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Key Author Analysis in Research Professionals' Relationship Network Using Citation indices and Centrality

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Abstract

In social network analysis, the importance of an actor can be found by using the centrality metrics. There are many centrality metrics available e.g. degree, closeness, betweenness, eigenvector etc. In research community authors forms a social network, which is called Research Professionals' Collaboration Network. This is similar to social network where each author is an actor and an article written together by some authors establishes collaboration between them. Each author acquires a certain value based on the citation of their articles. There are many citation indices are available such as citation count, h-index, g-index, i10-index etc. To analyze the Research Professionals' collaboration Network and for finding the key author, the citation indices can be used. In this paper, we compare and combine both social network analysis metrics and the citation indices to get better result in finding the key author.

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1. Introduction

A research professionals' relationship network is a set of researcher's which has connection in pair to represent their relationship. Two researchers are considered in a relationship if they have published articles in journal, conference and publish & edit books together. In such type of network, a researcher is called as "node" or "vertex" and the connection is an "edge". Research professionals are dedicated to the advancement of the knowledge and practice of professions through developing, supporting, regulating and promoting professional standards for technical and ethical competence. Research professionals' relationship network is represented by undirected weighted graph. This network represents only the collaboration of research professionals and no where related to how many papers published by each of these authors. Research professionals' relationship network is a type of social network. Different type of

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social network analysis metrics and citation indices are available for finding key actors in the network. In this paper we use different type of social network analysis metrics and citation indices for finding key author in the research professionals' relationship network.

2. Social Network Analysis (Methodology)

Social Network Analysis (SNA) views social relationships in terms of network theory, consisting of nodes, representing individual actors within the network, and ties which represent relationships between the individuals, such as friendship, kinship, organizations and sexual relationships^{1,3,4}. These networks are often depicted in a social network diagram, where nodes are represented as points and ties are represented as lines. Social network analysis^{7,14,29} is the mapping and measuring of relationships and flows between people, groups, organizations, computers, URLs, and other connected information/knowledge entities. The nodes in the network are the people and groups while the links show relationships or flows between the nodes. SNA provides both a visual and a mathematical analysis of human relationships^{8,9}.

In general, the benefit of analyzing social networks is that it can help people to understand how to share professional knowledge in an efficient way and to evaluate the performance of individuals, groups, or the entire social network³.

3. Social network analysis metrics and citation indices for key author analysis

Key or prominent actors are those that are linked or involved with other actors extensively. In the context of an organization, a person with extensive contacts (links) or communications with many other people in the organization is considered more important than a person with relatively fewer contacts.

Thus, several types of social network analysis metrics and citation indices are defined to find key actor in the social network. Here, we discuss degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, frequency, citation count, h-index, g-index and i10-index.

Degree Centrality: Degree centrality of a node refers to the number of edges that are adjacent to this node^{1,2,4}. Degree centrality represents the simplest instantiation of the notion of centrality since it measures only how many connection tie authors to their immediate neighbors in the network^{7,10}. Therefore important nodes usually have high degree. Degree centrality is an indicator of an actor's communication activity. The normalized degree centrality is defined as the number of links of an actor divided by the maximal possible number^{21,27,32}. The normalized degree centrality d_i of node i is given as

$$d_i = \frac{d(i)}{n-1} \quad (1)$$

Closeness Centrality: Closeness measures how close an individual is to all other individual in a network, directly or indirectly^{1,3}. This metric can only be used in the connected network which means every node has at least one path to the other^{11,13,24}. The closeness centrality $C_c(n)$ of a node n is defined as the reciprocal of the average shortest path length and is computed as follows:

$$C_c(n) = \frac{1}{\text{avg}(L(n, m))} \quad (2)$$

where $L(n, m)$ is the length of the shortest path between two nodes n and m . The closeness centrality of each node is a number between 0 and 1. Closeness centrality is a measure of how fast information spreads from a given node to other reachable node in the network.

Betweenness Centrality: Betweenness centrality is an indicator of an actor's potential control of communication within the network^{1,2,7}. Betweenness centrality is defined as the ratio of the number of shortest paths (between all pairs of nodes) that pass through a given node divided by the total number of shortest paths. The betweenness central-

ity $C_b(n)$ of a node n is computed as follows

$$C_b(n) = \sum_{s \neq n \neq t} \frac{\sigma_{st}(n)}{\sigma_{st}} \tag{3}$$

where s and t are nodes in the network different from n , σ_{st} denotes the number of shortest paths from s to t , and $\sigma_{st}(n)$ is the number of shortest paths from s to t that n lies on^{4,23}.

The betweenness value for each node n is normalized by dividing by the number of node pair excluding n : $(N-1)(N-2)/2$, where N is the total number of nodes in the connected component that n belongs to. Thus, the betweenness centrality of each node is a number between 0 and 1^{25,26,32}.

Eigenvector Centrality : Eigenvector centrality is a measure of the influence of a node in a network. Eigenvector centrality is extension of degree centrality¹². In degree centrality, degree centrality of a node is simply count the total no of nodes that are adjacent to that node, but in eigenvector centrality, not only consider the total no of adjacent nodes also consider the importance of the adjacent node. In eigenvector centrality, all connections are not equal. In general, connections with influence person will lend a person more influence than connection with less influence persons. In eigenvector centrality not only the connections are important also the score (eigenvector centrality) of the connected node. Eigenvector centrality is calculated by assessing how well connected an individuals to the parts of the network with the greatest connectivity¹⁵. Individuals with high eigenvector scores have many connections, and their connections have many connections, and their connections have many connections out to the end of the network. Eigenvector centrality is simply dominant of Eigenvector of the adjacency matrix. Philip Bonacich proposed eigenvector centrality in 1987 and Google’s PageRank is a variant of it^{16,19}.

Eigenvector centrality based on adjacency matrix : For a given graph $G:=(V,E)$ with $|V|$ number of vertices. Let $A = (a_{v,t})$ be the adjacency matrix of a graph G is the square matrix with rows and columns labeled by the vertices and edges^{16,20}
i.e

$$a_{v,t} = \begin{cases} 1, & \text{if vertex } v \text{ is linked to vertex } t, \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

If we denote the centrality score of vertex v by X_v , then we can allow for this effect by making X_v proportional to the average of the centralities of v ’s network neighbors:

$$X_v = \frac{1}{\lambda} \sum_{t \in M(v)} X_t = \frac{1}{\lambda} \sum_{t \in G} a_{v,t} X_t \tag{5}$$

Where $M(v)$ is a set of the neighbors of v and λ is a constant. With a small rearrangement this can be written in vector notation as the Eigenvector equation

$$AX = \lambda X \tag{6}$$

Hence we see that X is a eigenvector of the adjacency matrix of A with eigenvalue λ and λ must be the largest eigenvalue (using the Perron-Frobenius theorem) of adjacency matrix A and X is the corresponding eigenvector^{16,20}.

The gist of the eigenvector centrality is to compute the centrality of node as a function of the centralities of its neighbors¹⁶.

Eigenvector and Eigenvalue : An Eigenvector of a square matrix A is a non-zero vector v that when the matrix is multiplied by v , yields a constant multiple of v , the multiplier being commonly denoted by λ . That is

$$Av = \lambda v \tag{7}$$

The number λ is called eigenvalue of A corresponding to v .

High eigenvector centrality individuals, however, cannot necessarily perform the roles of high closeness and betweenness. They do not always have the greatest local influence and may have limited brokering potential.

Frequency: Frequency of an author is the total number of publication.

Citation count: A citation can represent many types of links, such as links between authors, publication, journals and conferences. When a researcher refers to another author's works in their own publication work, they cite it. A citation index is a compilation of all the cited references from articles published during a particular year or period. A citation index allows determining the researcher impact of publication according to the number of times it has been cited by other researchers. Self citation is not included in such citation count. However, using citation count alone to judge the quality of research contributions can be unfair to some researchers^{35,39}.

H-index: A popular method to measure the centrality of academic papers. H-index = number of your papers h that have been cited at least h times^{36,38}. The use of h-index aims at identifying researchers with more papers and relevant impact over a period of time. For any general set of papers one can arrange these papers in decreasing order of the number of citations they received. The h-index is then the largest rank $h = r$ such that the paper on this rank (and hence also all papers on rank 1 to h) has h or more citations^{34,35}. Hence the papers on ranks $h + 1$, $h + 2$, have not more than h citations.

G-index: The g-index is introduced as an improvement of the h-index of Hirsh to measure the global citation performance of a set of articles and effort to give some weightage to the highly cited paper³⁷. This set is ranked in decreasing order of the number of citations that they received, the g-index is the (unique) largest number such that the top g articles received (together) at least g^2 citations. The g-index of an author is greater or equal to h-index ($g \geq h$)^{34,36}.

I10-index: The i10-index indicates the number of academic publication an author has written that have at least 10 citations from other³³. It is only used by Google scholar.

4. Research Professionals' Relationship Network

In recent years, there has been a sharp increasing number of collaboration between research professionals. By publishing articles in association with other authors, researchers show their knowledge sharing activities, which are essential for knowledge creation. Most of the research activities are undertaken in the collaborative way because the research projects are too large for an individual researcher to handle, and also the domain of the project spans across multiple research areas. So it often needs collaboration from multiple researchers who are working prominently in those research areas.

An important result of research professionals' collaboration is the creation of new scientific/research knowledge, exchange knowledge, finding new research query, new publications, new invention, more number of articles publication. The product of research professionals' relationship is papers. These papers will impact the researchers who are read these articles, and researchers may found new ideas and express these ideas in an article. It is a cyclic process of spreading knowledge and innovation in research community.

5. Data collection, Cleansing and Analysis

In the process of publishing articles in journals and conferences, publishing and editing books, knowledge does not only exist in a particular researcher's mind but also kept in the papers. Currently, it is not clear which collaboration data is useful for evaluating the research community. Although, there is a large set of potential collaboration data and different source, the collaboration of data source is like joined conference organization, joined research proposal submissions, joined publications, joined conference attendance and teacher-student relationship and the data source is like IEEE Xplore, Google scholar, DBLP etc. For this analysis, we only considered joined publication as a measure and the data source is IEEE Xplore. IEEE Xplore provides the facility to search articles using various dimensions like date, publication type etc. The search result can be downloaded into CSV (Comma Separated Values) format. We search for articles detail topic wise for the period Jan-2000 to Jan-2014 and export the search result. Exported search result is in CSV format. The CSV file has 33 fields. The field names are as follows, "Document Title, Authors, Author Affiliations, Publication Title, Publication Date, Publication Year, Volume, Issue, Start Page, End Page, Abstract, ISSN, ISBN, EISBN, DOI, PDF Link, Author Keywords, IEEE Terms, INSPEC Controlled Terms, INSPEC Non-Controlled Terms, DOE Terms, PACS Terms, MeSH Terms, Article Citation Count, Patent Citation Count, Reference Count, Copyright Year, Online Date, Date Added To Xplore, Meeting Date, Publisher, Sponsors,

Document Identifier”. We have filtered the data and select only Document Title, Authors, Publication Title, Article Citation Count, Publisher and Document Identifier. Authors’ name of an articles are stored in a single column which is separated by a ”;”. Author and its co-author are extracted based on delimiter ”;” and store each author name in individual column.

After extraction of author’s name we found that some of author’s name is unable to read, so data cleaning has become necessary to clean such type of names by replacing actual name. We omitted the name of authors and marked each of them a personal number from 1 to 61546. After cleaning of publication data, 26802 publication and 61546 authors were finally available for analysis. We found that a paper has been written by minimum one author and maximum of 59 authors. Averagely each of these papers is written around two to four authors. In the dataset there are two papers that were composed by 59 authors which has the most co-published paper and 3230 papers is written by only one authors which has the least co-published paper. The most prolific writer is **Lau, Y.Y.**, who has published 54 papers. Author **Sasaki, M.** have maximum number of co-authors is 63 and some of authors work individually or have one or two co-authors.

6. Generating Relationship Network of Research Professionals’

Research professionals’ relationship network is drawn based on co-author; means an author have connection with those authors who have published articles in journal and conference together, publish and edit books together, publish articles in transaction together which can indicate individuals’ status and the scientific collaboration. Based on the available publication data of researcher, we can build a network matrix which is representing the relationship between researchers according to following technique: Lets, there are three papers: P1, P2 and P3. P1 and P2 are conference paper and P3 is journal. P1 has two authors’ a1 and a2 and citation is 12, P2 has three authors’ b1, a3 and b2 and citation is 2. P3 has five authors’ c1, a3, b2, c2 and b1 and citation is 11. It shows like this: P1-{a1, a2} P2-{b1, a3, b2} P3-{c1, a3, b2, c2, b1}

After that we extract author and its co-author which are involved in their research work and calculate the relationship weight according to their total citation count of all papers which is published together. We link the author {a1-a2}, {b1- a3, b1 - b2, a3 - b2}, {c1 - a3, c1 - b2, c1 - c2, c1 - b1, a3 - b2, a3 - c2, a3 - b1, b2 - c2, b2 - b1, c2 - b1} ^{5,7,31,18,30}. Here a node represents researchers and a link between two nodes represents the publication co-authorship relationship between nodes. After generating a network, we can start the analysis.

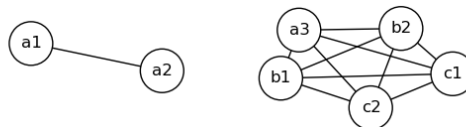


Fig. 1. Researcher relationship network an example

7. Key author analysis and result

In this part our aim is to find out key author in the research professionals’ relationship network. We generate research professionals’ relationship network based on available publication data and convey the frequency, citation count, h-index, g-index, i10-index, degree centrality, closeness centrality, betweenness centrality and eigenvector centrality. Now, we calculate frequency, citation count, h-index, g-index and i10-index of every researcher and also calculate normalized degree centrality, closeness centrality, betweenness centrality and eigenvector centrality by using python and networkx ¹⁷. After that we export all results in MYSQL database and arrange the authors in descending order, then select top 10 authors from each measures and combined it and obtain 51 important authors shown in Table 1, in which the sequence of the authors are listed firstly by the decreasing order of frequency and then by citation count, h-index, g-index, i10-index, degree centrality, betweenness centrality and eigenvector centrality of authors. These 51 authors’ data are available for analysis. After analysis, we found that only three authors Lau, Y.Y (Author id: 16947), Hirzinger, G. (Author id: 61365) and Gilgenbach, R.M (Author id: 8935) are present in all measure but they do not

having high value in all measures. According to frequency Lau, Y.Y is the key author, according to citation count Candes, E.J (author id: 189) becomes a key author, according to h-index, g-index and i10-index author Giannakis, G.B (author id: 29358) is the key author, according to degree centrality Hirzinger, G (author id: 61365) is the key author, according to closeness centrality Wang, Y. (author id: 13513) is the key author, Kim J. (author id: 41078) is the key author based on betweenness centrality and author Mizuno, T. (author id: 48688) is key author based on eigenvector centrality.

Table 1. Top 51 Authors By centrality and citation indices in Research professionals' relationship network

No.	Author ID	Frequency	Citation	h-index	g-index	i10-index	Degree Centrality	Closeness Centrality	Betweenness Centrality	Eigenvector Centrality
1	16947	54	159	8	12	6	0.0015584245	0.0597302006	0.0018587107	0.0000000013
2	61365	53	692	15	26	19	0.0017552781	0.0619001330	0.0046731385	0.0000000001
3	8935	47	152	8	12	7	0.0013287620	0.0597217937	0.0013977647	0.0000000013
4	56493	45	533	13	23	15	0.0006889877	0.0642255172	0.0035885079	0.0000000001
5	51188	42	720	17	26	23	0.0005085385	0.0632034440	0.0023709283	0.0000000017
6	29358	41	2223	23	41	32	0.0006889877	0.0644432554	0.0048778461	0.0000000005
7	53986	38	247	9	15	8	0.0008694368	0.0631794619	0.0013450811	0.0000036042
8	19686	34	223	9	14	7	0.0002952804	0.0565234339	0.0012528466	0.0000000000
9	10748	30	7	1	2	0	0.0005577519	0.0682436522	0.0006515796	0.0000000085
10	24476	29	354	11	18	12	0.0006397743	0.0588157407	0.0014161240	0.0000000001
11	51980	28	713	12	26	13	0.0008858413	0.0578717700	0.0040615117	0.0000000000
12	20117	27	182	6	13	4	0.0011647173	0.0653012831	0.0070899167	0.0000000002
13	42040	26	518	13	22	15	0.0005085385	0.0642873534	0.0033032907	0.0000000033
14	36257	24	965	15	24	17	0.0003773028	0.0502485463	0.0003132740	0.0000000000
15	1949	24	156	6	12	5	0.0010006726	0.0682135710	0.0098147929	0.0000000554
16	53589	23	978	14	23	16	0.0005577519	0.0589337943	0.0031531625	0.0000000058
17	21811	23	563	15	23	16	0.0005577519	0.0663969389	0.0041624579	0.0000000000
18	11373	22	672	8	22	7	0.0005085385	0.0453370786	0.0008980776	0.0000000000
19	56331	20	1284	15	20	18	0.0003444938	0.0546222400	0.0017207479	0.0000000000
20	25877	19	1188	12	19	15	0.0004265162	0.0598356220	0.0006995759	0.0000000001
21	58514	19	339	13	18	15	0.0005249430	0.0648566383	0.0006914223	0.0000000000
22	13513	16	112	5	10	2	0.0011647173	0.0739435385	0.0123000916	0.0000000871
23	56899	16	70	6	8	2	0.0013287620	0.0645821540	0.0051525725	0.0024905640
24	33095	15	201	7	14	7	0.0010334815	0.0718858696	0.0118138227	0.0000001434
25	46389	15	50	4	7	2	0.0012795485	0.0718250289	0.0134299745	0.0000000004
26	41078	14	111	4	10	1	0.0014764022	0.0725775985	0.0168249725	0.0000000200
27	25174	11	25	4	5	0	0.0009678636	0.0704856631	0.0067295431	0.0000000824
28	3667	10	52	4	7	2	0.0014107843	0.0645067771	0.0028558503	0.0113793075
29	24461	9	18	3	4	0	0.0007217966	0.0717564614	0.0076363362	0.0000000072
30	16530	7	89	3	7	2	0.0006561787	0.0703484486	0.0027333870	0.0000000432
31	27968	7	4	1	2	0	0.0006069653	0.0707822660	0.0079069144	0.0000000425
32	20621	6	11	2	3	0	0.0010334815	0.0719995838	0.0052392052	0.0000000833
33	48688	6	10	2	3	0	0.0016404469	0.0628135023	0.0013225435	0.1334739264
34	5340	5	6	2	2	0	0.0015912335	0.0624567989	0.0006998918	0.1333693085
35	56856	5	4	1	2	0	0.0015584245	0.0630196426	0.0012480845	0.1295166699
36	11029	4	2350	3	4	2	0.00011312357	0.0475522970	0.0003905120	0.0000000000
37	33989	4	55	2	4	2	0.0012795485	0.0721460914	0.0061896466	0.0000003761
38	36605	4	7	2	2	0	0.0011975262	0.0579120265	0.0000201996	0.1288715982
39	17849	4	6	2	2	0	0.0011319083	0.0579110066	0.0000020302	0.1284210454
40	189	3	2426	3	3	3	0.0000492134	0.0431370853	0.0000152403	0.0000000000
41	17217	3	1878	3	3	2	0.0000656179	0.0404585477	0.0000457187	0.0000000000
42	25056	3	1877	3	3	2	0.0000328089	0.0372173858	0.0000152403	0.0000000000
43	17718	3	1493	3	3	3	0.0000820223	0.0534990176	0.0000304795	0.0000000002
44	1370	3	5	2	2	0	0.0011319083	0.0579110066	0.0000020302	0.1284210454
45	11735	3	5	2	2	0	0.0011319083	0.0579110066	0.0000020302	0.1284210454
46	20758	3	5	2	2	0	0.0011319083	0.0579110066	0.0000020302	0.1284210454
47	22469	3	5	2	2	0	0.0011319083	0.0579110066	0.0000020302	0.1284210454
48	23930	3	5	2	2	0	0.0011319083	0.0579110066	0.0000020302	0.1284210454
49	18993	1	2333	1	1	1	0.0000328089	0.0431369438	0.0000000000	0.0000000000
50	16409	1	1449	1	1	1	0.0000328089	0.0479742511	0.0000000000	0.0000000000
51	33284	1	1449	1	1	1	0.0000328089	0.0479742511	0.0000000000	0.0000000000

Author with high frequency are key or prominent since they have published more number of papers with the others. But if an author published more number of papers with less quality or does not have any impact in research community then we can't say an author is prominent or key in the network. According to citation indices like citation count, h-index, g-index and i10-index the authors are prominent or key based on citation of their publication but mostly research work is done in the collaborative way and citation of each publication is equal to all authors means a paper has been written by 4 authors and citation is 12 then each author uses same citation count for their index calculation. So we can't say authors having high citation count, h-index, g-index and i10-index value are prominent. Author with high degree centrality are important since they have more relationship with the others but in this case we can't say an author having high degree centrality are important because if an author having a connection with more no of students then the degree centrality is high but their productivity is less. So, degree centrality is not suited for finding key author in the network. Authors who have a good closeness centrality are also significant means an author is nearest to average no. of authors. Authors who have a good betweenness centrality are also prominent means an author is frequently control information flow in the network and an author who have a good Eigenvector centrality is also prominent in the network means an author have a connection with a high score eigenvector centrality authors. Closeness and betweenness centrality are useful in information flow network but research professionals' relationship network is a co-authors relationship network. The product of research professionals' relationship network is research articles and the research articles quality is depends on authors of article, if the authors are highly qualified and they have relation with other high qualified researchers then have a probability to publish a good quality papers. So eigenvector centrality is more suited for finding key author in the network.

8. Conclusion

In this paper we have investigated the research professionals relationship network and find out the key author in the network based on different social network analysis metrics like normalized degree centrality, closeness centrality, betweenness centrality, eigenvector centrality and citation indices like frequency, citation count, h-index, g-index and i10-index. We found that different social network analysis metrics and citation indices gives different value for each researcher but some of the author having high value in all h-index, g-index and i10-index. It means a researcher who is the key author in network based on degree centrality; he/she is not guarantee to prominent based on other centrality and citation indices but some of the authors is present in all measure in top 10. So, we can say that these authors are key author in research professionals relationship network but they dont have high value in all measures. If we compare citation indices and all centrality measures, eigenvector centrality is more suited for finding key author in the network because the eigenvector centrality of nodes is depends on the neighbors node eigenvector centrality. If the neighbors eigenvector centrality is high then have a probability to gain high eigenvector centrality value of a node. A node having high eigenvector centrality than other is called key node in the network.

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