

gesis

Leibniz-Institut
für Sozialwissenschaften



Social Network Analysis with Digital Behavioral Data

Meet the Experts! – GESIS online talks

Haiko Lietz • November 25, 2021

Speaker



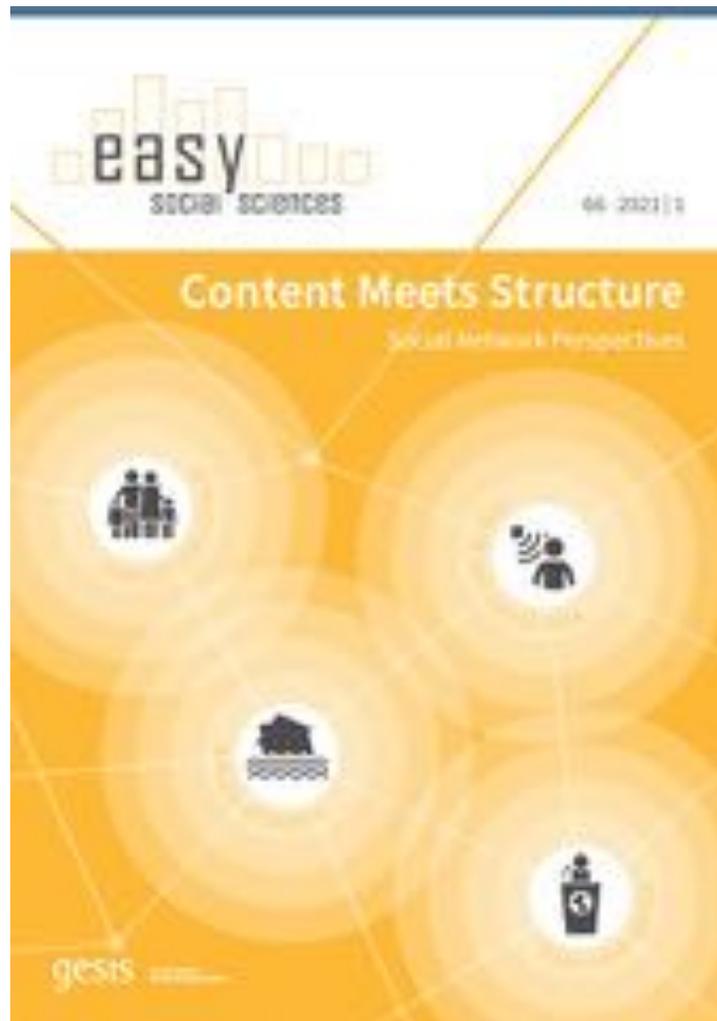
Dr. Haiko Lietz

- Postdoc in the team Digital Society Observatory, department of Computational Social Science at GESIS
- Ph.D. in sociology
- Social Network Science, Complexity Theory
- Contact: haiko.lietz@gesis.org

Logistics

- This talk will be recorded.
We do not record the Q&A session after the talk.
- Participants are muted during the session. Questions will be collected during presentation and answered after the talk.
- Please use the private chat function and send questions to the account "Q&A host (MTE)".
If you post in the general chat, your name and message will be visible to all participants. Of course, this is also possible; we kindly ask you to prefer the private chat to "Q&A host (MTE)" while the presentation is going on.
- Recording and slides will be made publicly available on the GESIS website and on our YouTube channel.

Paper accompanying this talk



Lietz, H., Schmitz, A., & Schaible, J. (2021)

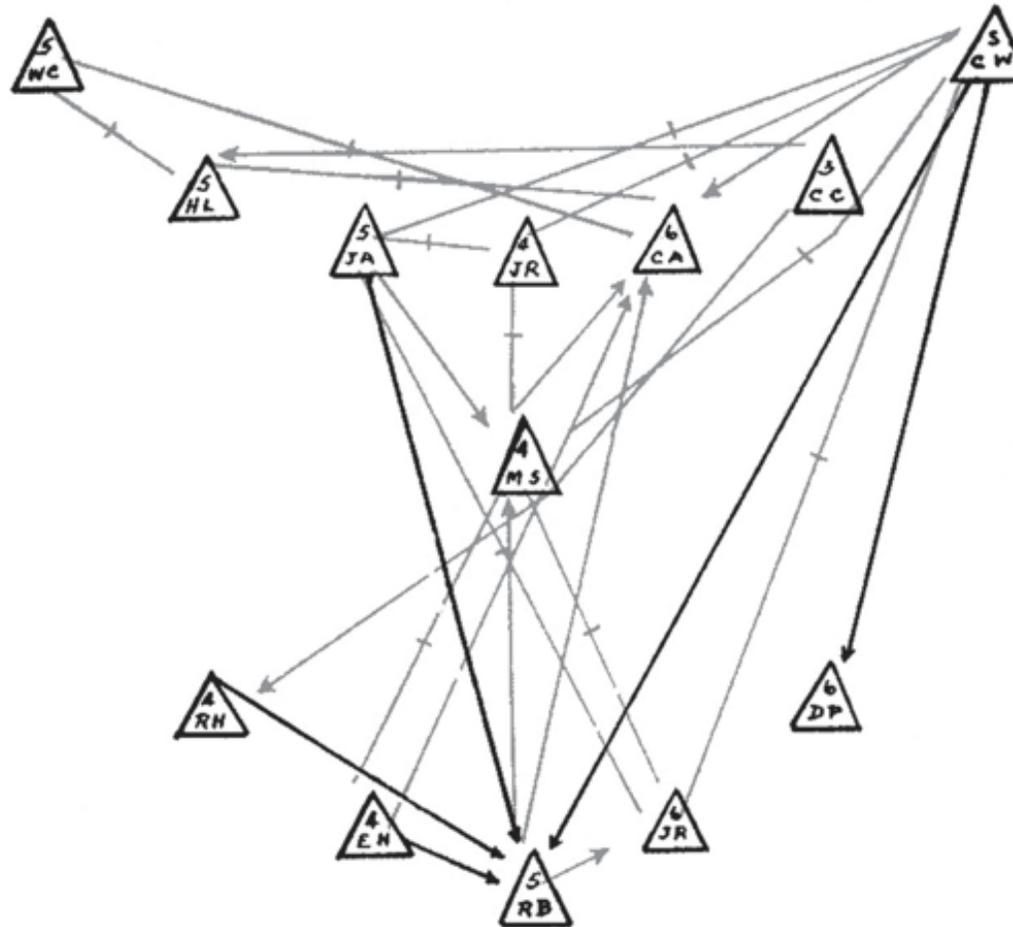
- Social Network Analysis with Digital Behavioral Data
- Analyse sozialer Netzwerke mit digitalen Verhaltensdaten

easy_social_sciences, 66

Agenda

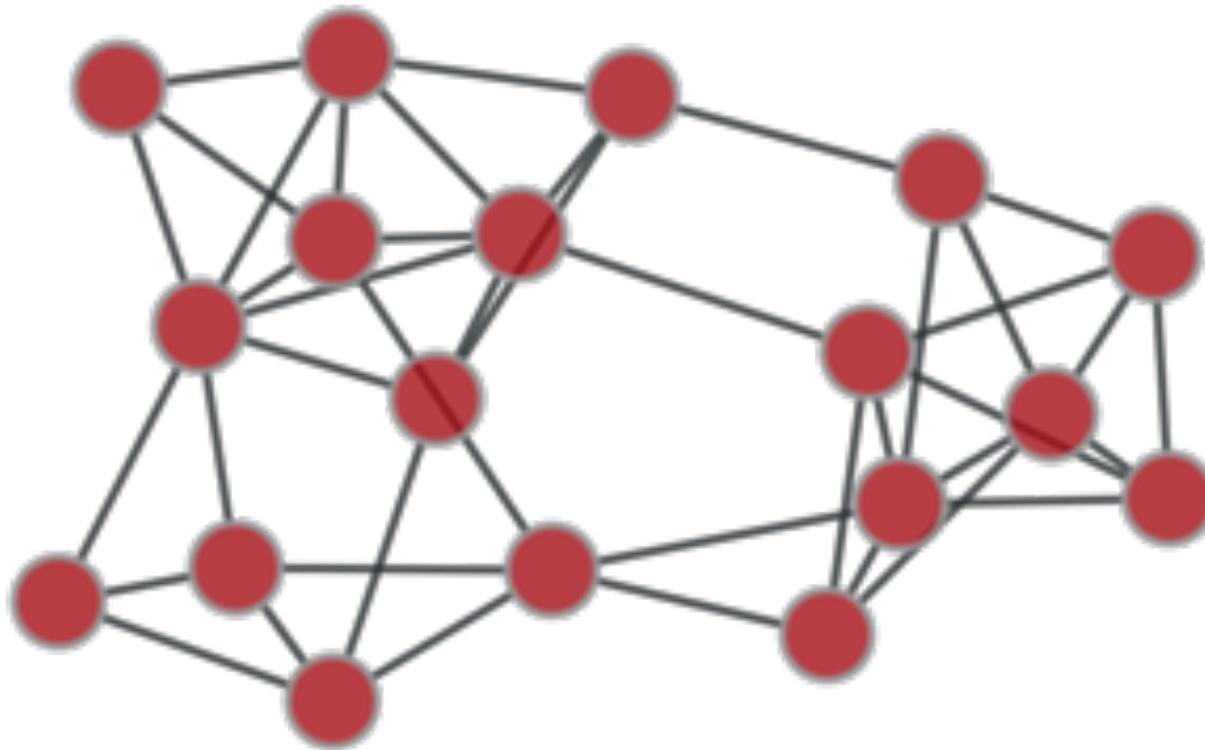
- Network Analysis
 - ▶ History
 - ▶ Philosophy
- Digital Behavioral Data
 - ▶ As transactions
 - ▶ Definition
 - ▶ 3 types
- Application scenarios
 - ▶ Socio-semantic analysis
 - ▶ Mechanistic modeling
- Challenges

Network analysis goes back to Moreno (1936)

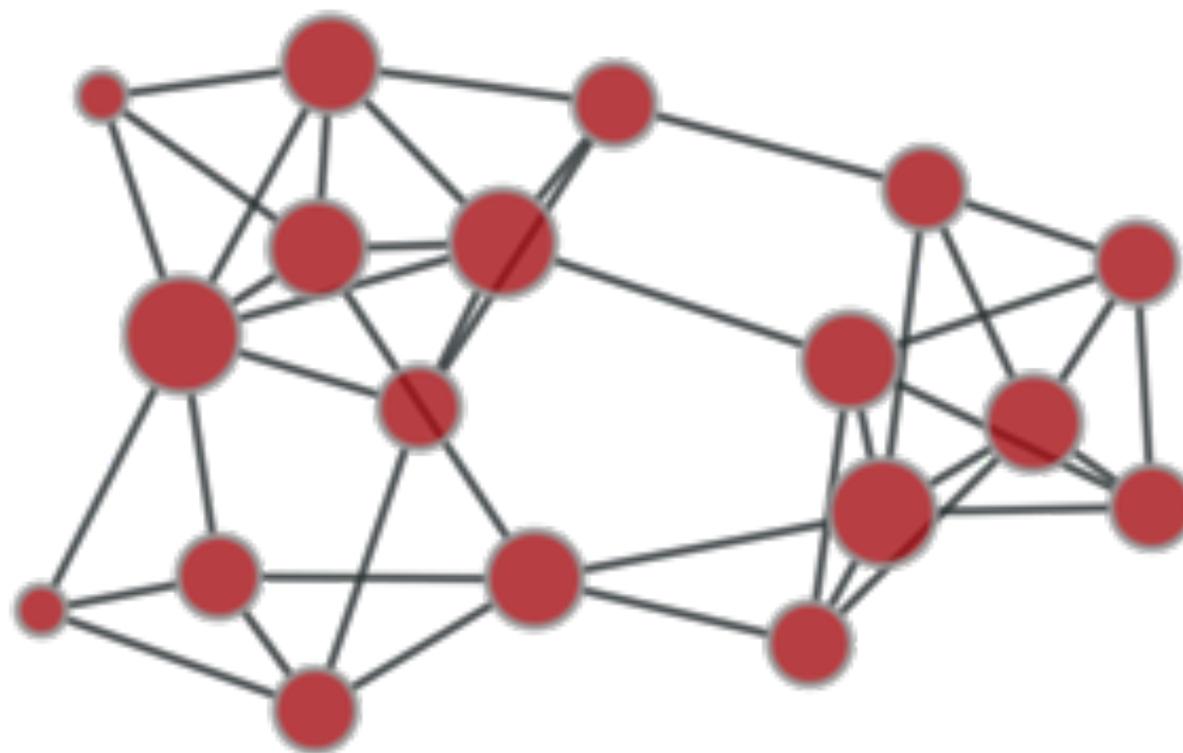


[1] Freeman, L. (2004). *The Development of Social Network Analysis*. Empirical Press.

Networks consist of nodes and edges

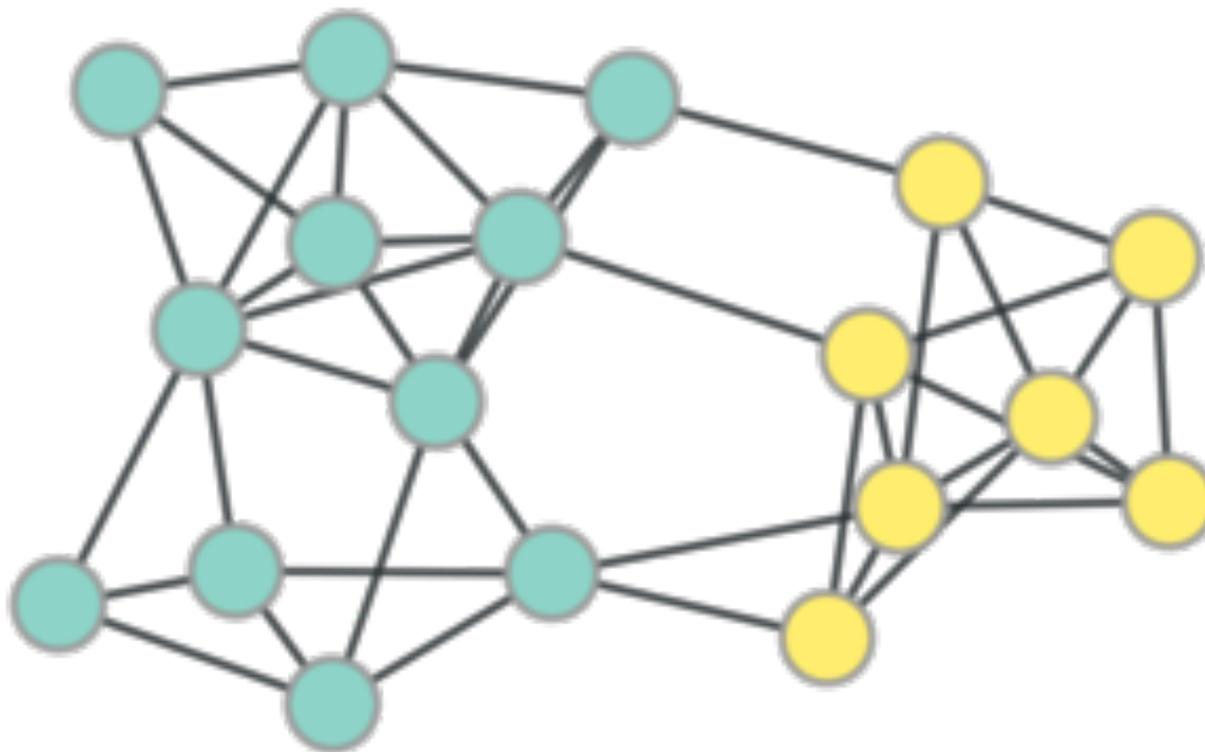


Micro (node) level analysis



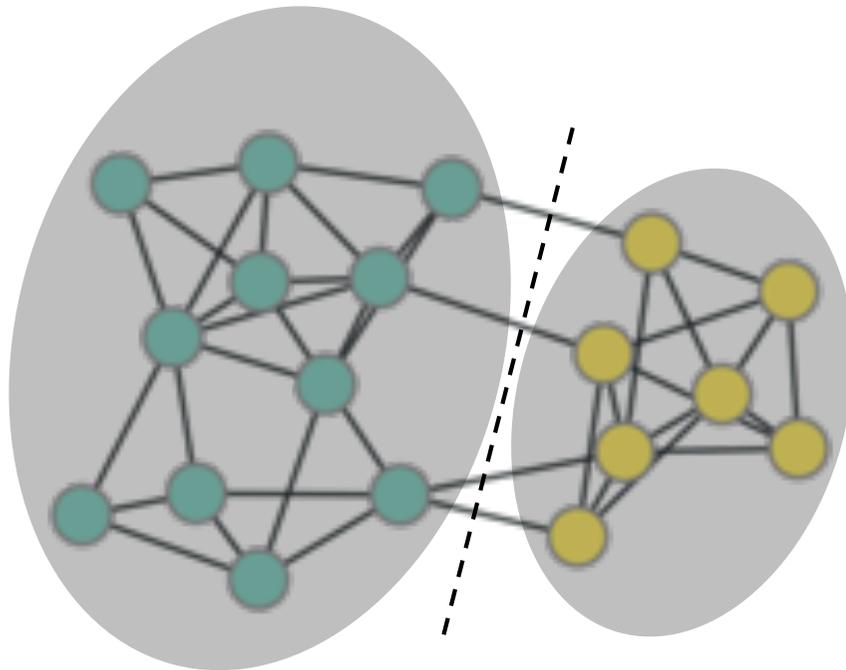
Node size depicts degree centrality

Macro (graph) level analysis



Node color depicts cluster belonging

Some insights in Social Network Analysis



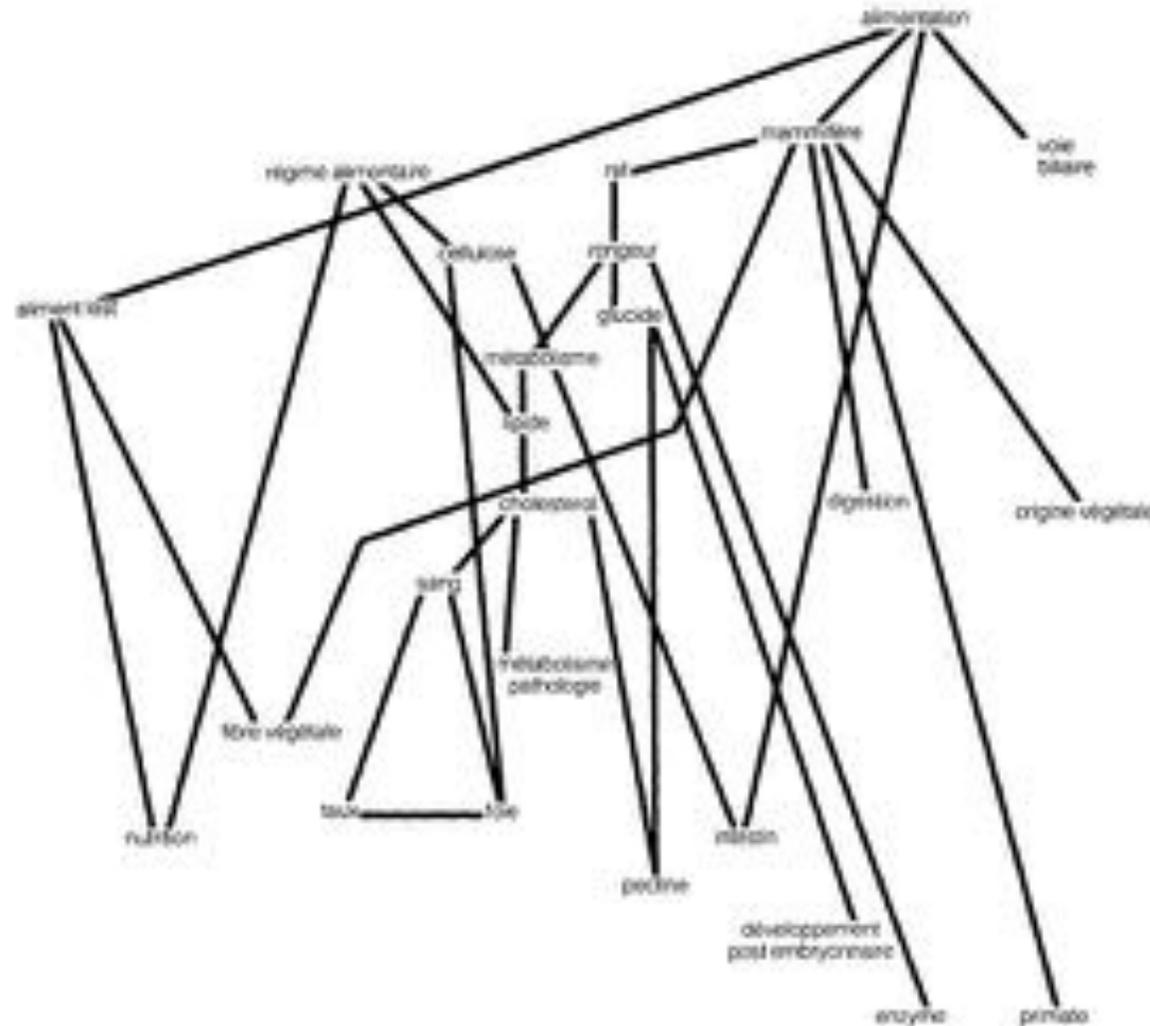
- Social networks consist of groups
- Often groups are homogeneous [2]
- There are structural holes between groups [3]
- Ties that bridge structural holes are sources of novelty [3,4]

[2] Kossinets, G. & Watts, D.J. (2009). *Am. J. Sociol.*, 115(2), 405–450.

[3] Burt, R.S. (1992). *Structural Holes*. Harvard University Press.

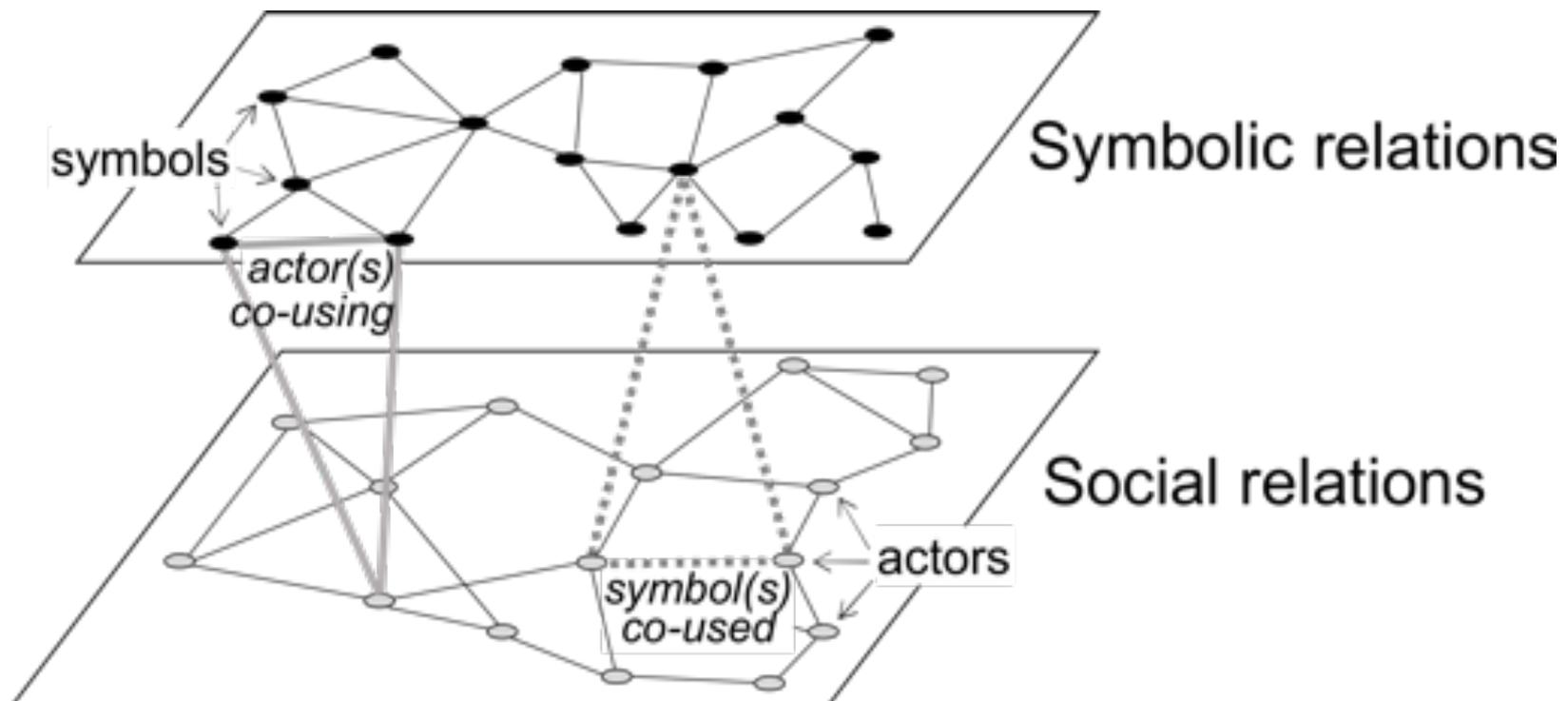
[4] Granovetter, M.S. (1973). *Am. J. Sociol.*, 78(6), 1360–1380.

Semantic networks emerged in the 80s

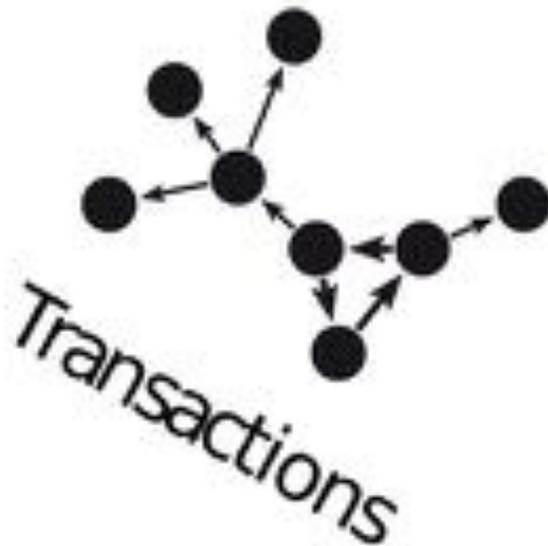


[5] Callon, M., et al. (1983). *Soc. Sci. Inf.*, 22(2), 191–235.

Socio-semantic networks emerged in the 90s



Relational epistemology



- Network analysis builds on full samples
 - Relations are units of observation
- Relations are *transactions* (as opposed to *selfactions* or *interactions*) [7]

Revolution in social science



[8] Watts, D.J. (2011). *Everything is Obvious*. Crown Business.

The „new telescope“ of social science



Digital
Behavioral
Data

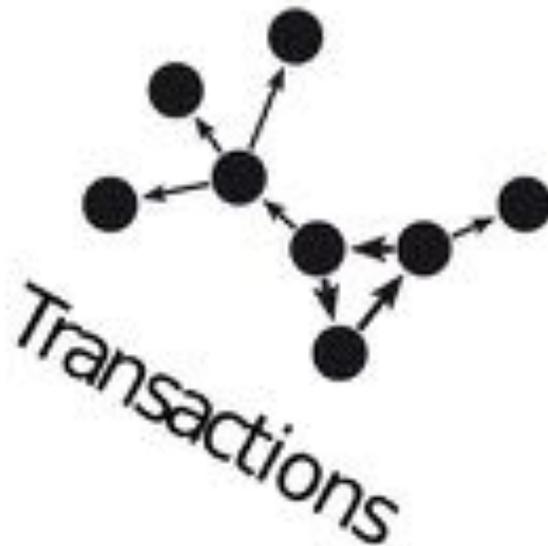
+



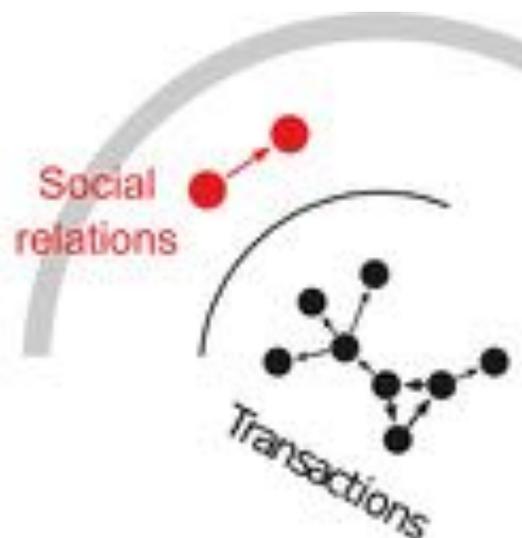
Hardware &
software to
analyze it

Digital Behavioral Data as transactions

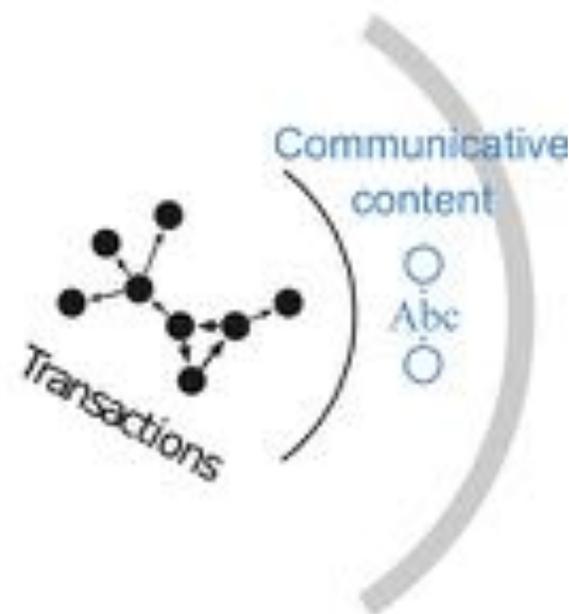
Digital Behavioral Data (DBD) are records of transactions [6]



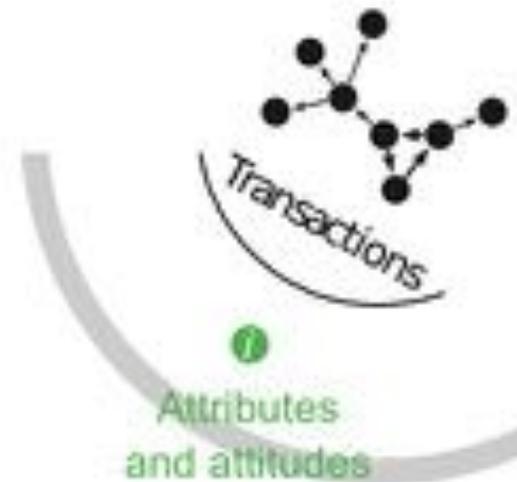
Four dimensions of transactions



Four dimensions of transactions



Four dimensions of transactions

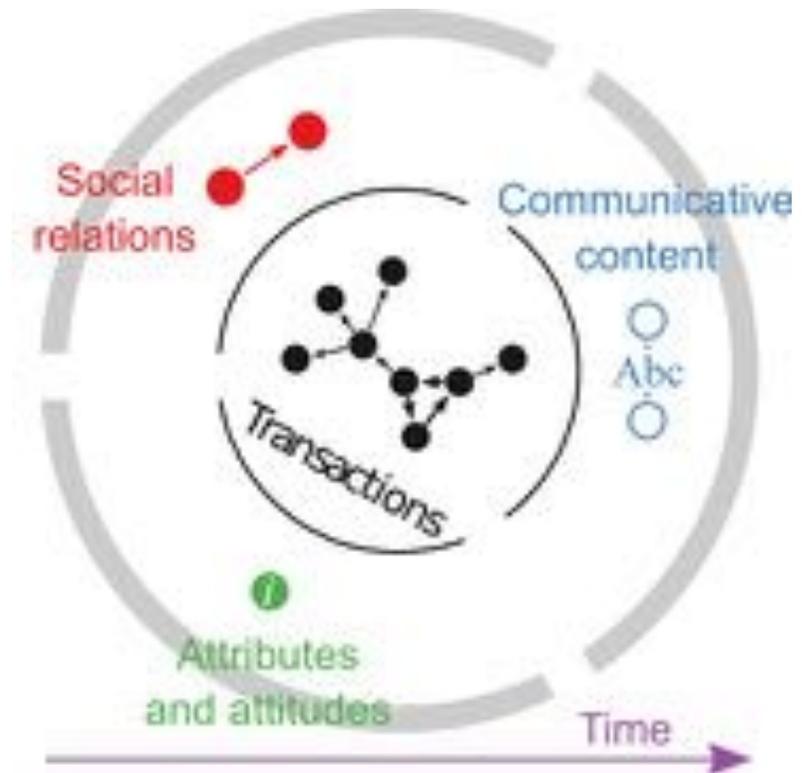


Four dimensions of transactions



Four dimensions of transactions

- Social relations
- Communicative content
- Attributes and attitudes
- Time



Definition of Digital Behavioral Data

Digital Behavioral Data (DBD) are traces of behavior left by uses of, or harnessed by, digital technology.

References for next slides:

[9] Howison, J., et al. (2011). *J. Assoc. Inf. Sys.*, 12(12), 767–797.

[10] Lazer, D. & Radford, J. (2017). *Annu. Rev. Sociol.*, 43(1), 19–39.

Traces of behavior

... are left by uses of digital technology?

Yes („found data“) [9]

... are actions and their tech. observation? [10]

Yes („digital life“)



e.g., Twitter

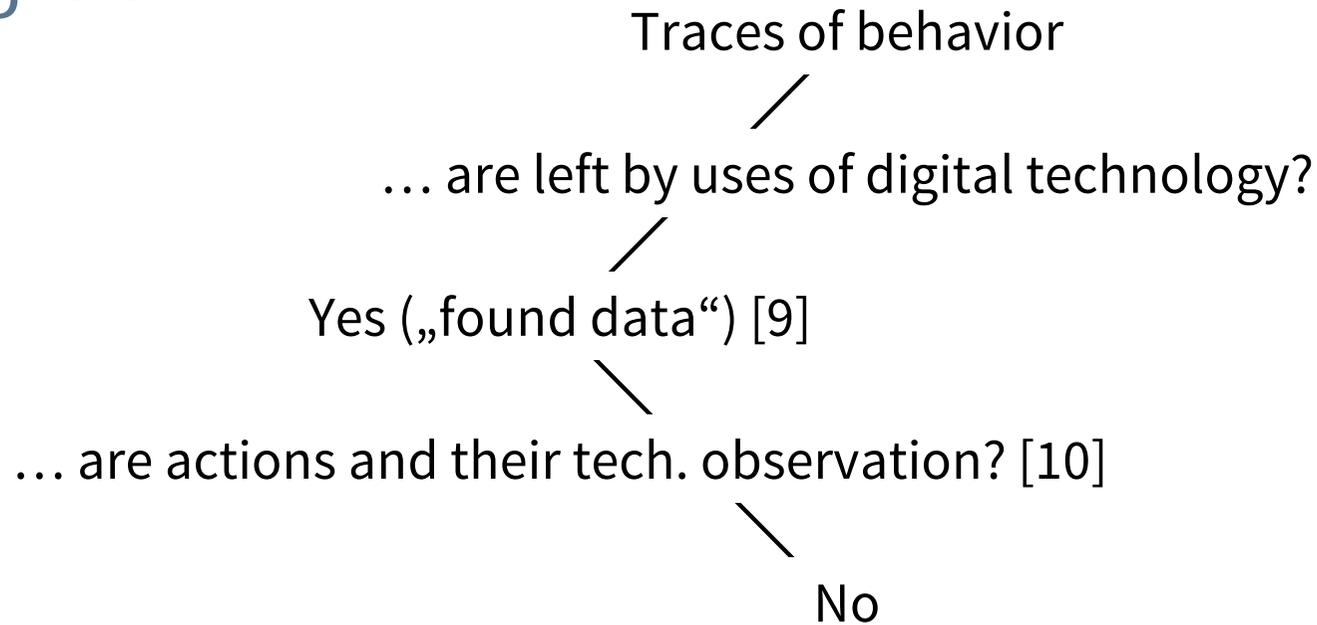
Type 1

Social relations ✓

Communicative content ✓

Attributes and attitudes ✓

Time ✓



e.g., E-Mail @

Type 2

Social relations ✓

Communicative content ✓

Attributes and attitudes

Time ✓

Traces of behavior

... are left by uses of digital technology?

No („designed data“)

„digitized life“

e.g., face-to-face interactions



Type 3

Social relations ✓

Communicative content

Attributes and attitudes

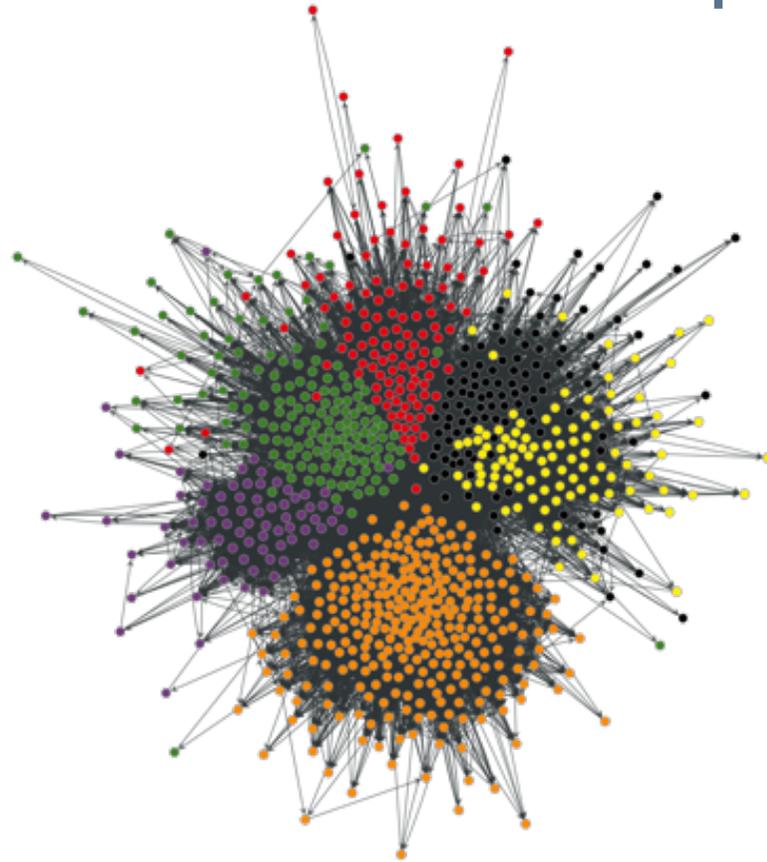
Time ✓

Types of Digital Behavioral Data

	Type 1	Type 2	Type 3
Example	Twitter	E-Mail	SocioPatterns
Social relations	✓	✓	✓
Communicative content	✓	✓	
Attributes and attitudes	✓		
Time	✓	✓	✓

- Application scenario 1: Socio-semantic analysis
- Application scenario 2: Mechanistic modeling

Patterns



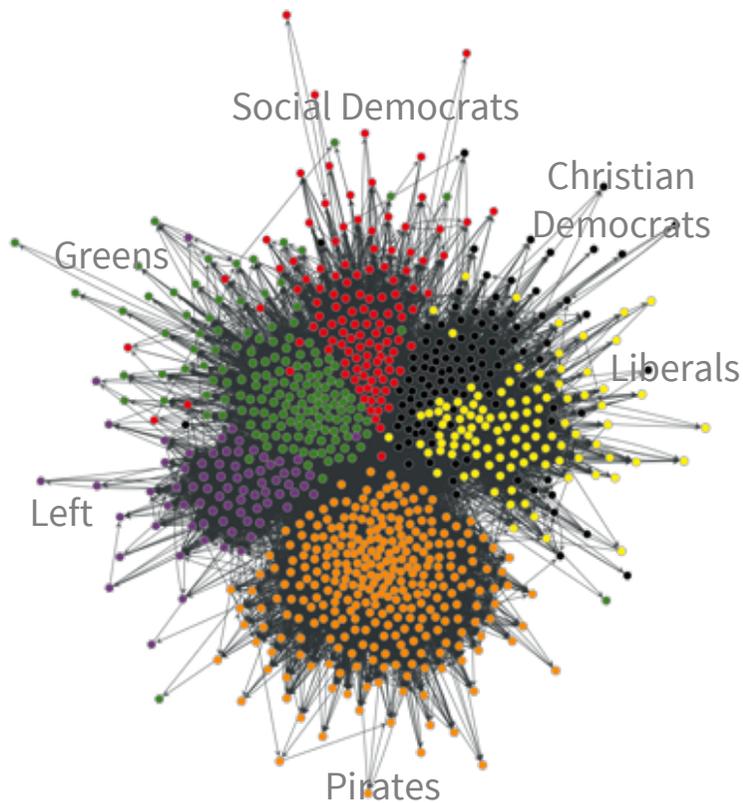
Follower network of politicians,
color indicates party affiliation [11]

Patterns are regularities
in the macrobehavior of
a system

→ e.g., existence of
groups of actors

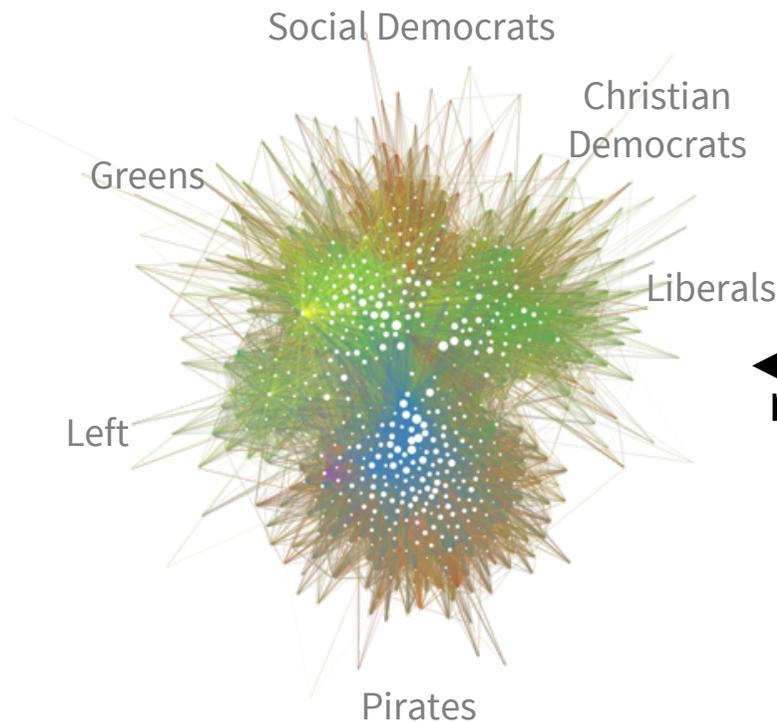
App. scenario 1: Socio-semantic analysis

Actors



Social network

App. scenario 1: Socio-semantic analysis



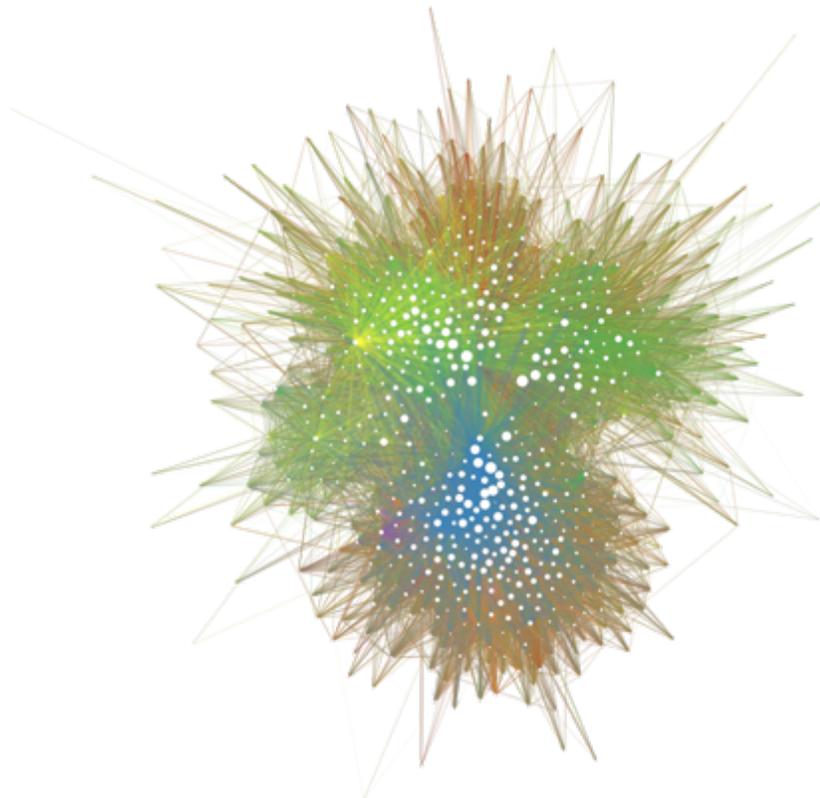
Socio-semantic network

← map



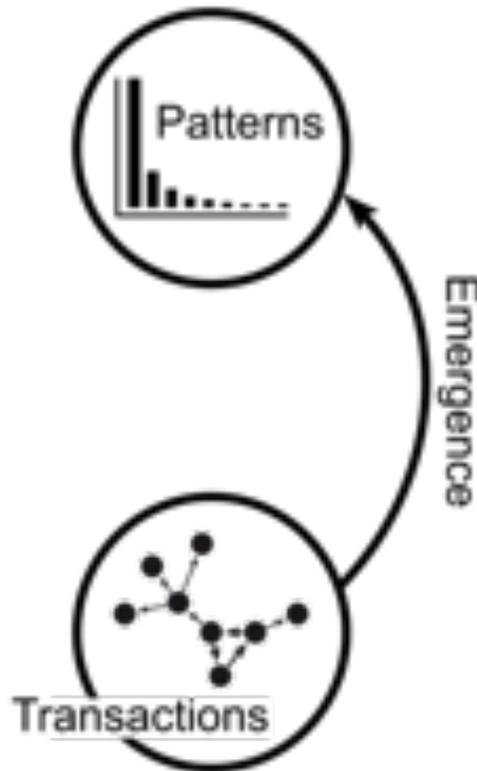
Semantic network

App. scenario 1: Socio-semantic analysis



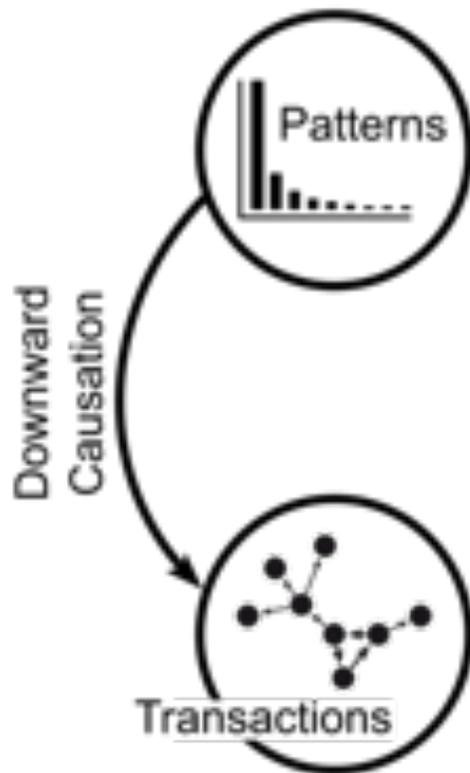
- Actors are just one entity among others
- Transactions are the unit of observation
- More approaches to socio-semantic analysis in *Poetics* [12]

Patterns in individualistic models of behavior



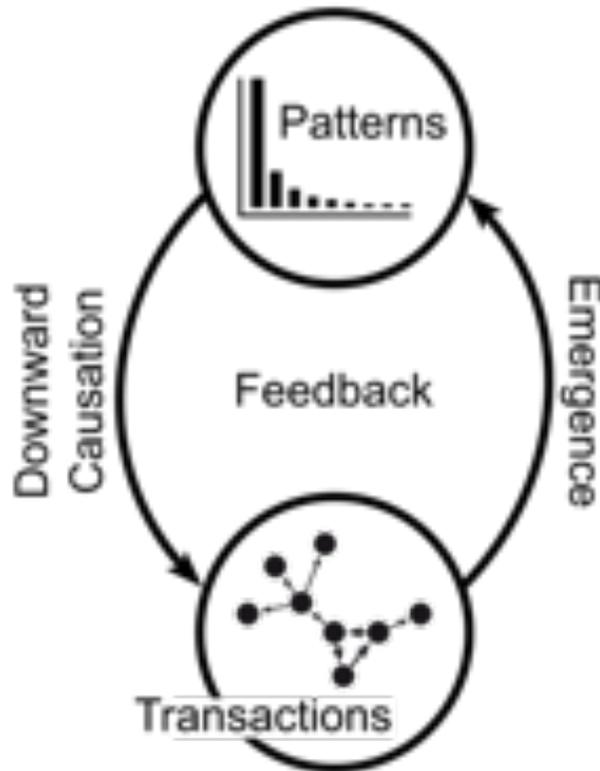
- Emergence: Patterns arise from transactions
 - e.g., methodological individualism
- *Undersocialized* conception of human action [13]

Patterns in functionalistic models of behavior



- Downward causation: Patterns influence transactions
 - e.g., structural functionalism
- Oversocialized conception of human action [13]

Patterns in analytical models of behavior



- Feedback: Patterns arise from, and later influence, transactions
 - e.g., enabling [3] vs. constraining [4] effect of structure
- Mechanistic conception of human action [14]

[3] Burt, R.S. (1992). *Structural Holes*. Harvard University Press.

[4] Granovetter, M.S. (1973). *Am. J. Sociol.*, 78(6), 1360–1380.

[14] Hedström, P. (2005). *Dissecting the Social*. Cambridge University Press

App. Scenario 2: Mechanistic modeling

Origins of Homophily in an Evolving Social Network¹

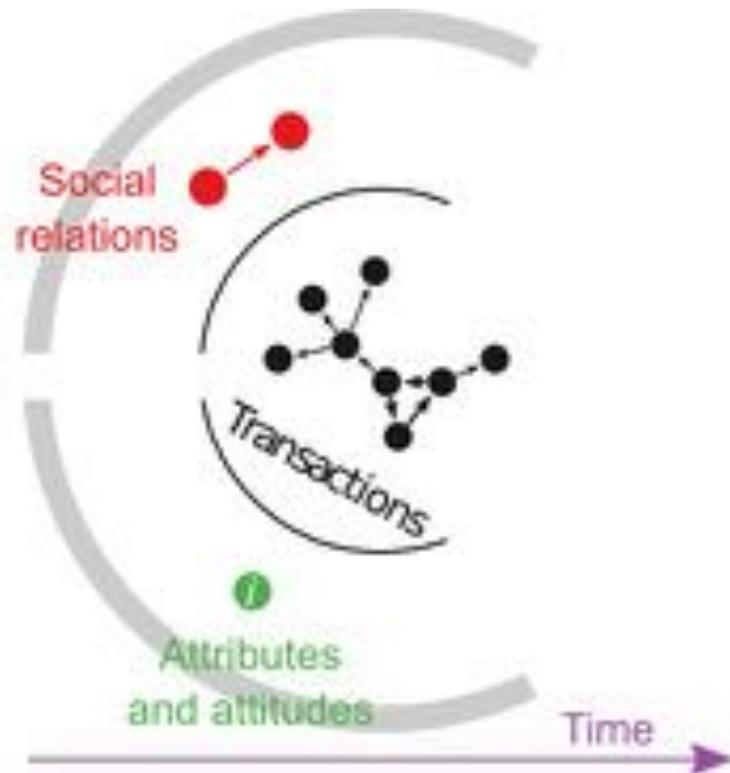
Gueorgi Kossinets
Google Inc.

Duncan J. Watts
Yahoo! Research

The authors investigate the origins of homophily in a large university community, using network data in which interactions, attributes, and affiliations are all recorded over time. The analysis indicates that highly similar pairs do show greater than average propensity to form new ties; however, it also finds that tie formation is heavily biased by triadic closure and focal closure, which effectively constrain the opportunities among which individuals may select. In the case of triadic closure, moreover, selection to “friend of a friend” status is determined by an analogous combination of individual preference and structural proximity. The authors conclude that the dynamic interplay of choice homophily and induced homophily, compounded over many “generations” of biased selection of similar individuals to structurally proximate positions, can amplify even a modest preference for similar others, via a cumulative advantage-like process, to produce striking patterns of observed homophily.

[2] Kossinets, G. & Watts, D.J. (2009). *Am. J. Sociol.*, 115(2), 405–450.

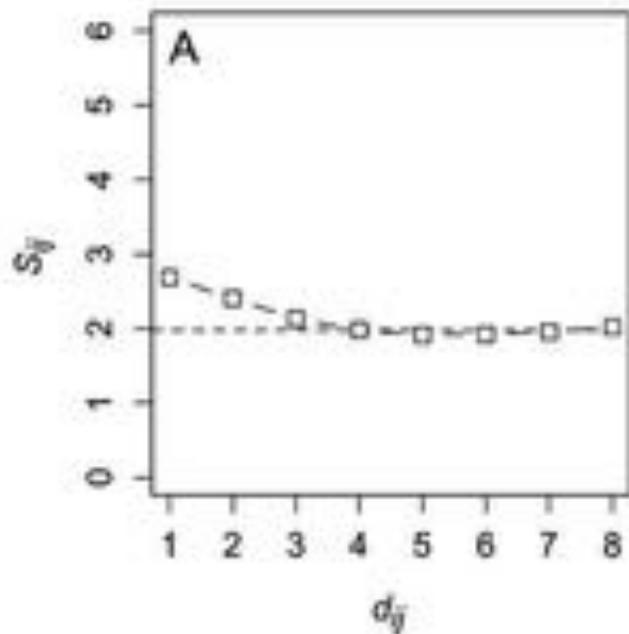
App. Scenario 2: Mechanistic modeling



Data

- Social relations: E-Mails by 30.396 persons with a university account
- 6 attributes: Gender, age, status, field, year, and state
- Time: 270 days

App. Scenario 2: Mechanistic modeling



Pattern

- Persons in short network distance d_{ij} have more attributes S_{ij} in common

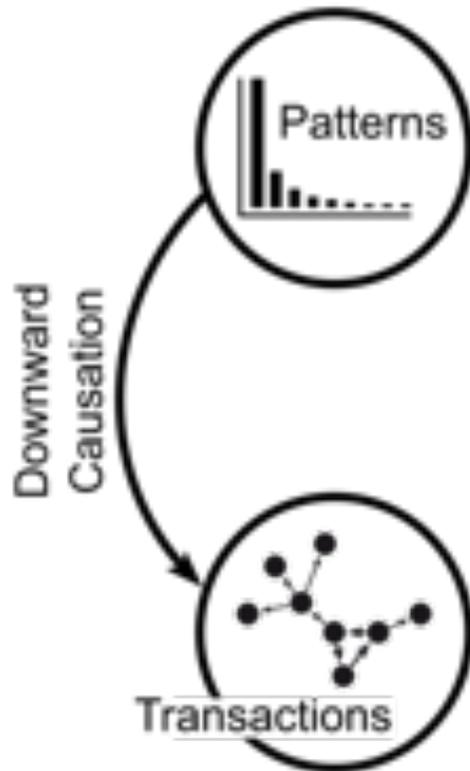
App. Scenario 2: Mechanistic modeling



Research question

- Do persons chose relations to similar others even though they could do otherwise?
- Choice homophily

App. Scenario 2: Mechanistic modeling



Research question

- Do persons chose relations to similar others because they have no other choice?
→ Induced homophily

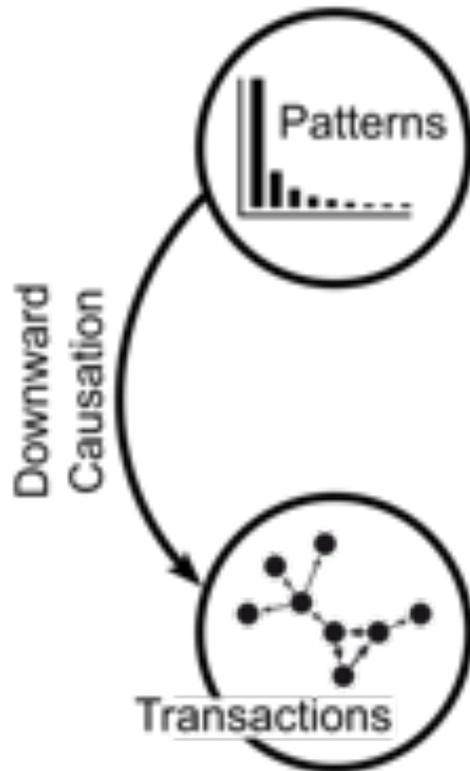
App. Scenario 2: Mechanistic modeling



Results

- The more similar two persons are, the more likely they are to send a mail on the next day
→ Choice homophily

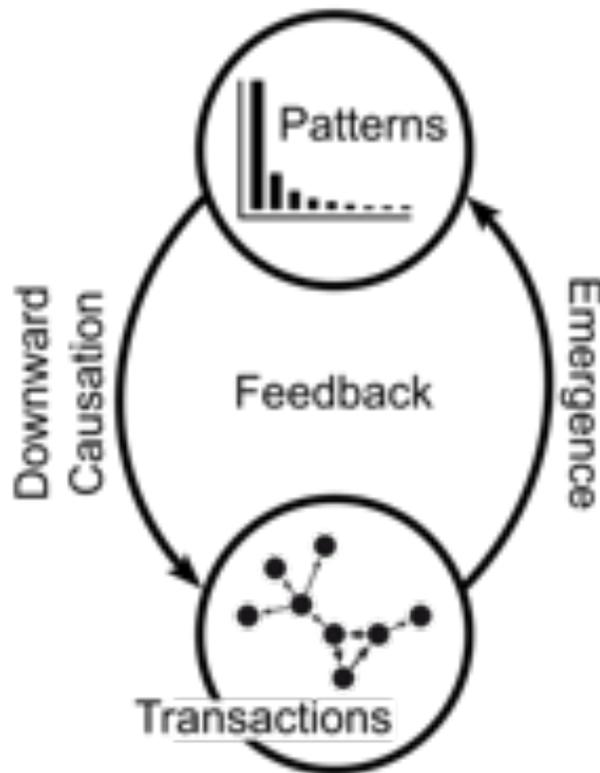
App. Scenario 2: Mechanistic modeling



Results

- The effect is weaker, the larger the distance in the network
 - The effect vanishes when persons share a focus (e.g., a class)
- Induced homophily

App. Scenario 2: Mechanistic modeling



Summary

- Network proximity and attribute similarity converge as distant but similar persons are drawn together, facilitated by shared activities
- Homophily as feedback mechanism

Conclusion

DBD offers fresh research opportunities

- Combination of social relations and communicative content (socio-semantic analysis)
- Enrichment of transactions by attributes and attitudes
- Availability of highly dynamic observations of behavior at scale (mechanistic modeling)

Challenges

1. Data management: Need to handle DBD
2. Data quality: Validity issues, measurement and representation errors
-  [Meet the Experts: Dr. F. Floeck & I. Sen: Digital traces of human behaviour in online platforms](#)
3. Reproducibility: Open data and methodology

Challenges

4. Reflexivity: Understanding modes of data generation
 - ▶ [Meet the Experts: Dr. Roberto Ulloa: Auditing Algorithms](#)
 - ▶ [Meet the Experts: Dr. K. Weller & O. Watteler: Ethics and Data Protection in Social Media Research](#)
5. Theory: Constitutive pillar for the consolidation of Computational Social Science

Thank you !

gesis

Leibniz-Institut
für Sozialwissenschaften

Leibniz
Leibniz
Gemeinschaft

Expert Contact & GESIS Consulting



Contact: you can reach the speaker/s via e-mail:
haiko.lietz@gesis.org

GESIS Consulting: GESIS offers individual consulting in a number of areas – including survey design & methodology, data archiving, digital behavioral data & computational social science – and across the research data cycle.

Please visit our website www.gesis.org for more [detailed information](#) on available services and terms.

More Services from GESIS

- Get materials for [capacity building in computational social science](#) and take advantage of our expanding expertise and resources in [digital behavioral data](#).
- Use GESIS data services for [finding data](#) for secondary analysis and [sharing your own data](#).
- Check out the [GESIS blog](#) "Growing Knowledge in the Social Sciences" for topics, methods and discussions from the GESIS cosmos – and beyond.
- Keep up with GESIS activities and subscribe to the monthly [newsletter](#).
-  for publications, tools & services.

More from CSS Experts in the Series

- June 24 Katrin Weller: **A Short Introduction to Computational Social Science and Digital Behavioral Data**
- July 01 Fabian Flöck, Indira Sen: **Digital Traces of Human Behavior from Online Platforms – Research Designs and Error Sources**
- July 08 Sebastian Stier, Johannes Breuer: **Combining Survey Data and Digital Behavioral Data**
- Sept 16 Katrin Weller, Oliver Watteler: **Ethics and Data Protection in Social Media Research**
- Sept 30 Roberto Ulloa: **Introduction to Online Data Acquisition**
- Oct 07 Roberto Ulloa: **Auditing Algorithms: How Platform Technologies Shape our Digital Environment**
- Oct 14 Marius Sältzer, Sebastian Stier: **The German Federal Election: Social Media Data for Scientific (Re-)Use**
- Nov 04 Arnim Bleier: **Introduction to Text Mining**
- Nov 25 Haiko Lietz: **Social Network Analysis with Digital Behavioral Data**
- Dec 2 Olga Zagovora, Katrin Weller: **Altmetrics: Analyzing Academic Communications from Social Media Data**
- Dec 16 Andreas Schmitz: **Online Dating: Data Types and Analytical Approaches**
- Jan 13 Gizem Bacaksizlar: **Political Behavior and Influence in Online Networks**
- Jan 27 David Brodesser: **SocioHub – A Collaboration Platform for the Social Sciences**