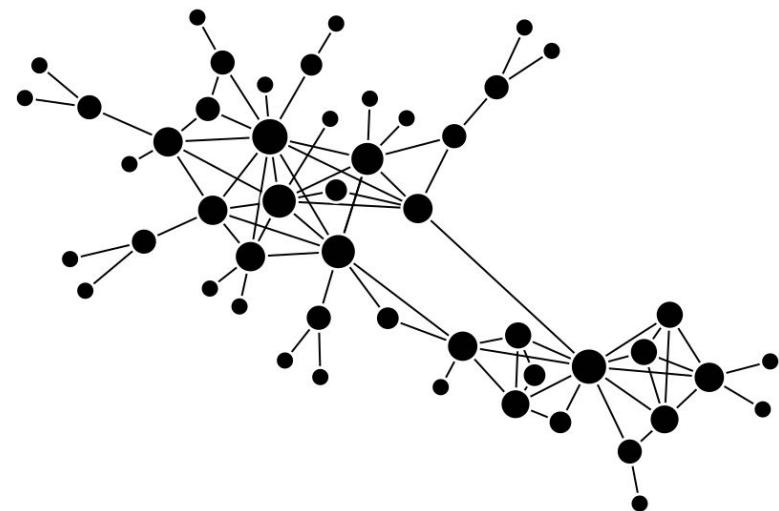


Translating Networks

Assessing correspondence
between network visualisation
and analytics

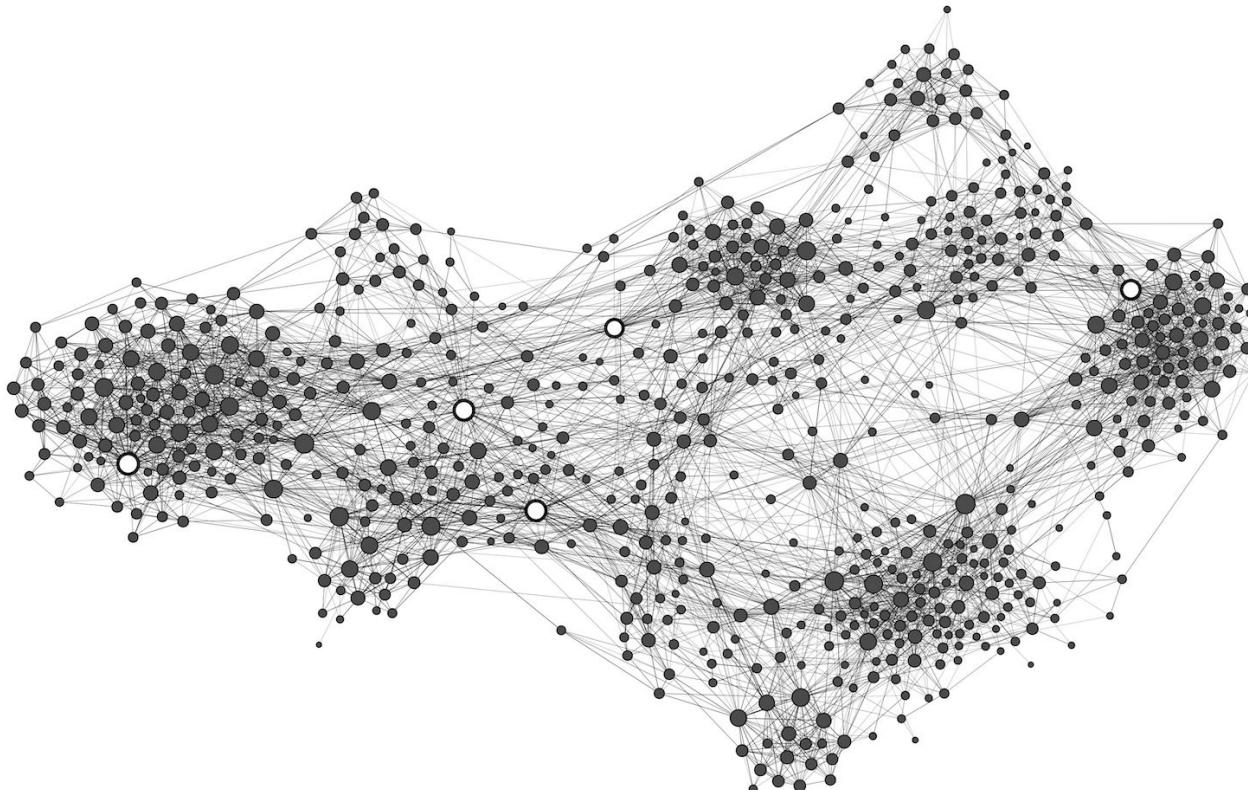
Martin GRANDJEAN, University of Lausanne (Switzerland)
Mathieu JACOMY, Aalborg University (Denmark)



TRANSLATING NETWORKS

Aim

How do we “read” networks and how do we “translate” them into the language of humanities research?



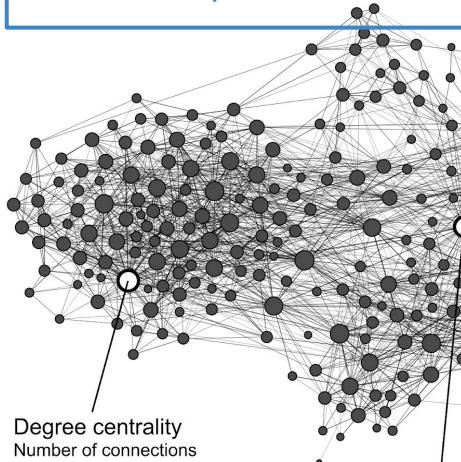
TRANSLATING NETWORKS

Aim

How do we “read” networks and how do we “translate” them into the language of humanities research?

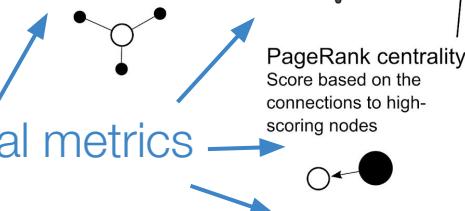
Visual analysis
Overall organisation
Clusters (highly connected)
Sparse areas (less connected)
Cliques and strongly connected components
Disconnected components
Center/Periphery

1. Visual patterns



Degree centrality
Number of connections

3. Local metrics



Betweenness centrality
Number of times being on the shortest path between two other nodes

Closeness centrality
Average length of the shortest path to all other nodes



Number of Triangles
Number of times connecting two nodes that are also connected together

2. Global metrics

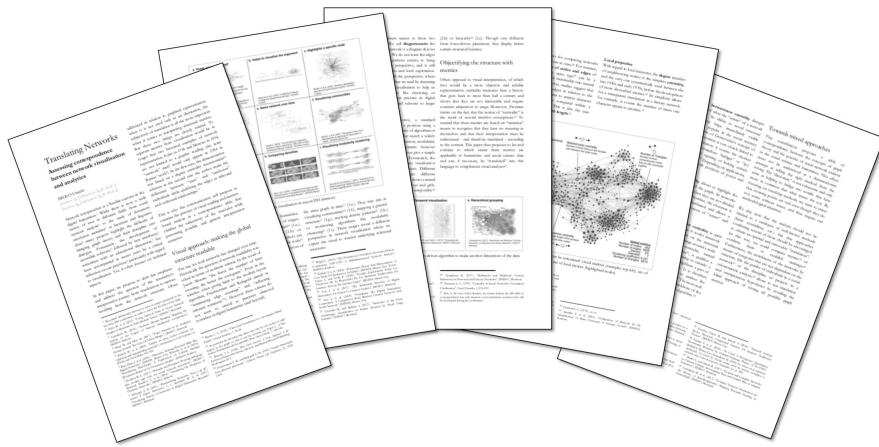
Global metrics
Number of nodes: 652
Number of edges: 5629
Density: 2%
Diameter: 7

TRANSLATING NETWORKS

Aim

How do we “read” networks and how do we “translate” them into the language of humanities research?

⇒ Building a correspondence **table** that clarifies the subjectivity of the translation while presenting possible and generic interpretation scenarios based on a wide literature review.

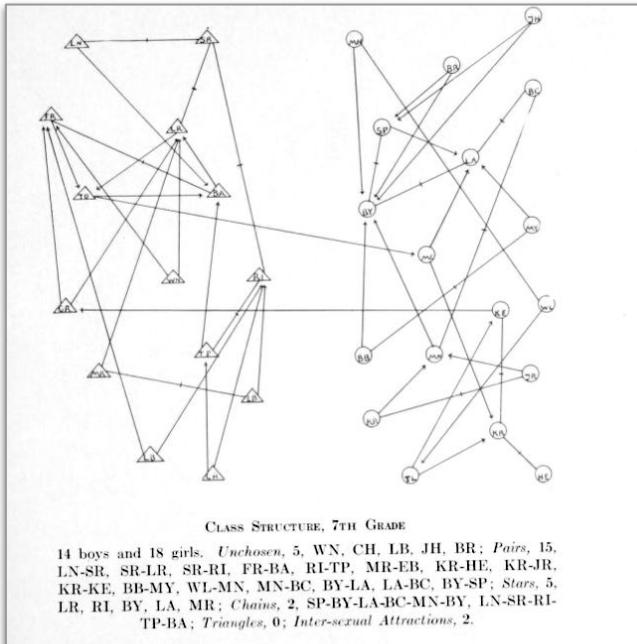


Network visual and topological patterns			
NETWORK	THEORETICAL ANALYSIS	COMPUTATIONAL ANALYSIS	INTERPRETATIVE PERSPECTIVE
Graphs and their properties	Graph theory	Theoretical analysis	Structural interpretation
Complex networks	Complexity	Computational analysis	Complexity interpretation
Dense clusters	Clustering	Computational analysis	Clustering interpretation
Small-world networks	Small-worldness	Computational analysis	Small-worldness interpretation
Modular structures	Modularity	Computational analysis	Modularity interpretation
Hierarchical structures	Hierarchy	Computational analysis	Hierarchy interpretation
Centralized structures	Centralization	Computational analysis	Centralization interpretation
Precise hierarchies	Precise hierarchy	Computational analysis	Precise hierarchy interpretation
Local clustering	Local clustering	Computational analysis	Local clustering interpretation
Network motifs	Network motifs	Computational analysis	Network motifs interpretation
Adversaries	Adversaries	Computational analysis	Adversaries interpretation
Opinion	Opinion	Computational analysis	Opinion interpretation

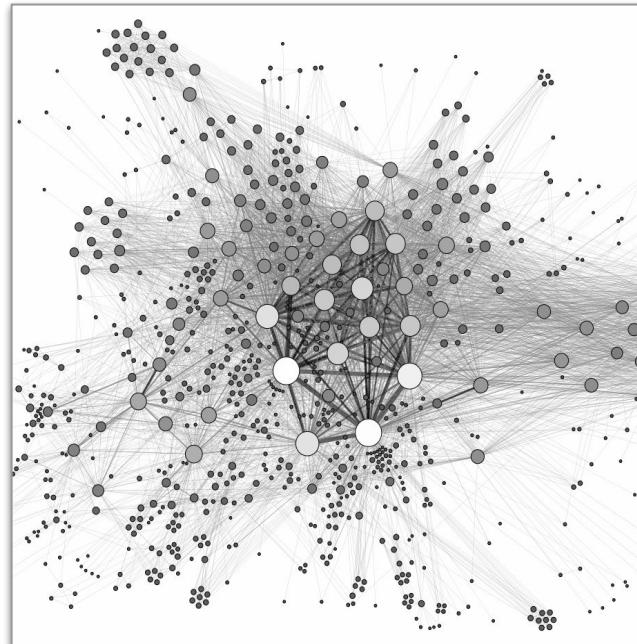
TRANSLATING NETWORKS

Visual approach

Diagrammatic



Topological



Visual approach

Examples from recent DH conferences

a. Image speaks for itself



"El resultado es una imagen real de lo que son hoy en día las Humanidades Digitales a nivel global"

Pino-Díaz J. and Fiomonte D. (2018). "La Geopolítica De Las Humanidades Digitales: Un Caso De Estudio De DH2017 Montréal", DH2018, Mexico City.

b. Helps to visualise the argument

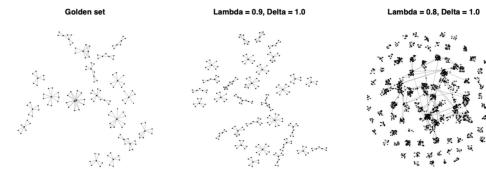


Figure 4. Largest components of social networks from golden set (left-most) and from disambiguated datasets (center and right-most).

Colavizza G. et al. (2016). "A Method for Record Linkage with Sparse Historical Data", DH2016, Krakow.

c. Highlights a specific node



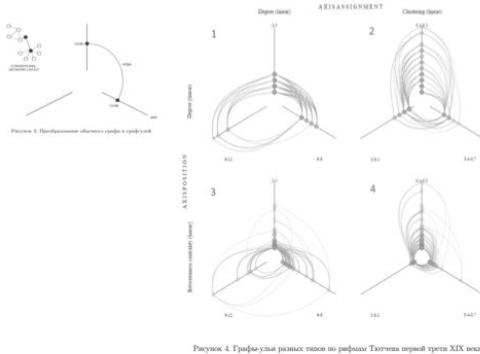
Moretti G. et al. (2016). "Building Large Persons Networks to Explore Digital Corpora", DH2016, Krakow.

TRANSLATING NETWORKS

Visual approach

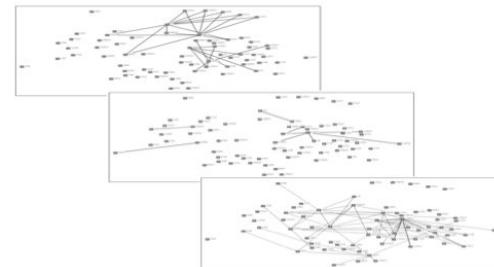
Examples from recent DH conferences

d. Comparing layouts



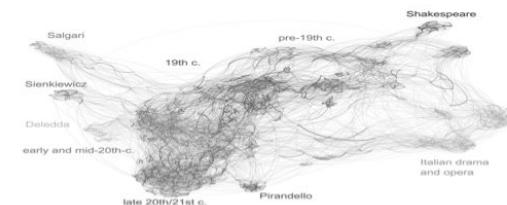
Sozina O. (2016). "Complex Networks-Based Approach to Russian Rhyme History Description: Linguostatistics and Database", DH2016, Krakow.

e. Same network over time



Wright C. (2016). "The Formation of Australia's Economic History Community, 1950–1970: A Multi-dimensional Network Analysis", DH2016, Krakow.

f. Visualising communities



Rybicki J. et al. (2018). "Polysystem Theory And Macroanalysis. A Case Study Of Sienkiewicz In Italian", DH2018, Mexico City.

TRANSLATING NETWORKS

Visual approach

Examples from recent DH conferences

g. Image presented as a map

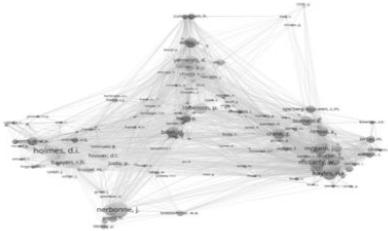
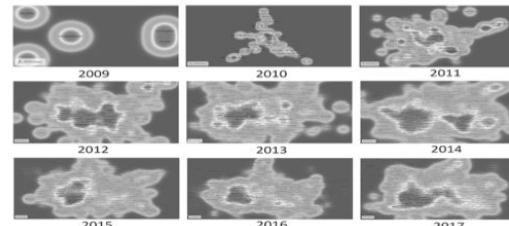


Figure 2. The provisional ACA network map in DH, data from journals *CHum*, *LLC/DSH*, and *DHQ*, 1966-2016, created using VOSviewer

Gao J. et al. (2017). "The Intellectual Structure of Digital Humanities: An Author Co-Citation Analysis", DH2017, Montréal.

h. Comparing densities



Gao J. et al. (2018). "Visualising The Digital Humanities Community: A Comparison Study Between Citation Network And Social Network", DH2018, Mexico.

i. Visualising modularity clustering

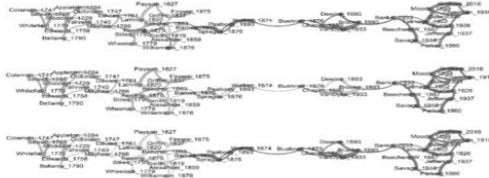


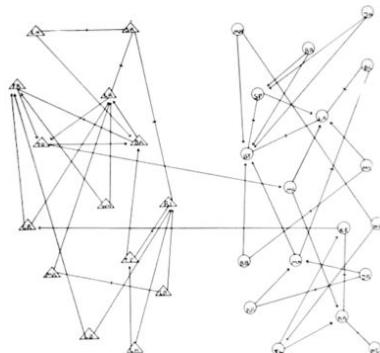
Figure 1. The four Great Awakenings in traditional classification (top); divided by modularity into 3 (center) and 4 (bottom) groups.

Choinski M. and Rybicki I. (2017). "Networks of the Great Awakenings: Classification of Puritan Sermons by Word Usage Statistics", DH2017, Montréal.

Visual approach

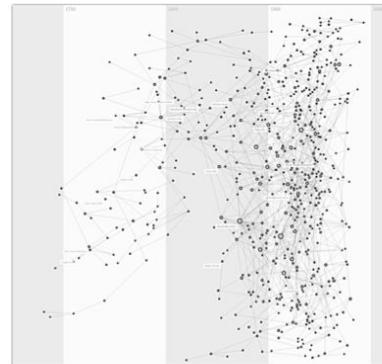
Making non-relational dimensions visually explicit

a. Grouping by category



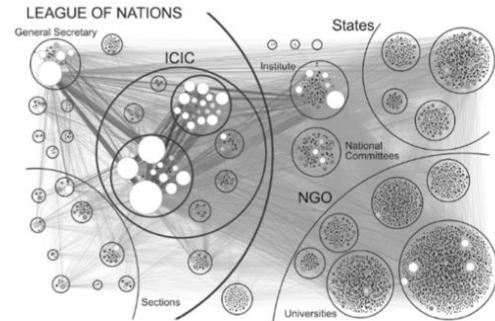
Moreno J. L. (1934). *Who Shall Survive? A New Approach to the Problem of Human Interrelations*, Nervous and Mental Disease Publishing, Washington D.C.

b. Temporal visualisation



Jänicke S. and Focht J. (2017). "Untangling the Social Network of Musicians", DH2017, Montreal.

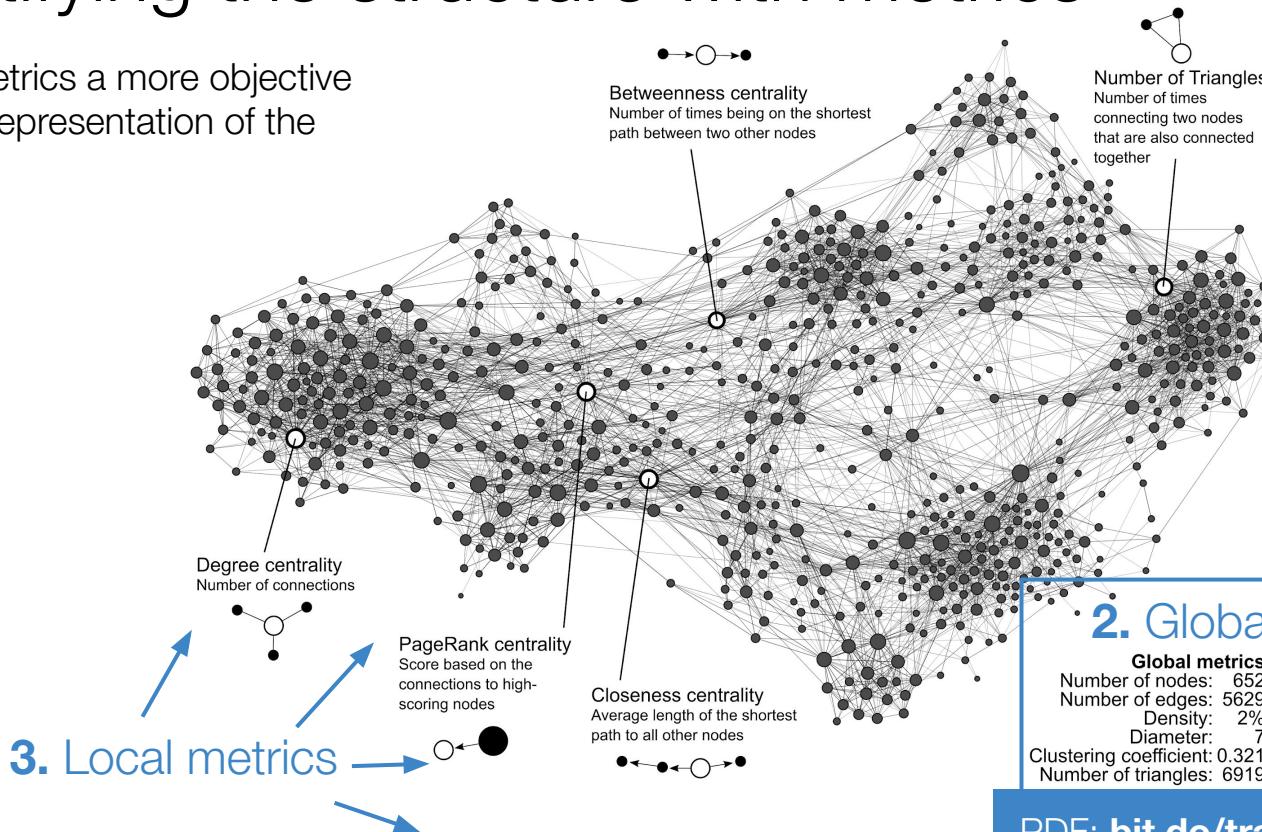
c. Hierarchical grouping



Grandjean M. (2017). "Multimode and Multilevel: Vertical Dimension in Historical and Literary Networks", DH2017, Montreal.

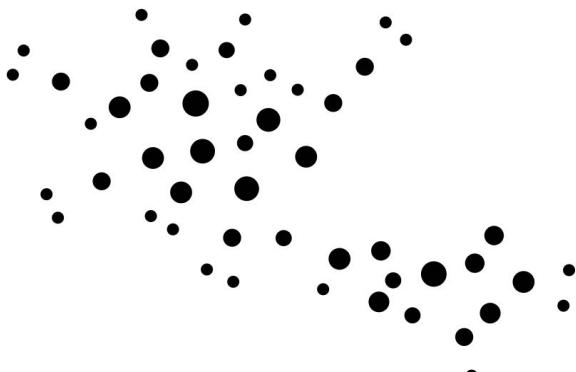
Objectifying the structure with metrics

Are graph metrics a more objective and reliable representation of the structure?



Global properties

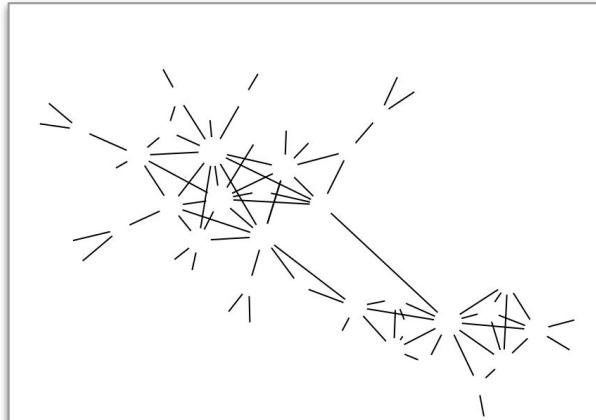
Analyze the **size** of the graph



NODES

Main “translation” equivalents:

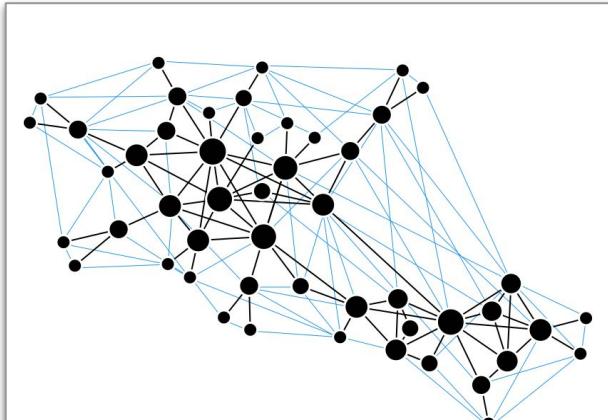
Size



EDGES

Main “translation” equivalents:

Size



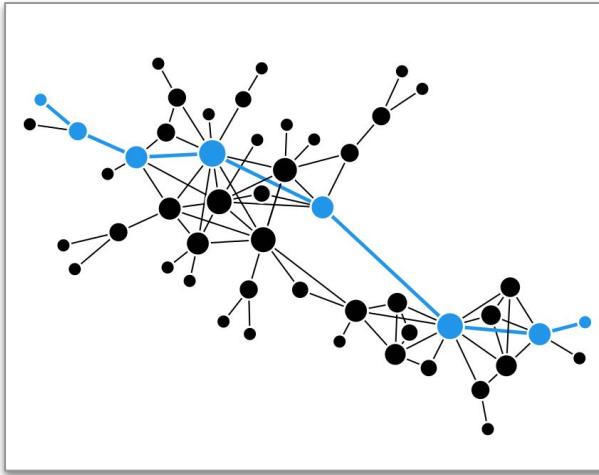
DENSITY

Main “translation” equivalents:

Complexity | Completeness

Global properties

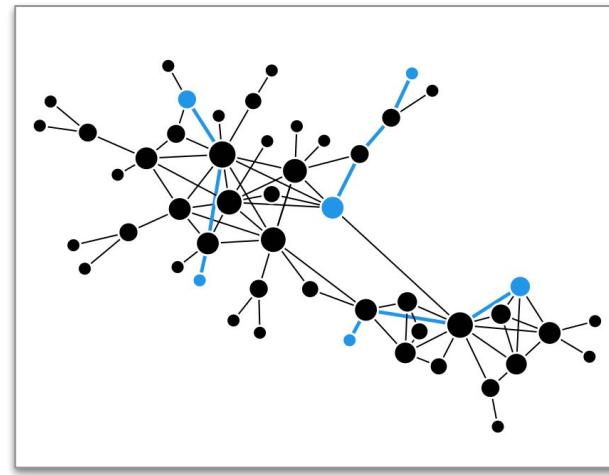
Analyze the **width** of the graph



DIAMETER

Main “translation” equivalents:

Size | Breadth | Width



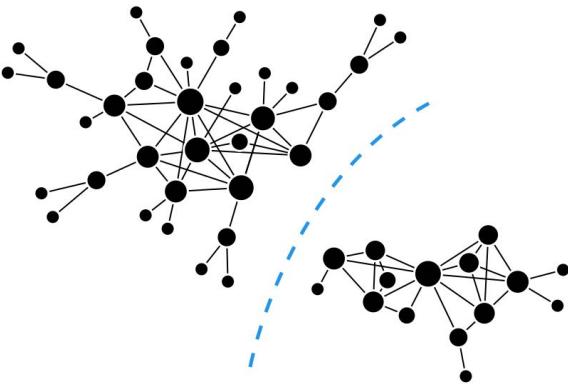
AVERAGE PATH LENGTH

Main “translation” equivalents:

Size | Width | Small world

Global properties

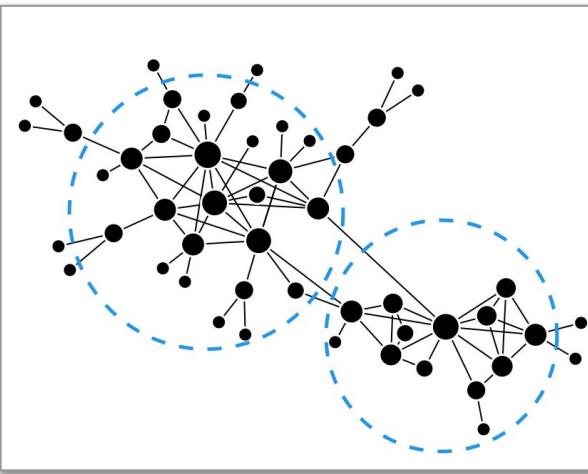
Analyze how the graph is **globally structured**



CONNECTEDNESS

Main “translation” equivalents:

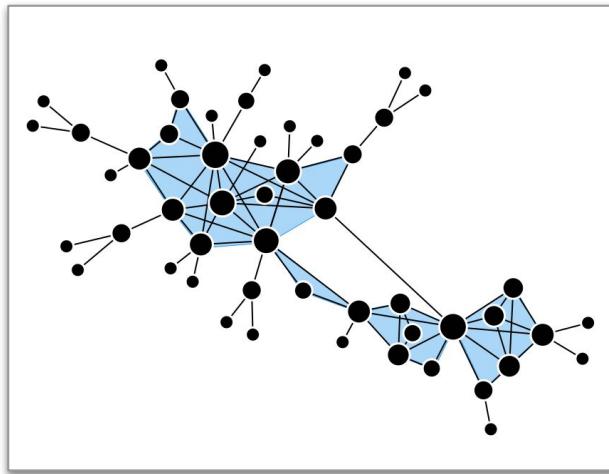
Continents | Archipelagos



CLUSTERS

Main “translation” equivalents:

Groups | Communities | Hubs



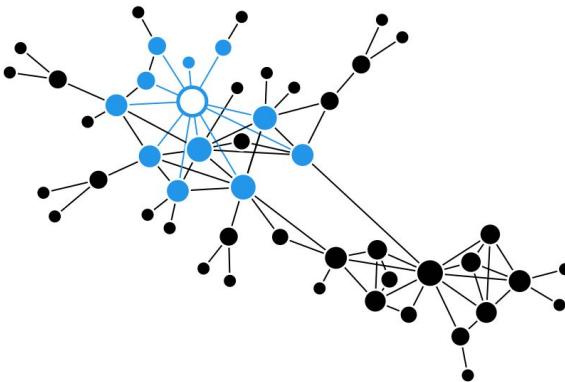
(GLOBAL) CLUSTERING COEF.

Main “translation” equivalents:

Entanglement | Intrication

Local properties

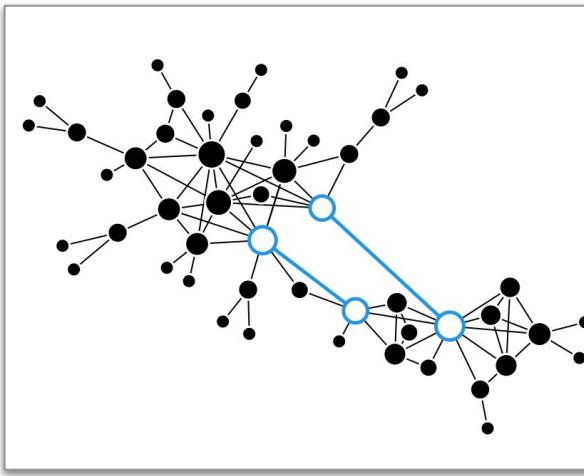
Analyze the **relation of a single node** to the rest of the graph.



DEGREE

Main “translation” equivalents:

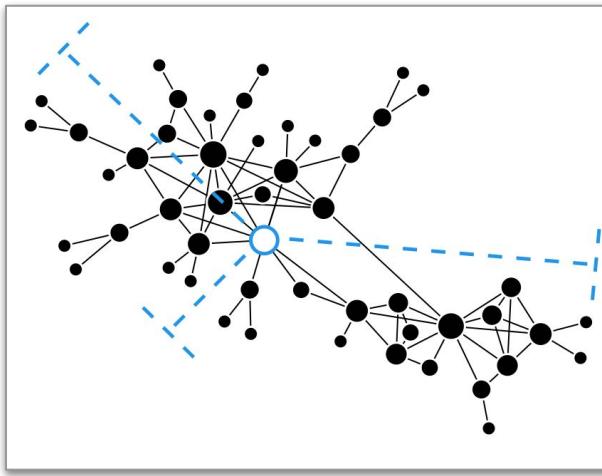
Connectivity | Neighbors



BETWEENNESS

Main “translation” equivalents:

**Bridge | Gateway | Broker |
Power | Vulnerability**



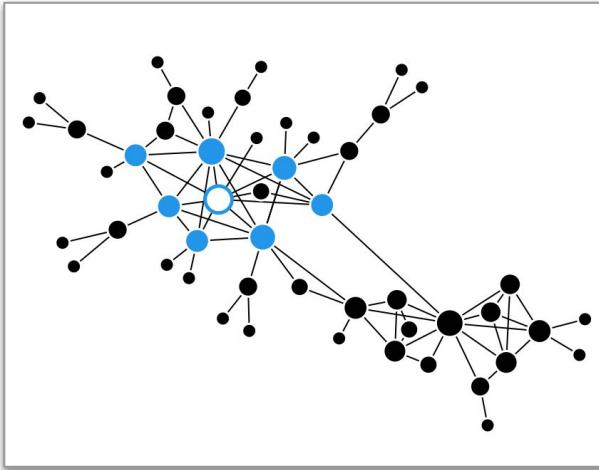
CLOSENESS

Main “translation” equivalents:

Center | Middle

Local properties

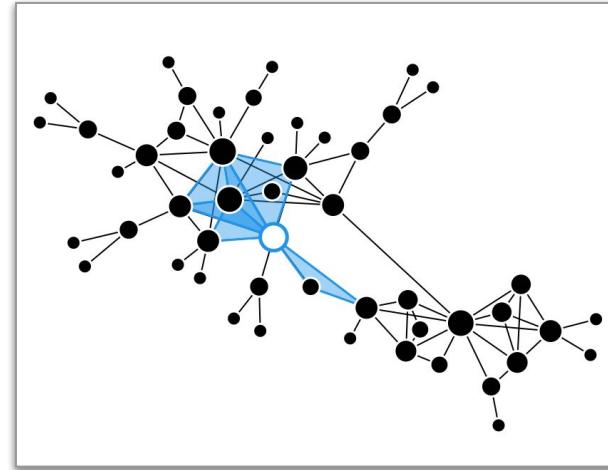
Analyze the **environment of a single node**.



EIGENVECTOR

Main “translation” equivalents:

Prestige | Authority | Influence



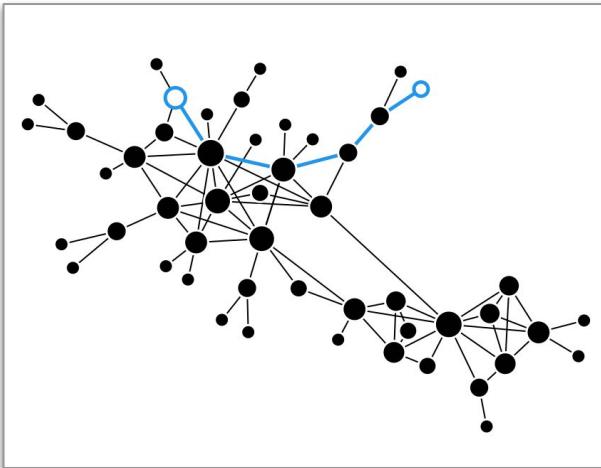
LOCAL CLUSTERING COEF.

Main “translation” equivalents:

Participation in a group

Local properties

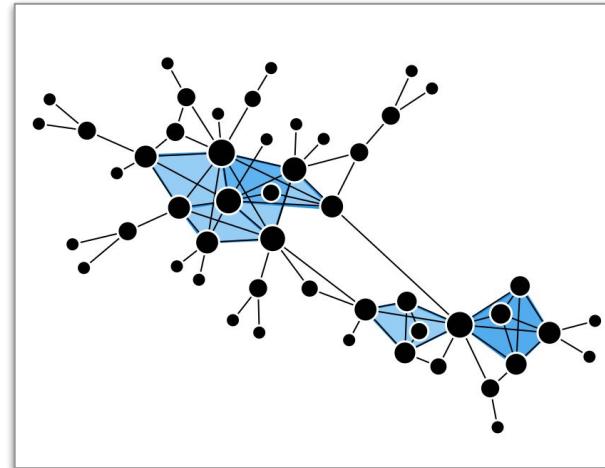
Search for a **specific feature**.



SHORTEST PATH

Main “translation” equivalents:

Distance



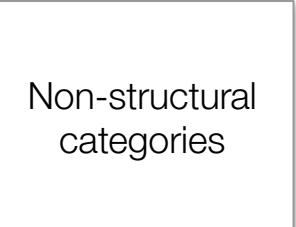
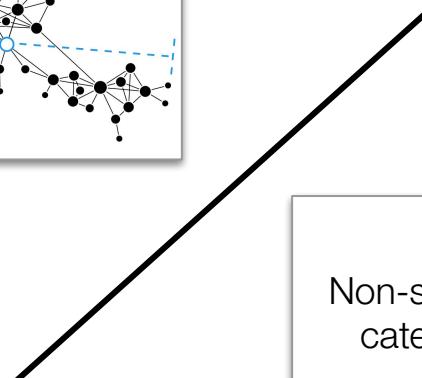
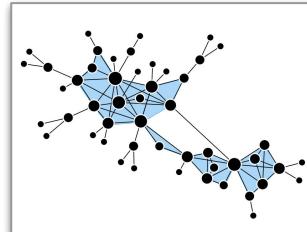
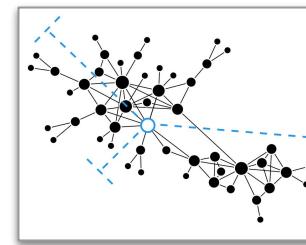
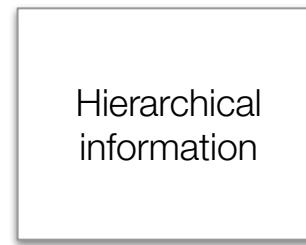
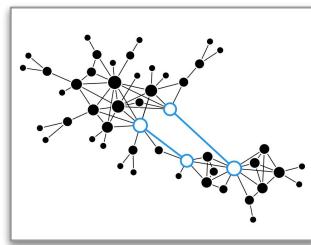
CLIQUEs

Main “translation” equivalents:

Communities | Neighborhoods

Toward mixed and enriched approaches

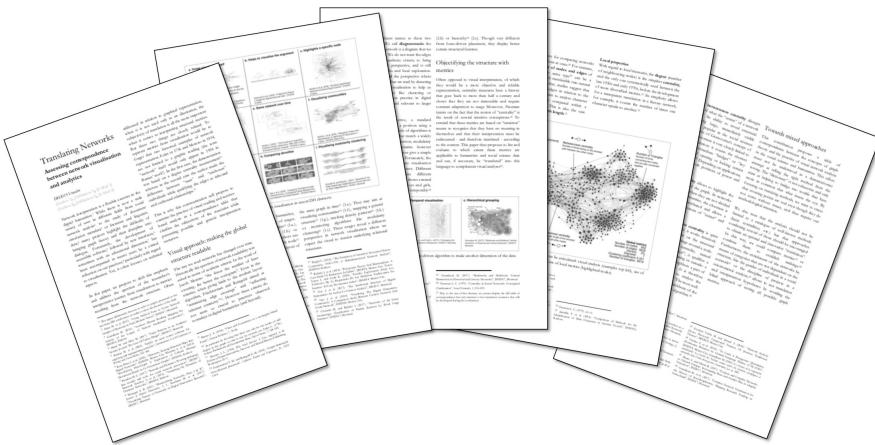
The previous table lists only the simplest concepts. But the analysis should not be limited to a catalogue of well-known methods (basic centralities, etc.) but that approaches combining several of those should be encouraged to obtain an optimal and innovative “translation”.



Next steps

How do we “read” networks and how do we “translate” them into the language of humanities research?

- ⇒ Discuss our practices in order to produce a catalogue that clarifies and fosters creativity.



Network visual and topological patterns				
NAME	THEORETICAL ANALYSIS	COMPUTATIONAL ANALYSIS	INTERPRETATIVE POTENTIALS	NAME
Graphs and nodes	Graphs are sets of nodes connected by edges. Nodes are the individual elements of the graph, and edges are the connections between them.	Graphs can be represented using various data structures, such as adjacency matrices or adjacency lists. Computational analysis often involves identifying specific subgraphs, such as cliques or clusters, and calculating metrics like centrality or degree distribution.	The interpretative potential of graphs and nodes lies in their ability to represent complex relationships and interactions. They can be used to analyze social networks, biological systems, or information flow in various domains.	Chains
Discrete structures	Discrete structures are sets of discrete elements that are not necessarily connected to each other. They can be represented as separate nodes or as separate components within a larger network.	Computational analysis of discrete structures often involves identifying distinct components and analyzing their properties. Interpretative potentials include understanding the relationships between different discrete entities and how they interact with the rest of the network.	Complex networks	
Bridges	Bridges are edges that connect two previously separate components of a network. They are crucial for maintaining connectivity in a network.	Computational analysis of bridges often involves identifying them and analyzing their impact on the network's structure. Interpretative potentials include understanding the role of bridges in maintaining network integrity and their potential for disrupting connectivity.	Centralized hubs	
Local clustering	Local clustering refers to the degree to which nodes in a network tend to form small, tightly-knit groups. It is often measured using metrics like the clustering coefficient.	Computational analysis of local clustering often involves calculating these metrics across the network. Interpretative potentials include understanding the degree of social cohesion or organizational structure within the network.	Precise fragments	
Community structure	Community structure refers to the presence of groups of nodes that are more densely connected to each other than to nodes outside the group. It is often identified using community detection algorithms.	Computational analysis of community structure often involves identifying communities and analyzing their properties. Interpretative potentials include understanding the functional or social significance of these communities within the network.	Linear paths	
Arrows	Arrows indicate the direction of flow or causality between nodes. They are often used in directed graphs to represent processes or relationships with a temporal or causal dimension.	Computational analysis of arrows often involves identifying directed paths and cycles. Interpretative potentials include understanding the flow of information or the sequence of events within the network.	Cycles	