

Article

Ranking Authors in an Academic Network Using Social Network Measures

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Abstract: Online social networks are widely used platforms that enable people to connect with each other. These social media channels provide an active communication platform for people, and they have opened new venues of research for the academic world and business. One of these research areas is measuring the influential users in online social networks; and the same is true for academic networks where finding influential authors is an area of interest. In an academic network, citation count, h-index and their variations are used to find top authors. In this article, we propose the adoption of established social network measures, including centrality and prestige, in an academic network to compute the rank of authors. For the empirical analysis, the widely-used dataset of the Digital Bibliography and Library Project (DBLP) is exploited in this research, and the micro-level properties of the network formed in the DBLP co-authorship network are studied. Afterwards, the results are computed using social network measures and evaluated using the standard ranking performance evaluation measures, including Kendall correlation, Overlapping Similarity (OSim) and Spearman rank-order correlation. The results reveal that the centrality measures are significantly correlated with the citation count and h-index. Consequently, social network measures have potential to be used in an academic network to rank the authors.

Keywords: social network measures; ranking authors; academic indexes; co-authorship network

1. Introduction

In the present era, online social networks are widely-used platforms that enable people to connect with other people for exchanging ideas, views and setting public opinion. Types of online social networks include, but are not limited to, Facebook, Flickr, Twitter, YouTube, etc. According to the statistics, Facebook had about 2.2 billion monthly active users in March 2018. Similarly, the total number of monthly active users of Twitter in January 2018 was 330 million, who share about 500 million tweets per day. Flickr is used by 92 million people worldwide and is a great place to store and share photos online [1]. These online social networking sites provide an active communication platform for people, and they have opened new venues of research for the academic world and businesses. One of these research areas is finding the influential users in the online social networks. According to the related research studies [2–6], the influence of top users is measured with the help of various techniques, such as the feature-based technique or link-based technique. Moreover, in all these techniques, the focus has been to find the top active or influential users.

Like online social networks, there are a number of online academic networks. These are also represented by the relationship among the entities or nodes, such as paper, author, journal or conference. These entities or nodes are connected through two types of relationships: co-citation and co-author, and result in two subtypes of academic network, which are the co-citation network and co-authorship network, respectively. In the citation network, one author cites the publication of other authors, whereas in the co-author network, links are formed between authors based on a publication. As in online social networks, finding influential authors in an academic network is an active research area as well, and the co-authorship network has been used to find the influential authors or the ranking of authors. The research domain of ranking of authors has vast applications such as finding the top supervisor in a specific research domain, offering research jobs, grant funding for research projects and nominating top authors for research awards [7]. In this regard, to rank the authors, using various indexing techniques, such as the h-index [8], g-index [9], m-index [10], R-index [11] and AR-index [11], are used. However, all these indexing techniques evaluate the author to only gauge the influence of authors, but rarely consider discipline or domain along with the impact of authors. To address this problem, centrality measure techniques from social network measures are borrowed. Moreover, authors have used PageRank [12] along with the centrality measure and compared the results with citation count. In another study [13], the authors used a technique from social network measures, i.e., Eigenvector to rank the journals of the PLOS database and compared the result with the citation count within a given journal. Moreover, the techniques borrowed from social network measures often focus on macro-level properties of the co-authorship network, yet no attention is paid to micro-level properties.

In this article, we propose the adoption of established social network measures in order to compute the centrality and significance of an author. Our contributions may be summarized as follows:

- We analyze the co-author network within the Digital Bibliography and Library Project (DBLP) research community at the macro-level by applying centrality measures (betweenness centrality, closeness centrality, degree centrality) and prestige measures (PageRank, Eigenvector) for author ranking.
- We also study the micro-level network properties of the co-author network using the average path length, the largest connected component and the average degree of a network.
- The results, compared with standard baseline methods using the standard performance evaluation measures, confirm that the network centrality measure provides an effective guideline to find the list of ranked authors.

The rest of the article is organized as follows: In Section 2, a literature review of social network measures and academic network metrics is described. The methodology is described in Section 3, which covers the proposed framework, the adoption of social network measures, a brief description of the dataset and the detail of the performance evaluation measures, used for ranking of authors. In Section 4, results are discussed and compared with the baseline indexes. Finally, the conclusions and future work directions are discussed in Section 5.

2. Related Work

In this section, we describe the earlier studies about the use of social network measures in different domains. In the first subsection, related literature from academic network is discussed. In the second subsection, related work from academic network measures is discussed, which are used to rank the authors in an academic network.

2.1. Academic Network Measures

In order to find the productivity and the impact of an author, different indexing schemes are introduced. In this regard, Hirsch [8] proposed the h-index to rank the authors and is considered a pioneer. The h-index takes into account both citation count and publication count. The h-index is

intended to measure both the quality and quantity of a scientific output. On the one hand, the h-index is most widely-used indexing technique; on the other hand, it has some shortcomings. One of the shortcomings is that once a paper is selected in the h-index, no further importance is given to that paper even if the paper doubles its citation [14]. To address the issue of the h-index, Egghe proposed another indexing technique named the g-index. It is an improved version of the h-index, and it firstly arranges the documents in decreasing order of their citation received as in the h-index. Afterwards, the g-index is calculated, which is the largest document number such that the top publications collectively receive at least g^2 citations. Although the g-index is widely used to find the impact of authors, it could not gain popularity like the h-index, because one very highly cited paper may affect the values of the g-index. Moreover, using the h-index, new authors could not get the desired credit, leading to another shortcoming of the h-index. The m-index [10] solved this issue by the clear distinction between old and new authors. It is computed by dividing the h-index by the number of the research's years as an author. Although the m-index is an enhanced version of h-index, for the m-index, a small change in the h-index values leads to a big change in the m-quotient, which is one of the major drawbacks of the m-index. The third issue linked with the h-index is that it cannot differentiate between the authors having the same h-index, but variation in the citation received. To overcome this issue, Jin et al. proposed a novel indexing technique named the R-index [11]. It is computed by calculating the h-index, adding all the citation counts involved in the h-index and finally calculating the square root of the cumulative sum of citations. Afterwards, a variation of the R-index was proposed by Jin et al. [11], named the AR-index, which takes into account the age of the article. In this regard, another indexing technique called the DS-index [7] was proposed. It differentiates among the authors having a very small change in the citation count. In the related literature, Arindam Pal and Sushmita Ruj proposed a graph-based analytics framework [15] to assign scores and to rank the paper, venue and author. The graph-based analytics framework used an algorithm that only considered the linked structures of the underlying graphs.

2.2. Social Network Measures

The related literature presents the use of various social network measures such as degree centrality, closeness centrality, betweenness centrality, PageRank and Eigenvector for finding the influential users. The social network measures rank users by their position in social networks. Thus, based on the position of a user, speed of information spread is affected by the user's centrality, which is an important attribute in a social network [16]. Centrality shows how important a user is for spreading the information over the social network. Moreover, the centrality value is affected by the graph layout and weights. Centrality has numerous measures for finding the influential users. Degree centrality [17] is the first measure, defined as the number of direct neighbors of any vertex or node. It measures the density of a graph. The second measure is closeness centrality [18], which is defined as the length of the minimum path to the other vertices. Subsequently, it measures how quickly data can proliferate from a vertex through the system. Betweenness centrality is the third measure, which requires numerous expensive shortest distance calculations [19]. Betweenness centrality measures how many times a particular node act as a bridge. An extension of degree centrality is the Eigenvector, another measure of centrality. In [20], a node is important if it is linked to another important node. Thus, it measures the influence of a node. The last measure is the PageRank algorithm, which is used to rank web pages. It is a widely-used measure utilized by the Google search engine for positioning websites according to their ranks. PageRank is a graph-based ranking algorithm, usually applied to directed graphs; however, its application to undirected graphs [21] is also possible. All these centrality measures are used to find the influential users. Diverse points of view of influence are being examined in academic networks. In the relevant literature, examples of academic network analysis include judgments of rising stars [22], link influence [23] and finding top conferences [24].

2.3. Applications of Social Network Measures

The social network measures are applied in different domains. To identify the influential users, Jianqiang, Xialin and Feng proposed the modified version of PageRank, named UIRank (user influence rank algorithm) in a micro-blog through the relationship of user interactions [25]. The results show that the UIRank algorithm outperformed other related algorithm in precision, recall and accuracy. Zhao et al. exploited social network measures such as degree centrality, PageRank and betweenness centrality for the analyzing urban traffic flow [26]. Kaple, Kulkarni and Potika also used social network measures to discover future needs in order to manage resources efficiently [27]. The authors applied PageRank on smart city data to find the influence on the behavior and choices of citizens and to increase the engagement of citizens in elections. Moreover, social network centrality measures are also used in the field of neural networks. Fletcher and Wennekers [28] examined the layout and activities of neurons with the help of the centrality of a neuron. The topological layout of a neural network explains the activity of the neurons within it. Fletcher applied an array of centrality measures, including betweenness, Eigenvector, Katz, PageRank, In-degree, closeness, hyperlink-induced topic search (HITS) and NeuronRank, to fire neural networks with different connectivity schemes. The results show that Katz centrality was the best predictor with optimized correlation in all the cases studied. Katz centrality produced best results because Katz centrality nicely captures disinhibition in neural networks.

2.4. Applications of Social Network Measures in Academic Network

Applications of social network measures in academic networks is also well recognized. For instance, Crossley et al. used social network measures for information exchanges between users, to understand the student retention in a massive open online course (MOOC) or to identify the student arrangements associated with course completion in an MOOC [29]. In an MOOC, betweenness centrality is computed to determine the central nodes. The participant's connections with other nodes are computed using closeness centrality. According to the results, a higher value of closeness centrality represents a participant's stronger connection to all other participants in a discussion. Moreover, for ranking of journals, Griffin et al. [30] used social network measures such as closeness, betweenness and degree. Similarly, Barnett et al. [31] used degree centrality, Eigenvector centrality and betweenness centrality to rank the journals. To identify the important keywords within documents, the authors in [32,33] used different social network measures. In this regard, Diallo et al. used the network centrality measures such as Eigenvector to identify the key paper within a journal [13]. Betweenness centrality was used by Chen to detect the emerging trends and patterns in scientific literature over time [34]. In academic networks, network centrality metrics, such as betweenness, determine the significance of papers within the community by examining their co-citation networks or their co-author network for social network analysis based on the flow of information between publications [35].

3. Materials and Methods

In this section, the proposed framework is explained, and social network measures used in this research are described in detail. Furthermore, the dataset used in this research study is discussed. In the last section, performance evaluation measures are discussed.

3.1. Proposed Framework

The proposed framework for finding the top authors using social network measures is shown in Figure 1. Firstly, data pre-processing is performed, where the extracted dataset available in XML form is transformed into the graph-based dataset using a custom-developed routine in Microsoft Visual Studio C.Net. Secondly, data analysis is carried out, which includes the calculation of micro-level measures including average path length and largest connected component. Thirdly, for finding top ranked author data, we apply the social network measures such as centrality measure and prestige measure to the dataset. Finally, the computed results are compared with the baseline techniques

such h-index and citation count using the performance evaluation measures: Kendall rank order correlation, OSim (also known as Overlapping Similarity or OSimilarity) [36] and Spearman's rank order correlation.

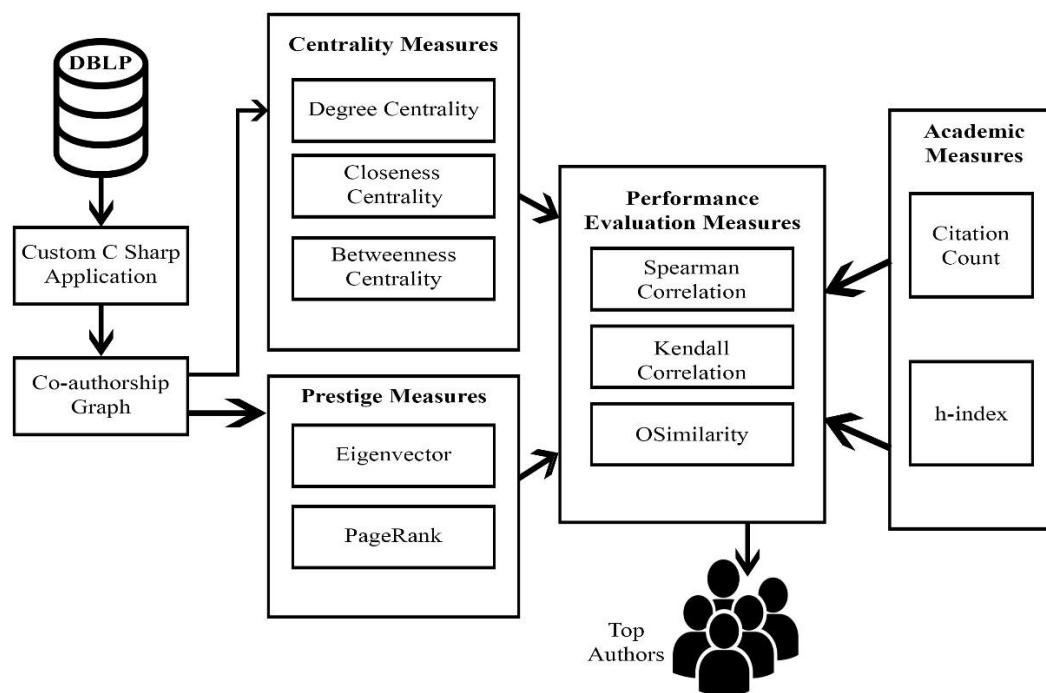


Figure 1. Ranking authors using social network measures. DBLP, the Digital Bibliography and Library Project.

3.2. Network Centrality Measures

Two measures, including centrality analysis and prestige analysis, are borrowed from social network analysis [12] and are applied in academic networks for ranking of authors. The centrality analysis determines the central position of an author in spreading the information over the network; whereas, the prestige analysis defines the importance of an author in a given network. Both measures are defined in detail in the following subsections.

3.2.1. Degree Centrality

Degree centrality of an author is defined as the total number of co-authors that are directly attached to a particular author. The degree centrality is computed using Equation (1).

$$C_D(a_i) = d(a_i) \quad (1)$$

where (a_i) represents an author in a set of authors and $d(a_i)$ represents the degree of an author a_i . The higher the degree of an author, the more the author central in a co-authorship network and tends to influence others at a greater capacity.

3.2.2. Closeness Centrality

Closeness is used to measure the importance of an author, which determines how much an author is close to the central position. For instance, an author who has a direct connection with many other authors has a high closeness centrality value, while an author that indirectly connects with many other authors has a lower value. Thus, the closeness centrality of an author is the average length of the

shortest path between the author and all other authors in the academic network. Closeness centrality is computed using Equation (2).

$$CC(a_i) = \left[\frac{\sum_j d(a_j, a_i)}{N-1} \right]^{-1} \quad (2)$$

where $CC(a_i)$ represents the closeness centrality of the given author and $d(a_j, a_i)$ is the distance between two given authors in the network of authors.

3.2.3. Betweenness Centrality

Betweenness centrality measures the number of times an author acts as a bridge or the shortest path between two other authors. Betweenness centrality is computed using Equation (3).

$$BC(a_i) = \sum_{a_i \neq a_j \neq a_k \in A} \frac{\sigma_{st}(a_i)}{\sigma_{st}} \quad (3)$$

where $BC(a_i)$ represents the betweenness centrality of the given author. σ_{st} represents the total number of shortest paths from author a_i to author a_j , and $\sigma_{st}(a_i)$ shows the number of those links that pass through author a_i .

3.2.4. PageRank

PageRank is used to determine the importance of an author within a graph. PageRank is computed using Equation (4).

$$PR(a_i) = \sum_{j=1}^n \frac{PR(a_j)}{OD(a_j)} + \frac{1-d}{N} \quad (4)$$

where d is the damping factor, $PR(a_j)$ is used to represent the PageRank of author a_j and $OD(a_j)$ represents the out-degree of author a_j .

3.2.5. Eigenvector

To find the influence of authors in an academic network, the Eigenvector is another measure. Authors with a high Eigenvector are recurrently co-authored with other significant authors and are considered significant. Thus, a highly-cited author contributes more to the account of the author being cited. In other words, a highly-cited author is connected with other highly-cited authors. The Eigenvector is computed by using Equation (5).

$$EV(a_i) = \frac{1}{\gamma} \times \sum_{j=1}^n a_{i,j} x_j \quad (5)$$

where $EV(a_i)$ represents the Eigenvector of an author a_i ; γ is a constant; $a_{i,j}$ represents the adjacency matrix; and x_j represents the Eigenvector of the author a_j .

3.3. Dataset

The DBLP (Digital Bibliography and Library Project) dataset, started in 1993 at the University of Trier, Germany, was used in this research. The DBLP is a computer science bibliography, which is a widely used in academic research [7].

The dataset was downloaded in the form of XML format, having a size of 2.93 GB. The downloaded dataset firstly was converted into the relational database and secondly converted into a graph structure of nodes. Finally, we created the co-authorship network in the form of a graph using an application developed in Microsoft Visual Studio C Sharp.Net. In this newly created graph, for a given publication, all the authors will be connected in an undirected graph. For instance, if a paper is written by three authors, then three undirected edges will connect all three authors. As our research is confined

to finding the influence among co-authors, considering those authors who publish alone is beyond the scope of this research study. All the characteristics of the dataset are shown in Table 1. The original DBLP dataset extracted from the source consisted of 3,818,185 research publications and 1,351,586 authors. To find the influential authors, experience was taken into account, and papers of the authors having a minimum of 20 years of research experience were considered. Resultantly, we came up with a dataset of 153,432 papers and 9072 authors. In addition, papers with single authorship were beyond our scope; thus, only those papers having at least two authors were considered, and we finally came up with a reduced dataset of 139,794 authors and 8959 authors.

Table 1. Characteristics of the DBLP dataset.

Attributes	Values
Vertex Type	Publication
Edge Type	Co-authorship
Size	8959 Vertices (author)
Volume	61,009 Edges (co-author)
Format	Undirected
Average Degree	13.62

3.4. Performance Evaluation Metrics

For performance evaluation, we applied three different measures, including Spearman rank order correlation, OSim and Kendall rank order correlation. These measures are discussed in the following subsections.

3.4.1. Spearman Rank Order Correlation

This represents the correlation between strength and direction of association between the two ranked lists [37]. It is calculated using Equation (6).

$$r_s = \frac{\sum (a_i - \bar{a})(b_i - \bar{b})}{\sqrt{(\sum (a_i - \bar{a})^2 - (\sum (b_i - \bar{b})^2)}} \quad (6)$$

3.4.2. OSimilarity

This measures the statistical relationship dependence between two ordered lists or variables. The nature of the relationship between the variables is assessed by the use of a monotonic function that preserves the order of the input data. The coverage similarity of the two-ordered lists R_1 and R_2 for M top values is measured using OSim [36]. It is calculated using Equation(7).

$$OSim = \frac{R_1 \cap R_2}{M} \quad (7)$$

3.4.3. Kendall Rank Order Correlation

This is a non-parametric and distribution-free test of independence that measures the association between two ordered lists or variables. It represents the variance analysis that helps in ranking differences between the ordered lists. It measures the similarity of the ordering of the data when ranked by each of the quantities [38]. It is computed using Equation(8).

$$\tau = \frac{(n_c) - (n_d)}{n(n-1)/2} \quad (8)$$

where n_c represents the concordant pairs and n_d represents the discordant pairs. Concordant pair means the ranks for both elements agree. Discordant means the ranks for both elements disagree.

3.4.4. Difference between Spearman and Kendall Correlations

The Spearman correlation is the difference between the rank orders. It detects the rare and unusual sensitivities that have very big discrepancies. However, Spearman's correlation is easier to calculate than Kendall's tau. In fact, the Kendall correlation is the difference between concordant and discordant pairs divided by the sum of concordant and discordant pairs. Thus, Kendall's tau has a more intuitive interpretation, and it represents the proportion of concordant pairs relative to discordant pairs. In addition, outputs better estimates of the corresponding population parameters, especially with smaller sample sizes. Consequently, it shows higher accuracy when the samples are smaller.

4. Results and Discussion

In this section, firstly, the experiments performed at the micro-level to extract the basic layout of the DBLP dataset are discussed, and the results related to average collaboration, largest connected component, average degree and average path length are explained. In the second subsection, macro-level properties were discussed over the DBLP dataset. The results of the centrality measure and prestige measures have been computed using Gephi, whereas the citation count and h-index values have been computed using the dataset. The results were correlated with the baseline such as citation count and h-index using Spearman rank order, Kendall rank order and OSim.

4.1. Micro-Level Overview of the Dataset

The micro-level properties of the dataset were computed using Gephi, which is a well-known tool for network-based analysis [39]. All the computed micro-level properties are shown in Table 2. There was a total of 39,497 papers in this network. The paper per author ratio was 4.42 papers, while the number of co-authors in a paper was 3.79 authors, and an author had 5.733 co-authors on average. The results showed that co-authorship has increased in the last decade from 2.24 [12] to 5.73. In [12], Ying Ding used the Library and Information Science (LIS) co-authorship network and found that papers per author ratio, authors per paper ratio and average co-authors were 2.40, 1.80 and 2.24, respectively. These results showed lower values as compared to the results computed in this research, as shown in Table 2. This means that now, the research domain of computer science has more collaborative work as compared to ten years ago. The largest connected component was the single largest component of connected authors that filled the maximum author volume of the graph. According to our results, the largest component of the network had a value of 17.17% of the total authors in the network, which shows that the DBLP collaborative network was not the largest connected component graph. Nascimento [40] reported that in Special Interest Group on Management of Data (SIGMOD), the largest component of the network had a value of 60% of all the authors in the network. The reported results showed that the value of the largest connected component was high. This high value was because of the nature of the bibliography, as it is a special interest group that shares common interests of the authors. In another research work, Newman [41] discussed the four co-authorship networks in biology, physics, high-energy physics and computer science databases, and it was found that the results of the largest component were 92.6%, 85.4%, 88.7% and 57.2%, respectively. The reported results were significantly higher than our results; however, a very high or very low value of the largest component does not confirm goodness or badness of the network; rather, a higher value is meant as convergence to the same interest, and a low value represents the diversity. Thus, as the discipline of computer science and information technology has a vast range of different interest groups, its largest connected component value is likely to be low as compared to other disciplines discussed in [40].

Table 2. Statistics of the DBLP co-authorship network.

Parameter	Values
Number of papers	139,794
Number of authors	9589
Average co-author	5.733
Paper per author	4.42
Author per paper	3.79
Average degree	13.62
Largest component	17.7%
Average path length	4.10
Diameter	10

Another characteristic of co-author network is average path length. According to the computed results, the average path length of the DBLP co-authorship network was 4.10, which was lower than the results (9.68) reported in the previous study [12] conducted in 2007. This shows that in the present era, authors collaborate more frequently and more widely with each other as compared to the past. Moreover, the values show that in the recent era, the information technology domain has become more collaborative as compared to previous research literature.

4.2. Network Analysis Using Centrality Measures

The original DBLP dataset with 3,818,185 research publications and 1,351,586 authors was used for network analysis. As per our analysis, the top 10 authors based on degree centrality are shown in Appendix A, Part (a), where Noga Alon had the highest degree centrality with a value of 158, which represents that Noga Alon was more central in a co-authorship network and tended to influence others to a greater degree. Consequently, the degree centrality values for all the top authors represented their frequent collaboration. Similarly, closeness centrality values are shown in Appendix A, Part (b), where Andreas Welermann, Djemel Ziu and all other authors had direct connections with many other authors and have high closeness centrality values. The rest of the authors in a network had lower values because they had indirect connections with many other authors in a network. The highest closeness centrality values for all top authors represented the independence of the individual authors. Betweenness centrality was the third measure, presented in Appendix A, Part (c), where Wei Wang had the highest betweenness centrality value and had the shortest path between two other authors in a network. The highest value of betweenness centrality for the top authors represented the flow of knowledge between other authors. In addition, the detailed analyses using centrality measures to find the top author using the reduced dataset are given in following sections.

4.3. Finding Top Authors Based on Social Network Measures

In this article, we computed the centrality of an author by using centrality measures such as betweenness centrality, closeness centrality and degree centrality. We also computed the prestige of an author by using PageRank and Eigenvector. Power law analysis [42] is an important statistical measure of social network analysis. It is carried out to show whether the degree and other measures follow the power law, i.e., the distribution on a log-log scale for the network (co-author network in our case). Our results verify that the computed measures followed the power law. The power law analysis of the social network measures is shown in Figure 2. Figure 2a,b shows that the distribution partially follows power law. Due to a very large number of data points, the distribution stayed smooth for a relatively high frequency.

Figure 2c–e follow the power law, which shows that fewer authors had a high value of degree centrality, PageRank and Eigenvector. The value of R^2 , which is known as the “co-efficient of regression”, represents the accuracy of the curve with respect to the data. It ranges from zero to one. It tells that how much variation is explained by the model. Therefore, 0.651 means that betweenness explains 65% of the variation within the data. Similarly, 0.57, 0.943, 0.947 and 0.944 mean that closeness

centrality, degree centrality, PageRank and Eigenvector explain 57%, 94%, 95% and 94%, respectively, of the variation within the data. A higher value represents more accurate results, which reveals a very high level of accuracy; whereas, the p -value tells us about the F statistics hypothesis testing. If the p -value is less than the significance level (0.05), then the model fits the data well. In our scenario, we had a high R^2 value and a low p -value, that is 0.00000332, which states that the model explained much of the variation within the data and that this was significant.

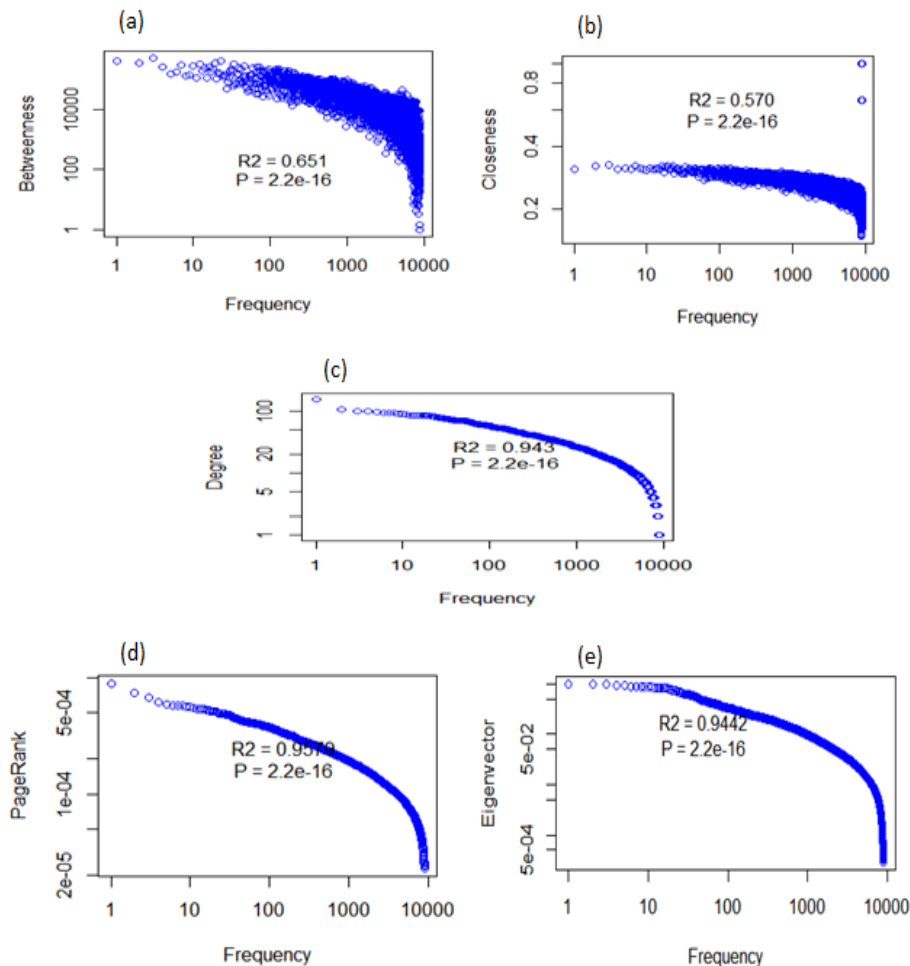


Figure 2. Power law analysis of (a) betweenness, (b) closeness, (c) degree, (d) PageRank and (e) Eigenvector.

4.4. Finding Top Authors Based on Centrality Measures

The results of the top 20 authors based on degree centrality, betweenness centrality and closeness centrality were calculated with the help of the co-authorship network and are shown in Table 3. The authors appearing consecutively in three centrality measures are shown prominently in bold font, and authors appearing in two centrality measures are marked with bold and italic font. According to the results, a few authors were consecutively highly ranked using all three centrality measures. The results are presented in the form of the triple of degree centrality, betweenness centrality and closeness centrality, respectively in parenthesis, of an author; for instance, for Elisa Bertino (2-3-16), Wei Wang (3-1-12), Christos Faloutsos (8-6-14), Ming Li (15-4-13), Philip S.Yu (16-11-19), Jiawei Han (19-9-17). Degree centrality values for all six authors represented their frequent collaboration; betweenness centrality values for each author showed the flow of knowledge between other authors; closeness centrality values for all six authors represented the independence of the individual author.

Table 3. Author rank according to centrality measures.

Rank	Authors	Degree	Authors	Betweenness	Authors	Closeness
1	Noga Alon	158	Wei Wang	517,151.36	Djemel Ziou	1
2	Elisa Bertino	108	Noga Alon	424,478.79	Modesto Orozco	1
3	Wei Wang	102	Elisa Bertino	369,459.22	Jan Flusser	1
4	Leonidas J. Guibas	101	Ming Li	349,935.03	F. Javier Luque	1
5	Gerhard Weikum	96	Thomas S. Huang	319,949.56	Edmond Bianco	1
6	Stefano Ceri	94	Christos Faloutsos	298,375.65	Jean-Michel Knippel	1
7	David Maier	93	John Mylopoulos	286,749.37	Andreas Weiermann	1
8	Christos Faloutsos	93	Leonidas J. Guibas	266,976.11	Michael Rathjen	1
9	Serge Abiteboul	92	Jiawei Han	266,191.03	Toms Suk	1
10	John Mylopoulos	90	Moshe Y. Vardi	235,958.04	Shengrui Wang	0.6666
11	Richard T. Snodgrass	88	Philip S. Yu	223,704.21	Salvatore Tabbone	0.6666
12	Thomas S. Huang	87	C. H. Papadimitriou	194,705.29	Wei Wang	0.3261
13	C. H. Papadimitriou	87	Stefano Ceri	179,227.78	Ming Li	0.3226
14	Moshe Y. Vardi	86	Kurt Mehlhorn	178,960.63	Christos Faloutsos	0.3215
15	Ming Li	85	Gerhard Weikum	150,870.43	Xin Li	0.3207
16	Philip S. Yu	85	Serge Abiteboul	146,865.46	Elisa Bertino	0.3203
17	Jeffrey D. Ullman	85	David Maier	133,393.66	Jiawei Han	0.3194
18	Kurt Mehlhorn	85	Richard T. Snodgrass	115,250.13	Wei Li	0.3168
19	Jiawei Han	85	Phillip A. Bernstein	112,711.00	Philip S. Yu	0.3164
20	Philip A. Bernstein	85	Jeffrey D. Ullman	106,383.54	Hao Wang	0.3154

Similarly, a few authors were consecutively highly ranked using two centrality measures. This means that some top authors according to the degree and betweenness centrality measures had a low closeness centrality value. For instance, Noga Alon had a high degree centrality, indicating that he had collaborated with many authors (147 authors), but his closeness centrality was relatively low, which ranked 25 out of 6441, which is why the author was not shown in the top 20 in Table 3. The reason behind the low closeness centrality was that a few of his co-authors (Micha Sharir, Michael Krivelevich, Amos Fiat, etc.) were located in Israel; thus, he was close to Israeli authors, whereas distant from the authors of other regions.

4.5. Comparison of Centrality Measures with the Baseline (Citation Count)

The results of the top 40 authors based on the citation count along with their rank of all three centrality measures are shown in Table 4. In this study, for comparative analysis of the results, citation count was used as a benchmark, as previously used in existing studies [11]. The results show that the citation rank was more in-line with the rank of degree centrality as compared to the other two measures of centrality.

However, in some cases, the authors with a high citation rank had low centrality rankings, as shown in Table 4. For instance, Jim Gray, Raymond A. Lorie, E. F. Codd, Won Kim and Nathan Goodman had a high citation count, but were very low for all three centrality measures. According to the results, Jim Gray had only seven co-authors who were located in America, and most of them were not cut-points; thus, he did not have a high centrality value. Cut-points are a kind of node whose removal increases the number of components. Jim Gray had four co-authors, H. Raymond Strong from New York, Gabor Herman from London, Limeshawar Dayal from North America and Rakesh Agrawal from New York. Moreover, Jim Gray had co-authored one paper in 2005, which had been cited 772 times. Because of the high citation of the paper, his citation count was high and his co-authorship was very limited; thus, he had low rank centrality measures for degree (62), betweenness (81) and closeness centralities (535). Similarly, Raymond A. Lorie had a publication count of 22, and a few of his publications were highly cited; he had eight co-authors only in the dataset. Furthermore, E. F. Codd had six papers in the dataset, and he had four co-authors. On the other hand, some authors had a high degree centrality, but low betweenness and closeness centrality. For instance, Michael J. Carey, Hector Garcia-Molina, Rakesh Agrawal and Raghu Ramakrishnan, although their centrality rankings corresponded to their citation rankings, only a portion of their publications were incorporated in our dataset, which may have affected the ranking results.

Table 4. Top 40 authors based on the citation count.

Authors	Citation Count		Centrality Measures Rank		
	Counts	Ranking	Degree	Closeness	Betweenness
Jeffrey D. Ullman	3412	1	13	38	117
Michael Stonebraker	2605	2	25	68	267
David J. Dewitt	2271	3	38	100	827
Philip A. Bernstein	1913	4	13	24	104
Jim Gray	1878	5	62	81	535
David Maier	1613	6	7	12	74
Serge Abiteboul	1570	7	8	39	58
Raymond A. Lorie	1494	8	83	1992	2481
E. F. Codd	1465	9	93	3844	6597
Michael J. Carey	1439	10	27	85	455
Won Kim	1392	11	63	239	278
Nathan Goodman	1360	12	82	1333	5342
Hector Garcia-Molina	1333	13	19	64	495
Yehoshua Sagiv	1288	14	63	357	1031
Catriel Beerl	1273	15	85	383	751
Rakesh Agrawal	1263	16	24	42	221
Raghu Ramakrishnan	1102	17	33	78	269
Umeshwar Dayal	1069	18	18	15	91
Francois Bancilhon	1066	19	70	921	2667
Donald D. Chamberlin	978	20	87	245	8083
Christos Faloutsos	964	21	7	5	8
Richard Hull	962	22	15	231	346
Ronald Fagin	950	23	53	336	759
Jennifer Widom	932	24	44	119	1022
Shamkant B. Navathe	886	25	42	76	82
Moshe Y. Vardi	843	26	12	13	17
Stefano Ceri	842	27	6	31	37
Bruce G. Lindsay	839	28	57	476	1827
Jeffrey F. Naughton	828	29	44	124	1253
Hamid Pirahesh	818	30	60	550	3224
C. Mohan	813	31	61	400	1182
Eugene Wong	806	32	87	1858	4390
Abraham Silberschatz	797	33	41	71	333
Peter P. Chen	776	34	81	2320	2274
Alberto O. Mendelzon	767	35	58	283	972
Nick Roussopoulos	724	36	61	176	606
Alfred V. Aho	716	37	71	370	862
Patrick Valduriez	715	38	78	378	651
Carlo Zaniolo	704	39	72	489	2093
H. V. Jagadish	692	40	32	48	372

4.6. Finding Top Authors Based on Prestige Measures

The results of the top 20 authors based on PageRank and Eigenvector calculated with the help of the co-authorship network are shown in Table 5. An author appearing consecutively in two prestige measures is shown prominently in bold font. According to the results, a few authors were consecutively highly ranked using both prestige measures. The results are presented in the form of the dual of PageRank and Eigenvector in parenthesis for an author; for instance, for Noga Alon (1-11), Wei Wang (2-13), Philip S. Yu (11-3), Stefano Ceri (13-12), Gerhard Weikum (15-2), Serge Abiteboul (17-8), and David Maier (18-1); where PageRank and Eigenvector values for all seven authors represent their prestige and importance within the given set of knowledge.

Table 5. Top 20 authors based on prestige measures.

Author Rank	Authors	PageRank	Authors	Eigenvector
1	Noga Alon	0.000897	David Maier	1
2	Wei Wang	0.000740	Gerhard Weikum	0.983821
3	Elisa Bertino	0.000674	Philip S. Yu	0.964201
4	Thomas S. Huang	0.000617	Richard T. Snodgrass	0.940632
5	Xin Li	0.000587	Hector Garcia-Molina	0.911671
6	Leonidas J. Guibas	0.000583	Jeffrey D. Ullman	0.904665
7	John Mylopoulos	0.000583	Laura M. Haas	0.901954
8	Ming Li	0.000573	Serge Abiteboul	0.898823
9	Wei Li	0.000569	Rakesh Agrawal	0.876175
10	Christos Faloutsos	0.000566	Michael Stonebraker	0.875162
11	Philip S. Yu	0.000548	Noga Alon	0.865516
12	Jiawei Han	0.000542	Stefano Ceri	0.854511
13	Stefano Ceri	0.000536	Wei Wang	0.849239
14	Ying Zhang	0.000535	Joseph M. Hellerstein	0.842421
15	Gerhard Weikum	0.000534	Michael J. Carey	0.823152
16	Jack Dongarra	0.000522	Yannis E. Ioannidis	0.81877
17	Serge Abiteboul	0.000521	Michael J. Franklin	0.813585
18	David Maier	0.000515	Jim Gray	0.782725
19	Kurt Mehlhorn	0.000515	David J. DeWitt	0.762307
20	Alberto L. Vincentelli	0.000513	Timos K. Sellis	0.756364

4.7. Comparison of Prestige Measures Using the Baseline (H-Index)

Table 6 lists the top 40 authors based on their h-index scores. The h-index [7] is a measure that considers both the productivity, as well as the citation received by the publications or an author. For comparison, the h-index is used as a benchmark, which is a widely-used metric by Google Scholar and other sources of scholarly literature to find the significance of research work of an author. The h-index is compared with prestige measures to check the prestige of an author. In Table 6, for each author, their respective centrality ranking within the top 40 rank is displayed in bold font along with their h-index rank. Table 6 shows some differences between the rankings of the h-index and centrality measures. The top three authors based on the h-index such as Won Kim, Catriel Beeri and Yehoshua Sagiv had low centrality. Won Kim, who enjoyed an h-index of 21 and had a substantial number of publications, i.e., 46, had fewer co-authors. The less number of co-authors may result in a low prestige score as computed from the values of the PageRank and Eigenvector of Won Kim, having low values of 185 and 195, respectively. Similarly, Catriel Beeri and Yehoshua Sagiv had 10 and 23, respectively, co-authors in the dataset and therefore a lower prestige score.

Table 6. Top 40 authors based on the h-index.

Author	H-Index		Prestige Measures	
	Counts	Ranking	PageRank	Eigenvector
Jeffrey D. Ullman	28	1	30	6
Michael Stonebraker	27	2	60	10
David J. DeWitt	24	3	113	19
Philip A. Bernstein	22	4	27	3
Won Kim	21	5	187	195
Catriel Beeri	20	6	174	87
Yehoshua Sagiv	20	6	127	100
Michael J. Carey	20	6	63	15
Rakesh Agrawal	20	6	56	9
Serge Abiteboul	19	10	334	2896
Nathan Goodman	19	10	324	854
Umeshwar Dayal	19	10	34	21

Table 6. Cont.

Author	H-Index		Prestige Measures	
	Counts	Ranking	PageRank	Eigenvector
Ronald Fagin	19	10	127	93
Jim Gray	18	14	98	18
David Maier	18	14	17	1
Raghu Ramakrishnan	18	14	87	24
Hector Garcia-Molina	18	14	41	5
Christos Faloutsos	18	14	9	37
Jeffrey F. Naughton	18	14	145	22
Jennifer Widom	17	20	142	23
Bruce G. Lindsay	17	20	196	56
C. Mohan	17	20	209	153
Shamkant B. Navathe	16	23	71	260
Hamid Pirahesh	16	23	221	48
Raymond A. Lorie	15	25	323	916
Francois Bancilhon	15	25	258	194
Richard Hull	15	25	150	200
Alberto O. Mendelzon	15	25	198	112
Peter Buneman	15	25	195	138
Carlo Zaniolo	15	25	268	378
Moshe Y. Vardi	15	25	20	38
Yannis E. Ioannidis	15	25	60	16
H. V. Jagadish	15	25	86	29
Stefano Ceri	14	34	12	12
Nick Roussopoulos	14	34	200	125
Abraham Silberschatz	14	34	110	50
Arie Shoshani	14	34	217	573
Gio Wiederhold	14	34	27	26
Eugene Wong	13	39	350	989
Goetz Graefe	13	39	382	611

4.8. Comparing Social Network Measures with Academics Indexes

The results of centrality and prestige measures were validated against the academic measures. For validation, Spearman, Kendall and OSim rank order correlations between prestige measures (PageRank and Eigenvector) and the h-index were used. We also found the correlation of degree centrality, betweenness and closeness with citation count using same correlation techniques.

The results of all three performance evaluation measures are described in Tables 7–9. According to the results, two prestige measures had a significant high correlation with the h-index for a p -value of 0.01, where the correlation coefficient of the Eigenvector was higher than PageRank. The high correlation of the h-index with prestige suggests that prestige measures have the potential to rank authors. In addition, according to the results of OSim based on the top 250 authors, the h-index and Eigenvector had the highest similarity with a value of 67%, whereas PageRank and Eigenvector had a similarity of 59%. Finally, the h-index and PageRank had the lowest similarity with a value of 52%.

Table 7. Spearman correlation between PageRank, Eigenvector and the h-index.

Technique	H-Index	PageRank	Eigenvector
H-index	1	0.84 **	0.79 **
PageRank	-	1	0.83 **
Eigenvector	-	-	1

** Correlation is significant at the level of 0.01.

Table 8. Kendall correlation between PageRank, Eigenvector and the h-index.

Technique	H-Index	PageRank	Eigenvector
H-index	1	0.72 **	1.0 **
PageRank	-	1	1.0 **
Eigenvector	-	-	1

** Correlation is significant at the level of 0.01.

Table 9. OSim between PageRank, Eigenvector and the h-index.

Technique	H-Index	PageRank	Eigenvector
H-index	1	0.52	0.67
PageRank	-	1	0.59
Eigenvector	-	-	1

Similarly, the results of all three correlation measures are described in Tables 10–12. According to the results, three centrality measures had a significant high correlation with the citation count at a p -value of 0.01, where the correlation coefficient of degree centrality was higher than other two centrality measures. The high correlation of citation count with centrality measures suggests that centrality measures also have potential to be used for authors' ranking. Moreover, the computed OSim values based on the top 250 authors, degree and closeness had the highest similarity with a value of 75%, whereas degree and betweenness had a similarity of 63%.

Table 10. Spearman correlation between degree, betweenness, closeness and citation count.

Technique	Citation Count	Degree	Betweenness	Closeness
Citation Count	1	0.63 **	0.45 **	0.59 **
Degree	-	1	0.88 **	0.87 **
Betweenness	-	-	1	0.81 **
Closeness	-	-	-	1

** Correlation is significant at the level of 0.01.

Table 11. Kendall correlation between degree, betweenness, closeness and citation count.

Technique	Citation Count	Degree	Betweenness	Closeness
Citation Count	1	1.0 **	0.19 **	0.29 **
Degree	-	1	0.72 **	1.00 **
Betweenness	-	-	1	0.62 **
Closeness	-	-	-	1

** Correlation is significant at the level of 0.01.

Table 12. OSim between degree, betweenness, closeness and citation count.

Technique	Citation Count	Degree	Betweenness	Closeness
Citation Count	1	0.63	0.40	0.53
Degree	-	1	0.66	0.75
Betweenness	-	-	1	0.55
Closeness	-	-	-	1

5. Conclusions and Future Work

This research study used social network measures to find the centrality and prestige of authors in an academic network. The results using both the centrality and prestige measures show that rank lists computed using all three centrality measures are consistent with each other. The results of the centrality and prestige measures are validated against the academic measures. The results show

that the degree centrality, betweenness centrality and closeness centrality measures are significantly correlated with citation counts. Among these three measures, degree centrality has a high correlation with the citation count. It confirms that the degree centrality has potential to be used for author ranking. However, in some cases, a few authors have a higher citation count, but they have low rank in the centrality measures. This shows that citation count measures the quality and influence of articles, whereas social network measures the quality of articles and the impact of the author's discipline, because citations and centralities measure different contents. Moreover, the results show that in the case of prestige measures, high correlation exists between Eigenvector and the h-index; whereas in the case of centrality measures, high correlation exists between degree centrality and citation count. According to the results, the degree centrality measures a scholar's co-authorship capacity; closeness centrality measures a scholar's position in a co-author network and the closest distance with other co-authors in the field; and betweenness centrality measures an author's importance for other authors in their virtual communication. Hence, centrality has its value in impact evaluation, since it integrates both article impact and author's field impact.

In the future, we aim to prepare the knowledge network by creating journal- and conference-level citation linkage, and then, the development of sub-disciplines will be identified. We will explore how research domains in computer science have evolved in the last two decades. This research study only considers authors in co-authorship networks without their affiliation, so in the future, we aim to consider the affiliation of the authors. We also aim to further explore the co-authorship network in order to find the actual contribution of an author within a research article.

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Conflicts of Interest: The authors declare that they have no competing financial interests.

Appendix A

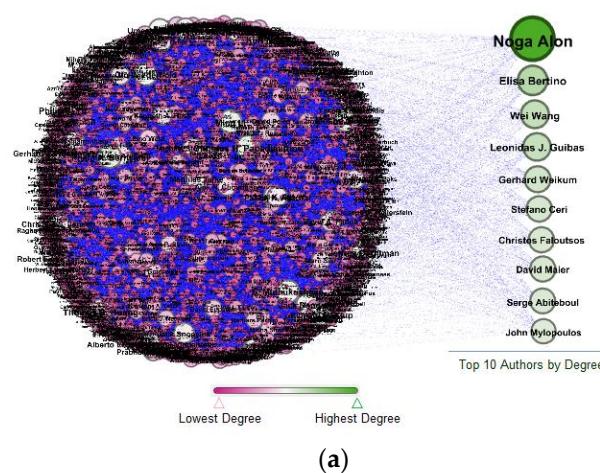


Figure A1. Cont.

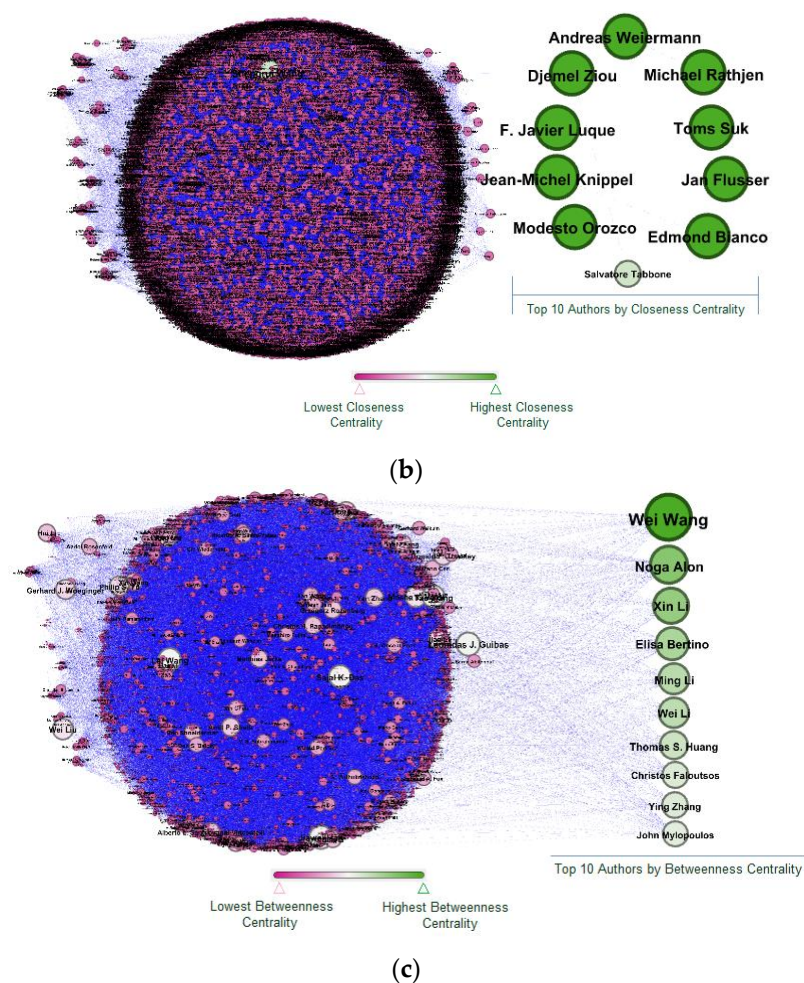


Figure A1. Part (a): Top 10 authors based on degree centrality, Part (b): Top 10 authors based on closeness centrality, Part (c): Top 10 authors based on betweenness centrality.

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