Agent-based modelling towards the future of social network research

Workshop on “Agent-based models of social networks”
Behave Lab and Computational Models and Designs Hub,
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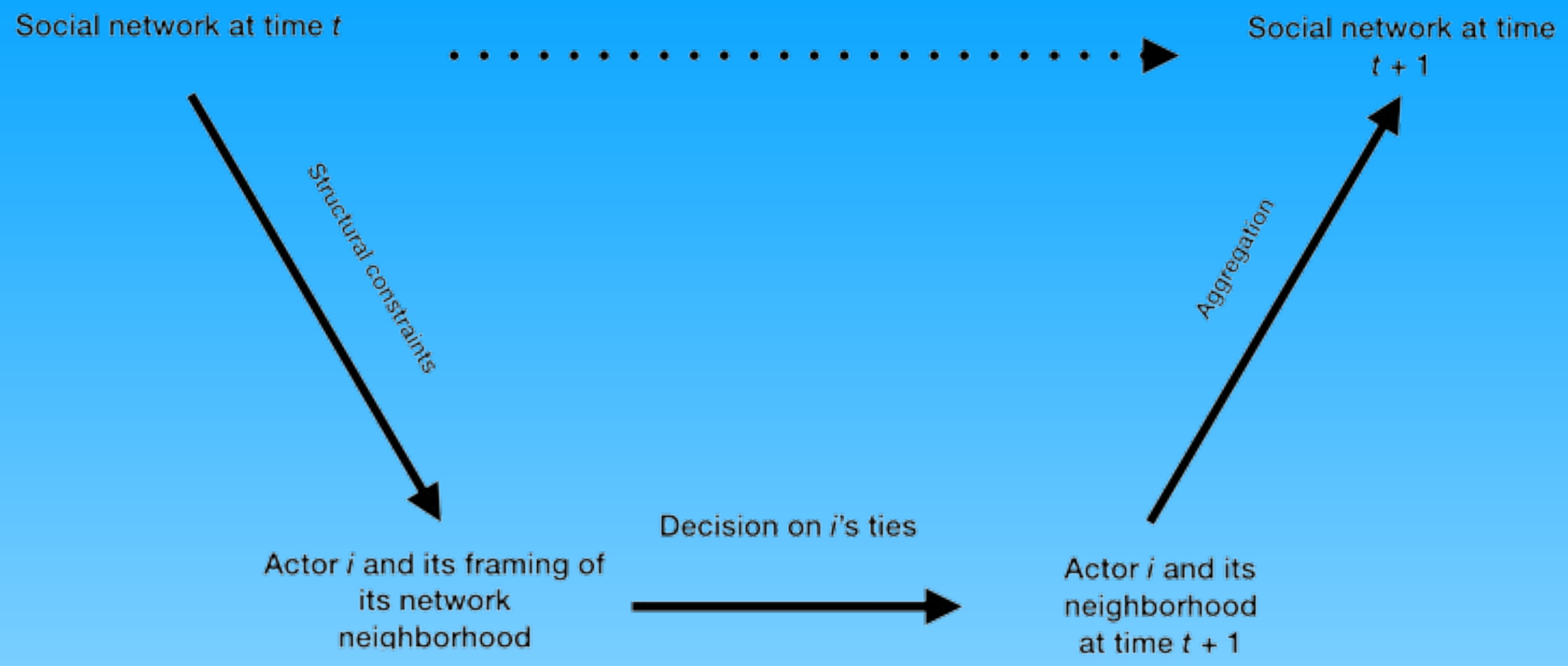
Federico Bianchi

Behave Lab, Department of Social and Political Sciences, University of Milan



Causal mechanisms of social network evolution

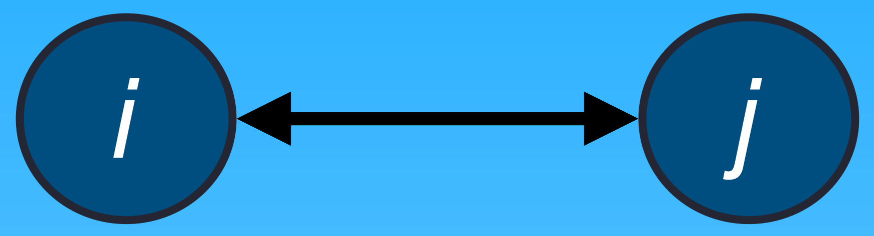
- Identifying the **causal mechanisms** of social network evolution
- Patterns of **social actors' inter(actions)** bringing about regular network structures or compositions (Hedström & Bearman, 2009)
  - **Motives** behind decisions (desires and preferences)
  - **Context framing** (cognition and culture)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

t = 0

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

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

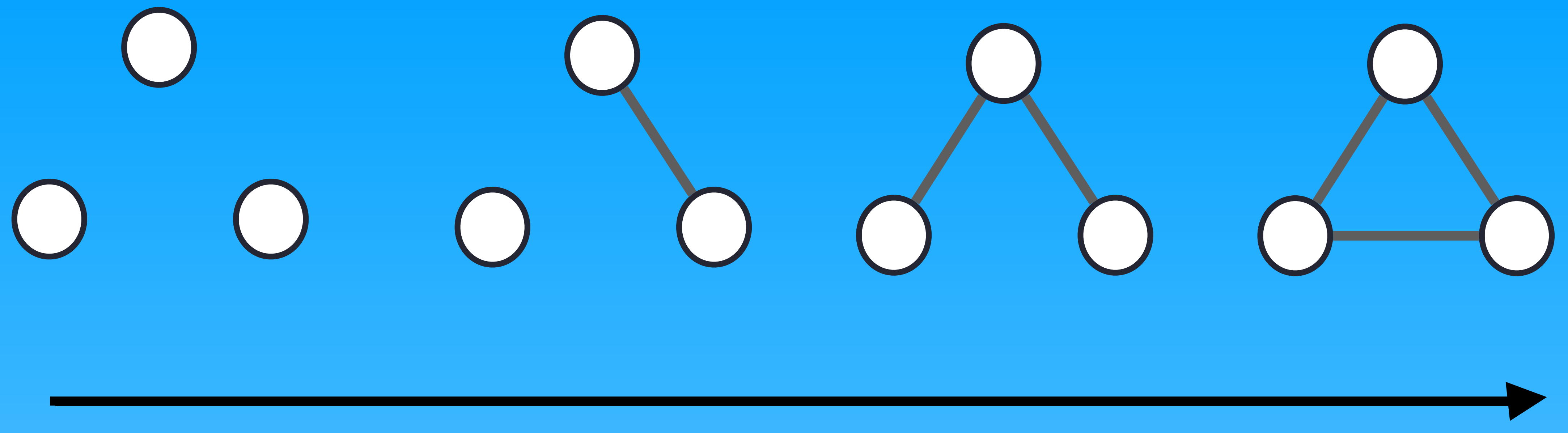
3. Controlling one's reputation (Buskens & Raub, 2005)

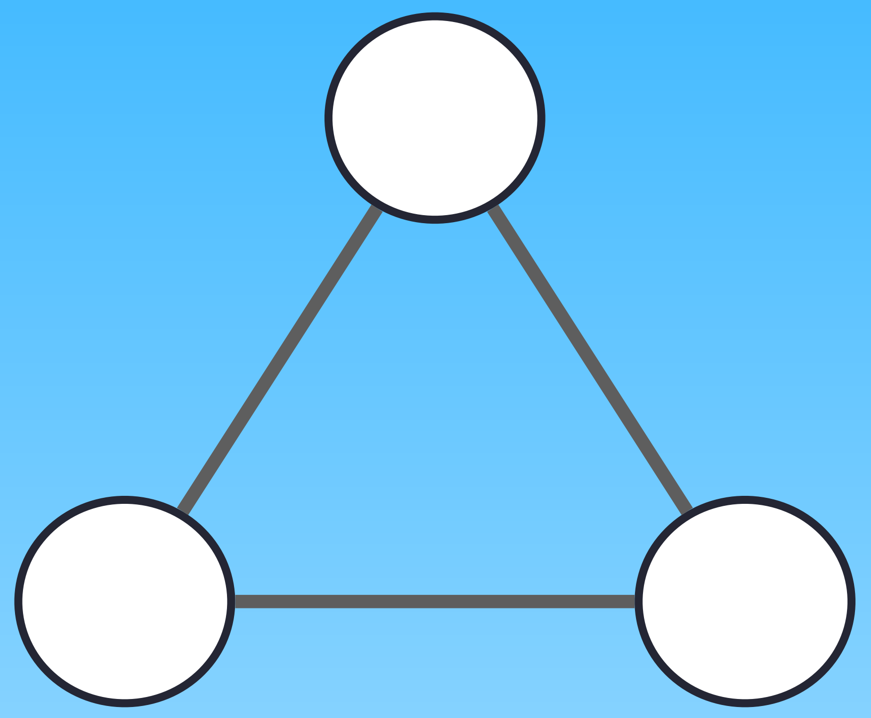


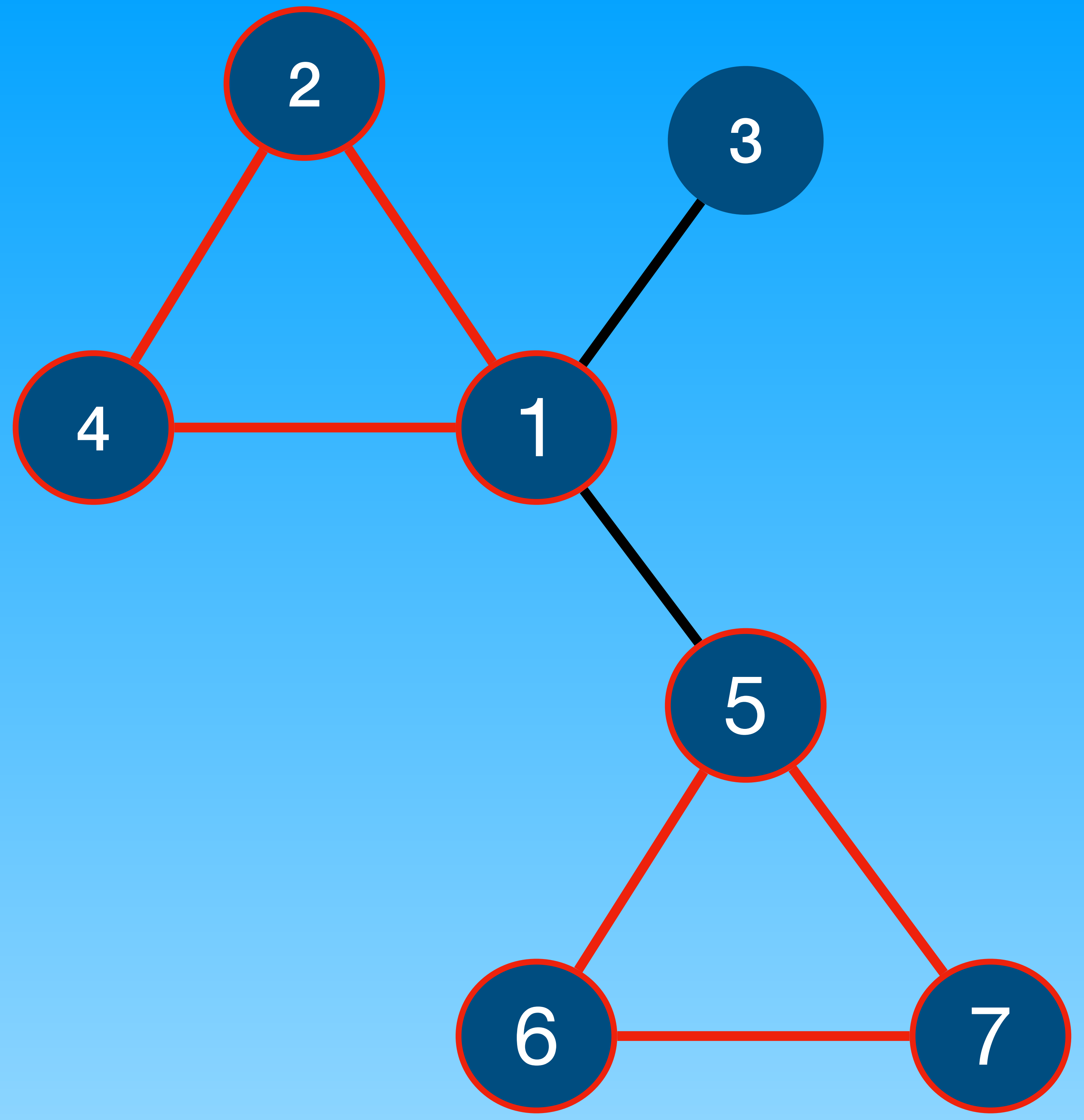
t = 1

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**

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

→

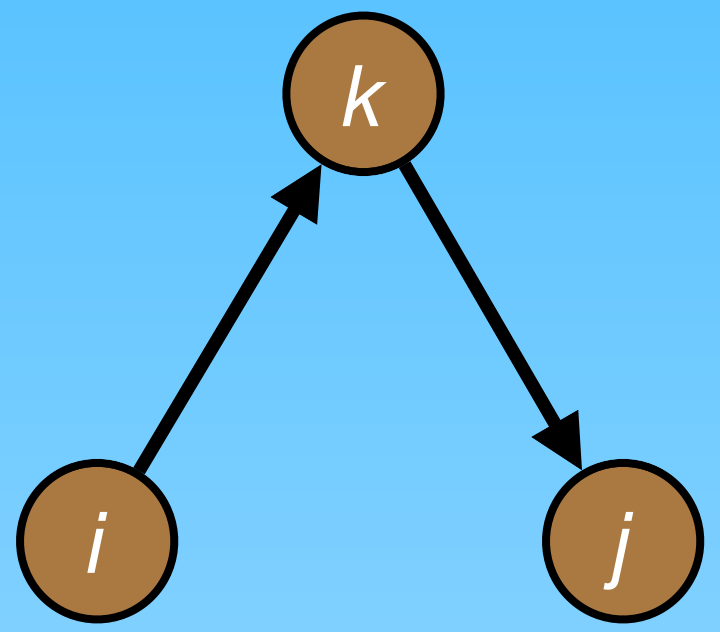
Agent-based model
- Agents
- Agents’ attributes
- Agents’ rules of behaviour
- Agents’ structural constraints

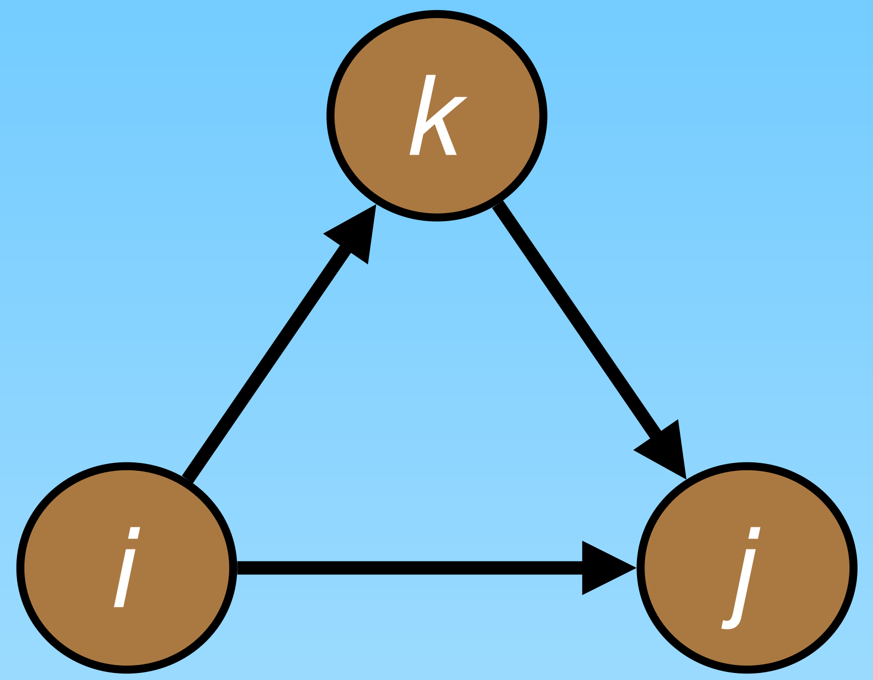
ABM:

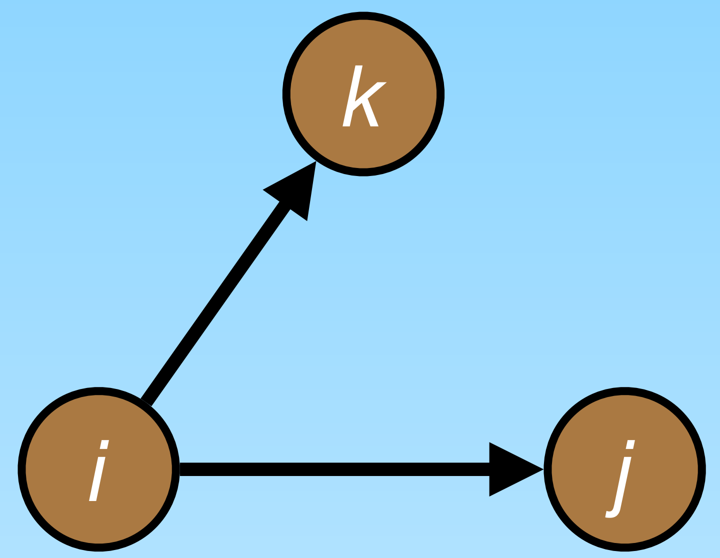
flexibility and granularity

- “**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

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





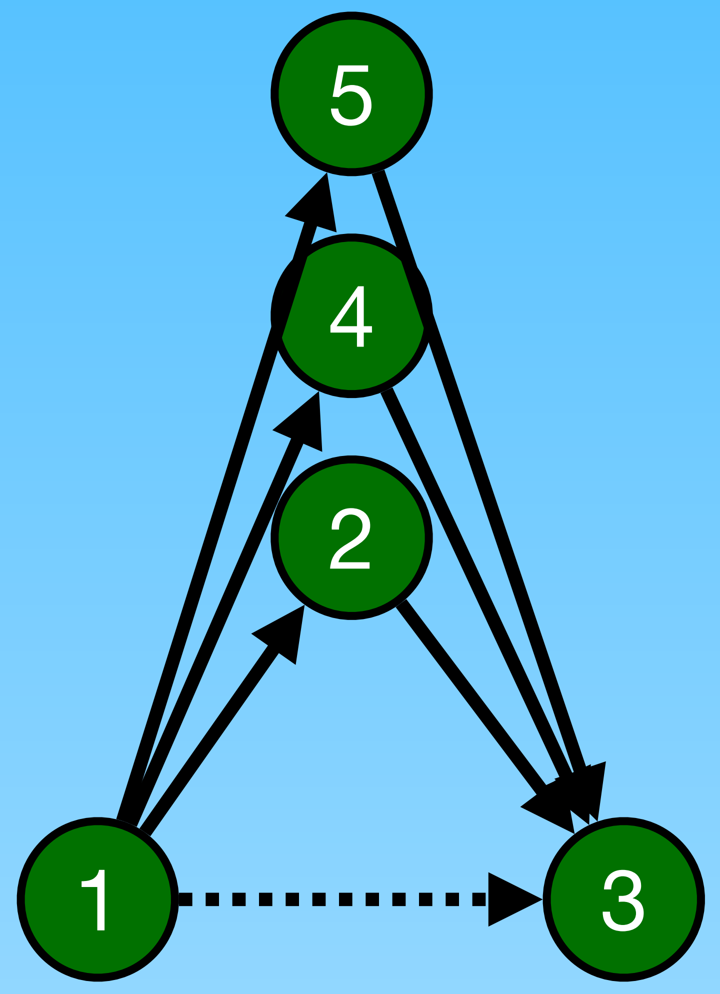


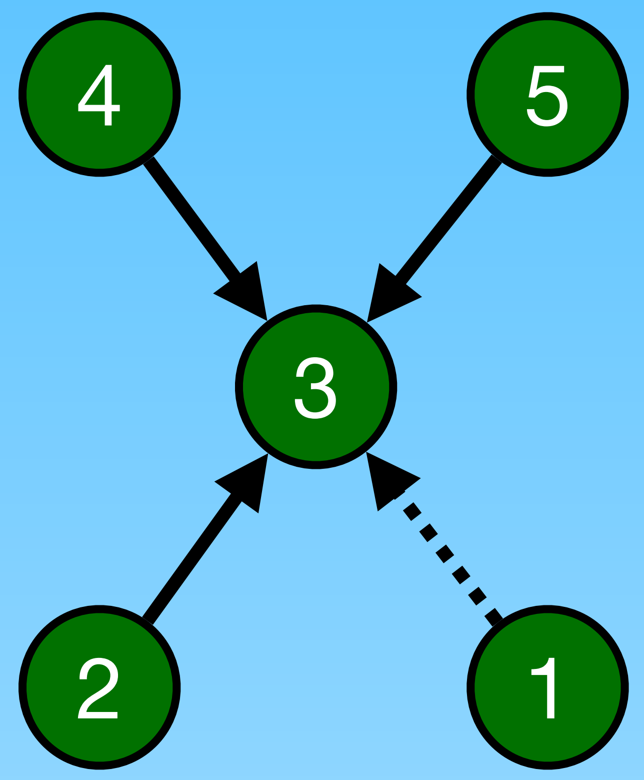
ABMs can complement for statistical models' limits concerning:

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

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

- 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)





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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)

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

ABMs can complement for statistical models' limits concerning:

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

- 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)

ABMs can complement for statistical models' limits concerning:

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- Tie-based models (e.g., ERGM-family) are indifferent to the specific tie sequences through which particular configurations emerge (Block et al., 2019)

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  - 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., **instrumental ties**, as in 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)
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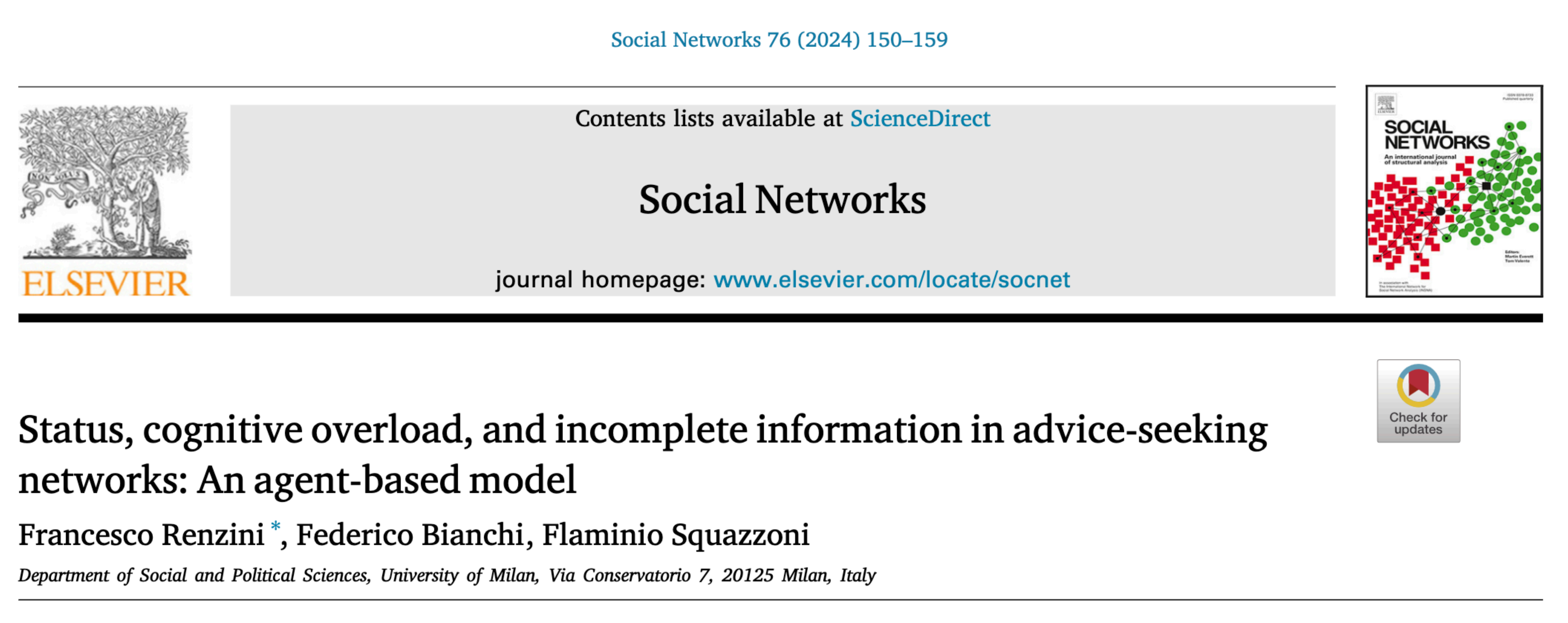

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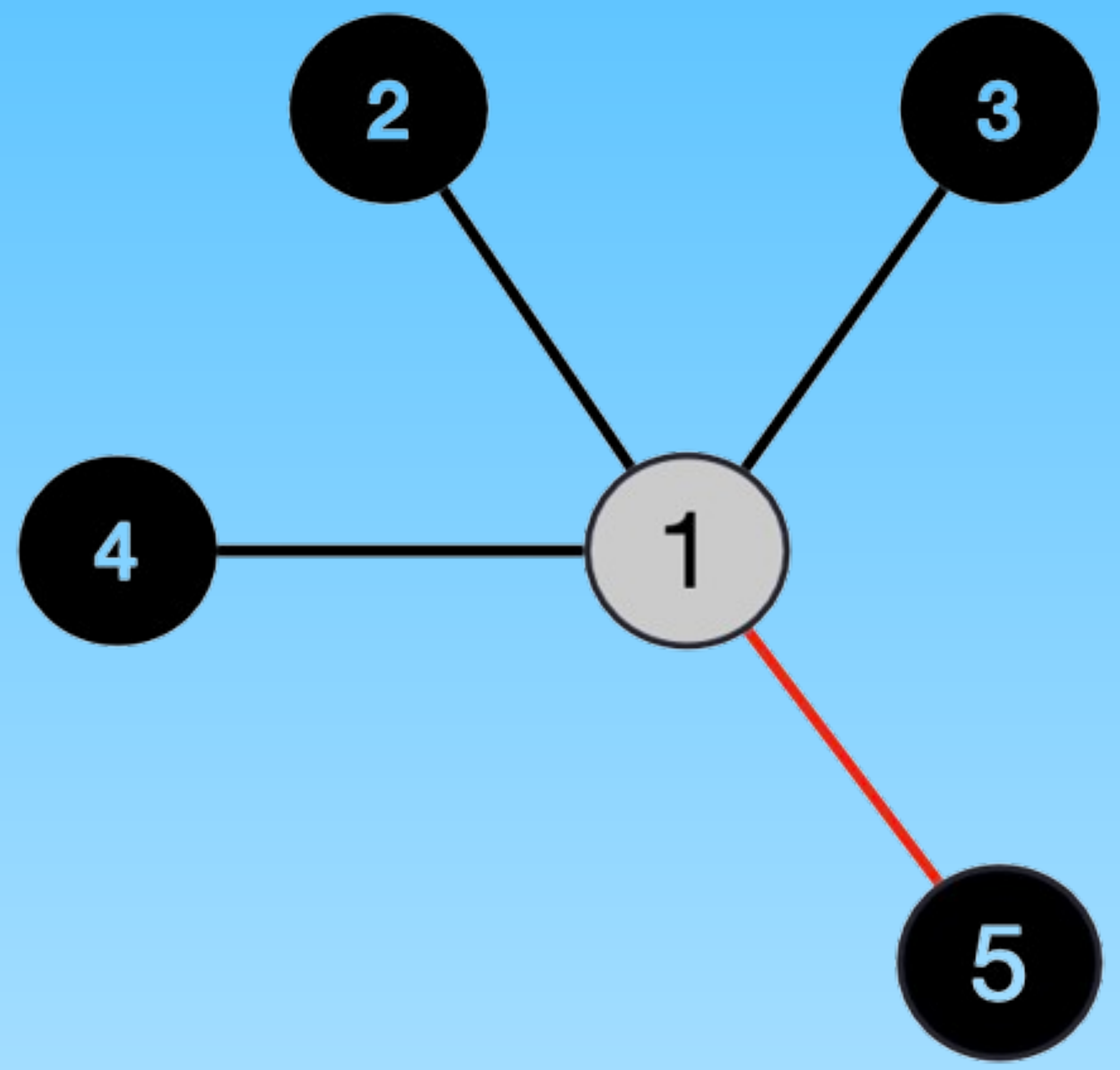
Status, cognitive overload, and incomplete information in advice-seeking networks: An agent-based model

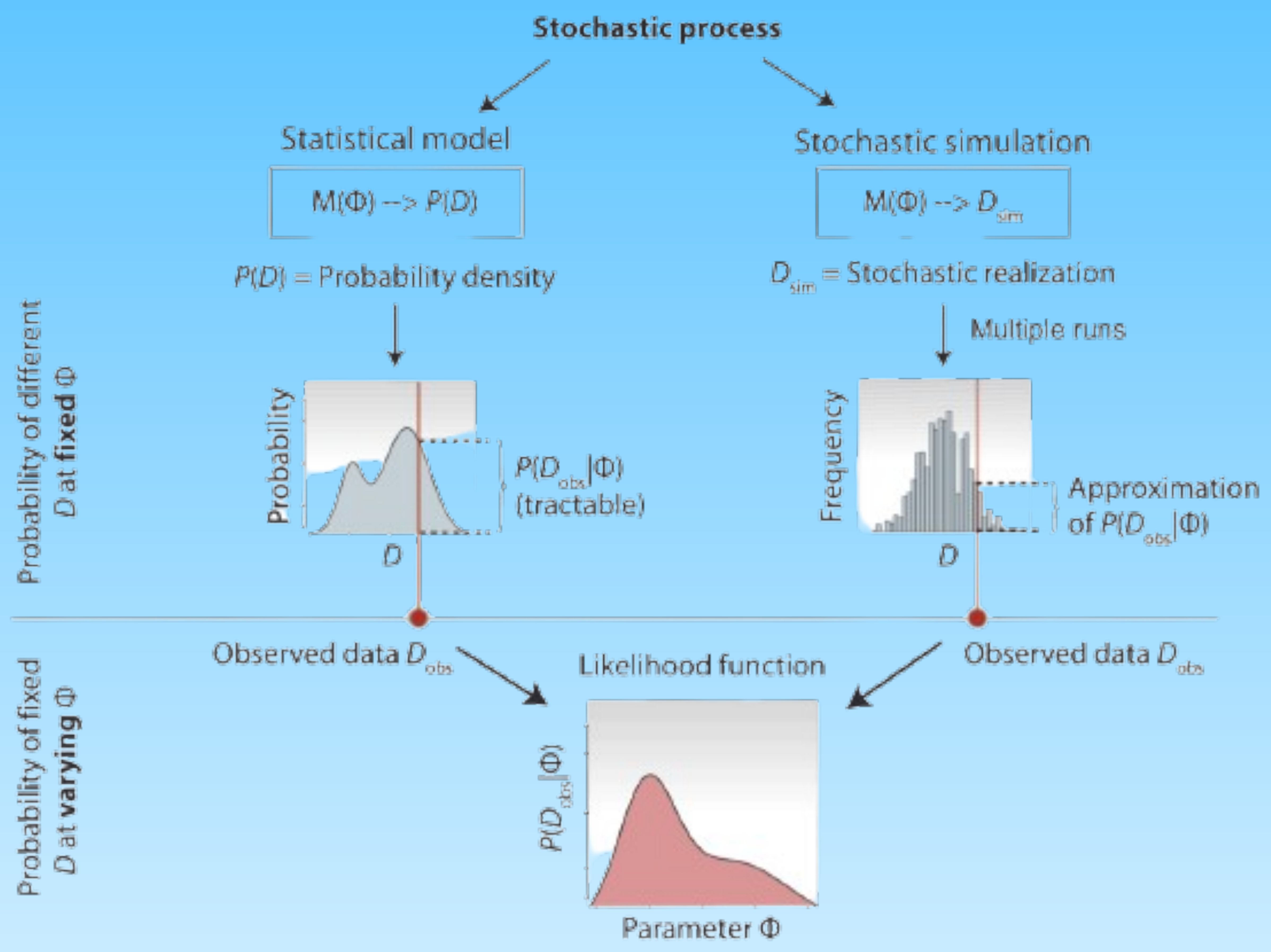
Francesco Renzini *, Federico Bianchi, Flaminio Squazzoni

Department of Social and Political Sciences, University of Milan, Via Conservatorio 7, 20125 Milan, Italy



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
- **Bellotti, Bianchi, & 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

Discussion

- **Explicitly modelling causal mechanisms**
- **Empirically testing** their explanatory power
- More realistic and parsimonious models (middle-range)
- Modelling the **unobserved** —> not giving up on **actors' cognition/culture** (experiments), **tie diversity**, and **social context**
- To what extent and how?

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