VRIJE UNIVERSITEIT AMSTERDAM

VU Research Portal

An adaptive temporal-causal network for representing changing opinions on music releases

van Gerwen, Sarah; van Meurs, Aram; Treur, Jan

published in
Distributed Computing and Artificial Intelligence, 15th International Conference [2018]
2019

DOI (link to publisher)
10.1007/978-3-319-94649-8_42

document version
Publisher's PDF, also known as Version of record

document license
Article 25fa Dutch Copyright Act

An Adaptive Temporal-Causal Network for Representing Changing Opinions on Music Releases

Sarah van Gerwen, Aram van Meurs, and Jan Treur(✉)

Behavioural Informatics Group, Vrije Universiteit Amsterdam, Amsterdam, Netherlands
sarahvangerwen@hotmail.com, aramvanmeurs@hotmail.com, j.treur@vu.nl

Abstract. In this paper a temporal-causal network model is introduced representing a shift of opinion about an artist after an album release. Simulation experiments are presented to illustrate the model. Furthermore, mathematical analysis has been done to verify the simulated model and validation by means of an empirical data set and parameter tuning has been addressed as well.

1 Introduction

For many people, music is an important part of daily life. Music can be useful in many situations. While entertainment immediately comes to mind as a primary function of music, it can also provide relief, distraction or emotional engagement (Lundqvist et al. 2008).

Because of the potential impact an artist, album or even a single song can have on someone, it is not surprising that strong fandoms can arise even from a single release. A fan of a specific artist has likely been influenced significantly by one or more releases in the artist's discography. As a result of this, fans do not only tend to monitor the artist's activity in the music business more closely, but they are also likely to have higher expectations of any new music releases that an artist may release in the future.

However, an artist may not always be able to live up to these expectations. They may 'lose their touch' over time, or release new material that is not in line with the expectations set by the artist's core fan base. In such a situation, part of the fan base may publicly declare their dislike for the new released material. In turn, they are likely to influence other members of the fan base as well. In the current era of easy digital communication through social media platforms such as Twitter, Facebook or Youtube, it is very easy to declare an opinion that is public and can be read by a potentially large amount of people. In this paper, we will research this phenomenon in social networks through an analysis and simulation of such situations.

The modeling approach used is the Network-Oriented Modeling approach described in (Treur 2016; 2017). This approach makes use of temporal-causal networks as a vehicle, enabling to model dynamic and adaptive aspects of networks. The network model presented here incorporates both social contagion and network evolution in the sense that network connections change over time by a homophily principle (Byrne

F. De La Prieta et al. (Eds.): DCAI 2018, AISC 800, pp. 357–367, 2019.
https://doi.org/10.1007/978-3-319-94649-8_42

1986; McPherson et al. 2001), which makes connections stronger when persons are more alike and weaker when they are less alike; see also (Mislove et al. 2010; Steglich et al. 2010; Sharpanskykh and Treur 2014; Macy et al. 2003).

In the paper, first in Sect. 2 the Network-Oriented Modeling approach is briefly summarized. Section 3 introduces the temporal-causal network that was designed. Section 4 discusses some simulation results. In Sect. 5 it is discussed how the model was verified by Mathematical Analysis. Section 6 shows how the model was validated by empirical data and parameter tuning. Finally, Sect. 7 is a discussion.

2 The Network-Oriented Modeling Approach Used

In this section the Network-Oriented Modeling approach used described in (Treur 2016), is briefly explained. This Network-Oriented Modeling approach is based on adaptive temporal-causal networks. Causal modeling, causal reasoning and causal simulation have a long tradition in AI; e.g., (Kuipers and Kassirer 1983; Kuipers 1984; Pearl 2000). The Network-Oriented Modeling approach described in (Treur 2016) can be viewed both as part of this causal modeling tradition, and from the perspective on mental states and their causal relations in Philosophy of Mind (e.g., (Kim 1996)). It is a widely usable generic dynamic AI modeling approach that distinguishes itself by incorporating a dynamic and adaptive temporal perspective, both on states and on causal relations. This dynamic perspective enables modeling of cyclic and adaptive networks, and also of timing of causal effects. This enables modelling by adaptive causal networks for connected mental states and for evolving social interaction.

As discussed in detail in (Treur 2016), Chap. 2, temporal-causal network models can be represented at two levels: by a conceptual representation and by a numerical representation. These model representations can be used not only to display graphical network pictures, but also for numerical simulation. Furthermore, they can be analyzed mathematically and validated by comparing their simulation results to empirical data. They usually include a number of parameters for domain, person, or social context-specific characteristics. A conceptual representation of a temporal-causal network model in the first place involves representing in a declarative manner states and connections between them that represent (causal) impacts of states on each other, as assumed to hold for the application domain addressed. The states are assumed to have (activation) levels that vary over time. In reality not all causal relations are equally strong, so some notion of *strength of a connection* is used. Furthermore, when more than one causal relation affects a state, some way to *aggregate multiple causal impacts* on a state is used. Moreover, a notion of *speed of change* of a state is used for timing of processes. These three notions are covered by elements in the Network-Oriented Modelling approach based on temporal-causal networks, and are part of a conceptual representation of a temporal-causal network model:

- **Strength of a connection** $\boldsymbol{\omega}_{X,Y}$ Each connection from a state X to a state Y has a *connection weight value* $\boldsymbol{\omega}_{X,Y}$ representing the strength of the connection, often between 0 and 1, but sometimes also below 0 (negative effect).

- **Combining multiple impacts on a state $\mathbf{c}_Y(..)$** For each state (a reference to) a *combination function* $\mathbf{c}_Y(..)$ is chosen to combine the causal impacts of other states on state Y.
- **Speed of change of a state $\boldsymbol{\eta}_Y$** For each state Y a *speed factor* $\boldsymbol{\eta}_Y$ is used to represent how fast a state is changing upon causal impact.

Combination functions can have different forms, as there are many different approaches possible to address the issue of combining multiple impacts. The applicability of a specific combination rule for this may depend much on the type of application addressed, and even on the type of states within an application. Therefore the Network-Oriented Modelling approach based on temporal-causal networks incorporates for each state, as a kind of parameter, a way to specify how multiple causal impacts on this state are aggregated. For this aggregation a number of standard combination functions are made available as options and a number of desirable properties of such combination functions have been identified (see Treur 2016, Chap. 2, Sects. 2.6 and 2.7), for example, the scaled sum function with scaling factor $\lambda > 0$:

$$\mathbf{ssum}_\lambda(V_1 + \ldots + V_k) = (V_1 + \ldots + V_k)/\lambda$$

A conceptual representation of temporal-causal network model can be transformed in a systematic or even automated manner into a numerical representation of the model as follows (Treur 2016, Chap. 2):

- at each time point t each state Y in the model has a real number value in the interval [0, 1], denoted by $Y(t)$
- at each time point t each state X connected to state Y has an impact on Y defined as $\mathbf{impact}_{X,Y}(t) = \boldsymbol{\omega}_{X,Y}\, X(t)$ where $\omega_{X,Y}$ is the weight of the connection from X to Y
- The *aggregated impact* of multiple states X_i on Y at t is determined using a *combination function* $\mathbf{c}_Y(..)$:

$$\begin{aligned}\mathbf{aggimpact}_Y(t) &= \mathbf{c}_Y(\mathbf{impact}_{X_1,Y}(t), \ldots, \mathbf{impact}_{X_k,Y}(t)) \\ &= \mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t))\end{aligned}$$

  where X_i are the states with outgoing connections to state Y
- The effect of $\mathbf{aggimpact}_Y(t)$ on Y is exerted over time gradually, depending on speed factor η_Y:

$$Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y[\mathbf{aggimpact}_Y(t) - Y(t)]\Delta t$$

$$\text{or} \quad \mathbf{d}Y(t)/\mathbf{d}t = \boldsymbol{\eta}_Y[\mathbf{aggimpact}_Y(t)) - Y(t)]$$

- Thus, the following *difference* and *differential equation* for Y are obtained:

$$\begin{aligned}&Y(t+\Delta t) = Y(t) + \boldsymbol{\eta}_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t)) - Y(t)]\Delta t \\ &\mathbf{d}Y(t)/\mathbf{d}t = \boldsymbol{\eta}_Y[\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t)) - Y(t)]\end{aligned}$$

The above three concepts (connection weight, speed factor, combination function) can be considered as parameters representing characteristics in a network model. In a non-adaptive network model these parameters are fixed over time. But to model processes by adaptive networks, not only the state levels, but also the values of these parameters can change over time.

3 The Temporal-Causal Network Model

In the current network we will model opinions and influences according to two principles. The first principle is social contagion, which can be explained as the principle that the opinions of people who are strongly connected will become more alike over time; this is a well-known principle. The second, a bit less known principle is called homophily (Byrne 1986; McPherson et al. 2001). Homophily can be explained as the principle that people whose opinions are more alike will become more strongly connected over time; in this way the network becomes adaptive. When a network follows both these principles, it creates a circular effect.

For the sake of simplicity, all persons are initially randomly connected in our network. Furthermore, two nodes will be added that are connected to all other nodes but are not affected by the homophily principle. One node will represent the overall opinion by summing the values of all nodes. The other node symbolizes the release of the album. This node will represent a sentiment, one can see it as the definition of the way the album is received i.e. if the album is received negatively the value of this node will be low, if the album is received positively the value of this node will be high. The value of this node stays constant over time for simplicity sake. See Fig. 1 for the conceptual representation.

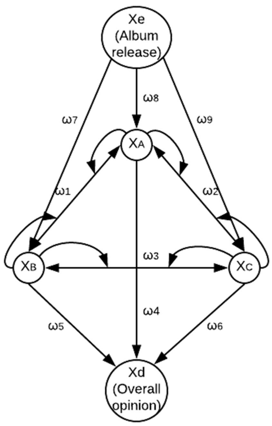

Fig. 1. Conceptual representation of the temporal-causal network model

A numerical representation of the social contagion part of the model, using the scaled sum function as combination function to calculate the aggregated impact, is as follows.

A. Modeling *social contagion* between the states X_B:

- Difference equation:

$$X_B(t+\Delta t) = X_B(t) + \boldsymbol{\eta}_{X_B}[\mathbf{c}_{X_B}(\boldsymbol{\omega}_{X_{A_1},X_B}X_{A_1}(t), \ldots, \boldsymbol{\omega}_{X_{A_k},X_B}X_{A_k}(t)) - X_B(t)]\,\Delta t$$

- Choosing combination function $\mathbf{ssum}_{\lambda}(..)$ with scaling factor $\lambda = \omega_{XB} = \boldsymbol{\omega}_{X_{A_1},X_B} + \ldots + \boldsymbol{\omega}_{X_{A_k},X_B}$ provides the following difference equation for $X_B(t)$:

$$\begin{aligned} X_B(t+\Delta t) &= X_B(t) + \boldsymbol{\eta}_{X_B}[\mathbf{ssum}\lambda(\boldsymbol{\omega}_{X_{A_1},X_B}X_{A_1}(t), \ldots, \boldsymbol{\omega}_{X_{A_k},X_B}X_{A_k}(t)) - X_B(t)]\Delta t \\ &= X_B(t) + \boldsymbol{\eta}_{X_B}[(\boldsymbol{\omega}_{X_{A_1},X_B}X_{A_1}(t) + \ldots + \boldsymbol{\omega}_{X_{A_k},XB}X_{A_k}(t))/\omega_{X_B} - X_B(t)]\Delta t \end{aligned}$$

- The corresponding differential equation is:

$$\mathbf{d}X_B(t)/\mathbf{d}t = \boldsymbol{\eta}_{X_B}[(\boldsymbol{\omega}_{X_{A_1},X_B}X_{A_1}(t) + \ldots + \boldsymbol{\omega}_{X_{A_k},X_B}X_{A_k}(t))/\omega_{X_B} - X_B(t)]$$

B. Modeling the *dynamics of the adaptive connection weights* ω, from X_A to X_B:

- Difference equation:

$$\begin{aligned} \omega_{X_A,X_B}(t+\Delta t) =& \omega_{X_A,X_B}(t) \\ & + \boldsymbol{\eta}_{\omega_{X_A,X_B}}[\mathbf{c}_{\omega_{X_A,X_B}}(X_A(t), X_B(t), \omega_{X_A,X_B}(t)) - \omega_{X_A,X_B}(t)]\,\Delta t \end{aligned}$$

- Choosing combination function $\mathbf{c}_{\omega_{X_A,X_B}}(..) = \mathbf{slhom}_{\alpha,\tau}(..)$:

$$\mathbf{slhom}_{\alpha,\tau}(V_1, V_2, W) = W + \alpha\, W(1 - W)\,(\tau - |V_1 - V_2|)$$

  provides the following difference equation for $\omega_{X_A,X_B}(t)$:

$$\begin{aligned} \omega_{X_A,X_B}(t+\Delta t) =& \omega_{X_A,X_B}(t) \\ & + \eta_{\omega_{X_A,X_B}}[\mathbf{slhom}_{\alpha,\tau}(X_A(t), X_B(t), \omega_{X_A,X_B}(t)) - \omega_{X_A,X_B}(t)]\,\Delta t \\ \omega_{X_A,X_B}(t+\Delta t) =& \omega_{X_A,X_B}(t) \\ & + \eta_{\omega_{X_A,X_B}}[\alpha\,\omega_{X_A,X_B}(t)(1 - \omega_{X_A,X_B}(t))(\tau - |X_A(t) - X_B(t)|)]\,\Delta t \end{aligned}$$

- The corresponding differential equation is:

$$\mathbf{d}\omega_{X_A,X_B}(t)/\mathbf{d}t = \eta_{\omega_{X_A,X_B}}[\alpha\,\omega_{X_A,X_B}(t)(1 - \omega_{X_A,X_B}(t))\,(\tau - |X_A(t) - X_B(t)|)]$$

4 Simulation Results

A first example scenario that was simulated in Python using the introduced model is as follows. Here, the scenario is that an album was received negatively but the overall opinions of people were not harshly affected by this. For this simulation, the model was set up for 100 persons, all interconnected with each other with values for the connection weights randomly assigned. Parameter settings are presented in Fig. 2. Initial values were set randomly. See Fig. 2 for a graph of the outcomes for the state values (For parameter values, see Table 1).

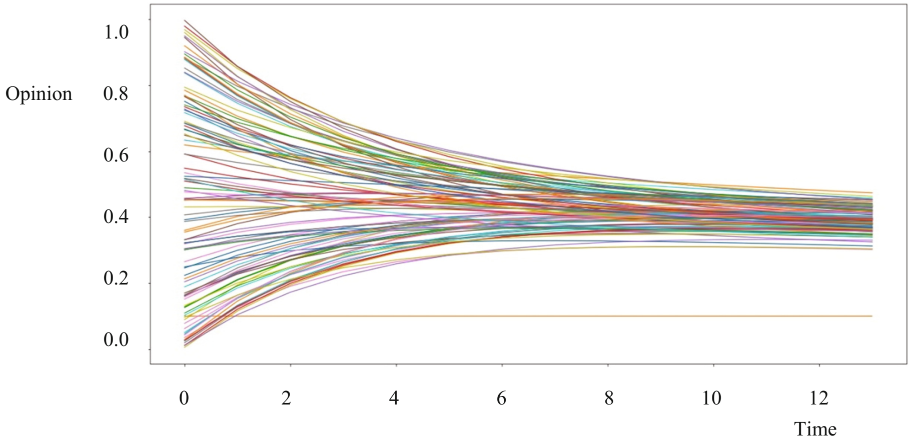

Fig. 2. Graphical representation of an example simulated scenario

Table 1. Parameter settings

Parameters	α	η_X	η_ω	τ	time	Δt
Values	0.5	0.5	0.5	0.05	14	0.5

The final network was also analyzed. Because all 102 nodes (except the overall opinion node and the album node) were interconnected in both directions, only modularity was examined. It was expected that subgroups would be found due to the homophily principle and social contagion principle. When people were more alike their connections became stronger, and the connections became weaker when they were different thus giving the opportunity for groups to arise. But the expectation was that modularity would be low due to the fact that all nodes were initially interconnected randomly and initial state values were set randomly. Modularity was 0.042 and four communities were found. These findings were in accordance with the expectations.

5 Verification of the Network Model by Mathematical Analysis

The behaviour of both parts of the model was mathematically verified, by analysing stationary points. A state Y has a stationary point at t if $\mathbf{d}Y(t)/\mathbf{d}t = 0$. The following criterion is useful; for more details, see (Treur 2016, Chap. 12; Treur 2017).

Criterion In a temporal-causal network model a state Y has a stationary point at t if and only if $\mathbf{c}_Y(\boldsymbol{\omega}_{X_1,Y}X_1(t), \ldots, \boldsymbol{\omega}_{X_k,Y}X_k(t)) = Y(t)$.

First, the social contagion part of the model was verified by using the above criterion. The state that has been verified is the overall-opinion node. See Table 2 for the overview for this state and Table 3 for the connections. The second row shows the time point considered, the third row the simulated state value at that time point (right hand side of the above criterion). The third row shows the outcome of the aggregated impact of the other states on this state (left hand side of the above criterion). The last row shows the difference between the two rows above it (the difference between left hand side and right hand side of the above criterion). The stationary point was accurate because the deviation was less than 0.01.

Table 2. Mathematical analysis of stationary point for the overall-opinion node

	Overall-opinion node
Time point	75
State value	0.25
Aggregated impact	0.24409
Deviation	0.00591

Secondly, in a similar manner the homophily part of the model was verified by again looking at stationary points. Here, according to the above criterion a connection $\omega_{XA,XB}$ is stationary at a point t in time if and only if $\omega_{X_A,X_B}\,(1 - \omega_{X_A,X_B})\,(\tau - |X_A(t) - X_B(t)|) = 0$. For every cluster of the simulated model, as presented in Fig. 2, one connection within each group has been verified. Furthermore, for every group, connections between groups have been verified. See Table 3 for the results. All stationary points were accurate (absolute deviation < 0.01).

Next, it is shown how the equilibrium values for the connection weights were determined by solving the equilibrium equations. Recall that the combination function for chosen homophily was $\mathbf{slhom}_{\alpha,\tau}(..)$. Therefore the criterion for a stationary point of ω_{X_A,X_B} is

$$\alpha\,\omega_{X_A,X_B}(t)\,(1 - \omega_{X_A,X_B}(t))\,(\tau - |X_A(t) - X_B(t)|) = 0$$
$$\omega_{X_A,X_B}(t) = 0 \text{ or } \omega_{X_A,X_B}(t) = 1 \text{ or } |X_A(t) - X_B(t)| = \tau$$

It was indeed found in the simulation experiments that in an equilibrium state all connection weights have one of these three values. Actually, only the values 0 and 1 occurred. The third option does not occur in simulations; it turns out non-attracting.

Table 3. Mathematical analysis of stationary points for connections in different groups

	ωs037, s053	ωs051, s002	ωs008, s060	ωs004, s027
Group	Green	Red	Blue	Purple
Time Point	199	147	199	148
τ	0.05	0.05	0.05	0.05
A	0.7533396	0.41653445752	0.732069432	0.37019925
B	0.7462730	0.4665799073	0.753700675	0.3170979
$\omega_{XA,XB}$	0.9735395	0.9947619214	0.99904304	0.3170979
Deviation	0.00006	-0.00000002	0.00002	-0.00002
Green	ω_s001, s003	ω_s001, s075	ω_s001, s017	
Group	Red	Blue	Purple	
Time point	199	199	199	
τ	0.05	0.05	0.05	
A	0.7550216029699692	0.7550216029699692	0.7550216029699692	
B	0.0706582564182544	0.31859763865295626	0.37415177835490465	
$\omega_{XA,XB}$	0.0013878034662381867	0.0071999214810507407	0.0057620295145630971	
Deviation	−0.0006	−0.0013	−0.008	
Red	ω_s003, s096	ω_s003, s009	ω_s003, s011	
Group	Blue	Green	Purple	
Time point	199	199	199	
τ	0.05	0.05	0.05	
A	0.0706582564182544	0.0706582564182544	0.0706582564182544	
B	0.7339988291681084	0.7525078027695329	0.7655270352677902	
$\omega_{XA,XB}$	0.00061083816794847766	0.003810955419157624	0.0049627422806713751	
Deviation	−0.0002	−0.0018	−0.0024	
Blue	ω_s021, s004	ω_s021, s100	ω_s021, s043	
Group	Purple	Red	Green	
Time point	185	152	151	
τ	0.05	0.05	0.05	
A	0.5643423754280926	0.40710342094874463	0.40240624936064046	
B	0.4985616546776945	0.45795017406714145	0.4529622564974337	
$\omega_{XA,XB}$	0.98564508572479936	0.99694175836884025	0.93834989764832599	
Deviation	−0.00003	−0.0000003	−0.000003	
Purple	ω_s027, s022	ω_s027, s065	ω_s027, s015	
Group	Green	Red	Blue	
Time point	199	199	199	
τ	0.05	0.05	0.05	
A	0.3406215358493736	0.3406215358493736	0.3406215358493736	
B	0.7123216865241855	0.7431349070323119	0.7538605497167643	
$\omega_{XA,XB}$	0.066607495201250019	0.025797442526141176	0.027427080454125591	
Deviation	−0.0084	−0.004	−0.0045	

6 Validation Using Empirical Data and Parameter Tuning

To validate the introduced model, a real life example was sought after. This example was the release of Eminem's new album, which is called "Revival". The focus was on the appreciation of this album. The release of this album was accompanied by very negative opinions and reviews, especially compared to Eminem's previous album release. Since the opinions about this new album were so vastly different from the preceding general opinions about Eminem, this seemed to be a good use case for validating the model. Data about the opinions on this album was collected by using the Twitter API. Twitter was used as the preferred social network, since it is a platform where people can very easily express their opinions about specific subjects. Since hashtags are very commonly used by Twitter users, it is easy for anyone to chime in and say something about any subject they desire. Additionally, these opinions can then be read by anyone who is interested in that hashtag. This makes Twitter an ideal platform for expressing opinions.

A Python script was written in order to interact with Twitter's API to collect relevant tweets about Eminem's 'Revival' album. To do this, the Python script was ordered to search for any tweets containing the hashtag '#Revival' during two different time spans. We wanted to measure opinions about the album both before and after the album was released on 15-12-2017. Therefore, the following time spans were used: before release (12-12-2017 to 14-12-2017), and after release (16-12-2017 to 18-12-2017). Ideally, longer time spans would be used. However, this was not possible due to the Twitter API's 7-day search limit. The search returned 175 results before the album's release, and 464 results after the release, all labeled with their sender. These tweets were then analysed using NLTK's sentiment analysis module. The results of this analysis are displayed in Table 4. The difference between the positive tweets and negative tweets from before the album release and after was not very large. Still, a small difference was found. Therefore, this data was still used to validate the network model by parameter tuning. Due to data-retrieval-constraints, connections between the different senders could not be identified. Therefore, all nodes were randomly connected with each other as they were in the previous simulation. Initial values were set to represent the attitudes before the release, 8 people received a value below the 0.5 while the others received a value above the 0.5, again randomly assigned. The album release node represented the negative impact. The value assigned to represent this negative sentiment was 0.35.

Using exhaustive search (with grain size 0.05), the optimal value of the speed factor for the contagion part of the model was identified, which was 0.6. As a result, the graphical representation presented in Fig. 3 was obtained.

Table 4. Data collected from Twitter API search and sentiment analysis

	Before release	After release
Positive tweets	160	410
Negative tweets	15	54
Negativity percentage	8.6%	11.6%

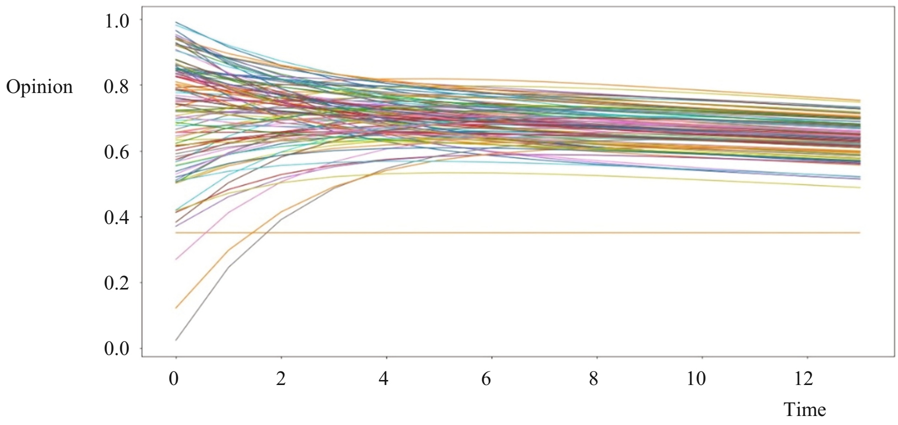

Fig. 3. Graphical representation of simulation of the final model

7 Discussion

In this paper a temporal causal network has been introduced representing a shift of opinion after an album release. One initial simulation experiment has been done. Furthermore, mathematical analysis has been done to verify the simulated model and validation by means of an empirical data set and parameter tuning has been addressed. The data set had some limitations as only data about states over time were available and no data about connections over time.

The Network-Oriented Modeling approach used is based on adaptive temporal-causal networks. Causal modeling has a long tradition in AI; e.g., (Kuipers and Kassirer 1983; Kuipers 1984; Pearl 2000). The Network-Oriented Modeling approach based on temporal-causal networks described in (Treur 2016) can be viewed as part of this causal modeling tradition. In (Treur 2017) it is shown that it is a widely usable generic dynamic modeling approach that distinguishes itself by incorporating a dynamic and adaptive temporal perspective, both on states and on causal relations. This dynamic perspective enables modeling of cyclic and adaptive networks, and also of timing of causal effects. This enables modelling by adaptive causal networks for connected mental states and for evolving social interaction. The model presented in the current paper shows these dynamics and adaptivity. In contrast to other literature such as (Mislove et al. 2010; Steglich et al. 2010; Sharpanskykh and Treur 2014; Macy et al. 2003) the work presented in the current paper addresses application to music appreciation and social media. Note that in the model the album-release node has a constant value for simplifying reasons though it could very well be imaginable that this sentiment shifts according to the overall opinion. Future research could therefore add a relation between these two nodes.

References

Byrne, D.: The attraction hypothesis: Do similar attitudes affect anything? J. Pers. Soc. Psychol. **51**, 1167–1170 (1986)

Kim, J.: Philosophy of Mind. Westview Press, Boulder (1996)

Kuipers, B.J.: Commonsense reasoning about causality: deriving behavior from structure. Artif. Intell. **24**, 169–203 (1984)

Kuipers, B.J., Kassirer, J.P.: How to discover a knowledge representation for causal reasoning by studying an expert physician. In: Proceedings of the 8th International Joint Conference on Artificial Intelligence, IJCAI 1983, Karlsruhe. William Kaufman, Los Altos, CA, pp. 49–56 (1983)

Lundqvist, L.O., Carlsson, F., Hilmersson, P., Juslin, P.N.: Emotional responses to music: experience, expression, and physiology. Psychol. Music **37**, 61–90 (2008)

Macy, M., Kitts, J.A., Flache, A.: Polarization in dynamic networks: a hopfield model of emergent structure. In: Dynamic Social Network Modeling and Analysis, pp. 162–173. National Academies Press, Washington, DC (2003)

McPherson, M., Smith-Lovin, L., Cook, J.M.: Birds of a feather: homophily in social networks. Annu. Rev. Sociol. **27**(1), 415–444 (2001)

Mislove, A., Viswanath, B., Gummadi, K.P., Druschel, P.: You are who you know: inferring user profiles in online social networks. In: Proceedings of the WSDM 2010, New York City, New York, USA, pp. 251–260 (2010)

Pearl, J.: Causality. Cambridge University Press, Cambridge (2000)

Sharpanskykh, A., Treur, J.: Modelling and analysis of social contagion in dynamic networks. Neurocomputing **146**, 140–150 (2014)

Steglich, C.E.G., Snijders, T.A.B., Pearson, M.: Dynamic networks and behavior: separating selection from influence. Sociol. Methodol. **40**, 329–393 (2010)

Treur, J.: Network-Oriented Modeling: Addressing Complexity of Cognitive, Affective and Social Interactions. Springer Publishers, Cham (2016). https://doi.org/10.1007/978-3-319-45213-5

Treur, J.: On the applicability of network-oriented modeling based on temporal-causal networks: why network models do not just model networks. J. Inf. Telecommun. **1**(1), 23–40 (2017)