INCREASING RESILIENCE AND ROBUSTNESS OF CRITICAL INFRASTRUCTURES TO HAZARDS USING ARTIFICIAL INTELLIGENCE AND STRUCTURAL MONITORING

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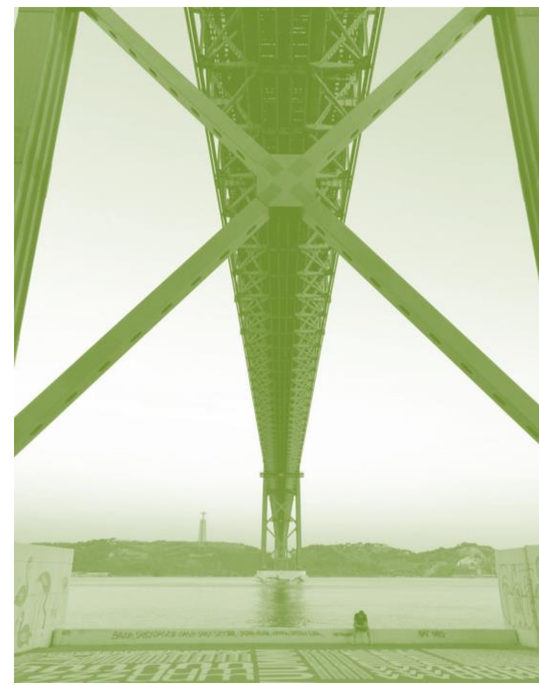

- Timeline
- Structural Health Monitoring
- From traditional inspection to intelligent monitoring
- Machine Learning
- Ensemble Models
- Deep learning
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- Milestones
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Timeline

Literature review: **Structural assessment based on data analysis and artificial intelligence methods**

Research Seminar in Structures / FEUP

PTI

Structural Health Monitoring

- Provide, through different technologies and algorithms, **information** about the behavior and condition of existing and new structures.

- Identify **changes/damages** in the structural systems.

- Widely accepted as a useful aid to **risk analysis and integrity management** of structures.

- Data acquisition
- Feature extraction
- Feature modelling
- Feature classification
- Damage identification

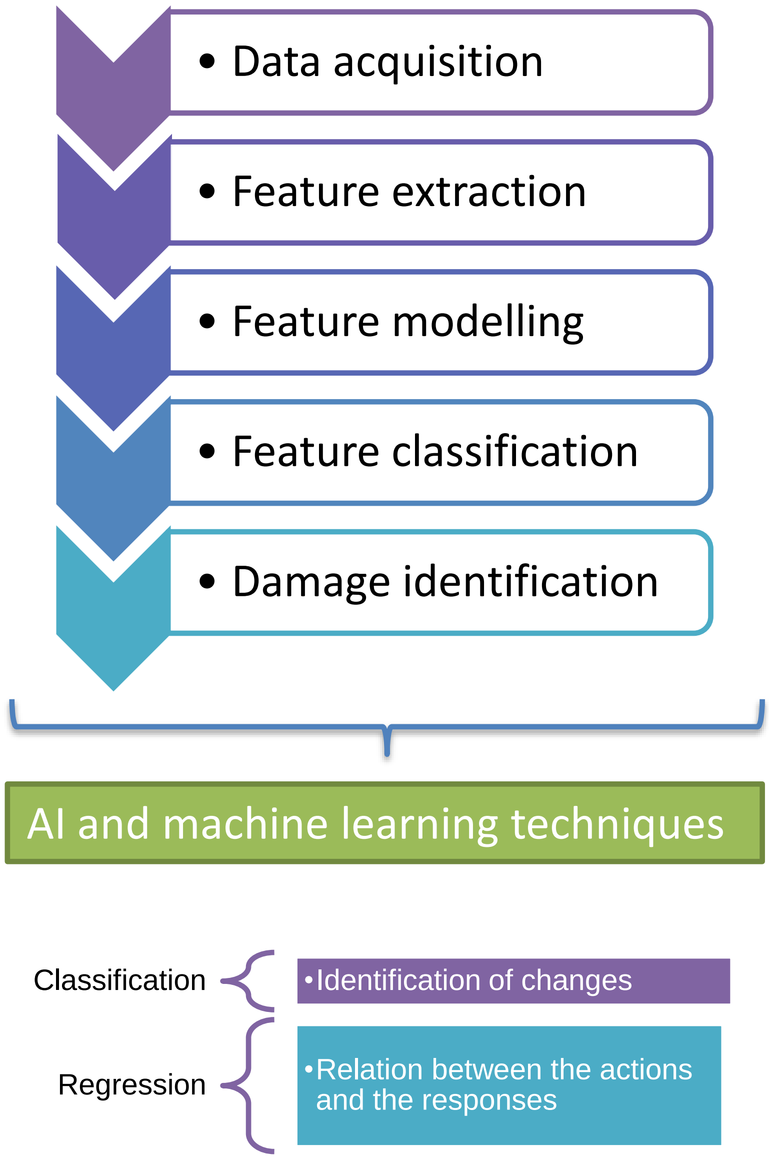
Structural Health Monitoring

- Generally, the SHM methods follows a **data-driven approach** (inverse; incorporated on the numerical models)

- Data obtained could contain important **incidence of false alerts**, that limit the efficiency of the following process

- It is **difficult to find sensitive and robust** damage indicators.

- The outputs are obtained through **deterministic methods**, based on upper and lower thresholds, not entirely adequate for decision making



From traditional inspection to intelligent monitoring

Detecting structural defects on structures

Visual inspection
Qualitative approach

- Labour-intensive
- Time-consuming
- Subjective
- Dependent on well-trained inspectors

1997

Strategies that benefit from **technological precision** for accurately **evaluating the structural health** of civil structures using **real-time monitored data**

Intelligent monitoring

"Structural damage is inevitable"

Sensing Technologies
Signal Analysis

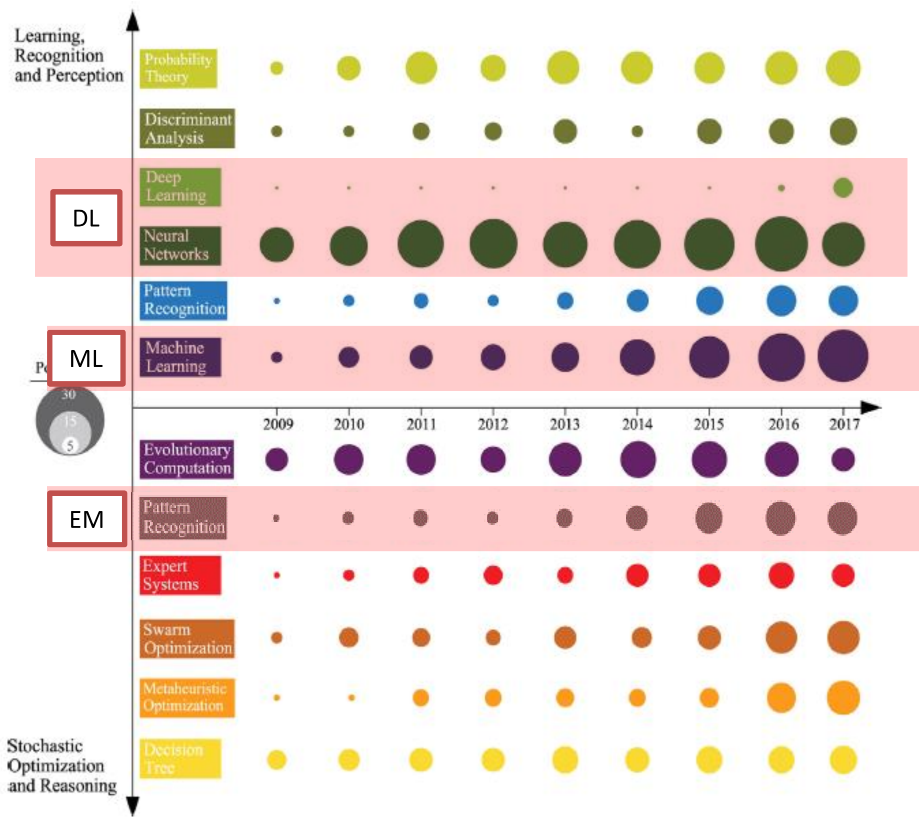
Sensors **cannot measure damage**, so signal processing and statistical classifications are necessary to **convert sensor data into damage information**

AI methods

From traditional inspection to intelligent monitoring

AI methods can deal with **uncertainty problems** within the context of **damage detection and system identification**

- Data analysis
- FEM updating



Intelligent SHM must deal with:

- Lack of **efficient and reliable** methodologies coupled with signal processing and big data
- Lack of **inexpensive sensors**

Recent technological advances:

- Sensor networks can now **measure large volumes of response data.**
- Data-driven **ML techniques** have been proposed
- **Neural networks** have been studied and developed

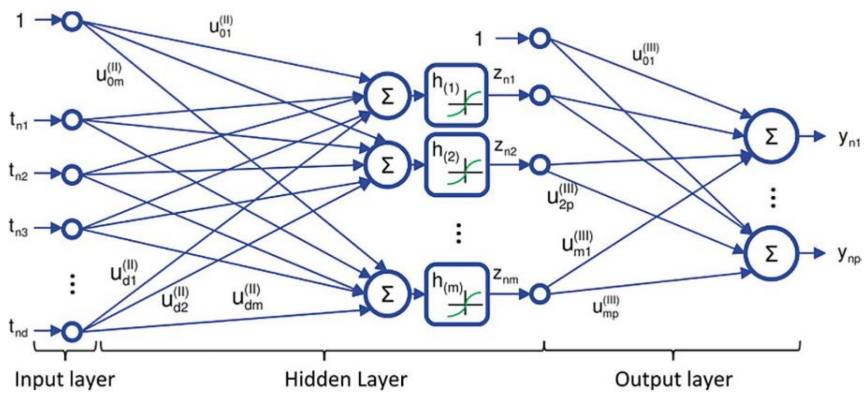
Based on Salehi, H., & Burgueño, R. (2018). Emerging artificial intelligence methods in structural engineering. *Engineering Structures*, *171*(November 2017), 170–189

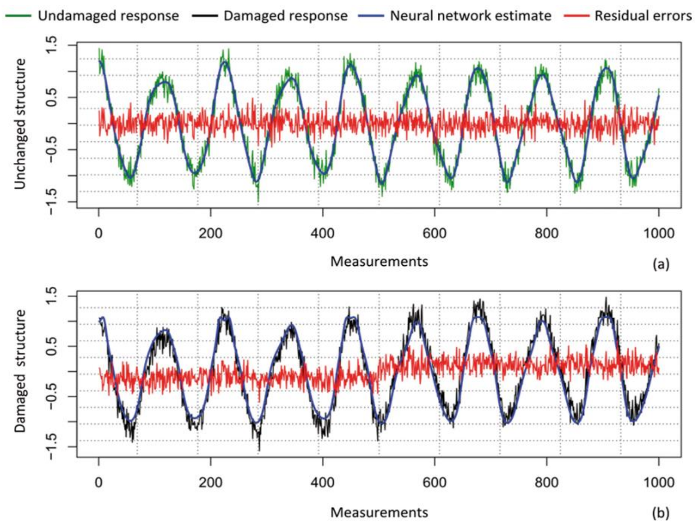
Machine Learning

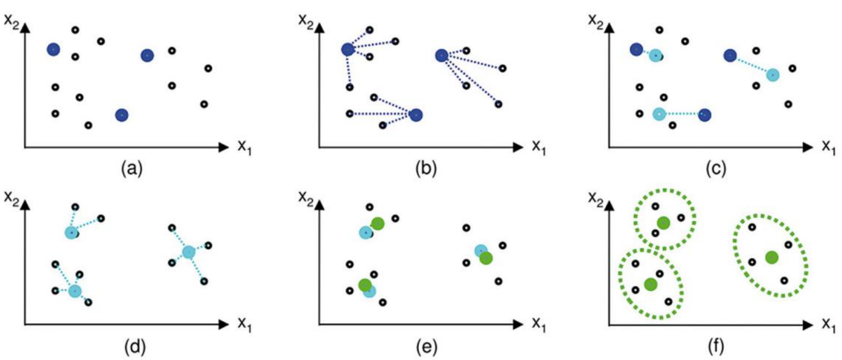
Shallow neural networks
Support vector machines
Linear and non-linear PCA
Clustering
Support vector machines
Decision trees

Multi-layer Perceptron (MLP)

To model the intrinsic relations between actions and responses







Clustering methods

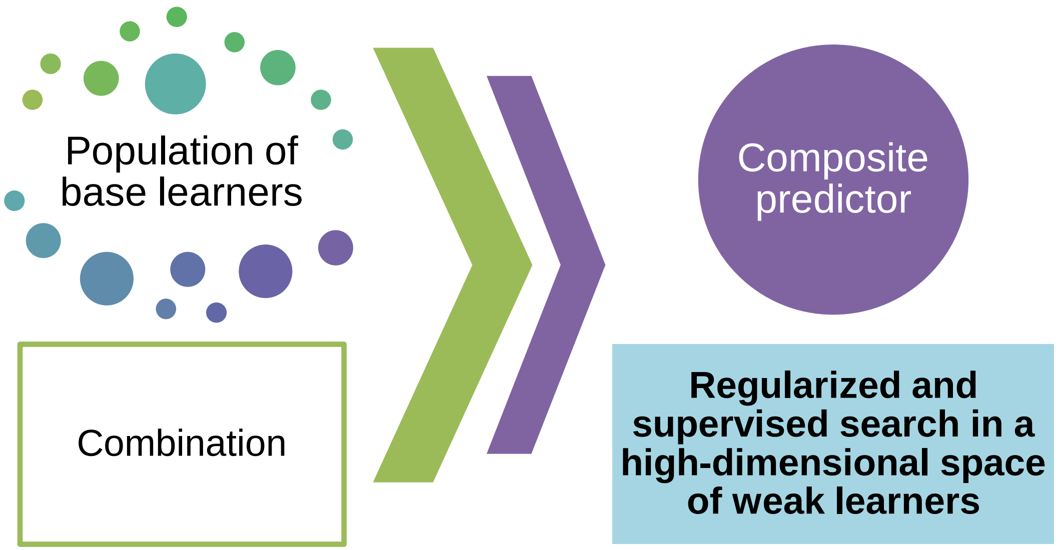
To minimize the dissimilarity between data objects assigned to the same cluster

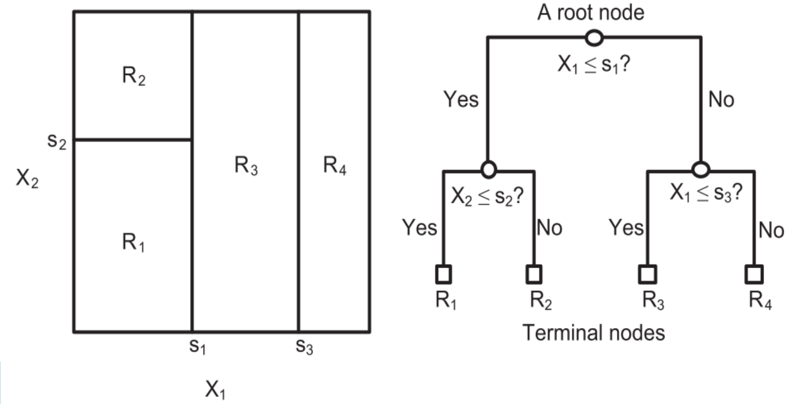
Real time damage detection

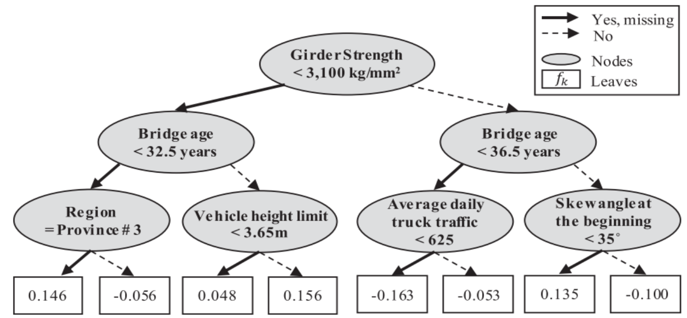
Ensemble models

Random Forest | Boosting | AdaBoost | XGBoost | Boosted regression trees | Model stacking

Machine learning approach that combines different models in order to obtain better predictive performance







Bagging: Help to improve the performance using weights and a classifier.

Boosting: Add iterations to evaluate correct classifications or incorrect classifications

Stacking: Adaptation of cross-validation to model averaging

Deep learning

Autoenco-ders

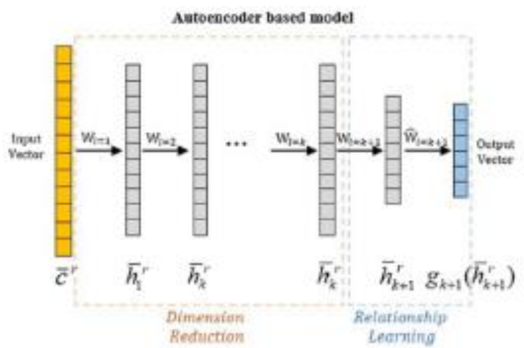
Restricted Boltzmann Machine

Convolutional NN (1D-2D)

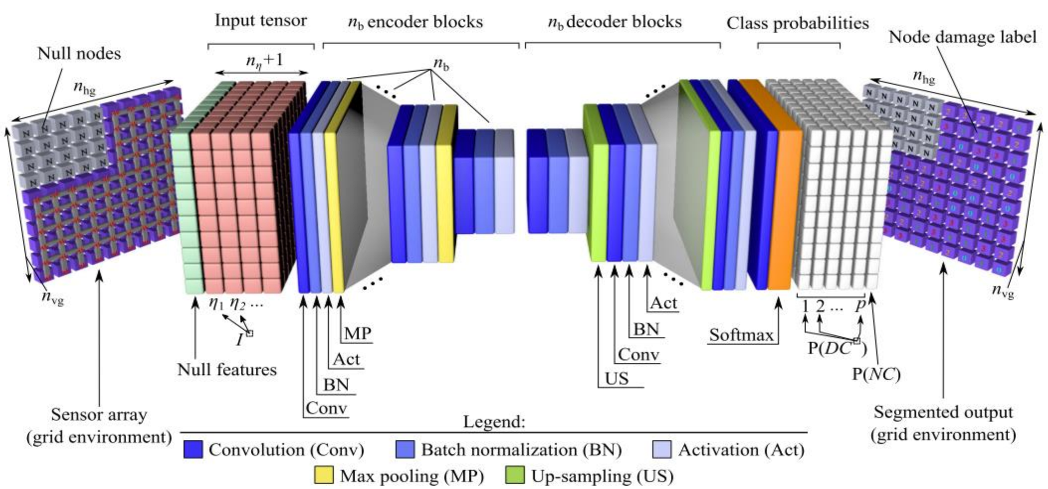
Recurrent NN

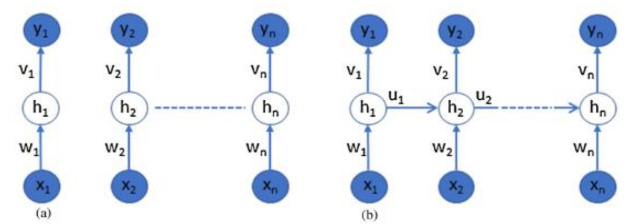
Long short-term memory

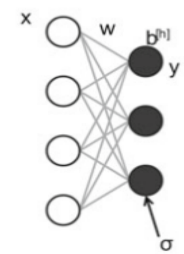
The term “deep learning” emphasizes the capacity to train deeper neural networks, and to focus attention on the theoretical importance of depth.



- DL architectures are based on ML knowledge.
- DL algorithms can learn not only to correlate the features to the desired output, but also to run the entire feature extraction process.
- DL algorithms can directly map from the raw inputs to the final outputs, allowing the system to perform complex tasks.



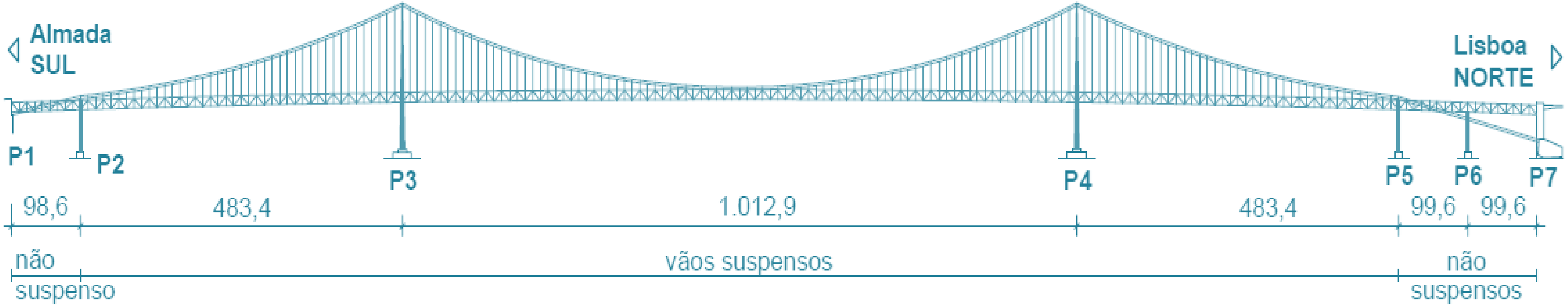




Case study: the Ponte 25 de Abril

The suspension bridge over the Tagus River in Lisbon is a structure with a total length of **2,277 m** between anchorages, including the **suspended central span with 1,013 m**, two suspended side spans with 483 m and, also three backstay spans with about 99 m each.

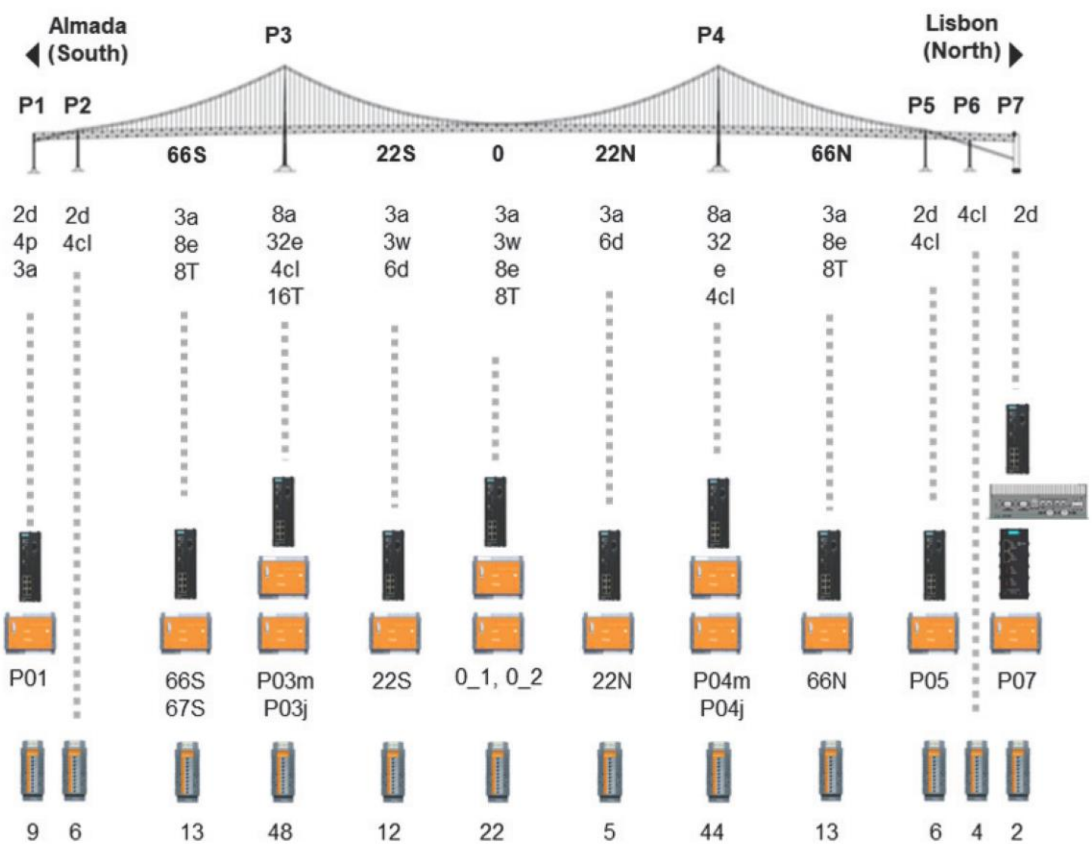
It was opened to the traffic in **1966** with a **4 lanes roadway deck**, located at the level of the upper chord of the stiffening truss. In **1999**, the bridge had construction works to **add a 2 lines railway deck**, at the level of the lower chord of the stiffening truss, and to widen the **roadway deck to 6 lanes**.



Monitoring system

The monitoring system proposed for the 25 de Abril's Bridge follows the program of (Silveira, 2013) with updates of (Santos,2015).

It considers **210 sensors** located in strategic sections of the bridge according its structural behaviour.



Legend:

d – longitudinal displacement (magnetostrictive transducers)
cl - rotation (electric gravity clinometers)
a - acceleration (uniaxial servo accelerometers)
e – stress 1D (bridge of electric resistance strain with one reading on each direction)
T - temperature (thermometers NPC)
w – wind velocity and direction (ultra sounds anemometer)
p – train weight-in-motion (rubber pads with F.Q. sensors)

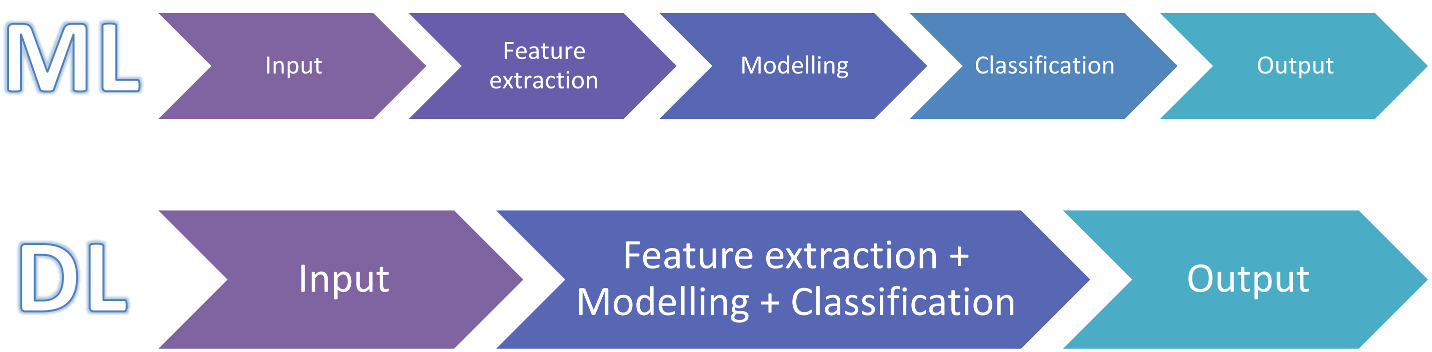
Data sets

500 measurements per second (378 million per hour) are transferred daily to the server and automatically filtered, the results are temporal series that then are going to be correlated and analysed with the structural behaviour of the bridge or possible anomalies:

- **Long-term responses influenced by slow actions:**
    - Most common SHM approach;
    - periods longer than 1 year;
    - hourly sampled;
    - detection of slight progressing damages;
    - fast effects filtered a priori;
- **Short-term fast responses influenced by all fast actions:**
    - periods not smaller than 7 days;
    - sampling rates not smaller than 10Hz;
    - real-time detection of slight sudden damages;
    - no filter or effects separation;

Concluding remarks from literature review

- ML algorithms parse data, learn from it and use that learning to autonomously make decisions regarding the existence of damage and the structural condition;
- ML algorithms are the basis of both Ensemble Methods and Deep Learning (DL) Algorithms;
- Ensemble methods are very effective and efficient since they are composed of many ML models;
- As opposed to legacy ML techniques, which require features to be identified before classification in order to be visible, so the learning algorithm could work, DL instead eliminates the need of feature extraction and learn high-level features from data in an incremental manner, optimizing the performance.



Is possible to perform data analysis with raw data as input!

Milestones to be reached

I. Increase the **sensitivity of damage** identification methods (reduce false negatives);

II. Increase of the **robustness of damage identification** methods (reduce false positives);

III. Contribute to the **standardization of the SHM systems**;

IV. Provide stakeholders with **automatic procedures** for safety assessment and decision-making based on predictive analysis of the structural condition;

V. Contribute to the achievement of **real-time damage identification** in practical applications of critical infrastructures.

Main objectives

Milestones

1. Apply the newest Machine Learning paradigms to SHM data acquired continuously onsite, namely EM and DL;
2. Assess the methods with the best performance considering site conditions, structural complexity and singularity, actions, hazards and sensorial limitations;

I, II, IV, V

3. Analyse raw SHM data acquired on site:
   - instead of features, which must be defined beforehand and are usually case- and objective-dependent;
   - without the need to separate effects from different actions/hazards;
4. Use only structural response data, thus avoiding the need to characterize complex actions acting in large structural systems (temperature, wind, traffic);

III, IV

5. Define the best SHM strategy based on the new SHM-ML paradigms;
6. Benchmark against the most common strategies used nowadays;

I - V

Thesis workflow / outline

Literature review

Experimental dataset preparation

Numerical damage scenario database (project SAFESUSPENSE)

Machine Learning application on SHM

Damage identification based on Ensemble Models

Damage identification based on Deep Learning

Method benchmark, strategy proposal and validation

Conclusions and future work

Chronogram of activities