Geomedia's Cube: A Multiscale Analysis of Media Flows in Space and Time

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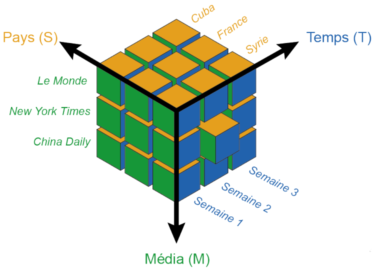
Laboratoire d'Informatique de Paris 6



In collaboration with:

Y. Demazeau	L. Tabourier
C. Grasland	F. Tarissan
B. Loveluck	J.-M. Vincent
H. Pecout	and many others

What is the state of the world?

International sections of daily newspapers

Which event made the news?

- At a given date?
- Regarding a given country?
- According to a given newspaper?

$\Rightarrow$ **Geomedia agenda-setting**

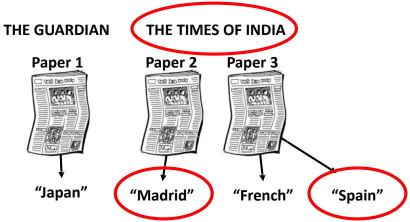
From **local observation**... ...to **global understanding**

Intro A tridimensional object

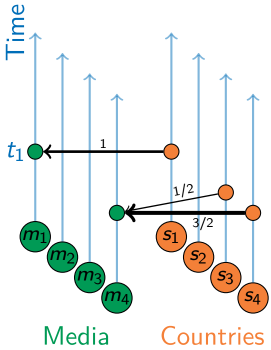
Part I Revealing its multiple facets

Part II Revealing its multiple scales

International Media Flows



Weighted temporal bipartite graph



Example:

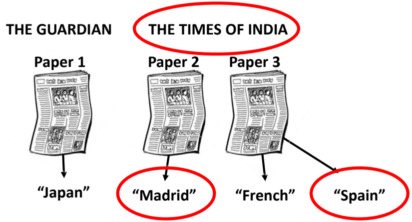
1 article published by media m_1 at time t_1 and citing country s_1

1 article published by media m_4 at time t_1 and citing country s_4

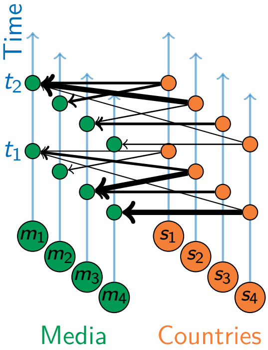
1 article published by media m_4 at time t_1 and citing countries s_3 and s_4

The Three Dimensions of Media Flows

International Media Flows



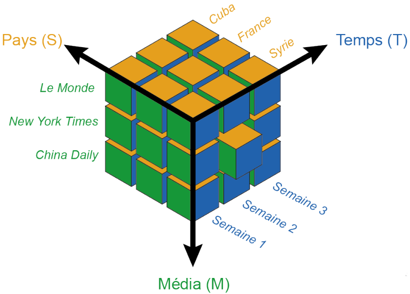
Weighted temporal bipartite graph



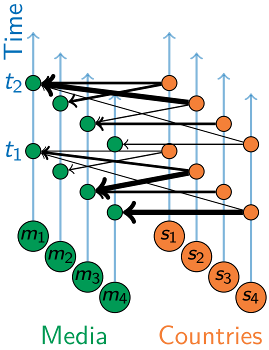
Data: 292 767 articles
published by **36 newspapers** (in 23 different states)
during **52 weeks** (from 28/04/2014 to 26/04/2015)
and citing **197 countries** (recognised by the UN)

The Three Dimensions of Media Flows

Geomedia Cube
(media × space × time)

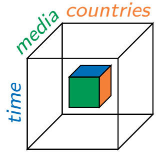


Weighted temporal bipartite graph



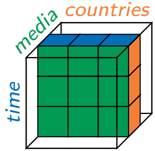
Data: 292 767 articles
published by **36 newspapers** (in 23 different states)
during **52 weeks** (from 28/04/2014 to 26/04/2015)
and citing **197 countries** (recognised by the UN)

What can be said about one observation?

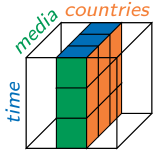


Cuba as been cited **16 times** by Le Monde during the week of December 15th, 2014.

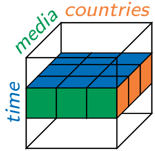
→ **Is that a lot?**



Knowing that Le Monde made 276 citations that week, and that it usually devotes 0.55% of its citations to Cuba?



Knowing that Le Monde made 276 citations that week, and that 9.0% of citations of all media that week were dedicated to Cuba?



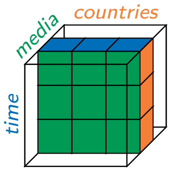
Knowing that Le Monde made 64 citations about Cuba within the whole corpus, and that 18.8% of all citations about Cuba where concentrated on that particular week?

Part I

The Multiple Facets of Media Flows

C. Grasland, R. Lamarche-Perrin, B. Loveluck, and H. Pecout. "L'agenda géomédiatique international : analyse multidimensionnelle des flux d'actualité". In *L'Espace Géographique*, vol. 45, issue 2016/1, p. 25-43. Éditions Belin, Paris, 2016.

ISTA Model: Internal Spatio-Temporal Agenda



Knowing that Le Monde made 276 citations that week, and that it usually devotes 0.55% of its citations to Cuba?

→ One would then expect **1.5 citations**, so **16** is a lot!

Given a media $m \in M$, detect spatio-temporal irregularities $(s_j, t_k) \in S \times T$.

m	s_1	s_2	s_3
t_1	3	4	3
t_2	3	5	4
t_3	2	7	1

⟶

m	s_1	s_2	s_3	
t_1				10
t_2				12
t_3				10
	8	16	8	32

⟶

m	s_1	s_2	s_3
t_1	2.5	5	2.5
t_2	3	6	3
t_3	2.5	5	2.5

Raw values:

$$v(m, s_j, t_k)$$

Marginal values:

$$v(m, ., t_k) = \sum_{s_j \in S} v(m, s_j, t_k)$$

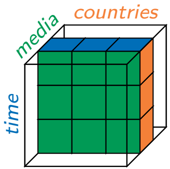
$$v(m, s_j, .) = \sum_{t_k \in T} v(m, s_j, t_k)$$

$$v(m, ., .) = \sum_{\substack{s_j \in S \\ t_k \in T}} v(m, s_j, t_k)$$

Expected values:

$$v^\star(m, s_j, t_k) = \frac{v(m, s_j, .)\ v(m, ., t_k)}{v(m, ., .)}$$

ISTA Model: Internal Spatio-Temporal Agenda



Knowing that Le Monde made 276 citations that week, and that it usually devotes 0.55% of its citations to Cuba?

→ One would then expect **1.5 citations**, so **16** is a lot!

Given a media $m \in M$, detect spatio-temporal irregularities $(s_j, t_k) \in S \times T$.

m	s_1	s_2	s_3
t_1	3	4	3
t_2	3	5	4
t_3	2	7	1

$\longrightarrow$

m	s_1	s_2	s_3
t_1	$+.51$	$-.12$	$+.51$
t_2	0	$-.11$	$+.63$
t_3	$-.09$	$+.73$	$-.43$

$\longleftarrow$

m	s_1	s_2	s_3
t_1	2.5	5	2.5
t_2	3	6	3
t_3	2.5	5	2.5

Raw values:

$v(m, s_j, t_k)$

Significativity:

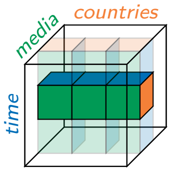
$$p(m, s_j, t_k) = \Pr(X \geq v(m, s_j, t_k))$$
with $X \sim \mathrm{Pois}(v^\star(m, s_j, t_k))$

$$\sigma(m, s_j, t_k) = 2p(m, s_j, t_k) - 1 \in [-1, +1]$$

Expected values:

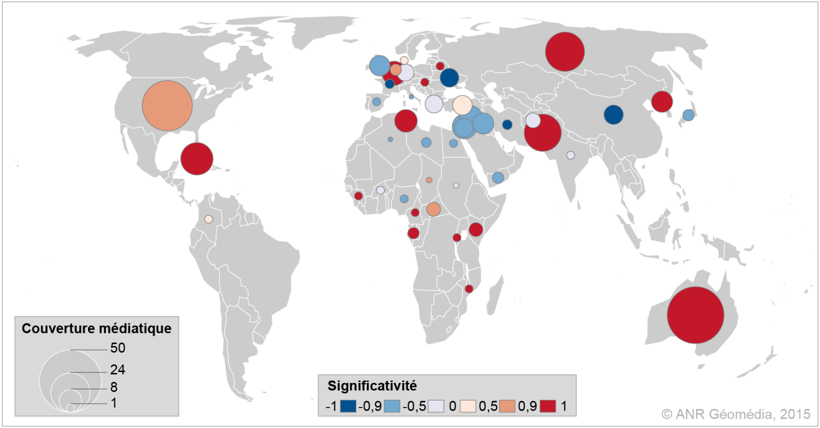
$$v^\star(m, s_j, t_k) = \frac{v(m, s_j, .)\ v(m, ., t_k)}{v(m, ., .)}$$

ISTA Model: Internal Spatio-Temporal Agenda

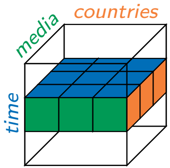


This data model measures significant divergences with respect to the **mean internal agenda** of a particular newspaper

(Le Monde, week of 15th December, 2014)



GSA Model: Global Spatial Agenda



Knowing that Le Monde made 276 citations that week, and that 9.0% of citations of all media that week were dedicated to Cuba?

→ One would then expect **25 citations**, so **16** is actually not much...

Given a time $t \in t$, detect spatio-media irregularities $(m_i, s_j) \in M \times S$.

t	s_1	s_2	s_3
m_1	3	4	3
m_2	3	5	4
m_3	2	7	1

⟶

t	s_1	s_2	s_3	
m_1				10
m_2				12
m_3				10
	8	16	8	32

⟶

t	s_1	s_2	s_3
m_1	2.5	5	2.5
m_2	3	6	3
m_3	2.5	5	2.5

Raw values:

$$v(m_i, s_j, t)$$

Marginal values:

$$v(m_i, ., t) = \sum_{m_i \in M} v(m_i, s_j, t)$$

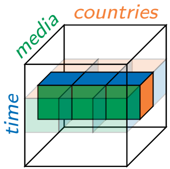
$$v(., s_j, t) = \sum_{s_j \in S} v(m_i, s_j, t)$$

$$v(., ., t) = \sum_{\substack{m_i \in M \\ s_j \in S}} v(m_i, s_j, t)$$

Expected values:

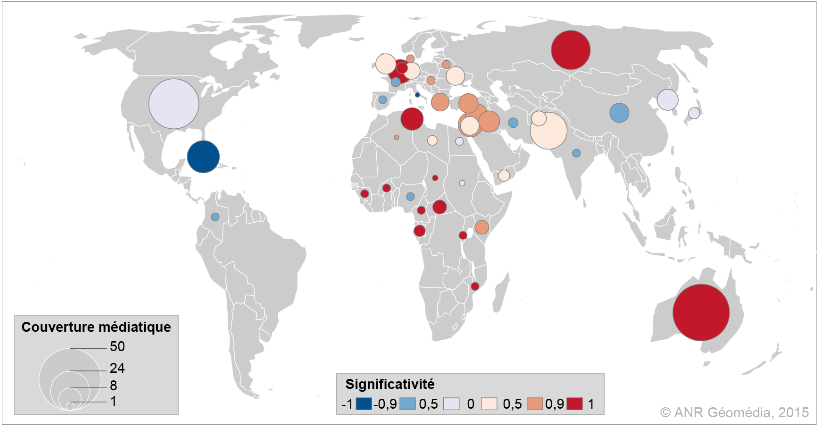
$$v^\star(m_i, s_j, t) = \frac{v(m_i, ., t)\, v(., s_j, t)}{v(., ., t)}$$

GSA Model: Global Spatial Agenda

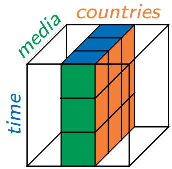


This data model measures significant divergences with respect to the **mean spatial agenda** of all media on a particular time period

(Le Monde, week of December 15th, 2014)



GTA Model: Global Temporal Agenda



Knowing that Le Monde made 64 citations about Cuba within the whole corpus, and that 18.8% of all citations about Cuba where concentrated on that particular week?

→ One would then expect **12 citations**, so **16** is a little bit more.

Given a country $s \in S$, detect tempo-media irregularities $(m_i, t_k) \in M \times T$.

s	t_1	t_2	t_3
m_1	3	4	3
m_2	3	5	4
m_3	2	7	1

$\longrightarrow$

s	t_1	t_2	t_3	
m_1				10
m_2				12
m_3				10
	8	16	8	32

$\longrightarrow$

s	t_1	t_2	t_3
m_1	2.5	5	2.5
m_2	3	6	3
m_3	2.5	5	2.5

Raw values:

$v(m_i, s, t_k)$

Marginal values:

$$v(m_i, s, .) = \sum_{m_i \in M} v(m_i, s, t_k)$$

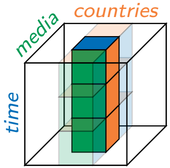
$$v(., s, t_k) = \sum_{t_k \in T} v(m_i, s, t_k)$$

$$v(., s, .) = \sum_{\substack{m_i \in M \\ t_k \in T}} v(m_i, s, t_k)$$

Expected values:

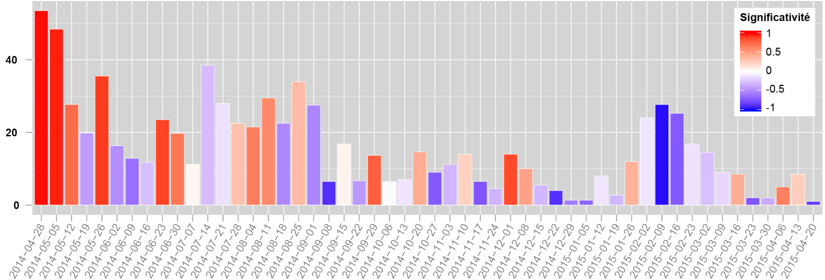
$$v^\star(m_i, s, t_k) = \frac{v(m_i, s, .)\, v(., s, t_k)}{v(., s, .)}$$

GTA Model: Global Temporal Agenda



This data model measures significant divergences with respect to the **mean temporal agenda** of all media regarding a particular country

(Ukraine, Le Monde)

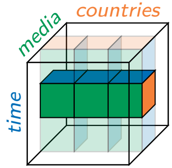


Part II

The Multiple Scales of Media Flows

R. Lamarche-Perrin, Y. Demazeau, and J.-M. Vincent. "Building Optimal Macroscopic Representations of Complex Multi-agent Systems". In *Transactions on Computational Collective Intelligence*, vol. XV, LNCS 8670, p. 1-27. Springer-Verlag Berlin, Heidelberg, 2014.

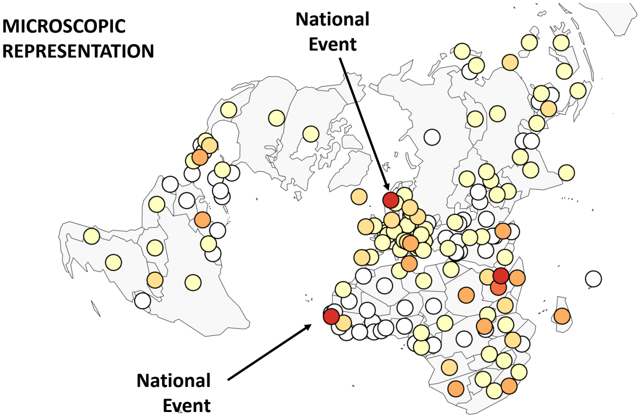
Looking for Geographical Scales



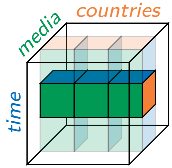
ISTA Model

Le Monde

July 2011



Looking for Geographical Scales

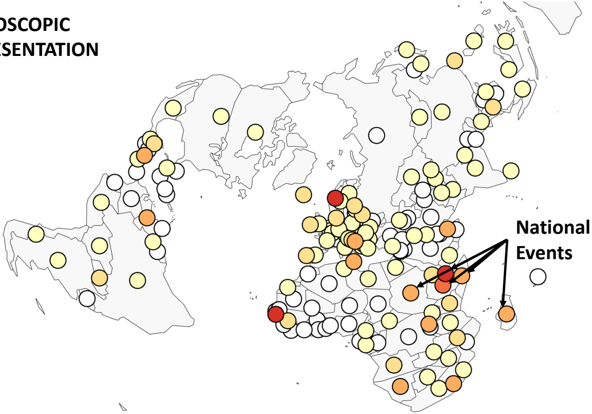


ISTA Model

Le Monde

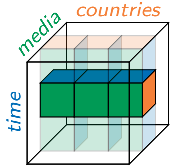
July 2011

MICROSCOPIC REPRESENTATION



m	s_1	s_2	s_3
t_1	3	3	4
t_2	3	6	3
t_3	2	7	1

Looking for Geographical Scales

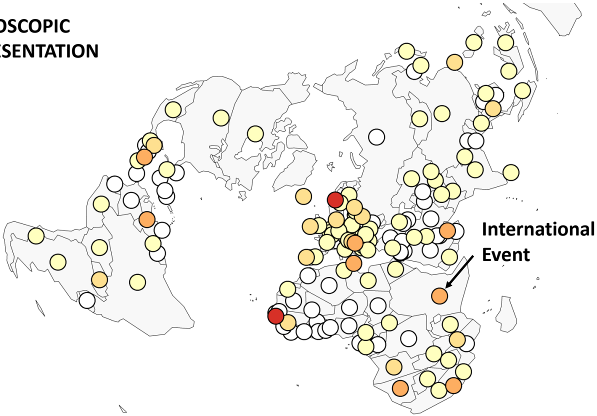


ISTA Model

Le Monde

July 2011

MICROSCOPIC REPRESENTATION

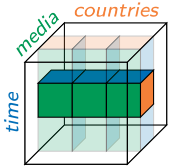


m	s_1	s_2	s_3
t_1	3	3	4
t_2	3	6	3
t_3	2	7	1

Aggregation $\longrightarrow$

m	s_1	s_2 s_3	
t_1	3	7	10
t_2	3	9	12
t_3	2	8	10
	8	16 8	32

Looking for Geographical Scales

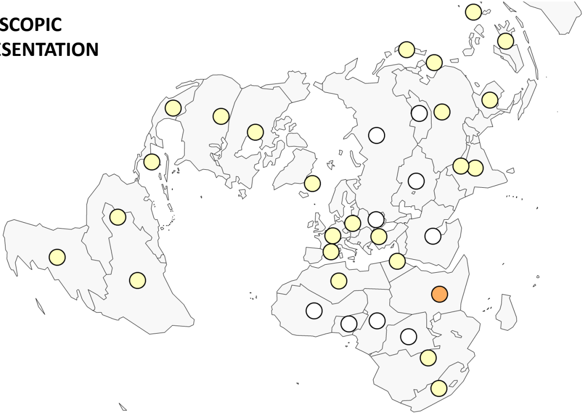


ISTA Model

Le Monde

July 2011

MESOSCOPIC REPRESENTATION



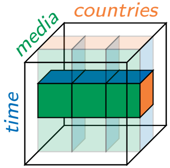
m	s_1	s_2	s_3
t_1	3	3	4
t_2	3	6	3
t_3	2	7	1

Aggregation

$\longrightarrow$

m	s_1	s_2 s_3	
t_1	3	7	10
t_2	3	9	12
t_3	2	8	10
	8	16 8	32

Looking for Geographical Scales

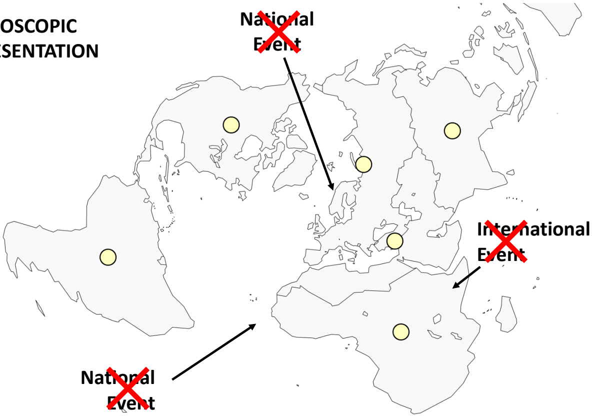


MACROSCOPIC REPRESENTATION

ISTA Model

Le Monde

July 2011

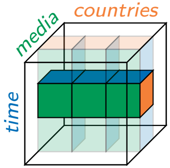


m	s_1	s_2	s_3
t_1	3	3	4
t_2	3	6	3
t_3	2	7	1

Aggregation $\longrightarrow$

m	s_1	s_2 s_3	
t_1	3	7	10
t_2	3	9	12
t_3	2	8	10
	8	16 8	32

Looking for Geographical Scales

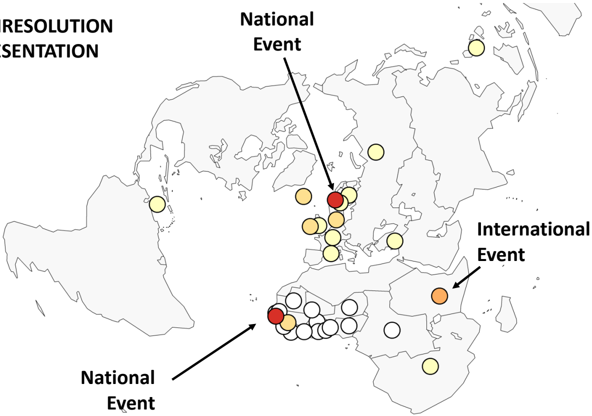


ISTA Model

Le Monde

July 2011

MULTIRESOLUTION REPRESENTATION

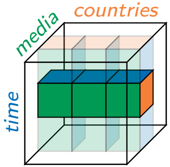


m	s_1	s_2	s_3
t_1	3	3	4
t_2	3	6	3
t_3	2	7	1

Aggregation $\longrightarrow$

m	s_1	s_2 s_3	
t_1	3	7	10
t_2	3	9	12
t_3	2	8	10
	8	16 8	32

Looking for Geographical Scales

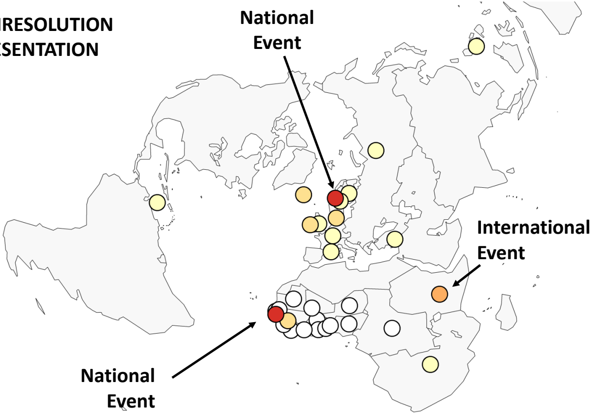


ISTA Model

Le Monde

July 2011

MULTIRESOLUTION REPRESENTATION



m	s_1	s_2	s_3
t_1	3	3	4
t_2	3	6	3
t_3	2	7	1

Aggregation $\longrightarrow$

m	s_1	s_2 s_3	
t_1	3	7	10
t_2	3	9	12
t_3	2	8	10
	8	16 8	32

Disaggregation $\longrightarrow$

m	s_1	s_2	s_3
t_1	3	4.7	2.3
t_2	3	6	3
t_3	2	5.3	2.7

Data Aggregation and Information Loss

	v_1	v_2	v_3	v_4	v_5
v_1	1	1	3	18	6
v_2	0	2	0	19	11
v_3	1	0	9	19	11
v_4	8	9	10	21	19
v_5	11	12	10	20	20

Empirical Distribution: $X \in V^2$

$$p_X(v, v') = \frac{w(v, v')}{|E|}$$

	v_1	v_2	v_3	v_4	v_5
v_1					
v_2					
v_3					
v_4					
v_5					

Compression Variable: $\hat{X} \in \mathcal{V}^2$

$$p_{\hat{X}|X}(M_i, M_j | v, v') = \mathbf{1}_{M_i \times M_j}(v, v')$$

	$\{v_1, v_2, v_3\}$	$\{v_4, v_5\}$
$\{v_3, v_2, v_1\}$	18	84
$\{v_5, v_4\}$	60	80

Compressed Distribution

$$p_{\hat{X}}(M_i, M_j) = \frac{w(M_i, M_j)}{|E|}$$

Information Loss
$D_{KL}(p_X \| q_X)$

	v_1	v_2	v_3	v_4	v_5
v_1	1	2	2	14	10
v_2	2	2	2	16	11
v_3	2	3	2	20	14
v_4	8	12	9	23	16
v_5	8	13	10	25	17

Decompressed Distribution

$$q_X(v, v') = \frac{w(M_i, M_j)\ w(v, .)\ w(., v')}{w(M_i, .)\ w(., M_j)\ |E|}$$

	v_1	v_2	v_3	v_4	v_5
v_1	3	4	3	12	8
v_2	3	4	3	13	9
v_3	4	6	4	17	11
v_4	6	9	7	27	19
v_5	6	10	7	29	20

Decompression Variable: $X^\star \in V^2$

$$u_{X^\star}(v, v') = \frac{w(v, .)\ w(., v')}{|E|}$$

	v_1	v_2	v_3	v_4	v_5	
v_1						29
v_2						32
v_3						41
v_4						67
v_5						73
	21	33	24	97	67	

External Information

Data Aggregation and Information Loss

	v_1	v_2	v_3	v_4	v_5
v_1	1	1	3	18	6
v_2	0	2	0	19	11
v_3	1	0	9	19	11
v_4	8	9	10	21	19
v_5	11	12	10	20	20

	v_1	v_2	v_3	v_4	v_5
v_1					
v_2					
v_3					
v_4					
v_5					

	$\{v_1, v_2, v_3\}$	$\{v_4, v_5\}$
$\{v_3, v_2, v_1\}$	18	84
$\{v_5, v_4\}$	60	80

Emp

istribution

$w(M_i, M_j)$ / $|E|$

Informat

$D_{KL}(p_X \|$

Information Loss using Kullback-Leibler Divergence

$$D_{KL}(p_X \| q_X) = \frac{1}{|E|} \sum_{\substack{(M_i, M_j) \in \mathcal{V}^2 \\ (v, v') \in M_i \times M_j}} w(v, v') \log_2 \left(\frac{w(v, v')}{w(M_i, M_j)} |M_i|\,|M_j| \right)$$

v_1	1	2	2	14	16
v_2	2	2	2	16	11
v_3	2	3	2	20	14
v_4	8	12	9	23	16
v_5	8	13	10	25	17

v_1	3	4	3	12	8
v_2	3	4	3	13	9
v_3	4	6	4	17	11
v_4	6	9	7	27	19
v_5	6	10	7	29	20

				v_4	v_5	
v_1						29
v_2						32
v_3						41
v_4						67
v_5						73
	21	33	24	97	67	

Decompressed Distribution

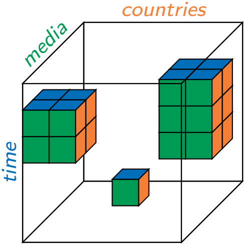
$$q_X(v, v') = \frac{w(M_i, M_j)\, w(v, .)\, w(., v')}{w(M_i, .)\, w(., M_j)\, |E|}$$

Decompression Variable: $X^\star \in V^2$

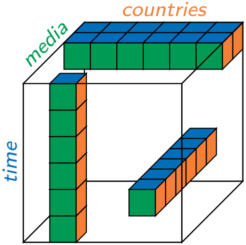
$$u_{X^\star}(v, v') = \frac{w(v, .)\, w(., v')}{|E|}$$

External Information

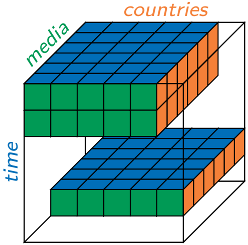
Multidimensional Aggregation in the Cube



No privileged dimension



One privileged dimension

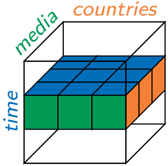


Two privileged dimensions

Disclaimer!

- **Epistemic bias:**
  What do citation networks really tell us about the social practice of news coverage?
- **Data bias:**
  Is our citation dataset in any way representative of the domain?
- **Method bias:**
  What does the aggregation method really tell us about the data?
- **Algorithmic bias:**
  Is the aggregation algorithm neutral with respect to the method?

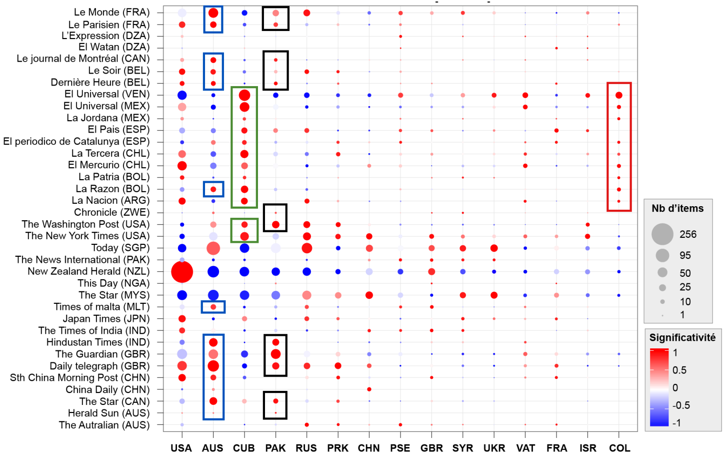
Media Aggregation



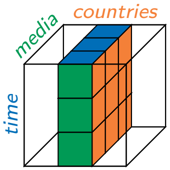
GSA Model

Week of

15/12/2014

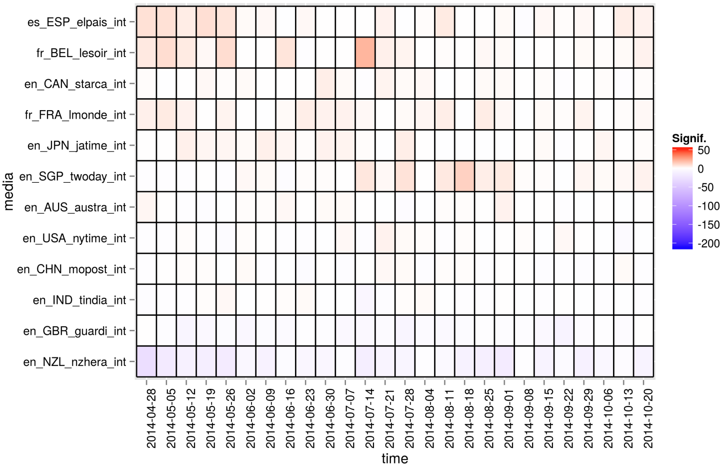


Media × Time Aggregation

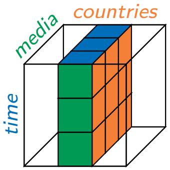


GSA Model

Ukraine

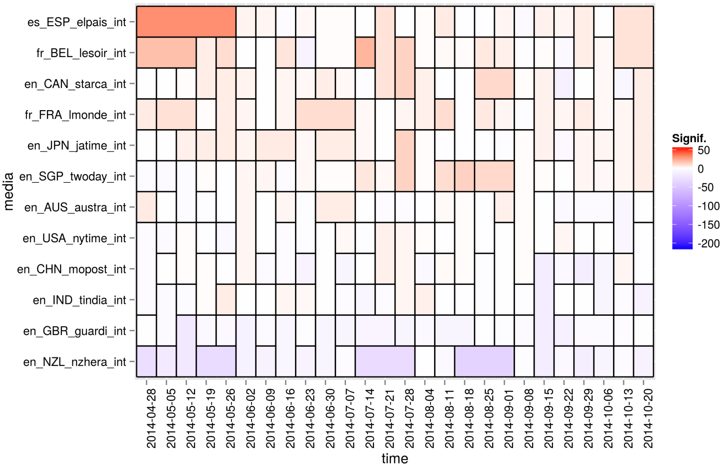


No information loss $\longrightarrow$ **312 aggregates**



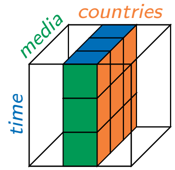
GSA Model

Ukraine



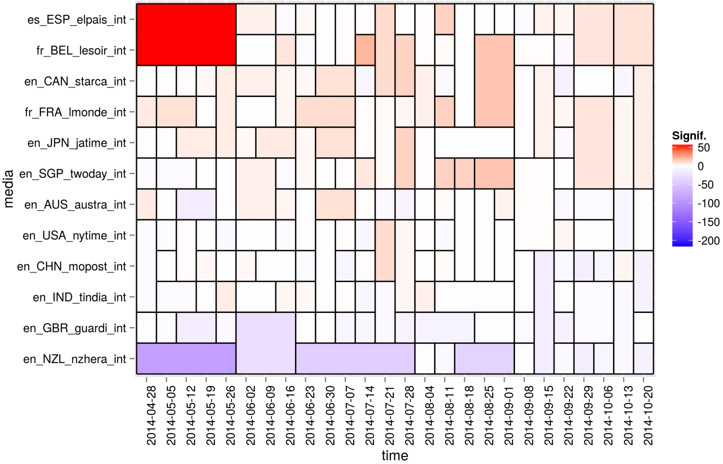
1.5% of information loss $\longrightarrow$ 118 aggregates

Media × Time Aggregation



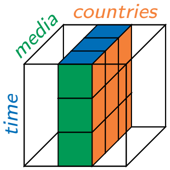
GSA Model

Ukraine



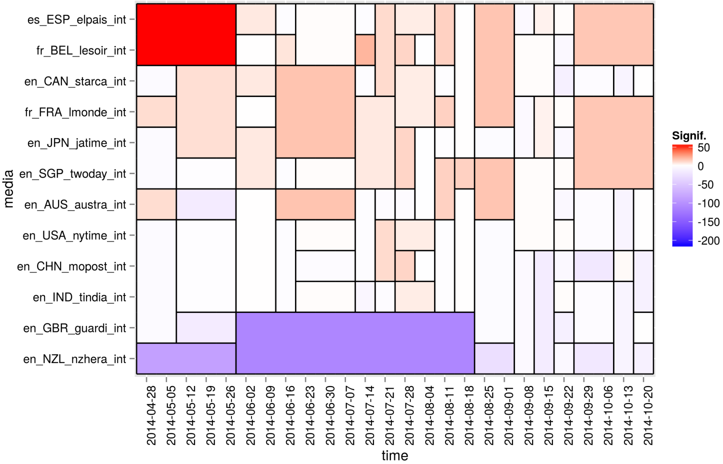
3.9% of information loss $\longrightarrow$ 86 aggregates

Media × Time Aggregation



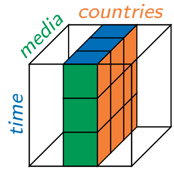
GSA Model

Ukraine



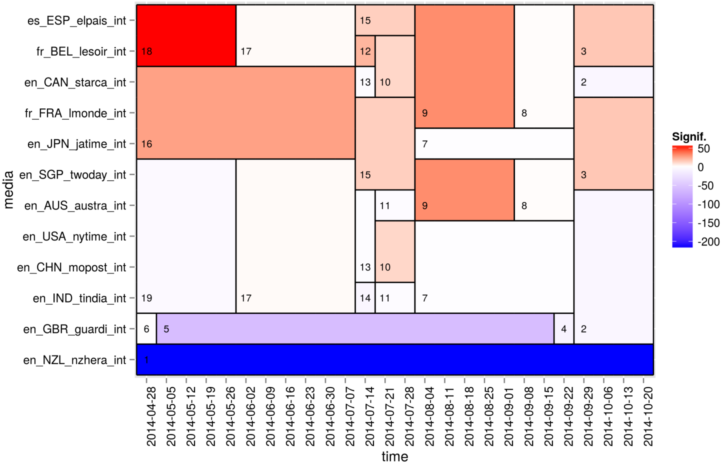
11.4% of information loss $\longrightarrow$ **46 aggregates**

Media × Time Aggregation



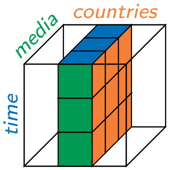
GSA Model

Ukraine



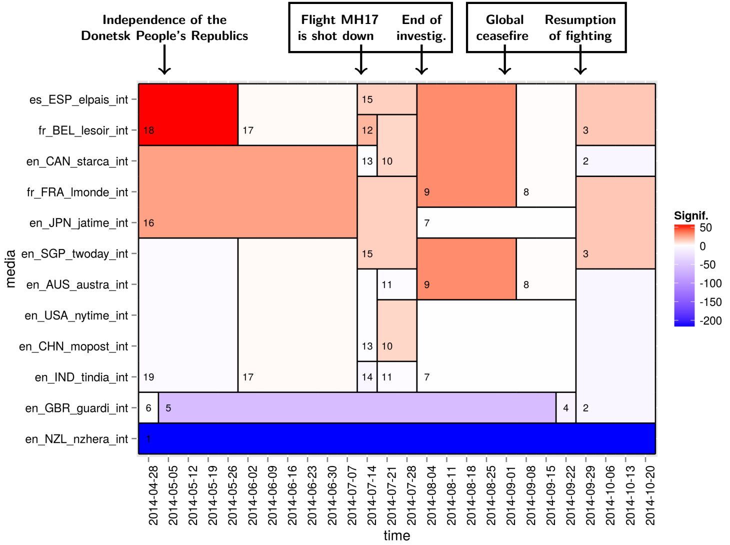
22.6% of information loss $\longrightarrow$ **19 aggregates**

Media × Time Aggregation



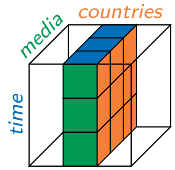
GSA Model

Ukraine



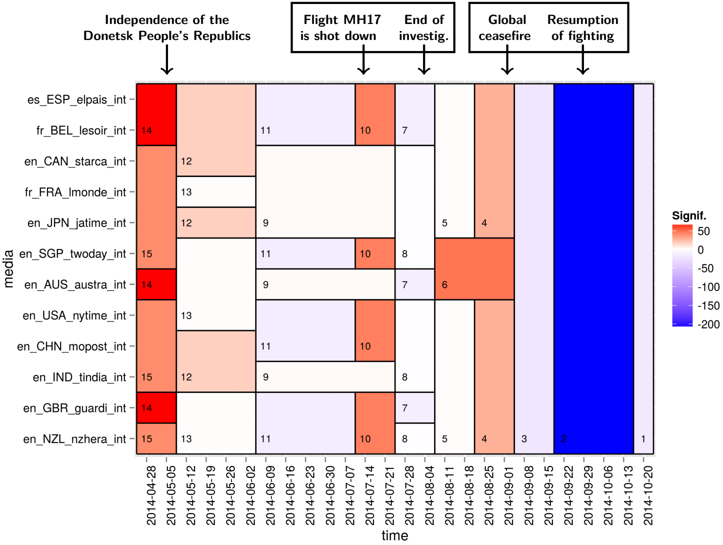
22.6% of information loss ⟶ **19 aggregates**

Media × Time Aggregation



ISTA Model

Ukraine



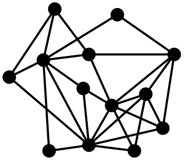
24.5% of information loss $\longrightarrow$ **15 aggregates**

Part III

The Semantics of Aggregates

R. Lamarche-Perrin, L. Tabourier, and F. Tarissan. "Information-theoretic Compression of Weighted Graphs". Poster session of the MSR-INRIA Join Center Workshop on "Networks: Learning, Information and Complexity", Paris, 18th-20th of May, 2016.

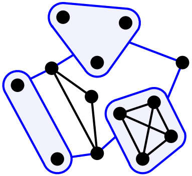
Constraints in Graph Aggregation



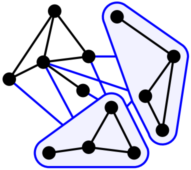
Initial graph

01000111 01110010
01100001 01110000
01101000 01100101
00100000 01111010
01101001 01110000
01110000 11000011
10101001 00100001

Unconstrained compression
(no constraint)

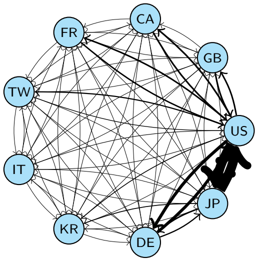


Modular Decomposition
(generic constraints)



Graph Rewriting
(strong constraints)

Power Graph Decomposition



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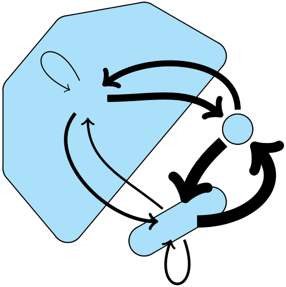
GB		3	5	1	2	0	11	23	82
CA	3		3	2	1	0	6	15	89
FR	5	3		1	3	1	14	28	83
TW	2	3	2		1	3	4	22	62
IT	2	1	3	1		0	7	12	31
KR	2	1	2	2	1		3	47	44
DE	11	6	12	2	6	1		78	167
JP	24	14	23	9	9	14	66		504
US	86	87	75	37	29	16	161	519	

National Patent Citations. Unit: 100 patents; Period: 1990–1999;
Source: NBER U.S. Patent Citations Data File (http://www.nber.org/patents/)

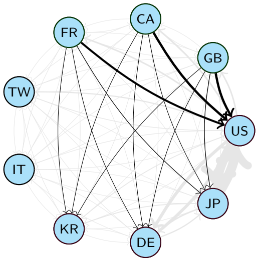
Power Graph Decomposition



	GB CA FR TW IT KR	DE JP	US
GB CA FR TW IT KR	59	192	391
DE JP	131	144	671
US	330	680	

National Patent Citations. Unit: 100 patents; Period: 1990–1999;
Source: NBER U.S. Patent Citations Data File (http://www.nber.org/patents/)

Power Graph Decomposition



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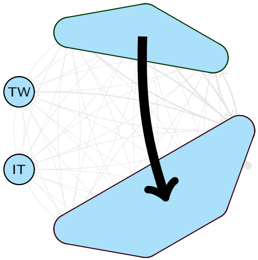
CA	3		3	2	1	0	6	15	89
FR	5	3		1	3	1	14	28	83
TW	2	3	2		1	3	4	22	62
IT	2	1	3	1		0	7	12	31
KR	2	1	2	2	1		3	47	44
DE	11	6	12	2	6	1		78	167
JP	24	14	23	9	9	14	66		504
US	86	87	75	37	29	16	161	519	

National Patent Citations. Unit: 100 patents; Period: 1990–1999;
Source: NBER U.S. Patent Citations Data File (http://www.nber.org/patents/)

Power Graph Decomposition



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<tr><th>GB</th><td></td><td>3</td><td>5</td><td>1</td><td>2</td><td rowspan="3" colspan="4">352</td></tr>
<tr><th>CA</th><td>3</td><td></td><td>3</td><td>2</td><td>1</td></tr>
<tr><th>FR</th><td>5</td><td>3</td><td></td><td>1</td><td>3</td></tr>
<tr><th>TW</th><td>2</td><td>3</td><td>2</td><td></td><td>1</td><td>3</td><td>4</td><td>22</td><td>62</td></tr>
<tr><th>IT</th><td>2</td><td>1</td><td>3</td><td>1</td><td></td><td>0</td><td>7</td><td>12</td><td>31</td></tr>
<tr><th>KR</th><td>2</td><td>1</td><td>2</td><td>2</td><td>1</td><td></td><td>3</td><td>47</td><td>44</td></tr>
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<tr><th>JP</th><td>24</td><td>14</td><td>23</td><td>9</td><td>9</td><td>14</td><td>66</td><td></td><td>504</td></tr>
<tr><th>US</th><td>86</td><td>87</td><td>75</td><td>37</td><td>29</td><td>16</td><td>161</td><td>519</td><td></td></tr>
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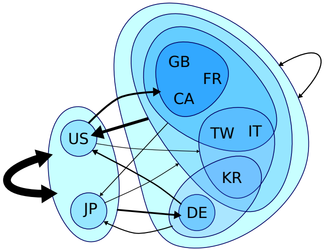
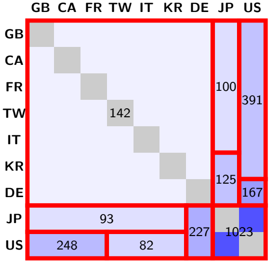
National Patent Citations. Unit: 100 patents; Period: 1990–1999;
Source: NBER U.S. Patent Citations Data File (http://www.nber.org/patents/)

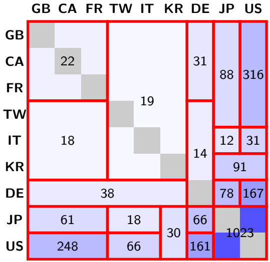
Power Graph Decomposition



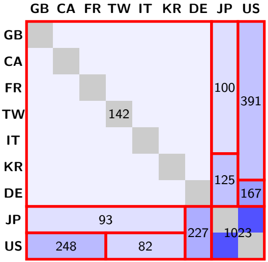


National Patent Citations. Unit: 100 patents; Period: 1990–1999;
Source: NBER U.S. Patent Citations Data File (http://www.nber.org/patents/)

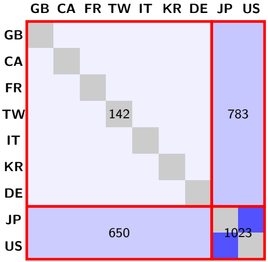
The Multiple Scales of Aggregation



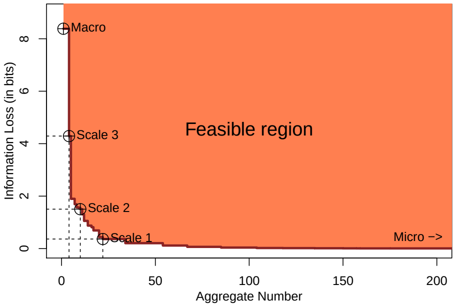
Scale 1: 22 aggregates
→ 96% of micro-information



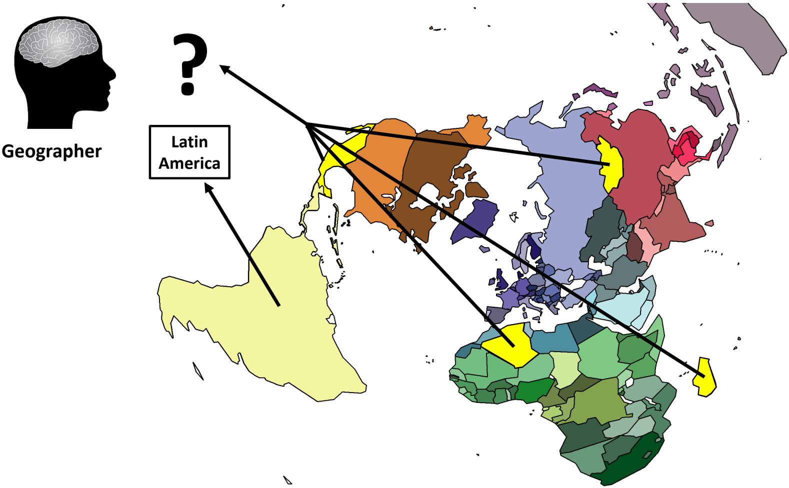
Scale 2: 10 aggregates
→ 82% of micro-information



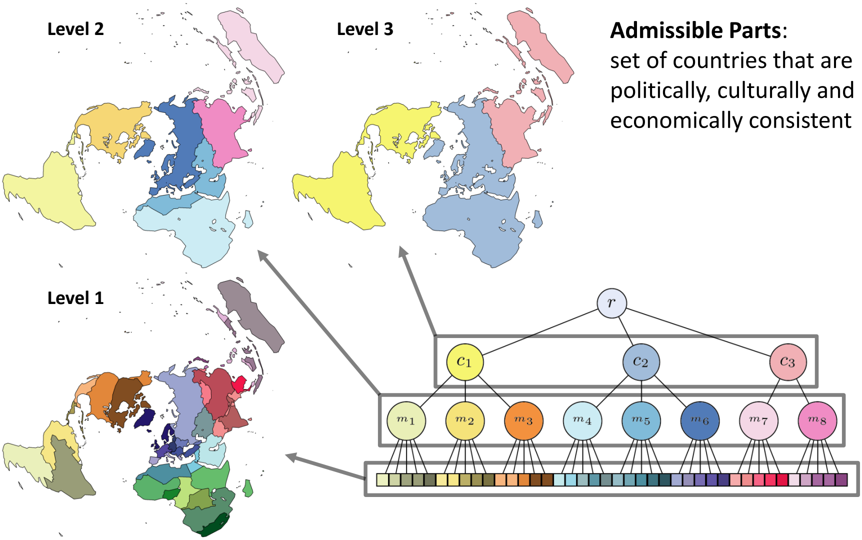
Scale 3: 4 aggregates
→ 49% of micro-information



Problem II: Semantics of Geographical Aggregates

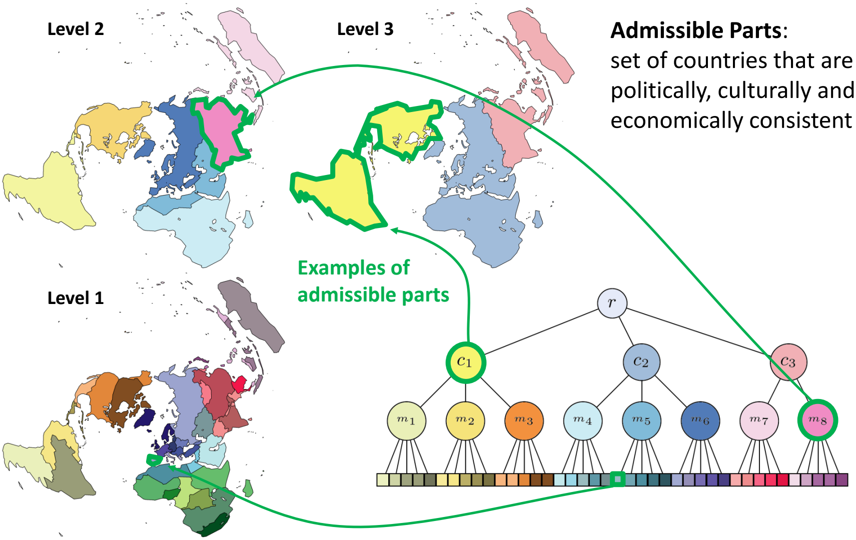


Hierarchical Structures in Geography



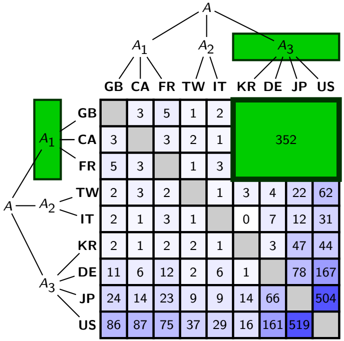
Admissible Parts:
set of countries that are politically, culturally and economically consistent

Hierarchical Structures in Geography



Admissible Parts:
set of countries that are politically, culturally and economically consistent

Hierarchical Aggregation of Interactions



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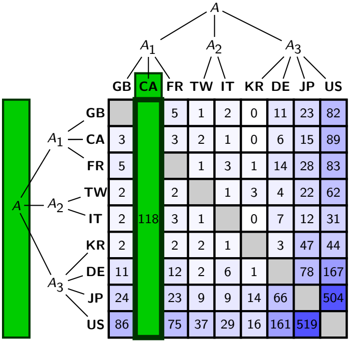
GB		3	5	1	2	352			
CA	3		3	2	1				
FR	5	3		1	3				
TW	2	3	2		1	3	4	22	62
IT	2	1	3	1		0	7	12	31
KR	2	1	2	2	1		3	47	44
DE	11	6	12	2	6	1		78	167
JP	24	14	23	9	9	14	66		504
US	86	87	75	37	29	16	161	519	

Admissible aggregate



	GB	CA	FR	TW	IT	KR	DE	JP	US
GB			5	1	2	0	11	23	82
CA	3		3	2	1	0	6	15	89
FR	5			1	3	1	14	28	83
TW	2		2		1	3	4	22	62
IT	2	118	3	1		0	7	12	31
KR	2		2	2	1		3	47	44
DE	11		12	2	6	1		78	167
JP	24		23	9	9	14	66		504
US	86		75	37	29	16	161	519	

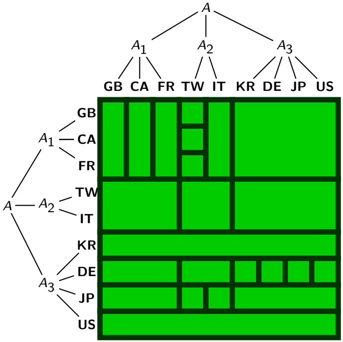
Admissible aggregate

Hierarchical Aggregation of Interactions

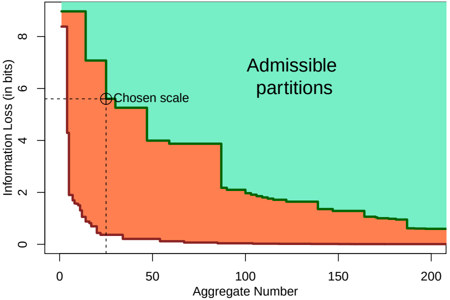
	GB	CA	FR	TW	IT	KR	DE	JP	US
GB		3	5	1	2	0	11	23	82
CA	3		3	2	1	0	6	15	89
FR	5	3		1	3	1	14	28	83
TW	2	3	2		1	3	4	22	62
IT	2	1	3	1		0	7	12	31
KR	2	25			1		3	47	44
DE	11				6	1		78	167
JP	24	14	23	9	9	14	66		504
US	86	87	75	37	29	16	161	519	

Unauthorised aggregate

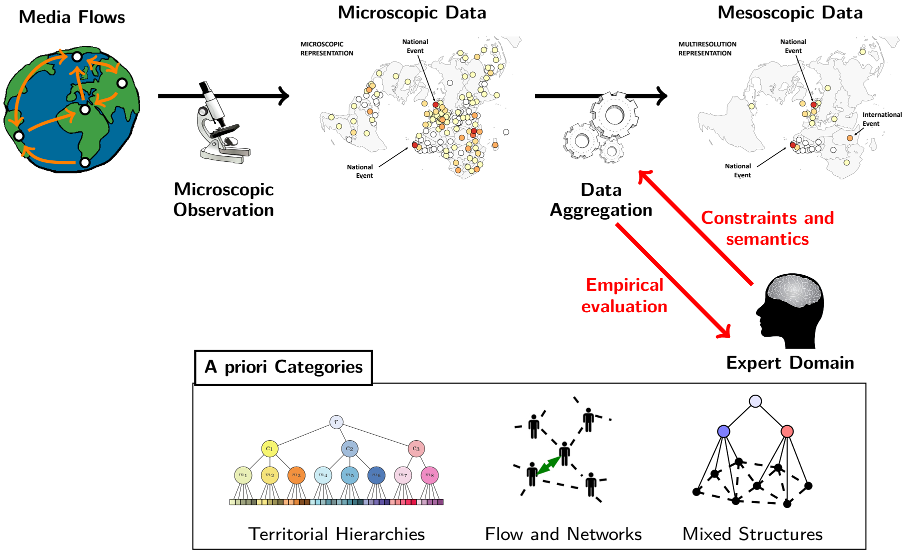
Hierarchical Aggregation of Interactions



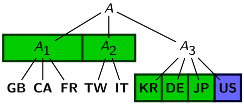
Admissible partition



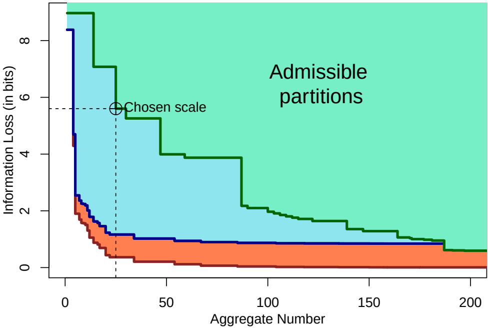
Multilevel Analysis of Social Systems

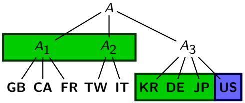


Building more appropriate multilevel structures

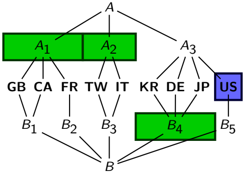


Classical Hierarchy

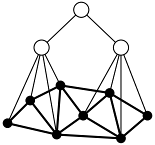




Relaxed hierarchy?

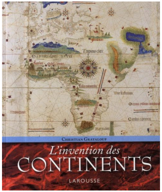


Two mixed hierarchies?



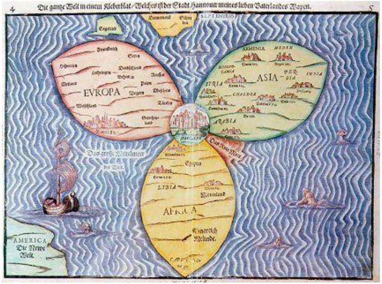
Hierarchy mixed with a graph?

Toward new geographical categories

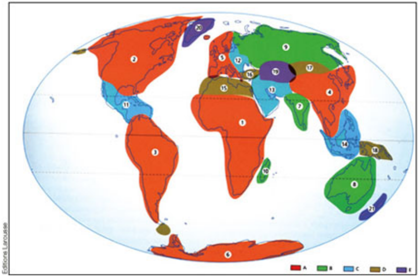


Christian Grataloup. 2009. *L'invention des continents : comment l'Europe a découpé le monde.* Paris, Larousse.

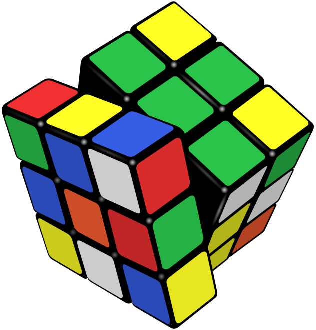
Outdated categories...



Building new ones?



Thank you for your attention



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Algo: github.com/Lamarche-Perrin/optimal_partition