Tensions and Treasures

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1. tensions
2. treasures
3. tell me who your friends
4. the road goes ever

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Tensions

though redundant to calculate $x(t_2)$ from $x(t_1)$, are retained because they facilitate the computation of the likelihood. Define $x^{(k)} = x(T_k)$; the digraphs $x^{(k)}$ and $x^{(k-1)}$ differ in element (I_k, J_k) provided $I_k \neq J_k$, and in no other elements.

The probability function of the sample path, conditional on $x(t_1)$, is given by

$$
\begin{aligned}
&p_{\mathrm{sp}}\{V = \big((i_1, j_1), \ldots, (i_R, j_R)\big); \alpha, \beta\} = \\
(14) \qquad &\qquad P_{\alpha,\beta}\{T_R \le t_2 < T_{R+1} \mid x^{(0)}, (i_1, j_1), \ldots, (i_R, j_R)\} \\
&\qquad \times \prod_{r=1}^{R} \pi_{i_r}(\alpha, x^{(r-1)})\, p_{i_r, j_r}(\beta, x^{(r-1)}) \ ,
\end{aligned}
$$

where π_i is defined in (2), and p_{ij} in and just after (5). Denote the first component of (14) by

$$
\begin{aligned}
(15) \quad &\kappa\big(\alpha, x^{(0)}, (i_1, j_1), \ldots, (i_R, j_R)\big) \\
&\qquad = P_{\alpha,\beta}\{T_R \le t_2 < T_{R+1} \mid x^{(0)}, (i_1, j_1), \ldots, (i_R, j_R)\} \ .
\end{aligned}
$$

Conditioning on $x^{(0)}, (i_1, j_1), (i_2, j_2), \ldots,$ (and not on $x(t_2)$!), the differences $T_{r+1} - T_r$ are independently exponentially distributed with parameters $\lambda(\alpha, x^{(r)})$. Hence under this conditioning the distribution of $T_R - t_1$ is

Tensions? No formulae (almost).

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How can these tensions be overcome?

.

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very impolitely ...

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   hard computation
2. gauge uncertainty in the results
   p-values, standard errors, posterior distributions
3. combining these:
   assess quality of models / theories
   to enable moving forward in the empirical cycle.

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about the models for complicated dependencies
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with some historical remarks)

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and then again about models for dependencies.

Models for network dependencies

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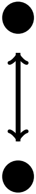
1. *Reciprocity* was noted by Moreno (1934) and has been investigated a lot.

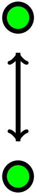
   An $n \times n$ adjacency matrix can be split into $\binom{n}{2}$ dyads;

   $\Rightarrow$ reciprocity is a manageable dependency.



2. *Homophily* was discovered by Lazarsfeld and Merton (1954) and is related to exogenous variables (as opposed to endogenous structure);

   ⇒ homophily is a manageable dependency.



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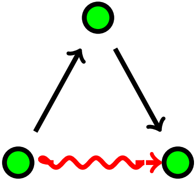
Transitivity was discussed already by Rapoport (1954).
Davis, Holland and Leinhardt (1970s) had an impressive research program demonstrating the ubiquity of transitivity in sociometric data.



Holland and Leinhardt (1976) systematized this to measures for *triadic dependencies*, evaluated under *null models*.

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Two different structural effects: this requires dependencies represented in estimated model, not only in statistics tested in a null model.

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This allows researchers
to model several theories simultaneously.

(Cf. control variables – simple version of this.)

Treasures

A great step was made by Frank and Strauss (1986)
who developed Markov graphs,
a model representing transitivity
in a kind of generalized linear model,
the probability of observing a particular network
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where the 'variables' X_k depend on the network itself :
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In the linear combination we can include also
exogenous effects: attributes of actors, etc.

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On to *probability models*,
then back to *dependencies*.

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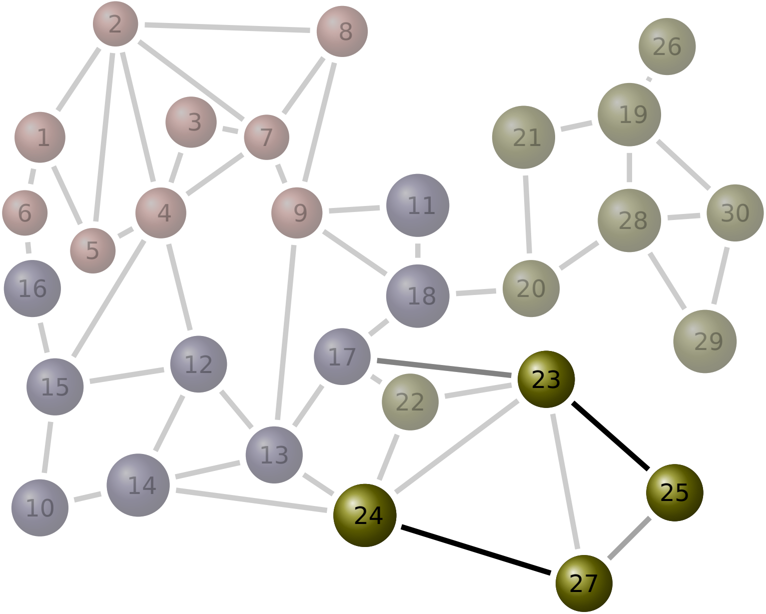
Assumptions can be about independence,
conditional independence, distributional shape, etc.

The model of Frank and Strauss, *Markov graph*,
was based on a conditional independence assumption
which they called Markov dependence:

non-adjacent ties are independent,
conditionally on the rest of the graph.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Frank and Strauss proved that this type of conditional independence corresponds to measuring transitivity by counting closed triangles or transitive triplets.

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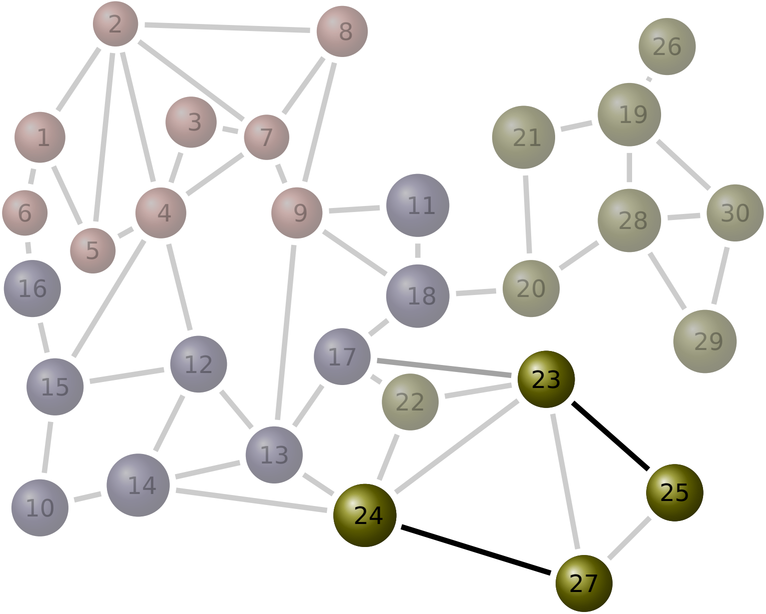
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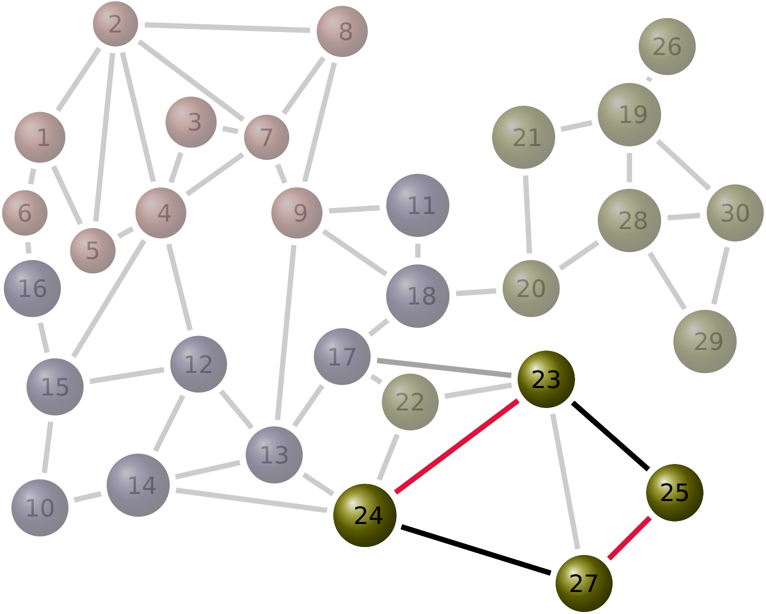
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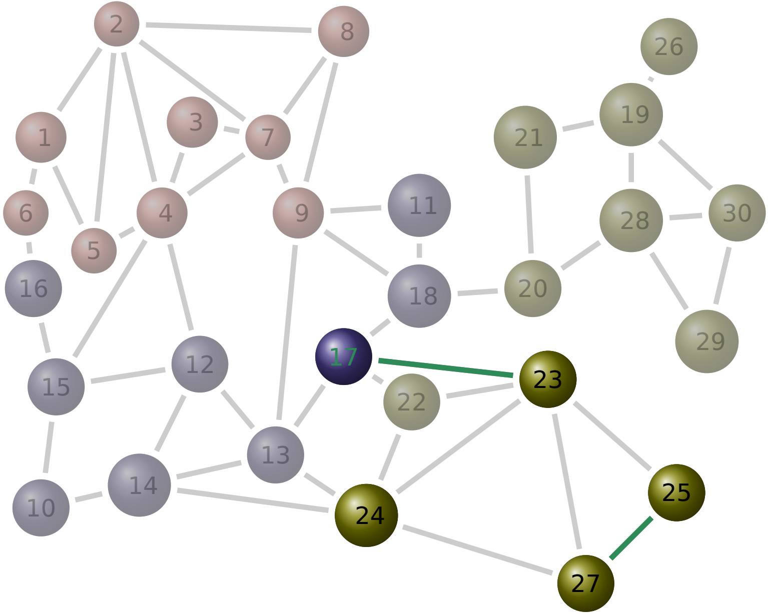
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- ⇒ represent many different kinds of dependencies;
- ⇒ include these dependencies simultaneously,
  also effects of measured (‘exogenous’) variables;
- ⇒ be estimated using Statnet and pnet,
  yielding also goodness of fit assessments.

How does this help in gauging uncertainty?

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The basic purpose of such assertions is
grappling with the question
(thanking Ivo Molenaar, 1988)

.

What would happen if you did it again?

The probability distributions stand for variability
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Random terms will stand for sources of variability left out of your model –
but also model approximations, etc.

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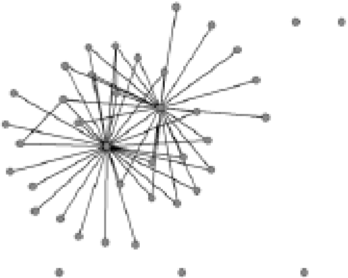
Statistical models for networks are based usually on, instead of independence: *exchangeability* of actors which sometimes
is more reasonable than some other times.

Garry Robins sampled this network from a particular specification of an ERGM.

A priori the nodes are exchangeable;



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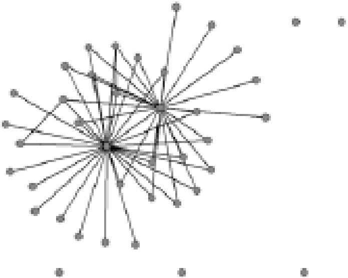

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estimates of variability for samples from this ERG distribution would themselves be highly variable...

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In modeling longitudinal data we can exploit
the arrow of time :
the present depends on the past, not on the future.

Holland & Leinhardt

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Elaborated by Stanley Wasserman (1977-1981)
in models representing (separately)
two types of dependence:
reciprocity and popularity.

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Again, linear predictor to combine theories,
dependencies, measured variables, controls ...

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⇒ estimation by Siena, now RSiena .

Some things we have learned

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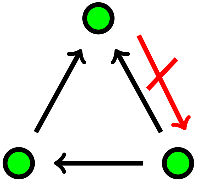
- In affective relations like friendship,
  reciprocation often has a strength of about 2
  on a logistic scale:
  for making new ties or maintaining existing ties,
  the tie being reciprocated
  increase chances by factor 5-10 ($e^2 = 7.389$).

- Affective relations often have a locally hierarchical nature: transitive triplets yes, 3-cycles no. (See already Davis 1970.)



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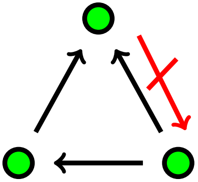
- Hierarchical structures (in-degrees $\sim$ high status) can be distinguished from locally transitive (clustered) structures.



- For effects of psychological traits on friendship dynamics:
  Big Five:
  openness, extraversion, agreeableness, neuroticism and conscientiousness.

- For effects of psychological traits on friendship dynamics:
  tendencies to homophily on
  openness, extraversion, agreeableness;
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  (Selfhout/van Zalk et al., *J. Personality*, 2010)

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  And, unsurprising perhaps:
  extraverts make more friends;
  agreeable persons get more friends.

Tell me who your friends are

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'homophily at distance 2'.

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4. negative *diversity, social capital* :
   alters bridging to different third actors.

¿ is there a tendency to homophily at distance 2,
while controlling for (regular) homophily ?

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↬ We also have to control for transitivity.

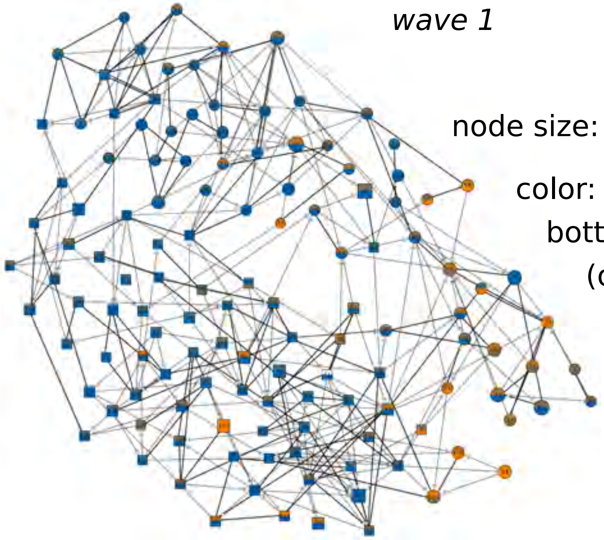
.

Example :

Study of smoking initiation and friendship
(following up on P. West, M. Pearson & others;
cf. Steglich, Snijders & Pearson, *Sociol. Methodology*, 2010).

One school year group from a Scottish secondary school starting at age 12-13 years, monitored over 3 years;
129 (out of 160) pupils present at all 3 observations;
three waves, at appr. 1 year intervals.

Smoking: values 1–3; drinking: values 1–5;
covariates:
gender, smoking of parents and siblings (binary),
money available (range 0–40 pounds/week).

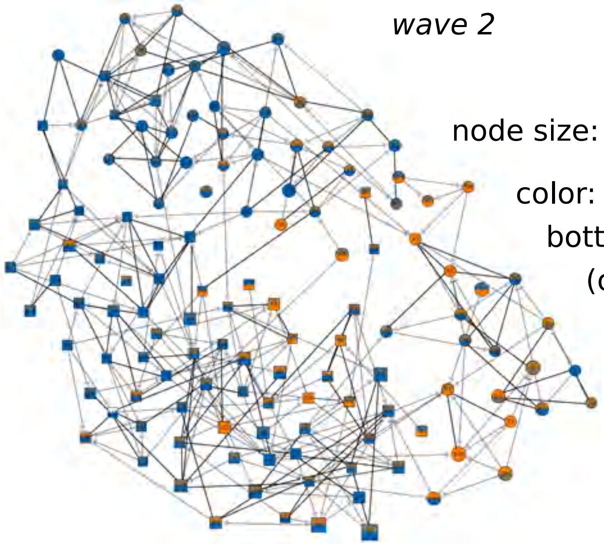


wave 1

girls: circles
boys: squares

node size: pocket money

color: top = drinking
bottom = smoking
(orange = high)

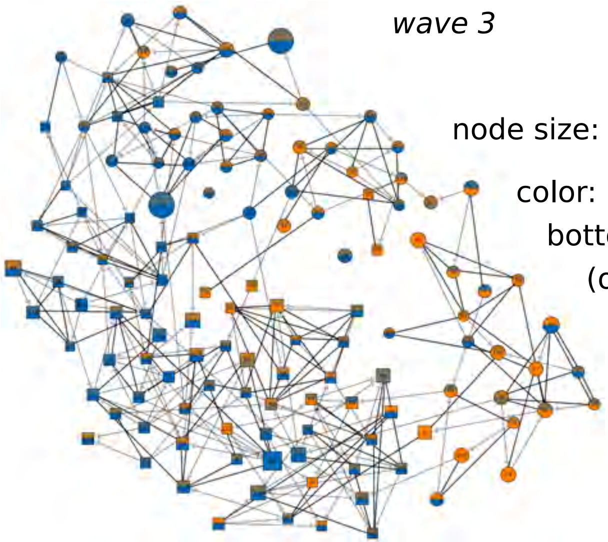


wave 2

girls: circles
boys: squares

node size: pocket money

color: top = drinking
bottom = smoking
(orange = high)



wave 3

girls: circles
boys: squares

node size: pocket money

color: top = drinking
bottom = smoking
(orange = high)

Some descriptives

Average degree varies between 3.5 and 3.7.

Table of tie changes

	$0 \Rightarrow 0$	$0 \Rightarrow 1$	$1 \Rightarrow 0$	$1 \Rightarrow 1$	Jaccard
Per. 1	15,800	235	265	212	$\frac{212}{235+265+212} = .30$
Per. 2	15,838	227	210	237	$\frac{237}{227+210+237} = .35$

Wave 1 $\Rightarrow$ wave 2: 235 ties created, 265 ties dissolved.
Wave 2 $\Rightarrow$ wave 3: 227 ties created, 210 ties dissolved.

Structural effects

		estimate	(s.e.)
1 .	outdegree (density)	−0.76*	(0.38)
2 .	reciprocity	1.94***	(0.12)
3 .	transitive triplets	0.45***	(0.05)
4 .	3-cycles	−0.21**	(0.09)
5 .	transitive ties	0.68***	(0.10)
6 .	indegree − popularity (sqrt)	*n.s.*	
7 .	outdegree − popularity (sqrt)	−0.86***	(0.12)
8 .	outdegree − activity (sqrt)	−0.65***	(0.10)

Attribute effects

		estimate	(s.e.)
9 .	sex alter	.	
10.	sex ego	.	
11.	sex similarity	.	
12.	sex similarity at distance 2	.	
13.	drinking similarity	.	
14.	drinking sim. at distance 2	.	
15.	smoking similarity	.	
16.	smoking sim. at distance 2	.	
17.	money alter	.	
18.	money similarity	.	
19.	money sim. at distance 2	.	

.

Attribute effects

		estimate	(s.e.)
9 .	sex alter	−0.08	(0.10)
10.	sex ego	0.13	(0.12)
11.	sex similarity	0.60***	(0.12)
12.	sex similarity at distance 2	0.64	(0.40)
13.	drinking similarity	0.27°	(0.15)
14.	drinking sim. at distance 2	3.64*	(1.66)
15.	smoking similarity	0.29*	(0.12)
16.	smoking sim. at distance 2	*n.s.*	.
17.	money alter	0.017**	(0.006)
18.	money similarity	1.25***	(0.31)
19.	money sim. at distance 2	*n.s.*	.

Conclusion :

Evidence for distance-2 homophily
for drinking behavior,
weakly for sex,
not for smoking or pocket money.

Other example :

Large-scale study of adolescent development
initiated by Håkan Stattin and Margaret Kerr (Ørebro).

All 12-18 year olds in a small town in Sweden,
yearly waves.

Here: 339 individuals,
cohort of all 13 year olds in given year, 3 waves.

Collaboration with Håkan Stattin, Margaret Kerr,
Bill Burk, Paulina Preciado Lopez.

Some descriptives

Relation: friends & important persons.

Average degree increases from 4.0 to 4.7.

Table of tie changes

	$0 \Rightarrow 0$	$0 \Rightarrow 1$	$1 \Rightarrow 0$	$1 \Rightarrow 1$	Jaccard
Per. 1	105,901	750	542	719	$\dfrac{719}{750+542+719} = .36$
Per. 2	108,450	630	588	888	$\dfrac{888}{630+588+888} = .42$

Wave 1 $\Rightarrow$ wave 2: 750 ties created, 542 ties dissolved.
Wave 2 $\Rightarrow$ wave 3: 630 ties created, 588 ties dissolved.

Structural effects

		estimate	(s.e.)
1 .	outdegree (density)	.	
2 .	reciprocity	.	
3 .	transitive triplets	.	
4 .	3-cycles	.	
5 .	indegree − popularity (sqrt)	.	
6 .	indegree − pop. (sqrt) × time	.	
7 .	outdegree − popularity (sqrt)	.	
8 .	outdegree − activity (sqrt)	.	

.

Structural effects

		estimate	(s.e.)
1 .	outdegree (density)	−2.81 * * *	(0.20)
2 .	reciprocity	2.34 * * *	(0.08)
3 .	transitive triplets	0.61 * * *	(0.02)
4 .	3-cycles	−0.54 * * *	(0.05)
5 .	indegree − popularity (sqrt)	0.11 *	(0.05)
6 .	indegree − pop. (sqrt) × time	−0.09 * *	(0.03)
7 .	outdegree − popularity (sqrt)	−0.92 * * *	(0.06)
8 .	outdegree − activity (sqrt)	−0.29 * * *	(0.05)

.

Settings effects

		estimate	(s.e.)
9 .	log distance	.	
10.	same school	.	
11.	same class	.	
12.	same class × time	.	
13.	same ethnicity	.	

.

Settings effects

		estimate	(s.e.)
9 .	log distance	-0.08^{***}	(0.02)
10.	same school	0.96^{***}	(0.06)
11.	same class	0.56^{***}	(0.05)
12.	same class × time	0.26^{**}	(0.08)
13.	same ethnicity	0.26^{**}	(0.08)

.

Attribute effects

		estimate	(s.e.)
14.	sex alter	.	
15.	sex ego	.	
16.	sex similarity	.	
17.	sex similarity at distance 2	.	
18.	delinquency alter	.	
19.	delinquency ego	.	
20.	delinquency similarity	.	
21.	delinquency sim. distance 2	.	

.

Attribute effects

		estimate	(s.e.)
14.	sex alter	0.07	(0.06)
15.	sex ego	0.08	(0.09)
16.	sex similarity	0.30**	(0.09)
17.	sex similarity at distance 2	1.08***	(0.32)
18.	delinquency alter	0.15***	(0.02)
19.	delinquency ego	0.04	(0.02)
20.	delinquency similarity	0.23*	(0.10)
21.	delinquency sim. distance 2	3.41***	(0.88)

Conclusion :

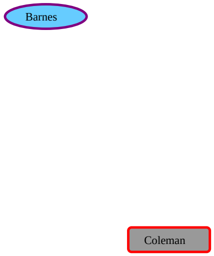
1. Evidence for distance-2 homophily
for sex and delinquent behavior.

Conclusion :

1. Evidence for distance-2 homophily
   for sex and delinquent behavior.
2. More generally:
   statistical modeling can bridge between
   network analysis and mainstream social science.

bridging intermezzo

1982



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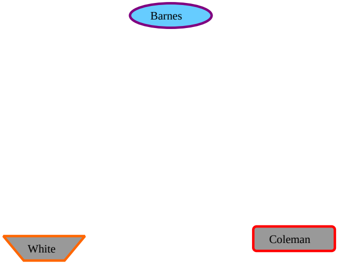

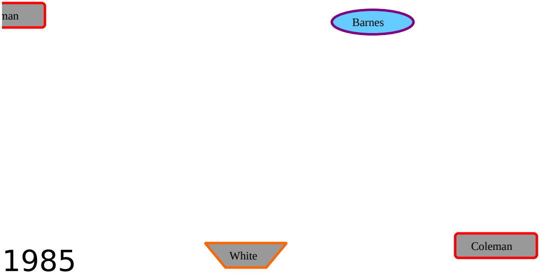
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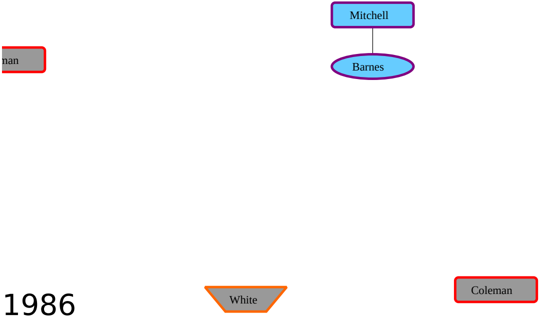

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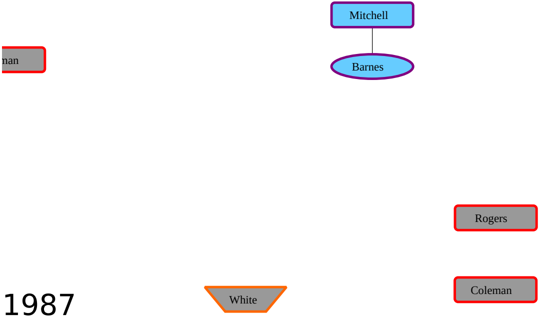

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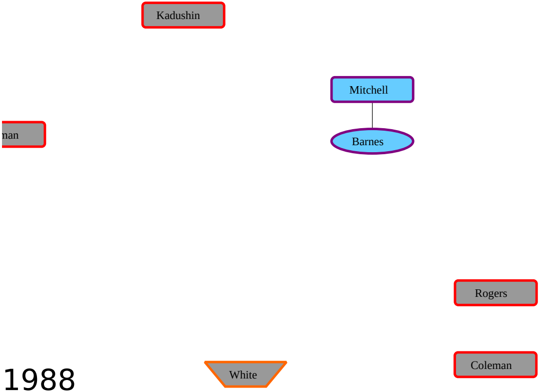

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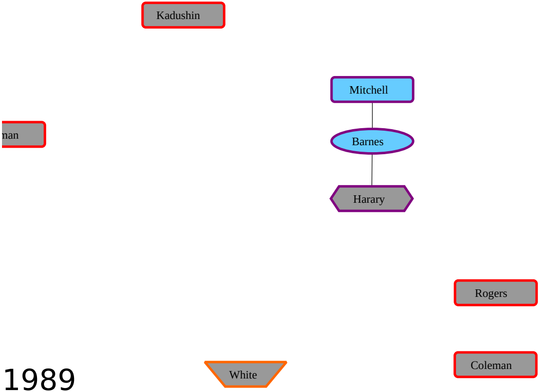

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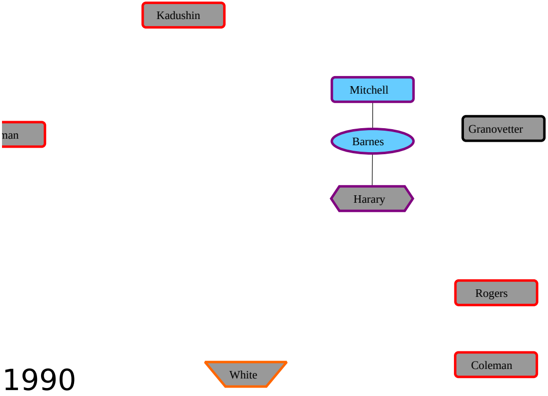
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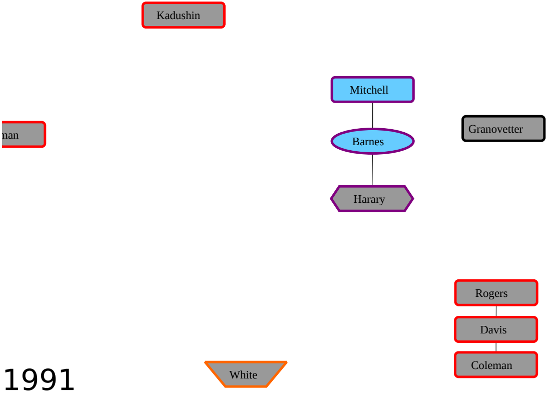
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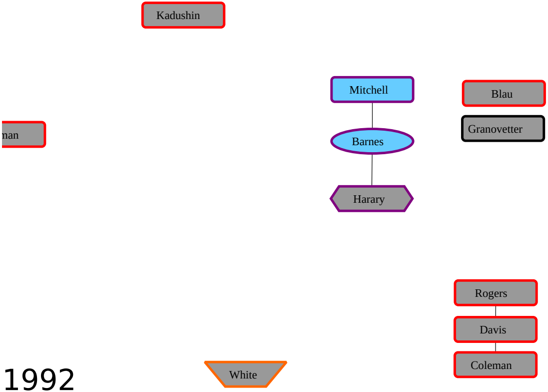
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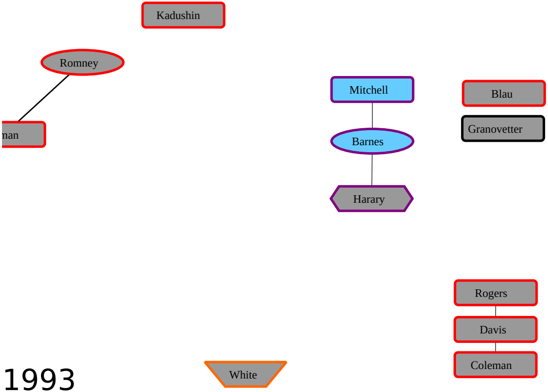
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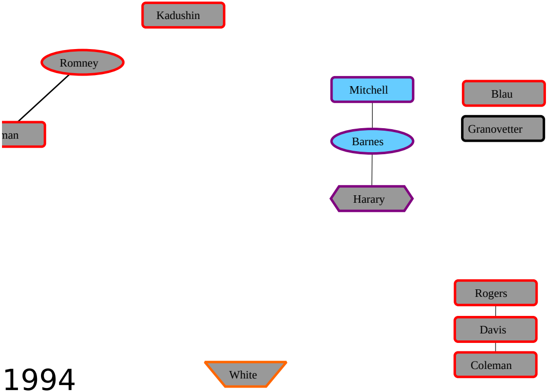
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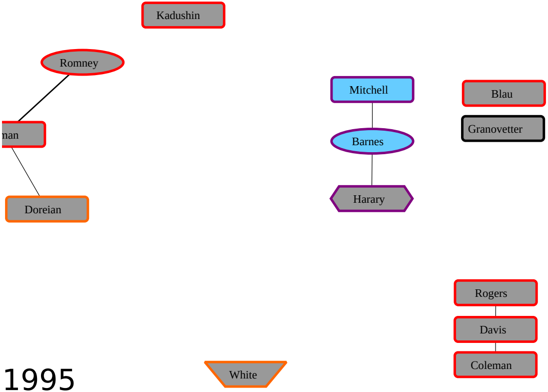
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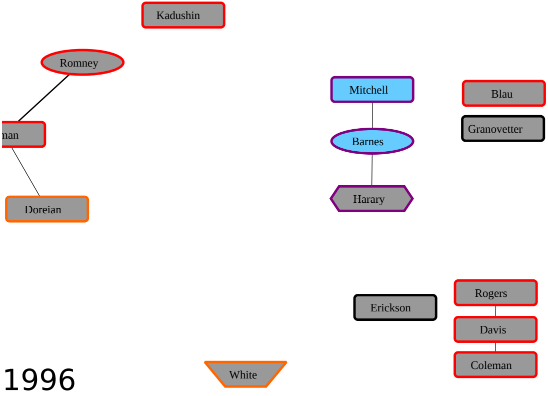
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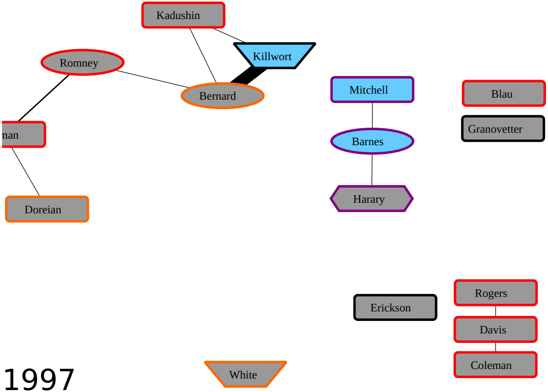
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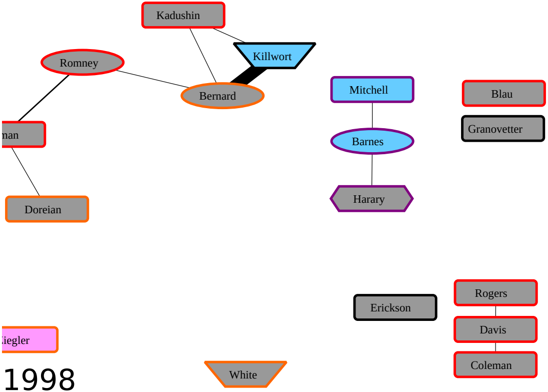
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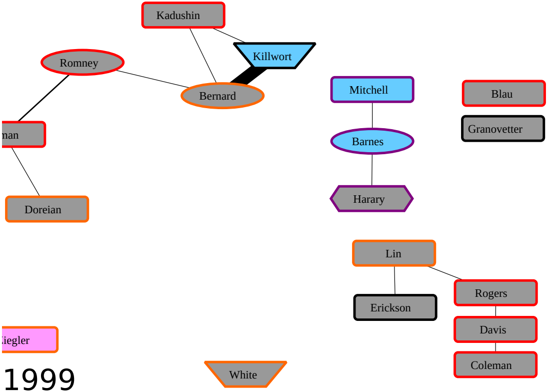
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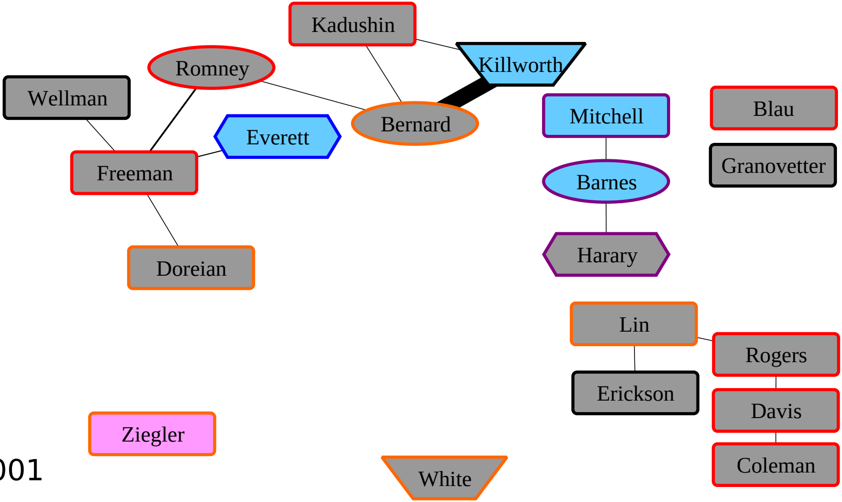
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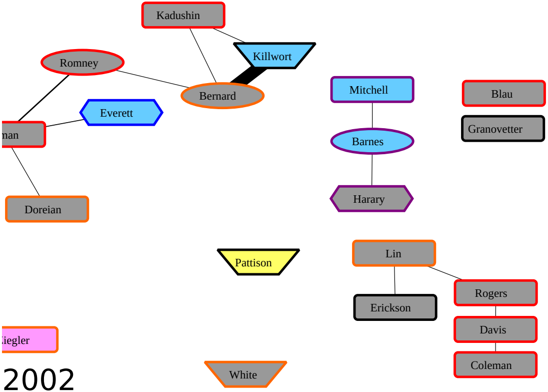
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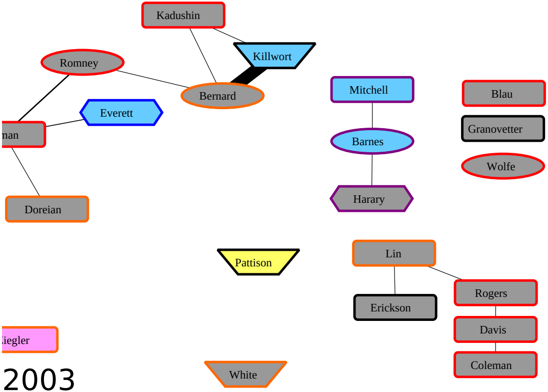
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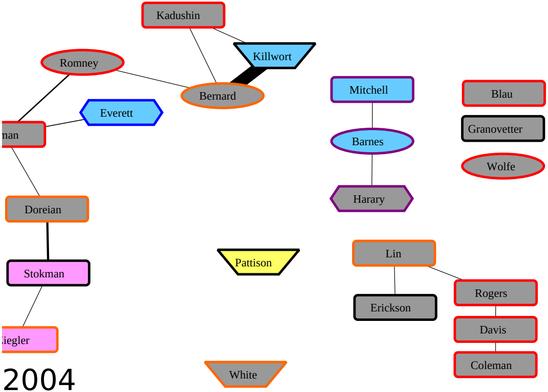
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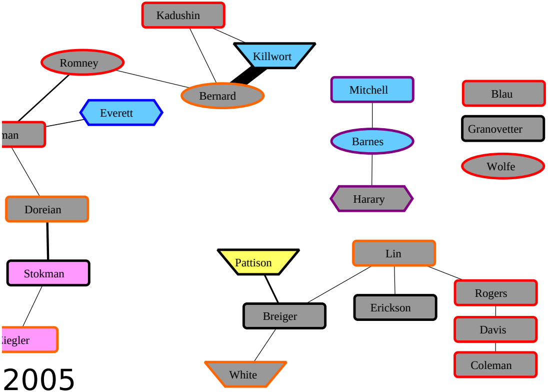
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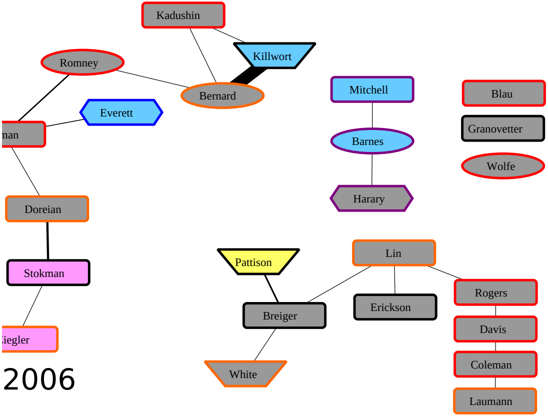
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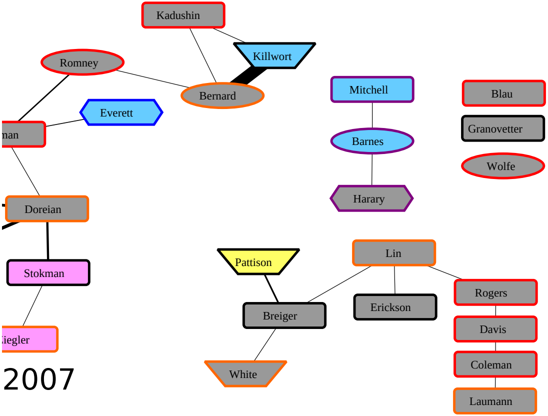
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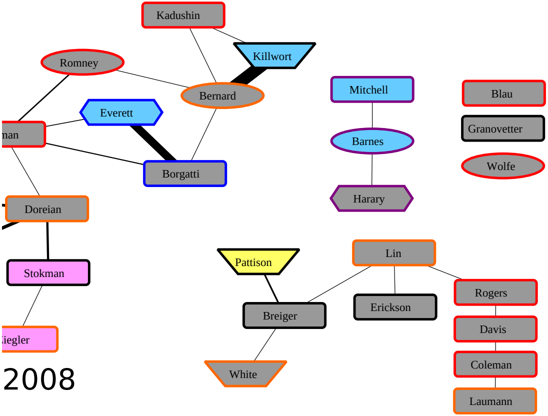
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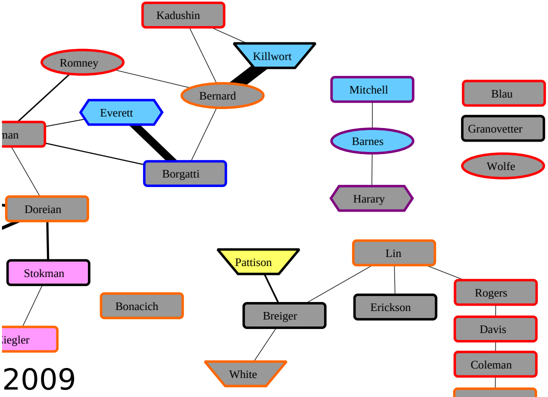
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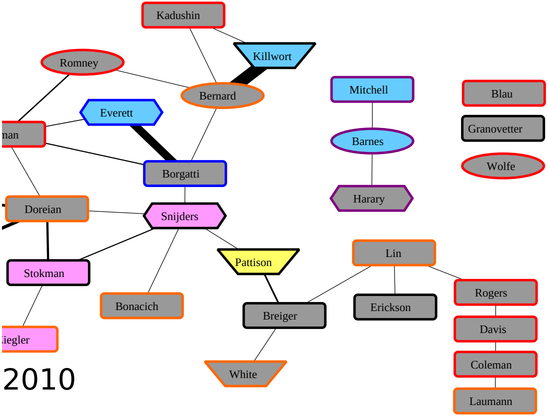
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2010

back to tensions,
treasures,
tell me who

The actor-oriented framework lends itself nicely for modeling *co-evolution*

network $\Longleftrightarrow$ individual outcomes

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network $\Longleftrightarrow$ individual outcomes

Networks are dependent
as well as independent variables.

Social capital theory
here clearly argues the connection:

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$\Rightarrow$ Our social network has an effect on us;

The actor-oriented framework lends itself nicely for modeling *co-evolution*

network $\Longleftrightarrow$ individual outcomes

Networks are dependent
as well as independent variables.

Social capital theory
here clearly argues the connection:

- $\Rightarrow$ Our social network has an effect on us;
- $\Rightarrow$ therefore we try to 'improve' our network.

Investigating network effects on individual outcomes now become fashionable as the study of

peer effects .

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Much non-network literature has an atomistic prejudice, regarding endogenous network choice as a nuisance, which best is being worked out of the model;
and using any ‘peer’ delineation that is available.

Investigating network effects on individual outcomes now become fashionable as the study of

peer effects .

Much non-network literature has an atomistic prejudice, regarding endogenous network choice as a nuisance, which best is being worked out of the model;
and using any ‘peer’ delineation that is available.

However –
the choice of our social neighborhood
is the essence of social science.

The question is not

The question is not

¿how much is added to R^2 by including network variables ?

The question is not

¿how much is added to R^2 by including network variables ?

but

¿what choice do actors have
in selecting their social surroundings,
and how does this affect their chances and outcomes ?

Christian Steglich, Tom Snijders, Mike Pearson,

Dynamic Networks and Behavior:

Separating Selection from Influence

(*Sociological Methodology, 2010*)

http://dx.doi.org/10.1111/j.1467-9531.2010.01225.x

discusses methods for studying peer effects

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- from an actor perspective
- based on explicitly modeling the feedback

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discusses methods for studying peer effects

- from an actor perspective
- based on explicitly modeling the feedback
  $$\text{network} \Longleftrightarrow \text{individual outcomes}$$
- incorporating the network as an interesting phenomenon rather than a nuisance.

'Selection and influence'

Co-evolution of networks and behavior:

model the mutually dependent dynamics of
networks ($\sim$ selection)
and behavior ($\sim$ influence)

'Selection and influence'

Co-evolution of networks and behavior:

model the mutually dependent dynamics of
networks ($\sim$ selection)
and behavior ($\sim$ influence)

as a way to studying peer effects
while simultaneously focusing on peer selection.

.

The advantage:

The advantage: more detail .

The advantage: more detail .

The difficulty:

The advantage: more detail .

The difficulty: dependence on the model.

Example, also from the Ørebro network studies:

See:

Burk et al., *Int. J. Behav. Development*, 2007;

Burk et al. *Revue Française de Sociologie*, 2008.

445 students initially aged 9–14 years (ave. 10.6):
all grade-4 pupils with complete data & their nominees;
5 waves, intervals 1 year.

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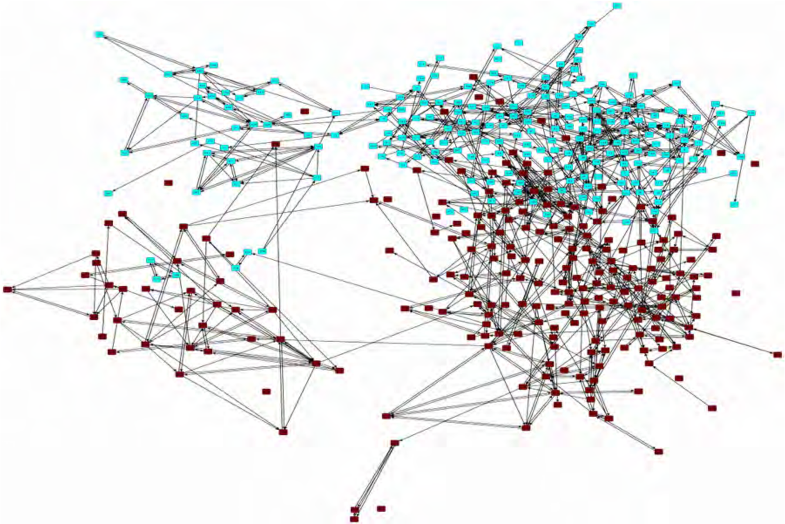
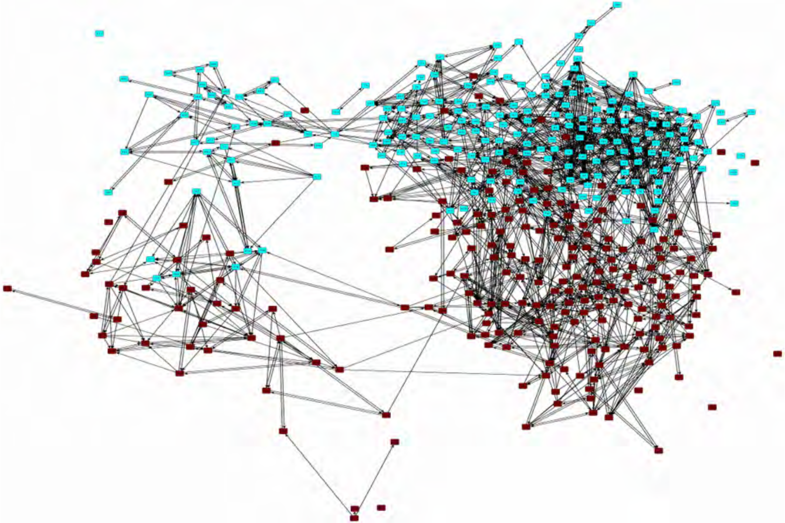
445 students initially aged 9–14 years (ave. 10.6):
all grade-4 pupils with complete data & their nominees;
5 waves, intervals 1 year.

Measures:
peer contacts (talk, hang out, do things);
delinquency; school involvement.

Descriptives

Wave	1	2	3	4	5
Mean degree	2.4	2.6	3.0	3.8	4.1
Reciprocity	0.42	0.46	0.45	0.49	0.49
Transitivity	0.31	0.38	0.37	0.45	0.46
Delinquency (1–3)	1.05	1.07	1.12	1.19	1.28
School inv. (1–5)	4.66	3.95	3.79	3.62	3.50





Friendship model

Outdegree	–2.73***	(0.23)
Reciprocity	2.59***	(0.07)
Transitive triplets	0.08***	(0.02)
Schoolmates	1.01***	(0.13)
Classmates	0.26	(0.45)
Age alter	0.24***	(0.03)
Age ego	–0.08*	(0.04)
Age similarity	1.94***	(0.18)
Sex (F) alter	–0.11	(0.06)
Sex ego	0.21*	(0.08)
Sex similarity	0.80***	(0.07)

Friendship model (continued)

Delinquency alter	0.15∗∗∗	(0.04)
Delinquency ego	–0.04	(0.13)
Delinquency similarity	1.55∗∗∗	(0.44)
School inv. alter	0.04	(0.02)
School inv. ego	0.00	(0.02)
School inv. similarity	0.35∗	(0.14)

Delinquency dynamics

Similarity to friends	1.444*	(0.643)
Age	0.152*	(0.075)
Sex (F)	–0.212*	(0.091)
School involvement	–0.008***	(0.001)

Delinquency dynamics

Similarity to friends	1.444*	(0.643)
Age	0.152*	(0.075)
Sex (F)	–0.212*	(0.091)
School involvement	–0.008***	(0.001)

School involvement dynamics

Similarity to friends	0.300	(0.189)
Age	0.007	(0.034)
Sex (F)	0.062	(0.045)
Delinquency	–0.064*	(0.030)

Conclusions

Friendship is influenced
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by similarity on delinquent behavior
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mutually negative influence (but not strong)
between school involvement and delinquency.

Network delineation issues

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1. What is
   – for a given relation and a given behavior –
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   – for a given relation and a given behavior –
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   direct ties; reciprocated ties; Simmelian ties;
   structurally equivalent others; larger setting ...
2. How are the results of these statistical models
   affected by network delineation?

Other statistical models ...

This talk has attempted to provide some elucidation and perspective for *some* statistical network models

but there are many more —

network sampling: work by Frank, Thompson, Handcock, Gile, Heckathorn, Salganik, etc.;

latent variable models;

see book by Eric Kolaczyk;

overview article Goldenberg, Zheng, Fienberg, Airoldi *Foundations and Trends in Machine Learning* (2010);

special issue *Annals of Applied Statistics* (soon).

The road goes ever on and on

We are only beginning to scratch the surface.

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research problems lead to new methods

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$\Rightarrow$ we are working with $N = \sharp$(networks) !

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7. mathematical proofs

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3. construction, documentation,
   dissemination of software.

... collaborators ....

Christian Steglich, Johan Koskinen,
Marijtje van Duijn, Mark Huisman, Michael Schweinberger,
Pip Pattison, Garry Robins, Mark Handcock,
with runners up Josh Lospinoso, Paulina Preciado Lopez,
Viviana Amati,
for methods development & & ;
John Light, Ruth Ripley, Krists Boitmanis,
for RSiena development & & ,

NWO, NIH for funding of software development;

.

... more collaborators ....

Gerhard van de Bunt, Evelien Zeggelink, Roger Leenders, Frans Stokman, Rafael Wittek, Siegwart Lindenberg, Andrea Knecht, Michael Pearson, John Light, John Scholz, Ainhoa de Federico de la Rúa, Chris Baerveldt, Emmanuel Lazega, Lise Mounier, Alessandro Lomi, Francesca Pallotti, Birgit Pauksztat, Mark Pickup, Paola Tubaro, Vanina Torlo, Bill Burk, Liesbeth Mercken, Isidro Maya Jariego, Håkan Stattin, Margaret Kerr, Maarten van Zalk, Filip Agneessens, Maurits de Klepper, Ulrik Brandes, Jürgen Lerner, Miranda Lubbers, José Luis Molina, Jo Halliday, Laurence Moore, ...

and others, for substantive discussions, theory, applications,