

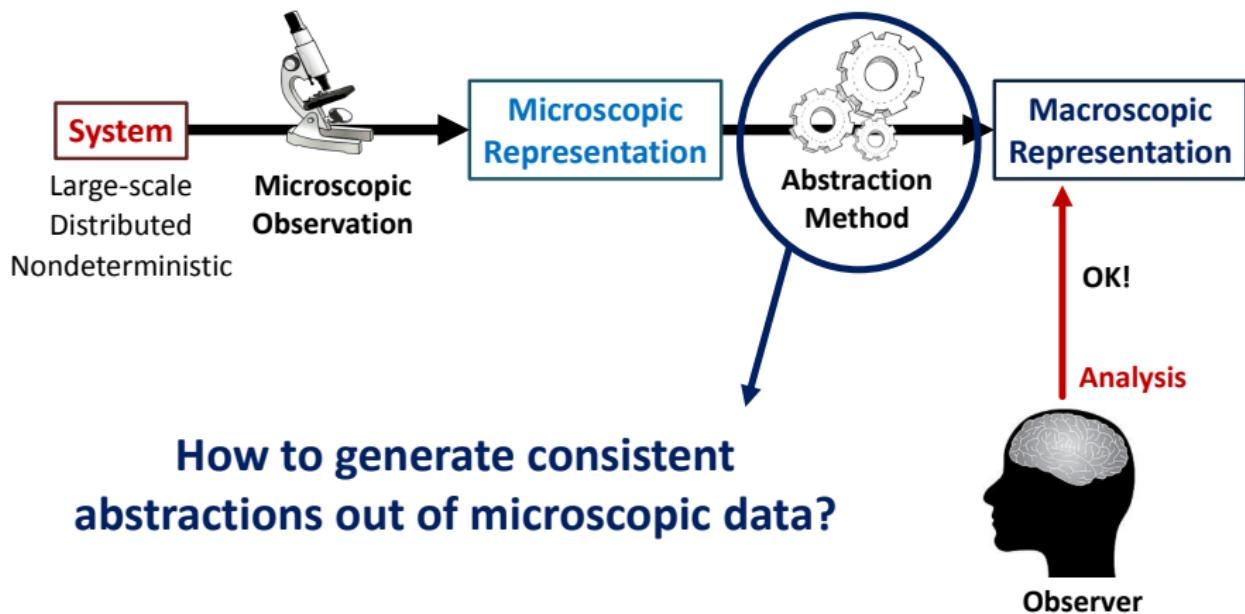
Multiscale Analysis of Social Systems

Robin Lamarche-Perrin



In collaboration with: Sven Banisch, Yves Demazeau,
Damien Dosimont, Claude Graland, Eckehard Olbrich,
Hugues Pecout, and Jean-Marc Vincent

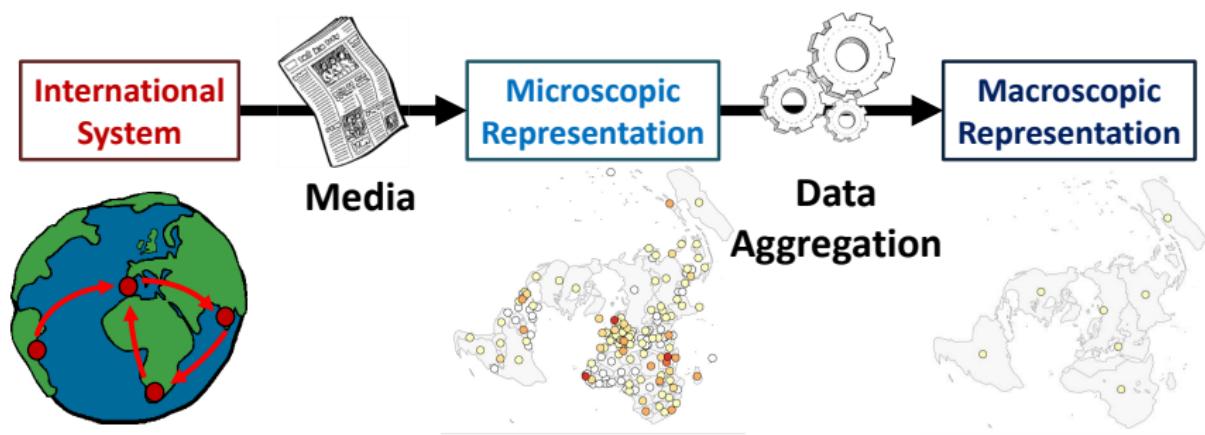
Macroscopic Analysis of Complex Systems



Macroscopic Analysis of Media Flows

Hypothesis: media constitute an adequate instrument to observe the national level

[Grasland *et al.*, 2011]



Raw Data

THE GUARDIAN

Paper 1



“Japan”

THE TIMES OF INDIA

Paper 2



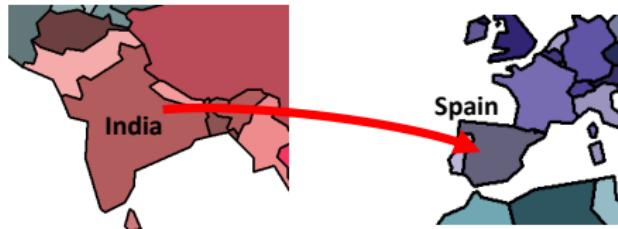
“Madrid”

Paper 3



“French”

“Spain”



The GEOMEDIA Database (ANR CORPUS GUI-AAP-04)

150 newspapers

1,944,000 papers

GEOGRAPHIC INFORMATION

193 countries (UN members)

THE GUARDIAN

Paper 1



“Japan”

30th May 2011

THE TIMES OF INDIA

Paper 2



“Madrid”

30th May 2011

Paper 3



“French”

19th July 2012

The GEOMEDIA Database (ANR CORPUS GUI-AAP-04)

150 newspapers

1,944,000 papers

GEOGRAPHIC INFORMATION

193 countries (UN members)

TEMPORAL INFORMATION

889 days / 127 weeks

(from the 3rd May 2011 to today)

Space

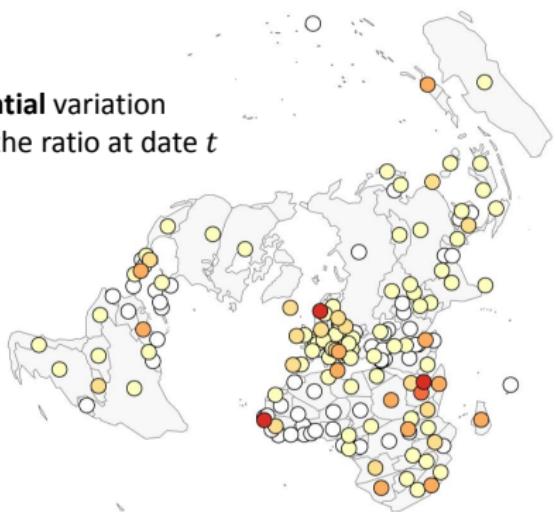
	USA	Libya	Syria	France	Israel	...	Total
2 May	25	12	11	10	4	...	142
9 May	14	6	12	12	5	...	108
16 May	20	11	12	6	9	...	142
23 May	15	9	6	13	5	...	120
30 May	10	16	17	9	4	...	137
6 June	14	16	16	9	4	...	114
13 June	15	14	17	9	6	...	119
20 June	17	13	12	12	7	...	123
27 June	7	6	7	20	2	...	103
4 July	12	13	8	10	6	...	129
11 July	21	10	10	14	3	...	107
18 July	7	3	8	4	5	...	61
25 July	16	7	6	13	4	...	128
1 Aug.	21	1	9	7	4	...	88
...
Total	423	308	260	248	153	...	3520

Time ↓

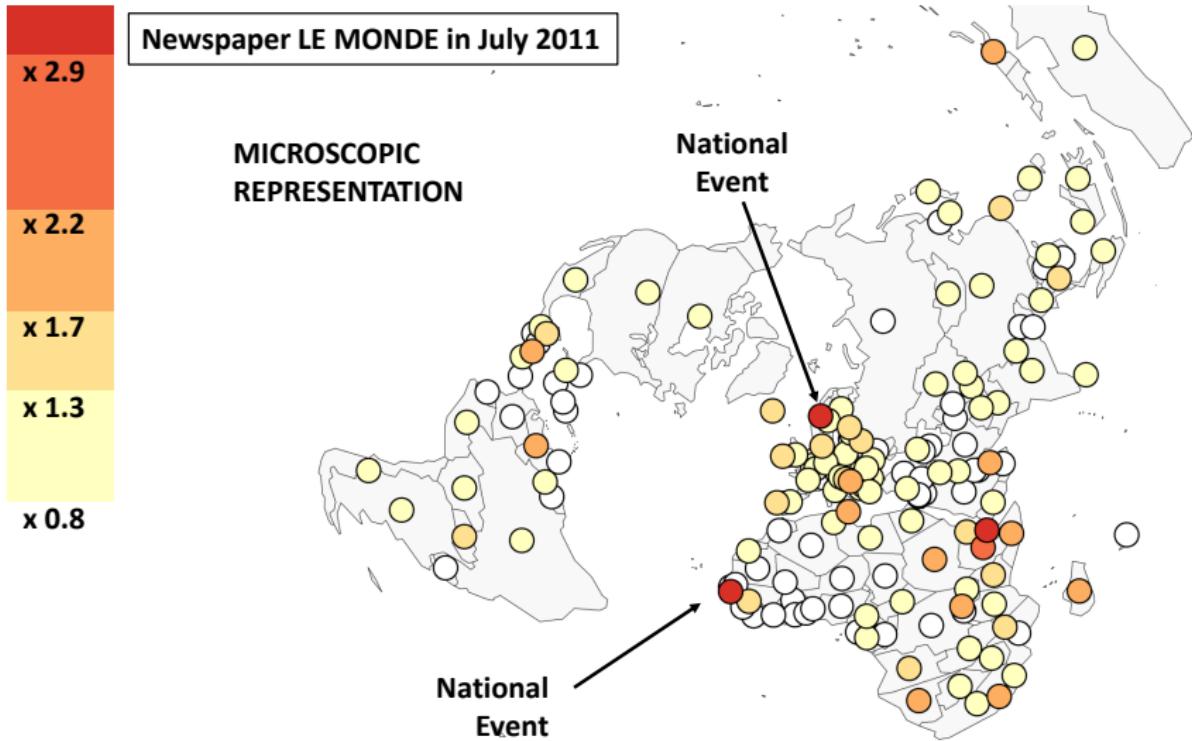
Observed-to-expected ratio of citation number

$$\rho(\pi, t) = \frac{v(\pi, t)}{v^*(\pi, t)} = \frac{v(\pi, t) v(., .)}{v(\pi, .) v(., t)}$$

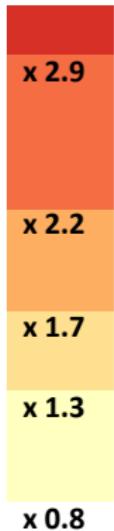
**Spatial variation
of the ratio at date t**



Detection of Media Events

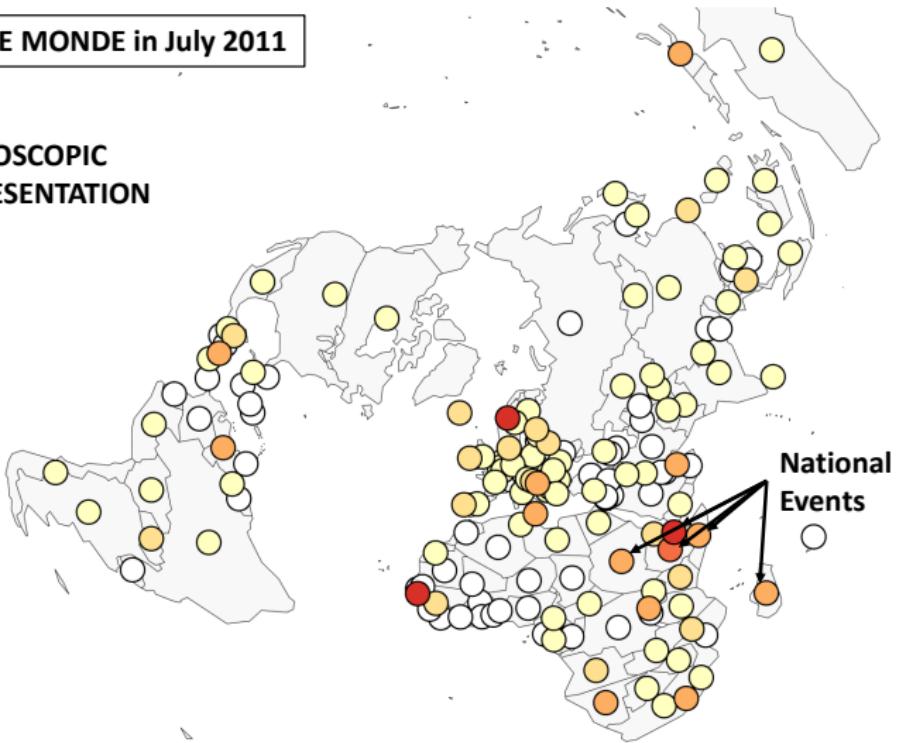


Detection of Media Events



Newspaper LE MONDE in July 2011

MICROSCOPIC
REPRESENTATION

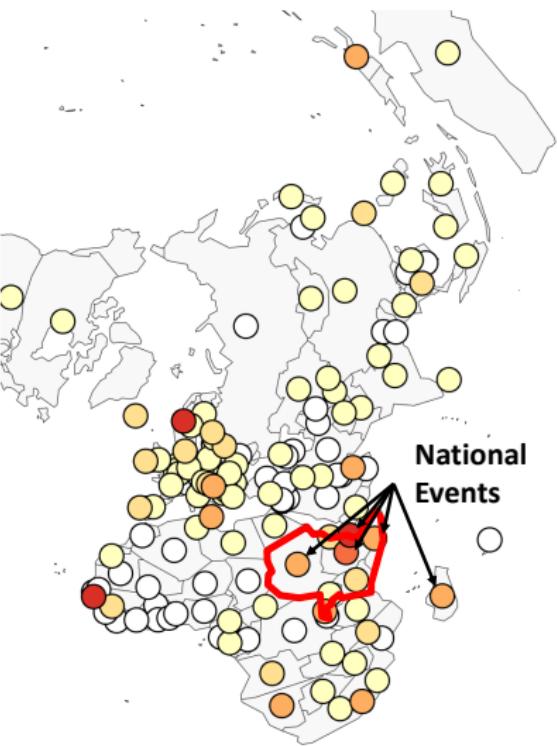


Detection of Media Events

$\pi_1 \quad \pi_2 \quad \pi_3$ **Space**

Time
t

	USA	Libya	Syria	France	Israel	...	Total
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9 May	14	6	12	12	5	...	108
16 May	20	11	12	6	9	...	142
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6 June	14	16	16	9	4	...	114
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27 June	7	6	7	20	2	...	103
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...
Total	423	308	260	248	153	...	3520



Detection of Media Events

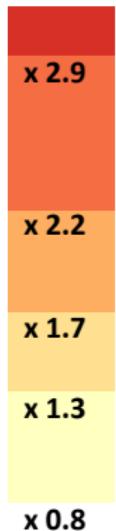
$\pi_1 \quad \pi_2 \quad \pi_3$ **Space**

Time

	USA	Aggregate			Total
		Israel	...		
2 May	25	13+11+10	4	...	142
9 May	14	6+12+12	5	...	108
16 May	20	11+12+6	9	...	142
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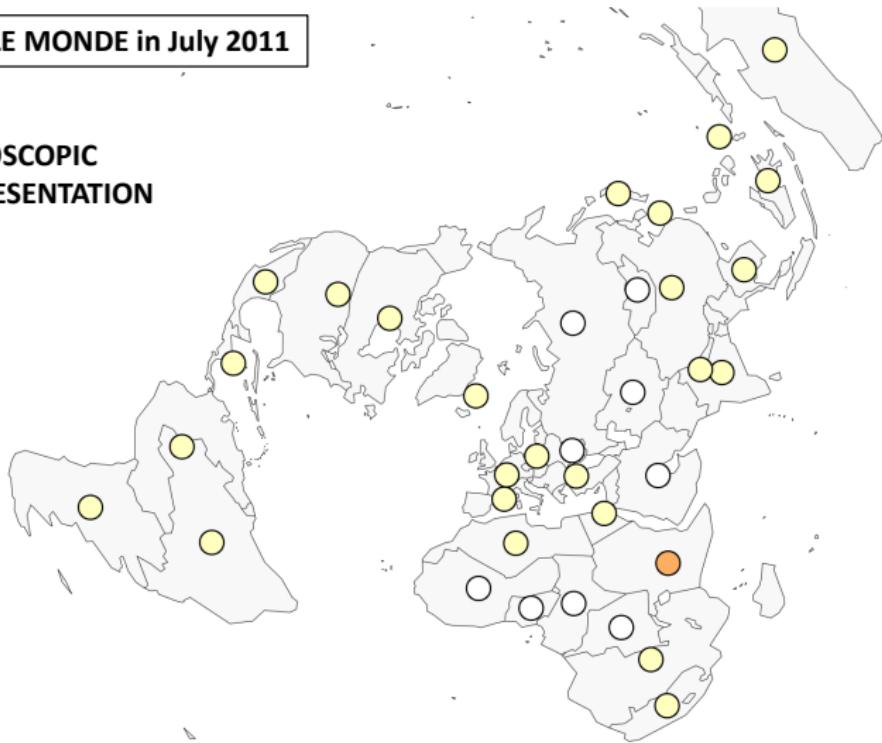


Problem I: Granularity of Geographical Information

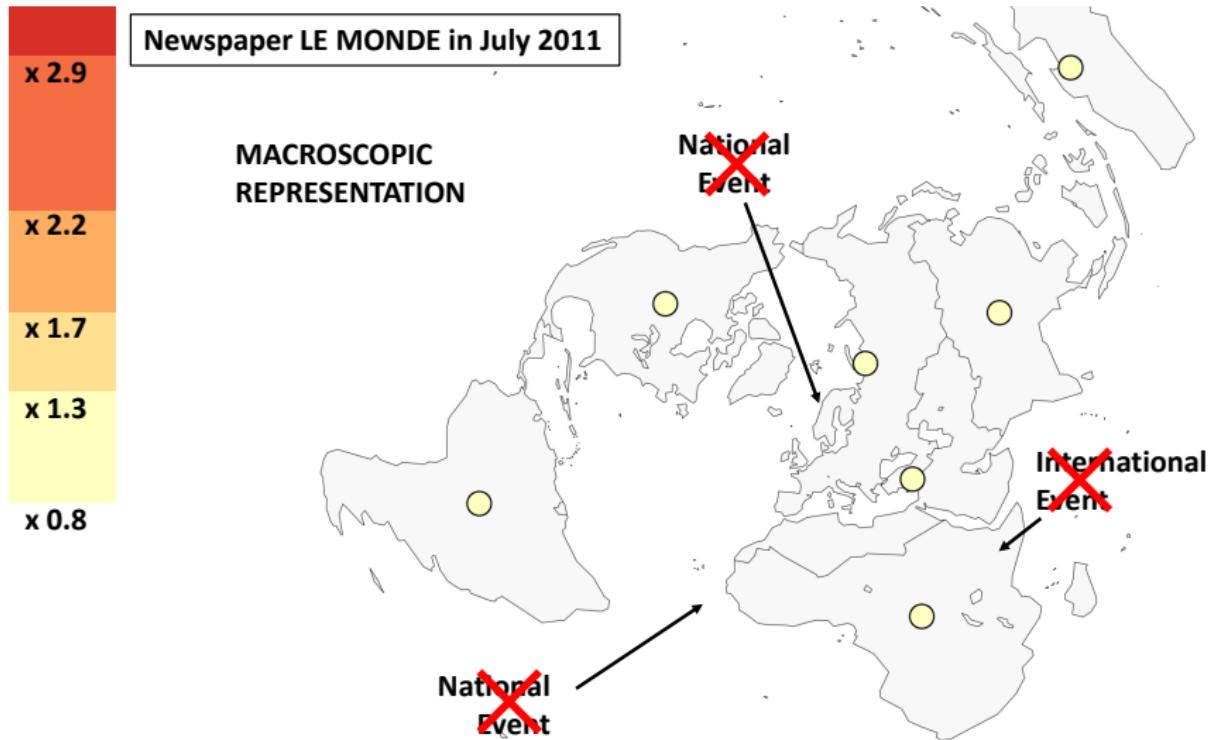


Newspaper LE MONDE in July 2011

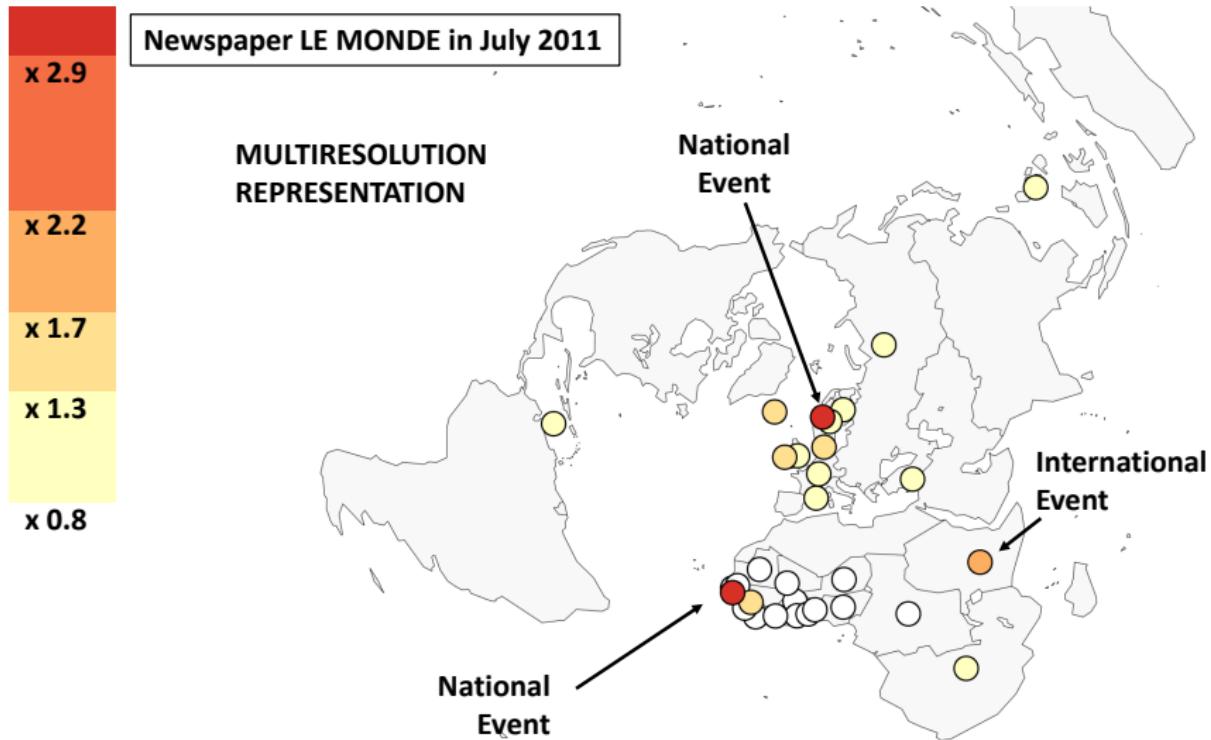
MESOSCOPIC
REPRESENTATION



Problem I: Granularity of Geographical Information



Problem I: Granularity of Geographical Information



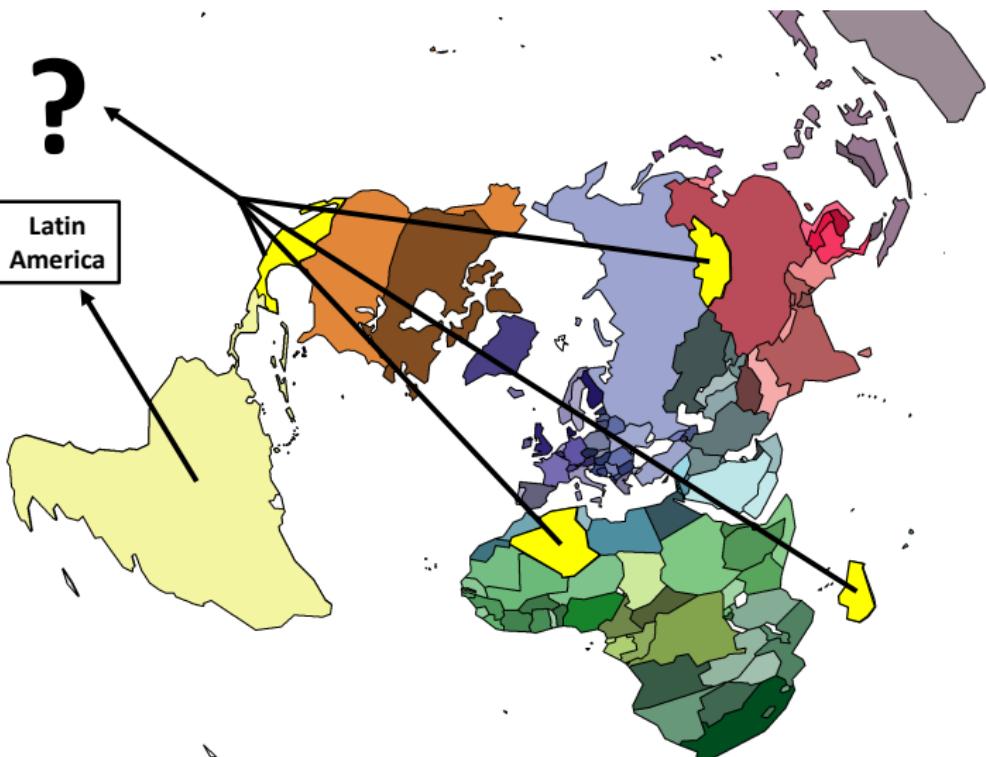
Problem II: Semantics of Geographical Aggregates



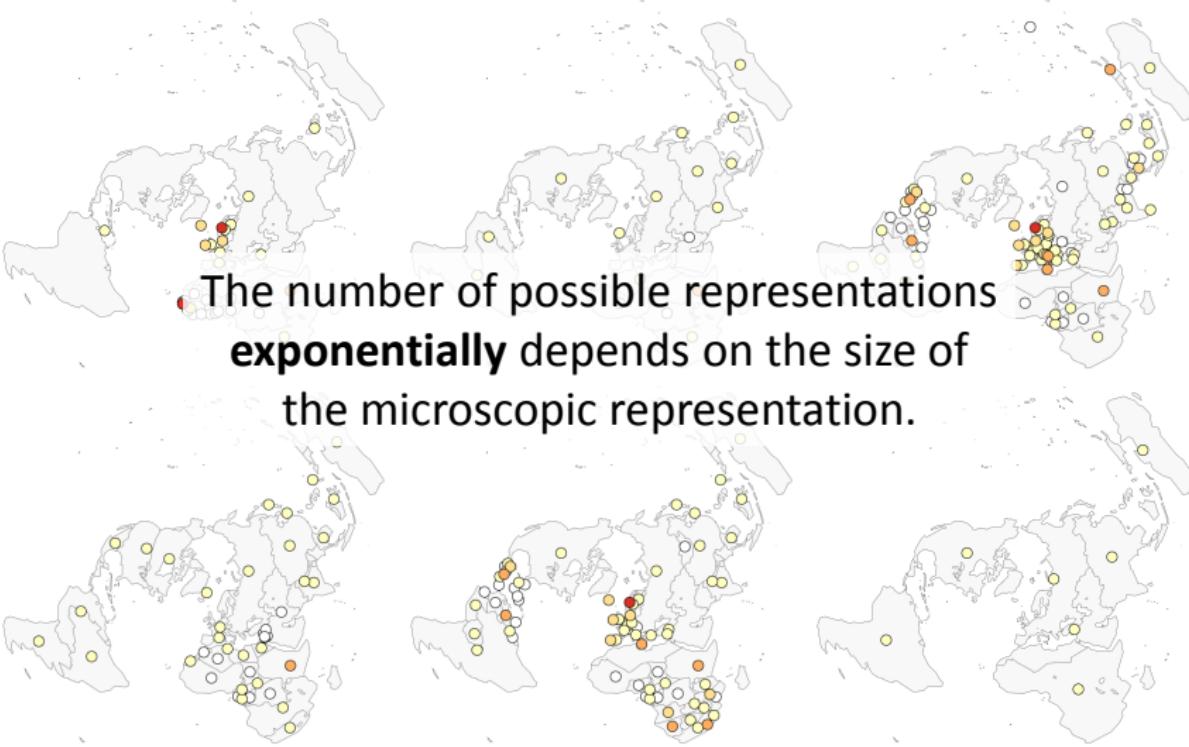
Geographer



Latin America



Problem III: Computation of Optimal Aggregates



The number of possible representations
exponentially depends on the size of
the microscopic representation.

Part I. Measuring Scales with Information Theory

Part II. Formalising Semantics with Combinatorial Constraints

Part III. Solving the Optimal Partition Problem

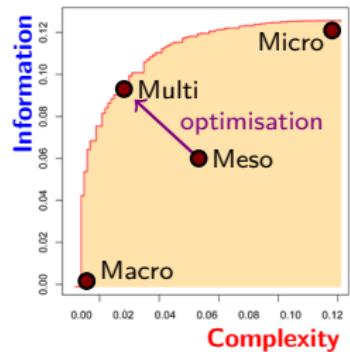
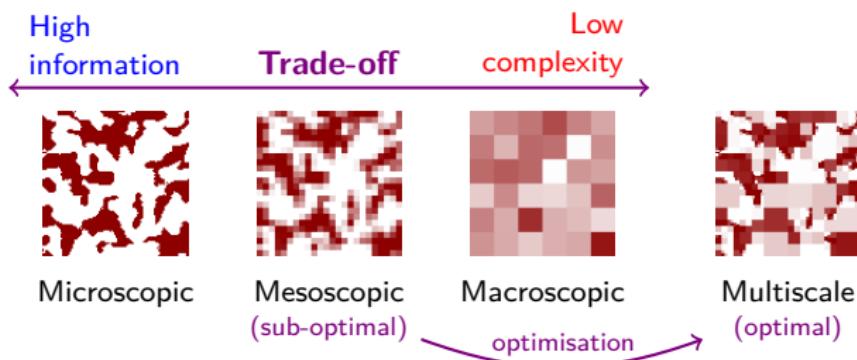
Part IV. Results and Experiments

Part I

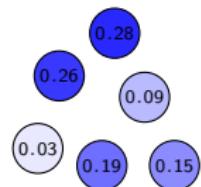
Measuring Scales with Information Theory

Trade-off between Information and Complexity

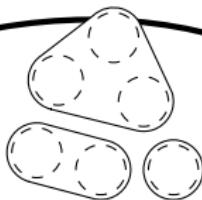
Objectives: Description / Explanation / Prediction of complex systems



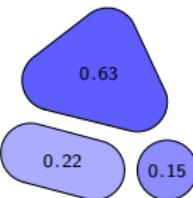
Kullback-Leibler Divergence for Information Loss



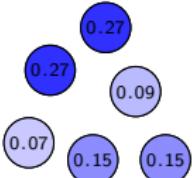
Initial Data
 $X \in \{x_1, \dots, x_n\}$
 $p(x_i) = \Pr(X = x_i)$



Aggregation
 $\hat{X} \in \{\hat{x}_1, \dots, \hat{x}_m\}$
 $p(\hat{x}_j|x_i) = \Pr(\hat{X} = \hat{x}_j|X = x_i)$

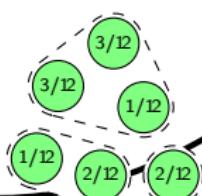


Information Loss
 $D_{KL}(p\|q) = \sum_i p(x_i) \log_2 \frac{p(x_i)}{q(x_i)}$

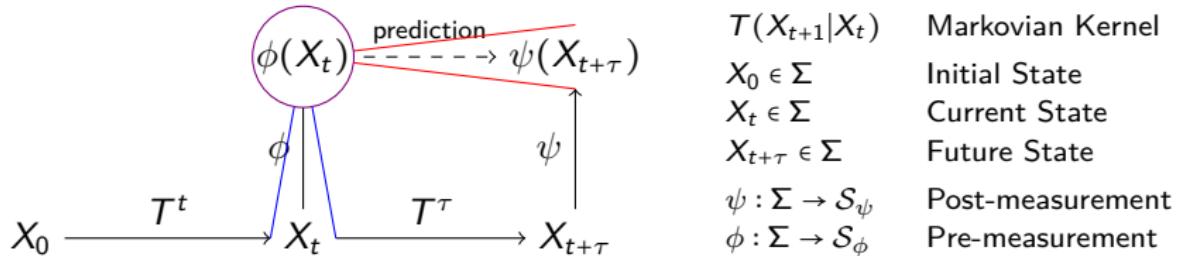


Disaggregated Data
 $q(x_i) = \sum_j q(x_i|\hat{x}_j)p(\hat{x}_j)$

Disaggregation
 $X^* \in \{x_1, \dots, x_n\}$
 $u(x_i) = \Pr(X^* = x_i)$
 $q(x_i|\hat{x}_j) = \frac{p(\hat{x}_j|x_i)u(x_i)}{\sum_{i'} p(\hat{x}_j|x_{i'})u(x_{i'})}$



Information Bottleneck for Optimal Prediction



Applying the Information Bottleneck Method: [Tishby *et al.*, 1999]

- Maximising the **Predictive Capacity** $\max_\phi I(\phi(X_t); \psi(X_{t+\tau}))$
- Minimising the **Measurement Complexity** $\min_\phi I(X_t; \phi(X_t))$
- Minimising the **Bottleneck Variational**

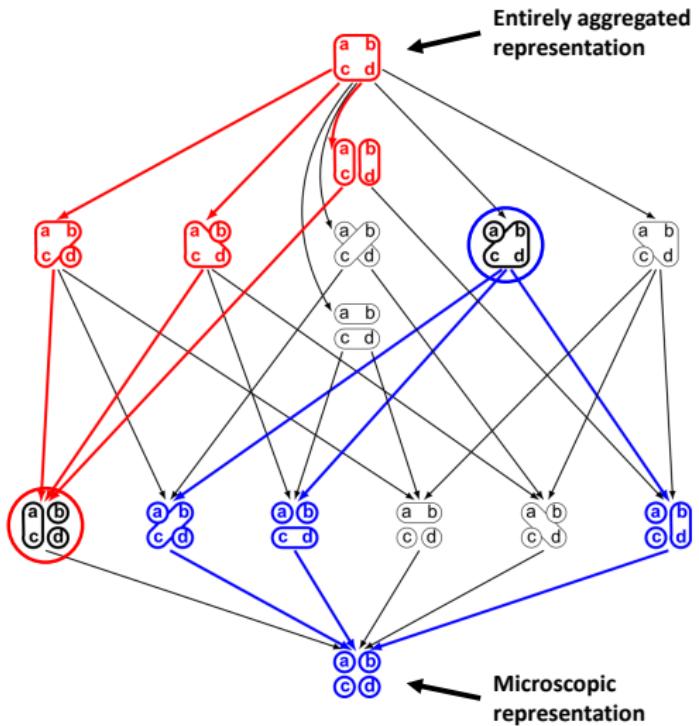
$$\min_\phi I(X_t; \phi(X_t)) - \beta I(\phi(X_t); \psi(X_{t+\tau})) \quad \text{with } \beta \in \mathbb{R}^+$$

where $I(X; Y)$ is the **Mutual Information** between X and Y

Part II

Formalising Semantics with Combinatorial Constraints

Solution Space: Set of Partitions



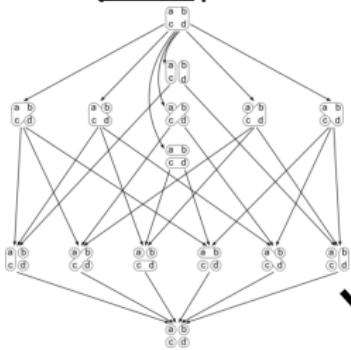
Algebraic Structure

A partial order on the set of possible partitions

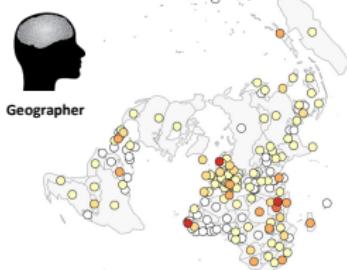
→ the refinement relation

Integrating the Semantics into the Aggregation Process

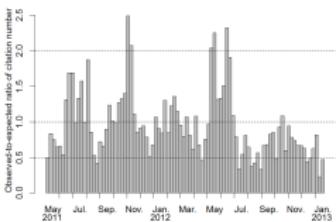
Set of possible partitions



Geographical Semantics

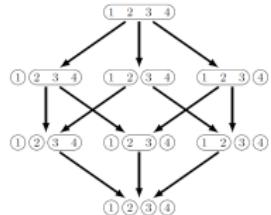
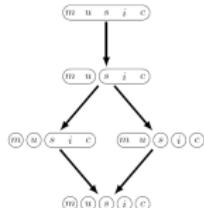


Temporal Semantics

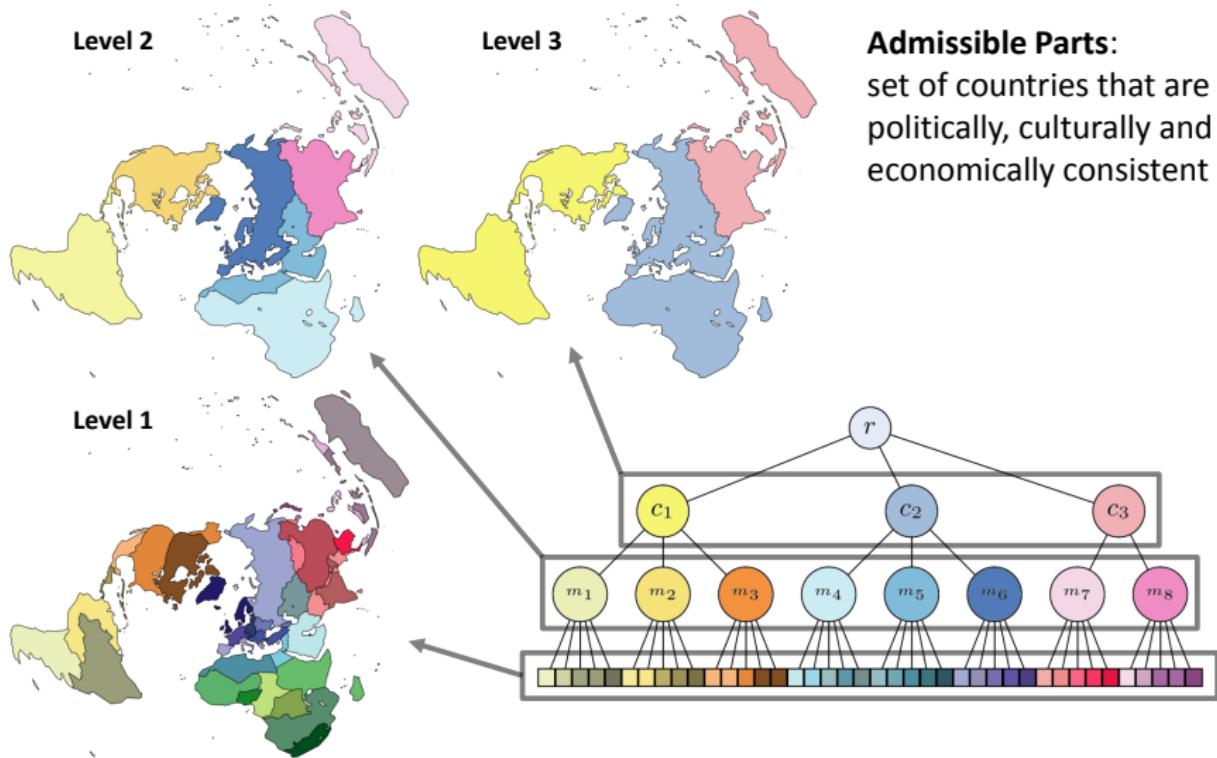


Constraints

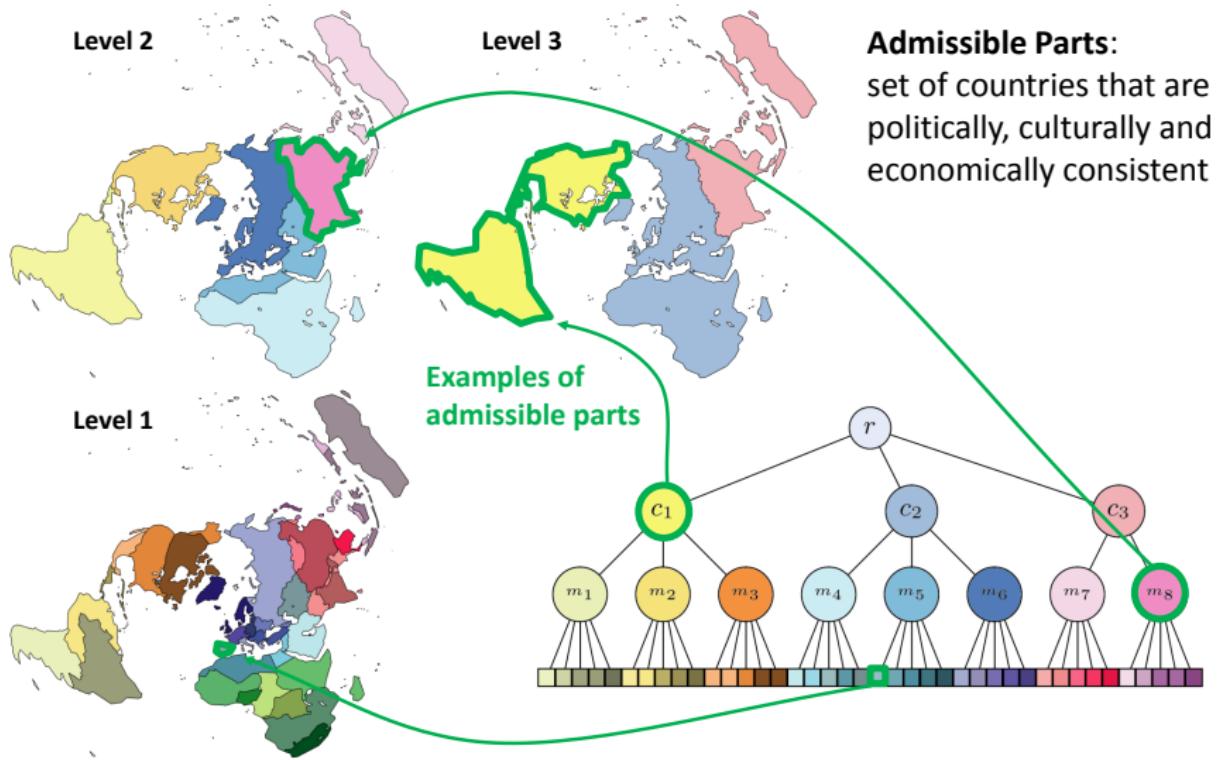
Set of admissible partitions



Preserving a Hierarchical Structure

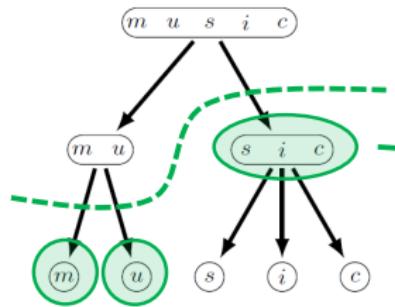


Preserving a Hierarchical Structure

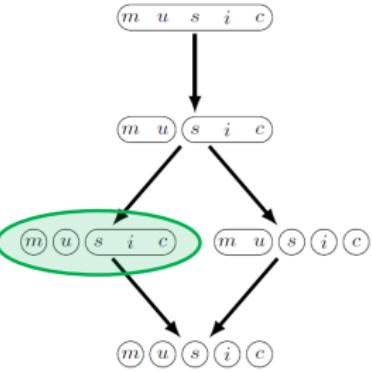


Preserving a Hierarchical Structure

Admissible Parts
(nodes of the hierarchy)

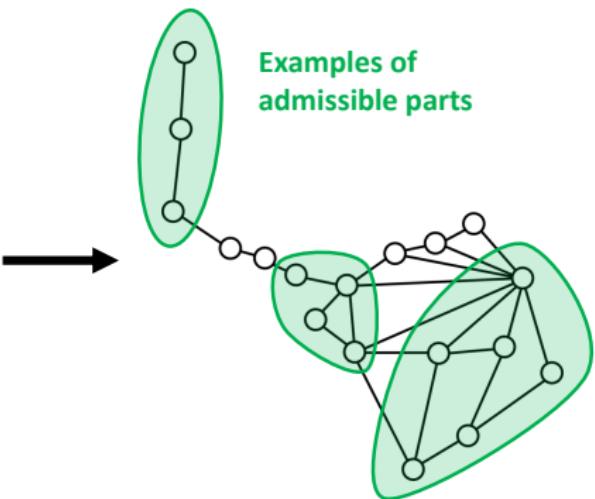


Admissible Partitions
(cuts of the hierarchy)

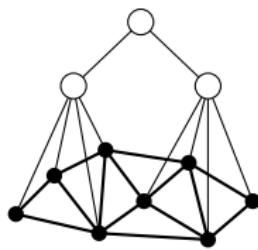


Preserving a Neighbourhood Relation

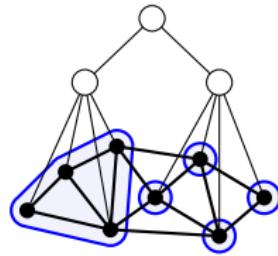
Admissible Parts: set of connected countries regarding the adjacency graph



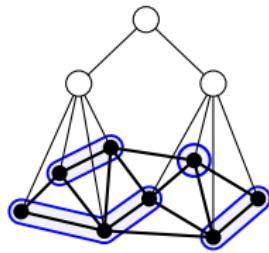
Preserving Mixed Structures



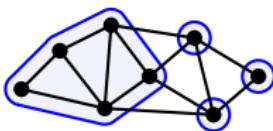
Mixed Structure
(graph + hierarchy)



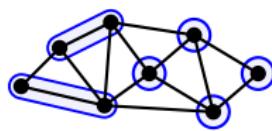
Hierarchical Aggregation
(consistent with the
graph)



Graph Aggregation
(not consistent with the
hierarchy)

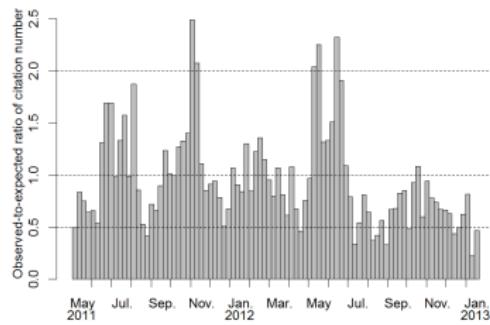


Union of Aggregates
(locally extends a node of the
hierarchy)



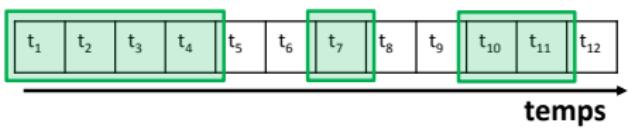
Intersection of Aggregates
(locally subdivides a node of the
hierarchy)

Preserving a Temporal Order



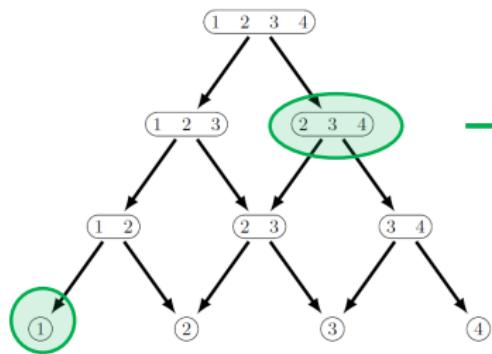
Admissible Parts:
time intervals

Examples of admissible parts

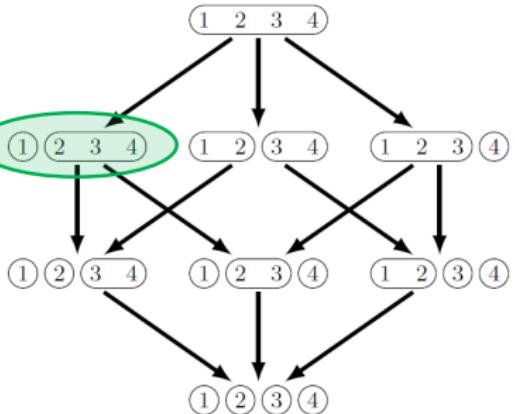


Preserving a Temporal Order

Admissible Parts (time intervals)

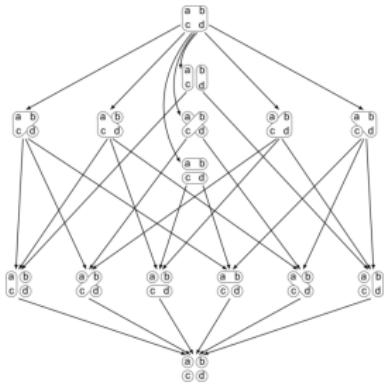


Admissible Partitions (interval sequences)



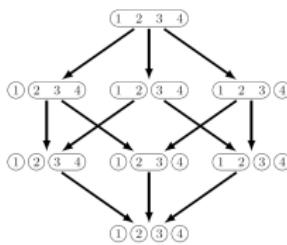
Complexity of Algebraic Structures

Non-constrained partitions

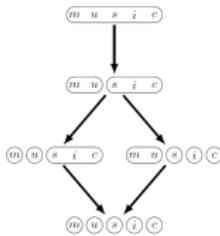


A horizontal double-headed arrow spanning the width of the page, divided into two main sections by a vertical line. The left section is labeled "Less constrained" at the top and "More complex" at the bottom. The right section is labeled "More constrained" at the top and "Less complex" at the bottom.

Admissible partitions
according to a **total order**



Admissible partitions according to a **hierarchy**



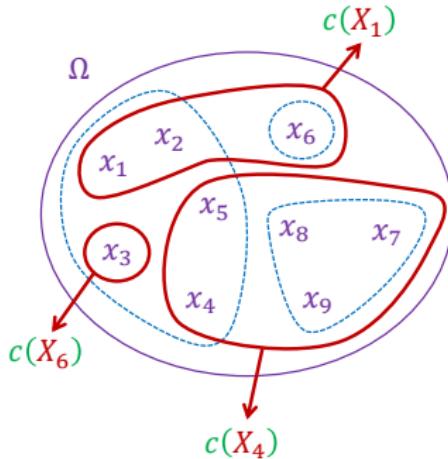
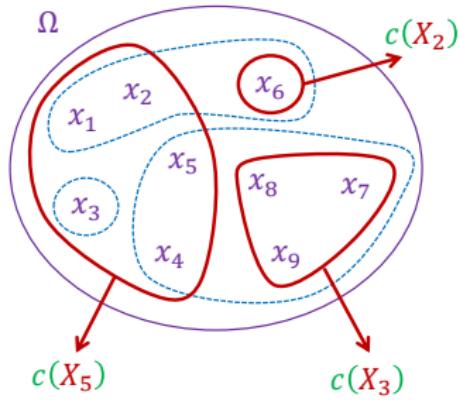
Part III

Solving the Optimal Partition Problem

The Set Partitioning Problem

Given:

- a set of individuals $\Omega = \{x_1, \dots, x_n\}$
- a set of admissible parts $\mathcal{P} = \{X_1, \dots, X_m\} \subset 2^\Omega$
- a cost function $c : \mathcal{P} \rightarrow \mathbb{R}$
- the corresponding set of admissible partitions $\mathfrak{P} = \{\mathcal{X} \subset \mathcal{P} \text{ such that } \mathcal{X} \text{ is a partition of } \Omega\}$

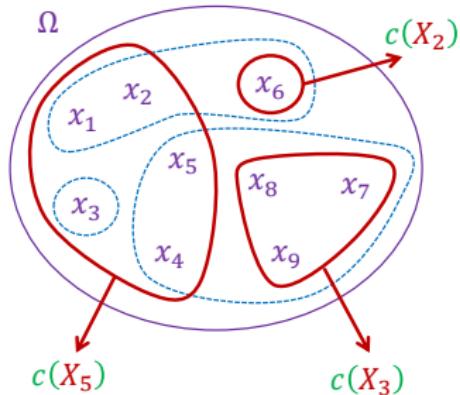


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Additional assumptions



Problem: Find an admissible partition that minimizes the cost function:

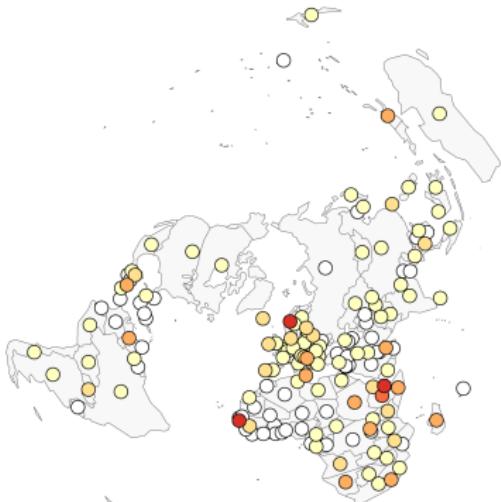
$$\mathcal{X}^* = \arg \min_{\mathcal{X} \in \mathfrak{P}} \left(\sum_{X \in \mathcal{X}} c(X) \right)$$

→ NP-complete!

Special Versions of the Set Partitioning Problem

Multilevel Geographical Analysis

- Ω = territorial units
- \mathcal{P} = admissible aggregates
- c = compression rate
- \mathfrak{P} = aggregated representations



Hierarchical SPP

- Assumption: \mathcal{P} forms a hierarchy
- Result: $\mathcal{O}(n)$ depth-first search
[\[Pons et al., 2011\]](#) [\[Lamarche-Perrin et al., 2014\]](#)

Graph SPP

- Assumption: \mathcal{P} are connected parts of a graph
- Result: NP-complete [\[Becker et al., 1998\]](#)



Special Versions of the Set Partitioning Problem

Multilevel Geographical Analysis

Hierarchical SPP

- Assumption: \mathcal{P} forms a hierarchy
- Result: $\mathcal{O}(n)$ depth-first search

[Pons *et al.*, 2011] [Lamarche-Perrin *et al.*, 2014]

Time Series Analysis

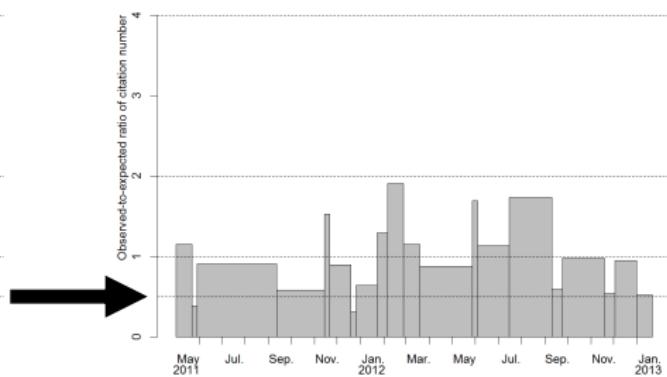
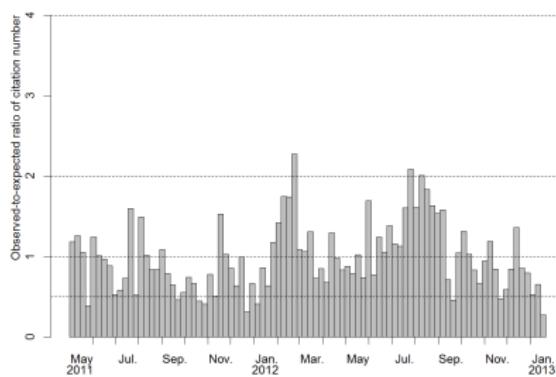
- Ω = ordered data points
- \mathcal{P} = time intervals
- c = compression rate
- \mathfrak{P} = aggregated time series

Graph SPP

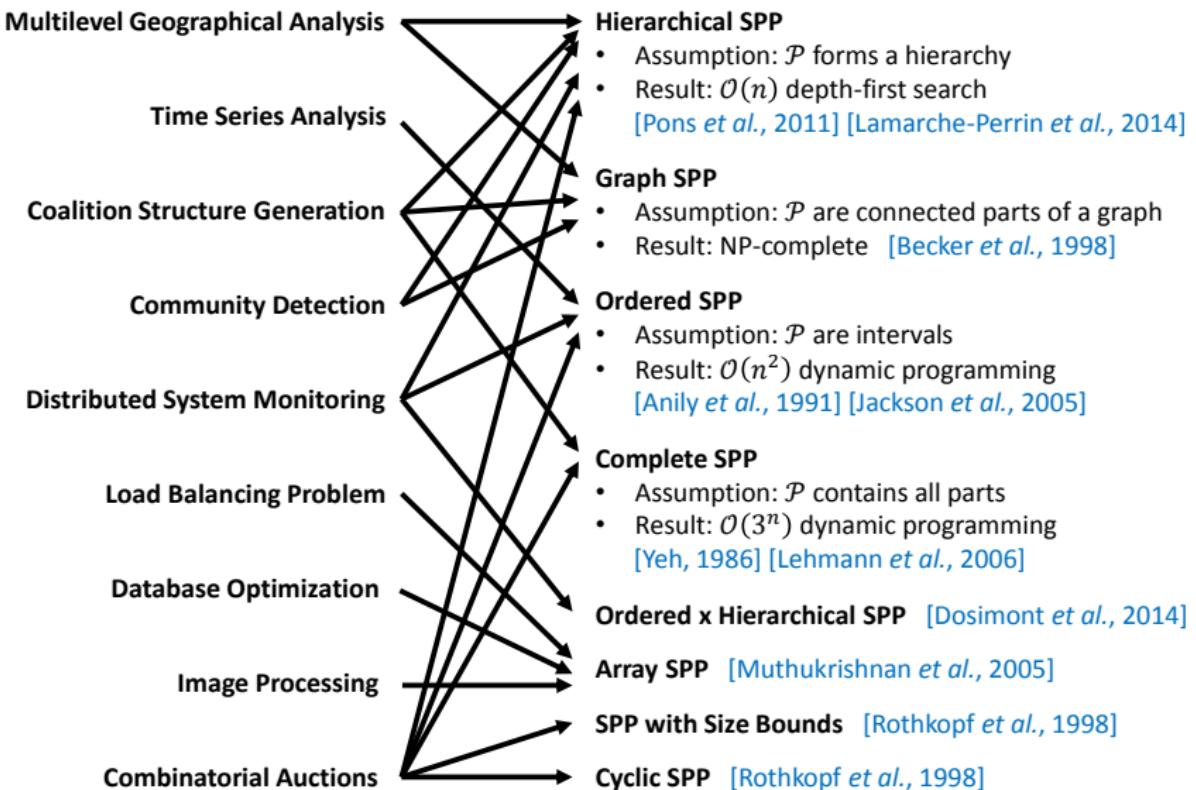
- Assumption: \mathcal{P} are connected parts of a graph
- Result: NP-complete [Becker *et al.*, 1998]

Ordered SPP

- Assumption: \mathcal{P} are intervals
- Result: $\mathcal{O}(n^2)$ dynamic programming [Anily *et al.*, 1991] [Jackson *et al.*, 2005]

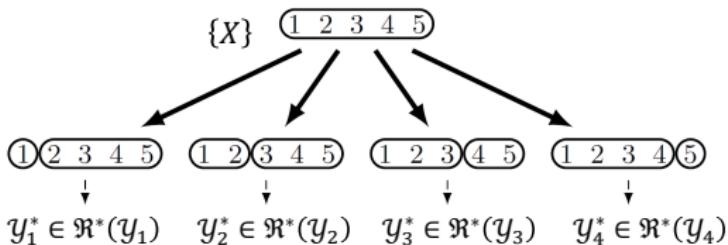


Special Versions of the Set Partitioning Problem



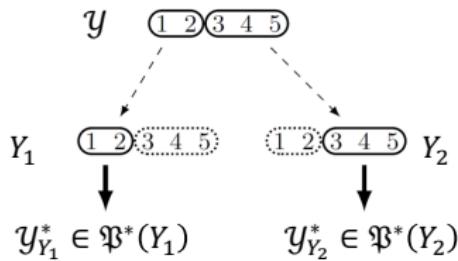
DIVIDE...

Branching the state space
according to the covering
relation

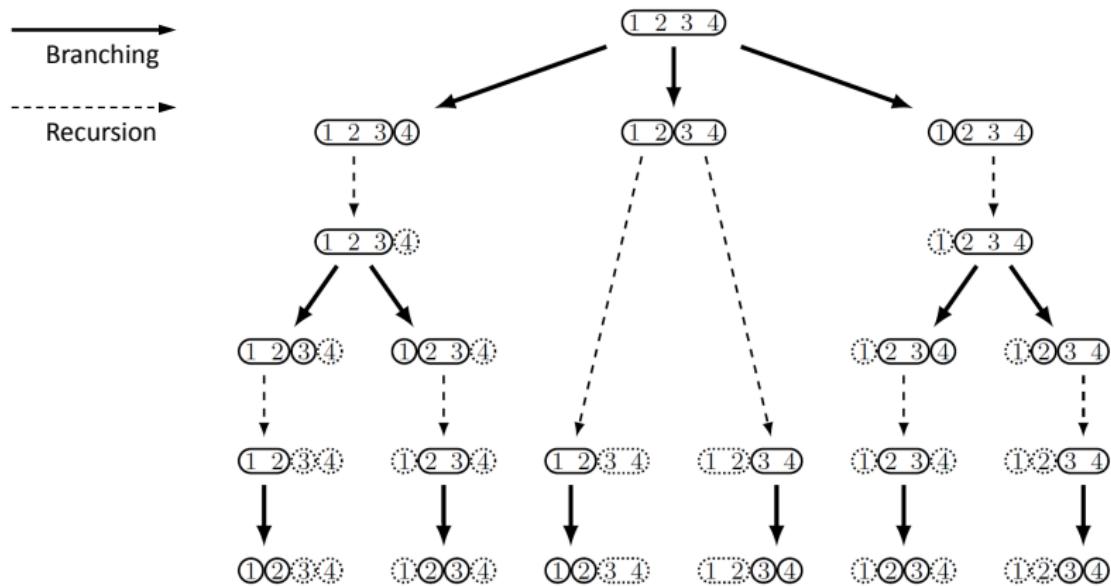


...AND CONQUER

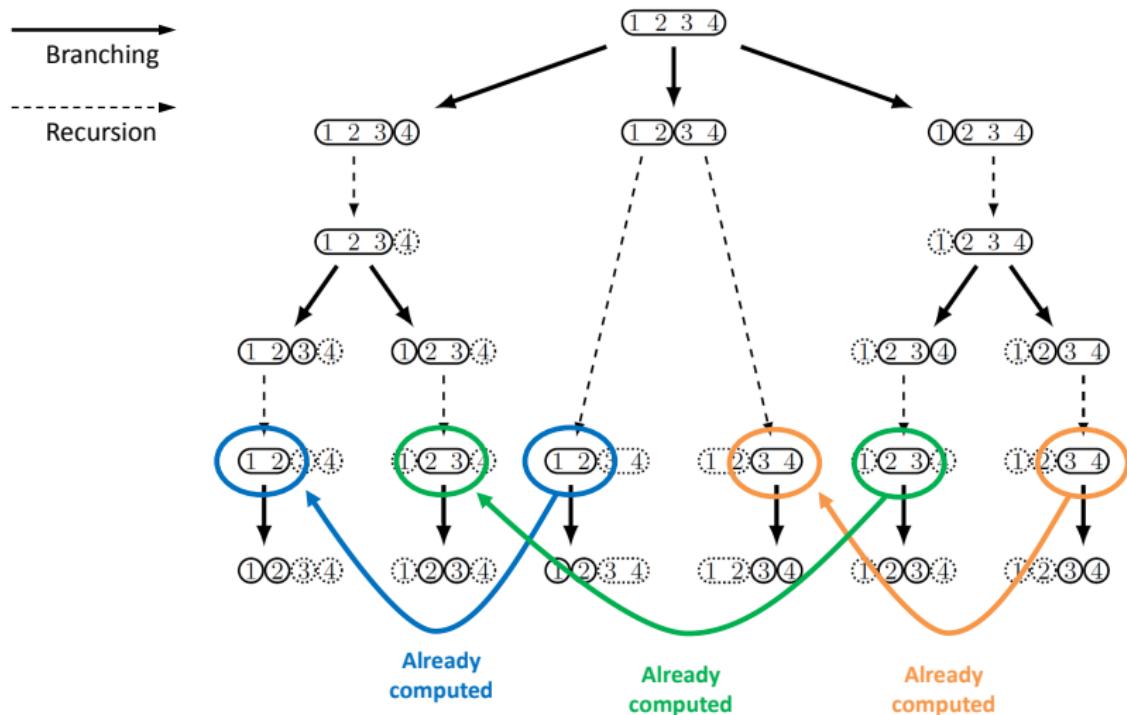
Recursion according to the
principle of optimality



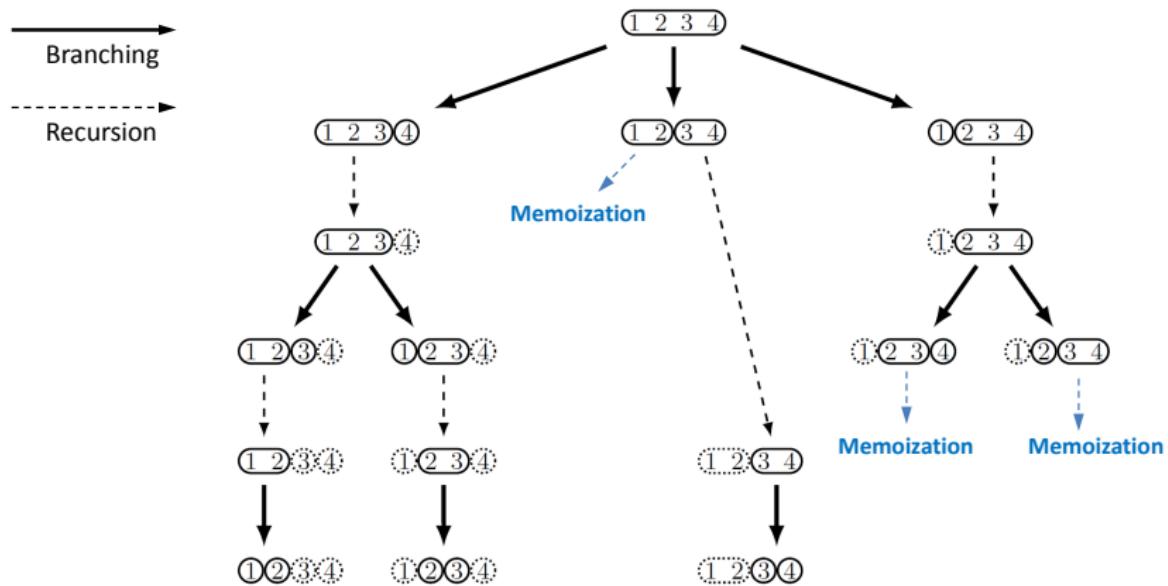
Dynamic Programming



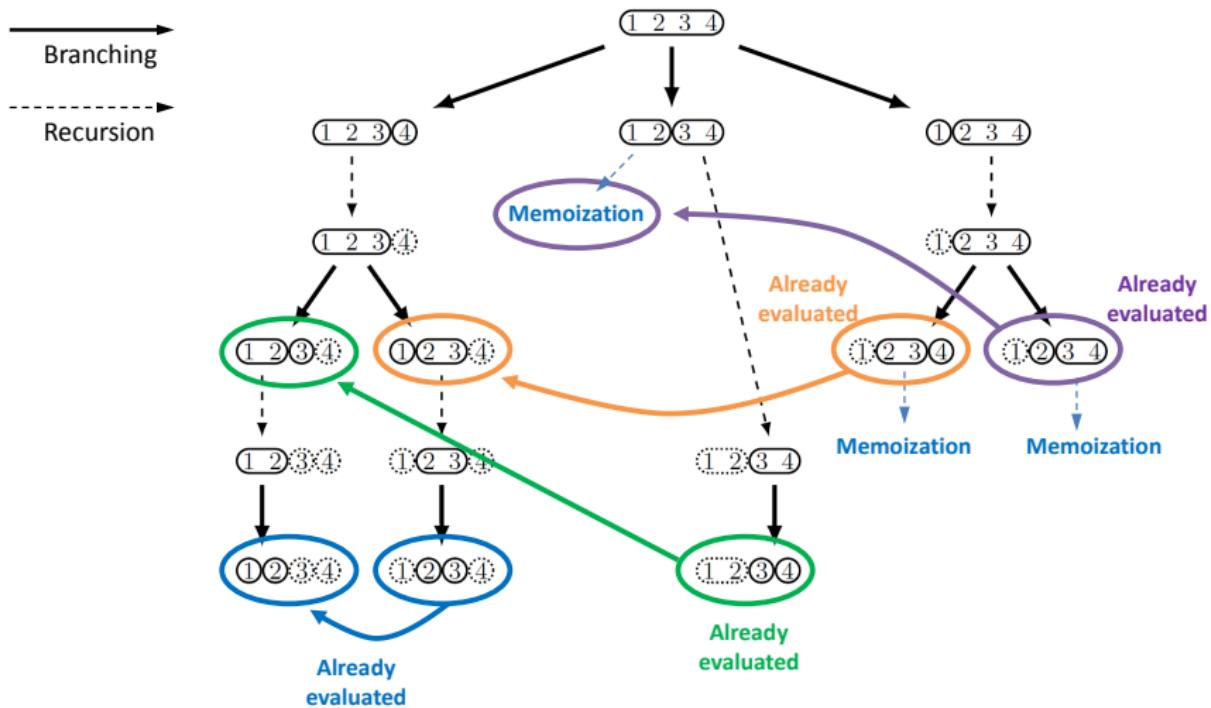
Dynamic Programming



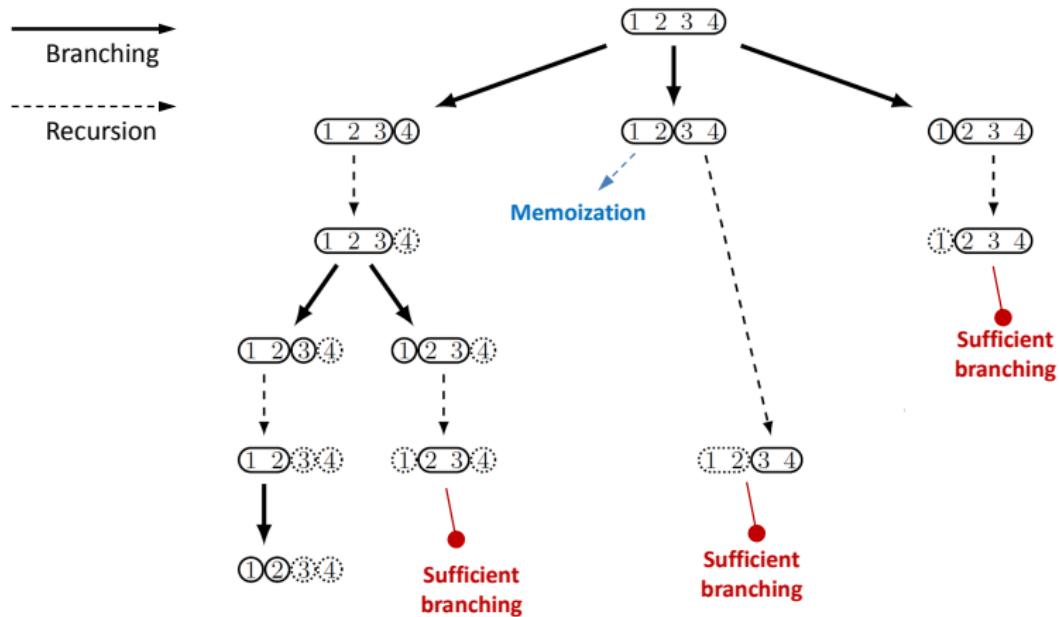
Dynamic Programming



Dynamic Programming



Dynamic Programming



Generic Algorithmic Framework

A Generic Algorithm to Solve the SPP

Global Inputs:

- c a cost function;
- \mathcal{P} a set of admissible parts defining admissible partitions;
- \mathcal{L} a set of locally-optimal admissible partitions of parts on which the algorithm has already been applied.

Local Inputs:

- X an admissible part;
- $\bar{\mathcal{X}}$ the complementary partition of X inherited from the “higher” call ($\bar{\mathcal{X}}$ is a partition of $\Omega \setminus X$);
- \mathcal{D} the set of admissible partitions which refinements have already been evaluated during “higher” calls.

Output:

\mathcal{X}^* a locally-optimal admissible partition of X .

- If the algorithm has already been applied to part X , return the locally-optimal partition recorded in \mathcal{L} .
- Initialization: $\mathcal{X}^* \leftarrow \{\{X\}\}$ and $\mathcal{D}' \leftarrow \mathcal{D}$.
- For each $\mathcal{Y} \in \mathfrak{C}(\{X\})$ such that $\bar{\mathcal{X}} \cup \mathcal{Y}$ does not refine any partition in \mathcal{D} , do the following:
 - For each part $Y \in \mathcal{Y}$, call the algorithm with local inputs $X \leftarrow Y$, $\bar{\mathcal{X}} \leftarrow \bar{\mathcal{X}} \cup \mathcal{Y} \setminus \{Y\}$, and $\mathcal{D} \leftarrow \mathcal{D}'$ to compute a locally-optimal partition $\mathcal{Y}_Y^* \in \mathfrak{P}^*(Y)$.
 - $\mathcal{Y}^* \leftarrow \bigcup_{Y \in \mathcal{Y}} \mathcal{Y}_Y^*$.
 - If $c(\mathcal{Y}^*) > c(\mathcal{X}^*)$, then $\mathcal{X}^* \leftarrow \mathcal{Y}^*$.
 - $\mathcal{D}' \leftarrow \mathcal{D}' \cup \{\mathcal{Y}\}$.
- Return \mathcal{X}^* and record this result in \mathcal{L} .

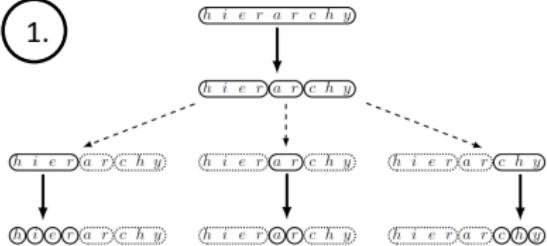
Generic: solve any instance of the SPP
→ but inefficient for special versions

Designing dedicated implementations:

- ① Analysing the generic execution
- ② Building appropriate data structures
- ③ Deriving a specialized algorithm

Generic Algorithmic Framework

1.



2.

Data Structure

- Set of parts: rooted tree
- Optimal partition: cut of the tree
- Algorithm: depth-first search

3.

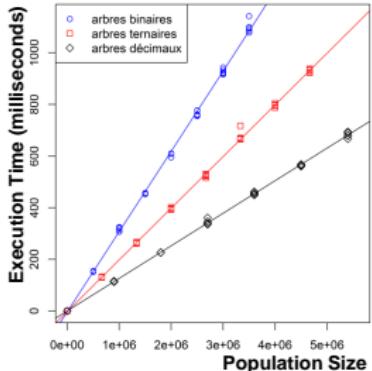
Algorithm 1 for the HSPP

Require: A tree with a label *cost* on each node representing the cost of the corresponding admissible part.

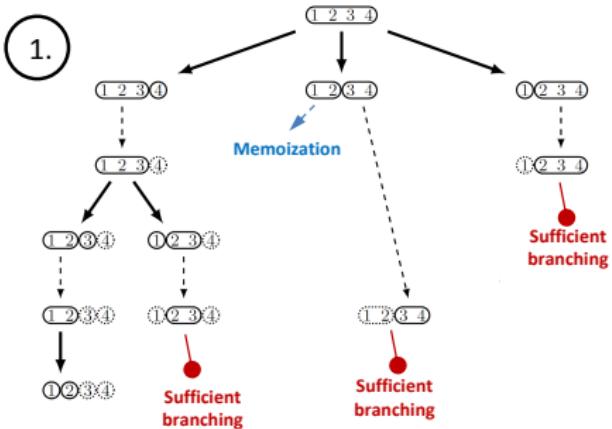
Ensure: Each node of the tree has a Boolean label *optimalCut* representing an optimal partition (see above).

```
procedure SOLVEHSPP(node)
    if node has no child then
        node.optimalCost ← node.cost
        node.optimalCut ← true
    else
        MCost ← node.cost
        μCost ← 0
        for each child of node do
            SOLVEHSPP(child)
            μCost ← μCost + child.optimalCost
        node.optimalCost ← max(μCost, MCost)
        node.optimalCut ← (μCost < MCost)
```

Linear Complexity



Generic Algorithmic Framework



2.

Data Structure

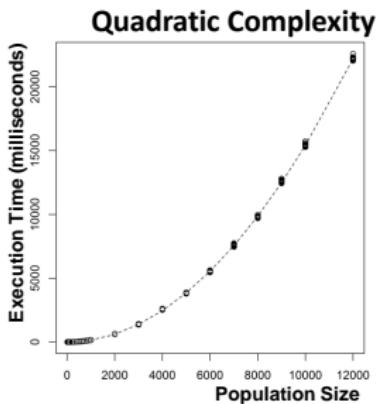
- Set of parts: triangular matrix
- Optimal partition: array of cuts
- Algorithm: dynamic programming

3.

Algorithm 2 for the OSPP

Require: A matrix $cost$ recording the costs of intervals.
Ensure: The vector $optimalCut$ represents an optimal partition (see text above).

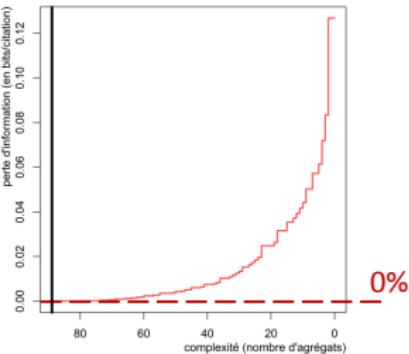
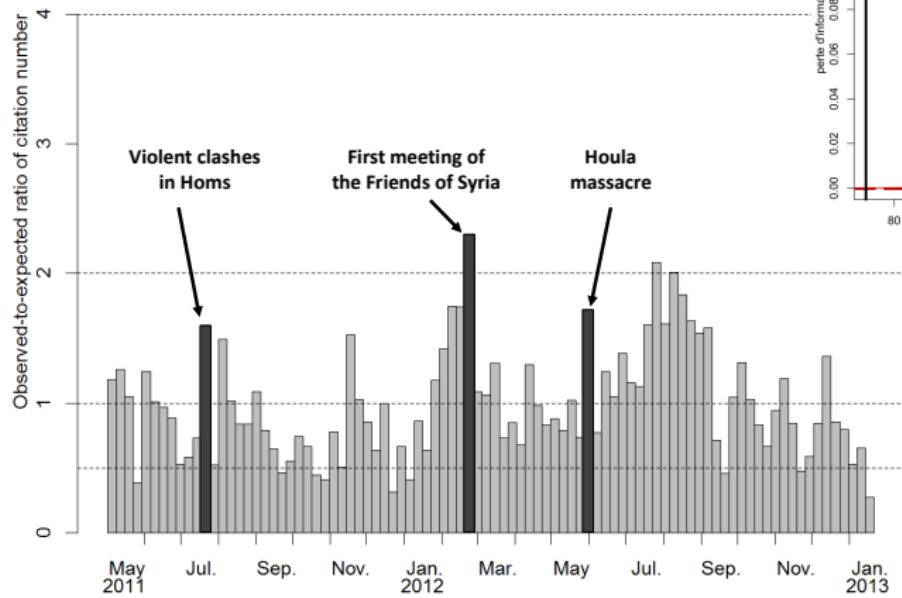
```
for  $j \in [1, n]$  do
     $optimalCost[j] \leftarrow cost[1, j]$ 
     $optimalCut[j] \leftarrow 1$ 
    for  $cut \in [2, j]$  do
         $\muCost \leftarrow optimalCost[cut - 1] + cost[cut, j]$ 
        if  $\muCost > optimalCost[j]$  then
             $optimalCost[j] \leftarrow \muCost$ 
             $optimalCut[j] \leftarrow cut$ 
```



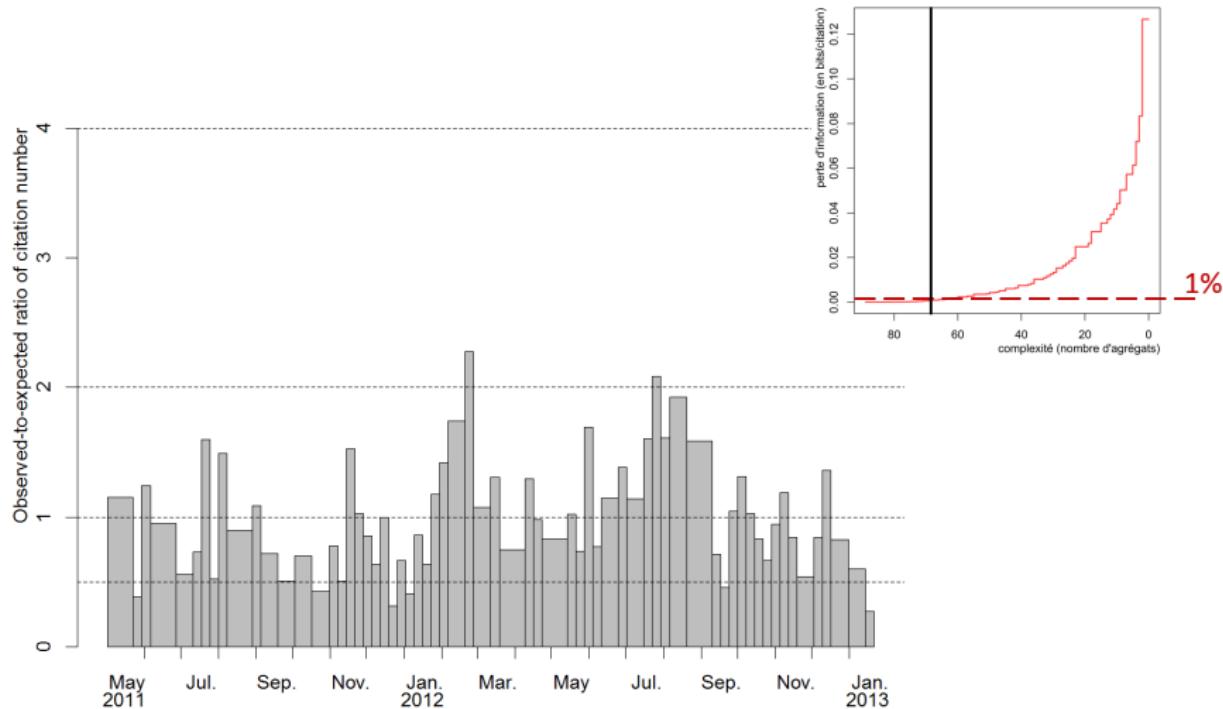
Part IV

Results and Experiments

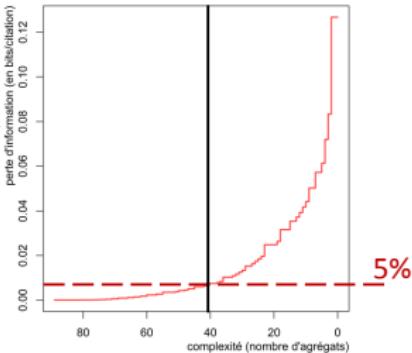
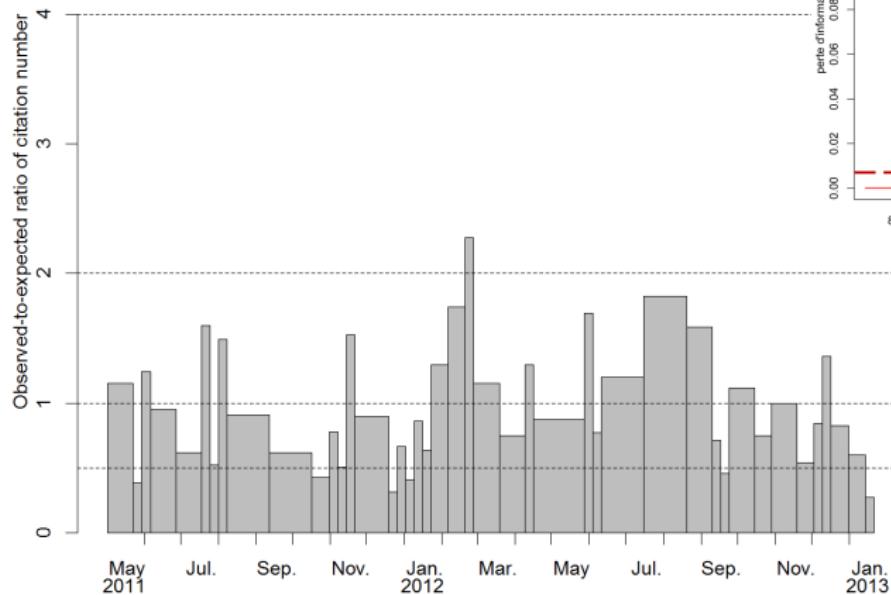
The Syrian Civil War according to *Le Monde* [TCCI 2014]



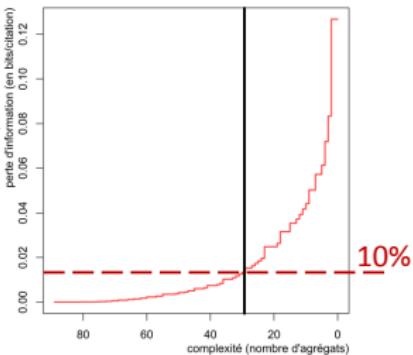
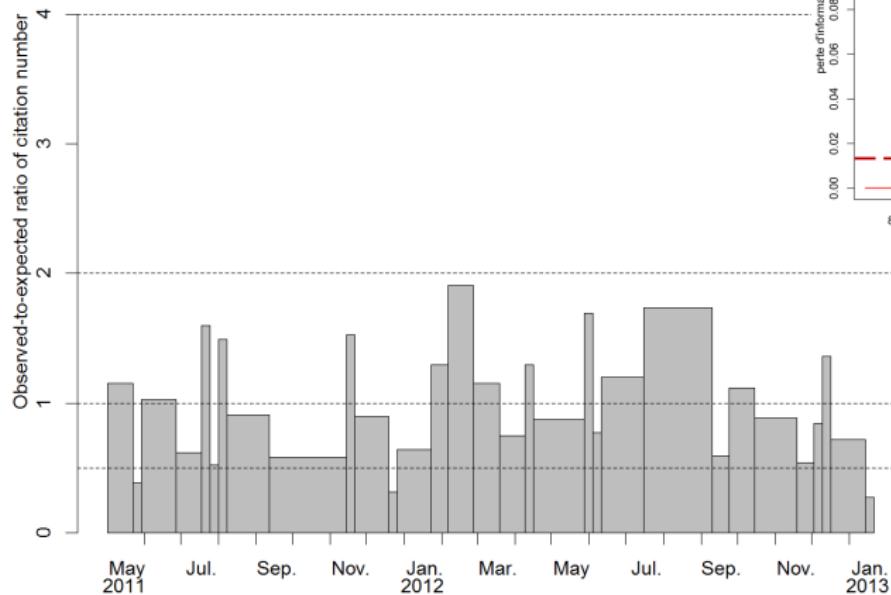
The Syrian Civil War according to *Le Monde* [TCCI 2014]



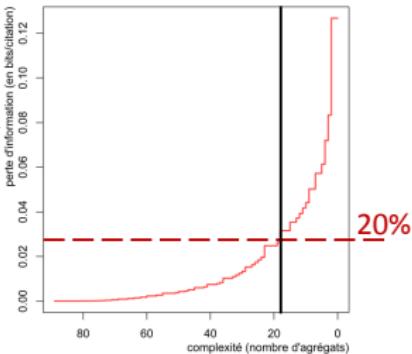
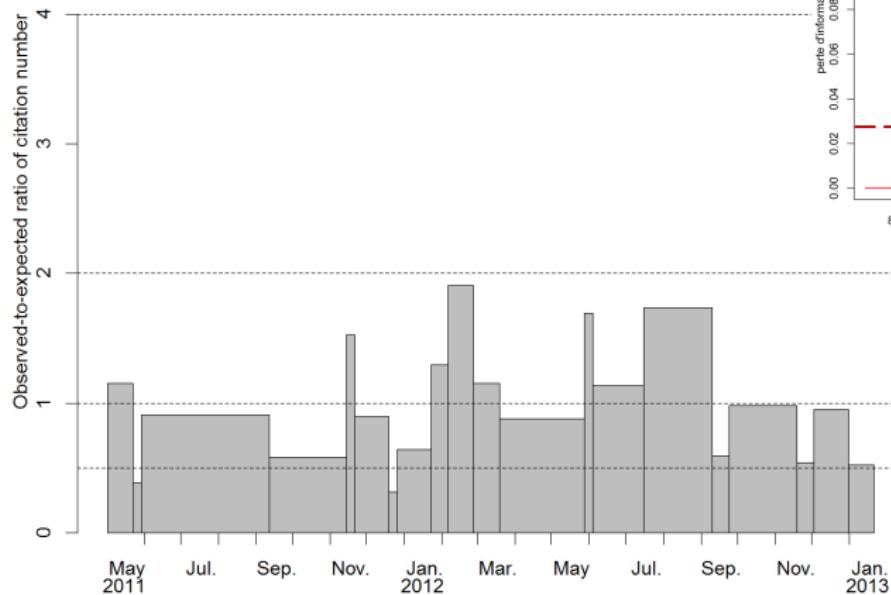
The Syrian Civil War according to *Le Monde* [TCCI 2014]



The Syrian Civil War according to *Le Monde* [TCCI 2014]



The Syrian Civil War according to *Le Monde* [TCCI 2014]

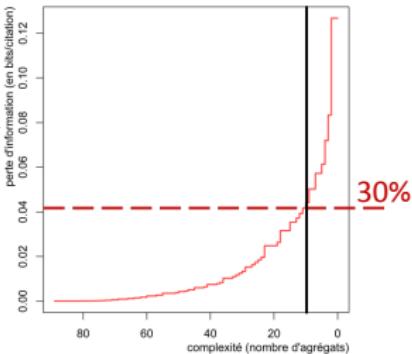
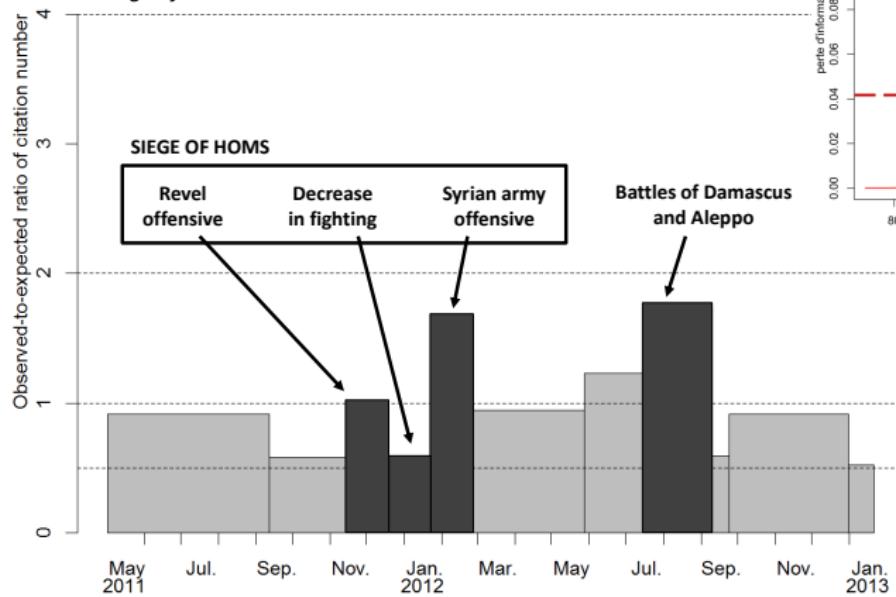


The Syrian Civil War according to *Le Monde* [TCCI 2014]

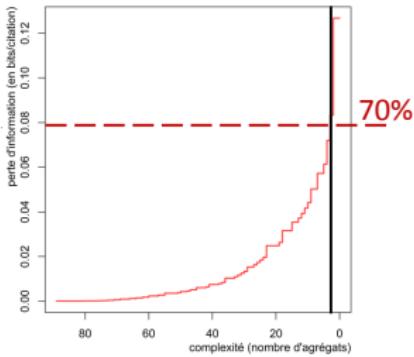
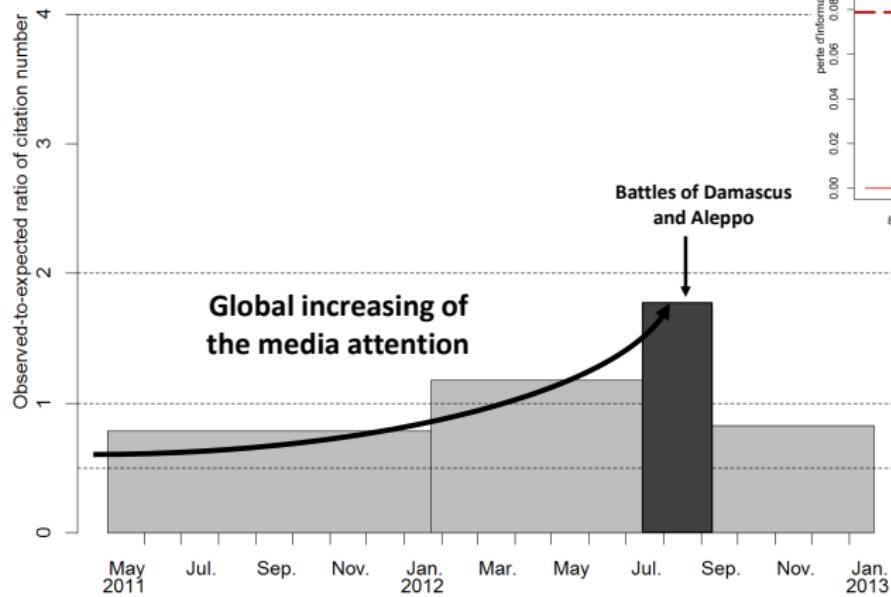
Source: Wikipedia

Timeline of the Syrian civil war

Siege of Homs



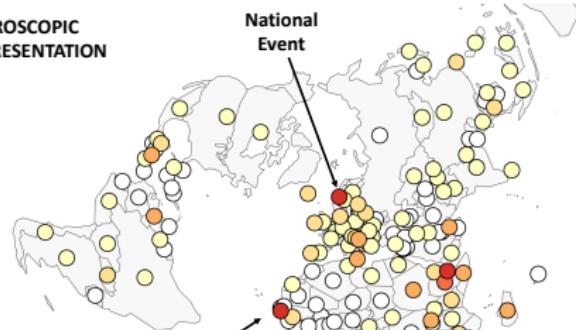
The Syrian Civil War according to *Le Monde* [TCCI 2014]



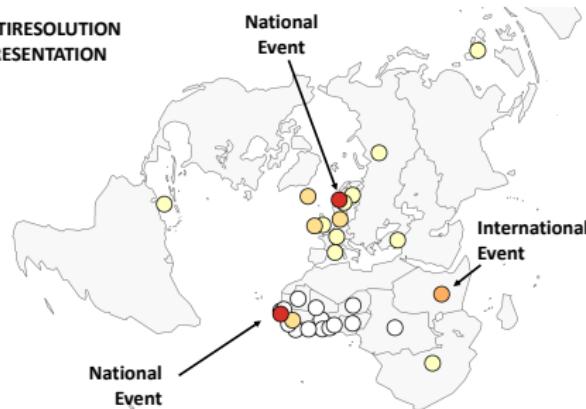
Geographical Aggregation

[TCCI 2014] News coverage of *Le Monde* in July 2011

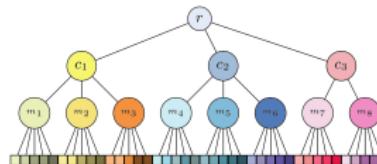
MICROSCOPIC
REPRESENTATION



MULTIRESOLUTION
REPRESENTATION

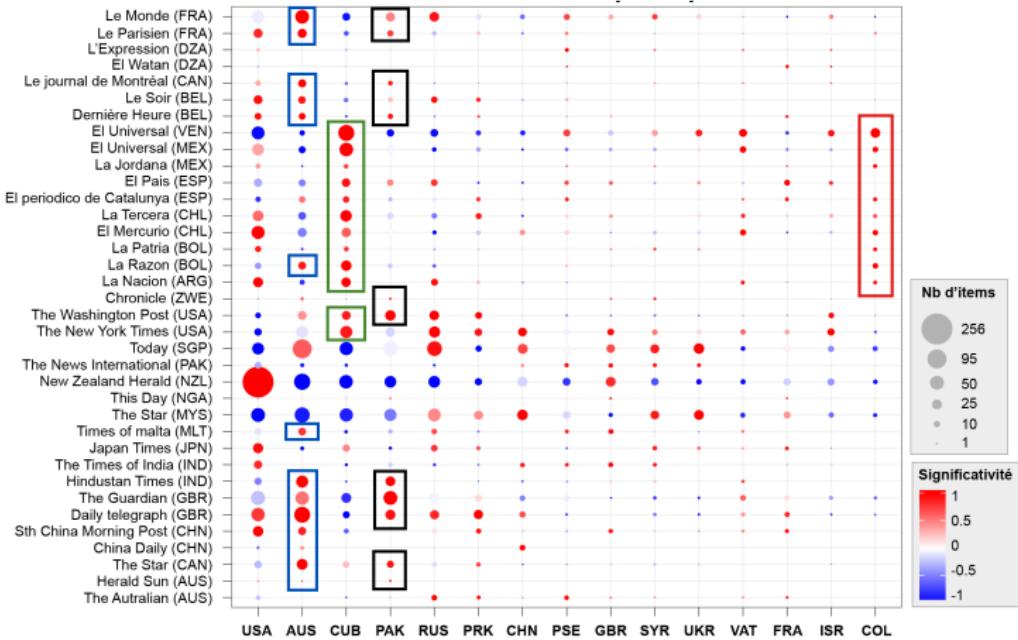


Territorial Hierarchy (WUTS)



Media Aggregation

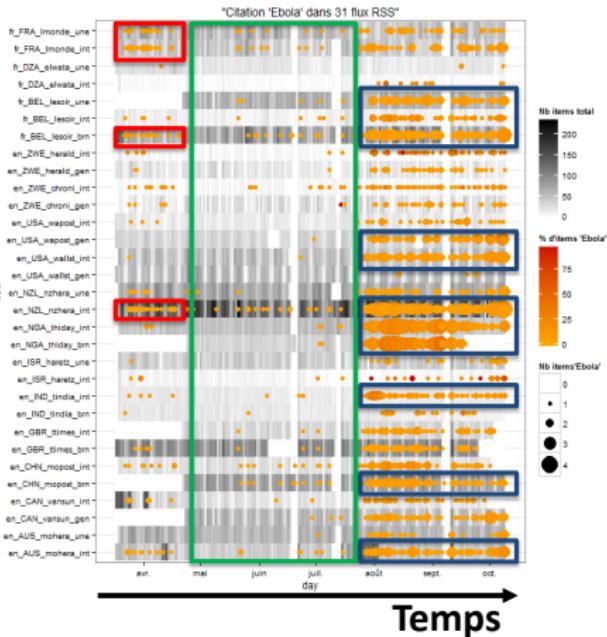
[Espace Géo 2016] News coverage the week of December 15, 2014



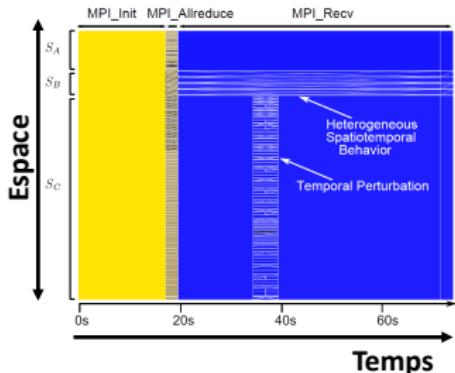
Multidimensional Aggregation

Journaux

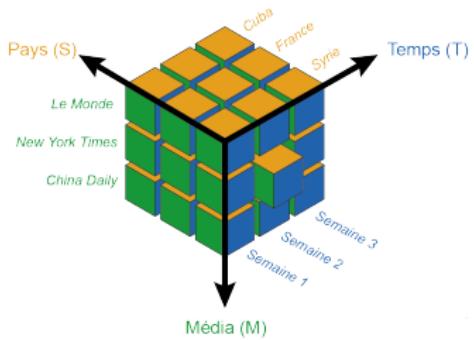
Media-temporal Aggregation



Spatio-temporal Aggregation



Geomedia Cube

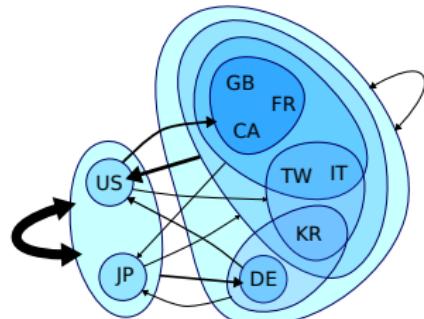
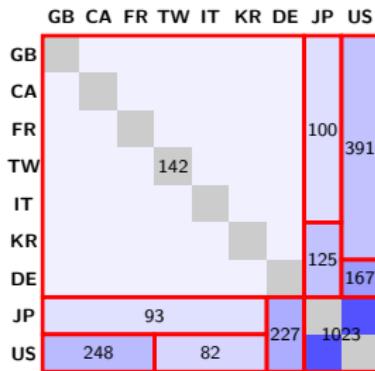
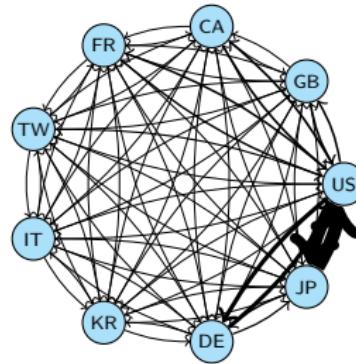


Aggregation of Social Relations

National Patent Citations. Unit: 100 patents; Period: 1990–1999;

Source: NBER U.S. Patent Citations Data File (<http://www.nber.org/patents/>)

	GB	CA	FR	TW	IT	KR	DE	JP	US
GB	3	5	1	2	0	11	23	82	
CA	3	3	2	1	0	6	15	89	
FR	5	3	1	3	1	14	28	83	
TW	2	3	2	1	3	4	22	62	
IT	2	1	3	1	0	7	12	31	
KR	2	1	2	2	1	3	47	44	
DE	11	6	12	2	6	1	78	167	
JP	24	14	23	9	9	14	66	504	
US	86	87	75	37	29	16	161	519	



Part V

Final Thoughts

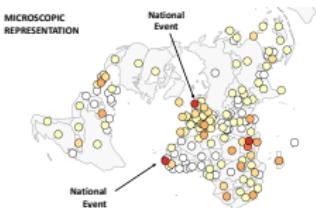
Conclusion

Complex System

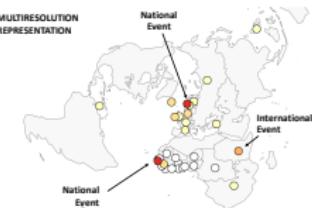


Microscopic Observation

Microscopic Data



Macroscopic Data



Data Aggregation

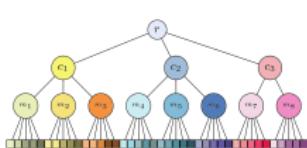
Constraints and semantics

Empirical evaluation

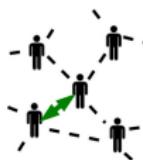


Domain Expert

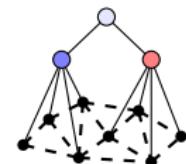
A priori Categories



Territorial Hierarchies

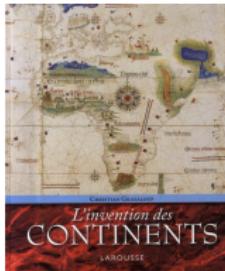


Flow and Networks



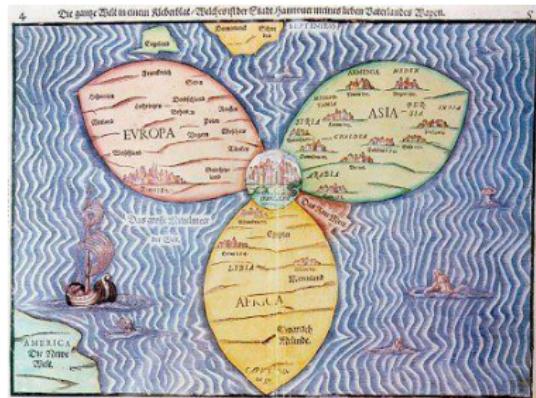
Mixed Structures

Toward new geographical categories

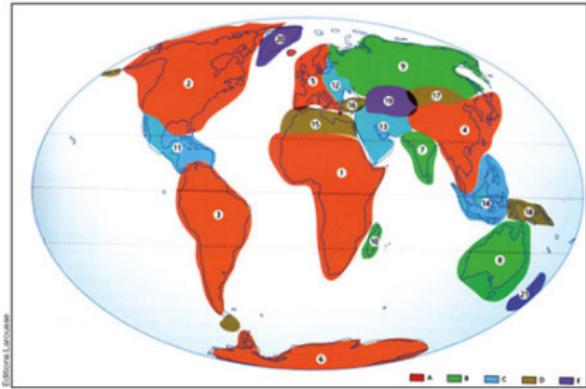


Christian Grataloup. 2009. *L'invention des continents : comment l'Europe a découpé le monde*. Paris, Larousse.

Outdated categories...



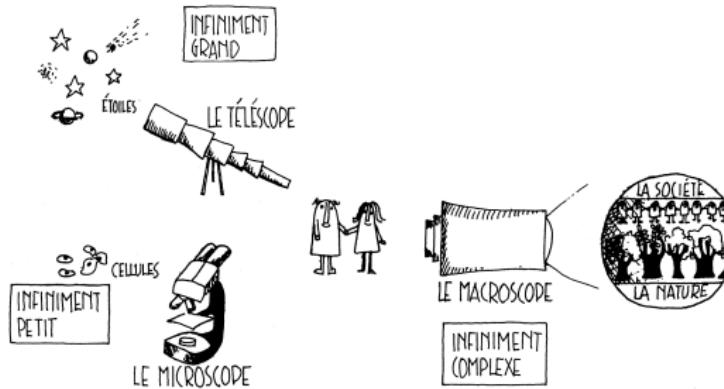
Building new ones?



Thank you for your attention

Mail: Robin.Lamarche-Perrin@lip6.fr

Web: www-complexnetworks.lip6.fr/~lamarche/



« Aujourd'hui, nous sommes confrontés à un autre infini : l'infiniment complexe. Mais cette fois, plus d'instrument. »

Joël de Rosnay. 1975. *Le Macroscope*.