Bayesian exponential random graph modeling of KWL Burial network

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Text of abstract

# Introduction

Burials provide valuable information about social structures that reflect not only the personal life and status of the deceased, but also the expressions of their descendants, from which we are able to detect the social differences that can relate to social inequality and complexity (Ehrhardt, 2009; Gamble and Zepeda, 2002; Janes, 2013; Johansen and Bauer, 2015). Mortuary practices such as burial forms, grave goods, and related ritual practices could represent the social relations between individuals and allow us to infer social structures, for examples, grave goods usually relate to social practices of trade, exchange, and gifting (Coward, 2013, p. 252). One way to study the relationships between individual is social network analysis (SNA), which can visualize, quantify, and statistically test hypotheses about the relationships to understand network structure and its effects on every part within the network (Freeman, 2004; Salvini, 2010). A social network contains a set of actors and a set of relationships connecting these actors, which could be groups, organizations or persons. Their relationships are flows of resources that reflect relations of control, dependence, and cooperation. In other words, actors are viewed as “nodes” in a wider network, in which nodes are connected by multiple relationships, or “edges”, to other nodes (Coward, 2013; Mizoguchi, 2013; Potgieter et al., 2008).

Exponential Random Graph Models (ERGMs) are an important family of statistical model for expressing properties of network structures with a focus directly on possible ties between nodes by viewing them as random variables (Robins et al., 2007). In traditional statistical model for network, each predictor variable for forming a tie between two nodes is measure separately by the presence of a tie without considering interactions among ties (Morris et al., 2008). By contrast, statistical models assumes social networks as dependent variables that can represent the network dependencies between tie variables (Snijders, 2011). In a network generated by ERGMs, the formation of a tie is influenced by the presence or absence of other ties or attributes of nodes/ties. Predictor variables, called network statistics, such as reciprocity, transitivity, homophily, are direct functions of the ties themselves where the probability of occurrence of the configuration of ties can be specified and hypothesized (Morris et al., 2008; Robins et al., 2007). With the development of Markov chain Monte Carlo (MCMC) algorithms that produce approximate maximum likelihood estimators and graph statistics for further specification of transitivity and heterogeneity, ERGMs can deal with complicated dependence patterns observed at one moment in time (Snijders et al., 2006). The advantage of networks specification under assumptions and contexts can be useful to explain archaeological network in a given time. Amati et al. (2019) demonstrate the use of ERGMs to reconstruct networks consist of a set of sites in the Caribbean during the period AD 100–400. They found out the structure of network can be efficiently explained by multiple interdependent mechanisms instead of hypotheses of distance and cultural homophily exclusively. However, they also point out some limitations of application such as static outcome and sensitive to missing data. The two major limitations ERGMs are difficult to compute because their normalizing constant depending on model parameters is intractable. A Bayesian framework allows for parameter inference using Markov chain Monte Carlo (MCMC) strategies which avoid the need for computationally intensive calculations of the normalizing constants (Caimo and Friel, 2011).

## Bayesian modeling

Bayesian approach to ERGMs is an efficient computational tool for social network analysis because it incorporates prior information about the network effects into the model and offers uncertainty quantification by evaluating the posterior distribution of the parameters associated with the network effects (Caimo and Lomi, 2015; Nemmers et al., 2019). This provides better estimations for complex social network models with heterogeneous data (Caimo et al., 2017). For archaeological data, missing data could be a problem leading to misinterpretation, which can be also reduced by using Bayesian modelling that provides average 80% correct prediction for the ties and allow 25% false with a third of data missing (Koskinen et al., 2010). - weighted data

Using the R language, we use Bayesian SNA to study burials from Kiwulan, an Iron Age site in northeast Taiwan. We view individual burials as actors or nodes in the social network with ties drawn between burials when the presence of the same variables that can represent the same “community” or social group. We test hypotheses about the distribution of influence in the network to identify network or corporate mode conditions. We ask the questions: 1. Do the observed burial data indicate a more clustered network than a distribution of random networks with similar qualities? 2. Whether European colonial activities in 17 century Taiwan resulted in the emergence of social inequality in an indigenous society can be detected by burials networks. 3. How the relations among burials may affect the quantity of burial goods? We expect the network to present a higher degree of clustering (e.g. the number of completed triangles in the network) in the European contact period that might hint at social heterogeneity during this period. This study helps to expand the use of burials in understanding the indirect effects of a colonial presence on indigenous groups. A Bayesian approach enables the efficient quantification for uncertainty, parametrization, and model evaluation of social network metrics.

# Archaeological background

The burial data we analyzed in this paper are collected from the upper component of Kiwulan site, an Iron Age settlement site (AD1350-AD1950) located in northeastern Taiwan which experienced the European colonial impacts in the 17th century and the large wave of Chinese immigrants in the 19th century. The excavation 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 were mostly located in the AD section, which is the largest open area at Kiwulan site that provides continuous stratigraphic sections suitable for comparison. Those burials are oriented in an east-west direction located on the north side of the house structures indicated by postholes and in-situ wooden posts. Previous research indicates the presence of economic inequality between burials, but there is debate about whether these represent an egalitarian or stratified society (Cheng, 2008; Hsieh, 2012). Cheng (2008) interprets the unequal distribution of prestige materials, such as the golden beads, between burials, as evidence for hierarchy. However, Hsieh (2012) suggests a relatively egalitarian form from the comparative analysis of frequency and proportion of burial goods. She finds that the rich burials were usually associated with elders, which might indicate achieved, rather than inherited, status. The use of prestige goods in burials might be traced back before the European arrival according to historical records from Spanish and Chinese [Borao Mateo (2009); Li and Wu (2006)). Analysing burial data will give an insight into the social reactions of Kiwulan residents and provide a way to examine and explain the changes in social inequality at Kiwulan before and after European contact.

Burials were assigned to the pre-European period, European and post-European period, and Chinese period for network comparison. Since the sedimentary characteristics show vertical and lateral continuity cross units of AD section, depth is used as the first criterion for burial chronology. The chronology is then evaluated by the burials with light grey glazed jars, also called An-ping jars produced most likely in China and circulated in Southeast Asia from the late 16th to 18th century but are often found at sites with the European occupation in the early 17th century in Taiwan (Berrocal et al., 2018; Hsieh, 1995; Ketel, 2011). In addition to the diagnostic porcelain, three radiocarbon dates of charcoal associated with three different burials are used as another evidence to evaluate the chronology (Chen, 2007). Some burials that were heavily disturbed by modern construction are excluded to avoid misinterpreting from incomplete data.

The archaeological sites in northeastern Taiwan show some evidence of accumulation of imported prestige goods in burials (Cheng, 2008), which might indicate the pursuit of prestige or wealth. In addition to prestige, European colonial powers could have provided military support to indigenous allies. For example, Voss’s (2005) study of a colonial outpost in California shows that colonial residents have different identities and higher social status than other local indigenous people. A general model to summarize these case studies might be that the support of a colonial power combined with high local values for imported goods, might lead to competition among individuals. In this study, I will use this model of competition to explain the changes in social inequality at Kiwulan before and after European contact.

Based on the quantity of grave goods among burials, we can reconstruct social networks from the distribution of prestige goods, including imported ceramic and beads based on the principle that prestige materials usually relate to social status. We build network where burials represent actors (nodes in the network) linked by sharing the same prestige goods.

We assume burial network represents the relations among people and social structure based on the argument that

# Methods

## data

We use burial data collected based on published excavation report, and original excavation records with detailed stratigraphy and context description. Burial data provides information about direction, size, depth, age, gender, classes and quantity of grave goods, and spatial relationship between them. We consider the effects of both exogenous and endogenous factors to generate meaningful explanation of the characteristics of burial network and tendency of burials correlate with each other. To be specific, our purpose is to understand the underlying mechanisms of the network structures and how the relationship influence on the pattern of accumulation of wealth during different foreign contact periods. We focus on connectivity, clusters, centralization, and homophily among those burials that could reflect the social relations between individuals guided by social structures. Previous studies have shown that there are some evidence of social inequality observed from Kiwulan but the degree over time and causes remain unclear. To answer our question for the shifts in social inequality to a more wealth differentiation during and after the arrival of the foreign presences, we hypothesize:

• Hypothesis 1: There are significant reciprocal structure effects in burial network before the contact • Hypothesis 2: There are significant transitivity structure effects in burial network after the contact • Hypothesis 3: There are significant popularity structure effects in in burial network after the contact

The computational processes in this paper were performed by the ergm package for simulation and model specification and then bergm package using R programming (Caimo and Friel, 2014; Hunter et al., 2008; Morris et al., 2008). We set the number of chains to eight. For each chain, the number of burn-in iterations is 200 and the number of iterations after the burn-in is 2000. We set the number of iterations used to simulate a network y′ at each iteration to 10000. The models are assessed by goodness-of-fit (GOF) diagnostics in the Bayesian framework, where the observed network is compared with a set of networks simulated from the estimated posterior distribution of the parameters of the model (Caimo and Friel, 2011; Caimo et al., 2017). This provides a statistical way to check how well the estimated posterior parameter distribution can reproduce networks similar to the general structural features of the observed network.

Since the accumulation of imported prestige goods in burials is commonly observed, we assign the burials into four classes, high, medium, low, and none, according to the total number of burial goods as an index of wealth.

## Model specification and estimation

it can accomodate binary network statistics to describe the weighted network topology (Snijders et al., 2006)

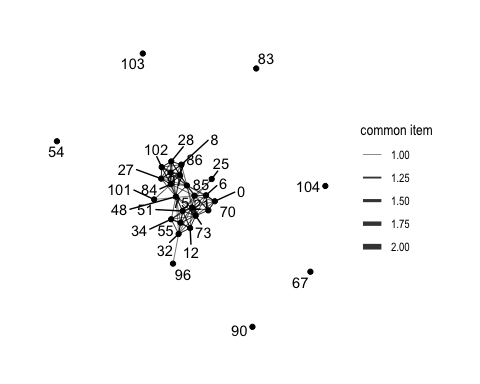
some concepts: - endogenous statistics that ties are modelled based on the existence of other ties - exogenous statistics that ties are formed according to monadic or dyadic node attributes

We used ergm package in R for the model specification. Every term in an ERGM must have an associated algorithm for computing its value for network (Morris et al., 2008). The terms we selected for network specification include:

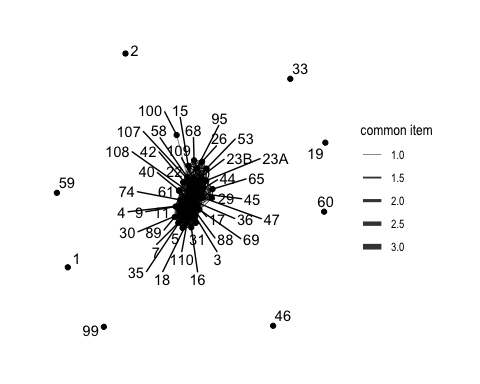
1. edges: ties, a measure of density, equal to kstar(1) for undirected networks
2. gwesp (geometrically weighted edgewise shared partners): triad-based clustering based on a dyad-based configurations (not node-based) that counts the number of times that both nodes have a tie to a third node. It is a measure of the tendency for two actors who are tied to have x partners in common. In other words, a tendency for those with shared partners to become tied, or tendency of ties to cluster together.
3. gwdegree (geometrically weighted degree distribution): a parametric form that represents the frequency distribution for nodal degree, each node counts only once. The local configuration is degrees and stars that are equivalent representations for the distribution of node-based edge counts. A measure of the tendency of the number of edges into a node. This statistic captures the tendency towards centralisation in the degree distribution of the network.
4. nodematch: uniform homophily between nodes that refers to the similarity of connected nodes. A statistics that counts the number of edges between nodes sharing the same covariate value or characteristics. We use wealth index and age as covariants that reflects the similarity between nodes.

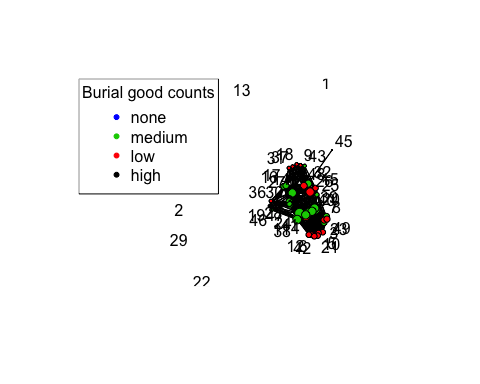
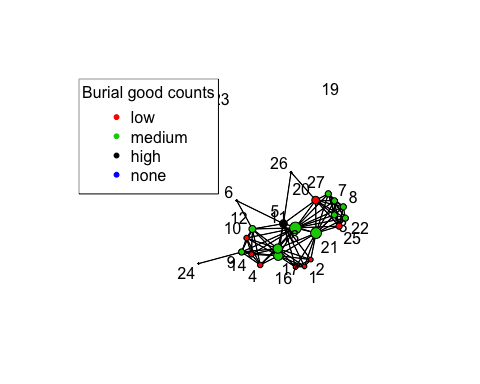
# Results

#> # A tbl\_graph: 29 nodes and 91 edges  
#> #  
#> # An undirected simple graph with 7 components  
#> #  
#> # Edge Data: 91 x 3 (active)  
#> from to common\_counts  
#> <int> <int> <dbl>  
#> 1 17 18 2  
#> 2 1 5 1  
#> 3 1 2 1  
#> 4 1 16 1  
#> 5 1 17 1  
#> 6 1 18 1  
#> # … with 85 more rows  
#> #  
#> # Node Data: 29 x 2  
#> id burial\_label  
#> <int> <chr>   
#> 1 1 0   
#> 2 2 6   
#> 3 3 8   
#> # … with 26 more rows



#> # A tbl\_graph: 49 nodes and 425 edges  
#> #  
#> # An undirected simple graph with 9 components  
#> #  
#> # Edge Data: 425 x 3 (active)  
#> from to common\_counts  
#> <int> <int> <dbl>  
#> 1 3 8 3  
#> 2 14 27 3  
#> 3 35 39 3  
#> 4 14 47 2  
#> 5 24 47 2  
#> 6 27 47 2  
#> # … with 419 more rows  
#> #  
#> # Node Data: 49 x 2  
#> id burial\_label  
#> <int> <chr>   
#> 1 1 1   
#> 2 2 2   
#> 3 3 3   
#> # … with 46 more rows





## ERGM parameter estimation

#> edges density triangle   
#> 91.0000000 0.2592593 182.0000000  
#> edges gwesp.fixed.0.2 gwdeg.fixed.0.8   
#> 91.0000 108.9881 48.1657  
#> edges nodematch.quantity nodematch.age nodematch.gender   
#> 91.00000 42.00000 41.00000 30.00000   
#> gwesp.fixed.0.75 gwnsp.fixed.0.75 gwdeg.fixed.0.2   
#> 181.64691 172.40227 27.79043

Normal distribution 𝜃 ∼ Nd (𝜇prior , Σprior ) is viewed as a suitable prior model for the model parameters of interests in network analysis if there is no previous observation for a network(Caimo et al., 2017). Since our original data presents a pattern of dense ties, we specified the prior based on our observation that assumes a high density and high transitivity network.

#>   
#> Posterior Density Estimate for Model: y ~ edges + nodematch("quantity") + nodematch("age") + nodematch("gender") + gwesp(0.75, fixed = TRUE) + gwnsp(0.75, fixed = TRUE) + gwdegree(0.2, fixed = TRUE)   
#>   
#> Mean SD Naive SE Time-series SE  
#> theta1 (edges) -9.34892351 3.7318956 0.0295032253 0.841121748  
#> theta2 (nodematch.quantity) 0.36976680 0.2441387 0.0019300858 0.029520986  
#> theta3 (nodematch.age) 0.06179467 0.3376027 0.0026689834 0.041719264  
#> theta4 (nodematch.gender) -0.12117994 0.3029788 0.0023952579 0.030976163  
#> theta5 (gwesp.fixed.0.75) 3.61915177 1.5705694 0.0124164415 0.349349077  
#> theta6 (gwnsp.fixed.0.75) -0.06692613 0.0844436 0.0006675853 0.009951691  
#> theta7 (gwdeg.fixed.0.2) 3.14710231 1.8359152 0.0145141840 0.359570351  
#>   
#> 2.5% 25% 50% 75%  
#> theta1 (edges) -16.8290605 -12.2157999 -7.84327277 -6.548409579  
#> theta2 (nodematch.quantity) -0.1529069 0.2281126 0.37458724 0.527753258  
#> theta3 (nodematch.age) -0.6527337 -0.1687237 0.08032933 0.313796309  
#> theta4 (nodematch.gender) -0.7031092 -0.3285914 -0.13254625 0.079765097  
#> theta5 (gwesp.fixed.0.75) 1.7426044 2.4740396 2.93408746 4.792082956  
#> theta6 (gwnsp.fixed.0.75) -0.2226152 -0.1322334 -0.07045418 -0.006332049  
#> theta7 (gwdeg.fixed.0.2) 0.6066086 1.7234536 2.52796773 4.627034926  
#> 97.5%  
#> theta1 (edges) -4.83144837  
#> theta2 (nodematch.quantity) 0.81271312  
#> theta3 (nodematch.age) 0.63801481  
#> theta4 (nodematch.gender) 0.48151605  
#> theta5 (gwesp.fixed.0.75) 6.85284815  
#> theta6 (gwnsp.fixed.0.75) 0.09451705  
#> theta7 (gwdeg.fixed.0.2) 6.89682380  
#>   
#> Acceptance rate: 0.21   
#>   
#>

## Structure Effects

The summary presents the statistics that each θ corresponds to the parameter specified in ERGM previously. In general, positive mean indicates positive correlation, while negative mean indicates negative correlation.

θ1 = number of ties θ2 = individuals with the same abundance of burial goods θ3 = gwesp, a positive sign suggests a tendency of burials in our sample to group together in closed transitive structures. In mortuary context, clustering implies a tendency of burials with the same status indicated by prestige goods to be organised in closed structures. Burials with multiple prestige goods in common are more likely to be directed connected. θ4 = gwdegree, negative estimates reflect an increased likelihood on ties to higher-degree nodes, or the strong edges are not necessarily centralised or dispersed in the degree distribution.

The plots from left to right show estimated marginal posterior densities, trace plots, and autocorrelation plots.

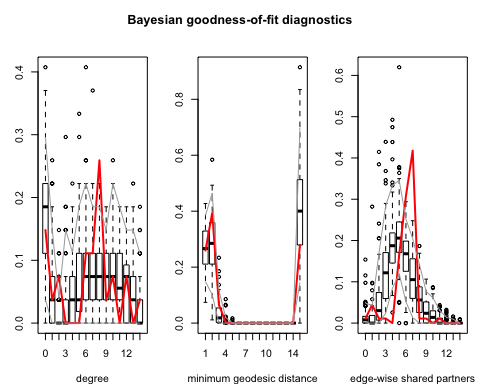


Figure shows the Bayesian goodness of fit diagnostics plots where the red lines represent the distributions of the observed data and the box plots represent the GOF distributions of 10000 network graphs simulated from ERGMs based on the estimated posterior distribution. The grey lines mark the 95% intervals. X-axis means the proportion of nodes

# Discussion

# Conclusion

# Acknowledgments

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### Colophon

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#> janitor 2.0.1 2020-04-12 [1] CRAN (R 3.6.2)  
#> jsonlite 1.6.1 2020-02-02 [1] CRAN (R 3.6.0)  
#> knitr 1.28 2020-02-06 [1] CRAN (R 3.6.1)  
#> labeling 0.3 2014-08-23 [1] CRAN (R 3.6.0)  
#> lattice 0.20-41 2020-04-02 [1] CRAN (R 3.6.2)  
#> lifecycle 0.2.0 2020-03-06 [1] CRAN (R 3.6.0)  
#> lpSolve 5.6.15 2020-01-24 [1] CRAN (R 3.6.0)  
#> lubridate 1.7.8 2020-04-06 [1] CRAN (R 3.6.2)  
#> magrittr 1.5 2014-11-22 [1] CRAN (R 3.6.0)  
#> MASS 7.3-51.5 2019-12-20 [1] CRAN (R 3.6.3)  
#> Matrix 1.2-18 2019-11-27 [1] CRAN (R 3.6.3)  
#> matrixcalc 1.0-3 2012-09-15 [1] CRAN (R 3.6.0)  
#> MatrixModels 0.4-1 2015-08-22 [1] CRAN (R 3.6.0)  
#> mcmc 0.9-7 2020-03-21 [1] CRAN (R 3.6.0)  
#> MCMCpack 1.4-6 2020-02-13 [1] CRAN (R 3.6.0)  
#> memoise 1.1.0 2017-04-21 [1] CRAN (R 3.6.0)  
#> modelr 0.1.6 2020-02-22 [1] CRAN (R 3.6.0)  
#> munsell 0.5.0 2018-06-12 [1] CRAN (R 3.6.0)  
#> mvtnorm 1.1-0 2020-02-24 [1] CRAN (R 3.6.0)  
#> network \* 1.16.0 2019-12-01 [1] CRAN (R 3.6.0)  
#> networkDynamic \* 0.10.1 2020-01-21 [1] CRAN (R 3.6.0)  
#> nlme 3.1-147 2020-04-13 [1] CRAN (R 3.6.2)  
#> pillar 1.4.3 2019-12-20 [1] CRAN (R 3.6.0)  
#> pkgbuild 1.0.6 2019-10-09 [1] CRAN (R 3.6.0)  
#> pkgconfig 2.0.3 2019-09-22 [1] CRAN (R 3.6.0)  
#> pkgload 1.0.2 2018-10-29 [1] CRAN (R 3.6.0)  
#> polyclip 1.10-0 2019-03-14 [1] CRAN (R 3.6.0)  
#> prettyunits 1.1.1 2020-01-24 [1] CRAN (R 3.6.0)  
#> processx 3.4.2 2020-02-09 [1] CRAN (R 3.6.0)  
#> ps 1.3.2 2020-02-13 [1] CRAN (R 3.6.0)  
#> purrr \* 0.3.3 2019-10-18 [1] CRAN (R 3.6.0)  
#> quantreg 5.55 2020-04-01 [1] CRAN (R 3.6.2)  
#> R6 2.4.1 2019-11-12 [1] CRAN (R 3.6.0)  
#> Rcpp 1.0.4.6 2020-04-09 [1] CRAN (R 3.6.3)  
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#> readxl \* 1.3.1 2019-03-13 [1] CRAN (R 3.6.0)  
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#> reprex 0.3.0 2019-05-16 [1] CRAN (R 3.6.0)  
#> rlang 0.4.5 2020-03-01 [1] CRAN (R 3.6.1)  
#> rmarkdown 2.1 2020-01-20 [1] CRAN (R 3.6.0)  
#> robustbase 0.93-6 2020-03-23 [1] CRAN (R 3.6.0)  
#> rprojroot 1.3-2 2018-01-03 [1] CRAN (R 3.6.0)  
#> rstudioapi 0.11 2020-02-07 [1] CRAN (R 3.6.1)  
#> rvest 0.3.5 2019-11-08 [1] CRAN (R 3.6.0)  
#> scales 1.1.0 2019-11-18 [1] CRAN (R 3.6.0)  
#> sessioninfo 1.1.1 2018-11-05 [1] CRAN (R 3.6.0)  
#> sna \* 2.5 2019-12-10 [1] CRAN (R 3.6.0)  
#> snakecase 0.11.0 2019-05-25 [1] CRAN (R 3.6.0)  
#> SparseM 1.78 2019-12-13 [1] CRAN (R 3.6.0)  
#> statnet \* 2019.6 2019-06-14 [1] CRAN (R 3.6.0)  
#> statnet.common \* 4.3.0 2019-06-02 [1] CRAN (R 3.6.0)  
#> stringi 1.4.6 2020-02-17 [1] CRAN (R 3.6.0)  
#> stringr \* 1.4.0 2019-02-10 [1] CRAN (R 3.6.0)  
#> tergm \* 3.6.1 2019-06-12 [1] CRAN (R 3.6.0)  
#> testthat 2.3.2 2020-03-02 [1] CRAN (R 3.6.0)  
#> tibble \* 3.0.0 2020-03-30 [1] CRAN (R 3.6.2)  
#> tidygraph \* 1.1.2 2019-02-18 [1] CRAN (R 3.6.0)  
#> tidyr \* 1.0.2 2020-01-24 [1] CRAN (R 3.6.1)  
#> tidyselect 1.0.0 2020-01-27 [1] CRAN (R 3.6.0)  
#> tidyverse \* 1.3.0 2019-11-21 [1] CRAN (R 3.6.0)  
#> trust 0.1-8 2020-01-10 [1] CRAN (R 3.6.0)  
#> tsna \* 0.3.1 2020-01-20 [1] CRAN (R 3.6.0)  
#> tweenr 1.0.1 2018-12-14 [1] CRAN (R 3.6.0)  
#> usethis 1.6.0 2020-04-09 [1] CRAN (R 3.6.3)  
#> utf8 1.1.4 2018-05-24 [1] CRAN (R 3.6.0)  
#> vctrs 0.2.4 2020-03-10 [1] CRAN (R 3.6.0)  
#> viridis 0.5.1 2018-03-29 [1] CRAN (R 3.6.0)  
#> viridisLite 0.3.0 2018-02-01 [1] CRAN (R 3.6.0)  
#> withr 2.1.2 2018-03-15 [1] CRAN (R 3.6.0)  
#> xfun 0.13 2020-04-13 [1] CRAN (R 3.6.2)  
#> xml2 1.3.1 2020-04-09 [1] CRAN (R 3.6.2)  
#> yaml 2.2.1 2020-02-01 [1] CRAN (R 3.6.1)  
#>   
#> [1] /Library/Frameworks/R.framework/Versions/3.6/Resources/library

The current Git commit details are:

#> Local: master /Users/EmilyWang/Desktop/School document/LW-Paper/kwl-burials-2020  
#> Remote: master @ origin (https://github.com/LiYingWang/kwlburials.git)  
#> Head: [4f9be97] 2020-04-15: update the code for post-Euro