

Applying SIENA

An Illustrative Analysis of the Coevolution of Adolescents' Friendship Networks, Taste in Music, and Alcohol Consumption

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Abstract. We give a nontechnical introduction into recently developed methods for analyzing the coevolution of social networks and behavior(s) of the network actors. This coevolution 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 coevolution process is sketched, and it is shown how to use the SIENA software for estimating these models. We illustrate the method by analyzing the coevolution of friendship networks, taste in music, and alcohol consumption of teenagers.

Keywords: network dynamics, longitudinal, social networks, stochastic modeling

Introduction

Social network analysis is concerned with how actors are related to each other (see Carrington, Scott, & Wasserman, 2005). The actors can be individual persons, but also organizations, countries, and so on, 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*, that is, the empirical finding that social ties occur more frequently among demographically or behaviorally similar actors than among dissimilar actors (Doreian, 1990). 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*, 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 article, an outline is provided of how such questions can be answered. We cover the case of an evolving "complete" network and coevolving 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 coevolution of networks and actor characteristics can be found in the literature (Carley, 1991; Dorogovtsev, Goltsev, & Mendes, 2002; Latané

& Nowak, 1997; Macy, Kitts, Flache, & Benard, 2003; Mark, 1998). The models presented in this article differ from these strands of literature in their explicit gearing toward 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 an 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, Steglich, Schweinberger, & Huisman, 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.

The article is structured as follows. In the next section, a family of stochastic, actor-driven models for the coevolution of social networks and individual behavior is sketched. These models build on earlier models for “pure” network dynamics that were recently extended to account for the joint dynamics of networks and behavior. This modeling approach is applied, in the third section, 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. We conclude with a brief recapitulation of our main messages.

A Family of Actor-Driven Models for the Coevolution 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 coevolving 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 two actors A and B, the state space would consist of the four possible dyad configurations (1) A and B unconnected (empty dyad), the two asymmetric dyads (2) A→B and (3) A←B, and the mutual dyad (4) A↔B. When increasing the number n of network actors, the number of states rises at a squared exponential rate¹, such that for a set of six actors, the state space already contains more than a million 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, that is, taken as the (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.
- actors do not coordinate their actions but act conditionally independent of each other, given the current state of the network.
- actors change at most one tie variable at a time, that is, create one new link or dissolve one existing link.

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 a random utility function (the so-called *objective function*), while task (b) is solved by specifying a distribution for the actors’ individual waiting times (with the parameter given by the so-called *rate function*). By this approach, the time dependence of the network evolution process is implicitly modeled as an 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 (a Markov assumption). For more details, we refer to the specific model analyzed in the next section, and to the other works cited in the beginning of this section.

So far, the model sketch covered only the dynamics of network evolution. The addition of coevolving 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 or her score on the behavioral dimension by moving at most one category upward 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

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

2 For the implications that 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 works cited in this section.

done by (a) specifying the Cartesian product of the separate state spaces as the joint state space, (b) assuming conditional independence of the occurrence of the different types of micro steps, and (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 coevolution 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 to change what they have under control (their outgoing ties and their 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 nonstationary process of network-behavioral dynamics, starting at the first observation, and then drifting toward 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 (Snijders, Steglich, & Schweinberger, in press) and also allows for simulation-based *maximum likelihood* and *Bayesian* estimation of models for pure network evolution (Koskinen, 2004). Extension of the likelihood-based estimation methods to the coevolution with behavioral dimensions is pending.

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 the 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. “Sameness 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) and for the manifestation of a status hierarchy (Bourdieu, 1984). Classic descriptions of fashion emphasize *differentiation* and *imitation* as driving forces underlying fashion dynamics (1899, Simmel, 1904; Veblen, 1899). According to these theories, actors at the top of the hierarchy attempt to differentiate themselves from 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 toward behavioral conformity among friends (the *assimilation hypothesis*).

Moving down in the postulated status hierarchy, schoolmates with a prominent music taste may also 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 the effects of the adolescents’ taste in music on their popularity (the *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 (the *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 (an acronym for Simulation Investigation for Empirical Network Analysis) is a computer program that carries out the statistical estimation of the dynamic actor-driven models introduced above. The best way to run SIENA is as part of the StOCNET program collection (Boer, Huisman, Snijders, & Zeggelink, 2003).

Data and Operationalization

We study the social network data collected in the *Teenage Friends and Lifestyle Study* (Michell & Amos, 1997; Michell & West, 1996; 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 re-

corded in three yearly waves, starting in 1995 with pupils aged 13 and ending in 1997. The number of participating respondents was 150 in the first wave, 146 in the second, and 137 in the third. More than two thirds of the changes in participation are due to pupils leaving or joining the school; the rest are occasional missings (for a detailed overview, see Bush, West, & Michell, 1997). In total, 160 pupils took part in the study, of which 129 were present at all measurement points. While in principle SIENA allows for special treatment of joiners and leavers (Huisman & Snijders, 2003), we decided to include only the complete cases in our analyses. The main reason for this was the resulting reduction of expected estimation time by about one third, combined with results of exploratory analyses that did not reveal any qualitative differences between the full sample and the complete cases subsample.

The friendship networks were assessed by a name generator that allowed for mentioning up to six friends. The restriction to a fixed maximum number of network neighbors can be problematic when one is interested in assessing local or global network structure (Holland & Leinhardt, 1973). On the one hand, in our data, the restricted format seems not to have cut off much. The median number of reported friends is four, and 88% of the respondents named less than the maximum number of six. On the other hand, the modeling approach we take relies on measures of local network structure that are, in principle, affected by an upper bound on the number of friends. To what degree this has an impact on the results of our analyses currently remains an open question.

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 is common in lifestyle research (e.g., Katz-Gerro, 1999), the original items had to be reduced to a manageable number of dimensions. We applied the following procedure: first, factor analyses were run, per measurement and on the pooled data. These suggested a three- or four-factor solution. Figure 1 shows a positioning of the items in three-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 fourth dimension, we decided to exclude these items.³ Fur-

ther, the item *60s/70s*, which in Figure 1 lies in between the rock and the classical groups, was special in 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). This item was also excluded. The final scales were obtained by a nonparametric 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 four dichotomous items), 0.83 for rock (four items), and 0.11 for classical (three 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 is 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 coevolving 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 above, the specification of an actor-driven model is done by defining, for each of the dimensions that coevolve, 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 what 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 coevolving dimensions, that is, 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 (Snijders, 2001; van de Bunt, van Duijn, & Snijders, 1999):

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

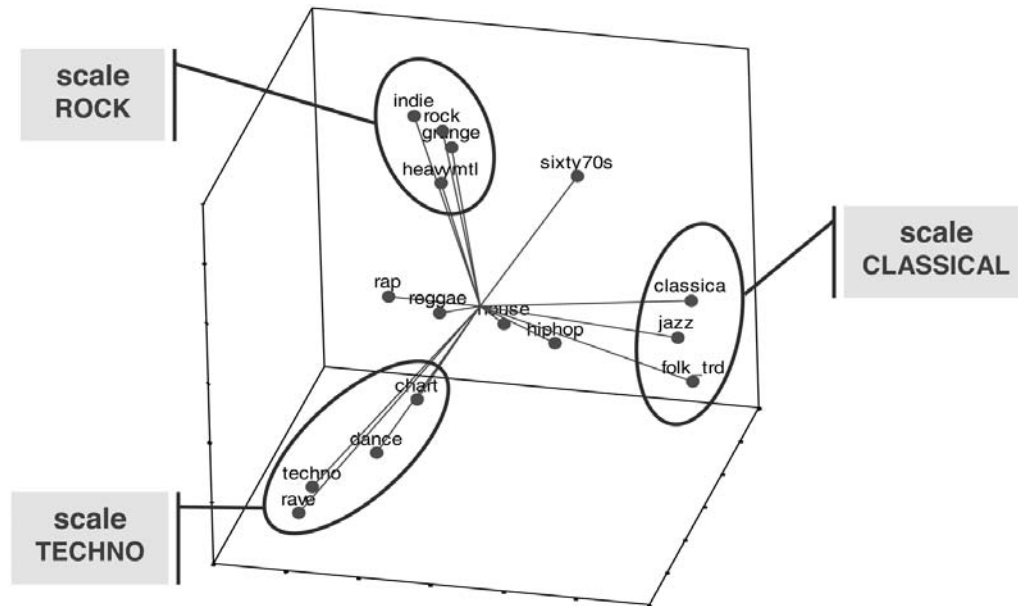


Figure 1. Music items in rotated three-dimensional principal-components space.

- *Outdegree effect*. Negative effect: Actors tend not to establish friendship with unspecific others.
- *Reciprocity effect*. Actors tend to reciprocate friendship.
- *Distance-2 effect*. Negative effect: Actors tend to avoid indirect relations via third parties.
- *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 the 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), 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 four 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 *similarity* on actor characteristics. It may suffice here to say that this similarity measure is standardized to the unit interval, with a score of 0 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 1 indicating that they have identical scores (of whatever scale value). A broader catalogue of possible effects than the one chosen for the present analysis is given by Steglich et al. (2004).

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 be tested directly by looking at the significance of the parameters estimated for the assimilation effect in the respective behavioral objective function. The *popularity-ranking hypothesis* can be tested indirectly by looking at the 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 the 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 that estimation of the parameters is

based on four consecutive and increasingly accurate sub-phases 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 3.0 GHz 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 tends to be avoided, unless there are additional desirable properties to the friendship tie—for example 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, that is, 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), homophily according to classical listening habits, and a positive effect of classical listening on activity (parameter classical ego). In Table 2, an overview calculation is given of the impact 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 only 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 on 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 di-

rection. 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 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 1 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 there is homophilous social selection. Both stand 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. The findings are in line, though, with previous research showing that tastes in music move during adolescence from mainstream “chart” music (included in our techno scale) to more specific genres later on (Roe, 1985, 1996).

Conclusion

We showed how panel data on the dynamics of social networks and behavioral dimensions can be analyzed by mak-

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 subquadratic dependence on the number of actors and to linear dependence on the number of parameters has meanwhile been achieved. These options will be available from SIENA release 3.0 onward.

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

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

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).

		Alter		
		Techno	Rock	Classical
Ego	Techno	-0.06	0.25	-1.39
	Rock	-0.15	0.54	-1.31
	Classical	0.02	0.50	1.73

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.

		Impact on odds		
		Techno	Rock	Classical
Increase	Techno	—	-40%	-60%
	Rock	-50%	—	+256%
	Classical	+29%	-49%	—

ing 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 that 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). 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, that is, 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, that is, 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, Abrams, Otten, & Hinkle, 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 article, 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 more simulations for generating artificial data sets on the coevolution 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).

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