FAULT DETECTION

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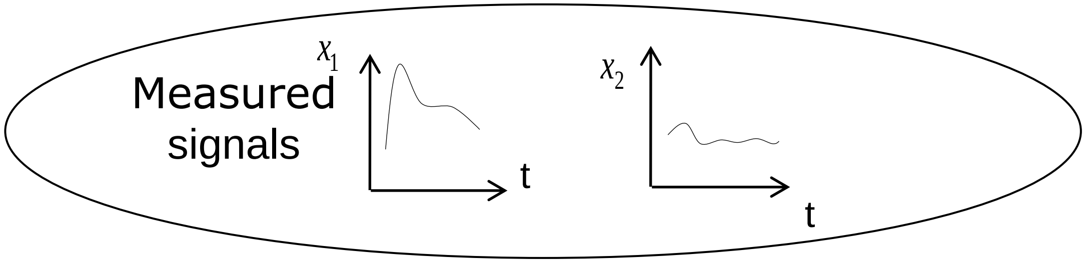
In This Lecture

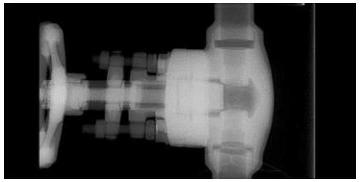
- Part 1: Model of the Equipment Behavior in Normal Condition
  - Principal Component Analysis (PCA)
- Part 2: Statistical Test
  - 2A) Thresholds-Based
  - 2B) Sequential Probability Ratio Test (SPRT)

Overview

Context: Prognostics and Health Management

Equipment (System, Structure or Component)


Measured signals



$$\frac{dx}{dt} = A\exp\left(-\frac{Q}{RT}\right)\varphi^n$$

Detect

- Anomalous operation
- Normal operation

Diagnose

- c_1
- c_2
- c_3

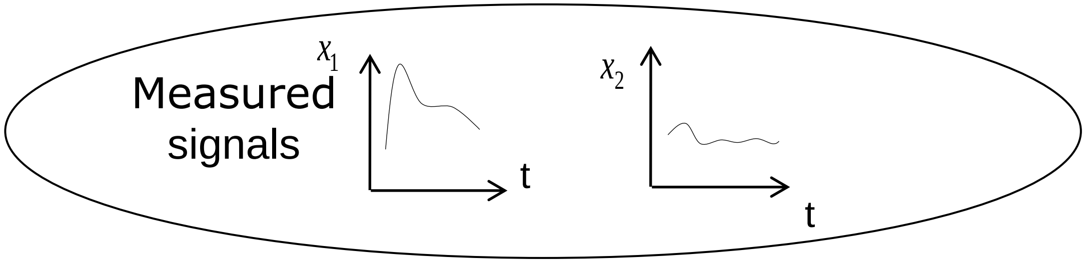
Malfunctioning type (classes)

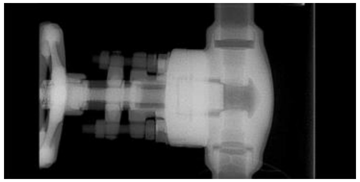
Predict

Remaining Useful Life (RUL)

In This Lecture: Fault Detection

Equipment (System, Structure or Component)





$$\frac{dx}{dt} = A\exp\left(-\frac{Q}{RT}\right)\varphi^{n}$$

Detect

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c_1 c_2 c_3

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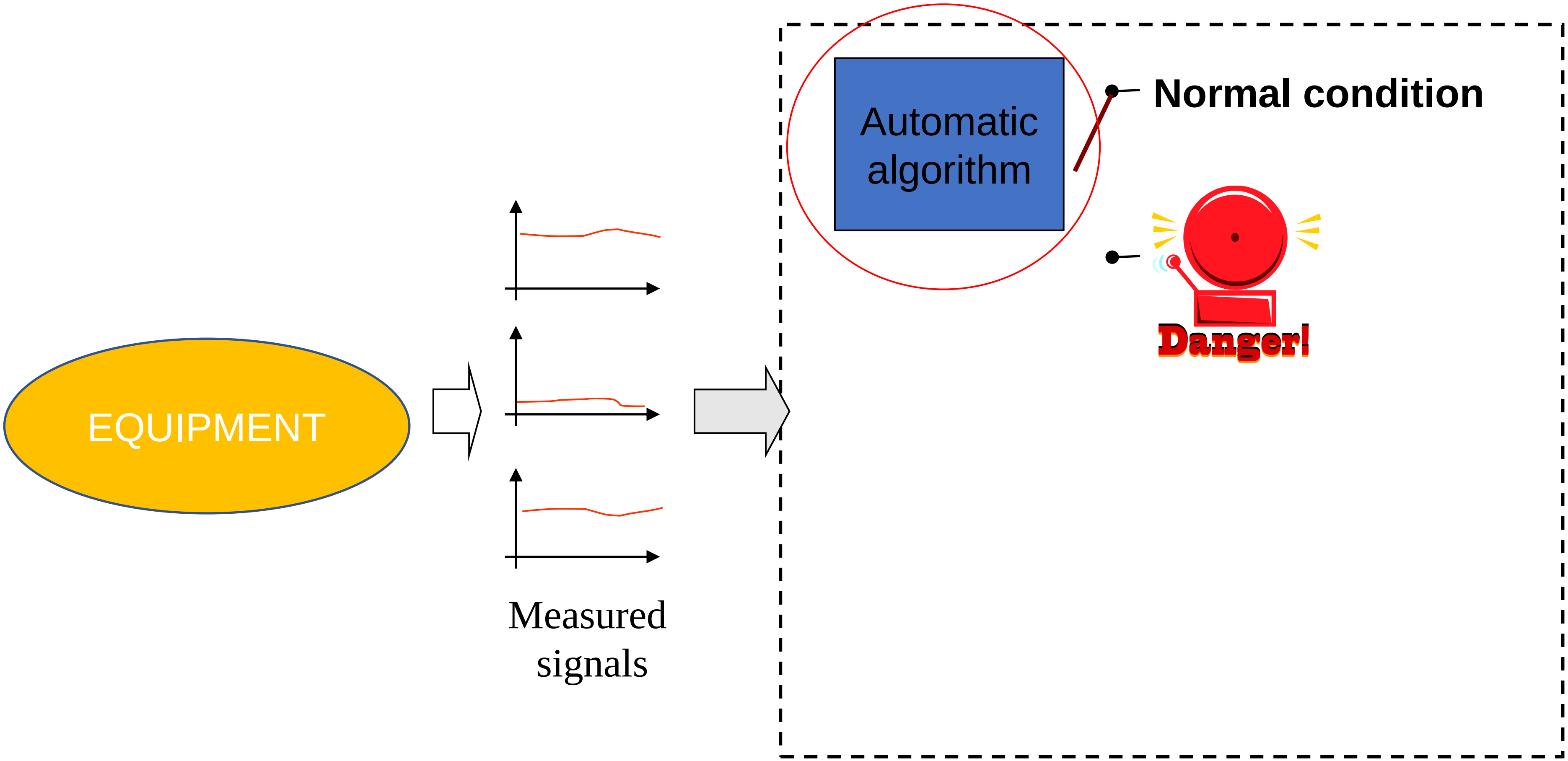
Fault Detection: What is?



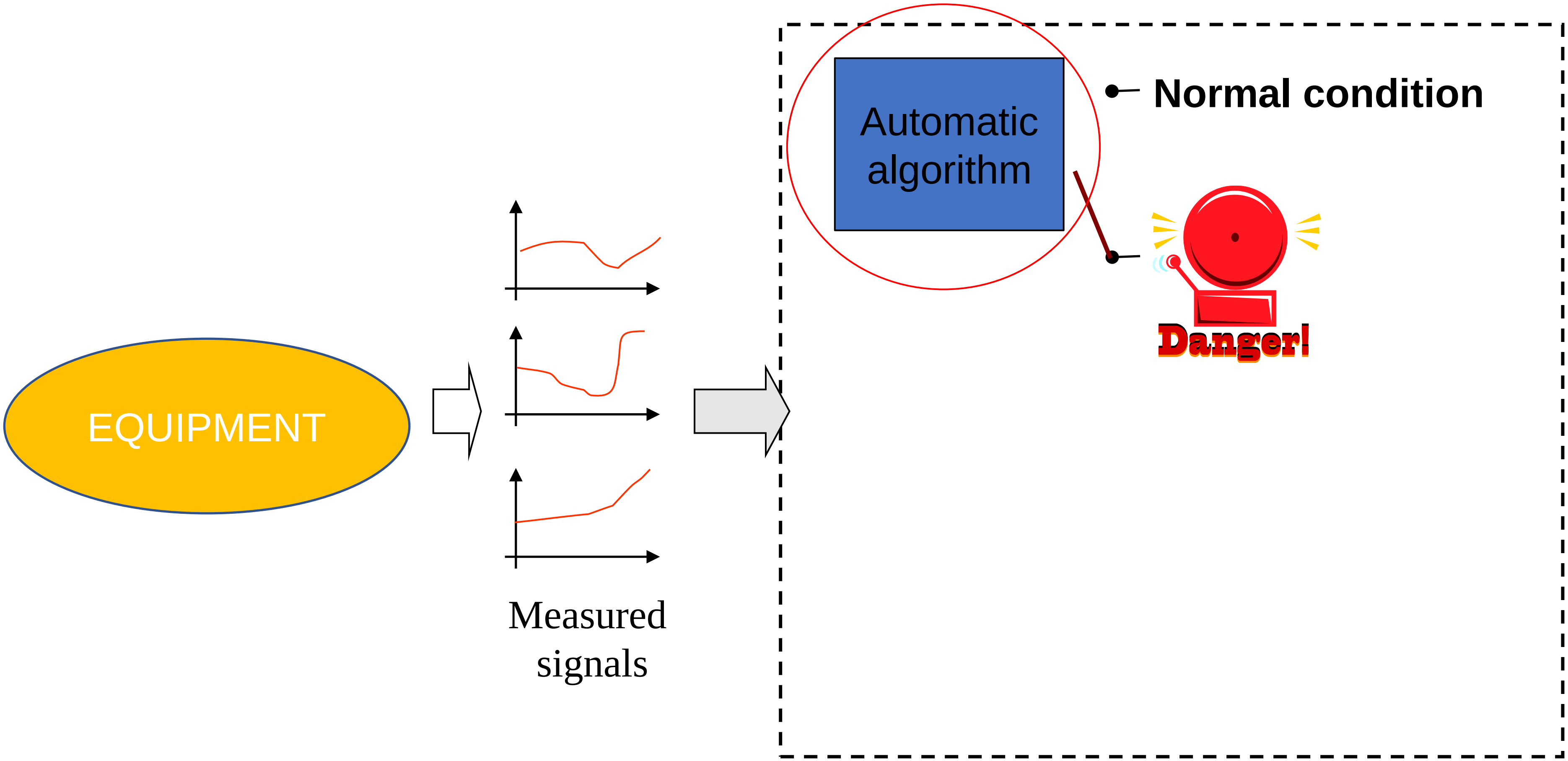
EQUIPMENT

Measured signals

Automatic algorithm

Normal condition

Fault Detection: What is?



EQUIPMENT

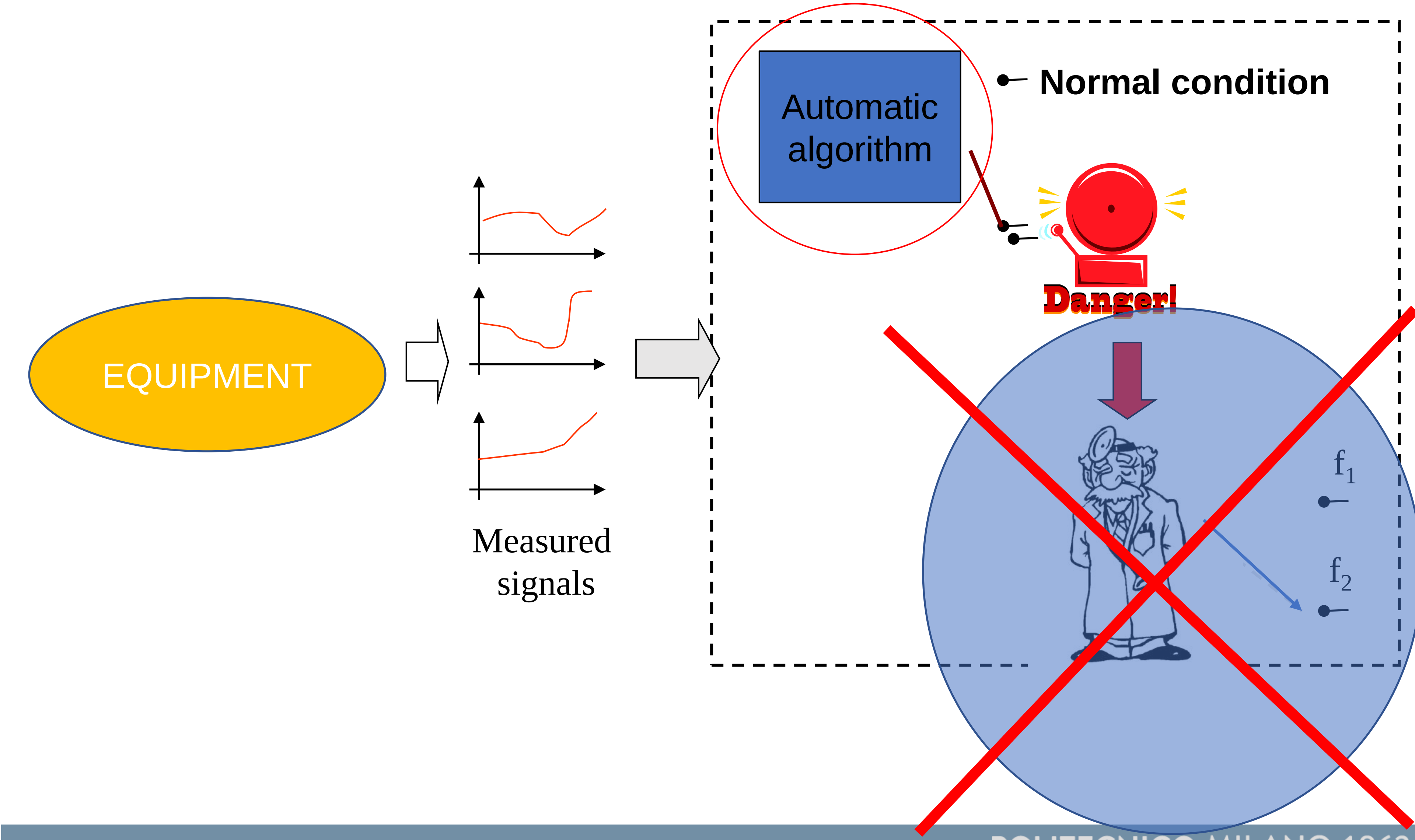
Measured signals

Automatic algorithm

Normal condition

Danger!

Fault Detection: What is not?



EQUIPMENT

Measured signals

Automatic algorithm

Normal condition

Danger!

f_1

f_2

Fault Detection: Approaches

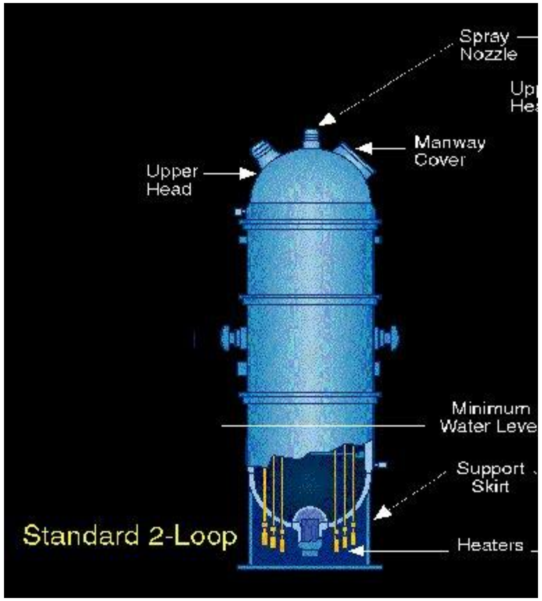
- Limit-based
- Model-based
- Data-driven

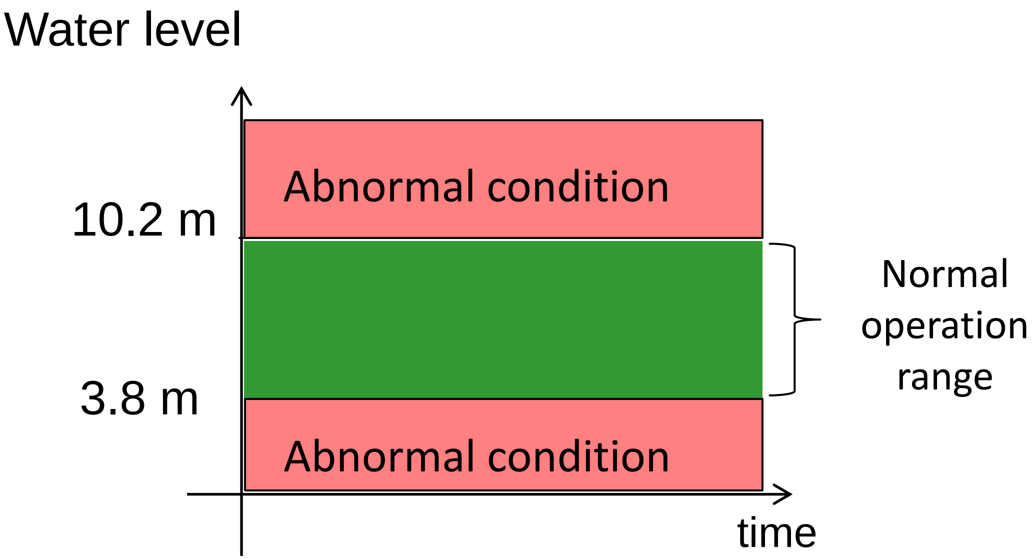
Limit-based fault detection: data & information

- Normal operation ranges of key signals

Example:

Pressurizer of a nuclear reactor





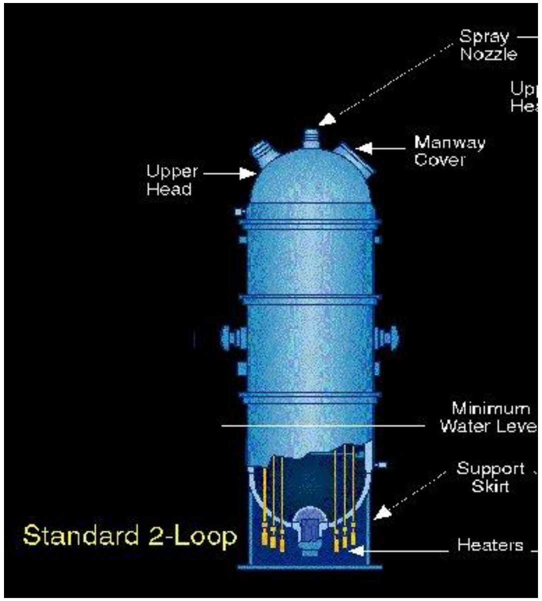
Limit-based fault detection: the method

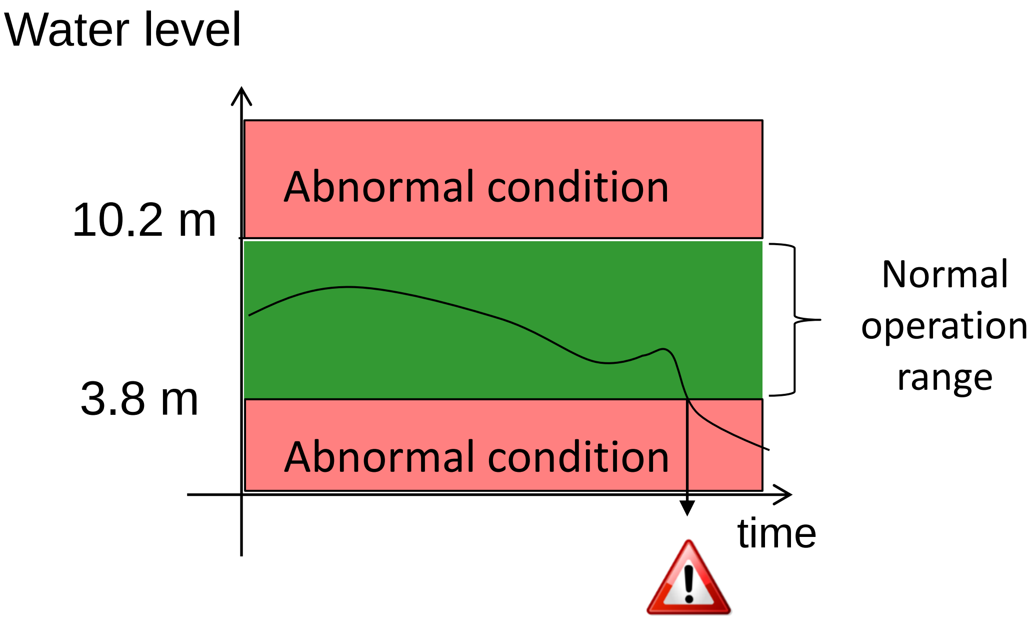
- Normal operation ranges of key signals

- Limit Value-Based Fault Detection

Example:

Pressurizer of a nuclear reactor





Limit-based fault detection: Limitations

- Normal operation ranges of key signals

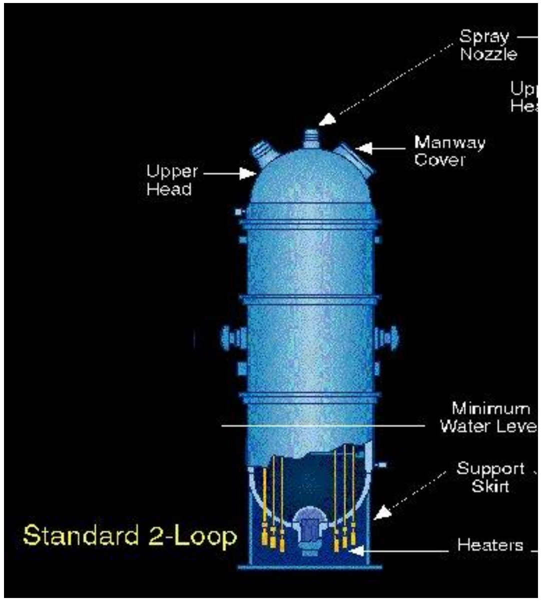
- Limit Value-Based Fault Detection

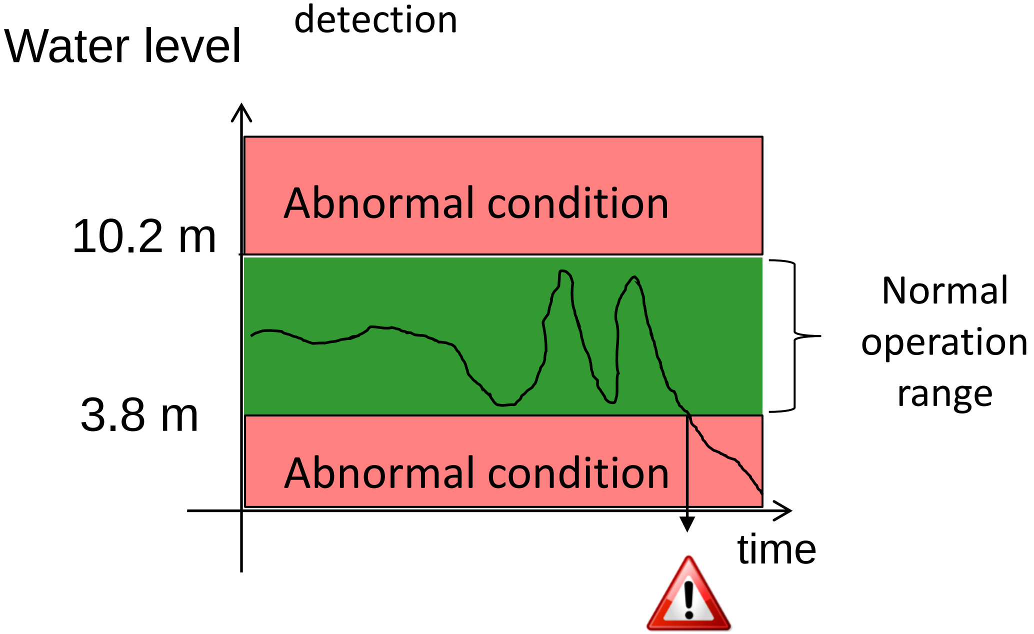
Limitations:

- No early detection
- Not applicable to fault detection during operational transients
- Control systems operations may hide small anomalies (the signal remains in the normal range although there is a process anomaly)
- Considering signal individually can delay detection

Example:

Pressurizer of a PWR nuclear reactor

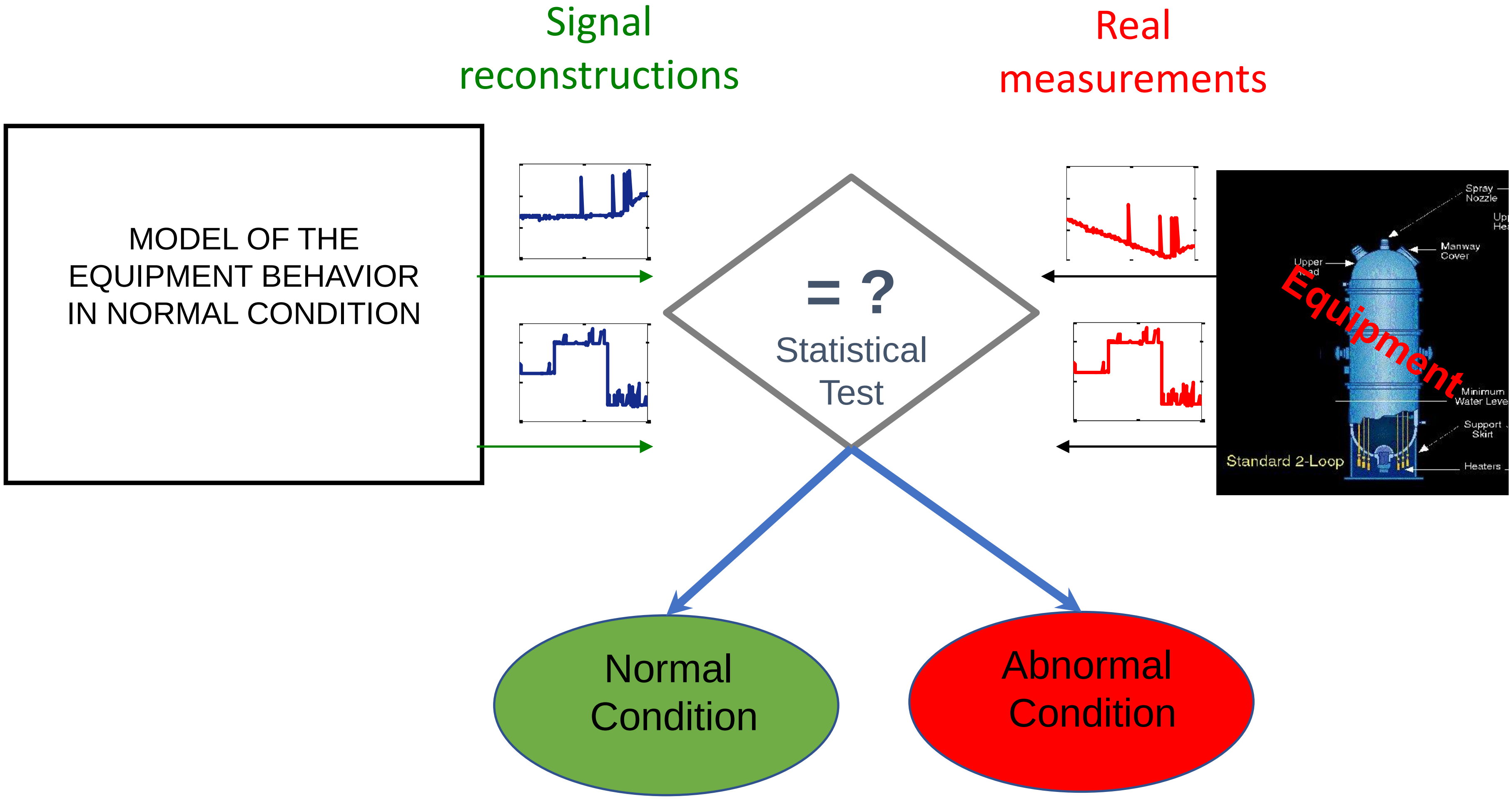




Fault Detection: Approaches

- Limit-based
- Model-based
- Data-driven

Model-based & Data-driven fault detection: basic idea



Signal reconstructions

Real measurements

MODEL OF THE EQUIPMENT BEHAVIOR IN NORMAL CONDITION

= ?

Statistical Test

Normal Condition

Abnormal Condition

Fault Detection: Approaches

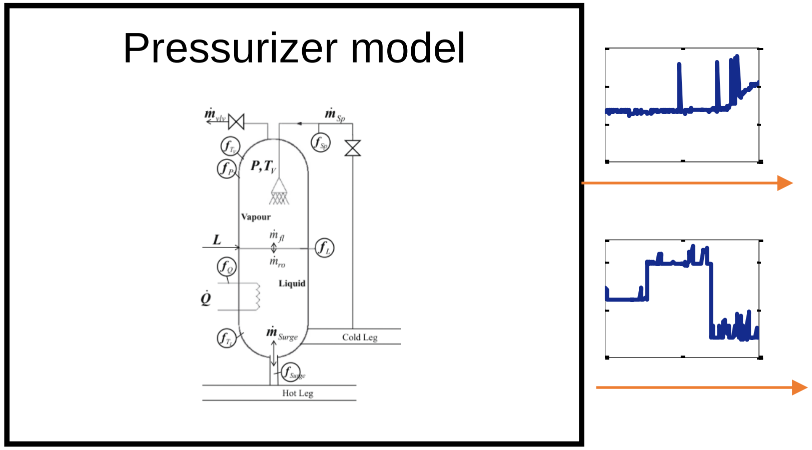
- Limit-based
- Model-based
- Data-driven

Model-based fault detection: data & information

- Physics-based model of the process (used to reproduce the expected behavior of the signals in normal condition)

Example:

Signal reconstructions



Pressurizer model

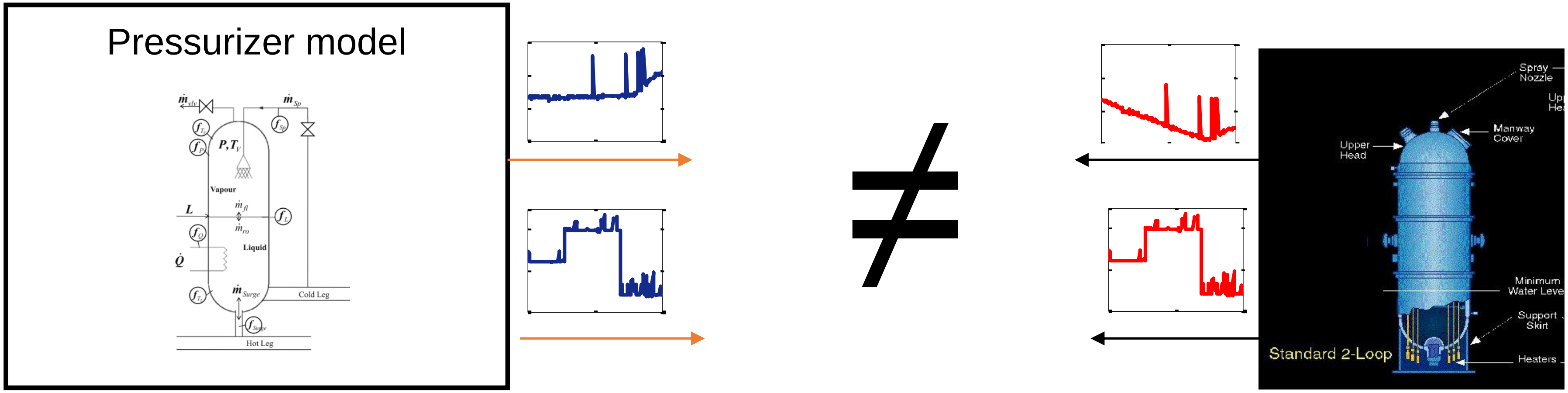
Model-based fault detection: limitations

- Physics-based model of the process (used to reproduce the expected behavior of the signals in normal condition)

Example:

Signal reconstructions

Real measurements



Pressurizer model

≠

Abnormal Condition

- ➢ Typically not available for complex systems
- ➢ Long computational time

Fault Detection: Approaches

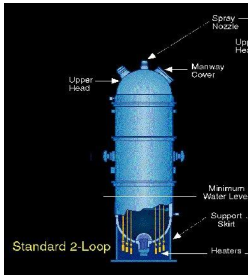
- Limit-Based
- Model Based
- Data-driven

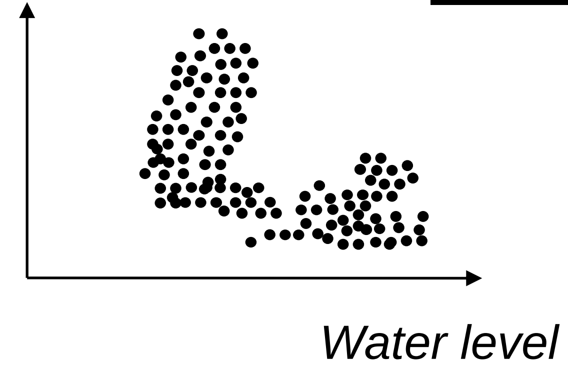
Data-driven fault detection: data & information

- Historical signal measurements in normal operation

Example:

Pressure	Liquid temperature	Steam temperature	Spray flow	Surge line flow	Heaters power	Level
150.2	321	362	539	244	0	7.2
150.4	322	363	681	304	0	7.5
150.3	323	364	690	335	1244	7.7
…	…	…	…	…	…	…





Data-driven fault detection: possible methods

- Statistical Approaches:
  - Principal Component Analysis (PCA)-based
  - AutoAssociative Kernel Regression (AAKR)
  - …
- Artificial Intelligence (AI)-based
  - Feedforward Neural Networks (FNNs)
  - AutoAssociative Neural Networks (AANNs)
  - AutoEncoders (AEs)
  - Self Organizing Maps
  - …

In This Lecture

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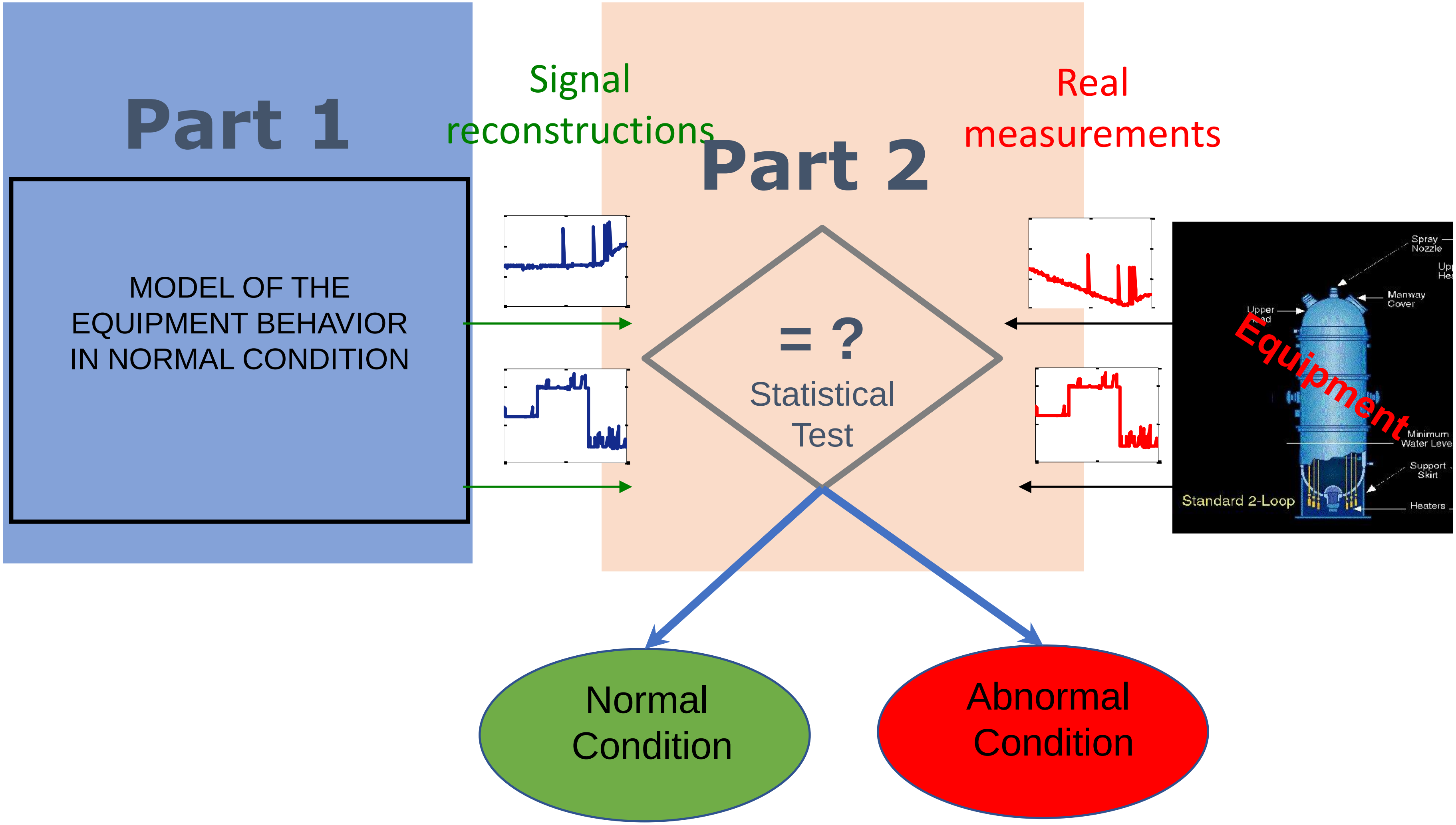
  - Principal Component Analysis (PCA)
- Part 2: Statistical Test
  - 2A) Thresholds-Based
  - 2B) Sequential Probability Ratio Test (SPRT)

In This Lecture

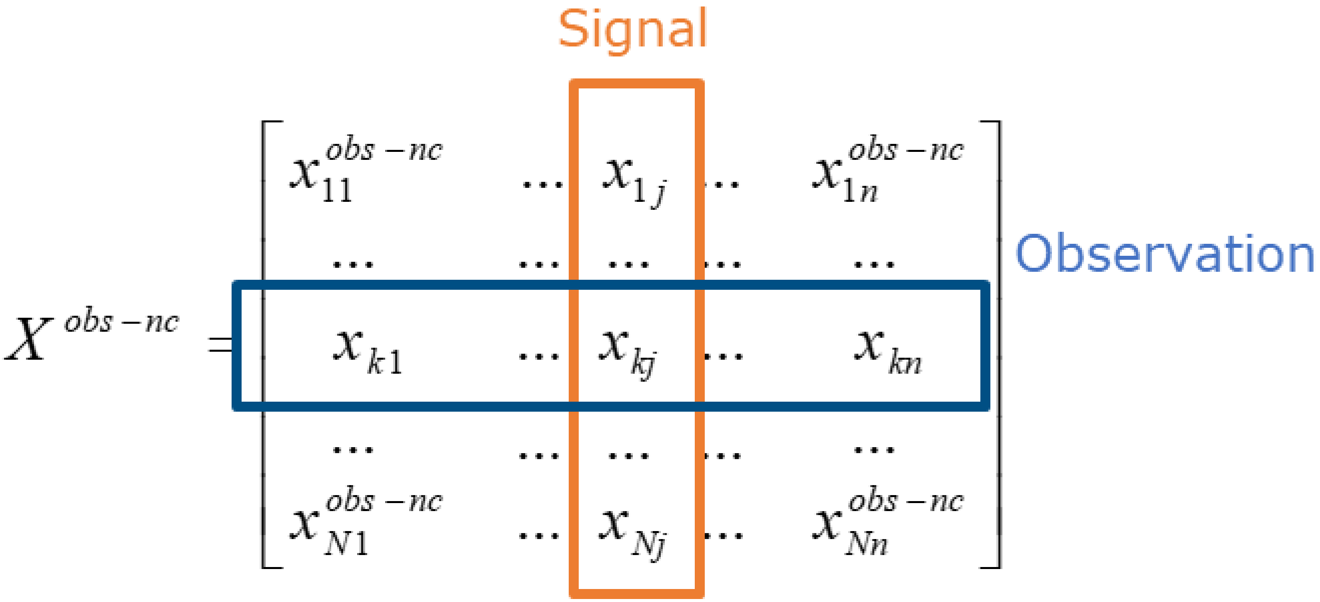


PART 1: Model of the Equipment Behaviour in Normal Condition

- Principal Component Analysis (PCA)

What do we need?

Data in normal conditions



Signal

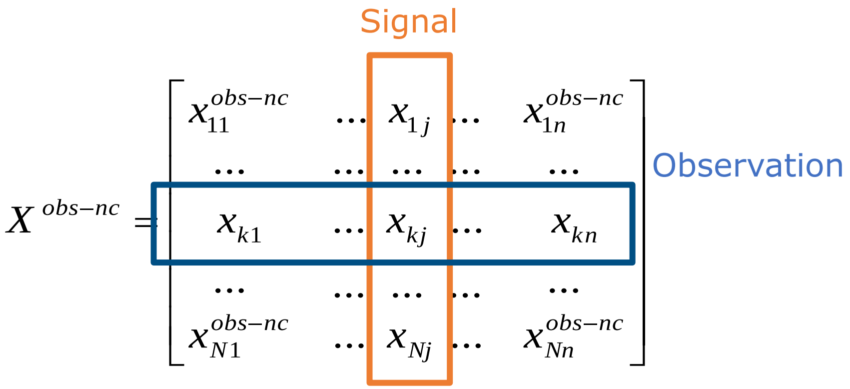
$$X^{obs-nc} = \begin{bmatrix} x_{11}^{obs-nc} & \cdots & x_{1j} & \cdots & x_{1n}^{obs-nc} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{k1} & \cdots & x_{kj} & \cdots & x_{kn} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{N1}^{obs-nc} & \cdots & x_{Nj} & \cdots & x_{Nn}^{obs-nc} \end{bmatrix}$$

Observation

obs-nc = observation in normal condition

Training set, input and output

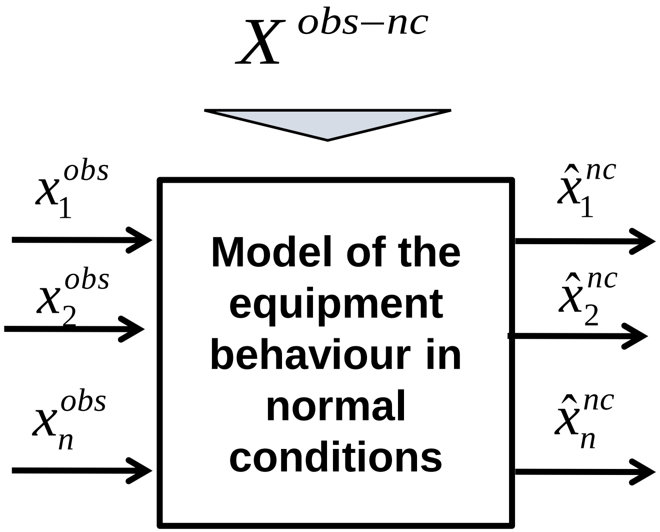
- Training patterns:
  Historical signal measurements
  in normal condition



$$X^{obs-nc} = \begin{bmatrix} x_{11}^{obs-nc} & \cdots & x_{1j} & \cdots & x_{1n}^{obs-nc} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{k1} & \cdots & x_{kj} & \cdots & x_{kn} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{N1}^{obs-nc} & \cdots & x_{Nj} & \cdots & x_{Nn}^{obs-nc} \end{bmatrix}$$

- Test input: $\vec{x}^{obs} = (x_1^{obs}, \ldots, x_n^{obs})$
  Signals measured at current time

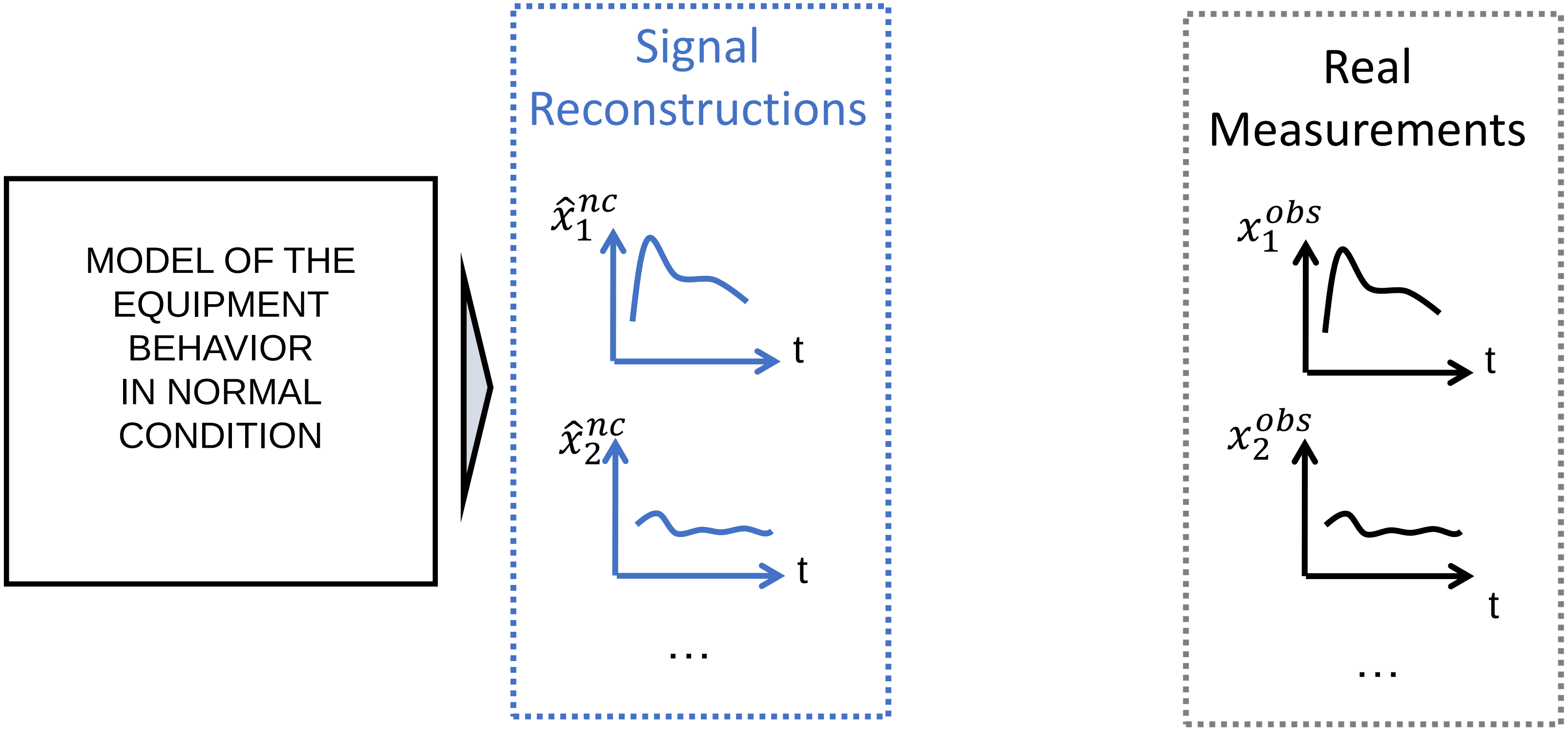
- Test Output: $\hat{\vec{x}}^{nc} = (\hat{x}_1^{nc}, \ldots, \hat{x}_n^{nc})$
  Signal reconstructions
  (expected values of the signals
  in normal condition)



Model of the equipment behaviour in normal conditions

Requirement I

- Equipment is in normal condition



MODEL OF THE EQUIPMENT BEHAVIOR IN NORMAL CONDITION

Signal Reconstructions

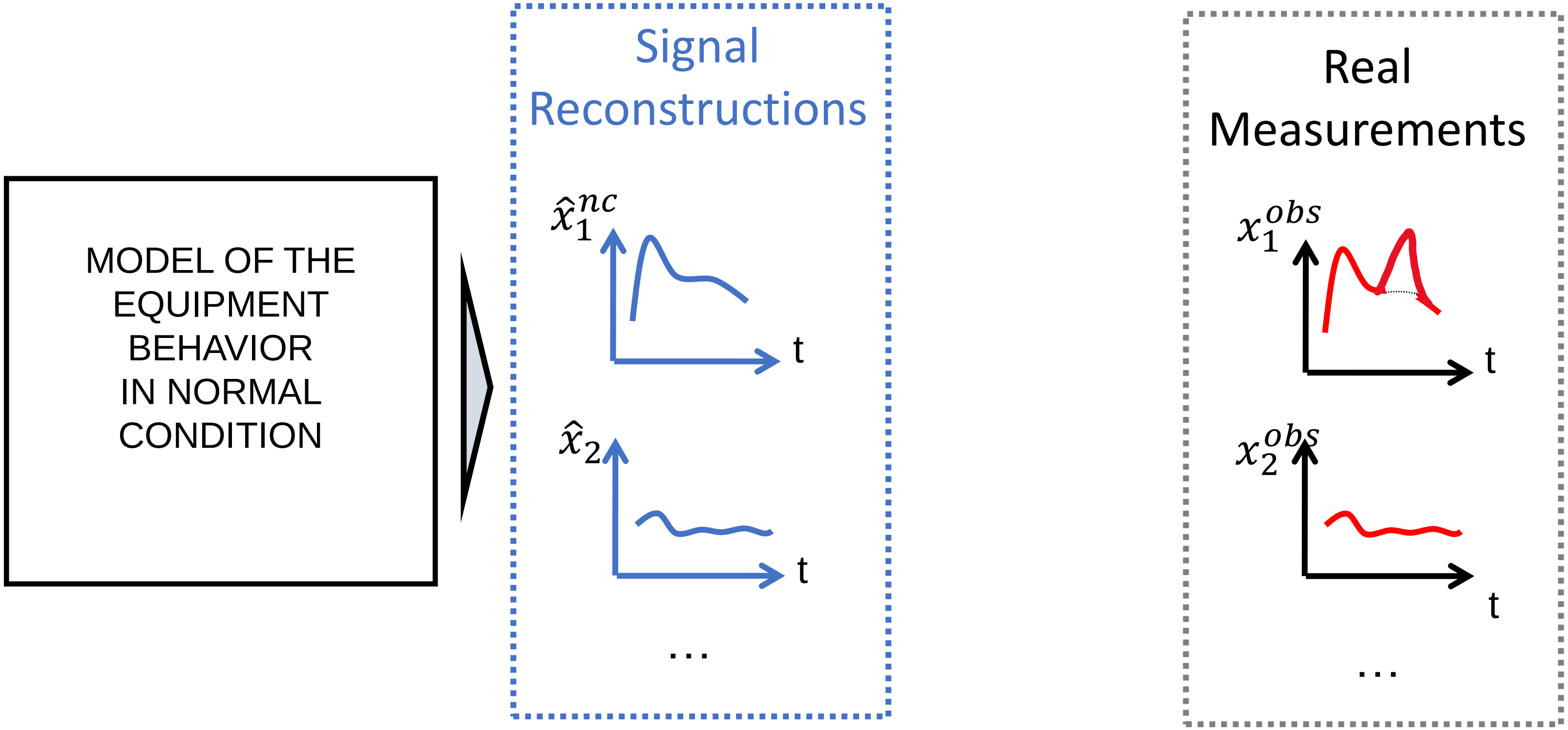
Real Measurements

$$\vec{\hat{x}}^{nc} \cong \vec{x}^{obs}$$

$\hat{}$ =reconstruction
nc= normal condition

Requirement II

- Equipment is in abnormal condition

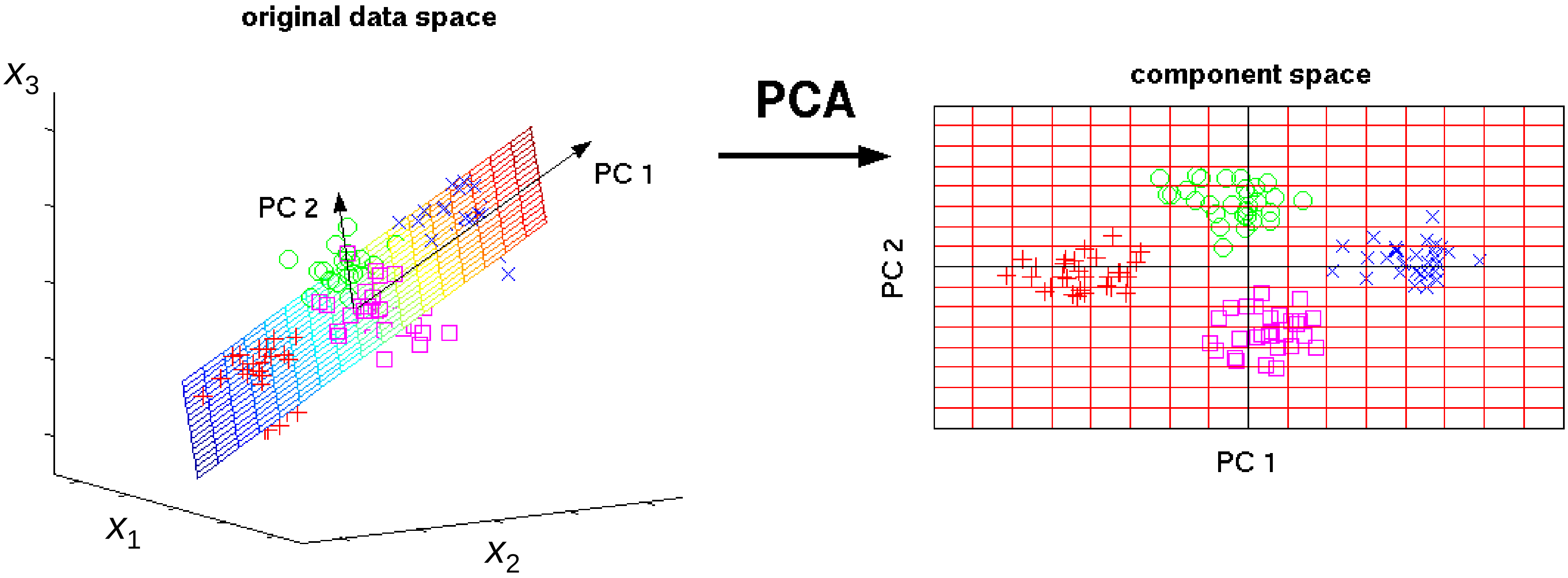


$$\vec{\hat{x}}^{nc} \neq \vec{x}^{obs}$$

PCA: What is it?

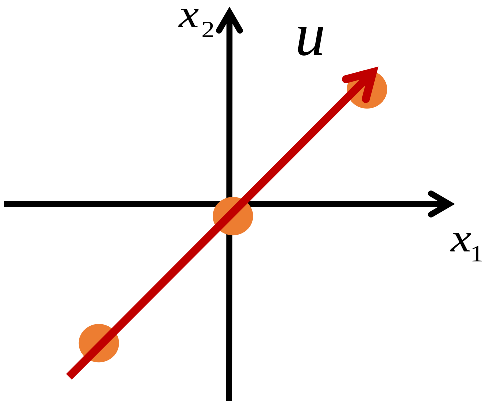
PCA:

- Space transformation
- From an *n*-dimensional space to a l-dimensional space ($l < n$)
- Retaining most of the information (loosing the least information)



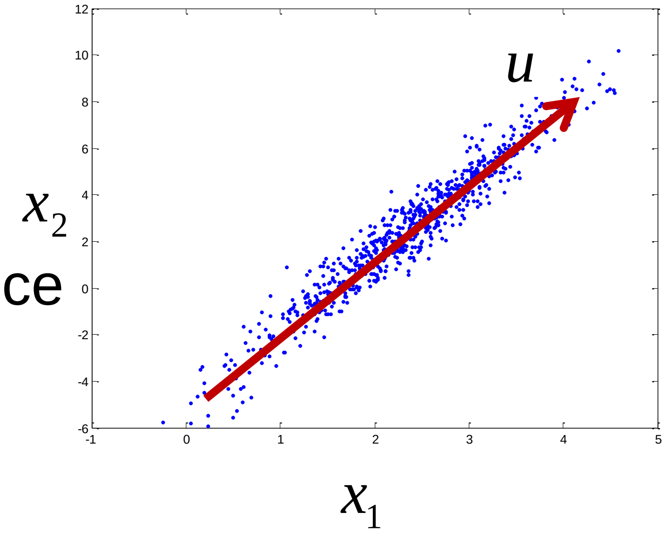
IDEA OF PCA

- Two signals are highly correlated or dependent
  ➔One is enough!



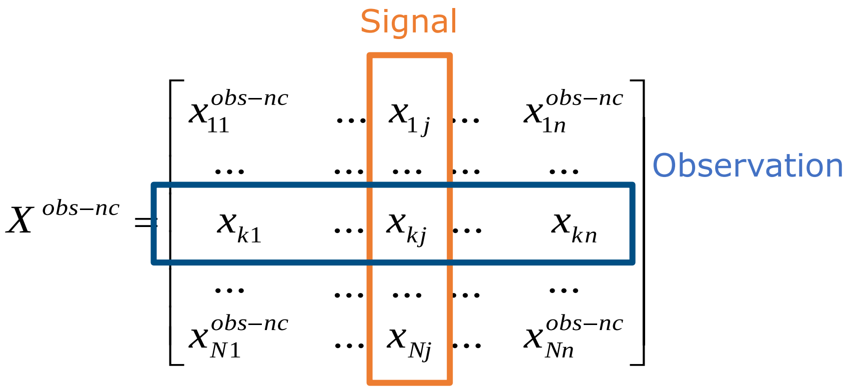
$$X = \begin{bmatrix} 1 & 1 \\ 0 & 0 \\ -1 & -1 \end{bmatrix}$$

- Key underlying phenomena
  ➔ Areas of variance in data
  ➔ Focus on directions along which the observations have largest variance



PCA: Training set, input and output = Slide 25

- Training patterns:
  Historical signal measurements
  in normal condition



$$X^{obs-nc} = \begin{bmatrix} x_{11}^{obs-nc} & \dots & x_{1j} & \dots & x_{1n}^{obs-nc} \\ \dots & \dots & \dots & \dots & \dots \\ x_{k1} & \dots & x_{kj} & \dots & x_{kn} \\ \dots & \dots & \dots & \dots & \dots \\ x_{N1}^{obs-nc} & \dots & x_{Nj} & \dots & x_{Nn}^{obs-nc} \end{bmatrix}$$

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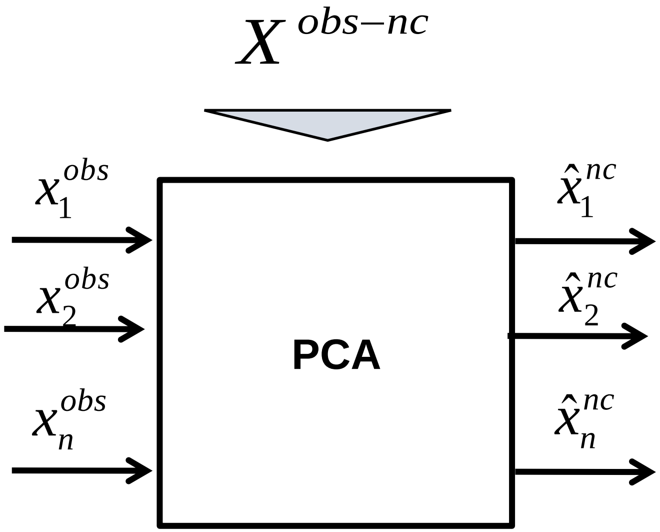


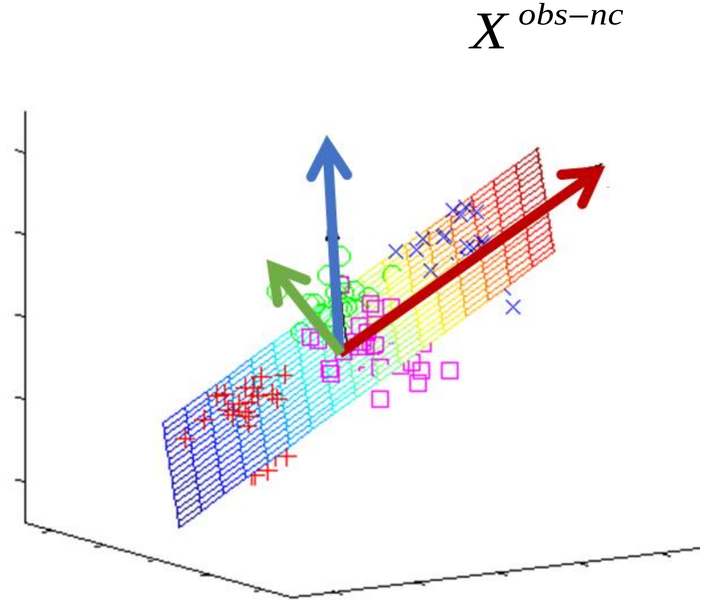
PCA for fault detection: operational steps (1)

Step 1: find Principal Components (PCs) in the training set X^{obs-nc}:

1) PC1 →
is the direction of maximum variance

2) PC2 →
is **orthogonal** to PC1 and describes the maximum residual variance

3) PC3 →
is **orthogonal** to PC1 and PC2 and describes the maximum residual variance



Step 1: Mathematical details (1A)

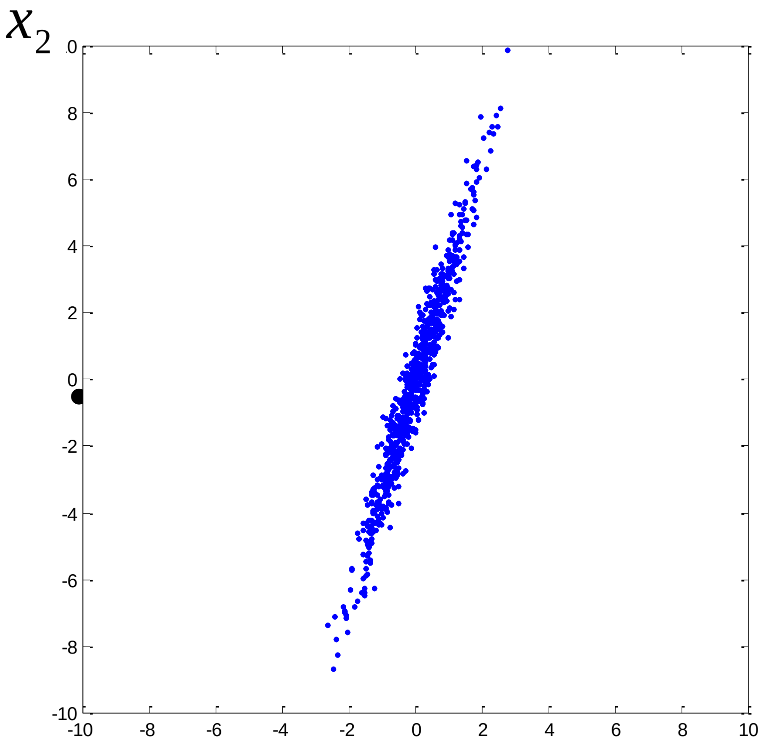
Objective: find principal components

Procedure:

- Compute V = covariance matrix of X^{obs-nc}

$$V = \left(X^{obs-nc} - \overline{X}^{obs-nc}\right)^T \left(X^{obs-nc} - \overline{X}^{obs-nc}\right)$$

Empirical
mean
matrix



x_1

$$\sum_{i=1}^{N} \left(x_{i1} - \bar{x}_i\right)^2$$

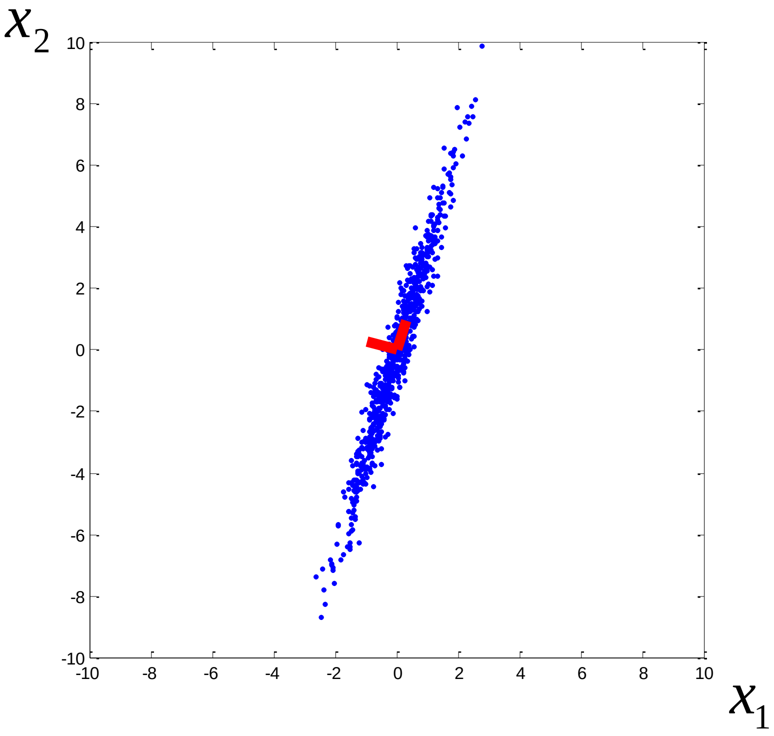
$$V = \begin{pmatrix} 0.79 & 2.55 \\ 2.55 & 8.75 \end{pmatrix}$$

Step 1: Mathematical Details (1B)

Objective: find principal components

Procedure:

- Compute V = covariance matrix of X^{obs-nc}
- Find the n eigenvectors $\vec{p}_1, \vec{p}_2, \ldots, \vec{p}_n$ of V and the corresponding eigenvalues $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \cdots \geq \lambda_n$



$$V\vec{p} = \lambda\vec{p}$$

λ_1=9.50 largest

λ_2=0.04 smallest

$$\vec{p}_1 = \begin{bmatrix} 0.28 & 0.96 \end{bmatrix}^T$$

$$\vec{p}_2 = \begin{bmatrix} -0.96 & 0.28 \end{bmatrix}^T$$

Step 1: Properties of the PCs (I)

$$P = [\vec{p}_1, \vec{p}_2] = \begin{bmatrix} 0.28 & -0.96 \\ 0.96 & 0.28 \end{bmatrix}$$

- *P* is an orthonormal basis:

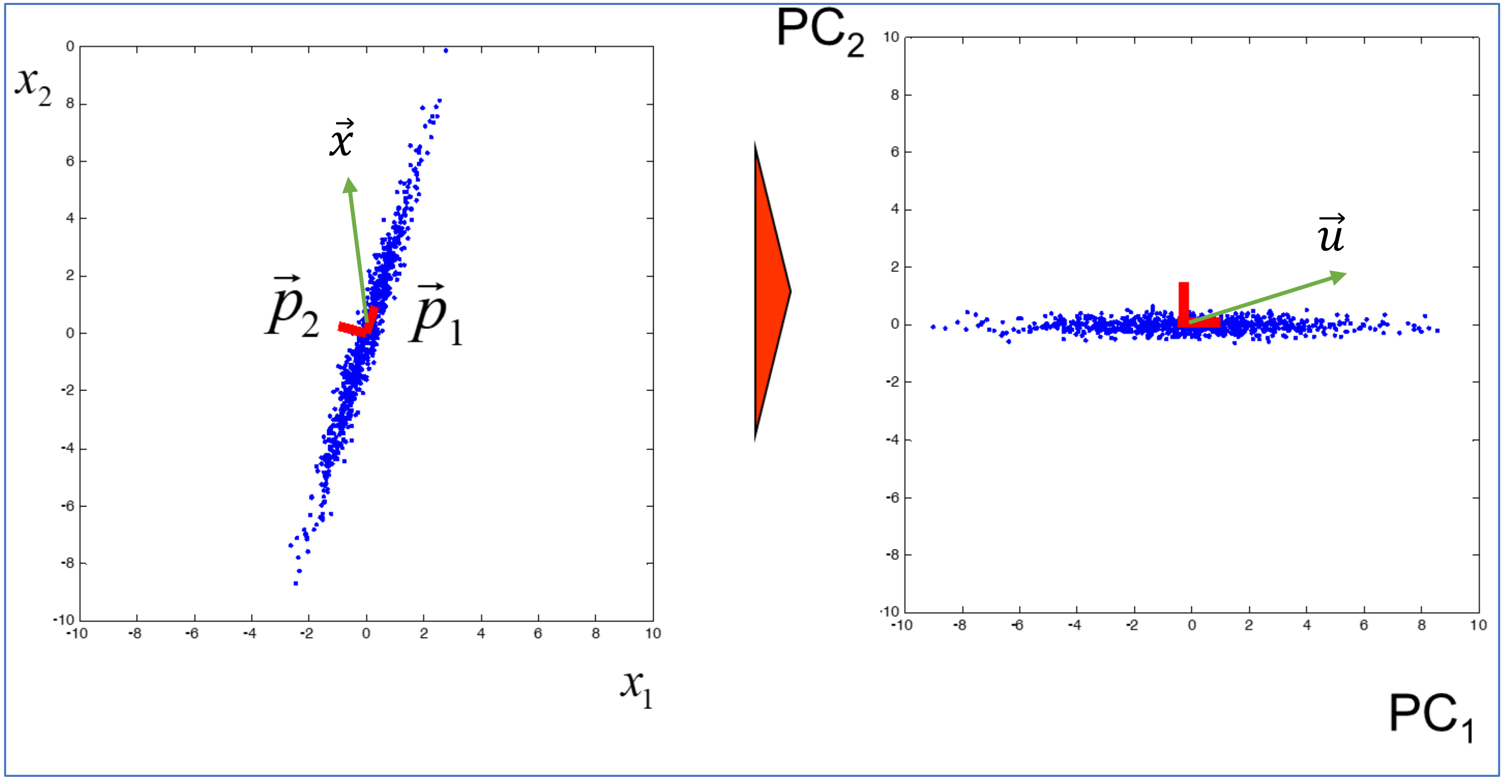
$$\vec{p}_i \perp \vec{p}_j \qquad \forall i \neq j$$

$$|\vec{p}_i| = 1$$

$$PP^T = I$$

Step 1: Properties of the PCs (II)

- *P* is an orthonormal basis:
- Data can be transformed from the original to the transformed bases and viceversa without any loss of information (multiplication for *P* and P^T)
  - $\vec{u}$ = the projection of $\vec{x}$ on the new basis is given by: $\vec{u} = \vec{x} \cdot P$



Step 1: Properties of the PCs (III)

- *P* is an orthonormal basis:
- Data can be transformed from the original to the transformed bases and viceversa without any loss of information (multiplication for *P* and P^T)
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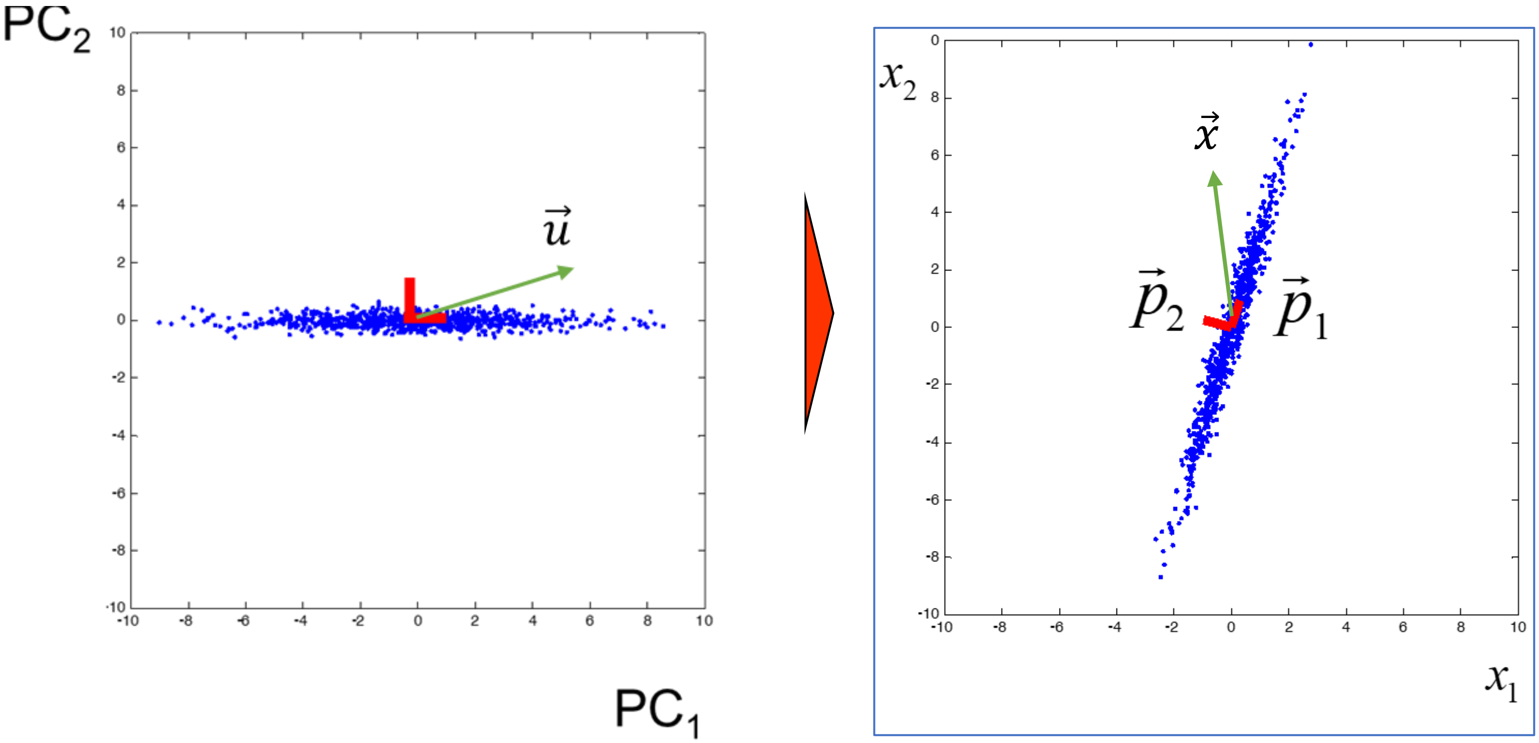
  - $\vec{x}$ can be obtained from $\vec{u}$ by: $\vec{x} = \vec{u} \cdot P^T$



Step 1: Properties of the PCs (III)

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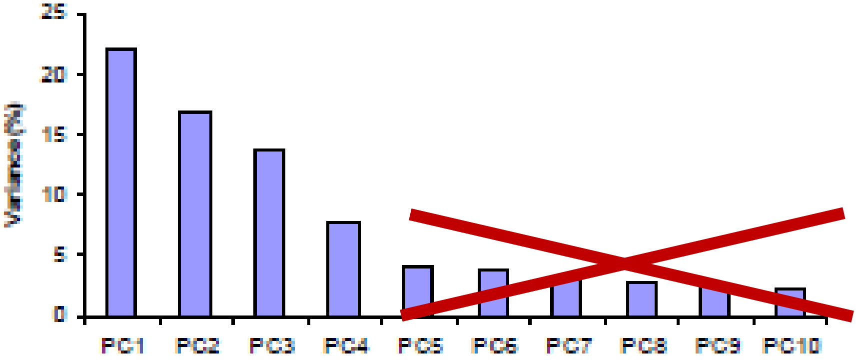
  - $\vec{x}$ can be obtained from $\vec{u}$ by: $\vec{x} = \vec{u} \cdot P^T$
- The percentage of variance retained by the *i*-th principal component is:

$$\%Var\left(PC_i\right) = \frac{\lambda_i}{\sum\limits_{i=1,\dots,n} \lambda_i}$$

PCA for fault detection: operational steps (1)

Step 2 [PCA approximation]: ignore the PCs of lower significance.



- Lost small information
- Reduce the number of dimensions from n=10 to = 4

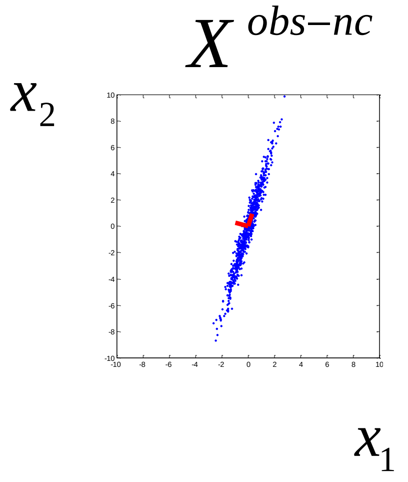
PCA for fault detection: operational steps (2)

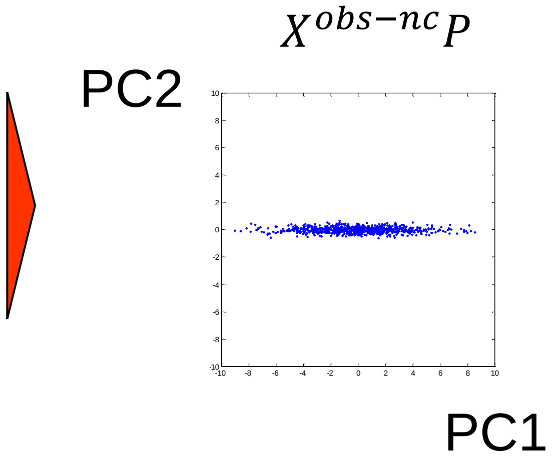
- Step 2 [PCA approximation]: ignore the PCs of lower significance.

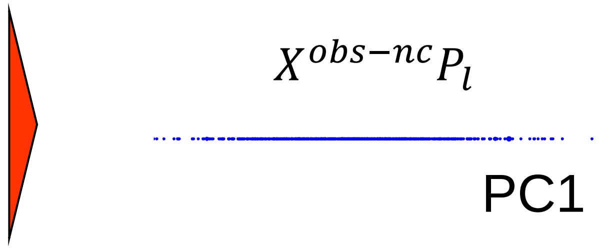
map the observation $\vec{x}^{obs}$ in a subspace $\Re^{l} \subset \Re^{n}$ identified by the first l< n eigenvectors $\vec{p}_1, \dots, \vec{p}_l$:

$\vec{x}^{obs} P_l$ with $P_l = [\vec{p}_1, \dots, \vec{p}_l]$

Example of application to the normal condition data: X^{obs-nc}







We consider only the directions that are most meaningful in normal condition (directions of maximum variance)

PCA for fault detection: operational steps (3)

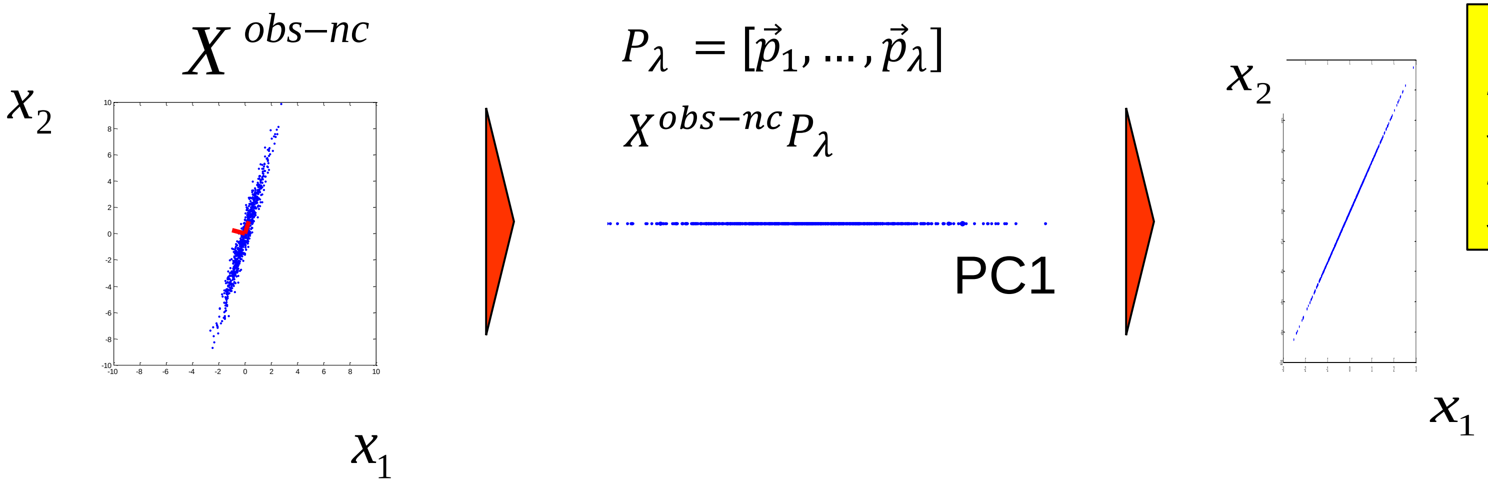
- Step 2 [PCA approximation]: ignore the PCs of lower significance.

map the observation $\vec{x}^{obs}$ in a subspace $\Re^l \subset \Re^n$ identified by the first $\mathrm{l} < n$ eigenvectors $\vec{p}_1, \ldots, \vec{p}_l$:

$$\vec{x}^{obs} P_l \quad \text{with } P_l = [\vec{p}_1, \ldots, \vec{p}_l]$$

- Step 3: [Antitransformation]: signal reconstructions $\hat{\vec{x}}^{nc} = \vec{x}^{obs} P_l \, P_l^T$

Example of application to the normal condition data: X^{obs-nc}



X^{obs-nc}

$P_\lambda = [\vec{p}_1, \ldots, \vec{p}_\lambda]$

$X^{obs-nc} P_\lambda$

We loose the noise in the space of the measured signals

PCA for fault detection: Summary

- Historical data $X^{obs-nc} = \begin{bmatrix} x_{11}^{obs-nc} & \dots & x_{1j} & \dots & x_{1n}^{obs-nc} \\ \dots & \dots & \dots & \dots & \dots \\ x_{k1} & \dots & x_{kj} & \dots & x_{kn} \\ \dots & \dots & \dots & \dots & \dots \\ x_{N1}^{obs-nc} & \dots & x_{Nj} & \dots & x_{Nn}^{obs-nc} \end{bmatrix}$

Find P_l from X^{obs-nc}

PCA for fault detection: Summary

- Historical data $X^{obs-nc} = \begin{bmatrix} x_{11}^{obs-nc} & \dots & x_{1j} & \dots & x_{1n}^{obs-nc} \\ \dots & \dots & \dots & \dots & \dots \\ x_{k1} & \dots & x_{kj} & \dots & x_{kn} \\ \dots & \dots & \dots & \dots & \dots \\ x_{N1}^{obs-nc} & \dots & x_{Nj} & \dots & x_{Nn}^{obs-nc} \end{bmatrix}$ Find P_l from X^{obs-nc}

- Measured signals at present time: $\vec{x}^{obs} = (x_1^{obs}, \dots, x_n^{obs})$

  - Transform and project $\vec{x}^{obs} P_l$

I'm looking at the measurements considering only the directions that are most meaningful in normal condition (directions of maximum variance)

  - Antitrnansform $\hat{\vec{x}}^{nc} = \vec{x}^{obs} P_l P_l^T$ Signal reconstructions

$\hat{\vec{x}}^{nc} \cong \vec{x}^{obs}$ → normal condition

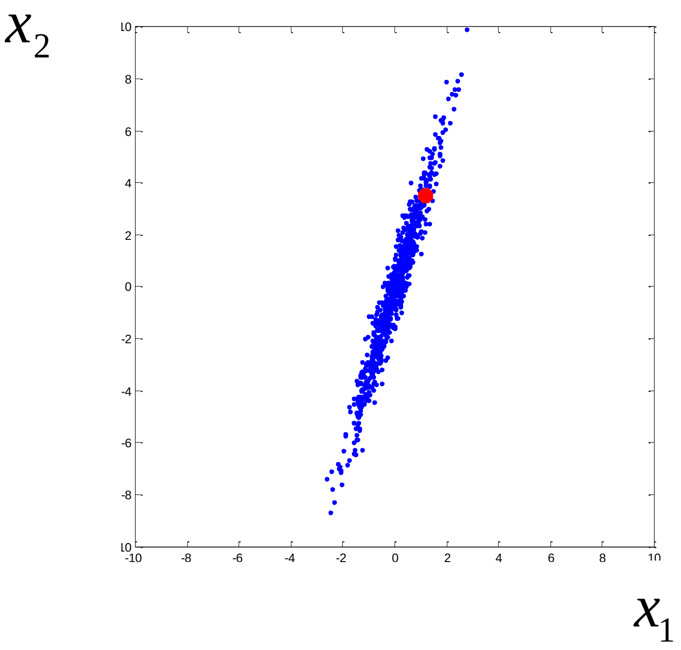
I loose only the irrelevant noise

$\hat{\vec{x}}^{nc} \neq \vec{x}^{obs}$ → abnormal condition

The process is changed

Exercise 1

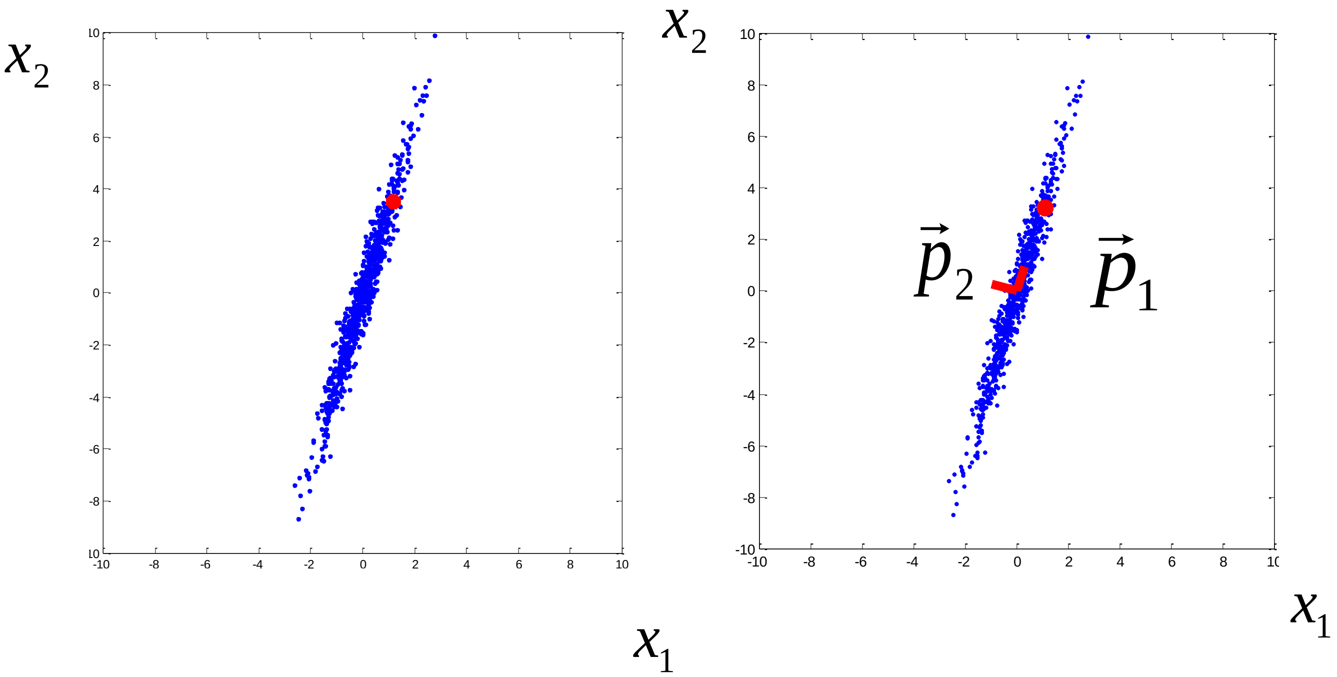
- Measured signals at present time: $\vec{x}^{obs} = (x_1^{obs}, x_2^{obs})$ ●
- Signal reconstructions?
- Normal or abnormal condition?



- available historical signal measurements in normal plant condition

Exercise 1: Solution

- Measured signals at present time: $\vec{x}^{obs} = (x_1^{obs}, x_2^{obs})$ ●
- Step 1: find principal components: $\vec{p}_1$, $\vec{p}_2$



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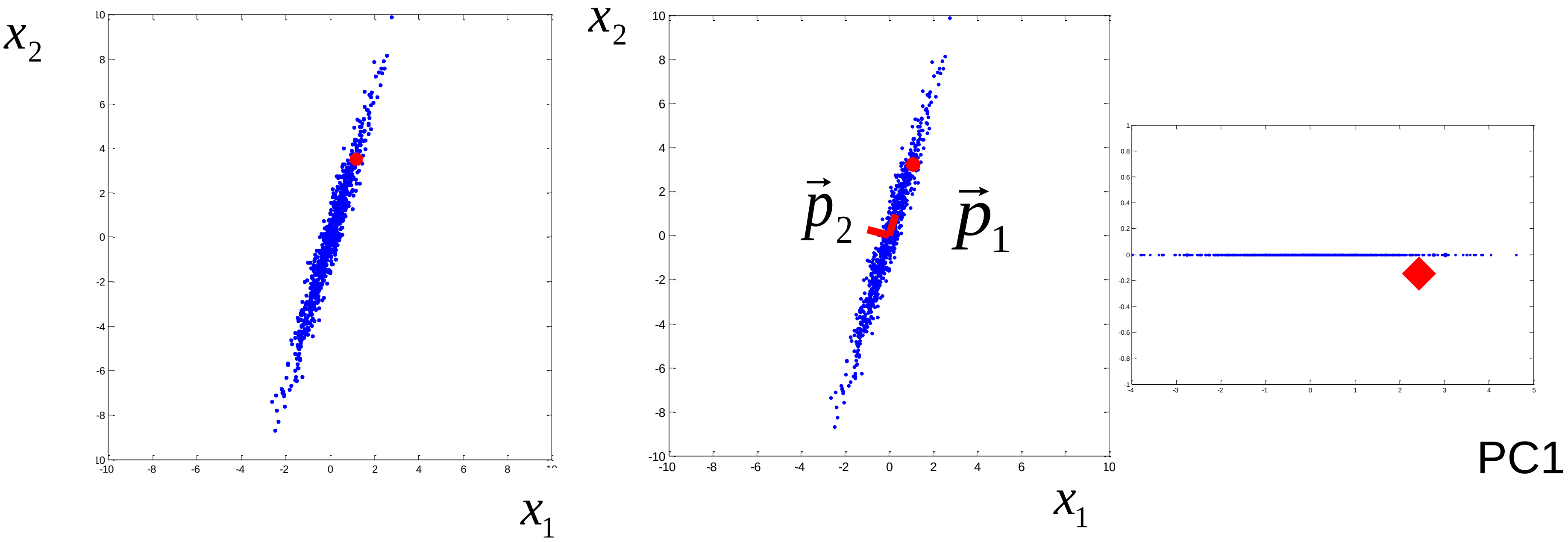
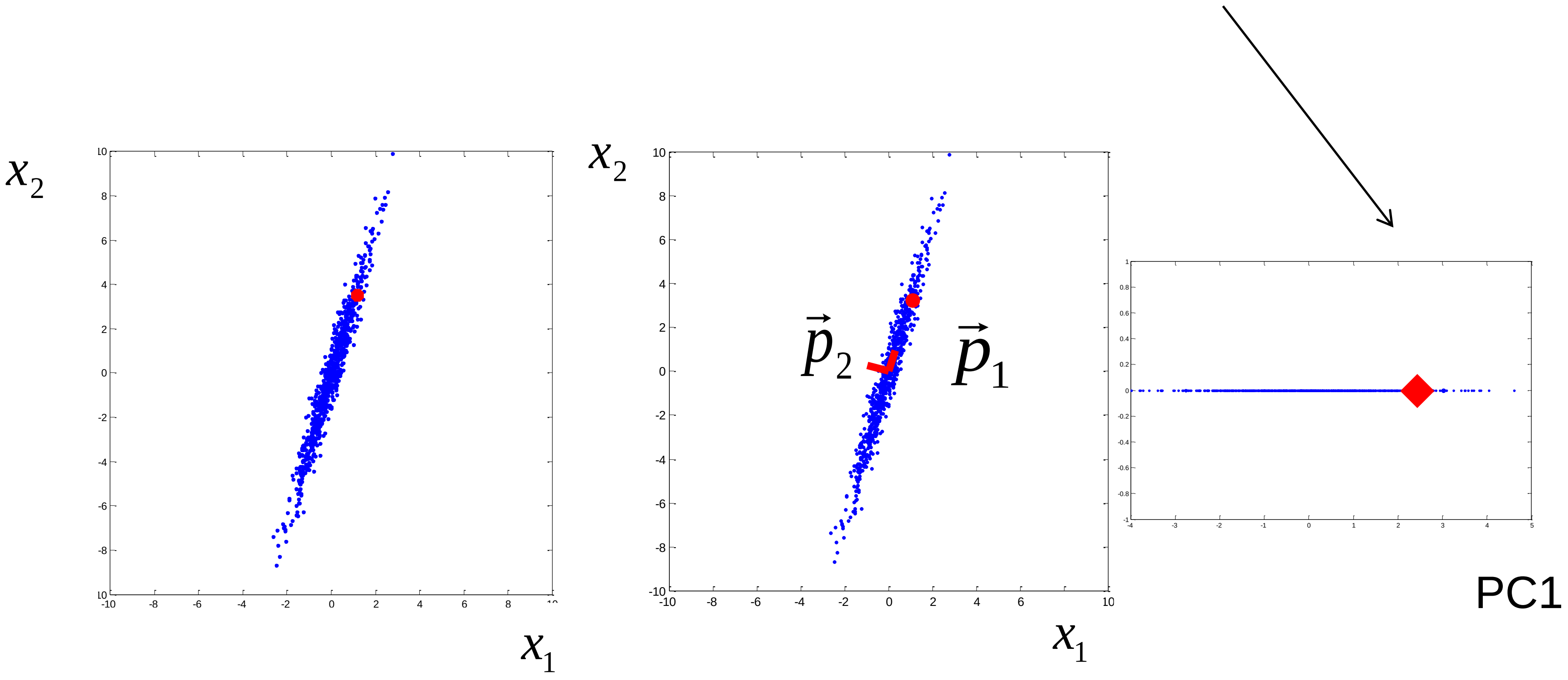


Exercise 1: Solution

- Measured signals at present time: $\vec{x}^{obs} = (x_1^{obs}, x_2^{obs})$ ●
- Step 1: find principal components $\vec{p}_1 , \vec{p}_2$
- Step 2 (PCA approximation): keep only 1 PC of ● ,i.e. $\vec{x}^{obs} \cdot \vec{p}_1$



Exercise 1: Solution

- Measured signals at present time: $\vec{x}^{obs} = (x_1^{obs}, x_2^{obs})$ ●
- Step 1: find principal components
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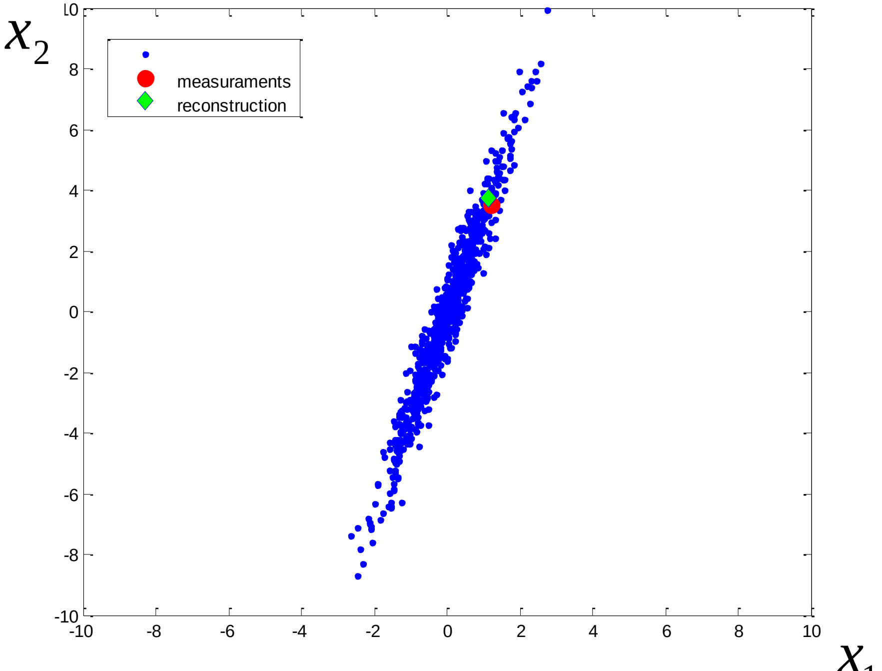
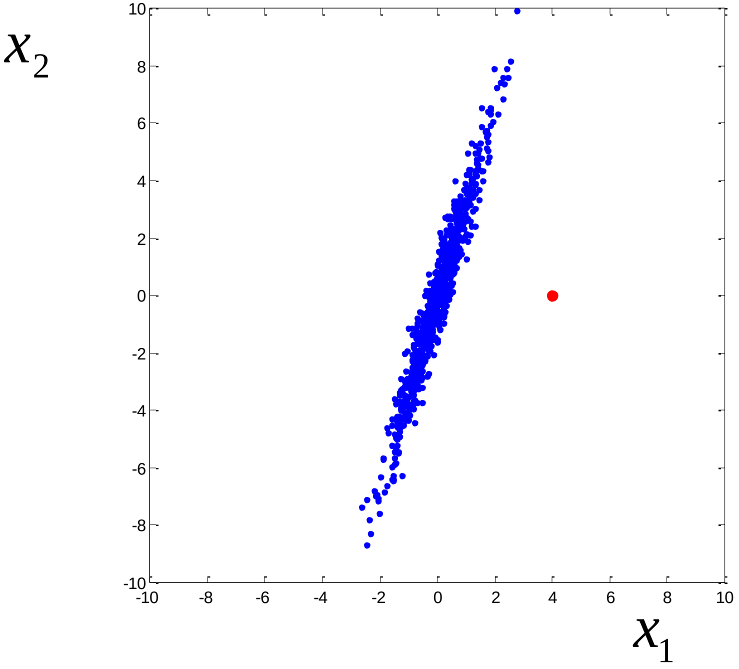
- Step 3 (antitransform): $\hat{\vec{x}}^{nc} = \vec{x}^{obs} P_l P_l^T$ ◆



$\vec{x}^{obs} \cong \hat{\vec{x}}^{nc}$ ➡ normal condition

Exercise 2

- Measured signals at present time: $\vec{x}^{obs} = (x_1^{obs}, x_2^{obs})$ ●
- Signal reconstructions?
- Normal or abnormal condition?



- available historical signal measurements in normal plant condition

Exercise 2: Solution

- Measured signals at present time: $\vec{x}^{obs} = (x_1^{obs}, x_2^{obs})$ ●
- Step 1: find principal components $\vec{p}_1$ $\vec{p}_2$
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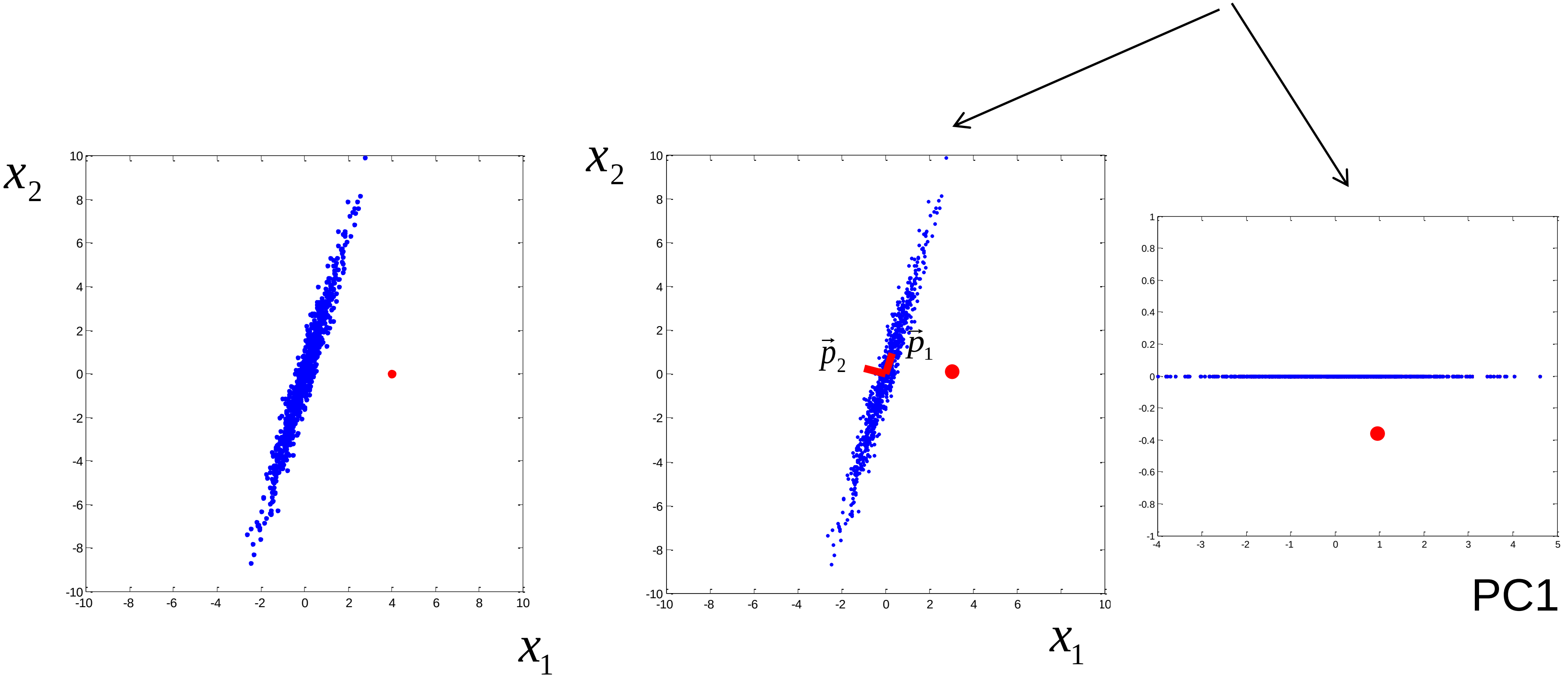
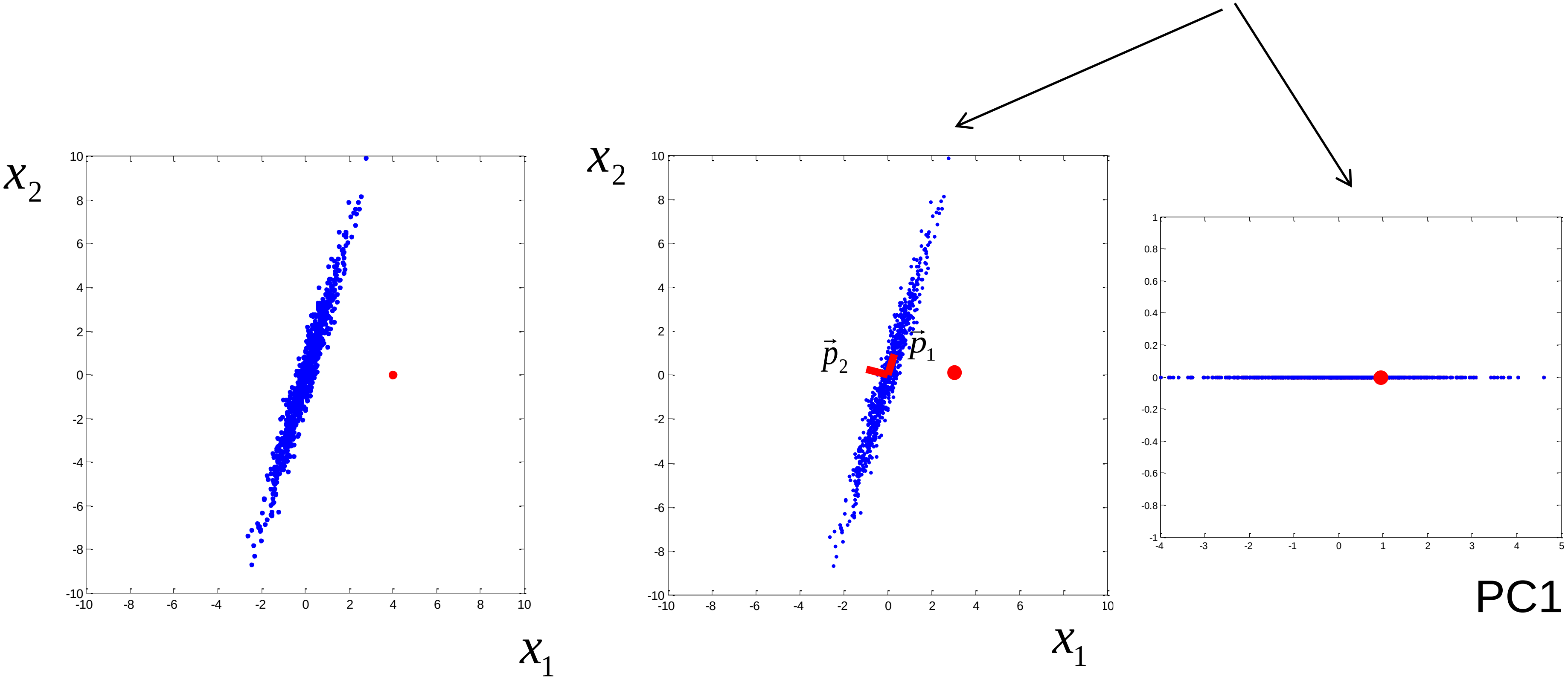


Exercise 2: Solution

- Measured signals at present time: $\vec{x}^{obs} = (x_1^{obs}, x_2^{obs})$ ●
- Step 1: find principal components $\vec{p}_1 \; \vec{p}_2$
- Step 2 (PCA approximation): keep only 1 PC of ● ,i.e. $\vec{x}^{obs} \cdot \vec{p}_1$



Exercise 2: Solution

- Measured signals at present time: $\vec{x}^{obs} = (x_1^{obs}, x_2^{obs})$ ●
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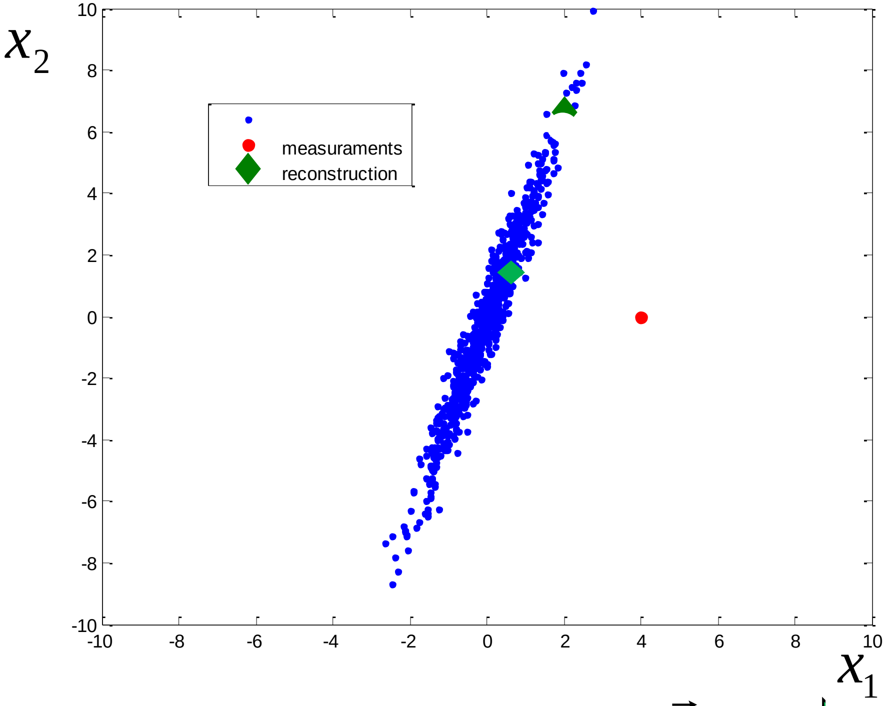
- Step 3 (antitransform): $\hat{\vec{x}}^{nc} = \vec{x}^{obs} P_l P_l^T$ ◆



$\vec{x}^{obs} \neq \hat{\vec{x}}^{nc}$ → Abnormal condition

PCA remarks: computational time

Computational time:

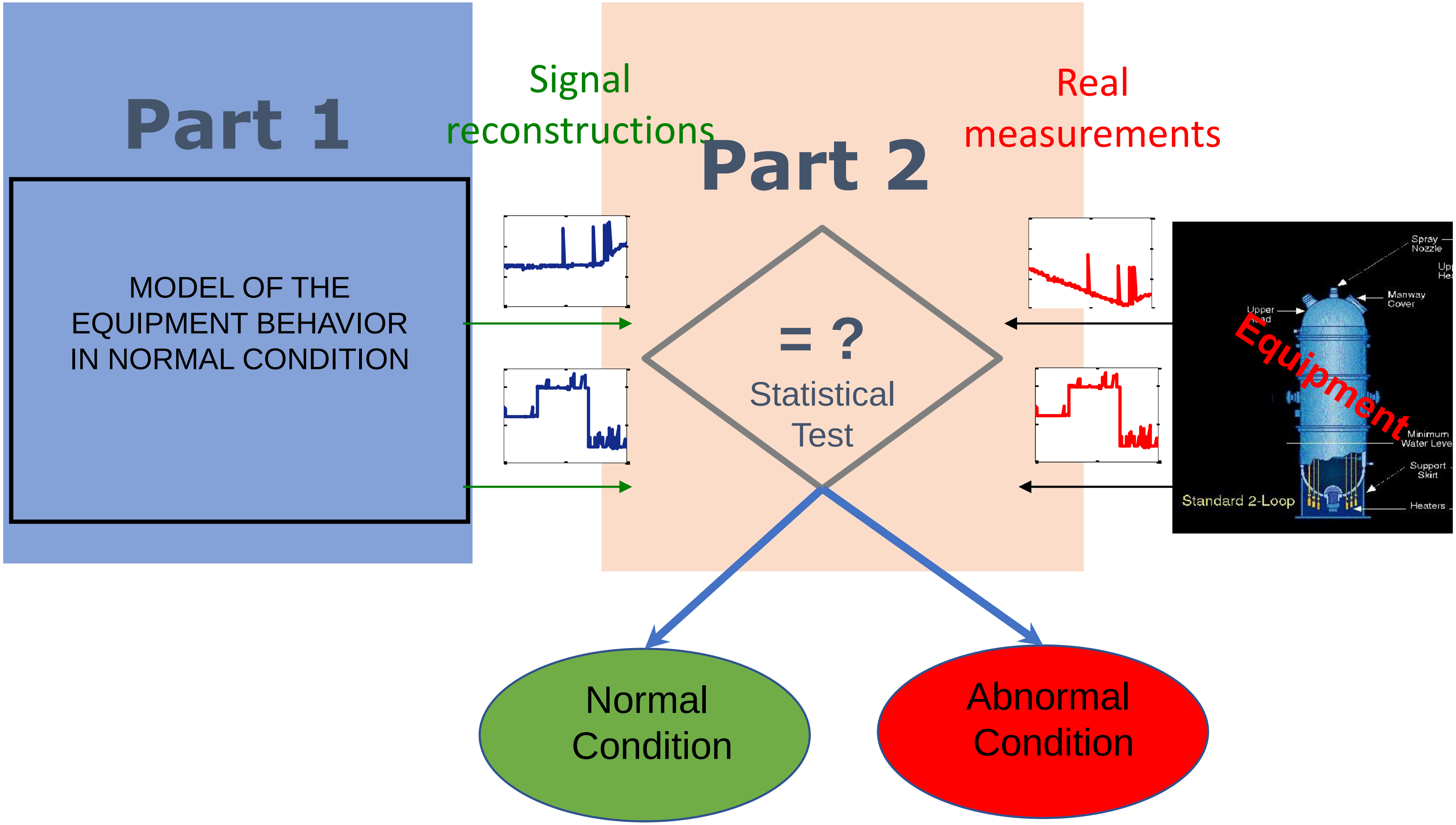
- Training time = computational time necessary to find the Principal Components is proportional to the number of measured signals n
- Execution time: very short (only 2 matrix multiplications) → OK for online applications

PCA remarks: complex structure

Performance:

Unsatisfactory for dataset characterized by highly non-linear relationships

Part 2: Statistical Test



Part 1

MODEL OF THE EQUIPMENT BEHAVIOR IN NORMAL CONDITION

Signal reconstructions

Part 2

Real measurements

= ?

Statistical Test

Equipment

Normal Condition

Abnormal Condition

In This Lecture

- Part 1: Model of the Equipment Behavior in Normal Condition
  - Principal Component Analysis (PCA)
- **Part 2: Statistical Test**
  - 2A) Thresholds-Based
  - 2B) Sequential Probability Ratio Test (SPRT)

PART 2: Statistical Test

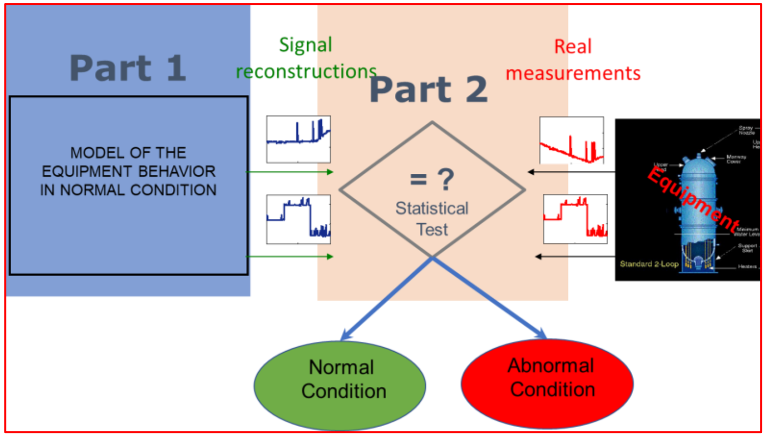
- Thresholds-based
- Sequential Probability Ratio Test (SPRT)

Abnormal condition detection: decision

- Basics of the decision: residual analysis

$$\vec{r} = \vec{x}^{obs} - \hat{\vec{x}}^{nc}$$

$$\begin{cases} \vec{r} \approx 0 \rightarrow & \text{Normal condition} \\ \vec{r} \neq 0 \rightarrow & \text{Abnormal condition} \end{cases}$$



Part 1

MODEL OF THE EQUIPMENT BEHAVIOR IN NORMAL CONDITION

Signal reconstructions

Part 2

Real measurements

= ?

Statistical Test

Equipment

Normal Condition

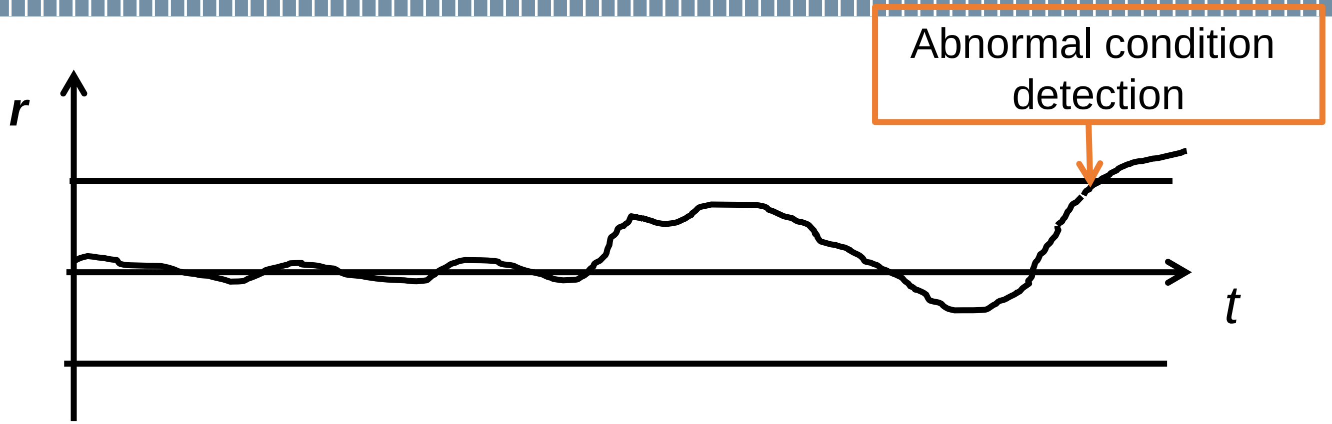
Abnormal Condition

- Methods
  - Thresholds-based approach
  - Stochastic approaches:
    - Q Statistics
    - Sequential Probability Ratio Test (SPRT)

PART 2 A: Statistical Test

- **Thresholds-based**
- Sequential Probability Ratio Test (SPRT)

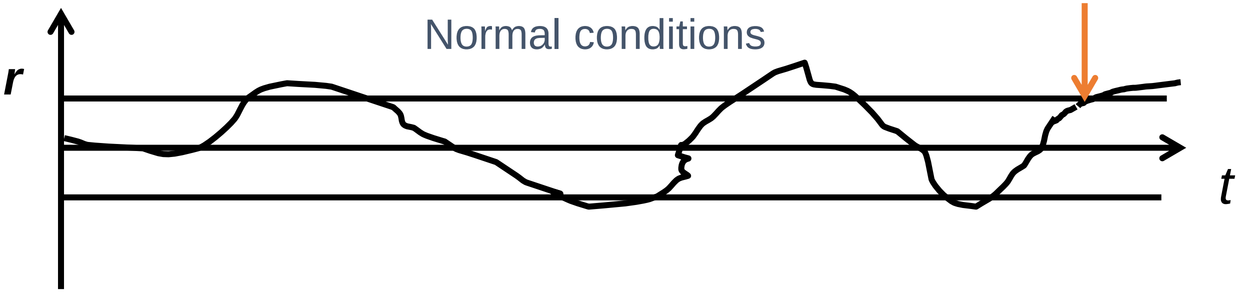
Thresholds-based



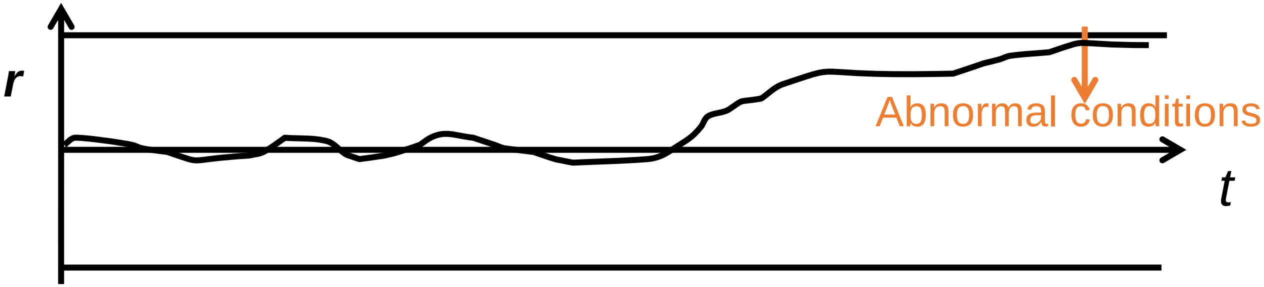
Thresholds-Based: Remarks

- Easy to apply
- Thresholds setting is difficult and error-prone

Too small thresholds → high false alarm rates (α)



Too large thresholds → high missing alarm rates (β)



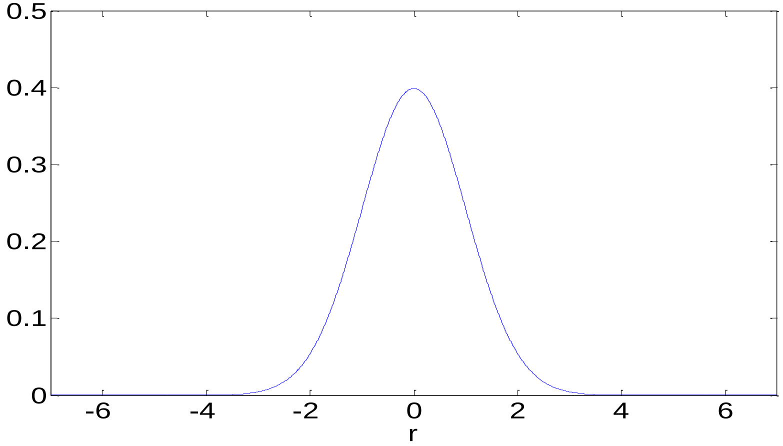
PART 2 B: Statistical Test

- General Idea
- **Sequential Probability Ratio Test (SPRT)**

Stochastic approaches

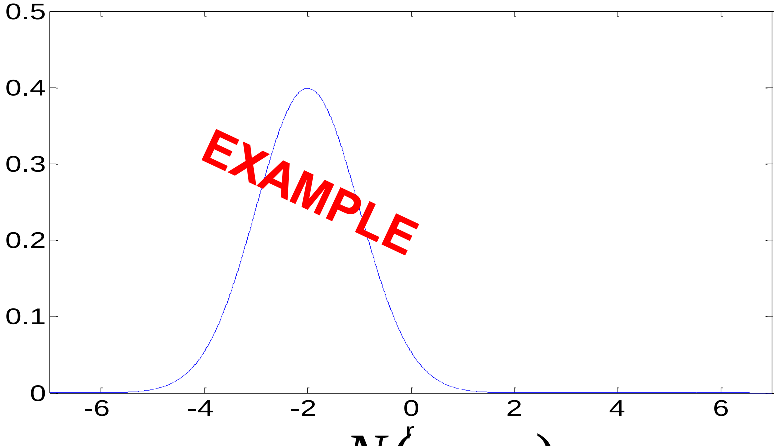
- Residual (*r*)= **random variable** described by a probability law
- The probability law is different in case of normal/abnormal condition

Normal condition



$$r \sim N(0,\sigma)$$

Abnormal condition

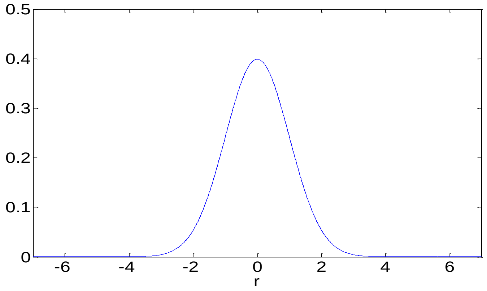


$$r \sim N(\mu_1,\sigma)$$

SPRT

- $R_T = \{r^{(1)}, \dots, r^{(T)}\}$ sequence of residuals at time $t = 1, \dots T$, where $r^{(t)} = x^{obs}(t) - \hat{x}^{nc}(t)$
- Binary hypothesis test:
  - Null hypothesis (H_0) ≡ Normal condition

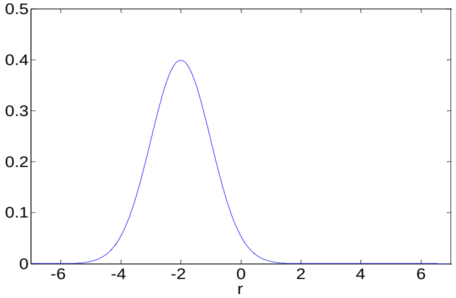
$$r^{(t)} \sim \mathcal{N}(0, \sigma), \forall t$$



$$f_0(r) \equiv N(0, \sigma)$$

  - Alternative hypothesis (H_1) ≡ Abnormal condition

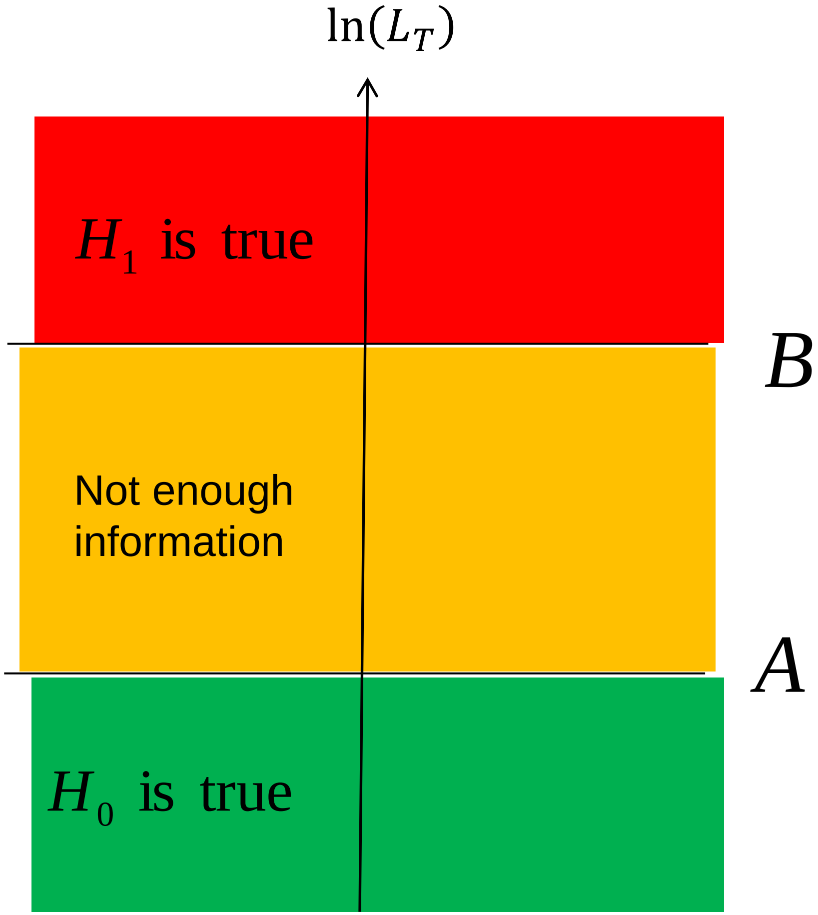
$$r^{(t)} \sim \mathcal{N}(\mu_1, \sigma), \forall t$$



$$f_1(r) \equiv N(\mu_1, \sigma)$$

SPRT: the decision

$$L_T = \frac{P\{R_T|H_1 \text{is true}\}}{P\{R_T|H_0 \text{is true}\}} = \frac{f_1\left(r^{(1)}\right) \cdot f_1\left(r^{(2)}\right) \cdot \ldots \cdot f_1\left(r^{(T)}\right)}{f_0\left(r^{(1)}\right) \cdot f_0\left(r^{(2)}\right) \cdot \ldots \cdot f_0\left(r^{(T)}\right)}$$



$\ln(L_T)$

H_1 is true

B

Not enough information

A

H_0 is true

SPRT Theorem

$$B = \ln \frac{1-\beta}{\alpha}$$

$$A = \ln \frac{\beta}{1-\alpha}$$

False alarm

$$P\left\{D_1 \mid H_0 \text{ is true}\right\} \le \alpha$$

$$P\left\{D_0 \mid H_1 \text{ is true}\right\} \le \beta$$

Missing alarm

SPRT for the positive mean test

- Null hypothesis (H_0) ≡ Normal condition $r^{(t)} \sim \mathcal{N}(0, \sigma)$
- Alternative hypothesis (H_1) ≡ Abnormal condition $r^{(t)} \sim \mathcal{N}(\mu_1, \sigma)$

$$L_T = \frac{P(r^{(1)}, \dots, r^{(T)} | H_1)}{P(r^{(1)}, \dots, r^{(T)} | H_0)} = e^{-\frac{1}{2\sigma^2} \sum_{t=1}^{T} \mu_1 (\mu_1 - 2r^{(t)})} = e^{\frac{\mu_1}{\sigma^2} \sum_{t=1}^{T} \left(r^{(t)} - \frac{\mu_1}{2}\right)}$$

$$\Downarrow$$

$$\ln(L_T) = \frac{\mu_1}{\sigma^2} \sum_{t=1}^{T} \left(r^{(t)} - \frac{\mu_1}{2}\right) = \frac{\mu_1}{\sigma^2} \sum_{t=1}^{T-1} \left(r^{(k)} - \frac{\mu_1}{2}\right) + \frac{\mu_1}{\sigma^2} \left(r^{T} - \frac{\mu_1}{2}\right)$$

$$= \ln(L_{T-1}) + \frac{\mu_1}{\sigma^2} \left(r^{(T)} - \frac{\mu_1}{2}\right)$$

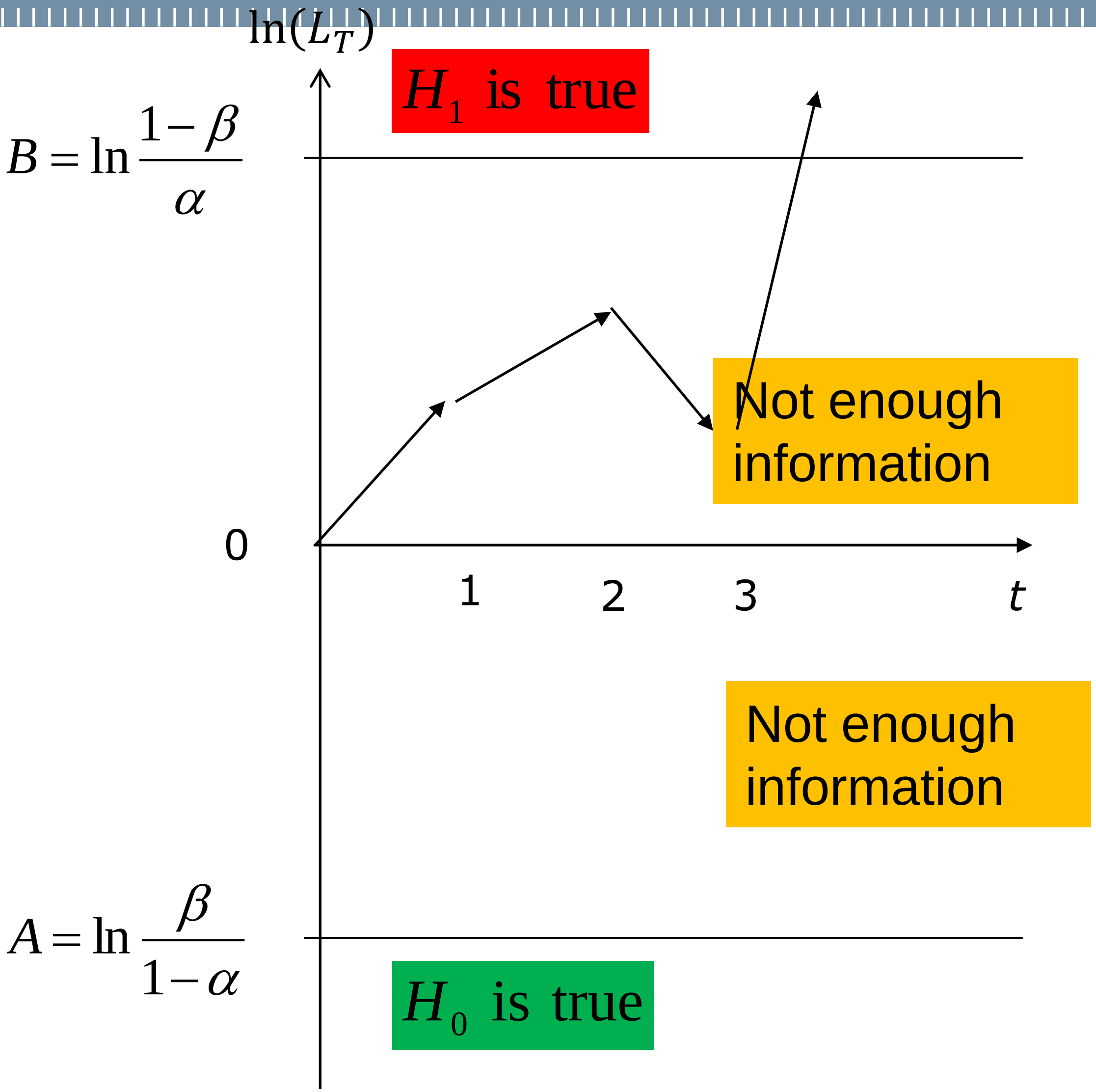
Sequential Formula!

SPRT: Example

$$L_0 = 1 \rightarrow \ln(L_0) = 0$$

$$\ln(L_1) = \ln(L_0) + \frac{\mu_1}{\sigma^2}\left(r^{(1)} - \frac{\mu_1}{2}\right)$$

$$\ln(L_2) = \ln(L_1) + \frac{\mu_1}{\sigma^2}\left(r^{(2)} - \frac{\mu_1}{2}\right)$$

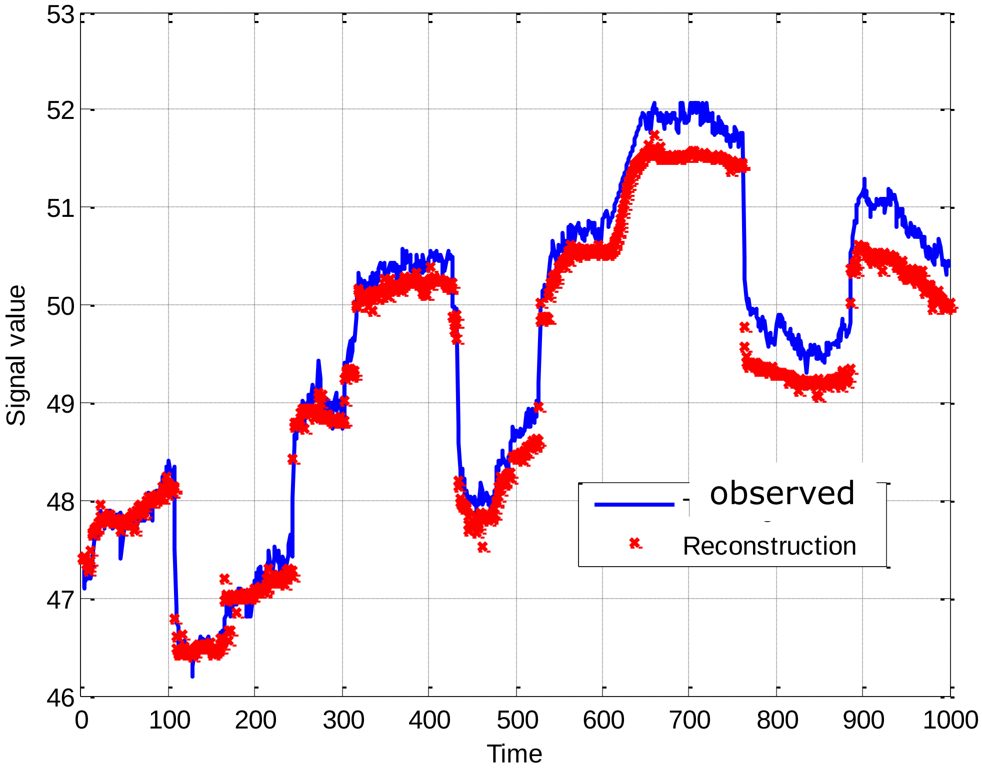


SPRT: parameters to be set

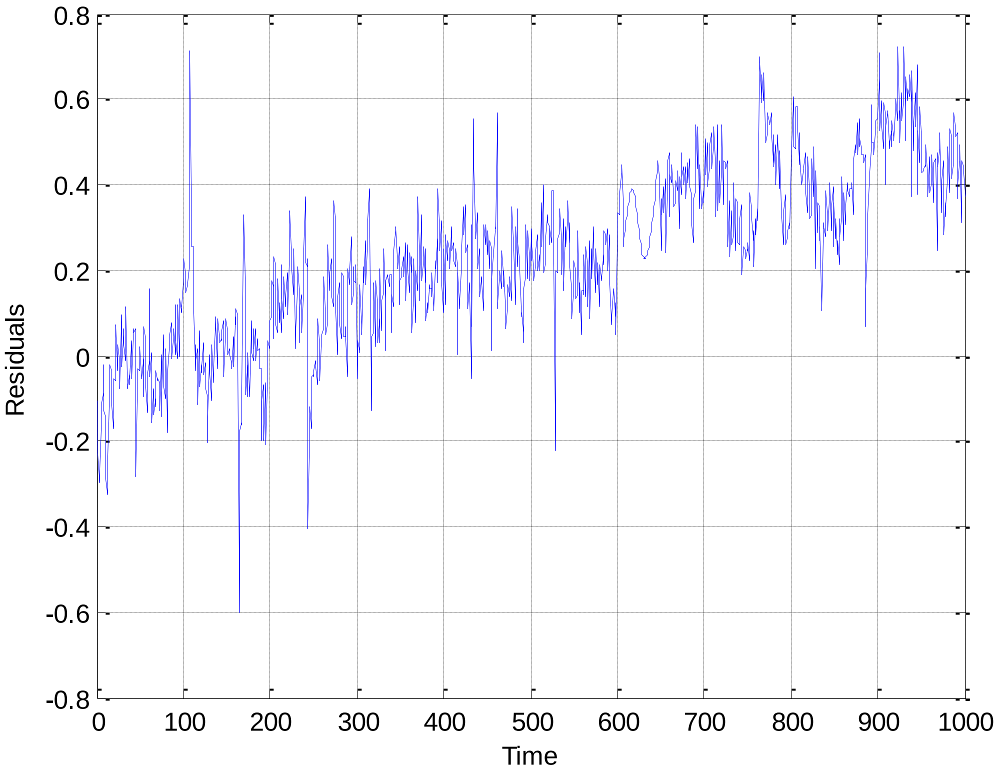
- the residual variance in normal condition (σ^2)
- the expected offset amplitude (μ_1)
- the maximum acceptable false alarm rate (α)
- the maximum acceptable missing alarm rate (β)

Example

Time interval	Simulated Offset
[0-200]	No
[201-400]	Yes (amplitude = 0.11)
[401-600]	Yes (amplitude = 0.23)
[601-800]	Yes (amplitude = 0.34)
[801-1000]	Yes (amplitude = 0.46)



Example: residuals



No offset

Maximum

offset

Example: SPRT

H_1 is true

Parameter	Value
α	0.01
B	0.01
μ_0	0
μ_1	0.46
σ^2	0.12

$$B = \ln \frac{1-\beta}{\alpha}$$

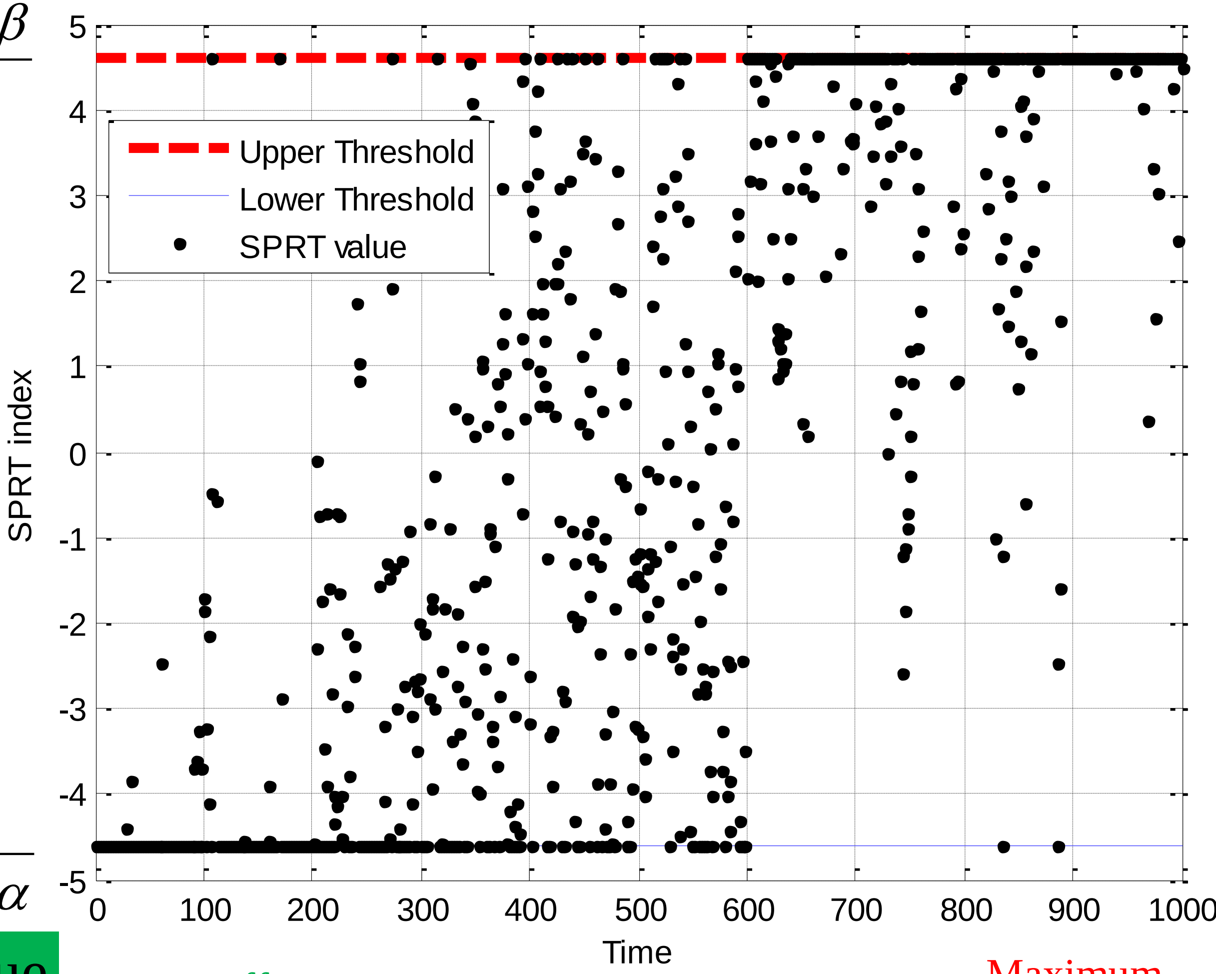
$$L_0 = 1 \rightarrow \ln(L_0) = 0$$

$$\ln(L_1) = \ln(L_0) + \frac{\mu_1}{\sigma^2}\left(r^{(1)} - \frac{\mu_1}{2}\right)$$

$$\ln(L_2) = \ln(L_1) + \frac{\mu_1}{\sigma^2}\left(r^{(2)} - \frac{\mu_1}{2}\right)$$

$$A = \ln \frac{\beta}{1-\alpha}$$

H_0 is true



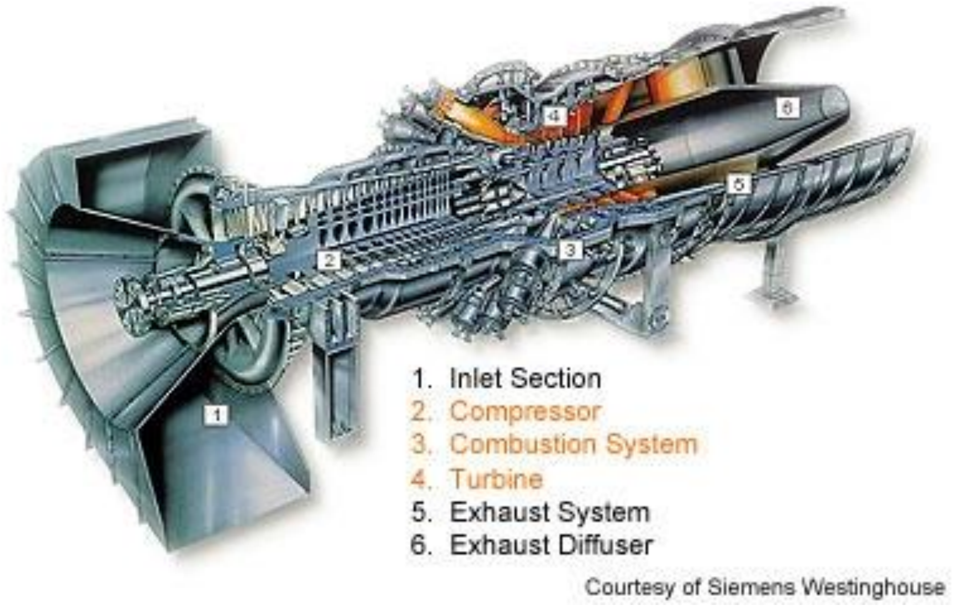
No offset

Maximum offset

Example of Applications

Example of Application 1

COMPONENT TO TO BE MONITORED GAS TURBINE

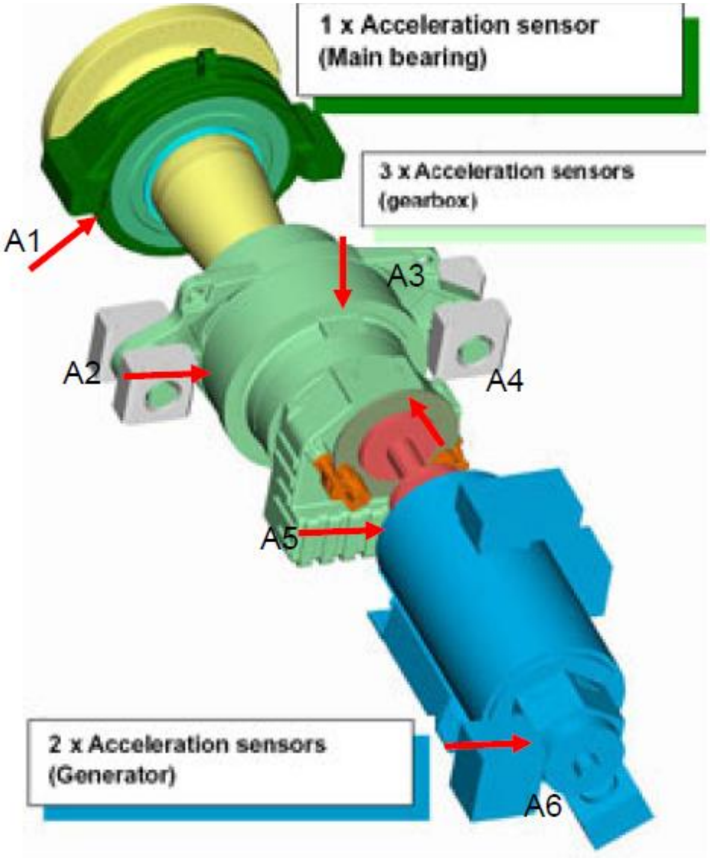


Courtesy of Siemens Westinghouse

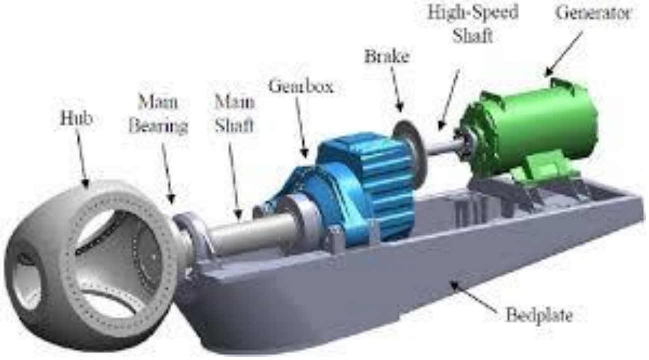
Measured Signals

Temperature location 1 (°C)
Temperature location 2 (°C)
Temperature location 3 (°C)
Temperature location 4 (°C)
Temperature location 5 (°C)
Temperature location 6 (°C)

Example of Application 2



Wind turbine farm

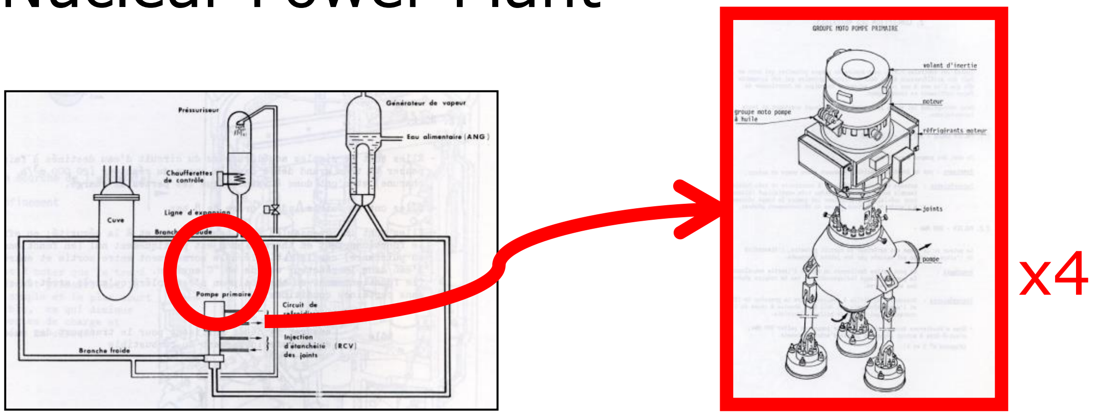


- Main Bearing+ Planetary Gear box + Gearbox + Generator
- **Monitoring system:** 6 accelerometers and 1 sensor measuring the rotating speed

Example of Application 3*

COMPONENT TO BE MONITORED

Reactor Coolant Pump of PWR Nuclear Power Plant



Measured signals	48 (Temperatures, pressures, flows,…)
Available data	Historical signal measurements in normal plant condition [1 year, frequency=1/30 Hz]

* Work developed with EDF-R&D