Mapping of Interconnected Social Groups in online Networks and Exploring Digital Spaces for community detection

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Abstract:
Social network analysis (SNA) is the examination of social networks to comprehend participant behaviour and organisation. With heterogeneity and interdependencies posing as a major challenge, social network analysis (SNA) acts as a sustainable technique to study large-scale complicated social interactions. It offers quantitative techniques and topological metrics to analyse a network's topology in order to support transdisciplinary applications. This paper delves into the intricate digital landscapes of online social networks, aiming to elucidate the interconnectedness among social groups within these dynamic spaces. Through an exploratory investigation, we employ advanced network analysis techniques to map out the intricate web of connections that define the social fabric of digital platforms. By scrutinizing the structural characteristics of these networks, we uncover clusters and communities that delineate the underlying social groups and their interactions. Our findings shed light on the complex dynamics of online social behaviour, offering insights into the formation, evolution, and interplay of interconnected social groups in digital spaces. This study not only enhances our understanding of online social networks but also provides valuable implications for various fields, including sociology, computer science, and digital marketing. An important problem in social networking analysis is community detection.

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Introduction:
One of the main areas of study for social netw ork analysis is finding communities.
Communities that are found through social networks enable their users to communicate with relatable people who share their interests. However, the massive expansion of social networks today necessitates a thorough analysis of current work done to uncover the community detection in social networks. This research compares the most popular optimization technique in the field of CD with recent methods that have been deployed.

The application areas where CD techniques ha ve been applied are also described. This directs and motivates scientists to explore and advance their work in the field of identifying communities in social networks. Virtual clusters or communities are created as a result of people's propensity to connect in social networks when they comparable preferences, choices, and tastes. Finding these communities can be useful for a variety of applications, including discovering a shared research area in collaboration networks, discovering a group of users who share similar interests for marketing and recommendation purposes, and discovering protein interaction networks in biological networks. In the literature, numerous community detection techniques have been put out and used in a variety of fields. This paper provides an overview of the current methods and algorithms for identifying communities in social networks. We also go over a few of the users for community detection.

User activity on web-based social networks have significantly increased recently, regardless of location or time. Huge datasets produced by this interaction provide a wealth of opportunities for uncovering intriguing user behavior and comprehending networks. A social network is a collection of relationships or a collection of individuals with a shared language and who exchange messages (directly or indirectly) a connection or interest. The majority of the time, social networks are represented using pictures [1]. SNA stands for social network analysis. the social network with the intention of understanding its basic structure and members' behavior. For SNA, the community detection (CD) method is incredibly prosperous place that is important for various fields, including business, healthcare and moreover marketing etc. To realize new insights in SNA, data analysis techniques like data mining and predictive modelling are being applied. Using social networks to identify communities would be very beneficial for understanding user behavior, target marketing, promotional activities, etc. The ability to recognize community division in a network captures the propensity of nodes to create clusters based on similarity and subsequently form communities. A community, sometimes called a cluster, is thought of as a collection of nodes having a lot of connections to one another and few connections to the rest of the network. Finding communities within networks will help to provide crucial information about the structural characteristics of the networks. In addition, it keeps track of communications within the nodes. Numerous real-world networks provide evidence of community structure (Girvan and Newman, 2002). Analyzing communities is essential to understanding the associations in the network that are structural and functional. The structural feature possesses applications that are significant in a variety of fields, including viral marketing, modelling the identifying crucial nodes in power systems, planning for disaster assistance, and the development of an epidemic where a cascading failure could occur if these nodes fail. Numerous studies on CD emphasize the conventional methods and different forms of social network representation[2]. The research described in these publications describes the domain's current research trends and well-known algorithms. In general, different types of data, situations, and applications cannot all be served by the same algorithm. Every algorithm has its own advantages, limitations, and areas for improvement. Cai et al. present a survey that highlights the application of evolutionary computational methods in the field of CD from social networks.

Social networks have the distinctive quality of displaying a community structure. We say that a network exhibits a community structure if its vertices can be divided into either disjoint or overlapping sets of vertices such that the number of edges within a set exceeds the number of edges between any two sets by a sizeable margin. In networks with a community structure, a hierarchical community structure is frequently present as well. Community detection is the process of locating cohesive groupings or clusters inside a network. It is a crucial component of social network analysis2. Many applications where decisions are made by groups can benefit from the detection of communities in social networks, such as multicasting an important message. An individual's interactions and interpersonal connections with other members of society help to build their social network. Social ties between people are modelled and represented via social networks. Using the Due to the web's quick development, user contact online has greatly increased. several social, in order to promote user involvement, networking websites like Facebook, Twitter, etc. have also been developed. As the quantity, it is getting more and more difficult to maintain track of these conversations as the number of exchanges has multiplied. People with comparable preferences and tastes are more likely to become friends with one another. the user-friendly social media enables people to expand their social lives in previously unimaginable ways because it is challenging to meet new acquaintances in the tangible world, but finding it is considerably simpler.

A community is a collection of items that are more similar to one another than the other entities in the dataset. Individuals create community through fostering interaction among group members. more often than with people who are not in the group. The degree of intimacy within a group can be measured through comparisons of things' similarity or distance. According to McPherson et al.5, "similarity connects people. They talked about several social elements that influence homophily or similar behavior in networks. Similar to clusters in networks, social networks have communities. one particular portrayed by a node in graphs, anything may not only belong to one community or one group; it may also be a component of numerous diverse or closely related. Due to the massive increase in social networking site users, the graphs used to illustrate these sites are getting increasingly complex and challenging to perceive and comprehend. Communities can be thought of as summarizes the entire network, making it simple to understand. The finding of these social network communities can be helpful in a variety of contexts[3].

Community Structure: Inthe network, people are more likely to form groups based on their common interests, backgrounds, hobbies, etc. Suchgroups are known as communities or clusters, which are defined as a set of dense nodes with more internal links thanexternal ones. People know more people in their community than outside their community (Fig. 1). Similarly, in theirarticle, define community as a group where individuals are grouped around a common interest, and therelations within the group are more important than those outside the group. On the other hand,studies suggests that there is no widely agreed-up meaning of the term “community”. Besides, thedetection and discovery process of these communities is known as community detection[4]Fig1: Community Structure

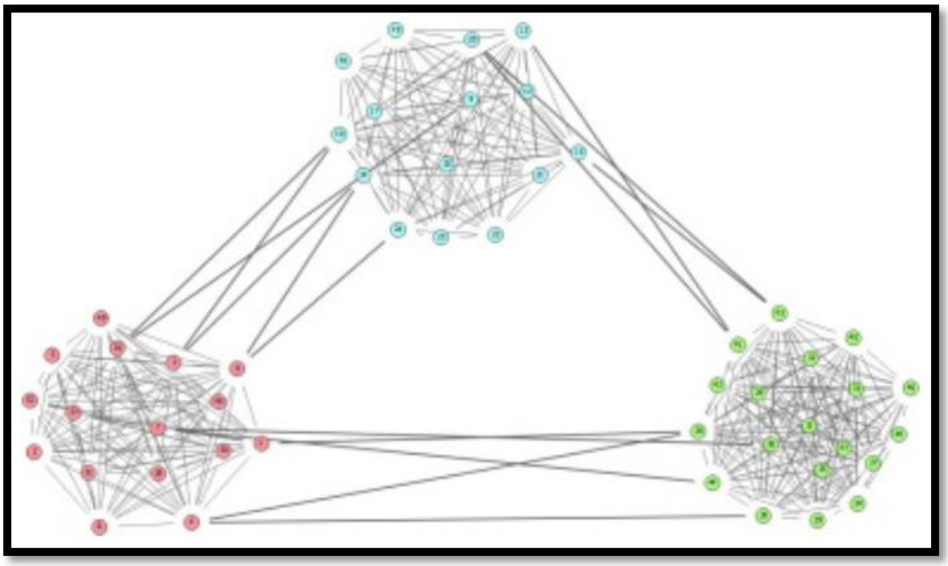

Figure 1: Community Structure.

An introduction of basics of community in social networks:

a) **Walk:** A walk in a network is defined as a collection of nodes that maintain relationships among one another. A stroll begins with the target node comes first, then the source node. while the stroll begins then that walk begins with a source node and concludes with the same node. is regarded as the closed stroll. A-B-C-FG is a walk in that network, and D-C-F-E-D is a closed walk, as shown in Fig2.The efficacy of random walks in building unstructured peer-to-peer networks and conducting searches. With a Supervised Random Walk, which combines the information on the properties of the network structure of the edge level properties and the nodes[5].

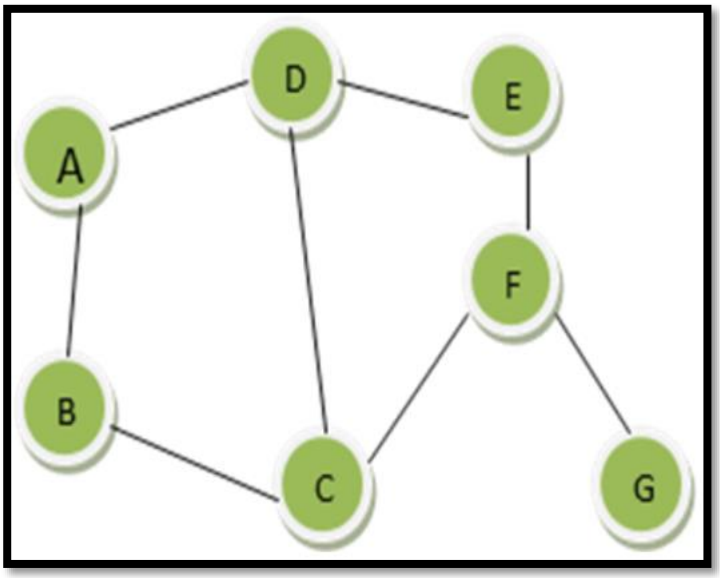

Fig 2: An undirected path is employed to depict walk, trail and path.

b) **Trail:** In a network, a trail is seen as a walk between nodes where a relation between nodes never occurs again. Although the same nodes in one trail may be a part of another trail multiple times, the same relationship between the nodes only happens once. Fig. 2 above shows how to take Because the relationship between D and E has already been established in the trail A-D-E and the graph is undirected, F-E-D is not a trail. The total number of relations in a trail determines how long it is. Trail does not divide the network into a hierarchy of distance-sensitive tracking for mobile objects in a network.

a) **Path:** In a network, a path is a walk where each node and each relationship is used a maximum of once. An individual When a path is closed, an exception is made to that rule. the same node serves as both the beginning and the end. C-D-E is depicted in Fig. 2 is a path, however since node D has a, D-A-B is not a path once more been employed before. Based on a number of factors, the length of a path depending on the overall number of its links. Two possible routes could connect the points A and E. Let E be the target node and A be the source node. A-D-E and A-B-C-F-E will then be the pathways. Whenever all nodes both of those paths have emerged.

b) Chain: In a social network, a chain is a walk that is only taken into account in directed graphs. Let's assume that Fig. 2 is a directed graph. If A-B-C then has a single flow from node A to node C is a chain, whereas C-B-A is not[6].

Literature Review:

Deep Learning Techniques: For graph embedding, methods based on deep neural networks and random walks are applied to the sampled paths to maintain the graph attributes carried by the paths. Deep Walk is the most well-known deep learning model that uses a random walk. The success of Deep Walk inspires numerous follow-up studies that use deep learning models. Word2Vec builds on Deep Walk's concept but modifies the settings of random walk sampling techniques. Deep models are applied to the entire graph using network embedding based on deep neural networks without random walks. AE and CNN are two well-known deep learning algorithms without random walk used in network embedding.

- **AE based network embedding methods**: A good data dimension compression algorithm is AE. The settings of either the loss function or the input vectors are frequently modified using AE based network embedding methods. The first-order and second-order closeness were combined to create a semi-supervised deep model using structural deep network embedding (SDNE) which enhanced the input vectors while maintaining the network structure. In order to accurately represent the local network structure, the model also included first-order proximity as supervisory information to the loss function. By jointly minimising AE loss and locality-preserving loss, deep network representations with adversarially regularised autoencoders (NetRA) improved the loss function. By jointly taking into account both locality-preserving and global reconstruction requirements, the model learnt smoothly regularised vertex representations that accurately depict the network structure[7].
- **CNN- Based network embedding methods**: Widespread network embedding uses CNN and its derivatives. The original CNN model, created for both Euclidean and non-Euclidean domains [16] through [18] and [19] through [21] domains, is directly used in CNN based network embedding. A CNN model was created by Xu et al. to extract and categorise pertinent information from the complicated network topology neighbouring matrix. In order to learn a neighbourhood representation using the CNN model, PATCHYSAN first chose a fixed-length node sequence from a graph and then assembled, normalised, and labelled the neighbourhood of the nodes. For a direct examination of 3D shapes to take use of their inherent geodesic connections usedMesh CNN. According to the various operations of the CNN-based graph embedding, it can also be separated into spectrum-based convolution and space-based convolution[8].
- **Machine Learning Approaches**: Biological interaction networks, such as those involving genes or proteins, have been investigated in a study. These biological networks' communities that have been retrieved are a group of genes or proteins that work together on a common biological task functionality. They provided a genetic algorithm-based solution, which depending on how closely related and interconnected genes are, a certain fitness function. The semantic has been utilised by them. They used similarity in a KEGG data collection as their score regarding community organisation. According to, it is calculated using a genetic ontology-based semantic similarity technique. An altered Deep walk algorithm is developed in light of another investigation given by the authors, which anticipated a connection in the protein-protein interaction network[9].
- In another study, the authors proposed a new tool named MOFSocialNet based on creating social networks using a metal–organic framework (MOF) database. MOFSocialNet is able to guide MOF researchers through the vast chemical space of existing and hypothetical MOFs. For a demonstration, they used social network analysis to identify the most representative MOFs in this research data set and to detect MOF communities[10].

- In another study carried out by in a study. a scalable and deterministic approach is proposed to identify communities using leader nodes called the community leader recognition approach. Their approach has two main steps: the first step is to retrieve the leaders and the second step is to identify the community using the similarities between the nodes. Two important issues in their work are community recognition and leader detection in complex networks.The network leader nodes are responsible for disseminating the influence and then, using the similarities between the nodes, the communities around the leader are formed. In social networks, the central nodes are responsible for spreading the intrusion. The advantage of this method is that there is no need for prior knowledge of the number of leaders and communities. They start by finding a leader to identify the most effective nodes and then extract the communities. For each leader, a community is obtained by calculating the similarity between the nodes. They distinguish communities based on the similarities of the nodes with the leader, who are all in the leader's neighbourhood. They used real social network data sets and used the Jaccard, Salton, Human Development Index (HDI) and Human Poverty Index (HPI) to calculate the similarity for finding out which works best in finding the leader of their method[11].
- In vast networks, a detection approach based on graph compression is introduced. It is the compressed graph achieved at first by constantly integrating degree one or two neighbours with higher degree levels. Afterward, two indexes, the quality and density of nodes are described as Analyse the likelihood of nodes acting as a community's seed. When these two standards are combined in a condensed social network, the how many communities there are and who the founding members of the connected community are chosen. They utilise the authentic social network data set to assess their approach. There isn't any resemblance HEA interaction is produced using node-to-node computation network[12].

- **Other Algorithms:** There has been a lot of research done on the community detection problem in relation to how important it is in social networks. These techniques are based on clustering techniques such as hierarchical clustering, density clustering, minimum-cut, clique, statistics, and others that are connected to social network analysis. These techniques did not take users' interest in online social networks into account and solely focused on communication and node architecture of social networks. Recent studies have shown that incorporating node or edge material in social networks can enhance the finding of prominent people and communities[13].
- Additionally, most methods—with the exception of the CMP technique and a few others—do not permit users to sign up for various communities, which is a concern. However, some experts think that each node belonging to a single community is sometimes more sufficient.Apart from this, table 1 below shows the contribution of different researchers towards the detection of communities from 2012 to 2017[14].

Table 1:

Year	Author	Techniques	Limitations
2012	De Meo et al.	Message propagations through random walks	Feasible for large network analysis,

			O(km) where k is a constant factor
2013	De Meo et al.	Random walk of bounded length	Increase in accuracy over three existing algorithms for CD
2013	Jin et al	modularity optimization based algorithm	An efficient and effective method for CD on medium and large networks.
2014	Liu et al	Agglomerative	A clustering algorithm without a number of the cluster as prerequisite input.
2015	Yin et al	Hierarchical	Introduced extensive modularity to overcome theproblem of the resolution limit.
2016	Hu et al.	Modularity Based	More stable and Robust version of LPA.
2017	Sun et al.	Modularity and Modular density	Community Detection for medium networks only.

Community Detection Algorithms:

1) **Louvain Method**: Using an algorithm, the Louvain approach can identify clusters of similar nodes in a network. The modularity score, which measures how well nodes are placed within communities, is optimised. This involves measuring how tightly linked the community's nodes are in comparison to a completely random network. In order to perform modularity clustering on compacted networks, the Louvain algorithm, a hierarchical clustering algorithm, recursively joins communities into a single node[15]. This method can be understood by taking the following example as given in figure 3 :

The goal is to show examples of the output and explain how to implement the algorithm in practise. This will be performed on a simplified social network graph consisting of only a few nodes connected in a certain way. Here's how the sample graph might look:

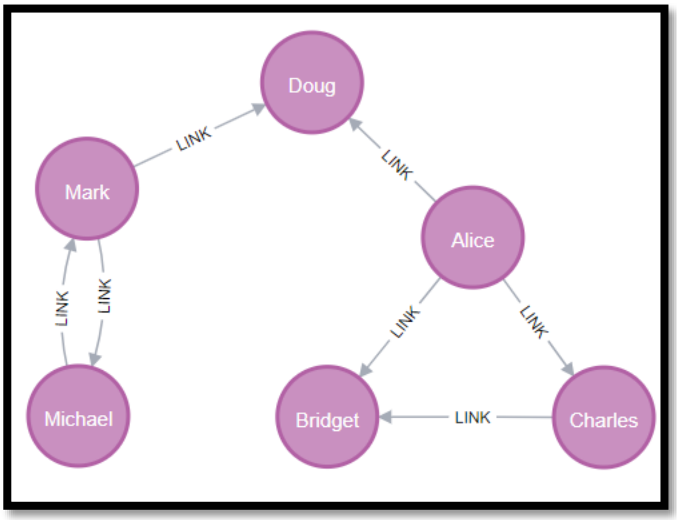

Figure 3: Louvain Method of CD.

Within this network, there are two tightly connected groups of users. There is only one edge connecting those groups. The strength of each connection between nodes in a given component is defined by a parameter called "weight."

2) **Modularity Optimization**: The goal of the Modularity Optimization technique is to identify modularity-based communities in a graph. Modularity is a measure of the structure of a graph, measuring the density of connections inside a module or community. A high modularity score indicates that the graph has numerous connections inside a community but few links to neighbouring communities. The technique checks to see if each node's modularity score would improve if it switched communities with a neighbouring node[16].

3) **Label Propagation**: Finding communities in a graph is fast work with the help of the Label Propagation algorithm (LPA). It discovers these communities without an objective function or any prior knowledge about them, instead relying solely on network structure. LPA forms communities based on label propagation, which is a process that spreads labels across the network. The idea behind the algorithm is that in a highly interconnected network, a single label can rise to the top fast, but in a less interconnected network, it will struggle to gain traction. When the algorithms are complete, nodes that end up with the same label are regarded to be part of the same community since the labels will become trapped inside of a densely connected group of nodes. The goal is to show examples of the output and explain how to implement the algorithm in practise[17]. This will be performed on a simplified social network graph consisting of only a few nodes connected in a certain way. Here's how the sample graph might look in figure 4:

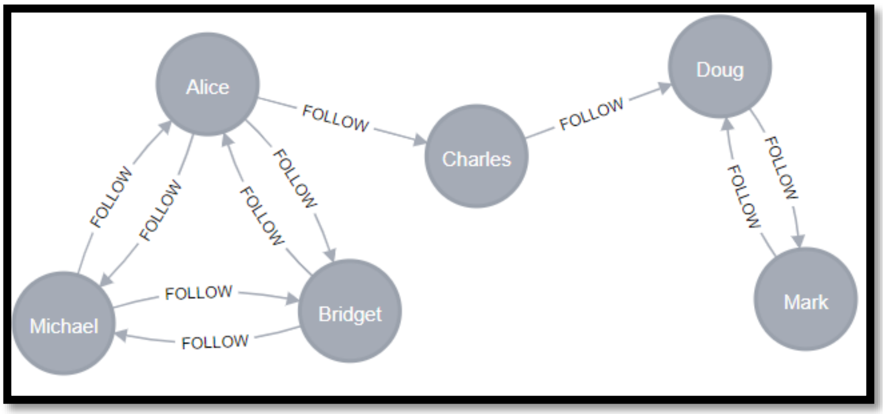

Figure 4: Label Propagation.

At the outset, each node is assigned a distinct label for its community (an identifier).These tags will be shared across the network. Each node's label is updated throughout each round of propagation to reflect the group to which the largest number of its neighbours now belong. All ties are broken at random but in a predetermined order. When every node has the same label as the majority of its neighbours, LPA has converged. Either when convergence is reached or when the maximum number of iterations set by the user is reached, LPA will end. Extremely well-connected clusters of nodes will quickly settle on a single label as word of the labels' validity spreads among them. Only a small fraction of the original labels will be left after the process of propagation is complete. Converging nodes are said to be part of the same community if they share the same community label. LPA's ability to provide preliminary labels to nodes to limit the search space is an intriguing feature. As a result, it can function as a semi-supervised method of discovering communities, in which we select certain seed communities for the algorithm to work with[18].

4) **Weekly Connected Components**: In an undirected graph, the WCC algorithm locates groups of connected nodes, where each group of nodes forms a connected component. To quickly grasp the structure of a graph, WCC is frequently employed at the outset of an investigation. When the graph structure is understood with WCC, other algorithms can be independently performed on the specified cluster. Identifying disconnected groups is a useful pre-processing step for directed graphs[19]. The example of WWC is shown below in figure 5:

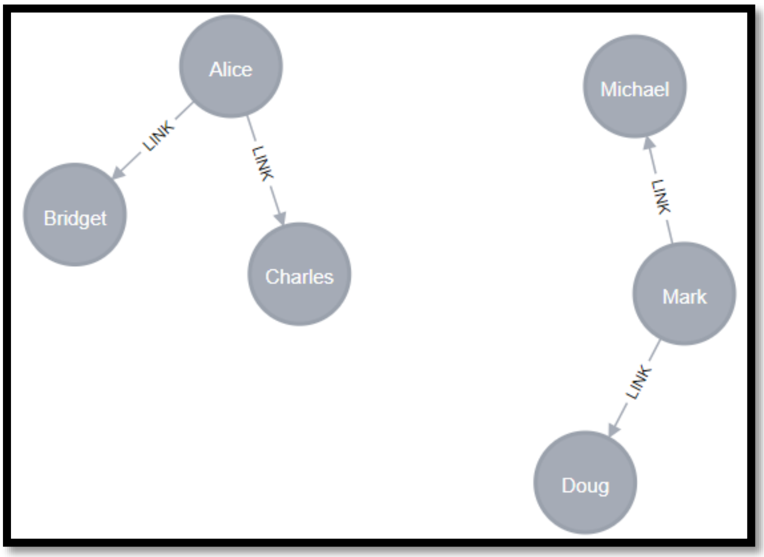

Figure 5: Weekly Connected Components.

There are six nodes total in this graph, split evenly between two connected sets of three. The strength of each connection between nodes in a given component is defined by a parameter called "weight."

5) **Strongly Connected Components:**In a directed graph, the Strongly Connected Components (SCC) technique locates groups of connected nodes where each node is reachable from every other node in the same set. Uses include the following:

Finding the group of companies where every member directly or indirectly holds shares in every other member is an important step in the analysis of large multinational enterprises. While this structure can improve trust and lower transaction costs, it also has the potential to reduce competition in the market.

Consider network connectivity when evaluating multihop wireless network routing performance.As the starting point for many graph algorithms that can only function on strongly connected graphs. A very tight network of ties exists between a set of individuals in a social setting (For example, students of a class or any other common place). Members of these communities often share interests and enjoy similar content. Finding these groups can be done with the SCC algorithms, which can then be used to recommend commonly liked pages or games to members of the group who have not yet liked those pages or games[20]. An example of SSC is shown below in figure 6:

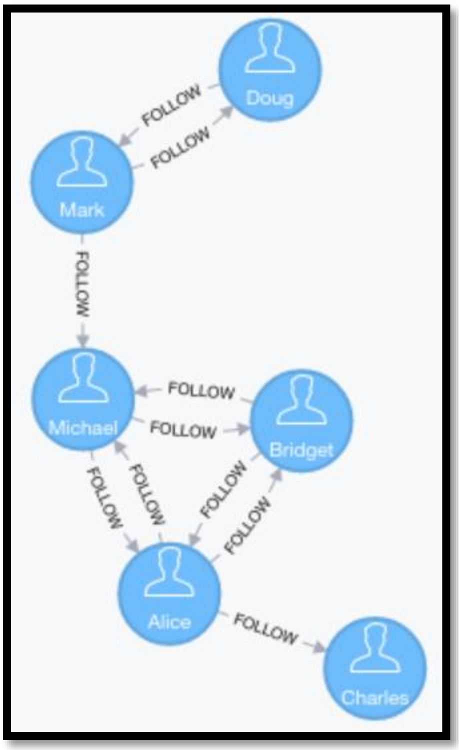

Figure 6: Strongly Connected Components.

Some Important Algorithms in Social Networks for Community Detection:

Graph portioning: The idea behind the graph partitioning approach is to separate the nodes into g groups of a certain size, so that the number of edges lying between the groupings, there is little. The quantity of flowing edges Cut size is the distance between clusters. Fig. 3 displays the answer to the issue with g = 2 and clusters of six nodes in a graph similar size. The graph partitioning problem has many NP-hard variations. There are a number of algorithms that can work well if the solutions aren't always the best. A graph's bisection is a common task for many algorithms. Typically, iterative bi-sectioning is used to achieve partitions into more than two groups. One of the earliest approaches to be developed is the Kernighan-Lin algorithm, which is still in use today. The authors were motivated by the challenge of organising electrical circuits onto circuit boards since the nodes on each board must be connected to one another using the fewest possible connections. The Kernighan-Lin approach was expanded to obtain partitions in any number of pieces, but the cost of run-time and storage skyrockets as cluster size increases. To calculate maximum flows in graphs, a number of effective routines exist, such as the Goldberg and Tarjan algorithm. In the Flake et al. have employed a graph of the World Wide Web in their research to identify communities, use the maximum flows. Internet graph the edges were undirected for the purposes of Flake et al. the calculation's goals. Each node's intrinsic degree in a, it must be less than its exterior degree community. Web communities are therefore considered to be powerful. An After including a synthetic sink t in the graph, one determines the maximum flows between a source node and a sink node: the community of nodes is identified by the appropriate minimal cut, if s shares a significant enough proportion[21].

Synchronization: An excellent process that occurs in systems and involves interactions between units in both nature and technology is synchronisation. At every moment, every component of the system is in the same state the time when the system is synced. To find the Communities in a real-world network can also synchronise to be used. A has been created in 2007 a technique for community detection using the idea of synchronisation.

Spectral Algorithms: The eigen vectors of the adjacency matrix may be localised if the graph has a distinct community structure, gave a thorough examination of the spectral characteristics of modular graphs in 2009. In 2007,study calculated the effective conductance's for pairs of nodes in a network using the eigenvalues and eigenvectors of the Laplacian matrix. By enabling the conductance for a random walker travelling around the graph, we compute the transition probabilities. From the transition probabilities, we may construct a similarity matrix between the node pairings. Using hierarchical clustering, nodes in communities are connected. The time required to compute the Laplacian matrix's entire spectrum.

Simulated Annealing: Simulated annealing is a probabilistic technique used in a variety of fields and challenges to provide global optimization. This process entails scanning the realm of potential states for a function's highest global optimum, used simulated annealing for modularity for the first-time optimization[22]. The common application of them mixes local motions—moves made by a single node—and global moves is randomly moved from one cluster to another; and moves, which include community mergers and divisions.

Newman Girvan Algorithm: The steps of this algorithm are as follows:

1. Determine the betweenness of each network edge.
2. Take away the border with the greatest betweenness.
3. Recalculate betweenness values for each edge that was removed.
4. Continue from step 2 until there are no more edges.

All shortest paths between various groups must follow one of the sparsely linked edges if a network comprises groups that are interconnected to one another. As a result, there will be a high edge betweenness on the edges joining groups[23]. The fast Newman algorithm, which calculates betweenness for every m edge in a graph of n vertices in time O, can be used to determine betweennesses (mn). Because the removal requires a single iteration of this calculation.

Applications of Community Detection: Several of the applications the benefits of community detection are briefly discussed below, shown in figure below.

Improving recommender systems with community detection: To provide recommendations, recommender systems employ data from people or objects that are similar to one another. This is comparable to the discovery of clusters or similar nodes in a graph. The potential for recommendation algorithms to benefit greatly from community detection. The traditional collaborative filtering method of recommender systems has been enhanced using a community detection-based technique. The mapping of the user-item matrix to the user similarity structure is the first step in the procedure.

1) **Optimization Technique**: optimization technique is used on this matrix to find communities. The user is then given recommendations for the products based on the communities that were found.
2) **Evolution of communities in social media**: The scope and purpose of social networking sites are growing in number along with the number of these websites. In terms of focus, the sites are becoming more varied. Other websites like Flickr for photo-sharing have also emerged in addition to popular ones like Facebook, Twitter, Myspace, and Bebo. An understanding of the community structure present in the Twitter network can be gained by analysing the tweet retweet and follower-followed networks on Twitter. Before applying community detection algorithms to determine the structure of communities, sentiment analysis of the tweets may be done as a preliminary step to determine their general nature. The community detection technique used to analyse a dataset of UK political tweets. The

various applications areas are shown in figure 7 below:

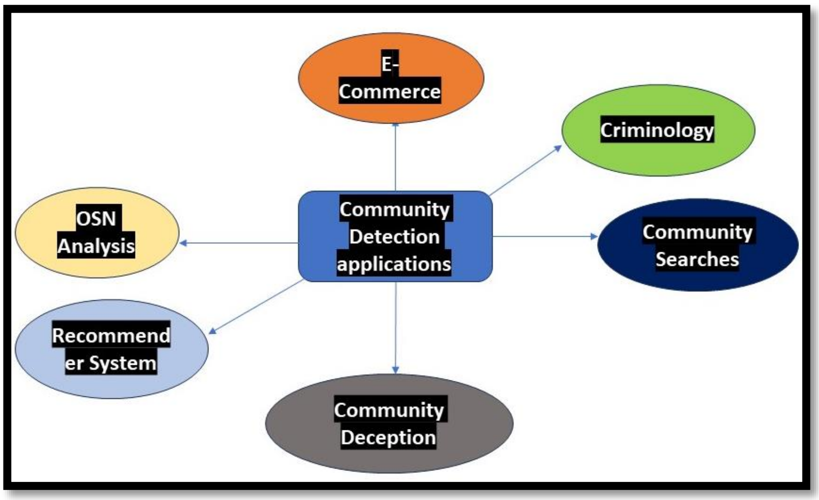

Fig 7: Applications of Community Detection.

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