Bayesian exponential random graph modeling of KWL Burial network

Author One

Author Two

18 November, 2020

Text of abstract

# Introduction

Burials analysis by archaeologists is an approach to understand past social structure through the study of the physical traces of mortuary practices. The material cultures and biological records of burial behaviors can represent the social ranking or identity of the deceased (Binford, 1971; Drennan et al., 2010; Saxe, 1970). Despite criticism that manipulation of burial rituals by the living can cause a disconnect between a person’s status in life and their status represented by burial contexts (Hodder, 1980; Pearson, 1982), burials can still provide valuable information to infer past societies (Chapman, 2003). For example, mortuary practices, including burial forms, grave goods, and ritual behaviors, that structure the material configuration of burials can represent social relations between members of a community, allowing the inference of social structures (Byrd and Monahan, 1995; Seikel, 2011). Based on network science and graph theories, the recent development of social network analysis provides many new tools to visualize and analyze relationships for archaeological data (Borgatti et al., 2009; Brughmans, 2013). Network science is the study of relational data where a phenomenon is conceptualized as a network through two steps, abstraction and representation, based on our specification in terms of network theories (Brandes et al., 2013; Collar et al., 2015). That is, a network can be viewed as a patterned aggregation that includes individual elements (i.e. individual burials), pair-wise relationships (the dyads, for example burials with similar types and amounts of grave goods), and an overall structure showing global patterns represented in the data.

A social network is generally visualized as a graph consisting of a set of socially-relevant nodes/actors, connected by edges/ties representing one or more relations, such as friendship, collaborations, information flow, trade ties, or any other forms of connection of interest (Marin and Wellman, 2011; Wasserman et al., 1994). The ties can be classified into four major types, including similarities, social relations, interactions, and flows (Borgatti et al., 2009). In archaeology, actors can be people, groups, objects, places, or events, with ties built on similarity, proximity, or co-presence of material culture to create patterns reflecting influence, geographical distance, or affiliations in social groups (**???**; Brughmans and Peeples, 2018; Mills, 2017). For example, past trade can be conceptualized as a network of individual entities connected by shared similarity, the flow of goods, to represent their interactions (Collar et al., 2015, p. 4). Similar concepts can be applied to a wide range of archaeological data with relational assumptions, such as burial contexts. Burial goods, especially high value goods, can reflect social practices in broader cultural contexts to represent personal wealth or social status from which we can infer social differentiation or complexity (Gamble and Zepeda, 2002; Janes, 2013). Burials with the same prestige goods could indicate some underlying social relations where individuals share similar access to trade, exchange, and gifting networks according to their status (eg. Coward, 2013, p. 252). This enables the exploration of the structure of the past social organization through the identification of the relationships among burials.

Network analysis has been increasingly applied by archaeologists in recent years to deal with past interactions and explore the underlying mechanisms. There are two common approaches to characterize network properties at two distinct scales: node/edge level and graph level (**???**). Node level focuses on the role of node in a network, such as centrality, representing the individual influence or social prominence in a group, while graph level assesses the whole network attributes, such as density, clustering in a network, to generalize relationship patterns (**???**; Mills, 2017). By quantifying those network properties, archaeologists can answer a wide range of research questions. Examples includes exploring the political centralization in the Kofun period in Japan through the hierarchical communication network constructed by prestige goods (Mizoguchi, 2013), the investigation of long term inter-site relationships from the Epipalaeolithic to the early Neolithic in the Near East according to trade items (Coward, 2013). Regarding burials, Sosna et al. (2013) examined spatial pattern of burials from the Early Bronze Age in Rebesovice with two hypothesized networks constructed according to cultural and chronological similarity between burials. Recently, complex network modeling evaluates networks at both node and graph level through simulations of particular processes and statistically testing the formation of network properties (Brughmans, 2013; Brughmans and Peeples, 2018; Freeman, 2004; Salvini, 2010). Such application includes simulations and testing food exchange modes for Ancestral Pueblos on the aggregation of households in the American Southwest simulation (Crabtree, 2015), or exploring the diffusion of fired bricks across Hellenistic Europe by comparing similarity networks of sites with random networks. Other examples show the assessment of hunter-gatherer exchange networks structure across the Kuril Islands using bootstrap simulation based on ceramic composition (Gjesfjeld, 2015). This paper will use a novel Bayesian modeling approach to investigate the formation of relationship between burials in northeastern Taiwan to explore the indirect impact of foreign contacts on social organization.

Archaeological sites in northeastern Taiwan show evidence of imported prestige goods, such as ornaments and porcelains, in burials and some accumulation patterns in residential areas around the same time as European contact in the 17th century (Chen, 2007; Wang and Marwick, 2020). The use of imported goods is also mentioned in historical records from the Spanish, indicative of the pursuit of prestige or wealth in those Indigenous societies (Borao Mateo, 2009; Li and Wu, 2006). For example, the document written by a Spanish Priest described that the Spanish soldier used carnelian beads to exchange natural resources with local Indigenous people since their high values in Indigenous culture (Li and Wu, 2006). In addition, an Indigenous person possessing more imported goods may have been recognized as more influential or having higher status by their community (Li and Wu, 2006). Despite we observed the uneven distribution of prestige goods in burials, the degree of differentiation across burials over time remain unclear. The introduction of prestige goods to local Indigenous communities might occur earlier before a European presence became established, but was amplified during the European colonial period (Borao Mateo, 2009; Li and Wu, 2006; Wang and Marwick, 2020). A general model to summarize this situation in northeastern Taiwan might be that the influence of a colonial power, combined with high local values of imported goods, might lead to increased social inequality due to competition among individuals, and unequal access to trade networks (Brumfiel, 1994; Clark and Blake, 1994). The observed uneven distribution may be explained as a result of social change from less social inequality to more social inequality when Indigenous societies in Northeastern Taiwan were involved in the complex trade network stimulated by the Europeans.

In this study, we use a pericolonial model to explore the changes in social inequality at Kiwulan, an Iron Age site in northeastern Taiwan, which covers the time before the European arrival, the presence of the Europeans, including the Spanish and the Dutch, in the 17th century, and finally the Chinese in the 19th century (Chen, 2007). We assume that the social changes at Kiwulan would be supported by chronological differences in the structure of burial networks. We examine burial networks before and after the foreign contacts, and test our hypothesis that increased social inequality can be observed in the network after the European arrival. We ask: (1) does the observed burial data after the start of European presence resemble the of network our hypothesized model? (2) did European colonial activities in 17th century Taiwan result in the emergence of social inequality in an Indigenous society in ways that can be detected by burials networks? (3) what are the major variables affecting or forming the higher degree of popularity (e.g. a few nodes have more relationships with other nodes) in the European contact period that might hint at social heterogeneity during this period? By answering these questions, this study helps to expand the use of burials in understanding the indirect effects of a colonial presence on Indigenous groups. This is important to understand the reactions of Kiwulan residents in the context of indirect impacts of European colonization.

# Exponential random graph models in a Baysesian framework

Exponential Random Graph Models (ERGMs) are an important family of statistical models for networks that allows direct modeling for the formation of edges, or ties, between nodes (Robins et al., 2007). The assumption is that possible ties in a network are random variables and dependent on actor variables or the presence or absence of other ties (Robins et al., 2007). ERGMs differs from traditional network approaches in that edges are only formed according to their corresponding predictors separately without taking into account the interactions among edges (Morris et al., 2008). In ERGMs, networks are viewed as dependent variables, the formation of a tie is also influenced by network dependencies, and the attributes of nodes/edges (Snijders, 2011). For example, nodes with similar attributes are more likely to form a relationship, such as friendship between people with the same hobby. Ties form a small structure in a network called a graph configuration, that describes the form of dependence, such as reciprocity (relationship between two actors), transitivity or clustering (relationship between two actors through a shared third actor), homophily (relationship between actors with a similar attribute), or popularity (actors have many relationships with others) (Morris et al., 2008; Robins et al., 2007; Snijders et al., 2006). Those configurations represent the structure or the property of a network and can be expressed by network statistics. We can model those network statistics as direct functions of ties, where the probability of occurrence of ties can be specified and hypothesized (Morris et al., 2008; Robins et al., 2007). By specifying the forms of configurations, we can build a hypothesis-based model to generate a distribution of random networks that represent our model. Such distribution consists of a large number of possible networks that enables statistical inference and comparison with an observed network (Robins et al., 2007). This helps us understand whether an observed network shows significantly more or less of a property of interest than the random networks generated from our model assumptions.

To date, ERGM has only been used once in archaeology, by Amati et al. (2019) who reconstructed three different networks consisting of 15 sites (AD 100 to 400) in the Caribbean to explore their interaction mechanisms. These network models evaluated different hypotheses about the importance of three variables, proximity, inter-cultural items, and pottery types, on the presence of hub sites they observed. They found that the presence of hubs can be efficiently explained by multiple interdependent mechanisms instead of only one variable exclusively. They also pointed out some limitations of ERGMs, such as static outcomes and sensitivity to missing data. In addition, it is difficult in ERGMs to estimate model parameters and interpret the result due to intractable likelihood normalizing constants and model degeneracy (Caimo and Friel, 2014; Jin et al., 2013). A normalizing constant is a function of the model parameter for making probability distributions integrate to one, which becomes harder to compute with larger set of networks (Caimo and Gollini, 2017). This is also termed “doubly intractable” since both the likelihood normalizing constant and the marginal likelihood (the evidence of the posterior) are hard to derive (Caimo and Friel, 2013; Lyne et al., 2015). Model degeneracy is another issue that probability models tend to overestimate a small number of extreme graphs by assigning too much weight, such as empty (all nodes unconnected) or complete graphs (all nodes connected) (Caimo and Friel, 2014; Schweinberger, 2011). One solution to these limitations is available by implementing ERGMs in a Bayesian framework.

Bayesian approaches to ERGMs are efficient computational tools for social network analysis because they incorporates prior information about the network configurations into the model and offers uncertainty quantification by evaluating the posterior distributions of the parameters associated with network configurations (Caimo and Lomi, 2015; Nemmers et al., 2019). In Bayesian analysis, posterior distribution is an updated probability distribution after combining the prior derived from previous data or assumptions and our data. The advantage that Bayesian modeling has over traditional ERGMs is the application of Markov chain Monte Carlo (MCMC) simulation using the approximate exchange algorithm (Caimo and Friel, 2011). MCMC avoids doubly-intractable computations by directly sampling from the not normalized part of the posterior, which alleviates the computational problems and gives a better convergence results. This enable us to deal with complicated dependence patterns with ease, providing better estimations for complex social network models with heterogeneous data (Caimo et al., 2017; Snijders et al., 2006). By fitting an ERMG with an MCMC algorithm, a Bayesian approach generates posterior probabilities that incorporates our sample data and prior information through summary statistics from estimates of the ERGM parameters. Posterior probability estimates the effect of ERGM parameters by looking at the posterior mean and 95% credible intervals, which can replace p-values for assessing a null hypothesis (Caimo and Gollini, 2017). The typical criteria for interpreting the posteriors is that an odds ratio greater than one means a positive effect of a parameter, while odds ratios less than one represents negative effect. In addition, Bayesian approaches are also useful to deal with missing data, which is often a problem leading to misinterpretation of networks, especially for archaeological studies. Koskinen et al. (2010) shows that the effect of missing data can be reduced with Bayesian modeling that can predict, on the average, 80% of the ties when a third of data missing.

# Burial data from Kiwulan, Northeastern Taiwan

We analyzed burial data collected from the upper component of Kiwulan, an Iron Age settlement (1350-1850 AD) located in northeastern Taiwan, which experienced European colonial impacts in the early 17th century and a large wave of Chinese immigrants in the 19th century (Chen, 2007). Excavations revealed abundant pottery sherds, imported ceramics and stonewares, wooden artifacts, stone tools, metal artifacts, imported glass beads and agates beads, and pipes (Chen, 2007). In addition to these artifacts, 90 burials, hundreds of middens, storage pits, and postholes with *in-situ* posts were also excavated. The burials are mostly located in the middle section of the excavation area, which is the largest open area at Kiwulan that provides continuous stratigraphic sections suitable for temporal comparison . Burials are oriented in an east-west direction on the north side of the residential area, indicated by post-holes and in-situ wooden posts, indicating a well organized spatial arrangement. Previous studies report an uneven distribution of prestige goods across burials without agreement about whether this uneven distribution hints at vertical social differences. For example, Cheng (2008) interpreted the unequal distribution of glass beads, especially the gold-foil beads between burials, as evidence for hierarchy, indicating a stratified society. However, Hsieh (2012) suggested a relatively egalitarian structure based on comparative analysis of the frequencies of all burial goods. She found that the burials with high value burial goods were usually associated with elders, which might indicate achieved, rather than inherited, status. One important limitation of these previous studies is that they did not use analytical units suitable for comparing pre-European social organization with post-European social organization. Here, we adopt a new chronological framework for the burials to test if network configurations differ from the pre-European period to the post-European period. The discord over the discussion of Kiwulan social organization could be associated with chronological differences that has not yet been well studied.

To compare burial networks, we assigned burials to the pre-European period (n = 29), European and post-European period (n = 49). Our assignments are based on an established fine-grained chronology that was reexamined and cross-validated by diagnostic materials, stratigraphic data, depth, and radiocarbon ages (Chen, 2007; Wang and Marwick, 2020). We excluded burials from the Chinese phase (n = 4) due to the smaller sample size. There are eight burials heavily disturbed by modern construction that are also excluded because we cannot determine their chronology. We reconstructed social relations between individuals by linking them according to similar prestige goods (cf. Coward, 2013, p. 252).Therefore, we built networks where burials represent actors (nodes in the network) that are linked when they have the same prestige goods in common. The prestige goods we identified include agate beads, gold-foil beads, imported Chinese porcelains, gold foils, and fish-shaped ornaments. Previous studies indicate that these items are considered as high-value across different archaeological contexts (**???**; Cheng, 2008; Hsieh, 2012, 2009). Historical accounts also support these items as prestige goods (Borao Mateo, 2009; Li and Wu, 2006).

# Methods

## Data and Hypothesis

We analyzed burial data collected from the published excavation reports, and the original fieldwork notes of Kiwulan. Gold-foil and agate beads are commonly found across burials with substantial differences in quantities, so we described each burial as having one of three levels, high (> 10), medium (> 1 and < 10), and low (= 1), of these beads. Glass beads are in levels of high (> 100), medium (> 99 and < 900), and low (< 100). That means if burial 1 and burial 2 both have high quantities of agate beads, then there will be a tie connecting them. For less frequent prestige goods, including imported porcelains, gold foils, and fish-shaped ornaments, we linked two burials when they possess each type of goods in common (i.e. presence or absence). Node attributes here include osteological data, such as age and sex, and cultural data, such as ritual pottery, and burial value index. Ritual pottery was identified as locally made ceramics placed above graves that suggests funeral feasting according to historical records. The burial value index is an important attribute for economical inequality that we assigned the burials into three classes, high (>30), medium (>11 and <30), and low (<12), as an index of wealth. The number is the sum of values of each type of prestige good, which is calculate by the total number of a prestige item from burial context over the number of prestige item in a burial. Since burials tend to have multiple prestige goods in common, the network ties are weighted instead of binary data (where the value 1 represents a tie and the value 0 otherwise) (Snijders, 2011). For example, if two burials have both low quantity of glass beads and porcelain in common, the tie is given a value of 2. Our networks are non-directed, which means ties have no orientation forming the relationship between actors to indicate a mutual relationship.

Our pericolonial impact hypothesis is that rare, high quality grave goods accumulated in only a few individuals’ burials after the European presence in the 17th century, because of increased social inequality at Kiwulan due to differential access to these goods. We can identify these high value trade goods had been from historical documents written by the Europeans and the Han Chinese (Borao Mateo, 2009; Li and Wu, 2006). A related effect of the European presence in northeastern Taiwan may have been manipulation of the European colonial image by ambitious local Indigenous individuals for building their personal status and power. If social inequality gradually increased in Kiwulan as we hypothesize, then we expect to observe a network with higher degree (popularity), less transitivity (cohesion), and strong inequality based on age difference (achieved status). To test this prediction, we use ERGM in a Bayesian framework to examine the formation of network ties and the underlying mechanisms that shape relationships between people at Kiwulan. By comparing networks from the pre-European period and the post-European period we can examine the effects of foreign contact on community relationships at Kiwulan.

## Model specification in a Bayesian framework

Table 1: The parameters of exponential random graph models for a undirected network to corresponding with archaeological evidence.

Property

Configurations (effect)

Description

Interpretation

Density

Edges

Numer of ties in the network

two burial having relationship

Cohesion or transitivity

Geometrically weighted edgewise shared partner

Tendency for nodes with shared partners to be tied

burial to be connected with a third shared burial

Multiple connectivity

Geometrically weighted non-edgewise shared partner

Tendency of nondirectly connected nodes to be connected through multiple others

burial to be connected without a third shared burial

Popularity

geometrically weighted degree distribution

Tendency towards centralization in distribution

burial being connected with mutiple partners

Node covariate (gender)

Homophily

Density of ties between nodes with same gender

burial having the same gender to be connected

Node covariate (age)

Homophily

Density of ties between nodes with same age

burial having the same age to be connected

Node covariate (wealth)

Homophily

Density of ties between nodes with same scale of wealth

burial having the same scale of wealth to be connected

Node covariate (ritual)

Homophily

Density of ties between nodes with same ritual treatment

burial having the same ritual treatment to be connected

We used Bayesian inference on exponential random graph models (ERGMs) to quantify the relations among burials and test our hypothesis of social change using the R programming language (R Core Team, 2019) with the bergm package (Caimo and Friel, 2014), which is built upon the statnet package for model specification and simulation procedures (Handcock et al., 2008; Hunter et al., 2008; Morris et al., 2008). Table 1 lists the configurations we used for the model specification for burials with the corresponding archaeological evidence. Every parameter in an ERGM has an associated algorithm for computing the probability of observing relations in terms of grave goods between two burials. Based on our hypothesis, we model a network with increased social inequality that is represented by endogenous network effects, low transitivity and high popularity. We include burial-specific attributes as covariate effects for homophily, such as age, gender, ritual activity, and the degree of wealth, to test whether burials with similar attributes tend to form relationships. For example, age-homophily means people of the same age to have the same burial goods. We also take into account the physical distance between burials as an indicator of a kinship-based relation since the deceased from the same family tend to be buried nearby (Li and Wu, 2006). Our model could reveal the emergence of social inequality via the presence of a few individuals as network centers, having more relations with others. This would be indicated by high popularity or degree values in the network statistics, with covariates to control the preferential tendency of formation of relationship. According to our hypothesis, the burial evidence from after the European arrival will show higher popularity compared with the burial evidence from before European contact.

After we set our model parameters, we simulated networks in a Bayesian framework using a Markov chain Monte Carlo (MCMC) algorithm. MCMC algorithms allow estimation of posterior distributions through direct random sampling the posterior without assuming the prior comes from any specific distribution (Hamra et al., 2013). We can obtain a posterior distribution by constructing a Markov chain that describes a sequence of moves from current state to the next state following probabilistic rules based on an algorithm. This enables a random or stochastic simulation in a long run where each move does not depend on the previous move. More chains ensures a more desirable posterior distribution that is close to the target distribution under study, or convergence. In Bayesian ERGMs, MCMC first selects a set of edges (or a set of empty pair of actors) with equal probability, and then switches to a pair of actors at random within the chosen set (Caimo and Friel, 2011). In our case, we set the number of chains to six. For each chain, the number of burn-in iterations was 200 and the number of iterations after the burn-in was 1000. We set the number of iterations used to simulate a network y′ at each iteration to 10^{4}.

Normal distribution for the priors is typical in network analysis studies that assume networks to have low density and high transitivity, as are commonly found in the real world (Caimo et al., 2017). Thus, we specified the prior of edge to low density for both network models. For covariates based on burial attributes, such as age, gender, and wealth index, we specified a vague prior information that follows a normal distribution with mean at 0 and standard deviation at 5 (i.e. N(0, 5)) for both models. For physical distance between burials, we set a negative covariate effect (N(-1, 5)) to infer the kinship-based proximity. To evaluate our anthropological assumption about increased social inequality over time, we incorporated different prior information for the network variables that are meaningful for social inequality, especially for gwesp and gwedegree representing transitivity and popularity. We set the priors to higher transitivity (N(5, 7)), lower popularity (N(4, 7)), and higher covariate effect based on the ritual (N(2, 5)) for network before European contact to indicate less social inequality. On the contrary, we set the prior for the network after the European arrival to lower transitivity (N(4, 8)), and higher popularity (N(8, 8)) to illustrate an increased social inequality. This prior information derives from the theory about horizontal hierarchy, which can be viewed as a spectrum that illustrates an increasing social inequality from a corporate mode at one end toward a network mode at the other end (Drennan et al., 2010; Feinman, 2000). The priors for density were also set differently with N(-17, 7) for earlier network and N(-20, 6) for later network. It should be noted the idea of those settings is to reflect the relative differences between two networks, and the standard deviation was adjusted in terms of different networks to indicate uncertainty.

To assess MCMC analysis, we first evaluate three diagnostics presented as visual summaries, including density plots, trace plots, and autocorrelation plots (Hamra et al., 2013). Those plots provide an informal way to diagnose model convergence by identifying any unexpected peaks or shapes in distribution. Then we access output from our two models by goodness-of-fit (GOF) diagnostics in the Bayesian framework, where the observed network is compared with the set of networks simulated from the estimated posterior distributions of the parameters of each model (Caimo and Friel, 2011; Caimo et al., 2017). Our Bayesian GOF summarized three distributions, including degree, minimum geodesic distance, and edgewise shared partner distributions. We set of 10000 network graphs simulated from the estimated posterior distribution in ERGMs. This provides a statistical approach to check how well the estimated posterior parameter distribution based on our hypotheses can reproduce networks similar to the general structural features of the observed network. We then compared the distribution of our observed networks, networks before and after the arrival of Europeans, with the distribution of our hypothesized models. We expect to see the models fit with our hypotheses, indicative of a increased social inequality after the foreign contact. In addition, the covariates can give some more clues for the underlying mechanisms for the formations of each network.

# Reproducibility and open source materials

The entire R code (R Core Team, 2019) used for all the analysis and visualizations contained in this paper is included in the Supplementary Online Materials at xxx to enable re-use of materials and improve reproducibility and transparency (Marwick, 2017). Also in this version-controlled compendium (Marwick et al., 2018) are the raw data for all the visualizations and tests reported here. All of the figures, tables, and statistical test results presented here can be independently reproduced with the code and data in this repository. The code is released under the MIT license, the data as CC-0, and figures as CC-BY, to enable maximum re-use.

# Results

We compared estimated statistics from the posterior distributions, networks before and after the European presence, to examine their differences in network structure (Table XX). For the former network, the nodal covariates, age-homophily and ritual-homophily, have significant effects on the relations between burials. The age homophiligy shows a negative effect that indicates burials of the same age tend to not share similar prestige goods, while the ritual-homophily demonstrates the positive effect that means burials with ritual pottery tend to form relations. Despite other covariates are positive, such as sex-homophily and burial value-homophily, they do not show a significant tendency to forming relations duo to value of zero in a confidence interval. Similarly, the dyadic covariate, physical distance, shows positive effects but not significantly. For the endogenous network effects, both gwesp and gwdegree present significant positive effects. The positive value of gwesp suggests a tendency of burials to be clustered in closed transitive structures, while positive gwdegree indicates a tendency toward centralization that means the presence of a limited number of burials with more relations.

For the network after the arrival of Europeans, there are no significant effects of nodal and dyadic covariates, but we still have a clue of possible tendency. The nodal covariates of age-homophily, sex-homophily, ritual-homophily, and dyadic covariate of physical distance all show positive effects, while the burial value-homophily has a negative effect. The interesting thing is that the burials in the same wealth level may tend not to form relations. Similar to the network before the European arrival, the endogenous network variables, gwesp and gwdegree, all demonstrate positive effects significantly. However, there are differences in values of positive effects between two networks. The later network has a smaller gwesp effect and a larger gwedegree effect that may suggest a less tendency toward clustering but more tendency toward centralization after the European presence. Both posterior estimates presents symmetric distributions because of the posterior means are close to posterior medians (Table XX).

To understand whether the differences in posterior distributions are affected by different network sizes, we conducted a sensitivity test using vertex bootstrap inference on networks that allows a comparison for multiple networks of different sizes (Chen et al., 2019). Vertex bootstrap is a non-parametric method that conducts resampling for all vertices (i.e. node) of a network to quantify standard errors in the network statistics estimation of interest. This enables the evaluation of uncertainty for networks and the comparison between networks by examining their confidence interval for the network population. We set the resampling size to 1,000 for network statistics, including density, clustering, and degree, for two networks. The result shows that the 95% confidence interval of each network statistic contains the observed network of both periods, which indicates our network is less sensitive to sample size. This suggests a limited sample size effect on both models. In addition, since the prior setting will have impacts on the posterior, we compared the posterior estimates with the same prior for all parameters, and those with the informative prior based on our assumptions for some parameters. In general, there are no significant changes in the posterior estimates using different sets of priors. But we can see the informative prior contributed to a better convergence of the MCMC according to the diagnostic plots showing more stationary distributions and decreased autocorrelation.

The Bayesian goodness of fit diagnostics plots allows an evaluation of our model fit by comparing our observed data with the simulated distributions. We compared two models based on diagnostic plots that a good fit to estimated ERGM is indicated by observed data falls inside the 95% intervals.

# Discussion

Age and gender attributes serve as indicators for distinguishing ascribed or achieved status in a society [citation].

# Conclusion

# Acknowledgments

##### pagebreak

# References

Amati, V., Mol, A., Shafie, T., Hofman, C., Brandes, U., 2019. A framework for reconstructing archaeological networks using exponential random graph models. Journal of Archaeological Method and Theory 1–28.

Binford, L., 1971. Mortuary practices: Their study and their potential. In approaches to the social dimensions of mortuary practices, in: Brown, J. (Ed.), Approaches to the Social Dimensions of Mortuary Practices. Memoirs of the Society for American Archaeology., pp. 6–29.

Borao Mateo, J.E., 2009. The spanish experience in Taiwan, 1626-1642 the baroque ending of a renaissance endeavor. Hong Kong University Press, Hong Kong.

Borgatti, S.P., Mehra, A., Brass, D.J., Labianca, G., 2009. Network analysis in the social sciences. science 323, 892–895.

Brandes, U., Robins, G., McCranie, A., Wasserman, S., 2013. What is network science? Network science 1, 1–15.

Brughmans, T., 2013. Thinking through networks: A review of formal network methods in archaeology. Journal of Archaeological Method and Theory 20, 623–662.

Brughmans, T., Peeples, M.A., 2018. Network science. The Encyclopedia of Archaeological Sciences 1–4.

Brumfiel, E.M., 1994. Factional competition and political development in the New World: An introduction, in: Brumfiel, E.M., Fox, J. (Eds.), Factional Competition and Political Development in the New World. Cambridge: Cambridge University Press, pp. 3–13.

Byrd, B.F., Monahan, C.M., 1995. Death, mortuary ritual, and natufian social structure. Journal of Anthropological Archaeology 14, 251–287.

Caimo, A., Friel, N., 2014. Bergm: Bayesian exponential random graphs in r. Journal of Statistical Software 61, 1–25.

Caimo, A., Friel, N., 2013. Bayesian model selection for exponential random graph models. Social Networks 35, 11–24.

Caimo, A., Friel, N., 2011. Bayesian inference for exponential random graph models. Social Networks 33, 41–55.

Caimo, A., Gollini, I., 2017. Bayesian computational algorithms for social network analysis. QSAR/QSPR.

Caimo, A., Lomi, A., 2015. Knowledge sharing in organizations: A bayesian analysis of the role of reciprocity and formal structure. Journal of Management 41, 665–691.

Caimo, A., Pallotti, F., Lomi, A., 2017. Bayesian exponential random graph modelling of interhospital patient referral networks. Statistics in medicine 36, 2902–2920.

Chapman, R., 2003. Death, society and archaeology: The social dimensions of mortuary practices. Mortality 8, 305–312.

Chen, Y., Gel, Y.R., Lyubchich, V., Nezafati, K., 2019. Snowboot: Bootstrap methods for network inference. arXiv preprint arXiv:1902.09029.

Chen, Y.-p., 2007. Qi wu lan yi zhi qiang jiu fa jue bao gao [report on the archaeological excavations at ki-wu-lan site]. Lanyang museum, Yilan, Taiwan.

Cheng, C.-f., 2008. Qi wu lan yi zhi yu she nei yi zhi chu tu bo li zhu de xiang guan yan jiu [studies of glass beads excavated from kivulan and shenei site, Taiwan] (Master’s thesis).

Clark, J.E., Blake, M., 1994. The power of prestige: Competitive generosity and the emergence of rank societies in lowland Mesoamerica, in: Brumfiel, E.M., Fox, J. (Eds.), Factional Competition and Political Development in the New World. Cambridge: Cambridge University Press, pp. 17–33.

Collar, A., Coward, F., Brughmans, T., Mills, B.J., 2015. Networks in archaeology: Phenomena, abstraction, representation. Journal of Archaeological Method and Theory 22, 1–32.

Coward, F., 2013. Grounding the net: Social networks, material culture and geography in the epipalaeolithic and early neolithic of the near east (  21,000–6,000 cal bce), in: Knappett, C. (Ed.), Network Analysis in Archaeology: New Regional Approaches to Interaction. Oxford University Press, Oxford, pp. 247–280.

Crabtree, S.A., 2015. Inferring ancestral pueblo social networks from simulation in the central mesa verde. Journal of Archaeological Method and Theory 22, 144–181.

Drennan, R.D., Peterson, C.E., Fox, J.R., 2010. Degrees and kinds of inequality, in: Feinman, G., Price, T.D. (Eds.), Pathways to Power: New Perspectives on the Emergence of Social Inequality. Springer, pp. 45–76.

Feinman, G.M., 2000. Corporate/network: New perspectives on models of political action and the Puebloan Southwest, in: Schiffer, M.B. (Ed.), Social Theory in Archaeology. University of Utah Press, pp. 31–51.

Freeman, L., 2004. The development of social network analysis. A Study in the Sociology of Science.

Gamble, L.H., Zepeda, I.C., 2002. Social differentiation and exchange among the kumeyaay indians during the historic period in california. Historical Archaeology 71–91.

Gjesfjeld, E., 2015. Network analysis of archaeological data from hunter-gatherers: Methodological problems and potential solutions. Journal of Archaeological Method and Theory 22, 182–205.

Hamra, G., MacLehose, R., Richardson, D., 2013. Markov chain monte carlo: An introduction for epidemiologists. International journal of epidemiology 42, 627–634.

Handcock, M.S., Hunter, D.R., Butts, C.T., Goodreau, S.M., Morris, M., 2008. Statnet: Software tools for the representation, visualization, analysis and simulation of network data. Journal of statistical software 24, 1548.

Hodder, I., 1980. Social structure and cemeteries: A critical appraisal, in: Rahtz, P., Dickinson, T., Watts, L. (Eds.), Anglo-Saxon Cemeteries. Oxford: British Archaeological Reports 82, pp. 6–29.

Hsieh, E., 2012. You pei zang pin de liang hua yan jiu kan qi wu lan yi zhi shang wen hua ceng zao qi nei bu de she hui guan xi [exploring the social relation: A quantitative analysis of burial goods for upper culture layer of kiwulan site].

Hsieh, E., 2009. Yi lan qi wu lan yi zhi chu tu wai lai tao ci qi zhi xiang guan yan jiu [the study of imported ceramics excavated at the ki-wu-lan site, i-lan] (Master’s thesis).

Hunter, D.R., Handcock, M.S., Butts, C.T., Goodreau, S.M., Morris, M., 2008. Ergm: A package to fit, simulate and diagnose exponential-family models for networks. Journal of statistical software 24, nihpa54860.

Janes, S., 2013. Death and burial in the age of the cypriot city-kingdoms: Social complexity based on the mortuary evidence. Bulletin of the American Schools of Oriental Research 145–168.

Jin, I.H., Yuan, Y., Liang, F., 2013. Bayesian analysis for exponential random graph models using the adaptive exchange sampler. Statistics and its interface 6, 559.

Koskinen, J.H., Robins, G.L., Pattison, P.E., 2010. Analysing exponential random graph (p-star) models with missing data using bayesian data augmentation. Statistical Methodology 7, 366–384.

Li, Y.-z., Wu, M.-z., 2006. Qing zai xi ban ya ren zai tai wan, 1626-1642 [the spanish in Taiwan]. Taiwan Historica, Nantou.

Lyne, A.-M., Girolami, M., Atchadé, Y., Strathmann, H., Simpson, D., others, 2015. On russian roulette estimates for bayesian inference with doubly-intractable likelihoods. Statistical science 30, 443–467.

Marin, A., Wellman, B., 2011. Social network analysis: An introduction. The SAGE handbook of social network analysis 11.

Marwick, B., 2017. Computational reproducibility in archaeological research: Basic principles and a case study of their implementation. Journal of Archaeological Method and Theory 24, 424–450. <https://doi.org/10.1007/s10816-015-9272-9>

Marwick, B., Boettiger, C., Mullen, L., 2018. Packaging data analytical work reproducibly using R (and friends). The American Statistician 72, 80–88.

Mills, B.J., 2017. Social network analysis in archaeology. Annual review of anthropology 46, 379–397.

Mizoguchi, K., 2013. Evolution of prestige good systems: An application of network analysis to the transformation of communication systems and their media, in: Knappett, C. (Ed.), Network Analysis in Archaeology: New Regional Approaches to Interaction. Oxford University Press, Oxford, pp. 151–180.

Morris, M., Handcock, M.S., Hunter, D.R., 2008. Specification of exponential-family random graph models: Terms and computational aspects. Journal of statistical software 24, 1548.

Nemmers, T., Narayan, A., Banerjee, S., 2019. Bayesian modeling and uncertainty quantification for descriptive social networks. Statistics and its interface 12, 181.

Pearson, P., 1982. Mortuary practices, society and ideology: An ethnoarchaeological study, in: Hodder, I. (Ed.), Symbolic and Structural Archaeology. Cambridge.

R Core Team, 2019. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Robins, G., Pattison, P., Kalish, Y., Lusher, D., 2007. An introduction to exponential random graph (p\*) models for social networks. Social networks 29, 173–191.

Salvini, A., 2010. Symbolic interactionism and social network analysis: An uncertain encounter. Symbolic Interaction 33, 364–388.

Saxe, A., 1970. Social dimensions of mortuary practices (PhD thesis). University of Michigan.

Schweinberger, M., 2011. Instability, sensitivity, and degeneracy of discrete exponential families. Journal of the American Statistical Association 106, 1361–1370.

Seikel, K., 2011. Mortuary contexts and social structure at nan madol, pohnpei. The Journal of Island and Coastal Archaeology 6, 442–460.

Snijders, T.A., 2011. Statistical models for social networks. Annual Review of Sociology 37.

Snijders, T.A., Pattison, P.E., Robins, G.L., Handcock, M.S., 2006. New specifications for exponential random graph models. Sociological methodology 36, 99–153.

Sosna, D., Galeta, P., Šmejda, L., Sladek, V., Bruzek, J., 2013. Burials and graphs: Relational approach to mortuary analysis. Social Science Computer Review 31, 56–70.

Wang, L.-Y., Marwick, B., 2020. Trade ornaments as indicators of social changes resulting from indirect effects of colonialism in northeastern taiwan. Archaeological Research in Asia.

Wasserman, S., Faust, K., others, 1994. Social network analysis: Methods and applications. Cambridge university press.

##### pagebreak

### Colophon

This report was generated on 2020-11-18 11:14:20 using the following computational environment and dependencies:

#> ─ Session info ───────────────────────────────────────────────────────────────  
#> setting value   
#> version R version 4.0.2 (2020-06-22)  
#> os macOS Catalina 10.15.6   
#> system x86\_64, darwin17.0   
#> ui X11   
#> language (EN)   
#> collate en\_US.UTF-8   
#> ctype en\_US.UTF-8   
#> tz America/Los\_Angeles   
#> date 2020-11-18   
#>   
#> ─ Packages ───────────────────────────────────────────────────────────────────  
#> package \* version date lib source   
#> assertthat 0.2.1 2019-03-21 [1] CRAN (R 4.0.0)  
#> backports 1.2.0 2020-11-02 [1] CRAN (R 4.0.2)  
#> blob 1.2.1 2020-01-20 [1] CRAN (R 4.0.0)  
#> bookdown 0.20 2020-06-23 [1] CRAN (R 4.0.0)  
#> broom 0.7.0 2020-07-09 [1] CRAN (R 4.0.2)  
#> callr 3.5.1 2020-10-13 [1] CRAN (R 4.0.2)  
#> cellranger 1.1.0 2016-07-27 [1] CRAN (R 4.0.0)  
#> cli 2.1.0 2020-10-12 [1] CRAN (R 4.0.2)  
#> colorspace 1.4-1 2019-03-18 [1] CRAN (R 4.0.2)  
#> crayon 1.3.4 2017-09-16 [1] CRAN (R 4.0.0)  
#> DBI 1.1.0 2019-12-15 [1] CRAN (R 4.0.0)  
#> dbplyr 1.4.4 2020-05-27 [1] CRAN (R 4.0.0)  
#> desc 1.2.0 2018-05-01 [1] CRAN (R 4.0.0)  
#> devtools 2.3.2 2020-09-18 [1] CRAN (R 4.0.2)  
#> digest 0.6.27 2020-10-24 [1] CRAN (R 4.0.2)  
#> dplyr \* 1.0.2 2020-08-18 [1] CRAN (R 4.0.2)  
#> ellipsis 0.3.1 2020-05-15 [1] CRAN (R 4.0.0)  
#> evaluate 0.14 2019-05-28 [1] CRAN (R 4.0.0)  
#> fansi 0.4.1 2020-01-08 [1] CRAN (R 4.0.0)  
#> forcats \* 0.5.0 2020-03-01 [1] CRAN (R 4.0.0)  
#> fs 1.5.0 2020-07-31 [1] CRAN (R 4.0.2)  
#> generics 0.0.2 2018-11-29 [1] CRAN (R 4.0.0)  
#> ggplot2 \* 3.3.2 2020-06-19 [1] CRAN (R 4.0.0)  
#> glue 1.4.2 2020-08-27 [1] CRAN (R 4.0.2)  
#> gtable 0.3.0 2019-03-25 [1] CRAN (R 4.0.0)  
#> haven 2.3.1 2020-06-01 [1] CRAN (R 4.0.0)  
#> here \* 0.1 2017-05-28 [1] CRAN (R 4.0.0)  
#> highr 0.8 2019-03-20 [1] CRAN (R 4.0.0)  
#> hms 0.5.3 2020-01-08 [1] CRAN (R 4.0.0)  
#> htmltools 0.5.0 2020-06-16 [1] CRAN (R 4.0.0)  
#> httr 1.4.2 2020-07-20 [1] CRAN (R 4.0.2)  
#> jsonlite 1.7.1 2020-09-07 [1] CRAN (R 4.0.2)  
#> kableExtra 1.2.1 2020-08-27 [1] CRAN (R 4.0.2)  
#> knitr 1.29 2020-06-23 [1] CRAN (R 4.0.0)  
#> lifecycle 0.2.0 2020-03-06 [1] CRAN (R 4.0.0)  
#> lubridate 1.7.9 2020-06-08 [1] CRAN (R 4.0.0)  
#> magrittr 1.5 2014-11-22 [1] CRAN (R 4.0.0)  
#> memoise 1.1.0 2017-04-21 [1] CRAN (R 4.0.0)  
#> modelr 0.1.8 2020-05-19 [1] CRAN (R 4.0.0)  
#> munsell 0.5.0 2018-06-12 [1] CRAN (R 4.0.0)  
#> pillar 1.4.6 2020-07-10 [1] CRAN (R 4.0.2)  
#> pkgbuild 1.1.0 2020-07-13 [1] CRAN (R 4.0.2)  
#> pkgconfig 2.0.3 2019-09-22 [1] CRAN (R 4.0.0)  
#> pkgload 1.1.0 2020-05-29 [1] CRAN (R 4.0.0)  
#> prettyunits 1.1.1 2020-01-24 [1] CRAN (R 4.0.0)  
#> processx 3.4.4 2020-09-03 [1] CRAN (R 4.0.2)  
#> ps 1.4.0 2020-10-07 [1] CRAN (R 4.0.2)  
#> purrr \* 0.3.4 2020-04-17 [1] CRAN (R 4.0.0)  
#> R6 2.5.0 2020-10-28 [1] CRAN (R 4.0.2)  
#> Rcpp 1.0.5 2020-07-06 [1] CRAN (R 4.0.0)  
#> readr \* 1.3.1 2018-12-21 [1] CRAN (R 4.0.0)  
#> readxl \* 1.3.1 2019-03-13 [1] CRAN (R 4.0.0)  
#> remotes 2.2.0 2020-07-21 [1] CRAN (R 4.0.2)  
#> reprex 0.3.0 2019-05-16 [1] CRAN (R 4.0.0)  
#> rlang 0.4.8 2020-10-08 [1] CRAN (R 4.0.2)  
#> rmarkdown 2.3 2020-06-18 [1] CRAN (R 4.0.0)  
#> rprojroot 1.3-2 2018-01-03 [1] CRAN (R 4.0.0)  
#> rstudioapi 0.13 2020-11-12 [1] CRAN (R 4.0.2)  
#> rvest 0.3.6 2020-07-25 [1] CRAN (R 4.0.2)  
#> scales 1.1.1 2020-05-11 [1] CRAN (R 4.0.0)  
#> sessioninfo 1.1.1 2018-11-05 [1] CRAN (R 4.0.0)  
#> stringi 1.5.3 2020-09-09 [1] CRAN (R 4.0.2)  
#> stringr \* 1.4.0 2019-02-10 [1] CRAN (R 4.0.0)  
#> testthat 3.0.0 2020-10-31 [1] CRAN (R 4.0.2)  
#> tibble \* 3.0.4 2020-10-12 [1] CRAN (R 4.0.2)  
#> tidyr \* 1.1.2 2020-08-27 [1] CRAN (R 4.0.2)  
#> tidyselect 1.1.0 2020-05-11 [1] CRAN (R 4.0.0)  
#> tidyverse \* 1.3.0 2019-11-21 [1] CRAN (R 4.0.2)  
#> usethis 1.6.3 2020-09-17 [1] CRAN (R 4.0.2)  
#> vctrs 0.3.4 2020-08-29 [1] CRAN (R 4.0.2)  
#> viridisLite 0.3.0 2018-02-01 [1] CRAN (R 4.0.0)  
#> webshot 0.5.2 2019-11-22 [1] CRAN (R 4.0.0)  
#> withr 2.3.0 2020-09-22 [1] CRAN (R 4.0.2)  
#> xfun 0.16 2020-07-24 [1] CRAN (R 4.0.2)  
#> xml2 1.3.2 2020-04-23 [1] CRAN (R 4.0.0)  
#> yaml 2.2.1 2020-02-01 [1] CRAN (R 4.0.0)  
#>   
#> [1] /Library/Frameworks/R.framework/Versions/4.0/Resources/library

The current Git commit details are:

#> Local: master /Users/EmilyWang/Desktop/School document/LW-Papers/kwl-burials-2020  
#> Remote: master @ origin (https://github.com/LiYingWang/kwlburials.git)  
#> Head: [b4883d1] 2020-11-17: work on network comparison para and adjust the setting for ties