



Seminario Tecnico

**Nuovi sviluppi nel monitoraggio dei versanti in frana:
esempi applicative nella pratica progettuale**

***Fondamenti dei modelli di machine learning
e loro utilizzo per valutare la stabilità dei pendii***

Michele Marino

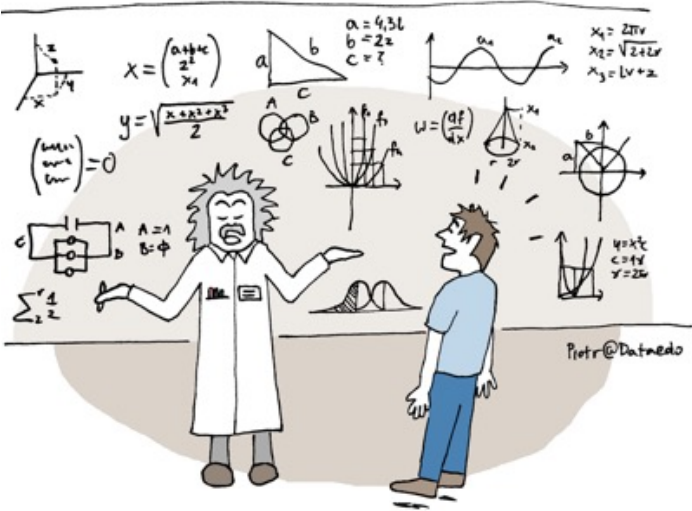
*Dipartimento di Ingegneria Civile e Ingegneria Informatica
Università degli Studi di Roma Tor Vergata*

*Ordine degli Ingegneri della Provincia di Roma
10 maggio 2024*

Introduction

► Critics to model-driven approaches

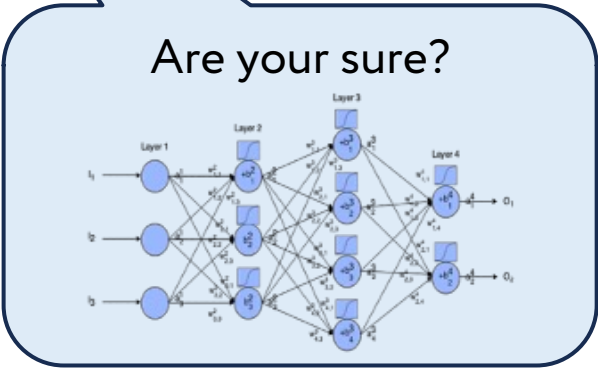
Models are often very complex, but fail to incorporate all data effectively!



NOW THAT YOU UNDERSTAND THE THEORY
MODELING IT SHOULD BE EASY...

So, do you incorporate data without the need of any model?

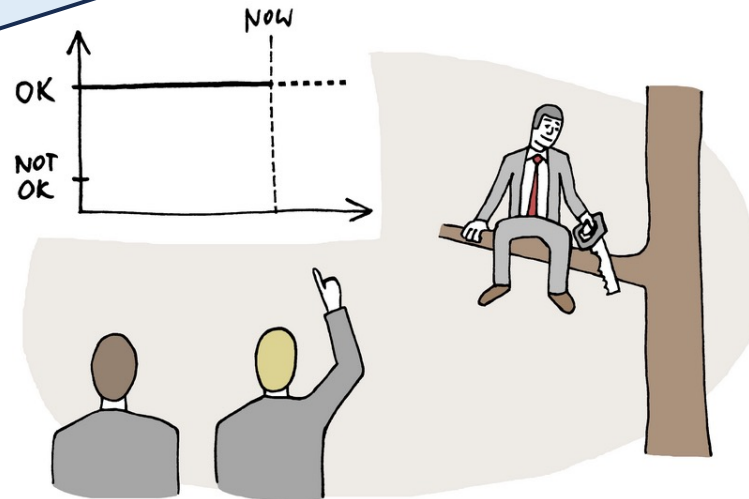
Yes, absolutely!



Introduction

► Critics to data-driven approaches

Correlation is not causation:
data-driven have low predictive capabilities!

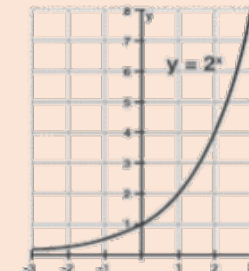


NOTHING TO WORRY ABOUT. HISTORICAL DATA
IS SHOWING THAT SITUATION IS STABLE.

So, are your models effective outside
of the parameters' calibration range?

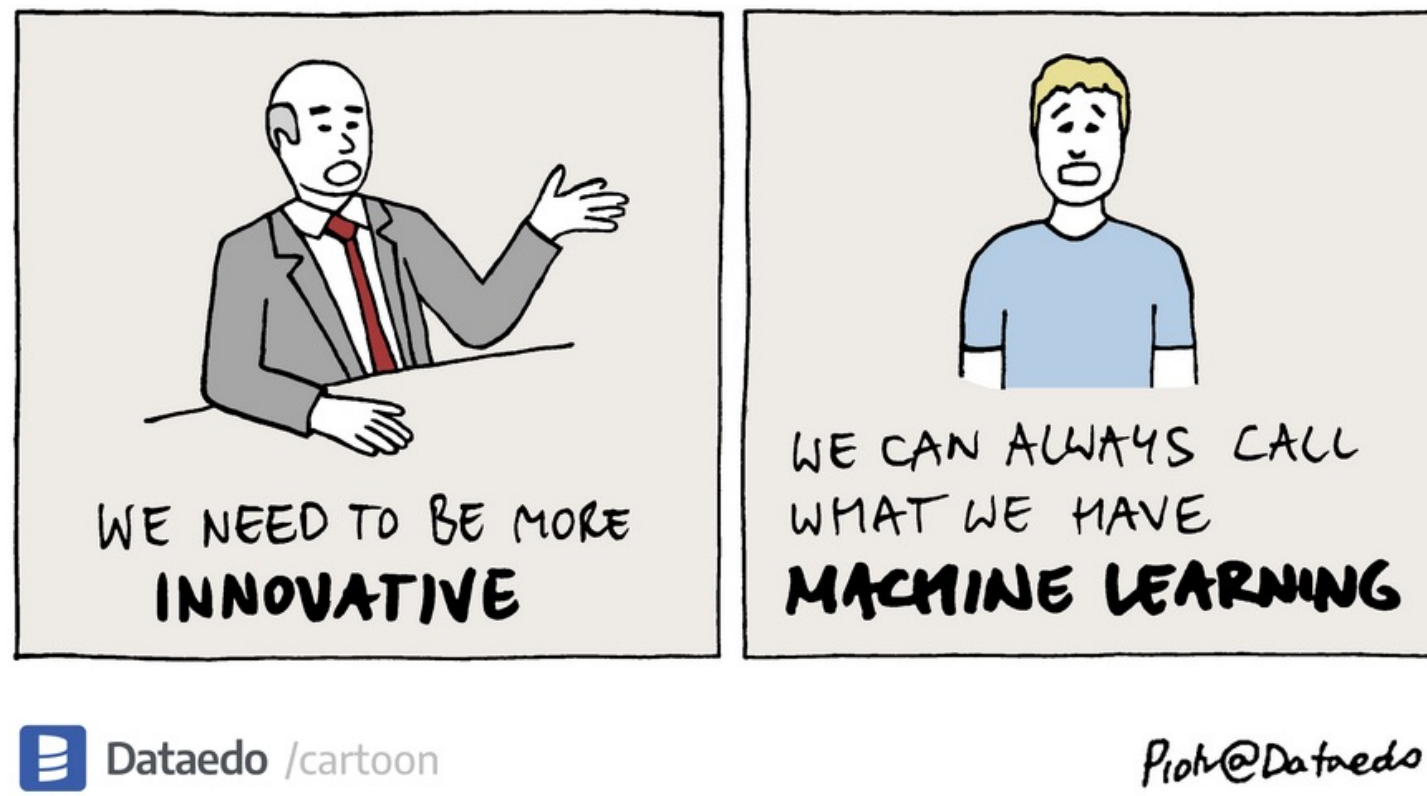
Yes, since our models
are physics-based!

Are your sure?



Introduction

- What is indeed sometimes going on...



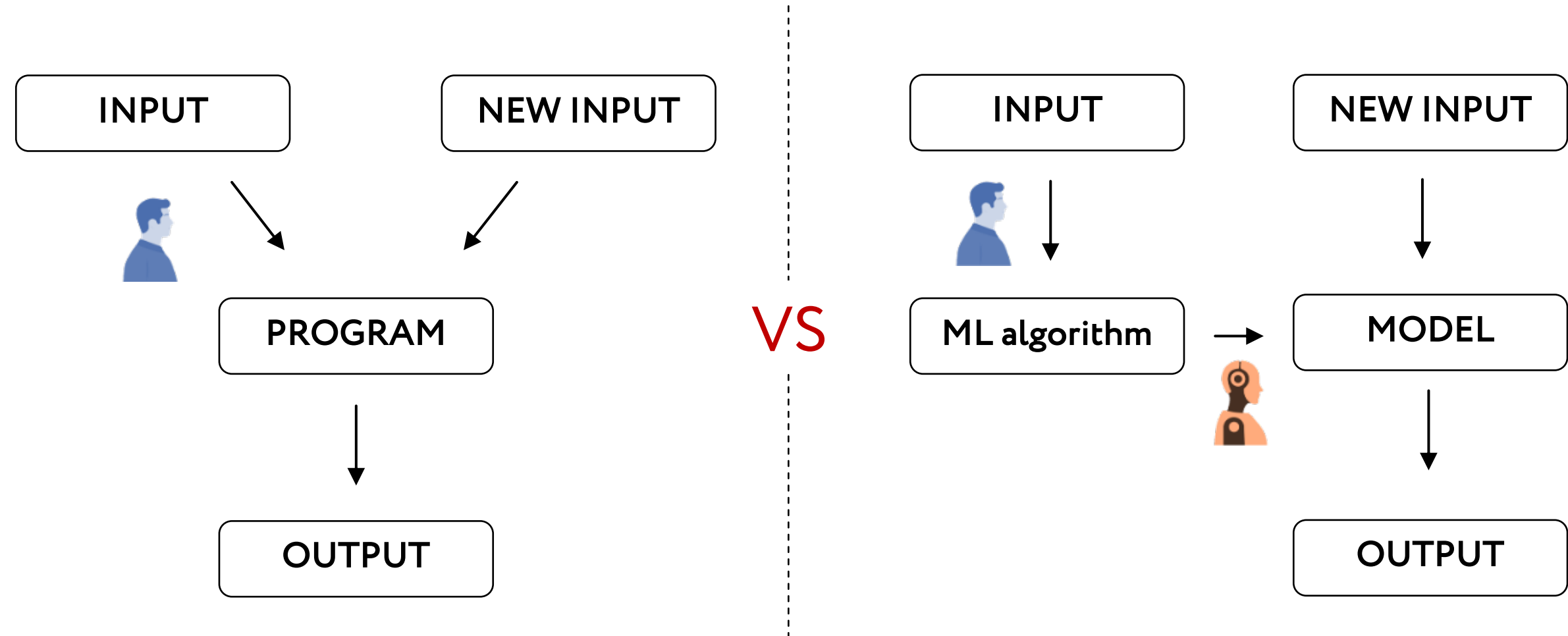
1959 *Arthur Lee Samuel*

Machine learning

is a field of study that gives
computers the ability to learn
without being explicitly
programmed



A Change of Paradigm



1998 *Tom Mitchell*

Machine learning is the study
of computer algorithms that
allow computer programs to
automatically improve
through **experience**



Introduction

- ▶ A computer program is said to learn from **experience E** with respect to some **task T** and some **performance measure P**, if its performance on **T**, as measured by **P**, improves with experience **E**

Experience E



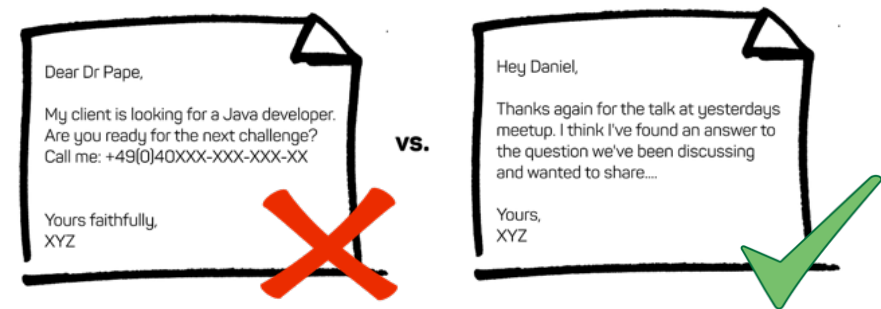
Over time Data

Task T



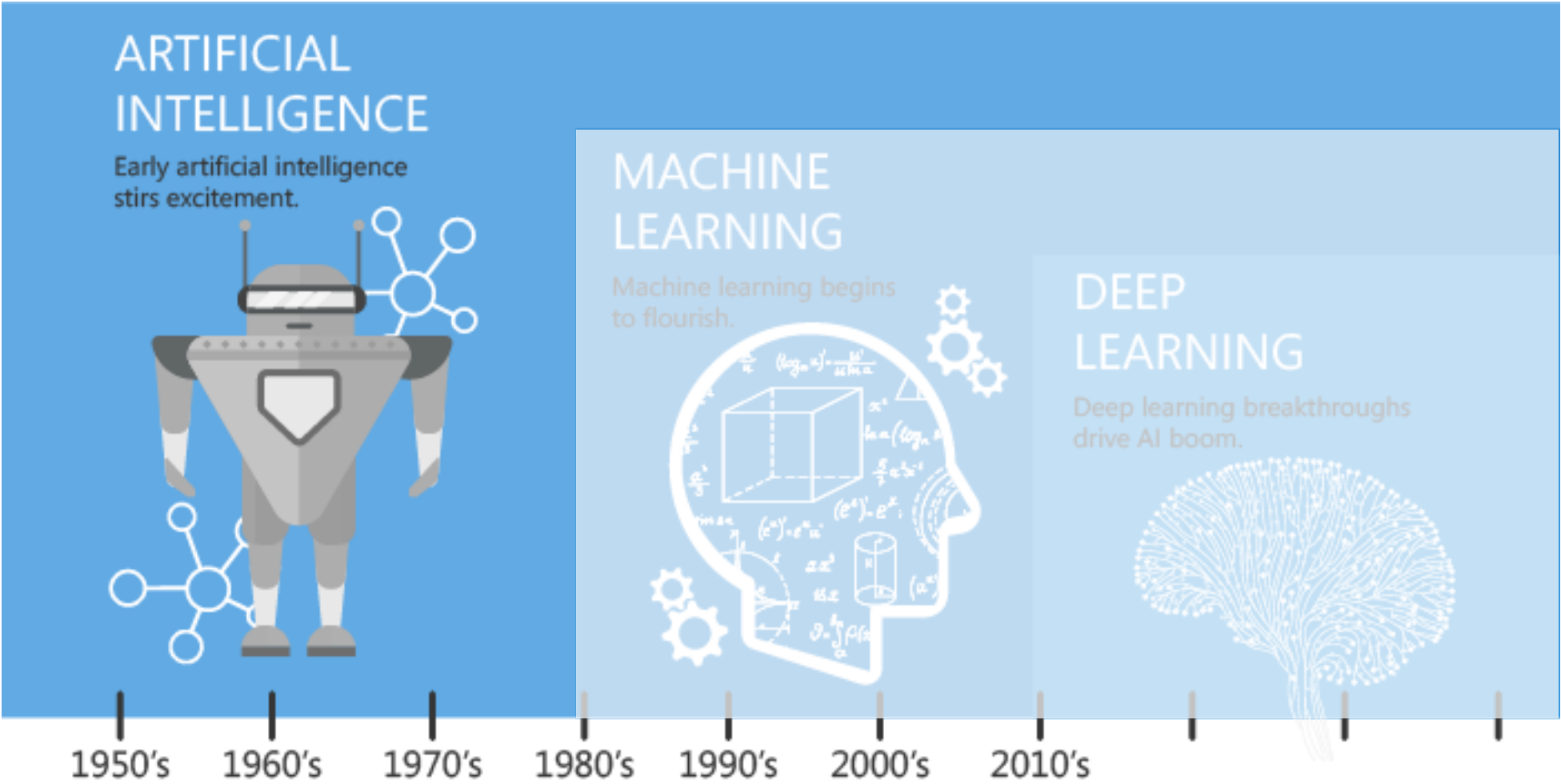
SPAM or NOT-SPAM?

Performance P

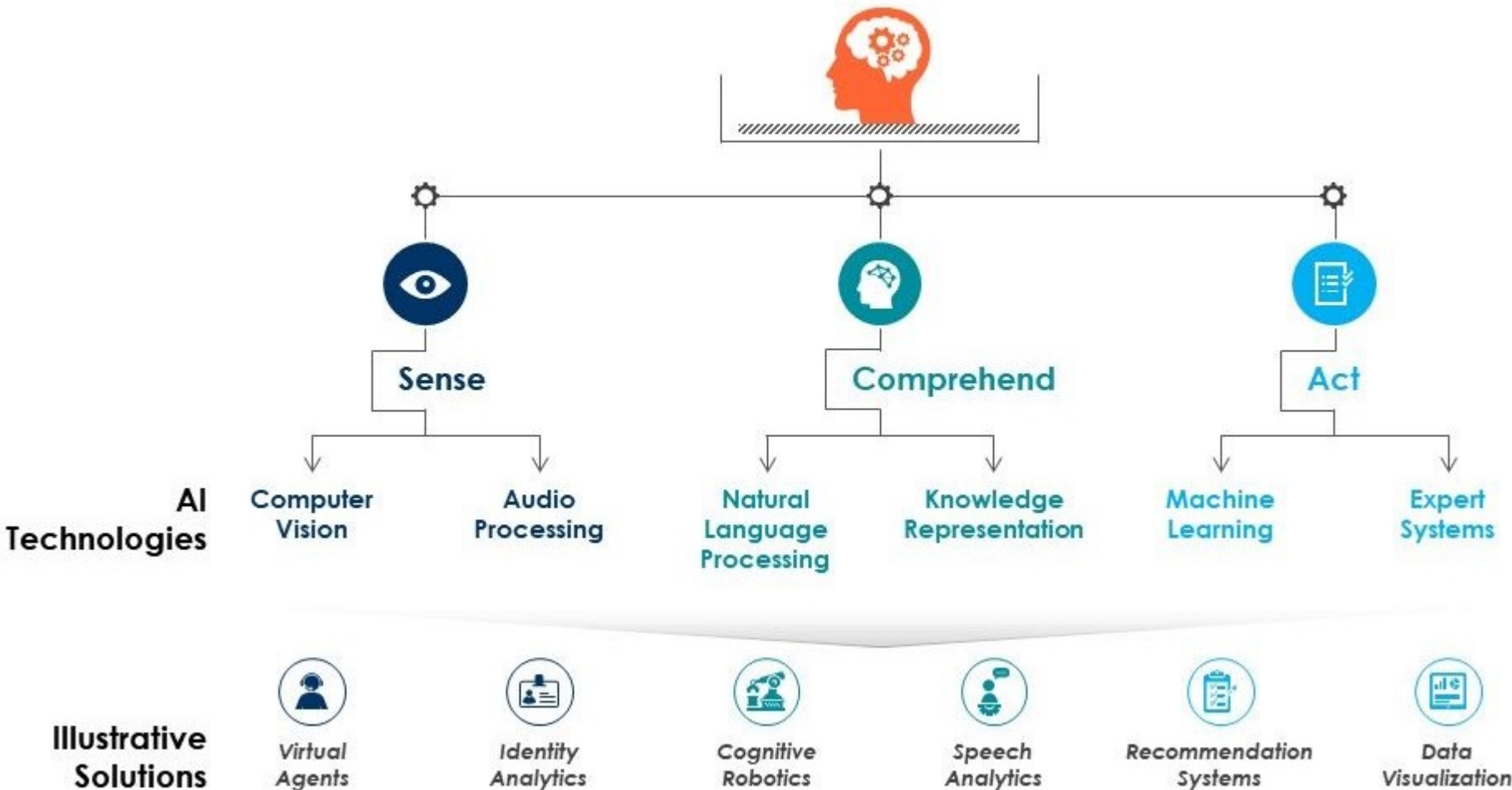


I have classified your e-mails

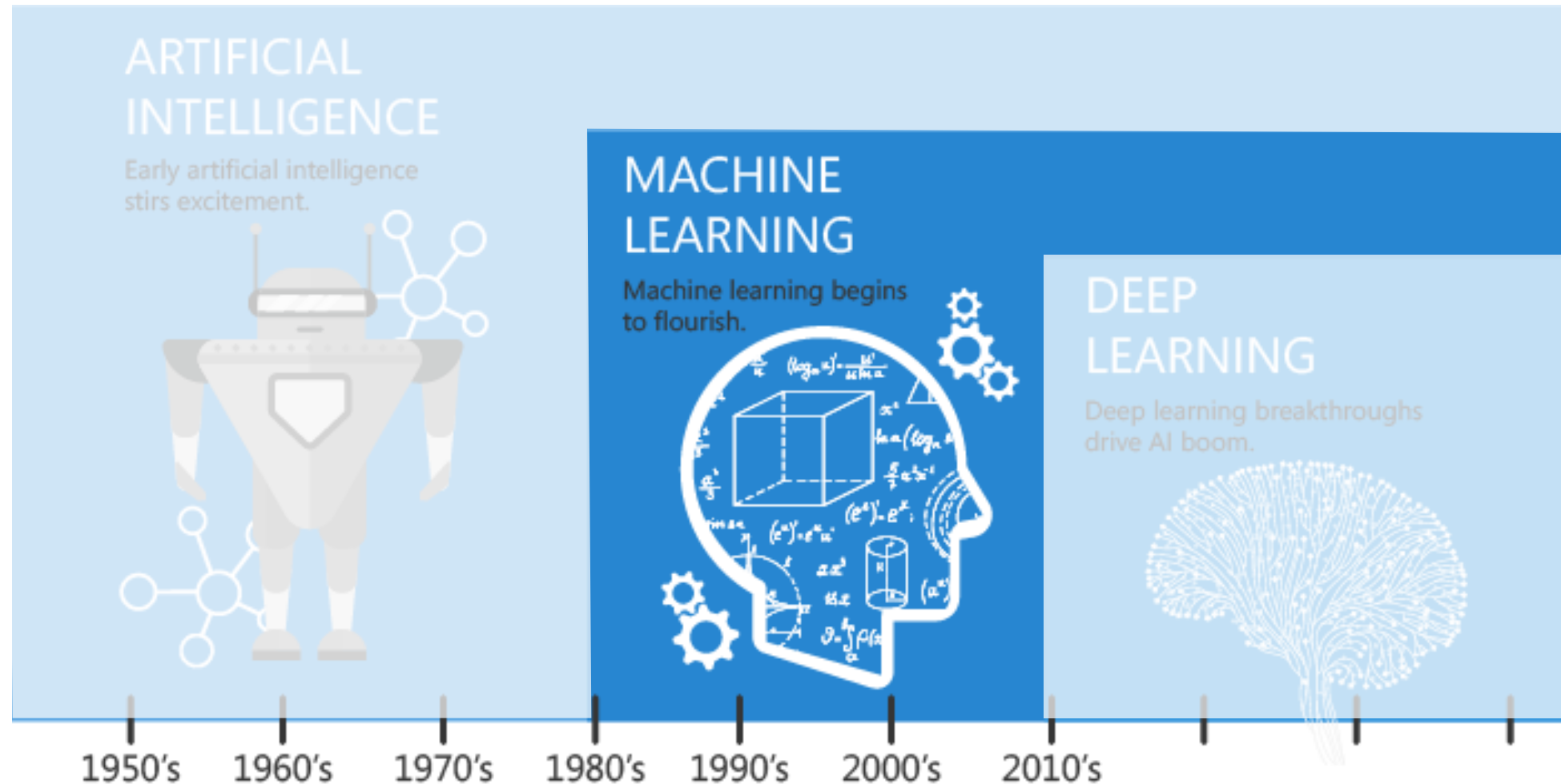
An (ordered) Overview



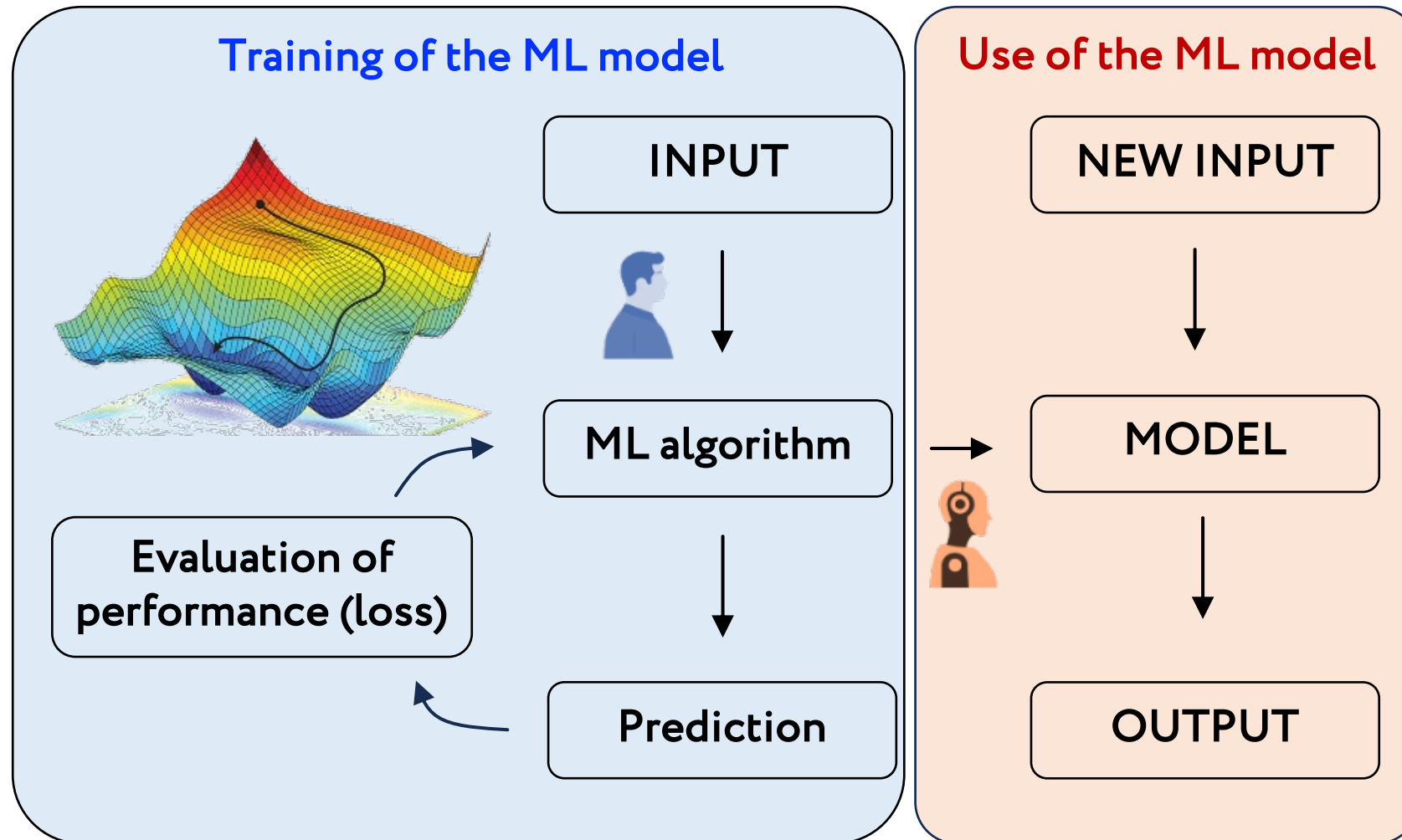
Artificial Intelligence: an ensemble of systems



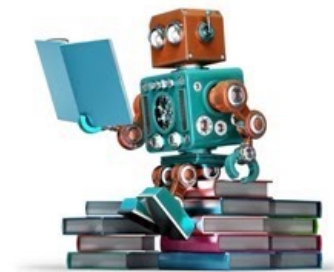
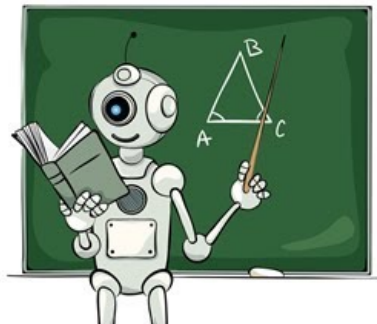
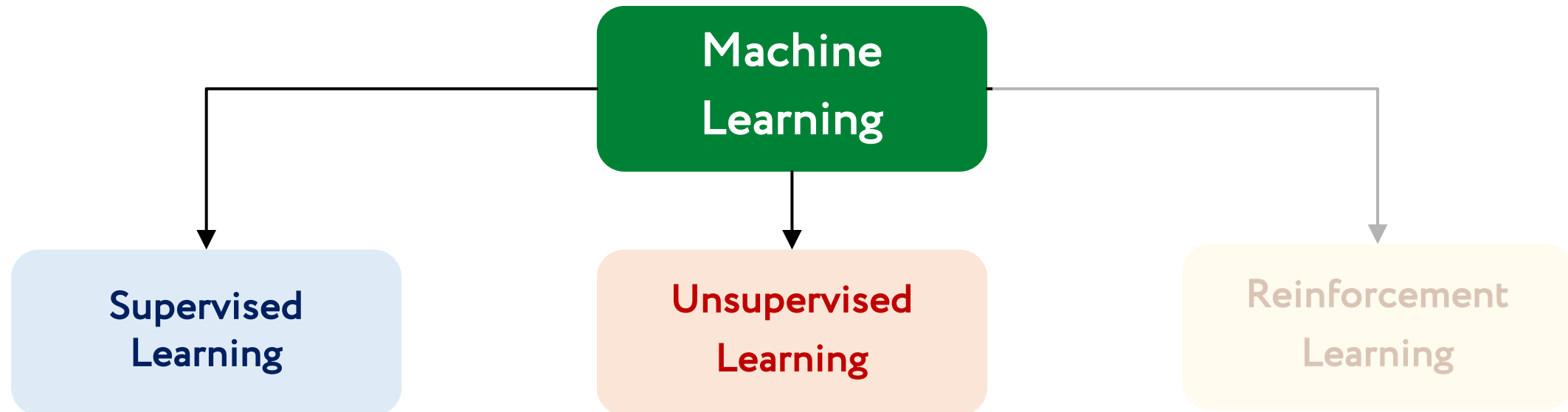
An (ordered) Overview



Fundamentals of Machine Learning

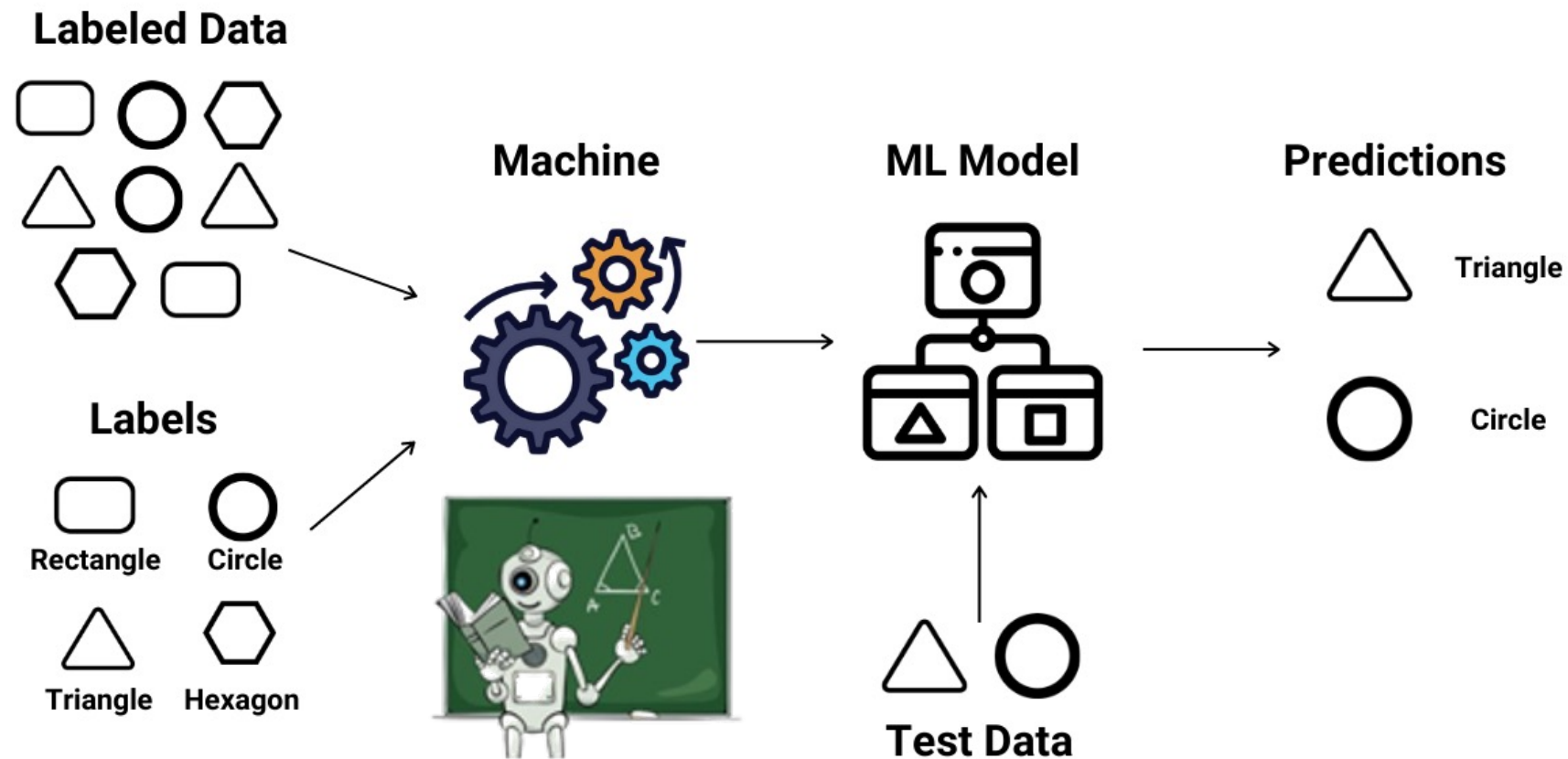


Fundamentals of Machine Learning



Fundamentals of Machine Learning

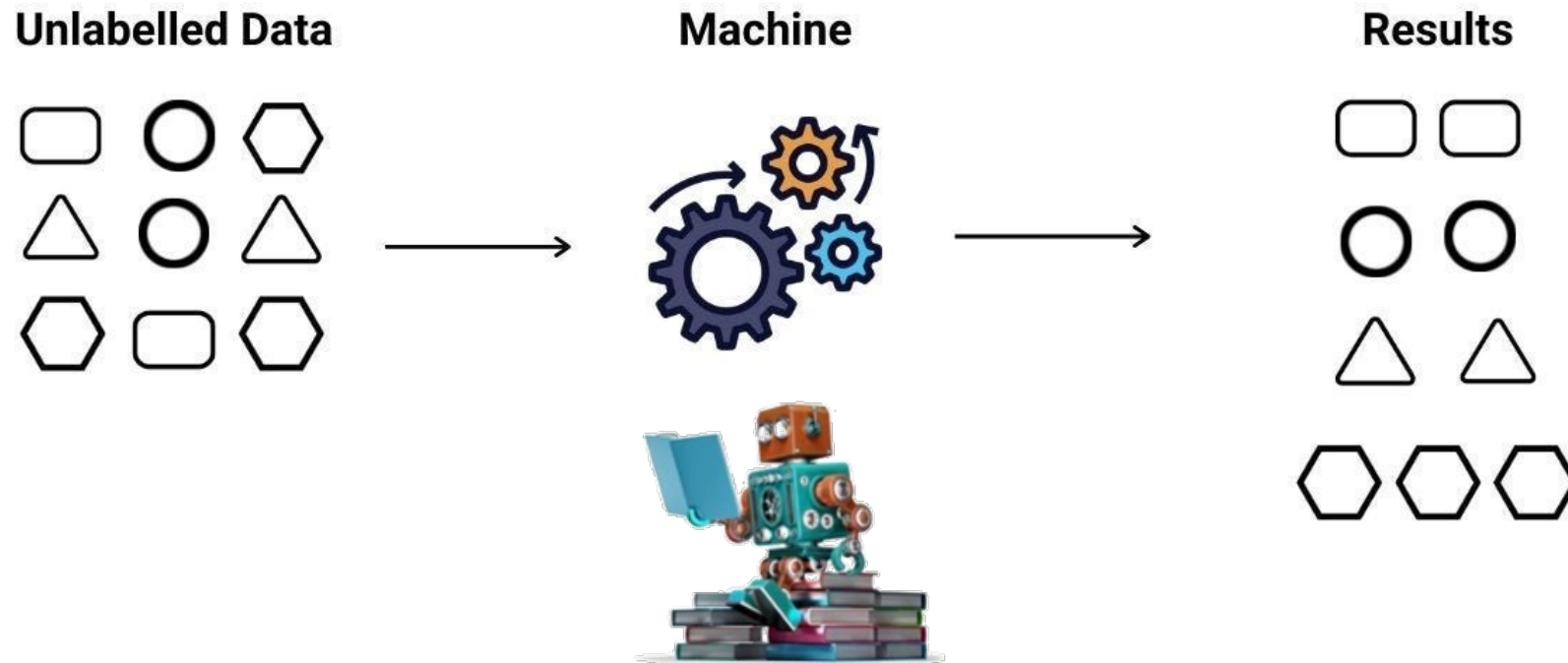
► Supervised vs Unsupervised learning



Credit: LinkedIn – Supervised Learning

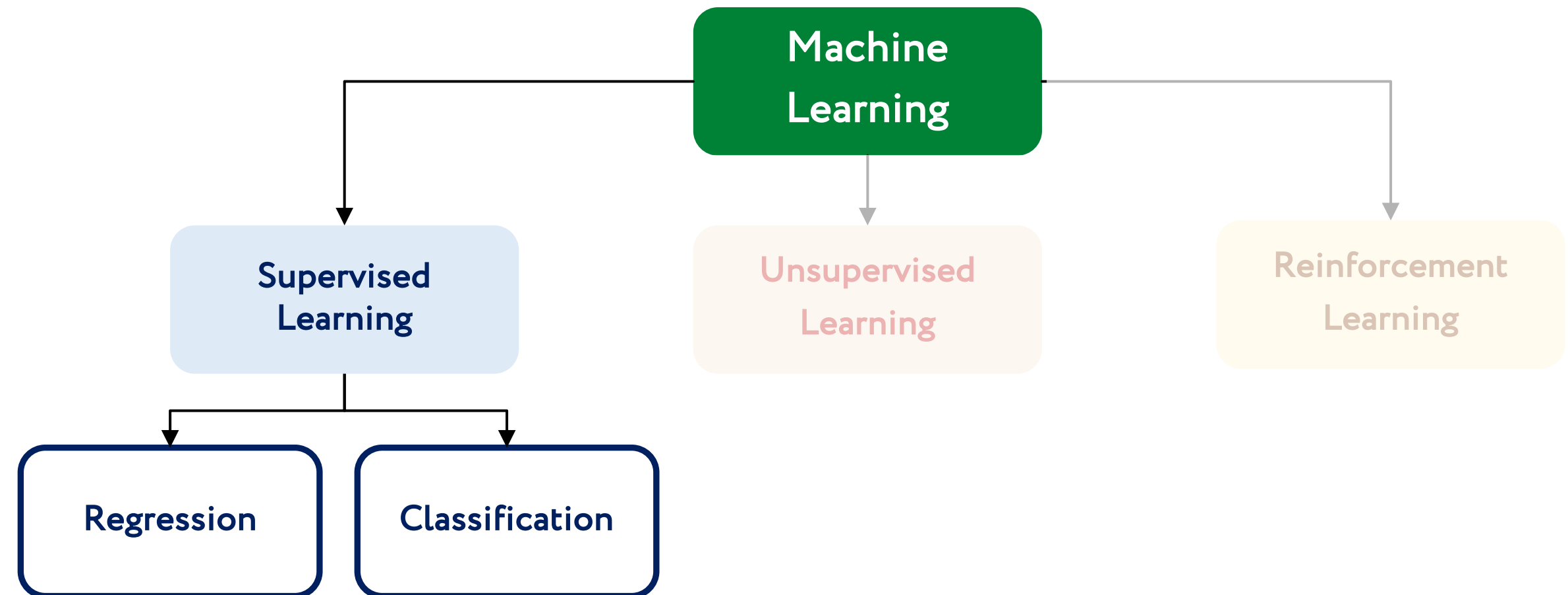
Fundamentals of Machine Learning

► Supervised vs **Unsupervised** learning



Credit: Medium – Navigating Unsupervised Learning

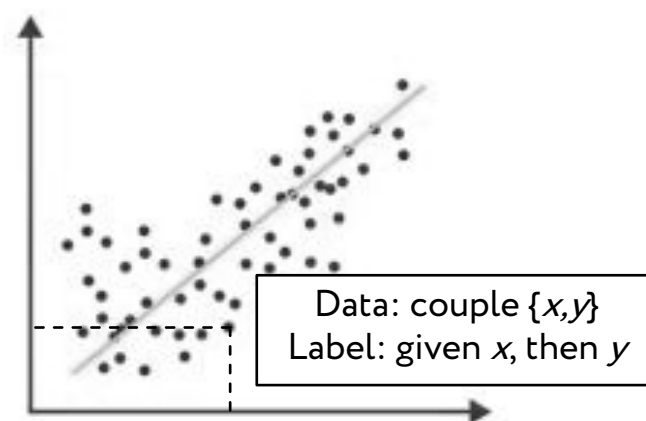
Fundamentals of Machine Learning



Fundamentals of Machine Learning

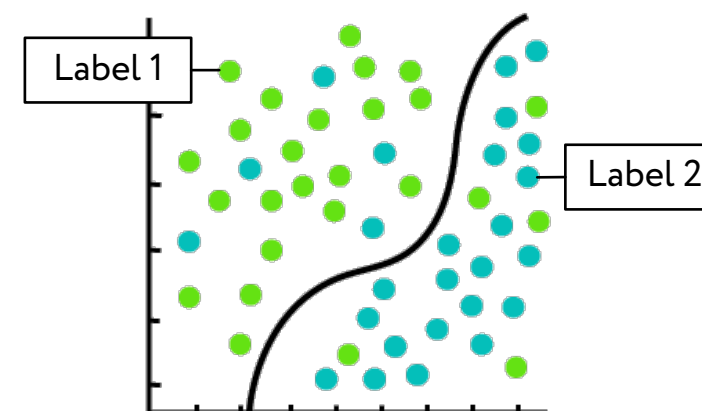
► Applications of supervised learning

Regression



Find the function
that allows to explain at best
the relationship between data

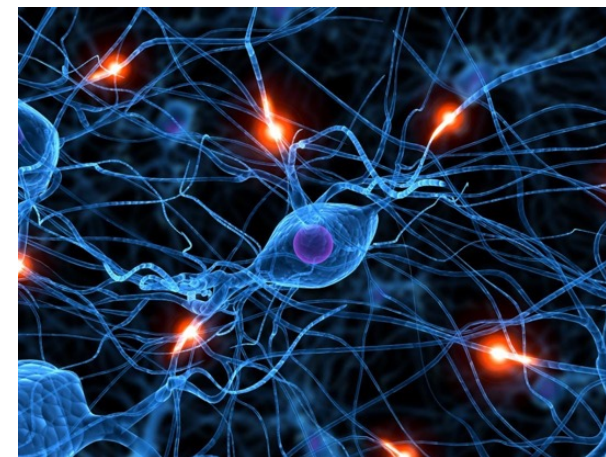
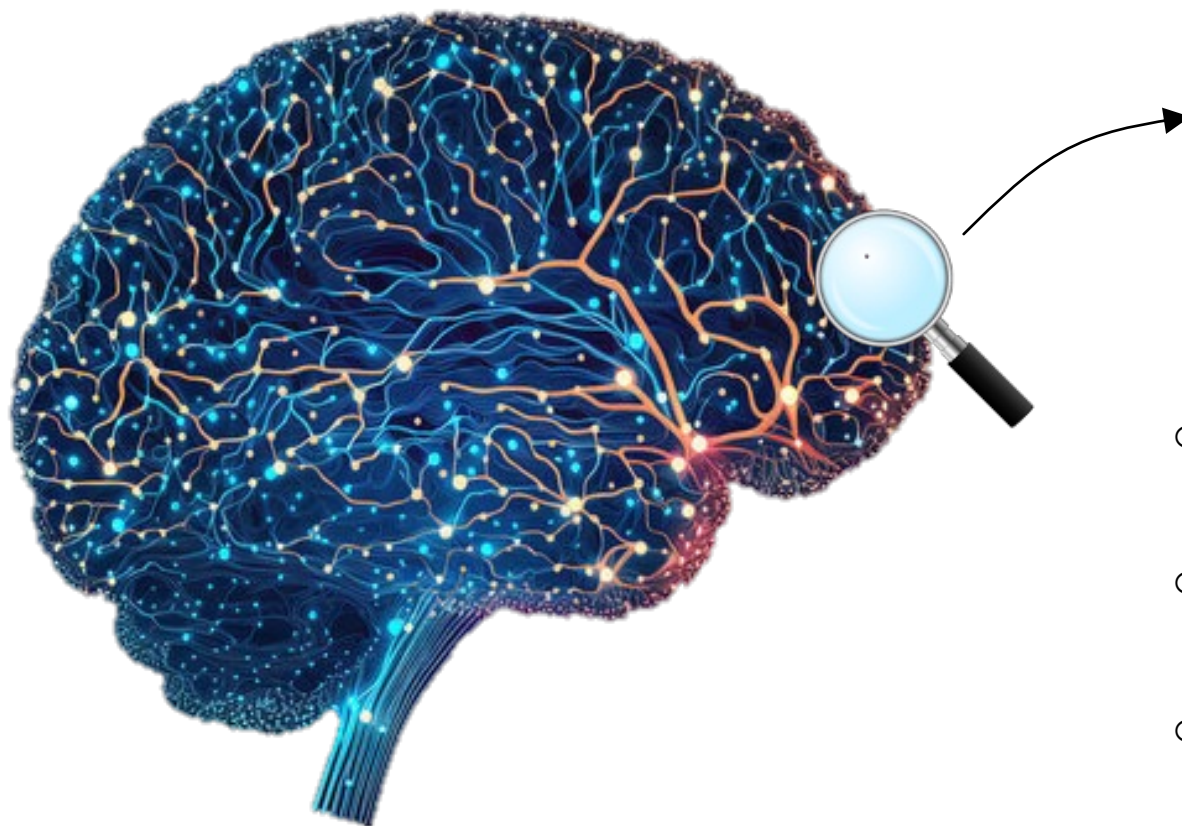
Classification



Find the function
that allows to separate
data into specific "classes"

Fundamentals of Machine Learning

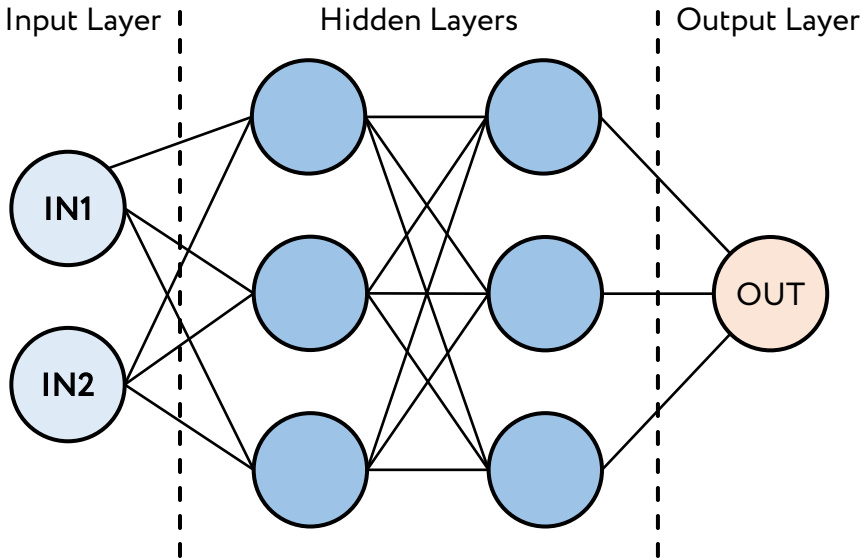
► A fundamental architecture: **Neural Networks**



- A neuron collects inputs from other neurons using dendrites.
- The neuron **sums** all the inputs and if the resulting value is greater than a threshold, it **fires**.
- The fired signal is then **sent** to other connected neurons through the axon.

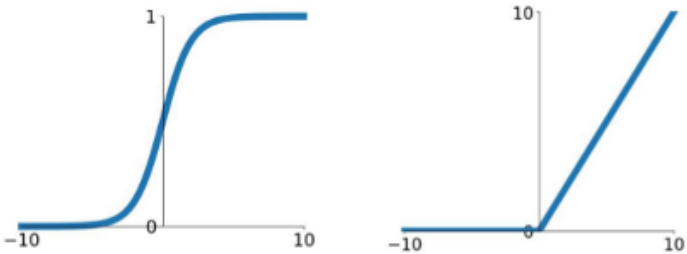
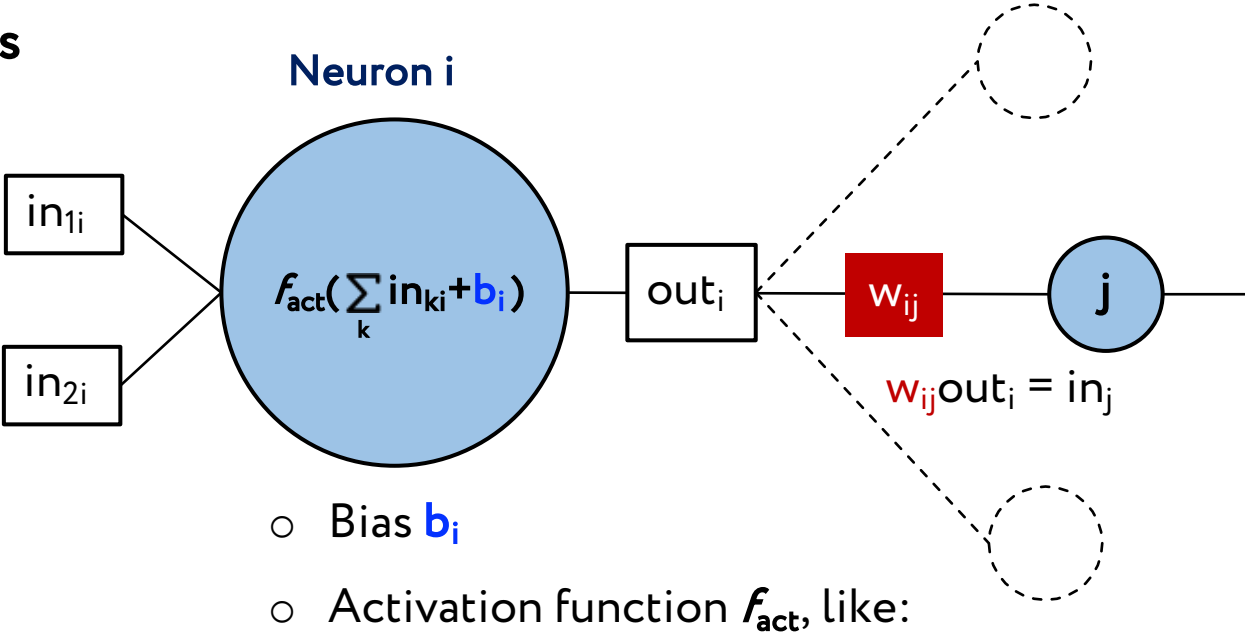
Fundamentals of Machine Learning

► A fundamental architecture: **Neural Networks**



Architecture definition:
number of layers, number of neurons per layer,
number and structure of connections, etc

(Hyper)parameters:
weights w_{ij} , biases b_i ← **TRAINING**



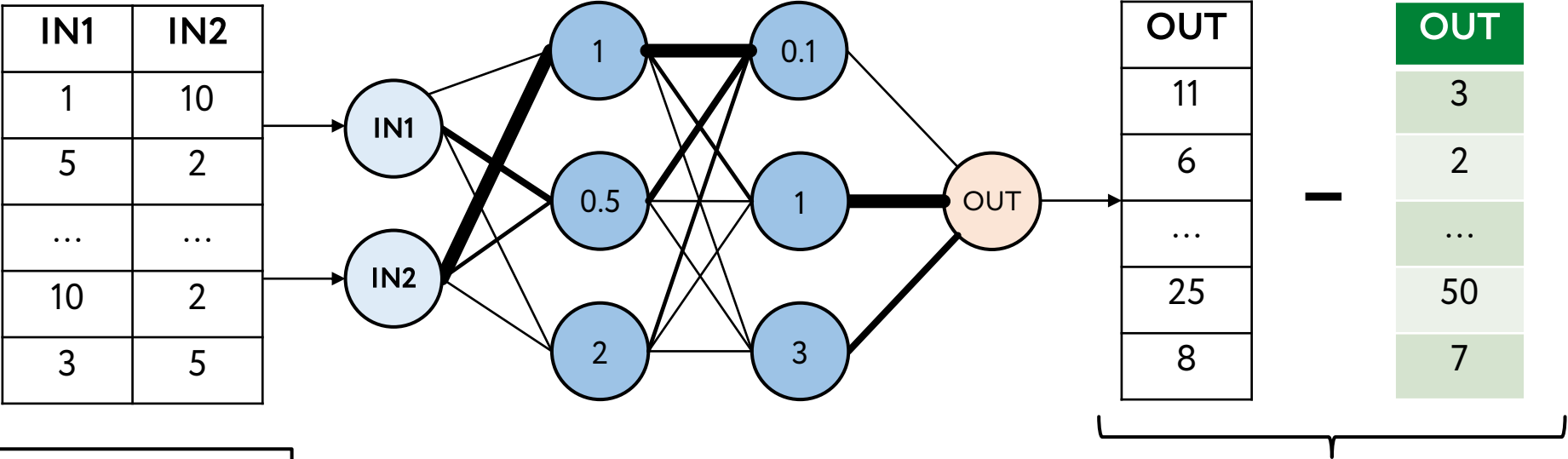
Fundamentals of Machine Learning

► A fundamental architecture: **Neural Networks**

Training dataset

IN1	IN2	OUT
1	10	3
5	2	2
...	...	...
10	2	50
3	5	7

Initialization: random choice of biases and weights



$$\Delta w_{ij} = -\eta \frac{\partial \mathcal{L}}{\partial w_{ij}}$$
$$\Delta b_i = -\eta \frac{\partial \mathcal{L}}{\partial b_i}$$

Backpropagation

η : learning rate

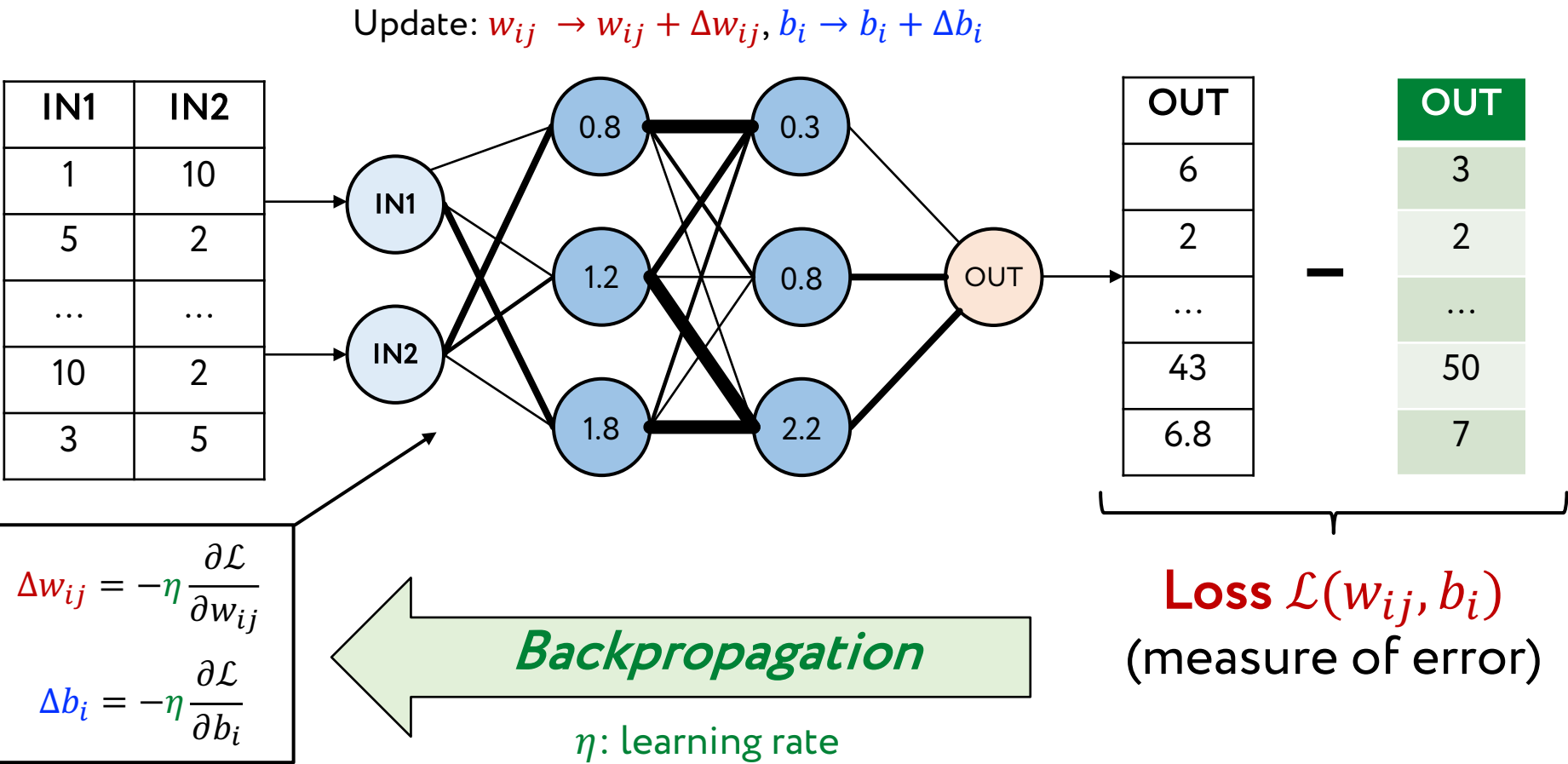
Loss $\mathcal{L}(w_{ij}, b_i)$
(measure of error)

Fundamentals of Machine Learning

► A fundamental architecture: **Neural Networks**

Training dataset

IN1	IN2	OUT
1	10	3
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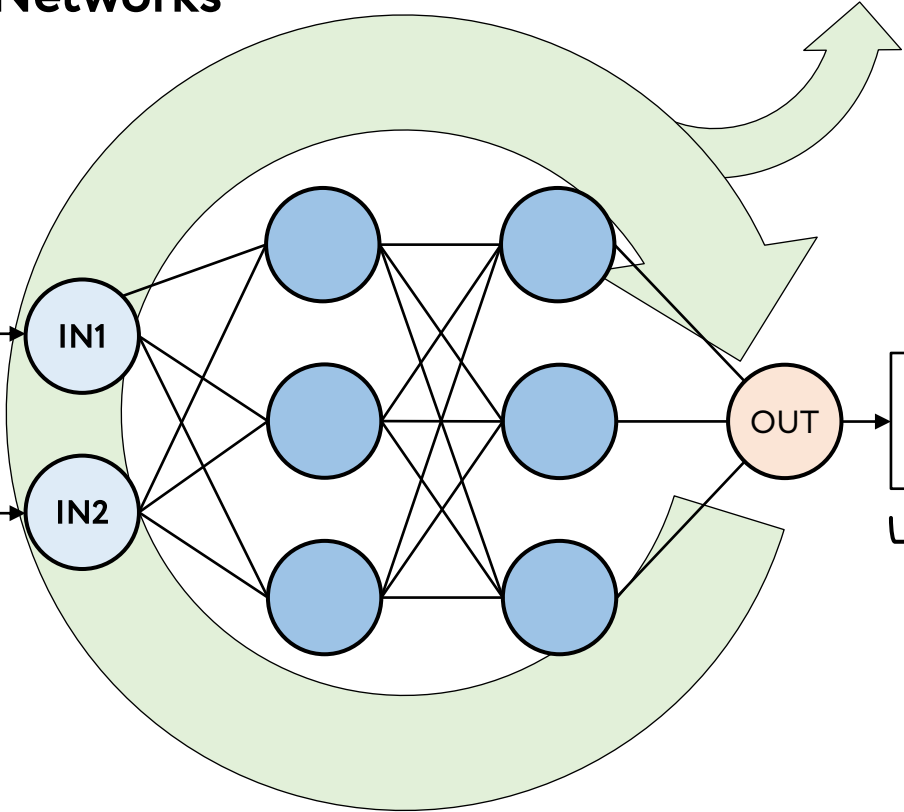
Fundamentals of Machine Learning

► A fundamental architecture: **Neural Networks**

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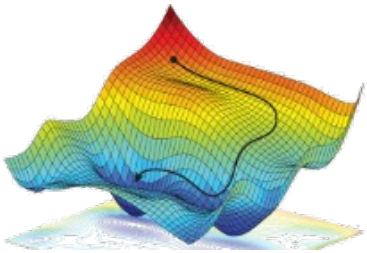
IN1	IN2	OUT
1	10	3
5	2	2
...	...	...
10	2	50
3	5	7

IN1	IN2
1	10
5	2
...	...
10	2
3	5



Training step/Epochs

UNTIL $Loss < Tol$
(or for a fixed number of epochs)



Predicted
OUT

–

Known
OUT

Loss $\mathcal{L}(w_{ij}, b_i)$
(measure of error)

Fundamentals of Machine Learning

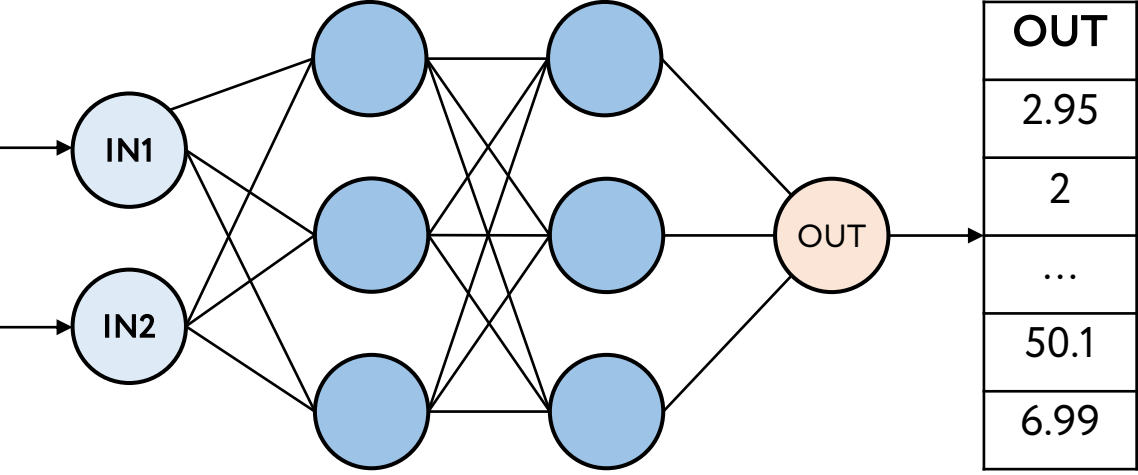
► A fundamental architecture: **Neural Networks**

✓ The NN is trained

Training dataset

IN1	IN2	OUT
1	10	3
5	2	2
...	...	...
10	2	50
3	5	7

IN1	IN2
1	10
5	2
...	...
10	2
3	5



OUT
2.95
2
...
50.1
6.99

≈

OUT
3
2
...
50
7

Validation dataset

2	8	6
...	...	...
4	5	12

2	8
...	...
4	5



Is it useful for predictions?

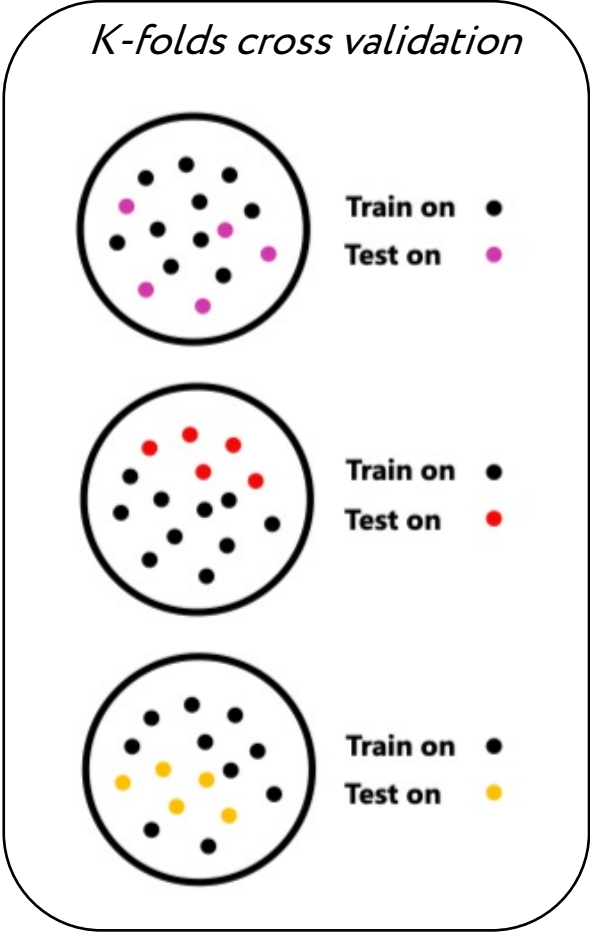
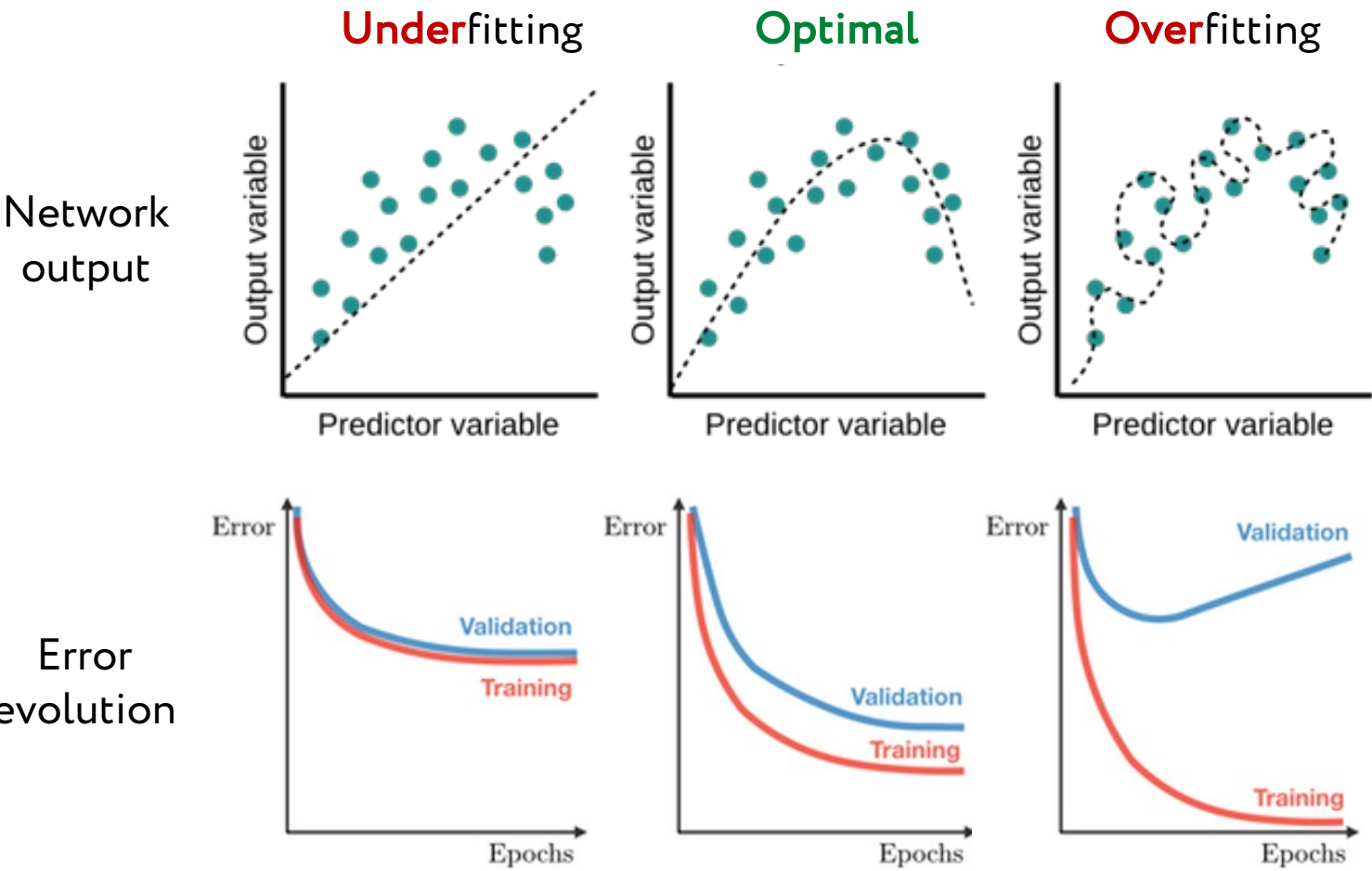
5.8
...
11.5



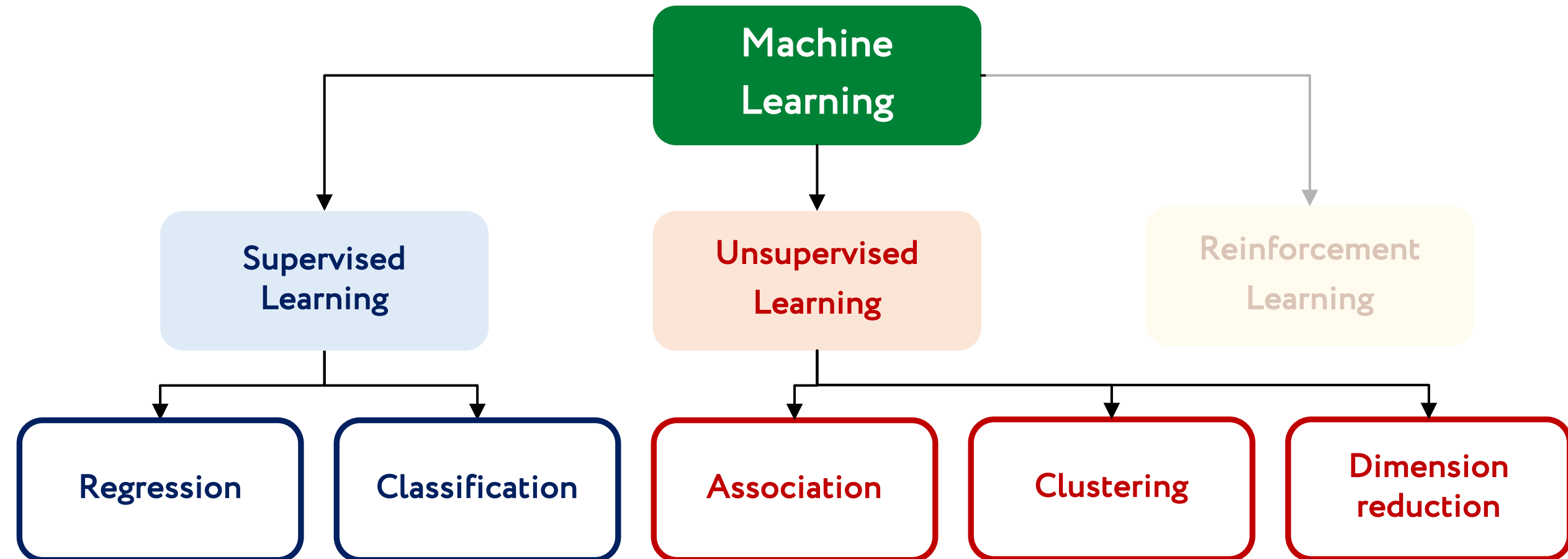
6
...
12

Fundamentals of Machine Learning

► A fundamental architecture: **Neural Networks**



Fundamentals of Machine Learning



Fundamentals of Machine Learning

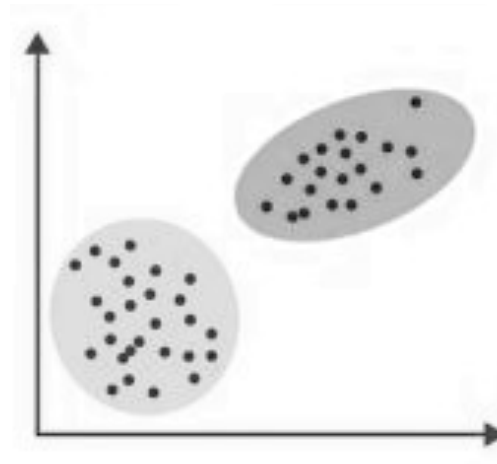
► Applications of unsupervised learning

Association



Discover relationships
between features

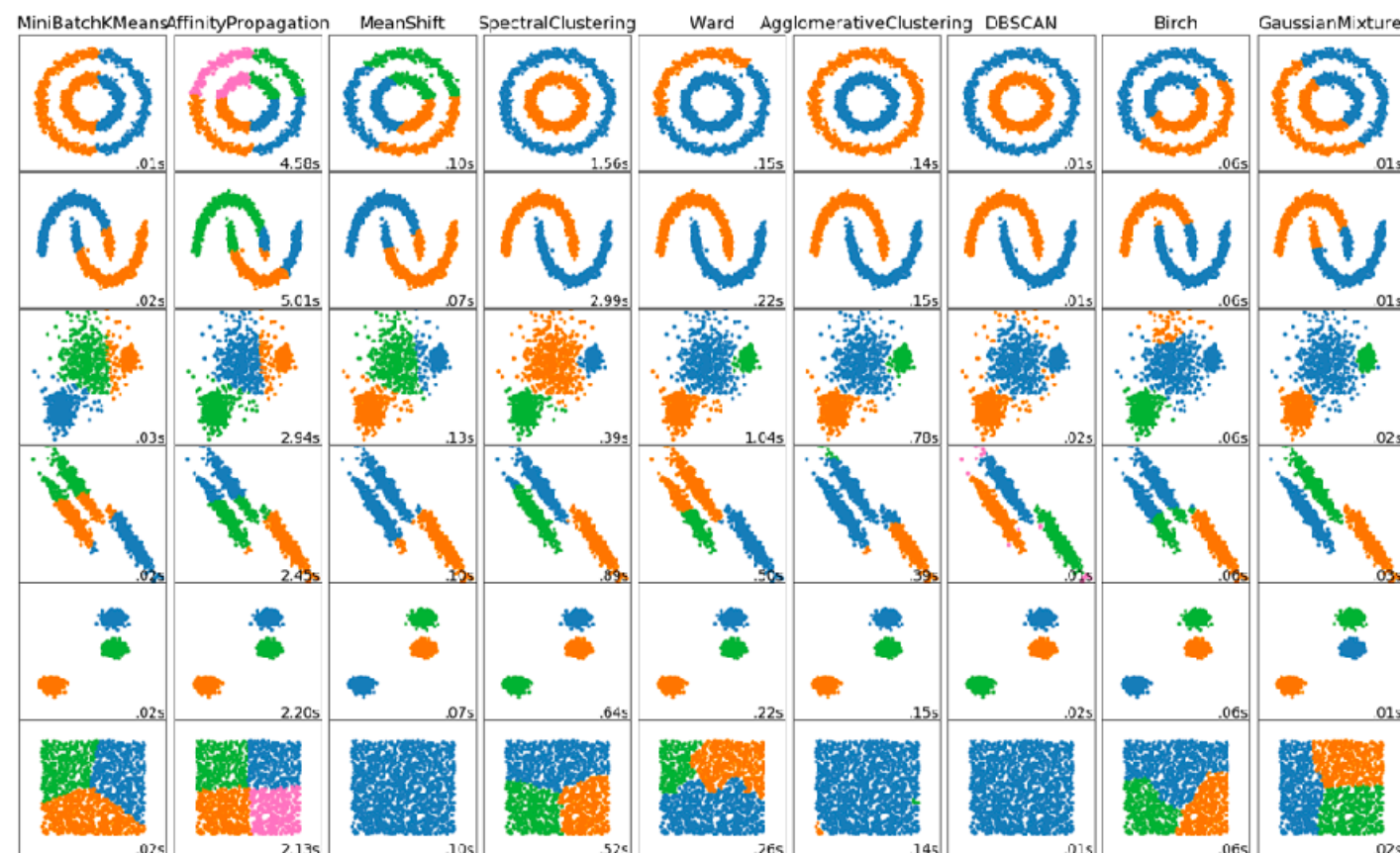
Clustering



Grouping data based on their
similarities and differences

Fundamentals of Machine Learning

- **Clustering:** automatically find the “internal structure” of data

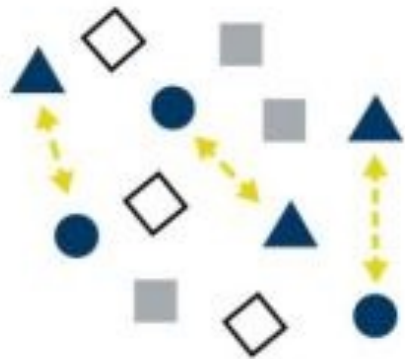


Source: http://scikit-learn.org/stable/auto_examples/cluster/plot_cluster_comparison.html

Fundamentals of Machine Learning

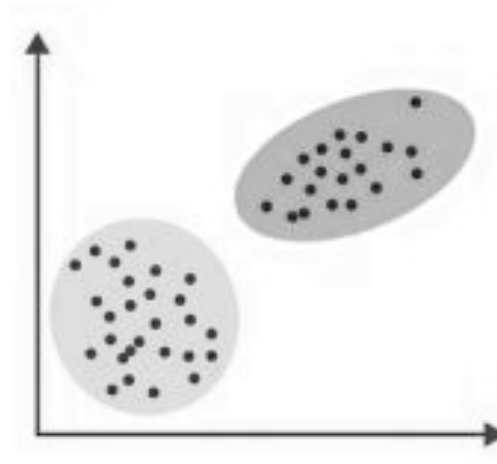
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Association



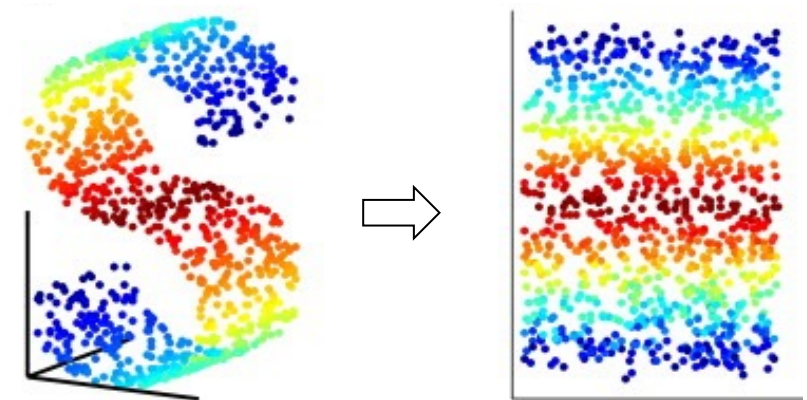
Discover relationships
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Clustering



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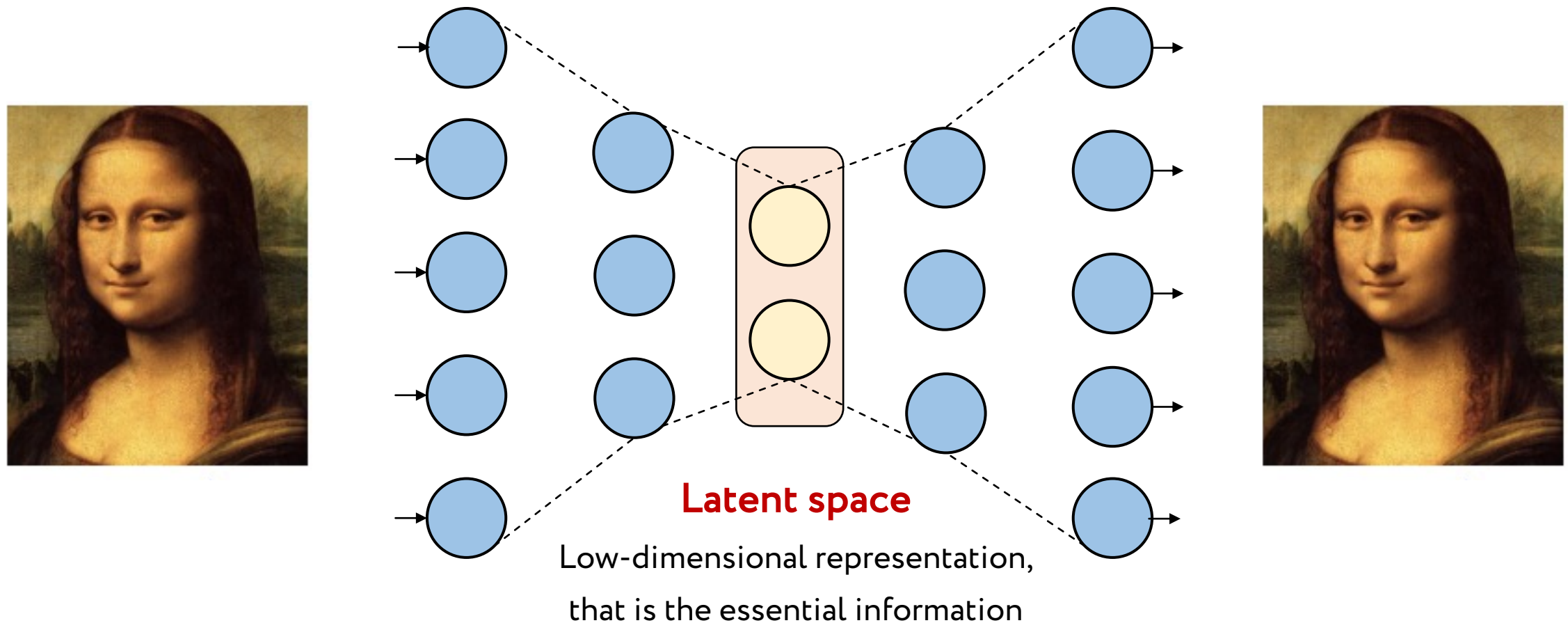
Dimension reduction



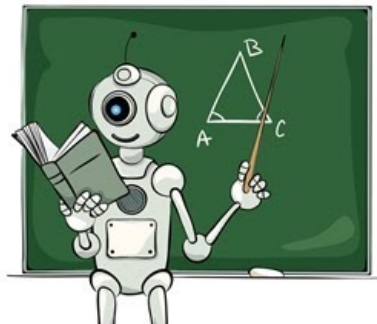
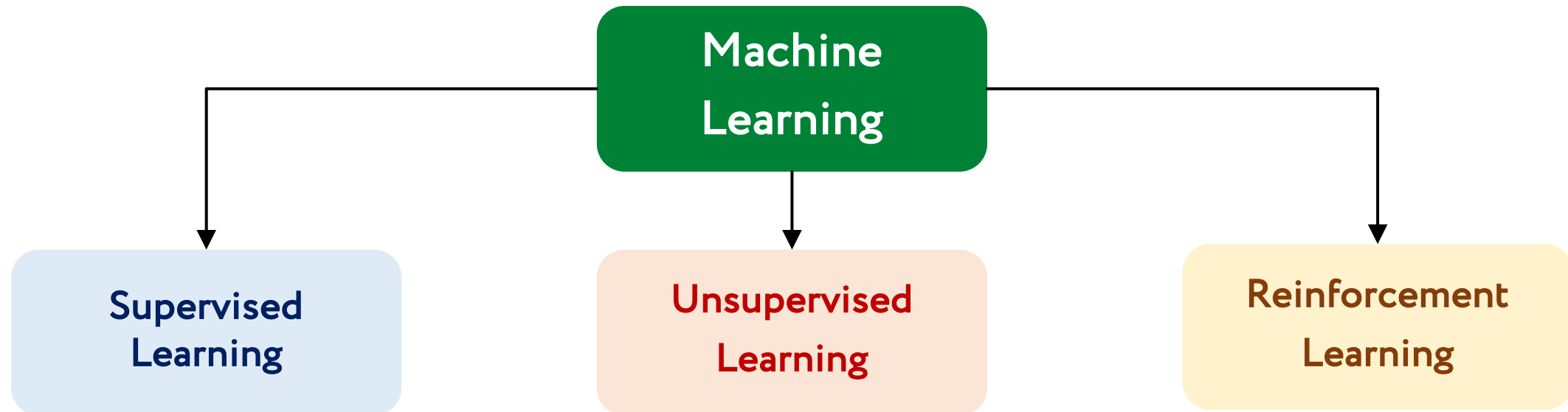
From high to low-dimensional
spaces without compromising data

Fundamentals of Machine Learning

- **Dimension reduction** via a powerful architecture: autoencoders



Fundamentals of Machine Learning



What do you want the machine learning system to do?

I want to see if there are natural clusters or dimensions in the data I have about different situations.

UNSUPERVISED LEARNING MAY BE APPROPRIATE

*clustering
anomaly detection*

I want to learn what actions to take in different situations.

SUPERVISED LEARNING MAY BE APPROPRIATE

*neural nets
support vector machines
regression
recommender systems*

Do you want the ML system to be active or passive?

ACTIVE

The system's own actions will affect the situations it sees in the future.

PASSIVE

The system will learn from data I give it.

No

Could there be patterns in these situations that humans haven't recognized before?

No

Yes

Could a knowledgeable human decide what actions to take based on the data you have about the situation?

Yes

Yes

Do you have access to data that describes a lot of examples of situations and appropriate actions for each situation?

No

Will the system be able to gather a lot of data by trying sequences of actions in many different situations and seeing the results?

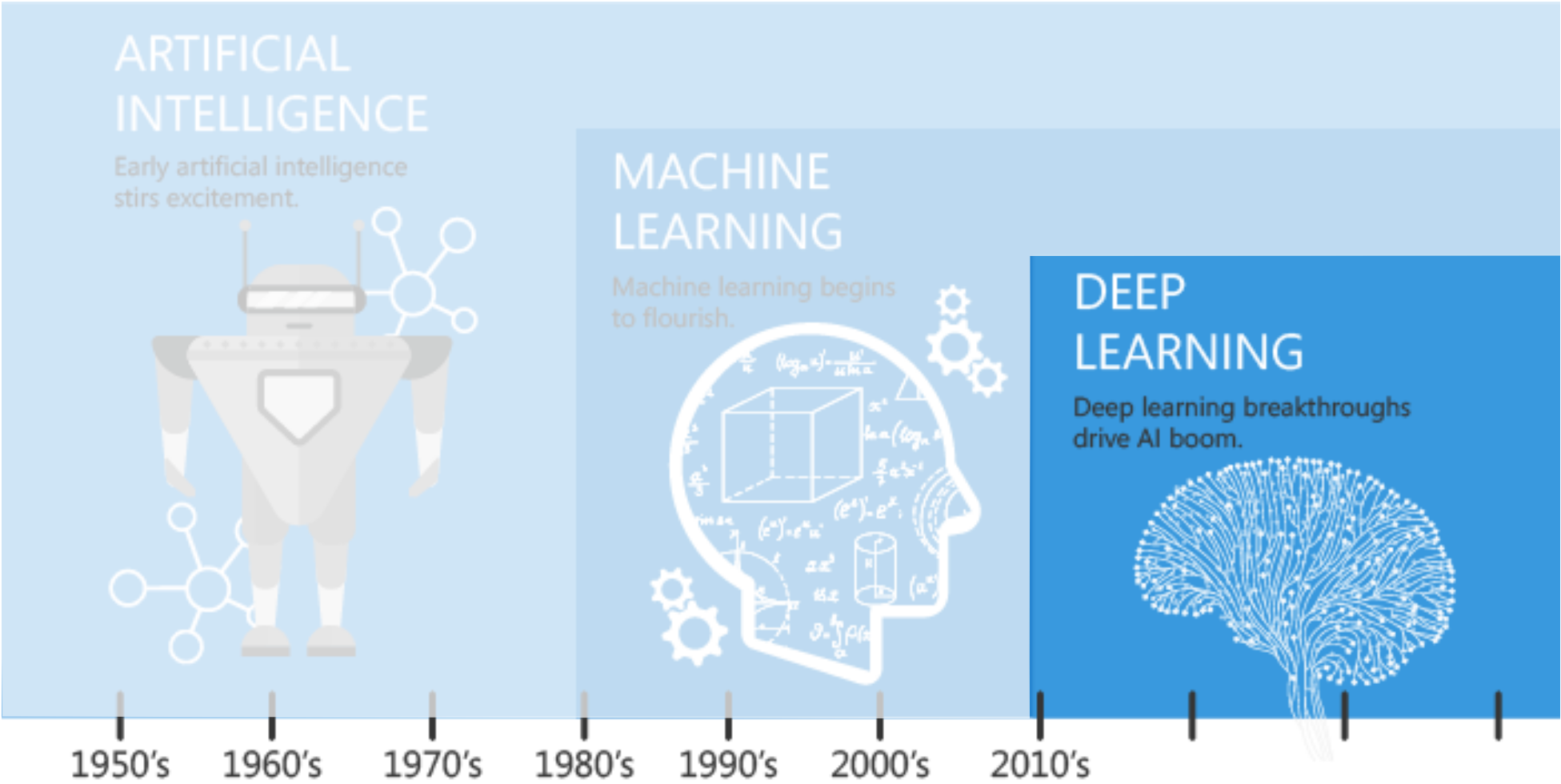
No

Yes

MACHINE LEARNING IS NOT USEFUL

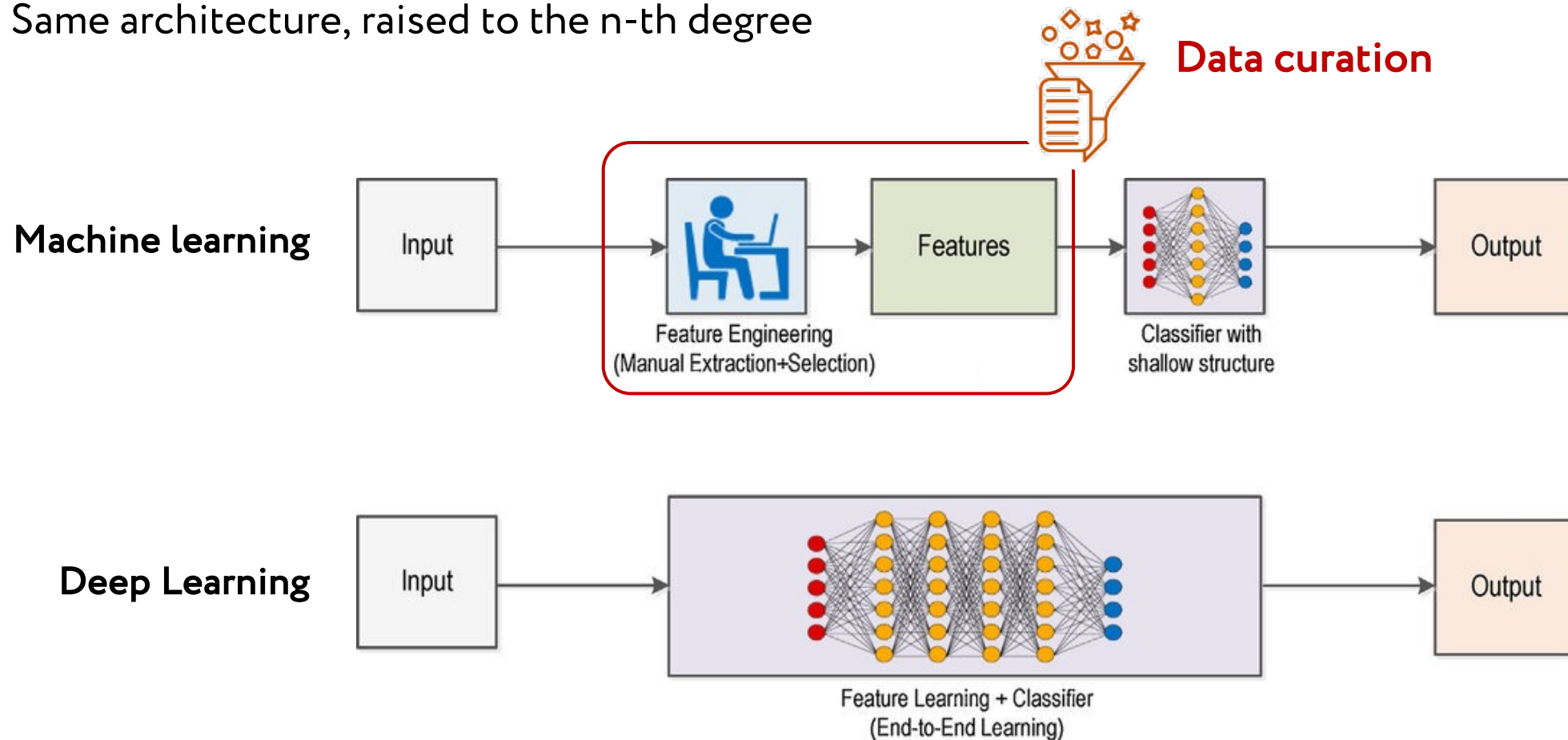
REINFORCEMENT LEARNING MAY BE APPROPRIATE

An (ordered) Overview



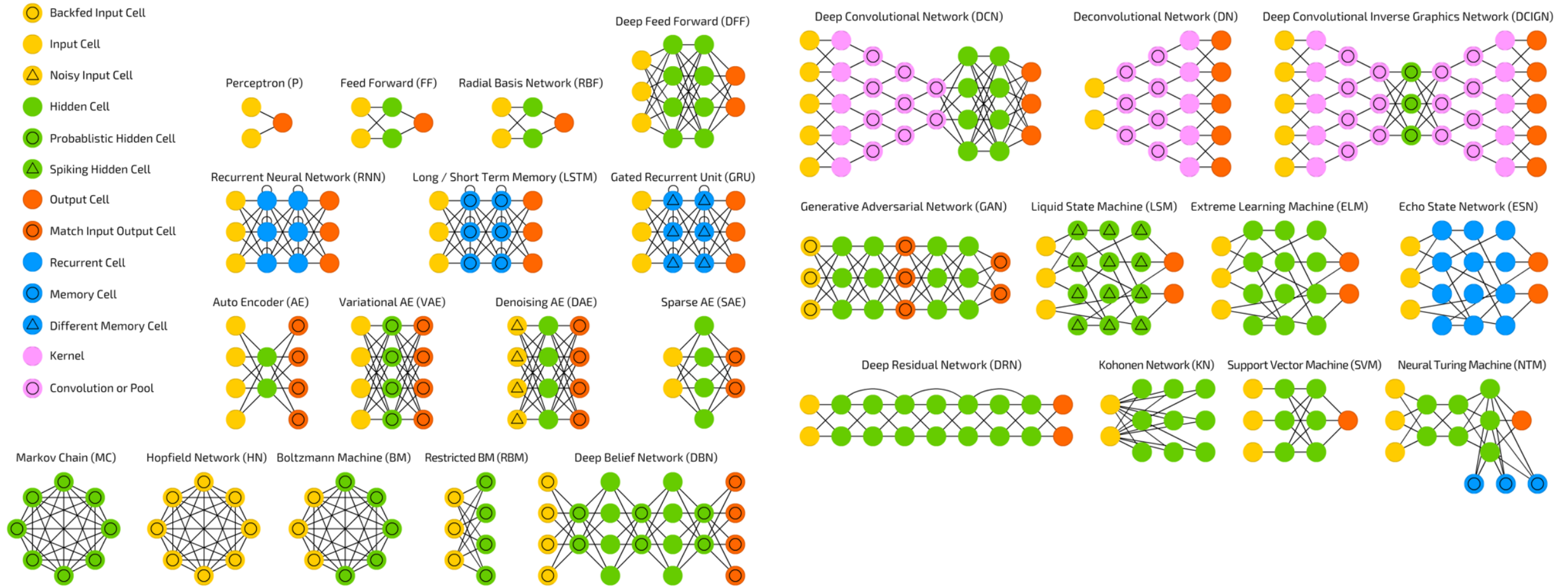
Machine Learning vs Deep Learning

- Same architecture, raised to the n-th degree

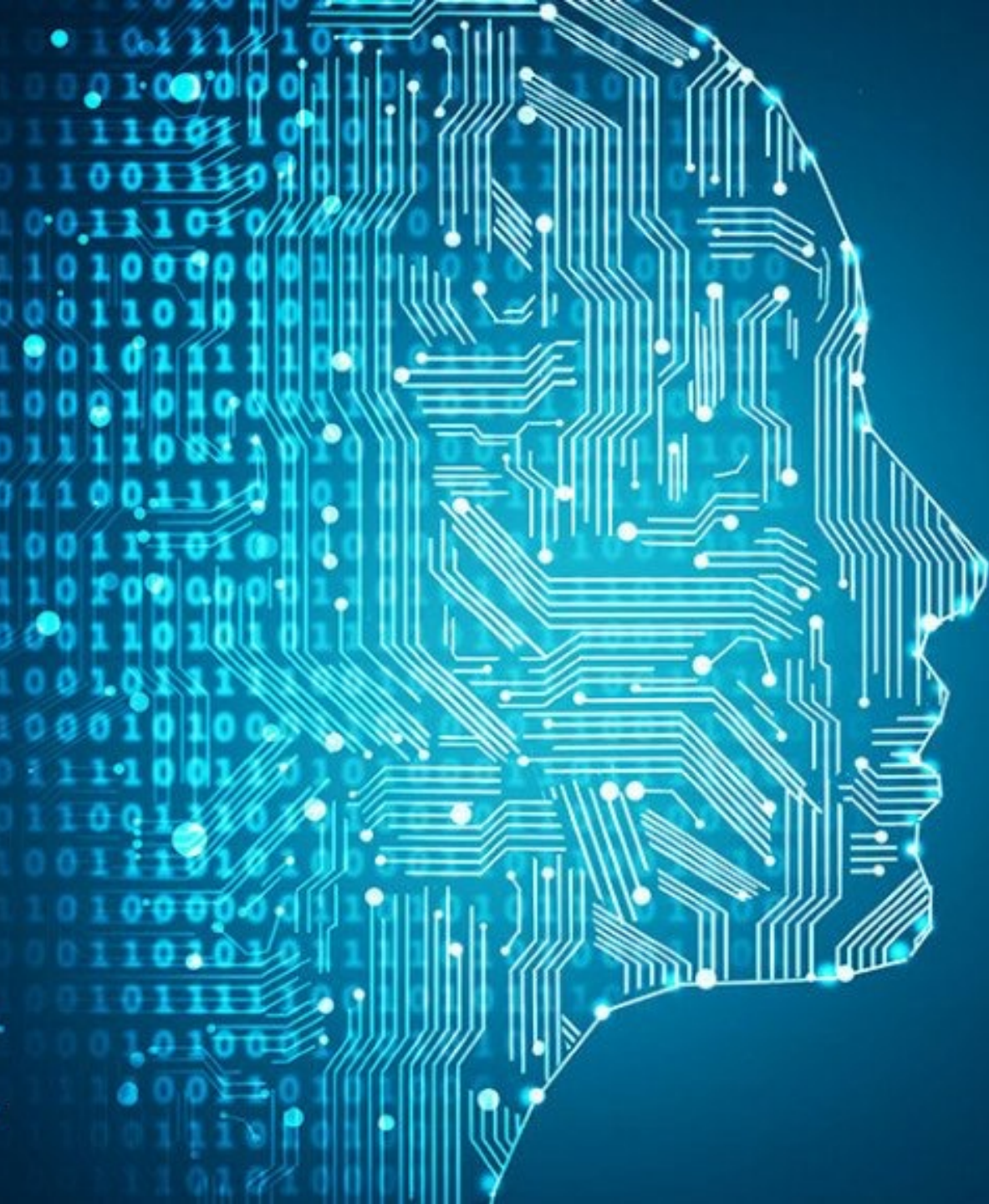


A mostly complete chart of Neural Networks

©2016 Fjodor van Veen - asimovinstitute.org



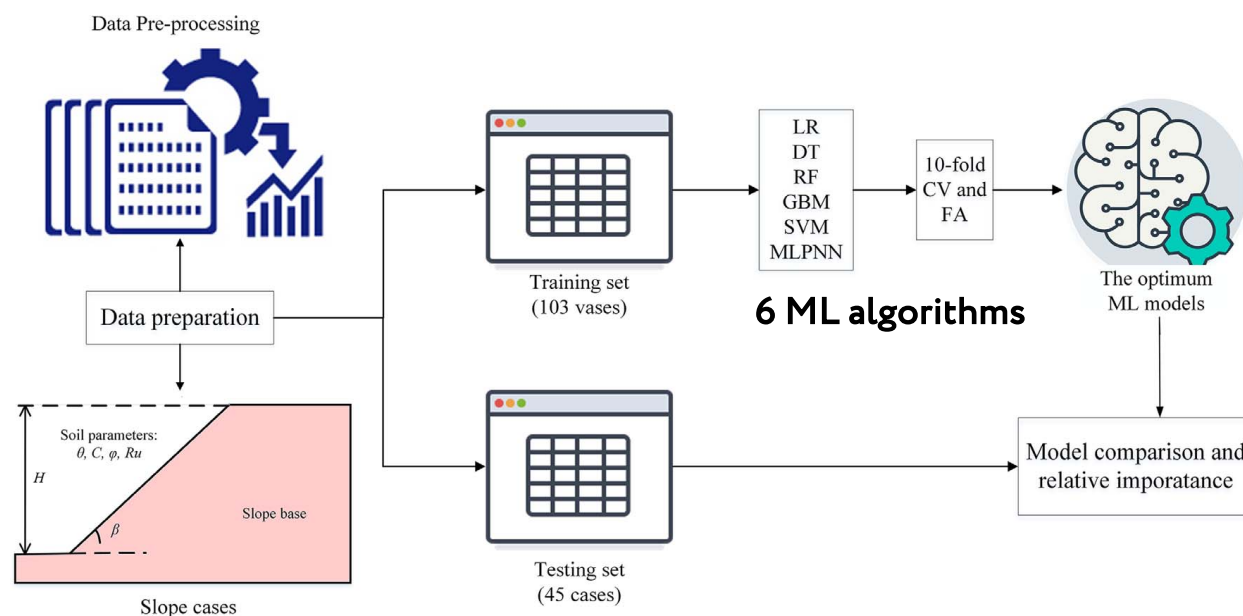
Source: Medium – The mostly complete chart of Neural Networks, explained



Representative examples

- Qi et al, 2018. Slope stability prediction using integrated metaheuristic and machine learning approaches: A comparative study. Computers & Industrial Engineering 118 (2018) 112–122

○ Classification problem: Stable vs Non-stable

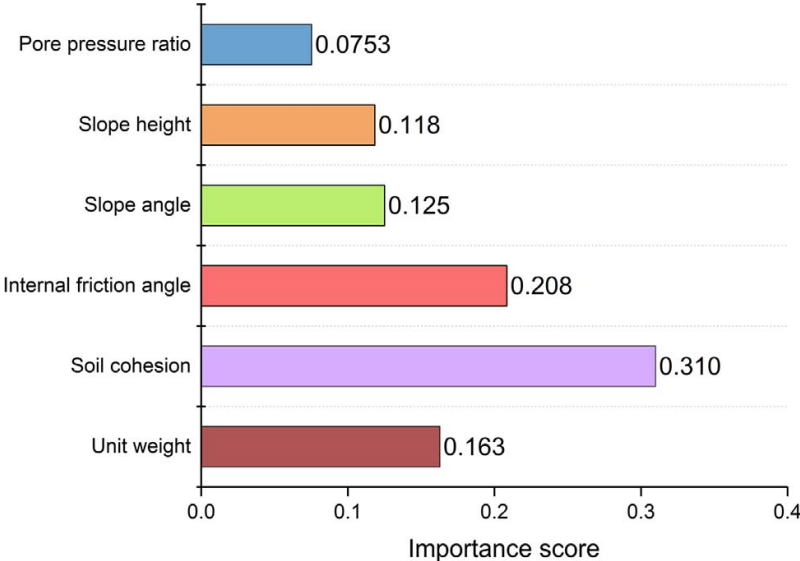
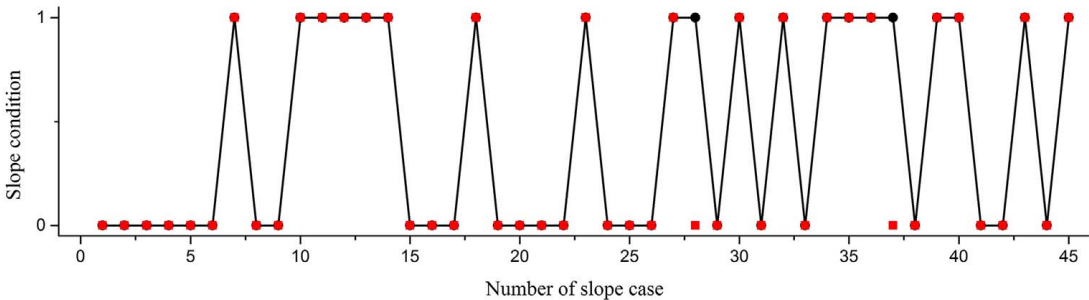


- Supervised learning (78 stable and 70 non-stable)
- 6 slopes attributes (e.g., height, angle, pore water ratio)
- Question 1: which ML algorithm works best?
- Question 2: which is the most important slope attribute?

Representative examples

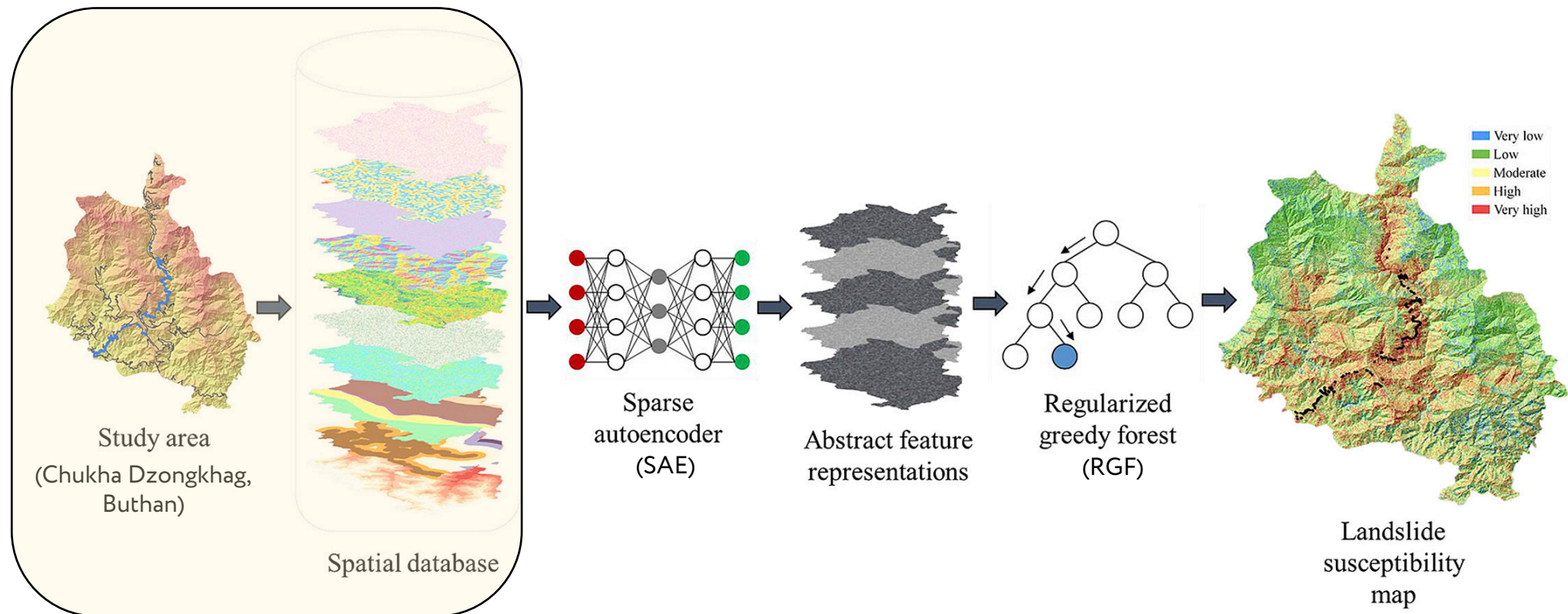
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Actual condition		Predicted condition		
		Youden's cutoff		
		Stable	Unstable	Accuracy
LR	Stable	17	3	0.82
	Unstable	5	20	
DT	Stable	15	5	0.80
	Unstable	4	21	
RF	Stable	20	0	0.93
	Unstable	3	22	
GBM	Stable	20	0	0.93
	Unstable	3	22	
SVM	Stable	18	2	0.96
	Unstable	0	25	
BPNN	Stable	17	3	0.84
	Unstable	4	21	



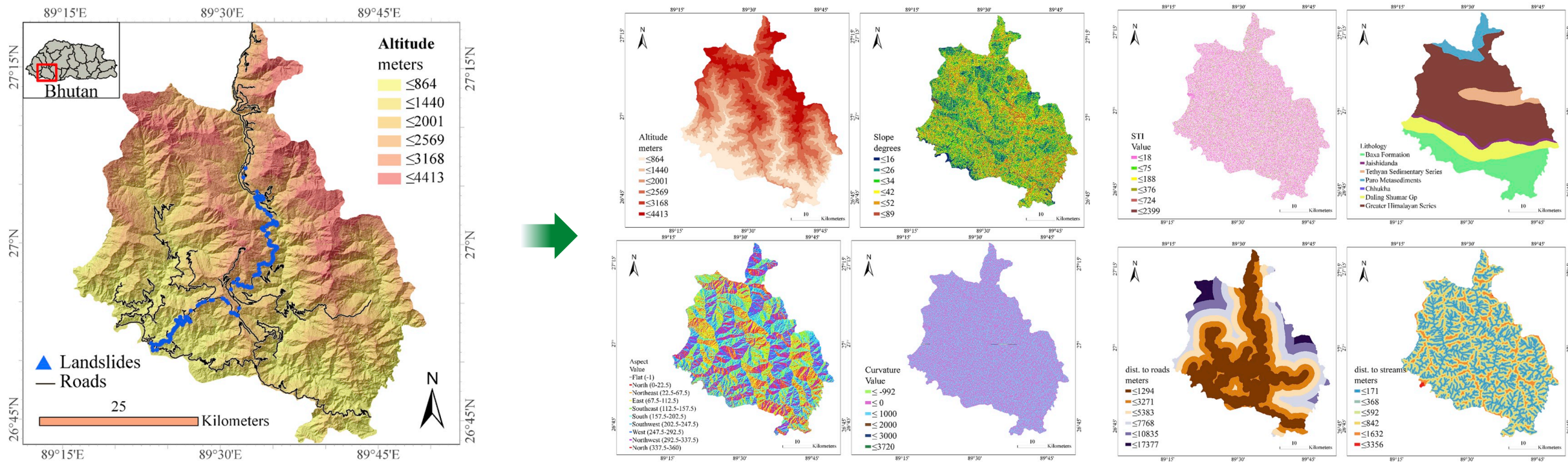
Representative examples

- ▶ Sameen et al, 2020. Landslide spatial modelling using unsupervised factor optimisation and regularised greedy forests. Computers & Geosciences 134 (2020) 104336
- **Spatial landslide susceptibility map reconstruction**



Representative examples

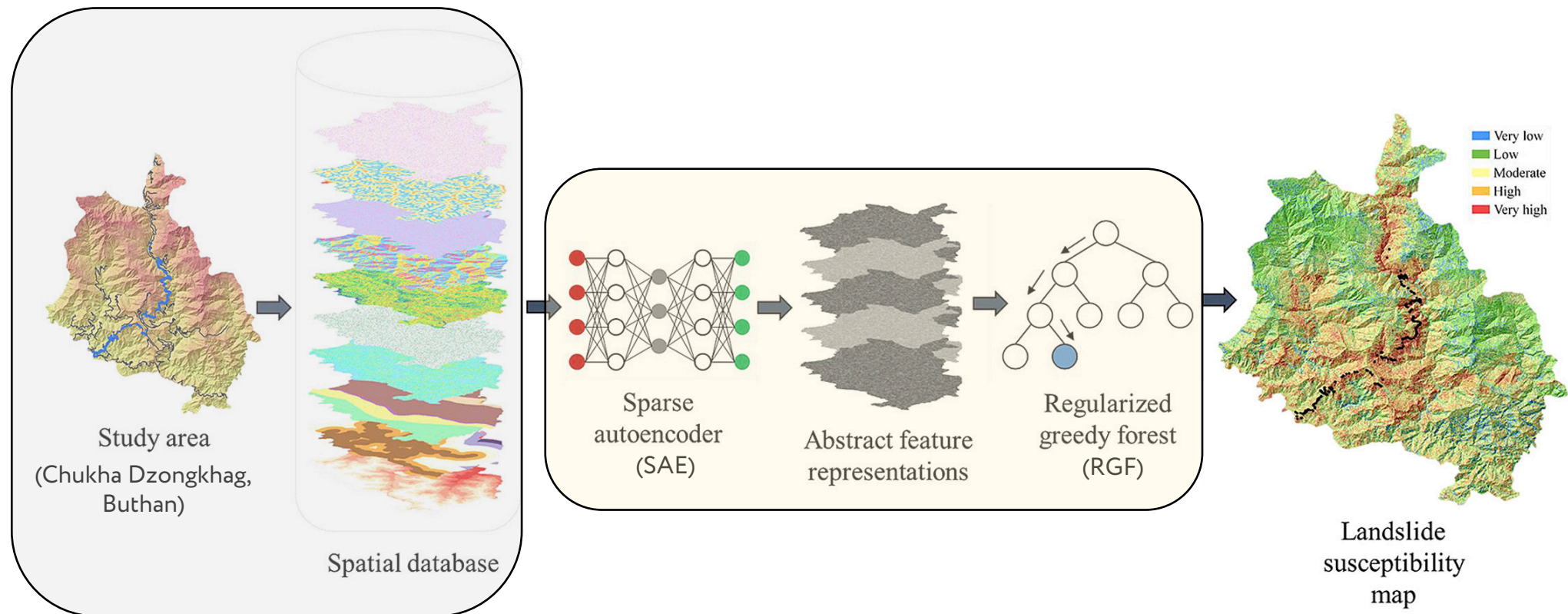
- Sameen et al, 2020. Landslide spatial modelling using unsupervised factor optimisation and regularised greedy forests. Computers & Geosciences 134 (2020) 104336



Landslide conditioning factor

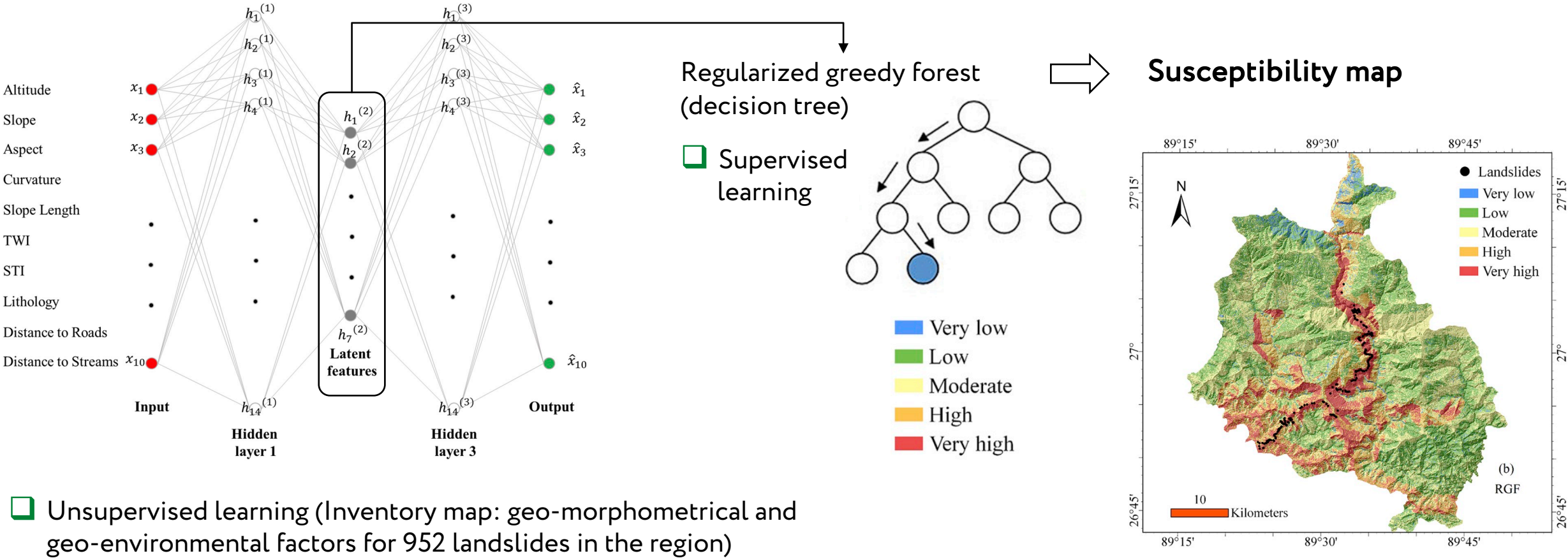
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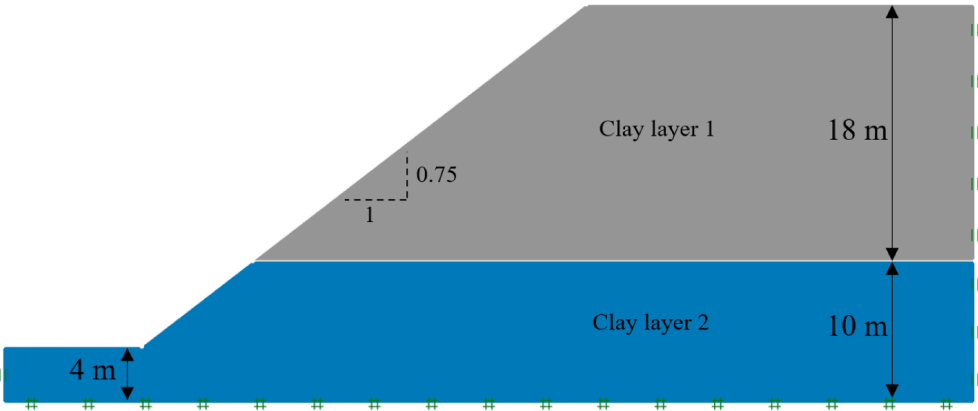
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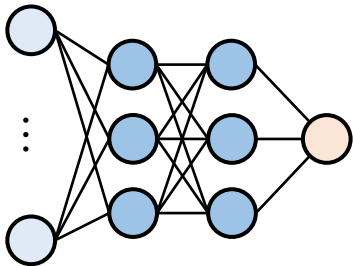
Representative examples

- ▶ Amnipour et al, 2023. Slope stability machine learning predictions on spatially variable random fields with and without factor of safety calculations. Computers & Geosciences 153 (2023) 105094
- Regression study: ML to account for uncertainty of geotechnical parameters

	Unit weight ($\frac{\text{kN}}{\text{m}^3}$)	Undrained shear strength (kPa)			
		Mean	COV	δ_h (m)	δ_v (m)
Clay layer 1	19	75	0.3	12	2
Clay layer 2	19	95	0.3	12	2

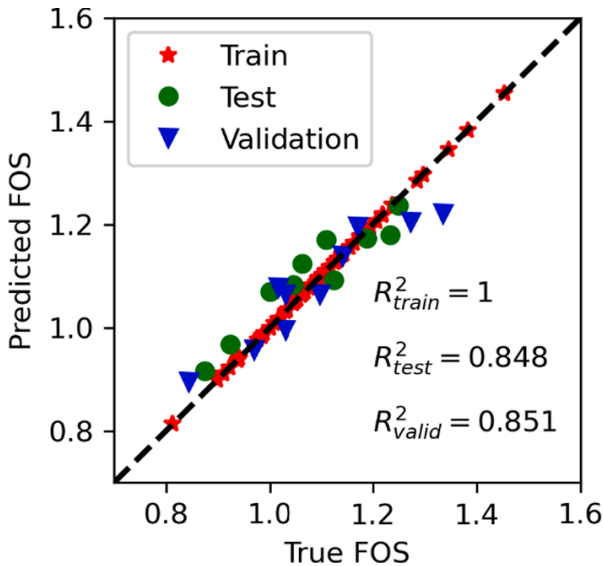


Elementwise undrained shear strength (4376 values)



Factor of Safety (FOS)

- Supervised learning (100 direct simulations)
- Research question: Effectiveness of ML algorithms to build a surrogate model



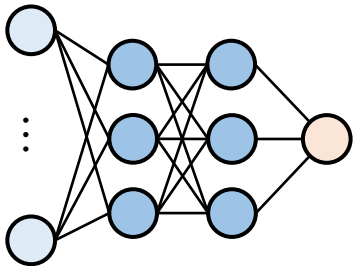
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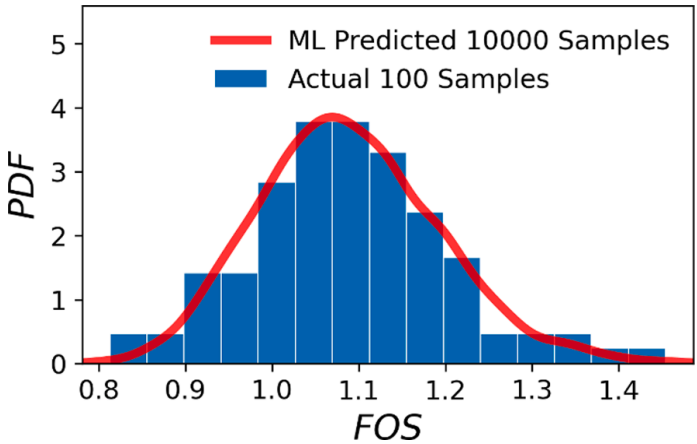
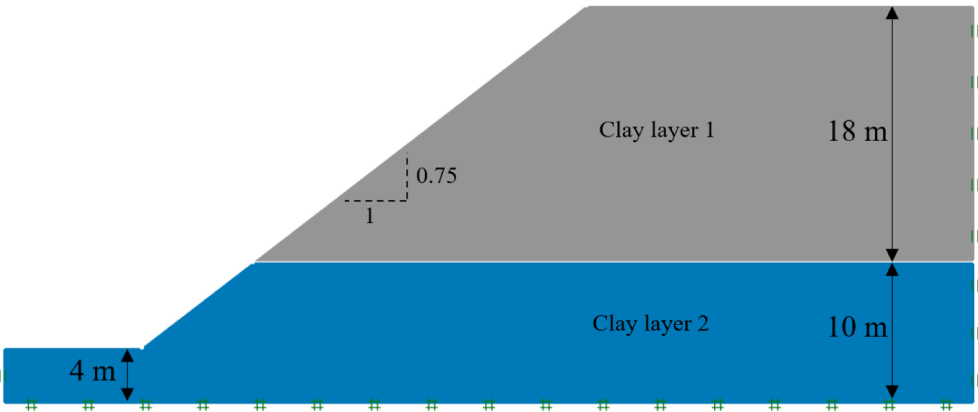
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Elementwise
undrained
shear strength
(4376 values)



Factor of Safety (FOS)



COMPUTATIONAL COST:

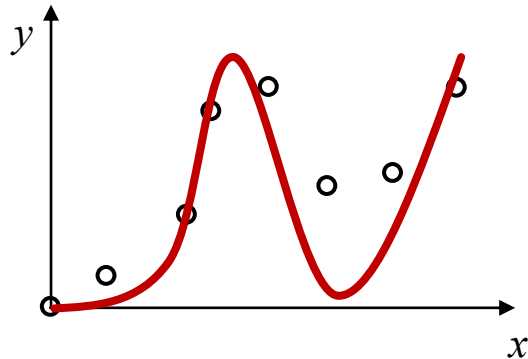
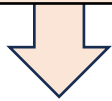
- ML surrogate: 8h
- Monte-Carlo simulation = 35 days

100x faster

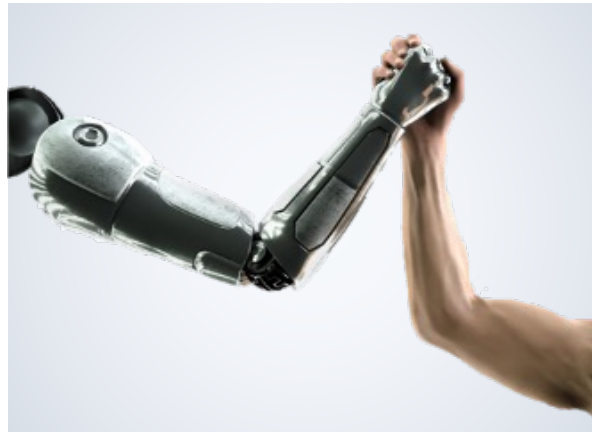
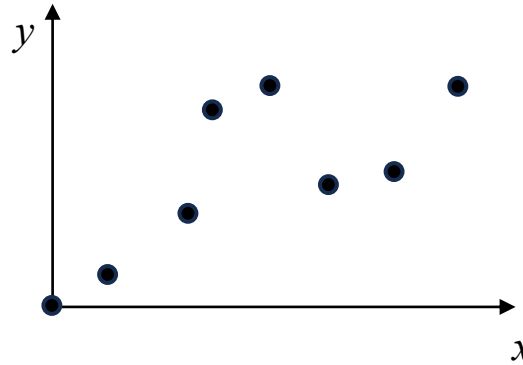
Conclusion: a futile struggle

Data-driven approaches:

Simulation methods able to integrate and perform data acquisition, reduction, assimilation and analysis (Chinesta et al, 2018)

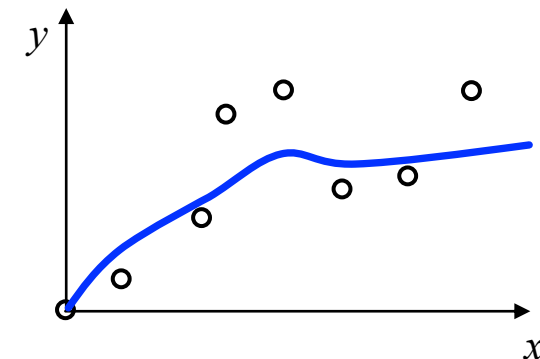
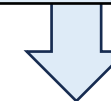


Kirchdoerfer and Ortiz, 2016; Liu et al, 2016; Eggersmann et al, 2019; Carrara et al, 2020; Logarzo et al, 2021; Yvonnet et al, 2023



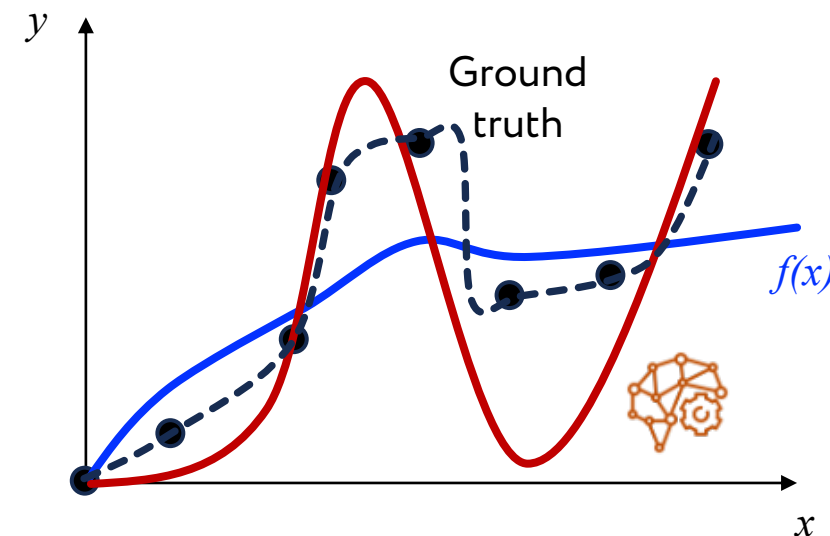
Model-driven approaches:

Simulation methods *a priori* incorporating constitutive relationships, defined such to be able to reproduce and explain available data



Since Galileo Galilei, Robert Hooke, Daniel Bernoulli, Claude-Louis Navier, and many others...

Conclusion: a futile struggle



Hybrid model-data driven approaches
PINN: Physics-Informed Neural Networks
Data augmentation and constraints enforcement

Michele MARINO

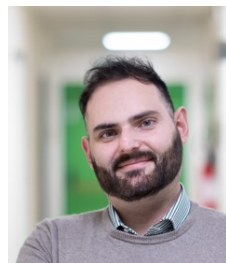
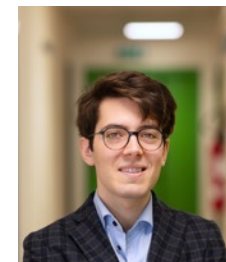


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