CONSIGLIO NAZIONALE DEGLI INGEGNERI

ANCE ASSOCIAZIONE NAZIONALE COSTRUTTORI EDILI

FORMEDIL ENTE UNICO FORMAZIONE E SICUREZZA

Utilizzo di tecnologie con Intelligenza Artificiale per la gestione in sicurezza del cantiere

Prof. Eng. Giuseppe C. Marano

Politecnico di Torino, DISEG, ArtIStE

CONTENUTI

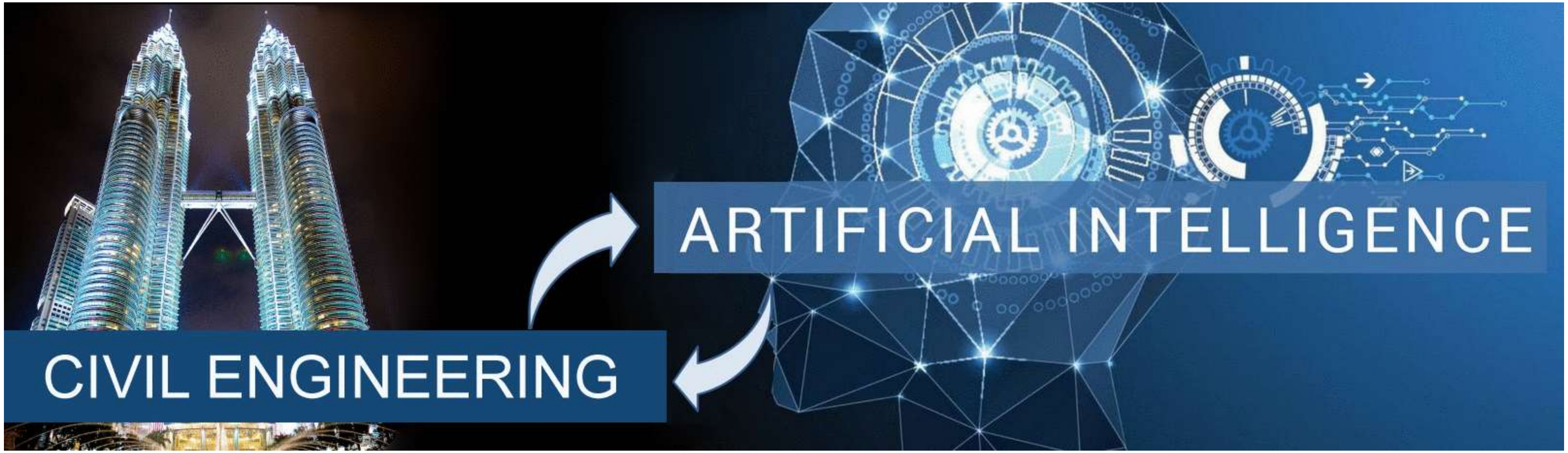
Panoramica sui tipi di Intelligenza Artificiale (IA) e il loro uso:

apprendimento automatico supervisionato e non

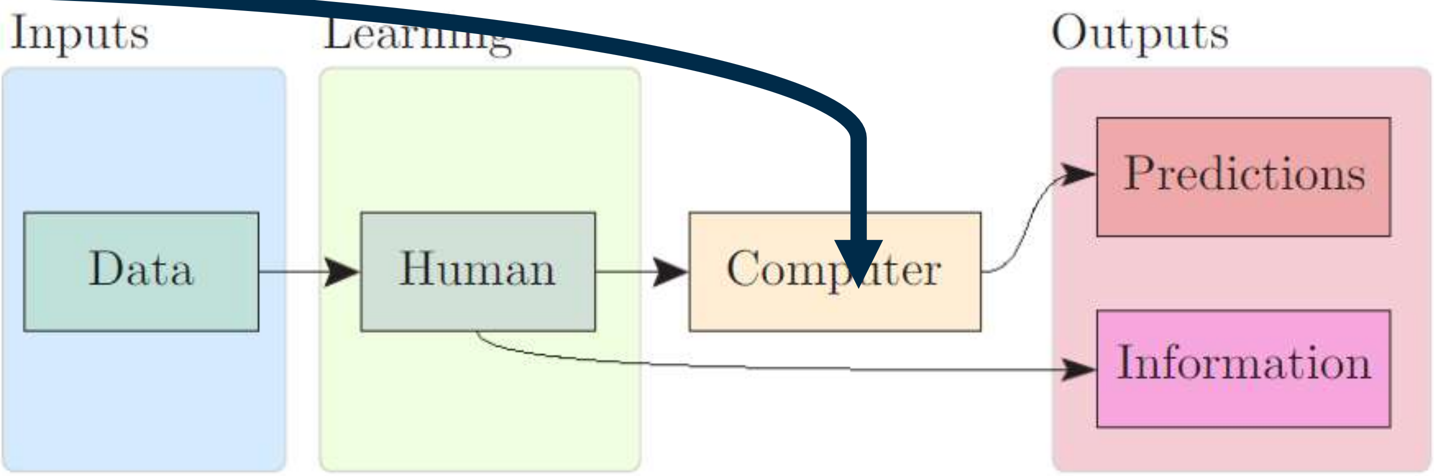
le reti neurali

Le Intelligenze artificiali discriminative e generative a supporto dell'ingegneria civile;

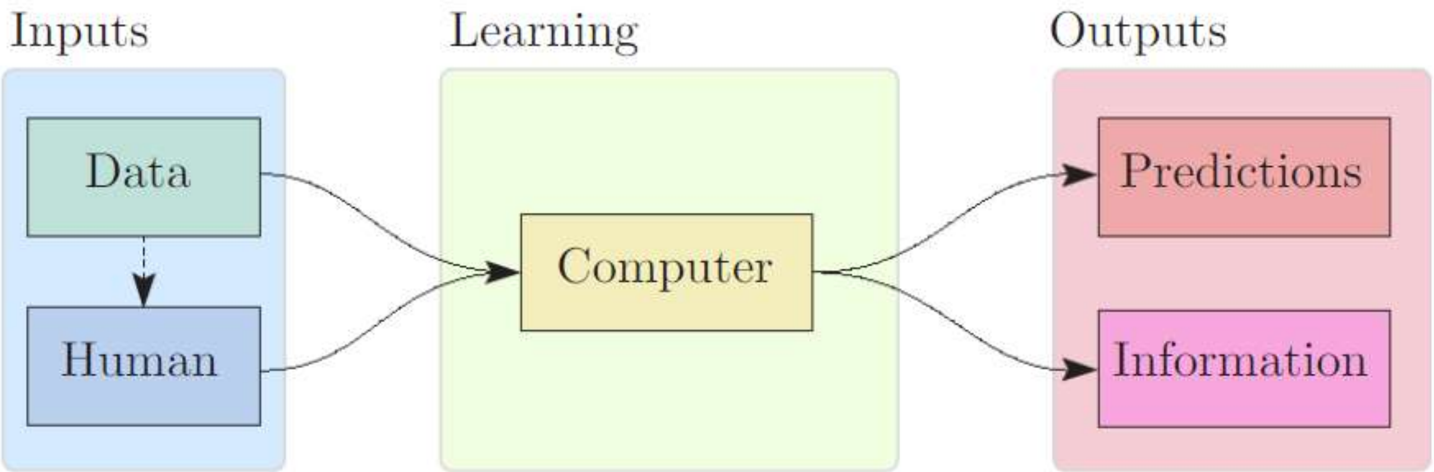
La nuova era dell Artificial Intelligence



```
4700 GOTO 5000
4790 :
4800 REM   --------------------
4801 REM   --- DARSTELLUNG ---
4802 REM   --- DES MANUALS ---
4803 REM   --------------------
4810 :
4820 PRINT"";
4825 W=V+1:IF W<0 THEN W=W+14
4830 FOR X=1 TO 2:PRINT"";
4835 FOR I=0 TO 23
4840 PRINT MD$(I+W);
4850 NEXT:PRINT:NEXT
4860 PRINT"";
4870 FOR I=0 TO 23
4880 IF MD$(I+W)=CHR$(32) THEN PRINT MB$
(I+1);:GOTO 4900
4890 PRINT MD$(I+W);
4900 NEXT
4910 PRINT:PRINT"";
4920 FOR I=2 TO 24 STEP 2
4925 PRINT"|";
4930 IF MD$(I+W-1)=" " THEN PRINT"
";:GOTO 4940
4935 PRINT" ";
4940 NEXT:PRINT""
4950 PRINT"";
4960 FOR I=2 TO 24 STEP 2
4965 PRINT"|";
4970 IF MD$(I+W-1)=" " THEN PRINT""
MB$(I)"";:GOTO 4980
4975 PRINT MB$(I);
4980 NEXT:PRINT""
```



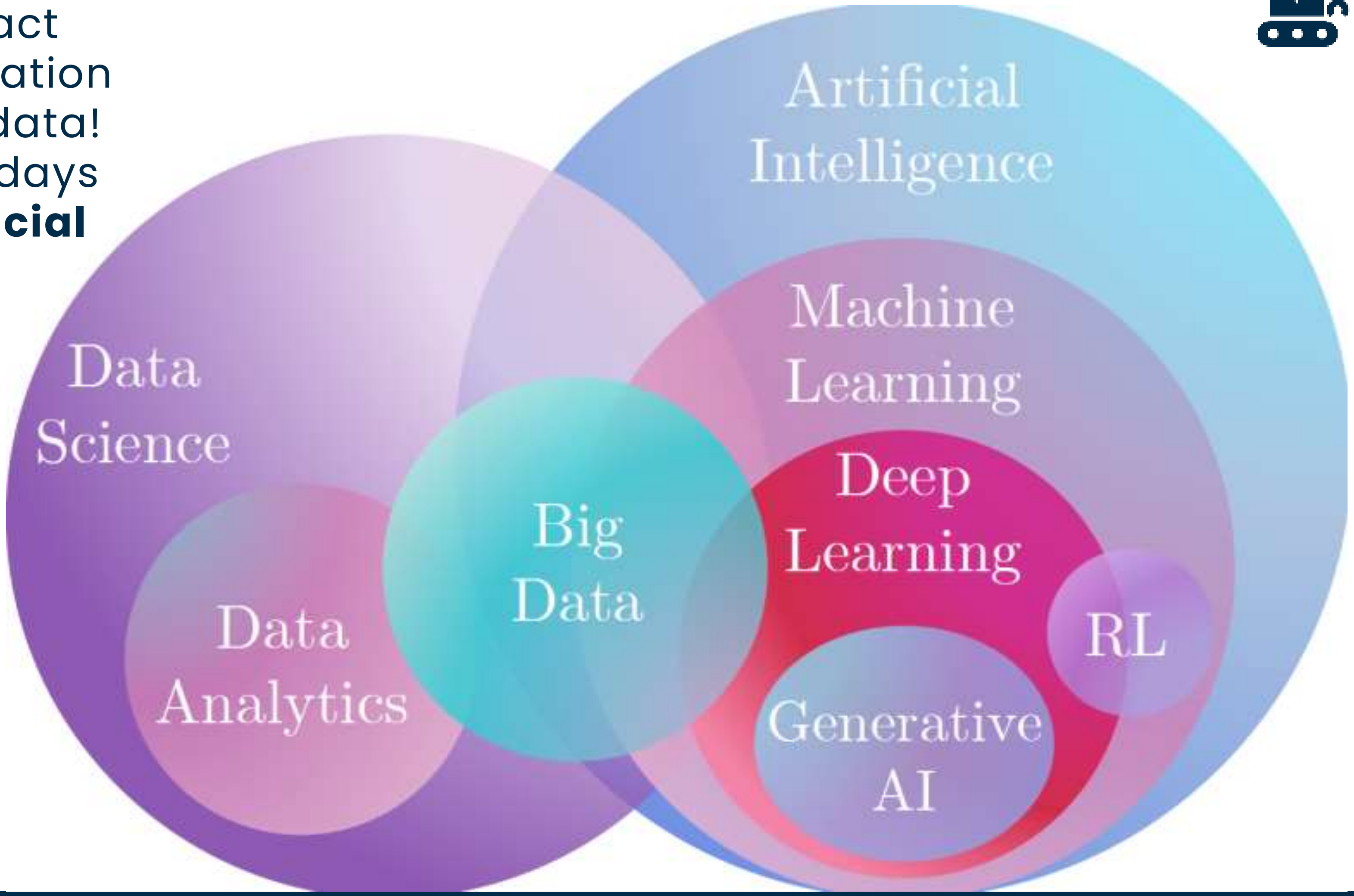
(a) Without machine learning



(b) With machine learning

Artificial Intelligence sottocampi:

Extract information from data! Nowadays is **crucial**

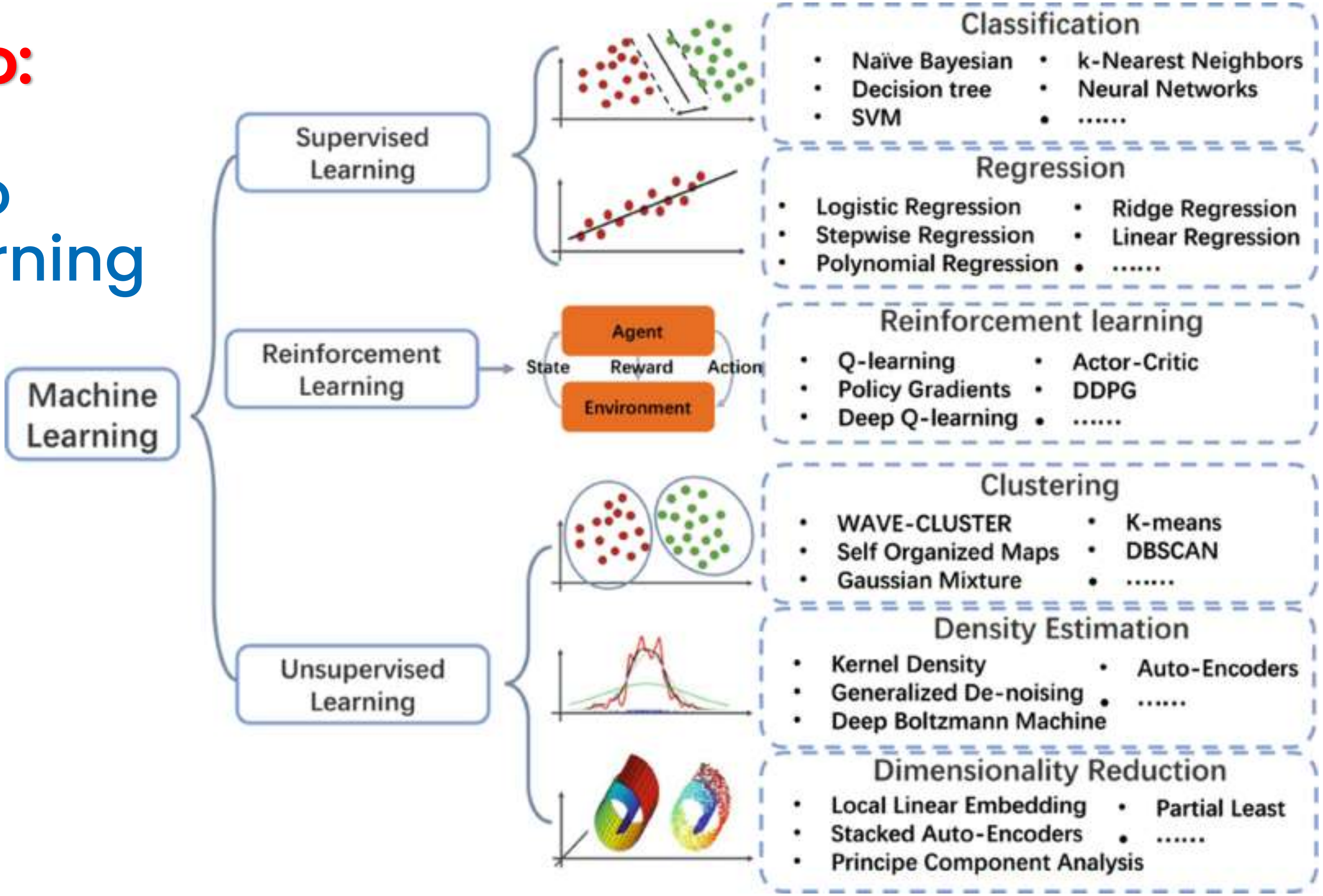


AI : simulation of Intelligent human-like behaviour

Machine Learning is a type of Artificial Intelligence that provides computers with the ability to learn without being explicitly programmed.
Learn from examples
Pattern Recognition

Tipi di Apprendimento:

- Supervisionato
- Non Supervisionato
- Reinforcement Learning

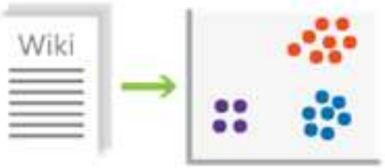


Machine Learning - Basics

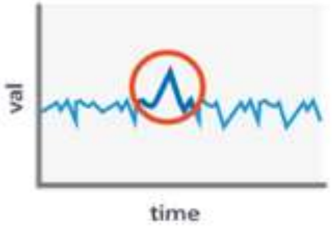
Problem Types

Classification
(supervised – predictive)

Regression
(supervised – predictive)

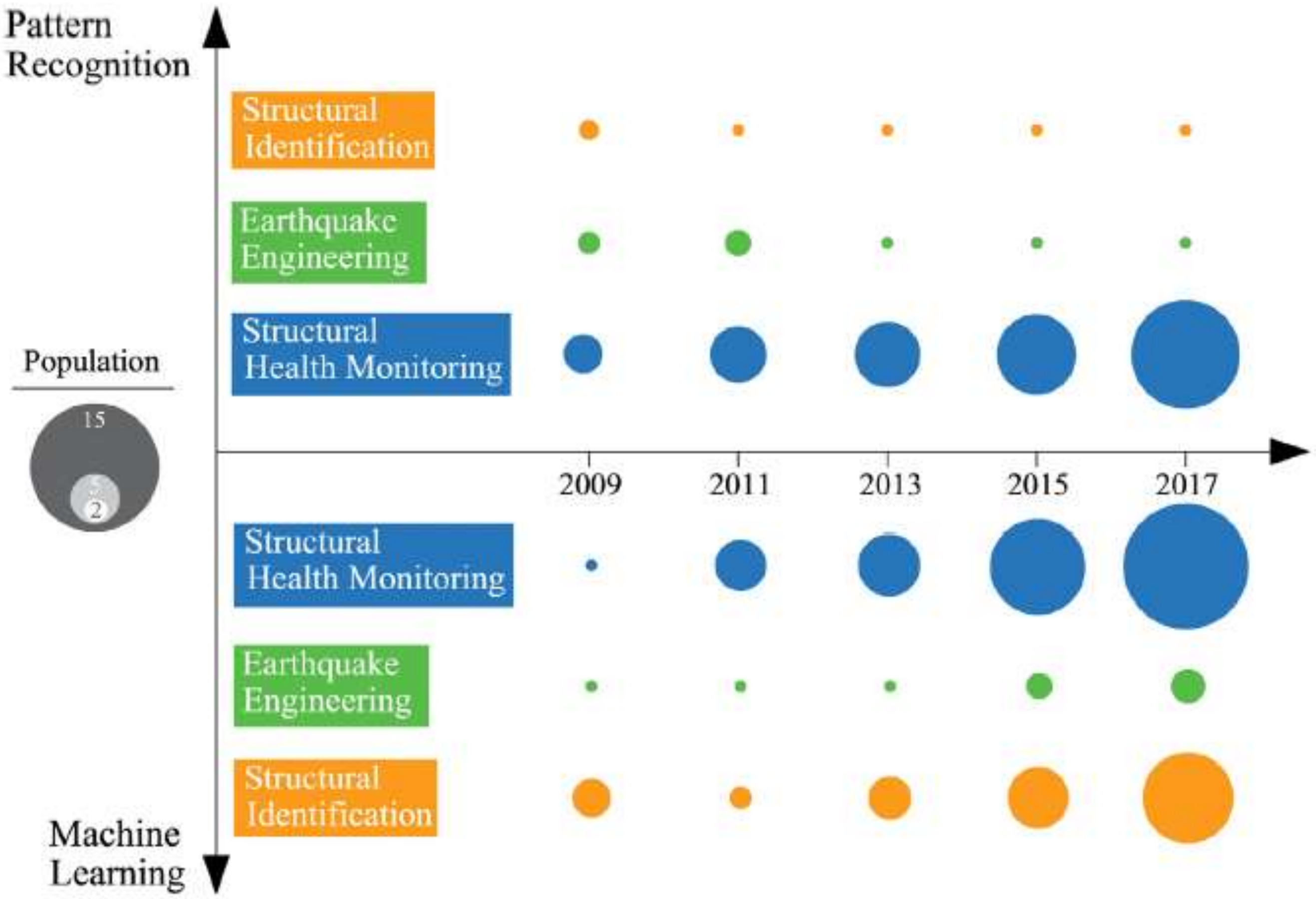


Clustering
(unsupervised – descriptive)

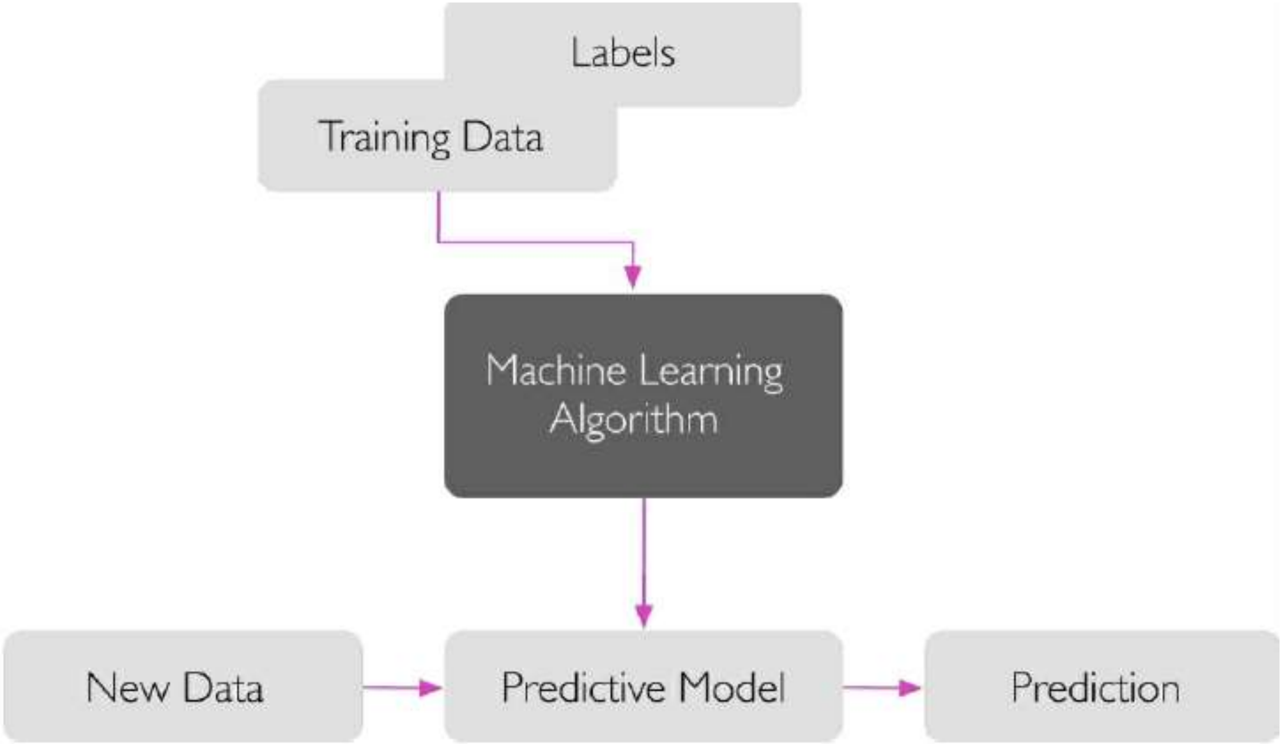


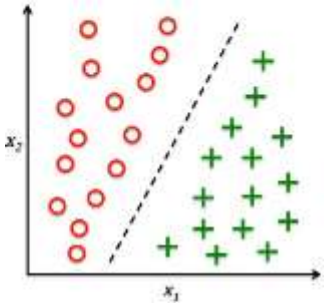
Anomaly Detection
(unsupervised– descriptive)

Applicazione del Machine learning(ML) e Pattern Recognition(PR)



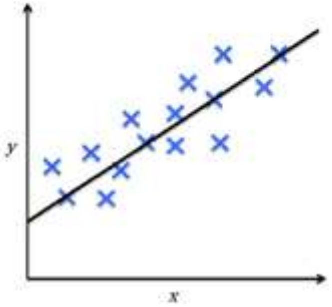
Supervised Learning





- **Classification Problem**

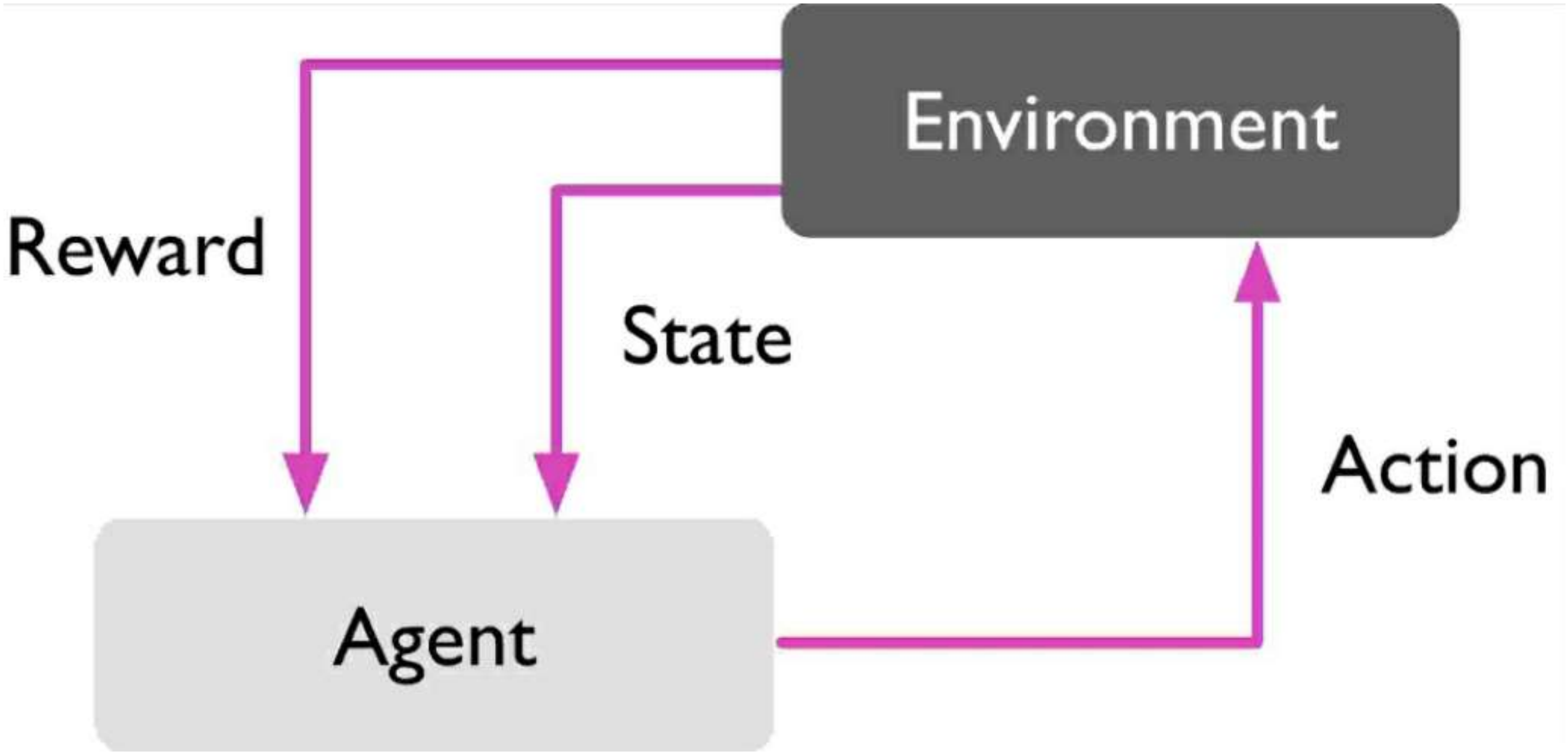
with discrete class labels



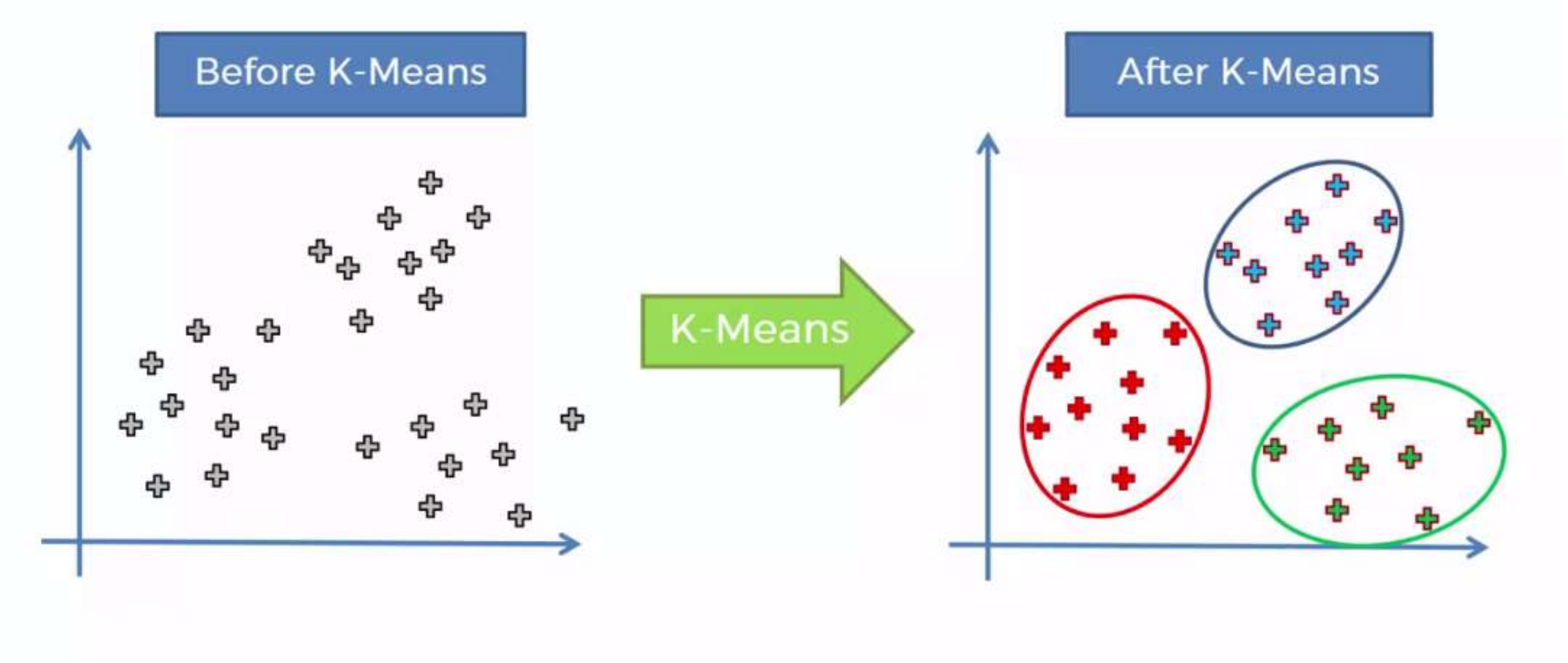
- **Regression Problem**

where the outcome is a continuous value

Reinforcement Learning

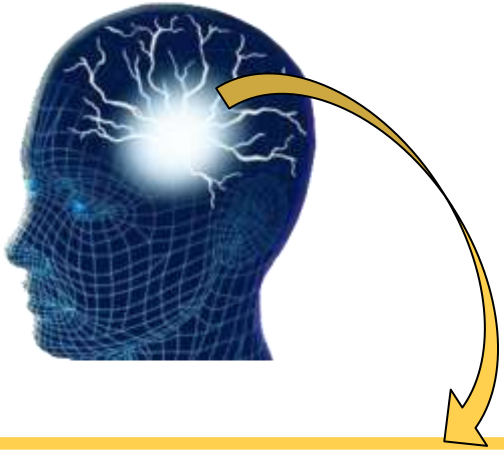


Unsupervised Learning Example of Clustering



Cosa e' il Deep Learning?

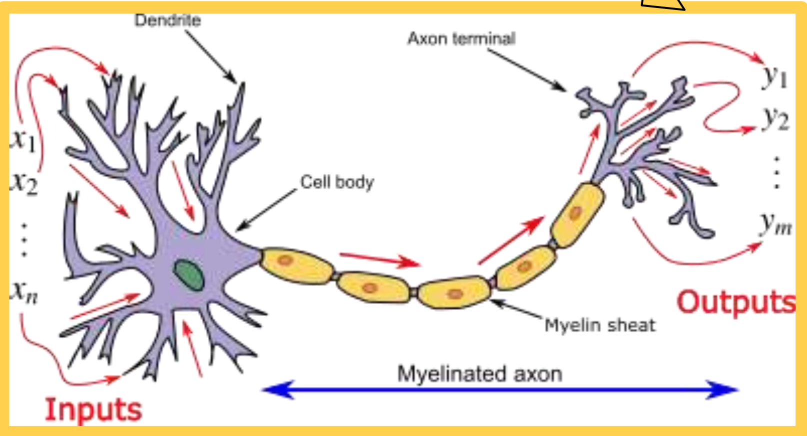
Inspired by Nature, Brain and Neuroscience



Part of the machine learning field of learning representations of data. Exceptional effective at learning patterns.

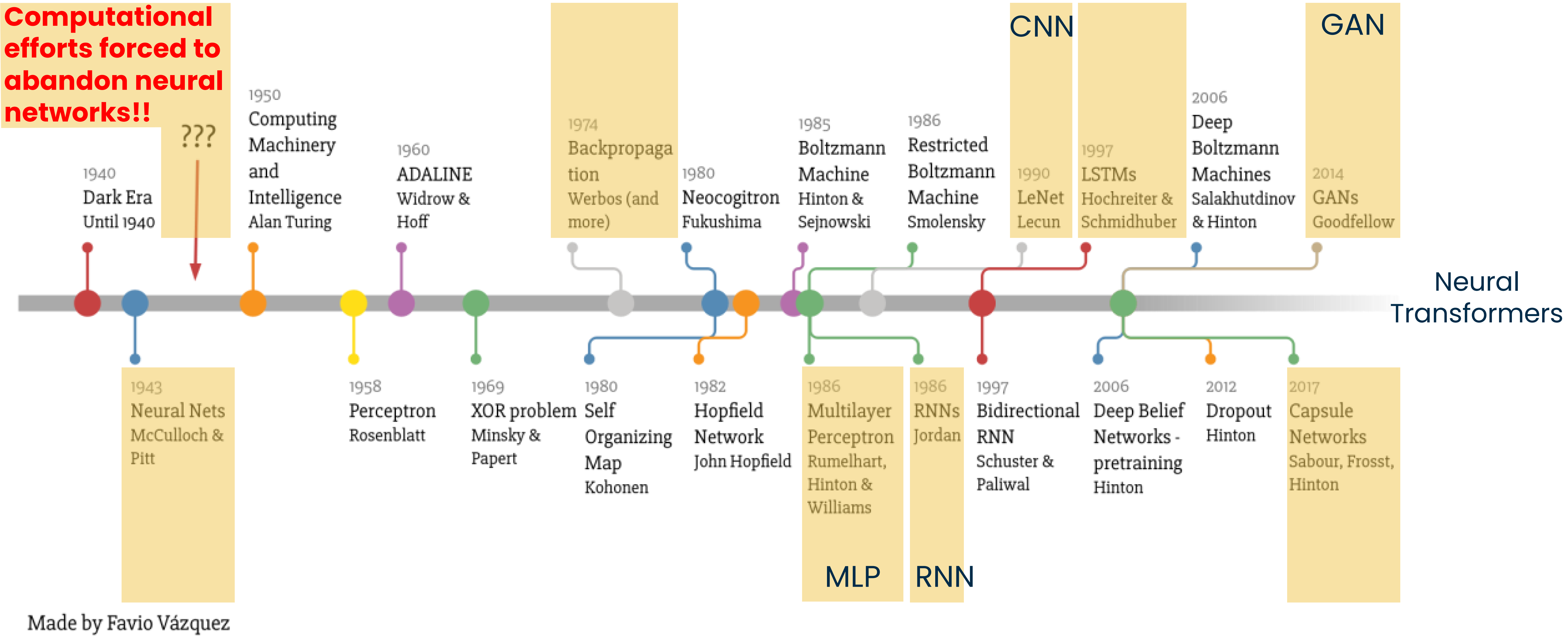
Utilizes learning algorithms that derive meaning out of data by using a hierarchy of multiple layers that mimic the neural networks of our brain.

If you provide the system tons of information, it begins to understand it and respond in useful ways.



Phenomenological model (schematization) of a neuron

Deep Learning Timeline

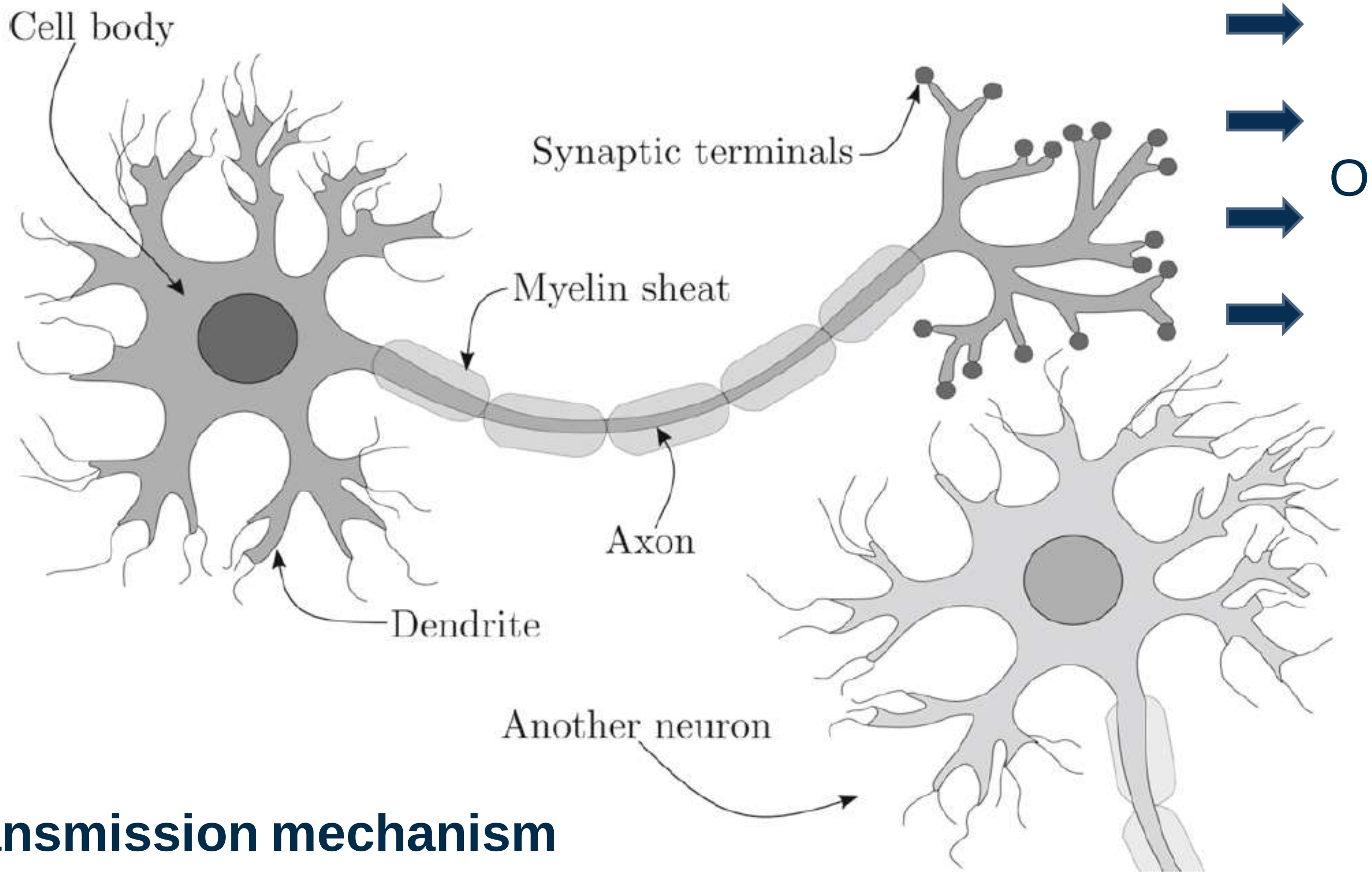


Artificial Neural Network (ANN)
McCullock-Pitts (MCP) Neuron (1943)

Historically, Neuroscience and Biology wanted to explain how the human brain works

Input signals

Coming from other neurons



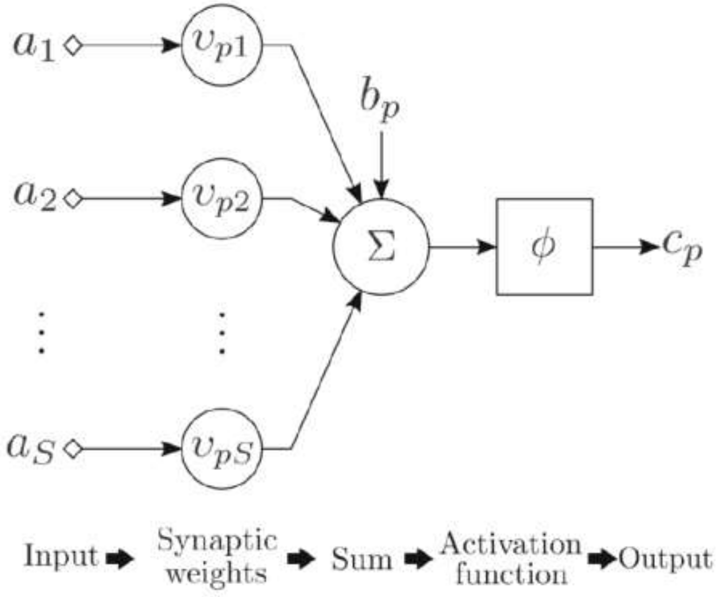
Output signals

Chemical or electrical transmission to other neurons

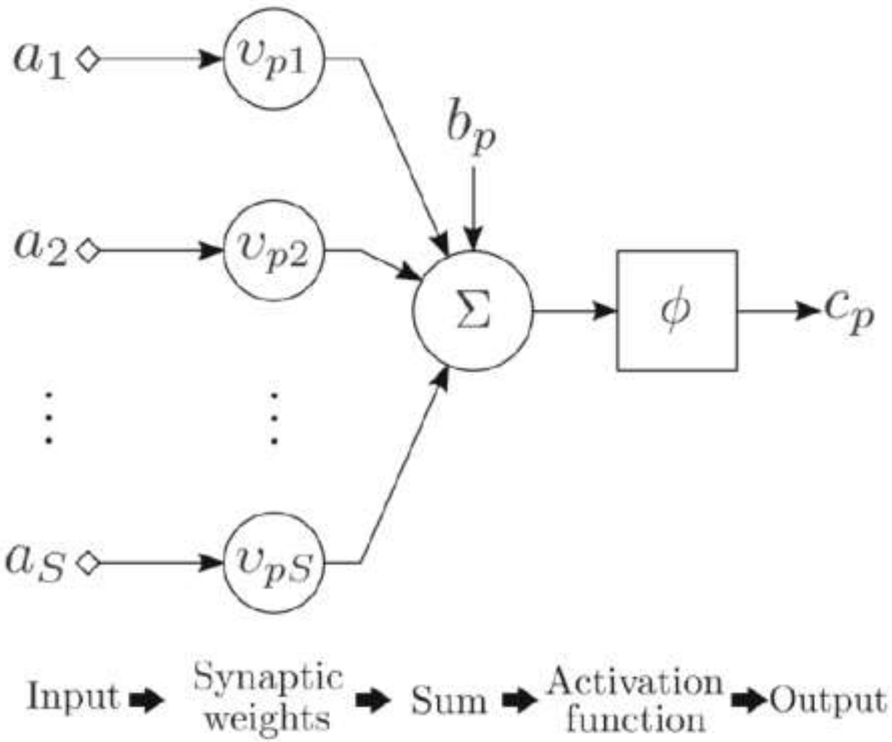
One-way signal transmission mechanism

Artificial Neural Network
McCullock-Pitts (MCP) Neuron (1943)

- Simplified as a logic gate with binary output [0,1] (or [-1,1])
- Accumulated input signal reach a threshold value the output signal is transmitted through the axon
- Few years later F. **Rosenblatt** formalize the **Perceptron rule (ANN with one neuron only)**



Artificial Neural Network
Perceptron (Rosenblatt 1957)



Simulation of a real neuron as information processing unit

- Input (a_q) at each synapsis get weighted (v_{pq}) by the neuron

$$\boldsymbol{v}^{\boldsymbol{T}} \cdot \boldsymbol{a}$$

- An external bias (b_p) could be considered
- An activation function (ϕ) governs the output (c_p)

$$c_p = \phi\left(\sum_{q=1}^{S} a_q v_{pq} + b_p\right)$$

- The bias could be considered in the weight vector as the first term associated to a unit input

$$\boldsymbol{v} = \left[b_p, v_{p1}, \dots, v_{pS}\right]^T \quad \Rightarrow \quad z = \boldsymbol{v}^{\boldsymbol{T}} \cdot \boldsymbol{a} \quad \Rightarrow \quad c_p = \phi(z)$$

$$\boldsymbol{a} = [1, a_1, \dots, a_S]^T$$

Funzioni di attivazione: input z è ridotto ad un binario

- **Heaviside** function (step function which output is comprised in [-1,1])

Threshold value

$$\phi(z) = \begin{cases} 1 & \text{if } z \geq \theta \\ -1 & \text{otherwise} \end{cases}$$

- **Sigmoid** function (continuous function, most adopted, output in [0,1])

$$\phi(z) = \frac{1}{1+e^{-z}}$$

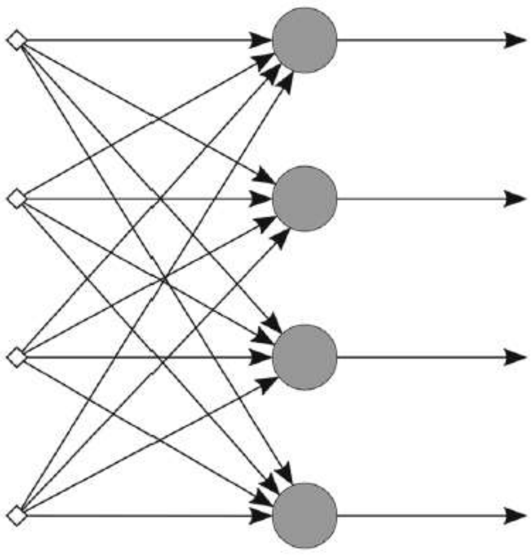
This model of perceptron is called **Feed-Forward Neuron.**

A Feed-forward Neural Network (**FNN**) combines more perceptron in layers

Training is done with **Back-propagation technique** (chain rule of derivatives)

Esempi di architetture per l'ANN combining a number of perceptrons

Single-layer FNN

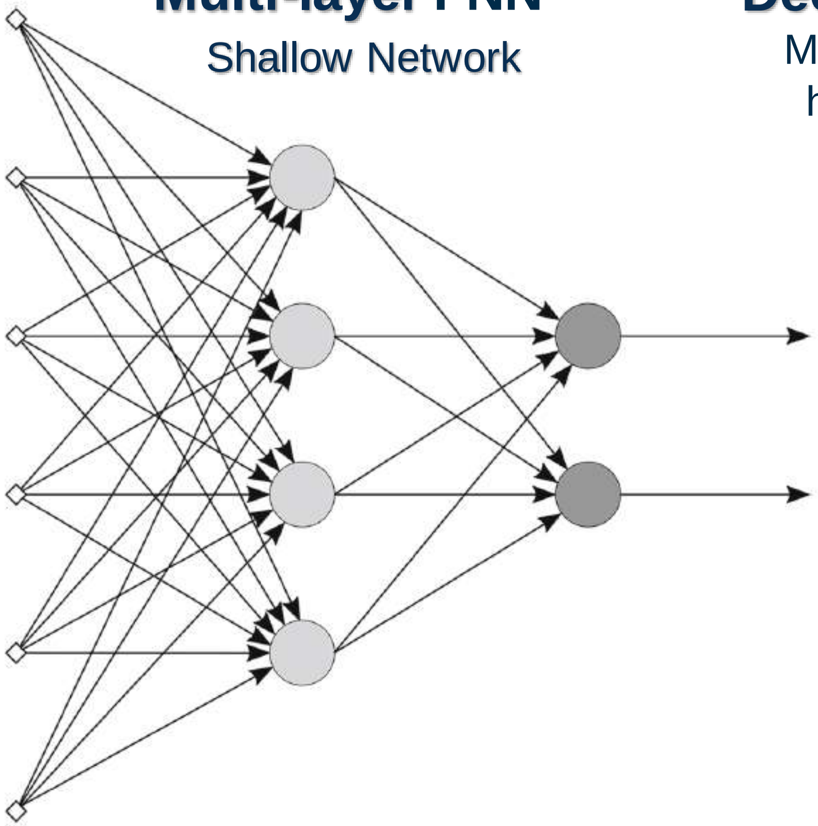


Input layer of source nodes

Output layer of artificial neurons

Multi-layer FNN

Shallow Network



Input layer of source nodes

Hidden layer

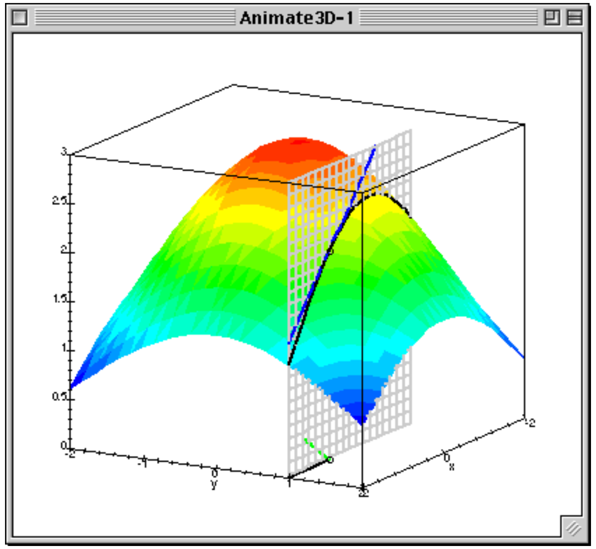
Output layer of artificial neurons

Deep Network

More than one hidden layer

Come le reti neurali apprendono…?
Gradient descendent algorithm and Backpropagation

The gradient of the error function w.r.t. the weights is needed. The derivatives are computed by using the backpropagation rule (chain rule among the neurons) Iterative



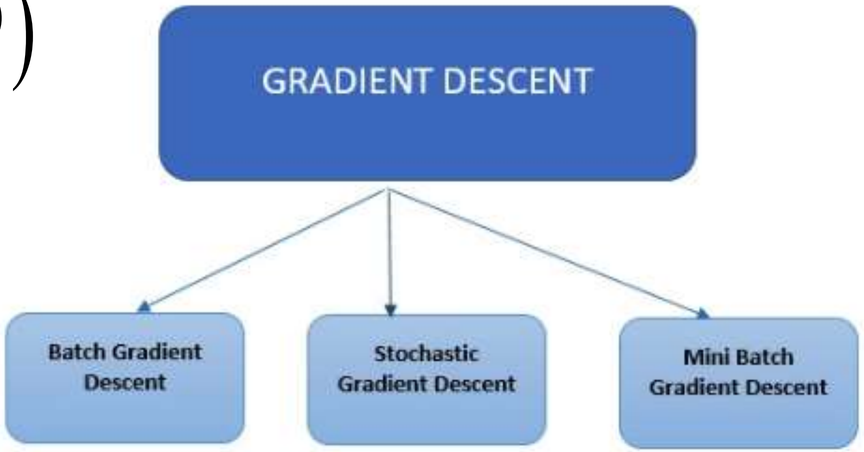
$$\theta^{(i+1)} = \theta^{(i)} + \mu^{(i)} f^{(i)}$$

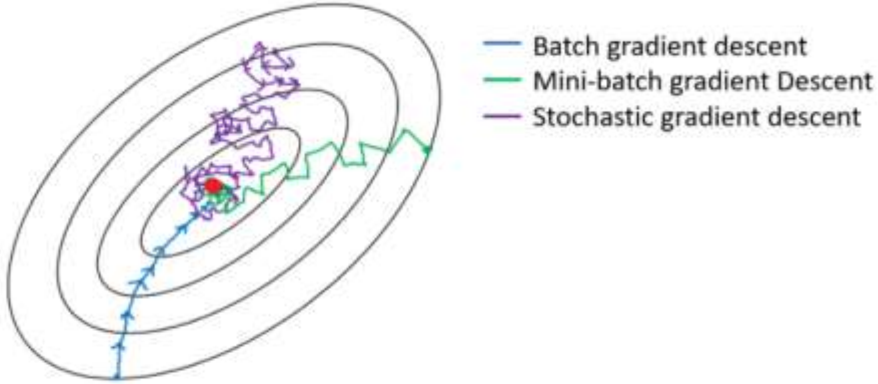
$$f^{(i)} = -G\left(\theta^{(i)}\right)$$

Gradient of the loss function w.r.t. the weights

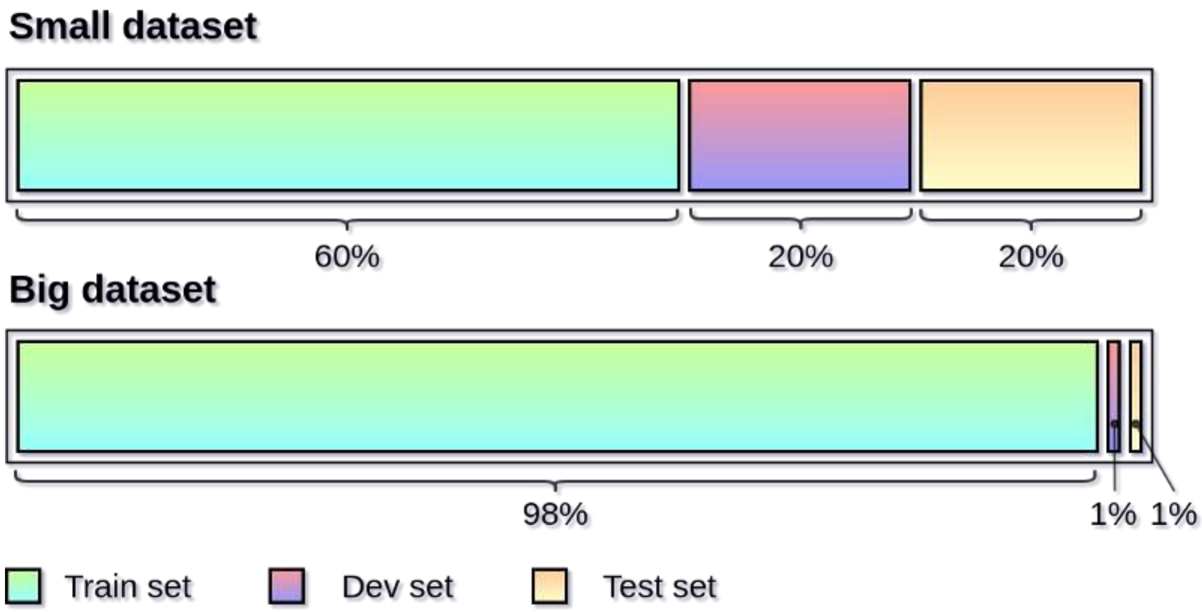
$$\theta^{(i+1)} = \theta^{(i)} - \mu^{(i)} G\left(\theta^{(i)}\right)$$

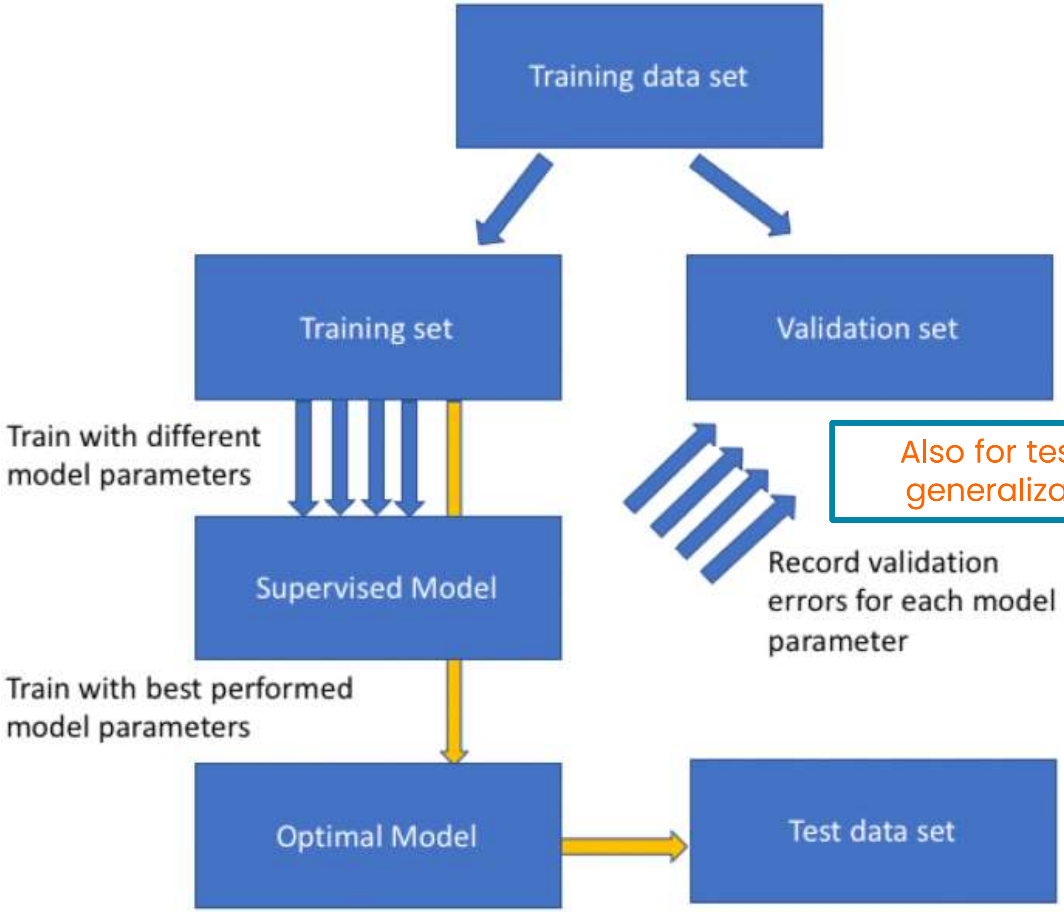
learning rate





Training set, validation set and test set





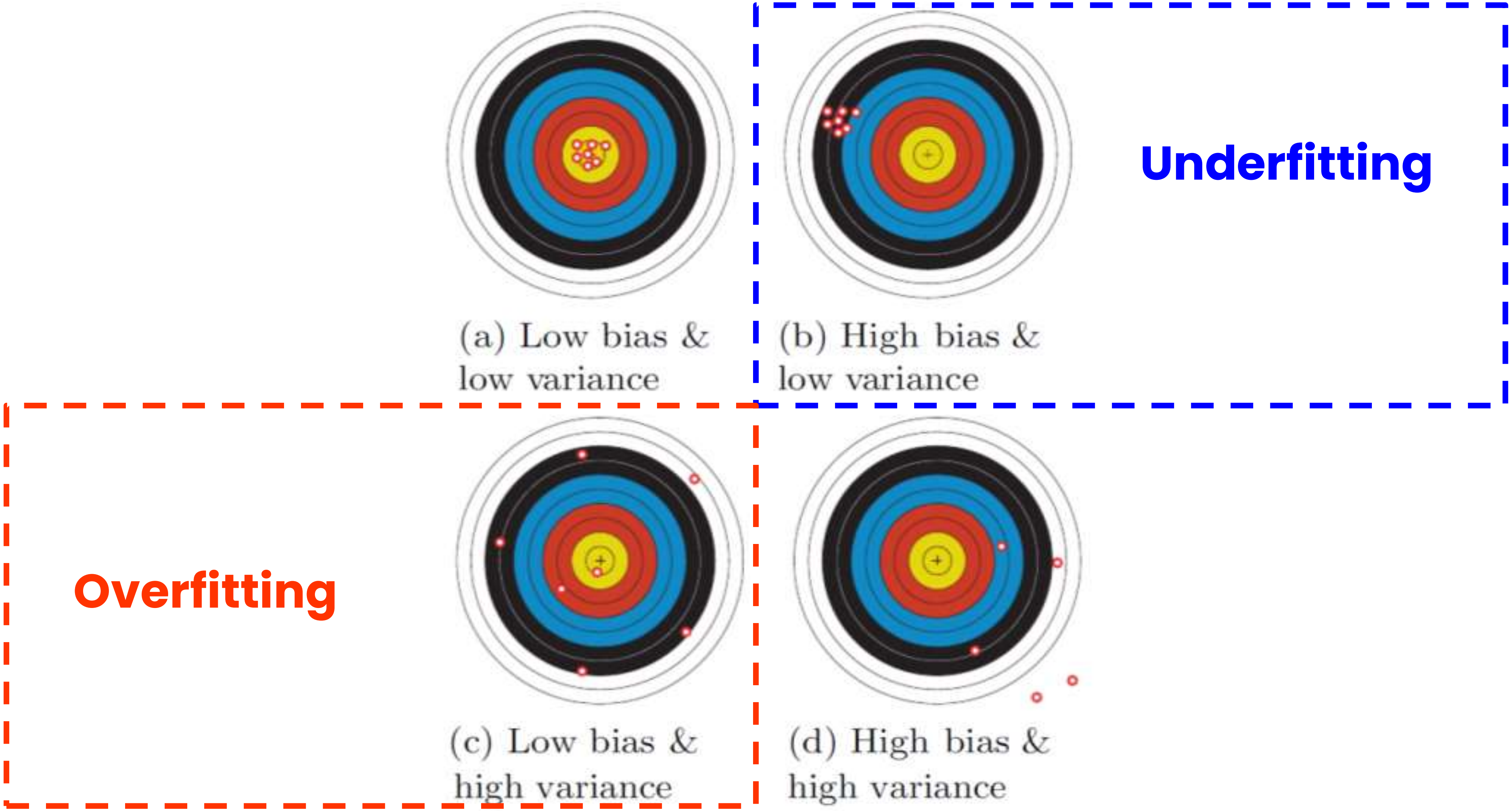
Also for testing generalization

Complessità: l'overfitting

The model is capable of adapting to the training data is said to have a large capacity.

Overfitting: model fits well training dataset, but it fails to provide good predictions for other covariates that were not seen during training.

Model complexity: overfitting and underfitting



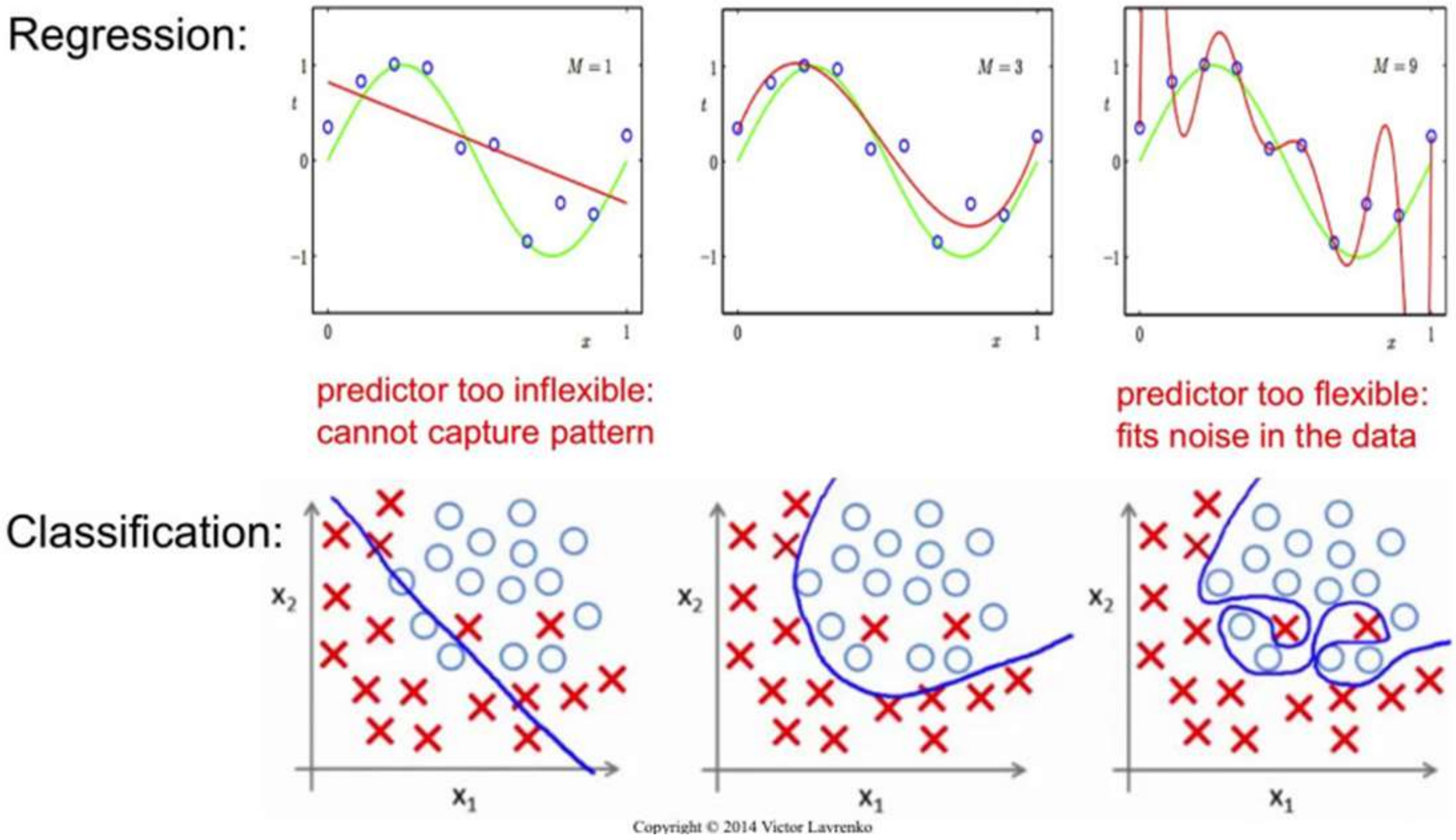
(a) Low bias & low variance

(b) High bias & low variance

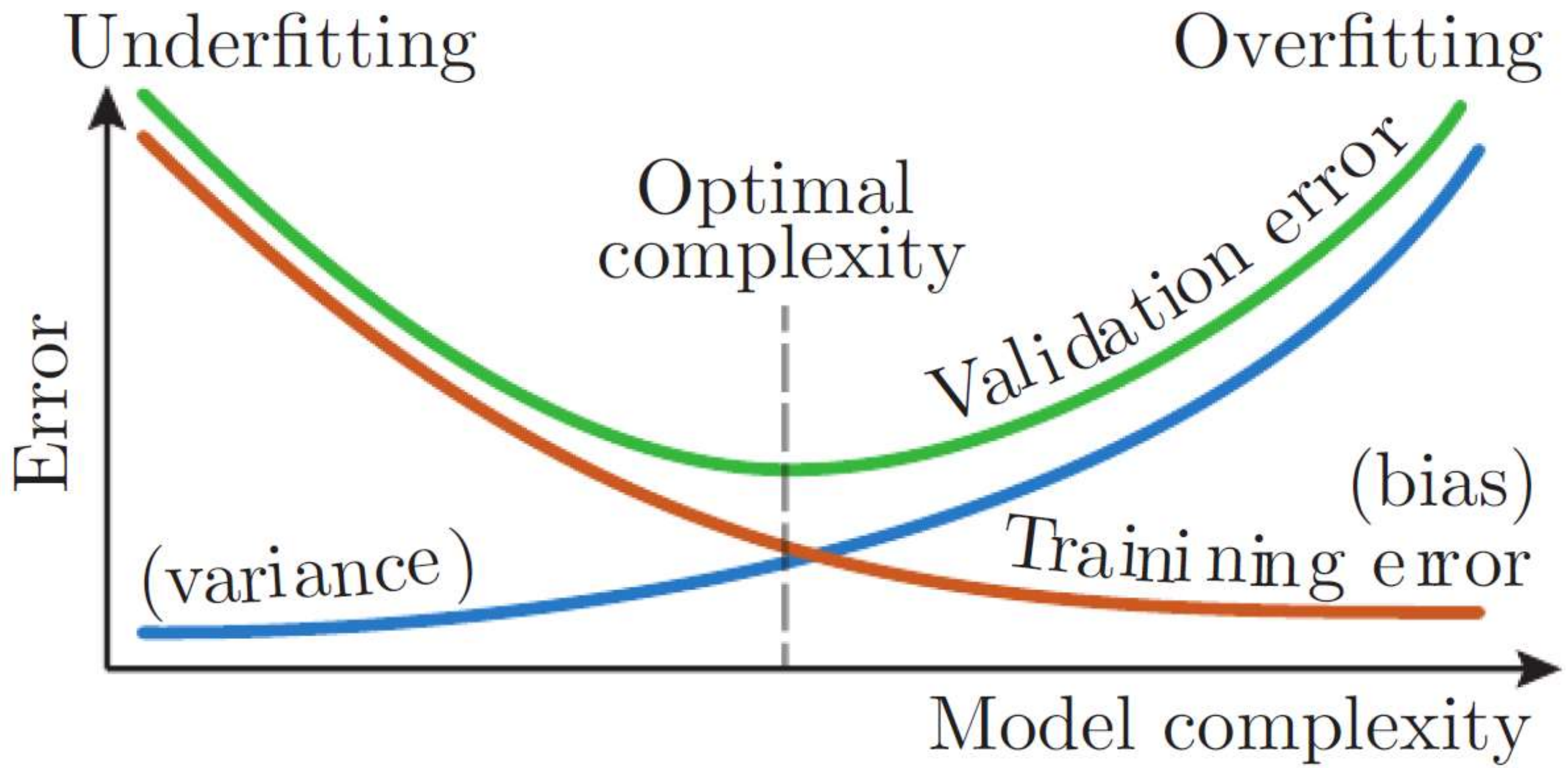
(c) Low bias & high variance

(d) High bias & high variance

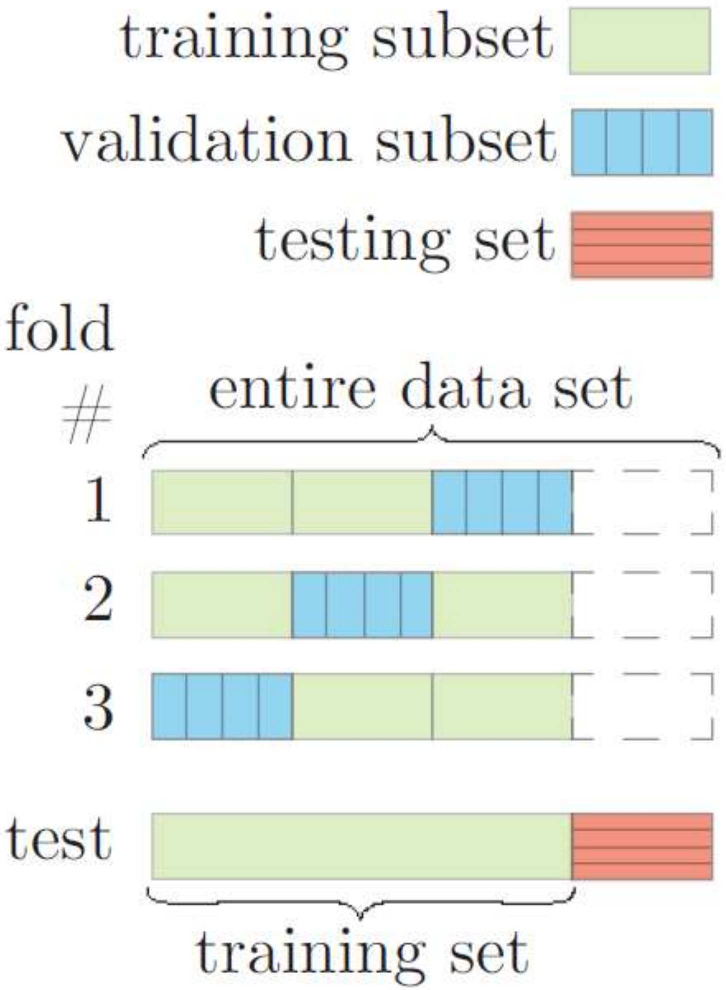
Underfitting and Overfitting



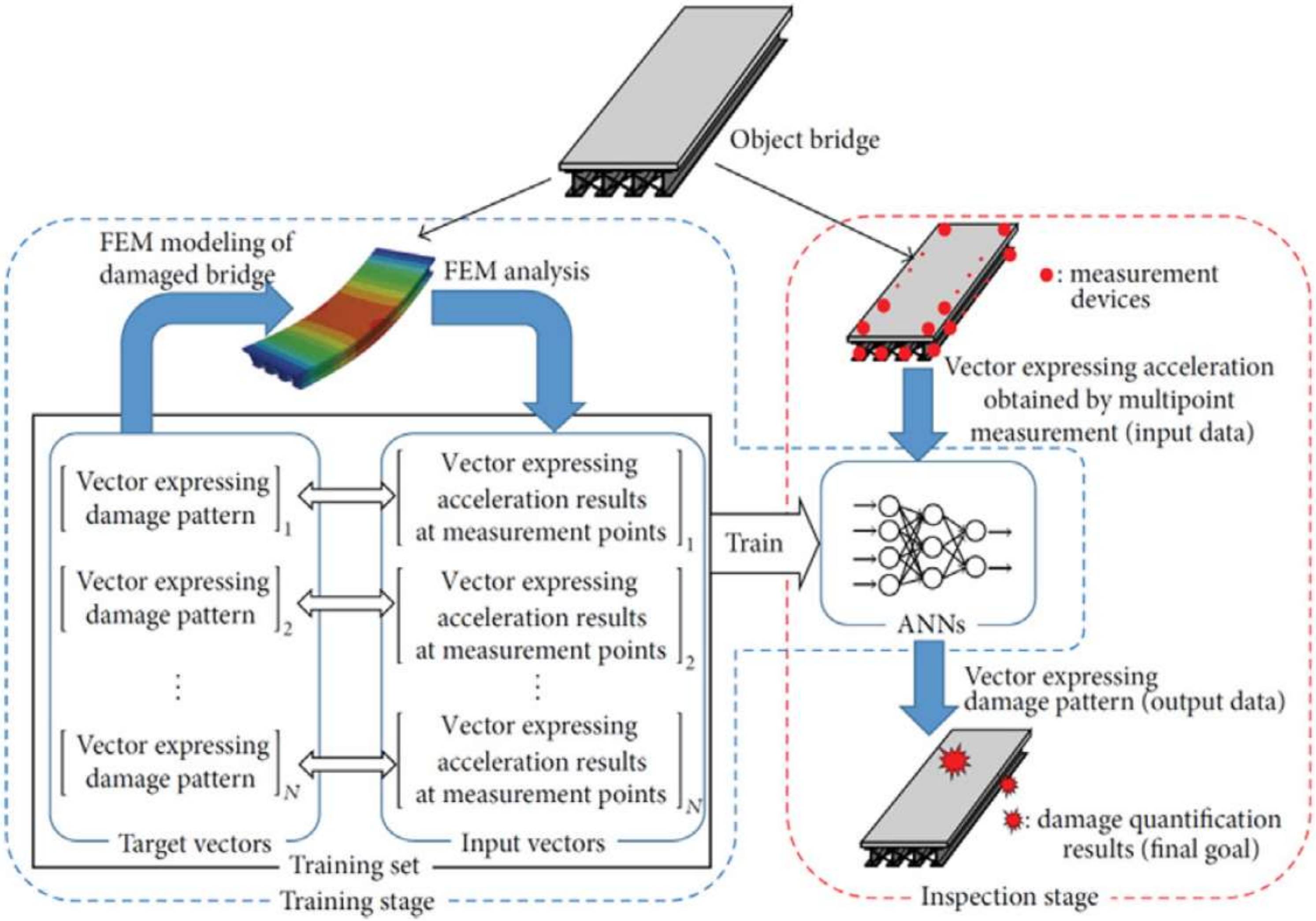
Model complexity: Bias-variance tradeoff



Model complexity: overfitting solutions



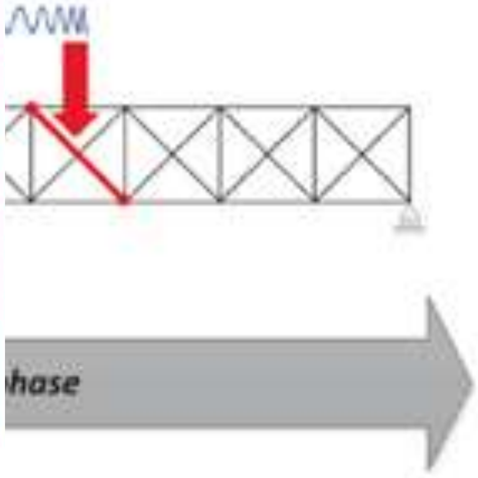
Esempi di ANNs nella ricerca del danno strutturale



Train ANNs on:

- Simulated damage scenarios
- real damage scenarios

(supervised learning not a suitable way because miss real or realistic Damaged consistent dataset)

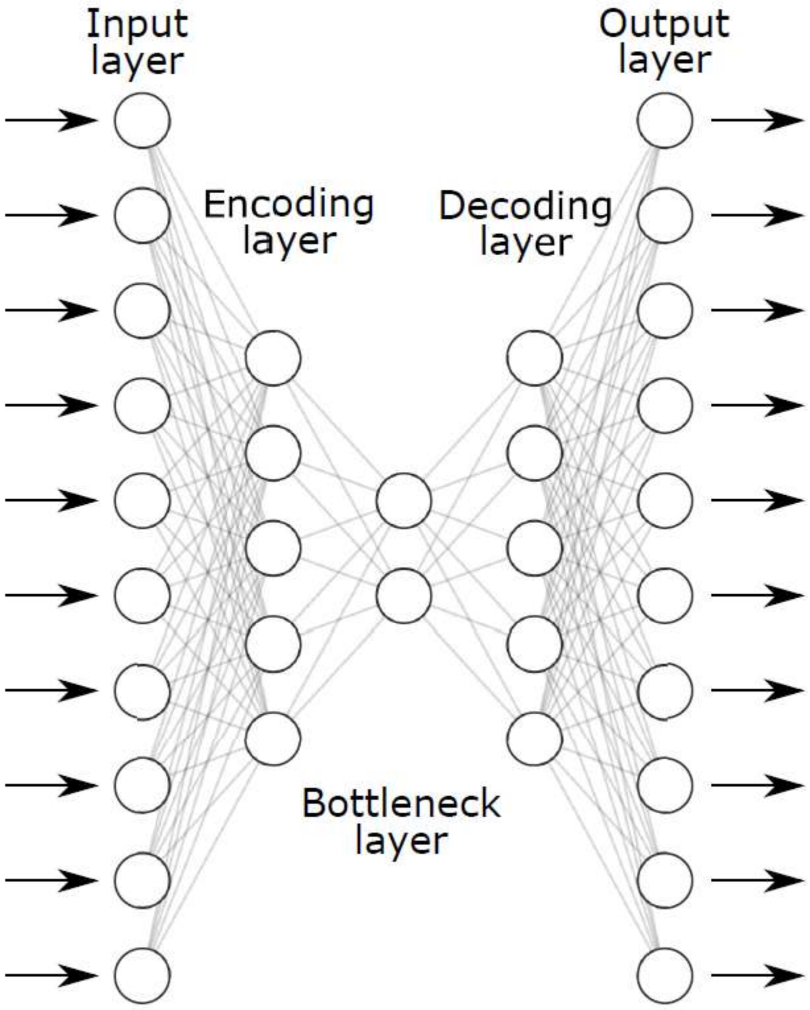


Directly trained on operational conditions

Reti Neurali Auto-Associative NN (AANN)

(unsupervised learning)

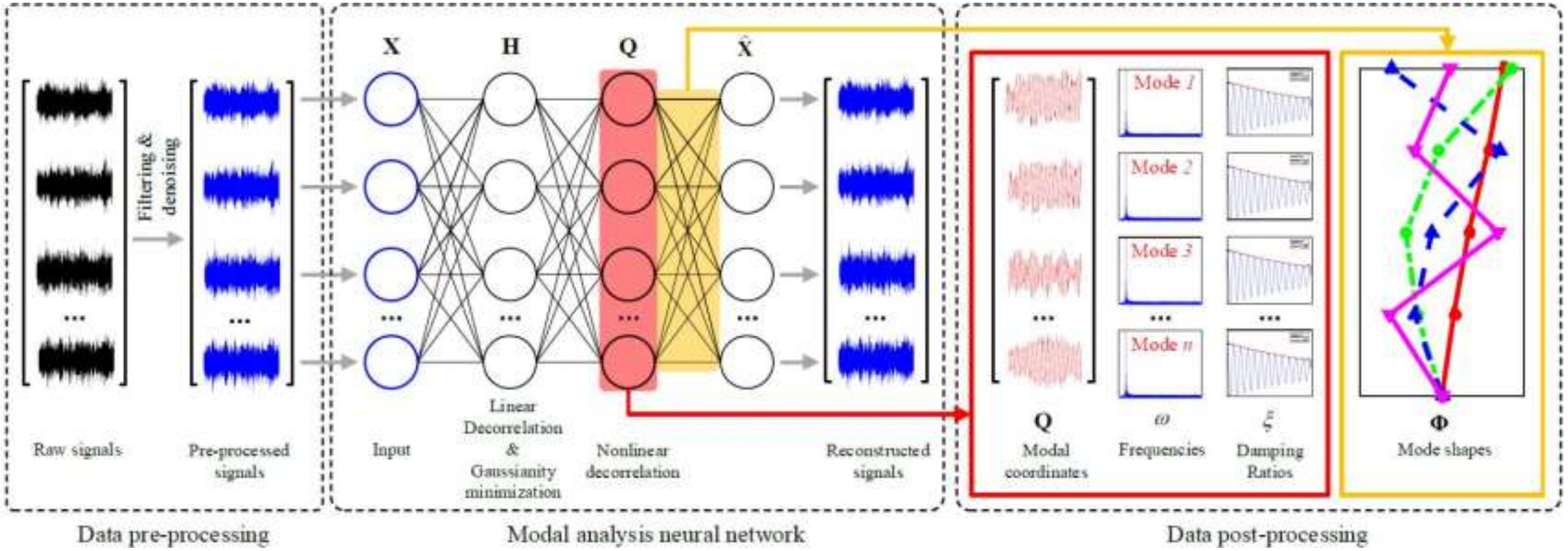
- Pass through a "bottleneck" layer to learn r
important feature and denoise the input si
- Once trained, if output signal is similar to ir
loss function (Damage index) almost zero,
otherwise a possible abnormal condition o
- **Autoencoder**

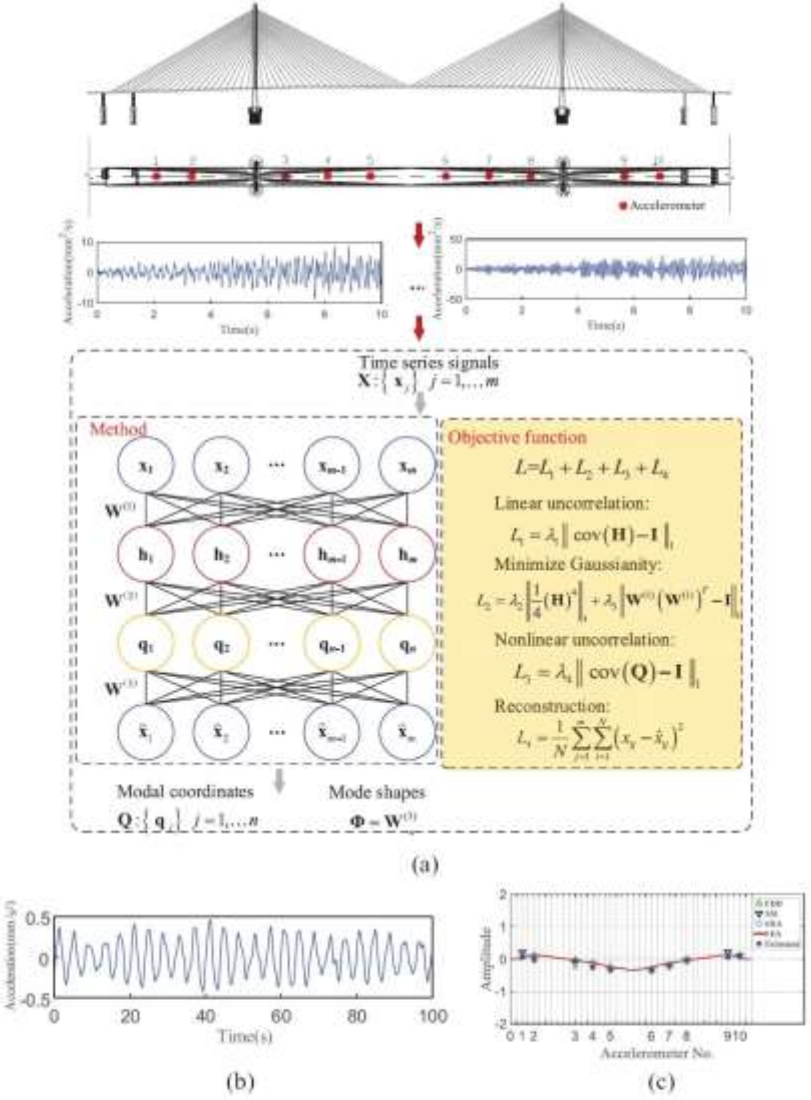


[Charles R. Farrar and Keith Worden. *Structural Health Monitoring: A Machine Learning Perspective*]

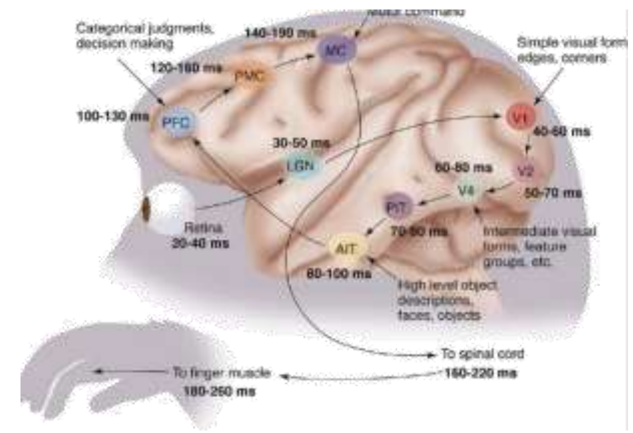
Ad hoc interpretable ANN implementations

Output-only SHM applications with ad hoc ANN implementations
To extract engineering paramters of interest (modal paramters)

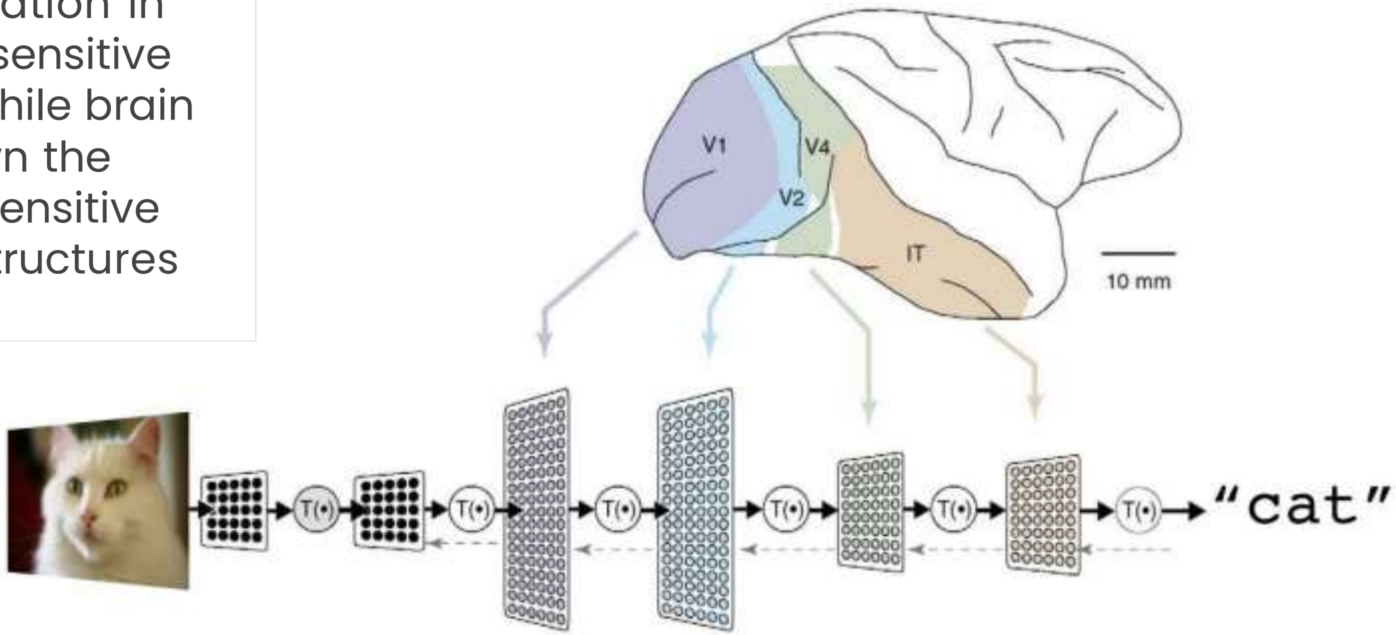


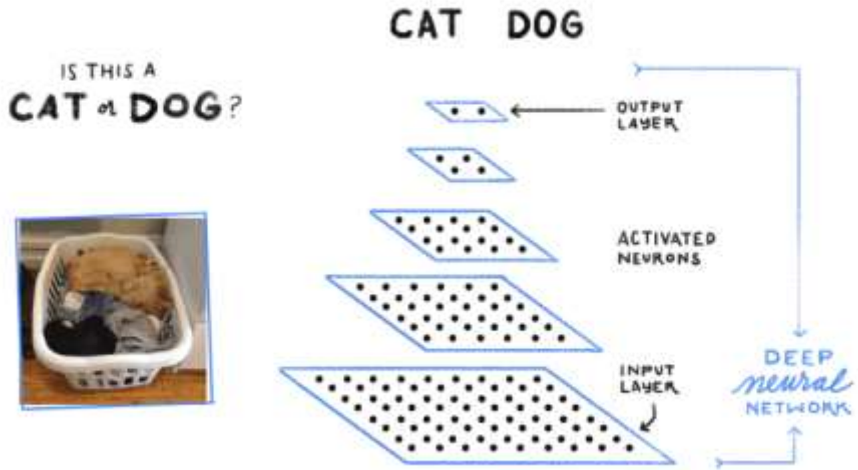


Convolutional Neural Networks (CNN)



The first hierarchy of neurons that receives information in the visual cortex is sensitive to specific edges while brain regions further down the visual pipeline are sensitive to more complex structures such as faces.





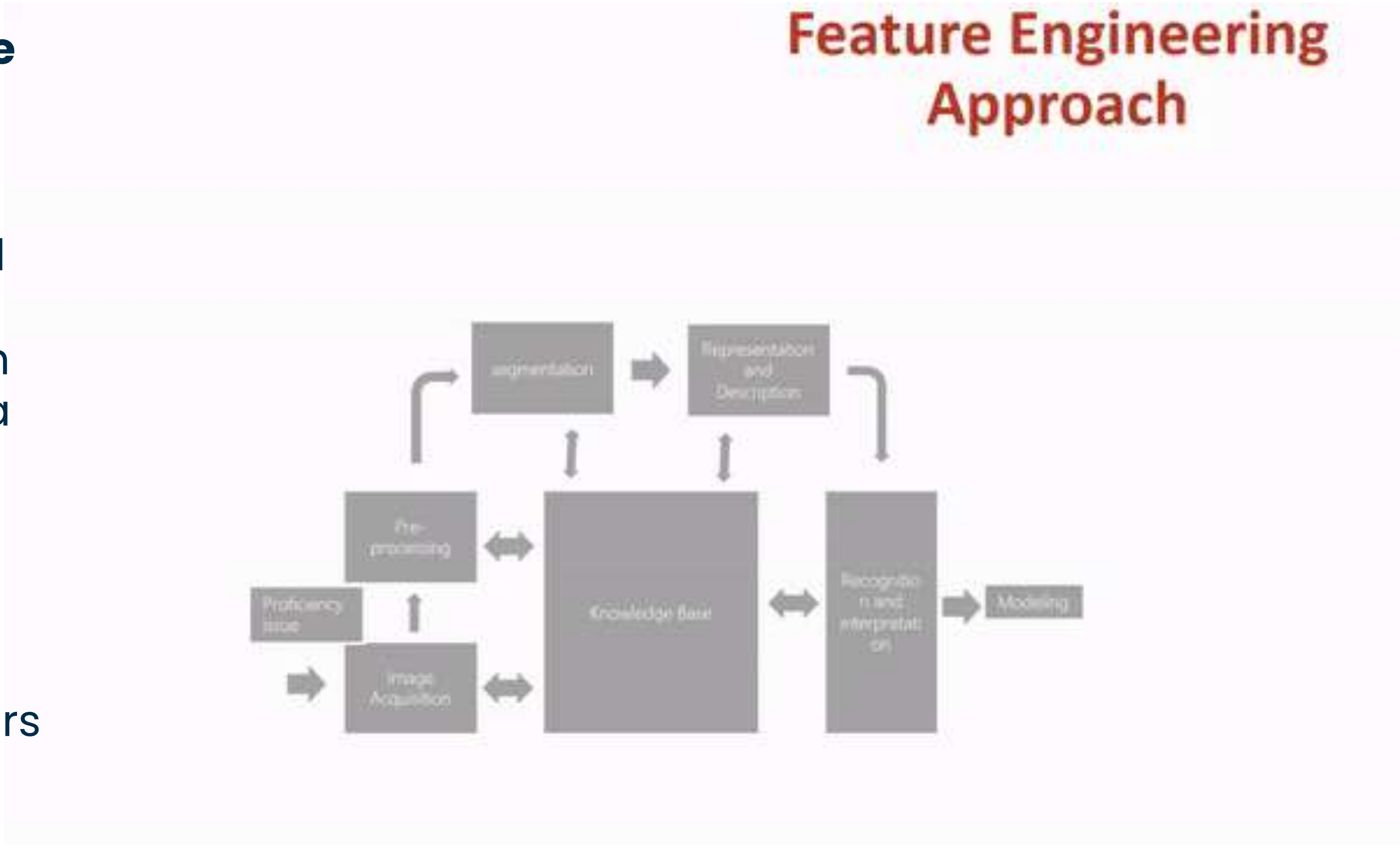
A deep neural network consists of a hierarchy of layers, whereby each layer transforms the input data into more abstract representations (e.g. edge -> nose -> face). The output layer combines those features to make predictions.

Convolutional Neural Networks (CNN)

The initial convolution part acts as an **automatic feature extractor**!

Feature maps are calculated by sliding learnable filters on the input images. Information are collected in tensors and a subsampling only retains the most useful information.

The classification/regression task is actually performed by the **fully connected** final layers

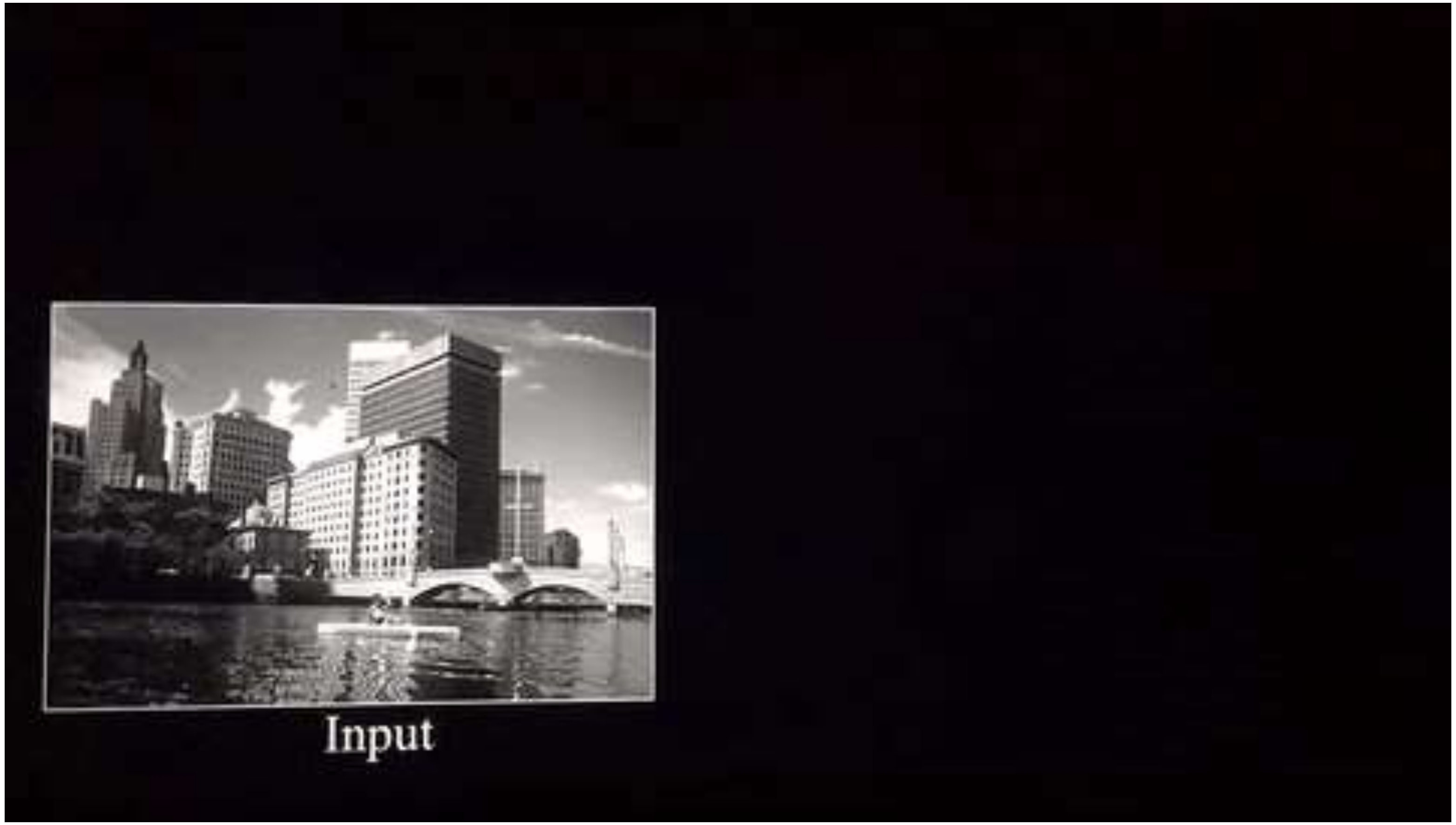


Convolutional Neural Networks (CNN)

The initial convolution part acts as an **automatic feature extractor**!

Feature maps are calculated by sliding learnable filters on the input images. Information are collected in tensors and a subsampling only retains the most useful information.

The classification/regression task is actually performed by the **fully connected** final layers



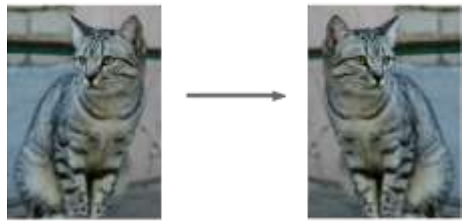
Convolutional Neural Networks (CNN)

More parameter to train → More data are needed!!
Therefore **Data augmentation** procedure can be adopted as regularization technique to increase db.

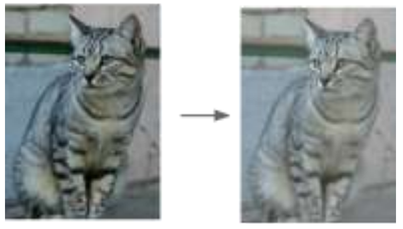
Random mix/combinations of :

- translation
- rotation
- stretching
- shearing,
- lens distortions, …

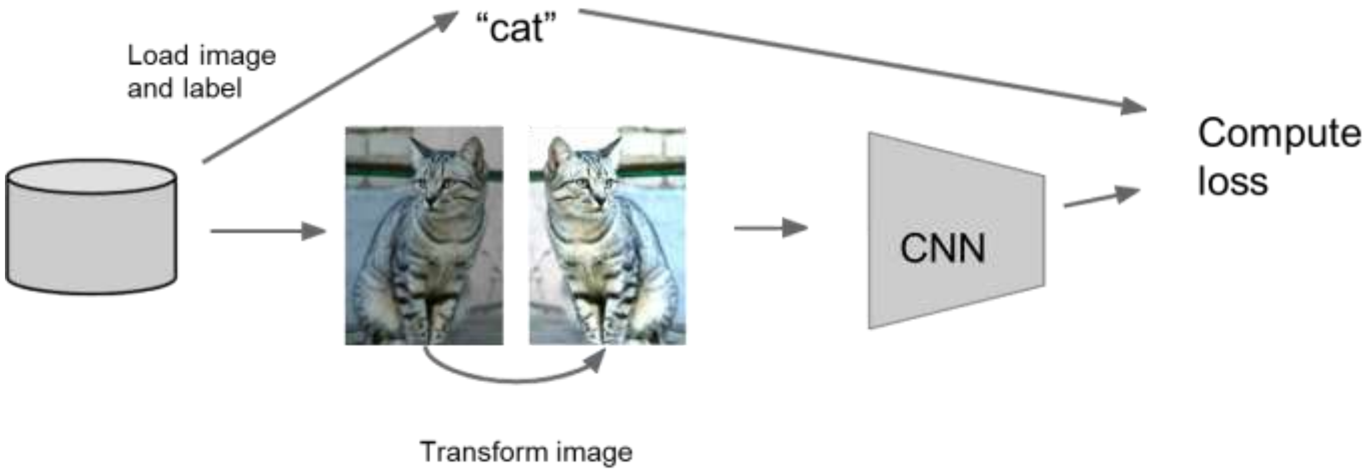
Horizontal Flips



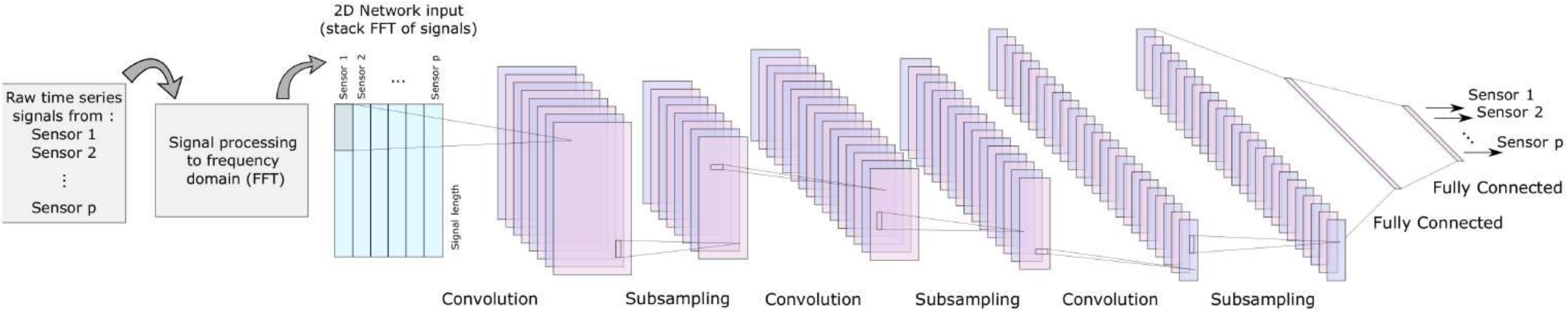
Color Jitter



Simple: randomize contrast and brightness



Convolutional Neural Networks (CNN)



Recurrent Neural Networks (RNN)

They are usually simple network which are called **recursively**.

We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

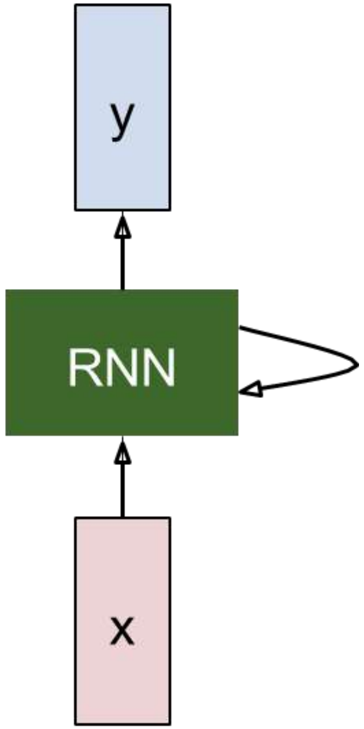
new state

some function with parameters W

old state

input vector at some time step

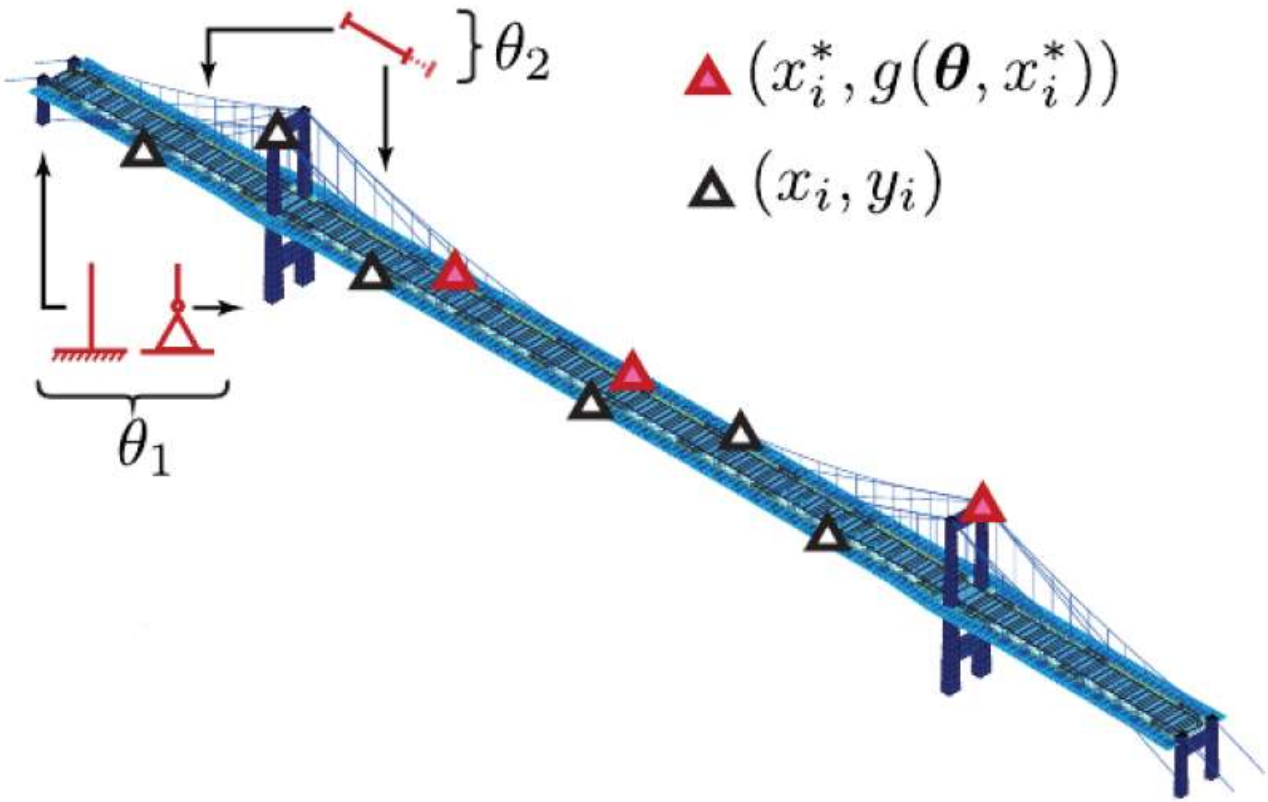
Notice: the same function and the same set of parameters are used at every time step.



Some more complex models have been proposed during years, especially to be suitable for dealing with very long sequence or time series, such as **LSTM** (Long Short Term Memory) or **GRU** (Gated Recurrent Unit)

Optimization: Model calibration and updating

- Foremost **Model parametrization**: Defines Parameter $\boldsymbol{\theta}$ to be updated
- Not all are directly observable
- *Deterministic Approaches*
- *Probabilistic Approaches* i.e. Bayesian Updating
- Observation may contains errors:



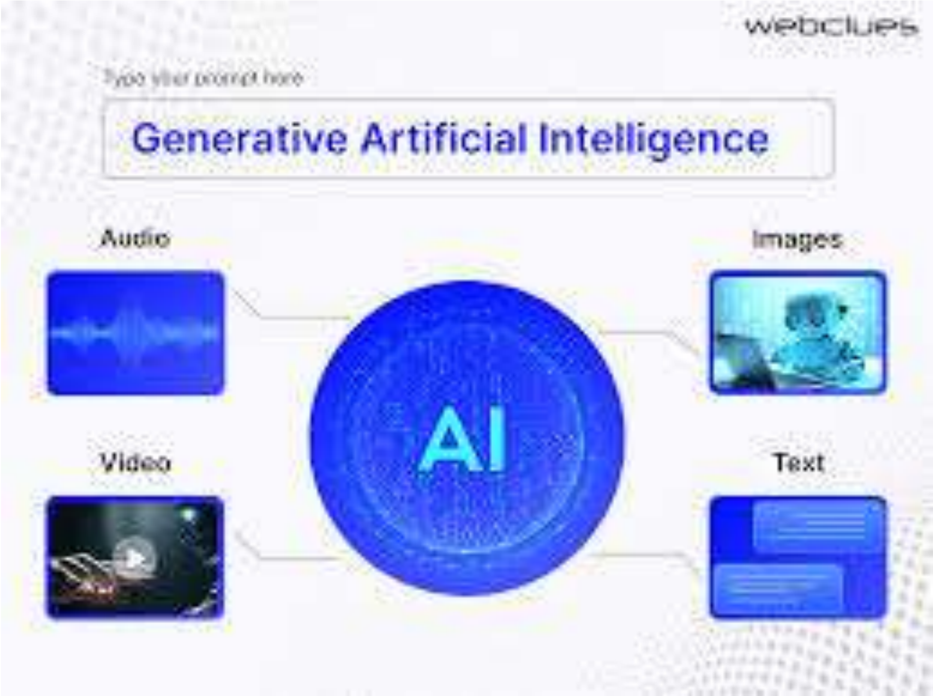
Prediction errors

$$\mathbf{y} = \mathbf{g}(\boldsymbol{\theta}, \mathbf{x}) + \mathbf{w}(\mathbf{x}) + \mathbf{v},$$

Covariates
Measurement errors
Model parameters
Deterministic predictions from a hard-coded model
Observations

AI GENERATIVA

- **Definizione**: L'IA generativa è una tecnologia di apprendimento automatico che crea nuovi contenuti come testi, immagini e musica.
- **Reti Neurali**: Utilizza reti neurali ispirate ai neuroni umani per riconoscere pattern nei dati.
- **Esempio**: Come un cuoco che crea nuovi piatti combinando ingredienti di diverse ricette, l'IA generativa crea nuovi contenuti combinando dati di addestramento.



Modelli di IA Generativa

GAN (Reti Generative Avversarie):

- Utilizzano un generatore e un discriminatore per creare e valutare nuovi dati.

Modelli Basati su Trasformatori:

- Eccellono in compiti dove il contesto è importante, come traduzione e generazione di testi.

GAN (Reti Generative Avversarie)

- **Componenti**: Generatore e Discriminatore.
- **Processo**: Il generatore crea nuovi dati che il discriminatore valuta rispetto ai dati reali.

Altri Modelli Popolari di AI Generativa

- **Autoencoder Variazionali (VAE)**: Codificano i dati in uno spazio ridotto e generano nuovi campioni.
- **Reti Neurali Ricorrenti (RNN)**: Ricordano gli input passati per gestire dati sequenziali.

Strumenti di IA Generativa

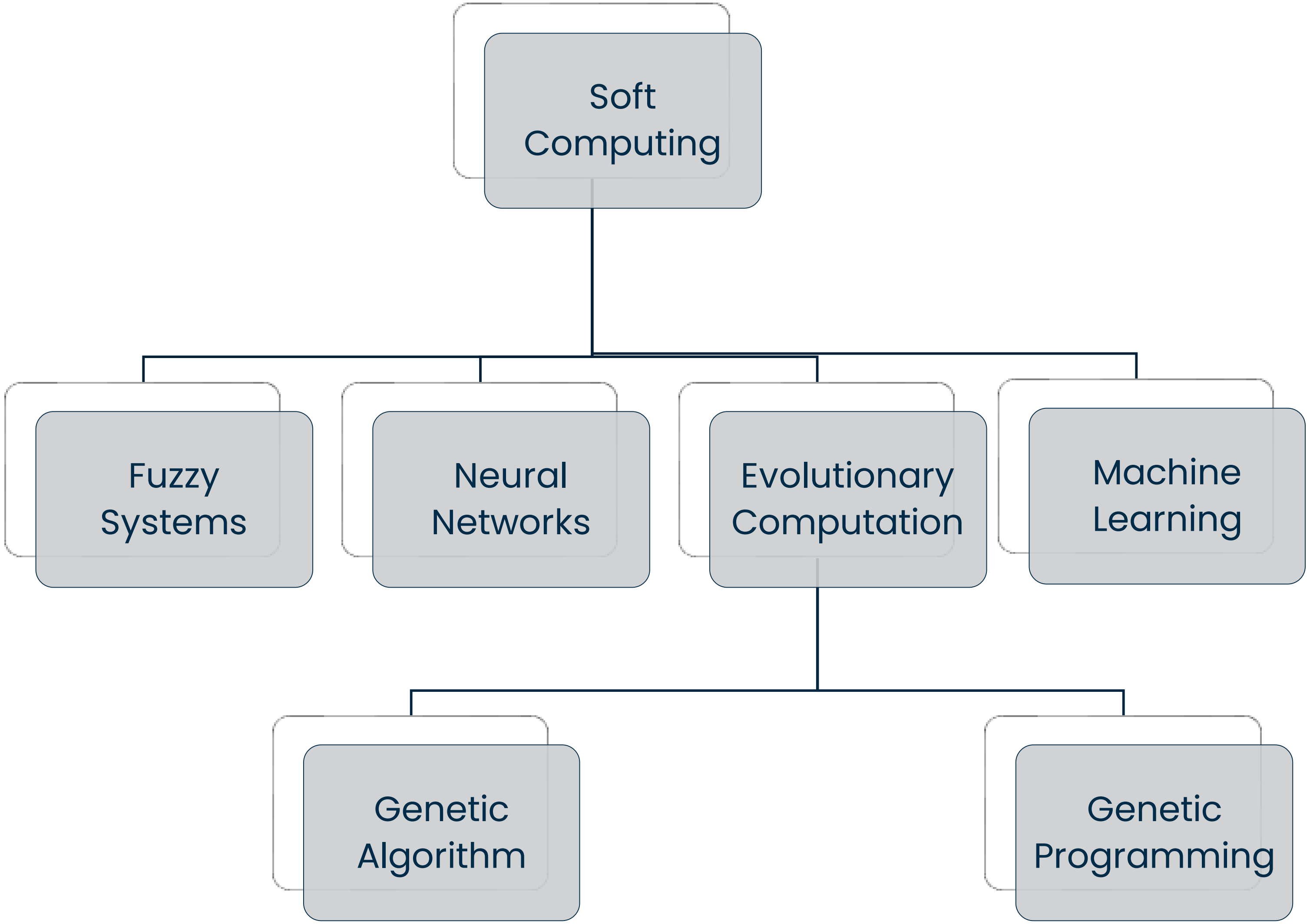
- **ChatGPT**: Risposte testuali realistiche e interattive.
- **Dall-E**: Genera immagini da descrizioni testuali.
- **Bard**: Chatbot di Google per risposte basate su linguaggio naturale.

Benefici dell'IA Generativa

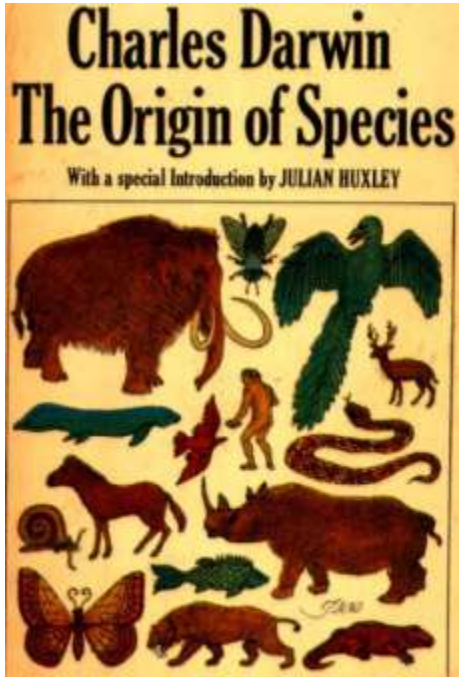
- **Efficienza**: Automatizza compiti ripetitivi.
- **Velocità**: Completa compiti rapidamente.
- **Creatività**: Genera nuove idee e design.
- **Decisioni Migliori**: Analizza dati per supportare decisioni

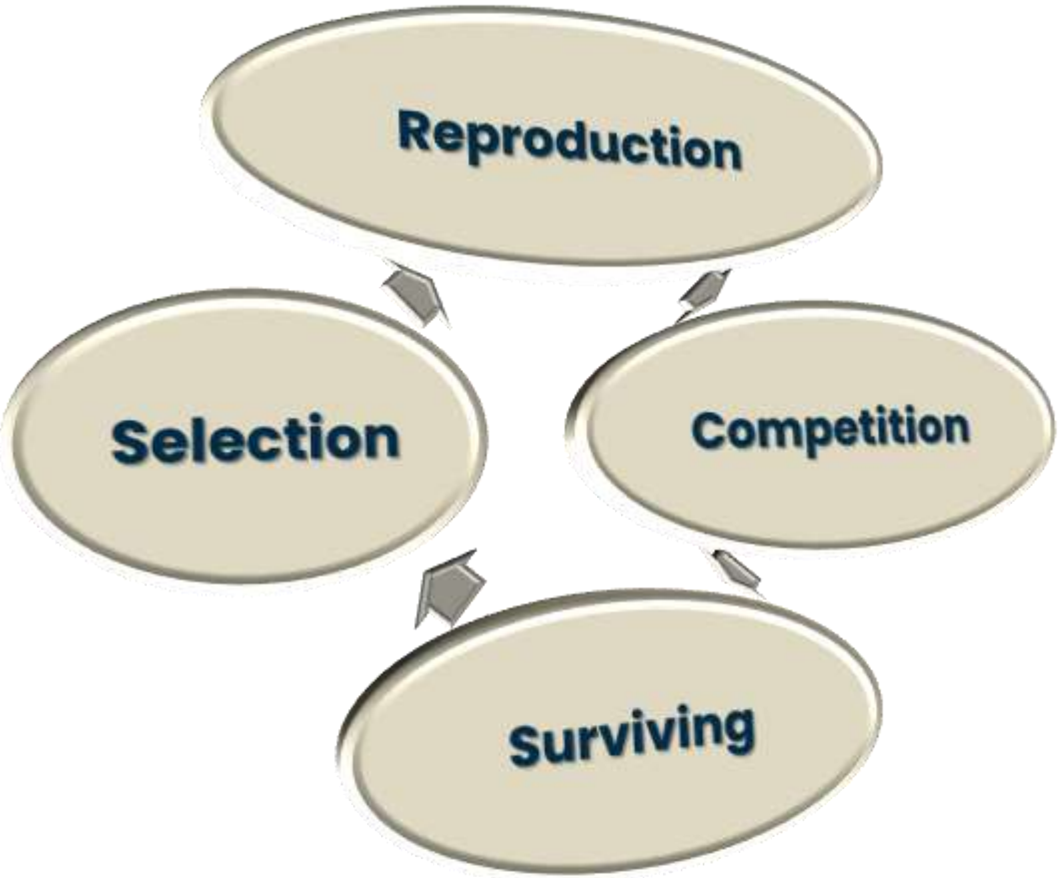
Limitazioni dell'IA Generativa

- **Controllo Limitato**: Difficile generare output con caratteristiche specifiche.
- **Qualità e Coerenza**: Dipende dalla qualità dei dati di addestramento.
- **Bias ed Etica**: Può replicare bias presenti nei dati di addestramento.


Soft Computing
Fuzzy Systems
Neural Networks
Evolutionary Computation
Machine Learning
Genetic Algorithm
Genetic Programming

Genetic Algorithms (GA)





GA's are based on Darwin's theory of evolution

Evolutionary computing evolved in the 1960's.

GA's were created by John Holland in the mid-70's.

Evolutionary Algorithms

Genetic algorithm

- One seeks the solution of a problem in the form of strings of numbers (traditionally binary, although the best representations are usually those that reflect something about the problem being solved), by applying operators such as recombination and mutation;

Genetic programming

- Here the solutions are in the form of computer programs, and their fitness is determined by their ability to solve a computational problem.

Evolutionary programming

- Similar to genetic programming, but the structure of the program is fixed and its numerical parameters are allowed to evolve;

Evolution strategy

- Works with vectors of real numbers as representations of solutions, and typically uses self-adaptive mutation rates;

Differential evolution

- Based on vector differences and is therefore primarily suited for numerical optimization problems.

Particle swarm optimization

- Based on the ideas of animal flocking behavior. Also primarily suited for numerical optimization problems.

Ant colony optimization

- Based on the ideas of ant foraging by pheromone communication to form paths. Primarily suited for combinatorial optimization problems.

Invasive weed optimization algorithm

- Based on the ideas of weed colony behavior in searching and finding a suitable place for growth and reproduction.

Harmony search

- Based on the ideas of musicians' behavior in searching for better harmonies. This algorithm is suitable for combinatorial optimization as well as parameter optimization.

Gaussian adaptation

- Based on information theory. Used for maximization of manufacturing yield, mean fitness or average information. See for instance Entropy in thermodynamics and information theory.

Exploration

- Search in regions with high uncertainty

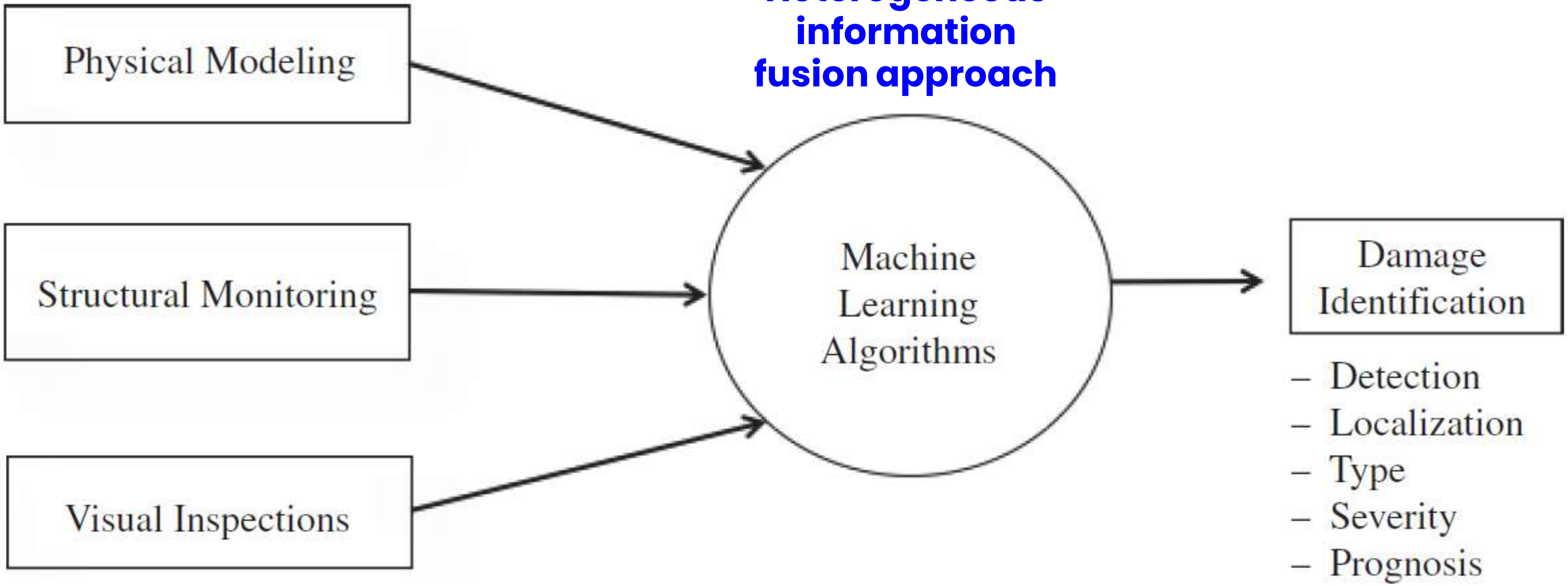
Exploitation

- Search in regions with high estimated value

Future directions: data fusion

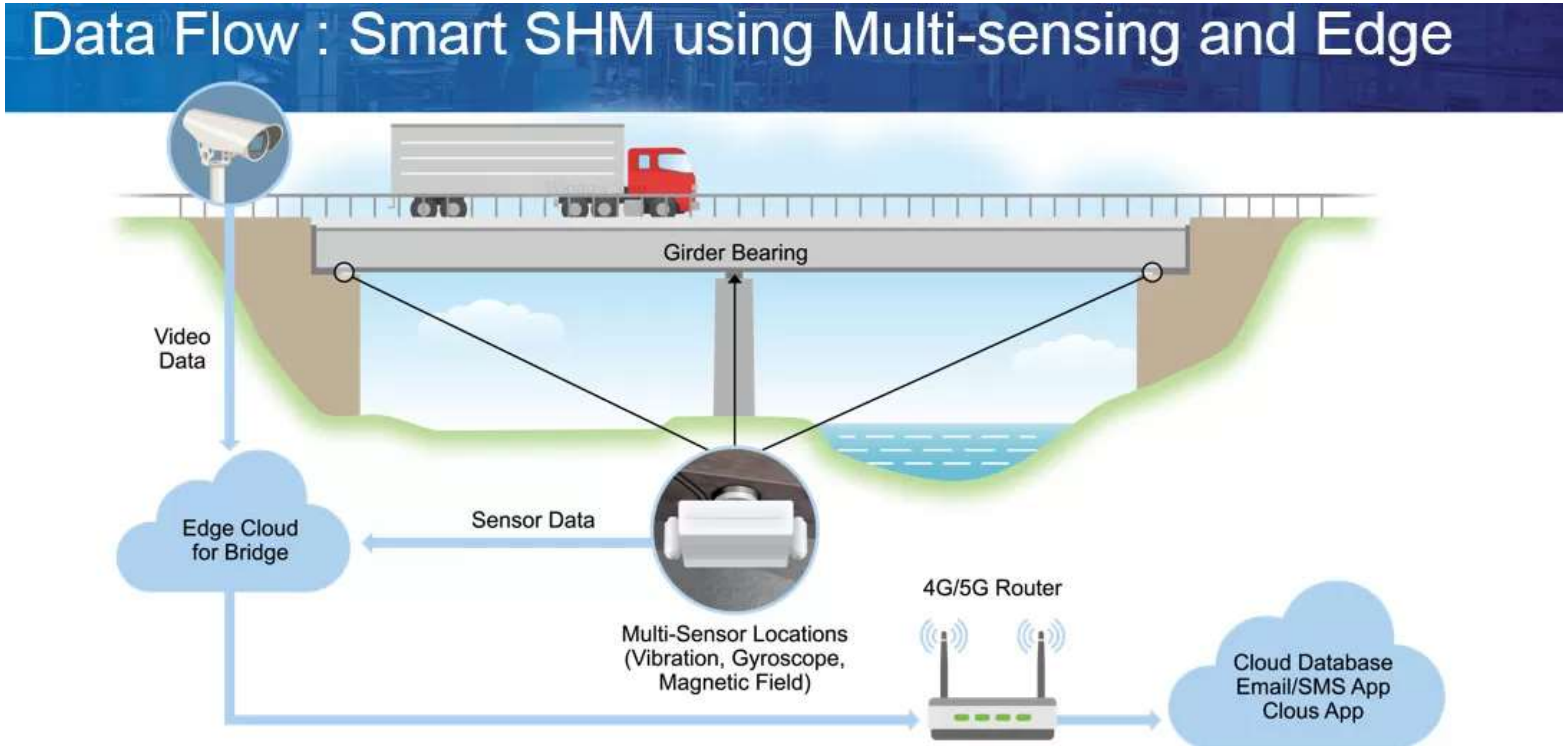
Integrated system to exploit advantages of both Data driven and physical modeling

Heterogeneous information fusion approach



Future directions: integrated solutions

Smart
Data Fusion
approaches



Correlate:

Data Traffic
TemperatureWind
…

↓

With vibrations
sensors data

MORE RELIABLE IDENTIFICATION SYSTEM