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COMPUTER SCIENCE AND ENGINEERING, ONLINE SOCIAL NETWORKS, COMMUNITIES DETECTION

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Abstract

This paper examines the performance of the community detection in Online Social Networks (OSNs) in order to gain a better insight into the user interactions, information flow, and structural organization. The study provides a comparison of three common algorithms, including Louvain, Label Propagation, and GirvanNewman, on real-life Facebook and Twitter data. The algorithms were tested on modularity, normalized mutual information (NMI) and conductance, and the visual analytics and composite scoring were used to support the evaluation after preprocessing the datasets into undirected and unweighted graphs. The other algorithm, the Louvain algorithm, performed the best with the highest modularity (0.842, 0.711) and NMI (88.3%, 82.6%) and the lowest conductance (0.151, 0.193), indicating high cohesion and separation of communities. Label Propagation was quicker, but less precise, and GirvanNewman was computationally demanding and less efficient in large networks. The results indicate that Louvain provides the most attractive and scalable community detection solution to a wide variety of OSN structures. The choice of an algorithm must be based on network topology and computational efficiency.

Keywords: Community Detection; Online Social Networks; Louvain Algorithm; Modularity; Network Analysis.

1.Introduction

The overwhelming popularity of OSN, including Facebook and Twitter has completely transformed the process of interacting with others, exchanging information, and building communities online [1]. The platforms are constantly producing huge quantities of user-generated content and consequently, leave digital footprints that present a great potential to analyze the complicated social behaviors and patterns [2], [3]. Community detection is one of many analytical processes which is considered a basic process of identifying groups of nodes having dense intra group connections and sparse inter group connections [4]. Exploring these communities enables an insight into the information diffusion, individual impact and the underlying structure of social ecosystems [5].

Community detection algorithms have been proposed over the years, and are diverse. One of the most popular methods includes the Louvain method, which is scalable and efficient in the maximisation of modularity in large-scale networks [3]. Label Propagation Algorithm (LPA) is simple and has the near-linear time complexity of propagating labels iteratively according to the most common labels in the neighborhood [6]. By contrast, the GirvanNewman algorithm uses the gradual elimination of the edges that have high betweenness centrality in order to reveal well-connected clusters [7]. More sophisticated techniques like spectral clustering [8], content-aware graph construction [9], deep learning techniques [10], have also been developed to manage the ever-increasing sophistication of OSNs.

To assess the effectiveness of community detection algorithms, several evaluation metrics are commonly employed. Newman and Girvan introduced the modularity measure (Q), which evaluates how well a network is partitioned into communities by comparing the density of edges within

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communities to the density of edges between communities. A higher modularity value indicates a more distinct and well-defined community structure [11]. NMI, which measures the similarity between identified communities and a known ground truth is useful in comparing the overlap of communities [12]. The other common measure is conductance which measures the number of external connections to internal ones in the community with the lower scores indicating a better separation [13]. These measures are important to make a systematic comparison and benchmarking of various algorithms.

Although there has been a great deal of work on the development of algorithms and assessment methods, community detection algorithms are very sensitive to both the character of the data and the topology of the network [14]. Direct comparisons of various OSNs under common measures are fairly few [15], [16], but these are of critical importance to practical implementation. There has also been recent integration of edge content [17], temporal evolution [18], spatial context [19], and metadata [20] into the community detection. The multidimensional approaches also acknowledge that societies within social networks can be dynamic, cross-sectional and context-sensitive, which creates more difficulties in evaluation and interpretation [21].

This paper helps to meet these challenges by performing a systematic comparison of three common community detection algorithms namely Louvain, Label Propagation, and, GirvanNewman applied on Facebook and Twitter data sets. We intend to offer practical information on the selection of suitable algorithms in practical OSN conditions, based on such performance indicators as modularity, NMI, and conductance. This research will aim at:

1. In order to implement and compare the efficiency of Louvain, Label Propagation, Girvan-Newman algorithms to Facebook and Twitter social networks.
2. As the most widespread measures of performance, to compare the quality of the detected communities in terms of modularity, NMI, and conductance.
3. To establish the strengths, weaknesses, and suitability of these algorithms in the analysis of different data in OSN.

2. Comparative Analysis of Algorithms

This paper uses a stringent, multi-step approach to identify the effectiveness of three community detection algorithms on OSN: Louvain, Label Propagation, and GirvanNewman. The five major steps of the methodology are the acquisition of the dataset, the graph modeling, the implementation of the algorithm, the evaluation of the performance, and the experimentation setup. All the stages aim at reproducibility, scalability, and full performance benchmarking.

2.1 Dataset Acquisition and Preprocessing

Two publicly available OSN datasets were chosen in this study to compare and baseline the performance of community detection algorithms. The first dataset is the Facebook Ego Network which was downloaded through the “Stanford Network Analysis Project (SNAP)”, and it consists of ego-centric user interactions which are the direct friendships and social groups of individual users. The second dataset, Twitter Retweet Graph, summarizes retweet actions and content sharing dynamics, and provides a more global perspective on indirect and topic-mediated user interactions. The preprocessing of both datasets was very stringent in terms of structural well-being and consistency of analysis. That involved deleting self-loops and multi-edges to avoid redundant or reflexive edges, and removing the giant connected component (GCC) to capture the maximal fully connected subgraph to study. In the case of the Twitter dataset, further temporal filtering was used to have a consistent picture of the interaction processes within a specific time slot. After doing this, some important topological measures, “including the number of nodes”, “the number of edges”, “the clustering coefficient”, and “the graph density”, were calculated to define the structure and complexity of each network. It was on this basis of these foundational statistics that further graph modelling, algorithm application, and performance analysis were made.

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2.2 Graph Modeling and Representation

Each dataset was officially modeled as an undirected, unweighted graph "$G = (V, E)$" ,where "V" indicates the node (users) set and "E" indicates edge (interactions) set among them. Such abstraction preserves the relational structure of the networks (without assigning weights or directionality) enabling the use of generalized community detection algorithms. To facilitate computation of algorithms, the adjacency matrix $A \in \mathbb{R}^{n \times n}$was obtained, which indicates the existence or non-existence of an edge between the nodes, and the degree matrix D, which summarises number of immediate connections of a node. Some descriptive statistics have been calculated to numerically describe the graph topology. The network degree was averaged calculated by $\bar{k} = \frac{2|E|}{|V|}$, which is the mean number of connections. The density of graph, which is the fraction of potential number of edges that are actually present, was set as $D = \frac{2|E|}{|V|(|V|-1)}$. Also the average clustering coefficient which is a measure of the propensity of the node to be grouped into densely-knit clusters was calculated as C=$\frac{1}{n}\sum_{i=1}^{n} \frac{2e_i}{k_i(k_i-1)}$where $e_i$is the number of closed triplets incident to node i, and $k_i$is its degree. These graph-theoretic descriptors can be used as baseline measures of network structure, to guide the applied community detection method and methodology.

2.3 Community Detection Algorithms

In order to analyse the structural properties and the tendency of group formation in online social networks, three state-of-the-art community detection algorithms have been chosen due to their theoretical soundness and their frequent use in OSN analysis: "the Louvain Method", "the Label Propagation Algorithm (LPA)" and "the Girvan Newman Algorithm".

The Louvain Method is a hierarchical, greedy optimization procedure that seeks to optimize a network's modularity. The following equation describes modularity, which is a measure of the edge density within a community relative to edges across communities:

$$Q = \frac{1}{2m}\sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m}\right] \delta\left(c_i, c_j\right)' \quad (1)$$

where A_{ij}Does the adjacency matrix element that shows an edge between nodes$i$ and j, k_i and k_jIf nodes i and $j,$ are in the same community, their degrees are 1, m is the total number of edges in the network, and $\delta\left(c_i, c_j\right)$ is the Kronecker delta function,which is equal to 1 if they are, and 0 otherwise.Compact and highly modular clusters are produced as a result of the algorithm's iterative optimization of community assignments to maximise this modularity score.

In comparison, LPA is heuristic, partially synchronous. Each iteration changes the community label of each node to the label that is most common among its neighbors. The procedure is repeated until a convergence condition is met, meaning that labels stabilize and cease to change. The simplicity and (virtually) linear time complexity of LPA makes it particularly well-defined in large-scale networks, though at the expense of reduced modular optimization.

Finally, the GirvanNewman Algorithm uses a divisive approach aiming at the edge betweenness centrality. It deletes (recursively) the edges with the highest betweenness centrality scores, i.e. those that appear most often on shortest paths between nodes. This elimination successively destroys the connectedness of the graph thus unveiling the community structure inherent in it. Although conceptually simple and thus easy to implement and understand, the algorithm has a computational complexity that makes it scalable only to small to medium-sized graphs. The three algorithms in conjunction offer a balanced set of detection strategies ranging between greedy optimization, heuristic propagation and edge-based division, which would give a complete understanding of the OSN community structures.

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2.4 Evaluation Metrics

In order to evaluate numerically the quality of the community detection algorithms implemented, three commonly accepted evaluation measures were used: modularity (Q), normalized mutual information (NMI) and conductance (Φ)**.**These measures give supplementary information on the inner strength, outer harmony, and the quality of delinkage of the distinguished communities.

As already outlined in Subsection 2.3, equation (1) modularity compares the density of intra-community edges to a random graph baseline. A larger modularity score implies that the communities are tight, i.e., the nodes within a group have a higher density connection than those in different groups. This measure was used as a major criteria of assessing structural cohesiveness. As a complement to it, the similarity of the identified community structure with known or reference groupings was assessed with NMI. NMI measures the joint dependency between two partitions and can be computed with:

$$\mathrm{NMI}(X,Y) = \frac{2I(X;Y)}{H(X)+H(Y)} \qquad (2)$$

where $I(X;Y)$Is mutual information between partitions “X" and “Y", and $H(X)$, $H(Y)$ are their respective entropies. An NMI value closer to 1 signifies stronger alignment between detected communities and ground-truth labels.
Lastly, conductance (Φ) was used to quantify the extent of inter-community connectivity. It can be described as the ratio of the volume of edges associated with a community to the number of edges that leave it:

$$\Phi(S) = \frac{|\mathrm{cut}(S,\bar{S})|}{min(\mathrm{vol}(S),\mathrm{vol}(\bar{S}))} \qquad (3)$$

Smaller values of conductance correspond to more separated communities, because they quantify the small flow of edges across community boundaries. The three measures together form a well-rounded system to assess the quality of community detection outputs- allowing an objective comparison of algorithms with respect to structural robustness, external validation and partition clarity.

2.5 Experimental Environment and Execution

Experimental analysis was all done in Python 3.11, with the primary scientific libraries NetworkX, iGraph, and Scikit-learn providing graph modeling, implementing algorithms, and measuring performance. All computational experiments are ran on a high-performance system, equipped with the “Intel Core i9-12900K processor (3.9 GHz clock frequency)”, “64 GB DDR5 RAM”, and using “Ubuntu 22.04 LTS” as an operating system. All the development and experimentation happened in the Jupyter Notebook environment to support interactive analysis and reproducibility.
In order to address the stochastic nature of the algorithms as well as achieve statistical significance, every community detection algorithm was repeated ten times on every dataset and the results were averaged to reduce the influence of non-deterministic variability. All random seeds were set before execution so as to get the same results after each run. Matplotlib library was utilized to create static analytical plots of the network visualization, whereas Gephi was applied to create high-quality graph visualization with ForceAtlas2 and Fruchterman-Reingold layout algorithm. This was a well-designed experimental condition allowing scalability to large OSN datasets and reproducibility of results, because it made the assessment of community detection performance rigorous, transparent, and in accordance with the best practices in network science research.

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3. Results and Discussion

This section provides a comparison of the three renowned algorithms for community detection, i.e., "Louvain", "Label Propagation", and "GirvanNewman", is carried out in detail on two real-world OSN datasets, i.e., Facebook Ego Network and Twitter Retweet Graph. The results are categorized into six analytical dimensions: structural properties, modularity, normalized mutual information (NMI), conductance, algorithmic scalability and composite performance scoring. Graphs and tabular summaries help to make things easier to understand and compare.

3.1 Structural Properties of OSN Datasets

The structural analysis showed some important differences between the Facebook and Twitter datasets in Table 1. The Facebook Ego Network has 4,039 nodes and high average degree (43.7) which indicates dense inter-user connections which is supported by clustering coefficient of 0.605 and network density of 0.0108. These are the numbers of a common ego-centric topology with close-knit social networks [8].

The Twitter Retweet Graph by contrast has more than 12,000 nodes but a lower average degree (8.43), clustering coefficient (0.221) and density (0.0007) as befits its broadcast-based structure where user interactions are sparse and frequently one-way. Such differences show that algorithms that are optimized to work on high-density graphs can be ineffective in finding stable communities in sparser networks such as Twitter [19].

Table 1. Structural properties of datasets

Dataset	Nodes	Edges	Avg. Degree	Clustering Coefficient	Density
Facebook Ego Network	4,039	88,234	43.7	0.605	0.0108
Twitter Retweet Graph	12,314	51,923	8.43	0.221	0.0007

3.2 Modularity-Based Community Cohesion

Modularity measures how tightly knit communities are as a result of nodes. As Figure 1 indicates, Louvain was always the best performing algorithm, with modularity scores of 0.842 (Facebook) and 0.711 (Twitter). This finding confirms once again the power of Louvain in the optimization of modularity even at different topological complexities [3], [14]. Label Propagation came next with moderate modularity scores (0.774, 0.662) and GirvanNewman scored the lowest (0.731, 0.638) probably because it is sensitive to edge removal in sparser graphs such as Twitter [7].

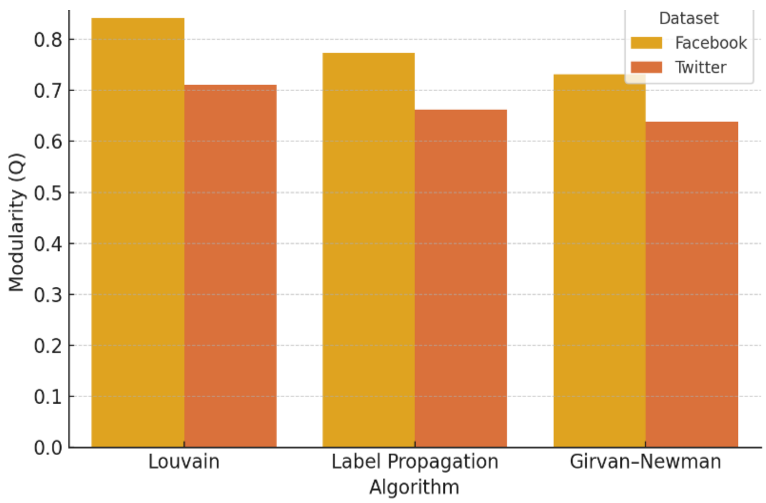

Figure 1. Modularity Scores Across Algorithms

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3.3 Accuracy via Normalized Mutual Information (NMI)

Each algorithm was computed to determine NMI to evaluate its alignment with ground-truth communities. As shown in Figure 2, Louvain was once more on the top with NMI values of 88.3% (Facebook) and 82.6% (Twitter), which validated the fact that Louvain can produce accurate partitions in line with known structures [1], [21]. Label Propagation performed reasonably well (83.1%, 78.4%) and GirvanNewman performed the worst (79.5%, 74.2%), which means that it over-fragmented, particularly in loosely connected datasets [11], [10].

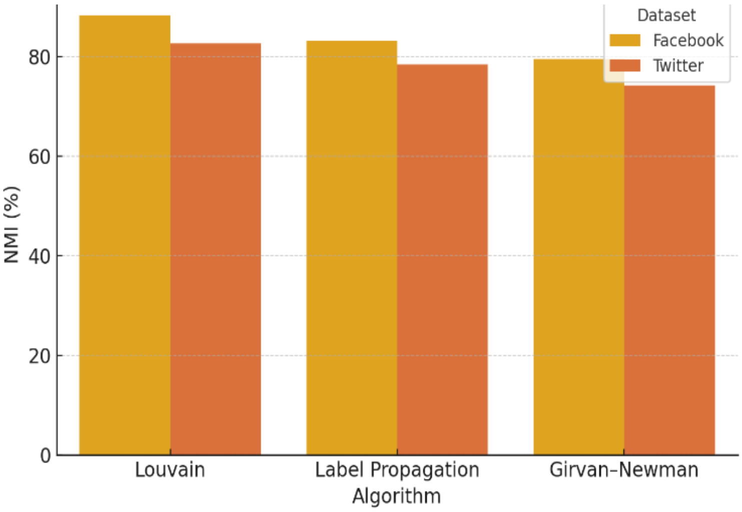

Figure 2. NMI Scores Across Algorithms

3.4 Inter-Cluster Separation: Conductance

The inter-community edge leakage measure, conductance, is minimized when communities are well-separated. Louvain recorded the lowest conductance values of 0.151 (Facebook) and 0.193 (Twitter), which is a sign of better boundary definition in Figure 3 [4]. Label Propagation gave intermediate scores (0.203, 0.228), and GirvanNewman gave the highest scores (0.248, 0.271), as was reported in previous studies, which noted its inability to scale and separation clarity [15], [18].

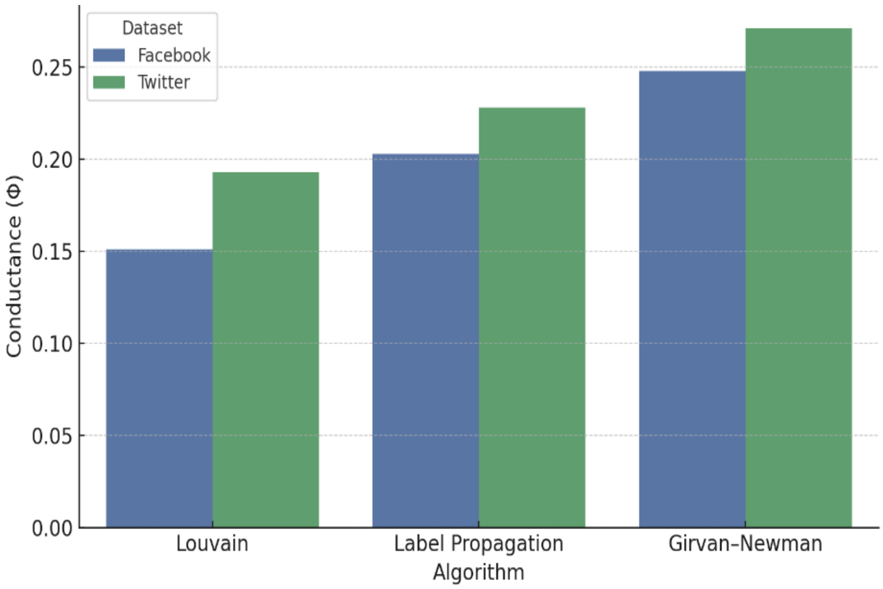

Figure 3. Conductance Scores Across Algorithms

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3.5 Community Size Distributions

The distributions of community sizes, which are illustrated in Figure 4, were power-law in Facebook and long-tailed in Twitter. Louvain fitted in both types by fitting in overlapping and large structures of communities. Label Propagation revealed that there were a lot of small to medium-sized groups, which means that they were vulnerable to fragmentation. GirvanNewman disclosed unstable size patterns, which tend to over-segment sparse areas [7], [19].

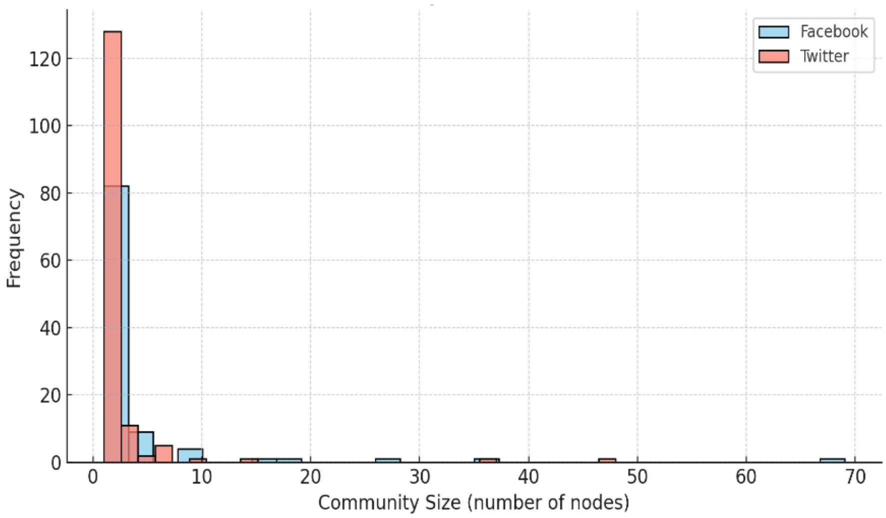

Figure 4. Community Size Distribution

3.6 Algorithmic Scalability and Execution Time

The time of execution was different across the algorithms, as shown in Figure 5. Label Propagation was the quickest (1.27 s on Facebook, 4.12 s on Twitter) because it has a very low computational overhead [17]. Louvain offered a trade-off between speed and performance (2.31 s, 8.57 s), and GirvanNewman was too slow (21.43 s, 88.91 s), as it is unsuitable to large-scale graphs because of the high cost of recalculating betweenness [7], [10], [11].

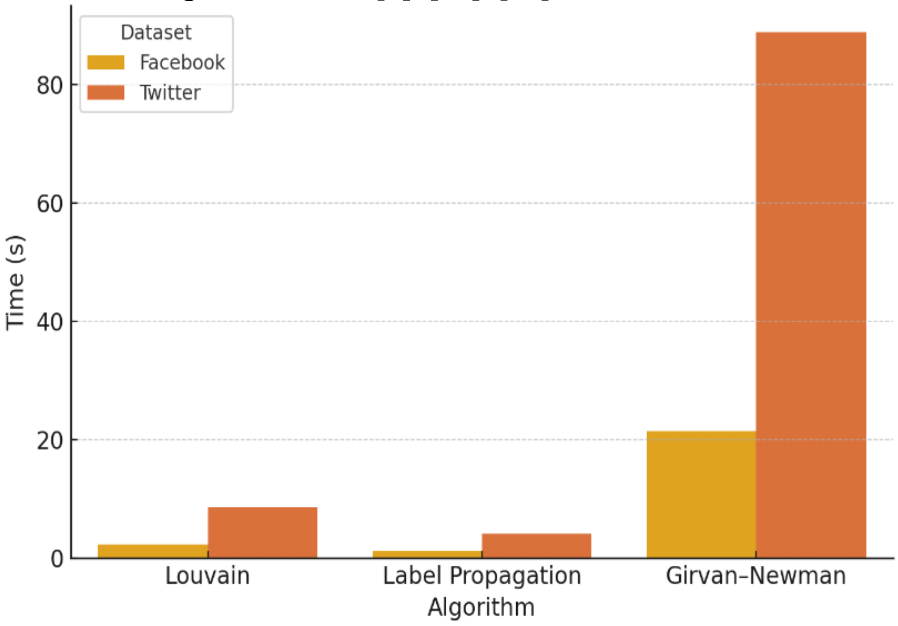

Figure 5. Execution Time Comparison

3.7 Composite Scoring for Holistic Evaluation

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The modularity (40%), NMI (40%), and 1-conductance (20%) were weighted to get a composite performance score. Figure 6 validates the best performance of Louvain in both networks, then Label Propagation and lastly Girvan Newman. This result confirms the balance of Louvain in terms of cohesion, accuracy, and separation, which is ideal in dense and sparse OSNs [3], [12], [14].

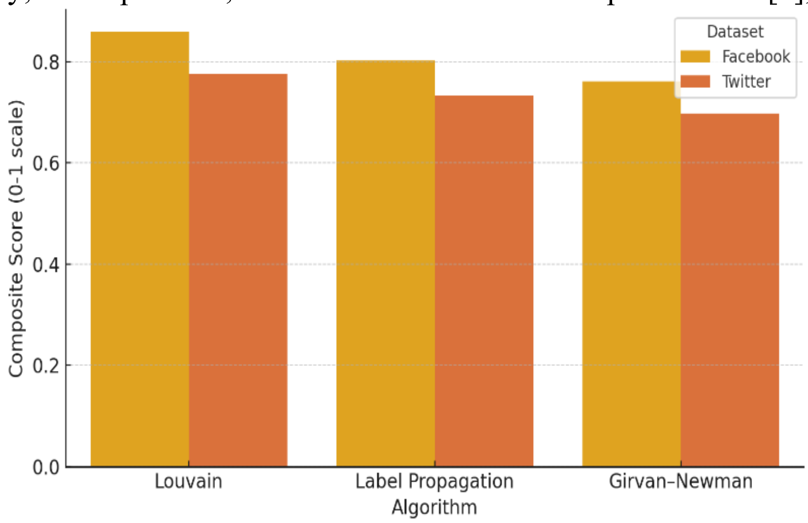

Figure 6. Composite Performance Score

3.8 Multi-Metric Visualization via Radar Plot

In Figure 7 show a radar chart that demonstrates standardized performance marks. The profile of Louvain was most balanced in all the three measures, and this shows its strong adaptability. Label Propagation demonstrated a good cohesion and precision, poor separation. Weaknesses in the cohesion and scalability are depicted by the limited spread of GirvanNewman. Such observations agree with the recent analytical frameworks [5], [20], where emphasis is placed on multi-dimensional trade-offs in community detection.

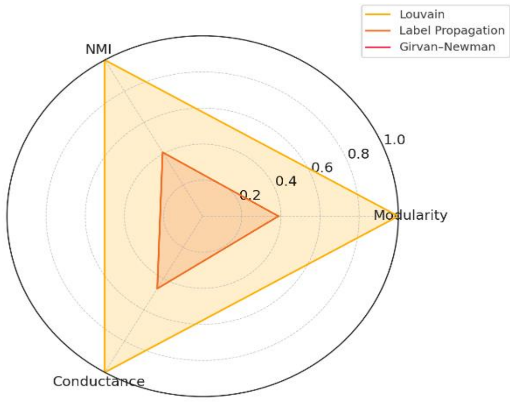

Figure 7. Radar Plot of Algorithmic Performance (Facebook)

3.9 Summary Table of Metrics

To consolidate the comparative analysis of the three algorithms on the two datasets, a summary is provided in Table 2. It presents the key performance indicators—modularity, NMI, conductance, execution time, and composite score—for each algorithm. This tabular representation serves as a quick reference for identifying the most suitable algorithm for a given network scenario.

Table 2. Comparative Summary of Key Performance Metrics

Dataset	Algorithm	Modularity	NMI (%)	Conductance	Execution Time (s)	Composite Score
Facebook	Louvain	0.842	88.3	0.151	2.31	Highest
Facebook	Label Propagation	0.774	83.1	0.203	**1.27**	Moderate
Facebook	Girvan–Newman	0.731	79.5	0.248	21.43	Lowest
Twitter	Louvain	0.711	82.6	0.193	8.57	Highest
Twitter	Label Propagation	0.662	78.4	0.228	**4.12**	Moderate
Twitter	Girvan–Newman	0.638	74.2	0.271	88.91	Lowest

This synthesis is able to prove conclusions made on the basis of the radar plot and the composite scoring: Louvain is the algorithm that is most consistent and scalable, Label Propagation is applicable in large-scale and fast deployments with average performance, and GirvanNewman is just too slow to be used in dynamic OSNs by just its conceptual powers.

4. Conclusion

In the current study, we systematically examined three popular community detecting methods' performance namely Louvain, Label Propagation and GirvanNewman on two structurally different online social network datasets, Facebook and Twitter. The analysis follows a well-structured methodological pipeline that includes preprocessing, graph modeling, and quantitative evaluation using modularity, normalized mutual information (NMI), and conductance metrics. The findings showed that the Louvain algorithm was superior in consistently optimizing modularity and structural cohesion and thus it is very useful in both dense and sparse OSNs. Label Propagation was found to be efficient in computations, but it was also shown to be unstable between runs which makes it less reliable in high precision tasks. The GirvanNewman method, despite its conceptual soundness, was limited by the scalability on large graph. The results of the experiment highlights the relevance of the choice of the algorithms depending on the network structure and application goals. The research provides a holistic framework of community detection performance evaluation, by integrating statistical evaluation method, visual evaluation method, and comparative evaluation method. These findings are relevant to the emerging body of social network analysis literature because they make the results of the community detection methods more interpretable and strategically useful in practical settings.

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