Interpretation of time-series trajectories of chronic pain using evidential clustering

V. Antoine

Université Clermont Auvergne, LIMOS, UMR CNRS 6158, France
https://perso.isima.fr/~viantoin

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[1] A. Soubeiga, V. Antoine, S. Moreno, J. Koko *Evidential clustering with view-weight learning for proximity data*, Neurocomputing, 2026.

Plan

Chronic pain

The burden of chronic pain

- 40% of French people concerned
- 10 million suffer the repercussion on their daily lives
  - Fatigue, sleep disorders, depression, anxiety, disability, isolation...
- Old treatments, not effective in the long term, with side effects

Chronic pain

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Difficulties in providing care

- Lack of knowledge and time for the doctors
- Pain centers overload
- Insufficient prescription of validated complementary therapies
- Diagnostic wandering and medical nomadism

Analgesia Foundation

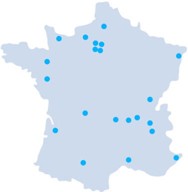
Foundation in the development of digital solutions for patients and their caregivers.

Analgesia
Fondation de Recherche sur la Douleur

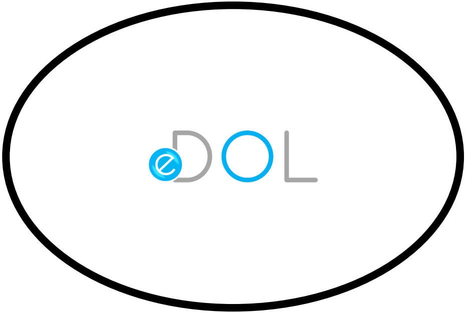
expert centers

research teams

patient association



eDOL project



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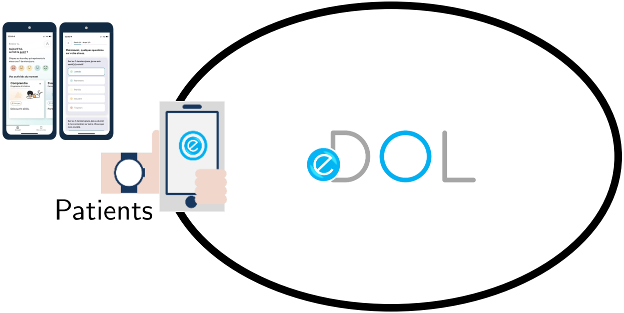

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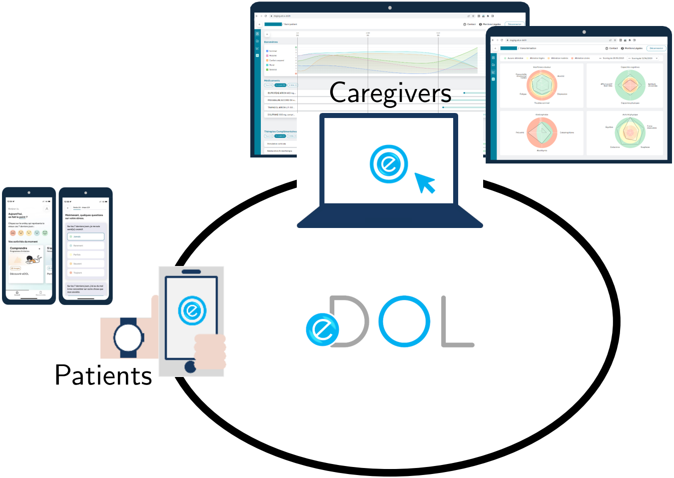

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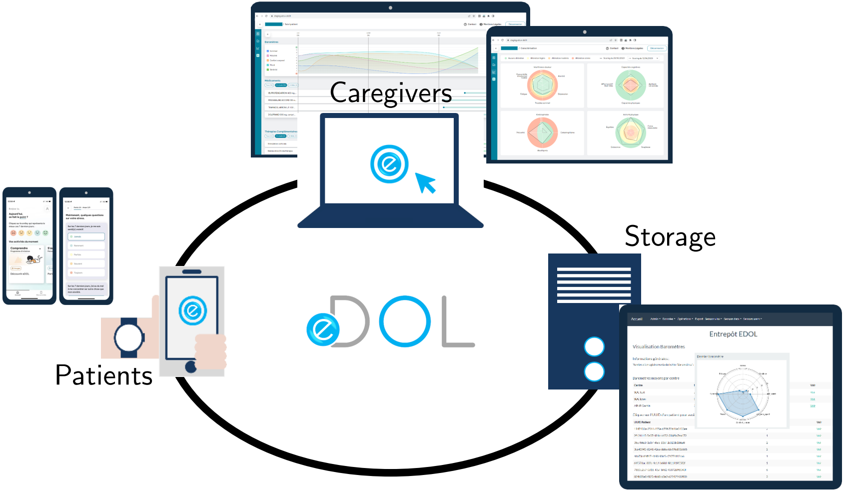
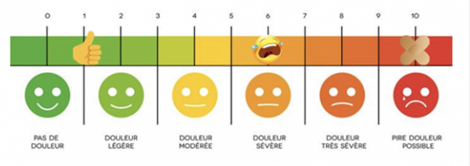


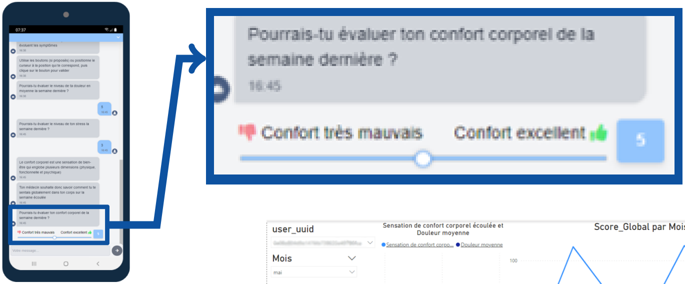
eDOL objective

Analysis of chronic pain patient profiles

- Better evaluate and monitor the pain (by barometers)
- Support general practitioner
  - alert
  - diagnostic
  - medical care

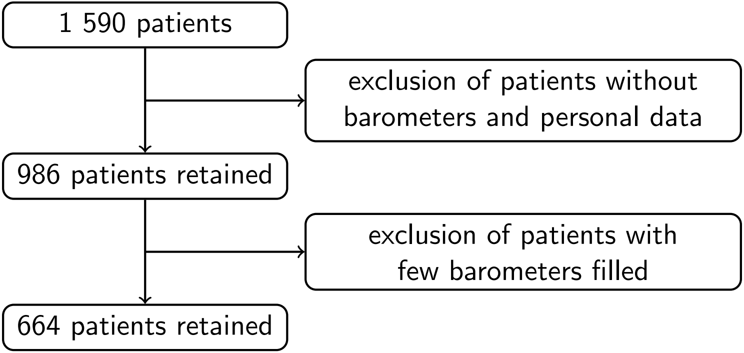


eDOL data



barometer	scale	polarity
Sleep		↗
Mood		↗
Fatigue	[0,10]	↘
Body confort		↗
Stress		↘
Pain		↘
Sport activity		↗
Non-sport act.		↗

eDOL data

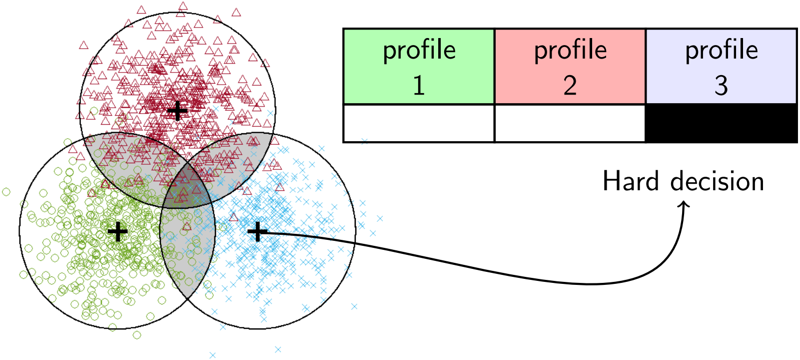


8 barometers accross 19 months

Patient profile ?

A lot of uncertainty

- intermediate states
- atypical states



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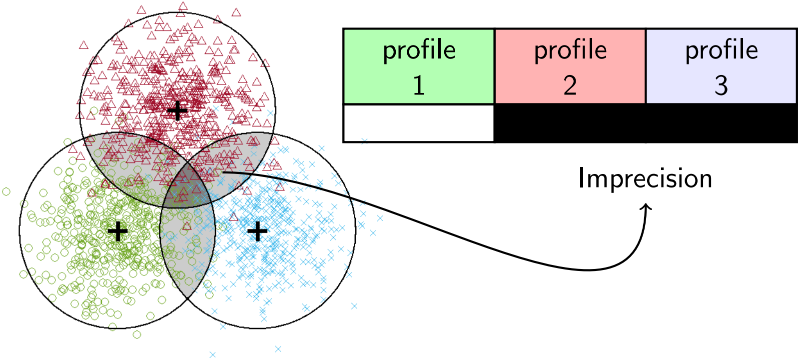

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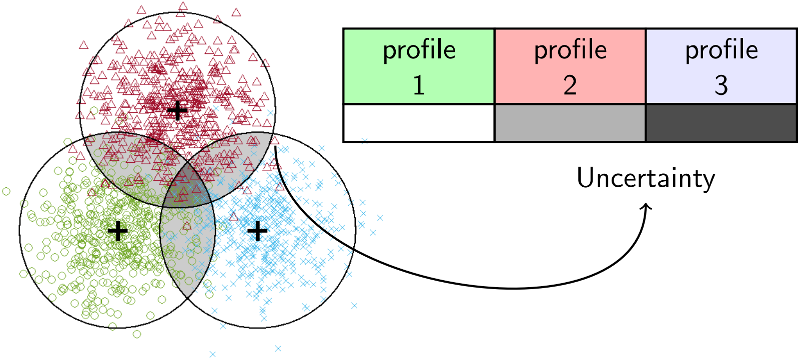

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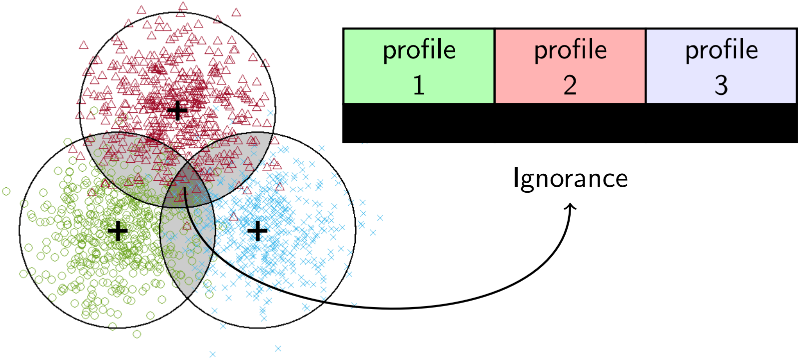

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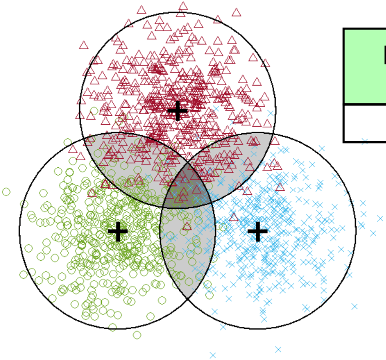
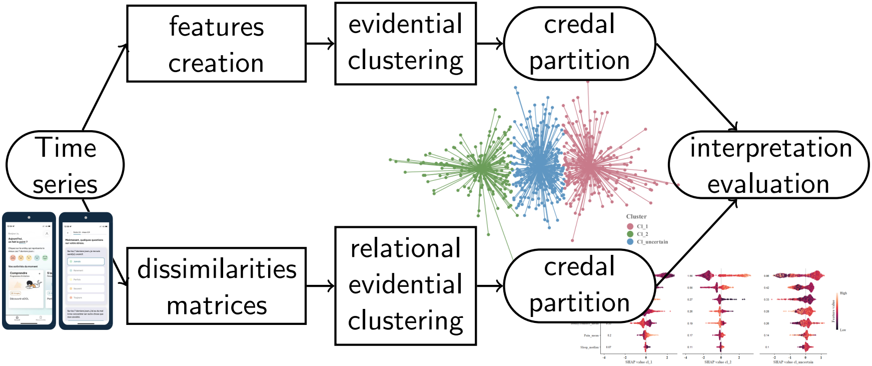


profile 1	profile 2	profile 3

Conflict

Scientific motivation



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Plan

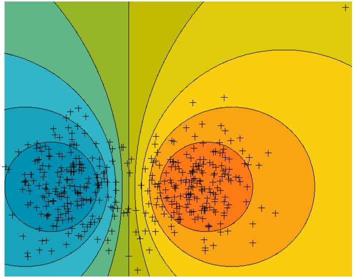
Fuzzy partition

- Each object has a membership degree for each cluster
- $\mathbf{U} = (u_{ik})$ such that $u_{ik} \in [0, 1]$, $\sum_{k=1}^{c} u_{ik} = 1$

Example

- ω_1 the class of squares
- ω_2 the class of circles

	p_{i1}	p_{i2}
	0	1
	1	0
	0.9	0.1
	0.5	0.5



Fuzzy c-means (FCM)

Geometrical model

- Each cluster ω_k is represented by a center $\mathbf{v}_k$
- Euclidean distance $d_{ik}^2 = (\mathbf{x}_i - \mathbf{v}_k)^T(\mathbf{x}_i - \mathbf{v}_k)$

Objective function

$$J_{FCM}(\mathbf{U},\mathbf{V}) = \sum_{i=1}^{n}\sum_{k=1}^{c} u_{ik}^{\beta} d_{ik}^2$$

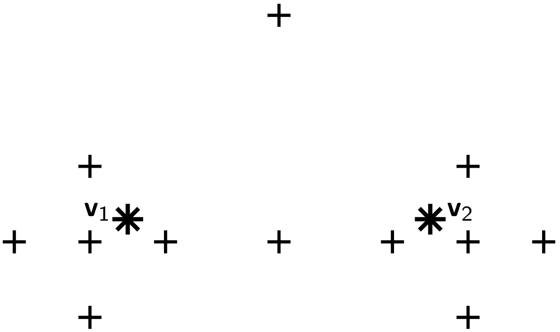
such that

$$\sum_{k=1}^{c} u_{ik} = 1 \text{ et } u_{ik} \geq 0 \quad \forall i,k$$

Gauss-Seidel optimization method

$$\min_{\mathbf{U}} J_{FCM} \quad \rightarrow \quad \min_{\mathbf{V}} J_{FCM} \quad \rightarrow \quad \ldots$$

Issue : imprecise assignments and atypical objects



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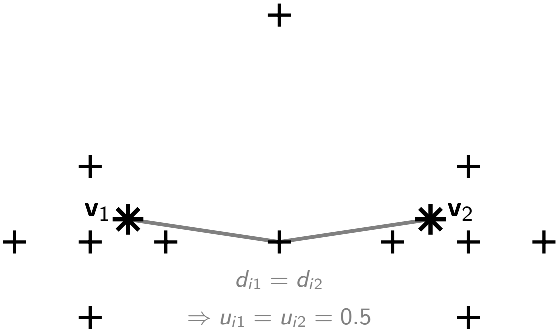
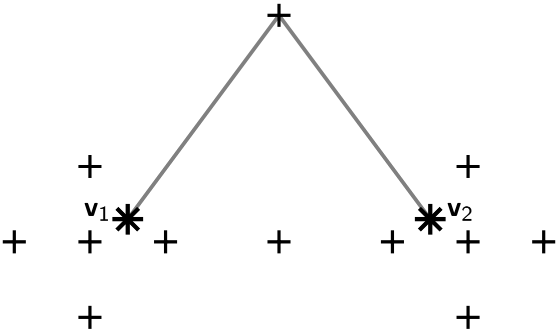


Issue : imprecise assignments and atypical objects

$$d_{i1} = d_{i2}$$

$$\Rightarrow u_{i1} = u_{i2} = 0.5$$



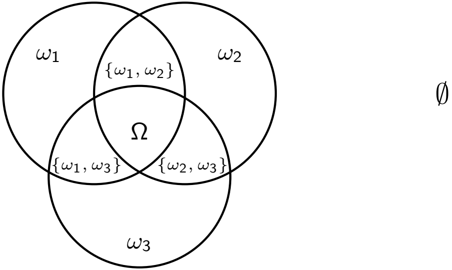
Belief function theory

Let Y be a variable taking values in a finite set Ω

Mass function $m : 2^{\Omega} \to [0,1]$

$$\sum_{A \subseteq \Omega} m(A) = 1$$

- $m(A)$: degree of belief specific to $Y \in A$
- If $m(A) > 0$ then A is a focal set

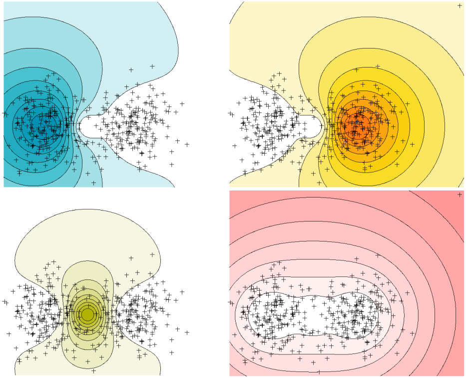


Credal partition

- Each object has a degree of belief for each subset $A_j \subseteq \Omega$
- $\mathbf{M} = (m_{ij})$ such that $m_{ij} \in [0,1]$, $\sum_{A_j \subseteq \Omega} m_{ij} = 1$

Example

	$m_{i\emptyset}$	$m_{i\omega_1}$	$m_{i\omega_2}$	$m_{i\Omega}$
	0	0	1	0
	0	1	0	0
	0	0.9	0.1	0
	0	0	0	1
	1	0	0	0



Credal transformation

Pignistic transformation to make decision

$$BetP(\omega) = \frac{1}{1 - m(\emptyset)} \sum_{\{A \subseteq \Omega | \omega \in A\}} \frac{m(A)}{|A|}$$

Credal partition

	$m_{i\emptyset}$	$m_{i\omega_1}$	$m_{i\omega_2}$	$m_{i\Omega}$
○	0	0	1	0
□	0	1	0	0
□	0	0.9	0.1	0
◗	0	0	0	1
☆	1	0	0	0

$\xrightarrow[\text{pignistic}]{\text{transformation}}$

Fuzzy partition

	$u_{i\omega_1}$	$u_{i\omega_2}$
○	0	1
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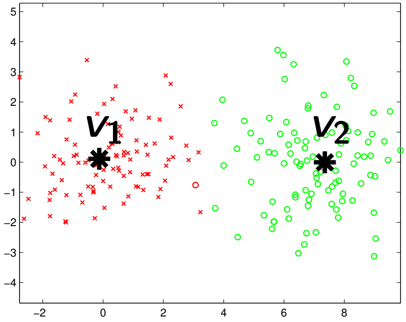
Evidential c-means (ECM)

- Each cluster ω_k is represented by a centroid $\mathbf{v}_k$
- Centroid $\bar{\mathbf{v}}_j$: barycenter of the centroids associated to the classes in $A_j \subseteq \Omega$
- Distance d_{ij}^2 between $\mathbf{x}_i$ and $\bar{\mathbf{v}}_j$



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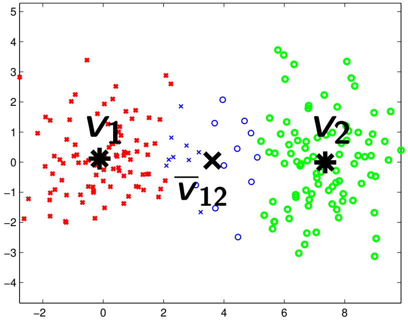

Evidential c-means (ECM)

Objective function

$$J_{ECM}(\mathbf{M},\mathbf{V}) = \sum_{i=1}^{n} \sum_{A_j \subseteq \Omega,\ A_j \neq \emptyset} |A_j|^{\alpha} m_{ij}^{\beta} d_{ij}^{2} + \sum_{i=1}^{n} \delta^2 m_{i\emptyset}^{\beta}$$

Such that

$$\sum_{A_j \subseteq \Omega,\ A_j \neq \emptyset} m_{ij} + m_i(\emptyset) = 1,\ m_i(A_j) \geq 0 \quad \forall i,j$$

Gauss-Seidel optimization method

$$\text{opt}(\mathbf{M}) \rightarrow \text{opt}(\mathbf{V}) \rightarrow \ldots$$

Evidential c-medoids (ECMdd)

Objective function

$$J_{ECMdd}(\mathbf{M},\mathbf{V}) = \sum_{i=1}^{n} \sum_{A_j \subseteq \Omega, A_j \neq \emptyset} |A_j|^{\alpha} m_{ij}^{\beta} \tau_{ij} + \sum_{i=1}^{n} \delta^2 m_{i\emptyset}^{\beta}$$

Such that

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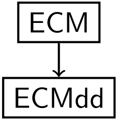
Difference with ECM

- use of a dissimilarity matrix $\mathcal{R} = (\tau_{ij})$
- use of medoids as centroids

Plan

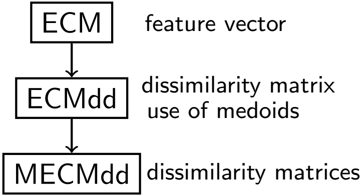
MECM: four variants



feature vector

dissimilarity matrix
use of medoids

MECM: four variants



MECM: four variants

ECM — feature vector

ECMdd — dissimilarity matrix, use of medoids

MECMdd — dissimilarity matrices

Global matrix estimation

$$\mathcal{R} = \sum_{l=1}^{p} \lambda_l^s \mathcal{R}_l$$

- sum constraint $$\sum_{l=1}^{p} \lambda_l^s = 1$$
- product constraint $$\prod_{l=1}^{p} \lambda_l^s = 1$$

Local matrix estimation

$$\forall A_j \subseteq \Omega, \mathcal{R} = \sum_{l=1}^{p} \lambda_{jl}^s \mathcal{R}_l$$

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MECM: four variants

global

or J_{MECMdd}

local

MECM: four variants

weights on dissimilarity matrices

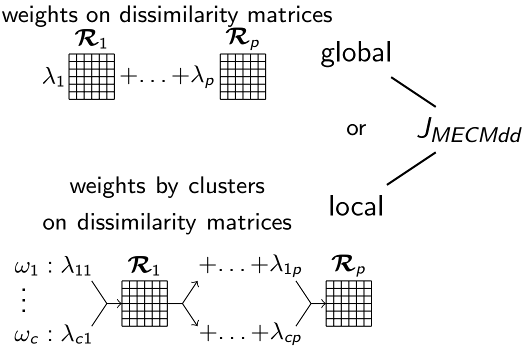
$$\lambda_1 \mathcal{R}_1 + \ldots + \lambda_p \mathcal{R}_p$$

global

or J_{MECMdd}

local

MECM: four variants



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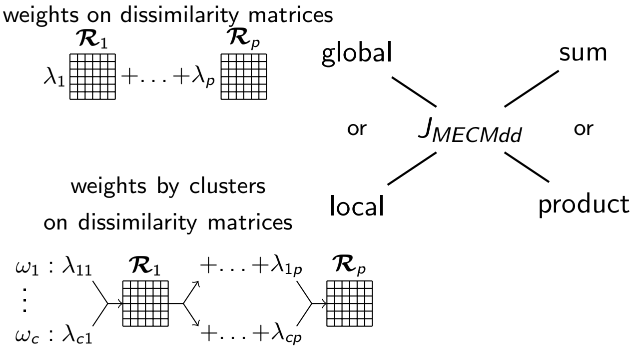


MECM: four variants

weights on dissimilarity matrices

$\lambda_1 \mathcal{R}_1 + \ldots + \lambda_p \mathcal{R}_p$

global

or

local

weights by clusters
on dissimilarity matrices

$\omega_1 : \lambda_{11} \mathcal{R}_1 + \ldots + \lambda_{1p} \mathcal{R}_p$

$\vdots$

$\omega_c : \lambda_{c1} \mathcal{R}_1 + \ldots + \lambda_{cp} \mathcal{R}_p$

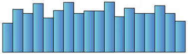
J_{MECMdd}

sum

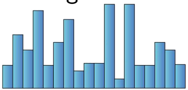
or

product

favor relatively balanced distribution of weights



wider dispersion of weights



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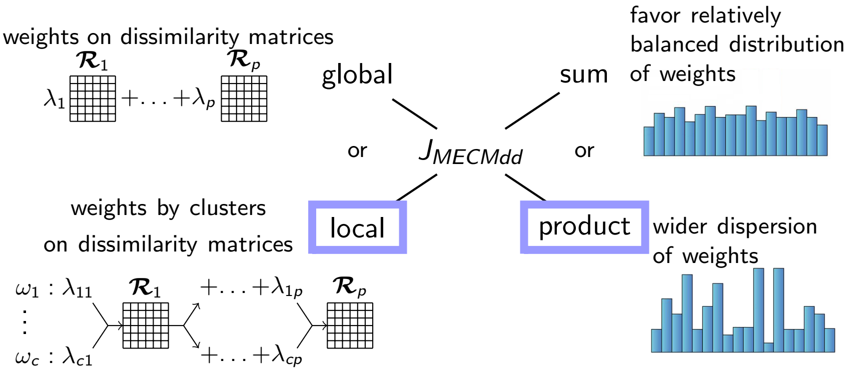


MECMdd with local weight estimation, product contraint

Objective function

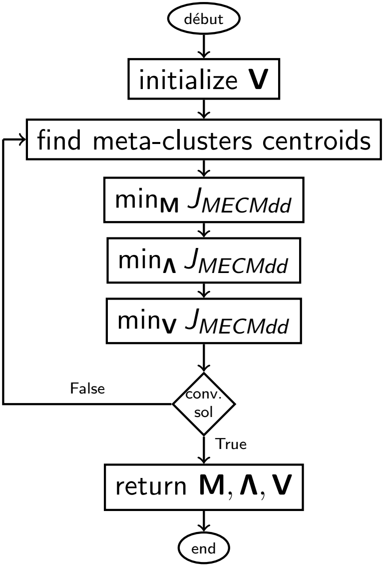
$$J_{MECMdd}(\mathbf{M}, \mathbf{V}, \boldsymbol{\Lambda}) = \sum_{i=1}^{n} \sum_{A_j \neq \emptyset} |A_j|^{\alpha} m_{ij}^{\beta} \sum_{l=1}^{p} \lambda_{jl} \tau_{ijl} + \sum_{l=1}^{p} \delta_l^2 \sum_{i=1}^{n} m_{i\emptyset}^{\beta}$$

Such that

$$\sum_{A_j \subseteq \Omega,\ A_j \neq \emptyset} m_{ij} + m_i(\emptyset) = 1,\ m_i(A_j) \geq 0 \quad \forall i, j$$

$$\prod_{l=1}^{p} \lambda_l = 1, \lambda_l > 0, \forall l$$

Alternate optimization



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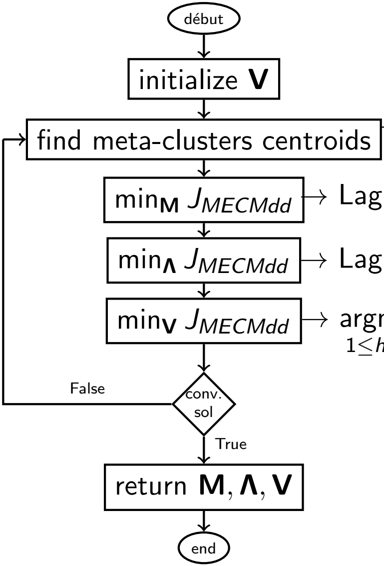


find meta-clusters centroids $\rightarrow$ $\underset{1 \leq h \leq n}{\operatorname{argmin}} \; \sigma_{ij}^2 + \eta \frac{1}{|A_j|} \sum_{\omega_k \in A_j} \sum_{l=1}^{p} \tau_{ikl}$

$\min_{\mathbf{M}} J_{MECMdd}$ $\rightarrow$ Lagrangian multipliers

$\min_{\mathbf{\Lambda}} J_{MECMdd}$ $\rightarrow$ Lagrangian multipliers

$\min_{\mathbf{V}} J_{MECMdd}$ $\rightarrow$ $\underset{1 \leq h \leq n}{\operatorname{argmin}} \sum_{i=1}^{n} m_{ij}^{\beta} \sum_{l=1}^{p} \lambda_{jl} \tau_{ijl}$

Plan

Evaluation

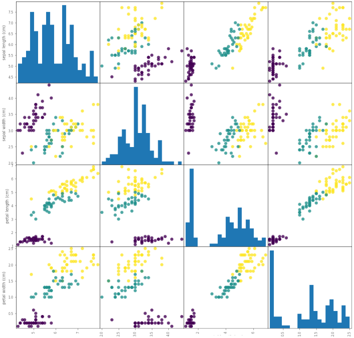
Datasets

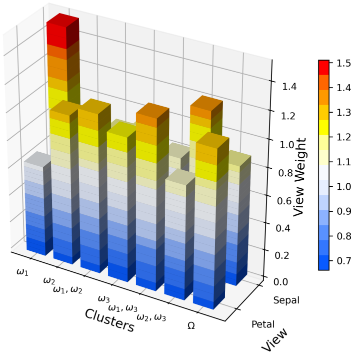
- 5 simple vector datasets
  - Abalone, Ecoli, Iris, Thyroid gland, Wine
- 3 categorical datasets
  - Car, Breast cancer, Zoo
- 4 multi-view datasets
  - Multiple features, Prokaryotic phyla, WebKB, MSRC
- 4 multivariate time series
  - UWaveGestureLibrary, StandWalkJump, BasicMotions, Biofam

Evaluation

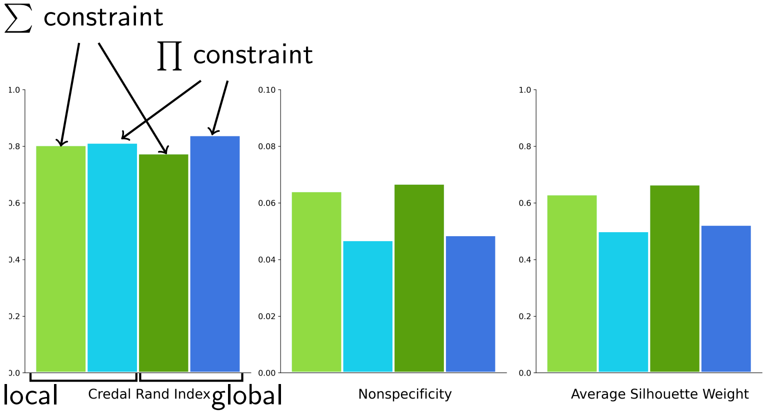
- Decision: Maximum of pignistic probability
- External criterion : Adjusted Rand Index
- Internal criterion : ASW and Non-Specificity

Behavior study with Iris





Behavior study with Iris



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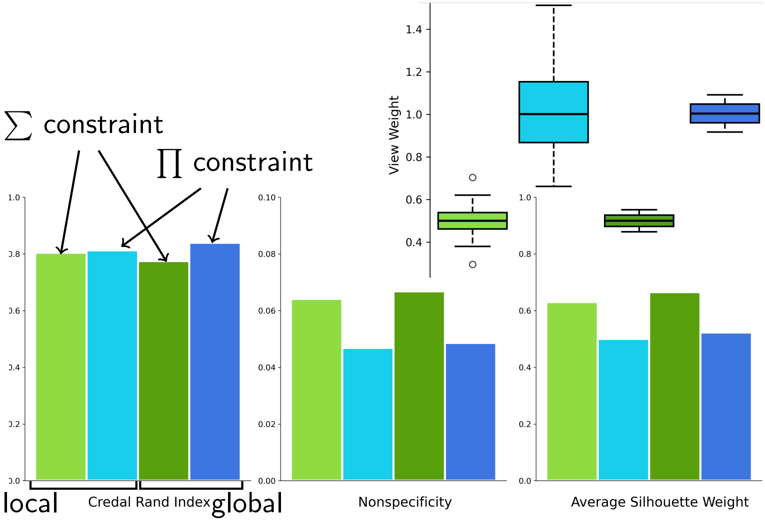
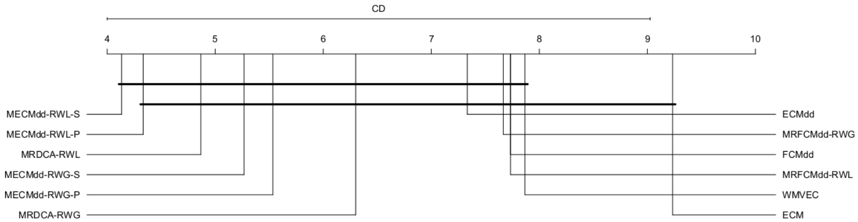
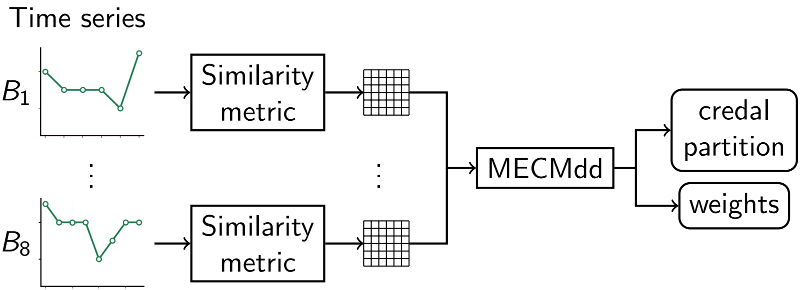


Comparison with relational algorithms



Application on eDOL dataset

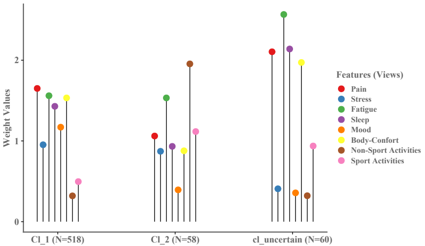


Similarity metrics tested

- Optimal Matching (OM)
- Time Warp Edit Distance (TWED)
- Dynamic Time Warping (DTW)

Results

	ASW	NS
OM	**0.68**	**0.09**
TWED	0.52	0.23
DTW	0.51	0.25



Interpretations

- MECMdd with product contraint
  - cluster 1: pain, stress, fatigue, sleep, mood, body confort
  - cluster 2: sport, non-sporting activities
- MECMdd using sum constraints
  - Similar results as [1]

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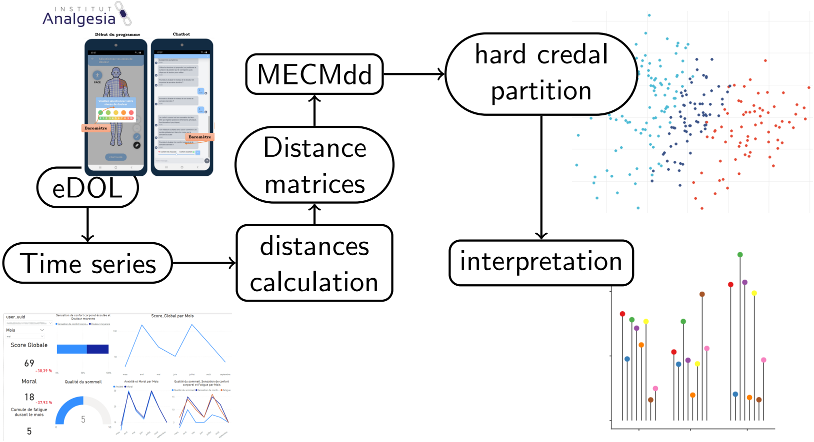
Plan

Conclusion ...



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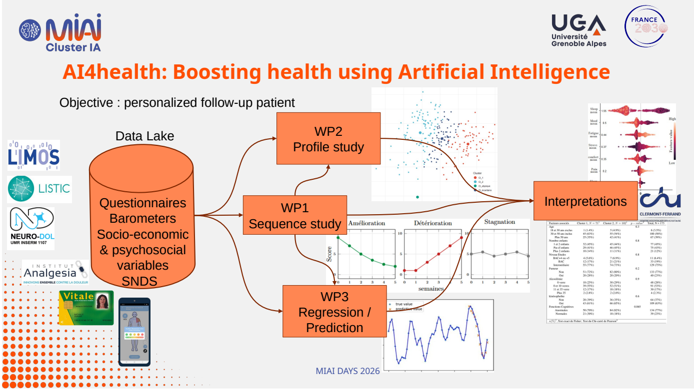
... and perspectives

Health

- Split patient's time series to take into account a sequence of states
- Chaining data with the SNDS



Thank you


advantages
obtained
belief function
medoid-based
matrices
overlapping
methods
credal partition
iterative
highlighting
assignment
proximity data
clustering
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