Synthetic Image Generation

with a focus on GANs

Koray Ulusan

University of Tübingen

koray.ulusan@student.uni-tuebingen.de

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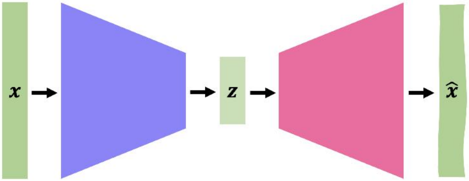
Overview

1. Earlier Approaches
2. Generative Adversarial Networks (GANs)
3. Modern Methods
4. Ethical Aspects
5. Q&A

Image Generation Before GANs

Deep generative models

- Deep Belief Networks [Hinton et al., 2006]
- VAEs [Kingma and Welling, 2013]



AutoEncoder

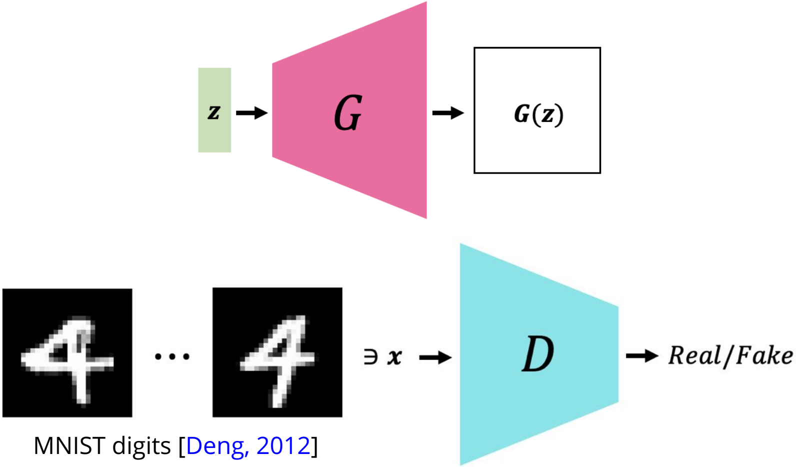
Slice of generated samples [Kingma and Welling, 2013]

Image Classification Models

- GoogLeNet [Szegedy et al., 2014]
- VGG [Simonyan and Zisserman, 2014]
- ResNet [He et al., 2015]

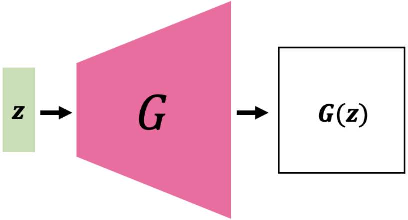
Generative Adversarial Networks (GANs)

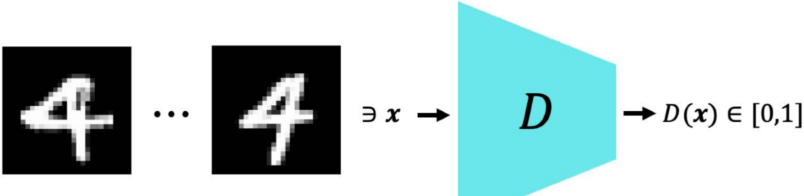
- Generative Adversarial Nets [Goodfellow et al., 2014]



MNIST digits [Deng, 2012]

Value Function





MNIST digits [Deng, 2012]

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]$$

Training Procedure I

GAN training algorithm [Goodfellow et al., 2014]

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

Training Procedure II

for number of training iterations **do**

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
  - Update the discriminator by ascending its stochastic gradient:

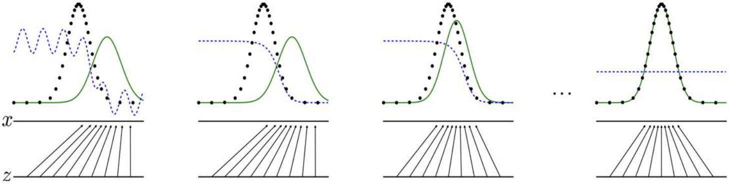
$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

  end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for



Several steps of training [Goodfellow et al., 2014]

Results

interpolation in z-space [Goodfellow et al., 2014]

Generated samples (using FC or Conv). Green ones are closest images in CIFAR-10 [Goodfellow et al., 2014]

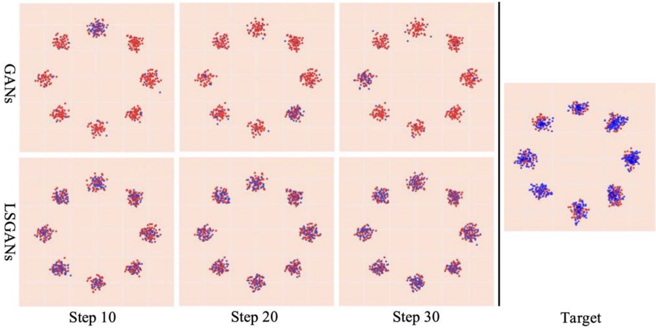
- Fréchet inception distance (FID) [Heusel et al., 2017]

Common Problems

- Mode collapse
- Vanishing gradients
- (non-) convergence

Apple

Orange



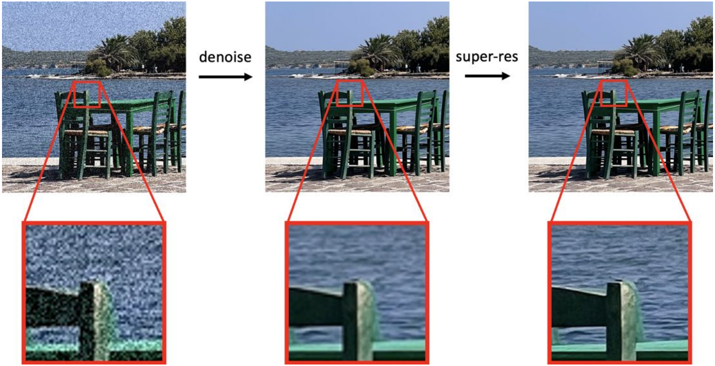
Regular GANs and LSGANs on CIFAR-10 [Shamsolmoali et al., 2020]

GAN Variants I

What can GANs do?

- image super-resolution
- image denoising
- image inpainting
- image fusion

[Shamsolmoali et al., 2020]



GAN Variants II

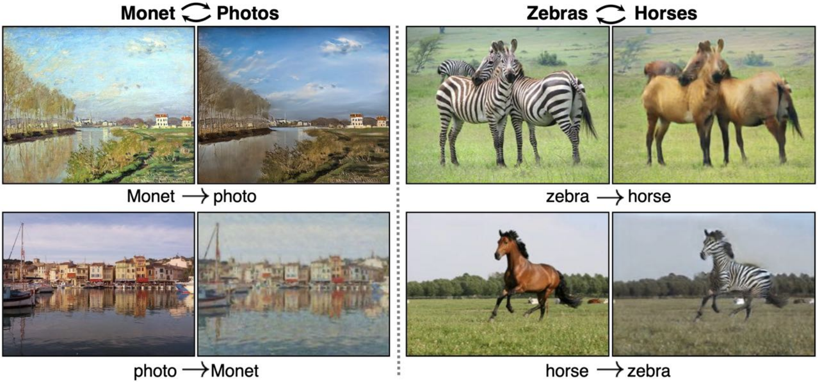
- image captioning
- text-to-image translation
- Multi-stage methods: StackGAN [Zhang et al., 2016]

Generated samples of flowers by StackGAN [Shamsolmoali et al., 2020]

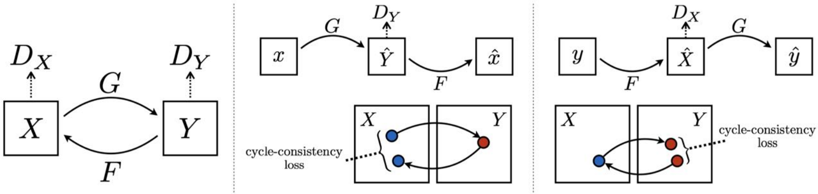
CycleGan I

- Adversarial Domain Adaptation:

  Unpaired Image-to-Image Translation using
  Cycle-Consistent Adversarial Networks [Zhu et al., 2017]



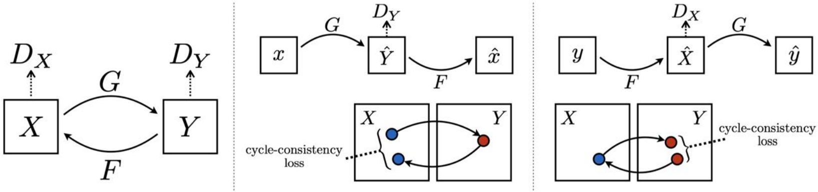
CycleGan II



CycleGAN architecture [Zhu et al., 2017]

“Horse $\rightarrow$ Zebra $\rightarrow$ Horse” cycle [Shamsolmoali et al., 2020]

CycleGan III



$$\mathcal{L}_{GAN}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{data}(y)}[\log D_Y(y)] + \mathbb{E}_{x \sim p_{data}(x)}[\log(1 - D_Y(G(x)))]$$

$$\mathcal{L}_{cyc}(G, F) = \mathbb{E}_{x \sim p_{data}(x)}[||F(G(x)) - x||_1] + \mathbb{E}_{y \sim p_{data}(y)}[||G(F(y)) - y||_1]$$

$$\mathcal{L}(G, F, D_X, D_Y) = \mathcal{L}_{GAN}(G, D_Y, X, Y) + \mathcal{L}_{GAN}(F, D_X, X, Y) + \lambda \cdot \mathcal{L}_{cyc}(G, F)$$

Note: $\lambda = 10$

State-of-the-Art

- Muse [Chang et al., 2023]
- by Google Research
- Text-To-Image Generation via Masked Generative *Transformers*

- CM3Leon (pronounced "Chameleon") [Yu et al., 2023] (exactly 90 days ago)
- by Meta AI (Facebook)
- *Autoregressive*
- Based on CM3 [Aghajanyan et al., 2022]
  "training ... image tokens (from a VQVAE-GAN) ..."

Ethical Aspects

Chest Radiograph [Desai, 2020]

Blended Signatures [Mattei, 2022]

Obama's Deepfake [MIT video]

"Théâtre D'opéra Spatial" [Roose, 2022]

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Questions and Answers

Q&A about:

- something you would like to explore further
- more on GAN training problems
- more on CycleGAN? extensions/limitations
- more on diffusion models
- ...