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Social Networks and Social Settings: Developing a Coevolutionary View

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Abstract One way to think about social context is as a sample of alters. To understand individual action, therefore, it matters greatly where these alters may be coming from, and how they are connected. According to one vision, connections among alters induce local dependencies—emergent rules of social interaction that generate endogenously the observed network structure of social settings. Social selection is the decision of interest in this perspective. According to a second vision, social settings are collections of social foci—physical or symbolic locales where actors meet. Because alters are more likely to be drawn from focused sets, shared social foci are frequently considered as the main generators of network ties, and hence of setting structure. Affiliation to social foci is the decision of central interest in this second view. In this paper we show how stochastic actor–oriented models (SAOMs) originally derived for studying the dynamics of multiple networks may be adopted to represent and examine these interconnected systems of decisions (selection and affiliation) within a unified analytical framework. We illustrate the empirical value of the model in the context of a longitudinal sample of adolescent participating in the Glasgow Teenage Friends and Lifestyle Study. Social selection decisions are examined in the context of networks of friendship relations. The analysis treats musical genres as the main social foci of interest.

Keywords Networks · Affiliation · Social networks · Social selection · Social foci · Stochastic actor-oriented models

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Soziale Netzwerke und Soziale Situationen: Ein co-evolutionäres Modell

Zusammenfassung Eine Möglichkeit, soziale Kontexte zu bestimmen, ist, sie als Stichprobe von Alteri zu definieren. Um individuelles Handeln zu verstehen, ist es wichtig zu wissen, woher diese Alteri kommen und wie sie miteinander verbunden sind. Einem Ansatz zufolge führen Beziehungen zwischen Alteri zu lokalen Abhängigkeiten. Es entstehen Regeln der sozialen Interaktion, die endogen die beobachtete Netzwerkstruktur von sozialen Situationen (settings) ausmachen. Hier geht es um die sozialen Wahlen. Einem anderen Ansatz nach sind soziale Situationen Sammlungen von sozialen Foci, also physischen oder symbolischen Räumen, in denen sich Personen treffen. Weil die Alteri eher aus den Foci stammen, werden soziale Foci häufig als die wichtigsten Ursachen für Netzwerk-Bindungen, und damit der Struktur der Situation, angesehen. Die Bindung an einen sozialen Focus ist das zentrale Interesse in diesem zweiten Ansatz. In unserem Beitrag zeigen wir, wie sich stochastische Akteurs-orientierte Modelle (SAOMs), die ursprünglich für die Analyse dynamischer multipler Netzwerke gedacht waren, auf miteinander verbundene Systeme von Entscheidungen (Wahl und Zugehörigkeit) in einem einheitlichen analytischen Bezugsrahmen anwenden lassen. Wir zeigen den empirischen Wert unseres Modells an einer Längsschnitt-Studie von Jugendlichen in der *Glasgow Teenage Friends and Lifestyle Study.* Die sozialen Wahlen werden im Kontext von Netzwerken von Freundschaften untersucht; dabei werden musikalische Genres als der wichtigste soziale Focus herausgearbeitet.

Schlüsselwörter Netzwerke · Soziale Wahlen · Zugehörigkeit · Soziale Foci · Stochastic actor-oriented models

1 Introduction

The notion of "alters"[1] as social context *(Die Anderen als sozialer Kontext)*—clearly articulated by Andreas Diekmann elsewhere in this special issue—brings to mind Jean Paul Sartre's vision of hell. It also prompts a fundamental question: Where do these alters come from? A major line of contemporary research in the analysis of social networks takes this question as the starting point for the specification of multiple dependence mechanisms between the network ties that link actors, and settings defined as subsets of possible alters (for recent comprehensive reviews see Rivera et al. 2010; Snijders 2011).

In a foundational contribution to the development of this line of research, Pattison and Robins (2002) propose the view of social networks as constructed locally through concatenation of local rules of social selection. These mechanisms operate in overlapping regions called social neighborhoods or—sites of interaction corresponding to subsets of possible network ties (Pattison and Robins 2002, p. 301). In

[1] Throughout the manuscript we use the less correct but more common plural form "alters" rather than "alteri".

this perspective, the composition of ego's social context (or setting)[2] is regulated by endogenous association-based mechanisms defined over local social neighborhoods. In recent years, substantial progress in statistical modeling of social networks has progressively refined and extended the menu of social mechanisms available for constructing and sustaining social settings (Snijders et al. 2006; Robins et al. 2007).

This view of social settings as local network neighborhoods that generate "Contingencies among possible network ties" (Pattison and Robins 2002, p. 305) is consistent with the notion of "setting as alters". This view also provides one possible analytical strategy to address associated questions about the mechanisms that regulate the selection of alters into social settings (Robins et al. 2001).

More recent research has revealed that local network neighborhoods are themselves embedded in larger structures that may span multiple levels of action—or layers of the social system (Wang et al. 2013). This is best illustrated by studies of formal organizations where individuals are members in units that are hierarchically nested in other—progressively more aggregate units connected by formal dependence relations (Borgatti and Foster 2003; Lazega et al. 2008; Lomi et al. 2014; Lusher et al. 2012; Rank et al. 2010).

The multilevel character of social settings that these more recent studies emphasize apparently exposes the view of "network neighborhoods as social settings" to the criticism that: "Unfortunately the study of social networks has often been carried out without concern for the origins in the larger social context. Most network analysis ends with the description and labeling of patterns; and when explanations of patterns are offered, they frequently rely upon inherent tendencies within networks to become consistent, balanced, or transitive" Feld 1981, p. 1015).

Clearly, this view is based on a sociological concept of context not simply as "alters," but rather as a collection of differentiated social foci or "Social, psychological, legal, or physical entit(ies) around which joint activities are organized (e.g., workplaces, voluntary organizations, families etc)" (Feld 1981, p. 1015). Like network neighborhoods, social foci tend to induce dependence relations among participants because: "[A]s a consequence of interaction associated with their joint activities, individuals whose activities are organized around the same focus will tend to become interpersonally tied and form a cluster" (Feld 1981, p. 1015). The consequence of this argument is that analysis of how individuals construct their social setting through interaction with a limited number of other individuals (their "alters") requires information about how individual interact in extra-network foci. According to Feld, (1981, p. 1016): "Without such contextual information, conclusions about networks and their consequences are likely to be incomplete and even misleading".

This argument reveals a clear tension in our theoretical understanding of social context and in our attempt to clarify the mechanisms through which contexts (settings) are constructed. Clearly, alters are not randomly sampled from populations of possible associates. Network ties create dependencies that affect this sampling process in predictable directions (Robins et al. 2005). Yet, alters are more likely to be

[2] Throughout the manuscript we do not provide explicitly different definitions for social "settings" and "contexts".

drawn from sets defined by joint participation in social foci—from "focused sets" in Feld's words (1982, p. 798).

In general, this discussion suggests that it would be desirable to have an analytical framework that allows both views to be integrated and their relative empirical value appraised. Such an analytical framework would be consistent with Pattison and Robins (2004) more comprehensive notion of social spaces—or contexts that are combined across multiple levels. To progress beyond programmatic statement, the notion of social space requires mutual articulation of the mechanisms through which actors construct their social setting, and the mechanisms through which actors choose the social foci in which they participate. The former set of mechanisms control social selection decisions ultimately giving rise to a social setting as defined by Pattison and Robins (2002). The latter set of mechanisms control participation in social foci ultimately giving rise to an affiliation network of individuals-by-foci, and hence to a social setting as defined by Feld (1981).

The objective of this paper is to illustrate how recent advances in Stochastic Actor Oriented Models (SAOMs) provide this analytical framework, and how such models may be adopted to reconcile the rival intellectual traditions we have briefly outlined. More specifically we adopt the recent SAOM for the co-evolution of one-mode and two-mode networks recently derived by Snijders et al. (2013) to specify multi-level mechanisms that connect individuals to social settings through social foci and social networks.

To establish the empirical value of the model we propose, we use data collected by Bush et al. (1997) in the context of the Glasgow Teenage Friends and Lifestyle Study. The analysis focuses on the coevolutionary relation linking change of friendship ties among adolescents and change in their preferences for music genres (See also Steglich et al. 2006 for a recent reanalysis of the same data). In the analysis we present, music genres play the role of social foci (Feld 1981)—occasions that facilitate the creation of direct network ties. The tendency of similarity in musical tastes (and patterns of cultural consumption in more general terms) to generate or stabilize social relation has been long recognized (Bryson 1996; van Eijck 2001; Lewis et al. 2008). We define affiliation-based closure as a multilevel network mechanism generating social relations through joint participation in focused activities (McPherson et al. 2001). We define association-based closure as a multilevel mechanism generating similarity in patterns of affiliation to social foci from the existence of network ties among adolescents (Wang et al. 2013). The objective of the analysis contained in the empirical part of the paper is to establish which one of these alternative mechanisms of multilevel closure better explains the coevolutionary dynamics of social setting and social networks among the adolescents in the sample.

2 Multilevel mechanisms linking networks and setting

Relations from nowhere do not exist. Like other social processes relations exist in settings. Settings are contingent times and places where actors meet and establish network ties—places in which individual action is situated (Abbott 1997).

For the purpose of the argument that we want to develop in this paper, the relevant feature of social settings is that they are internally differentiated in the sense that they: “Can be seen as consisting of a number of different foci and individuals, each individual is related to some foci and not to others” (Feld 1981, p. 1016). As we will see in the next section, it is precisely this internal articulation of social settings into differentiated foci that allows their representation as two-mode (or “affiliation”) networks—i.e., networks containing two distinct sets of elements and for which relations are defined only between elements in different sets (Wasserman and Faust 1994).

This representation is commonly found, more or less explicitly, in a variety of studies. Examples of social foci include, among many others: (i) committees in which politicians participate (Padgett 1990); (ii) social events that actors attend (Borgatti and Everett 1997; Davis et al. 1941); (iii) investment syndicates formed by venture capital firms (Sorenson and Stuart 2008); (iv) physical locations where individuals meet like, for example, streets, bars or shops (Whyte 1943); (v) facts that team members know (Carley 1991); (vi) companies that students may be willing to consider as potential employers (Snijders et al. 2013); (vii) issue areas attracting the attention of Supreme Court justices (Breiger 2000); (viii) social identities that relief organizations associate to administrative practices (Breiger and Mohr 2004; Mohr and Duquenne 1997); (ix) companies connected by shared members in their board of directors (Robins and Alexander 2004), and (x) projects in which different kinds of organizations are involved within broader civic arenas (Mische and Pattison 2000).

In all these examples, social settings (e.g., civic arenas) are collections of differentiated social foci (e.g., projects) in which actors (e.g., organizations) are jointly involved (Mische and Pattison 2000). In all these examples, individuals participating in the same social foci have been found to be more likely to become connected by direct network ties than individuals participating in different foci. This is the case because joint affiliation to specific social foci increases mutual awareness and provides opportunities for commensuration (Stinchcombe 2002)—i.e., for the discovery and appraisal of similarities and differences that are frequently considered as the main antecedents of network ties (McPherson et al. 2001). Therefore, while obviously different, the various examples of social foci we have listed are also fundamentally similar in that: “[I]ndividuals whose activities are organized around the same focus will tend to become interpersonally tied and form a cluster” (Feld 1981, p. 1016). The examples discussed are also similar in that they all involve forms of bipartite association between the rows (“actor”) and the columns (“foci”) of an affiliation network.

In network terms, Feld’s hypothesis implies that social settings affect the dynamics of social networks through a process of closure by affiliation or “affiliation-based closure”: individuals becoming connected through social relations generated by joint participation (or interest) in specific dimensions of their settings. The process postulated by Feld (1981) is “affiliation-based” because individual decisions to establish direct network ties depend on joint affiliation to social foci. The process may be defined as “closure” because it induces bipartite clustering as illustrated in the lower panel of Fig. 1. Affiliation-based closure involves a multilevel process because it involves relations between entities defined at different levels of analysis and observation: individuals (white circles) and social foci (red squares).

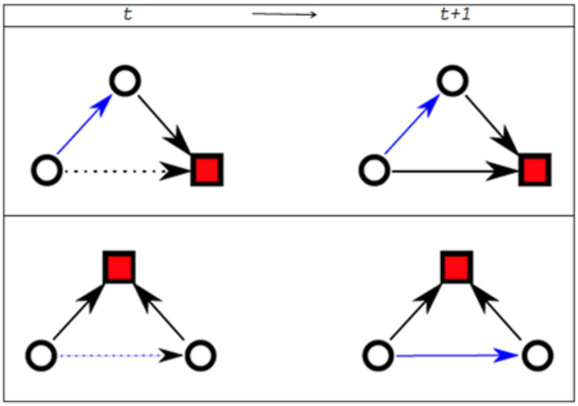


Fig. 1 Closure by association (*above*), and closure by affiliation (*below*). *White circles* are individuals. *Red squares* are social foci. *Blue edges* represent social relations between individuals. *Black edges* represent affiliation ties linking individuals to social foci. *Dashed edges* are connections not yet existing at time *t*

The argument that we have developed so far both hides, but at the same time reveals a fundamental duality linking individuals and social foci. Building on Breiger's notion of duality (2002, p. 303) we may say that a social focus "is" the set of actors jointly involved in it. In a fundamental sense, these actors "are" the multiple foci in which they participate. Relations between individuals, therefore, dually imply relations between social foci. This is probably what Feld had in mind when he recommended that (1981, p. 1019): "[I]t is important to remember that the formation of social networks and the relations to foci are interdependent. Once there is a tie between two individuals, these individuals will tend to find and develop new foci around which to organize their joint activity".

This view clearly resonates with the claim that social settings are contingent outcomes generated by social processes connecting individual actors (Pattison and Robins 2004). In this perspective, social networks may affect patterns of affiliation to social settings through a process of closure by association, or "association-based closure": individuals connected through social relations will be more likely to participate in (or build) shared social foci. This process is "association-based" because decisions to participate in specific foci are assumed to be driven by pre-existing social connections between actors. As before, we describe the process as "closure" because it induces a specific form of 2-mode network clustering as illustrated in the upper panel of Fig. 1.

Similarly to affiliation-based closure, association-based closure involves a multilevel process because it involves relations between individuals and social foci that are defined at different levels of analysis (Conaldi et al. 2012).

As it is readily apparent from Fig. 1 (see figures at time t+1 in the column to the right), affiliation-based and association-based closure mechanisms produce outcomes that are observationally indistinguishable in cross-sectional samples, i.e., connected individuals who are affiliated to the same foci. This is an outcome that that students of social networks typically associate with homophily (McPherson et al. 2001) or other forms of attribute-dependent assortative mixing (Rivera et al. 2010). The underlying trajectories responsible for this outcome, however, are very different and may reveal important details on how affiliation to social foci come to link social settings and social networks.

More specifically, mechanisms of affiliation-based closure are consistent with social selection arguments according to which individuals expressing preferences toward the same social foci are more likely to become connected by network ties (Snijders et al. 2013). Mechanisms of association-based closure are more consistent with social influence arguments according to which individuals connected by network ties tend to assimilate the preferences and behavioral orientations of their network partners. While the problem of separating the effects of social selection from those of social influence is well recognized in contemporary social network research (Steglich et al. 2010), available studies have restricted this problem to the analysis of social networks and individual behavioral outcomes. We are aware of no research that has recognized the multilevel character of social selection and social influence process. In the next section we outline a stochastic actor-oriented model recently derived by Snijders et al. (2013) for the coevolution of 1-mode and 2-mode networks that speaks directly to this concern.

3 Social networks coevolving with social settings

One way of linking social networks to social settings to facilitate empirical investigation is to see both as outcomes of coupled processes of change unfolding across different levels.

The first is the level of social ties between actors—the level at which change in network connections between individuals is observable. The second is the level of affiliation ties linking actors to constitutive dimensions of their social setting. Hypotheses about the specific coupling mechanisms connecting these two levels represent the core of the recent extension of stochastic actor-oriented models (SAOMs) proposed by Snijders et al. (2013). Wasserman and Iacobucci (1991) and Skvoretz and Faust (1999) provide earlier example of models inspired by a similar objective.

The model was originally derived for examining the coevolutionary dynamics of change in one-mode and two-mode networks. The model involves two interdependent processes. The first is a social selection process controlling change in network ties defined over the set of all possible ties that may connect social actors. The second is a bipartite affiliation process linking social actors to constitutive dimensions of their social setting ("social foci") defined over the set of all possible associations. The model provides an analytical framework to examine how network ties affect participation in social foci and—at the same time—how joint participation in those foci affects the dynamics of network ties. The former process, operating from ties to settings, is what we called association-based closure. The second process—operating from setting to ties—is what we have called affiliation-based closure. Both processes entail multilevel network closure mechanisms controlling tendencies toward clustering across levels of action (Wang et al. 2013).

To fix ideas, suppose that observations are available at T time points (with $T>2$) on a one-mode ("social") network X with node set N and directed tie variables Xij for $i, j \in N$ ($i \neq j$), indicating the presence of absence of a tie from actor i to actor j (Snijders et al. 2013). In network X, ties connect pairs of actors (i, j) through the existence of a specific social relation. In the empirical case that we present later in the paper, for example, social connectivity in X is determined by change in friendship ties between the adolescents analyzed by Steglich et al. (2006).

Suppose, further, that observations are also available at T time points (with T > 2) on a two-mode network Y with tie variables Yia (for i ∈ N, a ∈ A), and with Yia = 1 if actor i participates in activity a, and Yia = 0 otherwise (Snijders et al. 2013). In the network Y, ties (i, a) affiliate actors to activities, events, sites or any other object that may serve as social foci (Feld 1981). In the empirical example that we present later in the paper Y affiliates actors to musical genres interpreted as social foci (Bush et al. 1997; Pearson and West 2003).

The process of social selection operating on X may be defined in terms of change in network ties (Xij) controlled by the following network evaluation function:

$$f_i^x(x, y) = \sum\nolimits_k \beta_k^x s_{ki}^x(x, y), \tag{1}$$

The network evaluation function (1) represents the relative propensity of actor i to make a change toward state x of the social network, given that the affiliation network is in state y. In the network evaluation function, $s_{ki}^x(x, y)$ are called effects, and β_k^x are parameters which tell how strongly and in what direction the associated effect affects the change in the network of observed social relations.

The process of bipartite affiliation operating on Y may be defined similarly in terms of change in ties of association (Yia) controlled by the following setting evaluation function:

$$f_i^y(x, y) = \sum\nolimits_k \beta_k^y s_{ki}^y(x, y), \tag{2}$$

The setting evaluation function (2) represents the relative propensity of actor i to make a change toward state y of the two-mode network, given that the one-mode network has state x. As before, $s_{ki}^y(x, y)$ are called effects, and β_k^y are parameters which tell how strongly and in what direction the associated effect affects the change in the observed affiliation network.

A basic assumption of the model is that actors change at most one tie variable at a time, that is actors decide to create only one new link or dissolve only one existing link at a specific time point. Because in the model the ties are defined as dichotomous, changes in social and affiliation ties can be seen as a toggle of the tie variables, i.e., as changes of Yia or Xij into (1−Yia) or (1−Xij), respectively. Of course, the model also admits the possibility of no change (Snijders et al. 2013).

Both $s_{ki}^x(x, y)$ and $s_{ki}^y(x, y)$ are statistics computed on the observed social and affiliation networks, respectively. They may defined in terms of linear combinations of: (i) endogenous network dependencies created by mechanisms such as, for example, "reciprocity" and "transitivity"; (ii) endogenous 2-mode dependencies such as, for example, the tendency of specific elements of the social setting to attract affiliation ties ("popularity"), and (iii) cross-level dependencies such as, for example, the different types of closure that we have discussed in the prior section (Snijders et al. 2013). Finally, network effects may interact with actor-specific or relation-specific covariates such as, for example, gender, age and spatial distance to control for sources of exogenous variation in the dynamics of social and affiliation networks.

As discussed in Snijders et al. (2010) separate endowment functions may be defined to specify the factors that affect the termination, rather than the creation, of a tie. Such endowment functions may be defined for endogenous as well as exogenous effects. Endowment effects are both conceptually relevant as well as empirical important because a large proportion of observed relationships are replicated—i.e., they exist today because they existed in a prior time period. It is substantially important, therefore, to estimate models that specify mechanisms underlying the creation of new network ties, while controlling for the stabilizing force (or inertia) of preexisting ties. As we will see in the empirical part of the paper, different kinds of multilevel closure display asymmetric tendencies with respect to creation and dissolution processes.

In the section that follows, we situate the model in the analysis of an empirical case that we have selected to illustrate specific aspects of the coevolution of social networks and social settings. More specifically we will narrow the analytical focus on the specification and identification of different paths to multilevel closure as discussed in the prior section. The case is based on data originally collected by Bush et al. (1997) in the context of their Glasgow Teenage Friends and Lifestyle Study. Studies based on these data include Michell (1997); Michell and West (1996); Michell and Amos (1997), Pearson and Michell (2000), and Pearson and West (2003). More recent analyses may be found in Steglich et al. (2006), and in Steglich et al. (2010).

4 Illustration

4.1 Data

The data we use in the empirical part of the paper come from the "Teenage Friends and Lifestyle Study" (Michell and West 1996; Pearson and Michell 2000) that was conducted from 1995–1997 among teenage secondary school pupils in Glasgow, Scotland[3]. We focus on a cohort of 160 adolescent pupils aged 12–14 years at the beginning of the study. Data were collected in three waves with approximately one year between two subsequent measurements. All of the 129 pupils in the sample we analyze were present at the three measurement points.

The longitudinal data set include both individual and relational information. The individual part of the questionnaire is designed to elicit personal information on address, family background, and the consumption of tobacco, alcohol and drugs (Michell and West 1996). The questionnaire also elicited information on individual preferences for music genres (Steglich et al. 2006). The relational part of the questionnaire focused on friendship relations. Each participant could name up to six friends per wave that could potentially be outside the study cohort. On average, pupils named more than three friends within the cohort. In earlier studies, the change of friendship relations was investigated as a dynamic process that partly co-evolves with behavioral variables (not modeled as two-mode structures) such as alcohol consumption or music taste (Steglich et al. 2006; Steglich et al. 2010). We use music

[3] We use the data set that is publicly available and may be accessed by visiting: http://www.stats.ox.ac.uk/~snijders/siena/Glasgow_data.htm.

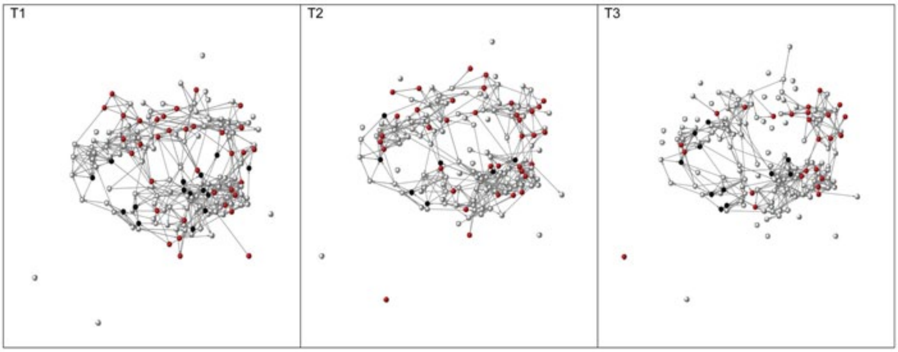


Fig. 2 Friendship networks in the three time periods. Different colors indicate different music tastes. *Back nodes* are "rockers" (adolescents declaring preference for rock music genres) *red nodes* are "ravers" (adolescents declaring preference for rave music genres). The three networks all have the same layout to make structural changes more readily comparable

genres as instances of social foci because received research has long recognized similarity in music tastes to affect the formation, stabilization and erosion of social relations (Lewis et al. 2008).

Figure 2 shows friendship relations among the 160 participants over three data collection waves (1995–1997). Students are marked as circles (nodes). An arrow from a person A to a person B indicates that A nominated B as a friend in the questionnaire of the corresponding wave. Many of the relations are reciprocal. Denser areas in the network indicate that social forces are at play that cause clustering. The colors of the people indicate music preferences: Black nodes are "rockers"—people who indicated their music preference to contain at least three types of rock music in one of the waves. Red nodes are "ravers" and listen to at least four types of electronic ("rave") music. This rough classification already indicates that music taste and friendship seem to be related: Colored nodes seem not to be randomly distributed in the networks but slightly cluster together.

Figure 3 shows the local relational structure of affiliation to seven exemplary music genres interpreted as social foci. As it should be clear from the figure, student one manifests less focused preferences than, say, student 2 who seems to like only rave—a genre (red square) that appears to be particularly popular in the sample. Less popular foci ("techno") are not direct generators of relations between the three adolescents (white circles) depicted in Fig. 3.

Figure 4 aggregates the personal affiliation networks to show the affiliation of all the 139 pupils to 15 different music genres in wave 3. As before, circles represent people, squares represent music genres. A link between a person and a music genre shows that this person indicated that he/she listen to this genre in wave 3. The very popular music genre "chart" is not represented to simplify the visualization. Proximity of two or more music genres in the plot indicates that the same people tend to listen to all these music genres. The visualization reveals several of such clusters of similar music types: electronic or rave music ("rave", "techno", "dance") in the upper part of the figure, rock music and sixties in the right part and classical ("folk", "jazz",

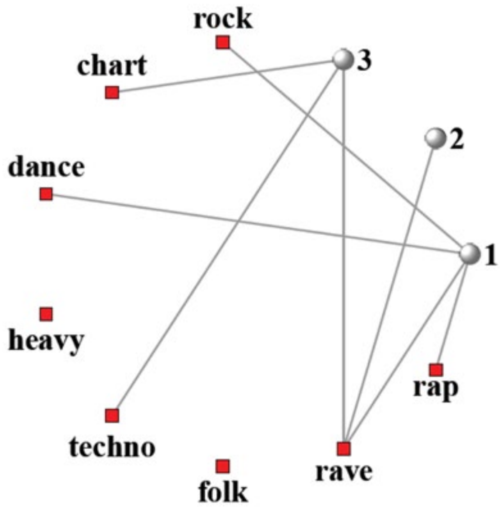


Fig. 3 Affiliation of students 1, 2 and 3 to 8 of 16 musical genres

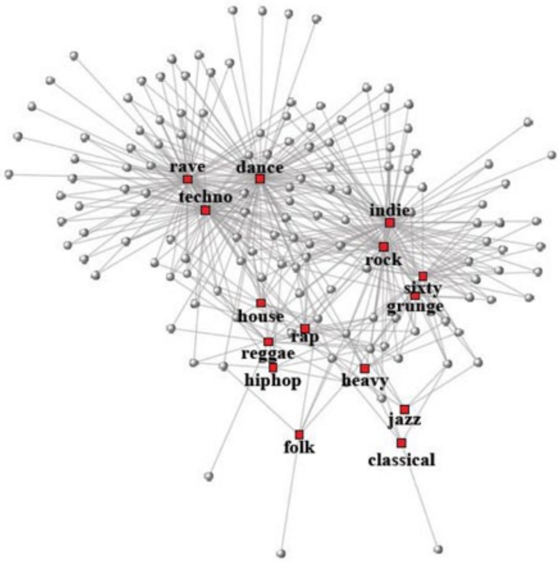


Fig. 4 Two-mode network describing the affiliation of students to 15 music genres (except for "chart"; wave 3 only). The presence of a tie denotes an expressed preference relation

"classical") in the lower part. This observation corresponds to the music genre classification derived by Steglich et al. (2006, p. 52).

Descriptive statistics of the friendship networks in the three data collection waves (1995–1997) are given in Table 1. The number of participants is 160 in total and ranges from 153 in wave 1 to 139 in wave 3. The network density varies between 2.2 and 2.6 % which corresponds to average degrees (number of nominated friends within the cohort) between 3.4 (wave 2) and 3.8 (wave 1). The percentage of reciprocal relations ranges between 53.9 % (wave 2) and 63.9 % (wave 3). Gender homoph-

Table 1 Network descriptive statistics

	Wave 1	Wave 2	Wave 3
Number of participants	153	152	139
Density (%)	2.5	2.2	2.6
Avg. degree	3.8	3.4	3.6
Reciprocity (%)	56.3	53.9	63.6
Same-gender ties (%)	88.6	90.1	90.1
Clustering coefficient (%)	35.8	30.9	41.8
Avg. music genre nominations	3.8	3.3	3.3

ily is an important social force in the formation of the observed friendship networks. This is indicated by the fact that 88.6–90.1 % of all friendship ties are between people of the same gender. Transitivity or local clustering seems to be relevant as well: The clustering coefficient that measures the proportion of closed triangular friendship structures over unclosed triads ranges from 35.8 % (wave 1) to 41.8 % (wave 3). The final descriptive explains the average number of music genre nominations of people which ranges from 3.3 to 3.8.

A further overview of the music genres is given in Table 2. It shows the sixteen music genres from the questionnaire in a ranked list per wave.

"Chart" (which was not shown in Fig. 4) is consistently the most popular music genre and is chosen by between 91 (wave 3) and 104 (wave 1) people. "Classical", on the other hand, is ranked last in two of three waves and only nominated by 4–5 people. The popularity of other music genres is less stable over time. The genres "Indie" and "Sixty" (rank 10 and 11 with 20 and 15 nominations in wave 1) become increasingly popular over time. In wave 3 they are ranked 4 and 7 with then 67 and 31 nominations. "Heavy" rock music (rank 9 with 20 nominations in wave 1) loses popularity. It is only ranked 13 in wave 3 with merely seven nominations.

4.2 Individual attributes and network mechanisms

In our analyses we use three demographic variables as controls: gender, age and spatial distances between parental homes of pupils. Descriptive statistics are reported in Table 3.

Female students represent 47.5 % of the sample. The average age in wave 1 is 13.3 years and ranges from 12.4 to 14.6 years. On average, the parental homes of the pupils are 1.6 km apart with a maximum distance of 9.2 km.

The network mechanisms included in the empirical model specification are summarized in Table 4. Note that the table includes both mechanisms operating at the network level (like, for example, reciprocity) as well as mechanisms operating across levels (like, for example, the various types of bipartite closure we have discussed).

The precise definition of the effects can be found in the R-Siena manual (Ripley et al. 2013). The one-mode effects in the table are defined and discussed in Snijders et al. (2010). Koskinen and Edling (2012), Conaldi et al. (2012) and Snijders et al. (2013) discuss and interpret some of the two-mode and mixed one-mode-two-mode effects included in the model and listed in Table 4. We refer interested readers to consult directly the original sources.

Table 2 Expressed preferences for music genres

Rank	Wave 1		Wave 2		Wave 3	
1	Chart	104	Chart	103	Chart	91
2	Rave	95	Dance	81	Dance	78
3	Dance	90	Rave	80	Rave	68
4	Techno	87	Techno	66	Indie	67
5	Rock	48	Rock	42	Techno	59
6	Rap	43	Indie	39	Rock	48
7	Reggae	33	Rap	30	Sixty	31
8	Grunge	23	Sixty	19	Rap	15
9	Heavy	20	Reggae	17	Reggae	14
10	Indie	20	Heavy	10	House	12
11	Sixty	15	House	10	Grunge	11
12	House	11	Grunge	10	Hiphop	8
13	Hiphop	9	Hiphop	8	Heavy	7
14	Jazz	5	Jazz	7	Folk	6
15	Classical	5	Folk	6	Jazz	5
16	Folk	3	Classical	4	Classical	5

Table 3 Sample descriptive statistics

	Mean	Std. dev.	Min	Max
Gender (% female)	47.5	50.1	0.0	100.0
Age in wave 1	13.3	0.3	12.4	14.6
Spatial distance (km)	1.6	1.2	0.0	9.2

4.3 Empirical model specification and estimation

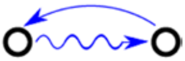
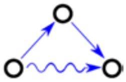
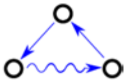
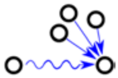
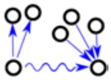
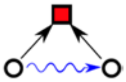
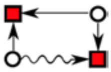
The model for the coevolution of one-mode (1M or "social") networks and two-mode (or 2M or "affiliation") networks derived by Snijders et al. (2013) is a recent addition to the class of Stochastic Actor Oriented or SAOMs (Snijders 1996). A non-technical introduction of SAOMs can be found in Snijders et al. (2010). More detailed treatments are provided in Snijders (2001), Snijders (2005), and Steglich et al. (2010).

Estimation of the 1M-2M SAOM requires repeated observations on a social network (X) and a related affiliation network (Y) of interest. Both networks are observed in discrete time but (unobserved) change between successive panels takes place in continuous time.

In SAOMs change is decomposed into a two component sub-processes. The first is the timing component which controls the number of opportunities for change that actors face per unit time—the amount of change, as it were. This is captured by a rate function that incorporates assumptions about the distribution of waiting times (Snijders 2005). In the model we estimate in the next section the time component is represented by period-specific rate parameters.

The second is the choice component which summarizes the preferences of the actors. In our case, preference driving change in social network ties are specified in the network evaluation function defined in (1). Preferences driving change in affiliation ties to settings are summarized by the setting evaluation function defined in (2). Further details on model specification are discussed in Snijders et al. (2013).

Table 4 Association and affiliation-based effects included in the model[a]

Effect	Qualitative pattern	Description
Outdegree (friendship)		Tendency to maintain a limited number of friends
Reciprocity		Tendency to reciprocate friendship ties
Transitive triplets		Tendency to become friend with friends of friends
Three-cycles		Tendency towards generalized exchange
Indegree popularity (friendship)		Tendency to nominate popular people as friends
Out-in degree assortativity		Assortative mixing of high outdegree with high indegree individuals: Tendency of students who mention many friends to mention students who are mentioned by many as friends
Affiliation-based closure		Choosing friends with a similar music taste (operationalized as the number of shared preferences)
Outdegree (music genre)		Tendency to maintain a limited set of music preferences
Four-cycles (similar music genre)		Tendency to adopt a music preference that is similar to the music preferences expressed by others with similar preferences
Indegree popularity (music genre)		Tendency to choose music genres that are liked by many others
Association-based closure		Choosing music genres that friends like as well (operationalized as the number of friends who like a particular music genre)

[a] *Red square* Social foci (music genres), *White circles* Individuals (adolescents), *Blue arrows* link between individuals (1-Mode connections), *Black arrows* affiliate individuals to foci (2-mode connections), *Squiggly arrows* potential ties at time t that may become observable at time t + 1

The models that we estimate in the next section contain both endogenous effects as well as covariate-related effects. In the friendship network endogenous effects are, for example, the tendency of people to maintain a limited outdegree, to reciprocate friendship nominations and to form and maintain transitive structures in the friendship network. We further control for degree-related effects like indegree popularity. In the music taste network we control for three endogenous effects: the outdegree, the tendency of people to like music tastes that are liked by others with similar preferences (four-cycle effect) and the tendency of individuals to choose music genres that are popular (have a high indegree).

Covariate-related effects in the friendship network are related to the three demographic variables in Table 3. We control for age homophily (the tendency to select friends who have a similar age) and gender homophily. Additionally, we allow differences in the number of sent and received friendship nominations between genders by including an “ego” (sender) and an “alter” (receiver) gender covariate. Further we test whether spatial distance between parental homes influences the tendency to become friends. In the music genre sub model we control whether people who choose a type of music from a certain category (e.g., the rock music genre “grunge”) are more likely to choose other music genres from the same category (e.g., the rock music genre “heavy”). Further parameters that are specified are two rate parameters per sub process that indicate the average number of changes per actor per period (e.g., from wave 1 to wave 2) in the two coupled dynamic networks (friendship and music genre affiliation).

Significantly positive (negative) parameters in the network evaluation function suggest that subjects act as if they preferred network configurations in which the correspondent effects have a higher (lower) value. For example, a positive reciprocity parameter may be taken as indication that subjects act *as if* they preferred reciprocated to non-reciprocated relations with partners. As discussed in Snijders et al. (2010) separate endowment functions may be defined to specify the factors that affect the termination, rather than the creation, of a tie. Significantly positive parameters corresponding to the endowment effect associated with reciprocity could be taken as evidence that reciprocated relations are costly to break. As a consequence organizations would prefer to maintain such relations.

In the section that follows, the parameters in the models are estimated by the method of moments using the stochastic approximation algorithms described in Snijders et al. (2007), and implemented in RSiena—an R-based software package designed for the analysis of SAOMs (Ripley et al. 2013).

5 Results

We estimate two models in which we focus on the distinction between “affiliation-based closure” and “association-based closure” while controlling for a number of additional variables.

Each model consists of two sub-models that describe changes in the friendship network and in the music genre affiliation network. By including “affiliation-based closure” in the friendship process and “association-based closure” in the music genre process, both processes become interdependent (coupled) sub processes.

In the first model, we test the general tendency to create *and* to maintain affiliation- and association-based closure structures. In the second model, we model the creation and maintenance of ties within selection and association-based closure structures as separate social processes. Beside these focal “cross-network effects” we control for a number of endogenous effects (changes in a network depending on the state of the same network) and covariate-related effects (changes in the network depending on covariates).

The results of the first model are presented in the left side of Table 5 (Model 1). The focal effects are shown in line 14 (affiliation-based closure) and line 21 (association-based closure). We find no evidence of affiliation-based closure in model 1. The estimate is positive but not significant. However, there is strong evidence for association-based closure. The estimate of 0.43 is highly significant and the effect

Table 5 Estimates of SAOMs for the coevolution of social networks and social settings

Model 1					Model 2				
	Effect	Estimate	S.E			Effect	Estimate	S.E	
1	Rate 1 (friendship)	14.68	1.41		1	Rate 1 (friendship)	14.80	1.63	
2	Rate 2 (friendship)	11.96	1.09		2	Rate 2 (friendship)	11.62	1.21	
3	Outdegree (friendship)	−2.77	0.19	***	3	Outdegree (friendship)	−2.68	0.19	***
4	Reciprocity	2.07	0.11	***	4	Reciprocity	2.11	0.11	***
5	Transitive triplets	0.73	0.04	***	5	Transitive triplets	0.74	0.05	***
6	Three-cycles	−0.41	0.09	***	6	Three-cycles	−0.42	0.09	***
7	Indegree popularity (friendship)	−0.01	0.03		7	Indegree popularity (friendship)	−0.01	0.03	
8	Out-in degree assortativity	−0.06	0.05		8	Out-in degree assortativity	−0.08	0.05	
9	Age difference	−0.03	0.11		9	Age difference	−0.03	0.11	
10	Spatial distance	−0.13	0.03	***	10	Spatial distance	−0.13	0.04	***
11	Alter female	−0.14	0.09		11	Alter female	−0.17	0.09	
12	Ego female	0.01	0.10		12	Ego female	0.03	0.10	
13	Same gender	0.77	0.09	***	13	Same gender	0.75	0.08	***
14	*Affiliation-based closure*	*0.04*	*0.04*		14	*Maintain: affiliation-based closure*	*− 0.38*	*0.17*	*
15	Rate 1 (music genre)	5.29	0.41		15	*Create: affiliation-based closure*	*0.43*	*0.18*	*
16	Rate 2 (music genre)	5.34	0.43		16	Rate 1 (music genre)	5.14	0.39	
17	Outdegree (music genre)	−1.72	0.06	***	17	Rate 2 (music genre)	5.14	0.38	
18	Four-cycles (sim. music tastes)x10	0.01	0.01		18	Outdegree (music genre)	− 1.68	0.07	***
19	Indegree popularity (musicgenre)x10	0.02	0.02		19	Four-cycles (sim. music tastes)x10	0.02	0.01	
20	Choosing music in the same category	0.14	0.03	***	20	Indegree popularity (music genre)x10	0.02	0.02	
21	*Association-based closure*	*0.43*	*0.05*	***	21	Choosing music in the same category	0.15	0.03	***
					22	*Maintain: association-based closure*	*0.17*	*0.10*	
					23	*Create: association-based closure*	*0.58*	*0.11*	***

*$p<0.10$; **$p<0.05$; ***$p<0.01$

size is large. Having a friend with a specific music taste increases the probability of adopting or maintaining the same genre preference by 53 % ($e^{0.43}$) compared to a genre no friend is affiliated to. If several friends are affiliated to a specific music genre, the influence effect gets even stronger. Three friends who share a music taste will increase the probability for creating or maintaining an affiliation with this music genre by 260 % ($e^{3*0.63}$) compared to a music genre that is not liked by a friend.

In model 2 (right side of Table 5), we distinguish between the creation and maintenance (using "creation" and "endowment" effects) of the focal closure mechanism. The effects for maintaining vs. creating a friendship tie with people who have the same music taste (affiliation-based closure) are in lines 14 and 15. The effects for maintaining vs. creating the preference for a music genre that is liked by friends are in lines 22 and 23.

Interestingly, now that we distinguish between these fine-grained social processes we indeed find two significant effects for affiliation-based closure that, however, point in different directions. The creation of ties with others who are similar regarding music taste is facilitated (positive "creation" effect 15) but these ties also tend to be easier dropped compared to friendship ties with people who have different music tastes (negative "maintenance" effect 14). The effects sizes are rather large. For example, the probability of becoming friends (create) with someone who shares a preference for a music genre is increased by 53 % ($e^{0.43}$) as compared to a person who does not share any music genre interests.

Both association-based closure effects are positive, however, only the creation effect is significant and the estimate is significantly higher. The general tendency towards association-based closure that we observed in model 1 is, therefore, mostly explained by a very strong creation effect. Students in the sample are very likely to establish ties of affiliation with new music genres based on what they learn from their friends. We find no significant evidence for the process that they will also be more likely to maintain these music tastes over time.

6 Discussion and conclusions

Considering alters as social contexts requires understanding of how the *actual* alters that compose personal networks are selected from populations of *potential* alters. One contemporary analytical tradition rooted in the work of Pattison and Robins (2002) on neighborhood-based models for social interaction addresses this question by emphasizing processes of network self-organization. The structure of social settings emerges from concatenation of local network dependencies involving subsets of relational entities providing possible sites of social interaction (see also Pattison and Robing 2004). A second tradition rooted in the work of Feld (1981, p. 1982) emphasizes the internal segmentation of social setting into social foci to which actors are differentially affiliated. In this perspective, the structure of social settings emerges from contingent patterns of overlapping affiliations to social foci.

Building on recent advances in stochastic actor-oriented models (Snijders et al. 2013), in this paper we have offered a model which attempts to integrate these two analytical traditions by portraying individual association and affiliation decisions as interdependent components of a broader co-evolutionary system. We have defined two multilevel closure mechanisms of theoretical interest: association and affiliation-based closure. We illustrated the empirical value of the model in the context of data on a sample of adolescents collected during the Glasgow Teenage Friends and Lifestyle Study (Bush et al. 1997; Pearson and Michell 2000; Pearson and West 2003). The data were recently re-analyzed by Steglich et al. (2010).

The model we presented was explicitly inspired by models for social space outlined by Pattison and Robins according to whom (2004, p. 11): "Social space cannot be specified simply in geographical, network or sociocultural terms but, rather, requires an understanding of the interdependence of relationships among different types of social entities, such as persons, groups, sociocultural resources and places. We also suggest that social space cannot be regarded as fixed: unlike the Euclidean space of Newtonian mechanics, social space is constructed, at least in part, by the social processes that it supports." The "social space" that Pattison and Robins (2004) define, encompasses both processes of association (generating network ties) and affiliation (generating connections to social foci).

The distinction that our model supports between mechanisms of closure by association (association-based closure), and closure by affiliation (affiliation-based closure) helped us to illuminate important dynamic aspects of the social context we have examined. For example, we found that adolescents affiliated to the same music genres (i.e., sharing membership in the same social foci) are more likely to establish friendship ties and hence become members of the same social neighborhood. Yet, the ties contributing to affiliation-based closure are more fragile than the less frequent ties established between adolescents affiliated to different music genres—ties that are part of open multilevel triads. This result is important because it demonstrate that social foci are not completely impermeable to cross-cutting ties (Lomi et al. 2014). We also found that adolescents associated through direct friendship ties are more likely to participate in similar social foci (association-based closure)—and hence construct overlapping social circles in a Simmelian sense (1955). We found no evidence, however, that friendship ties stabilize patterns of affiliation to social foci (music genres, in the case we have examined).

In conclusion, it seems appropriate to return to the need that Pattison and Robins (2004) identified in their prescient essay on social spaces to: "Introduce an explicit dynamic framework so that we can model the evolution of relational structures, and ultimately the joint evolution of interdependent social processes *at multiple levels of analysis*" (2004, p. 26. Emphasis in the original). One way to frame the contribution of the present paper is as an attempt to heed this call. Our intention has been to make a preliminary step towards establishing an analytical framework for combining social networks and social settings into a broader social space whose constructive mechanisms provide appropriate material for direct empirical investigation.

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