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Chapter 3

Archaeology as a Network Science: Basic Concepts and Measures

Claim 1	***Network science is the study of network models. […]***
Claim 2	***There are theories about network representation and network theories about phenomena: both constitute network theory. […]***
Claim 3	***Network science should be empirical – not exclusively so, but consistently – and its value assessed against alternative representations. […]***
Claim 4	***What sets network data apart is the incidence structure of its domain. […]***
Claim 5	***At the heart of network science is dependence, both between and within variables. […]***
Claim 6	***Network science is evolving into a mathematical science in its own right […]***
Claim 7	***Network science is itself more of an evolving network than a paradigm expanding from a big bang.***

Editorial of the first issue of *Network Science* (Brandes, et al. 2013)

This chapter introduces network approaches in archaeology by explaining some elementary concepts and measures that may be employed in the exploration of archaeological networks. Formal network approaches have a profound mathematical basis, based in graph theory and other topological mathematics. I will specifically discuss the structures of a graph theoretical network data set, concepts and measures of, grouping, cohesion and centrality. While, this chapter focuses on some of the more elementary formal network concepts and measures that have already been or could be applied in archaeological studies, it has to be noted that several general books present richer introductory texts or deeper explorations of graph theory and other mathematical analyses (e.g. Brandes and Erlebach 2005; Newman 2010;

Scott 2012). In addition, the network concepts and measures discussed here are by no means an exhaustive discussion on possible applications of network science in archaeology.

The concepts and measures discussed here will be illustrated by means of a hypothetical network case-study in which nine generic "artefact types" are distributed over twenty-six contemporaneously inhabited sites. These sites are all that remains of a fictional past island world called Chremanesia. The people of this island world had a peculiar tradition. They never moved to, never intermarried with, never befriended or had any other social interactions of any other kind with folk from other islands. The only exception to this norm was when a lone traveller crossed a channel to bring material culture to another island. Another peculiarity was that the inhabitants of Chremanesia only had nine different types of things and did not seem to have the need to alter these in any way or invent new things. This is especially strange since certain items were only produced at certain locations. The result is that only these nine types of things lay at the basis of supra-island culture and any inter-island politics must also have been completely founded on which island supplied which other island with their things. Of course such a system could not have survived for long and some unknown disaster wiped out the people of Chremanesia. A few centuries later archaeologists discover the remains of the Chremanesians. The only key to understanding their shared culture and society seems to be to make sense of how the nine types of things they left behind form an inter-island network.

The embedding of network science in archaeology

In the highly connected world of today, networks are everywhere. From everyday conversation to academia, they are the talk of the town. Networks are also big business. New online only companies like Facebook and Twitter rely on attracting as many members to their respective networks as possible. In these online networks many more people have much more "friends", "followers" or other types of social contacts over a far wider geographical landscape than traditional ideas on human group dynamics ever accounted for (Dunbar 1988; Dunbar, *et al.* 2010a). Indeed, the manner in which networks intrude into our everyday life seems to be unlike anything ever seen before. Fuelled by connected phenomena such as ICT revolutions and globalization, this gives rise to a number of completely new developments in the history of human society (Castells 2011).

In recent years network theories, models, and analyses have also enjoyed an enormous rise in popularity in academia, including archaeology (Brughmans 2013; Knappett 2013). As such, it seems that archaeology has fallen slightly behind the curve of an upsurge in network studies that occurred in other research fields around the turn of the millennium (Brandes, *et al.* 2013; Newman 2010). Having observed that this correlates with the growth of networks in our daily lives, it could be argued that the popularity of network-themed approaches in archaeology and beyond results mainly from the tangible reality of networks today. However, though we are now more concretely part of networks than before, this does not imply that the networks of today are categorically different than those from the past. In fact, networks of humans, computers, enzymes, academic papers or food webs are all analogous because as a system they are characterized by means of the relations between their nodal points. In principle these systems, from the most archaic and simple to the most advanced and complex, can be understood by applying a similar set of analyses arising from the incidence structure of relational data sets abstracted from real-world cases.

As a matter of fact, although we see a notable spike in publications on networks at the beginning of the present millennium, the study of networks is nothing new (Brandes, *et al.* 2013; Prell 2011: Chapter 2). Network-like approaches have also always been present in archaeology, even if they were not explicitly recognized as such. For example, one of the core methods and theories in archaeology, chronological or cultural seriation (Petrie 1899; Pitt-Rivers 1906), is an example of network ordering and visualization (Figure 3.1). Seriation is essentially network modelling of data *avant la lettre*: the diagrams are visualizations of systems of relations between site assemblages, objects or periods. Outside of the discipline of archaeology, such seriation models and diagrams have even been of wider interest

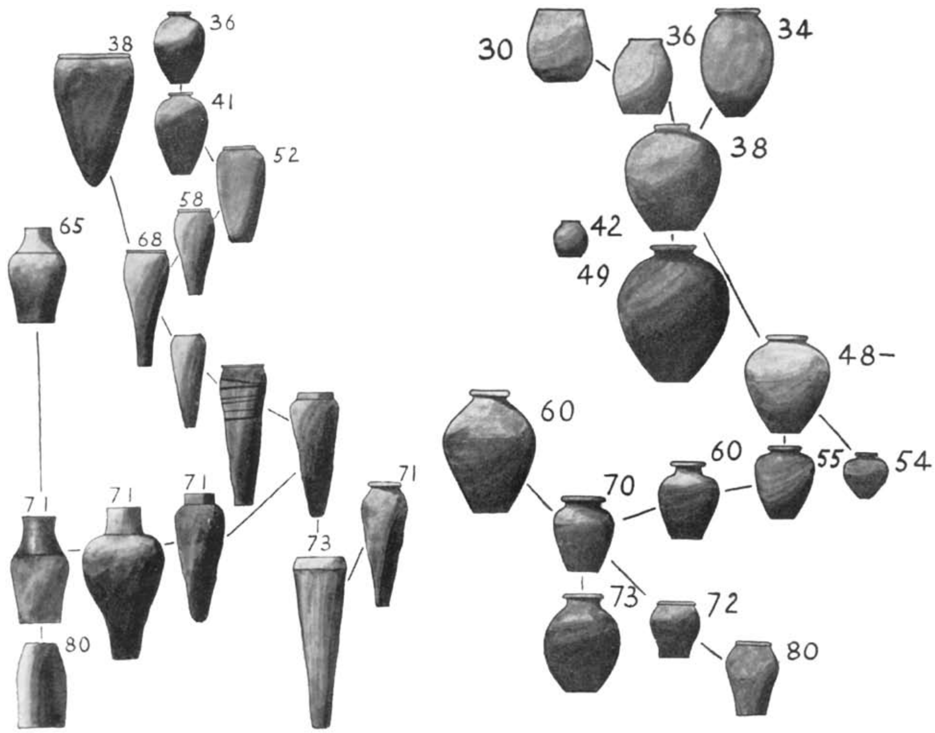

Figure 3.1: A seriation network by Flinders Petrie (1899). The depicted type-vessels are the nodes of the network. The ties are based on the cultural stratigraphy and development of one or multiple morphological traits. For the majority of nodes, there is only one route through the network (i.e. the network is phylogenetic and only partially ordered). In this sense the above network is comparable to what a network based on the modal approach by Rouse (1992; Figure 1.2) could resemble.

with regard to network studies – specifically in discussions concerning matrix re-ordering, a way of organizing that reveals regularity and patterning in a series of data points (Brandes, *et al.* 2012; Brandes, *et al.* 2013; Liiv 2010). Seriation is just one example of how networks are embedded in archaeology. The idea that "hidden" network theories are already an integral part of (Caribbean) archaeology has already been discussed in Chapter 1.

There are various reasons for the rise of network approaches in archaeology. At present their largest attraction seems to be that networks can provide a relational perspective. More specifically, however, a network science approach can provide both a set of models and analyses that intuitively seem to hold some value with regard to an advanced understanding of past (social) relations. Network analyses as "relational statistics" fill a niche that has only recently become available through the increasing size of archaeological data sets and the advent of ever more powerful methods and techniques enabling the study of relations in the archaeological record. Alongside these advances there have also been several developments in the broader network sciences themselves. Of specific significance is the increasing availability of network analytic software and the publication of popular science books on the topic (Terrell, personal communication 2010).

Although the call for a network approach to the study of the past can be heard throughout the discipline, formal network studies in archaeology can be termed as somewhat of a "grassroots movement". Even since their first usage during the 1970s (Kendall 1970; Terrell 1977), their application has arisen directly from questions and developments within regional archaeologies, rather than from an interest in the mechanics of networks themselves (e.g. Broodbank 2000; Cody 1990; Hardy 2008; Graham 2006; Knappett 2013; Knappett, *et al.* 2008; Mills, *et al.* 2013; Mol 2013; Terrell 2008).[1] This is perhaps the reason why, as Tom Brughmans (in press) has shown with a citation analysis of archaeological publications using formal network methods, network studies in archaeology are still paradoxically characterized by a distinct lack of connections between them. Fortunately, this situation is rapidly being remedied by means of new, cross-regionally integrated archaeological network studies (e.g. Knappett 2013), integration between historical and archaeological network analysis, and (upcoming) special journal publications and symposia.

Even if the applications thus far have been largely independent of each other, a number of general trends can be discerned regarding the application of networks within archaeology today. Firstly, the majority of studies make loose references to networks and apply them as a metaphor for trade or other types of exchange systems. Regrettably this is often without providing any form of argumentation or discussion on why it is important that trading, barter, gift or other exchange systems are networks and how they operates (e.g. Schortman and Ashmore 2012). If the term network is applied less loosely this is generally speaking done in order to emphasize the object of study forming a (social) network. This is akin to using the concept of the network as a heuristic device or theoretical perspective. Network

1 See Bentley and Maschner (2003)'s work on complex systems for a notable exception.

science is further integrated by theories drawn from the broader field of network studies (e.g. Collar 2007; Mol 2013; Terrell 2008). An example hereof is the recent work presented by Irad Malkin (2011). In his *A Small, Greek World* the idea of Greek cities forming a "small-world network" is used to discuss early Classical colonialism in the Mediterranean (cf. Watts 1999; see Chapter 1). The a-centrally organized Greek colonial system consisted of a group of city states, micro-regions which were only loosely or not at all affiliated in economic and political terms. Nonetheless, based on the connective power of the Mediterranean Sea and a small number of ties, a notion of shared group membership was strongly rooted in all of them. In other words, Malkin presents a perspective of how a "Greek" identity and language was dispersed throughout the Mediterranean and Black Sea area using the rhetoric of small-worlds.

Applied in this more rhetorical manner archaeological network perspectives are part of a meta-theoretical framework that can be referred to as relationism (e.g. Kaipayil 2009), methodological relationism (e.g. Ritzer and Gindoff 1992), or relational theory (e.g. Kineman 2011). Seen in this vein, network thinking is not new, especially not in the European academic tradition (Knappett 2005; LaBianca and Arnold Scham 2006; Malkin 2011: 41). The popularity of relational approaches in academia waxes and wanes, however. Archaeology is currently riding a wave of relational thinking and is (re-)connecting the pieces in the wake of the deconstructive efforts of post-processual Archaeology. It is therefore important to understand that using the concept of a network as a rhetorical device is not the same as applying network theory and analysis. In fact, sometimes the latter is even claimed to be antithetical or detrimental to the former (Ingold 2007a; Latour 2005; Malkin 2011). In Malkin's work an explicit network model or analysis is deliberately left out, since the author feels that network representations of multi-temporal, directional and dimensional connectivity too often lead to oversimplified models that still resemble "spaghetti-monsters" (*ibid.*: 18; e.g. Figure 1.4.2).

Although there is something to be said for this standpoint – there is much work to be done in the efficient visualization of networks, especially in archaeology –, his critique on "messy pictures" misconstrues the actual reason why more formal network approaches may be important new additions to archaeological method and theory. Networks, for example, can be employed as models for possible real-world connections. A good case in point is John Terrells's research on the likely structure of inter-community ties in New Guinea's north coast. For this he created the geographic relational modelling called Proximal Point Analysis already discussed in Chapter 2 (Terrell 1977; see also Broodbank 2000). As was shown there, PPA can serve to give base-line hypotheses for social, cultural and linguistic relations as underlain by geographic distances. Another example of geographic distance-based network modelling in archaeology is the case-study on Bronze Age Aegean inter-site connections presented by Knappett, Evans and Rivers. In order to test ideas on local maritime interaction they developed a software package, aptly named *ariadne* which runs a specific algorithm that was created for spatial modelling of cost-benefit relations in archaeological cases (Evans, *et al.* 2012; Knappett, *et al.* 2008). By means of this cost-benefit measure they looked into possible changes in Aegean

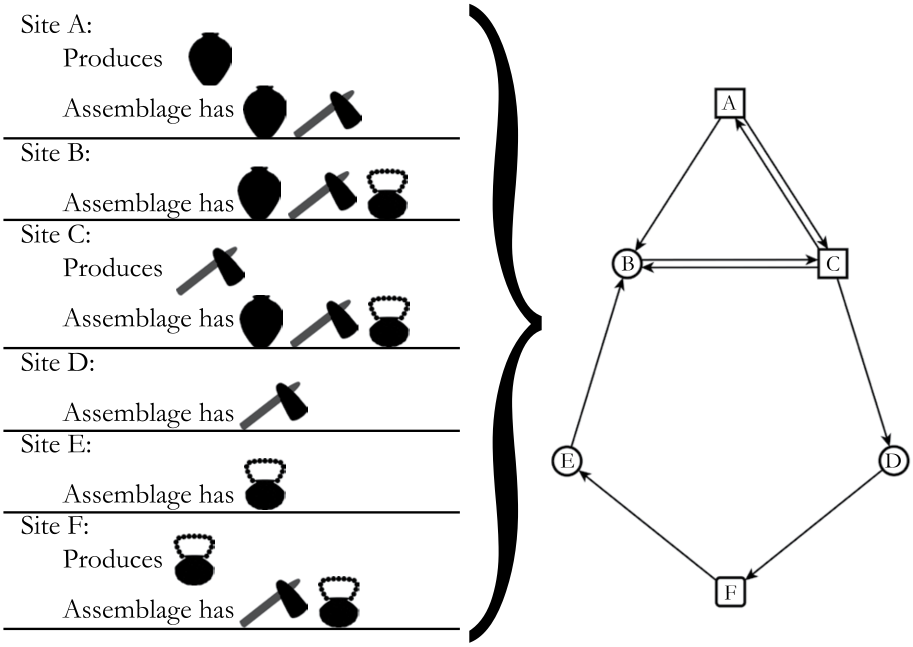

Figure 3.2: From archaeological assemblage to network. Here the archaeological record of the southern Chremanesian islands are combined and "incidences" (i.e. co-occurrences) of artefacts in assemblages and knowledge of production centres is abstracted into a network.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
A	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
B	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
D	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
E	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
H	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
J	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0
K	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
L	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	0	0
M	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0
N	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0
O	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
P	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0

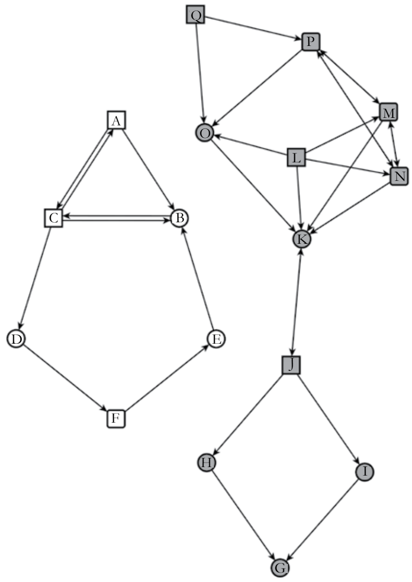

Figure 3.3: From matrix to network visualization. Here the matrix adapted from Chremanesia's fictional site assemblages is visualized as a network. In the matrix "1" indicates the presence of a tie, while a "0" means absence. A row of zeroes runs diagonally down the centre of the matrix, indicating there are no "loops" in this network (a tie from a node to itself). Moreover, due to the directed nature of this network, the matrix is not symmetrical.

networks based on the model's parameters and the absence or presence of site-nodes in the network. Among other things their model serves to illustrate the long-term network effects of the 17th century BC destruction (due to a large volcanic eruption) of the island of Thera, an important port of trade. According to this model the disappearance of the Thera node from the network caused overextension of maritime interaction routes which possibly heralded the demise of late Minoan culture approximately 50-100 years later (Knappett, *et al.* 2011).

These types of studies are interesting because their results can serve as base-line expectation models for what type of connectivity patterns one can expect in the region of study. This is exemplified by further research carried out by Terrell and his colleagues (Terrell 2010; Welsch, *et al.* 1992). Once again focusing on ties between communities on the New Guinea coast, linguistic affiliations were compared against a relational database based on Sepik material culture assemblages housed in the Field Museum of Natural History, Chicago. Both data-driven graphs were compared to a distance-based model and genetic affiliation, in both cases the model based on material culture similarities provided the better fit. This demonstrated, according to Terrell and his colleagues, that social boundaries in the region cannot be mapped to linguistic barriers, a correlation which is often taken for granted in archaeology. The corpus of data-driven network studies has been steadily growing and a selection of recent studies will be highlighted below

Site	Assemblage	Produces	Distributes	Comp.	Str. Comp.	Core	Clique
A	Type 1, 2	Type 1		#1		2-core	[A,B,C]
B	Type 1, 2, 3		Type 3	#1		2-core	[A,B,C]
C	Type 1, 2, 3	Type 2		#1		2-core	[A,B,C]
D	Type 2		Type 2	#1		2-core	
E	Type 3		Type 3	#1		2-core	
F	Type 2 and 3	Type 3		#1		2-core	
G	Type 4			#2		2-core	
H	Type 4		Type 4	#2		2-core	
I	Type 4		Type 4	#2		2-core	
J	Type 4, Type 5	Type 4		#2		2-core	
K	Type 4, 5, 6, 7, 8, 9		Type 5	#2		3-core	[K,L,M,N] & [K,L,O]
L	Type 5	Type 5		#2		3-core	[K,L,M,N] & [K,L,O]
M	Type 5,6,7,8	Type 6		#2	[M,N,P]	3-core	[K,L,M,N] & [M,N,P]
N	Type 5,6,7,8	Type 7		#2	[M,N,P]	3-core	[K,L,M,N] & [M,N,P]
O	Type 5,8,9		Type 9	#2		3-core	[K, L,M,N] & [O,P,Q]
P	Type 6,7,8,9	Type 8		#2	[M,N,P]	3-core	[M,N,P] & [O,P,Q]
Q	Type 9	Type 9		#2		2-core	[O,P,Q]

Table 3.1 Site nodes in the Chremanesian network. A list of the site assemblages of Chremanesia and production centres, followed by a list detailing to which components, strong components, cores and cliques a node belongs.

id	Degree %	Indegree %	Outdegree %	Closeness %	Betweenness %	Status %
A	4.8	3.2	6.5	5.6	0.0	3.3
B	6.5	9.7	3.2	5.2	8.1	8.6
C	8.1	6.5	9.7	7.7	11.7	6.5
D	3.2	3.2	3.2	4.1	6.3	3.3
E	3.2	3.2	3.2	4.8	6.3	2.6
F	3.2	3.2	3.2	4.4	6.3	2.7
G	3.2	6.5	0.0	0.0	0.0	5.3
H	3.2	3.2	3.2	2.5	3.6	3.1
I	3.2	3.2	3.2	2.5	3.6	3.1
J	6.5	3.2	9.7	7.9	18.9	5.5
K	9.7	16.1	3.2	4.9	21.6	17.0
L	6.5	0.0	12.9	11.1	0.0	0.0
M	9.7	9.7	9.7	9.3	2.0	10.2
N	9.7	9.7	9.7	9.3	2.0	10.2
O	6.5	9.7	3.2	4.8	6.0	8.2
P	9.7	9.7	9.7	7.5	3.6	10.2
Q	3.2	0.0	6.5	8.3	0.0	0.0

Table 3.2 Different measures of network centrality in Chremanesia.

(see also Brughmans 2013; Knappett 2013). Considering their rising popularity, it should be expected there will be more and more varied network studies in the near future.

To synthesize: networks in archaeology have been and can be applied in quite different ways (Isaksen 2013). Still, several general trends are visible in their implementation. At the threat of oversimplifying a dynamic situation, it can be said they are currently used in three different ways: (1) as conceptual metaphors and perspectives, (2) network models as base-lines, and (3) data-driven studies. As should be clear, these approaches are not mutually exclusive. In fact, I would argue that the usefulness of all three types of network is enhanced by combining all of them. If this is done there is much to be won by going beyond the traditional use of networks in archaeology as metaphors for exchange systems.

Key concepts and operation

Nodes and ties are the most basic elements of a network or graph. The term “node” has its roots in computer science and is also known as a “vertex” in mathematics and physics, “site” in physics, or “actor” in sociology. Ties or “edge”, “link” or “bonds” are the connections between nodes, creating the incidence structure of the network. Nodes and ties in a single network can literally be anything (e.g. Newman 2010: Chapters 2-5). This also applies to archaeological cases. However, when building a network it is required that nodes are equivalent in terms of their function in the network that is modelled and that they can be connected by relations that belong to an equivalent category. A network model of co-citations within a collection of academic papers, for example, would be drawn utilising references between papers and not based on whether the authors of the papers are personal acquaintances or not.[2] The same would be the case for an archaeological network. For instance, one can designate habitation sites as nodes and connect them if there is co-presence of artefact types in the site assemblage, as has been done in the hypothetical network presented in Figure 3.2 (e.g. Mills, *et al.* 2013; Sindbæk 2007). If one was to treat assemblages of regional surveys, activity sites and habitation sites as nodes in the same network this will presumably present us with a skewed picture. Needless to say, there could be a theory-driven motivation to do so.

The latter is important to keep in mind. A relational database and resulting network model is always contingent upon a theory that explains why a certain set of nodes and ties is deemed to be relevant for the question at hand. This is why formal network approaches always need to be applied in conjunction with a set of supporting ideas and hypotheses. It is entirely possible to create a network of the chronological connections between sites on the basis of stratigraphy, connecting site Y to site Z on the basis of the presence of cultural material in a similar geographic layer, for instance. However, such a network would not be only network theoretical but would also hinge on the geo-archaeological concept that such a geographic layer is indeed a valid type of relation (e.g. Waters 1992: 210-212). In this particular example, the theory is well-supported and it is also clear what such a relation entails: contemporaneous habitation of site Y and Z. However, in the case of shared artefact types across assemblages a shared artefact type will denote a tie. Whatever such a connection may imply in a societal or cultural sense is much more problematical to substantiate (see Chapter 4).

It is furthermore important that the choice of nodes and ties depends on the possibility to collect a database that can be acceptably "completed". It is problematical to measure networks when the structural holes – the empty spaces in the network – arise from missing data rather than actual absence of a tie. This is an especially problematical factor when working with archaeological data, because of the truism that absence of evidence is no evidence for absence. One can carry out a network study of habitation sites that have been excavated thus far, but the distribution of habitation sites will probably not fully correlate with the past distribution of contemporaneously occupied communities. When it is possible to collect a representative data set and abstract this into a collection of nodes and ties one should reflect beforehand upon the added value of a network approach. Analyses of very small data sets or networks with very few relations generally little more insight than can be gained from a cursory inspection of the original data. Nevertheless, network visualization can still effectively serve to communicate the networked nature of the data set.

2 One could contrast the citation network of scholars with their professional social networks in two separate networks.

In its basis, any archaeological feature can be investigated as part of a relational data set as long as the entities utilized as nodes can be meaningfully related. As a result, the inherent flexibility of that which constitutes a relational data set can be somewhat confusing at first. We find a number of obvious choices for node and tie-types in archaeology. As is clear from the literature, "sites" are most frequently selected as nodes. This echoes a general tendency in archaeology: the (habitation) site and its (ceramic) assemblage is the scalar unit of choice to understand past socio-cultural relations, even if there are many other types of archaeological features that can be used to construct networks (van Rossenberg 2012: 38-39). This is largely justified, since it is undeniable that places of habitation, ranging from the provisional shelter to the metropolis, are critical factors in any human network. Nonetheless, the prevalence of inter-site networks can blindside archaeological network approaches. Sites were indeed prime social, cultural, political and economic nodes precisely because they consisted of a myriad of micro-scale networks (Knappett 2011). In that sense it is remarkable that GIS-based proxemics and the studies of micro-practices, have not yet led to more formal network studies that emphasize networks of household assemblages or other more local scales of analyses (Mol and Mans 2013; Chapter 6). A similar remark can be made on network studies that draw relations between objects or object types based on their attributes (see Chapter 8). These smaller scale analyses could function as a network operationalization of design, materiality and object system theories.

In terms of the ties between site-nodes, distances in geographic or "Euclidean" space have often served as a basis. This development follows a line of earlier archaeological graph theoretical studies partly based on geography (cf. Brughmans 2013), such as publications by Terrell (1979) and later Broodbank (2000). Utilizing the geographic distance between sites provides a basic but profitable ground level for understanding past networks. This also showcases the close ties between archaeological network studies and GIS-based modelling, including space syntax approaches (Hillier and Hanson 1984; e.g. Mol 2012). Furthermore this geographic preference is presumably influenced by the fact that, although archaeologists cannot easily understand the human factors (cultural and social practices) that shaped a past network, physical factors such as distance between sites are more easily recovered. Site assemblage overlaps repeatedly serve as a basis for drawing ties between sites (e.g. Mills, *et al.* 2013; Sindbæk 2007; van Rossenberg 2012). Archaeological techniques that can be utilised in order to find the provenance of specific objects in a site assemblage can also be of great assistance when reconstructing more detailed relations between site assemblages (Golitko, *et al.* 2012; Graham 2006; Phillips 2011). If detailed knowledge can be acquired concerning inter-site steps in the *chaîne opératoire* of individual objects or specific artefact types this can enhance network modelling of archaeological relational data sets even more (Chapter 5).

An elementary form of graph theory, the type of mathematics underlying many network studies, was first put forth by Leonard Euler. In his essay dated 1736 he addressed a standing mathematical question based on the topography of the city of Königsberg (since 1945 Kaliningrad, Russia). This city was laid out across four landmasses connected by seven bridges. The question was whether it was possible to walk a route that covered the whole city without backtracking even once. This problem is similar to a modern diagram-tracing-puzzle in which one has to follow an "Eulerian route" in order to connect the dots and complete the picture. In a series of twenty-two paragraphs Euler first proceeded to abstract the problem, recognizing that its solution was not based on the layout of Königsberg or any other real world example, but on the routes between points – in Königsberg taking the form of bridges between city districts.[3] After surmising that the Königsberg problem had no solution, he then abstracted that for all cases, "if there are more than two areas to which an odd number of bridges lead, then such a journey is impossible." Yet when "the number of bridges is odd for exactly two areas, then the journey is possible if it starts in either of these two areas." Yet if there are no areas to which an odd number of bridges lead, then the required journey can be accomplished starting from any area (Euler in Hopkins and Wilson 2004). These abstractions and theorems later provided the base for what was to become known as "graph theory" – a term popularized in handbooks by the American mathematician Frank Harary (e.g. 1969).

This first example of graph theory delivers an elemental truth about network approaches. In order to find solution to problems regarding relations, one has to (1) abstract a general network theoretical problem, (2) abstract the nodes and the relations of the network, (3) analyse them and (4) abstract a conclusion from this (Scott 2000: Chapter 3). Therefore, in the case of the Chremanesian network an archaeologist may wish to investigate if the collection of sites in the data set forms groups of some kind and if group composition and similarity is centrally regulated or not. He or she could abstract this problem by asking whether there are any nodes in the collection of sites with more ties with each other than with other sets of nodes. If so, are there within these groups nodes with more network power than the average member of the group? The relations between the nodes can be discerned based on the presence or absence of a certain artefact type at a site. This is in turn based on another set of theories implying that such a pattern of presence and absence is meaningful for understanding communal systems in archaeology (e.g. Flannery 1976; Mills 2000). The outcome of the analyses might be based on the type of measure applied to understanding group composition and power within networks (Brandes and Erlebach 2005; Newman 2010: Chapter 6; see below).

Once this first steps has been taken a matrix of relations can be abstracted from a data set. A matrix is essentially a view of the mathematical structure of the graph. In a matrix, nodes make up the columns and rows, while ties are represented by means of the content of the matrix cells. The cells of the matrix of the most regular type of graphs do not have a discrete value, but will often contain binary data, a "1" marking the presence and a "0" marking the absence of a tie. In such a binary matrix, a node will not often be related to itself – a type of self-referential relation

3 In contrast to popular belief Euler did not draw a graph of the city of Königsberg but rather labelled the landmasses and routes with letters (Hopkins and Wilson 2004).

sometimes referred to as a “loop”. A binary matrix will typically consist of a series of zeroes running diagonally along the matrix, dividing it in half (Figure 3.3).

Not all network data will necessarily reflect two-way or reciprocal relations, but it is also possible to work with tie directions in graphs. If a graph is “undirected” it means that either all ties are considered to be reciprocal or that it does not matter for the model if ties are reciprocated or not. A matrix of an undirected graph can be easily recognized because it will be perfectly symmetrical. A visualization of such a graph will in principle show all ties as single lines. If not all ties in a network are necessarily reciprocal, this makes a graph “directed”. This is regularly visualized by means of an arrow-head at the end of a tie indicating its direction. Because certain nodes might be linked by only one directed tie, a directed graph will not (always) yield a symmetrical matrix. Although it is often difficult to understand the direction of relations in archaeological data sets, directed graphs might come into play in certain cases, e.g. a clear grasp on producers, distributors and consumers in a *chaîne opératoire*. In the network of Chremanesia ties have been given directionality based on a hypothetical – and admittedly rather perfect – data set that can identify producers, distributors and consumers. This data set therefore yields an a-symmetrical matrix (Figure 3.3). Finally, ties can also be provided with a value in a matrix. Especially in the case of archaeological networks this can often result in further insights into the specific historic processes shaping the network (Peeples and Roberts Jr. 2013). Once completed a matrix can then be explored and analysed further or be visualized as is.

2-mode networks and ego-networks

The majority of networks plot relations between nodes of the same kind – e.g. a person to other persons or one site to other sites. These types of networks are 1-mode networks. However, networks can also serve to understand the relations between nodes that are not of the same kind. This is based on tracing the incidences of ties between one type of node with another type of node. Such a 2-mode network, sometimes referred to as a bi-partite network, can present a rather different perspective. In a social network it might illustrate how academic scholars visit various congresses and how, through these meetings, they might become acquainted.

A 2-mode model can therefore present a radically different view of a network. There is, indeed, a different type of matrix underneath this graph, because it models information between two sets of nodes. A 1-mode graphs always consists of square matrices. A 2-mode matrix can have varying row and column lengths. It is possible to further explore group formation and other network features from a 2-mode matrix by transforming the matrix from a 2-mode to that of a 1-mode graph. Such a graph is known as an affiliation network. An affiliation network will display the ties between either the nodes in the rows or those in the columns by transposing the original 2-mode matrix into a 1-mode matrix.[4]

Where Figure 3.3 shows a 1-mode network, Figure 3.4 shows a 2-mode network. A 2-mode network can be of assistance with regard to the lack of detail inherent to many archaeological data sets. With many archaeological data sets, such as that of the hypothetical network above, one could also produce a 2-mode rather than a 1-mode graph based on relations between site assemblages and artefact types (Everett and Borgatti 2012). Even if archaeological data sets do not present us with any indication of direct relations between similar nodes, they do testify to the relation between nodes relative to categorically different nodes. Thus, whenever a detailed picture of a site's role in artefact type distributions is not feasible, an affiliation network – e.g. presence in the site assemblage – can be revealing. An archaeological 2-mode network showcases how networks of "people" (sites) and material culture (artefact types) can be part of mutually constitutive networks.

Chapter 6 will make use of ego-networks. The ego-network is not a network mode but rather another type of network altogether. Also known as centred graphs, they were pioneered by the sociologist Linton Freeman. Instead of focusing on the networks as a whole, ego-networks were designed to understand the effects a network has on a particular individual. In Freeman's original paper he observed how a group of academic professionals who had all been invited to a conference communicated with each other independently of the conference organizer. He found that after an initial period of communication, running via the conference organizer, small groups of scholars began to form. These groups dictated how future cooperation took place irrespective of the management of the conference organizer (Freeman 1982). More recently, the ego-network approach has also served to study and find remedies for structural holes – negative spaces in networks in which ties could exist, but for some reason do not (Prell 2011: 123-125).

The ego-network approach is thus all about visualizing and analysing networks that revolve around one node, referred to as the ego-node. The method to create an ego-network is rather straightforward: simply include nodes in the model with which Ego has a direct tie, then draw ties between all nodes that are also in direct contact with each other. This then allows for an analysis of Ego's direct network

4 There are two ways in which this can be done in UCInet 6.0: the cross-product method and the minimum method (Hanneman and Riddle 2005). The latter is applied to valued 2-mode data and will not be used here. Cross-product method transposition utilizes binary data (absence/presence).

	Group 1	*Group* 2	*Group* 3	*Group* 4
A	1	0	1	1
B	1	1	0	1

Suppose I wish to determine the affiliation of two row nodes "A" and "B" from the 2-mode network matrix above. This is done by taking entry A and multiplying it with the corresponding column entry of B. Proceed to do this for all other columns. Next the result of all columns is summed: (1 x 1) + (0 x 1) + (1 x 0) + (1 x 1) = 2. The outcome hereof is the strength of affiliation between the row nodes A and B as a tie with value 2. In order to fill a matrix with more than two row nodes the process is repeated for all rows. The same can be done with the Group nodes in the case-study network by multiplying across columns and adding up the rows.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
3	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0
6	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0
7	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	1	0
8	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	0
9	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1

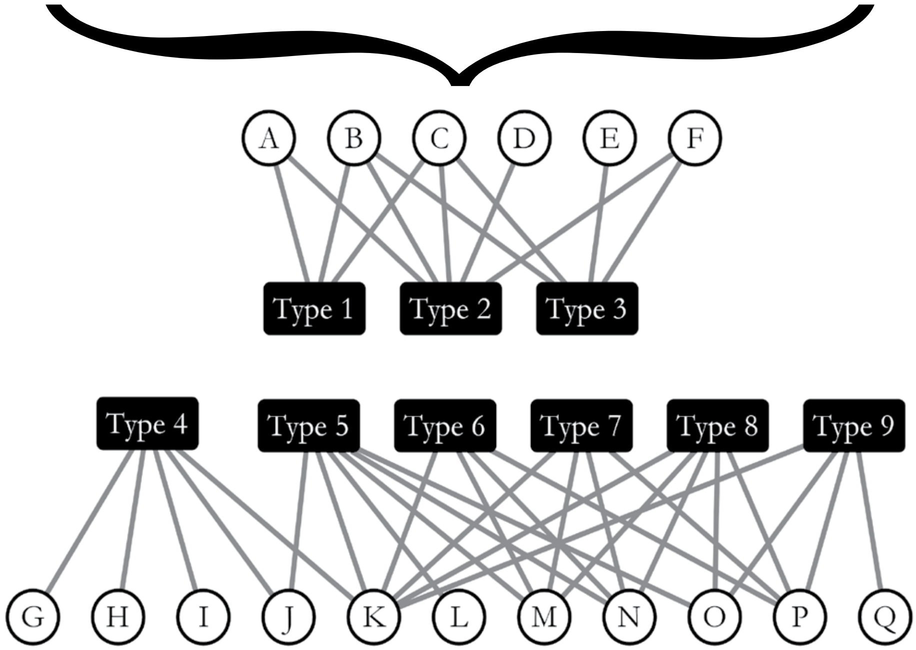

Figure 3.4: From matrix to 2-mode network. This shows a 2-mode network is based on the same archaeological record as the 1-mode network presented in Figure 3.3. Aside from information on site relations this also provides us with an intuitive view of which artefact types have the widest distribution in Chremanesia.

(Figure 3.5). This approach can also serve to compare the networks of different egos, which provides information on how different nodes can have completely different ego-networks and can thus be very different relational entities, even if they are part of the same network.

The fact that nodes and ties can literally be anything also applies to archaeological ego-networks. For example it is possible to designate a specific artefact as Ego and see how it connects to a wider web of things in order to better understand that specific artefact (type). Sites are once again an intuitive choice for an ego-network

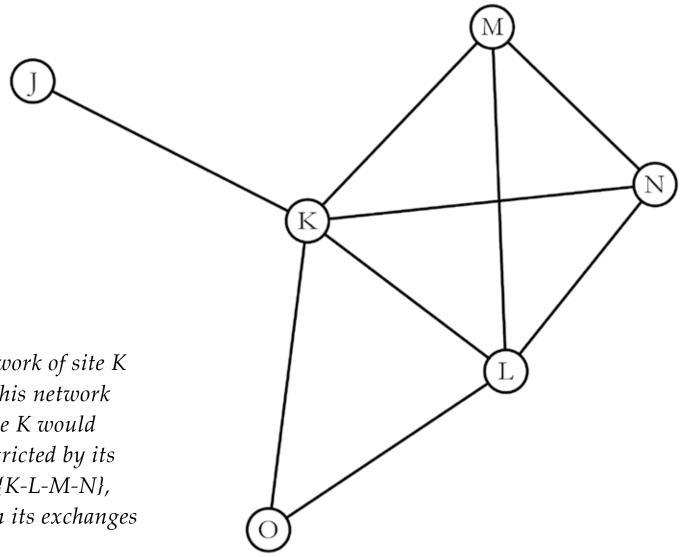

Figure 3.5: The ego-network of site K in Chremanesia. From this network we may suppose that site K would have been relatively restricted by its participation in Clique {K-L-M-N}, while it has free reign in its exchanges with J.

approach. While the majority of archaeological network studies sites connect to sites, a site ego-network model will connect a site to its own relational record. Through an ego-network we can begin to understand a site as a relational entity.

An ego-network is not a completely different type of network, however. Its analysis is also based on graphs and matrices. Thus, problems that affect regular archaeological network models and analyses also affect ego networks. They are for example not any less vulnerable to incomplete archaeological data sets. The reason being that, even if the network is centreed on one site, the same set of information on all other nodes in the network is also needed for the model to fully function. Furthermore, ego-networks need to be handled with care when working with multiple and multi-disciplinary data sets. When modelling an ego-network some relational data sets might turn out to be incompatible with others, even if they are part of the same site assemblage. Whether this is the case or not will be based on the type of data and, once again, a supporting set of theories.

Measuring and visualizing networks

One of the strengths of a graph theoretical approach is that it allows for aspects of networks such as systemic structure, group formation and power to be measured in many different ways. For example, while groups are often treated as (en)closed – you are either in the group or out of the group – network modelling allows for a more flexible perspective on group membership. A varied constellation of nodes can form different network groupings known as "subgraphs". Thus network measures can be used to explore and eventually analyse how, for example, artefacts can belong to multiple types, styles, assemblages or other categories.[5] This flexible view of multi-scalar and nested network cohesion might be applicable when analysing the archaeological record of the Caribbean as a network (see Chapter 8).

The same applies for understanding node power, the structural importance of one node relative to all other nodes, within networks. Looking at power in society it can be perceived to rest in the hands of an important public figure, a leader such as a chief, king or president. On the other hand various types of power can also be seen to lie with persons who have a more covert access to important institutions but who connect two different economies of power: the proverbial *eminence grises*. The same can be said regarding centrality in networks that can be recovered archaeologically. For example, based on settlement patterns it can be said that a site that is close to many other sites was likely an important location. A site may be connected to a few other sites but could still be central for other reasons. For example because it is positioned on a critical juncture of two trade routes. A different view of power will entail a different understanding of central places, processes, persons or things in a system. In other words, the kind of analysis of group formation or network power required depends on the concept of group or power that is relevant for the question at hand. Below I will briefly discuss several basic concepts and measures of network grouping and power before applying these to the case of Chremanesia.

The network measures employed in this work are relatively simple operations. Nevertheless, although it is theoretically possible to carry out graph-theoretical measures by hand, measuring even a small relational data set can be a laborious process. Fortunately, a range of analytic software can be useful for speeding up these calculations. It is necessary to understand the graph-theoretical basis of algorithms in order to comprehend the results of the analysis, yet the relatively easy-to-use interface and reports on many of these programs facilitate a more rapid and increased understanding of the data set. The result is that these relatively easily accessible network analytic programmes have given a boost to network studies across the board.

Although processing algorithms may require a large amount of computing power, the relatively small size of most archaeological networks mitigates this problem. The majority of analyses applied in recent archaeological network studies can be done on low-spec personal computers, with calculations taking only a short time. Of course, as the complexity of graph and other network theoretical models and measures continues to increase in archaeology, more complex calculations will require more computing. For now, most matrices can be created in a simple spreadsheet programme and then exported into a range of programs as a text (.txt) or comma delimited file (.csv) or created and edited in the network program itself. Other often used file types include .gml (Graph Modelling Language), .net (Pajek) and .dl (UCInet).

5 Subgraphs are indicated by accolades in the text: e.g. {M-N-P} for the subgraph consisting of nodes M, N and P.

The possibility of visualizing complex networks is a very powerful feature of network studies (Brandes, *et al.* 2006). A single figure depicting a network can illustrate something that a written discussion of a network's structure cannot hope to reveal in several pages. Furthermore, the intuitive mapping of a visualized network can communicate information to non-specialists that a matrix or formula cannot. A visualized network model can present more information than a matrix could hold. A number of network analytic programs offer the possibility to attach more qualities (colour, size, shape, *etc.*) or quantities to ties and even to nodes. These can then serve as visual keys for certain types of information. Larger node sizes are often used to indicate that a node is centrally positioned in the network. This can also be done with non-relational information (e.g. producer, distributor or consumer sites; Figure 3.3).

A growing choice in network analytic software is becoming commercially or freely available.[6] UCInet (Borgatti, *et al.* 2002a) is the most widely used program for network analysis in the social sciences. It is also the one most often found in archaeological network studies thus far. This shareware can handle large amounts of data, offers a relatively easy to use interface, direct saving and editing of matrices, automated matrix handling, and a range of analytic options. Specialized components can also be loaded into the main program in order to enhance its functions. Matrices can be visualized by means of the "Netdraw" software component (Borgatti, *et al.* 2002b). Although some models and measures here have been created or carried out with UCInet 6.0 (indicated per case), most have been done with visone 2.3 and later versions (Brandes and Wagner 2004).[7]

Visone is freeware and offers the possibility to create graphs directly by drawing them. From this network model the program creates the matrix of the graph that can be explored with several basic and advanced measures. These analyses can then also be easily visualized by means of a number of different settings. Nodes and ties can be provided with a different location or appearance and it is possible to attach extra information to them applying a built-in editor. Matrices can be exported and imported to other popular network analytic software, such as UCInet. In addition, the network visualizations can easily be exported into a number of other (graphic) file formats. Visone's visual input offers an efficient way to draw and explore smaller relational data sets. In combination with the option to attach and

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6 Currently, a Wikipedia article titled "Social Analysis Network Software" provides the most comprehensive and up-to-date list of available network analytic software (http://en.wikipedia.org/wiki/Social_network_analysis_software, accessed 25-8-2013).

7 When I started my analyses visone was not able to handle 2-mode data, as it automatically wrote a drawn graph as a 1-mode matrix. At that time I used UCInet for 2-mode to 1-mode transformation. The most recent versions of visone do support 2-mode data.

visualize extra attributes to nodes and ties, it is a practical and intuitive alternative to UCInet for (smaller) network archaeological studies.[8]

Measures of the network as a whole

There are many types of network measures. Perhaps the most elementary are those that measure the network as a whole. These can also be used to compare one network to another. Network density or sparseness, for example, is a measure related to the fraction of ties found versus the total possible number of ties. Even without any further analysis the network density can be insightful. One thing that will be clear from a first cursory glance is whether a network is excessively sparse or dense. Although network sparseness or density is not necessarily a defining feature of a network – networks with similar levels of density may have a completely different structural layout –, it does present an initial impression of structure, cohesiveness and connectedness of the overall network. For binary, non-loop matrices the density is easily calculable: $\frac{t}{n(n-1)}$, where t is the sum of all cells in the matrix (i.e. the total number of ties) and n is the total number of nodes. The outcome will be somewhere between 0 and 1, with an outcome of 0 indicating a collection of unconnected nodes and 1 a network that is maximally connected. Thus the density of the Chremanesian graph is, $\frac{31}{17 \times (17-1)} = 0.113$ or, in other words only 11.3% of the network's total capacity is utilized (Scott 2000: 78).[9]

In itself network density is not that informative. It is, however, more useful when contrasted to other networks. Particularly when compared to another, similar network this will establish some first structural similarities or differences between them. For example, Chremanesia's fantastical neighbouring archipelago, the Insulae Rerum, has the same strange practices and limited material assemblage. Closer inspection reveals that the network of the Insulae Rerum has a density of 65%, however. In comparison to Chremanesia this could imply that, regardless of the actual size of either network, greater cultural similarity and more egalitarian relations between sites should be expected in the Insulae Rerum.

Distance is another trait that can be of use for network comparisons. Distance between nodes in a network is always measured by its geodesic or shortest paths. As was already outlined by Euler, a path is a core concept of graph theory, signifying a sequence of ties in which each node and tie is distinct. The length of the path equals the number of ties in it. If a graph is directed, the direction of the arrows is normally taken into account. Thus in the case study the distance between A and

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8 At the time of writing no software packets were capable of dealing with archaeological relational data. ArcGIS does offer the possibility to apply "Network Analyst" as an extension, but I have no personal experience with this program. The *ariadne* program, created by Tim Evans, was developed in order to model the relations between sites or other geographic entities. It is primarily based on an algorithm of interaction cost and benefit especially created for research that Knappett, Evans and Rivers carried out on Minoan sites (Knappet, *et al.* 2008), but with a different file input can also be used for other (archaeo-)geographic network modelling. Unfortunately, due to a java-based error, it could not run on any of the computers I had access to.

9 It should be noted, however, that the density is here influenced by the fact that the graph is directed. Because non-directed graphs are symmetrical, a two node, non-directed graph will yield a matrix sum of 2, whereas one tie in a directed graph of two nodes will only yield a matrix sum of 1.

E is 4 (A→C→F→E). The diameter of a network or subgraph in the network is the length of the longest path between any pair of vertices for which a path actually exists (Newman 2010: 139-140). In Chremanesia there are several paths leading from node Q to G, but the shortest path between them has a length of 5 (Q → O → K → J → H or I →G). Especially when working with larger data sets measuring the diameter will present a first appreciation of the dynamics of distance in a network.

Subgraphs

Network groups or subgraph will be of especial interest in the case studies presented in later chapters. A dyad is the most basic grouping in a network. As a network entity the dyad is not very insightful, it simply means that a pair of nodes is connected by at least one tie. In fact, one could say that a network consisting only of otherwise unconnected dyads is not a network at all – or not a very interesting one at the very least. In order for a network structure to emerge, it needs to include dyads that intersect, i.e. have one node in common. Such dyads are called incident (Brandes, *et al.* 2013).

Not all (groups of) nodes in a graph are connected by a path. Indeed a network model may consist of discrete "sub-networks" called components, as is the case in the example of Chremanesia. These single nodes or groups of nodes cannot be connected with even a single path. Still, these are considered to be part of the same graph, but will never be part of the same subgraph. Within one graph we may find collections of nodes not related by any ties, other than for the fact they were selected for inclusion in the first place. It is possible to make a selection based on contemporaneity as has happened in the case of the hypothetical Chremanesia network, for instance. Nonetheless, even if there are only nine types of things there is indeed a break in this meagre material cultural repertoire, dividing Chremanesian culture and society into two components: North and South.

Components are the most inclusive form of subgraph. For a node to be part of a component it only has to be connected through minimally one path to all other nodes. When working with directed graphs it is also possible to differentiate between strong and weak components. Strong components are subgraphs with directed ties that still create a continuous path – in other words all relations between nodes are reciprocal – while weak components merely consist of nodes with ties of any type of direction. In the Chremanesian network the nodes {M-N-P} form a strong component while other subgraphs, like component 1 and 2, are simply weak components. The cycle is another type of grouping that dependends on paths between nodes, more specifically: a path that can return to the node from which it started, such as the site cycle C → D → F → E → B → C. Strong components like {M-N-P} are always cycles. Cyclical components are sets of cycles that intersect. Strong components, cycles and cyclical components are examples of further possible subgraph-divisions of a network (component).

Cores present yet another way of looking at groups within networks. A *k*-core is a set of nodes that is related because they are at least adjacent to *k* other nodes in the same component. At low numbers a core is a highly inclusive way of looking at groups in networks. It can, however, be further divided by distinguishing between *k*-core and *k*+1 core members – e.g. the *k*-core members are part of the group but the *k+1* core members have even more connections within that group. In the current example all nodes are members of 2-cores, but only 6, {K-L-M-N-O-P} are member of a 3-core.

A triad is a collection of three nodes that are maximally connected, i.e. every node is connected to all other nodes. There are certain fundamental differences between dyads and triads – as the sociologist George Simmel (1950: 135-137) had already noted. While a dyad is simply a pair of connected individuals, the addition of a third node transforms the network dynamics in crucial ways. With three nodes a so-called group effect is more likely to occur, which undermines the power and autonomy of the individual node (see Chapter 7). A clique is a more expansive, maximally connected subgraph – *ergo* all cliques contain at least one triad (Kosub 2005). Since it requires a subgraph in order to be maximally connected it is the most restricted and tightest form of group inside a network. Within the network of Chremanesia we find five cliques: (1) {A-B-C}; (2) {K-L-M-N}; (3) {K-L-O}; (4) {M-N-P}; and (5) {O-P-Q}. Note that a node can belong to several cliques at the same time, such as site K that belongs to two cliques. There are several variants on the base clique allowing its group membership to be more flexible. The concept of the *K*-cliques waters down the strict requirement of maximal connection in order to allow nodes to be a member of the clique if no more than *k* ties separate them and the other members of the clique. A *k*-clan is a stricter variant on the *k*-clique: specifying that nodes with distance *k* are clique members only if the diameter of the clique is no larger than *k*. Therefore, in the network model nodes A to E belong to a 2-clique but do not form a 2-clan because site D and E are only connected by non-clique member F. Finally, *k*-plexes are collection of cliques that have ties with all but *k* members of a clique.

These various ways of looking at groups inside the hypothetical network model presents us with alternate views of the same relational data set (see Table 3.1). In the hypothetical production and distribution network of Chremanesia the easiest subgraphs to identify are the two different components. Although components are generally easy to spot in any visualization or even in the data set itself, their analytical value should not be underestimated. For instance, it is easy to miss the breadth of the components by looking at a non-relational data set, because it consists of various sites that do not seem to be very connected. Further analysis of the component's connectivity might reveal interesting patterns. Site Q is a good example of this. From one perspective it could be described as a "backwater" of the graph. It functions as a producer of artefact type 9 which it distributes to site O and P. However, even if site Q shares no artefact types with site G, H, I, J, L, M and N, it is nevertheless still part of the same network component. In fact it is indeed part of the 2-clan {K-L-M-N-O-P-Q} and as such directly part of a group that includes the most powerful sets of nodes in the graph (see below).

Realising that this relational database can also be explored as an affiliation matrix of the 2-mode graph it is also possible to look at subgraphs through artefact type connection rather than site connections. The 2-mode graph shows how not only sites but also artefact types are holding the network together. Zooming in on type 6 it shows that this node, like site K, is a central "gathering place" in the network: i.e. it has many different members. In turn these are also members of other artefact types. This perspective can illustrate how an artefact (type) might diffuse through a network and even "interact" with other (types of) artefacts while doing so. Type 1 and 3, for example, are less well connected than type 2, so it could be hypothesized that the latter is more likely to spread through component 1. It also indicates how types themselves might interact at various locations, for example at site K, and thereby possible influence each other.

Centrality

The structural qualities of triads, cliques and other subgraphs demonstrates that aside from network groupings, the degree and paths by which individual nodes are connected are important features of a network. This can be further studied by looking at node "power" or "centrality" in networks (Brandes and Erlebach 2005: Part I; Newman 2010: Chapter 6). There is no common definition of power in networks, yet the concepts builds on the intuitive idea that power is defined by the relations a node is engaged in. Some measures of network power hold that the more connections a node has relative to other nodes the more powerful it is. Others look at relative importance of ties and paths that connect to a node instead of to other nodes. Mizoguchi (2009) provides an archaeological study of network power presenting examples of various centrality analyses in the context of early state formation during Japan's Kofun period.

Degree is the most basic of all the types of network centrality. It simply counts the number of ties that attach to a node and compares these to other the same count for all nodes in the network.[10] The idea behind degree analysis is that the more ties a node has the more influence it has over the rest of the network. Indegree and outdegree are subvariants of normal degree centrality for which respectively only the ties coming in or out count towards a node's centrality. [11, 12] In archaeology, indegree might be of use when researching a tribute-system in which only the incoming relations are of importance. Outdegree on the other hand may come into play when ranking which workshop or production centre has the highest number of consumer sites.

Closeness is a centrality measure based on network paths, rather than on the number of ties attached to a node. A node's closeness is the inverse of its farness, which is the total distance between a node and all other nodes in the graph.[13] Another centrality measure based on paths is betweenness. A node's betweenness

10 Degree measure (as calculated in visone, Brandes and Wagner 2004): : $c_v = \sum_{e \in \mathrm{instar(v)} \cup \mathrm{outstar(v)}} \omega(e)$

11 Indegree measure (as calculated in visone, *ibid.*): : $c_v = \sum_{e \in \mathrm{instar(v)}} \omega(e)$

12 Outdegree measure (as calculated in visone, *ibid.*): : $c_v = \sum_{e \in \mathrm{outstar(v)}} \omega(e)$

13 Closeness measure (as calculated in visone, *ibid.*): : $c_v = \frac{1}{\sum_{t \in V} \delta(\mathrm{v,t})}$

centrality can be gained by determining the shortest paths between a pair of nodes in a graph and calculating which fraction of the path runs through the node in question, repeat this measure for all pairs of node in the graph and summing up all of these fractions.[14] In essence, a node with a high betweenness rating functions as a gatekeeper, controlling access from nodes to other nodes in the graph. Thus, even it does not have the highest number of ties it may have a position that is strategically best. The real power of a node with high betweenness centrality depends for a large deal on the overall connectivity of the graph. If a graph is relatively dense there will be relatively many short paths and therefore a high betweenness will not be valued much: e.g. if all sites in a region have relatively easy access to a certain raw material the one with the easiest access only has marginally more power than if access to a certain resource is highly restricted.

Finally, in some cases status centrality measures, also known as "Katz' status centrality", will be applied.[15] Status centralities fall within a group of centrality measures based on Eigenvector analysis. Like degree, these measures are based on the idea that power in networks can be measured by the amount of ties to and from other nodes. Aside from tie quantity, status measures determine the power of a node based on the power of other nodes that it is tied to. Take the following situation: person A has ten contacts all of whom have fifty contacts and person B has one hundred contacts. Based on degree, B can be said to be the most powerful person. Yet a measure of Katz' status will indicate that A is the more powerful node. Imagine a situation in which a paramount chief C, who does not have a large following but does have ten subordinate chiefs who do, competes with a chief D with a good base of support. Who will be more powerful?

The answer is not immediately clear. Rather, it is dependent on what type of power structure is more applicable for the issue at hand. If it is about exerting influence directly (e.g. intra-communal power) chief D may be regarded as more powerful. If the type of power arises from a larger set of interactions, such as may be the case in larger distribution networks, chief C will be more powerful. This indicates that the selection of centrality analysis should be compatible with the type of network dynamics one is interested in. Beyond those discussed here, many other kinds of centrality analyses have been developed in order to measure specific variations of power in networks. With most network software, exploring power in networks is literally just a matter of selecting a different type of analysis from a menu. Because of this, adopting graph theoretical measures to comprehend power in networks can be deceptively easy. The type of analysis used for understanding centrality can heavily influence the final interpretation of the archaeological network.

In the hypothetical network model of distribution and consumer sites, depending on which type of degree centrality is applied, an individual node's network power will vary (Table 3.2). In terms of the total number of ties, or

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14 Betweenness measure (as calculated in visone, *ibid.*): : $c_v = \sum_{s \neq v \neq t \epsilon V} \frac{\sigma_{G(s,t|v)}}{\sigma_{G(s,t)}}$, where $\sigma_{G(s,t)}$ and $\sigma_{G(s,t|v)}$ are the number of all shortest *st*-paths and those passing through v.

15 Status measure (as calculated in visone, *ibid.*): $c_v = \alpha \cdot \sum_{(\mathrm{u,v}) \epsilon \mathrm{instar}} (1 + c_u)$, where $\alpha = \min\{\max_{v \epsilon V} \mathrm{indegree}(v), \max_{v \epsilon V} \mathrm{outdegree}\ (v)\}^{-1}$

degree, K, M, N and P have the same centrality. With the network of Chremanesia in mind this could be explained as evidence for a sprawling interaction sphere. Yet looking at betweenness and status, K's centrality is far higher than those of the other nodes. This implies that even if sites will have an equal part in the total amount of network interaction, some of them are more strategically located – betweenness – and have a higher total status due to their interactions with other powerful nodes. K would have occupied a very central position within the North component of Chremanesia.

Other types of centrality do not necessarily entail that anode has many connections. Node J, for example, has the second highest betweenness, even if it has only 6.5% of the total degree. Looking at the network model it becomes clear why: J is the bridge between two otherwise unconnected network regions. A similar thing applies for L, who actually has the highest closeness. K on the other hand is relatively far from most nodes, especially nodes P and Q in the outskirts of the network. In this hypothetical case being close to many other nodes can entail a different type of centrality. Suppose that occupants of site L wished to expand their distribution to other communities. A high closeness could indicate that this would require a relatively much smaller investment for L than for other sites in the region.

Network explorations

Chremanesia is an imperfect model for real archaeological networks – it is too perfect. It is a location where only a few ties based on the presence or absence of things form the basis of society and culture. There are furthermore only a few sites that display very little variation in the material cultural repertoire. Historical realities and archaeological records are far "messier" and less one-dimensional than Chremanesia's island world. Fortunately, network modelling and data-driven networks actually do not have to be based on such near "perfect" data sets. In fact, they rarely are (Isaksen 2013). Nevertheless, Chremanesia shows how it is possible to use archaeological assemblages by abstracting, visualizing and applying subgraph and centrality measures to them.

Technically speaking such a data-driven study of incident ties between items of material cultures in archaeological assemblages or other types of relational information should be referred to as "network exploration". This means that, rather than using statistical, analytical or theoretical modelling from the network sciences, concepts, visualizations and some basic measures are employed to lay bare and study in detail the inherent structures of archaeological and ethnohistorical sources of information. This type of bottom-up approach is a necessary first step and provides a good fit for some of the data sets and questions in the discipline itself. In addition, as was discussed in Chapter 1, the goal is not to use network science to find a general theory of pre-colonial network formation and development but rather to use it to check some of the "hidden" network assumptions of existing Caribbean archaeological theories. This will be done in Chapters 5 to 8. However, before that, it is necessary to delve deeper into the nature of the socio-material relations that would have structured the networks in these case studies.