Fast informed nonnegative matrix factorization for mobile sensor calibration

Farouk Yahaya[1] Matthieu Puigt[1] Olivier Vu thanh[2] Gilles Delmaire[1] Gilles Roussel[1]

[1] University of Littoral Côte d'Opale, LISIC, Calais, France
[2] University of Mons, Mons, Belgium

December 7th, 2021

Work partially funded by the Région Hauts-de-France and ULCO Research Pole MTE.
Experiments performed using the CALCULCO computing platform supported by SCoSI/ULCO.

Context

- centered on environmental monitoring
- Air pollution remains an issue $\Rightarrow \approx\ 400.000$ premature deaths per year in EU
- Need to monitor air quality

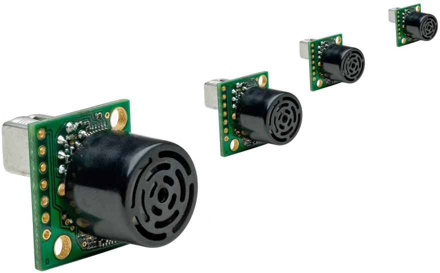
!!! Local effects not sensed and hard to model with a sparsely distributed sensor network

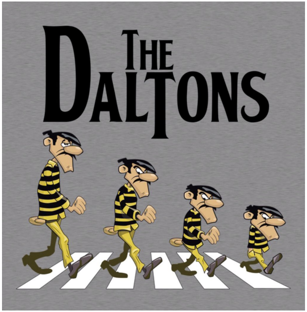
- Tremendous development of miniaturized sensors
- Allow a much denser deployment than authoritative sensing stations

➪ Some local effects become observable

!!! But **sensor drift** is an issue

The why of sensor calibration





- Observed phenomenon ➪ voltage
- Voltage ➪ Physical value?
  - ▶ Sensor calibration cannot be performed in lab
  - ➪ Data-driven approaches (a.k.a. *in situ* calibration techniques)
  - ▶ Presence of reference data

The how of sensor calibration

- Many existing methods (see, e.g., Maag *et al.* 2019, Delaine *et al.* 2020)
  - network topology
    - Mobile vs fixed sensors
    - Single sensor vs multiple sensors
  - calibration model
    - linear vs nonlinear
    - single vs multiple latent variables
  - calibration strategy
    - Macro vs Micro-calibration, etc

Dorffer *et al.*, 2015–2018: An original strategy

- Combine micro-calibration and macro-calibration
  - ➪ Highlighted as a promosing idea in (Maag *et al.*, 2019)
- Revisit mobile sensor calibration as an informed matrix factorization problem
  - ✔ Well-suited for much less dense networks (much less rendezvous needed)
  - ✔ Linear and nonlinear calibration models
  - ✔ Joint sensor calibration and physical phenomenon map
  - ✖ Limited to the calibration of a single sensor in sensing devices covering a small area over a short period

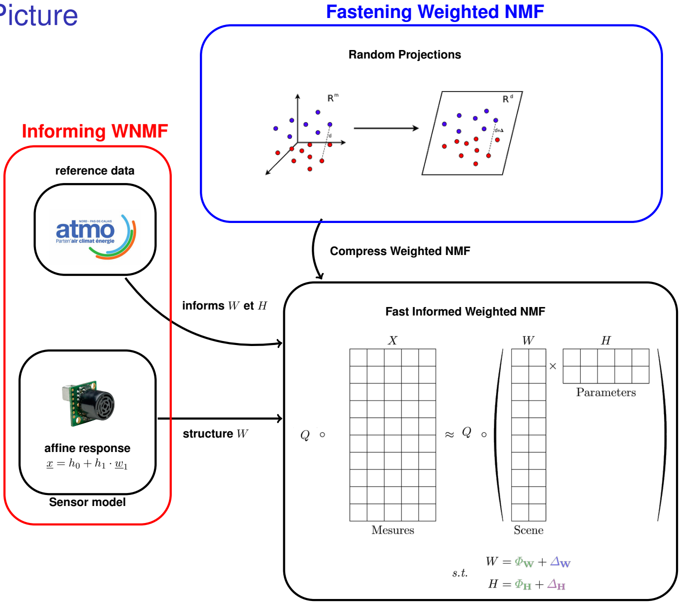
The how of sensor calibration

- Many existing methods (see, e.g., Maag *et al.* 2019, Delaine *et al.* 2020)
  - network topology
    - Mobile vs fixed sensors
    - Single sensor vs multiple sensors
  - calibration model
    - linear vs nonlinear
    - single vs multiple latent variables
  - calibration strategy
    - Macro vs Micro-calibration, etc

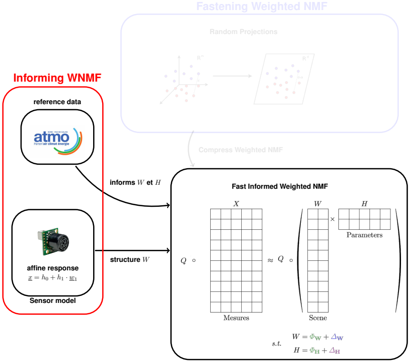
Dorffer *et al.*, 2015–2018: An original strategy

- Combine micro-calibration and macro-calibration
  - ➪ Highlighted as a promosing idea in (Maag *et al.*, 2019)
- Revisit mobile sensor calibration as an informed matrix factorization problem
  - ✔ Well-suited for much less dense networks (much less rendezvous needed)
  - ✔ Linear and nonlinear calibration models
  - ✔ Joint sensor calibration and physical phenomenon map
  - ✖ Limited to the calibration of a single sensor in sensing devices covering a small area over a short period

The Big Picture



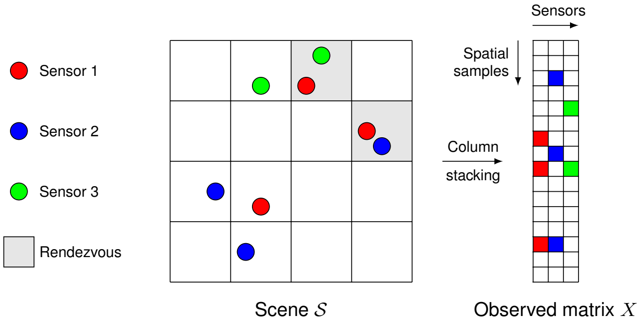
Part I: Revisiting in-situ calibration as an informed (semi-)NMF problem



1. Calibration of homogeneous sensors
2. Extension to p Heterogeneous sensors
3. A simple extension to T Scenes

Definitions

- A rendezvous is a temporal and spatial vicinity between two sensors (Saukh *et al.*, 2013).
- A scene $\mathcal{S}$ is a discretized area observed during a time interval $[t, t + \Delta t)$. A spatial pixel has a size lower than Δd, where Δt and Δd define the vicinity of the rendezvous (Dorffer *et al.*, 2018).



Assumptions & Problem Formalism (1)

- Sensor response (calibration function $\mathcal{H}(.)$ of Sensor j)

$$\underbrace{x(i,j)}_{\text{sensor-output voltage}} \simeq \mathcal{H}_j(w_1(i))$$

$$\simeq \underbrace{(w_1(i)}_{\text{physical phenomenom}} \cdot \overbrace{h_{1,j}) + h_{0,j}}^{\text{unknown gain and offset}}$$

➪ Matrix form (if **each** of the m sensor senses **all** the scene)

$$\underbrace{\begin{bmatrix} x(1,1) & \cdots & x(1,m) \\ \vdots & & \vdots \\ x(n,1) & \cdots & x(n,m) \end{bmatrix}}_{X} \simeq \underbrace{\begin{bmatrix} 1 & w_1(1) \\ \vdots & \vdots \\ 1 & w_1(n) \end{bmatrix}}_{W} \cdot \underbrace{\begin{bmatrix} h_{0,1} & h_{0,2} & \cdots & h_{0,m} \\ h_{1,1} & h_{1,2} & \cdots & h_{1,m} \end{bmatrix}}_{H}$$

- In practice, irregular sampling: $Q \circ X \simeq Q \circ (W \cdot H)$ with

$$Q(i,j) \triangleq \begin{cases} 0 & \text{if } x(i,j) \text{ is not available,} \\ \rho_j & \text{otherwise,} \end{cases}$$

where ρ_j is a weight coefficient associated with Sensor j

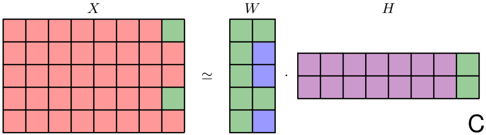
Assumptions & Problem Formalism (2)

- X, W, and H are nonnegative (air quality application)
- A known reference

➪ $\forall i = 1, \ldots, n, \quad x(i,m) = w_1(i)$ (i.e., $h_{1,m} = 1$, $h_{0,m} = 0$)

➪ Blind calibration revisited as an informed nonnegative matrix factorization problem

$$Q \circ \underbrace{\begin{bmatrix} x(1,1) & \cdots & x(1,m-1) & w_1(1) \\ x(2,1) & \cdots & x(2,m-1) & w_1(2) \\ \vdots & & \vdots & \vdots \\ x(n,1) & \cdots & x(n,m-1) & w_1(n) \end{bmatrix}}_{X} \simeq Q \circ \left(\underbrace{\begin{bmatrix} 1 & w_1(1) \\ 1 & w_1(2) \\ \vdots & \vdots \\ 1 & w_1(n) \end{bmatrix}}_{W} \cdot \underbrace{\begin{bmatrix} h_{0,1} & h_{0,2} & \cdots & h_{0,m-1} & 0 \\ h_{1,1} & h_{1,2} & \cdots & h_{1,m-1} & 1 \end{bmatrix}}_{H} \right)$$



$$W = \Phi_{\mathbf{W}} + \Delta_{\mathbf{W}}$$

$$H = \Phi_{\mathbf{H}} + \Delta_{\mathbf{H}}$$

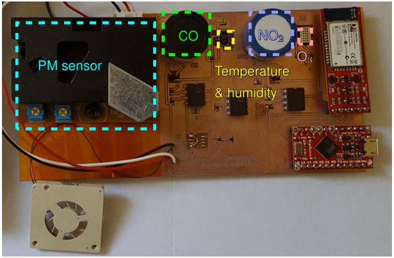
Calibration $\Longleftrightarrow$ Estimating H

Extension to p heterogeneous sensors (1)

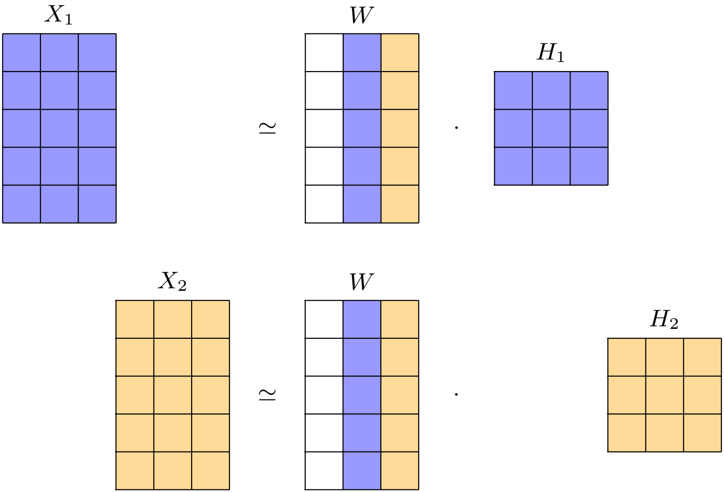
Cross-sensitive sensors

- Sensor readings may depend on other concentrations
  - NO_2 wrt O_3
  - O_3 wrt NO_2
- New calibration model (Maag *et al.* 2016, 2017)
  - for Sensor k ($k \in \{1, \ldots, p\}$):

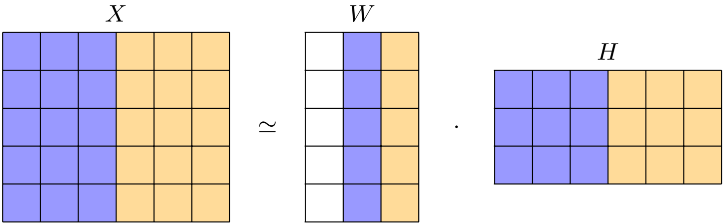
$$x_k(i,j) \simeq h_{0,j} + w_1(i) \cdot h_{1,j} + w_2(i) \cdot h_{2,j} + \ldots + w_p(i) \cdot h_{p,j}$$



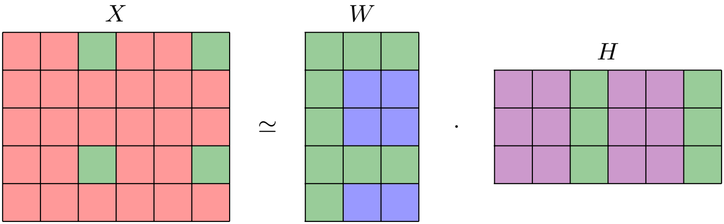
Extension to p heterogeneous sensors (2)



Extension to p heterogeneous sensors (2)



Extension to p heterogeneous sensors (2)



$$W = \Phi_{\mathbf{W}} + \Delta_{\mathbf{W}}$$

$$H = \Phi_{\mathbf{H}} + \Delta_{\mathbf{H}}$$

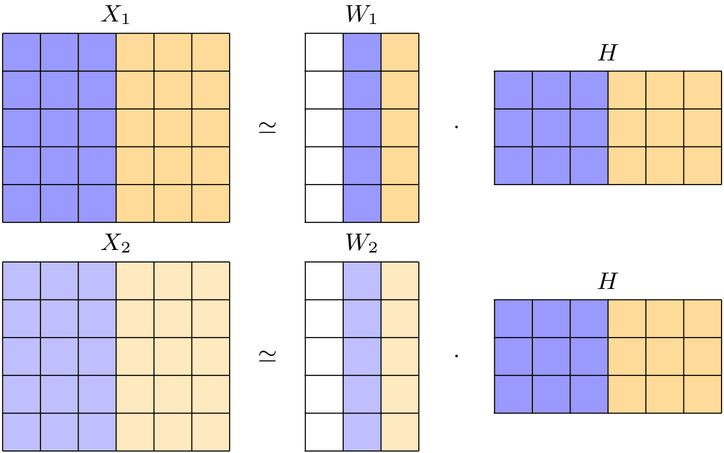
Similar problem as before (but with larger matrices)

A simple extension to T Scenes

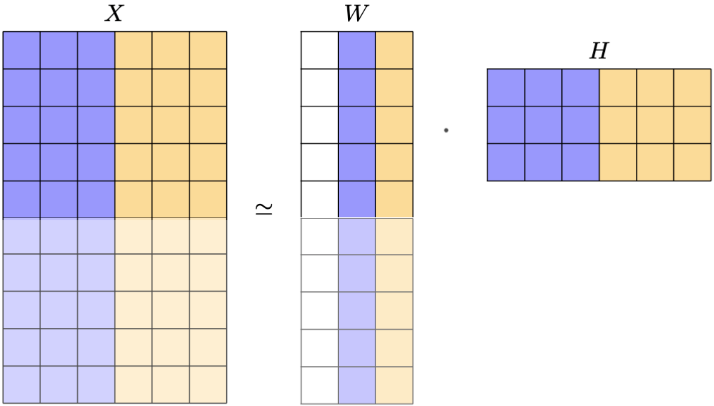
- Original approach by Dorffer *et al.* limited to a single scene
- We now consider a time series $\{X_1, \ldots, X_T\}$ of observed scenes
  - Calibration models remain (multi-)linear if considered on daily to weekly basis (Arfire *et al.*, 2015)
  - Sensor drift is usually not visible on such a short duration
  - ➩ For each X_i, we may consider a similar problem as before with a **common matrix** H

$$\forall i = 1, \ldots T, \quad Q_i \circ X_i \approx Q_i \circ (W_i \cdot H), \tag{1}$$

A simple extension to T Scenes

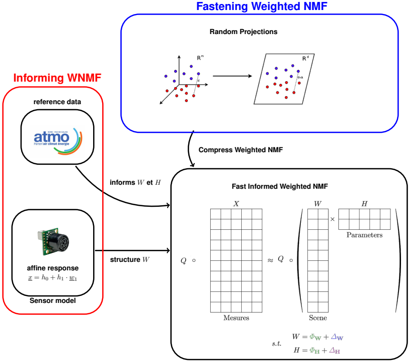


A simple extension to T Scenes



$$Q \circ X \approx Q \circ (W \cdot H). \tag{2}$$

Part II: Solving in-situ calibration with fast informed NMF techniques



1. Dorffer *et al.*'s IN-Cal
2. Fast IN-Cal (F-IN-Cal) (Vu than *et al.*, 2021)
3. Randomized F-IN-Cal (RF-IN-Cal) (Yahaya, 2021)

Proposed calibration methods (1/2)

All the above mobile calibration problems aim to solve:

$$\{\tilde{W}, \tilde{H}\} = \arg\min_{W,H\geq 0} \frac{1}{2} \cdot ||Q \circ (X - W \cdot H)||_{\mathcal{F}}^2 ,$$

$$\text{s.t.} \quad W = \Phi_{\mathbf{W}} + \Delta_{\mathbf{W}}$$

$$H = \Phi_{\mathbf{H}} + \Delta_{\mathbf{H}}$$

Proposed techniques:

1. IN-Cal: Infomed Nmf-based mobile sensor Calibration[1]
   - WNMF with multiplicative updates to update $\Delta_{\mathbf{W}}$ and $\Delta_{\mathbf{H}}$ only
   - $$H \leftarrow \Phi_{\mathbf{H}} + \Delta_{\mathbf{H}} \circ \left[\frac{W^T \cdot (Q \circ (X - W \cdot \Phi_{\mathbf{H}})^+)}{W^T \cdot (Q \circ (W \cdot \Delta_{\mathbf{H}}))} \right]$$

   ➪ Slow!

[1] Details in Dorffer *et al.*, IEEE TSIPN, 2018.

Proposed calibration methods (2/2)

2. Fast IN-Cal[2] (F-IN-Cal): uses an **EM framework** and applies a Nesterov gradient descent to update Δ_{W} and Δ_{H}
   - !!! Nesterov within EM much faster than a direct incorporation of the weights in the gradient expression (Dorffer *et al.*, 2017)
   - E-step: Estimate the unknown entries of X using the last estimates of W and H – see (Zhang *et al.*, 2006) for details
     ⇨ $X^{\text{comp}} = Q \circ X + (\mathbb{1} - Q) \circ (W \cdot H)$
   - M-step: Update Δ_{W} and Δ_{H} from X^{comp} using Nesterov gradient
3. Randomized F-IN-Cal[3] (RF-IN-Cal): combines F-IN-Cal with Compressive (W)NMF (Tepper & Sapiro, 2016, Yahaya *et al.*, 2019)
   - X is large and low-rank (typically rank 2 to 4)
   - At each E-step, we can derive compressed versions of X^{comp} (compression on the left and right side using **structured random projections**)
     - ✖ Extra CPU time in E-step wrt F-IN-Cal
     - ✔ Updates in M-step **much faster** than with F-IN-Cal

[2] Details in Vu than, Puigt, **FY**, Delmaire, Roussel, Proc. ICASSP 2021

[3] Details in **FY**, Ph.D. thesis, Nov. 2021

Proposed calibration methods (2/2)

2. Fast IN-Cal[2] (F-IN-Cal): uses an **EM framework** and applies a Nesterov gradient descent to update $\Delta_{\mathbf{W}}$ and $\Delta_{\mathbf{H}}$

   !!! Nesterov within EM much faster than a direct incorporation of the weights in the gradient expression (Dorffer *et al.*, 2017)

   - E-step: Estimate the unknown entries of X using the last estimates of W and H – see (Zhang *et al.*, 2006) for details

     ➯ $X^{\text{comp}} = Q \circ X + (\mathbb{1} - Q) \circ (W \cdot H)$

   - M-step: Update $\Delta_{\mathbf{W}}$ and $\Delta_{\mathbf{H}}$ from X^{comp} using Nesterov gradient

3. Randomized F-IN-Cal[3] (RF-IN-Cal): combines F-IN-Cal with Compressive (W)NMF (Tepper & Sapiro, 2016, Yahaya *et al.*, 2019)

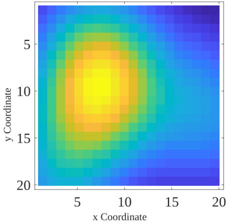
   - X is large and low-rank (typically rank 2 to 4)
   - At each E-step, we can derive compressed versions of X^{comp} (compression on the left and right side using **structured random projections**)
     - ✖ Extra CPU time in E-step wrt F-IN-Cal
     - ✔ Updates in M-step **much faster** than with F-IN-Cal

[2] Details in Vu than, Puigt, **FY**, Delmaire, Roussel, Proc. ICASSP 2021

[3] Details in **FY**, Ph.D. thesis, Nov. 2021

Simulations

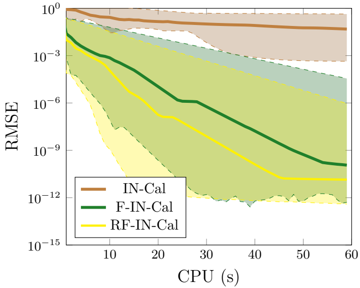
- We generate theoretical factor matrices W and H, then we calculate $X_{theo} \approx W \cdot H$
- The physical phenomena in the $\underline{w}_k$ columns of W are generated as mixtures of Gaussians with realistic concentrations



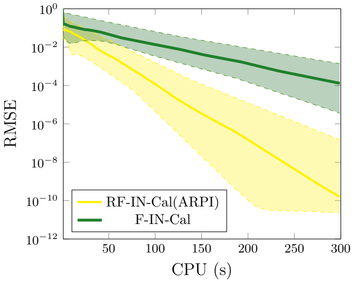
- Calibration parameters randomly chosen according to a manufacturer data sheet
- Observed data in X randomly chosen
- Each mobile sensor has **at most** one rendez-vous with a reference sensor
  - ► Complex scenario which can't be processed by most SotA techniques
  - ➩ We can only compare our proposed methods with IN-Cal

A few results

- We investigated the influence of several parameters (scene size, number of mobile sensors and of references, missing valeur proportion, rendezvous proportion, etc)
- We here just show the calibration accuracy (RMSE) versus CPU time (s)
  - 15 experiments in Matlab with the same initialization for each method
  - Enveloppe + median performance
- We fix several parameters and observe the performance below



(a) Single Scene Scenario



(b) Multiple Scene Scenario

Conclusion and Perspectives

- Mobile sensor calibration revisited as an informed NMF problem
- We extended previous work to the case of heterogeneous sensors and to multiple scenes
- We proposed accelerated WNMF methods using an EM framework
- The proposed methods are shown to be fast and well-suited for the considered problem
- A few perspectives:
  - As the present method is time independent, we could extend the calibration function to the case of single/multiple variables with time.
  - so far we do sampling of an area with square cells, in future one could imagine irregularly shaped locations.
  - in future we could apply the proposed methods to real mobile sensor data.

References

- Arfire, A., Marjovi, A., & Martinoli, A. (2015, November). Model-based rendezvous calibration of mobile sensor networks for monitoring air quality. In 2015 IEEE SENSORS (pp. 1-4). IEEE.
- Delaine, F., Lebental, B., & Rivano, H. (2019). In situ calibration algorithms for environmental sensor networks: A review. IEEE Sensors Journal, 19(15), 5968-5978.
- Dorffer, C., Puigt, M., Delmaire, G., & Roussel, G. (2017, February). Fast nonnegative matrix factorization and completion using Nesterov iterations. In Proc. LVA-ICA (pp. 26-35). Springer, Cham.
- Dorffer, C., Puigt, M., Delmaire, G., & Roussel, G. (2018). Informed nonnegative matrix factorization methods for mobile sensor network calibration. IEEE Transactions on Signal and Information Processing over Networks, 4(4), 667-682.
- Maag, B., Zhou, Z., Saukh, O., & Thiele, L. (2017). SCAN: Multi-hop calibration for mobile sensor arrays. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 1(2), 1-21.
- Maag, B., Zhou, Z., & Thiele, L. (2018). A survey on sensor calibration in air pollution monitoring deployments. IEEE Internet of Things Journal, 5(6), 4857-4870.
- Saukh, O., Hasenfratz, D., Walser, C., & Thiele, L. (2014). On rendezvous in mobile sensing networks. In Real-World Wireless Sensor Networks (pp. 29-42). Springer, Cham.
- Tepper, M., & Sapiro, G. (2016). Compressed nonnegative matrix factorization is fast and accurate. IEEE Transactions on Signal Processing, 64(9), 2269-2283.
- Vu thanh, O., Puigt, M., Yahaya, F., Delmaire, G., & Roussel, G. (2021, June). In situ calibration of cross-sensitive sensors in mobile sensor arrays using fast informed non-negative matrix factorization. In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 3515-3519). IEEE.
- Yahaya, F., Puigt, M., Delmaire, G., & Roussel, G. (2019, September). How to apply random projections to nonnegative matrix factorization with missing entries?. In 2019 27th European Signal Processing Conference (EUSIPCO) (pp. 1-5).
- Yahaya, F (2021, November). Compressive informed (semi-)non-negative matrix factorization methods for incomplete and large-scale data, with application to mobile crowd-sensing data. PhD thesis, ULCO.
- Zhang, S., Wang, W., Ford, J., & Makedon, F. (2006, April). Learning from incomplete ratings using non-negative matrix factorization. In Proceedings of the 2006 SIAM international conference on data mining (pp. 549-553). Society for Industrial and Applied Mathematics.

Merci de votre attention

Discover our work

1. **FY** *et al.*, in Proc. ICASSP 2021

   `https://dx.doi.org/10.1109/ICASSP39728.2021.9413496`
2. Vu thanh, Puigt, **FY**, Delmaire, Roussel, in Proc. ICASSP 2021

   `https://dx.doi.org/10.1109/ICASSP39728.2021.9414742`
3. **FY** *et al.*, in Proc. iTWIST 2020

   `https://hal.archives-ouvertes.fr/hal-02931454`
4. **FY** *et al.*, in Proc. EUSIPCO 2019

   `https://hal.archives-ouvertes.fr/hal-02151521`
5. **FY** *et al.*, in Proc. GRETSI 2019

   `https://hal.archives-ouvertes.fr/hal-02145705`
6. **FY** *et al.*, in Proc. iTWIST 2018

   `https://hal.archives-ouvertes.fr/hal-01859713`

   + Code: `https://github.com/faroya/Faster-than-Fast-NeNMF`