Understanding Homophily and More-Becomes-More Through Adaptive Temporal-Causal Network Models

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Abstract. This study describes the use of adaptive temporal-causal networks to model and simulate the development of mutually interacting opinion states and connections between individuals in social networks. The focus is on adaptive networks combining the homophily principle with the more becomes more principle. The model has been used to analyse a data set concerning opinions about the use of alcohol and tobacco, and friendship relations. The achieved results provide insights in the potential of the approach.

Keywords: Homophily · More becomes more · Temporal-causal networks · Alcohol · Tobacco

1 Introduction

Social networks model how individuals in a group relate to each other. The analysis of social networks has been studied in various domains, such as marketing, social life, mathematics, computer science and physics [1]. Wasserman and Galaskiewicz explain that in social network analysis the focus lies on social entities or actors (also called agents) in interaction with one another and how these interactions constitute a framework or structure that can be studied and analyzed in its own right [2]. A network can be represented conceptually as a graph in which the social actors are shown as *nodes* and their social links represented as *edges* [3]. The links between these actors are any connections of interest. When mapping these nodes and their connections one can get an overview of the social relations in such a network and how the nodes may influence one another. Adaptive networks can also change their shape over time: persons and their interests change and this in turn can influence the connections they share.

Peer groups are a primary context in which adolescents develop their identities [4]. This includes positive influences and changes, like academic achievements, but also negative influences, such as substance abuse. Studying such influences within a group can lead to insight on how these aspects develop over time. McGloin, Sullivan and Thomas investigated in [4] adolescent substance abuse and the effects of immediate friendships and broader schoolmate influences. They argue that the degree to which friendship groups and other social reference groups in an adolescent's life have similarities or dissimilarities

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should be considered, as it can have a meaningful impact on the social behavior. If the values of schoolmates are different from those of the proximate friendship group, effects on each other would decrease; if schoolmates are similar to one's friends, the values would be reinforced. Findings of the study indeed showed that the influence of the friendship groups on adolescents decreased if the friendship group substance use and the adolescent's substance use are more dissimilar. Similar findings were found in [5–8].

Within social networks the phenomenon that contact between similar persons occurs at a higher rate than among dissimilar persons is called *homophily* [9]. It has a circular character. Persons that share the same behaviors like each other more, and persons that like each other more, influence each other's behavior more by contagion. This has implications on the information people in a network receive, attitudes and beliefs they form and their mutual connections. Another principle by which mutual connections change, which also occurs at the same time, describes that very popular people seem worth connecting to more; this is sometimes called the *more becomes more* principle [10]. It is assumed that someone with many and stronger connections will over time receive even more and stronger connections. Both principles together describe a social network with connections that change over time: such a network is called adaptive.

In this paper, an adaptive temporal-causal network model is presented incorporating the homophily and more-becomes-more principle. The model was used to analyse a data set for longitudinal data on opinions on alcohol and tobacco consumption and friendships for high school students on a school in Glasgow [11]. One of the goals of this study is to test whether opinions on alcohol or tobacco are the most useful indicators of future development of friendships (modeled by adaptive connection weights) as well as opinions (modeled by dynamic state values) in early high-school students. The Glasgow data set provides data on both these aspects for approximately 13 Year-old students in the city of Glasgow. The students were questioned three years in a row, starting February 1995 and ending in January 1997. For creating the friendship network, they were asked to name up to six friends.

In the next section, the two principles that were addressed, homophily and more-becomes-more, respectively, are explained. In the subsequent section an example social network is defined. Using this example network, the effect of the combined principles on both the states and the connections is explored in some detail by designing an adaptive temporal-causal network model. Furthermore, the interaction between the two principles is elaborated on. Finally, the adaptive temporal-causal model is deployed on the Glasgow dataset to verify its validity and, subsequently, its usability for real-world applications.

2 Two Social Network Adaptation Principles

The adaptive temporal-causal network presented in this paper incorporates two adaptive social network principles: homophily and more becomes more. The homophily principle states that the more similar two nodes are, the stronger the connections between the two nodes will become ('birds of a feather, flock together'). The more

becomes more principle describes the phenomenon that nodes that have more and stronger connections than others, grow connections faster than nodes that are less connected. In this section the background of these principles is discussed and it is described how they are incorporated in the adaptive temporal-causal network model.

The connection weight from person A to person B is denoted by $\omega_{A,B}$, and the considered states for A and B are denoted by X_A and X_B. In Fig. 1 a conceptual representation of an adaptive temporal-causal network is presented for the *homophily* principle. An assumption made is that the connection weights $\omega_{A,B}$ are affected by the connected states X_A and X_B, as depicted by the arrows from X_A and X_B to $\omega_{A,B}$. To obtain a dynamic equation for the connection $\omega_{A,B}$ it is needed to determine how the activation levels affect this connection exactly.

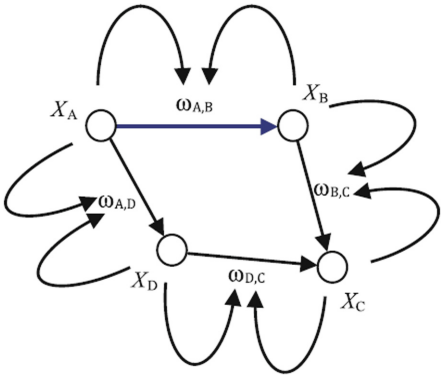

Fig. 1. Conceptual representation of the Homophily principle [10, Chap. 11].

Following the Network-Oriented Modeling approach described in [10], the homophily principle can be formalized numerically by a combination function $c_{A,B}(V_1, V_2, W)$:

$$\omega_{A,B}(t+\Delta t) = \omega_{A,B}(t) + \eta_{A,B}[c_{A,B}(X_A(t), X_B(t), \omega_{A,B}(t)) - \omega_{A,B}(t)]\Delta t$$
$$\mathbf{d}\omega_A, /\mathbf{d}t = \eta_{A,B}[c_{A,B}(X_A, X_B, \omega_{A,B}) - \omega_{A,B}]$$

Here the $X_A(t)$ and $X_B(t)$ represent the activation levels of the states X_A and X_B of person A and person B. The parameter $\eta_{A,B}$ is the update speed parameter of connection weight $\omega_{A,B}$. Assumptions are that the values of $\omega_{A,B}$ stay within the interval [0, 1], $c_{A,B}(V_1, V_2, W)$ is higher when $|V_1 - V_2|$ is smaller, $c_{A,B}(V_1, V_2, 0) \geq 0$ and $c_{A,B}(V_1, V_2, 1) \leq 1$. Here V_1 is the argument of the function $c_{A,B}(\ldots)$ used for $X_A(t)$, V_2 for $X_B(t)$, and W for $\omega_{A,B}(t)$. A relatively simple continuous function $c_{A,B}(V_1, V_2, W)$ that satisfies these requirements is obtained when a threshold value $\tau_{A,B}$ is assumed such that for $|V_1 - V_2|$ above this threshold, the connection weight decreases and under the threshold it increases:

$$c_{A,B}(V_1, V_2, W) = W + W(1 - W)(\tau_{A,B} - (V_1 - V_2)^2)$$

Using this combination function, the dynamic relations for $\omega_{A,B}$ are:

$$\mathbf{d}\omega_{A,B}/\mathbf{d}t = \eta_{A,B}\omega_{A,B}(1 - \omega_{A,B})(\tau_{A,B} - (X_A - X_B)^2)$$
$$\omega_{A,B}(t + \Delta t) = \omega_{A,B}(t) + \eta_{A,B}\omega_{A,B}(t)(1 - \omega_{A,B}(t))(\tau_{A,B} - (X_A(t) - X_B(t))^2)\Delta t$$

As discussed above, the more becomes more principle describes the phenomenon that well-connected nodes tend to get new or increased connections faster than nodes with less or weaker connections [10]. For example, when many other C's follow B on Twitter, B seems to be interesting to follow for A as well. This can be modeled taking into account the connection weights $\omega_{Ci,B}$ for $i = 1, \ldots, k$ of all connections from others C_i to B as follows; see also the conceptual representation depicted in Fig. 2. Based on the Network-Oriented Modeling approach from [10], the generic numerical representation is as follows:

$$\mathbf{d}\omega_{A,B}/\mathbf{d}t = \eta_{A,B}[c_{A,B}(\omega_{C_1,B}, \ldots, \omega_{C_k,B}) - \omega_{A,B}]\Delta t$$
$$\omega_{A,B}(t + \Delta t) = \omega_{A,B}(t) + \eta_{A,B}[c_{A,B}(\omega_{C_1,B}(t), \ldots, \omega_{C_k,B}(t)) - \omega_{A,B}(t)]\Delta t$$

Here $c_{A,B}(\ldots)$ is a combination function, for which in the current paper the advanced logistic function is chosen (for more detailed explanation, see [10, Chap. 2]):

$$c(V_1, \ldots, V_k) = \mathbf{alogistic}(V_1, \ldots, V_k) = \left[\frac{1}{1 + \mathbf{e}^{-\sigma(V_1 + .. + V_k - \tau)}} - \frac{1}{1 + \mathbf{e}^{\sigma\tau}}\right](1 + \mathbf{e}^{-\sigma\tau})$$

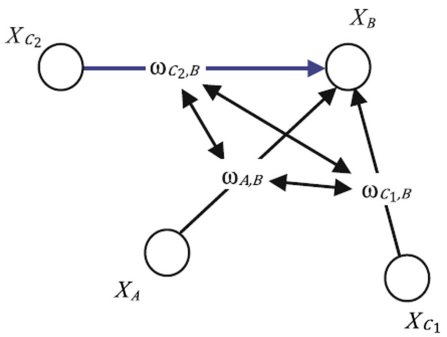

Fig. 2. Conceptual representation of the More Becomes More principle [10]

Both principles influence the connection weights between the nodes in the network over time. As in the real world they occur simultaneously, they have to be combined thus achieving an integrated model. Assume a parameter α between 0 and 1 that indicates the relative influence of the homophily principle, then $1 - \alpha$ indicates the relative influence of more becomes more. The overall combination function is the weighted sum of the above two combination functions with weights α and $1 - \alpha$, respectively:

$$\omega_{A,B}(t+\Delta t) = \omega_{A,B}(t) + [\alpha\eta_{A,B}^{\mathrm{HOM}}\omega_{A,B}(t)(1-\omega_{A,B}(t))(\tau_{A,B}-(X_A(t)-X_B(t))^2) + (1-\alpha)\eta_{A,B}^{\mathrm{MBM}}(\mathbf{alogistic}(\omega_{C_1,B}(t),\ldots,\omega_{C_k,B}(t)) - \omega_{A,B}(t))]\Delta t$$

In addition to this connection adaptation model, also a state contagion model was used based on a scaled sum function with the sum of the weights as scaling factor:

$$X_B(t+\Delta t) = X_B(t) + [(\omega_{C_1,B}X_{C_1}(t) + \cdots + \omega_{C_k,B}X_{C_k}(t))/(\omega_{C_1,B} + \cdots + \omega_{C_k,B}) - X_B(t)]\Delta t$$

3 An Example Social Network

The example network model analysed here (shown in Fig. 3) contains two groups of individuals that are connected through two hubs with outgoing connections to the other group (called bridges). Each group consists of 6 nodes. Their drinking opinions are assumed to be represented by values in the range of [0, 1], in which 0 represents someone very much against drinking, and 1 for someone that is addicted to alcohol. Two simulation experiments were conducted to investigate the effect of both principles in a network with strong initial bridge connections (0.8 between nodes 3, 4, 8 and 12). It is expected that due to the strong bridge connections, the more similar the initial values (and thus the more similar their opinions), the faster the two groups converge to the same value, and the stronger the two groups become connected to each other. If the initial values on opinions differ a lot, their opinions are expected to converge much more slowly. Under influence of homophily, the groups will reinforce their opinions within their group, but the bridges will eventually bring the groups together slowly (unless these bridge connections break). The initial connection weights can be found in Table 1. The example social network consists of 12 nodes and 31 edges, as shown in Fig. 3. As can be seen in the figure, the nodes with most connections are 3 and 4. The average number of connections of all nodes is 5.167. The two nodes 3 and 4 also form the main bridge connection between the two groups. A network analysis also reveals two communities, namely nodes 1, 2, 3, 5, 7 and 8 on one side and nodes 4, 6, 9, 10, 11 and 12 on the other, as was expected (for the chosen parameter values, see Table 2).

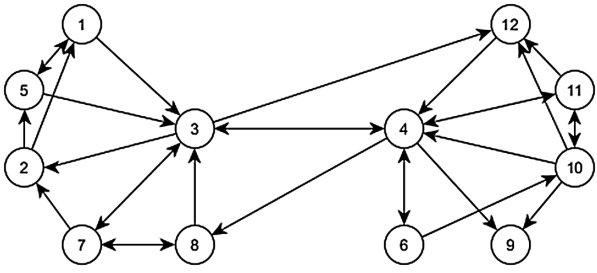

Fig. 3. Example social network

First, the parameter α was set at 0.5, meaning that the influence of the homophily and more becomes more principles are equal. The adaptation rates η are set at 0.4 for the weights and 0.3 for the states. The threshold value τ for homophily was set at 0.04. The value for the maximal time is 100 and the step size Δt is determined at 0.3. In Table 3 the initial values for the opinions for the two experiments are shown.

Table 1. Initial connection weights

	1	2	3	4	5	6	7	3	9	10	11	12
1	0	0	0.3	0	0.6	0	0	0	0	0	0	0
2	0.4	0	0	0	0.4	0	0	0	0	0	0	0
3	0	0.2	0	0.8	0	0	0.5	0	0	0	0	0.8
4	0	0	0.8	0	0	0.3	0	0.8	0.4	0	0.2	0
5	0.4	0	0.5	0	0	0	0	0	0	0	0	0
6	0	0	0	0.4	0	0	0	0	0	0.7	0	0
7	0	0.3	0.6	0	0	0	0	0.4	0	0	0	0
3	0	0	0.2	0	0	0	0.7	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0.3	0	0	0	0	0.7	0	0.5	0.6
11	0	0	0	0.5	0	0	0	0	0	0.6	0	0.7
12	0	0	0	0.4	0	0	0	0	0	0	0	0

Table 2. Network parameter values

Parameter	α	η weights	η states	τ homophily	Max. T	Δt
Value	0.5	0.4	0.3	0.04	150	0.3

Table 3. Initial node values

Node	1	2	3	4	5	6	7	8	9	10	11	12
Experiment I	0.2	0.1	0.2	0.9	0.3	0.7	0.3	0.3	0.8	0.9	0.7	0.8
Experiment II	0.4	0.3	0.5	0.6	0.3	0.7	0.4	0.3	0.7	0.8	0.6	0.7

In the *first example simulation* shown in Fig. 4 of the example social network from Fig. 3, the two groups differ more from each other in their opinions and use of alcohol: their opinions are dissimilar. The first group has higher initial values as they drink more often, these are the nodes 4, 6, 9, 10, 11 and 12. The values of this group range from 0.7 to 0.9. The second group, that is nodes 1, 2, 3, 5, 7 and 8, all have lower initial values as they do not drink that often. These range from 0.1 to 0.3. Within groups the nodes converge to a shared state value quickly due to their similarity. However, due to the bridge connections (of nodes 3, 4, 8 and 12) the groups themselves should still converge very slowly toward each other or break the two groups apart eventually. Figure 5 shows how the opinions of the groups change over time, with values for

homophily and more becomes more functions both set at 0.5 so their influence in the model is the same. It can be seen that both groups converge almost equally. The two groups converge together before time point 20, after which they reach a shared value of 0.5 where they remain constant. In the group with lower initial values (0.1 to 0.3) we see that node 8 tends to curve towards the other group at the start. This is explained by the connection that node 4 from the other group has on this node. With equal values for both principles, the influence of homophily is visible in the convergence of the state values of individuals in the subpopulations, and more becomes more in the convergence of the groups towards each other.

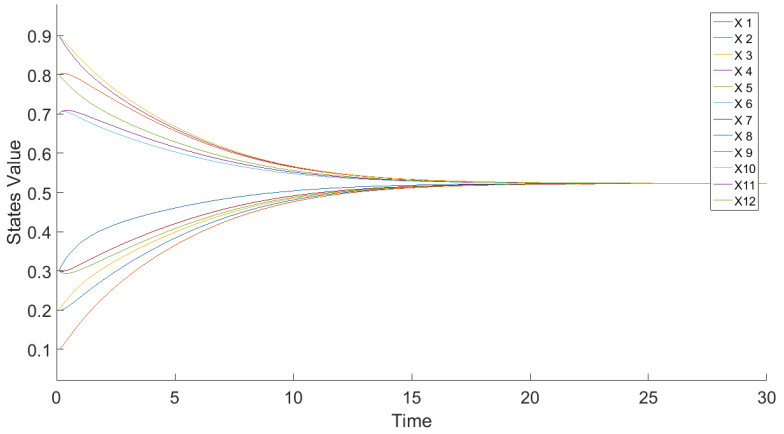

Fig. 4. Example simulation 1: the states (homophily 0.5, more becomes more 0.5)

In Fig. 5 the weights of all connections between the two groups are displayed. What is immediately visible is that all connections weights reach a value 1 after some time. Most connections start to increase from their initial value towards a value of 1. A few connections however first decrease to lower values (between 0.2 and 0.5) after which they curve upwards and eventually also reach 1.

The initial downward trend can be due to the influence of homophily, and the shifting upward trend due to the influence of the more becomes more principle. As nodes with many and strong connections get more and stronger connections over time, the main bridge connections (node 3 and node 4) contribute much to this pattern and it eventually leads to all connection weights reaching the same value.

Since no new connections are created in this example by design, the more becomes more only manifests itself in the strengthened connections. To make it more concrete: if everyone likes node 3 and 4, 10 will like them more as well, increasing the connection weights existing towards these nodes. There exists no connection to node 3 and no connections can be created in this example, but the more becomes more principle still influences the connection from node 10 to 4. Under the homophily principle, the states become more similar and the connections grow stronger even more. This self-enforcing force of more becomes more and homophily explain the fast connection strength growth after the initial poor start.

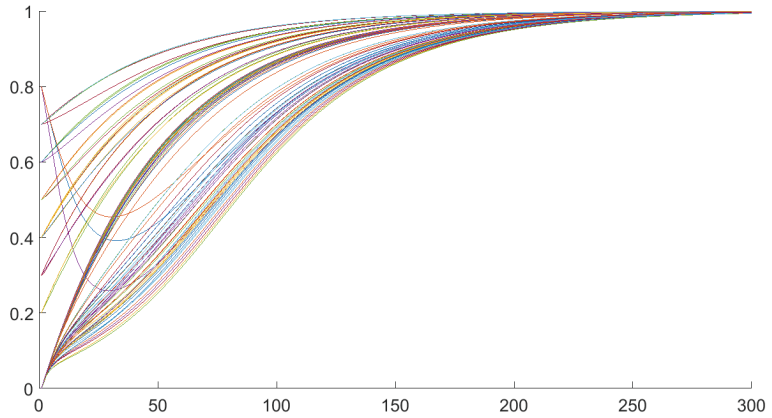

Fig. 5. Example simulation 1: the connection weights (homophily 0.5, more becomes more 0.5)

The contribution of homophily and more becomes more has also been investigated with different values for both principles. In Fig. 6 the homophily was given a value of 0.7 and a corresponding 0.3 value for more becomes more. As seen in the figure, the convergence of the groups among themselves is almost the same as in the previous example. The higher influence of the homophily is mainly seen in that the groups take slightly longer to converge towards each other. The curve at which they converge is also more straight than with equal influences of both the principles. They both join at the same value around 0.5 and remain constant there.

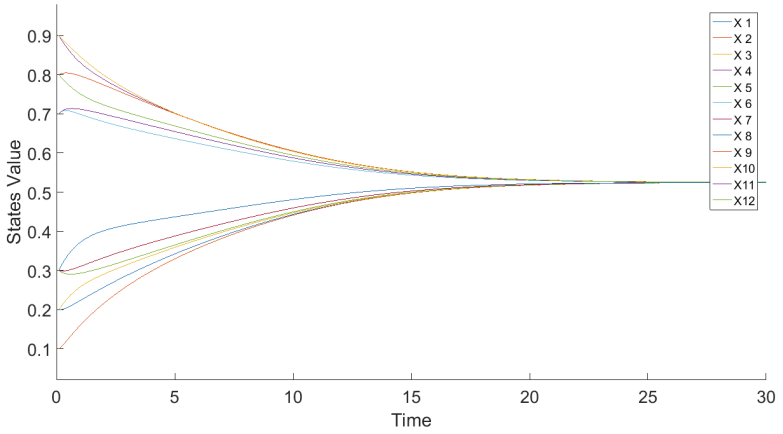

Fig. 6. Example simulation 1: the states (homophily 0.7, more becomes more 0.3)

In the Fig. 7, the homophily value has been set to 0.3 and the more becomes more value to 0.7. What is now visible is that, because the influence of homophily has decreased, the groups seem to converge towards each other sooner than with equal

influences of the principles. Although the actual convergence of the two groups is only a little sooner than previously, it is notable that the curve at which they converge towards each other is more steep. This is due to the more becomes more having a higher influence, and thus making the groups converge slightly faster. The nodes with the most connections (node 3 and 4) gather the groups more quickly. Once they meet both groups follow the same constant value of 0.5.

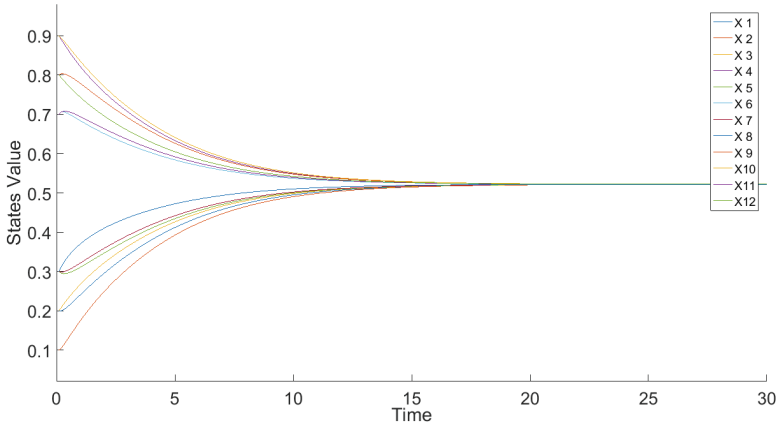

Fig. 7. Example simulation 1: the states (homophily 0.3, more becomes more 0.7)

In the *second simulation experiment* the initial values of the two groups are more similar to each other than in the previous simulation. The first group (node 1, 2, 3, 5, 7 and 8) now have initial values ranging from 0.3 to 0.5, while the initial values of group 2 range from 0.6 to 0.8. The values within the groups are still quite similar, but now the difference in values between the groups has become smaller. The groups now share more similar opinions on the use of alcohol and as a result of homophily and more becomes more, one would expect that the groups among themselves converge together quickly, but also that the two groups converge faster towards each other, as their opinions are more similar. In Fig. 8 the trend in opinions over time of the nodes can be seen with homophily and more becomes more values set a 0.5. The figure shows that the two groups do not converge as much among themselves in the beginning. Only a slight curve is seen in some nodes, that initially move towards their own group and away from the opposite group (the nodes with initial values of 0.4 and 0.5 of the first group, and the nodes with initial value of 0.6 in the other group). The nodes more or less gather all together than in two separate groups. The point where all nodes reach one value is only slightly sooner than compared to the simulation in which the groups were more dissimilar. The most notable difference now is that the nodes are more spread out at the beginning.

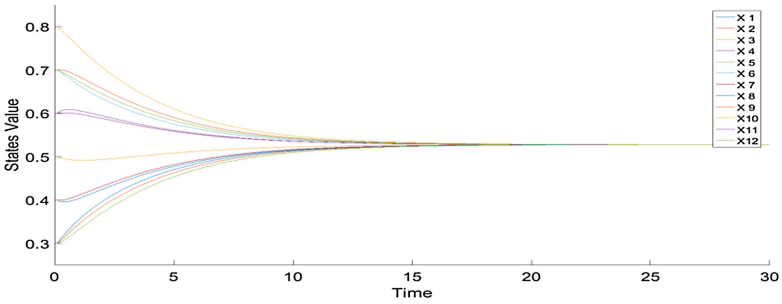

Fig. 8. Example simulation 2: the states (homophily 0.5, more becomes more 0.5)

4 Validation in a Real World Domain

In order to compare the temporal-causal network model with real world data, a longitudinal temporal real world data set was used on the tobacco and alcohol use among subjects aged approximately 13 at time point 0. The data spans three measurement points in a period of two years. For the model ten time steps a year were calculated to achieve a smooth simulation ($\Delta t = 1$, with 21 time points in total). The friendships were originally coded 0 (no friendship), 1 (best friends) or 2 (just friends). Since the simulation requires to allow new connections to be created to successfully simulate the more becomes more-principle, the new values were determined at 0.1 (no friendship), 0.5 (just friends) and 0.9 (best friends). The only connections with a value of 0, are the ones from states to themselves. The alcohol measures ranged from 1–5 (no drinking - more than once a week) and were mapped to a range from 0.1–0.9, in steps of 0.2 ([0.1, 0.3, 0.5, 0.7, 0.9]). Finally, the tobacco use measures were originally coded as [1–3] (no smoking, occasional, regular) and were mapped to [0.1, 0.5, 0.9]. In order to limit computational load, only the data on the first 50 of a total of 160 subjects was taken. Any subject for which the data on either tobacco or alcohol use, or on the relationships (due to the subject being removed from school for whatever reason) was missing, was completely removed from the network. As a result, a subset of 30 subjects remained.

The next step of comparison of the model to real world data is to optimize the model parameters, to see how much the best choice of simulated data deviates from the real-world data. The evaluation of the difference between simulation and real world data was measured by a Sum of Squared Residuals (SSR) error function, which is the sum of the squares of the differences between simulated values and empirical values. The fast Simulated Annealing algorithm in Matlab was applied to optimize the parameters, combining the SSR of states and connections in one error measure. Figures 9 and 10 show for the alcohol use data the SSR value plotted against the number of iterations. The temperature used is 100, re-initiating took place after every 100 iterations. The 50 initial iterations are shown in Fig. 10. Note that in the beginning, the SSR is very high due to the random initialization values that were taken. Also, due to the high temperature, a lot of variation occurs. Table 4 shows the found optimized parameter values and the corresponding performance measure separately for both the alcohol and the tobacco use data. Since it is assumed that no individual is immune to

influences from others on both their behavior and their relations, nor do they follow others blindly and immediately, the ranges of the speed factor parameters η for both the states and the relationships were limited to [0.1, 0.9]. The ranges for the parameters α, τ for homophily and τ for more becomes more were set at [0, 1], while the steepness parameter σ for more becomes more was limited to the interval [0, 10]. The latter was desired, as with the alogistic function a relatively low steepness parameter is required to simulate processes in a smooth gradual manner over the period of two years. Note that the speed factors for the states were individually tuned, but were not included in Table 4 for the sake of clarity.

The average deviation of the model for each state and relationship when compared to the real-world data from the Glasgow dataset was calculated by dividing the combined SSR by the number of data points used and then taking its square root. There were 1860 known data points (900 relationships and 30 state values) for time points 10 and 20. The data points from time point 0 are not included in this calculation, as they were used as initial values. This means that by definition there is a SSR of 0 over the first data points. The resulting values for tobacco of 0.12475 must be interpreted such that the model has an average predictive error of 12.475%. The predictive error of the model using alcohol use data is thus 11.231%.

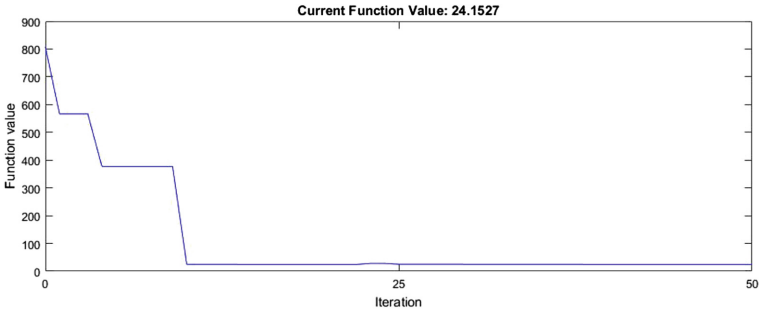

Fig. 9. The variation of the SSR value during the first 50 iterations of Simulated Annealing

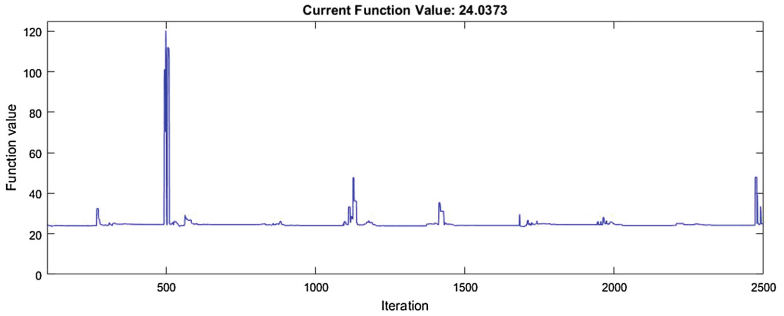

Fig. 10. Simulated annealing parameter tuning: development of the SSR value over 2500 iterations

Given few empirical data points available, the model may be considered to perform not too bad in simulating the development of real-world networks over time. The lack of information on more time points lowers the models predictive accuracy.

Table 4. Tuned parameter values

	η_ω	α	τ_{hom}	τ_{mbm}	σ_{mbm}	SSR	$\sqrt{(SSR/n)}$
Alcohol	0.80894	0.99851	0.01354	0.65446	8.74965	23.46141	0.11231
Tobacco	0.83675	0.99713	0.01396	0.54581	1.06990	28.94731	0.12475

5 Discussion

As shown in Table 4, the approach works better using the data on alcohol use than when using tobacco use data. This difference in accuracy may be explained by the fact that the alcohol states were measured on a 5-point scale, rather than on a 3-point scale like the tobacco data. As a result of this decreased data precision, less changes occur, but every change that occurs is more abrupt. For example, if a subject were to reduce his tobacco use in the real world from '0.65' to '0.35', this difference is not represented in the data points; they show a constant value of 0.5 due to rounding. Given the same scenario values for alcohol use, the data would show three data points with a clear, smooth trend: at data point the subject scores 0.7 on alcohol use, on time point 2 probably 0.5 and on the last data point 0.3. Although numbers are still being rounded, the mere knowledge that the substance use changes, helps better predict the substance use of all his friends as well. Therefore, the alcohol use data in this data set is more useful than the tobacco use data for simulating the development of social networks. The deviation of the simulated values from the real data points averages 11.2% on the alcohol use data and 12.5% on tobacco use data.

These findings could suggest that alcohol use is a more useful indicator for the development of social networks than alcohol use, although the effect of data precision should not be ignored. Another interesting finding are the optimal values for α, which are both higher than 0.99. This means that the more becomes more principle has less effect than 1% in this simulation. This might be the result of the data set, which allowed only a limited number of connections between subjects (6 per subject). This means that the data may limit the more becomes more principle in that it cannot generate as many new connections as one would hope. Finally, although this model appears to perform well on simulating longitudinal changes in substance use, it performed poorly on predicting the development of future relationships. This is caused by the dominance of relationships that did not exist at time point 0 that in the simulation never develop later on. Since there are approximately 750 static non-existent relationships (for which the value remains 0.1 throughout the experiment), the remaining about 150 relationships sharing the same η of the connections cannot be properly tuned. Ignoring the development of these future relationships, as proposed in an earlier study [12], therefore yields better results on the usability of temporal-causal network models for predicting - and potentially steering - behavior of people in social groups.

Further research can be done comparing the two given data on both alcohol and tobacco use on the same measure precision scale. Future research in this field would benefit if one of the biggest issues in the field is tackled: a lack of longitudinal data sets containing fine-grained data points on human behavior. The Glasgow subject-data set used in this study is valuable, but may as well be considered too outdated to develop present-day policies aimed at reduction of smoking among subjects, as it has been created years ago. Although it is useful for measuring the usability of approaches as done in this study, the results have to be replicated using more recent, and if possible, more fine-grained data before the findings of this study are turned into actions.

The adaptive temporal-causal network model presented here has an origin in [10, Chap. 11], just like the work reported in [11]. However, in the current work a different interpretation of the more becomes more principle was used, according to which the available connection weights are added to each other, after which a logistic function is applied. In [11] not a sum but the average was used of the available connections. That interpretation means that the connection is adapted to the average weight over the other connections. For example, more connections may have a decreasing effect when their weight is below the average of the weights of the other connections. In the approach in the current paper every extra connection has an additional positive effect. Another difference is that in the current paper, for the homophily principle a quadratic function in the difference between two states is used, whereas in [11] a linear function was used. Yet another difference is that in the current paper the data both for alcohol and for smoking have been considered, whereas in [11] only the data for alcohol were considered. For further refinements of the model, also more specific models for the contagion effects can be included, for example using inspiration from [13].

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