Article

Tweeting #RamNavami: A Comparison of Approaches to Analyzing Bipartite Networks

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Michael T. Heaney[1]

Abstract

Bipartite networks, also known as *two-mode networks* or *affiliation networks*, are a class of networks in which actors or objects are partitioned into two sets, with interactions taking place across but not within sets. These networks are omnipresent in society, encompassing phenomena such as student-teacher interactions, coalition structures and international treaty participation. With growing data availability and proliferation in statistical estimators and software, scholars have increasingly sought to understand the methods available to model the data-generating processes in these networks. This article compares three methods for doing so: (a) Logit (b) the bipartite Exponential Random Graph Model (ERGM) and (c) the Relational Event Model (REM). This comparison demonstrates the relevance of choices with respect to dependence structures, temporality, parameter specification and data structure. Considering the example of Ram Navami, a Hindu festival celebrating the birth of Lord Ram, the ego network of tweets using #RamNavami on 21April 2021 is examined. The results of the analysis illustrate that critical modelling choices make a difference in the estimated parameters and the conclusions to be drawn from them.

Keywords

Bipartite network, two-mode network, ERGM, REM, Twitter, Ram Navami

The last two decades have witnessed tremendous growth in scholarly interest in social network analysis. Several factors have helped to propel this growth. First, the rise of social media has made people more aware of networks and has given them tools to facilitate intentional networking. Second, data on social networks have become more widely available on a diversity of topics of social relevance, such as the spread of false information, joint business ventures, attacks on computer networks, migration, lobbying, disease transmission and friendship. Third, computer technologies have developed to facilitate the processing and analysis of the large and complex data sets that accompany social networks. Fourth, new statistical tools and software have made network analysis methods more accessible to a wider community of scholars and have made them more comparable to traditional statistical methods.

Bipartite networks, also known as *two-mode networks* or *affiliation networks*, are a particularly interesting and useful class of networks. This class is defined by the partition of networks into two sets of actors or objects. Such partitions occur naturally throughout the world. Examples include students (mode one) and their teachers (mode two); nations (mode one) and the treaties to which they are signatories (mode two); and people (mode one) and the events that they participate in (mode two). Bipartite networks differ from the classic one-mode network formulation (in which **A** is directly tied to **B**) by the introduction of an intermediary object (such as when **A** attends **Event 1** and **B** also attends **Event 1**), which then provides a context for the relationship between the actors. Despite the introduction of this extra step, the relevance of this connection is immediately recognized in many situations. For example, if **A** and **B** are both graduates of the **University of Delhi**, then the connection between them is usually realized if the two are introduced to one another, when employers are considering them for jobs, when journalists are writing about them in news stories and so on.

Social network scholars have long been attentive to bipartite networks and have established a variety of

[1] School of Social and Political Sciences, University of Glasgow, UK.

Corresponding author:
Michael T. Heaney, University of Glasgow, School of Social and Political Sciences, Adam Smith Building, Bute Gardens, Glasgow, G12 8RT, UK.
E-mail: michaeltheaney@gmail.com

methods to examine them (Brieger, 1974; Davis et al., 1941; Jasny & Lubell, 2015). One method to arrive on the scene recently is the two-mode Exponential Random Graph Model (ERGM), as described by Wang et al. (2009). Two-mode ERGMs enable the estimation of network parameters at a single point in time or in discrete time segments. Another emerging method is the Relational Event Model (REM), as described by Butts (2008). REMs enable the estimation of network parameters over a continuous, ordered time sequence.

The emergence of multiple methods for examining two-mode networks affords flexibility to scholars in how to approach bipartite network problems. At the same time, they create some confusion for scholars who many be unsure of which methods are most applicable in any given situation. The purpose of this short article is to illustrate the use of two-mode ERGMs and REMs using a simple, contemporary data set. To this end, tweets using the hashtag #RamNavami on 21 April 2021 were collected. Ram Navami is a spring festival and holiday that is celebrated in India and by Hindu people around the word. It is an observance of the birthday of Lord Ram, the seventh incarnation of Vishnu. This data set allows the demonstration of multiple analytic approaches to a simple, two-mode network, while also revealing how an ancient holiday is situated in the electronic communications of today's society.

The Data and the Network

Tweets that used the hashtag #RamNavami were collected using the Twitter API (Application Programming Interface) from midnight to 11am (Coordinated Universal Time) on 21 April 2021. This approach followed well-established procedures for gathering social network data from cyberspace (Steinert-Threlkeld, 2018). Initially, 1,319 tweets were assembled, excluding retweets and mentions. All hashtags (which are insensitive to capitalization) were extracted from the tweets to determine which were the most common hashtags related to #RamNavami. Hashtags could be written in any language, as long as they used the Latin/Roman alphabet. So hashtags written in Devanagari script (used for writing in Hindi) were not included in the analysis, a nontrivial limitation given the context.

From this initial set of tweets, two subsets were created: (a) a data set containing only hashtags that had been used two or more times (excluding #RamNavami, which was in *all* tweets by design), and (b) a data set containing only the top 30 hashtags. The first data set consists of 5,373 edges (i.e., sender-hashtag pairs), while the second consists of 3,128 edges.

Some appreciation for the nature of the data can be gleaned by considering the list of the top 30 hashtags listed in Table 1. Some of the most popular hashtags also made reference to Ram Navami but varied slightly from the specific hashtag that was used to identify the network, such as #ramnavami2021. Other hashtags made religious references, such as #navratri and #hindu. Still others alluded to the Covid pandemic sweeping India and the world at large, such as #staysafe and #stayhome. Hashtag coding was performed by graduate students fluent in Hindi and English.

The network processes related to #RamNavami are evident in Figure 1. In this graph, white circles represent

Table 1. Top 30 Hashtags in the Ego-Network for #RamNavami on 21 April 2021.

Hashtag	Count	Hashtag	Count
#ramnavami2021	468	#ramanavami2021	58
#jaishreeram	370	#ramanavami	56
#ramnavmi	224	#ramnavmi2021	56
#jaishriram	210	#festival	53
#ram	179	#wednesdaythought	53
#ayodhya	164	#rama	50
#india	117	#stayhome	49
#lordrama	116	#adipurush	47
#ramayana	108	#hinduism	47
#shriram	94	#happyramnavami2021	40
#hindu	92	#hanuman	38
#sitaram	79	#happyramnavami	38
#lordram	78	#ramayan	37
#navratri	70	#jayshreeram	35
#staysafe	67	#radhe	35

Source: https://developer.twitter.com/en/solutions/academic-research

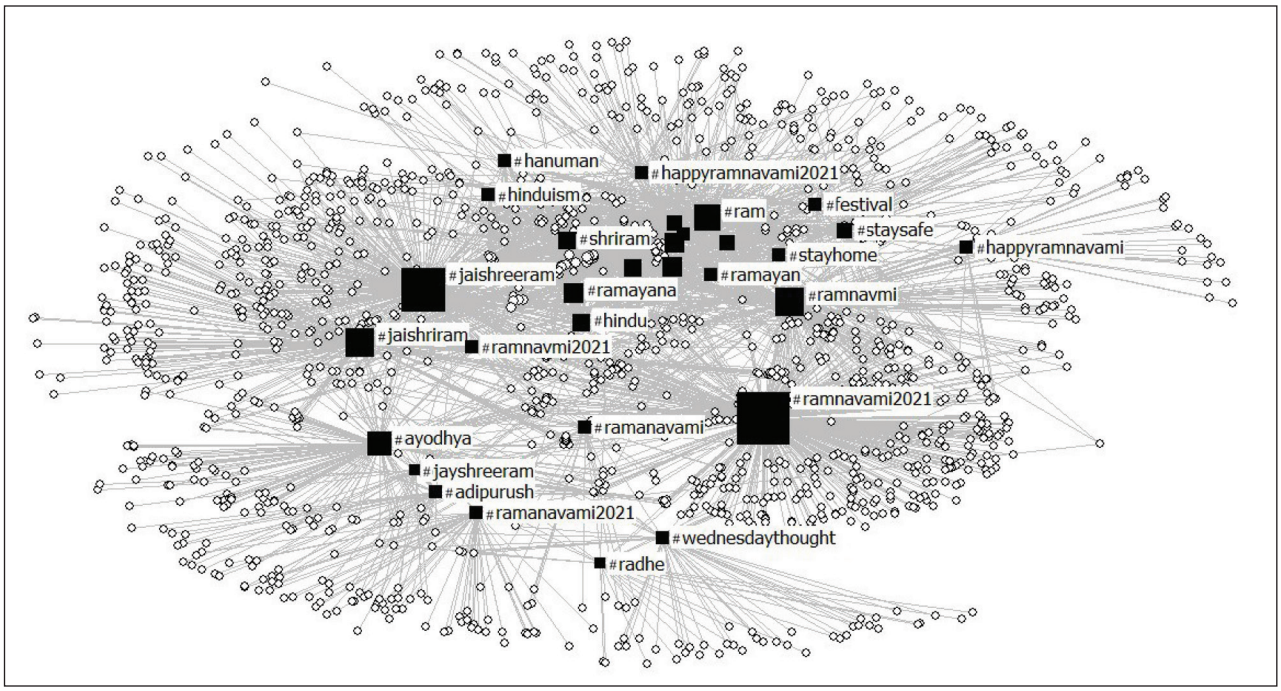

Figure 1. Ego Network for #RamNavami based on Top 30 Hashtags.

Source: https://developer.twitter.com/en/solutions/academic-research

Twitter users, while the black squares represent the top 30 hashtags in the ego network for #RamNavami. This graph was generated using the spring-embedding algorithm in Netdraw 2.168 (Borgatti, 2002), which draws points closer to one another based on minimizing tension in the graph. Not all of the labels for hashtags are included in the figure due to visibility issues. Some structures apparent in the data include the approximate co-location of #staysafe and #stayhome, both references to the Covid pandemic. Similarly, the near co-location of religiously themed hashtags, #hinduism and #hanuman, provides evidence for the relevance to religion on the network structure. Finally, there appear to be structural holes (Burt, 1992) between the denser top part of the network and the sparser bottom part of the network.

These casual observations may (or may not) be of interest to the reader. Yet, if we wish to truly understand the network generating processes behind these data, we require formal statistical tools, which are considered in the next section.

The Analysis of Bipartite Networks

No single approach to two-mode networks should dominate any other. Rather, there are different situations in which one approach may be preferred to others. Dyadic Logit models have been applied to topics such as the study of international conflict and alliances, though these models have been the target of extensive criticism (see Cranmer et al., 2021). The substance of the criticism is that dyads are often unlikely to be independent on one another, as is assumed by the Logit model. For example, a (hypothetical) attack by Pakistan on India is unlikely to be independent of a subsequent (hypothetical) attack by the United States on Pakistan; the crisis fomented by the first attack conditions the strategic logic governing the second attack. Nonetheless, it may be helpful to set the Logit model as a baseline for comparison, as it is widely understood by scholars. Also, it is possible that in some situations, it may be reasonable to assume dyadic independence, in which case a Logit model may be preferred.

Despite our familiarity with Logit, the advantage of ERGMs is that they allow the user to specify the network dependencies that may be present in the data generating process. For example, system behaviour may exhibit reciprocity, transitivity, preferential attachment, homophily or other endogenous network tendencies (Lusher et al., 2013). Thus, ERGMs enable the specification and assessment of network processes in the data, which may both address dependencies and yield substantively relevant knowledge. However, ERGMs do face limitations. While restricting the data to discrete time periods may not be a problem in many applications, in other cases, it may miss crucial elements of the problem. In examining tweets, for example, the sequence may be of special interest, requiring a continuous-time model. Additionally, ERGMs tend to

suffer from estimation difficulties resulting in degeneracies that make it impossible to estimate certain models. In these cases, it may be necessary to turn to other approaches to estimate network parameters.

The added value of REMs is that they incorporate continuous time into network models, provided that the assumption is made that no two events happen at the exact same time (Butts, 2008). Sequence statistics can be easily constructed in order to investigate how events relate to one another. However, current estimation procedures, such as those conducted using the informR package in R, limit the number of events (e.g., hashtags) that can be included in the estimation (Marcum & Butts, 2015). Further, including network attributes in REMs is not as straightforward as it is for ERGMs.

In light of these considerations, this article presents three simple models of the #RamNavami ego network using Logit, ERGM and REM estimators. In each case, variables are included for three hashtag characteristics: (a) direct reference to Ram Navami, (b) religious connotations (other than Ram Navami) and (c) reference to the Covid pandemic. These models are compared and then one extension is considered for each model.

Model Comparisons

Three models were estimated and are reported in Table 2. Model 1 used a Logit estimator including the three focus variables and a constant term (which is standard for this approach). Model 2 used an ERGM estimator with the three focus variables, an edges term (the analog to the constant term for ERGM) and an endogenous term for Twitter users that contributed at least two hashtags to the network. The inclusion of this endogenous term represents a minimal specification for the endogenous element of the network that is required to effectuate an ERGM. That is, without such a term, the ERGM would be equivalent to a Logit. Model 3 used a REM estimator that incorporated the unfolding of time during the 11 hours for which the data were collected. Sequence statistics were specified to approximate the variables in the Logit and ERGM models. The results of these exercises are reported in Table 2. The R code necessary to reproduce them is reported in the Appendix.

Comparison of the estimates of Models 1 and 2 indicates a very close match. Both models report that the coefficient on *Hashtag Reference to Ram Navami* is significant and negative, documenting that these hashtags had a less than typical chance of being coupled with other hashtags. The coefficient on *Hashtag Religious Connotation* is positive and significant, thus showing that these hashtags had a greater than typical chance to be combined with other hashtags. Both models display borderline significant coefficients on *Hashtag Covid Pandemic Reference*, with Model 1 just above the significance threshold and Model 2 just below it. The endogenous term in Model 2 is significant and negative, demonstrating that two hashtags by the same sender was less common in this network than was the case for randomly generated networks with the same size and parameters. The significance on this term establishes that the hypothesis of dyadic independence should be rejected. Nonetheless, the estimates of the Logit (which

Table 2. Logit, ERGM, and REM Models for the #RamNavami Ego Network.

Parameter	Model 1 *Logit*	Model 2 *ERGM* Coefficient (Standard Error)	Model 3 *REM*
Hashtag Reference to Ram Navami	–0.342 *	–0.347 *	1.980 *
	(0.049)	(0.048)	(0.159)
Hashtag Religious Connotation	0.560 *	0.562 *	0.080
	(0.047)	(0.049)	(0.288)
Hashtag Covid Pandemic Reference	0.173	0.178 *	3.514 *
	(0.089)	(0.087)	(0.532)
Constant / Edges	–2.879 *	–2.888 *	
	(0.042)	(0.044)	
Endogenous Term for Two Tweets by Same User		–0.527 *	
		(0.070)	
Akaike information criterion (AIC)	21,333	21,270	15,818
Bayesian information criterion (BIC)	21,368	21,313	15,835

Source: https://developer.twitter.com/en/solutions/academic-research
Note: * $p \leq 0.05$.

assumes dyadic independence) and the ERGM (which assumes dyadic dependence) lead to substantively very similar conclusions.

The REM estimates, which take into account the temporal ordering of the data, suggest substantive conclusions that are virtually opposite to those derived from Logit and ERGM. They show a positive and significant coefficient on *Hashtag Reference to Ram Navami,* thus suggesting an effect in the opposite direction of the Logit and ERGM. Unlike the Logit and ERGM results, the coefficient on *Hashtag Religious Connotation* is insignificant. In contrast to Model 1 and 2, the coefficient on *Hashtag Covid Pandemic Reference* is positive and statistically significant. These coefficients demonstrate that viewing the data through a temporal lens makes a considerable difference.

One implication of these results is that, at least for this dataset, the Logit and ERGM approaches are virtual substitutes for one another. While the ERGM estimates do demonstrate that the data generating process is dyad dependent, this dependence does not have severe consequences for the parameter estimates. Thus, it may be reasonable to extend the Logit to a range of data not feasible for ERGM estimation. However, this conclusion should not be generalized because if dyadic dependence was stronger in the network, then the resulting Logit estimate could be far off the mark.

A second implication of these results is that the researcher must be careful in choosing between discrete-time and continuous-time specifications. In this case, at least, the two approaches produce drastically different results. Consequently, it is necessary to carefully theorize whether or not time is expected to be a critical element of the problem at hand. More specifically, a key question is whether the sequence of events is expected to matter in generating the outcomes of interest. If yes, then REM is the obvious choice. If no, then ERGM (or possibly Logit) is more suitable.

Model Extensions

The three models reported in Table 2 were specified to make them as similar as possible, thus centring the discussions on the methods of estimation. Having considered these models, it is possible to investigate extensions of each approach. As mentioned earlier, the ERGM approach frequently suffers from degeneracy such that some models are not estimable. This problem is present in a case at hand, as Model 2 did not converge when sender characteristics were added to the specification. Hence, all the models were paired down to omit these characteristics. Now, since the Logit model is not commonly plagued with degeneracy issues, it is possible to consider an extension of this model to incorporate sender characteristics.

Since the informR software has limitations on the number of events that it can model for two-mode data (Marcum & Butts, 2015), all models were paired down to only 30 hashtags. Since ERGM does not suffer from this limitation, it is possible to consider an extension to a dataset with all hashtags used two or more times. The reason for setting the limit at two is that any hashtag used only once merely adds noise to the network structure, while at the same time threatening to prevent statistical convergence.

Finally, it is standard for REMs to include intercepts for each event in the model. This feature was suppressed in Model 3, with the goal of making the three models as comparable as possible. Now it is possible to relax that restriction and add event intercepts to the model, which is typical for REMs.

Three model extensions were estimated. Model 4 is a Logit that incorporates parameters for sender characteristics. Model 5 is an ERGM estimated on all hashtags with two or more appearances in the data. Model 6 is a REM that adds event intercepts for all events, except for the base category, #ramnavami2021, which was the single most popular hashtag in the #RamNavami ego network. The results of this estimation are reported in Table 3.

The model extensions reported in Table 3 add insights to the network generating processes beyond what was evident in Table 2. The Logit results in Model 4 contain a negative and statistically significant coefficient on *Sender Tweets*, indicating that senders who are more active on Twitter were less likely to contribute edges to this network. The coefficients on *Sender Accounts Followed* and *Sender Followers* are numerically very small and statistically insignificant. A reasonable speculation is that the relatively miniscule magnitude for all three sender coefficients explains why the ERGM would not converge when they were inserted in the specification. It is relevant to note that neither the direction nor the significance of the parameters on the hashtag attributes change in Model 4 when compared to Model 1.

Model 5 reflected an expansion of the data examined in comparison to Model 2. The extant software for ERGM estimation was able to manage the vastly expanded number of hashtags (516 instead of only 30) more routinely than is possible with the extant software for REM estimation. This increased information is consequential for model estimation. *Hashtag Reference to Ram Navami* switches from a significant, negative coefficient to a significant, positive coefficient. The coefficient on *Hashtag Covid Pandemic Reference* appears now as positive and significant, whereas it was insignificant in Model 2. Other parameters in Model 5 did not change their significance and direction in comparison to Model 2.

Model 6 extended the REM to incorporate intercepts for 29 of the top 30 hashtags, consistent with typical REM

Table 3. Extensions of Logit, ERGM, and REM Models.

Parameter	Model 4 *Logit*	Model 5 *ERGM* Coefficient (Standard Error)	Model 6 *REM*
Sender Accounts Followed	0.000		
	(0.000)		
Sender Followers	0.000		
	(0.000)		
Sender Tweets	–4 e^{-6} *		
	(1e^{-6})		
Hashtag Reference to Ram Navami	–0.343 *	2.181 *	0.929 *
	(0.048)	(0.040)	(0.169)
Hashtag Religious Connotation	0.560 *	1.344 *	–1.025 *
	(0.047)	(0.033)	(0.293)
Hashtag Covid Pandemic Reference	0.173	0.640 *	4.017 *
	(0.089)	(0.059)	(0.542)
Constant / Edges	–2.842 *	–5.996 *	
	(0.042)	(0.028)	
Endogenous Term for Two Tweets by Same User		–0.145 *	
		(0.065)	
#jaishreeram			–0.041
			(0.092)
#staysafe			–1.571 *
			(0.148)
#ramnavmi			–0.434 *
			(0.096)
#ramanavami2021			–2.735 *
			(0.250)
#ramnavmi2021			–1.887 *
			(0.172)
#stayhome			–1.794 *
			(0.161)
#ram			–0.436 *
			(0.102)
#jayshreeram			–2.717 *
			(0.251)
#wednesdaythought			–2.084 *
			(0.188)
#jaishiram			–0.601 *
			(0.105)
#hindu			–1.073 *
			(0.124)
#lordrama			–0.896 *
			(0.116)
#ayodhya			–0.896 *
			(0.116)
#adipurush			–2.116 *
			(0.190)
#rama			–1.766 *
			(0.163)
#lordram			–1.361 *
			(0.138)

(Table 3 continued)

(Table 3 continued)

Parameter	Model 4 *Logit*	Model 5 *ERGM* Coefficient (Standard Error)	Model 6 *REM*
#navratri			–1.507 *
			(0.147)
#shriram			–1.119 *
			(0.126)
#ramayan			–1.967 *
			(0.178)
#festival			–1.722 *
			(0.160)
#ramanavami			–1.700 *
			(0.159)
#happyramnavami			–2.842 *
			(0.266)
#india			–0.868 *
			(0.115)
#ramayana			–0.877 *
			(0.115)
#happyramnavami2021			–2.292 *
			(0.206)
#sitaram			–1.246 *
			(0.132)
#hanuman			–1.939 *
			(0.176)
#hinduism			–1.722 *
			(0.160)
#radhe			–2.459 *
			(0.222)
Akaike information criterion (AIC)	21,305	58,663	14,627
Bayesian information criterion (BIC)	21,366	58,722	14,812

Source: https://developer.twitter.com/en/solutions/academic-research
Note: * $p \leq 0.05$.

specifications. Almost all (28 of 29) of the coefficients on these intercepts are significant and negative due to the fact that the base category is the most commonly used hashtag; all other hashtags are less likely in comparison. These new model terms do not affect our conclusions about the *Hashtag Reference to Ram Navami* or *Hashtag Covid Pandemic Reference* variables. However, the parameter on *Hashtag Religious Connotation* is significant and negative in Model 6, where it was insignificant in Model 3.

Conclusion

Social media helped people to transmit greetings related to the Hindu festival of Ram Navami, even during the siege of an unprecedented global plague. These messages were not disseminated randomly but travelled through the cognitive and social structures that mould the internet. Models of bipartite networks afford scholars tools to investigate how these processes work (or do not work).

Firm conclusions about the network processes around #RamNavami cannot be drawn from the statistical results at hand. The estimated models displayed sensitivity to data selection criteria, the time scale of the analysis, parameter specification and the statistical estimator chosen. Moreover, the scope of the example data on which the analysis relied was starkly narrow, linking primarily to the use of one hashtag on one day.

Nevertheless, this article highlights critical choices to be made in the research design in the study of two-mode networks like the #RamNavami ego network. First, it is necessary to decide if the dyads in the network can be assumed to be independent (as is the case with Logit) or if

it is prudent to account for network dependence (as is possible with ERGM and REM). Second, time must be treated either in a discrete fashion (as is the case with Logit and ERGM) or handled as a continuous phenomenon (as is the case with REM). Third, decisions about the size of the data set and the variables to be included in the analysis have implications for model selection. While there are no hard and fast rules on this dimension, it is generally the case that Logit affords the widest berth, with ERGM allowing less flexibility and REM presenting even less latitude. These choices should be rooted in theoretical understanding of the case under study, as they are likely to make a difference in the resulting estimates.

The models discussed in this article are intentionally simple, though the ERGM and REM frameworks allow for more advanced applications. For example, Heaney and Leifeld (2018) demonstrates the utility of deploying structural zeros and structural ones in bipartite ERGMs to probe the intricacies of lobbying coalitions. Brandenberger (2018) illustrates how to test for reciprocity in congressional collaborations using REMs. These and other extensions are on the horizon in what is a rapidly evolving area of research.

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ORCID iD

Michael T. Heaney https://orcid.org/0000-0003-1678-1043

Appendix. R Code to Implement Network Models

```
# Tweeting #RamNavami
# Using R version 4.0.5 (2020-03-31) -- "Shake and Throw"
# April 26, 2021

# Set Working Directory

setwd(" USER'S DIRECTORY ")

# Open Libraries
# Note: statnet version 2019.6, created on 2019-06-13.
# Note: informR Version 1.0-5 created on 2015-03-09.

library(statnet)
library(informR)

# Read Data

Attributes_Two_or_More_Hashtags <- read.csv("Attributes_
Two_or_More_Hashtags.csv", header=TRUE)
Attributes_Top_30_Hashtags <- read.csv("Attributes_Top_30_
Hashtags.csv", header=TRUE)
Edges_Two_or_More_Hashtags <- read.csv("Edges_Two_or_
More_Hashtags.csv", header=TRUE)
Edges_Top_30_Hashtags <- read.csv("Edges_Top_30_Hashtags.
csv", header=TRUE)
eventlist <- read.csv("Eventlist_RamNavami.csv", header=TRUE)

# Convert Data to Network Form

Hashtag_Edges_Two_or_More_Matrix <- as.matrix(Edges_Two_
or_More_Hashtags, directed=FALSE)
Hashtag_Edges_Two_or_More_Network <-
as.network(Hashtag_Edges_Two_or_More_Matrix,
bipartite=1668, directed=FALSE)
Hashtag_Edges_Top_30_Matrix <- as.matrix(Edges_Top_30_
Hashtags, directed=FALSE)
Hashtag_Edges_Top_30_Network <- as.network(Hashtag_
Edges_Top_30_Matrix, bipartite=1389, directed=FALSE)

# Attach Attributes to Network

Hashtag_Edges_Two_or_More_Network %v% "B1_Followed"
<- Attributes_Two_or_More_Hashtags$B1_Followed
Hashtag_Edges_Two_or_More_Network %v% "B1_Followers"
<- Attributes_Two_or_More_Hashtags$B1_Followers
Hashtag_Edges_Two_or_More_Network %v% "B1_Tweets" <-
Attributes_Two_or_More_Hashtags$B1_Tweets
Hashtag_Edges_Two_or_More_Network %v% "B2_
DirectlyReferncesRamNavami" <- Attributes_Two_or_More_
Hashtags$B2_DirectlyReferncesRamNavami
Hashtag_Edges_Two_or_More_Network %v% "B2_
ReligiousConnotation" <- Attributes_Two_or_More_
Hashtags$B2_ReligiousConnotation
Hashtag_Edges_Two_or_More_Network %v% "B2_Covid" <-
Attributes_Two_or_More_Hashtags$B2_Covid

Hashtag_Edges_Top_30_Network %v% "B1_Followed" <-
Attributes_Top_30_Hashtags$B1_Followed
Hashtag_Edges_Top_30_Network %v% "B1_Followers" <-
Attributes_Top_30_Hashtags$B1_Followers
Hashtag_Edges_Top_30_Network %v% "B1_Tweets" <-
Attributes_Top_30_Hashtags$B1_Tweets
Hashtag_Edges_Top_30_Network %v% "B2_
DirectlyReferncesRamNavami" <- Attributes_Top_30_
Hashtags$B2_DirectlyReferncesRamNavami
Hashtag_Edges_Top_30_Network %v% "B2_
ReligiousConnotation" <- Attributes_Top_30_Hashtags$B2_
ReligiousConnotation
Hashtag_Edges_Top_30_Network %v% "B2_Covid" <-
Attributes_Top_30_Hashtags$B2_Covid

# Estimate Logit Model of Binary Network

Model_01 <- ergm(Hashtag_Edges_Top_30_Network ~ edges
        + nodecov("B2_DirectlyReferncesRamNavami")
        + nodecov("B2_ReligiousConnotation")
        + nodecov("B2_Covid"),
        control=control.ergm(12345)
        )
summary(Model_01)

# Estimate Binary ERGM
```

```
Model_02 <- ergm(Hashtag_Edges_Top_30_Network ~
        nodecov("B2_DirectlyReferncesRamNavami") +
        nodecov("B2_ReligiousConnotation") +
        nodecov("B2_Covid") +
        b1degree(2) +
        edges,
        control=control.ergm(12345)
        )
summary(Model_02)

# Estimate Relational Event Model (REM)

rawevents <- cbind(eventlist$Hashtag, eventlist$Sender)
evls <- gen.evl(rawevents)
names(evls)
evls$event.key
alpha.ints <- gen.intercepts(evls, basecat="bramnavami2021")

Hashtag_Characteristics <- c("c+d+e+f+v+w+z","a+h+i+k+l+m
+n+o+p+q+r+s+t+u+y+A+B+C+D","b+g")
Model_03.sforms <- gen.sformlist(evls, Hashtag_Characteristics)
Model_03.ints <- slbind(Model_03.sforms, alpha.ints)
Model_03.ints2 <- sldrop(Model_03.ints, c("bjaishreeram",
        "bramnavmi","bjaishriram","bram",
        "bayodhya","bindia","blordrama","bramayana",
        "bshriram","bhindu","bsitaram","blordram","bnavratri",
        "bstaysafe","bramanavami2021","bramanavami",
        "bramnavmi2021","bfestival","bwednesdaythought",
        "brama","bstayhome","badipurush","bhinduism",
        "bhappyramnavami2021","bhanuman",
        "bhappyramnavami","bramayan","bjayshreeram",
         "bradhe"))

Model_03 <- rem(evls$eventlist, Model_03.ints2, estimator =
        "BPM",
        prior.param=list(mu = 0, sigma = 100, nu = 4)
        )
summary(Model_03)

# Extension of Logit Model of Binary Network

Model_04 <- ergm(Hashtag_Edges_Top_30_Network ~ edges
        + nodecov("B1_Followed")
        + nodecov("B1_Followers")
        + nodecov("B1_Tweets")
        + nodecov("B2_DirectlyReferncesRamNavami")
        + nodecov("B2_ReligiousConnotation")
        + nodecov("B2_Covid"),
        control=control.ergm(12345)
        )
summary(Model_04)

# Extension of Binary ERGM

Model_05 <- ergm(Hashtag_Edges_Two_or_More_Network ~
        nodecov("B2_DirectlyReferncesRamNavami") +
        nodecov("B2_ReligiousConnotation") +
        nodecov("B2_Covid") +
        b1degree(2) +
        edges,
        control=control.ergm(12345)
        )
summary(Model_05)

# Extension of Relational Event Model (REM)

Model_06 <- rem(evls$eventlist, Model_03.ints, estimator =
        "BPM",
        prior.param=list(mu = 0, sigma = 100, nu = 4)
        )
summary(Model_06)
```

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