



GAN - Theory and Applications

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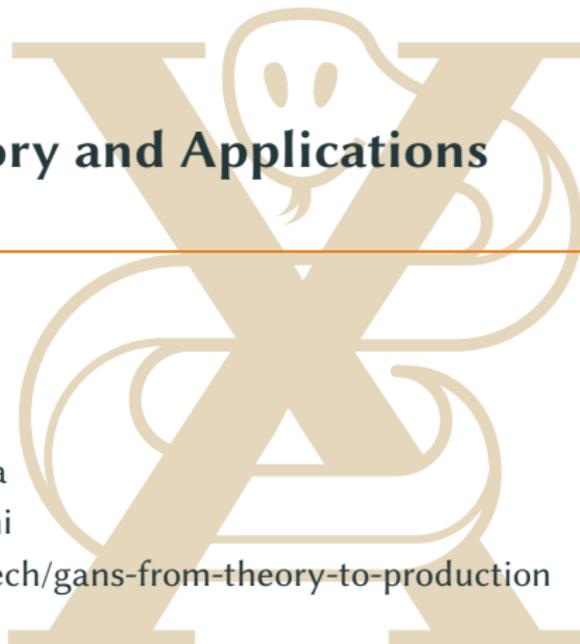
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github.com/zurutech/gans-from-theory-to-production

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PYCONX



Overview

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

Introduction

“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.

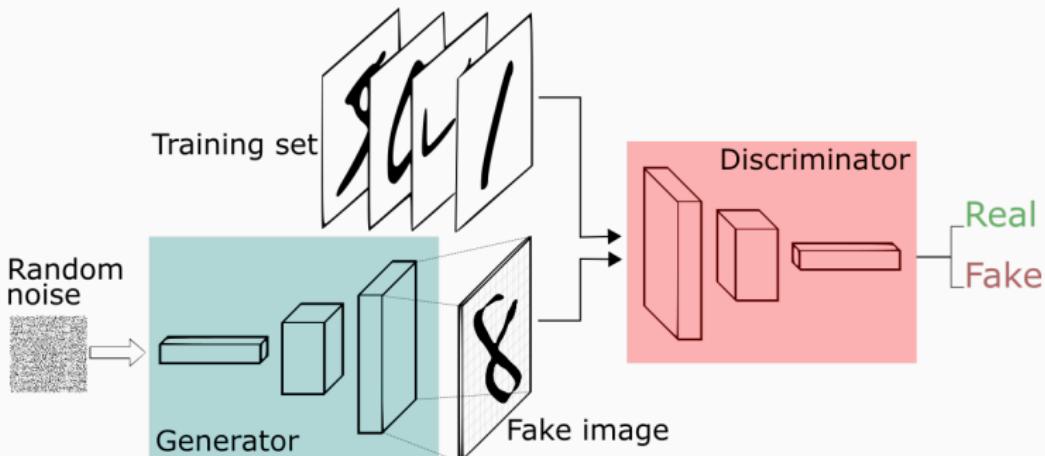


Figure 1: Credits: Silva

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

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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**

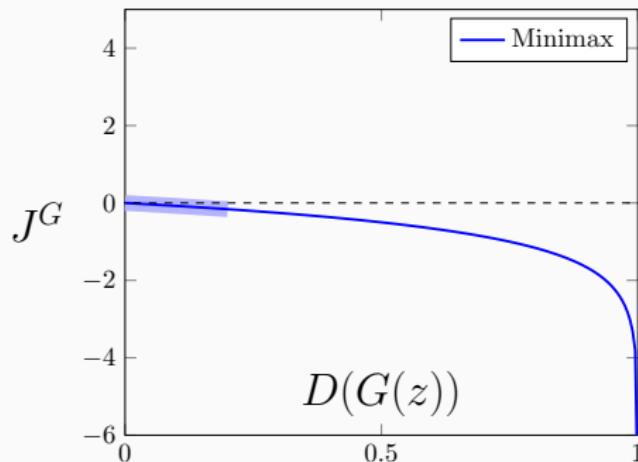
**IF A DISCRIMINATOR
DESIGNS ONE FOR YOU**

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:

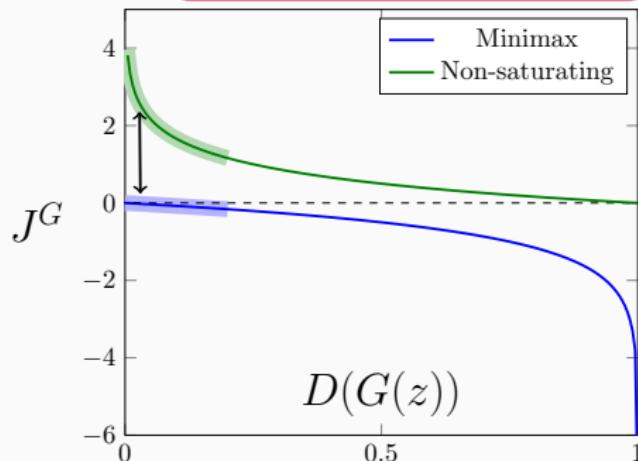
- Generate samples similar to the real ones:

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

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

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

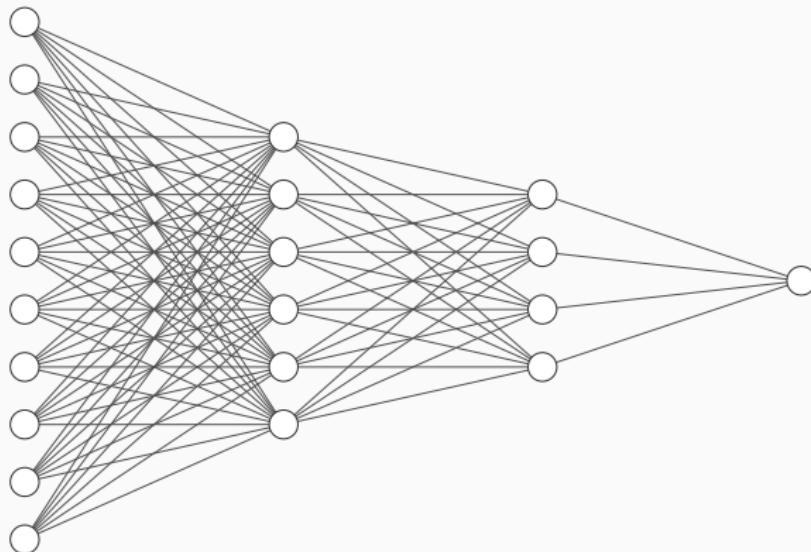
$$\min_G \mathbb{E}_{z \sim p_z(z)} [-\log(D(G(z)))]$$



Models definition

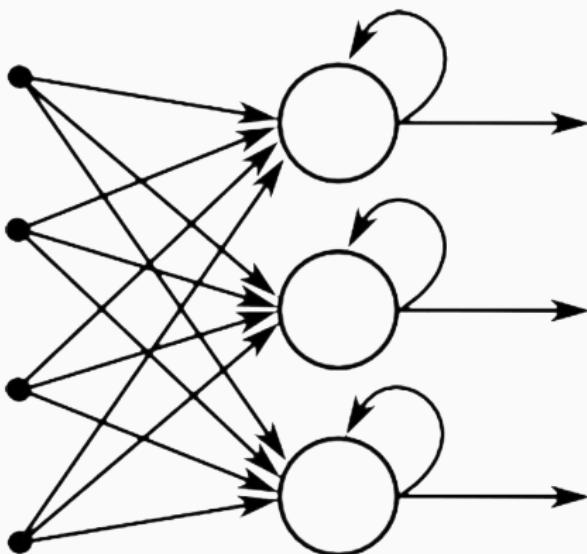
GANs - Models definition

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



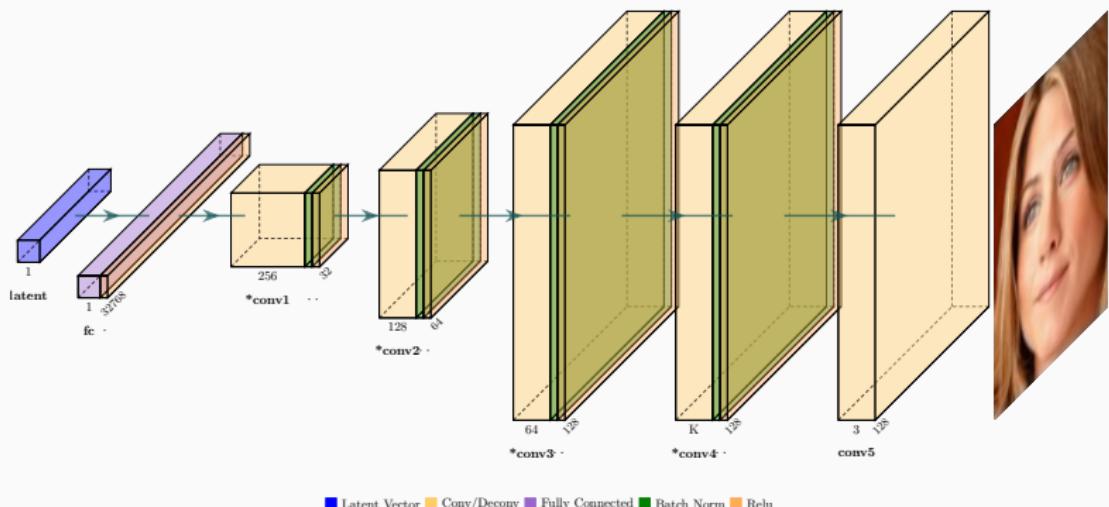
GANs - Models definition

- 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.

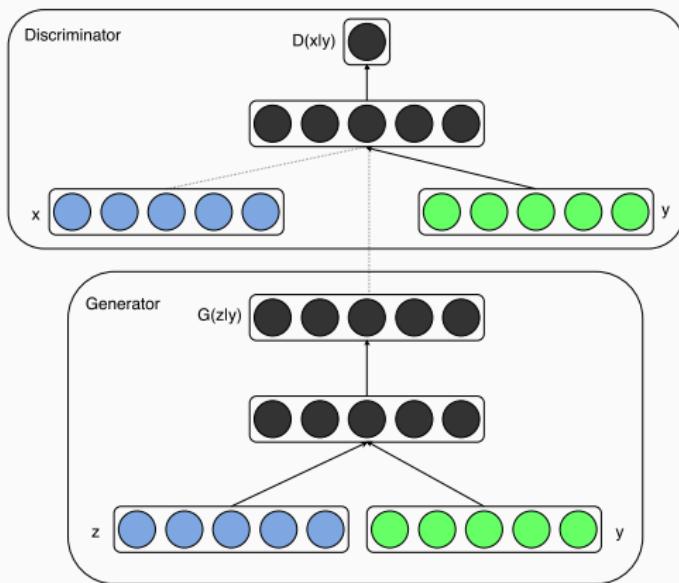


Figure 2: From Mirza and Osindero (2014)

Conditional GANs

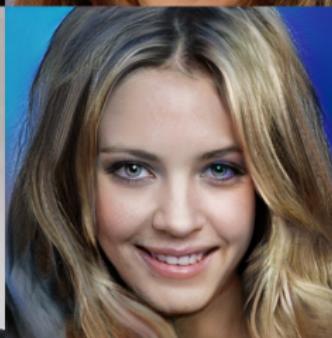
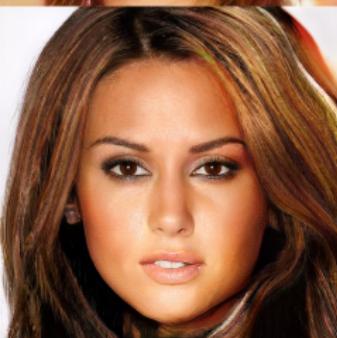
The GANs game becomes:

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

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

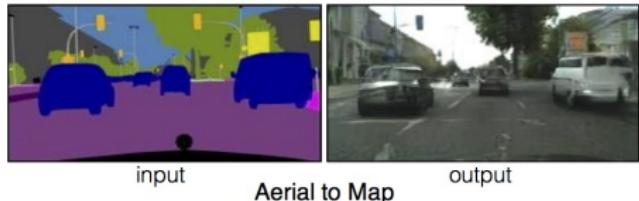
GANs Applications

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

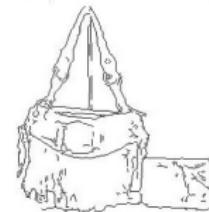
Input



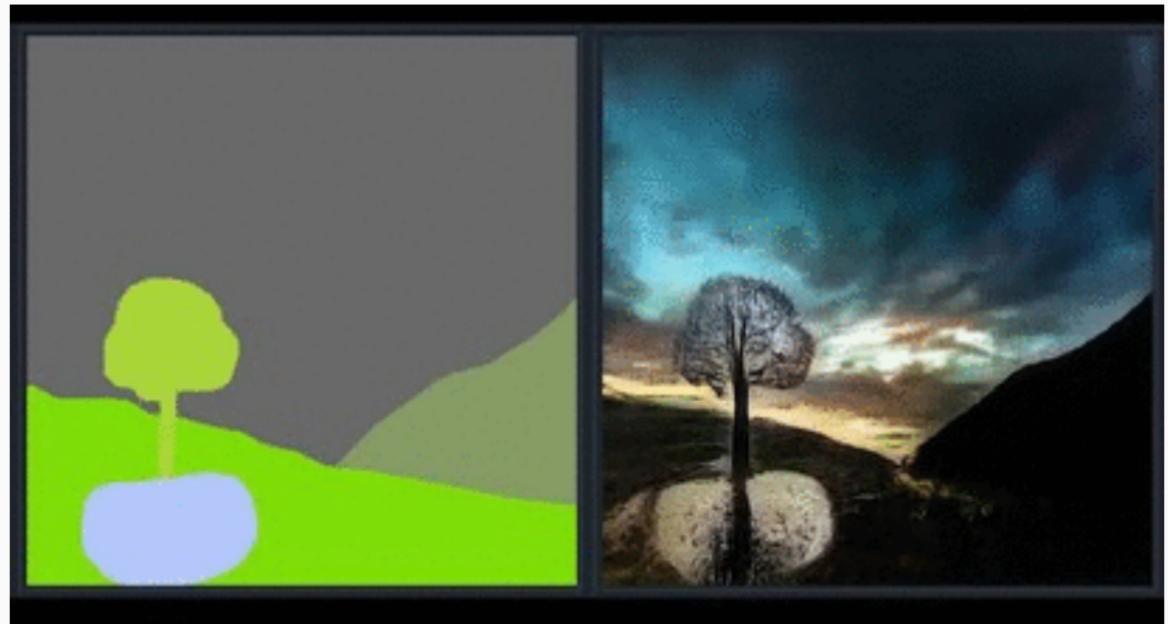
Ground truth



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

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