

M·O·D·A·L  
Mathematical mOdeling and  
Data Analysis Laboratory

# A brief Introduction to AI for Image processing

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University of Naples Federico II



**PHENET-EMPHASIS Data Management Training**

Paris, 4-6 December 2024

# Roadmap

...boring part...



PHENET  
PHENOTYPING & ENVIROTYPING  
SOLUTIONS FOR AGROECOLOGY



## PHENET-EMPHASIS Data Management Training

Paris, 4-6 December 2024

**Part 1-** Theoretical introduction to AI, Deep Learning  
and MathXAI

**Part 2 -** Laboratory of CNN

**Part 3 -** Laboratory of AI for Image

processing and PHENotyping data extraction

...exciting part...



# What is Artificial Intelligence (AI) ?

A1 Artificial Intelligence is the ability for a computer to think, learn and simulate human mental processes, such as perceiving, reasoning, and learning.



A2 It can also independently perform complex tasks that once required human input.

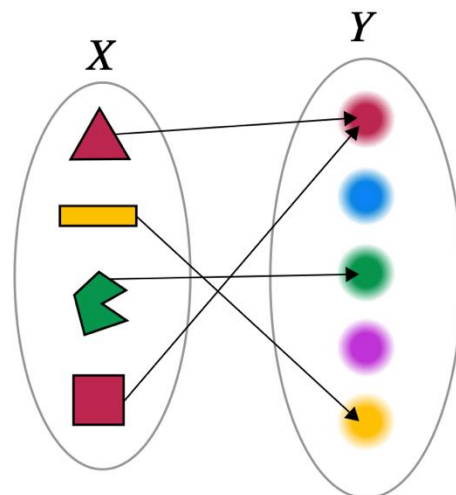


*The power of a machine to copy intelligent human behavior!*

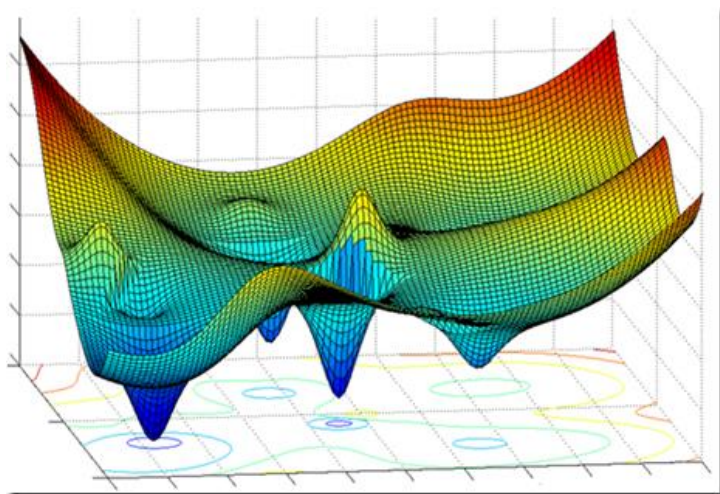
*AI is a MODEL that could be able to «think»*

# Rough Idea of a Model

✓ In a **level 0** math course



✓ In an **advanced** course



## Function

$$x \mapsto f(x)$$

Examples by **domain** and **codomain**

$$\mathbf{X} \rightarrow \mathbf{B}, \mathbf{B} \rightarrow \mathbf{X}, \mathbf{B}^n \rightarrow \mathbf{B}$$

$$\mathbf{X} \rightarrow \mathbf{Z}, \mathbf{Z} \rightarrow \mathbf{X}$$

$$\mathbf{X} \rightarrow \mathbf{R}, \mathbf{R} \rightarrow \mathbf{X}, \mathbf{R}^n \rightarrow \mathbf{X}$$

$$\mathbf{X} \rightarrow \mathbf{C}, \mathbf{C} \rightarrow \mathbf{X}, \mathbf{C}^n \rightarrow \mathbf{X}$$

## Classes/properties

Constant · Identity · Linear · Polynomial ·  
Rational · Algebraic · Analytic · Smooth ·  
Continuous · Measurable · Injective · Surjective  
Bijjective

## Constructions

Restriction · Composition ·  $\lambda$  · Inverse

## Generalizations

Partial · Multivalued · Implicit

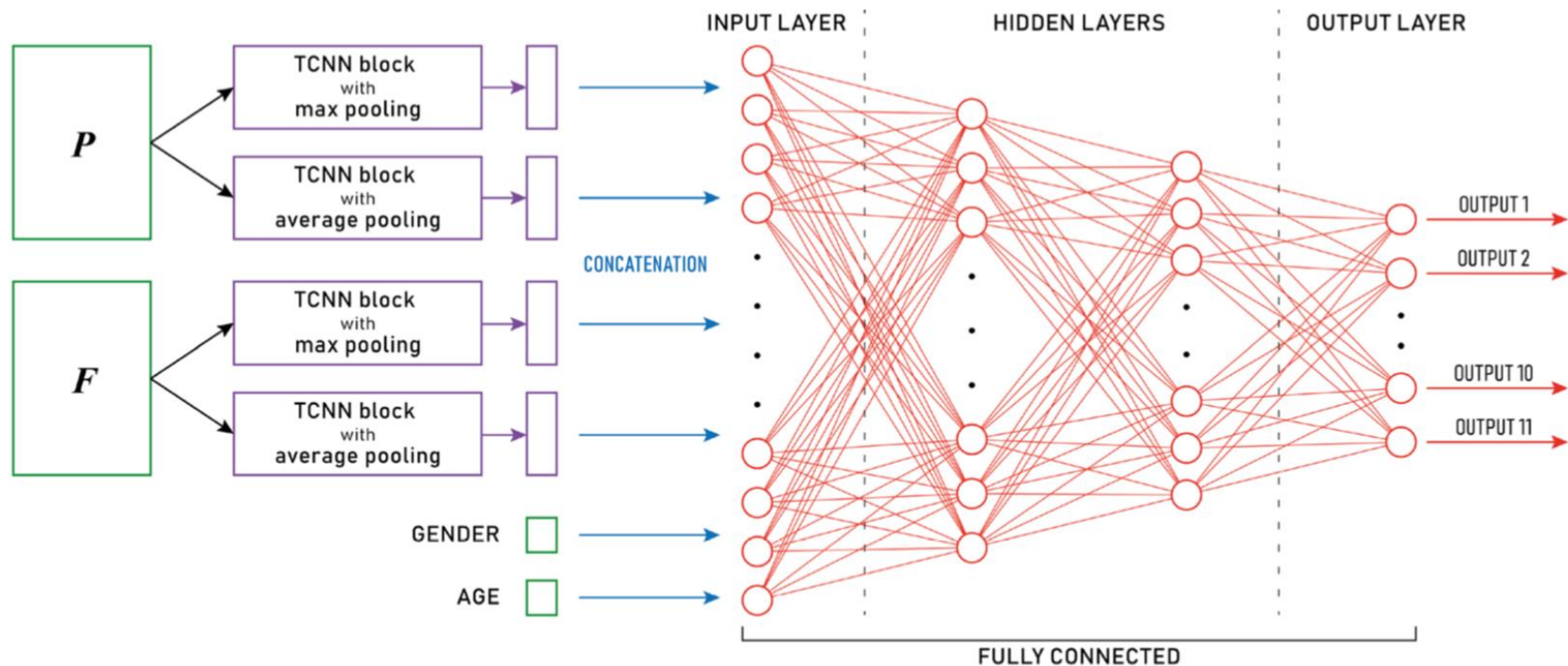
V · T · E

# Rough idea of Data

		Types of data		
		Continuous attributes	Categorical attributes	Mixed attributes
Cardinality of Relationship	Univariate Described by individual attributes (independence)	Type I Extreme value anomaly	Type II Rare class anomaly	Type III Simple mixed data anomaly
	Multivariate Described by multi-dimensionality (dependence)	Type IV Multidimensional numerical anomaly	Type V Multidimensional rare class anomaly	Type VI Multidimensional mixed data anomaly

# Relation between Data and Models

Nelle applicazioni

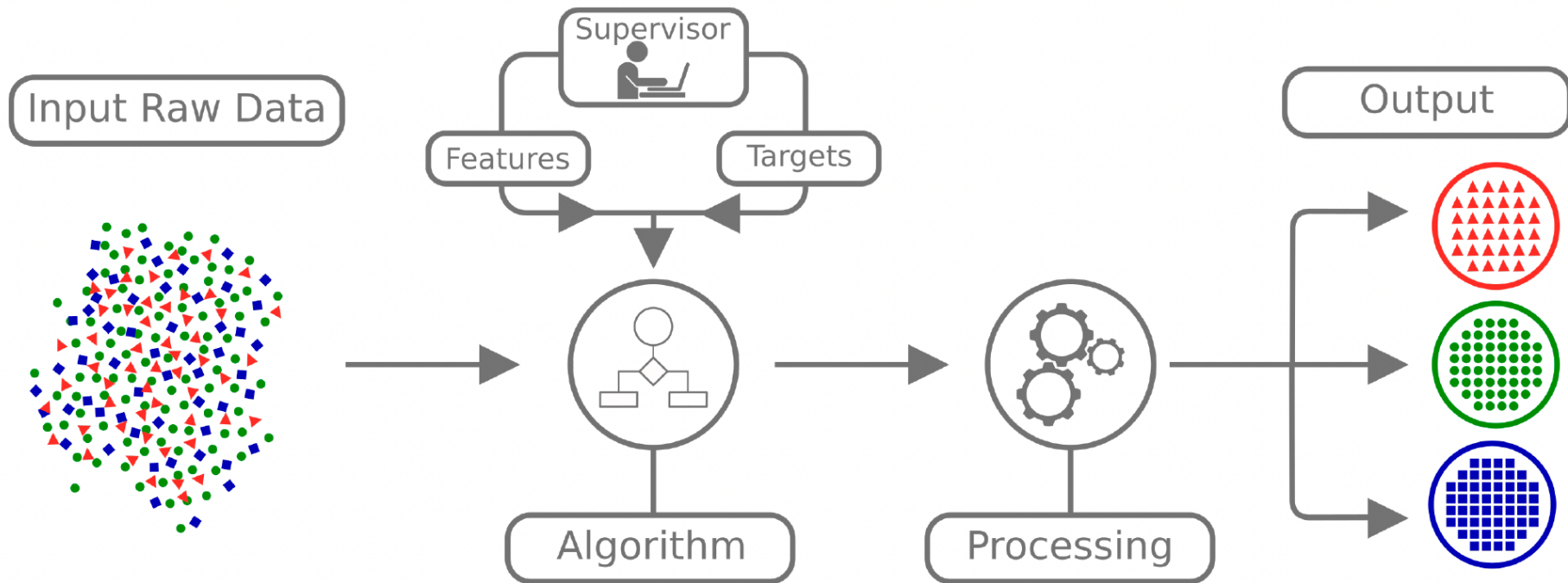


Modello

**Credits:** Piccialli, F., Cuomo, S., Crisci, D., Prezioso, E., & Mei, G. (2020). *A deep learning approach for facility patient attendance prediction based on medical booking data*. *Scientific Reports*, 10(1), 1-11.



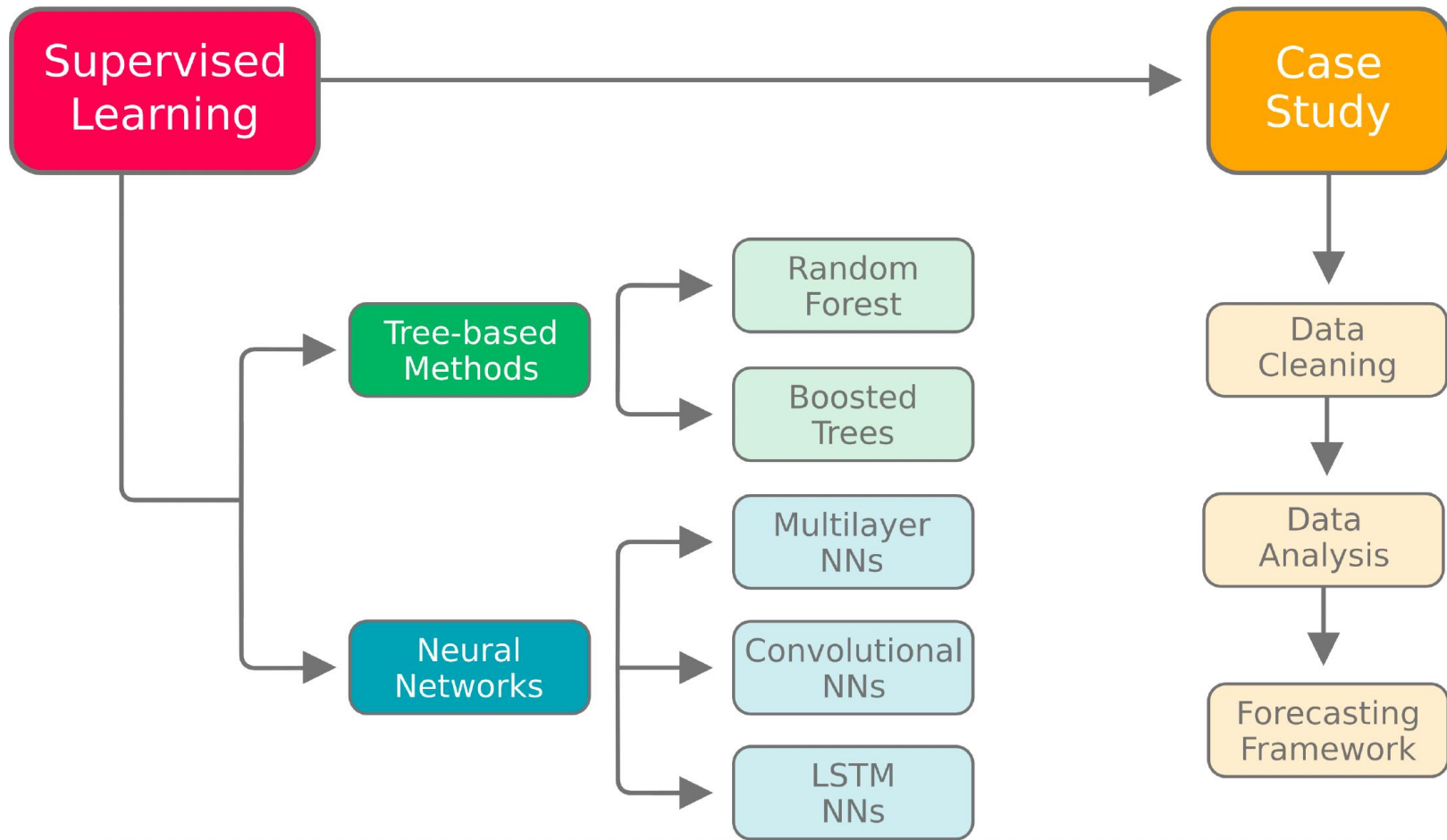
# ML:Supervised Learning



Supervised Learning is an area of ML where a set of **independent variables** are used to **analyse dependent variables and relations** between them.



# How are Neural Networks

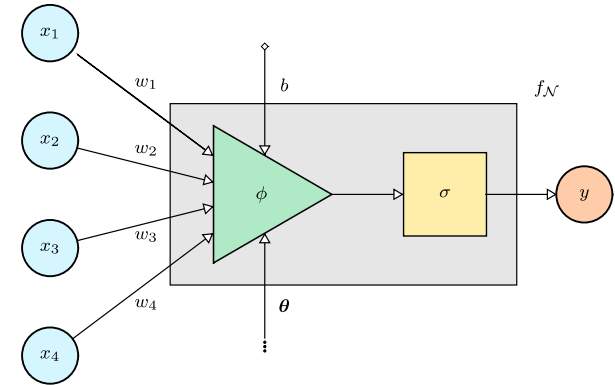


# A Neuron

## Definition (Neuron)

A neuron is defined as the set  $\mathcal{N} = \{\mathcal{M}, \mathbf{w}, b, \boldsymbol{\theta}, \phi, \sigma\}$

- $\mathcal{M} \subseteq \mathbb{R}^N$  is the input set;
- $\mathbf{w} \in \mathbb{R}^N$  is the weights vector;
- $b \in \mathbb{R}$  is the bias;
- $\boldsymbol{\theta} \in \mathbb{R}^P$  are additional parameters of the neuron;
- $\phi : \mathcal{M} \rightarrow \mathbb{R}$  is a parametric function with parameters  $\mathbf{w}$ ,  $b$  and  $\boldsymbol{\theta}$ , named the aggregation function;
- $\sigma : \mathbb{R} \rightarrow \mathbb{R}$  is the activation function of the neuron.



## Definition (Action of a neuron)

Given a neuron  $\mathcal{N} = \{\mathcal{M}, \mathbf{w}, b, \boldsymbol{\theta}, \phi, \sigma\}$ , the action of a neuron is defined as the following function  $f_{\mathcal{N}} : \mathcal{M} \rightarrow \mathbb{R}$  such that:

$$\mathbf{x} \mapsto f_{\mathcal{N}}(\mathbf{x}; \mathbf{w}, b, \boldsymbol{\theta}) = \sigma(\phi(\mathbf{x}; \mathbf{w}, b, \boldsymbol{\theta})) \quad (1)$$

# Feed Forward Neural Network

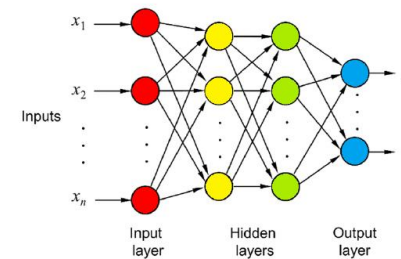
Let be

$$\eta^l = \begin{bmatrix} \eta_1^l \\ \vdots \\ \eta_{n_l}^l \end{bmatrix} \in \mathbb{R}^{1 \times n_l}, \quad \theta^l = \begin{bmatrix} \theta_1^l \\ \vdots \\ \theta_{n_l}^l \end{bmatrix} \in \mathbb{R}^{1 \times n_l}, \quad W^l = \left( w_{ij}^l \right)_{ij} \in \mathbb{R}^{n_l \times n_{l-1}},$$

- ▶  $l$  layer output:  $\eta^l = \mathcal{F}_a (W^l \cdot \eta^{l-1} + \theta^l)$
- ▶ defined:  $\mathcal{W}^l : x \in \mathbb{R}^{n_{l-1}} \mapsto W^l \cdot x + \theta^l \in \mathbb{R}^{n_l}$

The NN with  $L$  layers is  $F_{NN} : \mathbb{R}^n \rightarrow \mathbb{R}^m$ :

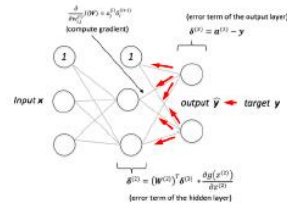
$$\begin{aligned} F_{NN}(x; \mathbf{W}, \boldsymbol{\theta}) &= \hat{y} = \mathcal{F}_a (W^L \cdot \eta^{L-1} + \theta^L) = \\ &= \mathcal{F}_a (W^L \cdot \mathcal{F}_a (W^{L-1} \cdot \eta^{L-2} + \theta^{L-1}) + \theta^L) = \dots = \\ &= (\mathcal{F}_a \circ W^L \circ \mathcal{F}_a \circ W^{L-1} \circ \dots \circ \mathcal{F}_a \circ W^2) (x) \end{aligned}$$



# Time line of the Deep Learning (DL)



1958 Perceptron



1974 Backpropagation



Convolution Neural Networks for Handwritten Recognition

1998



Google Brain Project on 16k Cores

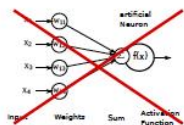
2012

awkward silence (AI winter)

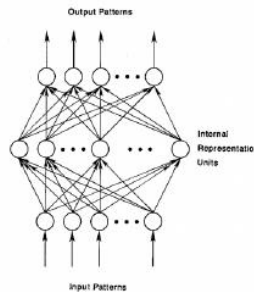


1969 Perceptrons book

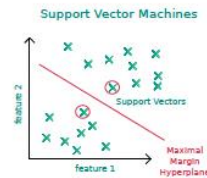
Perceptron criticized



~1980 Multilayer network



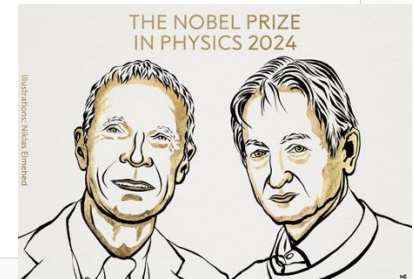
1995 SVM reigns



2006 Restricted Boltzmann Machine



2012 AlexNet wins ImageNet



John J. Hopfield Geoffrey E. Hinton

"for foundational discoveries and inventions that enable machine learning with artificial neural networks"

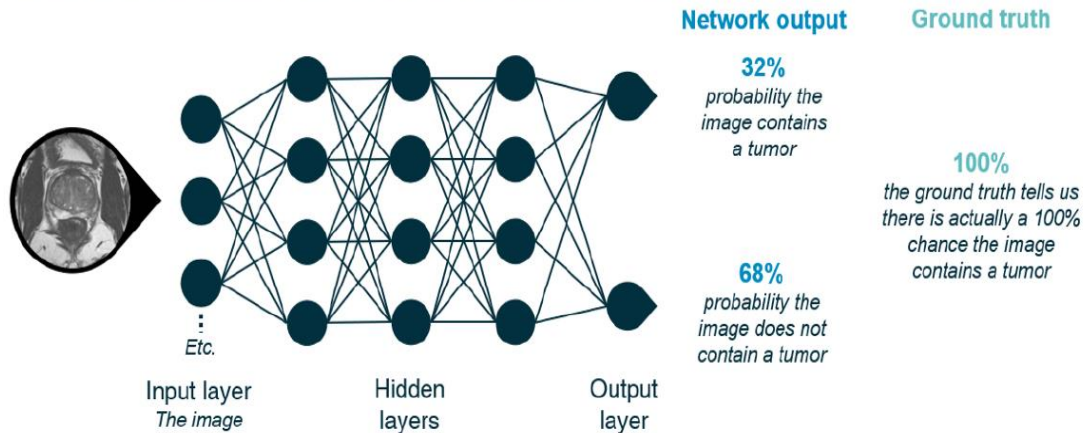
THE ROYAL SWEDISH ACADEMY OF SCIENCES

(Source: Lucas Masuch & Vincent Lepetit)

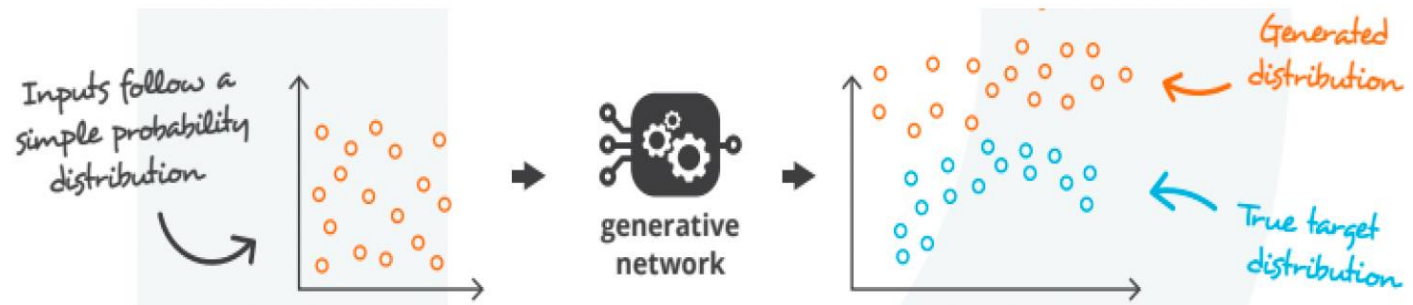
# DL – AI models

## DEEP LEARNING (DL)

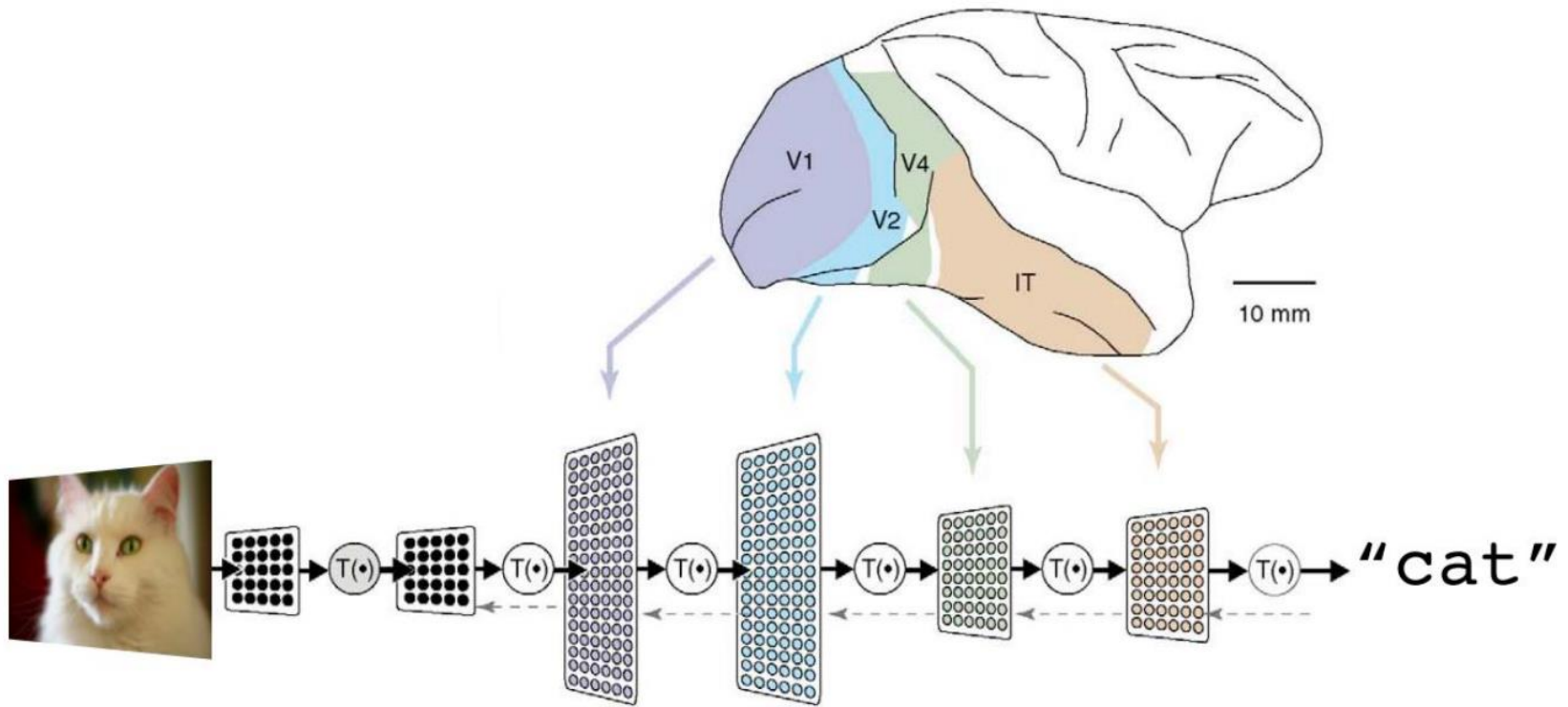
Example: Calculating the cost of a neural network



**GANs** are a class of **deep learning** methods



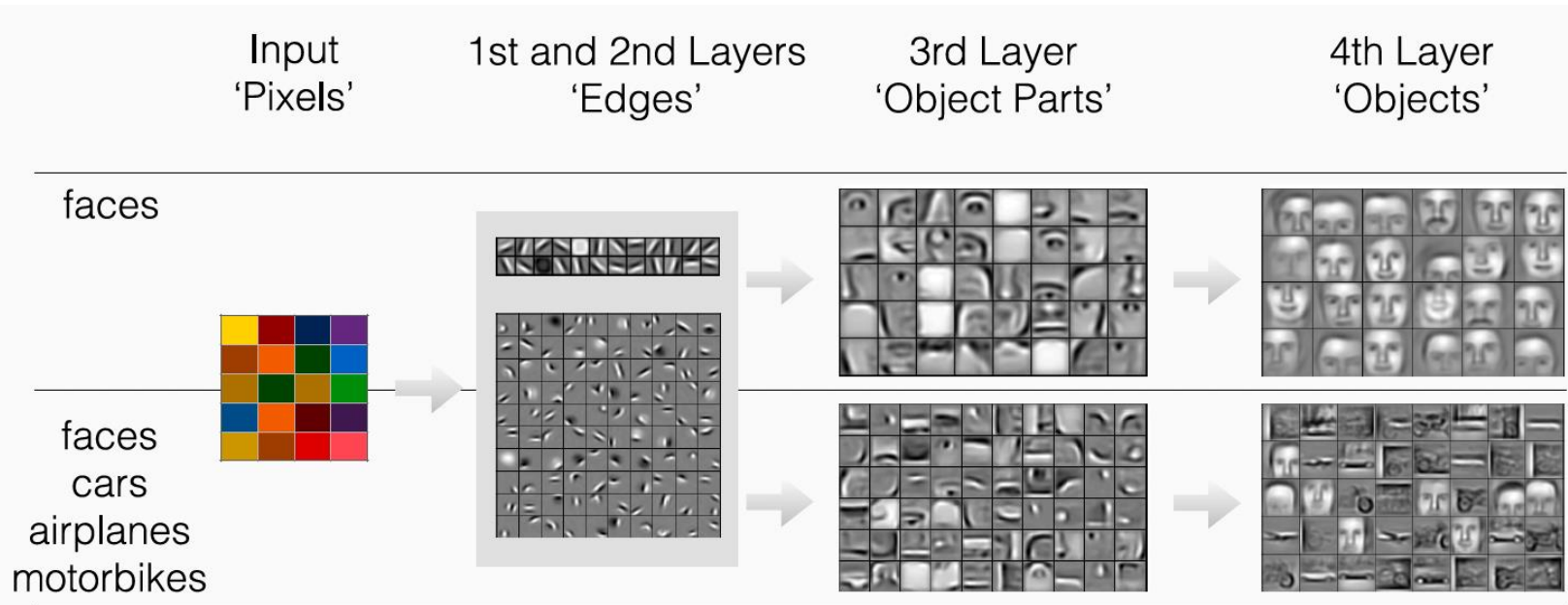
# DL basic architecture



A deep neural network consists of a **hierarchy of layers**, whereby each layer **transforms the input data** into more abstract representations (e.g. edge -> nose -> face). The output layer combines those features to make predictions.

(Source: Lucas Masuch)

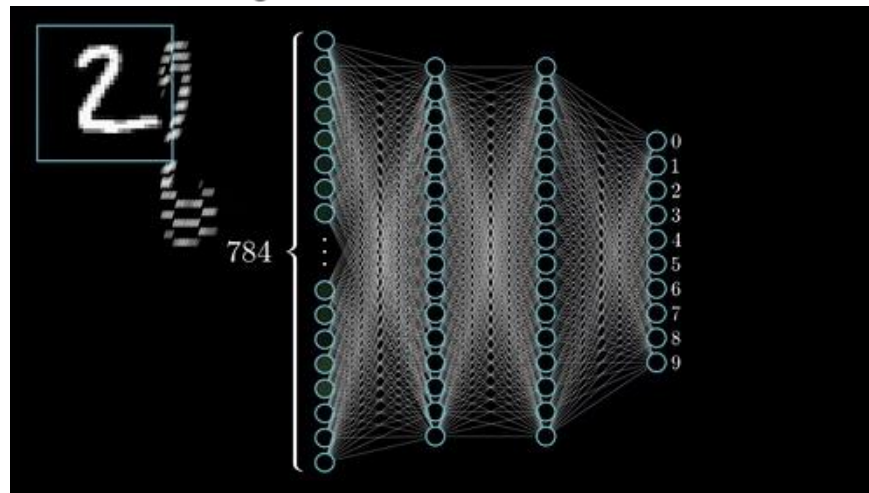
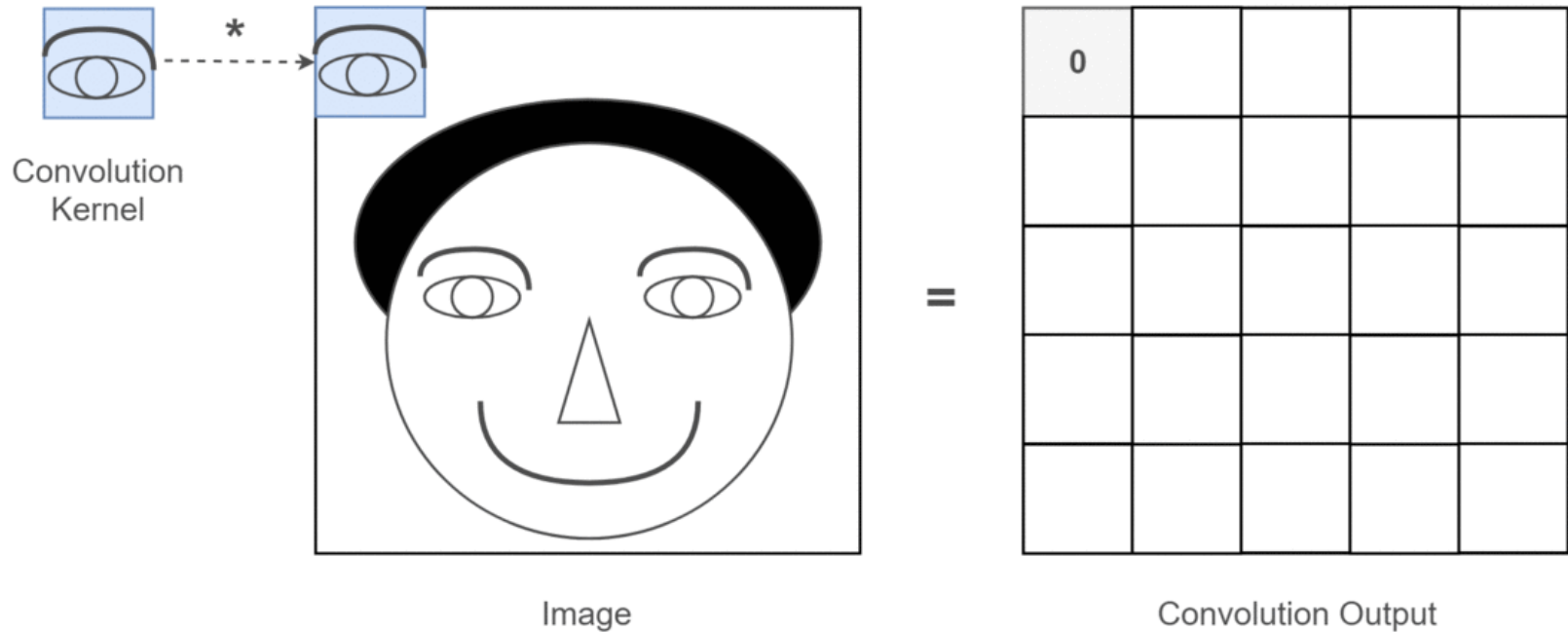
# DL feature hierarchy



Each layer **progressively extracts higher level features** of the input until the final layer essentially makes a decision about what the input shows. The more layers the network has, the higher level features it will learn.

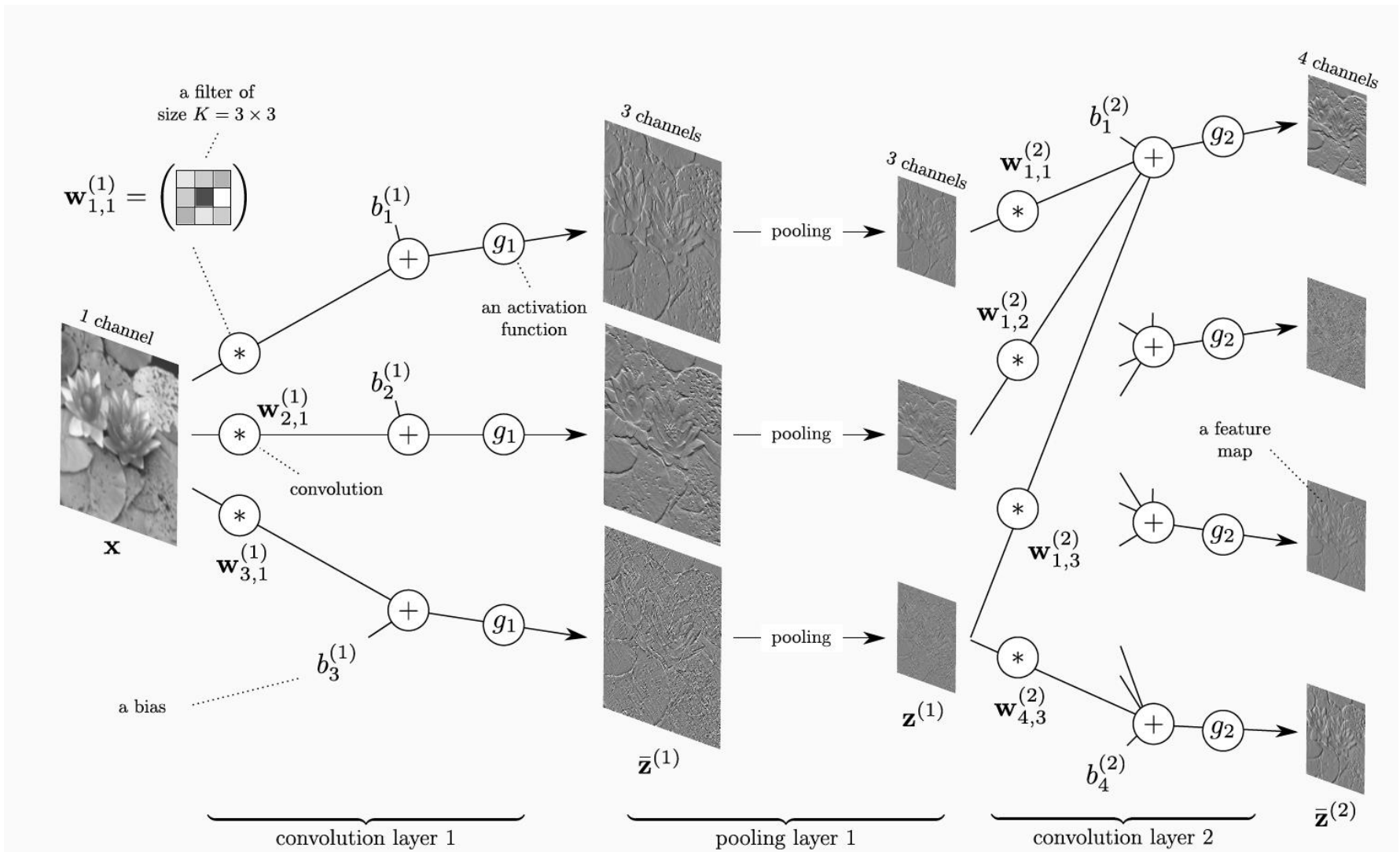
*(Source: Andrew Ng & Lucas Masuch & Caner Hazırbaş)*

# Convolutional Neural Networks

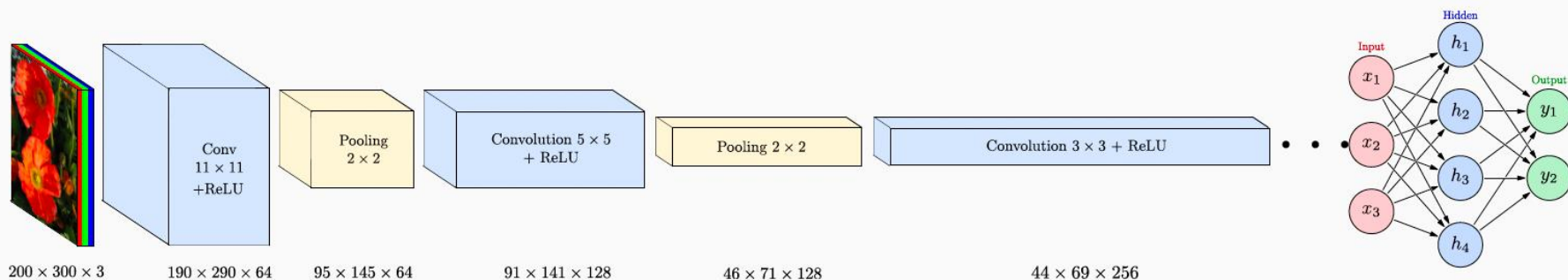




# CNN for Image Processing



# CNN main concepts



**CNN:** Alternate:  
Conv + ReLU + pooling

**End of network:**

Plug a standard neural network:

Fully connected hidden layers  
(linear) + ReLU

**Full network:**

- **CNN:** Extract features specific to spatial data
- **Fully connected part:** Use CNN features for specific regression/classification task
- **Training:** Learn regression/classification and feature extraction **jointly**

# Math and AI



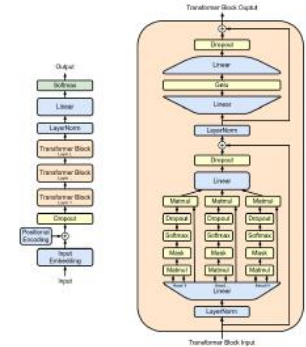
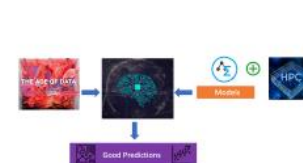
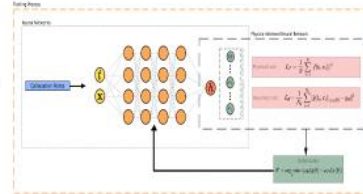
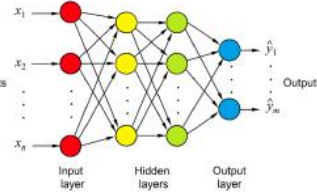
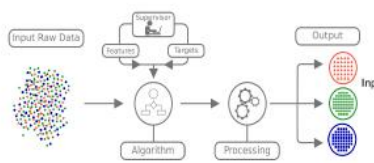
ML

ML+ NN

PINNs

SciML

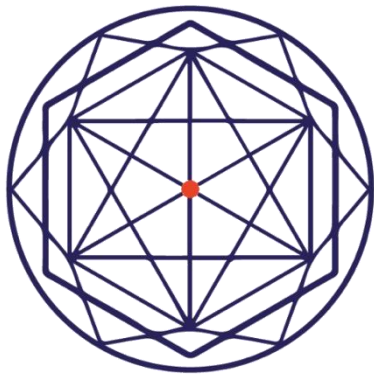
Generative AI Models



## About Mathematical Aspects



...end of the first part...



M • O • D • A • L

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— Data Analysis Laboratory

