



# GAN - Theory and Applications

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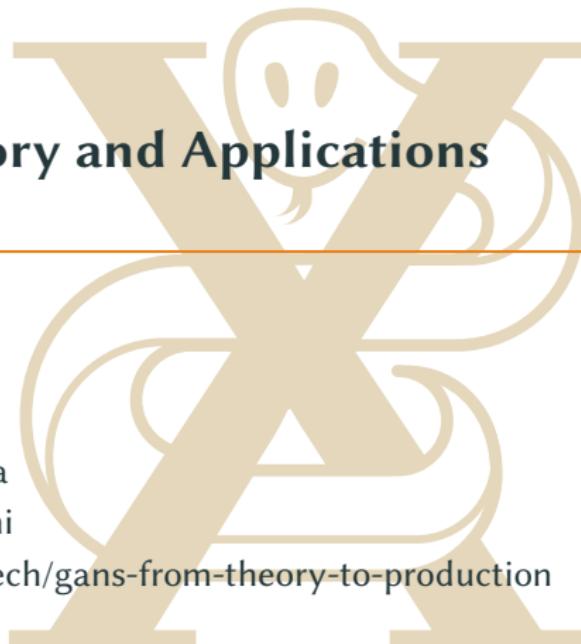
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[github.com/zurutech/gans-from-theory-to-production](https://github.com/zurutech/gans-from-theory-to-production)

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# PYCONX



# Overview

1. Introduction
2. Models definition
3. GANs Training
4. Types of GANs
5. GANs Applications

# Introduction

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**“Generative Adversarial Networks is the **most** interesting idea in the last ten years in machine learning.**

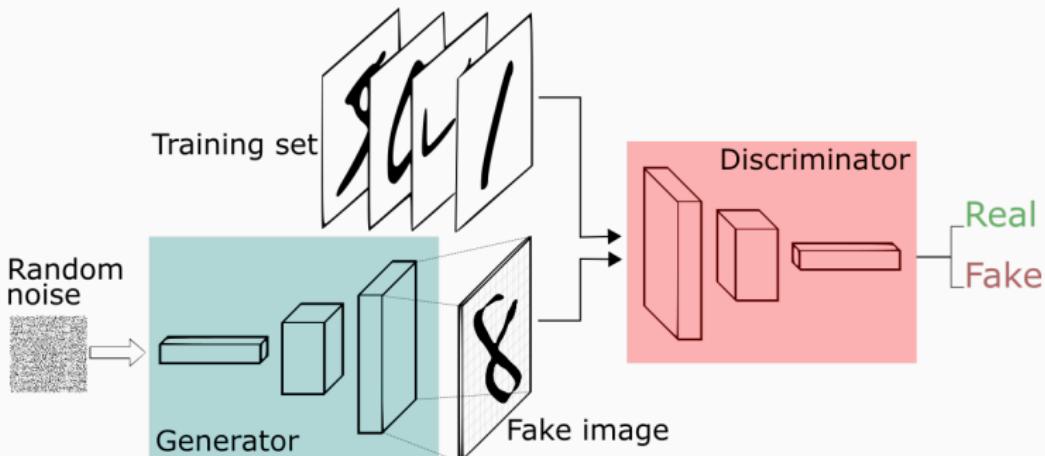
*Yann LeCun, Director, Facebook AI*



# Generative Adversarial Networks

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

- The **generator** G needs to capture the data distribution.
- The **discriminator** D estimates the probability that a sample comes 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:

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

$D(x) \rightarrow 1$

- Correctly classify **wrong** data:

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

$D(G(z)) \rightarrow 0$

- The discriminator is an **adaptive loss function**.



**YOU DON'T NEED TO  
DESIGN A LOSS FUNCTION**

**IF A DISCRIMINATOR  
DESIGNS ONE FOR YOU**

# GANs - Generator

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

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

$$D(G(z)) \rightarrow 1$$

# GANs - Generator

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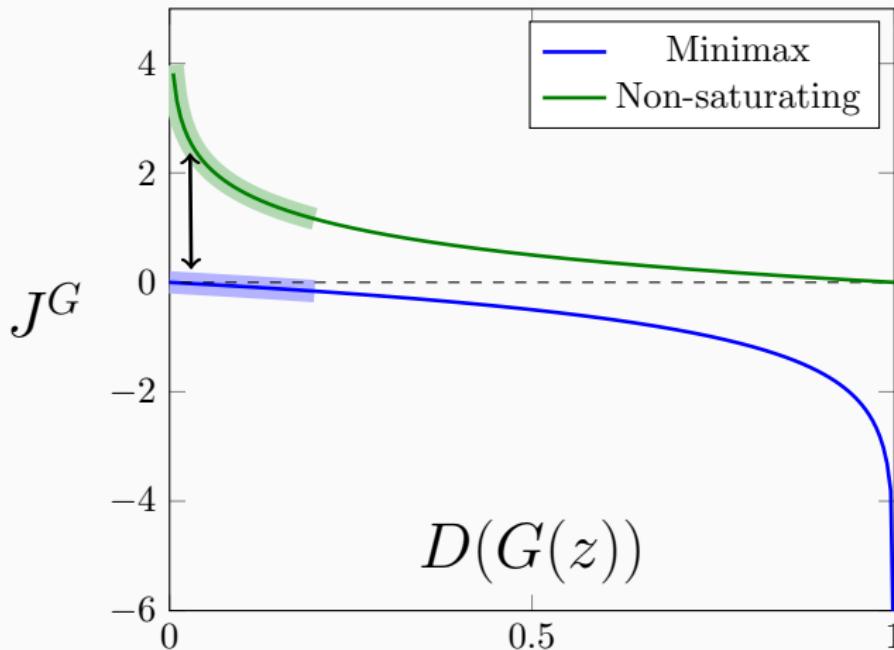
$$D(G(z)) \rightarrow 1$$

- Non saturating objective (Goodfellow et al., 2014):

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

## GANs - Generator Objectives

- Minimax:  $\log(1 - D(G(z)))$
- Non-saturating:  $-\log(D(G(z)))$

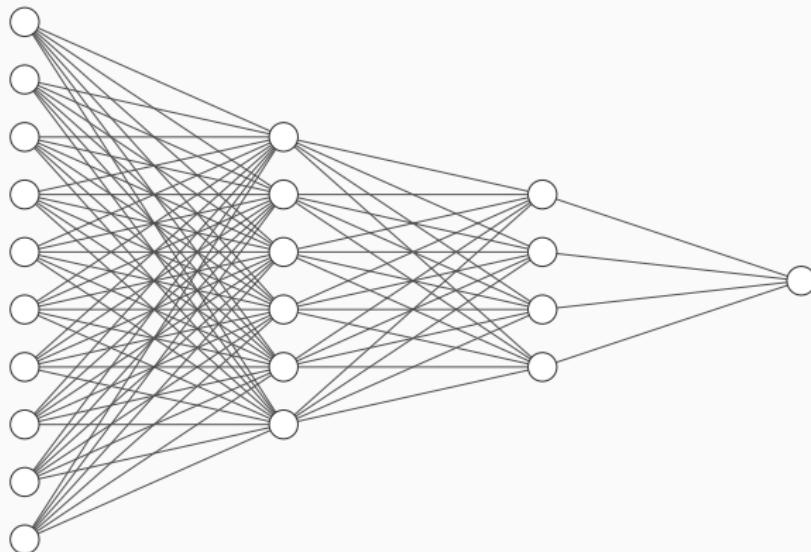


## **Models definition**

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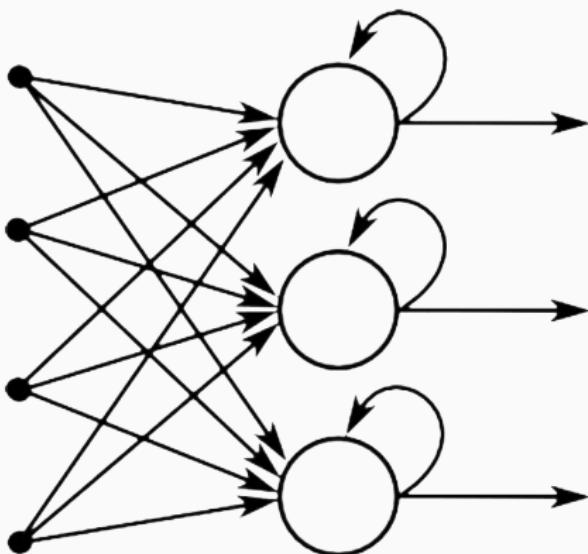
# GANs - Models definition

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



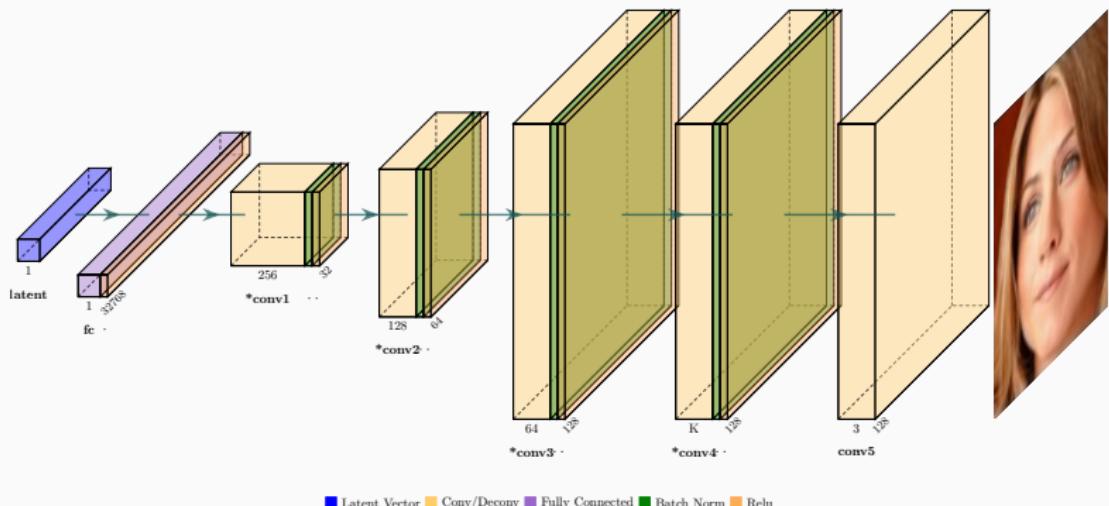
## GANs - Models definition

- 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

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## GANs - Training

- D and G 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  $p_z(z)$

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

$$J = \underbrace{\frac{1}{m} \sum_{i=1}^m \log D(x^{(i)}) + \log(1 - D(G(z^{(i)})))}_{D \text{ performance}}$$

$$\theta_d = \theta_d + \lambda \nabla_{\theta_d} J$$

## GANs - Training - Generator

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

Update executed **only once** after **D** updates:

1. Sample minibatch of  $m$  noise samples  $z^{(1)}, \dots, z^{(m)}$  from  $p_z(z)$

## GANs - Training - Generator

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

Update executed **only once** after **D** updates:

1. Sample minibatch of  $m$  noise samples  $z^{(1)}, \dots, z^{(m)}$  from  $p_z(z)$
2. Update **G**:

$$\mathbf{J} = \underbrace{\frac{1}{m} \sum_{i=1}^m \log(\mathbf{D}(\mathbf{G}(z^{(i)})))}_{\text{G performance}}$$

$$\theta_{\mathbf{g}} = \theta_{\mathbf{g}} + \lambda \nabla_{\theta_{\mathbf{g}}} \mathbf{J}$$

## GANs - Training - Considerations

- Optimizers: Adam, Momentum, RMSProp.
- **Arbitrary number** of steps or epochs.
- Training is completed when D is **completely fooled** by G.
- Goal: reach a **Nash Equilibrium** where the best D can do is random guessing.

## Types of GANs

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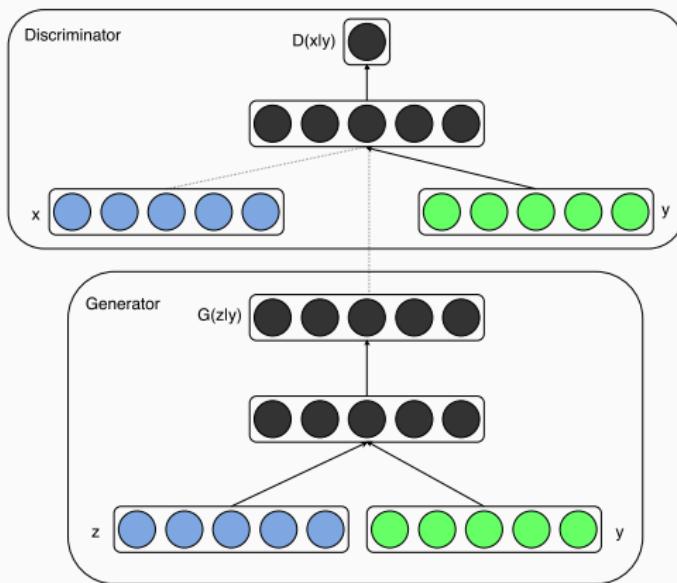
# Types of GANs

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:

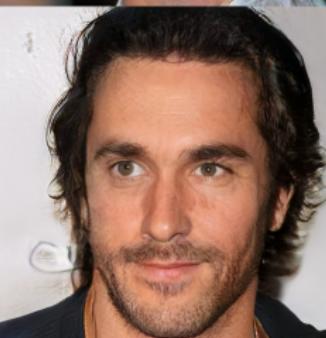
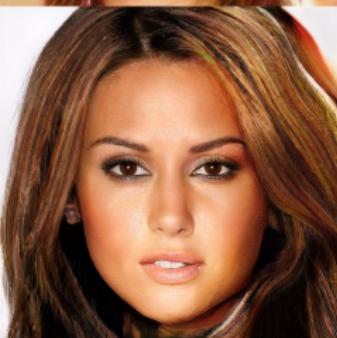
$$\min_G \max_D \mathbb{E}_{x \sim p_{data}(x|\mathbf{y})} [\log D(x, \mathbf{y})] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z|\mathbf{y}), \mathbf{y}))]$$

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

## GANs Applications

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# Unconditional - Face Generation - Karras et al. (2017)



# Conditional - Domain Translation - Isola et al. (2016)

Labels to Street Scene



input

output

Aerial to Map



input

output

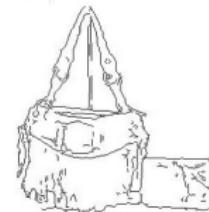
Input



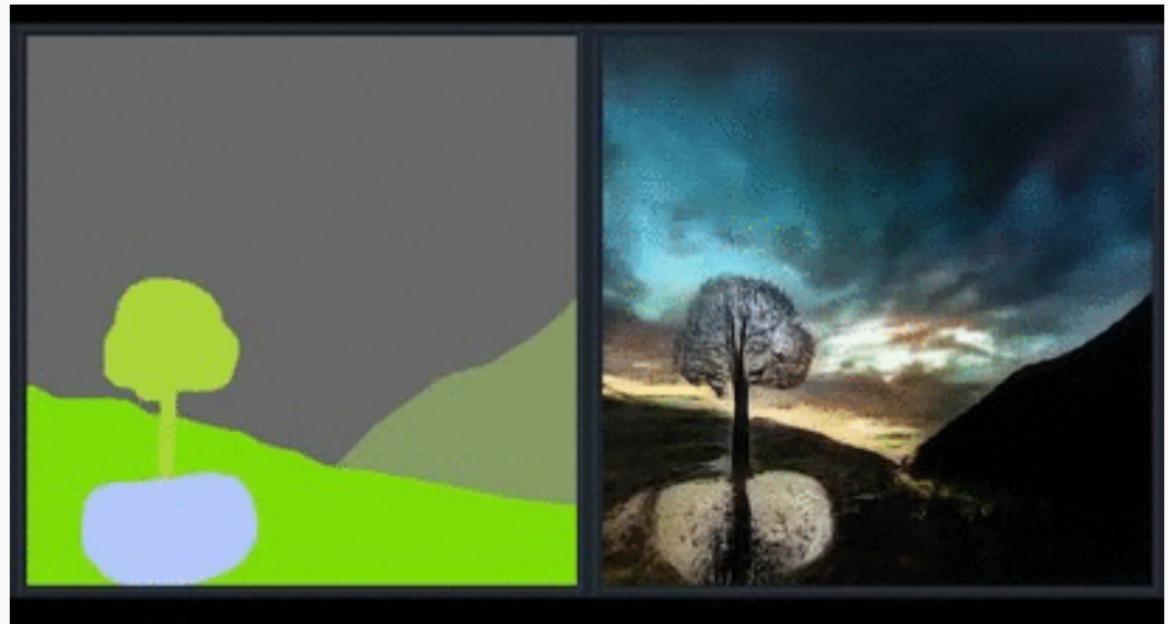
Ground truth



Output



# Conditional - Semantic Image Synthesis - Park et al. (2018)



# Conditional - Image Super Resolution - Ledig et al. (2016)



SRGAN



## Real-world GANs

- Semi-Supervised Learning (Salimans et al., 2016)
- Image Generation (almost all GAN papers)
- Image Captioning
- Anomalies Detection (Zenati et al., 2018)
- Program Synthesis (Ganin et al., 2018)
- Genomics and Proteomics (Killoran et al., 2017) (De Cao and Kipf, 2018)
- Personalized GANufactoring (Hwang et al., 2018)
- Planning

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