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# Sensor Calibration using Informed Matrix Factorisation for Air Quality Crowdsensing

Clement DORFFER, Matthieu PUIGT, Gilles DELMAIRE, and Gilles ROUSSEL

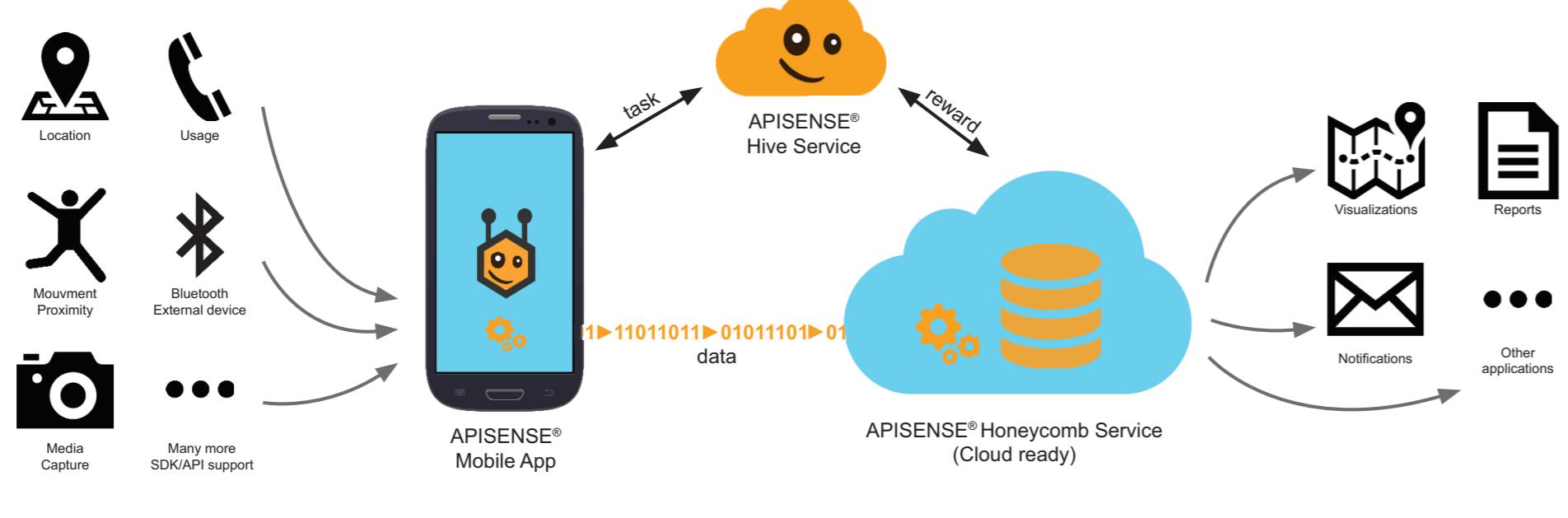
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## Context and Objectives

- Air quality monitoring performed by few fixed or mobile devices of the official air quality monitoring organisms (french AASQA)  $\diamond$  poor spatial coverage/important measurement cost
- Citizen weakly involved**
- Mobile crowd-sensing:** data acquisition from a crowd of sensors connected to smartphones
- Can we use both mobile crowd-sensing and official data to build dense pollution maps with high precision?
- Can we involve citizens into the monitoring process?

## From mobile crowd-sensing data to accurate estimation

- Low cost air quality device development:** arduino-based data acquisition device connected to smartphones
  - Devices build by high school students,
  - carried by volunteers who then know the quality of the air they breathe
- Energy- and privacy-preserving mobile crowd-sensing** acquisition with APISENSE® (<https://apisense.io>) [1]
 

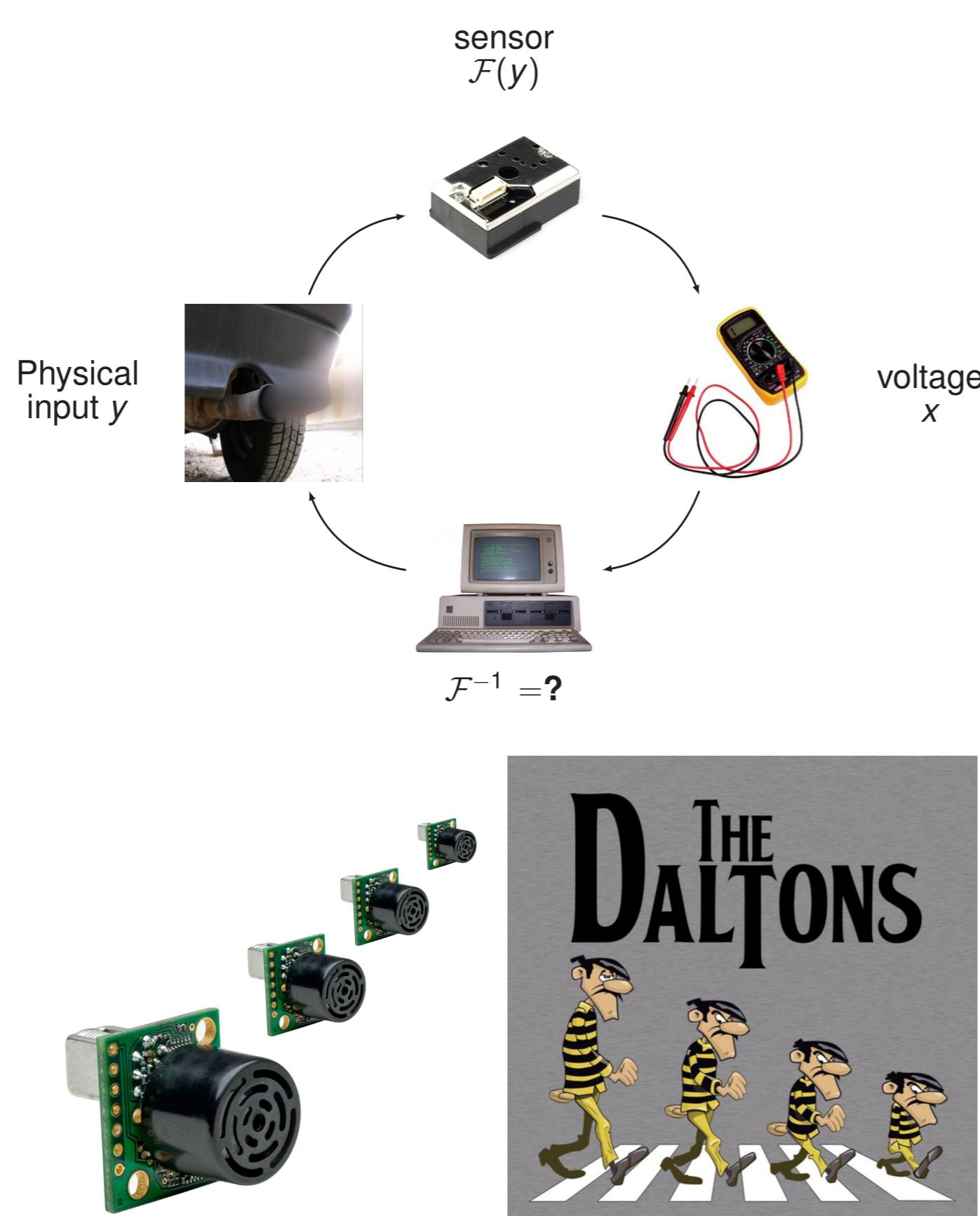
- Enhance data quality** by fusing data from both the mobile devices and the authoritative sensors (from ATMO in France)

## Calibrating the sensor network responses

- An electronic sensor breathes the air concentration  $y$  and provides an output voltage  $x$  linked to  $y$  through a calibration function  $\mathcal{F}$
- $\mathcal{F}$  is an unknown calibrating function to be estimated for each sensor (in laboratory)
  - $\diamond$  Polynomial approximation hypothesis of  $\mathcal{F}$

$$x \approx \mathcal{F}(y) \approx \sum_{k=0}^N f_k \cdot y^k$$

- $m$  mobile sensors  $\rightarrow m$  calibrating functions  $\mathcal{F}_j$  ( $j = 1 \dots m$ ) to estimate
  - $\diamond$  Aim: to get homogeneous physical measurements from different sensors for the same stimulus (Not a Daltons' distribution)
- If  $m$  is large, impossible to perform calibration in a laboratory (too expensive). How to do it remotely?



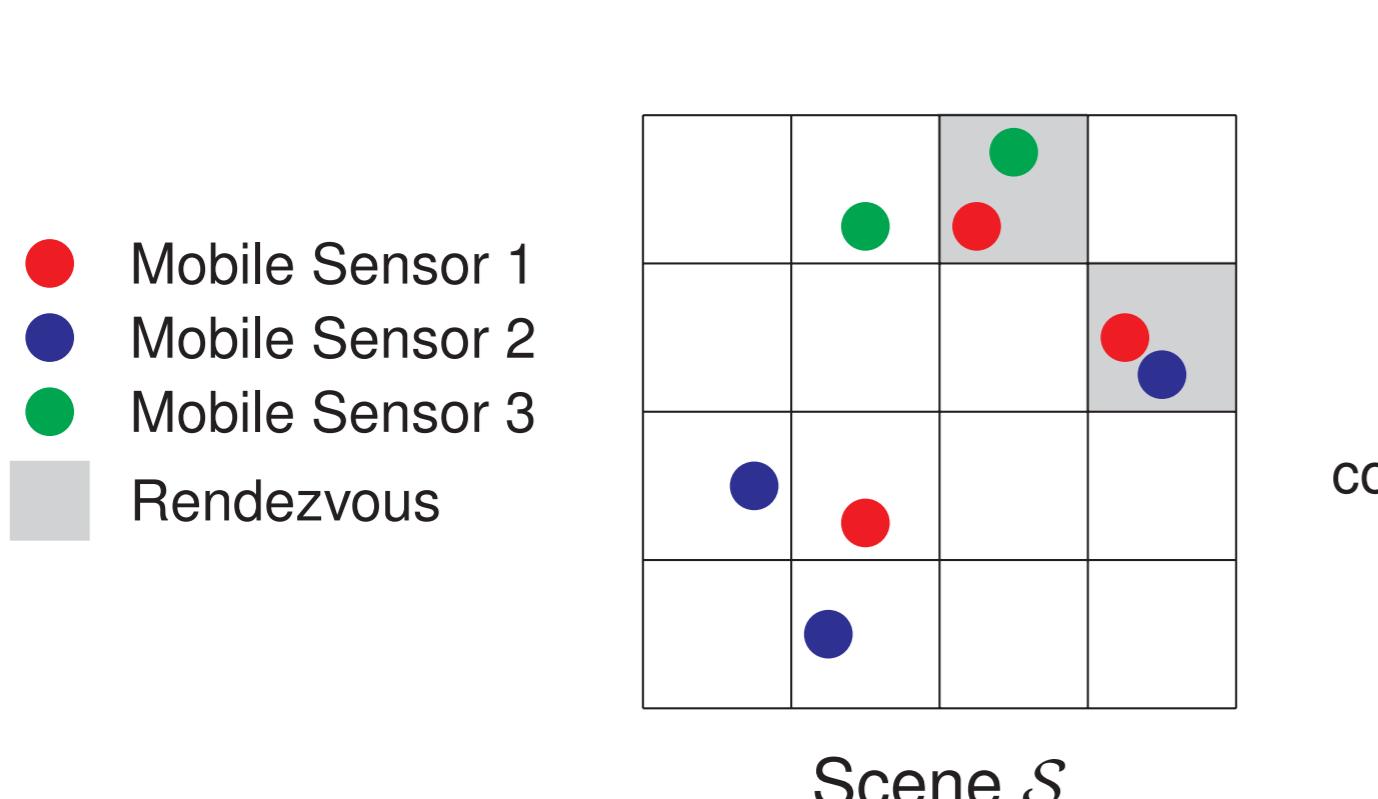
## Rendezvous principle

### Rendezvous [2]

A **Rendezvous** is a spatial and temporal vicinity between two sensors.

### Scene [3]

A **Scene** is a discretized area observed during a time interval  $[t, t + \Delta_t]$ . A spatial pixel has a size lower than  $\Delta_d$ , where  $\Delta_t$  and  $\Delta_d$  defines the vicinity of the rendezvous.



- General modelling of the sensor network observations [4]

$$x_{ij} \approx \mathcal{F}_j(y_i) \approx \sum_{k=0}^N f_{kj} \cdot y_i^k \quad \diamond \quad X \approx G \cdot F$$

where  $X$ ,  $G$ , and  $F$  respectively contain the sensor outputs, the calibration model (Vandermonde matrix), and the sensor parameters, i.e.,

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}, \quad G = \begin{bmatrix} 1 & y_1 & \dots & y_1^N \\ \vdots & \vdots & & \vdots \\ 1 & y_n & \dots & y_n^N \end{bmatrix}, \quad F = \begin{bmatrix} f_{01} & f_{02} & \dots & f_{0m} \\ \vdots & \vdots & & \vdots \\ f_{N1} & f_{N2} & \dots & f_{Nm} \end{bmatrix}.$$

- In practice, missing data in  $X$  (irregular sampling)  $\diamond$  binary mask  $W$

### Hypotheses:

- Dense network
- $X$  well conditioned
- Enough diversity in  $W \circ X$
- $X \geq 0$  (voltages)
- $G \geq 0$  (concentrations)
- $F$  of unconstrained sign

### Extra-information:

- Known values in  $G$  (model + reference data)
- Known values in  $F$  (reference sensors)

## Resolution process

- Weighted semi-nonnegative matrix factorization (Semi-NMF) problem with structured matrices

$$\{\hat{G}, \hat{F}\} = \arg \min_{G, F} \frac{1}{2} \|W \circ (X - G \cdot F)\|_F^2, \quad \text{s.c.} \quad \begin{cases} G \text{ is Vandermonde} \\ G = \Omega_G \circ \Phi_G + \bar{\Omega}_G \circ \Delta_G \geq 0 \\ F = \Omega_F \circ \Phi_F + \bar{\Omega}_F \circ \Delta_F \end{cases} \quad (1)$$

where  $\Omega_G \circ \Phi_G$  et  $\bar{\Omega}_G \circ \Delta_G$  stand for the known and free parts of  $\hat{G}$ , respectively, and  $\|\cdot\|_F$  is the Frobenius norm.

### Example

$$\begin{bmatrix} x_{1,1} & \dots & x_{1,3} & \dots \\ \vdots & \ddots & x_{2,2} & x_{2,3} & y_2 \\ x_{3,1} & \dots & \dots & \dots & \dots \\ \vdots & \ddots & x_{4,2} & \dots & y_4 \end{bmatrix} = W \circ \begin{pmatrix} 1 & y_1 & y_1^2 \\ 1 & y_2 & y_2^2 \\ 1 & y_3 & y_3^2 \\ 1 & y_4 & y_4^2 \end{pmatrix} \cdot \begin{pmatrix} f_{0,1} & f_{0,2} & f_{0,3} & 0 \\ f_{1,1} & f_{1,2} & f_{1,3} & 1 \\ f_{2,1} & f_{2,2} & f_{2,3} & 0 \end{pmatrix}$$

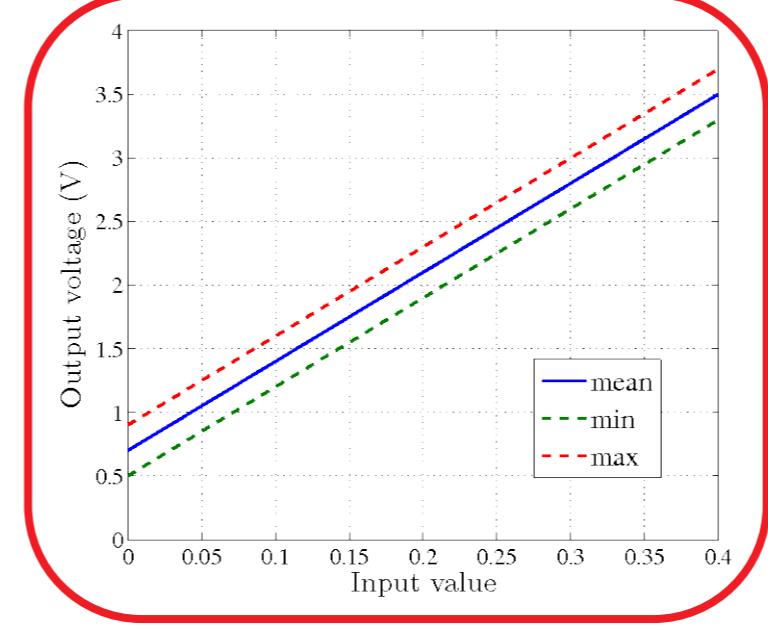
- Parameterization of the known and free parts:

$$G = \Omega_G \circ \Phi_G + \bar{\Omega}_G \circ \Delta_G = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \circ \begin{bmatrix} 1 & 0 & 0 \\ 1 & y_2 & y_2^2 \\ 1 & 0 & 0 \\ 1 & y_4 & y_4^2 \end{bmatrix} + \begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix} \circ \begin{bmatrix} 0 & y_1 & y_1^2 \\ 0 & 0 & 0 \\ 0 & y_3 & y_3^2 \\ 0 & 0 & 0 \end{bmatrix}$$

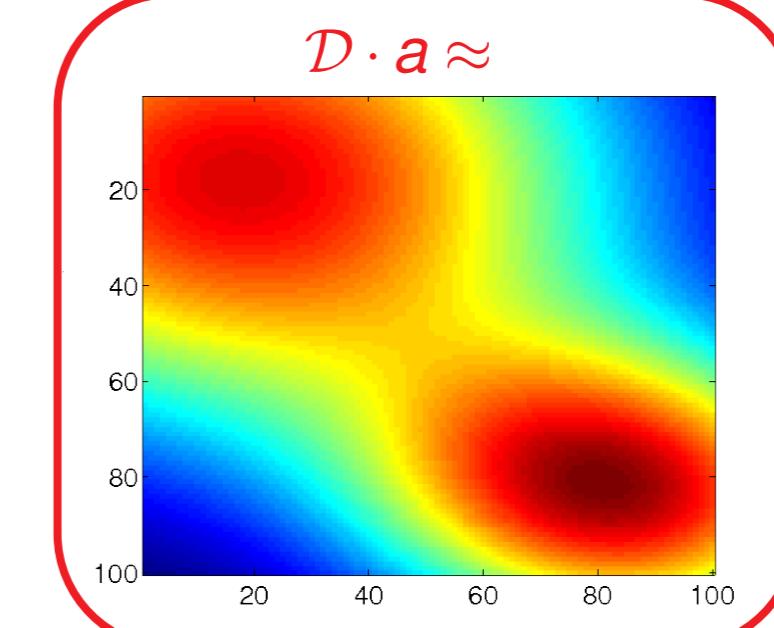
- 3 mobile sensors (Sensor 1 to 3)
- 1 reference (Sensor 4)  $\diamond x_{i,4} = y_i \quad \forall i$
- polynomial sensor response of degree  $N = 2$
- 2 measurements per sensor over a  $2 \times 2$  scene

## Extra information

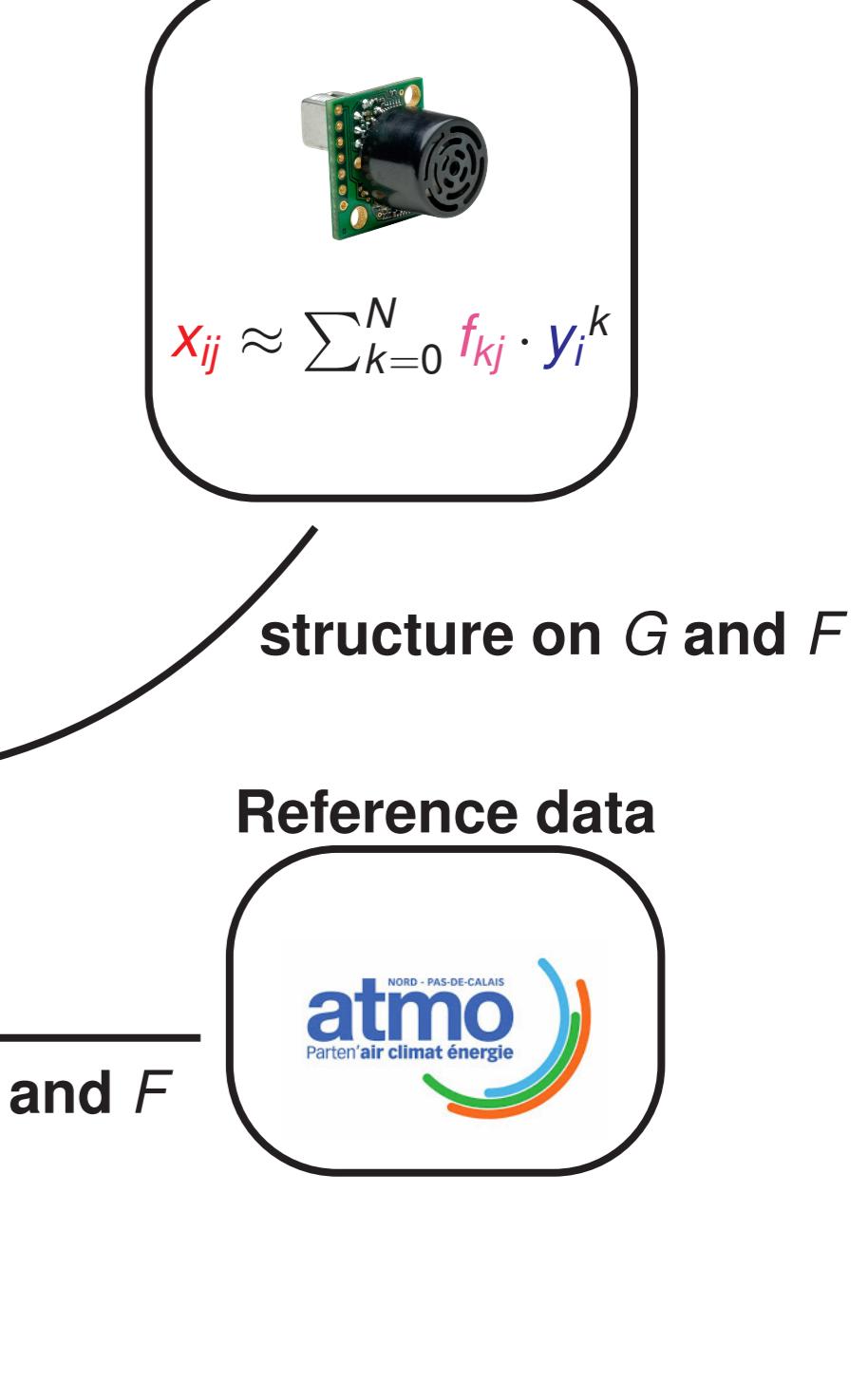
### Datasheet information [6]



### A priori knowledge [5, 6]



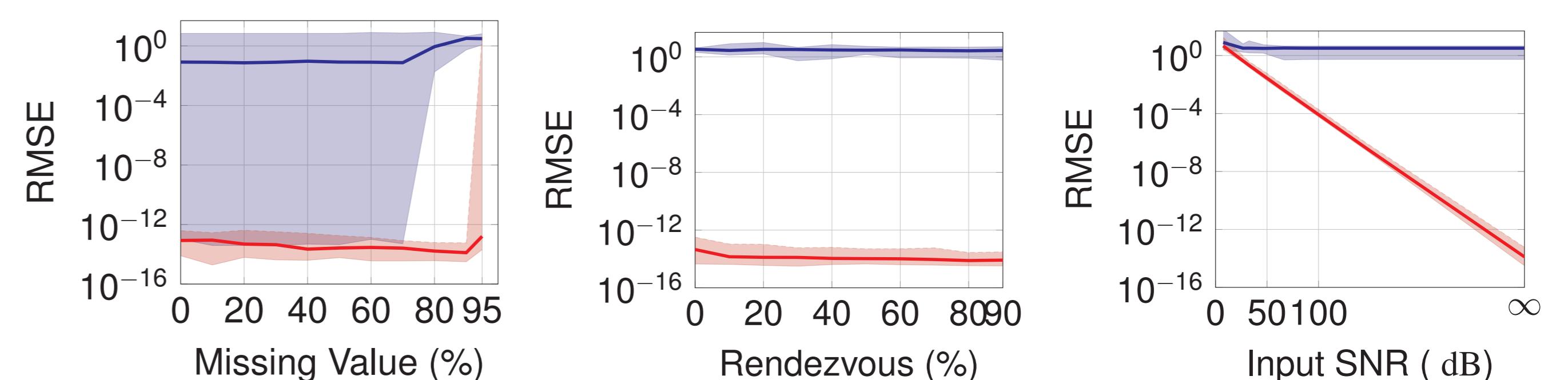
### Sensor response model



## Experiments

### Calibration performance (estimation of F)

- Simulations of crowdsensing-like air quality monitoring ( $N = 1$ , affine model,  $F$  nonnegative in this case)
- $m = 25$  sensors (+ 1 calibrated one)
- Performance criterion = RMSE between theoretical and estimated parameters
  - (blue): calibration using matrix completion and (red): proposed approach [5]
- Default parameters: prop. Rendezvous = 0.3; prop. Missing Value = 0.9; Input SNR =  $\infty$



### Field reconstruction (estimation of G)

#### Simulation parameters

- Theoretical field with  $100 \times 100$  cells observed by 50 mobile sensors
- 90% of missing value in the data matrix  $X$ ; 10 reference measurements
- Simulated dictionary composed of 60 atoms

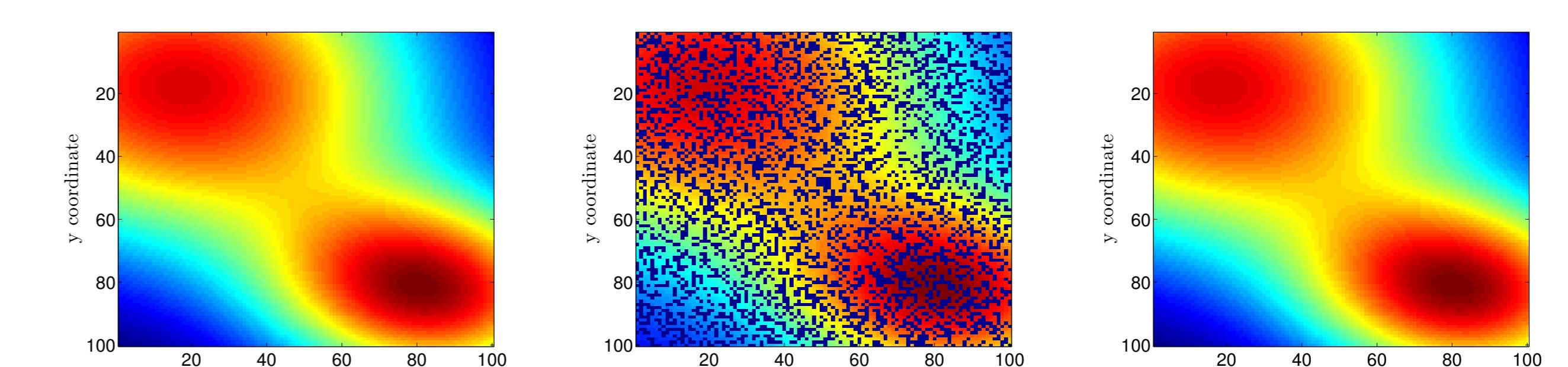


Figure: (left) theoretical field; (middle) Matrix Factorization (MF) based calibration; (right) MF and dictionary calibration

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