GAN - Theory and Applications

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> "Adversarial Training (also called GAN for Generative Adversarial Networks) is the most interesting idea in the last 10 years of ML."
>
> — Yann LeCun

Generative Adversarial Networks

Two components, the **generator** and the **discriminator**:

- The **generator** G, aim is to capture the data distribution.
- The **discriminator** D, estimates the probability that a sample came from the training data rather than from G.

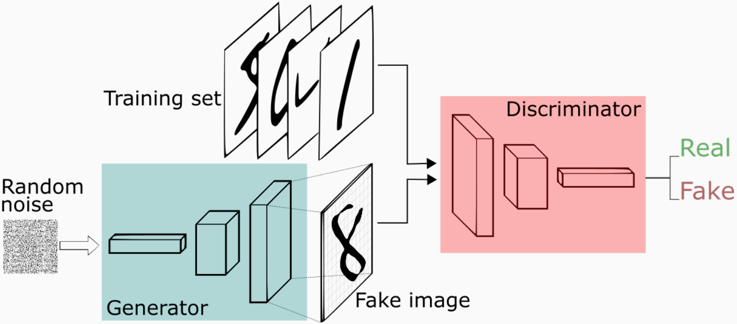

Figure 1: Credits: Silva

Generative Adversarial Networks

GANs game:

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

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GANs - Discriminator

Intuitive explanation:

- **Discriminator** needs to:
  - Correctly classify real data:

$$\boxed{\max_{D} \mathop{\mathbb{E}}_{x \sim p_{data}(x)} [\log D(x)].} \tag{2}$$

  - Correctly classify wrong data:

$$\boxed{\max_{D} \mathop{\mathbb{E}}_{z \sim p_z(z)} [\log(1 - D(G(z)))].} \tag{3}$$

- The discriminator is an **adaptive loss function** that gets discarded once the generator has been trained.

GANs - Generator

Intuitive explanation:

- **Generator** needs to **fool** the discriminator:
    - Generate samples similar to the real one:

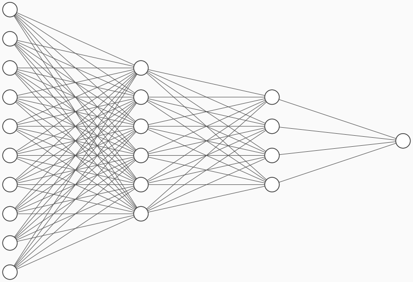
$$\boxed{\min_{G} \mathop{\mathbb{E}}_{z\sim p_z(z)}[\log(1 - D(G(z)))].} \tag{4}$$

    - Saturates easily Goodfellow et al. (2014).
    - Change loss for generator:

$$\boxed{\max_{G} \mathop{\mathbb{E}}_{z\sim p_z(z)}[\log(D(G(z)))].} \tag{5}$$

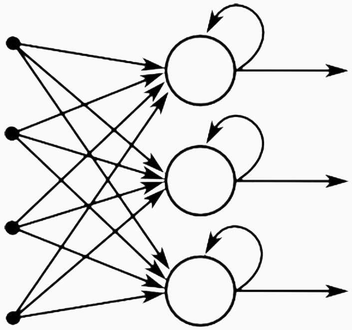
GANs - Models definition

- Both D and G can be parametrized functions (Neural Networks).
- Different architectures for different data types.
    - Tuple of numbers? Fully Connected Neural Networks



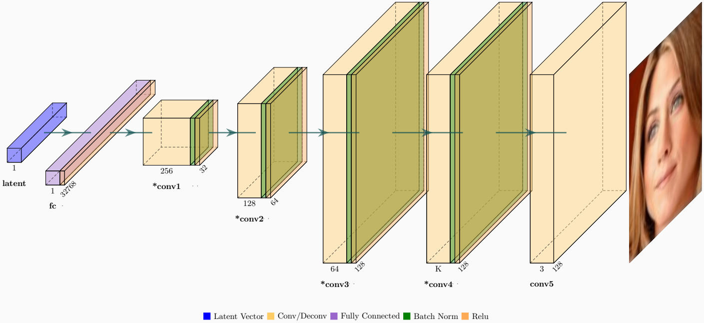
GANs - Models definition

- Both D and G can be parametrized functions (Neural Networks).
- Different architectures for different data types.
  - Text or sequences? Recurrent Neural Networks



GANs - Models definition

- Both D and G can be parametrized functions (Neural Networks).
- Different architectures for different data types.
  - Images? Convolutional Neural Networks



GANs Training

GANs - Training

- Discriminator and generator are **competing** against each other.
- **Alternating** execution of training steps.
- Use **minibatch stochastic gradient descent/ascent**.

GANs - Training - Discriminator

How to **train** the **discriminator**?

Repeat from 1 to **k**:

1. Sample minibatch of m noise samples $z^{(1)}, \dots, z^{(m)}$ from $p_g(z)$
2. Sample minibatch of m examples $x^{(1)}, \dots, x^{(m)}$ from $p_{data}(x)$
3. Train the **discriminator** by stochastic gradient **ascent**:

$$\nabla_{\theta_d} \underbrace{\frac{1}{m} \sum_{i=1}^{m} \underbrace{\log D(x^{(i)}) + \log(1 - D(G(z^{(i)})))}_{\text{Discriminator loss}}}_{\text{Loss estimation using m samples}}$$

GANs - Training - Generator

How to **train** the **generator**?

The update is executed **only once** and only after the turn of the discriminator is completed:

1. Sample minibatch of m noise samples $z^{(1)}, \dots, z^{(m)}$ from $p_g(z)$
2. Train the **generator** by stochastic gradient **ascent**:

$$\nabla_{\theta_g} \quad \underbrace{\frac{1}{m} \sum_{i=1}^{m} \underbrace{\log(D(G(z^{(i)})))}_{\text{Generator loss}}}_{\text{Loss estimation using m samples}}$$

GANs - Training - Considerations

- Optimizers: Adam, Momentum, RMSProp.
- Training phase can last for an **arbitrary number** of steps or epochs.
- Training is completed when the discriminator is **completely fooled** by the generator.
- Goal: reach a **Nash Equilibrium** where the best D can do is random guessing.

Types of GANs

Types of GANs

Two big families:

- **Unconditional** GANs (just described).
- **Conditional** GANs (Mirza and Osindero, 2014).

Conditional GANs

- **Both** G and D are **conditioned** on some extra information y.
- In **practice**: perform conditioning by feeding y into the discriminator and generator.

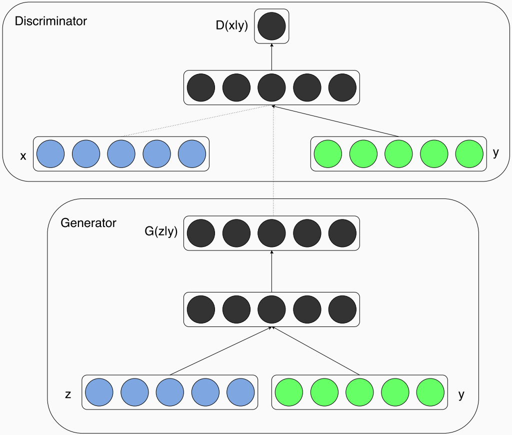


Figure 2: From Mirza and Osindero (2014)

Conditional GANs

The GANs game becomes:

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

Notice: the same representation of the condition has to be presented to both network.

GANs Applications

GANs Applications

GANs can be applied to different tasks:

- Face generation

Figure 3: From Karras et al. (2017)

GANs Applications

GANs can be applied to different tasks:

- Domain Translation

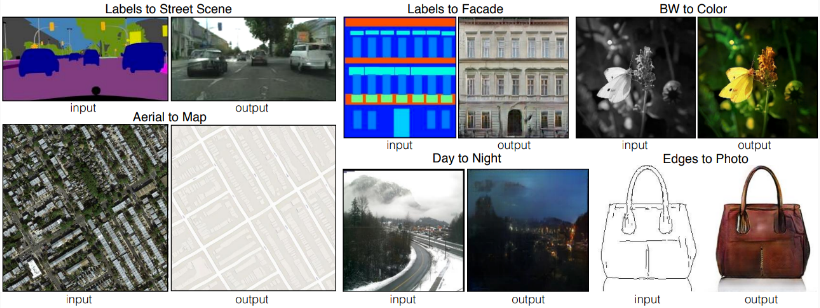


Figure 3: From Isola et al. (2016)

GANs Applications

GANs can be applied to different tasks:

- Super resolution applications

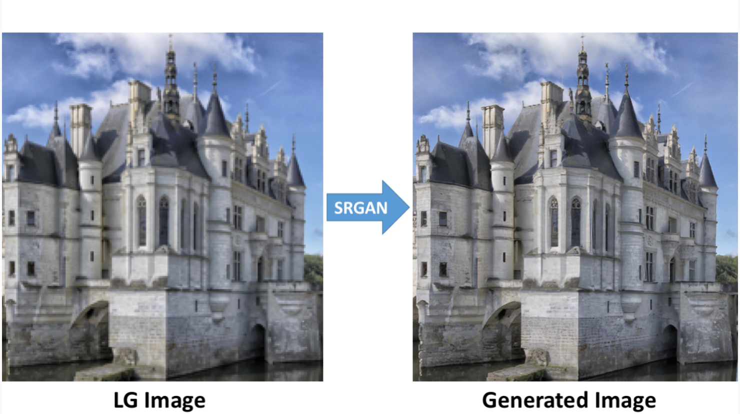


Figure 3: From Ledig et al. (2016)

Thank you for your attention!

Questions?

References

[Goodfellow et al. 2014] GOODFELLOW, Ian J. ; POUGET-ABADIE, Jean ; MIRZA, Mehdi ; XU, Bing ; WARDE-FARLEY, David ; OZAIR, Sherjil ; COURVILLE, Aaron ; BENGIO, Yoshua: Generative Adversarial Networks. (2014). – (2014)

[Isola et al. 2016] ISOLA, Phillip ; ZHU, Jun-Yan ; ZHOU, Tinghui ; EFROS, Alexei A.: Image-to-Image Translation with Conditional Adversarial Networks. (2016). – (2016)

[Karras et al. 2017] KARRAS, Tero ; AILA, Timo ; LAINE, Samuli ; LEHTINEN, Jaakko: Progressive Growing of GANs for Improved Quality, Stability, and Variation. (2017). – (2017)

[Ledig et al. 2016] LEDIG, Christian ; THEIS, Lucas ; HUSZAR, Ferenc ; CABALLERO, Jose ; CUNNINGHAM, Andrew ; ACOSTA, Alejandro ; AITKEN, Andrew ; TEJANI, Alykhan ; TOTZ, Johannes ; WANG, Zehan ; SHI, Wenzhe: Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. (2016). – (2016)

[Mirza and Osindero 2014] MIRZA, Mehdi ; OSINDERO, Simon: Conditional Generative Adversarial Nets. (2014). – (2014)

[Silva] SILVA, Thalles: *An Intuitive Introduction to Generative Adversarial Networks (GANs)*