CONSIGLIO NAZIONALE
DEGLI INGEGNERI

CONVEGNO ON LINE
MERCOLEDÌ 27 NOVEMBRE 2024, ORE 15.00 - 18.00

Design Intelligente, Manutenzione Predittiva, Realtà aumentata e virtuale nelle costruzioni

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Politecnico di Torino, DISEG, ArtIStE

AI Tradizionale vs AI Generativa

1. Obiettivo:

- AI Tradizionale: Classificare, predire o riconoscere dati.
- AI Generativa: Creare contenuti nuovi e originali.

2. Esempi:

- AI Tradizionale: Identificare un gatto in un'immagine.
- AI Generativa: Disegnare un gatto completamente nuovo.

3. Output:

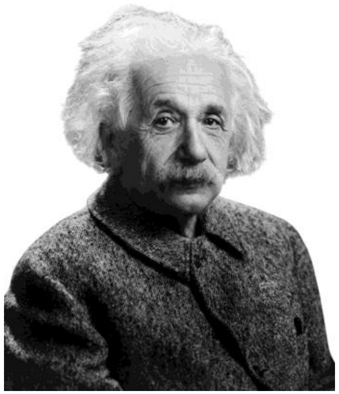
- AI Tradizionale: Etichette, numeri, decisioni.
- AI Generativa: Testo, immagini, video, suoni.

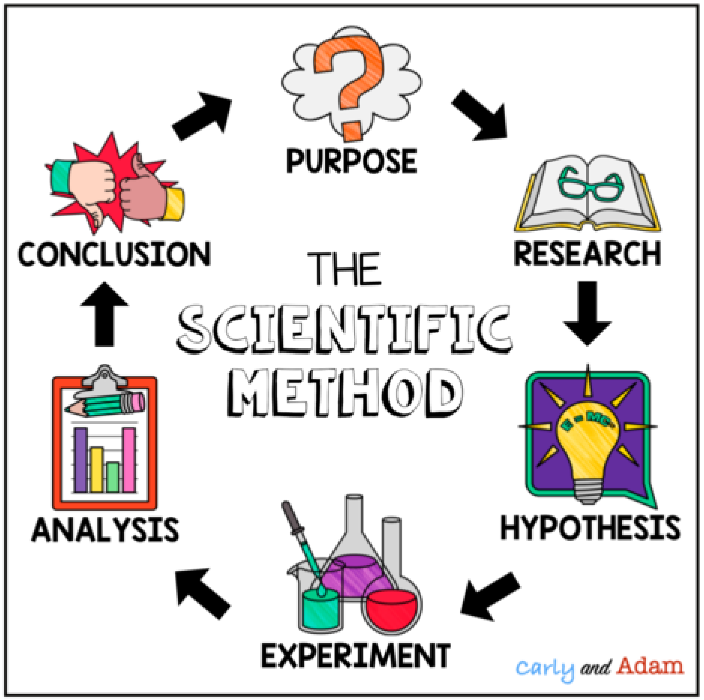
4. Modelli utilizzati:

- AI Tradizionale: Modelli discriminativi.
- AI Generativa: GANs, Transformers, Modelli Diffusivi.

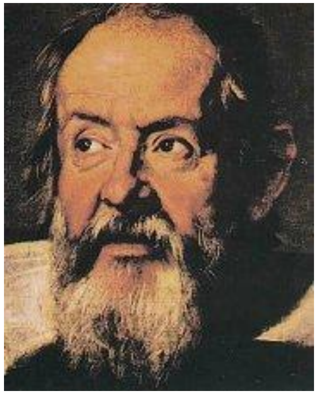
INNOVAZIONE ED INGEGNERIA:

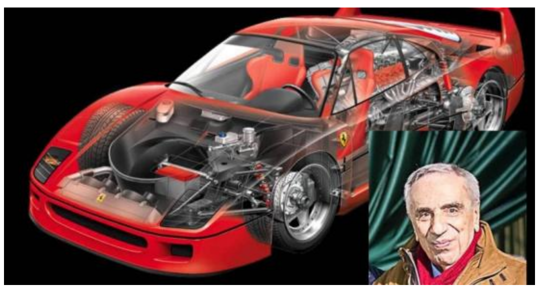
Un connubio imprescindibile

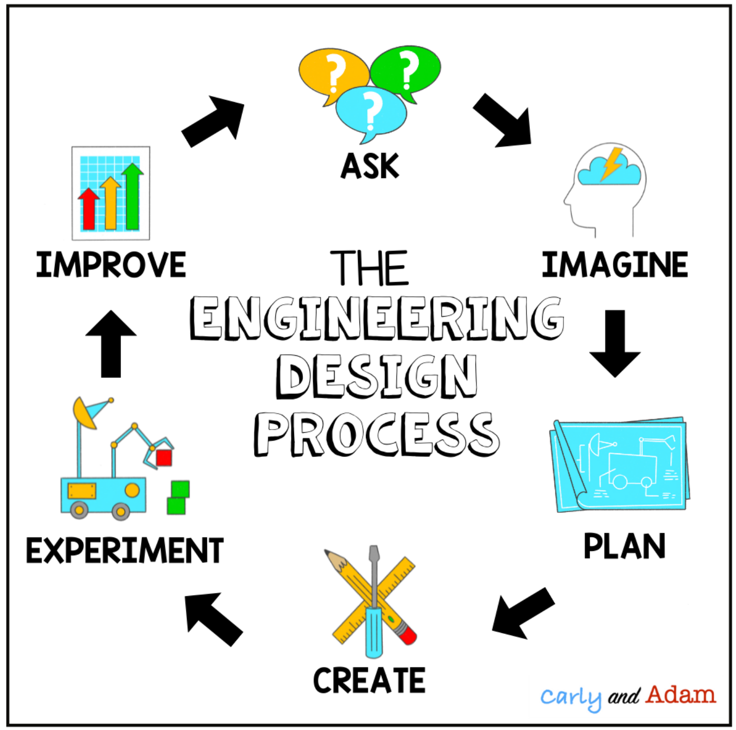




PURPOSE
RESEARCH
HYPOTHESIS
EXPERIMENT
ANALYSIS
CONCLUSION
THE
SCIENTIFIC
METHOD
Carly and Adam



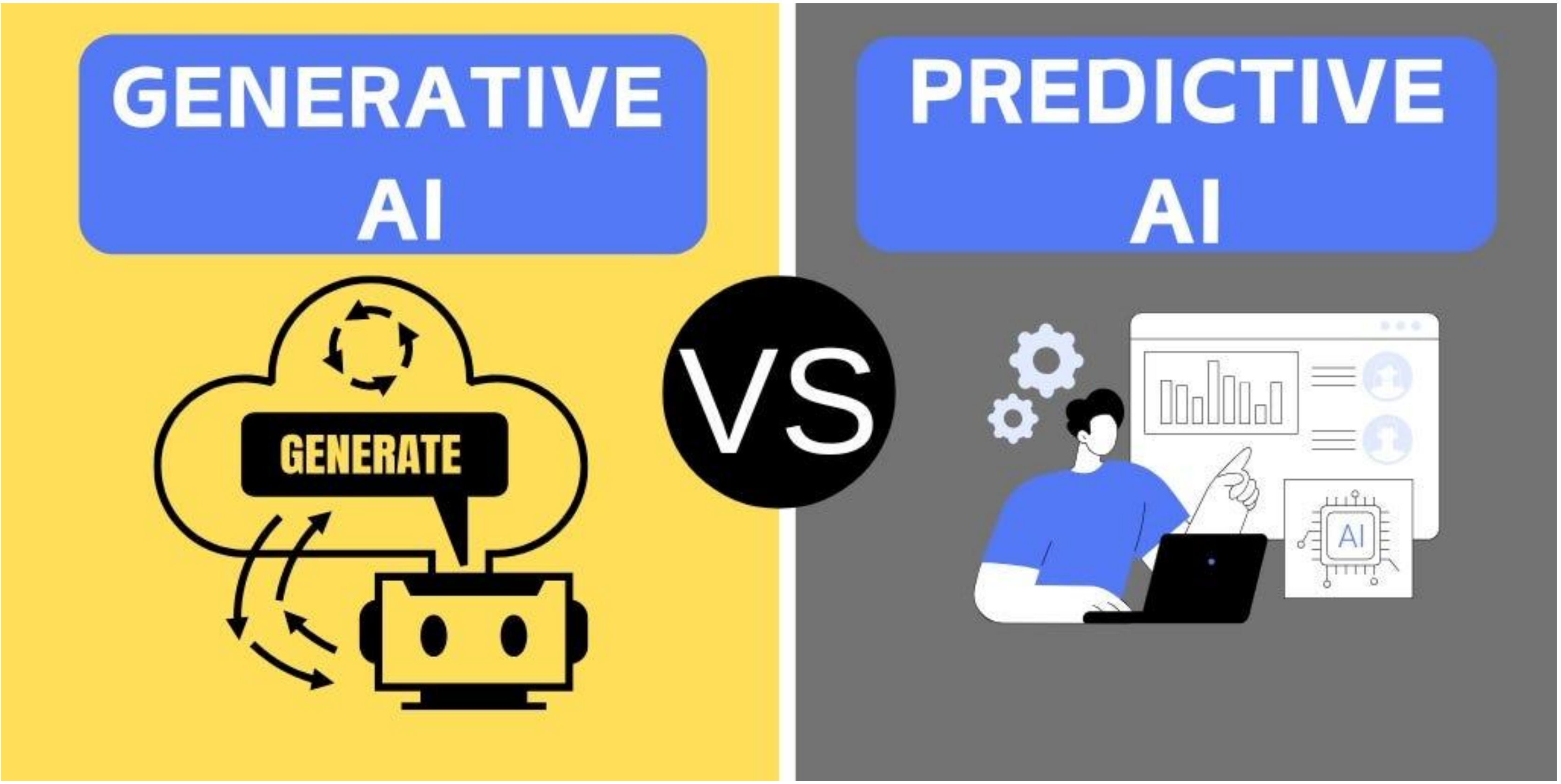



ASK
IMAGINE
PLAN
CREATE
EXPERIMENT
IMPROVE
THE ENGINEERING DESIGN PROCESS
Carly and Adam

SE NON SAI DOVE ANDARE, OGNI STRADA SARÀ SBAGLIATA

(H. Kissinger)

AI Tradizionale vs AI Generativa



Cos'è l'Intelligenza Artificiale?

L'AI è un insieme di tecnologie che permettono alle macchine di svolgere compiti che richiedono intelligenza umana, come riconoscere immagini, prendere decisioni o tradurre testi.

Due categorie principali:

AI "tradizionale" (o discriminativa): Si concentra sull'analisi e interpretazione dei dati.

AI generativa: Si concentra sulla creazione di nuovi contenuti.

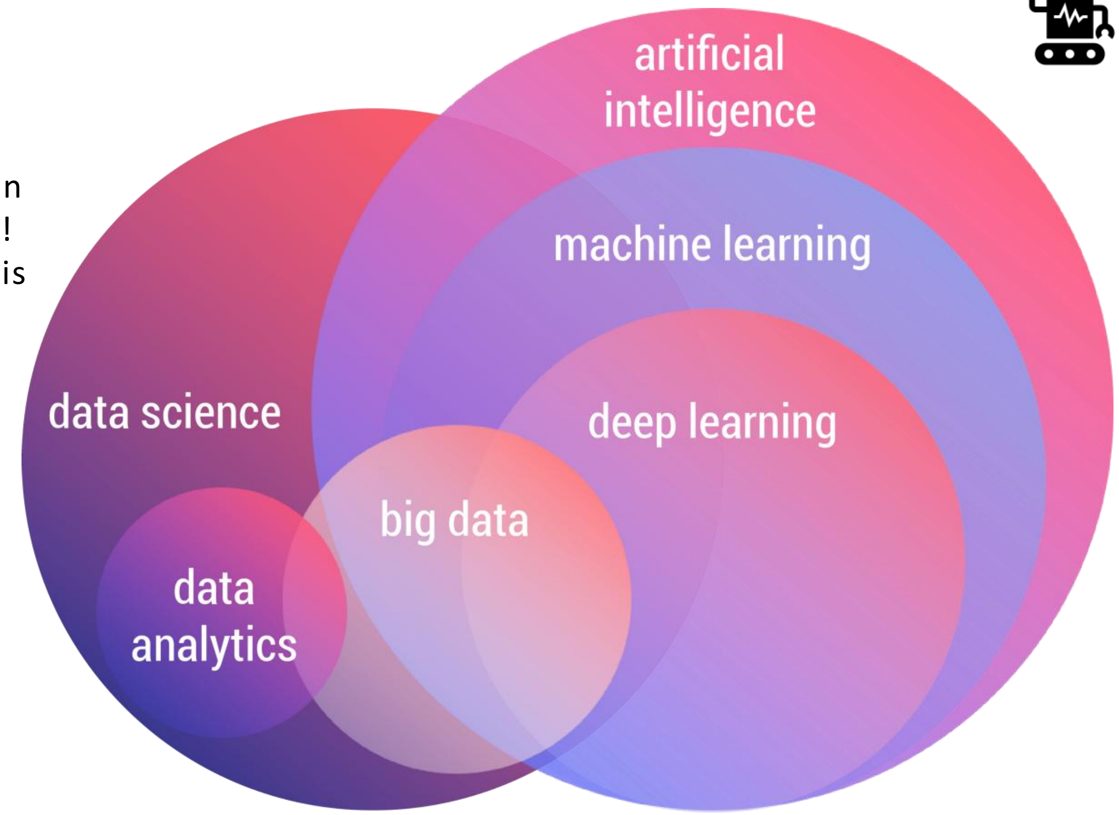
Generative AI	Predictive AI
Content Creation	Predict and Forecast
Text, image, video, voice, code as outputs	Report, analyze, diagnosis as outputs
Uses different data sets for training	Uses historical data for training
Neural networks, language models, transformers, GANs, diffusion models	Statistical models, regressions, random forests
Content creation, reasearch and survey, summarization, code generation etc.	Business analyze, risk management, management optimization, data diagnose etc.

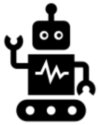
AI Tradizionale vs AI Generativa

Caratteristica	**AI Tradizionale**	**AI Generativa**
Obiettivo	Classificare, predire o riconoscere dati	Creare contenuti nuovi e originali
Esempi	Identificare un gatto in un'immagine	Disegnare un gatto completamente nuovo
Dati in output	Etichette, numeri, decisioni	Testo, immagini, video, suoni
Modelli usati	Modelli discriminativi	GANs, Transformers, Modelli Diffusivi

Artificial Intelligence suddivisione

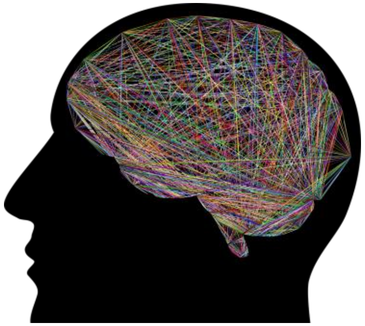
Extract information from data! Nowadays is **crucial**

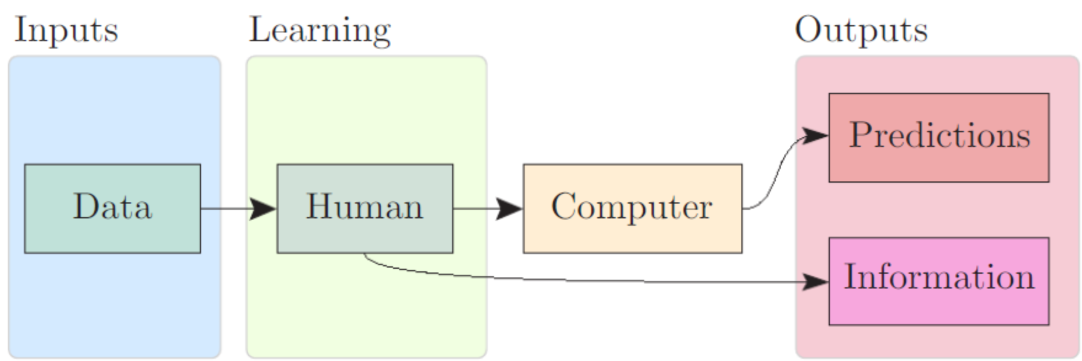




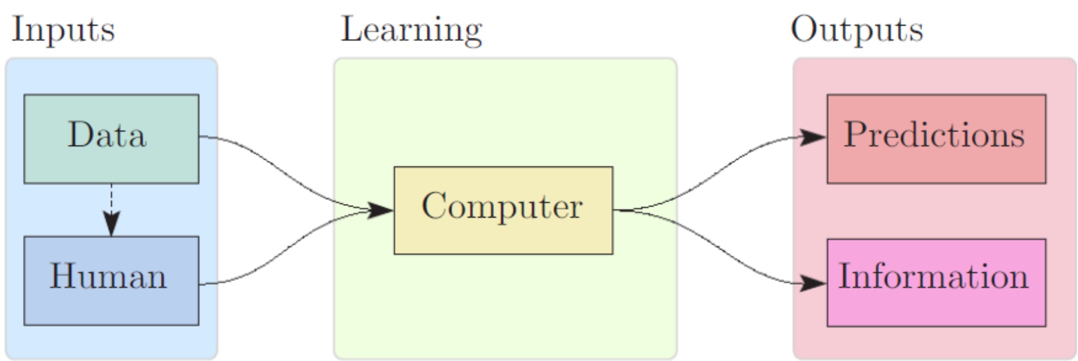
AI : simulation of Intelligent human-like behaviour

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



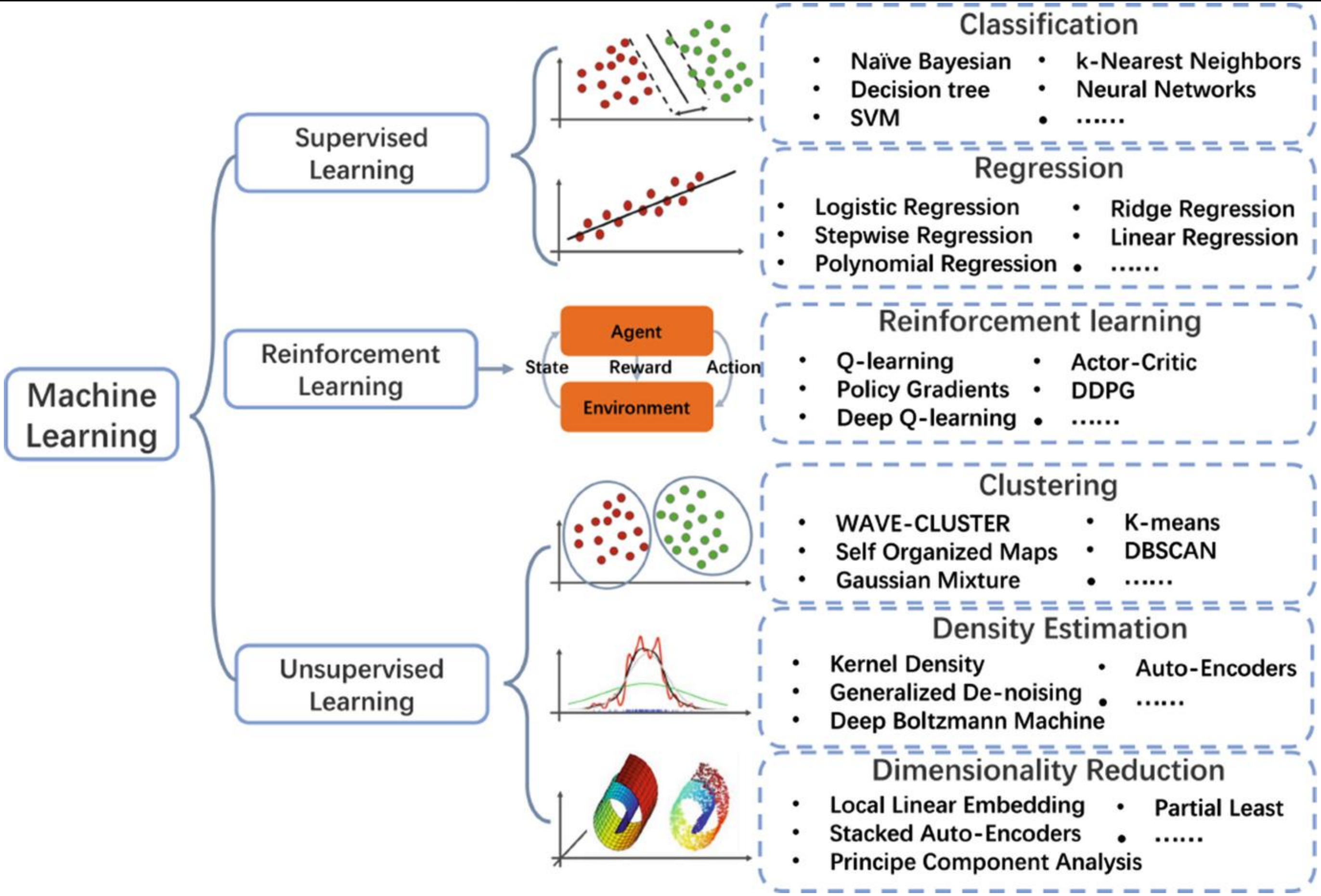


(a) Without machine learning



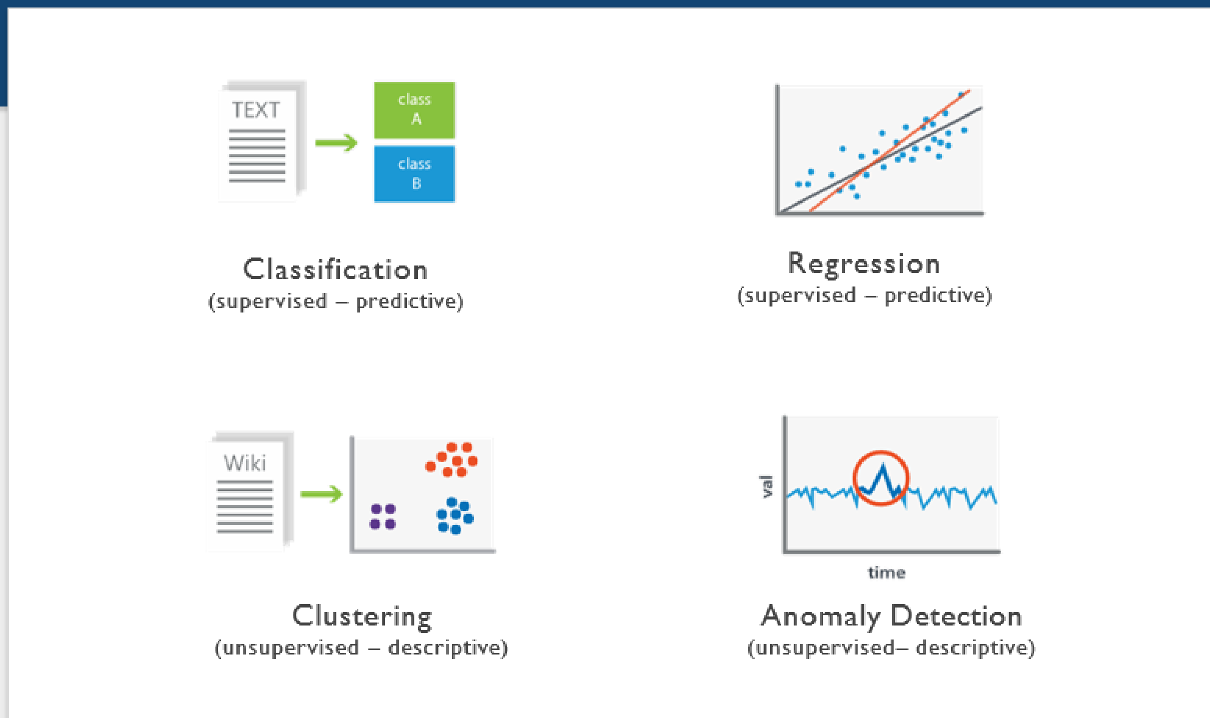
(b) With machine learning

Supervised, Unsupervised and Reinforcement Learning

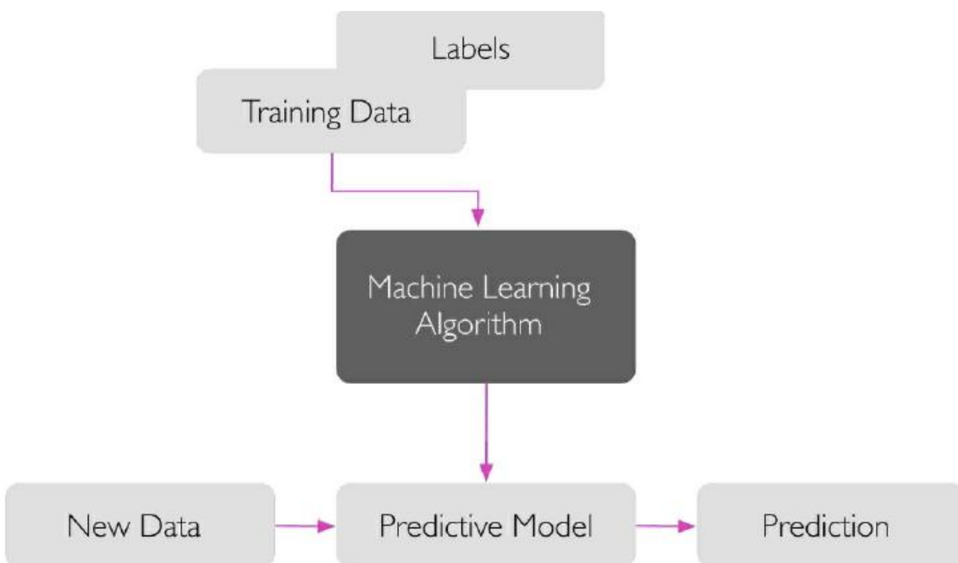


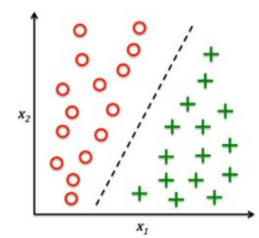
Machine Learning - Basics

Problem Types



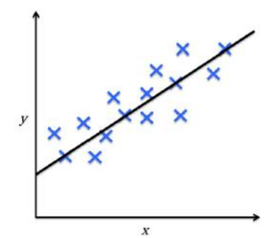
Learning phase and Predictive model





■ **Classification Problem**

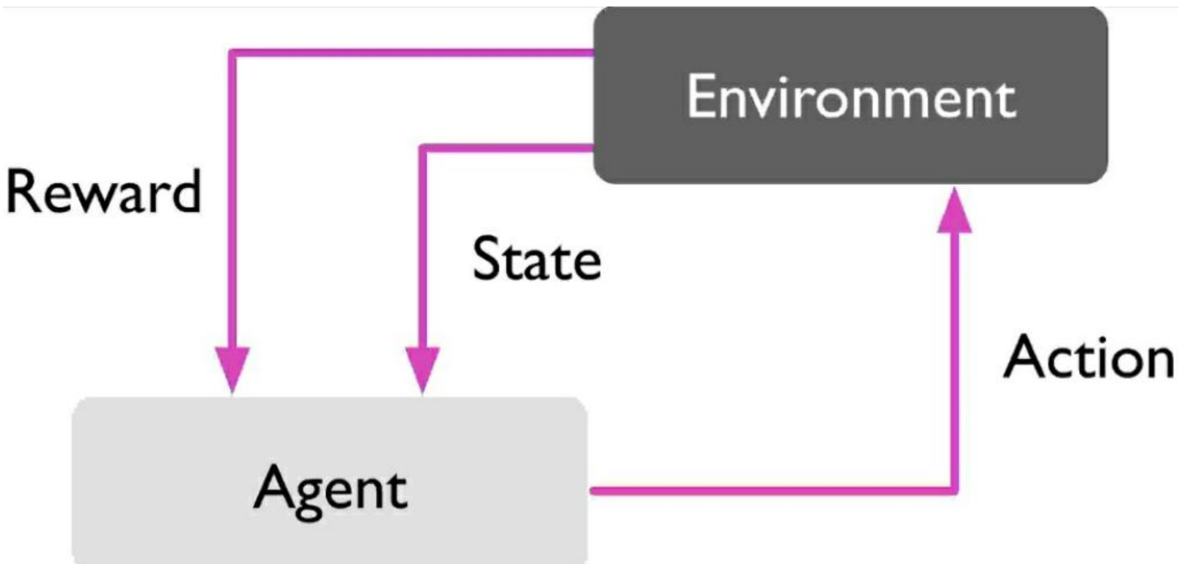
with discrete class labels



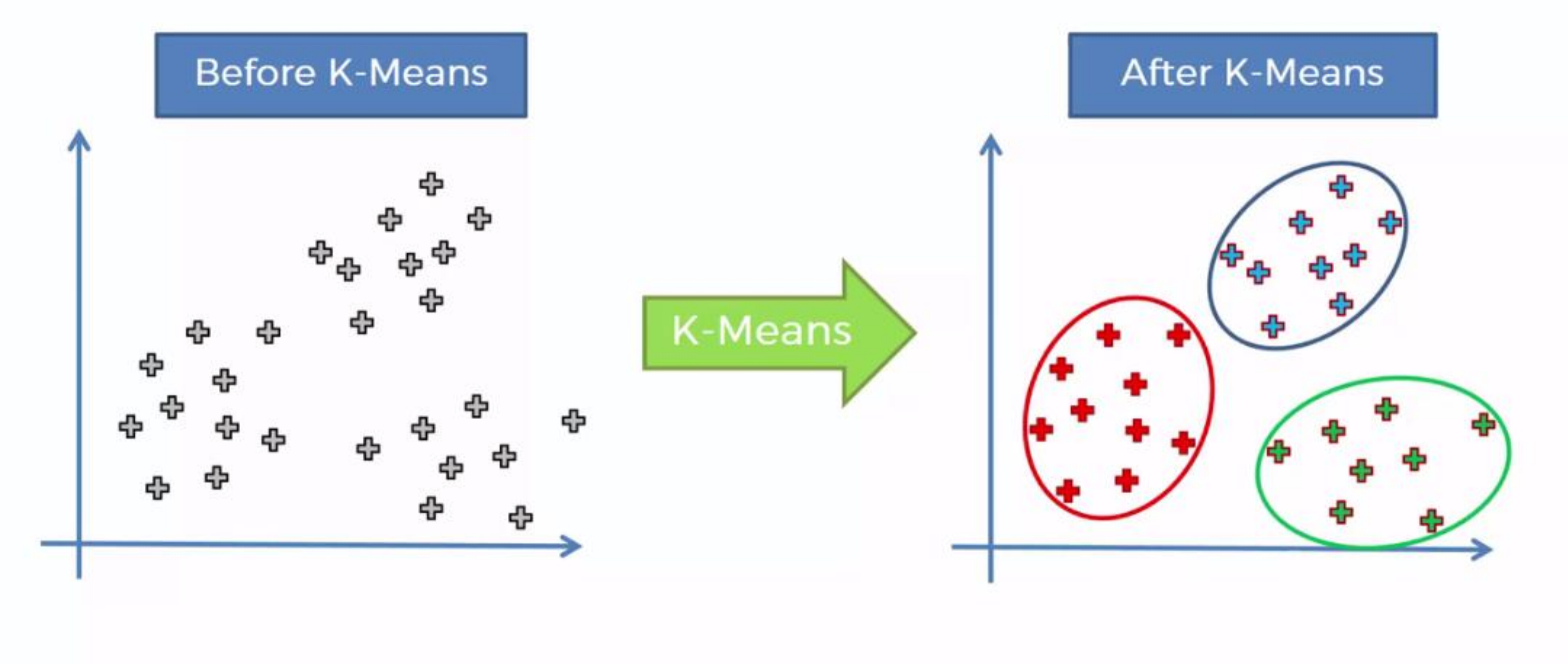
■ **Regression Problem**

where the outcome is a continuous value

Reinforcement Learning



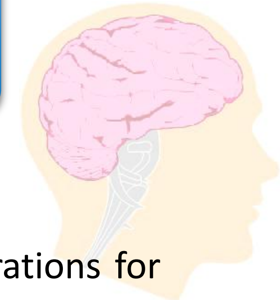
Unsupervised Learning Example of Clustering



Non-classical algorithms (Soft Computing)

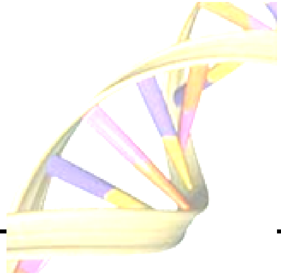
they deal with socially, phisically and/or biologically inspired paradigms

In this field, the most popular soft computing techniques are **Artificial Neural Networks** and **Evolutionary Algorithms (EA)**



Artificial Neural Networks (ANN) aim at reproducing some of the most important brain operations for virtue of two stages, the network training (or learning) phase and the validation phase.

Synthetically, during a succession of generations, **Evolutionary Algorithms** (EA) based methods generate new points in the admissible search space by applying operators on the current solution set and "statistically" move towards more optimal places in virtue of a given strife of survival.

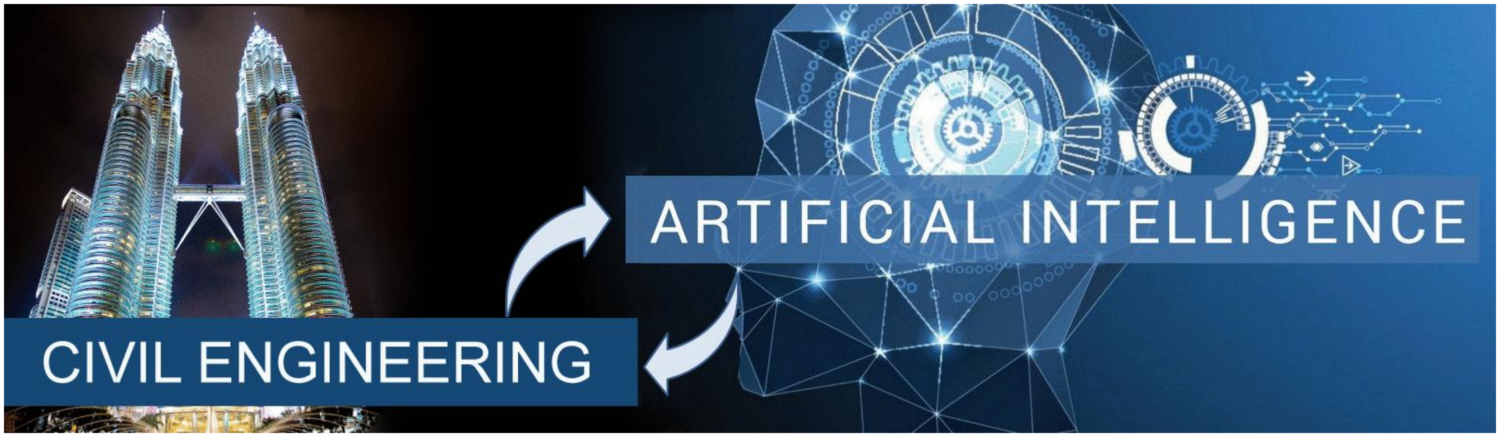


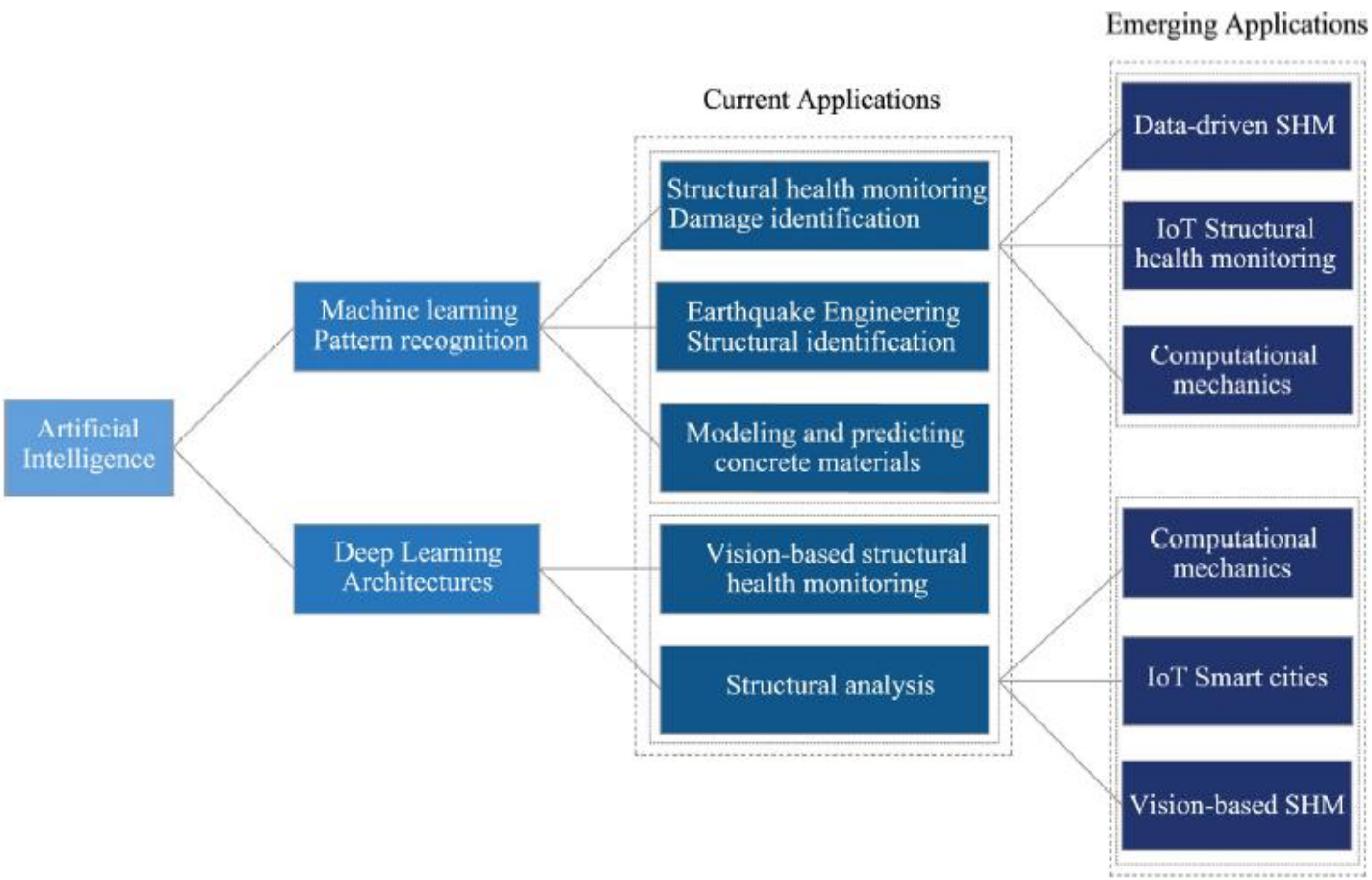
Soft computing

Conventional Computing

Hard Computing (Conventional)	Soft Computing
Requires precisely stated analytical model and a lot of computation time.	Tolerant of imprecision, uncertainty and approximation.
Based on binary logic, numerical analysis and crisp software.	Based on fuzzy logic, neural networks and probabilistic reasoning.
Requires programs to be written.	Can evolve its own programs.
Deterministic.	Incorporates stochasticity.
Strictly sequential.	Allows parallel computations.

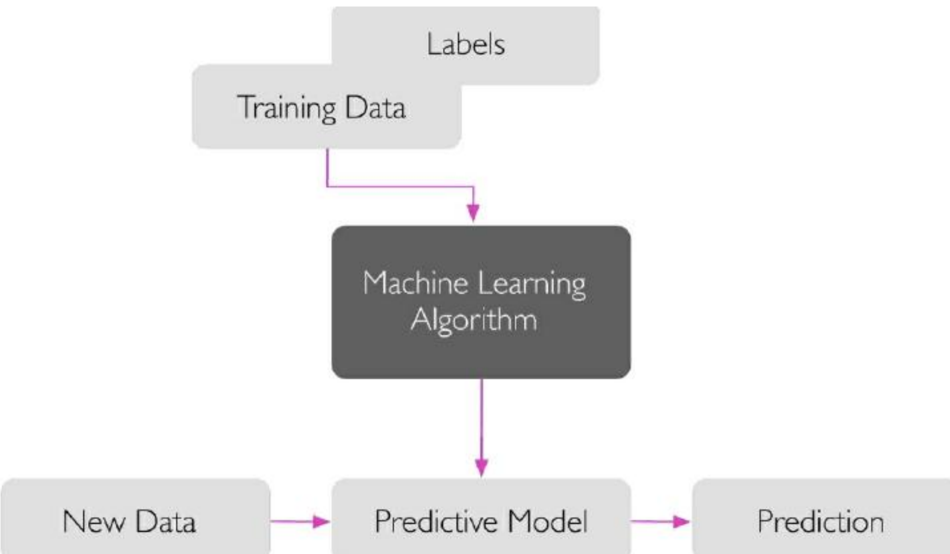
Artificial Intelligence and Engineering

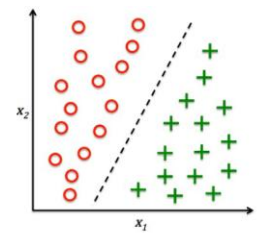



Emerging Applications
Current Applications
Artificial Intelligence
Machine learning Pattern recognition
Deep Learning Architectures
Structural health monitoring Damage identification
Earthquake Engineering Structural identification
Modeling and predicting concrete materials
Vision-based structural health monitoring
Structural analysis
Data-driven SHM
IoT Structural health monitoring
Computational mechanics
Computational mechanics
IoT Smart cities
Vision-based SHM

Learning phase and Predictive model

Supervised Learning





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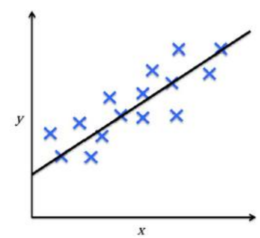
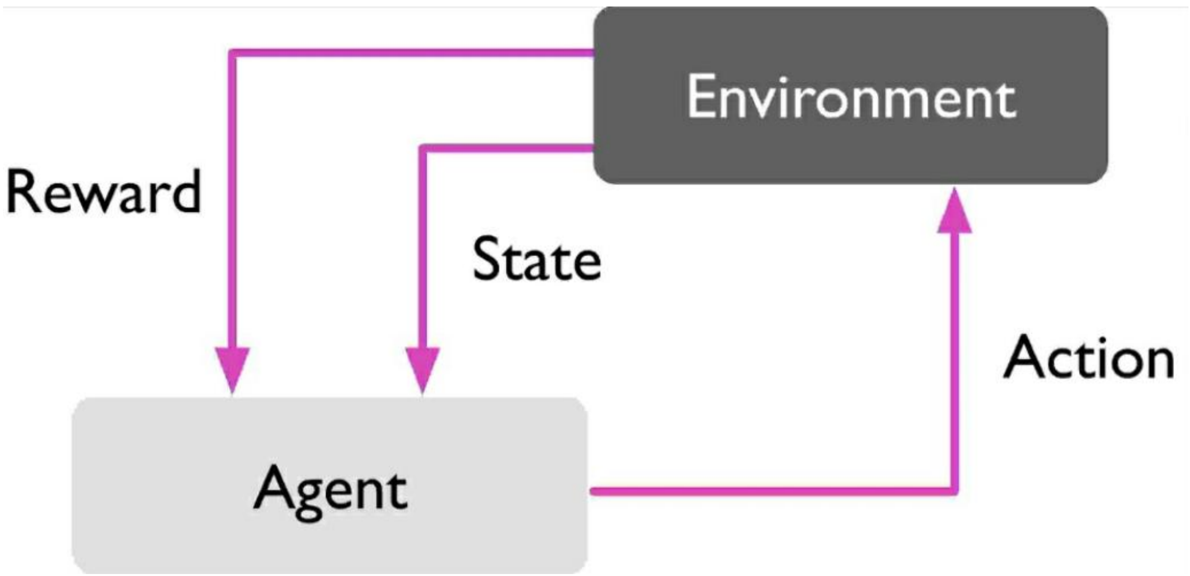


- **Regression Problem**

where the outcome is a continuous value

Reinforcement Learning



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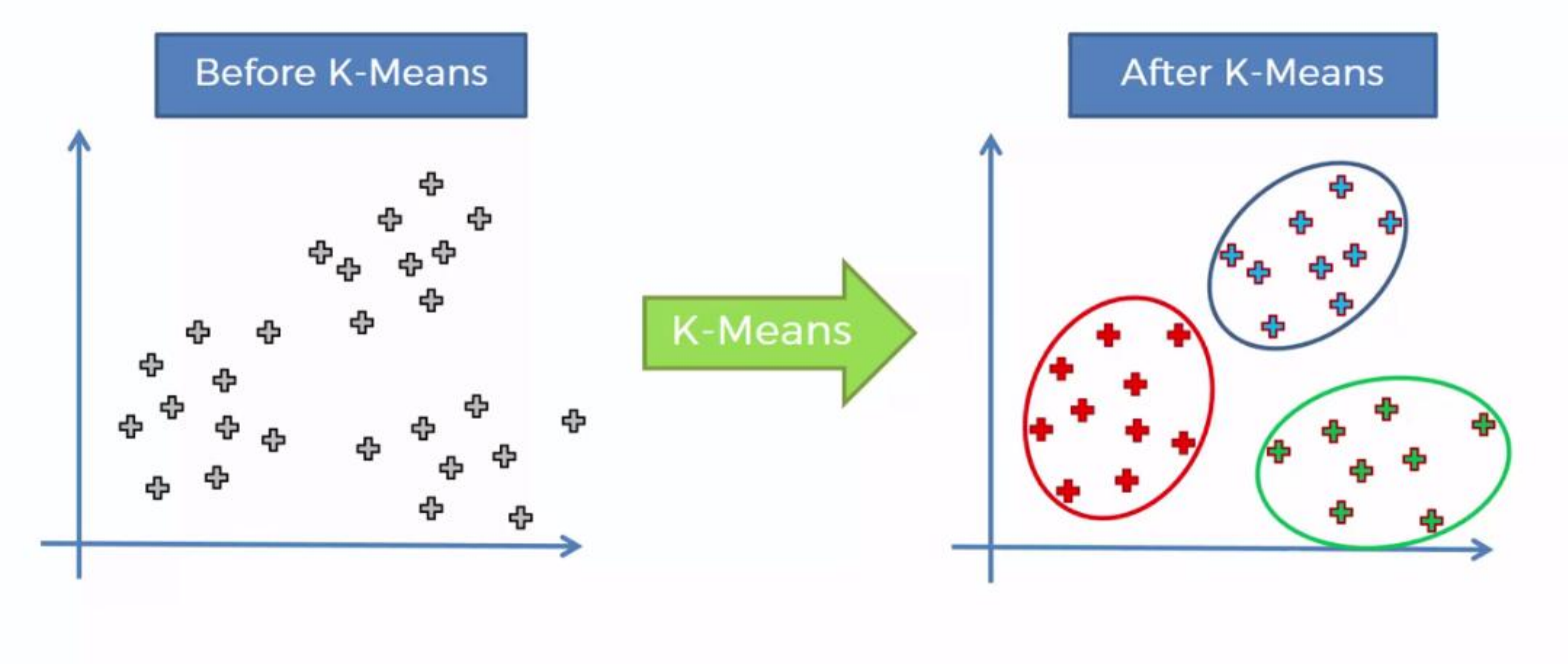


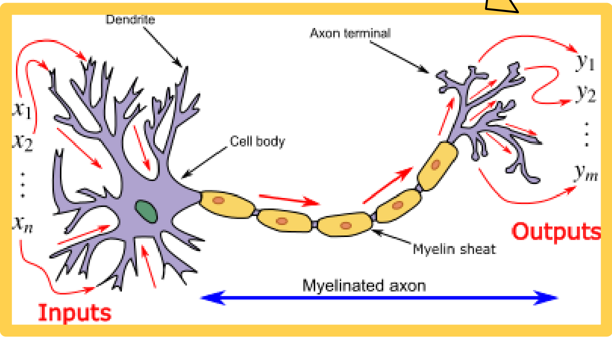
What is Deep Learning?

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.

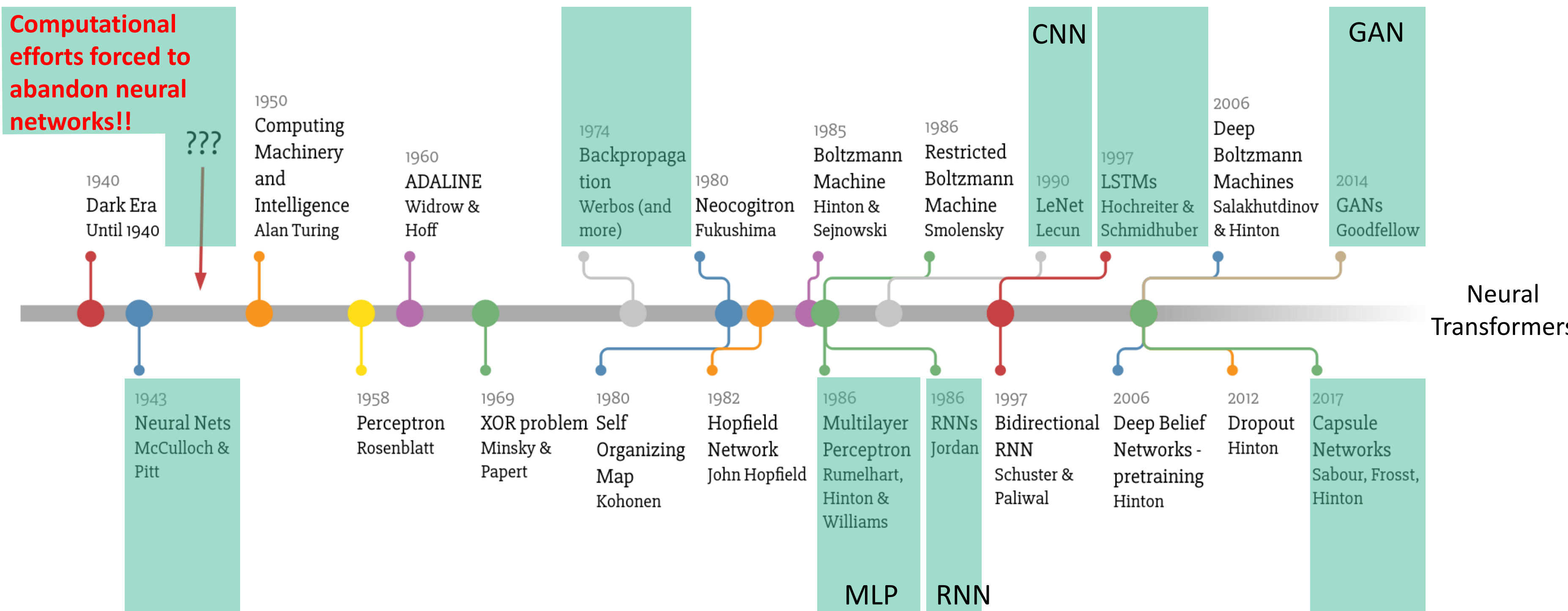
If you provide the system tons of information, it begins to understand it and respond in useful ways.

Inspired by Nature,
Brain and Neuroscience



Phenomenological model
(schematization) of a neuron

Deep Learning Timeline



Made by Favio Vázquez

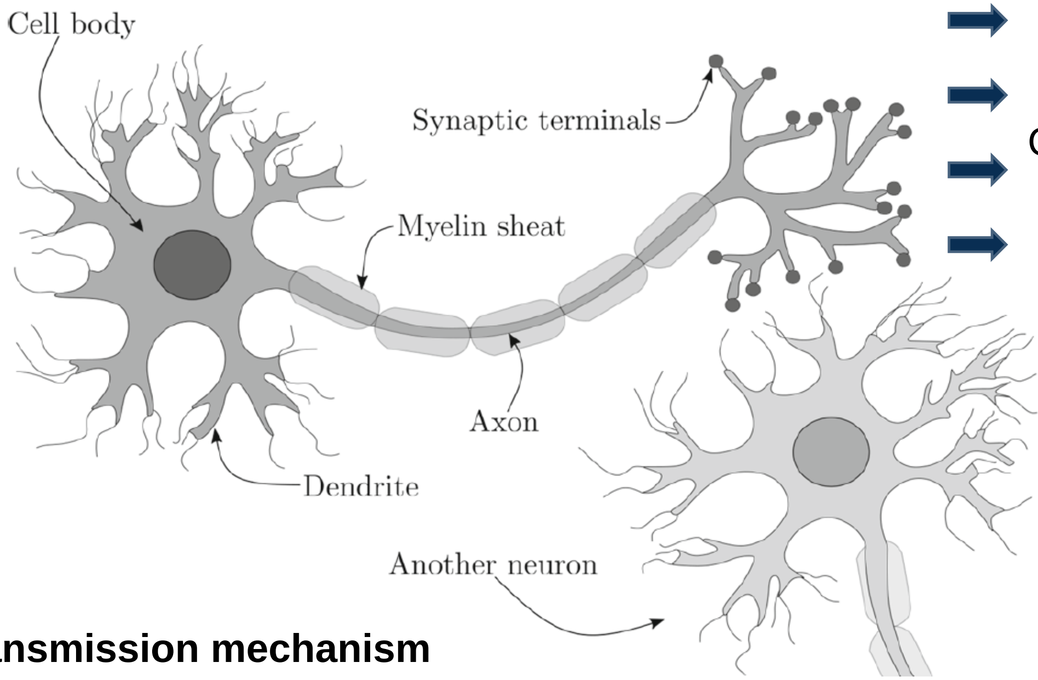
Artificial Neural Network (ANN)
McCullock-Pitts (MCP) Neuron (1943)

ANN

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

Input signals

Coming from other neurons



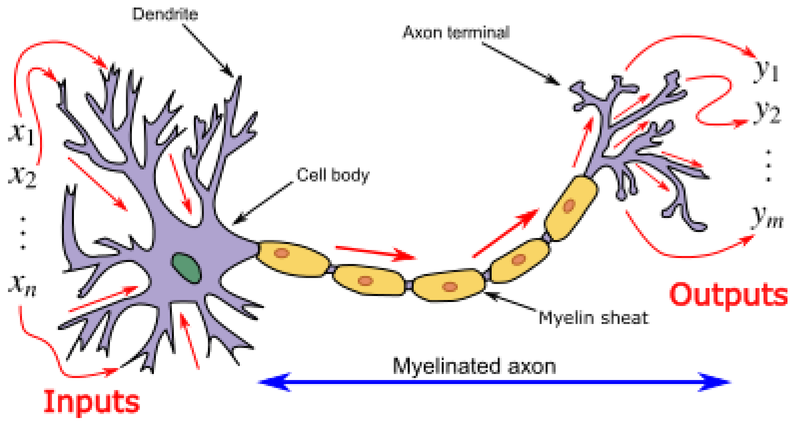
Output signals

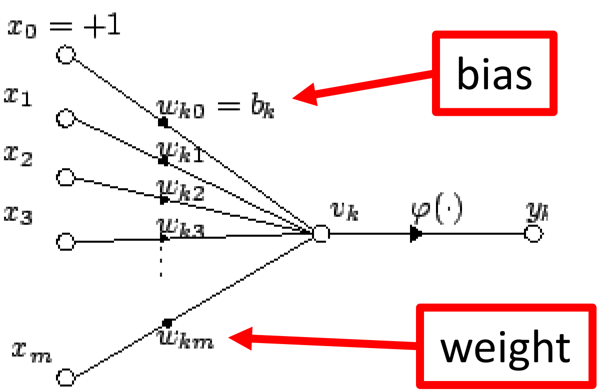
Chemical or electrical transmission to other neurons

One-way signal transmission mechanism

The neuron

$$y_k = \varphi\left(\sum_{j=0}^{m} w_{kj} x_j\right)$$



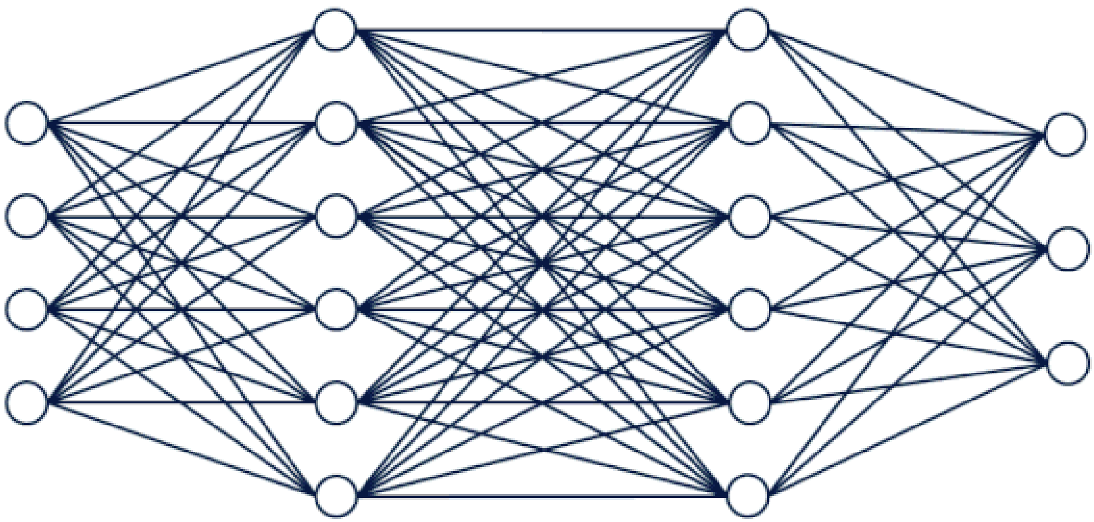


Neurons are trained to filter and detect specific features or patterns (e.g. edge, nose) by receiving weighted input, transforming it with the activation function and passing it to the outgoing connections.

An artificial neuron contains a nonlinear activation function and has several incoming and outgoing weighted connections.

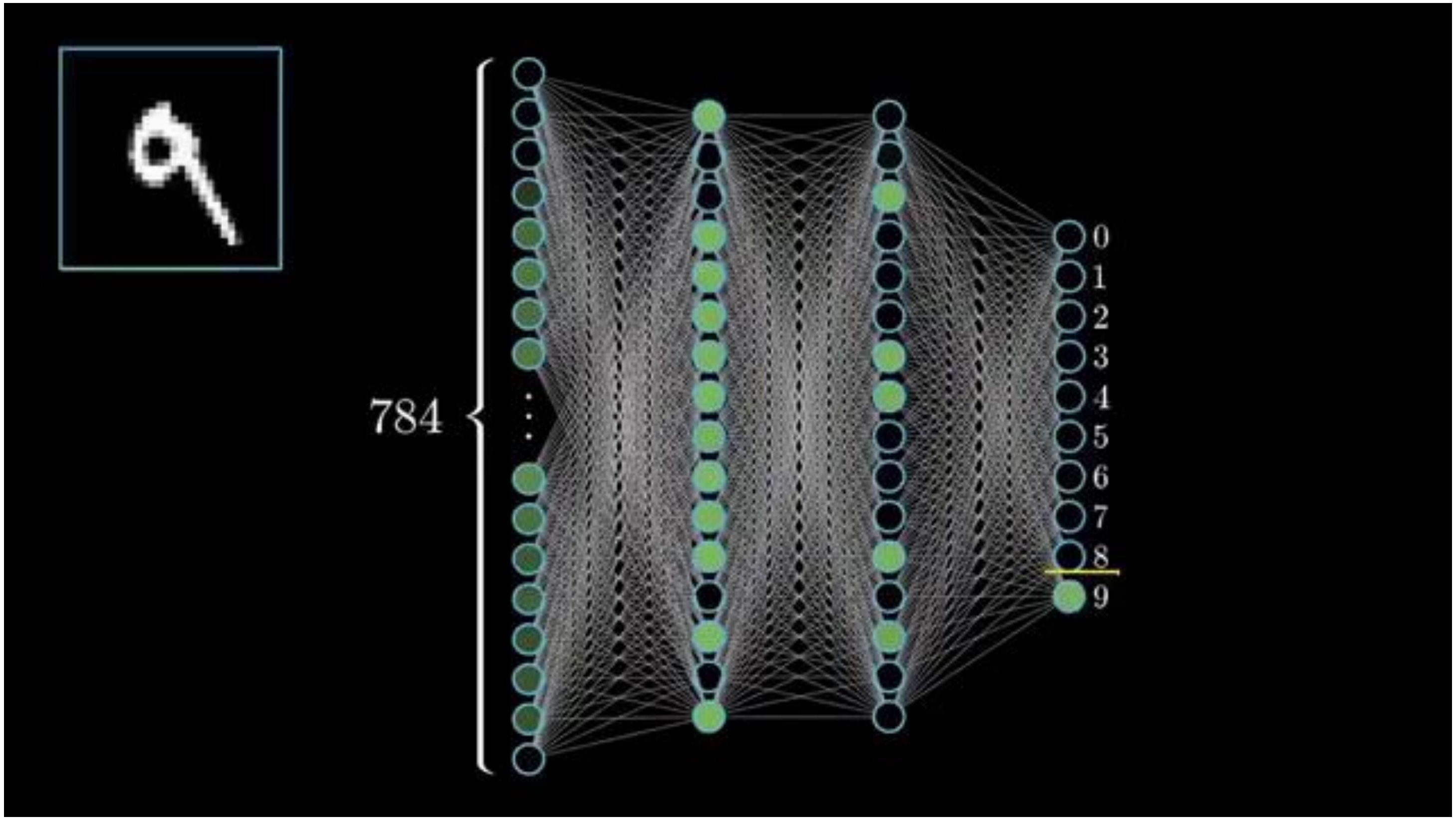
The Multilayer Perceptron (MLP)

feed-forward network mapping

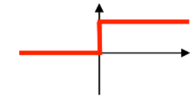
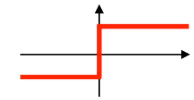
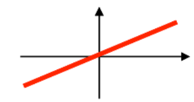
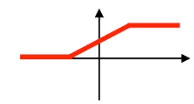
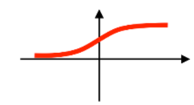
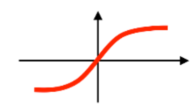
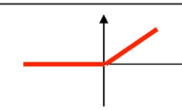
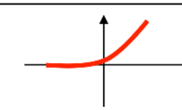


feed-forward network mapping

The Multilayer Perceptron (MLP)



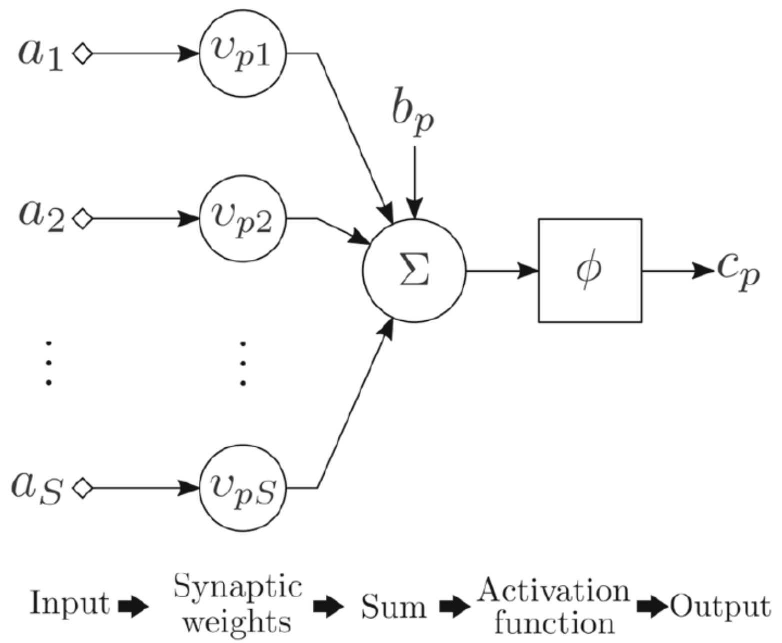
Activation functions

Activation function	Equation	Example	1D Graph
Unit step (Heaviside)	$\phi(z) = \begin{cases} 0, & z < 0, \\ 0.5, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Sign (Signum)	$\phi(z) = \begin{cases} -1, & z < 0, \\ 0, & z = 0, \\ 1, & z > 0, \end{cases}$	Perceptron variant	
Linear	$\phi(z) = z$	Adaline, linear regression	
Piece-wise linear	$\phi(z) = \begin{cases} 1, & z \geq \frac{1}{2}, \\ z + \frac{1}{2}, & -\frac{1}{2} < z < \frac{1}{2}, \\ 0, & z \leq -\frac{1}{2}, \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\phi(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, Multi-layer NN	
Hyperbolic tangent	$\phi(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$	Multi-layer Neural Networks	
Rectifier, ReLU (Rectified Linear Unit)	$\phi(z) = max(0, z)$	Multi-layer Neural Networks	
Rectifier, softplus	$\phi(z) = \ln(1 + e^{z})$	Multi-layer Neural Networks	

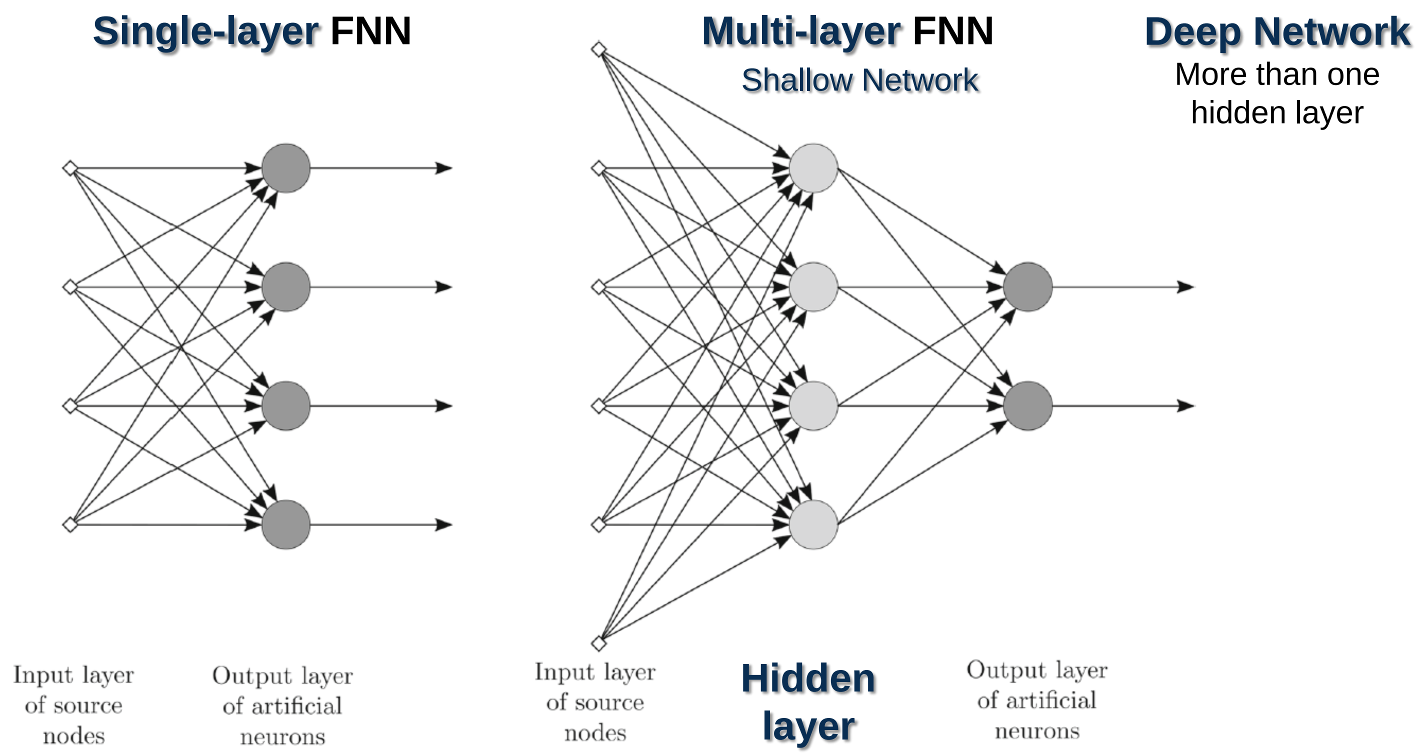
Non-linearity is needed to learn complex (non-linear) representations of data, otherwise the NN would be just a linear function.

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

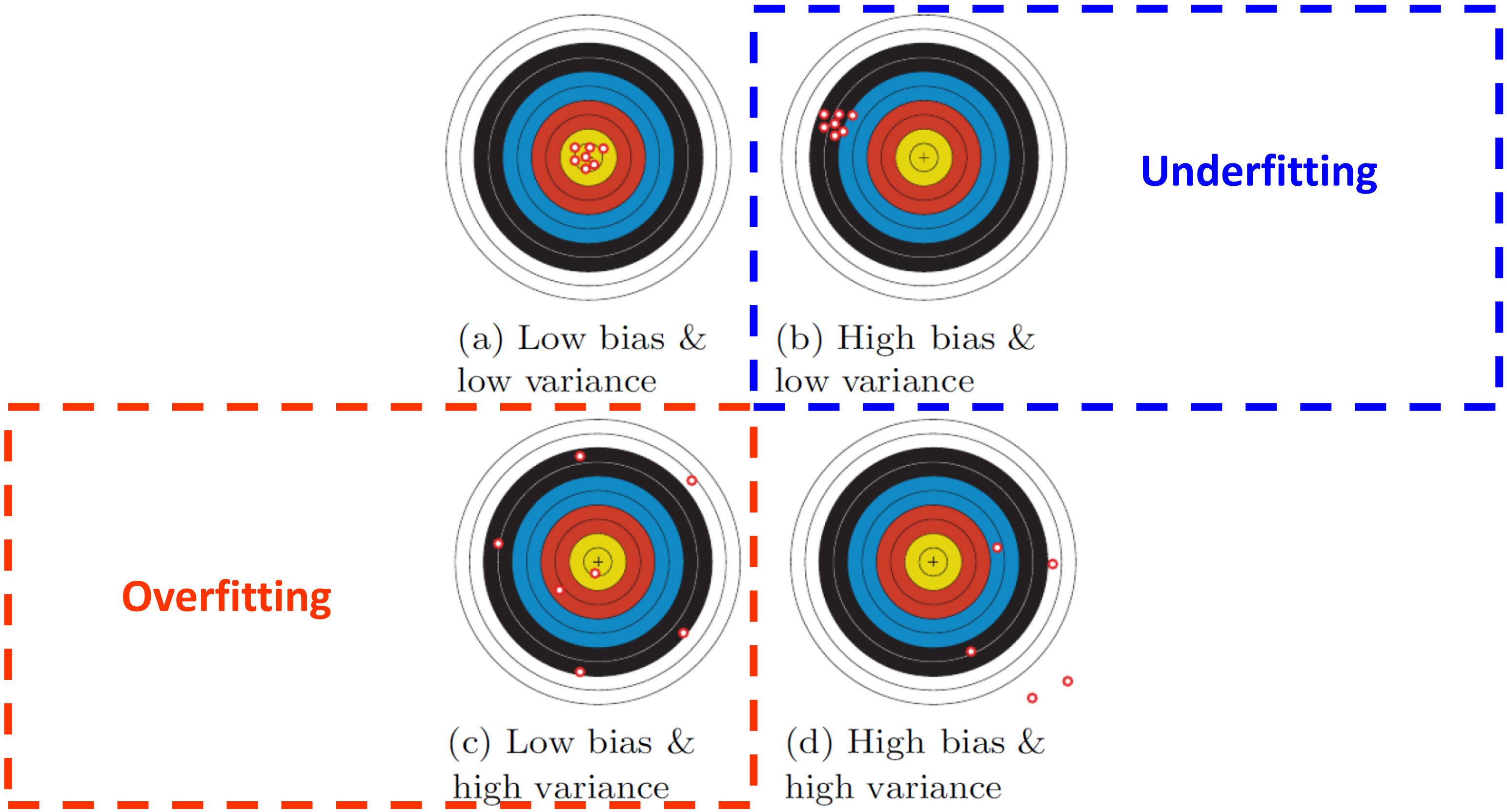
- Simplified as a logic gate with binary output [0,1] (or [-1,1])
- Accumulated input signal reach a threshold value the output signal is transmitted through the axon
- Few years later F. **Rosenblatt** formalize the **Perceptron rule (ANN with one neuron only)**



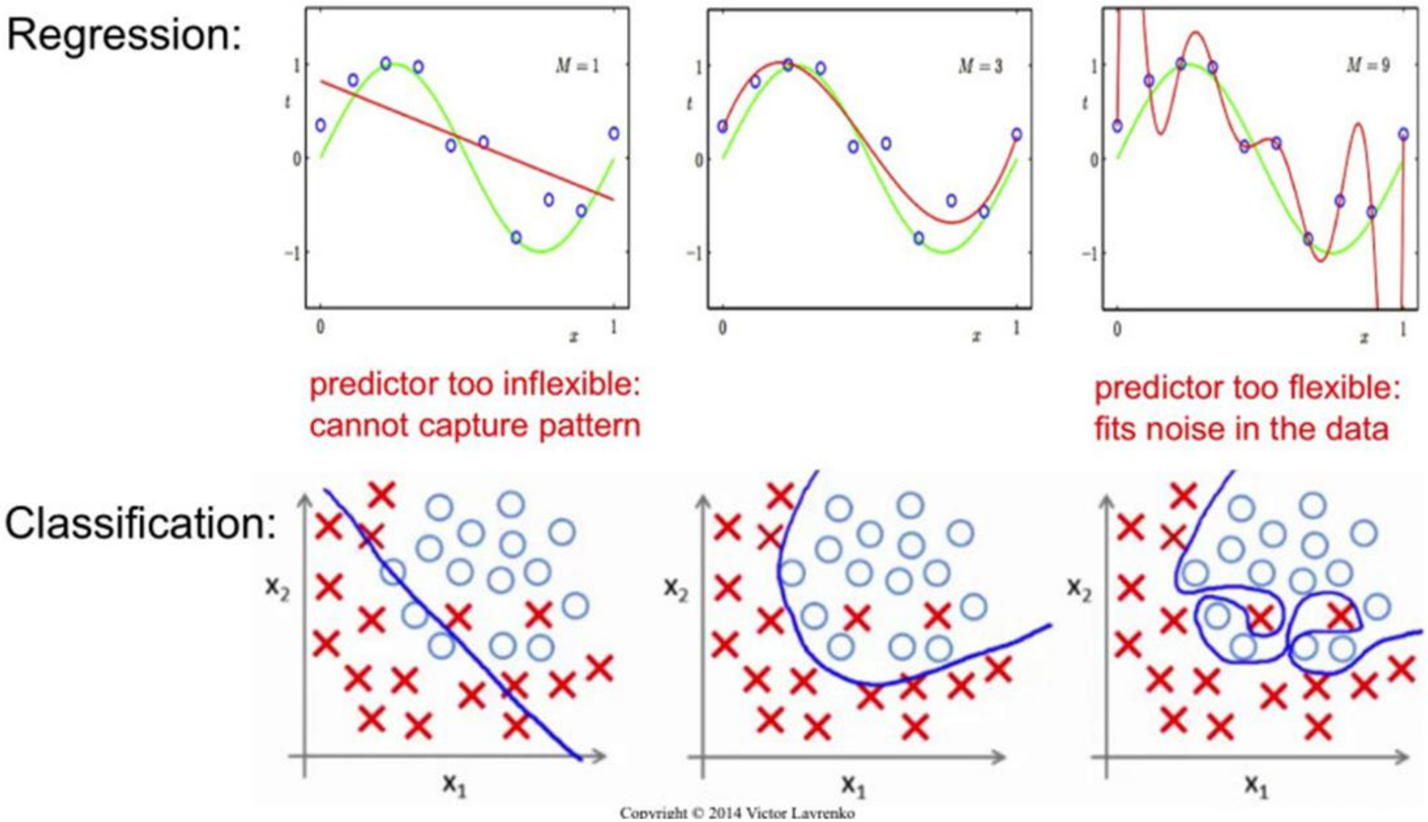
Examples of ANN architectures combining a number of perceptrons



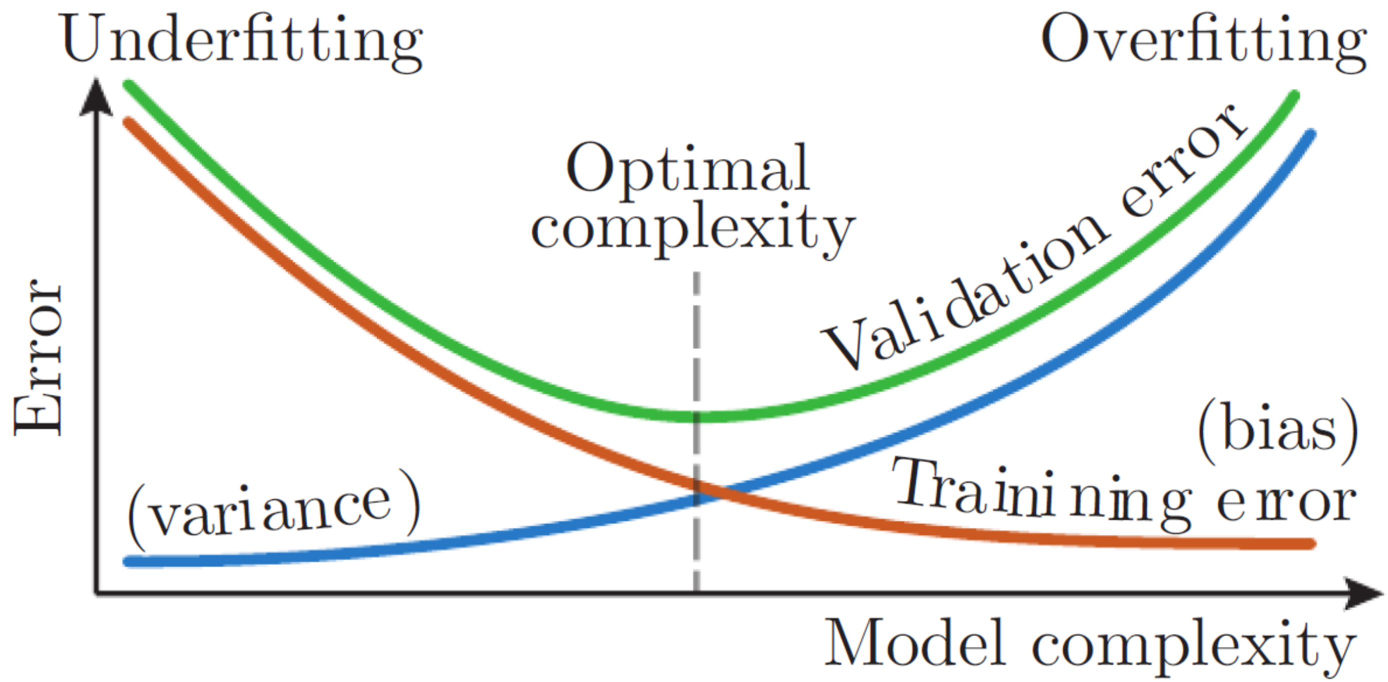
Model complexity: overfitting and underfitting



Underfitting and Overfitting



Model complexity: Bias-variance tradeoff



Model complexity: overfitting solutions

- ❑ Decrease model complexity

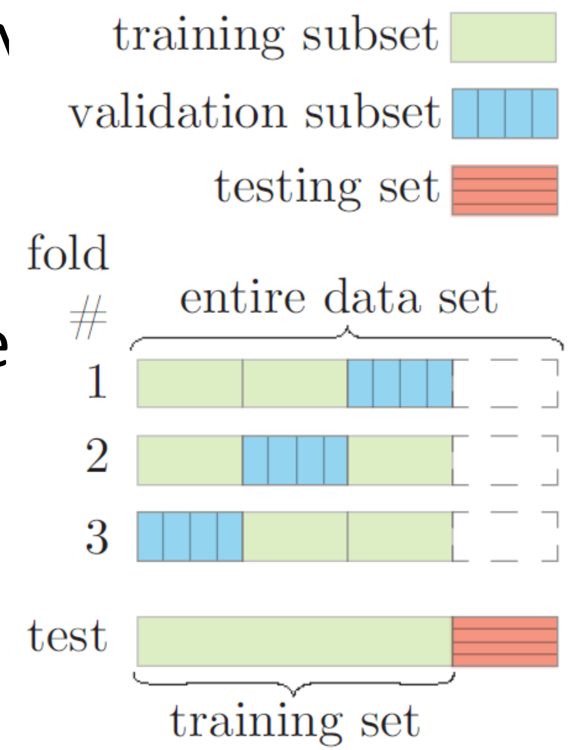
- ❑ Bayesian model selection instead of M d

estimation

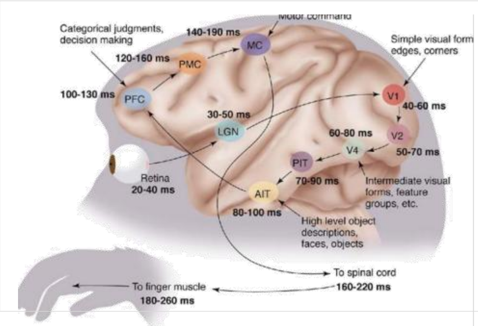
- ❑ Ridge regression and regularization te

constraints parameters

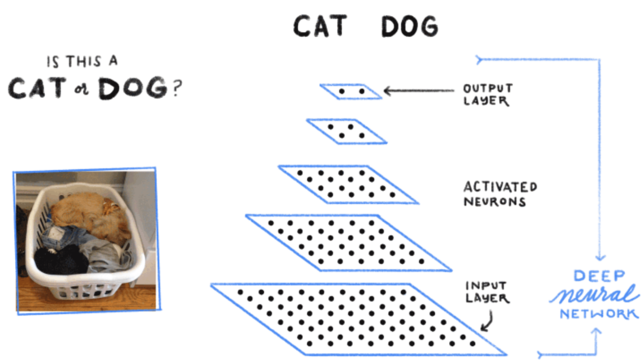
- ❑ N-folds Cross validation procedure

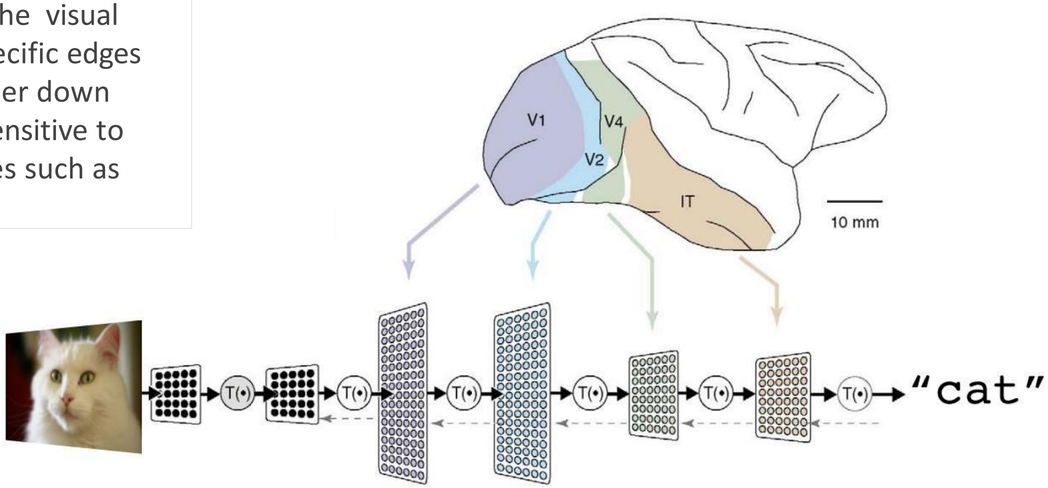


Convolutional Neural Networks (CNN)



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.





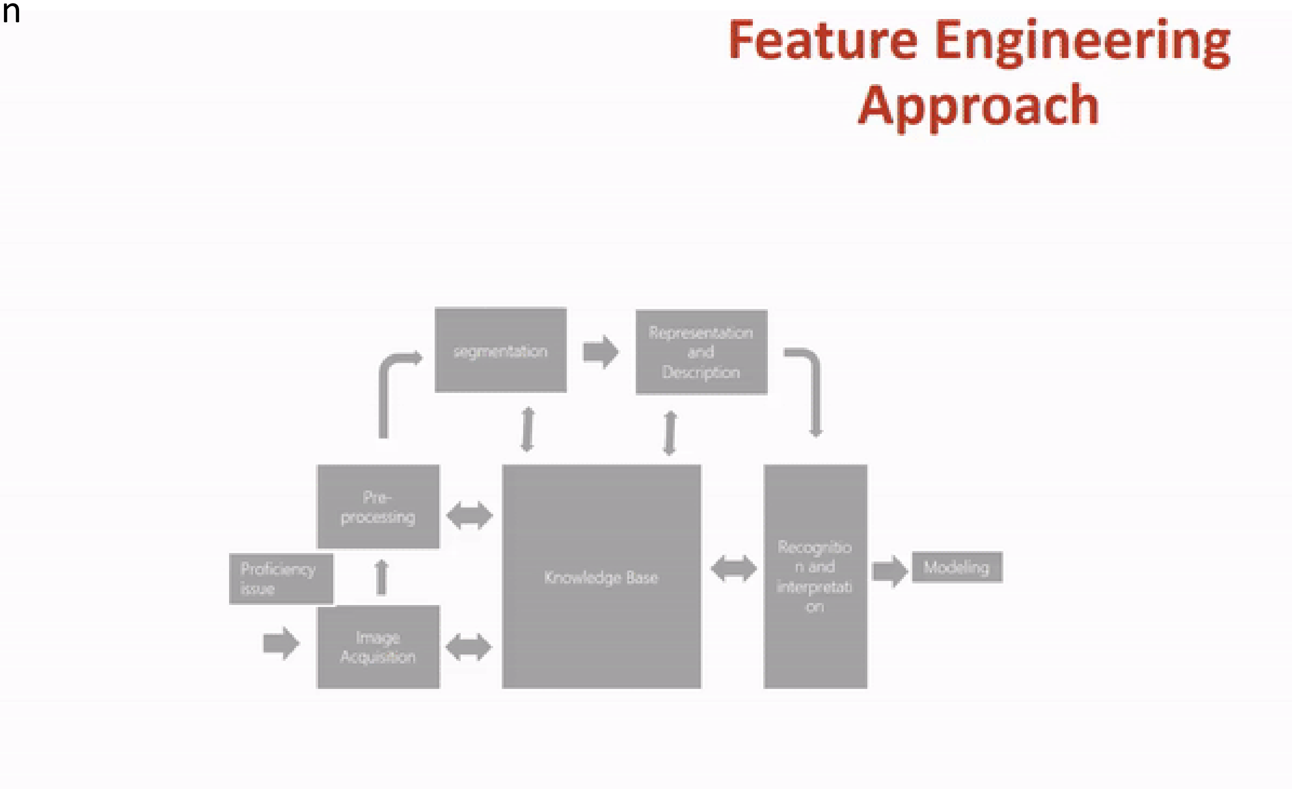
A deep neural network consists of a hierarchy of layers, whereby each layer transforms the input data into more abstract representations (e.g. edge -> nose -> face). The output layer combines those features to make predictions.

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



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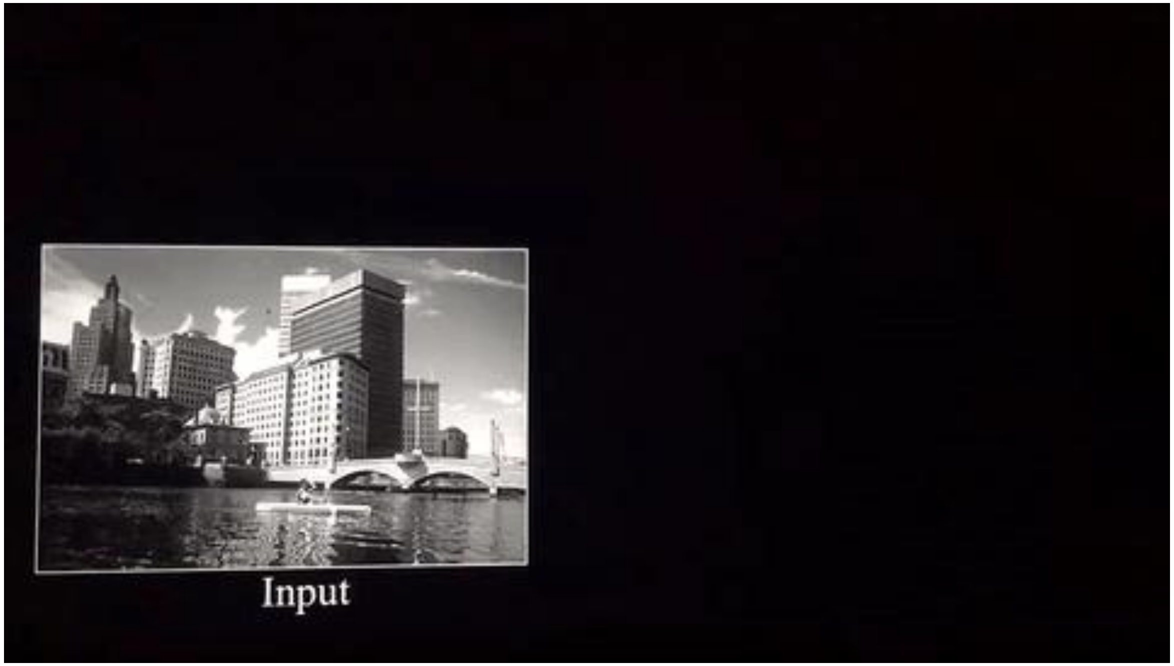
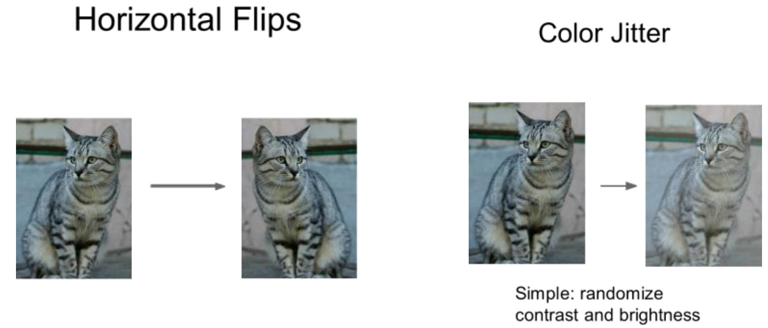


Convolutional Neural Networks (CNN)

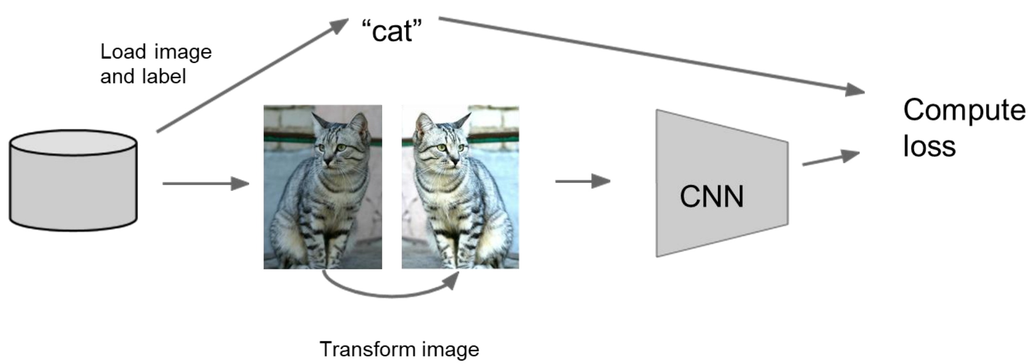
More parameter to train → More data are needed!!

Therefore **Data augmentation** procedure can be adopted as regularization technique to increase db.



Random mix/combinations of :

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

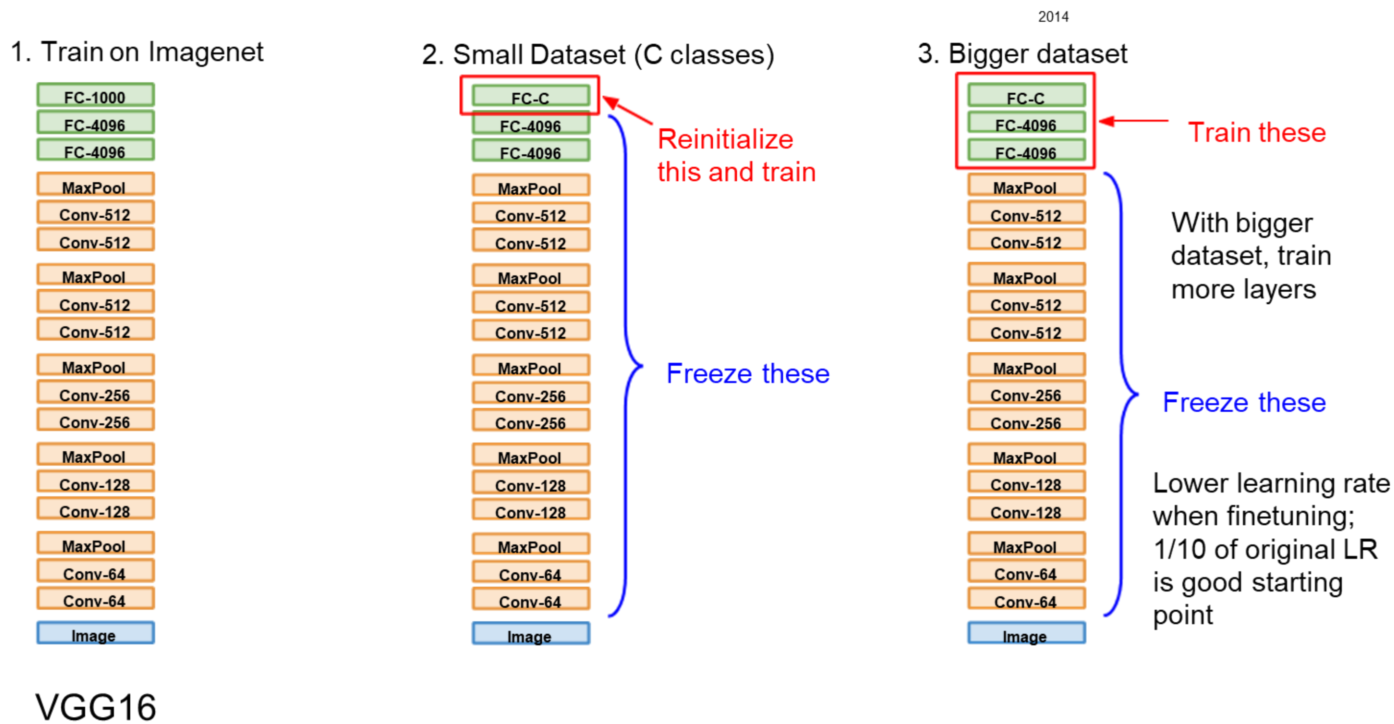


Transfer Learning

More parameter to train → ~~More data are needed!!~~ – It is possible to use **TRANSFER LEARNING** APPROACH!

With transfer learning, a pretrained model is adopted and only some layer are updated to become suitable for the problem at hand.

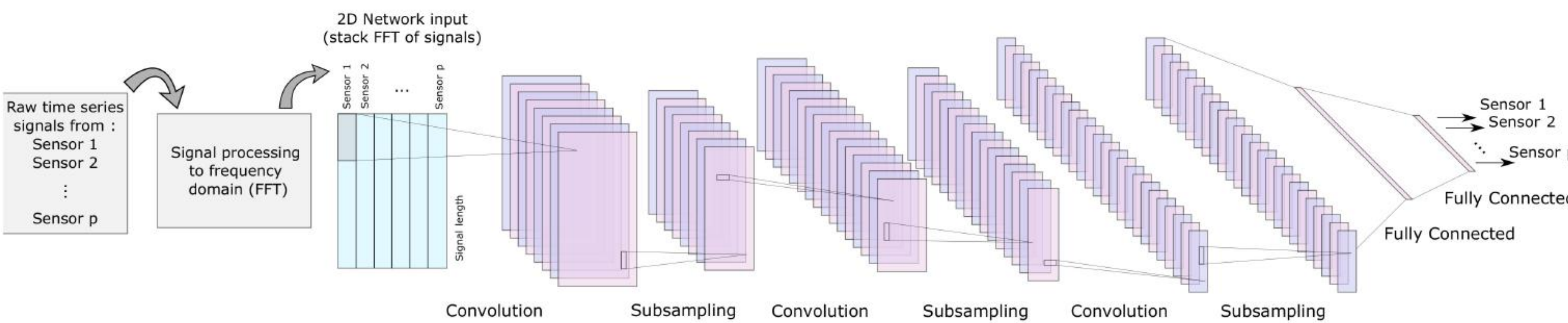
This approach is called **fine tuning**.



Convolutional Neural Networks (CNN)

Developed for Computer-Vision tasks, CNN have been extensively adopted in SHM because of their **automatic feature extraction** (with convolutional layers and pooling layers)

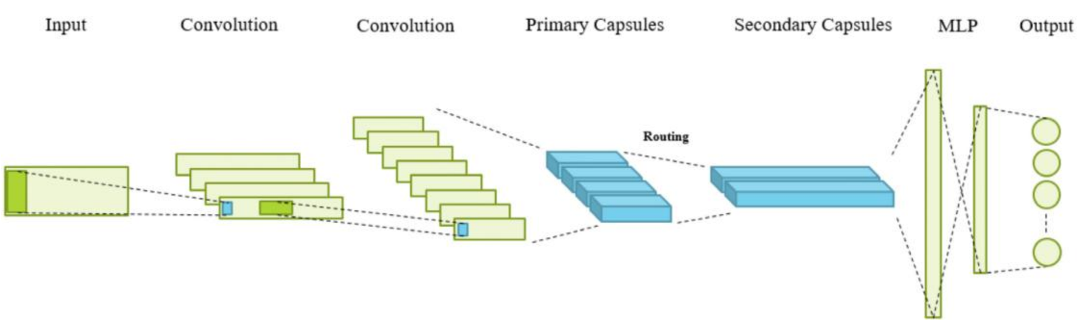
CNN requires a minimum preprocessing of data



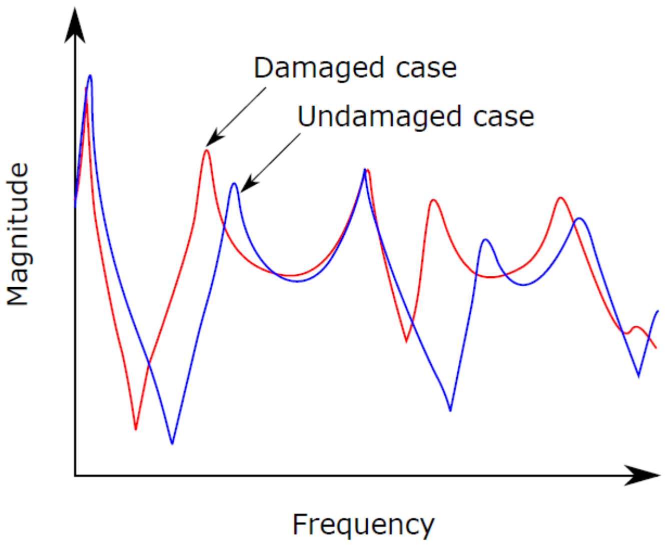
Deep Learning Recent Studies in SHM

Capsule Neural Network is an evolution of CNN to solve drawbacks of CNN and also taking into account relative position of extracted features in an image.

A CapsNet was trained to find frequecy peak shifts with damage progressively introduced in the structural elements



Transmissibility function



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:

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

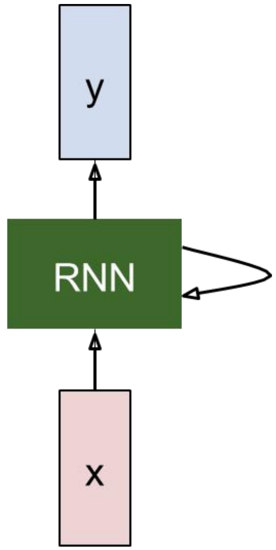
new state

some function with parameters W

old state

input vector at some time step

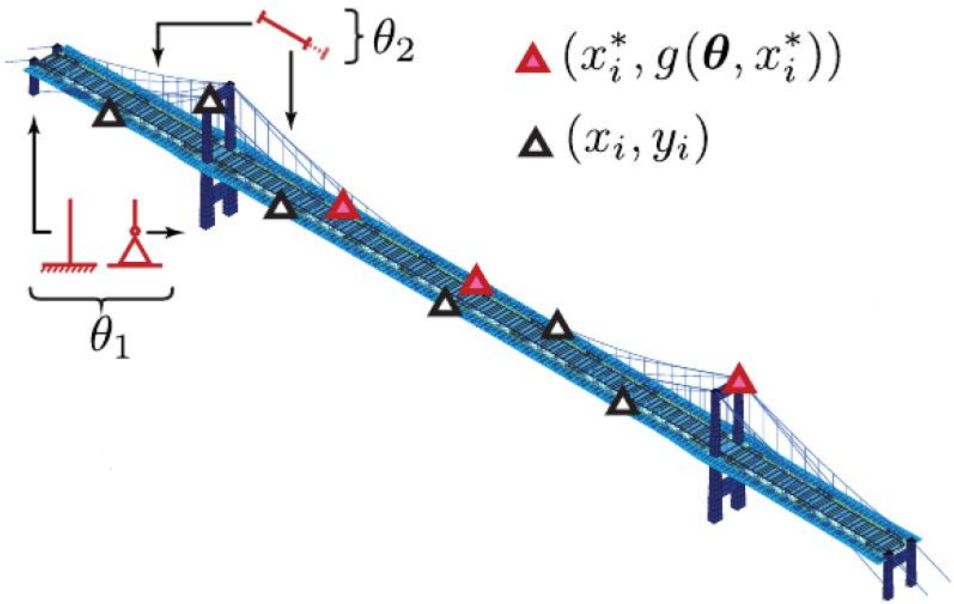
Notice: the same function and the same set of parameters are used at every time step.



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

Constrained Optimization Problems

Objective Function

tools

Paradigm

- Classical
- Non-classical

Design Vector

tools

Isaac Newton (1642-1727) (The development of differential calculus methods of optimization)

Joseph-Louis Lagrange (1736-1813) (Calculus of variations, minimization of functionals, method of optimization for constrained problems)

Augustin-Louis Cauchy (1789-1857) (Solution by direct substitution, steepest descent method for unconstrained optimization)

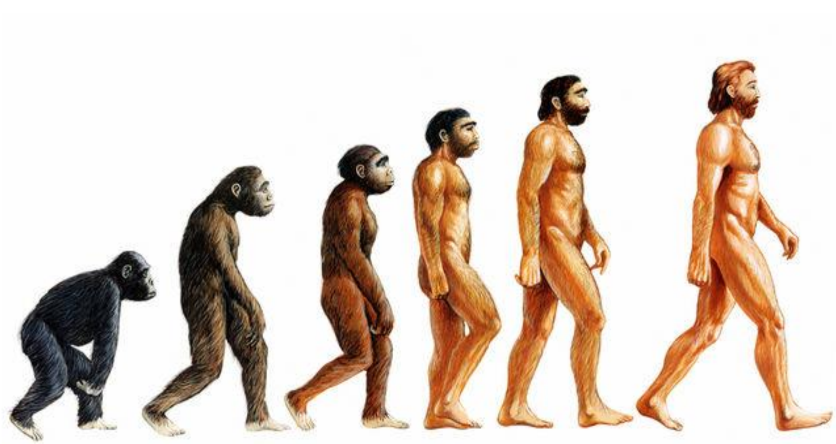
Leonhard Euler (1707-1783) (Calculus of variations, minimization of functionals)

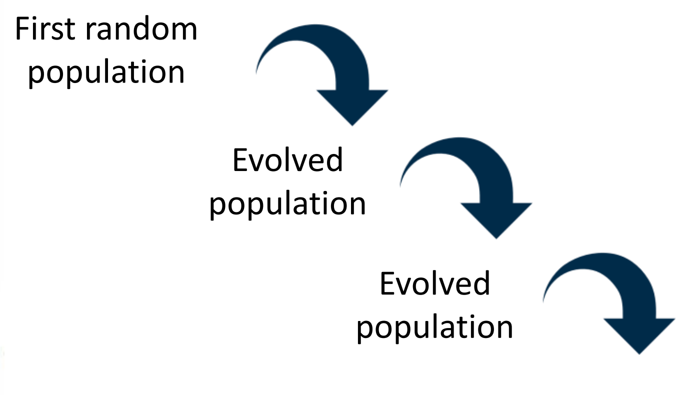
Gottfried Leibnitz (1646-1716)Differential calculus methods of optimization)

Harold William Kuhn (1925-2014) Necessary and sufficient conditions for the optimal solution of programming problems, game theory

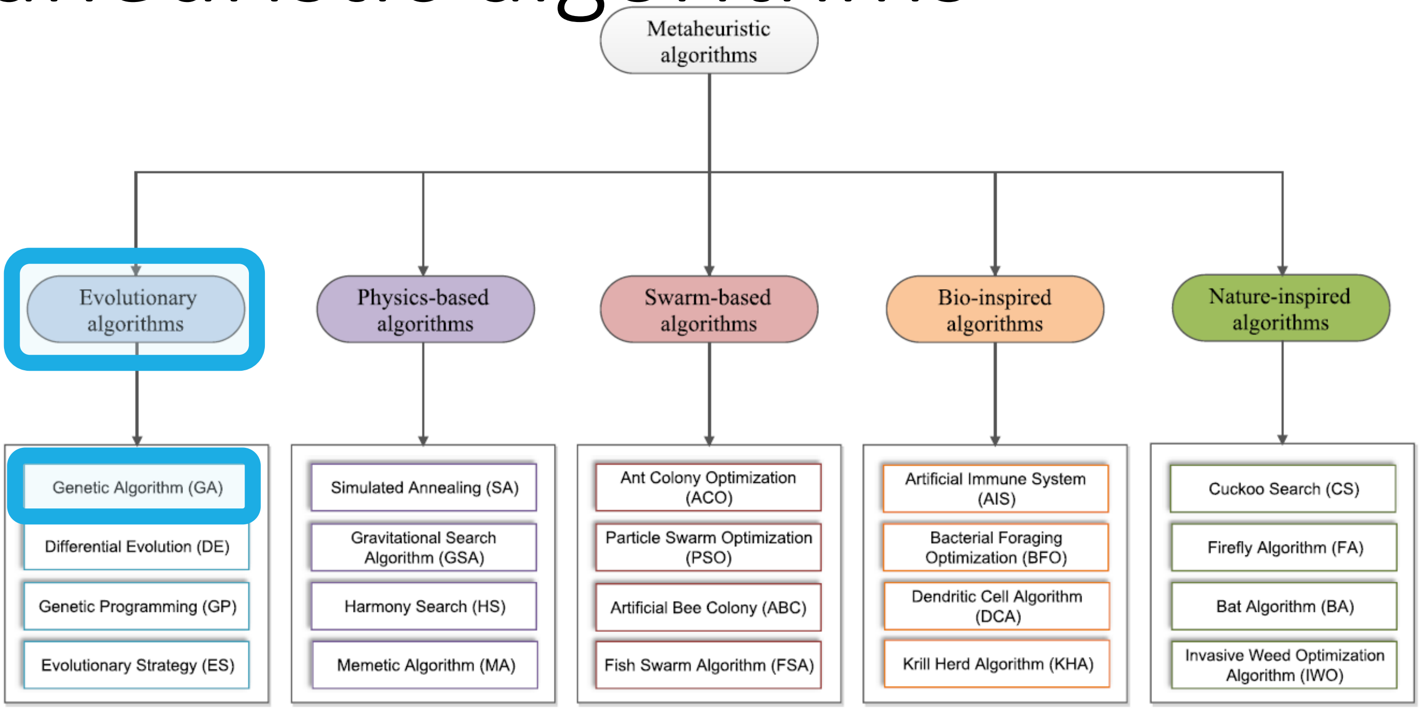
Evolutionary computation

- Evolutionary computation simulates **Darwinian Evolution's Theory** on a computer. The result of such a simulation is a series of optimization algorithms, usually based on a simple set of rules. Optimization iteratively improves the quality of solutions until an optimal, or at least feasible, solution is found.

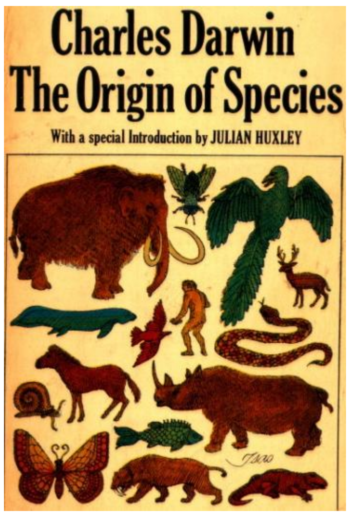


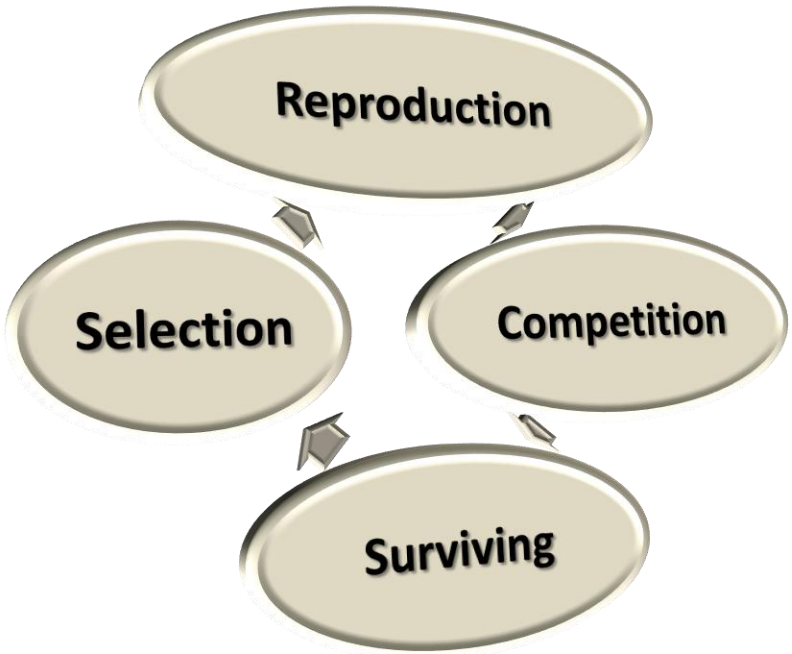


Metaheuristic algorithms



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.

Exploration

- Search in regions with high uncertainty

Exploitation

- Search in regions with high estimated value

Auto-Associative NN (AANN)

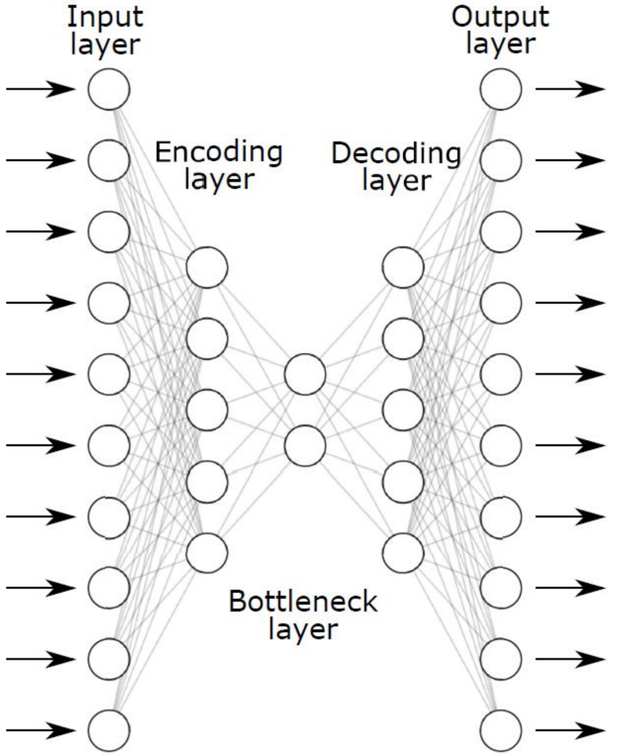
•Directly trained on operational conditions (undamaged situation)

•Try to reproduce the same input signal (unsupervised learning)

•Pass through a "bottleneck" layer to learn most importa
signal

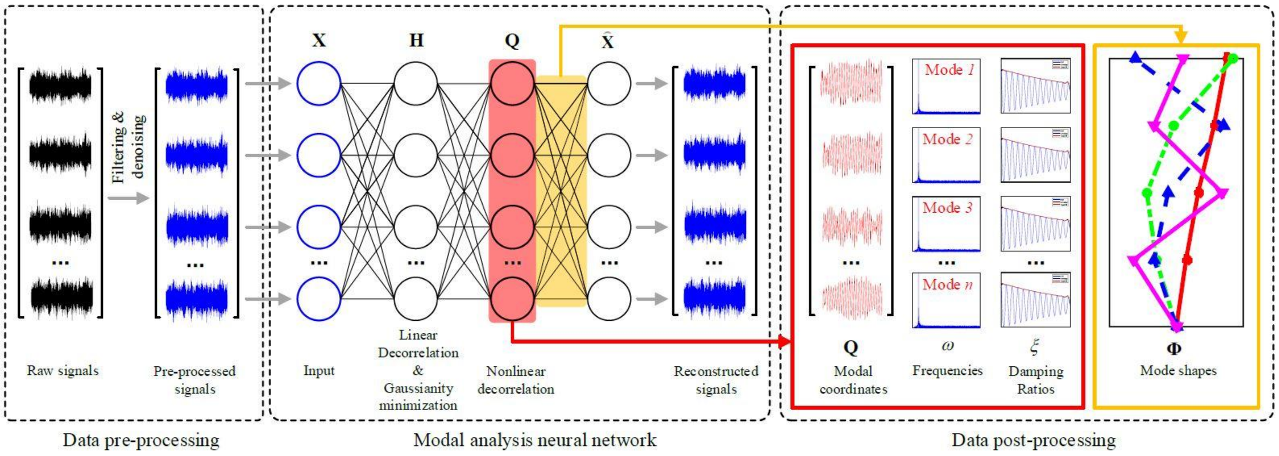
•Once trained, if output signal is similar to input, loss fu
otherwise a possible abnormal condition occurred

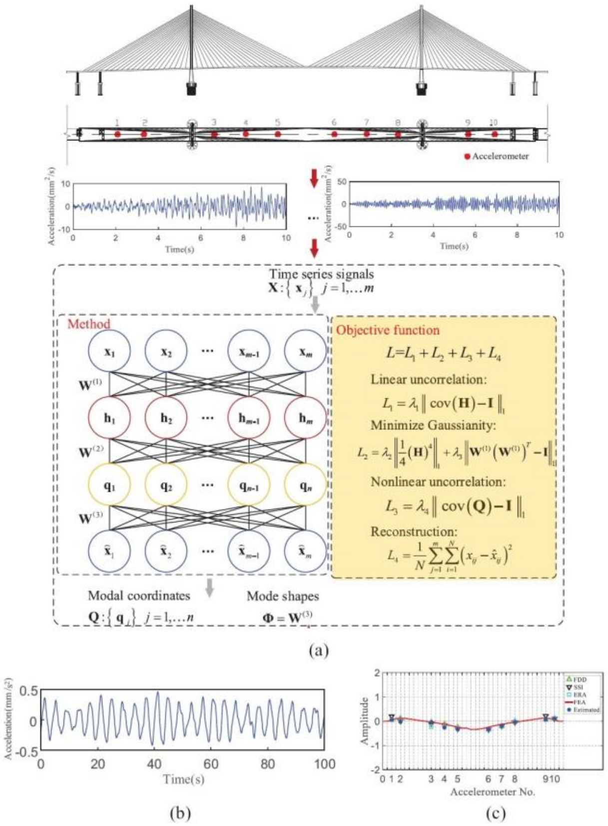
•Autoencoder



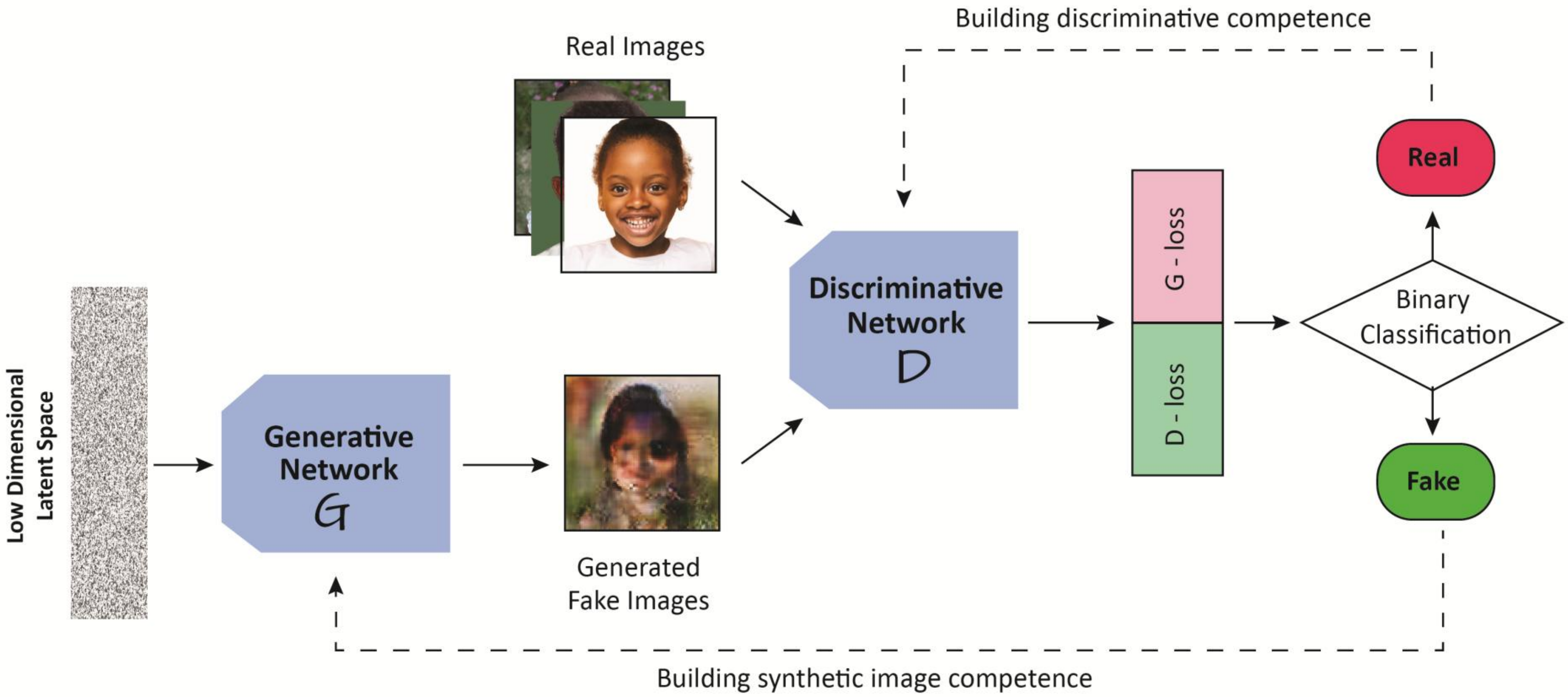
Ad hoc interpretable ANN implementations

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

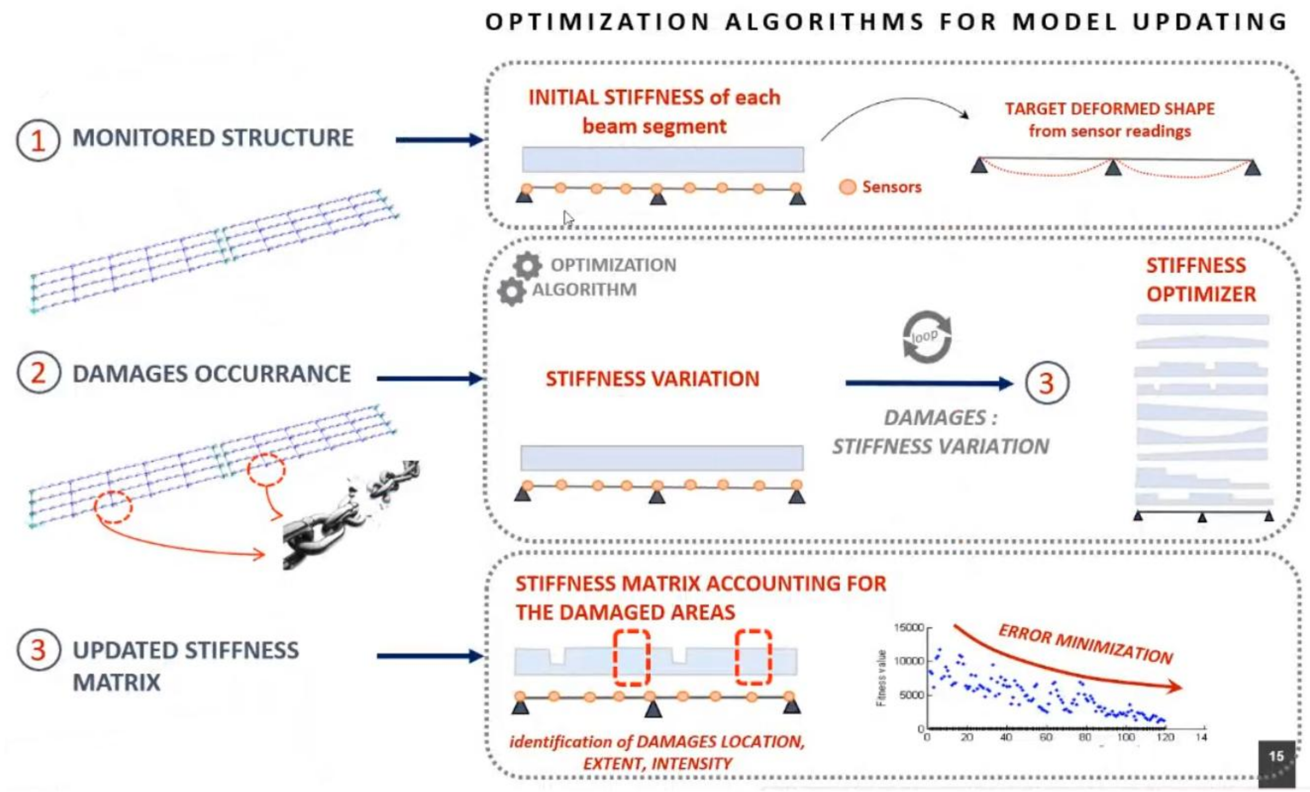




GAN – generative NN



Optimization: Parametric Model updating



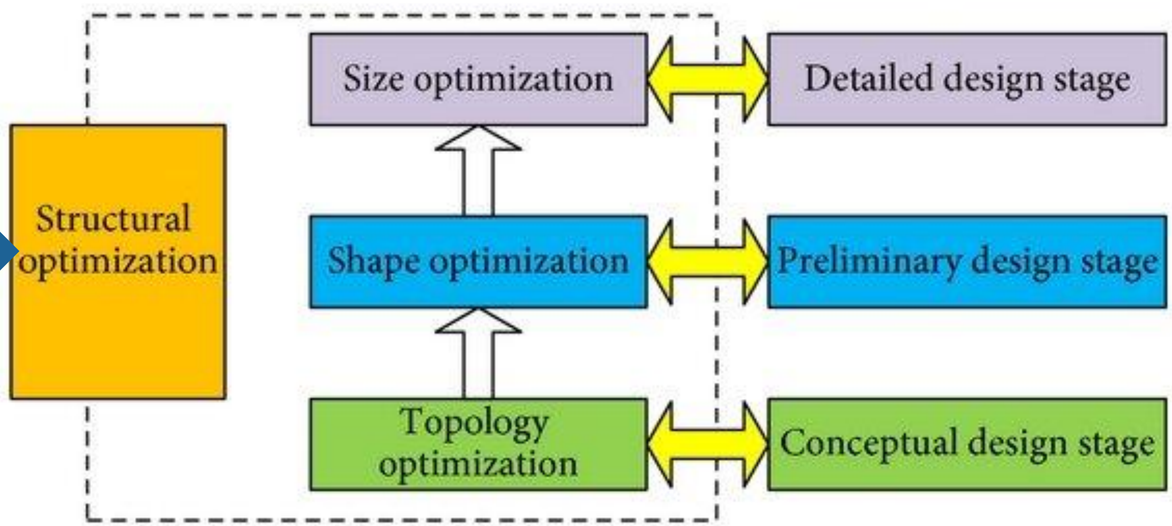
Constraints Handling in Evolutive Intelligence

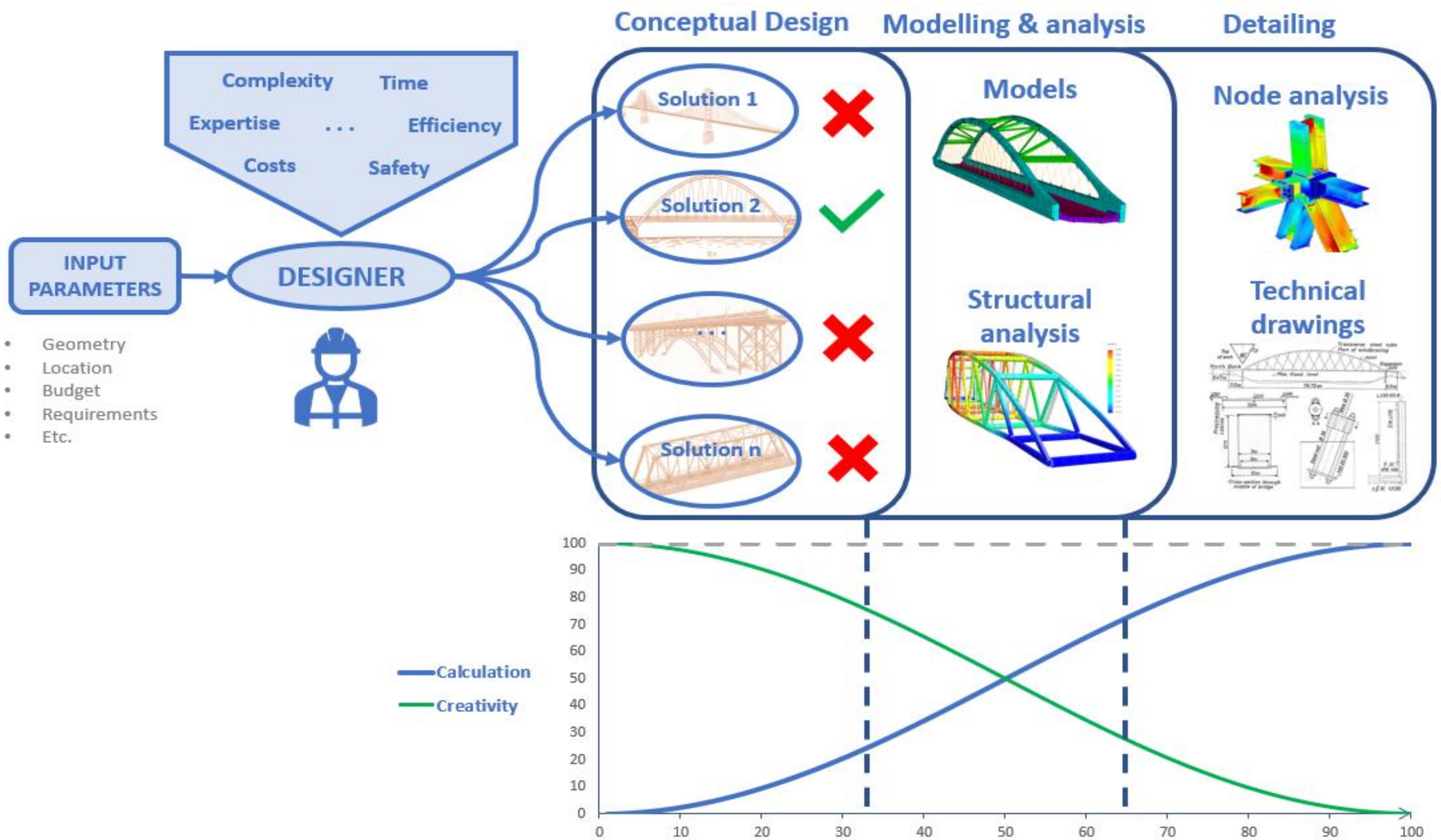
Methods have been classified by different authors into certain categories:

- **Penalty functions-based methods**
- **Methods based on repair algorithms**
- **Methods based on the separation between OF and constraints**
- **Hybrid methods**

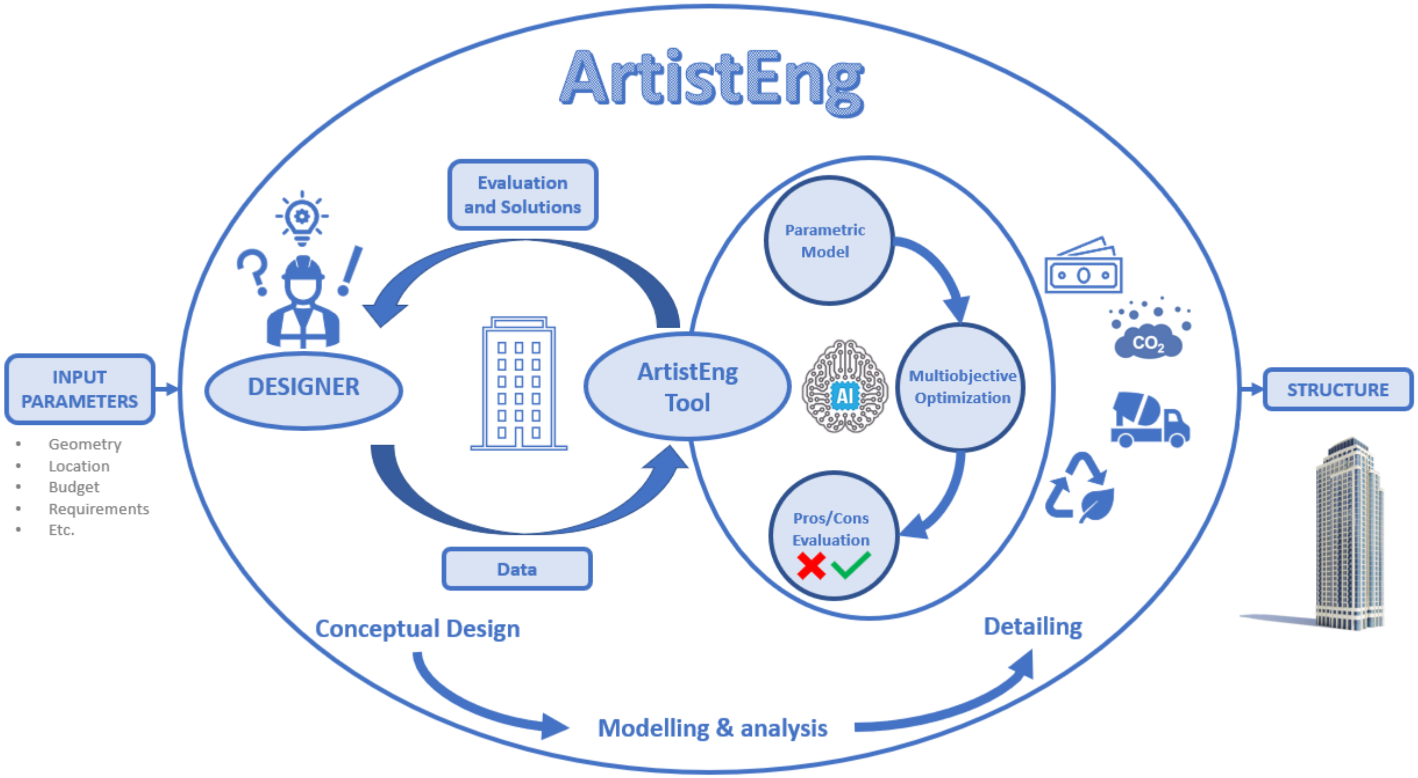
Levels of structural optimization

- Design variables
- Cost Function (OF)
- Constraints





Complexity
Time
Expertise
. . .
Efficiency
Costs
Safety
INPUT PARAMETERS
DESIGNER
Geometry
Location
Budget
Requirements
Etc.
Conceptual Design
Modelling & analysis
Detailing
Solution 1
Solution 2
Solution n
Models
Node analysis
Structural analysis
Technical drawings
Calculation
Creativity
100
90
80
70
60
50
40
30
20
10
0
0
10
20
30
40
50
60
70
80
90
100


ArtistEng
INPUT PARAMETERS
Geometry
Location
Budget
Requirements
Etc.
DESIGNER
Evaluation and Solutions
Data
ArtistEng Tool
Parametric Model
AI
Multiobjective Optimization
Pros/Cons Evaluation
CO_2
STRUCTURE
Conceptual Design
Modelling & analysis
Detailing

Initial Conceptual design - bridge

typology

number and
position of piers
span of deck

Design vector extremely variable

Initial Conceptual design - bridge

typology

Different cost models

<u>Volume</u>

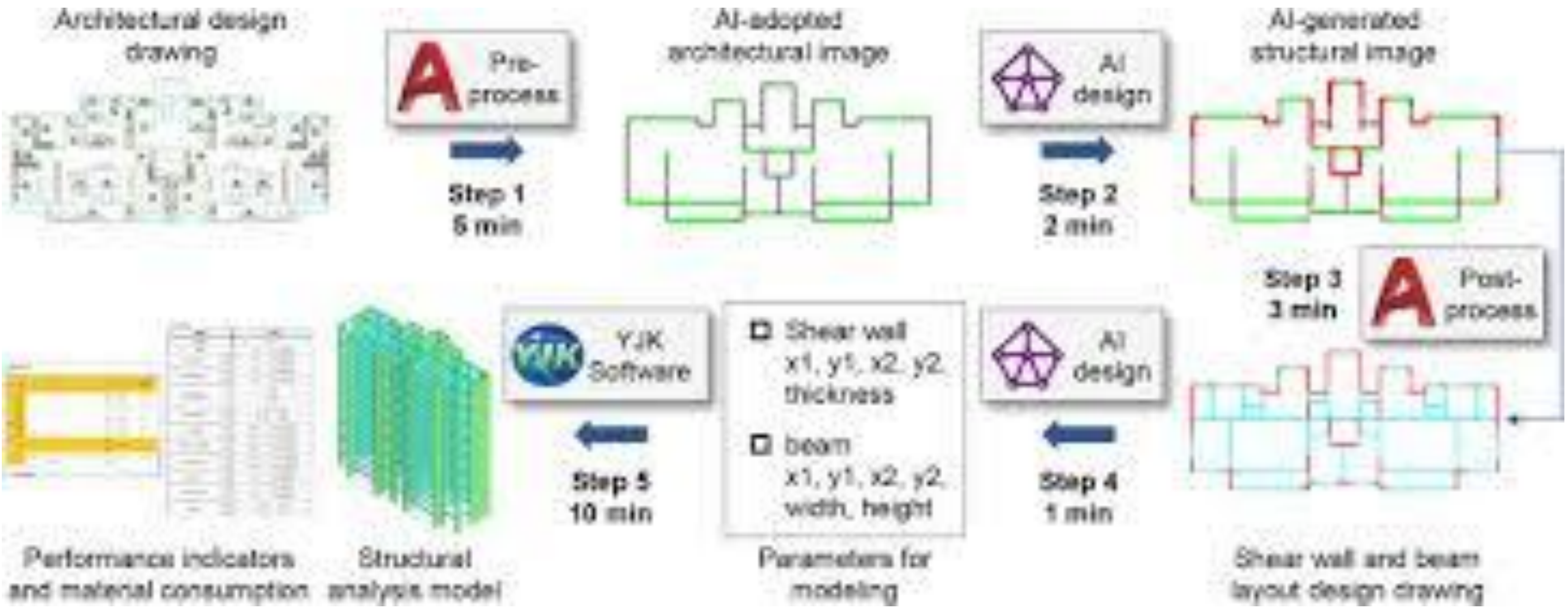
Transport/assembly/ construction / maintenance

Why an open source FEM (OpenSees) for a "multistage" structural optimization

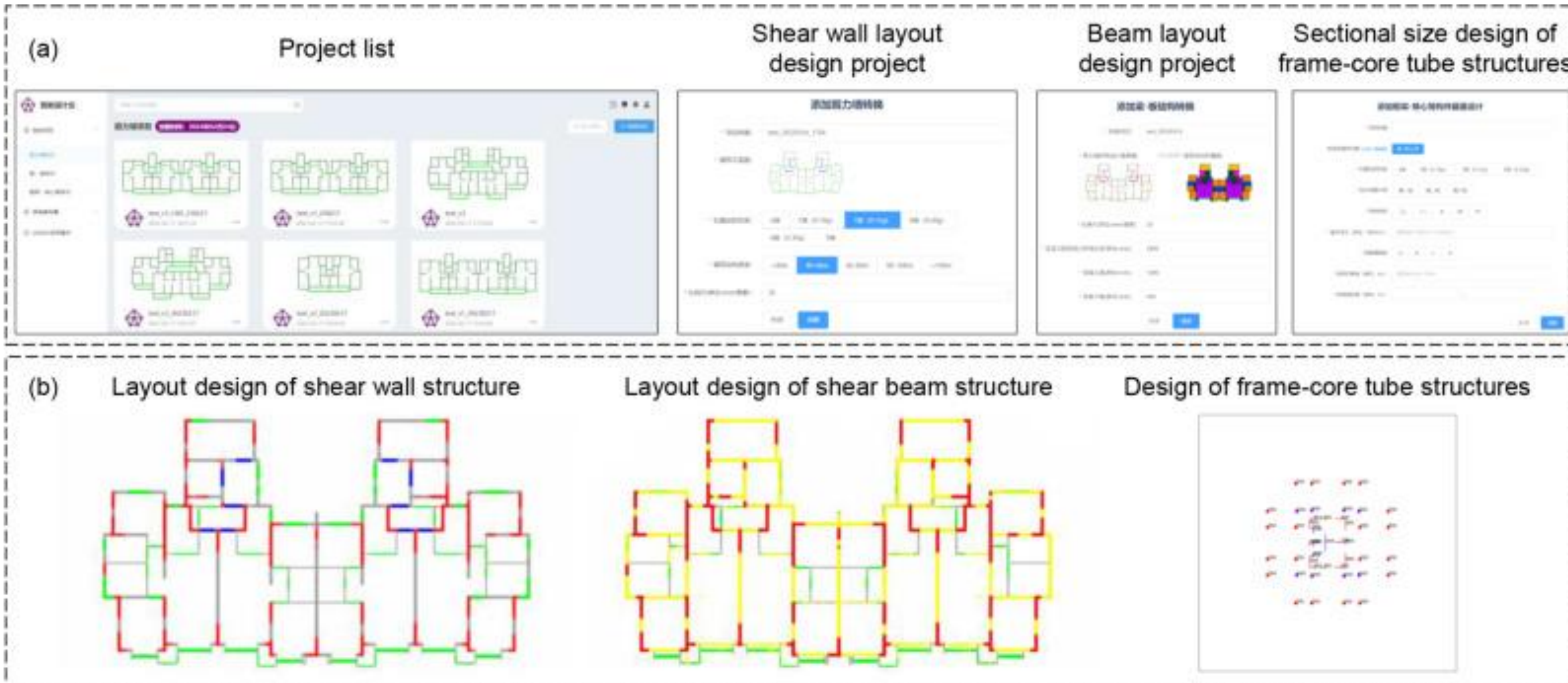
OpenSees

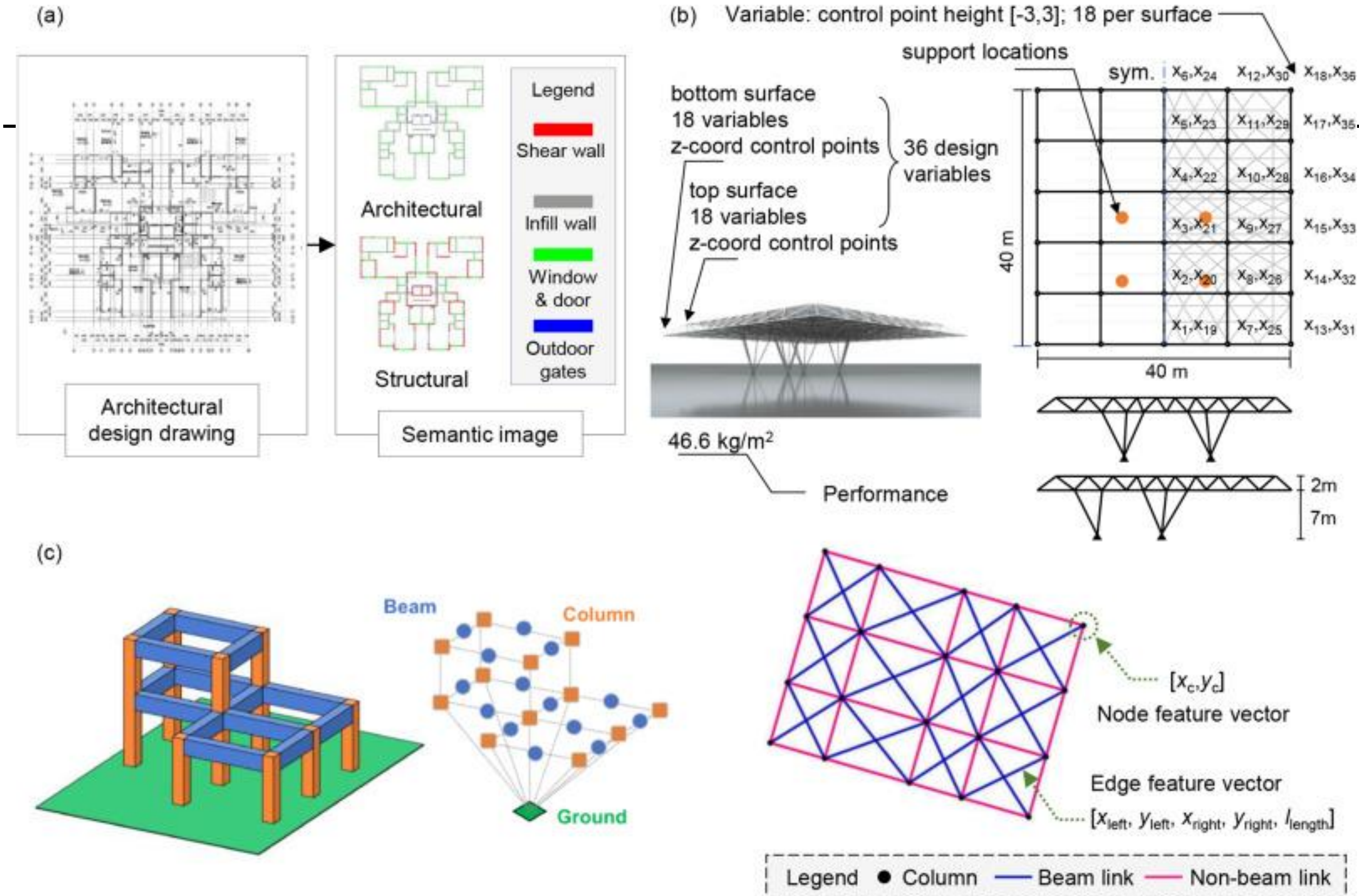
- scalable
- Easy implementation of different constraints
- Interface with external programs
- Different level of model complexity

Generative AI progettazione strutturale



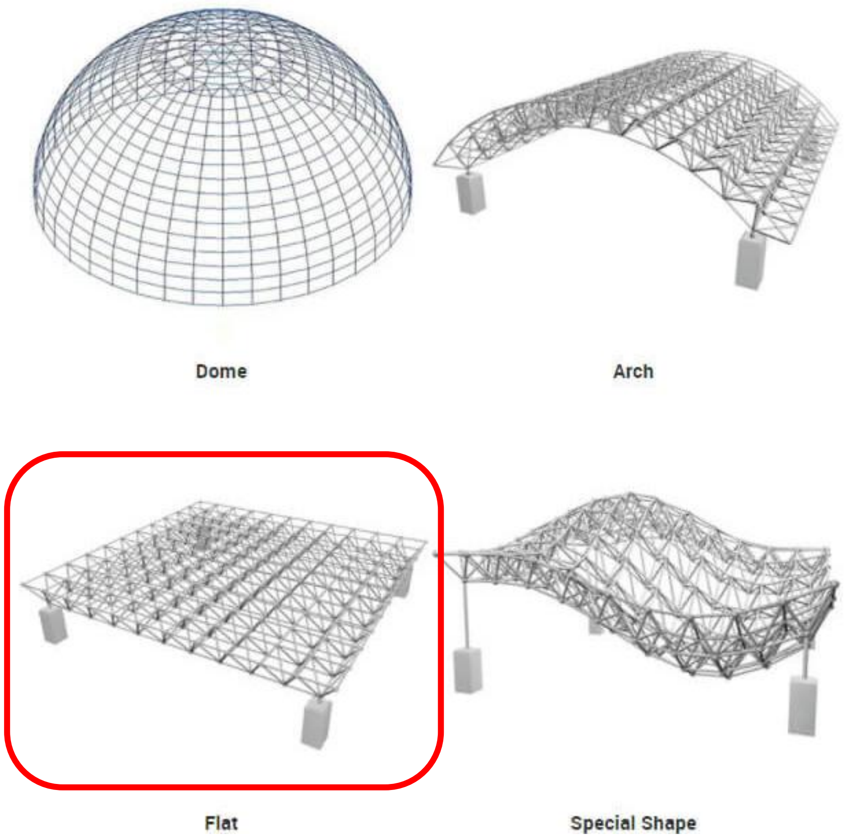
Generative AI progettazione strutturale





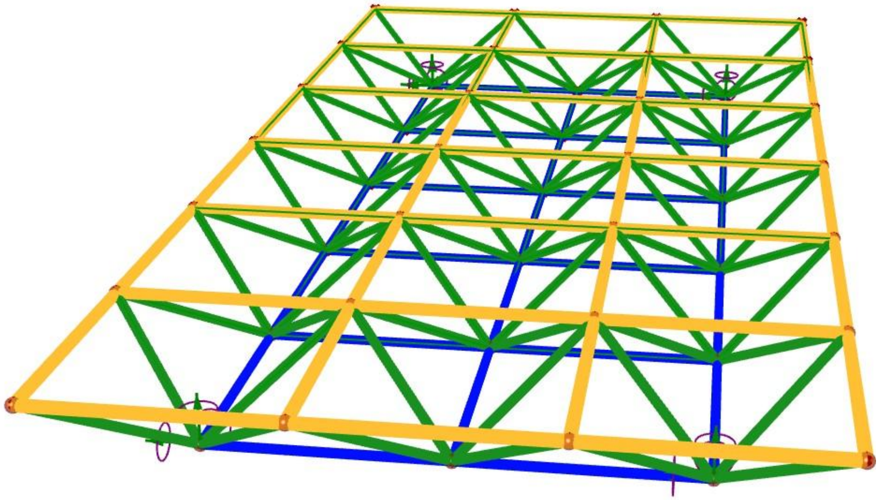
(a)
Architectural design drawing
Architectural
Structural
Legend
Shear wall
Infill wall
Window & door
Outdoor gates
Semantic image
(b)
Variable: control point height [-3,3]; 18 per surface
support locations
bottom surface
18 variables
z-coord control points
top surface
18 variables
z-coord control points
36 design variables
sym.
40 m
40 m
46.6 kg/m²
Performance
2m
7m
(c)
Beam
Column
Ground
[x_c, y_c]
Node feature vector
Edge feature vector
[x_left, y_left, x_right, y_right, l_length]
Legend
Column
Beam link
Non-beam link

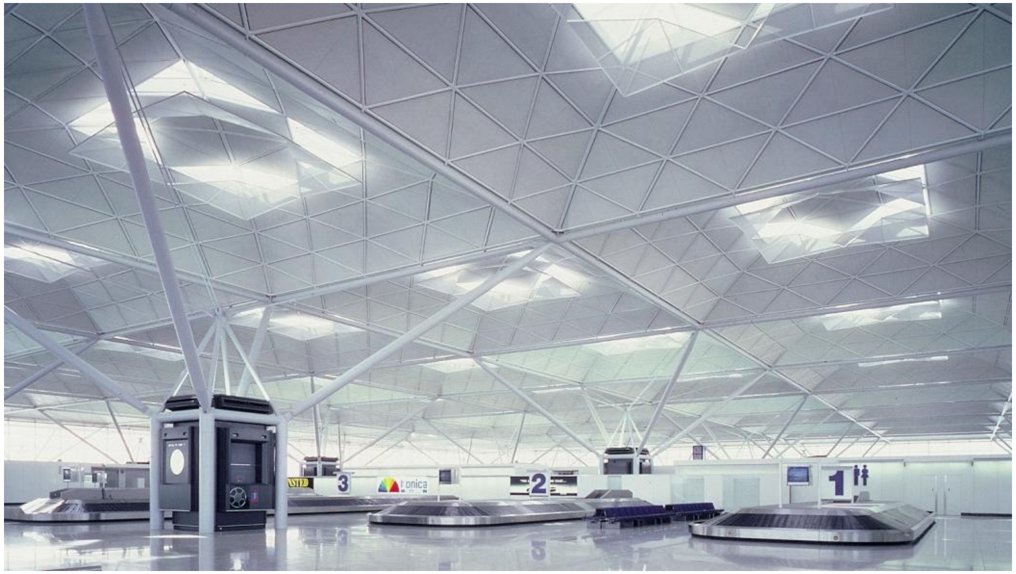
Space frame



Typology

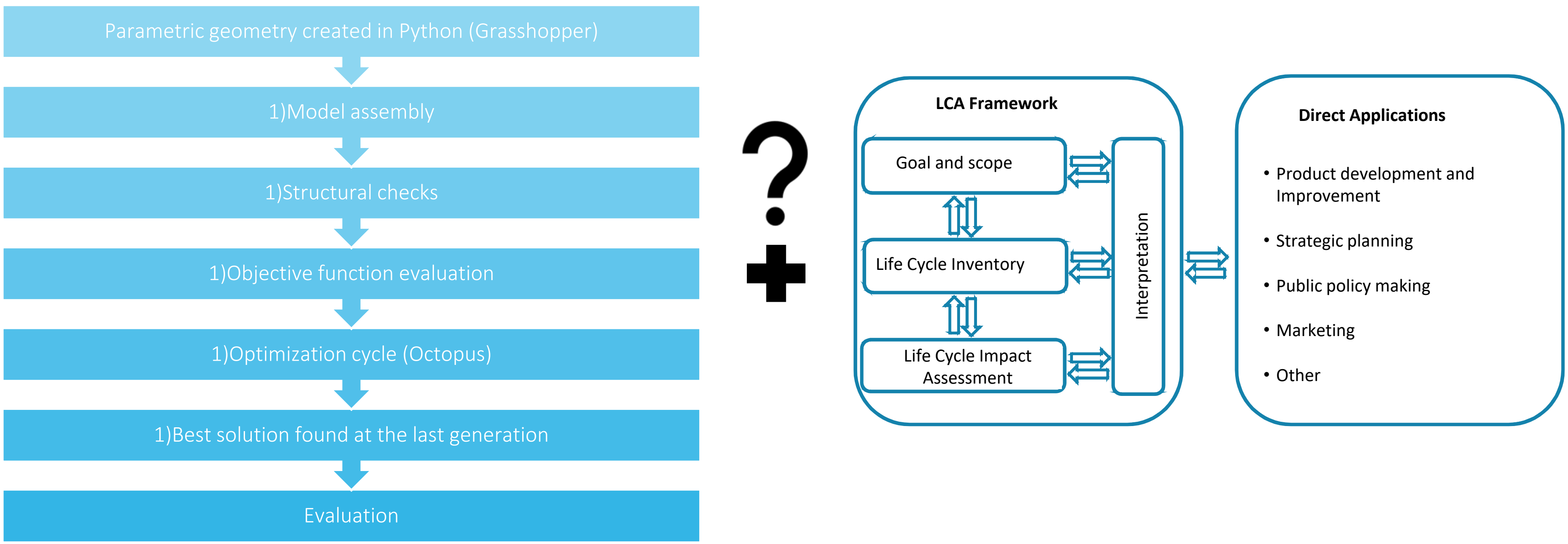
- Plane cover
- Double-layered grid
- Semi-octahedral module



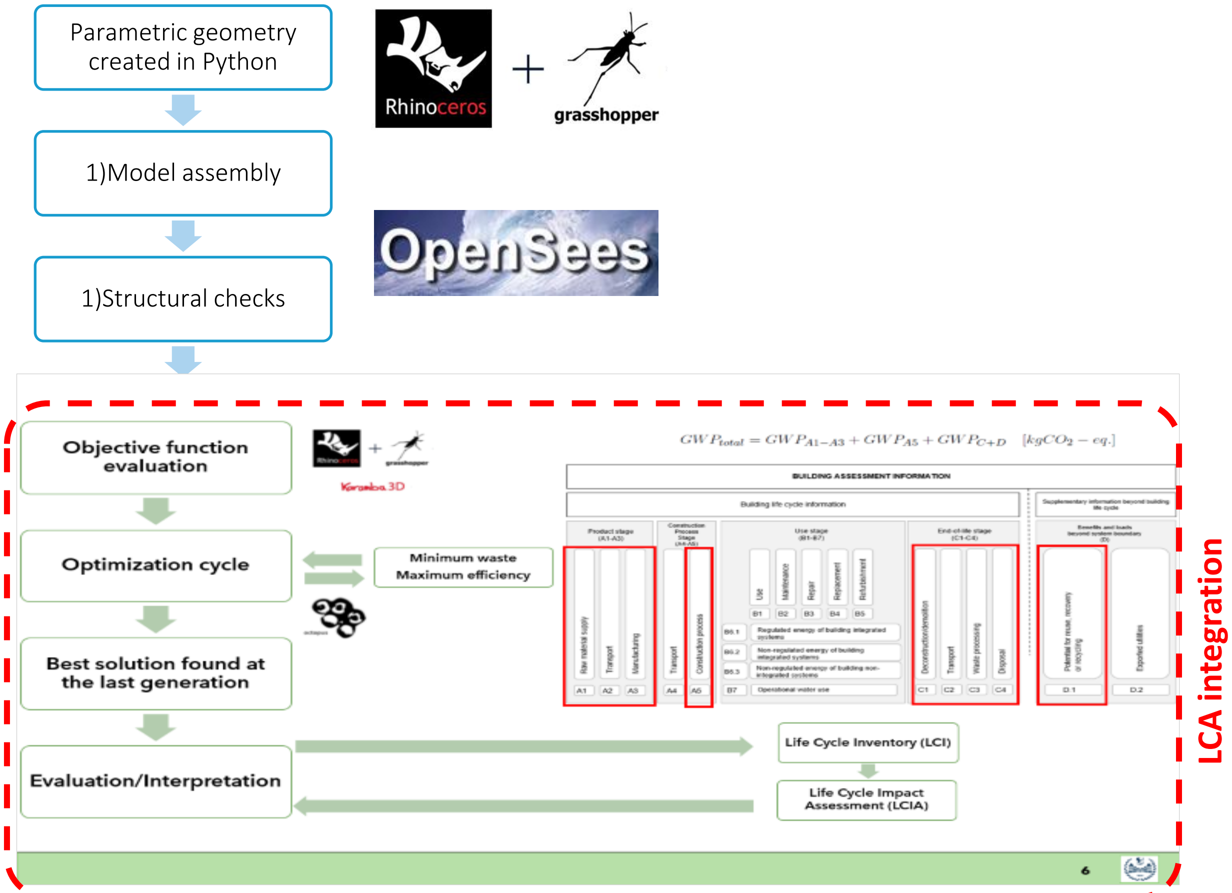


Stansted Airport

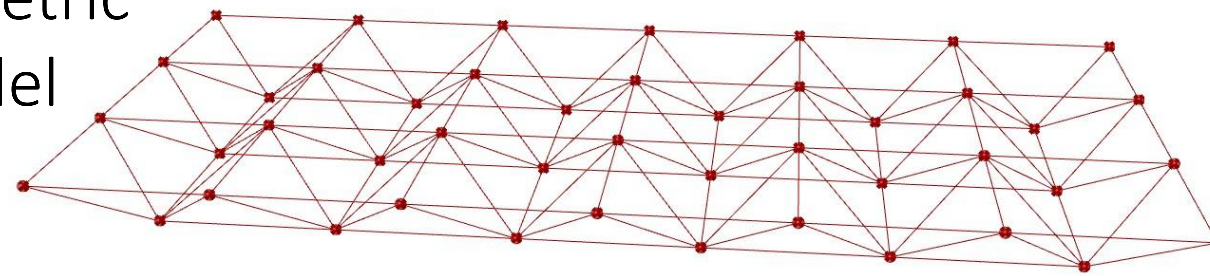
How to integrate the optimization process with LCA analyses?



Overall procedure flow - Methodology



Case study : Parametric geometry and model assembly



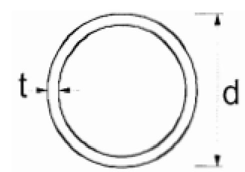
Space frame pre-design

$$1 \leq H \leq \frac{L}{15} \;\; [m]$$

Beam length: $1\ m \leq \Delta \leq 10\ m \rightarrow \frac{L}{\Delta_{max}} \leq Divisions \leq \frac{L}{\Delta_{min}}$

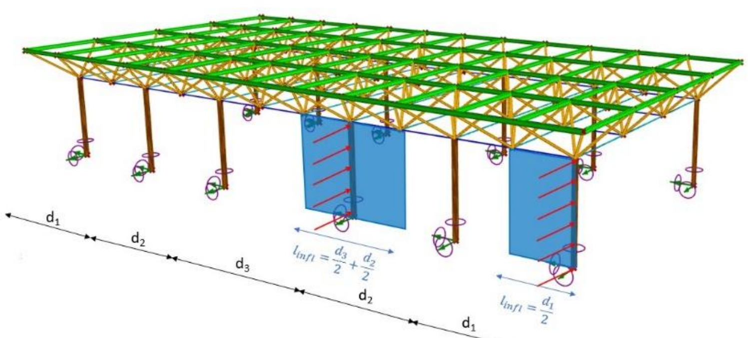
Beam cross-sections

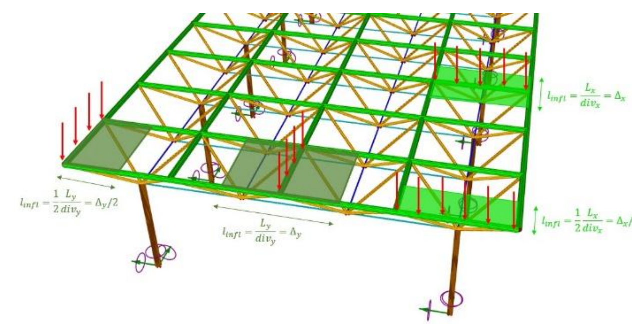
Steel S355, CHS (EN10219-2)



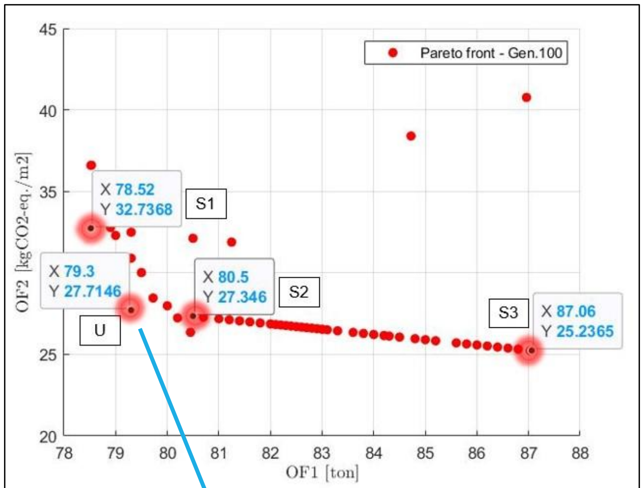
Applied Loads (ULS combination):

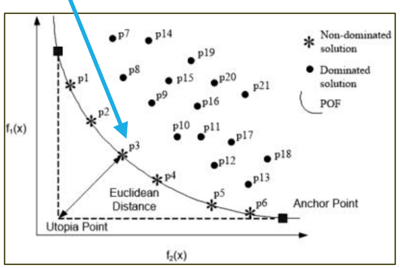
- **Gravitational and Horizontal loads**

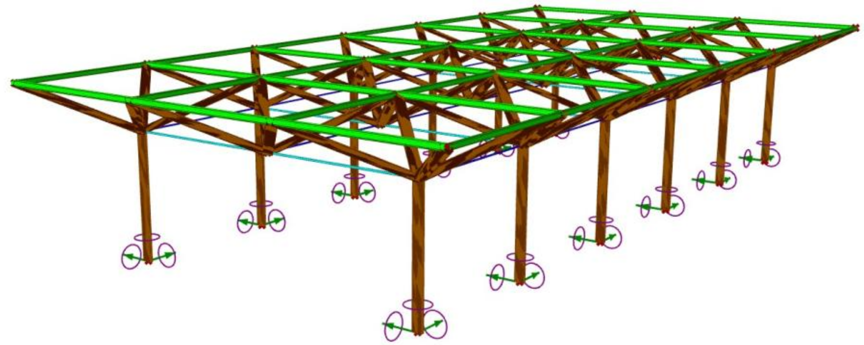




Case study: Results

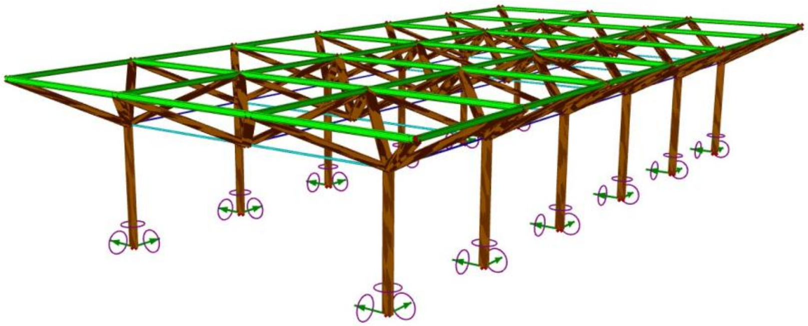




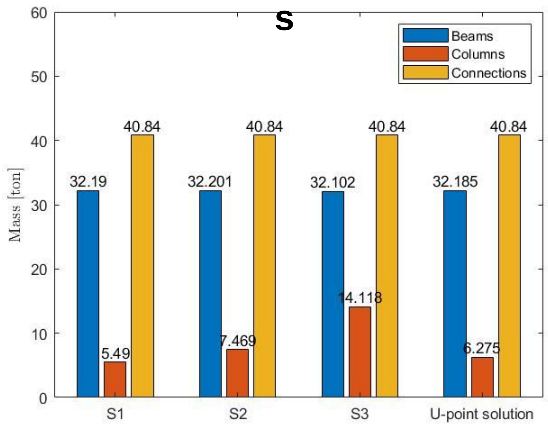


	U-point solution	S1	S2	S3
OF_1	79.3	79.3	80.51	87.06
OF_2	27.71	32.74	27.35	25.24
H	3	3	3	3
div_x	6	6	6	6
div_y	3	3	3	3
Up long.	CHS 355.6x6.3	CHS 355.6x6.3	CHS 355.6x6.3	CHS 355.6x6.3
Up transv.	CHS 406.4x6	CHS 406.4x6	CHS 406.4x6	CHS 406.4x6
Low long.	CHS 114.3x2.5	CHS 114.3x2.5	CHS 114.3x2.5	CHS 88.9x3
Low transv.	CHS 139.7x4	CHS 139.7x4	CHS 139.7x4	CHS 114.3x5
Diagonals	GL 365x570	GL 365x418	GL 365x570	GL 365x570
Columns	GL215x608	GL215x532	GL315x494	GL215x1368

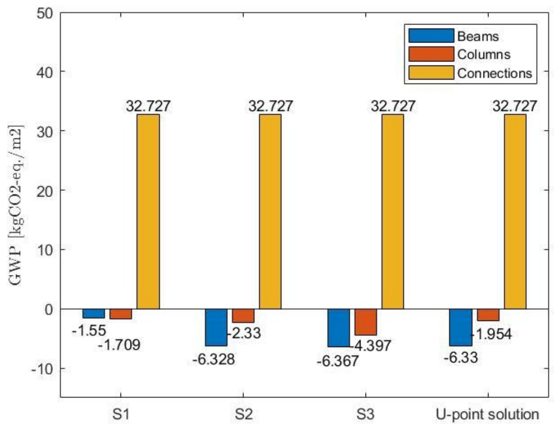
Case study : Results



Mas
s



CO2
Emission



EXOSKELETONS

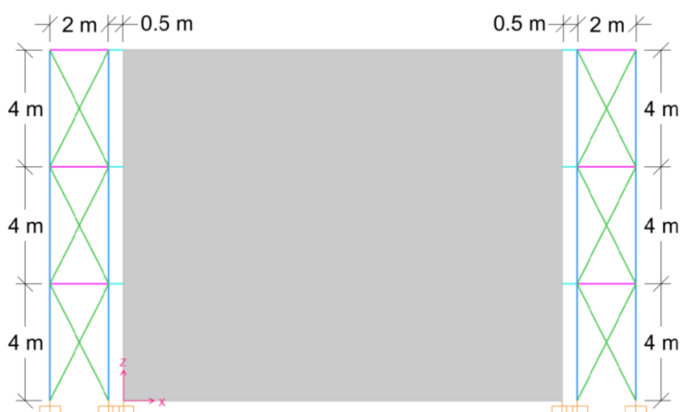
- **steel additive structures**
- inspired by nature: **biomimicry**

avoid the **interruption of the activities** carried out **inside** of the building

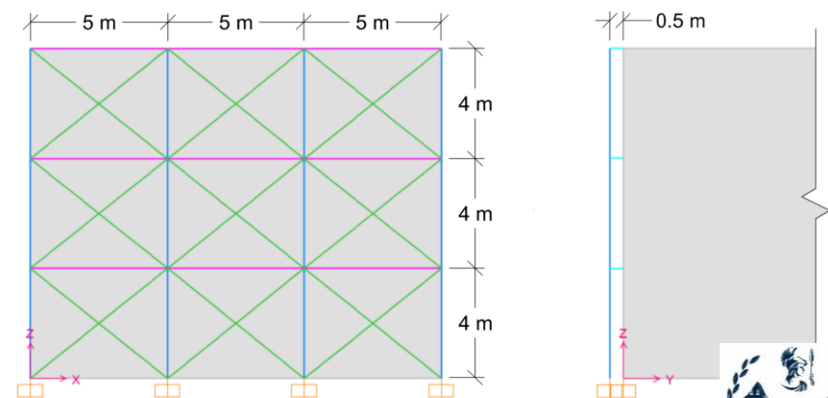
suitable for a **holistic intervention**: structural, energetic, architectonic

- applied **from outside**
- **low** construction **time and cost**

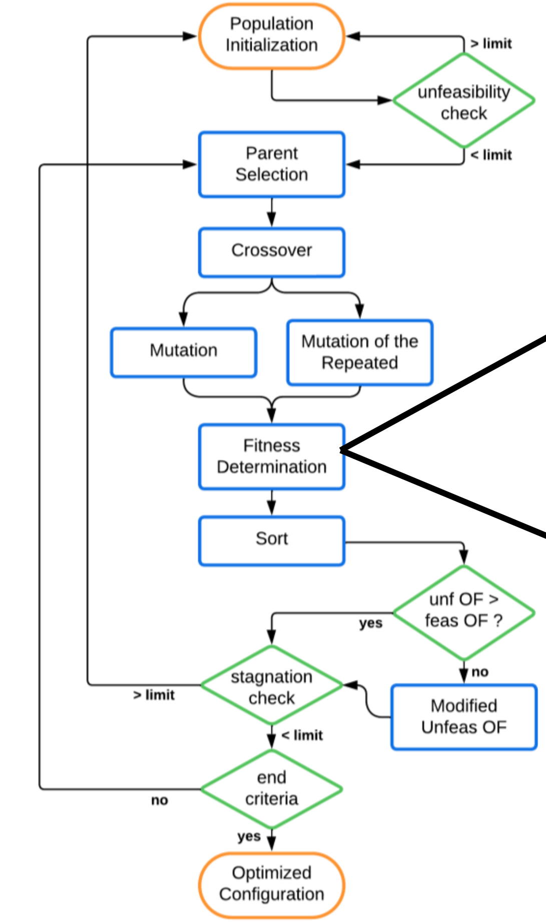
ORTHOGONAL

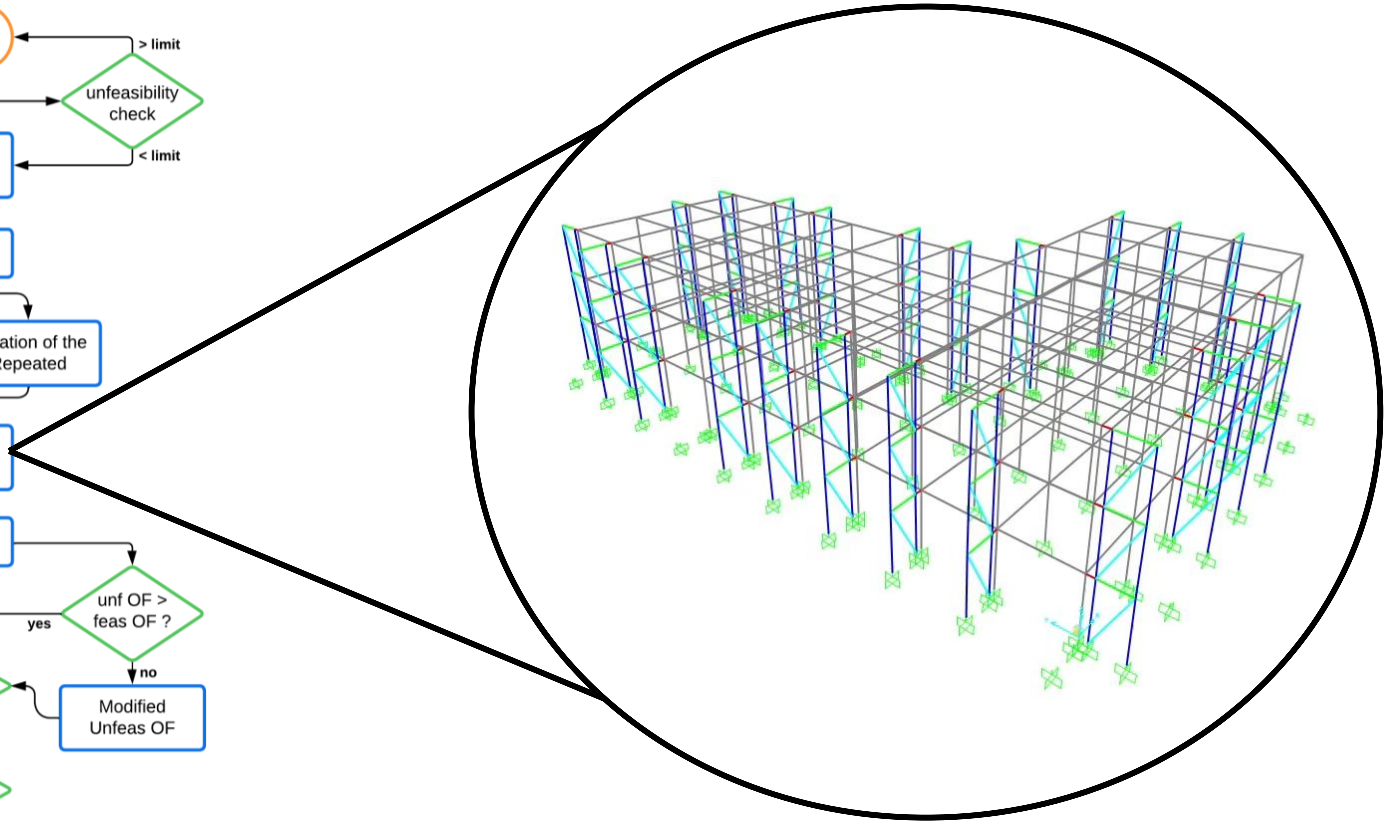


PARALLEL



OPTIMIZATION ALGORITHM & FEM ANALYSES





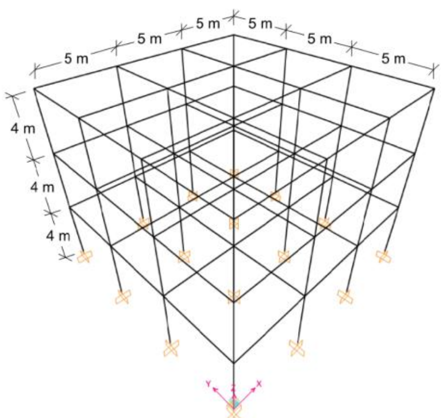
CASE STUDIES

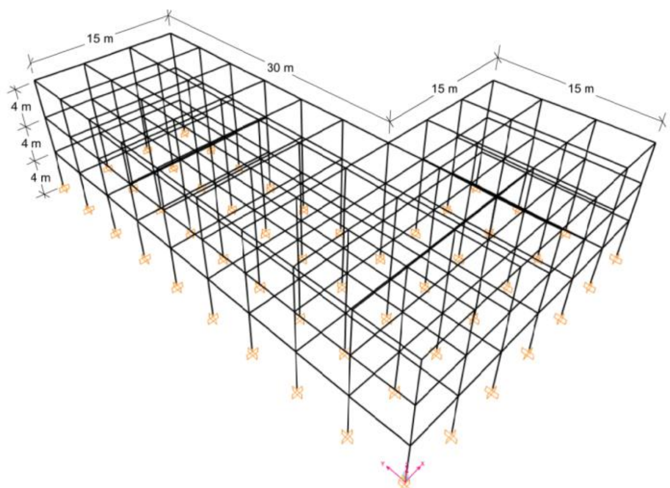
- **Reinforced Concrete** structures
- obtained by **replication of the base module**
- located in **Foggia, Italy**
- **0.4198 g** acceleration
- **5m x 5m** bay
- **4m** storey height

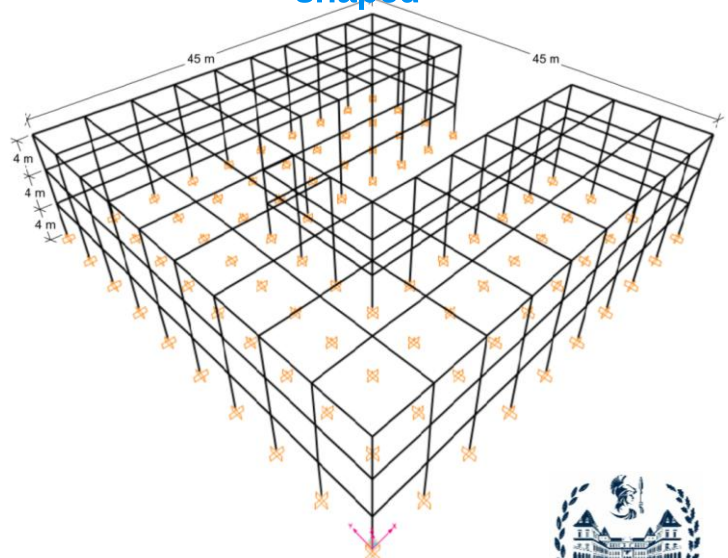
STRUCTURE 01 base module

STRUCTURE 02 L-shaped

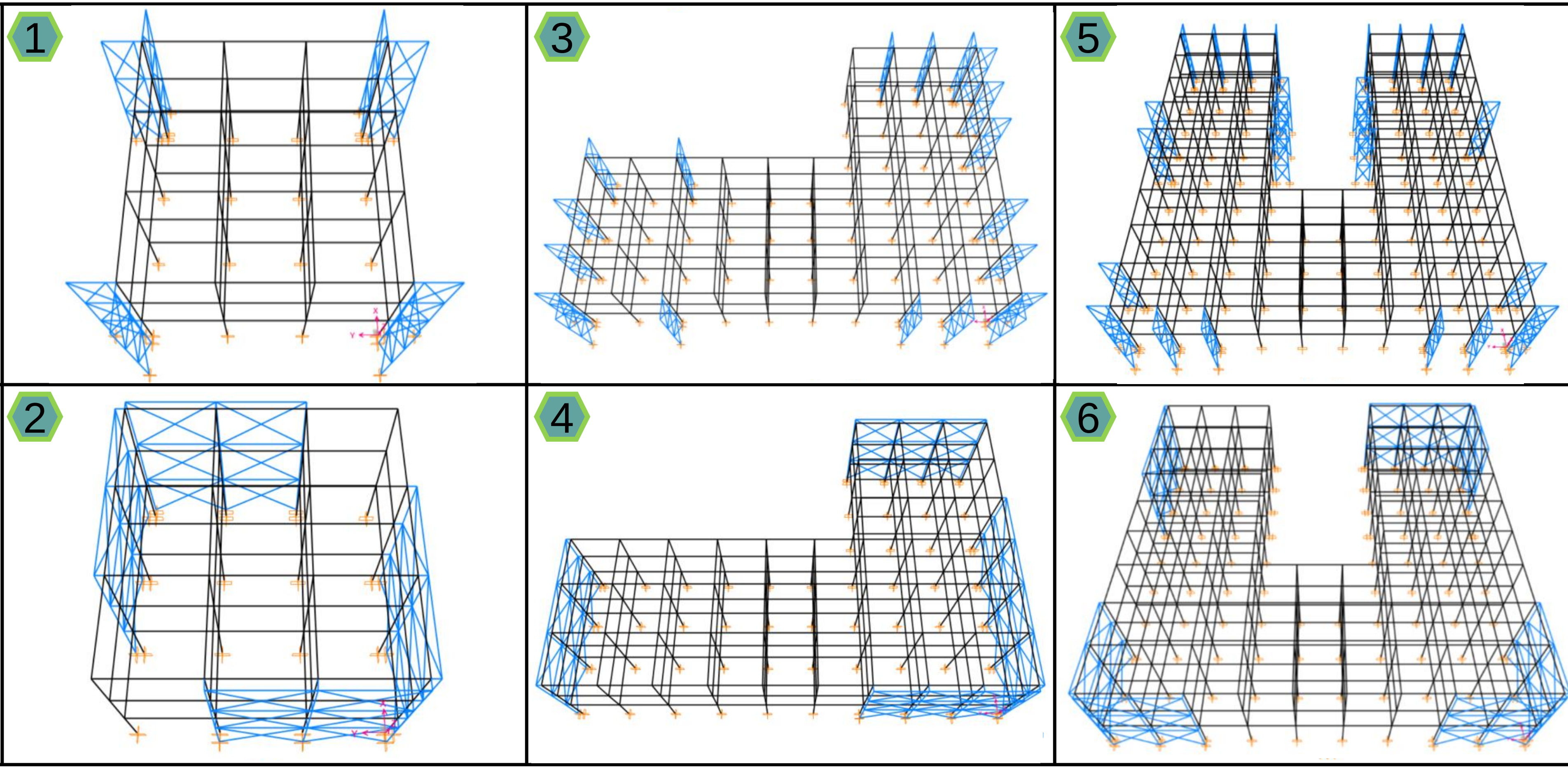
STRUCTURE 03 U-shaped



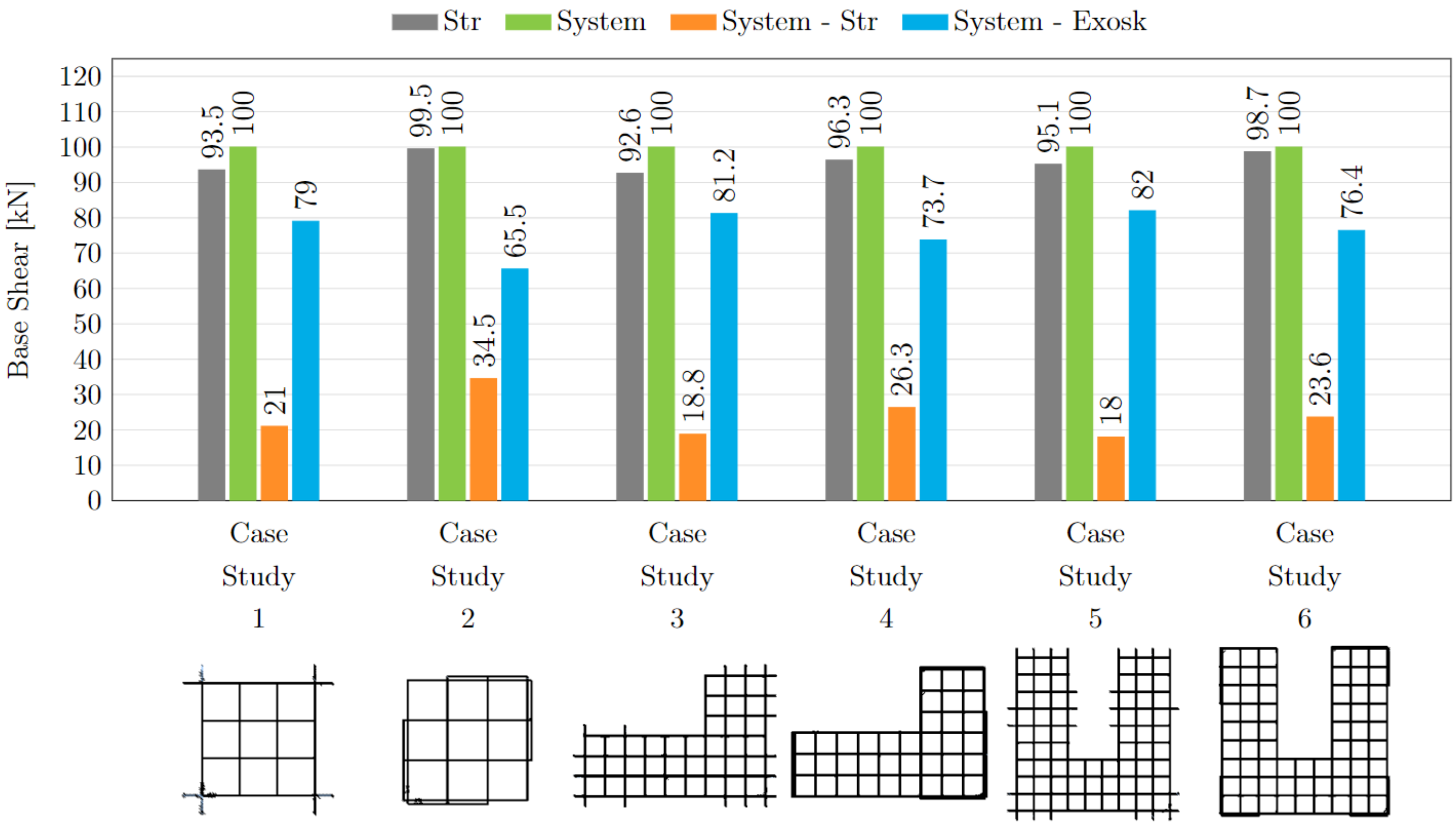




RESULTS: FINAL CONFIGURATIONS



RESULTS: BASE-SHEAR



AEROPORTI DI PUGLIA

BARI BRINDISI FOGGIA TARANTO

REGIONE PUGLIA

ADR INGEGNERIA PROGER RINA Benedetto Camerana Studio

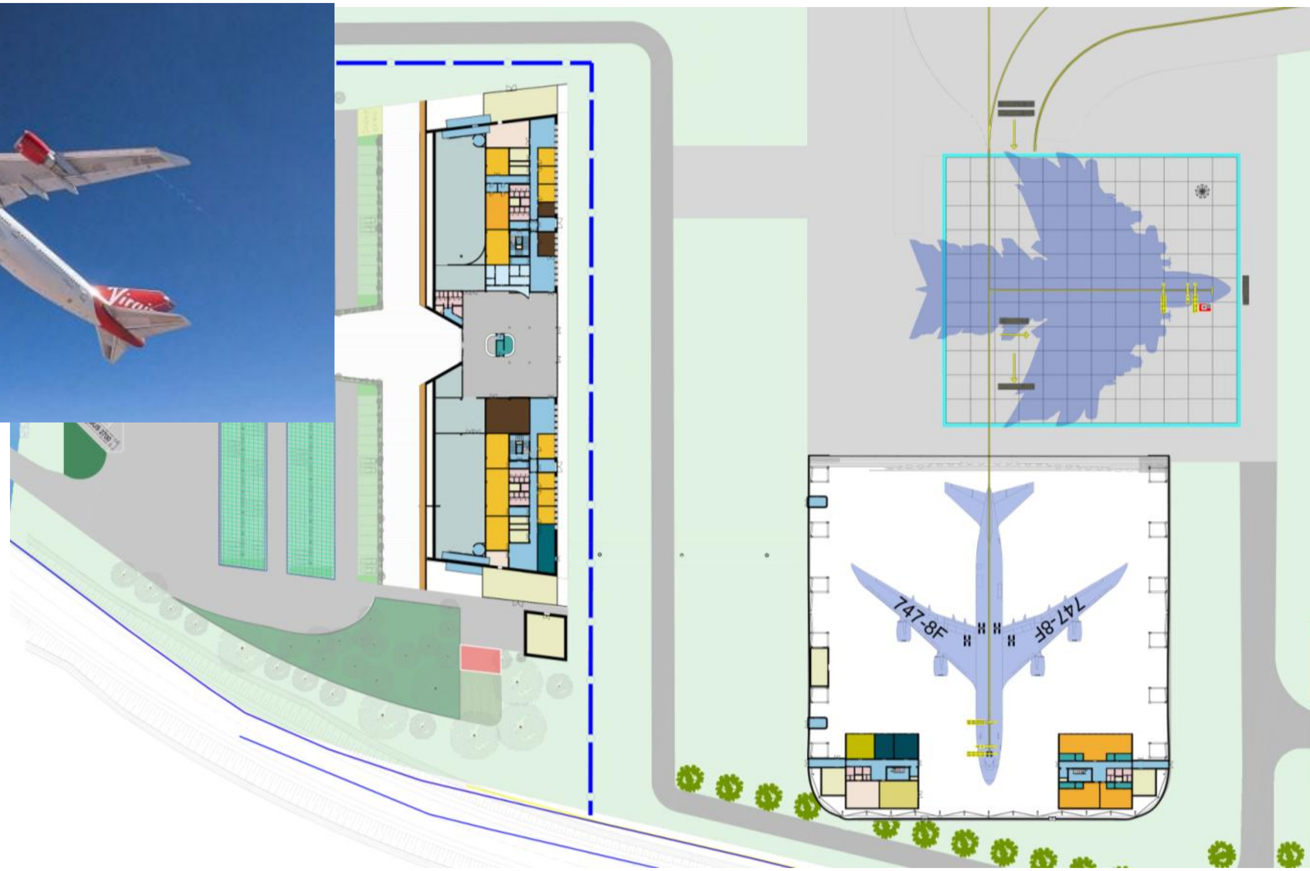
ALTEC Politecnico di Torino

Aeroporto di Grottaglie - Spazioporto

Attualizzazione del Piano di Sviluppo
Progetto di Fattibilità Tecnica ed Economica
delle opere per la realizzazione dello Spazioporto

16 febbraio 2024

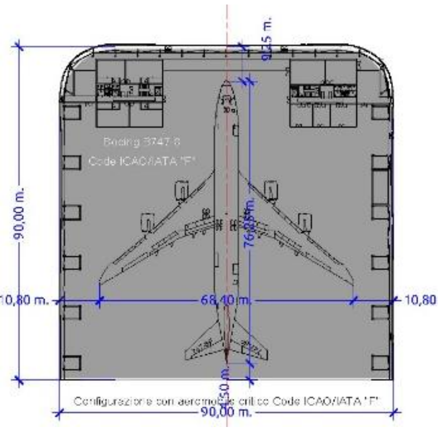
4. Il PFTE - Architettura



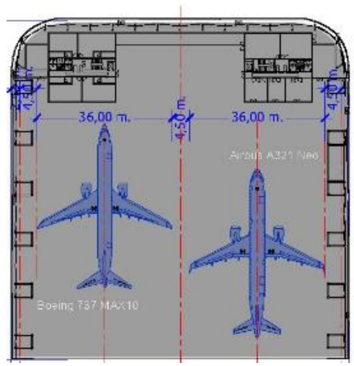
LEGENDA
- Hall
- Museo – Sale espositive
- Uffici – Laboratori
- Camera Pulita
- Sala conferenze
- Sala Medica
- Servizi igienici
- Area controlli
- Spogliatoi – Guardaroba
- Deposito
- Ristorante
- Distribuzione orizzontale e verticale
- Locali tecnici
- Officina

4. Il PFTE - Infrastrutture di volo

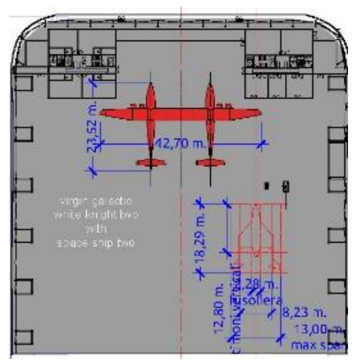
Allo stesso modo si è proceduto a dimensionare l'**HANGAR** a servizio delle operazioni di volo, in modo che possa accogliere la maggior parte dei velivoli con le tecnologie di volo ad oggi note.



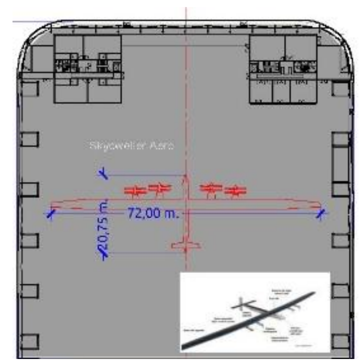
Configurazione
1 aeromobile EASA «F»



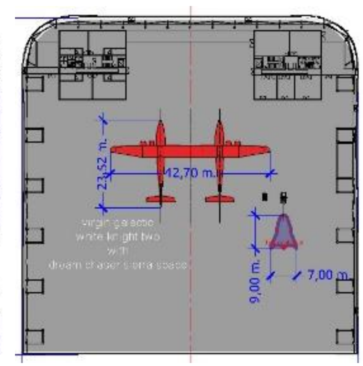
Configurazione
2 aeromobili EASA «C»



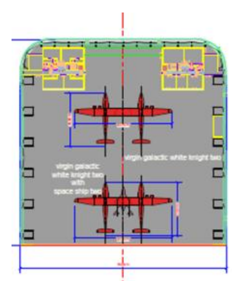
Configurazione
Virgin Galactic White Knight TWO
Space Ship Two



Configurazione
Skydweller Aero



Configurazione
Virgin Galactic White Knight TWO
Dream Chaser Sierra Space



Configurazione
2 Virgin Galactic White Knight TWO
Space Ship Two

4. Il PFTE - Architettura

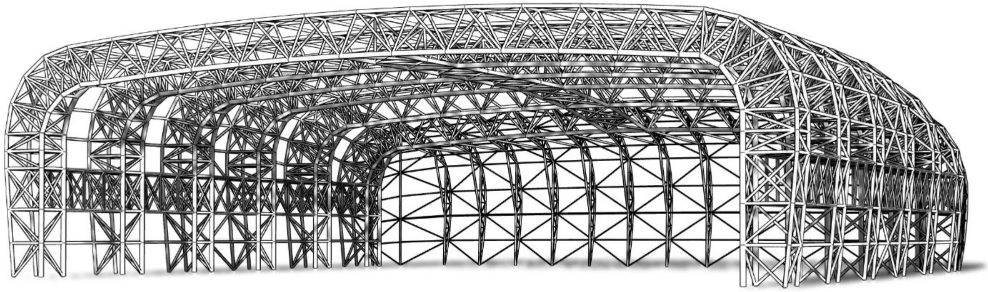
4. Il PFTE - Architettura

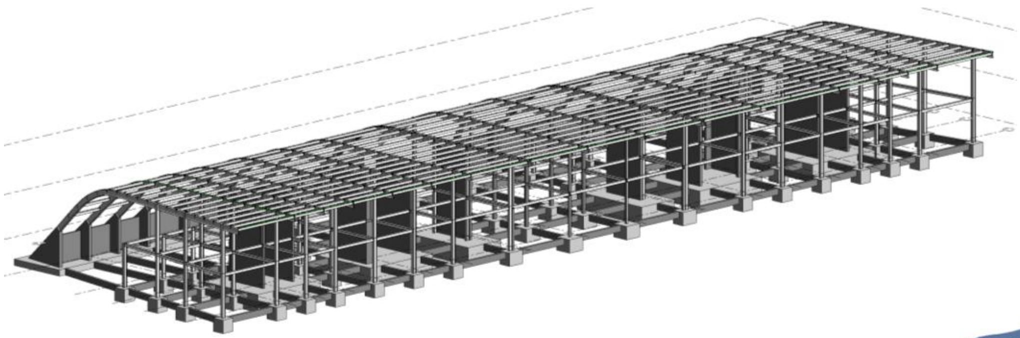
ADR INGEGNERIA PROGER RINA Benedetto Camerana Studio

6. La realizzazione delle Strutture

HANGAR

L'hangar è costituito da sei portali a struttura reticolare spaziale, posti ad interasse costante pari a 13.52m, aventi luce interna di 78.72m e altezza massima pari a 26.25m.



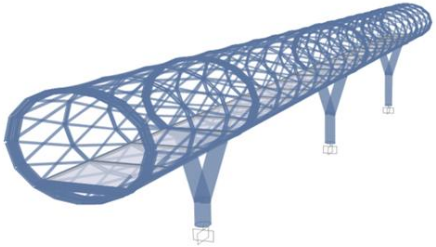


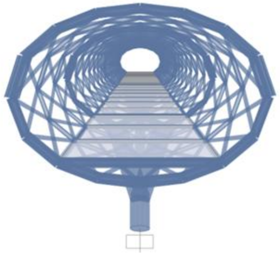
EDIFICIO POLIFUNZIONALE

fabbricato di due piani di altezza, esteso per oltre 120 m nella direzione longitudinale e circa 35 metri in quella trasversale

PASSERELLA PEDONALE

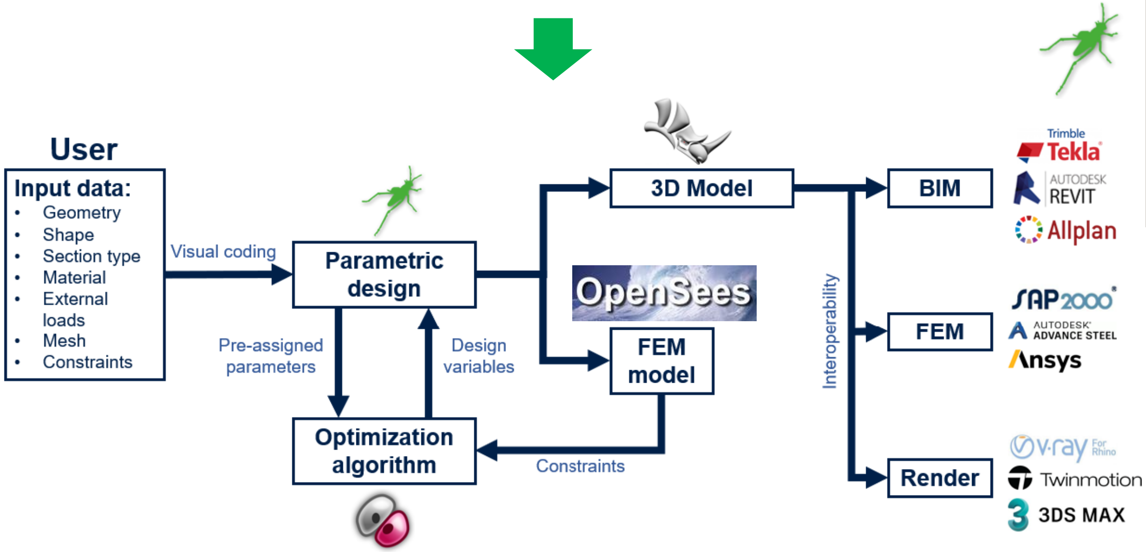
Guscio strutturale a graticcio (gridshell) a sezione ellissoidale di lunghezza pari a 60 m

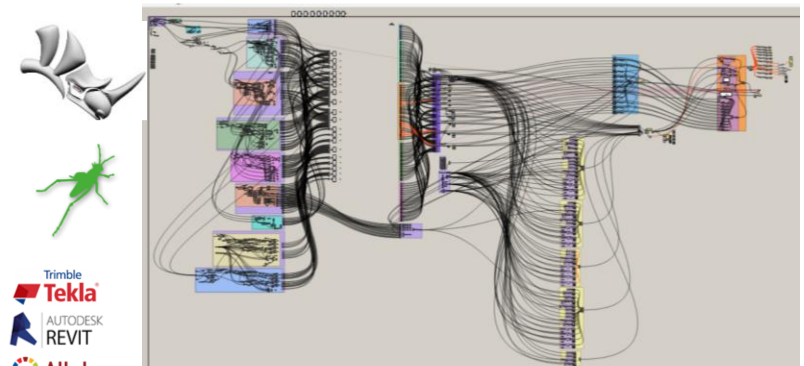


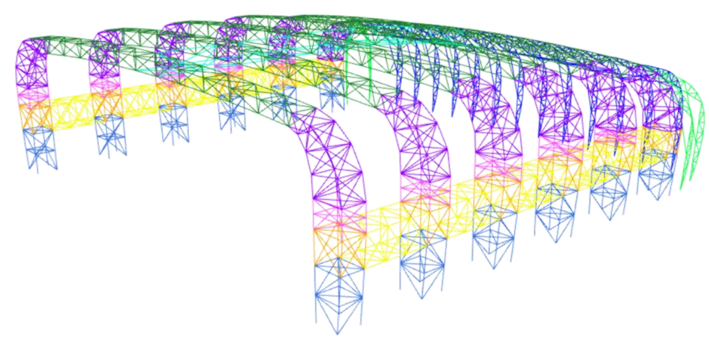


6. La realizzazione delle Strutture

HANGAR – parametric model

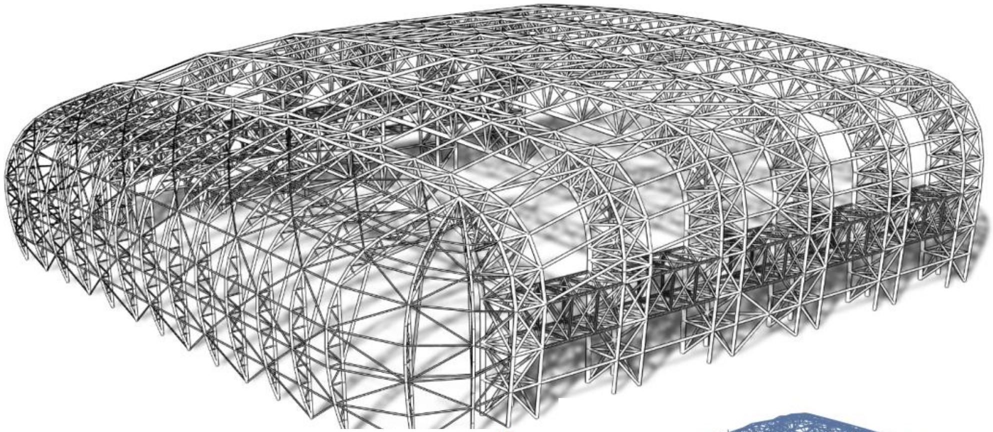


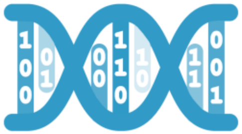


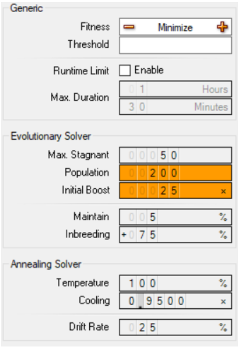


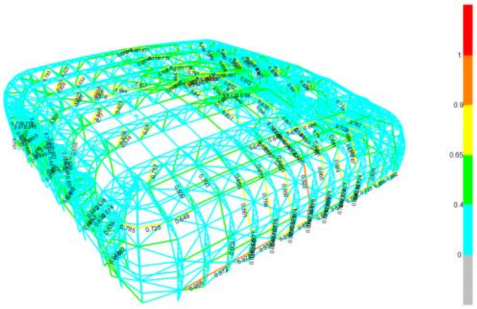
Opere per la realizzazione dello Spazioporto

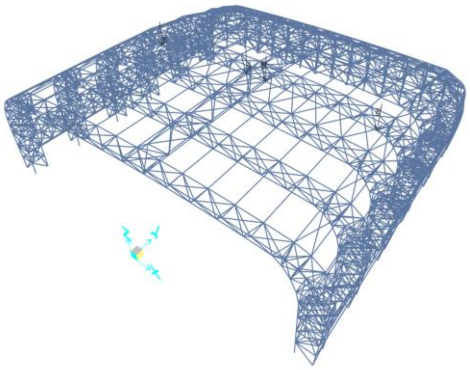
6. La realizzazione delle Strutture

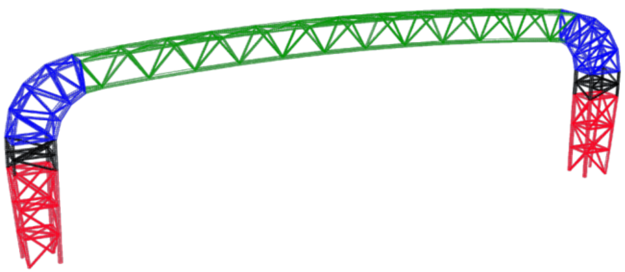












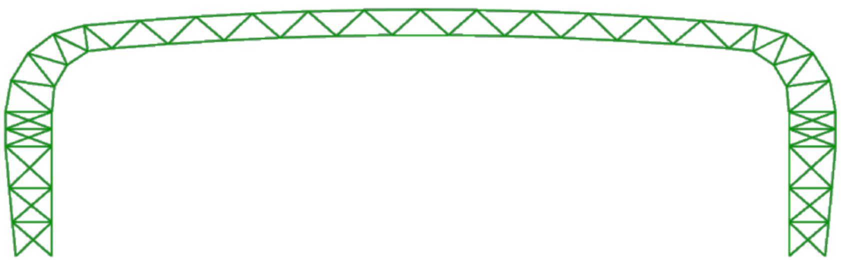
ADR INGEGNERIA PROGER RINA Benedetto Camerana Studio

Opere per la realizzazione dello Spazioporto

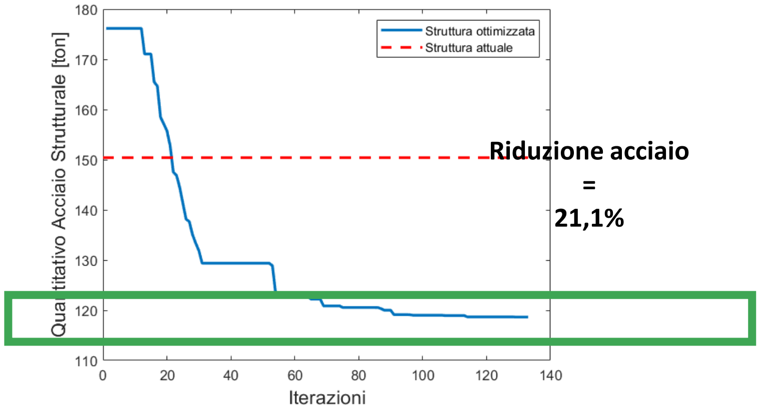
6. La realizzazione delle Strutture

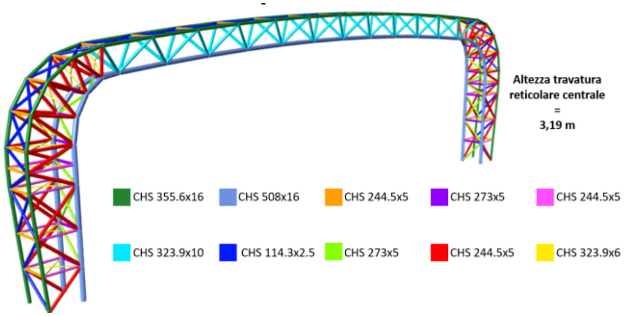
HANGAR – ESEMPIO OTTIMIZZAZIONE po

Il portale tipo è identificato come il **portale numero 1.** Il portale risulta essere il più critico per il passaggio del timone dell'aeromobile di progetto.



Risultati

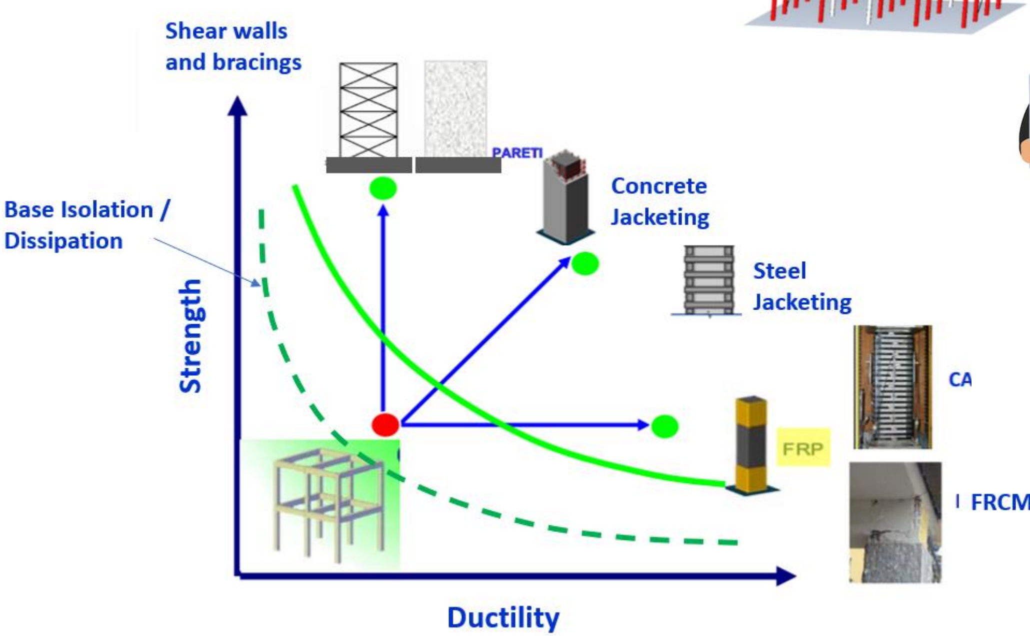


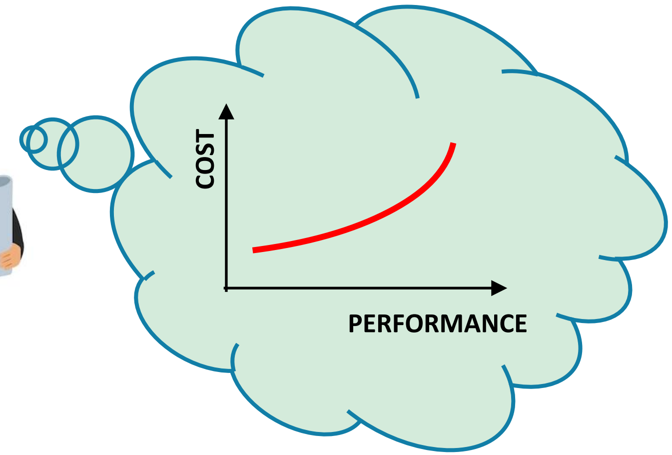


SEISMIC RISK REDUCTION STRATEGIES

Seismic Risk Mitigation

Retrofitting Systems

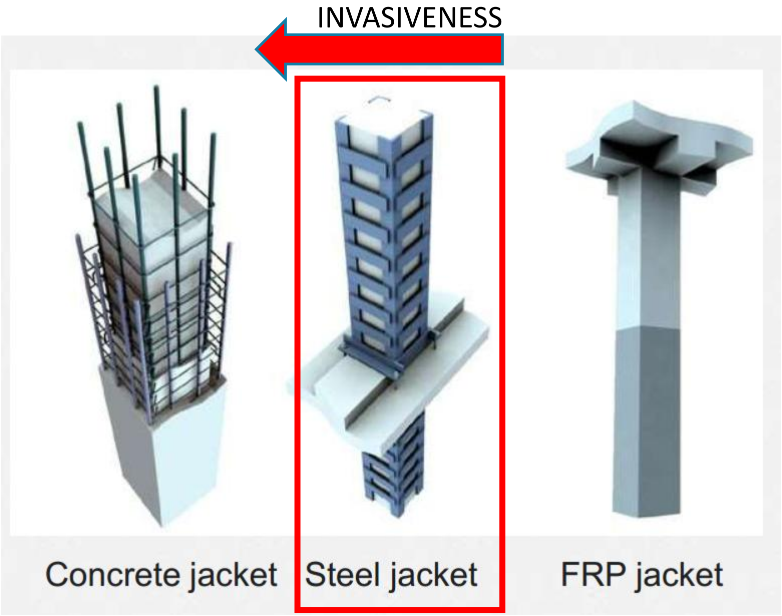




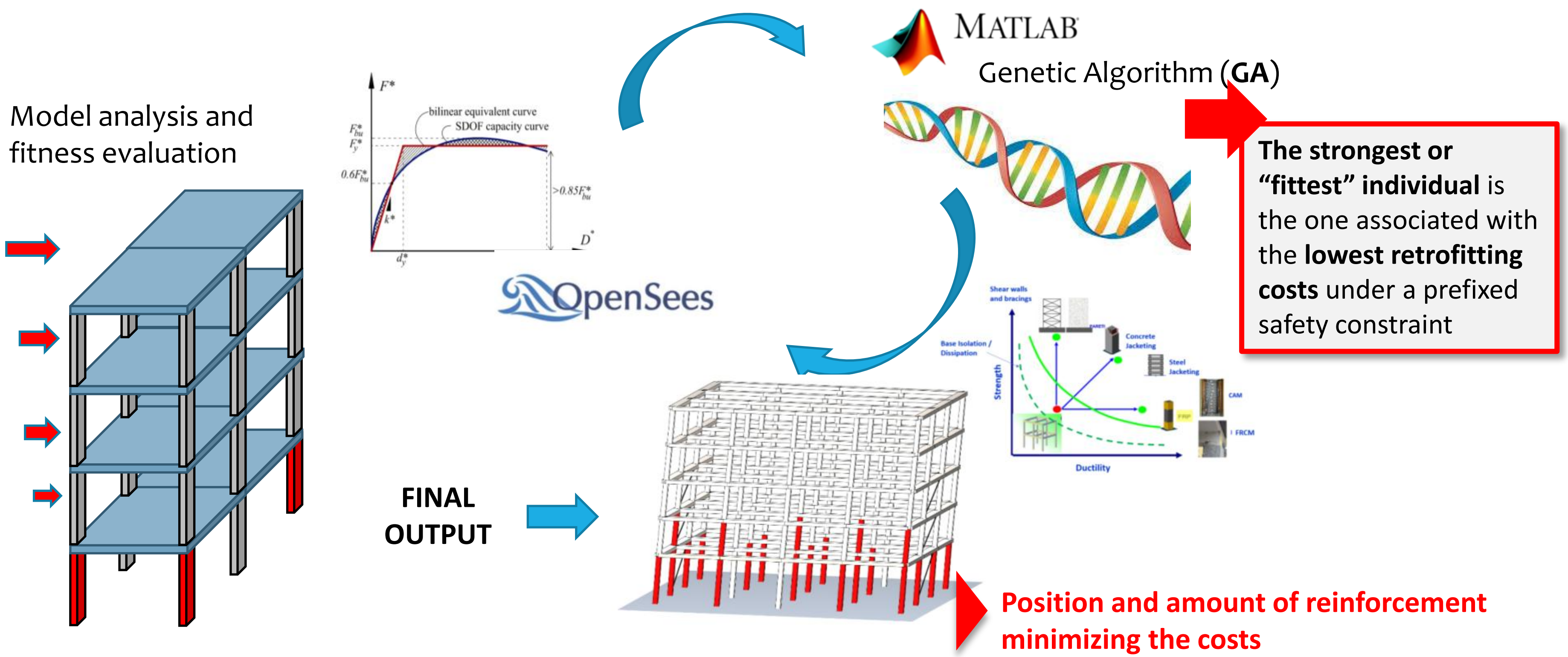
Impact

- Costs
- Invasiveness
- Downtime

APPLICATION TO RC COLUMNS RETROFITTING



Define an **Optimization Framework** aimed at **minimizing seismic retrofitting costs** of for existing RC frame structures



Why Genetic algorithms ?

Typical continuous optimization problem

$$\text{minimize} \quad f\ (\boldsymbol{b}$$

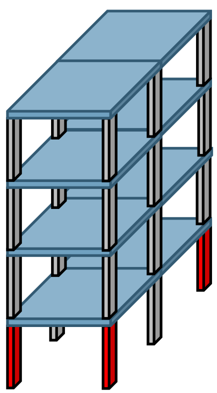
$$\text{subject to} \quad g\ (\boldsymbol{b} \ \leq 0, \quad i = 1, \ldots, m$$

$$)$$

Objective function (fitness) → Cost of the intervention as a function of the retrofitting configuration represented by the ***b*** vector called "**design vector**"

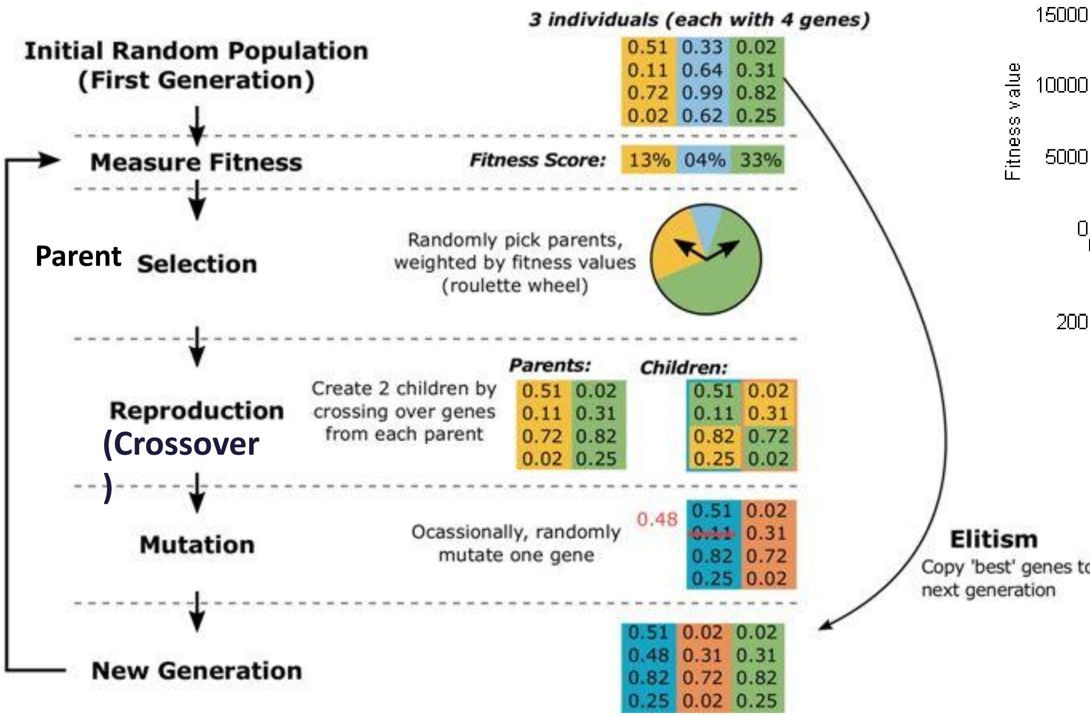
Constrains → Conditions to satisfy when minimizing ***f(b)*** (e.g. safety checks)

Discrete optimization



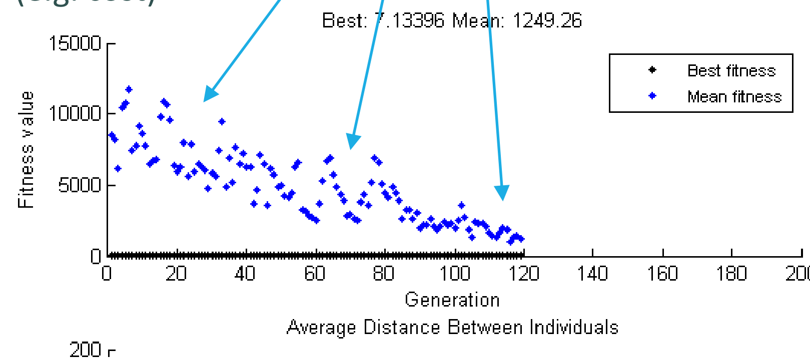
The objective function **is not continuous since it is composed of discrete variable or Boolean variables**

The iterative approach perceived by GA is suitable to solve these problems

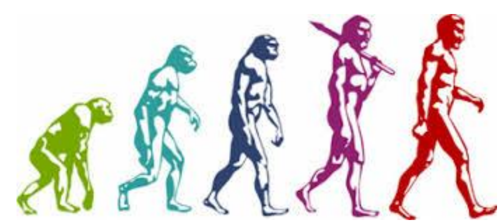


Generations of individuals

(e.g. cost)

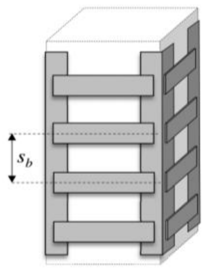


The GA imitates the evolution from generation to generation of a population (i.e. a group of structural designs) under the imposed constraints



Genetic algorithm – Design vector encoding

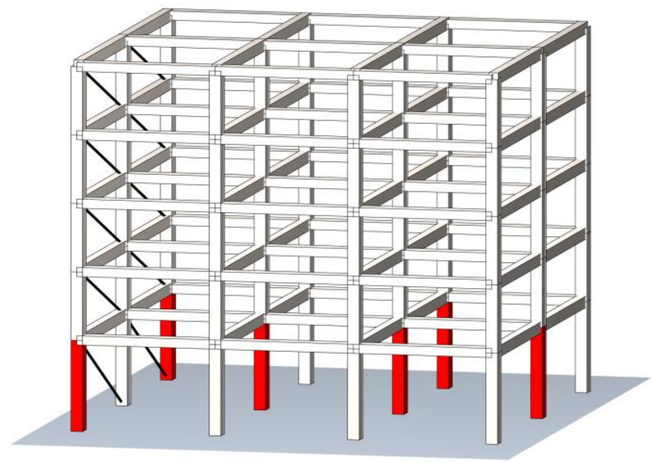
Genotype



0 → Unretrofitted column

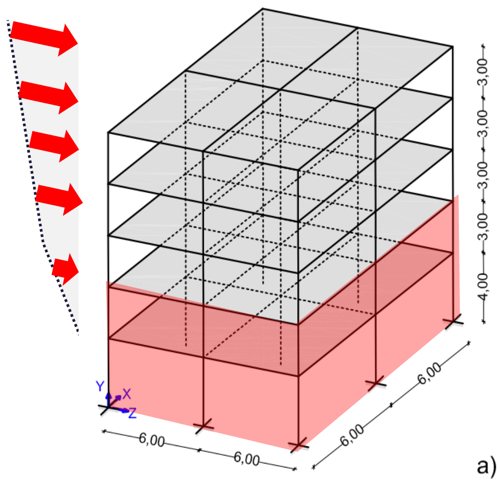
1 → Retrofitted column

Phenotype



Fitness

Cost of the intervention



a)

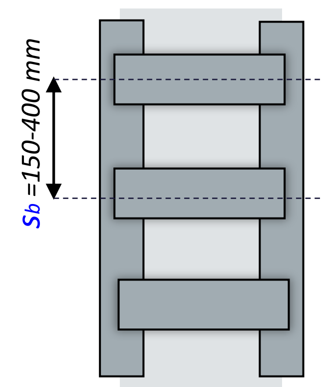
ENCODING

Battens spacing
(natural variables)

Column Reinforcement
(Boolean variables)

0 → unreinforced

1 → reinforced

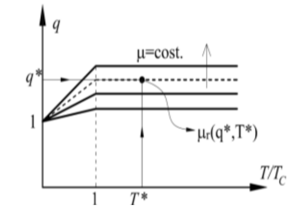


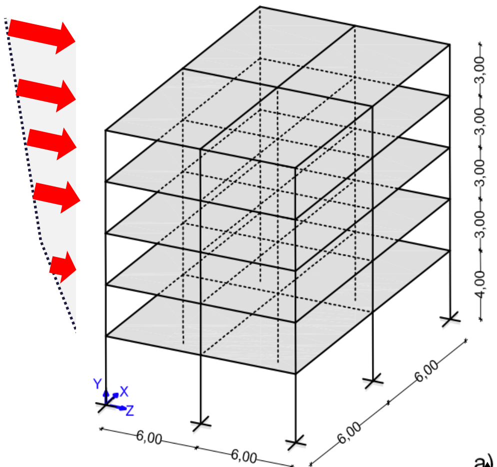
PROCESSING OF PUSHOVER RESULTS

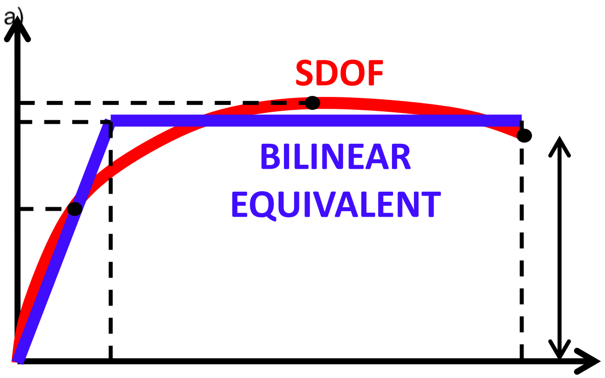
CAPACITY / DEMAND RATIO (ξ_μ)

Ductility capacity

Ductility demand







Assessment is satisfied (feasible solution)

Assessment is not satisfied (unfeasible solution)

THE OBJECTIVE FUNCTION

Costs of works on plasters and masonry

Material costs and the manpower costs to realize column steel jacketing

Number of retrofitted column

2000€/column

Number of retrofitted column

the total weight of the steel cage

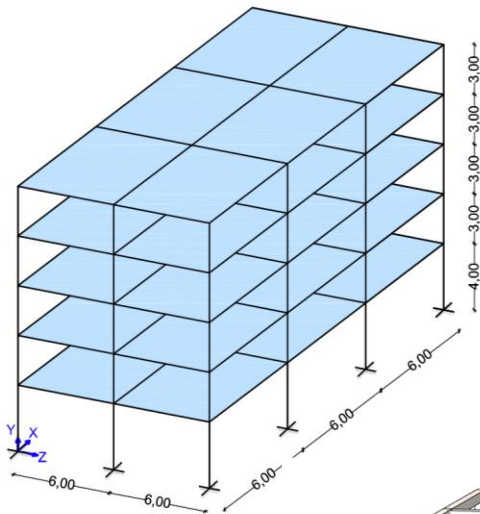
Cost per unit weigth (4.5 €/kg)

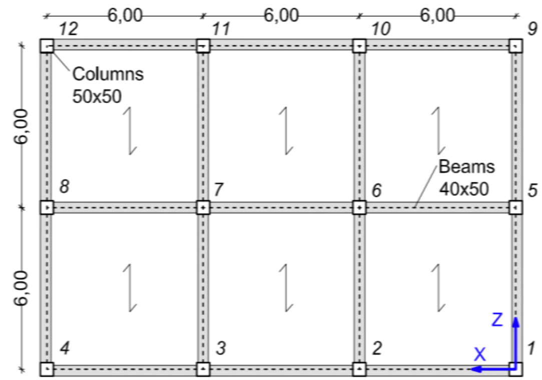
Battens volume

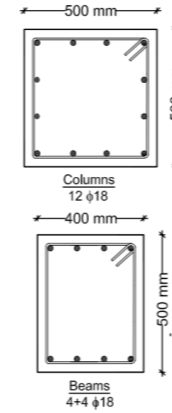
Angles weight

Battens weight

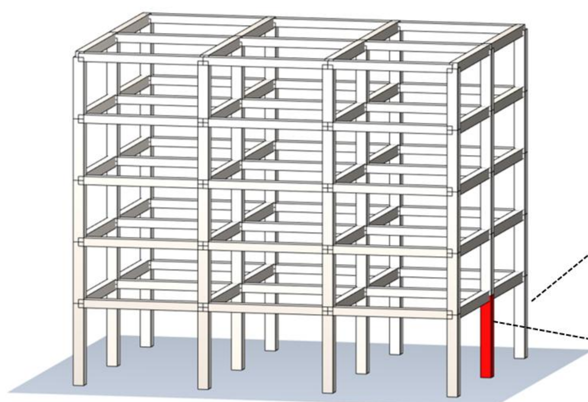
Design Parameters **nc** and **sb** are the only influencing the total cost

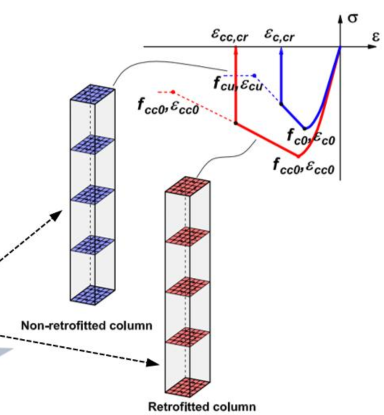

3,00
3,00
3,00
3,00
4,00
6,00
6,00
6,00
6,00
6,00
Y
X
Z


6,00
6,00
6,00
6,00
6,00
12
11
10
9
Columns
50x50
Beams
40x50
8
7
6
5
4
3
2
1
Z
X


500 mm
500 mm
Columns
12 ϕ18
400 mm
500 mm
Beams
4+4 ϕ18

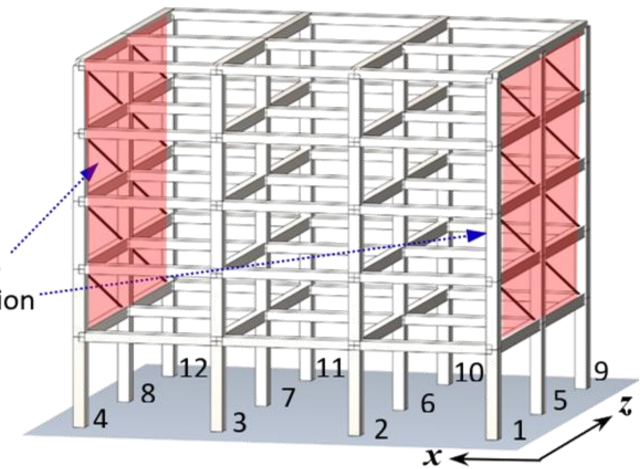
Model

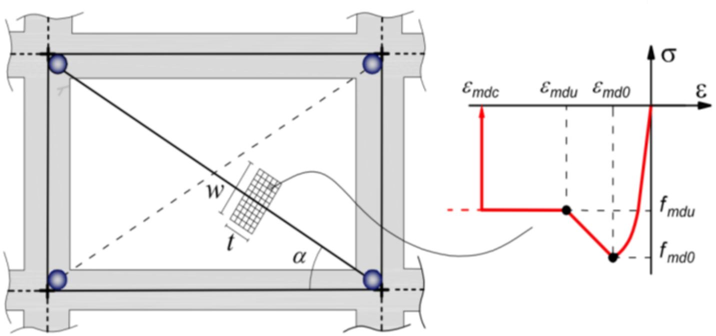



σ
ε
$\varepsilon_{cc,cr}$
$\varepsilon_{c,cr}$
f_{cu}, ε_{cu}
$f_{cc0}, \varepsilon_{cc0}$
f_{c0}, ε_{c0}
$f_{cc0}, \varepsilon_{cc0}$
Non-retrofitted column
Retrofitted column

Considered Sub-Cases

- Shear Critical Columns
- Shear resistant columns





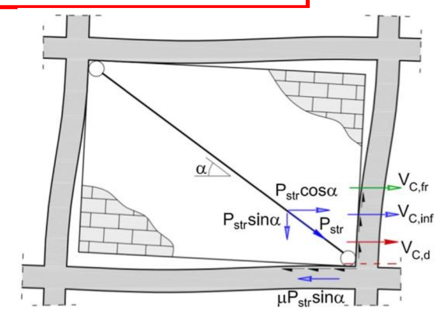
Shear Capacity

+

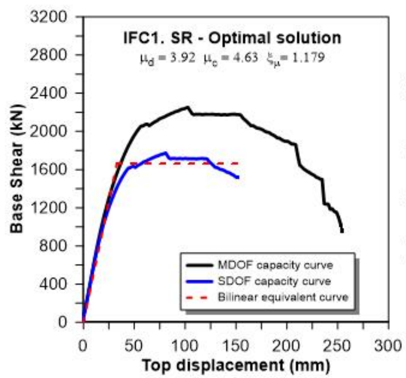
Shear Demand

Drift related shear

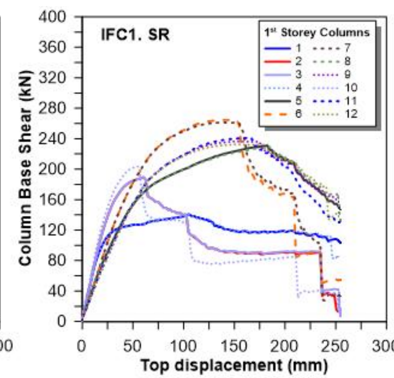
Infill related shear



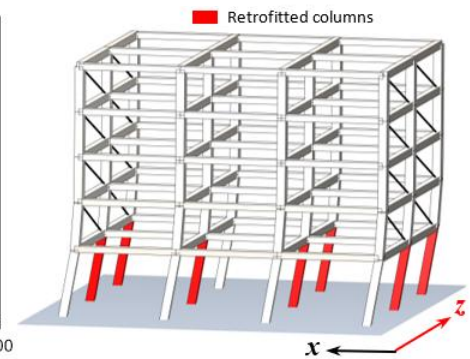
Shear Resistant Columns



(a)

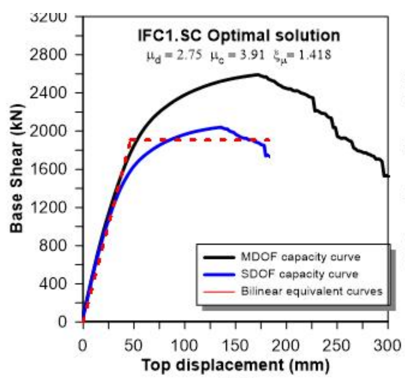


(b)

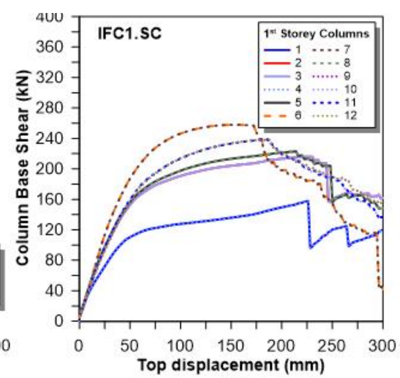


(c)

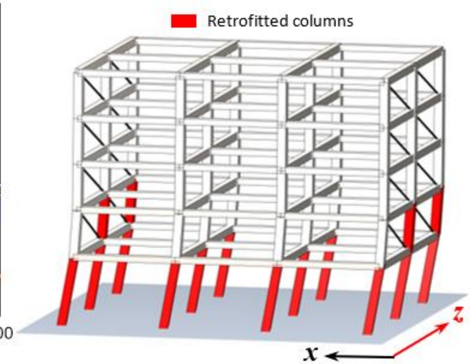
Shear Critical Columns



(a)



(b)



(c)

PONTI ITALIANI

Più di 60,000 ponti

Molti costruiti oltre 50 anni fa

Significativi processi di invecchiamento e degrado

Alcune crisi importanti

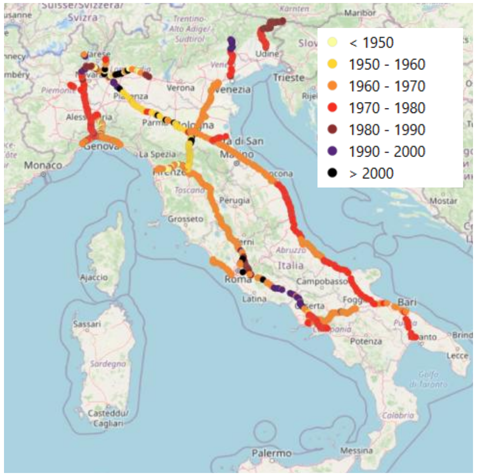
Polcevera bridge (2018)

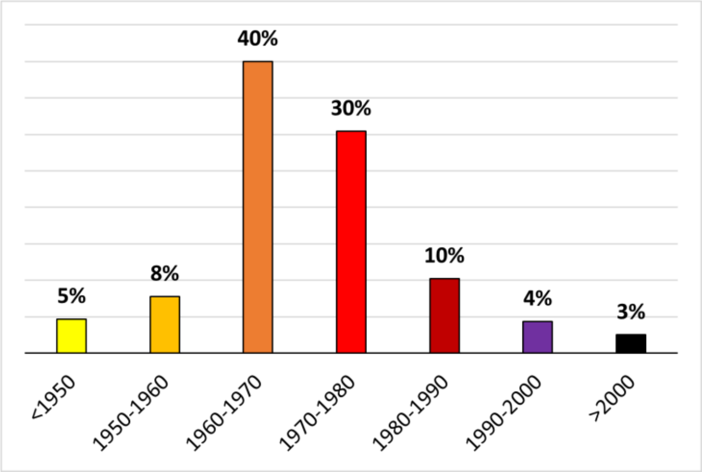
Annone bridge (2016)

Fossano bridge (2017)

Magra bridge (2020)

- ASPI ‘AutoStrade Per l’Italia’





Distribuzione dell’età dei ponti (luci>10 m) gestiti da ASPI

- La gestione di queste infrastrutture necessita di nuovi paradigmi operative per potre essere mantenuta in efficienza e garantire la fruibilità della rete di trasporto nazionale




Evoluzione del quadro tecnico – normativo

Crollo Ponte Morandi (2018)

- 1967 — Circolare n° 6736/61/AI
- 1991 — Circolare LL.PP n° 34233
- 1993 — 1.Norma C.N.R. (Boll. Uff. n° 165/93)
- 2008 — 1.NTC2008
- 2018 — 1.NTC2018 e Circolare Applicativa
- 2020 — 1.Nuove Linee Guida

Il sistema di gestione dei ponti secondo nuove Linee Guida 2020

Approccio multilivello

Ispezioni visive → Indicatore numerico del degrado → Classe di Attenzione del ponte → Interventi di manutenzione

Bassa Medio – bassa Media Medio – alta Alta

Indici numerici per la valutazione del degrado

I valori di difettosità relativa di ogni elemento del ponte vengono inseriti all'interno del database del **Bridge Management System**.

Bridge Management System (BMS)

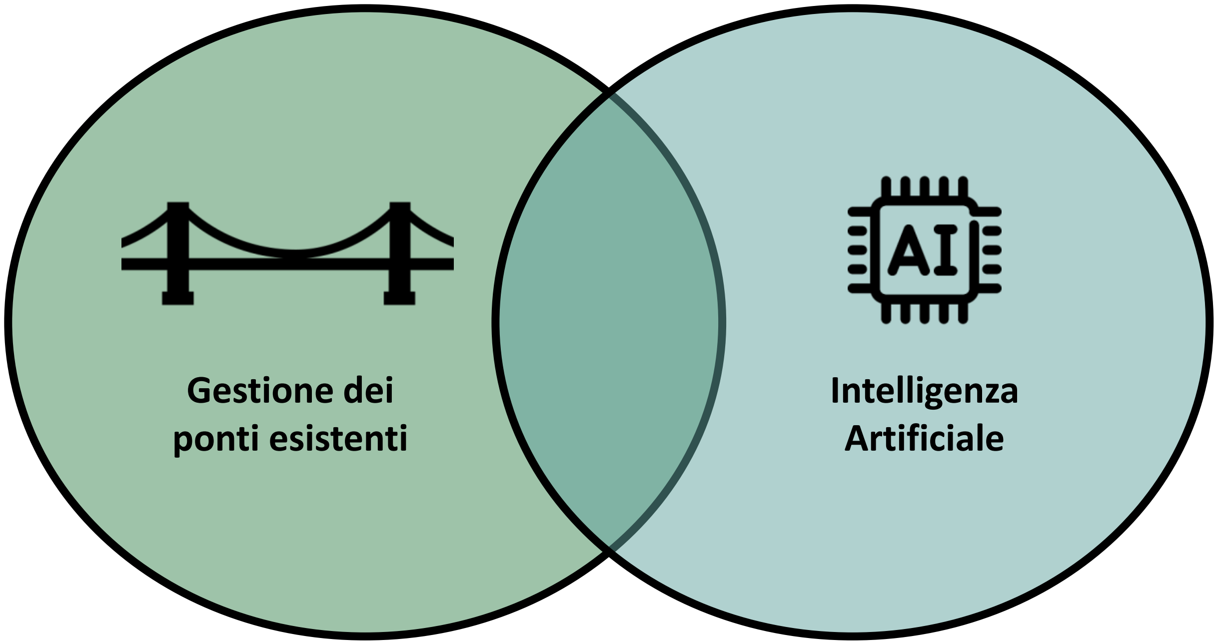
Database BMS

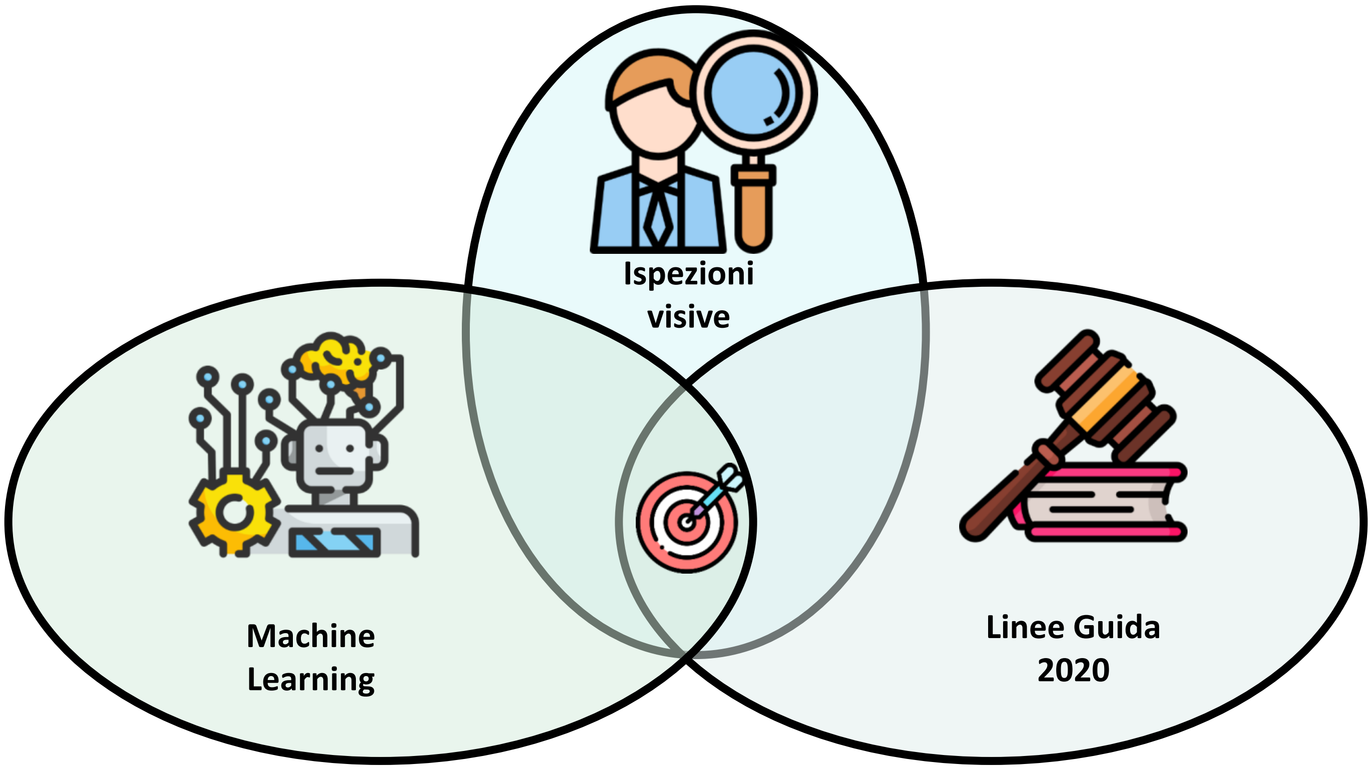
Modello di degrado

Modello dei costi

Modello di decisione

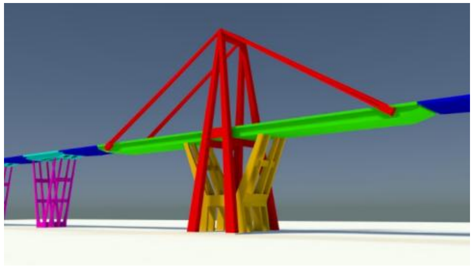
Pianificazione ottimizzata degli interventi di manutenzione


Gestione dei
ponti esistenti
Intelligenza
Artificiale
AI

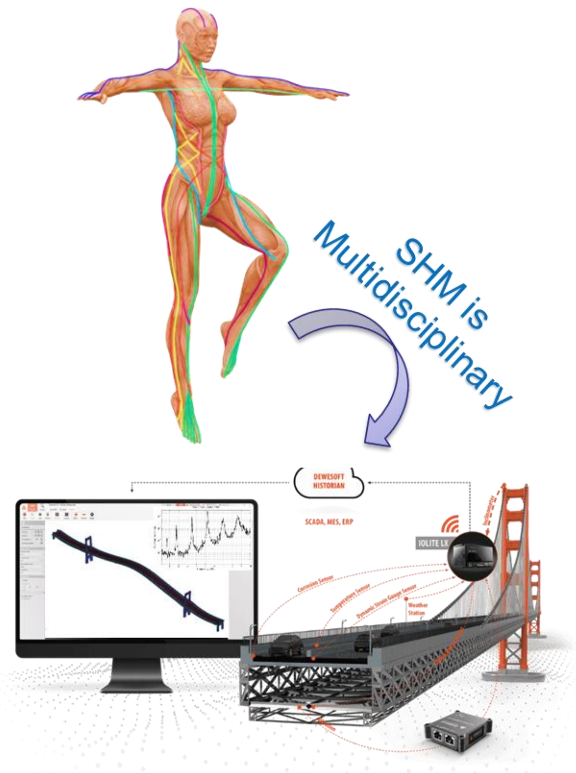

Ispezioni
visive
Machine
Learning
Linee Guida
2020

<u>MONITORAGGIO STRUTTURALE (SHM)</u>

MODEL-BASED (FEM)



DATA-BASED

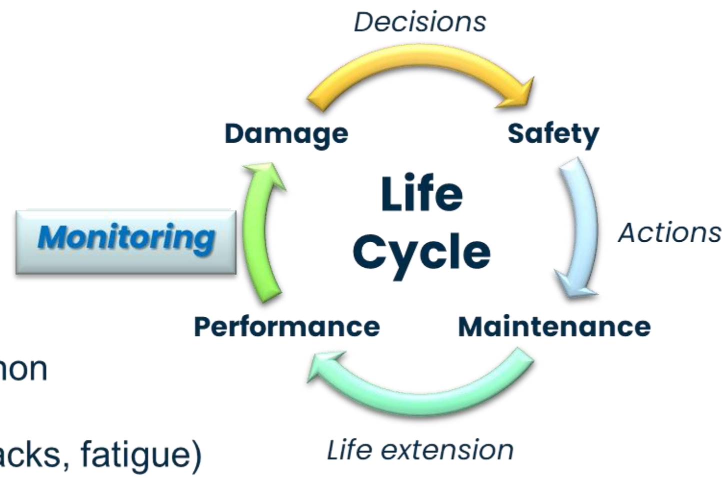


Motivations:

- prevent loss of life
- more reliable and safe systems
- mitigate risks
- assessment and diagnosis purposes to know the system's "health"
- no more with run-to-failure approach but time-based maintenance
- reduce management, repair or reconstruction costs

Monitoring task :

- Dynamic identification (operational, non linearities)
- Material issues (aging, corrosion, cracks, fatigue)
- Ductility, limit states (ultimate, service)
- Resilience
- Robustness
- Noise, modeling errors, uncertainties,…



"*Past*" of Structural Health Monitoring

- Detect cracks in railroad wheels since 1800s
- Systematic and deeper studies starting **from 1970s**
- **Multidisciplinary** approach (Aerospace, Mechanical, Civil Eng.)

- Motivations:
  - **prevent loss of life**
  - **more reliable and safe systems**
  - mitigate risks
  - **assessment and diagnosis** purposes to know the system's "health"
  - no more with run-to-failure approach but **time-based maintenance**
  - **reduce management, repair or reconstruction costs**

What is structural damage?

DAMAGE : *"an intentional or unintentional **changes** to the material and/or geometric properties of these systems, including changes to the boundary conditions and system connectivity, which adversely **affect the** current or future **performance** of these systems."*
[Farrar C.R., Worden K. "Structural Health Monitoring: A Machine Learning Perspective" (2012)]

- **Material imperfections**
  - Initial Imperfections (**defects at micro-scale**)
  - Occurring over time (**degradation, aging**)

Damage mitigation strategy related to the material science (e.g. manufacturing process, surface finish new self-healing materials)

- **Macroscopic damage** → Engineering **Assessment of Safety Levels**

How to study the Structural Damage

What to understand

- **Causes** and origins (environment, exceptional events)
- How to **prevent** or **mitigate** it
- Effects and **consequences** produced
- It is present now? **How fast** it grows?
- **How** all the factors **interact together**? (Challenging)

Miles Glacier Bridge (Alaska)

Long Island bridge in Quincy (USA)

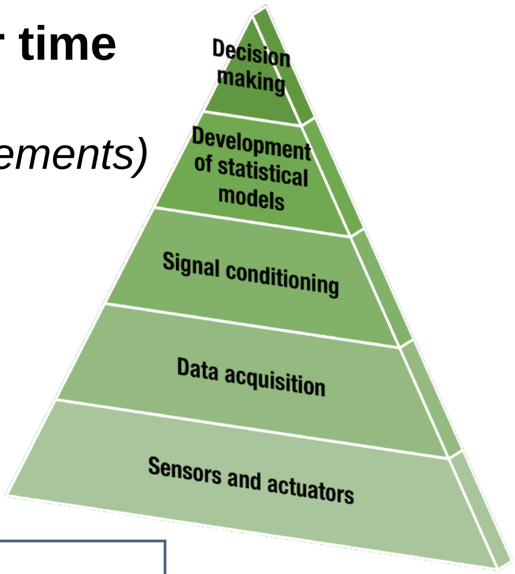
Structural Health Monitoring (SHM)

- SHM is a **Damage Detection Strategy and monitoring over time**

Observations of the structure over time (periodically spaced measurements)

Identification of the damage-sensitive feature

Safety Assessment



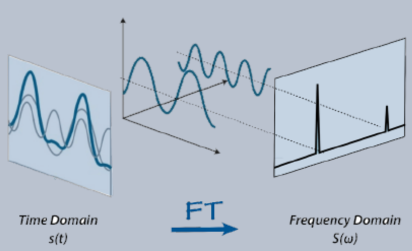
model-based approach (**parametric**)

data-driven approach (**non-parametric**)

Structural Health Monitoring outline

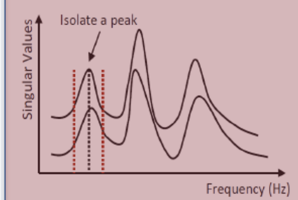
Signal Processing

From Time to Frequency Domain



Non Parametric ID

FDD method



Deliverables

$\omega_i, \zeta_i, \mathbf{\Phi}_i$

Parametric ID

Autoregressive Models

$$x[t] + \underbrace{\sum_{i=1}^{n_a} a_i \cdot x[t-i]}_{\text{AR part}} = w[t] + \underbrace{\sum_{i=1}^{n_c} c_i \cdot w[t-i]}_{\text{MA part}}$$

Deliverables

SISO Model & $\omega_i, \zeta_i, \mathbf{\Phi}_i$

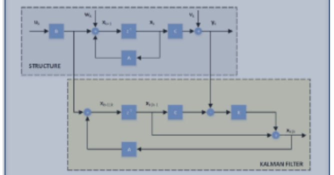
Subspace ID

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$
$$\mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u}$$

Deliverables

MIMO Model & $\omega_i, \zeta_i, \mathbf{\Phi}_i$

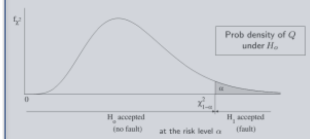
State Estimation



Deliverables

Estimate full response **x** from few measurements **y**

Damage Detection/SHM

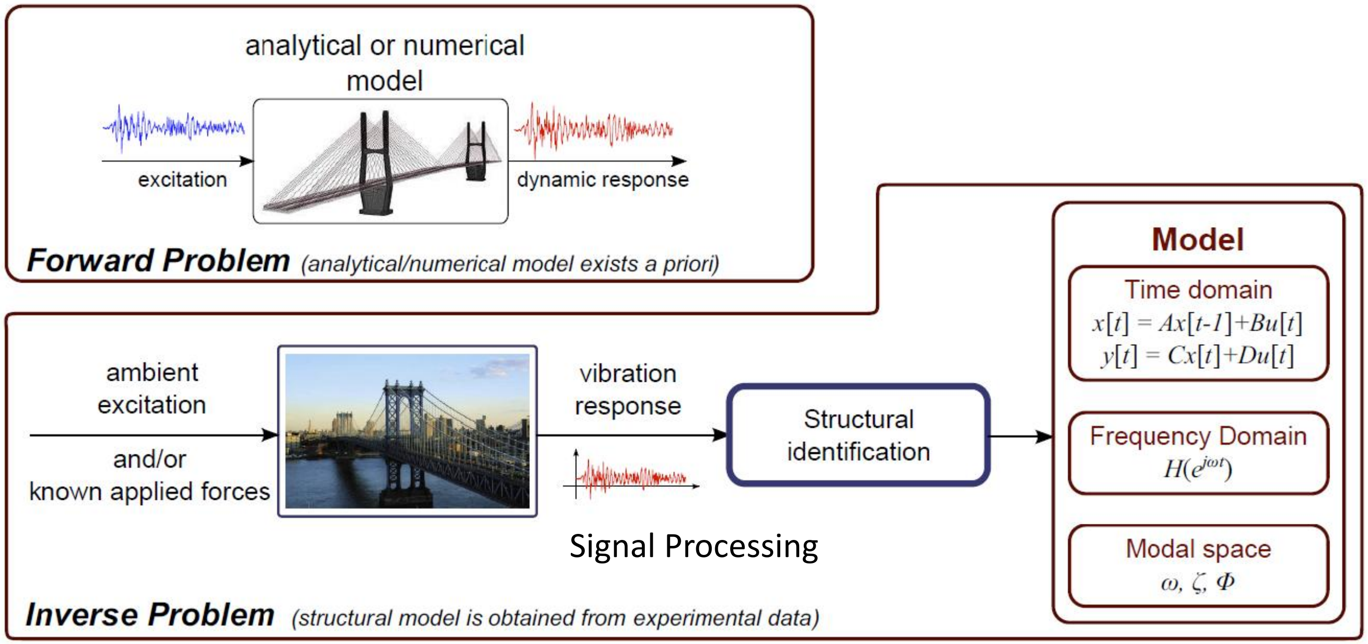


Deliverables

Identify possible damage in the system

System identification

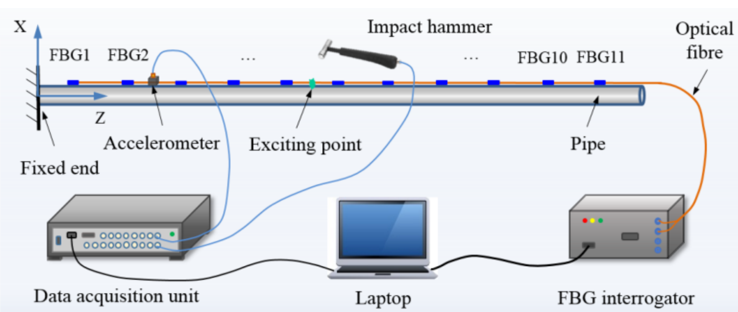
It is the process of developing or improving a mathematical representation of a physical system using experimental data.



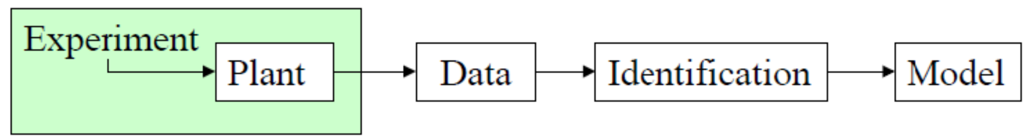
Experimental Modal Analsysi (EMA)

Experimental Modal Analysis (EMA) techniques aim at identifying vibration modes from the dynamic response measured on real structures.

Approaches:
Single Input – Single Output (SISO)
Single Input – Multiple Output (SIMO)
Multiple Input – Multiple Output (MIMO)



What is System Identification?

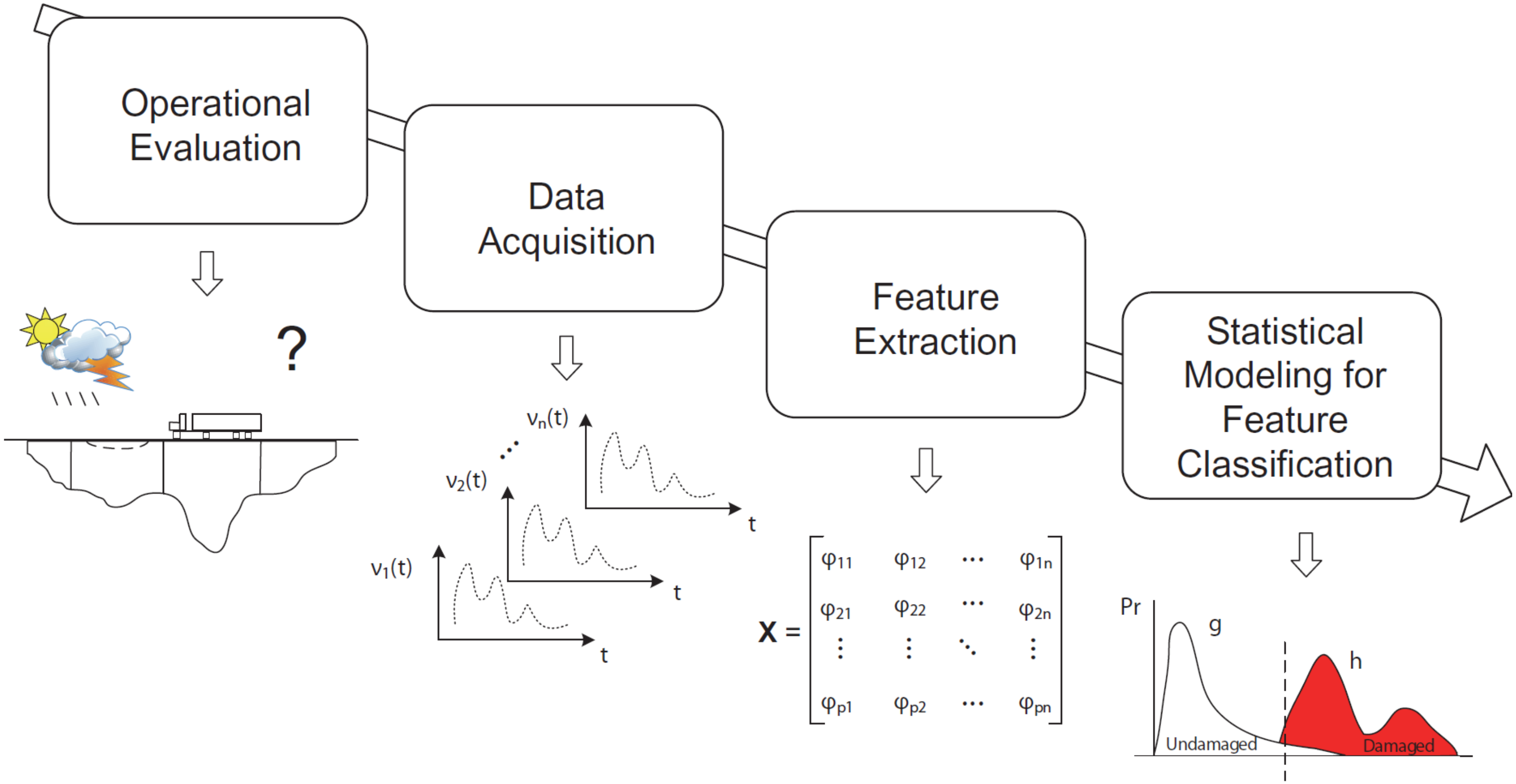


- White-box identification
  - estimate parameters of a physical model from data
  - Example: aircraft flight model
- Gray-box identification (e.g. phenomenological models)
  - given generic model structure estimate parameters from data
  - Example: neural network model of an engine

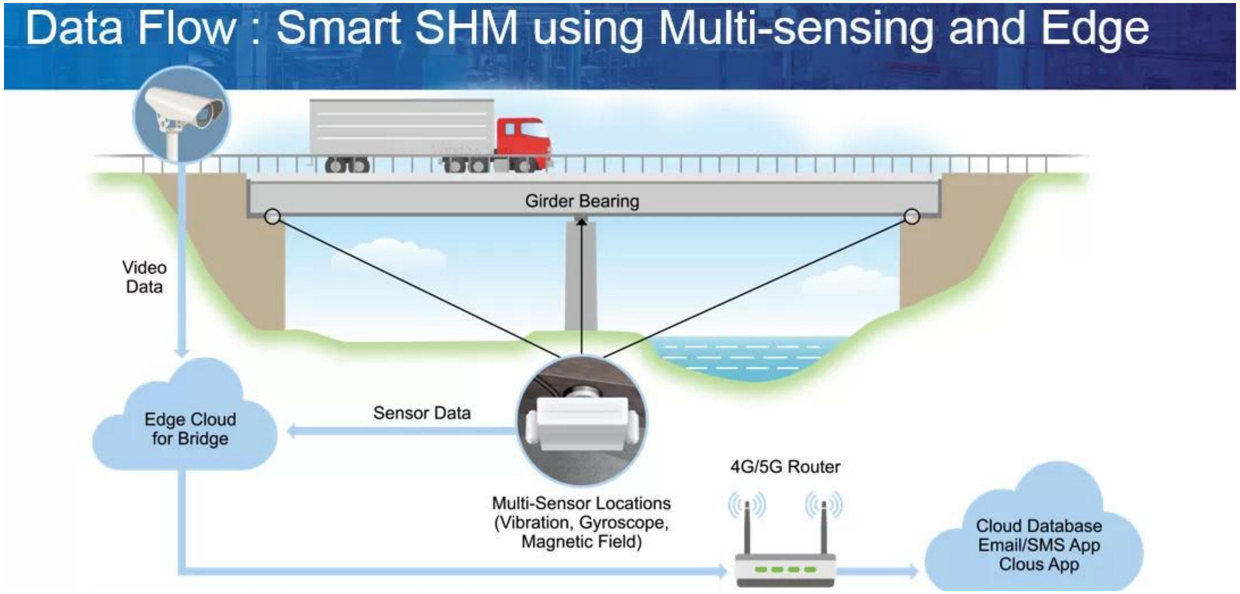
Rarely used in real-life control

- Black-box identification (i.e., nonparametric identification)
  - determine model structure and estimate parameters from data
  - Example: security pricing models for stock market

SHM Statistical Patter Recognition process



Futuri sviluppi: **integrated solutions**



Smart
Data Fusion
approaches

correlare:

Data Traffic
Temperature
Wind
…

↓

Sensori di
grandezze
cinematiche

MORE RELIABLE IDENTIFICATION SYSTEM