

Mapping Scientific Communities - Opening up the Black Box

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Opening up the “Black Box”

Black box “broadly: anything that has mysterious or unknown internal functions or mechanisms” [Merriam Webster Dictionary]

In science and technology studies: looking ‘under the hood’ at the social mechanics involved in producing scientific knowledge typically neglected and de-emphasized in the official account of how scientific results are obtained.

Opening up the Black Box

Part 1: How Scientific Communities Produce Knowledge – Insights Gained From Maps of Science

Part 2: How Maps of Science Are Produced – Discussion of Challenges Encountered

Mixed Method Approach

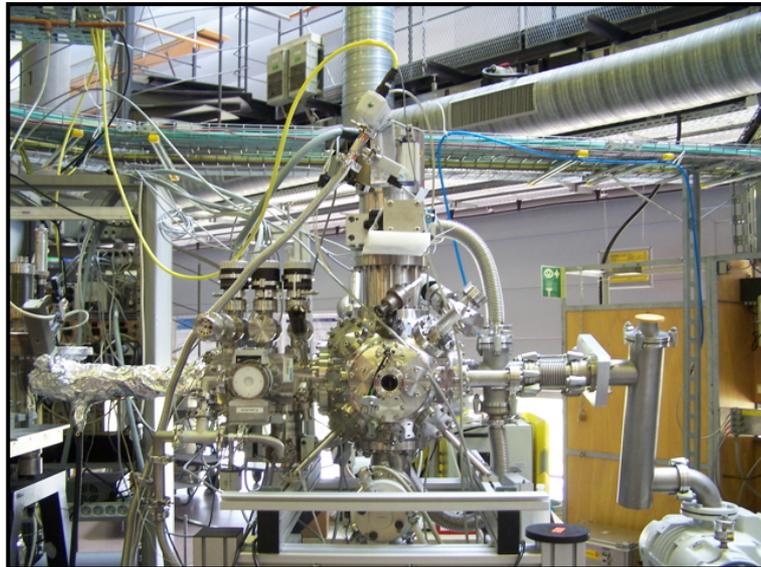
Network analysis

large publication networks (several 10,000 publications/authors)

&

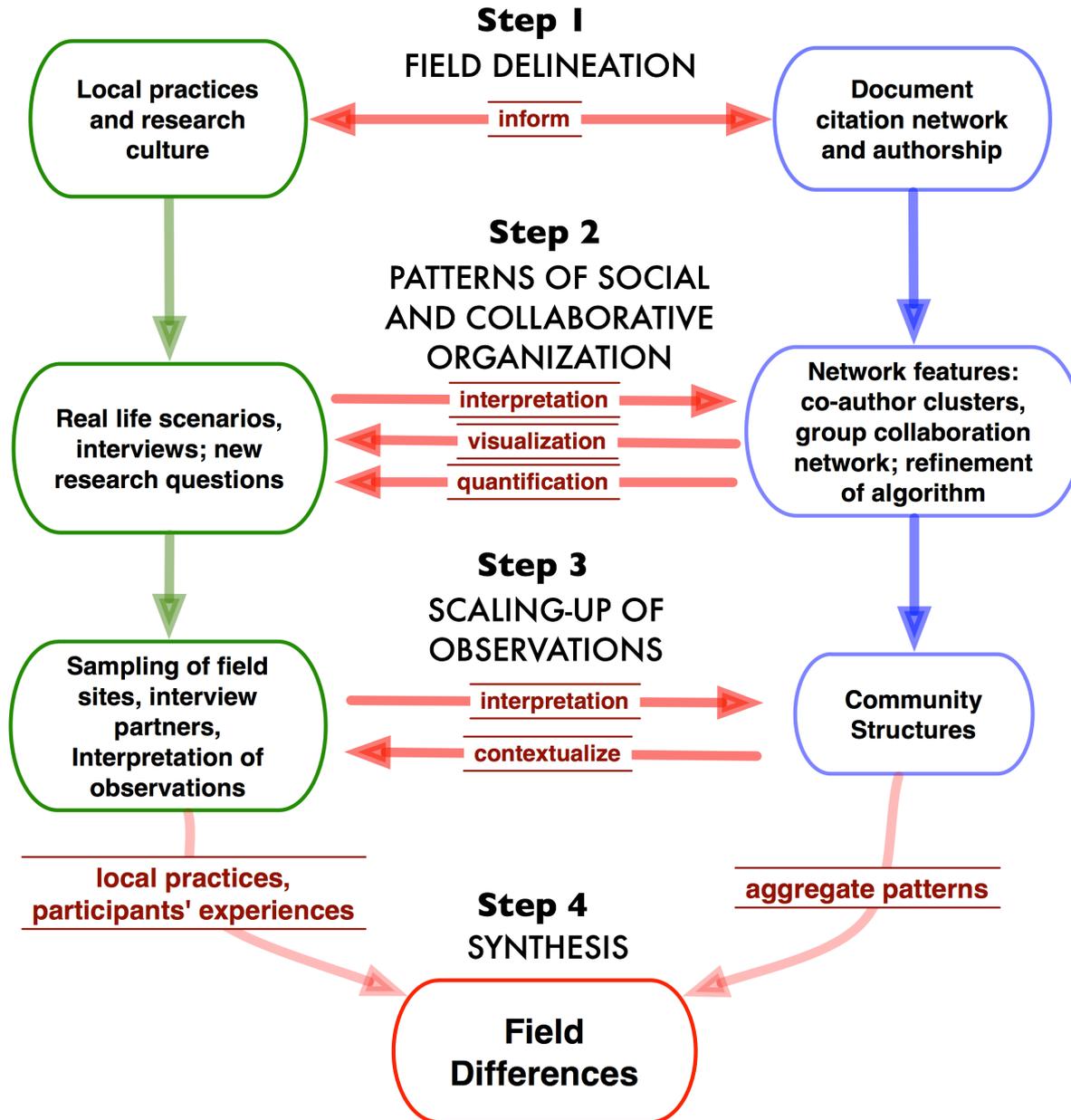
Ethnographic field studies

of scientific communities



Ethnographic Field Studies

Network Analysis



Co-author & citation networks

PART 1: MAPS OF SCIENCE

WoS Data

Lexical Query

Bibliographic Records

Co-author Network

Direct Citation Network

Clustering (infomap)

Clustering x 2 (infomap)

Research Groups

Topics

Filter Link Patterns

Calculate citation-based affinity

Group Collaboration Network

Topic Affinity Network

Socio-Cognitive Structures

'Social'

'Cognitive'

Data To Represent a Research Specialty

- Science Citation Index Expanded (SCI) edition, Web of Science (October 2013)
- Lexical query on title field
 - 20-year period (1991 - 2010)
 - Developed during ethnographic field studies between 2007-2009 to capture two research specialties in the physical and chemical sciences
 - Optimized recall and precision (Velden & Lagoze, JASIST 2013)
- Data preprocessing:
 - Include only records of type 'article'
 - Author name disambiguation (Velden et al, JCDL 2011)
 - Remove transient, one-time authors (~ 60%)
 - Final data sets:
 - For field A: **55,648 records** and **40,808 unique authors**
 - For field B: **13,910 records** and **9,116 unique authors**

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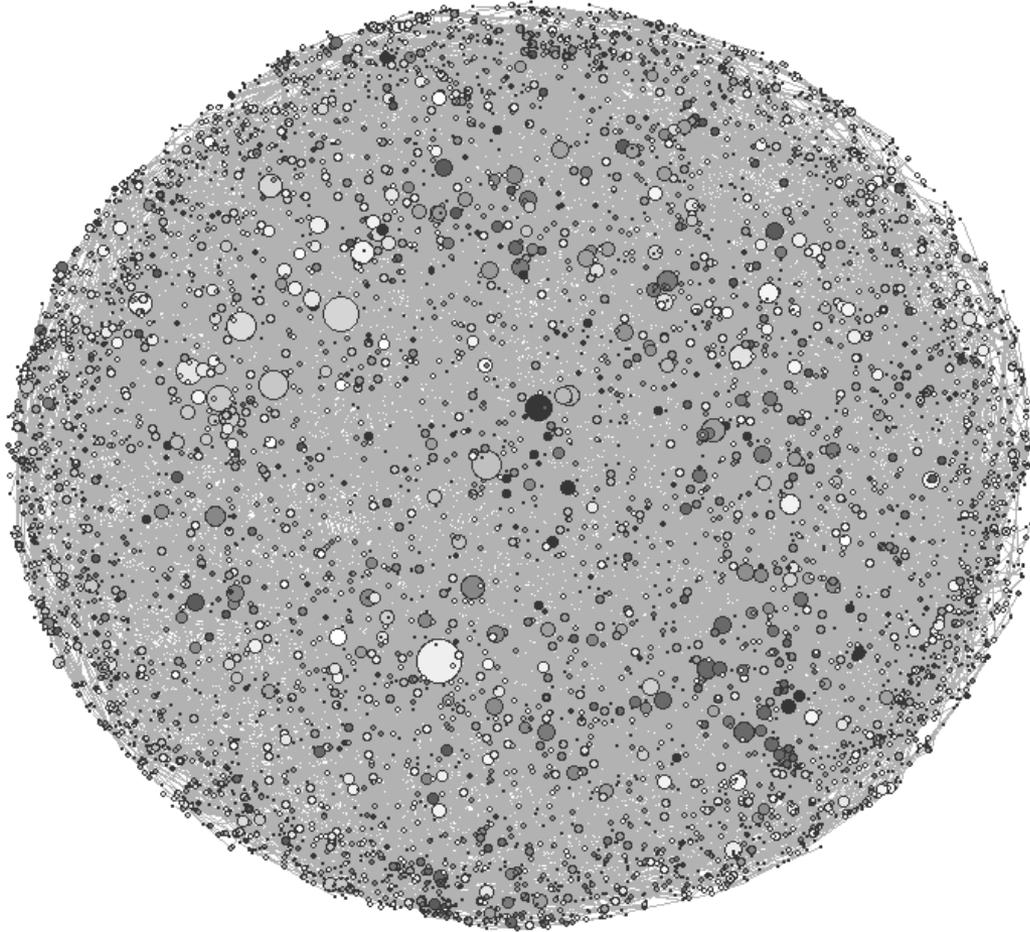
Topic Affinity Network

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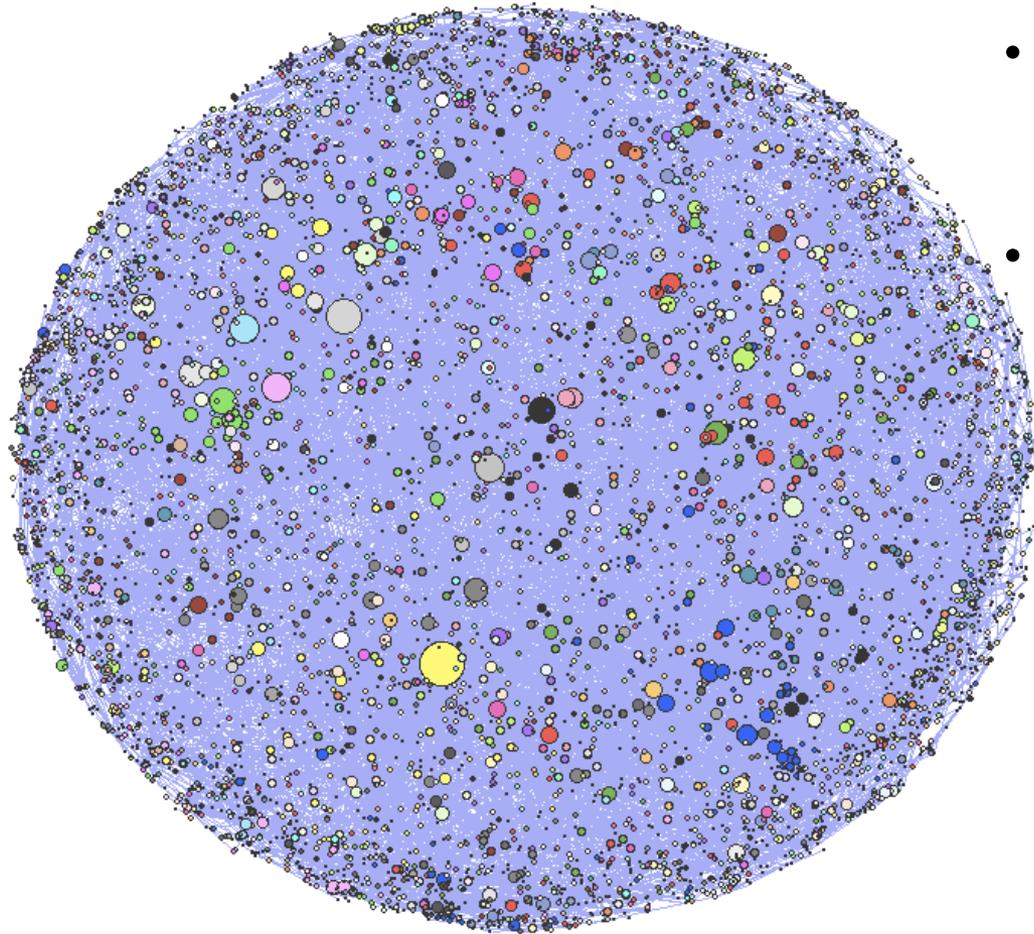
Co-Author Network



- weighted (weight = 1 per co-authored paper)
- undirected
- Field B: ~ 7,000 authors in giant component

Visualization: pajek,
Fruchterman Rheingold
algorithm

Clustered Coauthor Network

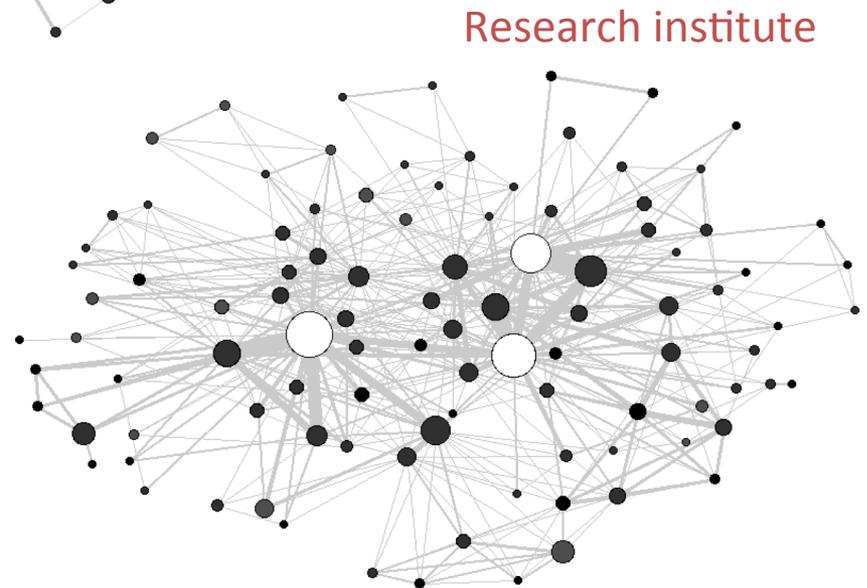
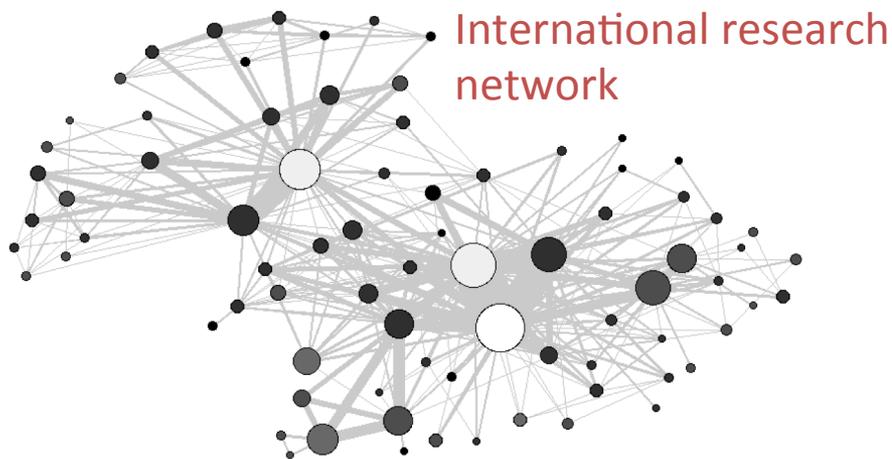
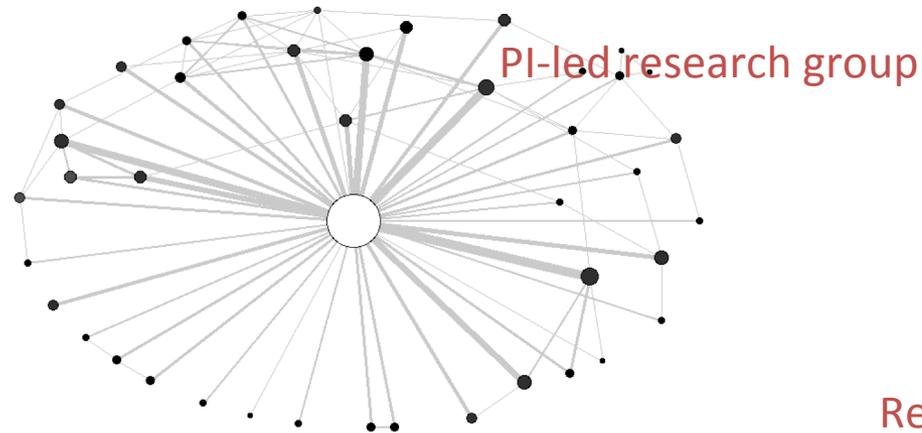


- Apply clustering algorithm to extract groups of closely collaborating authors
- Key properties of infomap algorithm:
 - Disjoint clusters
 - Unbiased cluster size
 - Fast

Clustering: Rosvall, M., & Bergstrom, C. (2007). An information-theoretic framework for resolving community structure in complex networks. PNAS, 104(18), 7327.

Co-Author Clusters

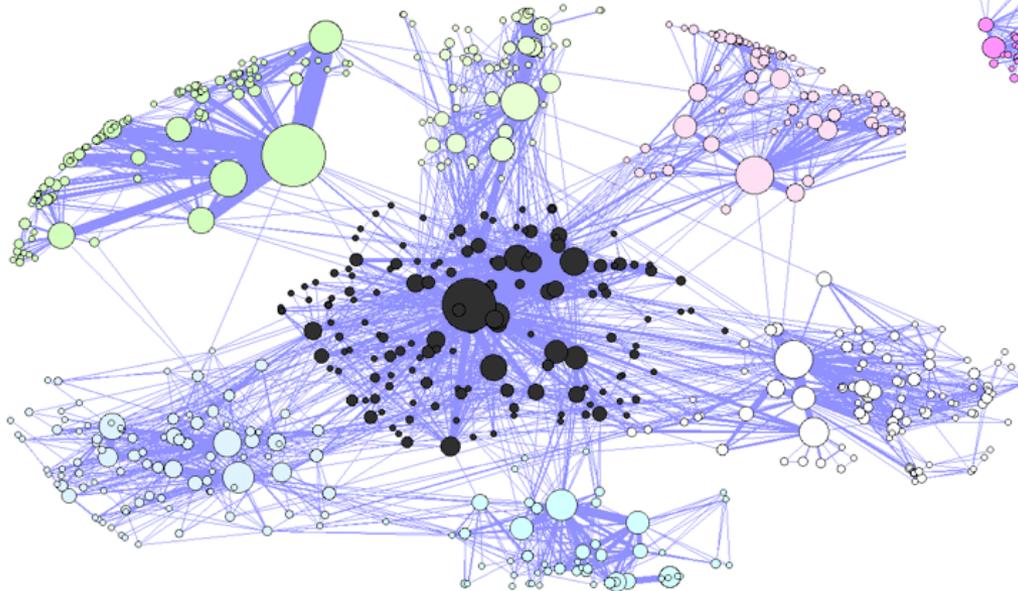
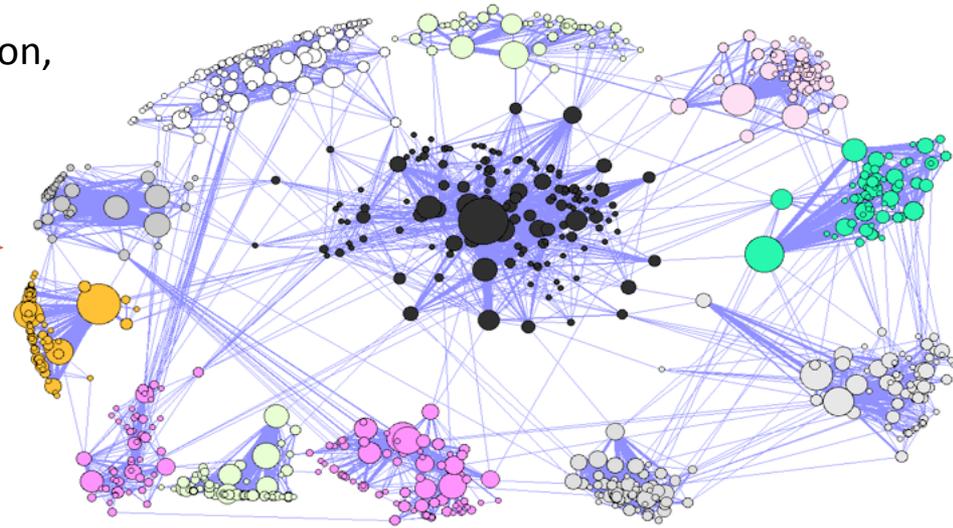
‘functional research groups’ [Seglen & Aksnes 2000, microbiology]



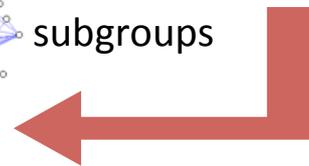
Mesoscopic Structure

Linking patterns between groups

Transfer links: career migration,
sample exchange, measurement
services

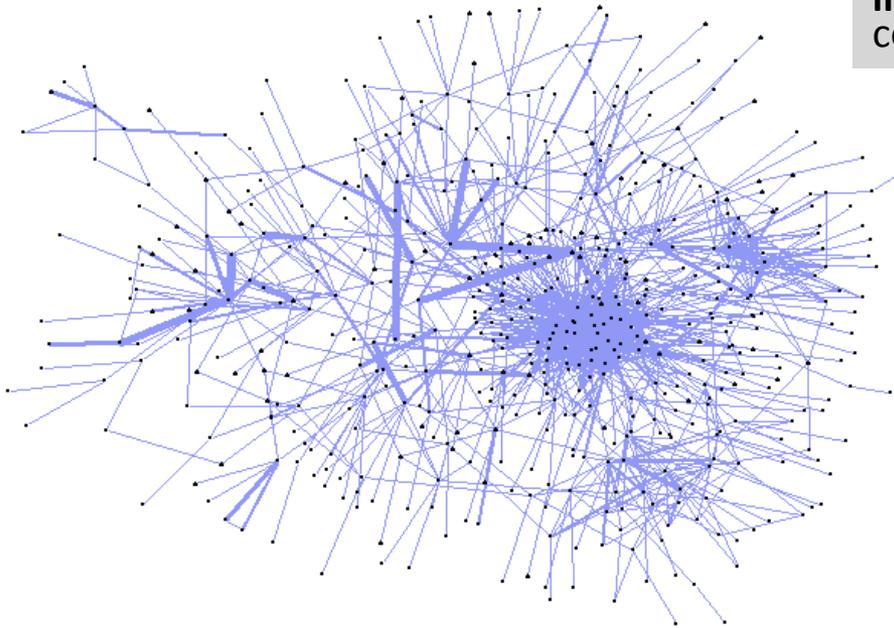


Inter Group Collaboration:
Intensive collaboration between
subgroups



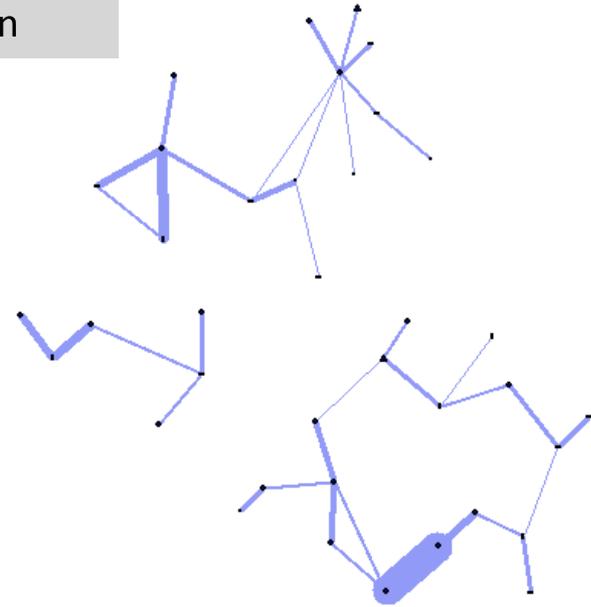
Field Differences: Group Collaboration Network

Field A



nodes: research groups
links: collaboration

Field B

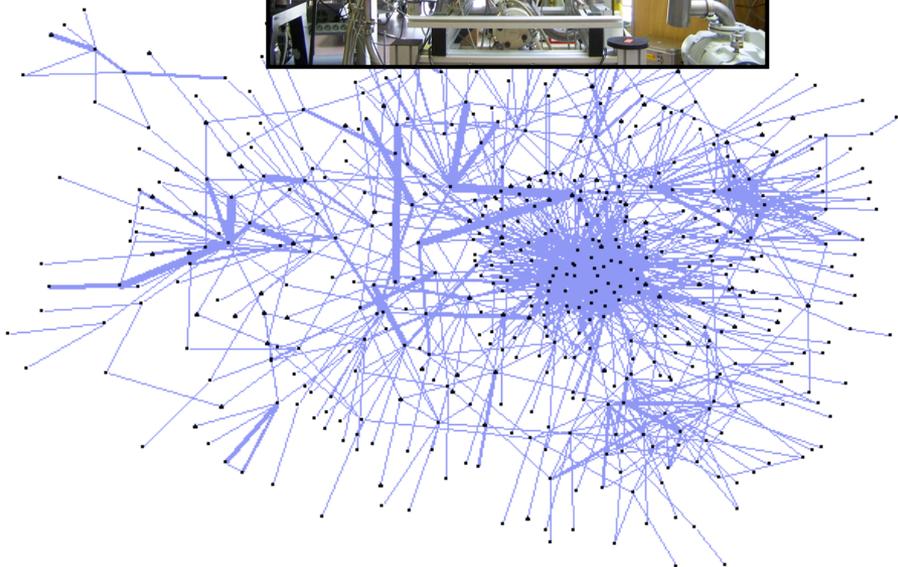
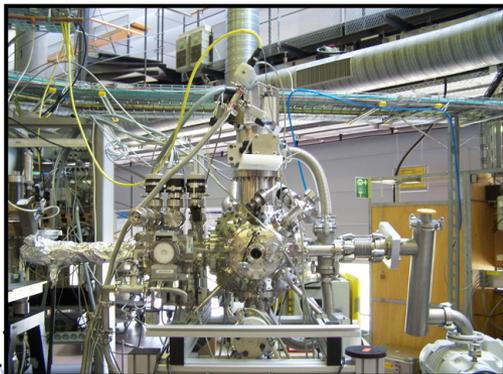


~ **23%** of groups from the giant component
of the co-author network collaborate
Large giant component

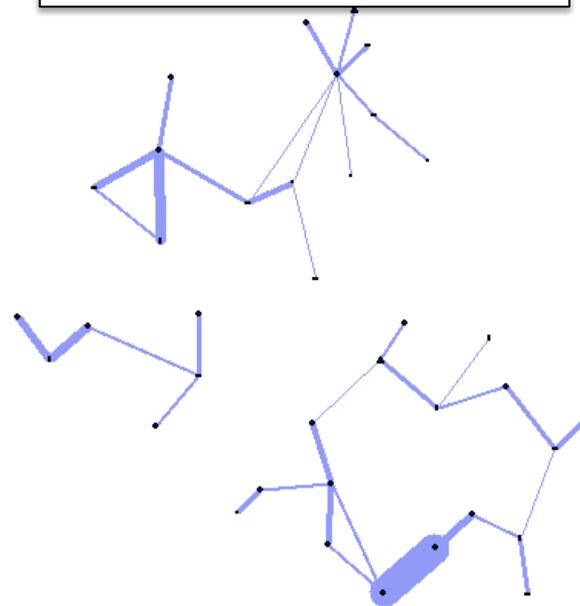
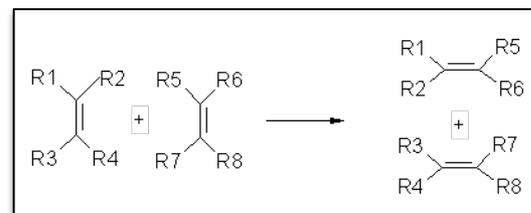
~ **9%** of groups from the giant component
of the co-author network collaborate
Small unconnected components

Field Differences: Group Collaboration Network

Field A: experimental physics



Field B: synthetic chemistry



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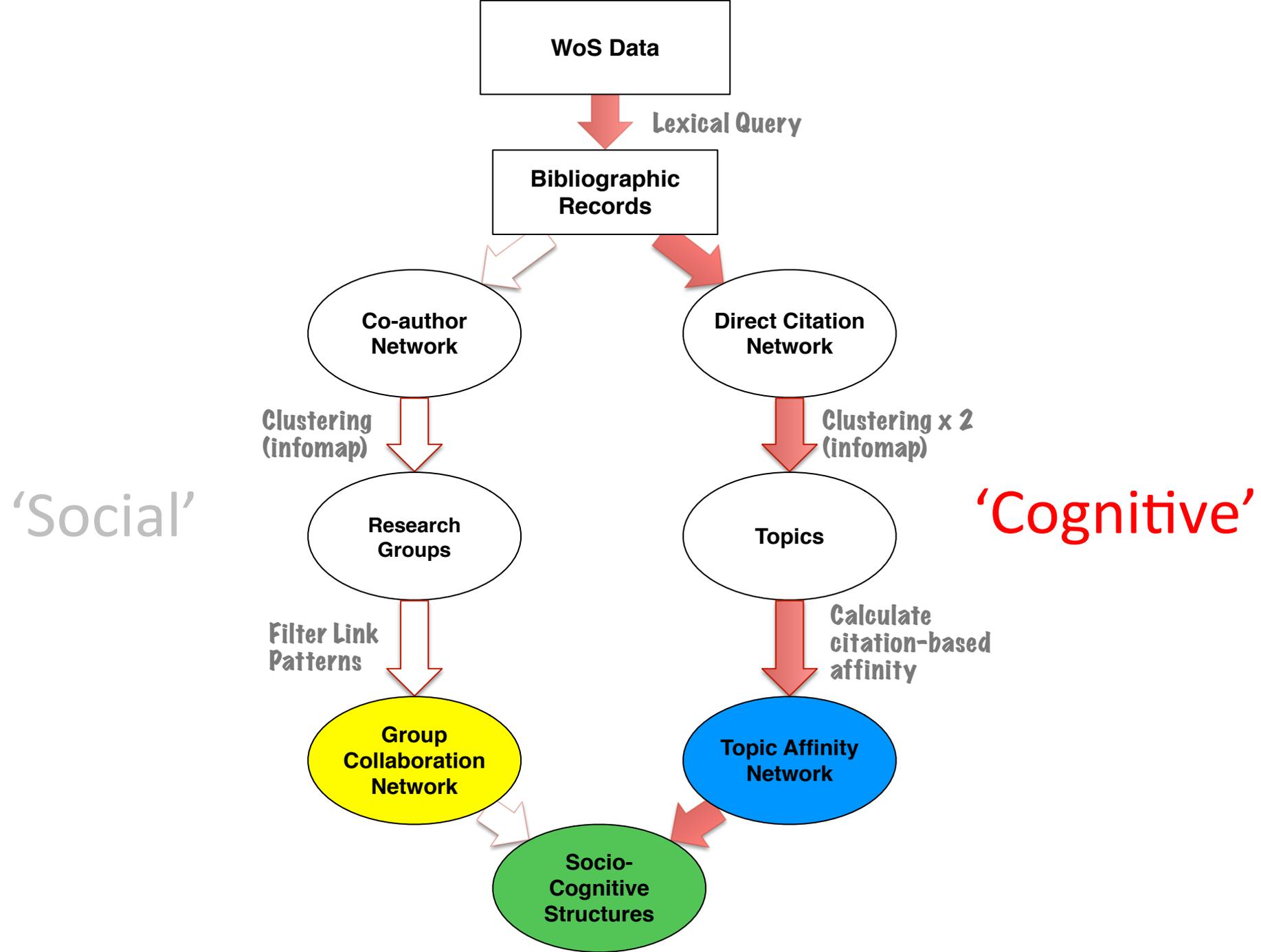
Group Collaboration Network

Topic Affinity Network

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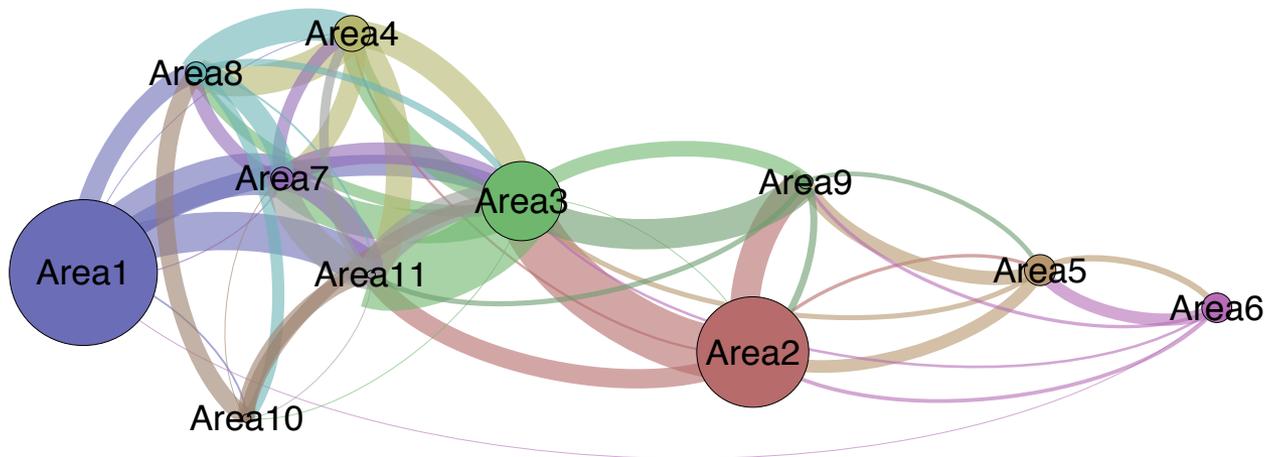
Topic Affinity Map

Topic: Clusters of clusters of documents (twice clustered citation network; infomap clustering algorithm)

Affinity: disproportionately strong citation links

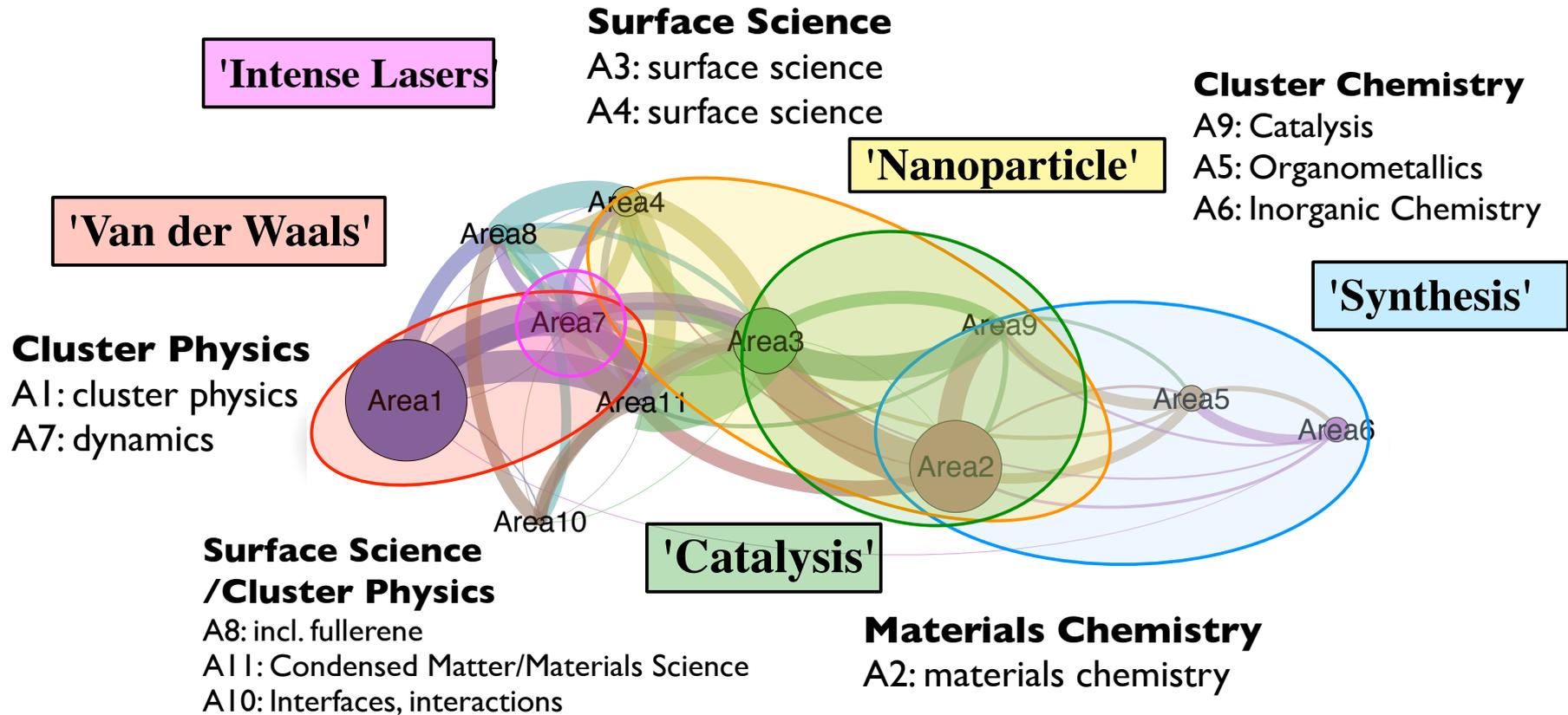
Affinity ($\text{area}_i \rightarrow \text{area}_j$) := $(\text{actual count} - \text{expected count}) / \sqrt{(\text{expected count})^2}$

where expected count is proportional to relative size of area_j



Topic Affinity Map

'Disciplinary Orientations'



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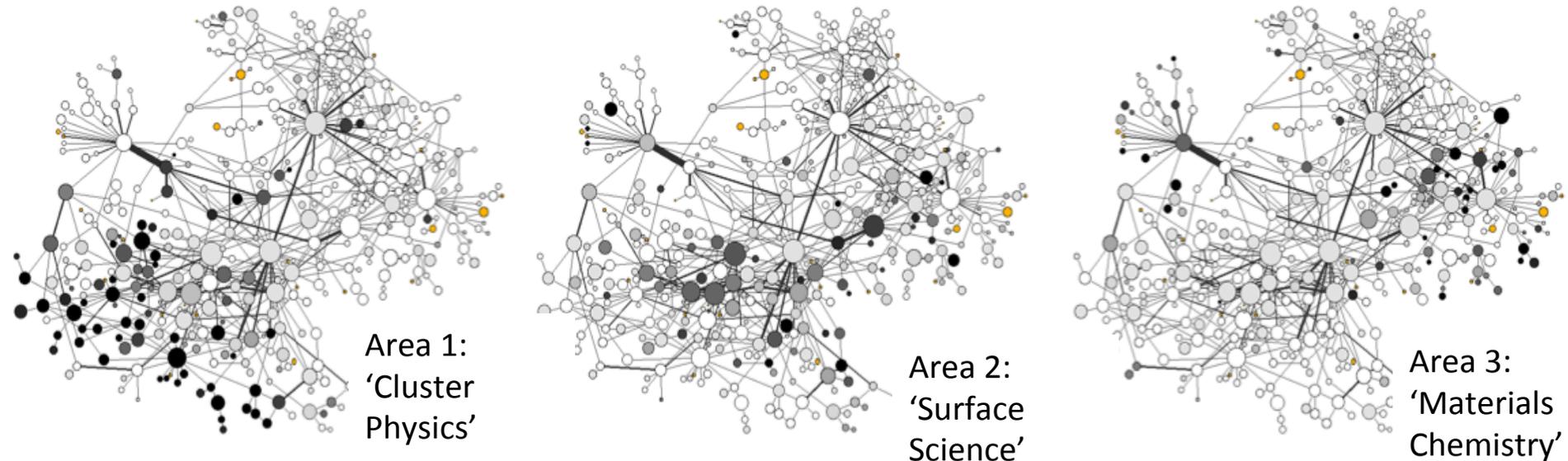
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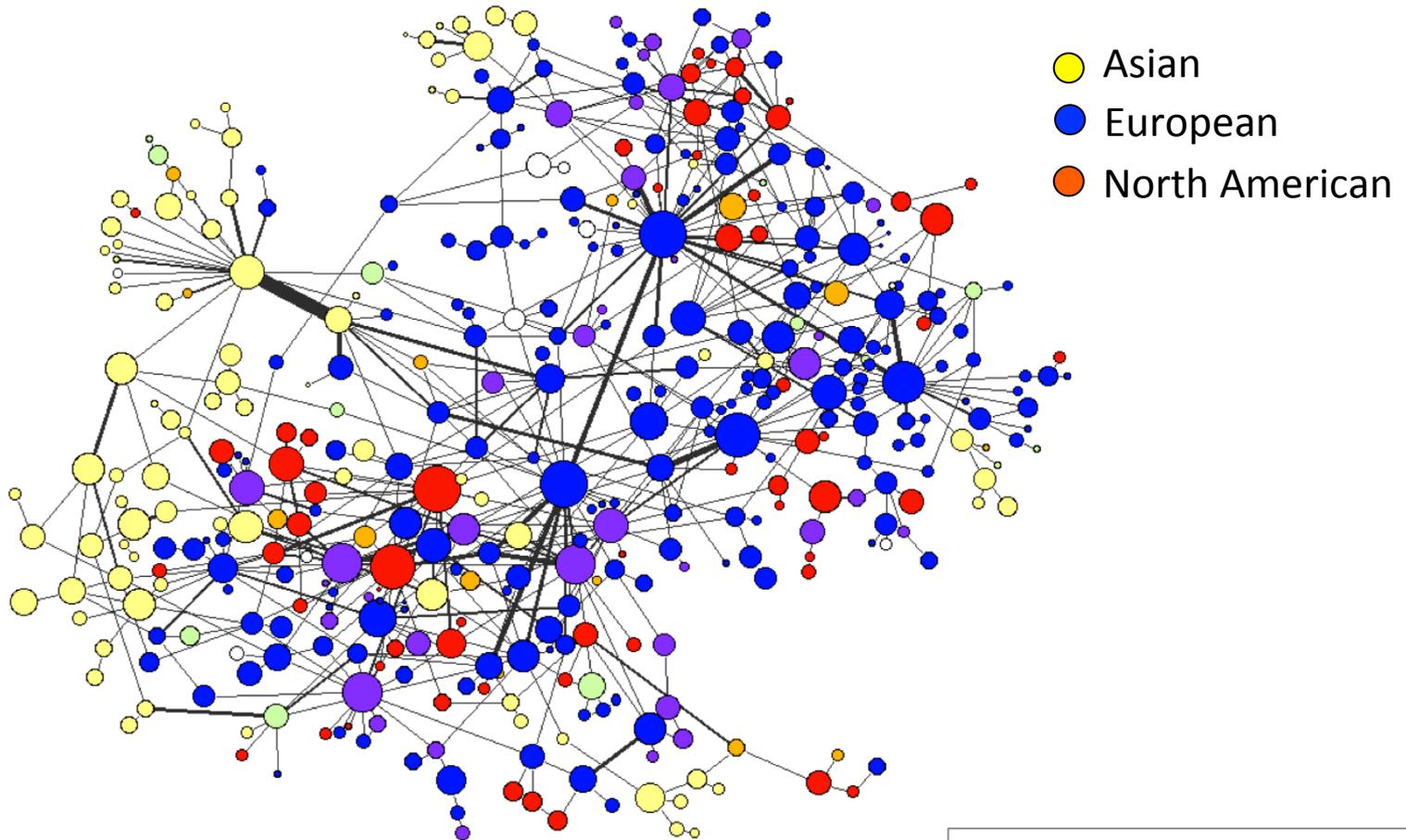
Visualization of the socio-cognitive fabric of a research field

Disciplinary Differential in Cohesiveness?



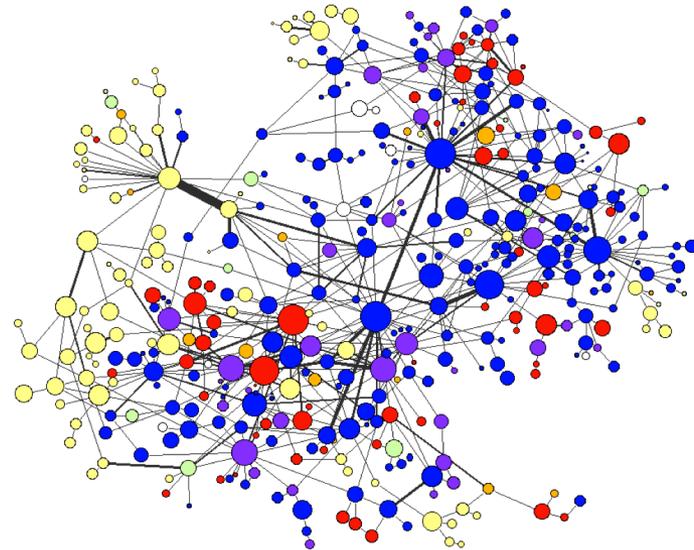
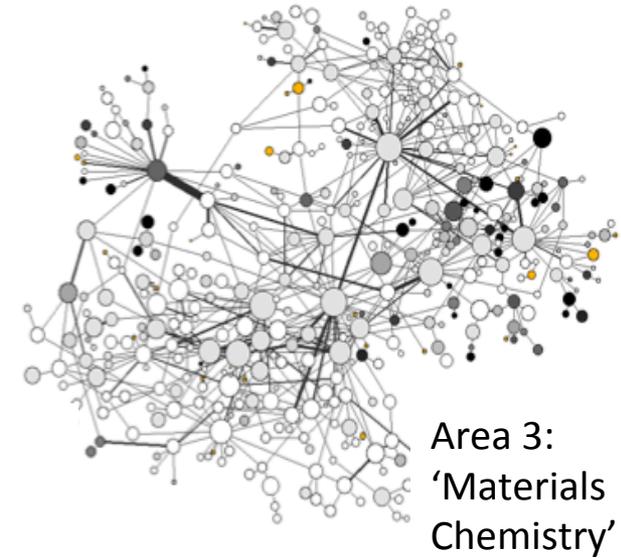
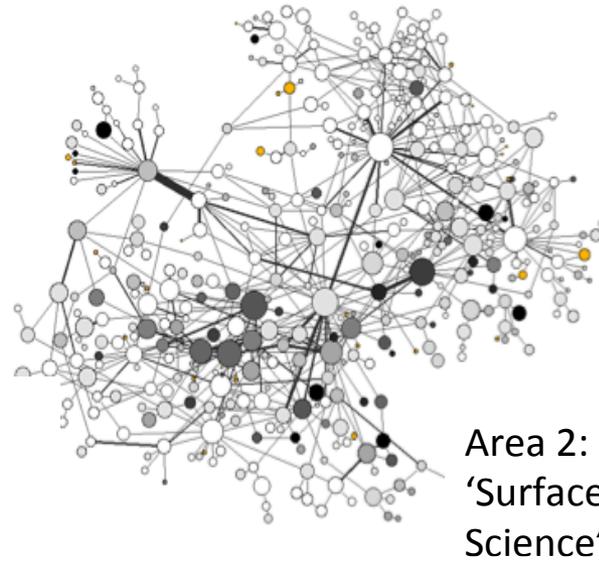
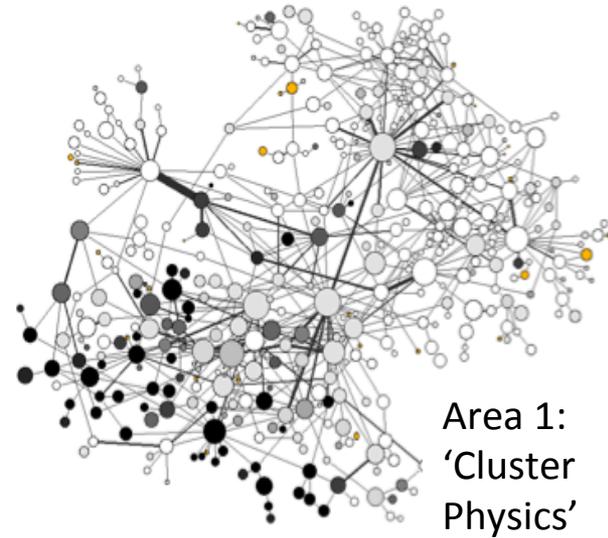
Group collaboration networks: color of nodes indicates intensity of (publication) activity of a group in the respective topic area.

International Group Collaboration Network



Visualization: pajek,
Kamada-Kawai algorithm

Topical versus Geographic Ordering of Collaboration Links



Data & Methods

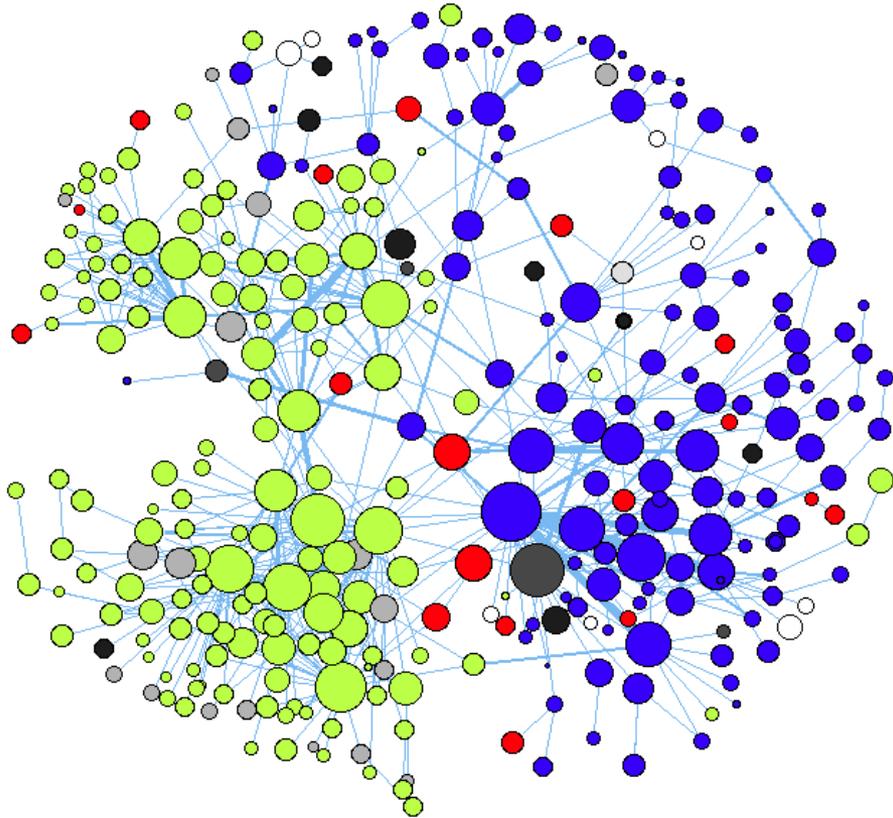
PART 2: MAJOR CHALLENGES IN THE MAKING OF MAPS OF SCIENCE

Data!

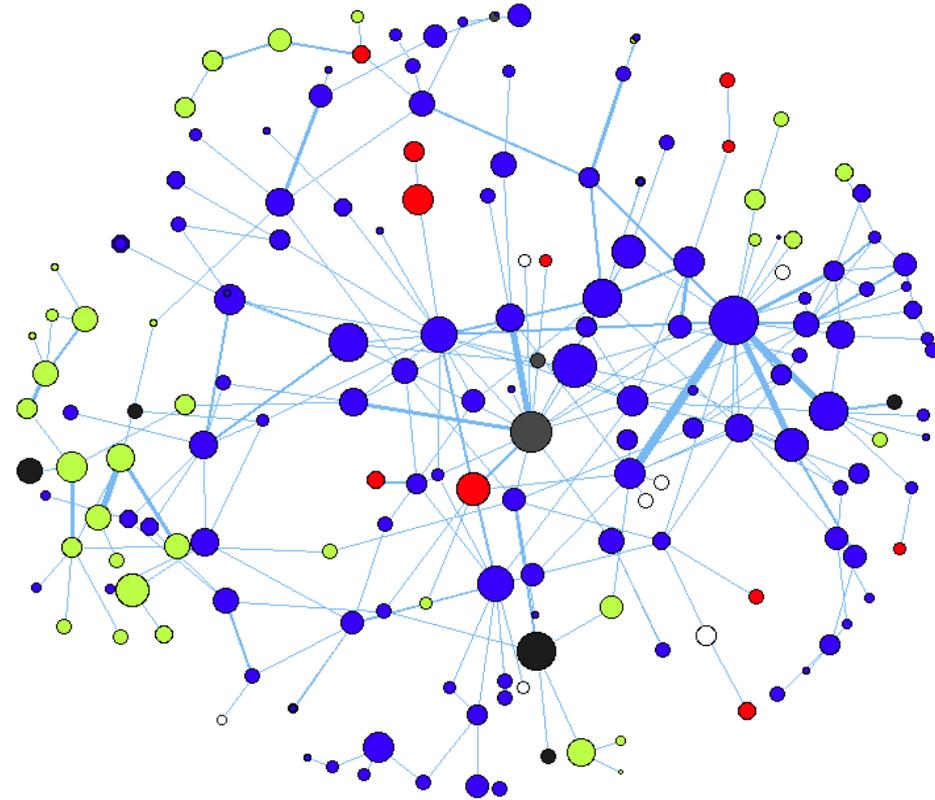
- Selection of Data:
 - Field delineation: how adequate is a data set to represent a field?
 - Research specialties have fuzzy boundaries (dynamic, overlapping, poly-hierarchical)
 - subject classification usually insufficient
 - Most thorough approaches (growing from seed) require comprehensive database access
- Access:
 - Can others reproduce or expand on my results?
- Quality:
 - Are references uniquely identified?
 - Author name disambiguation

Author Name Disambiguation

Before



After disambiguation



Proportion of Asian affiliated author clusters: reduced from 43% to 19%
average node degree decrease from 3.9 to 2.8

Velden, T., Haque, A. & Lagoze, C. (2011) Resolving Author Name Homonymy to Improve Resolution of Structures in Co-author Networks. JCDL 2011

Methods!

- Need for 'benchmarking' and validation
 - Often developed and fine-tuned in-house with lack of replication
 - Usually data set not available for replication
 - Limited understanding of origin and scale of differences in results obtained by different approaches

Example: Topic extraction

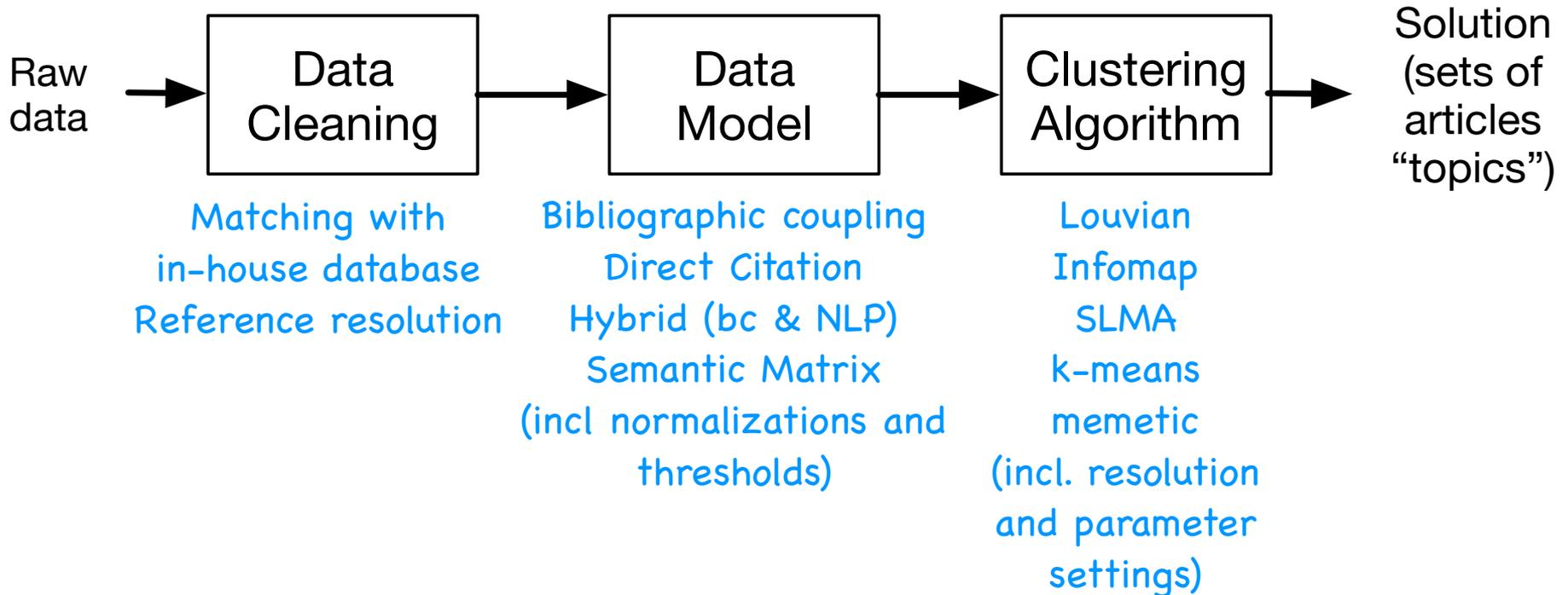
Same data, different results?

- How to group publications algorithmically into topics?
- Ongoing collaboration of several scientometric groups
- Start from same raw data set: ~ 111.000 publications from 59 journals in astronomy and astrophysics (Web of Science), 2003-2010

Kevin Boyack (SciTech Strategies) · Nees van Eck (CWTS Leiden) · Wolfgang Glänzel & Bart Thijs (ECOOM) · Jochen Gläser (TU Berlin) · Frank Havemann & Michael Heinz (HU Berlin) · Rob Koopman & Shenghui Wang (OCLC Research), Andrea Scharnhorst (DANS-KNAW), Theresa Velden (UMSI)

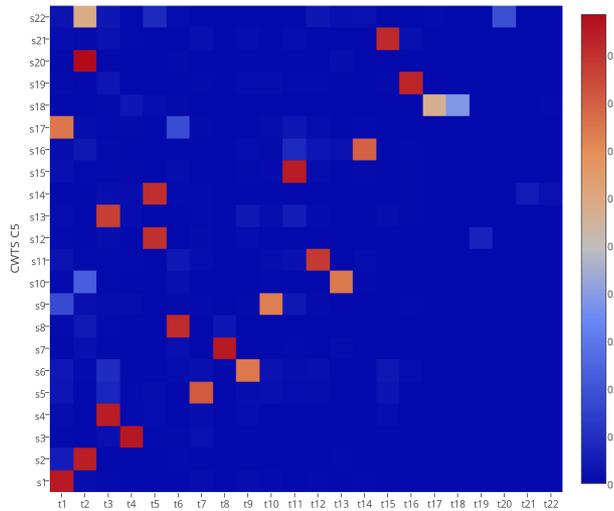
Workflow(s) for Topic Extraction

Sources for Variation

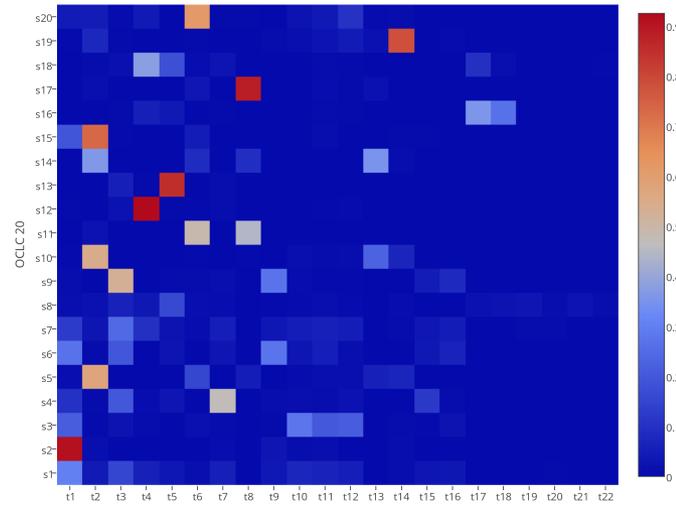


Sources of variability between solutions

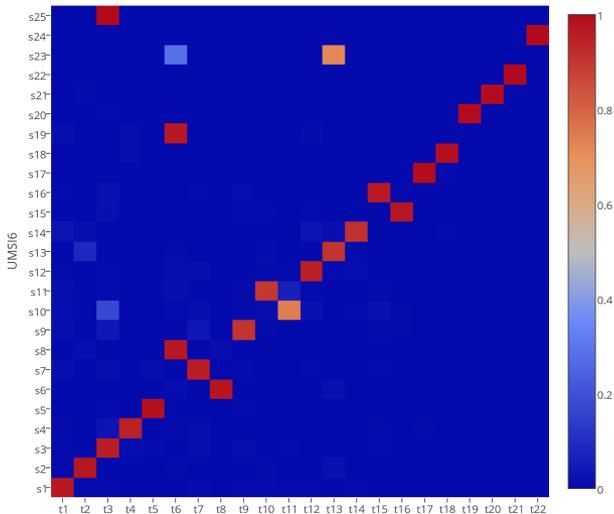
Same
model
&
different
algorithm



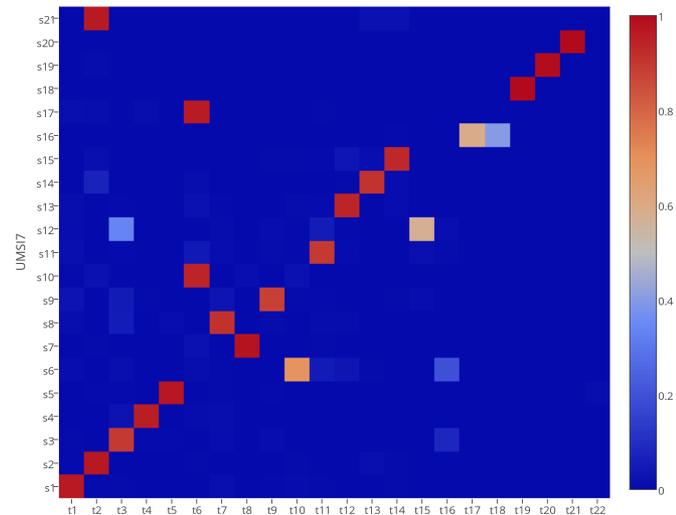
Different
model
& different
algorithm



Same
model
& same
algorithm



Same
model
& same
algorithm



Overlap Between Clusters: Comparison with UMSI0 Cluster Solution (22 clusters)

**Gravitational Physics,
Cosmology**

Astrophysics (Galaxies)

**Astrophysics
(Stars)**

Solar physics

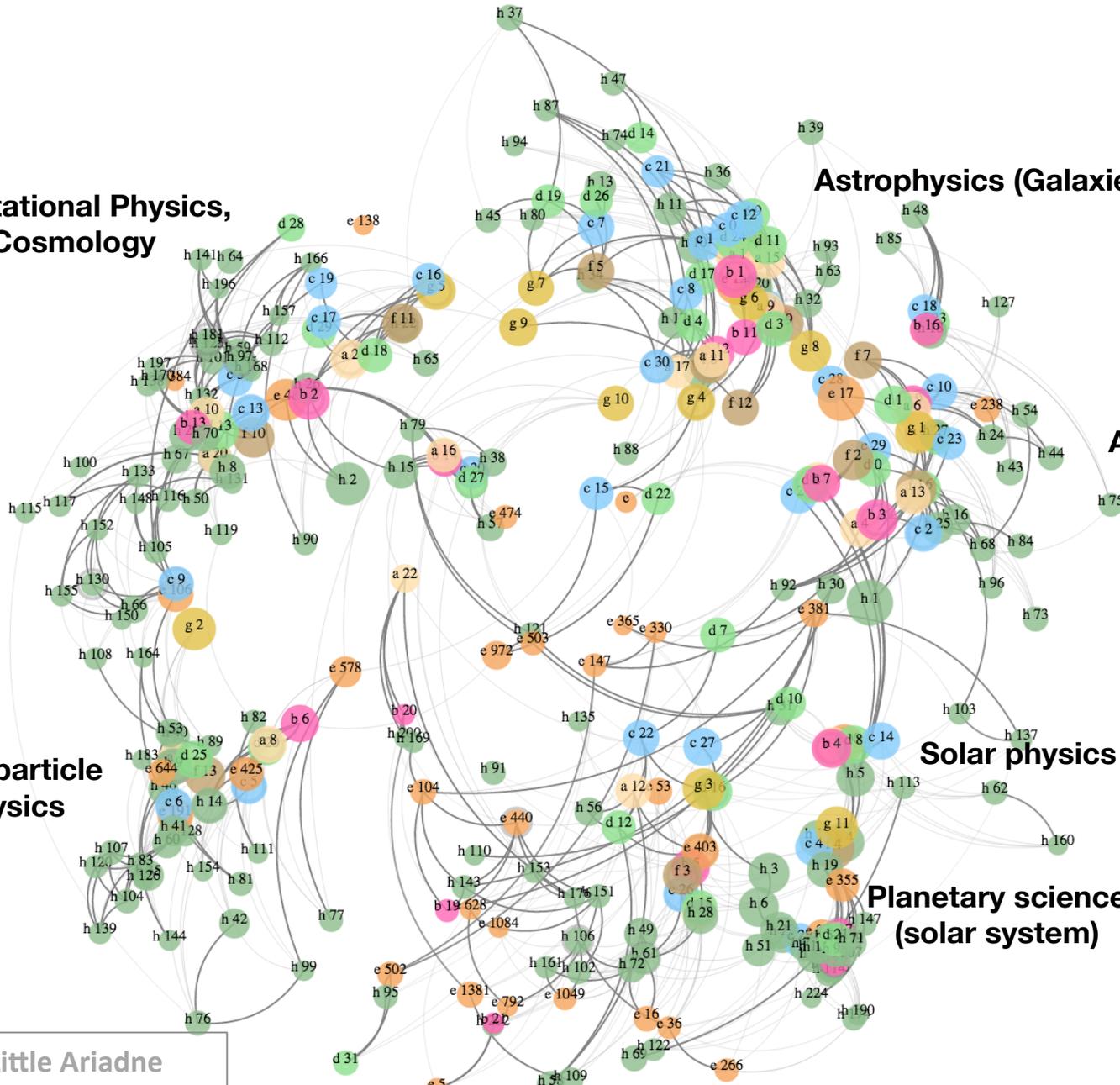
**Planetary science
(solar system)**

**Astroparticle
Physics**

Space science

Visualization: Little Ariadne
(OCLC)

- a:cwts
- b:umsi
- c:oclc_k
- d:oclc_l
- e:sts
- f:ecoom_bc
- g:ecoom_nlp
- h:hu



Stay tuned...

- Work in progress
- Special Issue for Scientometrics in Preparation
- In Planning: Topic extraction challenge
 - Invitation to other groups to provide their solutions for comparison

Conclusions

Visualizations for Science Policy

- Great potential for science maps, especially as an explorative and hypothesis generating tool
- Careful validation a key concern
 - Require comprehensive access to data to enable reproducibility and comparison
 - Need more rigorous comparison of methods
 - Benefit from mixed methods to ground interpretations



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