Knowledge Synthesis

3 Structures

Structures of Knowledge

- Drawing a big picture of scientific knowledge has always been desirable for various reasons
- Science mapping attempts to find representations of intellectual connections within the dynamically changing system of scientific knowledge (Small, 1997)
- Science mapping aims at displaying the structural and dynamic aspects of scientific research (Börner et al. 2003; Morris et al., 2008)
- Science mapping uses mainly the “structures of knowledge”

Three Structures of Knowledge
Discovering hidden patterns

Each community of scientists would have a complete overview of the main findings related to their specific field, following the evolution of theories and techniques

Science Mapping allows investigating scientific knowledge from a statistical point of view

CONCEPTUAL STRUCTURE → what science talks about, the main themes and trends

INTELLECTUAL STRUCTURE → how the work of an author influences a given scientific community

SOCIAL STRUCTURE → how authors, institutions and countries interact each other

Knowledge Synthesis

Conceptual Structure

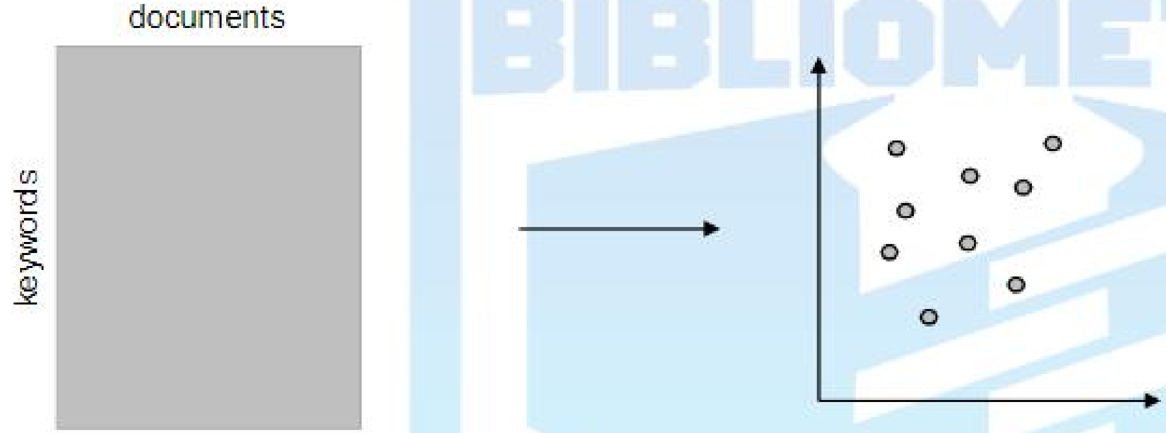
Conceptual Structure

Conceptual structure represents relations among concepts or words in a set of publications:

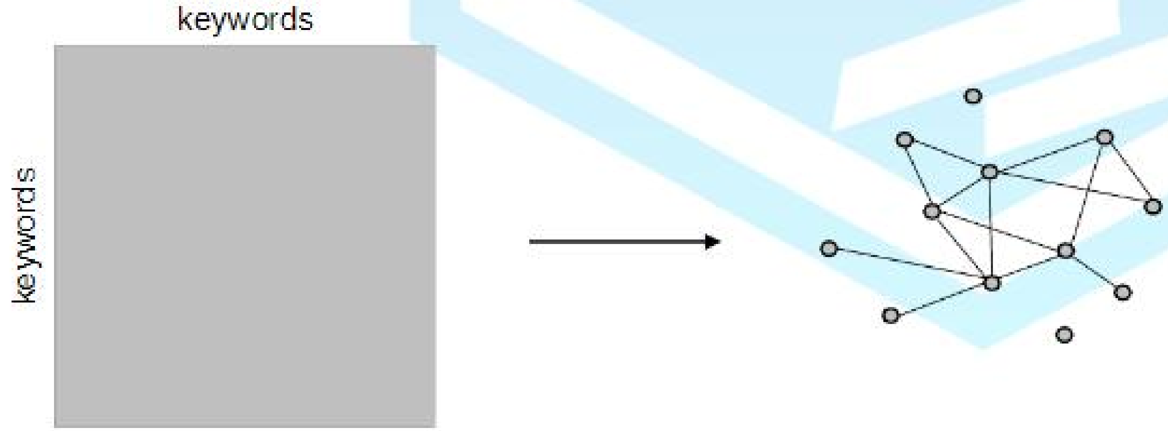
- Words, which appear together in a document, will be related in a network. It is also known as the **co-words network**. This structure is be used to understand the topics covered by a research field to define what are the most important and the most recent issues (so called, **research front**). It could also help in the study of the evolution of subjects over time.
- Similarly, to network analysis, **factorial analysis** (data reduction techniques) is helpful in identifying subfields. Various dimensionality reduction techniques can be applied, such as correspondence analysis (CA), multiple correspondence analysis (MCA), multidimensional scaling (MDS), principal component analysis (PCA). Clustering algorithms can be used in both cases of network or factorial analysis.
- **Mixed approach**. Starting from a conceptual network, you identify thematic networks that plot on a bi-dimensional matrix, where axis are function of centrality and density of the **thematic network**. Dividing the timespan in time slices, it is possible to represent the **thematic evolution** within a specific research field through an alluvial graph.

Mapping conceptual structure

The scope of a science mapping study can be a scientific discipline, a field of research, or topic areas concerning specific research questions



Factorial approach:
Correspondence Analysis
Multiple Correspondence Analysis
Multidimensional Scaling



Network approach
Co-word analysis

Factorial Approaches

The basic idea behind factorial approaches is to reduce the dimensionality of data and represent it in a low-dimensionality space.

Three alternative methodologies:

- Correspondence Analysis (CA)
- Multiple Correspondence Analysis (MCA)
- Multidimensional Scaling (MDS)

Factorial Approach: Interpretation

- The proximity between words corresponds to shared-substance:
  - keywords are close to each other because a large proportion of articles treat them together;
  - they are distant from each other when only a small fraction of articles uses these words together.
- The origin of the map represents the average position of all column profiles and therefore represents the center of the research field (meaning common and large shared topics) (Cuccurullo et al. 2016)

Conceptual Structure Tab

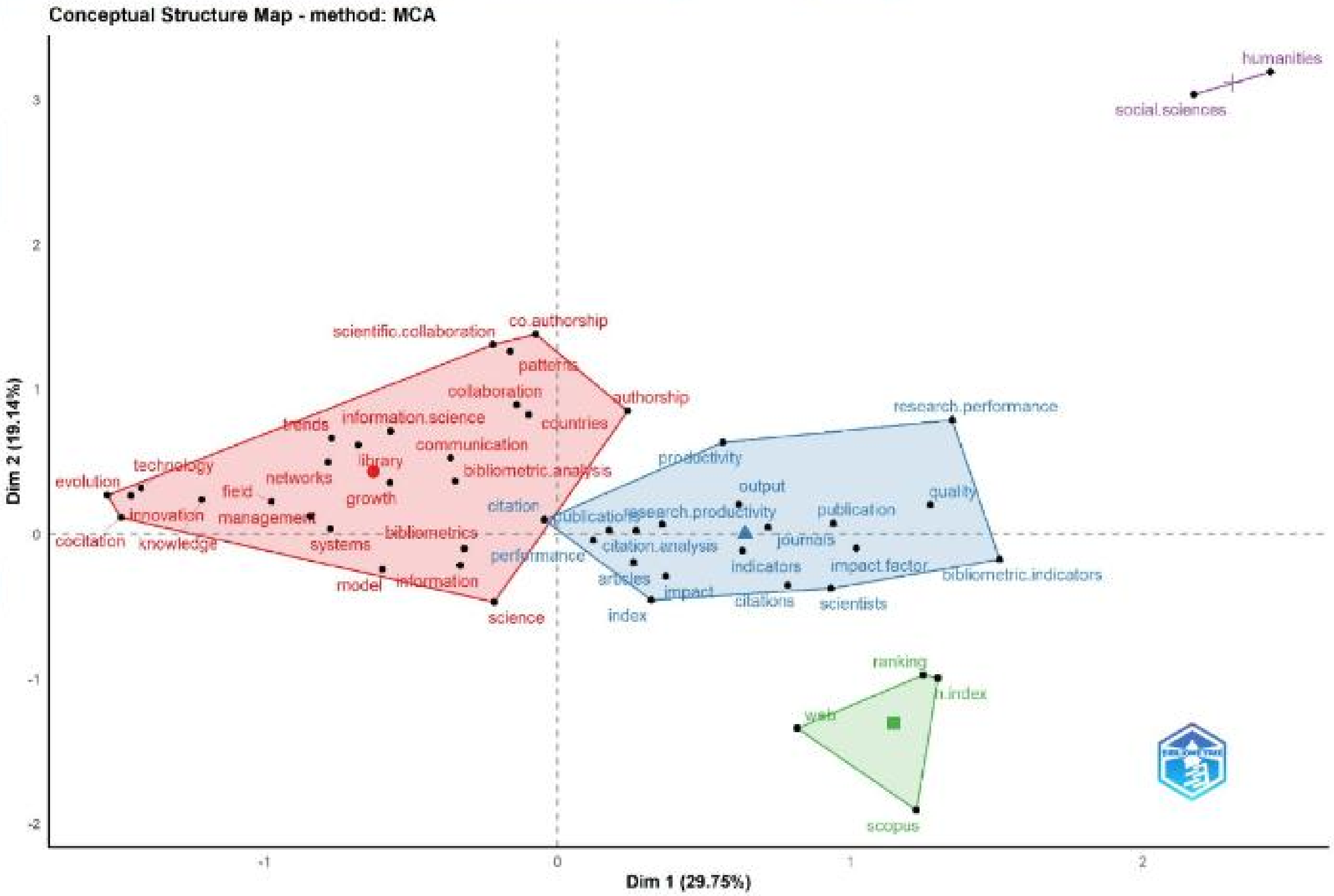
Correspondence Analysis and Clustering

Factorial Analysis

Map of words

Each color represents a cluster of word (a “topic”)

Clusters are identified by hierarchical clustering



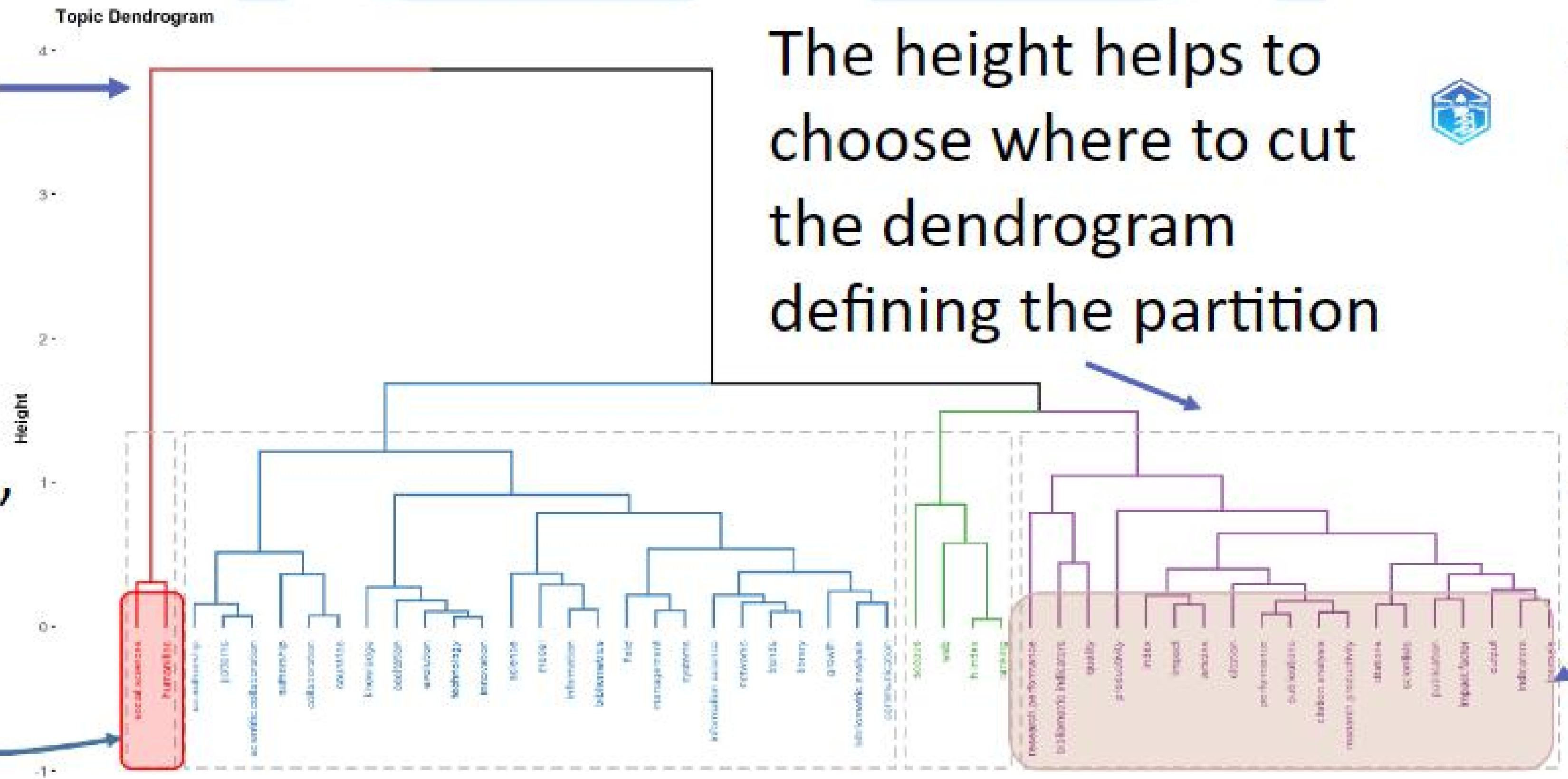
Conceptual Structure Tab

Factorial Analysis

Correspondence Analysis and Clustering

Dendrogram of words

The height measures the distance among words or cluster of words



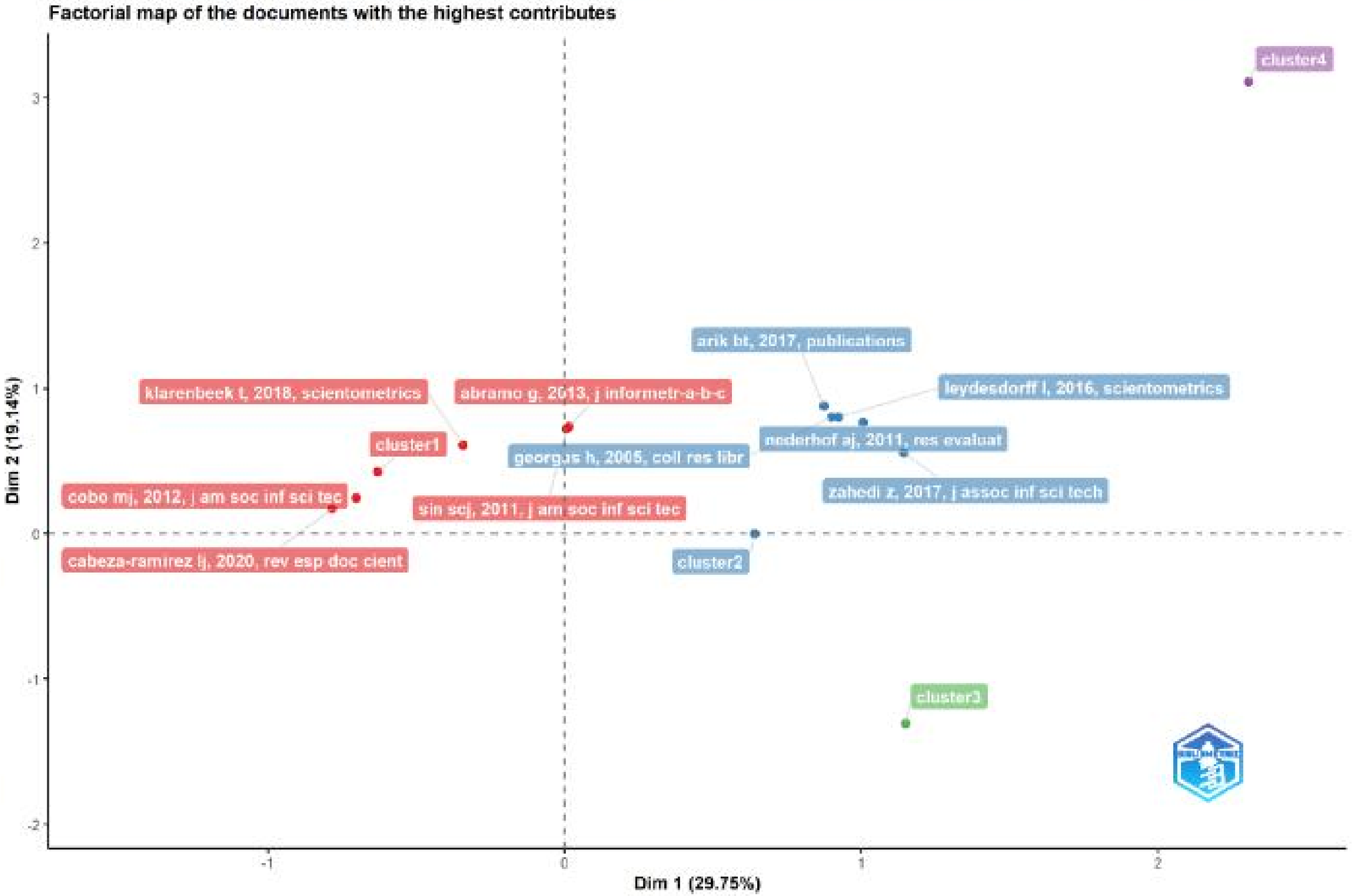
The height helps to choose where to cut the dendrogram defining the partition

“Similar words” which explain a similar “concept” or “topic”

“distant words” which define different “concept” or “topic”

Correspondence Analysis and Clustering
Most contributing documents

This graph allows to identify the link among topic and documents



The map plots the documents associated to the highest absolute contribution

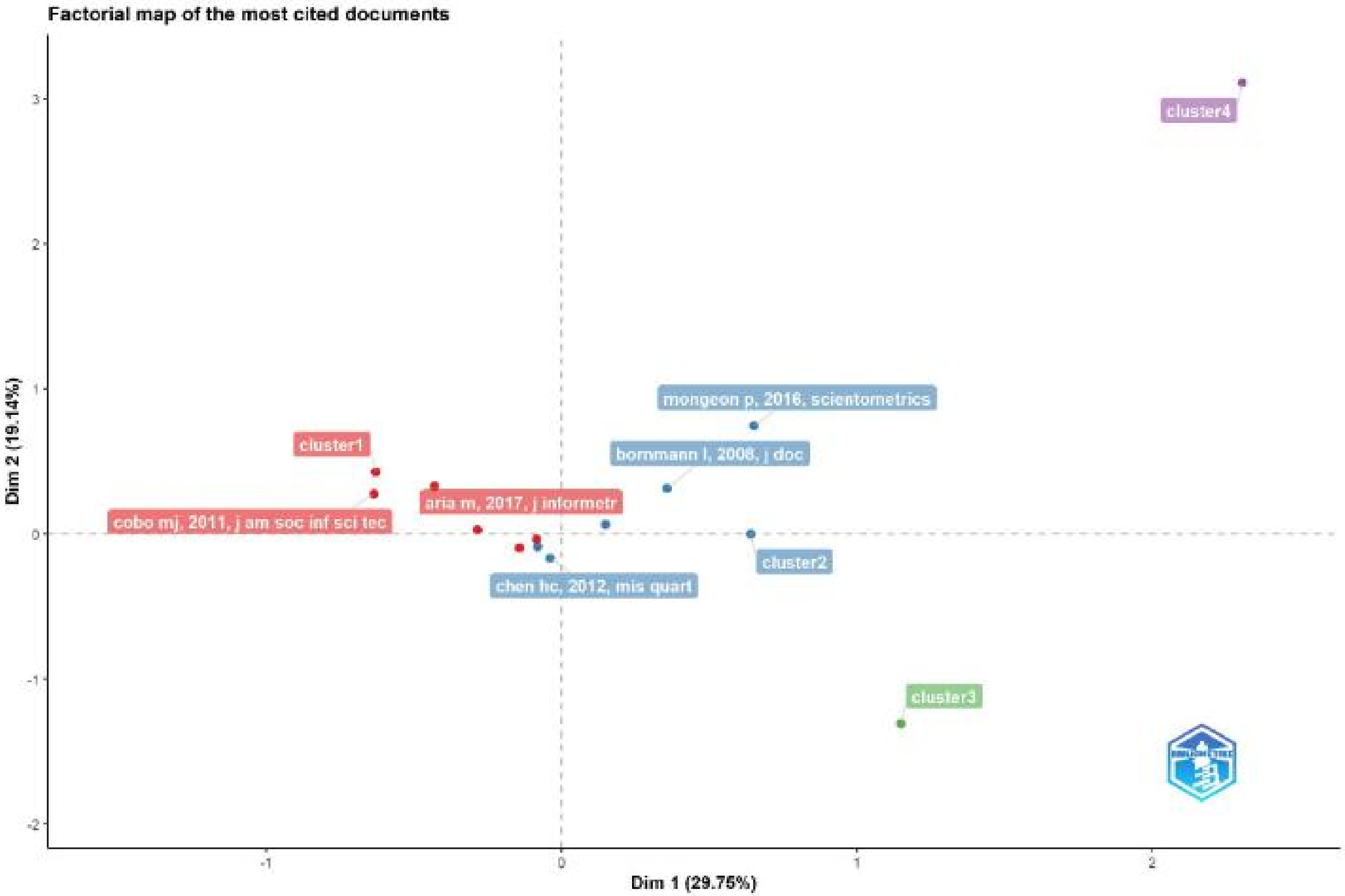
The **absolute contributions** measure the weight of each document in the information summarized by the two axes

The colors represent the clusters to which each document belongs

Conceptual Structure Tab

Factorial Analysis

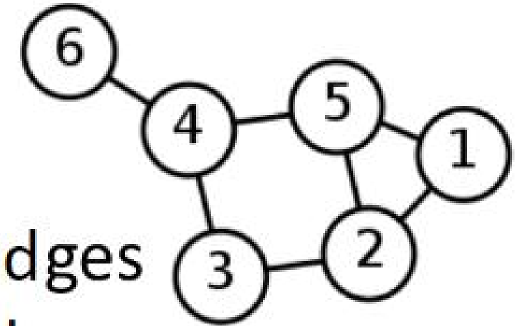
Correspondence Analysis and Clustering
Most cited documents



Network Analysis

- **Graph theory** is the study of graphs, which are mathematical structures used to model pairwise relations between objects

- A graph is made up of **vertices** (also called nodes or points) which are connected by **edges** (also called links or lines)



- A distinction is made between **undirected graphs,** where edges link two vertices symmetrically, and directed graphs, where edges, then called arrows, link two vertices asymmetrically

Network Analysis and Science Mapping

In Science mapping, a network graph is used to represent co-occurrences among bibliographic meta-data

The starting point is a co-occurrence matrix

Non-diagonal elements are the co-occurrence of two items in the collection

e.g in co-word analysis:

n_{32} measures how many times the words I_3 and I_2 appears together in the same corpus (keyword list, title, abstract, etc.)

$$\begin{array}{c|ccccccc} & I_1 & I_2 & I_3 & \cdots & I_p & \cdots & I_P \\ \hline I_1 & n_{11} & & & & & & \\ I_2 & & n_{22} & & & & & \\ I_3 & & n_{32} & & & & & \\ \cdots & & & & & & & \\ I_p & & & & & n_{pp} & & \\ \cdots & & & & & & & \\ I_P & & & & & & & n_{pp} \end{array}$$

Diagonal elements are the occurrence of each item in the collection

e.g in co-word analysis:

- Each items is words and
- an occurrence is the number of appearances of a particular word in the document collection.

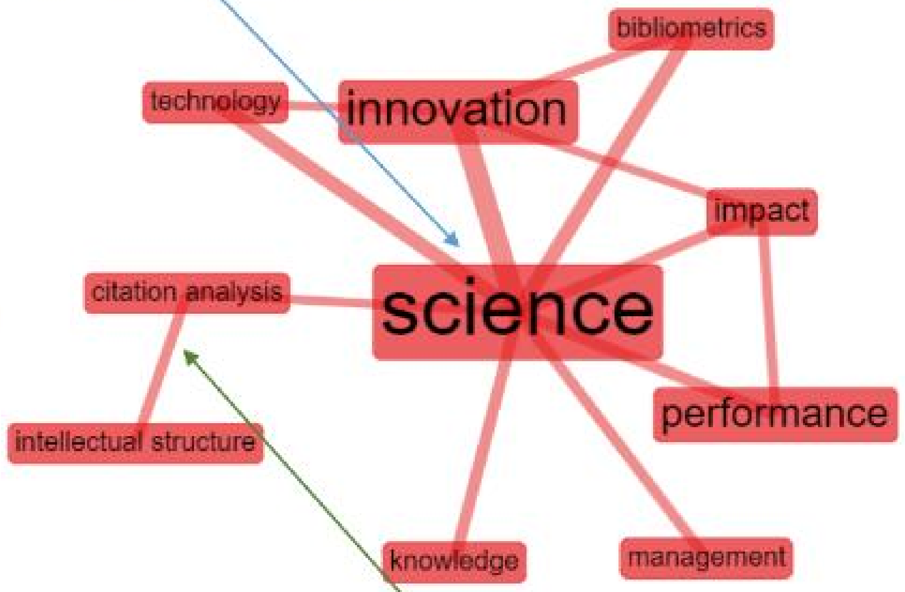
Network Analysis and Science Mapping

from the co-occurrence matrix to the network graph

	science	Know.	manag.	perf.	impact	bibliom.	innov.	tech.	cit.anal.	int.str.
science	100	17	16	21	20	25	40	26	10	0
knowledge	17	32	0	0	0	0	0	0	0	0
management	16	0	34	0	0	0	0	0	0	0
performance	21	0	0	70	15	0	0	0	0	0
impact	20	0	0	15	60	0	14	0	0	0
bibliometrics	25	0	0	0	0	38	13	0	0	0
innovation	40	0	0	0	14	13	80	0	0	0
technology	26	0	0	0	0	0	0	28	0	0
citation analysis	10	0	0	0	0	0	0	0	40	14
intellectual structure	0	0	0	0	0	0	0	0	14	36

Each ***vertex*** represents an item (in this example, each edge is a word)

The ***vertex size*** is proportional to the item occurrence (diagonal elements)

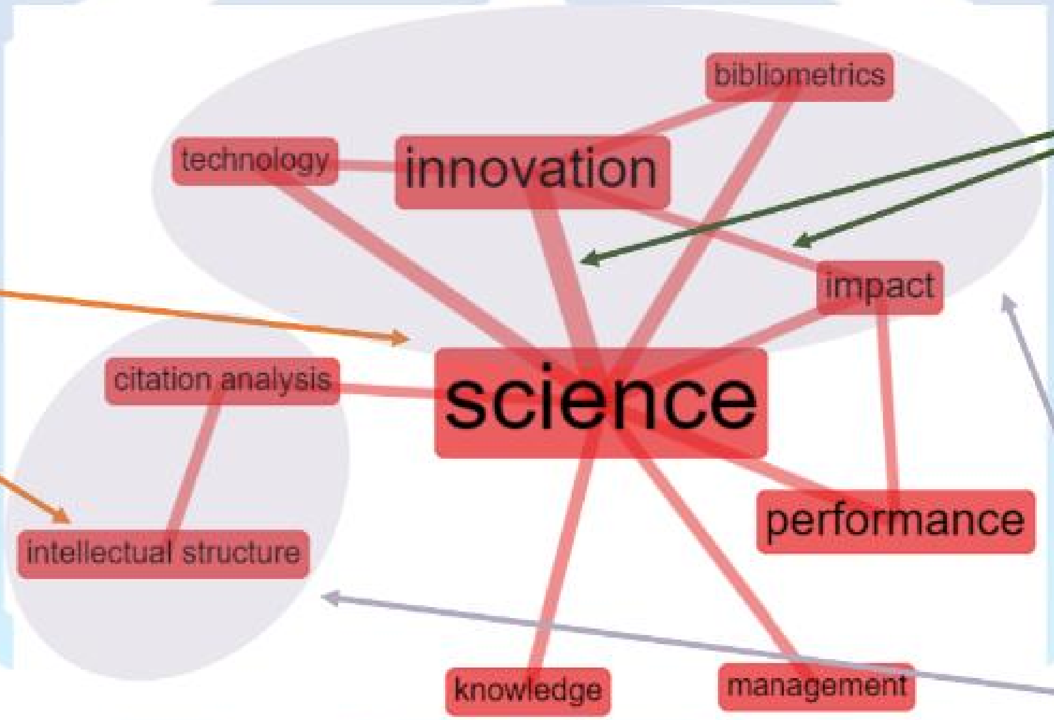


The ***edge size*** is proportional to item co-occurrences (non-diagonal elements)

Network Analysis and Science Mapping
How to read a network graph

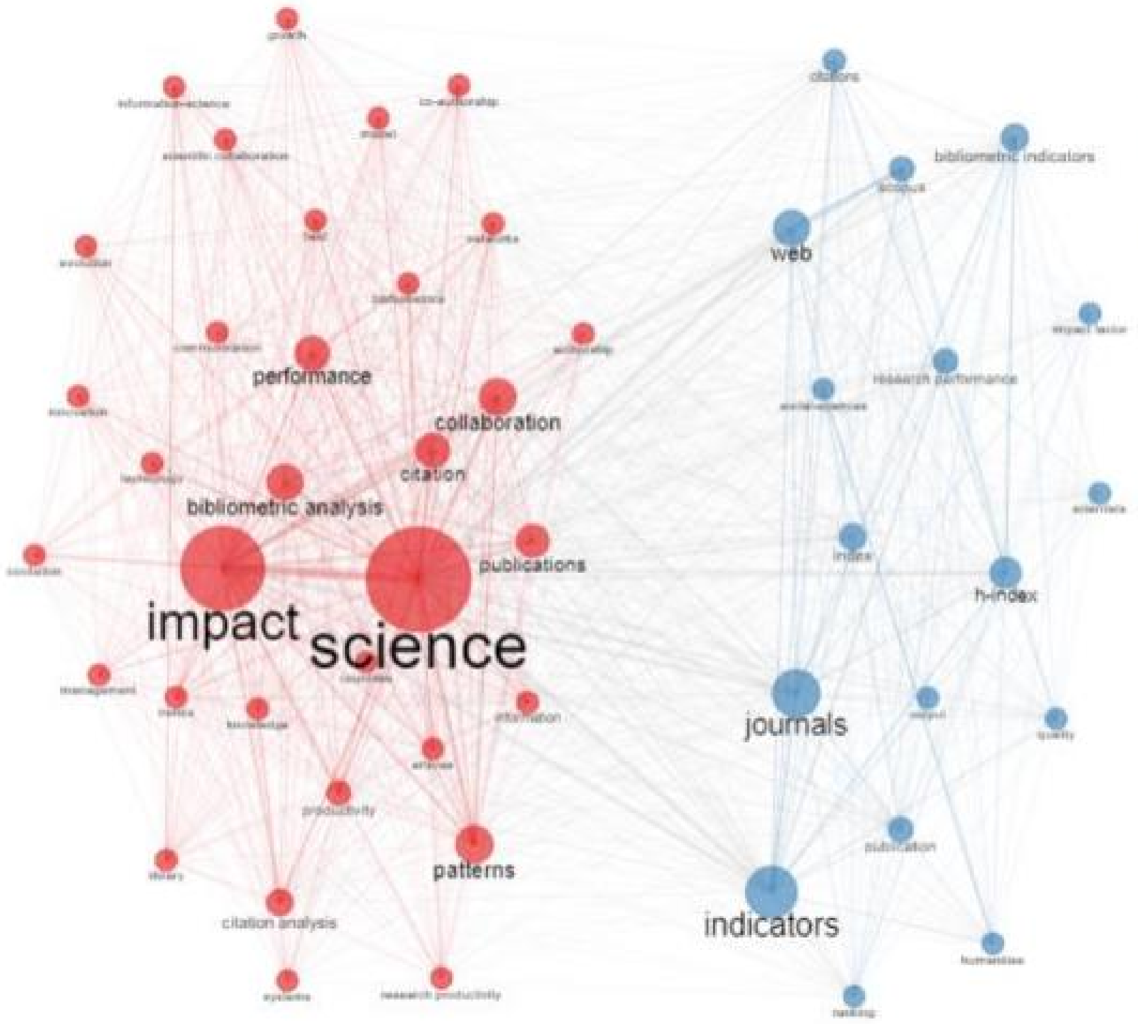
Vertex ***centrality vs***
Vertex ***farness***

Strength
of edges



Vertex Clustering
(community detection)

Co-occurrence Network



The colors represent the clusters to which each word belongs

Each cluster can be seen as a "topic"

Co-occurrence Network

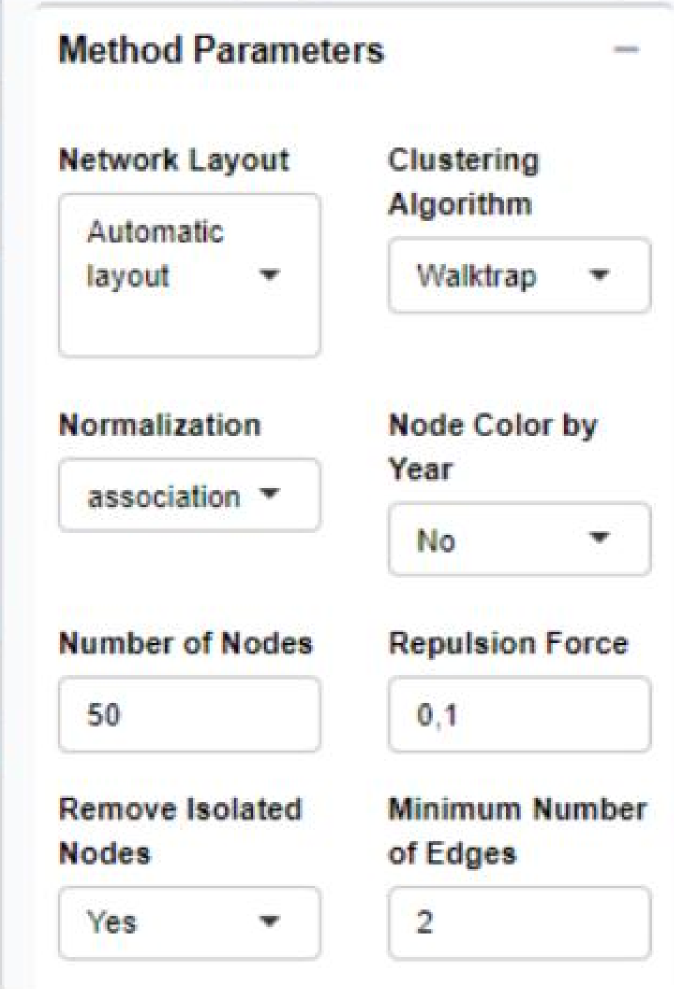
Layout

It is possible to choose among several network layout (Holten et al., 2009).

“Automatic Layout” automatically chooses the best layout in terms of graph readability

Normalization

Co-occurrences can be normalized by using similarity measures such as Salton's Cosine, Jaccard's Index, Equivalence Index, and Association Strength (van Eck et al.,2009).



Network options

Clustering

Several clustering algorithm are proposed. The best is “Walktrap” (Lancichinetti et al., 2009).

Repulsion Force

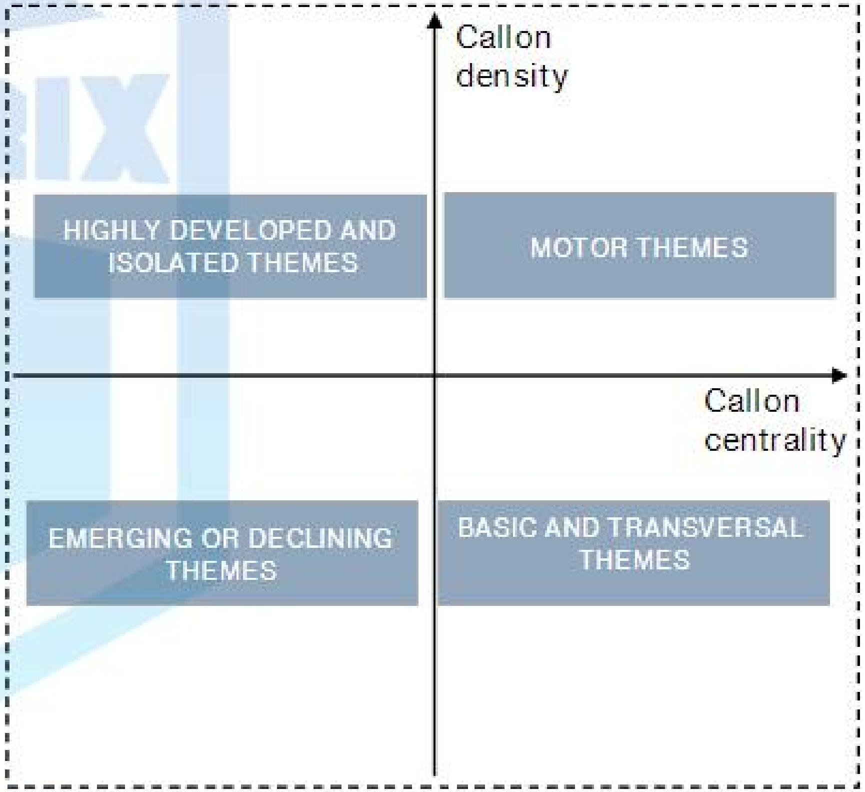
Repulsion force varies between 0 and 1, where 1 represents the maximum separation between the groups.

Thematic Map

By applying a clustering algorithm on the keyword network, it is possible to **highlight the different themes of a given domain**

Each cluster/theme can be represented on a particular plot known as *Strategic* or *Thematic map* (Cobo et al., 2011):

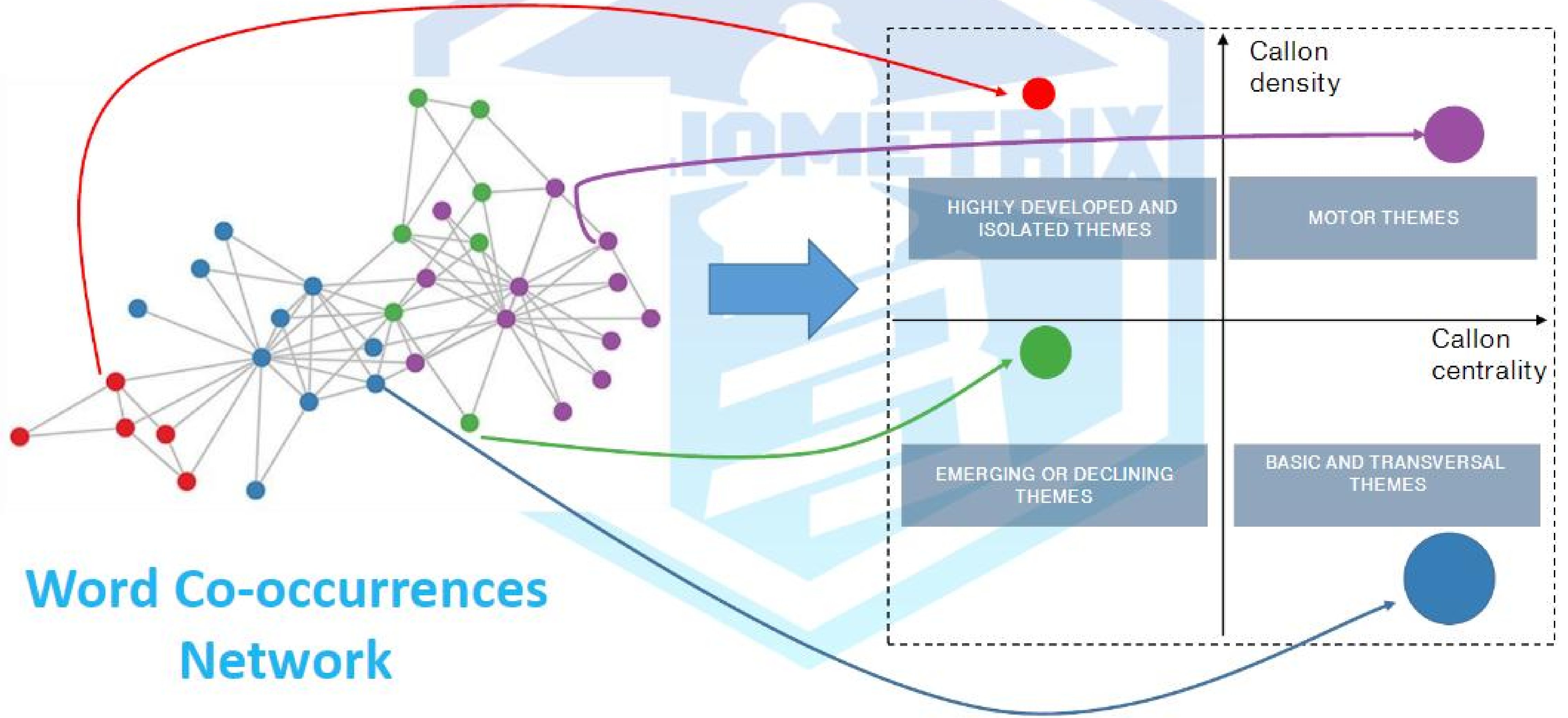
- Centrality is a measure of the theme's relevance
- Density is a measure of the theme's development



Limitations:

- Each keyword is associated only with one theme
- It is not possible to use themes for document categorization
- It is not possible to jointly analyse meta-information

Thematic Map
from a network to a bivariate map

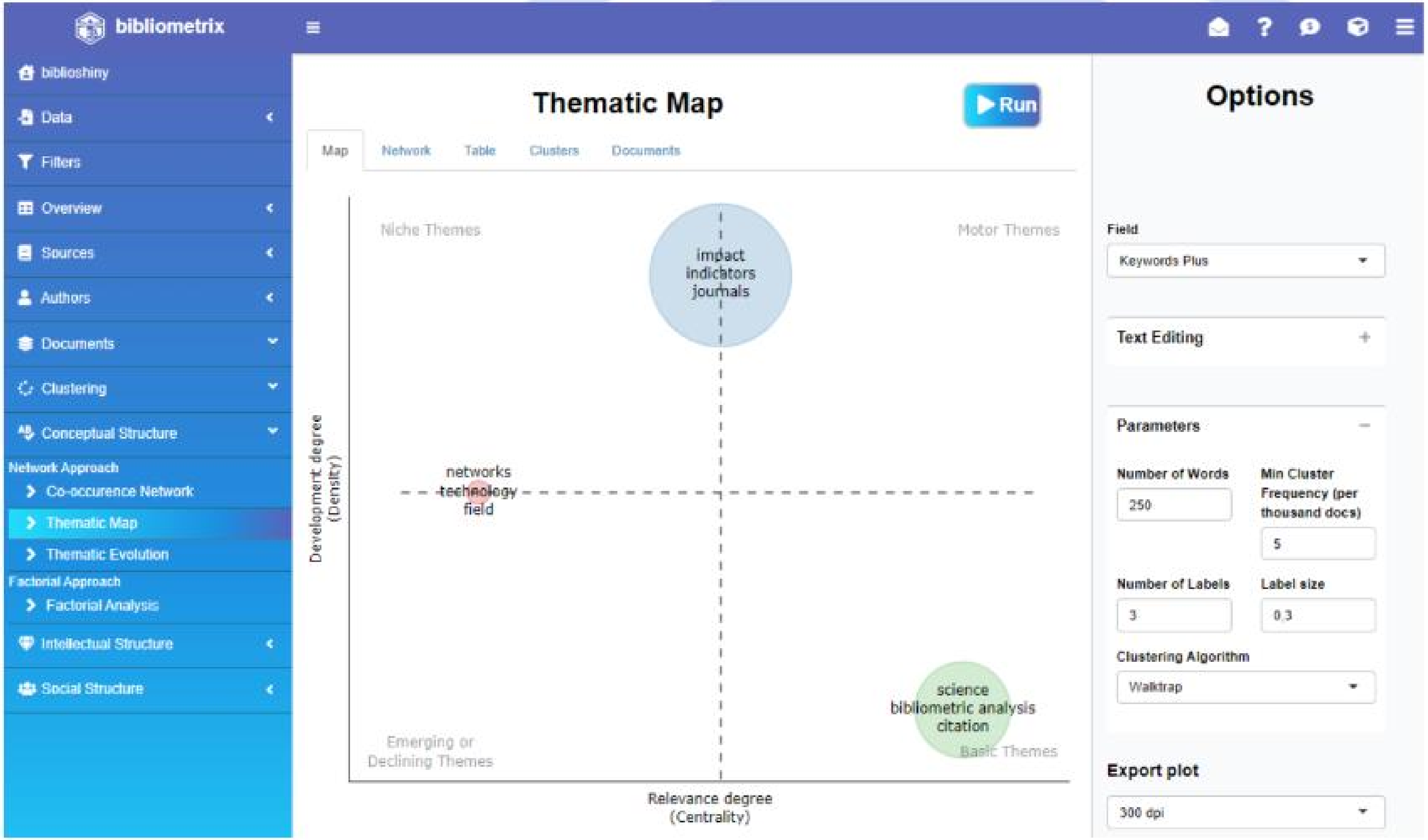


Word Co-occurrences Network

Conceptual Structure Tab

Thematic Map

Topics in business and management literature using bibliometrics

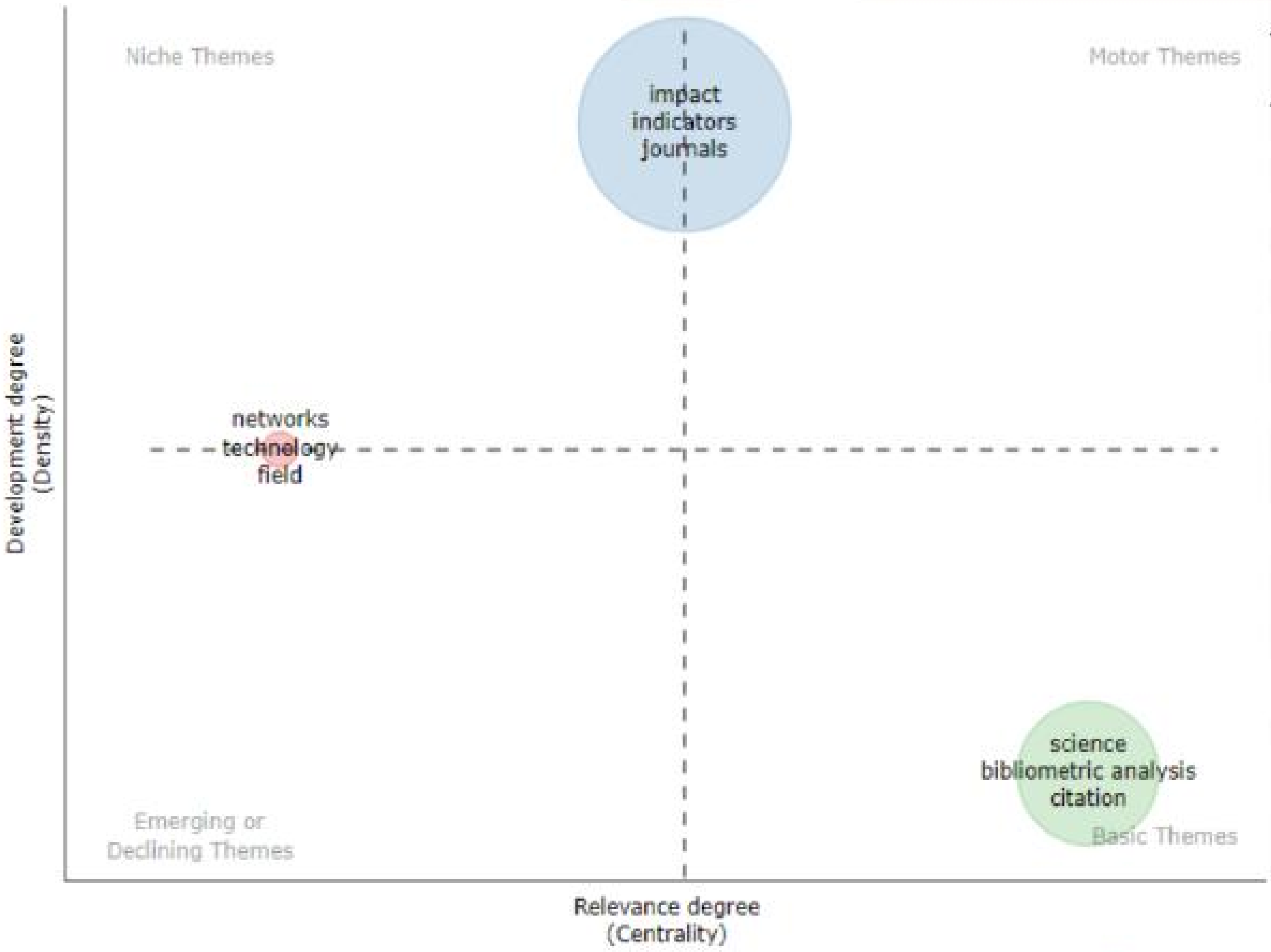


- Each bubble represents a network cluster
- The bubble names are words, belonging in the cluster, with the higher occurrence value
- The bubble size is proportional to the cluster word occurrences
- The bubble position is set according to the cluster Callon centrality and density

Conceptual Structure Tab

Thematic Map

Thematic Map
Cluster composition



Occurrences	Words	Cluster	Cluster_Label
All	All	All	All
127	networks	1	networks
124	technology	1	networks
111	field	1	networks
106	knowledge	1	networks
93	innovation	1	networks
87	evolution	1	networks
82	cocitation	1	networks
73	systems	1	networks
55	network	1	networks
47	intellectual structure	1	networks
45	internet	1	networks
40	dynamics	1	networks
39	research-and-development	1	networks
38	cocitation analysis	1	networks
37	maps	1	networks
36	interdisciplinarity	1	networks
34	retrieval	1	networks
33	author cocitation	1	networks
33	scientific literature	1	networks

Conceptual Structure Tab

Thematic Map

Thematic Map
Probability of belonging to a cluster

Thematic Map

▶ Run

Map · Network · Table · Clusters · Documents

Show 10 rows · Copy · CSV · Excel · PDF · Print

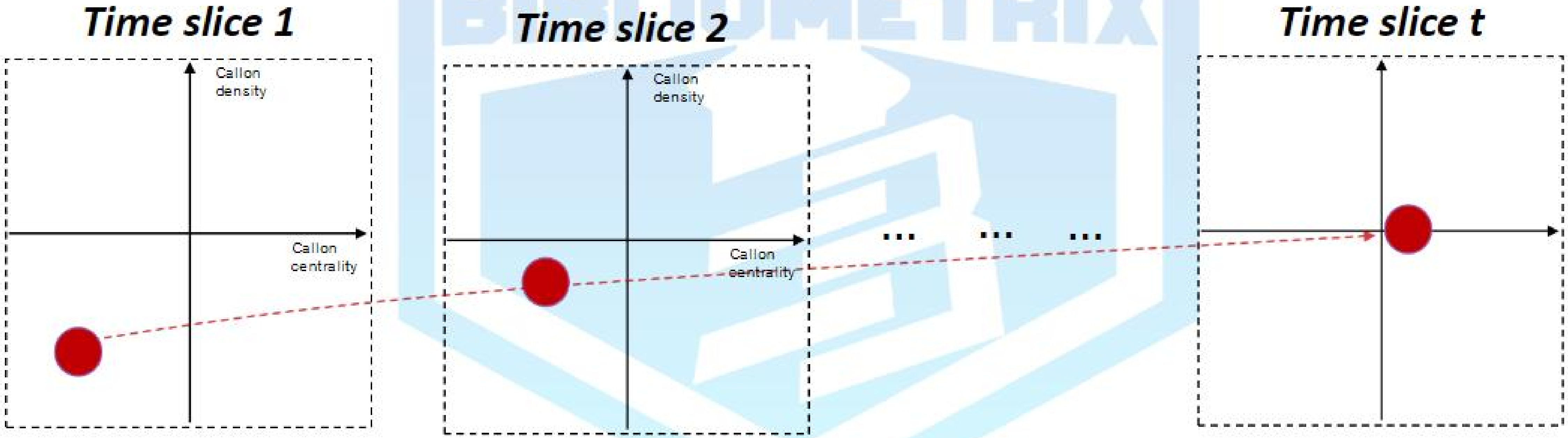
Search:

DOI	Authors	Title	Source	Year	TotalCitation	SR	impact	networks	science	Assigned_cluster
All	All	All	All	All	All	All	All	All	All	All
NA	CHEN HC;CHIANG RHL;STOREY VC	BUSINESS INTELLIGENCE AND ANALYTICS: FROM BIG DATA TO BIG IMPACT	MIS QUARTERLY	2012	2161	CHEN HC, 2012, MIS QUART	0.765	0.235	0.000	impact
10.1007/s11192-015-1765-5	MONGEON P;PAUL-HUS A	THE JOURNAL COVERAGE OF WEB OF SCIENCE AND SCOPUS: A COMPARATIVE ANALYSIS	SCIENTOMETRICS	2016	890	MONGEON P, 2016, SCIENTOMETRICS	1.000	0.000	0.000	impact
10.1108/00220410810844150	BORNMANN L;DANIEL HD	WHAT DO CITATION COUNTS MEASURE? A REVIEW OF STUDIES ON CITING BEHAVIOR	JOURNAL OF DOCUMENTATION	2008	712	BORNMANN L, 2008, J DOC	1.000	0.000	0.000	impact
10.1007/s11192-015-1798-9	HARZING AW;ALAKANGAS S	GOOGLE SCHOLAR, SCOPUS AND THE WEB OF SCIENCE: A LONGITUDINAL AND CROSS-DISCIPLINARY COMPARISON	SCIENTOMETRICS	2016	510	HARZING AW, 2016, SCIENTOMETRICS-a	1.000	0.000	0.000	impact
10.1016/j.joi.2009.04.001	ALONSO S;CABRERIZO FJ;HERRERA-VIEDMA E;HERRERA F	H-INDEX: A REVIEW FOCUSED IN ITS VARIANTS, COMPUTATION AND STANDARDIZATION FOR DIFFERENT SCIENTIFIC FIELDS	JOURNAL OF INFORMETRICS	2009	476	ALONSO S, 2009, J INFORMETR	0.987	0.000	0.013	impact
10.1007/s11192-005-0008-6	VAN RAAN AFJ	FATAL ATTRACTION: CONCEPTUAL AND METHODOLOGICAL PROBLEMS IN THE RANKING OF UNIVERSITIES BY BIBLIOMETRIC METHODS	SCIENTOMETRICS	2005	450	VAN RAAN AFJ, 2005, SCIENTOMETRICS	0.962	0.000	0.038	impact
10.1016/j.joi.2016.02.007	WALTMAN L	A REVIEW OF THE LITERATURE ON CITATION IMPACT INDICATORS	JOURNAL OF INFORMETRICS	2016	443	WALTMAN L, 2016, J INFORMETR	1.000	0.000	0.000	impact
10.1556/Scient.67.2006.3.10	VAN RAAN AFJ	COMPARISON OF THE HIRSCH-INDEX WITH STANDARD BIBLIOMETRIC INDICATORS AND WITH PEER JUDGMENT FOR 147 CHEMISTRY RESEARCH GROUPS	SCIENTOMETRICS	2006	405	VAN RAAN AFJ, 2006, SCIENTOMETRICS	1.000	0.000	0.000	impact

Papers with a probability of 0.8 or higher almost certainly belong to the cluster k.
Papers with a probability between 0.4 and 0.8 have a high probability of belonging to the cluster k.
A paper can deal with several topics, so it can also belong to more than one cluster.

Thematic Evolution
A longitudinal thematic map analysis

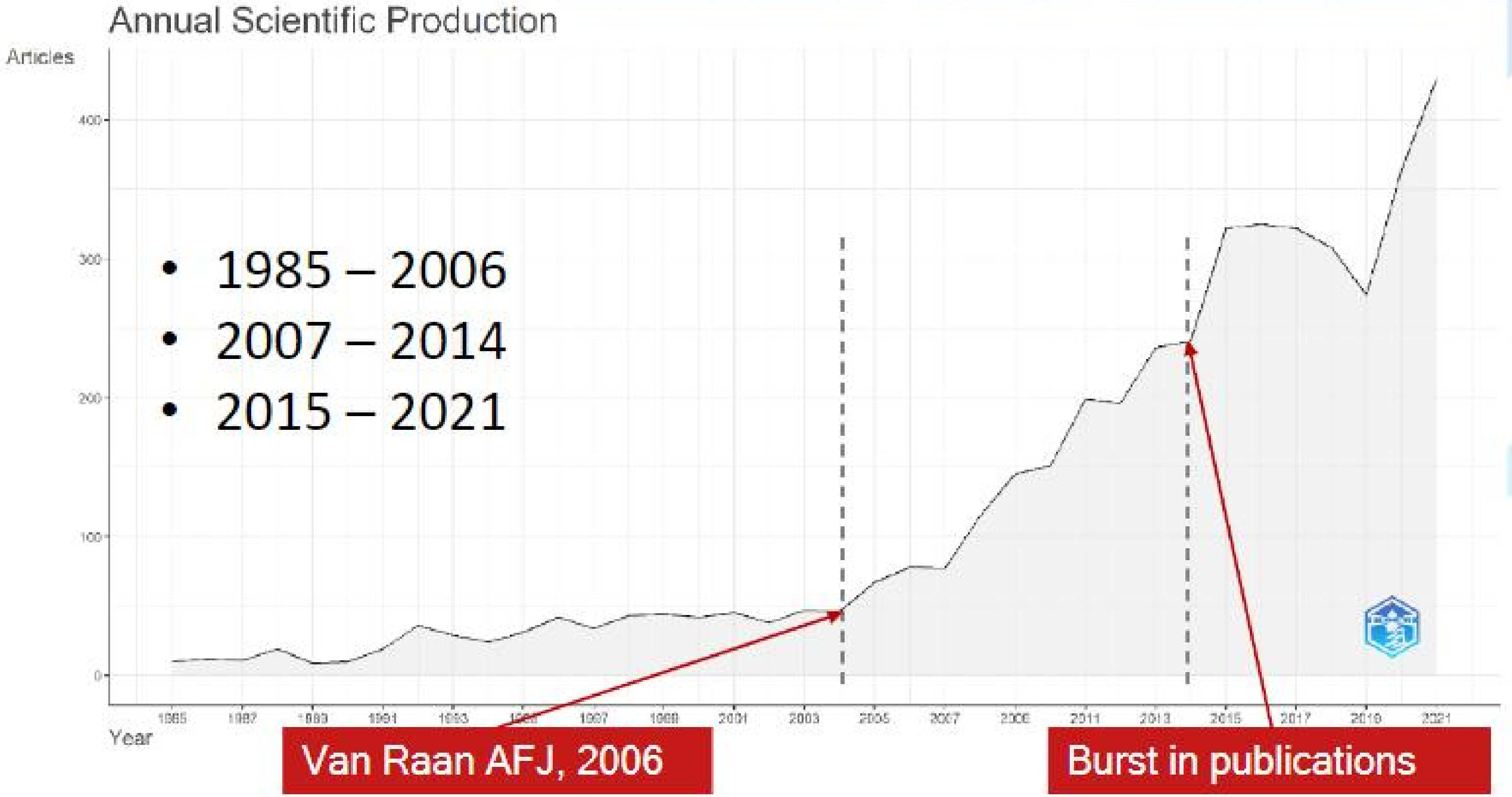
Dividing the time span in different time slices, it is possible to study and plot the topic evolution (in terms of trajectory along time)



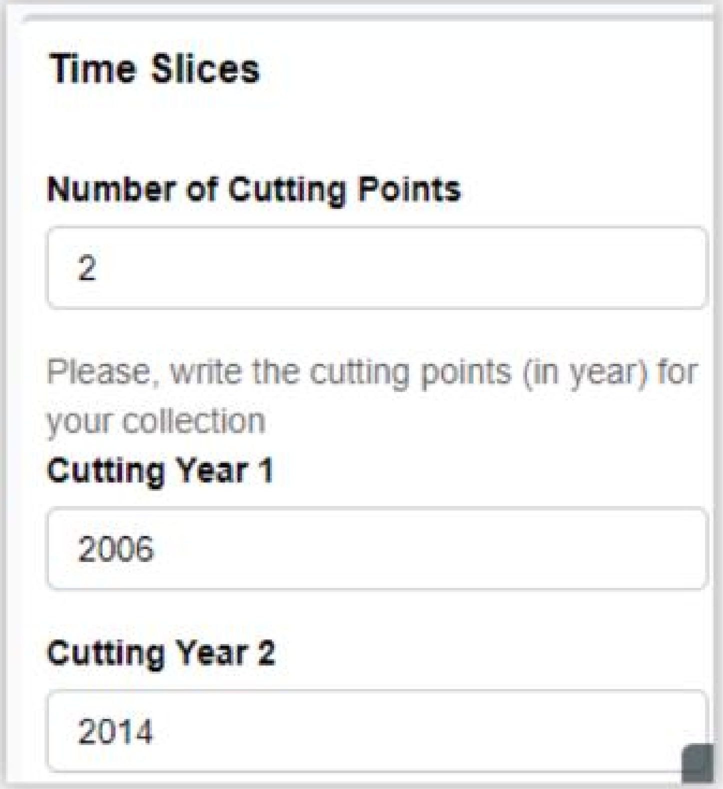
In this graph, the bubble represents an emerging topic that moves towards mainstream themes area

Thematic Evolution
Setting time slices

Looking at the distribution of publication per year, we decided to spit our collection into 3 time slices setting 2 cutting points 2006 and 2014:



- 1985 – 2006
- 2007 – 2014
- 2015 – 2021

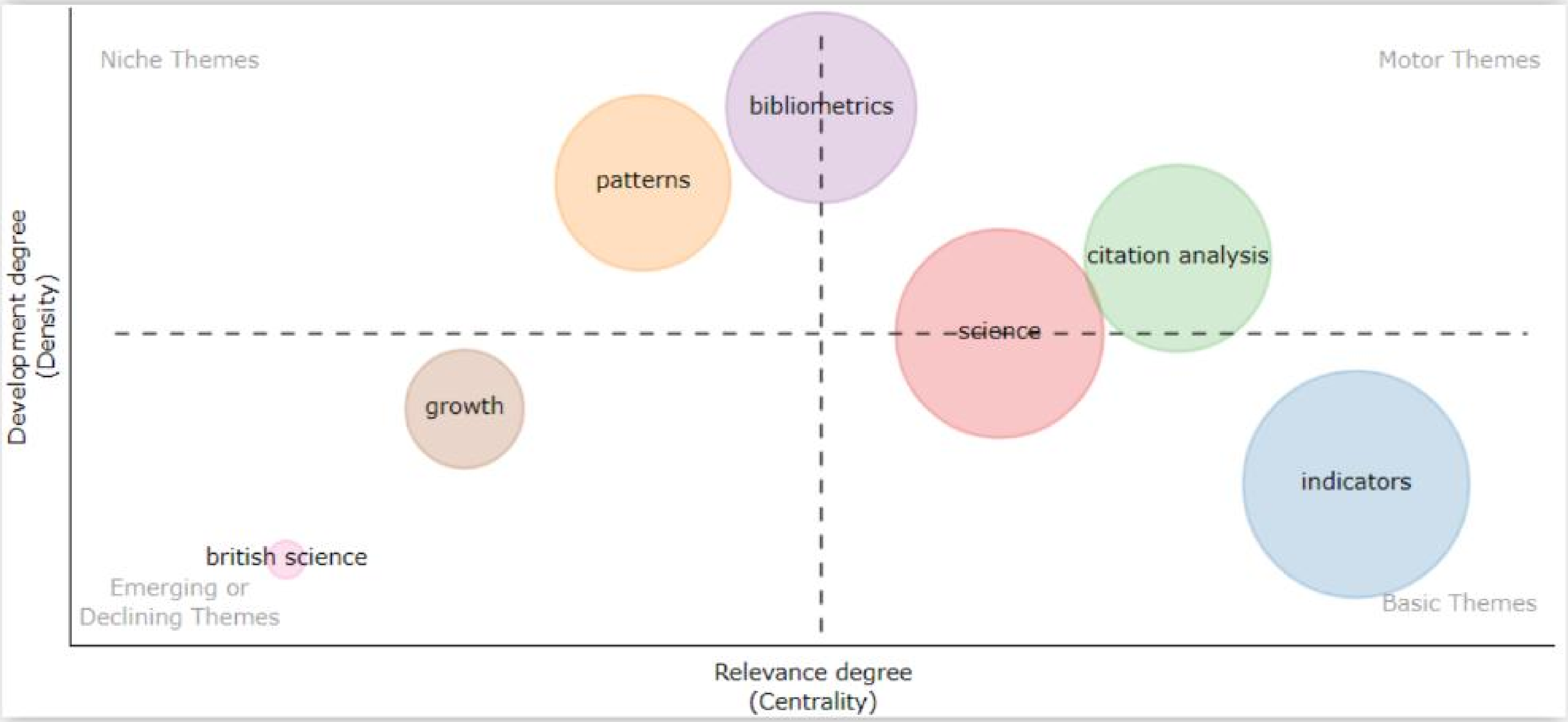


Conceptual Structure Tab

Thematic Evolution

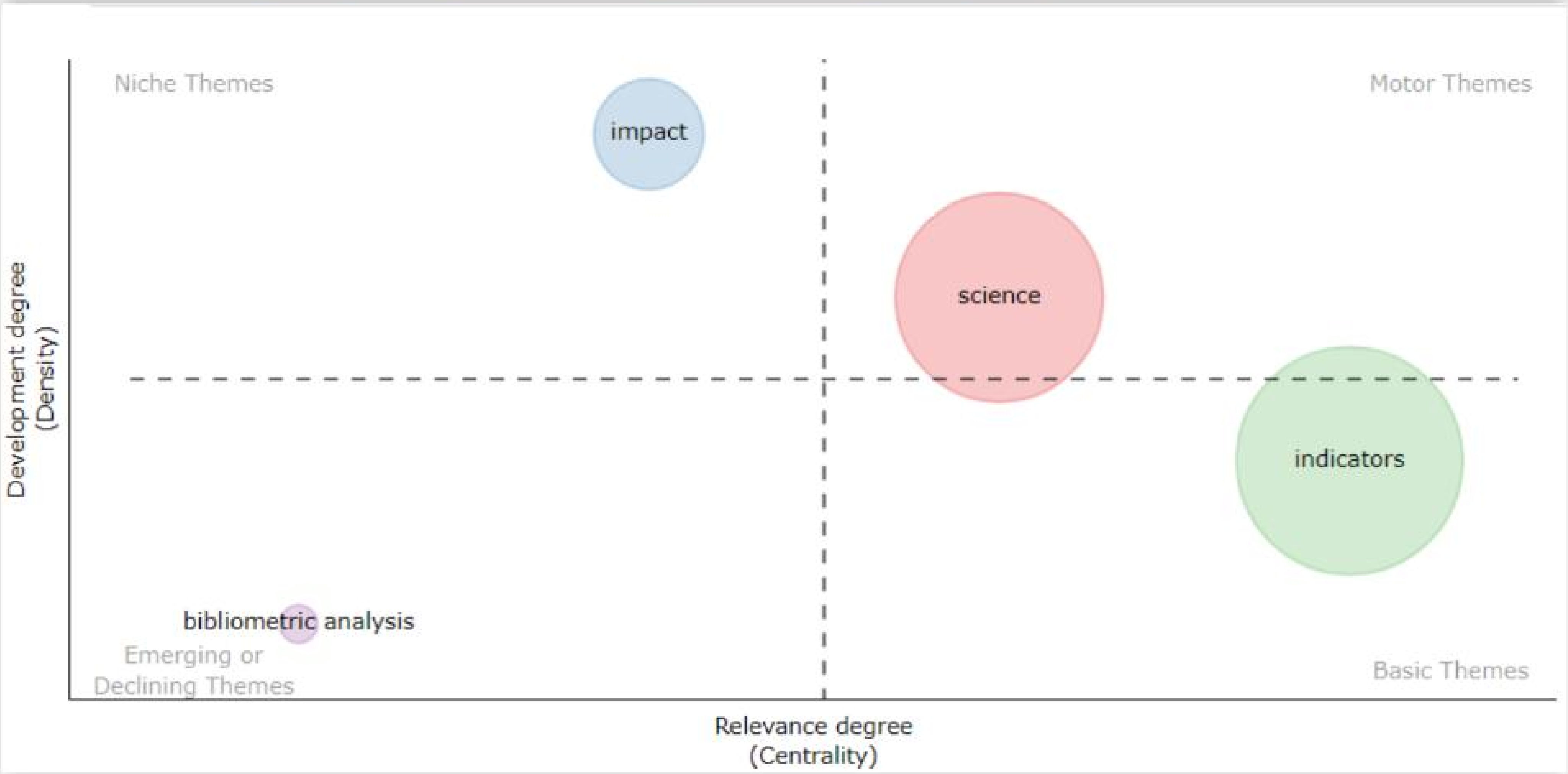
Thematic Evolution
A longitudinal thematic map analysis

Time slice
1985 - 2006



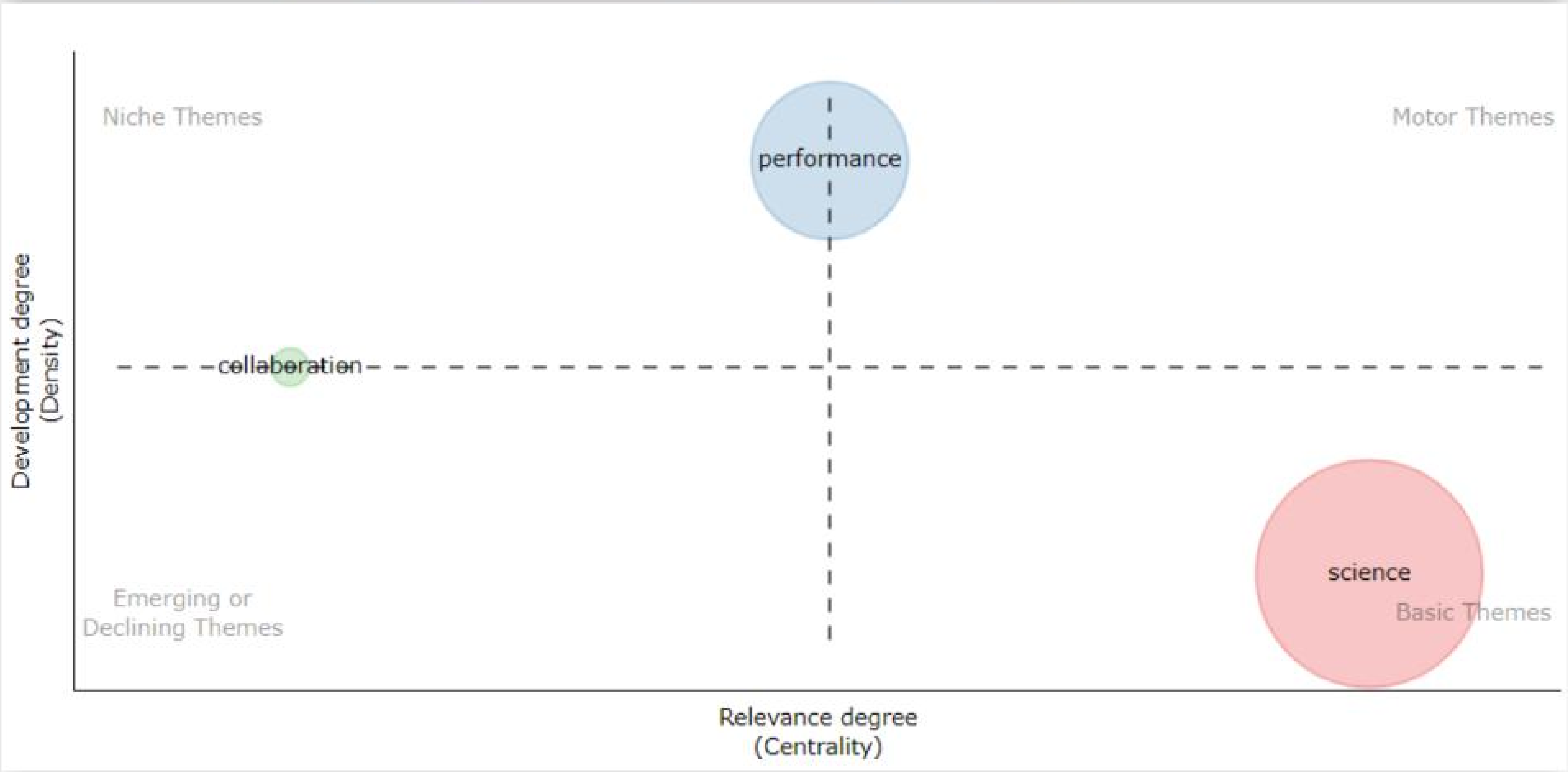
Thematic Evolution
A longitudinal thematic map analysis

Time slice 2007 - 2014



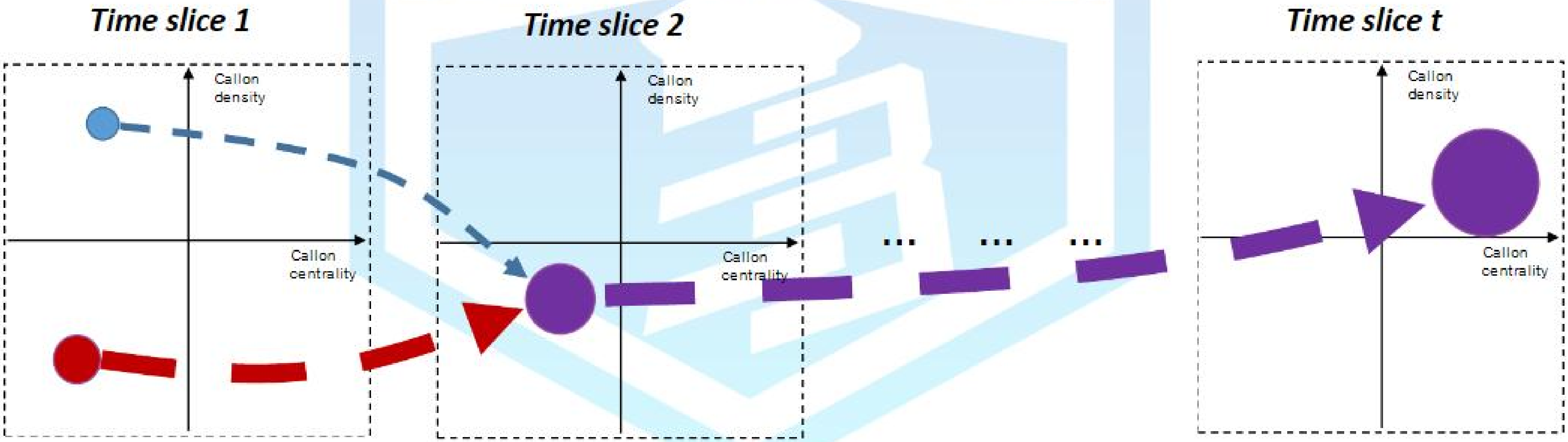
Thematic Evolution
A longitudinal thematic map analysis

Time slice 2015 - 2021



Thematic Evolution
A longitudinal thematic map analysis

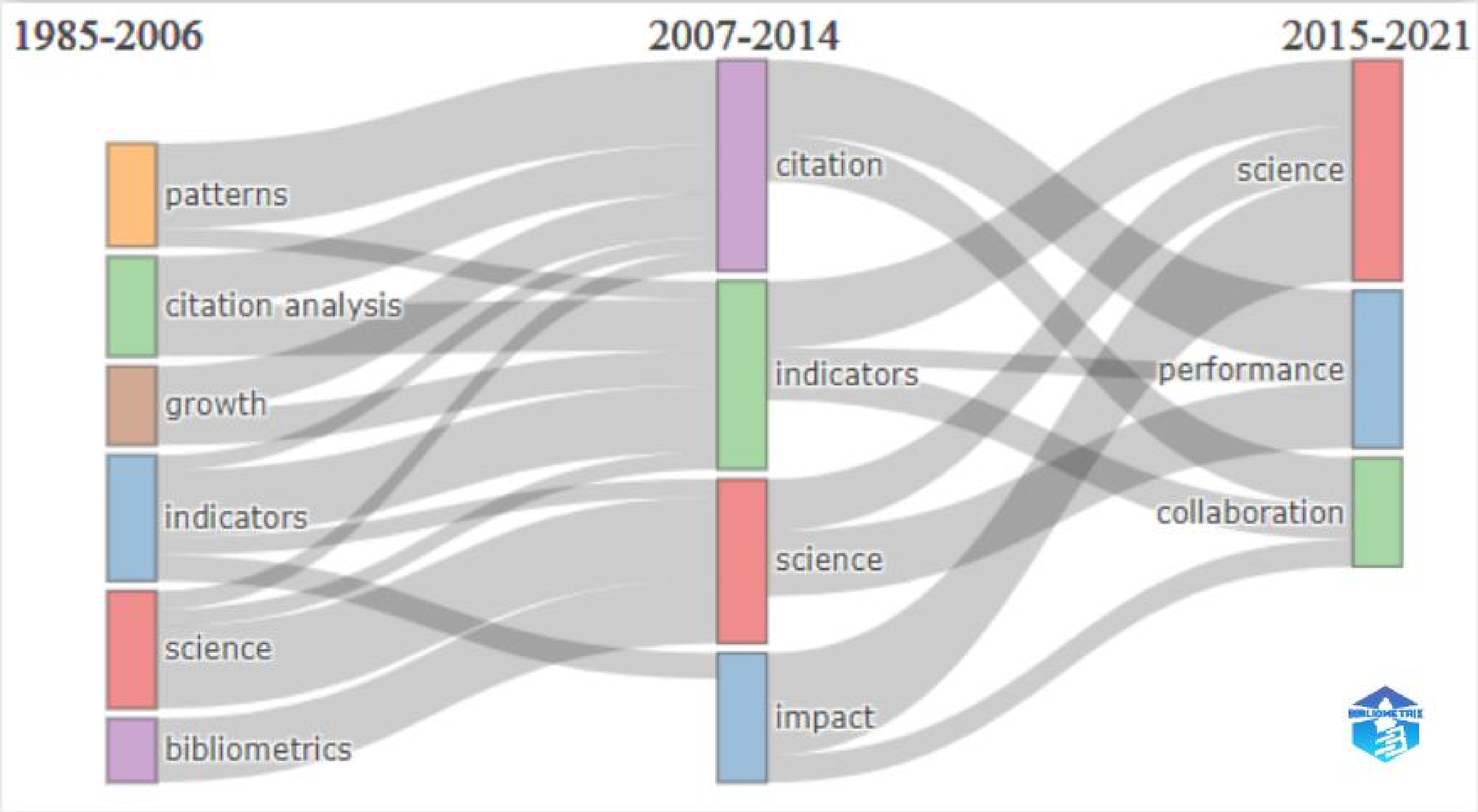
it is also possible to highlight the tendencies of some topics to merge together, or of a topic to split into several themes



Conceptual Structure Tab

Thematic Evolution

Thematic Evolution
A longitudinal thematic map analysis



Knowledge Synthesis

Intellectual Structure

Intellectual Structure

- Intellectual structure shows relationships between nodes which represent references
- Network edges can have different interpretations depending on the citation type (co-citation or direct citation)
- Citation analysis is the most common analysis in bibliometrics in the form of co-citation between authors or documents.
- Co-citation analysis, when examined over time, is helpful in detecting a shift in paradigms and schools of thought.

Intellectual Structure

Two type of analysis:

Co-citation network

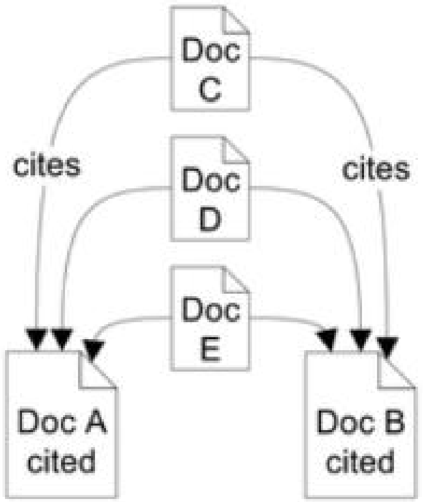
- Small, 1973

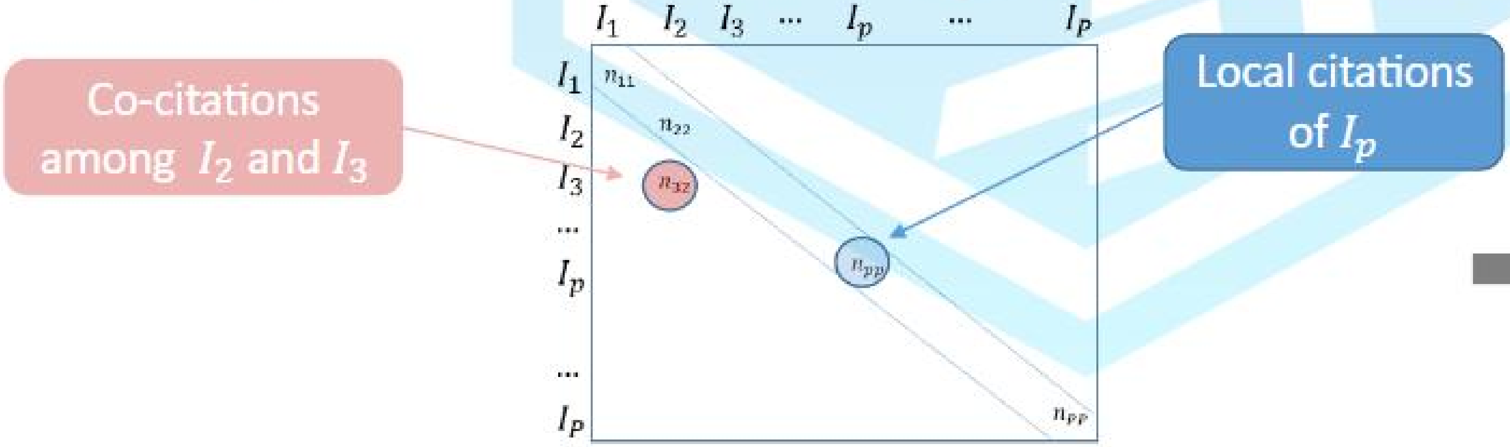
Historiographic mapping

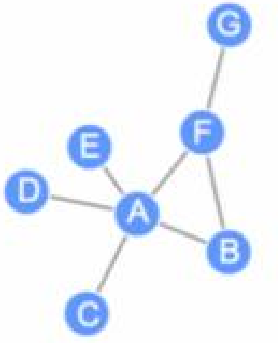
- Garfield, 2004

Co-citation analysis

- We talk about co-citation of two documents when both are cited in a third document
- Document “A” and “B” are “references” co-cited by documents “C”, “D” and “E”
- Co-citations can be represented in a co-occurrence matrix just like co-word analysis



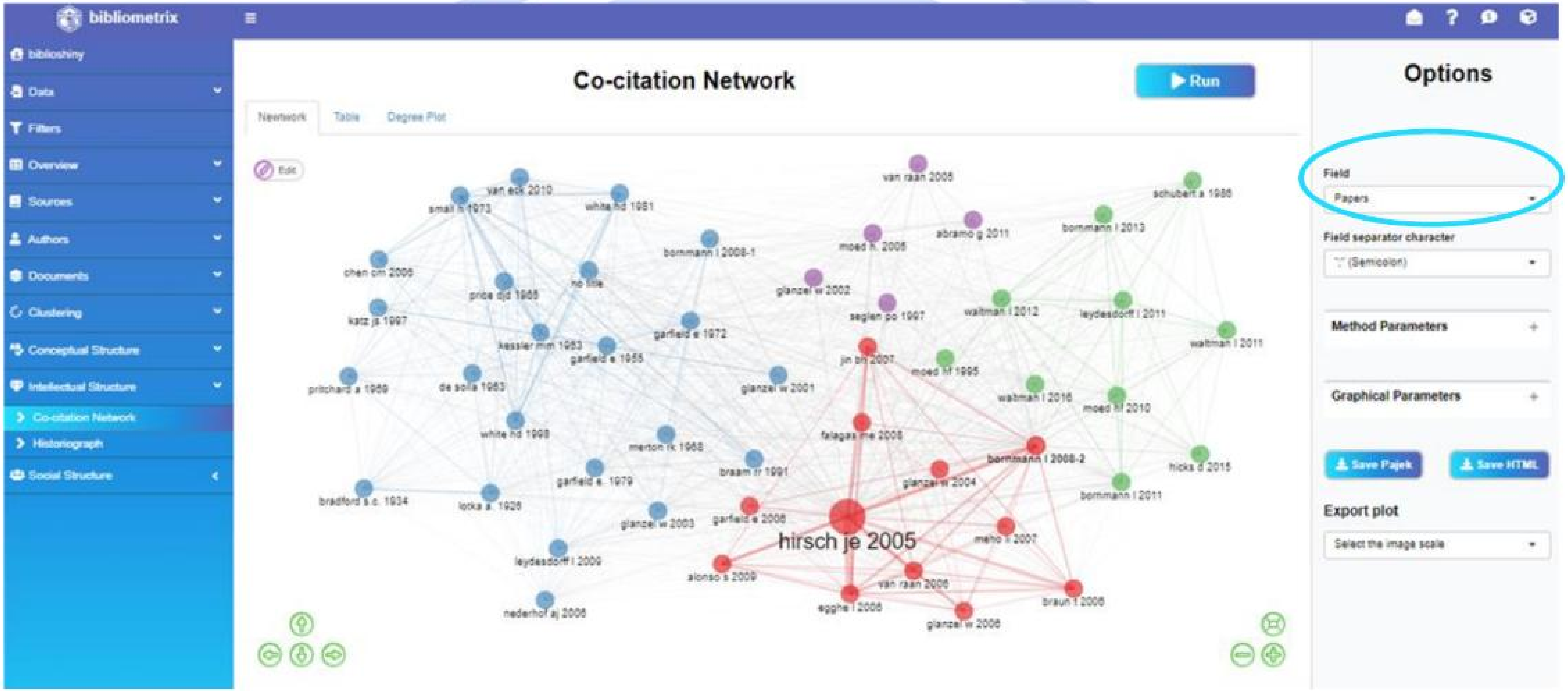




Intellectual Structure Tab

Co-citation network

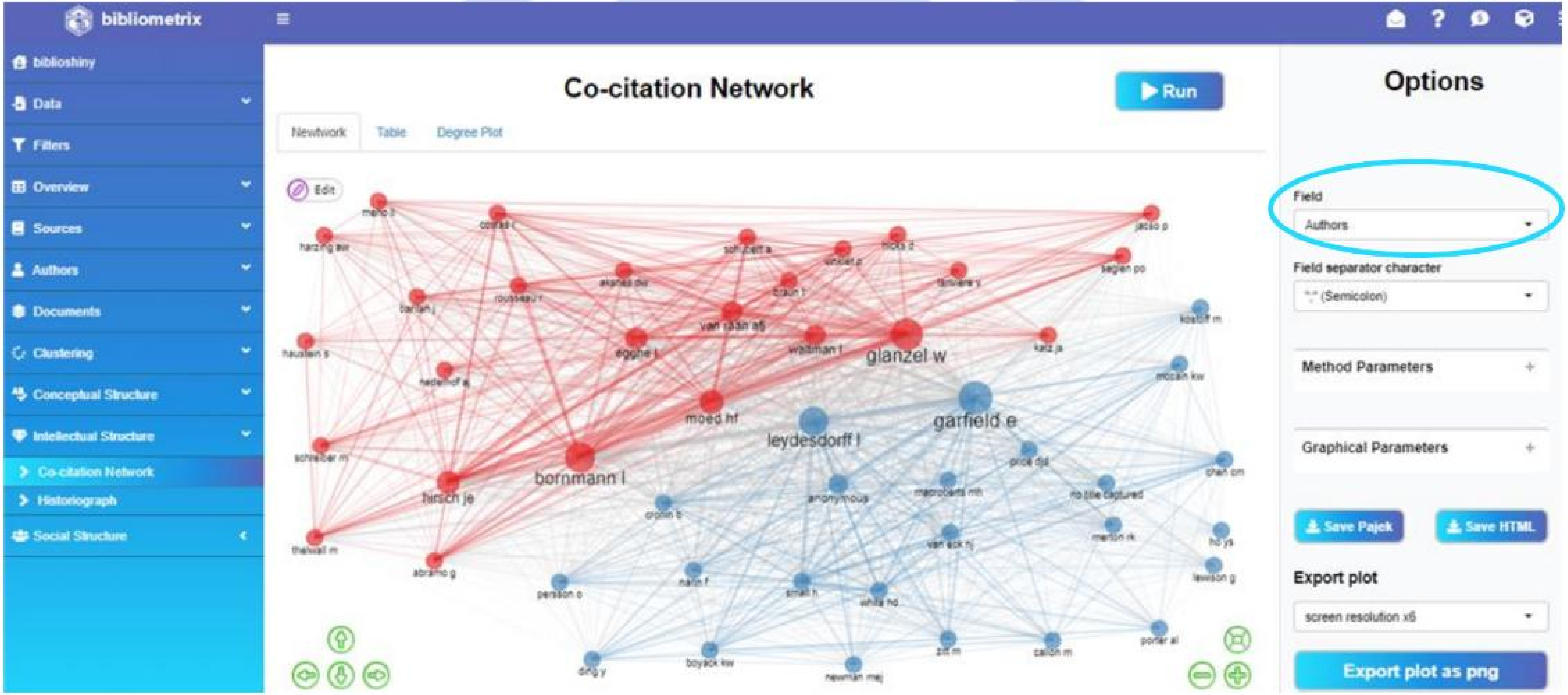
Co-citation network



Intellectual Structure Tab

Co-citation network

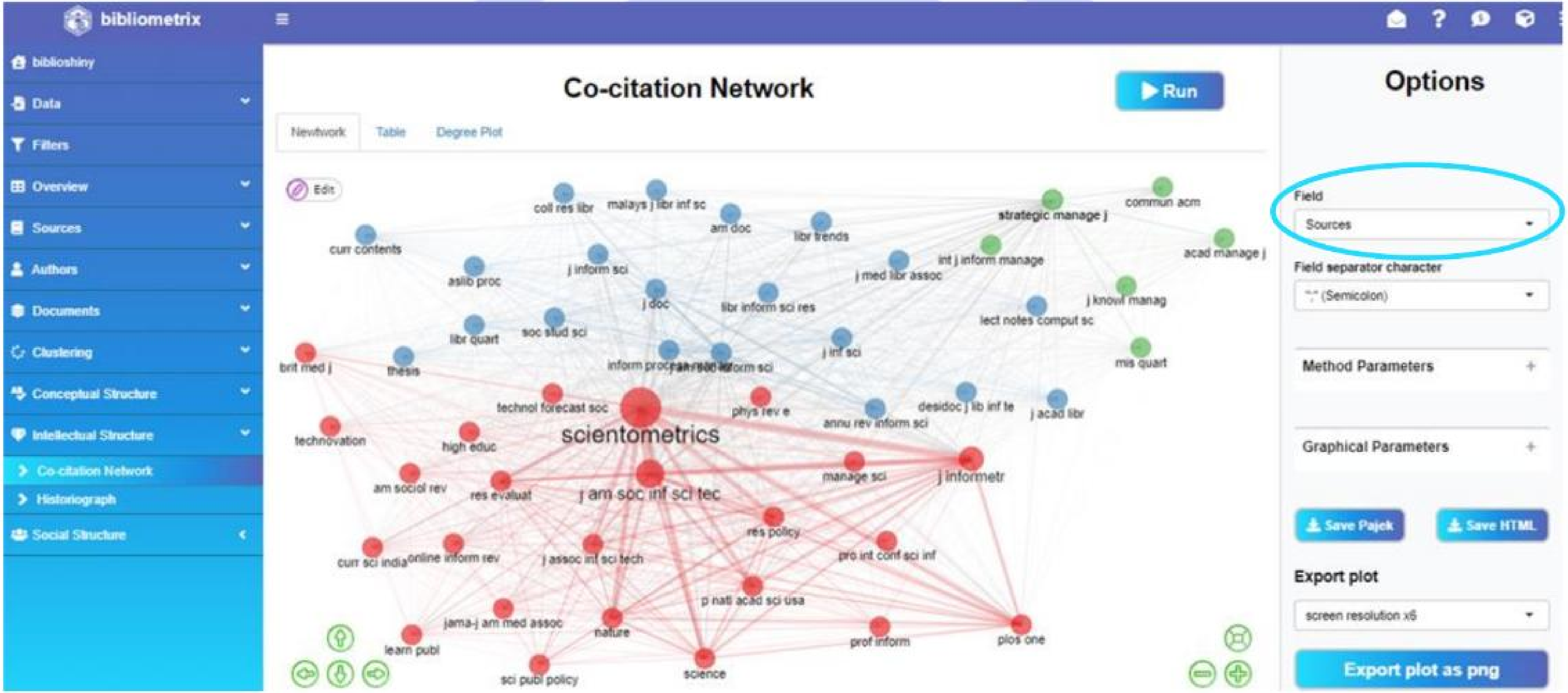
Co-citation network



Intellectual Structure Tab

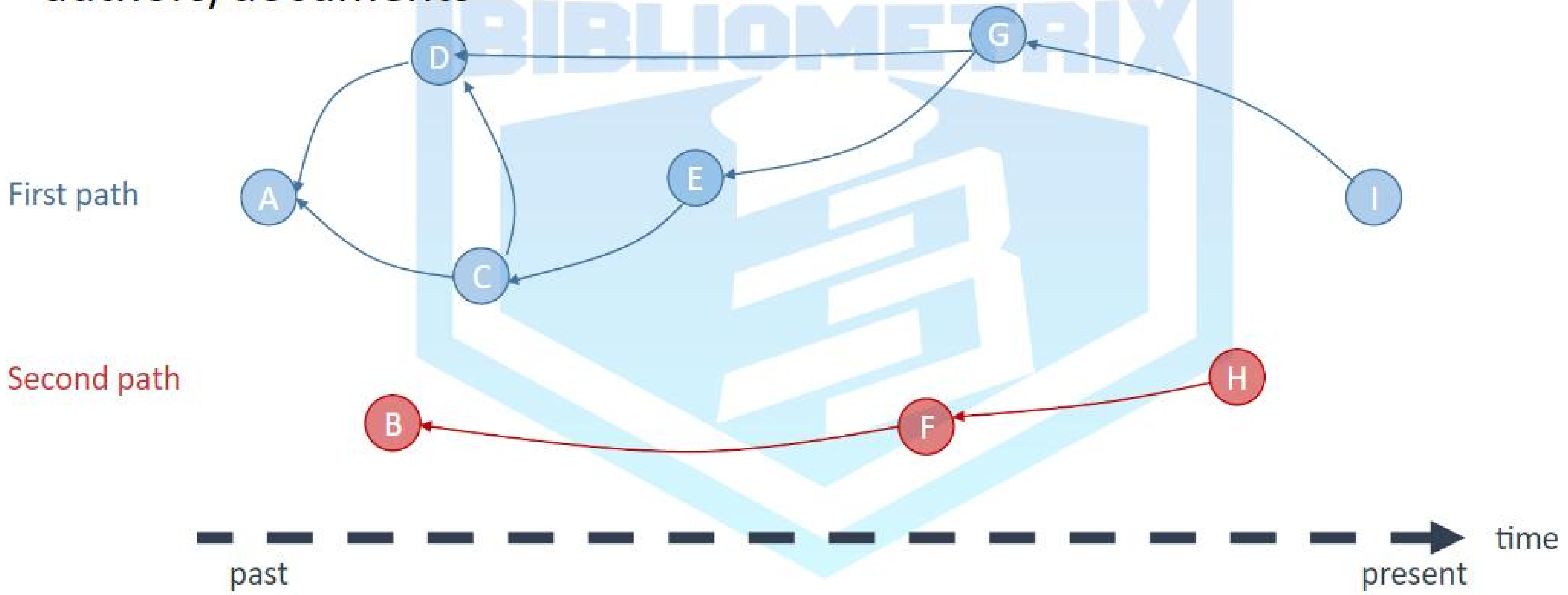
Co-citation network

Co-citation network



Historiographic mapping

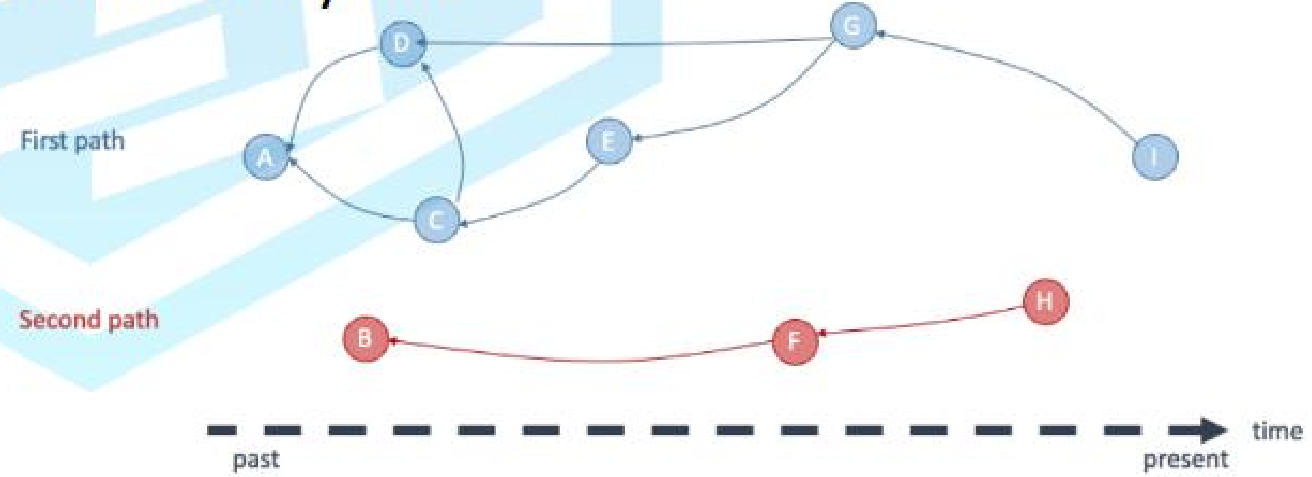
Each historical path identifies a research topic and its core authors/documents



Historiographic mapping

Some basic concepts about the historiograph:

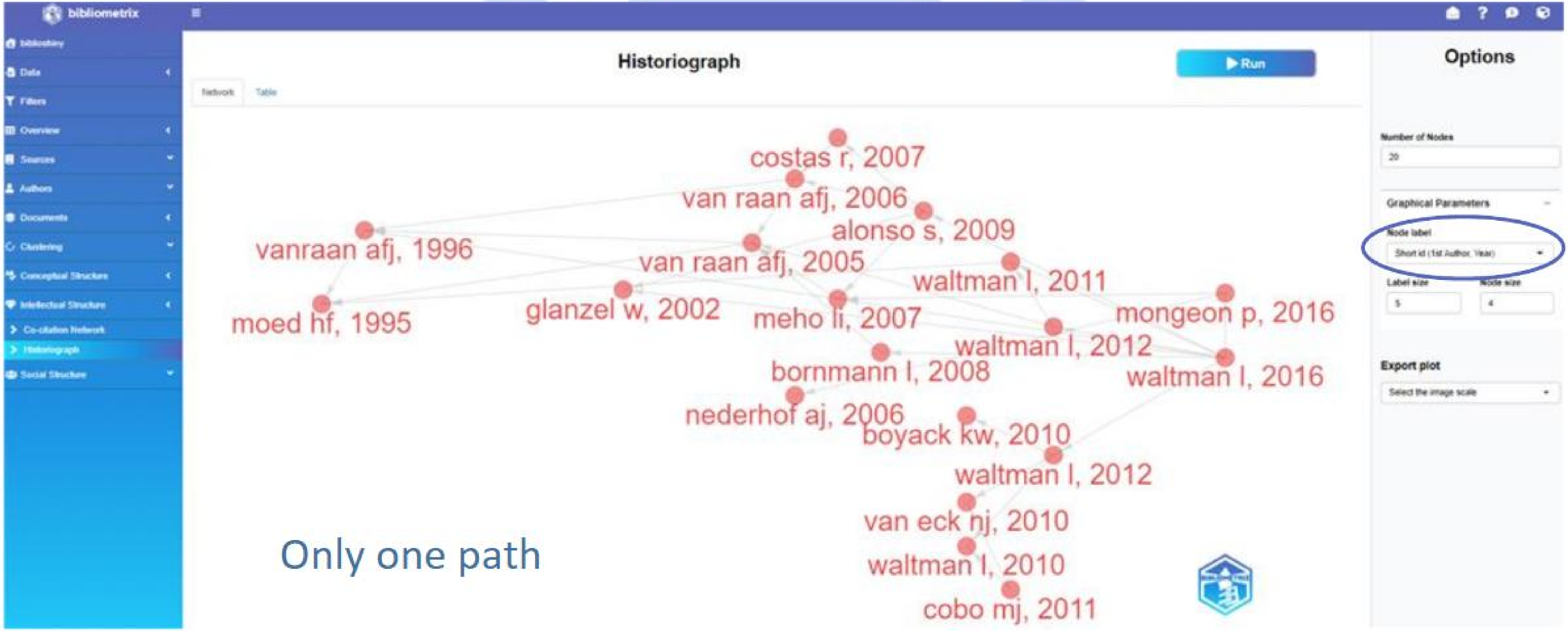
- Each node represents a document (included in the analyzed collection) cited by other documents
- Each edge represents a direct citation (e.g. D cited A; G cited D; etc.)
- Nodes and Edges are plotted on an oriented graph where the horizontal axis represents the publication years



Intellectual Structure Tab

Historiograph

Historiographic mapping



Only one path

Intellectual Structure Tab

Historiograph

Historiographic mapping

Only one path

Intellectual Structure Tab

Historiograph

Historiographic mapping

Authors' keywords

Keywords Plus

Intellectual Structure Tab

Historiograph

Historiographic mapping

Local citations

Global citations

Paper	Title	Author_Keywords	KeywordsPlus	DOI	Year	LCS	GCS	cluster
MOED HF, 1995, SCIENTOMETRICS DOI 10.1007/BF02017338	NEW BIBLIOMETRIC TOOLS FOR THE ASSESSMENT OF NATIONAL RESEARCH PERFORMANCE - DATABASE DESCRIPTION, OVERVIEW OF INDICATORS AND FIRST APPLICATIONS		SCIENTIFIC PUBLICATIONS; SUBFIELDS; JOURNALS	10.1007/BF02017338	1995	114	355	1
VAN RAAN AFJ, 2005, SCIENTOMETRICS DOI 10.1007/S11192-005-0008-6	FATAL ATTRACTION: CONCEPTUAL AND METHODOLOGICAL PROBLEMS IN THE RANKING OF UNIVERSITIES BY BIBLIOMETRIC METHODS		INTERNATIONAL COMPARISONS; IMPACT-FACTORS; SCIENCE; INDICATORS; COVERAGE	10.1007/s11192-005-0008-6	2005	98	450	1
VAN RAAN AFJ, 2006, SCIENTOMETRICS DOI 10.1556/SCIENT.67.2006.3.10	COMPARISON OF THE HIRSCH-INDEX WITH STANDARD BIBLIOMETRIC INDICATORS AND WITH PEER JUDGMENT FOR 147 CHEMISTRY RESEARCH GROUPS		RANKING	10.1556/Scient.67.2006.3.10	2006	147	405	1
MEHO LI, 2007, J AM SOC INF SCI TEC DOI 10.1002/ASI.20677	IMPACT OF DATA SOURCES ON CITATION COUNTS AND RANKINGS OF LIS FACULTY: WEB OF SCIENCE VERSUS SCOPUS AND GOOGLE SCHOLAR		BIBLIOMETRIC METHODS; INFORMATION-SCIENCE; H-INDEX; COMMUNICATION; PRODUCTIVITY; PERFORMANCE; INDICATORS	10.1002/asi.20677	2007	121	652	1
BORNMANN L, 2008, J DOC DOI 10.1108/00220410810844150	WHAT DO CITATION COUNTS MEASURE? A REVIEW OF STUDIES ON CITING BEHAVIOR	REFERENCE SERVICES; BIBLIOGRAPHIC SYSTEMS	ASSESSMENT EXERCISE RATINGS; CITED OLD PAPERS; 27 SCIENCE AREAS; SOCIAL-SCIENCES; BIBLIOMETRIC INDICATORS; CUMULATIVE ADVANTAGE; SCIENTOMETRIC WEIGHT; CONTEXT ANALYSIS; NORMATIVE THEORY; SELF-CITATION	10.1108/00220410810844150	2008	131	712	1
ALONSO S, 2009, J INFORMETR DOI 10.1016/J.JOI.2009.04.001	H-INDEX: A REVIEW FOCUSED IN ITS VARIANTS, COMPUTATION AND STANDARDIZATION FOR DIFFERENT SCIENTIFIC FIELDS	H-INDEX; BIBLIOMETRIC INDICATORS	HIRSCH-INDEX; CITATION ANALYSIS; SELF-CITATION; IMPACT; RANKING; INDICATORS; SCIENCE; SCOPUS; RESEARCHERS; WEB	10.1016/j.joi.2009.04.001	2009	97	476	1
WALTMAN L, 2011, J INFORMETR DOI 10.1016/J.JOI.2010.08.001	TOWARDS A NEW CROWN INDICATOR: SOME THEORETICAL CONSIDERATIONS	BIBLIOMETRIC INDICATOR; CONSISTENCY; CROWN INDICATOR; NORMALIZATION	RELATIVE INDICATORS; IMPACT; CHARTS	10.1016/j.joi.2010.08.001	2011	90	262	1
WALTMAN L, 2016, J INFORMETR DOI 10.1016/J.JOI.2016.02.007	A REVIEW OF THE LITERATURE ON CITATION IMPACT INDICATORS	BIBLIOGRAPHIC DATABASE; CITATION ANALYSIS; CITATION IMPACT INDICATOR; COUNTING METHOD; NORMALIZATION	AUTHOR SELF-CITATIONS; HIGHLY CITED PAPERS; SUB-FIELD NORMALIZATION; GOOGLE SCHOLAR COVERAGE; H-INDEX; JOURNAL IMPACT; SOCIAL-SCIENCES; BIBLIOMETRIC INDICATORS; RESEARCH PERFORMANCE; SCIENTIFIC IMPACT	10.1016/j.joi.2016.02.007	2016	103	443	1

Knowledge Synthesis

Social Structure

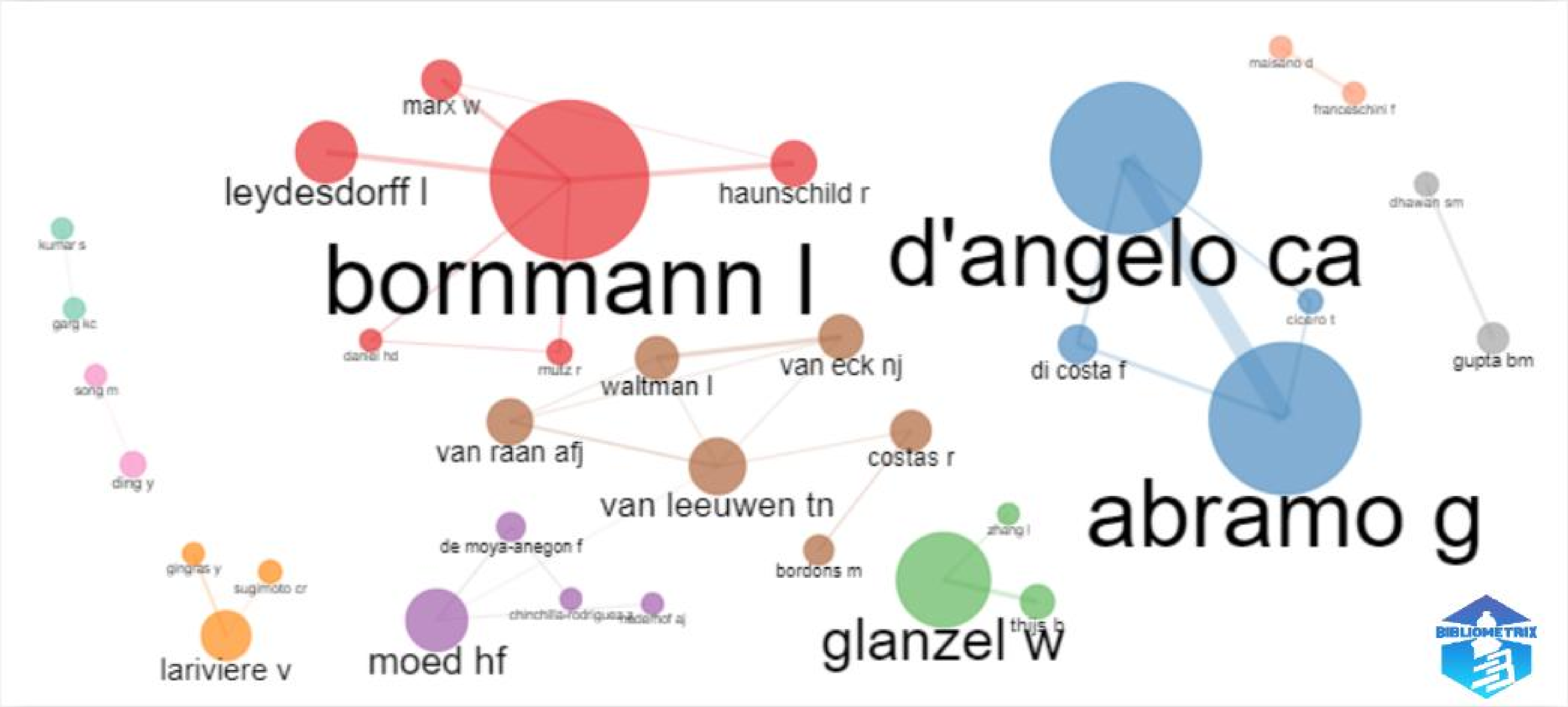
Social Structures

- **Social structure** shows how authors or institutions relate to others in the field of scientific research.
- The most common kind of social structure is **co-authorship network** (Peters et al. 1991)
- With co-authorship networks can be discovered, for example, groups of regular authors, influent authors, hidden communities of authors, relevant institutions in a specific research field, etc.

Social Structure Tab

Collaboration Network

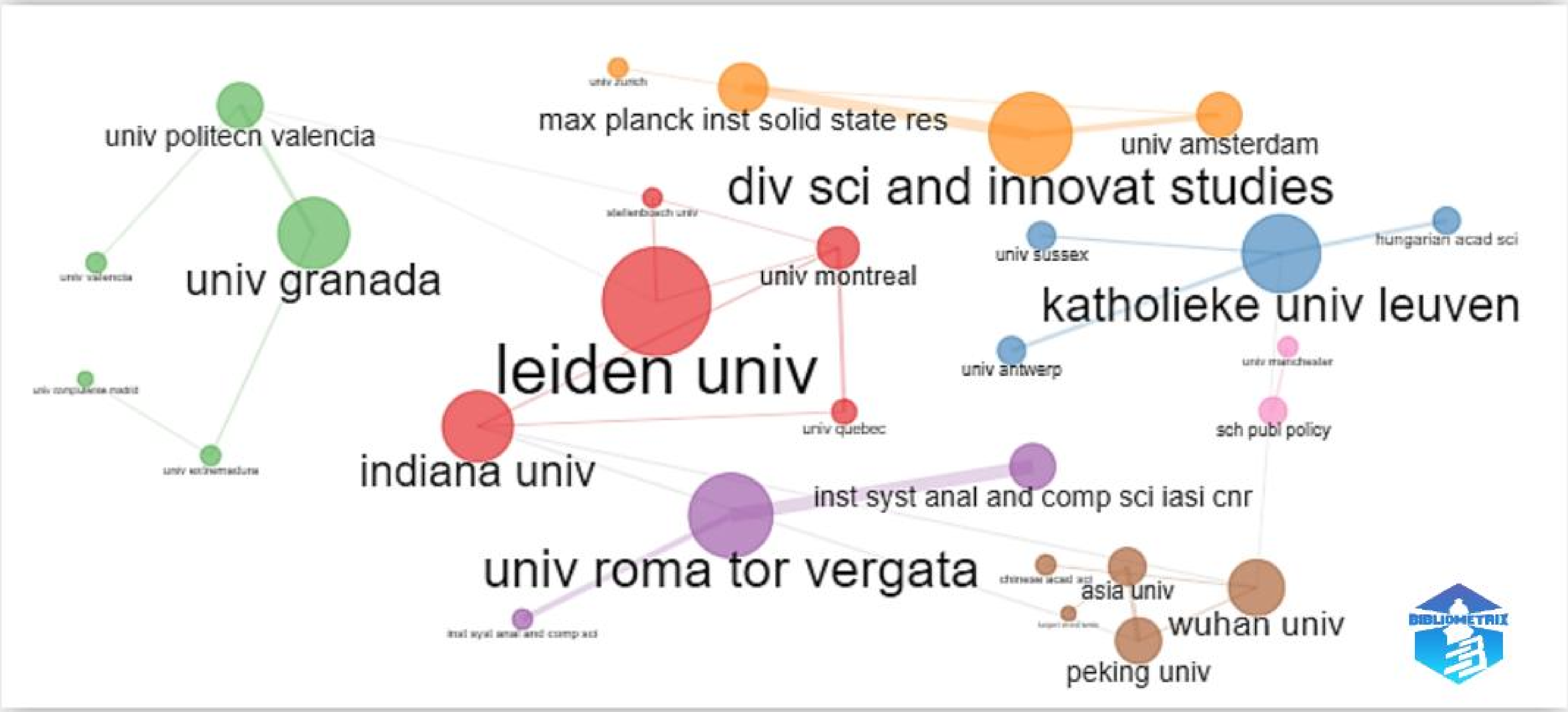
Author collaboration



Social Structure Tab

Collaboration Network

Institutions collaboration



Social Structure Tab

Collaboration World Map

Country collaboration

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