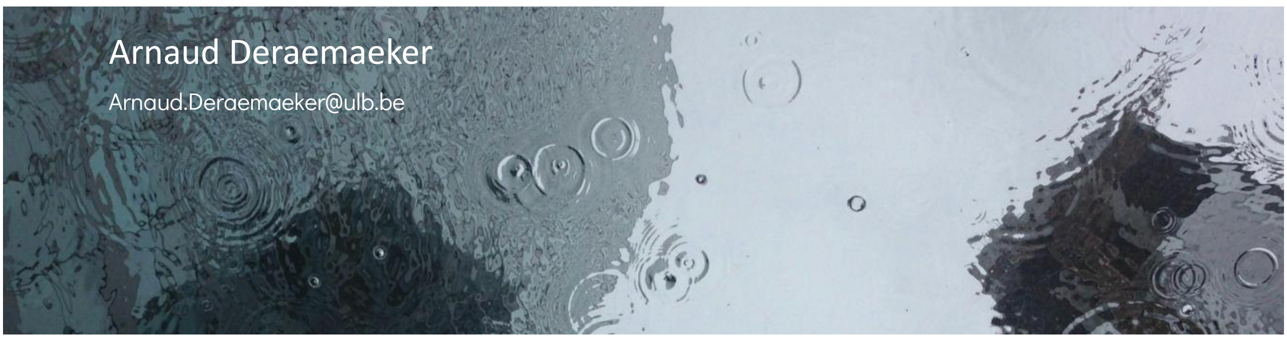
Mitigation of environmental effects in SHM – part I



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CONTEXT

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Is monitoring of concrete infrastructure necessary ?

Genoa bridge collapse, August, 2018

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Robustness of SHM systems

Sensor error/failure

Hardware problems

Software problems

False alarms !

Environmental/operational
factors

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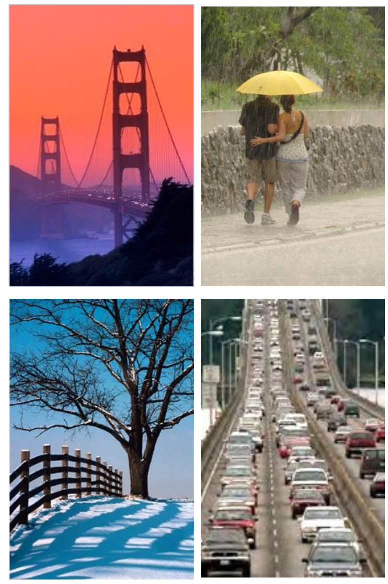
Environmental factors in SHM



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Strategy

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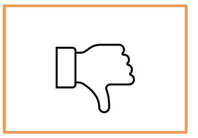
Physical understanding

Do we need to understand the effects to compensate for them ?

- Depends on type of measurements
- Depends on the structure/system



- Works for all

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The swiss knife theory

A swiss knife can do a lot of things, but is not the most efficient tool for a specific problem

General

A cork driver works better to remove a cork, but cannot be used do much else

Specific

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Are we using the tool properly ?

Cut cheese ?

- A good understanding of the physics is necessary to choose a specific tool.
- For a generic tool, this might not be necessary

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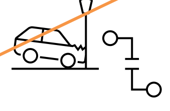
Measurement strategy in SHM

~~Damage sensors~~  do not exist

→ We need to evaluate damage from other measurements

- Vibration features, ultrasonic features, electric measurements, …

→ And to remove environmental trends from damage indicators

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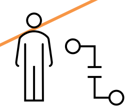
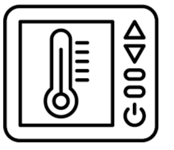
Analogy : comfort in houses

Comfort sensor  do not exist

→ We need to evaluate comfort from other measurements
- Temperature



→ But there could be other factors

- Humidity
- Temp gradients, … ?

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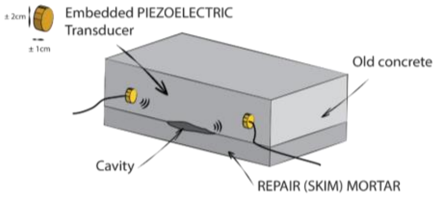
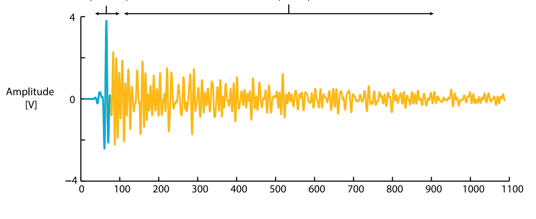
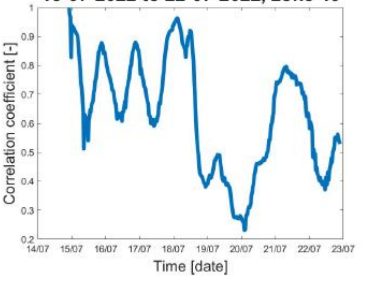
Does temperature explain it all ?

Ultrasonic measurements in Rogier tunnel



$$CC(S, S_0) = \frac{\int_{t_0}^{t_f} S(t)\, S_0\left(t\right)\, dt}{\sqrt{\int_{t_0}^{t_f} S^2(t)\, dt \int_{t_0}^{t_f} S_0^2\left(t\right)\, dt}}$$





Daily and seasonal variations

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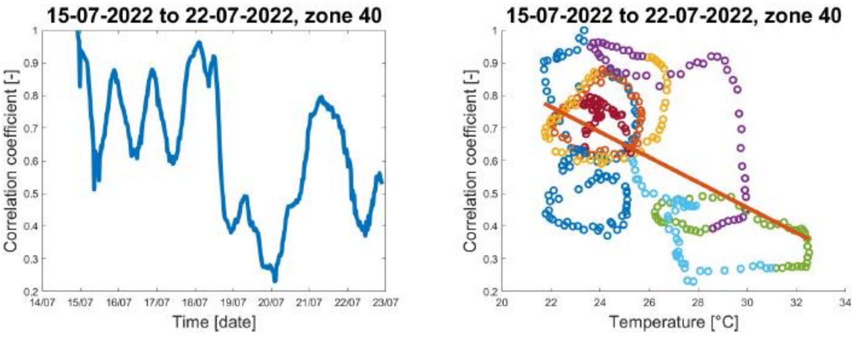
Does temperature explain it all ?



The relationship is not “one-to-one”

- Location of temperature probe ?
- Other factors ? (humidity, load, ...)
- Material hysteresis ?

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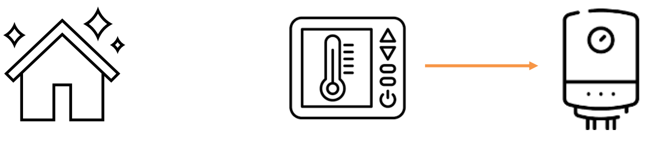
Analogy : temperature regulation in a house



Where should we measure ?

- Is the temperature uniform in the house?
- Is the heating capability uniform in the house ?
- Single or multiple thermostats ?

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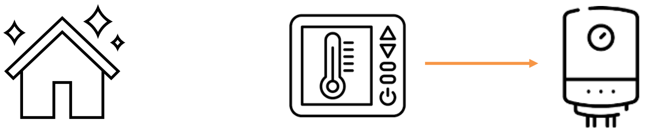
Analogy : temperature regulation in a house



What if the house is filled with water ?

- Is the regulation law still valid ?

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A cork driver example

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The cork driver for US monitoring of concrete

Two “identical” concrete blocks with embedded transducers are put in a climatic chamber (T° and humidity are controlled)

Constant humidity (60%)

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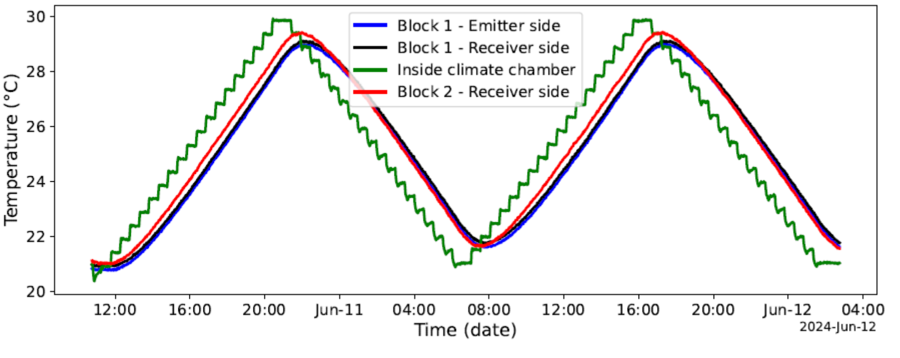
The cork driver for US monitoring of concrete



There is a time delay between the temp curves in the concrete and in the chamber

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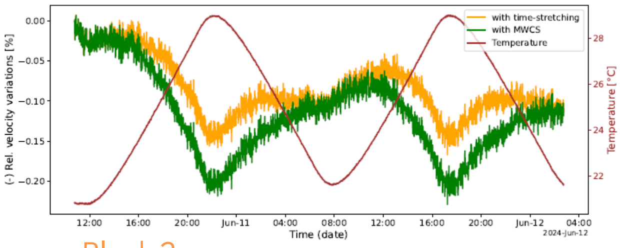
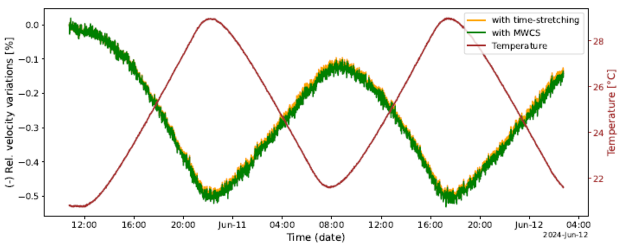
The cork driver for US monitoring of concrete

Block 1



(a) Estimated dv/v from concrete Block-1

Block 2



Wave velocity change is inversely proportional to temperature change

when humidity is kept constant

Although the concrete composition is identical, and the trend also is, the magnitude of change is different

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The cork driver and the swiss knife

- Need to learn a trend/behavior between damage indicator and environmental factors
- Will still be specific to the structure monitored
- Is useless if you are missing important environmental factors (wrong trend is inferred from measurements)

?

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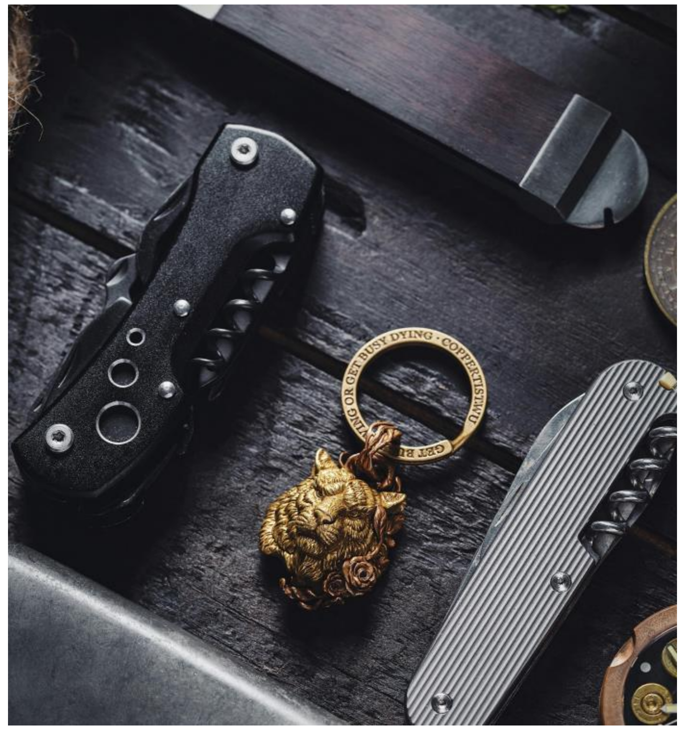
A swiss knife example



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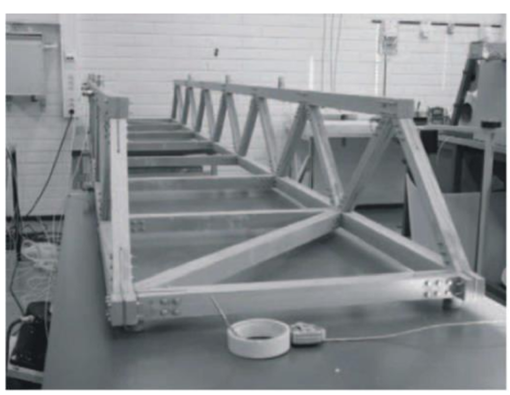
The wooden bridge example



No
temperature
measurement

- 15 accelerometers
- Monitoring over a long period with temperature changes
- 9 Mode shapes and eigenfrequencies extracted
- Samples 1-1880 undamaged, 5 added masses (damage)

[Jyrki Kullaa]

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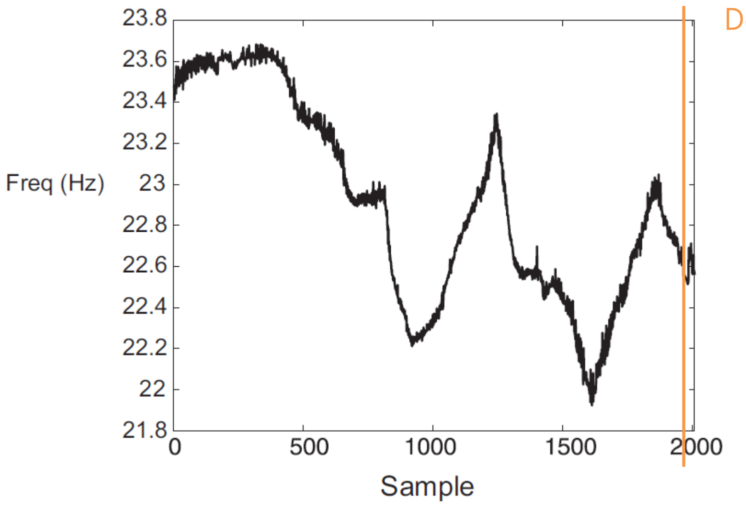
The wooden bridge example

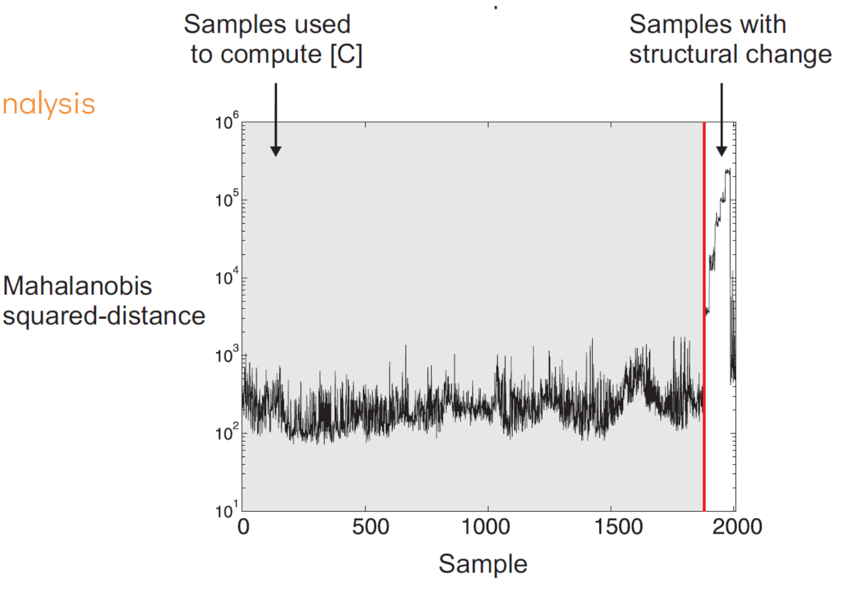
The effect of temperature on features is more important than the effect of damage



The wooden bridge example

- Statistical analysis

- No physical understanding
- Can be applied on any structure/specimen
- Requires a training period



Methods based on measurement of environmental factors

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Types of cork drivers

Data driven

<u>Aim:</u> to find a model and its parameters

that can reproduce the relationship between the EF and the Damage indicators

- Regression analysis
- Neural networks

The model is not known a priori

Model driven

<u>Aim:</u> to derive a model from physical knowledge and to find its parameters

so that the model can reproduce the relationship between the EF and the Damage indicators

- Analytical models
- Inverse problem

The model is derived from physics

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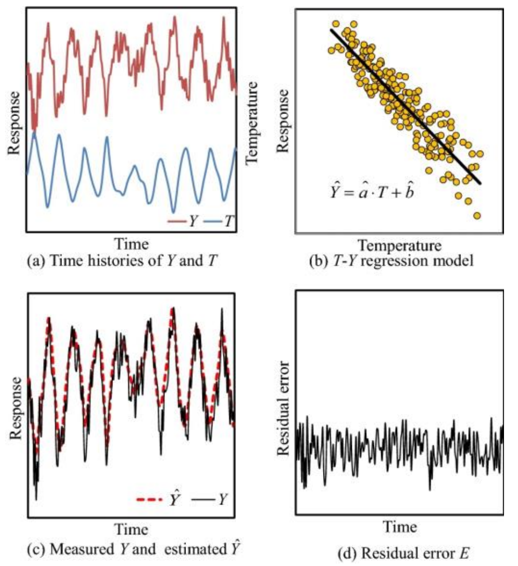
Linear regression



[Han2021]

Linear regression between

- measured temperature T
- structural response Y

allows to remove the trend

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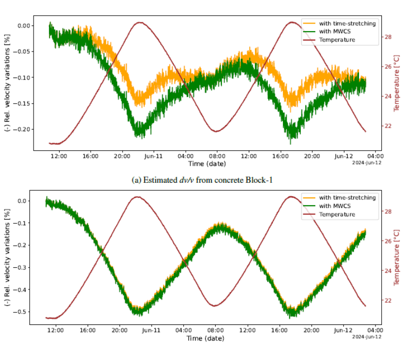
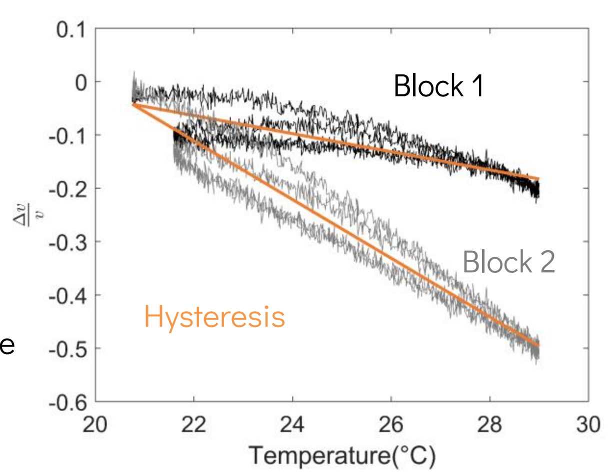
Two concrete blocks example





- Linear regression not accurate
- Time-dependent regression – autoregressive models (ARMAX)

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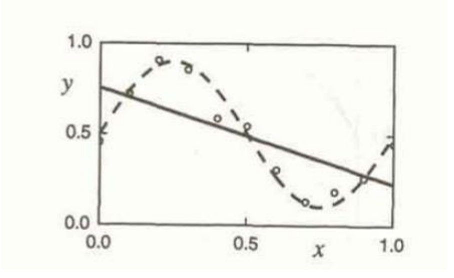
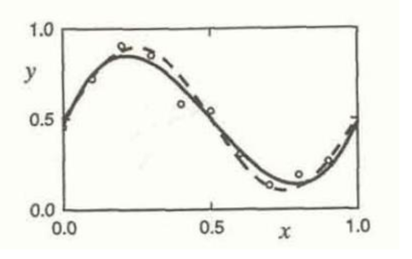
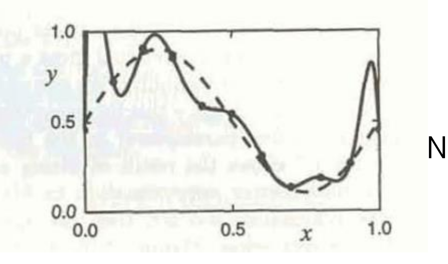
Polynomial fitting



N=1



N=3



N=10

[Bishop94]

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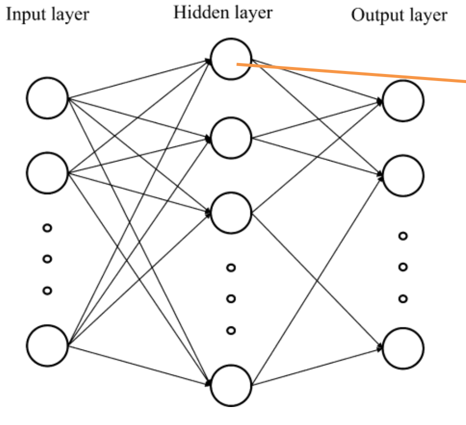
Artificial neural networks

Multi-layer perceptron

[Bishop94]



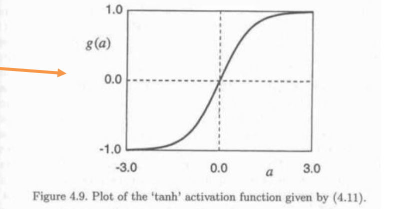


Figure 4.9. Plot of the 'tanh' activation function given by (4.11).

Threshold function makes the input/output relationship non-linear

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Artificial neural networks

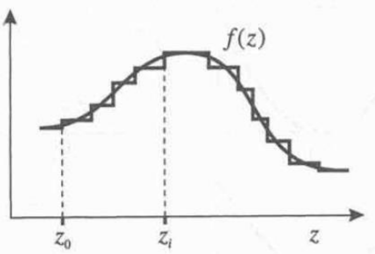

Figure 4.11. Approximation of a continuous function $f(z)$ by a linear superposition of threshold step functions. This forms the basis of a simple proof that a two-layer network having sigmoidal hidden units and linear output units can approximate a continuous function to arbitrary accuracy.

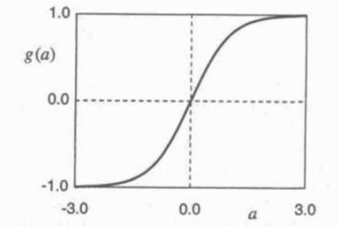

Figure 4.9. Plot of the 'tanh' activation function given by (4.11).

[Bishop94]

- The network needs to be trained
- Too many neurons in hidden layer = over-fitting !

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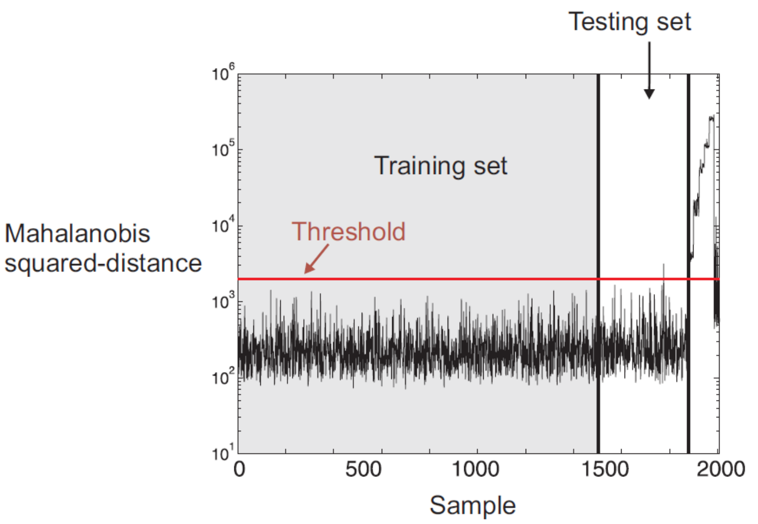
Training, testing, and validation sets



Helps to reduce risk of overfitting

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Methods not requiring the measurement of environmental factors

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What is the idea?

Measure multiple features (damage indicators) $y_1, y_2, y_3, \dots$

Use correlations to build a subspace including EF

Project damage indicators into orthogonal subspace

Linear methods

Non-linear methods

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Linear methods : a general methodology

$$\{\overline{y}\} = \frac{1}{N}\sum_{i=1}^{N}\{y_i\}$$ Mean

$$[C] = \frac{1}{N-1}\sum_{i=1}^{N}\left(\{y_i\}-\{\overline{y}\}\right)\left(\{y_i\}-\{\overline{y}\}\right)^T$$ Covariance matrix

$$D_\zeta^2 = \left(\{y_\zeta\}-\{\overline{y}\}\right)^T [C]^{-1}\left(\{y_\zeta\}-\{\overline{y}\}\right)$$ Mahalanobis squared distance

[Deraemaeker and Worden, 2018]

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Spectral decomposition of the covariance matrix

$$[C]\{U_i\} = \sigma_i^2\{U_i\}$$ Eigenvalue problem

$$[U]^T[C][U] = [S]$$
$$[U]^T[U] = Id$$
Orthogonality conditions

$$[C] = [U][S][U]^T$$ Covariance matrix

$$[C]^{-1} = [U][S]^{-1}[U]^T$$ Inverse of covariance matrix

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Transformation in the space of independent features

$$\{\eta_i\} = [U]^T \{y_i\}$$

Transformation

$$\{\overline{\eta}\} = \frac{1}{N}\sum_{i=1}^{N}\{\eta_i\} = [U]^T\{\overline{y}\}$$

Mean

$$\begin{aligned}[C]_\eta &= \frac{1}{N-1}\sum_{i=1}^{N}(\{\eta_i\}-\{\overline{\eta}\})(\{\eta_i\}-\{\overline{\eta}\})^T \\ &= [U]^T\frac{1}{N-1}\sum_{i=1}^{N}(\{y_i\}-\{\overline{y}\})(\{y_i\}-\{\overline{y}\})^T[U] \\ &= [U]^T[C][U] = \underline{[S]}\end{aligned}$$

Covariance matrix

diagonal covariance matrix

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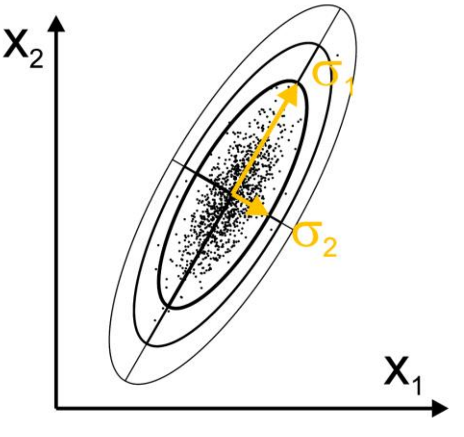
Transformation and Mahalanobis squared distance

$$\{y_i\} = [U]\{\eta_i\}$$

$$D_\zeta^2 = \sum_{i=1}^{n}\frac{1}{\sigma_i^2}(\eta_{\zeta i}-\overline{\eta}_i)^2$$



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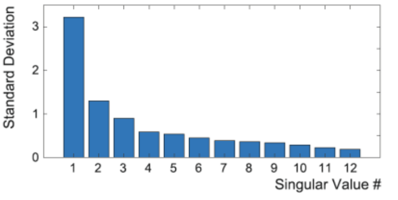
Transformation and Mahalanobis squared distance

$$I = \frac{\sum_{i=1}^{p} \sigma_i^2}{\sum_{i=1}^{n} \sigma_i^2} \qquad I > e(\%)$$



$$D_\zeta^2 = \underbrace{\sum_{i=1}^{p} \frac{1}{\sigma_i^2}(\eta_{\zeta i} - \overline{\eta}_i)^2}_{\text{Principal components}} + \underbrace{\sum_{i=p+1}^{n} \frac{1}{\sigma_i^2}(\eta_{\zeta i} - \overline{\eta}_i)^2}_{\text{Null- space}} = D_{1\zeta}^2 + D_{2\zeta}^2$$

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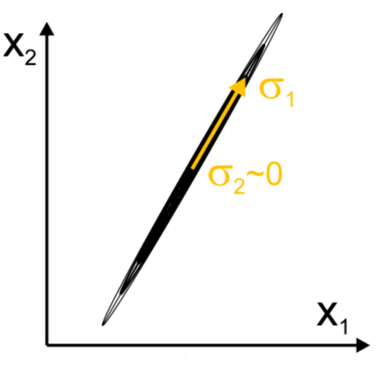
Transformation and Mahalanobis squared distance

$$D_\zeta^2 = \sum_{i=1}^{p} \frac{1}{\sigma_i^2}(\eta_{\zeta i} - \overline{\eta}_i)^2 + \boxed{\sum_{i=p+1}^{n} \frac{1}{\sigma_i^2}(\eta_{\zeta i} - \overline{\eta}_i)^2} = D_{1\zeta}^2 + \boxed{D_{2\zeta}^2}$$

σ_i is very large for i=1...p



- If EF are included in the training data, the Mahalanobis squared distance naturally filters these variations
- This is equivalent to projection in the space of minor components using PCA

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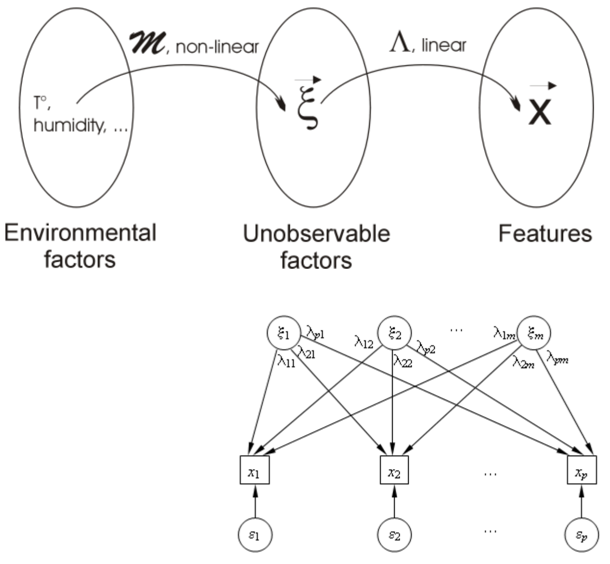
Factor analysis



- Assume a non-linear mapping between EF and « unobservable factors »
- Assume a linear mapping between « unobservable factors » and features
- This is equivalent to performing PCA

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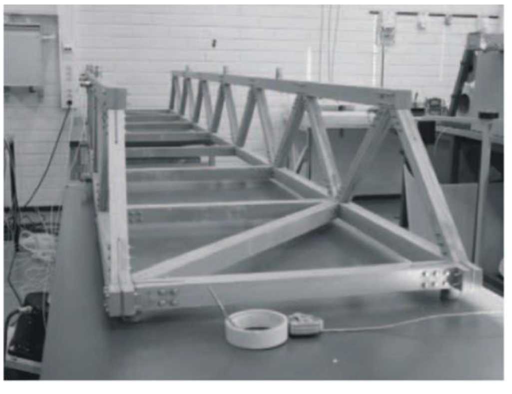
The wooden bridge example



No temperature measurement

- 15 accelerometers
- Monitoring over a long period with temperature changes
- 9 Mode shapes and eigenfrequencies extracted
- Samples 1-1880 undamaged, 5 added masses (damage)

[Jyrki Kullaa]

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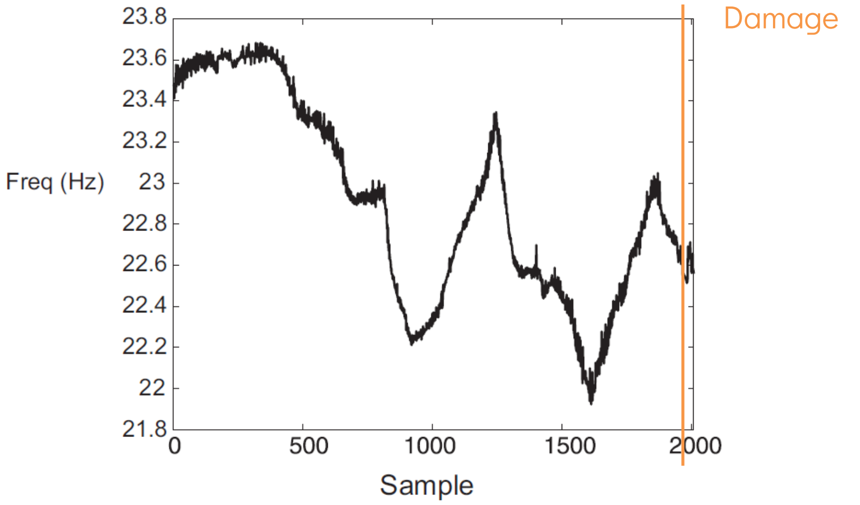
The wooden bridge example

The effect of temperature on features is more important than the effect of damage



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Application of Mahalanobis squared-distance

$$\{\overline{y}\} = \frac{1}{N}\sum_{i=1}^{N}\{y_i\}$$

$$[C] = \frac{1}{N-1}\sum_{i=1}^{N}\left(\{y_i\}-\{\overline{y}\}\right)\left(\{y_i\}-\{\overline{y}\}\right)^T$$

dim of *y* = *261*

N= 300, 1000, 1880

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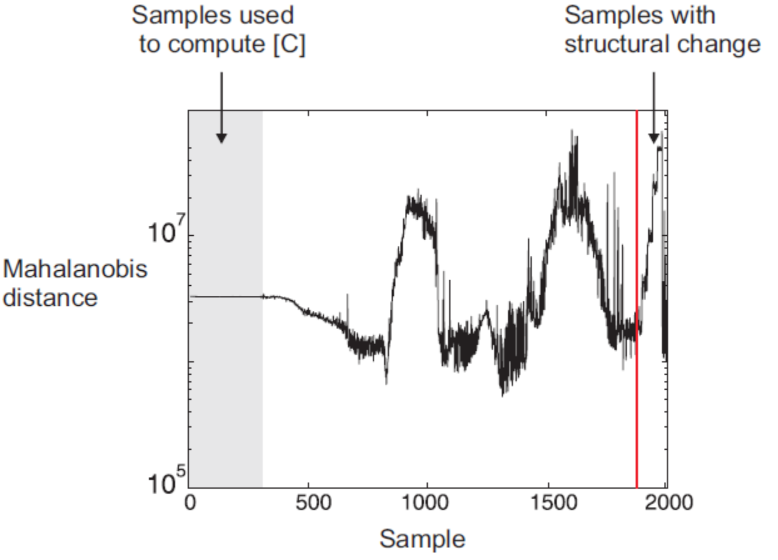
N=300



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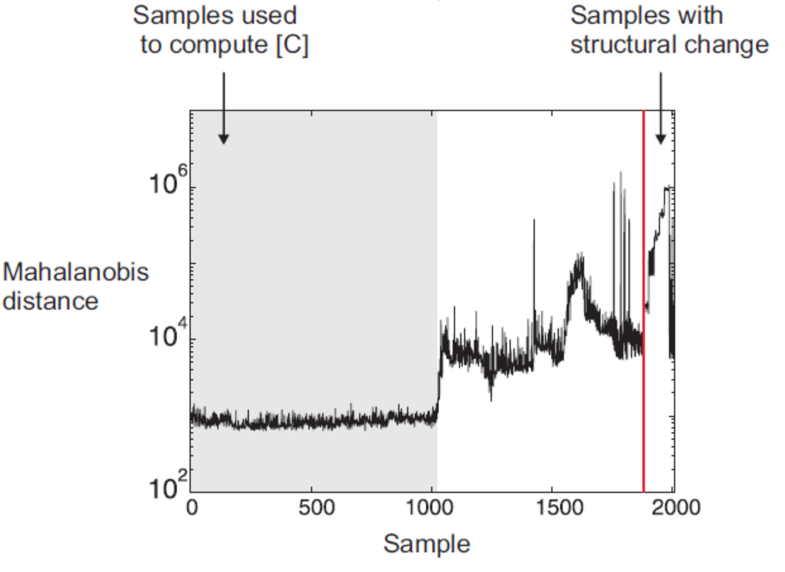
N=1000



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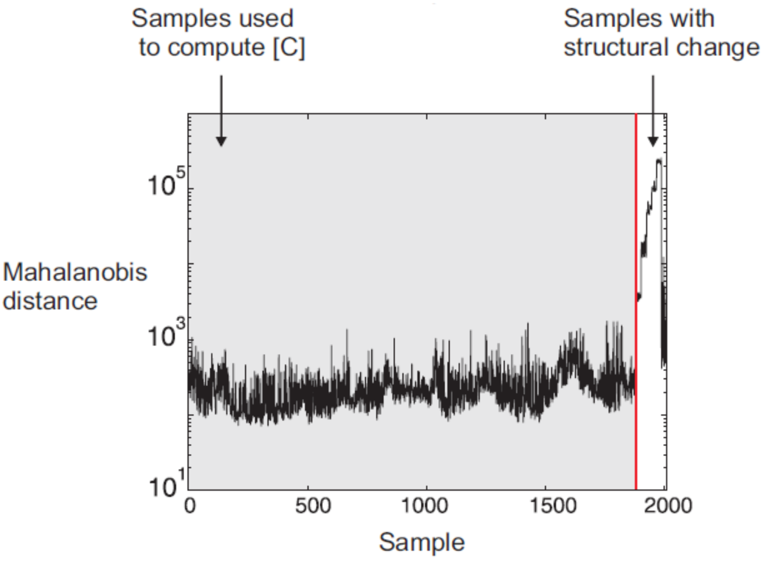
N=1880



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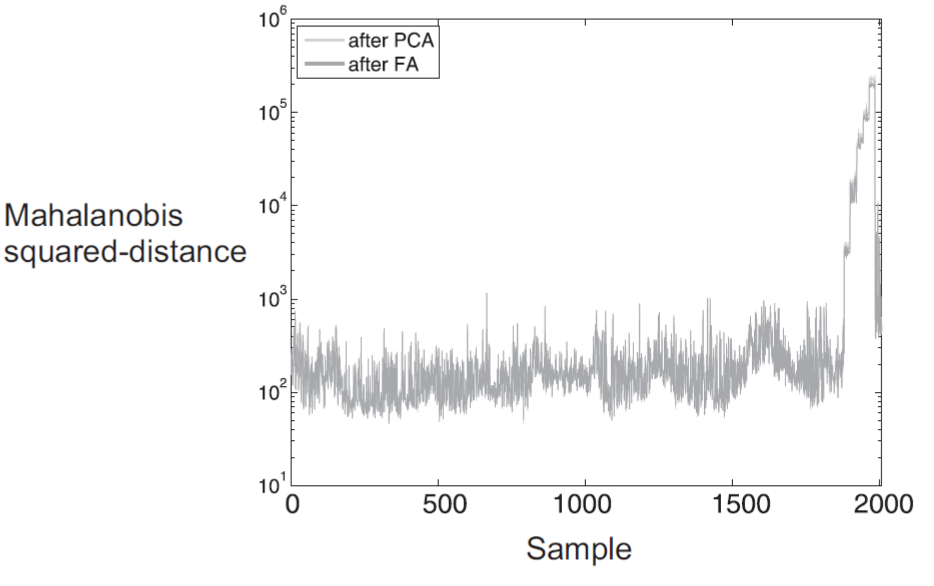
Factor analysis and PCA



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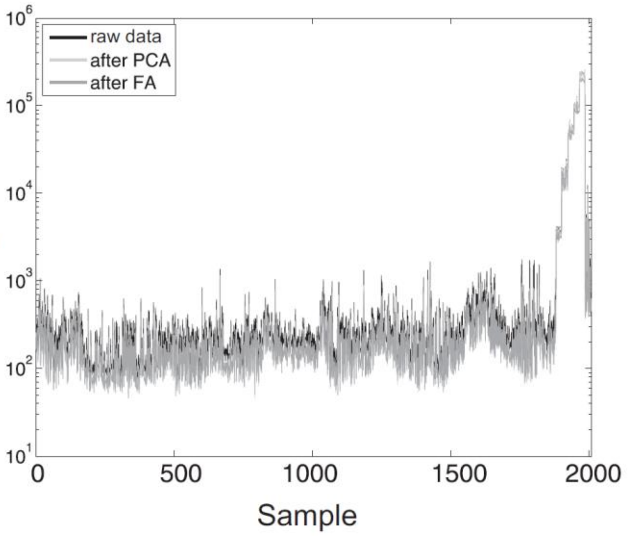
Equivalence of all methods

Mahalanobis squared-distance



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Linear vs Non-linear methods

Linear methods

- PCA
- Factor analysis
- Mahalanobis squared-distance

- Low computational cost
- Not restricted to linear relationship between EF and features
- Generally requires high-dimensional feature vector

Non-linear methods

- Non-linear PCA
- Non-linear factor analysis
- Auto-regressive neural networks

- High computational cost
- Can work with low-dimensional feature vector
- Trial and error to choose the non-linear model

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Setting thresholds

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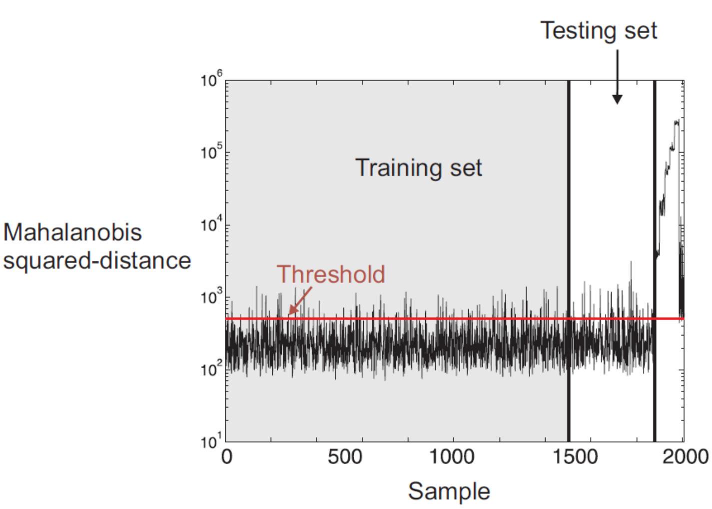
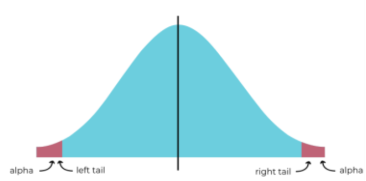
Normality assumption



Assume that the feature vector is multi-normal (gaussian)



Confidence level = 1/1000

Fails because tail of distributions is not fitted correctly

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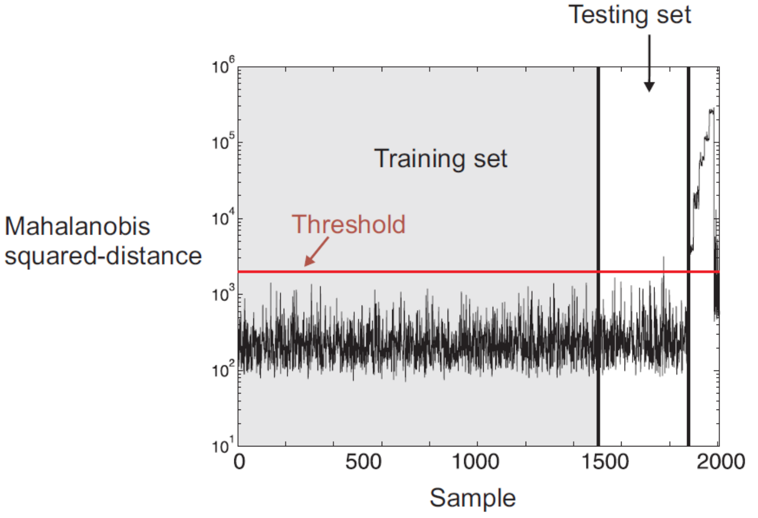
Extreme value statistics



Confidence level = 1/1000

Works because the focus is on fitting the tail of the distributions

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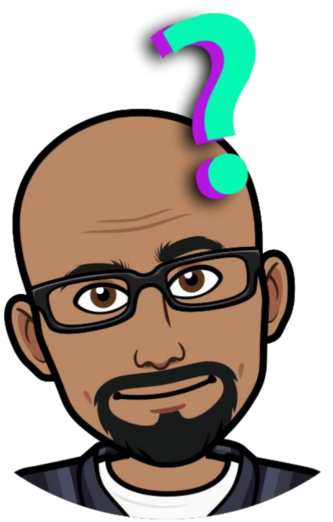

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