Social Network Analysis: Towards Complexity Problem

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Abstract

Social network analysis is a advances from field of social networks. The structuring of social actors, with data models and involving intelligence abstracted in mathematics, and without analysis it will not present the function of social networks. However, graph theory inherits process and computational procedures for social network analysis, and it proves that social network analysis is mathematical and computational dependent on the degree of nodes in the graph or the degree of social actors in social networks. Of course, the process of acquiring social networks bequeathed the same complexity toward the social network analysis, where the approach has used the social network extraction and formulated its consequences in computing.

Keywords

Star, Complete, Web, Nodes, Edges, Social Actors, Relationships, Relations.

Introduction

Physically and visually (Sun & Xie, 2019), a social network with a small number of social actors can be easily traced and understood (Mahon et al., 2006), and computationally it is not so complex (Wagner, 2003; Valverde-Rebeza & De Andrade Lopes, 2012). Of course, the results in social behavior, it is easily displayed through social network analysis manually or simple computations (Can & Alatas, 2019). However, in modern society, such social networks do not represent the overall characteristics of social communities summarized globally (Berger-Wolf & Saia, 2016). It is as a result of the important role of social actors in society (Prell et al., 2009). So, the networks are generally bound to the existence of nodes and edges with which social networks refer to social actors (Nasution, 2018a; Juma & Shaalan, 2021) and the relationship between social actors (Nasution, 2018b; Ahmadi et al, 2018).

Classically, the social network analysis focuses on social actors and the relationships that emerge subsequently whether they grow straight or widen (Freeman, 2004; Nasution et al., 2016). However, social networks are not only manifested in a small and static collection of social actors, social networks are expanding and dynamic – like the propagation of fertile plants – which do not stop to information technology such as the Internet and the Web (Javarone & Armano, 2013). The Internet and the Web are both sources of information as well as network resources such as nodes, social actors, relations, and edges (Nasution, 2016). Specifically, a social actor is a social member who writes, creates, or author/co-author of a web page or document whose name is on the web or document. It is not only presents virtual social networks, but also social networks semantics (Rytsarev et al, 2019), so social network analysis is not only related to social actors as a point in network resources, but the community allows it to be present as a point and have a special relationship with other communities. It resulted in the complexity of social network analysis being reduced, and this article proposes the study for the importance of social network analysis.

A Problem Definition

Suppose that social networks in general are social structures that consist of a set of social actors and a set of dyadic bonds, and other social interactions between social actors (Mills, 2017). In mathematics, the social networks are modeling social structures involving graph theory (Barnes, 1969). A graph consists of n nodes and m lines revealed in $G = \{V,E\}$, where $V = \{v_i|i = 1,\ldots,n\}$ is the set of nodes or vertices and $E = \{e_j|j = 1,\ldots,m\}$ is a set of lines or links (Blythe et al., 2005). Thus, to reveal the network from the source of information involves the transformation function namely $\gamma: D \rightarrow G$ by which D is the source of network information. In this case, the information source contains a set of social actors $A = \{a_i|i = 1,\ldots,n\}$ and a set of relationships between them $R = \{r_k|k = 1,\ldots,K\}$ so that the social network is $\gamma(1{:}1) : \{A,R\} \rightarrow \{V,E\}$ (Nasution, 2016; Ni et al., 2021).

Carrying out the social network analysis (SNA) depends on social network resources such as the social actors, the relationship between social actors, nodes, edges, edges, and information sources such as documents or information in big data (Nasution et al., 2015; Silva et al., 2020). Classically, social network analysis is stated as a process of investigating social structure through the use of graph and network theory (Tichy et al., 1979; Scott, 1987). Although social network analysis relies on nodes in general, the involvement of labels of edges show the widening of the task of social network analysis both based on the label level and based on the strength of the relationship, but it still involves the nodes as a foundation, especially the degree of node (Paolillo & Wright, 2006). However, what are the resources of social network analysis to be part of the study of Webology (Noruzi, 2016), therefore indirectly social network analysis reveals some support related to the web and its measurement metrics, as stated in Webometrics (Ismail et al., 2021) or Scientometric (Ciriminna et al., 2020). In this case, a pair of different nodes has symmetrical considerations according to the lines connecting them. Thus, social network analysis comes with various measurements such as clicks, centrality, betweenness, and others (Wasserman & Faust, 1994). All of that is related to determining the key roles that apply to each social actor both based on groups in social networks and as a whole social network (Dávid-Barrett & Dubar, 2013).

Conceptually, the social networks trivially form themselves automatically in society, from families until the community organizations (Fattore et al., 2009). However, the social network as an abstract of social structure is for the interest of decision making by determining the direction of social development based on communication connections and information flow (Kijkuit & Ende, 2007). Specifically, of course social network analysis aims to determine the role of social actors and predict the formation of social groups and their effects on other groups (Onnela et al., 2011).

Dynamically, the formation of social groups is based on time as the growth of social networks, with which groups have more density than the degree of node and the number of edges formed between members of the group (Li, 2011). The group, in this case, is composed of social actors who have relations with other and have relations with social actors who are separated from each other as a picture of the interactions that occur. Each group member has a role according to the position that occurs in the group: Social actors who have a central position have different roles from the marginal position in the group (Serret, 2009). However, any concept without theory or formalization into mathematics, social network analysis cannot be carried out. Interpretation of the purpose of a concept into mathematics is necessary so that computational results become evidence. Furthermore, social network analysis requires defining clicks, betweennes, and another.

An Approach

Social network analysis is a field that develops along with social networks (Nasution, 2016; Nasution, 2019) based on the usage perspective (Limongelli et al, 2021). When social networks are based on modest information, the analysis is based on resources with the abstraction of graph theory (Nasution, 2013). Suppose a_i, $i = 1,2,\dots,n$ are nodes in the social network G, or a_i in A, and e_j, $j = 1,\dots,m$ is the edges of the social networks G, or e_j in E. Social network analysis on nodes behavior called the degree of social actors (Chan & Liebowitz, 2006).

In the graph theory, each node has a degree, notated as *deg*(), that is number of edges that incident to (touches) node (Borgatti et al., 2009). In other words, the degree of a social actor $deg(a)$, a in A, is degree of node which also means the number of social actors $\Sigma_{i=1\dots N-1}\, a_i$ connected with a, or

$$deg(a) = \Sigma_{i=1\dots N-1}\, a_i \qquad (1)$$

where a_i in A. Degree of nodes in the range of $[0,n-1]$ for n nodes in a graph, and its states that the maximum degree in a graph is $\blacktriangledown(G) \leq n-1$, while the minimum degree in a graph is $\blacktriangle(G) \geq 0$, but $\blacktriangledown(G) > \blacktriangle(G)$. In a graph, therefore, it allows a node to have a degree $deg() = 0$, meaning it is not connected to another nodes with at least one edge (Meneely et al., 2008), but is social networks such social actors are not recognized. So the degree of social actors is in the range of 1 and n-1 for n social actors in networks, or $deg(a_i)$ in $[1,n-1]$. However, a computation of the degree of social actors depends on the kind of graph that present the social network (Pattilo et al., 2011). For two nodes essentially be counted as many layers according to the concept of a multi-graph, but in a social network one node represent only one social actor, and the number of degrees is

$$\Sigma_{i=1\dots n}\, deg(a_i) = 2|E| \qquad (2)$$

Manually computation follows intelligence that is implanted into formulas through changes in parameters then the factor is patterned into the domain of artificial intelligence based on data models that are allowed by computer programs. One approach to building social networks is the extraction of social network form information sources. The artificial intelligence domain using the unsupervised method for clustering information according to the data model for social network, i.e.

a. Determines the existence of social actors, $\gamma_1: \Omega \rightarrow A$, by which Ω is the source of information and $|\Omega|$ is a cardinality of information source, which is always expressed as $|\Omega_a| = \gamma_1(a) > 0$, a in A. Thus, for n social actors, the existence of social actors requires n processes (Barnes & Harary, 1983; Nasution, 2018a). In semantic, γ_1 is one of models in the semantic technology, i.e. it called as occurrence.

b. Specifies the existence of a relation between two social actors, γ_2: $\Omega \rightarrow A\times A$, which is always expressed as co-occurrence $|\Omega_a \cap \Omega_b| = \gamma_2(a,b) > 0$, a,b in A. Thus, to determine the presence or absence of a relation between two social actors $n(n\text{-}1)$ processes (Nasution, 2018b; Elfida et al., 2018). Therefore, γ_2 is one of models in the semantic technology.
c. Specifies the label of the social actor character, γ_3: $\Omega \rightarrow L_A$, where L_A is the set of labels with their weights. For each social actor it has the possibility of at least one label, and it requires nk processes, $k = 1,\ldots, K$ (Camacho et al., 2021).
d. Specifics the relationship weight, $\delta_{ab}(\Omega_a,\Omega_b,\Omega_a\cap\Omega_b)$ in [0,1] with a threshold of $\delta_{ab} \geq \alpha$, α constant. Based on the process of determining the existence of a relation between two social actors, the weight of the relation requires $n(n\text{-}1)$ computations (Nasution, 2016).
e. Specifies the relation label between two social actors, γ_4: $\Omega \rightarrow L_R$, where L_R is the set of relation labels with their weights. The process for getting one or l labels for $n(n\text{-}1)$ relations are n^2l (Camacho et al., 2021).

So, extracting social networks from information sources is modeling the relation between social actors, and social network extraction is at a complexity of $O(n^2)$. Modeling the relation between social actors is an abstraction of information sources to describe social structure based on virtual intelligence. Virtual intelligence is concerned with the source of information in the form of smart documents by which each part has an identify. Thus, social network extraction is expressed as the arrangement of social network resources $SNE = \langle V,E,A,R,L_A,L_R,\gamma_1,\gamma_2,\gamma_3,\gamma_4,\delta\rangle$ or abbreviated SNE. In this case, the γ function is the abstraction factor needed to express the social network in accordance with the interests of decision making (Nasution, 2016).

In particular, the extraction of social networks using the unsupervised method is always limited by the ability to device resources, such as search engines, while the extraction of social networks by the supervised method (classification) is always limited by the size of the corpus as source of information. However, social network analysis is not trapped by these considerations, but it still depends on the complexity inherited by social network extraction. Analysis of virtual social networks indicates the study of virtual social structures and their impact in analyzing social and cultural aspects. Thus, along with the limitations of the completeness of information sources and corpus, analysis of virtual social networks has grown massively along with the growth of information sources in cyberspace.

That way, the social network analysis requires indirect growth of nodes and edges in line with the growth of the degree of nodes that are the trigger. It shows the dependence between social network analysis with social networks and the degree of social actors as stated below.

Proposition 1: Social network analysis is the social network and the degrees of the social actors *deg*().

The Adaptive proof.

Simplification the statement in Proposition 1 can be abstracted as follow.

$$\mathrm{SNA} = \mathrm{SN} + deg() \qquad (3)$$

Or, Social Network Analysis (SNA) = Social Network (SN) + Nodes Degree, which reveal that if X is the results of SNA, then X comes from the social network SN and involves *deg*(), or if SN is social networks and computing involving *deg*() and it create X, then X is the result of SNA. In social network, each social actor has a different role in the network, although it is possible that some of them are in the same role.

Suppose A_k, $k = 1,\ldots, K$ are the subsets of social actors from A, where $|A_k|$ is the number of social actors in A_k. Eq. (3) has some proofs as follows.

1) Group in SNA

First, a *group* of social actors can be restated as a subset of A_k of the total set of social actors A, A_k is subset of A, with the following conditions:

a. For all nodes a_i in A_k applies $1 \leq deg(a_i) \leq |A_k| - 1 < n$.
b. There are a_c in A_k with $deg(a_c) \leq \blacktriangledown(G)(A_k) \leq - 1 < n$.

Thus, within the group some social actors have a central position, while others are leafs, but also sometimes become the path of communication of this group to the outside of the group. However, centrality illustrates the relative position of actors based on the context of social networks.

2) Clique in SNA

Second, suppose A_k is a subset of social actors A, A_k as part of the social network SN and is said to be a *clique* (click) if every A_i in A_k has the same nodes degree $deg(a_i) = |A_k|$-1, and there are several of a_i connected to other actors in A, or a_ia_l, a_l is not in A_k, a_l in A. It states that there is more than one or a maximum of $|A_k|-1 < n$, $deg(a_i) = |A_k| < n$.

A social network is said to be complete (the complete graph) if every social actor is connected to other social actors in a social network, or for $|A| = n$ all social actors a_I in A, $i = 1,\ldots,n$, $deg(a_i) = n$-1 or the number of edges in a complete-graph is ½n(n-1). Meanwhile, a social network is said to be a star (the star graph) if there is one actor as the central with the highest degree n-1 and another degree is 1 or the number of edges in a star-graph is n-1. So, the number of degrees for all nodes in a complete-shaped social network is

$$\Sigma_{i=1,\ldots,n}\, deg(a_i)_c = n^2-n. \quad (4)$$

Whereas, the number of degrees for all nodes in a star0shaped social network is,

$$\Sigma_{i=1,\ldots,n}\, deg(a_i)_s = 2n^2-2. \quad (5)$$

The comparison of Eq. (4) and Eq. (5) shows the facility of doing SNA according to the growth of social actors in the social network, as Fig. 1. The facility ε_x approaching zero the SNA will be more difficult.

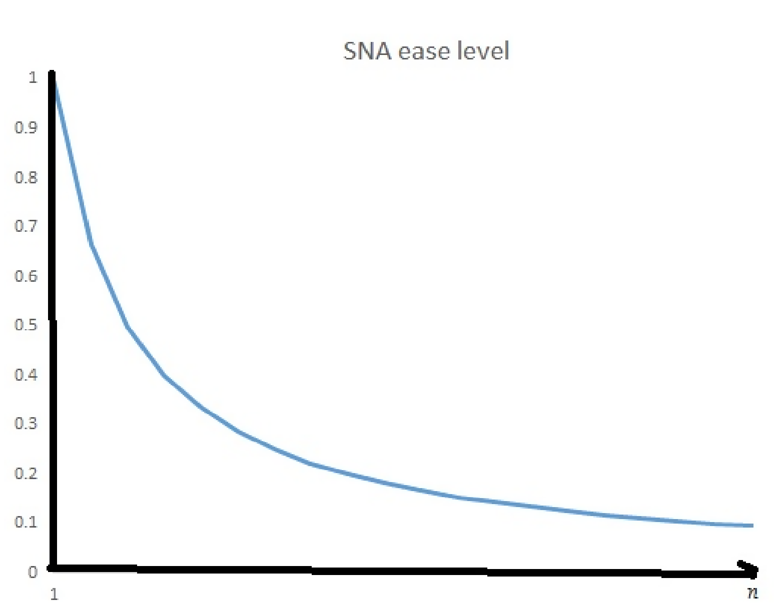

Fig. 1 Comparison the star and the complete graphs

3) Betweenness in SNA

Third, the *betweenness* is a kind of centrality through which social actors a_p control the flow of information between groups of social actors or between social actors individually. In this reality, every intermediary has exactly degrees $deg(a_p) < deg(a_c)$, a_c in A_k, for c, $k = 1,2,\ldots,K$.

In the case that a_p becomes a central node, if $deg(a_p)$ continues to approach one of $deg(a_c)$, the collection of social actors becomes a new group with more membership of groups.

4) Generalization for Area Advisability of SNA

Let the path in a social network consists of a number of social actors $a_1, a_2, \ldots, a_L$ where the edges are $\{a_l,a_{l+1}\}$, $l = 1,\ldots,L$-1, or a sequence of social actors and the link between two social actors, namely $a_1e_1a_2e_2\ldots a_L$ and the size of a path $l = |a_1e_1a_2e_2\ldots a_L| = L$-1. If l_k is all paths from a_1 *to* a_L, the shortest path is $l < l_{k\text{-}1}$. The size of $l = 1$ is trivial as the shortest path for two social actors. Therefore, the closeness between one social actor and another social actor in social network is the shortest path greater than 1, $2 \leq l < l_{k\text{-}1}$.

Furthermore, to reduce the complexity in getting closeness between one actor and another actors in social network can be done by ignoring social actors who have the degree $deg() = 1$. The closeness is related to the distance between one actor and another, and it only works when there are other social actors with degrees of at least $deg() \leq 2$. Thus, the problem results in the behavior of social actors with SNA is based on the degree of social actors as a whole.

The social network represented by complete graphs is the social network with the highest density represents by $\blacktriangledown()$. In the social network, every social actor has a maximum degree. Therefore, all forms of SNA computation cannot reveal anything from it. In contrast, a star-shaped social network has one central node and the other social actors are leafs. Thus, the measurement of SNA only functions when the social network is between complete and stars shapes. Fig. 2 shows the area advisability for doing SNA, that is an area in $n(n$-1), n-1, and n (or area with green color).

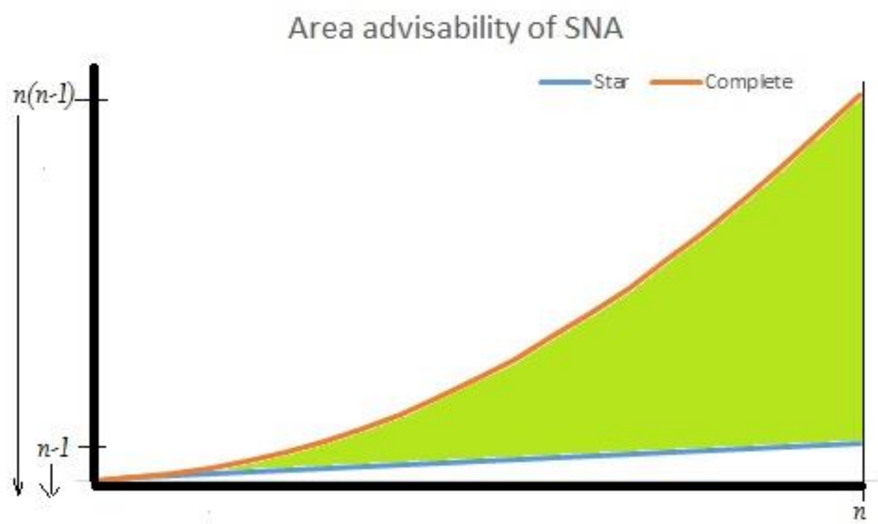

Fig. 2 The growth of edges based on star and complete graphs from i = 1,..,n

Thus, the measurement of SNA only works when the social network is between complete and star shapes, or the *X* area of SNA is the difference between Eq. (4) and Eq. (5), i.e.

$$x = n^2 - 3n + 2 \tag{7}$$

By comparing with Eq. (4), the result like in Fig. 3 reveal probability for the presence of a variety of key roles for the social actors in a social network (as an opportunity or a quantum).

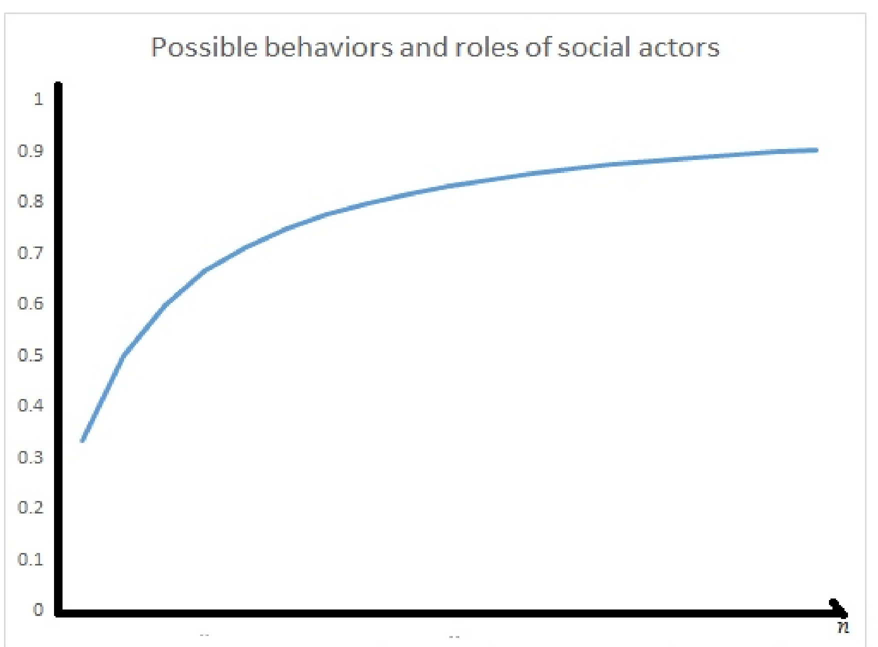

Fig. 3 Comparison number edges in non-complete and the complete graphs

The work area of SNA shown in Fig. 2 and the possible role of social actors in social networks such as Fig. 3, and it shows equality, so it showing that the implementation of SNA is increasingly complex as shown in Fig. 1. Of course, the determining factor in the SNA is the growth of social actors, and it is equivalent to the growth in the number of edges, so computing on SNA depends on the degree of the social actors. The growth of social actors and their relationships based on the time series of documents present, as evidence of their existence, shows the complexity that continues to apply to SNA.

Conclusion

SNA as by definition depends on social network resources: information source, nodes, and edges, whereby as a whole can be abstracted into a level of dependency, namely that SNA is nothing but the disclosure of the behavior or role or social actors based on the degree of social actors in social networks. The search for this role depends on the time series of documents present and is certainly computationally dependent on the complexity of the social network extractions process.

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