Hao et al. Hum. Cent. Comput. Inf. Sci. (2018) 8:8
https://doi.org/10.1186/s13673-018-0131-z

Human-centric Computing and Information Sciences

RESEARCH

Open Access

When social computing meets soft computing: opportunities and insights

Fei Hao[1,2], Doo-Soon Park[3*] and Zheng Pei[4]

*Correspondence: parkds@sch.ac.kr
[3] Department of Computer Software Engineering, Soonchunhyang University, ShinChang-Myun, 336-745 Asan, South Korea
Full list of author information is available at the end of the article

Abstract

The characteristics of the massive social media data, diverse mobile sensing devices as well as the highly complex and dynamic user's social behavioral patterns have led to the generation of huge amounts of high dimension, uncertain, imprecision and noisy data from social networks. Thanks to the emerging soft computing techniques which unlike the conventional hard computing. It is widely used for coping with the tolerant of imprecision, uncertainty, partial truth, and approximation. One of the most important and promising applications is social network analysis (SNA) that is the process of investigating social structures and relevant properties through the use of network and graph theories. This paper aims to survey various SNA approaches using soft computing techniques such as fuzzy logic, formal concept analysis, rough sets theory and soft set theory. In addition, the relevant software packages about SNA are clearly summarized.

Keywords: Social computing, Soft computing, Fuzzy logic, Formal concept analysis, Rough sets

Introduction

Social media are computer-mediated tools that allow people to create, share or exchange information, ideas, pictures, audio or videos in virtual communities by using open Internet. Among online social networking services, there exist very interesting and challengeable research works on how to improve an efficient social media computing and how to make an effective social network analysis and mining from the perspectives of both academia and industry. Therefore, social computing, as a research discipline, is emerging for handling those kind of data generated from social media. Normally, various social computing related techniques include statistical approaches, graph based approaches and so forth. However, a human nature is present in the social networks. This implies that the social networks are human-like-full of imprecise relations and connections between individuals, vague terms, groups and individuals with indefinite descriptions and characteristics of interests [1]. In order to better cope with these burning issues, advances on soft computing technologies, such as fuzzy set, formal concept analysis and rough set theories, probabilistic computing, as well as neural network and system, are paving a road to more valuable and feasible solutions to the emerging social media and big data, finally bringing a brilliant future of wisdom and intelligent social media network. This survey will be carried out for SNA from following various aspects, i.e., network representation, reputation/position analysis of users, social relationships characterization, topological structure analysis, social data analysis.

This paper is structured as follows: "Social computing" section overviews the main stream soft computing techniques; Then, a comprehensive taxonomy and its soft computing techniques based SNA approaches are presented in "Soft computing" section. Finally, "When social computing meets soft computing" section concludes this paper by presenting general remarks regarding the current stage of the research and a brief analysis of future perspectives.

Social computing

This section will present the basic definition of social computing as well as the potential applications.

Definition of social computing

The terminology of social computing was firstly proposed in 1994. However, there are various definitions for social computing. Schuler [2] pointed out that social computing can be any type of computing application that uses software as a medium or focus of social relations. Therefore, his opinion emphasized the importance of social softwares. Dryer et al. [3] stated that social computing is the interplay between persons, social behaviors, and interactions with computing technologies, its design model focuses on the reciprocal interaction of the system design, human behavior, social contribution and interaction results in the mobile computing system. Wang et al. [4, 5] provided the definition of social computing in the narrow/broad sense. Broadly speaking, social computing refers to the computational theory and method for social sciences. Narrowly speaking, social computing is a computational theory and method for social activities, social processes, social structures, social organizations and their functions and effects.

Figure 1 shows an architecture of social computing. The bottom level of this architecture illustrates that the real-life world is composed of physical world, mental world as well as artificial world. From practical point of view, it is easy to obtain a recognition that the social physics, social psychology and social computing are the certain products of the three worlds, respectively, and there is a significant overlap between them. Importantly, this recognition enables us to make full use of the model of artificial society, and use computers as experimental means under parallel system to check and demonstrate the hypothesis of social computing in the artificial world.

Research fields of social computing

Social computing is not only a technique but also a social phenomena. Basically, social computing has two main research trends: (1) social science-oriented social computing; (2) application-oriented social computing. And, these two research trends influence each other.

Social science-oriented social computing

Social science-oriented social computing is composed of social networks analysis and computational social science. First, social network analysis mainly covers the topics

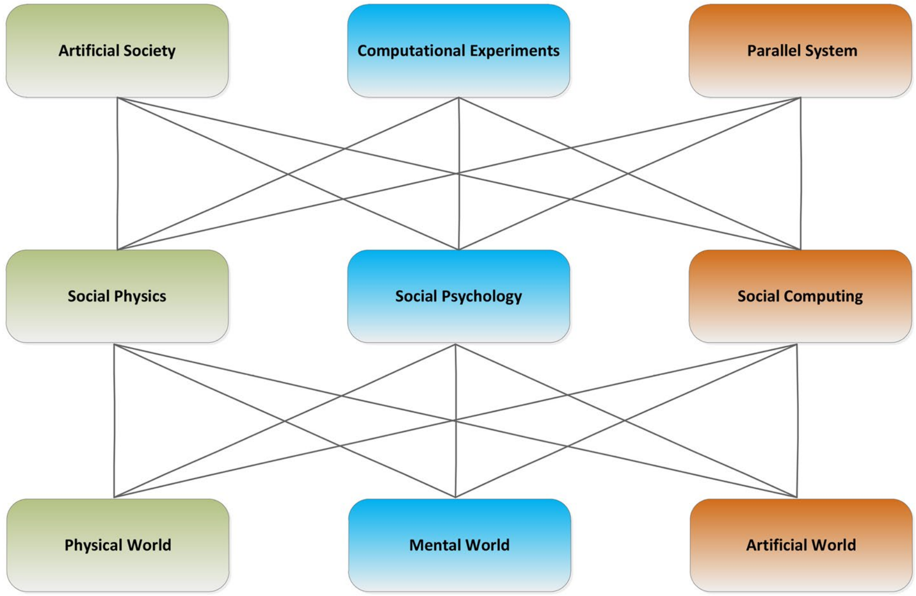


Fig. 1 Architecture of social computing

on social flows, healthcare, key nodes mining for disease dissemination, communities detection and so forth. The approaches about social network analysis are mainly categorized as: agent-based model, theoretical physics approach, and graph theory. Milgram et al. [6] and Watts et al. [7] pioneered the research on small-world. Based on their work, Barabasi et al. [8] found the connection between nodes followed the power-law distribution. In addition, there are other significant research achievements, such as strong and weak ties [9], structural holes [10], and information cascades [11], etc. Second, computational social science is a cross-discipline among systems science, control science, and complex science. It mainly focuses on the research on social simulation and social system modeling by using equation based modeling and computational modeling [12]. Technically, data mining as a key technology for computational social science, is to discover the interesting and useful patterns from massive data by using machine learning approaches.

Application-oriented social computing

Application-oriented social computing refers to a type of particular application which incorporating the methodologies and technologies about social computing, such as communities, social network, social phycology. Application-oriented social computing experienced three phases: group software, social software and social media [13]. Group software was proposed in 1970s, and it was used in many research institutes. The essence of group software is a collaborative technology with the aim of supporting the interactions collaboratively. For example, computer supported cooperative work and computer supported collaborative learning are two classic group software applications. In 2005, as the rapid development of Web 2.0 [14], social media is emerging. Social media emphasizes the active interaction from users, users can complete the social interactions by generating, consuming the contents over the social media. Recently, the wide usage of ubiquitous devices, such as mobile phones and smart devices, the mobile social media [15–17] attracts much attention from academia and industry.

Soft computing

Soft computing is defined as a collection of techniques spanning many fields that fall under various categories in computational intelligence [18]. Soft computing is a consortium of methodologies which work with real life problems and provides in one form or another flexible information processing capabilities for handling real-life and complex situations [19]. The guiding principle of soft computing is to explore the tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost that are not handled with conventional hard computing. Initially, soft computing is composed of three main branches: fuzzy systems [20, 21], evolutionary computation [22, 23], artificial neural computing [24]. Up to now, many new methods or techniques have been proposed for imprecision, uncertainty and partial truth, which are belong to soft computing. This paper makes a survey with the following soft computing techniques (as shown in Fig. 2) including fuzzy logic, formal concept analysis, rough sets analysis, and soft sets. The remainder of this section gives you the overview of these techniques.

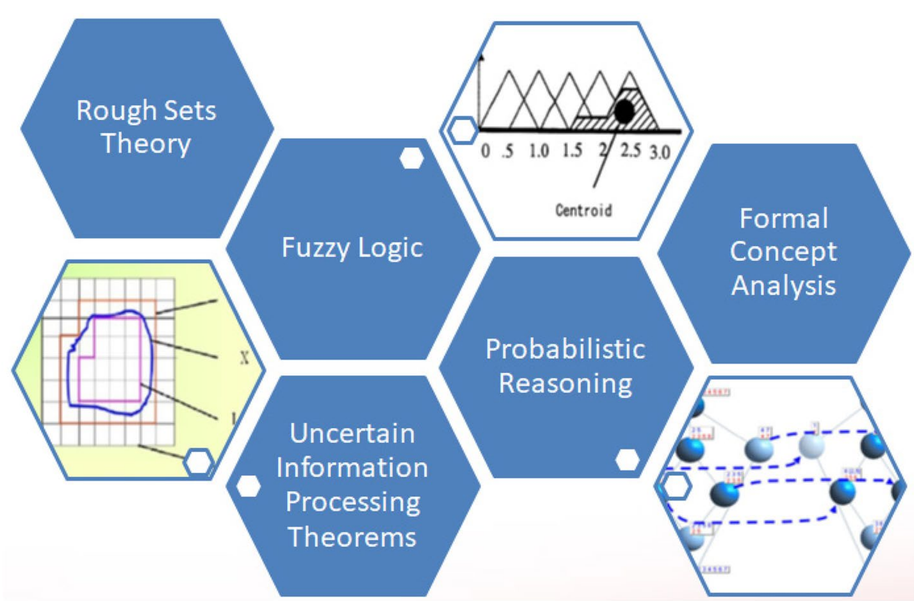


Fig. 2 Overview of main soft computing techniques

Fuzzy logic

Fuzzy logic (FL), a commonly used soft computing approach, provides a simple way to get a definite conclusion based upon vague, ambiguous, imprecise, noisy or missing information of inputs. The working principle of *FL* is to process the data by allowing partial set membership rather than crisp set membership or non-membership. Fuzzy expert system consists of fuzzification unit that converts crisp values into fuzzified input [25]. It consists of inference engine that contains if then else rules and a defuzzification unit to convert the result in a readable form. *FL* incorporates fuzzy rule based *IF X AND Y THEN Z* inference approach to solve problem rather than attempting to model a system mathematically. For example, fuzzy inference engine can be used for obtaining the trust relationship between mobile users in mobile social networks [26].

Formal concept analysis

Formal concept analysis (FCA) [27] is a typical computational intelligence technique for data analysis. FCA defines formal concepts to represent the relationships between objects and attributes in a domain. The objects and attributes are grouped into formal concepts, and then a conceptual hierarchy of all formal concepts (also called as formal concept lattice) can be constructed, which is a complete lattice. Therefore, giving a formal context, FCA can derive all formal concepts from this context and construct their formal concept lattice. Formally, relations of subsets of objects as well as attributes can be analyzed in the formal concept lattice, in addition, conceptual hierarchy provide information to order them according to a subconcept–superconcept relation [28, 29].

Rough set theory

Rough sets theory (RST) [30–32] has been widely used for processing the incomplete and uncertain information. Recent years have witnessed the ubiquitous applications of RST in machine learning, data mining, and decision support analysis fields. Theoretically, RST provides a useful method to understand unkownledge by using knowledge base, in fact, when the available information is not enough to determine the exact value of a given set, lower and upper approximations in RST can be used for the representation of this set. The approximation synthesis of concepts from the acquired data is the main objective of the rough set analysis [33]. In real world practices, if a subset is difficult to define a concept in a given knowledge base, then rough sets can "*approximate*" the subset with respect to the knowledge base.

Soft set theory

The soft set theory [34, 35] is used as a general mathematical tool for dealing with uncertainty. It is proved that soft set is the generalization of the fuzzy set [36], also a topological space (X, τ) can be represented by soft set. Up to now, many operations and applications of soft sets have been provided [37, 38]. Soft set, as efficient uncertain information processing mathematical methodology, is used to help us for finding the optimized solution under the uncertain environment. It can easily characterize the incomplete and uncertain information from the parameterization point of view, especially for the inconsistency and incompleteness of the uncertain information.

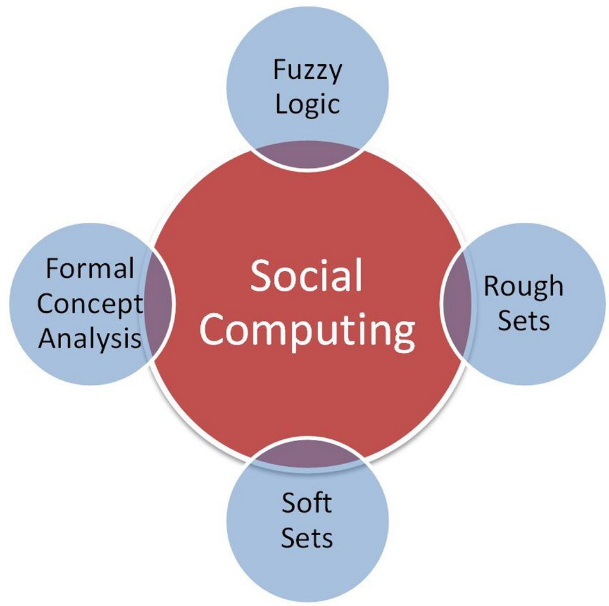


Fig. 3 When social computing meets soft computing, what is happening?

When social computing meets soft computing

When social computing meets soft computing, what opportunities can it bring to researchers from both communities of soft computing and social computing. Figure 3 illustrates a category of study on social networks analysis from a soft computing perspective. The survey on soft computing techniques based social networks analysis will be elaborated with the three main aspects: (1) structural analysis; (2) social data analysis; (3) social interaction analysis.

The rest of this section will provide the comprehensive survey on soft computing techniques (FL, FCA, RST) based social networks analysis from the aspects of structural analysis, social data analysis and social interaction analysis.

Representation of social networks

Social network is often modeled with a graph (sometimes an adjacency matrix) where the nodes indicating the individuals and edges indicating the relationships between the individuals. Most literatures considers the social relationships are binary value, i.e., 0 or 1. As a matter of fact, the social relationships between individuals are very complex and dynamic under different context, thus there exist much uncertainty or vagueness in social networks.

Fuzzy logic based representation approach

To overcome these uncertainty or vagueness, Refs. [39–46] applied fuzzy sets [36] for representing the social networks and analyzing the network. Commonly, a social network with vague relationships is represented with a fuzzy graph, so called fuzzy social networks [47]. The basic idea is described as follows: a fuzzy relation on a single set, $R \subseteq X \times X$, is defined through the membership function.

$$\mu_R: X \times X \rightarrow [0,1] \quad (1)$$

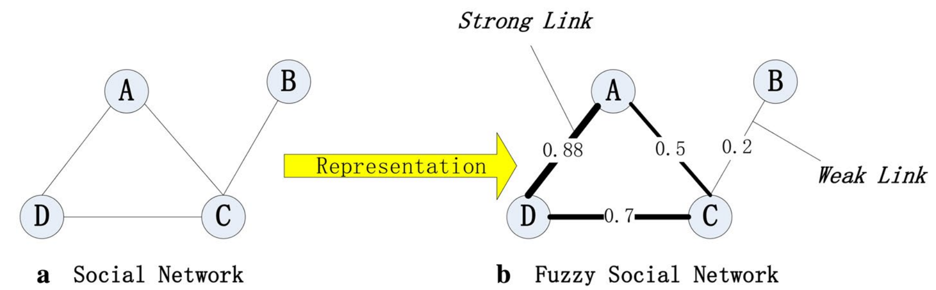


Fig. 4 Representation for social networks based on fuzzy logic

Equation (1) means that the social relationships between individuals are fuzzificated, denoted as $\mu_R(u_i, u_j)$. That is to say, the value of $\mu_R(u_i, u_j)$ is used to answer how strong is the relationship between u_i and u_j. Normally, the $\mu_R(u_i, u_j)$ has the following form:

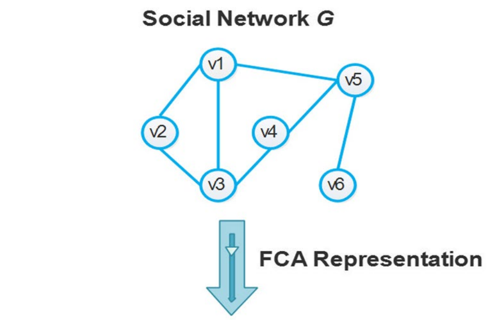
$$\mu_R(u_i, u_j) = \begin{cases} 1 & \text{if } u_i \text{ has the strongest relation with } u_j \\ (0, 1) & \text{if } u_i \text{ has a certain extent related to } u_j \\ 0 & \text{if } u_i \text{ is not related to } u_j \end{cases}$$

Figure 4 shows a representation for social networks based on FL. Clearly, a general social network as shown in Fig. 4a does not consider the strength of social relationships between individuals. Thanks to the FL and computing with words [48, 49], a fuzzy graph (fuzzy social network) can describe various types of relationships according to value of u_i and u_j (shown in Fig. 4b). For example, the relationship between A and D is a strong link with 0.88 degree of membership, but a weak link between B and C with 0.2 degree of membership.

FCA based representation approach

Recently years, FCA is also used for social networks analysis. Snael et al. [50] pioneered to represent the topology of a social network with a formal context. The solution of this representation approach as shown in Fig. 5 is to regard the individuals as both objects and attributes, and then construct the formal context according to the adjacency relation between individuals. A social network G can be modeled as a set of subjects, in which some of them have some relationships with others. This can be formalized as a classical mathematical relationship visualized as an undirected graph. Then, the modified adjacency matrix of G (denoted as $A^{'}$) is viewed as a formal context of G, namely $FC(G) = (V, V, I)$, in which I is the binary relationship between two vertices. Ref. [51] proved that the $FC(G)$ is equivalent to the modified adjacency matrix of G, i.e., $FC(G) \equiv A^{'}$.

Based on this representation approach, Hao et al. [51] first studied the k-balanced trusted cliques detection in signed social networks [23]. Further, they investigated the k-clique communities detection in social networks [29]. In both works [29] and [51], the authors initially converted the given social network into a formal context and then constructed the corresponding concept lattice. Finally, the important findings on equivalence between the equiconcepts and cliques are proved. In addition, Dorflein [52] stated and proved that the basic theorem on coherence networks of concept lattices as an extension of the basic theorem on concept lattices.



vertices as objectives / vertices as attributes

	v1	v2	v3	v4	v5	v6
v1	1	1	1		1	
v2	1	1				
v3	1	1	1	1		
v4			1	1	1	
v5					1	1
v6					1	1

Formal Context *FC(G)*
Modified Adjacency Matrix *A'*

Fig. 5 Solution of FCA-based representation for social network

Positional analysis

In social networks, the major purpose of positional analysis is to find similarities between individuals of a social network. One of the widely studied notions in the positional analysis of social networks is regular equivalence [53, 54]. As fuzzy social networks have received considerable attention, a regular equivalence to fuzzy social networks is generalized [42]. Based on FL, Portmann et al. [54] introduced a framework FORA to gain deeper insights into an organizations online reputation. Kudelka et al. [55] proposed a hybrid approach where the FCA is used for finding author's profiles based on keywords and fuzzy rules to learn the properties of the authors and to enhance the set of experts. Expert or influential people identification is an important task in social network positional analysis [56]. Kudelka et al. [54] introduced a new soft computing method for expert identification in social networks based on formal concept analysis and fuzzy rules. They proposed a hybrid approach where the formal concept analysis is used for finding author's profiles based on keywords and fuzzy rules to learn the properties of the authors and to enhance the set of experts.

Topological structure analysis

At present, most of previous work about topological structure mining mainly concentrate on cliques and communities mining from social networks. The framework of topological structure analysis with soft computing techniques is illustrated as shown in Fig. 6.

FL-based topological structure mining

The problem of fuzzy community detection in networks was early studied in [57, 58], it allows each vertex of the graph to belong to multiple communities at the same time, determined by exact numerical membership degrees, even in the presence of uncertainty in the data being analyzed. Golsefid et al. [59] proposed a fuzzy clustering model

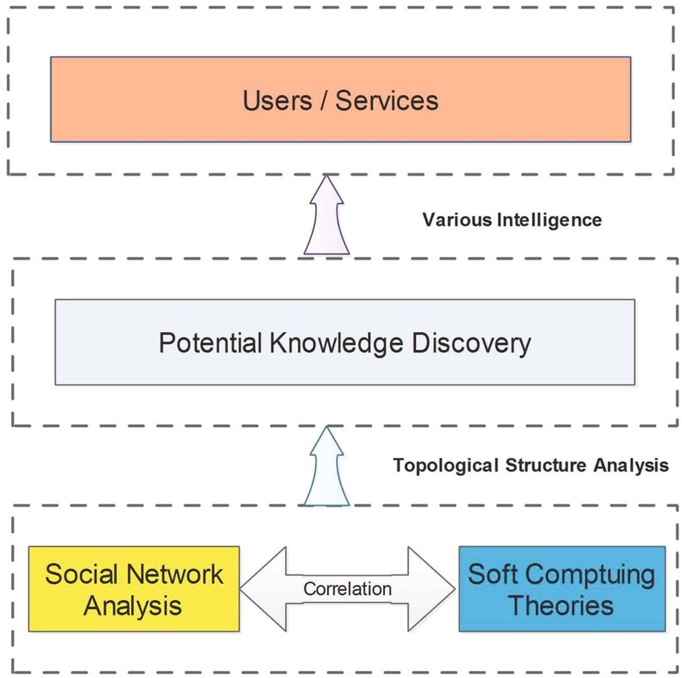


Fig. 6 The framework of topological structure analysis with soft computing techniques

for detecting overlapping communities in complex networks. Their proposed model was developed based on the CPM clustering model [60] and assigns each node to each cluster by degree of belonging over an interval [0,1]. Therefore, instead of one node belonging to exactly one cluster, it can belong to more than one cluster, and associated with each node was a set of membership levels. Davis et al. [46] attempted to identify fuzzy overlapping groups in social networks using stochastic model. They modeled the fuzzy overlapping group detection as an optimization problem. In summary, the ideas of these approaches are based on fuzzy membership function which is defined for the connections for one node to other communities.

FCA-based topological structure mining

Rome et al. [61] observed that the web subgraph can be viewed as a formal context and that web communities can be modeled by formal concepts. They utilized FCA to explore the community structure of the Web graph. Hao et al. [29] detected the *k*-balanced trusted cliques from signed social networks based on FCA. Further, Hao et al. [51] proposed a novel algorithm for mining the *k*-clique and *k*-clique communities based on FCA. They proved that all Equiconcepts[1] appearing in formal concept lattice of social network exactly match the cliques in social networks and also proved that the *k*-clique communities detection problem is equivalent to finding the *k*-intent Equiconcepts in the concept lattice of a social network. To reduce the high repetition rate between community-cores and isolated community, Fu et al. [62] presented an algorithm for detecting Blog community based on FCA. Initially, concept lattice was built from linkage relations

[1] Equiconcepts refer to a type of special formal concepts where the extent equals to the intent.

between Blogs, then clusters were divided from the lattice based on equivalence relation, finally communities were clustered in each cluster based on the similarity of concepts [63, 64]. Ali et al. [65] investigated the community detection based on FCA, their approach take the formal context of the given social network, and determine the partial communities. Then, the ignored nodes are re-assigned to the communities by maximizing GroupNode modularity function. Aiming to address the cliques discovery from big graph, our recent work [66] adopted the formal concept analysis techniques and proposed a novel framework, called "*cSketch*" for identifying the cliques from big graphs. This framework takes the graph stream as the initial input, and summarizes the original graph stream into the sketched graph by using Hashing function over the vertices; Based on the obtained sketched graph, formal concept analysis is utilized for mining the cliques from it. The resulting cliques is approximate to the cliques appearing in the original graph. Ref. [67] exploited the formation principle of maximal cliques in social networks based on formal concept analysis. The authors proposed a FCA-based approach for detecting the bases of maximal cliques and detection theorem. Their work provides a new research solution and direction for future topological structure analysis in various complex networking systems. Hao et al. [68] pioneered a novel approach for similarity evaluation between graphs based on FCA. The feature of this approach is able to characterize the relationships between nodes and further reveal the similarity between graphs. Therefore, the highlight of their proposed approach is to take vertices and edges into account simultaneously. Thus, the measuring accuracy for graph matching can be improved.

Overall, FCA-based topological structure mining is conducted based on the equivalence relation between equiconcepts and topological structures. These approaches are not dependent on the mathematical model, but also not dependent on the heuristics. Hence, this kind of approach provides a novel points for mining the topological structure from social networks.

RST-based topological structure mining

Regarding to this research branch, RST is often integrated with other traditional clustering algorithms in order to improve the detection performance of community discovery [69, 70]. Wang et al. [69] considered the difficulty of determining the value of K, and the relations among the cluster object or community node and the community. To overcome this disadvantage, they devised a community finding algorithm by incorporating the RST and k-mean clustering algorithm. Their proposed method is mainly used to find overlapping communities, and it can multi-anglely reflect the social network information better. In addition, our previous work [71] proposed rough k-clique theory that relaxes the conventional k-clique by using the newly defined upper/lower vertices approximation that are used for describing the boundary of the given subgraph. Therefore, the topological structure of any given subgraph can be characterized by the virtue of rough k-clique theory.

Social web mining

Social web mining, a specific web mining procedure over social media, may help to collect knowledge from the communities, hyperlink references, opinion graphs and most liked information. Thus, social web mining is a efficient way for discovering useful knowledge and extracting social intelligence from the web log data obtained from open source websites that are available on the web [72]. Social media web sites personalization is the procedure of modifying the content and structure of a web site to the precise requirements of each user taking benefit of the user's directional behavior. The main phases of the web personalization comprises of: (1) the collection of web data; (2) the preprocessing phase of these data; (3) the analysis of the collected data and (4) the purpose of the actions that should be performed. The log files are collected from the proxy server log. The gathered data are undergoing a preprocessing phase to remove the unwanted and noisy information. The web directories are discovered based on the user and session clustering. For grouping the user and session, the Neuro Fuzzy Clustering Approach (NFCA) is applied [19]. Additionally, Ant Colony Optimization (ACO), as an advanced soft computing methodology, is used for social web mining. Ahmad et al. [73] presented an ACO based approach for expert identification and query routing in social networks. Kwon et al. [74] proposed a novel method for sentiment trend analysis using ACO algorithm and SentiWordNet. They first collected social data in the form of Resource Description Framework (RDF) triples, and then used ACO algorithm to digitized the amassed RDF triples. Using ACO algorithm, the pheromone values were computed to extract the trends of the user's sentiments with the modified equations. Next, the user's sentiment scores were evaluated for the computed pheromone values with respect to the sentiment words with SentiWordNet. Finally, they analyzed the sentiment trend of the online user by time.

Social data analysis

Soft computing techniques based SNA provides several new social data analysis solutions for social networking services, such as folksonomy mining [75], tag recommendation, social marketing [76], social recommendation and sentiment analysis [77]. Jaschke et al. [78] proposed an algorithm for mining iceberg tri-lattices for mining the frequent tri-concepts. Hao et al. [79] proposed an approach of variable precision concept [80] based extended conceptual knowledge discovery in folksonomy for tag recommendation and resource suggestion. Based on FCA, [26] presented a novel approach for tag recommendation based on users' interest lattice matching (UILM). UILM constructs the users' interest lattice according to users' interest context extracted from tagging data. Lattice matching is then proposed and applied to obtain the users that are similar to the current user. Zhang et al. [81] studied the friends recommendation in social network. Basically, FCA is applied to analyzing the binary relation between users and terms of micro-blogs text. Then, a concept lattice was constructed to store the knowledge context based on the relationship among users and terms for assisting recommendation. By calculating the concept similarity and matching visited candidate users with the constructed concept lattice, the followee can be recommend in terms of these similarity. Recently, sentiment analysis, as an emerging topic, is becoming more and more important in social networks. Mukkamala et al. [82] presented an integrated modeling approach for analysis of social data with the sentiment analysis based on the FL. Trung et al. [55] proposed a fuzzy propagation modeling for opinion mining by sentiment analysis of online social networks. Further, a practical system named TweetScope, has been implemented to efficiently collect and analyze all possible tweets from customers. Considering the vague sentiment words in social networks, for example, the "excellent" and "good" are both expressed with positive sentiment, however, the positive degree of both words are not the same. To address this problem, Jusoh et al. [83] introduced the use of a fuzzy lexicon and fuzzy sets in deciding the degree of positive and negative. Regarding to the data sparse and information overload issues, Hao et al. [38] proposed a soft set-based recommendation model and devised the corresponding algorithm. Their approach is easier for implementation and recommendation; Besides, their approach not only recommend the items, but also make the feedback regarding to the results. Thus, there is no data sparse issue. Therefore, it is believed that the proposed approach can be applied into many other potential recommendation systems.

Human mobility analysis is another interesting research topic. Considering the human movement data including high levels of uncertainty and noise. Soft computing owns the necessary characteristics to extract accurate mobility models [84]. Proposed a novel approach to extract personal mobility patterns by means of the fuzzy c-means (FCM) algorithm. Their achievements will help to comprehensively capture and understand the movement of people in large spatial regions.

Medicine and healthcare services

The rapid development of ICT industrials is facilitating the advancement of medicine and healthcare. Particularly, healthcare has been promoted to an important social issue related to people's work and study. This past decade has witnessed the dramatic development of modern medical technologies by virtue of the wireless internet, the Internet of Things, and other ubiquitous technologies [85]. This section is devoted to overviewing the related literatures on soft computing-based social network analysis in medicine/healthcare services. Hao et al. [85] firstly represented the medical treatment data as an 3-order tensor that includes three dimensions of the objective, treatment phase, and treatment plan. Each element in this constructed tensor indicates an evaluation. Based on this representation model, a three-dimensional fuzzy evaluation model for selecting the sustainable medical treatment plan is further devised. In order to obtain a sustainable treatment plan, the membership functions for various evaluation linguistic terms are established. Then, a vertical aggregation was carried out (i.e., the degrees of membership are aggregated from the dimension of treatment phase), and then the overall degrees of membership were aggregated by a linear aggregation formula (i.e., horizontal aggregation). As we all known, medicine functions exploration is a challenge issue, a traditional clinic medical approach is to test it in both animal and human. Unfortunately, it usually consume a long time for identifying the functions of the medicine. To cope with this issue, Hao et al. [68] evaluated the similarity between the targeted graph (since the molecular structure of the targeted medicine can be modeled as a graph) and the graphs (i.e., other existing medicines) in the database via rough-k cliques theory which is a novel soft computing methodology [71]. Recently, the dramatic explosion of huge number of heterogeneous medical data in smart healthcare, is leading to many difficulties on both obtaining the intelligence, cognition and natural interactions between doctors and patients. Considering these challenges [86], proposed a big medical data cognitive system with the proposed methodology that is n-ary formal concept analysis. The unique

Table 1 Software packages for social network analysis

No Type	General software packages Academic/free	Specialized software packages Academic/free
1	Agna Applied graph and network analysis	Blanche Network dynamics
2	DyNet (SE and LS) [91] Data-driven visualizations	CID-ABM Competing idea diffusion agent based model
3	GUESS The graph exploration system	CFinder [92] Finding and visualizing dense groups
4	Pajek [93] Program for large network analysis	Commetrix [94] Dynamic network visualization and analysis
5	NodeXL [95]: viewing and analyzing network graphs	PGRAPH [96]: Kinship networks
6	igraph (R, Python, C) [97] Creating and manipulating graphs	SONIVIS Analyzing and visualizing virtual information space
7	NetVis [98]: dynamic visualization of social networks	E-Net [99]: Ego-NETwork analysis
8	ORA [100]: dynamic network analysis	EgoNet [101]: egocentric networks
9	SocNetV: social networks visualiser	KeyPlayer [102]: identifying nodes
10	UCINET 6 [103] Comprehensive social network analysis software	KliqFinder: cohesive subgroups
11	visone: analyis and visualization of social networks	Network genie: network surveys
12	JUNG (Java): Java Universal Network/graph frame-work	PNet: exponential random graph models (ERGMs)
13	libSNA (Python) Open-source library for social network analysis	SONIVIS Analyzing and visualizing virtual information spaces
14	NetworkX (Python) [104]: package for complex networks	StOCNET [105]: statistical analysis

Table 2 Visualization softwares for social networks analysis

No	Software name	Descriptions
1	aiSee [106]	Graph visualization
2	Apache Agora [107]	Visualizing virtual communities
3	Cytoscape [108]	Visualizing molecular interaction networks
4	Gephi [109]	Visualization and exploration platform
5	Graphviz [110]	Graph visualization
6	KrackPlot [111]	Social network visualization program

features of this cognitive system include efficient big data representation, high-quality data associations, and natural semantics interpretation among dimensions.

Relevant softwares for social computing

This section lists the softwares for social network analysis [87–90]. Then, several specific softwares for social network analysis based on soft computing are presented as well.

Table 1 summarizes the commonly-used general software packages and specialized software packages for social networks analysis.

In addition, this paper also lists the main visualization softwares for social networks, as shown in Table 2.

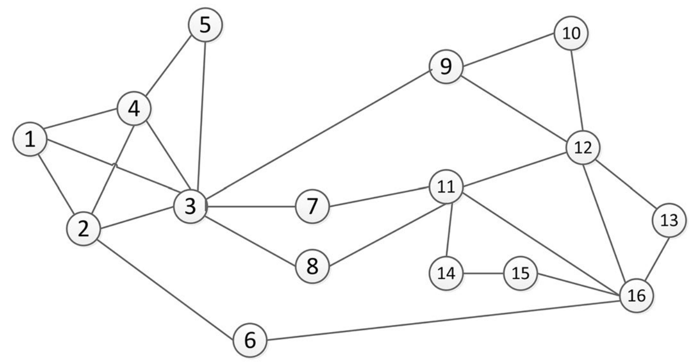


Fig. 7 A social network *g*

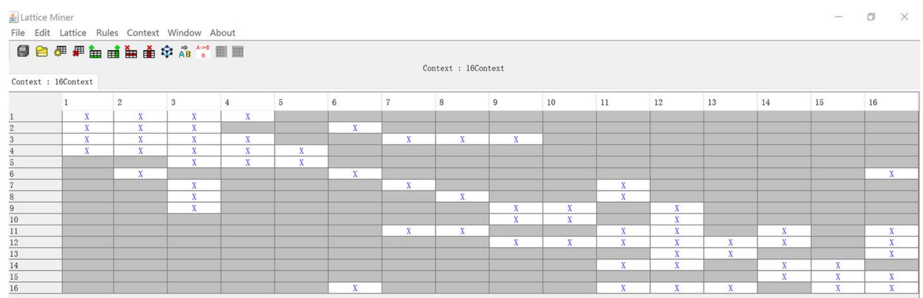


Fig. 8 Constructed formal context for social network *g*

To the best of our knowledge, the specific softwares for soft computing-based social network analysis are not available. However, we can adopt the soft computing softwares or tools for assisting the social network analysis. For example, FCA-based social network analysis, an emerging approach social network analysis, is widely used. Particularly, we illustrate how to analyze the social network with an open platform for lattices-Galicia [112].

- *Context construction* A given social network *g*, modeled as a graph as shown in Fig. 7. By using the construction approach [29], the formal contexts (as shown in Fig. 8) are easily obtained as follows.
- *Concept lattice building* According to the formal concept lattice generation algorithm presented in [29], the formal concept lattices of the given graph *g* is shown in Fig. 9.
- *Social computing issues* In this step, we can execute the topological structure mining and analysis based on the above extracted formal concepts. For example, our previous work [29] has proved that the equivalence relation between the equiconcepts and cliques. With this relation, we can extract the k-cliques, k-clique communities from social networks. Interestingly, the location-focused communities detection and evolutionary can be accomplished by observing the changing patterns of m-triadic concepts [113]. In field of graph matching, the formal concepts are regarded as the main features of the graphs for further evaluating the similarity between graphs [68].

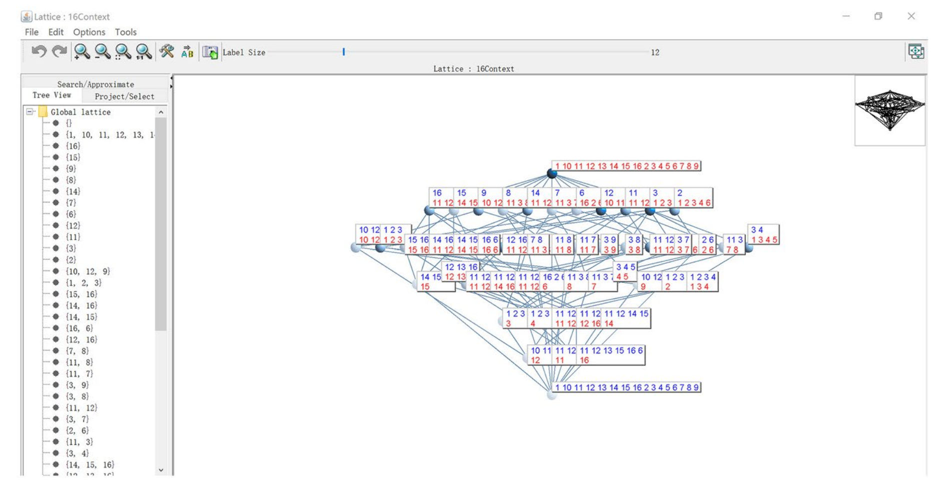


Fig. 9 The generated concept lattices for social network *g*

Conclusions

As the scale of social media and number of users are rapidly increasing, social network analysis (SNA) has become an important tool for experts and researchers in social computing. Specially, the necessary information is often distributed and hidden on social site servers, so there is an urgent demand for designing some new approaches for collection and analysis the social network. Soft computing methodologies like fuzzy sets, neural networks, genetic algorithms, rough sets, soft sets and their hybridizations, have recently been widely utilized to solve data mining problems. They strive to provide approximate solutions at low cost, thereby speeding up the process. In this paper, we firstly answered what happening when social computing meets soft computing. Then, we discussed the state-of-art on various soft computing techniques those are used for social networks analysis. It is believed that this paper can provide more insights for researchers from the both social computing and soft computing fields.

Authors' contributions

FH collected, reviewed and classified main literature for the paper, and also completed the writing of this work. DSP identified the insights of this work, especially the soft computing based social computing techniques in ubiquitous healthcare. ZP improved the part of soft computing techniques survey and presentation. All authors read and approved the final manuscript.

Author details

[1] Key Laboratory of Modern Teaching Technology, Ministry of Education, No.199, South Chang'an Road, 710062 Xi'an, China. [2] School of Computer Science, Shaanxi Normal University, No.620, West Chang'an Avenue, 710119 Xi'an, China. [3] Department of Computer Software Engineering, Soonchunhyang University, ShinChang-Myun, 336-745 Asan, South Korea. [4] Center for Radio Administration & Technology Development, Xihua University, 610039 Chengdu, China.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (Grant Nos. 61702317, 61372187) and MSIP (Ministry of Science, ICT and Future Planning), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2017-2014-0-00720) supervised by the IITP (Institute for Information & Communications Technology Promotion) and the National Research Foundation of Korea (No. NRF-2017R1A2B1008421) and was also supported by the Fundamental Research Funds for the Central Universities (GK201703059, GK201802013), and Fund Program for the Scientific Activities of Selected Returned Overseas Professionals in Shaanxi Province (Grant No. 2017024).

Competing interests

The authors declare that they have no competing interests.

Ethics approval and consent to participate

Not applicable.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Received: 30 January 2018 Accepted: 12 March 2018
Published online: 26 March 2018

References

1. Zadeh LA, Abbasov AM, Shahbazova SN (2015) Fuzzy-based techniques in human-like processing of social network data. Int J Uncertain Fuzziness Knowl Based Syst 23(Suppl. 1):1–14
2. Schuler D (1994) Social computing. Commun ACM 37(1):28–29
3. Dryer DC, Eisbach C, Ark WS (1999) At what cost pervasive? A social computing view of mobile computing systems. IBM Syst J 38(4):652–676
4. Wang FY (2007) Toward a paradigm shift in social computing: the ACP approach. IEEE Intell Syst 22(5):65–67
5. Wang FY, Carley KM, Zeng D, Mao W (2007) Social computing: from social informatics to social intelligence. IEEE Intell Syst 22(2):79–83
6. Milgram S (1967) The small-world problem. Psychol Today 1(1):61–67
7. Watts DJ, Strogatz SH (1998) Collective dynamics of "small-world" networks. Nature 393:440–442
8. Barabasi AL, Bonabeau E (2003) Scale-free networks. Sci Am 288(5):50–59
9. Granovetter M (1973) The strength of weak ties. Am J Sociol 78(6):1360–1380
10. Zhang E, Wang G, Gao K, Zhao X, Zhang Y (2013) Generalized structural holes finding algorithm by bisection in social communities. In: Sixth international conference on genetic and evolutionary computing. pp 276–279
11. Liu Q, Zhang L (2016) Information cascades in online reading: an empirical investigation of panel data. J Imaging Sci Technol 55(4):60504–1605048
12. Halpin B (1999) Simulation in sociology. Am Behav Sci 42(10):1488–1508
13. Lugano G (2013) Social computing: a classification of existing paradigms. In: Privacy, security, risk and trust. pp 377–382
14. O'Reilly T (2007) What is web 2.0: design patterns and business models for the next generation of software. Mpra Paper 97(7):253–259
15. Su Z, Xu Q, Qi Q (2016) Big data in mobile social networks: a qoe-oriented framework. IEEE Netw 30(1):52–57
16. Hao F, Min G, Lin M, Luo C, Yang LT (2014) MobiFuzzyTrust: an efficient fuzzy trust inference mechanism in mobile social networks. IEEE Trans Parallel Distrib Syst 25(11):2944–2955
17. Choi S (2016) Understanding people with human activities and social interactions for human-centered computing. Hum Centric Comput Inf Sci 6(1):9
18. Shamshirband S, Gocic M, Petkovic D, Saboohi H, Herawan T, Kiah MLM, Akib S (2015) Soft-computing methodologies for precipitation estimation: a case study. IEEE J Sel Top Appl Earth Obs Remote Sens 8(3):1353–1358
19. Shan F, Sharma MK (2017) Study for social media mining methods with soft computing. Int J Emerg Technol 8(1):1–4
20. Dong S, Su H, Shi P, Lu R, Wu Z-G (2017) Filtering for discrete-time switched fuzzy systems with quantization. IEEE Trans Fuzzy Syst 25(6):1616–1628
21. Feng Z, Zheng WX, Wu L (2017) Reachable set estimation of T–S fuzzy systems with time-varying delay. IEEE Trans Fuzzy Syst 25(4):878–891
22. Revay P, Cioffi-Revilla C (2018) Survey of evolutionary computation methods in social agent-based modeling studies. J Comput Soc Sci 1(1):115–146
23. Friedrich T, Neumann F (2017) What's hot in evolutionary computation. AAAI, Menlo Park, pp 5064–5066
24. Paradarami TK, Bastian ND, Wightman JL (2017) A hybrid recommender system using artificial neural networks. Expert Syst Appl 83:300–313
25. Douven I (2015) Review of r. belohlavek and g. klir (eds). Concepts and fuzzy logic (MIT Press, 2011). Studia Logica 102
26. Hao F, Zhong S (2010) Tag recommendation based on user interest lattice matching. In: IEEE international conference on computer science and information technology. pp 276–280
27. Ganter B, Wille R (1996) Formal concept analysis. Wissenschaftliche Zeitschrift-Technischen Universitat Dresden 45:8–13
28. Poelmans J, Elzinga P, Viaene S, Dedene G (2010) Formal concept analysis in knowledge discovery: a survey. In: International conference on conceptual structures: from information to intelligence. pp 139–153
29. Hao F, Min G, Pei Z, Park DS, Yang LT (2017) *k*-clique community detection in social networks based on formal concept analysis. IEEE Syst J 11(1):250–259
30. Pawlak Z (1982) Rough sets. Int J Comput Inf Sci 11(5):341–356
31. Pawlak Z, Skowron A (2007) Rudiments of rough sets. Inf Sci 177(1):3–27
32. Pawlak Z (1998) Rough set theory and its applications to data analysis. J Cybern 29(7):661–688
33. Zhou Q, Yongsheng LI, Yin C, Jingui LU (2003) Application of rough set theory in data mining. J Nanjing Univ Tech 25(2):44–48
34. Molodtsov D (1999) Soft set theory-first results. Comput Math Appl 37(4–5):19–31
35. Molodtsov DA, Leonov VY, Kovkov DV (2006) Soft sets technique and its application. Neuron 44(1):59–73
36. Zadeh LA (1965) Fuzzy sets. Inf Control 8(3):338–353
37. Feng F, Li Y, Leoreanu-Fotea V (2010) Application of level soft sets in decision making based on interval-valued fuzzy soft sets. Comput Math Appl 60(6):1756–1767
38. Fei H, Zheng P, Park DS, Phonexay V, Seo HS (2017) Mobile cloud services recommendation: a soft set-based approach. J Ambient Intell Humaniz Comput 9:1–9

39. Yager RR (2008) Intelligent social network analysis using granular computing. Int J Intell Syst 23(11):1197–1219
40. Yager RR (2010) Concept representation and database structures in fuzzy social relational networks. IEEE Trans Syst Man Cybern Part A Syst Hum 40(2):413–419
41. Nair PS, Sarasamma ST (2007) Data mining through fuzzy social network analysis. In: Fuzzy information processing society. Nafips'07 meeting of the North American. pp 251–255
42. Fan TF, Liau CJ, Lin TY (2007) Positional analysis in fuzzy social networks. In: GRC, p 423
43. Fan TF, Liau CJ, Lin TY (2008) A theoretical investigation of regular equivalences for fuzzy graphs. Int J Approx Reason 49(3):678–688
44. Newman MEJ (2004) Analysis of weighted networks. Phys Rev E Stat Nonlin Soft Matter Phys 70(5 Pt 2):056131
45. Brunelli M, Fedrizzi M (2009) A fuzzy approach to social network analysis. In: Social network analysis and mining. ASONAM'09. International conference on advances. pp 225–230
46. Davis GB, Carley KM (2008) Clearing the fog: fuzzy, overlapping groups for social networks. Soc Netw 30(3):201–212
47. Ciric M, Bogdanovic S (2010) Fuzzy social network analysis. pp 179–190
48. Zadeh LA (2002) Fuzzy logic = computing with words. IEEE Trans Fuzzy Syst 4(2):103–111
49. Li C-C, Dong Y, Herrera F, Herrera-Viedma E, Martínez L (2017) Personalized individual semantics in computing with words for supporting linguistic group decision making. An application on consensus reaching. Inf Fusion 33:29–40
50. Snasel V, Horak Z, Kocibova J, Abraham A (2009) Analyzing social networks using FCA: complexity aspects. In: IEEE/WIC/ACM international joint conferences on web intelligence and intelligent agent technologies. WI-IAT, pp 38–41
51. Hao F, Yau SS, Min G, Yang LT (2014) Detecting k-balanced trusted cliques in signed social networks. IEEE Internet Comput 18(2):24–31
52. Dörflein SK, Wille R (2005) Coherence networks of concept lattices: the basic theorem. In: International conference on formal concept analysis. Springer, Berlin, pp 344–359
53. Borgatti SP, Everett MG (1989) The class of all regular equivalences: algebraic structure and computation. Soc Netw 11(1):65–88
54. Kudelka M, Radvansky M, Horak Z, Krome P, Snasel V (2012) Soft identification of experts in DBLP using FCA and fuzzy rules. In: IEEE international conference on systems, man, and cybernetics. pp 1942–1947
55. Trung DN, Jung JJ (2014) Sentiment analysis based on fuzzy propagation in online social networks: a case study on TweetScope. Comput Sci Inf Syst 11(1):215–228
56. Zia MA, Zhang Z, Chen L, Ahmad H, Su S (2017) Identifying influential people based on interaction strength. J Inf Process Syst 13(4):987–999
57. Nepusz T, Petroczi A, Negyessy L, Bazso F (2008) Fuzzy communities and the concept of bridgeness in complex networks. Phys Rev E Stat Nonlin Soft Matter Phys 77(2):016107
58. Zhang S, Wang RS, Zhang XS (2007) Uncovering fuzzy community structure in complex networks. Phys Rev E Stat Nonlin Soft Matter Phys 76(2):046103
59. Golsefid SMM, Zarandi MHF, Bastani S (2015) Fuzzy community detection model in social networks. Int J Intell Syst 30(12):1227–1244
60. Gregori E, Lenzini L, Mainardi S (2013) Parallel k-clique community detection on large-scale networks. IEEE Trans Parallel Distrib Syst 24(8):1651–1660
61. Rome JE, Haralick RM (2005) Towards a formal concept analysis approach to exploring communities on the world wide web. In: International conference on formal concept analysis. Springer, Berlin, pp 33–48
62. Fu Y, Cui Z (2014) Research of blog community detection based on FCA. Int J Data Min Intell Inf Technol Appl 4(1):26
63. Formica A (2006) Ontology-based concept similarity in formal concept analysis. Inf Sci 176(18):2624–2641
64. Formica A (2008) Concept similarity in formal concept analysis: an information content approach. Knowl Based Syst 21(1):80–87
65. Ali SS, Bentayeb F, Missaoui R, Boussaid O (2014) An efficient method for community detection based on formal concept analysis. In: International symposium on methodologies for intelligent systems. pp 61–72
66. Hao F, Park DS (2017) csketch: a novel framework for capturing cliques from big graph. J Supercomput 1:1–13
67. Hao F, Park DS, Pei Z (2017) Exploiting the formation of maximal cliques in social networks. Symmetry 9(7):100
68. Hao F, Sim DS, Park DS, Seo HS (2017) Similarity evaluation between graphs: a formal concept analysis approach. J Inf Process Syst 13(5):1158–1167
69. Wang Z, Wang Z (2012) Research in social network based on rough set clustering algorithm. Int J Adv Comput Technol 4(15):295–301
70. Mitra A, Padhi P (2012) On application of rough set and neighborhood theory in social network. Int J Recent Trends Eng Technol 7(3):38
71. Hao F, Park DS, Shao Y (2016) A novel methodology on characterizing topological structure from complex networks. Adv Sci Lett 22(9):2404–2408
72. Cooley RW, Srivastava J (2000) Web usage mining: discovery and application of interesting patterns from web data. University of Minnesota, Minneapolis
73. Ahmad MA, Srivastava J (2008) An ant colony optimization approach to expert identification in social networks. Springer, Boston
74. Kwon K, Jeon Y, Cho C, Seo J, Chung IJ, Park H (2017) Sentiment trend analysis in social web environments. In: IEEE international conference on big data and smart computing
75. Hotho A (2006) BibSonomy: a social bookmark and publication sharing system. In: Conceptual structures tool interoperability workshop at the international conference on conceptual structures. pp 87–102
76. Ho CW, Wang YB (2015) Re-purchase intentions and virtual customer relationships on social media brand community. Hum Centric Comput Inf Sci 5(1):18
77. Singh J, Singh G, Singh R (2017) Optimization of sentiment analysis using machine learning classifiers. Hum Centric Comput Inf Sci 7(1):32

78. Jaschke R, Hotho A, Schmitz C, Ganter B, Stumme G (2007) TRIAS—an algorithm for mining iceberg tri-lattices. In: International conference on data mining. pp 907–911
79. Hao F, Zhong S (2010) ECKDF: Extended conceptual knowledge discovery in folksonomy. In: International conference on computational problem-solving. pp 71–76
80. Hao F, Zhong S (2009) Variable precision concepts and its applications for query expansion. In: Emerging intelligent computing technology and applications. With aspects of artificial intelligence. Proceedings international conference on intelligent computing, ICIC 2009, Ulsan, South Korea, 16–19 September. pp 154–165
81. Zhang W, Du Y, Song W (2015) Followee recommendation based formal concept analysis in social network. Int J Innov Comput Inf Control IJICIC 11(4):1155–1164
82. Mukkamala RR, Hussain A, Vatrapu R (2014) Fuzzy-set based sentiment analysis of big social data. In: Enterprise distributed object computing conference. pp 71–80
83. Jusoh S, Alfawareh HM (2013) Applying fuzzy sets for opinion mining. In: International conference on computer applications technology. pp 1–5
84. Cuenca-Jara J, Terroso-Saenz F, Valdes-Vela M, Gonzalez-Vidal A, Skarmeta AF (2017) Human mobility analysis based on social media and fuzzy clustering. In: Global internet of things summit (GIoTS). IEEE, New York, pp 1–6
85. Fei H, Doo-Soon P, Sang Yeon W, Se Dong M, Sewon P (2016) Treatment planning in smart medical: a sustainable strategy. J Inf Process Syst 12(4):711–723
86. Hao F, Park DS, Min SD, Park S (2016) Modeling a big medical data cognitive system with N-Ary formal concept analysis. In: Advanced multimedia and ubiquitous engineering. Springer, Singapore, pp 721–716
87. Hanneman RA, Riddle M (2005) Introduction to social network methods. Department of Sociology University of California Riverside, Riverside
88. Huisman M, Duijn MAJV (2005) Software for social network analysis. Models Methods Soc Netw Anal 270:e316
89. Loscalzo S, Yu L (2008) Social network analysis: tasks and tools. Springer, Boston, pp 151–159
90. Xu K, Tang C, Tang R, Ali G, Zhu J (2010) A comparative study of six software packages for complex network research. In: International conference on communication software and networks. pp 350–354
91. Neubig G, Dyer C, Goldberg Y, Matthews A, Ammar W, Anastasopoulos A, Ballesteros M, Chiang D, Clothiaux D, Cohn T (2017) Dynet: the dynamic neural network toolkit
92. Adamcsek B, Palla G, Farkas IJ, Derenyi I, Vicsek T (2006) CFinder: locating cliques and overlapping modules in biological networks. Bioinformatics 22(8):1021–1023
93. Mrvar A, Batagelj V (2002) Pajek—analysis and visualization of large networks. Lect Notes Comput Sci 2265:77–103
94. Trier M (2006) Towards a social network intelligence tool for visual analysis of virtual communication networks. TUDpress Verlag, Dresden
95. Smith MA, Shneiderman B, Milic-Frayling N, Mendes Rodrigues E, Barash V (2010) Analyzing (social media) networks with NodeXL. pp 277–284
96. White DR, Batagelj V, Mrvar A (2013) Kinship and marriage networks anthropology analyzing large kinship and marriage networks with Pgraph and Pajek. Soc Sci Comput Rev 17(3):245–274
97. Csardi G, Nepusz T (2006) The igraph software package for complex network research. Inter J Complex Syst 1695:1–9
98. Nicholls J, Peters D, Slawinski A, Spoor T, Vicol S, Happa J, Goldsmith M, Creese S (2013) Netvis: a visualization tool enabling multiple perspectives of network traffic data. Eurographics Association
99. Apostolato IA (2013) An overview of software applications for social network analysis. Int Rev Soc Res 3(3):71–77
100. Carley KM (2014) ORA: a toolkit for dynamic network analysis and visualization. Springer, New York, pp 1219–1228
101. Yang R, Bai Y, Qin Z, Yu T (2014) EgoNet: identification of human disease ego-network modules. BMC Genomics 15(1):314
102. http://www.maths.bris.ac.uk/R/web/packages/keyplayer/index.html
103. Johnson JD (1987) UCINET: a software tool for network analysis. Commun Educ 36(1):92–94
104. Hagberg A, Schult D, Swart P (2005) Networkx: Python software for the analysis of networks. Mathematical Modeling and Analysis, Los Alamos National Laboratory
105. Huisman M, Van Duijn MA (2003) StOCNET: software for the statistical analysis of social networks. Connections 68(4):1457–1458
106. http://freshmeat.sourceforge.net/projects/aisee
107. Weiss M, Moroiu G, Zhao P (2006) Evolution of open source communities. Springer, Boston, pp 21–32
108. Shannon P, Markiel A, Ozier O, Baliga NS, Wang JT, Ramage D, Amin N, Schwikowski B, Ideker T (2003) Cytoscape: a software environment for integrated models of biomolecular interaction networks. University of California Riverside, Riverside, pp 165–184
109. Bastian M, Heymann S, Jacomy M (2009) Gephi: an open source software for exploring and manipulating networks. In: Third international AAAI conference on weblogs and social media
110. Ellson J, Gansner E, Koutsofios L, North S, Woodhull G, Description S, Technologies L (2001) Graphviz-open source graph drawing tools. In: Lecture notes in computer science. Springer, Berlin, pp 483–484
111. Krackhardt D, Lundberg M, O'Rourke L (2014) Krackplot: a picture's worth a thousand words. Dermatol Times 72(2):200–222
112. Valtchev P, Roume C (2003) Galicia: an open platform for lattices. In: Using conceptual structures: contributions to ICCS'03. pp 241–254
113. Fei H, Park DS, Sim DS, Min JK, Jeong YS, Park JH, Seo HS (2017) An efficient approach to understanding social evolution of location-focused online communities in location-based services. Soft Comput. https://doi.org/10.1007/s00500-017-2627-2