Data Science Lab
Assignment 2 : GAN

Methods : f-GAN , Discriminator Rejection Sampling

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   - Hyperparameters tuning
   - Results
2. f-GAN
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   - Results
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Architecture description

Vanilla GAN

Generator Network (G) :

- **Input** : $z \in \mathbb{R}^{100}$
- **Output** : $G(z) \in \mathbb{R}^{784}$
- **Transformation** :

$$\mathrm{G(z)} = \tanh(W_4 \cdot \mathrm{LeakyReLU}(W_3 \cdot \mathrm{LeakyReLU}(W_2 \cdot \mathrm{LeakyReLU}(W_1 \cdot z + b_1) + b_2) + b_3) + b_4)$$

Discriminator Network (D) :

- **Input** : $x \in \mathbb{R}^{784}$
- **Output** : $D(x) \in [0, 1]$
- **Transformation** :

$$\mathrm{D(x)} = \sigma(W_4' \cdot \mathrm{LeakyReLU}(W_3' \cdot \mathrm{LeakyReLU}(W_2' \cdot \mathrm{LeakyReLU}(W_1' \cdot x + b_1') + b_2') + b_3') + b_4')$$

Hyperparameters tuning

Vanilla GAN

Epochs = 50

Batch Size = 64

Learning rate = 0.0001

Our Results
Vanilla GAN

Time	FID	Precision	Recall
111.4	52.44	0.52	0.18

Figure – Results of the vanilla GAN

- **Overview :**
  The f-GAN extends classic GANs by introducing a flexible divergence function f.
- **Differences from Classic GANs :**
  - Flexible divergence measure f replaces fixed divergence (e.g., KL divergence).
  - Allows customization of divergence, enhancing model adaptability.
- **Advantages :**
  - Improved stability in training.
  - Greater control over precision and recall.
  - Enhanced adaptability to specific application requirements.

Divergence Functions in GANs

f-GAN

Binary Cross-Entropy (BCE) :

$$\mathrm{BCE}(y, \hat{y}) = -\left(y \cdot \log(\hat{y}) + (1 - y) \cdot \log(1 - \hat{y})\right)$$

Kullback-Leibler Divergence (KLD) :

$$D_{\mathrm{KL}}(P \parallel Q) = \sum_i P(i) \cdot \log\left(\frac{P(i)}{Q(i)}\right)$$

Jensen-Shannon Divergence (JS) :

$$D_{\mathrm{JSD}}(P \parallel Q) = \frac{1}{2} D_{\mathrm{KL}}(P \parallel M) + \frac{1}{2} D_{\mathrm{KL}}(Q \parallel M)$$

f-GAN results - BCE

f-GAN

Epochs = 50 :

Epochs = 100 :

Epochs = 150 :

Epochs = 200 :

Epochs = 50 :

Epochs = 100 :

Epochs = 150 :

Epochs = 200 :

f-GAN results - JS

f-GAN

Epochs = 50 :

Epochs = 100 :

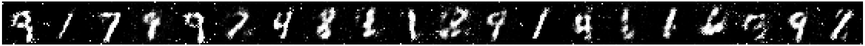
Epochs = 150 :

Epochs = 200 :

f-GAN results - small training

f-GAN

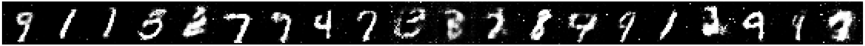
BCE, epochs $= 25$:



KLD, epochs $= 15$:

KLD, epochs $= 20$:

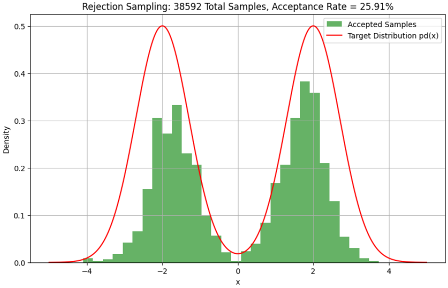
JS, epochs $= 20$:



JS, epochs $= 25$:

Discriminator Rejection Sampling (DRS)

- A statistical method for generating observations from a target distribution $p_d(x)$, which is difficult to sample from directly.
- Instead, samples are drawn from a simpler proposal distribution $p_g(x)$.
- A scaling factor M ensures $M \cdot p_g(x) \geq p_d(x)$ for all x in the domain of $p_d(x)$.
- Each sample y from $p_g(x)$ is accepted with a probability of $\frac{p_d(y)}{M \cdot p_g(y)}$, otherwise rejected.



Discriminator Rejection Sampling (DRS)

General Concept

DRS improves GAN sample quality by using the discriminator's assessment to accept or reject generator outputs. This technique refines the final data to better approximate the target distribution.

Implementation Highlights

- Samples are drawn from a trained generator and evaluated by the discriminator.
- A scaling factor M is dynamically updated based on the discriminator's output.
- Acceptance probabilities are modulated by a hyperparameter γ, enhancing the selection process.
- The process iterates, accepting samples that conform to a calculated threshold.

References

- Sebastian Nowozin, Botond Cseke & Ryota Tomioka, *f-GAN : Training Generative Neural Samplers using Variational Divergence Minimization.*
- Samaneh Azadi, Catherine Olsson, Trevor Darrell, Ian Goodfellow & Augustus Odena, *Discriminator Rejection Sampling.*

END OF THE PRESENTATION

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