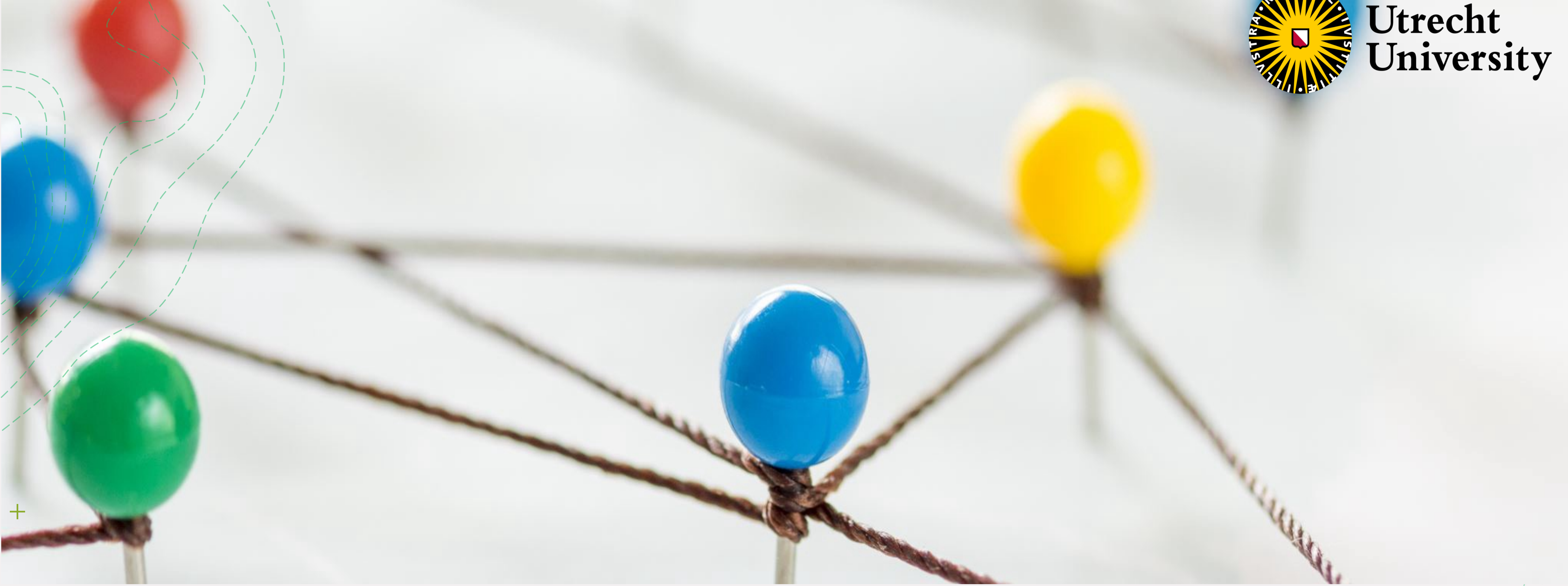


Social network analysis

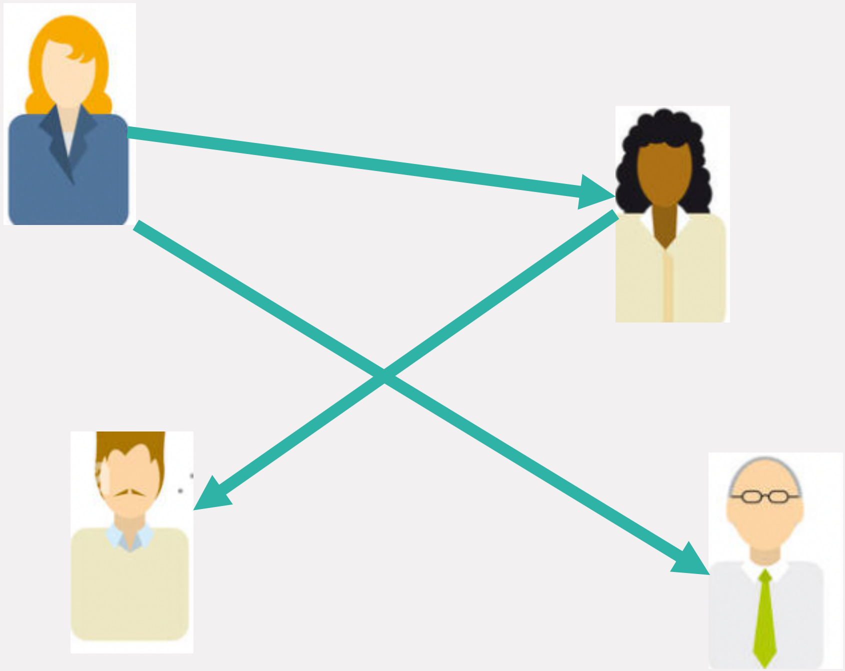
Mahdi Shafiee Kamalabad

Contents

- **Social networks**
- Relational Event History Data (**REH**)
- Relational Event Model (**REM**)
- **E**xponentioal **R**andom **G**raph **M**odel (**ERGM**)
- **S**tochastic **A**ctor **O**riented **M**odel (**SAOM**)
- Choosing your weapon in longitudinal network analysis: ERGMs, SOAM, TERGMs, REMs

Network

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



Social networks: Relations/interactions

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

For example,

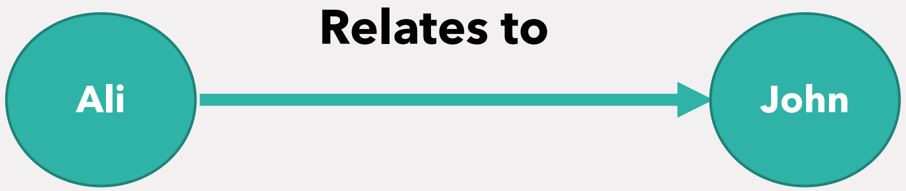
Ali goes to John for **advice**…

Ali considers John as a **friend**…

Ali sends an **email** to John…

Ali **calls** John…

Ali **communicates** with John…



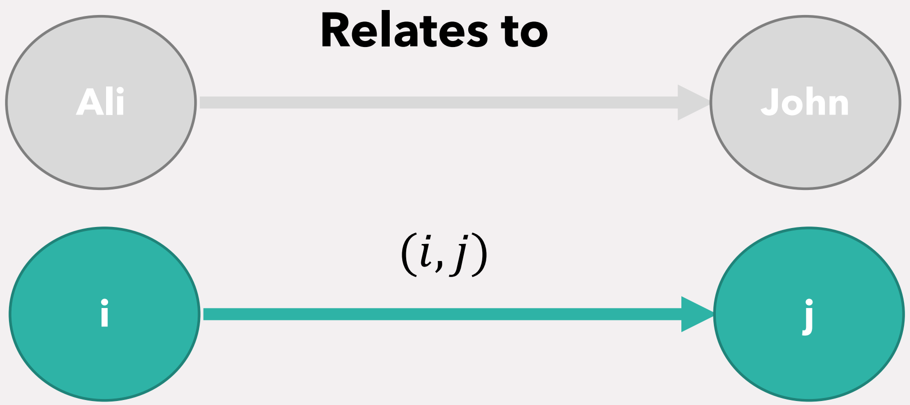
Tie present: On

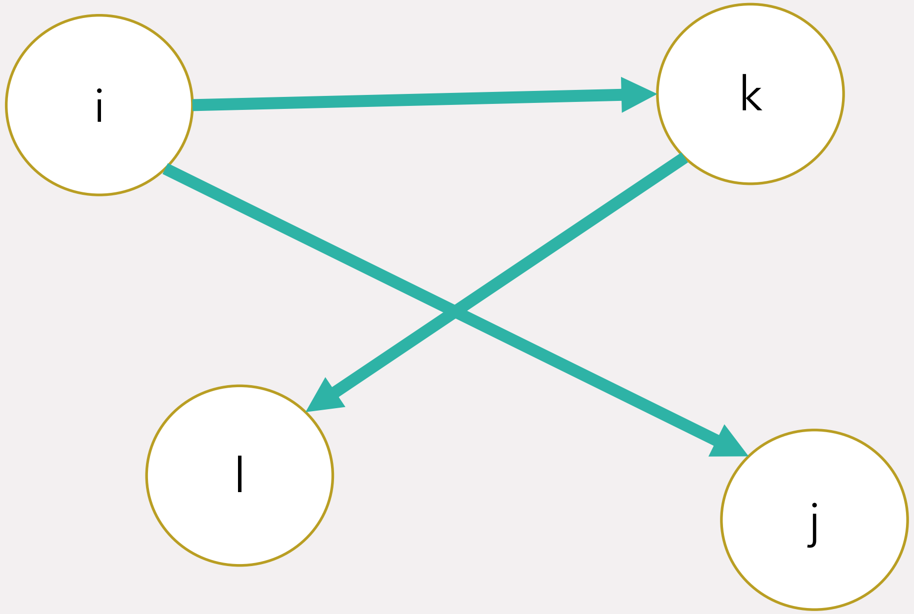
Tie absent: Off

Social networks

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

Actors / vertices: $V=\{1,2,\ldots,n\}$
Relations / edges: $E \subseteq \{(i,j) : i,j \in V\}$






Apollo 13

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 about ***what*** happened (message, email, etc.), ***when*** it happened (time), and ***who*** was involved (sender, receiver).
- REH data contain at least **receiver** (target), **sender** (source), 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?

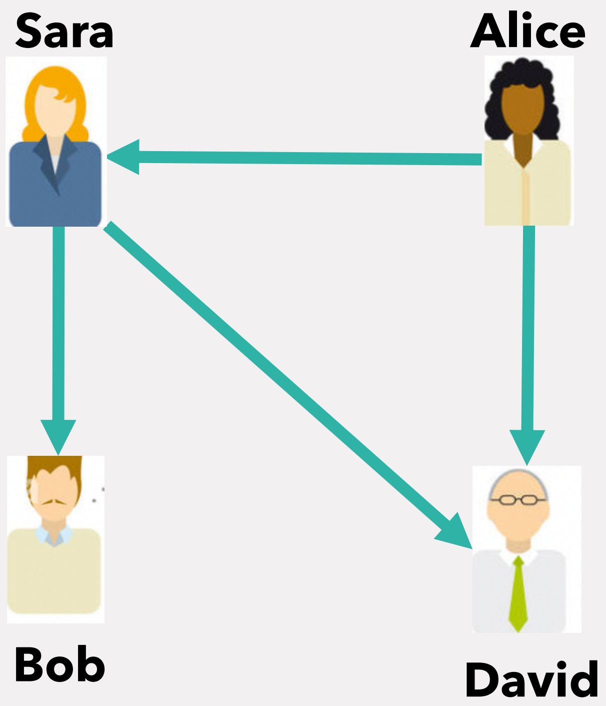
+ Relational events are everywhere, and ***increasingly available*** due to the development of technology.

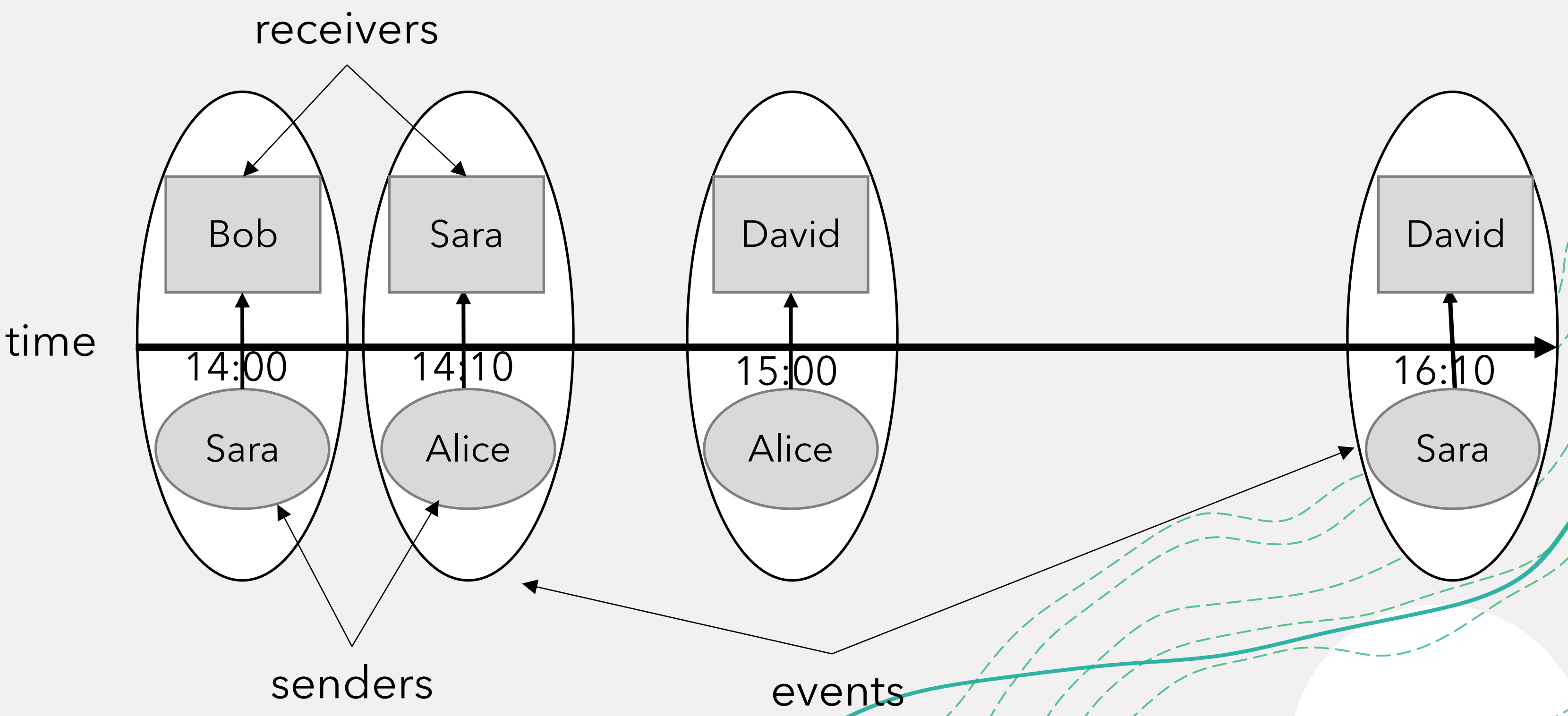
e.g.

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

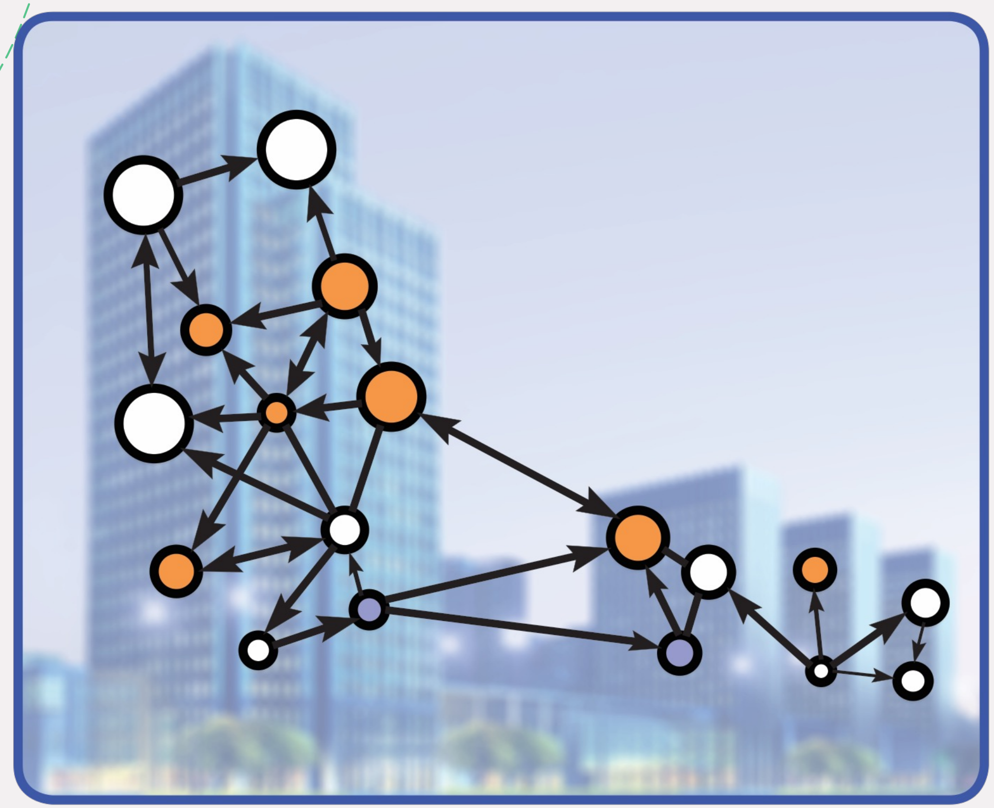
Why do we study relational events?

+ 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.



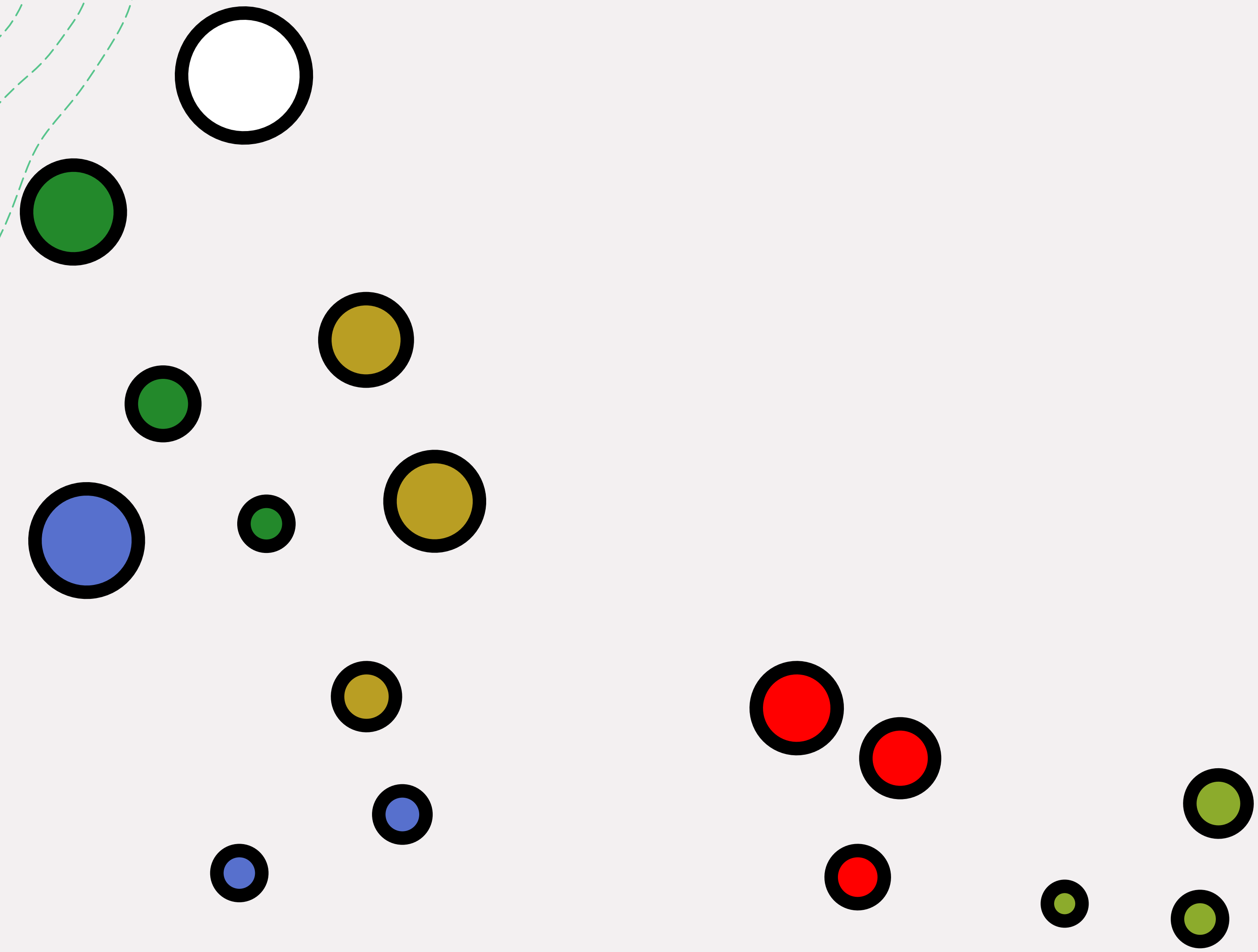


Example



Employees in organizations share information with each other via email.

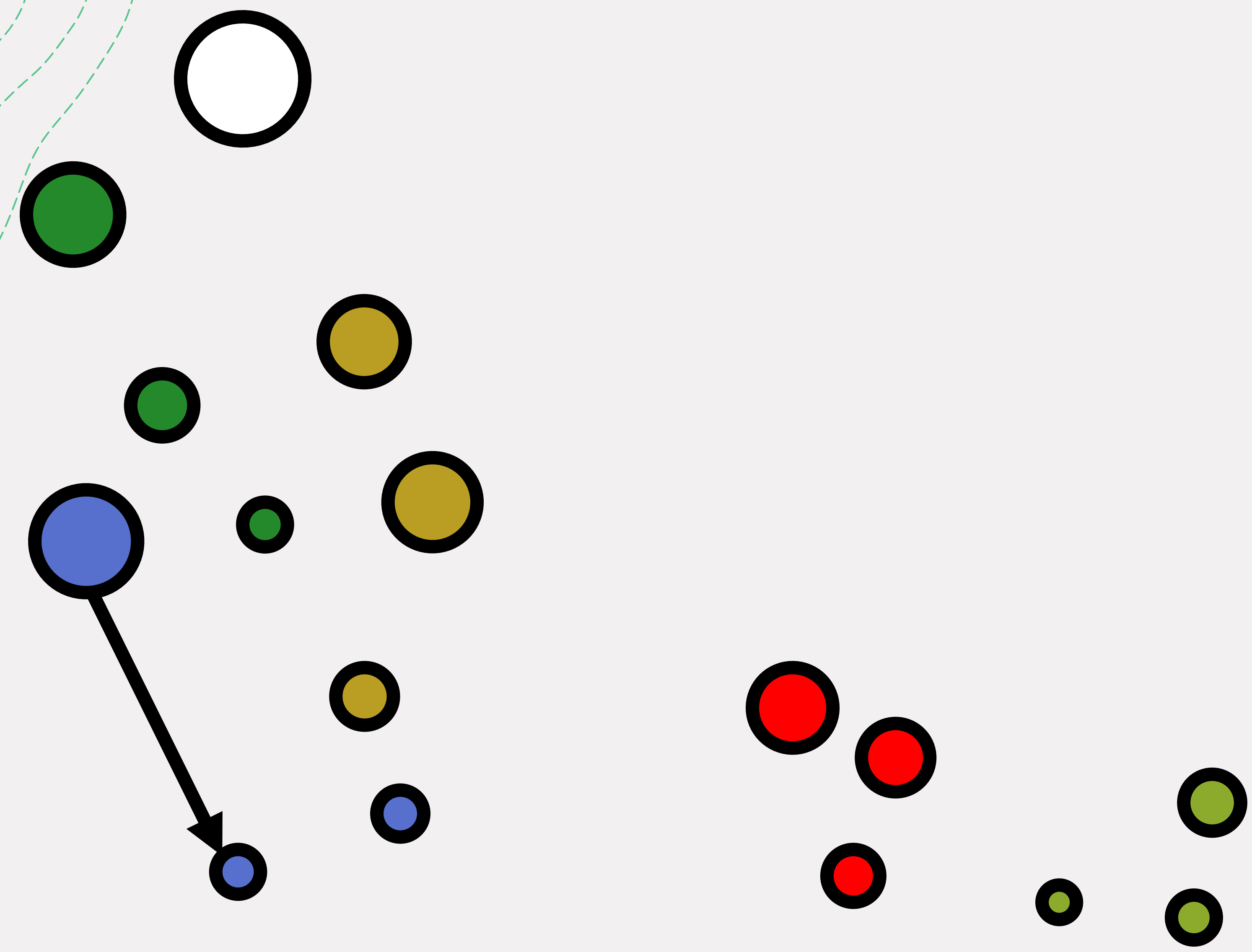
*How (**fast**) do employees share information with coworkers?*



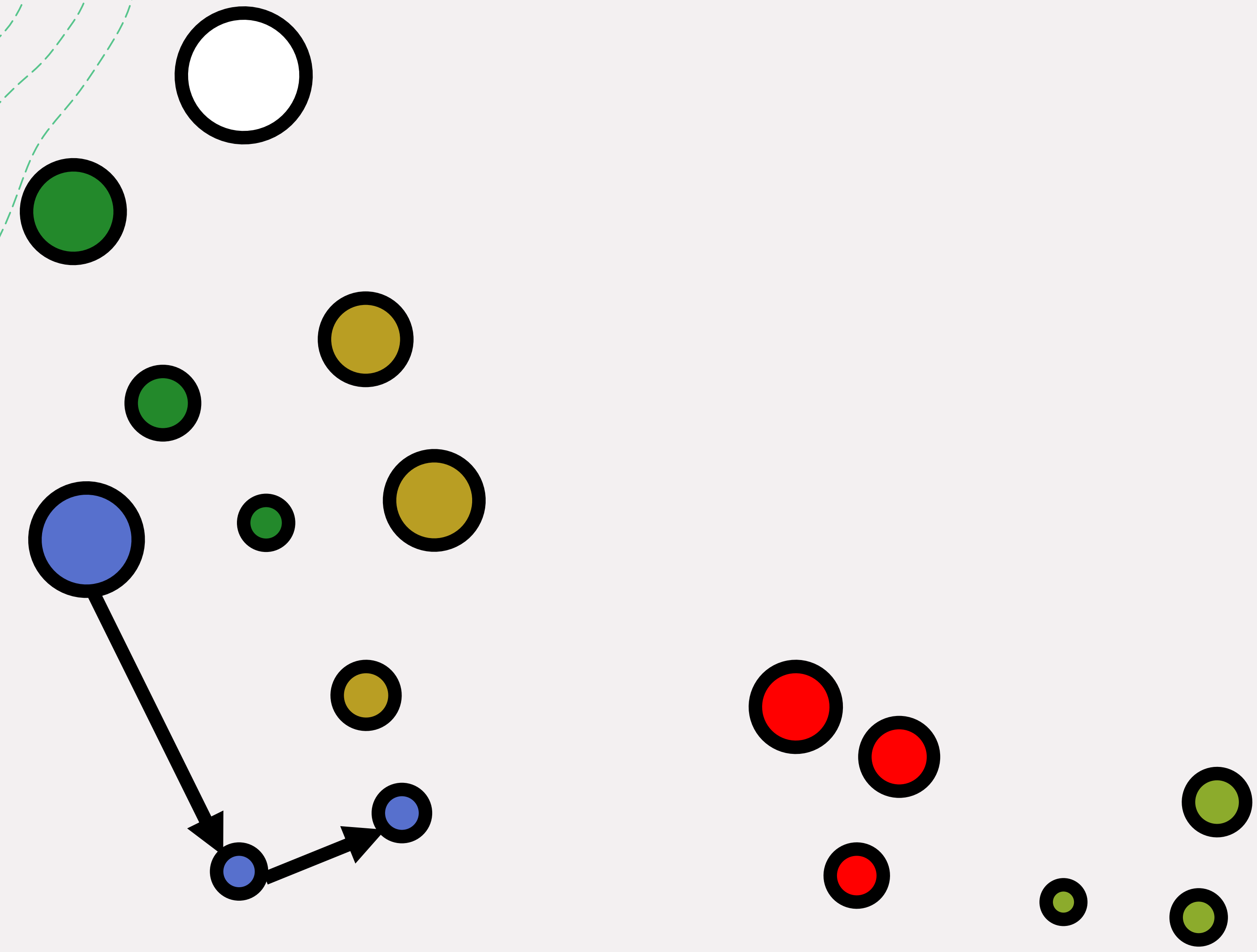
Relational Event History Data

time	sender	receiver

Relational Event History Data



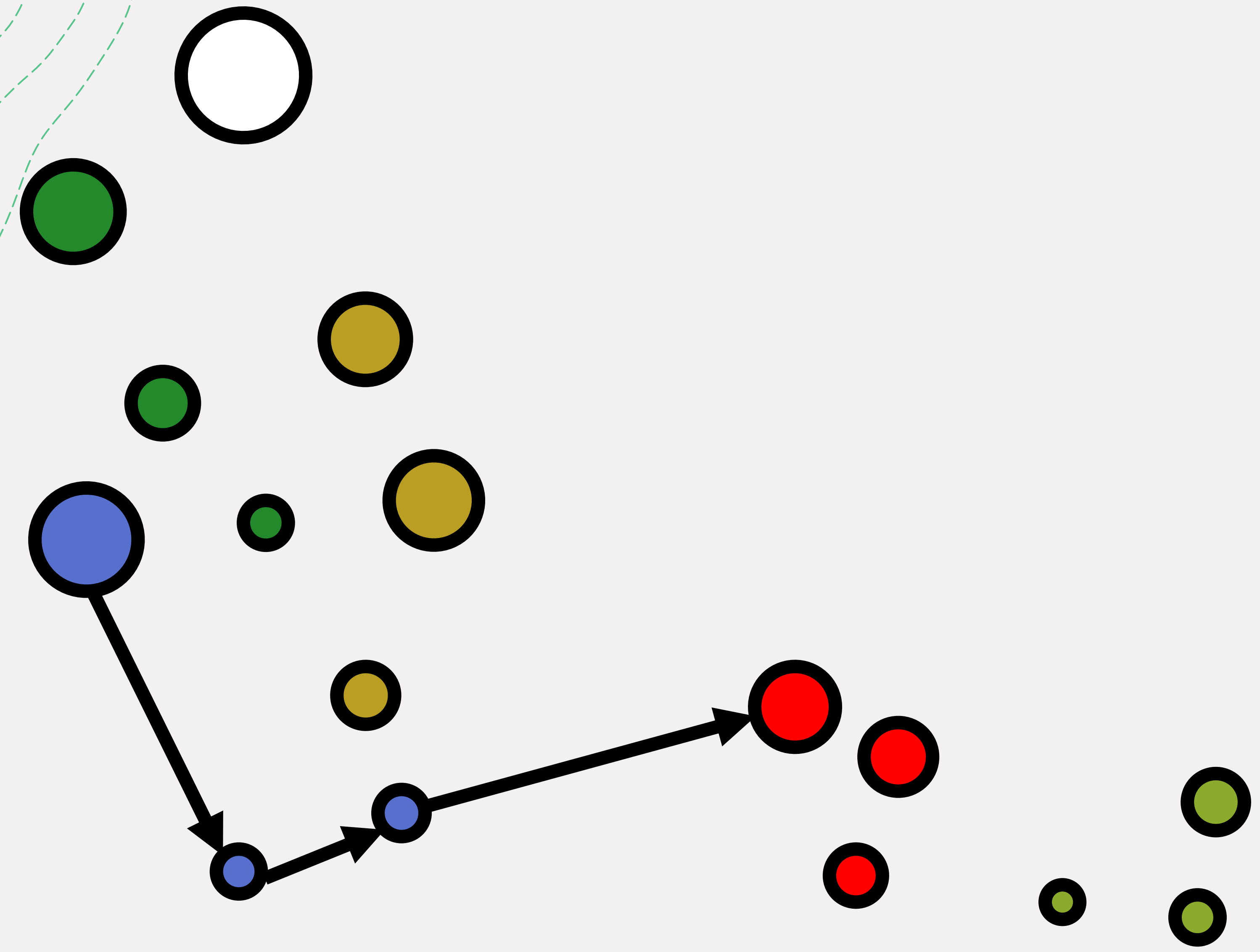
time	sender	receiver
00:03:34		



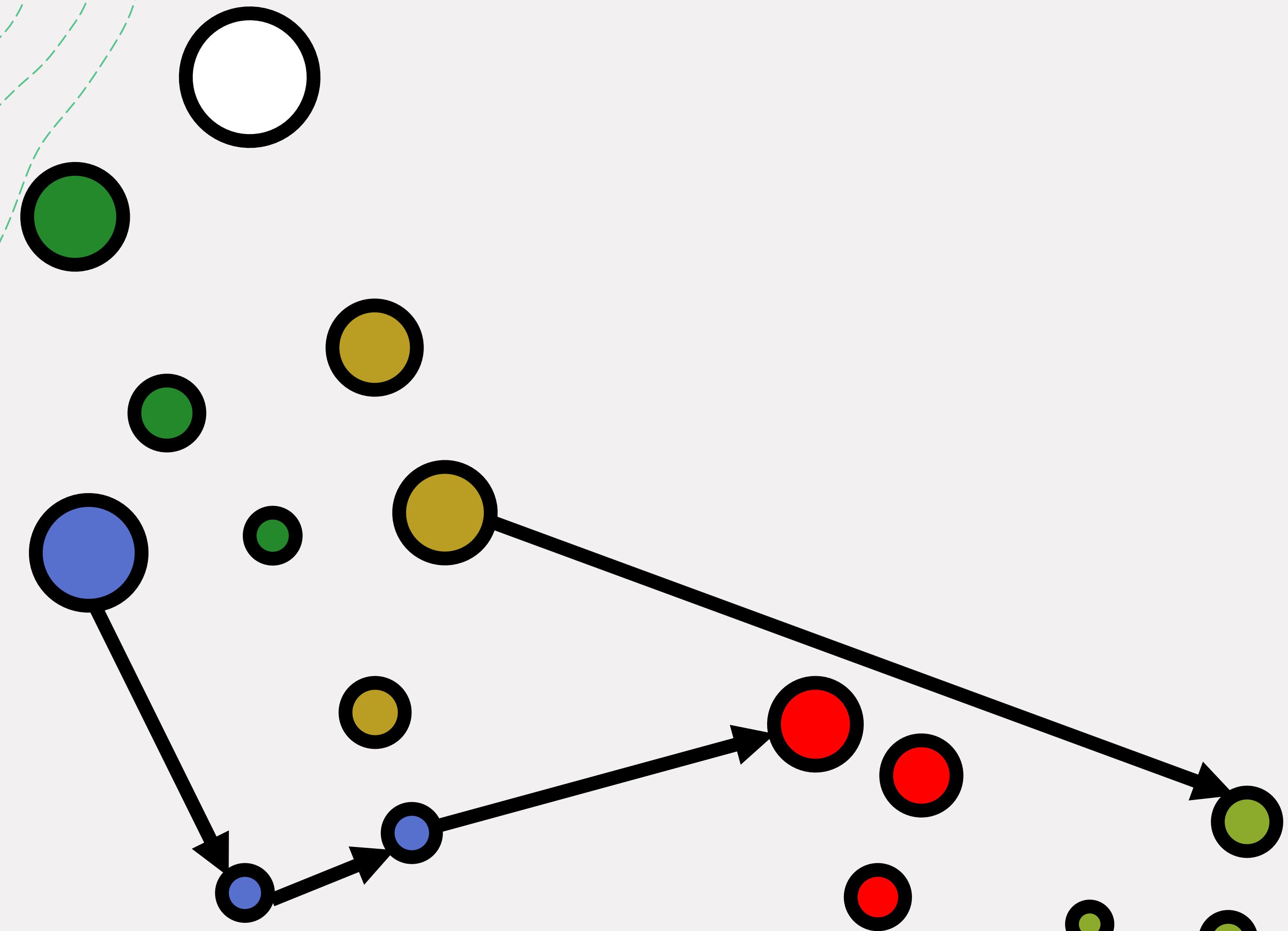
Relational Event History Data

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		



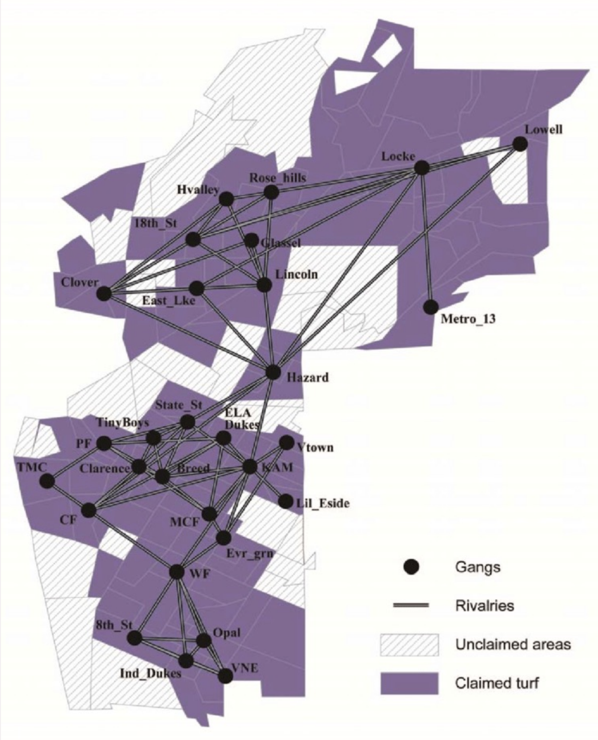
Relational Event History Data

time	sender	receiver
00:03:34		
00:09:12		
00:19:12		
00:25:10		
⋮	⋮	⋮

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
...	...	...

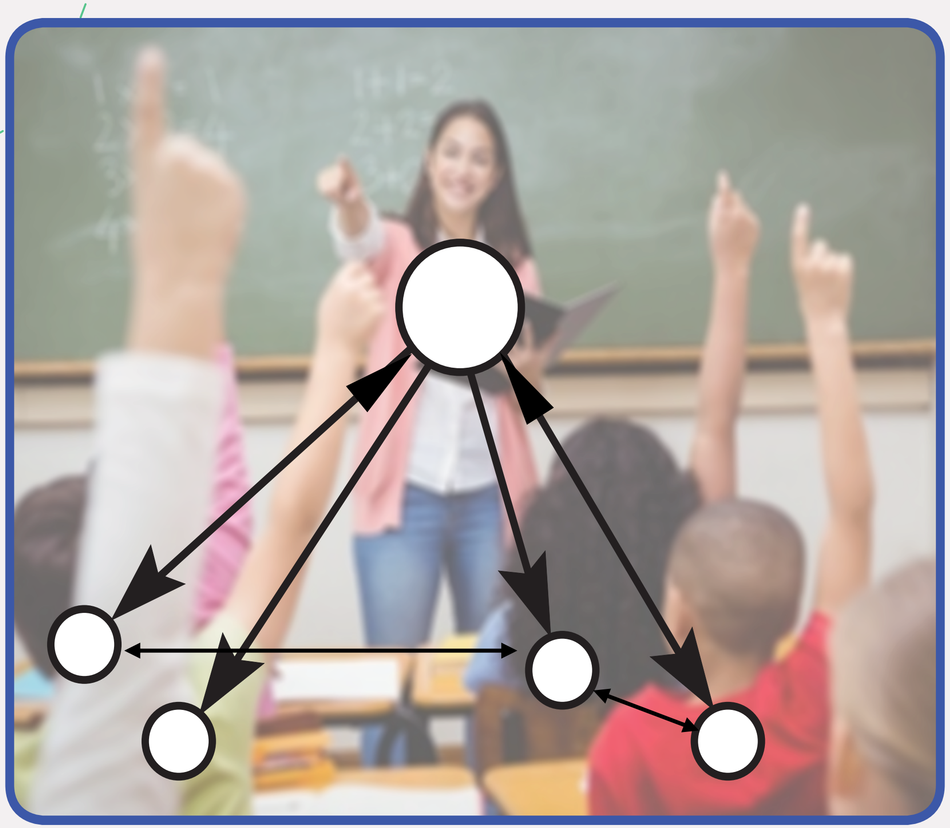


Research questions:

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?

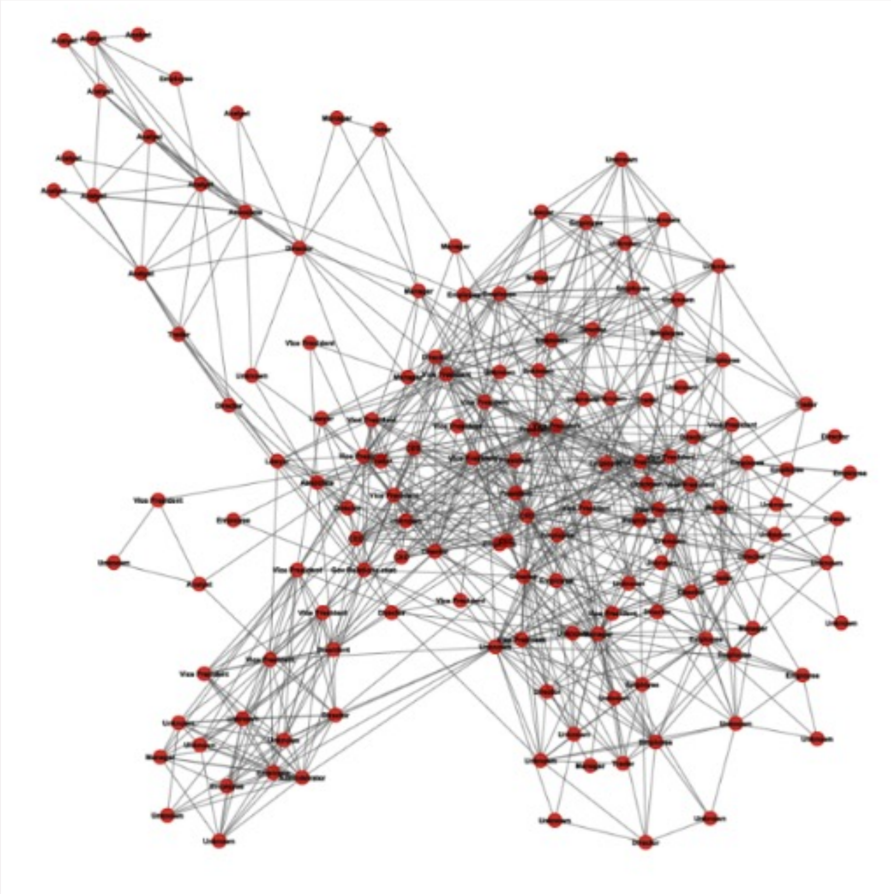
Can we predict ***when*** *defiant behavior will occur?*

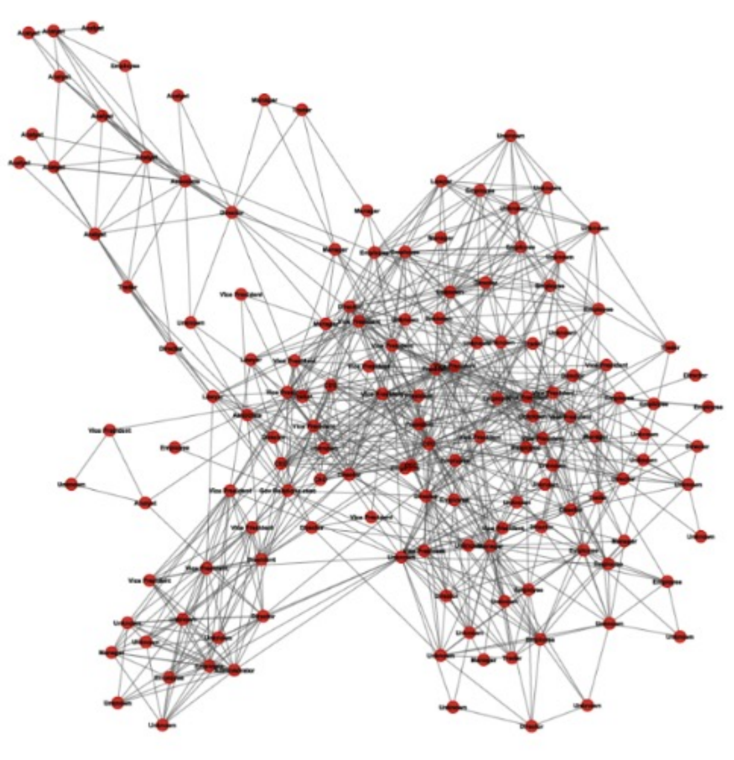
Classroom interactions

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

- **Collegial network**
- Made publicly avaliable 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 we are interested in knowing from these data

+ **Complex interaction behavior** in dynamic social networks.
+ **Who** does **what** and **when**?
+ Predicting **what/when** is the next event (next sender/receiver)?
+ How **interaction dynamics change** over time.
+ How the past **affects** the future.
+ What are the **true drivers of interaction** processes?
+ ...

Remark

+ Note that relational event data is distinct from network panel data in that ties are short lasting and occur in exact moments in time.

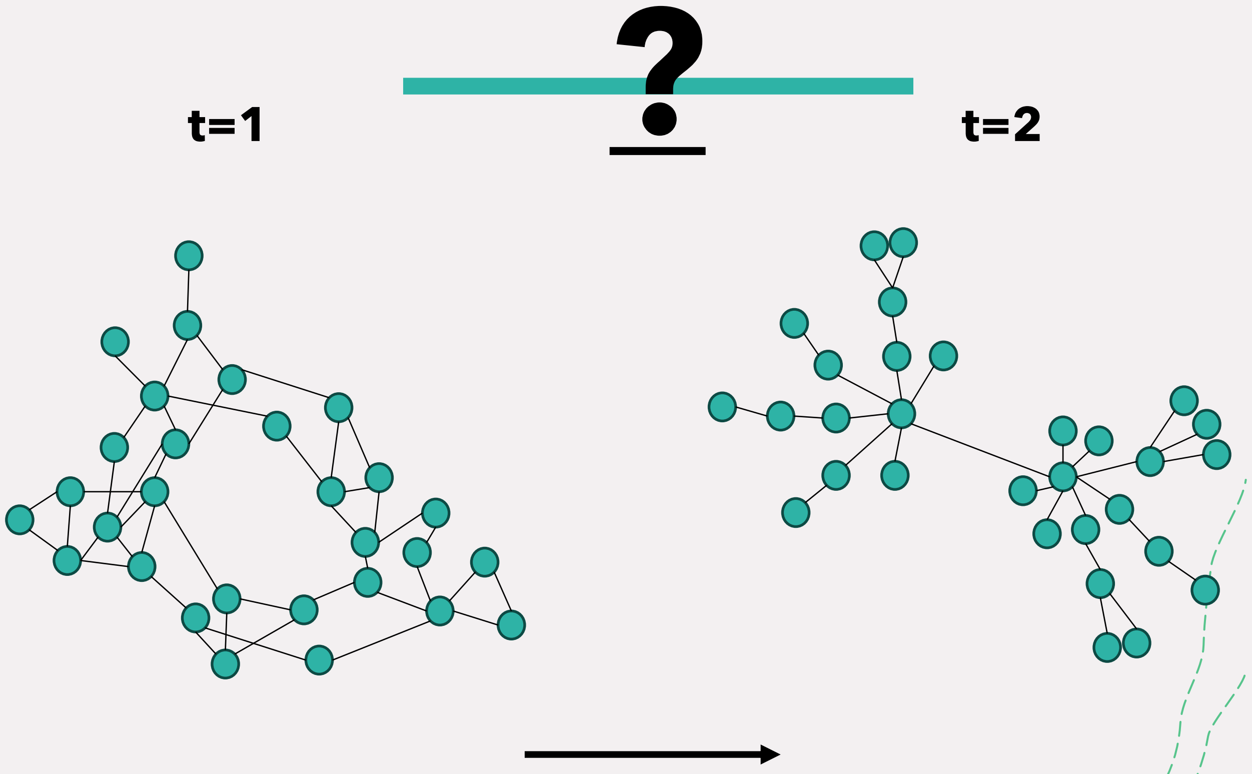
Network Panel Data

Coarse tie measurements

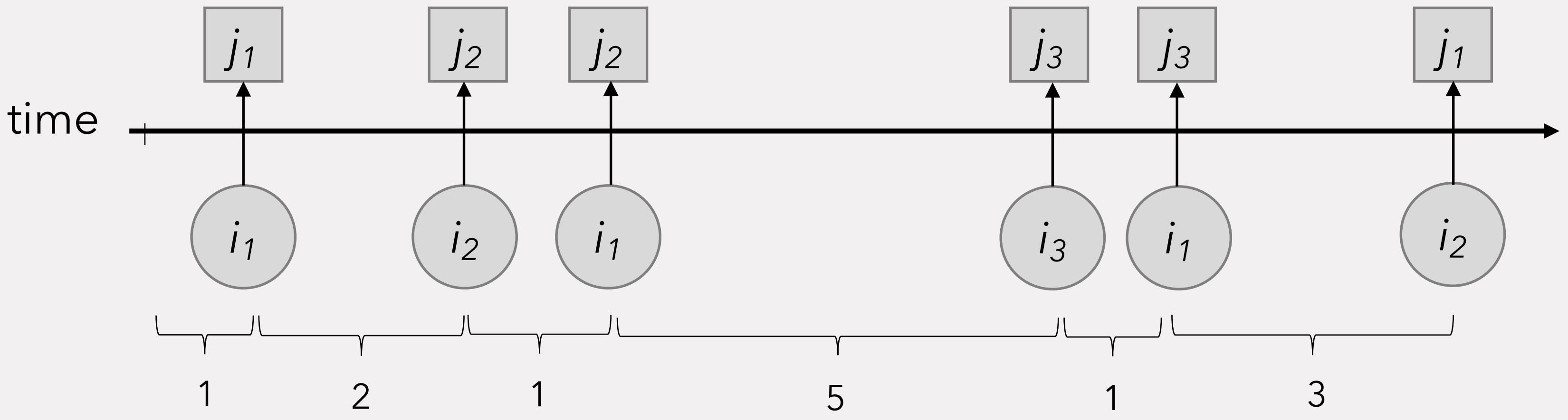
Measuring the same network at different points in time where the gap between measurements is usually large

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 reduces the demand on computer memory.

+ **Relational event model** 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

new **remstats**

remify

.

.

.

Relational Event Models (REMs)

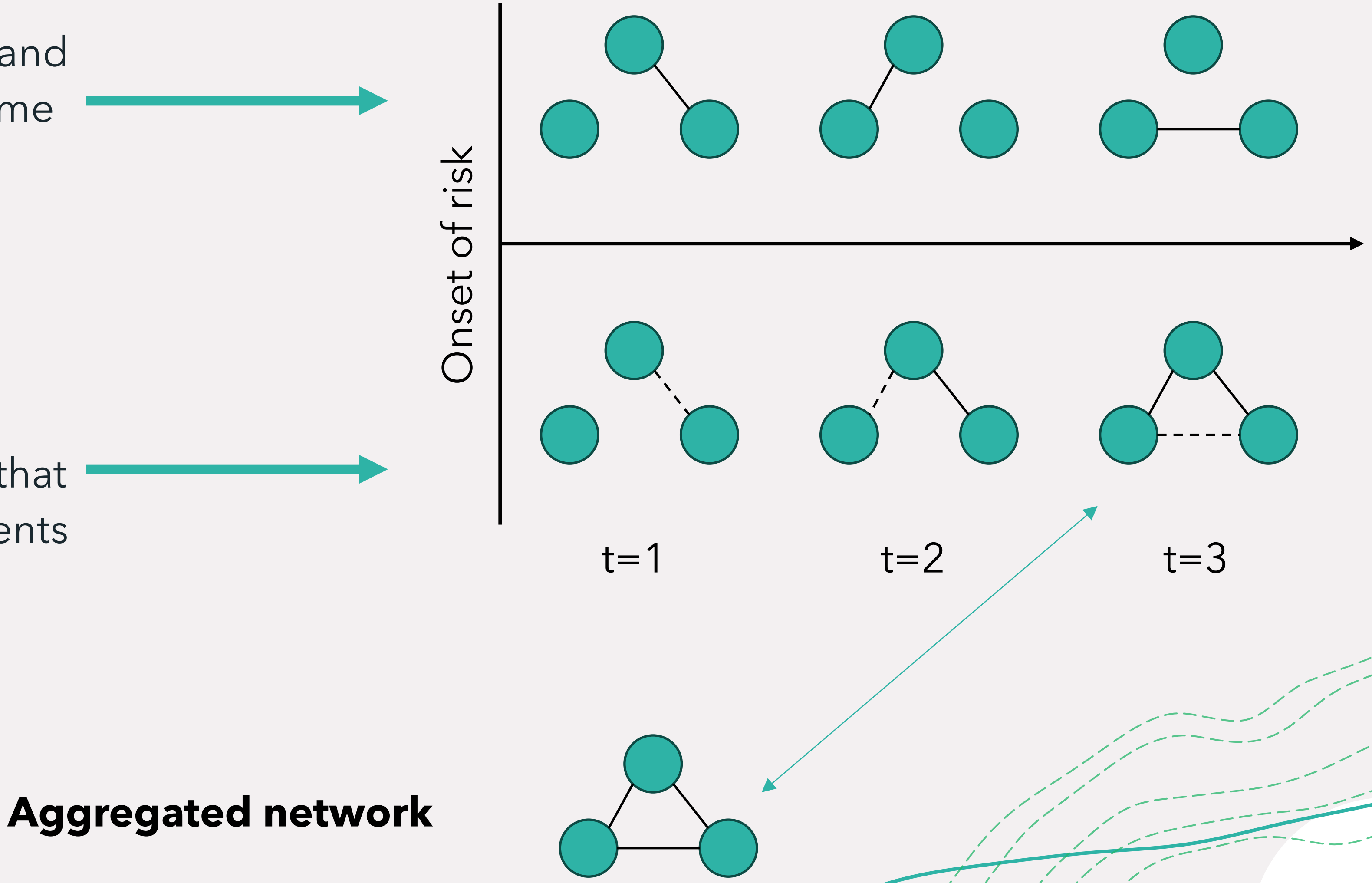
- First introduced by Butts (2008), modelling the time between events (or the frequency of events at each time period).

- Combination of **event history analysis** and **network analysis.**

Relational event modeling

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

+ We will take the *endogenous network structures into account* that accrue from histories of prior events



Relational Event Model (REM)

- In REM we model the ***interaction rate (hazard), λ,*** of relational event activity.
- **Interaction rate** is the propensity of an event to occur.
- Within the REM, interaction rates, λ, are parameterized as a function of network drivers (endogenous and exogenous statistics) that shape the social interactions over time.

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

- The model can handle continuous time or order of events.

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

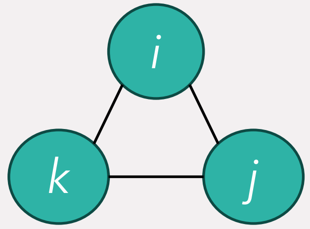
Relational Event Model (REM)

- **Prediction:** ***what*** will happen next, ***when*** will it happen, and ***who*** will be involved; like anticipating defiant behaviour in the classroom or violent interactions between gangs.

- **The dependent variable:** The **rate parameter** λ which is a **loglinear function** of predictors.
- Larger rates correspond to higher propensities.

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

Relational event models (REM):
The technical side: where does this rate parameter come from?



- We assume a **nonhomogeneous Poisson process** for the count of ties at each observation.
- Or we assume **exponential distribution** for modeling the time between events.

Relational Event Model (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***" *that could have occurred.*

λ is our *hazard rate.*

Higher values of λ indicate higher event frequencies at a given time period; lower values indicate lower event frequencies.

Remark

✓ We compute the statistics from the REH data.

✓ Coefficients, θ, represent the increase/decrease in the rate of event occurrence.

✓ λ_0 is the baseline hazard rate (how likely an event is to occur by random chance, conditional on other variables.

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

Interpretation of θ

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

We can interpret θ in three ways:

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

Which statistics, “x”, should be included in the REM?

- **The predictor variables/statistics**:
  - **Actor characteristics** (e.g. tenure of employees x_1, hierarchy, gender,...).
  - **Tie attribute** (e.g. same location, directed, undirected, etc.)
  - **The past** (e.g. volume of past interactions x_2, ...).
  - **External factors** (e.g. epidemic situation x_3, weekdays, ...).

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

Fitting a REM

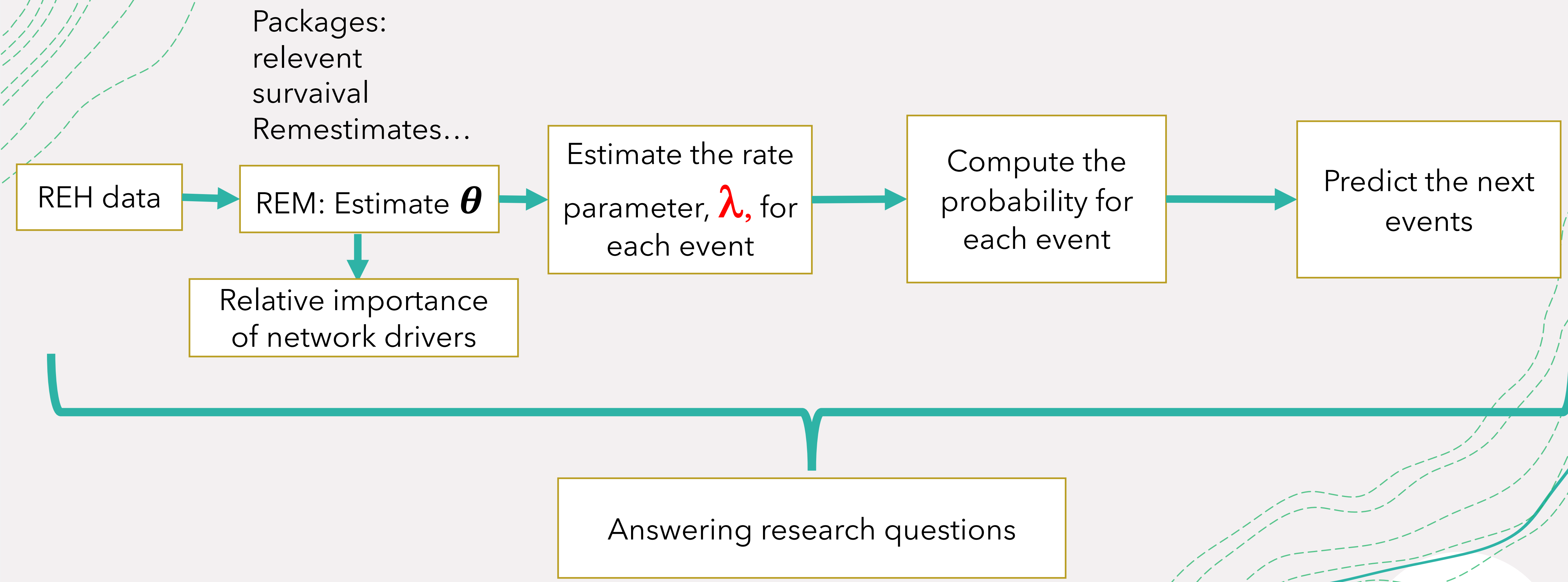
+ Requires an **estimation** of the $\lambda(i,j,t)$. That is, the estimation of θ.

+ **Note**: The rate for each dyad is a **function** of **statistics** such as **inertia**, **reciprocity**, **gender** of actors as well as **parameters** that represent the **sign** and **strength** of the statistics' effects.

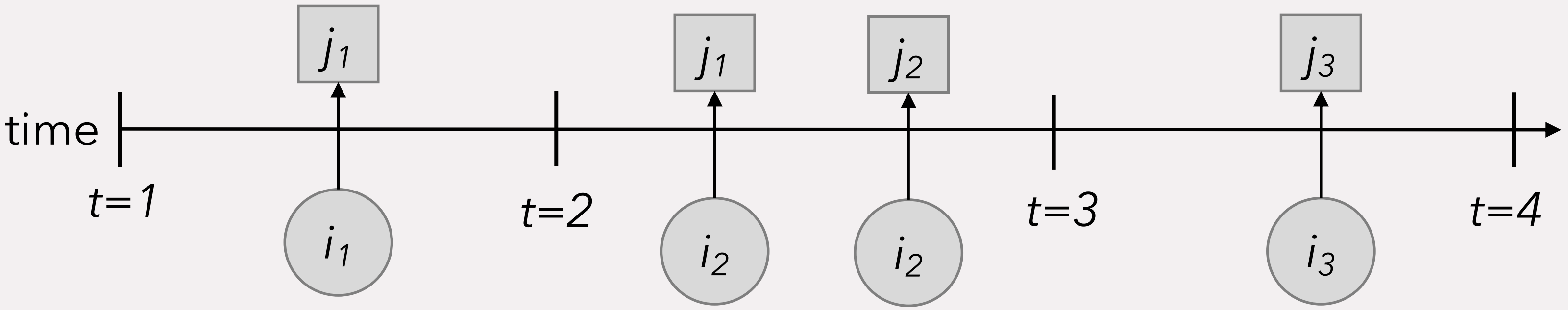
$$\log \lambda(i,j,t) = \lambda_0 + \theta_1 x_1(i,j,t) + \theta_2 x_2(i,j,t) + \theta_3 x_3(i,j,t) + \ldots$$

θ represents the magnitude of a particular effect (Stadtfeld et al., 2018).

Relational Event Models (REMs)

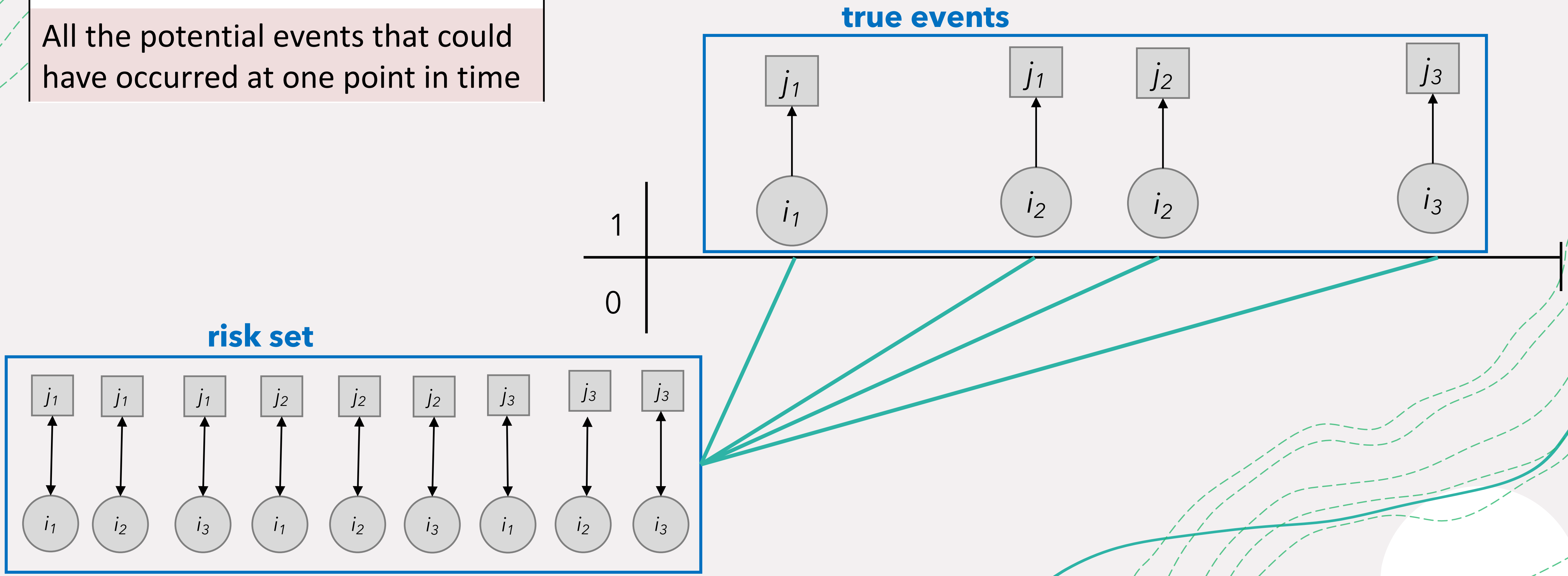


Risk set



risk set

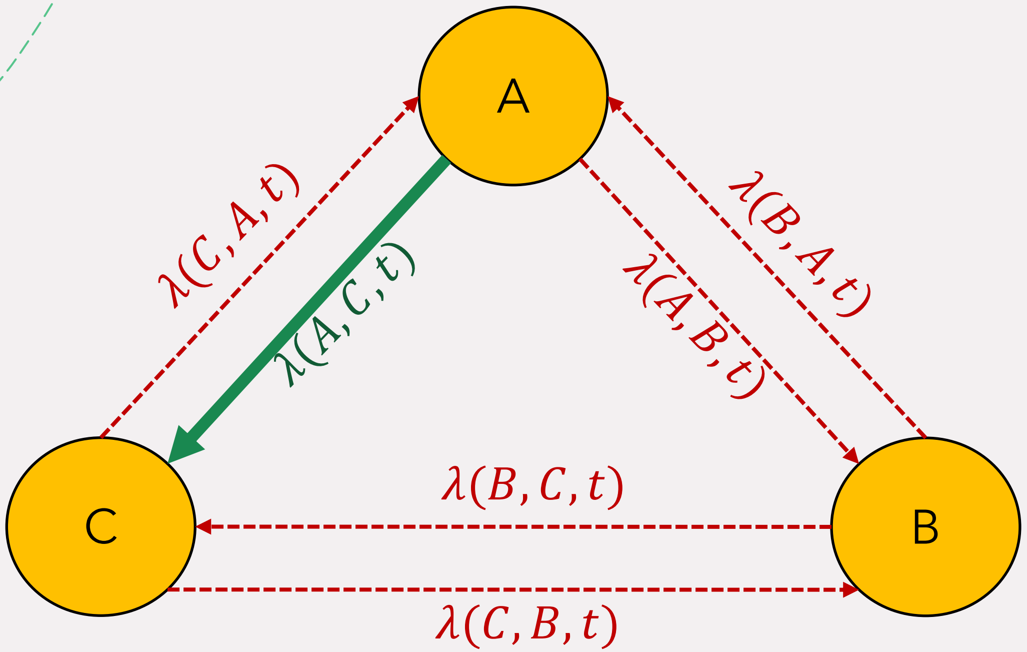
All the potential events that could have occurred at one point in time



Example: Relational Event History data (REH)

Sender (i)	Receiver (j)	Time (t)
A	C	2
C	A	2.4
B	A	3

Probability that a particular sequence of events transpired

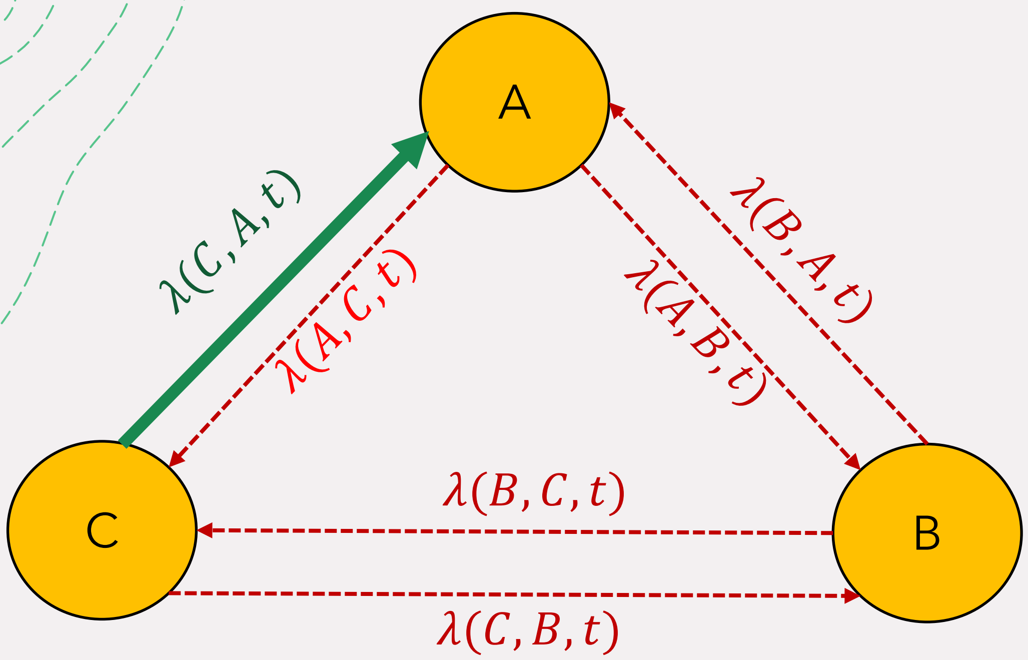


Sender (i)	Receiver (j)	Time (t)
A	**C**	**2**
C	A	2.4
B	A	3

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

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

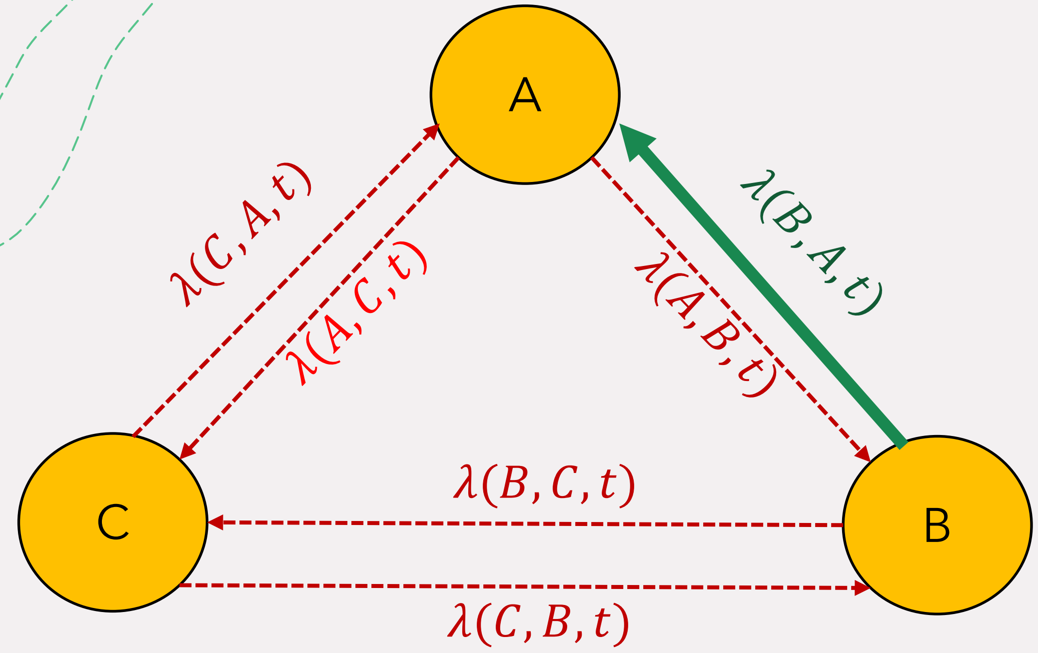
Probability that a particular sequence of events transpired



Sender (i)	Receiver (j)	Time (t)
A	C	2
C	**A**	**2.4**
B	A	3

- Which relational event: $P(C, A) = \frac{\lambda(C,A,t)}{\Sigma\lambda(s',r',t)}$
- $\Sigma\lambda(s',r',t)$ - all rates in a risk set at a specific time point.

Probability that a particular sequence of events transpired

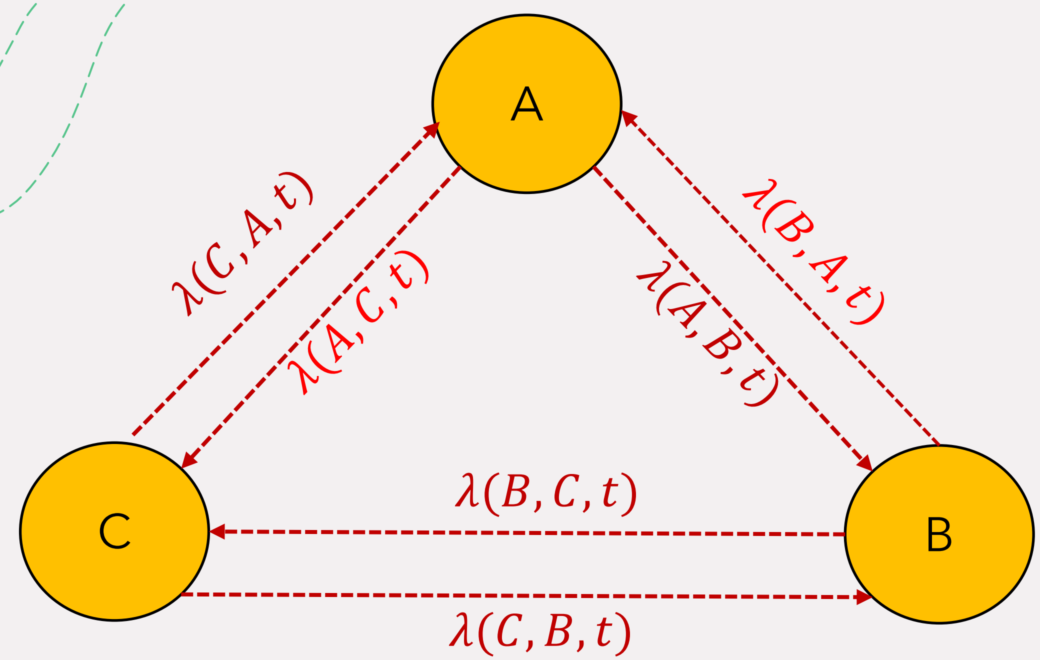


Sender (i)	Receiver (j)	Time (t)
A	C	2
C	A	2.4
B	**A**	**3**

- Which relational event: $P(B, A) = \dfrac{\lambda(B,A,\mathrm{t})}{\Sigma\,\lambda(s',r',\mathrm{t})}$
- $\Sigma\lambda(s', r', t)$ - all rates in a risk set at a specific time point.

Update all statistics and compute the probability

Prediction: Which one has the highest probability?



Sender (i)	Receiver (j)	Time (t)
A	C	2
C	A	2.4
B	**A**	**3**
+ **?**	**?**	**?**

+ Which relational event: $P(s, r) = \frac{\lambda(s,r,t)}{\Sigma \lambda(s',r',t)}$
+ $\Sigma\lambda(s',r',t)$ - all rates in a risk set at a specific time point.

R packages for implementing REM

For estimating the parameters:

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

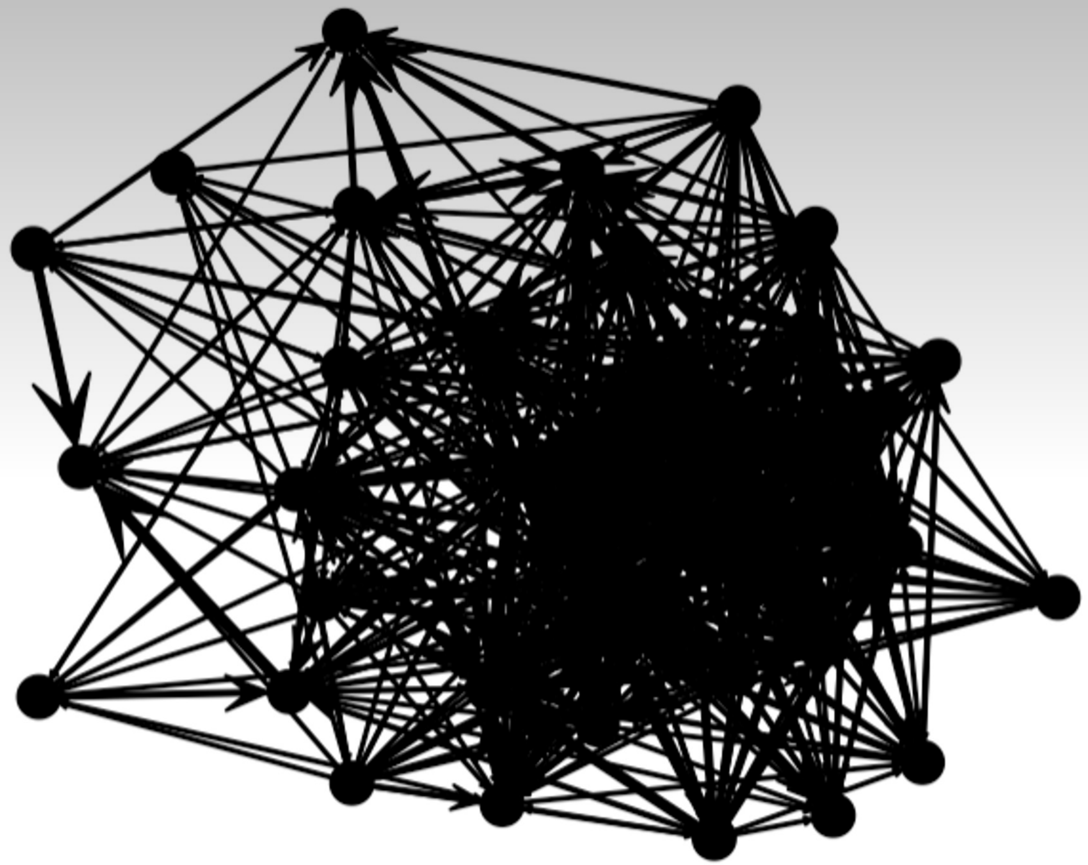
Estimation of the parameters

+ For computing statistics
+ remstats, remify, remulate…

Computing statistics and fitting the model

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

Twitter



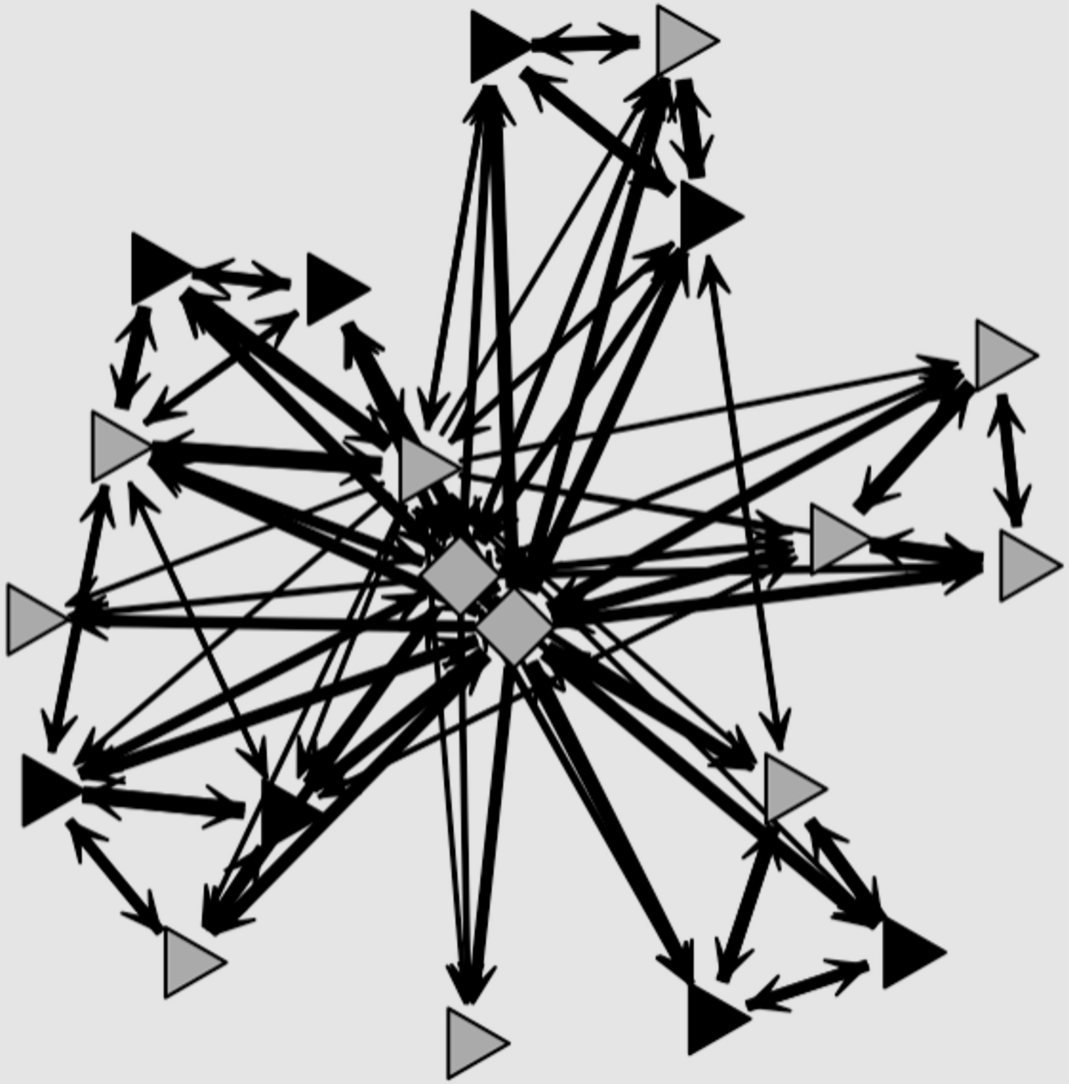
```
Twitter1 <-  rem.dyad(Twitter_data_rem3,n=39, effects = c("PSAB-BA", "PSAB-BY"), ordinal =
FALSE, hessian = TRUE)

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)

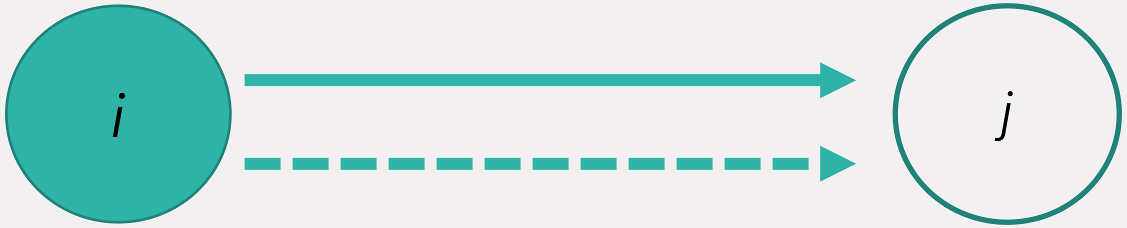
	Estimate	Std.Err	Z value	Pr(>|z|)
RRecSnd	2.429210	0.155367	15.6353	< 2.2e-16 ***
RSndSnd	-0.986720	0.144668	-6.8206	9.068e-12 ***
CovSnd.1	-5.003468	0.090610	-55.2197	< 2.2e-16 ***
CovRec.1	-0.722667	0.141950	-5.0910	3.562e-07 ***
PSAB-BA	4.622159	0.137602	33.5908	< 2.2e-16 ***
PSAB-BY	1.677639	0.164930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

Predictor variables/statistics: $(X_1, X_2, X_3, \ldots)$

+ Inertia…
+ Reciprocity
+ Transitivity
+ In(out) degree sender/receiver
+ …
+ Age
+ Hierarchy
+ 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*".



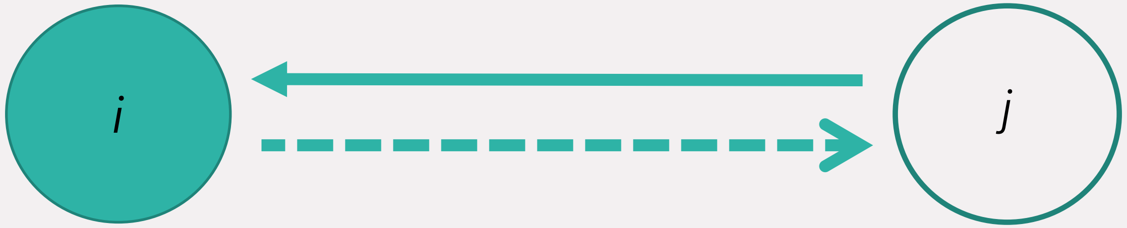
Example – Inertia

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

$$\log \lambda(i,j,t) = \lambda_0 + \boldsymbol{\beta}_{\boldsymbol{INERTIA}} * \mathrm{x}_{\mathbf{Inertia}}(i,j,t) + \theta_2\, \mathrm{x}_2(i,j,t) + \theta_3\, \mathrm{x}_3(i,j,t) + \ldots$$

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*".



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

Example – Reciprocity

+ The teacher initiates interaction with those students from whom she received a question in the past, e.g. creating a feedback loop that reinforces ongoing communication.

+ When this is the case, the effect of the reciprocity statistic should be large.

+ The results would show a tendency for reciprocating (i.e., connecting through a chain of questions and answers).

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

Example of Kitts et al. (2017)

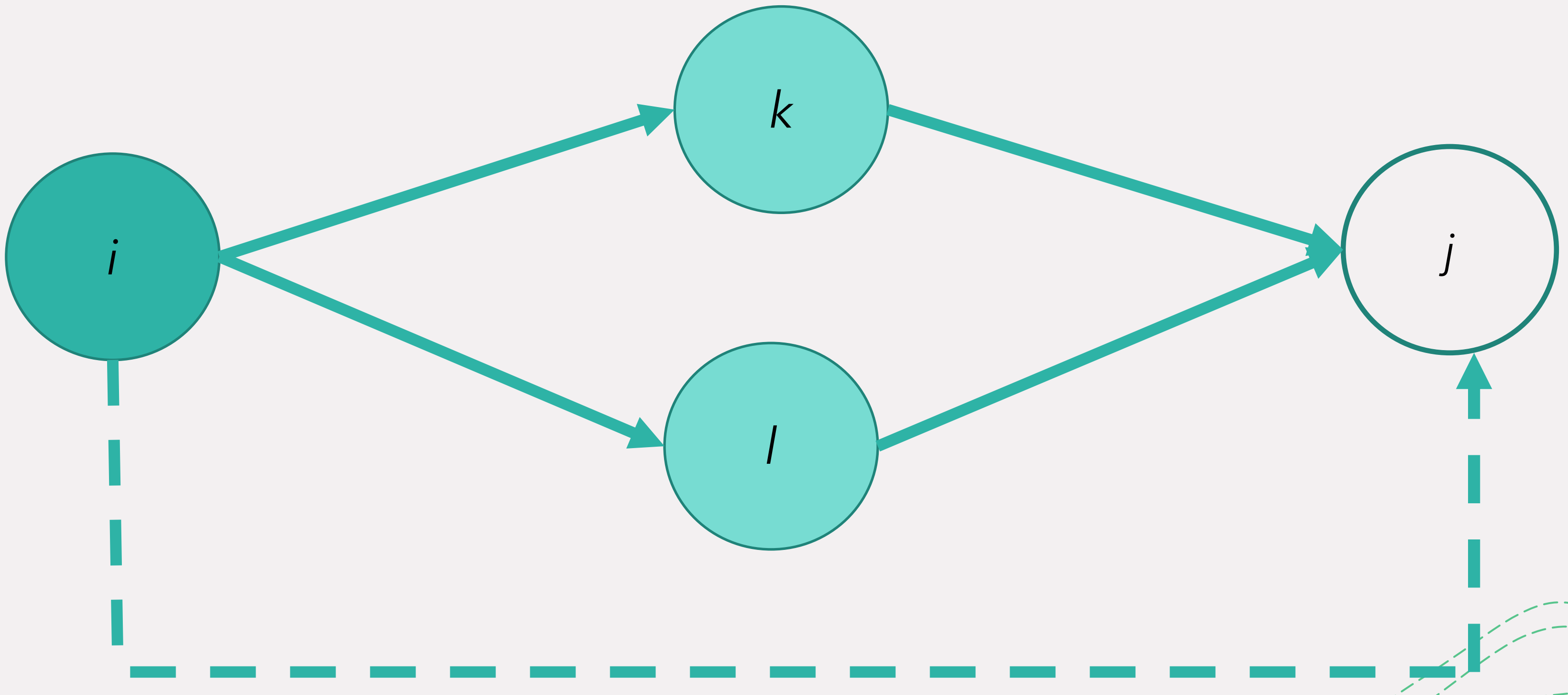
+ **Research question:** Do hospitals engage in the social norm of reciprocity when exchanging patients, instead of sending them to the hospital that can offer the best service for the patient?

+ 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, service quality, or hospital specialization.

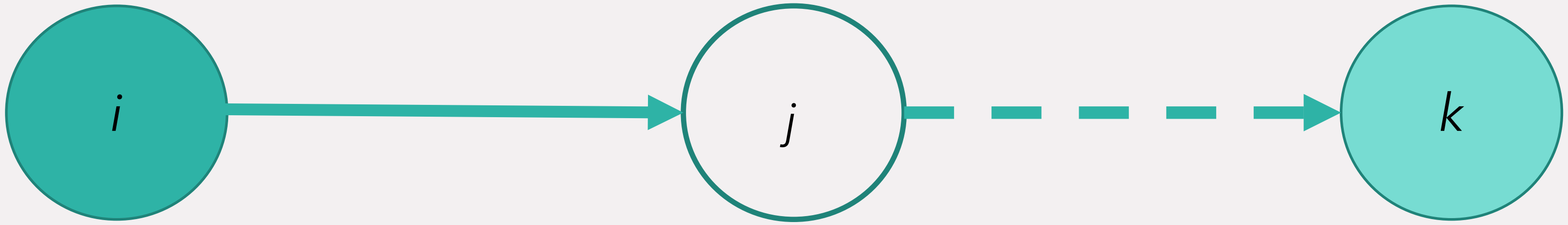
Transitivity

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



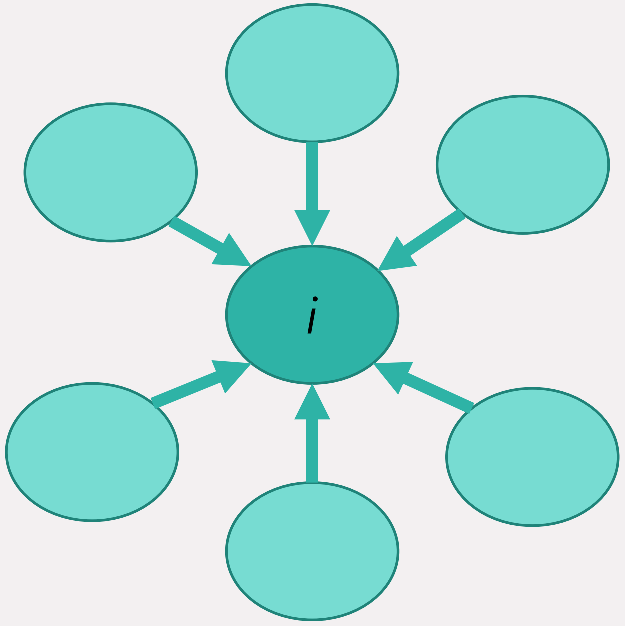
Participation shift AB-BY ("turn receiving")

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



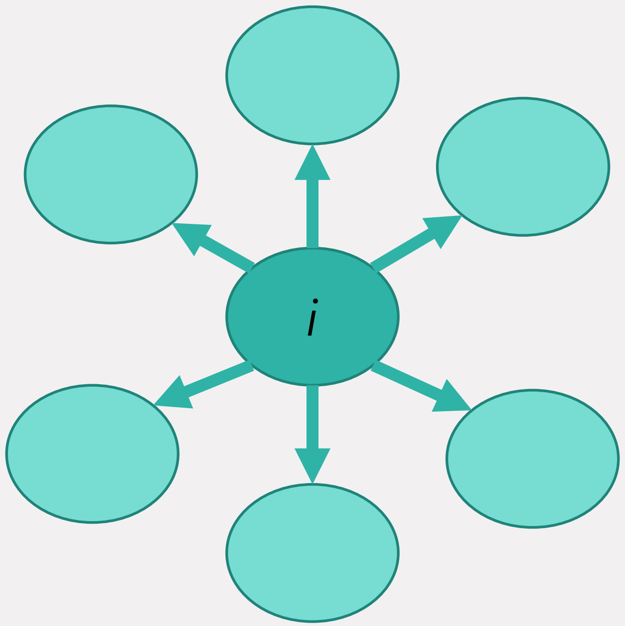
In-degree

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



Out-degree

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 importance of *network driver effects* θ.
- **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?

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

- The **choice** of a network inference model depends on **how the time is recorded**.

Four main network inference models:

- **Exponential Random Graph Models**
- Temporal Exponential Random Graph Models and
- Stochastic Actor Oriented Models (SAOMs)
- **Relational Event Models**

- Think about the application of this concept (e.g. in your field) for a few minutes and discuss that in pairs.

- Which data are there? Describe that: what/who is the sender/receiver?
- What is the research question?

Exponential Random Graph Model (ERGM)

R package: ergm

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

- Goal: "to **describe parsimoniously the <u>local selection forces</u> that shape the global structure of a network**" (Hunter et al. 2008). (The processes that influence link creation).

- 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**.

- Cross sectional model for network structure. (Single measurement of the network).

ERGM

- Let us say **G** is a graph.

- Network statistics: ***Z*(*G*)**
- Network statistics such as the **number of edges, reciprocated edges, etc.** in *G*.

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

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

c is a normalizing constant.

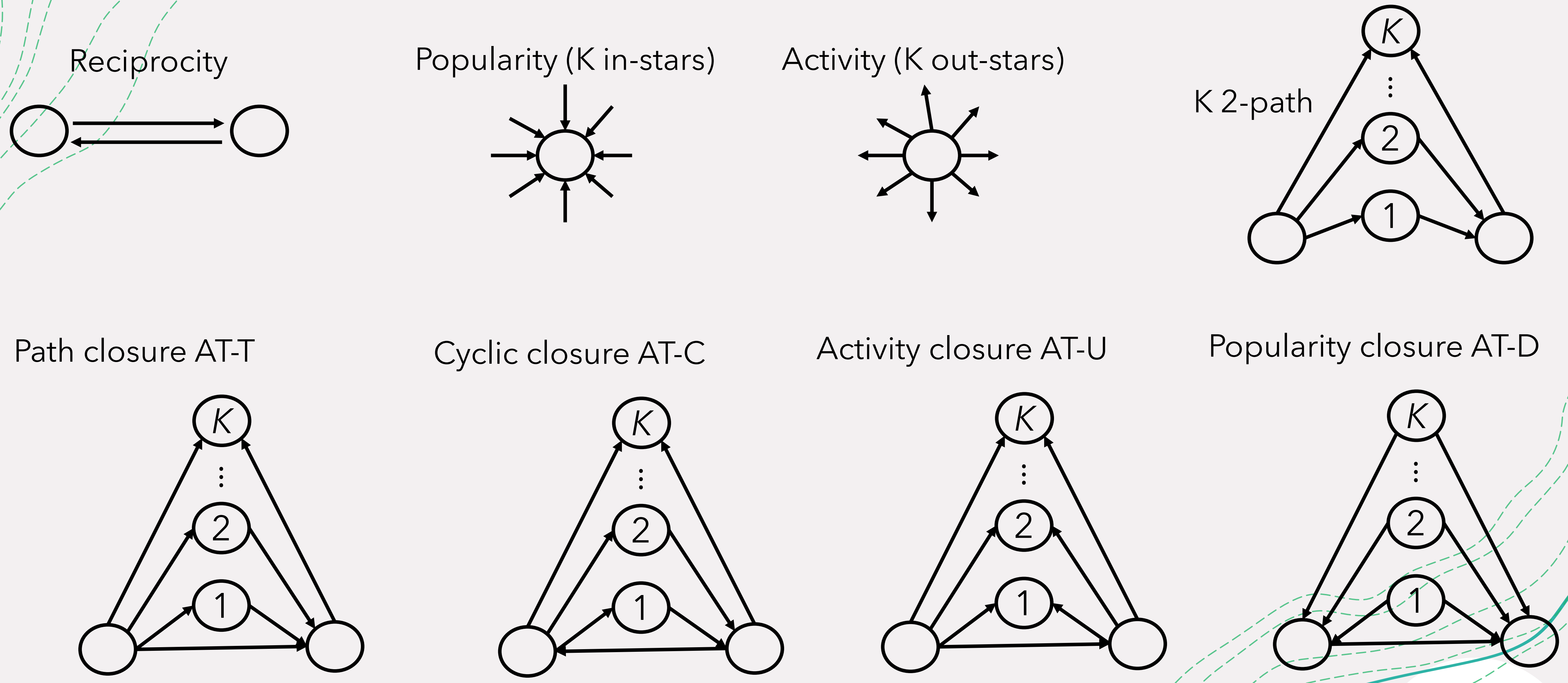
This is the probability of a given network.

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

Remark:

- **Random Sample assumption:** the observed network is a random sample from a larger population of possible networks.
- Ties between nodes in real social networks are not independent.
- This non-independence violates the most basic assumption of regression!
- Through simulation, ERGMs allow dyadic and higher-order dependencies to be modelled.

Different considered network statistics. More detailed explanations can be found in Lusher et al. (2013).



In a nutshell:

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

- Choose a set of configurations of theoretical interest.

↓

- Estimate parameters by applying ERGM.

↓

- Make inferences about the configurations – network patterns – in the data.

↓

- Make inferences about the type of social processes that are important in creating and sustaining the network.

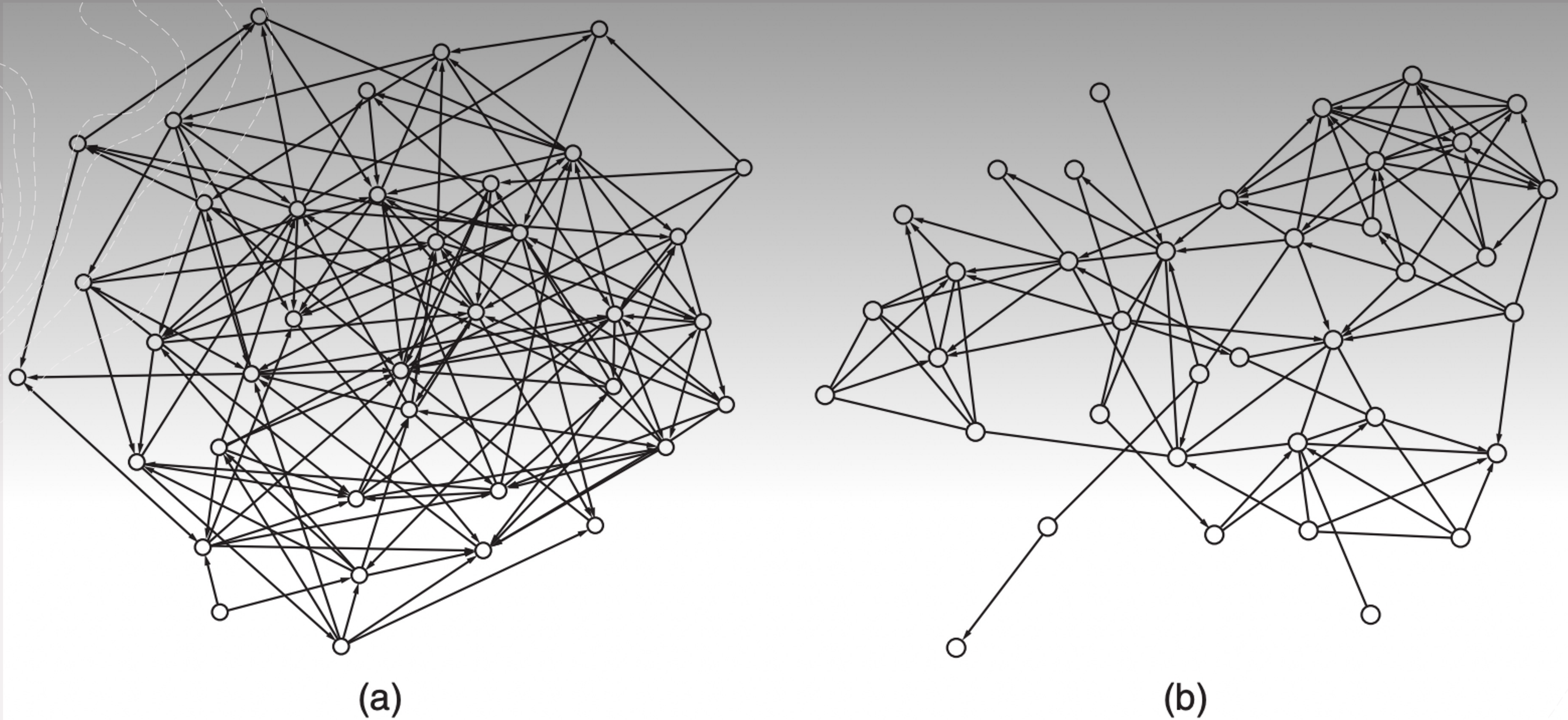


Figure 4.1. (a) Simple random network and (b) empirical communication network.

Lusher et al. (2013)

Selected network statistics for networks in Figure 4.1

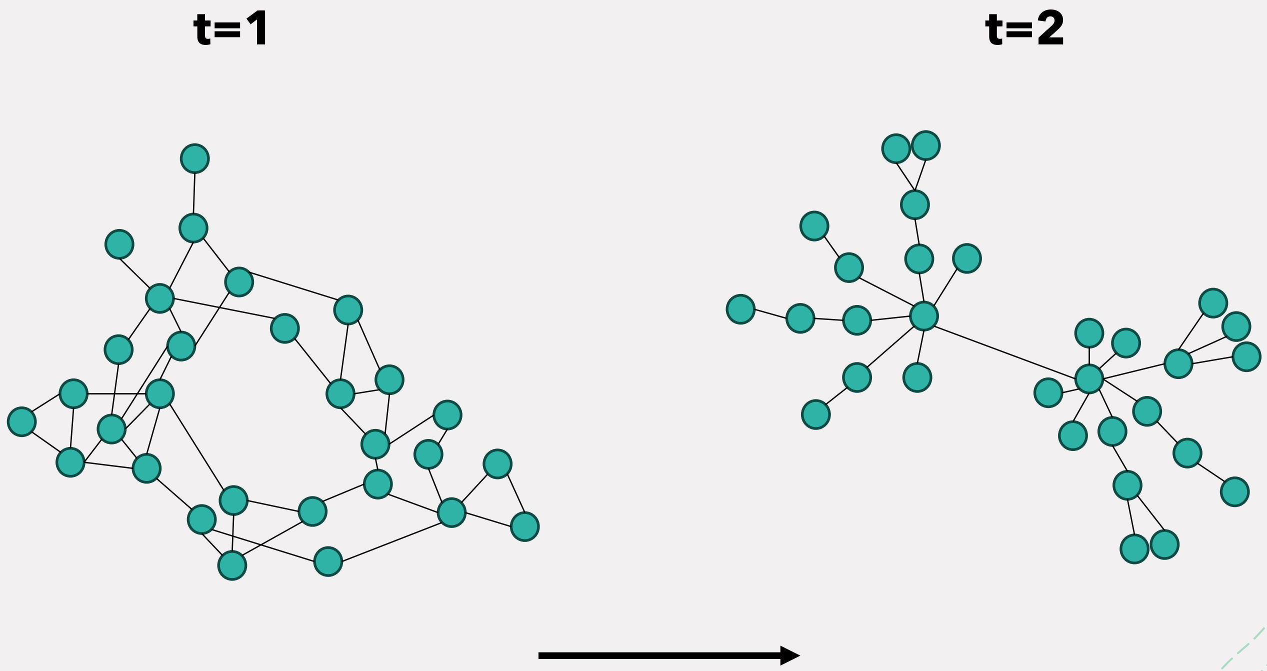
	Random network	Communication network
Actors	38	38
Arcs	146	146
Reciprocated arcs	6	44
Transitive triads	53	212
In-2-stars	292	313
Out-2-stars	254	283

Example 1

- **The presence of reciprocity** : There is a process that generates a significant number of **reciprocated structures** 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

+ Network Panels
+ Only the changes between Network panels



Stochastic Actor Oriented Models (SAOMs)

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

R package: RSiena

SAOMs

- Models for network **dynamics** and network **panel data.**

➢ **Network dynamic** through **simulations**.

➢ **Network panel** data are common for representing relations like **friendship**, **advice**, **collaboration**, exchange which can be regarded as *states* rather than *events.*

Application of SAOMs

a wide variety of domains:

- Study of selection patterns in school classrooms ,
- The evolution of communication networks in high-risk social-ecological systems,
- The role of teen drinking behaviour in friendship selection,
- ...

SAOMs

- 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.

- **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.

SAOM as a model of the network evolution

- All network changes are decomposed into very small steps, so-called **ministeps**, in which one actor creates or terminates one outgoing tie.

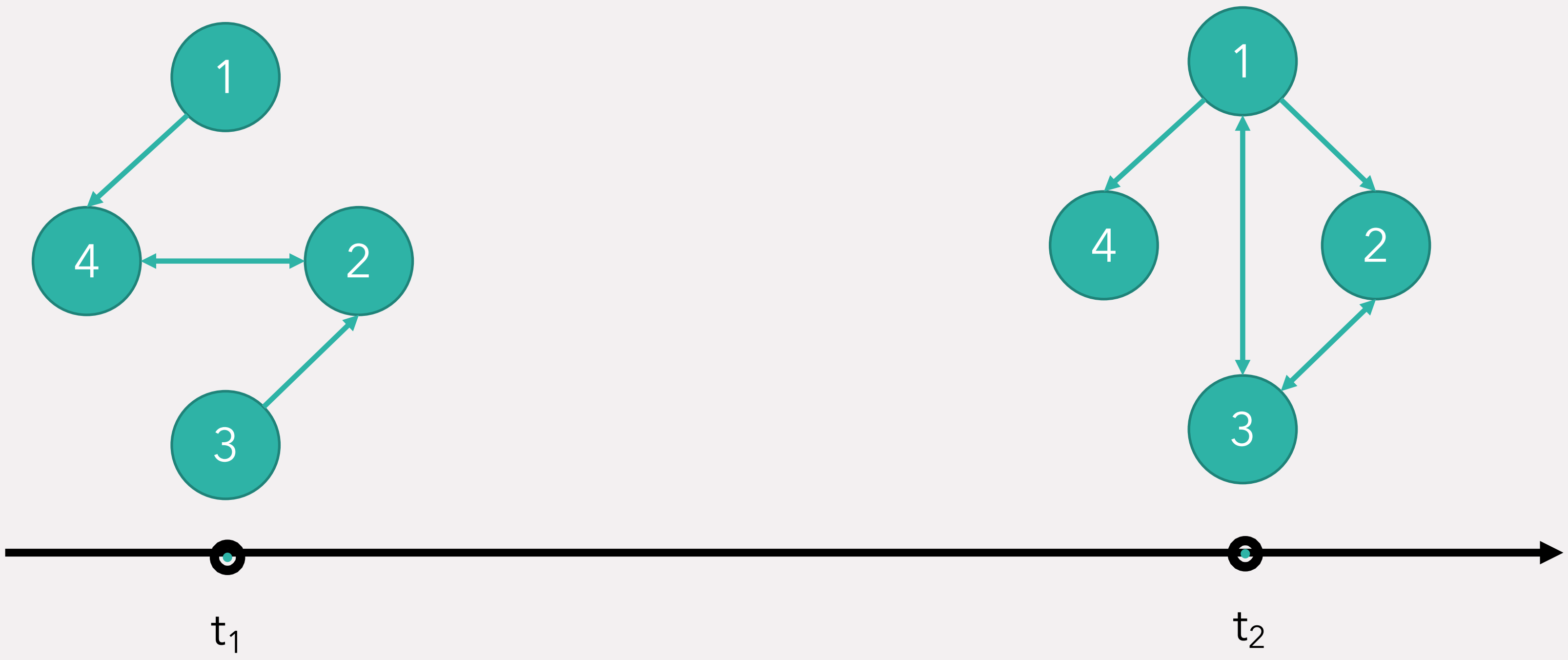
- These **ministeps** are **probabilistic** and made sequentially.

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

- This simulation model implements the statistical model for the **network dynamics**.

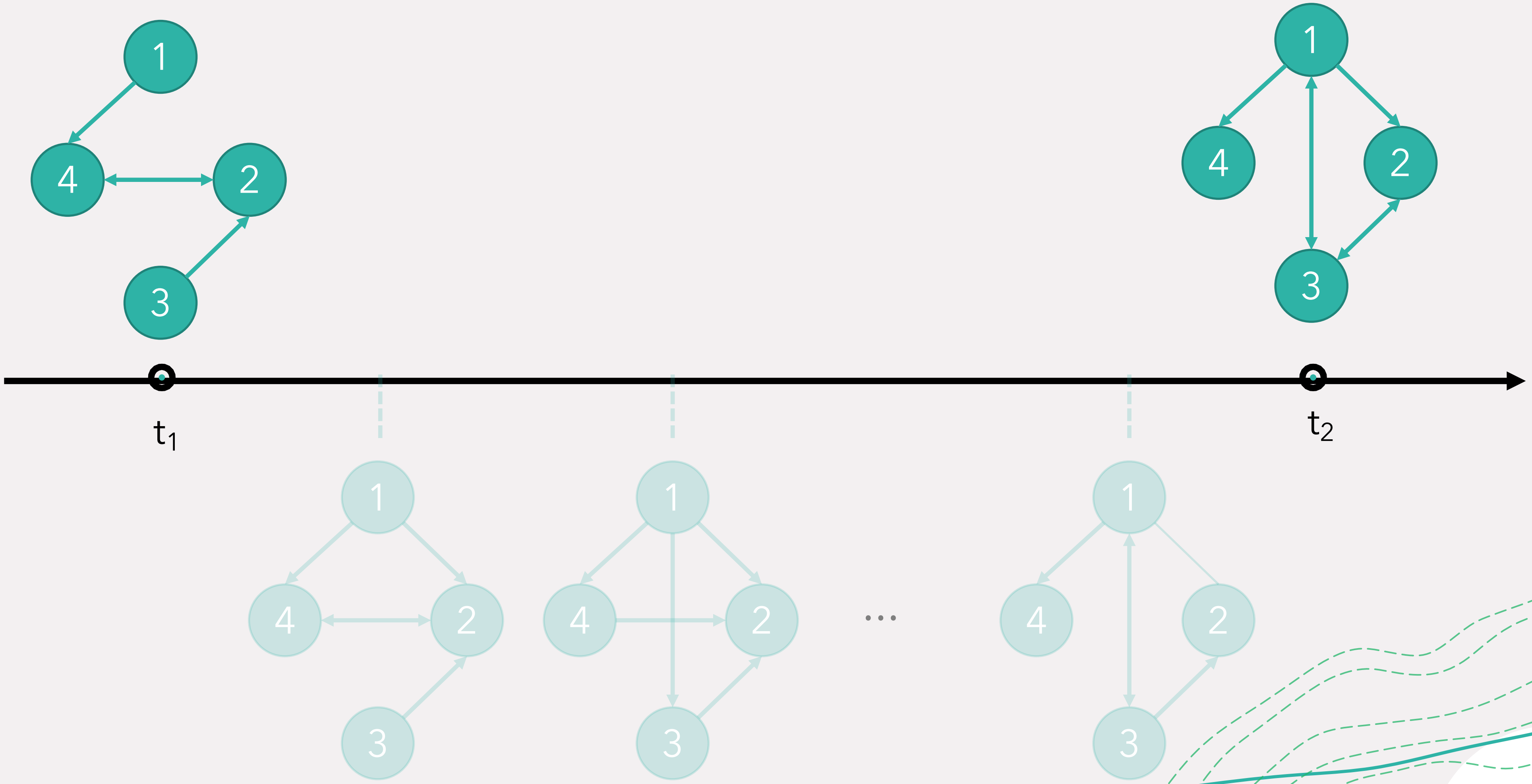
SAOMs

Model assumptions: consequences



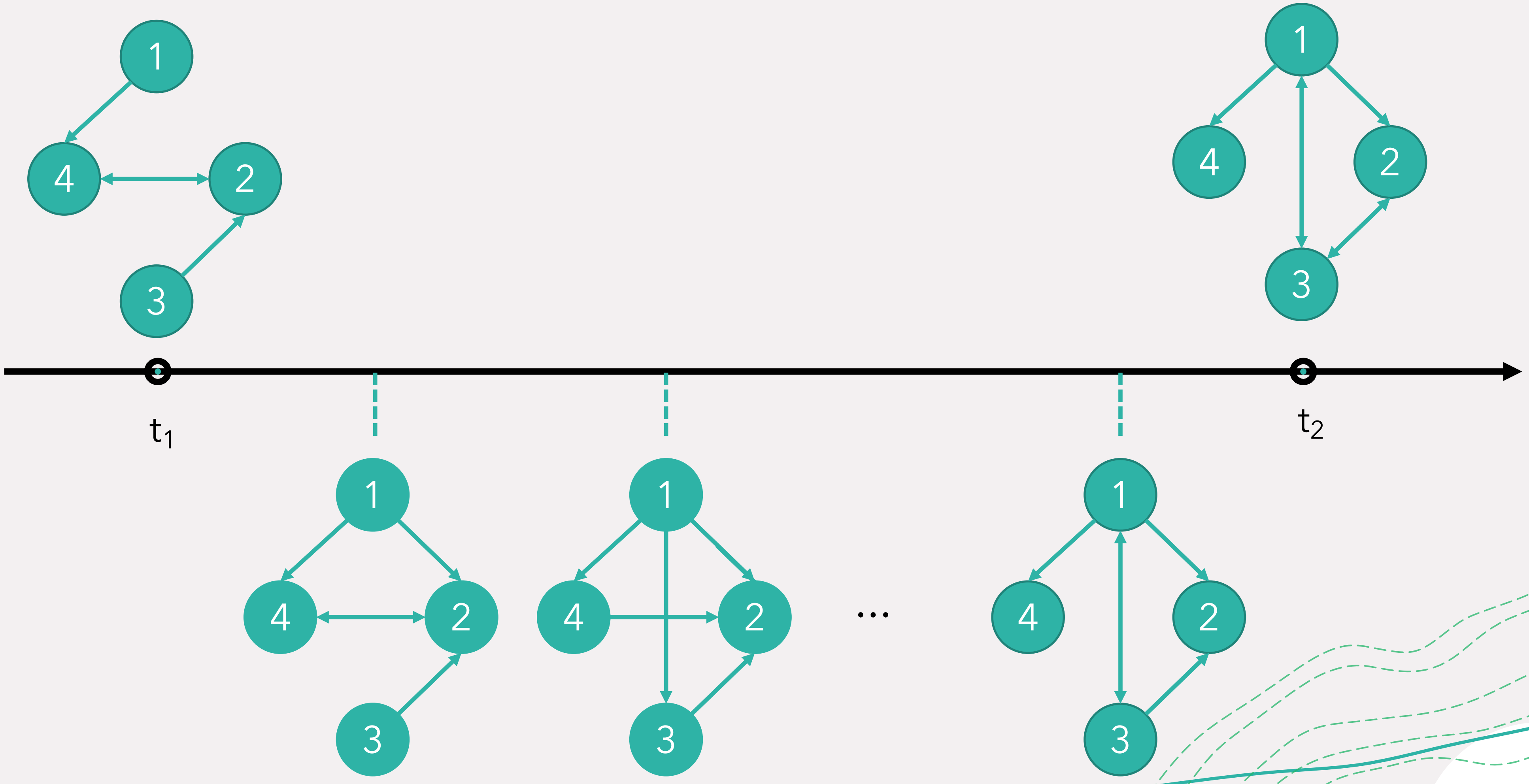
SAOMs

Model assumptions: illustration



SAOMs

Model assumptions: illustration



Modeling tie changes

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?

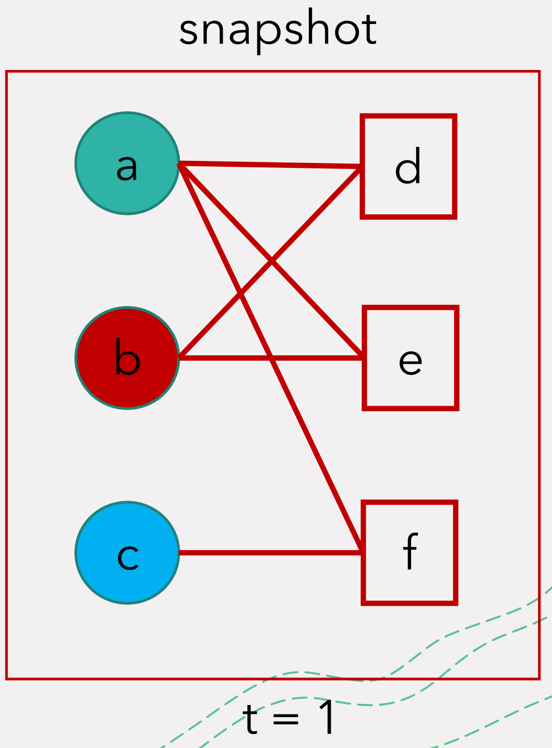
Next, we model **which tie change** is made. This is modelled in the objective function:

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

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

Longitudinal network analysis: ERGMs – SOAM, TERGMs - REMs

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



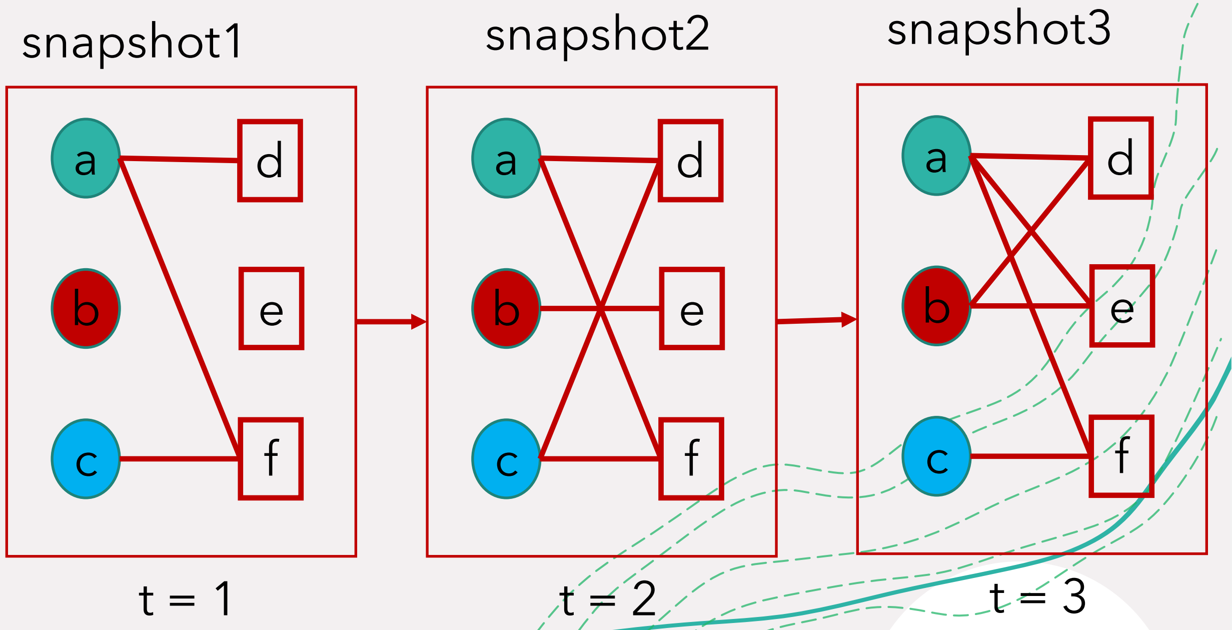
Research question
Which factors affect the structure of the network?

Longitudinal network analysis: ERGMs – SOAM, TERGMs - REMs

- If you have multiple snapshots of your network → run a tERGM or SAOM
- tERGM = temporal exponential random graph model

Research question

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

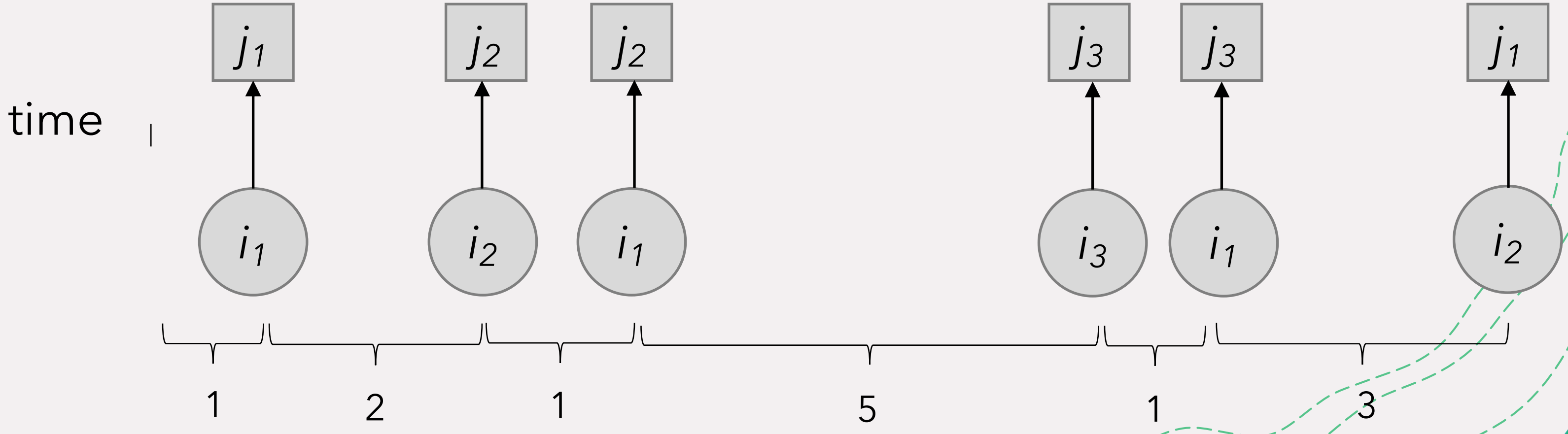


Longitudinal network analysis: ERGMs – SOAM, TERGMs - REMs

+ 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*?



References

+ Cranmer, S., Desmarais, B., & Morgan, J. (2020). *Inferential Network Analysis* (Analytical Methods for Social Research). Cambridge: Cambridge University Press. https:// 10.1017/9781316662915.
+ Butts, C. T. (2008). 4. A Relational Event Framework for Social Action. Sociological Methodology, 38(1), 155–200. https://doi.org/10.1111/j.1467-9531.2008.00203.x
+ Meijerink-Bosman, M., Back, M., Geukes, K., Leenders, R., & Mulder, J. (2022). Discovering trends of social interaction behavior over time: An introduction to relational event modeling. Behavior Research Methods. https://doi.org/10.3758/s13428-022-01821-8
+ Mulder, J., & Leenders, R. T. (2019). Modeling the evolution of interaction behavior in social networks: A dynamic relational event approach for real-time analysis. Chaos, Solitons & Fractals, 119, 73–85. https://doi.org/10.1016/j.chaos.2018.11.027
+ Lusher, D., Koskinen, J. and Robins, G. (2012), Exponential random graph models for social networks: Theory, methods, and applications, Cambridge University Press.
+ Snijders, T.A.B. (2011) Statistical models for social networks. Annual Review of Sociology, 37, 131–153.
+ Snijders, T.A.B., van de Bunt, G.G. & Steglich, C.E.G. (2010) Introduction to stochastic actor-based models for network dynamics. Social Networks, 32, 44–60
+ Snijders, T. A. B. (2017). "Stochastic actor-oriented models for network dynamics." Annual Review of Statistics and Its Application 4:343–363