Social Network Mining: A discussion

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Abstract. Social network is model in order to structuring social. In knowledge management, social structures need to be revealed to see social behavior and social change based on the interactions that have taken place. In knowledge technology, the semantic social structure is extracted from information sources to interpret social behavior and its changes, and the meaning is supported by social network analysis. However, social networks do not only reveal social structures and manage them, but social recognition by exploring the potential of social members (social actors) and the community so as to present competitiveness. Competence is defined by the existence of social actors, while the existence of social actors is expressed from the relationship between them whereby the relationship also proves the meaning the competence. By involving artificial intelligence (AI), the meaning can be affirmed in a variety of different ways depending on the treatment given to the source of information so that it is possible to predict and express on the characteristics and behavior of the data. It based on forensic data and information retrieval, for trustworthy information is generated. Moreover, social network mining is present by considering social network data and the resultant of extraction method so that social networks not only contain information but become knowledge. This serves to bridge the social network analysis gap based on primary and secondary data, so social engineering is possible by exploring all the potential presented by social network extraction.

1. Introduction
The advancement of information technology and computer networks have led to an abundance of data that can be utilized in the development of knowledge and decision making [1]. The advancement of this technology has formed the information space Ω as a shadow of the real world [2, 3, 4], which is recognized by the Internet and the Web [5, 6, 7, 8, 9, 10]. The main challenge comes from how to obtain useful data, arguing that traditional data analysis tools and techniques cannot be used due to measures that are sometimes too large and too small [11]. Therefore, new methods need to be developed, and it always formulated in the data mining related to social networks.

Data mining that contains the integration of traditional data analysis methods with sophisticated methods that have been translated into software to be able to process big data [12, 13]. However, data mining not only opens up opportunities to explore new types of data but also causes data have relations to entities as social actors either as subjects or objects of decision making socially and for importance of society [14]. Therefore this paper is to describe briefly the social network mining as a discussion.
2. A review with definitions

The rapid growth of data is directly related to social actors [15]: today the higher number of mobile phone sales compared to the world’s population [16]; the social media that not only delivers information, but also collects and interprets data [17]; the cloud computing continues to review data as predictions of change [18]; and the internet of thing that accumulates changes in the world based on complex automation [19]. Thus it is possible for every person who is knowledgeable or algorithmically capable to collect the latest data [20]. Data that is socially never separated from any social actor, which supports the competence of himself and has community [21, 22]. This is in the model stated as a social network, namely a collection of information about ties between all pairs of social actors where a tie connects a pair of actors by one or more relations [23]. A model based on graph theory for social actors (entities: people, organizations, or others) and their relations respectively in vertices and edges [24].

Awareness and ability of social actors opens opportunities for the presence of new types of data [25]. Based on the definition of social network extraction, for example, it has revealed the existence of new data types that represent vectors [26]. In this case, the social network extraction (SNE) is an effort for generating social networks from information sources [27]. Information sources, for example, are webpages and documents [28, 29]. Social actors are represented by vertices based on data types. In metadata not only are labeled by numbers but also labeled with the names of social actors, and each label has a value [30, 31]. In addition, the relationships described by the edge may have revealed two different actors or not, and this depends on how the social structure will be described. In terms of the relationship between social actors, the type of data produced by extraction depends on also the number of relationships revealed. Each relationship has a different vector than other relationships, with which this is caused by semantic different meaning labels [32]. SNE requires a different way of involving big data, including to give treatments [6]. Traditional approaches are no longer enough [33, 34]. This is different when the sample or corpus data is used [35]. Social network extraction methods are approaches that are supported by streams of: clustering and classification [36]. Even when the combination is not enough the heuristic method can be involved, of course with the aim of producing an achievement and optimization [37]. Classically, the clustering method is generally poor in meaning but fast in process, in the algorithm the classification method is generally rich interpretation but very slow to get outcome [5]. There is no method capable of doing both, except for new methods that adopt both capabilities, where algorithms are able to access information sources or big data [38]. Thus, based on that social network extraction involves new method that are not only able to recognize and analyze new data types, but allow old types of data to be recognized and analyzed by the new method.

SNE is not to recognize the structure of social networks. Interpretation of social networks that focus on vertices and edges in the network is carried out by methods collected in social network analysis [7]. Social network analysis (SNA) reveals the behavior of social structures based on the resultant of social network extraction methods (in change or not), but unable to predict changes [39]. However, SNA is expressed as a study of social networks for interpreting the structural relationships between actors [40]. So, when extraction has been done from an information source, interpretation can be done directly to interpret the structure [41]. Enrichment of extraction methods needs to be carried out to produce the latest social networks, but also historical success, so that the growth and tendency of social structures can be predicted [42]. Of course this is not easy to do with traditional methods, without updating existing methods. As a result, all methods involved in analyzing social networks need to be renewed so that the emphasis on meaning based on the degree of the meaning means predictions of change and social demand for more influential social actors.

Although, the SNA is not an extension of SNE, in general the SNA is involved so that social networks can be understood at that time. On the other hand, SNE requires SNA as an
extraction analysis tool. This implies that the methods support each other so that big data can we function. Big data with various types of data in the information source is extracted into structured information with new data types in the form of social networks, and structured information into new data can be processed by the appropriated methods so that knowledge is generated related to social networks [43]. This integration is expressed as a field of study of social network mining (SNM) [46], it expressed as a study to find useful information about actors and their relations automatically from information sources (as transformation of the big data to the knowledge). A field of study for enhancing the data mining methods where they generally do not consider the relationship between data [44], but rather it separates data to achieve the optimization stage in computing levels [45].

3. An approach with the review
Social network mining is used to express the social structurally with a variety of interests and in a variety of business intelligence applications such as social actor profiles, targeted outcomes, relationship management, impacts on change, reliability and forensic data [46, 47, 48]. Thus, the approach begins with the consideration that all of data are related to social actors, or in general it can be stated that the profile of social actors is all data that can be extracted by involving social actors from information sources [12]. Some of the data becomes information on determining the existence of social actors such as reducing ambiguity and giving meaning [21], with which this is done based on keywords [20].

The mining approach is driven to cover the shortcomings of all social networks analysis approaches. To cover the old and new concept/data gaps, and the various possibilities that can be used to improve the social network functions [46]. Several methods have been developed in data mining [44]. Traditionally, statistical approaches such as the mean and standard deviation aim to capture the various characteristics of values [49]. Characteristic disclosure can be improve by a variety of measurements: among them those that are directly related to frequency, namely modes, percentiles; or related to spread such as range and variance; or involve various attributes such as multivariate. The development of this characteristic disclosure is modeled in some streams in data mining [40]:

(i) Classification: Model assignment of objects to one of several predetermined categories. For example, approaches that involve decision trees and model evaluation, and some alternative models. The relationship between data is eliminated directly by related methods except those that are closely formed, all methods cannot reveal relationships that were not stated previously.

(ii) Clustering: Distribution of data into groups that are meaningful, useful, or both. The relationship between data may be built by involving the concept of similarity, but the relationship will strengthen or fade depending on data growth.

(iii) Association analysis: Discovering interesting relationship hidden in big data. It can be developed as a bookmark there is a relationship between various data, but it cannot be ascertained that the relationship is valid.

(iv) Anomaly detection: An approach to detect deviation, so that a value is found to be different from other values. Of course, this can be used to ensure that there is no connection between data.

Thus, the approach that will be implemented to mine social networks depends on the interests and targets that will be produced, including to design a scientific development activity [50, 51, 52].
Figure 1. Some social networks based on a seed

4. A review by an example

Social network extraction from big data is the first step in the social network mining. This step is to prepare structured and trusted information for an analysis activity. In the scientific world, for example, the Elsevier’s abstract and citation database or Scopus is involved, an online database that can be accessed by the authors themselves [53, 54]. In this concept, social network extraction uses a seed (or s) to express the growth of social networks, so there is at least one vertex \( v \in V \). For example, a name of author is taken, the well-defined name, namely "Mahyuddin K. M. Nasution" see Fig. 1(a), and found the names of other co-authors and will form another vertices so that there is a set of vertices \( V = \{ v_i | i = 1, \ldots, n \} \) in a social network [27], i.e. a set of actors \( A = \{ a, b, c, d, e, f, g, h, i, j, k, l, m, n, o, p, q, r, s, t, u, v, w, x, y, z, aa, ab, ac, ad, ae, af, ag \} \) with their documents in (intersection:personality), see Fig. 1(f). At the time of social networks
The growth of social networks based on documents of a seed

| Year | p   | n(v) | n(e) | n(ep) | n(ac) | Year | p   | n(v) | n(e) | n(ep) | n(ac) |
|------|-----|------|------|-------|-------|------|-----|------|------|-------|-------|
| 2010 | 1   | 1    | 1    | 1     | 1     | 2018 | 22  | 18   | 48   | 3     | 72    |
| 2011 | 2   | 1    | 1    | 1     | 2     | 23   | 21   | 54   | 6     | 78    |
| 2012 | 3   | 1    | 1    | 1     | 3     | 24   | 22   | 56   | 3     | 81    |
| 2014 | 4   | 1    | 1    | 0     | 3     | 25   | 22   | 57   | 6     | 87    |
| 2015 | 5   | 3    | 6    | 6     | 9     | 26   | 23   | 61   | 6     | 93    |
| 2016 | 6   | 3    | 6    | 0     | 9     | 27   | 23   | 62   | 3     | 96    |
| 2017 | 9   | 11   | 28   | 15    | 33    | 30   | 25   | 65   | 3     | 99    |
|      | 10  | 12   | 30   | 3     | 36    | 31   | 25   | 65   | 1     | 100   |
|      | 11  | 12   | 30   | 1     | 37    | 32   | 25   | 65   | 1     | 101   |
|      | 12  | 12   | 30   | 1     | 38    | 33   | 27   | 72   | 10    | 111   |
|      | 13  | 14   | 35   | 6     | 44    | 34   | 27   | 72   | 0     | 111   |
|      | 14  | 14   | 37   | 6     | 50    | 35   | 28   | 76   | 10    | 121   |
|      | 15  | 15   | 41   | 6     | 56    | 36   | 28   | 77   | 3     | 124   |
|      | 16  | 15   | 42   | 3     | 59    | 37   | 30   | 80   | 3     | 127   |
|      | 17  | 15   | 42   | 3     | 62    | 38   | 32   | 82   | 3     | 130   |
|      | 18  | 15   | 43   | 3     | 65    | 39   | 32   | 82   | 0     | 130   |
|      | 19  | 16   | 44   | 1     | 66    | 40   | 32   | 82   | 0     | 130   |
|      | 20  | 16   | 44   | 0     | 66    | 41   | 33   | 84   | 3     | 133   |
|      | 21  | 17   | 46   | 3     | 69    | 42   | 33   | 84   | 1     | 134   |

Each document may produce new social actors or produce relationships between them so that the degree of seed continues to increase, $\deg(s) = n - 1$. In each document or $p$, the authors will form a complete graph, which is a social network with $n(n-1)/2$ edges for $n$ vertices, where a set of edges $E = \{e_j : j = 1, \ldots, m\}$, see Fig. 1(b), (c), and (d). However, in accumulation the authors of a number of documents do not produce a complete graph, but also do not produce a tree, even though it is based on a seed. Maybe it is a candidate star graph [13].

In SNA, extracting social networks based on seeds is to reveal how a seed is able to survive as the center of social networks. The presence of new authors around the seeds shows the growth of new vertices. A new set of authors, with a complete graph, reveal the presence of a group of researchers in certain scientific fields as a branch of existing scientific fields, see Fig. 1(e). The large number of authors around the seed grows based on the time and number of documents showing scientific growth, with the slices of the group of authors in social networks showing scientific interaction has been carried out. Until, in time, there are new centers in social networks that show the influence of other authors on scientific development. So, SNA will be used to present a metric for measuring knowledge development. When research themes can be extracted from documents based on classification concepts, the trends and directions of scientific development can be explored based on the presence of related documents at all times. After all, the number of citations to one document not only presents that tendency, but also expresses the face of continuous knowledge development. This can mine both the research roadmap and the influence of other research groups.

Along with the increasing number of scientific documents published from time to time, the extraction (2010 to 2018) based on seeds there were 43 documents in the Scopus online database.
number of vertices as authors’ representatives has also increased, namely

\[ n(v) = n(v) + n(a) \]

where \( n(v) \) is the number of vertices in a social network while \( n(a) \) is an author number that has not been represented by vertices in a social network. At the same time, the number of edges \( n(e) \) also possible increases with the existence of a new relation based on the author-relationship from the next document, namely

\[ n(e) = n(e) + n(r) \]

where \( n(e) \) is the number of edges in social networks while \( n(r) \) is the number of relation that have not been represented by edges in social networks. Each document creates a complete graph with the numbers edge \( n(e_p) \) for the author \( n(a_p) \). Thus the accumulated number of edges is

\[ n(ac) = n(ac) + n(e_p) \]

where the intersection between edges in social networks and edges for the complete graphs to be \( n(e_{cg}) - n(e) \). In the complete graph, the number of edges \( n(e_p) \) shows two possible that is a document is written by one or more authors. As a professional in him/his field, the author present one by one documents that author wrote him/his self on behalf, and then in its development also remains the first author, whereas if acting as the second author and so on aims as scientific support or as guaranteed. Let’s just say, if someone has never written a scientific document in him/his own name, and then appears as a second or third author, the person actually puts name on the dissemination of knowledge so that there is scientific guarantee from others [55]. Thus, even though the degree of vertex \( deg(s) \) ≥ 2 or high, it is only seen as an administrative degree not as a sign of knowledge development or cannot be used as a seed to develop social networks. This is the meaning that can be mined from a set of documents.

Different treatments for a number of documents will result in social networks that strengthen existing social network. For example, in Table 1, no data about social actors and their relations is available before 2010 and after 2018, or to supplement the 2013 data, it can be done like extracting the strength relation like Fig. 2. This involves search engines, queries, and similarity metrics. However, to explore the potential of social network extracted in clustering is certainly different from exploring the potential of social networks extracted from different sources of information treatment. The data types that appear also differ according to the treatment given to the data mined. When the value of the strength relation, for example, is getting smaller, while the documentation evidence is available, an approach is needed to resolve this constraint,
such as involving the concept of information retrieval (primary data) [56], ontology [57, 58], or uncertainty [59]. The methods in the SNA can be implemented similarly to both social outcomes [60, 61], but to improve SNA performance optimally it use different approaches: The use of cluster approaches is controlled by naming and grouping relationships to enrich social network predictions (with secondary data), while the use of a classification approach is juxtaposed with the historical growth of vertex degrees in SNA for see growth trends. By involving the query and search engine, data treatment can be formed in accordance with the output that will be achieved, but the efficiency of the search engine must be considered [62].

The discussion about the social networks mining, to reveal the improvement of methods in data mining, requires a variety of extensions that need to be formulated formally so that from the point of implementation it can be computationally run.

5. Conclusion
Along with the presence of big data, the concept of data mining requires change. However, each data will be directly related to the characterization of social actors, and the data are connected to one another through social actors. Therefore, social network mining is an alternative solution to several weaknesses in data mining, namely by paying attention to the improvement of the methods used.

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