The co-evolution of one-mode and two-mode networks

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April 2009

Multiple Networks

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studying between-network dependencies can be illuminating.

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For statistical models:

multivariate p_1 model, Holland & Leinhardt (1981);
multivariate p^* model, Pattison & Wasserman (1999) .

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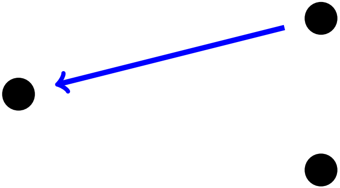
mixed popularity



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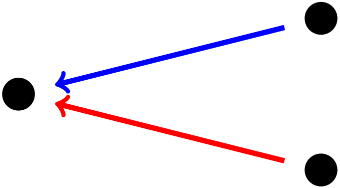

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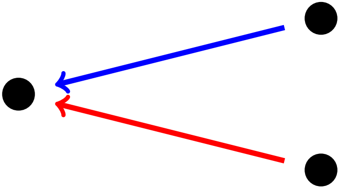

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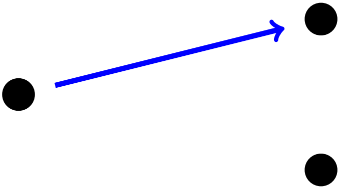

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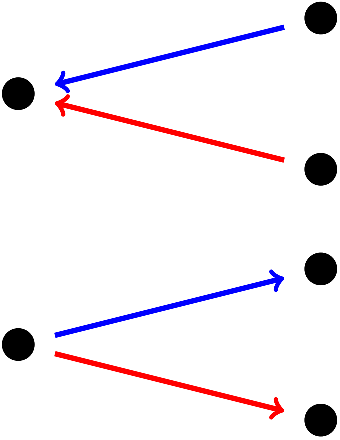
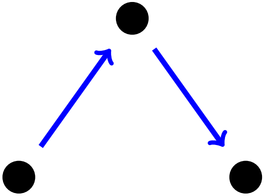


Next category: triads.

mixed transitive closure



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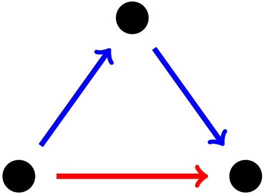

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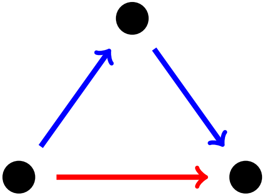
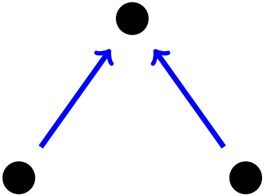


agreement ⇒
red tie



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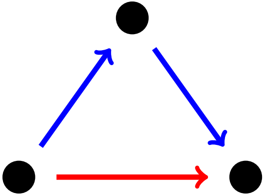

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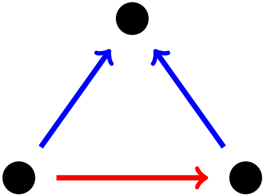

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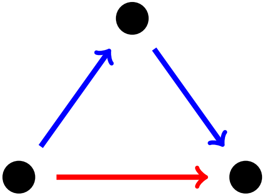

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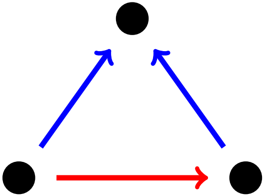

This type of cross-network dependencies is discussed for cross-sectional observations in Wasserman & Pattison (1999), with examples in Lazega & Pattison (1999).

For longitudinal observations the dependencies are multiplied, because we must distinguish between
the dependent and the explanatory
(antecedent – subsequent) relations.

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For the combination of a one-mode and a two-mode network, other mutual influences between the networks are possible.

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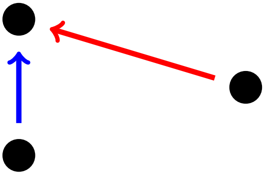

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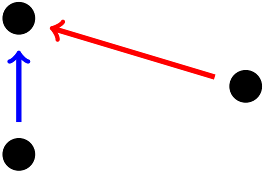

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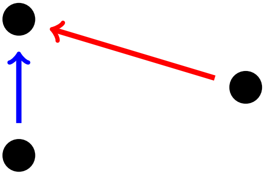

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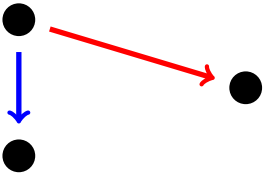

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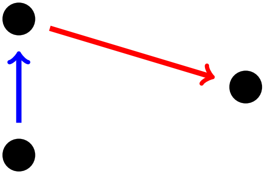

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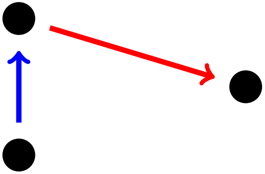

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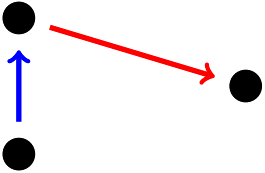

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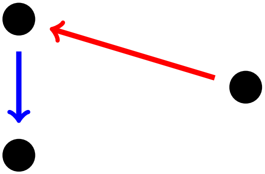

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An interlude:
for two-mode networks, other structures are important
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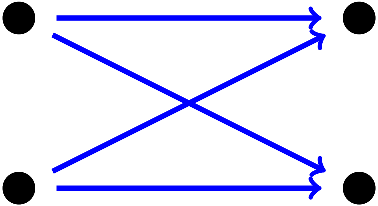

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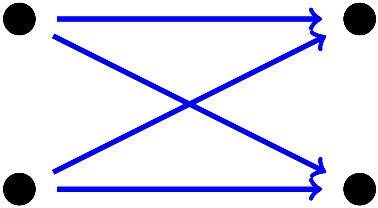
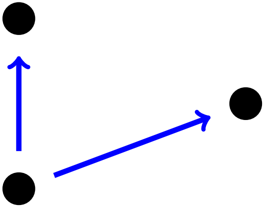


Closed triads are impossible in two-mode networks;
but they are possible as mixed patterns.

One-with-two-mode triads.

One-mode tie ⇒
two-mode agreement



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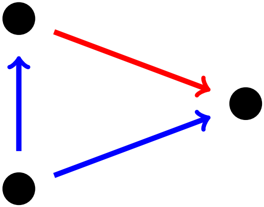

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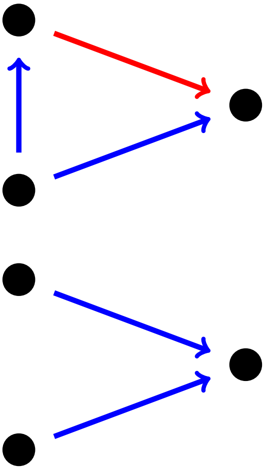

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Two-mode agreement ⇒
one-mode tie

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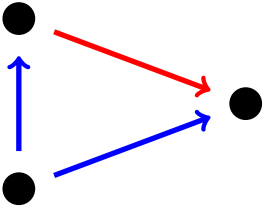

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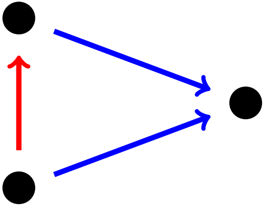

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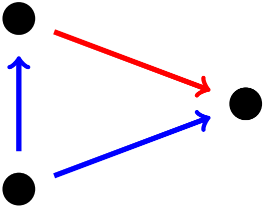

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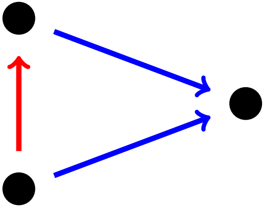

... etcetera ...

... outline of further presentation ...

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4. At any single moment in time,
only one tie variable may change.
5. The multiple relations together develop stochastically
according to a Markov process.

6. Changes in each network are modeled as choices by actors in their outgoing ties, with probabilities depending on '*objective functions*' of the network state that would obtain after this change.

These objective ('goal') functions are specified separately for each of the R networks.

Notation

Denote tie variable for r^{th} relation from i to j by

$$X_{ij}^{(r)} = \begin{cases} 1 & \text{if} \quad i \xrightarrow{r} j \\ 0 & \text{if} \quad \text{not } i \xrightarrow{r} j, \end{cases}$$

where this depends on time t.

By X we denote the collection of all R relations:
array $\left(X_{ij}^{(r)}\right)$ for $r = 1, \ldots, R;\ i = 1, \ldots, n;\ j = 1, \ldots, m_r$
($m_r = n$ if the r^{th} relation is one-mode).

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It is assumed that $\left(X_{ij}^{(r)}\right)$ is observed for time points $t_1, \ldots, t_M$:
panel data on multiple networks.

The statistical model is a *process model*:

an agent-based simulation model,
which simulates the development of the multiple networks
from one observation to the next;

statistical modeling consists of fitting such a simulation model
to the observed network data, and testing
which model components are required to give a good fit.

The model is defined by its smallest possible steps,
the ‘microsteps’, which consist of a change in one tie variable:

extend one new tie / withdraw one existing tie.

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$\Rightarrow$How rapidly does this happen?
$\Rightarrow$What is the probability of this particular tie change?

Decompose model in the average *frequency* of changes:

rate functions :

rate at which i can change r-relations is $\lambda_i^{(r)}(x)$;

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Focus on dynamics where rates of change
depend only on r: some relations change faster than others.

Denote $\lambda_+^{(r)} = \sum_i \lambda_i^{(r)}$ and $\lambda_+^{(+)} = \sum_r \lambda_+^{(r)}$.

Outline of model dynamics / algorithm

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   Step: Increment *t* by such a random variable.

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Model for microstep (smallest possible change):

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   Step: Increment *t* by such a random variable.
2. The probability that this is an event where actor *i* may change an *r*-tie is

$$\frac{\lambda_i^{(r)}}{\lambda_{+}^{(+)}} \ .$$

   Step: Choose *r*, *i* with this probability.

Outline of algorithm – continued

3. For this r and i, actor i may change one outgoing r-tie, or leave all outgoing tie variables $X_{ij}^{(r)}$ unchanged.
   The particular change toward a new situation x
   (x differs only in one tie variable from current situation!)
   is proportional to
   $$\exp\left(f_i^{(r)}(x)\right) .$$

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$$\frac{\exp\left(f_i^{(r)}(x \text{ changed in } x_{ij}^{(r)})\right)}{\sum_h \exp\left(f_i^{(r)}(x \text{ changed in } x_{ih}^{(r)})\right)} \; .$$

The objective function can be conveniently modeled as a weighted sum (cf. generalized linear modeling),

$$f_i^{(r)}(\beta, x) = \sum_{k=1}^{L} \beta_k^{(r)} \, s_{ik}^{(r)}(x) \, ,$$

where $s_{ik}^{(r)}(x)$ are 'effects' and $\beta_k^{(r)}$ their weights, which jointly drive the dynamics for relation r, given the current state of this *and all other* relations.

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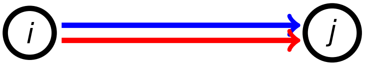
Here only a few examples of the latter are presented, with formulae for $s_{ik}^{(\mathrm{red})}(x)$.

Since this a component of the objective function for $X^{(\mathrm{red})}$, this network is the dependent relation – all others have an explanatory role.

direct association

$$\sum_{j=1}^{n} x^{(\text{blue})}(i,j)\, x^{(\text{red})}(i,j)$$



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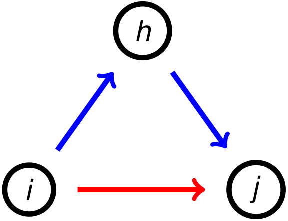
$$\sum_{j=1}^{n} x^{(\text{blue})}(i,j)\, x^{(\text{red})}(i,j)$$

mixed reciprocity

$$\sum_{j=1}^{n} x^{(\text{blue})}(j,i)\, x^{(\text{red})}(i,j)$$

mixed transitive closure

$$\sum_{j,h=1}^{n} x^{(\text{blue})}(i,h)\, x^{(\text{blue})}(h,j)\, x^{(\text{red})}(i,j)$$



Other formulae also are defined by mixed expressions
incorporating one network in the ‘dependent’
and the others in ‘explanatory’ roles.

Similar for combinations of one-mode and two-mode networks.

Estimation

For actor-based models for dynamics of single networks, the *method of moments* is a good estimation method in case panel data (repeated measures) of the network are available.

it operates by equating observed statistics
to their expected values given the parameter values
(note that the parameters are the variables in the equation).

For each parameter there must be a statistic
that is sensitive to this parameter.

This is implemented by an MCMC approximation
using the Robbins-Monro method of stochastic approximation.

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Which statistic is sensitive for the parameters expressing cross-network dependencies?

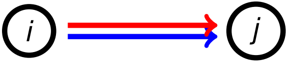
The example will be given for the parameter that is the weight of direct association,

$$\sum_{j=1}^{n} x^{(\text{blue})}(i,j)\, x^{(\text{red})}(i,j)$$

for the case of $M = 2$ repeated observations.

Consider direct association:

leading to



The statistic for fitting the corresponding parameter is

$$\sum_{i=1}^{n} \sum_{j=1}^{n} x^{(\text{blue})}(i,j)(t_1)\, x^{(\text{red})}(i,j)(t_2)$$

note the use of t_1 and t_2:
use explanatory network at previous observation,
dependent network at the next.

Example 1

Research with Rafael Wittek and Gerhard van de Bunt.

Kidney dialysis department in general hospital;
four waves, data collected by Gerhard van de Bunt.

49 employees; 4 waves, separated by a few months.

1. *Communication during work*:
   At least once a week.
2. *Trust*:
   Confiding for personal matters (work-related or private):
   strong or very strong trust.
3. *Advice*:
   Ask a colleague for advice or help at least once a week.

Descriptives

Average degrees:

- Communication: 15 – 20.
- Trust: 12 – 15.
- Advice: 3.7 – 5.4.

About 20 % missing data.

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Hypotheses, at this moment, are illustrations.

Hypotheses, dep. var. Communication

C1 *Direct association Advice* $\Rightarrow$ *Communication*:
Advice requires communication; therefore an advice tie will tend to lead to higher communication levels.

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C1 *Direct association Advice* ⇒ *Communication*:
Advice requires communication; therefore an advice tie will tend to lead to higher communication levels.

C2 ? *Direct association Trust* ⇒ *Advice*:
this is unclear, because trust makes communication easier but also may make it less necessary.

Hypothesis 1, dep. var. Trust

T1 *Direct association Mutual Communication* ⇒ *Trust*:
trust can be a byproduct of mutual communication,
mutual communication is required to establish trust.

(mutual C) ⇒ T

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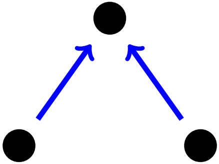
Hypothesis 2, dep. var. Trust

T2 *Agreement concerning Communication* ⇒ *Trust*:
others with whom both communicate
could provide social control
for the event that trust would be breached.

(agreement C) ⇒ T



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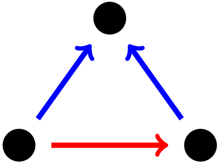

Hypotheses, dep. var. Advice

Basic notion: advice receiving can be risky
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A2 *Direct association Mutual Communication* $\Rightarrow$ *Advice*:
advice can be a byproduct of mutual communication.

A3 *Agreement concerning Trustees* $\Rightarrow$ *Advice*:
similar trustees are safeguard against
potential problems arising in advice relation.

The hypotheses were tested in the following way:

⇒ Specify for each relation a baseline model
of how the relation is influenced by itself:
effects of outdegree, reciprocity,
transitive triplets, 3-cycles;

⇒ for each relation, include both direct associations;

⇒ include also the tested effects.

Results: Communication

Effect	par.	(s.e.)
Out-degree	-1.423	(0.064)
Reciprocity	0.784	(0.085)
Transitive triplets	0.061	(0.003)
3-cycles	-0.101	(0.010)
Trust $\Rightarrow$ Communication (C2)	0.601	(0.097)
Advice $\Rightarrow$ Communication (C1)	0.741	(0.193)

Results: Trust

Effect	par.	(s.e.)
Out-degree	-2.461	(0.364)
Reciprocity	0.651	(0.120)
Transitive triplets	0.084	(0.008)
3-cycles	-0.147	(0.020)
Communication $\Rightarrow$ Trust	0.713	(0.224)
Advice $\Rightarrow$ Trust	0.252	(0.211)
Mutual Communication $\Rightarrow$ Trust (T1)	0.564	(0.233)
Communic. agreement$\Rightarrow$ Trust (T2)	0.022	(0.096)

Results: Advice

Effect	par.	(s.e.)
Out-degree	-2.341	(0.183)
Reciprocity	0.004	(0.262)
Transitive triplets	0.262	(0.033)
3-cycles	-0.534	(0.190)
Communication ⇒ Advice	0.917	(0.335)
Trust ⇒ Advice (A1)	0.288	(0.169)
Mutual Communication ⇒ Advice (A2)	0.064	(0.259)
Trust agreement⇒ Advice (A3)	–0.347	(0.236)

Conclusions

As hypothesized, increased/sustained communication follows on advice and trust;

the hypothesis that mutuality of communication is an antecedent for trust is borne out;
no significant effect for mutuality of communication on advice, when controlling for direct effect;

communicating with same others has no sign. effect on trust;

trusting the same others has no significant effect on advice.

Example 2

Research with Vanina Torlo and Alessandro Lomi.

International MBA program in Italy;
75 students; 3 waves.

1. *Friendship*
2. *Advice*:
   To whom do you go for help if you missed a class, etc.

Example 2

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1. *Friendship*
2. *Advice*:
   To whom do you go for help if you missed a class, etc.
3. Two mode: *organizational preference*:
   in which organizations are you interested
   as potential employer.
   A total of 100 organizations were mentioned.

Results: Friendship

Effect	par.	(s.e.)
Out-degree	–1.858	(0.089)
Reciprocity	1.261	(0.090)
Transitive triplets	0.189	(0.008)
3-cycles	–0.128	(0.021)
Indegree popularity ($\surd$)	0.088	(0.020)
Outdegree popularity ($\surd$)	–0.215	(0.051)
Performance similarity	0.836	(0.176)
Advice $\Rightarrow$ Friendship	1.153	(0.163)
'Incoming' advice $\Rightarrow$ Friendship	0.893	(0.196)
Indegree advice ($\surd$) $\Rightarrow$ Friendship	–0.138	(0.035)
Org. pref. agreement $\Rightarrow$ Friendship	–0.070	(0.080)

Results: Advice

Effect	par.	(s.e.)
Out-degree	–2.616	(0.084)
Reciprocity	0.561	(0.145)
Transitive triplets	0.375	(0.019)
3-cycles	–0.137	(0.039)
Performance alter	0.310	(0.038)
Performance ego	–0.080	(0.037)
Performance similarity	0.480	(0.307)
Friendship ⇒ Advice	1.395	(0.194)
‘Incoming’ friendship ⇒ Advice	0.592	(0.206)
Friendship agreement ⇒ Advice	–0.144	(0.021)
Org. pref. agreement ⇒ Advice	0.333	(0.110)

Results: Organizational Preference

Effect	par.	(s.e.)
Out-degree	–2.164	(0.110)
Four-cycles	–0.018	(0.014)
Indegree popularity ($\sqrt{}$)	–0.058	(0.039)
Friendship $\Rightarrow$ Org. pref. agreement	0.294	(0.101)

Thus, organizational preference is
influenced by preference of friends.
When the dynamics of organizational preference is analyzed
without influences of friends or advisers,
we find a strong '*indegree popularity*' ('Matthew') effect:

self-reinforcing differences between indegrees of organizations.

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we find a strong '*indegree popularity*' ('Matthew') effect:

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The co-evolution between friendship and organizational preference shows that this effect emerges from the influence between friends.

Discussion

⇒ Testing cross-network dependencies in dynamics of multiple networks gives interesting new possibilities for hypothesis testing.

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- ⇒ Testing cross-network dependencies in dynamics of multiple networks gives interesting new possibilities for hypothesis testing.
- ⇒ Elaborated along the lines of actor-based modeling.
- ⇒ Compared to modeling dynamics of single networks, this approach attenuates the Markov assumption by extending the state space to a multiple network.

⇒ New perspectives possible by combining one-mode and two-mode networks.

⇒ The method will be made available in Siena.
This will work for a small number (e.g., 2–6) of networks, and a limited number of actors (up to a few hundred).