# Course FSD311: Generative Adversarial Networks (GANs)

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## Contents

## Motivation

Yann Lecun (Director of Facebook AI Research Paris and Professor at NYU) on Twitter:

> "There are many interesting recent development in deep learning, probably too many for me to describe them all here. But there are a few ideas that caught my attention enough for me to get personally involved in research projects. **The most important one, in my opinion, is adversarial training** (also called GAN for Generative Adversarial Networks). This is an idea that was originally proposed by Ian Goodfellow when he was a student with Yoshua Bengio at the University of Montreal (he since moved to Google Brain and recently to OpenAI). **This, and the variations that are now being proposed is the most interesting idea in the last years in ML, in my opinion**."

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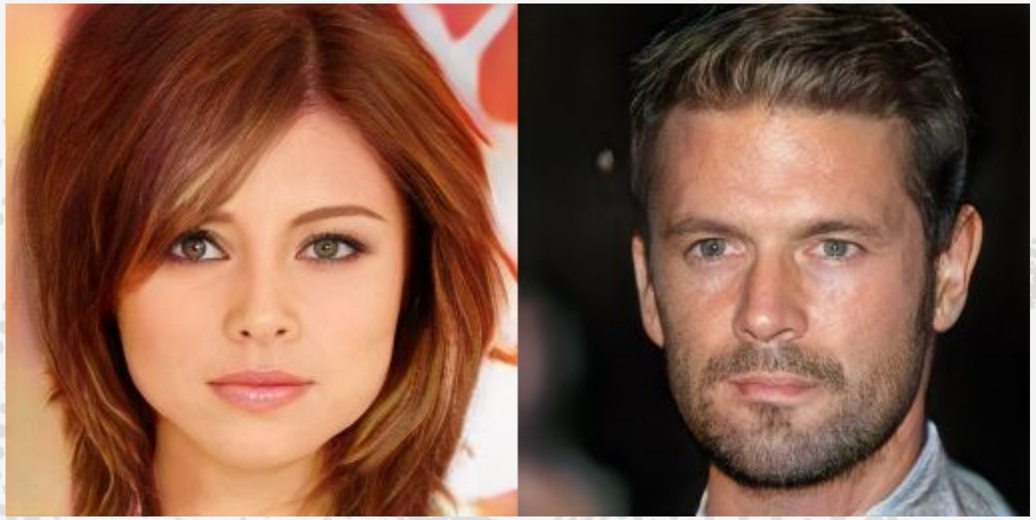
# Motivation

## Are those pictures real ?



## Motivation

### Are those pictures real ?

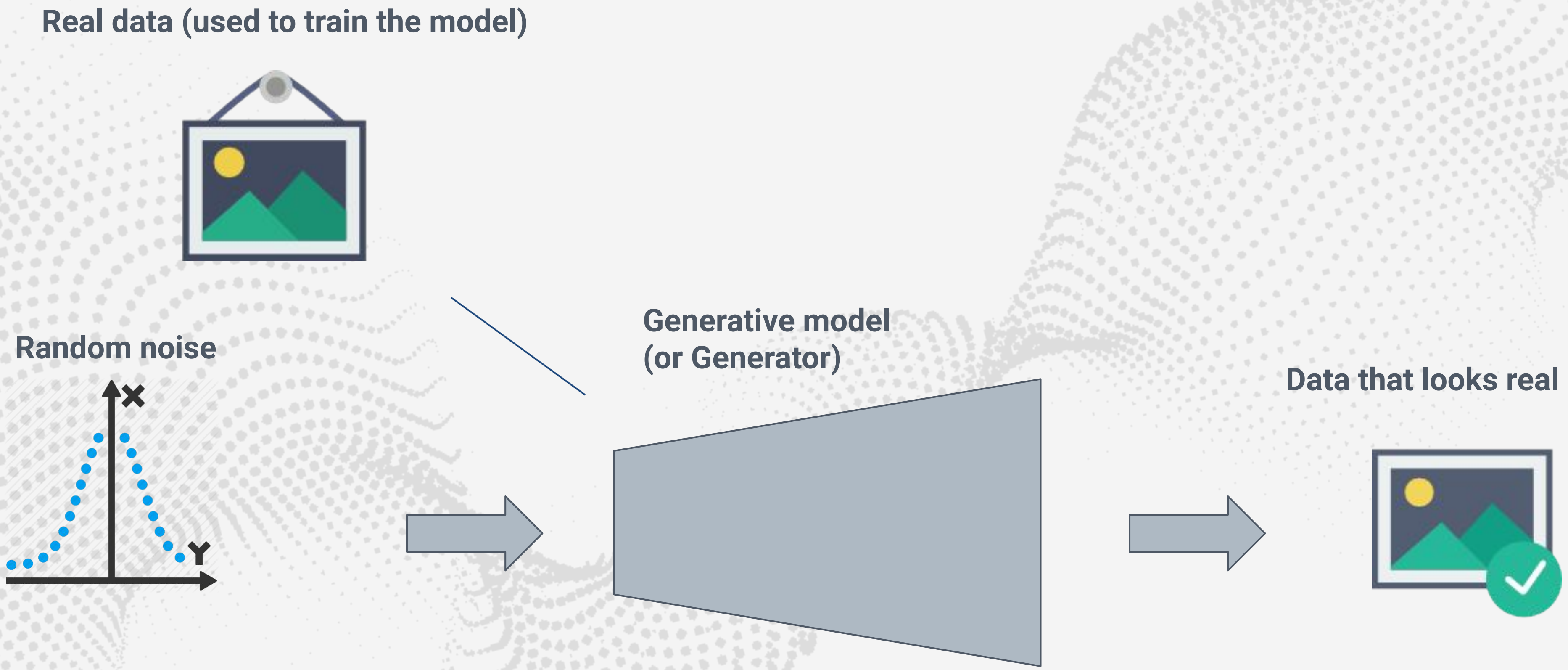
**No ! They've been dreamed by a neural network.**

Source : Progressive growing of gans paper

# Generative Models

- **Goal** : Generate with a model (in this case a NN) data that look real but does not already exist.
- **Example** : Generate pictures that look like pictures from a given dataset.
- **Problem** : No natural input in this situation.
- **Solution**: Random numbers as inputs.
- **Finally** : Model that maps a given distribution (ex: gaussian) towards our data distribution.

# Generative Models



# Generative Models

- Question : How to define a meaningful loss to train the model ?

- Possible solution : Minimize the distance between the generator output and its closest neighbour in the dataset.

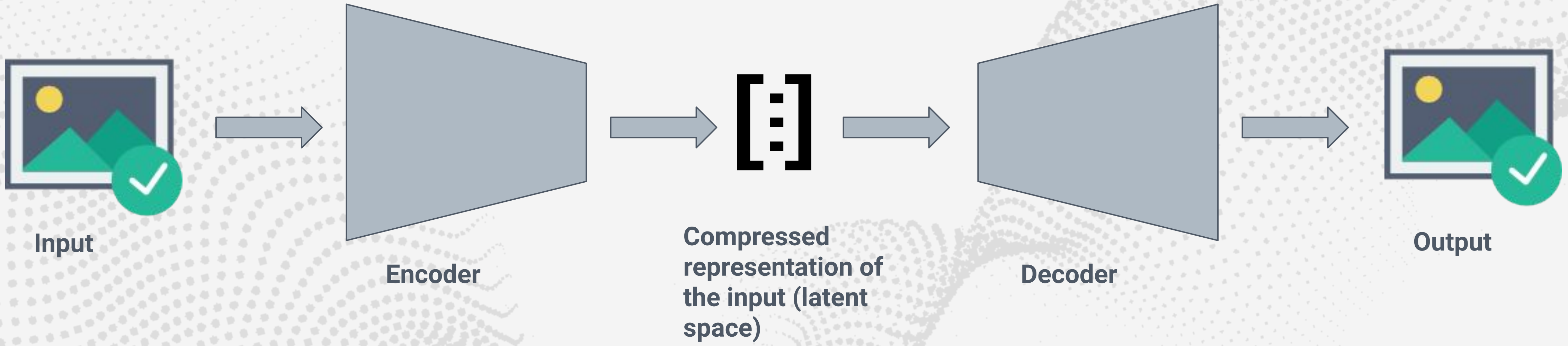
- Issue : Extremely expensive and leads to poor results.

- Solution : Use a second network to train the generator.
  - First possibility: VAE: Variational autoencoders
  - Second possibility: GANs: Generative Adversarial Networks

## Variational Autoencoders (VAE)

## Autoencoders

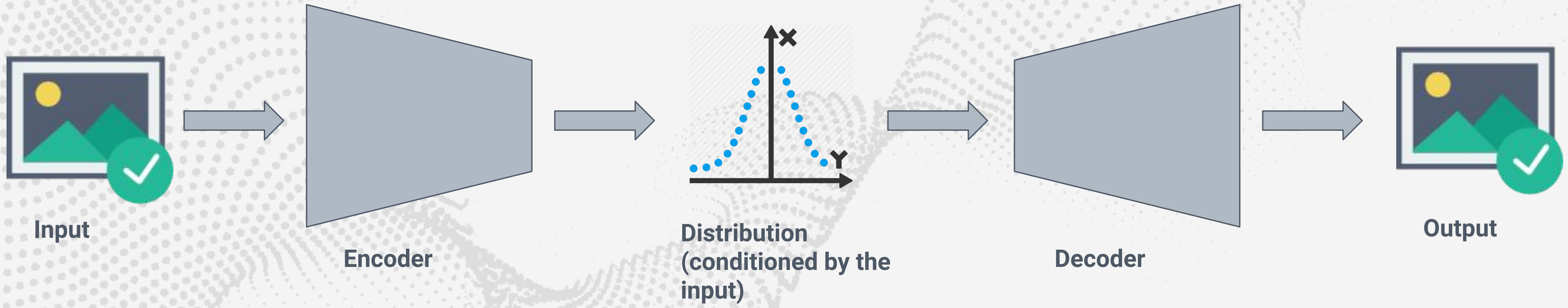
The autoencoder is trained to return an output that equals its input.
Thus, we minimize a distance between the network output and its input.



Autoencoder may be used for compression, to learn representations, but also as generative models.

# Variational Autoencoders

**Instead of learning deterministic representations, VAEs encode its input as a distribution. Then the decoder is trained to decode any vector sampled according to this distribution.**



**In practice, we assume the distribution to be a gaussian and the encoder network predicts a mean vector and  a covariance matrix.**

# Let's write it mathematically !

## Notations

- Inputs : $\mathbf{x} \in \mathcal{X}$
- Encoder : $q_\theta : x \in \mathcal{X} \rightarrow q_\theta(z|x)$
- Decoder : $p_\phi : z \sim q_\theta(z|x) \rightarrow x \in \mathcal{X}$

**Atomic loss (for one input):** $l_i(\theta, \phi) = -\mathbb{E}_{z \sim q_\theta(z|x_i)}[\log(p_\phi(x_i|z))] + \mathbb{KL}(q_\theta(z|x_i)||p(z))$

Reconstruction loss

Regularization loss

$p(z) \sim \mathcal{N}(0,1)$

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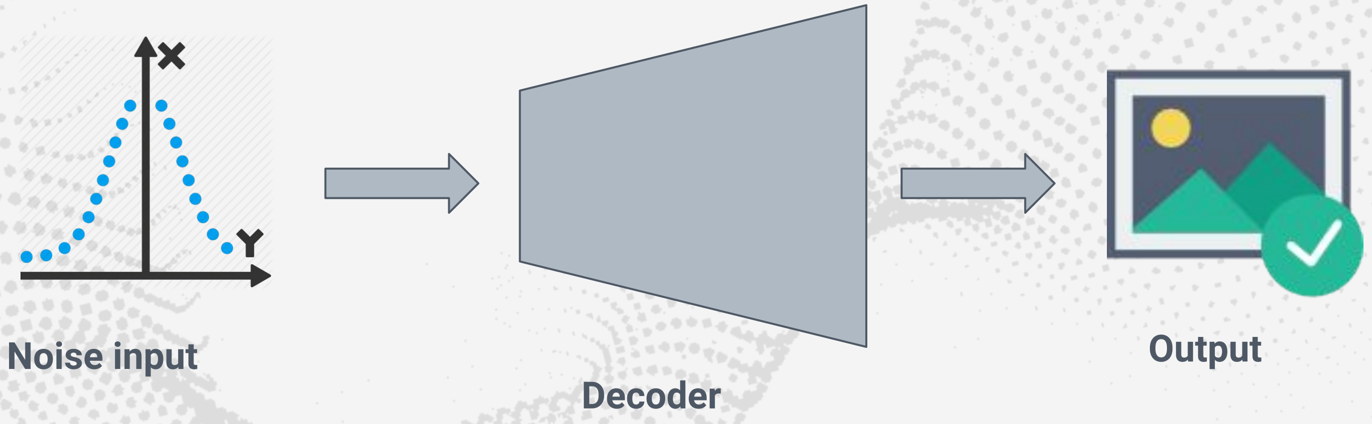
## VAE as a generative model

Once trained, the decoder can be used alone as a generative model. To use it, vectors are sampled according to a normal gaussian and decoded into data that looks real.



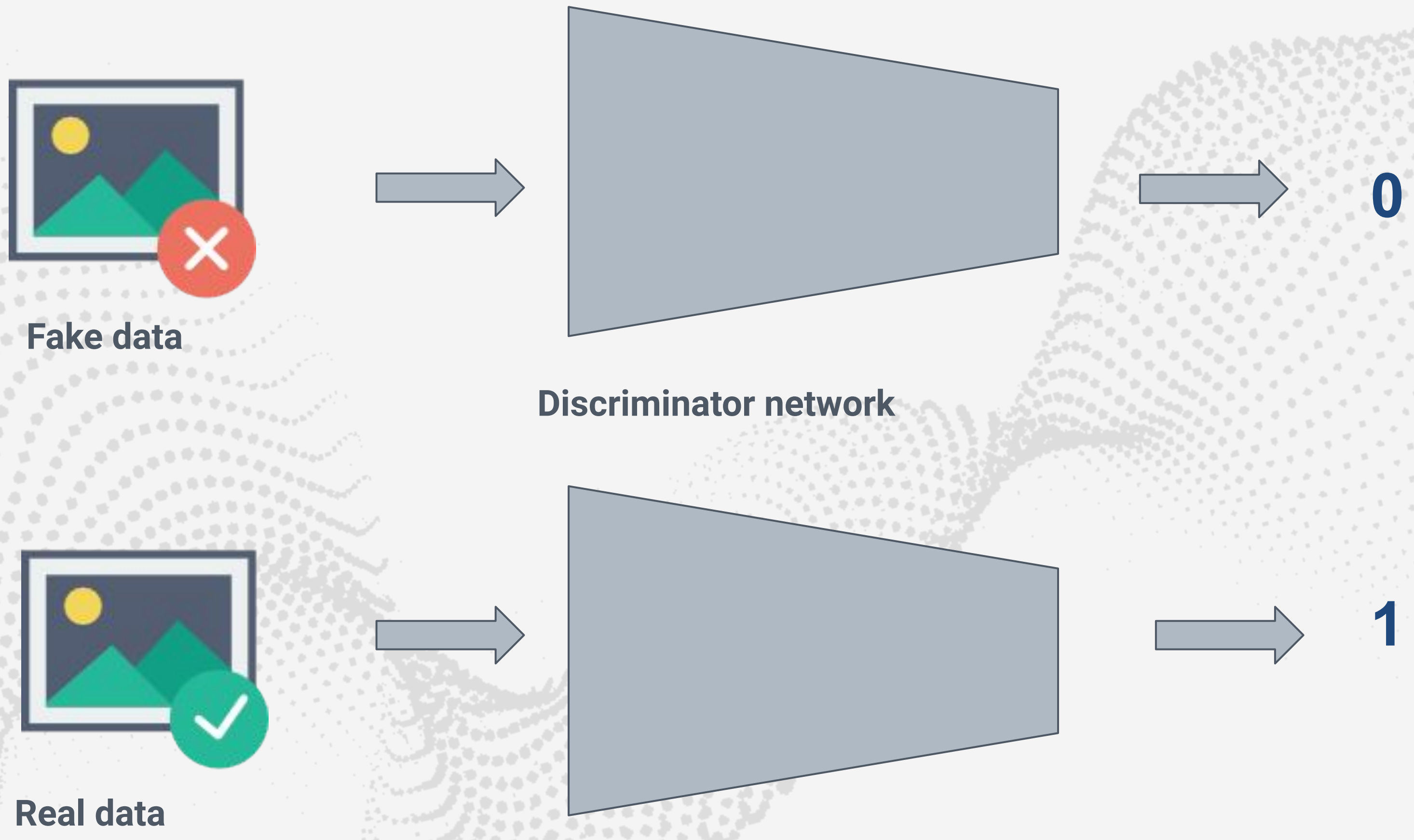
Major drawback: the reconstruction loss. When the input is a picture, considering a reconstruction loss on its pixels is not really meaningful and leads to poor results.

## Generative Adversarial Networks (GANs)

## GAN fundamental idea

- Defining meaningful distances between data (especially images) might very difficult and often require expert knowledge.
- In a GAN this distance, used to train the Generator, is learned implicitly through a second neural network called Discriminator.

# Discriminator network principle

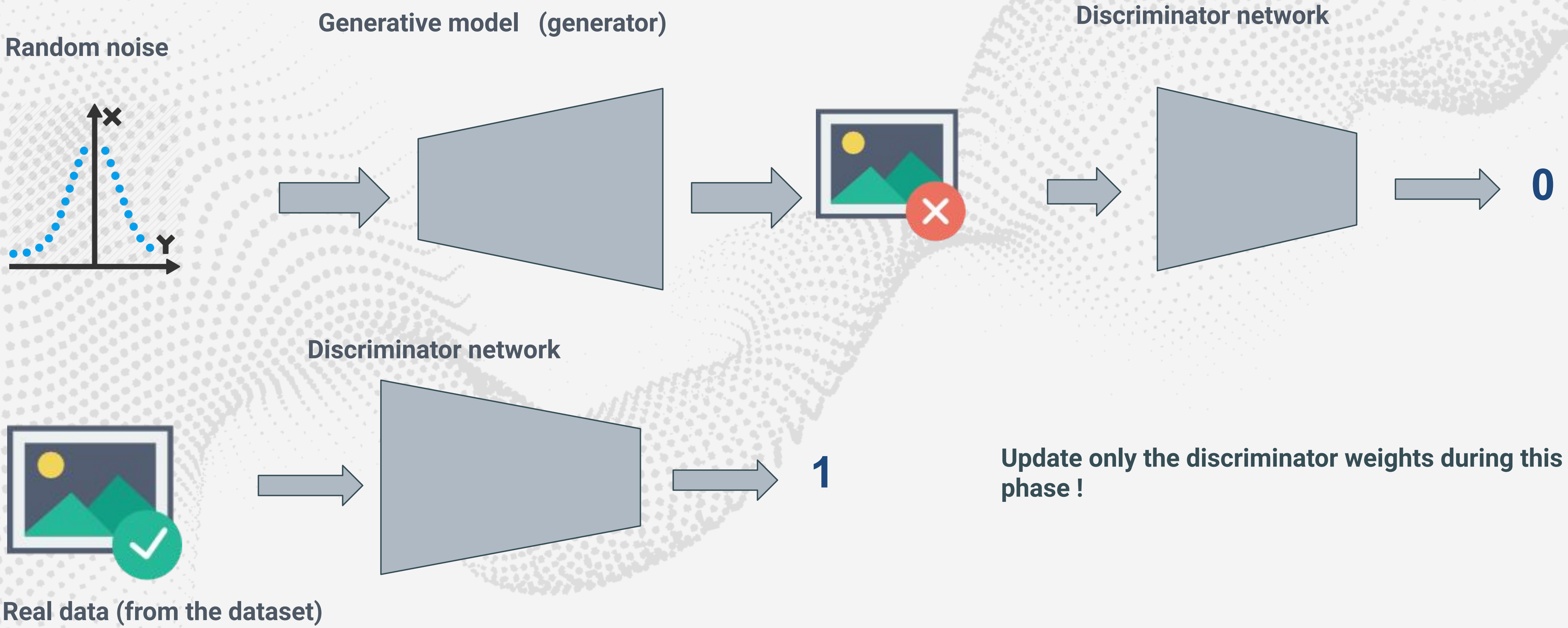


The discriminator returns the probability for a given input to be real.

## Adversarial training

- Train the discriminator to make the difference between fake and real data (standard supervised training).
- Train the generator to fool the discriminator.
- Repeat it until the discriminator is completely lost (returns always 0.5).
- At this point the generator returns data that looks real.

# Train the discriminator



Update only the discriminator weights during this phase !

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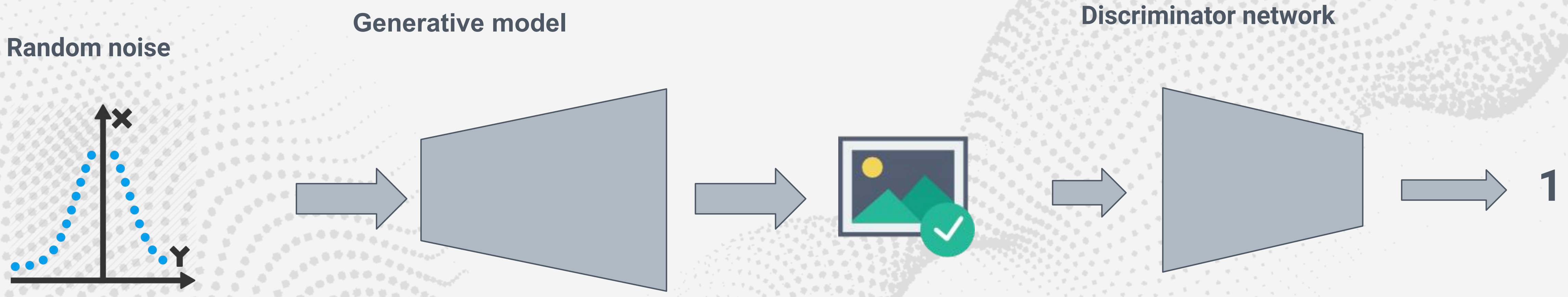
# Train the generator



Update only the generator weights during this phase !

## Let's write it mathematically !

Notations

- Inputs : $\mathbf{x} \in \mathcal{X}$
- Random noise : $\mathbf{z} \in \mathcal{G}, \quad \text{example} : \mathbf{z} \sim \mathcal{N}(0, 1)$
- Generator : $G \, : \, \mathcal{G} \longrightarrow \mathcal{X}$
- Discriminator : $D \, : \, \mathcal{X} \longrightarrow \mathbb{R}$

## How it works

- **Discriminator loss:**

$$L_D = -\sum_{i=1}^{n} \underbrace{\log\left(1 - D(G(z_i))\right)}_{L_D^{false}} + \underbrace{\log\left(D(x_i)\right)}_{L_D^{true}}$$

- **Generator loss:**

$$L_G = \sum_{i}^{n} \log\left(1 - D(G(z_i))\right)$$

**Warning:** I took the convention where the losses are to be **minimized**.

**Note:** As usual, the full sum is replaced with a sub-sum: we use mini-batches to compute the gradients.

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# Practical algorithm

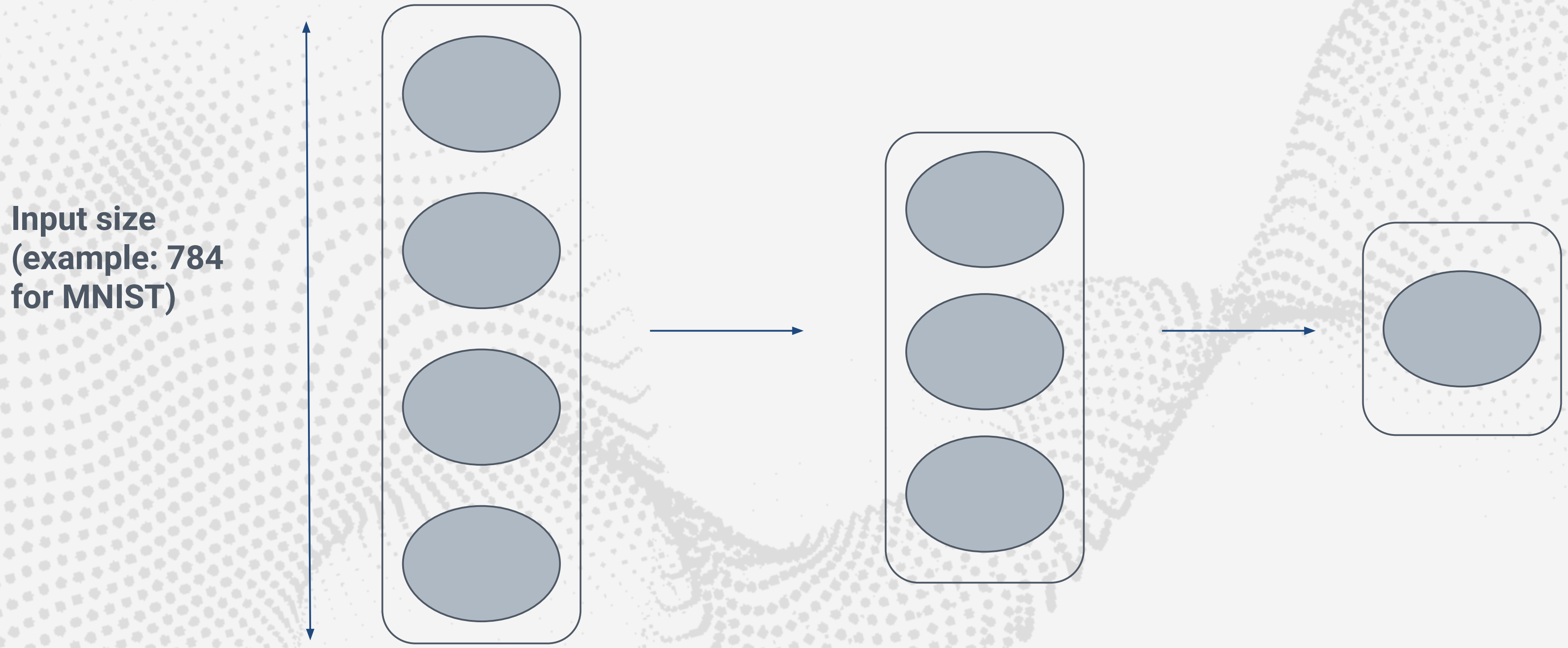
- **Initialize both networks**

- **Training:**
    - Sample a mini-batch of noise vectors and sample a mini-batch of input data.
    - Update the discriminator weights with those batches (gradient descent on its loss).
    - Sample a mini-batch of noise vectors.
    - Update the generator weights with this batch (gradient descent as well).

- **Repeat training phase until convergence**

# Architectures used in the original paper

## The discriminator (dense NN)

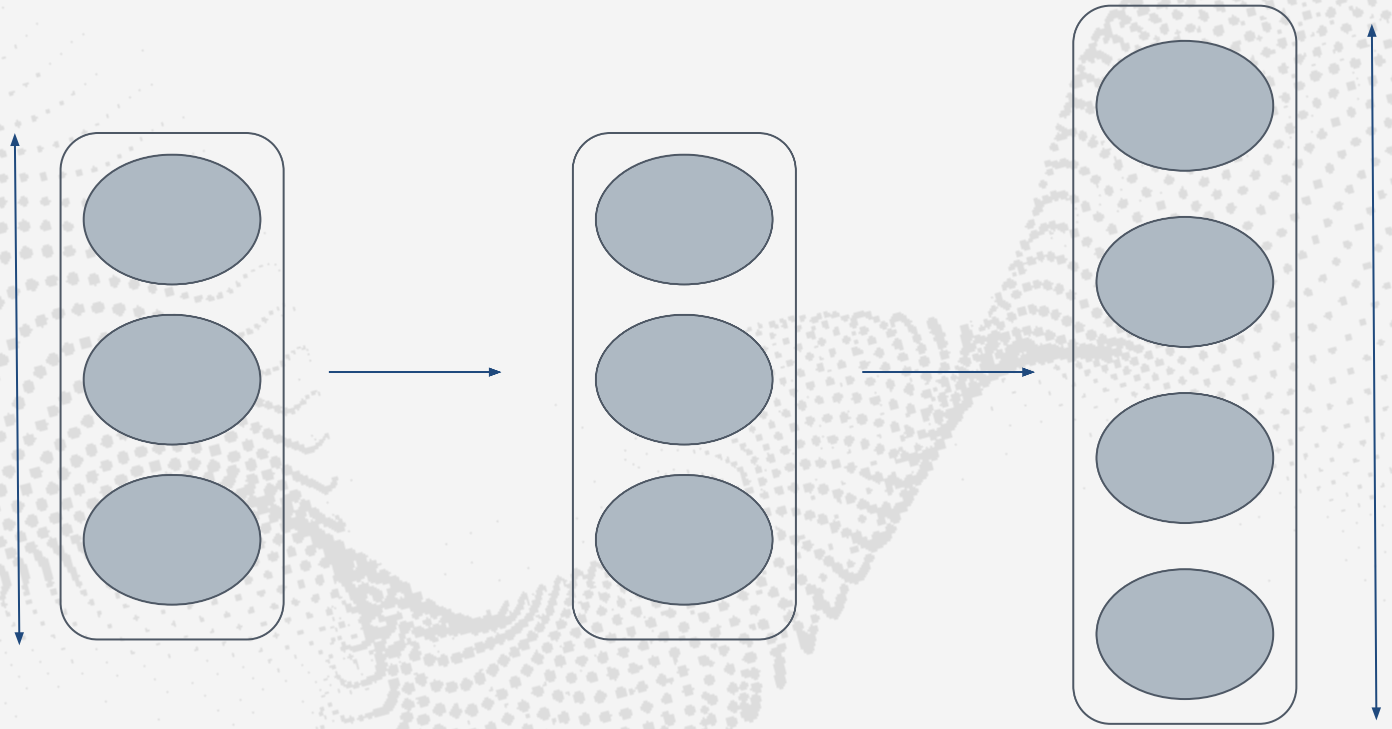


Takes a flattened image and returns a scalar value

# Architectures used in the original paper

## The generator (dense NN)

Noise vector size (example 100 in usual implementations)



Input size (example: 784 for MNIST)

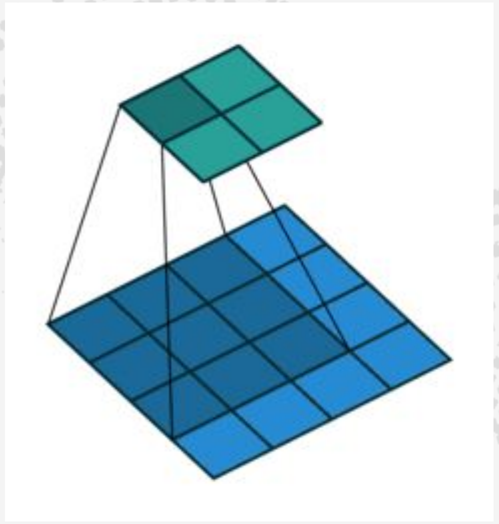
Takes a vector of random number and returns a flattened image

# Toward the DCGANs

- Now we want to work with large images.
- Problem: feed directly a large image into a dense NN will make the number of weights blow.
- Standard idea: use a convolutional NN instead of a fully dense NN.

# Reminder : convNets

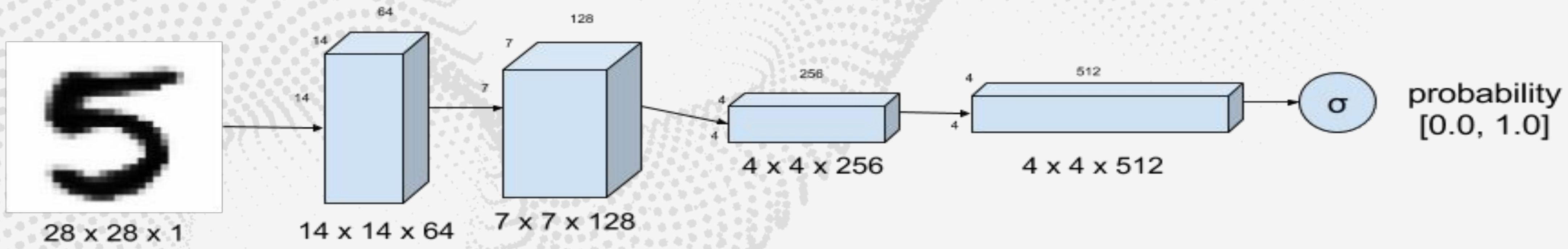
- Main idea : reduce input size (extract its features) before feeding it into a standard (dense) NN.
- Historically : hand-made feature engineering.
- Since 2012 : automatic feature extraction with convolution layers.



Example of convolution with a filter of size 3x3 on a 4x4 image. Result of the a convolution: a 2x2 image.

## Example for the discriminator

- Extract the input image features through several convolutional layers.
- Use the extracted features inside a NN layer to determine whether the image is real or fake.



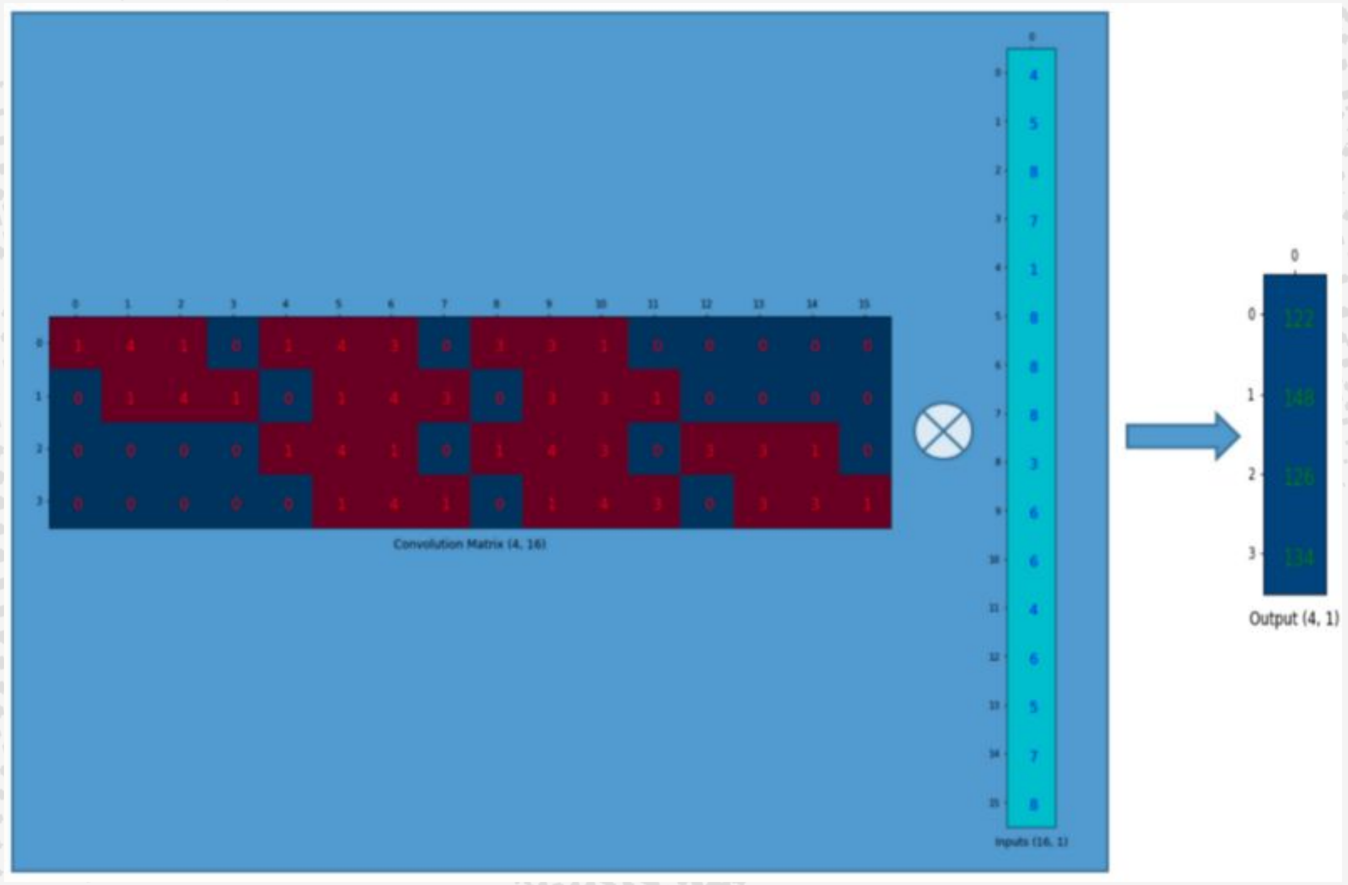
A discriminator example on MNIST

## What about the generator ?

- Convolution decreases the data size: it is perfect for the discriminator.
- However in the generator we need an operation that increases the data size !
- One might use standard interpolation techniques.
- But it leads to poor results (they are not really "learnable" ).
- Answer: the transposed convolution (also called deconvolution or up-sampling).

# Toward the transposed-convolution

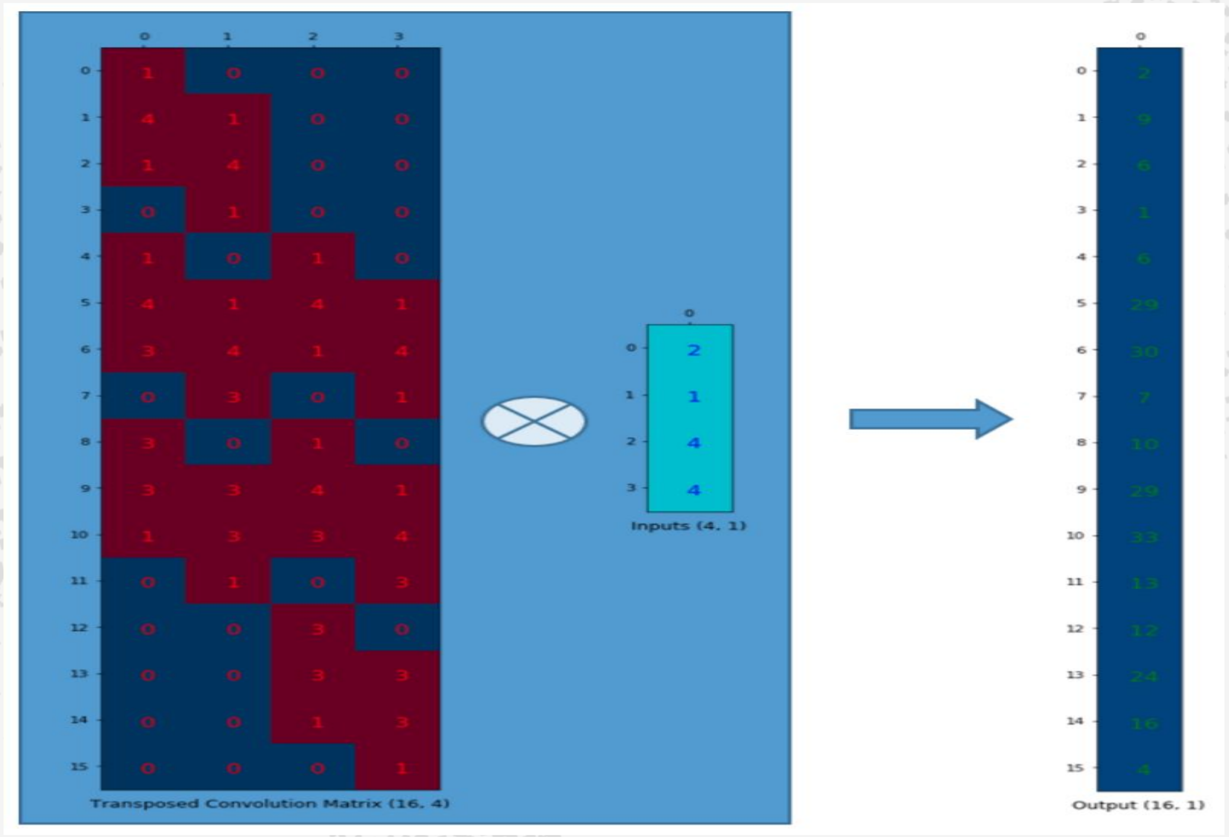
## Convolution as a matrix vector product operation.



Example: convolution over a 4x4 image (flattened as a vector of size 16) with a 3x3 filter. It gives a 2x2 image

# Toward the transposed-convolution

**We define the inverse operation: matrix vector product with the transposed convolution matrix.**



|  | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| 0 | 1 | 0 | 0 | 0 |
| 1 | 4 | 1 | 0 | 0 |
| 2 | 1 | 4 | 0 | 0 |
| 3 | 0 | 1 | 0 | 0 |
| 4 | 1 | 0 | 1 | 0 |
| 5 | 4 | 1 | 4 | 1 |
| 6 | 3 | 4 | 1 | 4 |
| 7 | 0 | 3 | 0 | 1 |
| 8 | 3 | 0 | 1 | 0 |
| 9 | 3 | 3 | 4 | 1 |
| 10 | 1 | 3 | 3 | 4 |
| 11 | 0 | 1 | 0 | 3 |
| 12 | 0 | 0 | 3 | 0 |
| 13 | 0 | 0 | 3 | 3 |
| 14 | 0 | 0 | 1 | 3 |
| 15 | 0 | 0 | 0 | 1 |

|  | 0 |
|---|---|
| 0 | 2 |
| 1 | 1 |
| 2 | 4 |
| 3 | 4 |

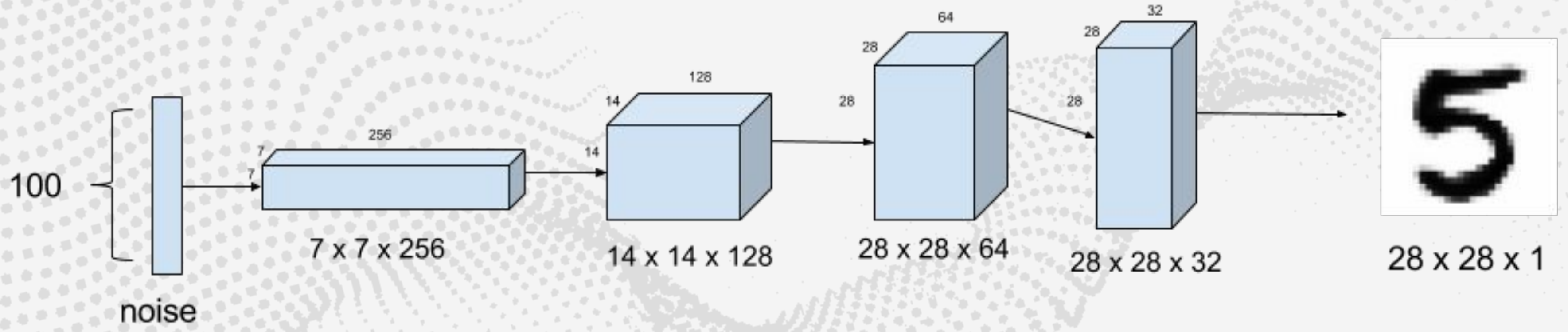
|  | 0 |
|---|---|
| 0 | 2 |
| 1 | 9 |
| 2 | 6 |
| 3 | 1 |
| 4 | 6 |
| 5 | 29 |
| 6 | 30 |
| 7 | 7 |
| 8 | 10 |
| 9 | 29 |
| 10 | 33 |
| 11 | 13 |
| 12 | 12 |
| 13 | 24 |
| 14 | 16 |
| 15 | 4 |

**As for the convolution, the matrix coefficients are learnt!**

**Example: deconvolution over a 2x2 image (flattened as a vector of size 4) with a 3x3 filter. It gives a 4x4 image**

# Example for the generator

- Perform up-sampling operations to transform the input noise vector into an image.



A generator example on MNIST

# DCGAN

- Radford *et al.* (2015) present the Deep Convolutional GAN (DCGAN).

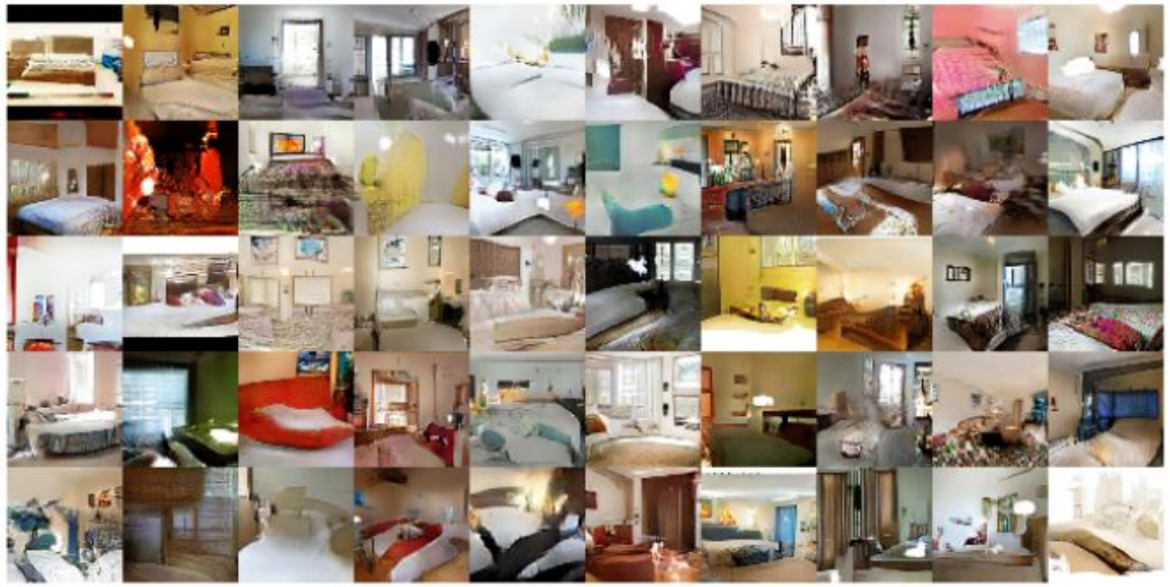


Figure 3: Generated bedrooms after five epochs of training. There appears to be evidence of visual under-fitting via repeated noise textures across multiple samples such as the base boards of some of the beds.

- They generate fake pictures of bedrooms to demonstrate their architecture efficiency.

# SRGAN

- Ledig *et al.* (2016): **super-resolution GAN model, SRGAN that can take a low resolution photo and generate a high-resolution sample.**

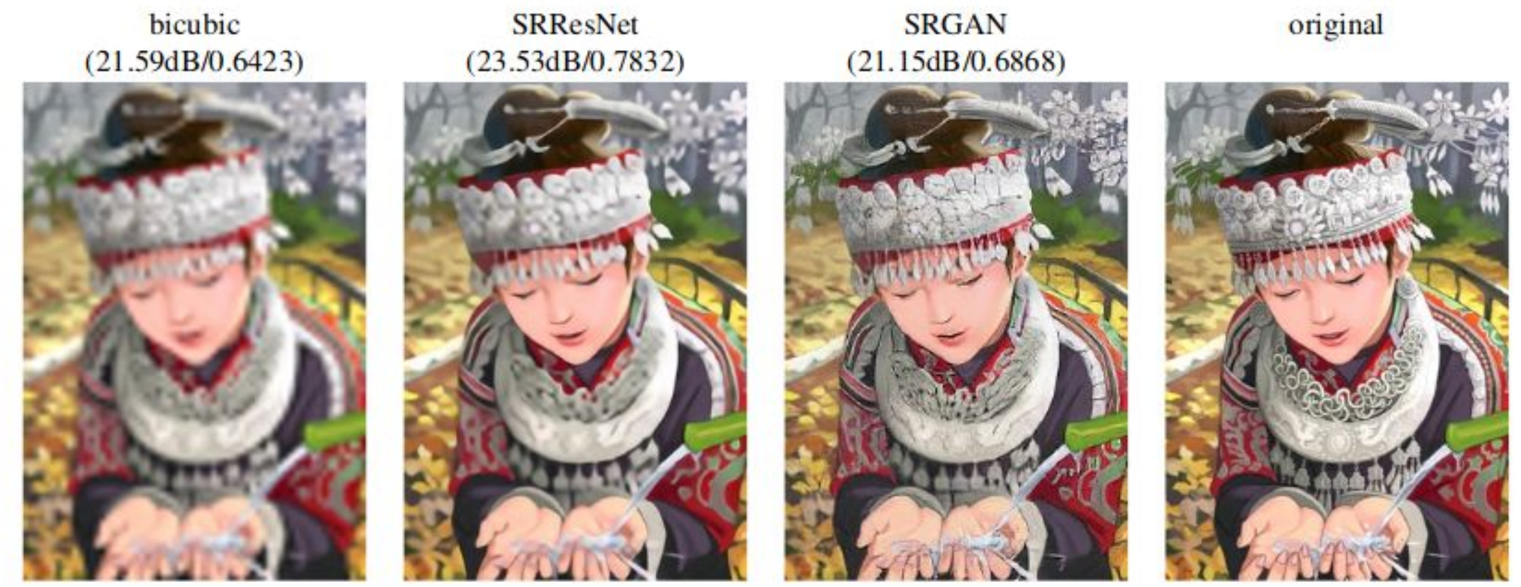


Figure 2: From left to right: bicubic interpolation, deep residual network optimized for MSE, deep residual generative adversarial network optimized for a loss more sensitive to human perception, original HR image. Corresponding PSNR and SSIM are shown in brackets. [4× upscaling]

- **This problem is classical supervised learning. Here, the GAN scheme is used as an alternative loss to the standard RMS (or L2) loss.**

## Conditional generative models

- GANs drawback: it generates data without “control on the output”.
- Example: if it learns to generate MNIST digits, it will generate any digit without distinction.
- One might desire to generate (with the same network) a given digit (a given label).
- Answer: we can condition the network output.
- In this case, we want to generate data given a condition c.
- Example: generate a MNIST digit given its label.

# Conditional GANs

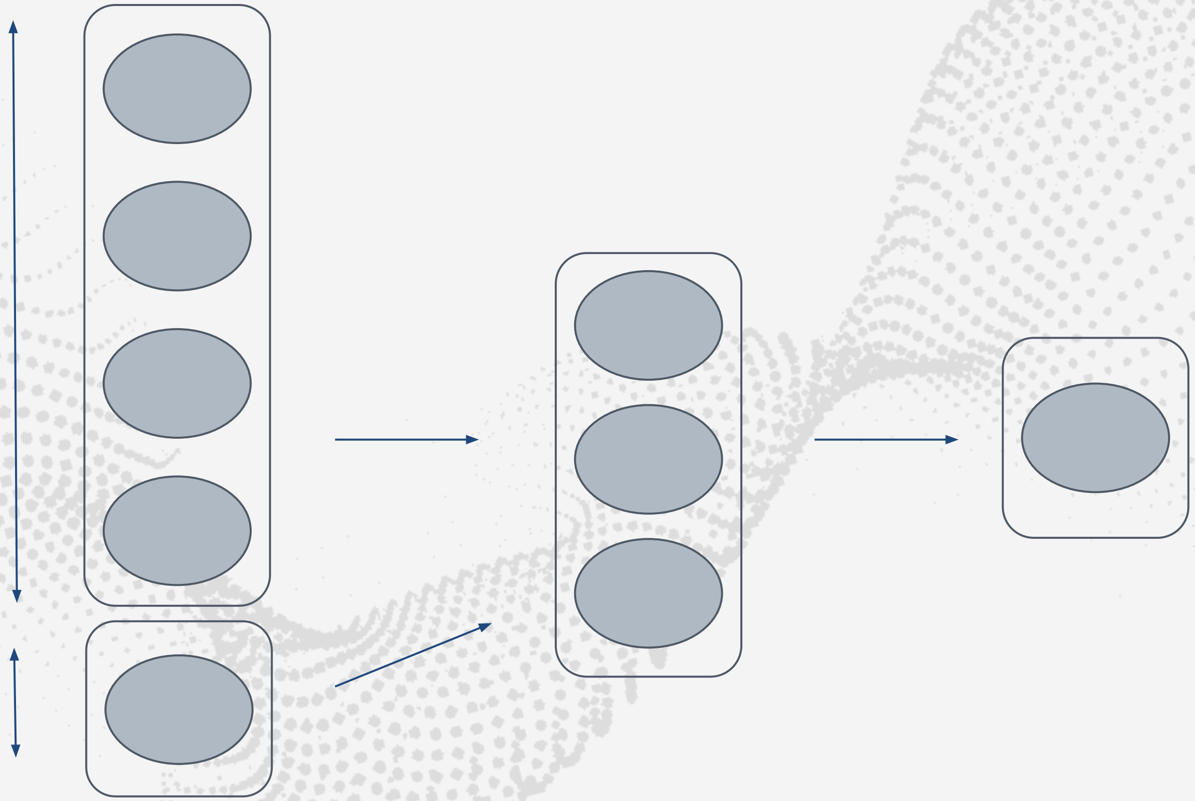
- **Adapt GAN to add a condition on the input: CGANs** (M. Mirza et al., 2014)
- **Simple idea: add an input to both the generator and the discriminator.**
- **The generator takes a noise vector and a condition (example a label) and generates conditioned (by this label) image.**
- **The discriminator takes an image and the condition and returns the conditioned (by this label) probability that this image is real.**
- **Note: most of the time the condition is a label, but it can be a description or other type of data.**

# CGAN architecture

## The discriminator (dense NN)

Input size (example: 784 for MNIST)

Condition size (example: 10 for MNIST) Labels are one-hot-encoded



Takes a flattened image and a condition and returns a scalar value.

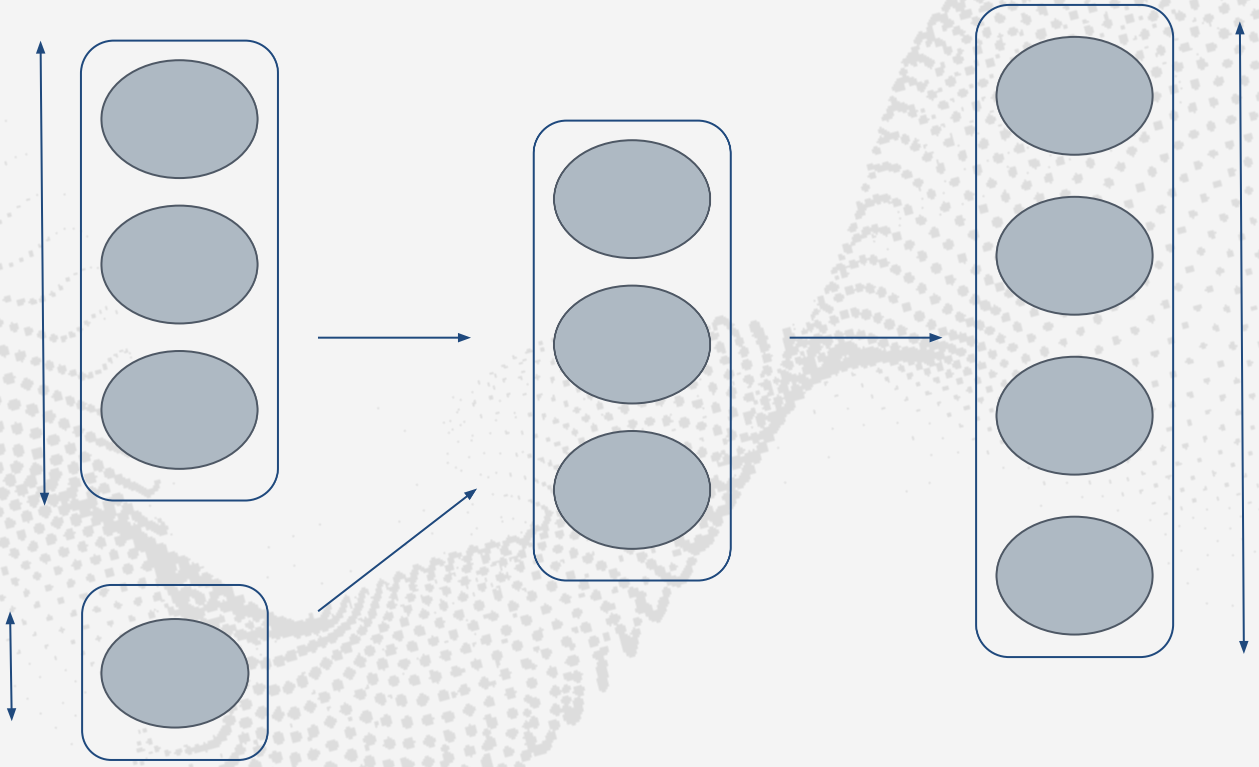
## CGAN architecture

### The generator (dense NN)

Noise vector size (example 100 in usual implementations)

Condition size (example: 10 for MNIST) Labels are one-hot-encoded

Input size (example: 784 for MNIST)



Takes a vector of random number and a condition and returns a flattened image.

# Adapt GAN losses to train the CGAN

- **Discriminator loss:**

$$L_D = -\sum_i^n \log\left(1 - D(G(z_i|c_i)|c_i)\right) + \log\left(D(x_i|c_i)\right)$$

- **Generator loss:**

$$L_G = \sum_i^n \log\left(1 - D(G(z_i|c_i))\right)$$

**Warning: To train the discriminator the same label must be fed into the generator and the discriminator.**

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## CGAN Practical algorithm

- **Initialize both networks**

- **Training:**
  - Sample a mini-batch of noise vectors, sample a mini-batch of input data and a batch of labels (c_i).
  - Update the discriminator weights with those batches (gradient descent on its loss).
  - Sample a mini-batch of noise vectors and a batch of labels.
  - Update the generator weights with this batch (gradient descent as well).

- **Repeat training phase until convergence**

# BigGan: DeepMind 2018

- **Of course, CGAN and DCGAN may be mixed !**

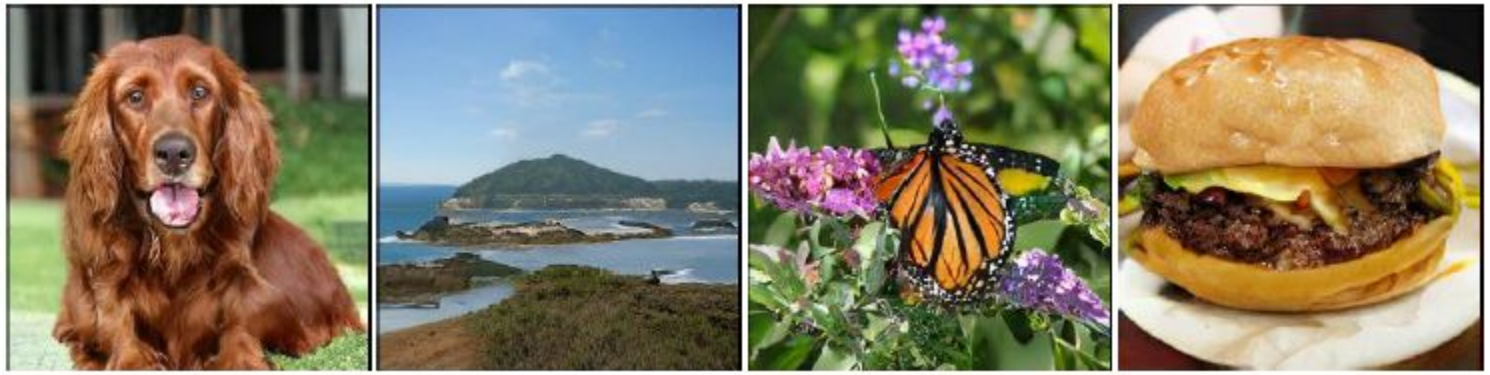
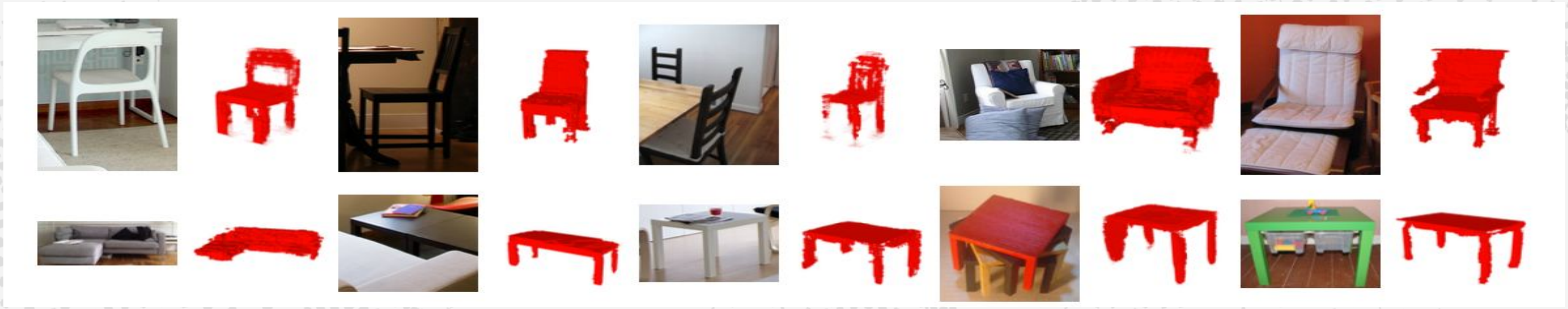


Figure 1: Class-conditional samples generated by our model.

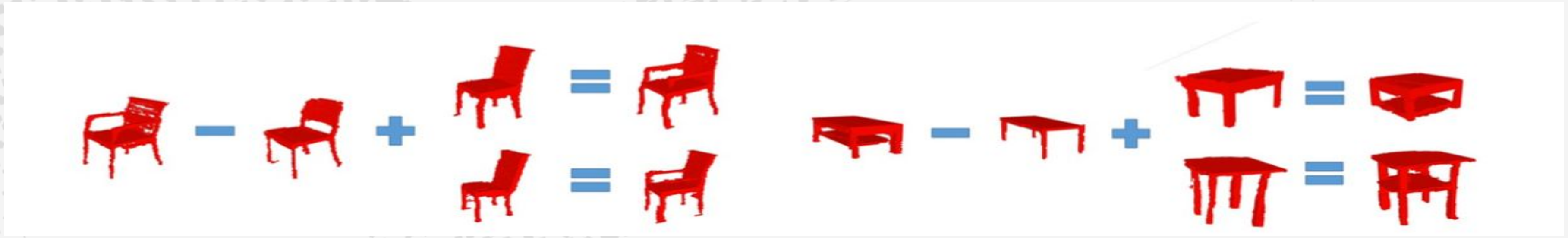
- **This year deepMind** (A. Brock et al., 2018) **proposed an algorithm BigGan that learns the conditional probability of the imageNet dataset (1000 classes !)**

# State of the Art: 3D

- GAN models can generate 3D objects, 3D environments and even VR environments.
- Wu *et al.* in a ground-breaking article recently published (Jan 2017) showed that it's possible to generate 3D furniture out of simple photos!



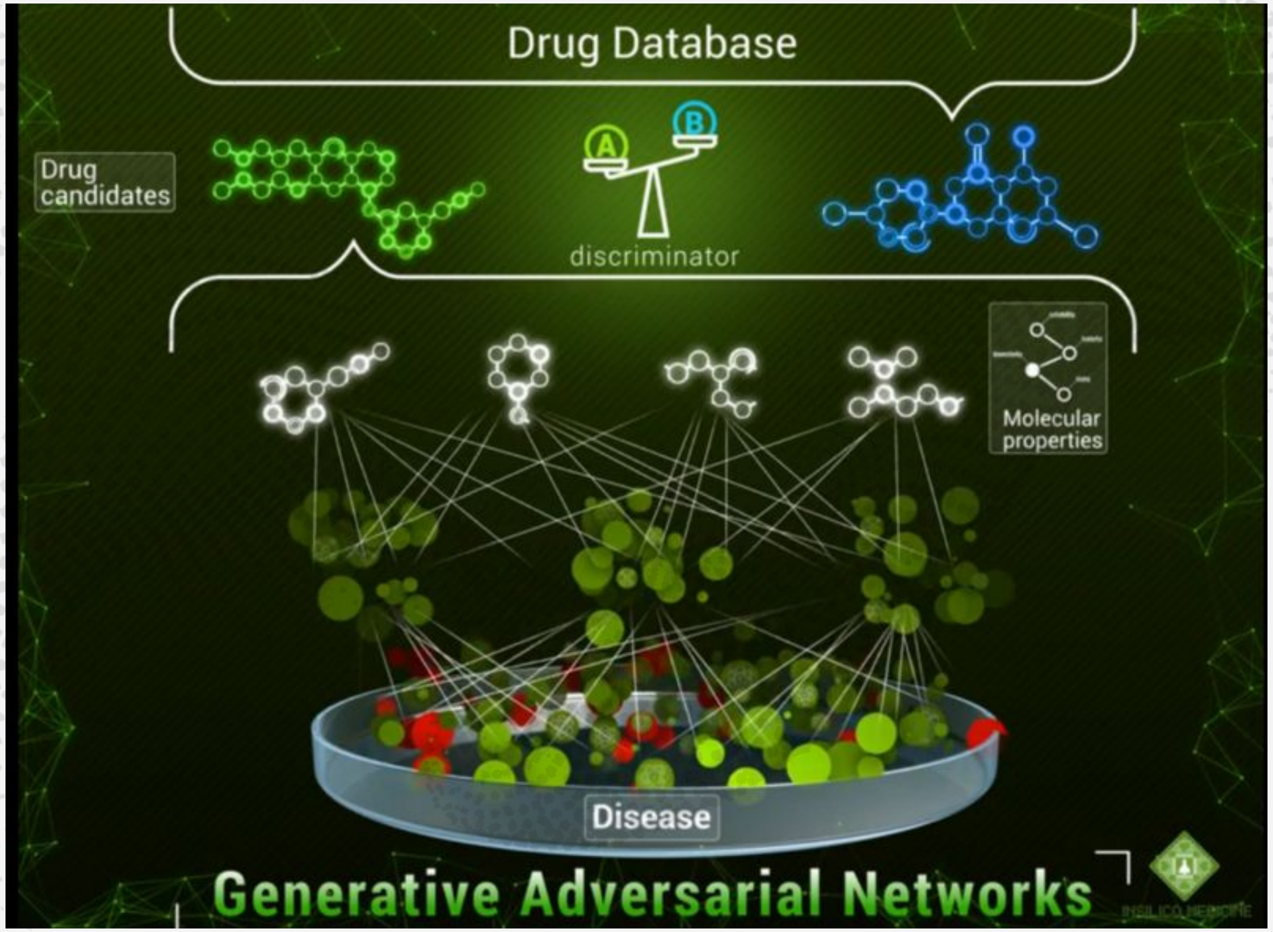
- Even more incredible you can even do arithmetic on these 3D models to create **new, never seen before furniture**!



- More state of the art examples: protein research, astronomy

# Other applications: drug discovery

**See:** https://medium.com/neuromation-io-blog/creating-molecules-from-scratch-i-drug-discovery-with-generative-adversarial-networks-9d42cc496fc6



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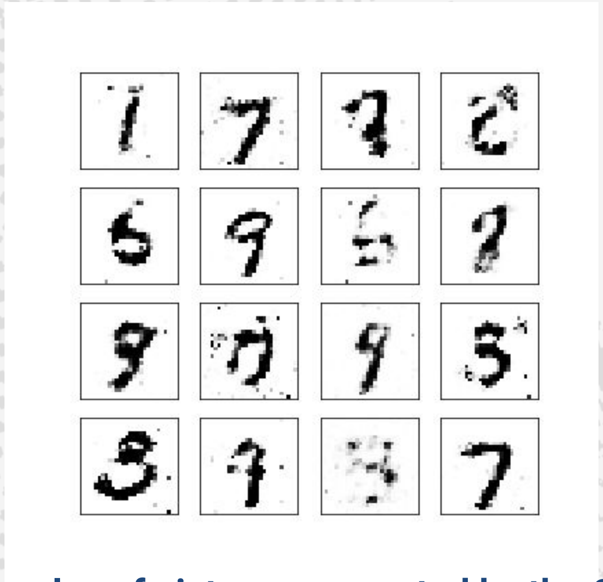
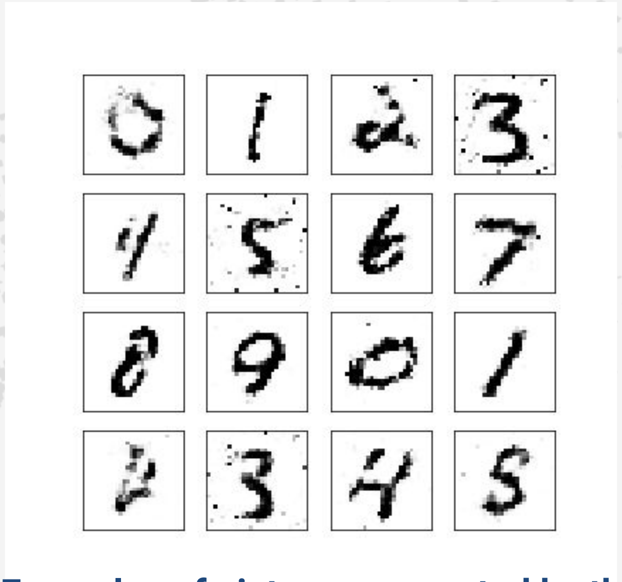
# Tutorials

- First part: download, read and complete the notebook “GAN-fill the gaps” that is available on GitHub.
- Second part: take this notebook and adapt it to train a CGAN on MNIST.



Examples of pictures generated by the GAN (we don’t control the digits generated).



Examples of pictures generated by the CGAN (we control the digits generated).

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