The Use of Centrality Measures in Scientific Evaluation: A Coauthorship Network Analysis

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Abstract
This article studies micro-level properties of a coauthorship network with the aim to apply centrality measures to impact analysis. Using coauthorship data from 16 journals in the field of library and information science (LIS) with a time span of 20 years (1988-2007), we construct an evolving coauthorship network and calculate four measures (closeness centrality, betweenness centrality, degree centrality, and PageRank) for authors in this network. We find that the four measures are significantly correlated with citation counts. We also discuss the usability of centrality measures in author ranking and suggest that centrality measures can be useful indicators for impact analysis.

Introduction
Social network analysis has developed as a specialty in parallel with scientometrics since the 1970s (Friedkin, 1991). The last decade has witnessed a new movement in the study of social networks with the main focus moving from the analysis of small networks to those with thousands or millions of vertices and with a renewed attention to the topology and dynamics of networks (Newman, 2001a). This new approach has been driven largely by improved computing technologies that allow us to gather and analyze data in large scales, which makes it possible to uncover the generic properties of social networks (Albert & Barabási, 2002).
Coauthorship network, an important form of social network, has been intensively studied in this movement. Many studies focus on macro-level network properties, such as mean distance, clustering coefficient, component and degree distribution; yet not enough attention is paid to micro-level structure, such as the power, stratification, ranking, and inequality in social structures (Wasserman & Faust, 1994). This article shows an example of studying micro-level structure by applying centrality measures to coauthorship network. Using twenty years (1988-2007) data from 16 LIS journals, we construct an evolving coauthorship network, with the focus of testing the usability of centrality measures in impact analysis.

Backgrounds
Centrality analysis is not new to sociology. In a ground laying piece, Freeman (1977) developed a set of measures of centrality based on betweenness. In a follow-up article, Freeman (1979) elaborated four concepts of centrality in a social network, which have since been further developed into degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality.
As for coauthorship networks, several studies have also applied centrality measures to coauthorship network analysis. Mutschke (2003) employed centrality to the coauthorship network of digital libraries research. Liu et al. (2005) applied centrality analysis to the coauthorship of the Joint Conference on Digital Libraries (JCDL) research community and discovered that betweenness centrality performed best among the three centrality measures when comparing the results with the ranking of JCDL program committee membership. Estrada and Rodriguez-Velazquez (2005) proposed a new centrality measure that

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characterizes the participation of each node in all subgraphs in a network. They found that this centrality displayed useful and desirable properties, such as clear ranking of nodes and scale-free characteristics. Chen (2006) used betweenness centrality to highlight potential pivotal points of paradigm shift in scientific literature over time. Yin et al. (2006) applied three centrality measures to the COLLNET community coauthorship network. Vidgen, Henneberg, and Naude (2007) applied six measures (degree, betweenness, closeness, eigenvector, flow betweenness, and structural holes) in ranking an information system community. Liu et al. (2007) applied betweenness centrality to the weighted coauthorship network of nature science research in China.

These articles applied centrality measures to bibliometric analysis; some stepped further in ranking the authors through different centrality measures and compared them with bibliometric measures (Liu et al., 2005; Yin et al., 2006). But they did not elaborate the relation of centrality with author impact, or the usability of centrality in scientific evaluation. In this article, we try to fill this gap by providing an approach of verifying the usability of centrality measures in scientific evaluation, and discussing its strengths and limitations.

Methodology

Centrality Measures

In this study, we apply three classic centrality measures (degree centrality, closeness centrality, and betweenness centrality) and PageRank (which is a variant of eigenvector centrality) to the coauthorship network.

Degree centrality. Degree centrality equals the number of ties that a vertex has with other vertices. The equation of it is as following, where $d(n_i)$ is the degree of n_i :

$$C_D(n_i) = d(n_i) \tag{1}$$

Generally, vertices with a higher degree or more connections are more central to the structure and tend to have a greater capacity to influence others.

Closeness centrality. A more sophisticated centrality measure is closeness (Freeman, 1979). It emphasizes the distance of a vertex to all others in the network by focusing on the geodesic distance from each vertex to all others. Closeness can be regarded as a measure of how long it will take information to spread from a given vertex to others in the network (Yin et al., 2006). Closeness centrality focuses on the extensivity of influence over the entire network. In the following equation, $\mathrm{C_c}(n_i)$ is the closeness centrality and $d(n_i, n_j)$ is the distance between two vertices in the network.

$$\mathrm{C_c}(n_i) = \sum_{i=1}^{N} \frac{1}{d(n_i, n_j)} \tag{2}$$

Betweenness centrality. Betweenness centrality is based on the number of shortest paths passing through a vertex. Vertices with high betweenness play the role of connecting different groups. In the following formula, g_{jik} is all geodesics linking node j and node k which pass through node i; g_{jk} is the geodesic distance between the vertices of j and k.

$$C_B(n_i) = \sum_{j,k \neq i} \frac{g_{jik}}{g_{jk}} \tag{3}$$

In social networks, vertices with high betweenness are the brokers and connectors who bring others together (Yin et al., 2006). Being between means that a vertex has the ability to control the flow of knowledge between most others. Individuals with high betweenness are the pivots in the network knowledge flow. The vertices with highest betweenness also result in the largest increase in typical distance between others when they are removed.

PageRank. PageRank is initially proposed by Page and Brin (1998), who developed a method for assigning a universal rank to web pages based on a weight-propagation algorithm called PageRank. A page has high rank if the sum of the ranks of its backlinks is high. This idea is captured in the PageRank formula as follows:

$$PR(p) - d\frac{1}{T} + (1-d)\sum_{i=1}^{k}\frac{PR(p_i)}{C(p_i)} \tag{4}$$

where T is the total number of pages on the Web, d is a damping factor, C(p) is the outdegree of p, and p_i denotes the inlinks of p. Actors in the PageRank of web information retrieval systems are web pages, and actors in the PageRank of coauthorship networks are authors. If author A coauthors with author B, this is similar to endowing one credit to B; if B has three collaborators, then each of her/his collaborators will have a third of B's credit; the procedure goes in this way until all authors have stable PageRank values. So PageRank does not merely count how many collaborators an author has but also considers the impacts of those collaborators.

Data processing

We chose the top 16 LIS journals based on ratings by deans and directors of North American programs accredited by the ALA (Nisonger & Davis, 2005) as well as on Journal Citation Reports (JCR) data for the years 1988-2007.We excluded from the rankings non-LIS journals such as *MIS Quarterly*, *Journal of the American Medical Informatics Association*, *Information Systems Research*, *Information & Management*, and *Journal of Management Information Systems*. Meanwhile, since some journals had changed their names during this time period, we also included these older titled journals in our data set (shown in parentheses below). These 16 journals are: *Annual Review of Information Science and Technology*, *Information Processing and Management*, *Scientometrics*, *Journal of the American Society for Information Science and Technology* (*Journal of the American Society for Information Science*), *Journal of Documentation*, *Journal of Information Science*, *Information Research*, *Library and Information Science Research*, *College and Research Libraries*, *Information Society*, *Online Information Review* (*Online and CD-ROM Review*, *On-Line Review*), *Library Resources and Technical Services*, *Library Quarterly*, *Journal of Academic Librarianship*, *Library Trends*, *Reference and User Services Quarterly*.

We download the twenty-year data of these 16 journals from the database of Web of Science. There are 22380 documents in all, in which we just focus on articles and review articles, and the number for them is 10344 (54 anonymous articles are excluded).

Results and analysis

An overview

After downloading the data from ISI Web of Science, we extract the coauthorship network through Network Workbench (NWB, 2006). Since some authors used middle name initials for some of their papers, while did not for the other paper. We combine the same authors manually by their affiliation information (e.g. we combine Meho, L and Meho, LI into one author in the network). We use CiteSpace (Chen, 2006) in obtaining the visualization, and due to the large scale of this network, we apply the pruning layout to it, as shown in Figure 1.

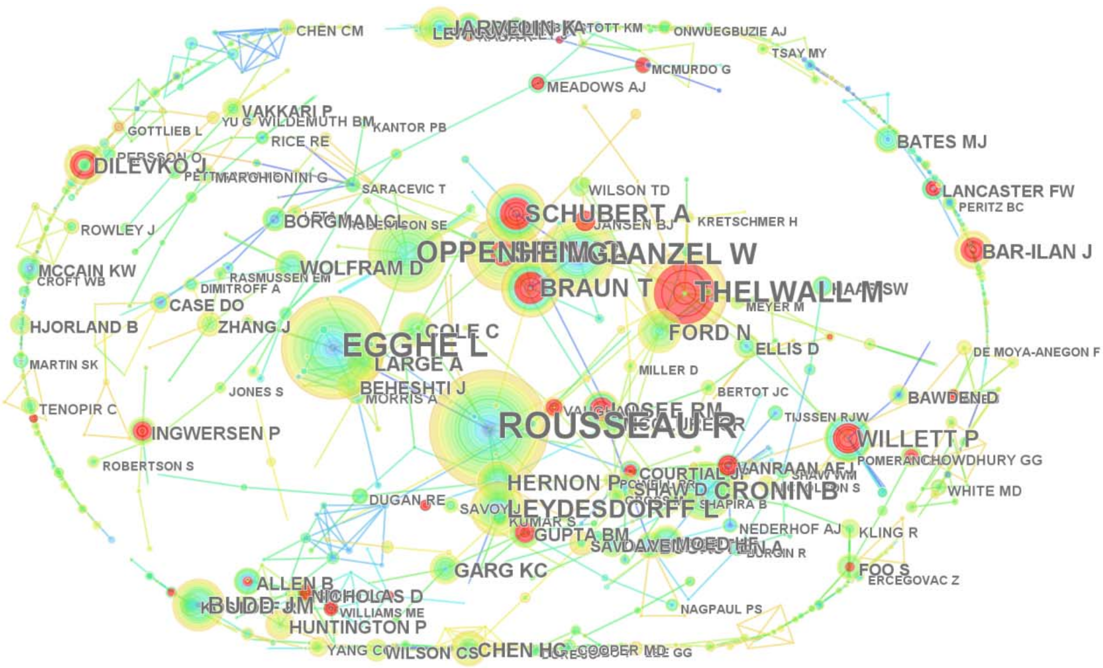

Figure 1.Network visualization by CiteSpace.

A component of a graph is a subset in which there is a path between a node and any other one of this subset (Nooy, Mrvar, & Batagelj, 2005). A coauthorship network consists of many disconnected components, and usually we focus on the largest component. The distance from vertex u to vertex v is the length of the geodesic from u to v. We export the network to Pajek (Program for Large Network Analysis) in gaining the largest component and mean distance.

Table 1. Properties of the evolving coauthorship network

Year	Number of authors	Number of papers	Mean collaborators	Largest component		
				Size	Ratio%	Distance
1988-1992	2262	2039	1.70	46	2.26	2.49
1988-1997	4357	4234	1.76	91	2.15	5.30
1988-2002	6941	6891	1.91	646	9.37	9.54
1988-2007	10579	10344	2.24	2197	21.24	9.68

Table 1 shows the properties of the evolving coauthorship network. Each author averagely has more collaborators, from 1.70 collaborators in the 1988-1992 period to 2.24 in 1988-2007 period. The increased mean collaborator means that authors collaborate more widely in recent years, which indicates that this field is becoming more collaborative. The values of the largest component exhibit some diverse facts. In their study on mathematics and neuro-science coauthorship networks, Barabási et al. (2002) found that the mean distance of the mathematics coauthorship network decreased from 16 in 1991 to 9 in 1998, and the mean distance of the neuro-science coauthorship network decreased from 10 in 1991 to 6 in 1998. However, the mean distance of the LIS coauthorship increases from 2.49 in 1992 to 9.68 in 2007. The discrepancy is due to the fact that more new authors are involved in this field each year, but their collaboration pattern is simple and collaboration scope is limited comparing to the well-developed field as biomedical science. More than ten year ago, Glänzel and Schoepflin (1994) found out that the field (scientometrics) is lacking consensus in basic questions and of internal communication. Scientometrics is only a sub-filed of LIS, but they share similar feature. Although LIS is increasingly becoming more collaborative, it has not arrived at its "phase transition” (Barabási, 2003) where authors collaborate with each other much more frequently and more widely, and from the perspective of network analysis, the mean distance will decrease after that phase.

Applying centrality measures to author ranking

Historically, most research on coauthorship network analysis focuses on overall topology of networks, whereas little research has been done to discover individual properties, fewer on the relationship between citations and centrality measures. In this study, we calculate four centrality measures for authors in the largest component through Pajek. Their frequency distributions are shown in Figure 2.

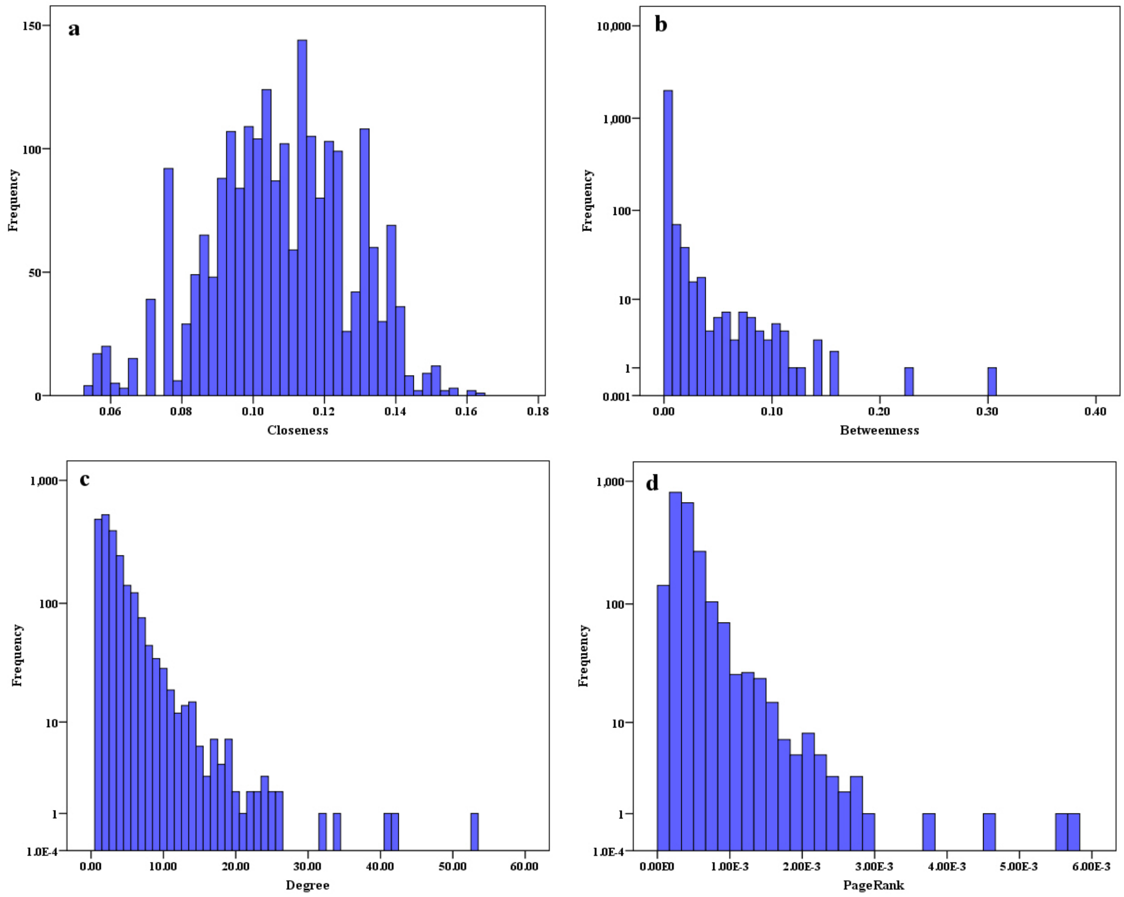

Figure 2. Frequency distribution of closeness (a), betweenness (b), degree (c) and PageRank (d) centrality.

The frequency of betweenness centrality, degree centrality, and PageRank follows power-law distribution where most authors have low centrality values while a few authors have high centrality values. On the other hand, the distribution of closeness centrality follows the normal curve. The power-law distribution of degree centrality also indicates that this coauthorship network has scale-free character (Barabási & Albert, 2002): the relationship between degree and its frequency probability matches the curve: $p(k) = 1.1788k^{-2.1514}$, with R^2=0.9186. This result is also consistent with Price’s network of citations (Price, 1965). He quoted a value of α = 2.5 to 3 for the exponent of his network. Other relevant researches on scale-free network also confirmed Price’s assumption (Newman, 2003).

Table 2 lists top 40 authors based on the number of citations to their publications. Corresponding centrality rankings within top 40 are displayed in bold font.

Table 2. Top 40 authors based on citation counts

Author	Citation*		Centrality Ranking			
	Counts	Ranking	Closeness	Betweenness	Degree	PageRank
Salton, G	1464	1	1199	259	216	229
Buckley, C	1389	2	1200	260	216	230
Dumais, ST	1323	3	1545	172	107	106
Landauer, TK	1295	4	1844	382	292	269
Harshman, R	1275	5	1845	672	554	667
Deerwester, S	1275	5	1845	672	554	667
Furnas, GW	1275	5	1845	672	554	667
Spink, A	1253	1	**1**	**2**	**4**	**4**
Saracevic, T	1141	2	**6**	**12**	47	84
Glanzel, W	969	3	384	34	**18**	**27**
Thelwall, M	884	4	**13**	**11**	**10**	**16**
Mccain, KW	835	5	1432	136	107	103
Ingwersen, P	791	5	41	74	76	52
Jansen, BJ	787	5	**23**	189	62	67
Egghe, L	747	8	206	147	107	79
Rousseau, R	705	9	**14**	**6**	**1**	**2**
Braun, T	704	10	897	175	47	56
Schubert, A	701	11	898	176	47	54
Borgman, CL	685	12	109	**18**	**7**	**11**
Ellis, D	654	13	**3**	**10**	31	33
Moed, HF	639	14	394	63	**13**	**20**
Kantor, P	635	15	**20**	**15**	**11**	36
Willett, P	609	16	**2**	**1**	**2**	**3**
White, HD	608	17	976	115	414	330
Vanraan, AFJ	590	18	728	284	62	85
Cronin, B	564	19	353	36	**12**	**7**
Harter, SP	526	20	1041	181	136	58
Leydesdorff, L	489	21	**21**	**13**	**6**	**6**
Fidel, R	426	22	666	117	47	83
Wilson, TD	414	23	**5**	44	136	162
Ford, N	378	24	**4**	40	**5**	**9**
Vakkari, P	361	25	**26**	**22**	47	37
Jarvelin, K	350	26	**12**	**28**	**9**	**5**
Marchionini, G	346	27	358	41	38	35
Wolfram, D	320	28	**8**	**21**	47	32
Oppenheim, C	295	29	1969	59	**3**	**1**
Large, A	291	30	427	270	41	59

Table 2 shows some discrepancies between the rankings of citations and the centrality measures. The most obvious one is that the seven most cited authors have very low centrality rankings. This is due to the fact that they are computer scientists and did not publish many articles in LIS journals; however, these papers are quite frequently cited (e.g., Deerwester, S, Dumais, ST, Landauer, TK, Furnas, GW and Harshman, R coauthored a paper cited 1275 times; Salton, G and Buckley, C coauthored two papers which have been cited 906 and 328 times). As a result, they do not have direct LIS collaborators: the closest collaborator is Fox, EA who has two degrees of separation from them, and, accordingly, they are in the periphery of the coauthorship network. Some less obvious instances including Ingwersen, P, Jansen, BJ, Marchionini, G and so on. Although their centrality rankings correspond to their citation rankings, only a portion of their publications are incorporated in our data set, which may affect their ranking results.

Discrepancies also exist within different centrality measures. For example, Glanzel, W has high degree centrality, indicating that he has collaborated with many authors (20 authors), but his closeness centrality is low, ranking only 384 out of 2197. The reason for this is that most of his collaborators are located in Europe – mainly Hungary, Germany, and the Netherlands. Thus, he is close to European authors but distant to authors in other regions (e.g., North America), and, as a result, his closeness centrality is low. McCain, KW has high citation ranking but low centrality rankings. This is because she only collaborates with 10 authors and all of her collaborators are located in the United States; thus, she does not have high centrality values. The same reasoning can also be applied to Ingwersen and Egghe: most of Ingwersen's collaborators are located in Denmark, and most of Egghe's collaborators are located in Belgium. By comparison, the majority of Rousseau's collaborators are located in Belgium, yet he also collaborates with authors from China, Japan, India, England and Canada, thus shortening his virtual distance from authors in the network.

Traditional scientific evaluation is heavily dependent on citations proposed by Garfield (Garfield & Sher, 1963). In the interest of testing the relationship between citation and centrality, we calculate the Pearson correlations for them, shown in Table 3.

Table 3. Pearson correlations between centrality measures and citation counts

	Citations	**Closeness**	**Betweenness**	**Degree**	**PageRank**
Citations	1	0.2433*	0.5332*	0.3929*	0.4067*
Closeness	0.2433*	1	0.1942*	0.2013*	0.1114*
Betweenness	0.5332*	0.1942*	1	0.6557*	0.7314*
Degree	0.3929*	0.2013*	0.6557*	1	0.9503*
PageRank	0.4067*	0.1114*	0.7314*	0.9503*	1

* Correlation is significant at the 0.01 level (2-tailed).

Table 3 shows that four centrality measures have significant correlation with citation counts at the 0.01 level, with PageRank has the highest correlation. The high correlation of citation counts with centrality suggests that centrality measures in certain degree also assess author's scientific productivity and quality. They can be indicators, or at least supplementary indicators for impact evaluation, providing alternative perspectives for current methods. Figure 3 shows the distribution of rankings of citation counts and centrality measures. Meanwhile, Ma, Guan, and Zhao (2008) found that for paper citation networks, citation has significant correlation (R=0.9) with PageRank. Comparing to this figure, the correlation for LIS coauthorship network is a bit low. One of the main factors contributed to this difference is the type of networks under study. Ties for paper citation network are citation relations. Comparing to coauthorship network whose ties are co-author relations, these networks are more pertinent to citations, and thus it is reasonable for them to have higher correlations with citation counts.

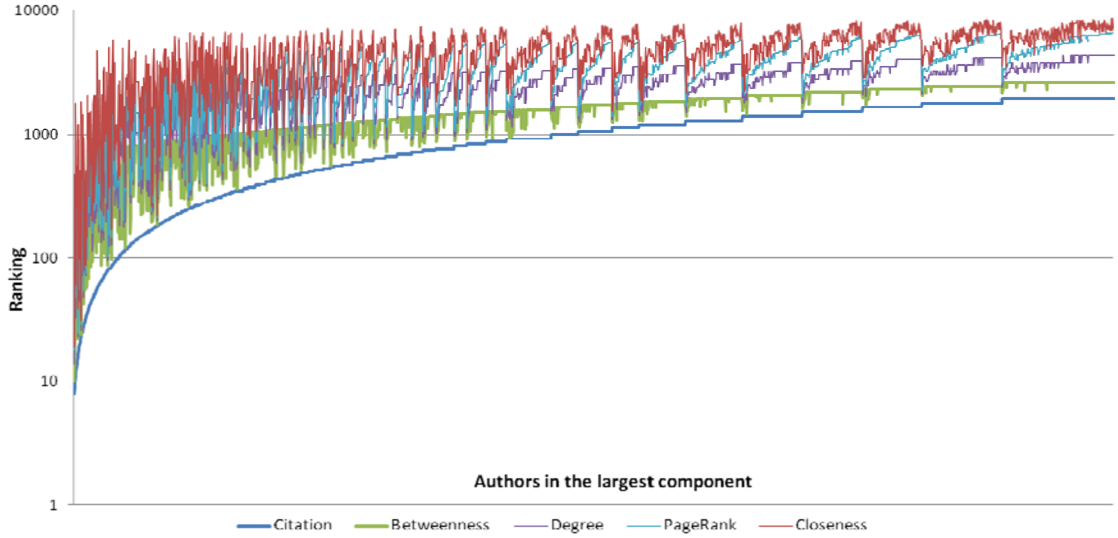

Figure 3. Distribution of rankings of citation counts and centrality measures.

Figure 3 shows the distribution of rankings of citation counts and centrality measures. X axis stands for all the authors in the largest component ranked by citation, Y axis stands for rankings, from 1st to 2197th. From Figure 3 we can discover that the overall distribution of the ranking of citation counts matches that of centrality measures, which is in accordance with the results shown in Spearman's correlations. Rankings of citation counts, PageRank, degree centrality and betweenness centrality correlate with each other more precisely; while rankings of closeness centrality have more inconsistent values.

Discussion and Conclusion

The coauthorship network is effective in revealing the collaboration patterns of authors. We find that all the four centrality measures are correlated with citation counts, whereas some inconsistencies occur. The discrepancy can be interpreted from two perspectives. First, citations and centralities measure different contents. Although the motivation for citation varies, citation counts measure the quality and impact of articles (Garfield & Sher, 1963; Frost, 1979; Lawani & Bayer, 1983; Baird & Oppenheim, 1994). Centrality measures, on the other hand, quantify an author's impact on the field which is, in effect, the counterpart of article impact, as illustrated in Figure 4.

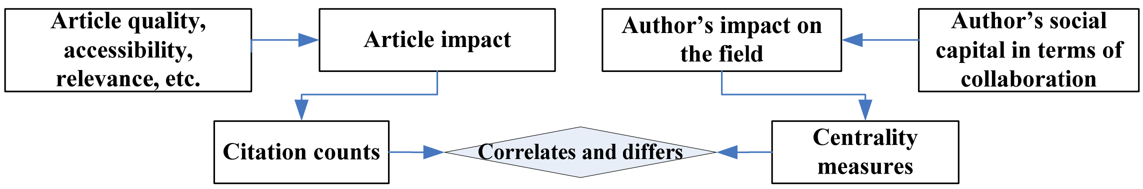

Figure 4. Relation between citation and centrality

As per this model social capital stands for the value for scientific collaboration. Betweenness in terms of structural holes is also a form of social capital. Betweenness reflects how close the sub-network to which the author belongs is and how important the author's role as a brokerage is. Thus, betweenness creates advantage by lowering the risk of collaboration and by increasing the value of collaboration (Burt, 2002). So authors with high betweenness centrality have more opportunity to broker the flow of information and, thus, have a higher social capital (Burt, 2002). Besides, degree centrality measures both strong ties and weak ties of authors, closeness centrality measures authors' position and their virtual distance from others in the field, and PageRank measures authors' impacts via their collaborators. Therefore degree centrality, closeness centrality, and PageRank also measure authors' impacts on the field and their social capital. Article impact can be quantified by citation counts; similarly, author impact on the field can also be quantified through centrality measures. Accordingly, citation is a metric of article impact, and centrality is a metric of author impact, so it is not surprising to find that they are correlated but also differ in their representation.

The limitations inherent to the current algorithm of centrality measures are another factor contributing to these discrepancies. Authors coauthoring with multiple authors have high degree centrality. For instance, if a paper is coauthored by 10 authors, each of these authors would have a degree centrality of 9. This is equivalent to 45 papers if they were coauthored by just two authors – obviously quite different academic impacts. Closeness centrality is a measure of network property rather than a direct measure of academic impact. Any author coauthoring an article with authors having high closeness centrality would also result in a high closeness centrality; however, this author may have little academic impact. Authors involved in interdisciplinary research would have a high betweenness centrality even through their role in the specific discipline of LIS may not be that significant. Centrality measures will be much more useful and valuable if these drawbacks could be eliminated.

In fact, some scholars have already embarked on this. Newman (2005) proposed a new betweenness measure that includes contributions from essentially all paths between nodes, not just the shortest, and meanwhile giving more weight to short paths. Brandes (2008) introduced variants of betweenness measures, as endpoint betweenness, proxies betweenness, and bounded distance betweenness. Liu et al. (2005) defined AuthorRank, a modification of PageRank which considers link weight. Other work aiming at improving PageRank in the context of author ranking includes Sidiropoulos and Manolopoulos (2005), and Fiala, Rousselot, and Ježek (2008).

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