Applying SIENA: An illustrative analysis of the co-evolution of adolescents' friendship networks, taste in music, and alcohol consumption.*

Christian Steglich†
Tom A.B. Snijders
University of Groningen

Patrick West
University of Glasgow

Abstract

We give a non-technical introduction into recently developed methods for analyzing the co-evolution of social networks and behavior(s) of the network actors. This co-evolution is crucial for a variety of research topics that currently receive a lot of attention, such as the role of peer groups in adolescent development. A family of dynamic actor-driven models for the co-evolution process is sketched, and it is shown how the SIENA software can be used for estimating these models. We illustrate the method by analyzing the co-evolution of friendship networks, taste in music, and alcohol consumption of teenagers.

1 Introduction

Social network analysis is concerned with how social actors are related to each other (cf. Carrington et al. 2005). The social actors can be individual persons, but also organizations, countries, etc., and the relations studied can be asymmetric (like investments of one company in another's stocks) or inherently symmetric (like two employees sharing an office). The basic data structure is the graph, which can be directed (for modeling potentially asymmetric relations) or undirected (for modeling symmetric relations). In a majority of applications of social network analysis, there is a natural interdependence between network structure and the individual characteristics of the network actors. The best-known pattern of this type may be *network autocorrelation*, i.e., the empirical finding that

*We thank the Chief Scientist's Office of the Scottish Home and Health Department for funding data collection. An earlier version of this paper was presented at the *XXV Sunbelt Social Network Conference*, Redondo Beach, February 16-20, 2005.

†The first author was funded by the Netherlands Organization for Scientific Research (NWO) under grant 401-01-550. All correspondence shall be directed to the first author, ICS / Department of Sociology, Grote Rozenstraat 31, 9712 TG Groningen, The Netherlands, e-mail: c.e.g.steglich@rug.nl.

social ties occur more frequently among demographically or behaviorally similar actors than among dissimilar actors (Doreian 1989). For explaining such patterns, it is necessary to uncover the processes by which the interdependencies come into existence. In general, there will be competing theories. Concerning the example of network autocorrelation, one prominent explanation is the *homophily principle*, which stands shorthand for the argument that it is easier or more rewarding for an actor to interact with a similar other than with a dissimilar other (McPherson, Smith-Lovin & Cook 2001). When this is the case, network ties tend to form according to similarity on some actor attribute, and network autocorrelation emerges as a consequence of tie selection over time. An alternative explanation of the same phenomenon is the *assimilation principle* according to which network actors adapt their own individual characteristics to match those of their social neighborhood (Friedkin 1998). Again, network autocorrelation emerges over time, but now due to processes of social influence.

Implicit in such explanatory approaches is often an assumption about change over time. It is obvious that selection according to the homophily principle requires the social network to be dynamic (i.e., changeable over time), while actor characteristics can be dynamic or static. The converse holds for social influence according to the assimilation principle. Here, the actor characteristics are required to be dynamic, while there is no requirement on the social network part. When in an application, the social network as well as the individual characteristic of interest are dynamic, both paradigms could occur. In such situations, it becomes an issue of empirical investigation to determine which of the two can better explain the observed patterns of network autocorrelation, by assessing the relative importance of either mechanism.

In this paper, an outline is provided of how such questions can be answered. We cover the case of an evolving 'complete' network and co-evolving behavioral dimensions, for which panel data have been collected. 'Completeness' of the network here refers to the boundaries of the set of actors on which the social network is studied. In general, the dynamic processes involved are hardly limited to a conveniently bounded group of actors, but we require that a meaningful approximation of the relevant 'carrier group' be made, by focusing on groups that contain within them a large part of the social processes relevant to the phenomenon that is investigated.

Some interesting models for the co-evolution of networks and actor characteristics can be found in the literature (Macy et al. 2003, Dorogovtsev, Goltsev & Mendes 2002, Mark 1998, Latané & Nowak 1997, Carley 1991). The models presented in this paper differ from these strands of literature in their explicit gear towards statistical inference. This imposes requirements of flexibility and a modicum of empirical realism, as the models must be useful for parameter estimation, hypothesis testing, fit assessment, and the improvement of fit by extending the model with additional components.

In the example discussed, the models are applied for investigating the joint dynamics of taste in music, alcohol consumption, and friendship ties among adolescents. As approximation of the social space in which these dynamics take place, we focus on a school cohort for which three waves of network-behavioral panel data were collected (Pearson & West 2003). The SIENA software (Snijders et al. 2005) is used for assessing the strength of homophily and assimilation processes. A transfer of the sketched method to other research domains involving interdependence between a social network and individual actor characteristics is easily possible.

Overview

In the following Section 2, a family of stochastic, actor-driven models for the co-evolution of social networks and individual behavior is sketched. These models build on earlier models for 'pure' network dynamics (Snijders 1996, 2001, 2005) that were recently extended to account for the joint dynamics of networks and behavior (Steglich, Snijders & Pearson 2004, Snijders, Steglich & Schweinberger 2005). This modeling approach is applied, in Section 3, to an empirical study of the joint dynamics of friendship networks, taste in music, and alcohol consumption among teenagers. For this purpose, we make use of the SIENA software (Snijders et al. 2005). In Section 4, recurring issues related to model identification and interpretation of the parameter estimates are discussed. We conclude with a brief recapitulation of our main messages in Section 5.

2 A family of actor-driven models for the co-evolution of social networks and behavior

Snijders (1996, 2001, 2005) introduced a family of stochastic, actor-driven models for the evolution of social networks 'alone' (i.e., not yet allowing for co-evolving individual dimensions). The basic idea is to take the totality of all possible network configurations (directed graphs) on a given set of actors as the state space of a stochastic process, and to model observed network dynamics by specifying parametric models for the transition probabilities between these states. For the simplest case of but two actors A and B, the state space would consist of the 4 possible dyad configurations (*i*) A and B unconnected (empty dyad), the two asymmetric dyads (*ii*) A $\rightarrow$ B and (*iii*) A $\leftarrow$ B, and the mutual dyad (*iv*) A $\leftrightarrow$ B. When increasing the number n of network actors, the number of states rises faster than exponentially[1], such that for a set of six actors, the state space already contains more than a million of possible network configurations.

When analyzing network panel data, each measurement of the network corresponds to one state in this (very large) state space. The explanation of the observed network dynamics (i.e., the 'jumping' from one observed state to the next) is formulated in terms of transition probabilities between the states, with the first observation being conditioned upon, i.e., taken as (exogenously given) starting value of the stochastic process. Because the set of possible transitions between the states also is very large, a series of simplifying assumptions are made in order to reduce the complexity of the modeling task[2]. It is assumed

- that the transitions between panel measurements are manifestations of an underlying process that takes place in continuous time,
- that actors do not coordinate their actions but act conditionally independent of each other, given the current state of the network, and
- that actors only change at most one tie variable at a time, i.e., create one new link or dissolve one existing link.

[1]The size of the state space is $2^{n(n-1)}$ for the case of directed, binary networks that we treat in this paper.

[2]For the implications which these assumptions have on the research topics that can be studied, as well as the possibilities to relax these assumptions, we refer to the pertinent discussions in the papers quoted in this section.

By these assumptions, the complex modeling task is reduced to the two smaller tasks of (a) modeling the change of one tie variable by one actor at a time (a so-called *network micro step*), and (b) modeling the occurrence of these micro steps over time. Task (a) is solved by specifying a multinomial logit distribution that instantiates the maximization of an individual random utility function (the so-called *objective function*), while task (b) is solved by specifying an exponential distribution for the actors' individual waiting times (with parameter given by the so-called *rate function*). By this approach, the time-dependence of the network evolution process is implicitly modeled as emergent consequence of the model-inherent progression of time, and need not be modeled explicitly. Both model parts allow for dependence on state (i.e., network structure), time, and actor, but not on the history of the process (Markov assumption). For more details, we refer to the specific model analyzed in Section 3, and to the other papers quoted in the beginning of this section.

So far, the model sketch covered only the dynamics of network evolution. The addition of co-evolving behavioral dimensions is done in a straightforward manner, by first transferring the modeling framework to behavioral evolution and then integrating the two models. For each behavioral variable, a separate behavioral state space is handled, consisting of all possible distributions of individual behavior scores (behavior is required to have discrete outcomes), and the observed transitions on each behavioral dimension are modeled by decomposition into *behavioral micro steps*, which consist of one actor adjusting his score on the behavioral dimension by moving at most one category up- or downward at a time. These micro steps again are modeled by a multinomial logit distribution based on a random utility objective function, and their occurrence by an exponential distribution based on a rate function.

Integration of the separate models for network evolution and the evolution of the separate behavioral dimensions is done by (a) specifying the Cartesian product of the separate state spaces as the joint state space, by (b) assuming conditional independence of the occurrence of the different types of micro steps, and by (c) extending the separate objective functions and rate functions to allow for dependence on the respective other dimensions of the state space. It is in step (c) that the interdependence between network dynamics and behavioral dynamics is introduced into the model. The resulting model for the co-evolution process of the network and the behavioral dimensions inherits its Markov property from the separate processes it is constructed from. The 'actor-driven' nature of the model family is reflected in the locus of action. It is the actors who get an opportunity for changing what they have under control (outgoing ties and own behavior), the relative frequencies of these opportunities being modeled by rate functions. And these actors base their decisions on evaluations of the expected immediate consequences of their decision, the evaluations being modeled by objective functions.

The Markov property implies that, for each set of model parameters, there exists a stationary (equilibrium) distribution of probabilities over the state space of all possible network-behavior configurations. In general, the configuration observed in the first wave of the panel will not be in the center of this equilibrium distribution. Because of this, the model defines a non-stationary process of network-behavioral dynamics, starting at the first observation, and then 'drifting' towards those states that have a relatively high probability under the equilibrium distribution. As can be guessed from the complexity of the model, neither the equilibrium distribution nor the likelihood of a data set under a given model parametrization can be calculated in closed form, except for some trivial special cases (Snijders & van Duijn 1997). However, simulations of the model-specific evolution process are possible, and by way of simulation-based inference, parameter estimates can be obtained. The SIENA software instantiates simulation-based *method of moments* estimation of these models, and also allows for simulation-based *maximum likelihood* and *Bayesian* estimation of models for pure network evolution (Snijders et al. 2005, Koskinen 2004). Extension of the likelihood-based estimation methods to the co-evolution with behavioral dimensions is pending.

3 An empirical study using SIENA

A domain in which the dynamics of social networks and individual behavior are likely to be strongly interrelated is the domain of fads and fashions. The particular fashion phenomenon studied in this section is the development of taste in music over time. We investigate to what degree and how the social network context mediates listening behavior of adolescents, and whether and how, in turn, their taste in music affects the social relations among them.

It is a characteristic of fashion phenomena that the tangible shape of a fashion signal (i.e., exactly which clothes to wear or which music to listen to) is not so important, compared to its use as an identity signal for communication among actors in the same social structure. 'Same-ness qua fashion' matters in the social context, while the individual fashion attribute has no inherent value to the actor ("fashions come and go"). It has been argued that fashion signals serve at the same time for the creation of social identity (Bryson 1996, SIRC 2004) and for the manifestation of a status hierarchy (Bourdieu 1984). Classic descriptions of fashion emphasize *differentiation* and *imitation* as driving forces underlying fashion dynamics (Veblen 1899, Simmel 1904). According to these theories, actors at the top of the hierarchy attempt to differentiate themselves from the those below by acting as 'trendsetters', while actors lower in the hierarchy attempt to imitate those above them (Suzuki & Best 2003).

In our application, we can reasonably expect that the trendsetters in the first place are the musicians listened to, who are themselves not part of the group of adolescent listeners studied. We accordingly hypothesize that the differentiation aspect of fashion dynamics (which takes place at the top of the postulated status hierarchy) plays a secondary role in the population studied, and that imitation will be the major determinant of the dynamics of adolescents' music listening behavior. Hence, we expect to find a strong tendency towards behavioral conformity among friends (*assimilation hypothesis*).

Moving down in the postulated status hierarchy, also schoolmates with a prominent music taste may act as a kind of localized trendsetter (the literature on product innovation here speaks of 'early adopters'). Assuming that it is not the individuality of these adolescents that causes them to act as proxy trendsetters, but the music taste they exhibit, we can expect adolescents who listen to more trendy music to be more popular as friends than those who listen to less trendy music. So, if taste in music indeed is an indicator for a status hierarchy, it should be possible to reveal this hierarchy by assessing effects of the adolescents' taste in music on their popularity (*popularity ranking hypothesis*).

Further, we expect an asymmetry of adaptation patterns: adolescents with lower-ranked taste in music should more easily start listening to higher-ranked music than vice versa (*adoption asymmetry hypothesis*).

The hypotheses about assimilation and adoption asymmetry refer to the behavioral part (dynamics of taste in music), while the hypothesis about the popularity ranking refers to the network part (dynamics of friendship). For testing them, we make use of the SIENA software (Snijders et al. 2005). SIENA (shorthand for Simulation Investigation for Empirical Network Analysis) is a computer program that carries out the statistical estimation of the dynamic actor-driven models introduced in Section 2. It can be downloaded for free at http://stat.gamma.rug.nl/stocnet/. The best way to run SIENA is as part of the StOCNET program collection (Boer et al. 2003), which is available at the same website.

Data and operationalization

We study the social network data collected in the *Teenage Friends and Lifestyle Study* (Michell & West 1996, Michell & Amos 1997, Pearson & West 2003). It covers a cohort of pupils at a school in the West of Scotland for which friendship network data, substance use, and several lifestyle variables (including 'music consumption') were recorded in three yearly waves, starting in 1995 with pupils aged 13, and ending in 1997. A total of 160 pupils took part in the study, of which 129 were present at all measurement points; these were included in our analyses. The friendship networks were assessed by a name generator that allowed for mentioning up to 6 friends.

Music taste was recorded by a 16-item inventory of music genres. Pupils were asked which type of music they liked listening to, with the options being *rock, indie, chart music, jazz, reggae, classical, dance, 60s/70s, heavy metal, house, techno, grunge, folk/traditional, rap, rave,* and *hip hop.* It may be argued that the fashion aspect of listening to music refers more to the particular musicians and songs that are popular than to the music style pupils listen to. However, we think that this is much more the case for later phases in life, when an 'own taste' has been acquired, than for the early phase of adolescence we investigate here, where experimenting plays a stronger role. Although certainly not the ideal operationalization, it seems acceptable to assume that among 13-15 year old pupils, preference for whole styles of music may (still) be treated as a fashion phenomenon.

As common in lifestyle research (e.g., Katz-Gerro 1999), the original items had to be reduced to a manageable amount of dimensions. We applied the following procedure: first, factor analyses were run, per measurement and on the pooled data. These suggested a 3 or 4 factor solution. Figure 1 shows a positioning of the items in 3-dimensional space according to a principal components analysis of the pooled data. The solutions differ in the role of the items *rap, reggae, house* and *hip hop*, which apparently form a weak scale on their own. Due to the comparatively little amount of independent information on this 4th dimension, we decided to exclude these items[3]. Further, the item *60s/70s*, which in Figure 1 lies in-between the "rock" and the "classical" group, was special in

[3] Running SIENA with strongly correlated variables is prone to lead to convergence problems of the stochastic approximation algorithm.

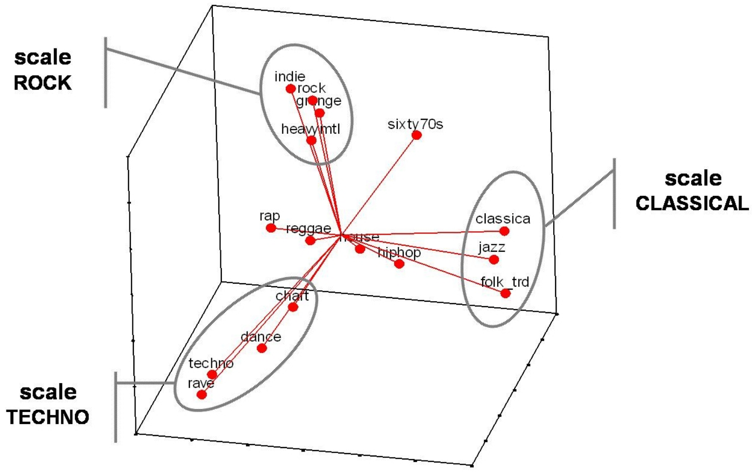

Figure 1: Music items in rotated 3D principal components space.

the sense that in separate factor analyses per measurement point, it 'moved' out of the "classical" group (in wave 1) into the "rock" group (in wave 3). Also this item was excluded. The final scales were obtained by a non-parametric Mokken scale analysis with MSP (Molenaar, Sijtsma & Boer 2000) on the pooled data, which gave the three scales solution as indicated in the figure. Although scale characteristics are weak for all the scales, with H-coefficients ranging from 0.35 (classical) to 0.40 (techno) and Cronbach's α ranging from 0.56 (rock) to 0.66 (techno), we continue to work with them because of their intuitive appeal and the illustrative character of the application. Scale averages over all three waves are 2.27 for techno (sum score of 4 dichotomous items), 0.83 for rock (4 items) and 01.1 for classical (3 items). The mainstream taste thus seems to be captured in the techno scale, followed at a distance by the rock scale. Listening to the music summarized in the classical scale seems to be confined to a rather small minority.

Earlier analyses on the same data set revealed that alcohol consumption was highly related to social network structure, both in terms of alcohol-based homophilous selection of friends and in terms of assimilation of alcohol consumption to the friends (Steglich, Snijders & Pearson 2004). In order to control for this major determinant of the friendship dynamics, we include the alcohol dimension as a co-evolving behavioral dimension into our study, next to the music consumption variables we are primarily interested in. Also, alcohol consumption is an element of adolescent lifestyle that may well be differentially associated with the three music styles we distinguish, and it seems desirable to assess its relation to taste in music. Alcohol is coded on a 5-point frequency scale ranging from 1 ('I don't drink') to 5 ('more than once a week').

Model specification

As indicated in Section 2, the specification of an actor-driven model is done by defining, for each of the dimensions that co-evolve, a *rate function* and an *objective function*. The rate function indicates the speed at which the network actors get an opportunity to change their behavior on the respective dimension, while the objective function indicates how such changes look like. In our application, this amounts to the specification of rate and objective functions for the network evolution part, for the three music dimensions identified, and for the alcohol dimension – a total of 10 functions. In order to keep things simple, we assume that the five rate functions are periodwise constant for each of the co-evolving dimensions, i.e., we estimate one basic rate parameter for each period and each dynamic dimension.

The objective functions are specified as follows. For network evolution, we assume that actors express some basic tendencies that are well-known to play a role in friendship networks (van de Bunt, can Duijn & Snijders 1999, Snijders 2001):

outdegree effect	Negative effect: actors tend not to establish friendship with just anyone.
reciprocity effect	Actors tend to reciprocate friendship.
distance-2 effect	Actors tend to prefer direct friendship to keeping friends' friends at a distance.
gender homophily effect	Actors tend to prefer same-gender friendships.
gender ego effect	Boys and girls may differ in their preferred number of friends.
gender alter effect	Boys and girls may differ in popularity.
behavior homophily effect	Actors may prefer friendship to others with same music taste and/or alcohol consumption level.
behavior ego effect	Music taste and/or alcohol consumption may determine social activity.
behavior alter effect	Music taste and/or alcohol consumption may determine popularity.

The first three components of this network objective function depend only on the network itself, while the others depend on characteristics of ego (the actor 'sending' the network tie), of alter (the actor 'receiving' the tie), or both (similarity between ego and alter). The homophily effects, expressing a preference for similar friends compared to dissimilar ones, may equivalently be characterized as 'heterophobia' effects – a point that can be helpful for interpreting parameter estimates. For behavioral evolution (and this concerns all 4 behavioral dimensions *listening to techno / rock / classical* and *alcohol consumption*), we assume that actors are affected by the following determinants:

tendency effect	Captures the overall preference for the three music dimensions and alcohol consumption.
assimilation effect	Actors tend to adapt to the music taste and/or alcohol consumption of their friends.
gender effect	Boys and girls may differ in music taste and/or alcohol consumption.

other behaviors' effects	Alcohol consumption and the preference for the three music dimensions may affect each other.

The homophily and assimilation effects are defined by a dyadic measure of *friendship similarity* on actor characteristics. It may suffice here to say that this similarity measure is standardized to the unit interval, with a score of zero indicating that two friends are maximally dissimilar on the actor characteristic (i.e., one of them has the minimum score and the other the maximum score), and a score of one indicating that they have identical scores (of whatever scale value).

When running SIENA in the StOCNET environment, model specification is done by checking the respective effects in the left column of the left part of the model specification screen (see Figure 2). The right part of the screen indicates the rate function (here modeled as periodwise constant).

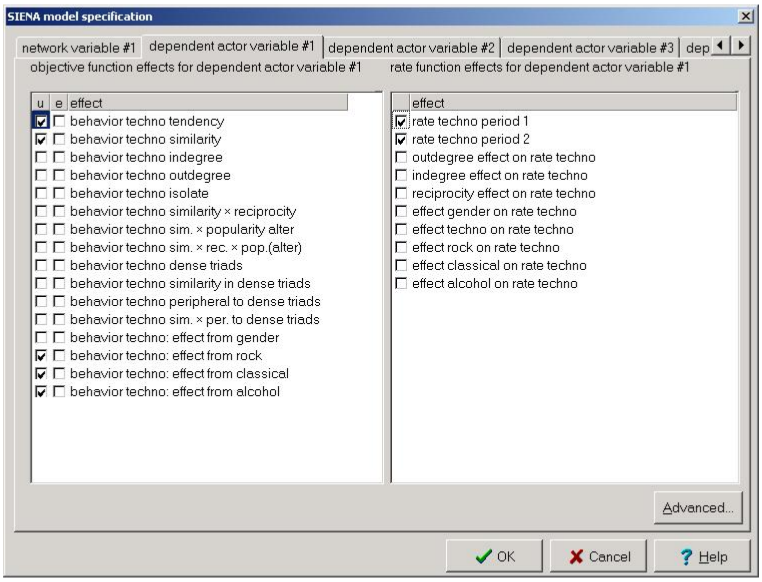

Figure 2: Screenshot of SIENA's model specification window.

For each of the effects included, a parameter is estimated, and some of these can be used for testing the hypotheses derived above. The *assimilation hypothesis* referring to the three dimensions of music taste can directly be tested by looking at significance of the parameters estimated for the assimilation effect in the respective behavioral objective function. The *popularity ranking hypothesis* can indirectly be tested by looking at significance of the parameters estimated for the effects *techno alter, rock alter,* and *classical alter.* If there is a popularity hierarchy revealed by music listening, the listening behavior of the friend (alter) should be linked to the pupil's preference for keeping or establishing the respective friendship tie. If such a hierarchy can be uncovered, the *adoption asymmetry hypothesis*, finally, can be tested by looking at significance of the main effects of the different music styles on each other. Here, we expect listening to the lower-ranked music style to have a stronger effect on listening to the higher-ranked music style than vice versa.

The model was estimated under the standard options of SIENA, which means: estimation of the parameters is based on 4 consecutive and increasingly accurate subphases of the Robbins-Monro moments estimation algorithm, and standard errors are calculated based on 500 additional simulation runs (Snijders et al. 2005). A total of 52 parameters were estimated with the SIENA software (version 2.0), which on a 3.0GHz Pentium 4 machine took 39 hours of estimation time[4].

Results

The results of our analysis are given in Table 1. We first address the results for the network part of the model, and then those for the behavioral dimensions.

In the friendship part of the model, a negative outdegree parameter indicates that friendship with arbitrary others is not stable, unless there are additional desirable properties to the friendship tie – e.g., reciprocation (positive reciprocity parameter), transitive embeddedness (negative distance-2 parameter), or a same-gender friendship (positive gender homophily parameter). Furthermore, girls tend to be more active in the friendship network than boys, i.e., tend to have more friends than boys, as indicated by the parameter of gender ego. Concerning the impact of music taste on friendship dynamics, one can say that there is a positive effect of listening to rock on popularity (parameter rock alter), there is homophily according to classical listening habits, and a positive effect of listening to classical on activity (parameter classical ego). In Table 2, an overview calculation is given of the impact which the different possible music taste configurations in a pair of actors have on the 'friendship value' between these actors (note that the table refers to situations in which each actor listens to but one music style). For the *popularity ranking hypothesis*, this means that if there is a status hierarchy based on music listening, it is the rock listeners that are highest in this hierarchy (parameter rock alter) while classical listeners are lowest (because they are equally shunned by techno as well as rock listeners, as expressed in the classical homophily / heterophobia parameter). As expected, alcohol consumption (the fourth behavioral dimension) has a strong impact on friendship dynamics in terms of homophily.

When looking at the music listening parts of the model, we see that the *assimilation hypothesis* can be confirmed only on the dimensions rock and techno, where the assimilation parameter is significant, but not for the classical dimension. The *adoption asymmetry hypothesis*, when applied to the diagnosed hierarchy, states that rock listeners (as the highest-ranked status group) should least easily adopt other music listening habits, and that classical listeners (as the lowest-ranked status group) should most easily adopt them, with techno listeners being located in-between these groups. Table 3 shows how changes on one music dimension affect the other music dimensions. What should be expected according to the *adoption asymmetry hypothesis* is a higher impact of lower-status music on the odds of listening to higher-status music than in the opposite direction. When confining our discussion to the parameters that are significant at $\alpha = 0.05$, the only statement we can make here is the comparison between the mutual effects of techno and rock on each other (all other main

[4]In the software version used for the reported analyses, computation time is roughly quadratic in the number of actors and in the number of parameters. A reduction to linear dependence on the number of parameters has meanwhile been achieved. This option will be available from SIENA release 2.2 onward.

effects are insignificant). An increase of the rock score by one reduces the odds of increasing the techno score versus decreasing it, by 50% (parameter rock on techno). Vice versa, an increase of the techno score by one reduces the respective odds for increasing the rock score, by just 40%. This means that comparatively less rock listeners tend to also listen to techno than techno listeners tend to also listen to rock, and can be counted as (weak) support of the adoption asymmetry hypothesis. Similarly, the comparison between techno and classical is in the predicted direction.

However, the most striking asymmetry in Table 3 concerns the comparison of rock and classical. Here, the hierarchy seems to be reversed: in contradiction to the *adoption asymmetry hypothesis*, a higher score on the rock scale increases the odds of listening more to the styles captured in the classical scale, while a higher score on the classical scale decreases the odds of listening more to the styles summarized in the rock scale.

Apparently, the classical dimension is special in several ways: there is no assimilation occurring on this dimension, but homophilous social selection. Both stands in diametrical contrast to the other music dimensions, which seem to be more 'socially acquired' and less 'socially steering' than the classical taste. The other dimensions also are not gender-specific, while there is a marginal positive effect of being female on classical (see also Roe 1985). The social hierarchy derived from the friendship dynamics puts classical at the lower end of the hierarchy, but this position is not confirmed by the music listening dynamics. Finally, classical is the only music taste associated to our controlling behavioral variable alcohol consumption: they tend to be incompatible.

As a result of our analyses, what emerges is a picture of a majority of pupils listening to music as summarized in the techno and rock scales, for whom the hypotheses are confirmed and where a preference for rock items seems to coincide with higher social status. And there is a small exceptional group of mainly (but not exclusively) girls, listening to music styles in the classical scale because of reasons exogenous to their school environment, barely drinking alcohol, and being avoided by most of their schoolmates. Their taste in music, though, seems to have appeal to the rock listeners, which makes it difficult to position these pupils on the social hierarchy. Previous research showing that tastes in music move during adolescence from mainstream 'chart' music (included in out techno scale) to more specific genres later on (Roe 1985, 1999) is confirmed by our analysis.

4 Notes on model assumptions, model identification, and interpretation of parameters

The threefold purpose of the following short discussion is (1) to give some hints on how to solve problems of parameter identifiability that may lead to divergence of the estimation algorithm. Related to this, we (2) point out the practical limitations incurred by making some standard model assumptions such as the assumption of homogeneity of rate and objective functions across actors. Finally, (3) some guidelines are given on how to interpret (and how not to interpret) parameter estimates. All parameters discussed in the previous section belong to the *objective functions* of the different submodels (network, the three music tastes, and alcohol). These functions are meant to capture stable mechanisms by which the network actors update their own behavior and outgoing network ties. Next to these, there also are the *rate functions'* parameters, which are used for modeling the progressing of time. The discussion starts with the rate parameters, followed by the parameters of the objective functions. For all parameter types, we use the empirical results from the previous section as illustration.

Rate parameters

The parameters of the rate functions specify the frequency by which an actor in the network is in a position to change his status quo on the respective submodel's dimension. Noting that actors are allowed not to change anything, the rate parameters may not be viewed as strictly behavioral indicators of change frequency, but as indicators for frequency of reconsideration, which may or may not lead to an actual change. When looking at the rate parameters in Table 1, we can see that in period 1, an actor on average got 12.45 times the opportunity to change one of his outgoing network ties, 3.40 times the opportunity to change his score on the techno dimension, 2.04 times the opportunity to change his rock score, et cetera. However, the rate parameters are sensitive to scale. This does not matter overly much when considering the network rate parameters, as the social network is 'naturally scaled' as long as tie variables are dichotomous. Here, each change means a change by ego of the friendship tie to one alter. For the behavioral dimensions, on the other hand, a change means one step up or down the scale, and for an M-point scale, the actor needs at least $M-1$ changes for moving from the lowest to the highest scale value, or vice versa. Hence, the rate parameters of the different behavioral dimensions can be compared to each other only after controlling for the scale (i.e., dividing by the range of the dependent behavior variable). In our data, all behavioral variables are measured on 5-point-scales, except for the classical dimension which is measured on a 4-point-scale. After controlling for scale, we (still) get the ordering *techno* $\succ$ *rock* $\succ$ *alcohol* $\succ$ *classical* in the first period and *techno* $\succ$ *alcohol* $\succ$ *rock* $\succ$ *classical* in the second period. By comparing the rates across periods, a global impression of the dynamics can be gained. The estimates obtained indicate that friendship stabilizes over time (the rate of change settles down), the two major music dimensions techno and rock stay about constant, while the dimensions classical and alcohol consumption show an increase in their 'reconsideration frequency' over time.

In the current application, no problems with the rate parameters were encountered. In general, however, high rate parameters are a cause of concern, as they indicate that under the given model specification, the actors have to undergo a tremendous if not unreasonable amount of small changes in order to come up with a global dynamic that resembles the observed one. In the worst and irreparable case, this can mean that the panel waves are too broadly spaced, such that earlier observations do not serve well for explaining later observations. If this is the case, it may make more sense to analyze the different measurements separately than to attempt a longitudinal SIENA analysis.

Other possible reasons for such divergence can be model misspecification, either in the objective function or in the rate function. Both functions should be able to account for sufficient heterogeneity of actors. Actors that have a strong impact on the estimation algorithm ('outliers' on some network or behavioral dimension) should be treated as the special cases they are, by including effects in the model specification that allow for singling them out. In the extreme case, even a mismatch between the whole model family and the data is possible. When it is impossible to reasonably and sufficiently model the observed actor heterogeneity (e.g., because heterogeneity at a later measurement point simply cannot be predicted from earlier observations, with the available data), it may make sense to recode the data such that they become more homogeneous.

For the user of SIENA, a situation of rate parameter divergence thus may most fruitfully be responded to by looking at outliers on the submodel's dependent variable and at the measurement point at the end of the period where the divergence occurred, and then adjust model or data accordingly.

Objective function parameters

For the interpretation of the objective functions' parameters (both network and behavioral), we recommend to safeguard against a couple of misunderstandings. Because the temporal progression is taken care of by the rate functions, the objective functions are inherently static. What they express thus is not a description of behavioral tendencies over time, but satisfaction measures that are suitable for explaining these observed changes under the assumption that actors are myopic satisfaction maximizers who, however, start out in a network neighborhood and with an own set of behaviors that may be far from optimal.

The parameter estimated for the outdegree effect in the network objective function is negative, which is the case in many empirical applications. The negative sign indicates that for the model actors, the existence of a tie to an arbitrary alter brings negative satisfaction - i.e., that ties are costly, and that the actor has a preference against having such ties unless other properties of the tie compensate for these costs. The negative sign does *not* mean that the total amount of ties would go down over time. It is true that the more negative this parameter gets, the smaller the average number of ties in the equilibrium distribution of the Markov process. However, whether or not the number of ties in the modeled network evolution process increases or decreases over time under a given configuration of parameter values, depends not on this equilibrium distribution alone, but also on the starting network. If there are very few ties in the beginning, the number is predicted to increase despite all costs involved - while if there are very many ties already, the number is likely to decrease. The same argument holds for the behavioral tendency parameters: they express tendencies in satisfaction, not tendencies over time.

In a similar way, the other parameters need to be interpreted as affecting satisfaction of the actor, and not as trends over time. E.g., the positive reciprocity effect that was estimated from our data means that the costs of having a tie to a random other (negative outdegree parameter) are more than compensated when this tie is reciprocated by the other – the net value of this tie to the actor being positive ($-1.89 + 2.34 = 0.45$). Likewise, the negative effect of classical on the rock dimension means that the general positive evaluation of rock that is expressed in the tendency parameter is zeroed out for scores of 2 or higher on the classical dimension ($0.59 - 2 \times 0.34 = -0.09$), the net value of listening to rock music being negative for such actors.

Also in the objective functions, model convergence can become an issue. Here, it is the classical issue of collinearity that plays a role. Accordingly, convergence problems related to objective function parameters can be addressed best by only including parameters into the model specification that are not overly correlated. However, there is considerable tolerance of the estimation algorithm even for correlation levels of 0.8 or higher between parameter estimators, which can and do occur among endogenous network parameters (e.g. the two transitivity-related parameters *distance-2* as used in the present analysis, and the effect of *transitive triplets* that is more broadly applied; Snijders 2001).

Finally, the random utility formalism of the model should not be mistaken to imply that all connotations evoked by the utility concept would hold. First, there are multiple objective functions instead of one overarching utility function, indicating that the model is closer to models of rational goal pursuit than to microeconomic utility models (Steglich 2003). Second, the myopic optimization character of the model means that the objective functions express what the actors seem to optimize on the short run, without any strategic foresight. And third, some effects may better be interpreted as constraints than as incentives or disincentives. For instance, the negative distance-2 parameter estimate, indicating that actors tend to shorten indirect links to friends' friends and turn them into direct friends, may better be interpreted as a result of opportunity structure than as a result of 'genuine preference'. When friends meet each other, they are likely to also be around with other friends, creating a social situation in which such transitive closure is more likely to happen than other types of friendship formation.

5 Conclusion

We showed how panel data on the dynamics of social networks and behavioral dimensions can be analyzed by making use of actor-driven models. Interdependent dynamics of this sort are characteristic for several active research topics, such as the spread of health-related behaviors in a network, the effects of communication networks on the individual, or the benefit which firms have from forming alliances. The particular application studied in the empirical part concerned the mutual effects of music listening and friendship on each other, which was investigated in a cohort of adolescents. It was shown how relatively complex hypotheses about status hierarchies underlying the dynamics of music listening could be tested in a straightforward way. The data were estimated with help of the SIENA software (Snijders et al. 2005) that can be downloaded for free at http://stat.gamma.rug.nl/stocnet/. Model estimates suggested a social hierarchy of music listening habits, in which the rock dimension dominated the techno dimension. Listening habits on the classical dimension were shown to be related to a special group of pupils, and could not be positioned in this hierarchy.

The limitations of the particular application we presented largely pertain to the operationalization of taste in music. On the one hand, while fashion waves in music are known to refer in the first place to the popularity of individual artists, our data was available only for whole music genres. On the other hand, the scales we constructed, while having intuitive appeal, showed relatively little internal consistency. This renders our results exploratory rather than conclusive. Further, the study was limited to straightforward tests of model parameters, which express 'micro behavior', i.e., the actions of individuals. An area still underexplored is the empirical relationship of such micro behavior of network actors to macro phenomena like segregation or segmentation of a social network (Baerveldt & Snijders 1994). In the study of fashion phenomena, this is of particular interest. According to Bourdieu (1984), fads and fashions serve for social differentiation and identity creation, i.e., for the creation of social boundaries. Such segregation phenomena have in the first place been studied in small group experiments in the context of social identity theory (Hogg et al. 2004) or on the macro level (Bourdieu 1984), but it is not clear to what degree the macro phenomena charted by the latter type of research can be explained by the individual-level processes identified by the former type of research.

A network study, which becomes possible with the actor oriented approach sketched in this paper, may be able to bridge the gap between the more cognitively oriented small group research and the segregation phenomena observed on the macro level. In the SIENA framework, it is easily possible to run simulations according to a given model parametrization. Usually, with the help of such simulation runs, model parameters are estimated from empirical data. However, once such 'realistic' model parameters have been obtained, they can also be used for running a couple more simulations for generating artificial data sets on the co-evolution of friendship and music taste. The statistical analysis of such empirically-informed simulations can be of help for assessing the impact of particular micro phenomena related to social identity (and expressed in model parameters) on properties of the emerging global dynamics (segregation on the macro level).

References

Baerveldt, C., and T.A.B. Snijders. 1994. Influences on and from the segmentation of networks: hypotheses and tests. *Social Networks*, **16**, 213 – 232.

Boer, P., M.E. Huisman, T.A.B. Snijders, and E.P.H. Zeggelink. 2003. *StOCNET: An open software system for the advanced statistical analysis of social networks. Version 1.4.* Groningen: *Pro*GAMMA/ICS. http://stat.gamma.rug.nl/stocnet/.

Bourdieu, P. 1984. *Distinction : a social critique of the judgement of taste.* London: Routledge & Kegan.

Bryson, B. 1996. Anything But Heavy Metal: Symbolic Exclusion and Musical Dislikes. *American Sociological Review*, **61**, 884 – 899.

Carley, K. 1991. A theory of group stability. *American Sociological Review*, **56**, 331 – 354.

Carrington, P., J. Scott, and S. Wasserman (Eds.). 2005. *Models and methods in social network analysis.* New York: Cambridge University Press.

Doreian, P. 1989. Network Autocorrelation Models: Problems and Prospects. In *Spatial Statistics: Past, Present, Future*, edited by Daniel A. Griffith. Ann Arbor: Michigan Document Services.

Dorogovtsev, S.N., A.V. Goltsev, and J.F.F. Mendes. 2002. Ising model on networks with an arbitrary distribution of connections. *Physical Review E*, **66**, 016104 1-5 (2002); cond-mat/0203227.

Friedkin, N. 1998. *A Structural Theory of Social Influence.* Cambridge: Cambridge University Press.

Hogg, M.A., D. Abrams, S. Otten and S. Hinkle. 2004. The Social Identity Perspective. Intergroup Relations, Self-Conception, and Small Groups. *Small Group Research*, **35**, 246 – 276.

Katz-Gerro, T. 1999. Cultural Consumption and Social Stratification: Leisure Activities, Musical Tastes, and Social Location. *Sociological Perspectives* **42**, 627 – 646.

Koskinen, J. 2004. *Esays on Bayesian Inference for Social Networks.* Dissertation. Department of Statistics, Stockholm University.

Latané, B., and A. Nowak. 1997. Self-Organizing Social Systems: Necessary and sufficient conditions for the emergence of clustering, consolidation and continuing diversity. *Progress in communication science*, **13**, 43 – 74.

Macy, M.W., J. Kitts, A. Flache, and S. Benard. 2003. Polarization in Dynamic Networks: A Hopfield model of emergent structure. Pp 162 – 173 in *Dynamic Social Network Modelling and Analysis: Workshop Summary and Papers*, edited by R. Breiger, K. Carley and P. Pattison. Washington: The National Academies Press.

Mark, N. 1998. Beyond individual differences: Social differentiation from first principles. *American Sociological Review*, **63**, 309 – 330.

McPherson, J.M., L. Smith-Lovin and J.M. Cook. 2001. Birds of a Feather: Homophily in Social Networks. *Annual Review of Sociology*, **27**, 415 – 444.

Michell, L., and A. Amos. 1997. Girls, pecking order and smoking. *Social Science and Medicine*, **44**, 1861 – 1869.

Michell, L., and P. West. 1996. Peer pressure to smoke: the meaning depends on the method. *Health Education Research Theory and Practice*, **11**, 39 – 49.

Molenaar, I.M., K. Sijtsma and P. Boer. 2000. *MSP5 for Windows. A program for Mokken scale analysis for polytomous items. Version 5.0.* University of Groningen: iec ProGAMMA.

Pearson, M., and P. West. 2003. Social network analysis and Markov processes in a longitudinal study of friendship groups and risk-taking. *Connections*, **25**, 59 – 76.

Roe, K. 1985. Swedish youth and music: listening patterns and motivations. *Comunication Research*, **12**, 353 – 362.

Roe, K. 1999. Music and identity among European youth: music as communication. *Journal on Media Culture*, **2**, ISSN 1567-7745.

Simmel, G. 1904. Fashion. *International Quarterly*, **10**, 130 – 155.

SIRC, The Social Issues Research Centre. 2004. *Smells Like Teen Spirit: Talking not taking in the teenage music tribe.* Report of The Social Issues Research Centre, Oxford.

Snijders, T.A.B. 1996. Stochastic actor-oriented models for network change. *Journal of Mathematical Sociology*, **21**, 149-176.

Snijders, T.A.B. 2001. The statistical evaluation of social network dynamics. Pp. 361-395 in *Sociological Methodology – 2001*, edited by M.E. Sobel and M.P. Becker. Boston and London: Basil Blackwell.

Snijders, T.A.B. 2005. Models for Longitudinal Network Data. Chapter 11 in Carrington, Scott & Wasserman (2005).

Snijders, T.A.B., and M.A.J. Van Duijn. 1997. Simulation for statistical inference in dynamic network models. Pp. 493 – 512 in *Simulating Social Phenomena*, edited by R. Conte, R. Hegselmann, and P. Terna. Berlin: Springer.

Snijders, T.A.B., Ch. Steglich, and M. Schweinberger. 2005. Modeling the co-evolution of networks and behavior. To appear in *Longitudinal models in the behavioral and related sciences*, edited by K. van Montfort, H. Oud and A. Satorra. Lawrence Erlbaum.

Snijders, T.A.B., Ch. Steglich, M. Schweinberger and M. Huisman. 2005. *Manual for SIENA version 2.1.* University of Groningen: ICS / Department of Sociology.

Steglich, Ch. 2003. *The Framing of Decision Situations. Automatic Goal Selection and Rational Goal Pursuit.* Dissertation. ICS / Faculty of Social and Behavioural Sciences, University of Groningen.

Steglich, Ch., T.A.B. Snijders, and M. Pearson. 2004. Dynamic Networks and Behavior: Separating Selection from Influence. *Under review.*

Suzuki, T., and J. Best. 2003. The emergence of trendsetters for fashions and fads: Kogaru in 1990s Japan. *Sociological Quarterly*, **44**, 61 – 79.

van de Bunt, G.G., M.A.J. van Duijn, and T.A.B. Snijders. 1999. Friendship networks through time: An actor-oriented statistical network model. *Computational and Mathematical Organization Theory*, **5**, 167 – 192.

Veblen, Th. 1899. *The Theory of the Leisure Class.* New York: Macmillan.

Submodel	**Parameter**	**Estimate**	**St. Error**	**p-value**
network	*outdegree*	−1.89	0.29	< 0.001
	reciprocity	2.34	0.12	< 0.001
	distance-2	−1.09	0.07	< 0.001
	gender homophily	0.80	0.12	< 0.001
	gender ego	0.24	0.11	0.030
	gender alter	−0.21	0.12	0.083
	techno homophily	0.08	0.33	0.798
	techno ego	−0.10	0.05	0.053
	techno alter	0.07	0.05	0.194
	rock homophily	0.11	0.41	0.791
	rock ego	−0.07	0.08	0.357
	rock alter	0.19	0.07	0.006
	classical homophily	1.44	0.69	0.039
	classical ego	0.40	0.17	0.015
	classical alter	0.15	0.17	0.362
	alcohol homophily	0.83	0.27	0.002
	alcohol ego	−0.03	0.03	0.397
	alcohol alter	−0.03	0.04	0.456
	rate period 1	12.45	1.54	< 0.001
	rate period 2	9.56	1.08	< 0.001
techno	tendency	0.01	0.25	0.960
	assimilation	0.45	0.18	0.014
	gender	0.25	0.12	0.035
	rock	−0.34	0.10	< 0.001
	classical	−0.13	0.23	0.577
	alcohol	0.07	0.10	0.500
	rate period 1	3.40	0.79	< 0.001
	rate period 2	3.46	0.78	< 0.001
rock	*tendency*	0.59	0.25	0.016
	assimilation	0.63	0.28	0.024
	gender	0.01	0.19	0.966
	techno	−0.25	0.09	0.003
	classical	−0.34	0.30	0.260
	alcohol	0.11	0.07	0.116
	rate period 1	2.04	0.42	< 0.001
	rate period 2	2.24	0.47	< 0.001
classical	tendency	0.67	1.30	0.606
	assimilation	0.42	1.17	0.716
	gender	1.57	0.83	0.057
	techno	−0.46	0.40	0.250
	rock	0.64	0.39	0.106
	alcohol	−1.03	0.34	0.002
	rate period 1	0.63	0.38	0.096
	rate period 2	1.43	0.55	0.010
alcohol	tendency	−0.30	0.37	0.420
	assimilation	0.94	0.27	< 0.001
	gender	−0.06	0.19	0.745
	techno	0.23	0.16	0.145
	rock	0.16	0.16	0.318
	classical	−0.59	0.32	0.067
	rate period 1	1.54	0.36	< 0.001
	rate period 2	2.50	0.54	< 0.001

Table 1: SIENA estimation results for the full model. Effects labeled in italics indicate significance at $\alpha = 0.05$ (two-sided test).

		alter		
		techno	**rock**	**classical**
	techno	−0.06	0.25	−1.39
ego	**rock**	−0.15	0.54	−1.31
	classical	0.02	0.50	1.73

Table 2: Contributions of music taste configurations to the network objective function, as derived from the estimates in Table 1 (calculations refer to highest possible scores and mutually exclusive music tastes).

		impact on odds		
		techno	**rock**	**classical**
	techno	—	−40%	−60%
increase	**rock**	−50%	—	+256%
	classical	+29%	−49%	—

Table 3: Impact of increasing the score on one music dimension on the odds of increasing versus decreasing the score on the other music dimensions, as derived from the estimates in Table 1.