Homophily Detection in Opinion Dynamics from Reddit Discussions

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Abstract. Homophily is an intuitive behavior in opinion dynamics, although its identification is not easy when using real data. In this paper, the Stochastic Actor-Oriented Model (SAOM) is proposed to detect homophily relationships emerging from Reddit discussions on three different topics: minorities discrimination, gun control, and politics. Homophily is characterized by the similarity of opinions between actors who connect over five sequential waves, each determined by collecting data over six months. Two indices to evaluate the tendency towards homophily-based connectivity are defined by considering the deviations of the actor's opinion from the average of all opinions and from that obtained by randomly choosing the same number of neighbors. The SAOM similarity score highlights situations in which homophily influences the variations of connections on consecutive waves and the Jaccard index is used to analyze the similarity of the graphs produced by the model with the experimental ones.

1 Introduction

Homophily can be defined as the tendency of individuals to interact with similar ones. It is a well-known phenomenon in social networks that can determine the formation and evolution of social structures since it implies that individuals tend to connect with those who share similar attributes, such as opinions, demographic characteristics, behaviors, and skills [26, 25]. Although homophily appears as a natural behavior in opinion dynamics [3], its detection starting from real data is not trivial and has not been much investigated in the literature, see [35] and the references therein. Recently, some Reddit discussions have been interpreted in terms of homophily for interactions along the social axis of the political compass and demographic attributes [8]. In this paper, we investigate possible homophily behaviors emerging from datasets of social interactions on Reddit dealing with three different topics, i.e., minorities discrimination, gun control, and politics [27], by using the Stochastic Actor-Oriented Model (SAOM).

SAOM represents a powerful tool to investigate homophily in dynamic social networks [31]. By providing statistical models that describe the co-evolution of networks and individual attributes over time, SAOM allows for the exploration of the interplay between behavior, influence, and network architecture [33, 32]. This model has been widely used in the literature to capture behaviors such as transitivity, similarity, or popularity. Our focus in this paper is on the concept of similarity, which aligns with the homophily principle.

In recent years, SAOM has been used to show evidence of homophily in different contexts. In order to better place our contribution within the international literature, it is interesting to provide a brief overview of how SAOM has been applied for detecting homophily behaviors in networks whose models have been determined by using real data.

1.1 SAOM for homophily with real data

A widely adopted framework consists of scholar communities in which homophily has been studied by considering different aspects characterizing young students such as ethnic identification [24, 23, 30], depressive symptoms [37, 14], familiar backgrounds [4], body mass index [11], socioeconomic status [7], gender [37, 14, 38, 19], and sports [16]. Another area of application of SAOM for homophily is represented by groups of academic students where communities related to performance (grades) [36, 34], emotional well-being [13], use of drugs [1], and gender [5, 2] have been highlighted.

Apart from student communities, SAOM has been applied also in other real scenarios of networking. The study [28] has examined the interactions among Kino-Eki (a Japanese system where shippers harvest trees from local mountains, receiving complementary currency in return) organizations. Using SAOM, the analysis of data from 2011 to 2019 has shown that organizations with similar locations and ages tend to participate together in policy forums.

In [22], 177 male inmates participating in a therapeutic community program at a Pennsylvania prison have been considered. Employing SAOM, it has resulted that inmates tend to interact more with peers who share similar levels of treatment engagement, and these interactions are reciprocated or transitive triads are formed.

The study [20] has analyzed collaboration networks among over 300 Iowa school districts through SAOM by showing that districts tend to collaborate with those they share mutual connections with or those considered popular. The analysis has also shown the preference for collaboration among districts with similar numbers of teachers with advanced degrees, spending per student, and geographic proximity.

The work [21] has analyzed the networks of developers involved in two open-source software projects, as indicated by their email exchanges. Applying SAOM, homophily has been highlighted when considering three attributes: commitment rate, significant file ownership, and minor contributor.

The study [15] has examined how networks of fighting and mating interactions among crickets, identified by vinyl tags and recorded by multiple cameras, evolve over time. SAOM results have indicated a strong positive interaction between the sexes, suggesting fights are mostly intra-sexual.

The study [9] has employed SAOM to examine floor sponsorship alliances in the Utah state legislature, focusing on networks of legislators in 2005–2008. An edge is directed from the author of a bill to its floor sponsors. The results have indicated that both party and gender homophily significantly predict which legislators are recruited as floor sponsors. In contrast, seniority and majority leadership homophily have not appeared to impact on the model.

The study [18] has analyzed transnational collaborations among more than 140 regulatory agencies across 18 years. The network size increases over time since new agencies join the collaborations. The analysis has shown a strong tendency toward triadic closure and homophily based on administrative tradition.

In [6], corporate acquisition transactions among over 200 electricity companies worldwide from 1994 to 2004 have been analyzed, considering their return on assets and retained earnings. The results have indicated that electricity companies are more likely to acquire others with similar performance levels.

The paper [39] has examined project-based collaborative networks among approximately 400 contractors and subcontractors involved in infrastructure development in China from 2001 to 2020. SAOM has shown that contractors are more likely to collaborate with subcontractors that belong to the same company group or are geographically close.

The authors in [29] have analyzed a Danish manufacturing company's network across three different time steps, involving over 100 employees. Using SAOM, they have investigated the coevolution of emotional job demands and work-based social ties. Their analysis has shown that employees facing high emotional job demands tend to foster positive work-based social ties, particularly with others experiencing similar demands.

In [12], SAOM has been applied to the Italian container terminal industry as a network system by investigating the homophily tendency in terms of indegree and outdegree.

1.2 Paper contributions and organization

The literature analysis presented above shows the presence of different and varied contexts in which SAOM has been applied for homophily detection. In spite of the wide range of applications considered, to the best of our knowledge this is the first time that SAOM is adopted with this objective by considering data coming from interactions in online social networks. In particular, we consider data of opinions derived from Reddit discussions on three different topics [27]. We show that the model derived from the application of SAOM can be used to highlight situations where similarities of opinions are relevant to the dynamics of network connections, which has been shown to not always be the case in Reddit discussions [10].

The rest of the paper is organized as follows. The datasets considered for the analysis and their preliminary elaborations are presented in Sec. 2. The application of SAOM for the homophily detection is discussed in Sec. 3. Section 4 summarizes conclusions and future work.

2 Datasets analysis

The datasets used for the analysis carried out in this paper are derived from Reddit data collected through the Pushshift API on three different topics: two subreddits related to minorities discrimination and gun control, and general discussions on the political sphere. The original data have been downloaded from a dedicated Github repository (`https://github.com/ValentinaPansanella/openmindedness-gunminpol`, accessed on 1 June 2024) and consists of five samples, in the following called *waves* so as typical in the SAOM terminology, each one corresponding to the collection of data over six months from January 2017 to July 2019. For each wave, the directed edges between pairs of interacting actors were available together with a scalar variable, which we call *opinion*, representing the orientation of the actor on that specific topic. The analysis of these data proposed in [27] has highlighted the presence of echo chamber communities based on three labels, called ideologies, derived through a quantization of the opinions, i.e., high (pro-trump), low (anti-trump), and medium (neutral) values of the opinions. In this paper, instead, the continuous values of the actors' opinions are considered for the homophily analysis.

A preliminary selection was adopted on the data. For each pair of consecutive waves the nodes with at least one link in both waves were selected. Then G_{ij} (M_{ij} and P_{ij}, respectively) represents the graph corresponding to this subset for the gun control (minorities discrimination and politics, respectively) topic by considering the i-th and the j-th consecutive waves, with $j = i + 1$ and $i = 1, 2, 3, 4$. The number of nodes and the number of edges for each of these graphs are reported in the first two rows of Tables 1, 2, and 3, respectively. In the following, the possible weights of the edges of the graphs are disregarded, thus considering only binary graphs.

	G_{12}	G_{23}	G_{34}	G_{45}
# nodes	110	109	115	128
# edges	639, 545	644, 452	413, 346	451, 469
$J_{\delta=0}$	0.22	0.17	0.15	0.12
h_μ	0.65, 0.75	0.62, 0.70	0.75, 0.74	0.76, 0.70
h_ν	0.56, 0.59	0.55, 0.62	0.67, 0.64	0.67, 0.63

Table 1. Pairs of waves for the gun control dataset (the two values, where present, refer to the initial wave and the next one, respectively).

In the third row of each table, the value of the Jaccard index is indicated. This index is used to identify the level of similarity between the graphs of two consecutive waves and is defined as

$$J_\delta = \frac{n_{11} + \delta n_{00}}{n_{11} + n_{10} + n_{01} + \delta n_{00}}, \tag{1}$$

where $n_{\alpha\beta}$, with $\alpha \in \{0, 1\}$ and $\beta \in \{0, 1\}$, is the number of edges with value α in the first wave and β in the second one, with the zero value meaning the absence

	M_{12}	M_{23}	M_{34}	M_{45}
# nodes	163	157	159	145
# edges	598, 498	476, 458	538, 534	472, 421
$J_{\delta=0}$	0.26	0.21	0.22	0.20
h_μ	0.80, 0.77	0.84, 0.66	0.82, 0.67	0.79, 0.77
h_ν	0.77, 0.66	0.75, 0.59	0.78, 0.59	0.75, 0.71

Table 2. Pairs of waves for the minorities discrimination dataset (the two values, where present, refer to the initial wave and the next one, respectively).

	P_{12}	P_{23}	P_{34}	P_{45}
# nodes	79	124	118	107
# edges	224, 216	295, 352	345, 292	226, 226
$J_{\delta=0}$	0.33	0.19	0.21	0.19
h_μ	0.81, 0.85	0.77, 0.77	0.78, 0.81	0.81, 0.74
h_ν	0.75, 0.77	0.72, 0.72	0.74, 0.74	0.73, 0.70

Table 3. Pairs of waves for the politics dataset (the two values, where present, refer to the initial wave and the next one, respectively).

of the edge, and the parameter $\delta \in \{0, 1\}$ selects between two possible values of the index. The characteristics of the different graphs can be also deduced from the clustering coefficient (density of the ego network) distribution shown in Fig. 1.

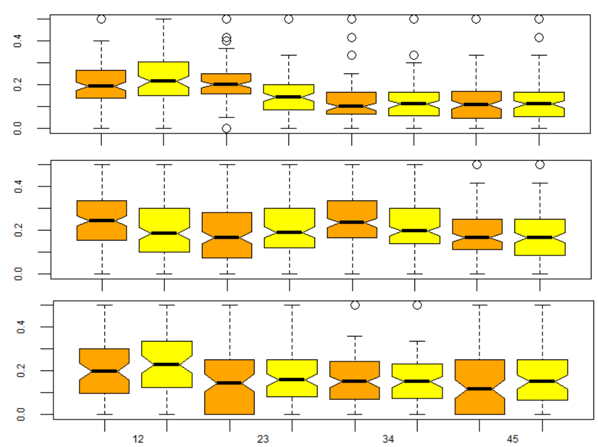

Fig. 1. Boxplot of the clustering coefficient distributions over the graphs related to gun control (top), minorities discrimination (middle), and politics (bottom) datasets; the values are for the initial (orange) and final (yellow) waves of each pair, respectively.

The pairwise analysis of the waves is also done in terms of opinions. Figure 2 shows the opinions for the different waves considered. A typical way for representing the homophily behavior in opinion dynamics consists of the so-called bounded confidence model [3]. Say $\mathcal{N}$ the set of all N actors and x_i the opin-

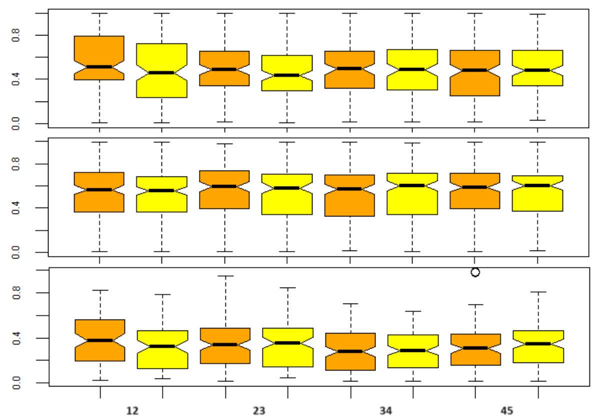

Fig. 2. Boxplot of the opinion distributions for gun control (top), minorities discrimination (middle), and politics (bottom) datasets; the opinions are for the initial (orange) and final (yellow) waves of each pair, respectively.

ion of the i-th actor at the current wave. In the so-called Hegselmann-Krause model [17], the opinion x_i, $i \in \mathcal{N}$, is assumed to update according to the following iterative averaging rule:

$$x_i^+ = \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} x_j = x_i + \frac{1}{|\mathcal{N}_i|} \sum_{j \in \mathcal{N}_i} (x_j - x_i), \tag{2}$$

where x_i^+ is the opinion at the next wave, $\mathcal{N}_i \subseteq \mathcal{N}$ is the set of the neighbors of the i-th actor at the current wave, and $|\mathcal{N}_i|$ is the size of this set, i.e., the number of neighbors of the i-th actor. Note that it is $i \in \mathcal{N}_i$, for all $i \in \mathcal{N}$. The interpretation of (2) is that the i-th opinion at the next wave is determined by taking the average of the neighbors' opinions or, in other words, by varying x_i according to the distance between x_i and that average.

Two different homophily-based connectivity tendency indices are defined. The first one analyzes the difference of the actor's opinion with respect to the average of the opinions over the network at that wave and is defined as

$$h_\mu = \frac{1}{N} \sum_{i \in \mathcal{N}} \mu_i, \tag{3}$$

where the binary variable takes value $\mu_i = 1$ if $|x_i^+ - x_i|$, with x_i^+ given by (2), is less than or equal to $|1/N \sum_{j \in \mathcal{N}} x_j - x_i|$ and $\mu_i = 0$ otherwise, $i \in \mathcal{N}$. The other index for homophily-based connectivity tendency is defined by computing how many times the classical update rule in bounded confidence opinion dynamics is less than a corresponding value obtained by choosing randomly the same number of neighbors of each actor:

$$h_\nu = \frac{1}{N} \sum_{i \in \mathcal{N}} \frac{1}{R} \sum_{r=1}^{R} \nu_i(r), \tag{4}$$

where the binary variable takes value $\nu_i(r) = 1$ if $|x_i^+ - x_i|$, with x_i^+ given by (2), is less than or equal to $|1/|\mathcal{N}_i^*(r)| \sum_{j\in\mathcal{N}_i^*(r)} x_j - x_i|$, with $\mathcal{N}_i^*(r)$ representing a set of $|\mathcal{N}_i|$ agents chosen randomly over the network for the r-th realization, $r = 1, \ldots, R$. The values of (3) and (4) shown in Tables 1, 2, and 3, as well as the distributions reported in Fig. 3, highlight the relevance of the rule assumed by the model (2) within the datasets. In particular, low values of $|x_i^+ - x_i|$ shown in Fig. 3 mean that the distance between the opinion of the actor and the average of its neighbors' opinion at the current wave is small, thus highlighting a tendency towards homophily.

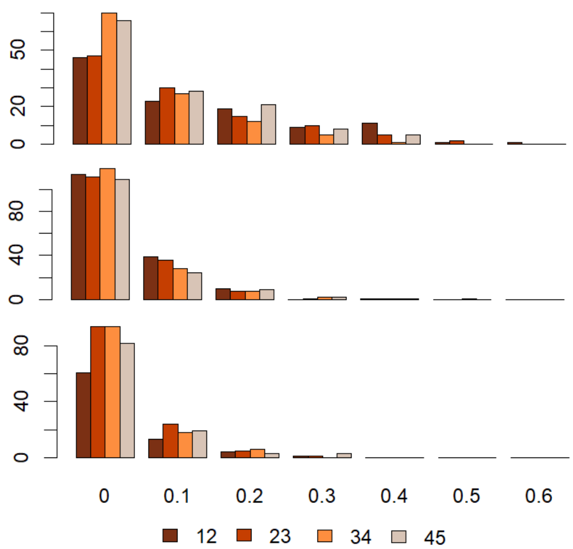

Fig. 3. Distributions of $|x_i^+ - x_i|$, with x_i^+ given by (2), $i \in \mathcal{N}$, for all graphs G_{hk} (top), M_{hk} (middle), and P_{hk} (bottom), $h = 1, 2, 3, 4$, $k = h + 1$.

3 SAOM for homophily

SAOM is a technique that aims to represent the dynamics of networks between two or more waves [31]. SAOM assumes that the network changes from one wave to the next through a sequence of mini-steps. At each mini-step, an actor (node) is selected according to some rate-function which indicates the frequency per unit of time with which each actor gets the opportunity to change an edge, given the current network state. The selected actor is allowed to take a decision regarding its outgoing edges: to add a new one, to remove one of the existing edges, or to keep them the same. The decision is taken according to the evaluation of an objective function, which can be expressed in the form $f_i(\mathcal{E}, x) = \sum_{k=1}^{K} \beta_k s_{ki}(\mathcal{E}, x)$, where s_{ki}, $k = 1, \dots, K$, are network statistics computed for the i-th agent, also called covariate effects in the SAOM nomenclature, β_k, $k = 1, \dots, K$, are weighting coefficients, $\mathcal{E}$ is the set of current edges, and x is the vector of the actors' opinions. For the selected actor i it is decided whether to add an outgoing edge, to cancel an outgoing edge, or to maintain the status quo by finding the solution which maximizes the variation of the objective function. The decision can be expressed as the solution of the problem $\max_{j, e_{ij}^+ \in \{0,1\}} (f_i(\mathcal{E}^+, x) - f_i(\mathcal{E}, x))$, where $\mathcal{E}^+ = (\mathcal{E} \setminus e_{ij}) \cup e_{ij}^+$ indicates the set of edges from which the element e_{ij} has been replaced with e_{ij}^+.

When the sequence of mini-steps has been completed, one compares the resulting network with the new wave in terms of the objective function. If the desired precision has been reached then the algorithm is finished, otherwise the procedure is restarted by choosing an increased value of the coefficient β_k corresponding to the network measurement vector s_k which shows the largest deviation between the wave and the simulated model. The output of the SAOM tuning is then given by the final values of the β_k coefficients, $k = 1, \dots, K$, the frequency per unit of time of the actors selection which is indicated with ρ, and the so-called t-ratio, i.e., the ratio between the average deviation and the standard deviation of the estimated coefficients β_k, $k = 1, \dots, K$.

In the case of the Reddit datasets considered in this paper, the use of SAOM for the detection of homophily is analyzed by considering $K = 2$, $s_{i1}(e) = \sum_{j=1, j \neq i}^{N} e_{ij}$, and $s_{i2}(e, x) = \sum_{j=1, j \neq i}^{N} e_{ij}(\sigma(x_i, x_j) - \bar{\sigma})$, where $\sigma(x_i, x_j) = \frac{\Delta - |x_i - x_j|}{\Delta}$ is the similarity score, $\Delta = \max_{ij} |x_i - x_j|$ is the maximum deviation between any two opinions in the network, and $\bar{\sigma}$ is the mean value of all similarity scores. The expression of s_{i2} shows that the proposed model benefits the creation of the edges between agents that have a larger similarity score; then if the resulting coefficient β_2 is large it means that this covariate effect is relevant in the wave by wave variations.

The results in Tables 4, 5, and 6 show the application of the model described above to the datasets analyzed in Sec. 2. Negative values of β_1 correspond to the tendency to eliminate edges from one wave to another rather than add new ones, which is coherent with the number of edges reported in Tables 1, 2, and 3. This characteristic is also highlighted by the high values of $J_{\delta=1}$ and low values of $J_{\delta=0}$, reported in the last two rows of Tables 4, 5, and 6. Positive values of β_2 indicate the preference in eliminating edges between actors with the most negative $\sigma(x_i, x_j) - \bar{\sigma}$ which means the lowest value of $\sigma(x_i, x_j)$ and then the largest difference of opinions between the actors.

4 Conclusion

In this work, the use of the SAOM technique for the analysis of homophily in online social networks has been proposed. Its application to data from Reddit discussions highlights the preference for connections between actors with similar opinions. Future work will involve validating the model with larger online social networks datasets and leveraging weighted graphs for homophily analysis.

	G_{12}	G_{23}	G_{34}	G_{45}
β_1 (s.e.)	-1.72 (0.03)	-1.82 (0.04)	-1.99 (0.04)	-1.89 (0.03)
β_2 (s.e.)	0.30 (0.13)	0.28 (0.16)	0.70 (0.20)	0.32 (0.13)
ρ	15.14	17.06	11.71	16.43
t-ratio	0.05	0.07	0.06	0.12
$J_{\delta=1}$	0.96	0.97	0.98	0.98
$J_{\delta=0}$	0.08	0.04	0.03	0.01

Table 4. SAOM results for the gun control dataset (in brackets the standard errors).

	M_{12}	M_{23}	M_{34}	M_{45}
β_1 (s.e.)	-2.42 (0.05)	-2.25 (0.04)	-2.26 (0.04)	-2.32 (0.05)
β_2 (s.e.)	2.13 (0.27)	1.33 (0.20)	2.03 (0.19)	2.15 (0.26)
ρ	8.67	8.56	9.77	10.41
t-ratio	0.07	0.06	0.06	0.04
$J_{\delta=1}$	0.99	0.99	0.99	0.99
$J_{\delta=0}$	0.14	0.08	0.09	0.09

Table 5. SAOM results for the minorities discrimination dataset (in brackets the standard errors).

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References

1. Barnett, N.P., DiGuiseppi, G.T., Tesdahl, E.A., Meisel, M.K.: Peer selection and influence for marijuana use in a complete network of first-year college students. Addictive Behaviors **124**, 107087 (2022)
2. Becker, K., Ebbers, J.J., Engel, Y.: Network to passion or passion to network? Disentangling entrepreneurial passion selection and contagion effects among peers and teams in a startup accelerator. J. of Business Venturing **38**(4), 106299 (2023)
3. Bernardo, C., Altafini, C., Proskurnikov, A., Vasca, F.: Bounded confidence opinion dynamics: A survey. Automatica **159**, 111302 (2024)
4. Block, P., Grund, T.: Multidimensional homophily in friendship networks. Network Science **2**(2), 189–212 (2014)
5. Boda, Z., Elmer, T., Vörös, A., Stadtfeld, C.: Short-term and long-term effects of a social network intervention on friendships among university students. Scientific Reports **10**(1), 2889 (2020)
6. Boukhris, M.B.A.: Does performance homophily matter in acquisition decisions? Evidence from acquisition network in the global electricity industry. J. of Social Sciences Research **5**(3), 715–722 (2019)
7. Chabot, T.: How does socioeconomic homophily emerge? Testing for the contribution of different processes to socioeconomic segregation in adolescent friendships. Social Networks **76**, 160–173 (2024)

	P_{12}	P_{23}	P_{34}	P_{45}
β_1 (s.e.)	-2.04 (0.08)	-2.10 (0.05)	-2.27 (0.08)	-2.21 (0.06)
β_2 (s.e.)	2.08 (0.39)	2.12 (0.30)	1.69 (0.06)	1.57 (0.41)
ρ	5.24	7.91	7.62	6.56
t-ratio	0.08	0.04	0.06	0.08
$J_{\delta=1}$	0.98	0.98	0.99	0.99
$J_{\delta=0}$	0.15	0.03	0.08	0.04

Table 6. SAOM results for the politics dataset (in brackets the standard errors).

8. Colacrai, E., Cinus, F., De Francisci Morales, G., Starnini, M.: Navigating multidimensional ideologies with Reddit's political compass: Economic conflict and social affinity. In: WWW24 Proc. ACM on Web Conf. pp. 1–13. Singapore (May 2022)
9. Davis, C.A., Redhead, D., Macfarlan, S.J.: Political alliance formation and cooperation networks in the Utah state legislature. Human Nature **33**(1), 1–21 (2022)
10. De Francisci Morales, G., Monti, C., Starnini, M.: No echo in the chambers of political interactions on Reddit. Scientific Reports **11**, 2818 (2021)
11. De La Haye, K., Robins, G., Mohr, P., Wilson, C.: Homophily and contagion as explanations for weight similarities among adolescent friends. J. of Adolescent Health **49**(4), 421–427 (2011)
12. De Martino, M., Giordano, G.: Equity joint ventures and new partnerships formation in terminal management: A stochastic actor oriented model. Int. J. of Transport Economics **48**(3-4), 359–379 (2021)
13. Elmer, T., Boda, Z., Stadtfeld, C.: The co-evolution of emotional well-being with weak and strong friendship ties. Network Science **5**(3), 278–307 (2017)
14. Ennett, S.T., Faris, R.W., Hussong, A.M., Gottfredson, N., Cole, V.: Depressive symptomology as a moderator of friend selection and influence on substance use involvement: Estimates from grades 6 to 12 in six longitudinal school-based social networks. J. of Youth and Adolescence **47**(11), 2337–2352 (2018)
15. Fisher, D.N., Rodríguez-Muñoz, R., Tregenza, T.: Dynamic networks of fighting and mating in a wild cricket population. Animal Behaviour **155**, 179–188 (2019)
16. Fujimoto, K., Snijders, T.A.B., Valente, T.W.: Multivariate dynamics of one-mode and two-mode networks: Explaining similarity in sports participation among friends. Network Science **6**(3), 370–395 (2018)
17. Hegselmann, R., Krause, U.: Opninion dynamics and bounded confidence models. Analysis and Simulation, JASSS **5**(3) (2002)
18. van der Heijden, M.: Agencies without borders: Explaining partner selection in the formation of transnational agreements between regulators. Regulation and Governance **15**(3), 725–744 (2021)
19. Hoffman, M., Chabot, T.: The role of selection in socioeconomic homophily: Evidence from an adolescent summer camp. Social Networks **74**, 259–274 (2023)
20. Hugg, V.G., Siciliano, M.D., Daly, A.J.: Public school district characteristics and the formation of longitudinal interdistrict collaboration networks. Educational Administration Quarterly **58**(4), 561–596 (2022)
21. Kavaler, D., Filkov, V.: Stochastic actor-oriented modeling for studying homophily and social influence in OSS projects. Empirical Software Engeering **22**(1), 407–435 (2017)
22. Kreager, D.A., Schaefer, D.R., Davidson, K.M., Zajac, G., Haynie, D.L., De Leon, G.: Evaluating peer-influence processes in a prison-based therapeutic community: a dynamic network approach. Drug and Alcohol Dependence **203**, 13–18 (2019)

23. Leszczensky, L., Pink, S.: Ethnic segregation of friendship networks in school: Testing a rational-choice argument of differences in ethnic homophily between classroom- and grade-level networks. Social Networks **42**, 18–26 (2015)
24. Leszczensky, L., Pink, S.: What drives ethnic homophily? A relational approach on how ethnic identification moderates preferences for same-ethnic friends. American Sociological Review **84**(3), 394–419 (2019)
25. Lobel, I., Sadler, E.: Preferences, homophily, and social learning. Operations Research **64**(3), 564–584 (2016)
26. McPherson, M., Smith-Lovin, L., Cook, J.M.: Birds of a feather: Homophily in social networks. Annual Review of Sociology **27**(1), 415–444 (2001)
27. Morini, V., Pollacci, L., Rossetti, G.: Toward a standard approach for echo chamber detection: Reddit case study. Applied Sciences **11**, 5390 (2021)
28. Nakazato, H., Izumi, R., Lim, S.: Joining policy forums together to develop Ki-no-Eki, a community currency system for forest management in Japan: Dynamics of policy communication networks. Land **11**(10), 1811 (2022)
29. Parker, A., Waldstrøm, C., Shah, N.P.: The coevolution of emotional job demands and work-based social ties and their effect on performance. J. of Management **49**(5), 1601–1632 (2023)
30. Schaefer, D.R., Khuu, T.V., Rambaran, J.A., Rivas-Drake, D., Umaña-Taylor, A.J.: How do youth choose activities? Assessing the relative importance of the micro-selection mechanisms behind adolescent extracurricular activity participation. Social Networks **77**, 139–150 (2024)
31. Snijders, T.A.: Stochastic actor-oriented models for network change. J. of Mathematical Sociology **21**(1-2), 149–172 (1996)
32. Snijders, T.A.: Stochastic actor-oriented models for network dynamics. Annual Review of Statistics and its Application **4**, 343–363 (2017)
33. Snijders, T.A., Van de Bunt, G.G., Steglich, C.E.: Introduction to stochastic actor-based models for network dynamics. Social Networks **32**(1), 44–60 (2010)
34. Snijders, T.A., Lomi, A.: Beyond homophily: Incorporating actor variables in statistical network models. Network Science **7**(1), 1–19 (2019)
35. Srivastava, T., Bernardo, C., Baccari, S., Vasca, F.: An experimental verification for Hegselmann–Krause opinion dynamics. In: 27th Int. Conf. on System Theory, Control and Computing. pp. 209–214. Timisoara, Romania (October 2023)
36. Torlò, V.J., Lomi, A.: The network dynamics of status: Assimilation and selection. Social Forces **96**(1), 389–422 (2017)
37. Yu, Y.F., et al.: The dynamics of adolescents' pubertal maturation, depressive symptoms and friendship networks: stochastic actor-oriented model. Current Psychology **42**(19), 16573–16586 (2023)
38. Zhao, L.: Networks in the making: Friendship segregation and ethnic homophily. Social Science Research **110**, 102813 (2023)
39. Zong, H., Wang, G., Cao, D.: Collaborative networks between contractors and subcontractors for infrastructure development: A comparative study of national quality award projects in China. Engineering, Construction and Architectural Management (2023)