The Duality of Networks and Foci: Generative Models of Two-Mode Networks from One-Mode Networks

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Abstract
Focus theory describes how shared social statuses, beliefs, and places (i.e., foci) can facilitate the formation of social ties, while two-mode projections provide a method for transforming two-mode data on individuals’ memberships in foci into a one-mode network of their co-memberships. In this paper, I explore the opposite process: how social ties can facilitate the formation of foci, and how two-mode data can be generated from a one-mode network. Drawing on theories of team, social group, and organization recruitment, I propose three models that describe how such foci might form from the relationships in a social network. I show that these models can be used to generate empirically plausible two-mode networks characterized by positively-skewed degree distributions and an over-representation of four- and six-cycles. I conclude by discussing these models’ limitations, and highlighting how they might be used to study two-mode networks representing social foci, and to investigate two-mode projection methods.

Keywords: bipartite, Blau space, generative models, group formation, organizations, projection, team formation

1. Introduction
A natural question in the social networks literature has been: Where do social networks come from? The answers have been diverse, and contributions have taken the form of both theoretical propositions for underlying mechanisms such as homophily (e.g., McPherson et al., 2001) and statistical frameworks for testing these propositions (e.g., Robins et al., 2007; Snijders et al., 2010). Focus theory proposed that social networks come from social foci such as events (e.g., parties) or group affiliations (e.g., clubs), which organize interaction and present opportunities for individuals to meet and form ties (Feld, 1981). However, this raises the obvious question: Where do social foci come from?

There is a duality of social networks and social foci, such that networks can come from foci, and foci can come from networks. A sketch of this duality was
already present in the initial articulation of focus theory (Feld, 1981). However, most subsequent work has examined how networks emerge from foci, while neglecting how foci emerge from networks. In this paper, I aim to elaborate the second half of this duality. Drawing from a range of disciplinary contexts, I develop three models for how foci can emerge from social networks: as teams (Guimera et al., 2005), as groups (Backstrom et al., 2006), and as organizations (McPherson, 2004). While these models offer insight into how foci can emerge from networks, they also contribute to the methodological literature as two-mode network generative models, which currently “are practically non-existent” in the literature (Filho & O’Neale, 2020a).

The remainder of the paper is organized in five sections. In section 2 I review how social networks can emerge from foci, and the methods used for generating social networks from affiliation data. Then, in section 3 I introduce three models for how foci can emerge from social networks. In section 4, I describe a set of simulations designed to explore these models’ ability to generate realistic two-mode networks representing individuals’ associations with foci. In section 5 I examine the characteristics of two-mode networks generated using these models, comparing them to characteristics typically found in real-world two-mode networks. Finally, in section 6 I conclude by considering these models’ limitations and their potential applications for building and testing both theories and methods.

2. Social networks emerge from social foci

Social networks can emerge through many different processes (Fuhse & Gondal, 2022; Yap & Harrigan, 2015). For example, ties may form through a process of preferential attachment, such that new ties tend to be formed with already well-connected others. Ties may also form through processes of balance that promote friendship cycles (i.e., A → B → C → A), or of status seeking that prohibit them. Among the most intuitive tie formation processes are those that unfold when individuals share something in common. Ties can form through homophily when individuals share an interest or demographic characteristic, through propinquity when they share a space, or through transitivity when they share a set of common friends.

Feld’s (1981) focus theory sought to clarify how these similarities can lead to the formation of ties at the micro-scale, and to networks and clusters at the macro-scale. Each of these similarities is a potential example of “a focus [which is] a social, psychological, legal, or physical entity around which joint activities are organized (e.g., workplaces, voluntary organizations, hangouts, families, etc.)” (Feld, 1981, p. 1016). The interactions that take place in these joint activities “bring people together in a mutually rewarding situation” because they are focused on something that is shared, and therefore these interactions are “positively valued” (Feld, 1981, p. 1017). Through these positively valued interactions, the participants “will develop positive sentiments toward each other”
and thus positive affective ties (Feld, 1981, p. 1026). Feld (1981) summarized the process by explaining that “As a consequence of interaction associated with their joint activities, individuals whose activities are organized around the same focus will tend to become interpersonally tied and form a cluster” (Feld, 1981, p. 1016).

The literature contains numerous examples where networks are assumed or shown to form through this process. Members of the global corporate elite are viewed as forming economically and politically consequential social ties through their shared membership on corporate boards of directors (e.g., Mizruchi, 1996; Burris, 2005). Residents of urban neighborhoods form social ties when they choose to visit the same stores and churches (e.g., Browning et al., 2015; Hipp & Perrin, 2009). Childrens’ peer social networks form through their membership in groups “who hang around together a lot” (e.g., Cairns & Cairns, 1994, p. 101). Politicians’ political alliances form as they collaborate on the passage of specific pieces of legislation (e.g., Fowler, 2006; Neal, 2020). Doctors’ behaviors are shaped by the social ties that form at conferences (e.g., Menchik, 2019). Actors’ form a network of collaboration by working together on films (Watts & Strogatz, 1998). These examples illustrate the general nature of the process described by focus theory, highlighting that although “foci may be many different things” (Feld, 1981, p. 1018), they often serve the same network-generating function.

Breiger’s (1974) description of two-mode projection can be viewed as a formalization of this network-generating process. Let $F$ be a binary incidence matrix that records the associations of individuals (rows) with foci (columns), such that $F_{ik} = 1$ if individual $i$ is associated with focus $k$, and otherwise $F_{ik} = 0$. Breiger (1974) used the example of 18 women’s attendance patterns at 14 social events, which served as foci organizing their joint activities. An integer-weighted adjacency matrix $N$ can be constructed as $N = FF'$, where $F'$ indicates the transpose of $F$. Each entry $N_{ij}$ in this matrix indicates the number of foci shared by individuals $i$ and $j$, or in Breiger’s (1974) example, the number of events jointly attended by each pair of women. To the extent that sharing foci leads to social ties, as focus theory contends, $N$ represents the social network predicted to emerge from these foci, with the edge weights capturing information about the likelihood of each tie.

Feld (1981) noted several implications of focus theory that have been confirmed by subsequent work adopting Breiger’s (1974) formalization. For example, he noted that “focus theory suggests the conditions under which transitivity should be expected, and thereby the conditions under which clusters are formed”

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1Feld (1981) refers to Homans (1950) for the claim that interactions focused on a shared characteristic will be valued and lead to positive interpersonal sentiments. This is reminiscent of the contact hypothesis (Allport, 1954), for which the empirical evidence is mixed (Pettigrew, 1998). For the sake of generality, I ignore whether the interactions are valued, and whether the sentiments and consequently formed social ties are positive.

2Although the network formation process described by Feld’s (1981) focus theory was directly captured by Breiger’s (1974) model, and indeed both rely on the same empirical work by Homans (1950) as a foundation, Feld (1981) did not refer to Breiger (1974).
Subsequent work on two-mode projections has confirmed that “even a random network – one that has no particular structure built into it at all – will be highly clustered” if the ties are formed through shared foci (Watts, 2008, p. 128; c.f., Feld, 1981; Neal, 2014; Latapy et al., 2008). He also noted that there are “variations among foci” and specifically that “the structure of a network is dependent upon the...size of the underlying foci” (Feld, 1981, p. 1019). Again, subsequent work on two-mode projections has confirmed that the column marginals of $F$ (i.e., each focus’s number of members) impact the interpretation of edge weights in $N$ (i.e., the likelihood two people are tied), and methods have been developed to take into account such variations when deriving a network from foci (Neal, 2014).

3. Social foci emerge from social networks

Focus theory offers a theoretical account for how a network can emerge from foci (i.e., foci $\rightarrow$ network). Similarly, two-mode projection offers a method for transforming data on individuals’ participation in foci into a possible network among individuals (i.e., two-mode network $\rightarrow$ one-mode network). But, what about the other direction? How might foci emerge from a social network (i.e., network $\rightarrow$ foci), and similarly how can data about individuals’ relationships be transformed into their possible foci participations (i.e., one-mode network $\rightarrow$ two-mode network)?

Feld (1981) acknowledged that foci can emerge from networks, noting that “Once there is a tie between two individuals, these individuals will tend to find and develop new foci around which to organize their joint activity.” Indeed, his diagram of the dynamics of the focus model is cyclical, with foci creating ties, which in turn create new foci. Schaefer et al. (2022) provided some of the most direct empirical evidence of this process, finding that direct influence from friends was the single most important exogeneous predictor of whether a high school student would form or join a new extracurricular activity. However, none of focus theory’s twenty propositions deal with how or when ties generate foci. Similarly, Schaefer et al. (2022) examined the circumstances under which individuals join existing foci, but not how new foci emerge. In this section I describe three theoretically-motivated models for how foci might emerge from social networks, and similarly how two-mode networks might be generated from one-mode networks. Each model describes how a specific type of focus (teams in a workplace, social groups such as parties, or organizations such as voluntary associations) might emerge from relationships in a social network, and is controlled by a tuning parameter $p$ that adjusts how closely the foci mirror cliques in this network.

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The goal of generating a two-mode network from a one-mode network is different from the goal of recovering a two-mode network from its two one-mode projections, which Everett & Borgatti (2013) show is possible under certain circumstances.
3.1. Teams

The teams model derives from an existing model of team formation. Guimera et al. (2005) suggested that the individuals who form teams in a given setting are embedded in a “complex network which is the result of past collaborations and the medium in which future collaborations will develop” (p. 697-8). That is, teams (the foci) emerge from a network of past collaborations. In their original model, all teams had a fixed size $m$. Each of the $m$ positions on a newly forming team were filled based on probabilities $p$ and $q$. Specifically, a position was filled with: (a) a new person joining the setting from an unlimited pool of outsiders with probability $1 - p$, (b) a person who is already a member of the setting with probability $p(1 - q)$, or (c) a person who is already a member of the setting and has previously collaborated with individuals on the new team with probability $pq$. Their model was dynamic because outsiders join the setting over time, and because each new team contributes to the network that influences the formation of future teams. It is also complex because it is parameterized by three values $m$, $p$, and $q$.

The teams model is a modification of Guimera et al.’s (2005) complex dynamic model, and allows teams of varying size to emerge from a static network based on a single parameter $p$. In a network of past collaborations, cliques represent sets of individuals who have all collaborated with one another, and thus represent prior teams. Each new team emerges from one of these prior teams, but can involve changes in membership. Because some of the prior team’s members (i.e. incumbents) may be unavailable or lack the necessary skills for the new team’s task, they must be replaced by individuals who were not members of the prior team (i.e. newcomers). The model outcome depends on a tuning parameter that specifies the probability with which incumbents are retained ($p$), rather than replaced by newcomers on new teams ($1 - p$). Accordingly, the tuning parameter $p$ controls how closely the memberships of new teams will match the memberships of old teams. When $p = 1$, where incumbents are always retained, the teams model reduces to the model described by Guillaume & Latapy (2004), where foci are equivalent to cliques.

Figure 1 provides a concrete example. Suppose the network on the left is a collaboration network among colleagues in an academic department, and the prior team $\{A,B,C\}$ (a randomly selected clique) represents a set of colleagues who collaborated on a grant proposal. A new three-member team is emerging from this prior three-member team to submit a revised proposal. For the sake of continuity and because they are initiating the new team’s formation, the first position on the new team must be filled by one of the prior team’s incumbents $\{A,B,C\}$. In this example, the first position is filled by incumbent $A$. The remaining two positions on the team are filled by selecting incumbents with probability $p$, and selecting newcomers with probability $1 - p$. In this example, the second position is filled by newcomer $D$, while the third position is filled by incumbent $B$. The new team $\{A,D,B\}$ could be the outcome of a situation in which newcomer $D$ replaced incumbent $C$ to address reviewers’ concerns with the team’s earlier proposal.
3.2. Groups

The *groups* model is informed by findings about how groups form in large social networks. Backstrom et al. (2006) used a decision tree approach to identify the set of conditions that influence whether or not a person embedded in two online social networks, LiveJournal and DBLP, joined a group (the focus). Although they investigated 19 characteristics of both the group and potential joiner, they identified two that were particularly influential. First, consistent with diffusion of innovation theory (Valente, 1996), the probability of joining a group (or adopting an innovation) depends on the number of friends one already has in the group (or who have already adopted). Second, consistent with social capital theory (Coleman, 1988), the probability of joining a group depends on the proportion of friends in the group who are friends with each other.

These two characteristics that promote group joining have implications for the density of groups. The fact that \( i \) tends to join a group when she has many friends \( j \) in the group increases the group’s density by increasing the likelihood of \( i-j \) edges. Additionally, the fact that \( i \) tends to join a group when her friends \( j \) in the group are also friends with each other increases the group’s density by increasing the likelihood of \( j-j \) edges. Therefore, groups whose formation is guided by the conditions identified by Backstrom et al. (2006) will be cohesive and have a relatively higher density than the overall network. From this implication, the groups model views groups as forming when existing members recruit their friends, who join on the condition that the group would maintain a minimum density \( p \). Accordingly, \( p \) functions as a tuning parameter that controls the group formation process. When \( p = 1 \), where new members join only if the new group would be a clique, the groups model reduces to the model described by Guillaume & Latapy (2004), where foci are equivalent to cliques.

Figure 2 provides a concrete example, where \( p = 0.7 \). Suppose the network on the left is a friendship network, within which a book club \{D,E,F,G\} (a
randomly selected clique) aims to recruit new members. To make their book club viable, they must recruit other friends to participate. The challenge is that these friends are socially anxious and only feel comfortable in group settings where at least 70% of the members are friends with each another. Initially C is the only candidate because they are friends with existing book club members. The book club attempts to recruit C, and C decides to join because doing so would result in a book club in which 70% of the members are friends with each other. Once C is a member, A and B become candidates for recruitment. The book club attempts to recruit A first, however A declines to join because doing so would yield a book club in which only 53% of members are friends with each other. The book club’s attempt to recruit B is unsuccessful for the same reason. Thus, the new book club’s members are \{D,E,F,G,C\}.

3.3. Organizations

The organizations model mirrors the Blau space model of organizational recruitment (McPherson, 1983, 2004). Blau space is a multidimensional space within which individuals are located based on their sociodemographic characteristics. As McPherson (2004) explains, Blau space has two important properties: it “at once organizes the social interactions among individuals, and structures the opportunities for the formation of social entities that are associated with individuals in that space” (p. 267). First, it organizes social interactions because individuals who are sociodemographically similar are located nearby in the space and, according to the principle of homophily (McPherson et al., 2001), are therefore more likely to interact with each other. This implies that network ties will tend to be local within Blau space. Second, it structures the formation of social entities because organizations recruit members from specific regions in this space, known as niches (Popielarz & Neal, 2007). For example, a youth yachting league might recruit its members from the region located at the lower end of the age dimension, but the upper end of the family wealth dimension.
The organizations model builds on these two properties, first estimating individuals’ positions in an unobserved Blau space from their distances in a social network, then simulating organizations’ recruitment of members from niches in this space. Individuals’ locations in Blau space can be estimated by embedding network geodesic distances in a $d$-dimensional space (Freeman, 1983; Péli & Bruggeman, 2006). The dimensionality of the space captures the complexity of the society’s social structure. I use a two-dimensional space because social networks tend to have low dimensionality (Freeman, 1983; Bonato et al., 2014), because many dimensions of social distinction are highly correlated (e.g., income and education), and because Blau space analysis is typically performed on low dimensionality spaces (Genkin et al., 2018). Organizations have $d$-dimensional circular niches within this space that reflect the type of member they seek to recruit. Organizations niche sizes vary, however most organizations are narrow-niche specialists, while a few are wide-niche generalists (Carroll, 1985). An organization’s success at recruiting members depends on whether the prospective members are inside its niche (with probability $p$) or outside its niche (with probability $1 - p$; Popielarz & McPherson, 1995). Accordingly, $p$ serves as a tuning parameter that controls the importance of niche location in individuals’ joining behavior.

Figure 3 provides a concrete example. Suppose the network on the left is a social network of neighborhood friends. The geodesic distances between individuals in the network can be used to embed them in a 2-dimensional space via multidimensional scaling. Friends (e.g., C & D) are close together in this space, while friends-of-friends (e.g., A & D) are further apart in this space, and friends-of-friends-of-friends (e.g., A & F) are furthest apart. The sociodemographic characteristics described two dimensions are unknown, but perhaps they are income and education; notice the two dimensions are highly correlated. A multi-level marketing company selling beauty products aims to recruit sales associates; its niche is people who have less income and education, which includes four people. It recruits each person inside this niche with probability $p$, and in this example successfully recruits A, B, and D. To recruit a fourth sales associate, it attempts to recruit those nearest the niche first, with probability $1 - p$. In this example, it fails to recruit E, but successfully recruits G, at which point recruitment ends. This yields a neighborhood sales team of \{A,B,D,G\}.

4. Methods

Each of the models described in section 3 can be viewed as a two-mode network generative model. Evaluating the quality of these generative models requires examining the extent to which they yield two-mode networks that

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4McPherson (1983) originally used (hyper)rectangular niches because they simplified calculation. The organizations model instead treats niches as hyperspheres, which more closely mirrors their definition in organizational ecology (Carroll, 1985; Péli & Bruggeman, 2006) and ‘Blau bubbles’ in contemporary formulations of Blau space (Suh et al., 2017).
resemble real-world two-mode networks representing foci memberships. Two types of characteristics are frequently observed in such empirical two-mode networks, and therefore should also appear in two-mode networks generated by these models: **positively skewed degree distributions** and **short cycles**.

A two-mode network representing individuals’ foci memberships is composed of two nodes, agents and foci, which each have their own degree distribution. The agent degree distribution captures the number of foci with which each agent is associated. Across many empirical contexts, this degree distribution tends to be positively skewed because most people are associated with just a few foci, while some people are associated with many foci. For example, most students participate in just a few extracurricular activities while some participate in many (Schaefer et al., 2022), most legislators sponsor just a few bills while some sponsor many (Neal, 2020), and most authors write just a few papers while some write many (Filho & O’Neale, 2020b).

The focus degree distribution captures the number of agents associated with each focus. Again, across many empirical contexts this degree distribution tends to be positively skewed because most foci have just a few members, while some foci have many members. For example, most extracurricular activities have just a few participants while some have many (Schaefer et al., 2022), most bills are sponsored by just a few legislators while some are sponsored by many (Neal, 2020), and most papers have just a few authors while some have many (Filho & O’Neale, 2020b).

Empirical two-mode networks also tend to contain more short cycles than random two-mode networks. Filho & O’Neale (2020b) observed that the abundance of four-cycles in two-mode networks helps explain the strong ties observed in social networks due to shared foci, while the abundance of six-cycles helps explain the triadic closure often observed in social networks. Accordingly, they find that both four- and six-cycles were over-represented in empirical two-mode networks.
networks capturing authors’ associations with papers in biology, mathematics, and physics, and a two-mode network capturing executives’ associations with corporate boards.

Figure 4 illustrates the design I use to evaluate whether these models generate realistic two-mode networks. First, I generate 500 small world networks containing 50 nodes and 150 edges (density = 0.112). I use small world networks because, while random, they closely resemble the structure of real-world social networks. Next, I use each model to generate a two-mode network at each level of the tuning parameter $p$ from 0.5 to 1 in 0.05 intervals. The figure illustrates a two-mode network generated from a small world network using the groups model when $p = 0.95$. Finally, for each generated two-mode network I compute the four characteristics of interest: agent degree skew, focus degree skew, over-representation of four-cycles, and over-representation of six-cycles. I expect both agent degree and focus degree to be positive, reflecting that most agents are associated with few foci and most foci have few members. I compute the over-representation of cycles as the ratio of the number of cycles in the observed two-mode network to the number in a random two-mode network with the same degree sequences. Therefore, I expect the cycle over-representation values to be larger than 1, reflecting that the generated two-mode network contains more cycles than a corresponding random network. This design involves examining 16,500 generated two-mode networks (i.e. 500 replications $\times$ 3 models $\times$ 11 tuning parameter values). The code necessary to replicate these analyses is available at https://osf.io/eyua4/.

5. Results

Figure 5A shows the skew in agent degrees (y-axis) in two-mode networks generated by the teams (red), groups (green), and organizations (blue) models using different tuning parameter values (x-axis). Solid lines show the mean over 500 replications, while the shaded regions around each line show the 95%
confidence interval. As desired, for all tuning parameter values, all models generate two-mode networks in which the agent degrees are positively skewed. This indicates that these models generate two-mode networks that are similar to empirically-observed focus memberships, where most people are associated with a few foci, but some people are associated with many foci.

Figure 5B shows the skew in focus degrees. As desired, for most tuning parameter values, all models generate two-mode networks in which the agent degrees are positively skewed. This indicates that these models generate two-mode networks that are similar to empirically-observed focus memberships, where most foci have a few members, but some foci have many members. For lower tuning parameter values the groups model yields two-mode networks with no or negative skew. This occurs because when $p < 0.7$ in the groups model, individuals are willing to join groups that are not particularly cohesive, which means that relatively large groups can form. For all tuning parameter values, the teams model yields two-mode networks with the same positive skew. This occurs because the size of foci in the teams model is not a function of the tuning parameter, but instead is a function of the size of cliques, the distribution of which is itself positively skewed.

Figure 6 shows the degree to which four-cycles (A) and six-cycles (B) are over-represented relative to a random two-mode network. As desired, for all tuning parameter values, all models generate two-mode networks in which both four-cycles and six-cycles are over-represented (i.e., values above 1). While these short cycles are always statistically significantly over-represented, their degree of over-representation is fairly modest. This occurs because the two-mode networks generated for this analysis are relatively small and dense; Filho & O’Neale (2020b) observed even more over-representation because they examined much larger and sparser two-mode networks.
6. Discussion

Over a century ago, Simmel (1955 [1922]) sketched the close association between individuals and groups. Building on these early ideas, Breiger (1974) demonstrated a method for deriving an interpersonal social network from individuals’ group memberships, while Feld (1981) proposed focus theory to explain how social ties emerge from shared ‘foci.’ Together, these methodological and theoretical contributions have facilitated research on how networks emerge from foci (e.g., Mizruchi, 1996; Burris, 2005; Browning et al., 2015; Hipp & Perrin, 2009; Cairns & Cairns, 1994; Fowler, 2006; Menchik, 2019; Neal, 2014, 2020).

However, this work has focused primarily on how foci lead to networks, while neglecting how networks can lead to foci. In this paper, building on ideas already present in focus theory and drawing on related theories of team Guimera et al. (2005), group Backstrom et al. (2006), and organization McPherson (1983) recruitment, I proposed three models for how a social network can lead to the formation of new foci. In the teams model, new teams are assembled from incumbents of, and newcomers to, prior teams. In the groups model, cohesive social groups form as existing members recruit friends whose decision to join depends on the group’s cohesiveness. Finally, in the organizations model, organizations recruit members from the interior and periphery of their socio-demographic niches.

These models can be viewed as two-mode network generative models, which are controlled by a tuning parameter $p$ that adjusts how closely the generated foci match cliques in the social network. A series of simulations demonstrated that under a range of tuning parameter values these models generate two-mode networks with (a) positively skewed agent degrees (i.e., most people belong to few foci), (b) positively skewed focus degrees (i.e., most foci have few members), and (c) more four-cycles and six-cycles than a random two-mode network. Together, these characteristics suggest that the models generate two-mode networks that are empirically plausible, closely resembling real-world data on individuals’ focus memberships.
6.1. Applications

Focus theory was initially proposed as a dynamic and cyclical process in which foci organize individuals’ activities, leading them to form positive social ties, which in turn lead them to create new foci (see figure 2 in Feld, 1981). The first half of this process has been widely adopted as a theoretical framework for understanding tie formation, while the conceptual teams, groups, and organizations models proposed here represent an initial step toward elaborating the second half of the process. Therefore, whereas the initial articulation of focus theory had theoretical applications for explaining network formation, these models have potential theoretical applications for exploring processes of group formation. As two-mode network generative models, they also have potential methodological applications. For example, just as small-world (Watts & Strogatz, 1998) and preferential-attachment (Barabási & Albert, 1999) models are used to generate random one-mode networks against which observed one-mode networks are compared, these models can generate random but realistic two-mode networks against which observed two-mode networks can be compared. Finally, linking theory and method, comparing an observed two-mode network to the two-mode networks generated by each of these models might provide insight into the generative process(es) responsible for its formation.

6.2. Limitations and future directions

These models and results are subject to some limitations, which highlight possible directions for future research. First, each model describes the emergence of independent foci, where individuals’ participation in one focus does not influence their participation in future foci. This simplifying assumption allows the models to require only one parameter, and may be a reasonable one as Schaefer et al. (2022) find the effect of ‘co-member influence’ is relatively weak. Nonetheless, in non-school contexts it may be an implausible assumption – if I join you for happy hour one Friday, I’m likely to join you for happy hour again the following week – that future models could seek to relax. Second, the results rely on relatively small (50 nodes) one-mode networks, from which relatively small (50 \times 50) two-mode networks were generated. The small sizes were necessary because counting six-cycles is computationally expensive, but the models themselves can be used to generate larger two-mode networks from larger one-mode networks. Therefore, future research should explore the scalability of these models, and should replicate these findings in larger networks. Finally, the evidence that these models generate empirically plausible two-mode networks rests on the observation that the generated two-mode networks have two features commonly observed in empirical two-mode networks: positively skewed degree sequences and an abundance of short cycles. As future research identifies other common properties of empirical two-mode networks, the plausibility of these models and the two-mode networks they generate should be re-evaluated. Additionally, future research may explore opportunities to validate these models by simultaneously collect data on a setting’s social network and its members’ focus memberships, which would permit examining how similar randomly generated foci are to empirically observed foci.
6.3. Conclusions

Theories (Feld, 1981) and methods (Breiger, 1974) have long acknowledged that individuals’ co-memberships in groups, co-locations in places, and co-participations in events can facilitate the formation of social ties. However, it is equally plausible that individuals’ social ties can facilitate the formation of new groups, places, and events. In this paper, I have sketched three conceptual models that describe how this might happen. These conceptual models can be used to generate random two-mode networks, which simulations suggest have many characteristics typically observed in empirical two-mode networks. Therefore, these models have the potential to advance theories of how groups form from networks, as well as to provide random two-mode networks against which empirical two-mode networks can be compared. Moreover, as theoretically-informed but stylized models, they also offer a starting point for the development of more complex and realistic models.

Data availability statement

The code to replicate these analyses is available at https://osf.io/eyua4/.

Disclosures

The author declares no conflicts of interest.

References

Allport, G. W. (1954). The nature of prejudice. Addison-Wesley.

Backstrom, L., Huttenlocher, D., Kleinberg, J., & Lan, X. (2006). Group formation in large social networks: membership, growth, and evolution. In Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 44–54). https://doi.org/10.1145/1150402.1150412.

Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. Science, 286, 509–512. https://doi.org/10.1126/science.286.5439.509.

Bonato, A., Gleich, D. F., Kim, M., Mitsche, D., Prałat, P., Tian, Y., & Young, S. J. (2014). Dimensionality of social networks using motifs and eigenvalues. PloS one, 9, e106052. https://doi.org/10.1371/journal.pone.0106052.

Breiger, R. L. (1974). The duality of persons and groups. Social forces, 53, 181–190. https://doi.org/10.1093/sf/53.2.181.

Browning, C. R., Soller, B., & Jackson, A. L. (2015). Neighborhoods and adolescent health-risk behavior: An ecological network approach. Social Science & Medicine, 125, 163–172. https://doi.org/10.1016/j.socscimed.2014.06.028.
Burris, V. (2005). Interlocking directorates and political cohesion among corporate elites. *American journal of sociology*, 111, 249–283. https://doi.org/10.1086/428817.

Cairns, R. B., & Cairns, B. D. (1994). *Lifelines and risks: Pathways of youth in our time*. Cambridge University Press.

Carroll, G. R. (1985). Concentration and specialization: Dynamics of niche width in populations of organizations. *American journal of sociology*, 90, 1262–1283. https://doi.org/10.1086/228210.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American journal of sociology*, 94, S95–S120. https://doi.org/10.1086/228943.

Everett, M. G., & Borgatti, S. P. (2013). The dual-projection approach for two-mode networks. *Social networks*, 35, 204–210. https://doi.org/10.1016/j.socnet.2012.05.004.

Feld, S. L. (1981). The focused organization of social ties. *American Journal of Sociology*, 86, 1015–1035. https://doi.org/10.1086/227352.

Filho, D. V., & O’Neale, D. R. (2020a). Latent space generative model for bipartite networks. In *International Conference on Network Science* (pp. 3–16). Springer. https://doi.org/10.1007/978-3-030-38965-9_1.

Filho, D. V., & O’Neale, D. R. (2020b). Transitivity and degree assortativity explained: The bipartite structure of social networks. *Physical Review E*, 101, 052305. https://doi.org/10.1103/PhysRevE.101.052305.

Fowler, J. H. (2006). Connecting the congress: A study of cosponsorship networks. *Political Analysis*, 14, 456–487. https://doi.org/10.1093/pan/mpl002.

Freeman, L. C. (1983). Spheres, cubes and boxes: graph dimensionality and network structure. *Social Networks*, 5, 139–156. https://doi.org/10.1016/0378-8733(83)90022-9.

Fuhse, J. A., & Gondal, N. (2022). Networks from culture: Mechanisms of tie-formation follow institutionalized rules in social fields. *Social Networks*, 150, 102564. https://doi.org/10.1016/j.socnet.2021.12.005.

Genkin, M., Wang, C., Berry, G., & Brashears, M. E. (2018). Blaunet: An r-based graphical user interface package to analyze blau space. *PloS one*, 13, e0204990. https://doi.org/10.1371/journal.pone.0204990.

Guillaume, J.-L., & Latapy, M. (2004). Bipartite structure of all complex networks. *Information processing letters*, 90, 215–221. https://doi.org/10.1016/j.ipl.2004.03.007.

Guimera, R., Uzzi, B., Spiro, J., & Amaral, L. A. N. (2005). Team assembly mechanisms determine collaboration network structure and team performance. *Science*, 308, 697–702. https://doi.org/10.1126/science.1106340.
Hipp, J. R., & Perrin, A. J. (2009). The simultaneous effect of social distance and physical distance on the formation of neighborhood ties. *City & Community, 8*, 5–25. https://doi.org/10.1111/j.1540-6040.2009.01267.x.

Homans, G. C. (1950). *The human group*. Harcourt, Brace & World.

Latapy, M., Magnien, C., & Del Vecchio, N. (2008). Basic notions for the analysis of large two-mode networks. *Social networks, 30*, 31–48. https://doi.org/10.1016/j.socnet.2007.04.006.

McPherson, M. (1983). An ecology of affiliation. *American Sociological Review*, (pp. 519–532). https://doi.org/10.2307/2117719.

McPherson, M. (2004). A blau space primer: prolegomenon to an ecology of affiliation. *Industrial and Corporate Change, 13*, 263–280. https://doi.org/10.1093/icc/13.1.263.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology, 27*, 415–444. https://doi.org/10.1146/annurev.soc.27.1.415.

Menchik, D. A. (2019). Tethered venues: Discerning distant influences on a field site. *Sociological Methods & Research, 48*, 850–876. https://doi.org/10.1177/0049124117729695.

Mizruchi, M. S. (1996). What do interlocks do? an analysis, critique, and assessment of research on interlocking directorates. *Annual review of sociology, 22*, 271–298. https://doi.org/10.1146/annurev.soc.22.1.271.

Neal, Z. P. (2014). The backbone of bipartite projections: Inferring relationships from co-authorship, co-sponsorship, co-attendance and other co-behaviors. *Social Networks, 39*, 84–97. https://doi.org/10.1016/j.socnet.2014.06.001.

Neal, Z. P. (2020). A sign of the times? weak and strong polarization in the us congress, 1973–2016. *Social Networks, 60*, 103–112. https://doi.org/10.1016/j.socnet.2018.07.007.

Péli, G., & Bruggeman, J. (2006). Networks embedded in n-dimensional space: The impact of dimensionality change. *Social networks, 28*, 449–453. https://doi.org/10.1016/j.socnet.2005.11.002.

Pettigrew, T. F. (1998). Intergroup contact theory. *Annual review of psychology, 49*, 65–85. https://doi.org/10.1146/annurev.psych.49.1.65.

Popielarz, P. A., & McPherson, J. M. (1995). On the edge or in between: Niche position, niche overlap, and the duration of voluntary association memberships. *American Journal of Sociology, 101*, 698–720. https://doi.org/10.1086/230757.
Popielarz, P. A., & Neal, Z. P. (2007). The niche as a theoretical tool. Annual Review of Sociology, 33, 65–84. https://doi.org/10.1146/annurev.soc.32.061604.123118.

Robins, G., Pattison, P., Kalish, Y., & Lusher, D. (2007). An introduction to exponential random graph (p*) models for social networks. Social networks, 29, 173–191. https://doi.org/10.1016/j.socnet.2006.08.002.

Schaefer, D. R., Khuu, T. V., Rambaran, J. A., Rivas-Drake, D., & Umaña-Taylor, A. J. (2022). How do youth choose activities? assessing the relative importance of the micro-selection mechanisms behind adolescent extracurricular activity participation. Social Networks, . https://doi.org/10.1016/j.socnet.2021.12.008.

Simmel, G. (1955 [1922]). The web of group affiliations. In K. H. Wolff (Ed.), Conflict and the web of group affiliations (pp. 127–195). Simon and Schuster.

Snijders, T. A., Van de Bunt, G. G., & Steglich, C. E. (2010). Introduction to stochastic actor-based models for network dynamics. Social networks, 32, 44–60. https://doi.org/10.1016/j.socnet.2009.02.004.

Suh, C. S., Shi, Y., & Brashears, M. E. (2017). Negligible connections? the role of familiar others in the diffusion of smoking among adolescents. Social Forces, 96, 423–448. https://doi.org/10.1093/sf/sox046.

Valente, T. W. (1996). Social network thresholds in the diffusion of innovations. Social networks, 18, 69–89. https://doi.org/10.1016/0378-8733(95)00256-1.

Watts, D. J. (2008). Six Degrees: The Science of a Connected Age. W. W. Norton.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’networks. nature, 393, 440–442. https://doi.org/10.1038/30918.

Yap, J., & Harrigan, N. (2015). Why does everybody hate me? balance, status, and homophily: The triumvirate of signed tie formation. Social Networks, 40, 103–122. https://doi.org/10.1016/j.socnet.2014.08.002.