

Social Networks 24 (2002) 231-259



www.elsevier.com/locate/socnet

# Scaling and statistical models for affiliation networks: patterns of participation among Soviet politicians during the Brezhnev era

Katherine Faust<sup>a,\*</sup>, Karin E. Willert<sup>b</sup>, David D. Rowlee<sup>b</sup>, John Skvoretz<sup>b</sup>

<sup>a</sup> Department of Sociology, University of South Carolina, 3265 Social Sciences Plaza B, Irvine, CA 92697, USA
 <sup>b</sup> Department of Sociology, University of South Carolina, Columbia, SC 29208, USA

#### Abstract

We use scaling and statistical models to study networks of ties among Soviet politicians during the Brezhnev era created by their co-attendance at events. The data consist of observations made by the National Foreign Assessment Center of the Central Intelligence Agency of appearances of Soviet political elites at official and social events for 8 years during the height of the Brezhnev era. Conventional wisdom characterizes the Soviet system as partimonial rather than bureaucratic in nature, that is, a system in which power is exercised through loyalties to key players often rooted in common regional and educational associations. One, therefore, might expect that co-attendance at events over these 8 years to be unrelated to actor's formal positions and the nature of the events. However, our scaling models reveal that participation is patterned by the state and party offices elites hold. Random graph models provide tests of hypotheses about structural features of this network and confirm the interaction between politicians' offices and the types of events which they jointly attend. Our discussion of the substantive implications of our analyses highlights the need for more detailed examination of "career tracks" through the co-participation space, particularly deviant career tracks and the need for a companion analysis of the structuring participations by informal power groups like those identified by Willerton [Soviet Stud. 34 (1987) 175]. © 2002 Elsevier Science B.V. All rights reserved.

# 1. Introduction

A hallmark and unifying principle underlying Romney's work has been the use of models for advancing scientific understanding of cultural and social phenomena. One inescapable message in his writings is that cumulative knowledge requires scientific investigation. This in turn involves developing general abstract models that are shown to be in correspondence

<sup>\*</sup> Corresponding author. Tel.: +1-949-824-9383; fax: +1-949-824-4717.

with empirical observations (Romney, 1989). In his work, Romney has put quantitative and statistical approaches in the social sciences on a par with models and scientific inquiry in the biological and physical sciences (Romney, 1980, 1989, 1999; Romney et al., 1972; Shepard et al., 1972).

Our paper draws on these aspects of Romney's work in a small way. We use two different modeling approaches to understand social interactions among a community of political elites. We begin by representing participation using correspondence analysis and principal components analysis. Patterns in these configurations are then evaluated using characteristics of the politicians and of events in which they participate. We then extend the analysis using random graph models to test hypotheses about specific structural properties underlying the observed network.

The question we address is how participation in events by Soviet political elites is shaped by actors' memberships in different governing bodies and by the nature of the events involved. Our data consist of observations of Soviet political elites at various official and social functions as recorded by the National Foreign Assessment Center of the Central Intelligence Agency for 8 years during the height of the Brezhnev era, 1972–1979 (Central Intelligence Agency, 1973–1980). Such observations were made, we suspect, because analysts thought that shifts in "behind the scenes" political alliances, indeed, membership in these contending groups, could be inferred from co-attendance at these events. This idea follows from a widely held view of "Soviet decision making in terms of the interplay of elite factions" (Ross, 1980).

Our research indirectly comments on this view. We examine the influence of the political offices held by the elite politicians on their co-attendance at the events and the nature of the events. We tackle this question using two general approaches. First we use scaling models, including correspondence analysis and principal components analysis, to represent patterns of actor co-attendance, both cumulatively for the 8 years and for each year separately, and to represent event overlap for each year. We then use random graph models to evaluate the importance of different actor and event configurations in accounting for the observed patterns of participation. Our aim is primarily methodological-to illustrate how scaling methods and random graph methods, two methods for modeling affiliation networks, relate to one another. We believe that the methods we describe are applicable to a wide range of substantive situations which can be represented as affiliation networks. Our substantive aim is very modest, to illustrate these methods on interactions between Soviet political elites and to evaluate the commonsensical claim that official position matters in the determination of co-attendance. We demonstrate support for this claim and then discuss possible further research springing from this unsurprising result that we suspect would be more revealing of the interaction between political elites and so of greater interest to students of Soviet politics.

### 2. Soviet politics in the Brezhnev era

Scholars of Soviet politics often note the importance of personal network connections, patron–client relationships and coalition building for advancement within the Soviet political system and ascension to elite status (Breslauer, 1980; Murphy, 1981; Willerton, 1987, 1992). Prior to the break-up of the Soviet Union in 1991, membership in the Communist

Party of the Soviet Union (CPSU) and state governance were intimately intertwined. In addition, unlike western democracies where political office holders are voted into office by the public at large or by their delegates, in the Soviet political system members of the highest bodies (the Politburo and the Secretariat) were admitted by agreement of standing members. As a consequence, personal contacts, sponsorship and coalition building were critical for advancement to elite status in the Soviet political system.

There is general agreement that top members of state and party bodies—full members of the Politburo, candidate members of the Politburo, members of the Secretariat of the CPSU and members of the Council of Ministers—comprised the Soviet political elite (Bielasiak, 1984; Miller et al., 1987; Willerton, 1987). Our data consist of observations on these politicians plus members of the Ministry of Defense.

Within this political elite there was a status ordering of groups. The Politburo outranked all other bodies. The Secretariat of the CPSU came next, outranking the Council of Ministers, which in turn outranked the Ministry of Defense. Within the Politburo there were two levels, full members who had voting rights and candidate members who did not vote. In practice, however, decisions were often consensual and the distinction had little practical significance in terms of voting rights.

A few comments about the responsibilities of, and relationships among, the bodies are in order. Officially, Party Congresses (held every 5 years) elected people to the various bodies (Dornberg, 1974). In practice, the Congress elected members of the Central Committee of the Communist Party (about 300 in number) which in turn chose the party leaders, party committees and members of the Politburo and Secretariat of the Central Committee (Gelman, 1984). The Politburo was generally a policy making body, whereas the Secretariat oversaw the day-to-day administrative tasks. The General Secretary chaired the CPSU Secretariat. In contrast to the Communist Party bodies, the Council of Ministers was a "government apparatus" and the Politburo's "primary vehicle for running the economy" (Gelman, 1984, pp. 57, 231). The Defense Ministry was under the Council of Ministers, but in practice answered to the Politburo (Gelman, 1984).

Our data cover the period 1972–1979, the height of Brezhnev's rule, though Brezhnev's political career began decades earlier and continued until his death in 1982. Brezhnev was a member of the Central Committee of the CPSU and candidate member of the Politburo starting in 1952. After Stalin's death in 1953, Brezhnev left these positions until 1956 when he returned to the CPSU Central Committee and was promoted to a full member of the Politburo in 1957.

In 1964, the trio of Leonid Brezhnev, Aleksey N. Kosygin and N.V. Podgorny ousted Nikita Khrushchev from his positions as First Secretary of the CPSU Central Committee and Chairman of the USSR Council of Ministers. At that time, Brezhnev became leader of the CPSU in the position of First Secretary of the CPSU Central Committee. Kosygin became head of the government, as Prime Minister, and Podgorny took over as chairman (President) of the Presidium (later the Politburo) of the Supreme Soviet, primarily a ceremonial role. In 1964, Brezhnev also became Second Secretary of the Central Committee of the CPSU. After considerable turnover among positions during Khrushchev's rule, Brezhnev sought to establish stability and during the Brezhnev era there was little turnover in political elite membership (Miller et al., 1987). He also sought to consolidate his own position by moving his supporters and proteges into key positions and by acquiring additional positions for

himself. In 1966, Brezhnev gained the title of General Secretary of the Central Committee of the CPSU (General Secretary of the Party). In 1977, Brezhnev replaced Podgorny as President in the role of Chairman of the Presidium of the Supreme Soviet. Brezhnev died in 1982 and was succeeded by Andropov as party leader. Admittedly, our data cover an 8-year period of relative stability in which patterns of co-attendance might be more routinized by protocol than during times of political flux or turnover in leadership. It would be informative to extend our analysis to the early years of Brezhnev's rule or before, but unfortunately the data for these years were not available to us.

# 3. The data

Our data consist of appearances of Soviet leaders at various events, as reported by the National Foreign Assessment Center of the Central Intelligence Agency (Central Intelligence Agency, 1973–1980). These observations record "known appearances of selected Soviet public figures" (Central Intelligence Agency, 1974, p. 3). According to the Central Intelligence Agency publication, these individuals include "members of the Politburo and Secretariat of the CPSU, Deputy Chairmen of the USSR Council of Ministers, leading officials of the Ministry of Defense and the Minister of Foreign Affairs" (Central Intelligence Agency, 1974, p. 3). Information was compiled from various sources. The sources are listed in the Central Intelligence Agency report but without definition or description.<sup>1</sup> Records are published for calendar years, 1 January through 31 December. We use the years 1972–1979, which cover Brezhnev's coalition building period (1972), height of power (1975), as well as the continued maintenance of his position through 1979. The events attended by the political figures are diverse and include both official gatherings and social occasions.<sup>2</sup> Many observations in the original records involve only a single person and are not included in the analyses because they do not bring multiple actors into contact.

The number of events attended by more than one political figure varies across years (from a low of 144 in 1977 to a high of 266 in 1978) as does the set of politicians that attend events in a given year. The number of people observed in a year ranges from 45 in 1972, 1974 and 1975 to 55 in 1976, 1978 and 1979. All together there are 67 people, 29 of whom are present in all years and the remainder of whom are present for only a portion of the time. There are 1816 events total across the 8 years. Most of these events are unique occurrences rather than events that reoccur across years. On average, each person attended 27.8 events per year and events averaged 6.1 political elites in attendance. The average number of events co-attended by each pair of actors ranges from a low of 2.31 in 1977 to a high of 9.38 in 1972. Table 1 reports the numbers of events and actors in each of the 8 years.

We also have information about the state and party bodies to which politicians belonged in each year. These bodies are: CPSU Politburo full member, CPSU Politburo candidate (non-voting) member, CPSU Secretariat, USSR Council of Ministers and the Ministry of

<sup>&</sup>lt;sup>1</sup> For example, some of the sources listed in 1973 include: Moscow Tass, Pravda, Kras Zved, Moscow Domestic, FBIS Dr II, Izvestiya, Krasnodar Domestic and Paris Domestic.

<sup>&</sup>lt;sup>2</sup> In 1972, for example, some of the events were: lunch with the Egyptian President, reception for the US President, opera with Bulgarian leaders, Agricultural Conference, Lenin birthday conference and a CPSU plenary session.

Year	Number of actors	Number of events	Average number of events attended	Average event size	Average number of events co-attended
1972	45	251	36.9	6.6	9.38
1973	46	246	30.2	5.6	7.01
1974	45	255	30.1	5.3	8.28
1975	45	211	27.6	5.9	6.15
1976	55	230	30.9	7.4	7.81
1977	53	144	13.6	5.0	2.31
1978	55	266	27.3	5.6	4.96
1979	55	213	24.5	6.3	4.50

 Table 1

 Event sizes, actor attendance and co-attendance frequency

Defense. A person could belong to more than one group in a given year. In that case, our analyses focus on the most prominent group (in order: full member of the Politburo, candidate member of the Politburo, Secretariat, Council of Ministers and Ministry of Defense). We have also coded whether the event was an official occasion or a social occasion. "Social" events involve some non-official activity or content, such as luncheon, dinner or concert. Otherwise an event is coded as "official". Two points should be made about the data. First, it could be argued that Defense officials were only minor players in Soviet elite politics (at least as compared to the other actors) and so, while their activities might of interest to the Central Intelligence Agency, they should not be included in the analyses. We view this point as easily addressable in future research but that, for present purposes, we think it prudent to use all the available data. Second, since the data are from public appearances, one may question whether they offer any substantive insight into the wider set of elite interactions surely occurring beyond public purview. This question of substantive meaningfulness cannot, however, be answered a priori. In our opinion one needs to develop the tools to do the analysis, then use these tools to describe the patterns of co-attendance and then attempt to assess such patterns against a larger and more comprehensive backdrop of substantive questions before settling on an answer.

These data form an affiliation network. An affiliation network consists of a set of actors and a set of events to which actors may belong (Wasserman and Faust, 1994). The events may be relatively enduring bodies, such as clubs or corporate boards or they may be more amorphous gatherings, such as the collection of people present at a party or lecture. In our case, the events are gatherings where the Central Intelligence Agency recorded the presence of Soviet political elites. Since there are two kinds of entities (actors and events) an affiliation network is a two-mode network. Moreover, the network is non-dyadic because the membership relation linking actors to events and events to actors relates subsets of arbitrary size, rather than simply pairs of entities. Actors may be present at multiple events and events may contain several actors.

An affiliation network is represented in a two-mode sociomatrix. The *N* rows of the matrix index actors and the *M* columns index events. We will use the notation *X* for the matrix, with entries  $x_{ij}$ , where  $x_{ij} = 1$  if actor *i* is in event *j* and 0 otherwise. The affiliation network for observations of Soviet political elites' attendance at events contains a total of 67 people and 1816 separate events recorded over 8 years.

There are a couple of wrinkles to consider in the data, both related to the longitudinal nature of the observations. First, actors come and go over the course of the 8 years. Some actors who are present at the beginning of the period are gone by the end (some have died and others have left, usually because they were "removed" from office or membership in one of the groups) and others have joined the set. As a consequence, all actors are not eligible to be included in the events in all years. Second, the events take place across a span of 8 years which, in addition to having different populations of political elites and unique events, might have different patterns of participation. This suggests that in addition to analyzing the data as a single set we should also take individual years into account in our analysis. We can do this either by fitting separate models to the different years or by incorporating the time dimension into a single model. We take the former approach in this paper.

Our analysis proceeds in several steps. First, we use correspondence analysis and principal components analysis to represent patterns of participations and we assess how characteristics of actors and events are related to the configurations. Second, we use random graph models to evaluate the importance of specific structural properties linking actors and events in the network.

There are a number of possible approaches that we could adopt for studying this network. Our research interests and features of the data frame our choice of approaches. First, we are interested in patterns of political participation and possible trends through time, as evidenced in social interaction. We are also interested in how the state and party bodies to which actors belong and the types of events involved, structure participation among actors. These interests suggest that we focus on two aspects of this network: first, the possible changes in patterns of attendance across the years; second, the relationships between actor offices and event types in patterning participation. First, we represent the pattern of participation, both in aggregate and by year. We are also interested in how official bodies (Politburo, Secretariat, Council of Ministers, etc.) structure participation. The ordering of these bodies in terms of political prestige and power, the varied functions of the bodies, and protocol for attendance leads us to expect that attendance should in part reflect memberships in these groups. As a secondary issue, we anticipate that patterns of co-attendance are related to the kind of event involved: social or official. Official events likely have better defined protocol for attendance, whereas social events may allow greater leeway in composition of the guest list. Furthermore, if events are occasions for signaling or reinforcing alliances, kinds of events may differ in the extent to which such alliances are apparent in patterns of co-attendance.

#### 4. Scaling models

We take two approaches to scaling the attendances of Soviet political elites at the various events. Our first analysis considers actor co-attendances for all years together and uses correspondence analysis to produce a single configuration in which each actor is represented for each year they are included in the observations. However, this result does not provide an event configuration, for reasons outlined below. Our second analysis scales the actor-by-event affiliation matrices using principal components analysis for each year separately. Here we obtain both actor and event configurations, with separate configurations for each of the 8 years.

#### 4.1. Correspondence analysis

Correspondence analysis (Greenacre and Blasius, 1994; Weller and Romney, 1990) is a data analytic technique for studying associations among categorical variables in two-way arrays, such as contingency tables or incidence matrices. It is one of a number of related approaches, including dual scaling (Nishisato, 1994), homogeneity analysis (Gifi, 1990) and optimal scaling. Correspondence analysis and closely related approaches frequently have been used to study social networks (Faust and Wasserman, 1993; Kumbasar et al., 1994; Levine, 1972; Nakao and Romney, 1993; Noma and Smith, 1985; Roberts Jr., 2000; Schweizer, 1991; Wasserman and Faust, 1989, 1994; Wasserman et al., 1990).

One goal of correspondence analysis is to represent the data in a low-dimensional space using scores for categories of the variables. These scores serve as coordinates in graphical displays in which points represent the categories of the variables and the distance between points represents the similarity between their respective categories.

Correspondence analysis is accomplished through a singular value decomposition of an appropriately scaled matrix. Entries in the original matrix are divided by the square root of the product of the row and column marginal totals, prior to singular value decomposition. Let, F be a rectangular matrix of positive entries.  $R^{-1/2}$  and  $C^{-1/2}$  are diagonal matrices with entries equal to reciprocals of the row and column totals of F, respectively. Correspondence analysis consists of a singular value decomposition of the matrix  $R^{-1/2}FC^{-1/2}$ :

 $\boldsymbol{R}^{-1/2}FC^{-1/2} = UDV$ 

where D is a diagonal matrix of singular values, and U and V are row and column vectors. For visual displays, U and V are re-scaled. We use principal coordinates, where, on each dimension, the weighted mean is equal to 0 and the weighted variance is equal to the singular value squared. We used UCINET 5.0 (Borgatti et al., 1999) for the correspondence analyses in this paper.

Correspondence analysis of F is equivalent, within re-scaling, to correspondence analysis of FF', a result that has important implications for scaling affiliation networks. If one is only interested in scores for actors and not for events in the affiliation network, one can analyze the actor co-attendance matrix (XX') rather than the actors-by-events matrix (X). Scores for rows (or columns, since the matrix is symmetric) are equivalent, within re-scaling, to row scores for X. This equivalence also facilitates a strategy for analyzing replicated networks or replicated similarity matrices by "stacking" comparable matrices from different sources into a single array (Kumbasar et al., 1994; Romney et al., 1995; Weller and Romney, 1990). Correspondence analysis of stacked matrices has been widely used for scaling domains when data come from multiple sources or time points. This approach has been used to study the relationships among multiple actors' perceptions of the network structure of the same group (Kumbasar et al., 1994), to study semantic similarities among animal terms from different respondents and using different data collection instruments (Romney et al., 1995) and to study the semantic structure of emotion terms from respondents in different language groups (Moore et al., 1999; Romney et al., 2000).

We use correspondence analysis of stacked matrices to examine actor co-participations for all years in a combined model. We begin with the actor co-attendance matrices (XX')for each of the 8 years. We then stack these eight matrices into a single two-way array. This stacked array has actors-by-years as its rows and actors as its columns. A couple of modifications are required to accommodate our data. First, in order to "stack" matrices they must have the same entities indexing columns in all stacked matrices. Since there are slightly different sets of actors in the different years in our data, we expand the matrix for each year to include the entire set of actors (67 in number) that were present at any time throughout the period. This population of 67 actors makes up the columns of the stacked array. Then, since actors not present in a given year could not attend events with other actors in that year, their matrix entries are by definition zero for that year. Since these entries are structurally zero, rows for actors absent in a given year are omitted, though their columns remain. Thus, the actor-by-actor co-attendance matrix in a given year may be rectangular. The resulting stacked matrix has 67 columns and 399 rows. Finally, since there are different numbers of events in the various years, we standardize each year separately by dividing entries by the number of events in that year. The resulting entries are the proportion of events in a given year to get the proportion of events in a given year that each pair of actors attended together.

Correspondence analysis of the stacked array results in two sets of scores: one for the 67 actors in the columns of the array—which might be thought of as the "stable" portions of actors positions across years—and a second for each actor in each year he was present. Since we are interested in patterns across years, we focus on the actor-by-year row scores.

Fig. 1 presents the correspondence analysis row scores for the first two dimensions. There are 399 points in this configuration—one for each actor in each year he was included in the observations. Overlaid on this plot are the 68.27% confidence ellipses for the actor groups (Politburo full member, Politburo candidate member, Secretariat of CPSU, Council of Ministers and Ministry of Defense). Each confidence ellipse is centered on the means of the dimension 1 and dimension 2 coordinates for its subset of actors (or events in the



Fig. 1. Correspondence analysis of stacked matrices, 1972–1979.

analyses presented below). The orientation of the ellipse is determined by the covariance of the two variables. Actors who belonged to more than one group are assigned to the higher ranking group, in the order of its status, described above. The first five dimensions of the correspondence analysis account for 9.6, 7.3, 5.1, 4.9 and 3.9% of the total variance, respectively. In Fig. 1, the first dimension shows a clear separation of the Ministry of Defense from the other bodies. The second dimension reveals some separation of the Council of Ministers from the other groups. Members of both levels of the Politburo and of the Secretariat are basically indistinguishable. It should be noted that in general the points for years drift from top to bottom of the figure, with centroids for points in years 1972–1975 in close proximity and a greater separation between those 4 years and the remaining years.<sup>3</sup>

## 4.2. Principal components analysis

Two drawbacks of scaling all years simultaneously by stacking actor co-attendance matrices are that we have no configuration for events and patterns characteristic of individual years may be obscured in the overall representation. Our second set of scaling results uses principal components analysis to model each year separately, with separate analyses and representations for actors and events. Two aspects of these results help interpret the patterns: the relationship between actor co-participation and office held by the politician, and between the type of event (official or social) and the configuration of events. This allows us to study the configurations of attendances among politicians and events in each year and the general trends in these patterns across years, even though most of the events are unique occurrences and the set of actors changes across years.

Principal components analysis can be expressed as the decomposition of a correlation matrix  $(\mathbf{R})$ :

$$\mathbf{R} = VDV'$$

where V is a set of eigenvectors of R and D the diagonal matrix of eigenvalues corresponding to the eigenvectors in V. Principal component loadings (L) are obtained by multiplying the eigenvectors by the square roots of their respective eigenvalues:

$$\boldsymbol{L} = V D^{1/2}$$

The loadings are then used as coordinates in graphical displays of the similarities among the points.

Principal components analysis of an affiliation network can be used either to represent similarities among actors (the rows of the matrix) or events (the columns of the matrix), depending on which mode is used to calculate the correlation matrix ( $\mathbf{R}$ ). If correlations are calculated between columns (events)  $\mathbf{R}$  is an  $M \times M$  matrix and the loadings pertain

<sup>&</sup>lt;sup>3</sup> In viewing the general north to south drift of years in Fig. 1, we suspect that this is due to gradual turnover in membership across successive years. We also suspect that the notable difference between the early years (1972–1975) versus the remaining years might be due to a 20% increase in the number of actors in the network between 1975 and 1976 rather than any substantive difference in participation patterns. Although assessing similarities and differences in patterns across years is an interesting direction of investigation, it is beyond the scope of the current paper.

to the events. On the other hand, if correlations are calculated between rows (actors) R is an  $N \times N$  matrix and the loadings pertain to the actors.

Some comments about alternative scaling approaches are in order. Often correspondence analysis, rather than principal components analysis, is used to scale affiliation networks (Wasserman and Faust, 1994; Roberts Jr., 2000). The two approaches are closely related, differing primarily in the matrix that is decomposed: principal components analysis is a decomposition of a correlation matrix, whereas correspondence analysis is a decomposition of a sums of cross-products matrix with entries divided by the product of square roots of the row and column totals (Weller and Romney, 1990). Because correlations are sums of cross-products of standardized variables (mean equal to zero and variance equal to one) correlations remove differences across variables in both mean and variance (Weller and Romney, 1990; Borg and Groenen, 1997). This standardization is important when variables differ greatly in variance.

An advantage of correspondence analysis as compared with principal components analysis is that, when applied to the affiliation matrix (X), it yields scores for both actors and events, with a mathematical duality between the two sets (Wasserman and Faust, 1994). Thus, actors and events can be represented in a 'joint space' depicting the relationship between the two sets. A disadvantage of correspondence analysis is that, as noted above, the resulting scores and thus the spatial configuration, encode aspects of the variance of the observations. This is a problem in our data because rates of participation (and thus variances, because the data are dichotomous) vary greatly among the actors and these rates are related to the offices actors hold. Full members of the Politburo and members of the Secretariat of the CPSU attend more events than do other groups and Ministers of Defense attend fewer. This can obscure patterns of co-attendance among actors.

Another alternative, as described by Brazill and Grofman (2002), is to do a metric multi-dimensional scaling of the proportion of positive matches between actors (or events). Just like principal components analysis and correspondence analysis, metric multi-dimensional scaling is a decomposition of a matrix into its basic structure (Weller and Romney, 1990). Thus, the major point of difference between the approach advocated by Brazill and Grofman (2002) and the one we use is the form of the input matrix: correlations in our case and proportion matches in theirs. Brazill and Grofman (2002) demonstrate that when applied to data of known low dimensionality (such as a perfect Guttman scale pattern), principal components analysis of correlations retrieves extra "bogus" dimensions, whereas metric multi-dimensional scaling of the proportion matches does not. This may lead to incorrect conclusions about the dimensionality of the solution. Since our concern is to represent possible patterning of participation by actor groups and event types, rather than detecting the "true" dimensionality of the solution, we used principal components analysis, as described above, despite the possible misrepresentation of dimensionality. Furthermore, since there are numerous possible measures of similarity that could be used as input to metric multi-dimensional scaling, this topic deserves further research.<sup>4</sup>

<sup>&</sup>lt;sup>4</sup> We should note that we did all of the analyses reported in this section using the three approaches just described: principal components analysis of correlations, correspondence analysis and metric multi-dimensional scaling of the proportion matches. The substantive conclusions from the three approaches are identical: participation is patterned by the actor groups not by the type of event.

Figs. 2 and 3 show the principal components analysis results for the 8 years. Table 2 gives the percent of variance accounted for by each of the first three dimensions in each year. In the plots for actors, actors are close to each other in space if they tended to be present at the same events and absent at the same events. As with the results combining all 8 years, in these figures we can see the patterning of actor co-participation by offices held. The separation of the Ministry of Defense from other groups can be seen in all years, as can the separation of the Council of Ministers from the Politburo and the Secretariat. In the plots for events, events are close to each other if the same people tended to be present and the same people absent at them. It appears that there is no distinction between official and social events in any of the years. A notable feature of the figures for 1972–1974 and 1976 is the "panhandle" of points protruding in the lower left of each figure. These events are generally small events attended by members of the Ministry of Defense.

These insights are confirmed by analyzing the distinctiveness of actor office groups and of event types in the principal component loadings for the first several dimensions. We follow



Fig. 2. Principal components loadings for actors in each of 8 years.



the procedure described in Romney et al. (1995) for calculating the "resolving power" of various data collection methods for distinguishing among different items. An analysis of variance (ANOVA) comparing loadings along several dimensions between different categorical groups (actor offices and event types) is used to determine the proportion reduction in error (PRE) in loadings due to the categorical grouping variables, as measured by the correlation ratio squared ( $\eta^2$ ). Table 3 presents these measures for the first three dimensions in each year. Results show that actor groups are distinct on the first two or three dimensions, but distinctions between official and social events are not important.

Taken together results of correspondence analysis and principal components analysis reveal that participations of Soviet political elites are patterned by the offices people hold, primarily distinguishing members of the Ministry of Defense from other groups and showing considerable overlap among members of the Politburo (both full and candidate members) and the Secretariat. However, official and social events do not appear to differ in terms of their participants.

Year	Dimension			
	1	2	3	
Event types				
1972	17.4	10.9	7.2	
1973	19.8	10.0	8.7	
1974	17.5	9.9	8.5	
1975	18.9	9.1	7.6	
1976	21.6	10.1	5.9	
1977	18.0	10.1	7.7	
1978	16.9	9.0	6.9	
1979	19.7	11.2	7.9	
Actor groups				
1972	23.6	10.4	7.8	
1973	21.6	13.2	7.8	
1974	21.3	11.1	9.5	
1975	20.9	11.6	8.5	
1976	22.0	13.8	5.8	
1977	19.6	13.1	6.3	
1978	18.7	12.9	5.4	
1979	16.9	13.3	6.4	

Table 2 Percent of variance accounted for by each dimension in the principal components analyses

Table 3

PRE measures for principal components analysis loadings by event types and actor groups, models for separate years

Year	Dimension			
	1	2	3	
Event types				
1972	0.0033	0.0002	0.1175	
1973	0.0529	0.0019	0.0641	
1974	0.0027	0.0030	0.0967	
1975	0.0059	0.0001	0.0016	
1976	0.0002	0.0019	0.0190	
1977	0.0019	0.0258	0.0002	
1978	0.0013	0.0010	0.0005	
1979	0.0001	0.0008	0.0363	
Actor groups				
1972	0.8582	0.8436	0.6447	
1973	0.8022	0.8986	0.7198	
1974	0.8052	0.8530	0.7498	
1975	0.8457	0.8707	0.7119	
1976	0.8893	0.8993	0.1725	
1977	0.9456	0.8461	0.1998	
1978	0.8062	0.7453	0.1402	
1979	0.9270	0.8360	0.2191	

Despite confirmation of these findings using ANOVA of dimension scores by actor groups and event types, subtler aspects of interactions between types of actors and types of events have not been explored in these analyses. For example, is the distinction between members of the Defense Ministry and others primarily due to participation in official events or in social events or both? Do members of the Politburo and Secretariat tend to meet in social or in official events? Essentially these questions address the possibility of an interaction between actor offices and the type of event in accounting for patterns of participation.

Evaluating these hypotheses requires statistical tests about structural features of the network of actor–event ties, including information about actor offices and types of events. Although scaling models depict patterns of actor co-participation or event overlap and we can use characteristics of these entities to interpret the spatial patterning, these models do not provide direct statistical tests about the underlying graph that generated the co-participation or overlap. We might attempt to tease apart the distinction between official and social events as the basis for patterns in actor co-participation by scaling co-participation in social and official events separately. Nevertheless, if we were to find differences in the spatial models of



Fig. 3. Principal components loadings for events in each of 8 years.



actor co-participation for the separate sets of events, we still would not know what specific configurations of actor–event ties were responsible for these differences, nor would we have a statistical test of the importance of specific configurations. To investigate this we turn to statistical models for social networks. These models allow us to test for the importance of specific structural properties in accounting for participation. Specifically we can evaluate the extent to which participation is patterned by combinations of actor offices and event types.

# 5. Statistical models for affiliation networks

Statistical models for social networks have a long history, though early models required overly simplistic assumptions about independence of observations of actors and dyads. Only recently have models with more realistic assumptions become available and sufficiently well-developed for general use. In this section, we describe one member of a class of statistical models, the p\* models and how this model can be adapted to examine the possible patterns present in the affiliation network of attendances of Soviet political leaders at various events. There are many papers describing p\* models (Anderson et al., 1999; Pattison and Wasserman, 1999; Robins et al., 1999; Wasserman and Pattison, 1996). A brief description of p\* models for networks for networks in general is provided in the Appendix A. In this section, we describe the simplifications and specifications that pertain to affiliation networks.

Statistical models for social networks adopt the stance that networks are random. That is, the ties in the network and the overall configuration of the graph representing the network are subject to probabilistic or stochastic processes. As a consequence, an observed network is only one of a possible number of graph realizations that could have arisen from a distribution of possible graphs. The goal is to model the probability of the observed graph as a function of various structural (graph) properties. For example, if the network under consideration consists of friendships in a small group, there may be a tendency for choices to be reciprocated; if actor *i* chooses actor *j* as friend, then there is a tendency for *j* to return the friendship choice to *i*. In that case, graphs for friendship networks with tendencies toward reciprocation would have larger probabilities than graphs in which ties tend not to be reciprocated. Reciprocity would be important structural feature determining the probability of the graph. Obviously there are numerous structural properties that might be considered for inclusion in a model and selection of which properties to include depends on theoretical expectations and the substance of the application. An important aspect of social networks is that network properties may be quantified at number of different levels: individual, dyadic, triadic, subgroup or group level. Properties at any of these levels may be important features of a graph and may be incorporated into the statistical models. Pattison and Wasserman (1999) and Anderson et al. (1999) describe a number of theoretically and substantively useful graph properties that can be studied using these models.

As described by Skvoretz and Faust (1999), the  $p^*$  models simplify for affiliation networks. Two wrinkles are immediately apparent given the nature of the affiliation relation. First, the relation is non-directional; actors belong to events and events contain actors. Thus, a tie may be either present or absent and reciprocity is not a consideration. Second, since an affiliation network is bipartite (there are two sets of social entities and all ties are between entities from different sets) subgraphs in which all ties originate from or terminate at a single node (stars) must be one of two types: stars centered on actors (actor stars) in which an actor has membership ties to events or stars centered on events (event stars) in which events have ties to their constituent members. In our models, we limit ourselves to stars of degree two (two ties from the actor or event in the center of the star). In addition, the models we use in this paper are simplifications of Markov random graph models. In a Markov random graph model, the tie in the (*i*, *j*) pair is assumed to depend only on the other ties and configurations in which *i* and *j* might be involved, but not on ties involving parties other than *i* and *j* (Frank and Strauss, 1986).

We argue that there are important processes underlying patterns of political elites' attendance at various events. We expect that patterns of alliances on the one hand and fission or exclusion on the other, will be evidenced in patterns of co-attendances among actors as they are brought together (or separated) in various events. Moreover, patterns of participation should in part be influenced by the state and party offices to which actors belong. Job responsibilities and protocol may play a large role in which actors are included in a given event. In contrast, for the most part events are "unique" occurrences, thus there is less theoretical importance in how events overlap through common members. In terms of the star configurations, actor stars capture the linking role of actors between events and would be theoretically important in studying the extent to which enduring events—such as corporate boards of directors—are linked through common members. Event stars capture the linking role of events in bringing actors together and are theoretically important when we are interested in coordinated activities among actors, as evidenced in common participations. As a consequence of these theoretical concerns, our models have homogeneous actor stars and use actor offices and event types to classify different kinds of event stars.<sup>5</sup>

Following our emphasis on actor offices and types of events shaping participations of Soviet politicians, we posit structural properties for the affiliation network that incorporate tendencies based on these features. The baseline model (model 1) includes only a single parameter, labeled "choice", that fits the overall density of ties in the network. We then add a parameter for two-stars, without distinguishing between actor and event two-stars (model 2). Model 3 distinguishes between two different kinds of two-stars, those centered on actors (actor two-stars) and those centered on events (event two-stars). We also present BIC statistics, described below, that allow direct comparison of model fits. As noted in the Appendix A, caution regarding  $\chi^2$  statistics is in order since estimates are pseudo-likelihood estimates. We then examine two models that are both nested within model 3. Model 4 includes homogeneous actor two-stars, but distinguishes between two kinds of event two-stars-those centered on official events and those centered on social events. Model 5 includes homogeneous actor two-stars, but distinguishes among event two-stars depending on the offices to which members of the actor pair belong (for example, both actors full members of the Politburo, one actor a member of the full Politburo and the other in the Ministry of Defense and so on). Including an "other" category for actors, there are 21 possible actor pair types. The final model (model 6) again includes homogeneous actor two-stars, but now distinguishes event two-stars by both the type of event (official or social) and the actor pair types. There are up to 42 different event two-stars when we classify both events (2 types) and actor pairs (21 types). Fig. 4 shows some examples of the possible kinds of event two-star configurations, classifying events by type and actor pairs by offices held.

Given the correspondence analysis results reported earlier, we might expect certain configurations to be important and others to be unimportant for understanding attendance patterns in this network. In general, we saw that actors tended to group by offices held. If actors tend to participate in events with similar others, then event two-star configurations that bring together pairs of actors from the same office should be important. Resulting parameter estimates for these configurations should be large and positive. Given the distinct position of the Ministry of Defense in all correspondence analysis results, we anticipate that there will be an especially strong effect of events bringing together members of the Ministry of Defense. Moreover, if actors have distinct arenas of participation and events tend not to include actors

 $<sup>^{5}</sup>$  Two-stars are intimately related to the variances of nodal degrees. Therefore, a model including only effects for the number of ties and two-stars (model 2 in Table 4) is quite limited in the structural effects it expresses, since it fits only the mean and variance of the degrees. Moreover, this model treats actor and event degrees as comparable, which may be undesirable.

5								
Model	1972	1973	1974	1975	1976	1977	1978	1979
(1) Choice	9436.390	8435.156	9023.103	7358.934	9977.004	4714.958	9890.778	8363.994
(2) Choice $+$ two-stars	8541.769	7431.112	7993.975	6401.136	7891.359	4043.057	8755.574	6687.736
(3) Choice + actor two-stars + event two-stars	8528.544	7107.531	7912.323	6371.401	7372.453	4011.218	8577.135	6625.584
(4) Choice + actor two-stars + official event	8263.827	7019.027	7899.801	5986.252	7347.334	4010.684	8034.062	6563.060
two-stars + social event two-stars (5) Choice ± order two-stars ± event two-store hu	7170 562 (22)	2060 200 (22)	(11) 0018 400	5308 872 (17)	5874 501 (22)	1287 178 (73)	(2015 517 (73)	5777 000 (73)
(v) Choice $T$ actor two-stats $T$ event two-stats of actor pair groups	(77) 700-011	(77) 0(7)00(0	(11) (01:07:0	(11) 7/0.0000	(77) 100-100	(r-) r-1.07r		(~7) ~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~
(6) Choice + actor two-stars + event two-stars by	6760.371 (42)	5714.103 (42)	6485.651 (32)	5058.903 (32)	5654.521 (42)	3143.231 (44)	6565.836 (44)	5511.925 (44)
actor pair groups and event types								
Number of model parameters in parentheses.								



Fig. 4. Examples of some event two-stars, including event type and actor pair groups.

from different groups, then parameter estimates for event two-star configurations containing different types of actors should be large and negative, indicating that graphs with such patterns have low probabilities. Again, looking at the correspondence analysis results, we anticipate that configurations linking members of the Ministry of Defense with members of the Politburo (either full or candidate members) and the Secretariat of the CPSU will be unlikely and parameter estimates for these configurations should be large and negative. On the other hand, given the overlap of full Politburo, candidate Politburo and Secretariat members in the correspondence analysis figures, we expect that event two-stars linking members between these different groups will be important and will have large and positive parameter estimates.

Since the principal components analysis of events shows no distinction between official and social events, we expect that any improvement in fit of models including this distinction should be minimal.

We present the  $p^*$  model results in two stages. First, we consider fits of the six models described above, looking at the impacts of actor offices and event types. We then examine the parameter estimates that quantify the importance of the different structural effects of actor and event two-star classifications for the most complex model. We fit models separately for each year.

Table 4 presents fit statistics  $(-2\log(\text{pseudo-likelihood}))$  for the six models for each of the 8 years. Since the magnitude of these statistics depends on both the number of parameters

in the model and the sample size (here the number of actor–event pairs) it is difficult to evaluate which models fit the data and to decide between competing models. The large sample sizes give rise to large pseudo-likelihood statistics and thus might lead us to reject a good model. An alternative model selection procedure relies on a Bayesian approach and employs the BIC statistic (Raftery, 1986, 1995). In comparing the fit of two models (M<sub>0</sub> and M<sub>1</sub>) the question becomes "given the data, which of M<sub>0</sub> and M<sub>1</sub> is more likely to be the true model?" (Raftery, 1986, p. 145). Taking the baseline model (model 1 in Table 4) for comparison, the BIC for model M is equal to  $-L^2_{(M_0)} + d.f._{(M_0)} \log N$ , where  $-L^2_{(M_0)}$  is the difference between the pseudo-likelihood ratio statistics for the two models being compared, d.f.<sub>(M<sub>0</sub>)</sub> the difference in degrees of freedom for the models and N is the number of observations. A negative BIC leads to the conclusion that model M is preferred over the null model. The BIC statistic can also be used to compare models that are not nested; the model with the more negative BIC is preferred. The BIC statistics for models 2–6, as compared with model 1, are presented in Table 5. We use these statistics to evaluate the relative fits of the models.

Comparing models 2 and 3, we can evaluate the impact of the distinction between actor and event two-stars, as compared with treating two-stars homogeneously. In all years, the distinction is important, though its impact is weaker in 1972 than in other years. The importance of the distinction between official and social events can be evaluated by comparing the fits of models 3 and 4. Here, the distinction appears to be important in all years except 1977, though it is weak in 1974. The impact of the offices held by pairs of people (regardless of whether the event was official or social) is evaluated by comparing models 3 and 5. The offices are important in all years. Finally, model 6 contains both event type and actor pair offices, and can be compared with model 4 to evaluate the impact of actor pair offices additional to the distinction between official and social events, and to model 5 to evaluate the impact of event type additional to actor pair offices. Comparing models 4 and 6, it appears that in all years the offices held by pairs of actors are important when added to a distinction between event types. Comparing models 5 and 6 shows that the distinction between event types is important when added to the classification of offices of pairs of actors in all years except 1977.

In summary, co-participations of pairs of actors in events are impacted by both whether the event is official or social and by the offices held by the two actors. In all years except 1977, model 6, which includes actor two-stars in addition to event two-stars that incorporate both actor offices and event types, is the preferred model. In 1977, model 5, which incorporates actor offices but not the type of event into the event two-stars is, the preferred model.

As a second step in interpreting the results of the  $p^*$  models, we examine the parameter estimates for the most complex model, model 6 in Table 4. Since there are dozens of parameter estimates, we simplify presentation in three ways. First, we present the exponentiated parameter estimates (exp *b*). These are interpreted as the effect of a one unit change in the independent variable on the odds of the dependent variable, given the other variables in the model. Effects above 1.0 indicate an increase in the odds, whereas effects below 1.0 indicate a decrease in the odds. Second we present only those estimates that are nominally significant at P < 0.01, keeping in mind that significance tests should be used cautiously with  $p^*$  models. For reasons described in the appendix, they should not be interpreted literally. Finally, we have grouped the estimates so that effects bringing together actors in

Table 5 BIC statistics for p* models as compared with t	the null model (r	nodel 1)						
Model	1972	1973	1974	1975	1976	1977	1978	1979
(2) Choice + two-stars	-885.29	-994.71	-1019.80	-948.64	-2076.20	-662.96	-1125.60	-1666.90
(3) Choice $+$ actor two-stars $+$ event	-889.18	-1309.00	-1092.10	-969.22	-2585.70	-685.86	-1294.50	-1719.70
two-stars								
(4) Choice + actor two-stars + official event	-1144.60	-1388.10	-1095.30	-1345.20	-2601.30	-677.45	-1827.90	-1772.80
two-stars + social event two-stars								
(5) Choice + actor two-stars + event	-2060.90	-2278.90	-1945.10	-2059.20	-3904.10	-1230.80	-2764.30	-2435.90
two-stars by actor pair groups								
(6) Choice + actor two-stars + event	-2293.40	-2338.40	-2247.70	-2309.20	-3935.20	-1187.30	-2912.50	-2449.20
two-stars by actor pair groups and event								
types								

the same office (for example, full Politburo members with each other) are presented in the one panel, effects bringing together actors from different offices (for example, full Politburo members with members of the Secretariat) are in the next panel and effects involving people not in one of the offices are in the final panel of the table.

Table 6 presents the exponentiated pseudo-likelihood estimates for the parameters in model 6 for each of the years. In addition to the overall "choice" parameter that fits the density of ties in the network, there is an effect for actor two-stars and effects for event two-stars classified by both the event type (official or social) and the combination of actor pair offices. If all possible actor and event types were present in a given year the full model would have 44 parameters. When some actor types are not present in a given year, there are fewer possible actor pair configurations and thus fewer parameters in the models.

Exponentiated parameter estimates greater than 1.0 indicate that networks with the corresponding configuration have larger probabilities; in other words, the presence of that configuration is an important feature of the network. On the other hand, exponentiated parameter estimates below 1.0 indicate that networks with the corresponding configuration have lower probabilities; the absence of that configuration is an important feature of the network and graphs with that property have lower probabilities.

In summarizing overall tendencies for positive or negative effects several trends can be seen. First, the most consistent positive effects bring together the following sets of actors and types of events.

## Within actor groups

Politburo full members with each other in official events (all years but 1975).

Politburo full members with each other in social events in the last 3 years (1977-1979).

- Defense Ministry members with each other in both official and social events (except in 1975 and 1977 for social events).
- Members of the Council of Ministers with each other in social events in the first 3 years and in 1979.

## Between actor groups

Politburo full and Politburo candidate members in official events (except in 1975 and 1977).

Politburo full and Politburo candidate members in social events (except in 1972, 1975 and 1978).

Politburo full members and Secretariat in official events (all years but 1979).

Politburo candidate members and Secretariat in official events (except 1977).

Second, there are negative effects for the following configurations.

### Within actor groups

Secretariat members with each other in social events (in 1972, 1973 and 1977). Members of the Council of Ministers with each other in official events in the first 3 years.

## Between actor groups

Politburo full members and members of the Ministry of Defense in official events (except in 1973, 1975 and 1978).

Table 6

Parameter	1972	1973	1974	1975	1976	1977	1978	1979
A two-stars	1.04	1.04	1.04	1.04	1.04	1.07	1.03	1.05
PP-O	1.25	1.24	1.37		1.24	1.35	1.12	1.38
PP-S						1.77	1.21	1.29
CC-O					0.80			1.21
CC-S	1.06		0.91	1.39	1.23			1.12
SS-O								1.46
SS-S	0.80	0.70				0.67		
MM-O	0.66	0.36	0.75					
MM-S	1.76	1.34	1.65			0.67		1.96
DD-O	1.86	2.20	1.97		1.82	1.61	1.77	1.95
DD-S	1.92	2.09	2.27		1.76	1.71		2.12
PC-O	1.24	1.25	1.13		1.24		1.42	1.11
PC-S		1.48	1.60		1.14	1.67		1.31
PD-O	0.91		0.89			0.78		0.87
PD-S			1.16	2.00				0.92
PM-O	1.09	1.12	0.94		1.13			
PM-S				3.87	1.47	1.4	2.05	1.63
PS-O	1.26	1.30	1.06	1.29	1.28	1.32	1.23	
PS-S				1.24			0.84	
CD-O				1.23				0.64
CD-S							1.11	
CM-O		1.19	1.37		1.19		1.08	
CM-S	0.94	1.16		0.88				
CS-O	1.75	1.69	1.68	2.35	1.97		1.75	1.59
CS-S		1.30			1.32	1.38		
SD-O				1.96				
SD-S					0.66			
SM-O	1.42		1.61	1.14	1.30			
SM-S	0.59							2.17
MD-O						0.26		0.69
MD-S		0.74						
CX-O			×	х				
CX-S	0.82		×	×				
PX-O			×	х		1.22	1.44	0.52
PX-S		1.72	×	х		1.84		
MX-O	1.41		×	X				2.34
MX-S			×	×				
DX-O			×	X			1.24	1.40
DX-S			×	×			2.95	
SX-O	0.55		×	×				
SX-S			X	X				
XX-O	×	×	×	X	×		0.15	
XX-S	X	×	X	X	X			
Choice	0.01	0.01	0.00	0.01	0.01	0.01	0.00	0.00

Exponentiated pseudo-likelihood estimates  $(\exp b)$  for parameters in model 6 (choice + actor two-stars + event two-stars by actor pair groups and event types)

Only estimates with P < 0.01 are reported; × indicates that the parameter was not included in the model; P: full Politburo; C: candidate Politburo; S: Secretariat CPSU; M: Council of Ministers; D: Ministry of Defense; X: other; -O: official event; -S: social event. Taken together these results confirm some aspects hinted at in the spatial configurations from the correspondence analysis and principal components analyses. Members of the Ministry of Defense form a relatively distinct set. Positive effects bring them together in both official and social events, but there are no consistent effects across years that bring them together with members of other groups and there are important effects that indicate that members of the Ministry of Defense do not attend official events with full Politburo members. The overlapping of full and candidate Politburo members with members of the Secretariat arises through the following configurations: full members of the Politburo come together in official events and with candidate Politburo members in both official and social events; both full and candidate Politburo members of the Secretariat in official events but members of the Secretariat do not participate with each other in social events nor do they participate with full Politburo members in social events in the later years. Members of the Council of Ministers do not show any clear pattern of participation or non-participation with members of other groups.

We can now address the issue of the convergence of our two different approaches. For the most part, our conclusions are consistent, though not entirely so. To the extent that there are positive p\* model effects bringing together actors in the same group, we see these groups clustering in the principal components analysis representations. For example, members of the Ministry of Defense form a relatively tight and distinct subset in the principal components analysis and also have positive within group p\* parameter estimates. In addition, positive p\* parameter estimates linking different groups (for example, between full Politburo and candidate Politburo members, between full Politburo members and members of the Secretariat and between candidate Politburo members and members of the Secretariat) are echoed in the principal components analysis representations where these three sets of actors consistently occupy overlapping regions of the space. On the other hand, there are instances where the strength and direction of the p<sup>\*</sup> parameter estimates is not clearly reflected in the principal components analysis representation. For example, members of the Council of Ministers have negative within group effects for attendance at official events in years 1972–1974, off-set by positive effects for social events in these years and nevertheless are quite closely clustered in the principal components results in all years.

We expect that in general a positive within group  $p^*$  effects will be reflected by relatively tight clustering of the group in the spatial representation, whereas negative within group  $p^*$  effects should lead to a more diffuse, less distinct clustering of the group. Positive between group effects should be seen in groups overlapping regions of the space, whereas negative between group effects should be seen in the two groups occupying different regions.

# 6. Summary

In this paper, we have used two different though complementary approaches to understand patterns of participation of Soviet political elites in official and social events. Scaling models, including correspondence analysis and principal components analysis, revealed that attendance was largely patterned by the state and party offices to which the politicians belonged. Statistical models confirmed this insight but also pointed to unanticipated features underlying observed patterns. In the scaling models, the distinction between social and official events was not apparent. Nevertheless, statistical tests of the interaction between types of events and actor offices indicated that social and official events operated in different ways for bringing together or separating, actors occupying different state or party offices.

We believe a strength of combining scaling and statistical models is that the depth of insight provided by visual representations can then be substantiated by statistical models. Statistical models can test hypotheses about specific structural configurations underlying the network. In our example, these statistical models provided unexpected insights into important features of the network.

The fact that political offices impact co-attendance at social and official events appears simply to confirm commonsense expectations. However, we note that while commonsense might lead us to expect that the offices would have the same effects over the years, they do not. Some combinations of offices and events do appear to consistently enhance or inhibit co-attendance, but others do not. Adducing substantive reasons for these departures may be a interesting research problem, but one that is beyond the scope of our methodological interests in this paper. Our point is that our methodology enables us to raise this problem in a systematic way. Also equally interesting but beyond our scope would be a project to relate the patterns in the co-participation of actors to the membership in informal power groups. Willerton (1987) would be a good start on this project since he identifies client–patron relations during the Brezhnev era among the same actors that we have studied.

Finally, it may be that, even upon closer analysis, no surprises occur in how co-attendance is influenced by political office. That is, the substantive significance of co-attendance may simply derive from the dictates and duties of the offices held rather than the informal "backstage" coalitions to which politicians belong. Yet, while the general rule would be participation determined by office, the rule would apply more or less accurately to particular individuals. We suggest that of more substantive interest against the backdrop of duty influenced participation would be significant departures from this backdrop by particular individuals. The analysis we envision here would look at the "careers" of particular individuals through the multi-dimensional space defined by co-attendance patterns. Of particular interest would be the trajectories that depart from the typical path and how those individuals fare in the contests for power and influence.

### Acknowledgements

We are grateful to Noshir Contractor and Stanley Wasserman for discussions of random graph models, to members of the USC Social Networks Seminar (Mourad Dakhli, Bill Jacoby, Melissa Marschall and Doug Nigh) for helpful comments on this research and to Devon Brewer and anonymous referees for comments on an earlier draft. A version of this paper was presented in the sessions in honor of A. Kimball Romney at the 29th Annual Meeting of the Society for Cross-Cultural Research, 23–27 February 2000, New Orleans, LA.

# Appendix A

This appendix describes p\* models for social networks in general. More detailed descriptions can be found in Anderson et al. (1999), Pattison and Wasserman (1999), Robins et al. (1999) and Wasserman and Pattison (1996).

Consider the graph of ties on relation  $\chi$  represented in matrix X. The entries  $x_{ij}$  in X are dichotomous: 1 if there is a tie from actor *i* to partner *j* and 0 otherwise. Our discussion is restricted to dichotomous relations, however, extensions of p<sup>\*</sup> models to valued relations are presented in Robins et al. (1999).

In these models the probability of the graph is expressed in terms of a collection of graph statistics. These graph statistics are explanatory variables in a model accounting for the probability of the graph and are calculated from the observed network. We will denote the graph statistics by  $z_k(x)$ , with the collection of statistics:

 $z_1(x), z_2(x), \ldots, z_k(x)$ 

A vast array of statistics may be considered for inclusion. The selection of statistics depends on what structural properties are hypothesized to be operating in generating the graph under study. These may include individual tendencies to send or receive ties, dyadic tendencies for reciprocity, triadic tendencies for transitivity, graph connectivity or graph centralization, among many others. The researcher's hypotheses specify expected dependencies among ties in the network expressed in these hypothesized structural tendencies and translate into the specific graph statistics that are to be included in the model. The probability of the graph is modeled as a function of the hypothesized structural properties. Model parameters ( $\theta$ 's) are coefficients in a linear equation for the probability of the graph:

$$\theta_1 z_1(x) + \theta_2 z_2(x) + \cdots + \theta_k z_k(x)$$

The  $\theta$ 's are unknown parameters to be estimated and quantify the importance of the respective graph properties for the probability of the graph. Parameters that are large and positive indicate that graphs with the respective property have larger probabilities, whereas parameters that are large and negative indicate that graphs with the respective property have lower probabilities. However, statistical tests are only approximate, for reasons discussed below.

The model for the probability of the observed graph x, Pr(X = x), is a function of the graph statistics, expressed in a log-linear form:

$$\Pr(\mathbf{X} = \mathbf{x}) = \frac{\exp\{\theta_1 z_1(\mathbf{x}) + \theta_2 z_2(\mathbf{x}) + \dots + \theta_k z_k(\mathbf{x})\}}{\kappa(\theta)}$$

The normalizing constant in the denominator of this equation ( $\kappa(\theta)$ ) is problematic and is difficult to estimate for all but small networks. What allows this model to be fit is an alternative version that expresses the response variable as the logarithm of the odds (logit) of a tie being present rather than absent and relies on a pseudo-likelihood estimation strategy described in Strauss and Ikeda (1990). In addition, the Hammersley–Clifford theorem (Besag, 1974) states that the probability of the graph is the product of the conditional probabilities of the individual ties. A little more notation is required. Let,  $X_{ij}^c$  be the complement graph (the network with everything but the *ij* tie),  $X_{ij}^+$  be the graph with the *ij* tie forced to be present ( $x_{ij} = 1$ ) and  $X_{ij}^-$  be the graph with the tie from *i* to *j* forced to be absent ( $x_{ij} = 0$ ). We then express the model in terms of conditional logits—the logarithm of the ratio of the conditional probability of the tie being present to the conditional probability of its absence. The logit version of the p\* model is:

$$\ln\left[\frac{\Pr(X_{ij}=1|X_{ij}^{c})}{\Pr(X_{ij}=0|X_{ij}^{c})}\right] = \frac{\exp\{\theta' z(x_{ij}^{+})\}}{\exp\{\theta' z(x_{ij}^{-})\}} = \exp\{\theta' [z(x_{ij}^{+}) - z(x_{ij}^{-})]\}$$

This form of the model shows that the conditional logit is a function of changes in the graph statistics when the *ij* tie changes from 1 to 0. Changes in graph statistics are calculated for each pair from the observed data by computing the statistic first with the tie present and then with the tie absent, and then taking the difference between the values of the two statistics. The  $p^*$  model can be fit approximately using standard logistic regression packages, such as SAS or SPSS.

The p\* model and simplifications including the Markov random graph model, are estimated using a pseudo-likelihood estimation strategy. This technique is widely used in spatial modeling where equations include intractable normalizing constants (Besag, 1974; Strauss and Ikeda, 1990). The resulting parameter estimates are pseudo-likelihood estimates rather than maximum likelihood estimates and the goodness of fit statistic (the usual  $-2\log(likelihood))$  is also a pseudo-likelihood statistic. As a result, statistical tests for parameter estimates and model goodness of fit statistics should be used cautiously.

The graph statistics in the  $p^*$  models express hypotheses about possible dependencies in the network. The simplest models are versions of the  $p_1$  model, which contains parameters for overall network density, the propensities for actors to send and receive ties, and the reciprocity of ties between pairs of actors (Holland and Leinhardt, 1981). In the  $p_1$  model, dyads are assumed to be independent. A slightly more realistic model, the Markov graph model (Frank and Strauss, 1986), posits that the tie from actor *i* to actor *j* is dependent only on ties that actors *i* and *j* might or might not have to other actors, but not on ties between pairs of actors not involving *i* and *j*. The models we describe and illustrate for affiliation networks are versions of Markov graph models which additionally take into account the bipartite nature of the affiliation network and also incorporate attributes of actors and events.

#### References

- Anderson, C.J., Wasserman, S., Crouch, B., 1999. A p\* primer: logit models for social networks. Social Networks 21, 37–66.
- Besag, J., 1974. Spatial interaction and the statistical analysis of lattice systems. Journal of the Royal Statistical Society. Series B. Methodological 36, 192–225.
- Bielasiak, J., 1984. Elite studies and communist systems. In: Linden, R.H., Rockman, B.A. (Eds.), Elite Studies and Communist Politics. University of Pittsburgh Press, Pittsburgh.
- Borg, I., Groenen, P., 1997. Modern Multi-dimensional Scaling, Theory and Applications. Springer, New York. Borgatti, S., Martin, E., Freeman, L., 1999. UCINET 5.0 for Windows. Analytic Technologies.

Brazill, T.J., Grofman, B., 2002. Factor analysis versus multi-dimensional scaling: binary choice roll-call voting and the US Supreme Court. Social Networks, this issue.

Breslauer, G.W., 1980. Political succession and the Soviet policy agenda. Problems of Communism 24, 34-52.

- Central Intelligence Agency, 1973–1980. Appearances of Soviet Leaders, January–December 1972 (Also 1973–1979). National Technical Information Service, Springfield, VA.
- Dornberg, J., 1974. Brezhnev: The Masks of Power. Basic Books, New York.
- Faust, K., Wasserman, S., 1993. Correlation and association models for studying measurements on ordinal relations. In: Marsden, P.V. (Ed.), Sociological Methodology, Vol. 23. Blackwell Scientific Publishers, Cambridge, MA, pp. 177–215.
- Frank, O., Strauss, D., 1986. Markov graphs. Journal of the American Statistical Association 81, 832-842.
- Gelman, H., 1984. The Brezhnev Politburo and the Decline of Detente. Cornell University Press, Ithaca, NY.
- Gifi, A., 1990. Non-Linear Multivariate Analysis. Wiley, New York.
- Greenacre, M., Blasius, J. (Eds.), 1994. Correspondence Analysis in the Social Sciences: Recent Developments and Applications. Academic Press, New York.
- Holland, P.W., Leinhardt, S., 1981. An exponential family of probability distributions for directed graphs (with discussion). Journal of the American Statistical Association 76, 33–65.
- Kumbasar, E., Romney, A.K., Batchelder, W.H., 1994. Systematic biases in social perception. American Journal of Sociology 100, 477–505.
- Levine, J., 1972. The sphere of influence. American Sociological Review 37, 14-27.
- Miller, R.F., Miller, J.H., Rigby, T.H. (Eds.), 1987. Gorbachev at the Helm: A New Era in Soviet Politics. Croom Helm, London.
- Moore, C.C., Romney, A.K., Hsia, T.-L., Rusch, C.D., 1999. The universality of the semantic structure of emotion terms: methods for the study of inter- and intra-cultural variability. American Anthropologist 101, 529–546.
- Murphy, P.J., 1981. Brezhnev: Soviet Politician. McFarland, Jefferson, NC.
- Nakao, K., Romney, A.K., 1993. Longitudinal approach to subgroup formation: re-analysis of Newcomb's fraternity data. Social Networks 15, 109–131.
- Nishisato, S., 1994. Elements of Dual Scaling: An Introduction to Practical Data Analysis. Lawrence Erlbaum, Hillsdale, NJ.
- Noma, E., Smith, D.R., 1985. Scaling sociomatrices by optimizing an explicit function: correspondence analysis of binary single response sociomatrices. Multivariate Behavioral Research 20, 179–197.
- Pattison, P., Wasserman, S., 1999. Logit models and logistic regressions for social networks. Part II. Multivariate relations. British Journal of Mathematical and Statistical Psychology 52, 169–193.
- Raftery, A.E., 1986. Choosing models for cross-classifications. American Sociological Review 51, 145–146.
- Raftery, A.E., 1995. Bayesian model selection in social research. In: Marsden, P.V. (Ed.), Sociological Methodology. Blackwell, Oxford, pp. 111–163.
- Roberts Jr., J.M., 2000. Correspondence analysis of two-mode network data. Social Networks 22, 65–72.
- Robins, G., Pattison, P., Wasserman, S., 1999. Logit models and logistic regressions for social networks. Part III. Valued relations. Psychometrika 64, 371–394.
- Romney, A.K., 1980. Multi-dimensional scaling applications in anthropology. In: Mitchell, J.C. (Ed.), Numerical Techniques in Social Anthropology. Institute for the Study of Human Issues, Philadelphia, pp. 71–84.
- Romney, A.K., 1989. Quantitative models, science and cumulative knowledge. Journal of Quantitative Anthropology 1, 153–223.
- Romney, A.K., 1999. Culture consensus as a statistical model. Current Anthropology 40, S103–S115.
- Romney, A.K., Shepard, R.N., Nerlove, S.B., 1972. Multi-Dimensional Scaling: Theory and Applications in the Behavioral Sciences. Applications, Vol. 2. Seminar Press, New York.
- Romney, A.K., Batchelder, W.H., Brazill, T., 1995. Scaling semantic domains. In: Luce, D., et al. (Eds.), Geometric Representations of Perceptual Phenomena: Papers in Honor of Tarow Indow's 70th Birthday. Lawrence Erlbaum, Hillsdale, NJ, pp. 267–294.
- Romney, A.K., Moore, C.C., Batchelder, W.H., Hsia, T.-L., 2000. Statistical methods for characterizing similarities and differences between semantic structures. Proceedings of the National Academy of Sciences 97, 518–523. Ross, D., 1980. Coalition maintenance in the Soviet Union. World Politics 32, 258–280.
- Schweizer, T., 1991. The power struggle in a Chinese community, 1950–1980: a social network analysis of the duality of actors and events. Journal of Quantitative Anthropology 3, 19–44.
- Shepard, R.N., Romney, A.K., Nerlove, S.B., 1972. Multi-Dimensional Scaling: Theory and Applications in the Behavioral Sciences. Theory, Vol. 1. Seminar Press, New York.
- Skvoretz, J., Faust, K., 1999. Logit models for affiliation networks. In: Sobel, M.E., Becker, M.P. (Eds.), Sociological Methodology. Basil Blackwell, Oxford, pp. 253–280.

- Strauss, D., Ikeda, M., 1990. Pseudo-likelihood estimation for social networks. Journal of the American Statistical Association 85, 204–212.
- Wasserman, S., Faust, K., 1989. Canonical analysis of the composition and structure of social networks. In: Clogg, C.C. (Ed.), Sociological Methodology, Vol. 19. Basil Blackwell, Cambridge, MA, pp. 1–42.
- Wasserman, S., Faust, K., 1994. Social Network Analysis: Methods and Applications. Cambridge University Press, Cambridge.
- Wasserman, S., Pattison, P., 1996. Logit models and logistic regressions for social networks. Part I. An introduction to Markov graphs and p<sup>\*</sup>. Psychometrika 61, 401–425.
- Wasserman, S., Faust, K., Galaskiewicz, J., 1990. Correspondence and canonical analysis of relational data. Journal of Mathematical Sociology 15, 11–64.

Weller, S.C., Romney, A.K., 1990. Metric Scaling: Correspondence Analysis. Sage, Newbury Park, CA.

Willerton, J.P., 1987. Patronage networks and coalition building in the Brezhnev era. Soviet Studies 34, 175–204.

Willerton, J.P., 1992. Patronage and Politics in the USSR. Cambridge University Press, Cambridge.