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Signs Over Time: Statistical and Visual Analysis of a Longitudinal Signed Network*

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Keywords: Network evolution; longitudinal network analysis; signed digraphs; multilevel logistic regression; actor-oriented approach; balance theory; field theory; practice theory; literary criticism

Abstract: *This paper presents the design and results of a statistical and visual analysis of a dynamic signed network. In addition to prevalent approaches to longitudinal networks, which analyze series of cross-sectional data, this paper focuses on network data measured in continuous time in order to explain the signs of lines rather than their occurrence. As a consequence, current stochastic actor-oriented models for network change cannot be applied. Instead, multilevel logistic regression analysis is used for uncovering the main statistical regularities of network evolution. Visualization by means of animated Scalable Vector Graphics with several options for interaction allows for in-depth inspection of network evolution and offers detailed information on the people involved in the network.*

The substantive focus of the paper is on the evaluations and complex labeling process among literary authors and critics illustrating the interplay between identity (literary style) and structure. It is hypothesized that actors do not just evaluate their immediate ego-network; they also try to survey and interpret the overall structure of the network and derive part of their identity from it. The latter, however, is a collective process involving communication, e.g., publicly labeling groups of actors in the network and adapting behavior to labels that have previously been assigned to actors. Including perceptions of overall network structure and classifications in dynamic network models would extend current actor-oriented models.

Technical prerequisites. The Scalable Vector Graphics image that can be opened by clicking the image below is rendered best in Internet Explorer with the latest SVG plug in from Adobe (http://www.adobe.com/svg/viewer/install/main.html). SVG allows zooming (Ctrl+left-click zooms in, Ctrl+Shift+left-click zooms out) and panning (Alt+drag). Right-click the SVG to open a menu of options.

Introduction

From an actor-oriented perspective, networks change because actors adjust their relations. At the same time, interactions between actors are affected by network changes. As a consequence, networks evolve in a complicated dynamic process, in which network structure is both a cause and a consequence. The structure of a network at a particular moment is merely a snapshot of this process, which is difficult to understand unless you know how it is generated from previous networks (Doreian 2001: 111; Snijders 2005: 215). Even if interacting individuals follow simple or at least traceable rules, conventions, or heuristics, the resulting overall network structure can be complex, seemingly random or chaotic.

As early as 1978, Stanley Wasserman listed several types of models for longitudinal network data, both in the social and natural sciences (Wasserman 1978). In the course of time, the focus of social network analysts has shifted from continuous-time Markov chain models (Holland and Leinhardt 1977; Wasserman 1977), to loglinear models (Fienberg and S. Wasserman 1981; Wasserman and Iacobucci 1988) and logistic regression (Frank 1991), to discrete-time Markov chain models (Banks and Carley 1996; Robins and Pattison 2001; Sanil et al. 1995), and back to continuous-time Markov chain models (Snijders 2001; Snijders 2005). Longitudinal sociometric data have traditionally been collected in waves by repeatedly administering questionnaires to a group of subjects. Therefore, various methods have been developed primarily for analyzing this type of data. To my knowledge, even more general methods like loglinear models or logistic regression analysis have only been applied to one or more waves of cross-sectional data, e.g., (Frank 1991; Frank and Strauss 1986).

At present, the actor-oriented continuous-time Markov chain model developed by Tom Snijders and implemented in the software program SIENA (part of the StOCNET software suite) offers the most sophisticated approach to analyzing the dynamics of social networks. Unfortunately, this and related approaches are not applicable to my data for two reasons.

The first reason is that Markov chain models need panel data, whereas my data consist of a historical series of events usually involving just two actors in the network. My observations are published literary reviews and interviews with literary authors from which I code evaluations that the critic passes on the reviewed author or the interviewed author passes on one or more of his colleagues. This data cannot be combined into a series of cross-sectional data because there are no short periods in which each actor in the network is able to evaluate every other member of the network. This is caused by the fact that external events, viz., the publication of a new book by an author, are usually the prerequisite for reviews and interviews.

The second reason why present models for network dynamics are not applicable to my data has to do with the nature of the dependent structural variable. Current models for longitudinal network data primarily try to explain the presence or absence of ties or the value of a line when zero line value indicates the absence of a line. In my case, the presence or absence of a line (literary evaluation) is not the important phenomenon to be explained because it depends on events and constraints outside the power of the actors in the network. As a rule, new reviews appear when an author publishes a new book. The decision to publish a book is made by the publisher, not by the authors or literary critics. Positive reviews may stimulate a publisher to publish a new book but, first of all, the author must produce a manuscript. The timing of this is hard to model.

The reviewing practice at newspapers and magazines poses another institutional constraint on who may review or interview whom. Only a small selection of new books can be reviewed in a particular paper or magazine. The coverage of a book, e.g., the number of periodicals reviewing it, is linked to the author's newsworthiness, e.g., see (Janssen 1988; Janssen 1998), which is determined by much more than the previous interaction among authors and critics. When a paper or magazine employs several critics, only one critic is assigned to review a particular book. The decision who reviews whom may be made by an editor, so the critic is not completely free to choose whom to review. In sum, it is not likely that the absence or presence of an evaluation between a critic and an author can be explained from the behavior of the critics and authors themselves. Modeling this aspect of network structure requires a different set of data, including decisions by publishers, editors, et cetera.

The overall outcome of the evaluation, that is, whether the author or book is evaluated positively or negatively, can be explained from previous evaluations and from characteristics of the actors involved in the evaluation. I would like to maintain that the pattern of signs also expresses structure. Dropping the signs from a graph really alters its structure (De Nooy 1999b: 283-5). Especially in the context of balance theory, which will be presented in a later section, the actual signs matter a lot. As we will see, it is possible and interesting to predict the sign of an evaluation, conditional on the presence of an evaluation, from the pattern of signs of previous evaluations. This paper's first aim is to explore analytic strategies, both statistical and visual, for this type of longitudinal data. I will demonstrate the use and usefulness of logistic regression analysis for predicting the sign of new lines in the network. This will uncover tendencies at the actor level that drive network evolution in terms of the distribution of signs and the genesis of balance-theoretic clusters.

The second aim is to expand the actor-oriented model to include both overall network structure and socially constructed meaning. Although an actor's interaction may primarily be driven by his or her immediate network neighborhood, I hypothesize that overall network structure also affects action, albeit mediated by the actors' perceptions and interpretations. It is my conjecture that actors try to overview the overall network structure in which they are participating, interpreting subgroups or factions within it as a system of identities relevant to their interaction. This is in line with the concept of Cognitive Social Structures that David Krackhardt introduced in 1987 (Krackhardt 1987). Krackhardt argued that we should look at the perceptions of network structure rather than the structure resulting from self-reported ties. The fact that he specifically referred to balance theory as an example makes his paper even more interesting to my research, which also uses balance theory.

In my research, meaning structures as constructed by the literary authors and critics consist of classifications according to literary style or movement that were published in the 1970s. These publications explicitly group literary authors and create literary identities: "Authors X, Y, and Z belong to the movement L." This can be seen as an example of the kind of labeling processes studied in symbolic interactionist research. I will test whether published classifications affect subsequent evaluations among members of style groups expressing solidarity within style groups and antagonism between style groups.

The literary field, however, does not operate within a social vacuum. It is part of a society that is subjected to internal conflicts and changes. These conflicts and changes are likely to affect the (inter)action within the literary field. Social tensions and contrasts that influence the odds of making or obtaining a negative rather than a positive evaluation in reviews and interviews become meaningful in the literary field; they acquire power or valence. They are most likely to become part of the self-conceptions and classifications of the actors in the field. Thus, social process at the actor level, overall network structure, social tensions, and meaning are dynamically interrelated. This is also how I implement the duality of culture and practice that is strongly advocated by John Mohr, e.g., (Mohr 2000), and rooted in practice theories of Clifford Geertz (Geertz 1973), Anthony Giddens (Giddens 1979), and Pierre Bourdieu (Bourdieu 1990; Bourdieu 1998). In this paper, I will explore the potential and limits of an actor-oriented model for testing these ideas. Is it possible and necessary to add processes of collective identity formation - social classification - to the modeling of network evolution?

Design

In light of adopting an actor-oriented approach, the causes and consequences of individual action (the micro level) are central to the analyses presented here. As stated above, the data represent interactions observed in continuous time rather than an entire network measured at distinct moments in time.

This paper uses multilevel MCMC logistic regression models for the statistical analysis of the causes or covariates of interaction. Ove Frank (Frank and Strauss 1986) proposed using logit or logistic regression analysis for graphs and also described the application to longitudinal graphs, that is, a series of cross-sectional graphs (Frank 1991). The applicability of logistic regression to Markov dependence graphs was proven by David Strauss and Michael Ikeda (Strauss and Ikeda 1990) and extended to the p* family of models by Stanley Wasserman and Philippa Pattison (Wasserman and Pattison 1996). However, serious reservations have arisen with respect to the statistical tests produced by the logistic regression procedure because the observations (ties) are clearly not independent (Wasserman and Robins 2005: 158). Within a cross-sectional network, each tie may both depend on and affect other ties if actors are assumed to take into account the ties in their network neighborhood, which is a central assumption in this type of network analysis.

Continuously observed longitudinal data offer an advantage here, because for each arc it is possible to determine the structure of the network as it existed at the time the arc was created. In my example, it is clear which evaluations had been published at the time that a particular critic or author passed judgment on a peer. An arc may only depend on previous arcs and it is independent of later arcs. In the case of arcs that appear at the same time, e.g., evaluations published on the same day, it is perfectly acceptable to assume that they cannot affect each other. In the case of literary evaluations, for instance, a review or interview has already been written and submitted for publication before the day it is published. This removes the circularity or mutual dependence among arcs.

Instead of the occurrence of an arc - the publication of an evaluation in this example - the sign of the arc is investigated: why is the evaluation positive or negative? Neutral evaluations - which are quite rare in the dataset - are excluded from the analysis. For each arc, we can imagine that the actor represented by the arc's tail (the critic or judge) evaluates his or her network environment and acts upon it by choosing between a positive and a negative sign. Each published evaluation is a case and its sign is the dependent variable.

This does not mean, however, that the observations are completely independent. In this case, dependence arises primarily from the selection of cases (evaluations) as a consequence of selecting a set of authors and critics. First, authors and critics were selected because they were involved in a debate on literary style groups at that time. Next, all evaluations among them published in reviews and interviews were collected. It is clear that the evaluations are to be seen as observations that are nested within the higher level observations of persons (authors and critics). Actually, the evaluations are doubly nested within the set of persons because one person is involved as the judge and another as the person who is being judged. Multilevel models account for this type of nesting with a crossed random effects design or a multiple roles design.

Having established the unit of analysis - each occurring evaluation - and the dependent variable - the sign of the evaluation - the explanatory variables in the logistic regression analysis are presented now. I distinguish between three types of explanatory variables: local structure, exogenous attributes, and endogenous attributes. Each type is discussed in a separate subsection, which also pays attention to the ways in which the effects are visualized. At the end, I discuss the consequences of micro action for overall network structure (meso level), introducing a micro-meso-macro perspective that combines causes and consequences of micro action.

Local structure

Actor-oriented approaches to networks are first and foremost interested in the effects of local network structure on behavior, which represent endogenous network processes. In the context of a signed graph, balance theory as introduced by Fritz Heider (Heider 1946; Heider 1958) is a well-known model for interpersonal relations. It assumes that people pursue a balanced situation, namely, a situation in which their friends' friends are their friends and their friends' enemies are their enemies. Note that the concept of friends should be taken broadly, referring to people connected by any kind of positive affective relation and not just by friendship. As Dorwin Cartwright and Frank Harary have shown, a signed graph is balanced if it contains balanced semicycles, that is, semicycles containing zero or an even number of negative lines (Cartwright and Harary 1956).

In the present study, semicycles of maximum length 4 are considered, assuming that authors and critics primarily respond to balance or imbalance among their closest contacts, that is, the people that they interact with directly (their neighbors) and the ones that their neighbors interact with. These are assumed to be the most salient contacts. Author or critic X passing judgment on colleague Y is quite likely to respond to previous evaluations from Y on himself or herself and take into account how Y has (been) evaluated (by) a third colleague Z. In addition to salience, cognitive limitations are likely to restrict the length of the semicycles (or diameter of the neighborhood) that an author or critic remembers in detail. This is in line with the types of effects tested in Tom Snijders' continuous-time Markov Chain model (Snijders 2005: 228-31). Although the actor's perception of the ties among their neighbors have not been measured, as David Krackhardt would suggest (Krackhardt 1987), the ties are published evaluations, so there is reason to assume that actors have similar perceptions of the ties. Finally, note that overall network structure is deemed to play a role in a different way, as explained in the section on endogenous attributes.

For each case (evaluation), I determine the number of balanced semicycles that a positive evaluation would create and I subtract the number of balanced semicycles created by a negative arc. A positive outcome on this index indicates that a positive evaluation is more likely or appropriate according to balance theory, whereas a negative outcome should lead to a negative evaluation. In sum, the constructed semicycle variable should be positively correlated with the odds of a positive over a negative evaluation in the logistic regression analysis. This approach is analogous to the way in which Stanley Wasserman and Philippa Pattison proposed to use logistic regression of network data (Wasserman and Pattison 1996). In a similar way, the effect of clusterability, which extends balance to situations with more than two factions, can be investigated by allowing an uneven number of negative arcs - but not one - in the semicycles created by an evaluation (Davis 1967).

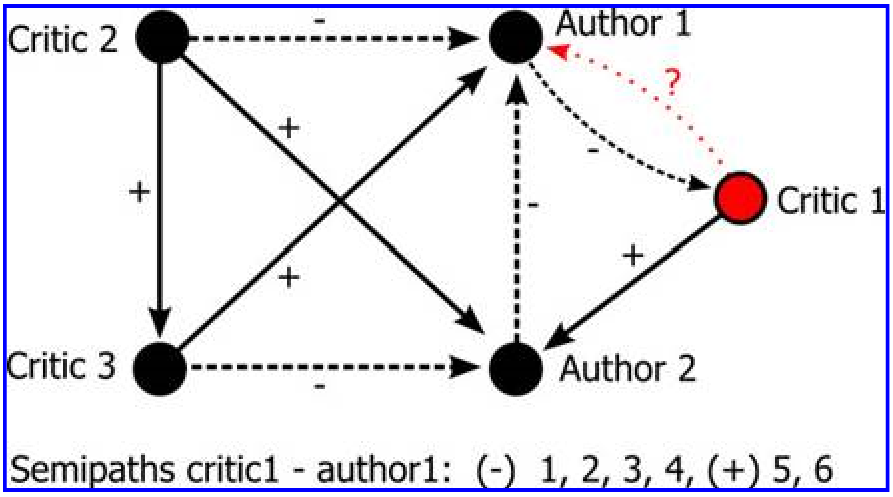

Figure 1 - Calculating the balance index (click on image for interactive SVG).

Figure 1 shows an example of calculating the balance index, in which positive evaluations are represented by solid arcs and negative evaluations by dashed arcs. The evaluation that critic1 is going to pass on author1 is the case for which the sign must be predicted; it is dotted to signify that its sign is not yet determined. Click on the picture to open the SVG file - see the technical requirements in the text box at the beginning of this article - and move the mouse over the numbers 1 to 4 to inspect the semicycles. Semipaths 1 through 4 connecting critic1 and author1 contain exactly one negative arc each, so critic1 should evaluate author1 negatively to obtain a balanced semicycle. Semipaths 5 and 6 require a positive evaluation because they contain two and no negative arcs respectively, but they are not considered because the resulting semicycles have length 5. Thus, the semicycle variable count amounts to 0 - 4 = -4, indicating that a negative evaluation would yield a surplus of four balanced semicycles in contrast to a positive evaluation. In this case, a negative evaluation is predicted by balance theory.

In the visualizations presented in a later section, an arc is colored blue if it creates more balanced than unbalanced semicycles. In the example above, if critic1's evaluation of author1 turns out to be negative, this arc is blue in the network visualization indicating that it conforms to balance theory.

One could take into account all previous evaluations or restrict the semicycle count to a limited period. It is likely that recent evaluations are more consequential than distant ones, so I restrict the retrospective time span to the 24 months preceding the evaluation under consideration. The number of months is set to 24 for practical reasons: it is the shortest period containing sufficient numbers of short semicycles and it yielded the best results in comparison to longer and shorter periods. Data have been collected from 1970, so the analysis starts in 1972. Clearly, the length of the retrospective period or moving window depends on the data set, especially the rate at which new arcs are created. Alternatively, one could also opt for a weighting procedure, assigning lower weights to arcs that are more distant (in time), combining the weights of arcs into a weight of the semipath in one way or another, but this is not done here.

Actor-oriented approaches usually include other types of structural effects, most notably reciprocity, conformity, popularity, expansiveness, and transitivity. Reciprocity 'in sign', that is, when the signs of reciprocated arcs are similar, is a special case of balance and so is transitivity if it is confined to positive arcs. Expansiveness seems quite meaningless if the arcs are exogenously given, but conformity, as a special case of balance, acquires a distinct meaning in the context of literary evaluations because it expresses a tendency for actors to stick to their previous evaluations. Therefore, it is distinguished from (other instances of) balance and clusterability in the statistical analysis. Popularity, expressed by the number of positive evaluations previously received, also has definite meaning in the context of literary criticism because it is a prime indicator of the author's or critic's literary standing. In addition to balance, conformity, clusterability, and popularity are used as explanatory variables in the logistic regression analysis but they are not color-coded in the visualization.

Exogenous attributes as identities

Attributes, that is characteristics of the actors, can be incorporated as explanatory variables in several ways. On the one hand, they can be used as a property of an actor, that is, as a (personal) covariate. In this case, the attribute represents an individual's propensity or capacity to be involved in a particular number or kind of ties, for instance, young critics may be more inclined to pass negative judgment than older critics or young authors may attract more negative evaluations than old authors.

On the other hand, attributes can be used as a dyadic covariate, viz., a property of the dyad involved in a tie. The most common application is determining the (dis)similarity of the head and tail of the arc with respect to an attribute, e.g., code a tie between a judge and a person judged as similar (usually coded as 1) if they have the same age or dissimilar (-1) if ages differ, using a neutral (0) code if the attribute is not known for both actors. This type of dyadic covariate expresses a solidarity or homophily effect, assuming that people tend to identify positively with alters that are similar.

Dyadic covariates, however, can also be used to express hierarchy on an attribute that is socially ranked, e.g., a younger person is more likely to evaluate an older person favorably whereas an older person tends to be more critical towards younger persons in a society that instills respect for seniority. This is linked to status or deference mechanisms. The dyadic covariate is then coded as 1 if an arc points from an actor with a lower score on the status variable to someone with a higher score, -1 if the arc points in the opposite direction, and 0 elsewhere.

In this paper, I distinguish between endogenous and exogenous attributes. Studying the literary field, endogenous attributes refer to characteristics of the actors that are established within the literary field, for instance, whether a person acts primarily as an author or as a critic or the literary style to which an author is assigned. I will discuss endogenous attributes in detail in the next section. Exogenous attributes, in contrast, are not established within the literary field; they are given from outside. I hypothesize that the following socio-demographic variables will have a homophily or deference effect: the person's sex, education type (elitist versus popular secondary education), type of occupation (commercial text writing versus other), and social class as represented by the parents' occupation (lower, middle, or higher middle class). Finally, the political signature of the paper or magazine publishing the review is considered to affect the sign of evaluations: leftwing papers are hypothesized to publish many negative judgments.

These variables cover basic sociological aspects of society that were quite prominent in The Netherlands in the 1970s: Feminism rose, the results of educational changes became visible (called the democratization of education), and new types of jobs appeared on the intersection of communication and commerce, e.g., in marketing. According to theories that distinguish between levels or domains of action in society having different norms, logics, or rules, e.g. institutionalist theory (Douglas 1986), New Institutionalism (Powell and DiMaggio 1991), and field theory (Bourdieu and Wacquant 1992), one should not merely assume that general social characteristics influence all types of action. For one thing, social attributes do not need to be influential all of the time. In addition, when a socially ranked attribute influences action, its effect can be opposite to the ranking order in society at large. Groups with less status or power in society, e.g., women or the young, may have more standing, that is, receive more positive evaluations, within the literary field. Alain Viala and Pierre Bourdieu called this the prismatic effect of a field (Bourdieu 1993: 181-2; Viala 1989). The literary field, having its own rules and practices, mediates between macro structure (overall society) and micro action, so it represents a meso level in this approach.

A major goal of my research project is to find out how we can determine whether and when general social distinctions affect literary evaluations. When are they part of the logic of practice within the literary field that constructs identities (De Nooy 2003)? Although elaborate theories exist on this matter, the methods used for testing them are rather crude. Researchers working along the lines of Bourdieu, for instance, use correspondence analysis mostly on cross-sectional data to reconstruct the major dimensions ordering a social space. The implications for the social valuation of particular attributes or actions literally must be read from the maps produced by correspondence analysis. More sophisticated approaches exist, e.g., Galois lattice analysis (Mohr and Duquenne 1997), but none of these include the actions and interactions among the population of a social field. It is my aim here to show that particular types of network analysis can achieve that.

Within the literary field, the social valuation of general properties of the authors and critics will show up in systematic effects of these properties on the literary evaluations. If books by women are evaluated negatively relatively often in comparison to books written by men in a particular period, sex has social valence within the practice of literary criticism at that time. Alternatively, one might say that the practice of being more critical of women's books produces the social valence of gender at that time. To show the temporal nature of social valuation, it is important to compare different periods, as I will do. Because of the possibility of prismatic effects, it is not feasible to formulate specific hypotheses; books by women may evaluated either more positively or more negatively. In addition, systematic differences may show up only among particular critics, e.g., among women or in evaluations between men and women. From sociological theory, however, it is to be expected that systematic differences will show up especially with respect to socio-demographic characteristics involved in overall changes in society at that time. Therefore, I will look for effects of gender, level of education, type of job, political orientation, and social class in the statistical analyses.

Effects of endogenous attributes are represented by red arcs in the visualizations. Positive evaluations among people with the same characteristic or negative evaluations among people with different characteristics (solidarity/homophily) are drawn as red arcs as well as positive arcs from lower to higher status occupants and negative arcs in the opposite direction (status/deference) or the other way around in the case of an inverted ranking. To distinguish between effects of different attributes, separate visualizations are created for different exogenous attributes with a major statistical effect on the signs of the evaluations.

Endogenous attributes as identities

As stated in the previous section, endogenous attributes refer to characteristics that are generated within the literary field. In principle, they can change according to events within the literary field, e.g., the interaction creating network structure. I will analyze the kind of role played within the literary field, viz., creative (author or author/critic) versus not creative (just critic), the actor's seniority indicated by the year in which his or her first literary book was published, the evaluated author's commercial success as indicated by the maximum number of reprints previously obtained for his or her literary books, shared affiliations to literary magazines, and the classification of the actors into literary styles, which I will review in more detail below.

Note that endogenous attributes are included in the analysis in exactly the same way as exogenous attributes (see the previous section). The kind of role played is used as a status/deference dyadic covariate, hypothesizing that authors have higher standing than critics due to their ascribed semi-divine creative power. Literary style is a solidarity/homophily dyadic covariate because style is hypothesized to be an important identity marker. In the visualizations, the solidarity/homophily effect of style is indicated by yellow positive arcs between members of the same literary style and yellow negative arcs between members of different literary styles. Commercial success is included as an individual covariate because commercially successful authors are expected to attract either many positive evaluations (from an economic or mass media point of view they are 'hot') or many negative evaluations according to Bourdieu's theory about the denial of the economy within artistic fields (Bourdieu 1983).

In contrast to most exogenous covariates, the endogenous covariates are usually dynamic, that is, they change over time. During an author's career, the maximum number of reprints may rise and he or she may be assigned to different literary styles or movements. As a consequence, an actor's score on these attributes must be assessed separately for each evaluation in which he or she is involved. Although this requires extra work in data preparation, it is inconsequential to the design of the multilevel logistic regression analysis. In the visualization, dynamic endogenous attributes result in changing properties of the vertices, e.g., a vertex representing an author who is assigned to a new or different literary style will change color.

Publications that literally group authors and label these groups as literary styles or movements - abbreviated to style classifications in this paper - are hypothesized to create identities that regulate subsequent evaluations among classified authors. As Bourdieu noted, "The names of schools or groups which have proliferated in recent painting (...) are pseudo-concepts, *practical* classifying tools which create resemblances and differences by naming them" (Bourdieu 1980: 289). During the 1970s, 11 classifications were published, each of which assigned a small number of authors to literary styles or movements. Note that these are not the publications that are used for coding literary evaluations (see below). The classifications, however, build upon and extend previous ones, so I constructed a cumulative classification which changes each time a new literary classification was published, adding newly classified authors and, if necessary, rearranging the clustering.

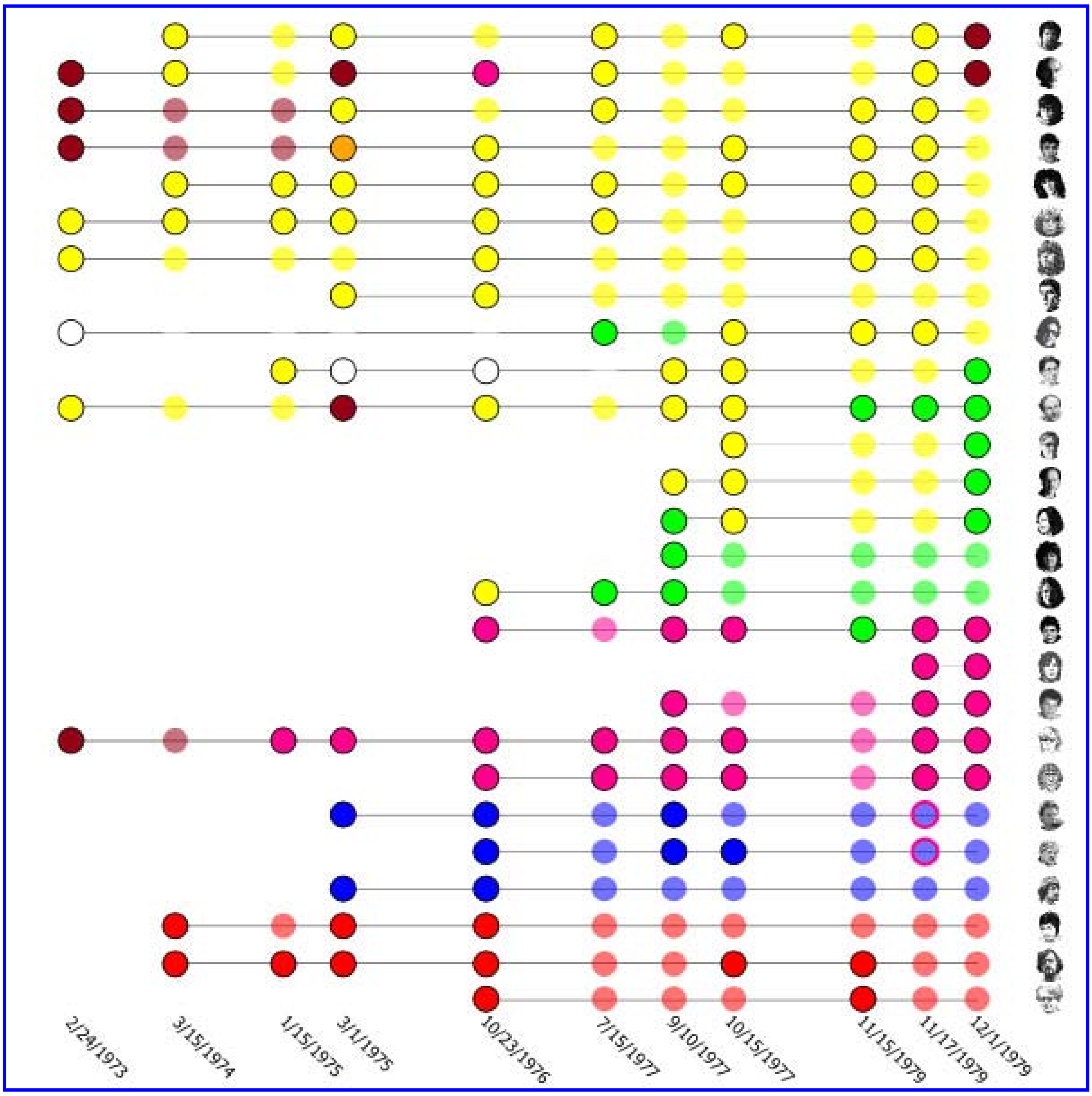

Figure 2 - Classifications over time (click for interactive SVG picture).

Figure 2 shows how the style classifications are combined. The authors define the rows (in the SVG picture, move the mouse over a face for biographic information - zoom in for more detail).

The publications of style classifications define the columns, which are ordered and labeled by publication date. An opaque circle indicates that an author was classified in the publication and its color refers to the style group to which the author was assigned. The SVG picture displays the label of the style group when the mouse moves over the circle. Within a column, circles with the same color identify the authors that were assigned to the same literary style group in a particular publication. The colors are chosen such that they change as little as possible between columns. White is used for authors who were explicitly excluded from the named style groups but who were not assigned a style. A transparent circle indicates that an author was not classified in a publication, so the previous classification is assumed to be still relevant.

In the visualization, vertex colors represent the current classification of authors according to literary style as shown in Figure 2. In the statistical analysis, the two persons involved in an evaluation belonged to the same (code 1) or to different style groups (code -1), or they were not both classified at the time the review was published (code 0). Note that the number of evaluations in which two previously classified authors are involved is rather low: only 61 cases out of 456. Therefore, the effect of literary classification must be quite strong to surface in the statistical analysis of this dataset.

Classifications according to literary style are assumed to represent the perception or interpretation of overall group structure by one or more actors in the literary field. Subgroups within the network of evaluations or other relevant social relations within the field are translated into literary identities. The perception of overall network structure may be imperfect and even strategically distorted as a product of wishful thinking, so the interpretation does not follow automatically from network structure and it must be included as a variable on its own in an explanatory model. Classification as interpretation and as an act of making sense represents the mental aspect of Heider's balance theory, which should be included according to Patrick Doreian (Doreian 2002: 108).

The classifications studied here were published in national papers or magazines, so it is safe to assume that they were known to everyone in the network. It is a fact that literary authors and critics scrutinize these media. Likewise, the evaluations are public and likely to be noted by all participants. In this particular application, it seems warranted to assume that all action is broadcasted to the entire group, so there is no need for restricting the knowledge of action to local settings (compare Hummon and Doreian 2003: 30).

Causes and consequences of individual action: a layered model

When we assemble the ideas about the evolution of the network of evaluations among literary authors and critics, a layered model arises. This is shown in Figure 3. It includes individual action at the micro level, which is represented by the publication of evaluations. The professional field, i.e., the literary field in this case, is the relevant context within which the evaluations are made and it is considered to be the meso level. It contains three types of factors that are hypothesized to affect the evaluations (red arcs): professional identity, local structure, and perceived meso structure represented by style classifications.

The actual network structure at the meso level follows immediately from the ties created by micro action (black arc), e.g., if the actors pursue local balance, the overall network structure may not be perfectly balanced (Hummon and Doreian 2003) but it will be quite easy to identify a blockmodel of clusters internally bound by positive ties and separated from other clusters by negative ties. As argued above, the overall network structure does not directly affect micro action because actors have to interpret it, e.g., translate it into a system of literary styles. However, making these classifications, actors can take into account other aspects as well, most notably their peers' attributes, which they derive either from the literary field or from society at large. The latter represents the macro level in the model.

In Bourdieu's field theory, as stated above, the practice within a particular field (of production) results from forces operating within the field and forces operating in the wider social field or field of social classes. It is my aim to distinguish between the two forces by separating the impact of exogenous attributes (representing structural properties of the social field) from the impact of endogenous forces (representing forces within the field of literary production). However, the effects on the clustering proposed by the style classifications, represented by blue arcs in Figure 3, will not be investigated in this paper.

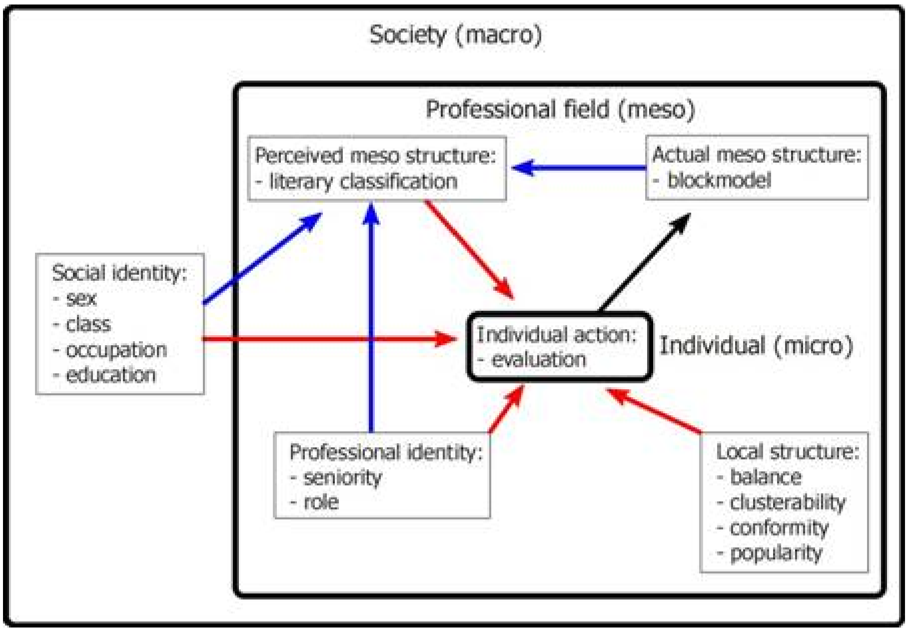

Figure 3 - A layered model of network evolution.

Data

This paper analyzes network data measured in continuous time: for a set of actors, it is known who acts towards whom at what moment. The actors are 40 Dutch literary authors and critics, most of whom made their appearance in the 1970s. The interaction consists of the evaluations among the authors and critics that were published in reviews and interviews in Dutch newspapers and magazines throughout the 1970s. In the analyses, 456 evaluations are used. Originally, the evaluations were coded on a 5-point scale: entirely negative - predominantly negative - neutral - predominantly positive - entirely positive. Intercoder reliability tests, however, showed that a 3-point scale was much more reliable. Because neutral evaluations are very rare, the analysis is restricted to evaluations that are either positive or negative. They are represented by signed directed ties. The data are described in more detail in (De Nooy 1991, 1999a). The publication dates arrange the evaluations in a continuous series, so the social process is observed step by step.

Statistical results

The statistical analysis is restricted to the explanation of micro action; the sign of the evaluations (positive versus negative) in this application. Because the dependent variable is a dichotomy, logistic regression analysis is applied, using the logit link function. Due to dependencies among the data that result from the selection of 40 authors or critics and, as a next step, all (456) evaluations passed among them in reviews and interviews, multilevel regression analysis is appropriate. The first (lowest) level consists of evaluations; the second level consists of persons acting in two roles, viz., as a person who passes judgment and as a person whose book is being judged.

I have used Bayesian MCMC estimation rather than quasi-likelihood estimates. MCMC estimates of fixed and random effects are better because the (1st order MQL) quasi-likelihood estimates are biased downwards (Browne 2004: 127). In addition, in the case of large variance components the known bias of quasi-likelihood estimates for the random factors may distort the estimated standard errors of the fixed effects (Snijders and Bosker 1999: 219). Finally, quasi-likelihood estimations do not yield reliable likelihood estimates that can be used for the evaluation of random effects (Snijders and Bosker 1999: 220). The Bayesian approach yields a DIC that can be used for this purpose, at least according to some (Spiegelhalter et al. 2002). In the MCMC estimation, the prior distributions that are standard in MLwiN software have been used: uniform for fixed parameters, Gamma for scalar variances, and Wishart for variance matrices. All numerical variables have been standardized to *z*-scores.

Table 1 - Variance components (MCMC multilevel logistic regression, N=456, 15,000 runs).

Model	**var tail (s.e.)**	**var head (s.e.)**	**pD**	**DIC**
- no random effects	-	-	1.04	595.46
- random effect: judge (tail)	0.459 (0.325)	-	15.63	579.25
- random effect: judged (head)	-	1.499 (0.675)	26.65	540.66
- crossed random effects: judge, judged	0.598 (0.381)	1.814 (0.826)	41.94	520.69
- multiple roles model: judge, judged+	3.128 (1.317)		28.35	537.25

* Dependent variable: the sign (positive or negative) of the evaluation.
+

Including 32 out of 40 persons that appear both as tail and head: N = 433.

As a first step in the analysis, I have evaluated the variance components or random effects to check whether I have to apply a multilevel model. The variance components are necessary if they improve the model fit. This is expressed by the Bayesian Deviance Information Criterion (DIC): a lower value on this statistic indicates a better fitting model (Spiegelhalter et al. 2002). In Table 1, we see that adding a random effect for the 33 persons that pass judgment (tail of the evaluation tie) improves model fit from 595.46 (the model without random effects) to 579.25. The variance in the judgment among the judges is 0.459 and the 33 persons involved are represented by approximately 15 (pD 15.63 - 1.04) effective parameters. The next row in the table tells us that the person judged (the head of the evaluation tie) accounts for more variance (1.499) in the judgment and that this random factor improves the fit of the model much more (DIC = 540.66) than the judges. This shows that the evaluations (positive/negative) vary more systematically among the persons who are evaluated than among the people who pass judgment. In other words, we find some differences between the judges with respect to their 'style' of criticism - some fault-finding critics that tend to pass negative judgment on their peers along with some enthusiasts that do not pass negative judgment - but the consensus on the literary quality of persons is more outspoken: there are more differences among the authors with respect to whether they are collectively evaluated positively or negatively.

Because each evaluation (tie) has a judge (tail) and person judged (head), we need a cross-classified model to include both random effects. This model fits better than each of the models including just one random effect. However, most people act in both roles: 33 persons pass judgment and 38 persons are being judged. This situation calls for a multiple roles model (Snijders and Bosker 1999: 161-162) or a multiple membership model (Browne 2004: 181-193). Table 1, however, shows that the multiple roles model fits worse (DIC = 537.25) than a simple cross-classified model (DIC = 520.69). This means that there is no interesting correlation between the way a person evaluates and is evaluated. Therefore, I will use the cross-classified model. There is, however, a little technical complication: the software (MLwiN) seems to ignore persons that do not act both as an evaluator and the subject of an evaluation.

Table 2 shows the model for the entire period resulting from a backward selection process, using Wald's test of significance for the parameters. Marginally significant estimates ($p < .10$) are retained as well as one insignificant effect (sex of evaluated person) needed to have a significant sex homophily effect. The Appendix contains the complete list of estimated effects. Among the many exogenous attributes, the evaluated person's seniority is the only predictor with a clear significant effect. The youngest level of authors and critics, starting their literary careers in the second half of the 1970s, have high odds for a positive judgment whereas the oldest generation (started before 1970, the reference category) have relatively high odds for a negative judgment. In general, younger people have better chances. These youngsters predominantly belong to the so-called Protest Generation in The Netherlands, which was very successful in society (Becker 1992). A marginal significant result is found for the difference in education type between the evaluator and the person evaluated. An author with elitist secondary education who is reviewed by a someone with a less prestigious type of education, has higher odds for being evaluated positively. The reverse, however, is not true. Higher odds for a negative evaluation are found more often between people with the same type of education than from higher to lower educated persons. Gender homophily appears only as a marginally significant effect if the gender of the evaluated person is also included even though that is not a significant effect itself.

Table 2 - Effects on the sign of the evaluation 1970-1980 (crossed random effects model, MCMC estimation, 150,000 runs, 454 cases).

Model	**parameter**	**posterior s.e.**	**(joint) posterior *p***
Seniority of evaluated person			.018
- 1970-1975	0.032	0.578	
- 1976-1980	2.158	0.794	
Educational background			.094
- to person with less elitist education	0.163	0.407	
- to person with more elitist education	0.878	0.416	

Evaluated person is female	1.198	0.852	.160
Sex homophily	1.005	0.574	.080
Evaluator is classified to a literary style	-0.874	0.351	.013
Conformity (standardized)	0.512	0.165	.002
Balance (standardized)	0.443	0.159	.005
Constant	-0.492	0.688	
Variance evaluator	1.259	0.693	
Variance evaluated person	0.262	0.270	

Endogenous attributes, that is, characteristics related to the literary field, have no significant impact on the sign of the evaluation except for the style classification of the person passing the judgment. Authors that have been assigned to literary style groups tend to pass negative judgment more often. This seems to indicate that literary styles function as banners for authors who are critical of their peers' work. Finally, two aspects of local structure have highly significant effects: conformity and balance. Within the literary field, people tend to stick to their judgments (conformity) and take into account the preferences among their colleagues.

The higher odds for the youngest authors and critics to obtain positive evaluations suggests that the second half of the decade, that is, the years in which they made their appearance, may be different from the first half. Following Bourdieu's conjecture that the impact of social factors within a production field may change, it is interesting to repeat the analysis separately for each half of the decade. (Adding interaction effects for period by each predictor yields too many parameters to be estimated.)

Table 3 contains the results for the years 1970-1975. The type and political signature of the periodical in which the evaluation was published is the only significant predictor in this period. As expected, critics in leftwing papers and magazines are much more likely to pass negative judgment than their colleagues in literary magazines. Rightwing or regional papers and periodicals in the political centre (reference category) are on neutral ground. Leftist men of literature attack the literature published by new authors. The wake of the 1968 Cultural Revolution is apparent here. Even more interesting is the fact that neither endogenous attributes nor local structure is systematically related to the contents of the evaluations. The absence of conformity may be caused by the fact that there are fewer instances of people evaluating the same author more than once. This, however, is not the case with balance. These results suggest that there are no clear group processes operating within the field in this period; in Bourdieu's terminology, the practice of literary evaluation is not clearly autonomous.

Table 3 - Effects on the sign of the evaluation 1970-1975 (crossed random effects model, MCMC estimation, 150,000 runs, 179 cases).

Model	parameter	posterior s.e.	(joint) posterior *p*
Type of periodical			0.030
- rightwing/regional	-0.320	0.650	
- leftwing	-3.165	1.100	
- literary magazine	0.349	0.664	
Constant	0.950	0.427	
Variance evaluator	1.378	0.999	
Variance evaluated person	0.563	0.709	

The second half of the 1970s shows a completely different picture (Table 4). Again, the type and political signature of the periodical has a significant effect, but now literary magazines have high odds for negative evaluations instead of the leftwing papers; the rightwing and regional papers are very much inclined to making positive evaluations. The type of periodical seems to have partly contrary effects in the two halves of the decade, which is why it does not show up in the results for the entire period. The effects of seniority and elitist education, which surfaced in the analysis of the entire period, actually pertain to the second period and they are more significant now. In addition, we find a highly significant effect for sex homophily; the new wave of feminism entered the literary field.

Table 4 - Effects on the sign of the evaluation 1976-1980 (crossed random effects model, MCMC estimation, 150,000 runs, 274 cases).

Model	parameter	posterior s.e.	(joint) posterior*p*
Type of periodical			0.004
- rightwing/regional	2.407	0.779	
- leftwing	-0.464	0.680	
- literary magazine	-1.296	0.828	
Seniority of evaluated person			0.006

- 1970-1975	0.824	0.601	
- 1976-1980	2.549	0.801	
Educational background			0.047
- to person with less elitist education	0.237	0.548	
- to person with more elitist education	1.386	0.566	
Sex homophily	1.491	0.561	0.008
Same type of occupation	1.340	0.577	0.020
Type of occupation evaluated person (commercial copywriter)	1.308	0.824	0.112
Evaluated person is classified as a member of a literary style	-1.257	0.570	0.027
Evaluated person is just a critic	-1.865	0.974	0.056
Creative role			0.034
- authors on critics	-1.842	0.789	
- critics on authors	0.297	0.534	
Balance (standardized)	0.701	0.217	0.001
Constant	-1.845	0.945	
Variance evaluator	0.436	0.731	
Variance evaluated person	0.127	0.250	

The type of main job (commercial copywriter or not) plays a complicated role, probably because its effect is related to the effects of a person's role within the literary field (also author versus just critic) and his or her perceived membership of a literary style group, which are two of the three endogenous attributes with (marginal) significant effects on the sign of the evaluation. Authors classified with a literary style group receive relatively many negative judgments. In the second half of the period, being classified works against you. Critics have higher odds for receiving negative judgments than authors, even more so if the evaluation is made by an author. The supremacy of the author as a creative genius seems to be re-established in the literary field.

Finally, there is a highly significant tendency towards balance: people tend to adjust their evaluations according to the principle that their friends' friends are their friends and their friends' enemies are their enemies. Thus, literary evaluations are subjected to a group process within the literary field; an autonomous process. The literary field seems to be in a process of restructuring itself, meanwhile dealing with changes in overall society such as feminism and educational changes.

Visualizations

The statistical results show which social attributes and aspects of network structure are important to the evaluations that are made and how their importance may change between periods. They disclose the basic mechanisms driving the literary evaluations in this period, but we cannot tell how the mechanisms play out and produce results in terms of network structure and positions. In addition, the backward selection process has shown that several effects are related: eliminating a non-significant effect has decreased the significance of other effects several times. This is true particularly for the classification according to literary style, which is central to this study. To investigate more closely the process going on within this literary field, the detected mechanisms are visualized. How do structure, action, and meaning co-occur and co-evolve?

The design section discussed the color coding for vertices (vertex color represents current literary style group, white means unclassified) and arcs:

- Red: homophily/deference on an exogenous attribute, either education type or sex, which had the most significant effects.
- Blue: balance (including conformity).
- Yellow: homophily on an endogenous attribute, viz., literary style group. Note that effects of dynamic (endogenous) attributes are determined at the time the evaluation was published. If the attribute changes afterwards, the arc's color may no longer match the color of the vertices.
- Black: the arc's sign does not conform to any of the effects.

Since an arc's sign may conform to more than one structural effect, it may have a mixed color, as indicated by the legend (Venn diagram) on the right of the animation. In the SVG picture, you may click anywhere in this legend or on the lettering around it to obtain a network containing a particular type of arc. For instance, clicking the blue part of the Venn diagram displays the arcs that only conform to balance. Clicking the purple part shows the arcs that only conform to balance and homophily, clicking the word *Balance* displays all arcs that conform to balance theory: blue, purple, green, or brown.

In addition, some remarks must be made about time, the layout of the vertices, and vertex size. To explore the relation between network structure and a newly published literary classification, each published classification is a stop in the animation. Classification dates are displayed on the right of the animated networks. At a stop, the network shows the relations in the previous 24 months. Proceeding to the next classification or going back to a previous one is done by clicking the triangular buttons at the bottom right, vertices move to new locations, and arcs that remain in the network move with them or gradually appear and disappear.

Note that the underlying network process is modeled in continuous time (discrete tie) (Bender-deMoll and McFarland 2006). As a consequence, the extent of overlap between consecutive networks depends on the time span between them. However, contrary to their recommendation, the duration of the animation is not proportional to the time passed between the publication of the two subsequent classifications because the periods vary from two weeks to more than two years. Some changes would be boringly slow while others would be too fast.

As recommended by Moody et al. (Moody et al. 2005: 1218-9), vertices move from their initial positions to their final positions in the layout in a straight line. Each publication of a literary classification represents a stop in the animation, providing new 'final' positions for the vertices in the layout. For each stop, I optimized the position of the vertices with the Fruchterman-Rheingold algorithm (as implemented in Pajek) such that positive arcs are rendered short and negative arcs are rendered long. Note that this optimization draws factions (plus clusters) within the network as tight clusters of vertices. Therefore, the placement of the vertices (authors and critics) shows whether and where polarization occurred. Thus, it is possible to survey overall network structure and relate it to the new literary classification, which mirrors network structure if the vertices are clustered by styles (vertex color). The optimal layout of the preceding network was the starting point for the optimization.

Finally, vertex size shows the commercial success of the author as measured by the maximum number of reprints of his or her books by that time. For critics without book publications, a fixed small vertex size is used. Representing success by vertex size shows how and when statistical tendencies in micro behavior produce winners and losers.

Technical note. Network animation is quite demanding, so use a fast computer or have patience.

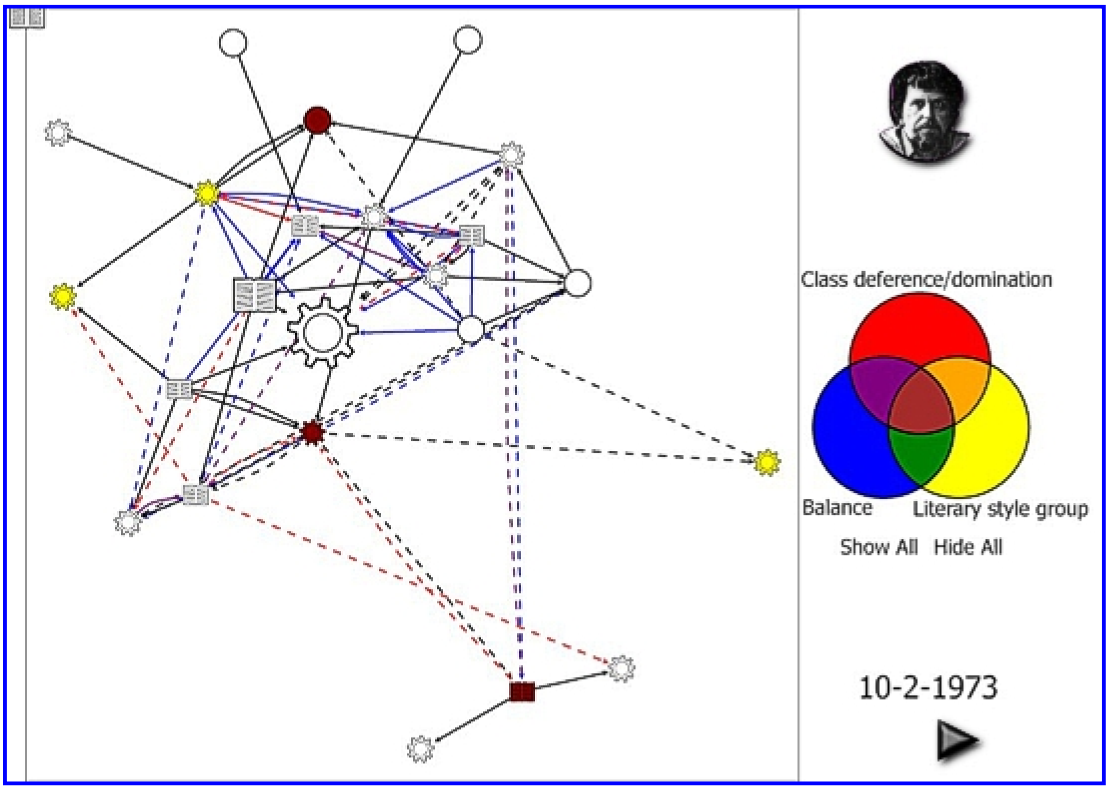

Figure 4 - Animated network with education type (deference - click to open).

Figure 4 (click on the image to open the animated SVG) shows the animated network with the deference effects of education type expressed by red arcs. Note that education type is represented by vertex shape: a book for elitist secondary education and a gearwheel for common education. Circles are used when the education type is not known. With the cursor on a vertex, the person's name pops up. Vertices without portrait represent people who are acting solely as critics (at least in the context of this case study).

Let us first have a look at general features of the evolving network before we take a closer look at the role of education type. I recommend browsing through the animation, paying attention to the composition of the network: who dominates the center and where do the largest, that is, most successful authors and critics, go? From 1973 to 1975, we see "gearwheels" (authors with less elitist secondary education) move into the center with some "books" hovering around. In 1976, (predominantly pink) books start to move to the center, which they really occupy by the end of September 1977.

By the end of 1979, the network is much more clearly divided in a center and a periphery. The center contains both "books" and "gearwheels" but three of the commercially most successful authors with a less elitist education are in the periphery. The periphery is dominated by "gearwheels," with "books" mainly concentrated in the (red) literary style group that was separated from the center throughout the entire period. In quintessence, we see the rise and fall of a generation of authors with non-elitist schooling. At the end, the cultural elite reclaims the center of the field.

How did this come about? We may have a look at the workings of balance, classification, and deference towards more elitist colleagues by clicking the appropriate labels around the Venn diagram at the right of the SVG. I will just briefly sketch some relevant trends and hope that the reader will play around with the animations and find additional results.

Focusing on the arcs that are in line with previous classifications (click the *Classification* label), I mainly see positive arcs among "gearwheels" until 1976. In the first half of the decade, style homophily meant positive evaluations within style groups. Afterwards, negative arcs between style groups prevail, showing polarization among both elitist and non-elitist actors; the separation of "gearwheels" into different style groups seems to end the previous solidarity among them. Style classifications, perhaps unintentionally, function as a divide and conquer strategy. Near the end of 1977, the pink books that gathered in the center supported one another. Afterwards, style classifications seem to play no role of importance anymore. Note that many arcs conforming to style classifications are green, which means that they are also in line with balance. Balance and literary classification seem to work together, which explains why style homophily has no significant contribution to the statistical model once balance is included.

Initially, the arcs expressing deference or domination with respect to the type of education (click the *Homophily/Status* label) were predominantly negative, which means that people with an elitist background pass negative judgment on their less elitist colleagues. Positive arcs, showing deference towards more elite authors and critics, dominated in 1976 and 1977. Showing their respect to the elite, the authors and critics of more common beginnings legitimize the elite's dominant position.

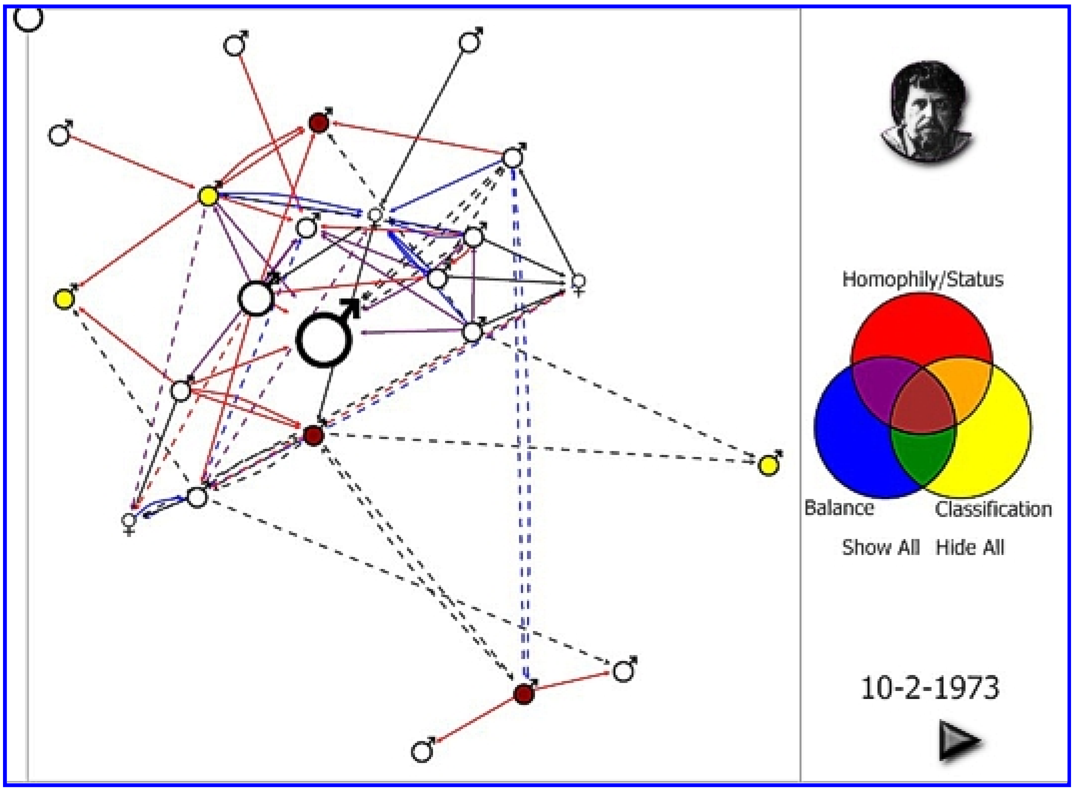

Figure 5 - Animated network with sex (solidarity/homophily - click to open).

A separate set of animations shows the role of sex in the evolution of the network. Open the SVG file and click the *Homophily/Status* label over the Venn diagram to inspect the evaluations that express intra-sex solidarity and inter-sex competition. I think that it is fascinating to see that positive arcs abound among men while they are very scarce among women. Until 1976, the inter-sex evaluations involved members of the "red" style group. In 1976, the situation changes due to the advent of new female authors, notably Hannes Meinkema, who would later be labeled as a Feminist author (October 1977). Meinkema systematically praises work by female authors and criticizes her male colleagues. However, praise among other female authors is still scarce. It is probably mainly because of Meinkema that sex became an issue within the literary field in the second half of the 1970s.

Conclusion and discussion

This paper's first aim is to explore analytic strategies, both statistical and visual, for longitudinal data measured in continuous time. This type of longitudinal data is found in all kinds of archives, in analog or digital format, but it can also be collected in field studies. With longitudinal network data, two questions may be raised: why does someone act at a particular moment towards a specific alter and why does s/he act in a particular way?

Analyses on a series of cross-sectional network data have focused on the first question, trying to predict that certain pairs of actors do relate whereas others do not. This approach presupposes that each actor is able to reconsider all of its ties and establish a new tie to any other member in the network within a particular time interval. If data measured in continuous time can be aggregated into time intervals for which this presupposition holds, the panel approach can be applied. However, if the assumption is not plausible for the data because ties among actors are constrained by the social context of the network or, in a more general way, when the formation and dissolution of ties is not primarily driven by the network of ties itself (Snijders et al. 2007), it is of no use trying to model the presence and absence of ties as an endogenous network process. This is the case with the network of literary evaluations investigated in this paper. The publication of reviews and interviews depends on events outside the network of evaluations, mainly the publication of new books. Probably, many more types of ties among people or organizations are constrained by events in their social context, e.g., e-mail correspondence. In these cases, explaining why there is a tie at a particular moment is different from explaining the effects of and on properties of existing ties, which brings us to the second question.

The second question, pertaining to the form or content of the (inter)action can be solved statistically on data in continuous time, provided that the (inter)action can take different forms, e.g., as a signed or valued relation, or if there are different types of relation (friendship or advice) in which the actor may engage. The analyses presented in this paper show how multilevel logistic regression analysis can be used to detect predictors of the sign of the (inter)action. The results reveal interesting regularities in the data that evoke the temporary construction of identities from both endogenous literary and exogenous social attributes. Although the formation of ties (their presence and absence) cannot be explained here, we still find interesting results for the characteristics of the ties. To my mind, this case shows that interesting structural aspects are not restricted to the presence or absence of ties.

Statistical analysis is a prerequisite for efficient visualization. Although or perhaps because a lot of information can be put into a visualization, hints on relevant factors are indispensable. Animations like the ones presented in this paper serve the inspection of known statistical trends rather than their detection. Just by knowing what to look for, it is possible to understand the statistical regularities in detail. In the visualizations, one can see at what moment a particular process is occurring and which actors are involved. Changes in the level or nature of effects occurring in 1976 and 1977, for example, corroborate the initial assumption that 1975 functions as a caesura in the data set analyzed here. In addition, visual inspection shows how statistical effects overlap or are intertwined. For instance, it shows how style homophily and tendencies towards balance are merged in a polarization process. Finally, visual inspection offers impressions of trends or changes within the process that are too weak or varied to be captured statistically. These impressions can be used as hypotheses in further research with more observations.

This paper's second aim is to expand the actor-oriented model to include both overall network structure and socially constructed meaning. At present, actor-oriented or actor-driven models take a restricted view of the actor: its interaction is supposed to be driven by its immediate network neighborhood. Can we do without overall network structure as a predictor or the way it is perceived and communicated among actors? I hypothesize that actors try to overview the overall network structure in which they are participating, interpreting subgroups or factions within it as a system of identities relevant to their interaction.

The present paper has used style classifications as communicated interpretations of network structure. Due to the small number of authors involved in each classification, it is not possible to test whether this is true, e.g., do classifications reflect plus clusters in a blockmodel of overall network structure (Doreian and Mrvar 1996)? I have tested whether the classification according to literary style affected the sign of evaluations. The results were meager: overall, members of style groups seemed to be more often inclined to pass negative judgment and, in the second half of the decade, they were evaluated rather negatively. The homophily effect expected between members of the same style group was not found. This may be a consequence of the low number of evaluations found within and among style groups or absorption of this effect by the variation among persons captured by the random effects in the model. In addition, classifications according to literary style and balance seem to go together in the visualizations. Anyway, I did not find evidence suggesting that one needs to go beyond the immediate network neighborhood in order to explain the signs of the ties. The actor-oriented approach that restricts attention to the immediate network neighborhood of the actor is sufficient in this case.

How could we include the genesis of identity in an analysis of networks over time? If identity can be measured as a one-dimensional quantitative property of the actors in the network, the approach to the co-evolution of networks and behavior proposed by Tom Snijders, Christian Steglich and Michael Schweinberger (Snijders et al. 2007) can be used, provided that network evolution is sufficiently endogenous (see above). This approach does not seem to be feasible for identity as a categorical variable, because the proposed model is based on small incremental increases or decreases in the values of behavioral variables. Perhaps an integral approach to the cyclic processes of micro action, network evolution, and identity formation requires a simulation study. The estimates from the regression analysis should offer realistic parameter values for a simulation model.

The results show that exogenous social attributes as well as endogenous literary characteristics at times affected the evaluations, which implies that they were meaningful at that time. This approach offers us a handle on the construction and function of identity in local action, which is at the core of both Symbolic Interactionism and practice theory. It shows how local action is symbolically interpreted and subsequently affects action as postulated in Symbolic Interactionism. But it also points out that the role played by the wider structure of society is being reproduced in local action, as claimed by practice theorists. The relative weights of local autonomy and structural constraints can be estimated with precision. In the case analyzed here, this was illustrated by the fact that effects of socio-demographic background (exogenous variables) changed over time and that they dominated in the first half of the decade.

At this point, I would like to advocate paying more attention to signed relations in social network analysis. A social constructivist perspective on meaning links symbols, e.g., words, to social entities, e.g., individuals or organizations, and their relations. Symbols derive their social meaning from the entities that they label. Analyzing discourse, one may discover the patterns of these linkages, thus disclosing the social meaning of symbols (Mohr and Duquenne 1997). In interaction, however, social meaning may be more easily constructed and observed through the ways in which social entities evaluate one another. Outside the domain of discourse, symbols and a social entity's relevant features remain unspecified, so they must be read indirectly from evaluation patterns. If actor X values actor Y, s/he may value any of Y's features. However, if X values a set of people, the features that they share are most likely to be perceived as the "thing" that X values in them. Thus, particular characteristics of the people involved in the network of interaction become socially meaningful in the sense that they affect interaction; they start to function as social identities.

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Appendix

All effects on the sign of the evaluation 1970-1980 (crossed random effects model, MCMC estimation, 150,000 runs, 454 cases).

Model	**parameter**	**posterior s.e.**
Local structure		
Conformity (standardized)	0.318	0.203
Popularity (grouped):		
- 0 (reference category)	-	-
- 1-5	-0.464	0.615
- 6-10	-0.645	0.717
- >10	-0.819	0.866
Balance (standardized)	0.474	0.219
Endogenous effects		
Seniority of evaluated person		
- before 1970 (reference category)	-	-
- 1970-1975	-0.807	1.387
- 1976-1980	5.895	2.449
Seniority difference:		
- head younger	0.534	0.898
- equal/NA (reference category)	-	-

Model	**parameter**	**posterior s.e.**
- head older	0.008	0.667
Commercial success:		
- no reprints (reference category)	-	-
- 1-2 reprints	-0.704	0.611
- >2 reprints	-0.441	0.629
Shared affiliations to literary magazines (I)		
- Editors of different magazines	-2.003	0.996
- Not both editors/NA (reference category)	-	-
- Editors of the same magazine(s)	0.819	1.687
Shared affiliations to literary magazines (II)		
- Authors of different magazines	-0.513	0.479
- Not both authors/NA (reference category)	-	-
- Authors of the same magazine(s)	-0.600	0.529
Evaluator's role: just a critic	-0.101	1.191
Evaluated person's role: just a critic	0.486	2.363
Evaluator is classified to a literary style	-1.202	1.041
Evaluated person is classified to a literary style	-0.484	0.550
Evaluator and evaluated are classified to the same literary style	1.233	1.218

Model	**parameter**	**posterior s.e.**
Exogenous effects		
Elitist education of evaluated person	-0.028	1.745
Educational background		
- to person with less elitist education	1.388	0.935
- equal/NA (reference category)	-	-
- to person with more elitist education	1.465	0.731
Evaluator is female	3.038	1.744
Evaluated person is female	3.226	1.548
Sex homophily	3.363	1.073
Social status of evaluated person:		
- low (reference category)	-	-
- middle	-1.720	1.342
- high	-0.126	1.661
Status difference:		
- to lower status	-.350	0.839
- equal/NA (reference category)	-	-
- to higher status	1.034	0.686
Creative occupation evaluator	-1.835	1.115

Model	**parameter**	**posterior s.e.**
Creative occupation evaluated person	1.071	0.874
Same type of occupation	1.311	0.616
Political signature paper		
- center (reference category)	-	-
- right wing/popular	-0.033	0.791
- left wing	-1.441	1.067
- literary magazine	0.687	0.761
Constant	-1.968	1.881
Variance evaluator	3.894	3.297
Variance evaluated person	3.329	2.441