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Thinking Through Networks: A Review of Formal Network Methods in Archaeology

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Abstract This review aims to expose the potential of formal network methods for archaeology by tracing the origins of the academic traditions, network models, and techniques that have been most influential to archaeologists. A brief discussion of graph theoretic applications in archaeology reveals how graph visualization and analysis was used since the 1960s in a very similar way to later network analysis applications, but did not seem to have influenced the more widespread adoption of network techniques over the past decade. These recent archaeological applications have been strongly influenced by two academic traditions, social network analysis and sociophysics. The most influential and promising techniques and models adopted from these traditions are critically discussed. This review reveals some general trends which are considered to be the result of two critical issues that will need to be addressed in future archaeological network analysis: (1) a general unawareness of the historicity and diversity of formal network methods both within and outside the archaeological discipline has resulted in a very limited methodological scope; (2) the adoption or development of network methods has very rarely been driven by specific archaeological research questions and is dominated by a few popular models and techniques, which has in some cases resulted in a routinized explanatory process. This review illustrates, however, the great potential of formal network methods for archaeology and argues that, if this potential is to be applied in a critical way, a broad multidisciplinary scope is necessary and specific archaeological research contexts should dominate applications.

Keywords Complex networks · Social networks · Networks · Graphs · Archaeology

Introduction

In a previous article (Brughmans 2010), I have argued that in the archaeological discipline, network methods have been insufficiently explored and have been

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dominated by a few popular perspectives that were sometimes uncritically adopted from other disciplines. Here, I will discuss this issue in more detail and argue that it seems to have resulted largely from a general unawareness of the historicity of network-based approaches, which span at least eight decades of multidisciplinary research. Many network analytical techniques that would only find a broader use in the last 10 years were in fact introduced in the archaeological discipline as early as the 1970s. Recent archaeological applications of formal network methods in particular have shown a tendency for adopting techniques and models that were fashionable in other disciplines at the time of publication rather than exploring other archaeological and non-archaeological approaches. This article does not claim that every archaeological network study should include a historiography. It merely wishes to stress the need to explore the full range of existing network techniques and models and select those that are most suitable for addressing particular research questions using the available archaeological data. I will illustrate that knowledge of the diversity of archaeological and non-archaeological network methods is crucial to their critical application and modification within archaeological research contexts.

This article aims to trace the origins of the academic traditions, network models, and techniques that have been most influential to archaeologists. Through this review, I will aim to expose the insufficiently explored potential for archaeology of formal network-based models and techniques, to raise some issues surrounding an uncritical adoption of such techniques, and to provide suggestions for dealing with these issues.

What are Networks?

The network has become a popular research perspective in disciplines as diverse as physics (*e.g.*, Newman 2010), economy (*e.g.*, Schweitzer *et al.* 2009), biology (*e.g.*, Bascompte 2009), neuroscience (*e.g.*, Sporns 2002), computer science (*e.g.*, Adamic and Huberman 2000a), and sociology (*e.g.*, Scott and Carrington 2011). In these disciplines, a network vocabulary is frequently used to describe structures as seemingly different as the World Wide Web, neurons in the brain, insect colonies, and the world economy. Developments in social network analysis (SNA) and social physics have been particularly influential to archaeologists, as this review article aims to illustrate. In archaeology, formal network methods have been applied to explore research topics as diverse as the transmission of ideas (*e.g.*, Graham 2006a), the movement of people and objects (*e.g.*, Brughmans 2010; Brughmans and Poblome 2012), the identification of social and cultural boundaries (*e.g.*, Terrell 2010a), interregional interaction (*e.g.*, Mizoguchi 2009), and maritime connectivity (*e.g.*, Knappett *et al.* 2008). These diverse applications in different disciplines have led to the development of distinct research traditions, different definitions of networks, and the associated vocabulary, specific quantitative techniques, and software to execute such techniques (*e.g.*, Pajek: de Nooy *et al.* 2005; UCINET: Borgatti *et al.* 2002; Cytoscape: Smoot *et al.* 2011; Gephi: Bastian *et al.* 2009; the igraph package in the statistic program R[1]; NodeXL for Microsoft Office Excel[2]; ESRI ArcGIS Network

[1] http://igraph.sourceforge.net/doc/R/00Index.html. Accessed 5 March 2012.
[2] http://nodexl.codeplex.com/. Accessed 5 March 2012.

Analyst extension[3]). Despite all these differences, there are some fundamental concepts that all network-based approaches have in common: a focus on relationships between entities and on the patterns that emerge from them.

Network-based approaches assume that the relationships between entities like people, objects or ideas matter. Rather than focusing on such entities in isolation, network scientists claim that relationships between entities should be examined explicitly if we are to understand the behavior of these entities (de Nooy *et al.* 2005; Wasserman and Faust 1994; Watts 2003). Although this might sound like a vague theoretical concept, it has a real and fundamental connection with how we understand the world around us. For example, how one drives from home to work every day depends on the way roads connect in the region. Not only the road network is influential to route selection; however, the decisions made by other drivers will affect one's actions as well. Everyone will try to avoid rush hour and busy roads, while collectively, we still create the traffic jams that no one wants to get stuck in. The message is simple: relationships are everywhere, they influence people's decisions, and through them information and objects spread and evolve. At least this is the assumption that underlies most network approaches, and it is why many network scientists believe a network-based research perspective holds the potential of providing a scientific framework to formally examine relationships and their effects directly (Cho 2009).

Traffic jams are an example of a real-world phenomenon that has been studied using formal network methods. It touches upon another assumption of network analysis, one that introduces the complexity of real-world networks: the entities cannot be understood independently of the connected whole and *vice versa*. In other and more familiar words: the whole is greater than the sum of its parts. This complexity arises from the open and evolving nature of systems "into and out of which matter and/or energy can flow" (Allen 1997, p. 42; in Bentley and Maschner 2003b, p. 2). For example, settlements emerged in past landscapes as time moved ever on, their populations rose, fell, or disappeared completely; within these settlements, objects and buildings were continually created, used, and fell into disuse, and people interacted with all of this. Such changes cause complex systems to constantly exhibit new properties appearing at each level of complexity (Anderson 1972, p. 393). But how does this happen exactly? How does the birth of a child or the creation of an object shape past landscapes? A fundamental question underlying this is "how does individual behaviour aggregate to collective behaviour?"—which is "one of the most fundamental and pervasive questions in all of science," according to Duncan Watts (2003, p. 24). Complexity scientists argue that a scientific method is needed to bridge the gap between "the reductionist study of parts…to the constructionist study of the related whole" (Bentley and Maschner 2003b, p. 1), and this is exactly what a networks perspective allows us to do.

According to these two concepts, all network applications are concerned with studying entities in interaction that collectively form a complex structure. This gives the network a few methodological advantages, as argued by Carl Knappett (2011):

1. "They force use to consider *relations* between entities."
2. "They are inherently spatial, with the flexibility to be both social and physical."
3. "Networks are a strong method for articulating scales."

[3] http://www.esri.com/software/arcgis/extensions/networkanalyst/index.html. Accessed 5 March 2012

4. “Networks can incorporate both people and objects.”
5. “More recent network analysis incorporates a temporal dimension” (Knappett 2011, p. 10).

Knappett goes on to illustrate how these methodological advantages can be wedded with a range of theoretical social concepts in a *network thinking* perspective that emphasizes the relations between objects and people on multiple scales. Although Knappett’s use of formal network methods is largely restricted to affiliation networks and complex network modeling (see below for both). I would argue that all of the techniques described in this review can work within the much-needed framework he developed.

Most formal network methods share a few other features that are closely linked to the way networks are often pictured: a set of points connected by lines (*e.g.*, Fig. 1). The points consist of the entities of research interest and can be seen as the smallest units within the formal analysis (although one can analyze smaller units as subnetworks embedded within network nodes as well as recognize their existence outside of formal analysis). Depending on the analyst’s research aims, entities can represent any conceivable discrete unit, ranging from neurons (Amaral *et al.* 2000; Watts and Strogatz 1998), individual people (Moreno 1960, p. 35; Ruffini 2008), and objects (Brughmans *et al.* 2012; Faloutsos *et al.* 1999) to entire sites (Broodbank 2000; Knappett *et al.* 2008) or even countries (Maoz 2011; Smith and White 1992). Most networks consist of only one type of node. When a network consists of different sets

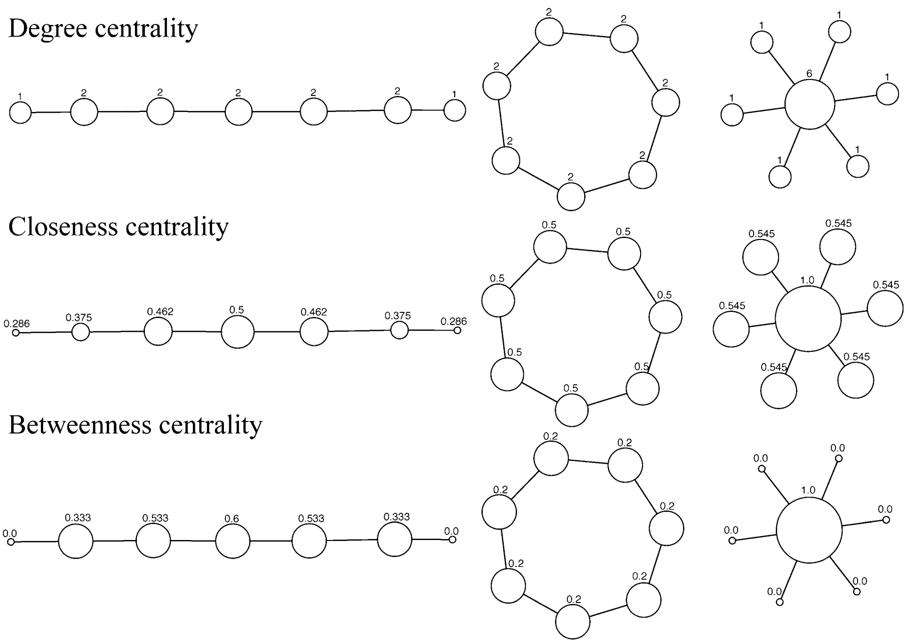

Fig. 1 An example of degree, closeness, and betweenness centrality for three undirected network structures. *Node size* and *labels* indicate centrality values. Degree centrality is the number of relationships a node has, closeness centrality is “the number of other vertices divided by the sum of all distances between the vertex and all others” (de Nooy *et al.* 2005, p. 127; Sabidussi 1966), and the betweenness centrality is the proportion of all shortest paths between pairs of other vertices that include this vertex (de Nooy *et al.* 2005, p. 131)

of nodes, however, we say that a network has multiple modes. A typical example of a two-mode network is an affiliation network (*e.g.*, Fig. 2; see below) in which one set of nodes represents the actors (like academics) and the second set represents the organizations or events the actors are affiliated with (like universities; Borgatti and Halgin 2011; de Nooy *et al.* 2005, p. 103; Wasserman and Faust 1994, p. 30).

The second fundamental building block of networks consists of the relational ties or relationships. These form the connections between the entities and can be equally diverse in nature. Some popular types of relationships include friendship (Carlson 1965), hyperlinks (Albert *et al.* 1999), co-authorship (Newman 2001), roads (Isaksen 2007, 2008), co-occurrence of objects on sites (Brughmans 2010; Brughmans and Poblome 2012; Mills *et al.* 2012), and affiliations (Newman and Park 2003; Watts *et al.* 2002). Relationships can have a value that can refer to an attribute of the tie (*e.g.*, the number of pottery sherds found on a site in Brughmans 2010; Brughmans and Poblome 2012). Ties can also be either directed (often called *arcs*) or undirected (often called *edges*). An arc typically points from a sending node to a receiving node. For example, if publication A cites publication B in a citation network, an arc will be drawn from A to B (for citation networks, see Garfield *et al.* 1964; Hummon and Doreian 1989). Selecting the best network representation for a specific archaeological study should depend strongly on the definitions of nodes, ties, and the network as a whole, as well as on the research questions being asked. In fact, defining the nature of the network and the data used, setting network boundaries (Laumann *et al.* 1992; Marsden 2005), and critically assessing the sample so that inferences can be drawn with confidence (Frank 2005; Orton 2000) are arguably the most important steps in any formal network analysis. All this will inform the selection and determine the interpretation of formal network analysis techniques.

The visualization of these points and lines is a crucial component of many formal network methods as it facilitates "an intuitive understanding of network concepts" (de Nooy *et al.* 2005, p. 14; Freeman 2005), although network visualization is by no means a necessity for network analysis. Network analysts adopted the graph as a model for network visualization from graph theory. A graph represents the structure

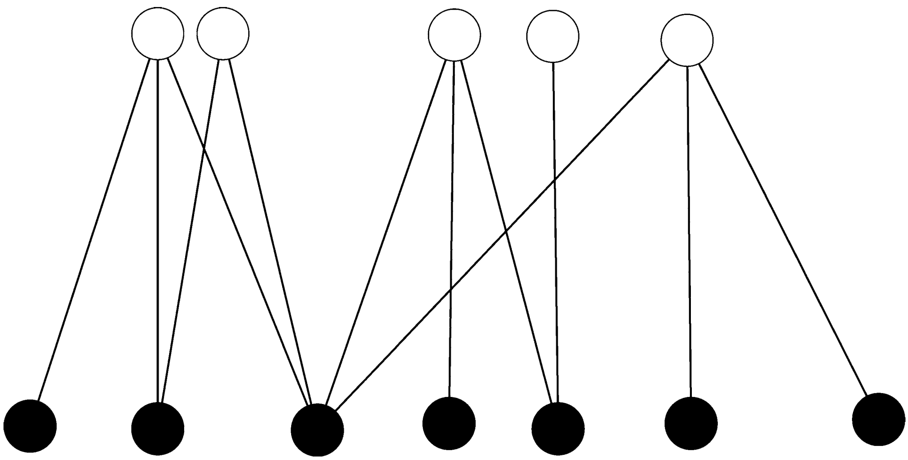

Fig. 2 Example of a two-mode network where white nodes can only connect to black nodes and *vice versa*

of a network of relationships, while “a network consists of a graph and additional information on the vertices or the lines of the graph” (de Nooy *et al.* 2005, p. 7; Wasserman and Faust 1994, p. 93). It consists of a set of vertices (also called points or nodes) which represent the entities of research interest and a set of lines (or ties) between these vertices which represent their relationships. Such network visualizations constructed of points and lines are often called node–link diagrams to distinguish them from other uses of the word *network* (for different node–link layout algorithms, see Freeman 2005; Golbeck and Mutton 2005; Krempel 2005; de Nooy *et al.* 2005, p. 16). However, the node–link diagram is not the only type of network visualization. Adjacency matrices, for example, hold the key advantage of being able to visualize absent relationships in addition to the ones that are present (Riche 2008). Node–link diagrams can perform poorly when visualizing large datasets, while adjacency matrices are often the better option in these cases.

This concept of networks has been used in a range of different methods by archaeologists. Many of them have their origins in graph theory, which is the focus of the following section. Archaeological applications of space syntax (*e.g.*, Brusasco 2004; Cutting 2003, 2006; Fairclough 1992; Foster 1989; Grahame 1997) also rely on the analysis of graphs, but will not be discussed in this review. They are directly influenced by the work of Bill Hillier and Hanson (1984) and not by the SNA and sociophysics traditions or the archaeological network applications that form the focus of this review (a critical review of the potential of space syntax for archaeology can be found in Cutting 2006).

Origins in Graph Theory?

The branch of mathematics concerned with the study of graphs is called graph theory, which is generally considered to be one of the major mathematical foundations of SNA (Barnes and Harary 1983; Wasserman and Faust 1994, p. 15) and underlies much of the work done in social physics. It is therefore not surprising that archaeological applications influenced by SNA and social physics are also strongly rooted in graph theory. However, as I will illustrate in this section, it would be wrong to claim that formal network methods were introduced to the archaeological discipline through graph theory.

The reason why graph theory and networks are such a happy couple lies in the fact that graph theory not only offered network analysts a way to visualize networks as vertices and lines, a representation that came to dominate the way we think of networks nowadays, but it also brought with it a descriptive and mathematical system. Harary *et al.* (1965, p. 3) described the potential of graph theory for SNA: (1) graph theory provides a vocabulary of concepts that can be used to describe properties of social structure; (2) it gives us a set of mathematical operations to quantify and measure these properties; and (3) given this vocabulary and mathematical operations, it allows us to prove theorems about social structure represented as graphs (Wasserman and Faust 1994, p. 93). It is crucial to stress that in SNA, graphs are used as models for social networks, which means that the nodes of graphs always represent social entities like individuals, communities, or organizations and that the lines or ties always represent relations with a social connotation like co-membership in organizations, kinship ties, or proximity to social entities (Wasserman and Faust 1994). The social nature of graphs is an assumption in SNA that underlies the creation and interpretation of graph theoretic techniques developed by social network analysts. In complex network modeling, the social nature of graphs is far less ubiquitous and less entangled with formal methods, which, as I will illustrate below, is a key distinguishing feature between these two network traditions.

Graph theoretic techniques have been used in archaeological research since at least the 1960s and have given rise to a number of interesting quantitative approaches to archaeological data. Very few of these influenced later archaeological network analyses directly, however, and in most, the graph was merely used to visualize relationships rather than analyze them. For example, in Doran and Hodson's 1975 monograph titled "Mathematics and Computers in Archaeology," a graph was introduced as "a set together with a relationship which may or may not exist between each pair of its elements" (Doran and Hodson 1975, p. 13). The authors largely limit their excursion into graph theory by introducing a number of graph theoretic concepts rather than elaborating on the mathematics of specific graph theoretic techniques. It seems that Doran and Hodson were mainly interested in the graph as a visualization of archaeological relational data or concepts that stimulate visual structural exploration. A number of scholars have also used graph theory and matrices for seriation (Kendall 1969, 1971a; Shuchat 1984), and Santley (1991) used graph theory to explore aspects of Aztec regional economic organization. Clive Orton, in his "Mathematics in Archaeology" (1980), does not elaborate on graphs explicitly, although he does suggest the graph as an alternative visualization for dissimilarity matrices (Orton 1980, pp. 44–47). His dissimilarity graph introduces one of the key features of "graph drawing aesthetics" (de Nooy *et al.* 2005, p. 14), namely, that "each object can be thought of as a point in a space, closer to objects which are more similar…and further from objects which are less similar" (Orton 1980, p. 45). Unlike Doran and Hodson, however, Orton stresses one of the weaknesses of graph visualization by showing that relational space often cannot be represented using nodes and links without considerable simplification. The studies of Oxfordshire parish registers by David Kendall (1971b) and Robert Hiorns (1971) also make limited use of graph theory. Both studies explored the degree of relatedness between parish communities in Oxfordshire using the same data sources. Robert Hiorns used marriage registers to investigate the effects on the relatedness of parishes' populations caused by movements between these parishes due to marriages (Hiorns 1971). The results of iterations of two mathematical models were visualized as graphs representing the hypothetical relatedness between parishes. These results were described and compared visually with graphs created from the marriage registers. David Kendall, on the other hand, explored the spatial relatedness between the same Oxfordshire parishes by using a multidimensional scaling algorithm known as MDSCAL (Kendall 1971b) to calculate the hypothetical locations of villages whose locations are no longer known (so-called *lost villages*) relative to the spatial location of known villages. John Terrell (1976, 1977a, b) also used graphs to explore spatial relationships. Influenced by the geographers Chorley and Haggett (1967; Haggett 1965), Terrell developed proximal point analysis (PPA) as a graph theoretical approach to think through interactions between island communities. This approach was later applied by Hunt (1988) for the study of exchange networks between Lapita island communities. In all of these examples, graphs were largely used to visually compare results and to explicitly address interactions between people, data, or places.

Mitchell Rothman's (1987) study of regional survey data from Middle Uruk, southwestern Iran, is also largely restricted to a visual comparison of graphs. Compared to Hiorns and Kendall, however, Rothman attributes a more central role to graph analysis in his arguments by presenting graph theory as an ideal method for the analysis of settlement pattern data. Rothman sums up a number of advantages of graph theory which include statements like "elements of the structure of settlement can be described objectively and analyzed using simpler and more appropriate assumptions than those of many currently used models," "[graph theory] can deal with the magnitude and direction of the movement of goods, information, or people between individual sites in a settlement system," and "[graph theory converts] a variety of empirical detail of regional systems into mathematical matrices ideal for the flexible, verifiable analysis of system characteristics and for objective comparison with other patterns" (Rothman 1987, p. 74). Both the descriptive and the analytical power of graph theory are stressed, but for neither of them are the author's arguments very convincing. Although Rothman is keen to point out the objective nature of graph theoretical techniques and the associated vocabulary, his discussion of what he calls "simpler and more appropriate assumptions" does involve a straightforward and seemingly restrictive social interpretation of graph theoretical concepts, which makes his use of graph theory very deterministic and simply prevents it from performing one of its main functions: comparing a variety of empirical data (the third advantage quoted above).

The graph theoretical work by the geographer Forrest Pitts (1965, 1979) on the Medieval river trade network of Russia seems to have been more influential to later archaeological network analysts (*e.g.*, Isaksen 2007, 2008; Peregrine 1991). Pitts was interested in exploring the connectivity of Moscow based solely on its position within the network of medieval trade routes to test the statements by Russian historians that the dominance of Moscow was at least in part due to its strategic position. His 1965 article is not very specific about the graph theoretic terms used. He does not define *connectivity* for example, but nevertheless suggests a measure for connectivity based on the graph diameter (the maximum number of steps between any pair of points in a connected network; Newman 2010, p. 140). In his 1979 article, Pitts modified his method to calculate what are essentially the *betweenness centrality* values of towns along the river trade network. At this time, he was a prominent member of the still very young SNA community, and it is therefore more likely that the influence of Pitts' early graph theoretical work on archaeological network analysts was the result of the influence of SNA rather than graph theory on the archaeological discipline.

One of the archaeologists influenced by the work of Pitts, Rothman, and Irwin-Williams (discussed below) was Peter Peregrine who explored the evolution of the prehistoric center Cahokia along the Mississippi, Missouri, and Illinois rivers by applying "the graph theoretic concept of centrality" (Peregrine 1991, p. 68). Peregrine aimed to mathematically test the hypothesis proposed by other archaeologists that Cahokia evolved into a major center thanks to its position near the confluence of major rivers, which allowed it to exercise control over riverine exchange in the Mississippi Basin. For this purpose, he visualized the rivers as a graph where points represented river heads and junctions, and lines represented the rivers themselves.

Peregrine used three centrality measures, as developed and described by the social network analyst Linton Freeman (1979), to analyze his graph and Cahokia's position on it. Peregrine therefore makes use of both graph visualization and analysis techniques, contrary to most of the studies described above.

The earlier article by Pitts, along with the network models for geography described by Chorley and Haggett (1970), dominated the graph theoretical techniques applied to Geoffrey Irwin's (1978) study of the development of a Papuan settlement and interaction system. Irwin was interested in exploring the role of Mailu Island as a manufacturing and trading center, which, in 1890 AD, had an atypical and more prominent economic development compared to other sites in the study area. He assumed that an effective communication network was of importance and decided to use graph theory, alongside other techniques, to explore consecutive hypothetical versions of this network for Mailu's prehistoric period (before 1890 AD). The centrality of nodes on these hypothetical networks was explored using the connection-array connectivity (the total number of alternative paths from a node) and short-path array connectivity (the path with a minimum number of links) measures as introduced by Pitts (1965) and discussed by Haggett (1970, pp. 636–637). Nodes were ranked according to the results of these measures, suggesting that Mailu was mildly more prominent than other sites, but not as much as its clearly advantageous position in 1890. The connectivity results were compared with a measure of accessibility by weighting the same networks with the actual distances between nodes, which seemed to lead to similar hypothetical inferences about the centrality of Mailu. Rather than having any predictive value, Irwin argues that the strength of this graph theoretical approach lies in making explicit and exploring the structure of an archaeological hypothesis. This study by Irwin makes clear that decisions made during the creation of networks dominate the choice of graph theoretical techniques as well as the usefulness of the results one can expect.

All of the archaeological studies discussed in this section used graph visualization or analysis techniques for different purposes and with varying success. Most of these graph theoretic applications, however, show similarities with SNA (excluding studies on seriation) by stressing the importance of attaching explicit social assumptions to graph theoretic concepts. Rothman, for example, introduced graph theory as a subset of network analysis (Rothman 1987, p. 74). It is not clear whether he was referring to work by the growing SNA community, but the social interpretations he attributes to his graph theoretic vocabulary seem to indicate that he was at least thinking in terms of past social networks. Although Peregrine considers his work to be graph theoretical, it is clearly influenced by developments in SNA through the works of Freeman (1979), Hage and Harary (1983) and Pitts (1965, 1979). However, none of these early archaeological applications seems to have had a significant impact on later archaeological network-based research.

This section on graph theory raised three issues: (1) the research potential of graph theory as an alternative approach for the visualization and analysis of social or geographical hypotheses in archaeology has been recognized at least since the 1960s; (2) in spite of the obvious similarities in approaches and the relevance to archaeological network analysts, the research potential illustrated by early graph theoretical work in archaeology has not been very influential to more recent network applications in the discipline; (3) as a result, the introduction of graph theory and

SNA into the archaeological discipline happened largely independently, and unlike social network analysts, archaeologists did not collaborate with graph theorists to develop mathematical techniques tailored for their needs. The specific graph theoretical techniques underlying network-based work in archaeology were developed in SNA and social physics and adopted into the archaeological discipline without much reference to their graph theoretical roots.

Social Network Analysis

Many archaeological network analysts have been strongly influenced by SNA, most of whom performed their SNA-related research only within the last 10 years (*e.g.*, Graham 2006a; Hart and Engelbrecht 2012; Isaksen 2007, 2008; Jenkins 2001; Mills *et al.* 2012; Mizoguchi 2009; Munson and Macri 2009). SNA has a long history throughout which a very large variety of network-based methods and applications was developed. This diversity is not reflected in the archaeological literature, and I will argue that it is worth exploring this since it might lead to original and valuable archaeological applications. In this section, I will briefly introduce the development of SNA and discuss some popular or promising research themes and techniques.

An Introduction to SNA

Social network analysis developed as a major research perspective in the social and behavioral sciences from its precursor, sociometry, which involves the measurement of interpersonal relations in small groups and was founded by Jacob Moreno after his invention of the sociogram in the early 1930s (Moreno 1934, 1946, 1960; Moreno and Jennings 1938). The sociogram is a means for depicting the interpersonal structure of groups as points and lines in two-dimensional space, like graphs. According to Linton Freeman (2004, p. 30), sociometry "was the first work that included all (…) of the defining features of social network analysis." Later, social network analysts built on Moreno's work as well as on the pioneering efforts by a group of Harvard scholars in the late 1920s to the early 1940s (Freeman 2004, pp. 43–64). Graph theory, statistical and probability theory, and algebraic models in particular found a place early on in mainstream social network methods (Wasserman and Faust 1994, pp. 10–17). SNA methods and applications have been further formalized by a number of extremely influential books throughout the last two decades (Carrington *et al.* 2005; Scott and Carrington 2011; Wasserman and Faust 1994), with contributions being largely limited to a dominant group of key players in the SNA community. The evolution of formal network methods within the SNA community is documented in the journals Social Networks (Elsevier) and Connections (INSNA), both first published in 1978.

Wasserman and Faust (1994, p. 4) have formulated a list of principles shared by SNA applications that clearly specifies the extent of the social assumptions of SNA:

- Actors and their actions are viewed as interdependent rather than independent, autonomous units.

- Relational ties (linkages) between actors are channels for transfer or "flow" of resources (either material or nonmaterial).
- Network models focusing on individuals view the network structural environment as providing opportunities for or constraints on individual action.
- Network models conceptualize structure (social, economic, political, and so forth) as lasting patterns of relations among actors.

These principles illustrate the main difference between SNA and other network-based approaches, namely, a restriction to social units as well as its implications. It is concerned with exploring social relationships as media for the flow of resources between active individuals, corporations, or communities. The focus on social entities in a networks perspective has been proven useful for approaching a wide range of research questions in the social and behavioral sciences. Wasserman and Faust (1994, pp. 5–6) provide a list of topics network analysts are traditionally interested in, including the diffusion and adaptation of innovations (Rogers 1979, 1995; Valente 1995, 2005), belief systems (Erickson 1988), markets (White 1981), exchange and power (Markovsky *et al.* 1988), and occupational mobility (Breiger 1981).

An Early Archaeological Model

From the above, it becomes clear that formal SNA methods have been around in some form or other since at least the 1930s and more coherently since the 1970s, yet it seems that archaeologists have only recently been interested in using SNA in their own research. This late adoption becomes even more striking when one considers how prominent anthropologists were in the SNA communities prior to 1970 and even after that (Freeman 2004; Johnson 1994; Mitchell 1974; Wolfe 1978, 2011). These anthropological network studies addressed many research themes that are of great interest to archaeologists (for reviews, see Johnson 1994; Wolfe 2011) and may have stimulated archaeologists to adopt SNA (especially in the USA, as one reviewer pointed out). There is at least one notable exception to this trend, however, which I believe might help us understand the limited use of SNA techniques in archaeology before the 2000s.

The potential of SNA for archaeology was clearly recognized no later than 1977 in Cynthia Irwin-Williams' (1977) network model for the analysis of prehistoric trade. She argued that in archaeology, the treatment of the exchange of material goods and services has tended to be simply descriptive and that a network model might provide a quantitative framework for this subject. Irwin-Williams limited her model to the exchange relations connecting settlements (described as network points), although it could easily be applied at different levels of archaeological analysis. The author still provided no less than six examples of measures of linkages within contemporaneous archaeological networks: "(1) within assemblages from a given settlement, the presence or absence of objects originating at another point; (2) the proportion of specific exchange goods from a particular origin to local goods of the same class; (3) the proportion of goods of the same class originating at various different points; (4) the directional dominance of the flow of goods, that is, the import–export ratio between settlement points; (5) the number of classes of objects exchanged between points; (6) the kinds of classes of objects exchanged between points" (Irwin-Williams

1977, pp. 142–143). She goes on to suggest the seven network-based approaches that make up her model: (1) three "points of view" for exchange networks are given: global (the whole network), zonal (part of a network, defined in geographical, cultural or other terms), and anchored (a so-called ego network focused on one point and its direct neighbors); (2) networks can be visualized as node–link diagrams and matrices; (3) the network density measure is introduced (this measure was adopted from Haggett and Chorley 1969 as well as Mitchell 1969); (4) a "first-order star" network is introduced as the ego and its direct neighbors, and a "first-order zone" is introduced as the relations between all members of the "first-order star" (a description adopted from Barnes 1972); (5) she introduces uniplex and multiplex links as relationships through which one or more classes of goods may circulate (adopted from Kapferer 1969); (6) it is possible to differentiate zones with maximum internal linkage bounded by zones of relative low density and few multiplex relations (an idea adopted from Kapferer 1969); (7) an effective network is characterized by large channels, multiplex linkages, and relatively great density, while relations within an extended network will be more attenuated and probably more specialized (ideas adopted from Epstein 1969). The author went on to argue for the potential of this network model as it might be applied to research on ancient Puebloan society in northwestern New Mexico, but she sadly did not elaborate on the results of this case study.

Some of the types of relationships mentioned by Irwin-Williams have formed the basis of later archaeological network analysis (*e.g.*, Brughmans 2010; Brughmans and Poblome 2012; Graham 2006b; Sindbæk 2007a, b), and the network analytic approaches she suggested are now part of the core set of network techniques used by archaeological network analysts. The network "points of view" are at the very least implicit in most archaeological network analyses, and graph and matrix formats are ubiquitous in these applications. I believe it is fair to argue that the ego network approach, link multiplexity and the identification of *zones* with certain topological features, all introduced by Irwin-Williams, have only recently been given more attention (*e.g.*, Brughmans 2012; Munson and Macri 2009). In light of all this, it seems striking that SNA techniques have received so little attention from archaeologists and, even more remarkable, that the clear potential illustrated by Irwin-Williams' model has influenced so few archaeological network analysts directly (including Peregrine 1991; Rothman 1987; Branting 2007). The reason for this might lie in the limited availability of cheap and potent computing power and large digital datasets in the late 1970s. Although Irwin-Williams clearly illustrated the potential of a networks approach, she did not illustrate how this should be applied to complicated networks in a large dataset. Many of the network techniques she described provide rather obvious results when applied to smaller datasets and often only reveal their real analytical strengths when applied to large datasets. As a consequence, the more widespread adoption of SNA by archaeologists was delayed until the necessary computing power was more generally available. However, this does not explain why the network concepts introduced by Irwin-Williams did not break through as more qualitative or small-scale approaches to think with. Knappett (2011, pp. 17–18) suggests that one reason for the reluctance of the New Archaeology to adopt networks might be that connectivity was generally conceived as interactions at the borders of zones around sites rather than as concrete geographical connections between sites.

The work by Irwin-Williams illustrates the core argument of the current article: the obvious potential for formal network-based methods in archaeology was discovered decades ago, but only a limited segment of this potential has been explored so far.

The rest of this section will introduce SNA research themes and analytical techniques that have either been particularly influential to archaeological network analysts or because they lend themselves particularly well to exploring archaeological data and addressing archaeological research questions.

Diffusion of Material and Immaterial Resources

The diffusion of material resources and information might prove of particular interest to the archaeological discipline. According to the social networks perspective, social relations are channels of social contagion and persuasion, and as such instrumental to the diffusion process (de Nooy *et al.* 2005, p. 161; Valente 2005, p. 98). Diffusion techniques focus on exploring the relation between the structural positions of actors and the moment at which they adopt an innovation. Most interestingly, the structure of the diffusion of innovations shows similarities to the spread of an infectious disease: the number of initial adopters is very limited, then large numbers adopt, and finally the growth rate decreases. Typical examples of this are network studies that explore the structure of the world economy (de Nooy *et al.* 2005, pp. 29–57; Snyder and Kick 1979). Calculating the density of social networks, the number and relationships of components, the centrality of key nodes, and the adoption rate allows network analysts to explore the structure of diffusion (de Nooy *et al.* 2005, pp. 161–183; Rogers 1995; Valente 1995). Some of these measures have been used in a study of Roman pottery distributed from the place of production to the place of deposition (Brughmans 2010; Brughmans and Poblome 2012) where we have stressed their potential for exploring large archaeological datasets and geographical hypotheses. This study also made it clear that there can be no straightforward and standardized interpretation to the results provided by SNA measures and that these results therefore require a re-contextualization in a wider sociopolitical, archaeological, and historical framework.

This issue is also very prominent in another archaeological example of the study of past diffusion processes: Shawn Graham's (2006a) analysis of Roman itineraries. Graham created a network of towns connected by the routes between them as mentioned in the Antonine Itineraries (a collection of route descriptions within the Roman Empire). He went on to calculate the average shortest path length,[4] the cohesion,[5] and the fragmentation curves[6] for a number of regions on this network. He concluded his SNA approach by stating that the structures identified have

[4] A shortest path (or geodesic path) in network terms is the shortest route over the network that runs from one vertex to another along the edges of the network, and the average shortest path length is the average of all shortest path scores between all possible pairs of vertices in the network (Newman, 2010, pp. 136–140; de Nooy *et al.* 2005, p. 127).

[5] Network cohesion (usually called density) is the fraction of the maximum possible number of edges in the network that is actually present (Newman, 2010, p. 134; Wasserman and Faust, 1994, pp. 101–103).

[6] The fragmentation curves represent the number of nodes that can be removed before the network falls apart in different components (unconnected parts of a network).

implications for how information was disseminated, and he explores this aspect more explicitly through an agent-based model, which will be discussed further on in this article. Graham seems to be very much aware of the fact that the results of his SNA approach inform him of the structure of a particular data source rather than the actual structure of past road networks. This implies, however, that the SNA techniques used are not necessarily linked to the study of past processes of the diffusion of information. In Graham's study, the results will at most reveal hypotheses on the spread of information as implied by this ancient source.

Network Centrality

Centrality measures are arguably the most popular tools in the social network analyst's arsenal. These allow for the identification of nodes that have better access to information and enhanced opportunities to spread information because of their central position or role as a necessary go-between in a social network. In SNA, centrality is commonly applied in analyses of the structure of organizations (Michael and Massey 1997; de Nooy *et al.* 2005, pp. 123–137). The identification of key people in the communication network of an organization, for example, will help tailor an optimized business-specific flow of information (Burt 2011). Degree[7] centrality, closeness centrality, betweenness centrality (Freeman 1979; Fig. 1), and eigenvector centrality (Bonacich 1972) are by far the most widely applied measures in archaeology (*e.g.*, Bernardini 2007; Isaksen 2007, 2008; Jenkins, 2001; Mills *et al.* 2012; Mizoguchi 2009; Peeples 2011; Peregrine 1991; Phillips 2011). These have been recently extended with measures for group centrality and centrality in two-mode networks (Everett and Borgatti 2005), of which there are no published archaeological examples yet, to my knowledge. In their work on the sociopolitical interactions of the Classic Maya, Munson and Macri (2009) used a renormalized degree centralization calculation (Butts 2006) that incorporates the size and density of the network and can therefore be used to compare different networks. The eigenvector centrality measure also takes the overall network structure into account (Bonacich 1972; Hanneman and Riddle 2005, pp. 68–70; Newman 2010, pp. 169–172) and can therefore be considered a good example of how SNA techniques can contribute to the search for global structure in networks, something social physicists are traditionally concerned with (see below). In a recent study of ceramic networks in the Late Hispanic US Southwest, Mills *et al.* (2012) have argued that eigenvector centrality also provides a more accurate reflection of complex flow processes measured by similarities in ceramic assemblages since it assumes that each node affects all of its neighbors at the same time (Borgatti 2005, p. 62).

Centrality measures have been used by archaeologists to explore properties of ancient transport networks (*e.g.*, Isaksen 2007, 2008; Jenkins 2001) in a very similar way to Peregrine's (1991) earlier work discussed above. David Jenkins (2001) aimed to analyze the significance of locational advantage relative to the Inka road network, administrative centers, productive enclaves, and storage sites. A network of 54 administrative, storage, or other sites connected by roads was created using published

[7] The degree of a node equals the number of nodes it is directly related to.

studies of the Inka road network as well as site reports and Spanish chronicles. Jenkins is very much aware that he is not studying the Inka road system itself directly. As I have stressed above for the work of Graham and Irwin, it is crucial to keep the network as a technique and as a past phenomenon clearly separated (Knox *et al.* 2006). Jenkins explored the structure of this hypothetical model using three centrality measures developed by Freeman (1979) and critically discussed their meaning in this specific archaeological context. To explore a hypothesis of wealth finance, Jenkins (2001, pp. 671–675) created a directed network representing the potential flow of what he defines as prestige goods from their origins at the periphery of the network toward the capital of Cuzco at the core. The latter network seems to be more a visualization of his hypothesis of wealth finance than anything else, given that the creation of this network was not discussed and he did not analyze it using centrality measures (which would require the use of modified graph theoretical algorithms). The same centrality measures (with the exception of degree centrality) were used by Leif Isaksen (2007, 2008) in his study of the transport system in Roman southern Spain. He combined data from the Antonine Itineraries with the river network based on the Vicarello Goblets, and with the Ravenna Cosmography. Isaksen proceeds with a critical description of the centrality results for each data source and the significant issues involved in interpreting them before he draws them all together in an attempt to explore aspects of the Roman transport framework of the region.

Another example of the archaeological use of centrality techniques is Koji Mizoguchi's (2009) study of the emergence of a centralized hierarchy in Japan's initial Kofun Period. Contrary to Isaksen and Jenkins, Mizoguchi compared the results of no less than six centrality measures: degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, Bonacich power centrality, and reach centrality. His descriptions of these techniques are taken from the SNA handbook by Hanneman and Riddle (2005), and he calculated them with the SNA software package UCINET (Borgatti *et al.* 2002). The author aimed to test the hypothesis that the relationships between social groups in the initial Kofun period were more significant to the emergence of interregional hierarchy than the attributes of these groups, such as the dominance over the exploitation of raw materials. To this purpose, he created two networks, one for the initial Kofun Period and one for the earlier Yayoi V Period. Sites were clumped together per region and represented as nodes. Mizoguchi drew edges between nodes according to the presence of non-locally produced prestige goods. The presence of non-local pottery and locally made pots according to non-local stylistic traditions in particular was considered evidence for interregional interactions. Although his use of centrality measures allows for an interesting and innovative evaluation of his archaeological hypothesis, his subsequent interpretation of the centrality results (see Mizoguchi 2009, p. 24) does reveal an issue related to the definition of network elements and their structural properties and the adoption of standard interpretations of network measures. The artifact distributions from which the network edges are created are assumed to be significant proxies for interregional interaction and sociocultural dependencies. Using such hypothetical networks of things to explain the emergence of an interregional hierarchy involves a significant leap of faith, for which Mizoguchi relies entirely on the centrality measures. However, the authors from whom Mizoguchi adopted the descriptions of these centrality indices themselves stress that "the definitions of what it means to be at the center differ. It is more correct to describe network approaches this way—measures of centrality—than as measures of power" (Hanneman and Riddle 2005, p. 62; for a good example, see Osa 2003). I would therefore argue that Mizoguchi successfully explored the structure of a hypothetical interpretation of a hypothetical network. The centrality measures allowed him to identify problems surrounding his hypothesis and data (Mizoguchi, personal communication) rather than to test his very interesting hypothesis, let alone refute alternative hypotheses like dominance over resources.

Affiliation Networks

A significant part of the social contexts in which individuals are embedded is shaped by their affiliations. When social network analysts examine affiliation networks, yet another popular topic, they assume that membership of an organization or participation in an event is a source of social ties (de Nooy *et al.* 2005, p. 101; Wasserman and Faust 1994, pp. 30, 291–343). Directors of different corporations, for example, might share information and make professional decisions at gatherings of the clubs they are members of. Alternatively, academics might be influenced by the novel ideas of other researchers at the conferences they attend. Affiliation networks are traditionally visualized as two-mode networks. The use of two-mode networks is not restricted to affiliations, however, since modes could represent two sets of actors (Wasserman and Faust 1994, p. 39–40) or indeed any data types (*e.g.*, Brughmans *et al.* 2012). A growing set of metrics to analyze two-mode affiliation networks is being developed (Everett and Borgatti 2005; Faust 2005). These techniques hint at the existence of the layered and heterogeneous nature of social relationships and could be considered a first step to exploring the complex web of interlocking contexts that make up social networks.

Published archaeological examples of affiliation networks are few. As I have argued elsewhere (Brughmans 2012), however, the approach holds great potential for dealing with the complexity of past social interactions by mapping broad generic (*e.g.*, known social, geographic, or political entities) or small specific contexts (*e.g.*, typologies, stratigraphic contexts) explicitly as affiliations. This potential is clearly illustrated by Carl Knappett's (2011) recent use of affiliation networks. On a more practical level, it can also help archaeologists deal with networks of multiple data types. In our study of Roman pottery distributions (Brughmans 2010; Brughmans and Poblome 2012), relationships were drawn between sites and the specific pottery forms excavated on them. This type of archaeological two-mode network was built on our assumption that sites with evidence of certain ceramic wares were in some way affiliated to the production centers or regions of those wares. This allowed us to explore and compare wares' distribution patterns in all their currently known diversity without restricting it to core regions. Similarly, Phillips (2011), in his work on lithic raw material consumption in the Kuril Islands, linked specific obsidian source groups with sites in affiliation networks. Phillips further explored the degree of association between the two classes in his affiliation networks by using correspondence analysis and the Jaccard similarity coefficient. While these studies were limited to exploring relationships between sites and a single data type, Søren Sindbæk (2007b), in his work on Early Medieval communication and exchange networks, illustrated how sites can be seen as affiliated to multiple data types in their assemblages. Sindbæk points out the exploratory nature of his approach, stressing that there is no direct relationship between shared artifacts and specific past processes (Sindbæk 2007b, p. 66).

Ego Networks

As a final example of social network analysis themes and tools, I will introduce the concept of ego networks as a technique to study the social environment surrounding individuals. An ego-centered approach focuses "on the position of one person in the network and his or her opportunities to broker or mediate between other people" (de Nooy *et al.* 2005, p. 144; for examples of ego network applications, see Boissevain 1973; Bott 1957). To this aim, ego networks are constructed consisting of one node (or the "ego"), its neighbors, and the ties among them, as in Fig. 3 (Hanneman and Riddle 2005, pp. 8–9; Marsden 2002; de Nooy *et al.* 2005, p. 145; Wasserman and Faust 1994, pp. 41–43). This approach is particularly useful in situations where it is not possible to track down the full network (Hanneman and Riddle 2005, p. 8) because the data are just not available or because the full network is not relevant to answering specific research questions. In fact, the ego network is a representation of the idea that individuals only have local knowledge of the social networks they are part of (Kleinberg 2000; Watts *et al.* 2002). By focusing on a single person, his or her direct relationships, and the relationships among them, we can begin to explore how the direct social environment influences one from an individual's point of view. However, in no way does this ego approach attribute an inherent simplicity to the process of influence and the evolution of entire social networks. Ego networks can be seen as attributes of individuals, representing one of the many reflections of social contexts they are embedded in (Granovetter 1985; Knox *et al.* 2006, p. 118).

Published examples of the archaeological use of ego networks are few. I would suggest, however, that an ego network approach is particularly promising for interpreting specific patterns or hypothetical processes from the bottom up. Like scholars in many other disciplines, archaeologists explore social relationships indirectly

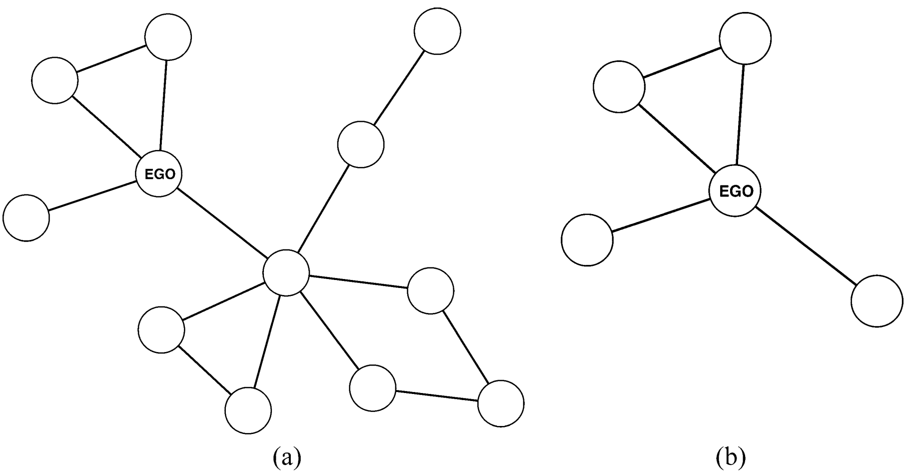

Fig. 3 Example of an undirected network (**a**) from which an ego-network (**b**), consisting of the ego, its direct neighbors, and the edges between them, was extracted

through the traces people leave behind. For historians, these traces might be found in textual data, and sociologists might use modern media like e-mail correspondence. As archaeologists, our data are typically the material residues of individuals' actions influenced by local knowledge of the social networks they were embedded in. It can only inform us of parts of social networks, and exploring entire social networks as a patchwork of “local knowledge” therefore becomes problematic. This essentially boils down to sampling issues that exist both on the whole network and the ego network analytical scales. Network techniques allow archaeologists to traverse these different scales within the same methodological framework. I believe that the results of an ego network study in particular can aid an interpretation of patterns identified in top-down network approaches, specifically in those cases where sampling issues on the whole network scale are considerable. For example, the structure of many complex social networks has been empirically proven to have a non-random degree distribution (Albert and Barabási 2002), a pattern that becomes clear on the level of the whole network. It has been shown, however, that this has a significant impact on the structure of ego networks (Newman 2003a; Roberts *et al.* 2009). Exploring differing structures of ego networks within a larger network can therefore provide an indication of whole-network patterning or help explain it. The analytical potential the multi-scalar nature of network approaches allows for has been recognized by archaeologists (*e.g.*, Coward 2010) and features prominently in Carl Knappett’s (2011) work. On his micro-networks scale of analysis, Knappett traced hypothetical relationships between individuals and artifacts using affiliation networks. A similar approach could be used to focus explicitly on key egos (or each ego in turn).

Discussion

In this section, I have illustrated how SNA tools and techniques have been used by archaeologists. Their applications are largely restricted to network visualization and exploring the static structure of archaeological datasets or social hypotheses. However, one can observe some general trends in the use of formal SNA methods. A number of methods, like centrality measures, seem to have been more popular than others, including affiliation and ego approaches. The reason for this might lie in their prominence within SNA itself as well as their clear aptness for exploring issues related to transport, power, and control. Whereas early SNA applications (*e.g.*, Irwin-Williams 1977) were strongly influenced by network methods in geography (Haggett 1965; Haggett and Chorley 1969), the more recent ones drew upon a number of key SNA reference works (Carrington *et al.* 2005; Hanneman and Riddle 2005; de Nooy *et al.* 2005; Wasserman and Faust 1994) as well as some well-known SNA theories and applications (Granovetter 1973; Hage and Harary 1996). This shift is at least in part a result of technological factors, thanks to the more general availability of potent computing power and large digital datasets which makes the application of many SNA techniques more worthwhile, and through the use of popular SNA software that is strongly linked with these SNA reference works. Although a growing number of software packages can be used to perform SNA techniques (for an overview, see Huisman and van Duijn 2005), most archaeologists used either Pajek (de Nooy *et al.* 2005) or UCINET (Borgatti *et al.* 2002), arguably the two most popular programs in SNA that are frequently expanded with new SNA techniques.

The most difficult hurdle for archaeological network analysts to overcome is not technological, however, nor is it related to a critical application of formal techniques. Indeed, SNA measures are largely adopted as they are available in software packages and are rarely adjusted to specific archaeological networks. It is the interpretative jump from identifying patterns in static network structures using SNA to explaining them in terms of past social processes that proved to be difficult in many cases. This is an issue present in any archaeological method, yet it is worth pointing out its influence in the particular case of SNA. Many SNA techniques come pre-packaged with traditional social explanations (block modeling is a particularly good example of this), and it is tempting to adopt these in archaeological studies. However, in many cases, the units of analysis are not social entities, which makes adopting traditional social explanations problematic. It should be recognized that identifying and explaining network patterns are two different things. Most archaeological network analysts are aware of this and stress that both are completely dependent on how network nodes, links, and measures are defined. We therefore cannot adopt SNA techniques into our discipline without question, although many of the topics and their traditional approaches discussed might prove useful for answering complex social research questions in archaeology. As argued elsewhere (Brughmans 2012), the nature of archaeological data makes the archaeological application of social network analysis as an interpretative tool problematic for a number of reasons. Firstly, the full complexity of past social interactions is not reflected in the archaeological record, and social network analysis does not succeed in representing this complexity. Secondly, the use of social network analysis as an explanatory tool is limited, and it poses the danger that the network as a social phenomenon and as an analytical tool are confused (Knox *et al.* 2006; Riles 2001). Thirdly, human actions are based on local knowledge of social networks, which makes the task of exploring past complex social systems through particular material remain problematic. These issues should not be considered unique to archaeology and archaeological data. An approach consisting of a number of aggregated SNA techniques has been suggested for understanding aspects of past social relationships. However, we will never be informed about the full complexity of past social relationships, and even if we were, SNA would not succeed in understanding this complexity (Brughmans 2012). The recently very popular research tradition of complex network simulation and social physics seems more promising in this respect, although it is by no means perfect itself. Indeed, neither SNA nor complex networks techniques are designed to unravel the full complexity of social interactions, and archaeologists should definitely not apply them as if they were. As I will argue below, it is a combination of SNA and complex network simulation techniques that seems to hold the true potential of networks for archaeology. We will now turn our attention to network perspectives developed to understand the properties of both human and non-human complex systems.

Complex Networks and Social Physics

Many of the ideas underlying the network-related work done by physicists are rooted in complexity theory. Melanie Mitchell recently defined a complex system as “a system in which large networks of components with no central control and simple rules of operation give rise to complex collective behavior, sophisticated information processing, and adaptation *via* learning or evolution" (Mitchell 2009, p. 13). A long list of very diverse real-world systems fit this definition, including the World Wide Web (Adamic and Huberman 2000a; Albert *et al.* 1999; Broder *et al.* 2000; Huberman and Adamic 1999), co-authorship of papers (Barabási *et al.* 2002; Newman 2001), the brain (Sporns 2002; Sporns *et al.* 2000; White *et al.* 1986), and even the web of human sexual contacts (Liljeros *et al.* 2001). Although such systems are quite different, they have some features in common on an abstract level, as summarized by Mitchell: complex collective behavior, signaling and information processing, and adaptation (Mitchell 2009, pp. 12–13). Notice how the first two are similar to Wasserman and Faust's first two principles of social network analysis introduced above. Indeed, network thinking is a popular perspective in complexity science as it forces one to think explicitly about how things relate and how local interaction between individual entities might give rise to patterning on a system-wide scale. Network thinking in complexity science is in part indebted to SNA as they share a research perspective, and some of the techniques used to analyze complex networks were originally developed by social network analysts. Although social network analysts recognize the importance of dynamically changing networks through adaptation and have developed some methods to confront this problem (Snijders 2005), most SNA applications still focus on the structural properties of static networks. Contrary to social network analysis, however, the adaptation and evolution of systems through learning or evolutionary processes is a key assumption in complexity science (Bentley and Maschner 2003b; Mitchell 2009).

Much of the work on complex systems aims to identify and explain self-organizing emergent properties. Such properties are called self-organizing because they are patterns visible at the scale of the system, but emerge without any internal or external planning or control. They are called emergent because they arise out of the relatively simple interactions between individual entities or actors, who collectively form more complex behavior (Mitchell 2009, p. 13). Examples include the large and immensely variable mounds constructed by termites or the way cities and even slums emerge without any top-down planning, but merely through the needs and actions of (groups of) individuals. Identifying such properties is but a first step to understanding the complexity of systems, both past and present, and network models have been developed to do just that. I will not elaborate more on complex systems (for an overview of complex systems in archaeology, see Bentey and Maschner 2003a, 2007; Bintliff 2004; Garnsey and McGlade 2006; Kohler 2012; Lane *et al.* 2009; McGlade 2005) and focus entirely on some of these complex network models.

A few very popular models have been developed to identify and simulate particular processes that lead to the emergence of properties that turn out to be extremely common in diverse real-world networks. Although these models are by no means the only techniques for understanding the properties of complex systems (for a few examples of other approaches to complex systems, see Bak *et al.* 1987; Buldyrev *et al.* 2010; Turcotte 1999; West *et al.* 1999), they have dominated research in complex networks for the past decade. Two complex network models have been particularly influential to archaeologists: the small-world model and the scale-free model.

Small-World Networks

In 1998, Duncan Watts and Steven Strogatz developed a simple model capturing a feature of complex networks that has puzzled sociologists for decades: the small-world problem (for the original paper, see Watts and Strogatz 1998; some very readable overviews of the model and its implications followed: Watts 2003, 2004; for an overview of pioneering work on the small-world problem, see Garfield 1979; Milgram 1967; de Sola Pool and Kochen 1978). The small-world problem was originally examined by Stanley Milgram (1967, 1992) (Korte and Milgram 1970) in his experiments of how letters are passed on between two individuals who do not know each other. Milgram concluded that any one individual on the planet can be reached by any other individual in an average of six interpersonal steps, giving rise to the concept of *six degrees of separation*. The reason for this, Watts and Strogatz discovered, lies in the fact that "real-world networks are neither completely ordered nor completely random, but rather exhibit important properties of both" (Watts 2004, p. 244; Watts and Strogatz 1998). They identified a broad region in between both states where networks are highly clustered while the average path length is as small as possible (Fig. 4). Clustering is measured by the clustering coefficient, which calculates the average probability that two neighbors of a vertex are themselves neighbors, as a ratio of the number of edges between the neighbors of a given node and the maximum number of edges that could possibly exist between these neighbors (Albert and Barabási 2002, p. 49; Newman 2010, pp. 262–266; Watts and Strogatz 1998, p. 441). They adopted the name *small-world networks* to refer to this class of networks, a term first used by Eugene Garfield in 1979. The specific structure of small-world networks has direct consequences for the way networks evolve and how information, objects, and people move through them. A crucial aspect of social networks this model does not address, however, is that human actions are limited by a strictly local knowledge of the networks they belong to and influenced by a general ignorance of the social system as a whole. Network analysts are aware of this (Kleinberg 2000; Watts *et al.* 2002), and the problems this poses for archaeological networks have been

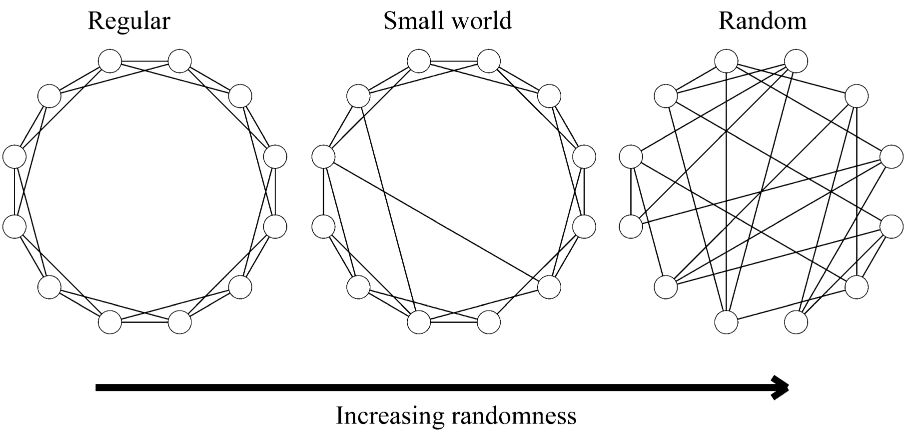

Fig. 4 Through a random rewiring procedure, a small-world network structure emerges as a state between regular and random networks (after Watts and Strogatz 1998, Fig. 1)

discussed elsewhere (Brughmans 2012). This issue does not undo the relevance and structural consequences of a small-world pattern, however. Long-distance relationships between social clusters existed in the past, and they did influence the lives of individuals, even if those people were not aware of their existence (*e.g.*, Malkin 2011). A most striking example of the importance of long-distance relationships is reflected in the way infectious diseases spread through human networks. Bacteria do not care about whether people know of their own relatedness because mere physical proximity suffices to jump between individuals. As such, long-distance relationships play a crucial role in transmitting diseases between largely independent communities (Newman 2003b; Watts 2003, pp. 162–194).

Scale-Free Networks and Power Laws

A second popular model was published shortly after Watts and Strogatz's work and was in fact developed using the same real-world network datasets to address a fundamental assumption of the former model. Albert-László Barabási and his student Réka Albert concluded in their groundbreaking paper published in Science in 1999 that in real-world networks, degree distribution (the fraction of nodes in a network with a certain number of relationships; Albert and Barabási 2002, p. 49; Newman 2010, pp. 243–247) is not normal, as Watts and Strogatz assumed, but is in fact highly skewed and follows the pattern of a power law distribution, as in Fig. 5 (for the original paper, see Barabási and Albert 1999; some very readable overviews of the model and its implications followed: Albert and Barabási 2002; Barabási 2002). The majority of vertices typically have less than the average number of relationships, while a small fraction of hubs are much better connected than on average. Barabási and Albert made a simple mathematical model where nodes are continually added

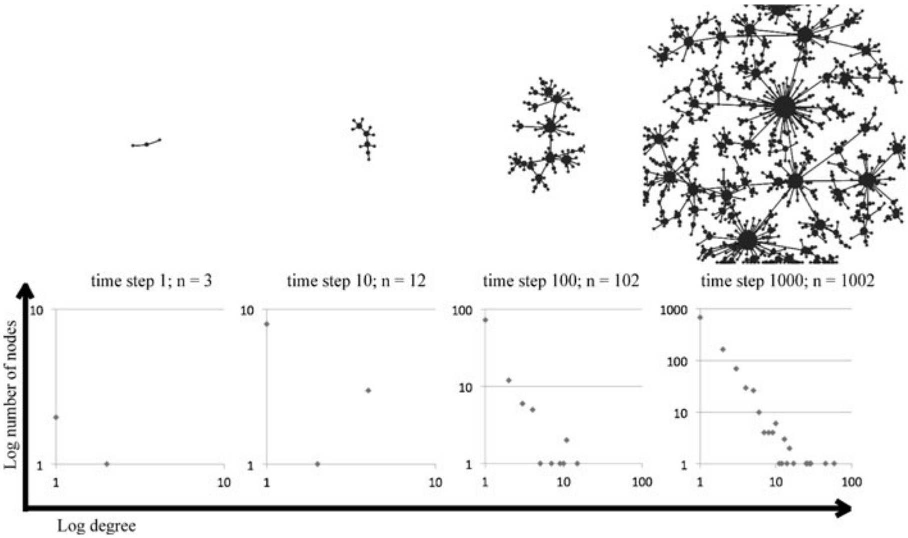

Fig. 5 Example of scale-free network growth (using a modified version of the model by Wilensky 2005 using Netlogo; Wilensky 1999). In the Barabási–Albert model, a new node is added to the network at every time step and attaches preferentially to an already well-connected other node. The degree distribution, when plotted on a chart with two logarithmic axes, shows an approximate power law for growing network size

and attach preferentially to those nodes that are already well connected, effectively giving rise to a rich-get-richer effect (Barabási 2002, pp. 79–92). Many real-world networks turn out to exhibit a scale-free structure. This realization had a significant impact on the way complex networks are approached because not only does it imply a dramatic change in perspective away from random graphs (at least this is what Barabási claims) but it also exhibits specific properties such as vulnerability to failures and attack that help us understand their functioning (Watts 2003, p. 109).

Small-World and Scale-Free Networks in Archaeology

The two real-world complex network models described in the previous two sections are by far the most widely applied in archaeology as well as in other disciplines. Social network analysts often criticize the claims to novelty by social physicists and others using these models, arguing that they ignore the advances made by the SNA communities over the years (*e.g.*, Scott 2011). I will illustrate below that social physicists and social network analysts are increasingly stressing the compatibility of their approaches and interests, a trend that I believe will allow for interesting archaeological applications as well. These two models and the multidisciplinary work they triggered did, however, give rise to a strong increase of network studies in archaeology. I will briefly discuss a number of archaeological applications of these two popular models in this section.

In her analysis of the complex social interactions between Ancient Near Eastern sites in the Epipalaeolithic and Early Neolithic, Fiona Coward (2010, 2012) combined a traditional social network analysis with a description of small-world network structure. Discrete ^{14}C-dated levels of sites formed the nodes in her networks, and these were linked by the co-occurrence of particular forms of material culture which were considered “a material reflection of some form of social relationship (in its widest sense) between those sites” (Coward 2010, p. 464). These networks were explored in 1,000-year time slices, and their density, centralization, average degree, and average path length were compared. The increases in network centralization, density, and average degree were considered highly significant, while the declining trend in the average shortest path length was not. Coward interpreted these results as a structure of dense kin- and proximity-based groups linked by *weak ties* (as described by Granovetter 1973, 1983), which appears to develop toward a small-world phenomenon. Based on her description of the results, however, the identification of weak links and a small-world structure is problematic. Coward gives no measure of clustering, but rather assumes a high degree of clustering from the increasing network density and average degree, and the decreasing average shortest path length. This was one of the issues Coward raised with the application of network measures to a patchy archaeological record.

Søren Sindbæk (2007b) developed a networks approach for the study of artifact-type distributions using small-world and scale-free networks. In his networks, Early Viking Age sites in South Scandinavia formed the nodes, and a connection between them was made when selected artifact types were co-present. Sindbæk stressed that “A shared artifact type does not show actual communication between sites, rather it indicates the existence of a group within which every site was connected to at least one other site” (Sindbæk 2007b, p. 66). Since Sindbæk was interested in the organization and dynamics of communication between these sites, he interpreted the archaeological network as an impression of the underlying complex network by using network models. He suggested that the existence of a small number of hubs with a far more than average degree indicates that the settlements might have communicated as a scale-free network. Sindbæk also identified a high level of geographical clustering, with each geographical region having some sites closely associated with the dense core of the network, which was interpreted as a probable small-world structure. Interpreting the archaeological evidence through these models suggests that “Communications across long distances were achieved through a spindly combination of hubs and weak ties” (Sindbæk 2007b, p. 70) and that this structure was also very vulnerable to targeted node removal. However, Sindbæk was very much aware of the issues involved in assigning the known behavior of dynamic models to a static structure visible in his archaeological network: “The fact that only a single phase is analyzed means that the dynamics involved are only hinted at” (Sindbæk 2007b, p. 70). Sindbæk shares this concern with almost all archaeological network analysts. Their general response to this issue involved the strict definition of network nodes, links, measures, models, and how to interpret the results, as well as a sense that one should not expect to understand more than a hint of past dynamic processes outside the static picture offered by the network. Complementing descriptions of static archaeological network structure with actual simulations of network models might help archaeological network analysts to move from the static to the dynamic, as I will argue below. A number of archaeologists used chronologically subsequent networks of archaeological data to explore changing network structure (*e.g.*, Brughmans 2010; Brughmans and Poblome 2012; Collar 2007, 2008; Graham 2006b), and we will now turn our attention to one of these applications.

Anna Collar (2007, 2008) made a more descriptive use of complex network models as concepts to think with in her study of religious innovation in the Roman Empire. Collar’s work aimed to explore why some religious movements succeed and spread while others ultimately fail. Rather than seeing this process as a direct consequence of the religions’ inherent properties, she adopted a bottom-up approach by exploring the social networks that linked the individuals who drove religious change. Through three case studies, Collar examined the power to communicate religious ideas of three types of social networks: the military networks that she argues were instrumental to the diffusion of the cult of Jupiter Dolichenus, the ethnic network of the Jewish Diaspora, and the religious network of the cult of Theos Hypsistos. Collar explored these social networks through a combination of a close reading of an exhaustive epigraphic dataset and archaeological networks generated from the spatial distribution of inscriptions. PPA, a technique previously used by Broodbank (2000) (discussed below) and developed by Terrell (1976, 1977a, 2010a), was used to create these networks. For all three case studies, Collar created a simple PPA network where sites with evidence of inscriptions were connected to their three geographically closest neighbors. The discussions of the resulting networks focus on the description of clusters, isolated communities, and centers. Collar repeatedly stressed that these networks are not a reflection of the actual connections that existed between sites. Rather, through PPA, she visualized and explored the assumption that communities interact most intensely with their closest geographical neighbors. Only in her final attempt to interpret the processes of diffusion that the discussed social networks hint at did Collar refer to concepts derived from small-world, scale-free, and complex systems research. She referred to the hypothesized roles of hubs, weak and strong links, information cascade, self-organized criticality, and stochastic network growth in the spread of religious innovation. In short, Collar illustrated how networks can be used to explore the distribution of archaeological data and think explicitly in terms of social networks without driving their interpretation. In addition, she used the vocabulary of complex networks to describe hypothetical processes.

A far more quantitative use of complex network models dominated Bentley and Maschner's (2003a) edited volume entitled “Complex Systems and Archaeology” (reviewed by Janssen 2005), a collection of papers with a particular focus on scale-free networks, punctuated change, and agency that grew from presentations at the Theoretical Archaeology Group meeting in 2000. In the first part of the volume, the editors provided an introduction to complex systems, discussing the potential use of the small-world and scale-free network models for archaeology (Bentley 2003a). They further illustrated how the emergence of social inequality in prehistoric societies can be explored through scale-free network growth (Bentley 2003b) in their analysis of house sizes on the North Pacific (Maschner and Bentley 2003). The authors argued that house size variability is indicative of the size of groups and the status of their headmen and can therefore be used to explore the emergence of social inequality. They argued that given “the nature of status striving among North Pacific hunter-gatherers,” competition and growth should feature prominently in their approach, which is why the scale-free network model was considered particularly well suited for their aims (Maschner and Bentley 2003, pp. 52–53). Trends in the frequency distributions of house sizes were interpreted in light of the rich-get-richer effect of scale-free networks: “a few households grow huge, with the remainder staying at levels similar to, or only slightly larger than, those in egalitarian societies” (Maschner and Bentley 2003, p. 57). In this example (and similar to the works of Collar, Coward, and Sindbæk discussed above), Maschner and Bentley consider static patterns in the archaeological record as an indication of the structure of complex network models, allowing them to attribute the dynamic behavior of these models to past processes. Contrary to all the studies discussed above, however, the authors also explored dynamic simulation approaches in this edited volume.

Few archaeologists have combined both SNA techniques and complex network modeling in a single approach. To some extent, Fiona Coward's (2010) work discussed above is an example of this. A particularly successful example is Graham's (2006b, 2009) study of the individuals active in the Roman brick industry in the Tiber valley. Graham created two types of networks. First, he looked at patronage networks in the brick industry, evidenced in the names of individuals appearing on brick stamps. Then he examined brick manufacturing networks where brick makers were connected if they shared the same clay sources (as derived from an archaeometrical analysis). These networks were considered to represent social relationships (of the kind petrified in bricks) between individuals and were analyzed in four chronologically subsequent periods (Julio-Claudian, Flavian, Nerva-Antonines, Severans). Graham combined SNA and complex network models in a method that switches between the local and the global scales. On a local level, Graham used the degree and Bonacich centrality measures to identify social *hubs* and *bridges* (Graham 2006b, p. 103). To explore patterns on a global level, he calculated the networks' average path lengths, degree distributions, and clustering coefficients. The results led Graham to conclude that the patronage and manufacturing networks exhibited what he called *egalitarian* (characterized by nodes roughly having the same degree) and *hierarchic* (characterized by the presence of a power law degree distribution, *i.e.*, a scale-free network) small-world structures at different periods. He went on to argue that the known behavior of small-world and scale-free networks can be attributed to the structure of different social networks in the Tiber valley brick industry at different times. Graham stressed that although his networks are at best static snapshots of an evolving industry, a comparison with the structure of complex network models still allows one "to explore how (and why) the industry assumed these different shapes at different times; it allows us to move from the static to the dynamic" (Graham 2006b, p. 97). By drawing together network techniques developed in different disciplines, Shawn Graham provided a real multi-scalar network perspective that allows one to explore social structure both from the bottom up and from the top down. I would like to argue, however, that Graham's interpretations of network structure are sensitive to the sampling issues typically surrounding archaeological data. Although network measures might indicate that archaeological data networks have a small-world and/or scale-free structure, interpreting this structure is quite another thing. The work by Stumpf *et al.* (2005) on the sampling properties of networks revealed the extent of this issue: "Only if the degree distributions of the network and randomly sampled subnets belong to the same family of probability distributions is it possible to extrapolate from subnet data to properties of the global network. We show that this condition is indeed satisfied for some important classes of networks, notably classical random graphs and exponential random graphs. For scale-free degree distributions, however, this is not the case. Thus, inferences about the scale-free nature of a network may have to be treated with some caution" (Stumpf *et al.* 2005, p. 4221). Graham's networks are relatively small, making their structure very likely to change dramatically through the addition of nodes and links. In fact, they might turn out not to have a small-world or scale-free structure at all. Graham did argue and illustrate that his hypotheses of preferential attachment, wealth condensation (Bouchaud and Mézard 2000), and cascading failures (Albert *et al.* 2000) are supported by historical events. As I argued above for SNA, however, it should be clear that the known behavior of complex networks cannot be extrapolated to the structure of archaeological data without question. Indeed, one could argue that this issue is present in all exploratory archaeological network analyses and that it favors network simulation approaches for testing hypothetical whole networks. As I will argue in the following section, identifying network structure and explaining it are two different things and requires one to move beyond a direct application of these popular models.

Discussion: Complex Networks Beyond Popular Models

Although they have received a disproportionate amount of attention, the models introduced above and the tsunami of papers they triggered in a wide range of disciplines are subject to some fundamental critiques, which should be acknowledged by archaeologists (for a brief overview, see Mitchell 2009, pp. 253–255). The mere identification of emergent self-organizing properties does not explain how this behavior came about and what it meant for the individuals creating it. Indeed, Kohler stressed that "characterizing a property as emergent is at best a general description and never an explanation" (Kohler 2012). Although these models imply that changes arise through interactions at every scale (individuals, communities, system-wide), the properties they allow us to identify do not tell us anything about specific human actions on a local scale. This shortcoming is particularly crucial in archaeology, in that we are typically confronted with the material reflections of isolated actions by individuals or small groups of individuals. This makes summing up our evidence to reveal system-wide patterns problematic and forces archaeologists to explore local actions. Similarly, Bentley (2003a, p. 15) raised the crucial point that merely identifying a power law distribution in archaeological data is close to meaningless (at least in part because these patterns are common in nature; Frank 2009). One has to understand what mechanisms created the power law and what it means. To be specific, preferential attachment should not be seen as the only cause for power law degree distribution in nature (Bentley and Shennan 2005; Mitchell 2009, p. 254; Shalizi 2011).

Archaeologists should also not forget that these models are minimizing abstractions of real-world networks; "they are overly simplified and based on unrealistic assumptions" (Mitchell 2009, p. 254). George Box captured the unrealistic nature of models perfectly by stressing that "all models are wrong, but some are useful" (Box and Draper 1987, p. 424). Mitchell mentioned that complex network models will never be able to represent the full complexity of real social systems as all nodes are often assumed to be identical, except for their degree, and all links are of the same type and have the same strength (Mitchell 2009, p. 255; although many models no longer share this assumption, *e.g.*, Evans *et al.* 2009). Physicists are indeed aware of these shortcomings (Watts 2003, 2004), and the "unimaginative" deterministic assumptions that follow from this form the favorite stick of social network analysts to beat them with (Carrington *et al.* 2005, p. 2; Scott 2011). For example, one key aspect of real-world systems that is not taken into account in these models is geographical space. Archaeologists seem more aware of this shortcoming than physicists, given the high number of archaeological network analyses that aim to explore spatial networks (*e.g.*, Allen 1990; Branting 2007; Brughmans and Poblome 2012; Coward 2010; Earl and Keay 2007; Knappett *et al.* 2008; Pouncett and Lock 2007; Terrell 2010b; Zubrow 1990), although it must be said that recently the spatial nature of real-world complex systems has come to the attention of physicists (*e.g.*, Barthélemy 2010; Gastner and Newman 2006) as well as the SNA community (Adams *et al.* 2012; see the special issue of Social Networks (34:1) dedicated to spatial networks).

Archaeologists should not expect complex network models to capture the full complexity of systems, nor should they attribute the most popular explanations to descriptions of emergent properties. In light of these issues, I would argue that archaeologists' focus on a few popular complex network models severely limits the potential descriptive power of network modeling and holds the danger of introducing a routinized explanatory process. The examples from the previous section clearly illustrate the potential for complex network models to describe and explore archaeological hypotheses. A wealth of alternative network models exists, however, simulating a range of different behaviors that might be used in different archaeological research contexts (for overviews, see: Costa *et al.* 2007; Newman 2010). The inability of many of these models to address more than one property of a complex network makes approaches that critically compare different models' behaviors with the archaeological record particularly promising (as in Bentley and Shennan's 2003 work described below). In fact, it is striking that random graph models (Erdős and Rényi 1959, 1960, 1961) that underlie much of the scale-free and small-world research have hardly been used in archaeology as comparative models (for an exception, see Graham 2006b), nor have spatial network models (Barthélemy 2010; Gastner and Newman 2006; for an exception, see Rihll and Wilson 1987, 1991). Archaeological problems might even drive the development of original complex network models (*e.g.*, Knappett *et al.* 2008, 2011; Evans *et al.* 2009, described below). Alternative network models allow for a wide range of applications, which again illustrates the need for archaeologists to clearly define network elements, contextualize results, and, where possible, validate these with empirical data (Graham 2006a). Some pioneering archaeological applications of alternative complex network models, discussed in the next section, illustrate that this is a research direction worth pursuing. The simulations used in these applications all require some advanced mathematical and computational knowledge, which might explain the relative lack of uptake in archaeology, but also give them the great advantage of being able to explore evolving network behavior.

Towards Dynamic Network Models

Bentley and Shennan's (2003) study of different processes of cultural transmission is a particularly good example of how the distinct behavior of slightly different network models can be compared in an archaeological context. The authors suggested three quantifiable types of cultural transmission with a testable difference: independent decisions in a highly simplified model show an exponential decay in variant frequencies (an artifact variant was assumed to have a discrete nature, existed for some finite time, and can be copied; Bentley and Shennan 2003, p. 461); unbiased cultural transmission is characterized by a power law or log-normal distribution; and biased cultural transmission deviates significantly from a null model of unbiased cultural transmission. Bentley and Shennan argued that Adamic and Huberman's (2000b) model of stochastic network growth is particularly applicable to unbiased cultural transmission. This model generates scale-free networks through a process slightly different from Barabási and Albert's (1999) model and was preferred since the process of preferential attachment can also occur in a network that is not growing. This model was adapted to represent biased cultural transmission by making preferential attachment proportional to an exponent of the number of connections of a node. Bentley and Shennan subsequently used three variations of this model with different values for the exponent in their case study to model change in linear Bandkeramik pottery motif frequencies from the Merzbach valley (Germany). In these networks, individual motifs (variants) formed the nodes and each copy of a motif was connected with an arc to the source motif. The authors concluded that they found a good fit between the stochastic network model for unbiased cultural transmission and the later-phase Merzbach pottery data. The earlier phase motifs, however, were suspected to have known a pro-novelty biased cultural transmission. As far as their use of networks is concerned, Bentley and Shennan have pioneered how complex network models can be adopted, critically modified to represent archaeological hypotheses, and how their resulting behavior can be compared with an archaeological dataset.

Together with Mark Lake, Bentley and Shennan also studied evolving networks using agent-based modeling (Bentley *et al.* 2005) to explore how an exchange network coevolves with the changing specializations of the agents within it. The authors argued that power law wealth distributions “are ubiquitous for a wide range of economic scales” and that this behavior might be linked to the benefits of specialization in exchange networks (Bentley *et al.* 2005, pp. 1346–1347). Their model therefore aimed “to test whether specialization and wealth inequalities are natural, self-organizing qualities of a small-scale economy” (Bentley *et al.* 2005, p. 1347). They modified a simple model to simulate exchange developed by Jin *et al.* (2001) by adding variables for agents’ possession of two different products (A and B) and a *strategy* variable, which determines the relative amount of A *vs.* B an agent produces per time step. A significant difference in the wealth distributions was identified for two scenarios where, on the one hand, two agents either trade when both possess sufficiently different amounts of a certain commodity (resulting in normal wealth distributions) and, on the other, where agents only trade if they both like the price of a commodity (resulting in highly skewed wealth distributions). The authors argued that this suggests “a basic analogy to the profound ideological differences that likely existed between certain indigenous populations and incoming agricultural colonists” (Bentley *et al.* 2005, p. 1353). Although the authors do not apply this model to an archaeological case study, it has clear potential for testing archaeological hypotheses concerning wealth distribution and exchange networks. In this agent-based approach, as well as in Bentley and Shennan’s (2003) work described above, the adopted network models are therefore not modified to represent attested static patterns in the archaeological record; rather, their value lies in thinking through a range of hypothetical dynamic networks as possible processes underlying the creation of the archaeological record.

Another combination of agent-based modeling and networks is Shawn Graham’s (2006a) study of Roman itineraries discussed above. Graham aimed at exploring the diffusion of information on the Antonine Itineraries by populating a map of the itineraries’ static network structure with digital agents who could interact and share a piece of knowledge. Contrary to the model of Bentley *et al.* (2005), the network used in Graham’s model was a pixelated map of the spatial representation of places connected by routes. Nodes represented places rather than the agents and played a far smaller role than the network edges in this model since agents were allowed to interact at any point on the network map. The model therefore did not allow Graham to make statements about the role of nodes. Rather, the author was interested in how the different structures of provinces as a whole affected the diffusion of information. The model simulates agents moving along the paths of the itinerary and passing on a message to agents who have not heard it. Graham concluded that there are distinctive regional differences in the fashion and speed of information diffusion. It is these simulated processes of diffusion that form the dynamic aspect of Graham’s work. Rather than network evolution through time, Graham explored the static structure of a conception of Roman space as presented in the Antonine Itineraries through hypothetical dynamic processes (for alternative network models of diffusion, see, *e.g.*, Cowan and Jonard 2004; Guardiola *et al.* 2002; Valente 2005; Zhuang *et al.* 2011).

A unique example of a complex network model developed for a specific archaeological research context is the model of Knappett *et al.* (2008, 2011) and Evans *et al.*

(2009) for maritime interaction in the Aegean Bronze Age, which emerged as a fruitful collaboration between one archaeologist (Carl Knappett) and two theoretical physicists (Tim Evans and Ray Rivers). The model was formulated as a reaction to more geographically deterministic network methods (Rihll and Wilson 1987, 1991) and the work of Cyprian Broodbank (2000), in particular. In his study of the Early Bronze Age Cyclades Broodbank examined networks consisting of archaeologically attested sites as well as hypothetical sites added to islands based on population estimates derived from site surveys. He used the PPA method (introduced above) to link each site to its three geographically closest neighbors. In this case, links were considered to be equal, which Knappett and colleagues argued was not the case for interactions in the Middle Bronze Age Aegean. The authors set about developing a complex network model that specifically addressed their assumptions about maritime interactions in the Middle Bronze Age Aegean. Thirty-nine archaeologically attested sites formed the *center of mass* for their immediate areas. These were represented as vertices that were assigned a fixed carrying capacity reflecting their local resources and a variable indicating each site's relative importance. The links between two sites were given a measure of the physical distance between them and a variable representing the effort one site puts into the interaction with the other (for technical details and the cost/benefit optimization function in this model, see Evans *et al.* 2009). Attributing such values to links is a key difference with the other archaeological applications of the complex network models described above. The authors used this model to explore the effect on Late Minoan civilization of the catastrophic destruction of Akrotiri on Thera (Santorini) by volcanic eruption (Knappett *et al.* 2011). For the pre-eruption period, the model revealed a high level of clustering with a number of weak and stronger links connecting clusters. The immediate post-eruption period was modeled by the removal of Akrotiri. The results indicated that the removal of a key node in this network had little immediate effect on the overall activity. The authors suggested that the removal of a key node might not lead to big changes initially, but will inevitably increase exchange costs. To test this hypothesis, they increased exchange costs. At first, total activity was not reduced substantially, but eventually, this hypothetical change led to fewer strong links, causing major sites to focus on maintaining fewer links. This was considered an unsustainable situation that might lead to collapse, represented by regional clusters in the network becoming disconnected. One could argue that the authors did not succeed in testing their hypothesis since it is the increase in exchange cost imposed by the authors that caused the network to disintegrate, not the removal of Akrotiri. It could be argued that this scenario should have been compared with one where the exchange costs are increased without removing Akrotiri. The works by Knappett, Evans, and Rivers also raise the issue of the role of archaeological data in complex network modeling. The model inputs are only based on the archaeological record to a very limited extent, and the results of their case study were not validated against empirical data. It should be clear, however, that the value of this model lies largely in its ability to make an archaeological hypothesis of interaction explicit by modeling it as a process on a network. The results should therefore not be interpreted as predictions of past processes, but rather as stressing the potential evolution of hypothetical structures that require subsequent validation. Knappett, Evans, and Rivers have illustrated that complex network models developed specifically to explore archaeological hypotheses can lead to innovative and useful ways of thinking about past processes that help guide future research efforts.

Conclusions

In the recently published SAGE handbook of social network analysis, John Scott (2011) severely criticized the claims to novelty made by social physicists (and Albert-Lázló Barabási, in particular; see also Bentley and Shennan 2005) given their "almost total ignorance shown concerning the vast amount of prior work in social network analysis" (Scott 2011, p. 55). Scott illustrated that there is a long history of social physics in sociology of which the new social physicists seem to "know little or nothing" (Scott 2011, p. 55). Indeed, citations to previous work in SNA by social physicists are largely limited to popular textbooks (Degenne and Forsé 1994; Scott 1991; Wasserman and Faust 1994). Scott seems particularly unhappy with Barabási's claim that the work in social physics triggered by Watts and Strogatz (1998) posed "the first serious challenge to the view that real networks are fundamentally random" (Barabási 2002, p. 15). Scott replied "that no sociologists, to the best of my knowledge, have ever thought that complex social networks are purely random phenomena" (Scott 2011, p. 58). It should be said in Barabási's defense that Scott only cites Barabási's popular science book *Linked* (2002). In fact, Scott himself seems quite unaware of the scope of recent work in social physics by Barabási and his followers. Scott concludes on a hopeful note, stressing that the work by some social physicists like Duncan Watts shows potentially valuable contributions to the social sciences. Scott considered much of the work by social network analysts and physicists to be complementary (complexity theory perspectives and agent-based dynamical modeling used by physicists in particular hold great potential for SNA) and argues strongly for collaborations between the two.

In this article, I have argued (although worded less strongly than John Scott) that a similar process is emerging in the archaeological use of formal network methods. A number of general trends can be identified that attest of a general unawareness of the historicity and potential diversity of existing network-based approaches or of suitable archaeological applications of known models and techniques and of the issues related to them (a similar development was recognized by Claire Lemercier 2012 for the discipline of history), which led me to believe that, as far as formal network methods are concerned, there is a clear need for multidisciplinary collaboration.

Firstly, archaeological applications of graph theory, which have been around since the 1960s, were not influential at all on more recent archaeological network studies. This is peculiar since many of the SNA techniques that only in the past decade have become more popular with archaeologists are rooted in graph theory. In fact, the archaeological applications of graph theory clearly illustrated the potential of the graph as a technique for visualization and analysis in research contexts that showed strong similarities with studies in social network analysis. The introduction of graph theory and social network analysis into archaeology therefore happened largely independently. Secondly, the potential of social network analysis techniques was explored (largely theoretically) through Cynthia Irwin-Williams' (1977) network model. Many of the techniques she described were not applied in archaeological research until the last 10 years, which might, at least in part, be due to technological factors. Like so many other quantitative methods in archaeology, the earliest network analyses in archaeology were also strongly influenced by the New Geography and the work of Chorley and Haggett (1970) (Haggett and Chorley 1969), in particular. Thirdly, social network analysis and social physics have been the most influential research traditions, yet only a very limited range of models and techniques have been explored by archaeologists so far. Centrality measures in SNA and the small-world and scale-free complex network models are among the most popular approaches, while a wealth of alternative complex network models (like the ones described in the previous section) and SNA techniques (including affiliation and ego networks) that I have argued show great potential for being applied to address archaeological research questions remain largely unexplored. Lastly and most crucially, there is a danger of falling toward a standardized explanation of attested network structure. It is as if every network method comes with a social interpretation that needs only be molded to fit the specific archaeological research context in question. This is definitely not the case as different processes can explain the emergence of the same structure.

These general trends are the result of two critical issues that will need to be addressed in future archaeological network analysis: (1) a general unawareness of the historicity and diversity of formal network methods both within and outside the archaeological discipline or of suitable archaeological applications of known models and techniques has resulted in a very limited methodological scope; (2) the adoption or development of network methods has very rarely been driven by specific archaeological research questions and is dominated by a few popular models and techniques, which has, in some cases, resulted in a routinized explanatory process.

These issues should not necessarily be seen as a critique toward existing archaeological applications of formal network methods. If anything, they stress that network methods have far greater potential than has already been explored by archaeologists. Moreover, the increasing number of archaeological applications in the last decade, largely triggered by the popularity of complex networks research in the early 2000s, seems to indicate that there is a genuine interest in formal network methods for archaeology. In order to channel this interest toward more diverse and more explicitly archaeological future applications, however, the above two issues will need to be confronted. To do this, I would argue that two things are crucial: taking a broad multidisciplinary scope and letting the specific archaeological research context dominate the application. These two might sound contradictory at first, but in light of this review of archaeological applications, their relevance and complementary nature becomes clear. Carl Knappett recently argued that "for new network approaches to be successful in archaeology they have to be as profoundly transdisciplinary as we can possibly make them" (Knappett 2011, p. 37). Indeed, we have seen that studies addressing a specific archaeological problem through a multidisciplinary collaboration (*e.g.*, Knappett *et al.* 2008, 2011) or through a combination of different network techniques (*e.g.*, Bentley and Shennan 2003; Graham 2006b) have often been the most fruitful ones. The combination of SNA techniques and complex network modeling (*e.g.*, Coward 2010; Graham 2006a, b), which is considered to have great potential according to John Scott (as well as other social network analysts, *e.g.*, Borgatti *et al.* 2009), is particularly promising for archaeology as it allows for a top-down as well as a bottom-up perspective to explore the multi-scalar nature of network thinking (Knappett 2011). The adoption or development of network methods should, however, always be motivated by specific archaeological research questions. The building blocks of every network (nodes, edges, and their parameters) as well as the techniques used should always be clearly defined from the outset as they will dominate the interpretation of the results. These results in turn require a re-contextualization within their wider archaeological framework before one can make the jump from the identification of network structure to its explanation in terms of past dynamic social processes.

In this review, I have illustrated through many archaeological and a few non-archaeological examples that networks can really be seen everywhere and that these can be studied through formal network methods. Archaeologists have successfully used network methods to visualize archaeological data or hypotheses (*e.g.*, Hart and Engelbrecht 2012), to explore the structure of large and complex datasets (*e.g.*, Brughmans 2010; Brughmans and Poblome 2012), to examine the structure of the spatial distribution of artifact assemblages (*e.g.*, Jiménez and Chapman 2002) or of archaeologically attested transportation or communication systems (*e.g.*, Isaksen 2008; Jenkins 2001; Swanson 2003), to trace the evolution of academic communities over time (*e.g.*, Schich and Coscia 2011), to compare different hypothetical processes of cultural transmission through dynamic modeling (*e.g.*, Bentley and Shennan 2003), to evaluate the effect of a natural disaster on an existing network of maritime interaction (*e.g.*, Knappett *et al.* 2008, 2011), and much more. Although it might seem like an already impressive range of different research topics, this is only the tip of the iceberg. Network thinking is a powerful research perspective allowing for a wealth of diverse formal methods that have great potential for archaeology. Moreover, it seems that the time is right for archaeologists to explore this potential. Over the last decade, a large cross-disciplinary community with a genuine interest in formal network methods has emerged to which, I am sure, archaeologists can make valuable contributions.

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