The Application of Social Network Analysis to Accounting and Auditing

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Abstract	This article aims to extend methodological possibilities for conducting research in accounting and auditing by providing an overview of how current developments in social network analysis (SNA) could serve as a powerful set of theoretical and methodological tools for this purpose. SNA focuses on structure and implication of network ties existing in particular empirical context. In contrast to classical quantitative methods (e.g. linear regression), SNA has the capacity to enable understanding of the emergence of the observed network by combining actors' attributes and structures of relational ties existing between them. The paper notes the concept of interdependency, which is inherent element in any social relationship and which is of paramount importance in any social context. This paper introduces a number of important SNA concepts and provides references to software that researchers could utilize for different analyses. The example of a one-mode network between audit partners is presented, to which a number of previously outlined concepts are applied and discussed. Finally, we describe the potential of a cutting-edge statistical method for SNA, exponential random graph model (ERGM), which act as a cutting-edge pattern-recognition device for network structure.
Key words	Innovativeness, Leadership, Technopark

1. Introduction

There is a fundamental divergence in the manner by which researchers interpret the world around them. On one hand, there are those who hold a substantialist perspective (i.e. an individualist entity approach), and on the other hand those who hold a relational perspective (Emirbrayer, 1997). The substantialist mode of thought is specific to their understanding of the world as a static "thing", while the relational perspective assumes that "things" are not independent one from another, and that their expediency and purposefulness is only reflected in their relationships with others. Such a relational view assumes that "things" derive meaning, significance, and identity from roles that evolve in interaction with others. This transactional perspective comprehends relations as unfolding, dynamic in nature, and always as ongoing processes rather than the static ties that exist between inert substances (Emirbrayer, 1997). Borgatti and Foster (2003) noted that the latter perspective has recently acquired prominence across different research disciplines.

An interest in relationships has encouraged the development and adaptation of new approaches to enable understanding of relational mechanisms which evolve between actors in a particular context. Social network analysis (SNA) is a method for research and interpretation of the world developed in the form of a tool which serves as a mean for exploring the relational perspective of a particular context. It provides a set of research tools for approaching the problem by putting the focus on '*relationships* among social entities, and on the patterns and implications of these relationships' (Wasserman and Faust, 1994). A network consists of a set of nodes and the relational ties between these nodes. This implies that the research focus is not on social actors as such, but relationships between the set of social actors. In disparate empirical contexts researchers have, so far, studied different types of ties between individuals, functional units, and organizations (Worrell *et al.*, 2013).

Hitherto, research on relationships and networks has not been salient to the context of accounting and auditing. Recent literature in this field has mainly discussed topics related to the introduction of technology to accounting and auditing procedures (Bierstaker *et al*., 2001; Coombs *et a*l., 1992; Debreceny, Lee *et al*., 2005); motives for auditor change (Fontaine et al., 2013), comfort provision (Guénin-Paracini *et al., 2014; Sarens et al., 2009)* etc. Researchers have also emphasized discussions of collaborative relationships (Sarens and De Beelde, 2006) which incorporate auditors on one side. Those studies mainly applied qualitative methods to inspect relationships by arguing that such an approach provides sufficient insights for theorization. Others, for example, used some other quantitative research methods e.g. linear regression, or logistic regression. Although each of the streams was included to study the research question from the relational perspective, SNA in such field has been neglected.

In the accounting field, some researchers discerned the importance of relational paradigm (Johansen and Pettersson, 2013; Morrison, 2002), but they have used linear regression methods for analysis. Those statistical methods assume that observations are independent from each other. Although one can use linear regression to examine social networks we argue that such tools are limited in their ability to properly examine the complex interdependencies naturally inherent in social contexts. This paper introduces social network analysis (SNA) as an alternative set of methodological tools for studies of accounting and auditing in order to provide a solution to methodological challenges which have constrained classical statistical approaches, and introduces some new network methods which take into consideration the issue of interdependency in a principled fashion. Most importantly, this paper does not aim to replace or criticize other methods, but to inform researchers within auditing and accounting field of the potential of SNA and how it may augment current analytic approaches.

The way in which intra-group relationships operate in the contexts of accounting and auditing have not yet been investigated nor used as the method for approaching the inner processes which determine the structure of social networks. Research in the field has observed relationships from the benefit exchange perspective as a driver to relationships emergence. However, the limitation in the use of a research tool has stopped researchers from integrating subjective actor attributes in order to model the process of network emergence. This article argues that in accounting and auditing context, networks of social relationships need to be explored in order to provide a better understanding of how interactions and relationships evolve (e.g. interlocking directorships, auditor selection, interpersonal relations in accounting teams and/with internal and external auditing departments, social selection process constraints in accounting and audit teams, longitudinal evolvement of social networks within the context) and that SNA is a useful methodology for approaching those issues.

Recently, scholars have developed a particular class of statistical network models that integrate the concept of *interdependency* inside the model (Wasserman and Pattison, 1996; Robins *et al*., 2007; Wang *et al*., 2013), and which therefore enables the limitations of previous methods to be overcome. The model represents today's cutting-edge statistical network method, Exponential Random Graph Models, and we dedicate special attention to ERGMs here.

This paper aims to introduce the network paradigm to the studies of accounting and auditing by presenting the capabilities of a network methodology and puts emphasis on appropriate concepts and tools. The aim of this paper is thus to provide an answer to the following question:

How can social network analysis be used in accounting and auditing research?

This paper is organized as follows: an introduction section is followed by the general concepts of social network analysis and the theoretical background of the study. After we review current research in accounting and auditing, we focus on potential applications of SNA. We introduce a list of concepts that might be used in research together with the resources for SNA and software applicable for network research. Lastly, we discuss the abilities of cutting-edge statistical models for social network analysis, Exponential Random Graph Models (ERGMs).

2. Social network analysis (SNA)

The term 'network' has been broadly used in diverse contexts and has different meanings (Worrell *et al*., 2013), but the concept of 'social network' refers to relationships that exist between empirically determined group of social actors. More specifically, it refers to the relationships between actors that form

specific configurations, and have an impact on the observed collective (Wassermann and Faust, 1994; Scott, 2013; Robins, 2015). Importantly, in today's digital age the term 'social network' is often inferred to relate only to 'social media' where one does 'social network*ing*'. Networks of social media are only a small part of the social networks that are studied by social network analysts, for the interconnection between boards and directors, and the labor mobility flows of executives amongst firms, and the advice-seeking relations of members of an organization, can all be considered social networks.

Several studies had a substantial role in the development of SNA. Starting from the argument that existing social relationships underpin economic behavior, Granovetter (1985) introduced the concept of network embeddedness. Moody and White (2003) extended the former argument by emphasizing that the network structure is comprised of ties, and the elimination of nested actors disturbs the cohesion of the group. Several assertions have been used as a baseline for other studies that discussed the small-world phenomenon (Watts, 1999), cognitive social structures (Krackhardt, 1987) and network emergence (Stuart and Sorenson, 2007).

However, social network is defined as a set of nodes (actors, vertices) and ties (relations, arcs) connecting them (Robins, 2015). Nevertheless, the term 'network' is different from that of a graph, and should not be mixed in the network studies, since graph represents a mathematical conceptualization of a network. Although the term 'social network' was attributed to Barnes (1954), SNA dates from the 1930s when Moreno and Jennings invented the sociogram (Wasserman and Faust, 1994) naming their approach *sociometry,* which served as a tool to depict interpersonal structures of in-group relationships. Anthropologist Radcliffe-Brown was the first to initiate social network analysis in its non-technical form (Scott, 2013). Unlike actor-oriented research approaches, network studies investigate actors through relationships by exploring the essence of their actions through relational ties.

In SNA, it is claimed that thick webs exist between social actors such as individuals, business entities, industries, etc. (Borgatti *et al.*, 2009). According to Robins (2015) social networks are comprised of actors and the relationships between them, with the relationships given in the form of dyadic *relational ties*. Relationships might differ in direction and the content they exchange, which further define the nature of the network. In terms of direction, networks could be classified as directed and undirected, which depends on whether ties represent orientation of one actor to another (Wasserman and Faust, 1994) or not. Therefore, directed networks differentiate between outgoing ($x_{ij} = 1$) and incoming ties ($x_{ji} = 1$).

Relational ties might acquire different meanings depending on the role they have in the research context. They can represent transactions, the spread of information, interchange of resources, and so on, but might also represent constrained actions and the restriction of particular behavioral patterns (Burt, 1992). Relationships might thus carry positive content, such as friendship, trust, transaction, and collaboration, or negative content, such as conflict and bullying. The nature of a network study is thus, to the greatest extent, dependent on the research context and research question. From the graph theory perspective, ties represent relationships where content, direction and strength depend on the context of investigation.

In conventional network research x_{ij} is a mathematical representation of a relational tie between two actors, namely *i* and *j*. All relationships have value. Ties might be binary, where $x_{ij} = 1$ indicates the presence of a tie, or $x_{ij} = 0$ indicates the absence of a tie. Conversely, ties may be weighted, where the weight of the relationship gives an indication of the strength of a tie. To this end, nodes and the edges commonly enable social actors to be seen as a micro-social system (Lusher et al., 2010). Essentially, the method circumvents the inspection of attributes in isolation and binds them together with the relational ties to simultaneously examine interdependencies between relationships, as well as any effects the attributes may have on the ties.

Nodes and ties might create different types of networks: (1) unipartite, (2) bipartite or (3) multilevel network (Robins, 2015). A unipartite network is comprised of one type of actor and the relational ties between them (e.g. all employees in an organization). A bipartite network is composed of two different groups of actors and the ties connecting them. Likewise, multilevel networks incorporate two groups of actors, while ties could both connect the same and different types of actors (i.e. relationships between managers, and relationships between projects). An examination of multiplex relationships is also feasible using this methodology (see Brennecke and Rank, 2016). Previous networks types are known as *sociocentric*

as they put focus on the overall network. Networks could also be observed from the perspective of a particular actor, and such networks are known as *egocentric*, *egonets,* or *personal networks* (Robins, 2015).

Borgatti *et al.* (2009) and Stuart and Sorenson (2007) observed an explosion of interest in network methodology among researchers. SNA was used as a useful tool for analyzing intra- and inter-group relationships in a variety of fields such as sociology, politics, medicine, social psychology, business, management, mathematics and anthropology. Even though network concepts had pioneering applications in sociology (Bauman *et al.*, 2007), psychology (Moreno, 1934) and anthropology, SNA has been extensively used in politics (Gil-Mendieta and Schmidt, 1996) health studies (Hirdes and Scott, 1998; Killworth *et al.*, 1998; Mikolajczyk and Kretzschmar, 2008) and for addictions (Braine *et al.*, 2008). SNA has also been applied in cultural studies (Chen, 2015; Ziegler, 2008), cognitive social structures (where each individual in the network reports on their perception of the ties among all other actors) and advice networks (Bondonio, 1998; Borgatti and Cross, 2003; Kilduff *et al.*, 2008; Krackhardt, 1987; Lomi *et al.*, 2013), social media (Lewis *et al.*, 2008; Tamburrini *et al.*, 2015), legislation (Desmarais *et al.*, 2015), research (Liberman and Wolf, 1997), and multiplayer online gaming (Shen and Chen, 2015).

3. Social network analysis concepts

In this section, we introduce several SNA concepts which are further used to discuss the empirical case of the network between audit partners. It is important to emphasize that some of the concepts are universally applicable to a broader range of studies, while the others are more specific and their use is limited. Thus, researchers are advised to develop their own list of concepts particular for their empirical case.

Degree and density

Density is one of the basic concepts and measures in formal social network analysis and represents the general level of linking between the nodes in the graph. In mathematical terms, density represents the proportion of present ties relative to all possible ties (Scott and Carrington, 2011). Density may range from 0, which indicates that all possible ties are absent, and 1, which signifies that all possible ties are present. A complete graph, though rare, has a density of 1, which means that all nodes are adjacent to one another (Scott, 2013). Density gives a measure of the overall connectedness between actors in the network. The size of the network directly impacts the density, thus networks that are larger in scope are likely to be less dense, although nodes might, in average, hold the same number of ties as in small-scale networks.

Despite its simplicity, the measure of density is crucial for understanding the general properties of network, and depends on inclusiveness and the sum of degrees of its points. Barnes (1974) distinguished between two perspectives from which the network could be distinguished, egocentric and socio-centric. If the density is determined from the perspective of a particular node then it is referred to as egocentric network, while if otherwise the overall network is accounted, the network is sociocentric.

The measure of *degree* gives information on the number of ties between a single node and all the other nodes in the network. In directed networks, it is possible to distinguish between in degree (the number of incoming ties to a node) and out degree (the number of outgoing ties from a node). Using the measure of degree, we can summarize the overall distribution of ties – known as the degree distribution – which gives information on the variability of ties between actors in the network.

Homophily

Researchers in various network studies have demonstrated that social actors tend to associate themselves with those similar to them in a particular way (Freeman, 2008; McPherson *et al.*, 2016). Homophily implies that ties are more likely to turn up between similar actors, and thus is one principle (of many) which explains why network ties emerge. In common parlance homophily refers to the observation that *birds of a feather flock together*. The homophily principle creates niches by localizing the positions of the vast majority of social differences that are present across society, and which can be classified as status or value homophily (McPherson *et al.*, 2001). SNA enables to identify which actor attributes seems to be important for the network emergence in a particular social setting (Lusher *et al.*, 2013). Homophily is referred to as a social selection process where ties come into being as nodes hold similar attributes.

Research has proven that this selection process is based on the equality in attributes of connected social actors, which could be age, gender, ethnicity, race, education or other context or profession-related similarities.

Reciprocity

Reciprocity is the tendency towards mutuality of relationships in a network, and is another principle that explains network tie formation. The concept is specific to directed networks because reciprocation and exchange are fundamental human social processes (Robins, 2015). Reciprocity can be described in lay terms as *you scratch my back and I'll scratch yours*. Reciprocation is often connected to the involvement of positive emotions. However, it should not be expected that one-sided relationships are reciprocal. In contexts like leadership and business hierarchy reciprocity is unlikely to occur due to the nature of relationships between social actors. Note that ties in undirected networks do not necessarily suggest reciprocity since the direction of the tie is not determined.

Triads

Triangulation is a process of establishing triads, which are comprised of three actors and the relationships between them (Cartwright and Harary, 1956). In lay terms, transitivity can be best depicted as "*a friend of a friend is a friend*". It also involves network closure since a 2-path becomes closed by an extra tie, which produces a triangle. Transitivity refers to the social mechanism that result in clustering or the cohesion of the network. Triads are seen as the smallest form of a group with a majority, and are thus seen as the building blocks of many social networks.

Studies usually report transitivity effects by calculating clustering coefficients, which in non-directed networks can be distinguished as (a) global and (b) local coefficients. The former coefficient represents clustering across the entire network, while the latter shows the density of alter-alter ties observed from the egonet perspective (Robins, 2015). In directed networks, transitivity is more complex to recognize as arcs connecting three nodes do not necessarily generate transitivity (Robins, 2015). An example of it is when three ties create a circle, and when A chooses B, B chooses C, and C chooses A. This is known as a cyclic triad, and represents the concept of generalized exchange. Triangulation has the potential to give an indication of how the network as a whole may be held together, by identifying clusters of actors present in the network.

Cohesive subgroups

Cohesive subgroups are understood as subsets of nodes which represent those social actors with substantially greater density compared to the rest of the network. The most common form of cohesive subgroup is named *clique*. That is a complete subgraph that contains all possible ties. Since cliques have tendencies to overlap, and detecting them might be an issue. Borgatti *et al.* (2013) have developed a method to overcome that problem.

Due to complexity and rareness, the literature has recognized the importance of relaxing the criteria for cliques. New form of cohesive network subsets emerged such as k-plex, k-cores and n-cliques (Robins, 2015; Scott, 2013). The literature emphasizes that, in the context of cohesive subgroups, the notion of density transmutes to the notion of connectivity, thus emphasizing the trade-off to geodesics from density, comparable with the rest of the network. Geodesic is an important concept for understanding cohesiveness. It represents the shortest possible path between two nodes, and the lower value they have, the more cohesive the subgroup is, which implies the presence of shorter paths that are known as small-world phenomenon (Watts, 1999). From a social perspective, subgroups are differentiated by norms, which suggest a different extent of cohesiveness within observed group (Wassermann and Faust, 1994).

Centrality

Centrality originates from the sociometric concept of a "star" (Scott, 2013) and reflects the prominence of a social actor within the observed network (Robins, 2015; Lusher *et al.*, 2013). Freeman (1979) has defined nine centrality measures according to three conceptual foundations, and Robins (2015) has outlined five different types of centralities for undirected graphs, stating that *degree centrality* and

betweenness centrality are the most widely used centrality measures in social network studies, while *closeness*, *eigenvector* and *beta centralities* are specific for particular types of studies.

Degree centrality is an intuitive notion of the activity of a single node, and since it isolates the most active or the most popular node, it is a measure of local centrality (Scott, 2013). According to Freeman (1979) local centrality is a relative measure of which the actual number is related to the maximum number a node could sustain. However, global centrality is expressed in terms of distances among nodes, if the node lies at short distances from many other points (Scott, 2013:86). On the other hand, the betweenness centrality of a node is built around the concept of local dependency, and represents the extent to which a particular point lies between various other points in a graph. This measure could also be interpreted as brokerage or control, which in empirical terms resembles to a function that an actor carries while communicate through the network.

For directed networks, centrality measures could further be split into the in-degree and out-degree, which accounts for the direction of arcs (Borgatti *et al.*, 2013; Knoke and Burt, 1983). It is also important to note that social actors might occupy a more central position in a network due to the other ties and attributes they have.

In general, the concept of centrality should be distinguished from centralization, since the latter extends the concept of density as it inspects how cohesion is organized around particular focal points. Centralization is a measure of the overall network and gives an indication of how centralized a network is, whereas centrality refers to the prominence of individual nodes within the network.

Structural equivalence

Structural equivalence is grounded in the argument that equivalent social actors tend to establish equivalent relational ties. The categorization of social actors with particular groups e.g. teams, departments, functions etc. is related to the concept of a *block*, which is defined as a set of structurally equivalent persons with respect to other such sets that lead to the development of blockmodels (White *et al.*, 1976; Robins, 2015). Since individuals belonging to the same block might be different to some extent, it is important to weaken the criteria for the analysis since the perfect match between individuals is very unusual in any social context.

In the particularity of the social context, the concept of structural equivalence is grounded on relative parities between social actors aggregated within the classes of positions they occupy (Scott, 2013; Wassermann and Faust, 1994). White *et al.* (1976) interpreted a blockmodel as an abstract pattern among a few aggregate units that characterize more detailed interactions between larger populations of individuals. In result, a reduced graph represents categories rather than individuals (Wassermann and Strauss, 1994).
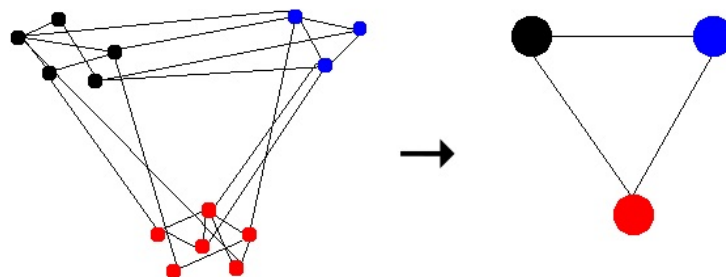

Figure 1. Visualization of the concept of structural equivalence (blockmodeling)

Structural holes, bridges and network brokerage

Social actors standing between different social groups are called bridges, and those individuals are critical for network cohesiveness. Such actors that bridge network regions are in a position to benefit from occupying a brokerage or network entrepreneurial position (Robins, 2015). In opposite, their removal affects the group's cohesiveness (de Nooy *et al.*, 2011). In mathematical terms, actors occupying brokerage positions tend to have higher values of betweenness centrality irrespective of degree centrality (Robins, 2015).

Burt (1992) proposed the theoretical concept of structural holes, and argued that social actors occupying such positions might yield different benefits. In this theory, Burt (1992) asserted that people are vehicles of structurally induced actions, whose incentives to occupy better social positions are grounded in the structure of social relationships for which actors compete. This theory is not a theory about competition as such, but rather a theory about the benefits that are the product of relationships (Burt, 1992). Burt suggests that the opportunity to yield benefits lies in the capacities of individuals to identify loose and not yet bridged subgroups, which may result in, for example, better ideas (see further, Burt, 2004). This is the result of an uneven spread of information as which first reach those that are better connected with others before the average actor receive the information. This is not related to the issue of secrecy but to network structuring principles, as well as trust (Burt, 1992). Therefore, for relationships and positions, *who* you know, is a more important question than *what* you know.

4. Collecting social network data

The collection of relational data is a complex task, and the process depends on a research question (Robins, 2015). As the data collection processes occur in an empirical setting (Robins, 2015), the properties of it determine the complexity of data collection procedures (Marsden, 2011). Prior to each data retrieval, a researcher should answer three questions, known as the 'boundary specification problem' (Marsden, 2011): (1) Who are the social actors and what attributes are relevant for the analysis? (2) What are the ties connecting them? and (3) What is the boundary?

A wide range of data collection methods are available in network studies, e.g. surveys (roster or recall method), interviews, observations, archival sources, contact diaries and longitudinal and relational event data (Robins, 2015). Regardless the method for data collection but the size of network, the process of transformation of raw data into the format suitable for analysis could be an extensive task. Of course, it is possible to use secondary data sources and construct networks for these data. Although researchers tend to focus on places in network where relations exist, in contrary, it is worth of emphasizing the places where ties are missing as that might provide additional input for understanding the properties of the network (White *et al.*, 1976).

To initiate data analysis, all relationship should be converted into 0 and 1 and generate an adjacency matrix. In the case of undirected ties, matrix contains the same information twice (from A to B, and from B to A), around both sides of a main diagonal. On the other hand, if the network consists of directed ties, then rows in the matrix represent the senders of the outgoing ties, while columns represent receivers of the incoming ties. In that case information around the main diagonal might differ, since ties do not necessarily imply reciprocal actions. The main diagonal refers to self-nominations which is often fixed to zero, as self-ties are nonsensical in networks (e.g. being one's own friend). The constructed matrix is not necessary useful for visualizing networks, because as a graphical representation of formal data there is little that is easily discernable from the raw adjacency matrix. However, there is a correspondence between a matrix and a sociograph. Figure 1 indicates a network representation for an undirected network.
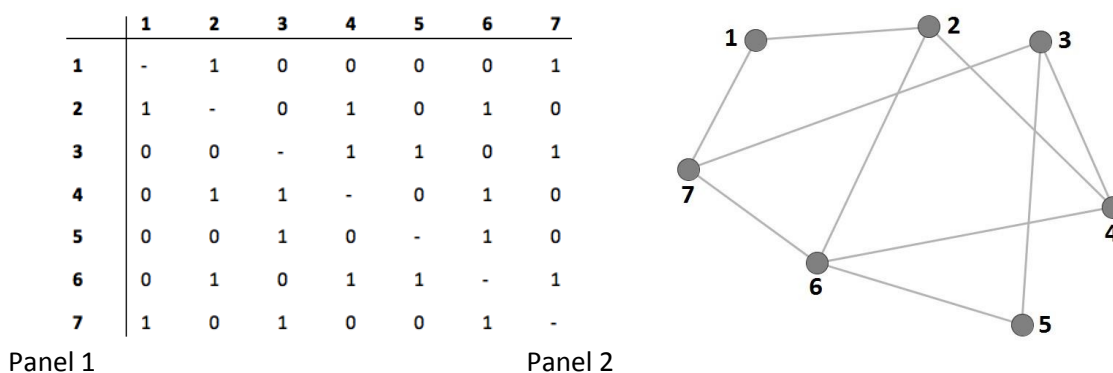

	1	2	3	4	5	6	7
1	-	1	0	0	0	0	1
2	1	-	0	1	0	1	0
3	0	0	-	1	1	0	1
4	0	1	1	-	0	1	0
5	0	0	1	0	-	1	0
6	0	1	0	1	1	-	1
7	1	0	1	0	0	1	-

Panel 1   Panel 2

Figure 1. Demonstration of audit partner collaboration network. Panel 1 represents a 7 x 7 collaboration sociomatrix ("who works with who"), and Panel 2 is a sociograph of the network that corresponds to the sociomatrix

5. Resources for social network analysis and software

A comprehensive introduction to methodological, theoretical, and practical aspects of SNA has been provided by Wasserman and Faust (1994). They have provided an exhaustive explanation of network-related concepts, including structural configurations, attributes and network dynamics. An edited work of Scott (2010) is also highly recommended introduction to SNA. Robins (2015) has developed a comprehensive introduction to network concepts for empirical research purposes, and provides guidelines and precautions for researchers, including ethics and other issues. An edited work by Lusher *et al.* (2013) on the theory, method and application of ERGMs has expanded the previous work by providing a one-stop-shop for complex methodologies related to statistical quantification of network interdependencies and substructures.

A wide range of software packages has been developed for network researchers to enable network analysis, but their capacities differ considerably. In general, software might be classified as network representations software, general data analysis or statistical modeling software. Not all of them are suitable for representations (or network graphs, or maps), but some are, such as Visone (Brandes and Wagner, 2004), Pajek (de Nooy *et al.*, 2011), Gephi (Bastian *et al.*, 2009), Netdraw (Borgatti, 2002), and NodeXL (Smith *et al.*, 2009), which is an add-on to Excel. Those wishing to conduct a large variety of statistical network analytics might use UCINET (Borgatti *et al.*, 2002), although most of those being previously mentioned have some of those functionalities. Exponential random graph models are recommended for complex statistical modeling of social networks since they utilize complex dependency assumptions. Available software for this purpose might be PNet (Wang *et al.*, 2006) and MPNet (Wang *et al.*, 2013), as well as Statnet (Handcock *et al.*, 2004). Finally, RSiena (Ripley *et al.*, 2016) is suitable for the statistical modelling of longitudinal networks as it uses a stochastic actor-oriented modelling approach to delineate social selection process by incorporating the concept of time, which is observed through the process of network change. Most of these programs are freely available for noncommercial use or for a minimal fee, which provides an opportunity for researchers in accounting and auditing to explore the current state of methodology for network analysis and inspect which software are most appropriate for their study.

6. Empirical case of social network in auditing context

This paper examines the case of an audit partner network in Denmark. An intention is to provide an outline of descriptive and explanatory capacities of SNA through the discussion of several previously represented network concepts. In Danish context, social component of auditing is established of two audit partners who manage an entire team on particular engagement. Over time, audit partners tend to change affiliation and collaborate with partners in other audit firms. The auditing context is particularly interesting because the later technological advancements (or other personal motives) accelerated the fluctuation of audit staff between audit firms, and outside the audit industry.

In our network, relational ties between audit partners represent their collaborations on an audit engagement. All collaborations are captured for the period from 2010 to 2014 including single partner engagements. Network considers no weighted effects. The case takes only those audit partners collaborating with publicly listed companies in Denmark (Nasdaq OMX Copenhagen) over the observed period. All Danish public companies are obligated to deliver their annual statements on an independent audit review. Information on signing auditors is publicly available and transparent due to regulatory requirements. This has enabled us to collect and transpose data into ties across the entire sample. The selected period enabled us to observe the agglomerate of auditors over time, and by plotting all the ties to inspect and discuss the group of delineated network concepts.

We followed Scott's (2011) argument that relational data could be obtained from documentary sources, surveys and ethnographic investigations. Documentary sources were main data collection method in use, and we combined (a) Danish registry of companies (*Virk.dk*) and (b) official company websites, to retrieve annual reports from and mine relational data for visualization and analysis. The final dataset includes 774 annual reports since those contain disclosed signed audit reports. The nature of data disenabled determination of the direction of ties, so in our case the network is undirected.

The data were extracted in the manner that the entire list of collaboration ties for each of five observed years to generate the unique database. Next, we converted audit partner names into IDs to facilitate data manipulation, based on which a binary matrix and visualizations were developed. We used a perennial approach as we assumed that the examination of a single year would not provide insightful results. A five-year period was considered to be sufficiently long to capture interactions between partners, as well to intercept their network positions across the overall structure. This has then enabled us to create the auditor network that is used for discussion of previously introduced network concepts.

6.1. Empirical example and statistics

The network presented in Figure 2 visualizes the collaboration network which has unfolded during the period of 2010-2014 among audit partners Denmark. Nodes represent a single audit partner connected with ties to formalize their collaborations on the unique audit engagement. Nodes are distinguished by shapes (triangle, square, rhombus, trapezoid and circle) which denote auditors' affiliation with the particular audit firm. Circle represent audit partners affiliated with non-Big 4, while the other shapes delineate representatives affiliated with Big 4. However, since the network captures periods of five years, only shapes from an initial auditors' affiliation have been taken into account in Figure 2 to properly interpret the network, regardless of the year in which particular auditor has first joined the network.
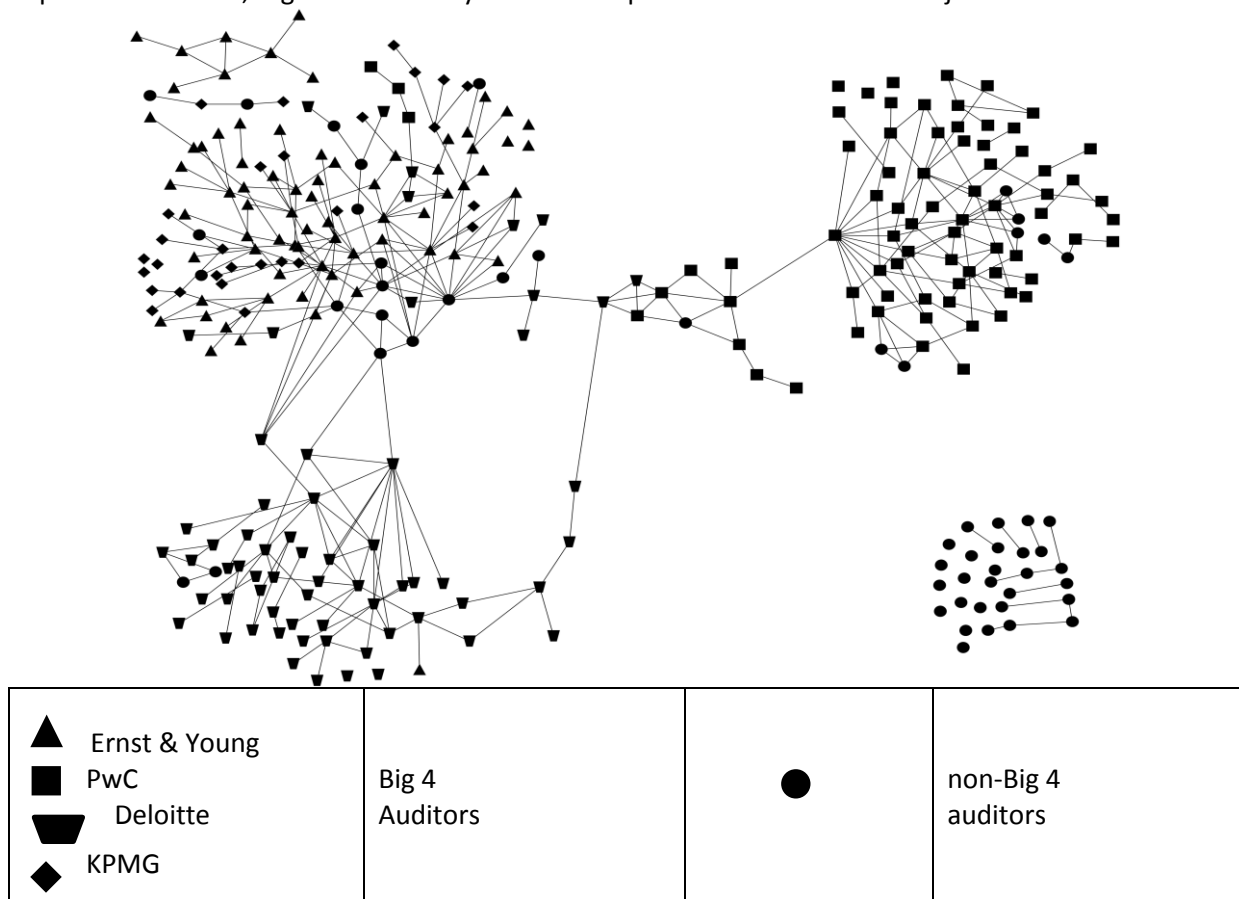

▲ Ernst & Young ■ PwC ⬛ Deloitte ◆ KPMG	Big 4 Auditors	●	non-Big 4 auditors

Figure 2. Representation of the audit partner collaboration network and affiliation change network
(n = 296, *x* = 718, Δ = 0,8%) for the period from 2010 to 2014

From Figure 2 it is notable that the network is composed of three mutually connected clusters where individuals belonging to the each are primarily partners initially affiliated with Big 4 firm. The upper right and lower left clusters significantly differ from the upper left cluster due to a relatively homogeneous structure of representatives. In those clusters, partners have retained initial affiliations over the entire period of observation, or have not been previously affiliated with any other audit firm. Such a clear structure implies that partners engaged with audit firms over longer period, were newcomers previously

affiliated with non-Big 4 company. On the other hand, it is notable that the upper left cluster is a highly intersected region. It is possible to propose that the lack of four highly clustered regions in the Danish context is a result of the two Big 4 mergers that occurred in 2008 and 2014, which resulted in the emergence of notably heterogeneous cluster. The bottom right group of isolated auditors is primarily comprised of non-Big 4 representatives. This is a sparsely tied locality where rare collaborations and auditors integrate those partners who were affiliated with the remaining eleven audit firms.

Table 1. Descriptive statistics of the observed network of audit partners in the Danish context

Network statistic	Description	Estimation
Number of ties	Total number of ties present in the observed network	718
Average degree	Average number of ties adjacent to a given vertex	2.426
Density	Ratio between present and all possible ties	0.008 (0.8%)
Graph centralization	Overall cohesion of the graph	0.0361 (3.61%)
Network centralization index (Betweenness centralization)	Network cohesion around the focal vertices	0.2049 (20.49%)
Transitivity	Density of transitive triplets in a network	0.069 (6.9%)
Overall graph clustering coefficient	Mean of open neighborhood of each vertex densities	0.264

Table 1 provides an outline of descriptive statistics of the network that we further discuss. The network captures 718 unique collaborations between 296 auditors, in total. Auditors have, on average, collaborated with 2.43 different auditors over the five-year period. The overall network has low density (Δ = 0.8%). This might be ascribed to different boundaries (regulatory), which constrain the number of engaged partners. The number of engagements of each auditor in a single year might also be predetermined at the audit firm level, e.g. internal agreements.

The graph has a degree centrality (overall network centralization) of 3.61%, which gives an indication of variance of degree inequality between present actors. In other words, this measure shows to what extent the number of collaboration ties oscillated around the average number of single collaborations for each auditor, expressed in percentage. This statistic indicates that, in general, auditors held relatively equal numbers of engagements, on average, as the oscillation is close to zero. A measure of betweenness centrality for each node represents the frequency of nodes occurrence on a geodesic, but, the overall network betweenness centralization gives an indication of what the network structure looks like. In our case, the index of 0.2049, which is closer to 0, shows that the observed network is less centralized, more scattered, and not likely to generate a hub.

The network has an overall clustering coefficient of 0.264, which represents the average measure of density in the open neighborhood for each node in the network. More specifically, it shows the degree to which two incident ties tend to become completed by a third to create triangles (3-loops) around each node and between each other adjacent node, measured on average. In our empirical case, the coefficient shows that a little over of 25% of total auditor collaborations tend to become transitive (i.e. form triangles, or triadic relations). The overall transitivity statistic is 6.9% for our network, which gives an indication of the density of triangles in the graph.

Structural hole theory (Burt, 1992) has gained prominence among researchers in areas such as organizational studies, absorptive capacity research, and more. The majority of those studies used this theory to give prominence to the knowledge spread that emerges from those who occupy such a position in the group, as they are more prone to generate good ideas and innovations (Tortoriello, 2015; Rodan, 2010; Burt, 2004), however, Ahuja (2000) explained that structural holes could have both positive and negative impact on innovation depending on the size of the structural hole. Our empirical case is complementary to Tan *et al*. (2015) who argued that only the actors present in low density networks may benefit from spanning structural holes, since denser networks and regions could weaken such effects and may turn out to be detrimental. In order to statistically examine which nodes occupy structural hole positions we utilized the UCINET software. The result of it is three nodes, indicated by arrows in Figure 3, which refer to auditors with the highest prominence in spanning highly clustered regions.
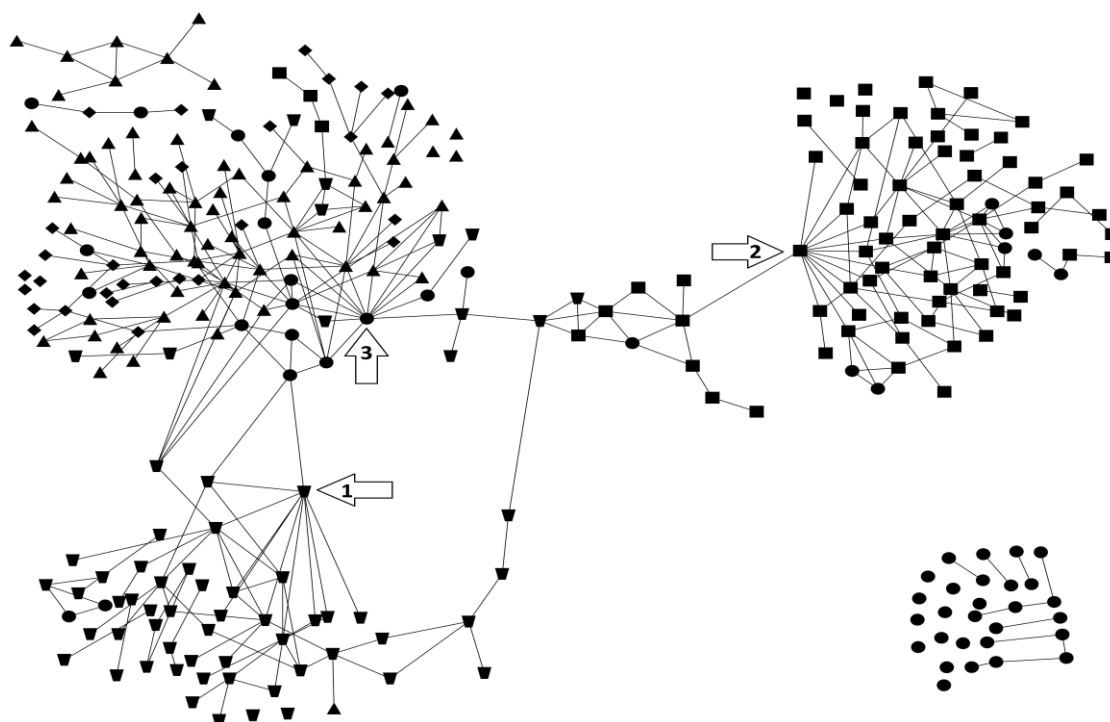
Figure 3. Audit partner collaboration network (n = 296, *x* = 718, Δ = 0,8%).
Arrows point to structural holes in the network; calculation performed by UCINET algorithm (Borgatti, *et al.*, 2002)

This implies that partners standing at sparse network regions also may gain significant prominence over others within denser regions; however, this empirical example further enriches a theoretical dilemma about whether the network closure effect or structural holes may yield better benefits from the perspective of network position. With this regard, it is possible that those auditors occupy position of structural hole are significantly attractive for collaboration. This means that some auditors might acquire high popularity if they change affiliation, as they might provide additional information input knowledge or experience.

7. Statistical models for social networks: Exponential random graph models (ERGM)

In accounting and auditing context, several studies previously have utilized network methodologies that were primarily based on linear regression methods. Regression hypothesizes that observations are independent one from another, and researchers using it might only be able to test how one or more independent variables influence a theoretically selected dependent variable. However, the assumption of independency of observations is not sustainable in network studies because networks' configurations unfold in local social processes, e.g. ties emerge as a response to other ties existing in network. This implies that the assumption of interdependency is more appropriate in network research than the classical dependent-independent assumption. As a result, a new class of statistical model, exponential random graph models (ERGMs), was developed to account for the presence and absence of network ties, and to enable modelling for network structure (Robins *et al.*, 2009; Robins *et al.*, 1999; Robins *et al.,* 2007; Wang *et al.*, 2013). In this section we present characteristics and power of this cutting-edge statistical model in order to inform readers of the logic, rationale and capacities.

ERGMs passed phases of development and had a long history before they arrived at their current state. Starting from the introduction of the network statistic approach (Moreno & Jennings, 1938), across Erdös and Rényi graph (Erdös and Rényi, 1959), Bernoulli graph distribution (Frank, 1981), the *p*1 model (Holland and Leinhardt, 1981), the *p** model (Wassermann and Pattison, 1996) and conditional independence assumption, Pattison and Robins (2002) arrived to the social circuit model on which the current ERGMs were underpinned. ERGMs are defined as tie-based statistical models for network structure which permits making inferences about how and why social network ties arise (Lusher et al., 2013:9), but

instead of observing random networks ties, ERGMs hold the premise that networks emerge in specific configurations of ties. Configurations are small local subgraphs whose probability of appearance determines how many of those configurations are present within the network. In turn, ERGMs work as pattern recognition devices and identify parameter values for a group of observed network configurations, which further informs researchers about the importance of each selected configuration for network emergence. Put more simply, a researcher selects a list of patterns that are based on theoretical interests and applies this to an observed social network to estimate parameters for each selected configuration. Model results permit making inferences about network patterns (Lusher *et al.*, 2013).

ERGMs hold an exceptionally important feature, i.e. network ties are dependent on one another (Pattison and Robins, 2002; Pattison and Wasserman, 1999; Wasserman, Pattison and Steinley, 2005, 2014; Pattison and Robins, 2002; Robins *et al.*, 2012). This process of network emergence is called network self-organization and assumes that the presence of one tie may affect the presence of the other ties – ties are conditionally dependent on one another if they share a node. ERGMs have taken further the assumption that individuals by definition are dependent, and assumed that the actual relationships between individuals are interdependent. This aligns the method closely with our theory of how the social world actually operates. There are many possible network substructures (or network effects) that a researcher might observe in one network. However, it depends on their interests and theoretical foundations, the selection of particular network configurations should be sufficient to provide parameter values for observed network patterns, with regard to the theory they want to contribute to. This also means that integrated configurations give a certain freedom to interpretation of results, but the level of freedom should be aligned with the particular theory on which the researcher builds the argument. For instance, if theoretical discussion in reciprocity is important to a researcher, then this should be included in an ERGM. Lusher *et al.* (2013) suggest what might be a good starting set of network effects to be included as a minimum for studies employing ERGMs.

The aim of ERGMs is not to predict the outcomes of individuals in the network (so-called social diffusion or social influence models) but to detect patterns that may inform on network formation processes, which also include the social selection process. ERGM is a pattern-recognition device identifies network substructures. Different social theories had significant influence on the development of social network analysis and ERGMs, which might explain why relational ties might be present in the network and how ties are associated with actor attributes (Lusher *et al.*, 2013). Literature recognizes three categories of tie formation processes: (a) network self-organization, (b) attribute-based processes, and (c) dyadic covariates. While the first assumes that network ties organize themselves into patterns because the presence of ties encourages the other ties to emerge, the second proposes that social actors bring their own capacities, capabilities and predispositions into the network (attributes). Finally, the third assumes that ties themselves have special characteristics, which, in turn, affect tie emergence.

ERGMs can be used for the examination of one-mode, multilevel, bipartite and multiplex networks. In addition, software called MPNet[1] (Wang *et al.*, 2013) is available for implementation of ERGMs to examine how selected variables affect network emergence. This software enables testing the existence of various network effects e.g.: homophily, reciprocity, centrality, clustering and/or many of the other available network effects, and all at once. It is important to note that ERGM methodology might be complex to master, but the aim of this is to inform readers in accounting and auditing of its capacity, and to draw attention to the fact that, for example, linear regression in network studies can either be used to predict attributes or the presence of ties, but not both of them at the same time. Since linear regression is inconsistent with the assumption of interdependence, the application of the method to network studies is considered problematic, and ERGM is a preferred method. To see more on ERGM theory, methods, and application please refer to Lusher, et al. (2013), an introductory article on ERGMs in sports teams (Lusher *et al.*, 2010), and examples of the application of ERGMs in social studies (Brennecke and Rank, 2016; Brennecke *et al.*, 2016; Lazega *et al.*, 2008; Lomi *et al.*, 2014). The focused organization of advice relations: a study in boundary crossing. Org. Sci. 25). Given the complexity of explaining ERGM, a paper detailing the application of ERGM to auditing and accounting is not presented here but is forthcoming.

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[1] Available at www.melnet.org.au

8. Conclusions

The aim of this paper was to outline main characteristics of SNA in order to inform researchers of how this method could serve as a powerful set of tools for approaching social relationships within the context of accounting and auditing. In this introductory article, we briefly outlined the history that brought the logic of the SNA to light. This is followed by a description of the characteristics of the methodology and fundamental network concepts. We delineated relational data and software resources that are available for network analysis, and give description of the exponential random graph models (ERGMs), as the cutting edge statistical model for social network analysis. To bring the method closer to the reader, we provide with an example of a collaboration network comprised of audit partners in Denmark, which evolved over a period of five years.

In a nutshell, SNA is able to integrate a different range of actor attributes and examine their influence on network structure. SNA is predominantly a quantitative-research method, and it enables researchers to simultaneously examine relationships and individual-level characteristics within the focal context. Unlike to classical quantitative research methods, current developments in SNA are able to account for interdependence, by providing estimations of selected network configurations that further enable theoretical inferences. This method replaces the measurement of individuals to networks and uses the network as the unit of the analysis, while still accounting for actor characteristics using them as an input to understand network structure. It is very important to note that this introductory article does not argue for the replacement of linear regression or other classical statistical methods, but for the use of SNA as an additional tool to previously developed quantitative methods, and emphasizes the appropriateness and legitimacy of this method for inspecting the evolution of network relationships in particular social contexts.

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