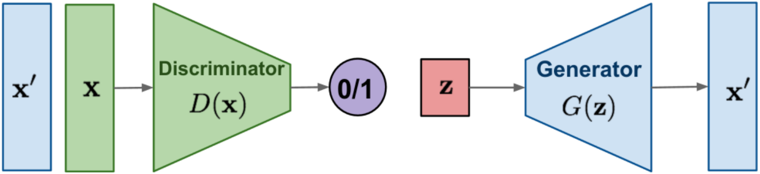


Figure 1: GAN Architecture

Min Max Problem

G and D are trained simultaneously to solve the following **min-max** problem:

$$\min_G \max_D \mathbb{E}_{x_r \sim P}[\log D(x)] + \mathbb{E}_{x_g \sim \hat{P}_G}[\log 1 - D(x)]$$

Dataset

- Use of 10.000 images of the **MNIST** Database
- Represent **handwritten digits** in grayscale
- Each image is 28x28 pixels

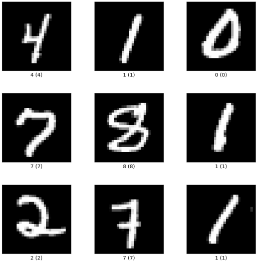


Figure 2: Example of MNIST images

Metrics Used

Fréchet Inception Distance (FID) measures similarity between real and generated images by comparing statistics of feature representations obtained from a pre-trained deep neural network.

- Correlates well with human judgment
- Computationally intensive

f-GAN

The f-GAN idea is to lower bound the distance between the true and generated distribution by using:

$$D_f(P\|Q) \geq \sup_{T \in \mathcal{T}} \left(\mathbb{E}_{x\sim P}[T(x)] - \mathbb{E}_{x\sim Q}[f^*(T(x))]\right)$$

Which yields the objective function:

$$F(\theta,\omega) = \mathbb{E}_{x\sim P}[g_f(V_\omega(x))] + \mathbb{E}_{x\sim Q_\theta}[-f^*(g_f(V_\omega(x)))]$$

FID for different f-Divergences

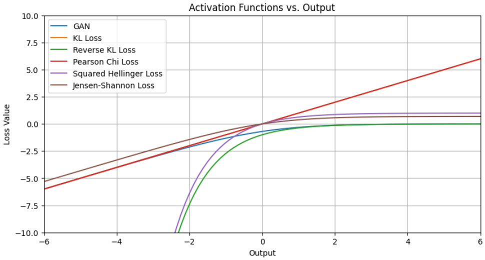


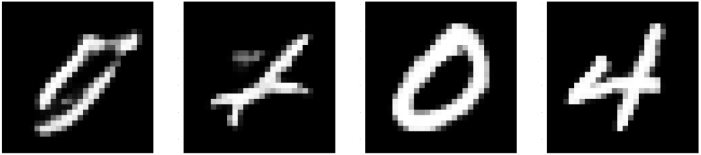
Figure 3: $g_f(x)$

Divergence	FID Score
GAN	49
KL	441
Reverse KL	230
Pearson X^2	196
Squared Hellinger	319
Jensen-Shannon	79

Table 1: FID Scores for Different Divergences

Principle of Latent Space Re-weighting

- It consists on managing the latent space after training, to do so :
  - We associate to each variable a weight that indicates its importance, those **weights** are **learned** during training
  - With the latent rejection sampling policy, we generate higher-quality samples by **rejecting** those that do not meet certain criteria defined in the latent space



$P_a(z) = 0.00$ $P_a(z) = 0.05$ $P_a(z) = 0.68$ $P_a(z) = 0.73$

Figure 4: Acceptance probabilities with the latentRS algorithm

Latent Space Re-weighting, algorithm and performance

Algorithm 2: LatentRS

Requires: Prior Z, Gen. G_θ, Importance weight network w^φ, maximum importance weight m;

while *True* **do**
- Sample $z \sim Z$;
- Sample $\alpha \sim \mathrm{Uniform}[0,1]$;
- **if** $\frac{w^\varphi(z)}{m} \geq \alpha$ **then**
  - break;
- **end**

end

$x \leftarrow G_\theta(z)$;

Result: Selected point x

Model	FID	Precision
Vanilla-GAN	49	0.23
Vanilla-GAN+LatentRS	46	0.38

Table 2: FID and Precision comparison

Results

Model	FID Score
f-divergence GAN	49
f-divergence KL	441
f-divergence Reverse KL	230
f-divergence Pearson X^2	196
f-divergence Squared Hellinger	319
f-divergence Jensen-Shannon	79

Table 3: FID Scores for Different Divergences

Model	FID Score	Precision
Vanilla-GAN	49	0.23
Vanilla-GAN + LatentRS	46	0.38

Table 4: FID and Precision with and without latent reweighting

Bibliography

- https://openaccess.thecvf.com/content/WACV2022/supplement
  $//arxiv.org/pdf/1606.00709.pdf$

sectionBibliography