International Journal of Computer Sciences and Engineering Open Access

Research Paper Vol.-6, Issue-9, Sept. 2018 E-ISSN: 2347-2693

Study of Clique Based Community Detection Algorithms

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Available online at: www.ijcseonline.org

Accepted: 16/Sept/2018, Published: 30/Sept/2018

Abstract**—** Social networks are generally represented as graphs (nodes represent users and edges represent their associations). Community in a social network means group of people which are more closely connected to each other as compared to their connection with rest of the people in the network. Clique in a graph is a subgraph such that each node in the subgraph is connected to every other node of this subgraph (complete subgraph). In this way clique is strict version of community. Community detection in social networks has attracted researchers effectively due to its wide range of applications. Cliques, having similar characteristics, prove to be highly applicable in community detection process. There are several community detection techniques in the literature which are developed around cliques. Generally these techniques fall into category of clique percolation methods. Clique percolation is a prominent approach that is based on k-cliques in the graph. This paper represents a detailed discussion of significant k-clique based techniques existing in community detection literature.

Keywords**—** Social Graph; Clique, Community Detection, Social Network Analysis.

I. INTRODUCTION

A clique is a closely connected group of individuals which follow a unique pattern of communication. The bonding between the members in a network has a certain characteristic that distinguishes them amongst one another. Networking involves combining new nodes and forming a relationship among them thus leading to formation of a structure. These structures are studied on a perspective that a set of methods are used for their analyses and on unmasking their patterns new theories and predictions statements are made. Certain criteria are taken into consideration including identification of local and global patterns in a network, to discover the influential entities, examining the dynamics of the network based on frequency and other attributes. Social network analysis has emerged as an interdisciplinary to sociology, statistics, psychology, graph theory, social sciences and behavioural sciences [1]. These network analysis methods uncover the patterns associated within the network.

With the increasing population and the usage of media the networks formed are complex and have communities, clusters and modules formed out of nodes linked together sharing a relationship. These communities could be functionally, behaviourally or structurally part of a network. Community discovery mechanism thus is a powerful tool to find these communities and understand their behaviour [2]. There have been many methods proposed to find the community in the network so as to study the overlapping attributes of the nodes. A clique is a complete subgraph whose nodes are densely connected and share a common trait and interest. Finding such complete graphs in a network where the number of nodes connected is largest is called maximum clique problem [3]. The social network have many applications including the clique problem such as community detection [4,5,6], information retrieving [7], recognising the patterns [8] and many more. Community detection is discovering the patterns occurring in the events when these communities are formed [9]. A major work has been already conducted to examine the changes taking place in the communities but the fall out was the static framework. The dynamic network study includes the changes in the nodes rapidly without notification of its resolution and dissolution. Thus dynamic network study analysis gives the topological changes with the growth in graph. Leskovec et al. [10] gave the graph generation model for studying the evolution of the communities. Backstrom et al. [11] describe the communities' structures and features using the decision tree and finding the probability of other individual nodes to join any of the communities.

Many researchers have been continuously working on the problem of community detection using different strategies and attributes. One of the methods of finding the community in the network is through the clique finding problem. There are different algorithms proposed involving of finding the clique either maximal or maximum. The maximum clique is the one which is the largest clique having largest number of nodes while maximal clique is the one whose nodes are not a part of nodes in the maximum clique. This paper studies few of the algorithms that have been proposed for community detection using the clique. The paper is divided into different sections that describes the following algorithms briefly and understand their limitations and goodness while discovering the community in the network. The different sections are stated as section 2 describes the terms associated and used in understanding the cliques with few methods that have their influence in working to find the community using clique. Clique based community detection techniques proposed by researchers are discussed in detail in section 3. The conclusion is given in section 4.

II. PRELIMINARIES

This section defines the notions that are associated in understanding the clique and community detection and the terms used in the algorithm. The figure 1 shows the structure with various communities linked together in a network. These communities are further represented in the form of a graph G (V, E) where V depicts the number of associated nodes or actors to the graph and E depicts the relationship formed between these nodes that are bonded with the edges. The clique is the complete subgraph and two cliques are said to be adjacent when k-1 number of nodes are shared amongst them. The adjacent cliques together form a connected component which is further referred to as the community

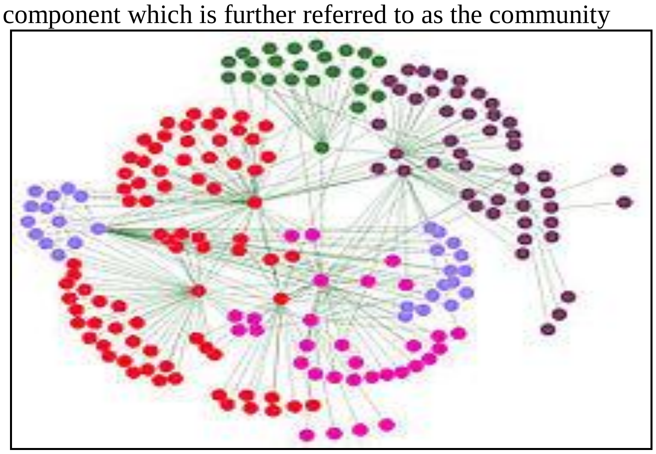

Figure 1 A network structure with communities shown with different colours.

Understanding the terms associated with the clique and community detection:

[1]. k-Clique: it is a graph whose all the vertices are joined to one other forming a complete graph whose total vertices equal to k.

[2]. k-clique adjacency: when a common vertex is shared between two cliques then two cliques are said to be adjacent.

[3]. k-clique chain: when adjacent cliques are joined together one after the other in sequence then they form clique chain.

[4]. k-clique connectedness: the subgraphs of the k-clique chain are k-clique connected.

[5]. k-clique percolation cluster: the combing of the k-clique connected cliques to particular k-clique for forming the maximal k-clique.

[6]. k-clique community: the collective combining of all the cliques where each clique is reachable through adjacent k-cliques.

[7]. Intersection Examining: In community detection to determine whether two cliques are adjacent to one another an intersection examining is conducted which gives the idea as to which clique would be part of the same community.

[8]. Maximal clique: It is a complete subgraph which depicts that when number of k-cliques are more in the same community then value of k is also larger and clique of size k are also larger in number thus maximal clique should remain intact thus not breaking k- cliques into smaller size cliques where the traversing of the graph with smaller size clique would unnecessary increase time.

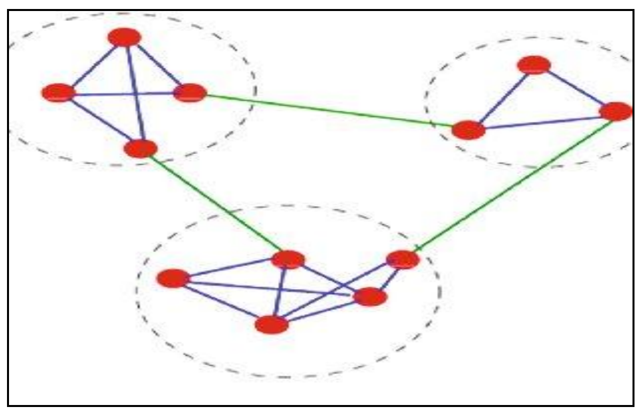

Figure 2 Mapping of one node to another and also mapping one clique to another.

The mapping of the nodes is done with either nodes or cliques where further cliques are mapped to other cliques adjacent to them and on the union of these mapping a community is found as shown in figure 2. The community is discovered by using different methods defined by research scholar to know their behaviour and feature. Various authors have published their work in finding the community in the network but most important is the attribute they have covered and taken into consideration. Asur et al. [12] analysed the community and their behaviour by defining the events occurring in the form of interaction. The factors taken into consideration included stability, sociability, popularity and trends with influential nodes. Falkowski et al. [13] analysed the community evolution by studying the stability and giving the fluctuations while depicting them to be part of the same community. The next section details certain methodologies which exist in literature and are used to detect community in a network.

III. Clique based community detection Methodologies

A. Clique Percolation Method

CPM is a community finding method which is used for overlapping communities shown as in figure 3. When two cliques are adjacent that means they share k-1 nodes and these cliques further join together to form community by percolation with each other. The algorithm involves two steps where the first step is to find the maximal clique and in the second step these cliques are converted to communities by joining. The brute force search mechanism finds the maximal cliques. The nodes with smaller number of vertices forming the clique are firstly considered. When cliques of all the sizes are found then their combining is started. Beginning with one node join with other or one node combined with the clique the chain is formed and cliques of larger sizes are discovered.

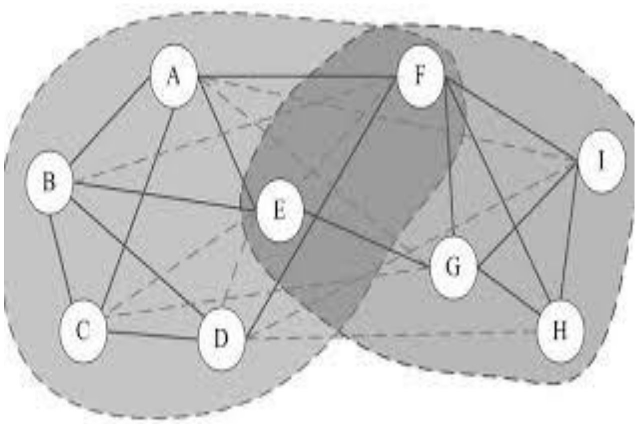

Figure 3 A clique percolating with another clique

One after another node is checked until the node with the desired size is the maximum rest the nodes are discarded. The proposed method by Derenyi et al. [14] considers the random graphs to associate the percolation of the cliques in which it is stated to be mandatory for a threshold value to be considered. The threshold value is the threshold probability p = pc(k) , where k is the size of the clique and pc(k) is given as in equation (1).

$$P_c(k) = \frac{1}{[(k-1)N]^{\frac{1}{(k-1)}}} \quad (1)$$

This is the percolating element that has 2 alternatives for mensuration however the foremost vital issue is selecting the value of the threshold that appears to be tough as setting its value to be high would discard many nodes thus these nodes if not thought of won't provide the acceptable results whereas on the other hand setting the value to be low then the percolated clique wouldn't be able to alter with this value therefore the value has to be somewhat close to an essential value so on alter the nodes and recognize the cliques. This paper conjointly offers bound alternative formulations once considering the various values for crisis.

Thus the constraints within the projected model ought to be additional reduced with bound modification considering the quality to be reduced and therefore the network is fully coated for dynamic teams with additional increase within the potency.

B. Sequential Clique Percolation Method

The clique percolation methodology given by Derenyi et al. [14] covers the overlapping communities and considers the native topology of the network whereas the algorithmic rule given by Kumpula et al. [15] Conjointly advocate the weighted and unweighted network. This algorithmic rule tracks the communities and at the same time adds one by one links to the constituent network then the process time is scaled linearly with relevancy range of cliques within the network.

This paper queries the constituents comprising the community. There is a wide range of the network that is to be thought-about and which might cause the required results may be a matter of truth that is strictly outlined thus on grasp either it’s a neighbourhood network or the values is foreseen as a global network. This methodology offers the clique percolation method for a neighbourhood topological networks finding the overlapping communities whereas there had been any researches for constant wherever the communities disagree. These papers are reviewed for the data purpose considering the protein interaction networks [16]. Proteins are the building blocks for the biological functions within the living organism whereas operating with people in general there's the neural networks to be studied. The neural networks embody the study of genomes wherever the characteristics within the proteins are to be analysed. The loop shaped within the structure of the people in general has huge connected networks that forms several communities on the common characteristics shared between them.

A whole structure wherever the 3D loops are studied and sure formulations are then generated. The study relies on the atom ideas and formulations provide the concept on however these connected structures are tagged and foreseen for the ordering project. The advantage of learning this algorithmic rule is to grasp the fitness within the conformation of the sides and nodes within the living organism.

The sequential clique percolation works on the principle that the links are inserted within the decreasing order of the load that detects the communities at the threshold that's chosen. On the basis of this the dendrogram is generated that represents the hierarchy during which these communities are maintained as shown in figure 4. The similar conception utilized by Derenyi et al. [14] is first taken into thought with the modification that cliques are detected and consecutive links are incorporated with the cliques forming the communities. This algorithmic rule covers the bipartite graphs with weighted edges and nodes. The performance is computed considering the network size and also the cliques found within the network. The paper conjointly offers the scaling pictured diagrammatically. This algorithmic rule is quick for analysing the bands once the scale of k is tiny therefore threshold worth isn't affected a lot whereas it will offer indifferent results when the scale of the clique will increase or a lot of nodes which high range are added.

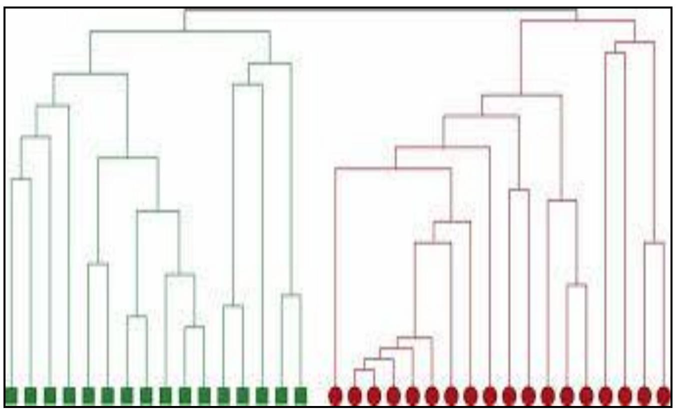

Figure 4 A dendrogram

C. Extended Clique Percolation Method

This is the modification to the sequential clique percolation technique in which the steps are projected as

I. The community structures are initially found that are used at successive step for the new community formation with taking them along the recently side nodes.
II. The communities are updated by considering the unnoticed nodes and taking care of the characteristics that are common amongst them.
III. The communities are united into one part that shares the common interests.

This formula given by Maity et al. [17] covers all the nodes within the network even the isolated nodes are considered. The vertex colouring formula helps to cover the nodes that share common characteristics which might simply distinguish the communities. The nodes that don't belong to any cluster are known and for all these nodes a replacement community is made. Once all the communities are fashioned and every one the nodes of the network are a part of any community then there's a break that some communities might share atleast a standard interest and that they are often fence like as one community. Therefore by merging the communities and changing the structures the analysis is completed.

The projected model offers the modularity as the measure for the community structure. The connected nodes are taken and also the isolated nodes that are still unnoticed are considered. The more the value of modularity the higher is the community structure. The limitation embrace that the extended version has higher quality than the clique percolation technique.

D. Distributed Clique Percolation Method Using MapReduce

The network with the increasing youth awareness of social media has become vast and thus this distributed network study has become a necessity so as to know the behaviour of the communities associated within the network. The small network in itself has a large number of cliques within them so to study large network a distributed algorithm based on the MapReduce mechanism is proposed by Varamesh et al. [18] which challenges to cover the entire network by extracting the cliques of larger size to be further used in the method processing.

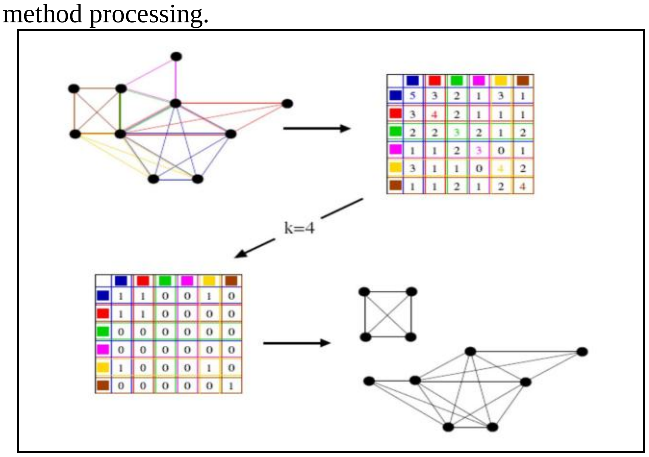

Figure 5 The Clique Percolation Method mapping with other cliques using Vertex colouring.

Figure 5 represents clique percolation using color coding which is then handled by MapReduce process shown in figure 6. MapReduce is a framework working with two functions Map and Reduce. These functions works so as to cover the large number of independent synchronised nodes and the processing is done in parallel. The Map function uses key pairs of the nodes as input to study them with respective other nodes in the network which then give some new key pairs to be read by the reduce function as the input if those pairs fulfil the criteria of the function the new key pairs are generated and processing is carried further else the pairs are reduced and then the key pairs generated are used for further processing.

MapReduce method is executed only after the algorithm for finding the cliques is executed and all the desirable cliques are known initially. On discovering the entire cliques the MapReduce method first percolates the cliques with one another to form the communities and finally the function maps the other nodes into the communities with the reduce function working simultaneously. The main issue to execute the finding of the community with large networks brings out of memory and IO work load which is reduce comparatively using this method. The execution time and IO work load is improvised by working in parallel and reducing the set by the functions.

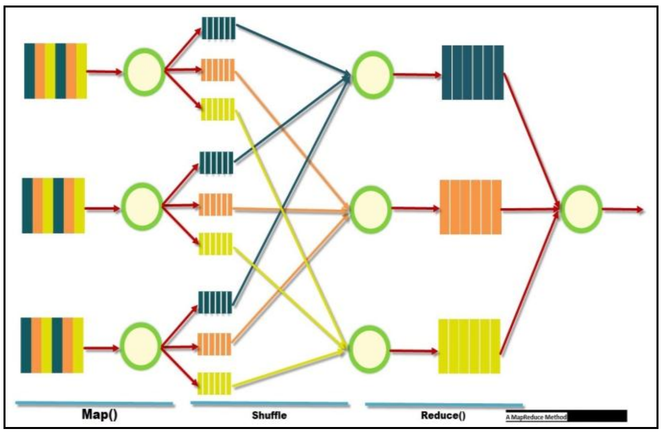

Figure 6 Working of the Map Reduce Function In the Network

Though the method has brought up improved results but the number of comparisons could not be reduced which makes the algorithm better in covering certain areas but if the comparisons and traversing of the graph could be reduced then this method could bring more efficient and better results with respect to time and efficiency.

E. Union-Find Function For Community Detection

This function is used as an improved method in solving the community detection problem. Union-Find function is represented as a tree based structure where the dynamic connectivity between the nodes and various cliques in the network could be clearly visible. Representing the structure to tree format can help it convert into the list structure to easily deform and study the changes occurring in the topology. Tree representation makes the structure highly efficient when insertion of nodes and query within nodes is to be done. The path compression and rank equilibrium maintenance allows the tree structure to easily executable.

The union operation joins the two trees only when they have a common ancestor existing between them thus there could be a relationship built and thus they can be assumed to be a part of the same community. The find operation thus finds the root node to the sub tree and in the process it also takes care of the path compression so that the tree remains balanced and new nodes can be added to the tree if they are part of it.

The main motive is to reduce the intersection tests between the cliques so as to reduce the number of comparisons and thus data set can be reduced which increases the time and efficiency. The method works on the principle of mapping the node with the clique or a clique with another clique as shown in figure 7.

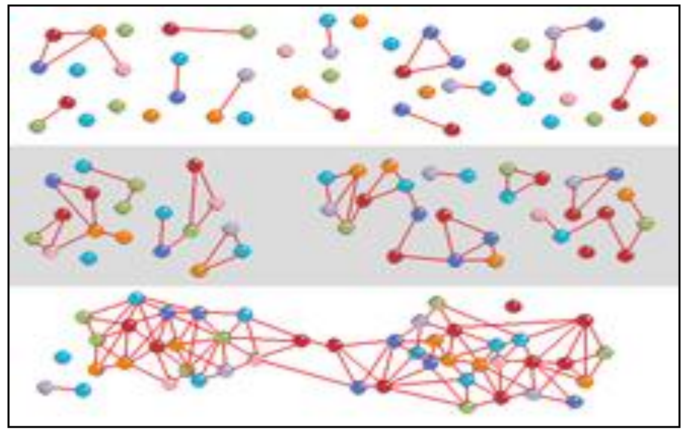

Figure 7 Node-Clique mapping which is later converted to Clique-Clique mapping.

The method is given by Jing et al. [19] begins with finding the entire set of largest possible cliques in the network and storing them with the ID. The network is then mapped using Node-Clique mapping and these nodes are further used to map Clique with other adjacent cliques. The cliques in the same community are then studied using the Union-Find function and the cliques in the communities are split with further checking them with other communities and the intersection tests gives the idea as to which all communities are reachable to each other and are adjacent. The method is terminated when the maximum size of the cliques adjacent to one another are known and joined to form a large community with using the DFS search the largest amongst them is known. The advantage of using this method in discovering the communities is that it reduces the traversing sets of nodes while updating the union-find function simultaneously which leads to covering the entire communities in a network within linear time reference.

F. Community Detection Using Formal Concept

The previous research work on discovering the community in the network covers various aspects which reduces the time or is efficient enough to deal with large networks. A formal concept analysis enhances the topological impact on the network and clearly makes it understandable which communities have similar traits and behaviour. Social network analysis includes the cyber space where people are connected through the friendship ties or relationship bonds but it is matter of fact to better relate and knows what has made the bonds attached to each other strongly.

An adjacency matrix is maintained along with the formal concepts visualization which finds the equiconcepts based on the formal statements defined. These equiconcepts finding problem is equivalent to finding the k-clique detection problem. Thus to better find solutions for the community detection the method proposed by Hao et al. [20] assigns social network vertices as objects and their relationship as attribute. The formal context is described relating both the objects and the attributes on account of the formal context. The adjacency matrix is modified with the objects and attributes relation. Table 1, table 2 and figure 8 represent complete process.

Table 1 Adjacency Matrix

	C1	C2	C3	C4	C5	C6	C7
f1	X			X		X	X
f2		X		X	X		X
f3			X		X	X	X

Table 2 Equiconcepts

T	{f1,f2,f3},{c7}
Concept 1	{f1,f2},{c4,c7}
Concept 2	{f1,f3},{c6,c7}
Concept 3	{f2,f3},{c5,c7}
Concept 4	{f1},{c1,c4,c6,c7}
Concept 5	{f2},{c2,c4,c5,c7}
Concept 6	{f3},{c3,c5,c6,c7}
⊥	{ϕ},{c1,c2,c3,c4,c5,c6,c7}

The formal concepts including the k-cliques are taken into account when equiconcepts for the cliques are defined as the formal concept and then the algorithm is executed to know the better behavioural influence of the community. Based on the intent equiconcepts the concept lattice is read and the modification in the process is done. FCA is the intelligent way to keep up the analysis as to how the object and attributes are interrelated. Table 3 represents a scenario where different people refer different breads. In figure 9 a lattice is prepared from table 3.

The main method categorizes into three different steps where initially formal context from the social network is extracted and addressed. In the second step the relation between the concept lattice is studied and its object and attribute relation is found. The last step detects the k-clique communities in the network. The every diagonal element whose value is smaller than k is replaced and the adjacency matrix is modified with the concept lattice.

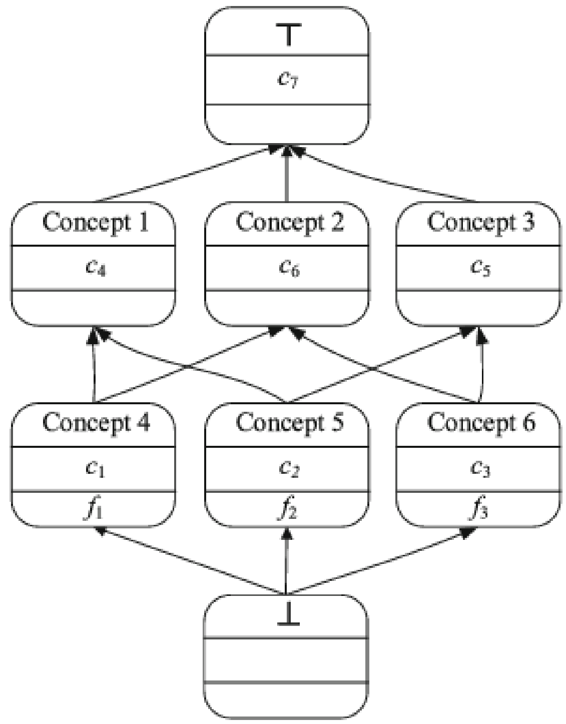

Figure 8 The formal concept defined and the adjacency matrix maintenance.

Table 3 An example of FCA-context about people and their preferred bread

People	People preferred bread			
	h1	h2	h3	h4
p1		x		
p2	x		x	x
p3	x		x	x
p4	x		x	
p5	x			
p6	x	x		x

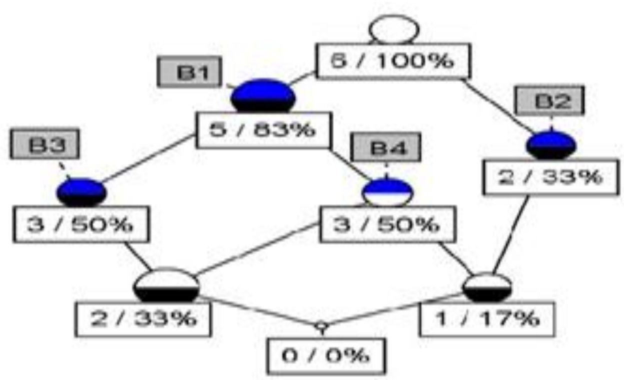

Figure 9 The Formal Concept Lattice built using the adjacency matrix.

The algorithm gives better results by significantly reducing the overlapping dimension list and the cost of computation is relatively reduced. Since there is no major requirement to find all the k-cliques only intent concepts work for the extraction thus the traversing steps number is also reduced. This method may have advancement and its application in mere future covering targeted marketing and E-health fields.

G. Weapon System Architecture Optimization with k-clique community detection

With the complexity attached to the weapon system architecture it has become evident that the system should perform well combat results with reusability and flexibility. The drawbacks in the traditional system included the isomerism of interfaces and the relation between their views was effected when attacked. Thus to address the efficient changes the viewpoint was enhanced and improved constructive processes with their services were identified and based on this good knowledge workers were allotted to make decisions.

The necessity of the system requirement made to know the better description of the communities in the system which is treated as the supporters to the activities and events taking place within the network. The System operation activity was studied with the set of relations operational to the global network. Based on the relationship between the actors the adjacency matrix is listed and this adjacency matrix is recreated using the transformation operations that find the clique from the network. The clique detection makes it easier to know which nodes are jointly connected and reachable to other nodes and thus community is evaluated. The major evident operations help to identify the services to be taken care of in weapon system architecture optimisation.

The WSA service optimisation method proposed by Wang et al. [21] illustrates the network using the gephi tool to show that different structures of the same network at other instant changes the point of view of the network. Thus GPS has the vital role in examining where the service needs to be provided by the change in the network view.

H. Influence Propagation Model for Community Detection

Social influence not only is now restricted to being available over networking sites but has increased the trend of being the active user with lots of followership. Thus this leads to the increased interaction rate amongst the users with the unknowns and forming various trend-setter communities. The proposed work by Alduaiji et al. [22] includes the network study based on the temporal interaction biased community detection as depicted in figure 10. The method follows four prominent steps to visualize the stable network interactions. The first step is the partition approach where the network is divided and certain cliques are built up out of the network covering the entire network. The second d=step uses the influence propagation approach and assigns the weights to the edges based on the frequency of the interactions held between them. In the third step the model is expanded to find the densely communicated relationship and the activities taking place between the communities is monitored. The final step gives the metric measures verifying the effectiveness of the approaches used in the data sets of the real world network.

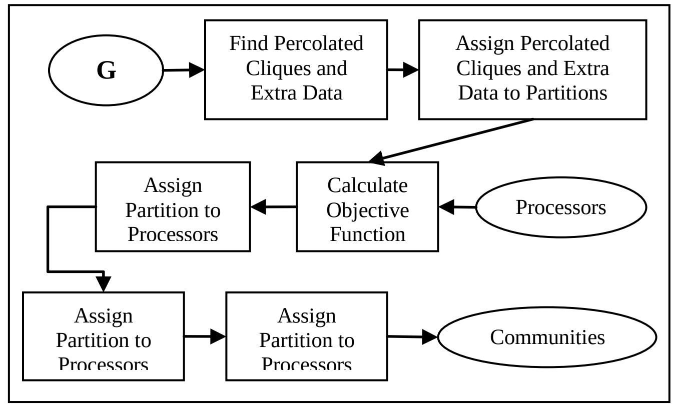

Figure 10 The framework working on finding the communities.

This paper closely considered the dynamic graphs for focusing on the influential and active communities thus giving the idea for the related activities prediction. This approach finds those active members who has a great impact on their adjacent neighbors and whose interactions make the communities increase their potential to add new members thus making the number to increase. The active members who are likely to become the most influential members of the community are recorded and their interactions are monitored in parallel so as to keep the record of the entire network. The overlapping nodes and communities are taken into account by executing the temporal biased interaction algorithm which maintains the densely connected nodes and the activity that occurs between them.

This approach not only works upon the strongly connected users but also challenges the weakly connected nodes to become the active users and an important element of the network. The author has redefined the definition of active edges and considered every node in the network to be influential enough as to change of the scenario is possible anytime. The method has its applications in various fields including prediction of the links, advertisements associated with the social network and knowing the members interested. This model works extremely well due to the portioning of the network which reduces its computation time with reduction in the comparison of steps.

IV. CONCLUSION

In this paper various prominent clique based community detection algorithms have been discussed. The different algorithms studied in this paper cover certain effecting issues which are removed with their methods defined and explained. The scope for finding the communities in the network has immensely raised its importance with the digital media gaining the awareness. Thus the need to establish better algorithms for community detection needs to be improved taking into account the remaining factors such as frequency, cohesiveness and many more. The above algorithms perform better considering the issue they have taken into account. Much work is already done and researchers are ready to leave no stone unturned by covering every aspect including the dynamic network communication and knowing the structure of the nodes and their attributes completely.

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