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Temporal Dynamics of Social Networks: A Study on Community and Hierarchical Evolution

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Abstract

Community and hierarchical structures are frequently created, disrupted, and reorganized in dynamic social networks. Understanding these dynamic processes is useful for a wide range of applications, including information diffusion, social innovation, and organizational management. In this research, we conduct a comprehensive evaluation of hierarchical reconstruction and community identification on three different datasets: the Email-EuAll network, Facebook Social Circles, and a synthetic dataset that simulates real-world network behavior. We assess the effectiveness of many well-known community detection techniques, including Louvain, Walktrap, Clique Percolation, and Label Propagation, in order to determine how well they recognize dynamic network patterns. Our findings demonstrate that while Louvain and Walktrap are successful in modularity-based scenarios, effectively detecting well-defined, densely interconnected communities, Label Propagation performs better in sparse networks with fewer, loosely coupled communities. Furthermore, Clique Percolation struggles in extremely dynamic environments yet provides valuable insights into overlapping community structures. Given that different algorithms yield varying degrees of accuracy and efficacy in dynamic situations, the results demonstrate that the best method to employ depends significantly on the structural characteristics of the network. The adaptable nature of hierarchical structures is further supported by empirical studies, which highlight how community patterns shift as a result of real-time network changes. The need for dynamic modeling techniques that can adjust to shifting network dynamics over time is supported by these findings.

Keywords: Community, Community Detection, Dynamic Social Network, Hierarchy, Network Analysis, Social Network Analysis.

Introduction

A social network represents relationships among individuals, each considered a social unit, with the network illustrating the distribution and strength of these connections. Statistically, social networks are modeled as graphs, where nodes represent individuals and edges denote their interactions (1). Dynamic social networks (DSNs) capture temporal patterns such as relationship formation and dissolution, community emergence, information spread, and structural evolution. Understanding these dynamics is crucial for revealing the mechanisms behind social interactions, diffusion processes, and collective behavior. With the rise of digital platforms and large datasets, DSNs have gained significant attention. Computational modeling, machine learning, and network analysis enable researchers to predict behaviors, analyze trends, and enhance network resilience. A strong grasp of temporal dynamics also helps address societal challenges and guide the development of new social network strategies. A Social Networks is formalized as a graph G = (V, E), where V and E denote the number of people and connections respectively. A snapshot $S_i = (V_i, E_i)$ of *G* shall signify graph that consists of the set of persons and interactions at specific time interval *i*. Every snapshot S_i comprises of k_i communities $C_i = (C_i^1, C_i^2, \ldots, C_i^{k_i})$ where every community C_i^j is also a graph denoted by (V_i^j, E_i^j) (2-4). Social network studies earlier have brought to study the role of community structure and strength of association in web analytics, marketing, homeland security and disease modelling domains (5-11). The constant changing nature of social networking is demonstrated through dynamic interactions such as emailing, joint authorships, emailing, joint authorships, and

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collaborations between actors (12-14). To observe topology changes and determine which nodes may be disproportionately influential, and also to enable well-informed decision-making, it is vital to have a glance at the community and hierarchical dynamics, in which hierarchies are conceptualized as Directed Acyclic Graphs incorporating notions of (high) intra-group similarity and community (15, 16). This study performs the analysis of community detection algorithms in three datasets and suggests suggestions on the improvements of dynamic modeling. This has been identified in the past as the limitation of hierarchical as well as scale-free networks especially in a cooperative environment and structural constraints (17). It has been seen that the emerging sophisticated algorithms perform better in community detection as compared to traditional techniques, that are of low-complexity validation in nature (18). Wikipedia notability scores and HSM framework has provided information about the changing online hierarchies and actor-group systems (15, 16, 19). Trust networks indicate the complication associated with hierarchy mining when there are mixed interactions present (20). Overlapping community tracking can be enhanced through techniques such as Tiles and hierarchical visualizations also make visualization more easily understood (21, 22). Surveys of interactive community discovery divide and classify algorithms according to principle and effectiveness, and more recent advances use neural representation learning and subgraph embeddings to apply such techniques to complex networks (23, 24). Angel algorithm also leads to enhanced overlapping communities identification because it presents a set of strong outcomes across various datasets (25).

Research Gaps

Despite significant progress in understanding social hierarchies and community structures, key research gaps remain. One major gap is the limited exploration of temporal dynamics—how communities and hierarchies evolve over time, especially given their interdependence. While methods like FacetNet and Tiles address community evolution, few techniques examine the organization of communities across time-sequential hierarchies (18, 21). Trust hierarchies, particularly within signed networks, are also understudied in dynamic settings due to challenges with mixed interactions (20). Additionally, there is a lack of standardized evaluation metrics for community detection and hierarchy assessment, unlike structured approaches such as ANGEL and HSM (15, 25). Most studies also focus on homogeneous networks, overlooking the complexities of attributed, heterogeneous, and dynamic networks (24). To better understand evolving network architectures and their adaptability, new algorithms and comprehensive evaluation frameworks are needed.

Our paper addresses these gaps by analyzing community and hierarchy patterns across three datasets—Facebook Social Circles, Email-EuAll, and a synthetic network. We evaluate key algorithms (Louvain, Walktrap, Label Propagation, and Clique Percolation) using standardized metrics such as modularity, clustering coefficient, and community size distribution. Unlike earlier studies, we examine how community and hierarchical structures evolve over time, highlighting the adaptive nature of social networks. Our results demonstrate algorithmic performance across diverse network types, bridging the gap in assessing methods for dynamic and heterogeneous networks. By incorporating insights into the temporal stability of these structures, our work contributes to the development of resilient and scalable approaches for real-world network applications.

Research Contributions

This study adds significantly to the field of dynamic social network analysis in a number of ways. The first step is a comparison analysis of three different datasets using well-known community detection techniques, such as Louvain, Walktrap, Label Propagation, and Clique Percolation. This enables a more sophisticated comprehension of how various methods function in various network scenarios. The study also looks into how social network structures change over time, showing how various algorithms adjust to the dynamic nature of community development and dissolution. Third, it presents the idea of using neighborhood theory to improve the scalability and efficacy of the conventional Clique Percolation method for identifying hierarchical structures in dynamic networks. The methodology for examining changing communities and hierarchies in intricate social systems is improved by these contributions taken together.

Organization of the Paper

This paper is organized as follows. The necessity for hierarchical development for networks has been demonstrated in section 2. Section 3 and 4 shall discuss about some of the aspects regarding hierarchy and community. Methodology alongside some real-life examples are illustrated in section 5. Development of hierarchical communities has been discussed with the idea of dynamic social network supported by some real-life example and simulation results have been provided for the existing algorithms with a dataset within Section 6. Finally, section 7 concludes the paper.

Need for the Study

Network modeling provides a versatile demonstration of objects and their relationship, which is often shown as a graph including nodes (members) and edges (information paths). There are three main models namely Random, Scale-free and Hierarchical networks which are represented in Figure 1. Random graphs (Figure 1A) are graphs whose edges have been placed at random, and so they lack an explicit structure and their degree distribution obeys a Poisson distribution. Scale-free networks (Figure 1B) show power-law distribution such that a small number of nodes are well-connected and most with a few connections (26, 27). Tree-structured networks (Figure 1C) are constructed without cycles (the cryptographic requirement of the hierarchy networks) and typically represent a tree-like hierarchy, more often than not a binary tree, with nodes in different layers varying in number as well as connectivity, documenting the layered relationships in an organization (17).

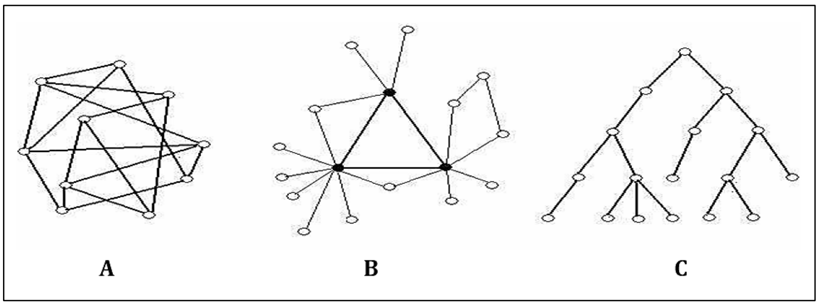

Figure 1: Representation of Network Structures (A) Random, (B) Scale-Free and (C) Hierarchical (17)

Historically, hierarchical networks have been formulated based on iterative algorithms that reproduce distinct topological properties such as scale-free topology and high clustering of nodes simultaneously. This type of network structure has more hubs and has a different distribution of clustering coefficients than the other two types. The Watts-Strogatz model generates graphs with small-world characteristics when used to a random graph generation mechanism: It creates graphs with strong clustering and shorter average path lengths. These characteristics are attained through interpolation between a regular ring lattice and randomised structures that can nearly resemble ER graphs. Subsequently, the model is capable of providing partial explanation concerning "small-world" phenomena among various networks (28, 29). The BA model is generally observed as a potent algorithm with preferential attachment and growth that is used to generate networks while analysing scale-free networks. The Internet, citation networks, and particular social networks are illustrations of both natural and artificial systems of scale-free networks. There are fewer nodes in these systems, known as hubs, which have a higher degree than alternative nodes within the network. A random graph generation model does not show power laws in degree distributions for such networks (30).

The difference in hierarchical models with other similar models lies in the fact that nodes whose links are greater are supposed to have a lower clustering coefficient. On the other hand, it is anticipated that the alternative models will maintain a degree-invariant clustering coefficient. Barabási-Albert model makes a prediction that average clustering coefficient would decrease with the increment in the number of nodes, but the size of a network and the average clustering coefficient are uncorrelated in hierarchical models (31). Moreover, hierarchical network model is built on few design goals that makes it better than other modeling approaches:

- **Hierarchy**: Reliability in a network infrastructure becomes easier when the network is modeled in a hierarchical manner. Fragmentation of complex problems in network design is done so that they become easier to manage.
- **Modularity**: Module wise separation of different functions within a network makes the design process simpler.
- **Resiliency**: Networks need to be available both under normal and abnormal conditions. Various normal conditions include predictable traffic movements and patterns, in addition to arranged processes like maintenance windows. In contrast, various abnormal conditions include hardware or software failures, unexpected traffic heaps, infrequent traffic arrangements, DoS events.
- **Flexibility:** The ability to modify some fragments of a network with the addition of novel services or enhancements to its capacity with very confined changes (32).

Some Aspects Regarding Hierarchy

Understanding the hierarchical structure of dynamic social networks is essential in social network analysis. As relationships and interactions evolve over time, capturing hierarchy becomes complex, yet it highlights each individual's role within the network. The process typically starts by dividing the network into cohesive units called communities, which form the basis for analyzing clustering patterns and subgroup dynamics. Once communities are identified, attention shifts to evaluating members' positions and significance in the broader context (33, 34).

Several methodologies have emerged to quantify individuals' roles within dynamic social networks. Network correspondence, for instance, provides a means to map individuals' positions across different snapshots of the evolving network, facilitating the identification of key players and evolving structures over time. Normalized degree D(v), closeness centrality C(v), betweenness centrality B(v), and eigenvector centrality E(v) are among the metrics utilized to gauge individuals' centrality and influence within their respective communities and the network as a whole. Maintaining the spectral properties of the network emerges as a fundamental objective in hierarchical analysis. This entails preserving the eigenvalues λ and eigenvectors v of the network, which encode crucial structural attributes such as graph connectivity, vertex centrality, and symmetry (35–38). The eigenvalues govern the stability of dynamic behaviors within the network, offering insights into its resilience and responsiveness to external stimuli. Meanwhile, eigenvectors shed light on additional properties, such as the propensity of random walks and information diffusion within the network, elucidating its navigational and communicative dynamics (39–41).

Developing hierarchical structures in dynamic networks requires a deep understanding of individual roles, community dynamics, and temporal network properties. By applying advanced methods and spectral analysis, researchers can uncover the mechanisms driving social interaction and information flow in these complex systems.

Hierarchical Clustering Algorithms

Hierarchical clustering algorithms form a family of unsupervised learning algorithms that place similar data-points in a tree-like hierarchy by nesting clusters. The agglomerative clustering method, the most usual one, consists of each point being a cluster by itself, and in successively joining similar clusters, where the linking criterion (e.g. the inter-cluster distance) may be one of single, complete, average, or Ward linkage. Conversely, divisive clustering starts with a web of every point in a single cluster and recursively cuts it up into two or more parts via such techniques as k-means or centroid partitioning. Such algorithms find broad use in computer science, biology and social network analysis, including document clustering and community discovery and gene expression analysis. However, although they are useful to disclose the complex data structures, hierarchical clustering techniques may be time-consuming and root-dependent, as well as linkage- and distance-measure-sensitive (41).

Spectral Analysis Techniques

Spectral analysis techniques are a class of methods used to analyze the properties of networks by examining the eigenvalues and eigenvectors of matrices derived from network representations. One common spectral analysis technique is spectral clustering, which leverages the spectral properties of matrices to partition nodes into clusters based on their connectivity patterns. Using a particular network adjacency or Laplacian matrix, spectral clustering would eigen decompose the network of interest into a corresponding low dimension and then use k-means, another conventional technique based on this data. A fourth spectral technique can be based on community detection using modularity maximisation, in which the adjacency matrix of any network is broken down into its various eigenvectors and associated, highest-value eigen-vectors that are used to identify networks by communities. By partitioning the network based on the sign of the entries in the leading eigenvector, spectral modularity optimization algorithms can efficiently detect communities in large networks (35).

Network properties like network centrality and structural equivalence are studied by spectral analysis techniques. The centrality measures like eigenvector centrality and PageRank assign importance scores to nodes based on their connectivity with other nodes and their position in the eigenvector space of the network. Structural equivalence analysis identifies nodes that have similar connectivity patterns by comparing their eigenvector representations. Principal component analysis (PCA) and singular value decomposition (SVD), two dimensionality reduction approaches, use spectral analysis techniques to convert high-dimensional network data into a lower-dimensional space while maintaining crucial structural information. These spectral analysis methods are effective for determining communities, assessing node centrality metrics, and comprehending the structural characteristics of networks. They shed light on the fundamental architecture of intricate networks and have potential applications in a number of fields, such as recommendation systems, biological networks, and social network analysis (36, 37).

Incorporating Temporal Aspects in Hierarchy Detection

Temporal consideration over hierarchy detection is associated with observing the dynamics of the development of the hierarchical structures within dynamic network. Conventionally, static snapshots tend to be the main idea of operation but, in dynamic networks, issues of influencing nodes and structure of groups have to be addressed in the approach. An example is done through dynamic centrality, where the rules are evolving centrality measures (like betweenness and eigenvector centrality) will be calculated in each time step to keep track of how the nodes become important and how they lose their significance over time, which will allow tracking hierarchies changing over time (40). Temporal evolution of the community can also be captured using dynamic clustering algorithm like dynamic modularity optimization and spectral clustering. Also, comparing frequency and persistence of network motifs can be used to imply changing relations of hierarchy, and mathematical models and time series analysis can also explain the changes of hierarchy formation and development in time (41).

This article defines hierarchy based on information flow and centrality. Nodes that have high ratings consistently in terms of their centrality the most particularly are those nodes betweenness and closeness; such are observed to be at higher positions in the hierarchy because of their influence factors and bridging functions. The trend of these centralities in time can be used to identify temporal levels of the hierarchy where nodes with high-centrality remain in a high hierarchy relative to other nodes. Verification of hierarchical structure happens longitudinally, whereby detected stratifications indicate a long term roles and not temporary pressures.

Community and its Detection

In social networks, communities represent clusters of individuals with interconnected relationships. A person may belong to multiple overlapping communities, such as school, college, friends, or family groups. Community detection involves identifying these clusters based on key structural features within the network. Various methods are used to uncover such groups, reflecting their wide range of applications. Typically, global quality functions are applied to detect meaningful substructures while satisfying local connectivity criteria (42–46).

Methods for Detecting Community Structure

Community definitions vary based on whether nodes can belong to one or multiple groups, depending on the analysis context. Community detection methods—static and dynamic—both identify densely connected node groups but differ in their treatment of time. Static methods analyze a single time snapshot using topology and edge weights, with common techniques including modularity optimization, hierarchical clustering, and spectral clustering. While computationally efficient, static methods lack temporal context and cannot capture evolving community structures.

Dynamic community detection aims to identify communities that evolve over time, capturing shifts, merges, splits, or dissolutions across time steps. These methods integrate topological information with temporal dependencies to track community evolution. While offering deeper insights into structural changes and temporal persistence, dynamic techniques are more computationally intensive and often require parameter tuning to balance noise resistance and sensitivity to fine-grained changes. The choice between static and dynamic approaches depends on the research goals, network characteristics, and the desired level of temporal detail (42).

Disjoint Community Detection

Many community detection algorithms also view the problem as that of hierarchical partitioning, and result in dendrograms that reflect nested subgroup relationships. Within this context, a person is progressively split into smaller subgroups until the whole network is broken, and the multi-level structure of community is exposed. A particularly important variant is disjoint community detection, that seeks to find a partition of nodes into disjoint parts, by trying to maximize internal connectivity by minimizing external links. This approach is extensively used in such fields as biological networks, social media analysis, or recommendation systems. Optimization of modularity as well as other algorithms evaluates the quality of a partition by contrasting rates of connections within a community versus rates of connections across communities, whereas alternatives, such as label propagation, hierarchical clustering as well as spectral, detect dense subnetworks based on divergent principles (43).

Nevertheless, disjoint community detection has serious challenges. Resolution limit issue means that small-scale communities cannot be easily identified, so scalable algorithms must be used and can work on a variety of granularity levels. The networks that exist in the real world even make the above more complicated because in the real world the networks are dynamic and therefore, communities keep evolving, form or break apart. The algorithms normally used to manage this are dynamic community detection algorithms, which monitor changes in a structure across time with the hope of observing the time changes of community organization. The need to have effective tools of identifying and assessing disjoint communities to provide the structural basis of complex networks and to facilitate developments in many aspects of analysis should be regarded as a priority.

Overlapping Communities

The existence of overlapping communities, in which nodes may have more than one membership at a time, can be seen as a feature of the multifaceted nature experienced in the real world networks like social, biological or other organizational networks (47, 48). As an example, a person can also involve in career, family and personal life simultaneously. Contrary to the segmented communities, overlapping ones provide a more detailed representation but are harder to identify because of the fuzzy notion of membership and complicated web of connections. The classical single-membership algorithms are not sufficient, thus more specialized, node-similarity based, based on local clustering coefficients, and based on community affiliation scores, methods have been developed. Overlapping modularity optimization enables the nodes to be in many communities and the optimization ensures that there is a high density within the communities. In addition, methods such as stochastic block models and mixed-membership models have been developed which scale the observed data to deal probabilistically with the uncertainty in community assignment. The approaches play an important role in both modelling a complex network structure across various quarters, including recommendation systems, social studies, and bioinformatics (47).

Mathematically, community detection can be formulated using optimization techniques aiming to maximize or minimize certain objective functions. For disjoint community detection, algorithms might seek in partitioning network in non-overlapping sets $C = C_1, C_2, \ldots, C_k$ where each C_i represents a distinct community $C = C_1, C_2, \ldots, C_k$ allowing nodes to belong to multiple communities. One commonly used metric for evaluating community detection algorithms is modularity Q, defined as:

$$Q = \frac{1}{2m}\sum_{ij} (A_{ij} - \frac{k_i k_j}{2m})\delta(C_i C_j) \quad [1]$$

Where A_{ij} is the adjacency matrix, k_i and k_j are the degrees of nodes i and j respectively, m is the total number of edges and $\delta(C_i C_j)$ is the Kronecker delta function which equals to 1 if the nodes i and j belongs to the same community and 0 otherwise. high modularity values indicate better community structure.

Methodology

A systematic approach has been used to analyze the changes of communities and hierarchies in the dynamic social networks including selecting a dataset, dividing the time into parts and using an algorithm. Three data sets were used: Facebook Social Circles, where the dense social relations available to users are described by friendships among the users; Email-EuAll, reflecting infrequent interaction by means of email messaging in a European research lab; a Synthetic data set generated to test the hypothesis of varied network density and structure under control conditions. All these datasets have made it possible to have in-depth analysis in various social contexts. All of the temporal snapshots were processed separately with the aim of evaluating structural dynamics across time using the static community detection algorithms, including Louvain, Walktrap, Label Propagation (LPA), Clique Percolation Algorithm (CPA), and others. The methodology allowed making a regular comparison of the performance and insight the strengths and weaknesses of the algorithms in relation to changing conditions of the networks.

Metrics and Algorithms for Detecting Communities

Social network community detection uses a range of metrics and methods to find clusters of nodes with strong connections between members and lesser connections to other nodes outside the group. One popular metric for evaluating a partition's quality is modularity, which shows how many edges there are in a community relative to what would be predicted by chance. The balance between internal density and outward connectivity is measured by other measures, such as coverage, conductance, and normalised cut, which assess the quality of community partitions. Community discovery algorithms include more contemporary techniques like the Louvain method, Infomap, and label propagation algorithms, as well as more conventional techniques like spectral clustering and hierarchical clustering. These algorithms iteratively optimize a quality function or perform iterative updates to partition nodes into communities based on network structure and connectivity patterns. Furthermore, dynamic community detection algorithms monitor how communities change over time, considering temporal relationships as well as topological information to capture the dynamic character of social networks (48).

Illustrating Some Hierarchical Communities in Real Life

Boxing club network: The communicative structure of boxing club with 34 members involves descriptions of social stratification that stemmed out of a dispute between the instructor and the club president (49). Applying the Hierarchical Structure of Members (HSM) strategy on the position of the instructor (node 34) we see a hierarchy to be visualized in Figure 2, with two levels emerging at first (k=2) corresponding to the real separation of the group, except by node 8 at the level boundary. When k is increased to three more separations are visible in the first level where we have lower-resolution (orange) and higher-resolution (red) subgroups. Additional increments of k divide the blue level into light and deep blue, the light blue nodes representing overlap among groups. Such a stratification of color accentuates the existence of multi-resolution structures in the community providing an understanding of overlapping memberships and depth of structural hierarchies (15).

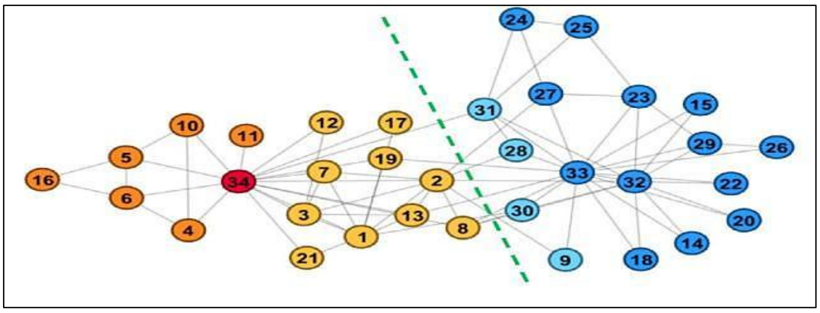

Figure 2: The Hierarchical Structure of All Members Forming a Network in the Boxing Club Each of Nodes at Distinct Levels is Represented with Different Colors, i.e. Orange, Yellow, Light Blue and Deep Blue. The Seed Node 34 is Colored in Red. The Green Dotted Line Specifies the Top 2 Levels (15)

University network: In this network, all staff members at a single university are represented by three distinct schools (50). The nodes shall represent a person while links shall represent friendship. The degree of friendship has been measured in terms of questionnaires which have subsequently been filled up by all the academic staff who have participated in this survey. The entire network has been partitioned into different communities according to the different schools of the university. This has been demonstrated in Figure 3(A). The grey nodes in the figure indicate the undetermined nodes. The HSM has been designed according to the seed nodes 50, 67, and 44, which correspond to three different schools. This has been demonstrated in the subsequent figures Figure 3 (C, D, E) where the dash line has accurately separated the real communities from others excluding a few of the overlapping nodes (15).

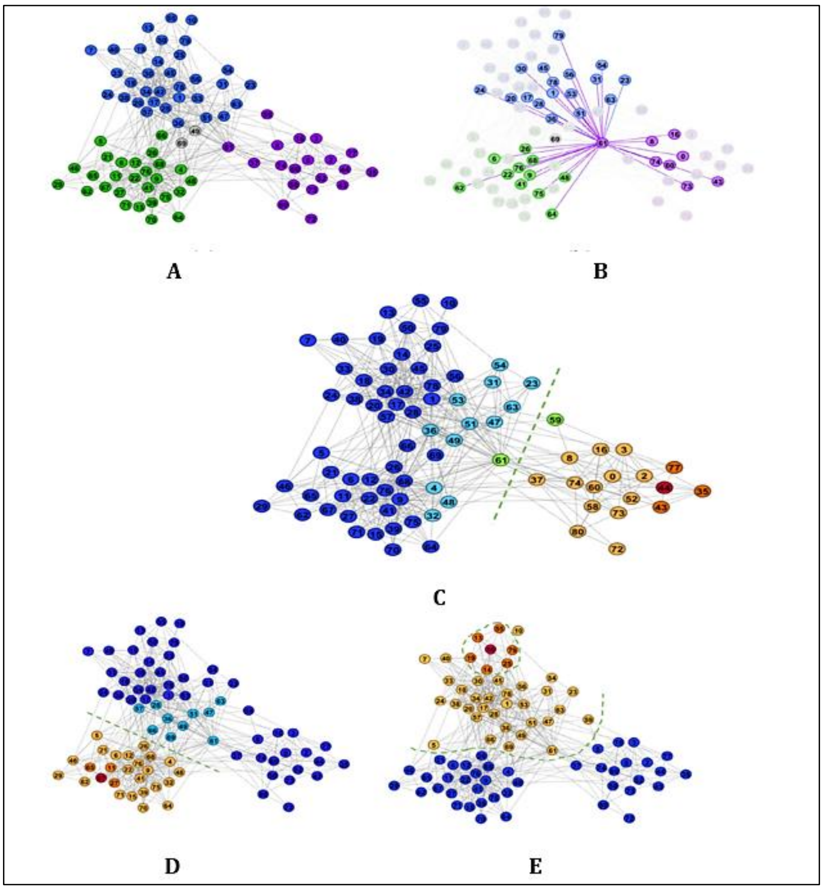

Figure 3: The University Network's Hierarchical Member Structure. (A) Displays Two Unknown Nodes (Grey) in Three Real Communities. (B) Displays the Area Where Node 61 Overlaps. (C-E) Three HSMs are Displayed, with Dashed Lines Indicating Automatically Determined Divisions and Levels Denoted by Various Colours (15)

Buy and sell groups in Facebook: Facebook's Marketplace feature allows individuals to create groups for buying and selling items via their pages. Promotional offers are often posted to attract large audiences, forming online social communities. Users who like the page or join the group are considered primary members. These groups are managed by a creator or admin, who can grant access to new participants. Reviews shared in comments or on the page wall allow users to express opinions about products. Instant messaging redirects buyers to the seller's Messenger for direct communication. A snapshot of such a group is shown in Figure 4.

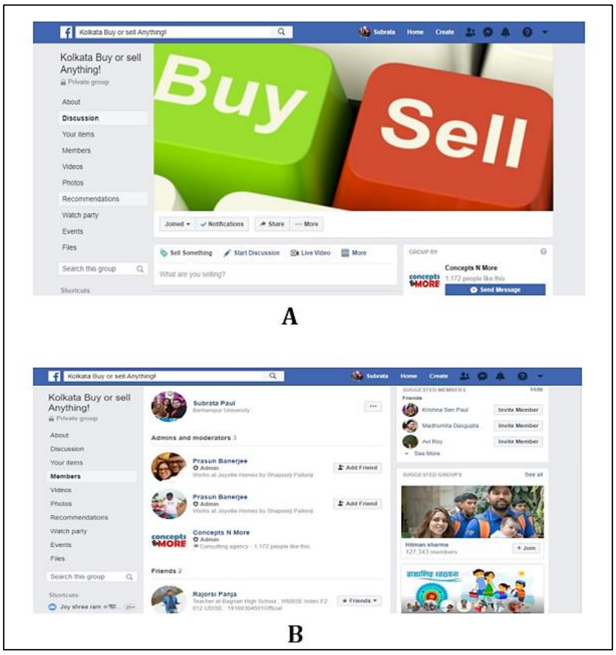

Figure 4: (A) Facebook Buy and Sell Group Inviting Members to Join the Group and Allowing the Members to Post Their Item in the Wall of the Page. (B) The Group Showing the Admins and Moderators of the Page, the Available Members are Shown, Whereas New Invitations for New Members to Join are Shown

Groups in WhatsApp: WhatsApp was a key source of communication between different groups of people within the office, colleges, and universities after it was developed. This messaging app has created a community with members acting as participants in every sphere of life. The group is centrally handled by an admin who has created the group and can add and remove participants from time to time. Assume there is an imperative message to be circulated among a group of people. Instead of calling and informing them one by one, the message is circulated instantly once this is posted in the official group. However, once everyone is online and has seen the message, the message is said to be shared. This information concerning how many of the people have seen the message, how many have read and to whom it has been delivered is available. It is regularly updated from time to time. Here is an example of a WhatsApp group given in Figure 5.

Defining Dynamic Communities

Dynamic communities are those which alter or develop with time. For an illustration, a social network might be considered alongside specific communities. The students staying in PGs form this kind of community. Static communities refer to the entire set of students who are the residents of the PG at any specified time. After a certain period of time, some students may leave the PG, and be replaced by some newcomers who move into their place. After a certain longer time period, none of the student neighbors are still residing in the PG; although, there is the existence of the corresponding community deprived of a slight disturbance. Such a community as a whole is described with a dynamic concept.

Figure 5: (A) Whatsapp Group Showing the Available Options Which Can be Done Within the Group. (B) An Invitation Link for Anyone Within the Contact List to Join the Group

Dynamic communities are explained by a fundamental network that evolves over time. There have been two probable demonstrations of these networks. Alternatively, these demonstrations may be presented as time-series for static networks, called time frames, or snapshots, where each such network corresponds to communications that can be constructed from collected data on the basis of a date, week, or month (Figure 6), or by inputting information on the basis of a flow of edges in real time. Such a network modeled using this procedure is referred to as temporal networks (51).

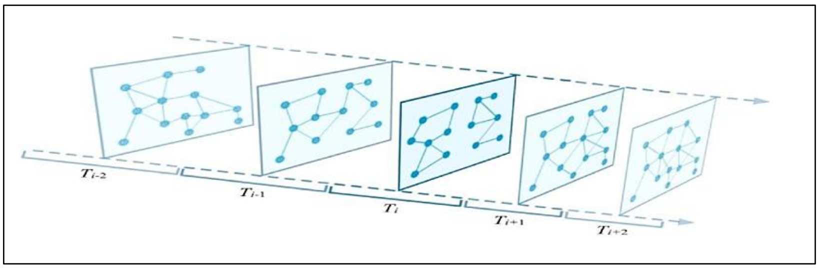

Figure 6: Demonstration of Dynamic Community (52)

In both the representation as well as in the conversion of snapshots into temporal networks, the path of dynamic communities is found to be similar. On the basis of whether the network is modeled by either of the two representations, there are two different procedures which might be discussed in regard to the development of a particular community:

- This phenomenon can be described as a sequence of changes occurring over consecutive time slots or, alternatively, as community variations observed in successive network snapshots.
- An initial static community and a succession of alterations within the specific community, in terms of names, integrating or excluding nodes.

Alterations within Dynamic Communities

The appearances of nodes and edges are the diverse operations which illustrate a dynamic network. Even though the alterations within communities appear to be simple, within the scale of a community, the alterations are more complex and referred to as "events" have focused on the detection of key events appearing within the community life cycle (52-55).

In the previously mentioned studies, several events are discussed which are quite comparable as well as being complementary (Figure 7). The general events within a community are Birth describing the emergence of a novel community at a specified time, Death illustrating the disappearance of a community where there is a loss of membership of every node within the given community, Growth discussing the attainment of new members or nodes within a community, Contraction describing the dropping of some members within a community, Merging where quite a few communities amalgamate to form a new community, Splitting, the process of division of a community into a few novel ones and Reappearance (56) defining disappearance and reappearance of a community subsequent to a specific duration of time.

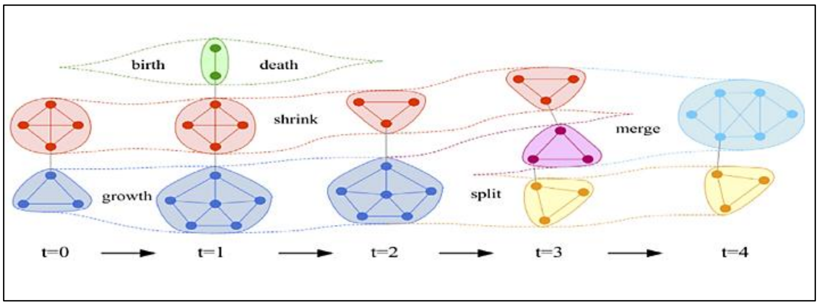

Figure 7: Community Evolution in Dynamic Social Network (55)

Dynamic Community Detection

For the purpose of the analysis of dynamic social networks, G is further divided into τ discrete and successive snapshots and therefore attaining a collection of graph which is represented as $G = (G_0, ..., G_\tau)$, where $G_i = (V_i, E_i)$ will denote graph consisting of only collection of nodes and edges which emerges within the interval (t_i, t_{i+1}). The k_i community which are distinguished within i^{th} snapshot is being symbolized as $C_i = (C_i^1, C_i^2, ..., C_i^{k_i})$ wherein the community $C_i^p \in C_i$, $1 \le p \le k_i$, is in addition a graph being indicated as (V_i^p, E_i^p). Identifying dynamic community's entails identifying analogous communities within diverse time snapshots. By pre-arranging its ingredient communities according to different time snapshots, the dynamic community can be represented. The dynamic community is formally represented as $DC = \{C_{t0}, C_{t1}, ..., C_{t\tau}\}$ wherein $t_0 < t_1 < ... < t_\tau$ and moreover C_{ti} shall correspond to the instance of a community at the time slot t_i (55).

Results and Discussion

The authors will provide a preliminary description of an example of a real-world dataset in this section, showing how communities and hierarchies are formed with each time period. Boxing Club and University Network real world examples have been considered for the purpose. Thereafter, the effectiveness of some of the existing algorithms for community detection has been implemented on some real-world dataset of a dynamic social network and simulation results were analyzed.

Illustrating Communities and Hierarchies in Dynamic Social Networks with Examples

Random communities are portrayed by the graph (in terms of nodes and edges) at dissimilar time slots within the Figure 6. Various scenarios are being considered where nodes and edges change over time. The real-life examples which are being discussed in section 3 are illustrated with brief descriptions where the hierarchical structure of the networks within the communities varies with time. Considering the example of the Boxing Club network, let us suppose that A and B are two instructors and C, D, E and F are the students. The four students are already interacting among themselves prior to joining the club because they are studying at the same university and the two instructors are in the same community (Time slot T_{i-2}). After the students enroll themselves in the boxing club, student's C and D come under the guidance of instructor A While E and F are guided by instructor B (Time slot T_{i-1}). Considering two skill set X and Y. The skill set X is mastered by instructor B while the skill set Y is mastered by instructor A. Students must be able to perform both skills sets in order to participate in the district championship. Therefore, at the first instant, E and F learn skill set X from instructor B while C and D learn skill set Y from instructor A (Time slot T_i). The students then exchange their respective instructors for a few minutes (Time slot T_{i+1}) to learn the alternative skill set. After the students have mastered all the skill sets, they again reunite and compete against each other (Time slot T_{i+2}). The development of hierarchies has been illustrated in Figure 8. There were 6 different communities that have developed with the 5 different time slots. During the initial time slots, there were two communities which developed to four in the subsequent two time slots. In the fourth time slot, there were further two new communities that existed for a single time slot. It is clearly viewed that community 1 and 2 only existed for the entire duration. This fact is illustrated in Figure 9.

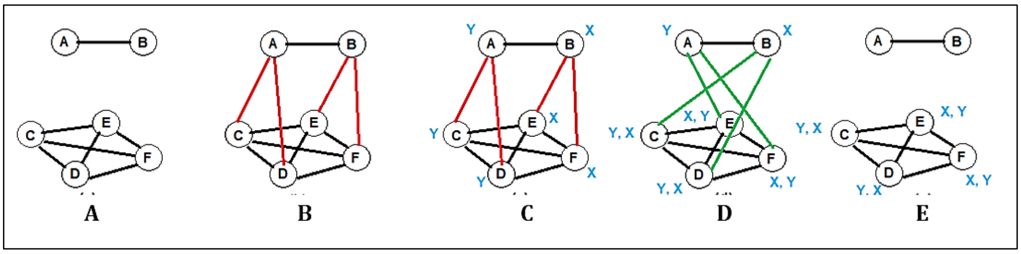

Figure 8: A Brief Illustration of the Development of Hierarchy with Each Time Slots in a Karate Club Network for (A) Time Slot T_{i-2}, (B) Time Slot T_{i-1}, (C) Time Slot T_i, (D) Time Slot T_{i+1}, (E) Time Slot T_{i+2}

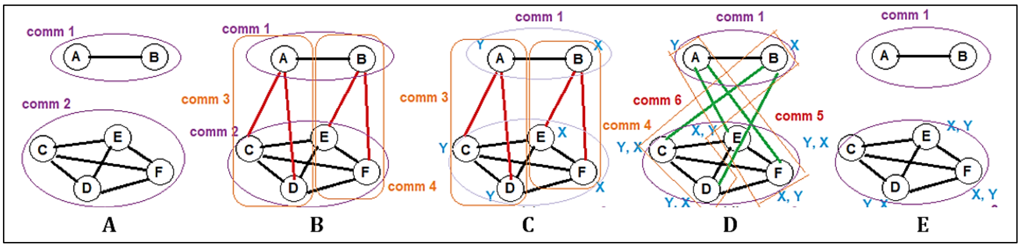

Figure 9: A Brief Illustration of the Development of Community along-with Hierarchy with Each Time Slots in a Karate Club Network for (A) Time Slot T_{i-2}, (B) Time Slot T_{i-1}, (C) Time Slot T_i, (D) Time Slot T_{i+1}, (E)Time Slot T_{i+2}

Considering the example of the University network, let us suppose that a professor A and professor B is associated with a common research interest whereas students C, D, E and F are performing their masters in the university (Time slot T_{i-2}). However, after some time, the research association will break up and Professor A will then work with his two research student's C and D on a particular topic, while E and F will be working in a same college (Time slot T_{i-1}). The scholar's C and D share common research interests up to the point where they unite (Time slot T_i), after which they perform their individual research work with their common guide Professor A (Time slot T_{i+1}). After the two scholar's C and D have completed their doctoral thesis and have submitted to the university, two new students come for the guidance of Professor B i.e research scholar E and F (Time slot T_{i+2}). The development of hierarchies and communicated have been illustrated in Figure 10. It is viewed that with each time slots there were development of new communities, only a single community i.e community 3 existed for the two subsequent time slots.

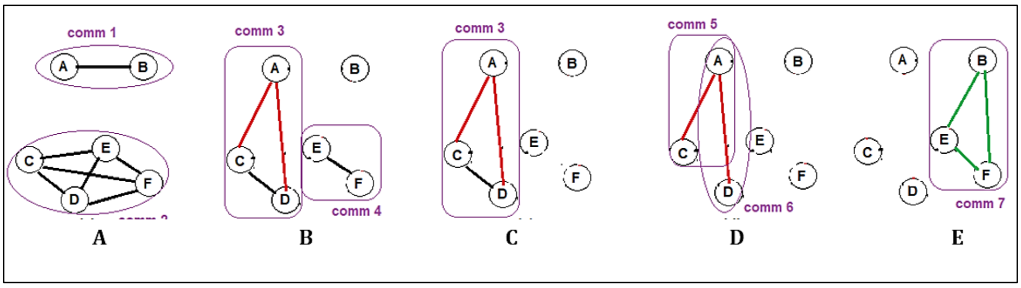

Figure 10: A Brief Illustration of the Development of Community along-with Hierarchy with Each Time Slots for an University Network at (A) Time Slot T_{i-2} , (B) Time Slot T_{i-1}, (C) Time Slot T_i, (D) Time Slot T_{i+1}, (E) Time Slot T_{i+2}

Considering the other example of the facebook buy and sell group, let us suppose that a person X has created an online store to sell his own handicraft items (t=0). Apart from having his own e-commerce website, the person took the help of the facebook buy and sell group to promote and sell his items. Therefore, he requests to the admins to join the group by filling all the credentials as specified in the sign-up page. The admin verifies his details and approves him to join the page. At the same time, P joins his page as a new member (t=1). The person upon getting permission posts his items in the wall of the page. He also invites new member Y and Z to the page so that his item is promoted and more people is exposed to his items. Although he sees that new invited friends have started liking the page as per his request, certain old members P are leaving the group (t=2). A new friends Y has invited has drawn enough inspiration from X that they decide to start their own business and therefore decides to split from the main Buy and Sell group (t=3) and finally they merge with another buy and sell community so that they can promote and sell their own items without the knowledge of X (t=4). The circumstance for the hierarchy and community development has been demonstrated in Figure 11. It is clearly viewed that there has been development of new communities with each time slots in time slots t=1 to t=4. Community 2 has been persistent in t=2 to t=5 while other communities has developed and perished with each time slot.

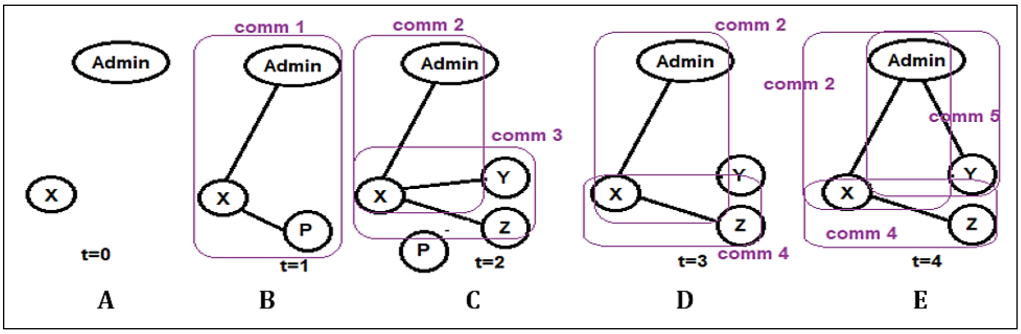

Figure 11: A Brief Illustration of the Development of Community along-with Hierarchy with Each Time Slots for a Facebook Buy and Sell Group

Let us suppose that a business conclave is going to be organized and therefore for a greater and efficient communication among the team members, the team head Mr X has created the whatsapp group (t=0). As per the necessity, the admin (Mr X) is adding the necessary team members P, Q, R, S and other people from the outside Y and Z so that a co-ordination is created (t=1). Many sub groups for each individual task are further created in the process with the knowledge of the team head keeping him in the loop (t=2). Some members having a difference in opinion from the team head have removed themselves from the group and further created their own group with the knowledge of the manager or the main organizer (t=3). They further unite with some of the subgroups for a better and efficient co-ordination as per the instruction of the manager (t=4). The illustration provided in Figure 12 shows the way the community and hierarchies developed in subsequent time slots. As seen, from t=0 to t=1 there has been an addition of new nodes within the network and in parallel communities also evolve. Some more communities develop and perish with the subsequent time slot. During the final time slot there has been a new addition of new nodes within the existing communities.

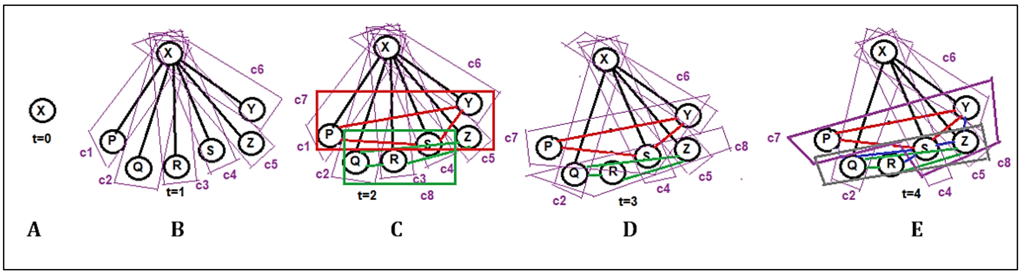

Figure 12: A Brief Illustration of the Development of Community along-with Hierarchy with Each Time Slots for a Facebook Buy and Sell Group

Simulation Results

Two real data sets namely Email-EuAll and Facebook Social Circles and one synthetic network data sets were analyzed to guarantee stability and cross-platform applicability. The facebook dataset is made up of 4039 nodes and 88 234 edges with an average clustering coefficient of 0.6055, having dense, user-centric interaction and anonymous node IDs as well as obscured feature vectors (57). The email-EuAll having 1005 nodes and 25571 edges is a medium scale organization network and contains internal as well as external edges (58, 59). To simulate controlled conditions of the network, a synthetic dataset with 100 nodes and 250 edges was also adopted. Fixed, non-overlapping comparison windows customized to the activity level of each data set 7 days, Email-EuAll; and longer in Facebook and synthetic data to eliminate repetition and information redundancy, and to maximize band structure signification. In order to measure their performance, the performance of community detection algorithms such as Clique Percolation, Label Propagation, Fluid Communities, Louvain and Walktrap were executed on 60,000 initial edges on Facebook, 500 unique edges on Email-EuAll and on all edges on the synthetic dataset (60-62).

Number of Communities (K) option specifies how many communities or clusters the algorithm should identify. The algorithms require this parameter as input, while others may decide it automatically based on network features or optimisation criteria. Average number of nodes per community is also an important criterion in defining the effectiveness of the algorithm. The greater number of nodes that fall within the community, the more efficient the algorithm is. The clustering coefficient is concerned with the number of neighbours that are connected to each given node. Consequently, it can be described as the extent to which a node's neighbours are connected to one another. The formula defines:

$$C_i = 2 \times \frac{L_i}{k_i(k_i - 1)} \qquad [2]$$

where $L_i$is number of links between the neighbors of node i. The value of Clustering co-efficient can only vary between 0 and 1. The quality of dividing a network into communities or clusters is measured by modularity that compares the number of edges in communities created by dividing a network into nodes with the number of edges that would be predicted if the network were rewired at random while maintaining the same degree distribution. The partition's ability to capture the network's community structure improves with increasing modularity. Mathematically, the modularity of a partition has already been defined earlier. The Facebook dataset that has been considered for algorithm implementation is a massive dataset with over 88,000 edges; as such, applying the algorithms to the entire dataset is a significant undertaking. Thus, for convenience, we have used the first 60,000 edges for research and analysis.

Table 1: Comparison of the Results Obtained on the Major Community Detection Algorithms on Social Circles: Facebook Dataset

Community Detection Algorithms	No. of Communities	Average No of Nodes per community	Average Clustering Coefficient	Average Modularity of Community
Clique- Percolation (CPA)	369	6.547	0.9342	0.0001
Label Propagation (LPA)	11	316.64	0.684	0.01215
Fluid Communities (FCA)	369	7.76	0.4423	0.00029
Louvain Community Detection (LCD)	12	290.25	0.6258	0.02716
Walktrap Community Detection (SCD)	9	387	0.5928	0.03233

As observed in Table 1, the clusters identified by spatial some of the algorithms CPA, LPA, FCA, LCD and WCD and vary widely because of variance in resolution parameters and detection methods, as well as the sensitivity to the particular characteristic in a network. Every algorithm focuses on different structural characteristics like interconnection patterns, and some are more effective to identify similar communities or deal with network noise. Variation is also due to network complexity, size and randomness in initialization of the network as well as parameter tuning. In spite of such differences of community number and mean node degree, clustering coefficients are rather constant between the algorithms. As Figure 13 shows, CPA shows the maximum average clustering coefficient, indicating a high local connectivity unlike other techniques which gives the value between 0.4 and 0.7.

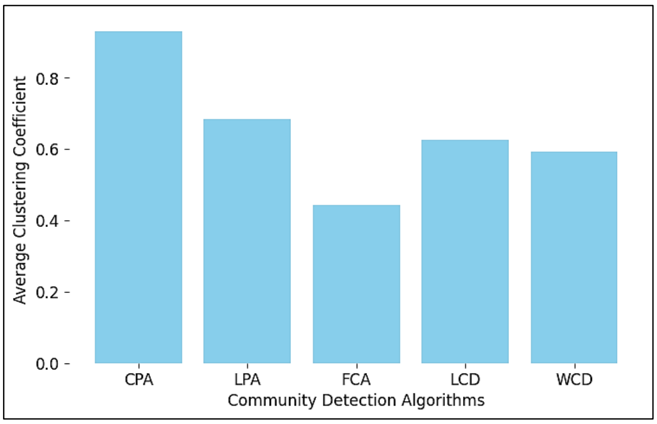

Figure 13: Comparison of the Average Clustering Coefficient Value for Evolved Community

Modularity-based methods can be adapted to dynamic networks, where tracking changes in modularity helps monitor community evolution, detect key events, and understand network dynamics. In dynamic social networks, a minimum modularity value should serve as a benchmark. As shown in Figure 14, LCD and WCD consistently yield higher partition quality, especially in the Email-EuAll dataset, indicating their effectiveness in identifying well-separated communities. In contrast, Clique Percolation and Fluid Communities produce lower average modularity values. However, with parameter tuning, these algorithms could contribute to developing more robust methods for detecting community evolution in dynamic social networks, as illustrated in the earlier real-time examples.

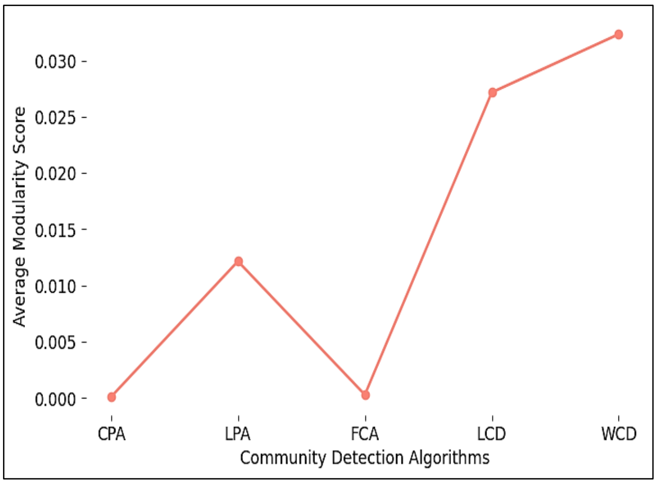

Figure 14: Comparison of the Average Modularity Value Per Community for Existing Algorithms

Table 2: Comparison of Results on Major Community Detection Algorithms on Email-Euall Network Dataset

Algorithm	No. of Communities	Average No of Nodes per Community	Average Clustering Coefficient	Average Modularity of Community
Clique Percolation (CPA)	3	132.334	0.412	
Label Propagation (LPA)	46	10.326	0.412	0.386
Louvain Community Detection (LCD)	32	14.844	0.412	0.461
Walktrap Community Detection (WCD)	39	12.179	0.412	0.446

The Email-EuAll dataset's community detection findings are provided in Table 2, which also shows the average modularity values and number of communities for each algorithm.

Table 3: Comparison of the Results Obtained on the Major Community Detection Algorithms on Synthetic Dataset

Algorithm	No. of Communities	Average No of Nodes per Community	Average Clustering Coefficient	Average Modularity of Community
Clique Percolation (CPA)	15	3.4	0.0474	
Label Propagation (LPA)	4	25.5	0.0474	0.047
Louvain Community Detection (LCD)	10	10.2	0.0474	0.427
Walktrap Community Detection (WCD)	9	11.333	0.0474	0.428

The performance metrics for the Synthetic dataset are shown in Table 3, which also illustrates how various algorithms react to simulated network dynamics.

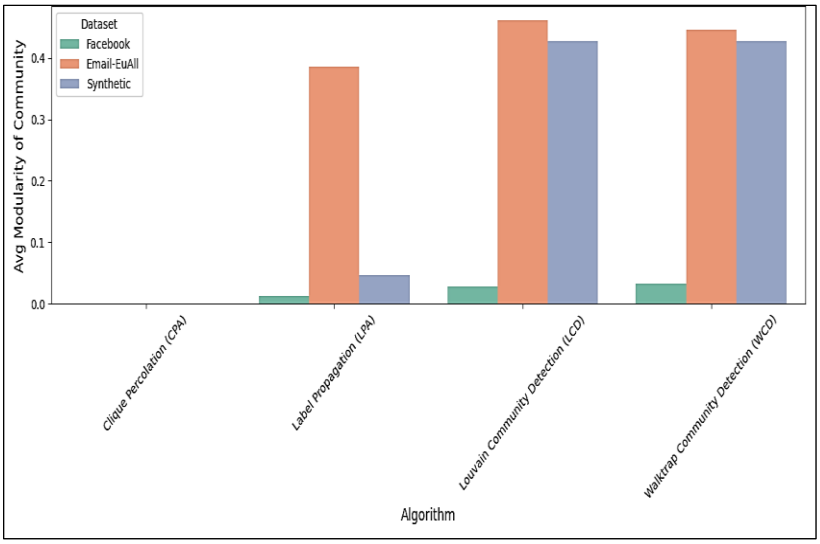

Figure 15: Comparison of Modularity Values of Different Community Detection Algorithms for Datasets

Performance pattern of community detection techniques are dissimilar based on statistical analysis of the three datasets. LCD and WCD always attain high modularity, in particular in sparse, well partitioned communities as those of Email-EuAll and Synthetic data, where the modularity takes values of 0.461 and 0.427, respectively (Figure 15). In comparison, CPA prefers small tight-knit clusters, thus leading to large modularity and small number of communities. LPA exhibits a more moderate modularity (0.386) in more sparse networks such as Email-EuAll but identifies smaller, but more communities in the Facebook dataset. Such observations are confirmed by correlation analysis as presented in Figure 16 where qualitative results demonstrate a positive relationship between modularity and community granularity and a weak relationship between clustering coefficient and modularity. As presented in Figure 17, LPA has a relatively moderate modularity when it creates fewer communities, which establishes the suitability of the algorithm again to sparse networks. At large, the two forms, LCD and WCD are resistant to modularity-oriented tasks, but CPA and LPA are competent in special settings.

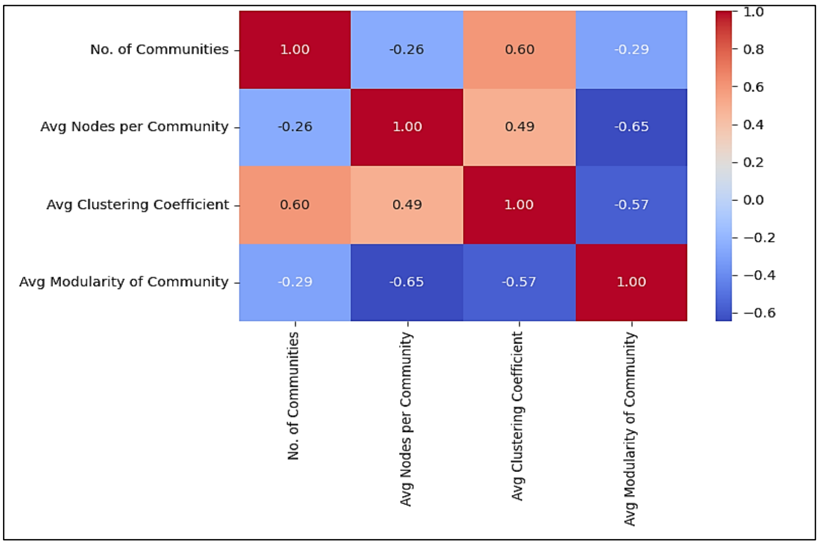

Figure 16: Correlation Matrix of Different Parameters for Datasets

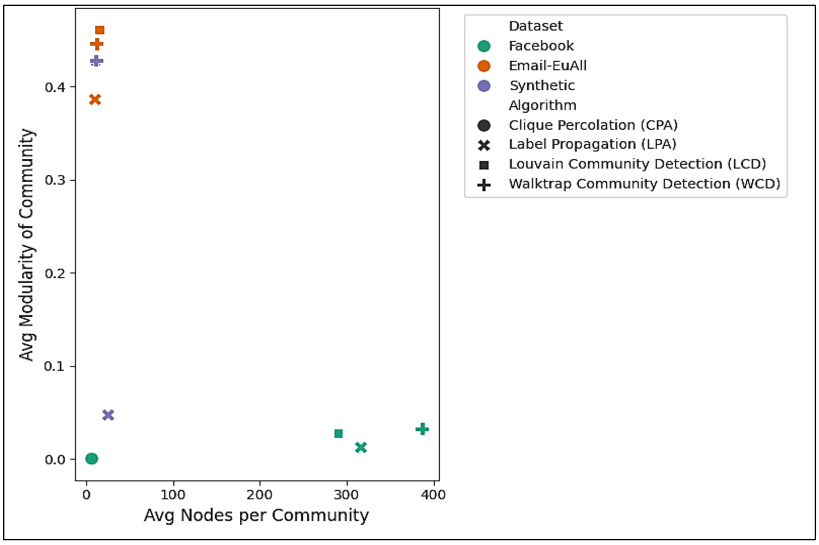

Figure 17: Scatter Plot of Average Modularity Value and Number of Nodes Per Community for Datasets

Scalability Considerations

Applying community detection to large, evolving real-world networks demands scalability. Louvain and Label Propagation (LPA) stand out for their efficiency. LPA, with near-linear time complexity and minimal global information needs, suits large, sparse networks. Louvain also scales well by reducing computation through hierarchical modularity optimization, making both suitable for dynamic networks. In contrast, algorithms like Clique Percolation and Walktrap struggle to scale due to higher time complexity and reliance on global structures. Clique Percolation's dependence on k-clique counting and Walktrap's use of random walks become computationally expensive in dense or large graphs. These limitations hinder their use in real-time systems without further optimization. Future work should focus on distributed frameworks, graph sampling, and incremental detection to adapt resource-intensive methods for high-scale, dynamic networks (63).

Practical Applications

Insights from studying community dynamics and hierarchical evolution in social networks have valuable practical applications. In corporate management, understanding shifting hierarchies and communication clusters can help detect isolated departments, identify informal leaders, and improve internal communication. In marketing and social innovation, tracking influential networks and their evolution supports targeted outreach, viral campaigns, and product adoption strategies. These insights enable organizations to align interventions with emerging social structures and influence patterns (18). Dynamic community detection enhances modeling in fields like epidemiology by enabling real-time tracking of disease transmission channels and supporting targeted interventions. In cybersecurity, detecting sudden changes in community behavior or hierarchy can reveal insider threats or coordinated malicious activity. Temporal modeling of user communities also improves personalization and relevance in recommendation systems and information retrieval platforms. Thus, the approaches discussed in this paper can support a wide range of systems that rely on evolving human interaction networks (18).

Comparative Analysis with Previous Studies

The performance of community detection methods that are established in the study has been determined to support a number of past researches. More specifically, modularity-based algorithms, including Louvain, showed better results in detecting well-separated communities in both Facebook and Email-EuAll data sets, which was also observed in the previous work (23,25). Label Propagation is a static approach, so it is natural that it has good performance on the sparse and dynamic settings as compared with the prior literature due to its tendency to work effectively on communication networks (18,54). These insights lead to the conclusion that some of the static algorithms naturally crop up dynamic settings and further the credibility of modularity as a metric of quality. There have been shortcomings of the

Clique Percolation Algorithm (CPA) in large or poorly connected networks because it relies on dense clique patterns. This finding is contrary to previous findings that pointed out the strong ability of CPA to identify small, overlapping communities (55). The difference can be explained by a gap in the scale and topology of datasets and the necessity to match the algorithm choice and the features of a network. The current paper adds to this realization by measuring how the modularity and clustering coefficient of CPA changes with increasing network sparsity.

Its issue with scalability on larger temporal snapshots was also discussed even though established to be very successful on smaller networks (61). The timing point of analysis in the proposed research should be contrasted with the majority of previous analyses conducted using a snap shot evaluation that indicate that the temporal implementation showed that the structural evolution over the years impacts detrimentally on the behavior of Walktrap. It was likewise discovered that despite Label Propagation being computationally efficient in large networks, modularity and stability remain dataset-dependent this is particularly in environments where there is a density of connections such as the case in Facebook (46). This work by introducing temporal variability and multiple-data set evaluation, further contributes to the evaluation of community detection methods, and increases the foundation of dynamic network analysis under diverse real-life circumstances.

Conclusion

Social networks continually evolve as nodes and edges are added or removed, and social events lead to varied interactions. This study applied Louvain, Walktrap, Label Propagation, and Clique Percolation to detect communities and hierarchies in three networks: Facebook Social Circles, Email-EuAll, and a synthetic dataset. Results showed that Clique Percolation maintained strong clustering coefficients, Label Propagation excelled in sparse networks, and Louvain and Walktrap performed well in terms of modularity. The findings highlight the adaptive nature of social networks and the importance of aligning algorithm choice with network characteristics. While static visualizations were used to illustrate temporal changes, they fall short in capturing the dynamic nature of social networks. Future research will explore interactive visualizations and time-lapse graph animations to better represent community formation, fusion, and dissolution over time. These tools may provide more intuitive interpretations and deeper insights into temporal behavior. Additionally, the study proposes enhancing the scalability and hierarchical detection of Clique Percolation by integrating neighborhood theory to better capture temporal evolution for practical applications.

Abbreviation

None.

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None.

Author Contributions

All authors have contributed equally.

Conflict of Interest

Author has declared there is no conflict of interest.

Ethics Approval

Ethical clearance for this study was based on the provision of informed consent from all participants, ensuring their voluntary participation and understanding of the research's purpose and procedures.

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