Social networks: mechanisms and models

University of Macerata, 25/3/26

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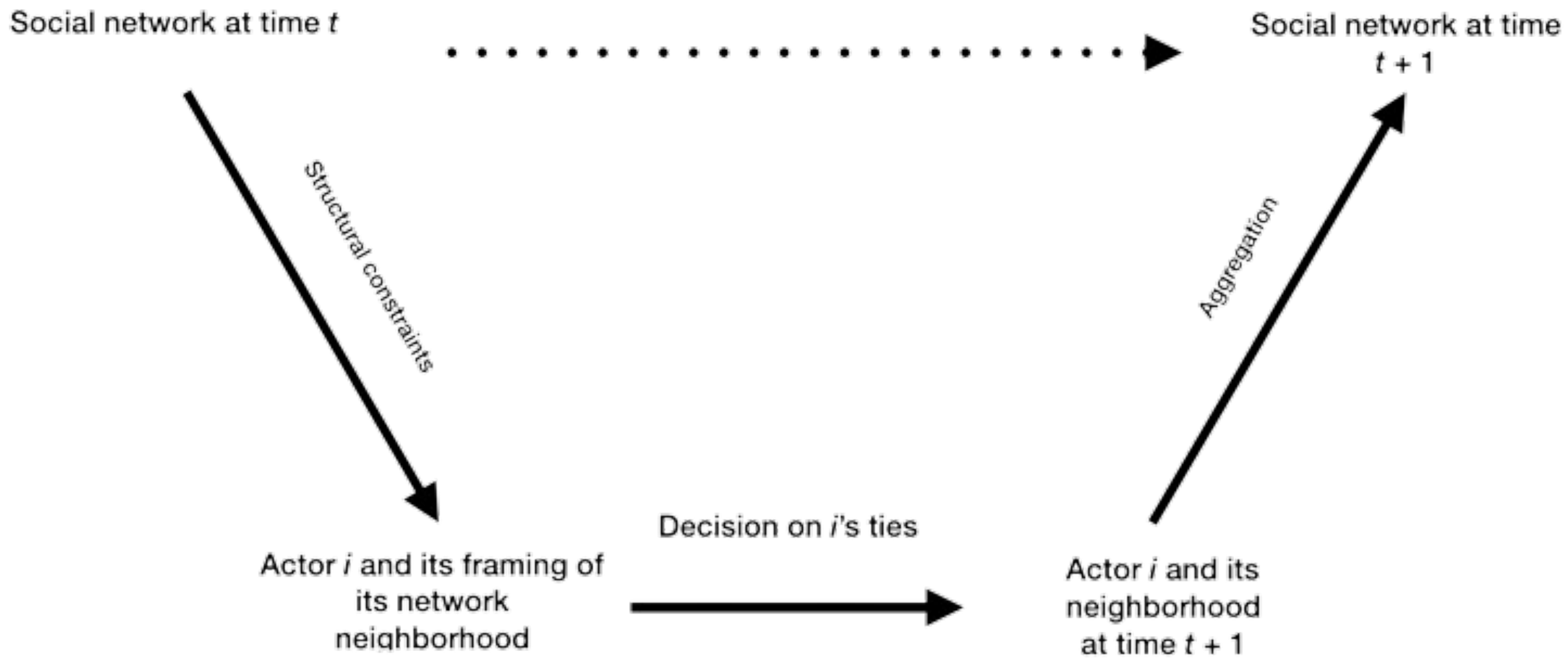
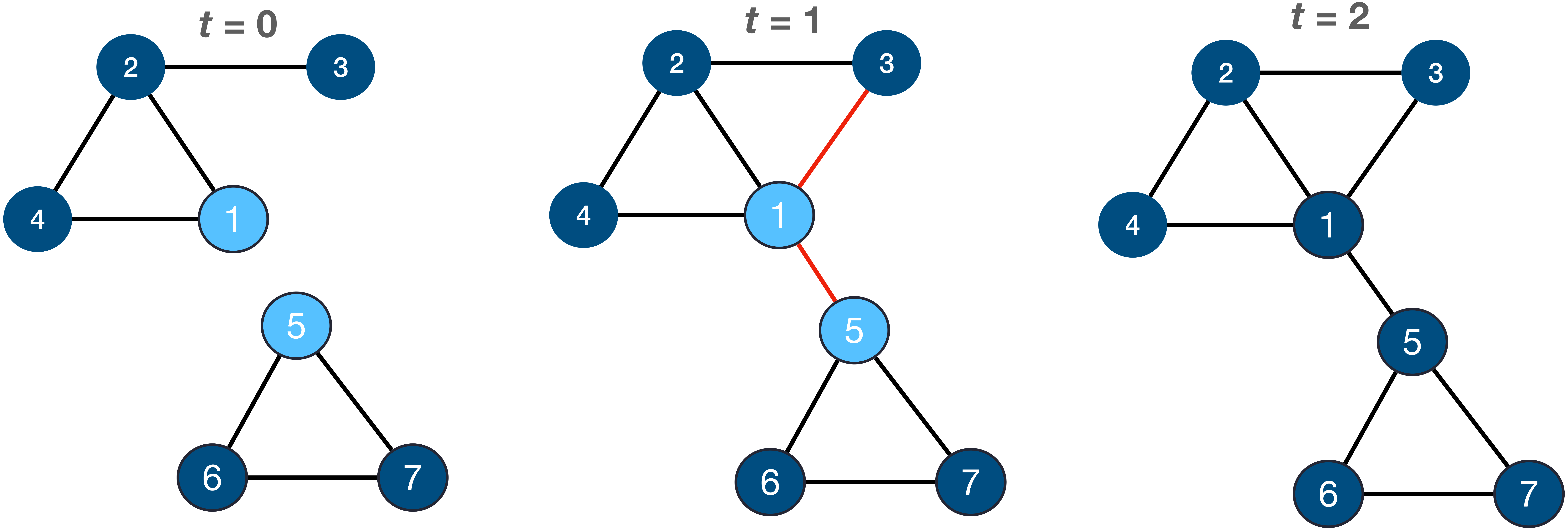


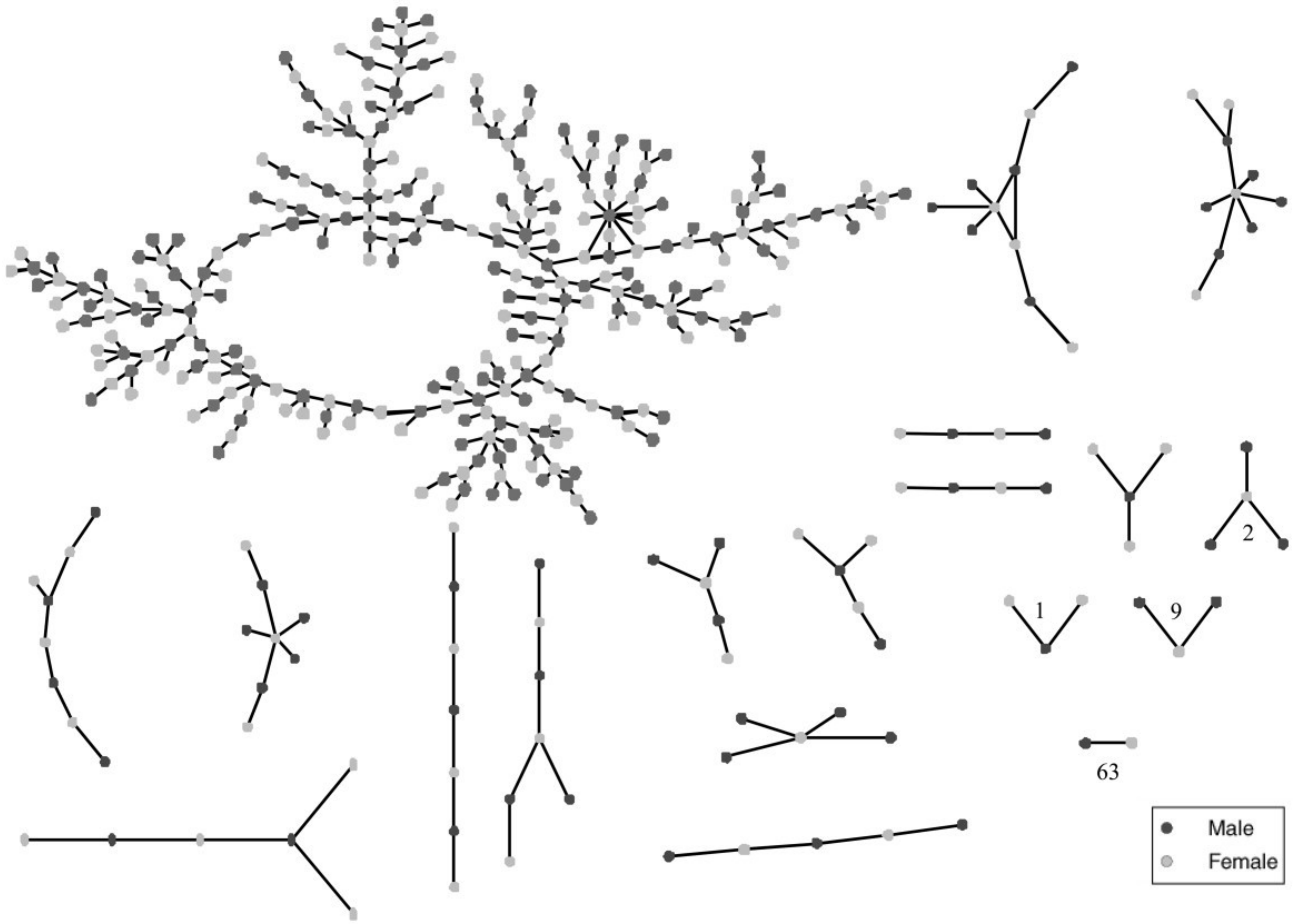
Causal mechanisms of social network evolution / 1

- Social networks as **models of relational data** (Brandes et al., 2013)
- Explaining social networks means identifying the **causal mechanisms** of their evolution
- Patterns of **social actors' inter(actions)** (Hedström & Bearman, 2009) bringing about regular network structures or compositions

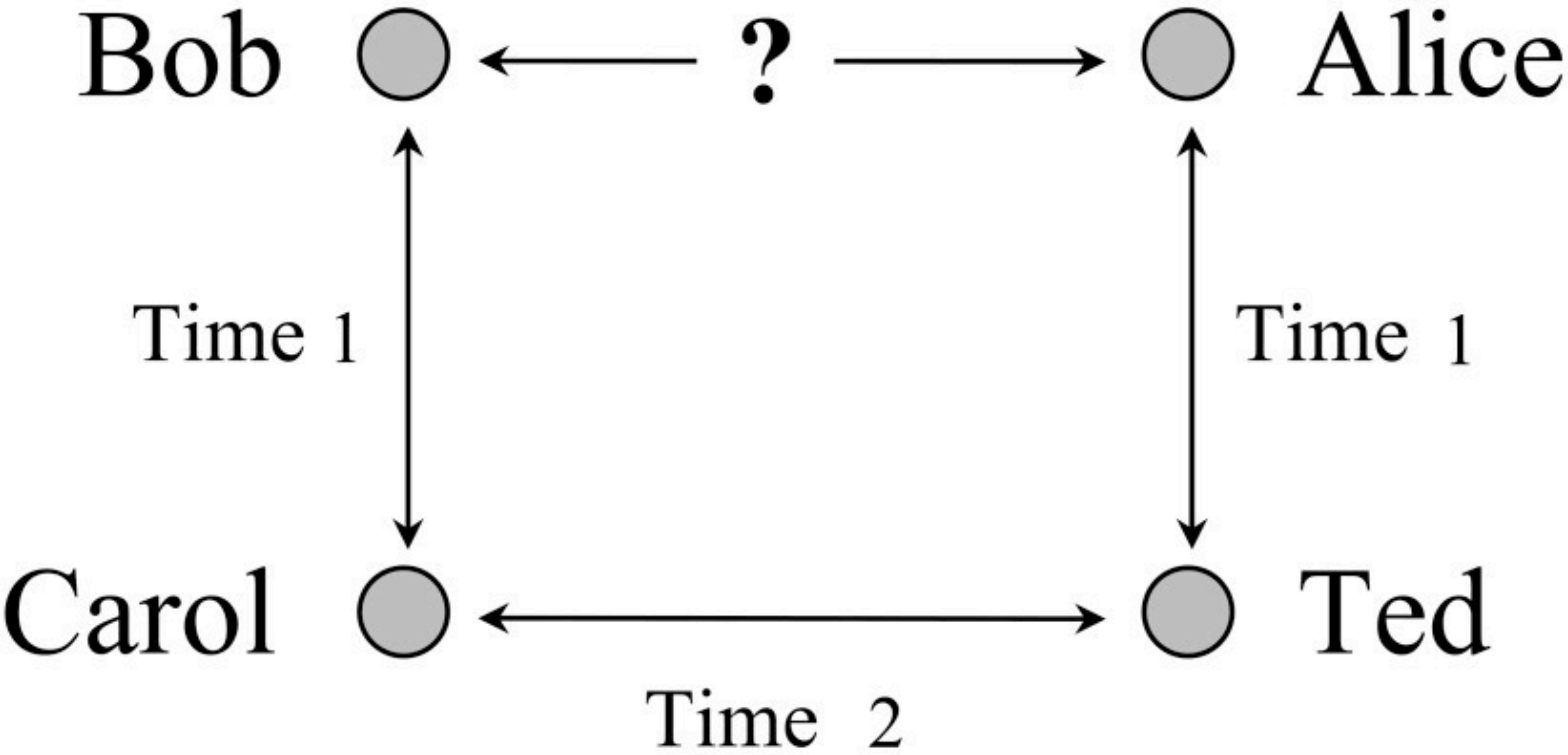


Causal mechanisms of social network evolution / 2

- Causal mechanism: “**entities** and **activities** that are organized in such a way that they regularly bring about a particular type of outcome” (Machamer et al., 2000)
- Entities: social actors (**nodes**)
- Activities: actions and interactions (**edges**)



Example: Bearman et al. (2004)



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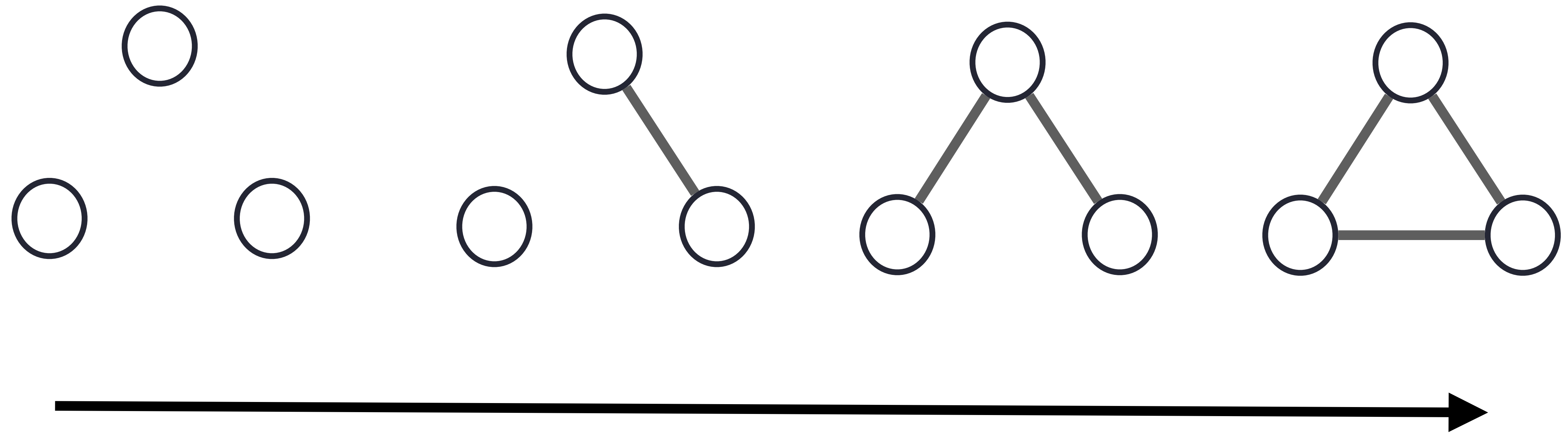
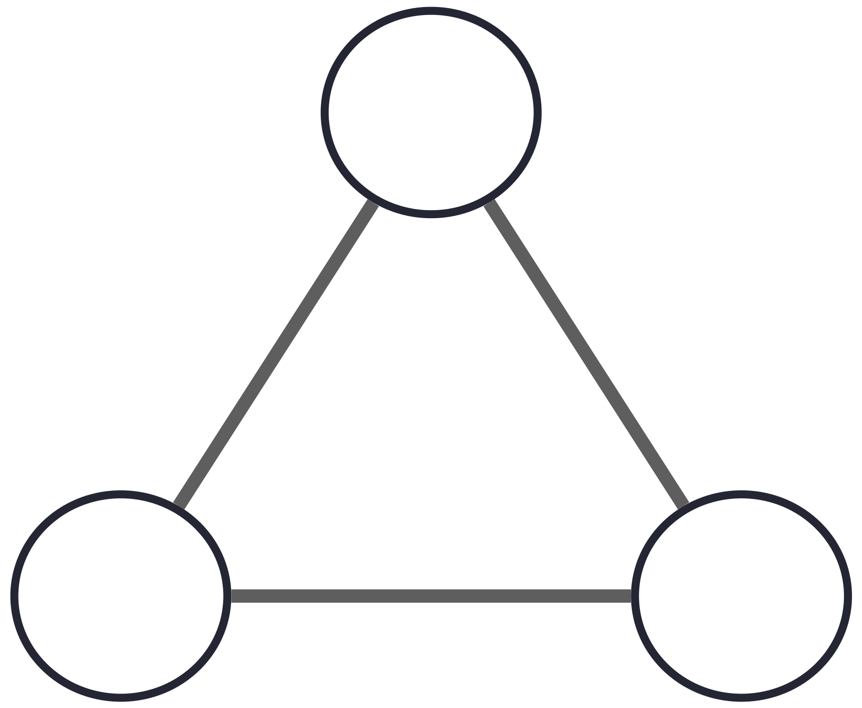
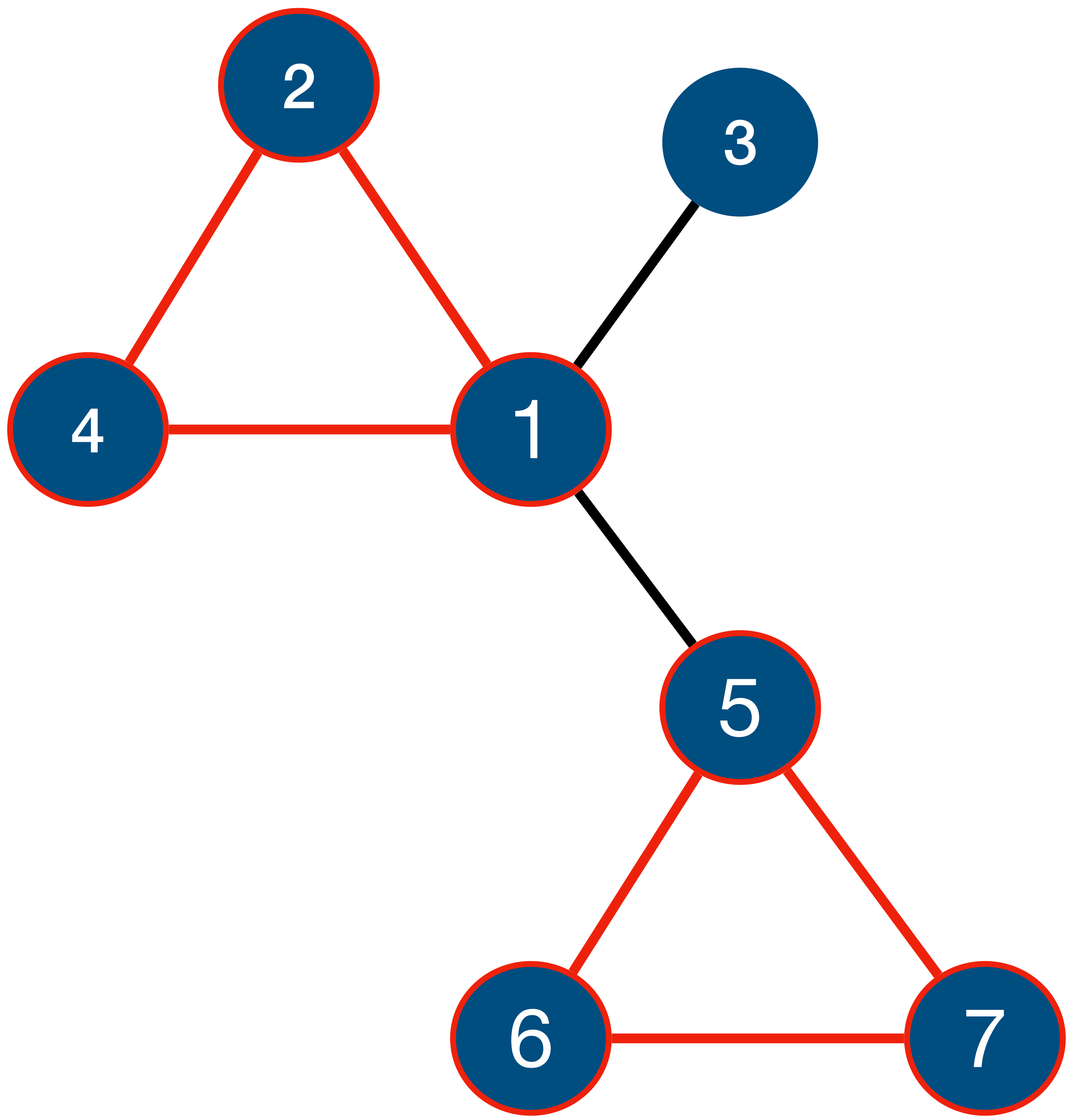
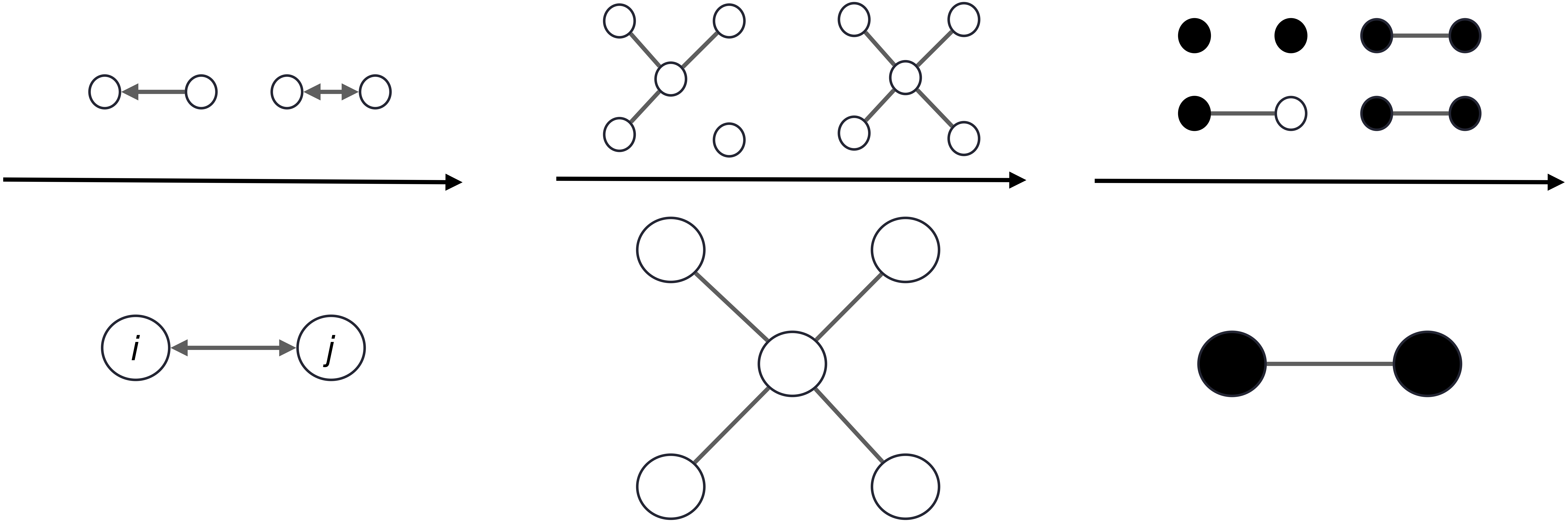






Statistical models of social networks

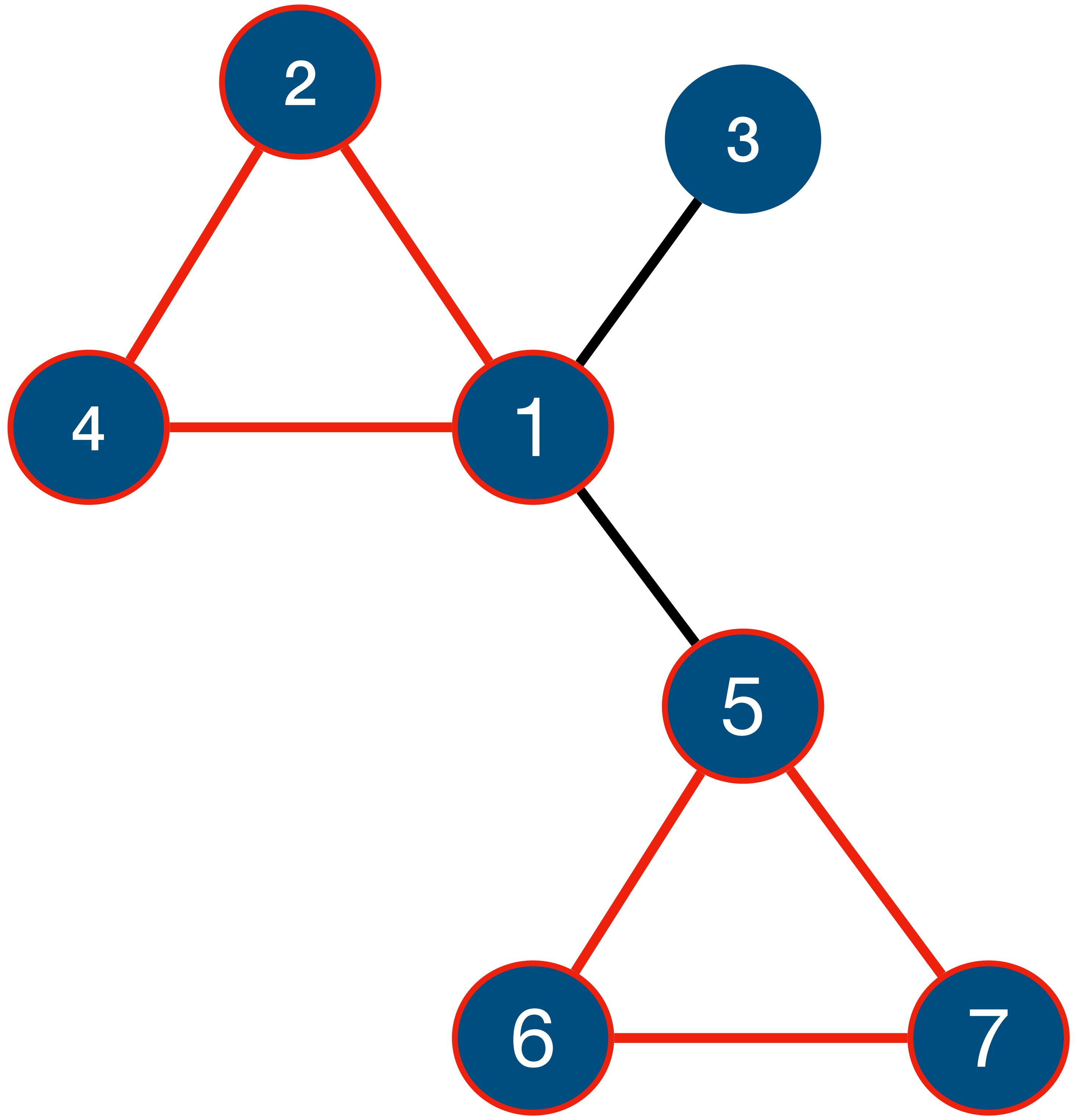
- Inferring the effect of **unobserved**, relational processes on the evolution of a network from the **prevalence** or **incidence** of certain **local configurations**
- Network local configurations as “archeological traces” left by relational processes (White, 1970; Lusher et al., 2013)
- The relative effect size of these processes can be estimated by computing **statistics of empirical network data** —> Maximum likelihood or method of moments (numerical simulations)

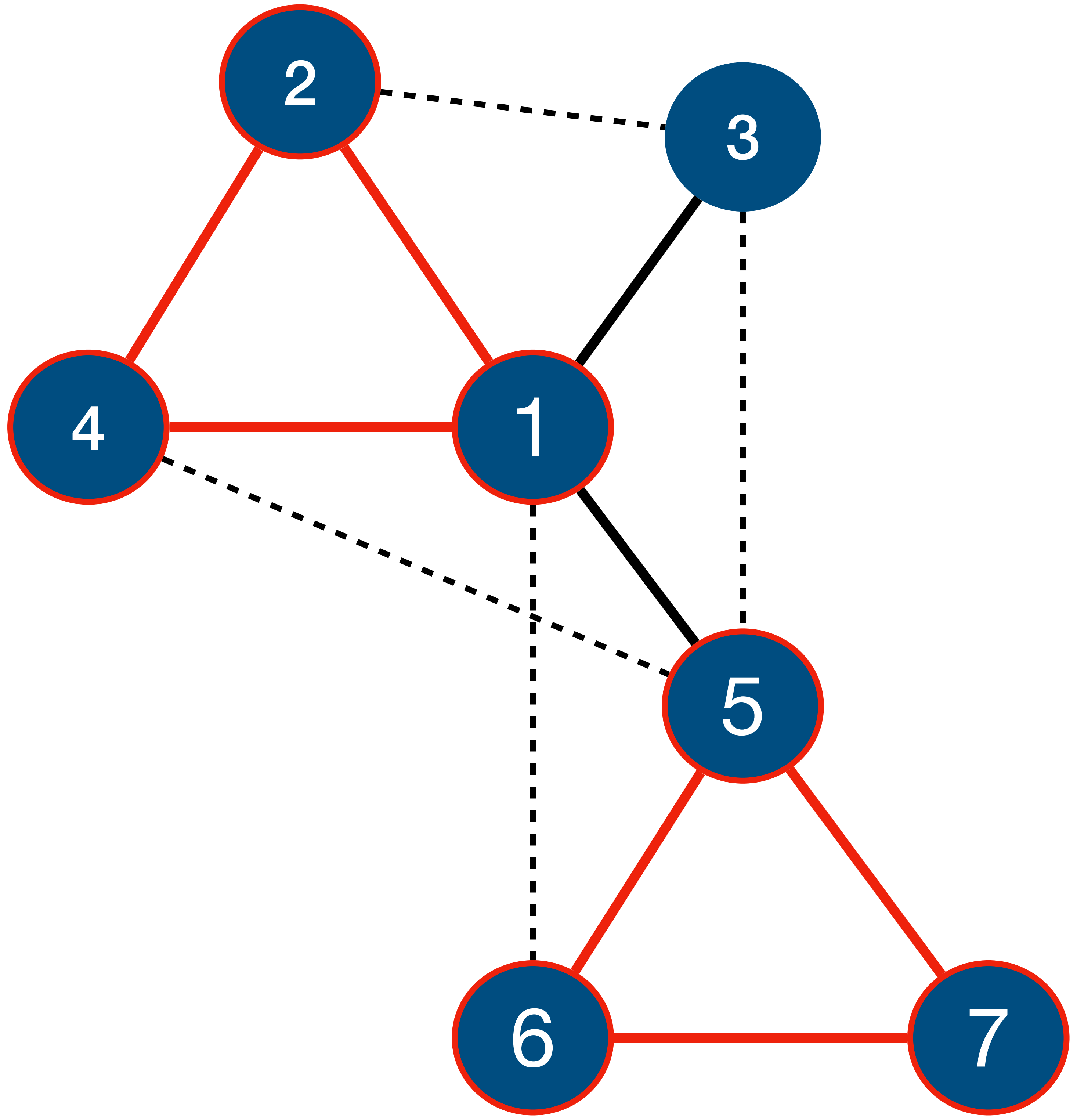


Statistical models of social networks:

stochastic dependency assumptions

- A relational process can be linked to a **local configuration**, of which **count statistics** can be computed
- Observations are **not independent**
- Each local configuration comes with a **stochastic dependency assumption**: es., $P(x_{ij}) \cap P(x_{ji}) = P(x_{ij} | x_{ji}) \cdot P(x_{ji})$

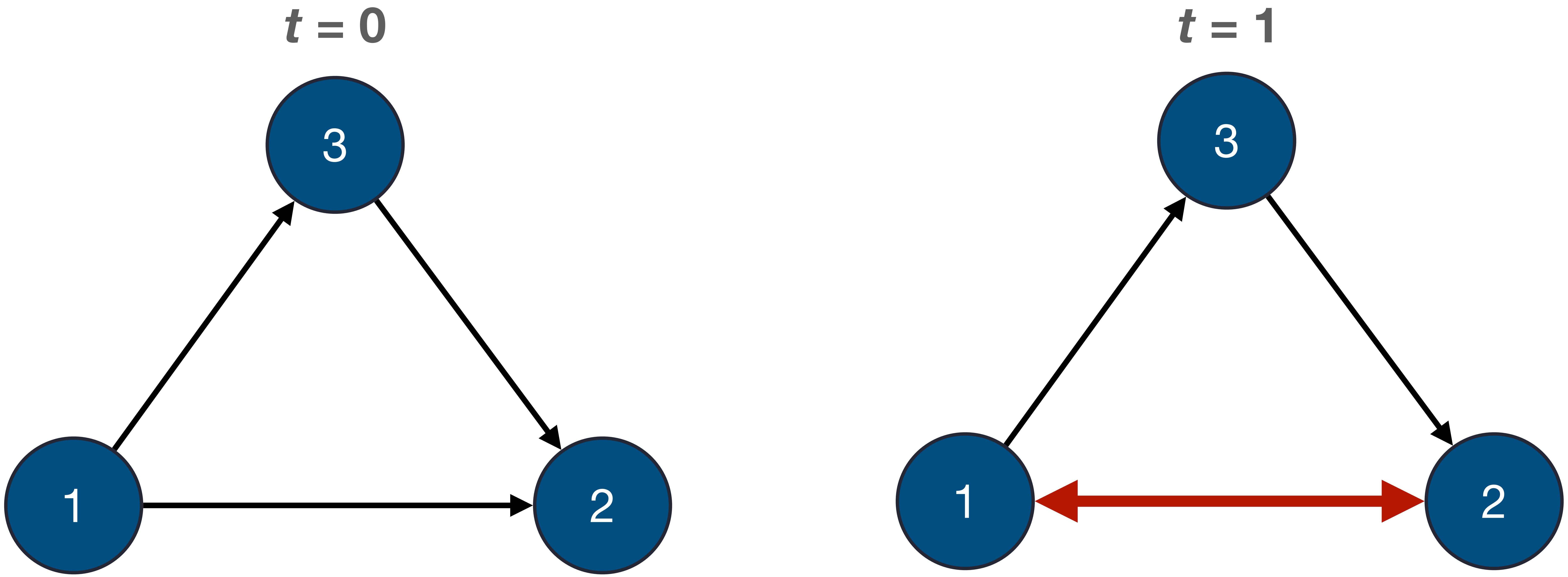




Statistical models of social networks:

hypothesis testing

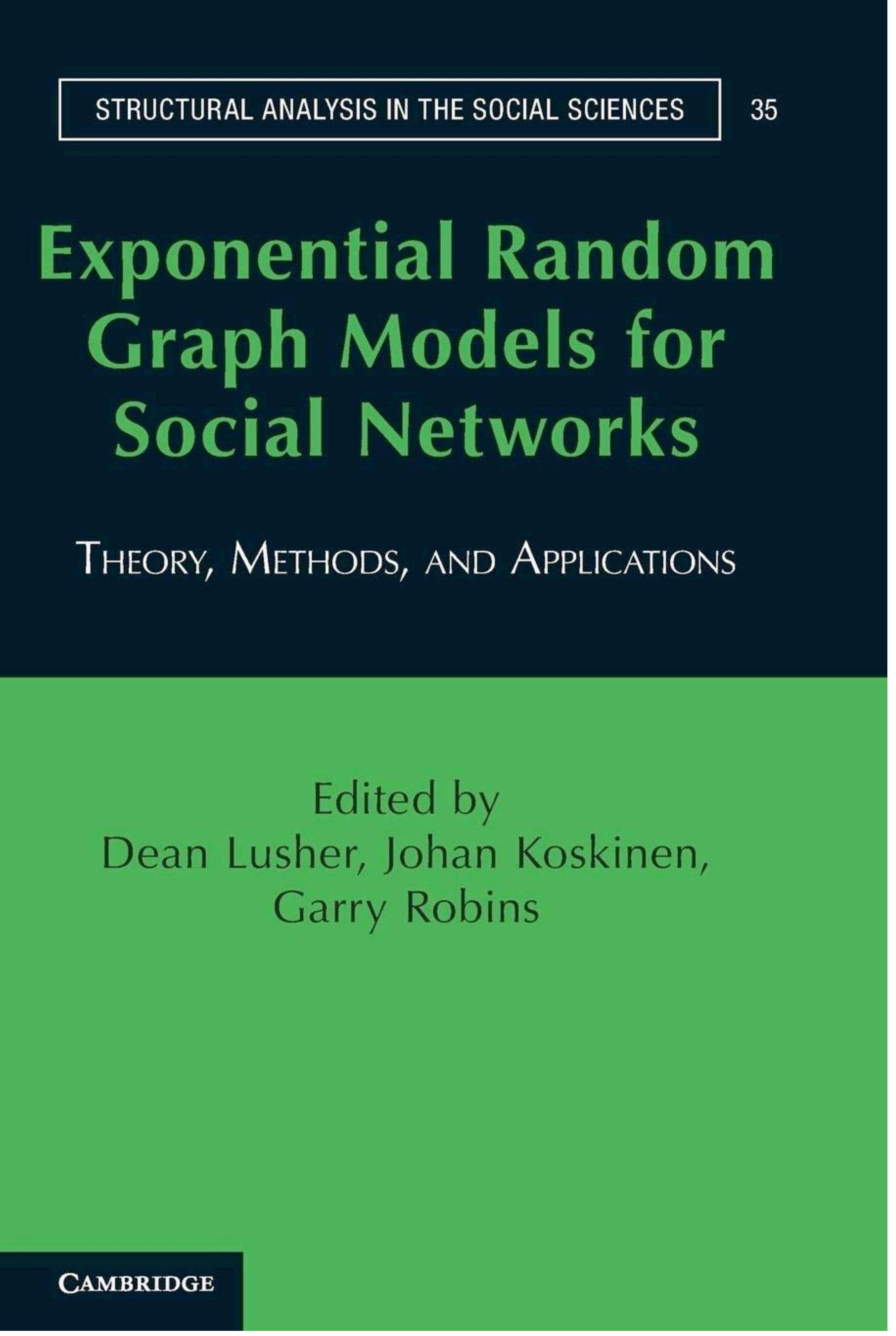
- Generating (simulating) a **random graph distribution** centred on the observed statistics
- Identifying a **parameter** vector
- Computing **uncertainty** measures (hypothesis testing)

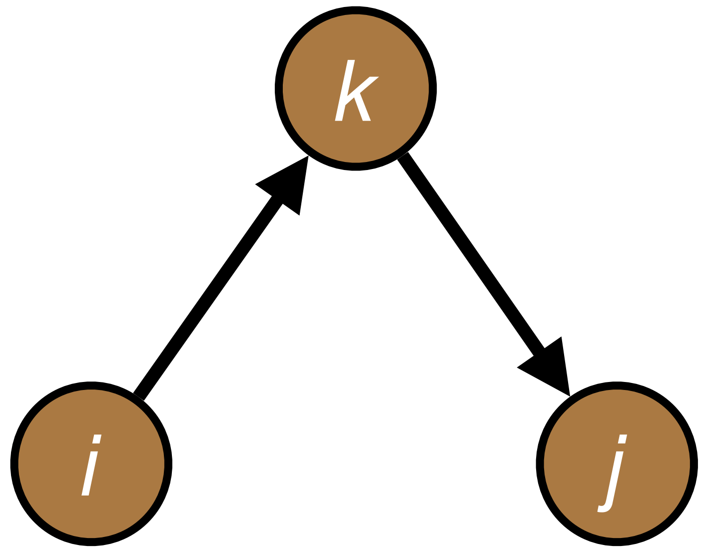


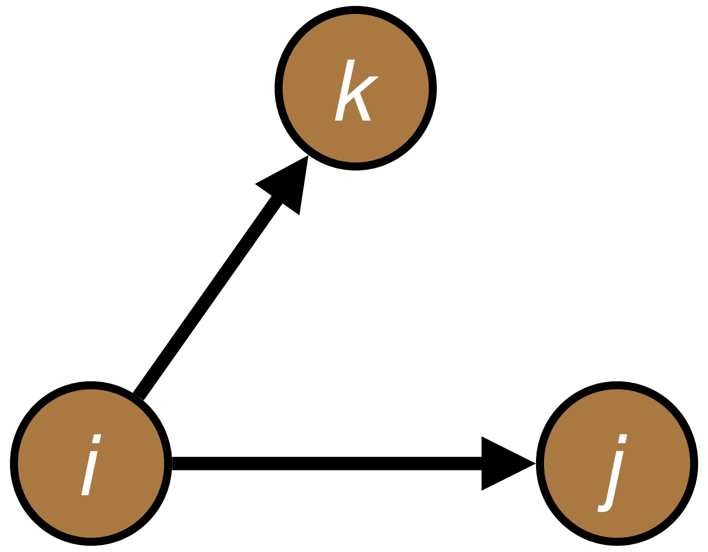
Statistical models of social networks:

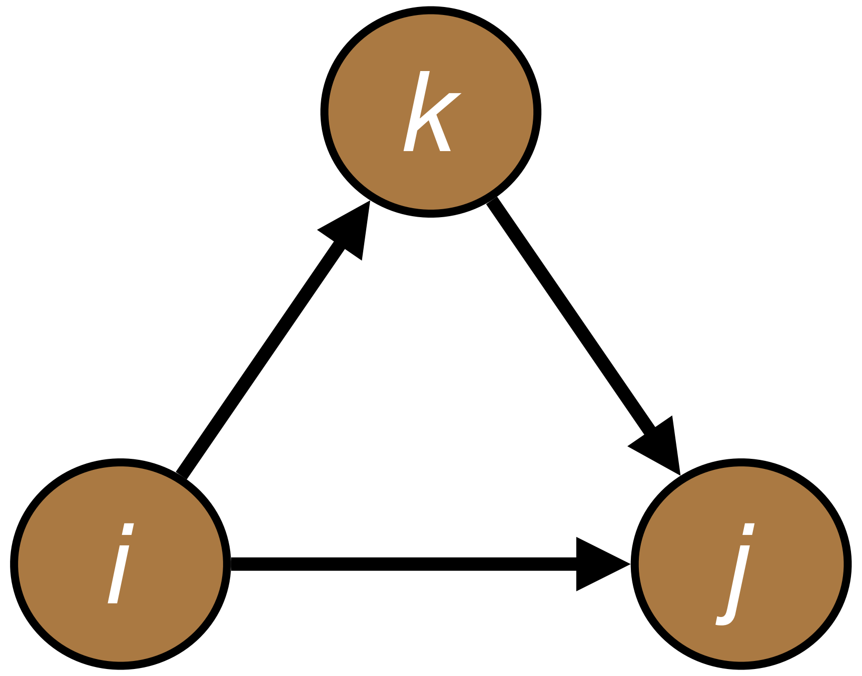
multivariate analysis

- Assessing the **relative effect** of **concurrent processes**
- E.g.: reciprocity or transitive closure?









$$Pr(x \rightarrow x^{\pm ij}; \theta) = \frac{1}{n(n-1)} \cdot \frac{\exp \sum_k \theta_k \Delta z_k(x, x^{\pm ij})}{1 + \exp \sum_k \theta_k \Delta z_k(x, x^{\pm ij})}$$

ERGM

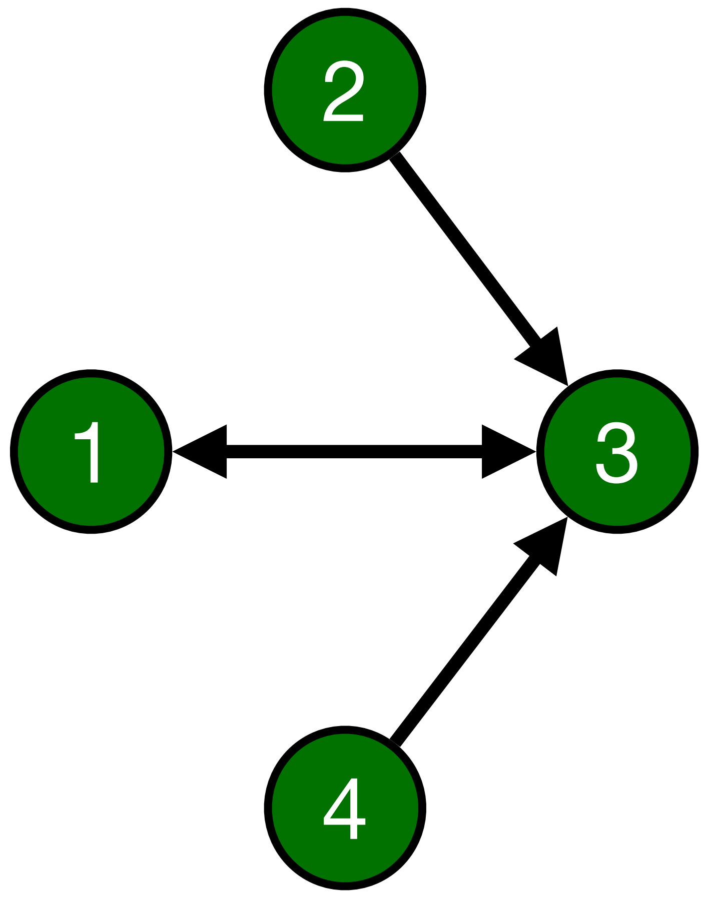
Exponential Random Graph Models

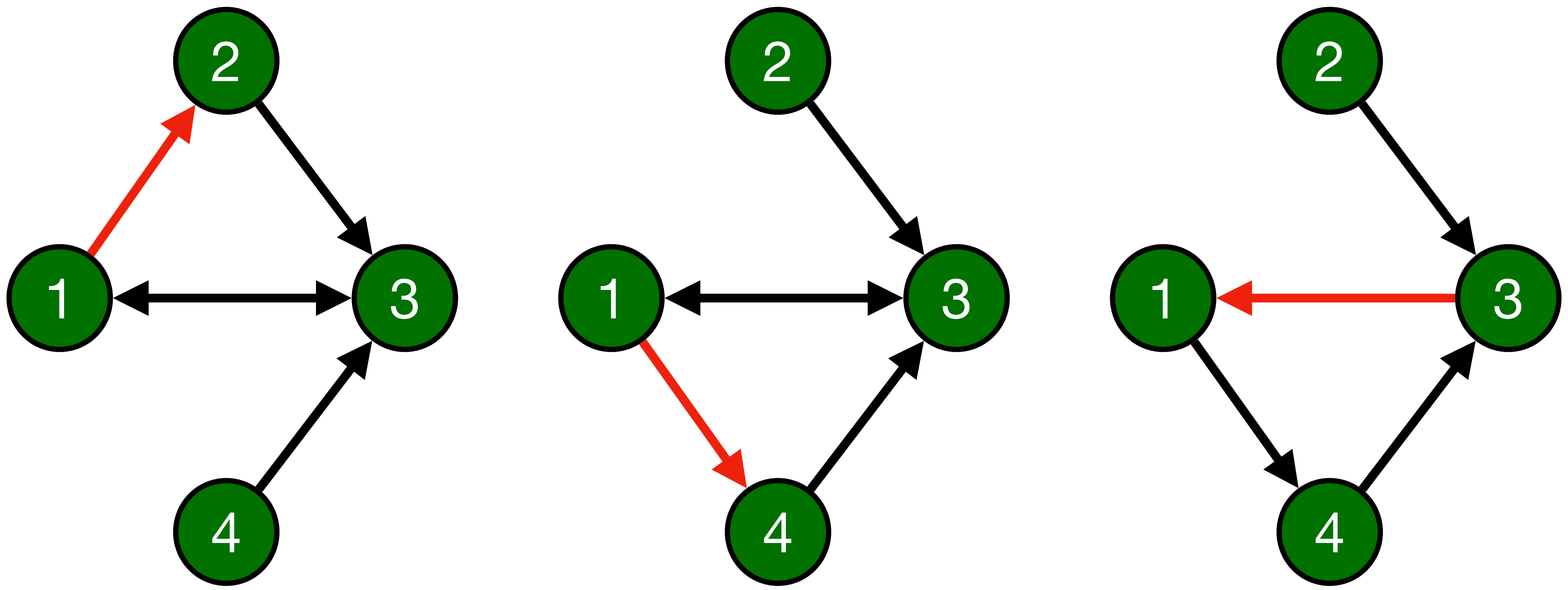
Tie-based models (ERGM-family; Lusher et al., 2013):

- the occurrence of a tie is assessed independently on agents' multinomial choice, typical of many decision-making contexts
- are **indifferent to the specific tie sequences** through which particular configurations emerge (Block et al., 2019)

SAOM

Stochastic Actor-Oriented Models

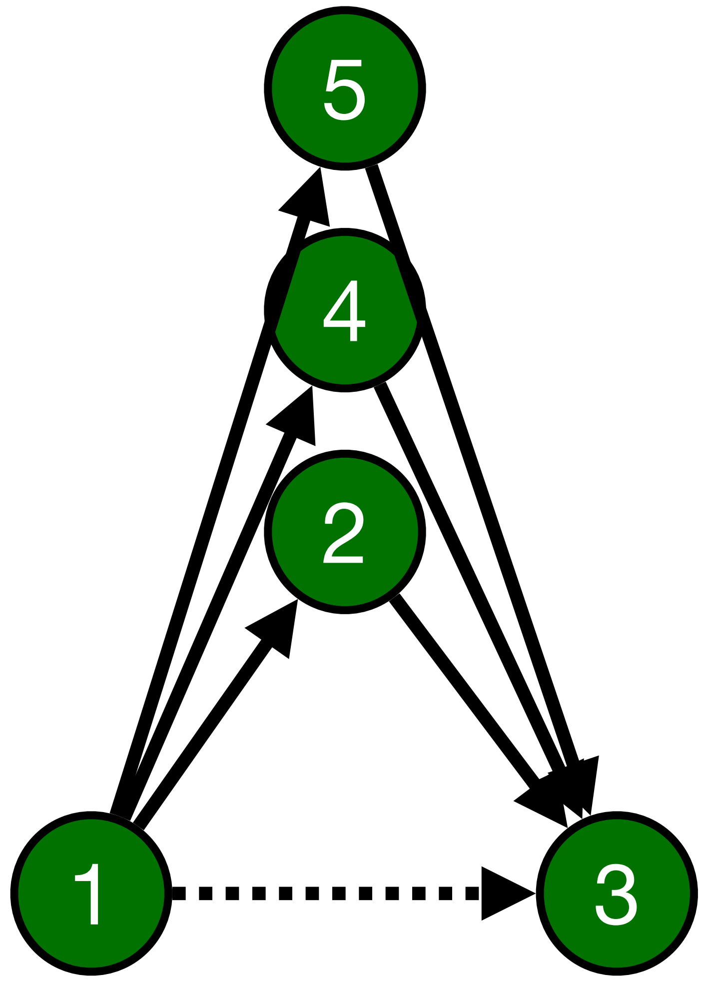


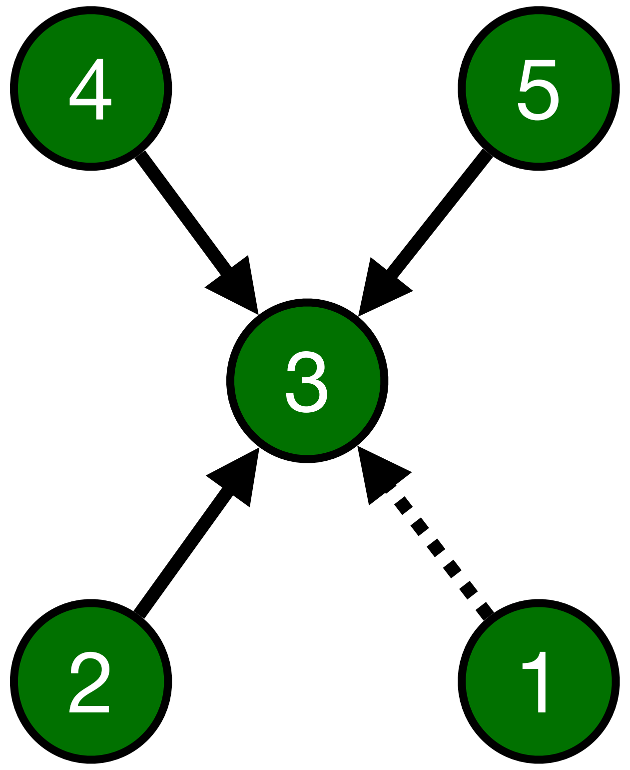


- ***Agent-based*** model: the likelihood of a tie to occurr is assessed as a function of a focal node-agent's neighborhood structure/composition

- Each agent decides whether to change the state of an outgoing dyad through a multinomial experiment (McFadden, 1973), by optimising an objective function $P(x \rightarrow x^{\pm ij}) = \dfrac{exp(f_i(\beta; x^{\pm ij}))}{\sum_{h=1}^{n} exp(\beta; f_i(x^{(ih\pm)}))}$

- The function parameters can be interpreted as the agents' **relative preferences** on the prevalence of certain local configurations





SAOM

Stochastic Actor-Oriented Models

To be **mathematically tractable**, (most) SAOMs (Snijders, 2017) assume agents':

- access to **information about the whole network** (e.g., geometrically weighted configurations): **unplausible for large networks** or **competitive contexts** where information is strategically concealed (e.g., Renzini et al., 2024) —> **idiosyncratic models**

- changing one tie at each simulation step: **prevents modelling coordination** and collective action (Leifeld & Cranmer, 2019) and **cascade dynamics** driven by threshold-based preferences (Renzini et al., 2024)

$$P(x \to x^{\pm ij}) = \frac{exp(f_i(\beta; x^{\pm ij}))}{\sum_{h=1}^{n} exp(\beta; f_i(x^{(ih\pm)}))}$$

SAOM

Stochastic Actor-Oriented Models

- tie selection as a **multinomial choice** based on **preference optimization**: **unplausible for cognitive relations** not requiring psychological investment (liking vs. disliking, status attribution)
- **myopia**: prevents modelling a) **backward-looking rationality** and **learning** processes; b) **forward-looking rationality** (strategic behaviour in competitive contexts)

$t = 0$

1. Complying to a solidarity norm (Lindenberg, 2015)

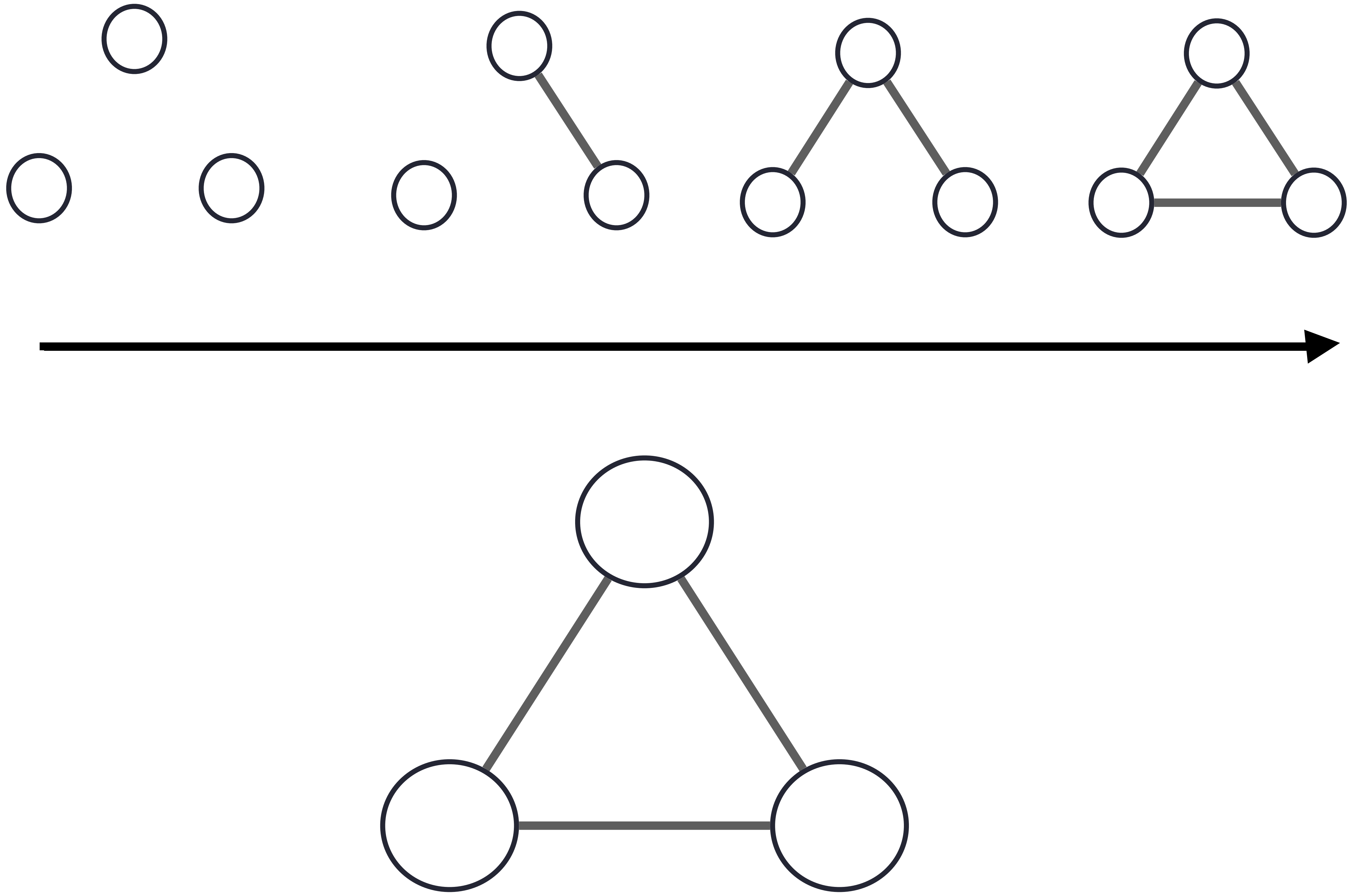
2. Strategically investing in a long-term relationship (Coleman, 1991)

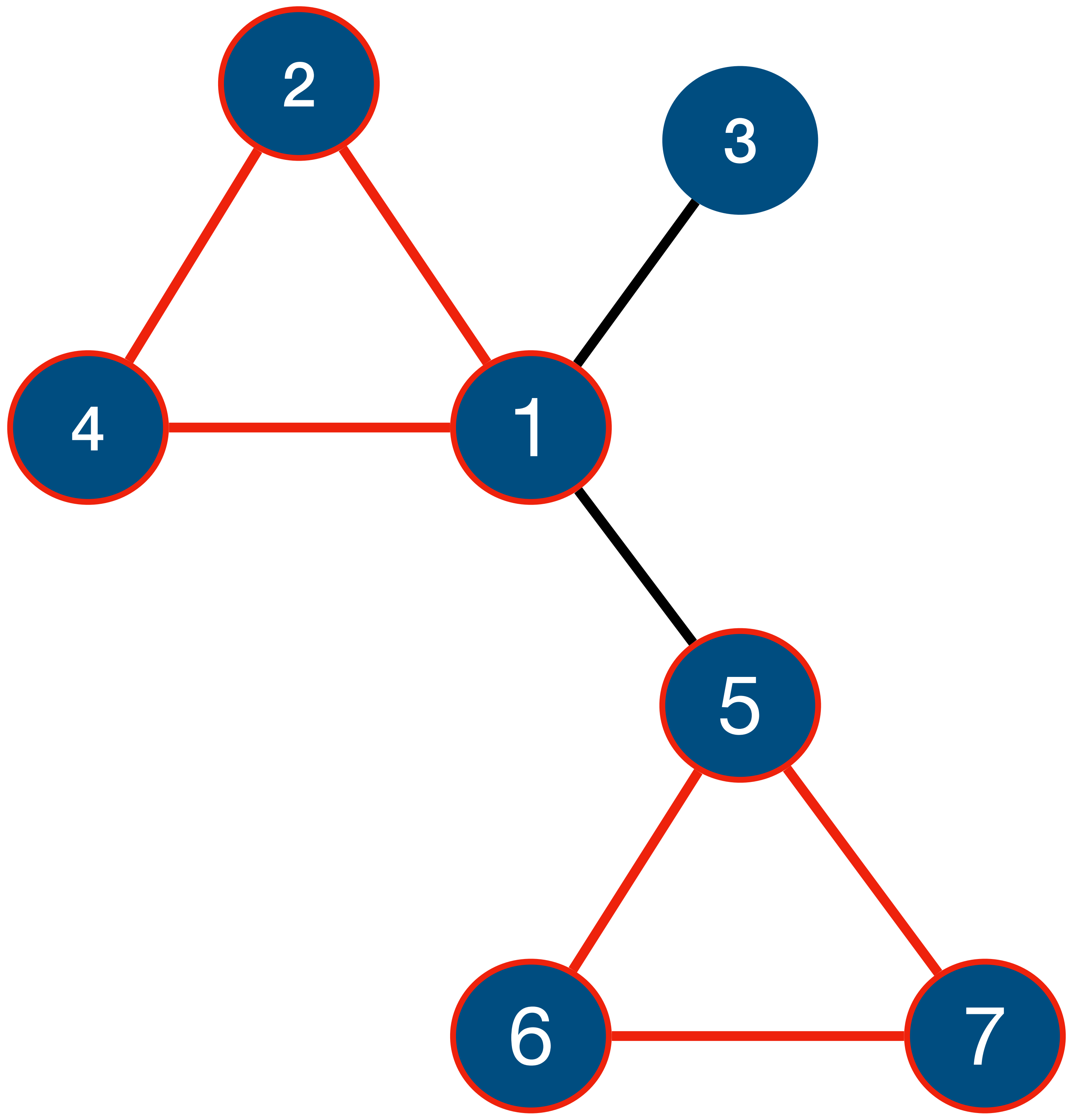
3. Controlling one's reputation (Buskens & Raub, 2005)

$t = 1$

Underdetermination of statistical models

- Statistical models of social networks usually provide **underdetermined evidence of causal mechanisms**
- "Network patterns" (Robins, 2015) or "network mechanisms" (Stadtfeld & Amati, 2021) underlie different possible causal mechanisms
- Statistical models cannot identify actors' **cognitive** and **cultural determinants of decisions** on extending, maintaining, or severing social relations





Why?

Methodological models

- Prevalence or incidence of the "**archeological traces**" of unobserved, past relational processes (White, 1970, 2008; Lusher et al., 2013)
- **Mathematical tractability**: sufficient statistics of local configurations + parameters estimated via robust algorithms (maximum likelihood or method of moments)
- "**Methodological models**" (Skvoretz, 1991): finding internal associations within aggregate-level data

if i is **low-skilled** (L) **then**
  Evaluate utility from removing ties to current advisors $(f_i^{L,rem})$
  Evaluate utility from sending requests to potential advisors $(f_i^{L,add})$
  Select $f_i^{L,*} = max\{f_i^{L,rem}, f_i^{L,add}\}$
  Compute $f_i^{L,N}$, the utility from doing nothing
  if $f_i^{L,*} > f_i^{L,N}$ and $f_i^{L,*} = f_i^{L,add}$ **then:**
    if New advisor is a H with In-Degree $(H) > \tau$ **then**
      Remove and redirect between 1 and τ low-skilled L asking to H
      for Every redirecting L **do**

Agent-based model as theoretical models

- **Computational, dynamic models** that formalize a population of **interdependent social actors** (i.e., *agents*) with specific **properties**, interacting according to a set of **behavioural rules** within certain **environmental constraints** (Gilbert & Troitzsch, 2005; Squazzoni, 2012; Hedström & Manzo, 2015)

- ABMs are "**theoretical models**" (Skvoretz, 1991; Hedström & Manzo, 2015): models of **logical or numerical propositions** of a theory assumed to explain a phenomenon

Real mechanism
- Actors
- Actors' properties
- Actors' (inter)actions
- Actors' relationships

→

Agent-based model
- Agents
- Agents' attributes
- Agents' rules of behaviour
- Agents' structural constraints

ABM:

flexibility and granularity

- "**Structural homology**" with causal mechanisms (Manzo, 2014):
    - **Cognitive** or **cultural** constituents of actors' decisions
    - Social **interactions**
    - **Institutional**, **relational**, or **spatial** constraints
- High **flexibility** —> wide **granularity** range of agent modelling (Wooldridge & Jennings, 1995)
    - **Social** characteristics: autonomy, interdependence, embeddedness, heterogeneity
    - **Cognitive** characteristics: reactivity, proactivity, heuristic-based rationality, adaptiveness

ABMs can complement for statistical models' limits concerning:

- **actors' behaviour**
- **tie types**
- **context**

- Tie-based models (e.g., ERGM-family) are indifferent to the specific tie sequences through which particular configurations emerge (Block et al., 2019)
- To be mathematically tractable, (most) SAOMs need assuming agents':
  - access to information about the whole network (e.g., geometrically weighted configurations): unplausible for large networks or competitive contexts where **information is strategically concealed** (e.g., Renzini et al., 2024)
  - tie selection as a multinomial choice based on preference optimization: unplausible for cognitive relations **not requiring psychological investment** (liking vs. disliking, status attribution)
  - myopia: prevents modelling a) **backward-looking rationality** and **learning** processes; b) **forward-looking rationality** (strategic behaviour in competitive contexts)
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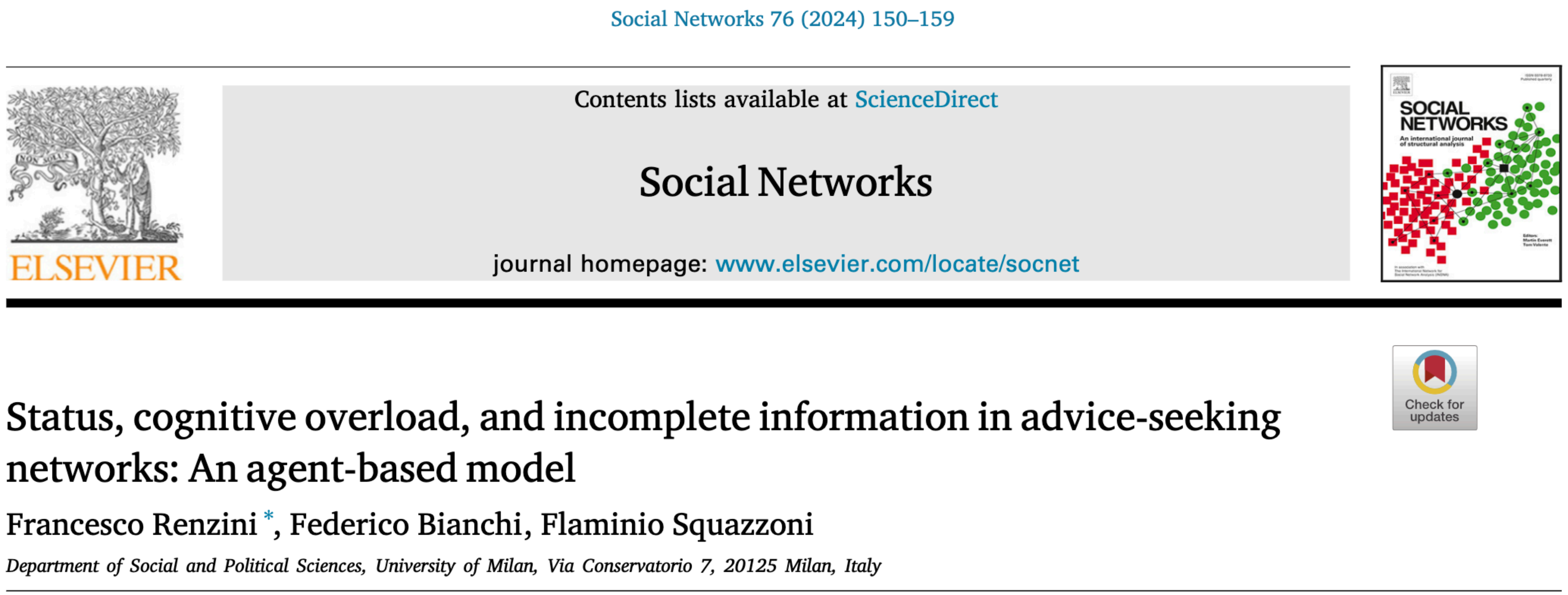

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Status, cognitive overload, and incomplete information in advice-seeking networks: An agent-based model

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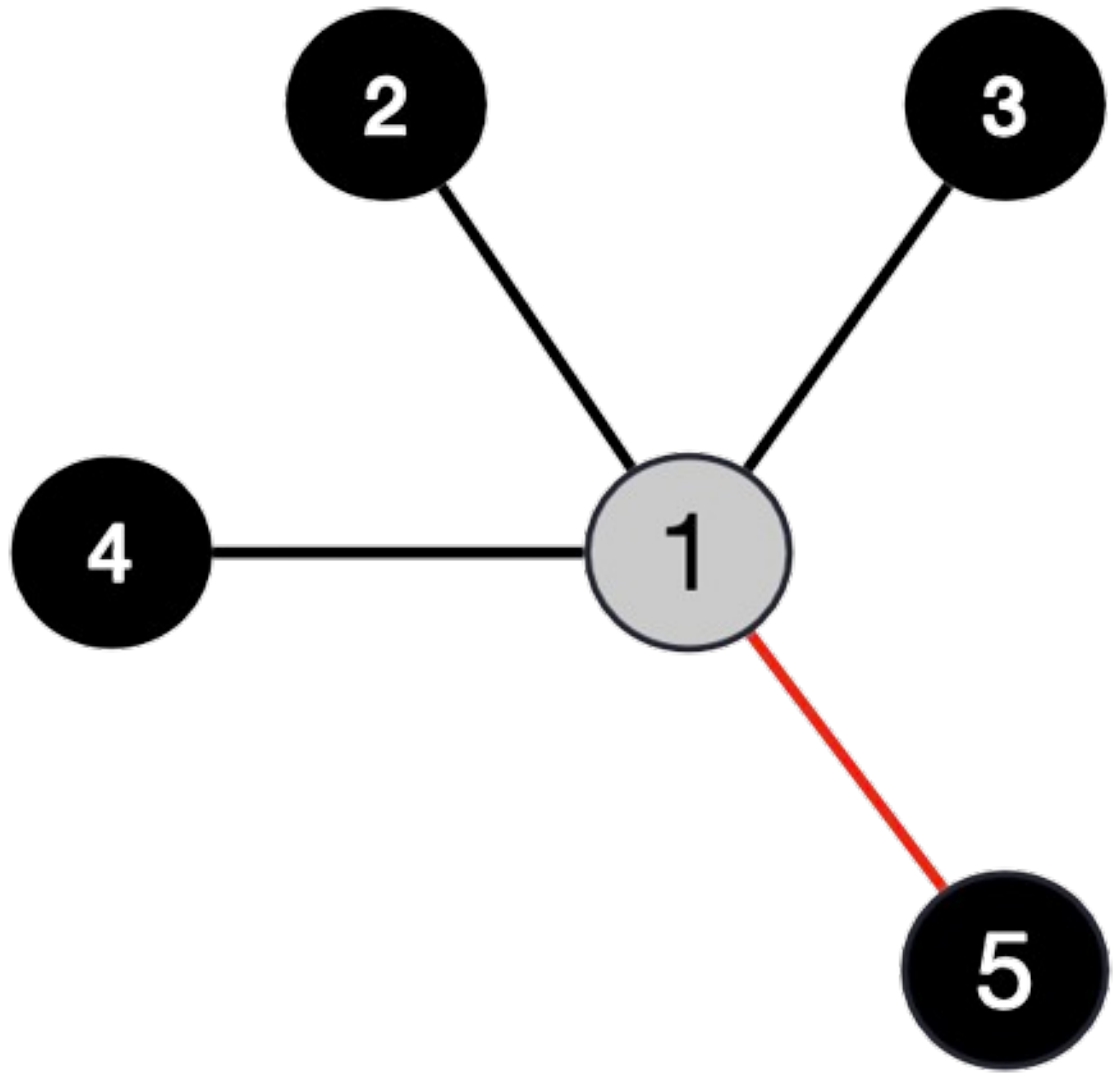
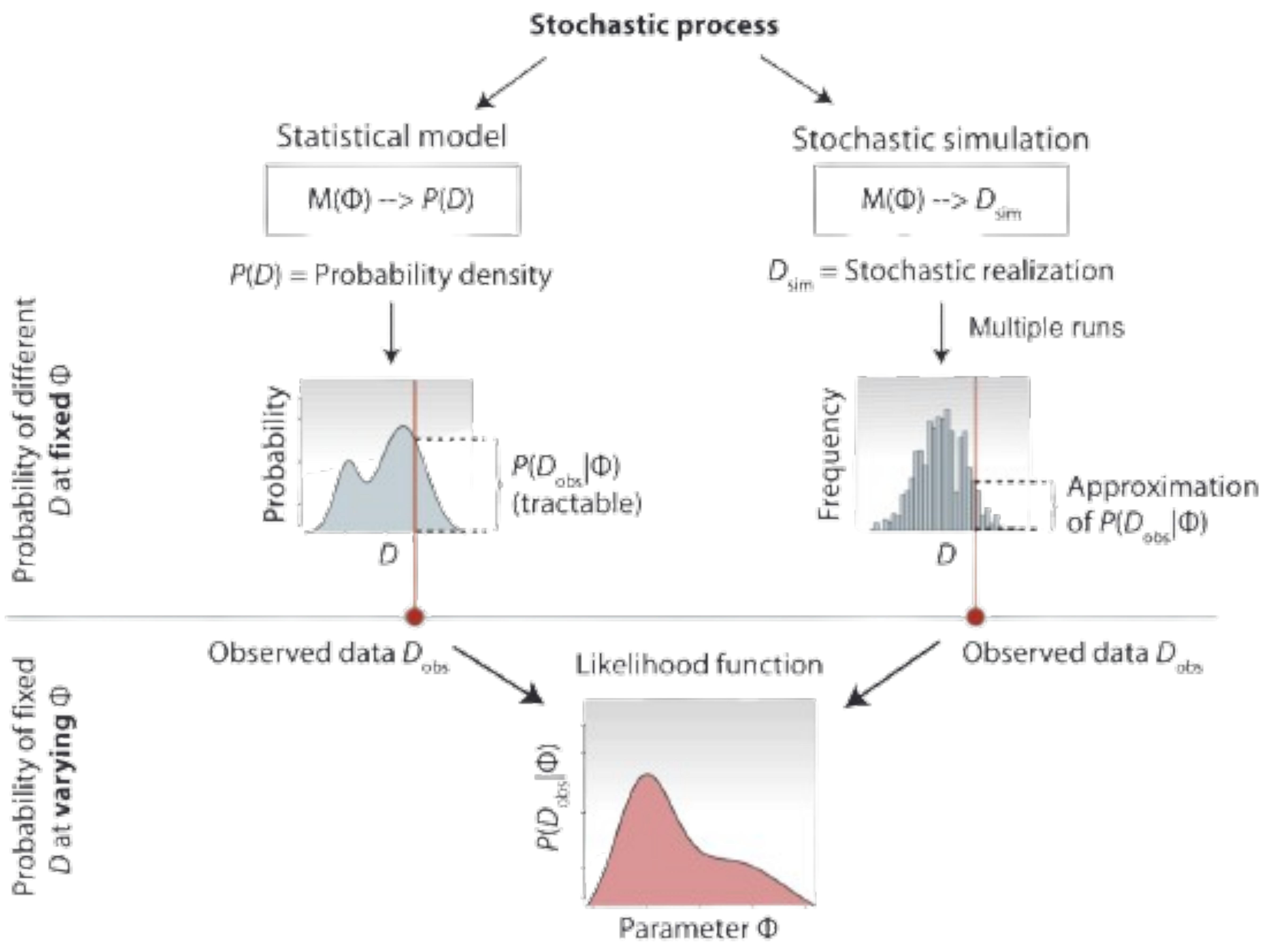


Examples of ABMs of social networks

- **Bianchi & Renzini (*work in progress*)**:
  - Explaining advice-seeking network formation as the outcome of context-dependent, time-varying heterogeneous framing of costs
  - Limited information, local heuristics, plausible and parsimonious model
- **Bellotti, Bianchi, Renzini, et al. (*work in progress*)**:
  - Explaining low adoption rates of malaria prevemptive practices in tribal villages in Meghalaya (India)
  - Complex contagion via information ties (threshold-based) * negative influence



Theoretical, yet empirical

- **Generativist method** (Epstein, 2006): **sequential complexification** of the modelled mechanism along with computer simulations **until the generated outcome fits the empirical observations** (summary statistics)
- **Testing for unobserved** (unobservable?) **mechanism components** (e.g., thresholds, motives, etc.)
- Simulation-based **estimates** of parameters and **uncertainty measures** for **untractable likelihood functions** (Hartig et al., 2011)
- **No need to rely on unplausible assumptions** to obtain a tractable likelihood function

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Conclusions

- ABM of social networks to estimate **unobserved** or **unobservable** processes
- Bringing back context-dependent **behaviour** and **cognition** (type of ties) to the core of explanations of social phenomena
- Middle-range social science

References

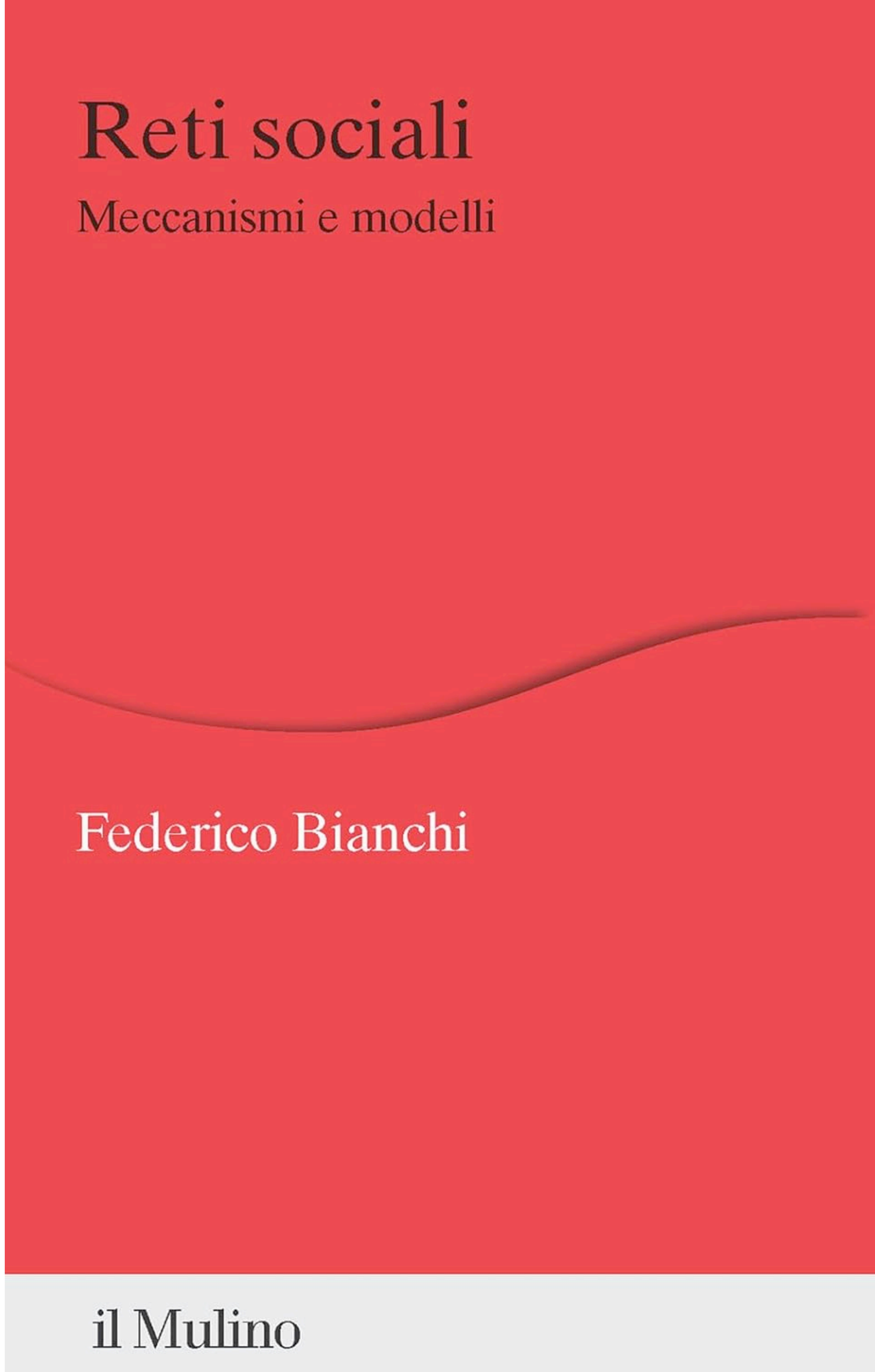
Bianchi, F. (2023). *Reti sociali. Meccanismi e modelli*. Bologna: Il Mulino.

Bianchi, F., Flache, A., Squazzoni, F., & Takács, K. (2027, *expected*). Agent-Based Modelling for Social Network Research. Special Issue of *Social Networks*.

Bianchi, F., & Renzini (2026, *expected*). Agent-based models of social networks. In: *Handbook of Research Methods of Social Network Analysis*, ed. F. Agneessens. Cheltenham: Elgar.

Bianchi, F., & Squazzoni, F. (2015). Agent-based models in sociology. *Wiley Interdisciplinary Research: Computational Statistics*, *7*: 284-306. doi: 10.1002/wics.1356

Renzini, F., Bianchi, F., & Squazzoni, F. (2024). Status, cognitive overload and incomplete information in advice-seeking networks: an agent-based model. *Social Networks*, *76*: 150–159.



Other references / 1

Bearman, P., Moody, J., & Stovel, K. (2004). Chains of affection: the structure of adolescent romantic and sexual networks. *American Journal of Sociology*, 110(1): 44-91. doi: 10.1086/386272

Block, P., Stadtfeld, C., & Snijders, T.A.B. (2019). Forms of dependence: Comparing SAOMs and ERGMs from basic principles. *Sociological Methods & Research*, *48*(1): 202-239. doi: 10.1177/0049124116672680

Brandes, U., Robins, G., McCranie, A.N.N., & Wasserman, S. (2013). What is network science?*. Network Science*, *1*(1): 1-15. doi: 10.1017/nws.2013.2

Epstein, J. (2006). *Generative Social Science: Studies in Agent-Based Computational Modeling*. Princeton, NJ: Princeton University Press.

Gilbert, N., & Troitzsch, K. (2005). *Simulation for the Social Scientist* (2nd ed.). Maidenhead: Open University Press.

Hartig, F., Calabrese, J.M., Reineking, B., Wiegand, T., & Huth, A. (2011). Statistical inference for stochastic simulation models - Theory and application. *Ecology Letters*, *14*(8): 816-827. doi: 10.1111/j.1461-0248.2011.01640.x

Hedström, P., & Bearman, P. (2009). What is analytical sociology all about? An introductory essay. In: *The Oxford Handbook of Analytical Sociology*, eds. P. Hedström & P. Bearman. Oxford: Oxford University Press, 3–24.

Hedström, P., & Manzo, G. (2015). Recent trends in agent-based computational research: A brief introduction. *Sociological Methods & Research*, *44*(2): 179-185. doi: 10.1177/0049124115581211.

Leifeld, P., & Cranmer, S.J. (2019). A theoretical and empirical comparison of the Temporal Exponential Random Graph Model and the Stochastic Actor-Oriented Model. *Network Science*, *7*(1), 20-51. doi: 10.1017/nws.2018.26

Other references / 2

Lusher, D., Koskinen, J., & Robins, G. (Eds.) (2013), *Exponential Random Graph Models. Theory, Methods, and Applications.* New York, NY: Cambridge University Press.

Machamer, P., Darden, L., & Craver, C.F. (2000). Thinking about mechanisms. *Philosophy of Science, 67*(1): 1–25. doi: 10.1086/392759

Manzo, G. (2014). Analytical Sociology: Actions and Networks. Chichester: Wiley.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In: *Frontiers in Econometrics* (pp. 105-142), ed. P. Zarembka. New York, NY: Academic Press.

Robins, G. (2015). *Doing Social Network Research. Network-Based Research Design for Social Scientists.* London: Sage.

Skvoretz, J. (1991). Theoretical and methodological models of networks and relations. *Social Networks*, *13*(3): 275-300.

Snijders, T.A.B. (2017). Stochastic Actor-Oriented Models for network dynamics. *Annual Review of Statistics and Its Applications*, 4: 434-363. doi: 10.1146/annurev-statistics-060116-054035

Squazzoni, F. (2012). *Agent-Based Computational Sociology*. Chichester: Wiley.

Stadtfeld, C., & Amati, V. (2021). Network mechanisms and network models. In: *Research Handbook on Analytical Sociology* (pp. 432-452), ed. G. Manzo. Cheltenham: Elgar.

White, H.C. (1970). Matching, vacancies, and mobility. *Journal of Political Economy*, *78*(1): 97-105.

Wooldridge, M., & Jennings, N.R. (1995). Intelligent agents: Theory and practice. *The Knowledge Engineering Review*, *10*(2): 115-152.