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An Effective Graph Theory-Based Methodologies for Social Network Analysis Based on Facebook Networks

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Abstract—Social network analysis is an active area of study beyond sociology. It gives insight into social processes and behaviours and reveals the unseen connections between participants in a network. Networks may be used to represent many real-world systems, and their examination can provide insight into the actual system. Graphs, often known as networks, are prevalent structures in a variety of fields. It is possible to direct the graphs, which results in non-symmetric edge semantics as the source node transfers some properties to the destination node but not the other way around. This study employs graph theory to analyse the Facebook social network, uncovering key insights into node connectivity, community structures, and network centrality. By computing centrality metrics such as betweenness and eigenvector centrality, influential nodes are identified, while in-degree and out-degree distributions reveal connectivity patterns, emphasising the network's power-law structure. Community detection techniques, including the Louvain Method and Label Propagation, are applied to detect dense node clusters, providing an in-depth understanding of the network's modularity. Graph traversal methods, such as Depth First Search (DFS) and Breadth First Search (BFS), explore node relationships, offering insights into connectivity and path lengths. Visualisations further illustrate network properties, highlighting key nodes and community structures. The findings showcase graph theory's efficacy in social network analysis, offering foundational insights for network research and practical applications.

Keywords—Social Media, Graph Theory, Social Network Analysis, Degree Centrality, Edges, Network Model.

I. Introduction

Social media is become a vital component of the majority of people's lives throughout the globe. Approximately 4.66 billion people worldwide are now utilising the internet, accounting for over 60% of the global population. With the introduction of social media, a huge and linked global ecosystem has emerged [1][2]. In the digital age, social media has become a key part of our daily lives, changing the way we communicate, receive information, establish social relationships, and engage in a variety of activities. Platforms such as Facebook, Twitter, Instagram, You-Tube or LinkedIn allow users to create and share content, communicate with other users, actively participate in discussions on various topics, and interact with brands, companies and celebrities. It's a place where events and trends spread rapidly, and information reaches millions of people in seconds. However, the enormous scale and complexity of these platforms means that the analysis of this digital ecosystem requires modern tools and methods [3]. The formalisation of the SNA began in the 1950s and 1960s with the work of researchers such as Alex Bavelas and Anatol Rapoport. It introduced mathematical graph theory to model social structures and interactions[4][5].

Graph theory provided a rigorous framework for representing social networks through nodes and edges [6][7], laying the groundwork for a more systematic and quantitative approach to the study of social relationships. Social network analysis (SNA) is a methodological approach that examines patterns of social relationships and interactions between individuals, groups, organisations, or other social actors [8][9]. It involves analysing the structure of social networks, identifying key actors or nodes in the network, and understanding the flow of information, resources or influences between these nodes. In a few words, the analysis of social networks (SNA) can be described as "the study of interpersonal relationships using graph theory" [10][11]. At its core, SNA is based on the understanding that social structures and relationships play a fundamental role in shaping individual behaviours, attitudes, and outcomes[12]. By representing social interactions as a network of nodes (representing individuals or entities) connected by edges (representing relationships), SNA provides a visual and quantitative framework for the study and analysis of these social structures[13][14][15]. A social network model is a graphical representation of the platform's interactions, shown as a graph with various nodes and edges [16][17][18]. It is possible to anticipate users' actions inside the network by extracting and analysing several subgraphs in accordance with each model [19]. The constructed models of social networks of Facebook are as follows.

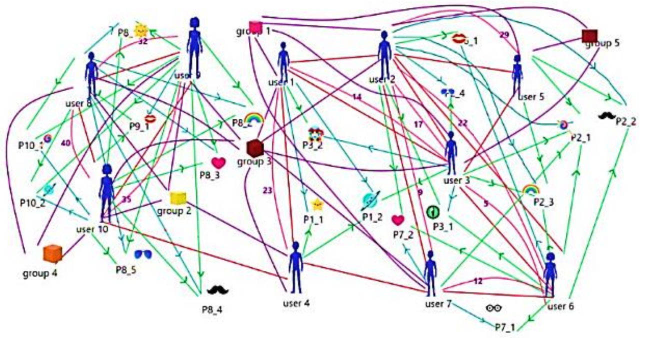

Fig. 1. Facebook network model

Users, posts, and groups are the three nodes that makeup Facebook's network model. Depending on the mathematical discipline, many formal definitions of networks exist [20]. The most common and adaptable explanation comes from graph theory; in this view, a social network is like a graph, with vertices (or nodes, units, or points) standing for social beings or things and lines (or relationships) connecting them. The extra data stored on the graph's vertices and lines makes a network more than just a graph [21][22][23]. The building blocks of graph theory, including standard representations and basic metrics, are essential for understanding and assessing social networks [24].

A. Contribution of the Study

The goal of this research is to use graph theory methods to better understand Facebook and other social networks. By analysing centrality measures, degree distributions, and community detection, the study aims to uncover patterns of influence, connectivity, and group formation. These insights are valuable for applications in social media analytics, user behaviour prediction, and network optimisation. The contributions of this study lie in the comprehensive analysis and application of graph theory techniques to the Facebook network dataset for social network analysis. The key contributions include:

- Utilize Facebook SNAP Network Data for social media network analysis.
- Computed and visualised edge centrality to identify influential connections in the network.
- Analyzed in-degree and out-degree distributions to explore network connectivity patterns.
- Applied and compared Label Propagation and Louvain methods for identifying network communities.
- Utilized DFS, DLS, and BFS algorithms for exploring node connectivity and reachability.
- Visualized the network using a spring layout for better structural representation.

B. Structure of paper

The remaining paper has been laid out in the following order. In section -II literature survey was reviewed, followed by section -III, where various approaches and methodologies were used with key phrases. Results and discussion are presented in Section IV, and the study concludes with a discussion of future work in Section V.

II. Literature Review

The literature on social network analysis as it pertains to graph theory is presented here.

G.H.J. Lanel et al. (2020), this study makes an effort to describe and analyse the online social media networks of LinkedIn, Facebook, and Twitter using principles from graph theory. Part one of the research involves cataloguing the aforementioned networks' activity and building a personalised graph model for every social media platform to reflect their activities. Evaluation of the built models of every social media platform independently to determine their usefulness in analysing user behaviour patterns and attributes is the subject of the next section of this research. The research concludes by suggesting a way to provide third parties access to pertinent data from online social networks in a way that does not compromise user privacy and enables competent decision-making [25].

D. Zhukov and J. Perova (2021), describes paradigm for identification of people’s affective states by means of using network media resources as potential auto-organized sociotechnical networks. The approaches applied in the graph theory and the neural network theory were integrated into the creation of the presented model. The first of them is collecting data such as comments from a particular user, the date and time of their presence, accessible user characteristics, news texts extracted from the network mass media. The next step is to construct a directed graph and an adjacency matrix (links) of comments made by news users and the comments made by each other using the data that has been received. The next step is to assign a numerical value on the segment [0,1] to represent one of the potential states by feeding the adjacency matrix into the input of a convolutional multilayer neural network. Several user categories were used to pre-compile a collection of patterns that the neural network was trained on. In fractions of a second, each of them conveyed the general public's disapproval of the self-organising social network. Then, you can use it to predict how public sentiment will change over time by evaluating the current state of automated news processing throughout the day (by assigning the current state to one of the CNN's states) and then averaging the results across all of the daily news[26].

Marco Brambilla et al. (2022), to evaluate the form and organisation of online discourse, suggests a framework based on graphs. Components of the investigation included intent analysis and network construction. Using keyword-based categorisation, we were able to discern users' intentions. Then, for uncategorised comments, we implemented classification methods based on machine learning. Subsequently, human-in-the-loop was used to enhance the categorisation based on keywords. They demonstrated the efficacy of our approach in two real-world trials and constructed conversation graphs using a directed multigraph network to extract crucial data about users' social media communication habits. Another study resulted in 90% correctness in its categorisations utilising genuine social media challenge data. The second study examined the responses to posts about the COVID-19 vaccine on parenting pages to determine how the comment section reacted to the parents’ comments and emotions. The top acknowledged patterns of online debate were then ‘extracted’ and ‘analysed’. They notice that the communication graph dynamics look similar to the more traditional modes of communication [27].

S. Arul et al. (2023), this abstract will focus on the applicability, current trends, and immediate employs of graph theory and network analysis concepts and methods to give an encapsulation of the above disciplines. Graph theory can be seen as a tool for modelling and evaluating the relations between what is presented by a node or vertex image and the relation or connection image or edge between nodes. Applying graph theory to the study of networks may shed light on the structure, relation and behaviour of complex systems. Therefore algorithms and graph theory makes rich source of data for characterising the detailed structure and connectivity of complicated systems, thus making real the idea of network analysis. It is a common case when graph theory and algorithms can be applied to social, transport, biological and other types of networks. The question of large-scale network analysis has not reached the state of fine art yet since the time when adequate algorithms and approaches appeared. Consequently, graph theory, as well as algorithms, are going to play an increasing role in the further development of networks [28].

P. Arya et al. (2024), the developed model employs the Bi-directional Attention Mechanism (BAM) for text-visual fusion and Genetic Algorithms (GAs) for hyperparameter tuning. Experiments carried out on Google, Facebook and Kaggle datasets show that compared to state-of-art models, our model has higher precision, recall, AUC, accuracy, specificity and performs less response time while detecting toxic content. The proposed MSCMGTB model consistently achieves superior precision, accuracy, recall, AUC, and specificity with rates ranging from 86.78% across varying dataset sizes, highlighting its efficacy in content moderation as well as reduced the delay time to classify social media contents as compared to Social Graph Neural Network (SGNN), CrediBot, and Adaptive LDA (ALDA) techniques. The model also preempts potentially harmful content posters, offering enhanced pre-emption metrics[29].

Sreenath Devineni et al. (2024), there are many different areas that might benefit from learning about graph theory and methods for social network analysis. Researchers are able to anticipate future interactions in social networks, discover hidden patterns, and identify prominent nodes or groups by using graph theory principles including link prediction tools, community discovery algorithms, and centrality metrics. Designing more successful marketing, public health, social media, and other initiatives that need an awareness of and ability to influence human behaviour may be accomplished with this information. Versatile with unique choices. A novel optimisation technique called MOORA has been put forward. In addition to indicating a matrix of possible responses, this objective approach suggests improved policies depending on the rates used. Firmly entrenched. Another multi-objective optimisation approach for comparison is the reference point method. This was determined to be the best strategy after several contests. Network models are ranked top in the results, whereas graph density is ranked fifth [30].

The following Table I provides the comparative analysis based on its methodology, key findings, applications, and future work.

TABLE I. SUMMARY OF RELATED WORK ON SOCIAL NETWORK ANALYSIS USING GRAPH THEORY

Author(s), Year	Study Focus	Methodology	Key Findings	Applications /Implications	Future Work
G.H.J. Lanel et al. (2020)	Social media network analysis using graph theory	Constructed and evaluated graph models for social media activities	Effective in analysing user behaviour; aids decision-making without privacy violation	Social media behaviour analysis, user activity modelling, privacy-preserving decision-making.	Extend models to more platforms and refine privacy measures.
D. Zhukov & J. Perova (2021)	Mood analysis of media users through self-organising systems	Built graph and adjacency matrix; used convolutional neural network	Predicts public sentiment dynamics; useful for automated sentiment analysis	Public sentiment monitoring, automated mood analysis for media, predictive sentiment analytics.	Incorporate more user attributes for better accuracy.
Marco Brambilla et al. (2022)	Online conversation analysis using intent and network generation	Keyword classification and directed multigraph conversation graphs	High accuracy in identifying communication patterns	Social media conversation analysis, sentiment and intent analysis, pattern mining in communication.	Expand dataset size and improve classification accuracy.
S. Arul et al. (2023)	Review of graph theory in network analysis	Overview of recent algorithms and graph theory applications	Powerful for complex systems analysis; advancements allow large-scale network analysis	Social networks, transportation networks, biological networks, large-scale network analysis.	Develop algorithms for real-time network analysis.
P. Arya et al. (2024)	Hybrid graph theory model for social media content moderation	Used Bi-directional Attention Mechanism and Genetic Algorithms	High precision in detecting harmful content, reduced response time	Content moderation, harmful content detection, social media security enhancement, and pre-emptive alerting.	Test on broader social media and content types
Sreenath Devineni et al. (2024)	Graph theory applications in social network analysis	Centrality, community detection, MOORA optimisation	Insights into human behaviour and information spread; MOORA optimisation effective in comparison	Marketing strategies, public health interventions, social media management, and predictive behaviour analysis.	Investigate optimisation in other network contexts.

III. METHODS AND MATERIALS

The methodology for social network analysis using graph theory involves several key steps to explore the structure and dynamics of networks. Initially, a dataset representing the social network, such as the Facebook network in this study, is loaded and examined for general information, including node and edge properties. The most important nodes in a network may be located by computing centrality metrics such edge centrality, betweenness centrality, and eigenvector centrality. In order to comprehend the communication patterns, the graph's in-degree and out-degree distributions are studied. Community detection techniques, such as Label Propagation and the Louvain Method, are applied to detect groups of densely connected nodes, with their effectiveness compared. Graph visualisations, such as a spring layout, are generated to better understand the network's structure. Additionally, graph traversal techniques, including DFS, DLS, and BFS, are employed to explore the graph's connectivity and node relationships. Finally, the graph's cycles are identified and counted to understand the presence of feedback loops within the network. These methods collectively provide a comprehensive analysis of social networks from a graph theory perspective.

A. *Data collection*

This dataset[1] it comprises friends lists/Facebook "circles" and ego networks gathered via a Facebook application, with node attributes and links. Here, changes by authors of Facebook data have been made to obscure the internal user IDs of real users by assigning them pseudo ID numbers, while feature labels have also been disguised. For example, original feature labels like 'political=Democratic Party' are transformed into such names as 'political=anonymized feature 1,' to enable a comparison between the users while preserving their anonymity.

[1] https://academictorrents.com/details/3efc53f35d49669b89039f2b4ec9de11ec1d73fd

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Facebook Graph Information
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Count of Nodes: 4039
Count of Edges: 88234
Directed Graph: True
Weakly Coonected : True
Strongly Connected : False
Graph Network Density: 0.0054099817517196435
Graph Transitivity   : 0.2027449891358539
Graph Clustering Coefficient: 0.3027733593100438
Graph Average Degree: 43.69101262688784
```

Fig. 2. Facebook graph information

B. Data Preprocessing

Following data collection, preprocessing prepares the data for effective analysis. This process is divided into three main steps:

- **Data Loading:** Import the dataset into the working environment, ensuring it is in a suitable format for graph analysis (e.g., edge list, adjacency matrix)[31][32].
- **Data Cleaning:** Check for and handle missing or inconsistent data, such as isolated nodes or incomplete edges, ensuring the network is well-formed for analysis [33].
- **Node and Edge Validation:** Check all about the nodes of the graphs and all edges to confirm the validity of all connections and the manner that depicts the network [34].
- **Graph Construction:** From the dataset build the graph starting from nodes and ends passing through edges considering the appropriate format to describe the network of the entities involved.
- **Normalization:** If the weights are present on the edges, then try to standardise it and eliminate the variations in the graph and its centrality parameters [35][36].
- **Graph Conversion:** If required, convert the graph for the analysis in the format according to need, either undirectional, directional, Weighted or unweighted [37].
- **Visualization Preparation:** Before visualising the graph a layout needs to applied on to the nodes such as spring layout to make the nodes more interpretable [38][39].

C. Depth First Search (DFS)

DFS is used on the network by going through nodes deeply in order to find the relationships of that network. Starting from a specified node, DFS navigates through each branch to the end before backtracking to explore other branches.[40][41][42] In this study, DFS is applied to identify the overall network constellations of nine key persons and explore their relationship to the last degree. That ensures that the nodes, as well as the edges, are visited once, making it easy to do things like checking connectivity or finding connected components in the connections of the network [43].

D. Depth Limited Search (DLS)

DLS is a subset of DFS that allows users to choose a depth limit for their searches. In the event that the search space is either infinitely deep or too big to be thoroughly searched, the depth limit will stop DFS from searching endlessly [44][45]. It uses DFS to search a graph and DLS to control depth. DLS limits traversal from focus nodes to 3 levels to reduce spread. Large populations benefit from this limited number of iterations since the search process can be stopped before it attempts all conceivable combinations and uses up all system memory. DLS can analyse hierarchical and structural parts and first-degree contacts by focussing on first-order connections [46].

E. Graph Analysis and Centrality Measures

Edge Centrality defines which edges really contribute to the network. Degree sequences reflect the centrality or influence of the nodes in a graph or network. The plotting of these distributions serves to identify certain structures by revealing the hubs or balanced structures or the fundamental connectivity.

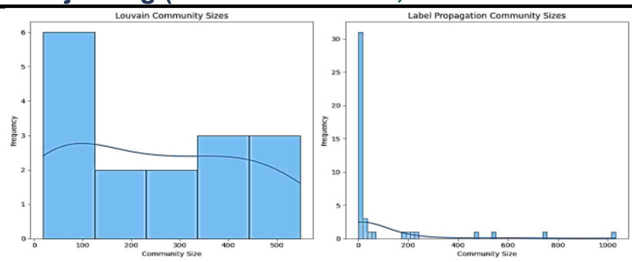

Fig. 3. Comparison of Community Detection Using Louvain and Label Propagation Methods

Figure 3 shows the Louvain Method identified 16 communities with more defined sizes, while the Label Propagation Method identified 44 communities with more dispersed sizes, which are more to the right-skewed, mostly small-size communities.

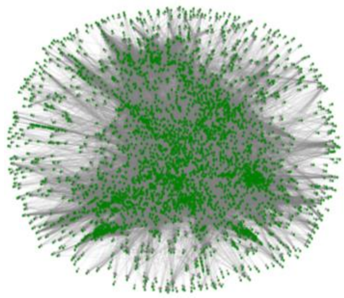

Fig. 4. Facebook Graph Visualization Using Spring Layout

Figure 4 represents a Facebook graph with the layout being a spring layout, the nodes, in this case, being users and the edges being acquaintances. Number of cycle in this graph is zero. The nodes in the centre show that they are much more connected than those areas that are located in the periphery of the observed network.

IV. Results Analysis And Discussion

The following experiment results of social media analysis using graph theory are provided in this section. The following table 2 shows the degree distribution.

TABLE II. CALCULATE DEGREE DISTRIBUTION

Graph	Degree
Maximum	1045
Minimum	1

Table II shows the degree distribution of the graph, with a maximum degree of 1045 (most connected node) and a minimum degree of 1 (least connected node), highlighting the variation in node connectivity.

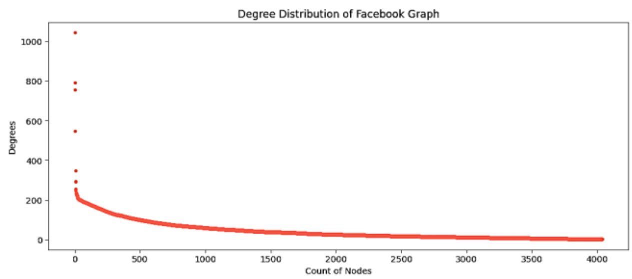

Fig. 5. Degree Distribution of Facebook Network Graph

Figure 5 represents the degree of a Facebook network, where the degrees vary from 1 to 1045. The overwhelming majority of nodes have small degrees, and some nodes have large degrees, making the distribution extremely stretched.

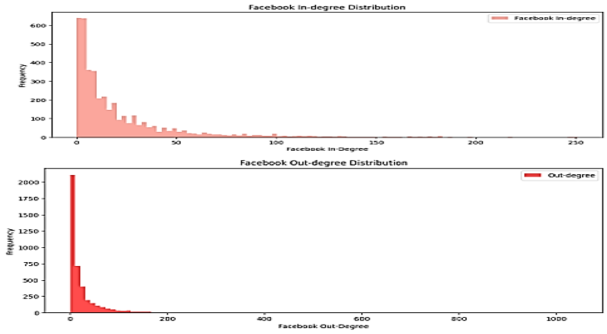

Fig. 6. In-degree and out-degree Distributions of Facebook Graph

Figure 6 shows that the majority of nodes in the Facebook network have low degrees and that the graph's in-degree and out-degree distributions are right-skewed. The in-degree distribution shows a peak around 0-10, with a long tail towards higher values, indicating hubs with many incoming edges. The out-degree distribution follows a similar pattern but has a slightly longer tail, suggesting more nodes with a higher number of outgoing edges.

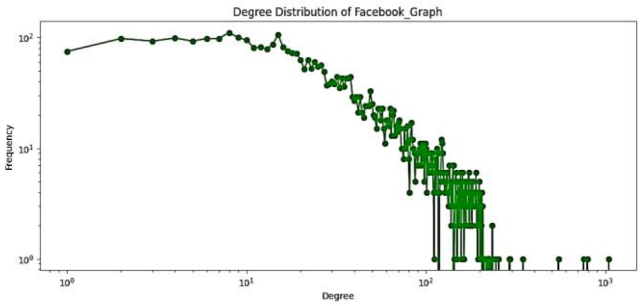

Fig. 7. Degree Distribution of Facebook Graph

Figure 7 displays the Facebook graph's degree distribution on a log-log scale. It reveals a power-law structure, with the majority of nodes having low degrees and a small number of nodes having very high degrees.

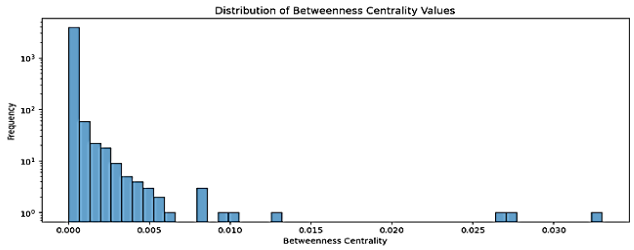

Fig. 8. Distribution of Betweenness Centrality Values

Figure 8 displays a distribution of betweenness centrality values, showing that most nodes have low centrality while a few have higher values, indicating they play key intermediary roles.

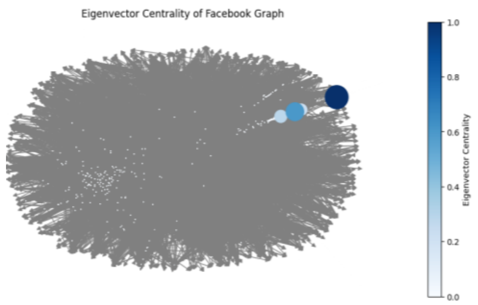

Fig. 9. Eigenvector Centrality of Facebook Graph.

Figure 9 shows the eigenvector centrality of a Facebook graph, with a colour gradient highlighting a few highly influential nodes in dark blue.

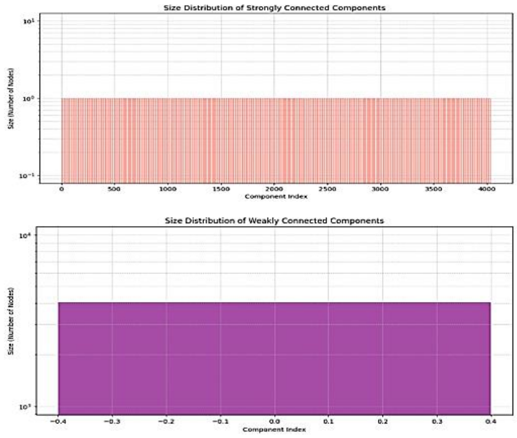

Fig. 10. Size Distribution of Strongly and Weakly Connected Components

Figure 10 size distribution of the strongly connected components is relatively uniform, with a few larger components, while the weakly connected components are dominated by one large component. This indicates that the Facebook graph is highly interconnected, with most nodes reachable from each other, and has a more distributed structure rather than being clustered into tightly connected groups.

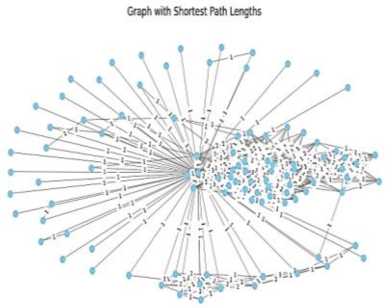

Fig. 11. Graph Showing Shortest Path Lengths

Figure 11 shows the shortest path lengths between nodes, highlighting central nodes with shorter paths to others.

DFS Traversal starting from node 0:

0 1 48 53 54 119 122 123 142 158 168 277 280 290 322 323 332 341 329 339 340 347 342 345 291 315 324 331 297 304 308 334 338 325 285 303 313 314 294 311 344 232 239 252 261 265 271 272 281 284 309 320 346 276 298 318 268 295 242 249 254 266 302 330 299 300 248 317 161 199

DLS Traversal starting from node 0 with depth limit 3:

0 1 48 53 54 57 73 80 88 119 126 130 180 199 203 271 299 302 320 322 330 332 92 94 101 187 194 196 204 242 249 254 266 346 133 141 183 188 224 232 236 276 280 315 2 20 41 44 111 115 149 162 214 226 312 326 333 343 116 140 144 3 9 21 25 26 30 56 66 67 69 72 75 79 85 105

The DFS traversal from node 0 explores the graph extensively, reaching many nodes at various depths. In contrast, the DLS traversal with a depth limit of 3 only includes nodes within three steps from node 0, resulting in a shorter list and a more localised exploration. This illustrates how depth constraints in DLS limit node coverage compared to the unrestricted reach of DFS.

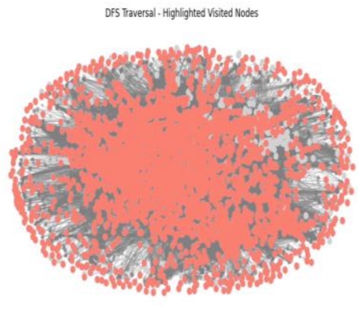

Fig. 12. Depth First Search Traversal Nodes in Graph

Figure 12 indicates the nodes highlighted with red colour which have been visited during the Depth-First Search (DFS) traversal. These highlighted nodes show the penetration created by DFS since it goes deeply through every path. The disconnected unvisited nodes are coloured in grey, representing those parts of the graph where this particular traversing will not go if a specific node is chosen. This slide shows how the DFS works in terms of spreading and penetration of the covering nodes in the network.

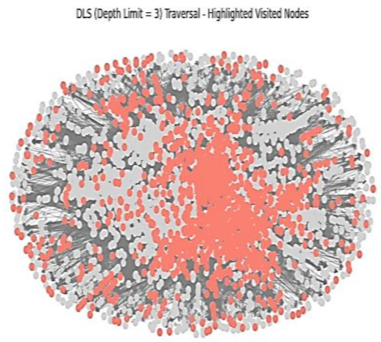

Fig. 13. Depth limit search Nodes in Graph

Figure 13 depicts nodes explored during Depth-Limited Search (DLS) with a depth limit of 3 entailing nodes explored during the search highlighted. The highlighted nodes are the subset of reachable from the starting node within three steps of hops and hence show more of a localised search compared to the unrestricted search above. Contours with grey colour represent the nodes which were not explored because the depth of traversal is limited, which shows that DLS works only in a limited capacity in comparison to other kinds of traversals starting with DFS.

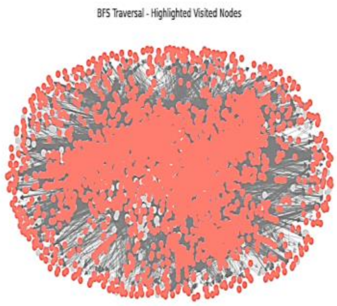

Fig. 14. Breadth-first search Nodes in Graph

Figure 14 illustrates that nodes that are visited during Breadth-First Search (BFS) traversal are painted in red colour. Starting with the level of connectivity, BFS traces through the graphs by visiting immediate neighbours of the node of origin. The shaded nodes in dark colour show that BFS covers all nodes in a graph with a width that is uniform to other searching algorithms, while the rest of the cells in grey colour demonstrate areas of the graph that were not explored. This visualisation on BFS demonstrates its property of layer-wise traversal of nodes starting from one node.

V. Conclusion And Future Scope

The need for social network analysis is being driven by the exponential growth of these platforms. An effective and significant tool for this kind of investigation is the visualisation of social networks. A wide variety of visualisation software programs are available. Graph theory, Python, and open-source tools are used in this article to create social network visualisations. The study of social networks based on graph theory enables identifying the structural and dynamic properties of large-scale, organised networks and relations, including the Facebook network considered in this paper. The most significant of all is the so-called power-law distribution of degrees, indicating that some nodes are densely linked while others are almost isolated to discern the existence of highly connected nodes such as hubs. Globally, betweenness centrality and eigenvector centrality identify key points, whereas the Louvain Method and Label Propagation identify modularity in revealing network partitions. DFS, DLS, and BFS are just the methods of graph exploration, and each one represents different ways to traverse the connected graph, as well as the peculiarities of the traversal. Visualisations offered a straightforward view of the hierarchy and clustering in the network, and thereby, the relevance of graph theory in the social network analysis was evident. It proves the fact that by using graph theory alongside right visualisations and traversal methods, social networks could be analysed efficiently. Future studies could build upon these results by adopting dynamic NPs that consider temporal dynamics and using other community detection methods.

References

[1] R. Kar, “To Study the Impact of Social Network Analysis on Social Media Marketing Using Graph Theory,” *Int. J. Softw. Sci. Comput. Intell.*, 2022, doi: 10.4018/ijssci.304437.

[2] B. Patel, V. K. Yarlagadda, N. Dhameliya, K. Mullangi, and S. C. R. Vennapusa, “Advancements in 5G Technology: Enhancing Connectivity and Performance in Communication Engineering,” *Eng. Int.*, vol. 10, no. 2, pp. 117–130, 2022, doi: 10.18034/ei.v10i2.715.

[3] H. Sinha, “Benchmarking Predictive Performance Of Machine Learning Approaches For Accurate Prediction Of Boston House Prices: An In-Depth Analysis,” *ternational J. Res. Anal. Rev.*, vol. 11, no. 3, pp. 181–187, 2024.

[4] H. Sinha, “Predicting Employee Performance in Business Environments Using Effective Machine Learning Models,” *Int. J. Nov. Res. Dev.*, vol. 9, no. 9, pp. 875–881, 2024.

[5] Muthuvel Raj Suyambu and Pawan Kumar Vishwakarma, “Improving Efficiency of Electric Vehicles: An Energy Management Approach Utilizing Fuzzy Logic,” *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 3, no. 2, pp. 737–748, Feb. 2023, doi: 10.48175/IJARSCT-9749V.

[6] S. Arora and P. Khare, “AI/ML-Enabled Optimization of Edge Infrastructure: Enhancing Performance and Security,” *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 4, no. 2, pp. 230–242, 2024.

[7] R. Tandon, “Social Media Texts Classification and Analysis Based on Large Language Models (LLMs),” *J. Emerg. Technol. Innov. Res.*, vol. 11, no. 9, pp. a751–a757, 2024.

[8] M. G. Galety, C. Al Atroshi, B. K. Balabantaray, and S. N. Mohanty, *Social network analysis: Theory and applications*. 2022. doi: 10.1002/9781119836759.

[9] M. R. S. Pawan Kumar Vishwakarma, “Data Analytics In Smart Grid With Renewable Energy Integration,” *IJSART*, vol. 10, no. 10, pp. 1–10, 2024.

[10] P. Khare, “Transforming KYC with AI : A Comprehensive Review of Artificial Intelligence-Based Identity Verification,” vol. 10, no. 12, pp. 525–531, 2023.

[11] M. Tsvetovat and A. Kouznetsov, *Social Network Analysis for Startups*. 2011.

[12] P. Khare and S. Srivastava, “SIGNATURE-BASED BIOMETRIC AUTHENTICATION: A DEEP DIVE INTO DEEP LEARNING APPROACHES,” *Int. Res. J. Mod. Eng. Technol. Sci.*, vol. 4, no. 8, Aug. 2022, doi: 10.56726/IRJMETS29522.

[13] S. Permata Dewi, R. Prihandini, D. Jannah, I. Izzah Makhfudloh, A. Agatha, and Y. Wulandari, “Social Network Analysis in Graph Theory and Its Application to Social Media Platforms,” 2024.

[14] M. R. S. and P. K. Vishwakarma, "The Assessments Of Financial Risk Based On Renewable Energy Industry," *Int. Res. J. Mod. Eng. Technol. Sci.*, vol. 06, no. 09, pp. 758–770, 2024.

[15] S. A. and A. Tewari, "AI-Driven Resilience: Enhancing Critical Infrastructure with Edge Computing," *Int. J. Curr. Eng. Technol.*, vol. 12, no. 02, pp. 151–157, 2022, doi: https://doi.org/10.14741/ijcet/v.12.2.9.

[16] V. V. Kumar, A. Sahoo, S. K. Balasubramanian, and S. Gholston, "Mitigating healthcare supply chain challenges under disaster conditions: a holistic AI-based analysis of social media data," *Int. J. Prod. Res.*, 2024, doi: 10.1080/00207543.2024.2316884.

[17] M. R. S. and P. K. Vishwakarma, "An Efficient Machine Learning Based Solutions for Renewable Energy System," *Int. J. Res. Anal. Rev.*, vol. 9, no. 4, pp. 951–958, 2022.

[18] S. A. and A. Tewari, "Security Vulnerabilities in Edge Computing: A Comprehensive Review," *Int. J. Res. Anal. Rev.*, vol. 9, no. 4, pp. 936–941, 2022.

[19] S. Arora, P. Khare, and S. Gupta, "AI-Driven DDoS Mitigation at the Edge: Leveraging Machine Learning for Real-Time Threat Detection and Response," in *2024 International Conference on Data Science and Network Security (ICDSNS)*, IEEE, Jul. 2024, pp. 1–7. doi: 10.1109/ICDSNS62112.2024.10690930.

[20] V. Kumar, V. V. Kumar, N. Mishra, F. T. S. Chan, and B. Gnanasekar, "Warranty failure analysis in service supply Chain a multi-agent framework," in *SCMIS 2010 - Proceedings of 2010 8th International Conference on Supply Chain Management and Information Systems: Logistics Systems and Engineering*, 2010.

[21] Sahil Arora and Apoorva Tewari, "Fortifying Critical Infrastructures: Secure Data Management with Edge Computing," *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 3, no. 2, pp. 946–955, Aug. 2023, doi: 10.48175/IJARSCT-12743E.

[22] A. Chakraborty, T. Dutta, S. Mondal, and A. Nath, "Application of Graph Theory in Social Media," *Int. J. Comput. Sci. Eng.*, vol. 6, pp. 722–729, 2018, doi: 10.26438/ijcse/v6i10.722729.

[23] M. E. J. Newman, "A measure of betweenness centrality based on random walks," *Soc. Networks*, vol. 27, no. 1, pp. 39–54, 2005, doi: https://doi.org/10.1016/j.socnet.2004.11.009.

[24] H. Sinha, "ANALYZING MOVIE REVIEW SENTIMENTS ADVANCED MACHINE LEARNING AND NATURAL LANGUAGE PROCESSING METHODS," *Int. Res. J. Mod. Eng. Technol. Sci. (*, vol. 06, no. 08, pp. 1326–1337, 2024.

[25] G. H. J. Lanel and H. S. S. P. Jayawardena, "A Study on Graph Theory Properties of On-line Social Networks," *Int. J. Sci. Res. Publ.*, vol. 10, no. 3, p. p9929, Mar. 2020, doi: 10.29322/IJSRP.10.03.2020.p9929.

[26] D. Zhukov and J. Perova, "A Model for Analyzing User Moods of Self-organizing Social Network Structures Based on Graph Theory and the Use of Neural Networks," in *Proceedings - 2021 3rd International Conference on Control Systems, Mathematical Modeling, Automation and Energy Efficiency, SUMMA 2021*, 2021. doi: 10.1109/SUMMA53307.2021.9632203.

[27] M. Brambilla, A. Javadian Sabet, K. Kharmale, and A. E. Sulistiawati, "Graph-Based Conversation Analysis in Social Media," *Big Data Cogn. Comput.*, 2022, doi: 10.3390/bdcc6040113.

[28] S. M. Arul, G. Senthil, S. Jayasudha, A. Alkhayyat, K. Azam, and R. Elangovan, "Graph Theory and Algorithms for Network Analysis," *E3S Web Conf.*, vol. 399, no. March, pp. 52–60, 2023, doi: 10.1051/e3sconf/202339908002.

[29] P. Arya *et al.*, "MSCMGTB: A Novel Approach for Multimodal Social Media Content Moderation Using Hybrid Graph Theory and Bio-Inspired Optimization," *IEEE Access*, vol. 12, pp. 73700–73718, 2024, doi: 10.1109/ACCESS.2024.3400815.

[30] B. G. Sreenath Devineni, "Graph Theory and Algorithms for Social Network Analysis," *REST J. Data Anal. Artif. Intell.*, vol. 3, no. 1, pp. 52–60, Apr. 2024, doi: 10.46632/jdaai/3/1/7.

[31] J. Thomas, "A Survey of E-Commerce Integration in Supply Chain Management for Retail and Consumer Goods in Emerging Markets," *J. Emerg. Technol. Innov. Res.*, vol. 10, no. 12, 2023.

[32] Mani Gopalsamy, "An Optimal Artificial Intelligence (AI) technique for cybersecurity threat detection in IoT Networks," *Int. J. Sci. Res. Arch.*, vol. 7, no. 2, pp. 661–671, Dec. 2022, doi: 10.30574/ijsra.2022.7.2.0235.

[33] M. Gopalsamy, "Identification and Classification of Phishing Emails Based on Machine Learning Techniques to Improvise Cybersecurity," *Int. J. Sci. Adv. Res. Technol.*, vol. 10, no. 10, pp. 47–57, 2024.

[34] P. P. Jubin Thomas, "Predictive big data analytics for supply chain demand forecasting," *Int. J. Creat. Res. Thoughts*, vol. 10, no. June 2022, pp. 301–330, 2022.

[35] K. Mullangi *et al.*, "AI-Augmented Decision-Making in Management Using Quantum Networks," *Asian Bus. Rev.*, vol. 13, no. 2, pp. 73–86, Aug. 2023, doi: 10.18034/abr.v13i2.718.

[36] N. Richardson, R. Pydipalli, S. S. Maddula, S. K. R. Anumandla, and V. K. Yarlagadda, "Role-Based Access Control in SAS Programming: Enhancing Security and Authorization," *Int. J. Reciprocal Symmetry Theor. Phys.*, 2019.

[37] J. Thomas, "The Effect and Challenges of the Internet of Things (IoT) on the Management of Supply Chains," *Int. J. Res. Anal. Rev.*, vol. 8, no. 3, pp. 874–878, 2021.

[38] V. V Kumar, M. Tripathi, S. K. Tyagi, S. K. Shukla, and M. K. Tiwari, "An integrated real time optimization approach (IRTO) for physical programming based redundancy allocation problem," *3rd Int. Conf. Reliab. Saf. Eng.*, pp. 692–704, 2007.

[39] M. R. Kishore Mullangi, Vamsi Krishna Yarlagadda, Niravkumar Dhameliya, "Integrating AI and Reciprocal Symmetry in Financial Management: A Pathway to Enhanced Decision-Making," *Int. J. Reciprocal Symmetry Theor. Phys.*, vol. 5, no. 1, pp. 42–52, 2018.

[40] A. Soni, R. Arora, and A. Kumar, "Enhancing Security in Cloud Native Applications: A Blockchain-Based Approach for Container Image Integrity," Sep. 2024. doi: 10.21203/rs.3.rs-5063708/v1.

[41] S. E. Putri, T. Tulus, and N. Napitupulu, "Implementation and Analysis of Depth-First Search (DFS) Algorithm for Finding The Longest Path," 2011. doi: 10.13140/2.1.2878.2721.

[42] A. Soni, R. Arora, A. Kumar, and D. Panwar, "Evaluating Domain Coverage in Low-Resource Generative Chatbots: A Comparative Study of Open-Domain and Closed-Domain Approaches Using BLEU Scores," 2024. doi: 10.21203/rs.3.rs-5063895/v1.

[43] J. Thomas, "Optimizing Bio-energy Supply Chain to Achieve Alternative Energy Targets," *J. Electr. Syst.*, vol. 20, no. 6s, pp. 2260–2273, Apr. 2024, doi: 10.52783/jes.3176.

[44] R. K. R. P., T. Vadlapatla, S. Azmeera, A. Komaraneni, and A. Jula, "Performance Comparison of Depth Limited Search and A* Algorithm: A Case Study," *E3S Web Conf.*, vol. 391, 2023, doi: 10.1051/e3sconf/202339101140.

[45] H. S. Chandu, "Enhancing Manufacturing Efficiency : Predictive Maintenance Models Utilizing IoT Sensor Data," *IJSART*, vol. 10, no. 9, 2024.

[46] J. Thomas and V. Vedi, "Enhancing Supply Chain Resilience Through Cloud-Based SCM and Advanced Machine Learning: A Case Study of Logistics," *J. Emerg. Technol. Innov. Res.*, vol. 8, no. 9, 2021.