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Collaboration Network Analysis Based on Normalized Citation Count and Eigenvector Centrality

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ABSTRACT

In the research community, the estimation of the scholarly impact of an individual is based on either citation-based indicators or network centrality measures. The network-based centrality measures like degree, closeness, betweenness & eigenvector centrality and the citation-based indicators such as h-index, g-index & i10-index, etc., are used and all of the indicators give full credit to all of the authors of a particular article. This is although the contribution of the authors are different. To determine the actual contribution of an author in a particular article, we have applied arithmetic, geometric and harmonic counting methods for finding the actual contribution of an individual. To find the prominent actor in the network, we have applied eigenvector centrality. To authenticate the proposed analysis, an experimental study has been conducted on 186007 authors collaboration network, that is extracted from IEEE Xplore. The experimental results show that the geometric counting-based credit distribution among scholars gives better results than others.

KEYWORDS

Collaboration Network, Eigenvector Centrality, Normalized Citation Count, Social Network

1. INTRODUCTION

In the research community, the collaboration between researchers plays an important role to develop a new technology. It may span over multiple subject areas, multiple organization or country. But one of the major tasks is to estimate the scholarly impact of individual and discovered the most prominent actor in the whole network as well as in a particular community. For this, several analyses and research are done by eminent researchers and much research and analyses are currently ongoing. Several bibliometric indicators and social network analysis metrics were proposed to estimate the scholarly impact of individual and for finding the key author in the community. In general, it seems that all of the indicators consider full credit of an article, but rarely the contribution of all authors are equal. To share or distribute the citation of an article to all authors is one of the major tasks. De Solla Price, (1981) mentioned that the contribution of all authors is equal, then the credit share of each author is 1/k. Where k is the total number of authors. However, hardly they contribute equally. Thus, it is not fair to share credit equally among all authors. Egghe et al., (2000) and Wan et al.

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(2007) used geometric series to distribute credit among authors in the multi-author article. TRuenba and Guerrero (2004) discuss the arithmetic counting and Hagen, (2008) discusses the harmonic counting to distribute share credit among authors. To evaluate the scientific impact of an individual not only the actual contribution is important, the neighbors' researcher is also playing an important role. To consider the impact of neighbors' researchers, the network-based centrality measures can be used. The network centrality measures like degree, closeness, betweenness, and the eigenvector centrality are generally used. The degree centrality considers only the number of connected authors, closeness considers how many neighbors are in the average distance, betweenness considers how many communications happens through the particular nodes and eigenvector centrality consider the total numbers of neighbors as well as the impact of the neighbors' node. So, the eigenvector centrality is more suitable than others for calculating the impact of a node in the collaboration network. In this paper, our prime objective is to discover the most influenced actor in the network. For this first, we discuss the arithmetic, geometric and harmonic counting methods for finding the actual contribution of the individual author of an article. After that, the eigenvector centrality is used for scientific assessment of authors and also used for discovering the prominent author in the network. To do this, first, we set the initial impact of every node is the total share credit of individual from all articles and the collaboration weight is the correlation coefficient based on the normalized citation count by different counting methods.

2. RELATED WORK

Newman (2001) discussed the weighted collaboration network of co-authors. Here, authors mentioned that the node represents the individual author and the edge between nodes represents the collaboration and the weight of the edge represents the collaborative strength. Farkas et al. (2007) discussed the weighted collaboration network for appraising the scholarly impact of authors where weight is the geometric mean of citation count earn by the collaborators.

Abbasi et al. (2011) discuss the weighted collaboration of researcher and used social network analysis metrics to evaluate the scientific impact of individuals. In this article, the author used the total number of publications as a collaboration weight between collaborators.

Wang et al. (2011) discuss the weighted co-authorship network and used component analysis, publication frequency and degree centrality for finding the prominent actor in the network.

Liu et al. (2005) formed the collaboration network of digital library research community and proposed a new method for evaluation of the scientific impact of an individual called author rank and mentioned that this method gives a better result than social network analysis metrics. In this article author, consider the sum of the proportional counting of the total number of authors excluding self in a particular paper as a collaboration weight.

Liu et al. (2015) discuss the new method to construct a collaboration network. Here author used geometric series for calculation of share credit to all authors in a particular paper and the collaboration weight computed based on the law of gravity.

Bihari et al. (2015) discuss the citation count weighted network of collaboration network and convey the social network analysis metrics like degree centrality, closeness centrality, betweenness centrality & eigenvector centrality and citation-based indicators like h-index, g-index and i10-index for prominent actor finding.

Bihari et al. (2015) discussed the eigenvector centrality and its application in the collaboration network. In this article, the author used the degree centrality of the node as an initial impact of a node and the collaboration weight is the total number of citation count earned by all those publications which were published together.

Bihari et al. (2016) implements the maximum spanning tree to remove all those edges which has less impact in their research and find out the most influential actor in the community by using centrality measures.

Bihari et al. (2016) discuss the feature of collaboration network and discover the key author in the network based on normalized citations and eigenvector centrality. In this article, the author used geometric series for credit allocation and that credit is used as an initial impact of every author in eigenvector centrality and the collaboration weight is the correlation coefficient value based on the normalized citation count.

3. METHODOLOGY

In this section, we have discussed the methodologies that are used in the experimental analysis.

3.1. Correlation Coefficient

The correlation coefficient has been used to calculate the cross relationship between two different entities which worked together. In this article, we have used the correlation coefficient for calculation of the total collaboration impact of each authors pair based on their normalized citation count. The derived mathematical formula of the correlation coefficient is as follows:

$$CR\left(m,n\right)=\frac{\sum_{l=1}^{k}\left(m_l-\overline{m}\right)\left(n_l-\overline{n}\right)}{\left(k-1\right)ST_m ST_n} \tag{1}$$

Where m and n represent two different entity (Author's individual citation), k is the total number of elements, ST_m and STn is the standard deviation of m and n.

3.2. Arithmetic Counting

In the multi-authored article, every author gives some contribution to complete the work. Therefore, instead of total share credit, the credit share must be shared with every author to evaluate the scientific impact of authors. For this, arithmetic counting is used for credit allocation. In this credit allocation system, the first author gets more credit than the second one and the second author will get more credit than the third one and so on. Let an article has been written by the k number of authors and their relative rank (r) is 1, 2, …, k. Then the credit allocation of the T^{th} author is defined as follows:

$$CA_T=\frac{2\left(k-T+1\right)}{k\left(k+1\right)} \tag{2}$$

3.3. Geometric Counting

In the geometric counting, credit allocation of the T^{th} author is defined as follows:

$$CA_T=\frac{2^{\left(k-T\right)}}{2^k-1} \tag{3}$$

3.4. Harmonic Counting

The credit allocation of the T^{th} author is defined as follows:

$$CA_T = \frac{\left(\frac{1}{T}\right)}{\left[1 + \left(\frac{1}{2}\right) + \ldots\ldots\ldots + \left(\frac{1}{L}\right)\right]} \tag{4}$$

Where L represents the total number of authors in an article.

To distribute the citation counts of an article among all authors, then multiply the total share credit into the citation count of that article. The total shared citation count of an author is the sum of the all articles normalized citation count.

3.5. Eigenvector Centrality

It is an imperative technique to compute the significance of a node in the social network. It is the variant of well-known web page ranking algorithm PageRank. The main objective of this measure is to evaluate the performance of a node in the network based on their neighbor's nodes impact [17,18]. If a node has a fewer number of neighbors, but their productive strength is high, then the performance of that node is much better than the node has a number of neighbors but their productive strength is very less. The mathematical background of this method is the eigenvalue and eigenvector. Mathematically, it is defined as follows:

$$E_v = \frac{1}{\lambda}\sum_{k \in P(v)} E_k = \frac{1}{\lambda}\sum_{k \in GP} Ad_{v,k} E_k \tag{5}$$

Where P(v) is the set of neighbors of v, λ is a constant which represents the eigenvalue, $Ad_{v,k}$ is the adjacency value between node v and k.

4. COLLABORATION NETWORK

In order to estimate the scholarly impact of authors, the collaboration network construction is required. For this, we have used the following technique to construct a collaboration network. Let an article published by author P, Q, J, T, and R. Then the collaboration between all those authors exist. Therefore, first, we extract the collaboration pair of authors, then calculate the correlation coefficient based on the individual normalized citation count, that is considered as a collaborative strength between nodes. To calculate the collaboration strength between nodes, the normalized citation count is used. The collaboration between author P & Q, P & J, P & T, P & R, Q & J, Q & T, Q & R, J & T, J & R and R & T are exist because all works together. For example, we consider two articles for the collaboration network. The article details are shown in Table 1. For network construction, we have used the python and networkX as a platform [19].

The Network is like

5. DATASET DESCRIPTION

For experimental analysis of collaboration network as well as scientific evaluation of individual author required collaboration data. For this, we have extracted the publication data from IEEE Xplore, which are published in the different journal, conference proceedings and transaction with computer science & engineering keywords for the period of Jan-2010 to July-2016. The raw publication data is in CSV format and has many fields. For this study, we have filtered only a few numbers of fields such as

Table 1. Publication and author details

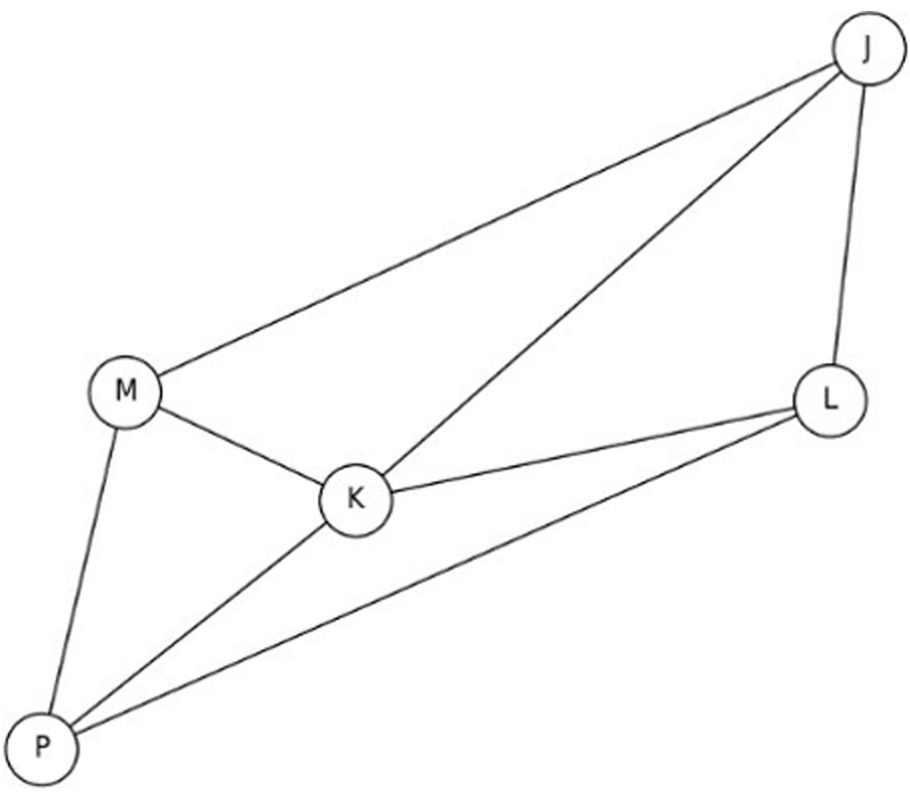
Article	Authors	Citation Count
Pub1	J, K, L, M	100
Pub2	K, L, P, M	20

article name, author's name, citation count and publication year. Raw data requires a data cleaning process for cleaning noisy data. In the raw data, some publication data have incomplete information, so we remove such type of publication data and also some of the authors' name are not readable due to their naming style. Another cleaning process is done for author name cleaning, in this section, we simply replace the ambiguous author name to their original name. After cleaning of publication data 96503 articles and 186007 author's data are available for the experiment. In our dataset, we found that 47% of articles published by the two authors and only 4% of articles were published by one author. Two articles published by 156 authors, which is called the most co-published article.

6. EXPERIMENTAL RESULT AND ANALYSIS

In this section, our prime objective is to estimate the scholarly impact of authors and discover the most influential author in the network. Our experiment follows the following steps:

Figure 1. Collaboration network an example



1. Computation of normalized citation count for every author based on arithmetic, geometric and harmonic counting methods individually.
2. Extract collaboration pair from each publication based on technique discussed in section 4.
3. In general, the collaboration impact between authors is either total publications count or total citation count of articles that were published together. But in this approach, we calculate the collaboration impact between authors pair using a correlation coefficient formula based on the normalized citation count of authors. This mechanism shows the significance of the total citation count and the total number of publication count.
4. In social network analysis, several centrality measures are available for finding social capital in the network. But in a scientific collaboration network, all measures are not suited to apprise the scholarly impact of authors. To do so, we have used Eigenvector centrality, because it considers the overall impact of a node as well as give credit to the neighbors' node in the evaluation. In the researcher community, the performance of an individual author also depends on the neighbors' authors. To calculate the eigenvector centrality, we have used Python and NetworkX as an experimental platform. For computation of eigenvector centrality, it necessitates the initial impact of every node as well as the collaboration weight between pairs. Whereas In traditional eigenvector centrality, the initial impact of each node is 1/n, where n is the total number of nodes. That means the initial amount of influence is equal for all authors. But in the research community, every author has its own impact. To fulfill the requirement of evaluation of individual author, we modified the eigenvector centrality algorithm of NetworkX and set the initial impact of a node is the total normalized citation count earned by the individuals. Another issue we discovered in this algorithm is the correlation weight is equal to all author pairs and is always 1. But it is not fair, because in the research community every collaboration has own definition and impact. To resolve this issue, the correlation coefficient has been used to calculate the correlation weight between author pairs and set it as a collaboration weight.
5. Finally, we conduct the experiment using python and NetworkX.

For analyzing the performance of individual author, we construct three different weighted networks such as arithmetic, geometric and harmonic counting-based correlation value and convey the eigenvector centrality with normalized citation count as an initial amount of influence. Then select top 20 authors from different weighted network shown in Table 2, Table 3 and Table 4.

After that, we combine all those data into a single place shown in Table 5. After analysis of the top 20 data, we have found that some of the authors present in the top 20 in all measures, but their value is greatly different. The difference between values shows the significance of the credit sharing method. After analysis of these data, we have found that the geometric counting-based correlation coefficient weighted network gives better results than the arithmetic and harmonic counting-based correlation coefficient weighted network. In this collaboration network author "Jing Liu", "Hirzinger, G." and "Thompson, D. J." are called prominent in arithmetic, geometric and harmonic counting the weighted network respectively.

7. CONCLUSION

In this article, we have discussed the different citation distribution technique among authors. In the research community, most of the research articles are written by the group of authors and hardly they contribute equally. To distribute, share credit among all authors, we have used arithmetic, geometric and harmonic counting methods. To evaluate the overall performance of an individual author, the eigenvector centrality is used. The main objective of the use of the eigenvector centrality in the collaboration network is to compute the scholarly impact of an author based on its own impact as well the impact of neighbors' researchers. In this experimental analysis, the initial impact of every node is the total normalized citation count and the correlation weight between node pairs is the correlation

Table 2. Result of eigenvector centrality of Top 20 authors in arithmetic counting weighted network

Sl. No.	Author Name	Eigenvector Centrality
		(Arithmetic)
1	Jing Liu	0.2060
2	MacMullin, S.	0.2055
3	Gehman, V.M.	0.2055
4	Yuen-Dat Chan	0.2055
5	Johnson, R.A.	0.2055
6	Kroninger, K.	0.2055
7	Jordan, D.V.	0.2055
8	Kazkaz, K.	0.2055
9	Boswell, M.	0.2055
10	Marino, M.G.	0.2055
11	Xiang Liu	0.2055
12	Schubert, A.G.	0.2055
13	Volynets, O.	0.2055
14	Finnerty, P.	0.2055
15	Schubert, J.	0.2055
16	Lenz, D.	0.2055
17	Pandola, L.	0.2055
18	Tomei, C.	0.2055
19	Leviner, L.	0.2055
20	Mokhtarani, A.	0.2055

coefficient value calculated based on individual normalized citation count of both authors. Our analysis shows that the geometric counting-based mechanism gives better results than the other ones. Therefore, we can say that the geometric counting is more suited to share credit among all authors in the multi-authored articles.

Table 3. Result of eigenvector centrality of Top 20 authors in geometric counting weighted network

Sl. No.	Author Name	Eigenvector Centrality (Geometric)
1	Hirzinger, G.	0.2903
2	Albu-Schaffer, A.	0.2062
3	Rodriguez, J.	0.1977
4	Bin Wu	0.1958
5	Pou, J.	0.1947
6	Franquelo, L.G.	0.1941
7	Leon, J.I.	0.1941
8	Perez, M.A.	0.1941
9	Kouro, S.	0.1941
10	Malinowski, M.	0.1941
11	Gopakumar, K.	0.1941
12	Wimbock, T.	0.1934
13	Eiberger, O.	0.1886
14	Grebenstein, M.	0.1823
15	Friedl, W.	0.1698
16	Haddadin, S.	0.1620
17	Wolf, S.	0.1460
18	Ott, C.	0.1459
19	Jorg, S.	0.1392
20	Seitz, N.	0.1392

Table 4. Result of eigenvector centrality of Top 20 authors in harmonic counting weighted network

Sl. No.	Author Name	Eigenvector Centrality (Harmonic)
1	Thompson, D. J.	0.1636
2	Kuss, M.	0.1534
3	Ampe, J.	0.1512
4	Johnson, R. P.	0.1480
5	Phlips, B.F.	0.1480
6	Sadrozinski, H.F.-W.	0.1480
7	Kroeger, W.	0.1480
8	Hartman, R. C.	0.1472
9	Rowe, W.A.	0.1458
10	Kotani, T.	0.1456
11	Kamae, T.	0.1455
12	Dubois, R.	0.1437
13	Krizmanic, J.	0.1429
14	Godfrey, G.	0.1423
15	Webster, A.	0.1406
16	Handa, T.	0.1405
17	Kavelaars, A.	0.1391
18	Russell, J. J.	0.1386
19	Ormes, J.F.	0.1386
20	Spandre, G.	0.1373

Table 5. Top 20 authors eigenvector centrality result in the normalized citation weighted network

Sl. No.	Author Name	Eigenvector Centrality (Arithmetic)	Eigenvector Centrality (Geometric)	Eigenvector Centrality (Harmonic)
1	Hirzinger, G.	0.0021	0.2903	0.0114
2	Albu-Schaffer, A.	0.0031	0.2062	0.0114
3	Rodriguez, J.	0.0025	0.1977	0.0094
4	Bin Wu	0.0014	0.1958	0.0093
5	Pou, J.	0.0021	0.1947	0.0093
6	Perez, M.A.	0.0026	0.1941	0.0031
7	Leon, J.I.	0.0025	0.1941	0.0031
8	Franquelo, L.G.	0.0023	0.1941	0.0031
9	Gopakumar, K.	0.0015	0.1941	0.0024
10	Malinowski, M.	0.0013	0.1941	0.0024
11	Kouro, S.	0.0012	0.1941	0.0024
12	Wimbock, T.	0.0017	0.1934	0.0024
13	Eiberger, O.	0.0013	0.1886	0.0024
14	Grebenstein, M.	0.0012	0.1823	0.0024
15	Friedl, W.	0.0015	0.1698	0.0024
16	Haddadin, S.	0.0015	0.1620	0.0024
17	Wolf, S.	0.0021	0.1460	0.0024
18	Ott, C.	0.0021	0.1459	0.0024
19	Jorg, S.	0.0022	0.1392	0.0024
20	Seitz, N.	0.0010	0.1392	0.0024
21	Phlips, B.F.	0.0253	0.0296	0.1480
22	Ampe, J.	0.0123	0.0296	0.1512
23	Thompson, D. J.	0.0017	0.0296	0.1636
24	Kuss, M.	0.0000	0.0296	0.1534
25	Sadrozinski, H.F.-W.	0.1230	0.0281	0.1480
26	Johnson, R. P.	0.0258	0.0269	0.1480
27	Hartman, R. C.	0.0183	0.0251	0.1472
28	Rowe, W.A.	0.0231	0.0222	0.1458
29	Kamae, T.	0.0152	0.0222	0.1455
30	Kotani, T.	0.0125	0.0222	0.1456
31	Dubois, R.	0.0198	0.0196	0.1437
32	Krizmanic, J.	0.2010	0.0190	0.1429
33	Godfrey, G.	0.1230	0.0171	0.1423
34	Webster, A.	0.1830	0.0161	0.1406
35	Handa, T.	0.0145	0.0160	0.1405
36	Kavelaars, A.	0.0189	0.0157	0.1391
37	Russell, J. J.	0.0153	0.0155	0.1386
38	Ormes, J.F.	0.1200	0.0155	0.1386
39	Spandre, G.	0.0153	0.0149	0.1373
40	Kroeger, W.	0.0145	0.0148	0.1480
41	Kazkaz, K.	0.2055	0.0017	0.0016
42	Jordan, D.V.	0.2055	0.0016	0.0016
43	Schubert, A.G.	0.2055	0.0016	0.0016
44	Lenz, D.	0.2055	0.0016	0.0016
45	Jing Liu	0.2060	0.0015	0.0016
46	Gehman, V.M.	0.2055	0.0015	0.0016
47	Yuen-Dat Chan	0.2055	0.0015	0.0016
48	Johnson, R.A.	0.2055	0.0014	0.0016
49	Kroninger, K.	0.2055	0.0014	0.0016
50	Finnerty, P.	0.2055	0.0014	0.0016
51	Xiang Liu	0.2055	0.0013	0.0016
52	Schubert, J.	0.2055	0.0013	0.0016
53	Mokhtarani, A.	0.2055	0.0013	0.0016
54	MacMullin, S.	0.2055	0.0012	0.0016
55	Volynets, O.	0.2055	0.0012	0.0016
56	Leviner, L.	0.2055	0.0012	0.0016
57	Boswell, M.	0.2055	0.0011	0.0016
58	Tomei, C.	0.2055	0.0011	0.0016
59	Marino, M.G.	0.2055	0.0010	0.0016
60	Pandola, L.	0.2055	0.0010	0.0016

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