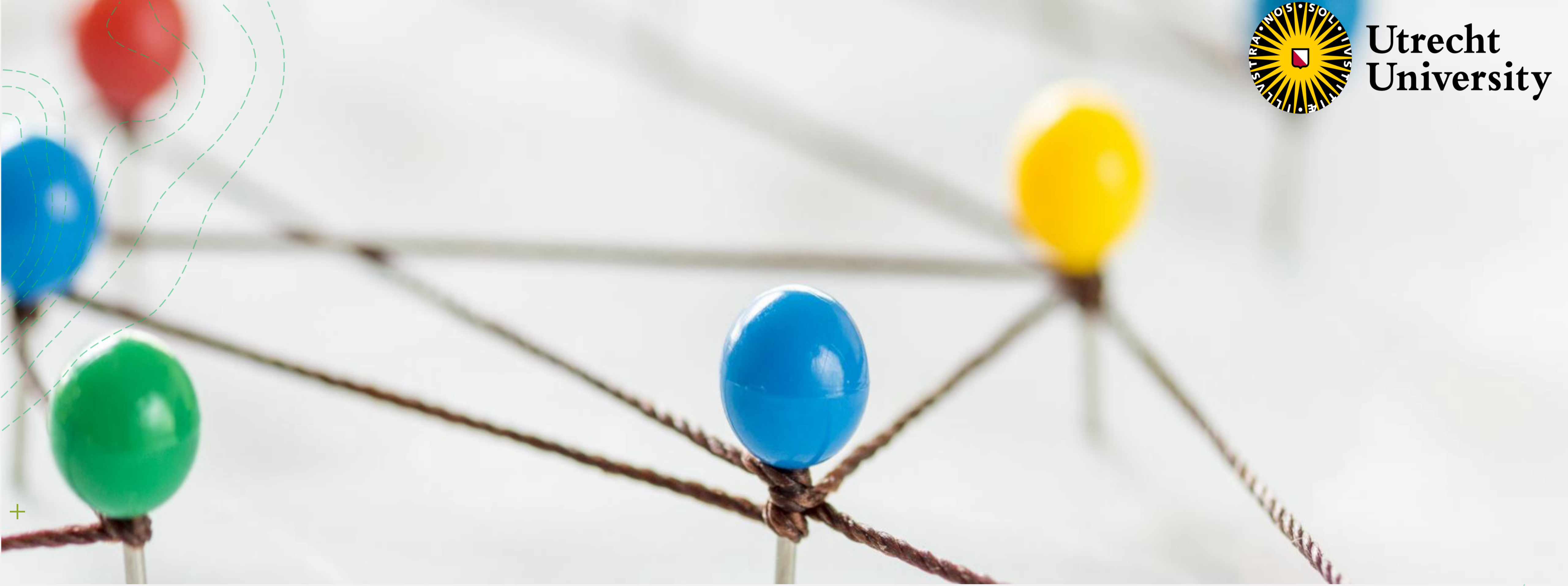
Utrecht University



Social network analysis

Mahdi Shafiee Kamalabad

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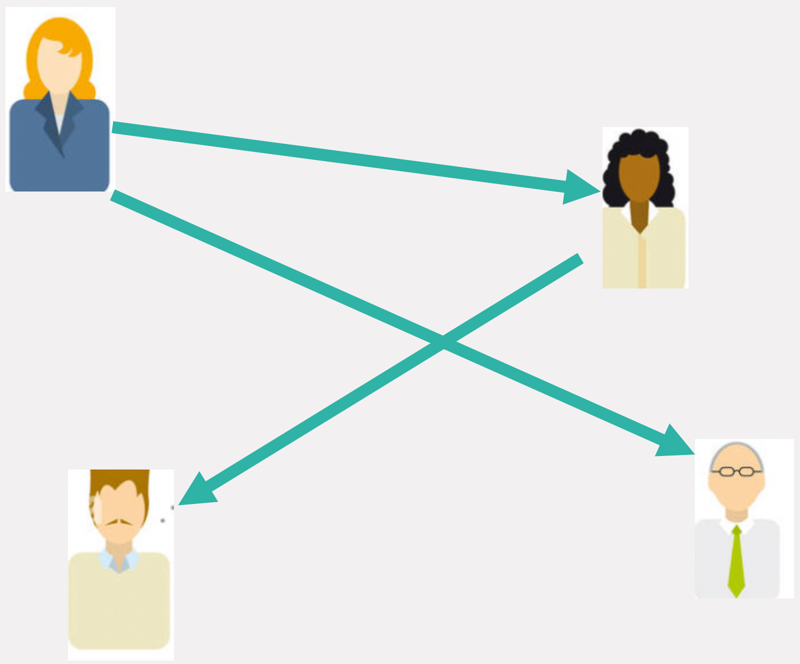
+ **S**tochastic **A**ctor **O**riented **M**odel (**SAOM**)
+ Choosing your weapon in longitudinal network analysis: **ERGMs, SOAM, TERGMs, REMs**

Social Network

+ Representations of **relational data**.
+ **Nodes** (actors/vertices) represent **entities** while the **links** (edges/ties) connecting them represent any form of **interaction** or **connection** between the entities.

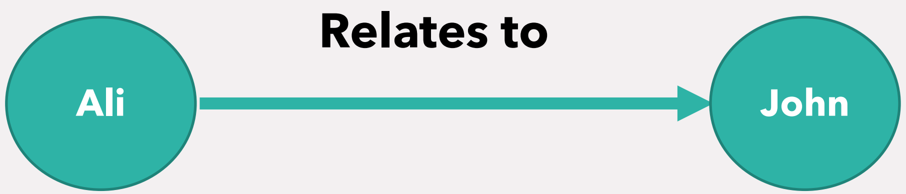


Social networks: Relations/interactions

+ A **Relation** defined on a collection of **individuals (actors).**

For example,

- Ali goes to John for **advice**…
- Ali considers John as a **friend**…
- Ali sends an **email** to John…
- Ali **calls** Join…
- **…**



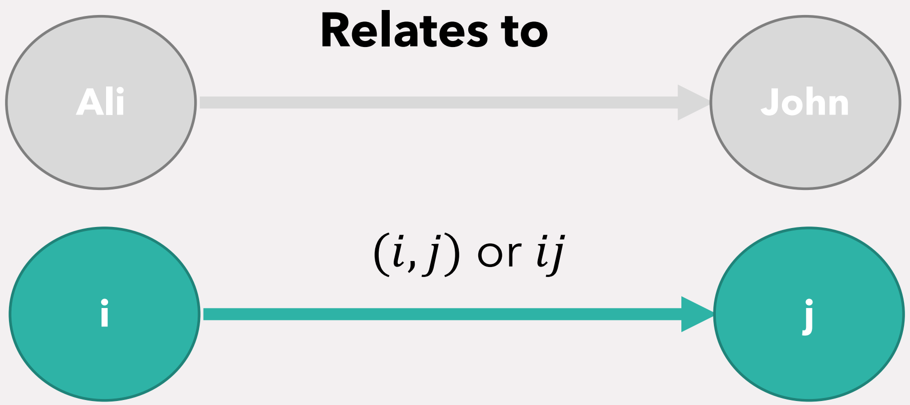
Tie present: On

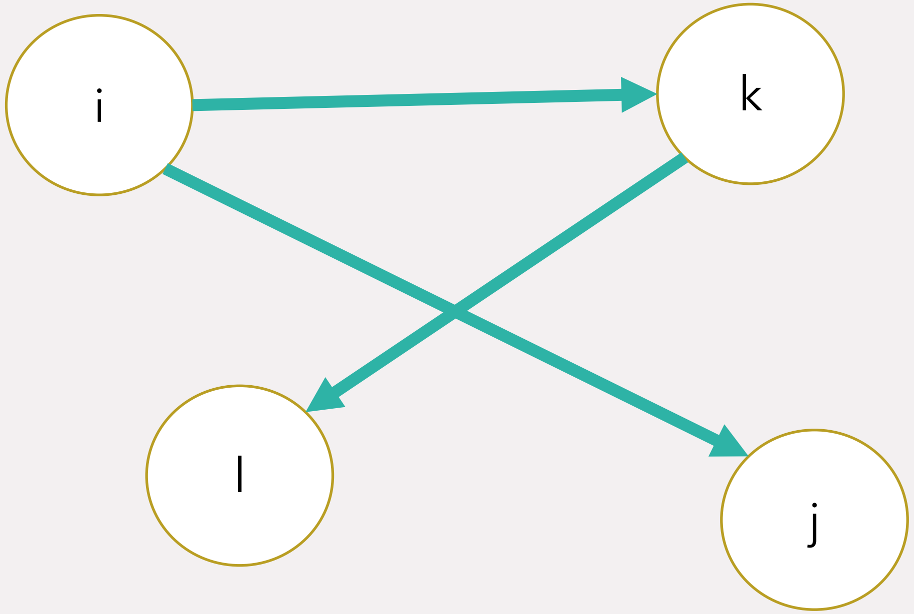
Tie absent: Off

Social networks

A network is a **Graph**: $G(V, E)$, on

Individuals / actors: $V=\{1,2,\ldots,n\}$
Relation / edges: $E \subseteq \{(i,j) : i,j \in V\}$





Note, actors can be any entities such as :

- Countries
- Humans
- Animals
- Organiazations
- …

Relational Event History Data (REH data)

Relational Event History Data (REH data)

+ They are **social network data** where **one actor as a sender** (person, organization, team, etc.) **interacts** in some way **over time** with **another actor as a receiver**.

+ REH data contain detailed information ***what*** happened (message, email, etc.), ***when*** it happened (time), and ***who*** were involved (sender, receiver).

+ REH data contains at least **receiver** (target), **sender** (sourse), and **time/order**.

+ Event = (sender, receiver, time, …)

- **Why “history”?**

- **Example of REH data?**

Examples:

- **Relational event data**
  - **Social media**
    - Twitter
    - Wiki edits
    - Forum posts
  - **Communication**
    - Email
    - Classroom talk
    - Team interaction
    - Phone calls
  - **Collaboration**
    - Participation in meetings
  - **Animal behavior**
    - Food sharing: Jackdaws
    - Cow interactions

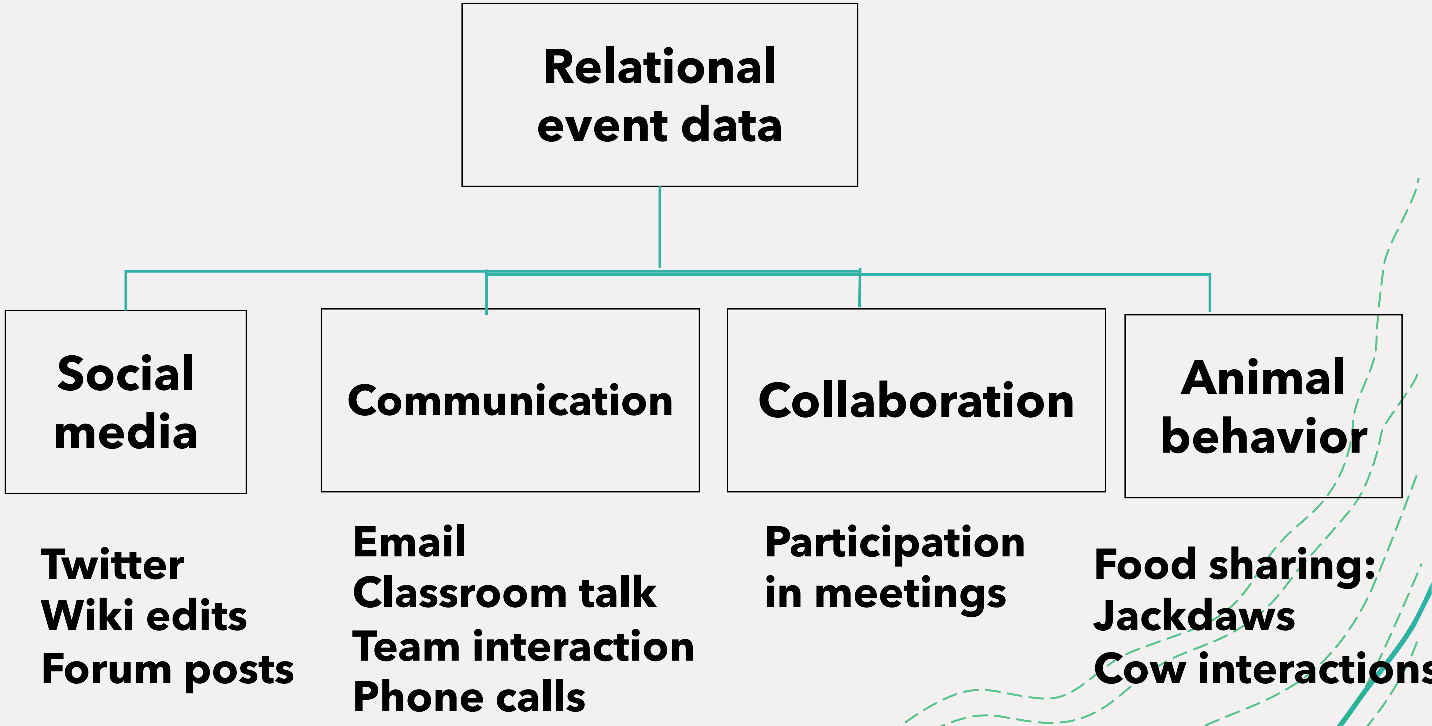
Why do we want to study relational events history data?

Why do we study relational events history data?

- Relational events are everywhere, and ***increasingly available*** due to the development of technology.
- Often in the form of Big Data

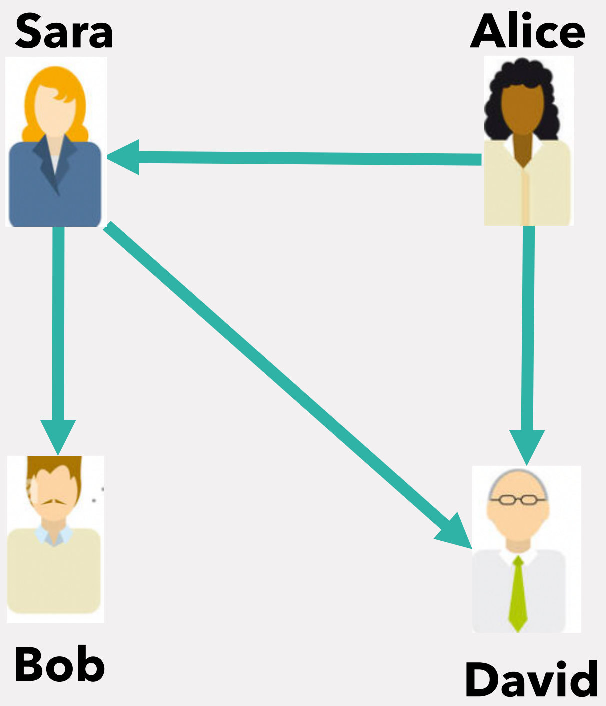
e.g.

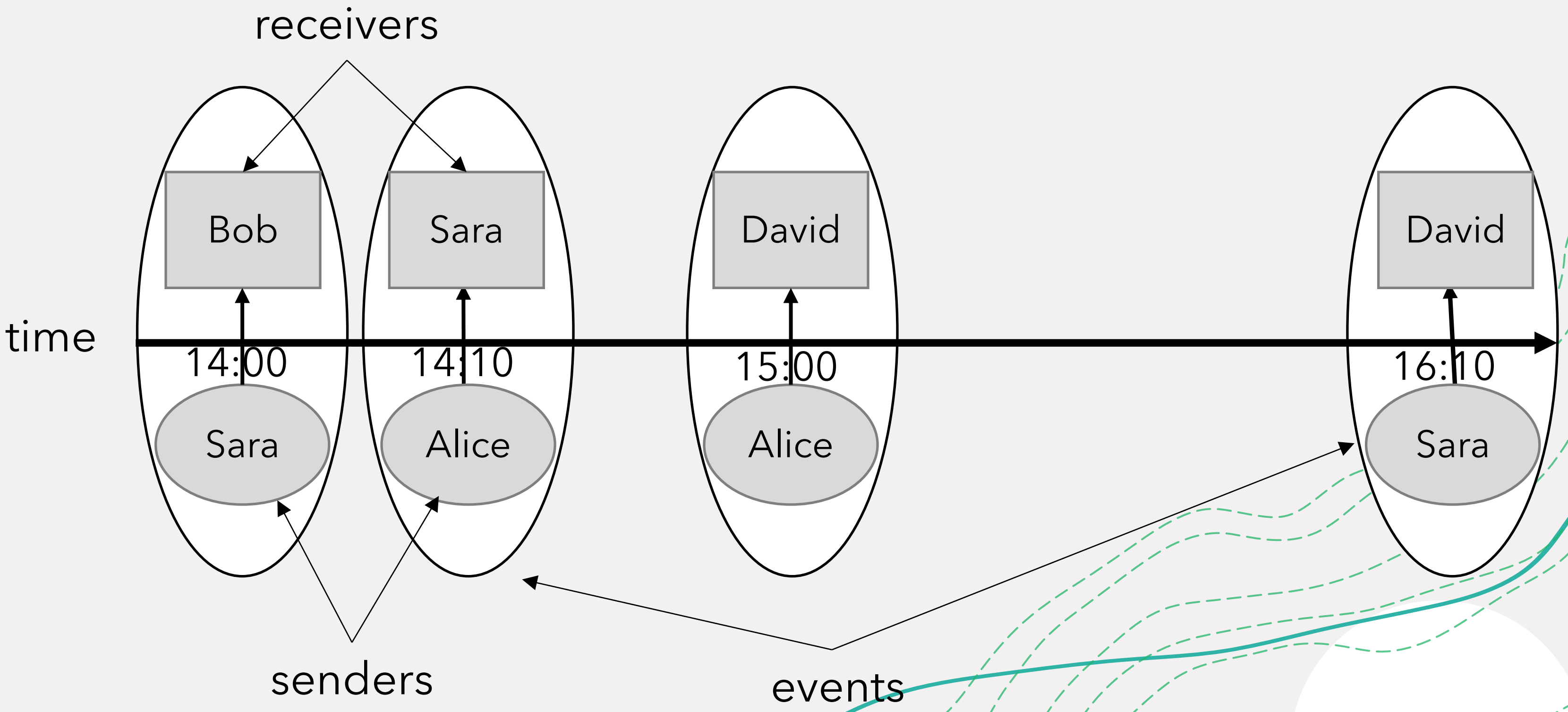
- Sociometric badges, digital communication (email), video monitoring, etc.



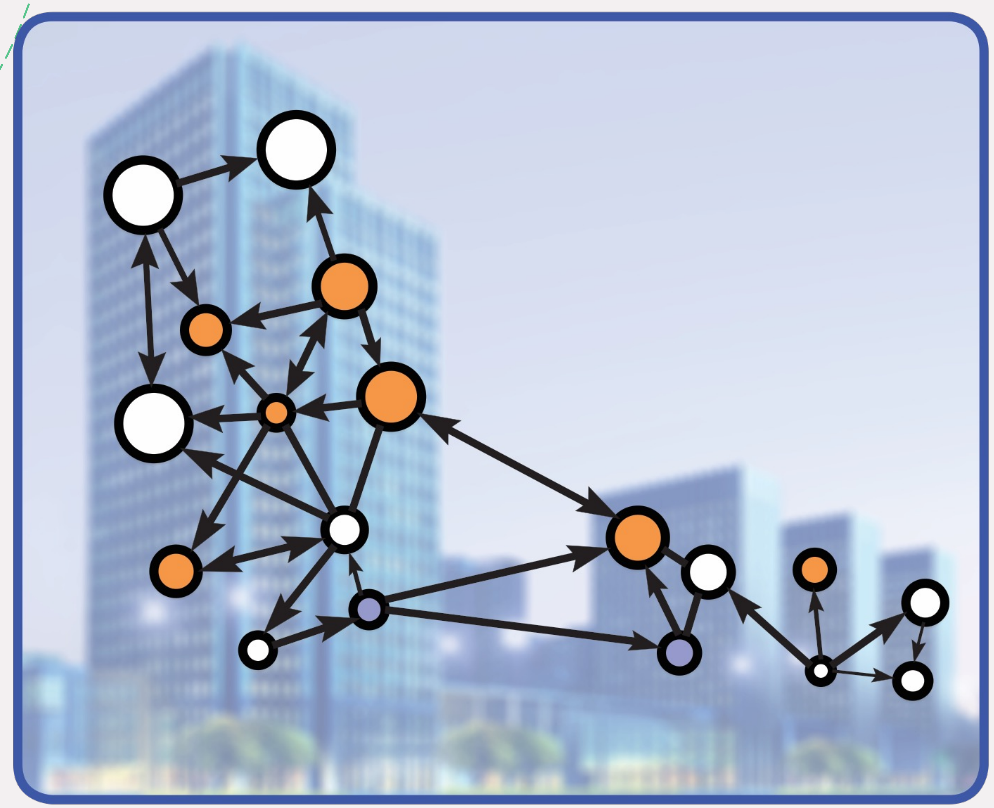
Why do we study relational events?

+ They are of high-resolution precision.
+ They contain the history of events/interactions.
+ Edges are any sorts of interactions, e.g. phone calls, emails, classroom interactions, collaborations, etc.





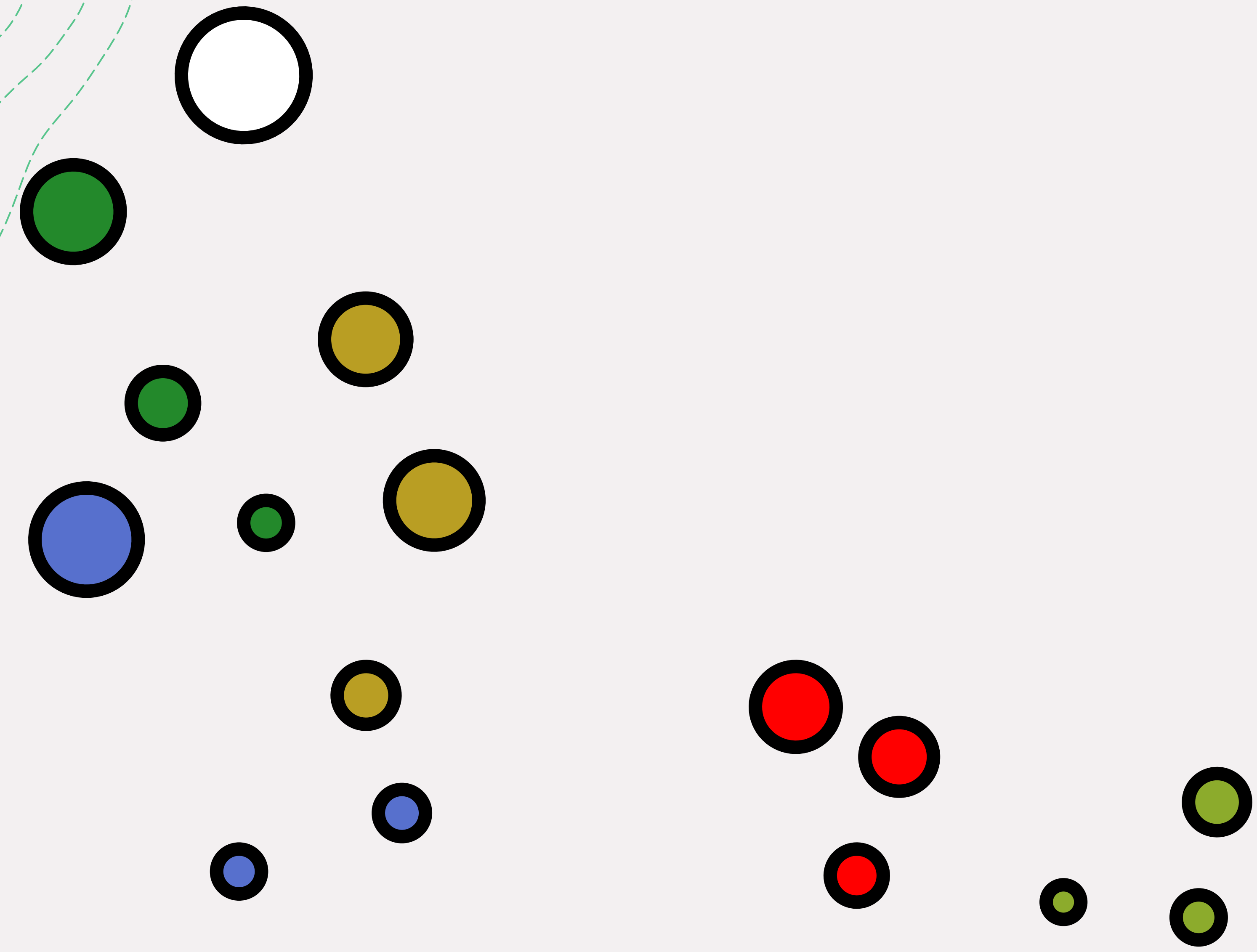
Example



Employees in organizations share information with each other via email.

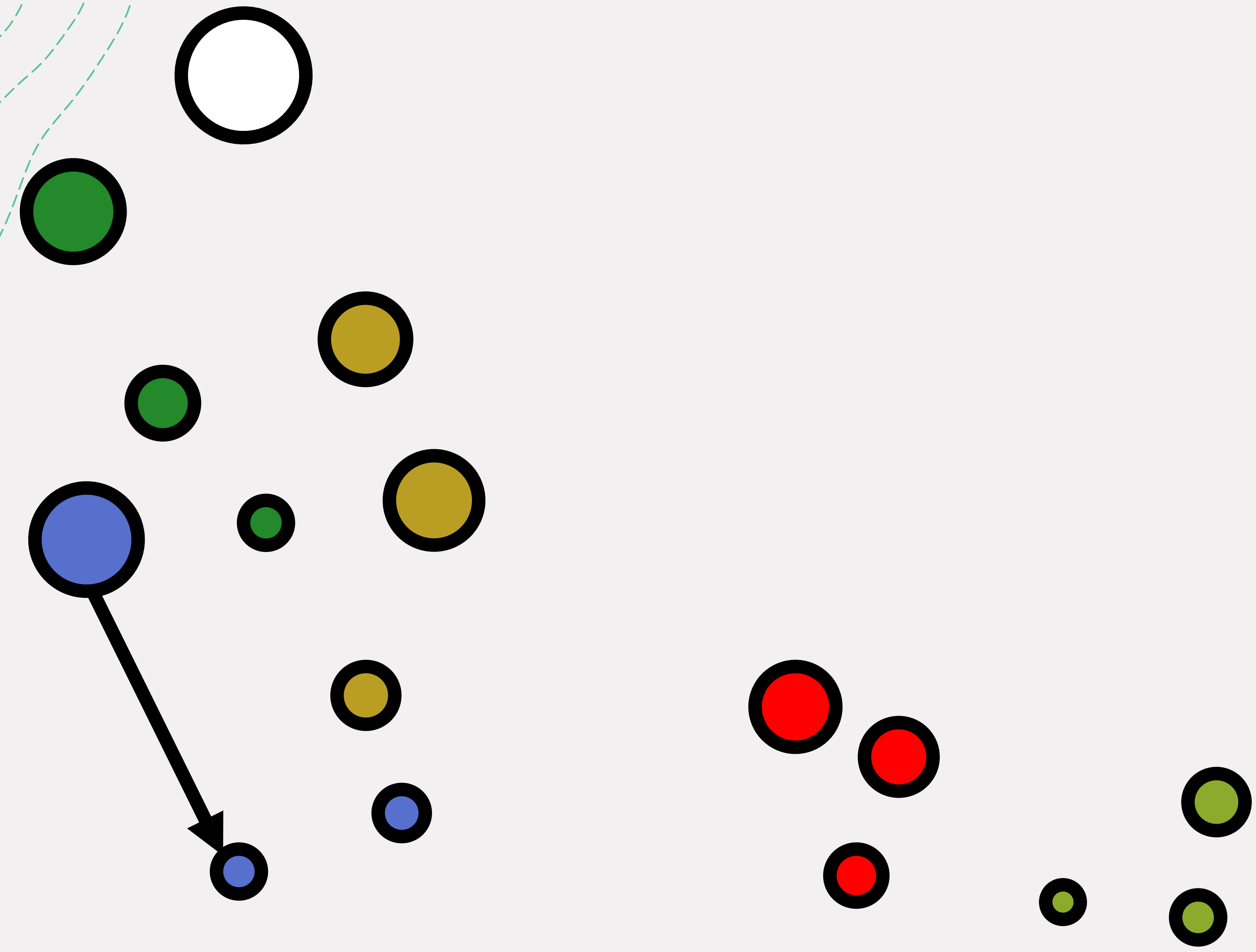
*How (**fast**) do employees share information with coworkers?*

Relational Event History Data



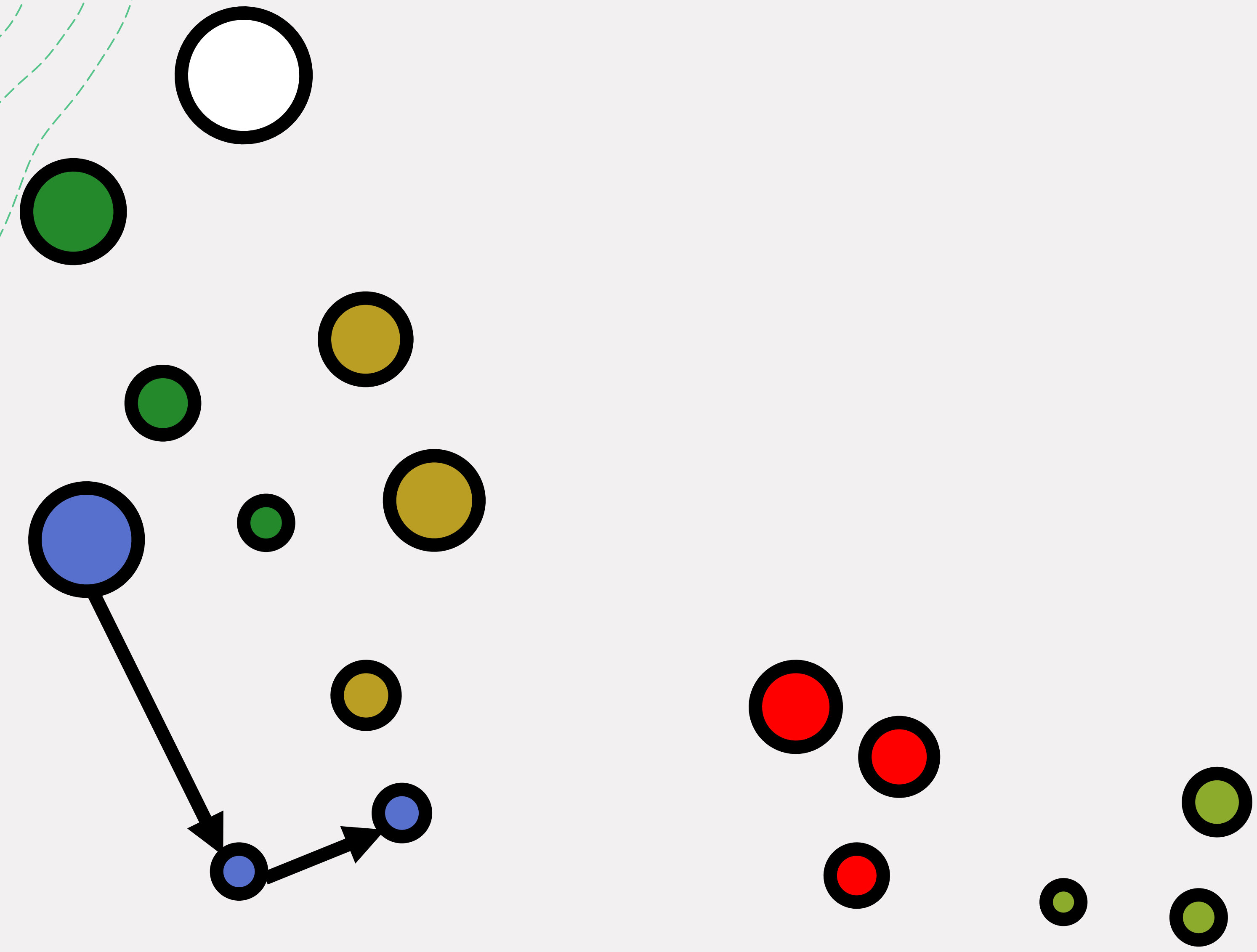
time	sender	receiver

Relational Event History Data



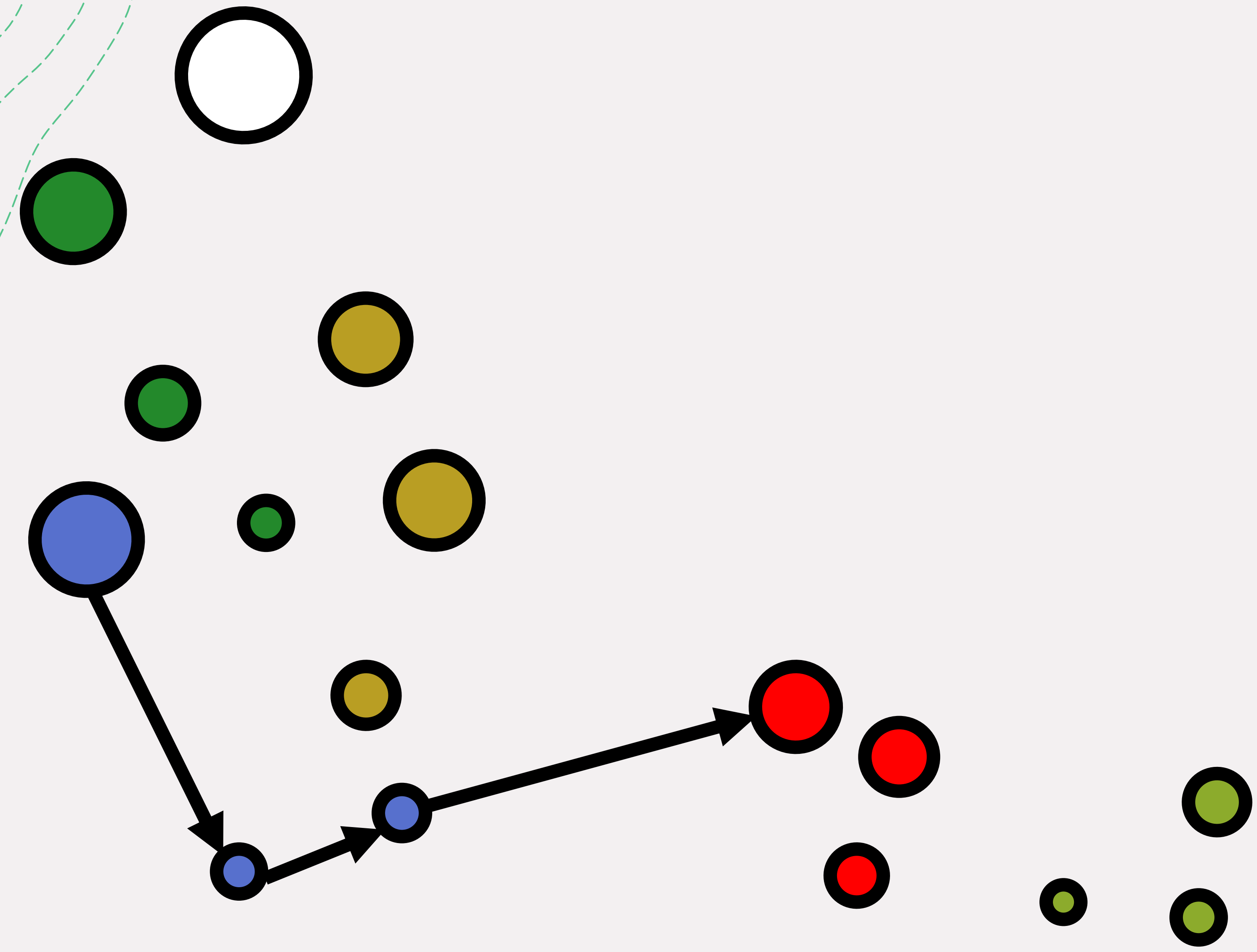
time	sender	receiver
00:03:34		

Relational Event History Data



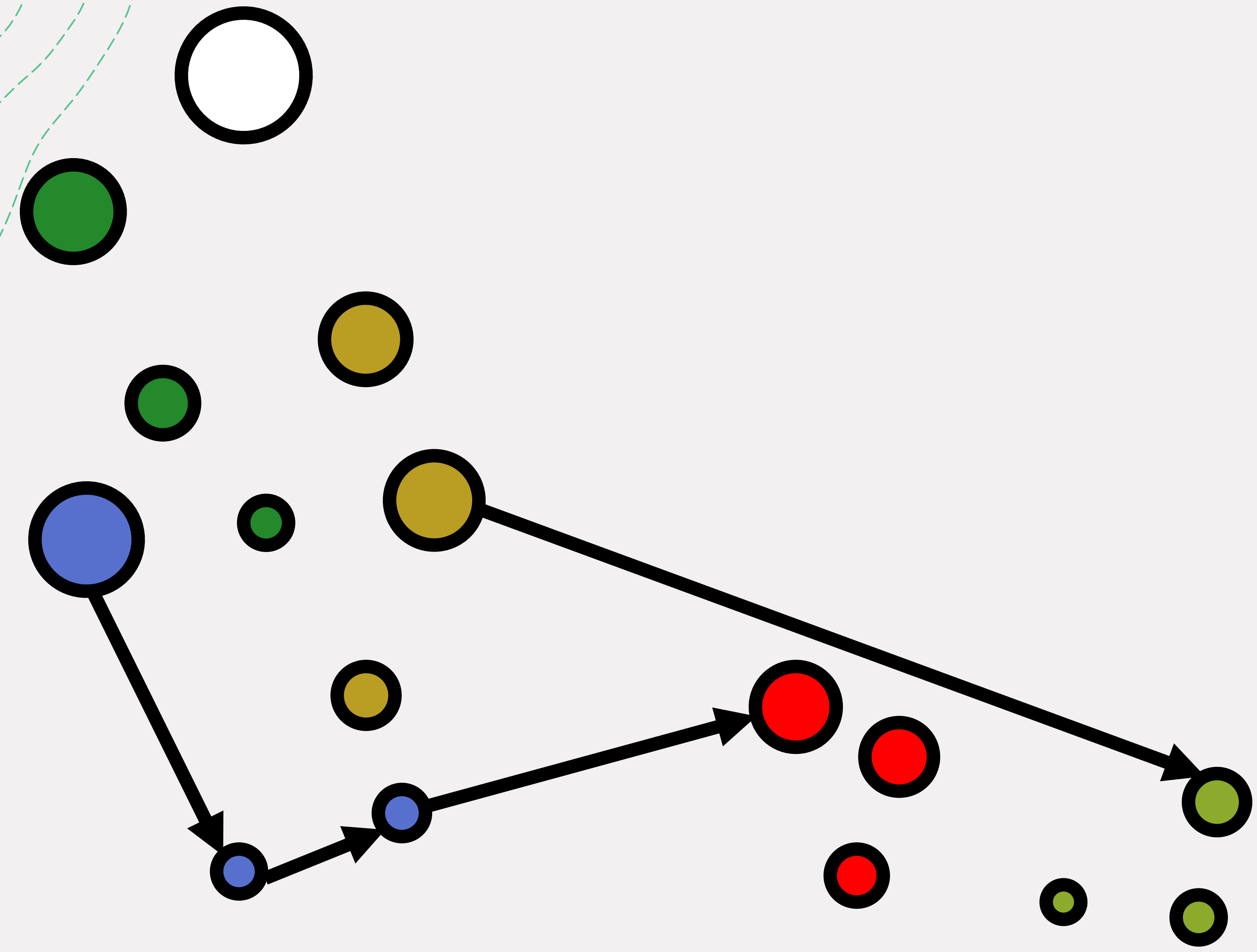
time	sender	receiver
00:03:34		
00:09:12		

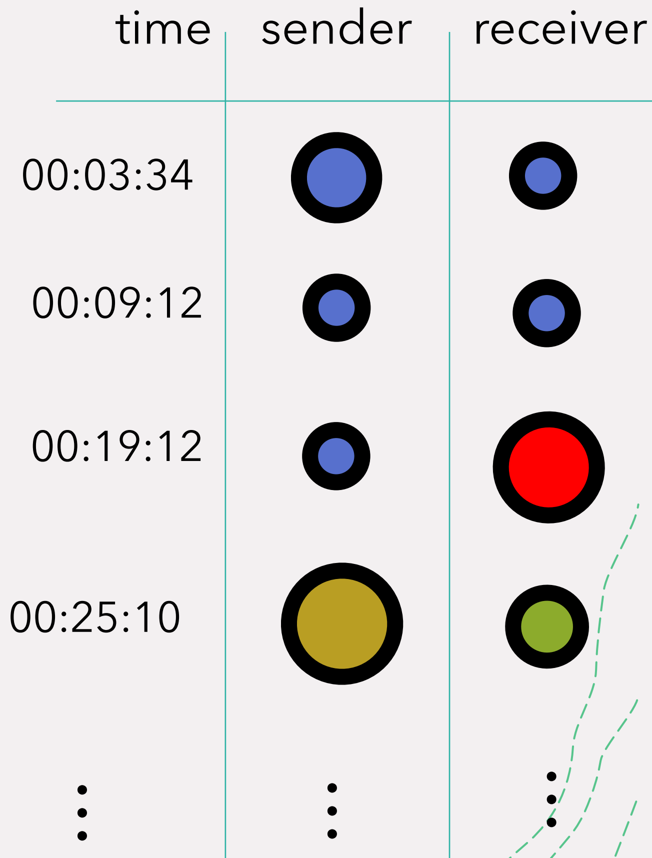
Relational Event History Data



time	sender	receiver
00:03:34		
00:09:12		
00:19:12		

Relational Event History Data

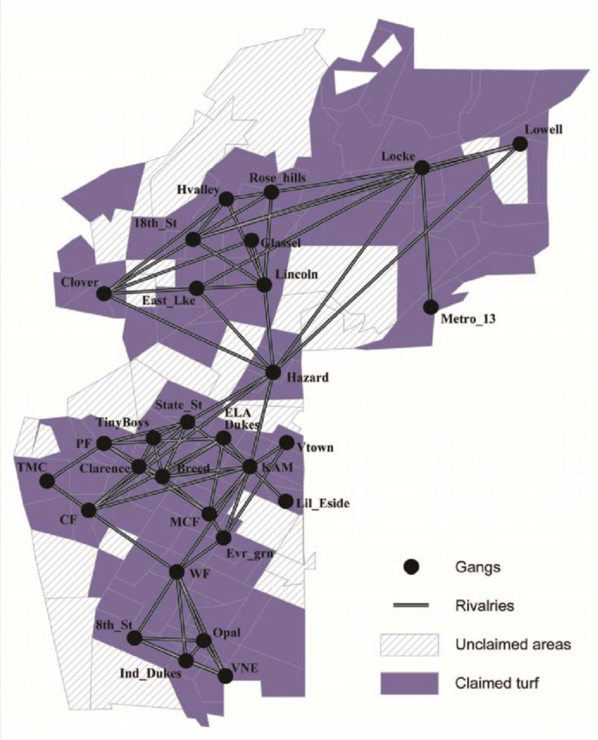




Violent interactions between criminal gangs

(Attempted) homicides between gang members as relational events, Tita et.al. 2003).

date & time	suspect	victim
...	...	...
11/16/1999 19:00	KAM	STATE ST
11/17/1999 15:50	MC FORCE	EVERGREEN
11/18/1999 14:15	TMC	CUATRO FLATS
11/20/1999 15:55	TINY BOYS	BREED ST
11/26/1999 23:20	STATE ST	TINY BOYS
11/27/1999 21:00	VNE	8TH STREET
12/2/1999 14:30	18TH STREET	KAM
...	...	...

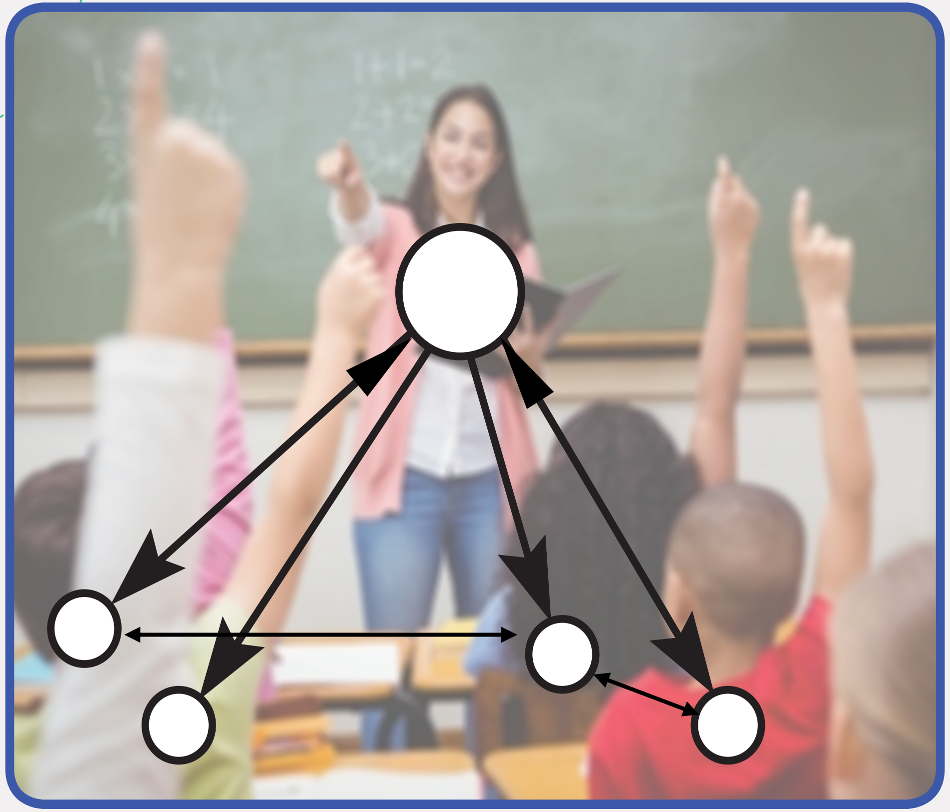


Research questions:

How do gangs interact over time? Which factors influence their interactions?

Aim: Reducing violence in Hallenbeck (LA)

Classroom interactions



Teachers and students interact with each other in classrooms

How *do the teachers and students interact?*

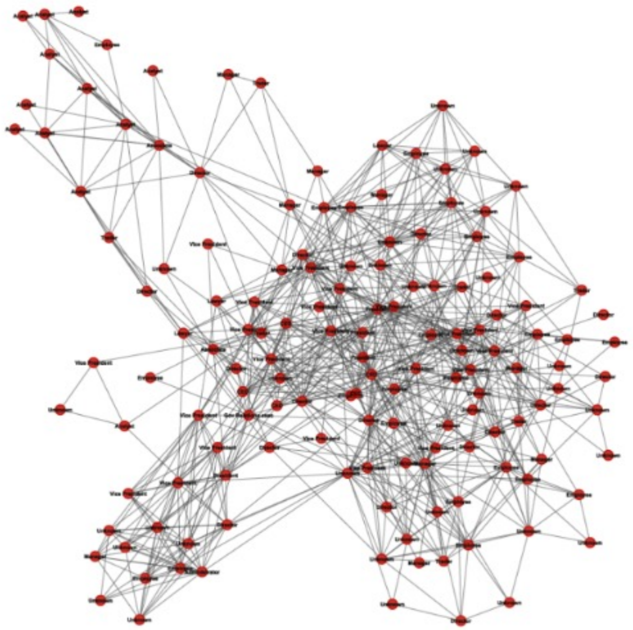
How their interactions change over time?

Can we predict ***when*** *defiant behavior will occur?*

Classroom interactions

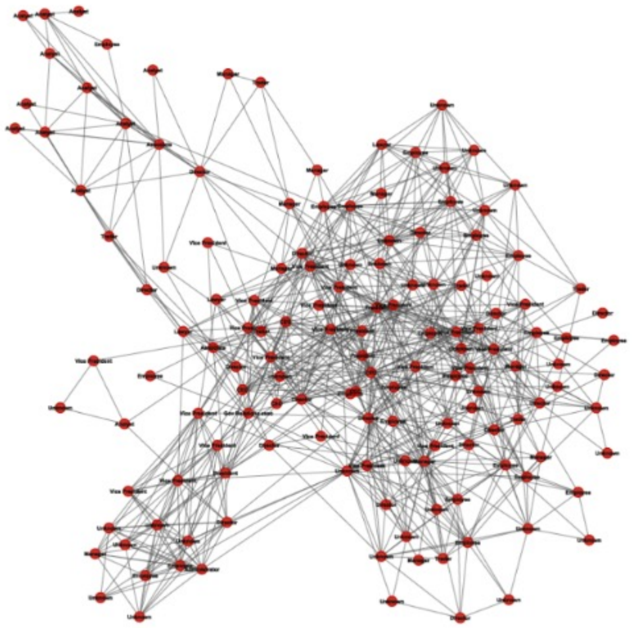
Time	Sender	Receiver	Message
10:10	Teacher	Class	Who can summarize the main idea of the text?
10:12	Ruby	Teacher	The text was about climate change and its effect on the planet.
10:13	Teacher	Ruby	Excellent! Can you tell me a specific example of how climate change is affecting the planet?
10: 14	Ruby	Tom	Do you know an example?
10:17	Teacher	Tom	Tom, can you help Ruby out with an example?
10:20	Tom	Teacher	Uh… I think they mentioned something about melting ice causing sea levels to rise.
10:21	Teacher	Class	Exactly. Can anyone else give another example?

Enron email data



Enron email data (Zhou et al., 2007; Collingsworth & Menezes, 2009)

- Collegial network
- Made publicly available during an investigation into fraudulent accounting practices.
- Observational period: November 13, 1998 and June 21, 2002
- $M = 21,635$ messages ('events').
- $N = 156$ actors.



time	sender	receiver
⋮	⋮	⋮
1999-08-04 13:01:00	138	130
1999-08-05 06:01:00	109	98, 53
1999-08-05 10:34:00	91	117
1999-08-05 12:14:00	138	120, 130
1999-08-06 01:55:00	138	59
1999-08-06 01:56:00	120	138
⋮	⋮	⋮

What insights can we gain from these data?

+ **Complex Interaction Patterns** in dynamic social networks - uncover complex relationships.
+ **Who did What, How & When** - pinpoint actors, actions, modalities, and timing.
+ **Predicting Upcoming Interactions** - forecast the next sender, receiver, and moment of engagement.
+ **Evolution of Interaction Dynamics** - how the interactions change over time and why they change.
+ **From Past to Future** - gauge how earlier interactions shape later interactions and network structure.
+ **Key Drivers & Contexts** - identify roles, content, patterns, and situational factors that propel or inhibit interactions.
+ **Scenario Simulation & "What-Ifs"** - model the impact of interventions, policy changes, or external shocks.
+ **...**

Network Panel Data and relational event history data

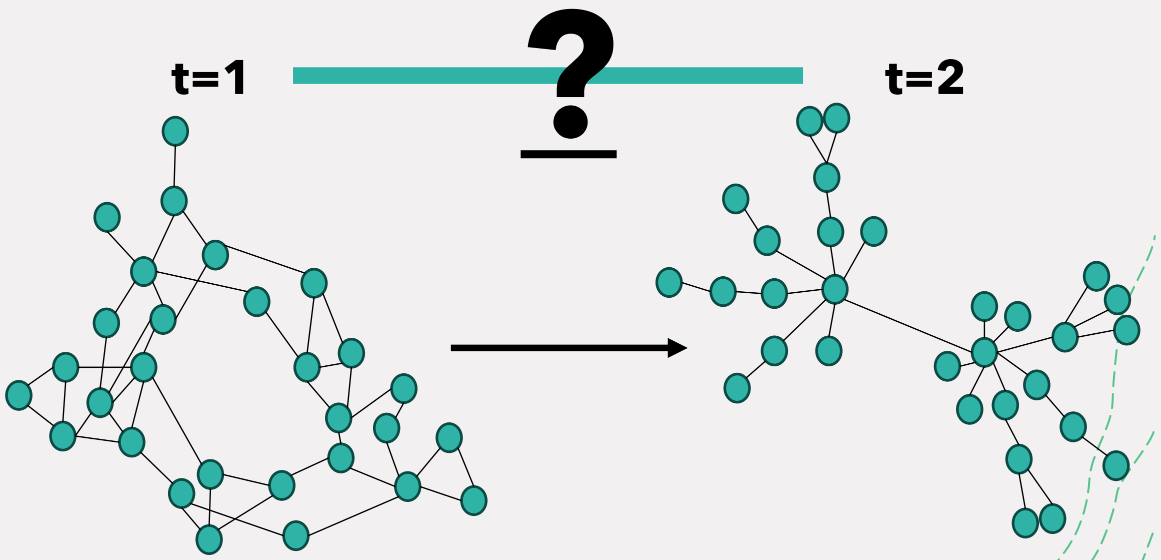
Network Panel Data:

Coarse tie measurements

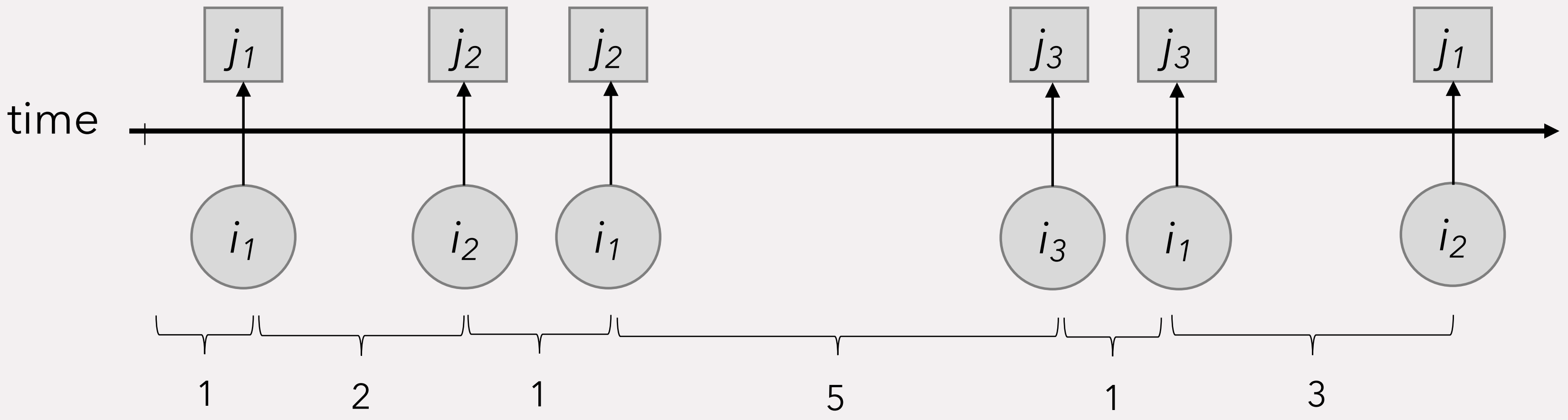
Measuring the same network at different points in time where the gap between measurements is usually large

Typically, ties are assumed to be long lasting E.g., friendships, business relationships.

We know the network changed between panels, but we don’t know the order of those changes



REH Data



Event sequence translated into a data frame: edgelist

time	sender/source	receiver/ target
0	i_1	j_1
3	i_2	j_2
4	i_1	j_2
9	i_3	j_3
10	i_1	j_3
13	i_2	j_1

Edgelist reduced demands on computer memory

Relational event model (REM)

(Butts (2008))

+ The REM is a gold standard for analyzing REH data and addressing those research questions.

Model to analyze REH data:

Relational Event Models (REMs)

R packages:

relevent

survival

remstimates

remstats

remify

.

.

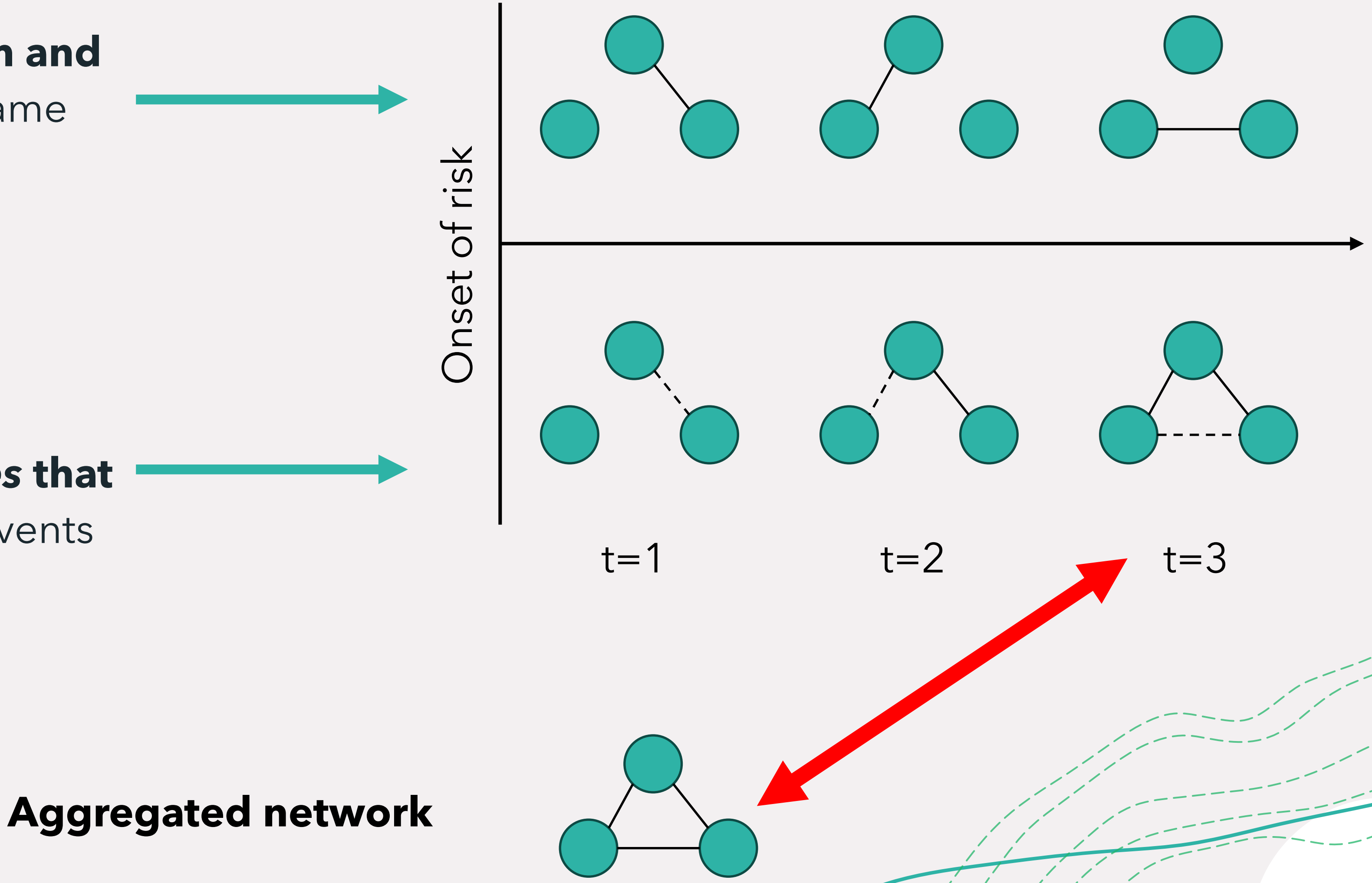
.

new

Relational event modeling

+ A model that **allows ties to form and dissipate** in their natural time frame

+ We also need to account for the ***endogenous network structures* that accrue from histories** of prior events



How does REM work?

- In REM we model the ***interaction rate (hazard), λ,*** of relational event activity.
- **Interaction rate** is the propensity of an event to occur.

- In a REM, the interaction rate (λ) is influenced by **various factors - called network drivers -** that help explain why people interact. These can come from the history of the network itself (endogenous) or from outside information (exogenous).

$$\log \lambda(i,j,t) = \lambda_0 + \theta_{inertia} X_{inertia}(i,j,t) + \theta_{reciprocity} X_{reciprocity}(i,j,t) + \theta_{same\ gender} X_{same\ gender}(i,j,t) + \theta_{same\ education} X_{same\ education}(i,j,t) + \ldots$$

- The model can handle continuous time or ordinal time.

- Note: We'll focus on the *dyadic* case that treats **the dyad as the unit of analysis**.

Statistics : Endogenous and Exogenous

Type	Description	Examples
Endogenous	Come from the interaction history within the network	Reciprocity, triadic closure, popularity
Exogenous	Come from outside the network, e.g. prior actor traits or edge attributes. They're fixed or given before any ties form.	Roles, gender, same location, membership

Relational Event Model (REM)

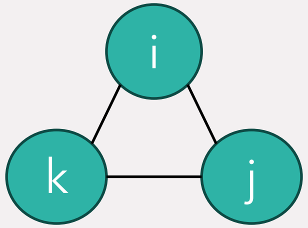
- **The dependent variable can be:**
- ***what*** will happen next, ***when*** will it happen, and ***who*** will be involved.
- The **rate parameter** λ which is a **loglinear function** of predictors.
- Larger rate correspond to higher propensities.

$$\log \lambda(i,j,t) = \lambda_0 + \theta_{inertia} X_{inertia}(i,j,t) + \theta_{reciprocity} X_{reciprocity}(i,j,t) + \theta_{same\ gender} X_{same\ gender}(i,j,t) + \theta_{same\ education} X_{same\ education}(i,j,t) + \ldots$$

- **Each θ is a weight that shows how important that variable is.**

What is the origin of the ***interaction rate (hazard), λ***?

Relational event models (REM): The technical side



+ We assume **a Poisson process** for the count of events (or ties) up to interaction time *t*.
+ ***<u>Or</u>*** we assume **exponential distribution** for modeling the time between events
+ Both of these models have this ***interaction rate (hazard),*** λ.

Relational event models (REM): The technical side

+ A Poisson probability model for the frequency of events at each time period:

$$\Pr(n_{ij}(t)) = \frac{\lambda_{ij}(t)^{n_{ij}(t)} \cdot \exp(\lambda_{ij}(t))}{n_{ij}(t)!}$$

n is the number of events per time period ***t***

$\boldsymbol{\lambda_{ij}}$ is our *hazard rate*.

Higher values of $\boldsymbol{\lambda_{ij}}$ indicate higher event frequencies at a given time period; lower values indicate lower event frequencies.

Fitting a REM :

- ✓ Requires the **estimation** of the $\lambda(i,j,t)$. **How?**
- ✓ We compute the statistics of interest from the REH data, which serve as explanatory variables in the REM.
- ✓ Note: The statistics translate the observed relationships/interactions as explanatory variables.
- ✓ We estimate coefficients, θs,
  - ➢ θs represent the increase/decrease in the rate of event occurrence
  - ➢ Each θ tells us how strongly that variable influences the event rate.)
- ✓ λ_0 is the baseline hazard rate (how likely an event is to occur by random chance)

$$\log \lambda(i,j,t) = \lambda_0 + \theta_{inertia} X_{inertia}(i,j,t) + \theta_{reciprocity} X_{reciprocity}(i,j,t) + \theta_{same\ gender} X_{same\ gender}(i,j,t) + \theta_{same\ education} X_{same\ education}(i,j,t) + \ldots$$

What do the coefficients (θ) mean?

$$\log \lambda(i,j,t) = \lambda_0 + \theta_{inertia}\, X_{inertia}(i,j,t) + \theta_{reciprocity}\, X_{reciprocity}(i,j,t) + \theta_{same\ gender}\, X_{same\ gender}(i,j,t) + \theta_{same\ education}\, X_{same\ education}(i,j,t) + \ldots$$

We simply can interpret θ as follows:

- Whether the corresponding statistics plays an important role in shaping the interactions (look at magnitude of θ).
- Note that higher values of λ indicate that a focal (i,j) connection is more likely at a given time period.

Statistical interpretation:

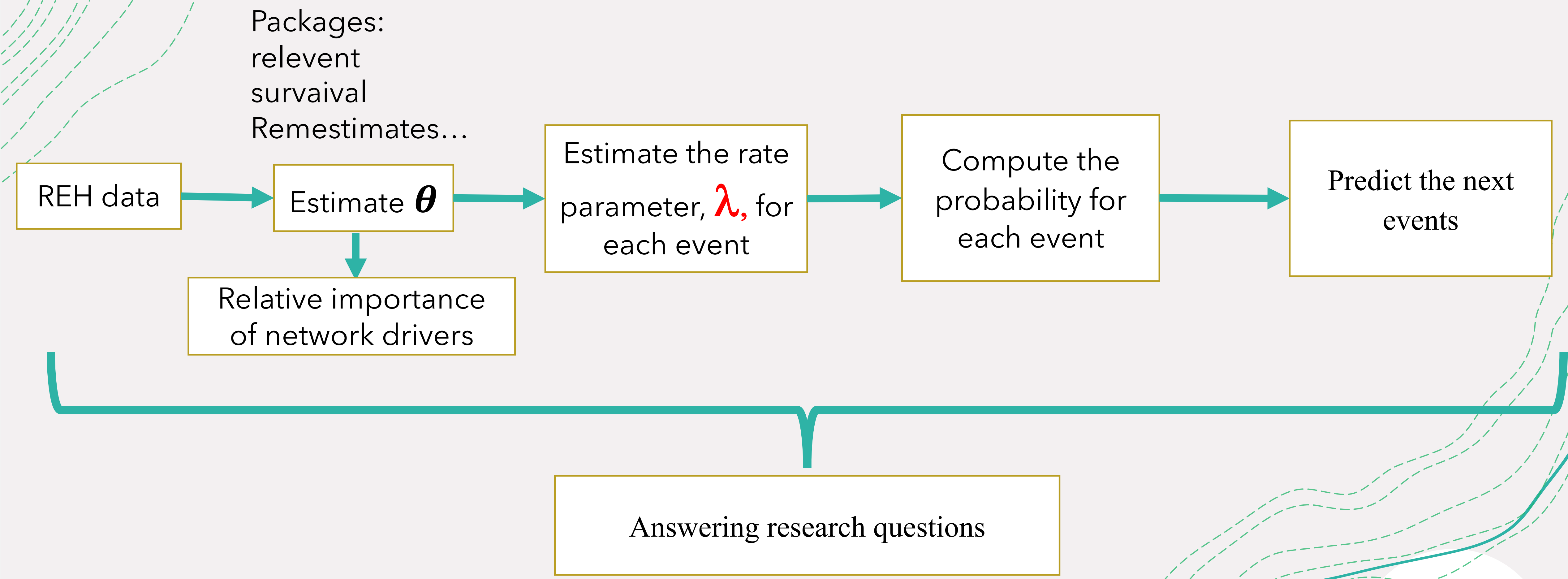
Interpretation	Meaning of θ	How to Understand the Sign and Magnitude
Rate Multiplier	A one-unit increase in predictor **X** multiplies the event rate λ by **exp(θ)**.	• **θ > 0** → λ increases (faster rate) • **θ < 0** → λ decreases (slower rate)
Event Frequency	A higher θ means λ is higher, which results in **more expected events** over a fixed time interval.	• **exp(θ)=1.5** → **50% more** expected events in same time interval • **exp(θ)=0.5** → interactions are happening **50% less frequently**
Waiting Time (Timing)	Higher θ increases λ, which leads to **shorter expected delays** between events (since wait time = 1/λ).	• **θ > 0** → shorter wait • **θ < 0** → longer wait

Statistics in Relational Event Models (REMs)

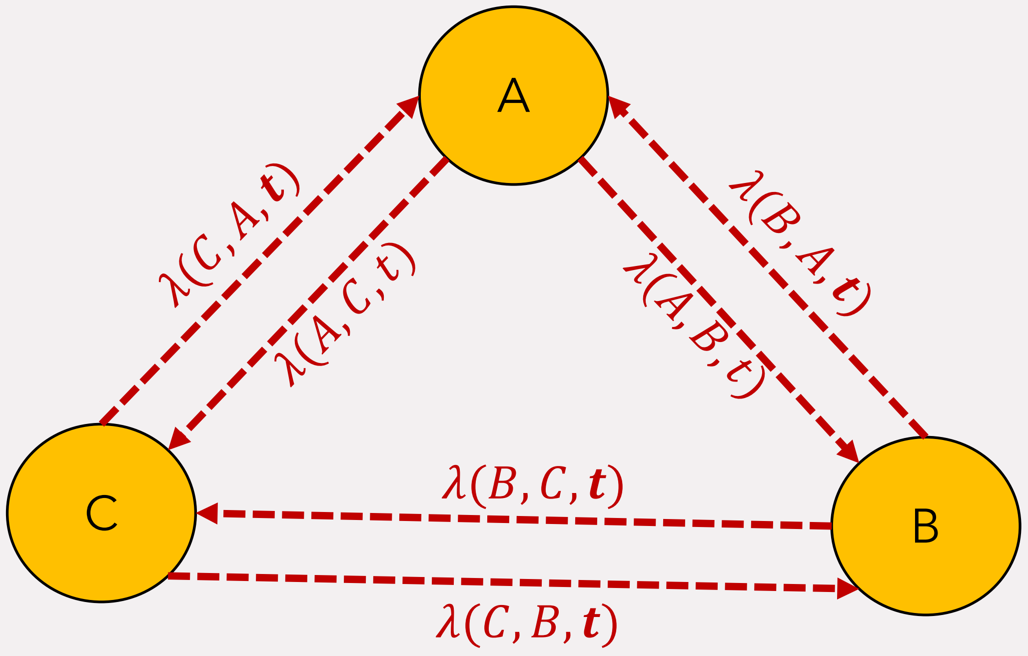
+ **Actor characteristics** (x_1: e.g. tenure of employees, hierarchy, gender, age)
+ **Tie characteristics** (x_2: e.g. same location, same gender)
+ **The past** (x_3: e.g. volume of past interactions, inertia, ...)
+ **External factors** (x_4 : e.g. epidemic situation)
+ **...**

$$\log \lambda(i,j,t) = \lambda_0 + \theta_1\, x_1(i,j,t) + \theta_2\, x_2(i,j,t) + \theta_3\, x_3(i,j,t) + \ldots$$

Relational Event Models (REMs)

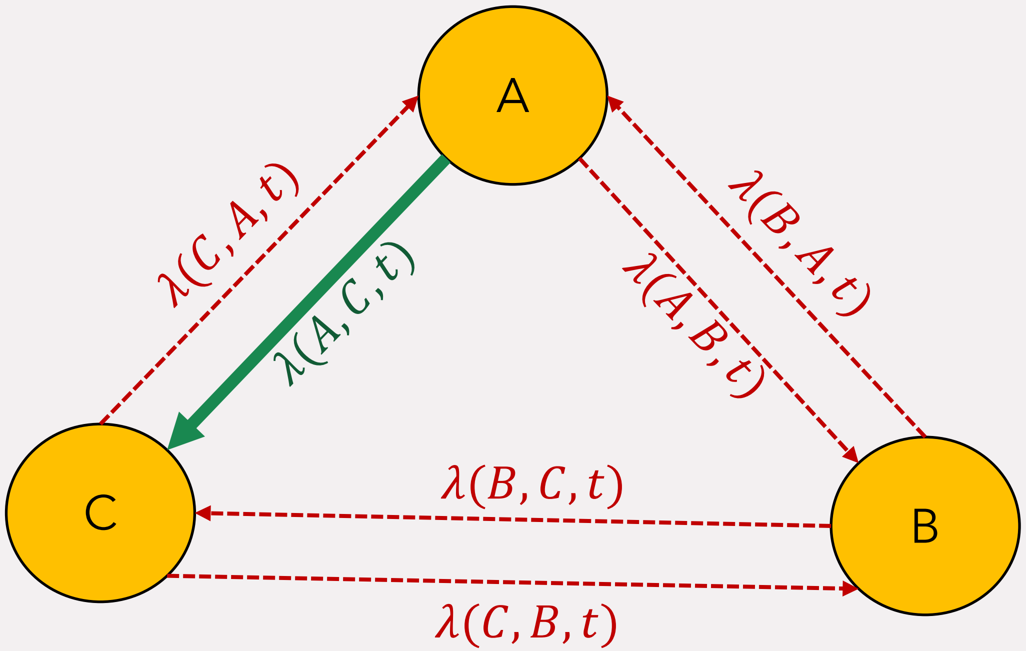


Probability that a particular sequence of events transpired



Risk set: the set of all potential events at time $\underline{t}$

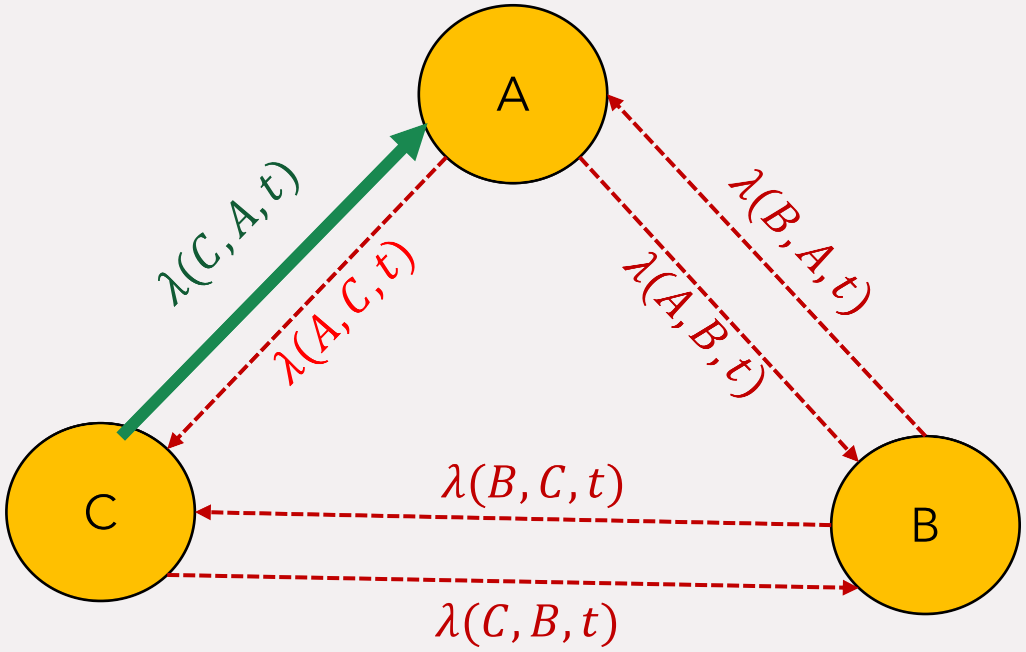
Probability that a particular sequence of events transpired



+ Which relational event: $P(A, C) = \dfrac{\lambda(A,C,\mathrm{t})}{\Sigma\,\lambda(s',r',\mathrm{t})}$

$\Sigma\lambda(s',r',t)$ - all rates in a risk set at a specific time point.

Probability that a particular sequence of events transpired



+ Which relational event: $P(C, A) = \dfrac{\lambda(C,A,\mathrm{t})}{\Sigma\,\lambda(s',r',\mathrm{t})}$

R packages for implementing REM

For estomating the parameters:

- relevent -------(**rem.dyad(), rem()**)
- survival --------(**coxph()**)

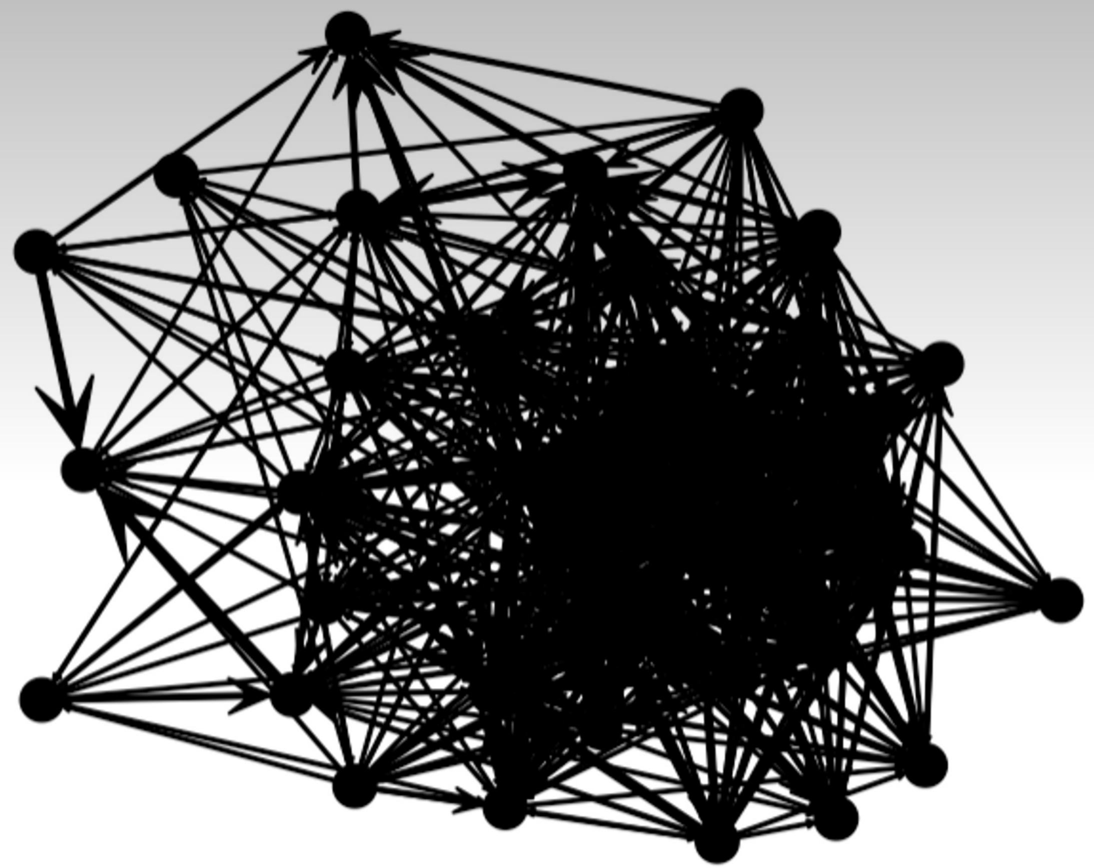
Estimation of the parameters

- For computing statistics
- remstats, remify, remulate…

Computing statistics and fit the model

- **Note**: For **relevent::rem(),** and **survival::coxph()** you need to compute the statistics first.
- But **relevent::rem.dyad(),** compute statistics internally**.**

Twitter



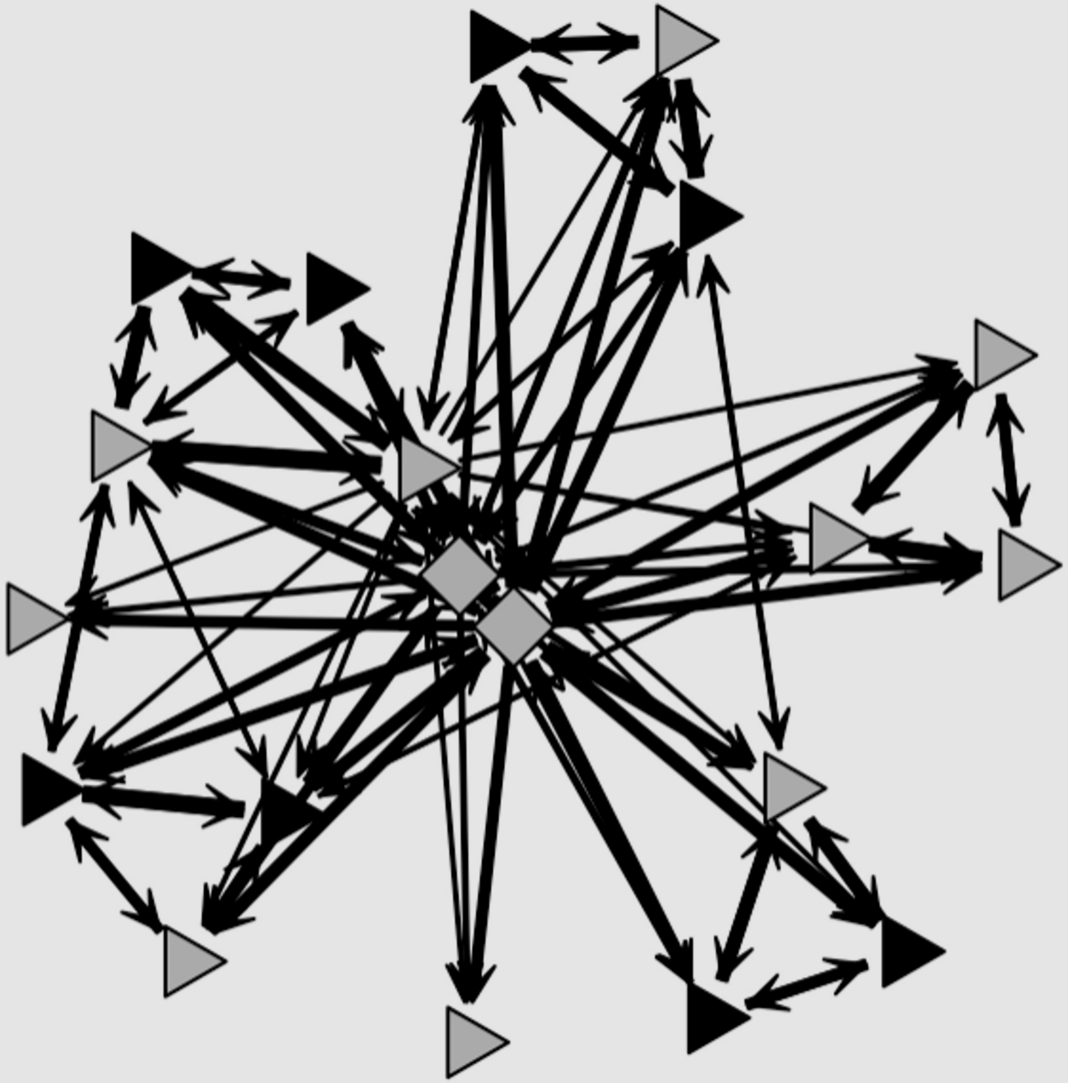
```
Twitter1 <-  rem.dyad(Twitter_data_rem3,n=39, effects = c("PSAB-BA", "PSAB-BY"), ordinal = FALSE, hessian = TRUE)

summary(twitter1)
```

Relational Event Model (Temporal Likelihood)

	Estimate	Std.Err	Z value	Pr(>|z|)
PSAB-BA	-6.757	0.5777.	-11.697	< 2.2e-16 ***
PSAB-BY	-8.285.	0.2040.	-40.611	< 2.2e-16 ***

Signif. codes:
0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’
0.1 ‘ ’ 1

Class



```
classfit5<-rem.dyad(Class,n=20,effects=c("CovSnd","CovRec","RRecSnd","RSndSnd",
"PSAB-BA","PSAB-AY","PSAB-BY"), covar=
list(CovSnd=cbind(ClassIntercept,ClassIsTeacher),
CovRec= cbind(ClassIsTeacher,ClassIsFemale))

summary(classfit5)
```

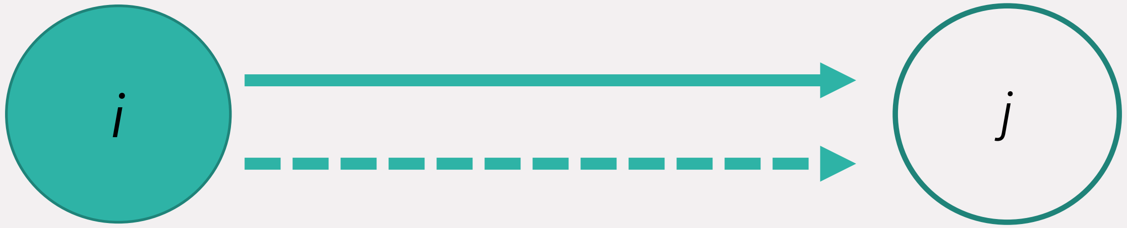
	Estimate	Std.Err	Z value	Pr(>|z|)
+ **RRecSnd**	2.429210	0.155367	15.6353	< 2.2e-16 ***
+ **RSndSnd**	-0.986720	0.144668	-6.8206	9.068e-12 ***
+ **CovSnd.1**	-5.003468	0.090610	-55.2197	< 2.2e-16 ***
+ **CovRec.1**	-0.722667	0.141950	-5.0910	3.562e-07 ***
+ **PSAB-BA**	4.622159	0.137602	33.5908	< 2.2e-16 ***
+ **PSAB-BY**	1.677639	0.164930	10.1718	< 2.2e-16 ***
+ **PSAB-AY**	2.869985	0.103114	27.8330	< 2.2e-16 ***

The predictor variables/statistics: $(X_1, X_2, X_3, \dots)$

- Inertia…
- Reciprocity
- Transitivity
- In(out) degree sender/receiver
- And many more
- Age
- Hirarchy
- Same location
- … whatever you beleive is important

Inertia

The **tendency** of person *i* to continue to initiate events towards person *j*, as a function of the **volume of past events** from *i* to *j*.



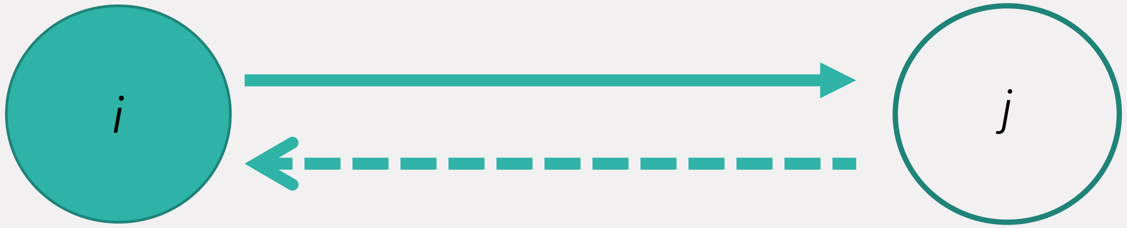
Example-- Inertia

+ A teacher exhibits a tendency to ask students they have been frequently asked questions in the past.
+ Then the true effect value $\beta_{INERTIA}$ of inertia statistics is positive, and the REM should find a positive and significant estimate.

$$\log \lambda(i,j,t) = \lambda_0 + \boldsymbol{\beta_{INERTIA}} * \textbf{Inertia}(i,j,t) + \theta_2\, x_2(i,j,t) + \theta_3\, x_3(i,j,t) + \ldots$$

Reciprocity

The tendency of person *i* to initiate events towards person *j*, as a function of the volume of past events *i* received from *j*.



$$\log \lambda(i,j,t) = \lambda_0 + \beta_{INERTIA} * \textbf{Inertia}(i,j,t) + \beta_{recipro} * \textbf{Recipro}(i,j,t) + \theta_3\, x_3(i,j,t) + \ldots$$

Example-- Reciprocity

- In some classrooms, teachers and students **systematically respond to each other** based on past interactions.
- For example, a teacher may be **more likely to call on a student just because that student previously asked a question**.
- In this case, the **reciprocity effect** in the model should be **large**.
- That means the model would show **strong tendency for back-and-forth exchanges** (e.g., question–answer chains).

- $\log \lambda(i,j,t) = \lambda_0 + \beta_{INERTIA} * \textbf{Inertia}(i,j,t) + \beta_{recipro} * \textbf{Recipro}(i,j,t) + \theta_3\, x_3(i,j,t) + \ldots$

Example of Kitts et al. (2017)

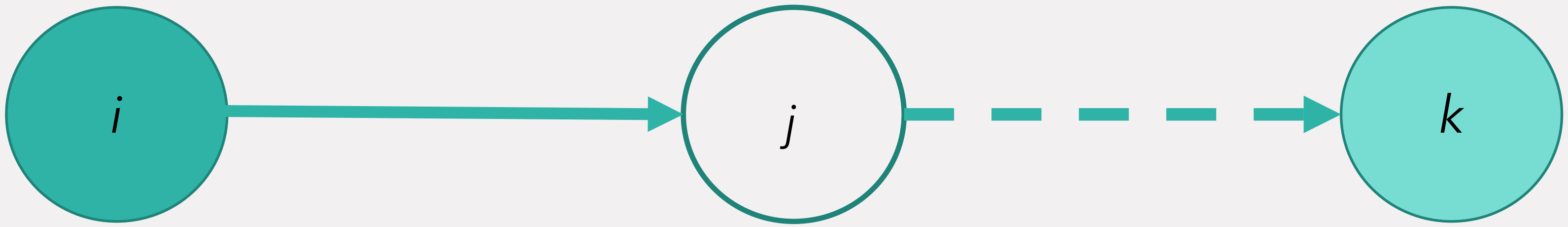
+ **Research question:** Do hospitals engage in the social norm of reciprocity when exchanging patients, instead of sending them to the hospital that can offer the best service for the patient?

+ Using REM, they examined reciprocity in over 4,000 patient exchanges between 21 hospitals in a region of Italy, spanning 5 years.

+ **Result**: hospitals do reciprocate patient exchanges over time in ways that are not explained by the availability of beds, the quality of service, or the specialization of hospitals.

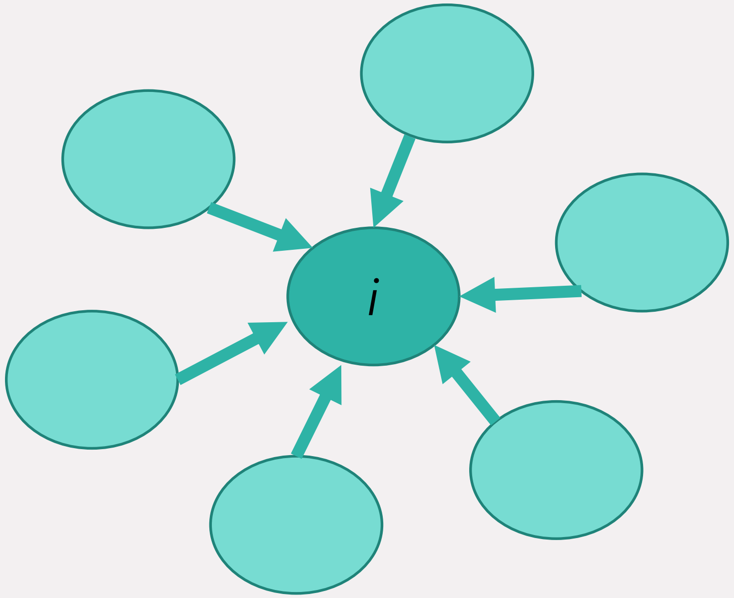
Participation shift AB-BY ("turn receiving")

The tendency of an initial receiver *j* of an event to, **in turn**, direct the next event to another person *k*.



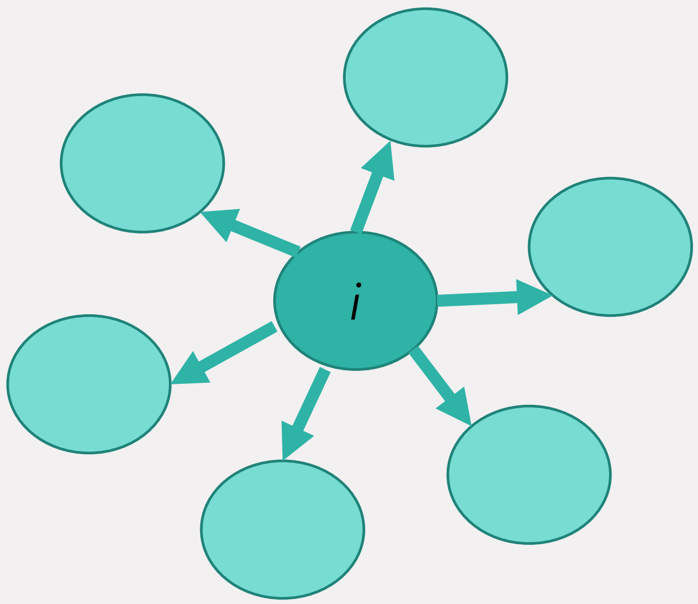
In-degree

In-degree is the number of connections that point inward at a vertex. Actors with high in-degree are impacted by multiple other actors.



Outdegree

Out-degree is the number of connections that originate at a vertex and point outward to other vertices.



In a nutshell, REM is suitable for

+ **Estimating** the relative important of *network driver effects* β.
+ **Testing** *temporal social theories* via competing statistical models.

+ **Predicting** future events, *what* will happen next, *when* it will happen, and *who* will be involved. REMs predict the occurrence of the next event in a temporally distributed sequence of events (Marcum & Butts, 2015)
+ This means that, in REM, the dependent variable can be the occurrence of the next event in a sequence, which is modelled as a function of the sequence of past events.

+ **Understanding** how interaction behavior *changes in continuous time*.
+ Why did some node tie to another at this point in time and not previously?

Class activity

+ Can you identify a potential application of this concept in your field, or in any area you find valuable?

  - **What do the data look like?**
    - Describe that: what/who is the sender/receiver?
  - **What is your research question?**
  - **Prepare a brief proposal summarizing your idea.**

Longitudinal network analysis: TERGMs (ERGMs) – SAOMS and REMs

+ The **choice** of network inference model depends on **how time is recorded.**

Four main network inference models:

+ **Relational Event Models**
+ **Exponential Random Graph Models**
+ **Temporal Exponential Random Graph Models and**
+ Stochastic Actor Oriented Model (SAOM)

Exponential Random Graph Model (ERGM)

R package: ergm

ERGM: **E**xponential **R**andom **G**raph **M**odel

- **Cross sectional model** for network structure. (single measurement of the network)
- Goal: “to describe parsimoniously the **local selection forces** that shape the global structure of a network.” (Hunter et al. 2008).
- Why do we observe this particular network structure as opposed to some other possible network configuration?
- ERGMs are tie-based statistical models for understanding **how and why social network ties arise**.

Example: What drives friendships in high school?

You collect data on who is friends with whom, and you notice some patterns:

- Students tend to become friends with people of the **same grade**.
- Friendships are often **mutual** (if A is friends with B, B is usually friends with A).
- **Triads** are common (if A is friends with B, and B is friends with C, then A often becomes friends with C).

How ERGM helps:

Test whether these patterns (same grade, reciprocity, triads) explain the network.
Estimate how much each pattern contributes.

ERGM helps you say, *"these are the reasons they became friends."*

ERGM

- Let say **G** is a graph.
- **Summary measures *z*(*G*):** or "network statistics,"

- Network statistics such as the **number of edges, triangles, popularity**.

- The ERGM assigns probability to graphs according to these statistics:

$$P_{\theta}(G) = c e^{\theta_1 z_1(G) + \theta_2 z_2(G) + \cdots + \theta_p z_p(G)}$$

c is a normalizing constant.

This is the probability of a given network.

The parameters inform us of the **importance** of each configuration.

In nutshell:

- Include variables in the model that are hypothesised to explain the observed network.

- The ERGM will provide information relative to the statistical significance of the included variable.

- Choose a set of configurations of theoretical interest.
- Estimate the parameters by applying ERGM
- Do inferences about the configurations – the network patterns – in the data.
- Do inferences about the type of social processes that are important in creating and sustaining the network

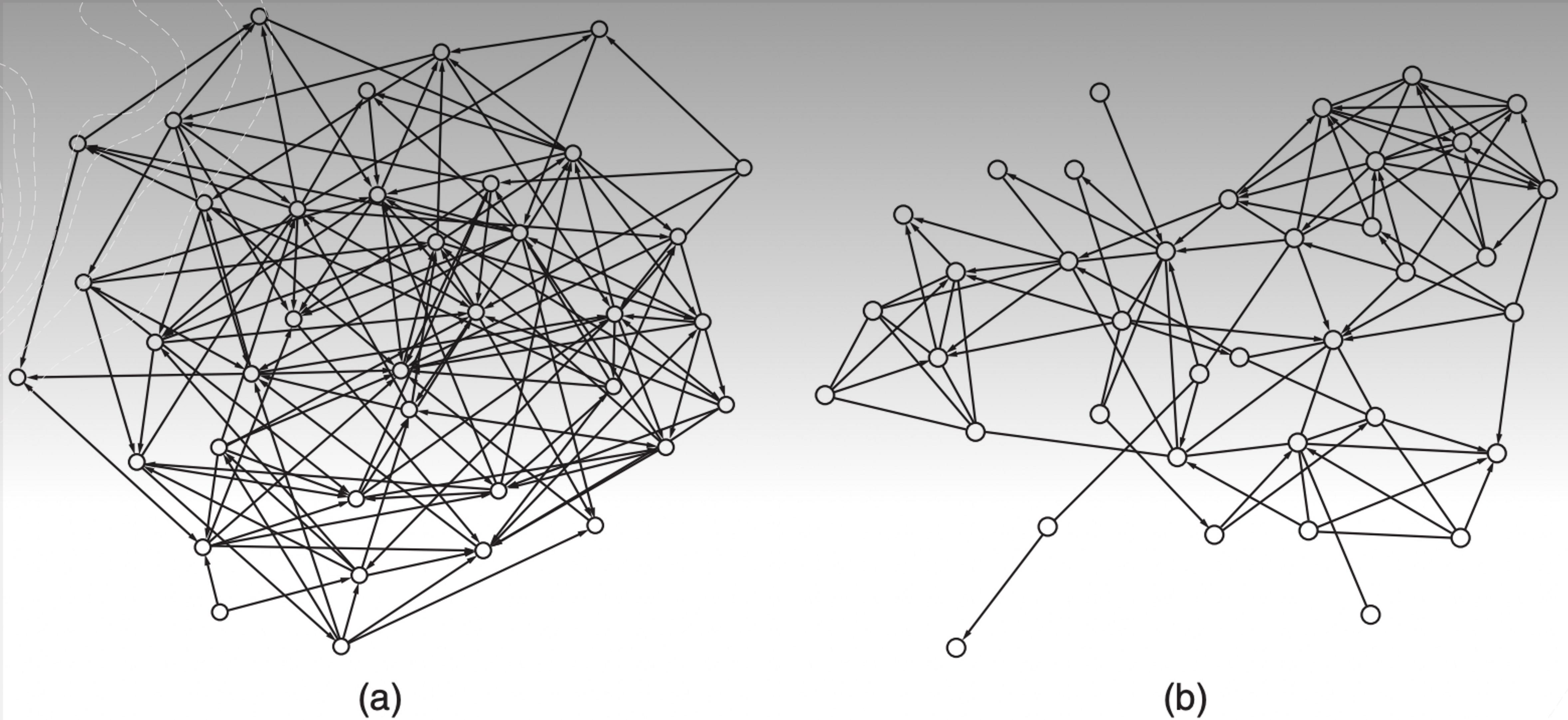


Figure 4.1. (a) Simple random network and (b) empirical communication network.

Lusher et al. (2013)

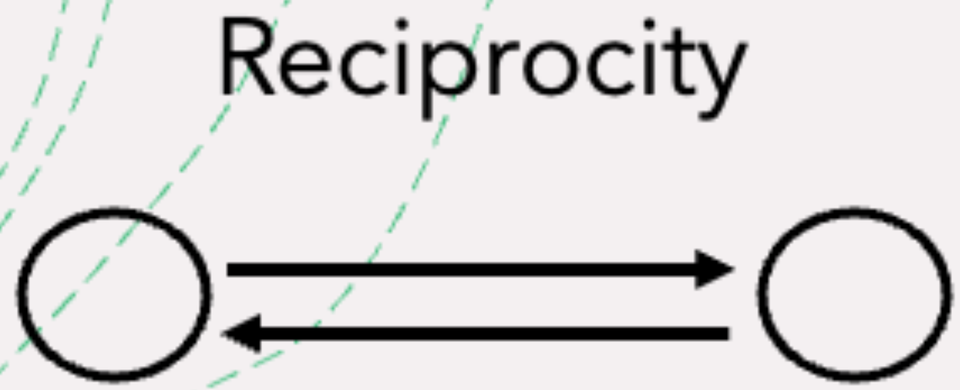
Table 4.1. *Selected network statistics for networks in Figure 4.1*

	Random network	Communication network
Actors	38	38
Arcs	146	146
Reciprocated arcs	6	44
Transitive triads	53	212
In-2-stars	292	313
Out-2-stars	254	283

Example

+ **The presence of reciprocity** :

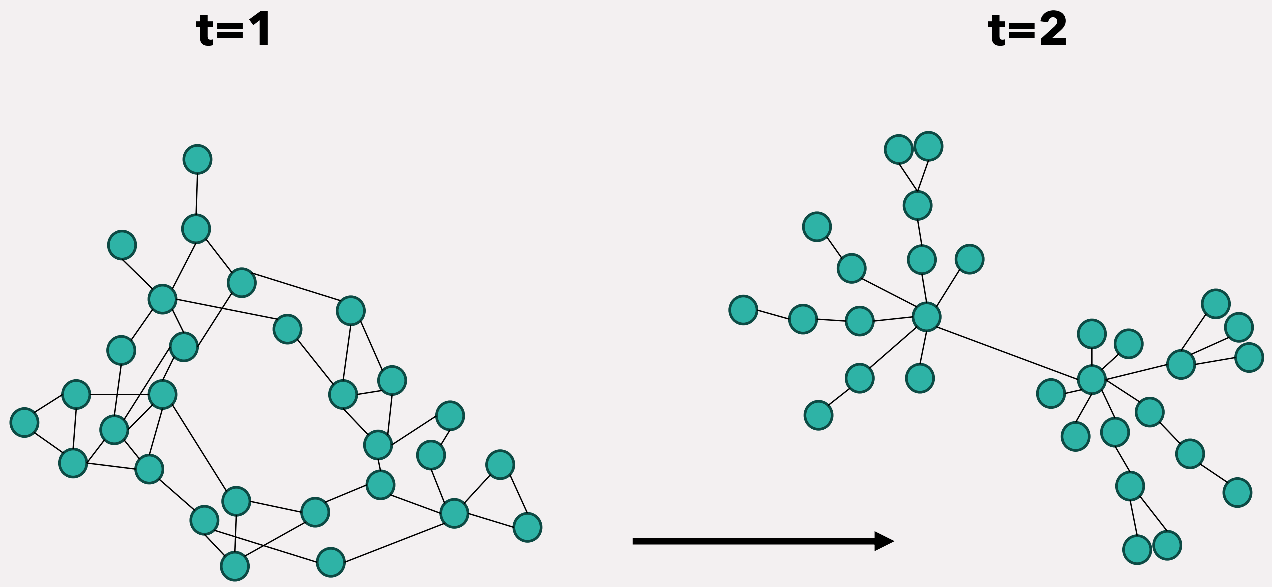
  There is a process that generates a significant number of **reciprocated structure** that **is not** the result of **random link creation** e.g., a tendency to create a link between common friends.



TERGM is the temporal version of ERGM

+ Models for network dynamics and network panel data (**longitudinal social network** data)
+ **Network panel** data are common for representing relations like **friendship**, **advice**, **collaboration**, <u>exchange which can be regarded as *states* rather than *events*.</u>

+ Only the changes between Network panels



Concept	ERGM	TERGM
Time	**One snapshot**	**Multiple time points** (network panels)
Goal	**Explain why a network has the structure it does**	**Explain how/why it changes over time**
Data	**One network**	**Sequence of networks** (e.g., t = 1, 2, 3…)

Stochastic Actor Oriented Models (SAOMs)

(Snijders, 1996; Snijders et al., 2010)

R package: RSiena

SAOMs

- are models for network **dynamics** and network **panel data**
- developed for the analysis of **longitudinal social network** data, collected by taking two or more "snapshots" ("**panels**" or "**waves**") of a network as it evolves over time.
- focus on the **decisions of individual actors (people)** over time.
- **are agent-based ('actor-oriented')** : They model changes from the perspective of the actors (**creating, maintaining or terminating ties** to other actors (a series of "**choices**") within a (potentially) changing network.
- investigate **network dynamic** through **simulations between panels**.

How SAOM works?

- You observe the network at several time points (like in TERGM).

- SAOM assumes:
  1. Changes happen in **small steps (mini steps) which** are **probabilistic** and made sequentially based on some rules.
  2. **One actor at a time** can make a change (e.g., add/drop a tie).
  3. Actors try to improve their network position based on rules (like reciprocity, homophily).

- The **transition** from the observation at **one wave** to the **next** is done by means of a large number of ministeps. These **changes** are not individually observed, but they are **simulated.**

- Over time, the model simulates this decision-making process and estimates the **influence of each rule**.

Application of SAOMs

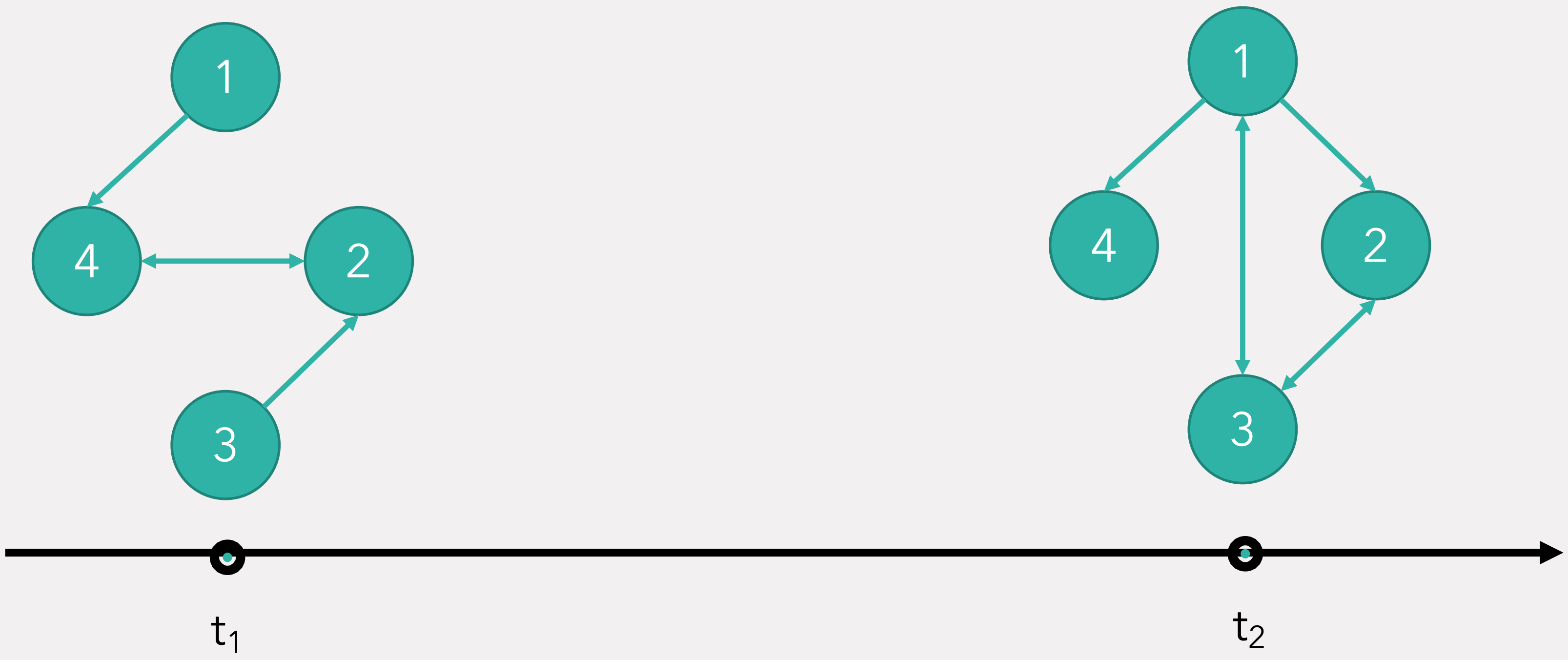
Domain	**Typical research question**
Adolescent friendship & health	*Do teens start smoking/drinking because their friends do (influence), or do they pick friends who already behave that way (selection)?*
Peer effects & online activity	*How do social-media contacts shape risky or prosocial online behaviour, and vice-versa?*
Organisational & team collaboration	*Which structural or behavioural rules drive who collaborates with whom inside firms or open-source projects?*
Scientific co-authorship	*Do researchers preferentially co-author with similar experts, and how does that affect knowledge diffusion?*

Key difference between SAOM and TERGM:

Feature	**TERGM**	**SAOM**
Focus	Whole network evolution	**Individual choices** over time
Process	looks at the overall changes between full network snapshots.	Models **who changes ties, how and why**, step-by-step
Assumption	• No information about the sequence or decision-makers • Network changes follow statistical patterns based on structure (e.g. triads)	• **actors make deliberate choices (**tie changes) over time to improve their position or satisfy preferences (e.g. prefer friends who are similar). It models behavior explicitly.

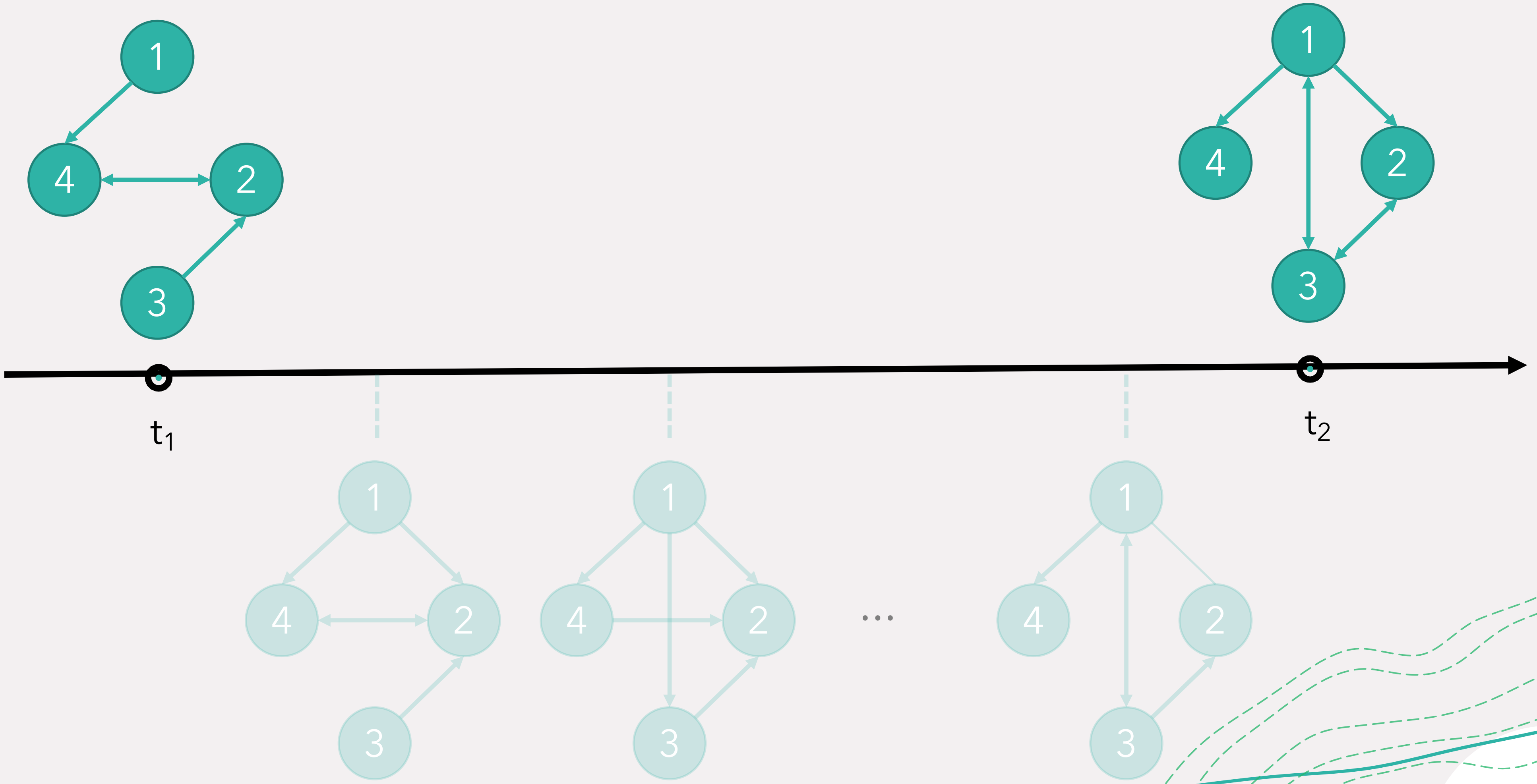
SAOMs

Model assumptions: consequences



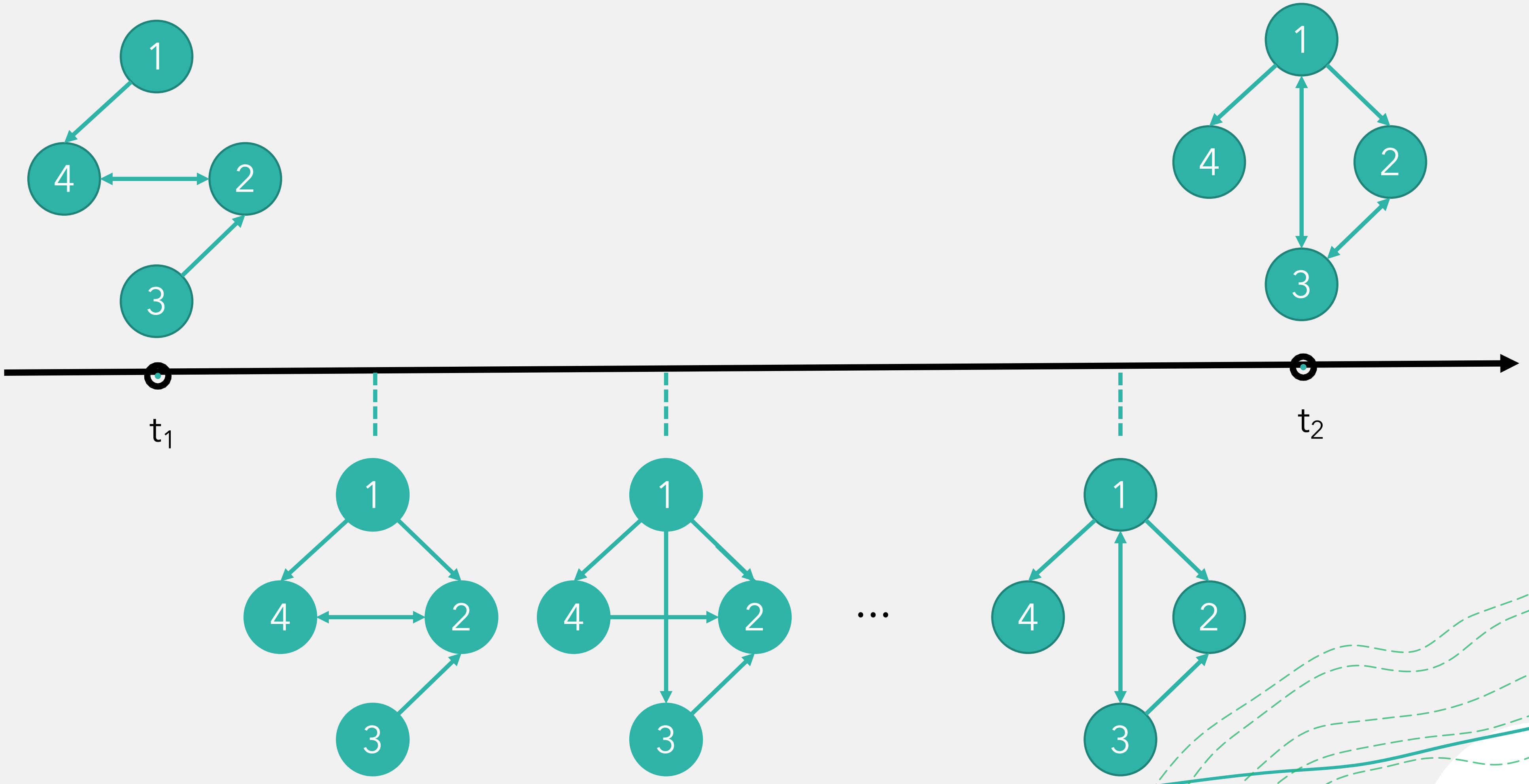
SAOMs

Model assumptions : illustration



SAOMs

Model assumptions: illustration



Modeling tie changes in SAOM

- **Who gets the opportunity for a tie change and when?**

A **person** from the network is chosen to make a change according to **the rate function**.
For actor i, the waiting time until the next opportunity for change is exponentially distributed with rate parameter

$$\boldsymbol{\lambda_i(x, v) = \exp(\textstyle\sum_k \alpha_k\, r_{i,k}(\mathrm{x}, \mathrm{v}))}$$

- **To whom?**

Next, we model **which tie change** is made. This is modelled in the objective function:

$$\boldsymbol{f(\beta, x, v, w) = exp(\textstyle\sum_k \beta_k\, s_{i,k}(\mathrm{x}, \mathrm{v}, \mathrm{w})}$$

At each time step, the actors move in a direction that **maximizes their particular objective function**

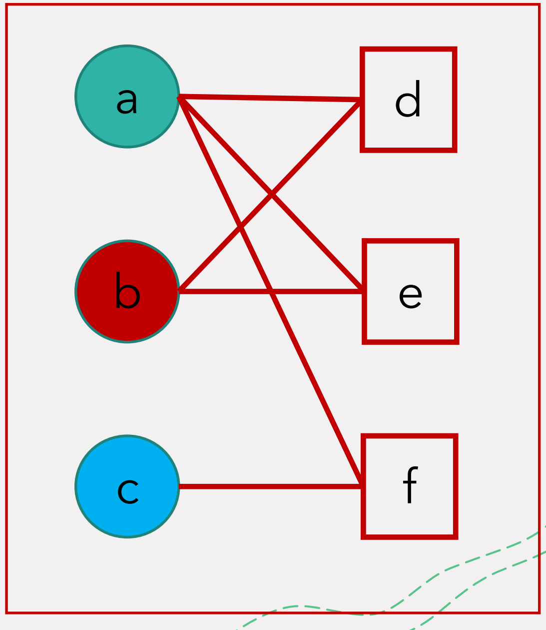
REM vs ERGM vs TERGM vs SAOM:

Which model fits your data best?

Longitudinal network analysis: ERGMs – SOAM, TERGMs - REMs

- If you have 1 snapshot of your network → run an ERGM
- ERGM = exponential random graph model

snapshot



t = 1

Research question

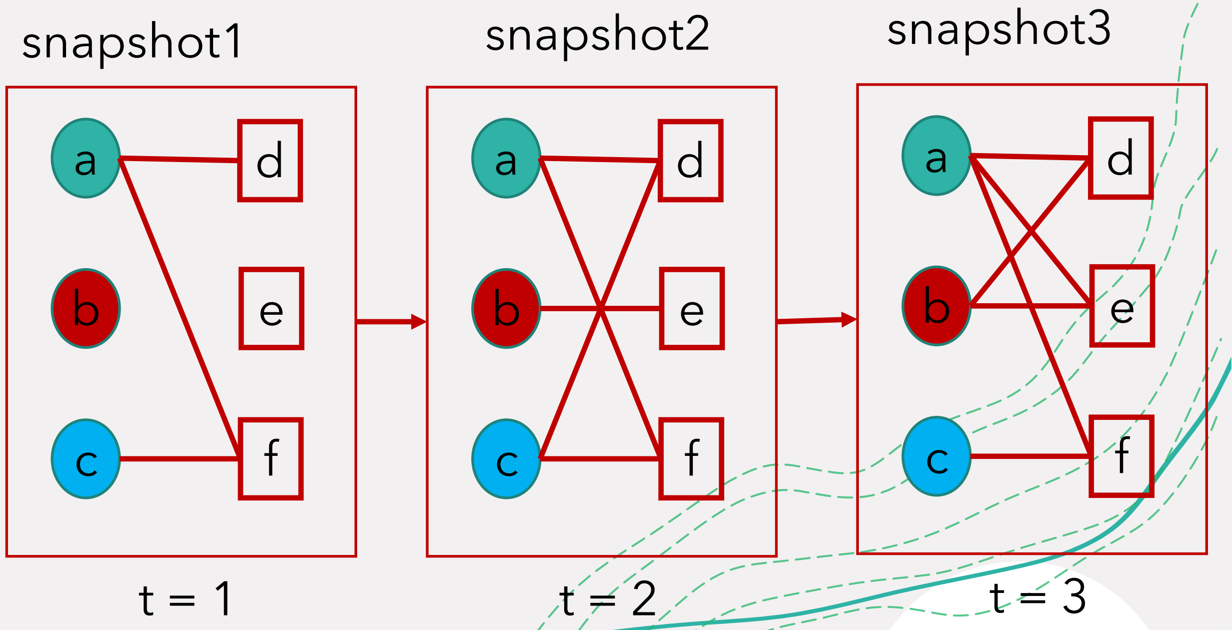
Which factors affect the structure of the network?

Longitudinal network analysis: ERGMs – SOAM, TERGMs - REMs

- If you have multiple snapshots of your network → run an TERGM or SAOM

Research question

Which factors affect the structure of the networks and how do networks change over time?

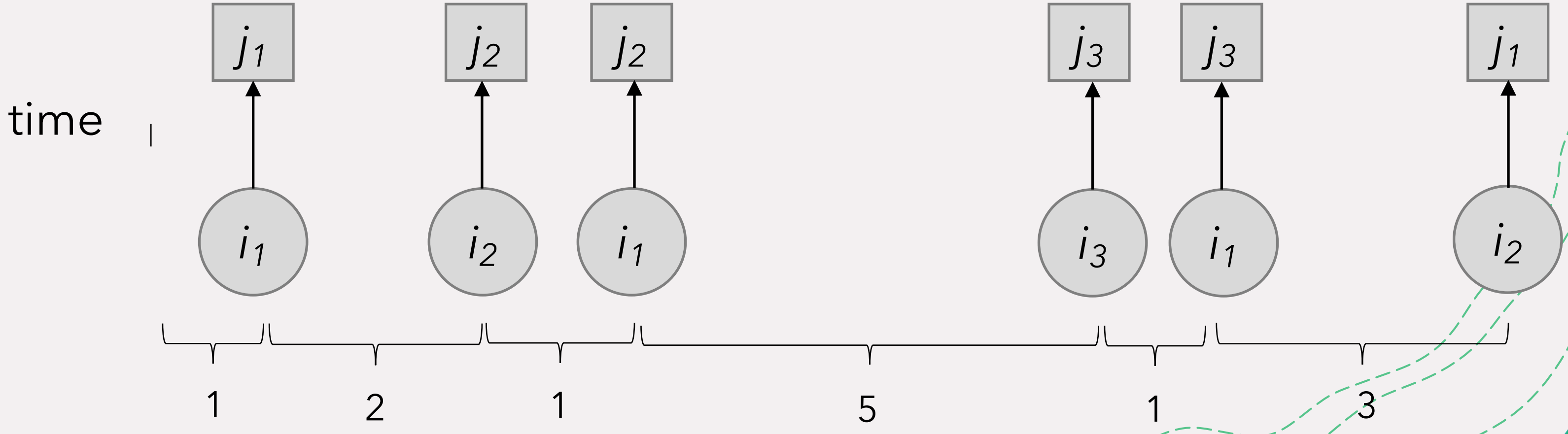


Longitudinal network analysis: ERGMs – SOAM, TERGMs - REMs

- If you know the **time/order** each tie is created in a network → run a REM
- … recorded in exact time or ordered

Research question

Which factors affect the probability of an edge forming at time point *t*?



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