

# A Story On Anomaly Localisation

From Science to Data Science

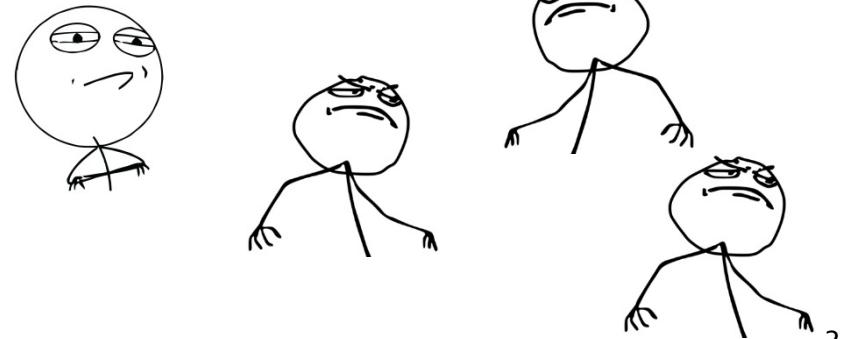
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# A true story...

THALES

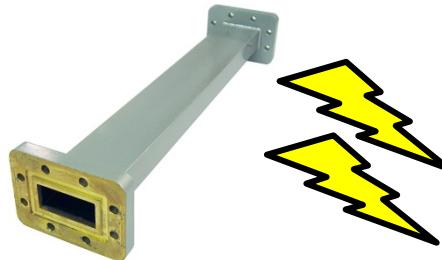


CHALLENGE ACCEPTED



# What was the problem ?

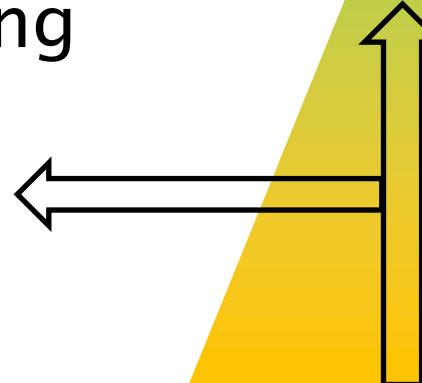
- ▶ A wave guide was exciting an electronic card



~10 vars



- ▶ Built-in tests: real-time monitoring and reporting

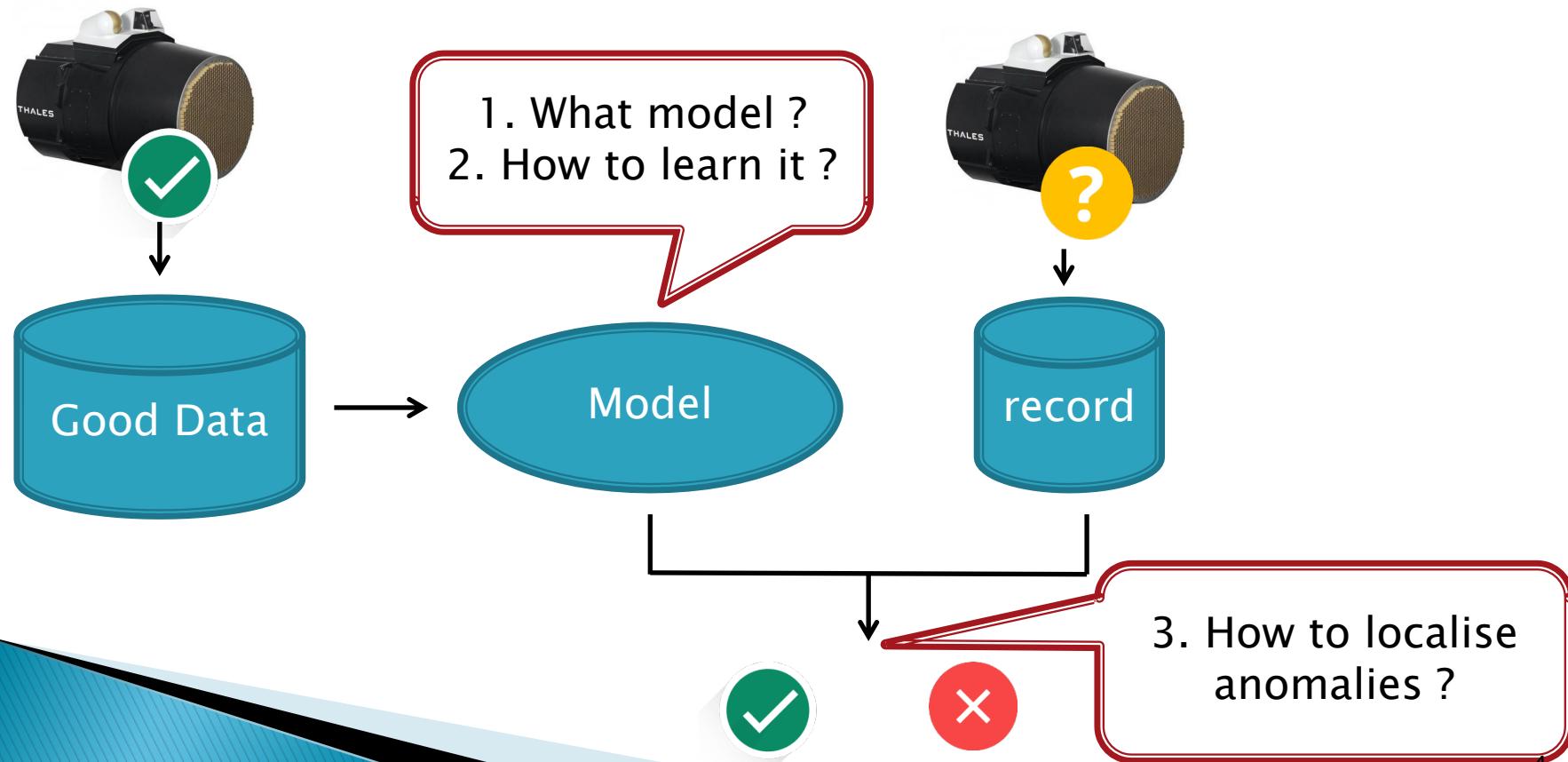


~10 000 vars



# How to improve the built-in tests,

- ▶ It is impossible to list all breakdowns.
- ▶ ~ 10 000 variables !

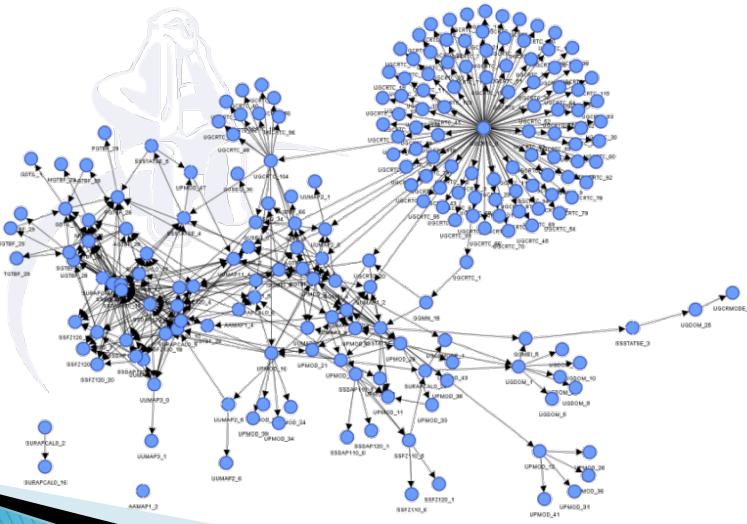
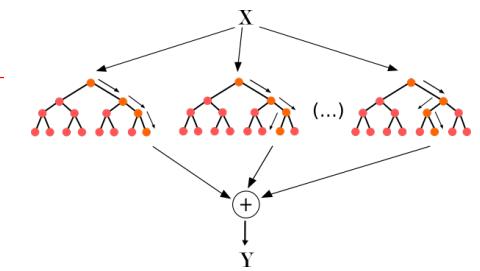
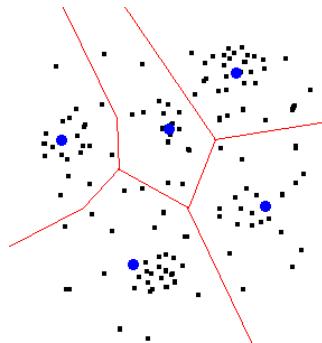
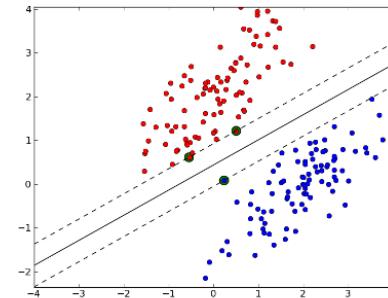
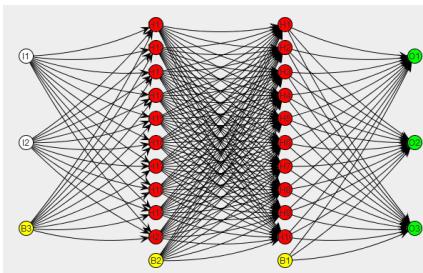


# With some constraints...

- ▶ Scalable method ( $> 10\ 000$  variables)
- ▶ Batch data file  $\sim 10$  Go
- ▶ Online method
  - With no false alarms !
- ▶ Low computation power
  - $\sim$  Gaming PC
- ▶ User friendly
- ▶ Heterogeneous data
  - Physical measures
  - Categorical variables

# What ML tool for localisation ?

- ▶ Plenty of approaches to detect anomalies

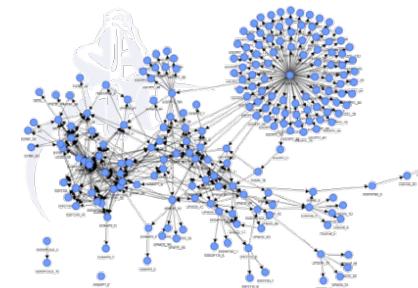


- ▶ Most of them are *Blackbox*...

# What is a graphical model ?

- ▶ Machine to compute probabilities
  - $P(Temp = 35^{\circ}C \mid State = Finland) = ??$
- ▶ The density might be intractable
  - E.g. :  $n$  binary variables  $\leftrightarrow 2^n - 1$  parameters
  - $2^{35} - 1 \approx 32.10^9$  parameters
- ▶ Association between a density and a graph.

$$P(X_1, \dots, X_n)$$



## 1. What kind of model ?

# What is a graphical model ?

- Idea : simplify the density into a product of factors using independances in  $P$

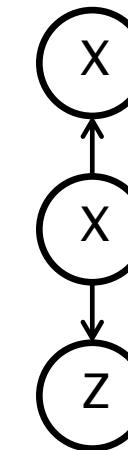
$$P(X, Y, Z) = P(X)P(Y|X)P(Z|X)$$

X	Y	Z	$P(X, Y, Z)$
0	0	0	0,14
0	0	1	0,06
0	1	0	0,02
0	1	1	0,18
1	0	0	0,084
1	0	1	0,036
1	1	0	0,048
1	1	1	0,432

X	$P(X)$
0	0,4
1	0,6

Y	X	$P(Y X)$
0	0	0,5
0	1	0,2
1	0	0,5
1	1	0,8

Z	X	$P(Z X)$
0	0	0,7
0	1	0,1
1	0	0,3
1	1	0,9



*Ice creams*

*Summer*

*Skin cancer*

# Pairwise Markov Models

- ▶ Pairwise Exponential Family:
  - Given a graph  $(V, E)$ ,

$$P_{\theta}(X) \propto \exp \left( \sum_{i \in V} \theta_i B_i(X_i) + \sum_{(i,j) \in E} \theta_{ij} B_i(X_i) B_j(X_j) + \sum_i C_i(X_i) \right)$$

- ▶  $\{B_i(\cdot)\}_i$  and  $\{C_i(\cdot)\}_i$  depends on the choice of the family

# Some Exponential families

- ▶ (zero-mean) Gaussian distribution:

$$B_i(X_i) = \frac{X_i}{\sigma_i}, \quad C_i(X_i) = \frac{-X_i^2}{2\sigma_i^2}$$

- ▶ Poisson distribution:

$$B_i(X_i) = X_i, \quad C_i(X_i) = -\log(X_i!)$$

- ▶ Ising/Potts distribution:

$$B_i(X_i) = X_i, \quad C_i(X_i) = 0$$

- ▶ We can mix them too !

# Mixed exponential families

## ▶ Gaussian + Ising

- $X \in \mathbb{R}^p, Y \in \{0,1\}^q : p(X, Y)$  is valid!



## ▶ Poisson + Ising

- $X \in \mathbb{N}^p, Y \in \{0,1\}^q : p(X, Y)$  is valid!



## ▶ Gaussian + Poisson

- $X \in \mathbb{R}^p, Y \in \mathbb{N}^q : p(X, Y)$  is invalid...



# Learning a model

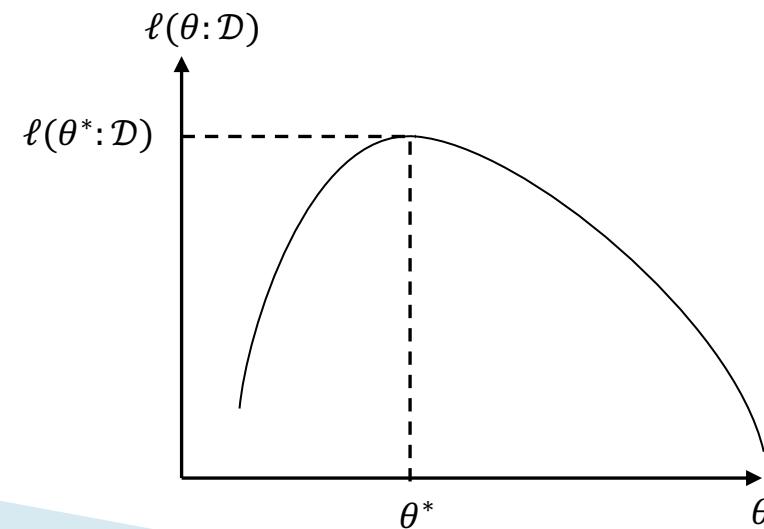
- ▶ Training set  $\mathcal{D} = (X^{(t)})_{t \in \mathcal{T}}$ .
- ▶ We denotes  $\theta = (\theta_i, i \in V) \cup (\theta_{ij}, ij \in E)$

$$P_\theta(X) = \frac{1}{Z_\theta} \exp \left( \sum_{i \in V} \theta_i B_i(X_i) + \sum_{(i,j) \in E} \theta_{ij} B_i(X_i) B_j(X_j) + \sum_i C_i(X_i) \right)$$

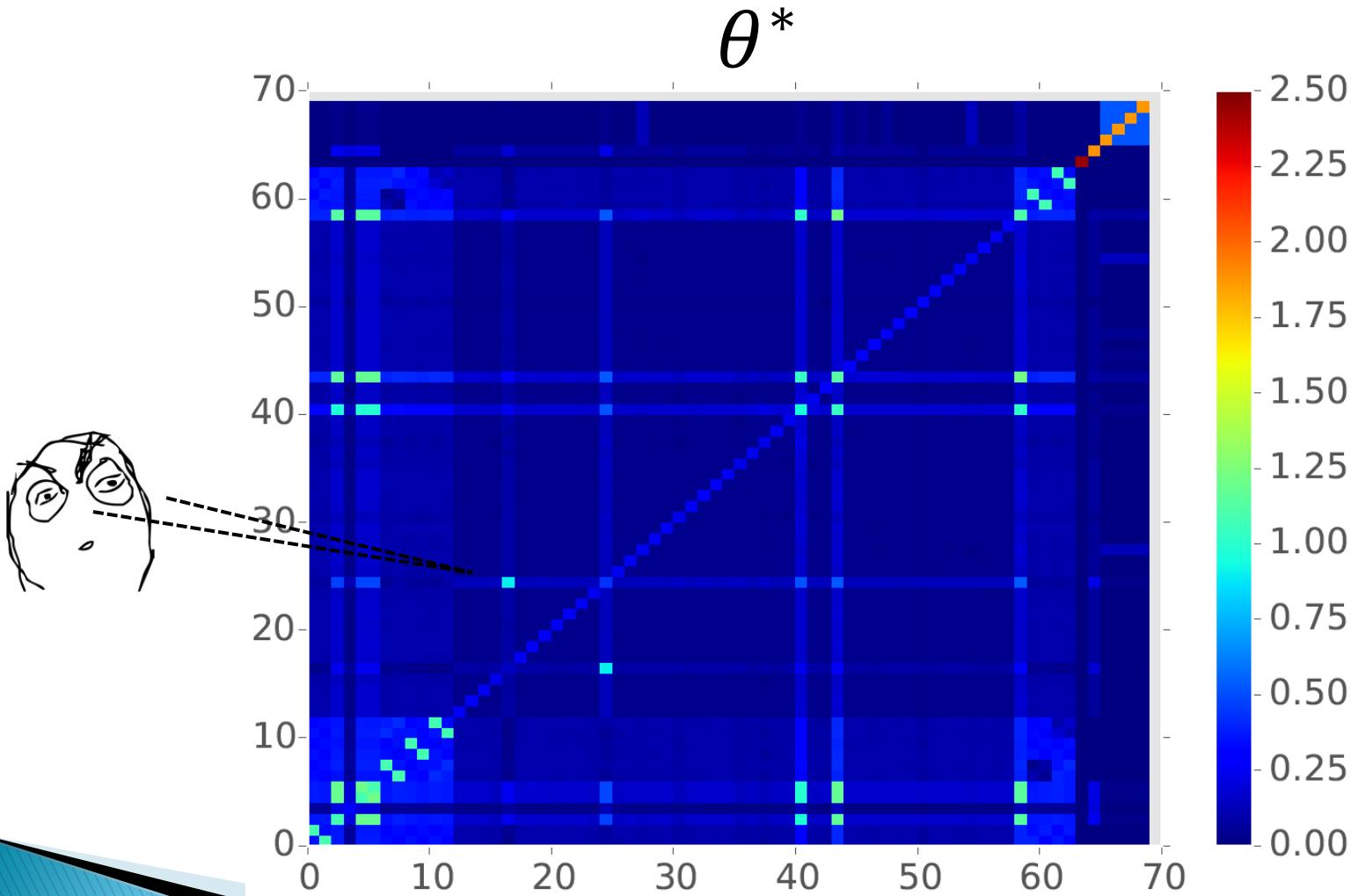
- ▶ Optimise the likelihood function

$$\ell(\theta | \mathcal{D}) = \sum_{t \in \mathcal{T}} \log P_\theta(X^{(t)})$$

$$\theta^* = \operatorname{argmax}_{\theta \in \Theta} \ell(\theta | \mathcal{D})$$

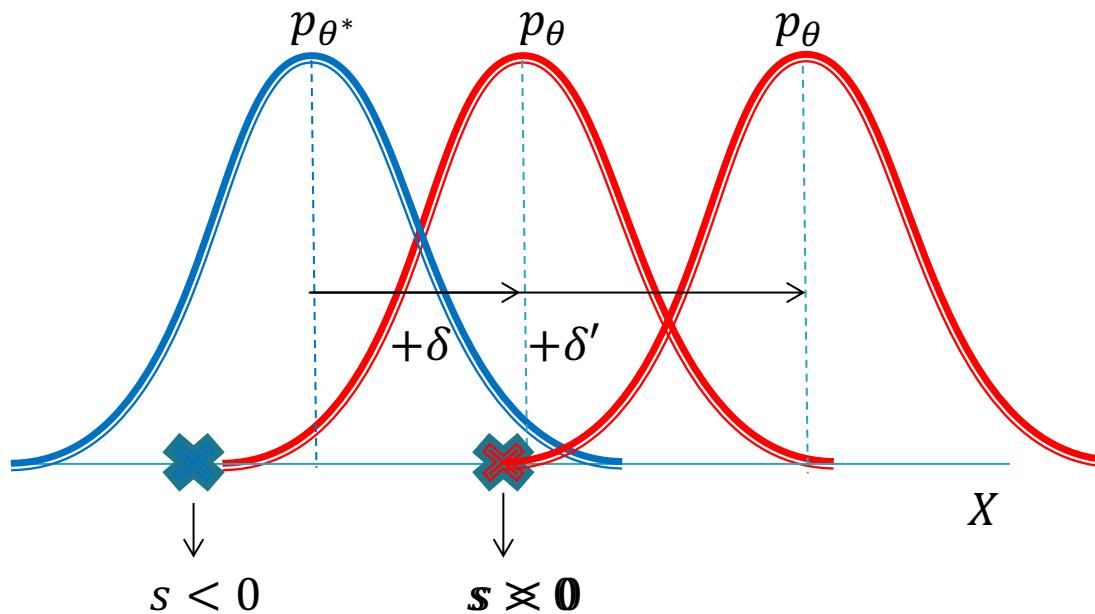


# Learning a model



# How to detect an anomaly ?

- ▶ We learned  $p_{\theta^*} = \mathcal{N}(\mu, \sigma^2)$
- ▶ We define an anomalous density  $p = \mathcal{N}(\mu + \delta, \sigma^2)$

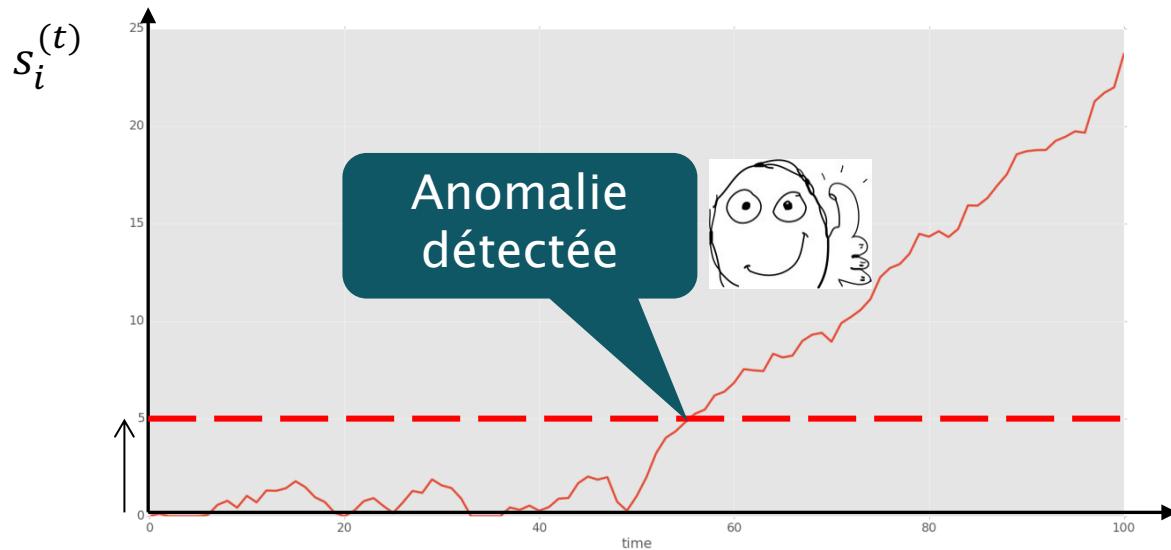


$$s(X) = \log \frac{p(X)}{p_{\theta^*}(X)}$$

$\delta$  controls the sensibility of the detection.

# Anomaly localisation

- ▶ Do the same for every variable !



$$s_i(t) = \log \frac{p_{\theta_i}(X_i|X_{-i})}{p_{\theta^*}(X_i|X_{-i})}$$

$$S_i(0) = 0$$

$$S_i(t) = (S_i(t) + s_i(t))^+$$

$$p_{\theta}(X_i|X_{-i}) \propto \exp \left( B_i(X_i) \left( \theta_i + \sum_j \theta_{ij} B_j(X_j) \right) + C_i(X_i) \right)$$

# What are we doing ...

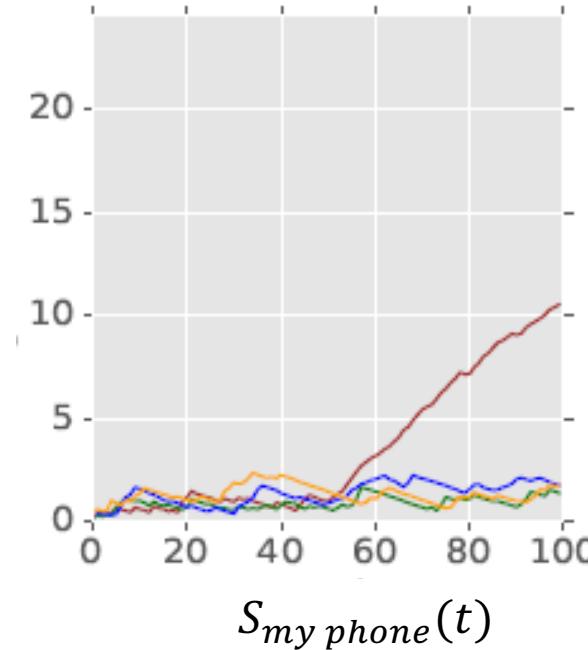
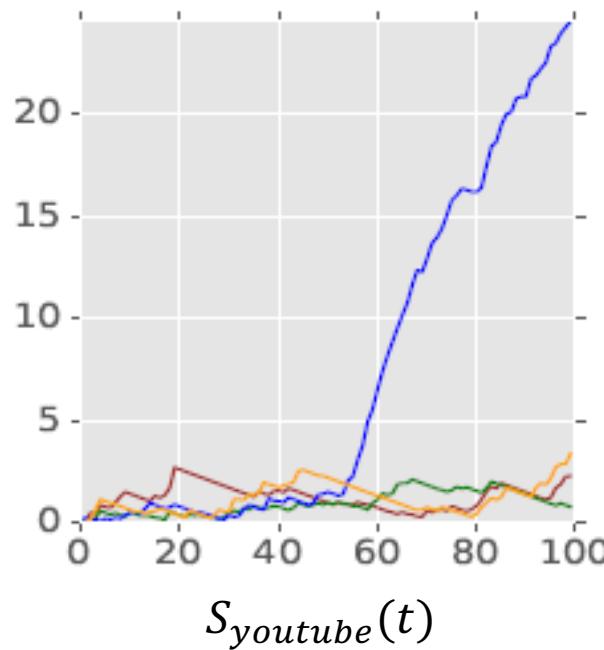
- ▶ We find the change time  $t_0$ :
  - $X^{(t)} \sim P_{\theta^*}$  for  $t < t_0$
  - $X^{(t)} \sim P_{\theta}$  for  $t > t_0$
- ▶ We have located a change in the parameters  $\theta^*$
- ▶ Localisation = finding a change in the parameters of the implicit distribution

# Network traffic control

- ▶  $N$  devices
- ▶ Each device  $i$  sends  $X_i^{(t)}$  frames through WIFI during  $t$  and  $t + 1$
- ▶ Hypothesis :  $X_i | X_{-i} \sim Poisson(\lambda_i)$
- ▶ Anomalous density :  $Poisson(\lambda_i + 50)$

# Network traffic control

- ▶ At  $t = 50$ , I started watching a Youtube video

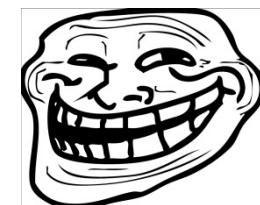


# Back to the company world...



- ▶ 40% : understand the data
- ▶ 30% : communicate
  - Proof of concept, updates, plannings, ...
- ▶ 20% : research
  - The simplest works often fine !
- ▶ Remaining 10% : useless meetings

**THALES**



# Thanks for your attention !