

A Review of Recent Improvements of Generative Adversarial Networks

Progressive Growing of GANs

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Figure 1: ...



Figure 1: People imagined by a numpy random number generator¹.

¹Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”.

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Introduction

Generative Adversarial Networks

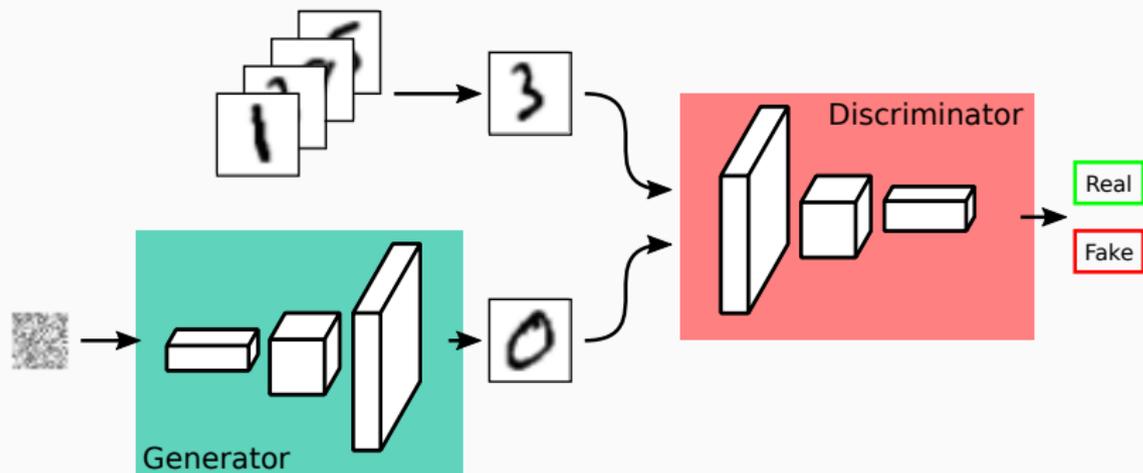


Figure 2: GAN framework²

² Image reference by Thalles Silva

<https://medium.freecodecamp.org/an-intuitive-introduction-to-generative-adversarial-networks-gans-7a2264a81394>

Results from the Original Paper



Figure 3: Results from the original GAN paper³.

³Goodfellow et al., “Generative adversarial nets”.

Problems and Solutions

Variation of Generated Images

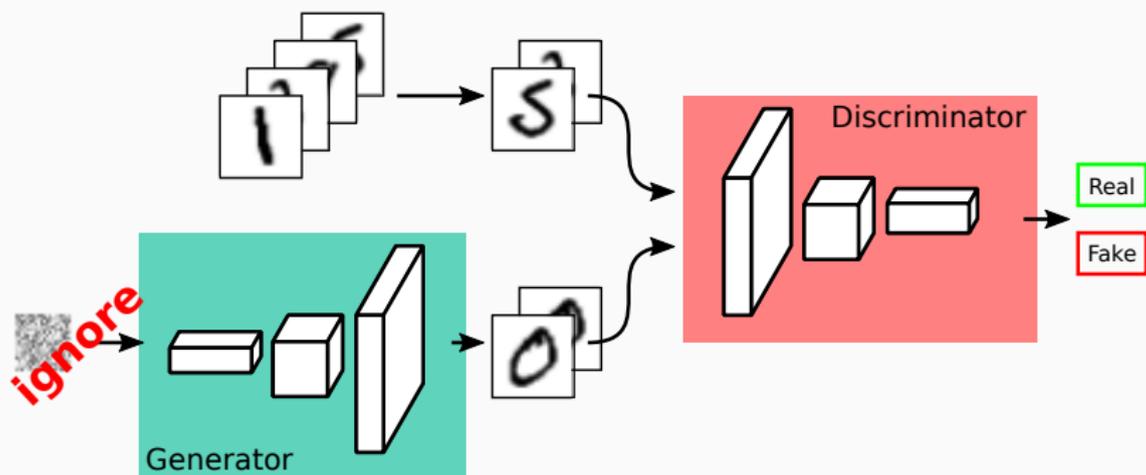


Figure 4: The latent vector can be ignored and only one good image generated.

Variation of Generated Images

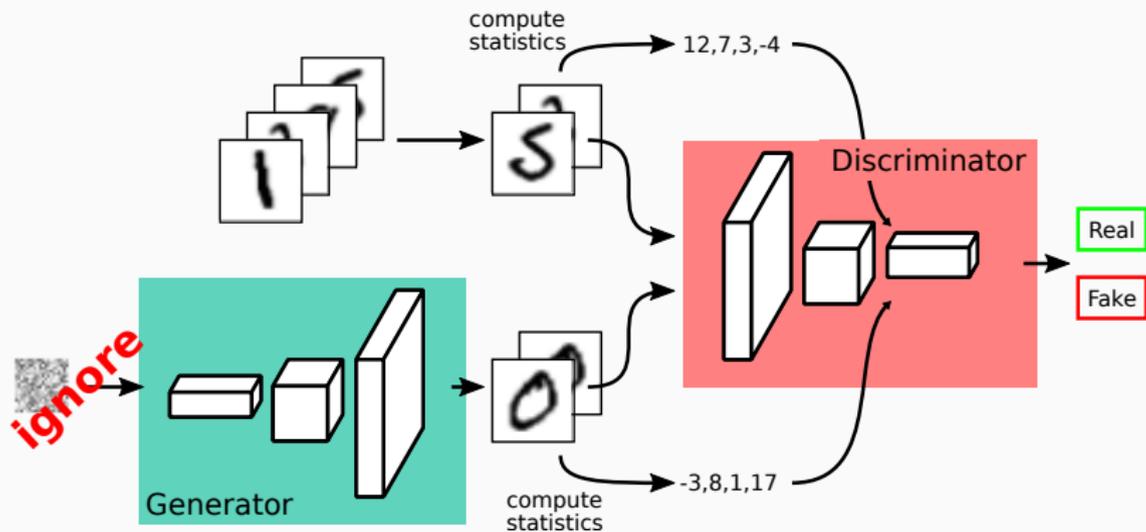


Figure 5: Compute statistics over minibatch and make them available to the discriminator.

High-Resolution Images

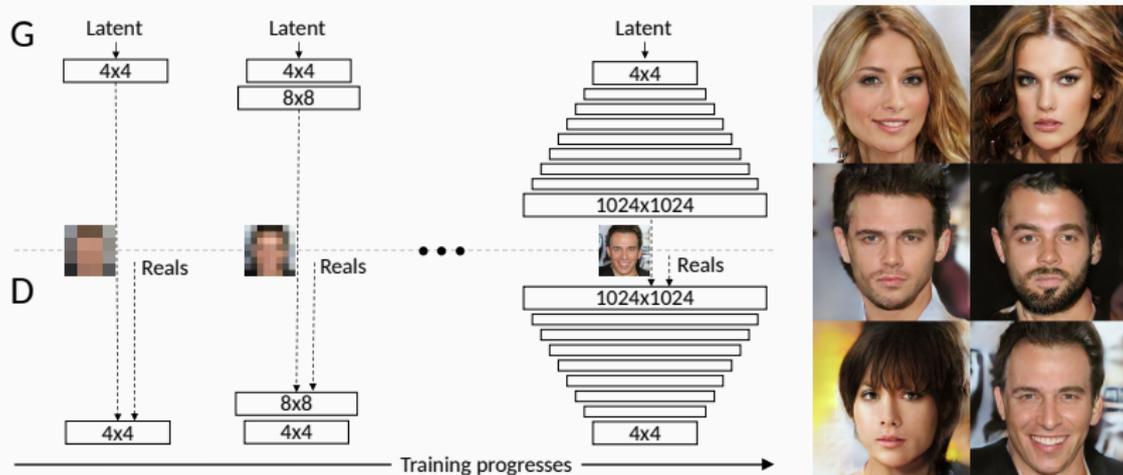


Figure 6: Progressive Growing⁴.

⁴Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation".

High-Resolution Images

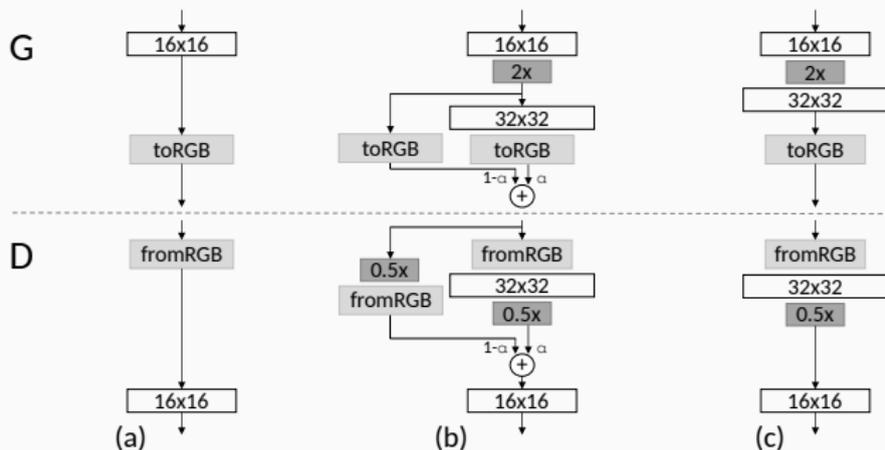


Figure 7: Fading in of new layers⁵.

⁵Karras et al., "Progressive Growing of GANs for Improved Quality, Stability, and Variation".

High-Resolution Images



Figure 8: Progressive Growing results⁶.

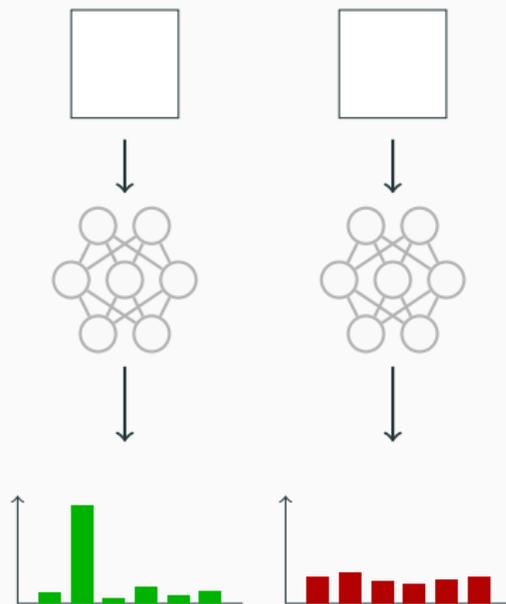
⁶Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”.

How good are the generated images?

Assessing Results

Option 1: Inception Score (IS)⁷

- If an Inception network gives a good prediction the images are realistic
- If it predicts all classes the variation is good

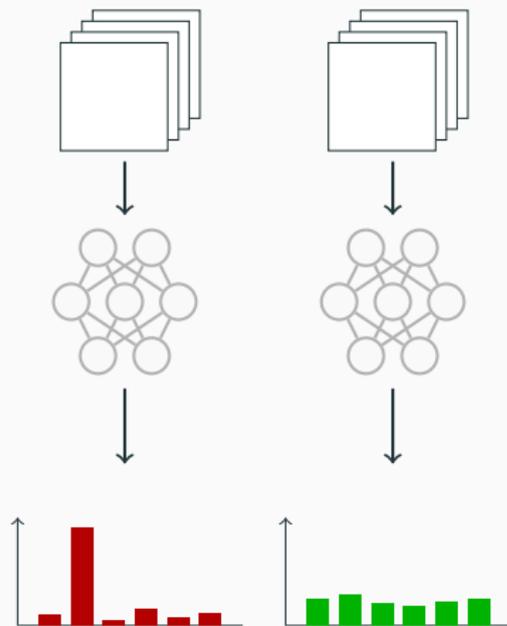


⁷Salimans et al., “Improved techniques for training gans”.

Assessing Results

Option 1: Inception Score (IS)⁷

- If an Inception network gives a good prediction the images are realistic
- If it predicts all classes the variation is good



⁷Salimans et al., “Improved techniques for training gans”.

Option 2: Fréchet Inception Distance (FID)⁸

- Improvement of the IS
- Use features by an intermediate layer
- Compute μ and Σ for real images and generated images
- Compares statistics

⁸Heusel et al., “Gans trained by a two time-scale update rule converge to a local nash equilibrium” .

Option 3: Sliced Wasserstein Distance⁹

- Compute laplacian pyramids of real images and generated images
- Sample image patches on one level
- Compute the sliced Wasserstein distance between the patches

⁹Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”.

Evaluation

Original Results from the Paper



Figure 9: Progressive Growing results¹⁰.

¹⁰Karras et al., “Progressive Growing of GANs for Improved Quality, Stability, and Variation”.

Generated Images



Figure 10: Images generated with the source code and weights from the paper¹².

¹²https://github.com/tkarras/progressive_growing_of_gans

Generated Images



Figure 11: Images generated with the source code and weights from the paper.

Style-Based GANs



Figure 12: Generated images from the Style-Based GANs paper¹³.

¹³Karras, Laine, and Aila, “A Style-Based Generator Architecture for Generative Adversarial Networks”.

Style-Based GANs



Figure 13: Generated images from the Style-Based GANs paper.

Style-Based GANs



Figure 14: Images generated with the source code and weights from the Style-Based GANs paper¹⁵.

¹⁵<http://stylegan.xyz/code>

Style-Based GANs



Figure 15: Images generated with the source code and weights from the Style-Based GANs paper.

Conclusion

- General idea of GANs
- Problems and Solutions
 - Variation
 - High-resolution
 - Assessing of results
- Generated images



Questions?

References

-  Goodfellow, Ian et al. “Generative adversarial nets”. In: *Advances in neural information processing systems*. 2014, pp. 2672–2680.
-  Heusel, Martin et al. “Gans trained by a two time-scale update rule converge to a local nash equilibrium”. In: *Advances in Neural Information Processing Systems*. 2017, pp. 6626–6637.
-  Karras, Tero, Samuli Laine, and Timo Aila. “A Style-Based Generator Architecture for Generative Adversarial Networks”. In: *arXiv preprint arXiv:1812.04948* (2018).

-  Karras, Tero et al. “Progressive Growing of GANs for Improved Quality, Stability, and Variation”. In: *International Conference on Learning Representations*. 2018. URL: <https://openreview.net/forum?id=Hk99zCeAb>.
-  Salimans, Tim et al. “Improved techniques for training gans”. In: *Advances in Neural Information Processing Systems*. 2016, pp. 2234–2242.

Progressive Growing of GANs: <https://youtu.be/G06dEcZ-QTg>

Style-Based GANs: <https://youtu.be/kSLJria0umA>