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MODELING AND ANALYSIS OF A CO-AUTHORSHIP SYSTEM USING COMPLEX NETWORK APPROACH: A CASE STUDY

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Abstract

Complex systems across various domains including biological, social, environmental, technological, communication, and transportation can be effectively modeled as complex networks. These networks are typically large and intricate due to the vast number of nodes and interconnections among them.This study apply a network science approach to model and analyze co-authorship networks derived from the Journal of Lightwave Technology (JLT). The analysis is conducted using key network metrics such as degree centrality, clustering coefficient, and betweenness centrality.The results indicate that the network exhibit high clustering, short average path lengths, and an inhomogeneous distribution of weighted degree. Furthermore, the findings reveal the presence of influential authors acting as hubs who frequently appear across multiple issues.

1. Introduction

Complex network analysis is an interdisciplinary research area widely applied in fields such as engineering, sociology, physics, and biology. Various modeling techniques have been developed to represent and analyze real-world systems, enabling better understanding and system design. A network typically consists of entities (nodes or vertices) and also the relationships between them also refered (edges)[1].

Many real-world systems can be represented as networks, however over the past decade; researchers have increasingly used network-based approaches to explore the behavior and structure of large-scale systems. Social networks, for example, consist of individuals or groups connected through relationships or interactions. A simple example is a friendship network [2].

Early models of complex networks were introduced by mathematicians, who proposed structures such as regular networks (lattices and grids), random networks, small world networks, and the scale free networks[3]. The concept of the "small-world" phenomenon was popularized by Stanley Milgram in the 1960s[4].

Networks are present in many domains, including social networks, collaboration networks (where authors are linked through co-authorship), the World Wide Web, and biological systems such as gene and protein networks. These real-world systems can be effectively studied using network modeling techniques[6].

2. .Network Matrics

Several centrality measures are used to analyze networks, including degree, betweenness, and clustering coefficient. These metrics help in understanding the importance and structure of nodes within a network.

2.1 Degree Centrality

Degree centrality is one of the simple measures of node importance. It represents the a node has number of direct connections within network [7]. A node with a higher degree is considered more influential because it interacts with many other nodes.In the coauthorship networks, the degree related to an author corresponds to the number of available co-authors they have collaborated with [8]. The degree of any node ki of node i is computed based on its connections with other nodes within the network, that is shown in following equation 1.

$$K_i = \sum_{i=1}^{N} aij \qquad \text{Equation. 1}$$

In this mathematical framework, ki denotes the degree of node i, while aij represents the adjacency matrix element. A value of aij = 1 indicates a direct connection between nodes, whereas a value of 0 signifies the absence of an edge. The variable N is utilized to represent the total number of nodes within the network population.

2.2 Betweenness Centrality

The significance of any node in betweenness centrality measures is based on its position in the shortest paths among other nodes [7]. Nodes with high betweenness act as bridges, facilitating communication across different parts of the network.This concept was formally introduced by Linton Freeman. A node having high betweenness centrality often plays an essential role in controlling information flow within the network [9]. Betweenness computed as assumed in the following equation.

$$CB(k) = \sum_{j}^{N} \sum_{i}^{N} \frac{hji(k)}{hji}, i \neq j \qquad \text{Equation. 2}$$

In this context, CB(i) represents the betweenness centrality for a specific node i. The variable hji signifies the total number of shortest paths existing between any two nodes j and l, while hji(i) indicates the subset of those shortest routes that pass through node i. The specific calculation for betweenness centrality, as proposed by Opsahl, is detailed in above Equation [10].

2.3 Clustering Co-efficient

The clustering coefficient measures are used as the likelihood that the neighbours of a node remain connected with each other. It reflects the inclination of nodes to create tightly connected groups or clusters [11].

The range of value from 0 to 1, whereas 0 indicates no clustering and 1 shows complete clustering [12]. Clustering can be measured using local and global approaches.

3. Modeling Co Authorship Dataset As A network

In this study, co-authorship data from JLT(Journal of lightwave) is modeled as two-mode networks. The datasets include attributes such as author names, paper titles, publication year, and co-authors. In a two-mode network, one set of nodes represents authors, while the other represents papers. Connections exist between authors and the papers they have contributed to. This structure allows for analyzing collaboration patterns effectively.

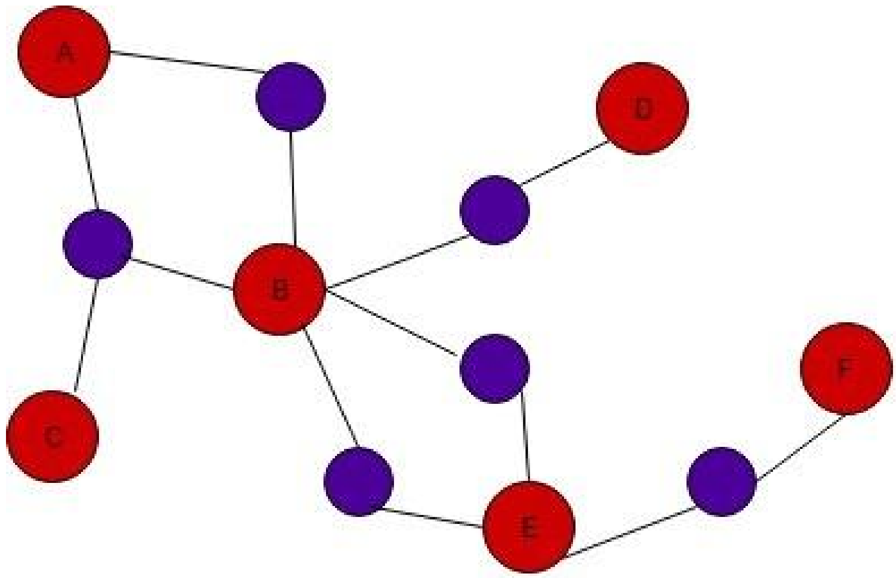

Fig .1. A two-mode network(simple bipartite)

A two mode network can be described as triplet G=$(T, \perp, E)$, in this T denotes the set that includes top nodes, bottom nodes are denoted by $\perp$, and $E \subseteq T \times \perp$ is a set of associations [13].

4. Findings

4.1 Node Degree and Strength

Within the framework of node centrality measures, degree centrality is recognized as the most fundamental indicator. It quantifies the number of direct edges connecting a specific node to others within the network. By analyzing the distribution of these connections, one can characterize the overall structural integrity and behavioral strength of the network. As detailed in Table 1, the two-mode degree centrality for the top ten authors in the *Journal of Lightwave Technology (JLT)* dataset reveals that Author ID 144 is the most central researcher, maintaining a one-mode degree of 21 despite a two-mode degree of 15. Furthermore, Authors 172 and 853 share a two-mode degree of 13, but their extensive collaborations connecting with 46 and 43 authors respectively, mark them as prominent figures in the field. Other significant researchers include IDs 337 and 912 with 12 links, ID 757 with 11, and IDs 148, 278, 453, and 844, all of whom maintain 10 degrees. This collaborative landscape is visualized in Figure 3, where the horizontal axis represents the author count and the vertical axis illustrates the number of papers.

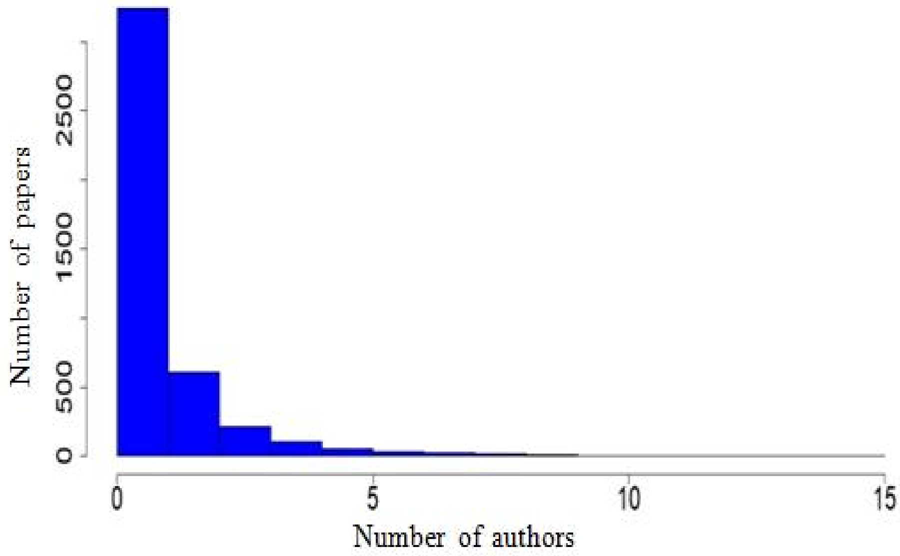

Fig.2. Histogram of two-mode degree of authors in JLT

Table.1: *Different degree measures of JLT*

Two-Mode Degree		One-Mode Degree		Strength Of Node	
Author_ID	Degree	Binary	Newman Method	Binary	Newman
144	15	21	21	21	12
172	13	46	46	46	13
853	13	43	43	43	13
337	12	69	69	69	12
912	12	27	27	27	12
757	11	16	16	16	10
148	10	37	37	37	10
278	10	13	13	13	9
453	10	16	16	16	8
844	10	83	83	83	10

4.2 Betweenness Centrality

Betweenness centrality identifies researchers who serve as vital bridges, connecting scientists who have not previously collaborated by occupying the shortest paths between them. According to the data in Table 3, the *Journal of Lightwave Technology (JLT)* network is anchored by key intermediaries, specifically IDs 844, 3508, 269, 423, 773, 1871, 633, 883, 713, and 840. Author 844 holds the most significant "brokerage" position with the highest betweenness score, followed closely by ID 3508. The line distribution for this metric indicates that while the majority of researchers maintain limited connectivity, over 100 authors in the JLT network possess high betweenness values. This concentration of central roles suggests a high link weight and a robustly integrated collaborative structure.

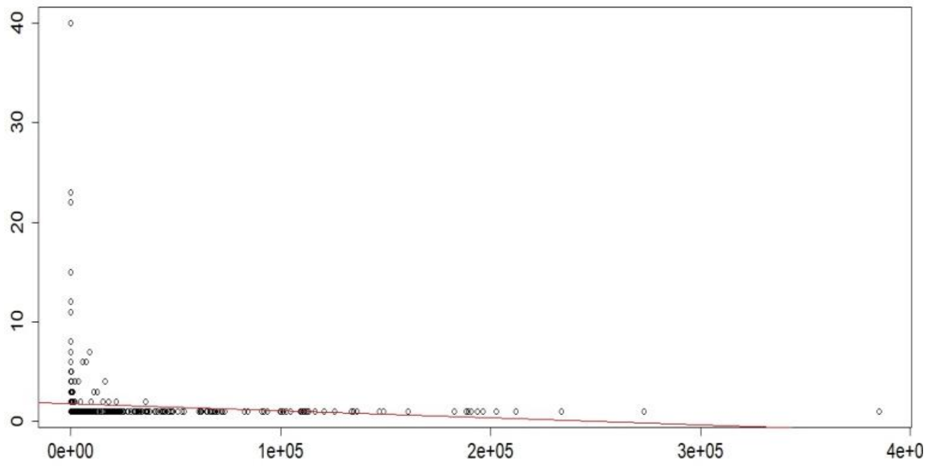

Fig.3. Journal of lightwave (JLT) Line Distribution using Betweenness method

Table 2: *Betweenness centralities of JLT networks*

Betweenness Centrality JLT	
Author_ID	**Newman Method**
844	385172.5
3508	2497
269	149020
423	273208.1
773	69087
1871	112770.8
633	92104.17
883	196312.6
713	202627.2
840	104520

4.3 Global Clustering Coefficient JLT Network

Analysis of the global clustering coefficient for the *Journal of Lightwave Technology* (JLT) network indicates a high degree of clustering regarding co-authorship and connection weights. Table 3 and Figure 4 compare five distinct methods for calculating this coefficient. Among the weighted approaches, the Minimum method yielded the highest clustering value, primarily driven by authors with high two-mode degrees. Conversely, the Maximum method produced the lowest value, suggesting that only a small fraction of links within the network carry high weights. The Geometric Mean outperformed both the Maximum and Arithmetic Mean methods, as it effectively accounts for closed 4-paths. Finally, the Binary results confirm a highly clustered structure, characterized by numerous closed 4-paths relative to the network's limited node count.

Table 3: *Global clustering coefficient of Journal of light (JLT)*

Global Clustering Coefficient				
AM	*GM*	*Max*	*Min*	*Binary*
0.65288	0.6632207	0.6228764	0.7037688	0.6830588

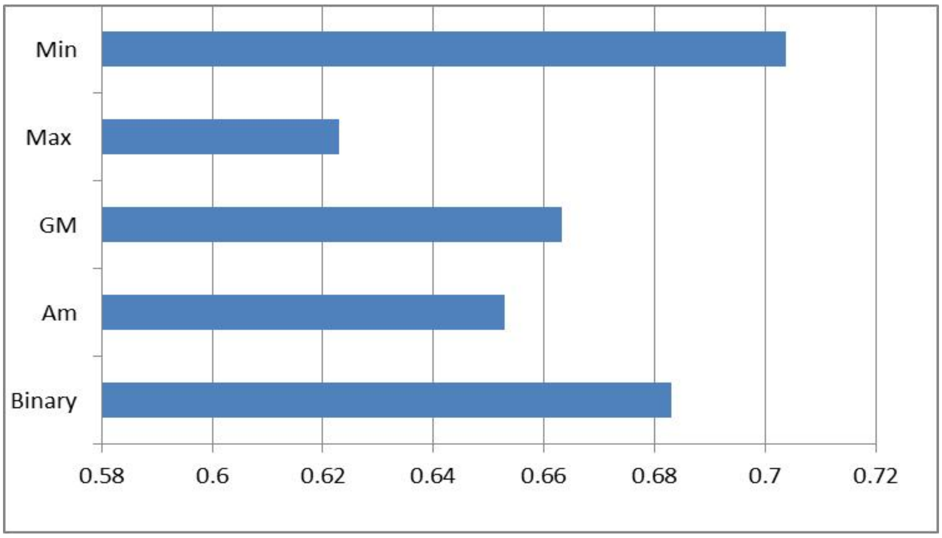

Fig.4. The Journal of lightwave (JLT) graph shows the comparison of different global clustering methods applied on the two-mode network

Table 4: *Network Analysis Findings of Journal of light (JLT).*

Journal of light (JLT)		
Methods	High Score	Low Score
Two-mode degree	15	1
One-mode degree	21	1
Betweenness Centrality	3851725.5	0.166
Global Clustering Coefficient	0.70337688	0.6228764

5. Conclusion

This research models and evaluates a co-authorship network through the lens of complex network theory. While existing literature extensively explores partnership patterns within academic collaborations, this study specifically utilizes an international dataset from the *Journal of Lightwave Technology (JLT)*. By applying complex network metrics, the study identifies the structural properties of two-mode networks and compares the topological framework of technology-focused journals. The findings indicate that the JLT network exhibits superior structural values across key metrics, including betweenness centrality, two-mode degree, and one-mode degree. Furthermore, the global clustering coefficient is notably high, driven by a subset of authors with expansive two-mode degrees. These topological characteristics are essential for gaining a comprehensive understanding of the network's underlying physical and collaborative properties.

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