Detecting Community Structures Within Complex Networks Using a Discrete Unconscious Search Algorithm

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ABSTRACT

Detecting the communities that exist within complex social networks has a wide range of application in business, engineering, and sociopolitical settings. As a result, many community detection methods are being developed by researchers in the academic community. If the communities within social networks can be more accurately detected, the behavior or characteristics of each community within the networks can be better understood, which implies that better decisions can be made. In this paper, a discrete version of an unconscious search algorithm was applied to three widely explored complex networks. After these networks were formulated as optimization problems, the unconscious search algorithm was applied, and the results were compared against the results found from a comprehensive review of state-of-the-art community detection methods. The comparative study shows that the unconscious search algorithm consistently produced the highest modularity that was discovered through the comprehensive review of the literature.

KEYWORDS

Evolutionary Searched-Based Algorithms, Modularity, Social Networks, Unweighted and Undirected Networks

INTRODUCTION

The amount of research dedicated to complex networks has increased over the last decades due to its wide range of applications. For example, by researching complex networks, the research community has investigated various phenomena within economic, social, and technological settings (Chen & Redner, 2010). Within these problem areas, social structures can also be represented as a complex network. Social networks consist of a set of communities, which are sometimes referred to as called clusters or modules. This particular area of study is also receiving more attention from the research community. For example, Internet social networks (Lambiotte & Ausloos, 2005), scientific reference networks (Chen & Redner, 2010), biological networks (Diao, Li, Feng, Yin, & Pan, 2007), neurological networks (Schwarz, Gozzi, & Bifone, 2008), epidemiology networks (Sun & Gao, 2007), transportation networks (Barigozzi, Fagiolo, & Mangioni, 2011), and even political networks (Porter, Mucha, Newman, & Friend, 2007) are some of the areas being investigated by practitioners and researchers.

Detecting the structure of the communities within a network receives a lot of attention from the research community because it plays a vital role in understanding the behavior among the various communities within a network (Gleich & Seshadhri, 2012). To detect the structure of the communities within a complex network, a clustering operation is used (Zhou, Yang, Xie, Yang, & Huang, 2019).

As a result, decision-makers can make better, more informed, and more effective decisions depending on the application of the complex network being investigated.

Detecting communities in a social network is an NP-hard problem. Given this complexity, several methods have been proposed in the literature involving this particular problem. For example, spectral methods, divisive methods, agglomerative methods, maximization of the modularity, local methods, method selection, and roles of vertices are methods dedicated to detecting the structure of the communities within complex networks (Costa, Rodrigues, Travieso, & Villas Boas, 2007). The unconscious search (US) algorithm is a method that is designed to tackle the continuous optimization problems (Ardjmand, Park, Weckman, & Amin-Naseri, 2014). However, the unconscious search algorithm can be modified to solve discrete optimization problems. In this paper, the US algorithm is explored as a community detection method. Using the US algorithm as a method for detecting community structures has not been previously explored by researchers. Thus, the focus of the research presented in this paper involves a comprehensive comparative study of how well the US method preforms when comparing its results against other state-of-the-art methods found within recent academic research.

The comprehensive comparative study presented in this paper is primarily based on the concept of modularity, which is a popular measure in community detection literature. This measure is utilized to determine the strength of the division of a network. In other words, to detect the structure of the communities within a social network, a network N can be partitioned in a manner that creates a subset of nodes containing a maximum number of internal links while minimizes the number of possible links with nodes outside of a given cluster (Girvan & Newman, 2002).

LITERATURE REVIEW

Several methods have appeared in the literature that attempt to define the communities hidden within complex networks. These methods include, but are certainly not limited to the spectral bisection algorithm (Fiedler, 1973), Kernighan-Lin algorithm (Kernighan & Lin, 1970), spectral partitioning (Elsner, 1997; Fjällström, 1998), and hierarchical clustering (Wasserman & Faust, 1994). As noted, detecting community structures within complex networks is an emerging field of study. As a result, it is not surprising that the methods explored by researchers are quite diverse and the creativity exhibited from the research community is not lacking. For example, the theory of dynamics of excitable systems has used to developed a method to detect community structures (Li, Li, Hu, Di, & Fan, 2010). Also, a novel cellular learning automate-based algorithm was developed to tackle the community detection problem within social networks that were both undirected and unweighted (Khomami, Rezvanian, & Meybodi, 2018).

Detecting communities within social networks associate itself naturally to clustering methods. For example, a dynamic clustering method that utilizes a cluster's desynchronization properties of phase oscillators has been explored (Boccaletti, Ivanchenko, Latora, Pluchino, & Rapisarda, 2007). It is quite common to find clustering methods being used to detect communities within structures. At times, the fundamental properties of the clusters are used to identify the communities within a network. However, clustering methods have also been used to enhance the development of community detection algorithms. For example, k-means clustering has been used in conjunction with a simulated annealing metaheuristic algorithm to detect communities within complex networks (Liu & Liu, 2010). Clustering methods are classified as unsupervised learning methods. Although they are commonly used to detect communities within networks, they are not the only unsupervised learning methods that have been used by researchers. For example, a vector partitioning approach was adopted to detect community structures within network graphs (Wang, Shen, & Ouyang, 2008).

In terms of community detection methods, many researchers have developed their methodologies around the premise of maximizing the modularity of a network, but they differ in their approach (Gach & Hao, 2013). For example, a simulated annealing algorithm has been used as a method to

maximize the modularity within a network (Medus, Acuna, & Dorso, 2005). Though the concept of maximizing modularity has been integrated into many methods throughout the years, it still is a popular choice among researchers exploring more flexible algorithms to tackle the community detection problem (Zhou et al., 2019).

Research articles often focus on comparing the benefits and limitations of community detection methods. One consideration that researchers must consider is a method's ability to accurately detect the communities within networks. They must also take into account the time required to implement and produce accurate clusters within large networks. Some methods have been noted to be computationally expensive, while others were successfully applied to large datasets. For example, one method maximizing the modularity measure was applied to a network of 'collaboration among physicists' which was composed of about 50 thousand nodes (Newman, 2004). The researchers concluded that the algorithm was highly capable of detecting community structures in a short amount of time relative to other benchmark methods explored. Other methods can be found in the literature that aims to rapidly locate the core of each cluster residing inside a network (Chen, Fu, & Shang, 2009). In addition, large undirected and unweighted networks with linear time complexity have also been used to examine an online community structure (Pan, Wangsheng, Zhaohui, & Shijian, 2014).

From an efficiency standpoint, detecting communities within excessively large networks can be a considerable challenge that researchers must overcome. For example, label propagation has been used and was found to be an efficient approach from a computational time perspective when detecting the structure of the communities within excessively large networks (Liu & Murata, 2010). However, traditional agglomerative algorithms have also been applied successfully to extremely large networks as well (Clauset, Newman, & Moore, 2004). Although agglomerative approaches have been introduced as a method to determine community structures some time ago, they remain a popular choice among active researchers. For example, a degenerate agglomerative hierarchical clustering algorithm based on a reachability matrix was recently introduced by researchers (Maria Fiscarelli, Brust, Danoy, & Bouvry, 2019).

Even though modularity remains to be the primary measure when determining the structure of communities within networks, it is certainly not the only measure being used by researchers. For example, a maximum flow factor has been utilized within community detection methods that are designed to eliminate the weakest links within a network (Mann, Matula, & Olinick, 2008). Methods of this nature have the benefit of simplifying the overall structure of the complex network being investigated. A measure of node similarity has also been applied to complex networks and it was considered to be a fast and efficient method for detecting community structures within complex networks (Pan, Li, Liu, & Liang, 2010). Other methodologies that use a measure other than modularity also exist. For example, a method leveraging structural similarity was applied to unweighted and undirected networks with promising results (Dabaghi Zarandi & Kuchaki Rafsanjani, 2018). In addition, a communicability measure, which was inspired by how an epidemic pattern propagates through a network (Estrada & Hatano, 2008, 2009; Rajtmajer & Vukičević, 2010), has been used to determine a network's structure. It is clear from the literature, that there is not a shortage of inspiration when it comes to creating various measures detecting the communities within structures. For example, information discrepancy has also been used as a measure for community detection. Like other measures, it aims to determine the quality of detecting communities within complex networks (Zhang, Zhang, & Zhang, 2008).

As noted, one consistent theme found in the literature is that many methods are developed to maximizing the modularity measure within complex networks. However, it is becoming more popular for researchers to develop community detection algorithms that utilize more than one measure. In addition to modularity, many examples within the literature can be found that formulate the structure of networks with other measures. For example, researchers have presented a parallel partitioning strategy based on two distinct measures for community detection. More specifically, researchers have developed an approach that accounts for the modularity of a network as well as a network's

community recursive coefficient (Shen, Pei, Wang, Li, & Wang, 2008). Another hybrid approach uses the affinity between nodes to determine the stability among the communities that are detected. This particular method strikes a balance between normalized mutual information and modularity to discover the communities hidden within complex networks (Zeng, Chenxi Shao, Xingfu Wang, & Miao, 2020). Many other hybrid systems can also be found in the literature. For example, a community detection algorithm was developed that utilizes a graphlet measure to determine the structure of a social network (Abduljabbar, Hashim, & Sallehuddin, 2020). For this novel work, the authors proposed two contradictory optimization functions, which are inspired by the cooperation between the neighborhood relationships and the signature similarity measures. In terms of another hybrid approach, attracting and recommending degree measures were utilized within an AR-clustering framework to strengthen the similarities among the vertices within social networks (Zhou, Li, Li, Zhang, & Cui, 2017).

Although clustering methods are classified as unsupervised learning methods, the act of detecting communities within social networks is not limited to traditional clustering-based approaches. For example, a semi-supervised method for solving network community structure detection problems have also been introduced (Ma, Gao, Yong, & Fu, 2010). The problems relating to community detection have also been formulated as optimization problems (Duch & Arenas, 2005), which has led many researchers to formulate additional community detection methods based on evolutionary algorithms. Evolutionary algorithms are emerging in the literature for community detection and they often utilize measures of modularity to investigate the structure of complex networks (Guerrero, Montoya, Baños, Alcayde, & Gil, 2017). One reason genetic algorithms are becoming a popular choice among researchers is because of their ability to model large complex networks (Li, Liu, & Lao, 2013) and it is clear that these methods continue to evolve in their performance (Moradi & Parsa, 2019). For example, quantum-inspired evolutionary algorithms are now being applied to very complex social networks (Yuanyuan & Xiyu, 2018). Many other forms of evolutionary-based methods are now being explored. For example, a clonal section algorithm that maximizes modularity has been developed (Cai, Gong, Ma, & Jiao, 2015). In addition, a discrete bat algorithm has been used to estimate the global optimality of community detection within complex networks (Song, Mingbo, Xuehai, Wei, & Ke, 2016). Finally, a novel multi-objective optimization algorithm using an ant colony algorithm was used to confront the community detection problem (Shahabi Sani, Manthouri, & Farivar, 2018).

The research dedicated to social networks has increased dramatically over the last decade. Research relating to social networks is becoming more popular to cope with a great variety of phenomena and systems that have been classified as complex systems. Additionally, due to the sensitivity of the information on social networks, further privacy issues should be also considered. The main applications to the social network are the telecommunication industry, marketing purposes, online communities, search engines, etc. For these reasons and areas of application, methods dedicated to detecting community structures within complex networks are needed. Therefore, the motivation of the research contained in this article relates to exploring a new method for detecting community structures within complex networks that have not been previously explored. The dissemination of this research is considered significant given the novelty and the overall accuracy that was obtained by testing the performance of the algorithm on several complex networks that regularly appear in research dedicated to this specific topic. Investigating new methods of detecting community structures is significant because they can ultimately lead to advances in several areas of engineering, business, and other technology-focused fields of study. The evolutionary search-based method proposed in this article is based on the extremal optimization method (Duch & Arenas, 2005). The method employs the discrete version of an optimization algorithm known as the unconscious search (US) algorithm (Ardjmand & Amin-Naseri, 2012) to search for the optimum value of modularity.

The remainder of the article is organized as follows: Section 3 is devoted to a discussion of the US algorithm. Section 4 contains the results of the US method to popular benchmark networks that often appear in research exploring new methods for community detection. These commonly referenced networks include the 'Computer-Generated,' the 'Karate Club,' and the 'Dolphin' networks. Finally,

Section 5 contains the conclusions reached by the authors using the US method as a community detection method with respect to the comprehensive comparative investigation that was performed.

METHODOLOGY

The methodology in this paper is based on the maximization of network modularity (Q) by using an unconscious search (US) algorithm. In the following sections, the concepts of community and modularity are introduced and the proposed algorithm is described.

Community

A community is represented by a group of nodes, which can be fully or partially interconnected to other nodes within the cluster (Newman, 2006). Figure 1 depicts a general representation of a structure with three distinct communities. In general, there are more connections that link the nodes of a community together than there are links connecting the communities within a network (Kenward & Carrott, 2006). For example, the connections in groups A, B, and C are denser than between groups. There are 6, 11, and 10 between groups A, B, and C, respectively.

Mathematically speaking, a network N may be represented by a set of nodes $\left\{ n_i \mid i = 1,\ldots,n \right\}$ and a set of links $\left\{ l_{ij} \mid i = 1,\ldots,n, j = 1,\ldots,n \right\}$. In this particular framework, $l_{ij} = 0$ if there are no connections between the corresponding nodes n_i and n_j. Thus, $l_{ij} = 1$ if a connection is present. Complex networks are usually characterized by their edge weights. Considering these characteristics, complex networks can be classified into two types, unweighted networks and weighted networks (Buttner & Krieter, 2018). In an unweighted network, the edge weights are ignored, and the structure of the graph defines the characteristics of the network. In a weighted network, the edge weights and structure of the graph play an important role in understanding the behavior of the network being investigated. Additionally, the networks can be classified as either undirected networks or directed networks. In an undirected network, there is only one edge that connects two notes together. This is unlike directed networks where there could be multiple edges between certain nodes (Newman, 2003b). Our proposed algorithm in this paper investigates unweighted and undirected networks, where $l_{ij} = l_{ji}$.

Figure 1. An Example Community Structure with Three Communities
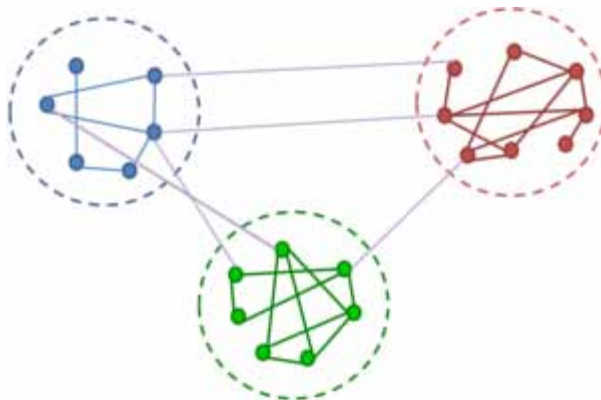
Modularity (Q)

For example, a typical partition P of network N is composed of p communities P_1, P_2, …, P_p. Considering a $p \times p$ symmetric matrix e where, e_{ij} denotes the ratio of all edges that connected vertices in P_i to vertices in P_j. Furthermore, the trace of matrix e ($Tre = \sum_i e_{ii}$) presents the fraction of edges in the network, and $\left|e^2\right|$ estimates the sum of all elements of the matrix e Newman, 2003a; Newman & Girvan, 2004). Thus, modularity can be calculated by Equation 1, which is shown below:

$$Q = \sum_i e_{ii} - \sum_{ijk} e_{ij} e_{ki} = Tre - \left|e^2\right| \tag{1}$$

In Equation 1, the modularity is represented by Q and it is indicative of the ratio of internal links in a given community to the total number of links less than the expected value of the same ratio for the case where the links are distributed randomly across the network (Fan et al., 2018). Thus, the value of Q must lie within the range between -1 and +1. If the value is closer to 1, it implies that P can reflect the quality of modularity in a graph. As a result, the problem of detecting the community structure in a network comes down to choosing the partition P such that the corresponding value of Q is maximized. The degree of modularity can be also determined by Equation 2, were L represents the total number of links in the network and l_s signifies the number of links in the sth module, while d_s denotes the total of the degrees of nodes in the sth module:

$$Q = \sum_{s=1}^{p} \left[\frac{l_s}{L} - \left(\frac{d_s}{2L}\right)^2 \right] \tag{2}$$

The Unconscious Search Algorithm

The unconscious search (US) algorithm is a meta-heuristic propounded by Ardjmand and Amin-Naseri (2012) and later adopted and applied by Xing and Gao (2014) and Molina et al. (2020). The US algorithm is a multi-start, memory-based metaheuristic that mimics the process of psychoanalytic psychotherapy proposed by Sigmund Freud, where the therapist tried to find the root cause of a patient's mental disorder based on their unconscious (Freud & Strachey, 1996).

In each step, the US algorithm maintains a list of the best solutions that have been found in a set called a measurement matrix (MM). Once solutions are found, the US algorithm tries to find a good starting point and direction for the next search. For this purpose, US uses two types of measures, which are called displacement and condensational memories. Displacement memory attempts to learn the most promising starting point, while condensational memory attempts to find the most promising search directions. Whenever US finds a solution, it compares the performance results produced by the solutions within the MM against the performance of new solutions. In this manner, only the best performing solutions are stored, and the algorithm continues to test solutions until there is not an improvement to its modularity.

The US algorithm has four main steps, which include construction, construction review, a local search, and a measurement matrix update. In the construction step, a new solution is constructed. In the construction review, a solution is generated based on the results from the prior solutions that were found. These candidate solutions are based on a search that shows a promising direction. A local search

enhances the best solution found in the first two phases, while in the last step, the measurement matrix is updated. The construction review phase in the US is mainly designed for continuous optimization problems. Several studies have utilized the US method to solve problems. For example, it has been used to solve an uncapacitated facility location problem (Ardjmand et al., 2014), and it has been used to solve a production planning with price uncertainty problem (Ardjmand, Weckman, Young, Sanei Bajgiran, & Aminipour, 2016). However, the proposed methodology presented in this article is applied to discrete problems (i.e. number of clusters), which means that this particular phase is not needed (Ardjmand et al., 2014). As a result, the proposed US algorithm will only have three phases, which include construction, a local search, and a measurement matrix update.

To apply the US to community detection problems within complex networks, a network is initially divided into two partitions in such a way that the modularity measure is maximized. Next, the two partitions are divided into two sub-partitions to ensure that the modularity of each sub-partition is maximized. The procedure is repeated, using the US algorithm, until the modularity measure, which is shown in Equation 2, is not improved upon. The process of using the US algorithm for the community detection problem is summarized in Figure 2.

In the first iteration of the US algorithm, a set of random solutions (i.e. a network with nodes randomly assigned to two clusters) is generated. These solutions are stored in a measurement matrix (MM). The size of the MM is shown by $|MM|$ and this measurement defines the number of best-performing solutions that are stored. Thus, if $|MM| = 10$, the 10 best-performing solutions are stored.

To construct a new solution, the US assigns each node of the network to a cluster. For example, based on the best solutions stored in MM, if a node is assigned to Cluster 1 60% of the time, and it is assigned to Cluster 2 40% of the time, then based on the new solution, the node will have a 60% chance of being assigned to Cluster 1, and a 40% chance being assigned Cluster 2. In terms of creating new solutions, this type of memory is referred to as displacement memory (Ardjmand & Amin-Naseri, 2012).

Figure 2. US algorithm for Clustering Networks
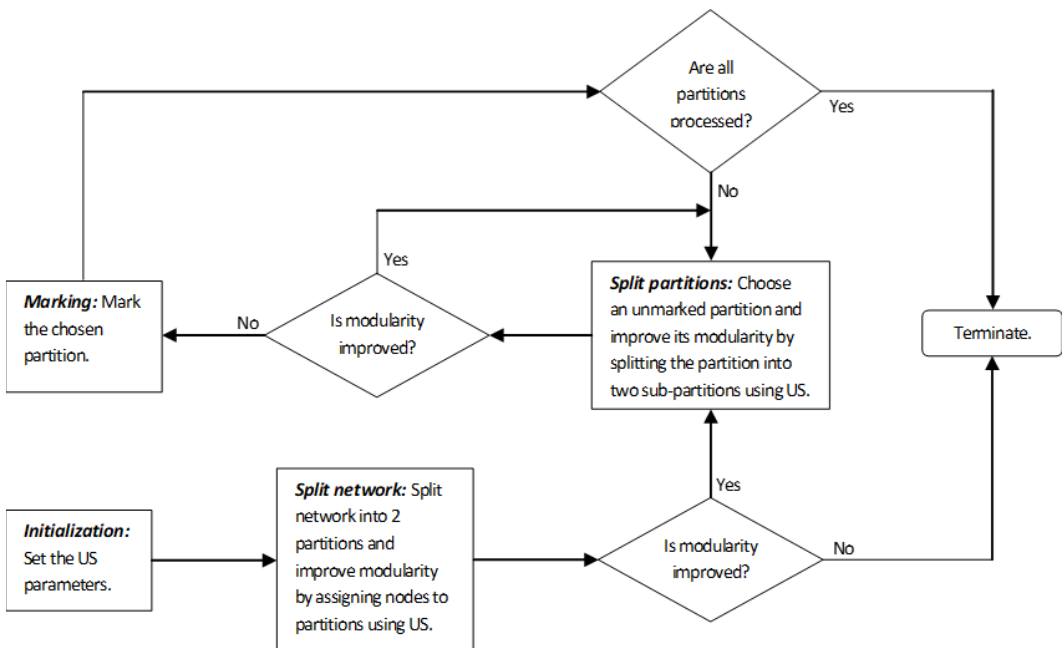
For the local search, after a solution is constructed, a node will be picked randomly and transferred from one cluster to another. If this move improves the modularity, the assignment will be accepted. Otherwise, if this is not the case, the solution will be rejected. This process continues until the modularity ceases to improve any further.

The last step of the US algorithm is the local search. In this step, if a given solution is an improvement over the worst-performing solution stored in MM, the new solution will be inserted in MM and the worst performing solution found in the MM will be discarded. Likewise, if the new solution does not perform better than the worst solution stored in MM, it will be discarded, and the MM will not be updated.

RESULTS

To evaluate the performance of the US algorithm as a new community detection method, three complex networks were explored. These particular networks are commonly used by researchers exploring new methods for community detection. Given the popularity of these benchmark networks, the results obtained from the US algorithm were compared to the results published by authors exploring community detection methods. Computer-Generated Networks (CGN).
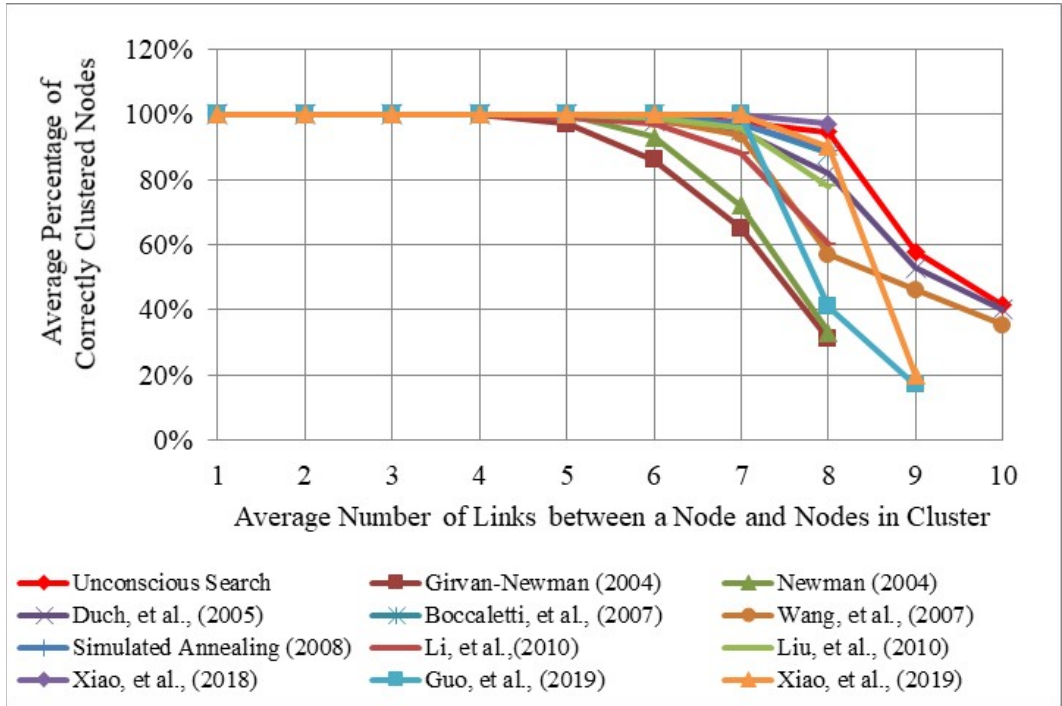
The first complex network that was investigated in this research was the Computer-Generated Network (CGN). CGN involves a series of graphs representing pre-identified community structures. The CGN consists of 128 nodes and four pre-defined clusters. Each node was linked with an average of z_{in} number of nodes to the same cluster, and an average of z_{out} number of nodes to other clusters, such that $z_{in} + z_{out} = 16$. To produce measures that can be compared against other published results, a large number of graphs were created from the US algorithm that consisted of z_{out} values that ranged between 0 to 10. The CGN problem has been explored by many researchers. Figure 3 shows a summary of the results obtained by other researchers who investigated the CGN problem with various community detection algorithms. In particular, the graph shows the percentage of nodes that were correctly clustered by each community detection algorithm. The US algorithm's ability to detect community structures for values of $z_{out} \leq 8$ preformed just as well or better than the other results found in the literature. However, for $z_{out} > 8$ the US outperformed all other methods recorded from the literature.

Karate Club Network

The Karate Club Network (KCN) problem was the second complex network that was explored. This network was first introduced by Zachary (1977) but has remained popular with researchers exploring community detection algorithms. The KCN consists of 34 nodes and 78 links, where the network represents the membership of a karate club and the friendship between the members. The objective of this problem is to detect the communities within the social network. When the US algorithm was applied to the KCN, it produced a modularity of 0.420. The graph network based on the US solution is shown in Figure 4, where four communities or clusters were detected.

As noted, the KCN is popular among researchers investigating new community detection methods. To assess how well the US algorithm performed as a community detection method, a comprehensive review of the literature was conducted. As a result of this investigation, a total of 26 references were found that solved the KCN with a variety of community detection methods. The summary of this review is shown in Figure 5, where research utilizing the KCN dates back as far back as 2005 and includes studies as recent as 2020. The US algorithm was able to produce a modularity of 0.42 for the KCN network. In terms of this metric, the US algorithm was able to outperform many other techniques that were found during the comprehensive review of the literature. The US algorithm produced the highest modularity that has discovered during the review of existing literature exploring the KCN. However, as shown in Figure 4, many other methods were capable of producing this value of modularity as well. It should be noted that additional information about the studies shown in Figure 4 is provided in Section 5.

Figure 3. Benchmark Results for the Computer-Generated Network

Dolphin Network

The third and final complex network that was evaluated in this study was the Dolphin Network. Just like the two previous networks investigated, this network has been utilized by many other researchers exploring community detection algorithms. The Dolphin Network problem involves a network of 62 nodes and 159 links, which represent the interaction between dolphins in the network. The US

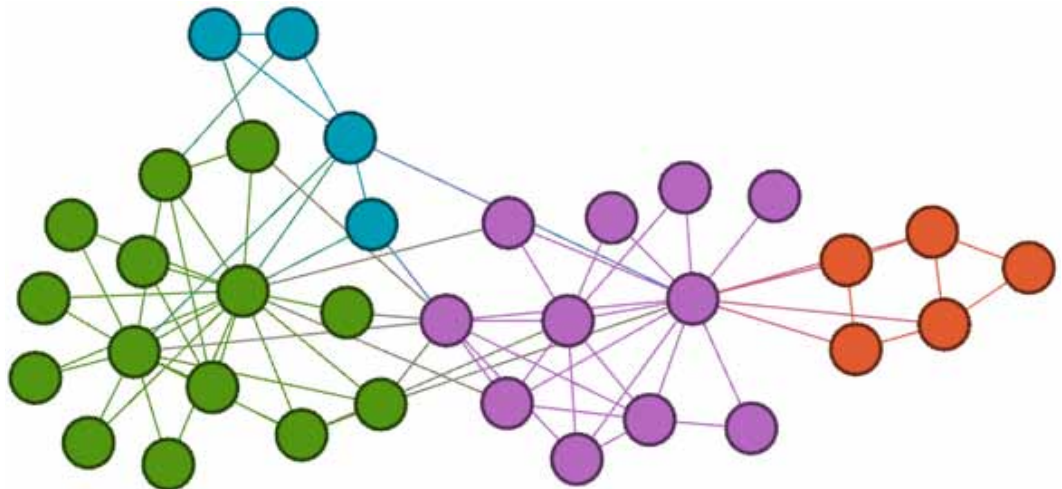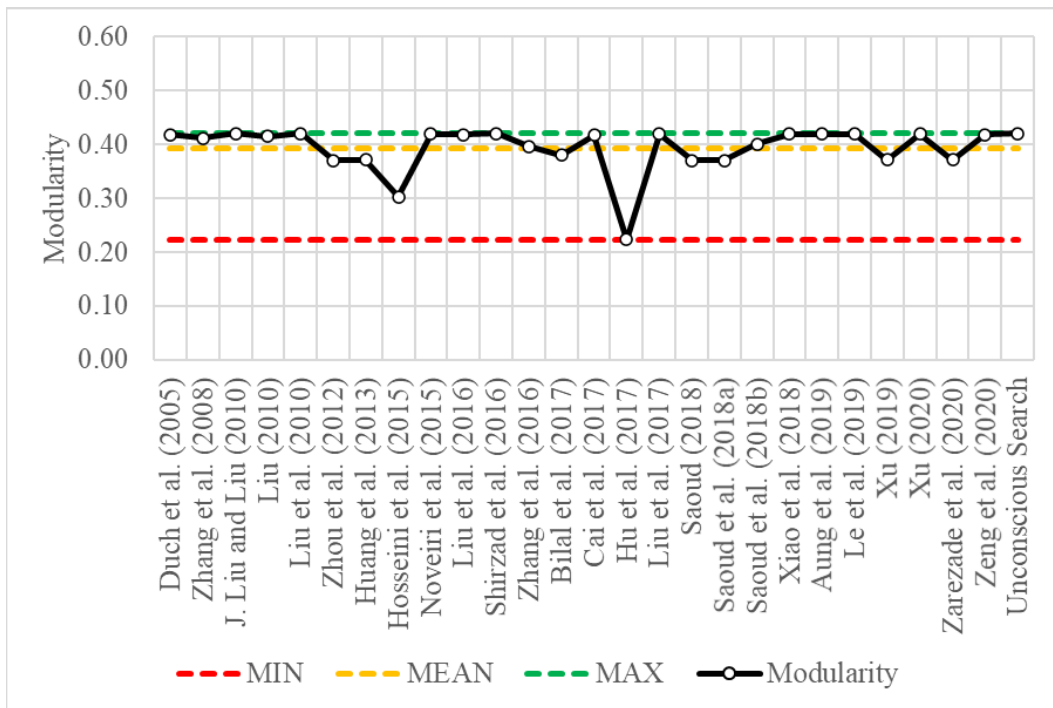Figure 4. Unconscious Search Algorithm Results for the Karate Club Network

Figure 5. Benchmark Results for the Karate Club Network

algorithm was used to partition the network into four subsets. The communities detected by the US algorithm are illustrated in Figure 6, where the resulting modularity was found to be 0.527.

Given its complexity and size, the Dolphin Network is another network that is widely used by researchers exploring advances within community detection algorithms. In total, 24 references utilizing the Dolphin Network were found through the process of reviewing the literature. Based on the review of literature, the studies that were found that utilized the Dolphin Network ranged in years from 2010 to 2020. As shown in Figure 7, the US algorithm produced a modularity of 0.527 for the Dolphin Network. Based on the comparative study, these results were similar to the outcome of the KCN study. In other words, the US algorithm was able to outperform many other community detection methods; however, even though it produced the highest value of modularity that was observed, it was not the only method to do so.

CONCLUSION

The US algorithm is a multi-start, memory-based metaheuristic that mimics the process of psychoanalytic psychotherapy. In this article, the US algorithm was adapted to solve community detection problems of small dimensional scale. Several complex networks appear in the related literature surrounding community detection. Of these networks, three were selected and used to compare the results of the US algorithm to the results based on other state-of-the-art methodologies that have appeared recently in the literature. These networks included the Computer-Generated Network (CGN), the Karate Club Network (KCN), and the Dolphin Network.

With respect to the networks explored in this study, the use of the US algorithm showed promising results. For example, the US method was able to produce results that were among the highest, or in certain situations, was the highest performing method when applied as a community detection

Figure 6. Unconscious Search Algorithm Results for the Dolphin Network
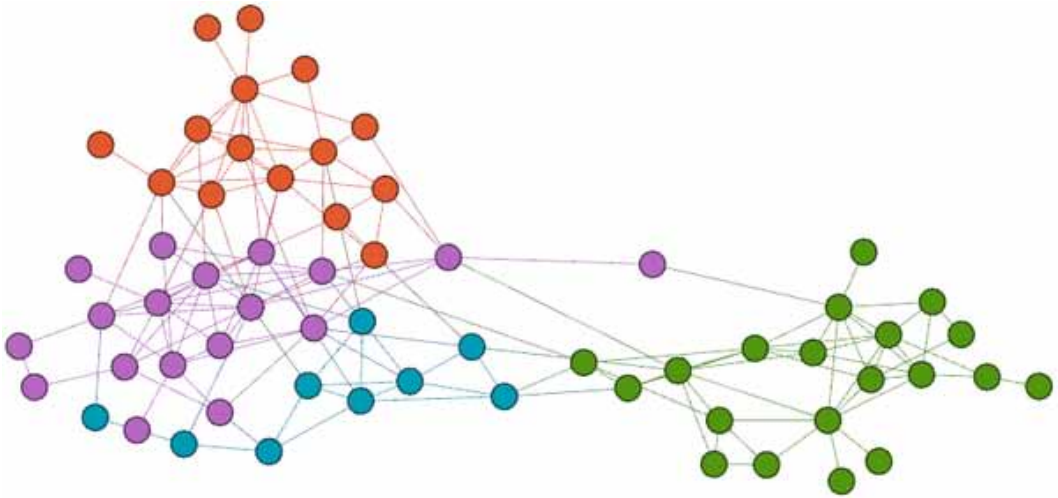

Figure 7. Benchmark Results for the Dolphin Network
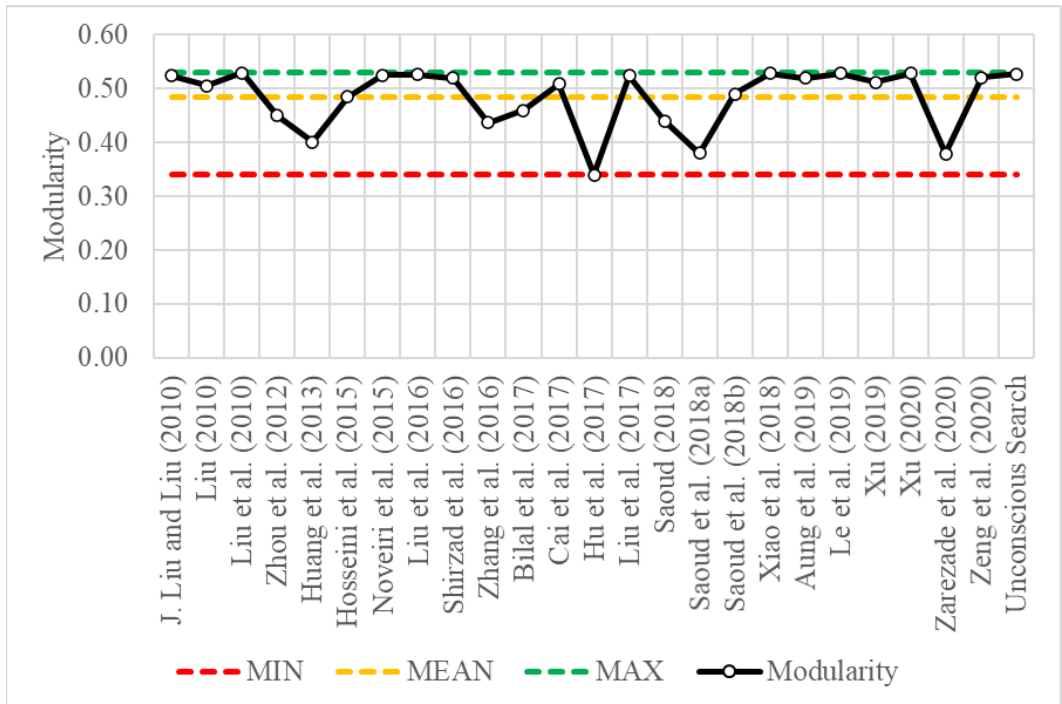
method to the CGN. For the KCN and Dolphin Network problems, the modularity obtained by the US algorithm performed equally as well as the best results that were discovered from a comprehensive review of related literature. Table 1 contains additional information related to the comprehensive review of state-of-the-art community detection methods for the KCN and the Dolphin Network. As the table shows, the US algorithm consistently produced highly accurate results.

Table 1. Comparison Summary of Community Detection Algorithm

Reference	Karate Club	Dolphin	Community Detection Method Description
Zhou, et al., (2012)	0.370	0.450	Greedy Algorithm
Saoud, et al., (2018b)	0.401	0.490	Detection Based on Node Similarity and Modularity
Bilal, et al., (2017)	0.380	0.460	Evolutionary algorithm
Huang, et al., (2013)	0.371	0.401	Multi-Agent based decentralized algorithm
Xu, (2019)	0.372	0.511	Communicability Distance Algorithm
Xu, (2020)	0.419	0.528	Spectral algorithm
Aung, et al., (2019)	0.419	0.520	Discrete artificial bee colony algorithm
Le, et al., (2019)	0.419	0.528	Meta-Heuristic based label propagation
Zarezade, et al., (2020)	0.371	0.379	SD-GCN Algorithm
Zeng, et al., (2020)	0.418	0.521	Affinity Between Nodes & Stability of Community
Xiao, et al., (2018)	0.419	0.528	Differential Evolution Algorithm
Saoud, et al., (2018a)	0.370	0.380	Genetic Algorithm
Liu, et al., (2017)	0.419	0.524	A Biogeography-based Optimization Algorithm
Hu, et al., (2017)	0.223	0.340	Novel Algorithm J-SC
Cai, et al., (2017)	0.417	0.508	Particle Swarm Optimization Algorithm
Liu, et al., (2016)	0.418	0.526	Genetic algorithm
Zhang, et al., (2016)	0.396	0.436	Fuzzy community detection approach
Hosseini, et al., (2015)	0.303	0.485	Memory-based Label Propagation Algorithm
Noveiri, et al., (2015)	0.419	0.524	Ant Colony Algorithm and Fuzzy Clustering
Liu, (2010)	0.415	0.505	Simulated Annealing Strategy
Saoud, (2018)	0.370	0.440	Artificial Bee Colony
Liu and Liu (2010)	0.420	0.523	Simulated Annealing with k-means Algorithms
Duch, et al., (2005)	0.418	-	Extremal Optimization Method
Liu, et al., (2010)	0.420	0.529	Label Propagation Algorithm
Zhang, et al., (2008)	0.411	-	Iterative Procedure based on Information Discrepancy
Shirzad, et al., (2016)	0.420	0.520	Hierarchical approach
Unconscious Search	0.420	0.527	Unconscious Search Algorithm

In conclusion, the US algorithm was able to produce results that were consistently among the best results found from a comprehensive review of recent literature. The networks that were explored were small in scale; however, these networks are consistently used by the research community to judge how well algorithms discover the communities that are hidden within complex networks.

The downside of the algorithm was the local optimal solution. In this case, the immigration operator should be applied when there is no improvement in the generations due to the premature convergence to a local optimum. This relaxation helped the US algorithm to reach the optimal solution in many situations. Additionally, the research conducted in this article was restricted to small-scale unweighted and undirected networks. The proposed algorithm solved the three complex networks that were selected for this study in only a few minutes. In all cases that were explored, the US algorithm detected the communities within two minutes. Given the scope of the research conducted,

the performance of the US algorithm on large-scale, weighted, and directed networks is unknown. Researchers are advised to take this under consideration until these types of are explored, Thus, future research will focus on using the US method to detect community structures within larger complex networks that are weighted and directed.

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