Book presentation

Reti sociali. Meccanismi e modelli. Bologna: Il Mulino, 2023.

Quantitative Social Science Seminars,
Department of Political and Social Sciences, University of Bologna
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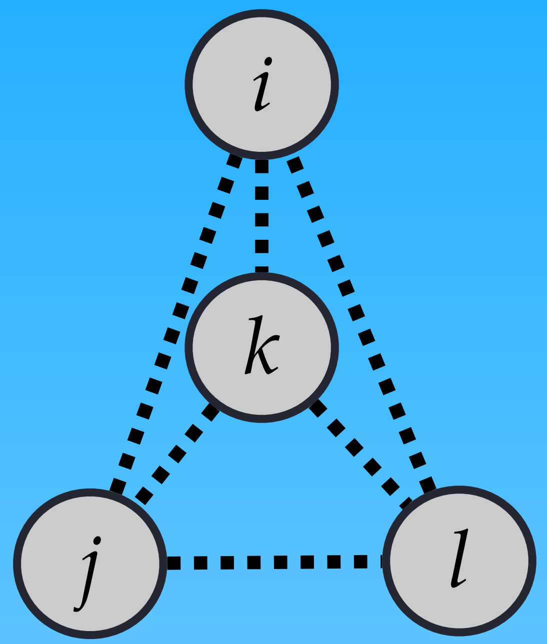
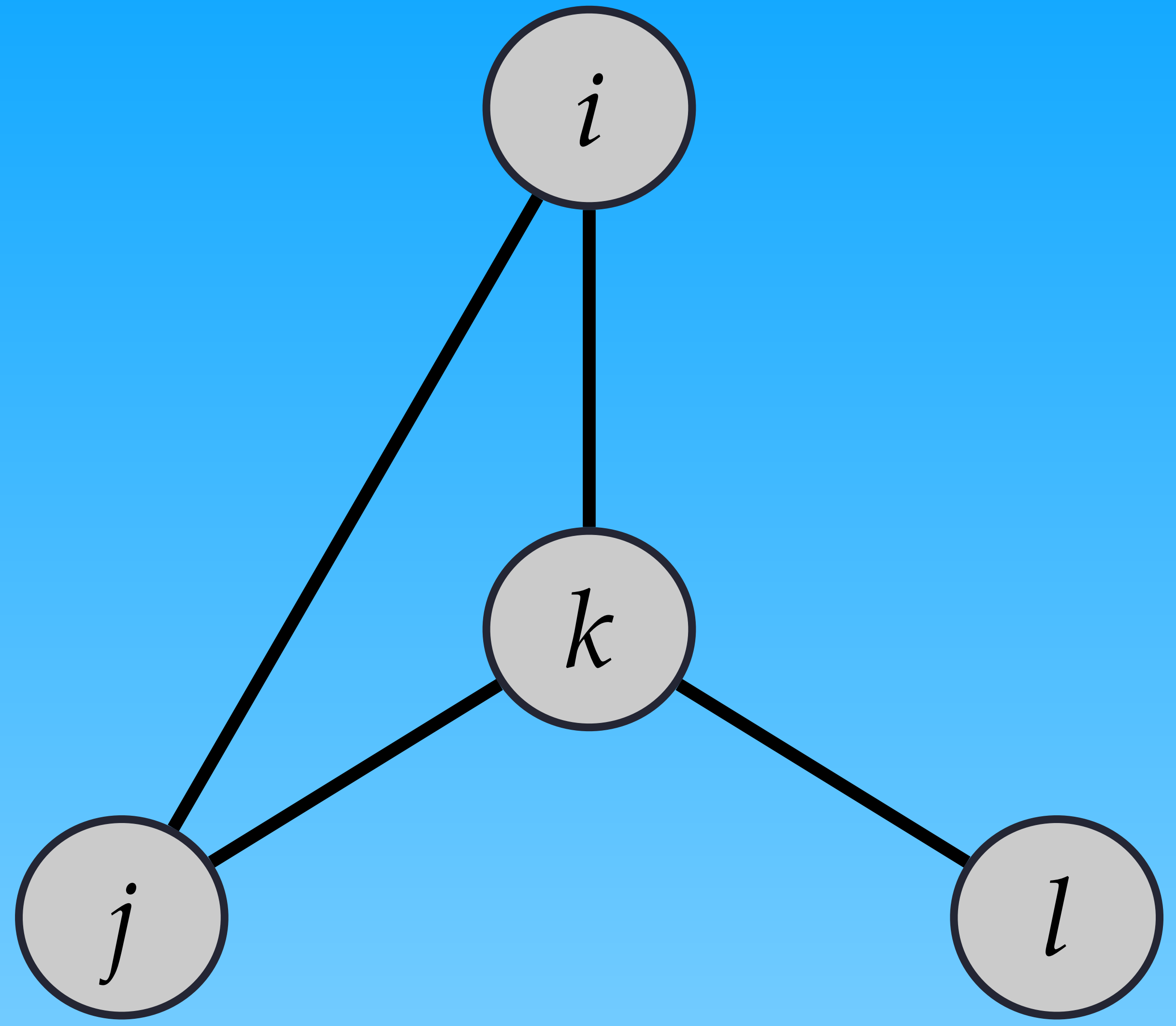




Why this book / 1:

From descriptive to inferential network analysis

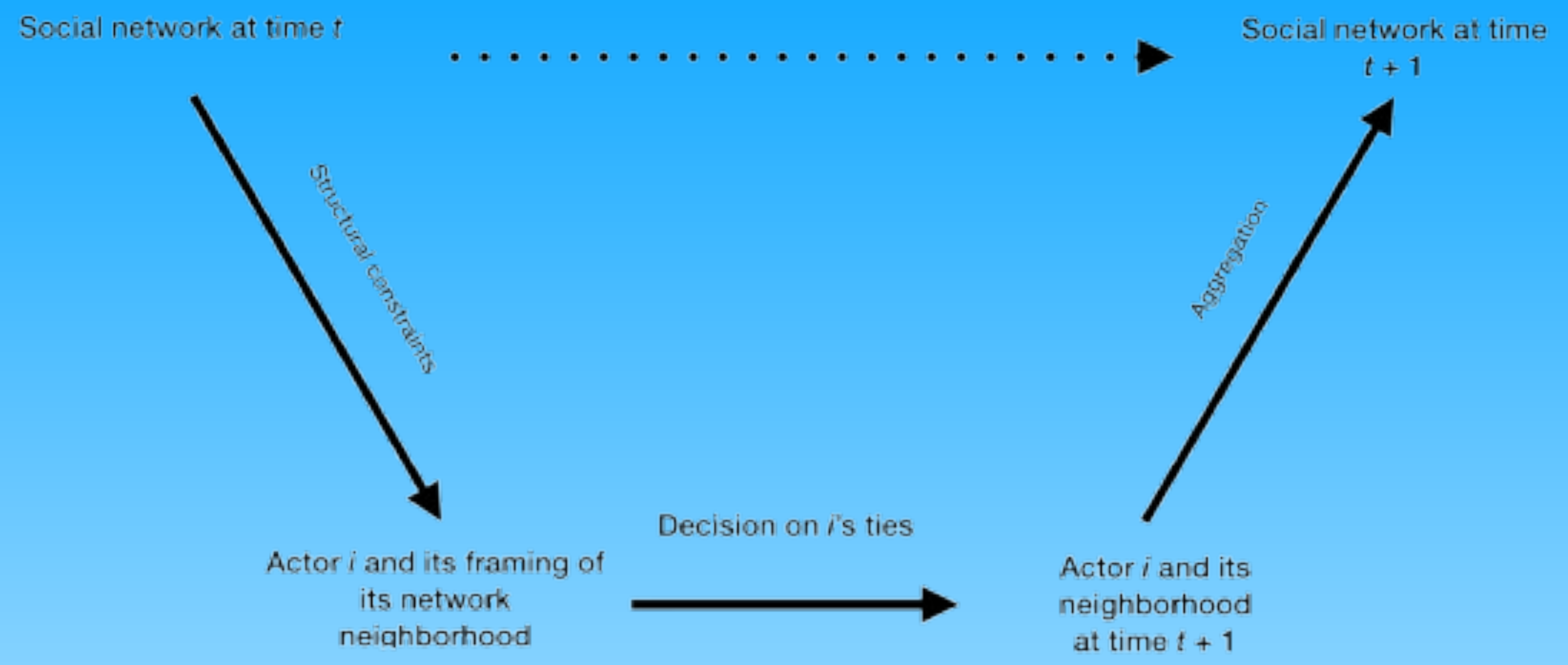
- Updated introduction to **statistical and computational modelling** techniques
- 1990s-2000s: convergence of multiple research groups efforts (Indiana/Melbourne and Groningen) + access to computational power —> statistical models (p^*) for hypothesis testing and multivariate analysis
- ***Exponential Random Graph Models*** (ERGM; Lusher et al., 2013) and ***Stochastic Actor-Oriented Models*** (SAOM; Snijders, 2017)

Social network analysis in Italy

- Focus on metatheoretical issues: translations by Fortunata Piselli (1995) with an introductory essay; Enrica Amaturo's preface to the Italian edition of Scott (1997 [1991]).
- An introduction to SNA techniques by Antonio M. Chiesi (1980, 1981, 1999).

Why this book / 2:

Social networks as causal mechanism models

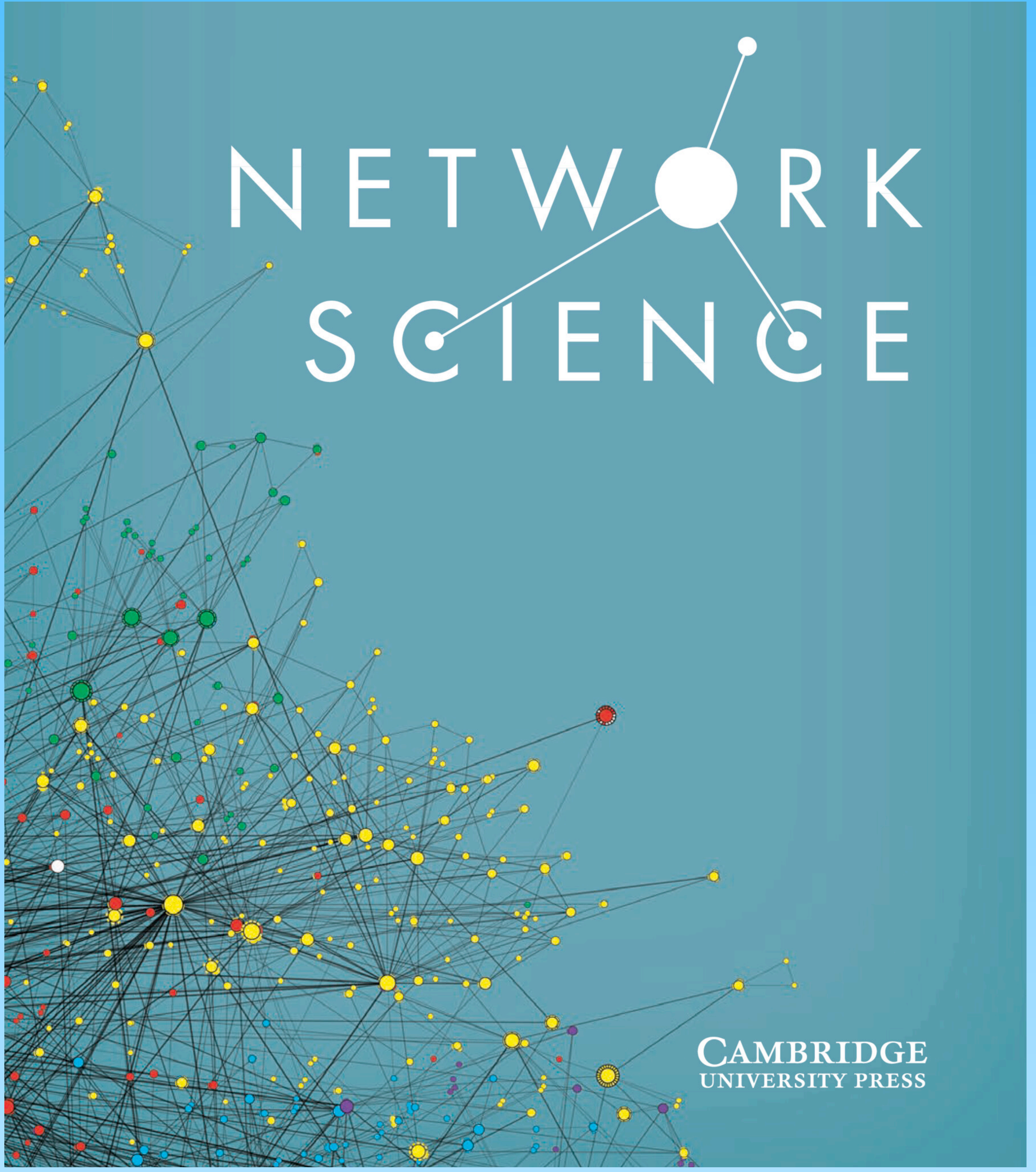


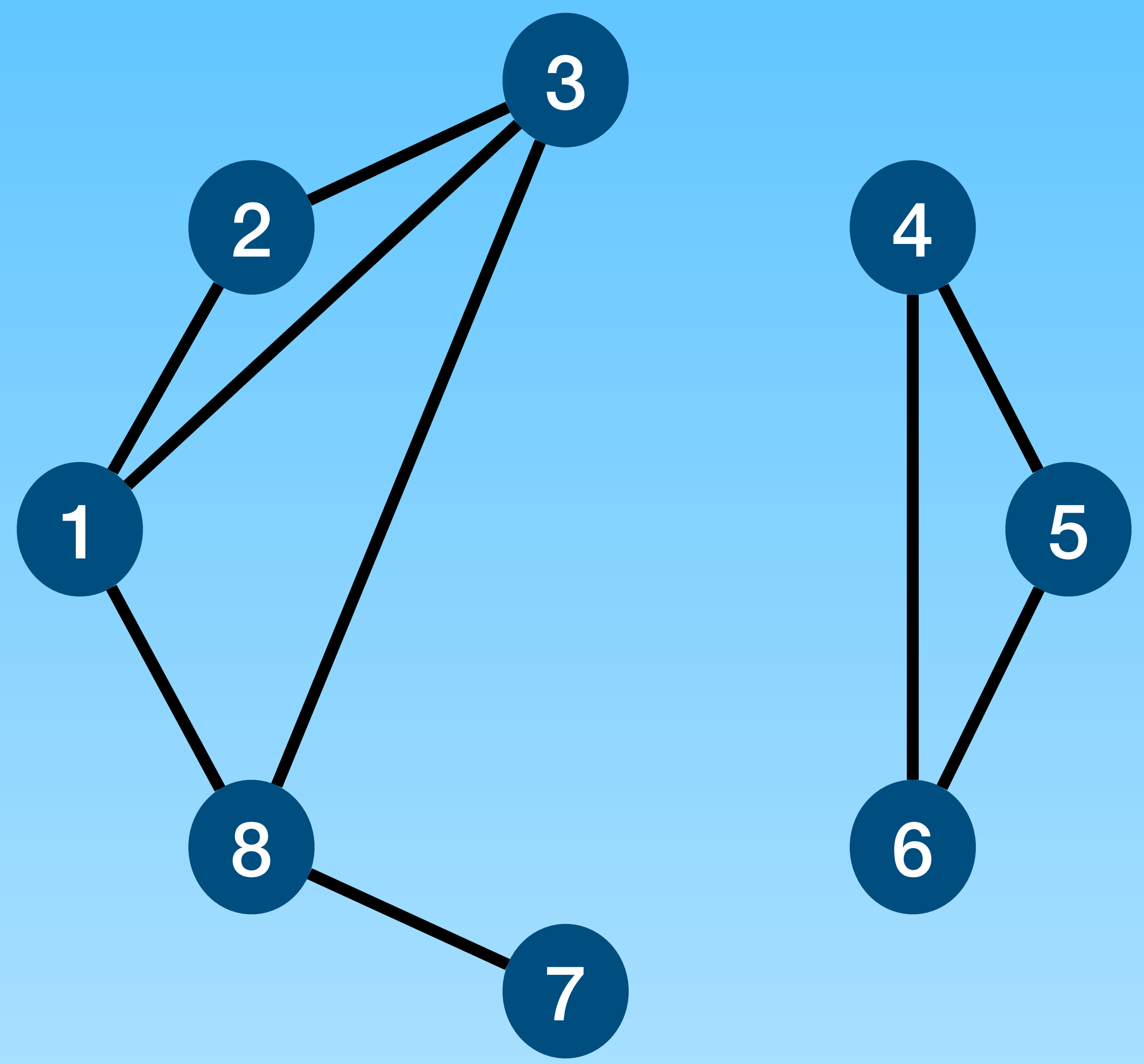
- Social network analysis as a method to **formally model causal mechanisms** of social phenomena

- Two steps:

    1. bringing back actors' **behaviour** (cognition and culture) to the core of the analysis of social relationships —> context-dependent *framing* of relationships and decision-making heuristics

    2. integrating **agent-based modelling** into social network analysis



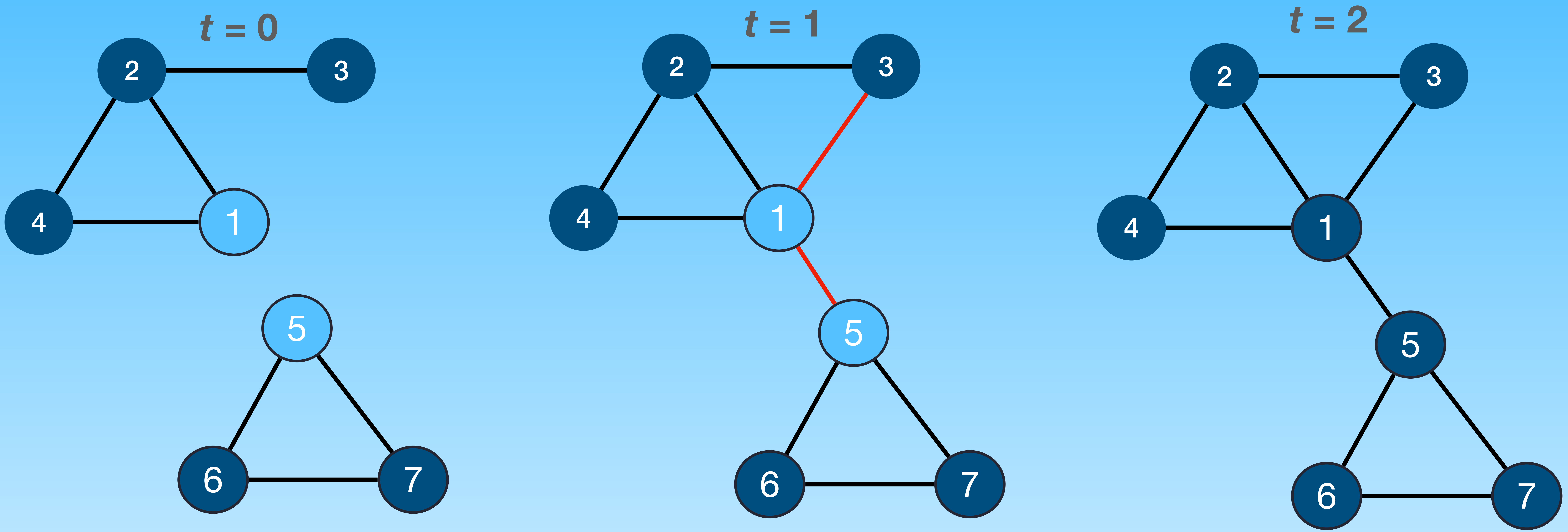


	1	2	3	4	5	6	7	8
1	0	1	1	0	0	0	0	1
2	1	0	1	0	0	0	0	0
3	1	1	0	0	0	0	0	1
4	0	0	0	0	1	1	0	0
5	0	0	0	1	0	1	0	0
6	0	0	0	1	1	0	0	0
7	0	0	0	0	0	0	0	1
8	1	0	1	0	0	0	1	0

Premise:

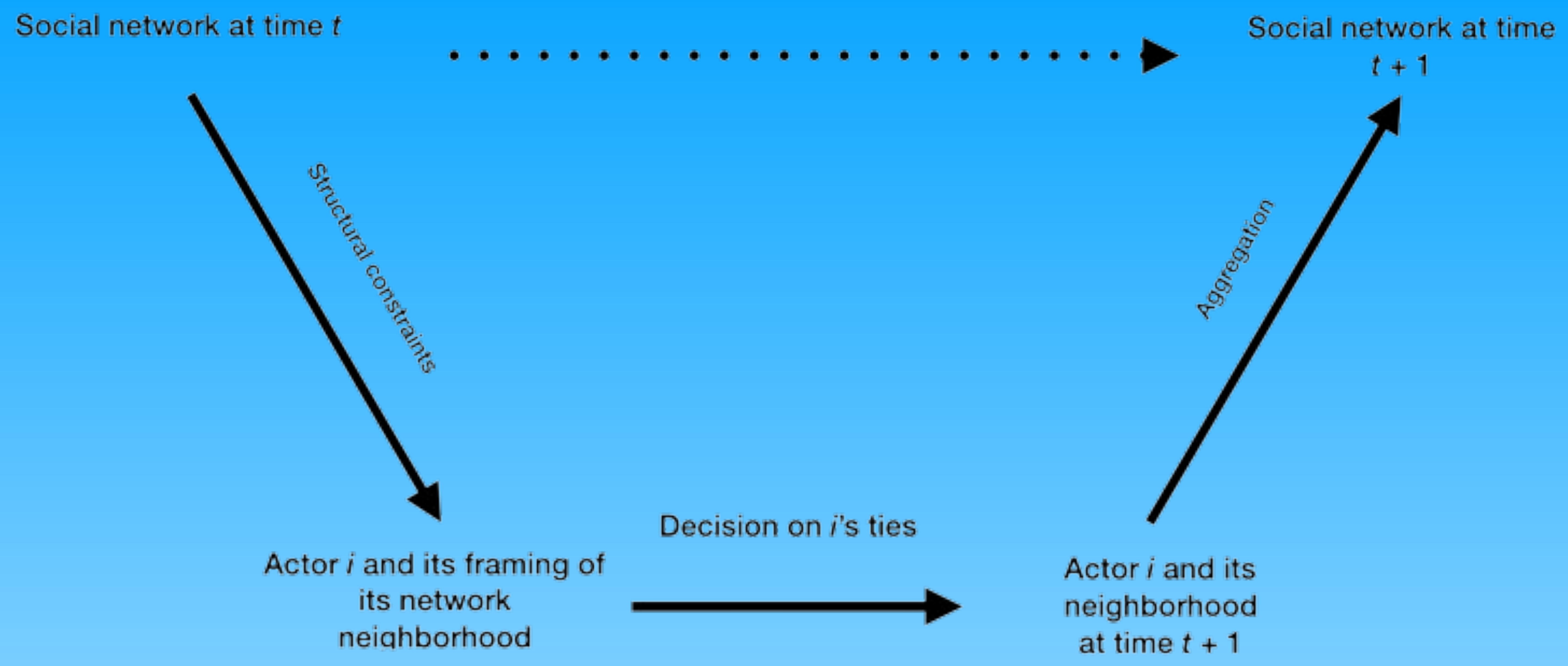
Networks as models of social phenomena

- “*Network science is the study of network models*” (Brandes et al., 2013, p. 4) —> “*network analysis*” vs. “*network theory*”
- Methods and techniques to analyse **relational data**, i.e. information on a certain relationship defined within a pair of entities
- Social network analysis is not necessarily the key to access the inherently relational structure of social reality



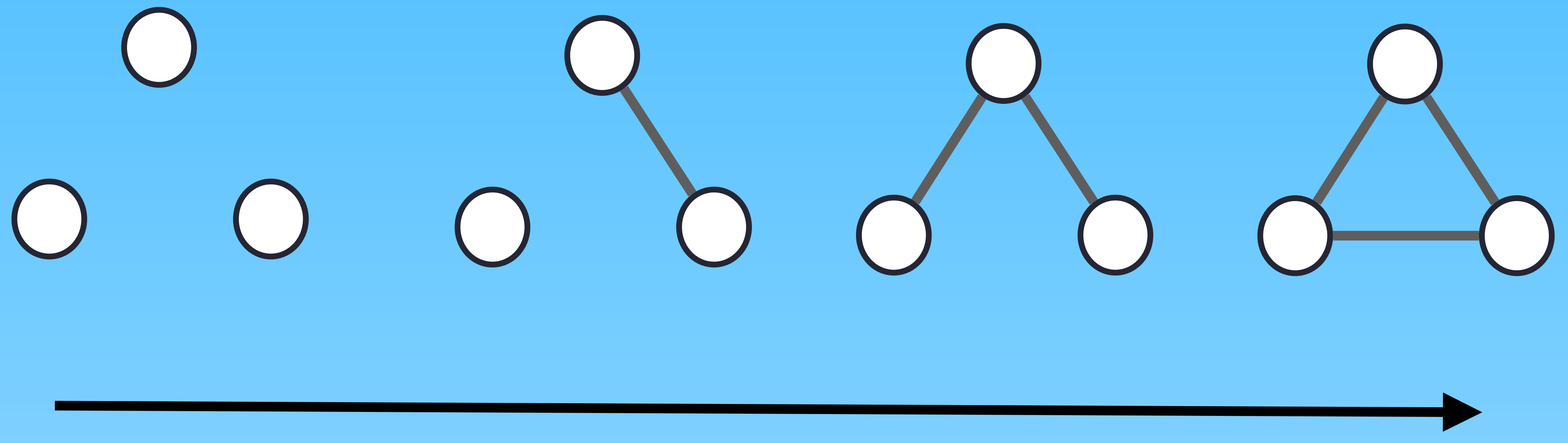
Social networks as models of social mechanisms

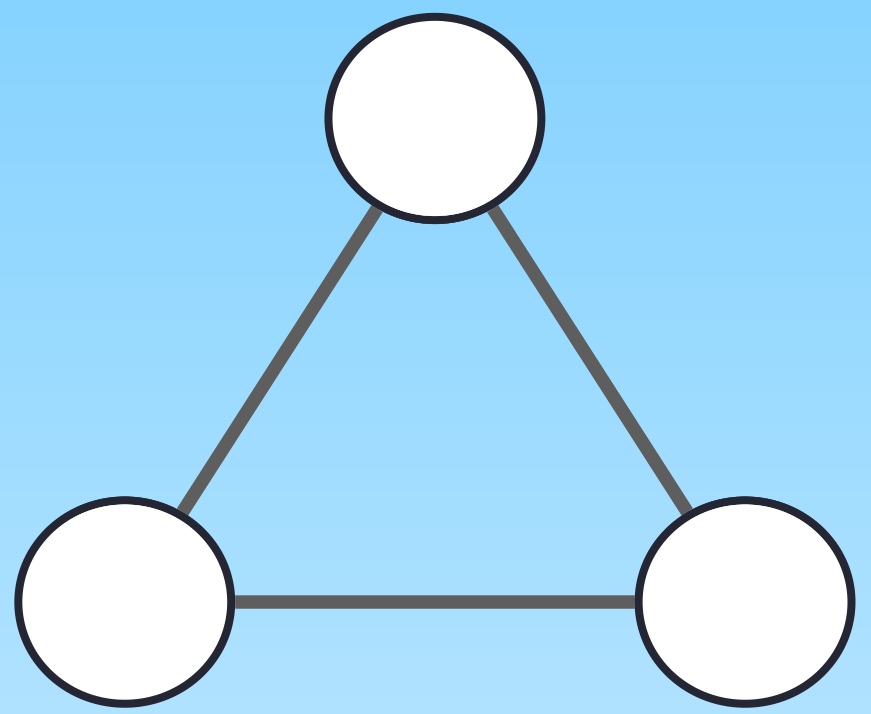
- Identifying a **social mechanism** —> describing a regular pattern of actions and interactions within a population of social actors (Hedström & Bearman, 2009)
- Dynamic social interactions: **vertices (actors)** and **edges (interactions)** in a graph
- Edges: relational “events” (e.g., transferring symbolic or material resources) or “states” (e.g., friendship, solidarity, etc.) (Borgatti et al., 2009)

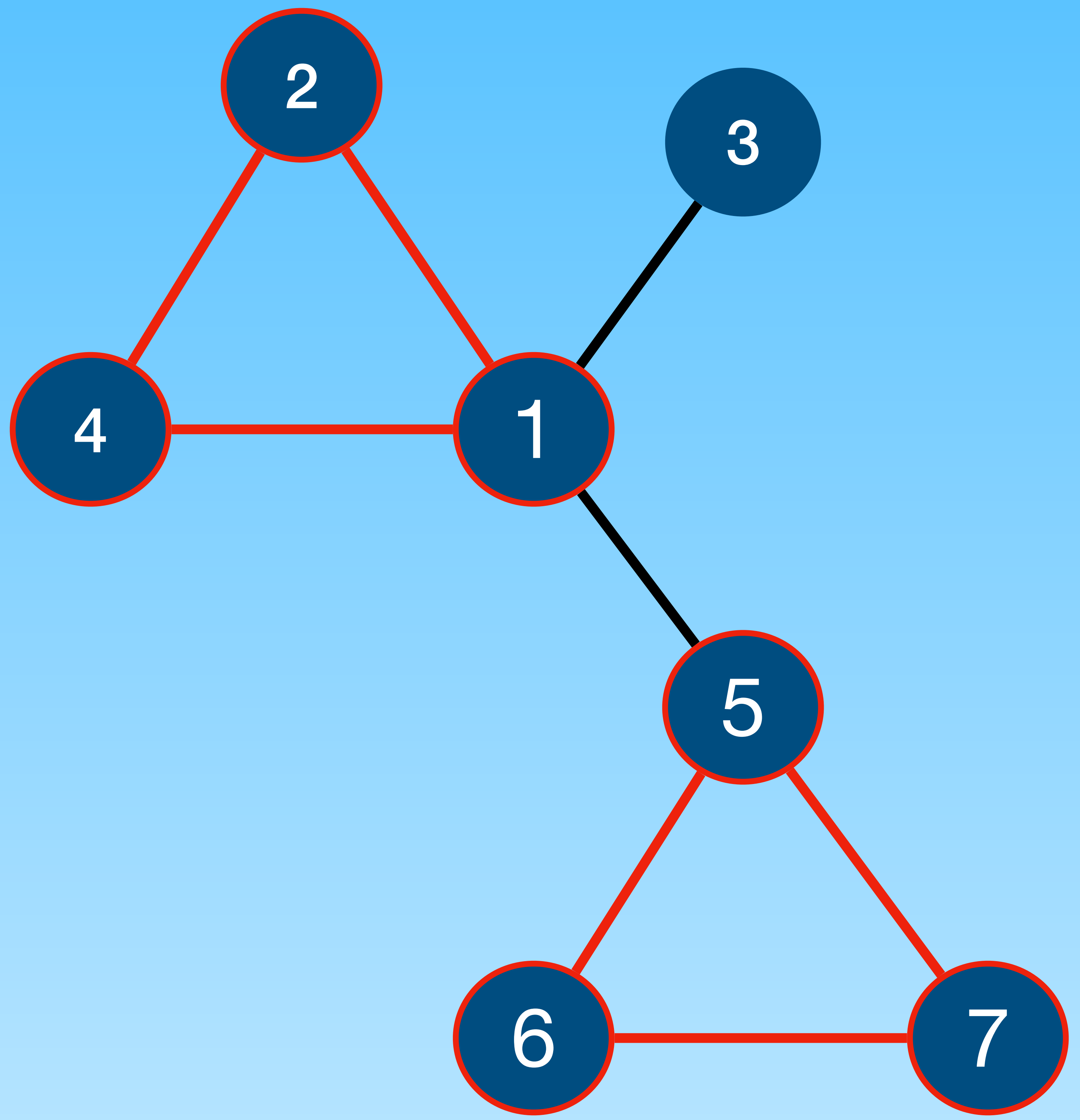


Causal mechanisms of social network evolution

- Identifying the **causal mechanisms** of social network evolution
- Patterns of **social actors' inter(actions)** bringing about regular network structures or compositions (Hedström & Bearman, 2009)
  - **Motives** behind decisions (desires and preferences)
  - **Context framing** (cognition and culture)
  - **Types of ties** (events or states; Borgatti et al., 2009)





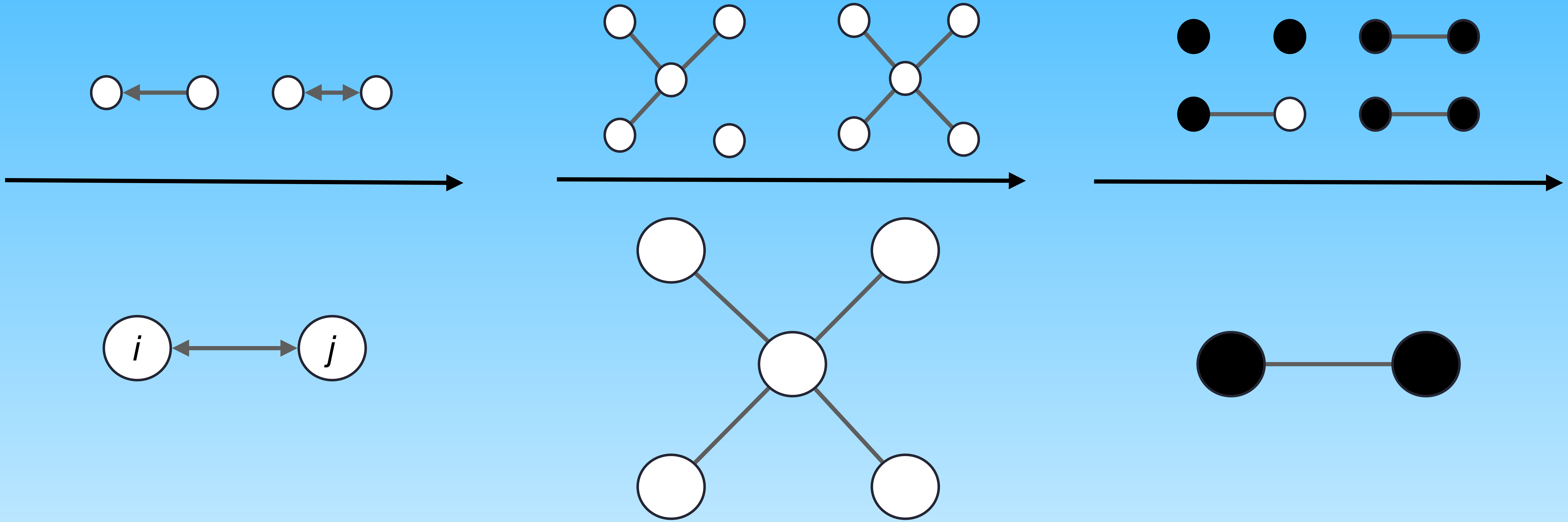


Statistical models of social networks

- Inferring the effect of **unobserved**, dynamic 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 causal mechanisms (White, 1970; Lusher et al., 2013)

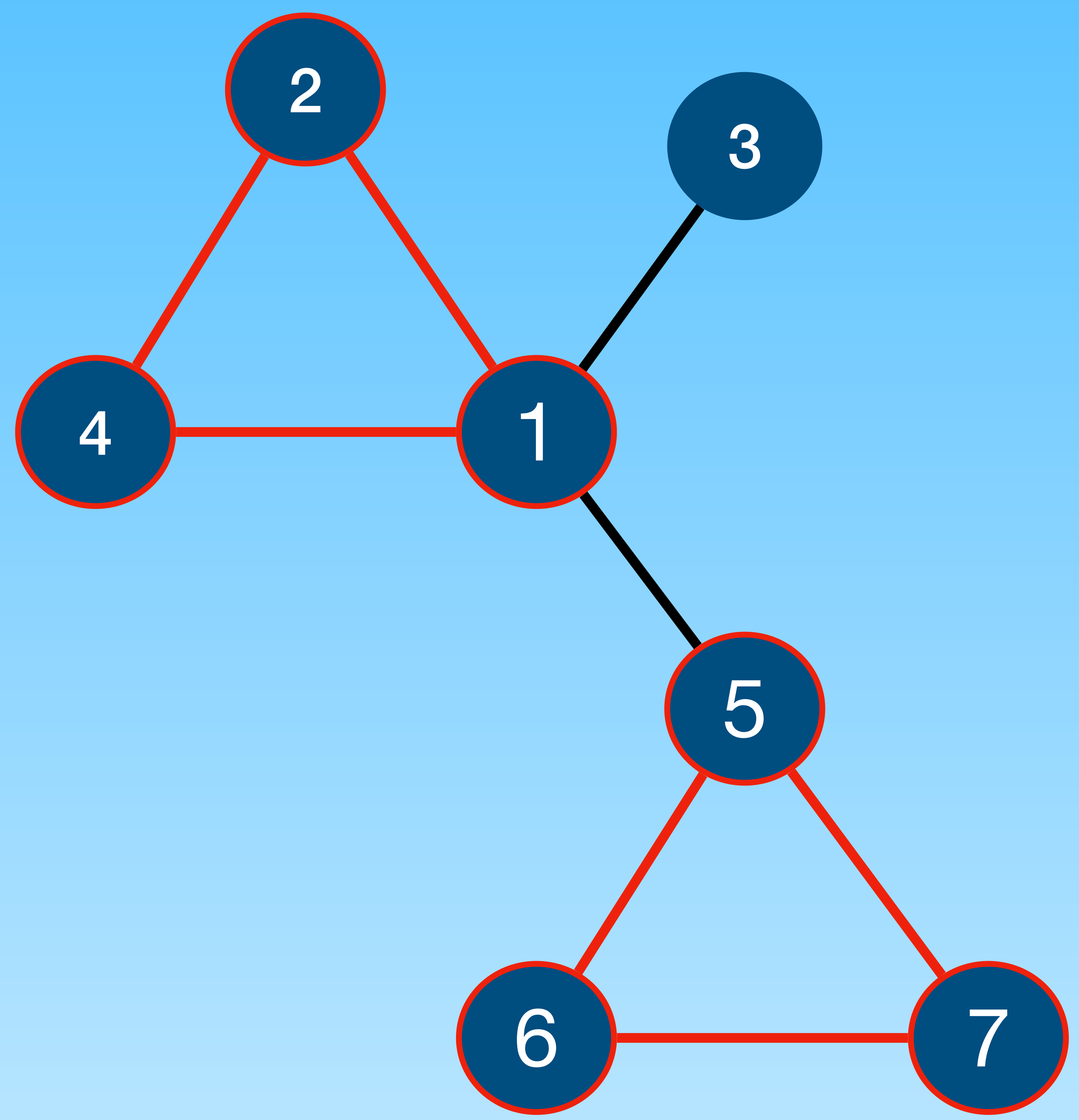
- The relative effect size of these processes can be estimated by computing **statistics of empirical network data** —> Maximum likelihood or method of moments (numerical simulations)

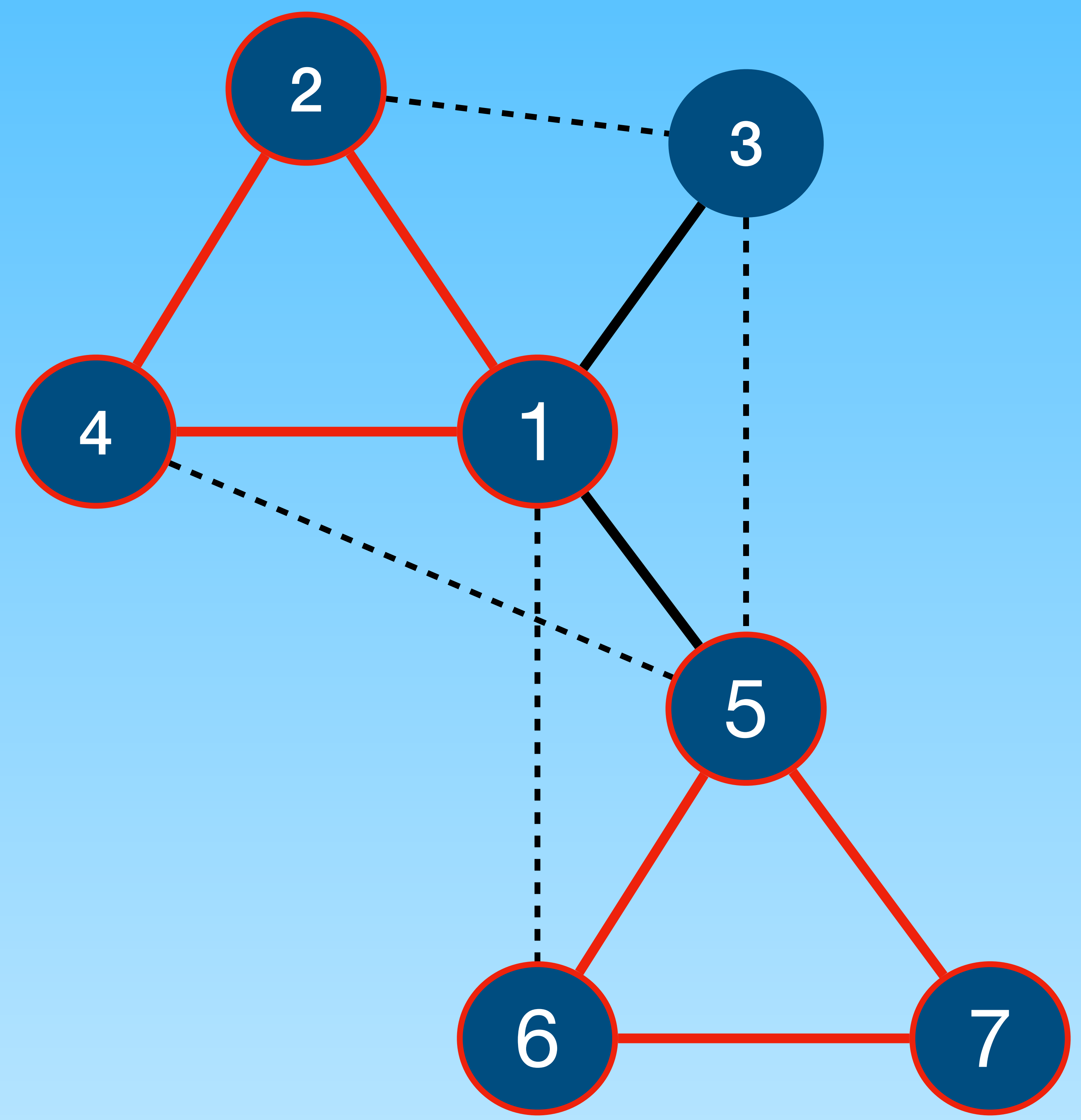


Statistical models of social networks:

local configurations and 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., $P(x_{ij}) \cap P(x_{ji}) = P(x_{ij} | x_{ji}) \cdot P(x_{ji})$

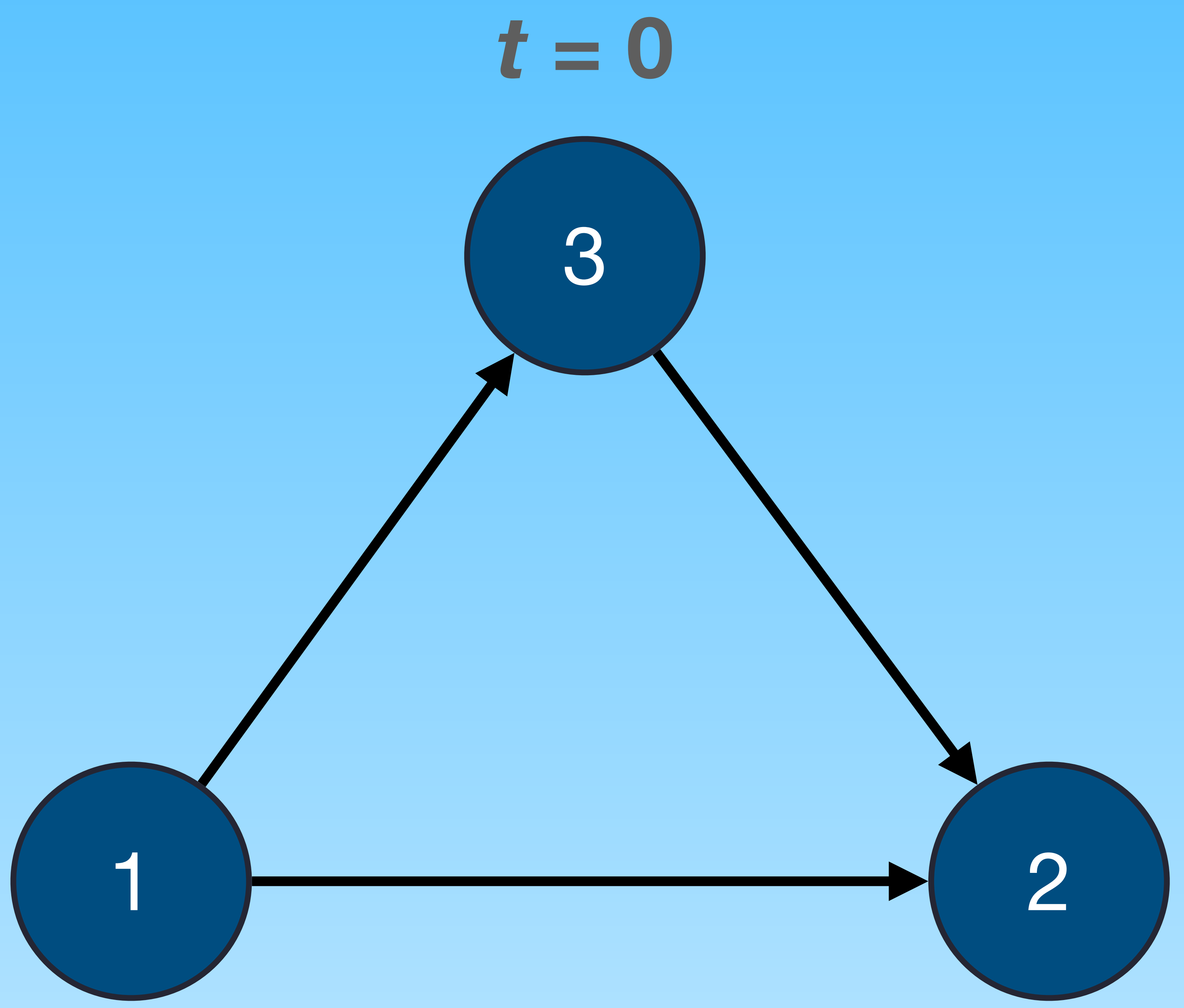


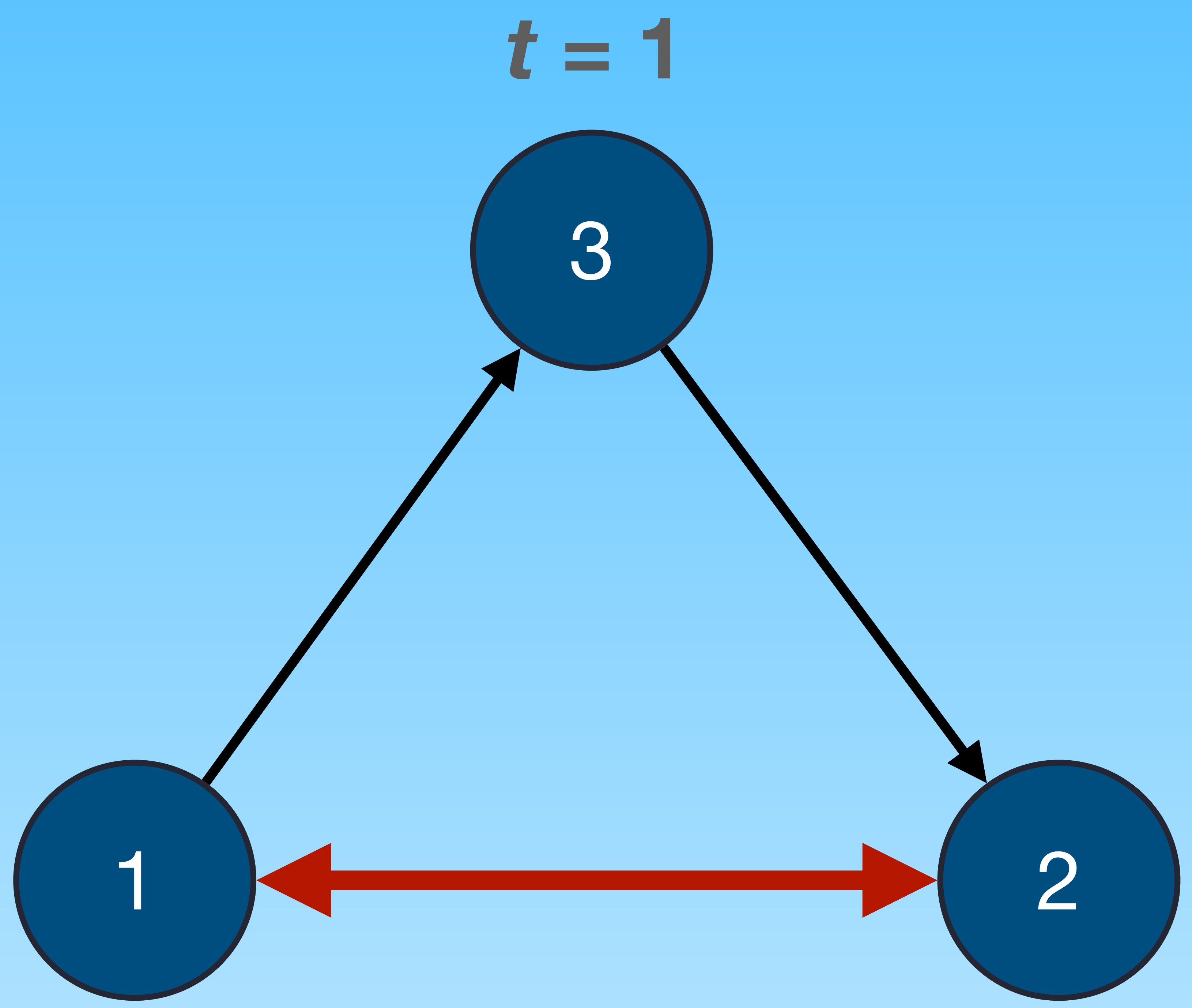


Statistical models of social networks:

hypothesis testing

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

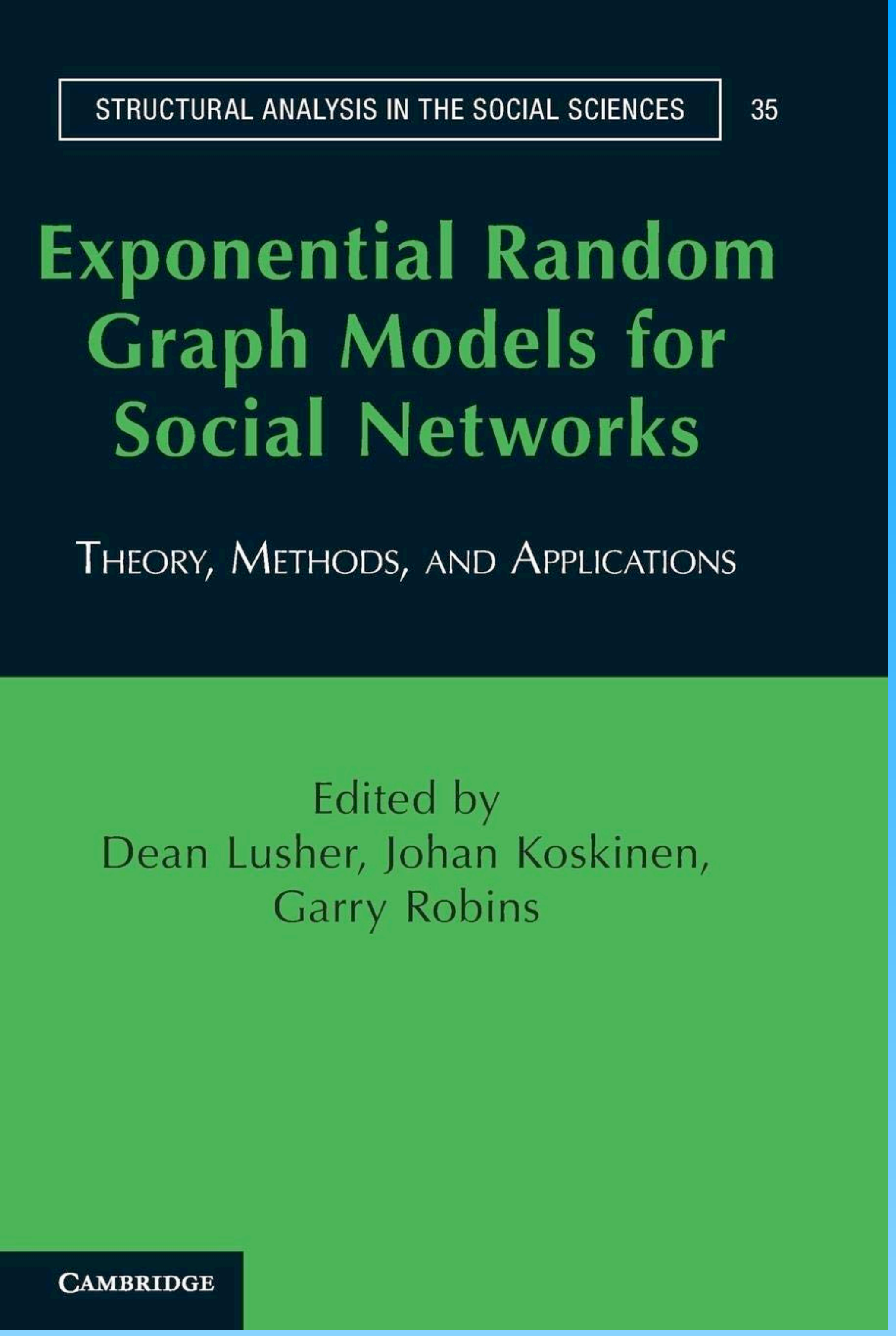


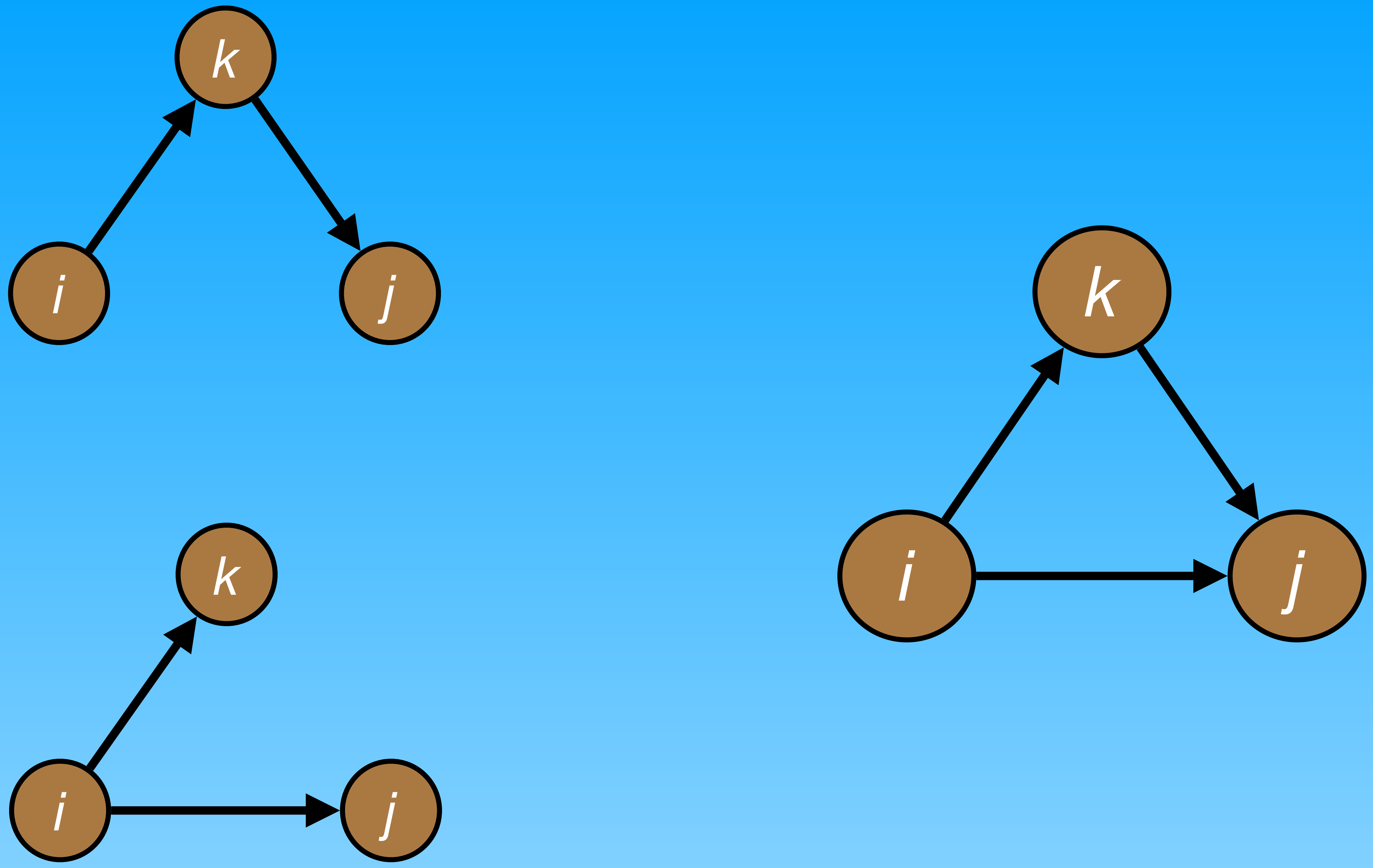


Statistical models of social networks:

multivariate analysis

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





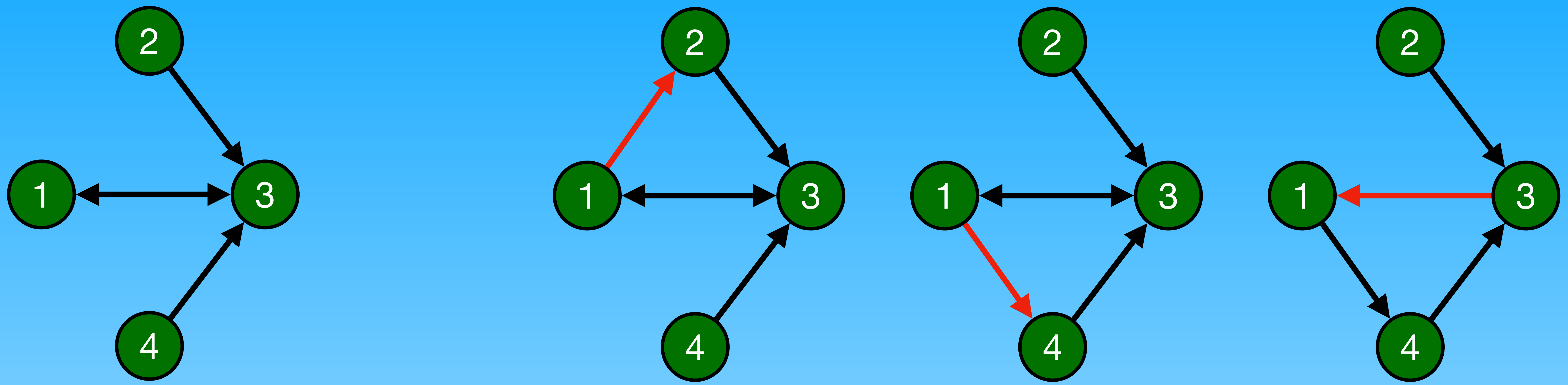
$$Pr(x \to x^{\pm ij}; \theta) = \frac{1}{n(n-1)} \cdot \frac{\exp \sum_k \theta_k \Delta z_k(x, x^{\pm ij})}{1 + \exp \sum_k \theta_k \Delta z_k(x, x^{\pm ij})}$$

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)



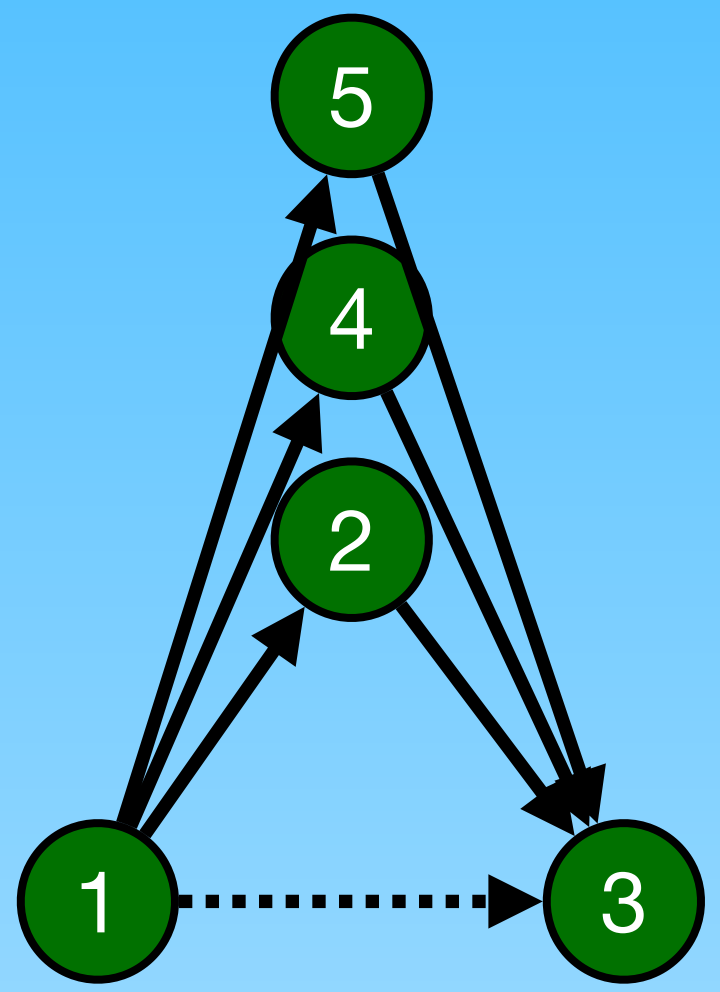
- ***Agent-based*** model: the likelihood of a tie to occurr is assessed as a function of a focal node-agent's neighborhood structure/composition

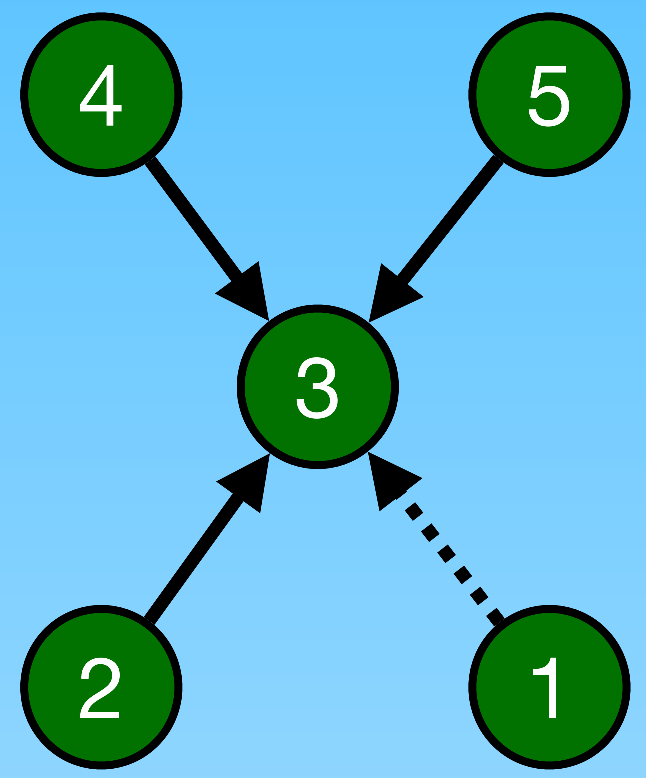
- Each agent decides whether to change the state of an outgoing dyad through a multinomial experiment (McFadden, 1973), by optimising an objective function $P(x \rightarrow x^{\pm ij}) = \dfrac{exp(f_i(\beta; x^{\pm ij}))}{\sum_{h=1}^{n} exp(\beta; f_i(x^{(ih\pm)}))}$

SAOM

Stochastic Actor-Oriented Models

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





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., 2023) —> **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., 2023)

SAOM

Stochastic Actor-Oriented Models

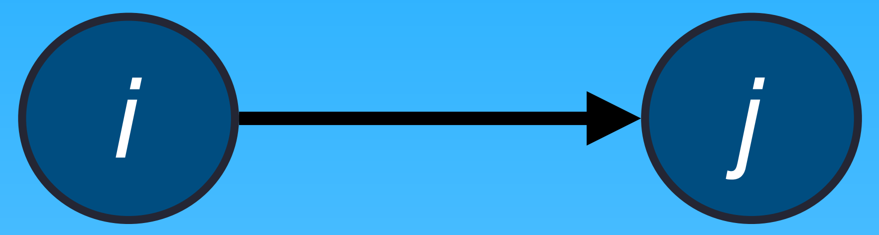
$$P(x \to x^{\pm ij}) = \frac{exp(f_i(\beta; x^{\pm ij}))}{\sum_{h=1}^{n} exp(\beta; f_i(x^{(ih\pm)}))}$$

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)

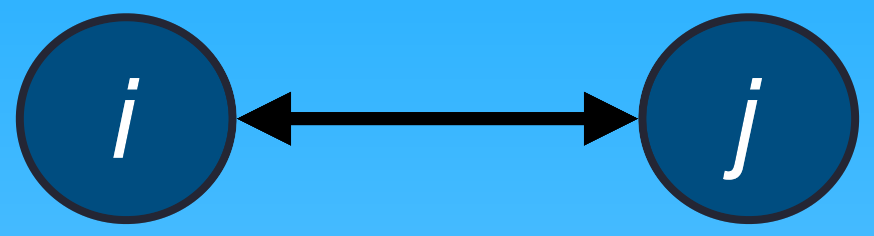


$t = 0$

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

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

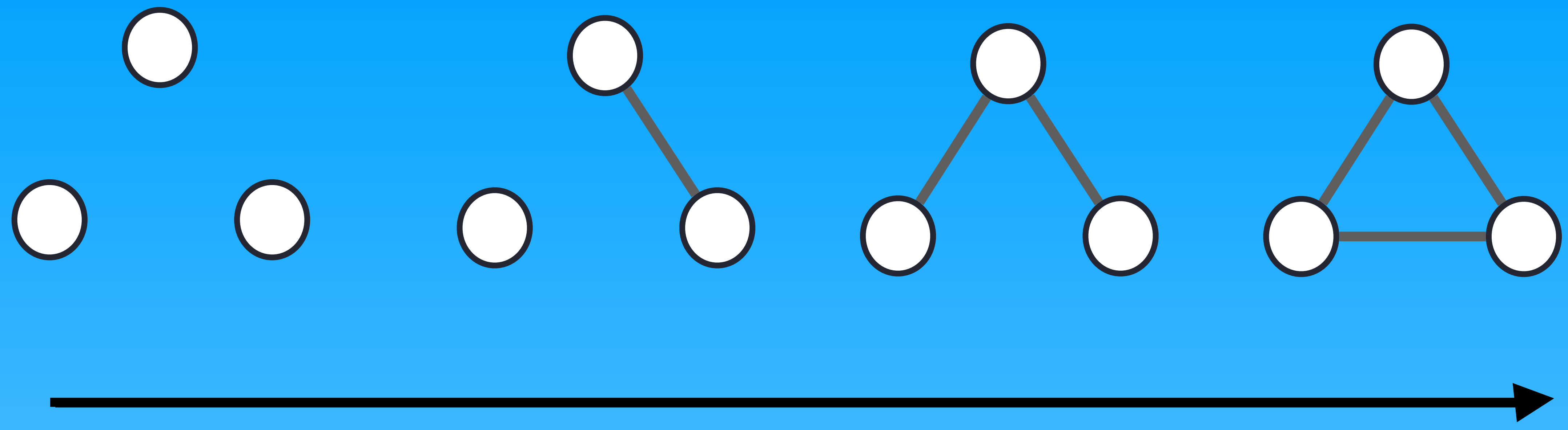
3. Controlling one's reputation (Buskens & Raub, 2005)

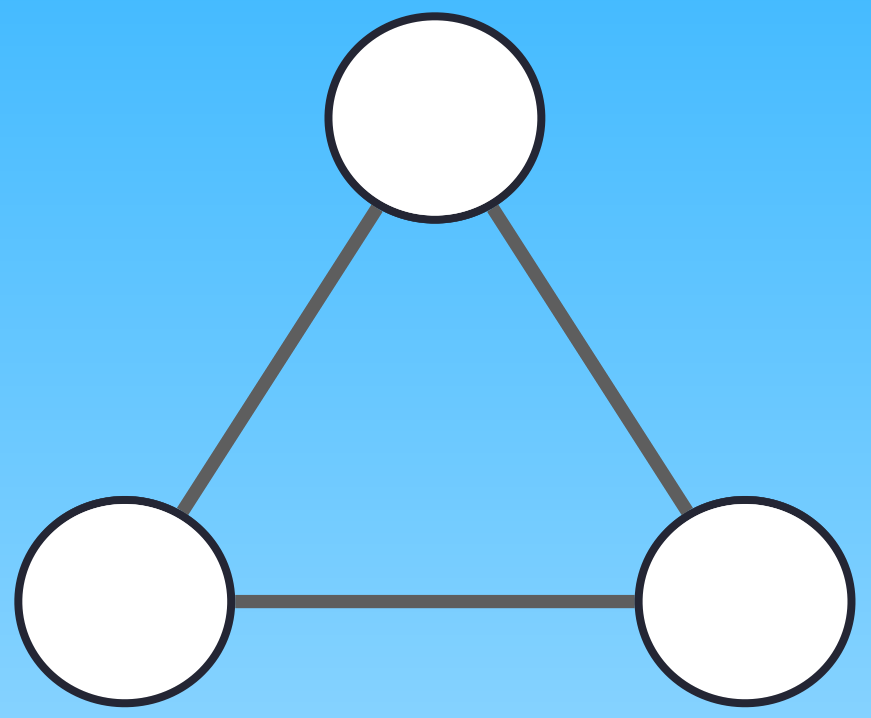


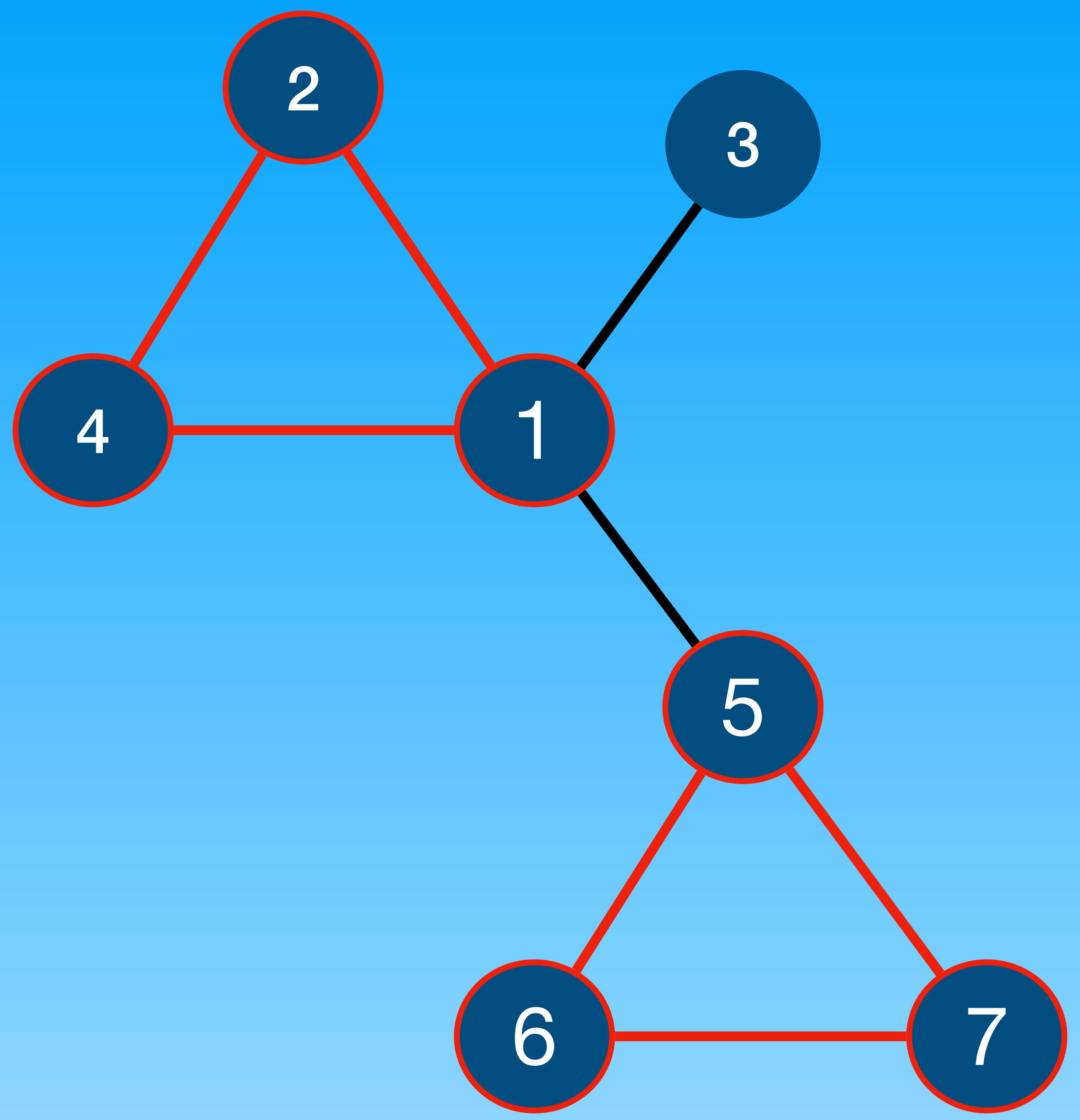
$t = 1$

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







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; Sørensen, 1998): 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., 2023)
  - 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)
  - 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., 2019)

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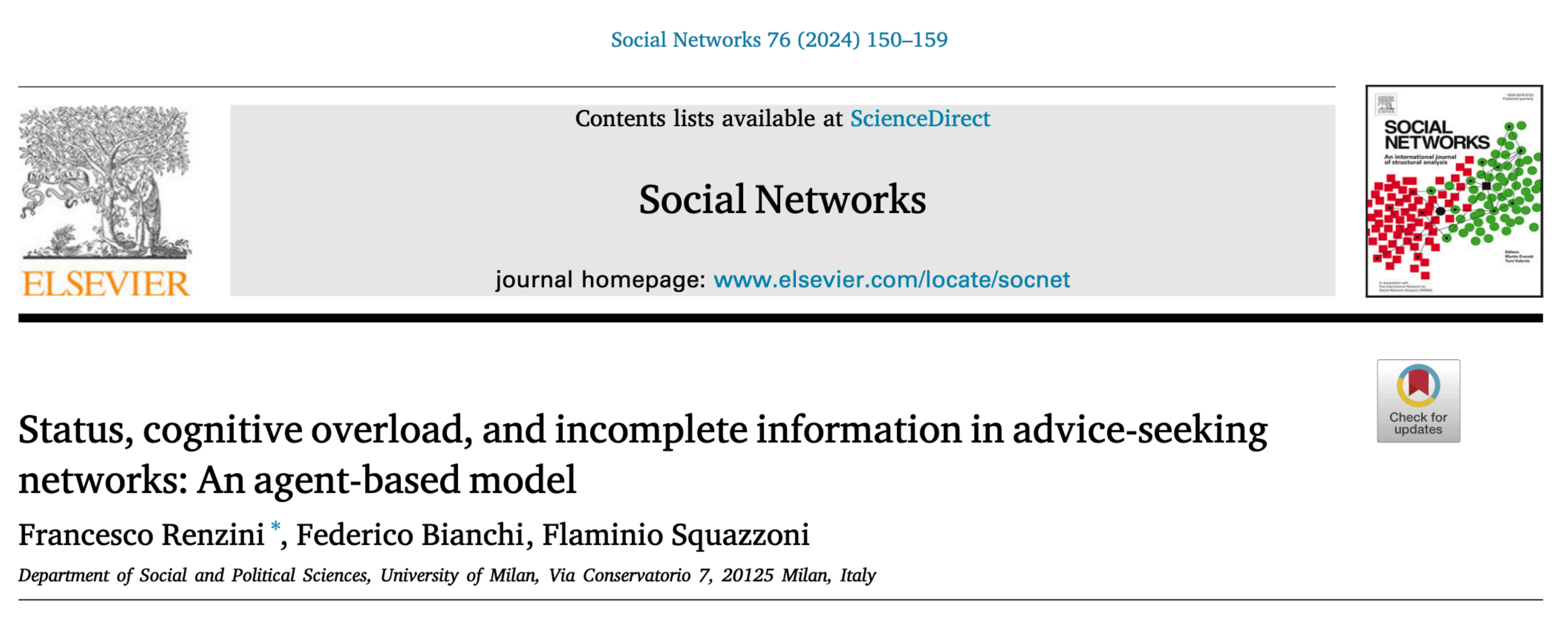
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Status, cognitive overload, and incomplete information in advice-seeking networks: An agent-based model

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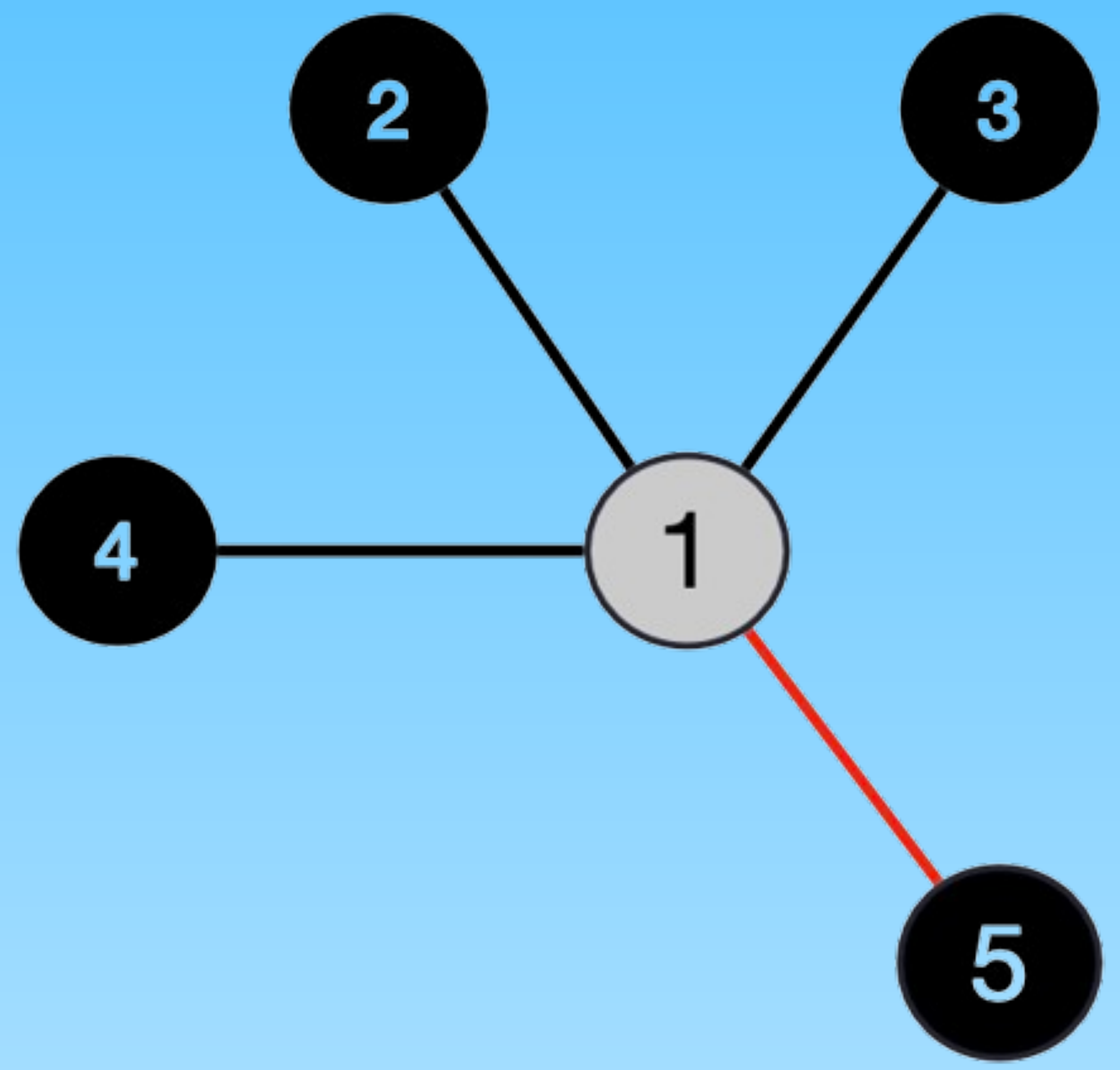
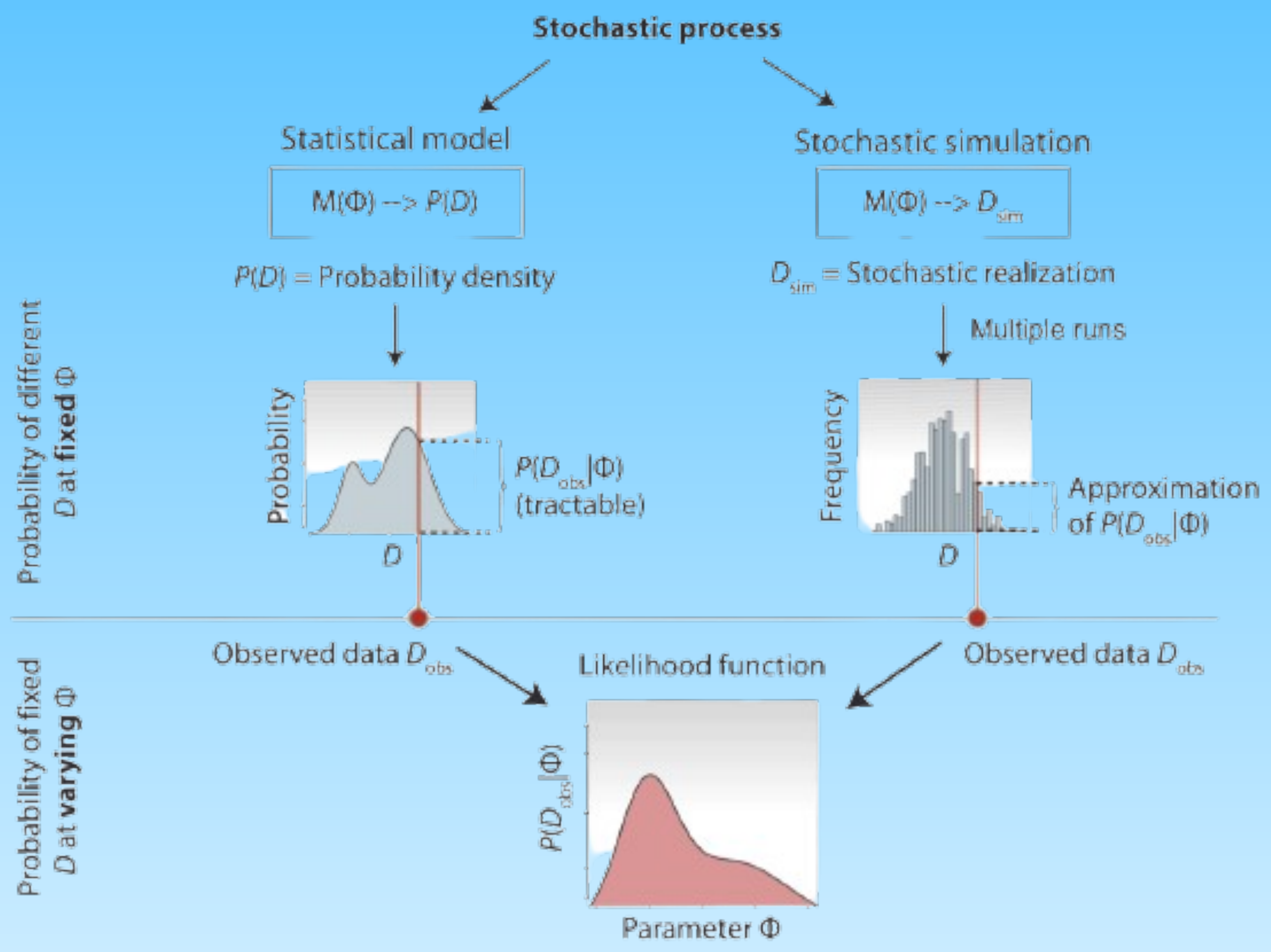


Examples of ABMs of social networks

- **Renzini, Bianchi, & Squazzoni (2023)**:
  - Explaining advice-seeking network formation as the outcome of request overload (threshold-based)
  - Limited information, local heuristics, plausible and parsimonious model
  - Fitted to classic Lazega's (2001) network
- **Bianchi, Bellotti, & Renzini (*wip*)**:
  - 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 **point estimates** of parameters and **uncertainty measures** for **untractable likelihood functions** (Hartig et al., 2011; Carrella, 2021)
- **No need to rely on unplausible assumptions** to obtain a tractable likelihood function

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
- Experiment (Brashears & Gladstone, 2020)
- Middle-range social science

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