Improving GAN on MNIST

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Content

1. f-GAN
2. Wasserstein GAN
3. Mode-Seeking GAN
4. Mode Seeking Regularization
5. Generation Optimization Techniques
6. Conclusion

f-GAN

f-GAN: a generalized approach to extending GANs to any f-divergence.

f-divergence:

$$D_f(\mathcal{P} \parallel \mathcal{Q}) = \int_x q(x) f\left(\frac{p(x)}{q(x)}\right) dx$$

where f is a convex f

Training Objective Function:

(GAN)

(f-GAN)

$$F(\theta, \omega) = \mathbb{E}_{x \sim P}\left[\log D_\omega(x)\right] + \mathbb{E}_{x \sim Q_\theta}\left[\log(1 - D_\omega(x))\right]$$

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

f-GAN

From Vanilla GAN to f-GAN:

- The final layer activation function of the discriminator: sigmoid(v) to g_f
- Loss function: f*(t) for computing D_fake_loss, G_loss
- Accuracy metrics: f'(1) for defining the decision boundary in the discriminator's output

Name	**Output activation** g_f	**Conjugate** $f^*(t)$	**Threshold** $f'(1)$
Kullback-Leibler (KL)	v	$\exp(t-1)$	1
Reverse KL	$-\exp(-v)$	$-1-\log(-t)$	-1
Jensen-Shannon	$\log(2)-\log(1+\exp(-v))$	$-\log(2-\exp(t))$	0

Table 1: Activation functions, Conjugates, Thresholds for various f-divergences.

f-GAN

- Performance can vary significantly depending on the divergence used.

  Best performance FID 45.53 with JS divergence. Convergence difficulty with KL divergence

- Require gradient clipping or learning rate adjustments. Adding complexity to the training process.

- Find out the most effective divergence for application is time-consuming and resource-intensive.

Wasserstein GAN

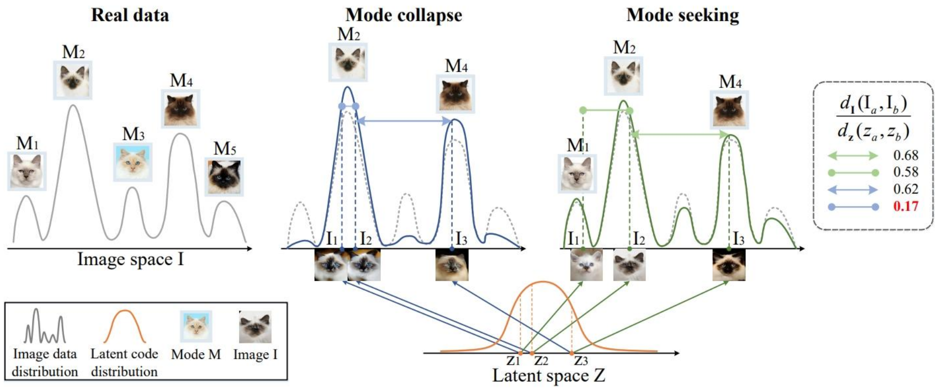
Uses Wasserstein distance:

$$W(P_r, P_g) = \inf_{\gamma \in \Pi(P_r, P_g)} E_{(x,y)\sim\gamma}[||x - y||]$$

FID: 87.54

Mode-Seeking GAN

Illustration of motivation



In mode collapse data distribution

- When distance between two latent vectors Z1 and Z2 is decreasing, the mapped images distance I1 and I2 will become shorter in a disproportionate rate
  - This lead the generator generate nearly identical images, even when the inputs are different.

Mode Seeking Regularization

Regularization Term:

$$L_{ms} = \max_{G} \left(\frac{d_I(G(c, z_1), G(c, z_2))}{d_Z(z_1, z_2)} \right)$$

Maximize the ratio of distances to enhance diversity in generated samples.

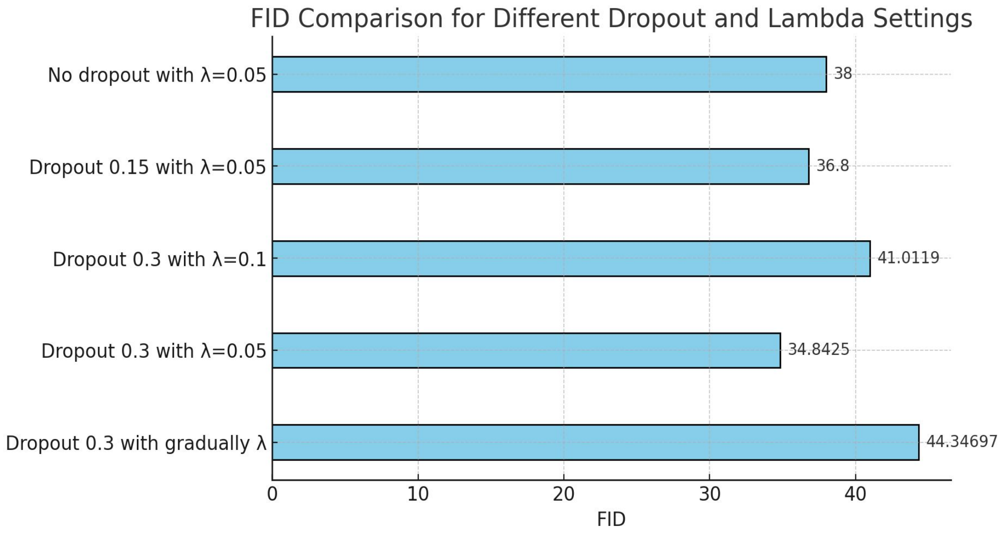
Integration:

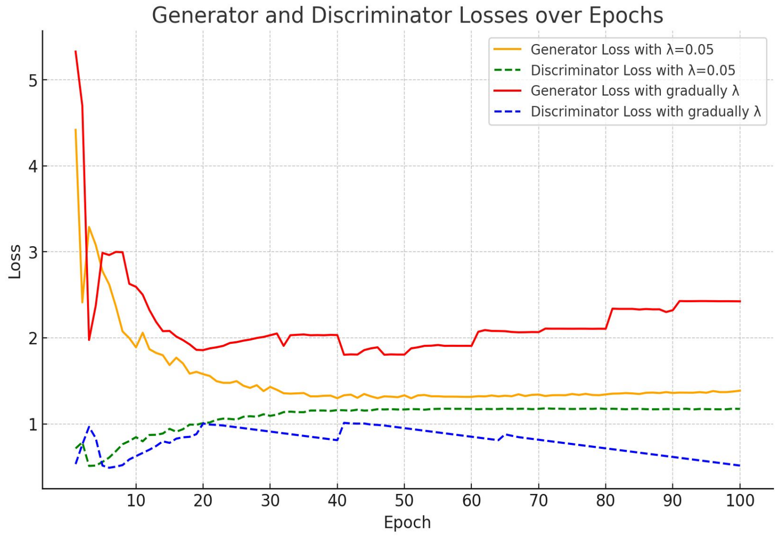
$$L_{new} = L_{ori} + \lambda_{ms} L_{ms}$$

Hyperparameter Selection

Dropout: 0.15

Mode-Seeking Loss Parameter λ: 0.05





Generation Optimization Techniques

Rejection Sampling

Uses the discriminator to score each generated image, selecting only those above a confidence threshold.

Latent Space Interpolation

Introduces smooth transitions between generated samples by interpolating between two latent vectors.

Final result: FID 27.72, Precision 0.49, Recall 0.16

Conclusion

- f-GAN: Flexible with divergence choices but struggles with mode collapse and convergence stability.

- Mode-Seeking GAN: Maximize diversity, more resistant to mode collapse, especially on simple datasets.

- For future research, introducing a semi-supervised approach may improve training stability and sample quality by leveraging labeled data more effectively.