Community Detection by using cliques : A survey

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Abstract:
One of the most crucial fields that aids in understanding and analyzing the structure of huge and complex networks, such as social networks, collaborative networks, and web graphs, is communities' detection. The significant elements of research is the extraction of pertinent information from these networks. The goal of community detection is to reduction the application-generated graph into smaller communities with comparable nodes. The counting of cliques in a larger network is a fundamental problem in graph theory. There is many algorithm used for detecting communities and find the cliques, the maximum clique algorithm.
In this paper, a detailed survey of various methods applied for finding communities is given first. Then, the technique of clique , maximum clique and maximal clique is discussed and the main works that have been reported to detect social networks communities using these techniques is summarized.
Keywords—(social network, Community detection , Clique-based algorithm , Maximum clique-based algorithm).

I. INTRODUCTION

Complex networks refer to a collection of interconnected nodes that communicate and interact in various ways. These networks can be observed in social, biological, and technical systems. [1].

In social network analysis, nodes represent entities and edges represent their communication or interaction patterns. Typically, these networks exhibit sparse global connections and dense local connections, indicating the presence of community structures. The identification of influential nodes in dynamic social networks has gained significant attention due to the ever-changing nature of interactions between entities. Networks like Facebook, Twitter, and LinkedIn are dynamic in nature, with edges continuously being added or removed.[2][3]. Consequently, the selection and attraction of influential users play a crucial role. Understanding the structural and functional properties of complex networks requires a comprehensive understanding of the communities that bring entities together. [4[5]

A full understanding of the structural and functional properties of a vast network requires a thorough comprehension of the community that makes entities come together [6].

Community detection analysis is the procedure of identifying the clusters or communities on social networks. It is one of the most crucial components of a social network. It used graphs to analyze relationships between users on social networks to cluster users in different communities, which can be helpful in many applications in the real world[7].

community detection is the divided of network into clusters of strongly related nodes . To put it another way, nodes within the same community should be highly connected to one another while being weakly connected to nodes outside of that community. [8]. Weighted networks assign weights to the connections between nodes, and sparse networks have fewer links compared to their maximum potential. Connections in complex networks can manifest as various types of relationships, such as friendship, collaboration, or trade, with different capacities and intensities[9].

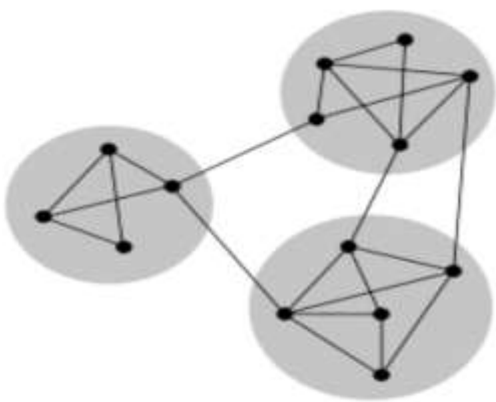

Fig.1 graph of community structure with three groups with dense internal connection and sparser connection between groups

I. Clique based community detection

The clique is a subset of undirected graph vertices where each pair of different vertices is neighboring. The clique is made up of paired neighboring nodes that are connected by edges, each of which represents a full sub-graph. [10].

Clique is used to identify shared nodes in a graph to create a community. Finding the communities in a network depends heavily on cliques. The fact that the nodes in the cliques are totally connected to one another which indicates that they must belong to the same community. [11].

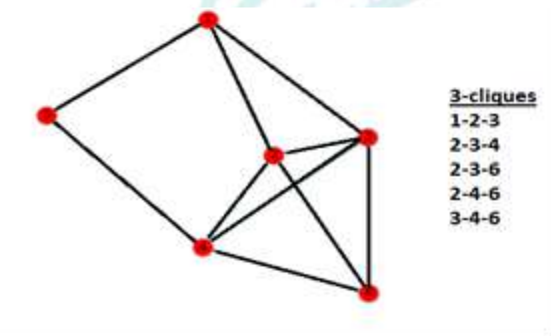

Fig. 2. A Graph with 5 cliques of size 3

Palla et al. [12] proposed the Clique percolation method for community detection. According to the theory of "clique percolation," edges within the same community can produce a clique, but edges within other communities cannot. Using these method, community structures may be interpreted effectively and quickly. They can also uncover sub graphs with a high degree of connectivity in order to estimate the communities that exist. As per Clique percolation, a predefined graph G is analyzed and all cliques of size cq are detected.

in [13] the author employed the graph coloring approach and the LDC algorithm to identify cliques in huge graphs, such as social networks. The new method uses an algorithm to color a graph, starting with the node with the highest degree in a certain graph. This research builds on previously completed work by adding features. Our feature, which uses a graph coloring algorithm to detect cliques, showed promising results when compared to other brute force and numeration algorithms. The results show that the improved algorithm performs better and runs faster than the other algorithms in terms of time complexity. where the research In [14] built a hierarchical clustering procedure on user relationships and interests networks to find the clique of communities. They used semantic analysis and the following/follower relationships to calculate edge weight to improve community detection. The original network changed into a new network, including the undirected and weighted edges. The weights generate using the direction and interest vectors in the original network, and the edge weights are used to find the similarity between edges. The hierarchical clustering algorithm is used to identify communities based on the edge-weighted similarity.

In[15] Three clique generalization problems were put forth by the author. They are the maximum weighted co-2-plex problem, the minimal k-core problem, and the minimal k-core problem. The method used to resolve these issues advances the field of study regarding clique generalizations. They talked about the minimal k-core issue and how it relates to the investigation of associative memory. They specifically explained how the closure of a minimal k-core relates to the idea of cell construction. and investigated two potential solutions to the MWC2P problem for {claw, bull} - Free graphs. Ultimately, they offered a solution for the least k-core problem. The two methods presented can both be solved in polynomial time. In this study, they underline the possibility of a more effective solution when some additional inequalities are added to the LP relaxation of an IP.

The authors in [16] proposed a new overlapping community detection algorithm based on density peaks (OCDDP) to detect cliques. A distance matrix computation approach is initially presented. After that, a three-step technique for selecting community cores is used to calculate the centers of the clusters. Finally, they developed a node allocation mechanism based on membership vectors. The efficiency of OCDDP performs well when dealing with simple networks compared with the existing techniques, while OCDDP still performs well with complex networks. Where the research in [17] proposed Attracting and Recommending Degree (AR-Cluster) graph clustering algorithm to detect communities in social networks. A novel collaborative similarity metric is used to cluster nodes together in the AR-cluster approach based on calculated similarities among vertices to calculate node similarities. A K-Medoids framework adopts to clustering graph. The results have shown that the AR-Cluster approach performs well compared to the other three techniques (W-Cluster, SA-Cluster, IGC-CSM). This approach is challenging to use for large social networks.

In[18] The authors reduce the temporal complexity of the Louvain algorithm. As the first step of the algorithm, a clique-Louvain algorithm was suggested to detect cliques with at least three members. In essence, every clique or node in the graph that is not a member of a clique is a community. A clique's members are more likely to practically belong to the same community. Hence, it is possible to draw the conclusion that cliques, which are thought of as the center of communities enhance the algorithm's performance while maintaining relatively high quality. Where the research in [19] offer Pivoter, an exact clique counting algorithm that counts all k-cliques faster than other cutting-edge parallel algorithms. The use of pivoting to build the SCT (concise Clique Tree) a concise representation of all the cliques of the graph, is one of the important concepts. We might be able to create a parallel SCT solution that is effective and considerably quicker than our existing one. when evaluations against alternative techniques demonstrate the usefulness of the suggested approach.

Maximal clique

Community detection is a fundamental task in graph analysis that aims to identify groups of densely interconnected vertices. One popular approach for community detection is the utilization of maximal cliques, which are subsets of vertices where every pair of vertices is directly connected[11]. A graph's maximal clique is a portion of the graph in which the clique's characteristic is lost when a node is added. An independent vertex set that cannot be enlarged to another independent vertex set by the addition of any vertex in the graph is said to have a maximal independent vertex set. [21].

In this literature review, we examine several studies that have focused on the application of maximal cliques for community detection in graphs.

The influence maximization problem was initially introduced by Domingos and Richardson [22], suggesting a probabilistic solution. They proposed a greedy algorithm that considered the maximal effect as an algorithmic problem and a stochastic Markov approach to obtain a probabilistic solution to the effect propagation process. Their greedy algorithm is very inefficient, especially in large social networks with a lot of nodes. From another view, several heuristics have been offered as potential IM time-saving measures. But The research in [23] introduced shared memory parallel techniques (ParTTT), For enumerating the most maximal cliques from a graph. ParTTT is A work-effective parallelization of a sequential algorithm . When compared to the present state-of-the-art on MCE (Maximal Clique Enumeration), our techniques significantly outperform it. According to our tests, ParMCE speeds up significantly as compared to an effective sequential baseline. Prior shared memory parallel MCE approaches, in contrast, either ran out of memory or were unable to process the same graphs in a reasonable amount of time.

in [24] This paper explores a technique proposed by Ding et al. [2008] for locating a maximal clique in a graph. The efficiency and runtime of the technique, measured by mean CPU-runtime, are examined using different types of graphs and a range of adjacency matrix sizes. The authors utilize manually constructed adjacency matrix structures, random graphs, and random intersection graphs to evaluate the technique's performance. The results shed light on the effectiveness of the approach in identifying maximal cliques. and the research In [25] creates a number of fresh approaches to maximal clique search in ambiguous graphs. To be more precise, we first suggest an effective core-based pruning method to remove nodes from an uncertain network that are not part of any maximal clique. We suggest a novel algorithm to compute one of the maximum cliques based on multiple carefully thought-out upper-bounding techniques, as well as a new strategy to enumerate all maximal cliques on the pruned uncertain graph. The usefulness and efficiency of our algorithms are demonstrated by extensive trials on six real-world datasets.

in[26] The author described a technique for finding communities in graphs. Our approach is focused on finding the maximal clique network and making the maximal clique graph. The SCoDA (Streaming Community

Detection Algorithm) and OSLOM (Order Statistics Local Optimization Method) algorithms were modified to include a pre-process phase in which a maximal clique network was created. The revised methods were given the names MSCoDA and MOSLOM. The addition of this pre-processing stage was done in order to increase the precision of community detection in graphs with overlapped communities and complex community structures. In all of the test graphs, we showed that our new approach, MSCoDA, performed better than SCoDA. But the research in [27] propose a method to identify nearly fully linked cliques in graphs by counting approximate maximal cliques. They highlight that starting with a triangle as a seed guarantees the presence of at least one clique among its projected vertex sets. The objective is to employ heuristic search to locate all approximate maximal cliques that meet the heuristic's constraints within each triangle's projection. The study utilizes the A* search algorithm to select the best approximate maximal clique while eliminating less interesting nodes.

The work in [28] introduce MacroIE, an OpenIE system that is non-autoregressive. It relieves the burden of forecasting the extraction order of many facts in previous autoregressive OpenIE models by predicting the fact set at once based on a novel view of OpenIE as a maximal clique discovery issue. Experiments on two public datasets demonstrate that our suggested networks surpass cutting-edge baselines in every metric. Whereas the research in [29] address the issue of overlapping maximal cliques in graphs. They propose four types of clique summaries, including τ-visible summary (clique-based), expected τ-visible summary (clique-based), τ-cover (vertex-based), and expected τ-cover (vertex-based). The problem of finding the τ-visible summary is proven to be NP-hard, and two deterministic strategies using local and global filters are investigated. The study also presents an optimal sampling technique for determining the anticipated τ-visible summary, ensuring accurate coverage of all maximal cliques while maintaining conciseness.

In]30[The authors of thisreserachfocus on the structural and algorithmic aspects of probable maximal cliques and minimal separators. They particularly examine graphs with a small number of minimum terized complexity. The study establishes separators and investigate parame a new relationship between the structural properties of graphs, their number of minimal separators, and likely maximal cliques. Notably, they he demonstrate that an exponential function of the vertex cover number or t modular width provides an upper bound on the number of minimal .separators and likely maximal cliques in any graph

III. Maximum clique based Community detection

Introduction: Maximal cliques are an important concept in graph theory that plays a crucial role in various applications, including community detection, network analysis, and optimization problems. This literature review explores the definition and properties of maximal cliques, as well as recent research efforts in solving the maximum clique problem and utilizing maximal cliques for graph analysis[31].

Definition and Properties: A maximal clique is a subset of vertices in a graph where each pair of vertices is connected by an edge and cannot be extended further without violating the clique property. It represents a fully connected subgraph within the larger graph. It is worth noting that a maximal clique may not necessarily be the largest clique in terms of the number of vertices, while a maximum clique refers to the clique with the maximum number of vertices in a graph[32].

The maximum clique problem aims to find the largest clique in a given graph. It is a well-known NP-hard problem that has attracted significant research attention. The clique number, denoted as $\omega(G)$, represents the number of vertices in a maximum clique of graph G. Additionally, the concept of maximum clique transversal refers to a subset of vertices that must be present in every maximum clique of the graph.

In Fig. 3 nodes {1, 2, 4, 5}a maximum clique of size four means that No clique larger than four nodes can be generated.[11].

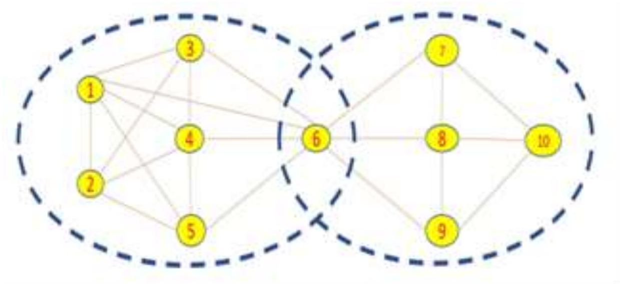

Fig. 3 .Community structure

Recent Research Efforts: In recent years, several studies have focused on addressing the maximum clique problem and exploring the applications of graph analysis. These studies offer valuable insights and maximal cliques in propose efficient algorithms for solving the problem and utilizing maximal .cliques in various domains

In[33] In order to further improve the MCP's (maximum clique problem) exact solution, a better coloring approach can be used to estimate the upper bound. Due to the different structure of graphs, we can find that a few algorithms outperform all others when using local search techniques. including numerous search operators into a single algorithm and including dynamic capabilities to choose the most permissible operators to be triggered during the search process may be one solution to address this shortcoming. Where the research in [34] introduces the RMC (Recursive Maximum Clique) algorithm, which employs a binary search schema to find maximum cliques. By maintaining lower and upper bounds on the clique size, RMC iteratively searches for a clique of target size within each iteration. The authors present a novel iterative brute-force searching approach called divSeed to update the maximum clique when the seed set is exhausted. Experimental results demonstrate the effectiveness of the RMC algorithm.

In the context of continuous formulations for the maximum clique problem, a study [35] introduces a new formulation based on symmetric rank-one nonnegative matrix approximation. The authors establish a correspondence between maximal cliques and local optimal solutions of the continuous formulation, and propose a clique discovery procedure using a projected gradient method. Experimental comparisons with other continuous and discrete methods validate the effectiveness of the proposed algorithm. But the research In [36] provided a hybrid approach For the maximum clique problem,. The heuristic approach HTS (Hybrid Tabu Search) is utilized to build cliques, and these are enhanced by tabu search and some straightforward optimizations. This algorithm used A pseudoexact algorithm with some particular pruning . Preprocessing is advantageous in several situations. The algorithm's effectiveness is demonstrated using both established and novel benchmarks.

Another research effort [37] By converting instances of MCC-Sparse into instances of KCF(f k-clique finding)-Dense, we created a link between MCC (Maximum Clique Computation) over sparse graphs (MCC-Sparse) and MCC over dense graphs (MCC-Dense), and we created a branch-reduce-&-bound framework for KCF-Dense. We created the ego-centric heuristic algorithm MC-EGO as well as the exact algorithm MC-BRB. The usefulness and efficiency of our methods were demonstrated by experimental results on huge actual graphs. Where the research in [38] is proposed a metaheuristic algorithm to solve the maximum clique problem in social networks. The algorithm, based on the ABC (Artificial Bee Colony) optimization method, addresses the NP-hard nature of the problem and provides efficient solutions. Evaluation on both large-scale instances from the Facebook social network dataset and standard examples from the literature demonstrates the effectiveness of the proposed approach.

In [39] The authors of this study propose a three-stage method for community detection using maximum cliques. The stages include central node identification, label propagation, and community merger. Central node identification involves identifying central nodes based on node distances. Label propagation assigns the same color to nodes that exhibit maximum similarity. Finally, communities are merged if it results in an increase in modularity. The complexity of this approach is noted to be high for large networks. Where the research in[40] was proposed The reverse enumerative approach, or REA, as a better heuristic approach that improved the upper bound of the EA algorithm. The clique size induced on each vertex is stored in extra memory and later used while pruning the branch.

The technique stores the greatest clique discovered before for each vertex into a unique array called b. Therefore, when looking backward, b[i] is the greatest clique for the i-the vertex. But the research in [41] Using neural networks and AI techniques, the author created a novel method for locating the largest clique on a protein graph. It is a fresh method that has never been created before, and its outcomes demonstrate a surprising acceleration in identifying the proper maximal clique on the product graph. Fast algorithms that can solve the maximum clique problem are crucial for discovering new medications and understanding protein function. We developed several variations of the new MCQD-ML ((Maximum Clique Dynamic-Machine Learning)) algorithm by applying a few machine learning techniques to a regression problem in order to accelerate a dynamic algorithm for maximum clique search.

IV. CONCOCTION AND SUGGEST FUTURE WORKS

Nowadays, community detection is one of the interesting areas of networks analysis because of the rapid growth of the social network. Including information into the nodes and community can help discover the perfect community. There are several types of algorithms that used to detect community’s ,By studying these algorithms, we noticed that this algorithms contains many problems in communities detection, including not getting good results in identifying communities. in this paper we used the clique , maximum clique algorithm and maximal clique .Maximum and maximal cliques are fundamental structures in graph theory with numerous applications in graph analysis. Recent research efforts have focused on solving the maximum clique problem and utilizing maximal cliques for community detection, clustering, and optimization tasks. The proposed algorithms and techniques have shown promising results, although scalability and computational efficiency remain ongoing challenges. Further research in this area can contribute to the development of more effective algorithms and the exploration of novel applications of maximal cliques in diverse domains.

As a future work we decided to combine the maximum clique algorithm and Leiden algorithm to increase the possibility of obtaining good results in discovering communities.

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