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Statistical Analysis of Complete Social Networks

Co-evolution of Networks & Behaviour

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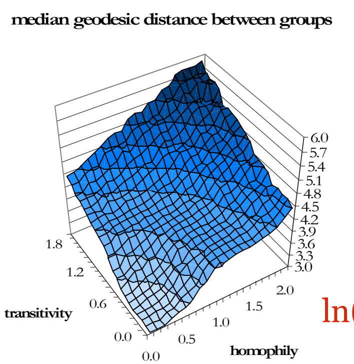
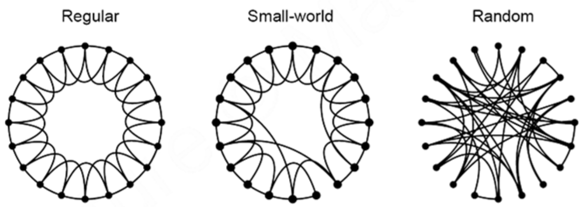




$$\ln\left(\frac{\Pr(x^c \to_i x^b)}{\Pr(x^c \to_i x^a)}\right) = \sum_{k=1}^{K} \beta_k \left(s_{ik}(x^b) - s_{ik}(x^a) \right)$$

Co-evolution models for networks and behaviour

A. Interdependence of networks and behaviour

B. Extension of the stochastic actor-based modelling framework to "behaviour" dimensions

C. The case of *homogeneity bias / network autocorrelation*

D. An example:
Co-evolution of music taste, alcohol & friendship

E. Notes on the modelling of peer influence

A: Interdependence of networks and behavior

As could be seen already, social network dynamics can depend on actors' individual characteristics.

Some examples:

- homophily: interaction with similar others can be more rewarding than interaction with dissimilar others
- heterophily / exchange: selection of partners such that they complement own abilities and resources
- popularity: some properties make actors more attractive as network partners than other actors
- activity: some properties make actors send more network ties than other actors do

Vice versa, also actors' characteristics can depend on the social network

Changeable individual characteristics can be affected by others in the network: behaviour proper, but also opinions, attitudes, intentions, etc. – we use the word ***behaviour*** for all of these!

Some examples:

- contagion / assimilation: innovations spreading in a professional community; adolescents adopting friends' attitudes; investment bankers copying behaviour of successful competitors
- differentiation: division of tasks in a work team
- effects of isolation: lack of connections in a network may lead to behaviour that well-connected actors do not exhibit

There often is a "natural pairing" of effects in both directions

Example: *Suppose "success attracts sponsors". This will lead to a positive association between success and indegree in any cross-sectional data collection. The same cross-sectional association, however, can also be explained by "sponsors make you successful".*

More generally, any *cross-sectional association* between network features and individual characteristics could come about by at least two *competing mechanisms*:

1. The network leads to behavioural alignment.
2. Actors' behaviour leads to network alignment.

Aim: construction of a model that allows a teasing apart.

B. Extension of the network modelling framework

- Stochastic process in the (extended!) space of all possible network-behaviour configurations

beh

net

r^n states, where **r** is the range of the <u>ordinal</u> behaviour variable **z**

$2^{n(n-1)}$ states in the case of a (binary) directed network variable **x**

- Again, the first observation is not modelled but conditioned upon as the process' starting value.
- Discrete change is modelled as occurring in continuous time, but now there are two types of change.

Actor based approach now in two domains

- Network actors drive the process: individual decisions.
  - two domains of decisions:
    - decisions about network neighbours,
    - decisions about own behaviour.
  - per decision domain two model parts:
    - *When* can actor **i** make a decision? (rate functions λ^{net}, λ^{beh})
    - *Which* decision does actor **i** make? (objective functions f^{net}, f^{beh})

By again sampling waiting times and identifying the shortest one, it becomes clear *who* makes *which type* of change.

Monte Carlo simulation

Initialise system at 1st observation

Each actor draws one waiting time for his/her next network change and one for his/her next behaviour change

rate functions
$\lambda^{net}, \lambda^{beh}$

Actor and change type of the shortest waiting time are identified

Is time up?

yes

Terminate and return system state

no

objective functions
f^{net}, f^{beh}

Actor implements change of given type

Time is updated

Schematic overview of model components

	Timing of decisions	**Decision rules**
Network evolution	Network rate function $\lambda^{\mathbf{net}}$	Network objective function $\mathbf{f}^{\mathbf{net}}$
Behavioural evolution	Behaviour rate function $\lambda^{\mathbf{beh}}$	Behaviour objective function $\mathbf{f}^{\mathbf{beh}}$

- By simultaneously operating both processes on the same state space (conditionally independent, given the current state), *feedback processes* are instantiated.
- Processes of network evolution and of behavioural evolution therefore are *controlled for each other's occurrence*!

Micro steps that are modelled explicitly

Let $(x,z)(t)$ be the state of the co-evolution process at time point t (where x stands for the network part and z for the behaviour vector).

Micro steps are defined as "smallest possible changes":

network micro steps

$(x,z)(t_1)$ and $(x,z)(t_2)$ differ in one tie variable x_{ij} only.

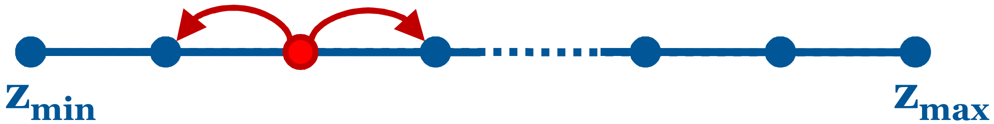
behaviour micro steps

$(x,z)(t_1)$ and $(x,z)(t_2)$ differ by one in one behavioural score variable z_i only.

Model for behavioural change

Choice options:

(1) increase, (2) decrease, or (3) keep current score
on the ordinal behavioural variable, provided the range is not left



Choice probabilities:

Analogous to network part: multinomial logit model based on evaluations of options according to behavioural objective function.

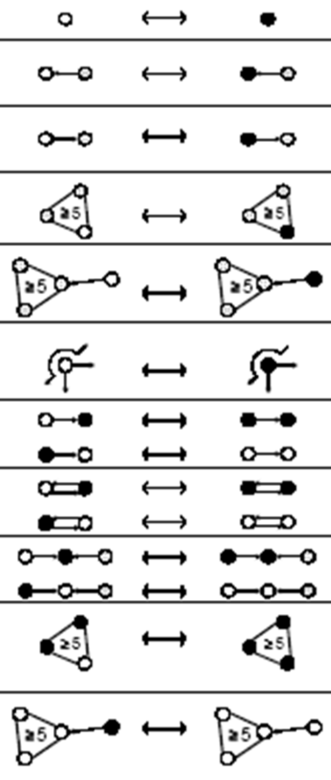
Explanatory model for behaviour change:

By inclusion of effect statistics in the objective function.

Also here, many effects are possible to include in the objective function…

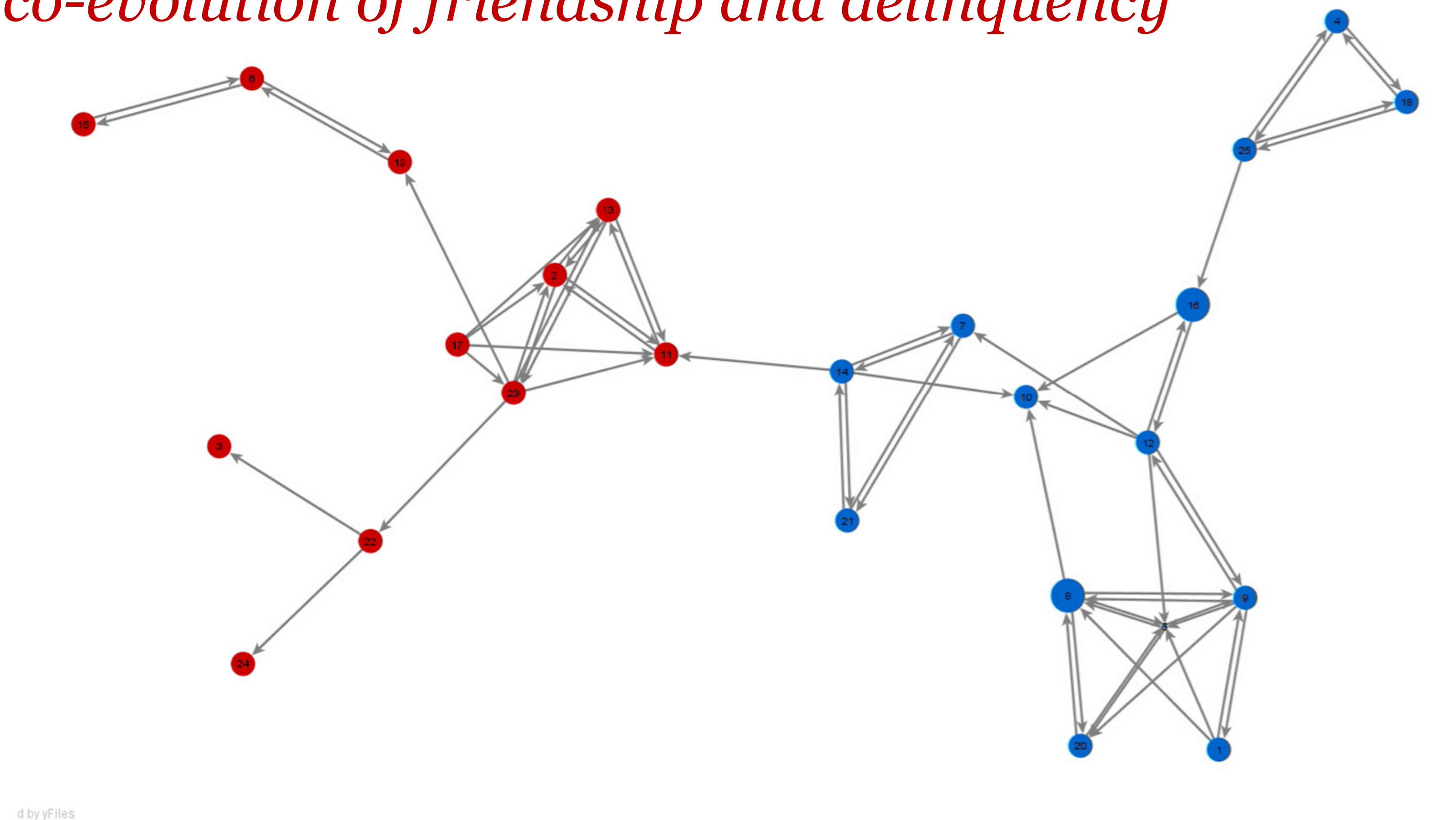
TABLE 3

SELECTION OF POSSIBLE EFFECTS FOR MODELING BEHAVIORAL EVOLUTION

effect	network statistic	effective transitions in network*	verbal description
1. tendency	z_i		main behavioral tendency
2. indegree × behavior	$z_i \sum_j x_{ji}$		effect of own popularity on behavior
3. outdegree × behavior	$z_i \sum_j x_{ij}$		effect of own activity on behavior
4. dense triads × behavior	$z_i \sum_{jh} \text{group}(ijh)$		effect of belonging to cohesive subgroups on behavior
5. peripheral × behavior	$z_i \sum_{jhk} \text{peripheral}(i;jhk)$		effect of being peripheral to cohesive subgroups on behavior
6. isolation × behavior	$z_i \, \text{isolate}(i)$		effect of being isolated in the network on behavior
7. similarity	$\sum_j x_{ij} \, \text{sim}_{ij}$		assimilation to friends (contagion / influence)
8. similarity × reciprocity	$\sum_j x_{ij} x_{ji} \, \text{sim}_{ij}$		assimilation to reciprocating friends
9. similarity × pop. alter	$\sum_j x_{ij} \, \text{sim}_{ij} \sum_k x_{kj}$		assimilation to popular friends
10. similarity × dense triads	$\sum_{jh} \text{group}(ijh)(\text{sim}_{ij} + \text{sim}_{ih})$		assimilation to the majority behavior in a cohesive subgroup
11. similarity × peripheral	$\sum_{jhk} \left(\text{peripheral}(i;jhk) \times (\text{sim}_{ij} + \text{sim}_{ih} + \text{sim}_{ik})\right)$		assimilation to those cohesive subgroups one unilaterally attaches to

* In the *effective transitions* illustrations, it is assumed that the behavioral dependent variable is dichotomous and centered at zero; the color coding is ○ = low score (negative), ● = high score (positive), ○ = arbitrary score. Actor i is the actor who changes color z_i in the transition indicated by the double arrows. Illustrations are not exhaustive.

Example data: (Andrea Knecht, 2003/04)
co-evolution of friendship and delinquency



Estimation of co-evolution models

- The estimating equations algorithm needs to be modified slightly because the default equations for ‘competing process explanations’ are identical and would imply an unsolvable collinear system of equations.
- Solution: work with *cross-lagged statistics* in the estimating equations!
  - Network change in response to prior behaviour,
  - behaviour change in response to prior network.

Estimating equations

When **X**, **Z** are model-based simulated data and **x**, **z** the empirical data, the following statistics are used:

› For parameters in the network objective function:

$$\mathbf{S}_{\square}(\mathbf{X},\mathbf{Z}) = \sum_{k} \sum_{i} \mathbf{s}_{ih}^{net} \left(\mathbf{X}(\mathbf{t}_{k+1}), \mathbf{z}(\mathbf{t}_{k})\right)$$

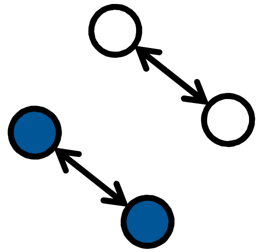
› For parameters in the behaviour objective function:

$$\mathbf{S}_{\square}(\mathbf{X},\mathbf{Z}) = \sum_{k} \sum_{i} \mathbf{s}_{ih}^{beh} \left(\mathbf{x}(\mathbf{t}_{k}), \mathbf{Z}(\mathbf{t}_{k+1})\right)$$

The estimating equations are $\mathbf{E}(\mathbf{S}_{\square}(\mathbf{X},\mathbf{Z})) = \mathbf{S}_{\square}(\mathbf{x},\mathbf{z})$; everything else remains as in the case of the simple network evolution model.

C. Explaining homogeneity bias

In networks connected actors are often behaviourally more similar than non-connected actors. Technically, this has been termed *homogeneity bias* or *network autocorrelation*.

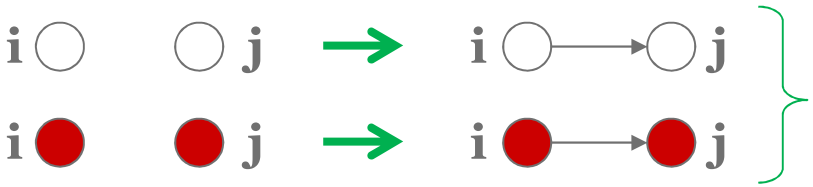


One measure (implemented in SIENA) is the *network similarity statistic* $\sum_j x_{ij}\mathrm{sim}_{ij}$, where sim_{ij} is a standardised measure of similarity of two actors based on their distance on a variable z , $\mathrm{sim}_{ij} = 1 - \left(\left| z_i - z_j \right| / \mathrm{range}_z \right)$.

$\mathrm{sim}_{ij}=1$ means scores of i and j are identical; $\mathrm{sim}_{ij}=0$ means they are maximally apart (one maximal, the other minimal).

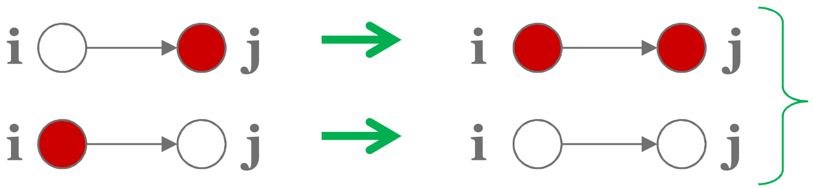
Competing explanatory stories

Actors base their social relations on similarity of individual features.



homophily (social selection)

Actors adjust their individual features to the features of their social environment.



assimilation (social influence)

Modelling selection and influence

By including the network similarity statistic $\sum_j x_{ij} \mathrm{sim}_{ij}$

…in the ***network objective function***, homophilous selection is modelled,

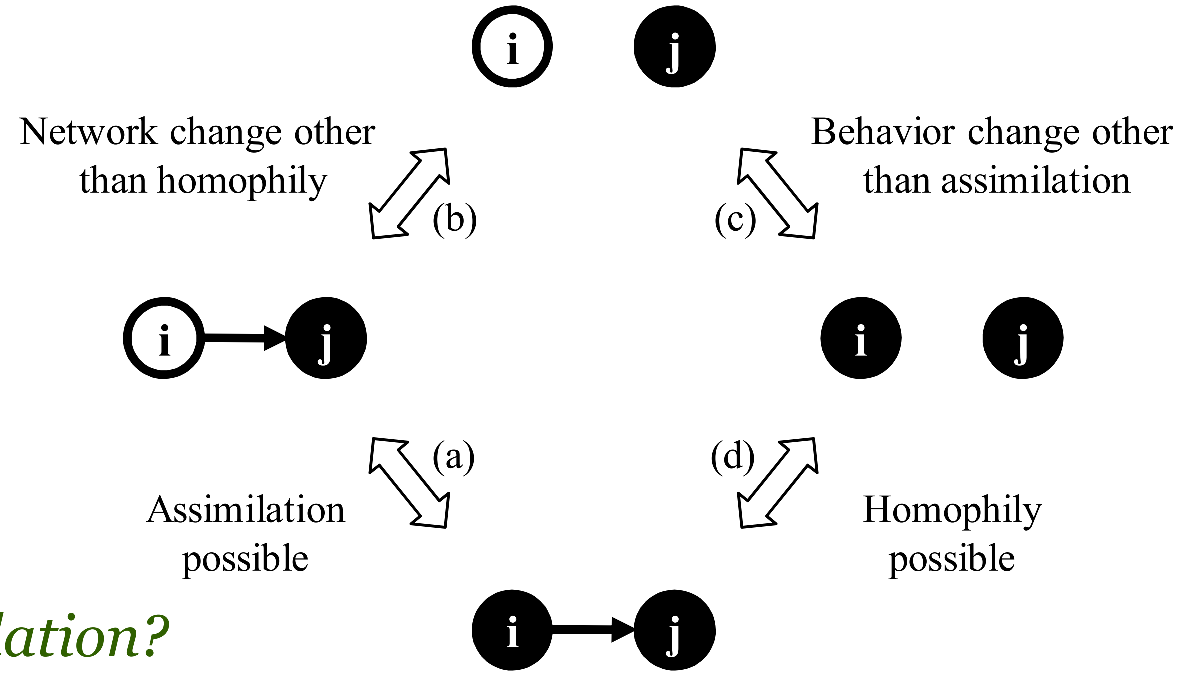
…in the ***behaviour objective function***, assimilation / social influence is modelled.

It can be of crucial importance to be able to control one effect for the occurrence of the other – e.g., in the design of social interventions to reduce smoking at school.

An advantage of / reason for continuous time modelling

Suppose in a given data set, transition (a) on the right has been observed from one observation moment to the next.

May one diagnose this observation as occurrence of assimilation?



The continuous time approach allows to control for other explanations such as (b)-(c)-(d); discrete time models cannot do this!

D: Example co-evolution analysis*

A set of illustrative research questions:

1. *To what degree is music taste acquired via friendship ties?*
2. *Does music taste (co-)determine the selection of friends?*
3. *What is the role played by alcohol consumption in both friendship evolution and the dynamics of music taste?*

Data: Medical Research Council's *Teenage Friends & Lifestyle Study* (Bush, Michell & West, 1997)

three waves, 129 pupils (13-15 year old) at one Glasgow-based school; pupils named up to 6 friends

* see Steglich, Snijders & West, *Methodology* 2: 48-56 (2006)

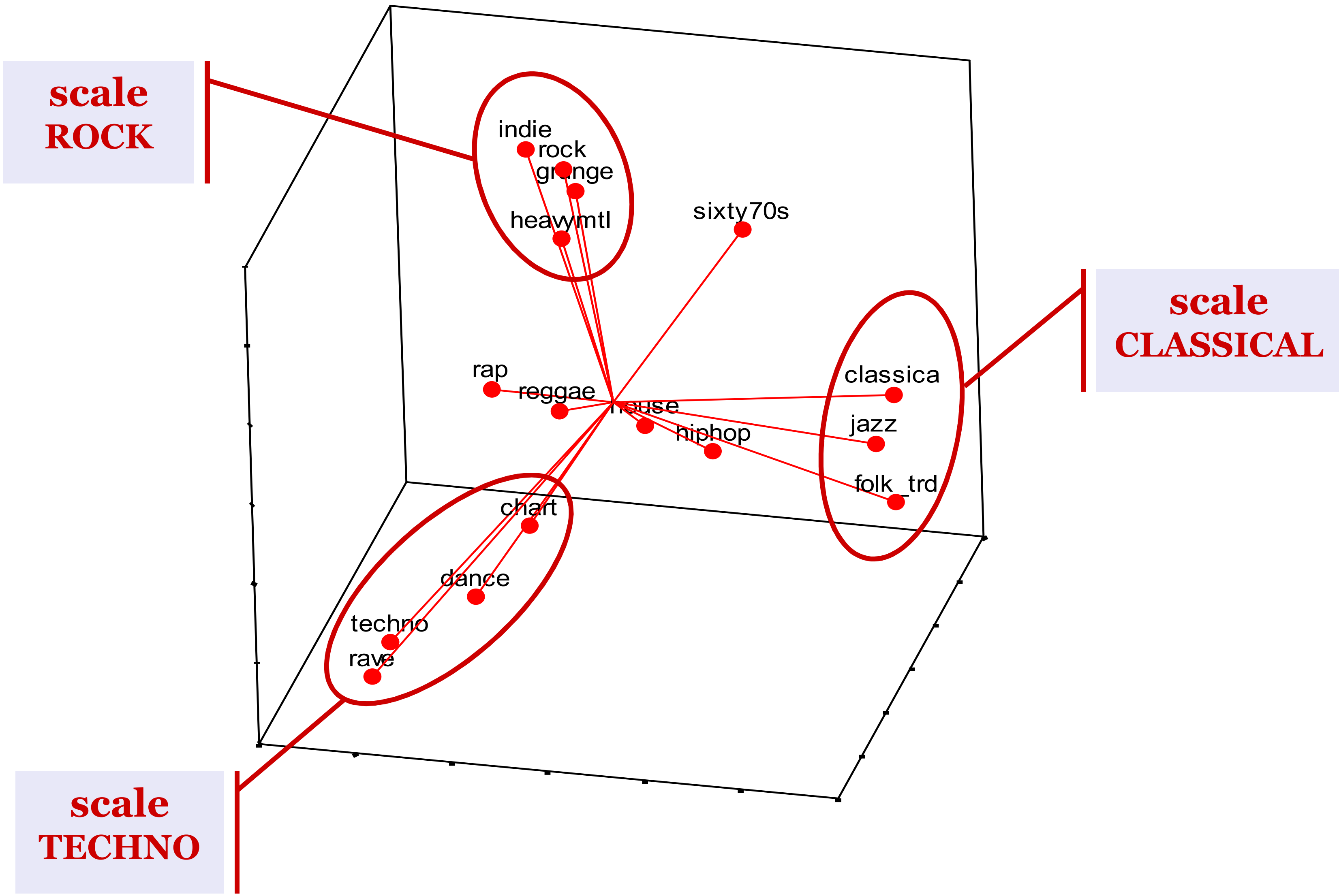
43. Which of the following types of music do you like listening to? Tick one or more boxes.

Rock	☐	*Indie*	☐
Chart music	☐	*Jazz*	☐
Reggae	☐	*Classical*	☐
Dance	☐	*60's/70's*	☐
Heavy Metal	☐	*House*	☐
Techno	☐	*Grunge*	☐
Folk/Tradit.	☐	*Rap*	☐
Rave	☐	*Hip Hop*	☐

Other (what?)......................................

Before applying SIENA: data reduction to informative dimensions...

Principal components analysis (confirmed by Mokken scaling) yields three music listening dimensions…

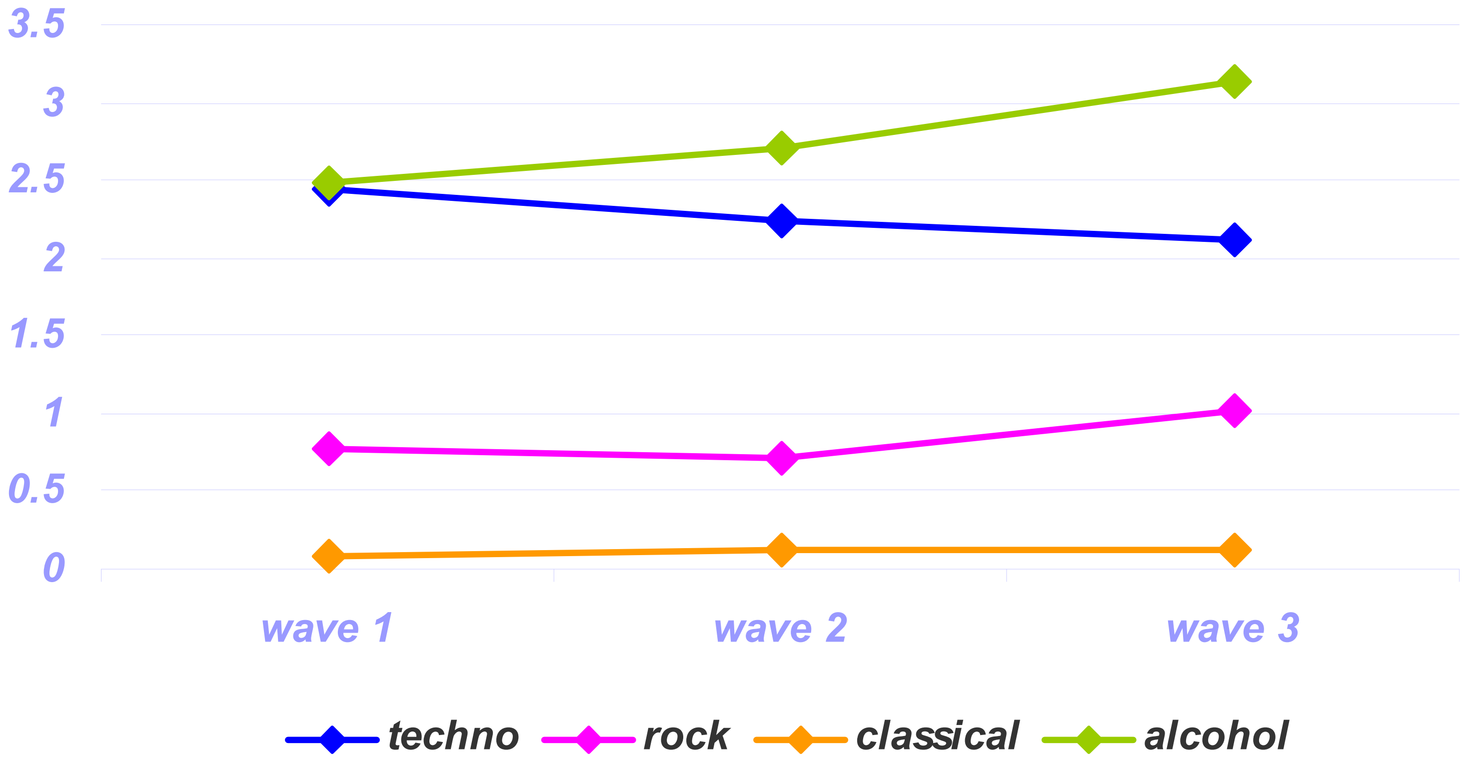


Alcohol question: five point scale

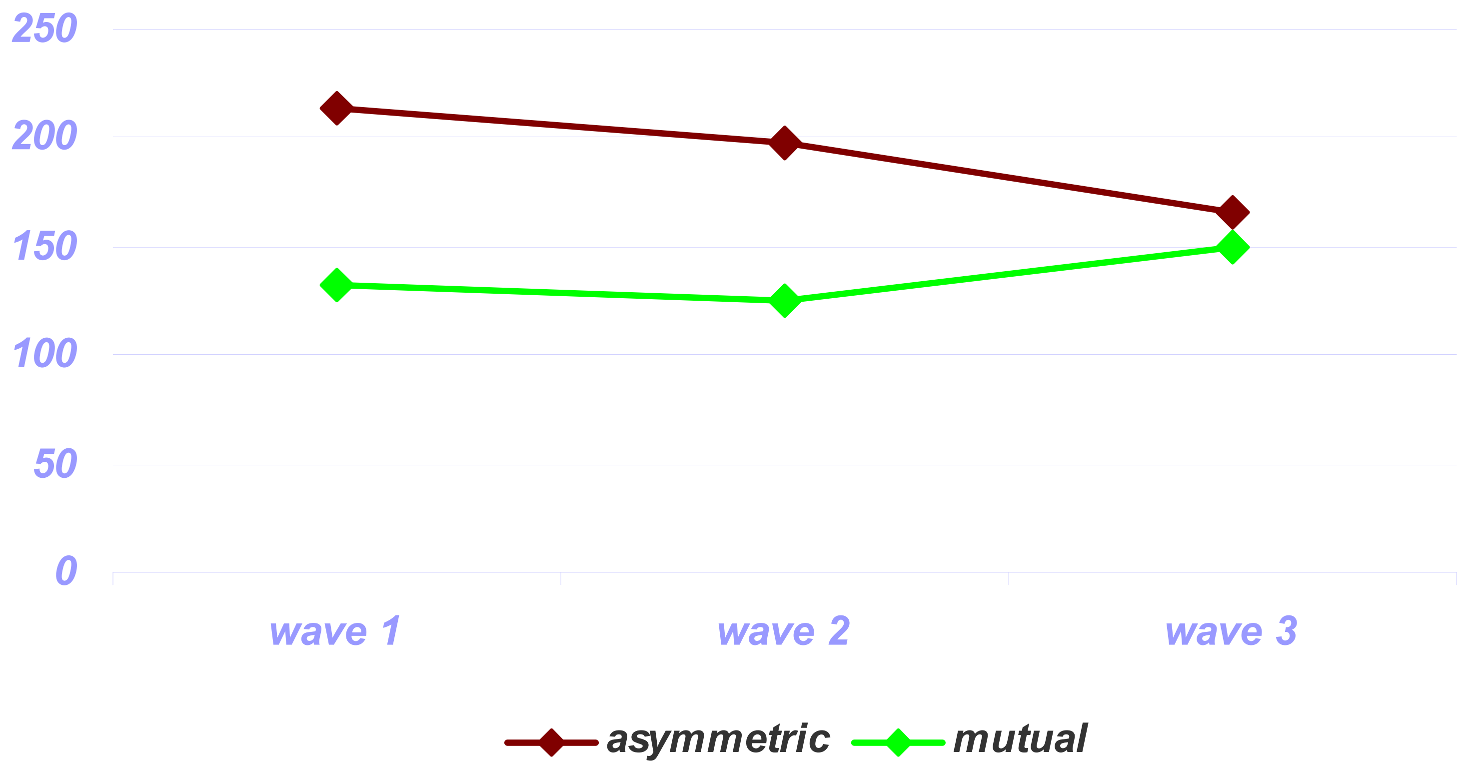
32. How often do you drink alcohol? Tick <u>one</u> box only.

More than once a week	☐	**5**
About once a week	☐	**4**
About once a month	☐	**3**
Once or twice a year	☐	**2**
I don't drink (alcohol)	☐	**1**

Average dynamics of the four behavioural variables…



...and global dynamics of friendship (dyad counts)



Analysis of the music taste data

Network objective function:

– intercept:
  outdegree

– covariate-determined:
  gender homophily
  gender ego
  gender alter

– network-endogenous:
  reciprocity
  distance-2

– behaviour-determined:
  beh. homophily
  beh. ego
  beh. alter

Rate functions were kept as simple as possible (periodwise constant).

"behaviour" stands shorthand for the three music taste dimensions and alcohol consumption.

Behaviour objective function(s):

– intercept:
 tendency

– network-determined:
 assimilation to neighbours

– covariate-determined:
 gender main effect

– behaviour-determined:
 behaviour main effect

The following slides show the original estimation results (2006, Steglich, Snijders & West).

Results: network evolution

		parameter	s.e.	t-score
outdegree		-1.89	0.29	-6.51
reciprocity		2.34	0.12	20.08
distance-2		-1.09	0.07	-14.89
gender	sim	0.80	0.12	6.72
	alter	-0.21	0.12	-1.73
	ego	0.24	0.11	2.17
techno	sim	0.08	0.33	0.26
	alter	0.07	0.05	1.30
	ego	-0.10	0.05	-1.93
rock	sim	0.11	0.41	0.26
	alter	0.19	0.07	2.75
	ego	-0.07	0.08	-0.92
classical	sim	1.44	0.69	2.07
	alter	0.15	0.17	0.91
	ego	0.40	0.17	2.42
alcohol	sim	0.83	0.27	3.08
	alter	-0.03	0.04	-0.75
	ego	-0.03	0.03	-0.85

Low overall density in these networks.

Reciprocation is important for friendship.

There is a tendency towards transitive closure.

Results: network evolution

		parameter	s.e.	t-score
outdegree		-1.89	0.29	-6.51
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	alter	-0.21	0.12	-1.73
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alcohol	sim	0.83	0.27	3.08
	alter	-0.03	0.04	-0.75
	ego	-0.03	0.03	-0.85

There is gender homophily:

		alter: boy	alter: girl
ego	boy	0.38	-0.62
ego	girl	-0.18	0.41

table gives gender-related contributions to the objective function

There is alcohol homophily:

		alter: low	alter: high
ego	low	0.36	-0.59
ego	high	-0.59	0.13

table shows contributions to the objective function for highest / lowest possible scores

Results: network evolution

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outdegree		**-1.89**	**0.29**	**-6.51**
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	alter	-0.03	0.04	-0.75
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Techno style listeners are marginally less active in sending friendship nominations.

Rock style listeners are more popular as friends.

Classical style listeners select each other as friends!

Classical style listeners are more active in sending friendship nominations.

Results: behavioural evolution

	alcohol		techno		rock		classical	
	par.	s.e.	par.	s.e.	par.	s.e.	par.	s.e.
intercept	-0.30	0.37	0.01	0.25	**0.59**	**0.25**	0.67	1.30
assimilation	**0.94**	**0.27**	**0.45**	**0.18**	**0.63**	**0.28**	0.42	1.17
gender	-0.06	0.19	0.25	0.12	0.01	0.19	1.57	0.83
techno	0.23	0.16	---	---	**-0.25**	**0.09**	-0.46	0.40
rock	0.16	0.16	**-0.34**	**0.10**	---	---	0.64	0.39
classical	-0.59	0.32	-0.13	0.23	-0.34	0.30	---	---
alcohol	---	---	0.07	0.10	-0.11	0.07	**-1.03**	**0.34**

- Assimilation to friends occurs: –on the alcohol dimension,
  – on the techno dimension,
  – on the rock dimension.

Results: behavioural evolution

	alcohol		techno		rock		classical	
	par.	s.e.	par.	s.e.	par.	s.e.	par.	s.e.
intercept	-0.30	0.37	0.01	0.25	**0.59**	**0.25**	0.67	1.30
assimilation	**0.94**	**0.27**	**0.45**	**0.18**	**0.63**	**0.28**	0.42	1.17
gender	-0.06	0.19	0.25	0.12	0.01	0.19	1.57	0.83
techno	0.23	0.16	---	---	**-0.25**	**0.09**	-0.46	0.40
rock	0.16	0.16	**-0.34**	**0.10**	---	---	0.64	0.39
classical	-0.59	0.32	-0.13	0.23	-0.34	0.30	---	---
alcohol	---	---	0.07	0.10	-0.11	0.07	**-1.03**	**0.34**

- There is evidence for mutual exclusiveness of:
  - listening to techno and listening to rock,
  - listening to classical and drinking alcohol.
- The classical listeners tend to be girls.

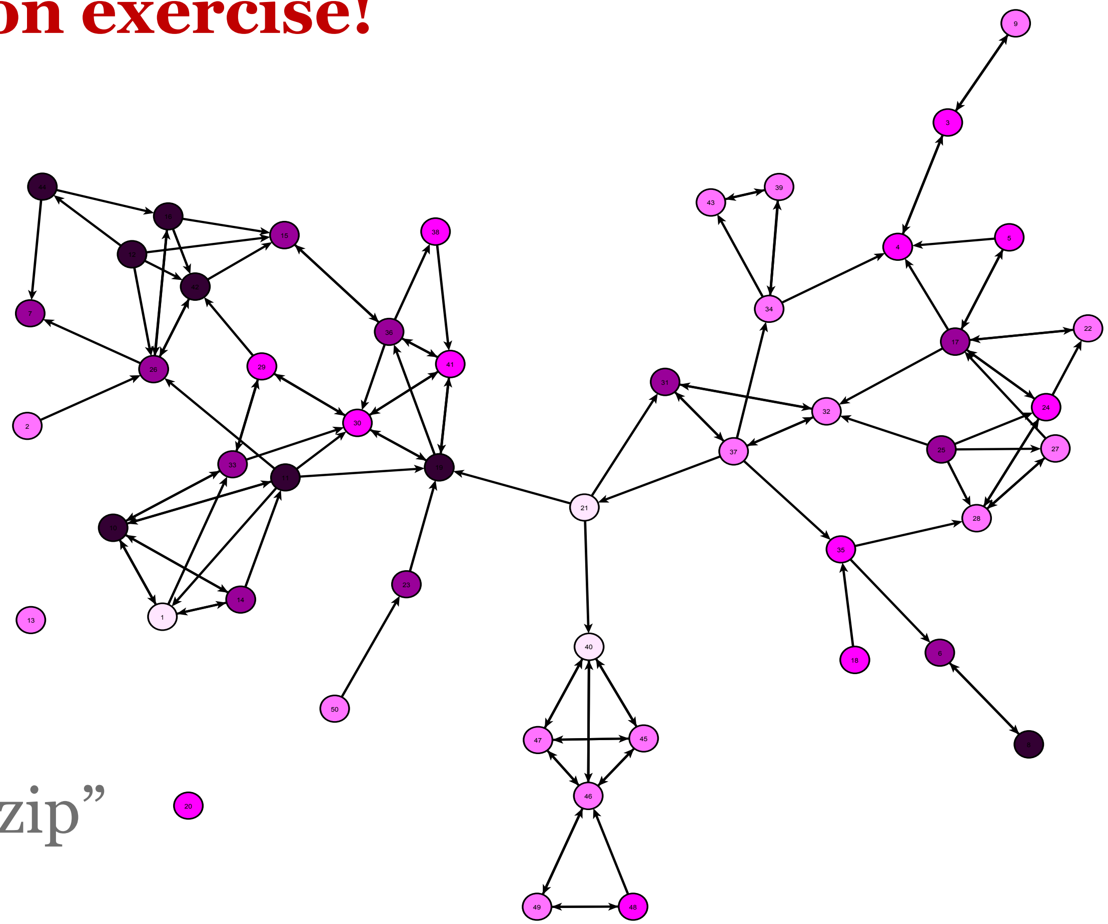
Time for a hands-on exercise!

Scottish s50 data

- friendship
- alcohol use

- 50 teenage girls

See “lab-coevolution.zip”



E: More on peer influence modelling

› Peer influence doesn't necessarily mean *"connected people becoming / staying more similar over time"*

- For strongly skewed variables, peer influence may even coincide with connected people becoming less similar.

  Example: When entering secondary school, students initially are all non-delinquent, i.e., perfectly similar. Any subsequent movement implies a reduction of similarity.

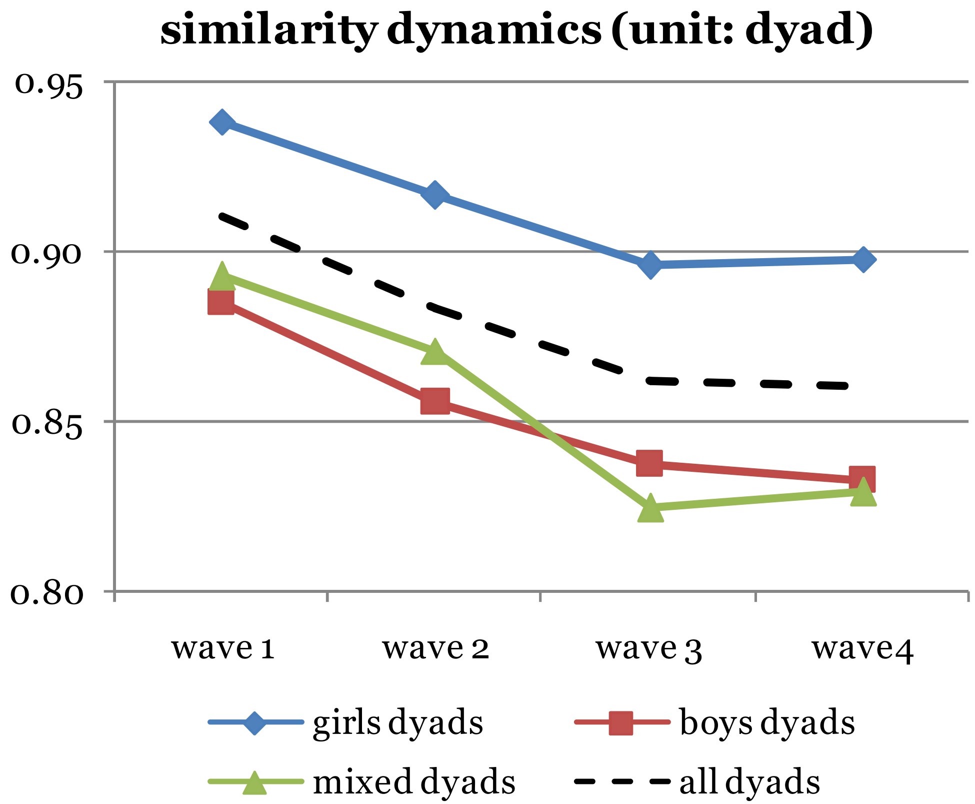
- In such cases, the *similarity based* measures can be *wrong specifications* of peer influence!

  Correlational measures may be the better choice here; see Knecht et al. (Social Development, 2010) & following slides.

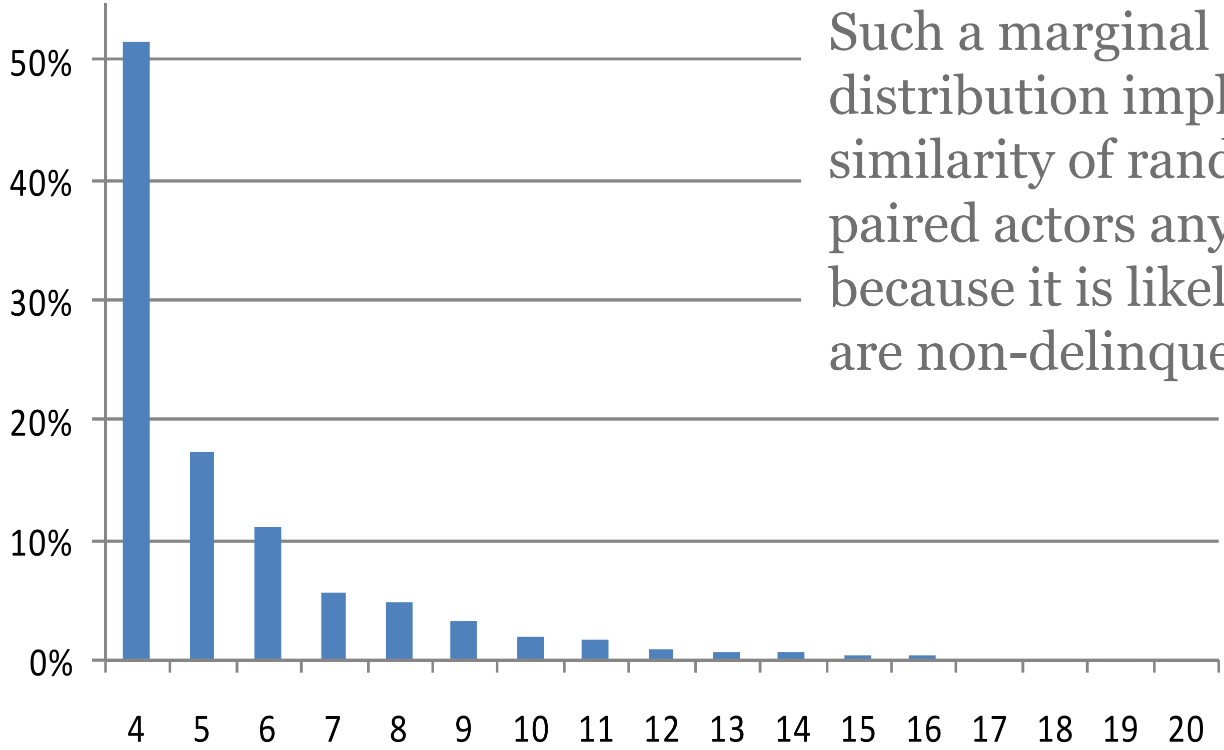
Minor delinquency & friendship

A <u>negative</u> effect of 'getting similar' was estimated!

- Huh?
- *<u>Do students want to differ from their friends</u>*, on the delinquency dimension?
- Take closer look!

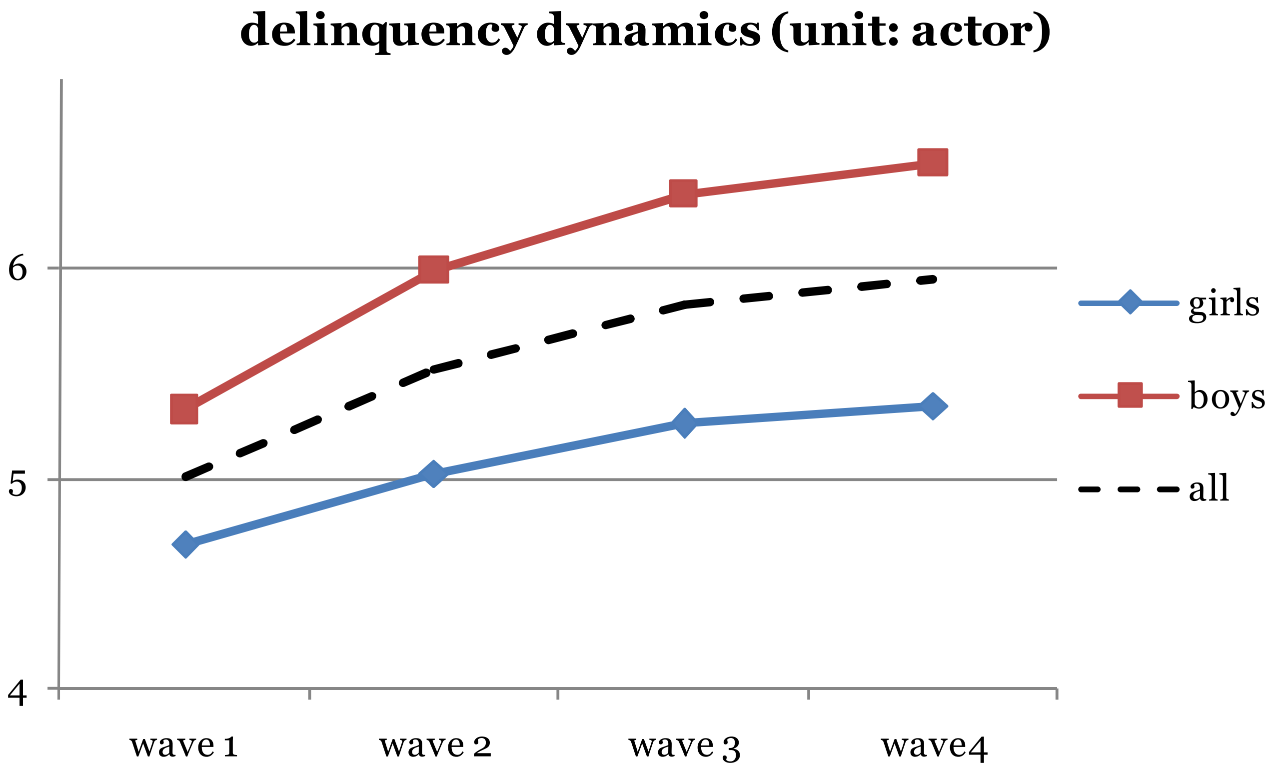


A. Very skewed distribution.



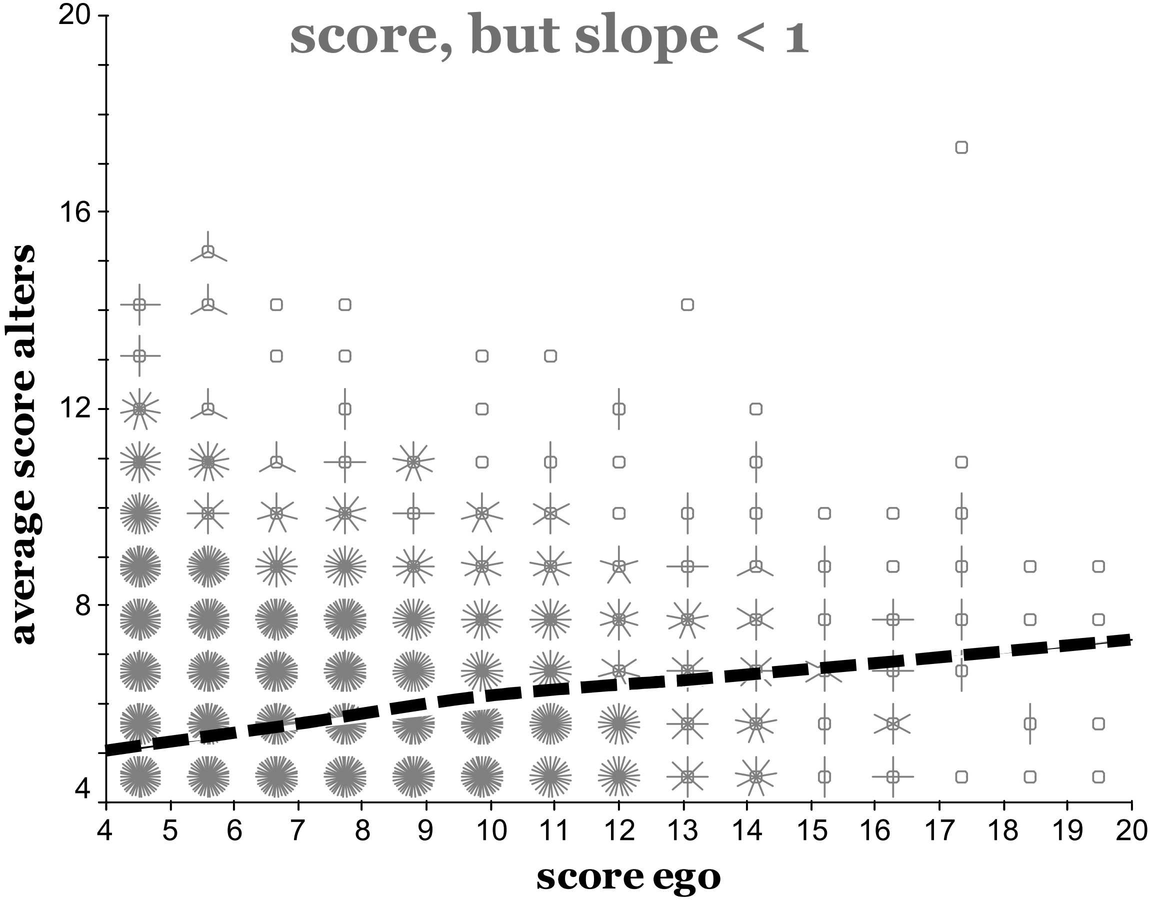
Such a marginal distribution implies a high similarity of randomly paired actors anyway, because it is likely that both are non-delinquent…

B. Increase over time



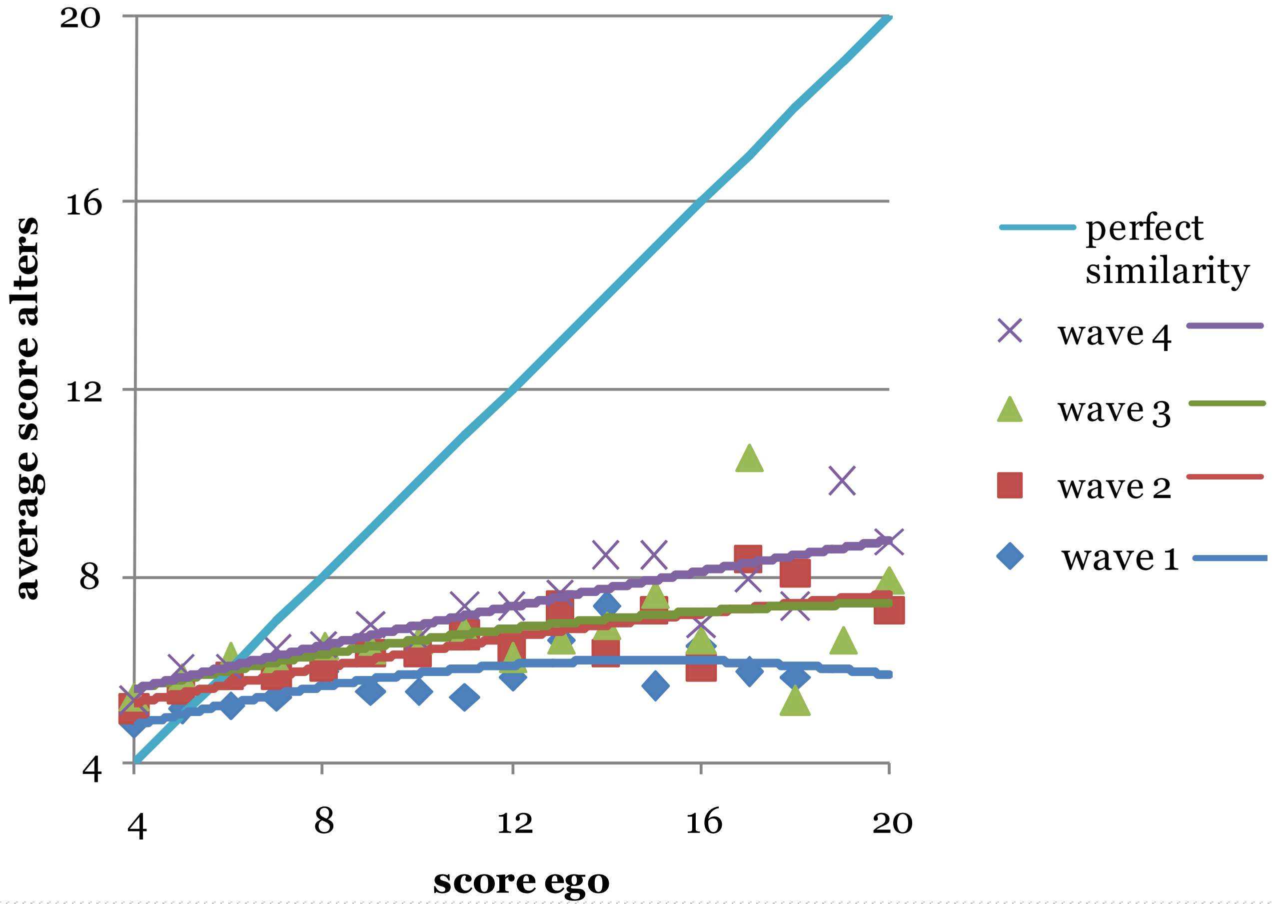
If the dynamic process starts with perfect similarity (“nobody delinquent”) it can only get less similar from there on…

C. Average of friends increases with ego score, but slope < 1



The positive alignment of alter averages and ego scores suggests there might be influence, after all… just not of the sort captured in the distance-based similarity measure!

Use a correlational measure for social influence instead!



Include the statistic

$$\sum_j x_{ij} z_i z_j$$

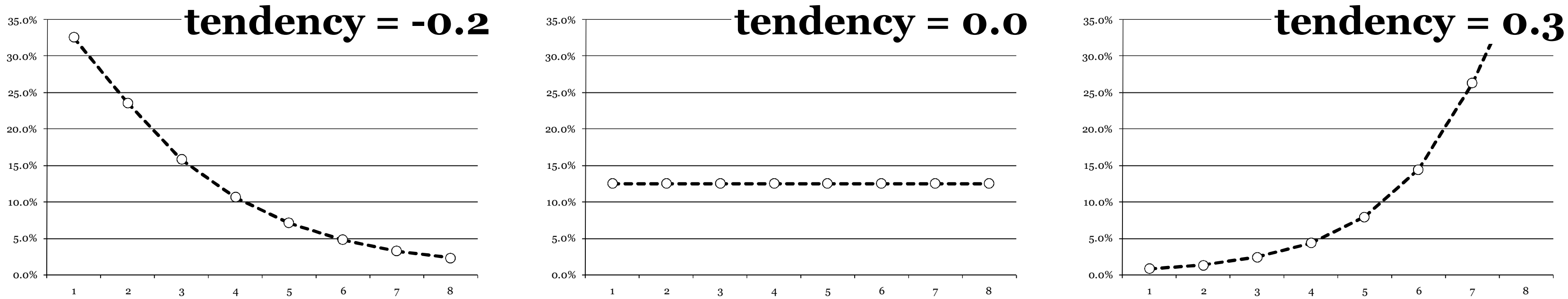
as – in this case: more appropriate – alternative operationalisation of social influence into the model part expressing behaviour change.

To remember:

- "Influence" is not unequivocally tied to one specific operationalisation!
- It is not always about "similarity" – sometimes "alignment" / "association" is the better way to phrase it – and sometimes it is a "connectedness" issue.
- Always take a close look at your data set to find out what makes sense in your context.
- In the stochastic actor-based framework, goodness of fit tests (score type) facilitate the technical part of decision making – but doesn't substitute thought!

Next issue: Consider distributional shape!

› The simple 'intercept' or 'tendency' (now 'linear shape') parameter used by Steglich, Snijders & West (2006) is not a good baseline model for behaviour variables:



› It can <u>only</u> express monotonous, not too extremely skewed baseline distributions as the result of behaviour change in the long run.

But… empirical distributions often are <u>unimodal</u> or <u>U-shaped</u>!

Why is this a problem?

- If a distributional shape persists over time, this stability will be captured by parameter estimates.

  Example: If a behaviour variable is empirically over- or under-dispersed with respect to its best-fitting 'linear shape' model, the residual dispersion can bias peer influence estimates.

  An illustration is the paper by Baerveldt et al., 2008.

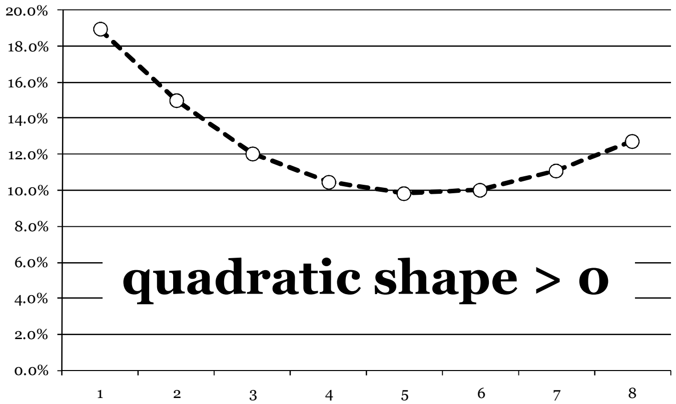
- Best is to work with empirically meaningful baseline distributions – including U-shapes and unimodality.

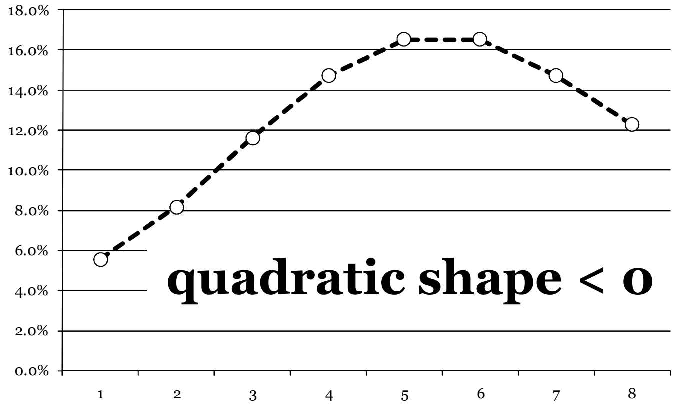
  U-shape or strong skewness are cases of overdispersion; unimodality is a case of underdispersion w.r.t. the linear shape model.

- So… enhance 'baseline capabilities' of the behaviour model!

The 'quadratic shape' parameter

› The addition of a 'quadratic shape' parameter allows the modelling of also unimodal, U-shaped, and strongly skewed baseline distributions as long-run result of behaviour change:





› Note, however, that there still can be other, weird empirical distributional shapes! *Always check, recode if too weird!*

Interpretation of 'quadratic shape' estimates

› Besides the rather technical dispersion interpretation, the 'quadratic shape' parameter can be interpreted as follows:

positive sign: *"The higher the behaviour already is, the higher the tendency to increase it even more."* Change dynamics self-accelerating towards extremes. Behaviour is potentially 'addictive'. Polarisation of the group on this behaviour dimension is likely.

negative sign: *"The higher the behaviour already is, the lower the tendency to still increase it further."* Change dynamics self-correcting towards the mean. Behaviour is potentially governed by norms of moderation that hold in the whole group. Consensus formation on this behaviour is likely.

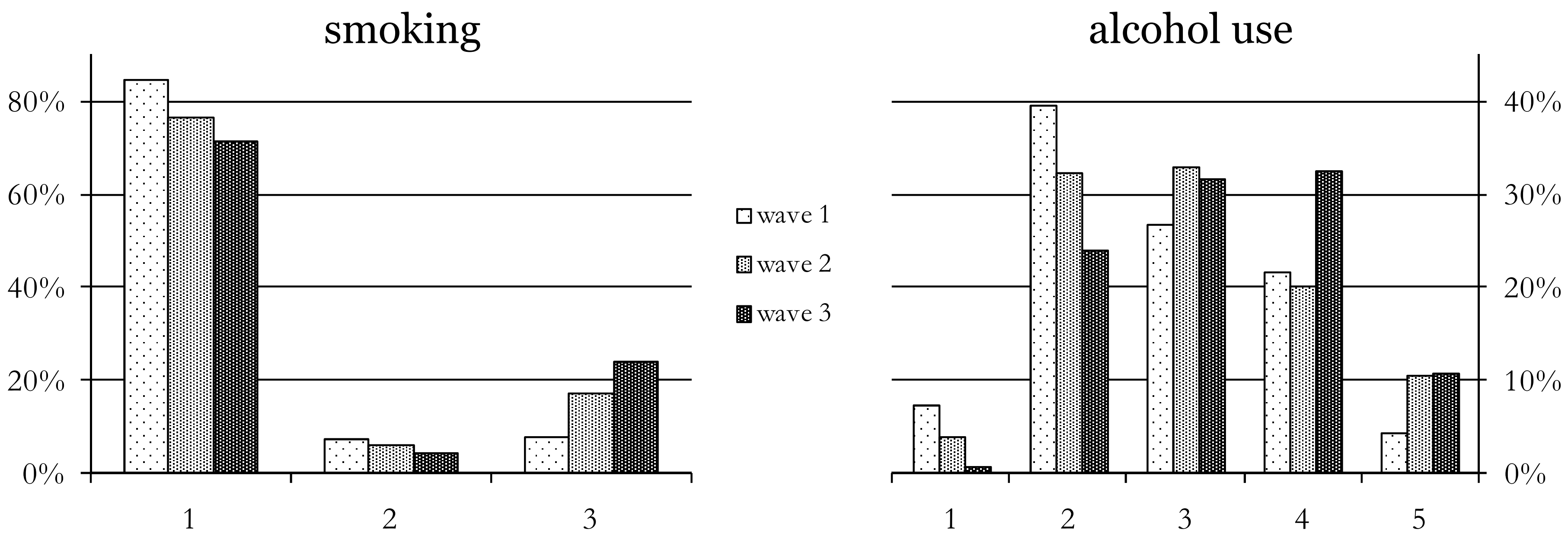
Some results obtained with this model
(Steglich, Snijders & Pearson, 2010)

- Shape (see next slide) does not necessarily dominate influence.

	ALCOHOL			SMOKING		
	estimate	*st.error*	*p-value*	*estimate*	*st.error*	*p-value*
shape: linear	0.41	(0.14)	0.004	-2.61	(0.42)	<0.001
shape: quadratic	0.01	(0.11)	0.926	2.62	(0.31)	<0.001
average similarity	6.70	(2.18)	0.002	2.63	(1.06)	0.014

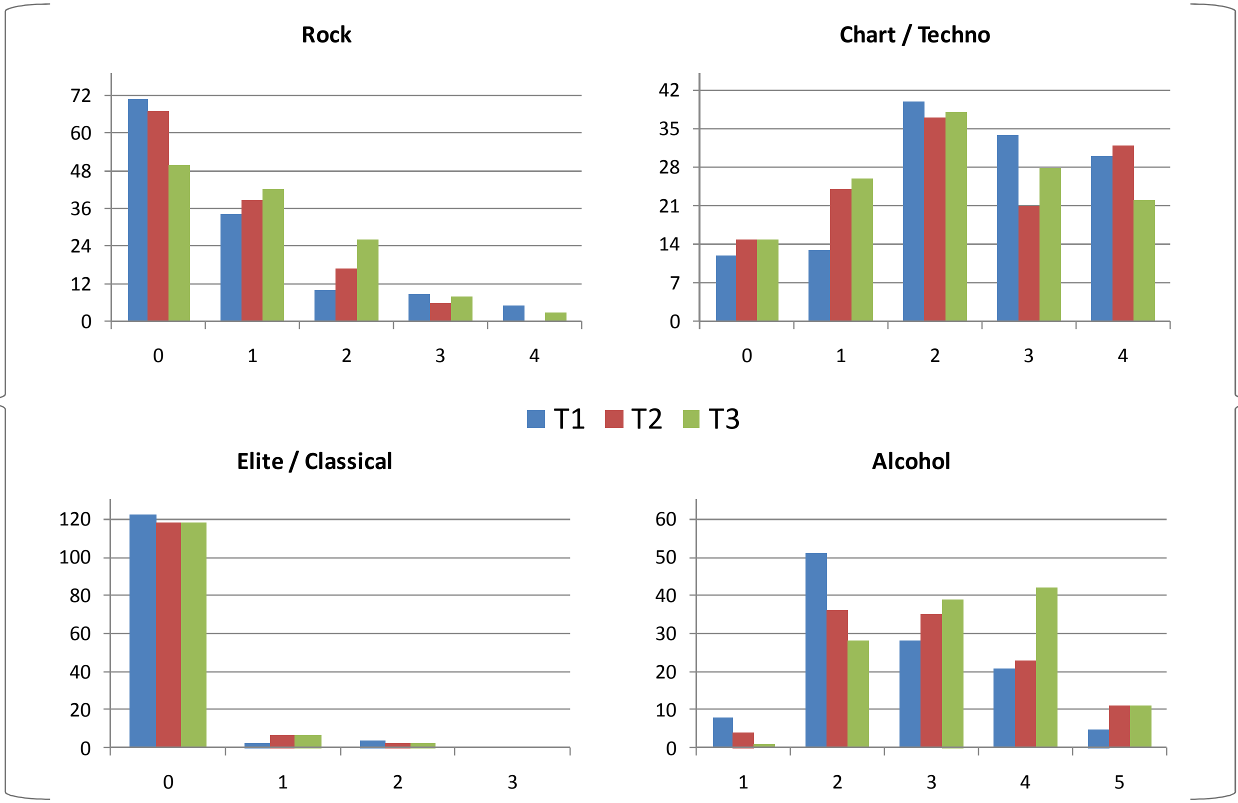
- Alcohol: “real influence” (network partners attract)
- Smoking: both influence and general polarisation trend.

Distribution of the corresponding variables



What about the distributional shapes of the four behaviour variables in Steglich, Snijders & West (2006)?

rock & ***classical*** skewed, the latter strongly



alcohol & ***techno*** unimodal, more or less

Robustness check of results reported by Steglich, Snijders & West upon addition of 'quadratic shape' effect to the model

quadratic shape parameters:

- weakly negative ($p=0.08$) for *alcohol consumption* (unimodal)
- positive ($p=0.01$) for *classical / elite* (strongly skewed)
- n.s. ($p>0.6$) for *rock* and *techno / chart*

change in peer influence results:

- result for *rock* drops to n.s. ($p=0.16$)
- result for *techno / chart* drops to weak effect ($p=0.08$)

change in homophily-based selection:

- result for *classical / elite* drops to weak effect ($p=0.08$)

Overall "slightly less spectacular results", it seems.

Interpretation of robustness check results

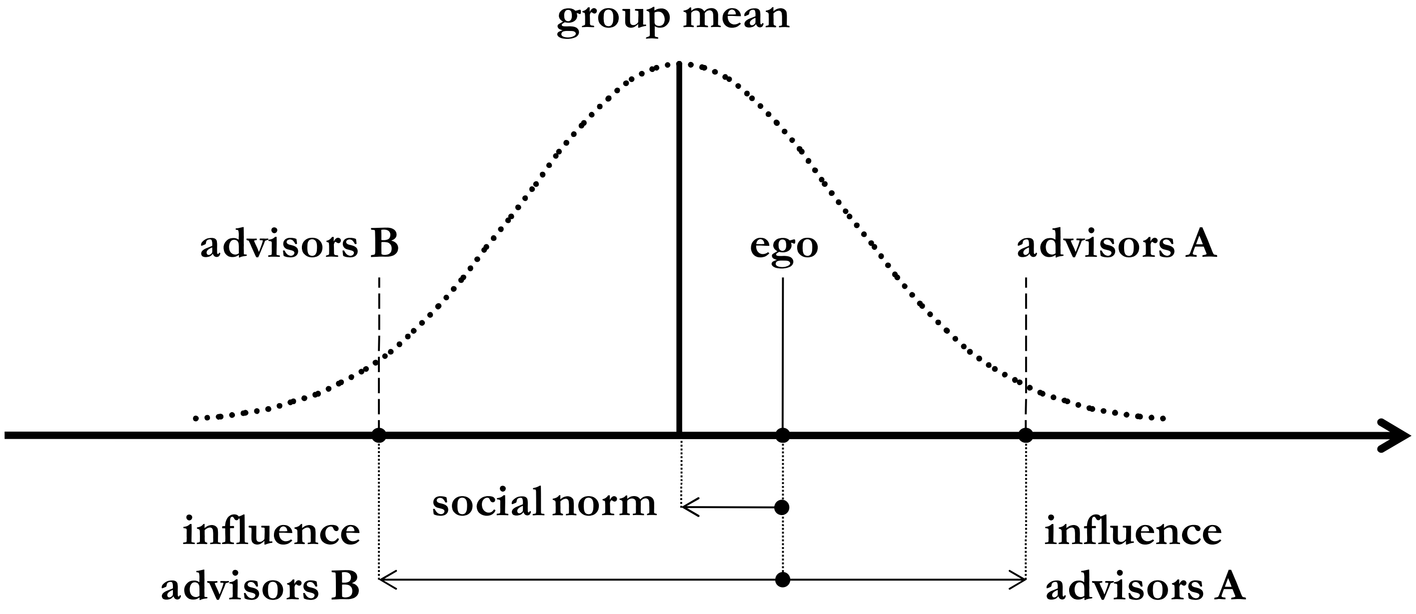
- The overall drop in significance of almost all effects can be a result of adding four more parameters to an already large model, which implies a reduction of statistical power.
- The strongest drop in significance occurs for the 'assimilation rock' effect: Controlling for the whole cohort's behavioural tendencies, it is not possible to tell anymore whether friends adjusted their rock listening habits to those of their friends.
- Besides these comments, the new results seem in line with the earlier reported ones.

To remember:

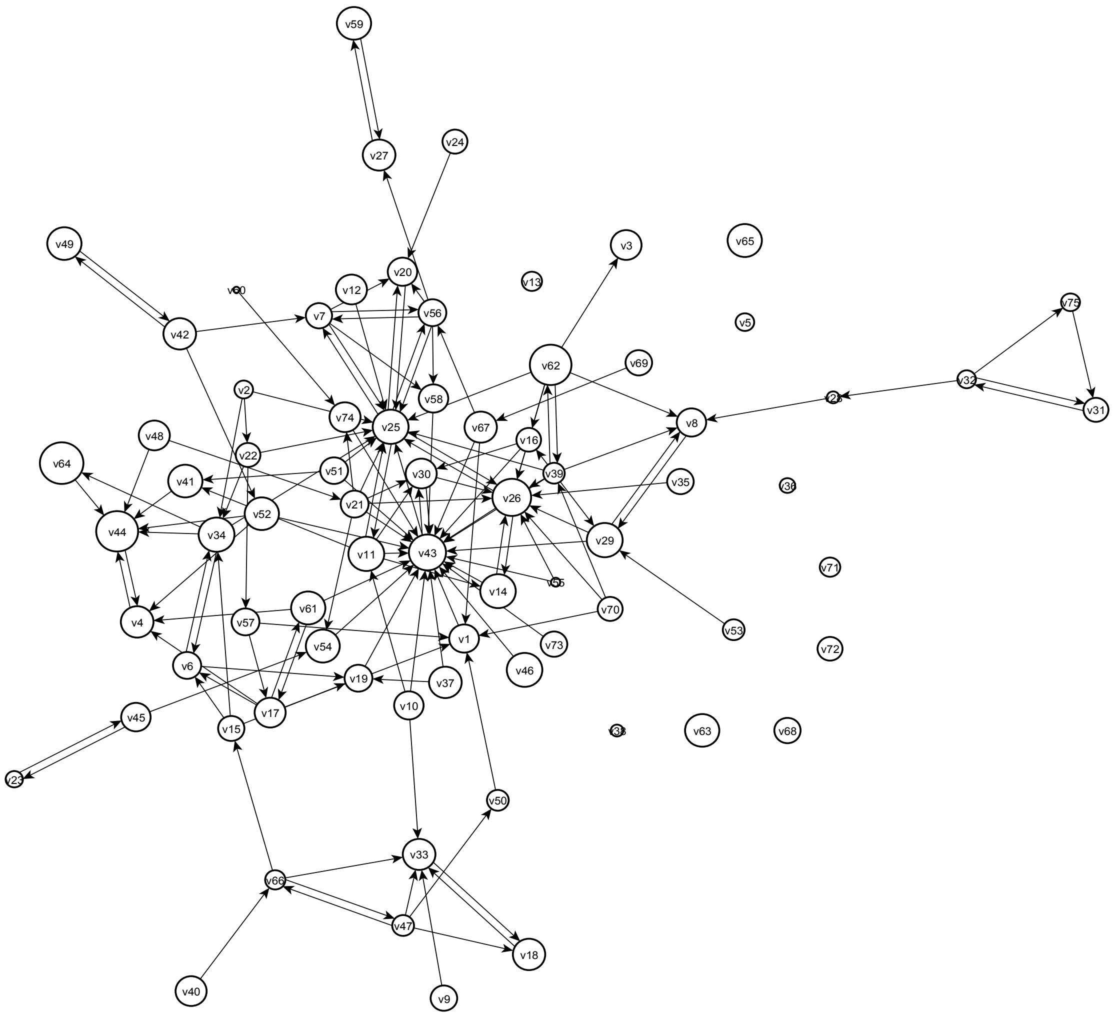
- “Network influence” can be diagnosed while actually there is no network level influence operating!
- Control for distributional shape of the behaviour variable – otherwise the model might pick it up with its network influence parameter, i.e., sell you shape as influence.
- Results show both patterns can be identified in appropriate data sets.

But how to interpret this quadratic parameter?
Can we attach a meaning (e.g., social norm)?

Does the group average exert a pull on individuals?



The *quadratic shape effect* expresses the squared distance from the global average of the behaviour variable (if centered). Modify it a bit...

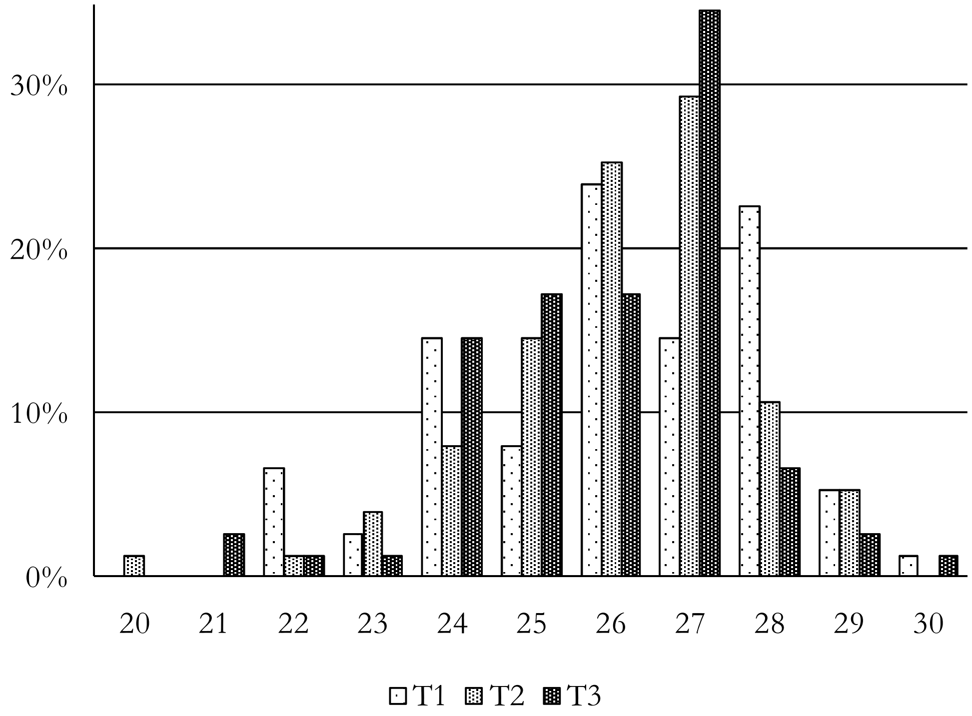


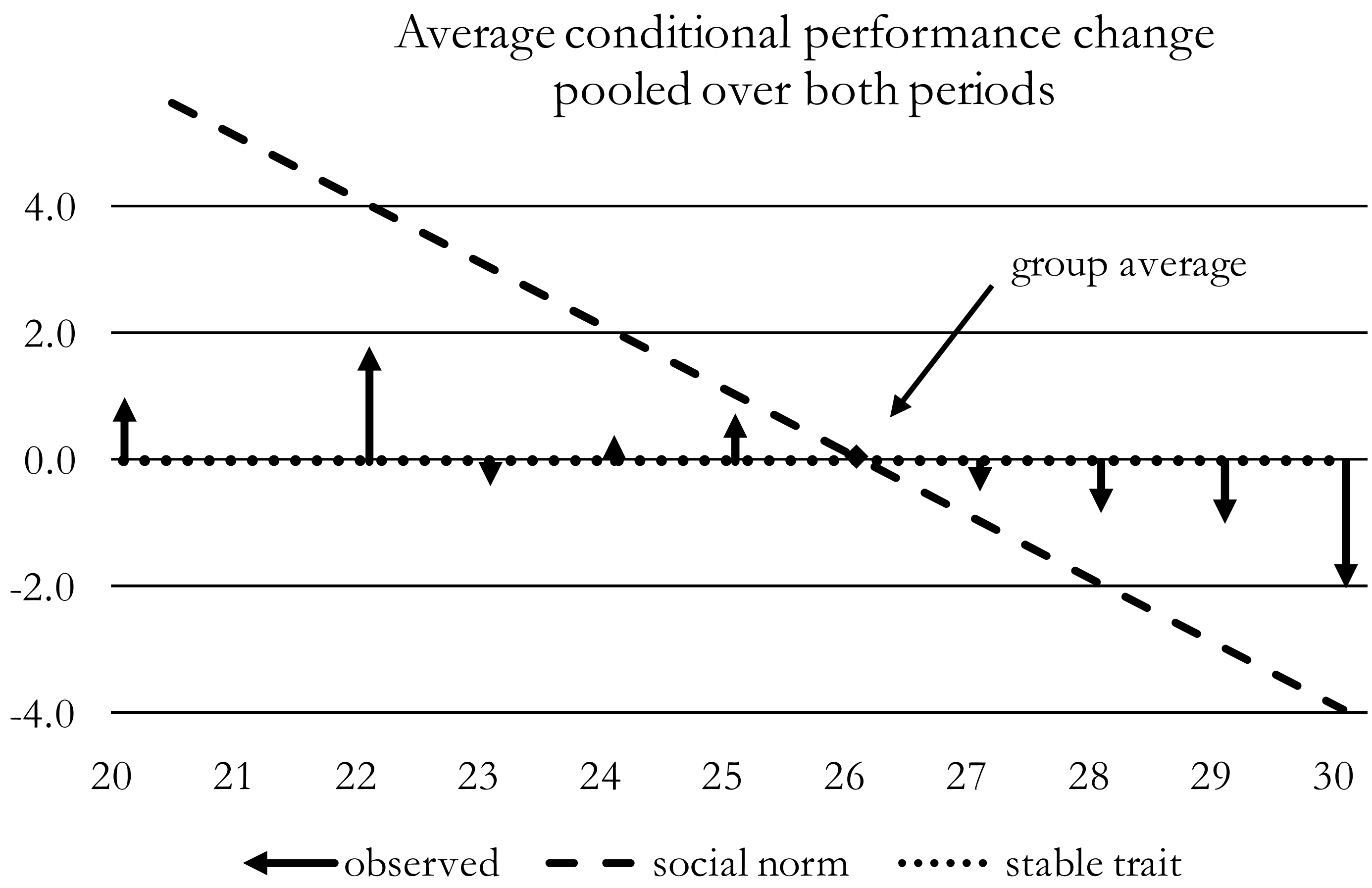
Example

(Torlò, Lomi, Snijders & Steglich, 2010)

Advice seeking & performance among 75 MBA students in Rome

Performance distribution




Average conditional performance change
pooled over both periods
4.0
2.0
0.0
-2.0
-4.0
group average
20
21
22
23
24
25
26
27
28
29
30
observed
social norm
stable trait

In this data set, network influence is indistinguishable from group level influence!

Results for a specification with network influence only:

PERFORMANCE	***estimate***	***st.error***	***p-value***
tendency	-0.236	0.113	0.037
distance to advisors	-0.599	0.179	<0.001

Results for a specification controlling for group influence:

PERFORMANCE	***estimate***	***st.error***	***p-value***
tendency	0.546	0.679	0.421
distance to advisors	-0.389	0.250	0.119
distance to social norm	-0.413	0.358	0.249

Wrapping up

Main messages:

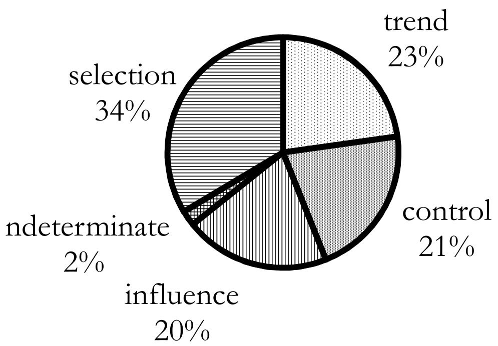
- Assessment of peer influence effects requires control for peer selection effects
- As far as possible, also context effects need to be taken into account.
  - *Validity of results obtained by stochastic actor-based modelling is conditional on having all relevant variables inside the model specification!*
- The model assumption of *decomposability into smallest possible steps* is crucial for separating peer influence and peer selection effects.

Further aspects not covered in this presentation

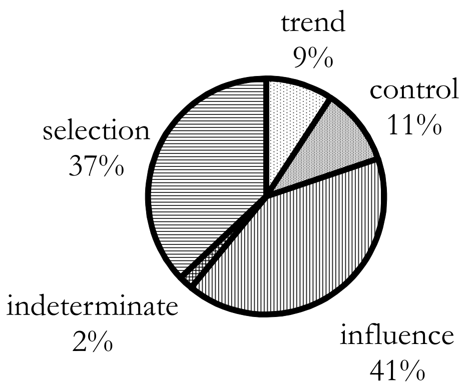
The issue of comparing the strength of influence and selection .

› Requires joint metric for comparison, e.g. *network autocorrelation coefficients* (Moran, Geary); see

Steglich, Snijders & Pearson, 2010. Dynamic Networks and Behavior: Separating Selection from Influence. *Sociological Methodology* 40: 329-393.



SMOKING MODELS



ALCOHOL MODELS

An autocorrelation fit measure

- To what degree are performance of advice giver and advice recipient associated?
- Indicator Moran's autocorrelation:

$$I = \frac{n\sum_{ij} x_{ij}(z_i - \overline{z})(z_j - \overline{z})}{\left(\sum_{ij} x_{ij}\right)\left(\sum_i (z_i - \overline{z})^2\right)}$$

- Compared are (partially) nested models including these components:
  T rend (rewiring, perf. drift, etc.)
  C ontrol (sex, experience, etc.)
  S election (homophily, etc.)
  I nfluence (assimilation, etc.)