Deep Learning Lesson 4

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Credits: PYCONX GAN Theory and Applications slides, by Ghelfi, Galeone, Di Mattia, De Simoni

SAPIENZA
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Overview

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

“*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.

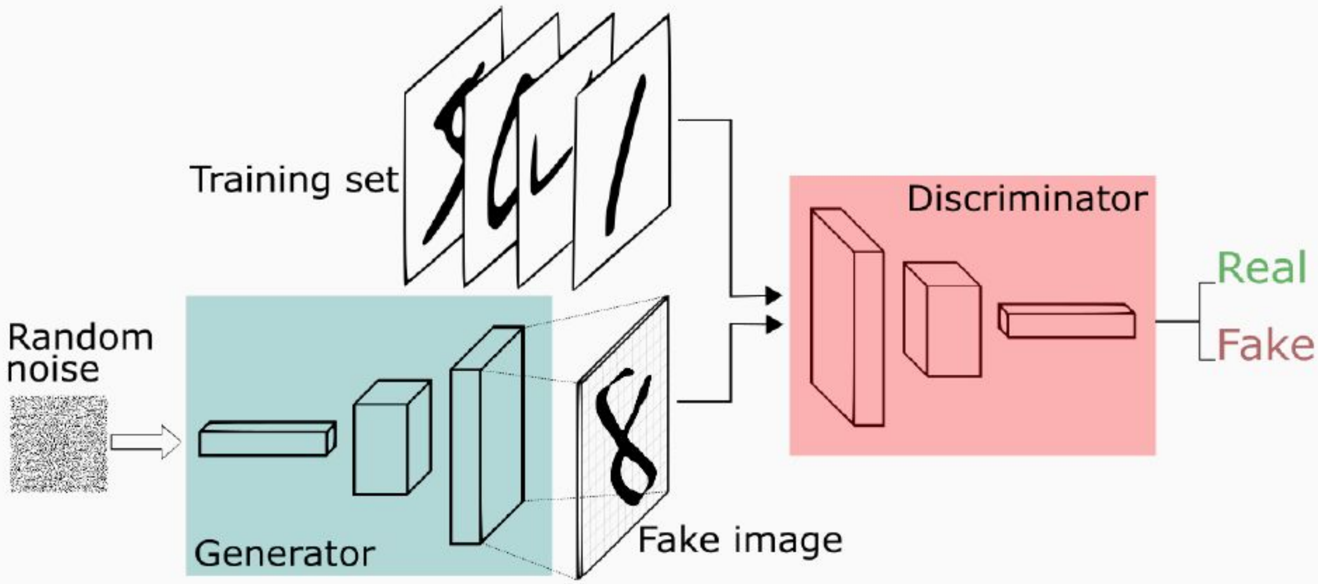


Figure 1: Credits: Silva

Generative Adversarial Networks

GANs game:

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

GANs - Discriminator

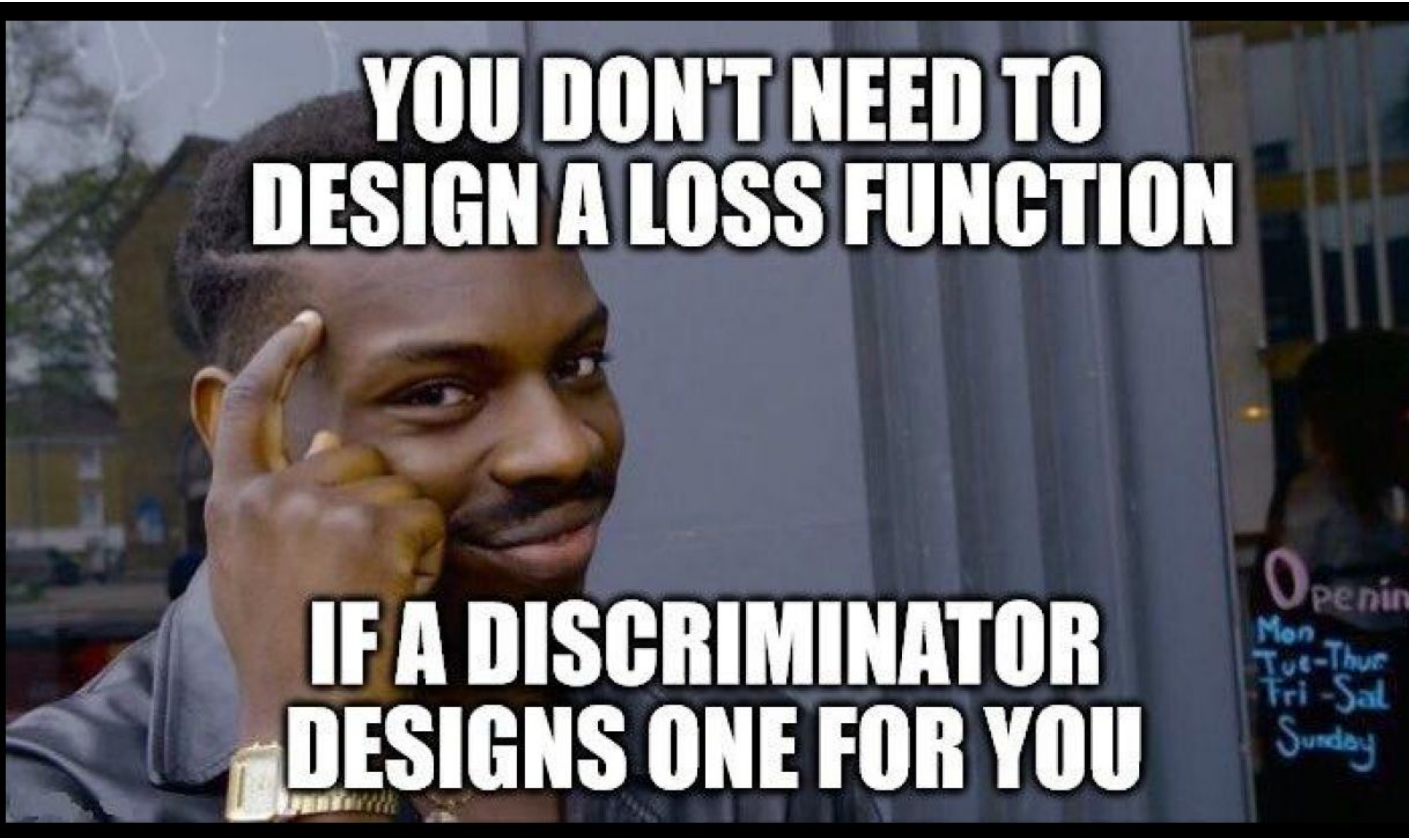
- **Discriminator** needs to:
  - Correctly classify real data:

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

  - 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

GANs - Generator

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

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

GANs - Generator

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

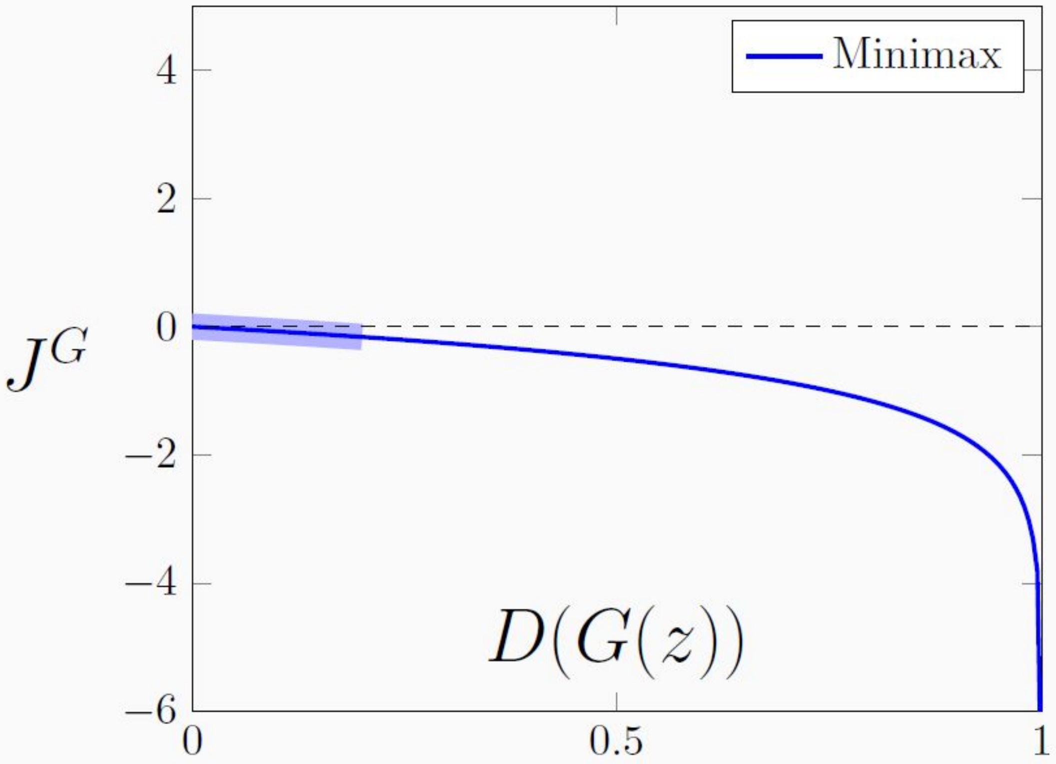
$$\boxed{\min_{G} \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]} \qquad D(G(z)) \to 1$$

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

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

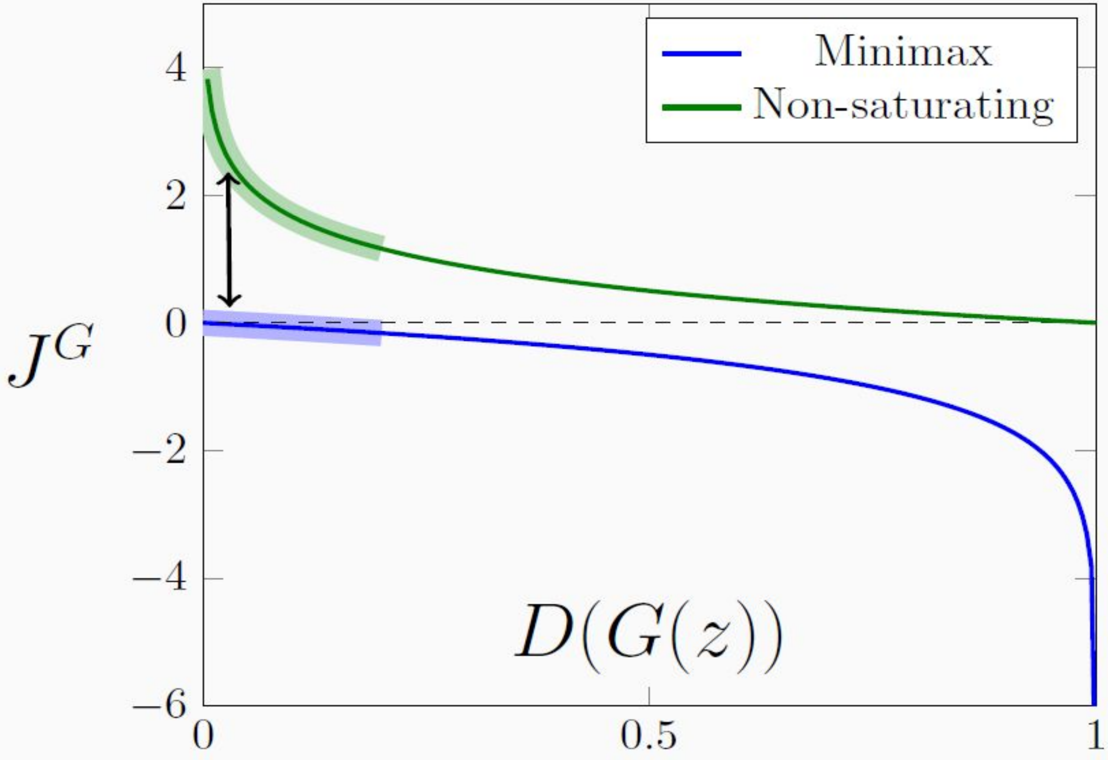
GANs - Generator Objectives

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



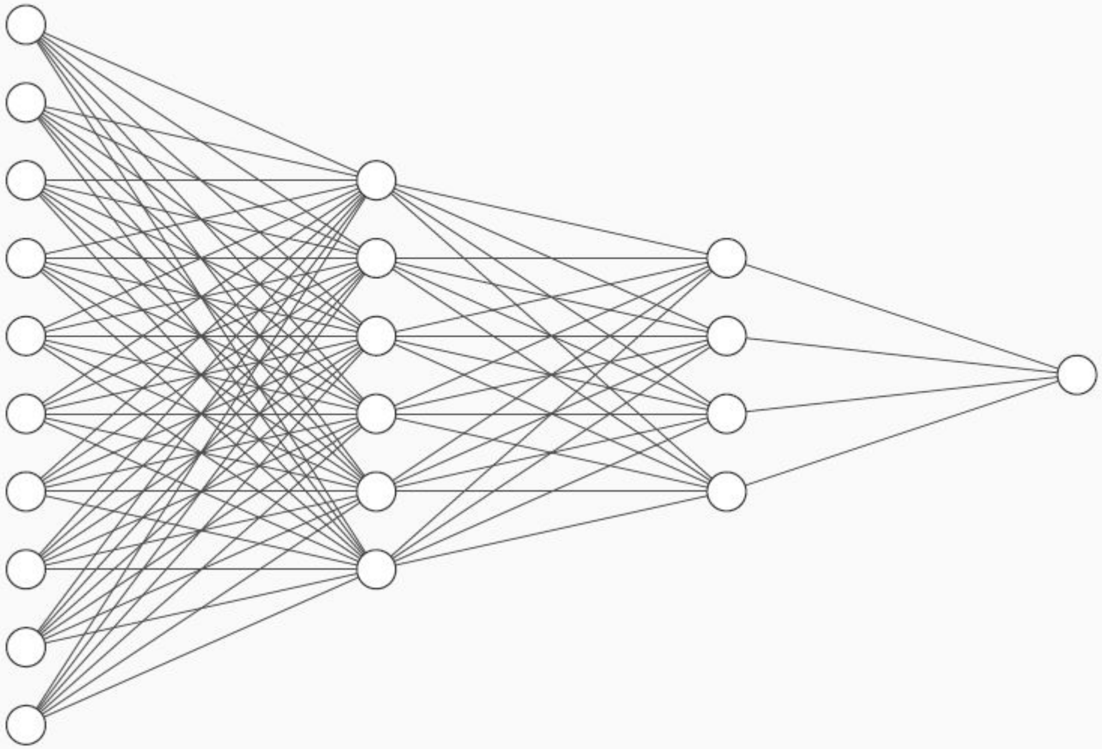
GANs - Generator Objectives

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



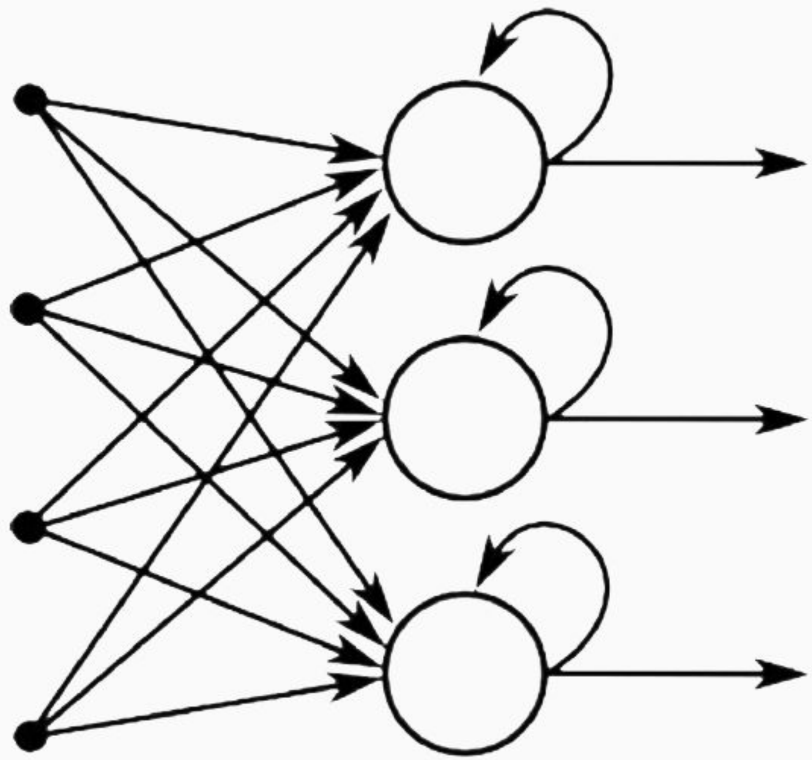
Models definition

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



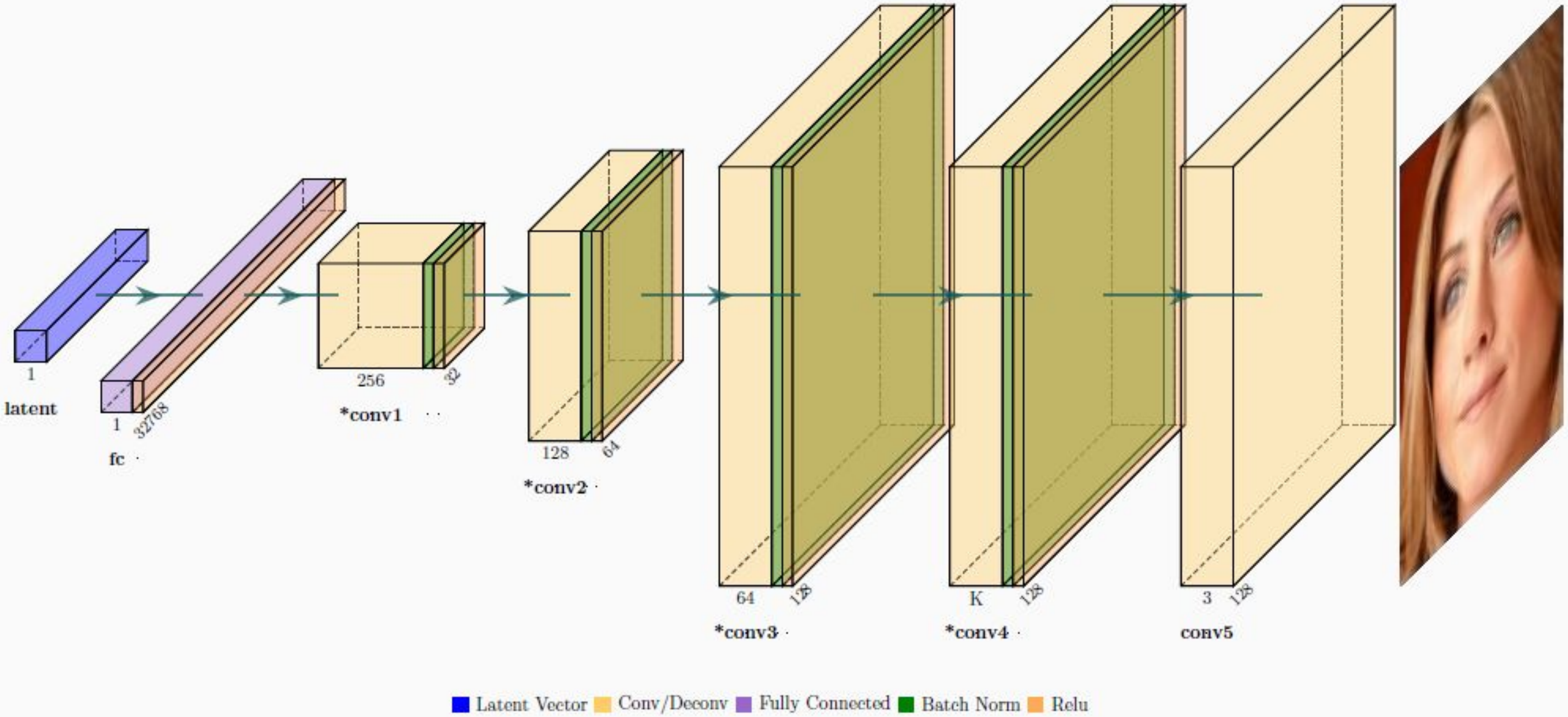
Models definition

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



Models definition

- Different architectures for different data types.
  - Images? Convolutional Neural Networks



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 $z^{(1)}, \ldots, z^{(m)}$ 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**:

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

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

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

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.

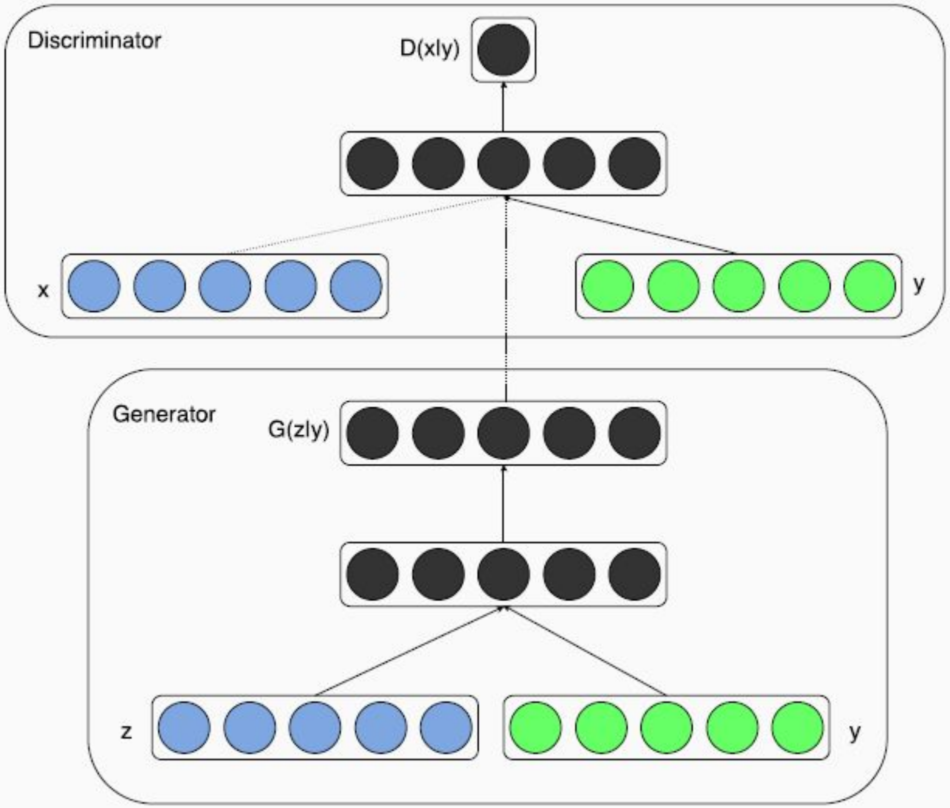


Figure 2: From Mirza and Osindero (2014)

Conditional GANs

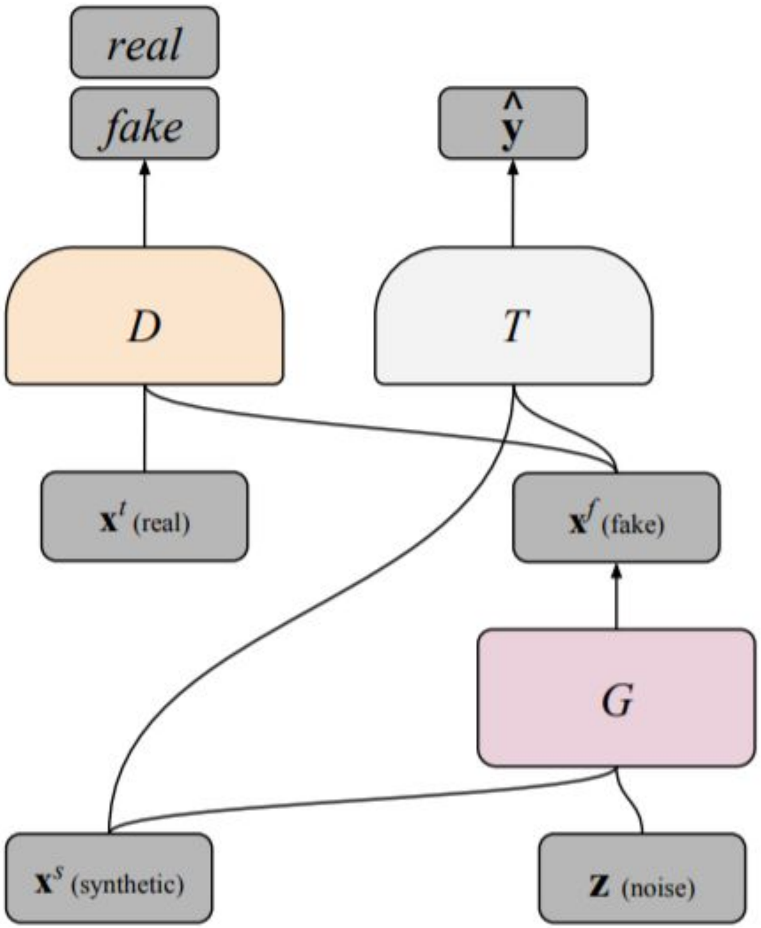
The GANs game becomes:

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

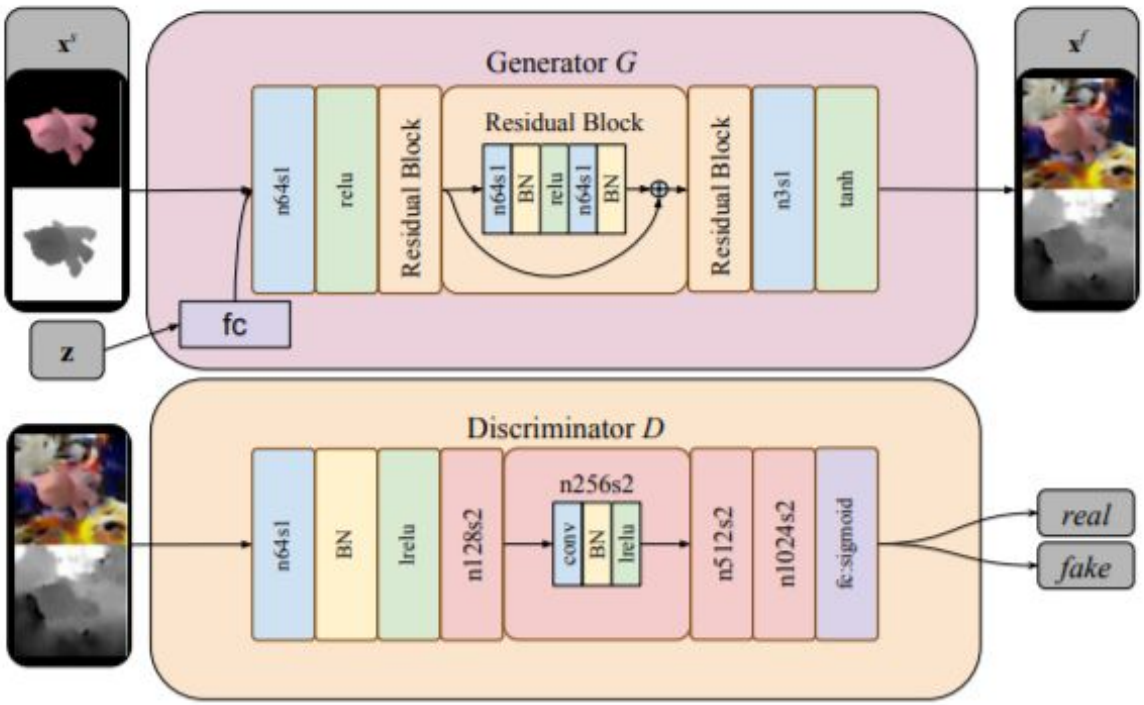
Notice: the same representation of the condition has to be presented to both network.

PixelDA

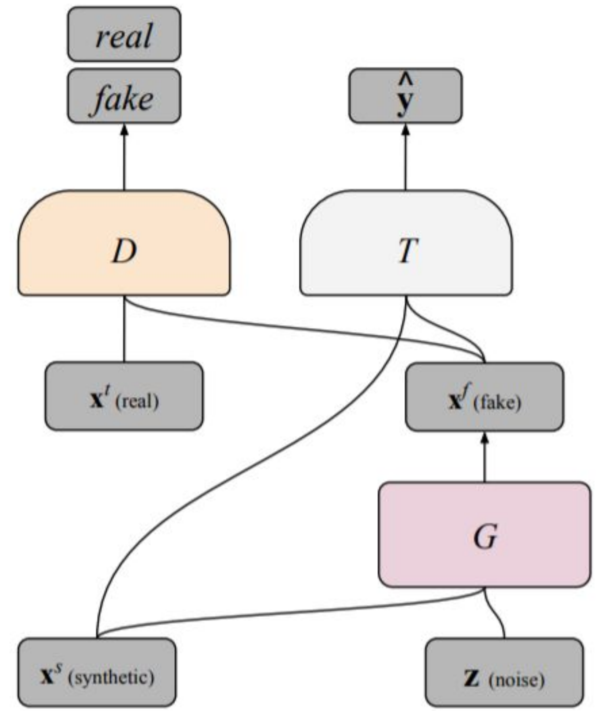
- *“Unsupervised Pixel–Level Domain Adaptation with Generative Adversarial Networks”*
- Developed by DeepMind (Google AI lab)
- It works by using a simple resnet-like generator and DCGAN-like discriminator, together with an auxiliar classifier!



PixelDA

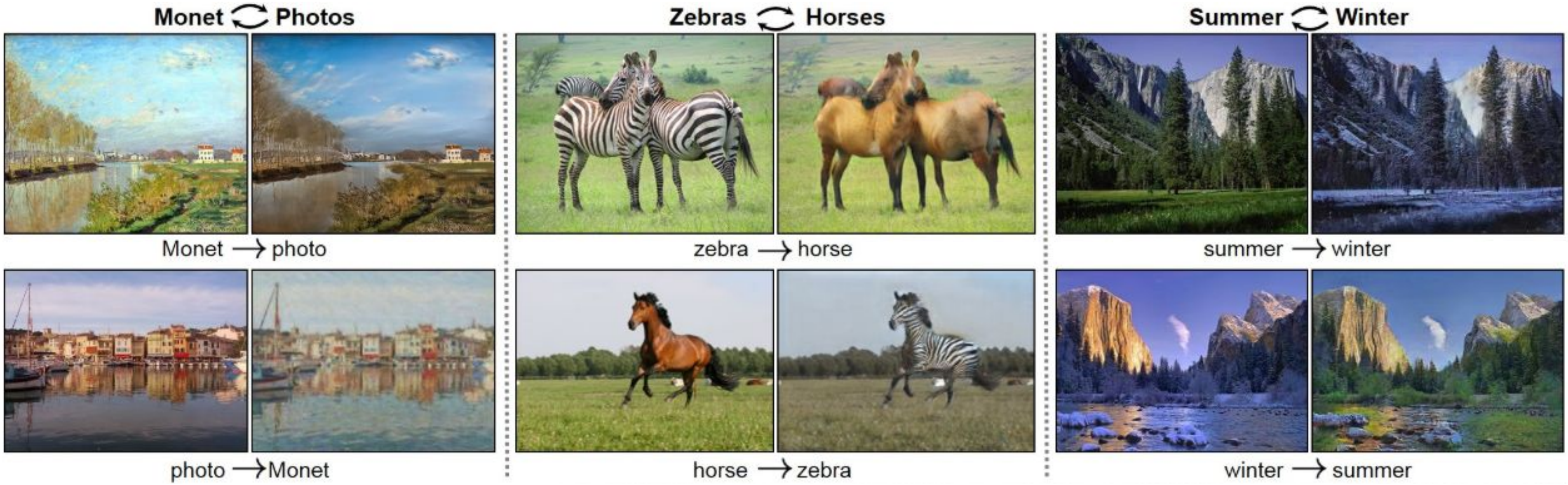


Generator G
Residual Block
n64s1
relu
BN
tanh
n3s1
fc
z
Discriminator D
n128s2
n256s2
conv
lrelu
n512s2
n1024s2
fc:sigmoid
real
fake



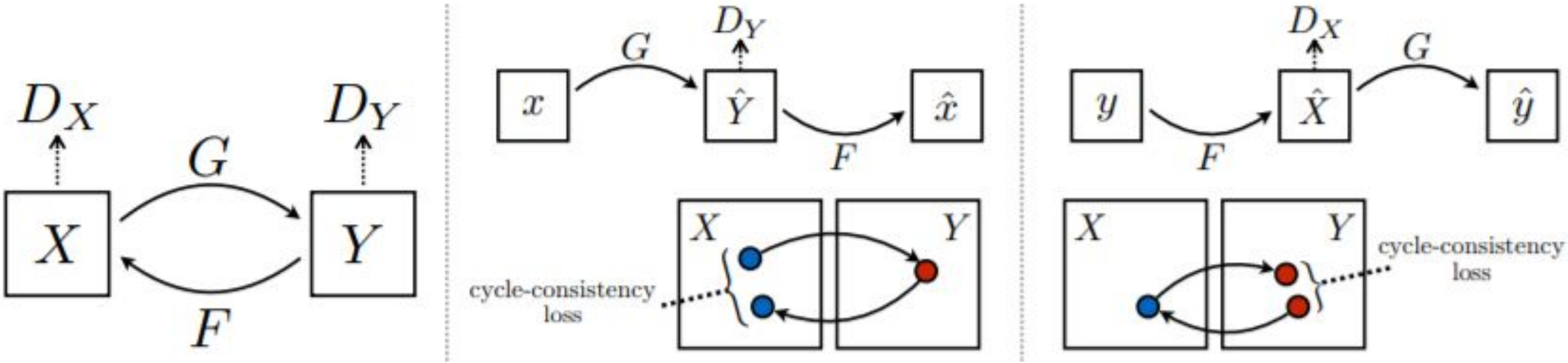
real
fake
D
T
G
(real)
(fake)
(synthetic)
(noise)

CycleGAN



- ICCV 2017 groundbreaking paper
- First work, together with DiscoGAN, that exploits 2 GAN models for source → target and target → source mapping at the same time!
- Used as baseline method for several other models

CycleGAN



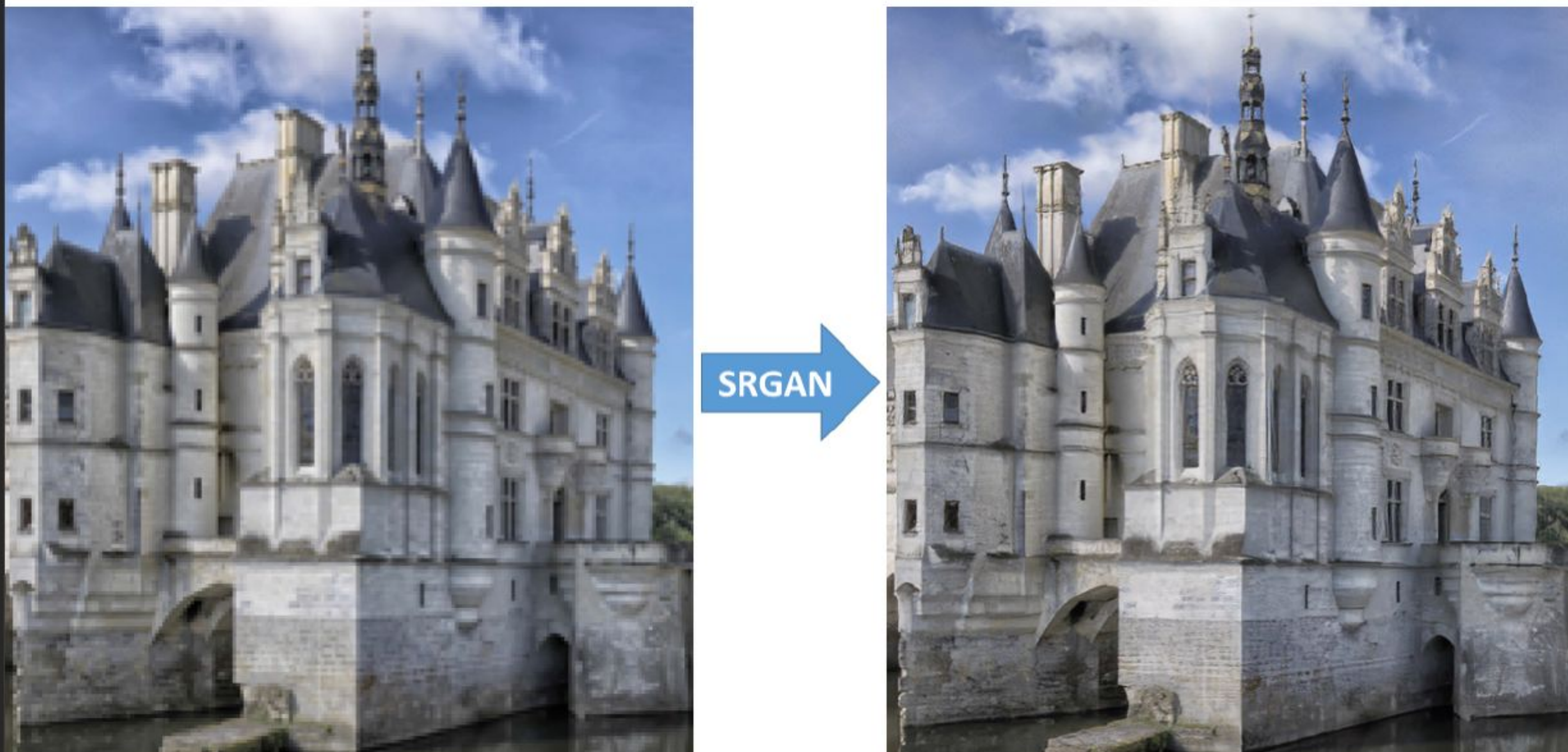
- One generator learns the function G from X to Y, another one learns the function F from Y to X. Each generator has a corresponding discriminator for real/fake traditional GAN training.
- In addition, a *cycle consistency loss* is added to the system:
  F(G(X)) ≈ X (and vice versa) → $|F(G(X))-X|_1$ to be minimized (L1 norm)

Conditional - Domain Translation
Isola et al. (2016)

Unconditional - Face Generation
Karras et al. (2017)

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

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



Project

- The project main theme is a standard training of a classifier
- If you own enough expertise and computational power, you can choose to implement and run a GAN method, or in general you can ask for more freedom of choice for a more complicated project.
- You choose the dataset for the training. Obviously, it must be labelled, at least 2 classes, and enough challenging for a deep learning run! If there is no training/test split, you do the splits (80/20).
- You have to run two separate experiments: one with a pretrained network (VGG, ResNet, Inception, or whatever you like!), and another one with a simple custom CNN you build (which will produce worse performance of course).

Project

- For each experiment, run a new training with 2-3 data augmentation techniques. If you want, try to play also with learning rate, with solvers,
- Write a presentation (slides) in which you tell us what you have done, what you was expecting, and what you got. Analyze the accuracy for each experiments and tell us your considerations – why this data augmentation technique worked so nicely? Why you chose to not use another particular data aug. ? Why your custom network failed so miserably? ;-)
- The project and presentation can be done in a group of 2 or 3 people. We encourage you to work in group, but if you are really a lone wolf, you can do it in solo.

Project

- Before starting the project, send me an email with your project proposal, in which you tell me which dataset you wanna use and a small description of your project – no project group can work on the same dataset! So, please send me a plan A (preferred) dataset, but also a plan B dataset if the first one have been already chosen by someone else!
- Do not, DO NOT, **DO NOT** copy code and experiments from other groups. It is a silly move, you will not learn anything good from that, and copy = failed exam. The main aim of this project is to make you learn how to work with deep learning ☺

That's all!