PRIVACY-PRESERVING USE OF INDIVIDUAL SMART METERING DATA FOR CUSTOMER SERVICES

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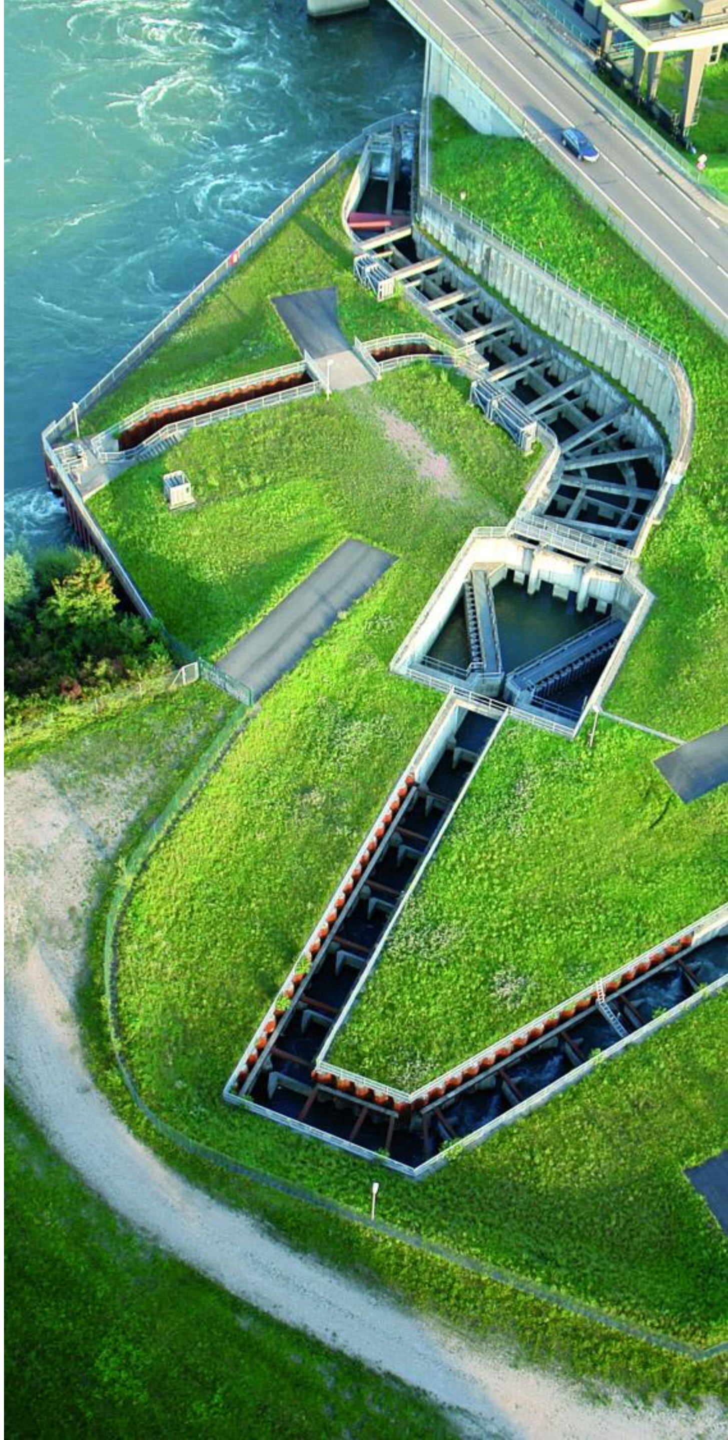
Séminaire “Data Science sur un plateau”

11 Octobre 2017

EDF Lab Saclay




Smart Grid
... We're Watching


Linky
BiG LiNKY
is WATCHiNG
You!
UFC-Que Choisir
Biz

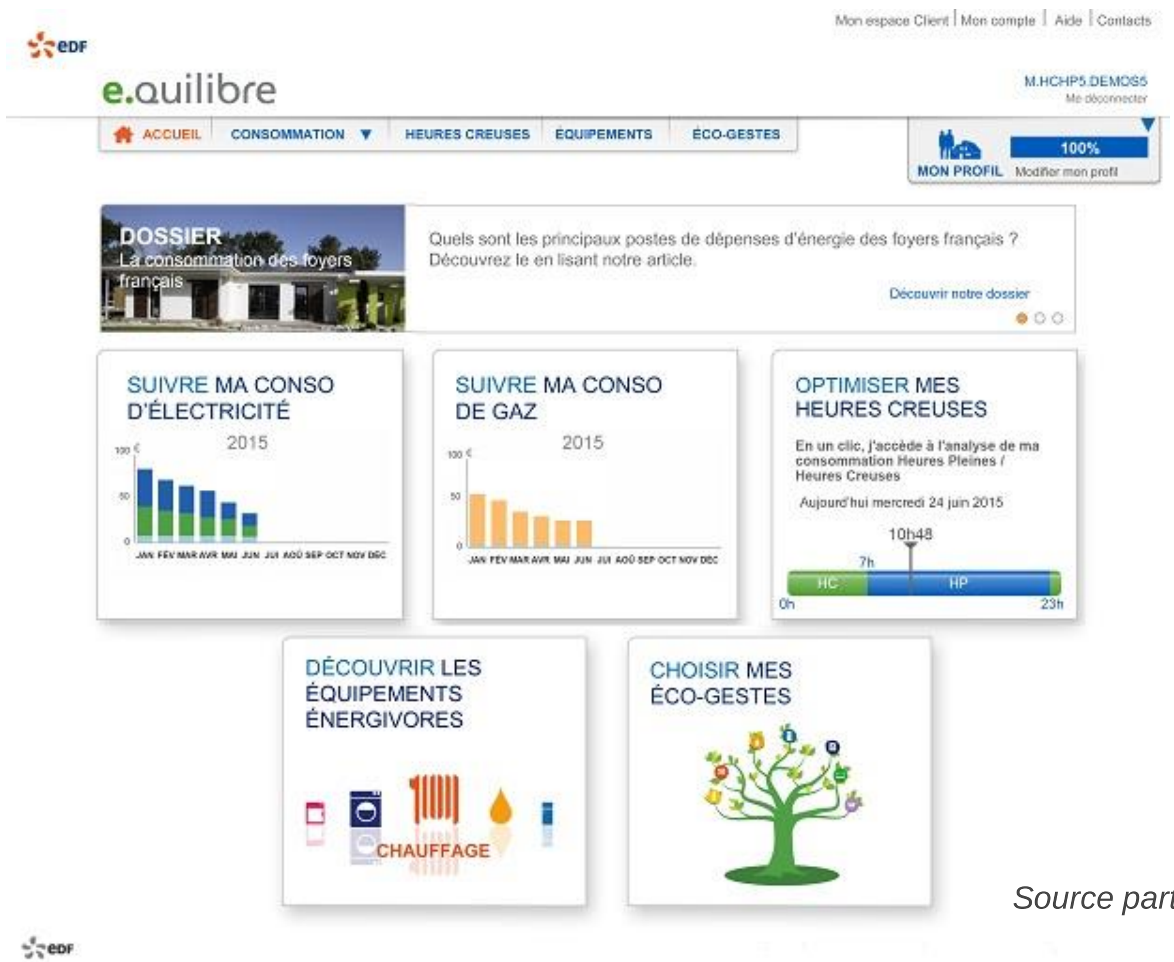
SMART METERS AND CONNECTED OBJECTS

- **Deployment of smart meters** (Linky project in France)
  - From 2016 to 2020 (35M meters) – 8M end of 2017
  - Remote turning power on/off, remote readings and billing
  - Readings up to every 10 minutes to the supplier/distributor
  - Readings up to 2s on premisses

- **Deployment of connected objects in households** ('smart home')

NEW SERVICES TO CUSTOMERS

- **Using smart meter readings for energy efficiency diagnosis and advice**



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NEW SERVICES TO CUSTOMERS

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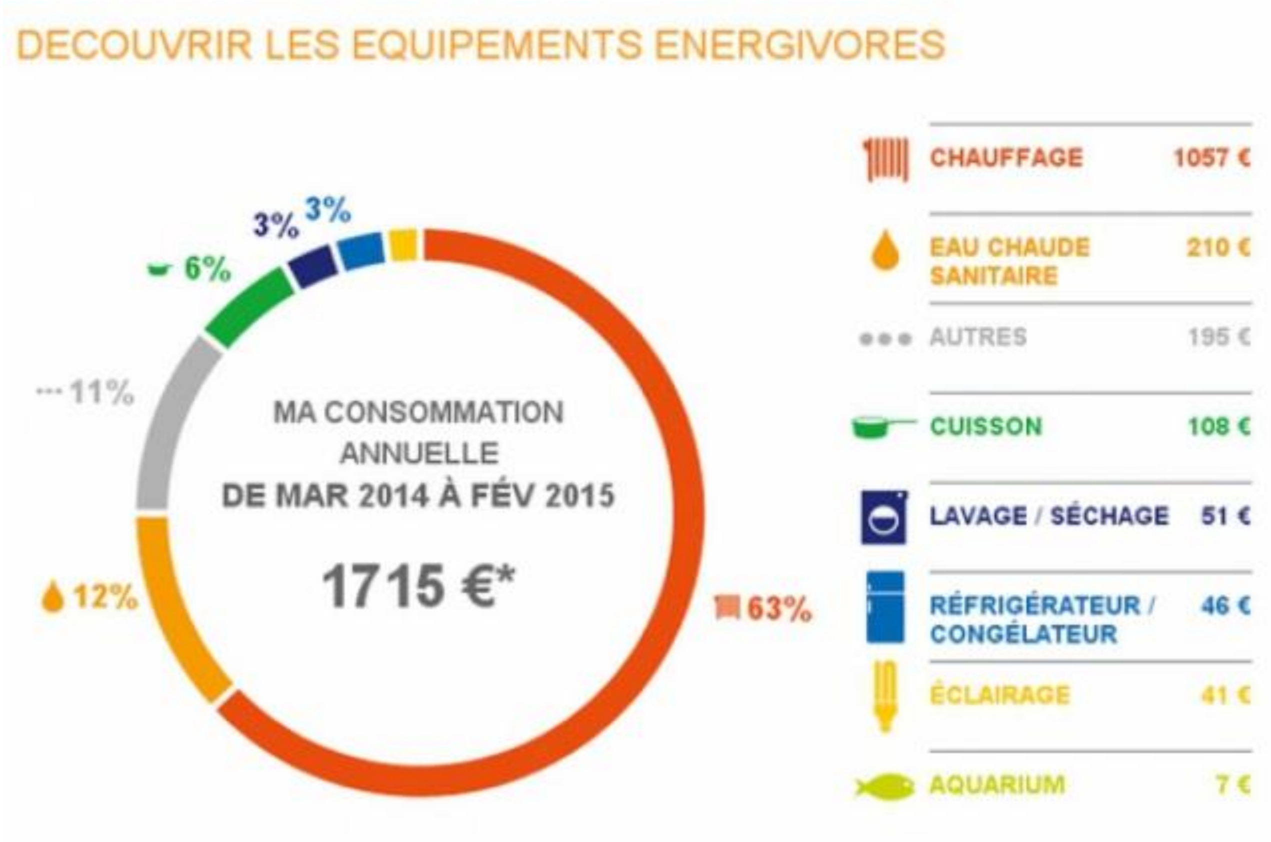

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NEW SERVICES TO CUSTOMERS

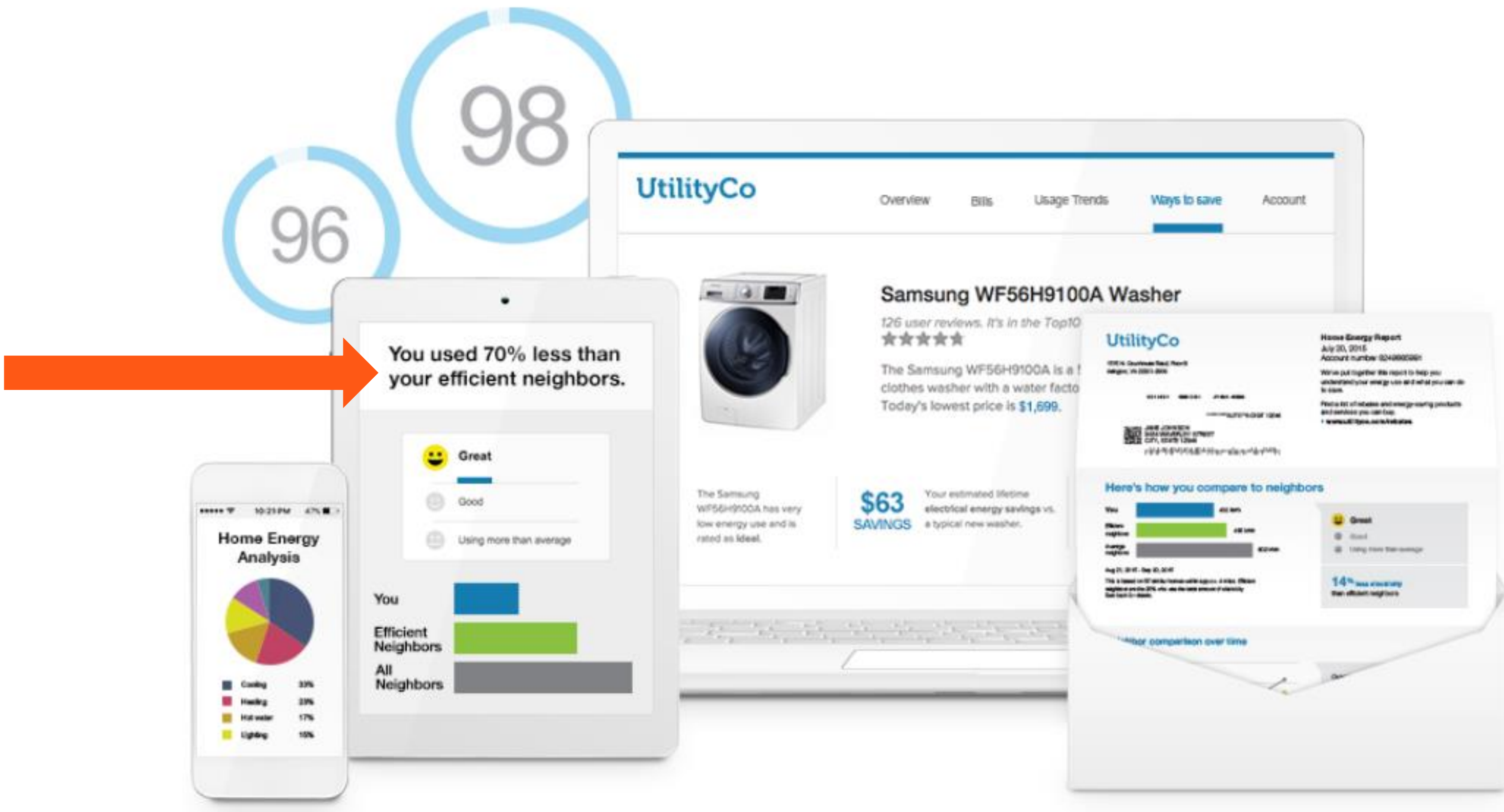
- **Using smart meter readings for energy efficiency diagnosis and advice**

Green Button Download My Data ®

Green Button Connect My Data

NEW SERVICES TO CUSTOMERS

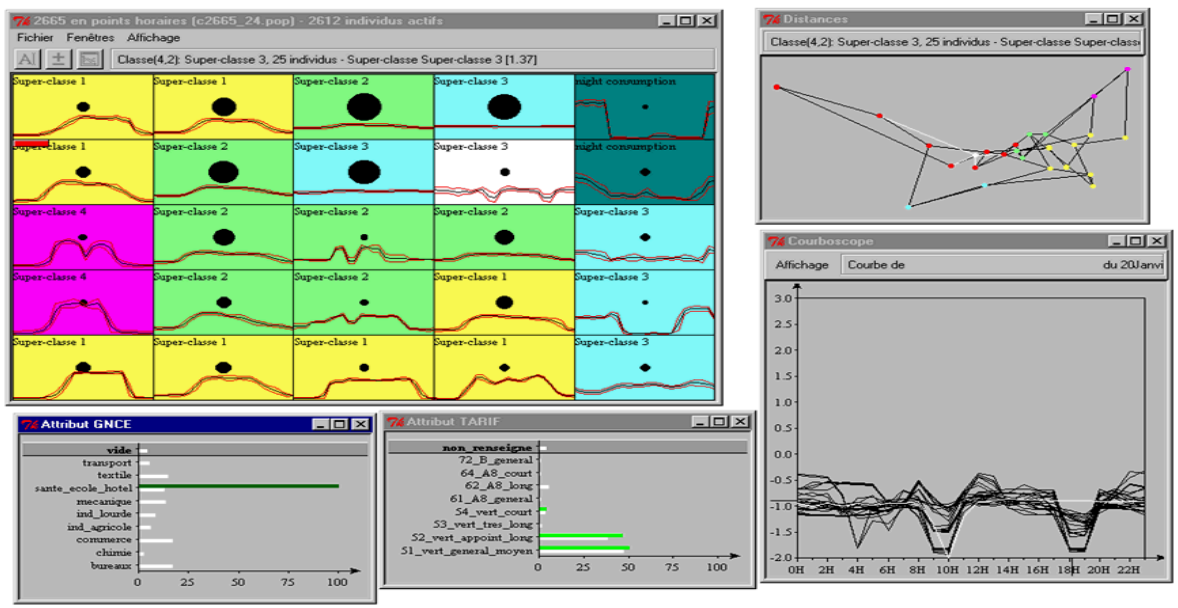
- **Using smart meter readings for energy efficiency diagnosis and advice**



Source www.opower.com

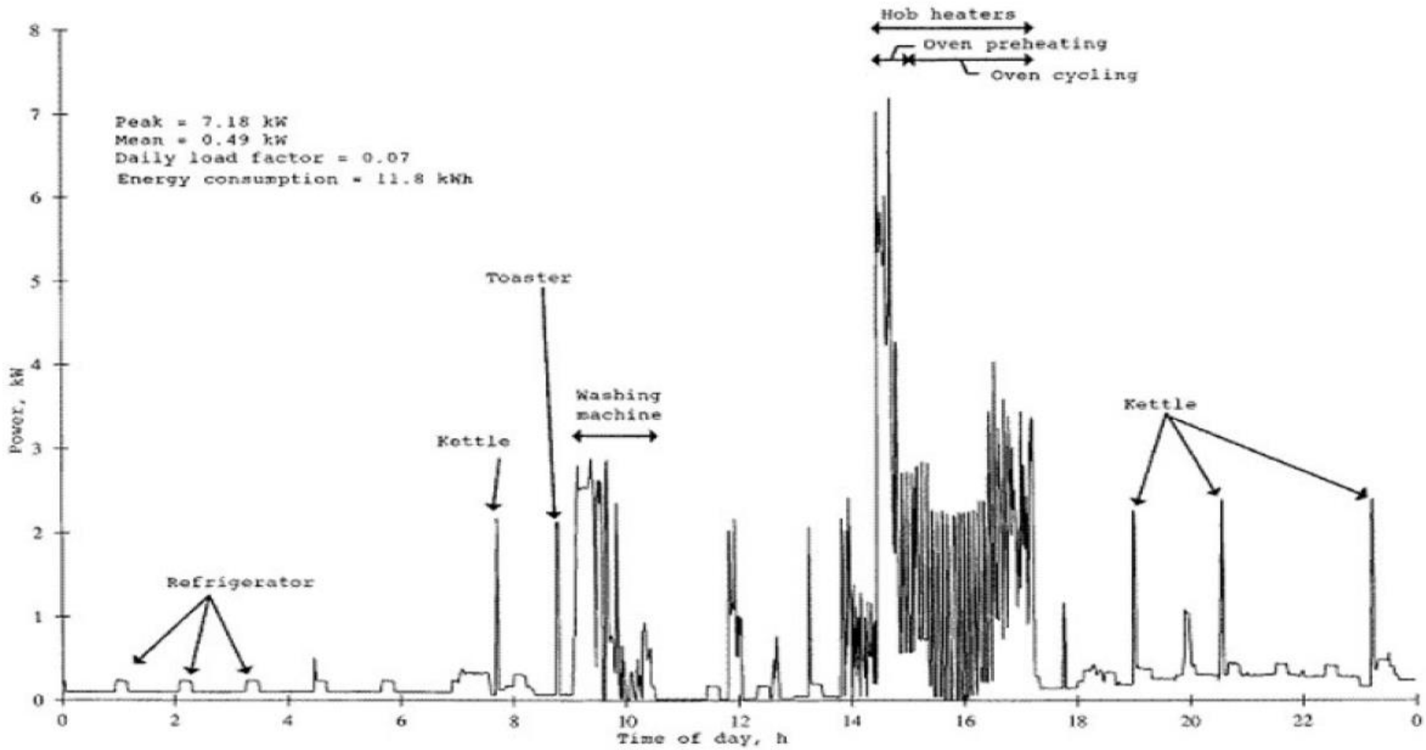
NEW SERVICES TO CUSTOMERS

- **Using smart meter readings for energy efficiency diagnosis and advice**
  - One standard approach: comparison to « neighbors »
    - Storage of individual consumption curves in a centralized data warehouse
    - Construction of (daily/weekly) profiles by clustering of individual curves
    - Association of house/equipment/occupants characteristics to clusters
    - Comparison of individual data with profiles



GREAT … BUT …

- **Consumption data becomes more sensitive at a higher sampling rate**
  - Presence/absence, number of people in the house
  - Human activity (cooking, shower, TV, …)



Household electrical consumption example

Newborough et P. Augood, « Demand-side management opportunities for the UK domestic sector », Generation, Transmission and Distribution, IEE Proceedings-, vol. 146, n° 3, p. 283 -293, mai 1999.

PRIVACY-PRESERVING SERVICES TO CUSTOMERS

Do the same job but with privacy preservation of individual electric power consumption curve !

→ « Chiaroscuro »

- **Basic idea**
  - Customer advice is computed locally (can easily be private)
  - Construction of profiles with associated household characteristics

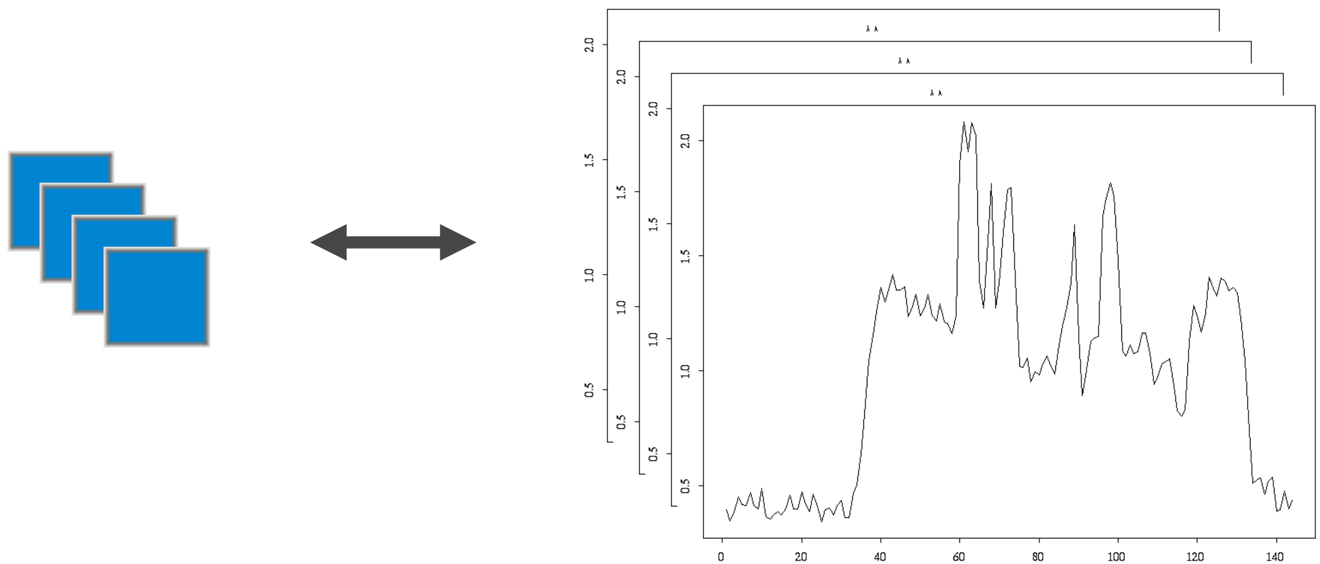
  → New approach of privacy-preserving clustering of individual consumption curves

PRIVACY-PRESERVING TIME SERIES CLUSTERING

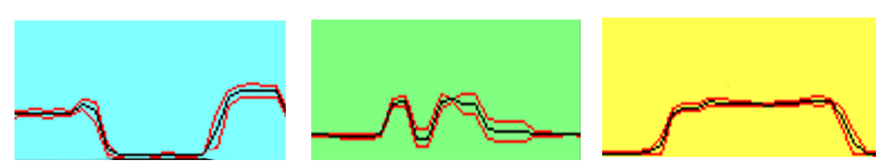
- **Privacy-preserving distributed clustering**
- **P2P infrastructure**
- **Evaluation**

PRIVACY-PRESERVING DISTRIBUTED CLUSTERING

- **Data input**
  - N geographically distributed individual daily electric power consumption time series
  - 24 dimensions vectors if hourly data, 144 dimensions data if 10’ data
  - Euclidian distance on (normalized) coordinates

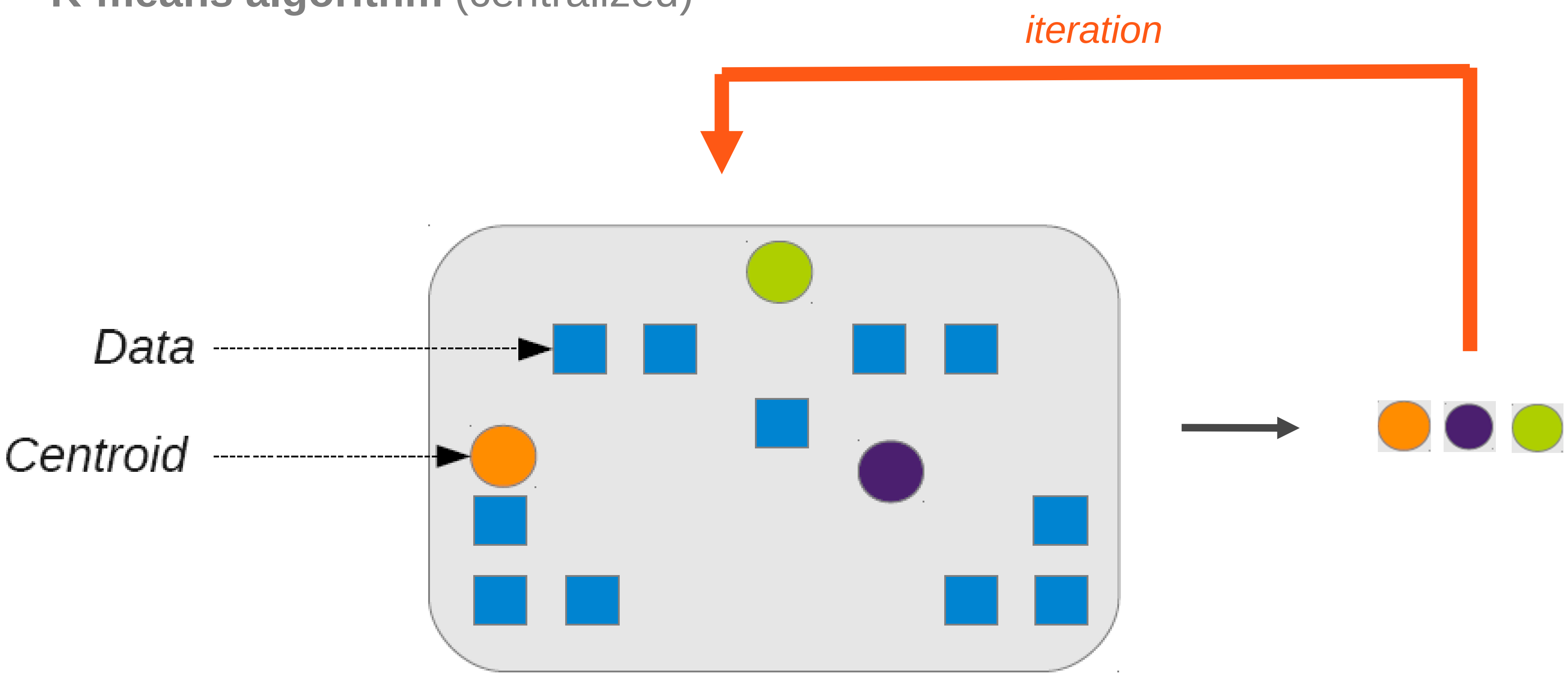


- **Output result**
  - K time-series profiles (24 ou 144 dimensions)



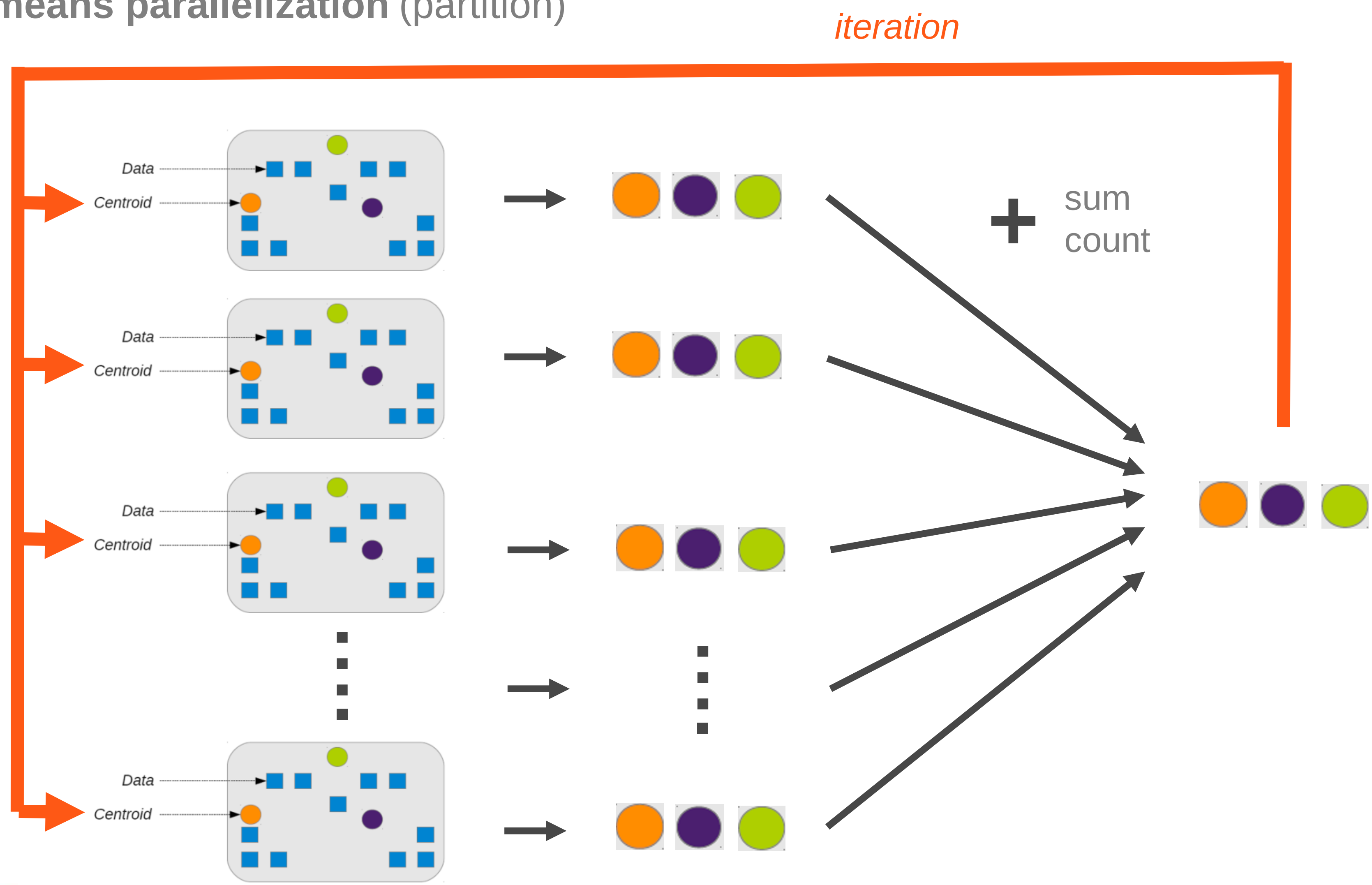
PRIVACY-PRESERVING DISTRIBUTED CLUSTERING

- **K-means algorithm** (centralized)



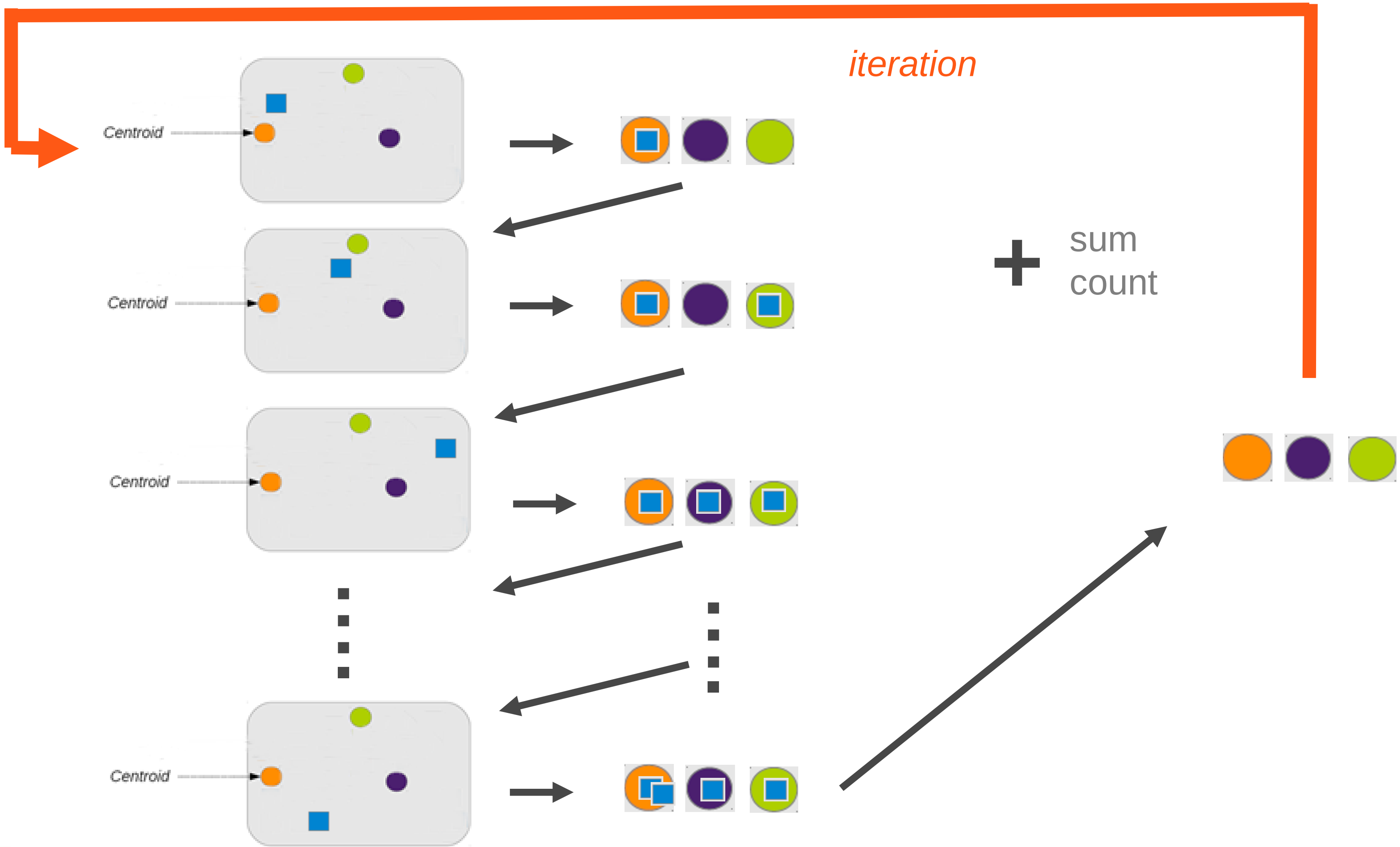
PRIVACY-PRESERVING DISTRIBUTED CLUSTERING

- **K-means parallelization** (partition)



PRIVACY-PRESERVING DISTRIBUTED CLUSTERING

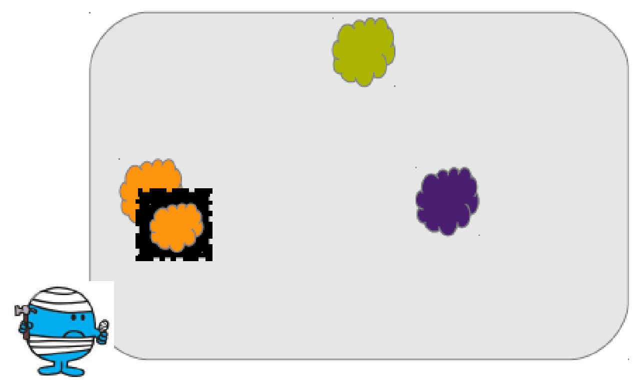
- **K-means:** *circulation* of centroïds among individuals



PRIVACY-PRESERVING DISTRIBUTED CLUSTERING

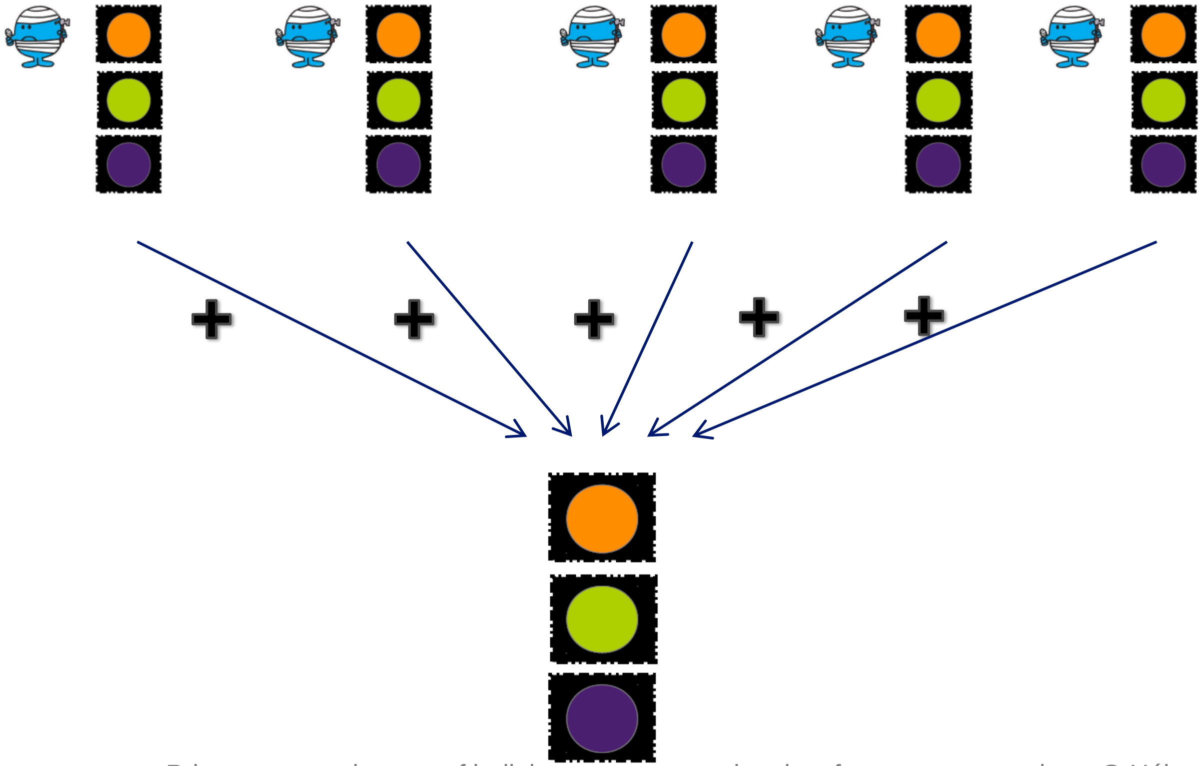
- **Circulation of 2 centroïd structures among individual participants**
  - Cleartext centroïds for local assignment of individual time series to the closest cluster
  - Encrypted centroïds built gradually from assignments for the next iteration

	
Cleartext centroids **perturbed** (differential privacy)	**Encrypted** means (additively-homomorphic)



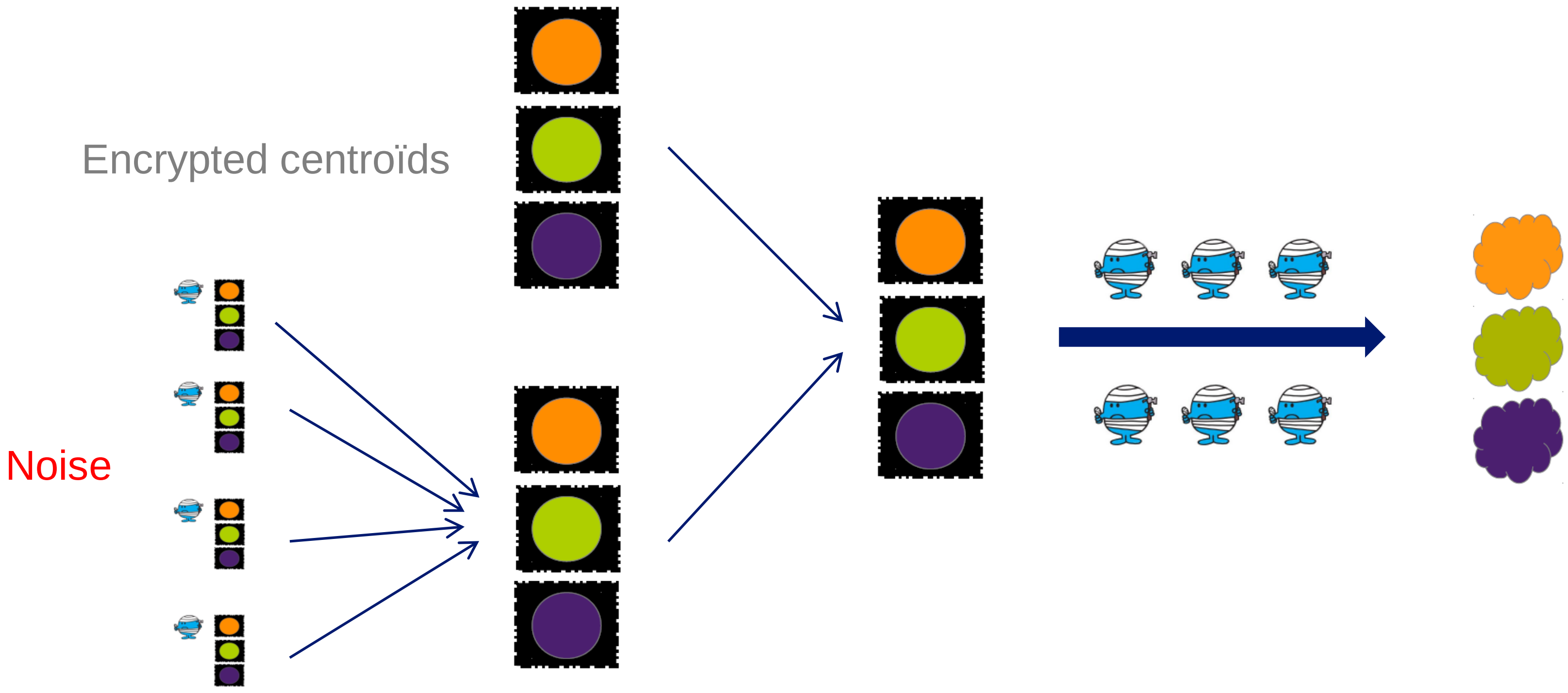
PRIVACY-PRESERVING DISTRIBUTED CLUSTERING

- **Centroïd computation within an iteration**
  - Two additive parts: SUM and COUNT
  - Use of additive homomorphic encryption *(allows addition directly on encrypted data)*



PRIVACY-PRESERVING DISTRIBUTED CLUSTERING

- **End of iteration**
  - Decryption of centroïds for the next iteration but:
    - Introduction of noise in centroïds before decryption (differential privacy)
  - Collaborative decryption



PRIVACY-PRESERVING DISTRIBUTED CLUSTERING

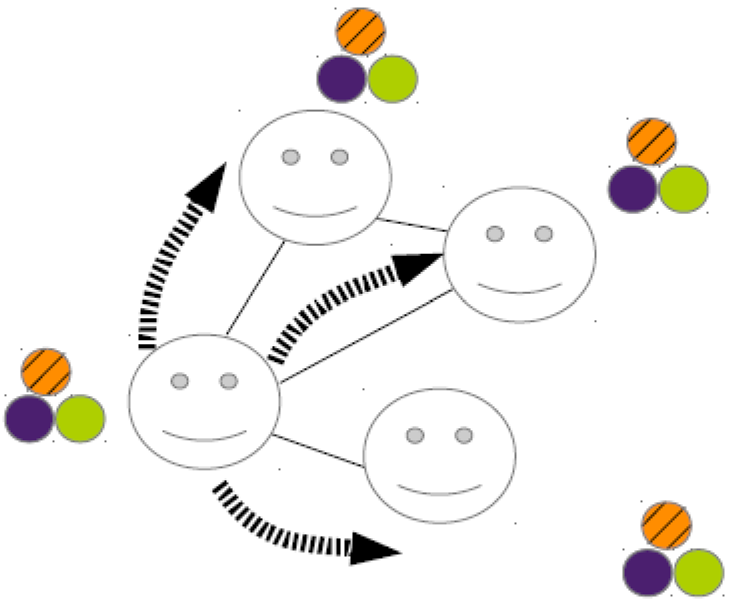
- **Association of house/equipment/occupants characteristics to clusters**
  - Last iteration
  - Counting for each combination *characteristic x cluster*
  - Similar protection: encryption + noise + collaborative decryption

PRIVACY-PRESERVING TIME-SERIES CLUSTERING

- **Privacy-preserving distributed clustering**
- **P2P infrastructure**
- **Evaluation**

PRIVACY-PRESERVING TIME-SERIES CLUSTERING

- **P2P (peer-to-peer) architecture**
  - No central server (local operations preserving privacy)
  - Scalability to millions of customers
  - Robustness to connections / disconnections (churn)
  - Sum computations using a « **gossiping** » algorithm
    - repeated averages between participants (adaptation of usual gossip sum algorithm)



PRIVACY-PRESERVING TIME-SERIES CLUSTERING

- **Privacy-preserving distributed clustering**
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PRIVACY-PRESERVING TIME-SERIES CLUSTERING

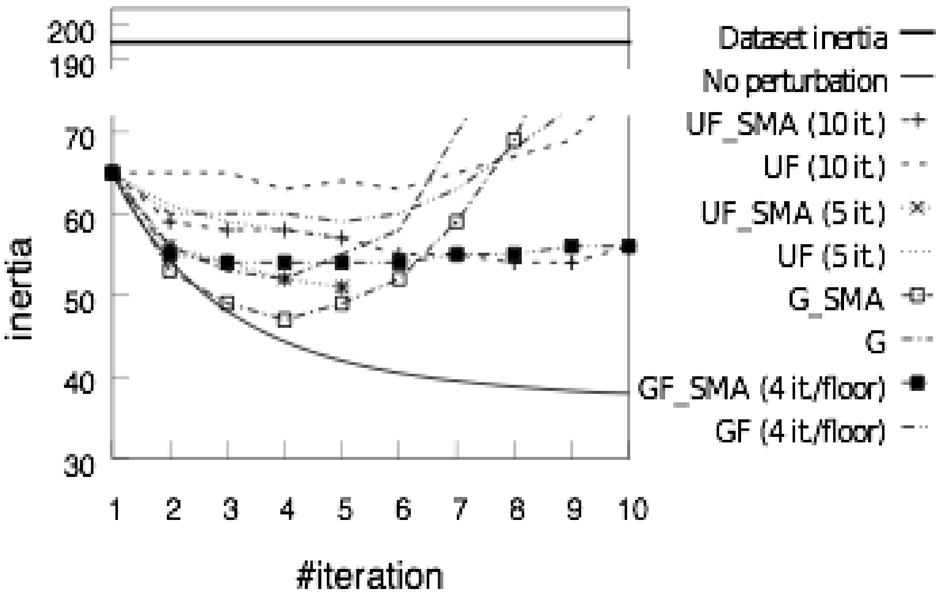
- **Evaluation questions:**
  - **Quality of clustering:**
    - Perturbed centralized k-means implementation
    - Measured by the intra-cluster inertia
    - Datasets : Irish CER (3M real electrical consumption time-series) and NUMED (1.2M synthetic tumor growth time-series)
  - **Latencies** of gossip algorithms: distributed computing simulator (Peersim)
  - **Local performances** (*i.e.,* CPU times, bandwidth consumption): laptop with *current average*+ resources

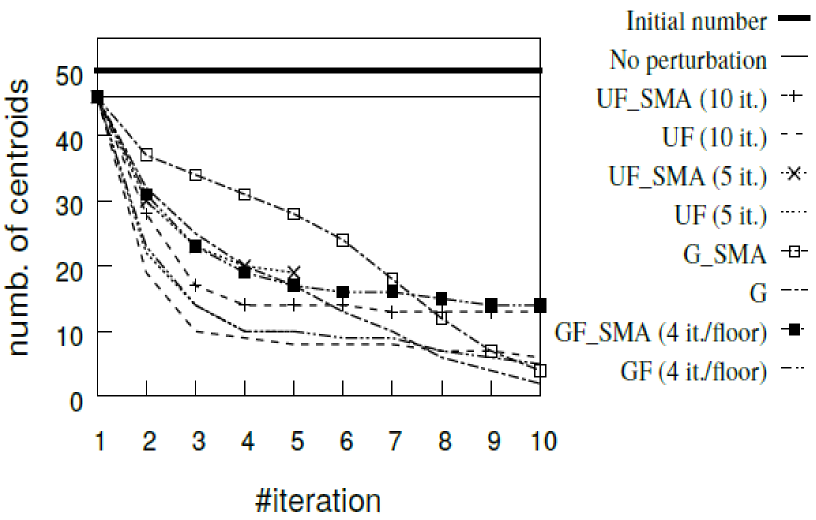
PRIVACY-PRESERVING TIME-SERIES CLUSTERING

- **Quality of clustering**
  - Varying participants for each iteration (connections/disconnections)
  - Introduction of noise
    - High perturbation for small clusters
    - Large clusters « eat » small clusters
  - Distribution of privacy budget between iterations
  - Smoothing time series after noise introduction
  - Early stopping

PRIVACY-PRESERVING TIME-SERIES CLUSTERING

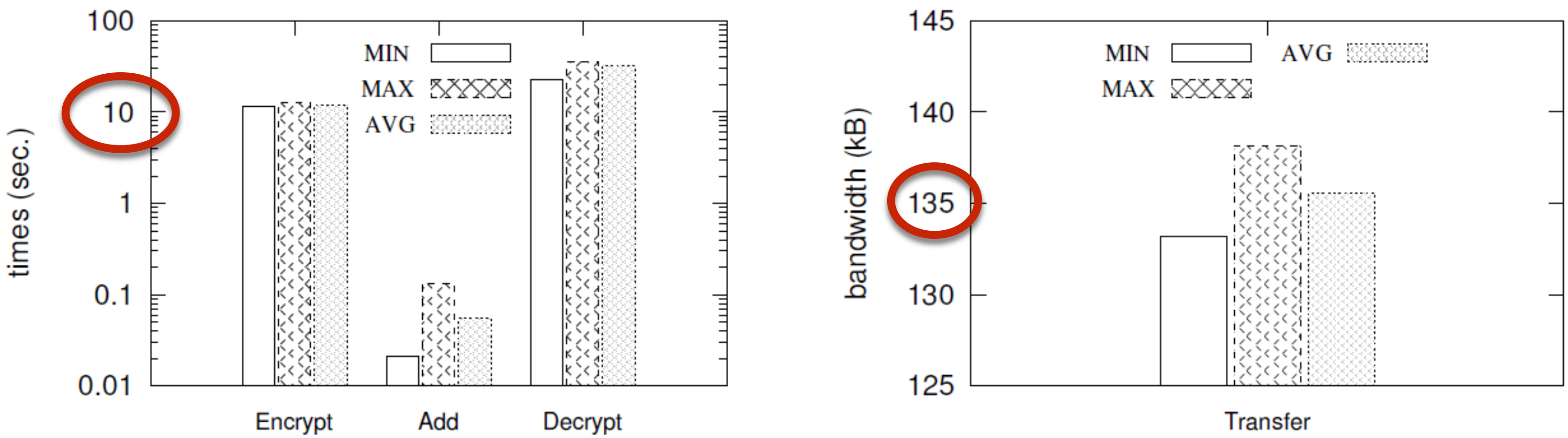
- **Quality of clustering: example of settings**
  - Clustering : k = 50 centroids, CER dataset, 24 numbers per time-series
  - Security : differential privacy budget ε = 0.69, encryption key length 1024 bits





PRIVACY-PRESERVING TIME-SERIES CLUSTERING

- **Affordable communication and computation costs**
  - NUMED dataset: 1.2M time series of size 20



(a) Times Consumption for Encrypting or Decrypting One set of Means, or Adding Together Two Sets of Means (seconds)

(b) Bandwidth Consumption for Transferring One Set of Means (kilo-bytes)

Unitary Local Costs for a Set of 50 Means, 20 Measures per Mean, and a 1024 Bits Encryption Key

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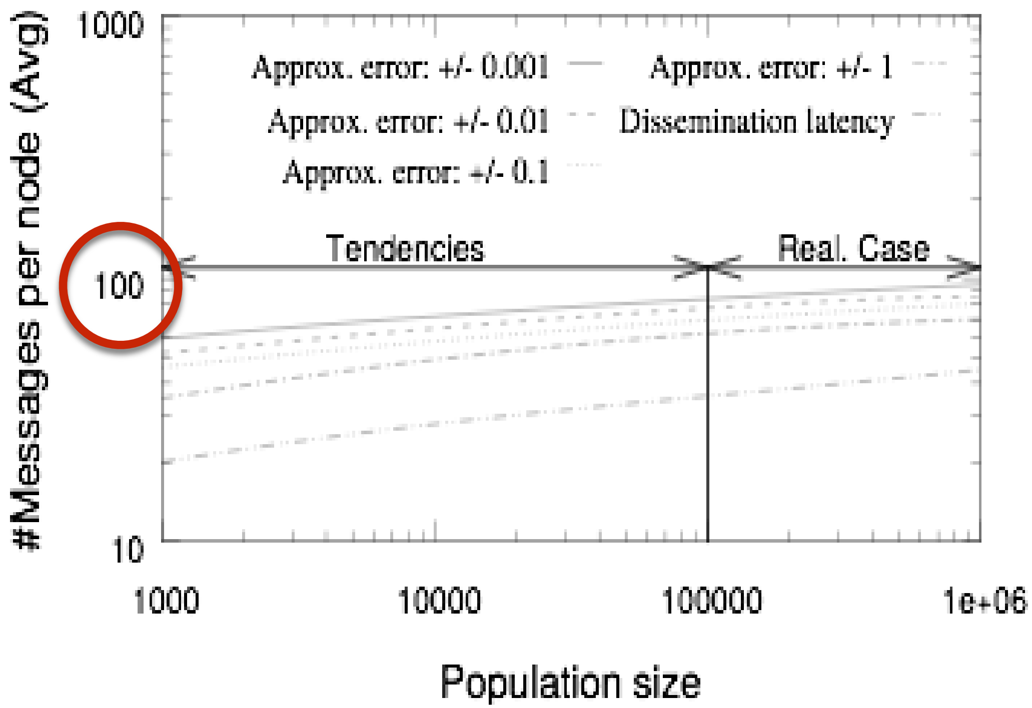

CONCLUSION

- **Chiaroscuro :**
  - First massively distributed privacy-preserving clustering solution for time series
  - Clustering: *k*-means-like algorithm (simplicity)
  - Distribution: Gossip-based (scalability and fault-tolerance)
  - Privacy: encryption and differential privacy

- **Future work :**
  - Functional representation of time series
  - Malicious participants
  - Other analytical algorithms

REFERENCES

"Chiaroscuro: Transparency and Privacy for Massive Personal Time-Series Clustering", T.Allard, G.Hébrail, F.Masseglia, E.Pacitti, Proceedings of the 2015 ACM SIGMOD.

" A New Privacy-Preserving Solution for Clustering Massively Distributed Personal Times-Series", T.Allard, G.Hébrail, F.Masseglia, E.Pacitti, 2016 ICDE demonstration.

"Differential privacy", C. Dwork, in ICALP, 2006, p. 1–12.

"A Generalisation, a Simplification and Some Applications of Paillier's Probabilistic Public-Key System", Damgaard et M. Jurik, in Proceedings of the 4th International Workshop on Practice and Theory in Public Key Cryptography: Public Key Cryptography, London, UK, UK, 2001, p. 119–136.

"Gossip-Based Computation of Aggregate Information", D. Kempe, A. Dobra, et J. Gehrke, in FOCS, Washington, DC, USA, 2003, p. 482–491, 2003.