

# 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

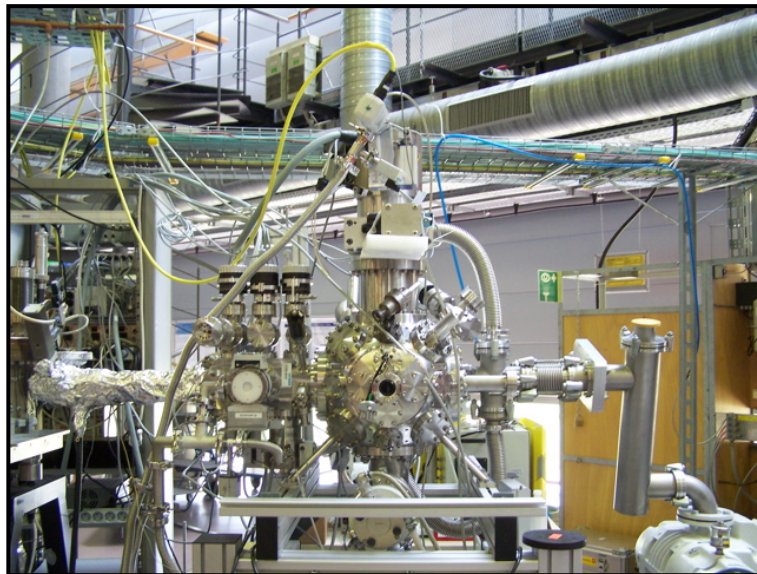
## ***Network analysis***

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

&

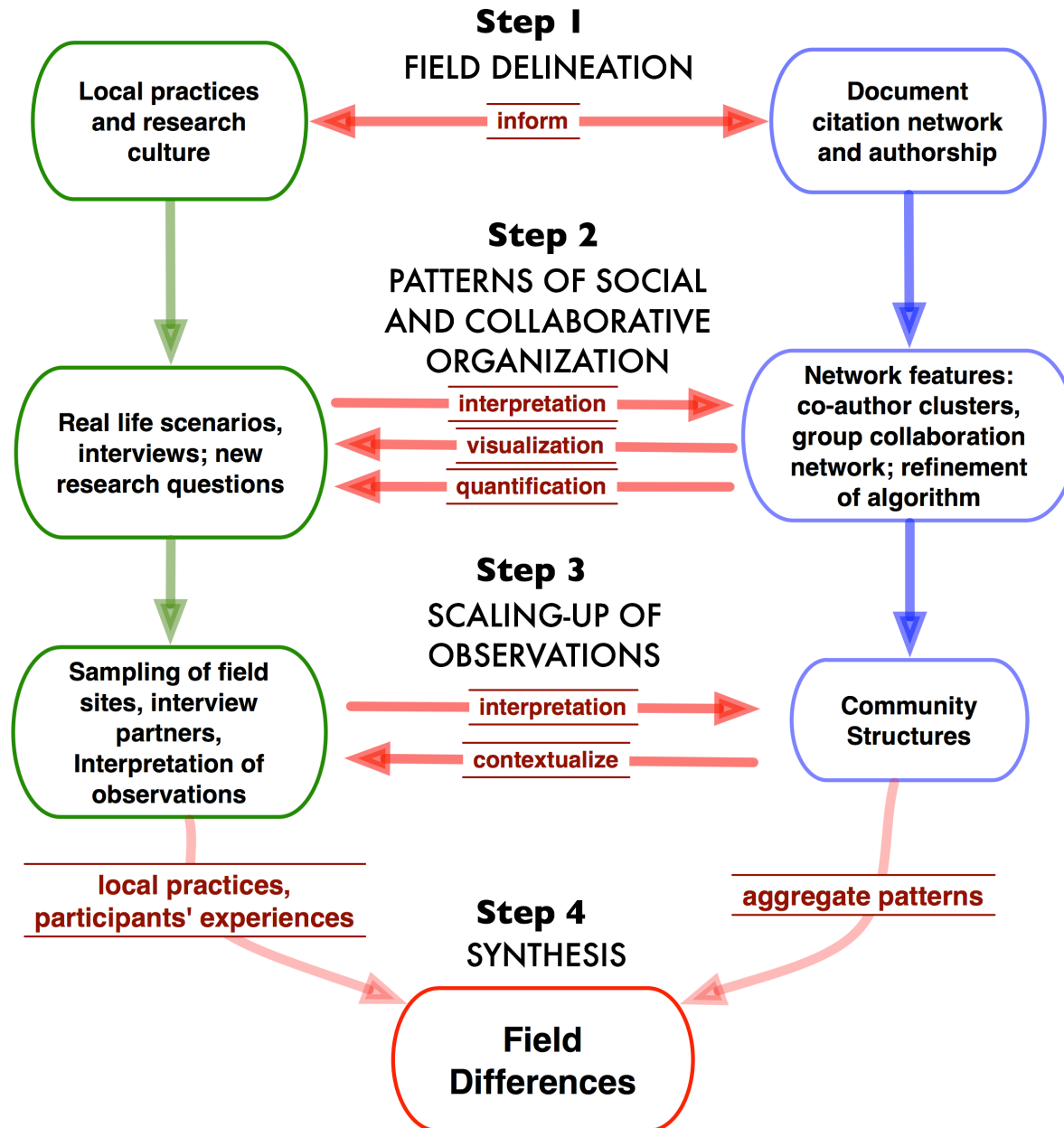
## ***Ethnographic field studies***

of scientific communities



# Ethnographic Field Studies

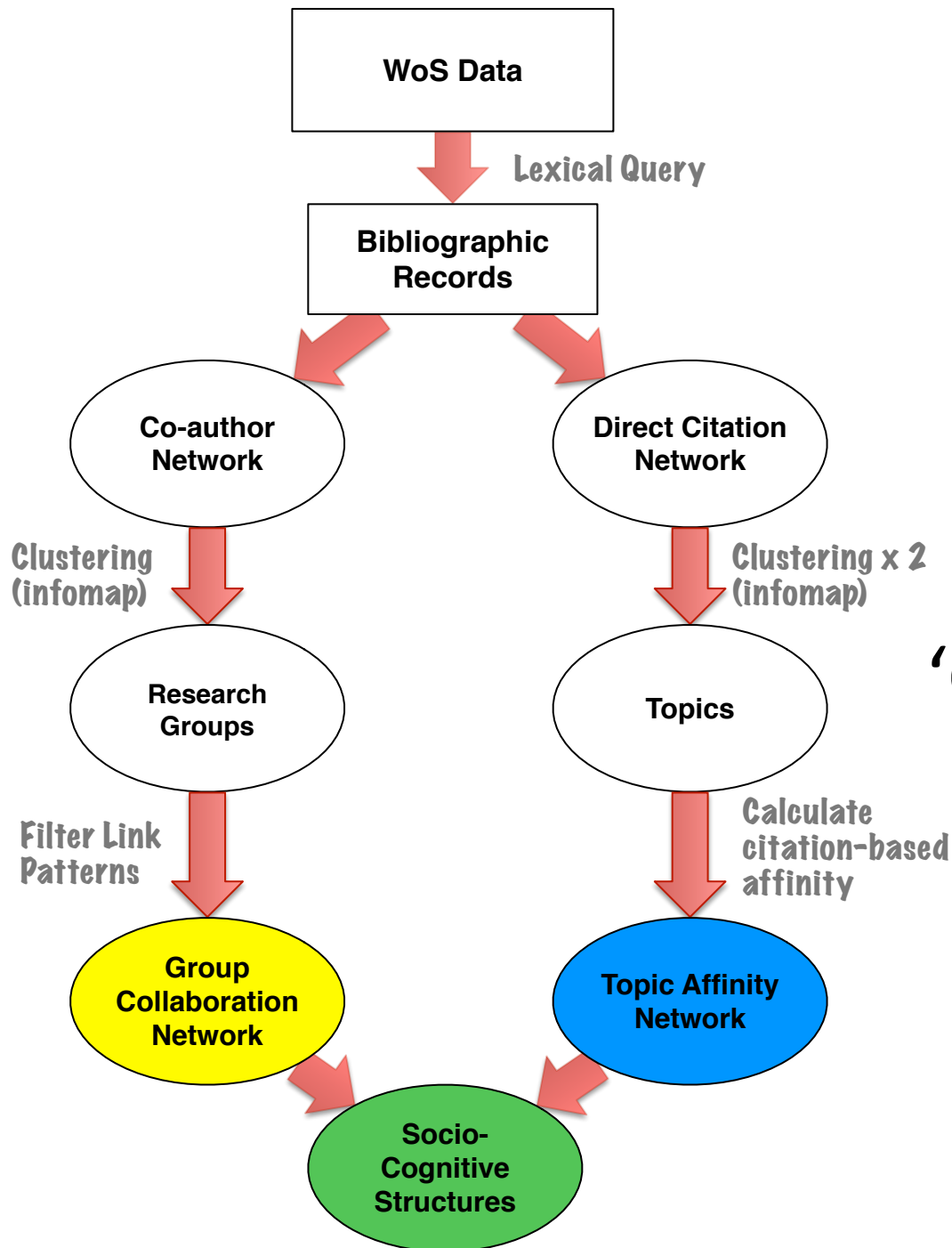
# Network Analysis



*Co-author & citation networks*

# **PART 1: MAPS OF SCIENCE**

‘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**



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

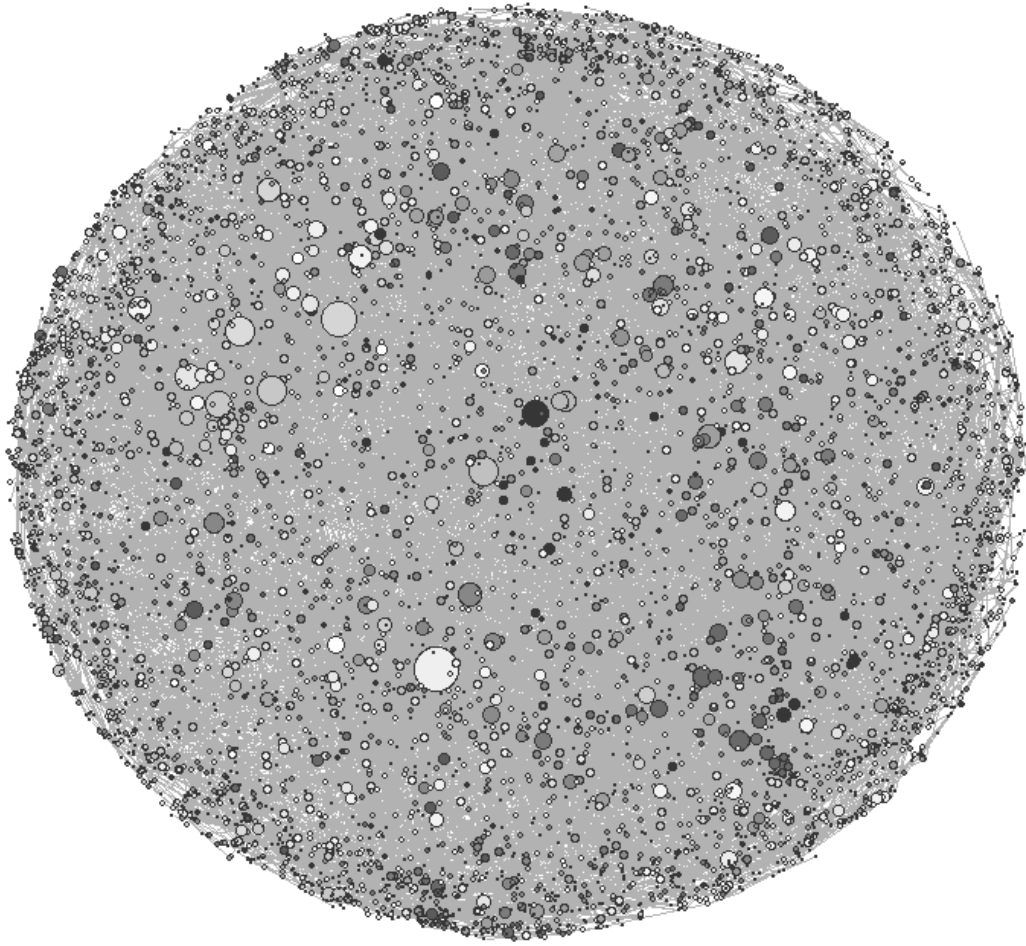


Socio-  
Cognitive  
Structures

‘Social’

‘Cognitive’

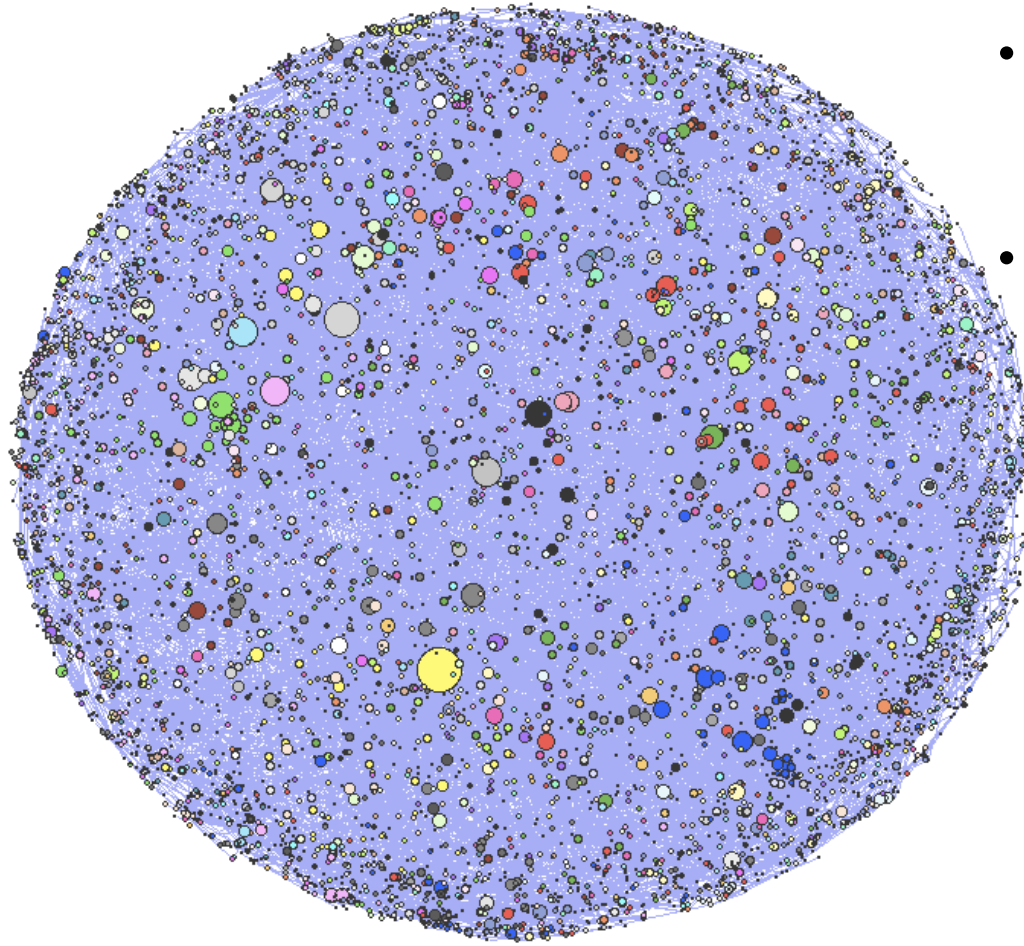
# Co-Author Network



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

Visualization: pajek,  
Fruchterman Rheingold  
algorithm

# Clustered Coauthor Network

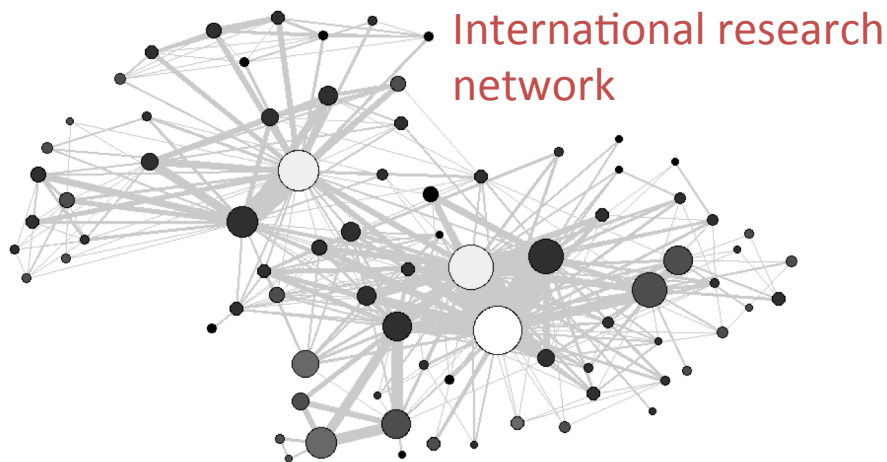
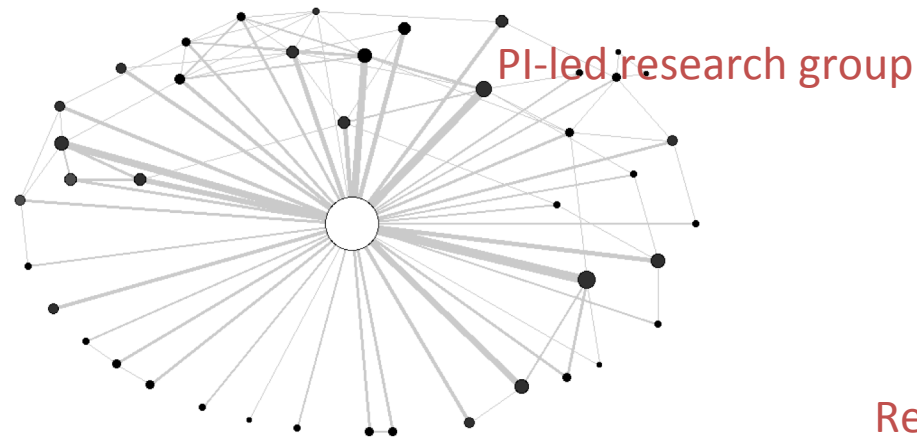


- Apply clustering algorithm to extract groups of closely collaborating authors
- Key properties of infomap algorithm:
  - Disjoint clusters
  - Unbiased cluster size
  - Fast

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

# Co-Author Clusters

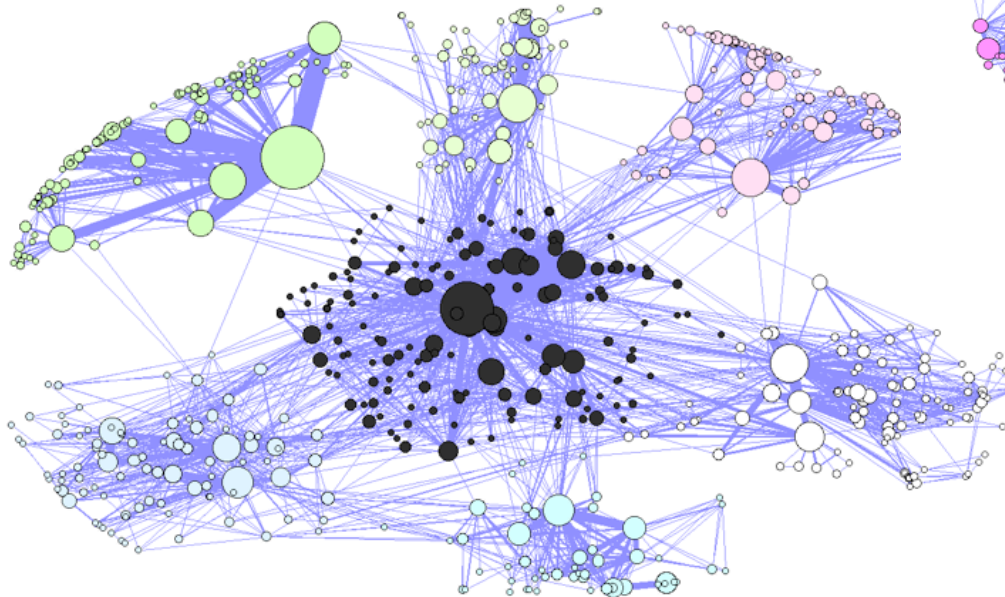
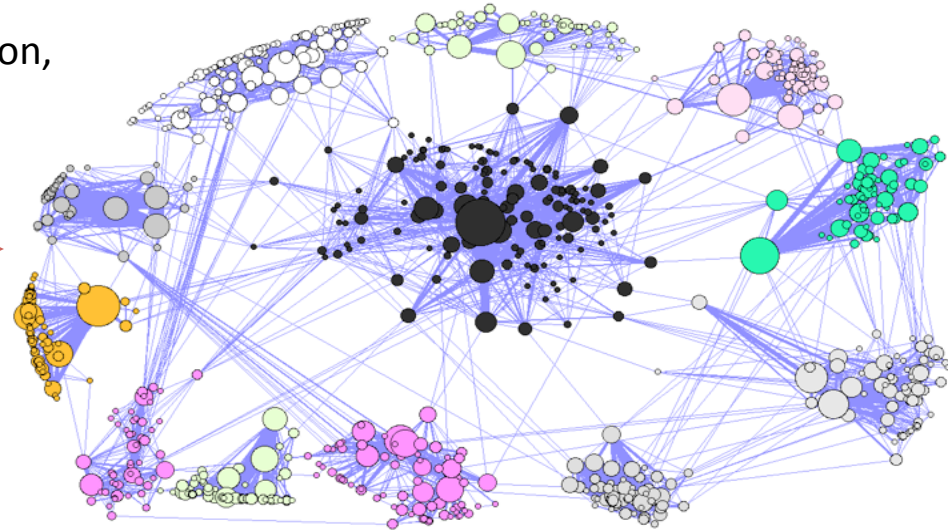
‘functional research groups’ [Seglen & Aksnes 2000, microbiology]



# Mesososcopic Structure

## *Linking patterns between groups*

**Transfer links:** career migration,  
sample exchange, measurement  
services

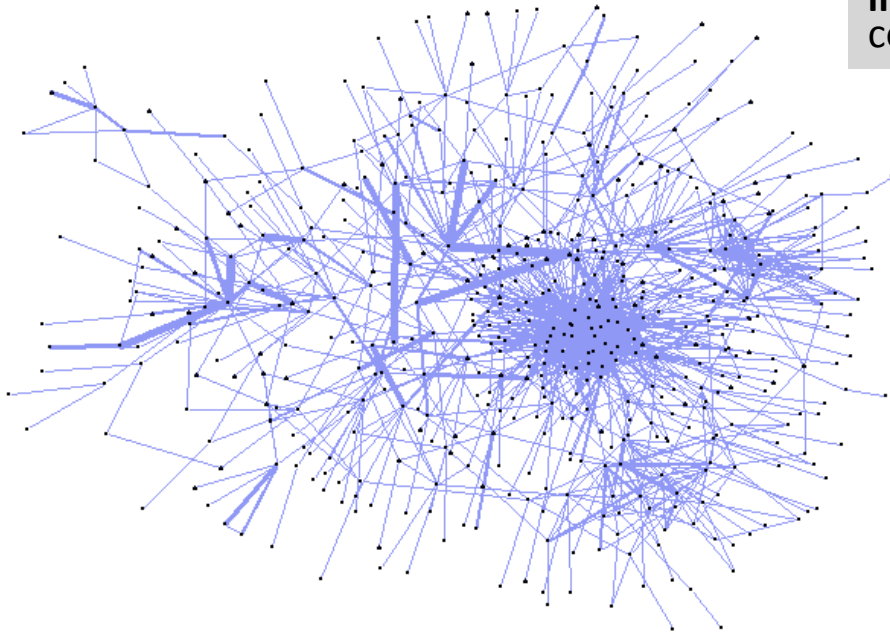


**Inter Group Collaboration:**  
Intensive collaboration between  
subgroups



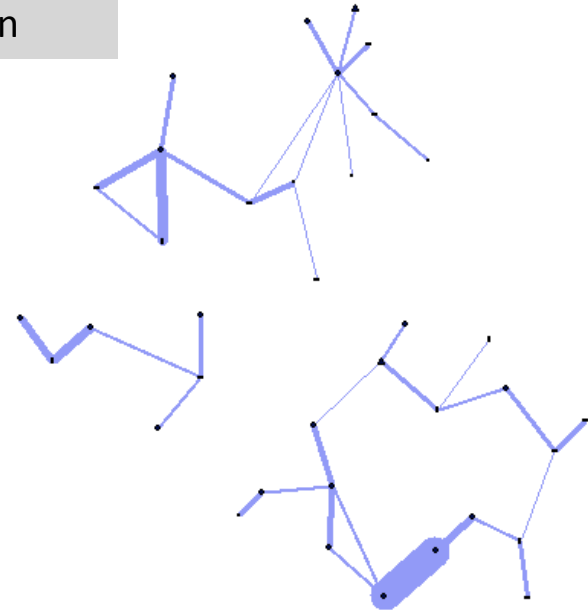
# Field Differences: Group Collaboration Network

Field A



**nodes:** research  
groups  
**links:**  
collaboration

Field B



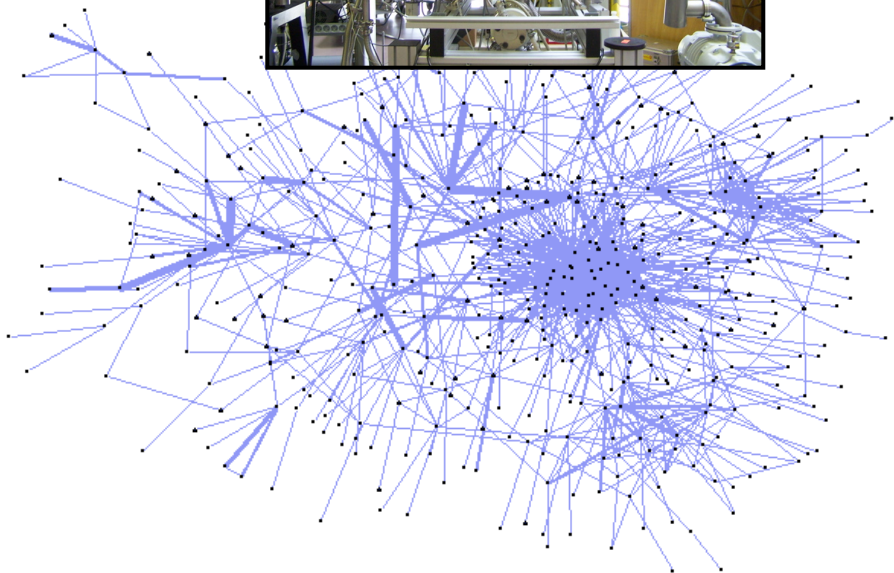
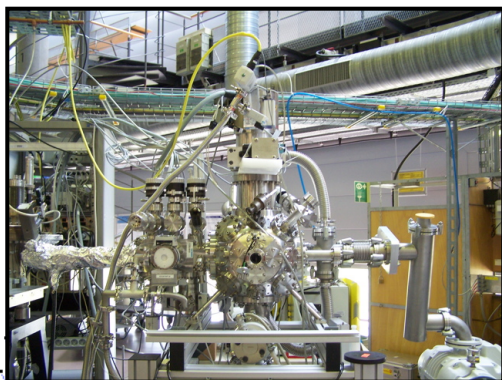
~ **23%** of groups from the giant component  
of the co-author network collaborate  
**Large giant component**

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

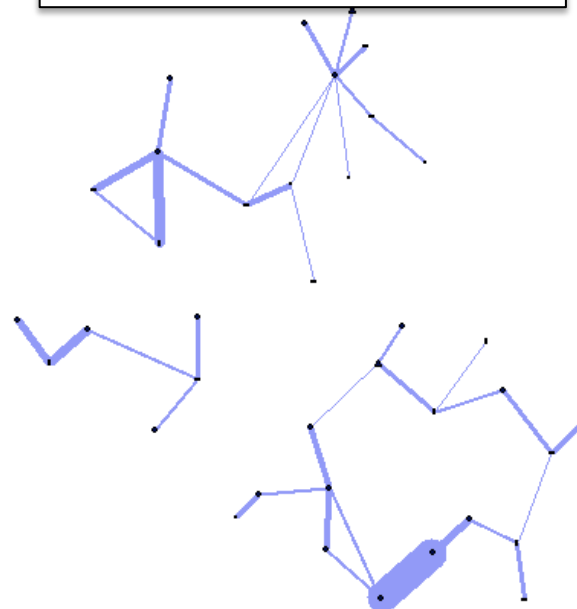
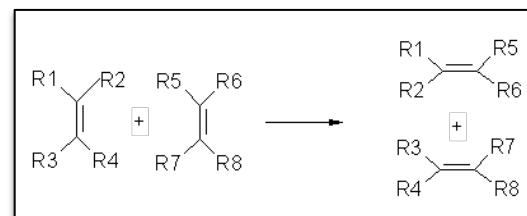


# Field Differences: Group Collaboration Network

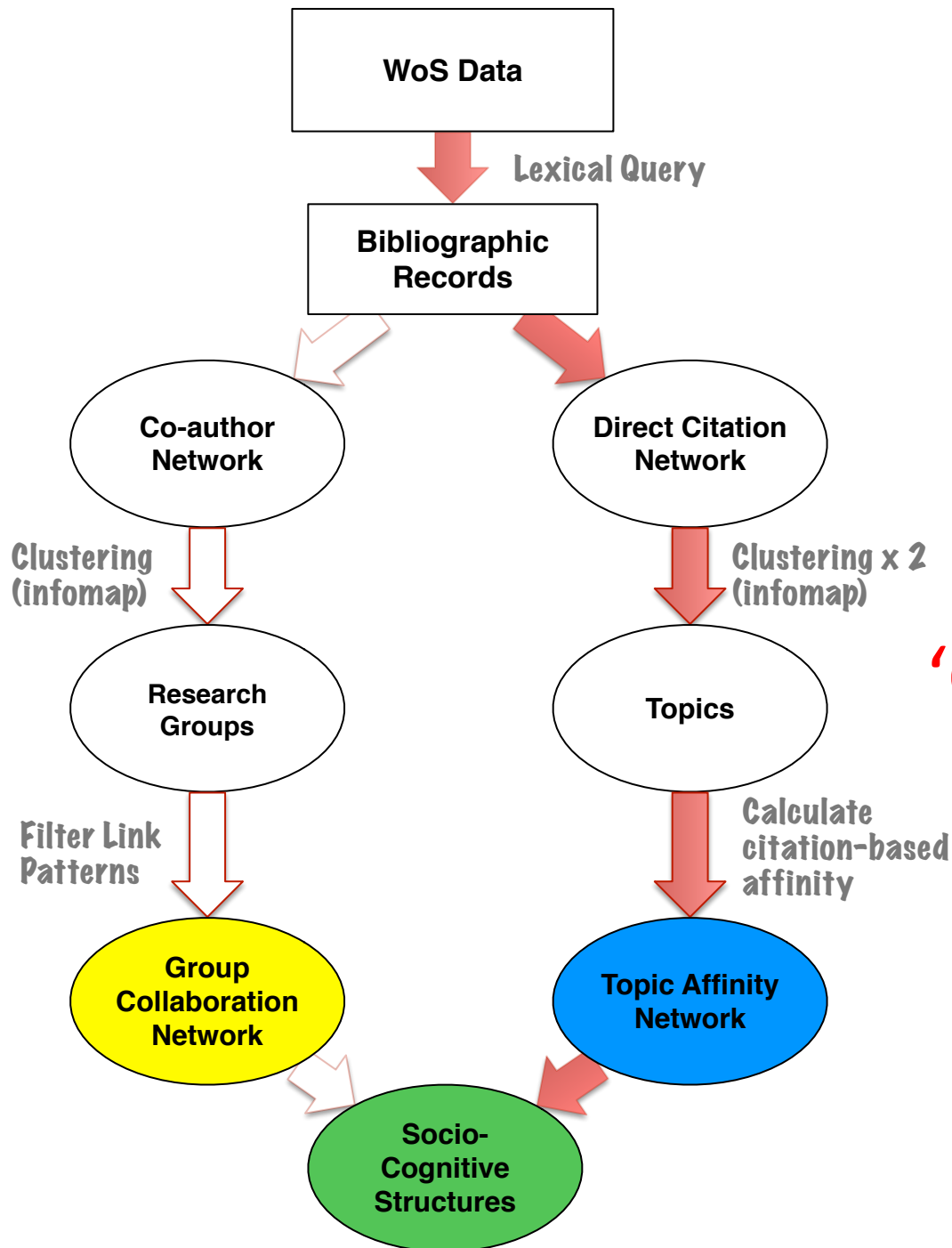
Field A: experimental physics



Field B: synthetic chemistry



‘Social’



‘Cognitive’



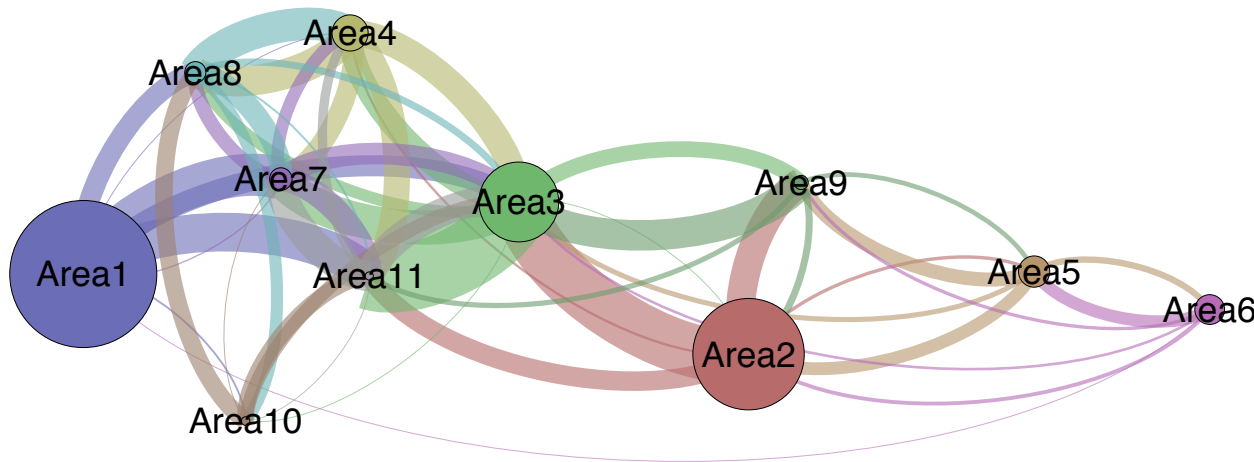
# Topic Affinity Map

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

**Affinity: disproportionately strong citation links**

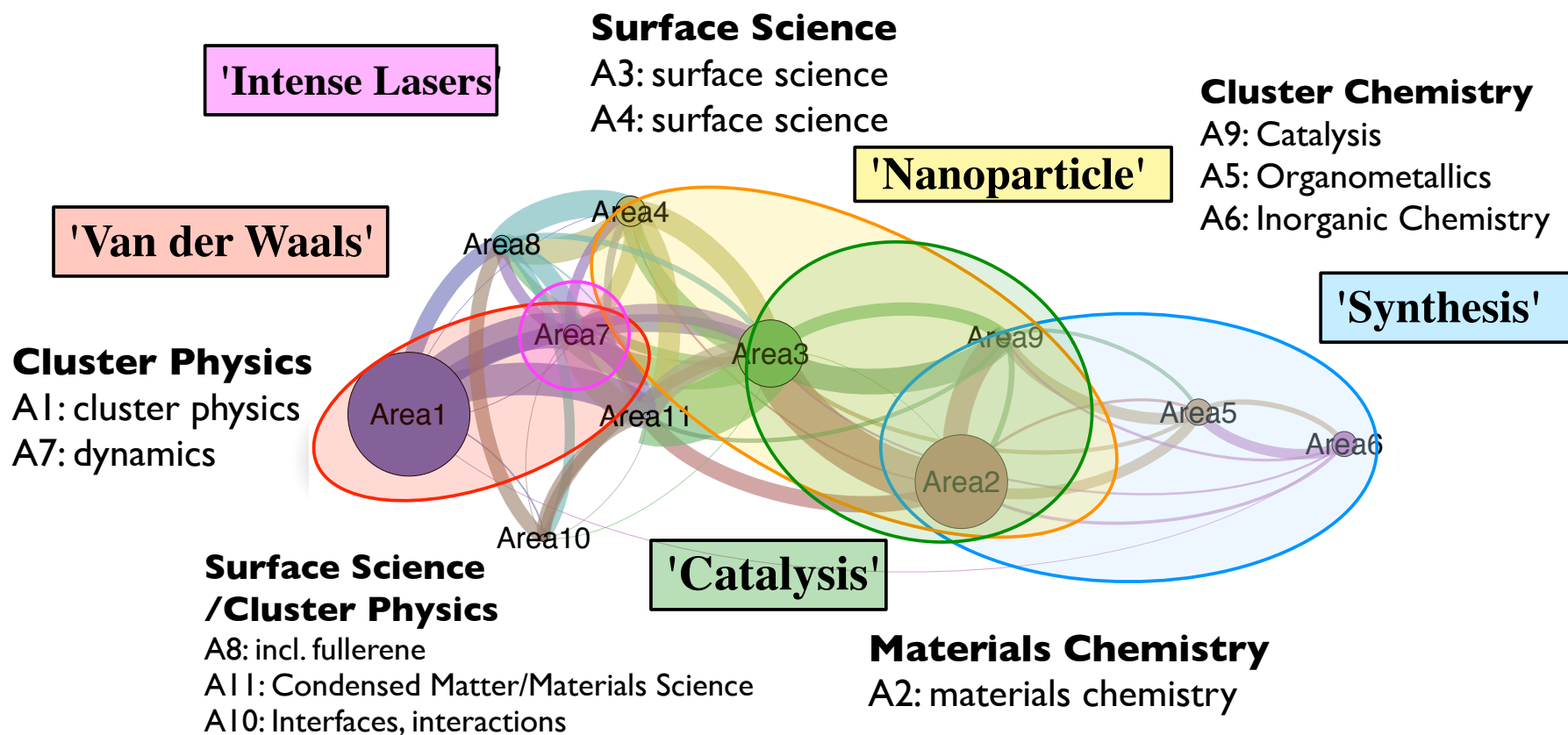
Affinity ( $\text{area}_i \rightarrow \text{area}_j$ ) :=  $(\text{actual count} - \text{expected count}) / \sqrt{(\text{expected count})^2}$

where expected count is proportional to relative size of  $\text{area}_j$

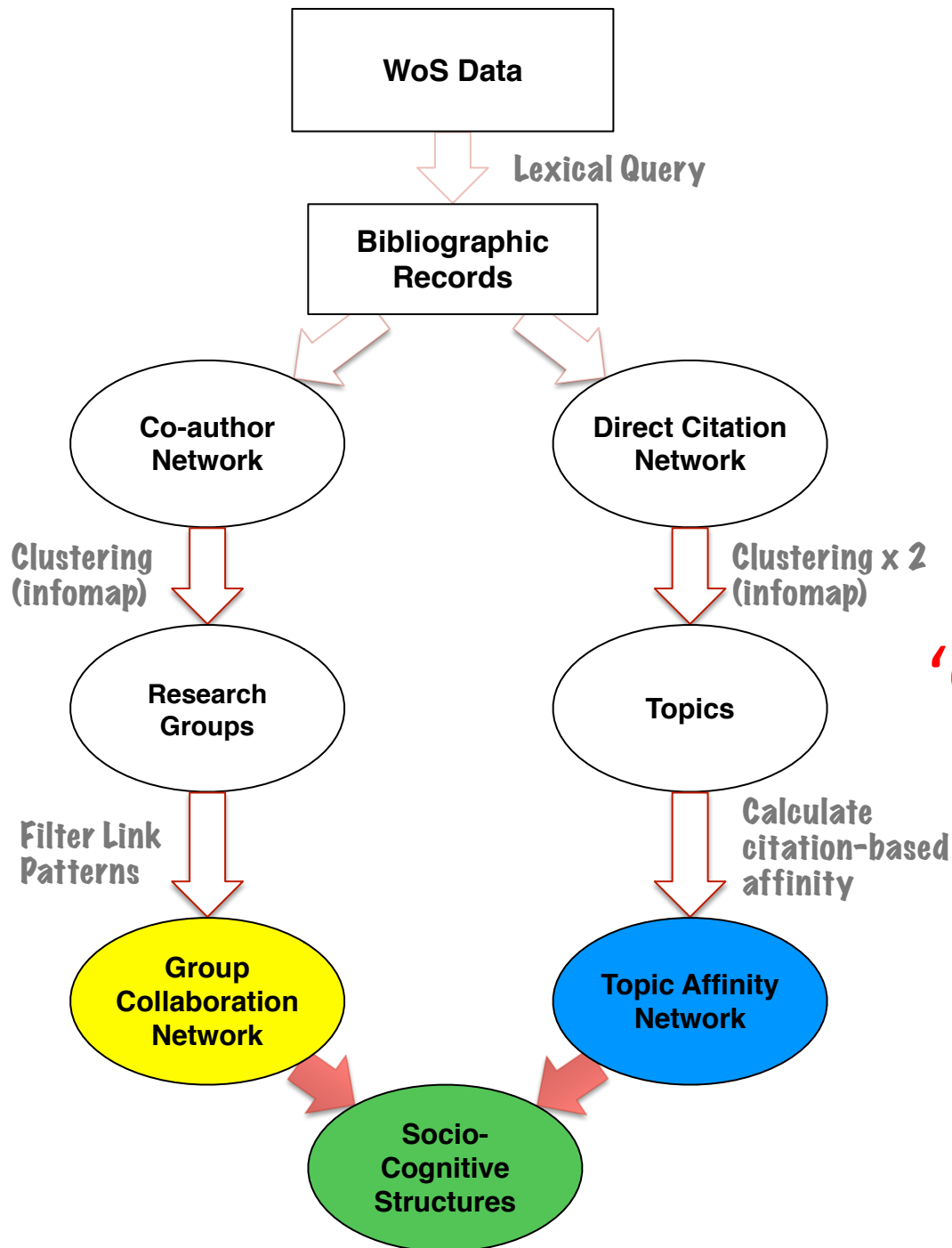


# Topic Affinity Map

## *'Disciplinary Orientations'*



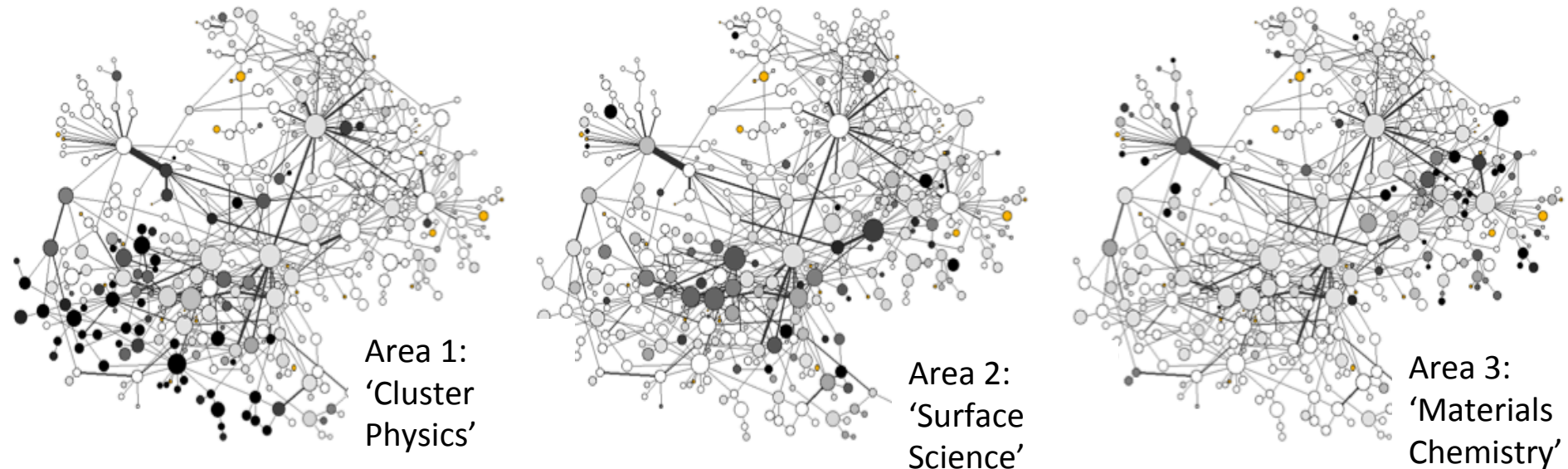
**‘Social’**



**‘Cognitive’**

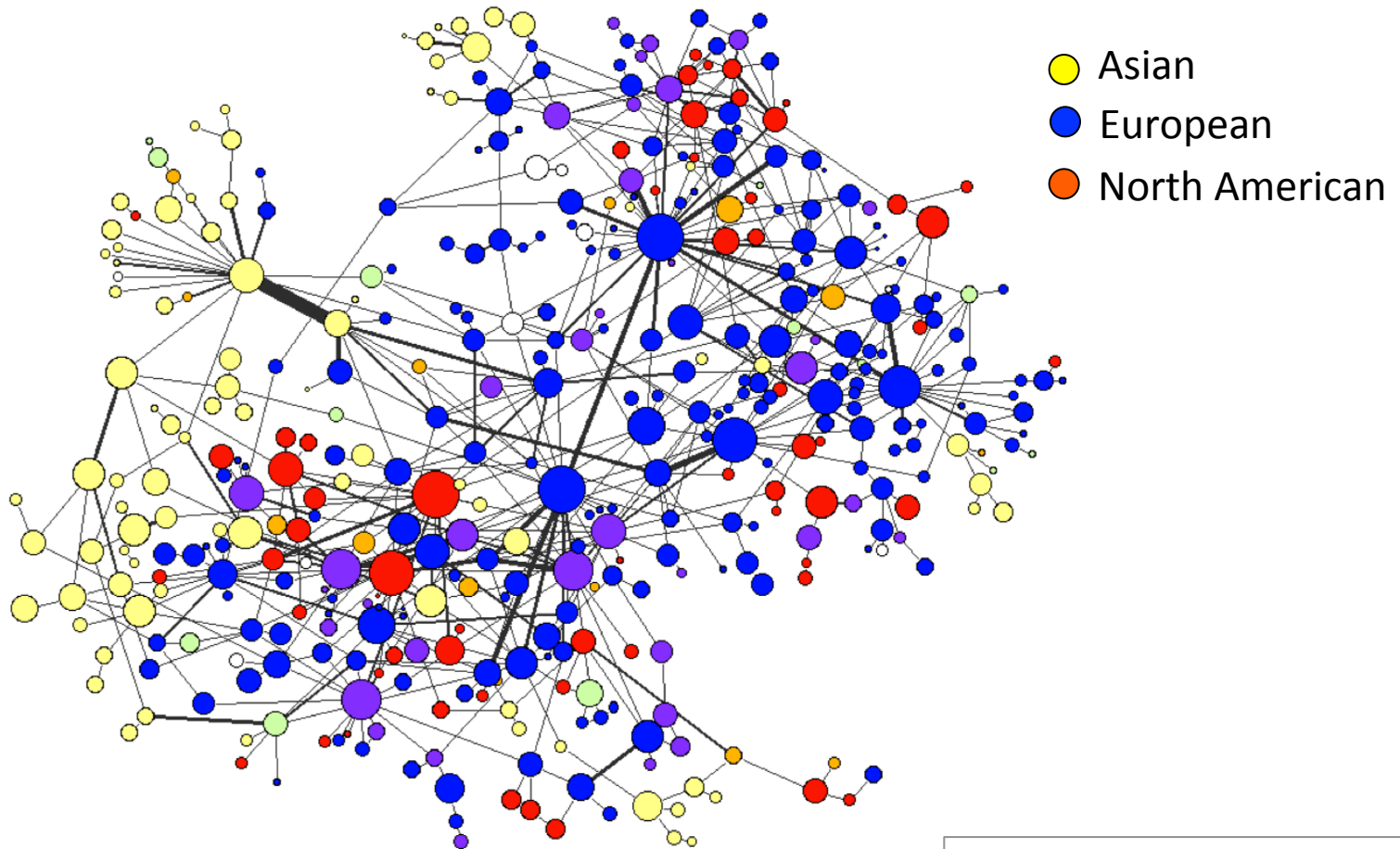
# Visualization of the socio-cognitive fabric of a research field

*Disciplinary Differential in Cohesiveness?*



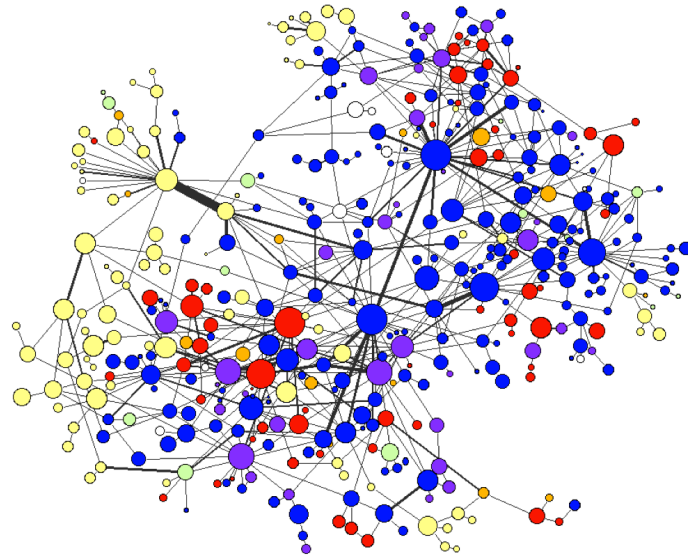
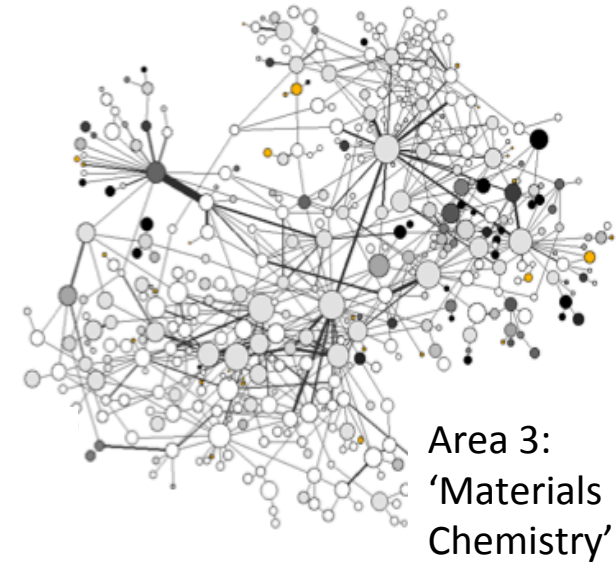
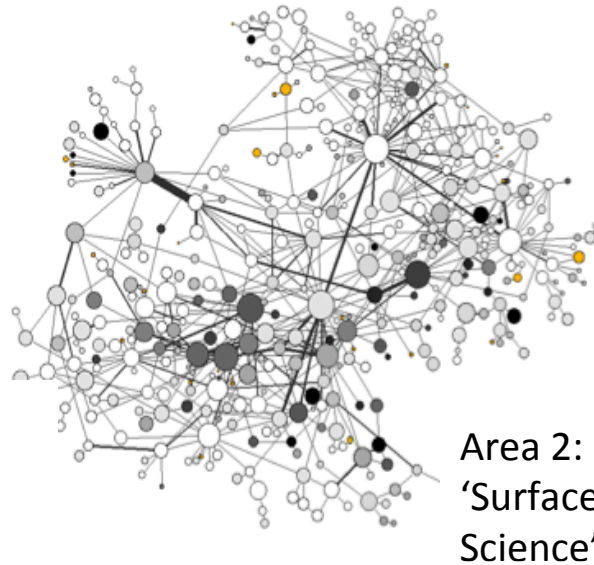
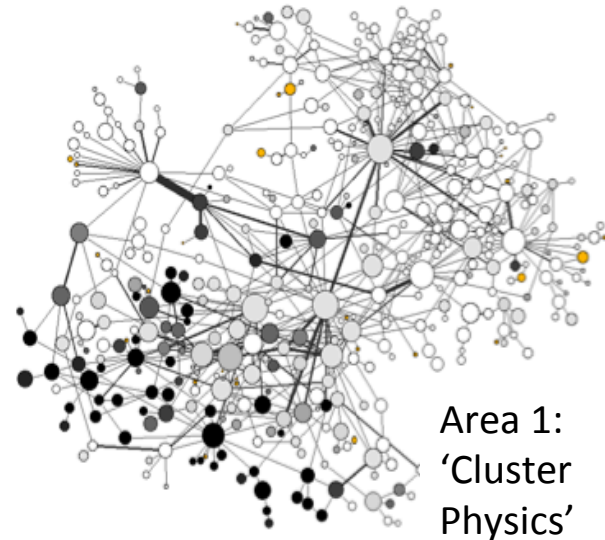
Group collaboration networks: color of nodes indicates intensity of (publication) activity of a group in the respective topic area.

# International Group Collaboration Network



Visualization: pajek,  
Kamada-Kawai algorithm

# Topical versus Geographic Ordering of Collaboration Links



Geographic affiliation

Data & Methods

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

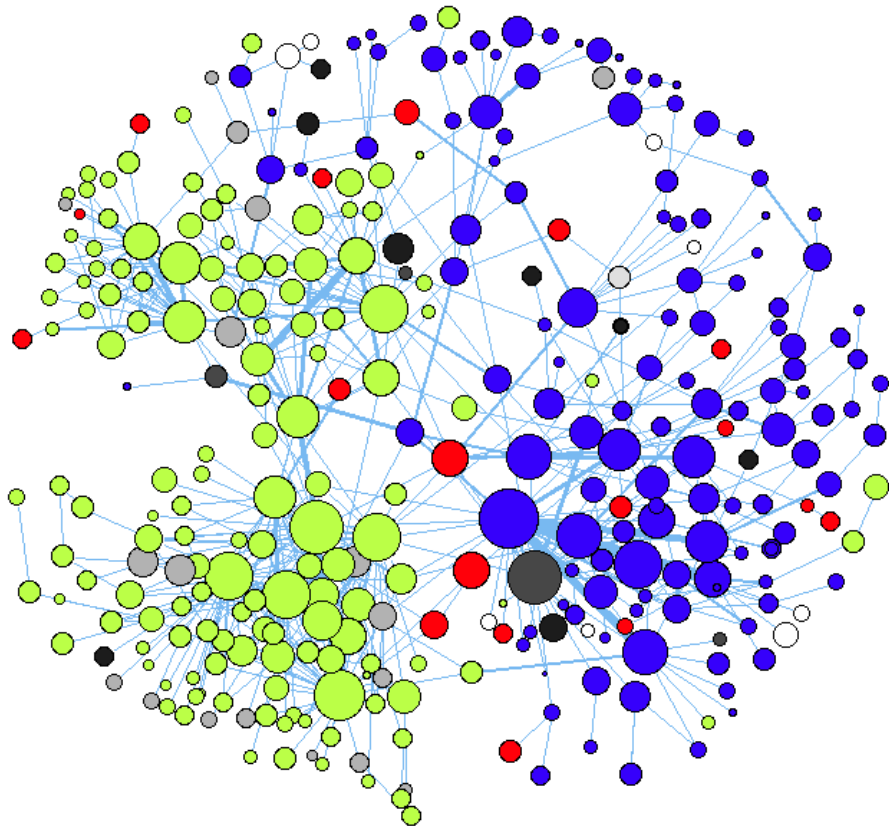
# Data!

- 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

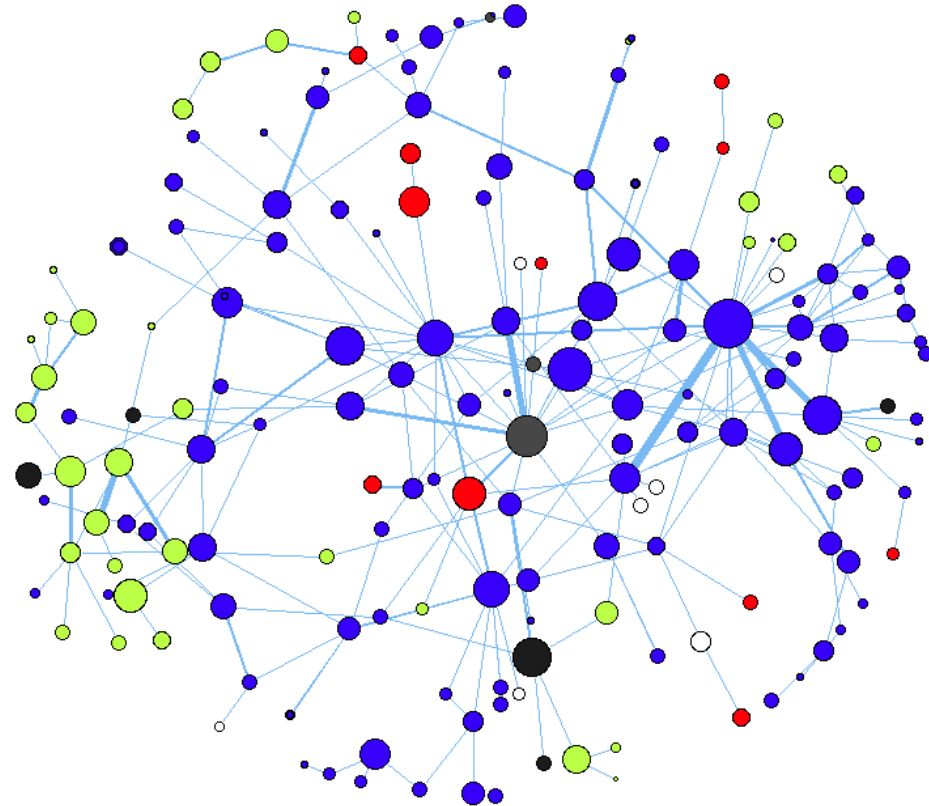


# Author Name Disambiguation

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

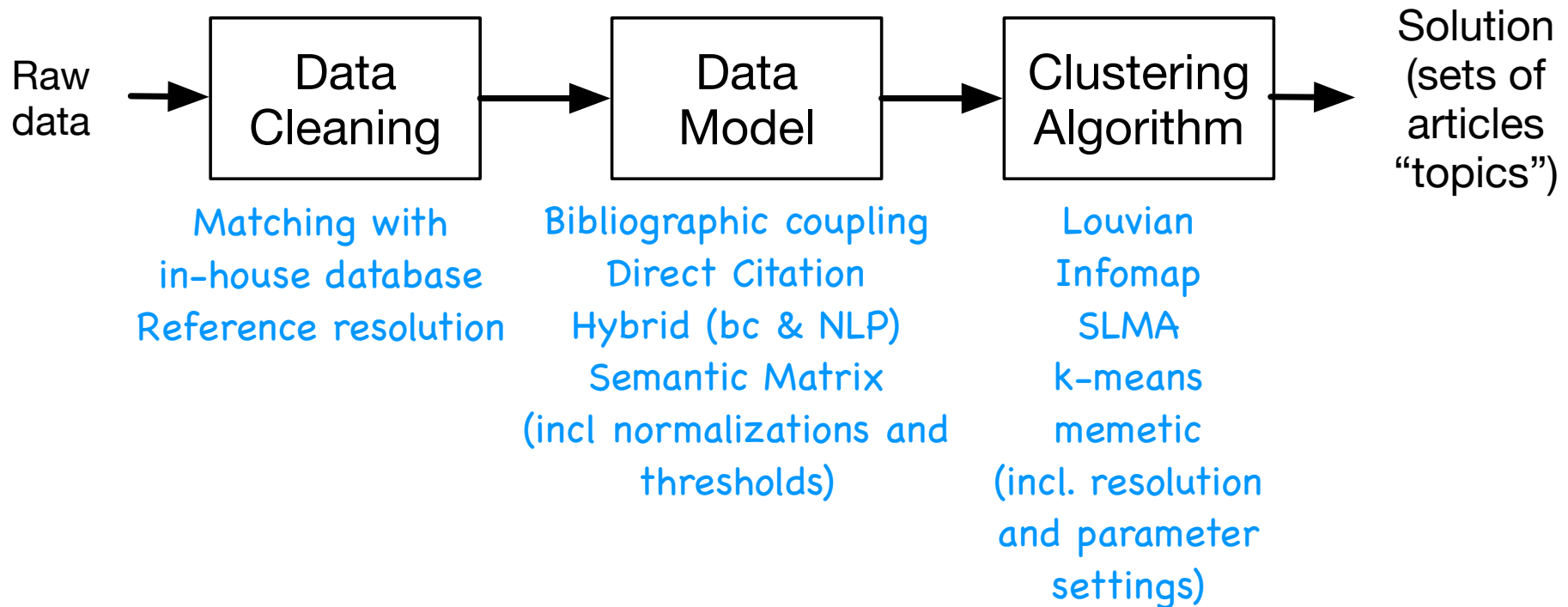
*Same data, different results?*

- 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)

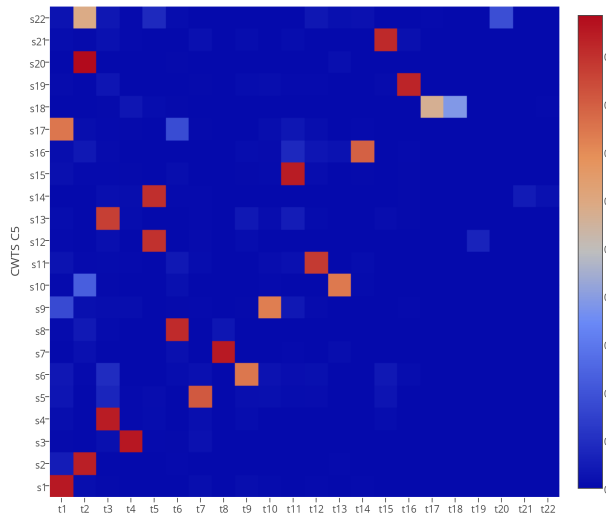
# Workflow(s) for Topic Extraction

## *Sources for Variation*

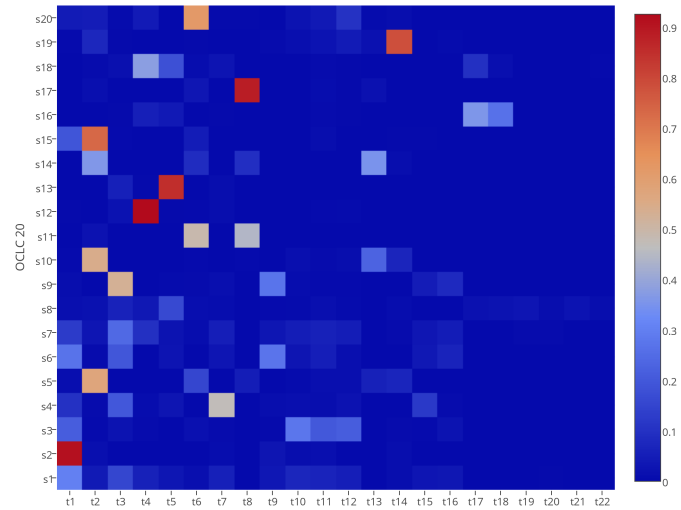


# Sources of variability between solutions

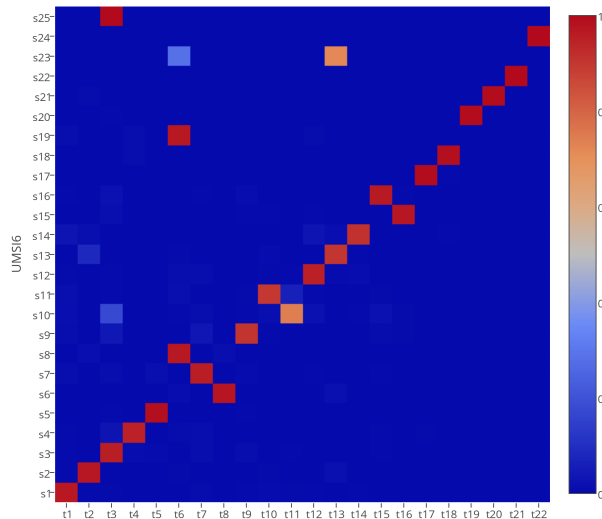
Same  
model  
&  
different  
algorithm



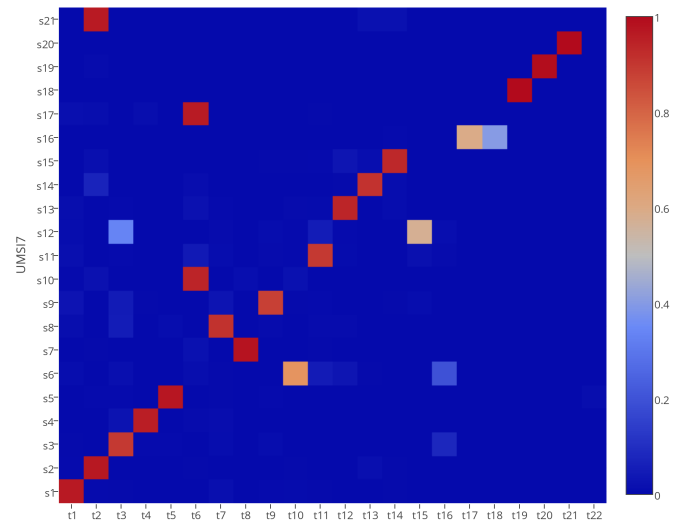
Different  
model  
& different  
algorithm



Same  
model  
& same  
algorithm



Same  
model  
& same  
algorithm



Overlap Between Clusters: Comparison with UMS10 Cluster Solution (22 clusters)



# 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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