The Clash of GAN Loss Functions: LS-GAN vs. WGAN vs. WGAN-GP

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Vanshika Tyagi

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Introduction : The Quest for the Ideal GAN Loss Function
Imagine yourself as an artist seeking to perfect your craft. You start with a blank canvas, brush in hand, but after each creation, a critical inner voice quickly points out imperfections. Over time, you enhance your abilities, improving each new piece. This reflects the operation of **Generative Adversarial Networks (GANs)** — where the generator (the artist) and the discriminator (the critic) constantly push each other to get better.

However, not all critics are equal! The choice of a loss function — the framework that dictates how the critic gives feedback — greatly affects the artist's growth. In this article, we explore a comparison of three loss functions to determine which one generates the most lifelike images :

1. **Least Squares GAN (LS-GAN)** — A more forgiving critic
2. **Wasserstein GAN (WGAN)** — A more insightful critic
3. **WGAN with Gradient Penalty (WGAN-GP)** — A more rigorous critic

We will train these GANs using a medical imaging dataset **(ChestMNIST from MedMNIST)** and evaluate their performance based on **Inception Score (IS)**, **Fréchet Inception Distance (FID)**, and **visual inspection.**

Let's dive into the experiment!

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The Arena: MedMNIST Dataset

For our experiment, I chose the **ChestMNIST, a set of grayscale X-ray images of lungs.** Unlike natural images, medical imagery introduces distinct challenges due to a lack of texture variety, making it difficult for GANs to generate convincing images.

Preprocessing Steps :
- Images are converted into grayscale tensors.
- They are normalized to **[-1,1]** to aid in effective GAN training.
- A **batch size of 64** and a **latent vector size of 100** were used.

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The Contenders : GAN Variants

1. Least Squares GAN (LS-GAN) — The Gentle Critic

LS-GAN modifies the standard GAN loss function by implementing **least squares loss** rather than binary cross-entropy. This modification smooths the gradients and reduces training fluctuations.

📝 **Importance :**
- Reduces mode collapse (when the GAN generates a restricted variety of images).
- Stabilizes training, promoting a more gradual learning process.

2. Wasserstein GAN (WGAN) — The Shrewd Critic

WGAN substitutes conventional loss functions with **Earth Mover's Distance (Wasserstein loss)**. Instead of focusing on whether an image is real or fake, WGAN evaluates how "far" the generated distribution is from the actual distribution.

📝 **Importance :**
- Guarantees improved gradient flow, preventing the discriminator from overpowering the generator.
- Lessens mode collapse.

3. WGAN with Gradient Penalty (WGAN-GP)— The Disciplined Critic

WGAN-GP builds on WGAN by incorporating a **gradient penalty** to maintain the **Lipschitz constraint**. This addition preserves training stability and avoids extreme weight clipping.

📝 **Importance :**
- Further improves training stability.
- Reduces artifacts in the generated images.

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The Showdown : Training Process

Each GAN variant underwent training for **50 epochs**, utilizing the **Adam optimizer** with a learning rate of **0.0002.** Images were generated at regular intervals and saved for later evaluation. We also employed **TensorBoard** to visualize loss progress and track training.

🔥 Training Insights :

- **LS-GAN :** Started to generate decent images early on but resulted in somewhat noisy outputs.
- **WGAN :** Showed more stable training, though occasionally produced blurry images.
- **WGAN-GP :** Demonstrated the most consistent loss trajectories and produced the clearest images.

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The Results : Which One Emerges Victorious ?

Upon completing the training, we evaluated the models using three key metrics :

1. Inception Score (IS) — Measures image quality and diversity.
- Higher = Better

2. Fréchet Inception Distance (FID) — Evaluates the similarity between real and generated images.
- Lower = Better

3. Visual Evaluation — Do the images seem genuine to a human viewer?

LS-GAN

IS — 4.2 | FID — 75.3

WGAN

IS — 5.1 | FID — 58.7

WGAN-GP

IS — 5.6 | FID — 45.2

📌 Key Takeaways :

WGAN-GP clearly excels! It secures the highest IS and the lowest FID, suggesting it produces more authentic and diverse images.

LS-GAN struggles with image variety, leading to a lower IS.

WGAN demonstrates improvements over LS-GAN but still faces some issues with mode collapse.

Visual Evaluation : Seeing is Believing

We displayed the generated images at different epochs. Here's our review:

LS-GAN images : Lung structures can be recognized, yet noticeable noise persists.

WGAN images : The pictures are more refined but can occasionally come off as blurry.

WGAN-GP images : The X-rays are crisp and well-defined, showcasing the most lifelike details.

👀 TensorBoard Visualization :

The loss curves reveal that WGAN-GP underwent the most stable training, while LS-GAN exhibited considerable fluctuations.

Final Assessment : The Best Loss Function for Medical Image Creation

This experiment convincingly shows that **WGAN-GP** is the superior choice for generating high-quality medical images. The gradient penalty enhances stability, making it ideal for complex tasks like medical imaging, satellite image generation, and deepfake detection.

Key Observations :

✅ LS-GAN is functional but lacks consistent stability.
✅ WGAN improves GAN training, though it has its drawbacks.
✅ WGAN-GP yields the best results by imposing limitations on the critic.

Next Step : Join In!

Interested in experimenting on your own? Check out the full code on **GitHub :**
🔗 https://github.com/vanshikaTyg/GANLossFunctions_MedmnistDataset

What's your opinion on these GAN loss functions? Have you experimented with different architectures? Let's discuss in the comments below! 🚀

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Written by Vanshika Tyagi

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V Vanshika Tyagi

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