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Survey on a Model for Examining the Role of Nodal Attributes in Dynamic Social Media Networks Using Natergm

C RAVI KISHORE REDDY [*1], ERANTI MOUNIKA[2]

[*1] ASSISTANT PROFESSOR,DEPARTMENT OF MCA, VIGNAN'S LARA INSTITUTE OF TECHNOLOGY&SCIENCE, VADLAMUDI, GUNTUR, ANDHRA PRADESH, INDIA.
[2]MCA STUDENT, DEPARTMENT OF MCA, VIGNAN'S LARA INSTITUTE OF TECHNOLOGY&SCIENCE, VADLAMUDI, GUNTUR, ANDHRA PRADESH, INDIA

ABSTRACT

Social media networks are dynamic. All things considered, the request in which organize ties create is an imperative part of the system flow. This examination proposes a novel dynamic system demonstrate, the Nodal Attribute-based Temporal Exponential Random Graph Model (NATERGM) for dynamic system investigation. The proposed demonstrate centers around how the nodal traits of a system influence the request in which the system ties create. Worldly examples in social media networks are demonstrated in light of the nodal qualities of people and the time data of system ties. Utilizing social media information gathered from a knowledge sharing group, observational tests were led to assess the execution of the NATERGM on distinguishing the transient examples and foreseeing the qualities without bounds networks. Results demonstrated that the NATERGM showed an improved example testing ability and an expanded expectation precision of system attributes contrasted with benchmark models. The proposed NATERGM show clarifies the parts of nodal qualities in the arrangement procedure of dynamic networks.

Keywords: Social networking, graphs and networks, web mining, knowledge sharing

I.INTRODUCTION

Social media networks are developing on the web networks that basically associate people. These networks con-sist of hubs that speak to singular social media clients and ties that speak to different connections between the clients. Cases of social media networks incorporate online companionship networks [1], [2], following-adherent networks [3], and content sharing networks [4], [5]. The connections between the online clients are regularly open data, which gives chances to utilizing social system investigation (SNA) to better understand how and why people set up social associations online [6]. Subsequently, a developing number of studies have utilized SNA to look at social media networks [7], [4], [8], [5], [9].

Social media networks have two essential qualities. Initially, they are dynamic in nature. System ties create in a request, however not all the while. All things considered, connections between people may change after some time. Second, social media clients vary in different properties, for example, sex, useful part in online groups, and notoriety. Therefore, social media networks are multimode networks [10], [11] and distinctive hub writes exist in the system. An outcome of these two qualities is that the apparently same system examples can come about because of various system arrangement forms, contingent upon the request in which the system ties create. For instance, Fig. 1 shows two procedures in shaping a two-star design. Here, we expect that the dark hubs speak to very dynamic people (e.g., people who every now and again come on the web and leave messages) in online groups and the numbers beside organize ties demonstrate the request in which the connections create. The Pattern A delineates a procedure where very dynamic people are organized over others when creating connections, while the example B shows the contrary inclination. On the off chance that the request in which the system ties create is disregarded, we can't separate between these two examples and understand how very dynamic people take part in the dynamic procedure of system development.

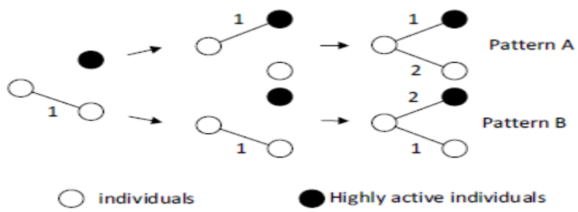


Fig. 1. Different Processes Leading to the Same Network Pattern

Differentiating between various temporal patterns is thus critical to understand the formation mechanisms of social media networks. However, current social network research usually adopts a static view of networks based on the assumption that all network ties have developed con-currently upon observation. This assumption, while con-tributing to simplicity and being useful for identifying static patterns of networks, leads to reduced representa-tion of real social media networks. As a result, the ability of social network analysis to identify network patterns may be negatively affected. The problem can further re-duce the practical value of social network analysis to un-derstand various network phenomena in social media con-texts.

In this study, we propose a novel dynamic network model, the Nodal Attribute-based Temporal Exponential Random Graph Model (NATERGM), for dynamic network analysis. NATERGM is an extension of TERGM [12] and focuses on how nodal attributes of networks affect the or-der in which network ties develop. The proposed model extracts nodal attributes of individuals and time infor-mation of network ties from social media networks, based on which various temporal patterns are modeled and their likelihoods of occurrence are estimated. Extending prior work [13], with empirical data we demonstrate that NA-TERGM provides an enhanced pattern testing capability compared to TERGM. Moreover, NATERGM is able to pre-dict the characteristics of social media networks in future and we show that our approach outperforms TERGM-based prediction models. The major objective of this study is to provide a framework to explore, analyze, and explain the formation mechanisms of social media networks.

II.RELATED WORK

In this segment we first audit late investigations examining so-cial media networks. At that point, we audit developing system models for dynamic system examination.

2.1 Social Media Networks

In view of a hypothetical conceptualization of system ties [14], four sorts of social media organize ties have been outlined in earlier research [6]. Vicinity ties speak to that two people have a place with a similar sub-groups (e.g., Facebook Group) or locational zones. Social connection ties speak to social associations between people, for example, virtual companionships and membership connections in mi-cro-blogging destinations [15], [16]. Connection ties speak to between dynamic practices between people, for example, data trades through message answers [17]. Stream ties speak to the development of products or data between organize hubs, for example, retweets.

A few analysts have contended that these sorts of ties are not really decoupled, but rather speak to a continuum [18]. For instance, vicinity may additionally prompt social relations; collaborations and streams of knowledge may happen in the meantime.

Social media networks have been contemplated for various purposes. When all is said in done, the examination goals of these investigations can be grouped into three classifications. The main stream of research centers around clarifying system instruments. This kind of research goes for understanding in what conditions people will probably set up social associations on the web. For instance, statistic homophily was found to exist in online fellowship networks [19]. Understudies of a similar sexual orientation, major, and habitation territory will probably set up social associations in Facebook kinship networks. Earlier research has likewise discovered that immediate correspondence, circuitous correspondence, and special connection happen every now and again in online web gatherings [20]. The second stream of research looks at how the structure of a social media arrange influences the results of people in the system. This sort of research is alluded to as basic capital investigations [21]. For instance, an examination of kinship networks in an online small scale loaning stage prompted disclosures that the odds of effective financing were fundamentally influenced by the quantity of fellowship ties and by the kinds of companionship [2]. Research has discovered that people in an associated organize can anticipate results of a given issue all the more precisely, contrasted with the situations when they are detached [22]. Another famous research region is to segment the system into sub-graphs and recognize sub-groups. These investigations for the most part go for distinguishing key gatherings or players in the system and understanding the qualities of these sub-groups. For instance, in light of centrality and coreness measures, center gatherings and key individuals in the center gathering who were most dynamic were distinguished in a clinical talk discussion [17]. Another investigation recognized Twitter client bunches from following-devotee networks in Twitter.com and analyzed the impact of intra-aggregate ties, between amass ties, and middle person ties on retweeting practices [3].

Previous studies focusing on community detection mainly use clustering or modularity optimization algo-rithms [23]. In structural capital studies, regression analy-sis has been frequently used to examine the relationships between network structures and individual outcomes. De-pendent variables are the outcomes of network nodes, such as funding success [2] and online users' activity levels [16]. Independent variables can be various network metrics of the nodes, such as degree centrality, betweenness central-ity [24], and structural holes [25]. To explain the mecha-nisms of network formation, network models can be used, such as the Latent Space Model [26], p1 models [27], and the Exponential Random Graph Model [28]. In social me-dia network research, ERGM has received increased atten-tion recently [20], [19], [29]. ERGMs are statistical models that test whether observed networks show theoretically hypothesized structural tendencies [30], [28]. These struc-tural tendencies, or configurations, are subsets of nodes and ties in the network, reflecting certain types of network sub-structures. Examples of typical configurations can be "triangle" and "k-star" [31], [32]. In addition, nodal attrib-utes can be incorporated in a configuration. Equation (1) specifies the expression of ERGM, where YY is a matrix of random variables representing network ties and yy is its re-alization; $\eta\eta AA$ is a parameter corresponding to configuration A, positively related to the likelihood of configuration A to occur; $ggAA(yy)$ is network statistics corresponding to A; $\kappa\kappa$ is a normalizing constant ensuring that $\Pr(YY)$ is a probabilistic distribution.

$$\Pr(Y = y) = \left(\frac{1}{\kappa}\right) \exp\left\{\sum_{A} \eta_A \, g_A(y)\right\} \qquad (1)$$

Given an observed network, the primary task of ERGM is to examine which configurations appeared statistically more than by chance. If a parameter $\eta\eta AA$ is estimated to be significant, it will suggest that the corresponding configu-ration has better chances to occur in the network, which further suggests that the corresponding effect plays an im-portant role in the formation process of the network.

Although various analytical methods have been used to study social media networks, studies that address the dy-namics of social media networks are still scarce. Only a few studies have taken into account the time information relat-ing to when network ties are developed. For instance, Shriver et al. [16] considered the number of friendship ties at previous time points in their time series regressions. An-other study analyzed the order in which retweeting links were activated in micro-blogging sites, and found that the extent to which an individual could reach other parts of the network positively affected the popularity of the content posted by that individual [33]. Overall, the dynamics of so-cial media networks have been addressed in few prior studies. Nevertheless, dynamic network analysis is an emerging area of network research, and relevant studies have been conducted in biology, neural science, healthcare, and social science domains. We review existing dynamic network analysis approaches next.

2.2 Dynamic Network Analysis

Generally, two different approaches can be used for dy-namic network analysis. Cross-sectional approaches ana-lyze network data where time information is embedded within the network. Longitudinal approaches observe net-works at multiple time points and track the evolution of networks based on comparisons [10]. Previous research has proposed various dynamic network models, including both types of approaches, for studying the dynamic pro-cess of network formation, evolution, and dissolution. We review selected dynamic network models next.

Temporal Exponential Random Graph Model (TERGM) is an extension of the ERGM for dynamic networks [34], [12], [35]. A simple TERGM model under the first-order Markov dependency can be written as:

$$\Pr(Y^t = y^t | Y^{t-1} = y^{t-1}) = \left(\frac{1}{\kappa(y^{t-1})}\right) \exp\left\{\sum_{A} \eta_A \, g_A(y^t, y^{t-1})\right\} \qquad (2)$$

Note that the major difference between (1) and (2) is the specification of network statistics for each temporal pat-tern A, which is now determined by network realizations in multiple observational time points (observed at t and t-1 in this case). Given multiple observations, TERGM can be used to test whether a certain temporal pattern is more likely to occur than by chance. For example, as illustrated in Fig. 2, three different temporal patterns can be derived from a transitivity pattern, depending on the order in which the three ties develop. Compared to the conven-tional ERGM where only a tendency for transitivity can be tested, TERGM differentiates between three different dy-namic patterns of network ties formation which all finally lead to the same transitivity structure in (a). TERGM can further test the likelihood of each temporal pattern to occur.

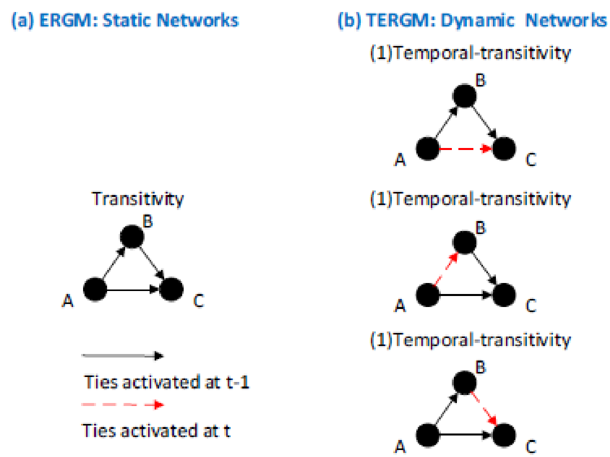


Fig. 2. Three Different Temporal Patterns Derived From Transitivity

In addition to the transitivity in this example, TERGM can also include network configurations of many other types such as temporal stability and temporal reciprocity [12], [36]. TERGM can also be applied to cross-sectional data if time duration information for network ties is pro-vided. However, none of the TERGM research has consid-ered how nodal attributes can affect the order in which net-work ties develop.

Separable Temporal Exponential Random Graph Model (STERGM) separates TERGM into a formation model and a dissolution model, thereby modeling not only the tem-poral patterns of network formation, but also the temporal patterns of network dissolution [37], [38], [36]. STERGM addresses the concern that some existing network ties might disappear over time, such as a broken friendship, for example. STERGM identifies new connections and dis-solved ties by comparing networks at multiple time points. A variant of STERGM for cross-sectional data is also pro-posed for the case when longitudinal data is unavailable [38].

Hidden Temporal Exponential Random Graph Model (HTERGM) is a model that combines TERGM with hidden Markov models [34]. It assumes that (1) network structure at time t, Yt, is dependent on the structure of the network in the previous time point Yt-1, and (2) nodal attributes of the network, xt, are dependent on the network structure Yt. It further assumes that only nodal attributes are observa-ble, while network structures are hidden states. The major aim of HTERGM is to estimate the transition probabilities P(Yt|Yt-1) and emission matrices Λ = P(xt|Yt) so that hid-den network structures can be inferred given time series of nodal attributes x1, x2, …, xt. However, HTERGM does not explain how nodal attributes affect the formation process of networks.

Temporally Randomized Reference Models (TRRM) in-vestigates the dynamic characteristics of networks by com-paring observed networks with an ensemble of temporally randomized networks [39], [40], [41]. Temporal randomi-zation generates new networks by rewiring ties in the orig-inal networks or changing time information associated with the ties. Typical randomization methods include ran-domized edges, randomly permutated times, random times, edge randomization, and time reversal [40]. Fig. 3 shows examples of randomized edges and randomly per-mutated times. By comparing original networks with tem-porally randomized networks, key dynamic characteristics of original networks can be understood. For example, Holme [39] compared e-mail networks with their tempo-rally randomized samples and found that in general the average time it took to pass information between network nodes is longer in the original email networks.

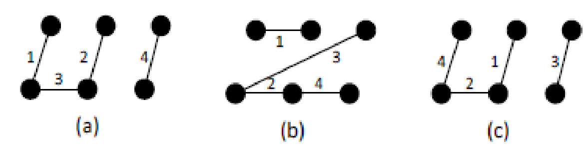


Fig. 3. Network Temporal Randomization with (a) an original network with numbers indicating the order of tie activation; (b) a randomized net-work by iteratively rewiring network ties among four selected nodes; and another randomized network by permuting the time associated with ties.

Latent space models [26] assume that each node in a net-work is associated with a latent position in a low dimen-sional space. The probabilities of tie occurrences are deter-mined by the distances between nodes in the latent space. The latent space model estimates the parameters associ-ated with latent positions based on the observed networks. The estimated model can be used to visualize a spatial rep-resentation of network relationships [26], [42]. Dynamic Latent Space Model (DLSM) is an extension of the latent space model and allows the latent positions to change over time [43], [44].

2.3 Research Gaps

Based on the prior literature, several research gaps can be identified. First, social media networks are dynamic in na-ture. However, little research has explained the mecha-nisms of network formation with a dynamic perspective. Dynamic network analysis has been frequently used to de-tect communities from networks [10], [11], but not to ex-plain the mechanisms of network formation. Most network mechanisms studies focused on identifying static network patterns, but did not explain how these patterns developed dynamically. Second, emerging network research has given rise to various approaches for examining temporal networks and has suggested that the order of network ties is an important aspect of network dynamics [12], [40], [33]. Recent TERGM models examine different dynamic pat-terns of network tie formation in dyadic and triadic rela-tionships when all the nodes are considered to be of the same type. STERGM additionally examines the order in which network ties dissolve. However, none of the existing models explain even more complex patterns created by the interactions of network tie order and nodal attributes. We need a model to carefully examine such interactions in or-der to understand how nodal attributes affect the order in which network ties develop. In addition, network predic-tion has been an under-studied research area [45]. Alt-hough prior research has helped identify dynamic network patterns, little has been done to predict future networks based on the identified patterns.

III. NODAL ATTRIBUTE-BASED TEMPORAL EXPONENTIAL RANDOM GRAPH MODEL

The proposed NATERGM focuses on how nodal attributes of networks affect the order in which network ties develop. Because the order of network ties needs to be tracked ac-curately, NATERGM examines cross-sectional network data with time information for network ties. Figure 4 pre-sents the framework of NATERGM. The major compo-nents include network extraction, temporal pattern analy-sis, and network prediction. In the network extraction step, social connections are identified between individuals in so-cial media, along with the timestamps of these relation-ships and nodal attributes of the individuals. Temporal patterns of the networks are modeled, and the likelihood of each pattern is estimated in the temporal pattern analy-sis step. Based on the estimated model, new networks are simulated and compared to the original network to evalu-ate how effectively the model can predict future networks.

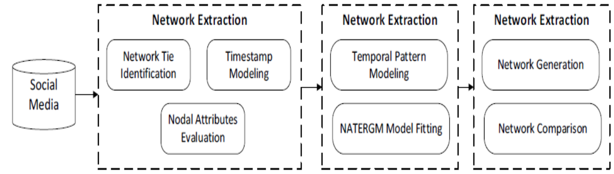


Fig. 4. NATERGM Framework

First, network ties are extracted from social media based on relationships between online users. Among the various types of social media network ties summarized by Kane et al. [6], the interaction/flow and social relation ties are the ones that are the most dynamically established (i.e., these ties are often associated with timestamps). Different types of network ties can be identified depending on specific so-cial media contexts. For example, directed interac-tion/flow ties can be established if an individual sends greetings to another individual; undirected social relation ties can be established if two individuals become friends by using friending functions provided in social media plat-forms. After identifying network ties between all possible pairs of individuals, a network with N nodes is repre-sented by a matrix Y=[Yij], (i, j =1, 2,…N). For undirected networks, Yij=1 if a tie exists between nodes (i.e., individu-als) i and j, and Yij=0 otherwise. For directed networks, Yij=1 if a tie starts from i and ends at j, and Yij=0 otherwise.

For timestamp modeling, we use Tij to represent the time when each network tie (i, j) is established. A matrix T=[Tij], (i, j =1,2,…N) records the timestamps for all net-work ties and can be used to model the order of network ties. For example, if T12<T21, it would represent a process where node 1 sent out a tie to node 2 first, and then re-ceived a tie from the node 2 in return.

Nodal attributes of individuals can be evaluated using different approaches. Prior studies have characterized in-dividual social media users based on three types of fea-tures. Platform-based features refer to individual attrib-utes that are directly provided by social media platforms. For example, registered users are often associated with usernames while an unregistered user is represented by a "visitor" tag or an IP address in the name space. Some so-cial media platforms also assign functional roles to users such as members or administrators. This type of infor-mation can be directly used as nodal attributes of individ-uals. Textual features refer to attributes that are inferred by texts posted by the individuals. Social media users typi-cally leave many textual traces, such as private messages and message postings. Various characteristics of social me-dia users can be evaluated based on these texts, such as general opinions, writing proficiency, and topics of inter-ests. Social network features refer to individual attributes that are inferred by their connections or positions in the network. Social relations between individuals in part re-flect their personality, status, and roles. For example, an in-dividual who is linked with many others is expected to have a high level of popularity compared to others who have fewer connections. Such information can thus be used as nodal attributes of individuals. After evaluating the nodal attributes of individuals, they are represented by a vector X=(x1, x2, ..., xN).

3.2 Temporal Pattern Analysis

To model temporal patterns, the nodal attributes and timestamps of network ties are used to represent various temporal patterns regarding the dynamics of network formation. By taking into account the order in which network ties develop, common static network patterns such as reciprocity, k-star, transitivity, and cyclicity can have different temporal variations. Tables 1 to 5 list examples of temporal patterns for directed networks. White nodes represent individuals in general and black nodes represent individuals with key nodal attributes (e.g., highly active individuals). Dashed arrows represent network ties that developed after solid ones.

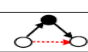
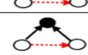
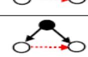
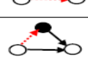
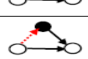
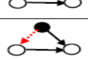
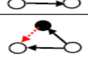
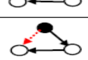
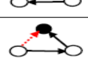
TABLE 1.
NATERGM Temporal Patterns for Directed Networks: Reciprocity

Legend: General nodes; Nodes with key attributes; Ties activated at T_1; Ties activated at T_2 ($T_1 < T_2$)

Static Pattern	Temporal Pattern	Illustration	Hypothesis
reciprocity	feedback		Nodes with some attribute have a high tendency to receive feedback.
	response		Nodes with some attribute have a high tendency to respond to incoming ties.

TABLE 2.
NATERGM Temporal Patterns for Directed Networks: Transitivity

Legend: General nodes; Nodes with key attributes; Ties activated at T_1; Ties activated at T_2 ($T_1 < T_2$)

Static Pattern	Temporal Pattern	Illustration	Hypothesis
transitivity	bridge		Nodes with some attribute have a high tendency to bridge new relationships between others.
	co-supporting		If two nodes are supporting a common node with some attribute, they have a high tendency to build a new relationship.
	co-supported		If two nodes are supported by a common node with some attribute, they have a high tendency to build a new relationship.
	remarked-supporter		A node with some attribute has a high tendency to receive attention from another node, if both co-support a common node.
	remarked-supported		A node with some attribute has a high tendency to receive attention from another node, if they are supported by a common node.
	remarking-supporter		A node with some attribute has a high tendency to pay attention to another node, if they co-support a common node.
	remarking-supported		A node with some attribute has a high tendency to pay attention to another node, if they are supported by a common node.
	follow-up		A node with some attribute has a high tendency to pay attention to another node, if a third node bridges their relationship.
	reference		A node with some attribute has a high tendency to receive attention from another node, if a third node bridges their relationship.

As can be seen from the table, the temporal patterns modeled by NATERGM provide an extended hypotheses testing capability about network formation compared to static patterns. In particular, these temporal patterns can be used to examine the roles of nodal attributes in deter-mining the order of network ties.

TABLE 3.
NATERGM Temporal Patterns for Directed Networks: K-out-star

Legend: General nodes; Nodes with key attributes; Ties activated at T_1; Ties activated at T_2 ($T_1 < T_2$)

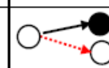
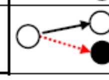
Static Pat-	Temporal Pattern	Illustra-tion	Hypothesis
k-out-star	prioritization		Nodes with some attribute have a high tendency to be prioritized when forming relationships.
	de-prioritiza-tion		Nodes with some attribute have a high tendency to be de-prioritized when forming relationships.

TABLE 4.
NATERGM Temporal Patterns for Directed Networks: K-in-star

Legend: General nodes; Nodes with key attributes; Ties activated at T_1; Ties activated at T_2 ($T_1 < T_2$)

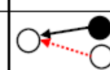
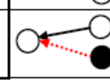
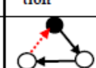
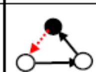
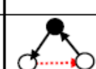
Static Pat-	Temporal Pattern	Illustra-tion	Hypothesis
k-in-star	initiative		Nodes with some attribute have a high tendency to take the initiative in multi-actor relationships.
	laziness		Nodes with some attribute have a high tendency to hold off in multi-actor relationships.

TABLE 5.
NATERGM Temporal Patterns for Directed Networks: Cyclicity

Legend: General nodes; Nodes with key attributes; Ties activated at T_1; Ties activated at T_2 ($T_1 < T_2$)

Static Pat-	Temporal Pattern	Illustra-tion	Hypothesis
cyclicity	reversed-refenrence		A node with some attribute has a high tendency to receive attention from another node, if a third node
	reversed-fol-low-up		A node with some attribute has a high tendency to pay attention to another node, if a third node bridges their relationship reversely.
	reversed-bridge		Nodes with some attribute have a high tendency to reversely bridge new relationships between others.

For example, assuming that we are interested in the role of highly active individu-als in developing message flows in social media, the static reciprocity pattern would only model a tendency for two individuals (at least one of them being highly active) to ex-change messages. In comparison, if we observed many ”feedback” patterns in the network, it would suggest a ten-dency for highly active individuals to receive returning messages after they sent out messages first; if we observed many "response" patterns, it would suggest a tendency for highly active individuals to respond to others' incoming messages. Although both "feedback" and "response" pat-terns finally lead to the same "reciprocity" pattern, they model two distinct dynamic processes. In a similar way, NATERGM extends other static patterns (i.e., k-star, tran-sitivity, and cyclicity) to their temporal variations by con-sidering the possible order of network ties, which provides richer insight about the dynamic process of network for-mation.

Given the list of temporal patterns in Tables 1 to 5, the major objective of NATERGM is to test which of these tem-poral patterns are more likely to be observed than to occur by chance in a network. The NATERGM model can be written as: Pr(𝑌𝑌=𝑦𝑦|𝜼𝜼)=1𝜅𝜅exp𝜂𝜂𝑎𝑎𝑎𝑎𝑎𝑎𝑎𝑎 𝑔𝑔𝑎𝑎(𝑦𝑦,𝑻𝑻,𝑿𝑿) (3)

In (3), A is a set of temporal patterns to be tested, $\boldsymbol{\eta\eta}$ = [$\eta\eta$a] is a vector of parameters representing the strength of each temporal pattern's effect in network formation, and $\kappa\kappa$ is a scaling parameter to ensure (3) is a probability distri-bution. ggaa(•) is the network statistic of temporal pattern a, evaluated with network yy, timestamp matrix TT, and vector of nodal attributes X. Table 6 provides definition of $ggaa$(•) for each temporal pattern listed in Tables 2 to 5, with the assumption that nodal attributes are binary or categorical. I() is an indication function that takes the value 1 if and only if the expression inside results in TRUE values. For categorical attributes, I(Xj) takes the value 1 if node i be-longs to the desired category in X. For cases when nodal attributes are continuous variables, I(Xi) is replaced by the value of Xi.

The likelihood of occurrence for each temporal pattern can be assessed by estimating the parameters $\boldsymbol{\eta\eta}$. If a param-eter is positive and significant, it indicates that the corre-sponding temporal pattern appears more frequently than by chance in the network. For parameter estimation, the Markov Chain Monte Carlo (MCMC) method is used, fol-lowing prior ERGM literature [46]. The procedure is mod-ified to adapt to temporal settings.

TABLE 6.
Specification of NATERGM Terms
(Directed Network, Binary or Categorical Attributes)

NATERGM Term	Network Statistic
reciprocity	
feedback	$g_F(y,T,X) = \sum_{i\neq j} y_{ij} \cdot y_{ji} \cdot I(X_i) \cdot I(T_{ij} < T_{ji})$
response	$g_R(y,T,X) = \sum_{i\neq j} y_{ij} \cdot y_{ji} \cdot I(X_i) \cdot I(T_{ij} > T_{ji})$
2-out-star	
prioritization	$g_P(y,T,X) = \sum_{i\neq j\neq k} y_{ki} \cdot y_{kj} \cdot I(X_i) \cdot I(T_{ki} < T_{kj})$
deprioritization	$g_D(y,T,X) = \sum_{i\neq j\neq k} y_{ki} \cdot y_{kj} \cdot I(X_i) \cdot I(T_{ki} > T_{kj})$
2-in-star	
initiative	$g_I(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ik} < T_{jk})$
laziness	$g_L(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ik} > T_{jk})$
transitivity	
bridge	$g_B(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{jk} > T_{ji}, T_{ik})$
cosupporting	$g_{CS}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{jk} > T_{ji}, T_{ki})$
cosupported	$g_{CSD}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{jk} > T_{ij}, T_{ik})$
remarked-supporter	$g_{RS}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ji} > T_{ik}, T_{jk})$
remarked-supported	$g_{RSD}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ji} > T_{ki}, T_{kj})$
remarking-supporter	$g_{RMSR}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ij} > T_{ik}, T_{jk})$
remarking-supported	$g_{RMSD}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ij} > T_{ki}, T_{kj})$
follow-up	$g_{FU}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ij} > T_{ik}, T_{kj})$
reference	$g_{REF}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ji} > T_{jk}, T_{ki})$
cyclicity	
reversed_reference	$g_{RREF}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ki} > T_{ij}, T_{jk})$
reversed_followup	$g_{RFU}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{ij} > T_{ki}, T_{jk})$
reversed_bridge	$g_{RB}(y,T,X) = \sum_{i\neq j\neq k} y_{ik} \cdot y_{ij} \cdot y_{jk} \cdot I(X_i) \cdot I(T_{jk} > T_{ij}, T_{ki})$

In general, the model fitting procedure iteratively gen-erates random networks based on the given set of parame-ters and updates the parameters based on the difference between the generated networks and the observed net-work. For a given set of parameters $\boldsymbol{\eta\eta}$ = [$\eta\eta aa$], Algorithm 1 is used to generate random networks on a given set of nodes.

Algorithm 1. NATERGM Random Network Generation
Initialize network as $Y = Y^{(t=0)}$
repeat until maximum rounds of iterations are made
for each element Y_{ij} in $Y^{(t)}$:
change the value of Y_{ij} based on the
conditional distribution defined by
$$logit\{\Pr(Y_{ij} = 1 | Y_{kl} = y_{kl}\ for\ all\ (k,l) \neq (i,j))\} = \boldsymbol{\eta}^T \left(\boldsymbol{g}(y^{(ij1)}, T_{Gibbs}, X) - \boldsymbol{g}(y^{(ij0)}, T_{Gibbs}, X)\right)$$
end for
t←t+1
return Y(t)

Given the random network generation procedure, Al-gorithm 2 is used to estimate parameter values. It calcu-lates the differences for a set of network statistics between generated networks and the actual network, and use the differences to adjust the parameters used to generate the networks.

Algorithm 2. NATERGM Parameter Updating

initialize $\boldsymbol{\eta} = \boldsymbol{\eta}^{(0)}$

repeat from n=0:

generate K networks ($y_1, y_2 \dots y_K$) independently based on $\boldsymbol{\eta}^{(n)}$ and Algorithm 1

define

$$\bar{\boldsymbol{g}} = \left(\frac{1}{K}\right)\sum_{k=1}^{K}[p_k^{(n)}\boldsymbol{g}(1-y_k^{(n)}) + (1-p_k^{(n)})\boldsymbol{g}(y_k^{(n)}) - \boldsymbol{g}_0]$$

$$\boldsymbol{D}_0 = diag\{\left(\frac{1}{K}\right)\sum_{k=1}^{K}[p_k^{(n)}\boldsymbol{g}^T(1-y_k^{(n)})\boldsymbol{g}(1-y_k^{(n)}) + (1-p_k^{(n)})\boldsymbol{g}^T(y_k^{(n)})\boldsymbol{g}(y_k^{(n)}) - \bar{\boldsymbol{g}}^T\bar{\boldsymbol{g}}]\}$$

calculate

$$\boldsymbol{Z}^{(n)} = (Z_1^{(n)}, Z_2^{(n)}, \dots, Z_K^{(n)}),$$

$$Z_K^{(n)} = p_k^{(n)}(y)(1-y_k^{(n)}) + (1-p_k^{(n)}(y))\boldsymbol{g}(y_k^{(n)}) - \boldsymbol{g}_0]$$

where

$$p_k^{(n)}(y) = \frac{\exp(\boldsymbol{\eta}^{T(n)}\boldsymbol{g}(1-y_k))}{\exp(\boldsymbol{\eta}^{T(n)}\boldsymbol{g}(1-y_k)) + \exp(\boldsymbol{\eta}^{T(n)}\boldsymbol{g}(y_k))}$$

until convergence criterion is met

sn is a sequence of positive numbers converging to 0. In this study we used sn=2exp(n)/10 , as suggested in prior research [46]. For convergence criterion, we also used the t-ratio methods in [46].

3.3 Network Prediction

After estimating the parameters in NATERGM, the fitted model can be used to predict the characteristics of future networks with the following procedures.

Based on the actual network observed at time point t-1, NATERGM parameters □□□□−□□ are estimated. A number (=K) of networks at time point t are then simulated based on the parameters □□□□−□□ using Algorithm 1. However, network at the time point t-1 is used as the initial network, instead of a randomly initialized network.

Each generated network at time point t does not neces-sarily look exactly like the actual network at time point t. However, global network statistics averaged over K gener-ated networks should resemble those of the actual net-work. An assumption made here is that global network property does not change dramatically in a short term [55], and thus a network model estimated at time t-1 should be able to generate networks that are also similar to networks in time t in terms of global network statistics. Moreover, the parameters □□□□−□□ used for network generation in the proposed model are related to the tendency of correspond-ing temporal patterns, which should be reflected gradually over time in networks. Therefore, we use the similarity be-tween generated networks with the actual network in the next time period to evaluate the prediction performance.

In order to evaluate how close the generated networks are to the actual network in the next period, we calculate the absolute difference (AD) for each network statistic a'ЄA' at prediction period t:

CONCLUSION

Dynamic collaboration between different sorts of people in social media is a mind boggling process and the request of system ties is an imperative part of social media arrange flow. We spoke to different fleeting examples of system arrangement in light of nodal properties and the request of system ties advancement and created NATERGM show for dynamic system examination. We directed observational tests to assess the execution of NATERGM and results demonstrated that NATERGM has an improved example testing ability and conceivably better forecast precision of system attributes contrasted with past unique system models. Contrasted with existing TERGM-based models, our proposed model can test more perplexing dynamic examples coming about because of the cooperation between arrange tie development and nodal traits, along these lines finding how different nodal qualities are influencing the arrangement procedure of a dynamic system. By and by, the proposed model can be utilized to assess the effect of people's traits in the development procedure of dynamic social media networks. By examining these properties, social media fashioners can understand what factors are basic to the social system advancement and figure out what functionalities to include or advance in their stages.

I.

II. The commitments of this examination are complex. To begin with, this investigation gives a stretched out ERGM-based system model to look at transient examples in powerful networks. The expanded model can look at how nodal qualities of networks influence the request in which organize ties create. Past models were not able look at the system flow from this point of view. Second, this investigation gives a rundown of worldly terms that expands static ERGM terms and dynamic TERM terms without nodal qualities. The rundown of fleeting terms is intended to be versatile to any broad system. Given another system, these transient terms can be utilized to understand the effect of other nodal traits past the qualities utilized as cases in this investigation. Moreover, this examination gives a system forecast outline work in view of worldly examples distinguishing proof, which has been an under-considered zone in social system investigate. In our present model, every transient example just thinks about one characteristic at any given moment. We intend to stretch out starting here and consider the communications of different qualities in future research.

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