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A Performance Evaluation of Community Detection Algorithms Using Modularity and NMI across Diverse Social Network Datasets

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Abstract

Community detection is crucial in the analysis of social networks. Its main goal is to find groups of users densely connected among them, and sparsely connected between themselves. There are so many algorithms which makes it difficult for researchers to choose the best one for a specific dataset. In this paper, we provide a thorough comparison between five Community Detection (CD) algorithms- Girman-Newman (GN), Clauset-Newman-Moore (CNM), Label Propagation Algorithm (LPA), Louvain and Leiden. To evaluate in real social network datasets like Zachary's Karate Club, Dolphin networks and bigger ones such as Facebook, Twitter, LinkedIn along with citation networks we used different metrics modularity and NMI. We employed Normalized Mutual Information (NMI) to quantify the agreement of detected communities with their true ground-truth score and modularity for evaluating the overall quality of partitions given by diverse methods. Our experiments show that greedy and modularity-optimization algorithms are particularly well-suited. Notably, the Leiden algorithm had a better modularity value than Louvain (Q = 0.9141 and Q = 0.9051 of LinkedIn Network respectively) in most of the dataset. The NMI plot provided more explanation about Clauset-Newman-Moore (CNM), Louvain and Label Propagation Algorithm (LPA)which are in good agreement on community detection and their NMI score. These results would allow us to choose more rationally among the different community detection algorithms for social network analysis, by providing accurate quantitative benchmarks.

Keywords: Social Network, Social Network Analysis, Community Detection, NMI, Modularity.

1. Introduction

A network is a representation of relationships among individuals which is modeled as a graph $G = (V, E)$, where Vdenotes the set of nodes (vertices) representing entities, and Edenotes the set of edges (links) representing relationships, or connections between them. For example, just imagine you are holding fishing net where every node is connected directly to another which represents direct link between them. Hence social network is a vast web of individual which are tied together by different means, such as school, work, activities just like a fishing net. It forms a community of people trading information, assistance and interests.

Social network analysis (SNA) is the systematic study of relationships between different individuals which help us to understand different patterns of interactions and clusters among tightly connected groups (communities). Just as a coach studies strength and weakness of each and every player in the team and strategize accordingly in any team sport, similarly

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SNA observes how people share ideas, form alliances, or spread information in a social network. By analyzing these connections mathematically and visually, SNA provide insights about how relationships explain behaviors, uncovering hidden structures like influential individuals, key communities, and pathways through which information flow.

When we talk about our favorite sports team. Just like a team, a community is a group of people who might live in the same area, enjoy the same type of music, or have the same beliefs. They have something in common that bonds them together and provides them with a sense of togetherness and unity.

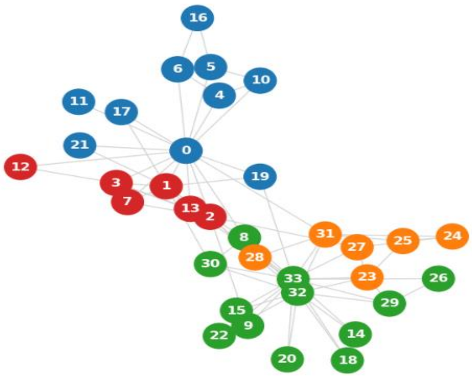

Fig. 1.Communities in social networks

Community detection is the concept to identify naturally clustered groups in a social network, such as clusters of little circles amidst a large crowd, for instance friends who hang out with each other, fans sharing favorite teams, or individuals working in same job or on same project. Community detection does that automatically through graph theory and computational techniques. This may give us some insight into how relationships between different individuals in any community are structured, how information flows through different channels, as well as the nature of cliques or group of people that can be clustered in accordance with their interest.

Phenomenon of clustering in social network is where one tries to partition the people into groups based on similarity or “closeness” within the system. It's based on data mining and machine learning algorithm such as clustering which is applied to network data. In a social network, clustering may be structural in nature, where members are clustered if they have similarities in terms of the structures through which they are linked liked common friends or frequent interactions. It could also be attribute based, where the similarity of user profiles, interests or their behaviors are used to form clusters, which may be the combination of structural links and node attributes such as connections and contents (i.e., tweets) shared.

The words “community” and “clustering” are often used interchangeably in social network analysis, but they are really two different things. A community is a naturally forming group within a social network, characterized by dense internal connections and sparse links to the rest of the network. Communities emerge organically from the network’s structure and often correspond to real-world social groups such as friend circles, interest-based communities, or professional networks. For example, on Facebook, a community might represent your close friend circle, where everyone frequently interacts, comments on each other’s posts, and shares common interests. On the other hand, clustering is a broader data-driven process of grouping nodes based on similarity measures, which may not always correspond to natural interaction patterns. For instance, an e-commerce platform like Amazon might cluster users

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into groups based on similar purchase histories or browsing patterns, even if those users have no direct connection with one another. Clustering methods, such as K-Means or Spectral Clustering, rely on mathematical distances in an embedding or feature space and typically produce non overlapping partitions, whereas communities obtained through community detection may overlap, which allow a node to belong to multiple groups simultaneously. In essence, community detection emphasizes uncovering the inherent organizational structure of a network, while clustering focuses on algorithmically partitioning nodes based on selected similarity metrics, which may or may not fully align with the social dynamics of the network.

Social networks such as Twitter have become vital platforms for customer interaction, propagation of information, and diffusion. Community detection in densely connected groups or in clusters of customers is key to understand network topology and customer behavior. Existing community detection techniques are largely founded on structural measures such as pattern-of-connectivity without making use of textual content written by customers. However, communities in social sites usually emerge over topics or interests embedded in users' textual updates. Structural data alone may therefore overlook semantically pertinent relationships.

2. Literature survey

Bedi and Sharma conducted a comprehensive survey of community detection in social networks. They emphasized the growing importance of analyzing large-scale online social activities. Their research techniques involved at least six areas which are graph partitioning, clustering, genetic algorithms, label propagation, semantic approach and Overlapping community detection. The study referred to algorithms that were widely used, such as Girvan-Newman, Louvain, modularity optimization methods, and random walk-based detection techniques, as well as new expressions that combined semantic information with big data frameworks. Also included in the analysis were evaluation metrics like modularity and clustering coefficients. At last, they discussed about applications of community detection in recommendation systems, biology networks, collaborative identification of research teams [1].

Thangaranjan et al. (2023) empirically comparing different community detection algorithms in their paper such as Louvain, Label Propagation, Girvan--Newman and k-clique percolation methods, on rich dataset with large networks like those of Github's social developer networks. They introduced machine learning and deep learning particularly extending the Graph Neural Networks (GNNs) for the prediction of the ideal number of communities and increased accuracy detection. According to their analysis, Louvain can be a better result (M = 0.8), and NMI (0.9) which reaches the highest score for overlapping community and k-clique performed the best tune for non-overlapping communities. Furthermore, their experimental results confirmed the GNN-based hybrid method’s effectiveness for a feature–dense dynamic network [2].

Rustamaji et al. (2024) enhanced GMD (Greedy Modularity Disassembly) strategy was proposed for community detection to overcome the problem of standard modularity-based methods which are easily trapped in local minima. They propose node and community disassembly (e.g., weak nodes, low embeddedness, triad based) to improve both the modularity and detection accuracy. Extensive experimentation on real and synthetic data has confirmed the superior performance in comparison with state-of-the-art methods such as

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Louvain, Leiden or Girvan-Newman especially for modularity optimization, breaking resolution limits [3].

Yen et al. investigated how community formations were affected by social network interaction in collaborative online environment discussion. Using social network analysis (SNA), the study measured betweenness, closeness and eigenvector centralities to chart how students standing changed within online learning communities. The results showed that learners closeness centrality became higher over time, contributing to stronger study groups. Self-regulated learning skills demonstration led to critical thinking, collaboration and active participation of students in the digital domain [4].

Du et al. examined the potential for large–scale online communities of AI-driven automatic text generation using deep learning. The result showed how GPT-2 generated human-like responses that were context relevant and hence highly appreciated by learners, which making them feel comfortable. Then he proposed a model of educational community discovery which integrates two types of deep learning- Deep Recurrent Neural Networks and Convolution Neural Networks. Recurrent Neural Networks (DRCNN) and hyper spectral feature selection [5].

Gao and Zhang gave an extensive survey on graph diffusion-based community detection, where they showed that it performs equally well for local as well global detection. The work also classified different framework categories such as edge-based, higher-order model and techniques such as Personalized Page-Rank (PPR) and heat kernel diffusion. The review, in particular highlighted how well graph diffusion captured similarity. Hence it improved community quality and relevant domains from social, biological to information networks [6].

Tharani et al. developed a model for community detection in educational networks using Deep Recurrent Convolutional Neural Networks (DRCNNs), along with hyper spectral feature selection, to study the communication features of online educational networks. The technique employed Box-Cox Normalization, the estimation of community pattern interest rate (CPIR) and lynchpin academic communities. Better accuracy and consistency have been achieved compared with traditional machine learning algorithms [7].

Newman analyzed the problem of community detection in graph partitioning. It is a nontrivial way to design algorithms that can take full advantage of traditional marginal models such as the stochastic block model in partitioning communities for network data. This method enabled us to use methods like spectral partitioning which further achieved performance that was both fast and competitive in terms of accuracy. To the best of our knowledge, the work is first to unify probabilistic inference and classical graph partitioning based algorithms, leading a theoretically founded way for answering the community detection question [8].

Karrer and Newman proposed a degree-corrected stochastic block model (DC-SBM), to enhance the quality of communities especially in networks exhibiting heterogeneous degree distributions. In contrast to traditional block models, DC-SBM takes into consideration of the degree heterogeneity between nodes and demonstrates a robust performance on real networks. They showed that the inclusion of degree correction provides better-fitting models and improved performance on synthetic benchmarks, as well as a variety of real-world datasets [9].

Karatas and Sahin (2018) extended the research by comprehensively reviewing the fields of community detection applied within criminology, public health, politics, marketing, recommendation systems, and privacy protection. They described community detection methods as spectral, statistical inference, optimization-based and dynamic. Despite the

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amount of attention given to the issue before the studies were written, they discussed their limitations. They recommend nurturing this increasing preference with a bit of practical assistance. Moreover, it has gone far beyond previous considerations by traditional me drawn from our discussion. The scanning method is also subject to new questions such as fraud detection epidemic modelling and link prediction. Now, to cater for the rapid increase in demand take advantage of the more appropriate term Community Detection for present day applications as they prefer it for real-time processing. [10].

Hoffmann et al. proposed a method for extracting communities from multivariate time series data without explicit network edges. This end-to-end framework carries signal uncertainties from data raw waves to community labels, produces multi-scale detection and it compares different community detection models. Applications to finance and climate data showcased its effectiveness in uncovering latent community structures in scenarios where relationships are implicit or unobservable [11].

Jin et al. outlined the latest developments in community detection, splitting them into two categories: stochastic block models (SBMs) that comprise probabilistic graphical models (such as factor analysis, matrix factorization and topic models) and deep learning approaches (including auto-encoders). Their work introduced an integrated framework that unifies the methods, therefore emphasizing trends like dynamic SBMs, mixed-membership models and learning-based representations. They also underlined the change from topology-based approaches to represent the learning and multiple information fusion. In this way, they have opened up possibilities for deep learning models of ever-increasing complexity on complex network community detection [12].

In recent systematic reviews, machine learning-based community detection methods proposed by Nooribakhsh et al. were systematically mapped with 246 peer-reviewed papers for machine learning-based community detection method. According to their results, unsupervised learning approaches (e.g., k-means, DBSCAN, spectral clustering) dominate the literature due to their scalability and low computational complexity. Deep learning approaches after 2020 in particular have however shown significant progress based on their performance in handling high-dimensional data and dynamic structures [13].

Common algorithms used to detect disjoint and overlapping communities are Louvain, Label Propagation [14], Girvan-Newman and k-clique percolation. The Louvain algorithm optimizes modularity for finding community structures, Label Propagation applies node label diffusion across the graph, Girvan-Newman repeatedly removes edges between communities by edge betweenness, and k-clique finds densely connected sub graphs as communities. Deep learning models, particularly Graph Neural Networks (GNNs), have recently been proposed for community detection because they are able to capture complex node and edge patterns. These models perform better than traditional methods in large dynamic networks with node features and structural information at the same time.

The literature is also concerned with classification of communities as overlapping, non-overlapping, and hidden. Though static networks were the focus of the majority of earlier works but since dynamic, attributed, and temporal networks are increasing widely it makes a big challenge in dynamic community structure and multiple edge types. Moreover, metrics like Normalized Mutual Information (NMI) and modularity remain the default for performance measurement, and Zachary's Karate Club is among the most widely used benchmark datasets.

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Louvain is renowned for its scalability and effectiveness in optimizing modularity. Spectral methods rely on eigen decomposition of graph Laplacians but require predefined cluster counts. Graph embedding techniques, such as Node2Vec [15] and Deep Walk learns about low-dimensional node representations preserving structural context. More recently, Graph Neural Networks (GNNs) have been explored for representing learning in attributed networks.

We compare different community detection methods by highlighting the size of networks they can manage, along with their strengths and weaknesses. Such a comparison helps in understanding which algorithm is more suitable for large-scale networks, and what trade-offs come with each approach (refer Table I).

TABLE I. COMPARISION OF COMMUNITY DETCTION ALGORITHMS

Method	*Can handle no. of nodes*	*Advantages*	*Limitations*
Edge betweenness (Girvan-Newman Algorithm)	~1,000 - 5,000	• Conceptually simple and easy to understand	• Extremely slow and not practical for large networks
Hierarchical clustering (Clauset-Newman-Moore Algorithm)	~500,000 – a few million	• Much faster than Girvan-Newman. • Good for medium to large networks. • Simple, greedy approach is efficient.	• Suffers from a resolution limit (can't find small communities
Graph Partitioning-Louvain Algorithm	Millions to Billions	• Very fast and highly scalable. • The long-time standard for large networks. • Finds high-quality communities.	• Can produce poorly connected or even disconnected communities. • Finds high-quality communities.
Graph Partitioning-Leiden Algorithm	Millions to Billions	• Fixes Louvain's key flaw: Guarantees that all communities are well-connected. • More accurate and reliable results. • The new standard for modularity	• Slightly slower per iteration than Louvain (but a worthwhile trade-off).
Label propagation Algorithm	Millions to Billions	• The fastest algorithm available. • Extremely simple to implement. • Excellent for a quick first look at a massive network.	• Unstable: Results can vary between runs due to randomness

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3. Application Areas of Community Detection

Community detection is not a mere theoretical concept but a conceptual tool applicable to diverse fields. Detecting groups and hidden structures allows community detection to serve many purposes such as the analysis of social interactions, patterns detection, enhanced decision making, and predicting next steps. Additionally, community detection can be used in both a static and dynamic sense, across both online and real-world settings [10].

a) **Criminology:** Finding hidden structures within criminal networks is made easier with the aid of community detection. It can identify criminal groups, spot fraudulent trends in telecom or financial data, and find coordinated cyberattacks or botnets. Law enforcement can more effectively monitor terrorist cells and organized crime by mapping relationships.

b) **Politics:** Community detection is used in political contexts to investigate how politicians, political parties, or ideologies affect society. It is also employed to reveal "astroturfing"- a practice in which automated systems or phony accounts fabricate the appearance of popular support for a campaign or policy.

c) **Marketing and Advertising:** Knowing their customers is a major concern for most companies. In the past, marketers treated all buyers the same. Community detection helps businesses, divide buyers into groups of shared interests or behaviors. Once a business recognizes their audiences, they may further refine their ads to be even more targeted, provide unique offerings, or even change product recommendations. For first time in a marketer's career, they can make marketing feel less random and more relevant to the people they are trying to reach.

d) **Recommendation Systems:** Recommendation engines like the ones used on Netflix, Amazon, or Spotify do a better job if they have a good idea of which groups you belong to. Community detection works by grouping users with similar preferences. If members of your "community" read a certain book, watch a certain movie, or listen to a certain musician, you're likely to do the same. This is why recommendations feel so astoundingly accurate.

e) **Social Network Analysis:** Social media sites, including Facebook, Twitter, or LinkedIn, have lots of relationship data. Community detection organizes the data into clusters for friends, groups of professionals or groups with shared interests. The clusters created show not only how individuals interact online, but also explore the potential for meaningful real-world relationships and influences.

f) **Privacy and Network Summarization:** In some cases, too much data is shared, and an individual-level analysis of the networks would be unmanageable. By creating communities of groups in a social network, patterns can be analyzed without revealing private details. This can help to preserve privacy when the information is eventually shared with other organizations or researchers. In other instances, such as information shared from crypto currency networks, the information can reveal the connections between accounts meant to be anonymous.

g) **Community Evolution Prediction:** Communities are dynamic that they grow, shrink, split, and die. At the evolution of communities over time, it might be possible to predict their future of their growth, or ultimate demise. This is typically done using machine-learning tools in conjunction with community detection, and allows researchers to predict social movements, customer patterns, or political movements.

h) **Citation and co-authorship networks:** Within academia and research, community detection is also a widely used method of analyzing collaborative activity. By looking at who is citing who, or who is publishing papers together, academics may be able to detect research communities that are formed. This will not only allow academics the opportunity to identify new fields of inquiry, demonstrate groups of leading scientists in respective fields, but may also offer some indication of possible future collaborations.

4. Community Detection Algorithms

a) Divisive (Top-Down): Starts with the whole network and progressively splits it. Example: Girvan-Newman Algorithm. The Girvan Neuman (GN) algorithm is also known as the edge betweenness algorithm to identify communities within a network [18][19].The edge betweenness represents bridge edges between communities in the network.

b) Overlapping Community Detection: Acknowledges that nodes can belong to multiple communities (e.g., a person can be in a "family" community and a "work" community). Example: Clique Percolation Method (CPM) whichfinds communities by searching for adjacent cliques (fully connected subgraphs) [21].

c) Agglomerative (Bottom-Up): Starts with each node as its own community and progressively merges the "closest" pairs.

- Louvain Method which is highly efficient and popular algorithm that optimizes modularity in two phases: local node moving and network aggregation. It's known for its speed and accuracy [16].
- Clauset Newman Moore is aim for greedy modularity optimization based on merging communities to enhance modularity. It is faster than Girman-Newman but slower than Louvain [27].

d) Label Propagation:A very fast method where nodes adopt the community label of the majority of their neighbors. Example: Label Propagation Algorithm (LPA) which is simple, fast, but can have non-deterministic results [17].

e) Leiden Algorithm: It recursively merges community into single nodes by using greedy optimization, then optimizing the modularity and the process repeated in the contracted graph[20]. This work just like Louvain, optimizes modularity in three phases: local movement, refinement and aggregation. It fixes the Louvain's disconnected modularity.

5. Experimental analysis

In this section, we worked on five publicly available social network datasets to evaluate the community detection algorithms mentioned in section 4.

5.1 Experimental Setup

We used several key Python libraries for the experiments and all experiments were implemented in Python 3.10 and executed on Google Colab Pro and Jupyter.

- pandas: Essential for importing, cleaning, and managing network data in a structured data frame format before analysis.
- networkx and igraph:Used for creating, manipulating, and studying structure and dynamics of complex networks.
- leidenalg: It is a specialized, high-performance library for implement the leiden algorithm.
- cdlib: This is community discovery library, best for many different algorithms.

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- igraph; It is a great option for being very fast and powerful, making it suitable for very large network.
- scikit-learn: It provides standardized metrics, such as normalized_mutual_info_score to evaluate and compare community detection results.

5.2 Features used in Community detection

- Node Degree [22][25]: The number of connections a node has.
- Clustering Coefficient [22][23]: This measures how close a node's neighbors are to being a clique.
- Common Neighbors [24]: The number of shared neighbors between two nodes.
- Edge Betweenness [18][19]: The number of shortest paths between node pairs that pass through an edge.

5.3 Measures for community detection (Evaluation Metrics)

- Modularity (Q): The most popular metric. It measures the fraction of edges that fall within the given communities minus the expected fraction if edges were distributed randomly. Range [0 to 1] a value close to 1 indicates strong community structure. Excellent for comparing different partitions on the same network when you don't have a ground truth [1][24].

$$Q = \left(\frac{1}{2m}\right) \sum_{u,v} \left[A_{uv} - \frac{(k_u k_v)}{2m}\right] \delta(c_u, c_v) \quad (1)$$

Where Q is Modularity, A_{uv} is the adjacency matrix, k_u and k_v represent node degrees, m is the total number of edges, and $\delta(c_u, c_v)$ indicates whether nodes u and j belong to the same community.

- Normalized Mutual Information (NMI): Compares a known "ground truth" set of communities in the detected communities. Range [0 to 1] a value of 1 means the detected communities perfectly match the ground truth. The gold standard for evaluating algorithm accuracy on benchmark datasets where the true communities are known [1][26].

$$\mathrm{NMI}(S,T) = 2 * \mathrm{I}(S,T)/[\mathrm{H}(S) + \mathrm{H}(T)] \quad (2)$$

Where $\mathrm{I}(S,T)$is mutual information between the two partitions (S and T), measuring their shared information, $\mathrm{H}(S)$ is the entropy of partition (a measure of the uncertainty or randomness is the community assignments), and $\mathrm{H}(T)$is the entropy of partition T.

5.3 Dataset:

TABLE II. DATASETS DESCRIPTION

S. No.	*Dataset*	*Numbers. of nodes*	*Numbers of edges*
1	Zachary's Karate Club	34	78
2	Dolphin Network	62	159
3	LinkedIn Network	6,726,011	19,360,690
4	Facebook dataset	4039	88234
5	Twitter dataset	81,306	13,42,310
6	Citation network (Arxiv High Energy Physics paper citation network)	34546	420921

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5.4 Dataset Implementation

a) ***Zachary's club Dataset:*** Table III summarize the performance of various CD algorithms on Zachary's Club dataset in terms of Modularity and NMI. In terms of modularity, Louvain algorithm achieved the highest value (0.4266) while detecting four communities. When evaluated against the ground truth using NMI, Girvan-Newman achieved the highest score (0.8365). This result indicates that while Louvain provides strong modularity-based partitions, Girvan-Newman best captures the true community structure as reflected by NMI metric.

TABLE III. MODULARITY AND NMI SCORE ANALYSIS OF DIFFERENT ALGORITHMS ON ZACHARY'S CLUB DATASET

Algorithm	*Modularity*	*Community Found*	*NMI*
Louvain Algorithm	0.4266	4	0.7003
Leiden Algorithm	0.4198	2	0.6873
Girvan-Newman (GN)	0.3477	2	0.4448
Label Propagation (LPA)	0.3095	3	0.8365
Clauset-Newman-Moore (CNM)	0.4110	3	0.6925

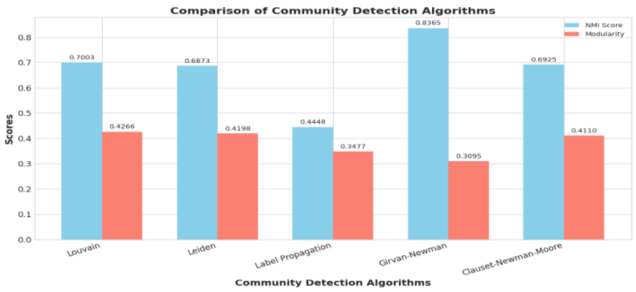

Fig. 2. Comparison of Modularity and NMI scores for different community detection algorithms on Zachary's Club dataset

b) **Dolphin's Network Dataset:** In Table IV, Modularity of Leiden yields the highest value (0.5241), closely to Louvain, both discovering similar number of communities. Fig. 4 is the heat map representation of the NMI score provides a visual summary of the similarity between the community structure detected by different algorithms for the dataset. Each cell shows the NMI value between two algorithms. Diagonal grids are 1.0000 (since each algorithm is identical to itself), and the highest value (0.9646) indicates that Louvain and Leiden find similar communities.

TABLE IV. MODULARITY ANALYSIS OF DIFFERENT ALGORITHMS ON DOLPHIN'S NETWORK DATASET

Algorithm	*Modularity*	*Community Found*
Louvain Algorithm	0.5196	6

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Leiden Algorithm	0.5241	5
Girvan-Newman (GN)	0.3787	2
Label Propagation (LPA)	0.4986	6
Clauset-Newman-Moore (CNM)	0.4955	4

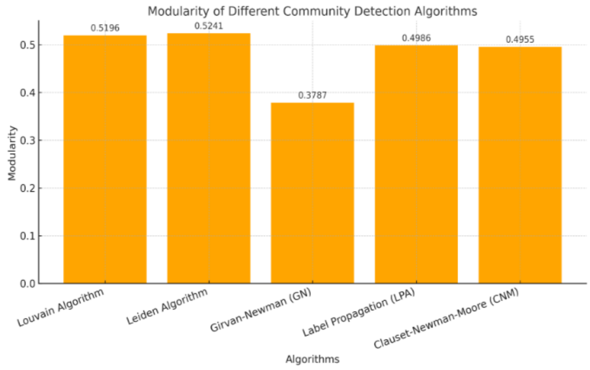

Fig. 3. Comparison of Modularity for different community detection algorithms on Dolphin's Network dataset

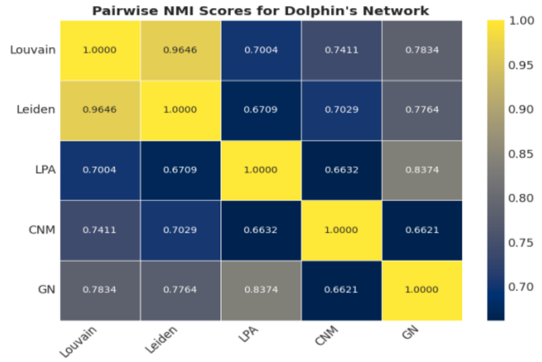

Fig. 4. The heatmap representation of the NMI score on Dolphin's Network

c) Twitter's Network Dataset: Table V summarizes the modularity of different community detection algorithms on Twitter's network dataset. Higher values indicate better-defined communities. Both Louvain (0.8077) and Leiden (0.8069) algorithms achieve very similar and high modularity, indicating both are effective in identifying significant community structures despite the large size and complexity of network. GN and CNM algorithms are not applied due to their computational inefficiency on networks with highest numbers of nodes and edges, as both algorithms have higher time complexity making them impractical for large-scale graphs. Fig. 6, heatmap represents NMI scores between two algorithms; Louvain and Leiden have a high score of 0.8596, indicating strong agreement in the structure of communities they detect. Both have moderate agreement with LPA (0.7168 and 0.7245, respectively).

TABLE V. MODULARITY ANALYSIS OF DIFFERENT ALGORITHMS ON TWITTER'S NETWORK DATASET

Algorithm	*Modularity*	*Community Found*
Louvain Algorithm	0.8077	77
Leiden Algorithm	0.8069	74
Label Propagation (LPA)	0.7562	897
Girvan-Newman (GN)	-	-
Clauset-Newman-Moore (CNM)	-	-

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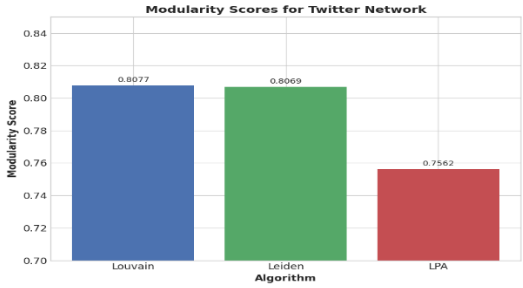

Fig. 5. Comparison of Modularity for different community detection algorithms on Twitter's Network dataset

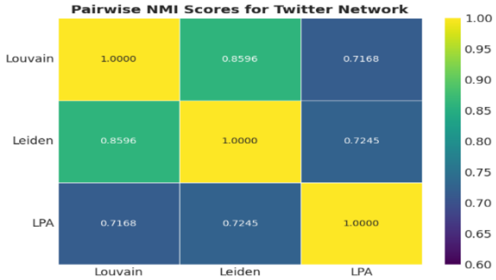

Fig. 6. The heatmap representation of the NMI score on Twitter's Network

d) Facebook's Network Dataset: In Table VI, Louvain and Leiden provide similar, high modularity scores (0.8349 and 0.8355), each discovering a moderate number of communities, indicting well -defined and robust community structures for Facebook's network. GN indicates very low modularity and finds only two communities, reflecting poor fit for this dataset (demonstrates its limitations for such complex social graphs). Fig.8 represents NMI scores between two different algorithms, Louvain and Leiden show moderate similarity (0.4654), consistent with their close modularity scores and number of communities. Comparison with LPA indicates higher NMI value for Louvain (0.8075) and CNM (0.8568), discovering that these methods agree more closely. CNM and GN show a very low NMI (0.1782), highlighting significant differences in detected structure.

TABLE VI. MODULARITY ANALYSIS OF DIFFERENT ALGORITHMS ON FACEBOOK'S NETWORK DATASET

Algorithm	*Modularity*	*Community Found*
Louvain Algorithm	0.8349	15
Leiden Algorithm	0.8355	16
Girvan-Newman (GN)	0.0439	2
Label Propagation (LPA)	0.7368	44
Clauset-Newman-Moore (CNM)	0.7774	13

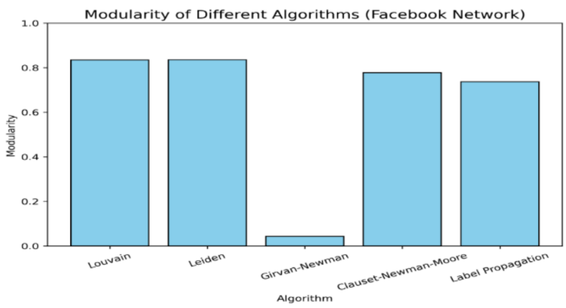

Fig. 7. Comparison of Modularity for different community detection algorithms on Facebook's Network

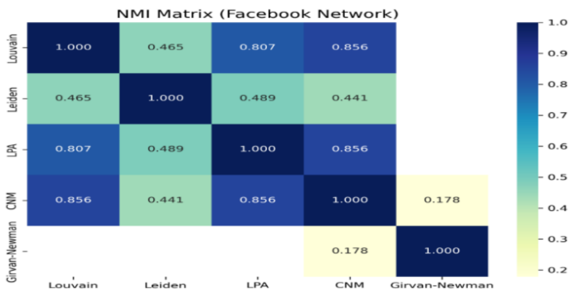

Fig. 8. The heatmap representation of the NMI score on Facebook's Network

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e) LinkedIn's Network Dataset: Table VII summarize the modularity on LinkedIn's network dataset. Leiden yields a very high modularity (0.9141) with 1384 communities, showing effective and clear partitioning of the network. Louvain produces slightly lesser modularity (0.9051) but identifies 293 communities. LPA gives a much lower modularity and finds an extremely larger number of very small communities, possible over-segmentation. As described previously that GN and CNM algorithms are not applied due to their computational inefficiency. Fig. 10, heatmap represents NMI scores, LPA and Leiden show moderate similarity (0.5074), indicating actual assignments overlap only partially. While Louvain and Leiden both achieving high modularity, also show only moderate agreement (0.6679), showing that Leiden's more granular community structure differs from Louvain's coarser partition even though both achieve similarly high-quality separations.

TABLE VII. MODULARITY ANALYSIS OF DIFFERENT ALGORITHMS ON LINKEDIN'S NETWORK DATASET

Algorithm	*Modularity*	*Community Found*
Louvain Algorithm	0.9051	293
Leiden Algorithm	0.9141	1384
Label Propagation (LPA)	0.7477	421223
Girvan-Newman (GN)	-	-
Clauset-Newman-Moore (CNM)	-	-

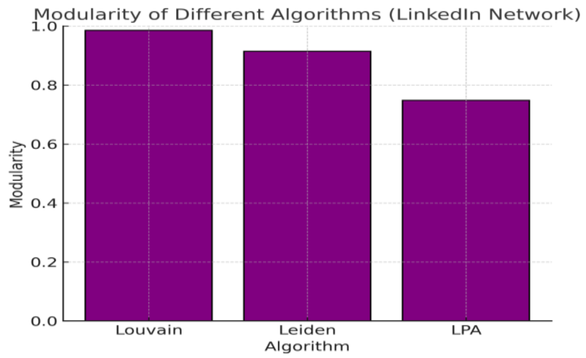

Fig. 9.Comparison of Modularity for different community detection algorithms on LinkedIn's Network dataset

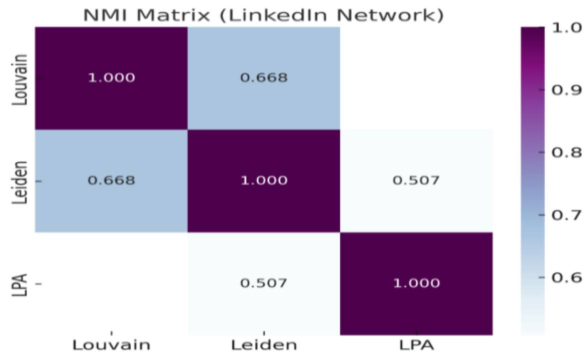

Fig. 10. The heatmap representation of the NMI score on LinkedIn Network

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f) **Citation's Network Dataset:** Citation's Network Dataset Table VIII is modularity analysis for the Citation Network dataset, Leiden achieves the highest modularity (0.7352), closely followed by Louvain (0.7269), with both algorithms finding around 86-85 communities, showing similarity robust and meaningful partition. CNM and LPA identifies far more communities but with lower modularity, showing over-partitioning and weaker structure. GN is not applicable in this network due to computational constraints or incompatibility. Fig. 12 represents heat map of NMI scores, Louvain and Leiden show strong agreement (0.7749), reflecting their similar modularity and community counts. Both have lower similarity with CNM and LPA, consisting larger number of smaller communities.

TABLE VIII. MODULARITY ANALYSIS OF DIFFERENT ALGORITHMS ON CITATION'S NETWORK DATASET

Algorithm	*Modularity*	*Community Found*
Louvain	0.7269	85
Leiden	0.7352	86
Clauset-Newman-Moore	0.5516	197
Label Propagation (LPA)	0.6686	725
Girman-Newman	-	-

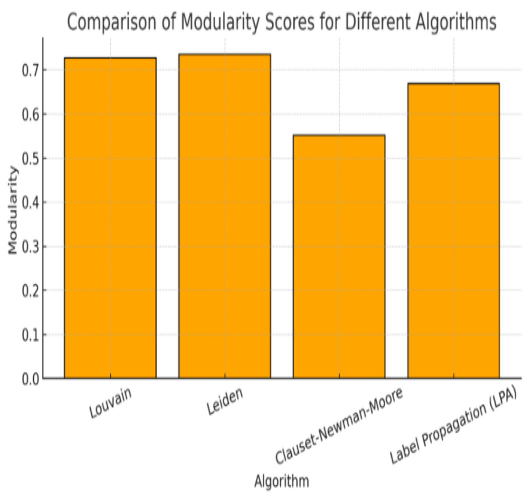

Fig. 11. Comparison of Modularity for different community detection algorithms on Citation's Network dataset

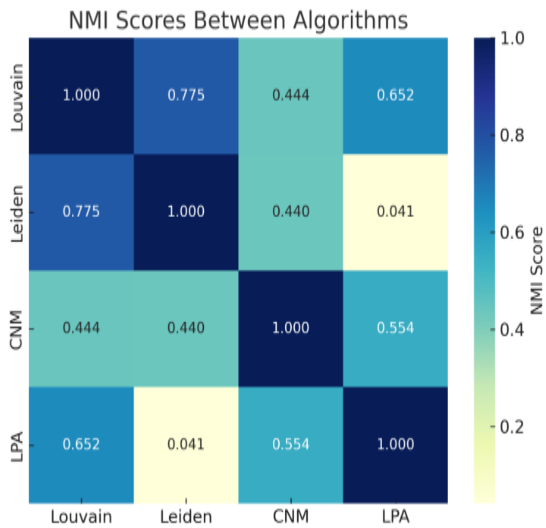

Fig. 12. The heatmap representation of the NMI score on Citation's Network

6. Conclusion

This review has rigorously assessed the performance of some of the most influential community detection algorithms, Louvain, Leiden, Label Propagation (LPA), Girvan-Newman, and Clauset-Newman-Moore (CNM)on social networks of diverse scale and structure. The results show that there is no unified "best" algorithm, but rather the best choice depends on the particular features of the network and the aims of the analysis. For maximizing the modularity score, the Louvain and Leiden algorithms performed invariably better, with the best scores on all the tested datasets. However, the key observation is supported by the NMI scores which maximized modularity does not necessarily translate to equal community structures. This was strongly observed in the case of Facebook, where both Louvain and Leiden generated different partitions although their modularity scores were almost identical.

Scalability is a factor which determines feasibility of practical use. While hierarchical methods like Girvan-Newman provide a benchmark, their computational burden makes them impractical for real-world large networks, as it is already not available to be carried out on large dataset. Nevertheless, the Louvain, Leiden and LPA algorithms scale well, although they may give very different community resolutions (indeed LPA can over detect and find a lot more smaller size communities).

The development of algorithms that balance scalability and sensitive detection is a priority for future work, particularly for time-evolving networks and overlapping community identification, which better accommodate the multiplex nature of human social interactions.

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