



# GAN - Theory and Applications

Emanuele Ghelfi

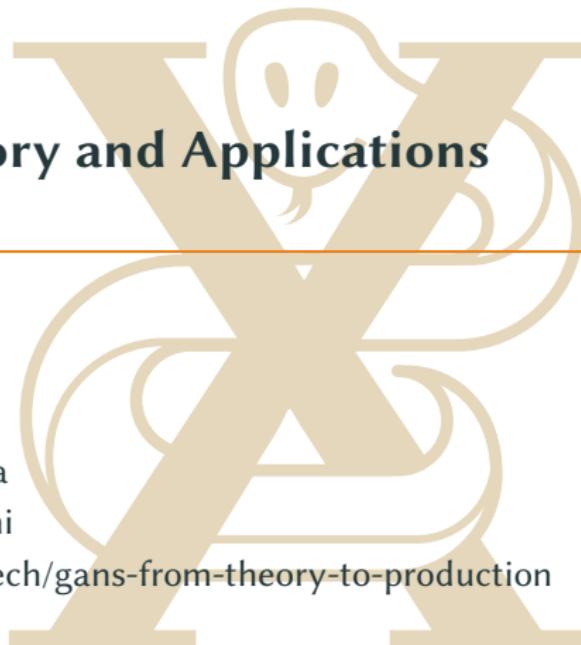
Paolo Galeone

Federico Di Mattia

Michele De Simoni

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

May 2, 2019



# PYCONX



# Overview

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

# Introduction

---

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

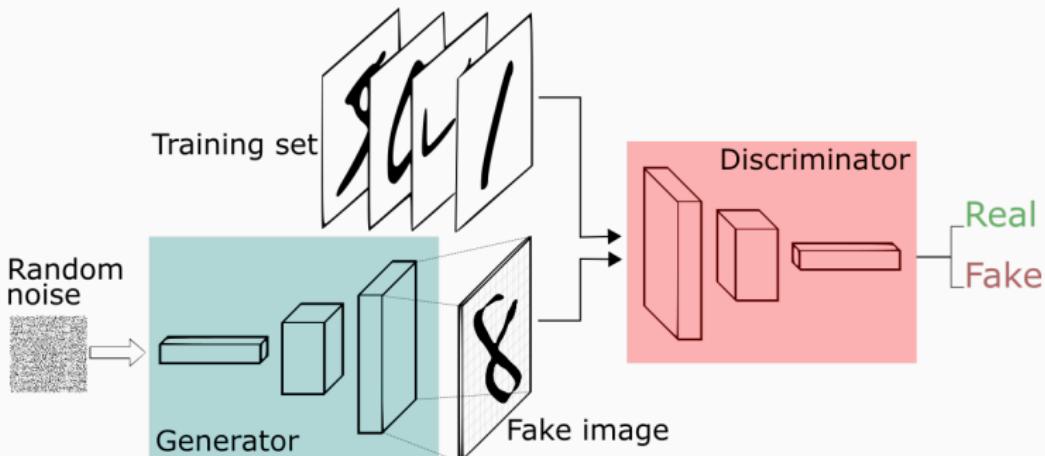
*Yann LeCun, Director, Facebook AI*



# 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:

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

# Generative Adversarial Networks

GANs game:

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

# Generative Adversarial Networks

GANs game:

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

# 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**

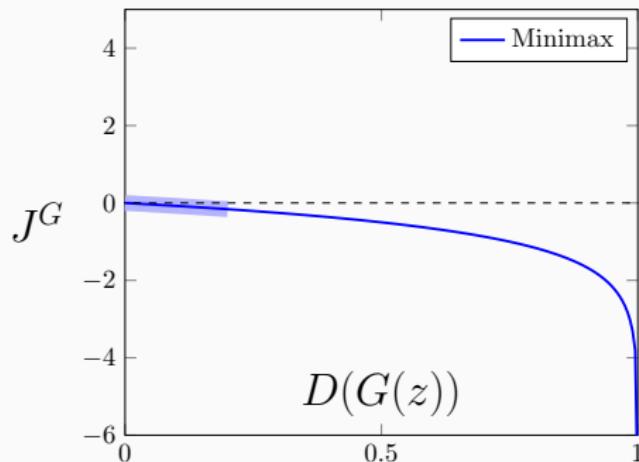
**IF A DISCRIMINATOR  
DESIGNS ONE FOR YOU**

# 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

- **Generator** needs to **fool** the discriminator:

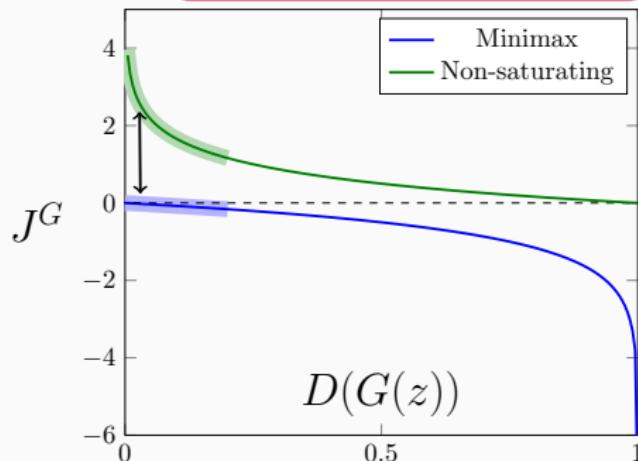
- Generate samples similar to the real ones:

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

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

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

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

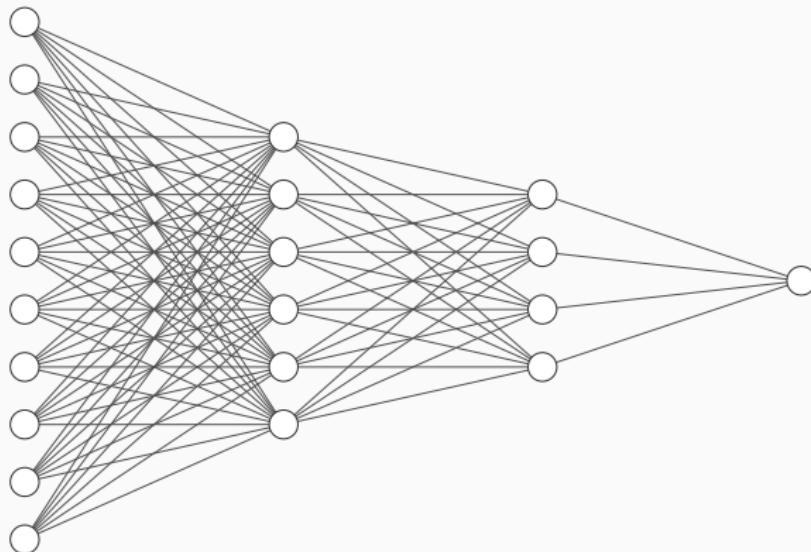


## **Models definition**

---

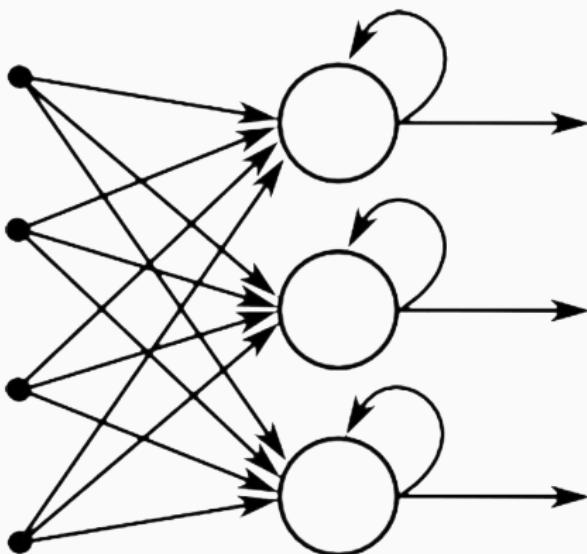
# GANs - Models definition

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



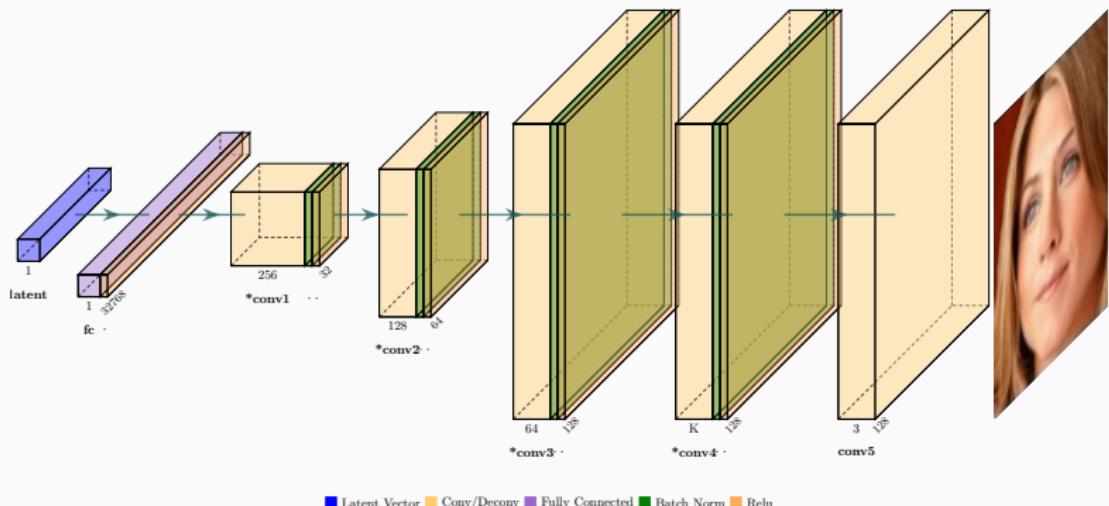
## GANs - Models definition

- 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

- 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  $p_z(z)$

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

## 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  $p_z(z)$
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

---

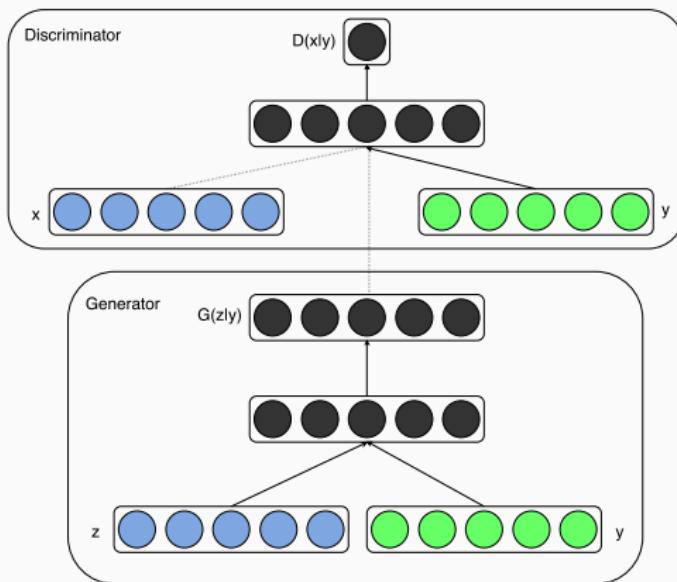
# Types of GANs

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:

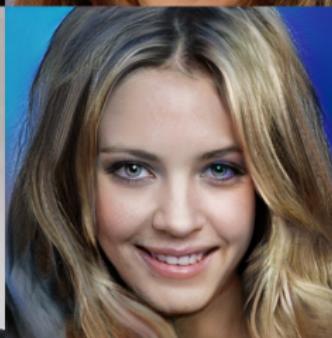
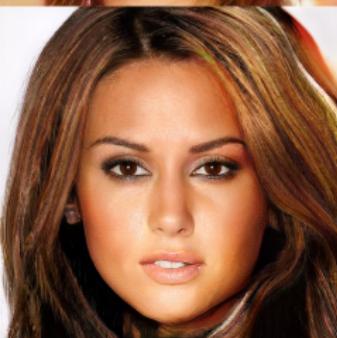
$$\min_G \max_D \mathbb{E}_{x \sim p_{data}(x|\mathbf{y})} [\log D(x, \mathbf{y})] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z|\mathbf{y}), \mathbf{y}))]$$

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

## GANs Applications

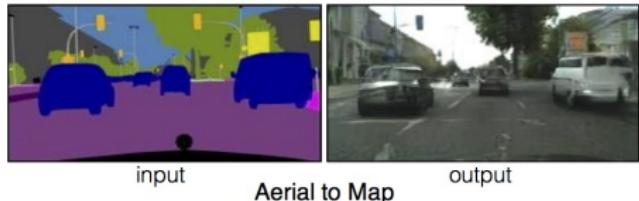
---

# 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

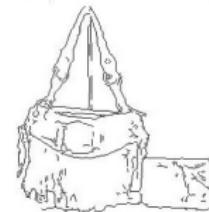
Input



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

## References

---

- [De Cao and Kipf 2018] DE CAO, Nicola ; KIPF, Thomas: MolGAN: An Implicit Generative Model for Small Molecular Graphs. (2018). – (2018)
- [Ganin et al. 2018] GANIN, Yaroslav ; KULKARNI, Tejas ; BABUSCHKIN, Igor ; ESLAMI, S. M. A. ; VINYALS, Oriol: Synthesizing Programs for Images Using Reinforced Adversarial Learning. (2018). – (2018)
- [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)

- [Hwang et al. 2018] HWANG, Jyh-Jing ; AZERNIKOV, Sergei ; EFROS, Alexei A. ; Yu, Stella X.: Learning Beyond Human Expertise with Generative Models for Dental Restorations. (2018). – (2018)
- [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)
- [Killoran et al. 2017] KILLORAN, Nathan ; LEE, Leo J. ; DELONG, Andrew ; DUVENAUD, David ; FREY, Brendan J.: Generating and Designing DNA with Deep Generative Models. (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)

[Park et al. 2018] PARK, Taesung ; LIU, Ming-Yu ; WANG, Ting-Chun ; ZHU, Jun-Yan: Semantic Image Synthesis with Spatially-Adaptive Normalization. (2018). – (2018)

[Salimans et al. 2016] SALIMANS, Tim ; GOODFELLOW, Ian ; ZAREMBA, Wojciech ; CHEUNG, Vicki ; RADFORD, Alec ; CHEN, Xi: Improved Techniques for Training GANs. (2016). – (2016)

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

[Zenati et al. 2018] ZENATI, Houssam ; Foo, Chuan S. ; LECOUAT, Bruno ; MANEK, Gaurav ; CHANDRASEKHAR, Vijay R.: Efficient GAN-Based Anomaly Detection. (2018). – (2018)