

MAPPING COLLABORATIVE: CO-AUTHORSHIP NETWORK ANALYSIS IN THE JOURNAL OF GRAPH THEORY (2001-2015)

(Memetakan Kolaboratif: Analisis Rangkaian Penulisan Bersama dalam
Journal of Graph Theory (2001-2015))

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ABSTRACT

The co-authorship of articles in peer-reviewed journals contributes to knowledge based on the research community. Co-authorship can be termed as a collaboration between two or more authors if they publish a scientific work together. The main goal of this study is to analyse the co-authorship network of scientists who published their articles in the Journal of Graph Theory. The co-authorship data of 810 articles published in the journal from 2001 until 2015 was collected. We used the principle of network sciences in which the network nodes represent authors who are connected with the edges if they co-authored papers. The analysis was conducted using the network science indicators and visualisations of the co-authorship network and thereafter centrality measures such as degree centrality, betweenness centrality, and closeness centrality are used to identify the authors' connectedness and influence in the network. The study identifies key influential authors based on centrality measures, demonstrating their pivotal roles in the network. Furthermore, the prevalence of multi-author collaborations underscores the collaborative nature of research in this domain.

Keywords: social network analysis; co-authorship analysis; network science; centrality

ABSTRAK

Penulisan bersama dalam artikel-artikel yang diterbitkan dalam jurnal berwasit menyumbang kepada perkembangan ilmu pengetahuan dalam kalangan komuniti penyelidikan. Penulisan bersama boleh ditakrifkan sebagai kolaborasi antara dua atau lebih pengarang apabila mereka menerbitkan hasil karya saintifik secara bersama. Matlamat utama kajian ini adalah untuk menganalisis rangkaian penulisan bersama dalam kalangan saintis yang menerbitkan artikel mereka dalam *Journal of Graph Theory*. Data penulisan bersama daripada 810 artikel yang diterbitkan dalam jurnal tersebut dari tahun 2001 hingga 2015 telah dikumpul. Kami menggunakan prinsip sains rangkaian di mana nod dalam rangkaian mewakili pengarang yang dihubungkan dengan sisi jika mereka menulis bersama artikel. Analisis dijalankan menggunakan indikator sains rangkaian dan visualisasi rangkaian penulisan bersama, diikuti dengan ukuran keterhubungan seperti *degree centrality*, *betweenness centrality*, dan *closeness centrality* bagi mengenal pasti keterhubungan dan pengaruh pengarang dalam rangkaian tersebut. Kajian ini mengenal pasti penulis berpengaruh utama berdasarkan ukuran keutamaan (*centrality measures*), yang menunjukkan peranan penting mereka dalam rangkaian tersebut. Selain itu, prevalensi kerjasama pelbagai penulis menekankan sifat kolaboratif penyelidikan dalam bidang ini.

Kata kunci: analisis rangkaian social; analisis penulisan bersama; sains rangkaian; keterhubungan

1. Introduction

Since social interactions come from different contexts, social networks have already existed in our society. Social networks provide people with resources, including trust, knowledge, and power (Coleman 1994). Since the 1930s, the social network has been analysed in some form (Scott 2017) and one of the networks that occur in academia is the co-authorship network. A co-authorship network is a social network of authors focusing on one area of a specific study. This is also known as a collaboration network between two or more authors when they publish a paper. There would be some fascinating trends within this network that can be analysed and thus improved by creating an enhanced structure for collaboration. Co-authorship network analysis can be done with various statistical measures by applying the principle of social network analysis (SNA). The present study is based on relational data detailing the authors' connection describing the structures of co-authorship network. Indeed, the connection is important to be reviewed to understand the progress in developing collaboration to increase the productivity of authors.

Nodes (or vertices) which represent an object or in the case of the social network, are the individuals or an organization who play a role in the network. While edges drawn as the line are the link or connection between the nodes. An edge in a network can take on two distinct forms, undirected edges and directed edges. Undirected edge shows the direction of a network that goes both ways while the directed edge exhibits the direction. Examining co-authorship networks holds a pivotal role in bibliometric analysis as mentioned in relevant references (Melin & Persson 1996; Razak *et al.* 2019; Sapini *et al.* 2022; Mohd Zu & Yow 2024). Through this network, we can analyse the pattern and connection between the authors.

A collaborative study of co-authorship research using data from publications has been carried out extensively and has issued various important information that is useful to the scientific community (Newman 2001). Every co-author is important in academic research because the collaboration between authors has an impact on their publication. In addition, this collaboration also allows the authors to expand and share their knowledge in particular research. In past studies of networks, the analysis had shown the significance and benefits of why the collaboration of authors in the publication is a necessity. One of the benefits is a collaboration with other authors allows an author to enhance their limited skills and gain from the capabilities of others. In general, an academic paper that is written by more than one author shows more information and depth in their specific study. Thus, this contributes to an increase in the quality of the research. In-depth research increases the image of academic researchers and thus creates opportunities for better research funds from sponsors (Knoke & Yang 2008; Li *et al.* 2013).

In addition, it would take less time to write a paper with a co-author than an author writes the paper alone. This would increase the productivity of the research as well as increase the area and scope of the research. Moreover, within the realm of co-authorship networks and given the advancements in communication technology, authors or researchers now have the chance to identify more suitable co-authors across various global regions, hence improving the outcome (Englebrecht *et al.* 2008; Fleischman & Schuele 2009). Analysis of the co-authorship network should be enlarged in every field of study with suitable measures from social network analysis. The analysis would point out every opportunity and link that is still not realized by researchers. Besides, expert authors in the specific area of study can be identified and emphasise the importance of linking up with the main authors in the network rather than connecting to a wide number of authors who may not be influential and well-known (Yang *et al.* 2017).

Among the recent co-authorship networking available in the literature, Carchiolo *et al.* (2022) proposed an analysis of the co-author network of Italian researchers, and

Mohammadamin *et al.* (2012) examined the co-authorship network in the field of Scientometrics for the years 1980 to 2012. For more research on co-authorship networking analysis please refer to Kılıç *et al.* (2019), Kumar & Markscheffel (2016), King & Settle (2019), Di Bella *et al.* (2021), Hasni *et al.* (2023), Muhammad Luqman *et al.* (2022) and references therein. In line with this research, this paper examines the co-authorship in the field of Graph Theory (extracted from *Journal of Graph Theory*) using social network analysis to elucidate the research collaboration in this community. For the rest of the paper, we abbreviate the *Journal of Graph Theory* as *J. Graph Theory*.

2. Methodology

In this study, there are four steps, the first of which is data collection and preparation, followed by data pre-processing in the second step. The third step is applying the centrality measures, and the last step is to analyse the results. The first step of this research process, data collection and preparation are conducted with suitable methods and tools. Relational data that are used in for co-authorship network analysis may be inherently unwieldy due to the number of connections everyone might have. The boundaries must therefore be set by the researchers themselves.

In this paper, the scope is the co-authorship of articles in the *J. Graph Theory*. Overall, the data of this research includes 810 articles published from 2001 through to the end of 2015 in the journal. Articles in this timeframe are collected including volume, issue, date of first publication, title, and most importantly the name of the author list. Those data are entered into a Microsoft Excel spreadsheet. For network visualisation and analysis of co-authorship, Gephi which is an open-source network analysis and visualisation on software is chosen to be used in this study. Users can customise the look of nodes, edges, and labels using a variety of choices as this technique increases network clarity and readability.

In the second step which is data pre-processing, a task such as data cleaning and data reduction is conducted. Some authors might use a different name in different articles, but in this process, their names are listed using the most recently used in the timeframe. Besides that, one author might have the same name as another author so it might look like their articles were written by a single author. These issues were resolved and errors in the name of authors were minimised as manual checking was conducted (Kumar & Markscheffel 2016).

During the data reduction process, articles with a single author were filtered and excluded from the data record as in this study, only the articles with two or more authors are considered the co-author network. A directed analysis indicates one individual affects the other while undirected analysis does not show a direction of influence, just that the individuals have a link. Hence, the co-authorship network will be constructed using undirected analysis since there is no fundamental hierarchy between co-authors. Moreover, this study cannot use directed analysis as the collected data of the authors does not indicate any ways of influence each author holds for each other (King & Settle 2019). Then, by using Gephi, the co-authorship network analysis and visualisation are developed. Figure 1 shows how data elements from the records in spreadsheets are extracted into Gephi and construct a co-authorship network that represents this journal.

The entire co-authorship network is plotted as one big network. The important network indicators such as the number of nodes, edges, network components, network density, the number of degrees, network diameter, the number of largest components, average degree, and average path length that are considered useful in this study are recorded. In addition, the largest connected component in the network is also investigated in detail. In consequence, all the data from Gephi representing social network attributes for nodes and edges are reported in the result section. After every task in the second step is completed, calculation from recorded data of

important network indicators is performed in the third step using three main centrality measures which are degree centrality, betweenness centrality, and closeness centrality. These measures can be calculated by using statistical functions in the Gephi tool (Freeman 1978).

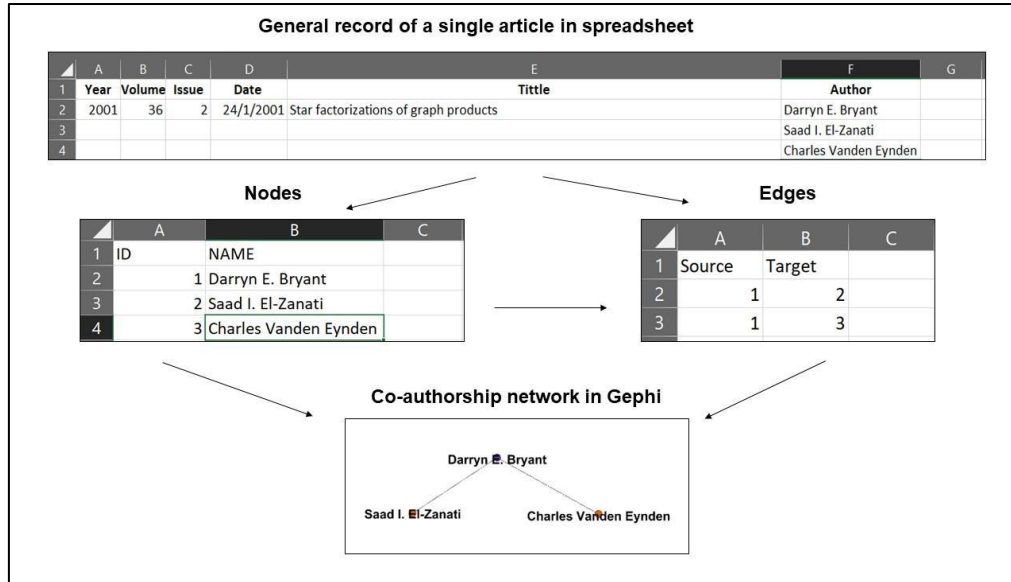


Figure 1. Example of the extraction of graph data from spreadsheet and the construction of a co-authorship network in Gephi

2.1. Degree centrality

The simplest way to measure node centrality is by measuring the degree of the node in the graph. The formula to calculate the degree centrality of a node p_k is:

$$C_D(p_k) = \sum_{i=1}^n a(p_i, p_k), \quad (1)$$

where n is the number of nodes in the network and $a(p_i, p_k)$ is a distance function, $a(p_i, p_k) = 1$, if and only if the node p_i and node p_k are connected one edge away, and $a(p_i, p_k) = 0$ otherwise (Freeman 1978). Nodes with a higher degree are more central and tend to have a greater capacity to influence others. This is indicated that authors with a high degree prefer to co-author with many different authors in a single article than co-authored in many articles.

2.2. Betweenness centrality

Betweenness centrality measures the frequency with which the node appears in the shortest path. The formula to calculate the betweenness of a node p_k is:

$$C_B(p_k) = \sum_i^n \sum_{j \neq k} \frac{g_{ij}(p_k)}{g_{ij}}, \quad i \neq j \neq k, \quad (2)$$

where g_{ij} is the number of geodesics (shortest paths) linking to node p_i and node p_j and $g_{ij}(p_k)$ is the number of geodesics linking to node p_i and node p_j that contain node p_k (Freeman 1978). Nodes with higher betweenness are connectors that bring authors together and connect different groups

2.3. Closeness centrality

Closeness centrality is a measure of detecting nodes that can spread information very efficiently in a graph. This measure identifies how long it will take information to spread from a given node to another in a network. The formula to compute the closeness centrality of a node p_k is:

$$C_c(p_k) = \sum_{i=1}^n d(p_i, p_k), \quad (3)$$

where $d(p_i, p_k)$ is the number of edges in the geodesic linking p_i and p_k (Freeman 1978). This centrality measures the capacity of an author to reach other authors directly without relying on intermediaries. Hence, high closeness rates the author as most responsible for spreading information constantly to other authors.

For the last step, the results from visualisation and calculation in the second step and third step are fully analysed. The ranking of the authors with high centrality based on the result is presented in the form of a table. Discussion to achieve the objectives of the study as well as all the data collected are written in detail.

3. Analysis and Results

In this work, 810 articles from *J. Graph Theory* which involves 44 volumes of the journal were analysed. Articles between the years 2001 and 2015 from the journal were written by 1131 authors. From the article's analysis, there were 425 articles with two authors (52.4691%), 241 articles with three authors (29.7531%), 82 articles with four authors (10.1235%), 62 articles with five authors and above (7.6543%) which consist of two articles produced by eight authors and five articles by seven authors as the highest authors. Article productivity throughout 15 years and multi-authored articles have slightly increased over those range of years is shown in Table 1. Observation from this analysis shows an increase in two, four, and five above-authored articles but a decline in those by three authors (Figure 2). Figure 3 shows the total number of multi-authored articles over the years reached its peak in 2012 with 81 articles and the lowest total is 45 which is in the year 2009. Overall, the graph shows an uneven trend in the articles produced throughout the 15 years.

Table 1: Co-authorship structure of *J. Graph Theory* over the period 2001 to 2015.

Number of Authors	Number of Articles			Total
	2001-2005	2006-2010	2011-2015	
Two	124	135	166	425
Three	72	89	80	241
Four	20	28	34	82
Five and Above	24	13	25	62
Total	240	265	305	810

Analysis of author productivity was also carried out to identify which authors have the most articles produced. Out of 1131 authors, 745 authors (65.8709%) and 186 authors (16.4456%) have produced one and two articles each, respectively. 181 authors (16.0035%) have produced three to nine articles while another 19 authors (1.6799%) produced ten articles and above. The most productive authors are; Xuding Zhu with 25 articles produced, Alexandr V. Kostochka with 17 articles, András Gyárfás and Douglas B. West with 14 articles. Therefore, Xuding Zhu has been significantly more productive than the rest of the authors.

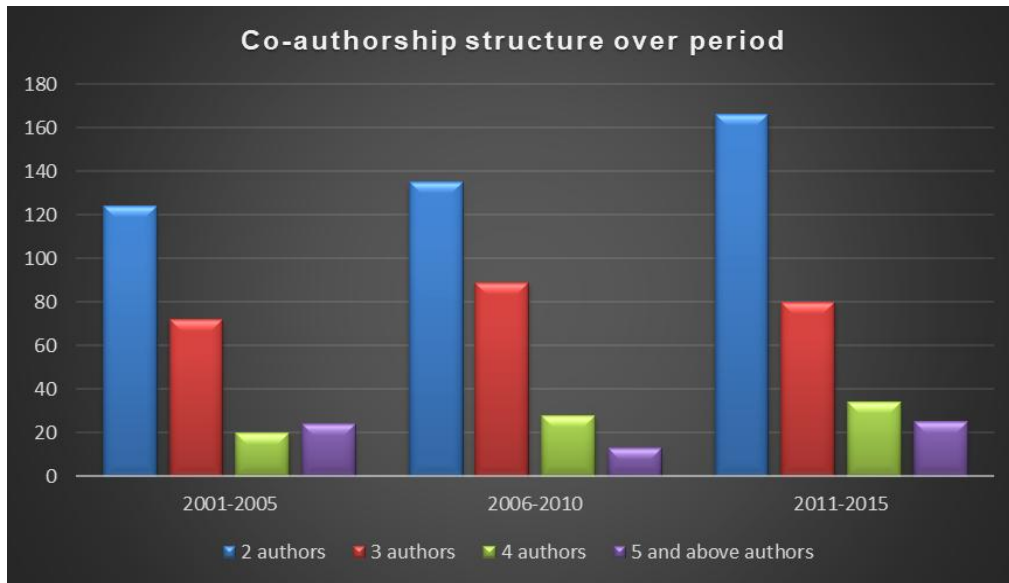


Figure 2. Column chart of co-authorship structure of J. Graph Theory over the period

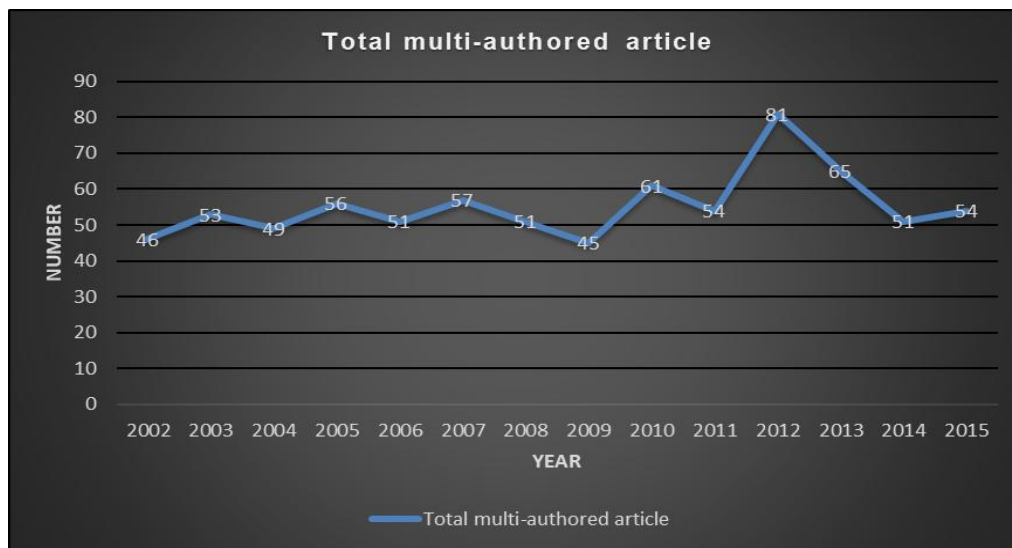


Figure 3. Line chart of total multi-authored articles per year

In this section, the details of co-authorship network visualisation and statistical report of the network are displayed in Table 2. By using some features and tools in Gephi, various network visualisations are obtained to show interesting properties of different nodes that have different values of influence based on the type of network measures. Each of the properties has its interpretation in terms of co-authorship network for this study. The number of degrees indicated an author's total number of co-authors from 2001 to 2015 in the journal. In this study, the maximum degree is 90 and the minimum is 1. The degree of a node in this network must be greater than or equal to one as data collection contains all articles with more than one author. The measure of average degree shows the average number of co-authors for each author in the network.

Table 2: Summary statistics for co-authorship network in *J. Graph Theory*

Network Properties	Result
Nodes	1131
Edges	4790
Maximum degree	90
Average degree	8.47
Network Diameter	14
Average path length	5.611097827754919
Graph density	0.007
Connected component	120
Average clustering coefficient	0.742
Total triangles	1592

The measurement of the longest of all shortest paths in a network is called network diameter. In the co-authorship network, this measurement is used to count the shortest distance between the two most distant authors in the network. Average path length in a co-authorship network can be thought of as the average number of steps taken by each author in the network along the shortest path to another author.

Graph density exhibits the number of existing relationships relative to the possible number each node has. King & Settle (2019) defined graph density as the proportion of the network that is made up of connections between authors as opposed to isolated authors. As a result, the network's density would be 1 if every author were directly connected to every other author. For the case of this study, the value of the graph density of the co-authorship network is 0.007 because not all the authors are connected to every other author which known as single author. 120 connected components are detected in the co-authorship network of this journal.

Other network overviews that were recorded include the average clustering coefficient and total triangles. Both overviews measured the degree of nodes. The average clustering coefficient measures the overall indication of authors in the network that construct a cluster together and 1592 total triangles showed the total cluster of co-authors in the network. Network visualisations play a crucial role in the co-authorship analysis as this technology helps the process to identify the possible relationship that occurs by the distribution of the authors and the connection they had in the network. In this study, every single network is developed using Gephi tools. By using some useful features, the visualisation can be constructed to make the different appearance of the network as there are various attributes to choose from the analysis. Figure 4 illustrates the co-authorship data of articles in this journal within 15 years. This overall network was drawn using the Yifan Hu layout without any annotations to the network with Gephi.

As stated in Table 2, the network in Figure 4 consists of 1131 nodes and 4790 edges, resulting in 120 connected components. There is an obvious giant component in the middle of the network. The largest component is enlarged in Figure 5 occupies 66.14% of the overall network, consisting of 748 nodes and 3901 edges. A giant component that has a big part in a network may be an indication of frequent collaboration interaction. Knowledge exchanges in such networks are faster because they are not prone to the disruptions that would have occurred if the large component had been small, and the entire network had multiple smaller segments of components.

Figure 6 shows the largest network with degree attributes. In the figure, the node size and colour are related to the number of degrees. The bigger the nodes, the higher the number of degrees the node has. Other than that, the colour of the node indicated the degree of centrality. The blue colour represents the nodes with a high degree and the red represents the nodes with a low degree. There are a few nodes that show a high degree while some show an intermediate degree and the rest have a low degree. The degree indicates the number of other nodes connected to a node.

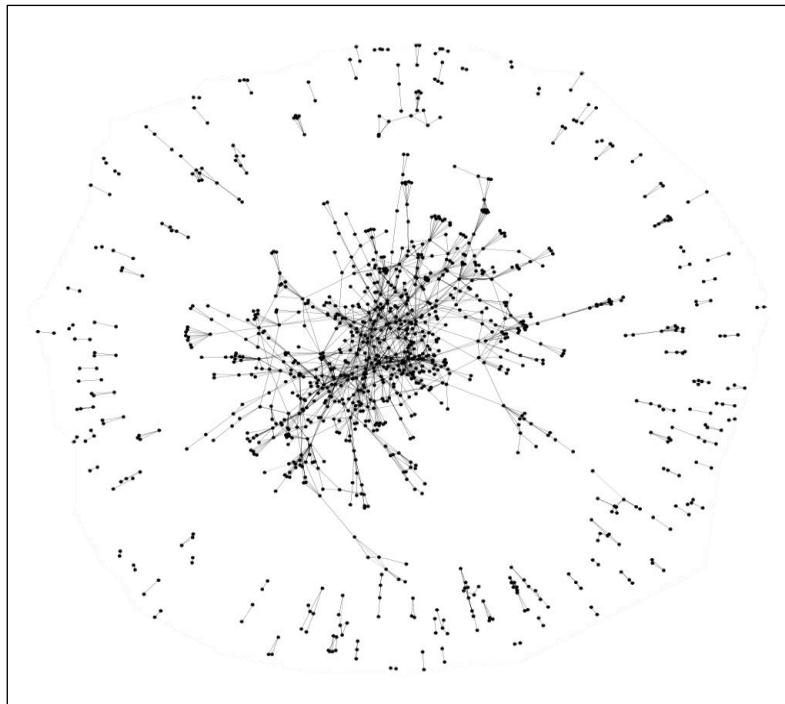


Figure 4: Co-authorship network of articles in J. Graph Theory from 2001 to 2015

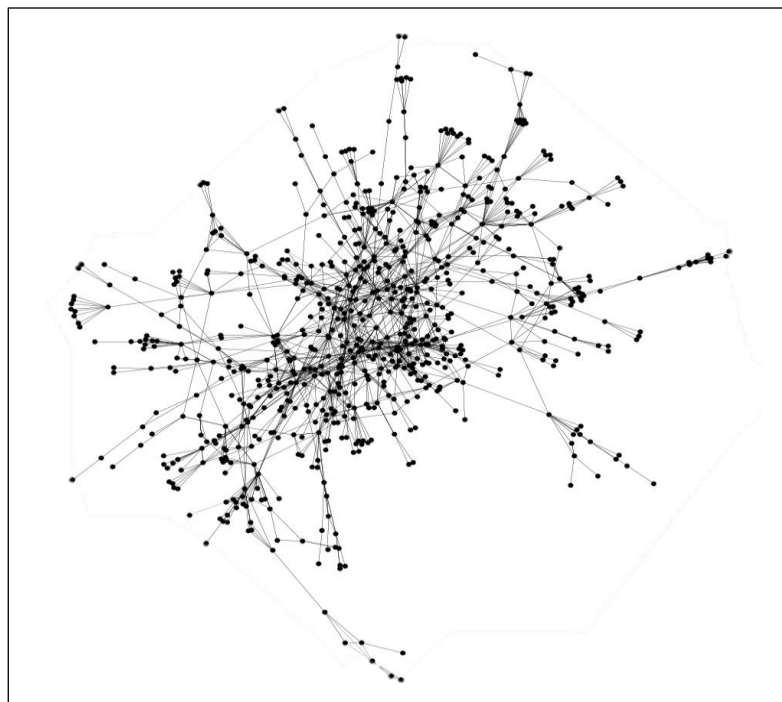


Figure 5: Largest connected component of the co-authorship network

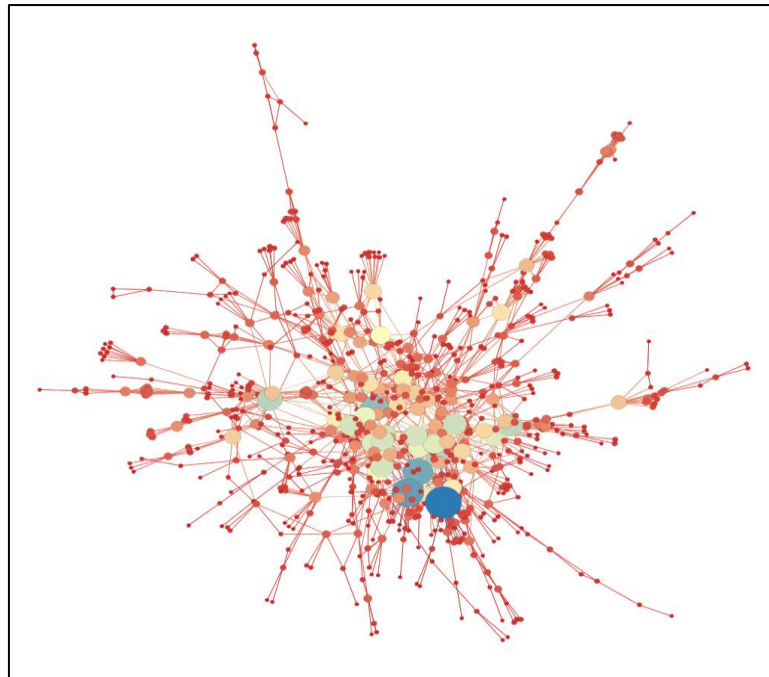


Figure 6. Largest component with degree attribute

Figure 7 shows the largest component is constructed with the betweenness centrality attribute. The node with green colour and the biggest node size indicates the highest value of betweenness centrality while the nodes with brown colour and the smallest in size are nodes that have low betweenness centrality. The rest size and colour have in-between values. The betweenness centrality measure is used to identify how many authors will transit via a given author to reach another author with the fewest hops. The author who has the most traversals has the highest betweenness centrality value.

Closeness centrality in the largest network is visualized as shown in Figure 8. While on Figure 9, with the same attribute but applied to the whole co-authorship network shows a contradiction in colour and size between the nodes. The small orange nodes indicate the lower closeness centrality value. On the other hand, the big purple nodes indicate higher closeness centrality. For this centrality attribute, then different closeness centrality values are significantly shown as the centre which is the largest component is majority have small closeness value rather than other components which are located far from the largest component. Closeness centrality counts the average distance from a given starting node to all other nodes in the network. Therefore, the network shown disconnected communities have weaker closeness and centrality and authors that connect to other communities have a higher proximity centrality.

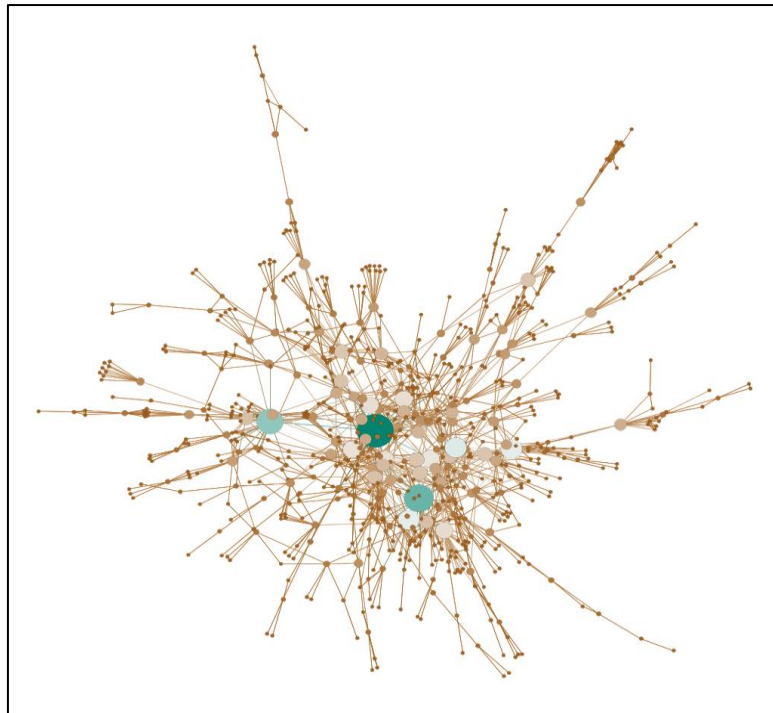


Figure 7. Largest component with betweenness centrality attribute

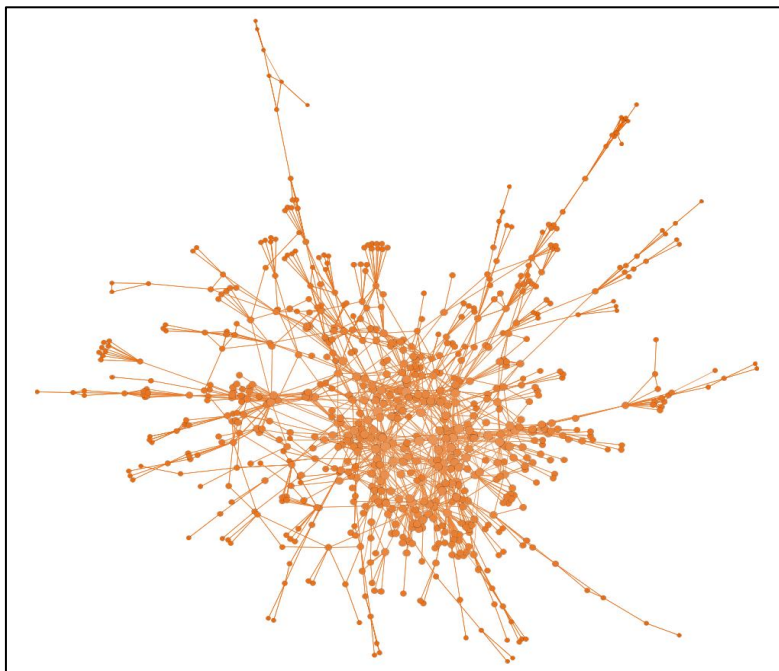


Figure 8. Largest network with closeness centrality attribute

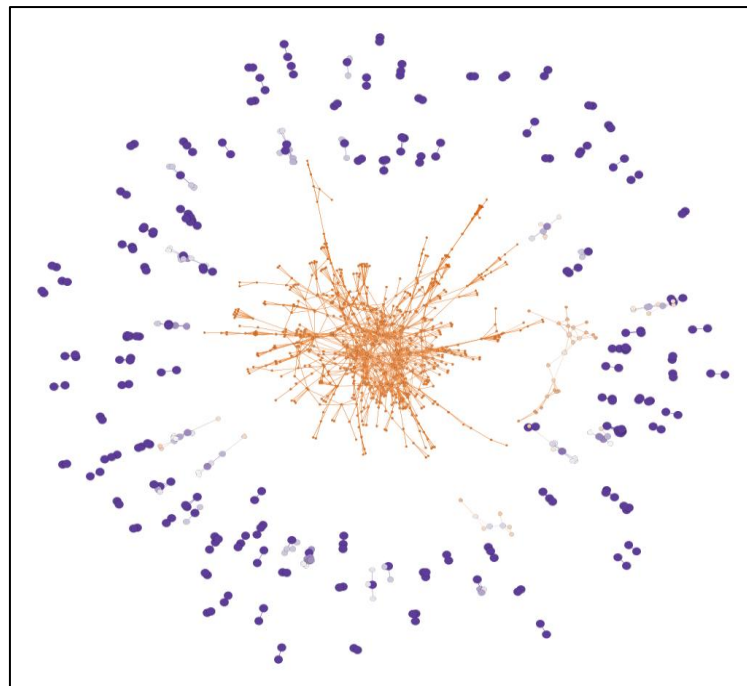


Figure 9. The co-authorship network with closeness centrality attribute

Tables 3, 4 and 5 show the top 10 rankings of authors in three centrality measures which are degree centrality, betweenness centrality, and closeness centrality. On that account, there will be more than one author in some rank since they have the same value of centrality.

Table 3. Top 10 ranking in degree centrality

Ranking	Author	Degree centrality
1	Xuding Zhu	90
2	Douglas B. West	78
3	Alexandr V. Kostochka	74
4	András Gyárfás	68
5	André Raspaud Noga Alon	60
6	H. J. Broersma	59
7	Zdeněk Ryjáček	56
8	Akira Saito Ken-ichi Kawarabayashi Michael S. Jacobson Ralph J. Faudree Ronald J. Gould	54
9	Daniel Král' Guantao Chen Mickaël Montassier	52
10	Ingo Schiermeyer	50

Table 4. Top 10 ranking in betweenness centrality

Ranking	Author	Betweenness centrality
1	András Gyárfás	44928.31202
2	Alexandr V. Kostochka	35239.04179
3	Noga Alon	31599.09558
4	Zdeněk Ryjáček	24589.45885
5	Douglas B. West	23863.0567
6	H. J. Broersma	23687.49979
7	Michael Stiebitz	20060.22156
8	Ken-ichi Kawarabayashi	19761.95465
9	Akira Saito	19304.43465
10	Michael A. Henning	19112.74121

Table 5. Top 10 ranking in closeness centrality

Ranking	Author	Closeness centrality
1	252 authors	1
2	L. Sunil Chandran	0.875
3	Yan-Quan Feng Ron Aharoni Endre Boros Vladimir Gurvich	0.833333
4	Jian-Liang Wu	0.818182
5	Lin Xiaohui A. Abouelaoualim C. A. Martinhon M. Karpinski R. Saad W. Fernandez de la Vega Y. Manoussakis Bernardo Llano Eduardo Rivera-Campo Paul Horn	0.8
6	Jian-Feng Hou Fan Chung Haidong Wu Paul Horn Talmage James Reid	0.75
7	Darryn Bryant Charles Vanden Eynden Saad I. El-Zanati	0.727273
8	Jin Ho Kwak Eli Berger Igor Zverovich J. Gimbert J. Gómez Y. Wu	0.714286
9	Guizhen Liu	0.692308
10	24 authors	0.666667

From the ranking above, Xuding Zhu is in first place in ranking for highest degree centrality and most connected author with the value of 90. András Gyárfás with 44928.31202 is the top author with the highest betweenness centrality. This author was the main author who connects and brings other authors together and at the same time connects different groups. In addition, they do not have intermediaries in their way to reach the other authors they connect to. Hence, they are authors who are closer to other authors and will be more likely to co-author an article together.

Throughout the list of authors in those ranking tables, there are a few names that were listed in more than one table. The authors are András Gyárfás, Alexandr V. Kostochka, Noga Alon, Zdeněk Ryjáček, Douglas B. West, H. J. Broersma, Ken-ichi Kawarabayashi, and Akira Saito. For András Gyárfás, Alexandr V. Kostochka, Noga Alon, Zdeněk Ryjáček, and Douglas B. West and they are the top 5 in betweenness centrality and the top 7 in degree centrality. These five authors were the prominent authors in creating connections with others in the network and among the influential authors in this journal through the period of time study.

4. Conclusion and Future Work

This study focuses on the co-authorship network analysis of articles published in *J. Graph Theory* from 2001 to 2015. By employing tools, measures, and visualisations from social network analysis, the co-authorship network was effectively interpreted. Additionally, the data collection revealed the frequency of co-authored articles published during this period. This analysis aims to foster both article and author productivity in graph theory research, particularly in promoting collaborative efforts. Furthermore, the study identified several influential authors, providing valuable insights for other researchers to strengthen their connections and enhance research outputs in the field.

Graph invariants were applied using network analysis principles to study the co-authorship network using Gephi tools. Centrality measures such as degree centrality, closeness centrality, and betweenness centrality provided values or indices to nodes (authors) based on their positions in the network. The overall co-authorship network comprised 1,131 nodes and 4,790 edges, with the largest connected component consisting of 748 nodes and 3,901 edges. Authors were ranked based on their values across the three centrality measures, highlighting their connectedness and influence within the network. Notably, András Gyárfás, Alexandr V. Kostochka, Noga Alon, Zdeněk Ryjáček, and Douglas B. West appeared in the rankings for both betweenness centrality and degree centrality, underscoring their significant influence in the network.

Future research should incorporate additional centrality measures, such as eigenvector centrality, PageRank centrality, and clustering coefficient, to provide deeper insights into author influence. Complementary bibliometric analyses, such as co-citation analysis, could identify highly cited and impactful research within graph theory. Furthermore, addressing gaps in the availability of institutional and regional data about authors could enhance the scope and applicability of subsequent studies.

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