

Initiation à l'apprentissage automatique en science des matériaux

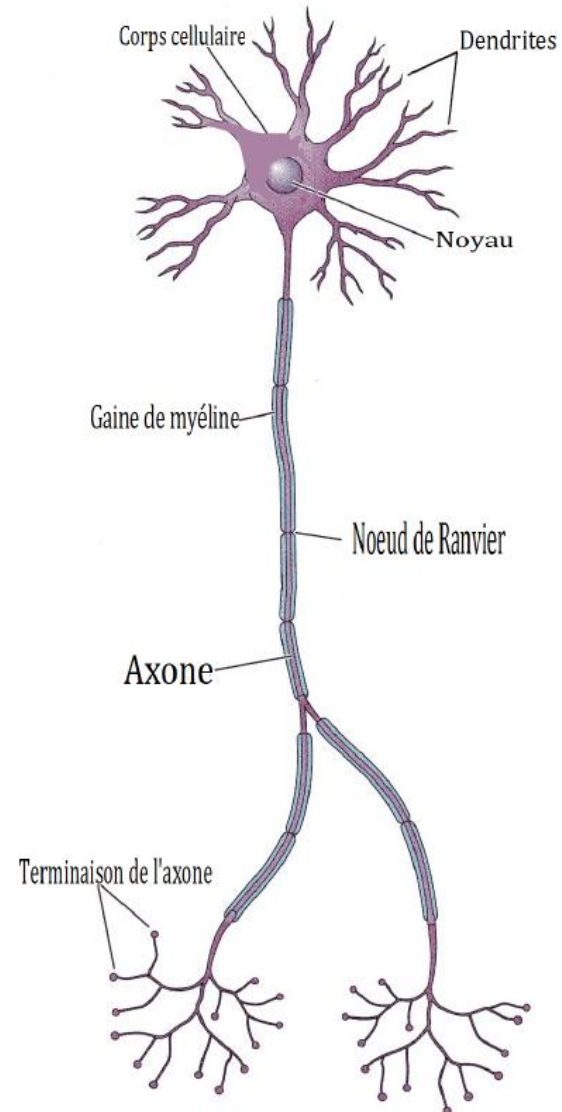
5. Neural Network

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Inspired by nature



Human:

$100 \cdot 10^9$ neurons

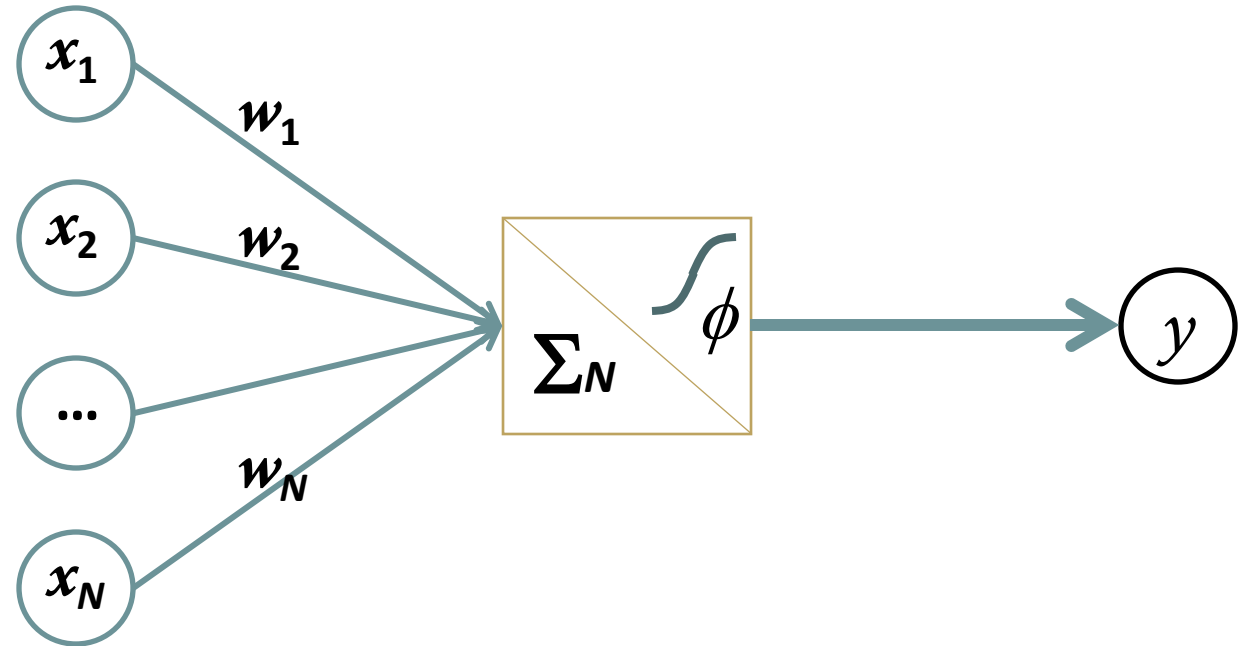
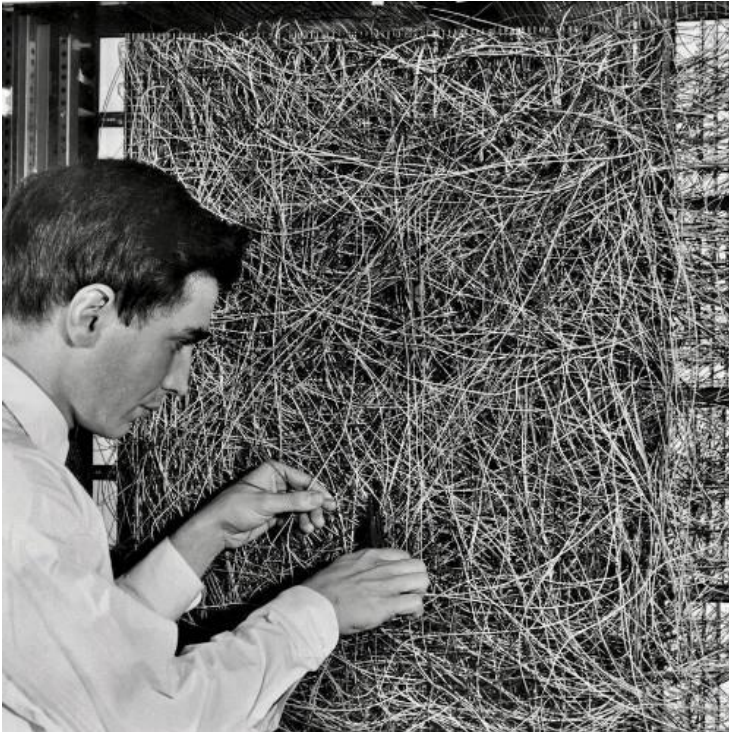
10^3 synapses/neurons

$200 \cdot 10^3$ electric bonds

Artificial neuron

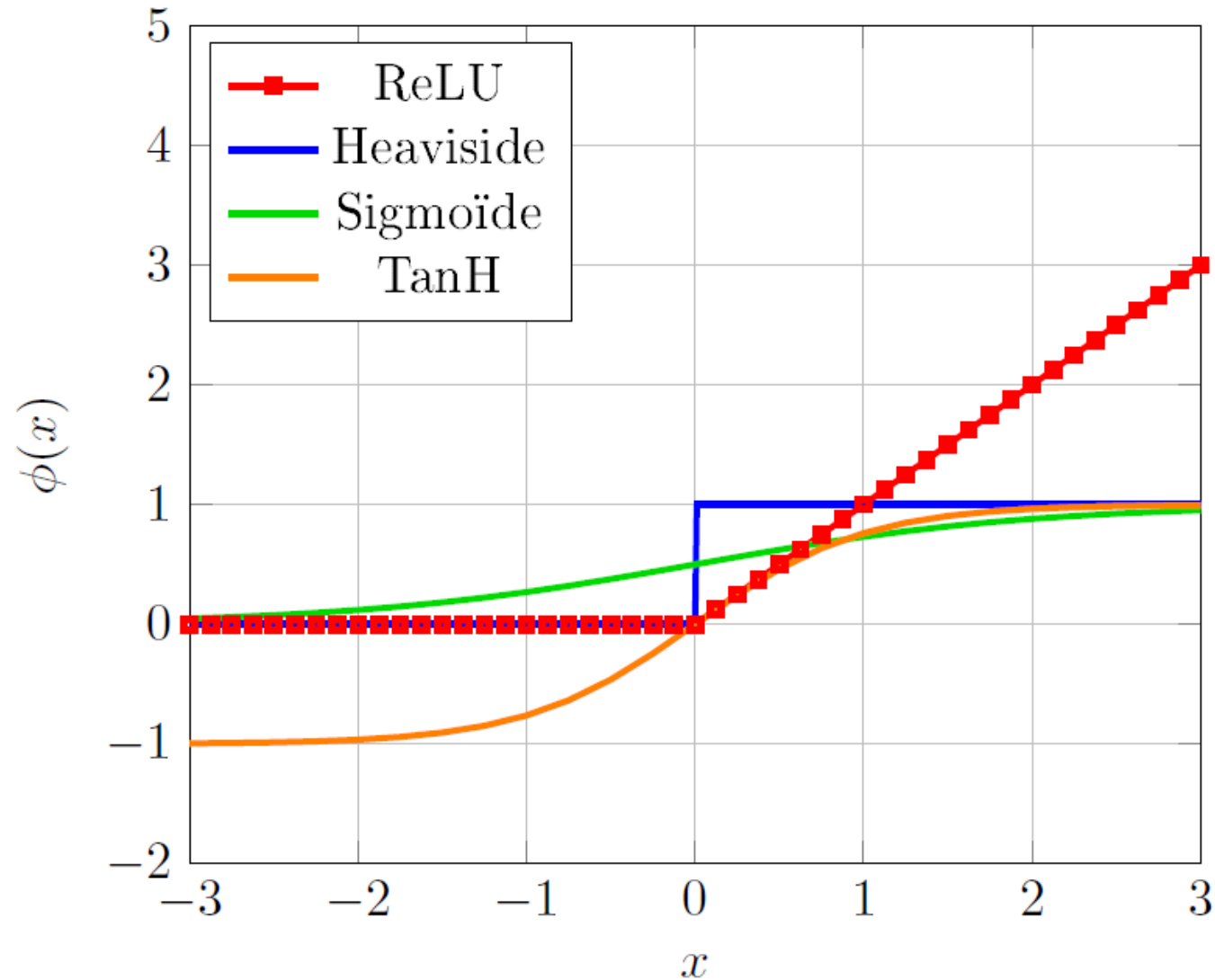
1957

Perceptron, 1957



$$y = \phi \left(\sum_{n=1}^N \omega_n x_n - \omega_0 \right)$$

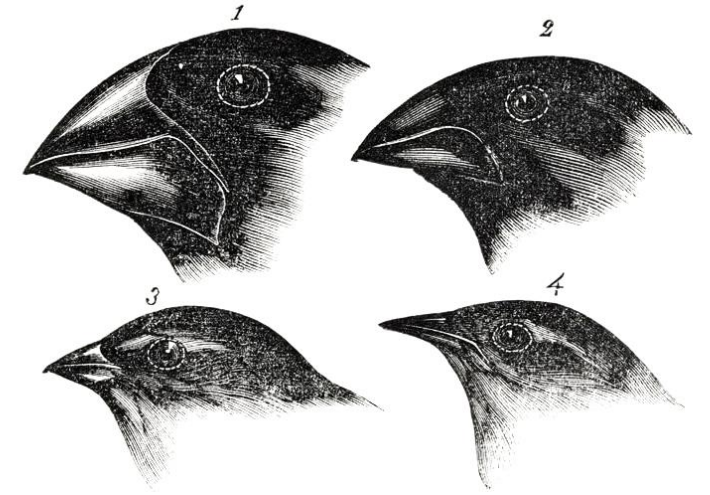
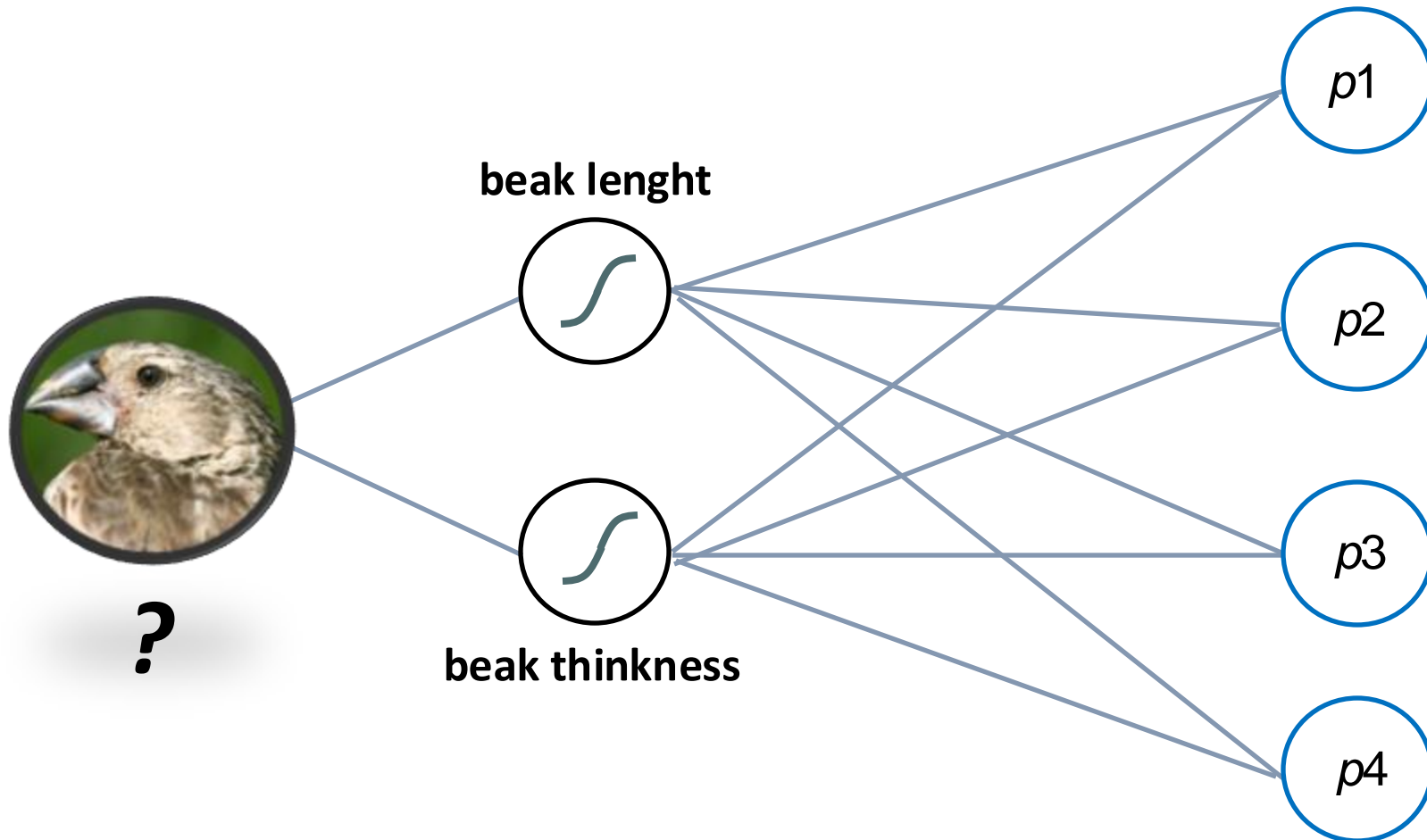
Activation function



$$y = \phi \left(\sum_{n=1}^N \omega_n x_n - \omega_0 \right)$$

The artificial neural network

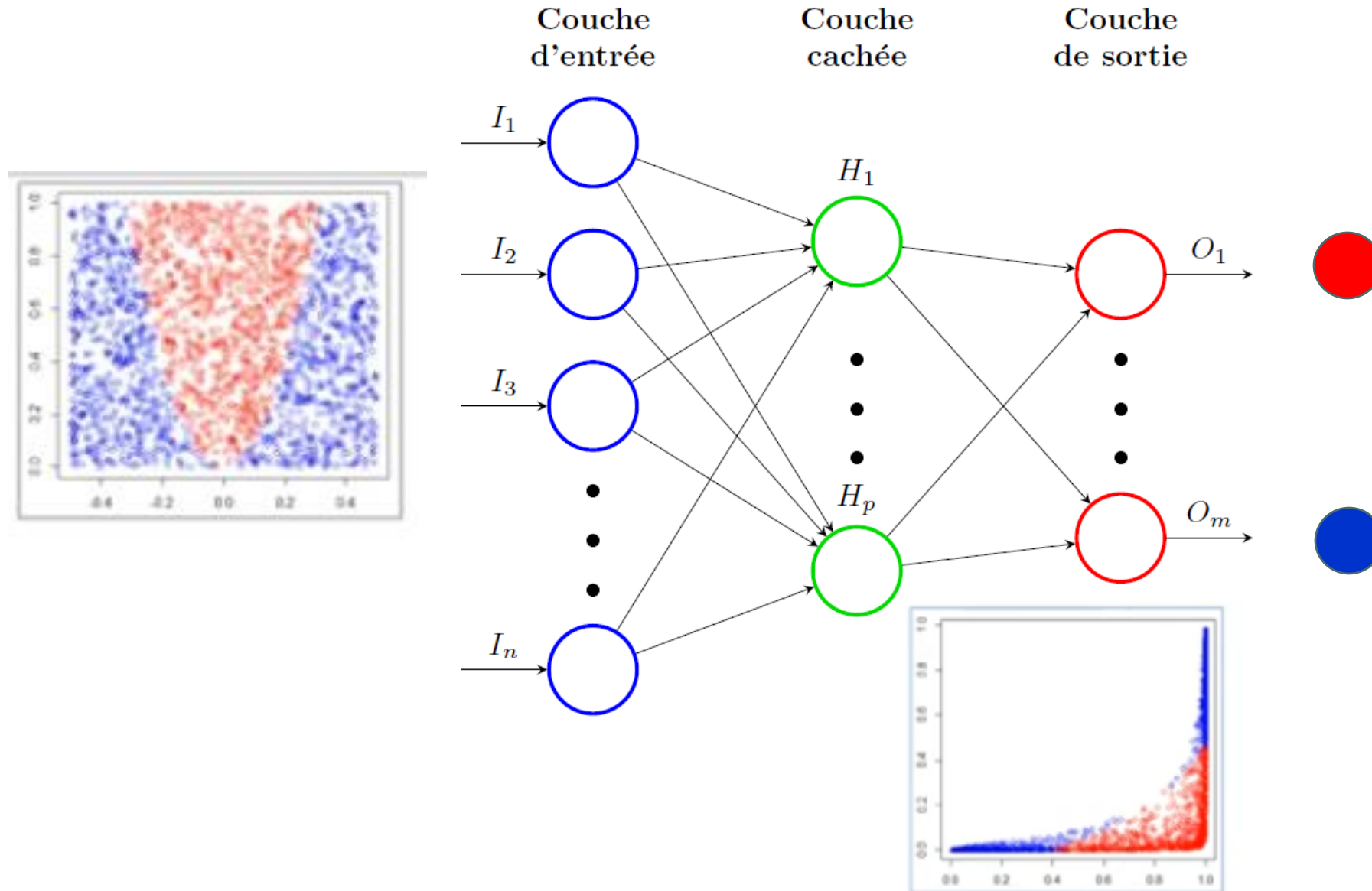
Classification of Darwin's finches



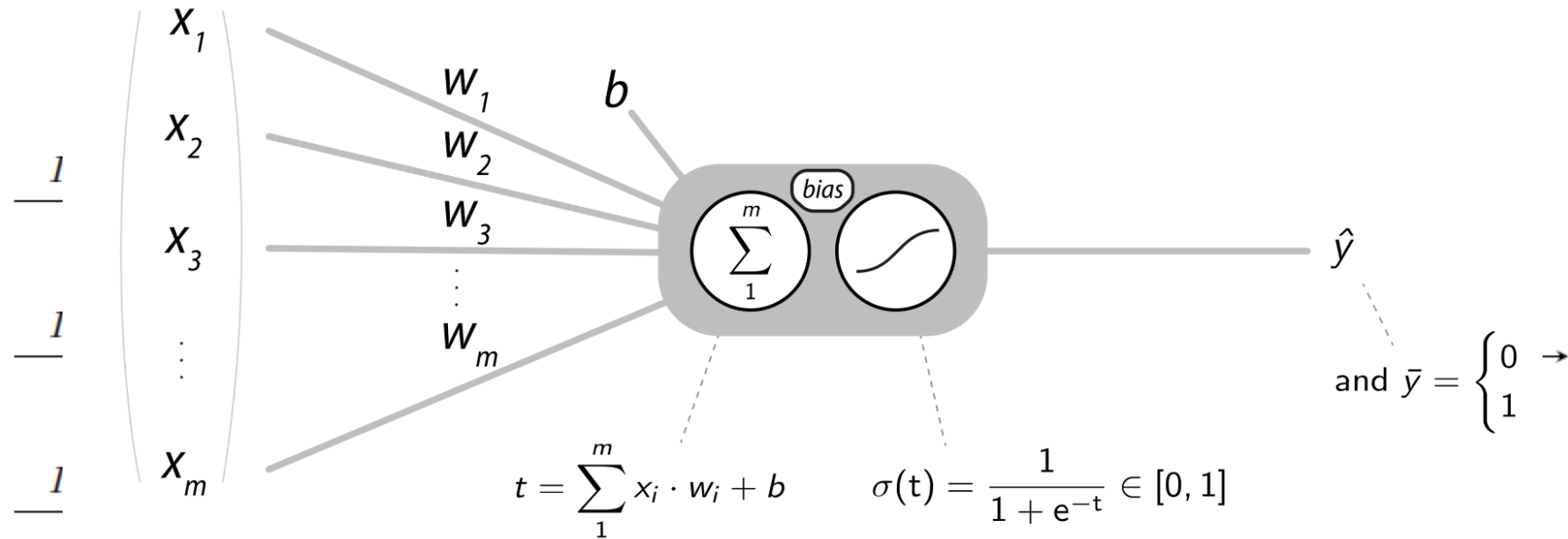
1. *Geospiza magnirostris*
3. *Geospiza parvula*

2. *Geospiza fortis*
4. *Certhidea olivacea*

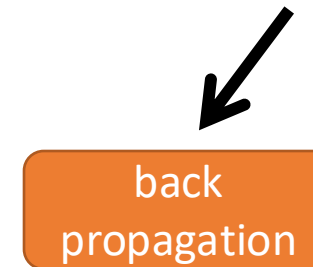
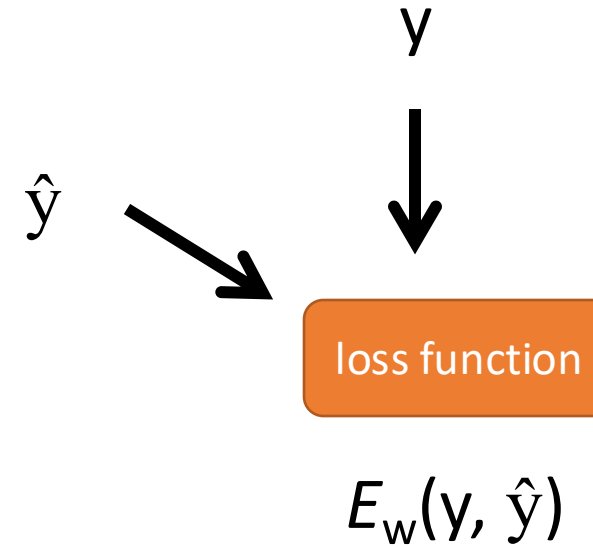
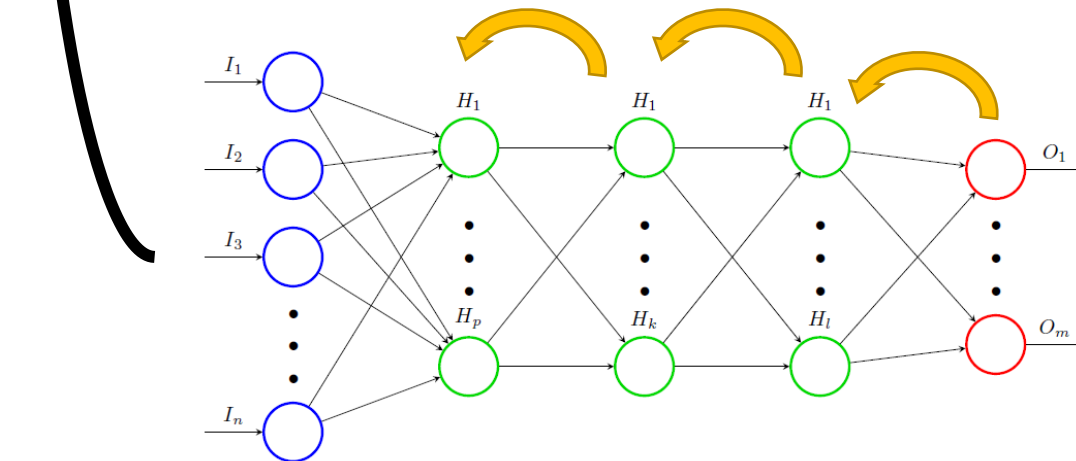
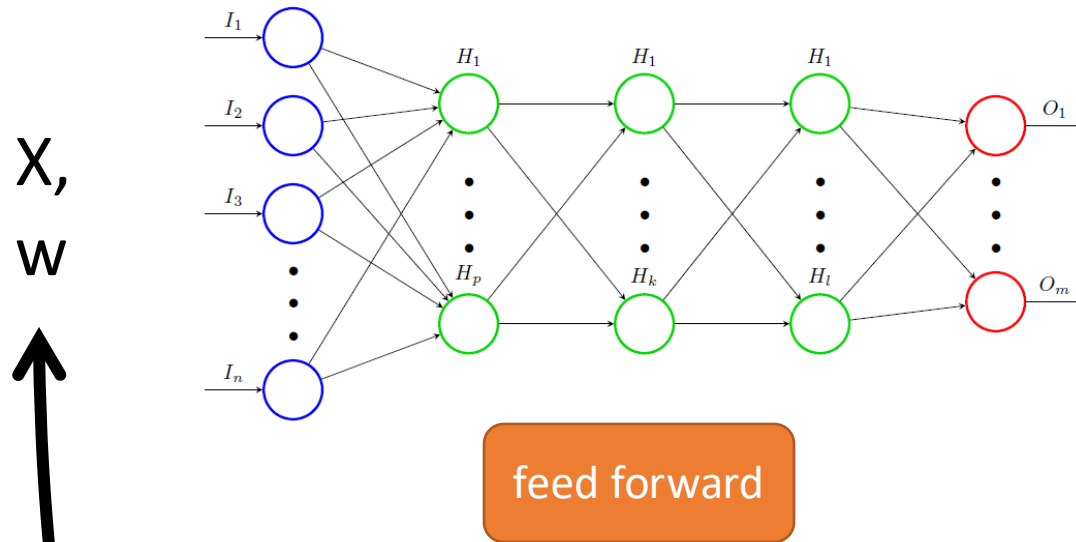
Neural network / Perceptron multicouche MLP



multilayer perceptron MLP



Back-propagation



$$W_{ij} = W_{ij} - \alpha \frac{dE}{dw}$$

How to adjust w_{ij} ?

$$w_{ij} = w_{ij} - \alpha \frac{dE}{dw}$$

α : learning rate

$$\text{if } E_w(y, \hat{y}) = \frac{1}{2} (\hat{y} - y)^2 \\ \rightarrow \frac{dE}{dy} = \hat{y} - y$$

$$\begin{aligned} \frac{dE}{dX} &= \frac{dE}{dy} \frac{dy}{dX} \\ &= \frac{dE}{dy} \frac{d}{dX} \phi(X) \\ &= (\hat{y} - y) \frac{d}{dX} \phi(X) \end{aligned}$$

$$\begin{aligned} \frac{dE}{dw} &= \frac{dE}{dX} \frac{dX}{dw} \\ &= \frac{dE}{dX} y \end{aligned}$$

<https://playground.tensorflow.org/>



Epoch
000,176

Learning rate
0.03

Activation
Tanh

Regularization
None

Regularization rate
0

Problem type
Classification

DATA

Which dataset do you want to use?



Ratio of training to test data: 50%

Noise: 0

Batch size: 10

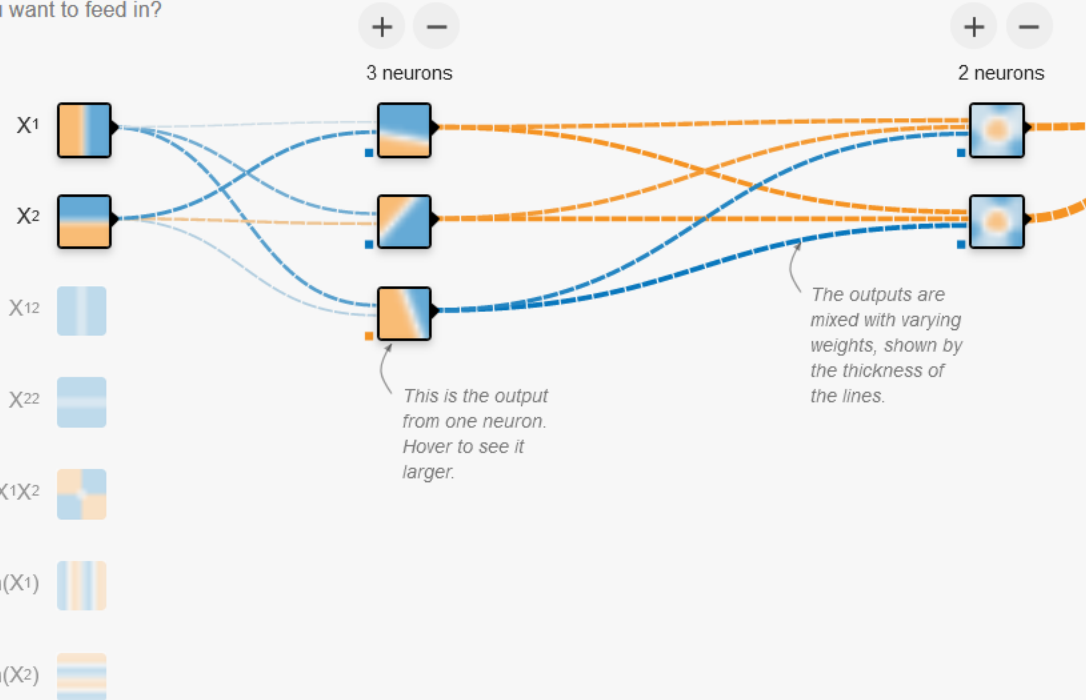
REGENERATE

FEATURES

Which properties do you want to feed in?

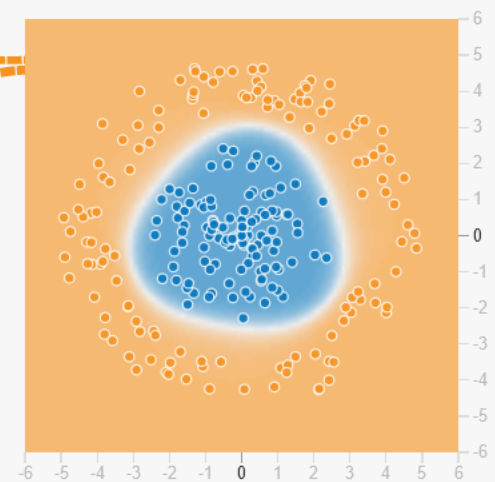
- X1
- X2
- X1²
- sin(X1)
- sin(X2)

2 HIDDEN LAYERS

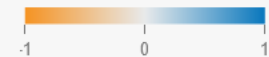


OUTPUT

Test loss 0.004
Training loss 0.003



Colors shows data, neuron and weight values.



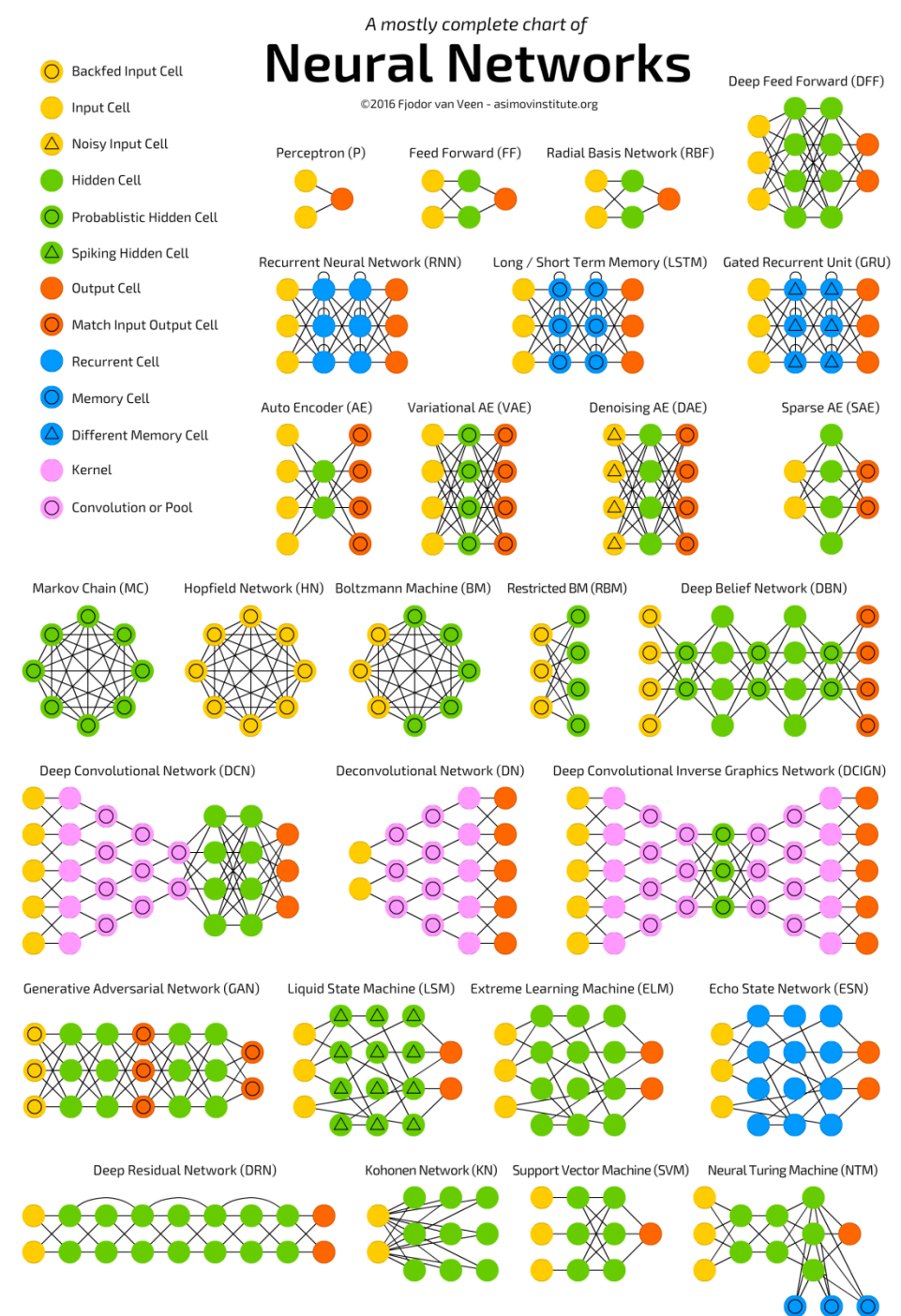
Neural network

Strengths:

- Model can read any data without any knowledge
- Consideration of complex correlations
- Really efficient

Weaknesses:

- Black box
- Too many connections
- Slow to learn

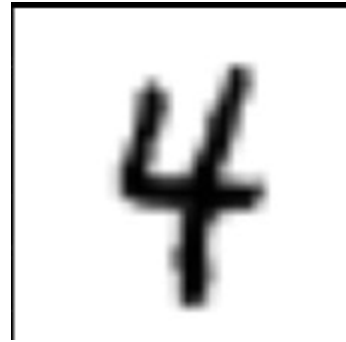


About images

0.0008 Mpixels

28x28 px

8 bits



24 Mpixels

3*8bits

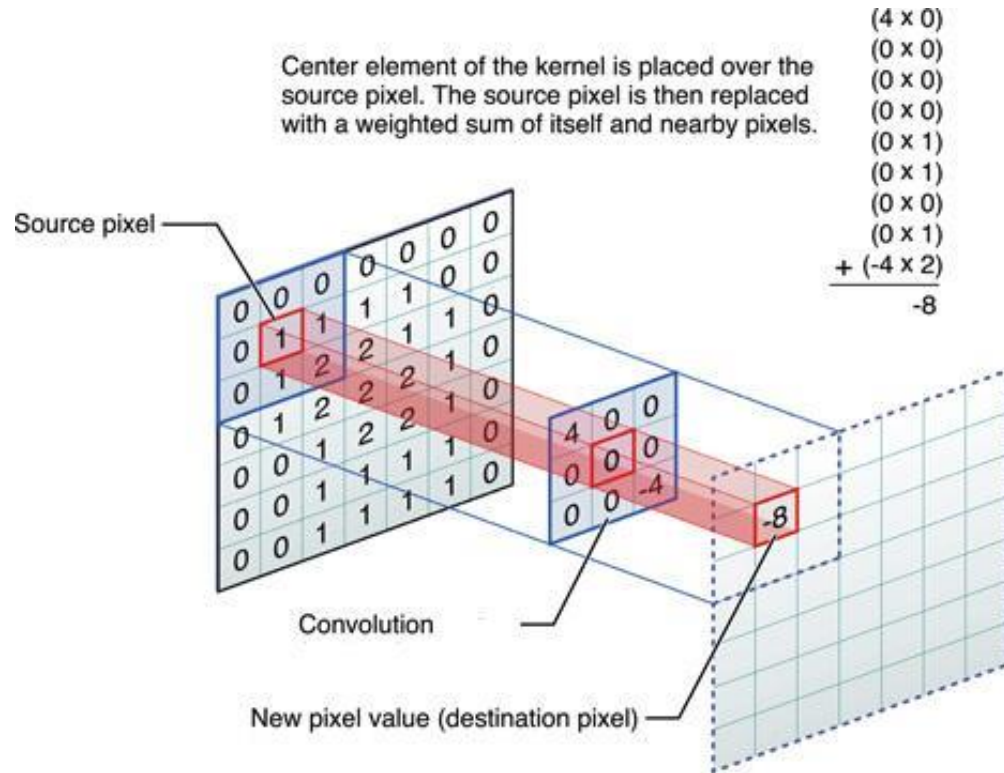


With a fully connected NN of 1000 neurones:

→ 785 000 parameters

→ $72 \cdot 10^9$ parameters

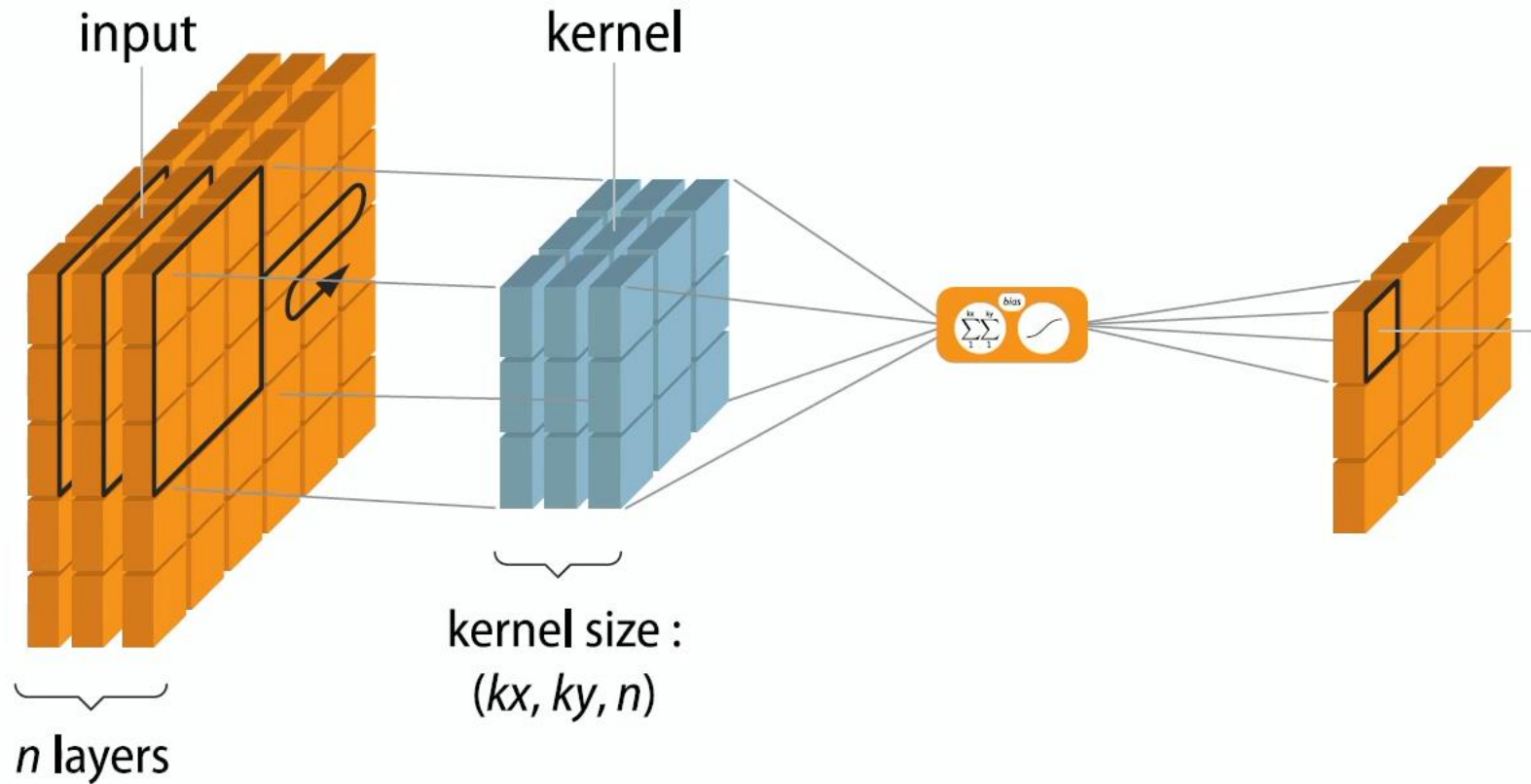
Image convolution



Hanamard product by a kernel

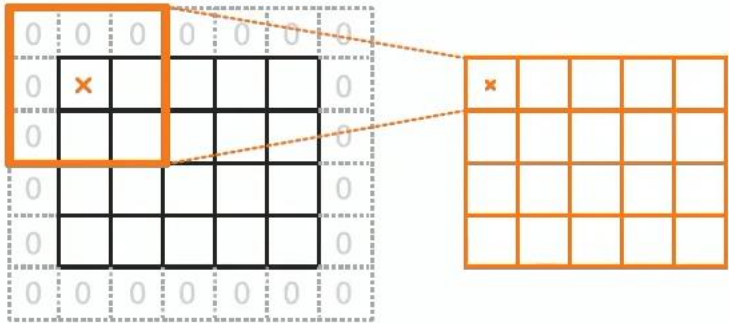
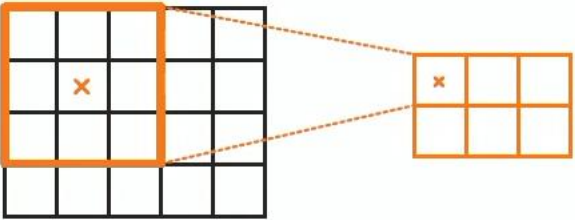
Operation	Filter	Convolved Image
Identity	$ \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} $	
Edge detection	$ \begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix} $	
	$ \begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix} $	
	$ \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} $	
Sharpen	$ \begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix} $	
Box blur (normalized)	$ \frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} $	
Gaussian blur (approximation)	$ \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} $	

Convolution

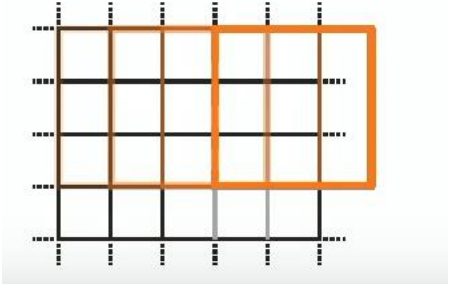


Several operations

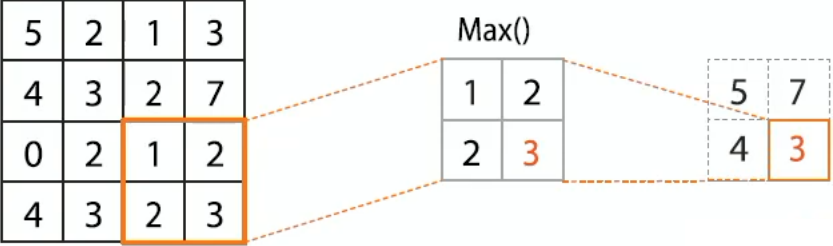
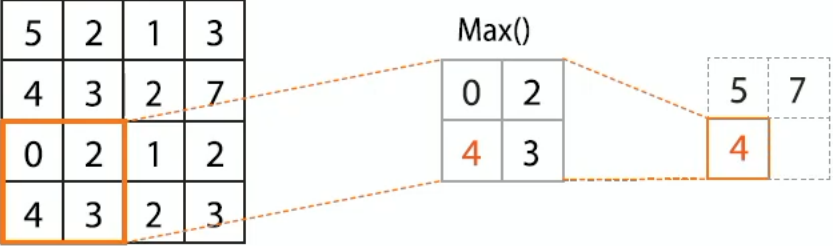
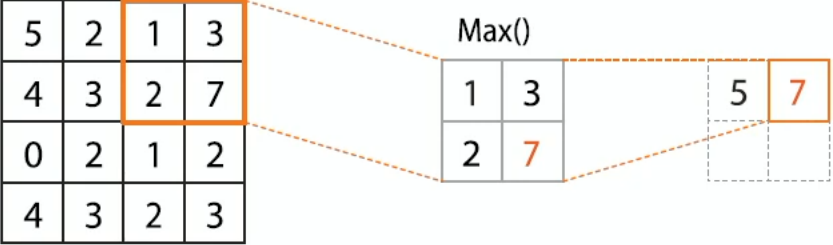
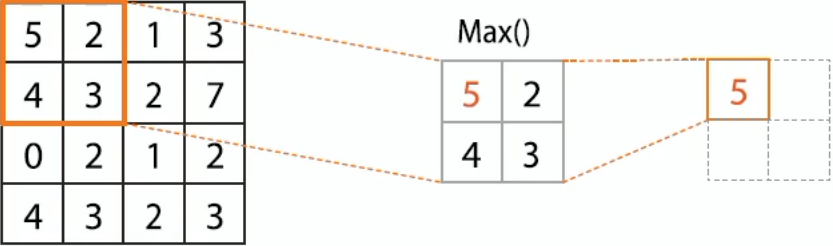
padding



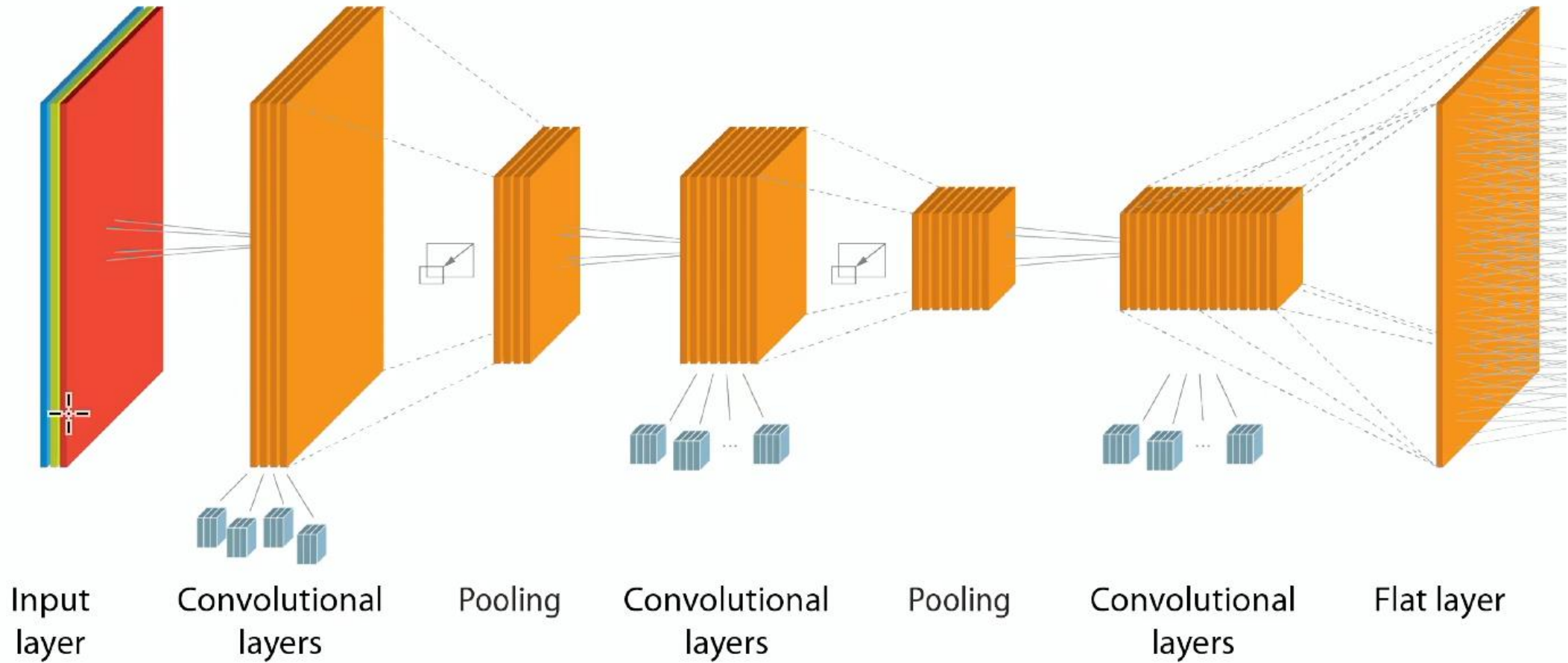
strides



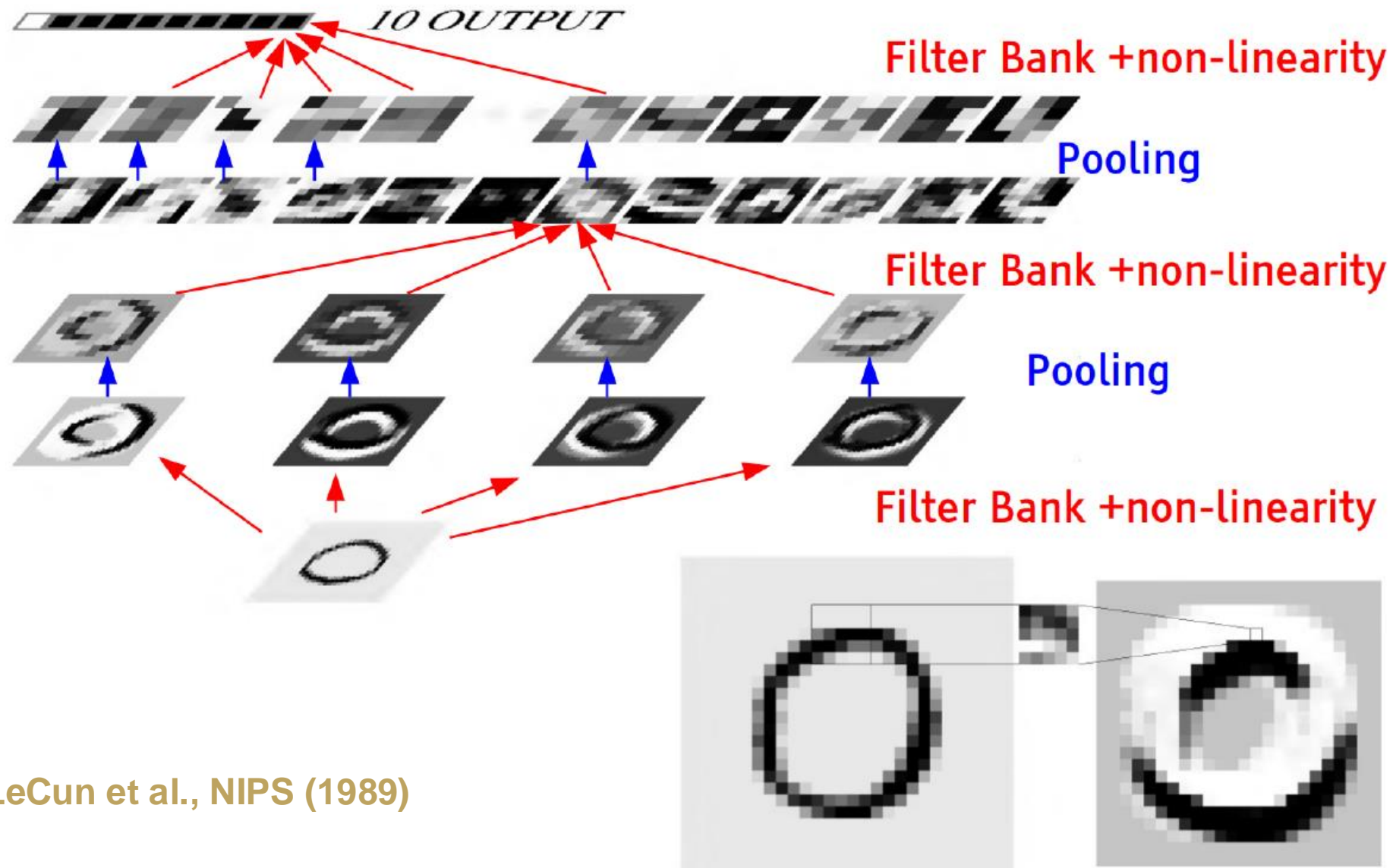
pooling



Convolution



Convolution for classification



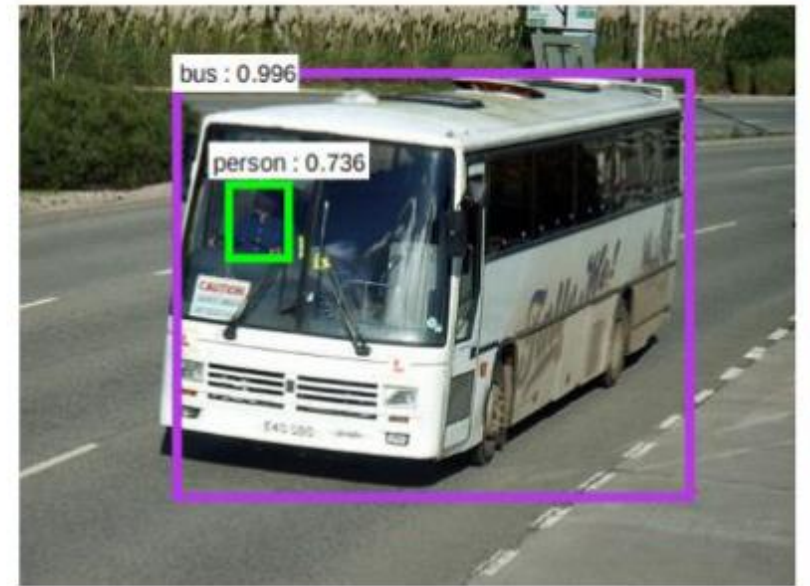
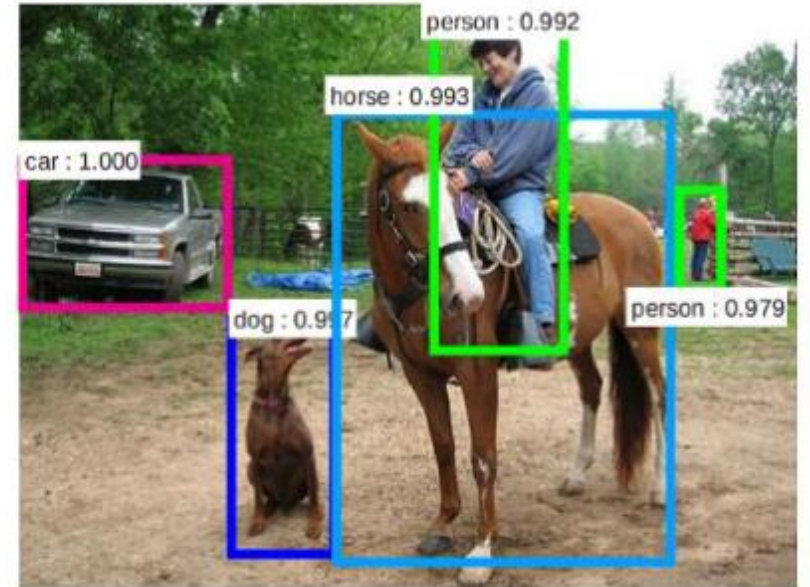
Convolution network

Strengths:

- Can treat complex images
- More simple than MPL (same weight)
- Reduce size by pooling
- Learn from deep information hidden by data
- Adapted for GPU (60 times faster)

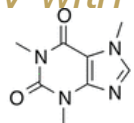
Weaknesses:

- Black box
- Slow to learn
- Need a large DB



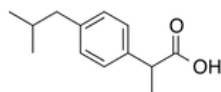
Generative methods

Segler *et al.* ACS central science (2018)
Generating Focused Molecule Libraries for Drug Discovery with Recurrent Neural Networks



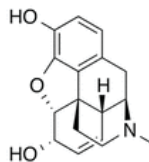
Caffeine

CN1c2ncn(C)c2C(=O)N(C)C1=O



Ibuprofen

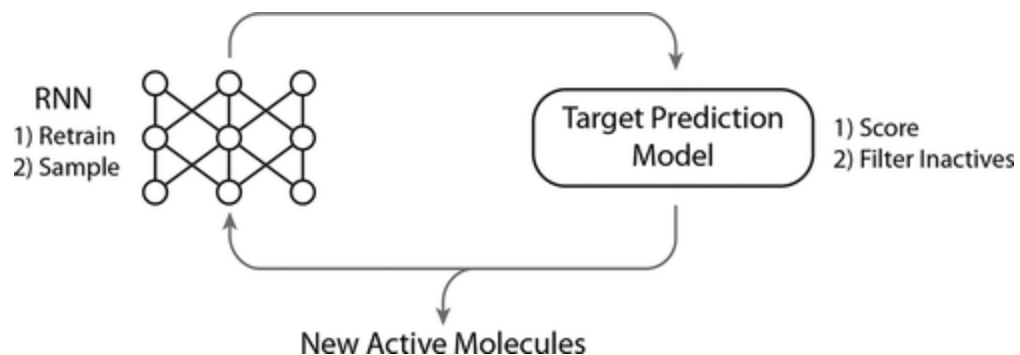
CC(C)Cc1ccc(cc1)C(C)C(=O)O



Morphine

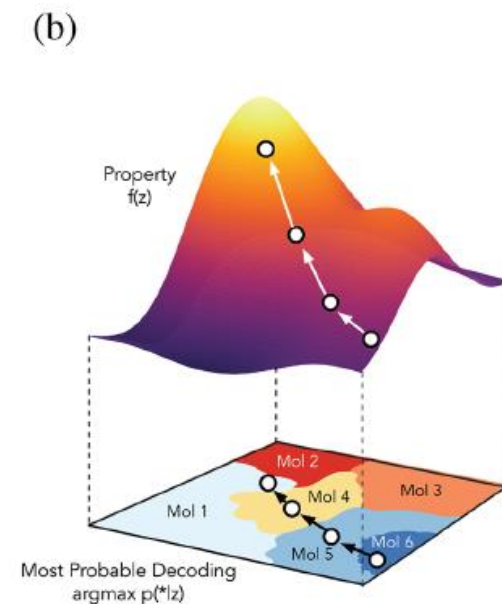
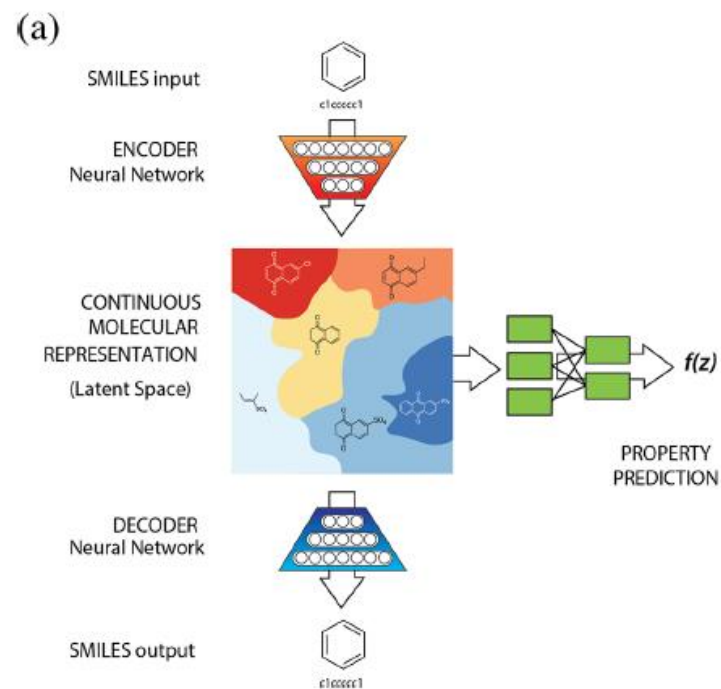
[H][C@]12C=C[C@H](O)[C@@H]3OC4C5C(C[C@H]1N(C)CC[C@@]235)ccc4O

Batch	Generated Example	valid
0	<chem>Oc.BK5i%ur+7oAFc7L3T=F8B5e=n)CS6RCTAR((OVCp1CApb)</chem>	no
1000	<chem>OF=CCC20CCCC)C2)C1CNC2CCCCCCCCCCCCCCCCCCCCC</chem>	no
2000	<chem>O=C(N)C(=O)N(c1occc1OC)c2ccccc2OC</chem>	yes
3000	<chem>O=C1C=2N(c3cc(ccc3OC2CCC1)CCCc4cn(c5c(C1)cccc54)C)C</chem>	yes

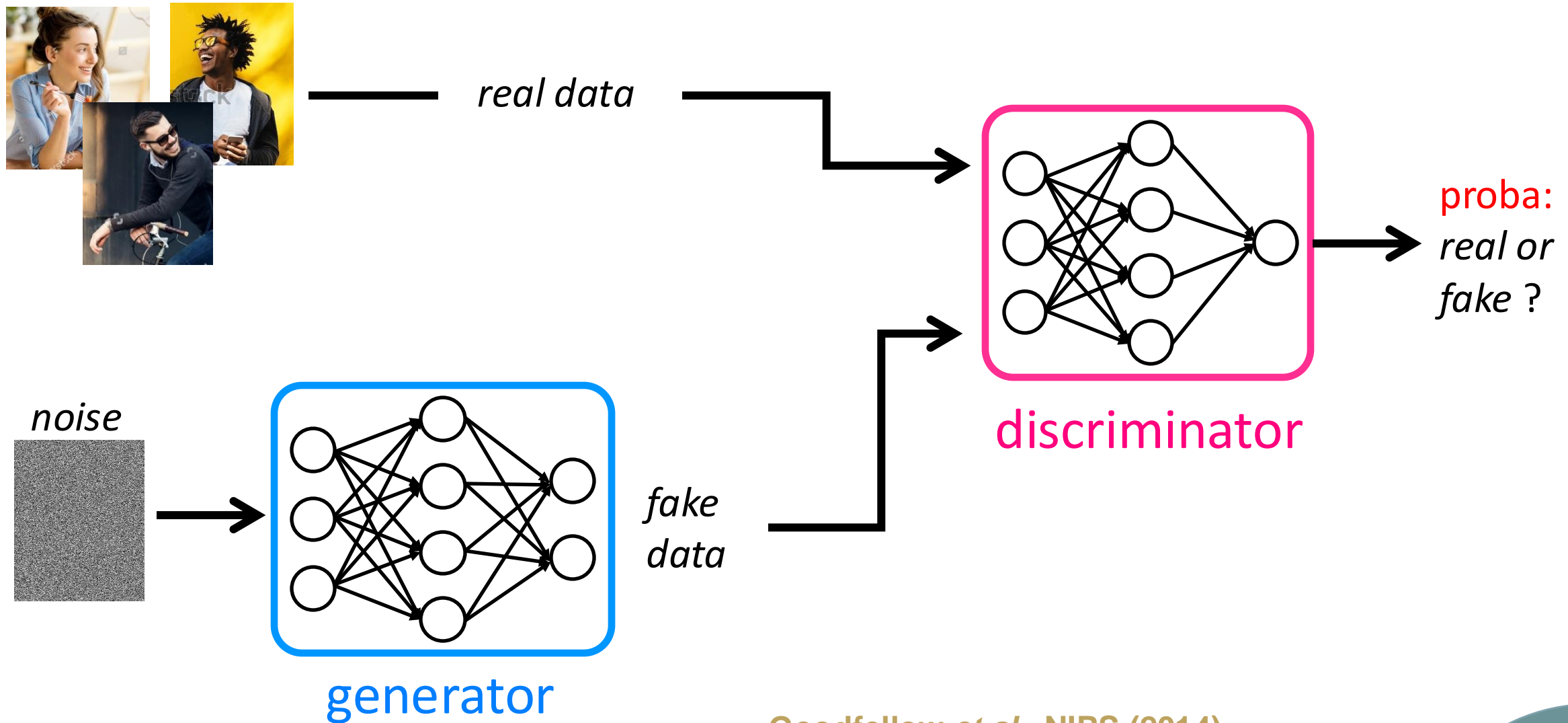


Gomez-Bombarelli *et al.* ACS central science (2018)

Automatic Chemical Design Using a Data-Driven Continuous Representation of Molecules

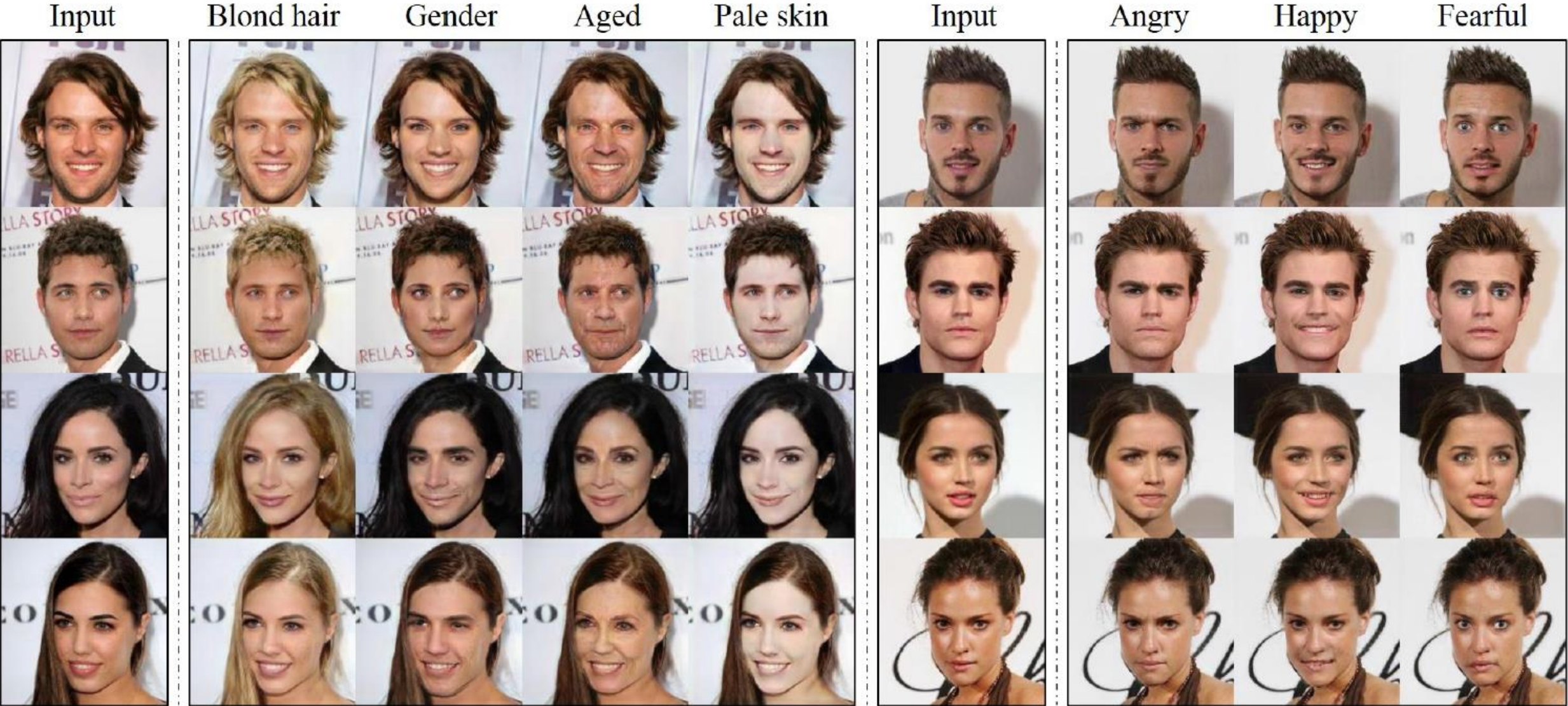


Generative adversarial networks (GAN)

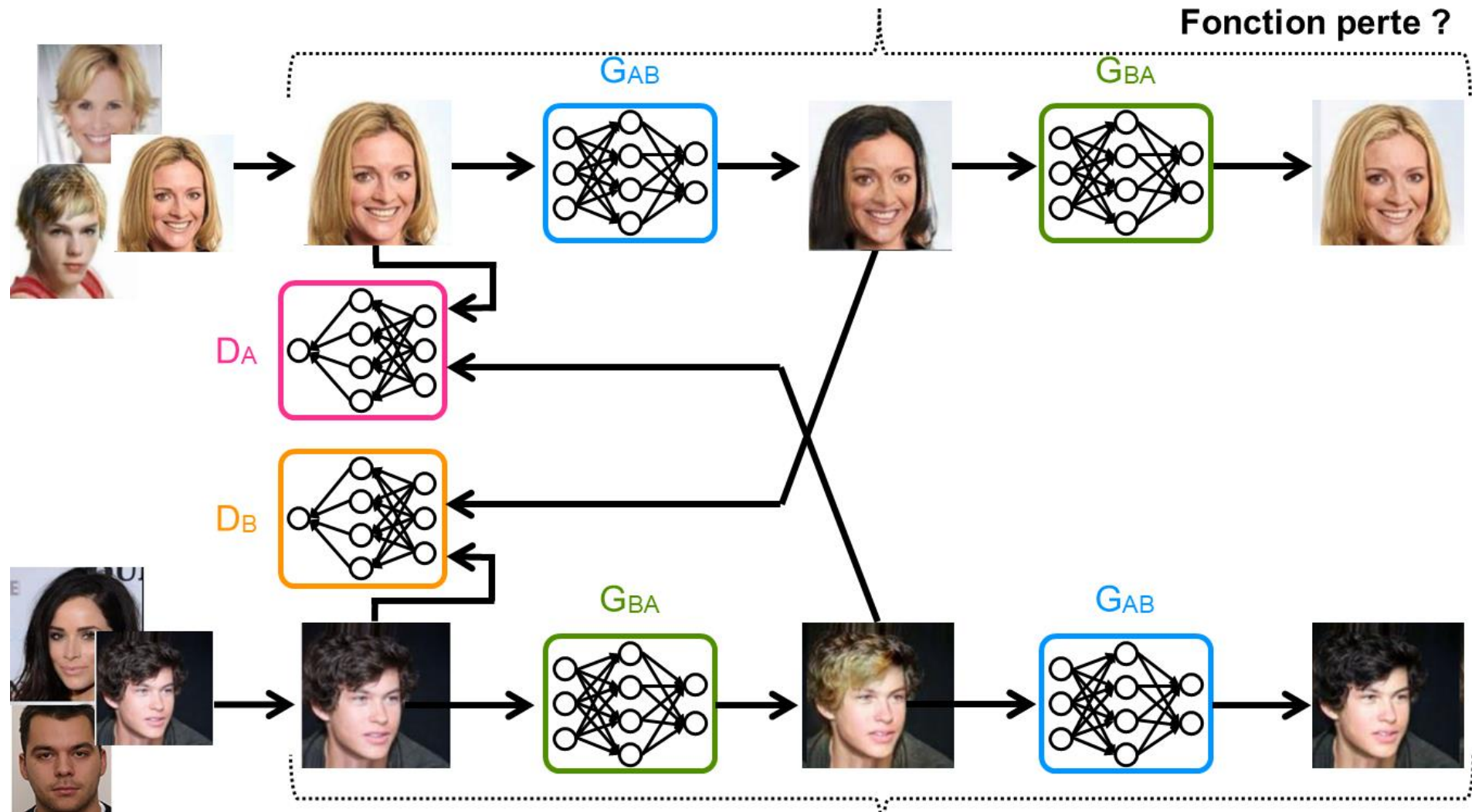


Goodfellow et al., NIPS (2014)

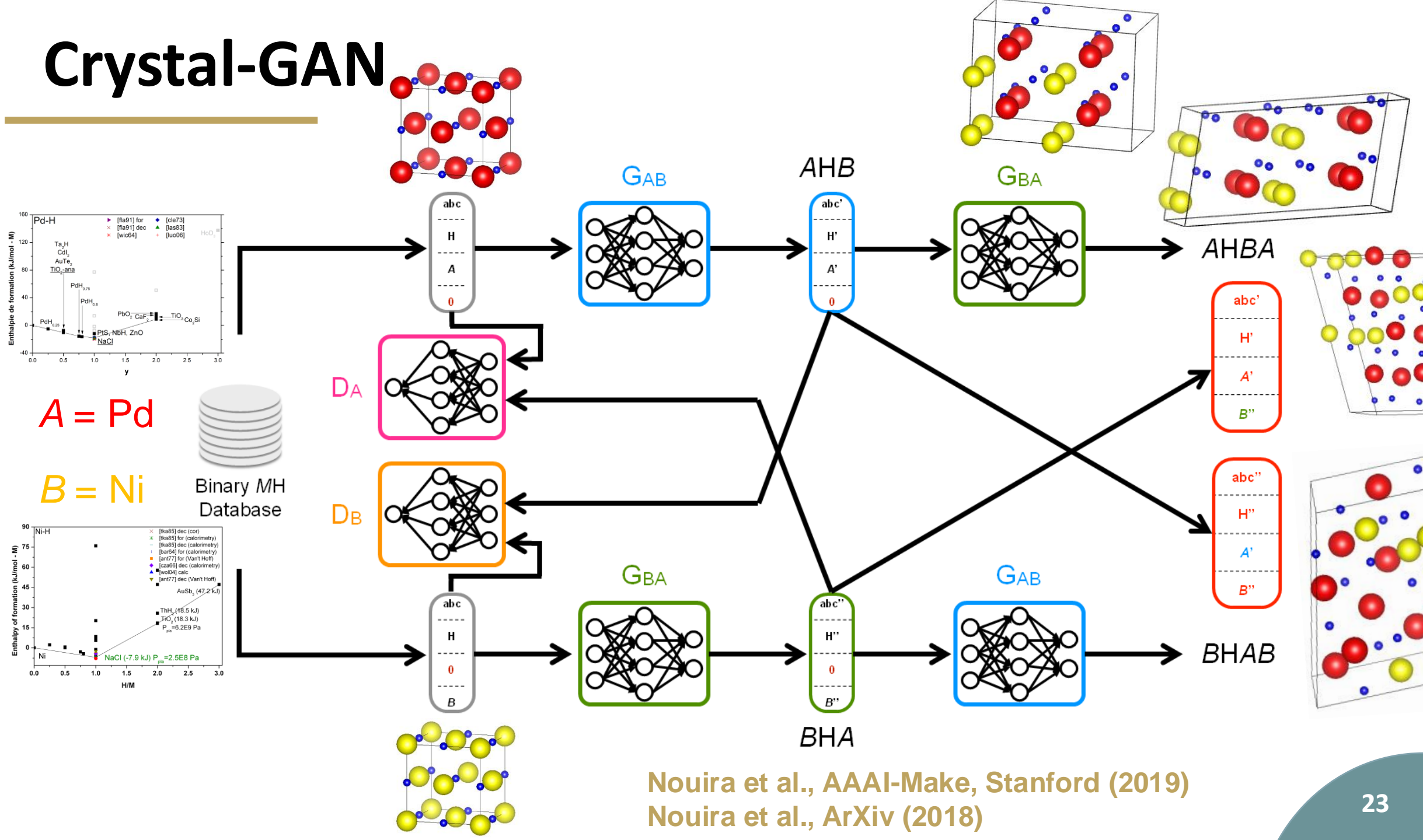
Generative adversarial networks (GAN)



Cross-domain GAN (DiscoGAN)



Crystal-GAN



Nouira et al., AAAI-Make, Stanford (2019)
 Nouira et al., ArXiv (2018)

Generative methods: many applications

Generate a picture

“a cabin in the mountains”

https://huggingface.co/spaces/akhaliq/VQGAN_CLIP

2020: DALLE3



Generate a narration (GPT3)

<https://play.aidungeon.io>

2023: GPT4 (1000 G parameters)



Generate a sound track

<https://openai.com/blog/jukebox/>