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Master IASD
Data Science Lab
Generative adversarial network

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Introduction

Problem Statement

- **MNIST :** Hand-written digit images ranging from 0 to 9.
- **Objective :** Training a Generative Adversarial Network (GAN) to generate 10K synthetic samples from the MNIST dataset.
- **Evaluation Metric :** The Frechet Inception Distance (FID) :

$$FID = \sqrt{\sum_i (\mu_1(i) - \mu_2(i))^2 + \mathrm{Tr}(C_1 + C_2 - 2\sqrt{C_1 C_2})}$$

where $\mu_1(i)$ and $\mu_2(i)$ represent means and C_1 and C_2 represent covariances of features in real and generated samples, respectively.

Training and Results (Vanilla GAN)

Hyperparameters	Training Time (s)	FID	Precision	Recall
Default values	106.2	379.21	0.0	0.0
Optimized values	113.74	42.5	0.57	0.22

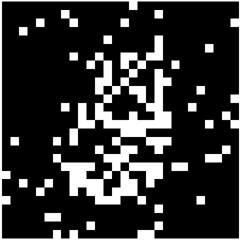


Figure – Generated by model trained with default Hyperparameters

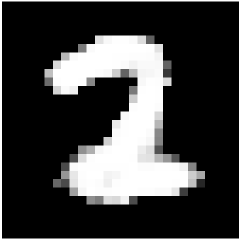


Figure – Generated by model trained with optimized hyperparameters

Vanilla GAN

Structure

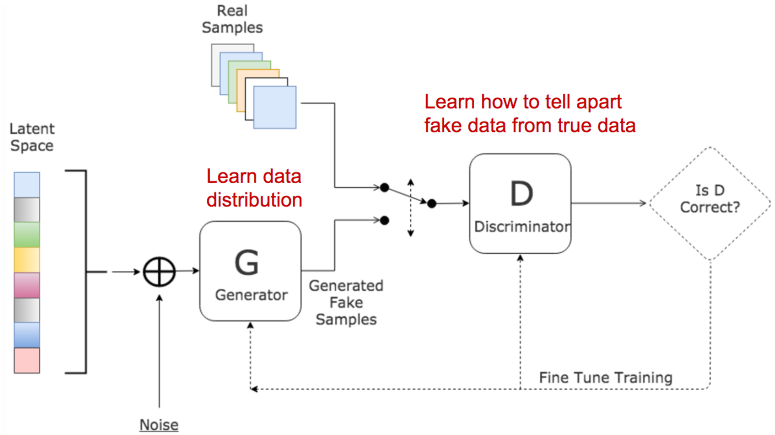
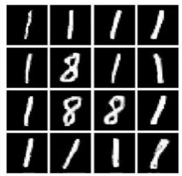
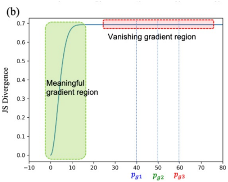


Figure – Structure of a Vanilla Generative Adversarial Network (GAN)

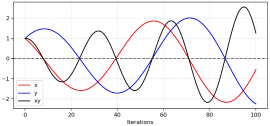
Problems



(a) Figure 1
Mode collapse



(b) Figure 2
Vanishing Gradient



(c) Figure 3
Nash Equilibrium

Figure – Common problems in training GANs.

Wasserstein GAN

Structure

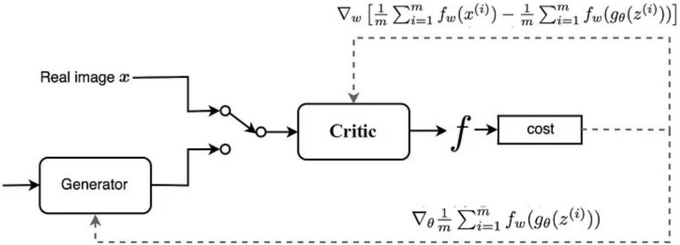


Figure – Structure of a Wasserstein GAN (WGAN)

- **W-Loss :** $L = \min_g \max_f \mathbb{E}(f(x)) - \mathbb{E}(f(g(z)))$

solution to problems

- **Vanishing gradient :** critic function needs to be **K-Lipschitz continuous**
  - weight cliping :forces the weigth of critic to a fixed interval [-c, c]
  - regularization term :penalize gradient far from **K**

$$\lambda \left(\|\nabla\ f(\hat{x})\|_2 - K \right)^2$$

  where $\hat{x} = \varepsilon x + (1 - \varepsilon) g(z)$

- **Mode collapse :** The Wasserstein loss in WGANs is more informative and continuous and encourages diverse data distribution coverage, unlike the binary cross-entropy loss in traditional GANs that may lead to single-mode focus.

Bibliography

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