

ZURU™

GAN - Theory and Applications

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PYCONX

Generative Adversarial Networks

“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.

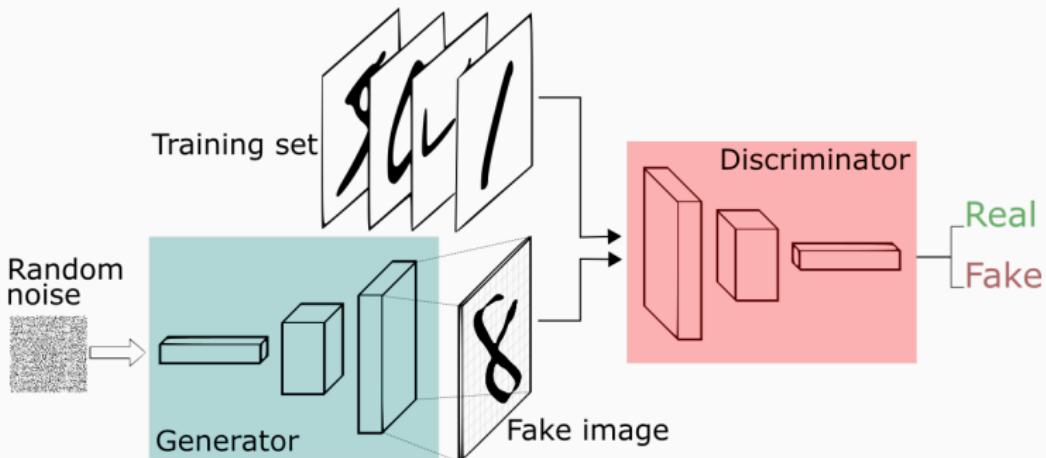


Figure 1: Credits: Silva

Generative Adversarial Networks

GANs game:

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

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GANs - Discriminator

- **Discriminator** needs to:

- Correctly classify **real** data:

$$\max_D \mathbb{E}_{x \sim p_{data}(x)} [\log D(x)]. \quad (2)$$

- Correctly classify **wrong** data:

$$\max_D \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))] \quad (3)$$

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

GANs - Generator

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

$$\min_G \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))] \quad (4)$$

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

$$\max_G \mathbb{E}_{z \sim p_z(z)} [\log(D(G(z)))] \quad (5)$$

GANs - Generator

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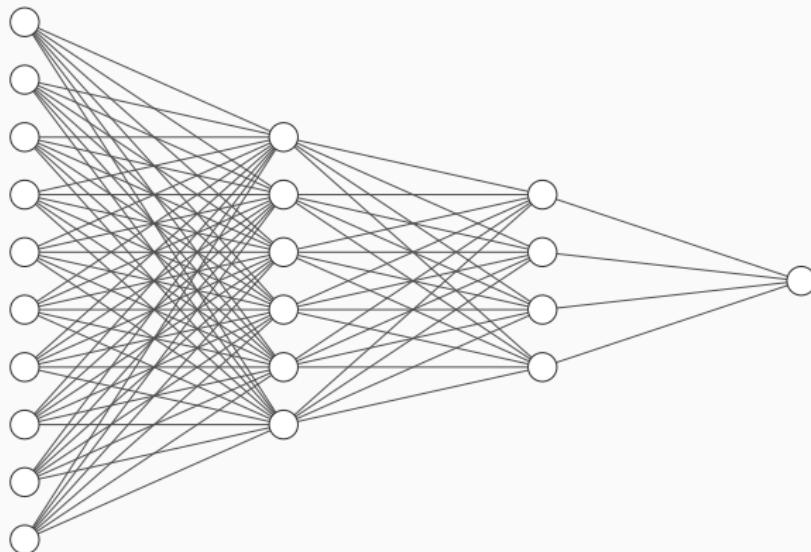
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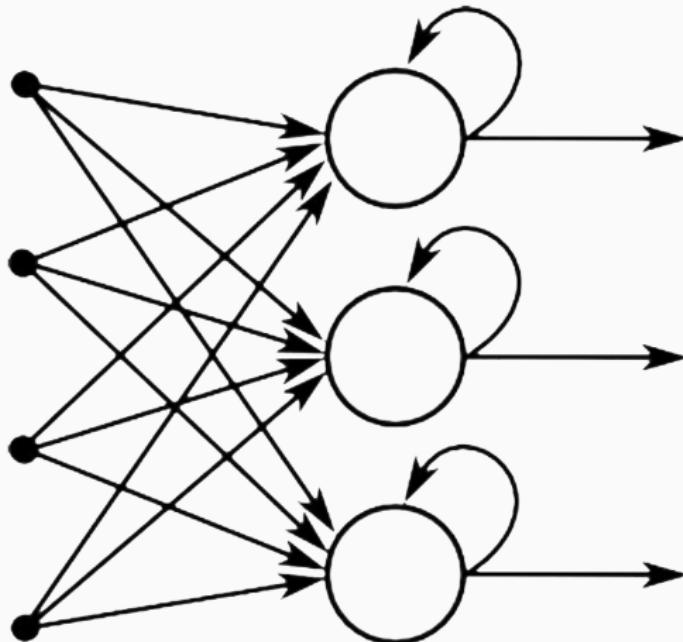
GANs - Models definition

- Different architectures for different data types.
 - Tuple of numbers? **Fully Connected Neural Networks**



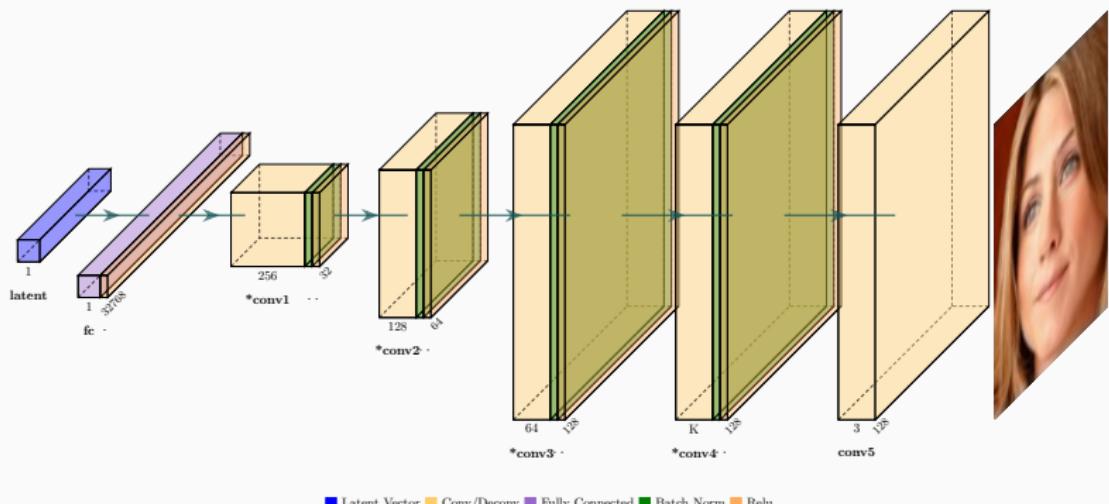
GANs - Models definition

- Different architectures for different data types.
 - Text or sequences? Recurrent Neural Networks



GANs - Models definition

- 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 $p_g(z)$

GANs - Training - Discriminator

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2. Sample minibatch of m examples $x^{(1)}, \dots, x^{(m)}$ from $p_{data}(x)$

GANs - Training - Discriminator

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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**:

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

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 $p_g(z)$

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**:

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

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.

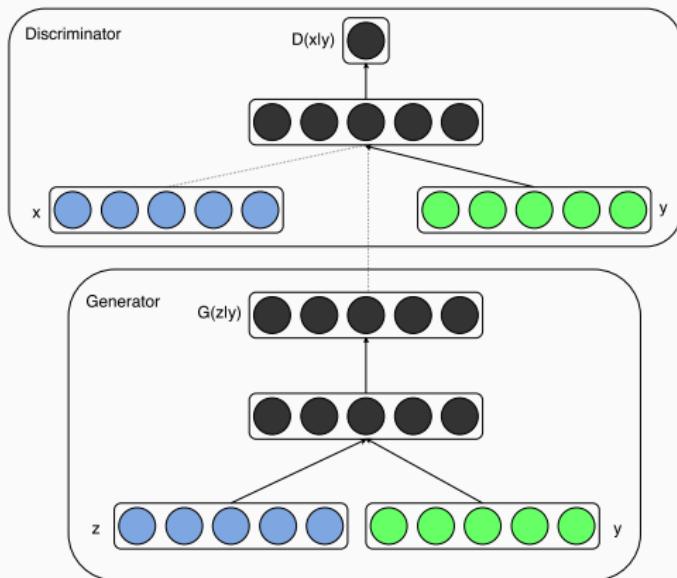


Figure 2: From Mirza and Osindero (2014)

Conditional GANs

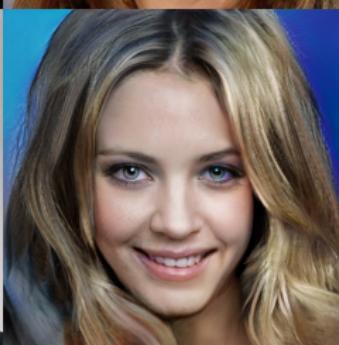
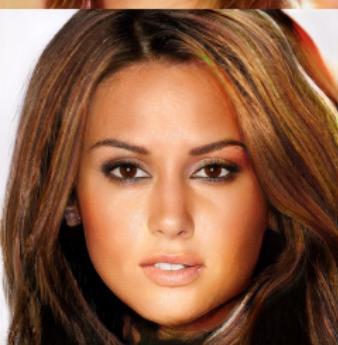
The GANs game becomes:

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

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

GANs Applications

Face Generation - Karras et al. (2017)



Domain Translation - Isola et al. (2016)

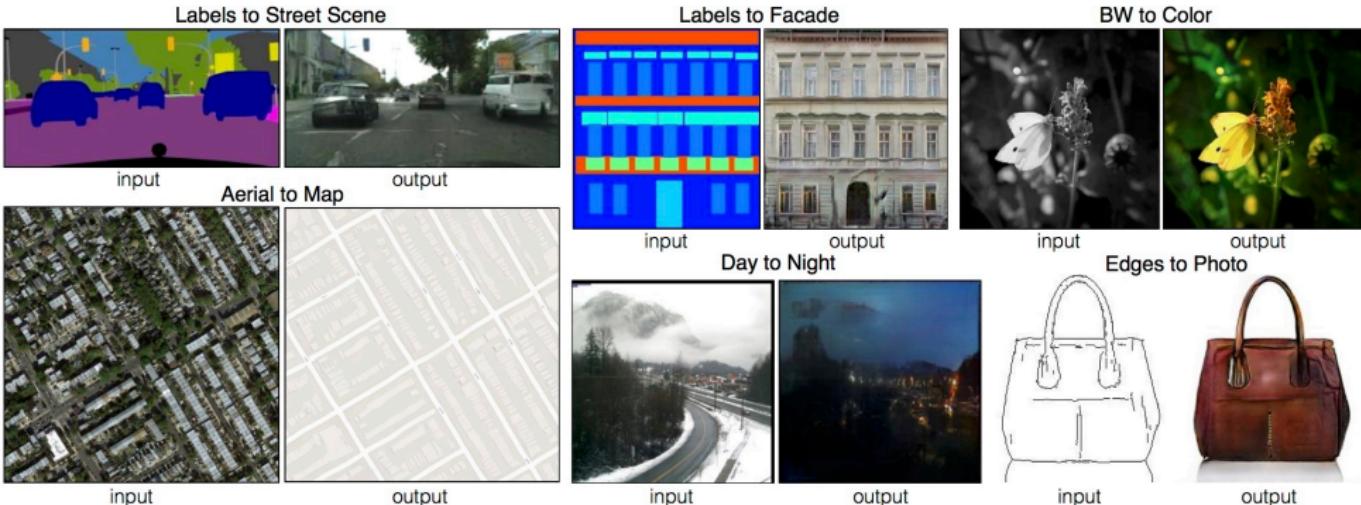


Image Super Resolution - Ledig et al. (2016)



LG Image



Generated Image

Thank you for your attention!
Questions?

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