Network Dependencies in Social Space, Geographical Space, and Temporal Space. Part II [1]

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[1] More material at http://www.stats.ox.ac.uk/siena/; Material from Snijders greatly acknowledged

Topics

- ‘Change we can believe in’ - network regression v continuous-time (Block et al., 2018)
- Missing data - some clarifications
- Multiplex models
- One-mode plus two-mode
- Multilevel with all types-of-ties - multilevel as one-mode
- Continous attributes
- Diffusion model
- Settings - SAOM for thousands of nodes
- Multilevel/repeated measures SAOM - multigroup, meta-analysis, `sienaBayes`

Recap of basic modelling assumptions

The model is actor-oriented in so much as:
at random points in (continuous) time an actor *i* is chosen w.p.

$$\frac{\lambda_i}{\sum_i \lambda_i} \tag{1}$$

to make a change. The chosen actor changes (or not) one of their out-going ties

Notation and assumptions

1. Actors: $i = 1, \ldots, n$ (individuals in the network),
2. Adjacency matrix: pattern X of ties between actors;
   $X_{ij} = 1$, or 0 according to whether there is a tie from i to j.

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4. Continuous time parameter t, observation moments $t_1, \ldots, t_M$.
5. Current state of network $X(t)$ is dynamic constraint for its own change process: Markov process.

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   only one variable $X_{ij}(t)$ may change.

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

Remarks on assumptions

Agency: The change probabilities can (but need not) be interpreted as arising from goal-directed behavior, in the weak sense of myopic stochastic optimization.

Objective function interpreted as
'that which the actors seem to strive after in the short run'.

Next to actor-driven models,
also tie-driven models are possible (e.g. Snijders & Koskinen, Ch. 11 ERGM book; Koskinen & Lomi, J Stat Phys 2010).

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which implies a dependence between the actors over time;
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one tie may lead to another one.

This implies strong dependence between what the actors do,
but it is completely generated by the time order:
the actors are dependent because they constitute
each other's changing environment.
NB: no path dependencies OR strategic action

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   rate functions;

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2. probabilities of changing (toggling) X_{ij}, conditional on such an opportunity for change:
   objective functions.

The distinction between rate function and objective function separates the model for *how many* changes are made from the model for *which* changes are made.

Specification: rate function

Given the current state x the time until i is given an opportunity is exponentially distributed with rate $\lambda_i(\alpha, \rho, x)$ independently for all $i \in V$

Consequently:

- ✓ the prob. i is ‘winner’: $\lambda_i(\alpha, \rho, x)/\lambda_+(\alpha, \rho, x)$
- ✓ the distribution of quickest time: $\lambda_+(\alpha, \rho, x)$

where

$$\lambda_+(\alpha, \rho, x) = \sum_i \lambda_i(\alpha, \rho, x) \; .$$

Specification: objective function

The objective function $f_i(\beta, x)$ indicates preferred changes.
β is a statistical parameter, i is the actor (node), x the network.

When actor i gets an opportunity for change,
he has the possibility to change *one* outgoing tie variable X_{ij},
or leave everything unchanged.

By $x(i \rightsquigarrow j)$ is denoted the network obtained
when x_{ij} is changed ('toggled') into $1 - x_{ij}$
Formally, $x(i \rightsquigarrow i)$ is defined to be equal to x.

Modelling the ministep

Conditional on actor i being allowed to make a chance

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One-step jump probability

$$p_{ij}(\beta, x) = \frac{\exp\left(f_i(\beta, x(i \rightsquigarrow j))\right)}{\sum_{h=1}^{n} \exp\left(f_i(\beta, x(i \rightsquigarrow h))\right)} \,,$$

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where

- $x(i \rightsquigarrow j)$ is the network resulting from the change
- β are statistical parameters
- f_i describes the attractiveness of $x(i \rightsquigarrow j)$ to i

Interpretation as conditional random utility model

One way of obtaining this model specification is to suppose that actors make changes such as to optimize the objective function $f_i(\beta, x)$ plus a random disturbance that has a Gumbel distribution: *myopic stochastic optimization*, multinomial logit models.

Actor i chooses the “best” j by maximizing

$$f_i\big(\beta, x(i \leadsto j)\big) \quad + \quad U_i(t, x, j)\,.$$

$$\Uparrow$$

random component

(with the formal definition $x(i \leadsto i) = x$).

Thus given that i is allowed to make a change,
the probability that i changes the tie variable to j,
or leaves the tie variables unchanged (denoted by $j = i$), is

$$p_{ij}(\beta, x) = \frac{\exp\big(f(i,j)\big)}{\sum_{h=1}^{n} \exp\big(f(i,h)\big)}$$

where

$$f(i,j) = f_i\big(\beta, x(i \rightsquigarrow j)\big)$$

and p_{ii} is the probability of not changing anything.

This is the multinomial logit form of a *random utility* model.

Objective functions will be defined as sum of:

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Evaluation function and endowment function modeled as linear combinations of theoretically argued components of preferred directions of change. The weights in the linear combination are the statistical parameters.

The focus of modeling is first on the evaluation function; then on the rate and endowment functions.

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The evaluation and endowment functions express how the dynamics of the network process depends on its current state.

Micro-step

At random moments (frequency determined by rate function),
a random actor gets the opportunity
to make a change in one tie variable:
the *micro-step* (on $\Rightarrow$ off, or off $\Rightarrow$ on.)

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to make a change in one tie variable:
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This actor tries to improve his/her objective function
and looks only to its value immediately after this micro-step
(*myopia*) .

This absence of strategy or farsightedness in the model
implies the *definition* of effects as
“what the actors try to achieve in the short run”.

Simple model specification:

- The actors all receive opportunities to change a tie at random moments, at the same rate ρ.

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- The actors all receive opportunities to change a tie at random moments, at the same rate ρ.
- Each actor tries to optimize an *evaluation function* with respect to the network configuration,

$$f_i(\beta, x)\,, \quad i = 1, ..., n, \;\; x \in \mathcal{X}\,,$$

which indicates the preference of actor i for the relational situation represented by x; objective function depends on *parameter* β.

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Change we can believe in: Comparing longitudinal network models on consistency, interpretability and predictive power

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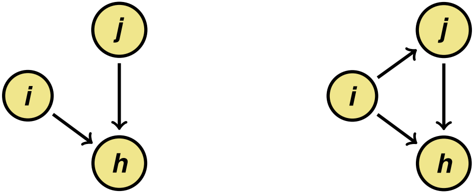
ABSTRACT

While several models for analysing longitudinal network data have been proposed, their main differences, especially regarding the treatment of time, have not been discussed extensively in the literature. However, differences in treatment of time strongly impact the conclusions that can be drawn from data. In this article we compare auto-regressive network models using the example of TERGMs – a temporal extensions of ERGMs – and process-based models using SAOMs as an example. We conclude that the TERGM has, in contrast to the ERGM, no consistent interpretation on tie-level probabilities, as well as no consistent interpretation on processes of network change. Further, parameters in the TERGM are strongly dependent on the interval length between two time-points. Neither limitation is true for process-based network models such as the SAOM. Finally, both compared models perform poorly in out-of-sample prediction compared to trivial predictive models.

Continuous-time v discrete-time

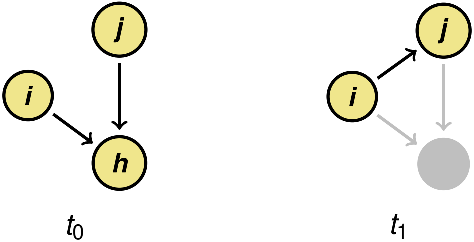
Assume network $X(t_0)$ and $X(t_1)$
and that we are happy to fix $X(t_0)$
How do we model closure?



t_0 t_1

Network regression

$\sharp$ ties at t_1 close open triples at t_0



This approach does not care what happened to the mixed path $i \rightarrow h \leftarrow j$ ERGO: you may find closure even though closure has decreased!

Network regression

Basic problem ties at t_1 are modelled as independent conditional on t_0

Is there any way around this?

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Is there any way around this?

Robins & Pattison (2001, Random graph models for temporal processes in social networks. J. Math. Sociol.) propose:

$$X(t_1)|X(t_0) \sim ERGM(\theta)$$

with $X(t_0)$ as covariate network.

This is permissible BUT model cannot be interpreted in terms of *change* as $X(t_1)$ is in equilibrium (Block et al., 2018)

Network regression

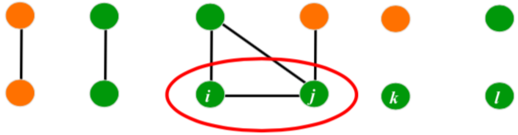
Dependencies in $X(t_1)$ cannot be accounted for through $X(t_0)$

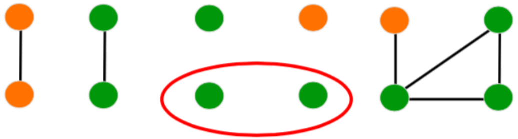
Unless you assume *continuous-time* process.

What is the effect on prediction?

Prediction: example ERGM

Colour homophily and clustering do not distinguish between:





ERGM (and stationary SAOM) is permutation invariant

How does SAOM account for dependence?

SAOM induces marginal dependence in ties of $X(t_1)$ through assuming incremental changes in continuous time where a change only dependens on the past

What type of data do we want to explain

If an element x_{ij} has changed

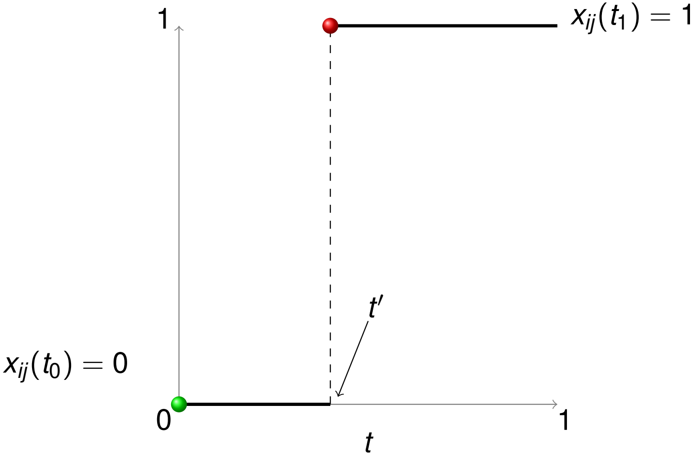
from

$$x_{ij}(t_0) = 0$$

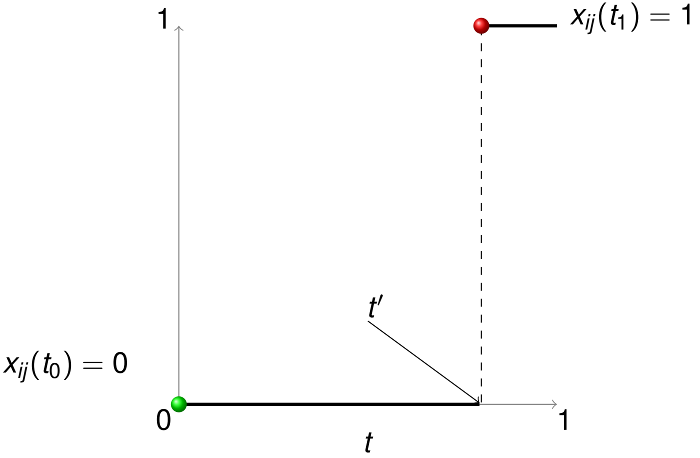
to

$$x_{ij}(t_1) = 1$$

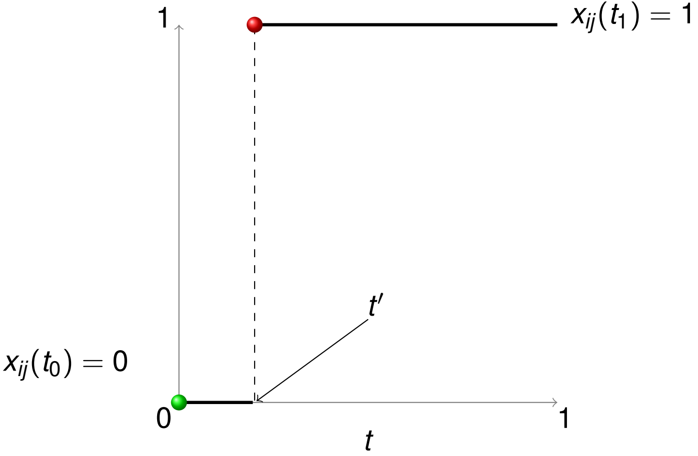
something has changed inbetween t_0 and t_1



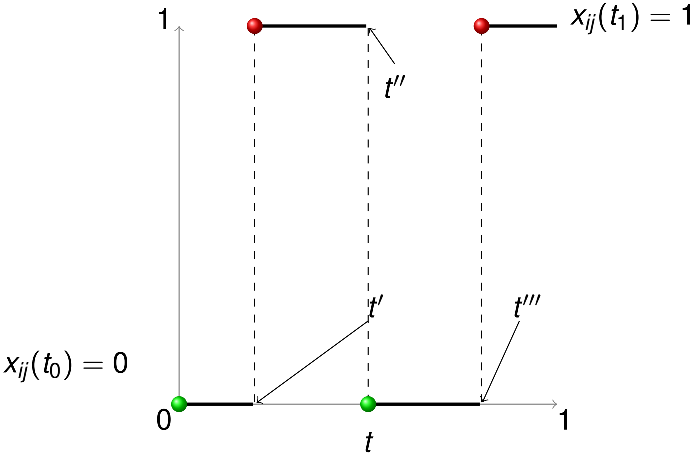
Change at t'



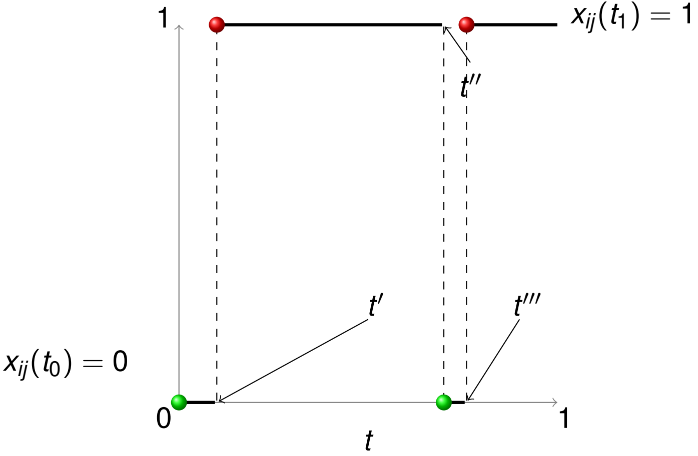
Change at t'



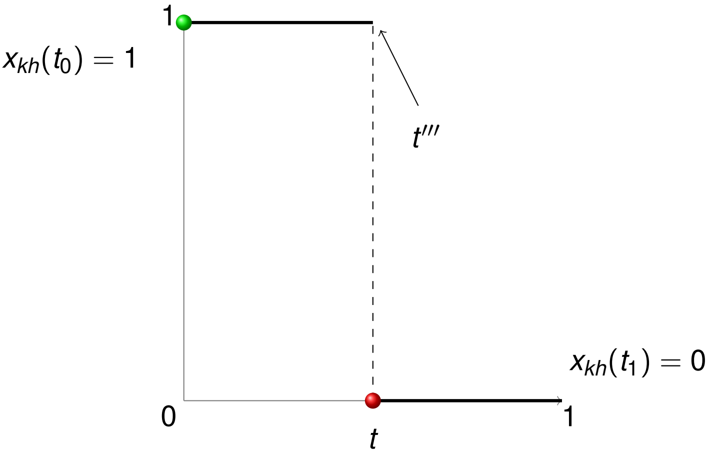
Change at t'



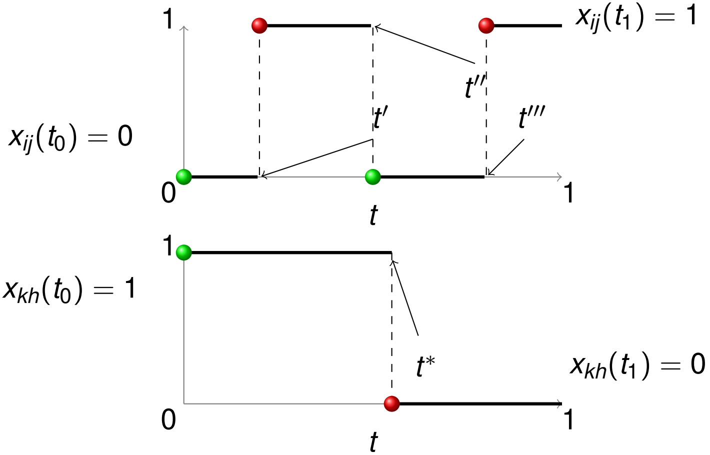
Change at t', t'', *and* t''

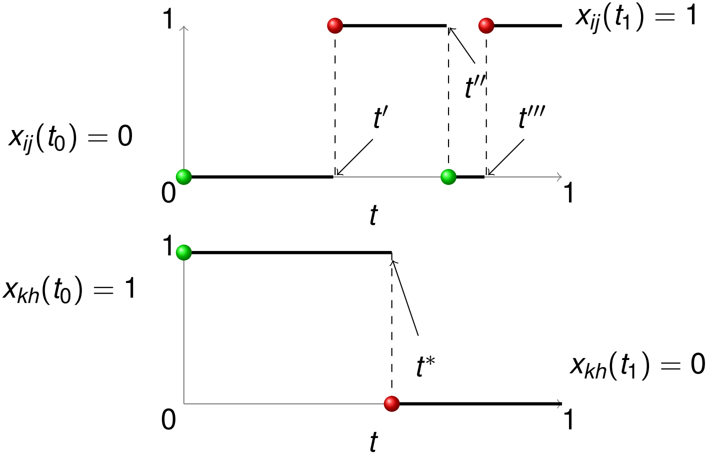


Change at t', t'', *and* t''



Change at t'''


1
$x_{ij}(t_1) = 1$
t''
t'
t'''
$x_{ij}(t_0) = 0$
0
1
t
1
$x_{kh}(t_0) = 1$
t^*
$x_{kh}(t_1) = 0$
0
1
t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t''
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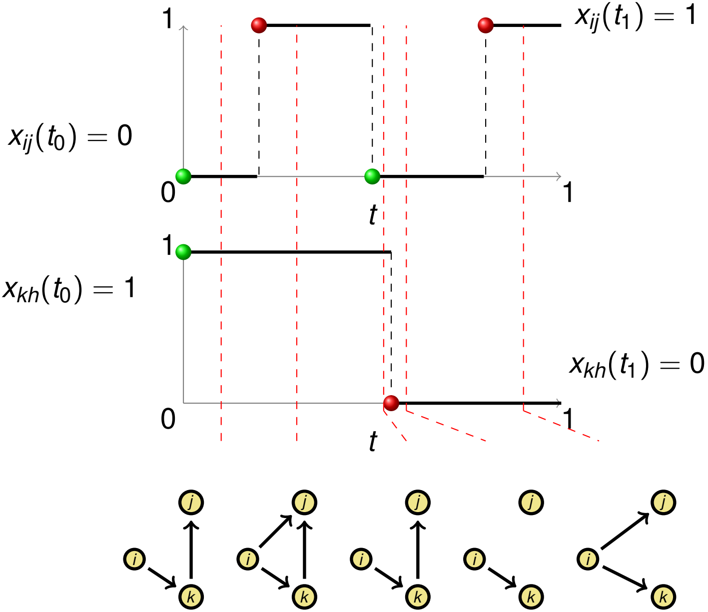
t'
t'''
0
1
t
1
$x_{kh}(t_0) = 1$
t^*
$x_{kh}(t_1) = 0$
0
1
t


1
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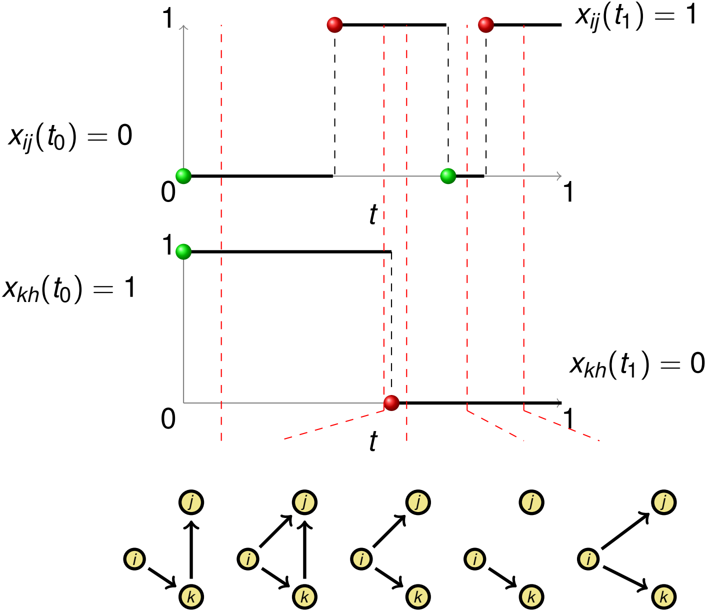
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$x_{ij}(t_1) = 1$
$x_{ij}(t_0) = 0$
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1
$x_{kh}(t_0) = 1$
$x_{kh}(t_1) = 0$
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j
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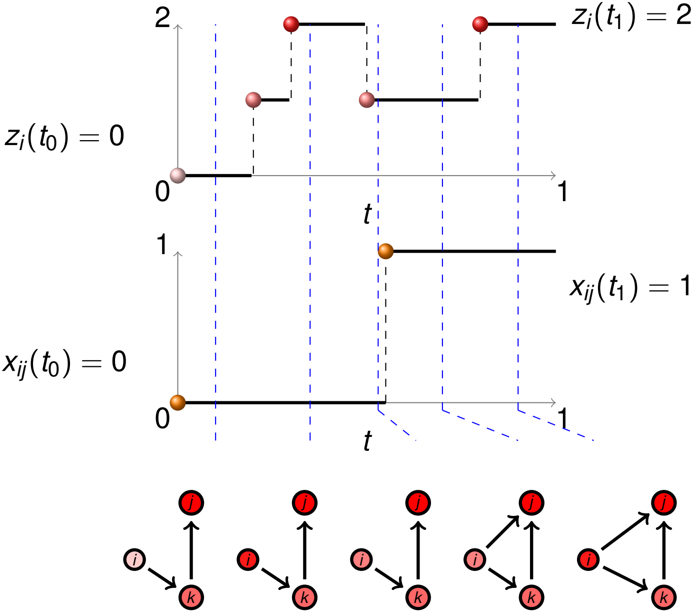
Actor-driven models

Network change process and behavior change process
run simultaneously, and influence each other
being each other's changing constraints.


2
$z_i(t_1) = 2$
$z_i(t_0) = 0$
0
1
t
1
$x_{ij}(t_1) = 1$
$x_{ij}(t_0) = 0$
0
1
t
j
i
k

Missing data in RSiena - MoM

For waves t_0, t_1, t_2
Default (MoM):

- if $X_{ij}(t_0) = NA$, $X_{ij}(t_0) := 0$, becuase networks are sparse
- if x, $X_{ij}(t_1)$ is simulated according to the model but $X_{ij}^{\text{sim}}(t_1)$ is not used in calculating target statistics (Hipp et al. 2015, incorrect interpretation)
- if $X_{ij}(t_1) = NA$ and $X_{ij}(t_2) = NA$, $X_{ij}(t_2) := X_{ij}^{\text{sim}}(t_1)$

Covariates are imputed using mean.
Hipp et al. (2015) and Krause et al. (2018) impute $X_{ij}(t_0)$ using ERGM/stationary SAOM.

Missing data in RSiena - Likelihood based

For ML (Snijders, Koskinen, Schweinberger, 2010) and Bayes (Koskinen and SNijders, 2007):
Missing values are integrated out (by simulation from fully conditional posterior)
aver 1: no distribution for t_0 so imputed independently
aber 2: for reasons of parralelisation, if $X_{ij}(t_1) = NA$:
$X_{ij}^{\mathrm{sim}}(t_1)$ imputed for interval $t_0 \rightarrow t_1$, but
$X_{ij}(t_1) = NA$ is treated as a 'first' observation (i.e. imputed independently)

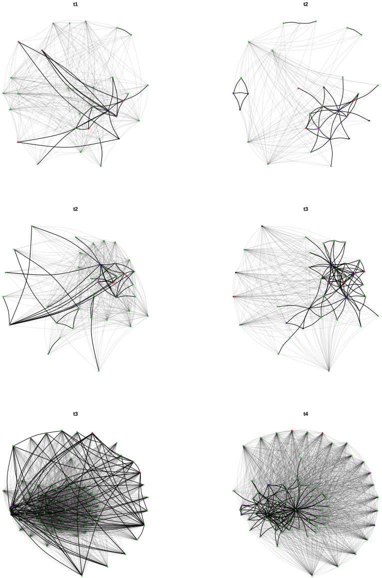
Missing data in RSiena - Likelihood based

Sampling paths for MoM are simulated forwards (unconstrained)

Sampling parths for ML/Bayes are simulated constrained, so that

$X_{ij}^{\text{sim}}(t_m) = X_{ij}^{\text{obs}}(t_m)$, for $m > 0$.

Missing data for ML/Bayes hence reduces constrains and make estimation 'easier' (but less precise)



Waves t_0 through t_3 plotted pariwise $\{t_m, t_{m+1}\}$ Grey: missing dyad (Bright, Koskinen, Malm, 2019)

Changing composition and missing data

Changing composition of node-sets can be dealt with in three (and a half different ways):

- using `sienaCompositionChange` where actors actually enter and leave
- coding ties of leavers as structural zeros, code: `10`
- simlar to composition change, actor must have entered and left at some point, at which point their ties were NA

Using the Markov property, all can be combined with the multigroup option `sienaGroupCreate` by interval to reduce NA.

Using changing coposition

50 actors across 6 waves with 11, 20, and 33 entering and leaving

```
comp <- rep(list(c(1,6)), 50)
comp[[11]] <- c(3,6)
comp[[20]] <- c(1,4)
comp[[33]] <- c(1.5,3, 4.01,6)
changes <- sienaCompositionChange(comp)
```

33 enters halway between waves 1 and 3 with no ties; no one can have tie to 33 betwwen waves 3 and 4.

Structural zeros

For actor with tie-value `10`

they are in the network

if all outgoing ties are `10`, they can still be chosen

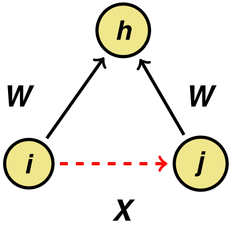
if exact times not known, equivalent to `sienaGroupCreate`

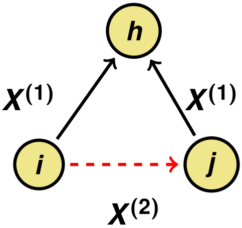
Changing composition through missings

If actor leaves inbetween t_m and t_{m+1}
setting ties at t_{m+1} to `10` loses information at t_m
using NA allows actor to choose and be chosen up until t_{m+1}

Multiplex networks

Any effect for a dyadic covariate *W* on network *X*
(e.g. *from W agreement*)





can be defined in terms of network $X^{(s)}$ on network $X^{(u)}$, for $s, u \in \mathcal{R} = \{1, \ldots, R\}$.

Two dependent networks - no problem

Let $r = 1$: friendship

and $r = 2$: romantic

```
friendship <- sienaDependent(friendshipData)
```

```
romantic <- sienaDependent(romanticData)
```

from W agreement

Let $r = 1$: friendship

and $r = 2$: romantic

Closure of friendship by romantic:

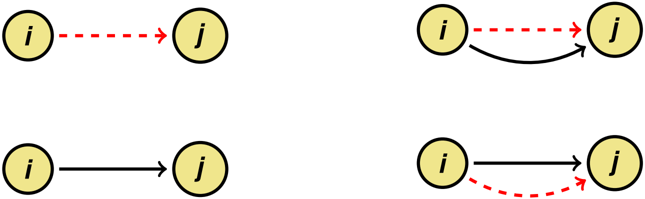
```
myeff <- includeEffects(myeff, name = 'romantic' , from,
  interaction1 = 'friendship')
```

Closu

of romantic by friendship:

```
myeff <- includeEffects(myeff, name = 'friendship' ,from,
     interaction1 =  'romantic' )
```

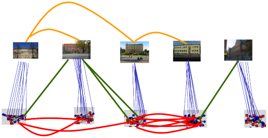
Note that, for alignment, to investigate:



You need to use likelihood-based inference

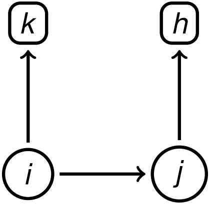
Multilevel Analysis of Networks

Multilevel Network Analysis



Analysing one-mode + two-mode networks

Set of people $V = \{1, \ldots, n\}$ and,
corporate boards/concepts/activities $M = \{1, \ldots, m\}$.



As actor oriented (rates only λ_i for one type of node $i \in V$)
$k \in M$ cannot create ties (hence no ties in $M \times M$)

Data structure - two distinct node-sets

Define two different node sets

```
people <- sienaNodeSet(nrppl, nodeSetName="people")
affiliations <- sienaNodeSet(nraffiliations,
nodeSetName="affiliations")
```

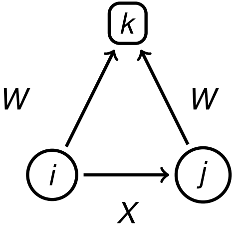
dependent variables

```
friendship <- sienaDependent(friendshipData)
aff <- sienaDependent(array(c(affiliations1, affiliations2),
dim=c(nrppl, nraffiliations,2)),
"bipartite", nodeSet=c("people", "affiliations"))
```

and the suite of effects is given by `getEffects`

What type of effects?

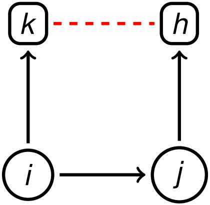
As for multiplex networks,
some effects with multiple types of ties defined (others not)
(*from W agreement*)



But as *M* not actors no dependent attribute on top-level

Multilevel Network Analysis

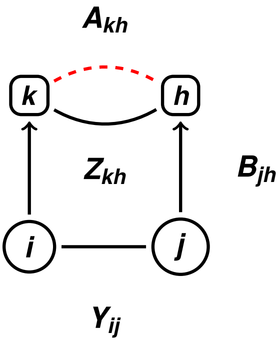
Set of people $V = \{1, \ldots, n\}$ and,
what if $M = \{1, \ldots, m\}$ have ties in $M \times M$?



. . . or have dependent attributes?

Define relevant networks

Example of people-people ties (Y_{ij}), people-concepts (B_{ik}), and concept-concept (Z_{kh}), with dyadic covariate (A_{kh})



The James Hollway trick

Define three blocked matrices

$$\underset{(m+n)\times(m+n)}{\mathbf{D}} = \begin{pmatrix} \mathbf{Z} & \mathbf{0}_{m\times n} \\ \mathbf{0}_{n\times m} & \mathbf{0}_{n\times n} \end{pmatrix}$$

$$\underset{(m+n)\times(m+n)}{\mathbf{U}} = \begin{pmatrix} \mathbf{0}_{m\times m} & \mathbf{0}_{m\times n} \\ \mathbf{0}_{n\times m} & \mathbf{Y} \end{pmatrix}$$

$$\underset{(m+n)\times(m+n)}{\mathbf{V}} = \begin{pmatrix} \mathbf{0}_{m\times m} & \mathbf{B}^{\top} \\ \mathbf{B} & \mathbf{0}_{n\times n} \end{pmatrix}$$

where **0** are blocks of structural zeros.

The James Hollway trick

The dyadic covariate for the concept-concept ties can be defined similarly

$$\underset{(|\mathcal{N}|+n)\times(|\mathcal{N}|+n)}{\mathbf{C}} = \begin{pmatrix} \mathbf{A} & \mathbf{0}_{|\mathcal{N}|\times n} \\ \mathbf{0}_{n\times|\mathcal{N}|} & \mathbf{0}_{n\times n} \end{pmatrix}$$

and the same for other dyadic covariates

Blocked SAOM for Basov's sociosemantic network

Reading in the networks

```
MatC <- as.matrix( read.table("blocked_c.txt") )
MatD <- as.matrix( read.table("blocked_d.txt") )
MatV <- as.matrix( read.table("blocked_v.txt") )
MatU <- as.matrix( read.table("blocked_u.txt") )
N <- dim(MatC)[1]
```

Defining the dependent variables and expert network covariate

```
LocalNet <- sienaDependent(
            array( c( MatD,MatD ),
            dim = c(N,N , 2 ) ) ,
            allowOnly=FALSE  )
SocialNet <- sienaDependent(
            array( c( MatU,MatU ),
            dim = c(N,N , 2 ) ) ,
            allowOnly=FALSE  )
UsageNet <- sienaDependent(
            array( c( MatV,MatV ),
            dim = c(N,N , 2 ) ) ,
            allowOnly=FALSE  )
ExpertNet <- coDyadCovar(MatC, centered=FALSE)
```

Defining the siena data structure

```
Blockdata <- sienaDataCreate( LocalNet,
                    SocialNet ,
                    UsageNet ,
                    ExpertNet )
```

Parameter	Point estimate	S.E.	Convergence
rate basic rate parameter LocalNet	0.5		
LocalNet: degree (density)	1.046	17.455	0.0234
LocalNet: transitive triads	0.096	0.0763	0.0578
LocalNet: ExpertNet	0.923	0.2183	0.0204
LocalNet: WW on X closure of ExpertNet	−0.003	0.0116	0.0284
LocalNet: shared incoming UsageNet	0.2	0.0274	0.0131
rate basic rate parameter SocialNet	50		
SocialNet: degree (density)	−1.259	0.265	0.125
SocialNet: transitive triads	0.475	0.2401	0.1154
basic rate parameter UsageNet	50		
UsageNet: outdegree (density)	−0.175	0.0423	0.0014
UsageNet: degree sqrt LocalNet pop.	0.563	0.0615	0.0429

Co-evolution with continous outcomes

For the behaviours, the formula of the change probabilities is

$$p_{ihv}(\beta, z) = \frac{\exp(f(i,h,v))}{\sum_{k,u} \exp(f(i,k,u))}$$

where $f(i,h,v)$ is the objective function calculated for the potential new situation after a behaviour change,

$$f(i,h,v) = f_i^Z(\beta, z(i, h \rightsquigarrow v)) \ .$$

A multinomial logit form.

Co-evolution with continous outcomes

What if $Z_i \in R$ or $Z_i \in \{0, \ldots T\}$ for T LARGE?

to go from a value 0 to, say, 50, an actor has to make at least 50 changes w.p.

$$p_{ihv}(\beta, z) = \frac{\exp(f(i,h,v))}{\sum_{k,u} \exp(f(i,k,u))}$$

This attenuates the effects and lead to large rates

Co-evolution with continous outcomes

Solution, assume Brownian motion and apply stochastic differential equation:
Niezink, Snijders (2017). Co-evolution of Social Networks and Continuous Actor Attributes. The Annals of Applied Statistics (NB: MoM)

Diffusion in stochastic oriented networks

Standard co-evolution of influence and selection in RSiena assumes
The behaviour switches on and off with multinomial probabilities an unlimited number of times inbetween t_m and t_{m+1}
This does not afford:

- diffusion/contagion/adaption of something that monotonically increasing
- drawing on previous survival analysis techniques (e.g. Strang and Tuma, 1993)

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Diffusion in stochastic oriented networks

Luckily:

Diffusion of innovations in dynamic networks

Charlotte C. Greenan

University of Oxford, Oxford, UK.

Summary. The evolution of a dynamic social network and the diffusion of an innovation are jointly modelled, dependent on one another, using an extension of a stochastic actor oriented model developed by Snijders (2001), which is modified so that the adoption times follow a proportional hazards model. The asymptotic behaviour of the method of moments estimator is examined. The model is demonstrated on a dataset involving of the initiation of cannabis smoking amongst adolescents, and a simulation study is presented.

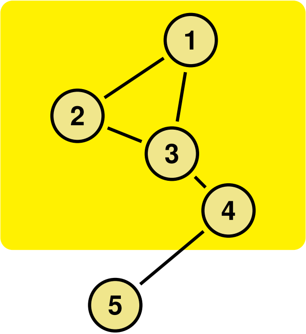
Keywords: Diffusion of innovations; Longitudinal analysis of network data; Method of moments; Proportional hazards; Stochastic actor oriented models.

Introduction

Greenan, (2015). Diffusion of Innovations in Dynamic Networks. JRSS A

The settings model for thousands of nodes

Primary setting of *i*: everyone at distance less than or equal to 2



EGO: $\boldsymbol{i = 1}$

Ego ONLY evaluates primary setting

this changes dynamically

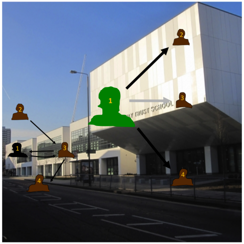
Multilevel analysis of networks

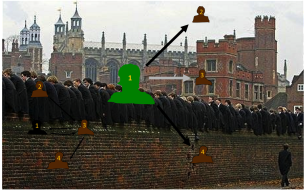
What if we have the same type of network observed in multiple, independent contexts?

How do dynamics play out in different contexts

should we have different models $p_{ij}^{[g]}(\beta^{[g]}, x^{[g]})$ for different groups g ?

How do dynamics play out in different contexts





should we have different models $p_{ij}^{[g]}(\beta^{[g]}, x^{[g]})$
for different groups g ?

Data structure

Independently for groups $g = 1, 2, \ldots, G$ we have observations


$$x_{t_1}^{[1]}, \ldots, x_{t_M}^{[1]}$$
$$x_{t_1}^{[2]}, \ldots, x_{t_M}^{[2]}$$
$$x_{t_1}^{[2]}, \ldots, x_{t_M}^{[2]}$$
$$\vdots$$
$$x_{t_1}^{[G-1]}, \ldots, x_{t_M}^{[G-1]}$$
$$x_{t_1}^{[G]}, \ldots, x_{t_M}^{[G]}$$


Multilevel Data structure

Independently for egos $g = 1, 2, \ldots, G$ we have observations

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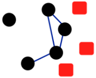
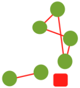


$$x_{t_1}^{[2]}, \ldots, x_{t_M}^{[2]}$$

$\vdots$



$$x_{t_1}^{[G]}, \ldots, x_{t_M}^{[G]}$$

Data structure

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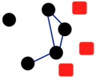
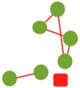


$x_{t_1}^{[2]}, \ldots, x_{t_M}^{[2]}$

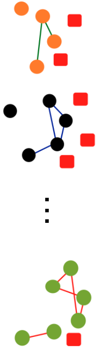
$\vdots$



$x_{t_1}^{[G]}, \ldots, x_{t_M}^{[G]}$

Approach one: separate analysis

Independently for egos $g = 1, 2, \ldots, G$ we have observations



$x_{t_1}^{[1]}, \ldots, x_{t_M}^{[1]}$

$x_{t_1}^{[2]}, \ldots, x_{t_M}^{[2]}$

$\vdots$

$x_{t_1}^{[G]}, \ldots, x_{t_M}^{[G]}$

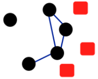
Fit separate (unrestricted) models

- G unique explanations
- confounds systematic processes and context
- tedious
- egonets with little info.

Approach two: multigroup

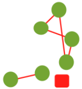
Independently for egos $g = 1, 2, \ldots, G$ we have observations

$x_{t_1}^{[1]}, \ldots, x_{t_M}^{[1]}$



$x_{t_1}^{[2]}, \ldots, x_{t_M}^{[2]}$

$\vdots$



$x_{t_1}^{[G]}, \ldots, x_{t_M}^{[G]}$

Fit identical models assuming $\theta^{[g]} = \theta$

- strong assumption
- does not account for different contexts
- dominated by 'large' egos

Could use structural zeros but more efficient

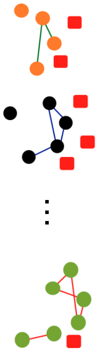
```
Group1 <- sienaDependent(array(c(N3401, HN3401),
  dim=c(45, 45, 2)))
Group3 <- sienaDependent(array(c(N3403, HN3403),
     dim=c(37, 37, 2)))
Group4 <- sienaDependent(array(c(N3404, HN3404),
     dim=c(33, 33, 2)))
Group6 <- sienaDependent(array(c(N3406, HN3406),
   dim=c(36, 36, 2)))
  dataset.1 <- sienaDataCreate(Friends = Group1)
  dataset.3 <- sienaDataCreate(Friends = Group3)
  dataset.4 <- sienaDataCreate(Friends = Group4)
  dataset.6 <- sienaDataCreate(Friends = Group6)
```

Then model can be defined as usula

```
FourGroups <- sienaGroupCreate(
       list(dataset.1, dataset.3, dataset.4, dataset.6))
 FourEffects <- getEffects(FourGroups)
 FourEffects <- includeEffects(FourEffects, transTrip)
```

Approach three: meta-analysis

Independently for egos $g = 1, 2, \ldots, G$ we have observations



$x_{t_1}^{[1]}, \ldots, x_{t_M}^{[1]}$

$x_{t_1}^{[2]}, \ldots, x_{t_M}^{[2]}$

$\vdots$

$x_{t_1}^{[G]}, \ldots, x_{t_M}^{[G]}$

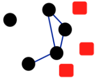
Fit separate identical models but parameters differ. POOL estimates

- ✓ assumes $(x_{t_m}^{[g]})$ from distribution of networks
- ✓ estimate the effects $\bar{\theta}$ "net of context"
- ✓ test differences across g
- ⊙ $\hat{\theta}^{[g]}$ not estimable for small g
- ⊙ pools $\hat{\theta}_r^{[g]}$ independently (for effects $r = 1, \ldots, p$)
- ⊙ no ego covariates

Proposed approach: Hierarchical SAOM

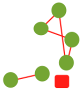
Independently for egos $g = 1, 2, \ldots, G$ we have observations

$x_{t_1}^{[1]}, \ldots, x_{t_M}^{[1]}$



$x_{t_1}^{[2]}, \ldots, x_{t_M}^{[2]}$

$\vdots$



$x_{t_1}^{[G]}, \ldots, x_{t_M}^{[G]}$

Assume a parametric model $\theta^{[g]} \sim N(\mu, \Sigma)$, and conditionally on this identical models

- ✓ estimate μ and Σ rather than $\theta^{[g]}$
- ✓ assumes $(x_{t_m}^{[g]})$ from distribution of network models

Proposed approach: Hierarchical SAOM

Independently for egos $g = 1, 2, \ldots, G$ we have observations

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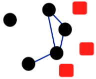
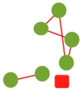


$x_{t_1}^{[2]}, \ldots, x_{t_M}^{[2]}$

$\vdots$



$x_{t_1}^{[G]}, \ldots, x_{t_M}^{[G]}$

Assume a parametric model $\theta^{[g]} \sim N(\mu, \Sigma)$, and conditionally on this identical models

- ✓ estimate μ and Σ rather than $\theta^{[g]}$
- ✓ assumes $(x_{t_m}^{[g]})$ from distribution of network models
- ✓ $\hat{\theta}^{[g]}$ **does not have to** be estimable for all g
- ✓ pools $\hat{\theta}_r^{[g]}$ **consistently** (for effects $r = 1, , p$)
- ✓ includes ego **covariates**

Use the multigroup option

```
FourEffects <- includeEffects(FourEffects, transTrip)
FourEffects <- setEffect(FourEffects, density, random=TRUE)
FourEffects <- setEffect(FourEffects, recip, random=TRUE)
print(FourEffects, includeRandoms=TRUE)
```

now you can chose to set some effecfs to vary across groups

Hierarchical SAOM: model and prior

Assuming the conjugate prior,

- $\Sigma^{-1} \sim \mathrm{wishart}_p(\Lambda_0^{-1}, \nu_0)$, and conditionally on Σ
- $\mu \mid \Sigma \sim N_p(\mu_0, \Sigma/\kappa_0)$.

The joint p.d.f., for data $x^{[1]}, \ldots, x^{[G]}$, is

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$$f_{\text{InvWish}}\left(\Sigma \mid \Lambda_0^{-1}, \nu_0\right) \phi_p\left(\mu \mid \mu_0, \Sigma/\kappa_0\right) \quad \text{prior}$$

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$\times \prod_{g=1}^{G} \phi_p(\theta^{[g]} \mid \mu, \Sigma)$	hierarchical model

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$\times \prod_{g=1}^{G} \phi_p(\theta^{[g]} \mid \mu, \Sigma)$	hierarchical model
$\times \prod_{g=1}^{G} p_{\mathrm{SAOM}}(x^{[g]} \mid \theta^{[g]})$	network model

EXAMPLE OF MULTIPLE GROUPS

traditional nested data-structure

Example: data Andrea Knecht

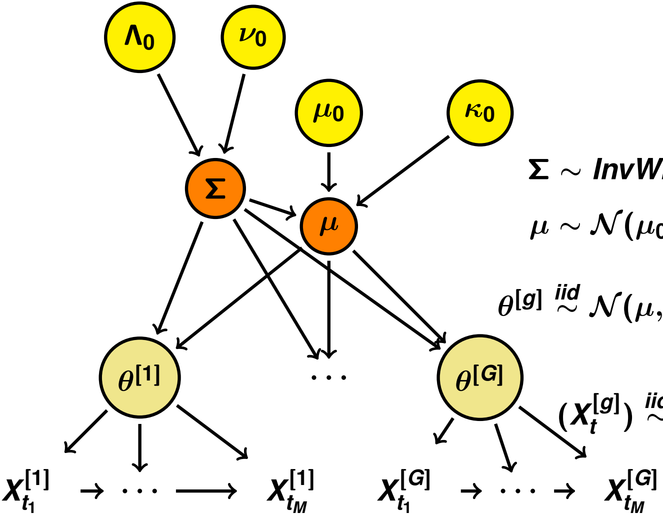
$G = 21$ school classes (Andrea Knecht, PhD thesis Utrecht, 2008; see Knecht, Snijders, Baerveldt, Steglich, & Raub, 2010)
We consider a model for a longitudinal study with 2 waves, and with 9 parameters:
rate of change; outdegree; reciprocity; transitive triplets; 3-cycles; delinquency ego, alter, ego $\times$ alter; sex similarity.

Use the multigroup option

```
groupModel.e <- sienaBayes(GroupsAlgo, data = TwentyOne_Group
initgainGlobal=0.1, initgainGroupwise = 0.001,
                effects = FourEffects, priorMu = Mu, priorSig
priorKappa = 0.01,
prevAns = ans,
nwarm=200, nmain=1000, nrunMHBatches=40,
                nbrNodes=7, silentstart=FALSE)
```

now you can chose to set some effecfs to vary across groups

HSAOM (DAG)



$$\boldsymbol{\Sigma} \sim InvWish_{p_1}(\Lambda_0^{-1}, \nu_0)$$

$$\mu \sim \mathcal{N}(\mu_0, \boldsymbol{\Sigma}/\kappa_0)$$

$$\theta^{[g]} \overset{iid}{\sim} \mathcal{N}(\mu, \boldsymbol{\Sigma})$$

$$(X_t^{[g]}) \overset{iid}{\sim} SAOM(\theta^{[g]})$$

Hierarchical SAOM: estimation

We use a Bayesian MCMC inference scheme:

Draw posterior variates

$$(v^{[1]}, \ldots, v^{[G]}, \theta^{[1]}, \ldots, \theta^{[G]}, \mu, \Sigma)$$

by iteratively drawing from the full conditional posteriors

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- $(v^{[1]}, \dots, v^{[G]}) \sim [v^{[1]}, \dots, v^{[G]} | \theta^{[1]}, \dots, \theta^{[G]}, x^{[1]}, \dots, x^{[G]}]$ (unobserved sample paths)

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- $(\theta^{[1]}, \ldots, \theta^{[G]}) \sim [\theta^{[1]}, \ldots, \theta^{[G]} | v^{[1]}, \ldots, v^{[G]}, x^{[1]}, \ldots, x^{[G]}, \mu, \Sigma]$ (group-level parameters)
- $(\mu, \Sigma) \sim [\mu, \Sigma | \theta^{[1]}, \ldots, \theta^{[G]}]$ (global parameters)

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  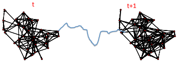

  (unobserved sample paths)
- $(\theta^{[1]}, \dots, \theta^{[G]}) \sim [\theta^{[1]}, \dots, \theta^{[G]} | v^{[1]}, \dots, v^{[G]}, x^{[1]}, \dots, x^{[G]}, \mu, \Sigma]$ (group-level parameters)
- $(\mu, \Sigma) \sim [\mu, \Sigma | \theta^{[1]}, \dots, \theta^{[G]}]$ (global parameters)

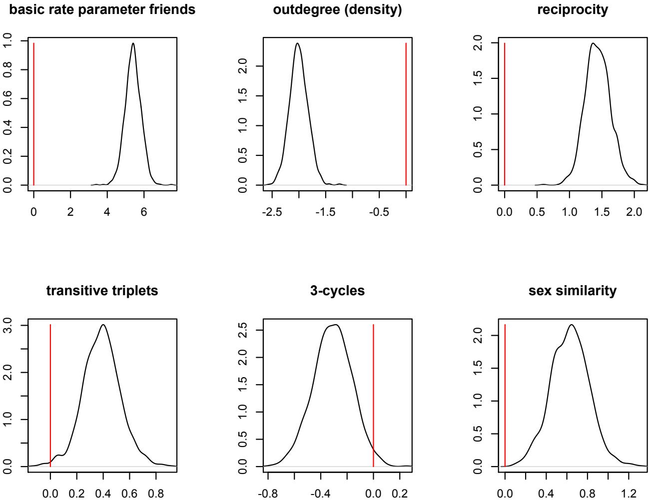

Figure: Posterior distributions μ

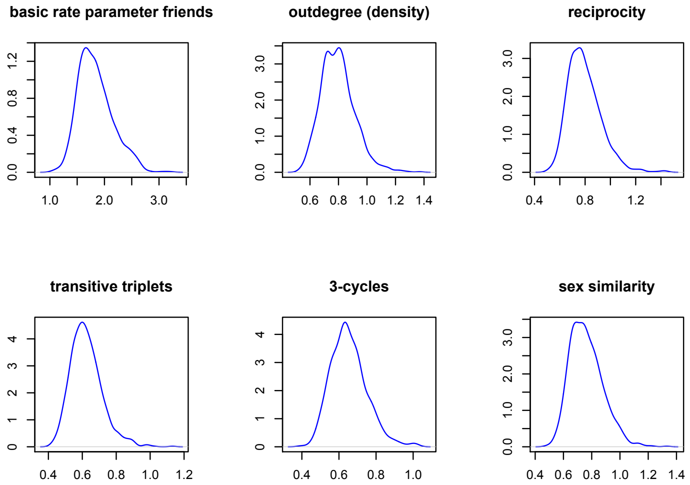

Figure: Posterior distributions SDs, square roots of diag elements Σ

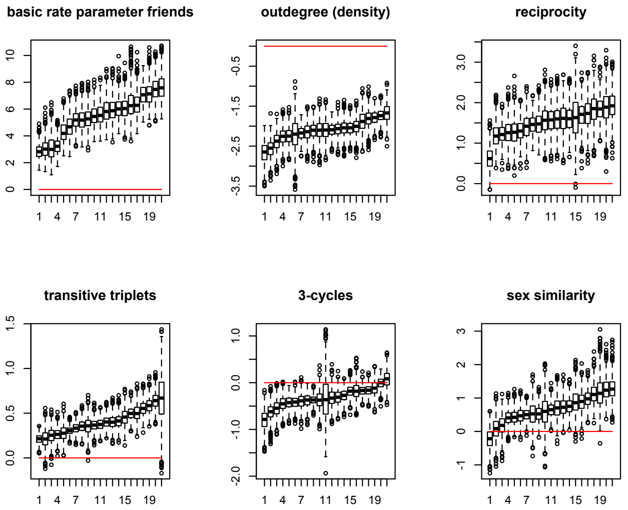

Figure: Posterior predictive distributions for $\theta^{[g]}$ (ordered)

Bayesian analysis of SAOM - final remarks

- estimation in `sienaBayes` that is in `RSienaTest` (download from RForge)
- implementation is robust but slow (should be improved in future implementations)
- A paper (started in 2010)is under review and a preprint available at http://arxiv.org/abs/2201.12713

Last words

A lot of material
– programs, manuals, papers, workshop announcements –
can be found at the Siena website:

http://www.stats.ox.ac.uk/siena/

There used to be a user's group:

http://groups.yahoo.com/groups/stocnet/

That has now moved to GitHub:

https://github.com/snlab-nl/rsiena/wiki/