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A Graph-Theoretic Clustering Approach to Social Network Analysis

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Abstract

Networking websites such as LinkedIn have now become rich sources of data that represent real world career connections. Unraveling the underlying community structure of such websites is critical in many domains, including recruitment, organizational analysis, and professional networking. In this work, the authors utilize graph theoretical community detection techniques to study LinkedIn professional network data. nodes denote the LinkedIn members, and links denote the professional relationships among these members. To create an edge weight for this graph, three metrics of similarity were used: location, profession (using Jaccard similarity index) and age group. There are two algorithms utilized to detect communities: **Louvain algorithm** and **Girvan-Newman algorithm**. Some of the graph measures calculated include betweenness centrality, clustering coefficient, density, and modularity. This experiment is conducted on the dataset containing 148 hand curated LinkedIn profiles. The result produced by Louvain algorithm shows 6 distinct communities in the network, with a modularity score of 0.508 that indicates high modularity in the network. On the other hand, Girvan-Newman algorithm did not perform well with the current dataset. It was found that professional role is the most important variable that influences community detection. Betweenness centrality is employed in detecting five important bridge professionals. the above mentioned study shows that graph theory approaches can be effectively used for investigating the underlying structures in professional social networks. The findings of this experiment will add value to the field of social network analysis in terms of the structural clustering.

Keywords: *Clustering Algorithm, Girvan-Newman Algorithm, Louvain Algorithm, Betweenness Centrality, Community Detection*

1 Introduction

LinkedIn has now become one of the leading professional networking sites due to its extensive reach through millions of people in all sorts of professions and careers. This extensive reach forms a professional social web that is complicated and inter-connected. However, it is still difficult to understand the structure hidden in professional relations within the network. Conventional ways of analyzing data consider LinkedIn data as isolated users or simple tables having no information beyond their characteristics such as job title, company, or skills.

These approaches, while being very informative, do not take into account network connectivity, community building, and information exchange. Given that LinkedIn is a platform based on connections, the neglect of the network may result in misleading conclusions. The main goal of the present research is to overcome the mentioned drawback by using a graph-based approach to model LinkedIn data and applying graph theory clustering algorithms to discover the hidden communities of professionals, patterns of relationships, and handle the problem of large scale networks.

2 Review of Literature

Many people have been engaged in social network analysis and have been trying to comprehend the process of formation and interaction among the network. The idea of modularity was introduced by Newman and Girvan [6] for assessing the community structure of a complex network. Modularity compares a network partition with a random network in order to assess its quality. Newman [7] improved the methods of optimizing modularity.

The use of graph theory in social network analysis to find influential nodes through the study of structural properties like centrality, clustering, and connectivity has been studied by Dutta [1]. Likewise, Dutta [2] has reviewed some recent graph theoretical techniques used in modern social networks.

Jamadar [4] concentrated on the role of graph theory in the solving of network-related issues such as finding the shortest path between two vertices, the problem of flow and connectivity in the network. The research stresses the significance of graph models in analyzing the structure and dynamics of different types of complex systems, for example, transport and communication networks. Goledzinowski and Błocki [3] provided an overview of graph-theoretic methods in social network analysis by considering the theoretical ideas and practical application of the methods. The researchers considered such methods as centrality

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measures, clustering, and community detection stressing the multidisciplinary character of network science involving computer science, data analytics, and sociology.

The practical application of graph theory in social network analysis was explored by Mamatha, Sunitha, and Shivakumar [5]. The study concentrated on the use of centrality measures, clustering, and graph visualization in the analysis of social networks.

Community Detection Method using Random Walks by Pons and Latapy [8] is a probabilistic method for community detection. The method works on the assumption that the random walks will tend to stay within the same community. Hence it helps identify densely connected clusters in a network. The community detection method based on random walk significantly increased the efficiency of community detection, especially for larger networks. Raghavan [9] developed a community detection algorithm that works in near linear time. The algorithm had significant computational efficiency due to which it was suitable for community detection in large networks. Fortunato [10] gave an overview of various community detection algorithms along with their limitations.

3. Motivation and Objectives

The rise of LinkedIn's popularity requires a thorough investigation into the way professionals' social communities develop and are linked together. The current research aims at investigating key community groups and influential members through applying graph methods and getting insights into professional interactions and communication patterns. Real data from LinkedIn will make it possible to derive conclusions relevant to real-life social networks of professionals.

1. Detect communities and professional groups through applying clustering algorithms.
2. Estimate structural characteristics of the network, such as:
    - Centrality
    - Modularity
    - Clustering coefficient
    - Network density
3. Study the connection between user characteristics and network clusters.
4. Show practical value for:
    - Professional networking
    - Recruitment
    - Information exchange

4. Data and Variables

The data that were used for this research were gathered manually through LinkedIn profiles for an authentic presentation of the professional networking context. In total, **148 professional profiles** were gathered, and the obtained data were recorded using the Microsoft Excel software. Each profile describes an individual professional and has three characteristics: **age group, professional interests, and geographical location**. They were chosen due to their significant impact on professional relationships and communities creation in social networks.

The **age group** characteristic reflects the career level of the professional and can be presented in terms of young, middle-aged, and senior professionals. Professionals who have the same age groups tend to create professional connections and communication in the network.

The **professional interests** characteristic describes the fields of activity and competencies of professionals. The users having the same interests are more likely to connect, cooperate and share knowledge, which makes this characteristic crucial in determining the similarity of profiles.

The **geographic location** is defined by the city or region where a professional belongs. Proximity in geography might have an impact on networking activities and regional cooperation.

All three attributes were used to build the weighted professional network. In the graph form, a node refers to a LinkedIn profile, whereas the weights of the edges between nodes depend on the similarity of the users with regard to their age, professional interest, and geographic location.

5 Mathematical Formulation

Data Preprocessing:

The application of graph based techniques necessitated preprocessing of the LinkedIn data set and transforming it into a format appropriate for network analysis. The preprocessing involved transforming the profile attributes to quantitative similarities. In order to avoid biased clustering and achieve unsupervised community detection, the professional attribute was not considered during the preprocessing stage.

Dataset Representation:

Let the LinkedIn data set be denoted by:

$$D = \{u_1, u_2, \ldots, u_{148}\}$$

with u_i being the representation of individual LinkedIn professional profiles. The attributes associated with each profile given by:

$$u_i = (a_i, s_i, l_i)$$

where:

- a_i is the age of the professional,
- s_i refers to the interests of the professional,
- l_i indicates the location

Age Normalization:

To ensure comparability across profiles, the age attribute was normalized using min–max scaling. Let a_{min} and a_{max} denote the minimum and maximum ages in the dataset. The normalized age is computed as:

$$a_i' = \frac{a_i - a_{\min}}{a_{\max} - a_{\min}}$$

This transformation maps age values to the interval [0, 1].

Location Similarity Measure:

Geographical similarity between two profiles u_i and u_j is defined as:

$$L_{ij} = \begin{cases} 1, & \text{if } l_i = l_j \\ 0, & \text{otherwise} \end{cases}$$

This binary function captures the influence of geographical proximity on professional networking.

Professional Interest Similarity:

Professional interests are represented as sets of keywords. The similarity between two profiles is computed using the Jaccard similarity index:

$$I_{ij} = \left| \frac{s_i \bigcap s_j}{s_i \bigcup s_j} \right|$$

A higher value of I_{ij} indicates greater overlap in professional interests.

Age Similarity Measure:

Age-based similarity between two profiles is computed as:

$$A_{ij} = 1 - |a_i' - a_j'|$$

This measure assigns higher similarity scores to professionals at similar career stages.

Edge Weight Construction:

The overall similarity between profiles u_i and u_j is represented by a weighted edge defined as:

$$w_{ij} = \alpha L_{ij} + \beta I_{ij} + \gamma A_{ij}$$

subject to the constraint:

$$\alpha + \beta + \gamma = 1$$

where α, β, and γ are weighting parameters that control the relative importance of location, interests, and age similarity, respectively.

Graph Formation:

Using the computed edge weights, the LinkedIn dataset is transformed into a weighted undirected graph:

$$G = (V, E, W)$$

where:

- $V = \{u_1, u_2, \ldots, u_n\}$ represents the set of nodes,
- $E = \{(u_i, u_j) \mid w_{ij} > 0\}$ represents the set of edges,
- $W = \{w_{ij}\}$ represents the corresponding edge weights.

Graph Measures Calculation:

After detecting communities using the Louvain and Girvan–Newman algorithms, several structural properties of the LinkedIn network are computed to analyze the network's characteristics. Let the preprocessed LinkedIn network be represented as a weighted undirected graph $G = (V, E, W)$, where V denotes nodes (LinkedIn profiles), E denotes edges, and

W denotes edge weights based on age, professional interests, and location similarity.

Betweenness Centrality:

Betweenness centrality measures the extent to which a node lies on shortest paths between other nodes:

$$C_B(u_i) = \sum_{s \neq t \in V} \frac{\sigma_{st}(u_i)}{\sigma_{st}}$$

where σst is the total number of shortest paths between nodes s and t, and $\sigma_{st}(u_i)$ is the number of those paths that pass through u_i. Nodes with high betweenness act as bridges connecting different professional communities.

Clustering Coefficient:

The local clustering coefficient of a node u_i measures how tightly its neighbors are interconnected:

$$C_i = \frac{2e_i}{k_i(k_i - 1)}$$

where e_i is the number of edges among neighbors of u_i, and k_i is the degree of node u_i.

For weighted networks, following Onnela et al. (2005):

$$C_i^{(w)} = \frac{1}{k_i(k_i - 1)} \sum_{j,k} (\hat{w}_{ij}\hat{w}_{ik}\hat{w}_{jk})^{1/3}$$

where $w_{ij} = w_{ij}/\max(W)$ is the normalized edge weight.

Network Density:

The overall connectivity of the network is measured using network density:

$$D = \frac{2|E|}{|V|(|V| - 1)}$$

For weighted networks:

$$D_w = \frac{\sum_{i,j} w_{ij}}{|V|(|V| - 1)}$$

Modularity:

Modularity Q evaluates the quality of the detected communities:

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

where:

- c_i is the community assigned to node u_i,
- $\delta(c_i, c_j) = 1$ if u_i and u_j belong to the same community, 0 otherwise,
- k_i is the degree of node u_i,
- $m = \frac{1}{2}\sum_{ij} A_{ij}$ is the total edge weight in the network.

Attribute-Based Analysis and Visualization:

After detecting communities using the Louvain or Girvan–Newman algorithms, the detected communities are analyzed in relation to user attributes including age, professional interests, and geographical location. This analysis helps to interpret the structural patterns of the network and understand the underlying factors driving community formation.

5.1 Louvain Algorithm

Community detection is an essential task in network analysis that tries to discover sets of vertices that are more strongly connected to each other than to the rest of the graph. Those subsets of nodes, called *communities* (or *clusters*), demonstrate the structure of the complex networks.

One of the most popular approaches to community detection is the **Louvain algorithm** the developed by Blondel. It is based on maximization of **modularity (Q)** that is introduced in section 5.

5.2. Girvan-Newman Algorithm

The Girvan-Newman algorithm is one of the first methods proposed for the discovery of communities in networks. It was introduced by Michelle Girvan and Mark E. J. Newman (2002). Unlike methods that attempt to directly cluster nodes, Girvan–Newman identifies communities by **removing inter-community edges** those that serve as bridges between tightly connected regions based on a measure known as **edge betweenness centrality**.

Edge Betweenness Centrality

The edge betweenness centrality measures the significance of the edge as the number of shortest paths passing through the edge The definition of this metric is ：

$$B(e) = \sum_{s \neq t \in V} \frac{\sigma_{st}(e)}{\sigma_{st}}$$

where (σ_{st}) denotes the total number of shortest paths between nodes (s) and (t), and ($\sigma_{st}(e)$) denotes the number of those shortest paths that pass through edge (e). Edges with high betweenness centrality act as bridges between communities and are therefore removed first during the community detection process.

Algorithmic Process

The Girvan-Newman algorithm performs the following actions:

1. Calculate the edge betweenness centrality for all edges in the network.
2. Delete the edge(s) with the largest edge betweenness score.
3. Recalculate the edge betweenness after deleting an edge.
4. Repeat the procedure until the required community structure is achieved or all the edges are deleted.

The network will get divided into several disconnected sub-networks with the iterative deletion of edges, where each subgraph represents a possible community.

The effectiveness of discovered communities is measured using the modularity (Q) described in section 5.

The partition with the maximum modularity value is treated as the best community structure.

The Girvan-Newman algorithm offers a well-defined hierarchy for network division and is highly efficient in detecting community boundaries within small to medium-size networks.

6. Results

6.1. Results of Louvain Algorithm

In this research, the use of the Louvain method helped to analyze the communities in the professional network, and the results were obvious and reasonable. Six communities were found in this professional network, indicating that people can indeed be classified into several groups according to the connections between them. The result of the analysis of the modularity is around 0.508, which shows a good community structure in the network. Louvain algorithm was used on the weighted network graph that contained 148 nodes. This algorithm revealed **six different professional communities** having a value of modularity of $Q = 0.508$.

Table 1: *Louvain Algorithm Results Summary*

Metric	Value
Total Nodes (Professionals)	148
Number of Communities Detected	6
Modularity Score (Q)	0.508
Primary Driver of Clustering	Professional Role
Algorithm Complexity	$O(n \log n)$

With a modularity index of $Q = 0.508$, this is an outstanding outcome as it surpasses the accepted value of $Q = 0.3$, which is considered significant for the formation of communities within a network. This indicates that the six clusters discovered are not randomly formed, rather they are a result of structurally existing connections between individuals.

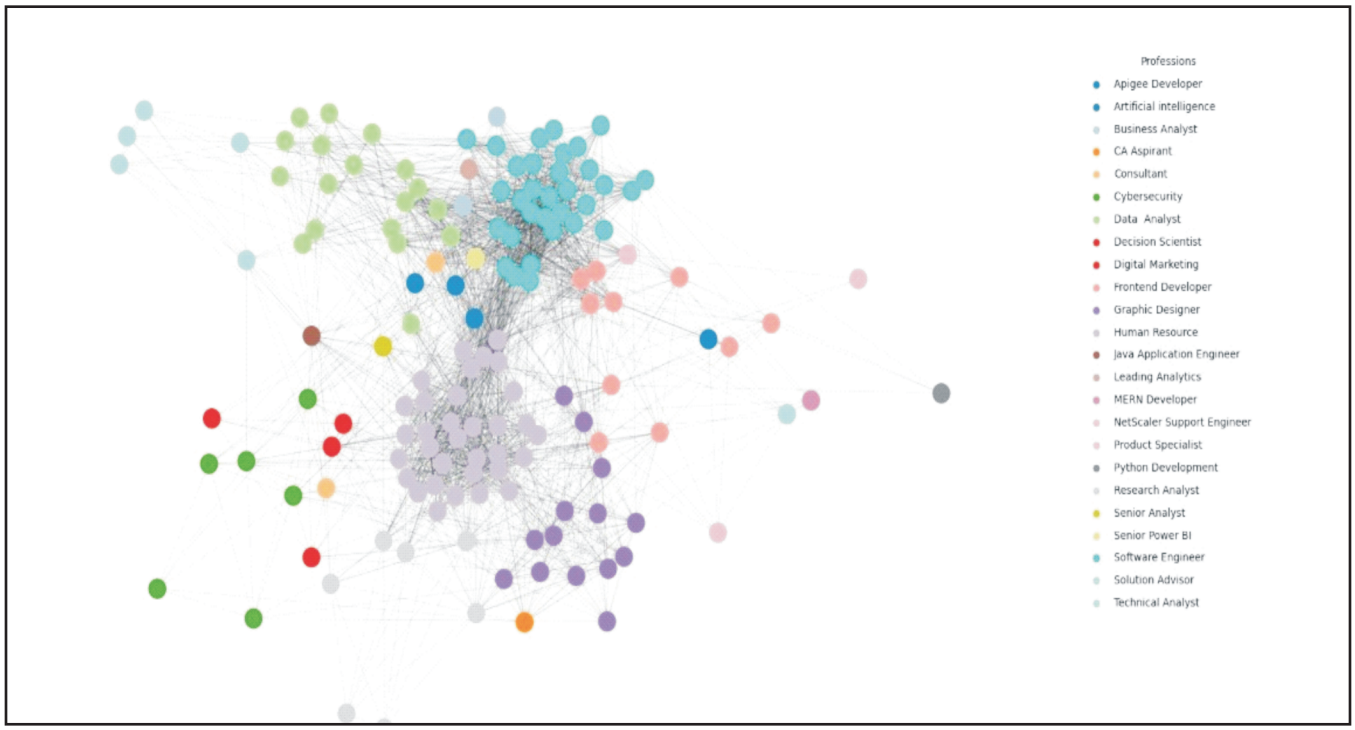


Figure 1: *Professional Network Visualization (color = Profession)*

Community Composition:

The six clusters identified through the Louvain method are representative of professional groups matching well defined occupational clusters :

- **Community 1:** Made up of front end developers and other professionals like Apigee Developer ,Python Developer , Business Analyst and Solution Advisor ,thus making it a diverse technology community .
- **Community 2:** This is a Data Analyst Community which is quite homogeneous in nature with similar professional backgrounds .
- **Community 3:** This is a Software Engineer community which is homogenous in nature .
- **Community 4:** This includes Research Analysts ,Technical Analysts ,Senior Analysts ,and Digital Marketing professionals thus making it a research and analytics driven community .
- **Community 5:** This community comprises of Graphic Designer and Cybersecurity ,Digital Marketing ,MERN professionals and hence is creative community with diversity in technology background .
- **Community 6:** This is a Human Resource Community which is homogeneous in nature and is not a technological community .

Key Graph Metrics:

Table 2: *Structural Graph Metrics for the Professional Network*

Graph Measure	Value	Interpretation
Average Clustering Coefficient	0.298	cohesion within the professional network
Network Density	0.226	Sufficient connectivity (not too high nor too low)
Modularity (Louvain)	0.508	High modularity of clusters
Modularity (Girvan–Newman best)	0.000228	Extremely low modularity
Number of Louvain Communities	6	Clearly defined professional clusters

Interpretation of the Clustering Coefficient:

With an average clustering coefficient of C = 0.298, there is moderate clustering within the network. It means that the professionals have formed a community wherein their connections are themselves connected to one another. Simply put, people

who work on the same subjects or have common interests will have stronger connectivity between them, hence forming cohesive clusters. Yet, the value does not suggest extremely high clustering; therefore, there is still some diversity within the network.

Interpretation of Network Density:

A network density of 0.226 represents a relatively interconnected network. This implies that not all possible links are present, although the number of connections within the network is high enough for interactions to be conducted effectively within the network. A well-connected network with such a density level usually occurs in professional networks where connections are made selectively rather than randomly.

Interpretation of Modularity:

The modularity score of 0.508 achieved through the Louvain algorithm shows a highly structured community formation process. The result reveals that there is an effective division of the network into communities whereby nodes within a community are connected much more strongly than the nodes connecting different communities. Unlike the Louvain approach, the modularity score achieved using the Girvan–Newman algorithm was 0.000228. The extremely small modularity score achieved by the latter method shows that no useful community structures were found in the network under analysis.

6.2. Results of Girvan-Newman

The Girvan–Newman algorithm was applied to identify communities in the pro-fessional network by removing important edges with high betweenness centrality. As more edges were removed, the network gradually split into multiple groups. The best result was obtained when the network was divided into five communities. However, the modularity values remained low, indicating weak community structure. These results suggest that although the algorithm can reveal network divisions, it is not highly effective for professional social networks. Overall, the study highlights that different community detection methods can produce different outcomes, and some approaches may be more suitable for identifying meaningful communities in such networks.

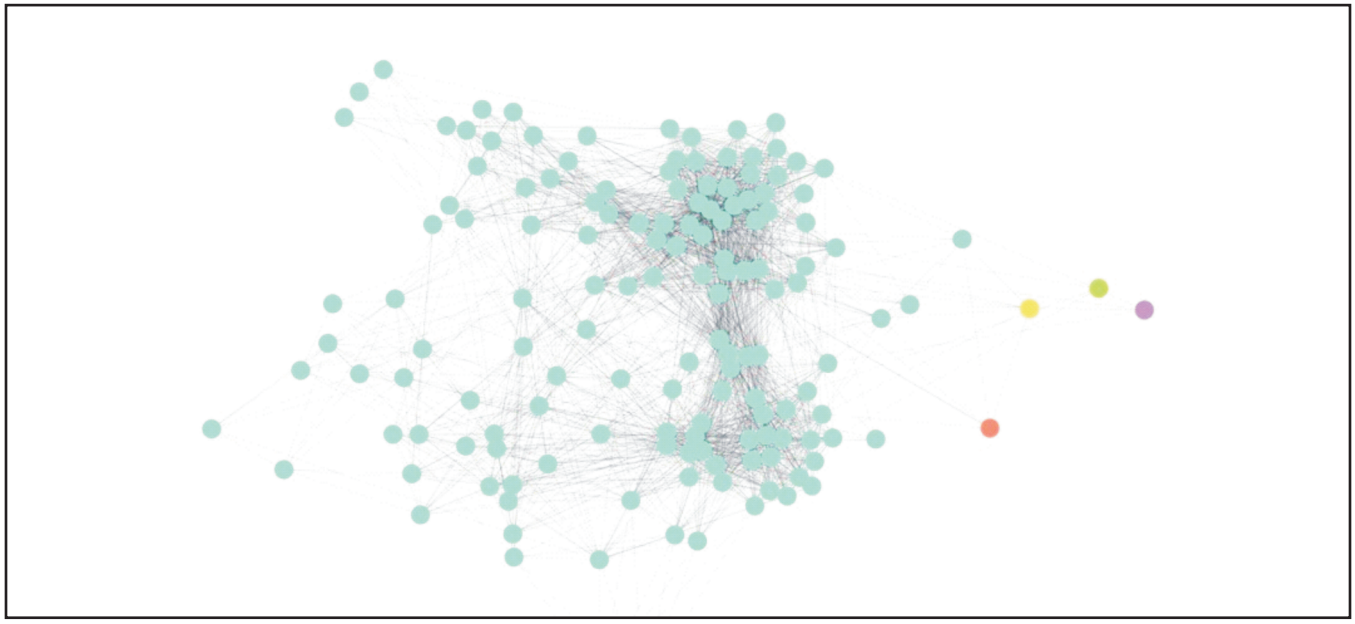


Figure 2: *Girvan-Newman community structure*

Table 3: *Girvan–Newman Algorithm: Modularity at Different Levels*

Level	Communities	Modularity (Q)
Level 1	2	- 7.0861
Level 2	3	- 1.7290
Level 3	4	- 4.9036
Level 4	5	+0.000228←Best
Level 5	6	+0 000216

Modularity gained by the Girvan-Newman method (Q = 0.000228) is almost negligible in comparison with the one obtained using the Louvain method, which equals Q = 0.508. The negative value of modularity for early stages suggests that the divisions made at the start are detrimental since they unite professionals who have structural differences, while splitting up similar ones.

Betweenness Centrality:

Betweenness centrality was used to identify the most influential users who act as bridges between different groups in the network. The analysis showed that a few users had higher betweenness centrality values, indicating their important role in connecting separate communities. These users help facilitate communication and information flow across the network. Their presence reduces fragmentation and strengthens overall connectivity. Therefore, betweenness centrality provides valuable insight into the network structure by highlighting key individuals who link different groups together.

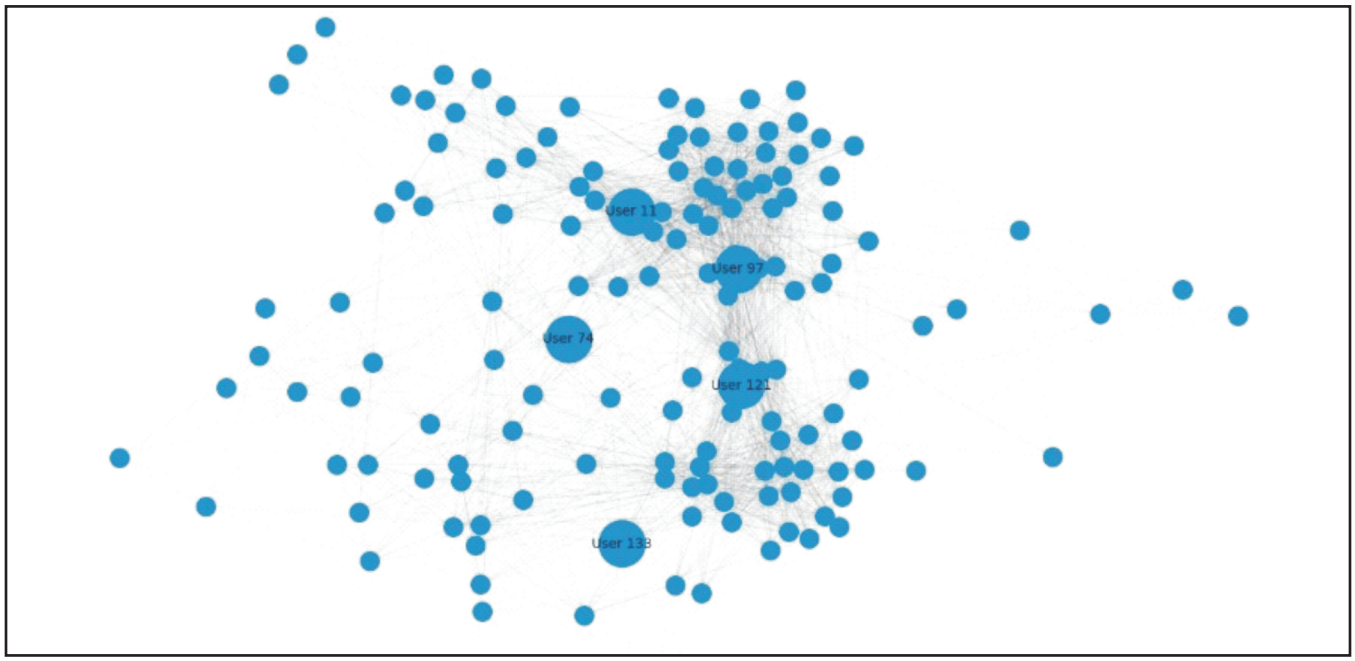


Figure 3: *Bridge Professional Based on Betweenness Centrality*

Table 4: *Top 5 Bridge Professionals by Betweenness Centrality*

Rank	User	Betweenness Score	Role
1	User 97	0.0497	Inter-community connector
2	User 133	0.0404	Cross-domain bridge
3	User 74	0.0388	Intra-domain facilitator
4	User 121	0.0386	Geographic bridge
5	User 11	0.0355	Age-group bridge

Practical Implications of Bridge Professionals:

The role of bridge practitioners in the design of professional networks is very practical in nature since they link different parties together.

- **Cross-team collaboration:** Since bridge employees are already associated with many teams, their jobs are ideal for situations where collaboration with several teams is involved. Because they are connected to various teams, they can communicate and connect with people without much effort. The process will facilitate coordination between different teams and avoid conflicts among them.
- **Information exchange:** It is due to their position as an intersection in the organization that it is easier for them to pass on critical knowledge and information across teams which do not interact with each other. They ensure that all parties share information and get informed about any changes taking place. It eliminates any information barriers between teams.
- **Leadership and influence:** People who have high levels of betweenness tend to exercise a lot of influence over others. This is because of the connections they form with other communities, making it easy for them to disseminate new ideas, practices, and work patterns.
- **Talent identification:** The importance of bridgers lies in the fact that they can be helpful for recruitment as well as human resources teams since they have broader networks and experience in various fields. In addition, they will have a broader range of competencies as well as knowledge regarding different positions.

Attribute-Based Community Analysis:

This part discusses the effect of various characteristics, including profession, age, and geographical location, on the formation of communities in the network. It is observed that these characteristics do not hold equal importance; rather, each one is more important than the other in forming such communities. Through the analysis of various characteristics, this study sheds light on why specific communities have been created.

Role of Professional Interest:

The analysis showed that profession is one of the most important factors influencing community formation in the network. Individuals with similar professional backgrounds tended to connect more frequently and form distinct groups. Communities were often formed around shared fields such as technology, data science, and artificial intelligence. The results also indicated that giving greater importance to professional interests improved community detection and increased modularity values. This suggests that professional similarity strengthens connections among individuals and plays a key role in shaping well-connected communities.

Role of Age and Career Stage:

It was also discovered that age played an important role in clustering; however, it had less impact than professional interest. It is clear from the research findings that people who are of the same age tend to make up distinct clusters in the network. Young professionals, specifically the 19-24 years and 24-28 years age groups, are more often placed into the same cluster. This is probably due to the fact that they are at the same stage in their career development, and share common problems like career establishment and mentorship seeking. The reason for this is that both groups will have a lot in common, making them relate better to one another. For example, they could be searching for jobs or even experimenting with new technological tools in order to develop in their careers.

Conversely, the professionals aged above 30 years were noted to occupy different groups from each other. The professionals within this category have been noted to have higher levels of experience and career stability. They usually connect through technical skills and professional success. This makes their groups more organized than those of young professionals.

Role of Location:

The analysis showed that location has some influence on community formation, as people from the same city are more likely to connect with each other. However, location alone does not determine community structure. Many individuals from different cities were found in the same communities because of shared professional interests. This highlights the role of online networking, which allows people to build connections regardless of geographical distance. Therefore, while location can support networking, professional similarity plays a more important role in forming strong and connected communities.

7. Comparative Analysis

7.1 Comparative Analysis of Community Detection and Network Measures

In this research work, the performance of the Louvain and Girvan–Newman algorithms for detecting the communities was compared using a LinkedIn professional network. In order to do that, community detection performance, modularity, and betweenness centrality measures have been utilized.

Six communities with high modularity equal to 0.508 were detected by the Louvain algorithm, showing a presence of strong community structure. Detected communities corresponded to professional roles like Software Engineers, Human Resources, Data Analysts, Graphic Designers, Front-end Developers, and Research Analysts.

Five communities with modularity of 0.000228 were found by the Girvan–Newman algorithm; comparing it to the Louvain one, a weaker community partitioning result has been obtained.

Analysis of betweenness centrality measure helped to find key influencers in the LinkedIn social network, who were acting as bridges between the communities. The most important users are Users 97 (0.0497), 133 (0.0405), 74 (0.0389), 121 (0.0386), and 11 (0.0356)

The results of both algorithms' performances are summarized in Figures 4 and 5. As can be seen from the figures, the Louvain algorithm has shown higher community detection performance.

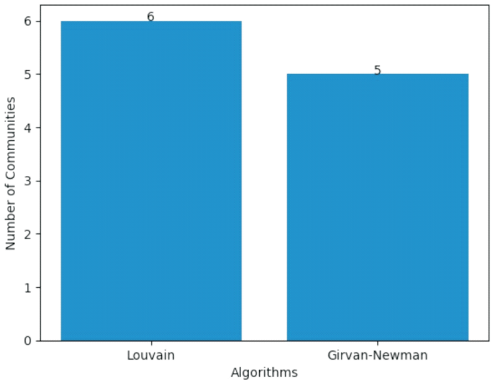


Figure 4: *Community Detection Comparison*

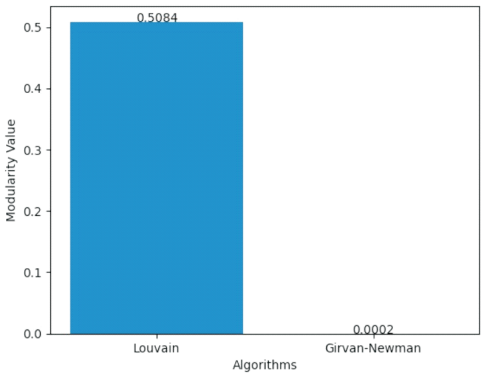


Figure 5: *Modularity comparison of algorithms*

8. Conclusion

In this research, an approach based on graph theory for exploring professional social networks by using the LinkedIn dataset has been introduced. Through modeling professional profiles as nodes and the similarity among them as weighted edges, the proposed approach has successfully detected the community structure of the network.

The resulting communities are meaningful and professional in nature, indicating the usefulness of the graph-theoretic approach to detect communities.

Comparative analysis of the Louvain and Girvan-Newman algorithms indicates that the Louvain algorithm is more appropriate for the purpose of detecting community structures within the studied LinkedIn network. Moreover, through the betweenness centrality analysis, the influential individuals who are acting as bridges between communities have been identified.

Through the results obtained in this study, the utility of the graph-theoretic approach can be explored for various applications like professional networking, discovering talent, recruitment processes, recommendation system, and knowledge sharing.

9. Limitations and Future Scope of Research

- The experiment was carried out on the basis of a LinkedIn data set that contains only **148 professional profiles**, which can hardly reflect the characteristics of large professional networks.
- Only three attributes were analyzed: **professional interests, age group, and geographical location**. Such attributes as education, work experience, skills, and industry have been ignored in the process of analysis.
- A **static graph** of the LinkedIn professional network has been used, thus not taking into account the dynamics of changes in the network.
- Only two methods for detecting communities in graphs have been studied: **Louvain and Girvan-Newman algorithms**.
- Extend the experimental research on a larger dataset of LinkedIn profiles.
- Add other attributes to be analyzed to get the most accurate community structure.
- Perform **dynamic (temporal) network analysis** to study the evolution of communities in the network.
- Test the proposed framework against other algorithms for detecting communities in graphs.
- Employ novel graph learning technologies, such as **Graph Neural Networks (GNNs)** and graph embeddings, for enhanced community detection and network analysis.
- Use the proposed system in practical applications, such as **business networking, recruitment, talent management, recommender systems, and information exchange**.

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Conflict of Interest Statement

The author declare that they have no conflicts of interest related to the publication of this research paper.

Ethical Declaration

This research did not involve human participants, animals, or any procedures requiring ethical approval. All data and materials were obtained, processed, and analyzed in accordance with established academic standards and ethical guidelines.

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