GAN - Theory and Applications

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https://bit.ly/2Y1nqay

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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.

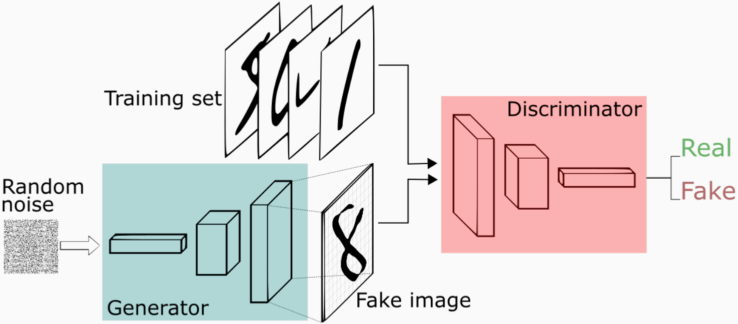


Figure 1: Credits: Silva

Generative Adversarial Networks

GANs game:

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

Generative Adversarial Networks

GANs game:

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

Generative Adversarial Networks

GANs game:

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

GANs - Discriminator

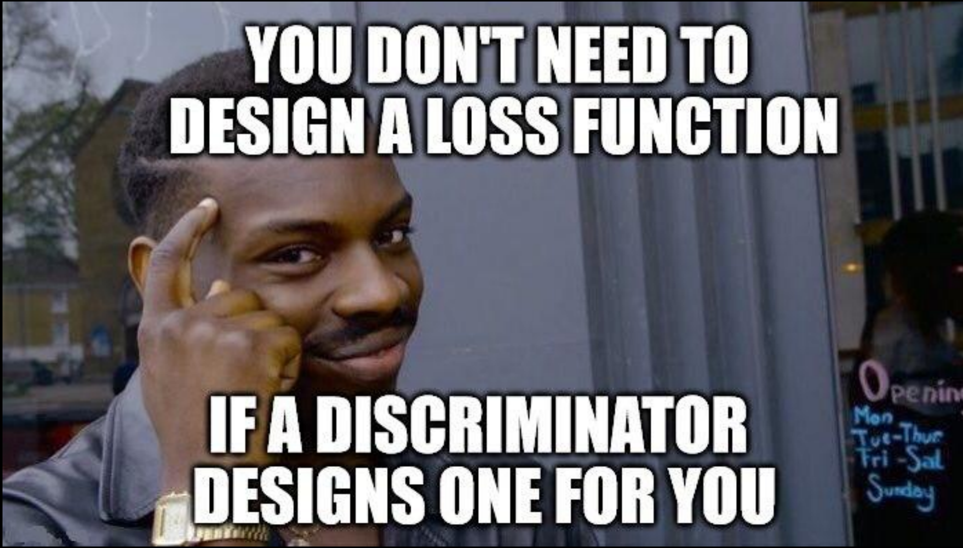
- **Discriminator** needs to:
  - Correctly classify real data:

$$\boxed{\max_D \mathop{\mathbb{E}}_{x \sim p_{data}(x)} [\log D(x)]} \qquad D(x) \to 1$$

  - Correctly classify wrong data:

$$\boxed{\max_D \mathop{\mathbb{E}}_{z \sim p_z(z)} [\log(1 - D(G(z)))]} \qquad D(G(z)) \to 0$$

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


YOU DON'T NEED TO
DESIGN A LOSS FUNCTION
IF A DISCRIMINATOR
DESIGNS ONE FOR YOU
Mon
Tue-Thur
Fri -Sat
Sunday

GANs - Generator

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

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

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

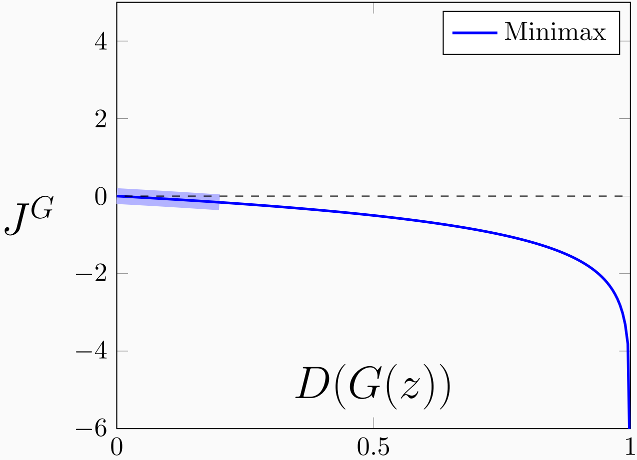
$$\boxed{\min_{G} \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]} \qquad D(G(z)) \rightarrow 1$$

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

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

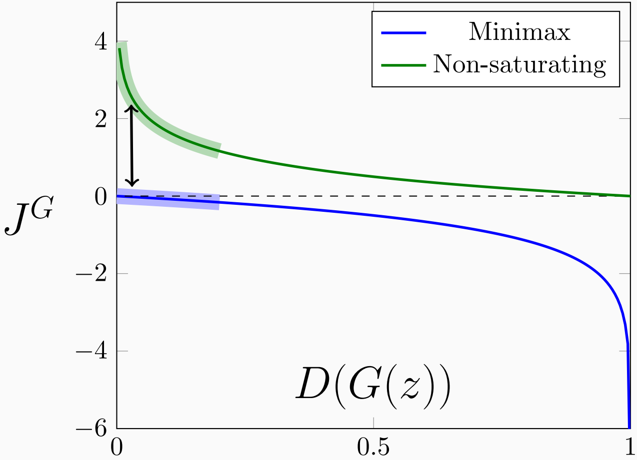
GANs - Generator Objectives

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



GANs - Generator Objectives

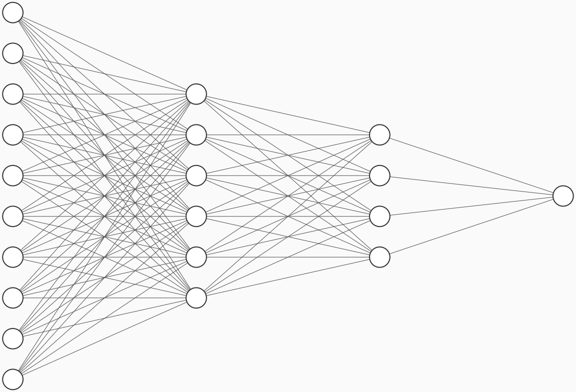
- Minimax: $\log(1 - D(G(z)))$
- Non-saturating: $-\log(D(G(z)))$



Models definition

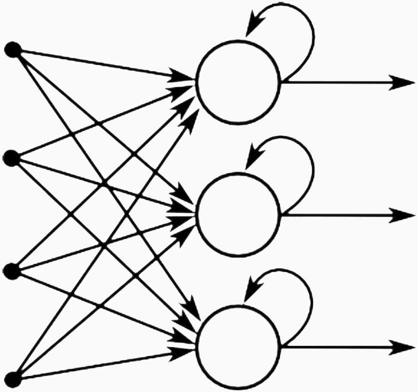
GANs - Models definition

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



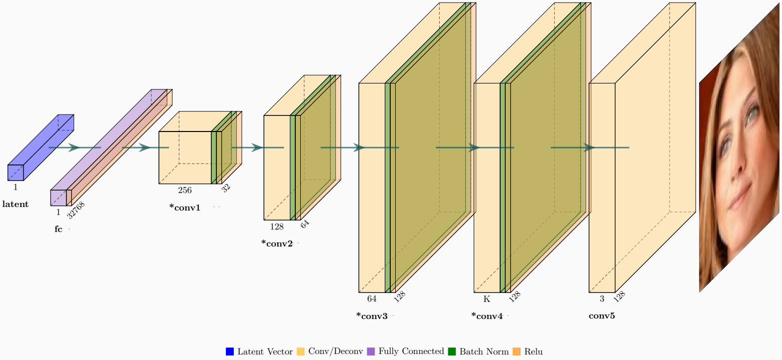
GANs - Models definition

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

GANs - Training - Discriminator

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

Repeat from 1 to **k**:

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

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

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

GANs - Training - Generator

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

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

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

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

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

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 D and G.

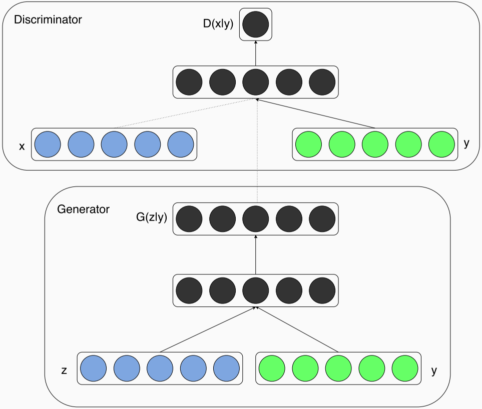


Figure 2: From Mirza and Osindero (2014)

Conditional GANs

The GANs game becomes:

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

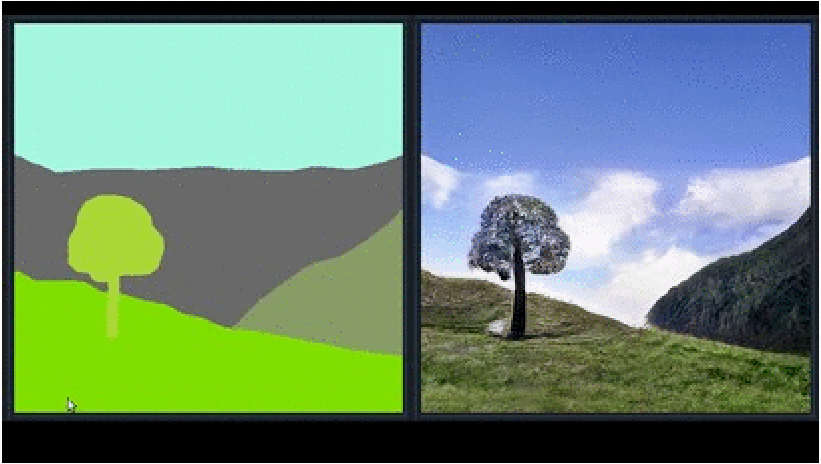
Notice: the same representation of the condition has to be presented to both network.

GANs Applications

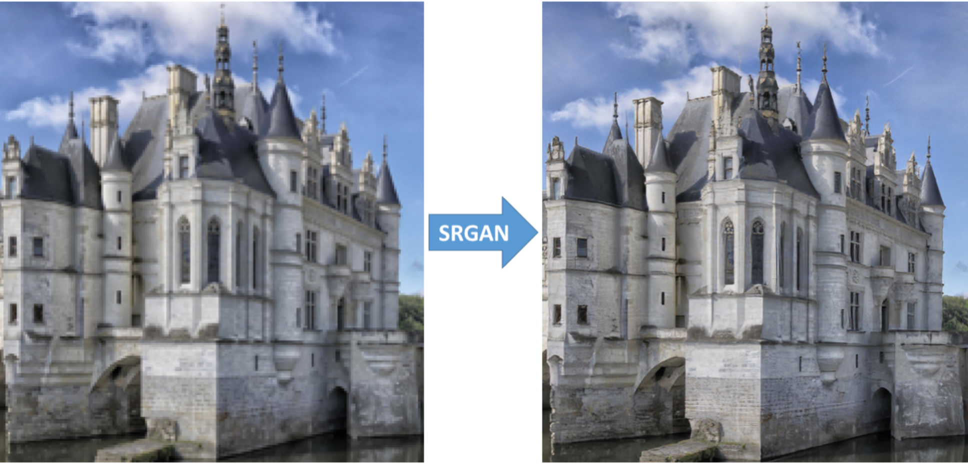
Unconditional - Face Generation - Karras et al. (2017)

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

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



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



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)