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Ranking themes on co-word networks: Exploring the relationships among different metrics

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ABSTRACT

As network analysis methods prevail, more metrics are applied to co-word networks to reveal hot topics in a field. However, few studies have examined the relationships among these metrics. To bridge this gap, this study explores the relationships among different ranking metrics, including one frequency-based and six network-based metrics, in order to understand the impact of network structural features on ranking themes on co-word networks. We collected bibliographic data from three disciplines from Web of Science (WoS), and generated 40 simulation networks following the preferential attachment assumption. Correlation analysis on the empirical and simulated networks shows strong relationships among the metrics. Their relationships are consistent across disciplines. The metrics can be categorized into three groups according to the strength of their correlations, where Degree Centrality, H-index, and Coreness are in one group, Betweenness Centrality, Clustering Coefficient, and frequency in another, and Weighted PageRank by itself. Regression analysis on the simulation networks reveals that network topology properties, such as connectivity, sparsity, and aggregation, influence the relationships among selected metrics. In addition, when comparing the top keywords ranked by the metrics in the three disciplines, we found the metrics exhibit different discriminative capacity. Coreness and H-index may be better suited for categorizing keywords rather than ranking keywords. Findings from this study contribute to a better understanding of the relationships among different metrics and provide guidance for using them effectively in different contexts.

1. Introduction

Keywords of scientific articles, either manually assigned (author keywords and subject descriptors) or automatically generated, are widely used to reveal themes, structures, and development of a field, for example, through co-word analysis (Callon, Courtial, Turner, & Bauin, 1983). Unlike other bibliometric methods, such as co-citation analysis or co-author analysis, co-word analysis is a content-based method from which the results can be directly interpreted according to their semantics. Term frequency, defined as the number of occurrences of a term in a collection, is often used to identify important themes of a field (Khasseh, Soheili, Moghaddam, & Chelak, 2017). The assumption is that a frequently investigated topic could be an important theme in the field. Identifying themes by frequency is simple and convenient. However, this metric ignores the co-occurrence relationships among keywords, which can be captured by co-word networks. The structures of co-word networks carry information beyond term frequency, which can be used to measure the importance of keywords.

As social network analysis becomes popular, co-word analysis shifts to network-based metrics for measuring important themes

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(Song & Cai, 2012). Network-based metrics rank the nodes (i.e. keywords) in co-word networks by considering the network topology. For example, Degree Centrality measures the importance of nodes through the number of incident edges. Nodes with higher values of degree centrality are regarded as more important. Some researchers have applied network-based metrics to co-word networks for identifying important themes in a research field (Ronda-Pupo & Guerras-Martin, 2012; Song & Cai, 2012). However, few studies have examined the relationships among traditional metrics (e.g., frequency) and network-based metrics on co-word networks. In this study, we explore the relationships among frequency and a number of popular network-based metrics, including Degree Centrality, Betweenness Centrality, Clustering Coefficient, Coreness, H-index, and Weighted PageRank. Our first research question is:

- What are the differences and correlations of these seven metrics in ranking themes revealed by keywords in a research field? In particular, are there any differences between frequency-based and network-based methods?

A further goal of this study is to examine the impact of structural features of co-word networks on the relationships among frequency-based and network-based metrics. The research question is:

- Do the relationships among different metrics differ depending on different disciplines or the different properties of networks, such as density, the number of vertices, the number of edges, etc.? If so, what are the factors that influence their relationships?

To address these questions, the seven metrics were compared using two groups of data. One group was the empirical data from three fields, and the other group was a collection of simulated co-word networks with different scales and other structural features. The simulated co-word networks were generated by following the generation process of real co-word networks, and were used to investigate the impact of structural features on the relationships between the seven metrics. The findings of this study help to understand the relationships among different methods in identifying important themes on a co-word network and provide guidance on how to use them effectively in different contexts.

This study extends previous work that has attempted the random walk method on co-word networks (Chiu & Lu, 2015), and aims to provide a more comprehensive understanding of the metrics. In particular, this study includes more datasets, a more comprehensive list of network-based metrics, and a simulation method for co-word networks.

2. Literature review

Work related to this study can be found in the following areas: co-word analysis method, metrics for co-word networks, and network simulation.

2.1. Co-word analysis method

As a commonly used method in information science over the past decades, co-word analysis is well known for its ability to reveal themes, structures, and development of a field by examining co-occurrences of term pairs from different parts of papers. Terms from titles (Besselaar & Heimeriks, 2006), abstracts (Ravikumar, Agrahari, & Singh, 2015), and full-texts (Janssens, Leta, Glänzel, & Moor, 2006) are frequently used. Also, author keywords (Cho, 2014) and subject terms (Ocholla, Onyancha, & Britz, 2010) are recently used in co-word analysis, the results of which have shed light on the structure and development of a research field.

Co-word analysis has been through two stages: the first stage is characterized by frequency-based analysis methods, while the second stage places more emphasis on term co-occurrences and the resulting network structure. In the first stage, co-word analysis is often combined with multidimensional scaling (MDS) or other clustering methods. It has been used to reveal the development of concepts (Ronda-Pupo & Guerras-Martin, 2012) or domains (Gan & Wang, 2015; Viedma-Del-Jesus, Perakakis, Muñoz, López-Herrera, & Vila, 2011), and to find hot topics (Liu, Chen, Liu, & Xie, 2016) or hidden topics (Milojević, Sugimoto, Yan, & Ding, 2011; Muñoz-Leiva, Sánchez-Fernández, Liébana-Cabanillas, & López-Herrera, 2012). However, research in this stage does not consider network structures. In the second stage, network analysis is applied to co-word networks (Hong et al., 2016; Liu, Hu, & Wang, 2012), which provides different metrics to measure network properties. These metrics can be categorized into global indicators that describe the overall properties of a network (e.g. density, diameter, and average degree), and local indicators that delineate the importance of individual vertices in a network (e.g. centrality). Many network-based metrics can be used to identify important themes on a co-word network. However, previous studies have not comprehensively investigated the relationships among different metrics for this purpose.

2.2. Metrics for co-word networks

Global metrics describe the entire network, especially the topology of a network. For example, the numbers of vertices and edges are the two simplest global metrics that define the size of a network. According to Wang, Li, and Chen (2012), connectivity, sparsity, aggregation, uniformity, and assortativity are five perspectives that reflect network topology. Connectivity concerns how strongly vertices connect with each, and thus it mainly focuses on the largest component of a network, which is a connected component of a network that has the most vertices. Common metrics of connectivity include metrics related to edges, such as the number of edges whose weights are 1. Unlike connectivity, sparsity focuses on network degree, which is often revealed by average degree and density. Aggregation reflects how closely vertices are connected with each other, which is usually measured by average distance and

Clustering Coefficient. Degree distribution is the most common way to examine network uniformity. By modeling or plotting degree distribution, one can discover whether the network follows some specific regularities, like power-law. As for assortativity, degree correlation is an essential indicator of whether vertices tend to connect to similar vertices or dissimilar ones. If high degree vertices tend to connect with other high degree vertices, the network is considered assortative. Otherwise, the network is disassortative.

Compared with global metrics, local metrics are more popular in co-word network analysis due to their ability to reveal important themes (Ronda-Pupo & Guerras-Martin, 2012; Song & Cai, 2012). The most popular are variations of centrality. According to Yan and Ding (2014), commonly used centrality measures in scholarly networks analysis include Degree Centrality, Betweenness Centrality, Closeness Centrality, and Eigenvector Centrality. Degree Centrality mainly measures local influence as it only considers directly connected vertices. Both Betweenness Centrality and Closeness Centrality reflect global centrality. Closeness Centrality focuses on the geodetic distance between nodes and is more regularly used in collaboration networks (Abbasi, Hossain, & Leydesdorff, 2012) and citation networks (Linden, Barbosa, & Digiampietri, 2017). In the context of co-word networks, Betweenness Centrality better reflects the bridging effect of keywords. Eigenvector Centrality is closely related to PageRank (Yan & Ding, 2009) which will be discussed below. Therefore, in this study, we selected Degree Centrality and Betweenness Centrality, two commonly used centrality metrics in co-word networks. Clustering Coefficient, usually recognized as a global metric (Zhu & Guan, 2013), has a local version as well (Newman, 2010). The local version of Clustering Coefficient represents the average probability that nodes connected to a node are also connected with each other, which measures the connectivity among the neighbors of a node. According to Newman (2010), compared with Degree Centrality, Clustering Coefficient can reveal node importance from a different perspective, namely, how solidary a node's neighborhood is, and can be used as a probe for “structural holes” in a network. Another indicator, Coreness, not only weights the nodes, but also categorizes them (He et al., 2015). It originates from the k-shell decomposition, and provides a deeper perspective on which level a node belongs to. The higher Coreness level a node is at, the closer this node is to the core of the network (Shen, Yuan, & Guan, 2013). Coreness has been successfully applied to a variety of networks, such as bibliographic networks (Yang, Wu, & Cui, 2012) and institution networks (Zong et al., 2013). More recently, H-index has been applied to network analysis. It is one of the most popular metrics in ranking authors (Dehdarirad & Nasini, 2017), articles (Bornmann, Mutz, & Daniel, 2008), and journals (Harzing & Ron, 2009). The H-index of a node n is defined as the largest integer k such that n has maximum k neighbors with degrees at least k (Korn, Schubert, & Telcs, 2009). Lü, Zhou, Zhang, and Stanley (2016), have discovered that degree, Coreness, and H-index, which seem to be unrelated, are actually highly correlated. In addition, an increasing number of network-based metrics are also introduced to co-word network analysis, for example, the weighted random walk (Chiu & Lu, 2015).

Random walk is one of the simulation models showing random moves on a network. It simulates stochastic processes on a network according to the given parameters of the network and movements. Originated from information retrieval (Page, Brin, Motwani, & Winograd, 1999), random walk has been applied to other research areas, such as ranking tags (Liang et al., 2014). The difference between random walk and other network-based metrics is that random walk changes vertices' status iteratively, which does not apply to other metrics. As the most popular branch of random walk, PageRank has been applied to co-citation networks, for ranking journals (Cheang, Chu, Li, & Lim, 2014) and papers (Song & Kim, 2013), and co-author networks (Liu et al., 2015) for ranking authors. Studies have shown that PageRank is feasible and reliable in measuring the impact of entities.

In light of the commonly used metrics for co-word networks and other networks, this study selects seven metrics, including Frequency, Degree Centrality, Betweenness Centrality, Clustering Coefficient, Coreness, H-index, and Weighted Random Walk. These metrics well represent different perspectives of assessing the importance of nodes in a network.

2.3. Simulation for scholarly networks

Applying mathematical models to simulate how real science works is an important way of studying the mechanisms of science. Price (1956) used an exponent curve to describe the growth of science. Later, Price (1965) modeled citation networks of scientific papers through which some quantitative rules about references and citations were investigated. Recent studies have mainly focused on modeling empirical data with scholarly networks (Yan, 2012) and investigating the properties of the networks. Among all the scholarly networks, co-author networks (Guimera, Uzzi, Spiro, & Amaral, 2005) and citation networks (Garfield, 1970) have attracted the most attention. However, one limitation of empirical studies is the insufficient amount of data which hinders the ability to generalize beyond the datasets used. Most empirical studies only collect one or a few datasets from popular citation databases, such as Web of Science or Scopus. A simulation approach can overcome this issue in that almost unlimited artificial data can be generated in an automated manner. In addition, parameters in simulation models can be easily tuned to allow studies on how network properties impact the structures of scholarly networks, which reveals the underlying mechanisms of science. Attributing to these benefits, some recent studies have started to apply simulation approaches to understand the innate process of academic phenomena. To study research teams in a research specialty, Morris and Goldstein (2007) proposed a team growth model that considers the two phenomena of collaboration and author productivity simultaneously. The key simulated process was the author behavior: to write an article as the result of a research task in the team, and to select co-authors from/outside of the team. Goldberg, Anthony, and Evans (2015) proposed three models to simulate citation networks to study the variations of citation distribution per year, from which three phenomena were uncovered, including cumulative advantage of cited papers, aging effect of core papers, and local search of citations.

However, to our knowledge, the process of generating co-word networks has not been attempted, although some related mechanisms of paper keywords are studied empirically. The keyword frequency distribution has been shown to be a power law distribution in many research fields (Liu et al., 2012; Liu, Qi, Xue, & Xie, 2014), which reflects how different keywords grow in the collection. Another mechanism is the decay of popular keywords in a field (Zhang, Lü, Liu, & Zhou, 2008). These mechanisms can be considered when simulating co-word networks.

In summary, a brief review of the literature suggests that co-word analysis has seen a shift to network-based metrics; however, very few studies have examined the relationships among different ways of ranking terms on co-word networks. This motivates us to explore the relationship among different ways of identifying important themes on co-word networks through empirical data and simulation studies.

3. Method

To address the research questions proposed earlier, two approaches are adopted: first, empirical studies on three co-word networks from three research fields are conducted to compare different methods on empirical networks; then, a simulation study is carried out to generate co-word networks with different scales to examine the impact of network properties on the relationships among different metrics. The combination of the two approaches provides a more thorough understanding of the research questions.

3.1. Empirical studies on co-word networks

3.1.1. Data collections

The top 20 journals with the highest impact factor according to the 2014 Journal Citation Report were selected from three fields: *Information Science & Library* (LIS), *Sociology* (Socio), and *Physics, Fluids & Plasma* (Phys). LIS was selected due to the expertise of the authors. Two additional fields, Socio and Phys, were selected to represent social sciences and natural sciences, respectively. The selection of the top 20 journals is an arbitrary cut intending to select representative and high quality literature in a field. Bibliographic records of articles published in these journals for the period January 2006–December 2015 were downloaded from Web of Science (WoS). This resulted in 14,048, 11,978, and 65,603 articles for LIS, Socio, and Phys, respectively (Appendix A).

Using term sources from controlled vocabularies is generally preferable for co-word analysis as different expressions of the same concept are standardized (Looze & Lemarie, 1997; Qin, 2000). We chose the *KeyWords Plus* field in which the keywords are automatically selected from the titles of a paper's references (Garfield, 1990). Other term sources, such as author keywords or title words, can also be used. The author keywords field in WoS is obtained from publishers and varies greatly across journals. Some journals don't request author keywords, which results in a high ratio of missing data. This is observed in the Phys data we collected, where 69% of the articles miss author keywords. This would greatly skew the topics generated from the author keywords field. In addition, according to Zhang, Yu, Zheng, Long, Lu, and Duan (2016), *Keywords Plus* terms cover the majority of author keywords, and are more comprehensive and better fitted to analyze the structure of scientific fields than author keywords, although author keywords are more specific. On the other hand, title words are free-text with many variations. Therefore, *Keywords Plus* field is used for co-word analysis in this study. After removing bibliographic records without *KeyWords Plus* fields, 11,530, 7166, and 61,301 articles for respective LIS, Socio, and Phys fields were used as the empirical data.

3.1.2. Data processing

The WoS bibliographic data was loaded into a local MySQL database, and co-occurrence pairs of the keywords from the *KeyWords Plus* field were tallied. Then, Java programs were developed to generate .net files used by the network analysis tool Pajek (Batagelj & Mrvar, 1998).

3.2. Co-word network simulation

To obtain a larger number of networks that represent different situations, a simulation study was conducted. In this study, we simulated co-word networks based on the process of composing scientific papers. The key of the simulation lies in the growth of keywords, which is similar to the growth of authors (Morris & Goldstein, 2007) in the sense that the growth of keywords/authors can be accomplished via two critical steps incrementally, i.e., to generate a paper and to generate keywords/authors for the paper. A co-word network was formed by cumulating co-occurrences of keywords in the papers of the collection.

The generation of keywords for papers is governed by inherent rules in scholarly communication. For example, the keywords in the *KeyWords Plus* field are selected from the titles of the paper's references. Essentially, the keywords of a new paper are either selected from existing keywords used in previous papers or newly added. We assume that the keyword selection follows the preference attachment (PA) mechanism. The preferential attachment guides the keyword selection by producing a power law distribution for item occurrences (Mitzenmacher, 2004). Therefore, the more frequently a keyword occurs in previous papers, the higher the probability that it will be chosen as a keyword for the new paper. In addition to picking an extant keyword for the new paper, there is a chance to generate an unseen keyword that has not appeared in previous papers. This is implemented by applying a damping factor.

Formally, we define a collection as a tuple $\{P, K, A, N\}$, where P is the paper set, K is the distinct keyword set, A is the keyword assignments for the papers where A^i denotes the set of keywords assigned to the paper p_i, and N is the weighted co-word network which is a graph $\{V, E\}$. The simulation process is as follows:

1) Generate a paper p_i in the collection. Since we are only interested in the keywords of p_i not its content, here p_i is just a sequential number.
2) Determine the number of keywords to be assigned to p_i, μ (the size of A^i, i.e., $|A^i|$), according to the probability distribution of the

number of keywords γ observed in empirical data. In this study, the probability distribution γ is set as:

$$P(\mu|\gamma) = \begin{cases} \frac{1-\delta}{9}, & \mu = 1, 2, \cdots, 9 \\ \delta, & \mu = 10 \end{cases} \tag{1}$$

where μ is the number of keywords in the paper and δ is the probability that the paper has 10 keywords. This is based on the observation that a majority of papers are assigned with 10 keywords and the rest share roughly equal probability of having from 1 to 9 keywords (Appendix B).

3) Keyword selection:
   a. Select a keyword for p_i by applying preferential attachment as in Simon model (Simon, 1955): with a probability of $1-\alpha$ to pick a keyword from the existing keyword set K, and the probability of picking a keyword is proportional to the frequency of the keyword:

$$P(k) = (1-\alpha)\frac{n_k}{\iota} \tag{2}$$

   where n_k is the current frequency of the keyword k and ι is the sum of the frequencies of all keywords in the collection.
   b. In addition, with a probability α (damping factor) to pick a keyword from a new keyword outside of K.

   It should be mentioned that the keywords of a paper should be distinct.

4) Form co-word network edges from A^i: For each pair of keywords in the paper, if the edge connecting two keywords already exists in the edge set E, increase the weight of the edge by 1, otherwise create a new edge with a weight of 1 that connects the two keywords and add it to the edge set E.
5) Repeat steps 1–4 M times to generate the co-word network for a collection with M papers ($1 \le i \le M$).

For example, to generate the 10th paper in simulated data (i = 10), five keywords are assigned to the paper according to the probability distribution γ (Appendix B). It's assumed that at this point there are 20 keywords in the existing keyword set (K) with a total frequency of 50 ($\iota = 50$). Then, each of the 5 keywords is sampled from the 20 keywords according to the distribution $P(k)$ ($= (1-\alpha)\frac{n_k}{50}$, $k = 1,2,\ldots,20$), or newly generated with a probability of α. Any new keyword is added to the keyword set. The 5 keywords of this paper form new edges or increase the weight of existing edges in the co-word network.

When simulating the final co-word networks for analysis, the damping factor α was set to 0.17 and δ equaled 0.36, which were determined manually by comparing the network properties between initial simulated data and the empirical data. The number of papers in the collection (M) varied from 2500 to 100,000 with an interval of 2500. In total, 40 co-word networks were generated.

3.3. Metrics of keyword importance in co-word network

Seven metrics that measure the importance of keywords in a co-word network were calculated, namely, Frequency (fr), Degree Centrality (dc), Betweenness Centrality (bc), Clustering Coefficient (cc), Coreness (co), H-index (hi), and Weighted PageRank (pr). They are categorized into frequency-based and network-based metrics (Table 1).

Frequency, H-index, and Weighted PageRank were computed using a Java program developed by the authors, and the other metrics were obtained from Pajek.

Table 1
Brief description of frequency-based and network-based metrics.

Frequency-based metric	
Frequency (fr)	the number of times a keyword occurs in the collection
Network-based metrics	
Degree Centrality (dc)	measured by the degree of a node
Betweenness Centrality (bc)	describes the probability of a keyword being in the middle of the shortest route of other two randomly selected keywords (Newman, 2010)
Clustering Coefficient (cc)	measured by the ratio of triangles connected to the keyword to triples connected to the keyword. Triangles are triples whose nodes connect to each other (Newman, 2010)
Coreness (co)	used to identify influential spreaders of information at network cores and reveal the level of edges being in the central of the network (Alvarez-Hamelin et al., 2005)
H-index (hi)	adopted from the definition of H-index in Lü et al. (2016)
Weighted PageRank (pr)	adopted from Chiu and Lu (2015). The difference between Weighted PageRank we used and PageRank is that we used co-occurrence of two keywords as the weight of the corresponding edge.

Table 2
Descriptive information of the data sets and co-word networks.

Attributes	Information Science & Library	Sociology	Physics, Fluids & Plasma
# of articles	11,530	7,166	61,301
Keywords per article	6.6	7.1	6.4
Edges	182,449	146,966	841,627
Nodes	12,165	10,499	50,106
Density	0.0025	0.0027	0.0007
Average degree	29.996	27.996	33.594
Clustering Coefficient	0.0982	0.1108	0.0568
Diameter	6	6	7
Average distance	2.766	2.815	2.847
# of unreachable pairs of nodes	3,217,912	1,714,952	29,275,752

4. Results

There were 12,165, 10,499, and 50,106 unique keywords assigned to articles in LIS, Socio, and Phys, respectively. Descriptive information of the data collections and co-word networks are presented in Table 2. It is interesting to note that although the sizes of the co-word networks differ, the average distances (the average length of shortest paths between any two nodes in the networks) are very similar (2.77 for LIS, 2.82 for Socio, and 2.85 for Phys), so are the diameters of the networks (6 for LIS and Socio, and 7 for Phys).

The frequency distributions of the keywords in the collections are shown in Figs. 1–3. The frequency distributions of the keywords in simulated networks with similar sizes are overlaid in the figures to provide visual comparisons between the empirical and simulated networks. The figures suggest that the frequency distributions of the keywords in simulated networks and empirical networks are similar, both are Zipf-like. This, to some extent, validates the simulation process which generates simulated networks sharing similar basic properties with empirical co-word networks in this study.

4.1. Correlation analysis on empirical data

Spearman's correlation coefficient was used to measure the strength of the associations among the seven metrics as a normal distribution is not assumed. Fig. 4 presents a summary of the correlation results in LIS, Socio, and Phys. Heat maps are used to show the strength of the correlations. All seven metrics are significantly ($p < .01$, two-tailed tests) and strongly correlated with each other with the lowest values well above 0.80. The values of correlations are similar across the three fields, which suggests that their relationships are consistent across these disciplines. It is worth noting that Clustering Coefficient has all negative correlations with the other metrics, which suggests that a higher value in Clustering Coefficient associates with lower values in the other metrics.

The highest values of correlations are observed among Frequency, Betweenness Centrality, and Clustering Coefficient, and Degree Centrality, H-index, and Coreness. With that, it seems that Frequency, Betweenness Centrality, and Clustering Coefficient are the closest to each other, and Degree Centrality, H-index, and Coreness are the closest. In addition, Weighted PageRank is strongly correlated with other metrics; however, its correlations with the others are not among the strongest.

To provide detailed results from these metrics, tables in Appendix C, D, and E list the top 20 keywords by different metrics in the three fields (the bottom 20 keywords from Clustering Coefficient due to its negative correlations with the other metrics). Many keywords are shared by different metrics, which is not surprising given the strong correlations among them. Both general keywords and relatively specific keywords can be found in the tables. For example, in the LIS field, general keywords like “INFORMATION”,

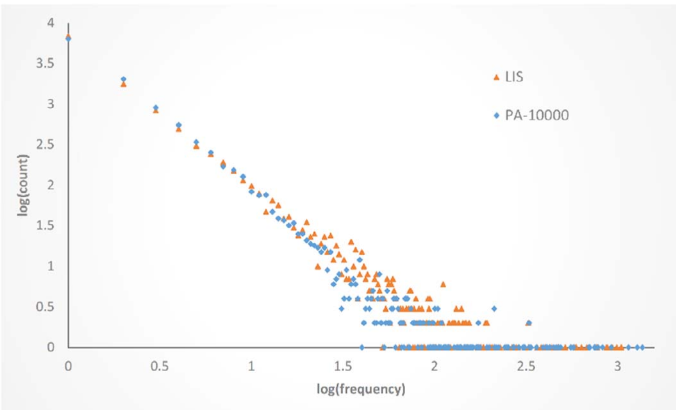

Fig. 1. Frequency distribution of keywords in Information Science & Library and PA-10,000 (PA-10,000 indicates the simulated network with 10,000 articles).

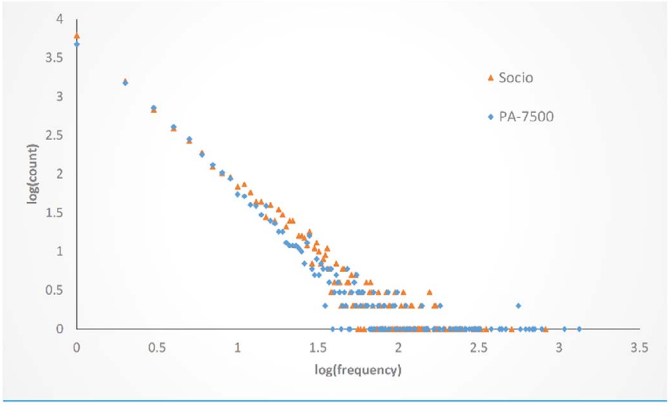

Fig. 2. Frequency distribution of keywords in Sociology and PA-7500 (PA-7500 denotes the simulated network with 7500 articles).

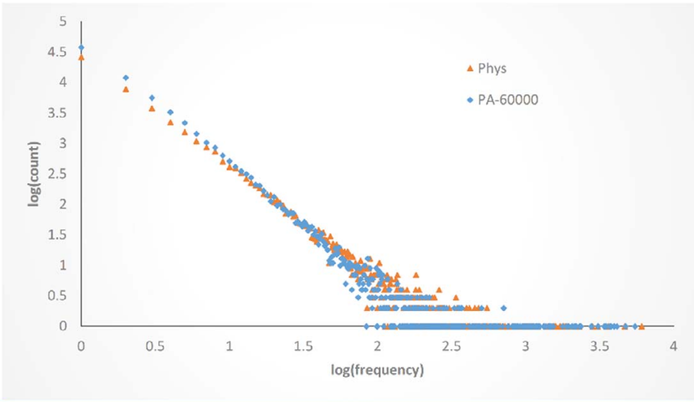

Fig. 3. Frequency distribution of keywords in Physics, Fluids & Plasma and PA-60,000 (PA-60,000 indicates the simulated network with 60,000 articles).

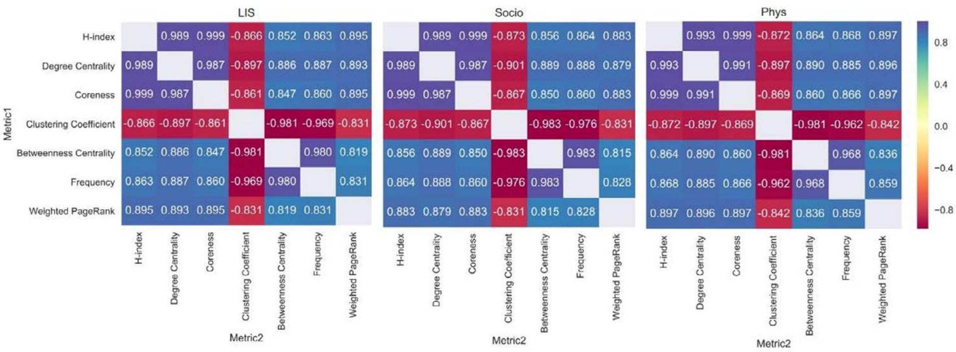

Fig. 4. Heat maps of Spearman's correlation results for empirical networks (Left is LIS, middle is Socio, and right is Phys).

"KNOWLEDGE", "TECHNOLOGY", and "MODEL" are listed. More specific ones, like "SYSTEMS", "BEHAVIOR", "QUALITY", and "IMPACT" which reveal important themes in the LIS field (e.g. information system, information behavior, and informetrics), are also in the top 20 across different metrics. Some keywords are only ranked within the top 20 by some metrics but not the others. For example, in Appendix C, "ORGANIZATIONS" is only listed by Degree Centrality, Frequency, and Weighted PageRank, "UNITED-STATES" is only listed by Clustering Coefficient and Betweenness Centrality, and "INNOVATION" is found by all the metrics except Clustering Coefficient and Betweenness Centrality. There are many ties among the top keywords from H-index and Coreness. For example, twelve of the top 20 keywords from H-index share the same ranks, and 290 keywords ties at the first place for Coreness. Similarly, for H-index, 10 keywords tie in *Socio* and 14 keywords tie in *Phys*. For Coreness, 144 keywords tie in *Socio* and 383 keywords tie in *Phys*. This indicates that H-index and Coreness are less able to differentiate among the top keywords.

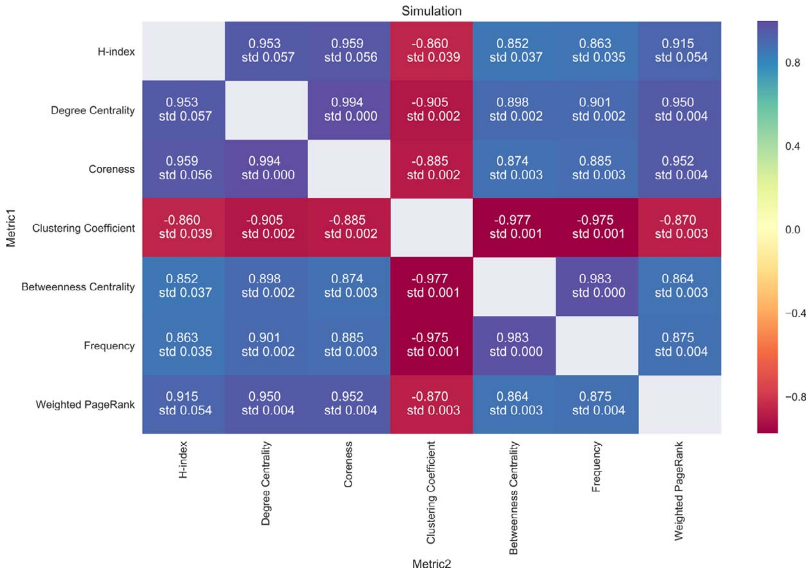

Fig. 5. Heat map of correlation results for simulation networks ($N = 40$).

4.2. Correlation analysis on simulated networks

Fig. 5 shows the correlation results from 40 simulated networks. All pairs are strongly correlated according to Spearman's correlation tests. The small values of standard deviations, except for the pairs involving H-index, indicate that little variation exists in the correlation values. Similar to the results from empirical networks (Fig. 4), Frequency, Between Centrality, and Clustering Coefficient are the closest to each other, and Degree Centrality, H-index, and Coreness are the closest among themselves. This further validates the simulation method.

Fig. 6 plots the correlations between the pairs of metrics against the sizes of simulated networks. It shows that the correlation curves involving H-index behave differently from others with a drop (a rise for Cluster Coefficient due to the negative correlations) as the number of articles increases beyond 55,000. This explains the higher standard deviations for the pairs involving H-index in Fig. 5. Other correlations are more stable as the size of the network grows. The reason for the exception of H-index is unclear and warrants further investigation.

Regression analysis was conducted on the simulated data to examine the potential factors that may influence the relationships among different metrics. We selected nine network property metrics as independent variables (Table 3), and categorized them into different types according to Wang et al. (2012). The dependent variable is the correlation between different metrics.

Regression results (Table 4) show that global attributes of networks do affect the correlations between different metrics, except for the number of edges whose weights are 1 (x2) and the number of edges (x9). Most regression models have high adjusted R^2 values above 0.75, meaning these models are of good fit. Three groups of correlations, including fr*bc, dc*co, and dc*cc, are not affected by any independent variables. For fr*bc and dc*co, their standard deviations are smaller than 0.000, meaning they seldom change. Some regression models share one or more common factors. For example, x4 (average degree) and x6 (average distance of reachable nodes) are shared by pr*fr, pr*bc, pr*cc, fr*cc, and co*cc. This means the correlations between the five pairs are influenced by x4 and x6. Independent variables x3 (the number of edges whose weights are not 1) and x4 are common factors for pr*bc, pr*hi, and bc*cc. Independent variables x1 (the number of unreachable node pairs) and x3 are common factors of pr*hi, dc*hi, and hi*co. In addition, a few other correlations share single common factors. For example, x6 is shared by pr*dc and pr*co, and x1 is shared by fr*hi, bc*hi, and hi*cc. It's interesting to note that correlations between H-index and all other metrics are negatively influenced by the common factor x1, and correlations between Weighted PageRank and all the other metrics, except with H-index, share x6 as their common factor. Similarly, x5 (density) is shared by fr*dc, fr*co, and bc*cc, and x7 (diameter) is shared by dc*bc, bc*co, and bc*cc.

The results in Table 4 also show that there are interaction effects in the regression models for pr*bc, pr*hi, dc*hi, bc*cc, and hi*co. An interaction effect indicates that the impact of one independent variable varies depending on the value of another independent variable. To visualize the interaction effects, we discretized the values of x1, x3, x4, x5, x7, and x8 into two groups where "high" represents values that are higher than their corresponding median, and "low" represents the values that are equal to or lower than the median. The results of some interaction effects are shown in Fig. 7. For example, Fig. 7(a) suggests when the values of x4 are high, the impact of x3 on the correlation between pr and bc is greater than when x4 is low, and the same kind of interaction effect is observed between x8 and x4 as in x3 and x4. Fig. 7(b) suggests when the values of x4 are high, the impact of x3 (or x1) on the correlation between pr and hi is greater than when x4 is low. Similar interpretations can also be given to the rest of the plots in Fig. 7. These interaction effects show more complex relationship between the independent variables and the correlations.

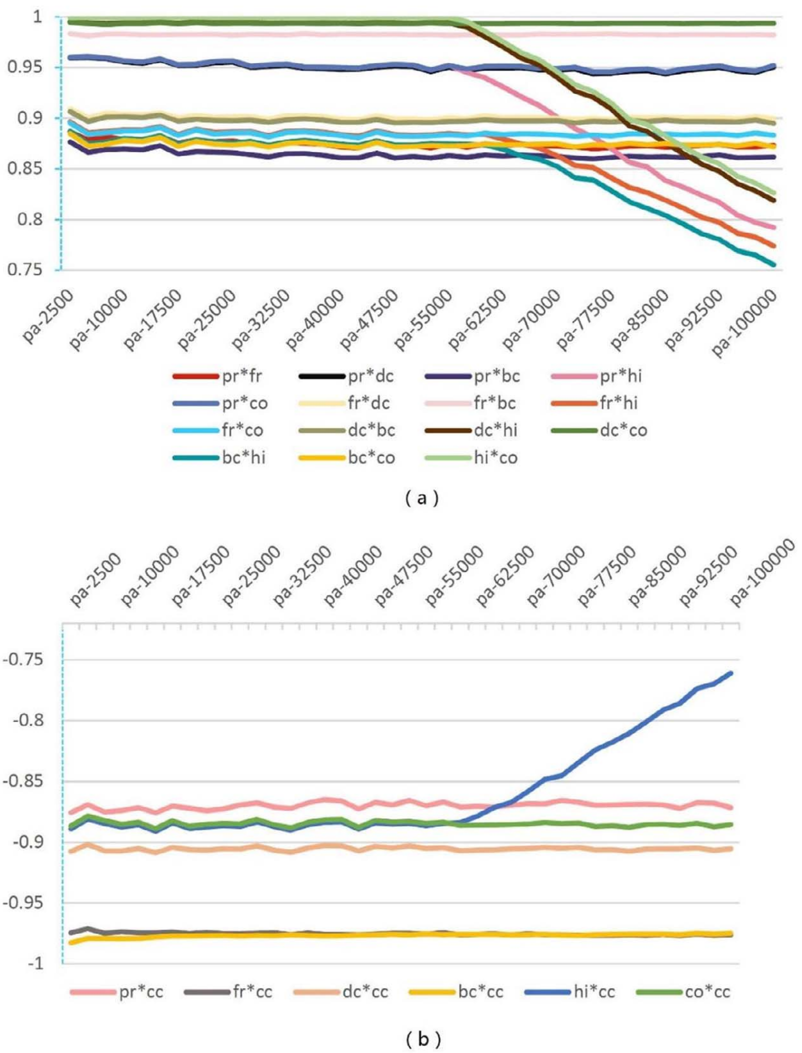

Fig. 6. Correlation results from simulation networks. (a) shows correlations without Clustering Coefficient involved, and (b) shows correlations involving Clustering Coefficient.

Table 3
Independent variables for regression analysis.

Independent variables
Connectivity
x1 the number of unreachable node pairs
x2 the number of edges whose weights are 1
x3 the number of edges whose weights are not 1
Sparsity
x4 average degree
x5 density
Aggregation
x6 average distance of reachable nodes
x7 diameter
Basic indicators
x8 the number of vertices
x9 the number of edges

Table 4
Regression analysis on simulation networks ($N = 40$).

Dependant variables (correlations)	Significant main effect	Significant interaction effect	R^2	adjusted R^2
1 pr*fr	x4(+), x6(-)	\	0.810	0.800
2 pr*dc	x6(-)	\	0.817	0.813
3 $(pr*bc)^{-169.8112}$	x3(+), x4(-), x6(+), x8(-)	x3*x4, x4*x8	0.758	0.731
4 pr*hi	x1(-), x3(+), x4(-)	x1*x3, x1*x4, x3*x4	0.965	0.962
5 pr*co	x6(-)	\	0.798	0.793
6 pr*cc	x4(-), x6(+)	\	0.519	0.493
7 $(fr*dc)^{-228.7784}$	x5(-)		0.268	0.248
8 fr*bc	\	\	\	\
9 $(fr*hi)^{25.4622}$	x1(-)	\	0.916	0.914
10 $(fr*co)^{-162.2933}$	x5(-)	\	0.242	0.222
11 fr*cc	x4(-), x6(+)	\	0.812	0.802
12 $(dc*bc)^{-236.3315}$	x7(+)	\	0.388	0.372
13 dc*hi	x1(-), x3(+)	x1*x3	0.962	0.960
14 dc*co	\	\	\	\
15 dc*cc	\	\	\	\
16 $(bc*hi)^{23.432}$	x1(-)	\	0.914	0.911
17 $(bc*co)^{-181.7074}$	x7(+)	\	0.231	0.211
18 bc*cc	x3(+), x4(-), x5(-), x7(+)	x5*x3, x5*x4, x3*x7, x3*x4	0.942	0.936
19 hi*co	x1(-), x3(+)	x1*x3	0.962	0.960
20 $(-hi*cc)^{23.3602}$	x1(-)	\	0.893	0.890
21 $(-co*cc)^{82.6251}$	x4(+), x6(-)	\	0.349	0.313

Note: The asterisk signs (*) in the dependent variables column are used to indicate the correlation between two metrics. Since the raw models didn't meet the assumptions of regression analysis, we used Boxcox method to transform pr*bc, fr*dc, fr*hi, fr*co, dc*bc, bc*hi, bc*cc, hi*co and co*cc. After Boxcox transformation, we also deleted one of the indicators (x3) for model 20, which is less correlated with dependent variable, since it affects heteroscedasticity of the model. '+' and '-' means positive and negative coefficient correspondingly. All effects are significant at 0.05 level

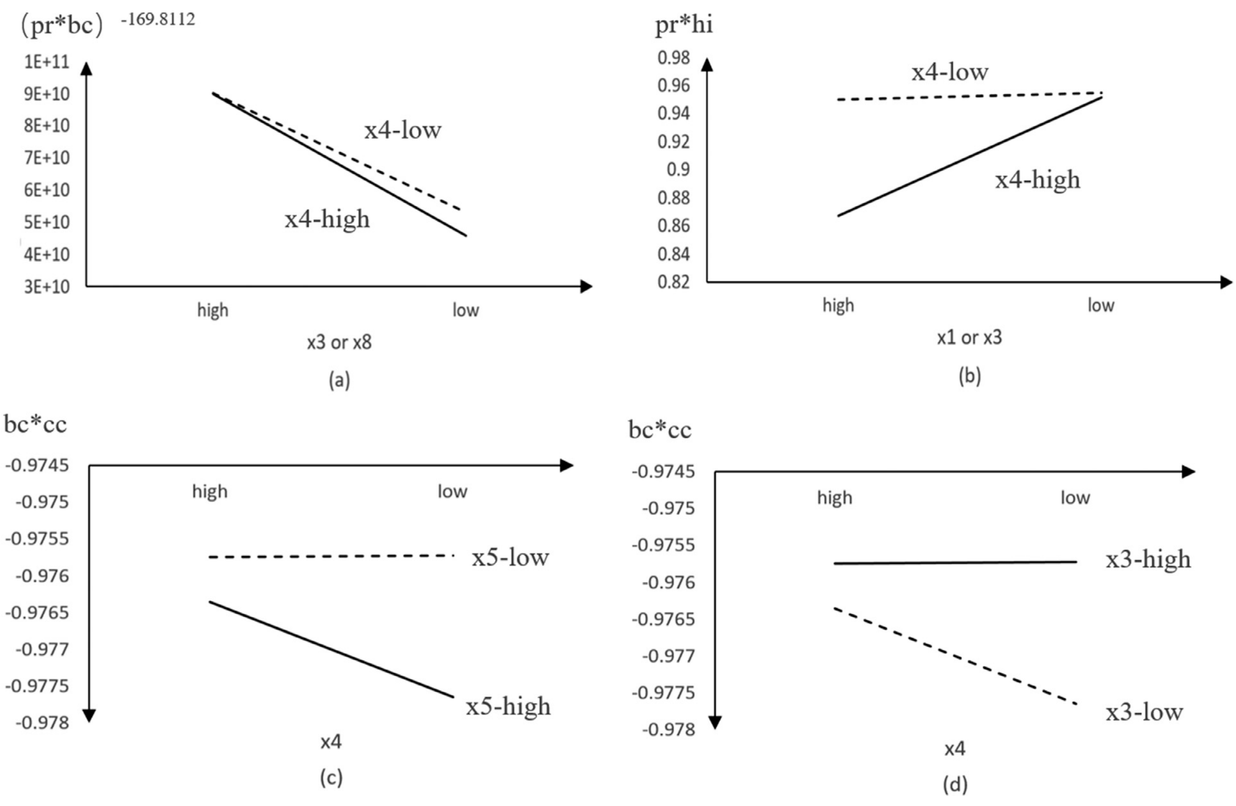

Fig. 7. Visual examples of interaction effects.

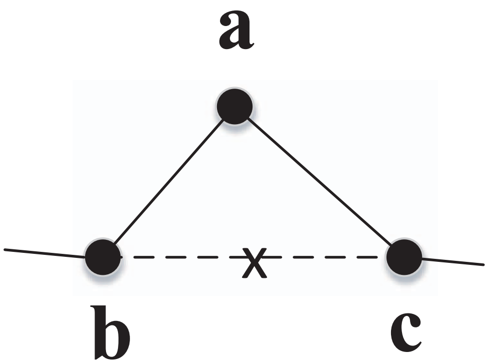

Fig. 8. Direct links among three nodes.

5. Discussion

5.1. Relationships among different metrics

All metrics are strongly correlated according to both empirical and simulated co-word networks. Empirical results show relationships among metrics are consistent across the three disciplines. According to their correlations, the seven metrics can be classified into 3 groups: group 1 includes Degree Centrality, H-index, and Coreness; group 2 includes Betweenness Centrality, Clustering Coefficient, and Frequency; and group 3 has Weighted PageRank.

The metrics in group 1 concern directly linked nodes. Lü et al. (2016) found that Degree Centrality, H-index, and Coreness are strongly related. More specifically, Degree Centrality and Coreness are different forms of H-index, where Degree Centrality corresponds to zero order of H-index and Coreness corresponds to the highest order, in other words, the converged form of H-index. The results from our study confirm the strong relationship among Degree Centrality, H-index, and Coreness in the context of co-word networks.

The three metrics in group 2 appear unrelated but turn out to be highly correlated. The high correlation between Betweenness Centrality and Clustering Coefficient can be partially explained by their definitions. Betweenness Centrality describes the probability of a keyword being on the shortest route of any other two keywords (Newman, 2010). Clustering Coefficient measures the connectivity among the neighbors of a node (Newman, 2010). Conceptually, Betweenness Centrality reflects bridging effect where one keyword bridges two other keywords, and Clustering Coefficient concerns complete mutual connections among keywords. It turns out these are two opposite concepts. If we only focus on direct links, Betweenness Centrality depicts to which extent the neighbors of a node are not connected with each other (In Fig. 8, if a node *a* is on the shortest path of the other two nodes *b* and *c*, then *b* and *c* must not be directly linked. Otherwise, the shortest path between *b* and *c* is their direct link.), which is exactly the opposite of Clustering Coefficient. This partially explains why Betweenness Centrality and Clustering Coefficient are negatively correlated. The strong positive correlation between Frequency and Betweenness Centrality suggests that the more frequently a keyword occurs, the more likely it serves as a bridge for other keywords.

As for Weighted PageRank, unlike other metrics discussed above, it considers more network features. First, Weighted PageRank considers the edge importance based on the co-occurrences of connected nodes, which is neglected in other metrics. Secondly, Weighed PageRank is not a static metric, but involving iterations until convergence, which essentially accounts for the global topology of the network.

5.2. Factors influencing relationships among metrics

Empirical results show no evidence of disciplinary differences for the relationships among the metrics. Regression analysis on the simulation networks shows that some network topology factors influence the relationships among different metrics. Common factors of pr*hi, dc*hi, and hi*co, the number of unreachable node pairs (x1) and the number of edges whose weights are not 1 (x3), are metrics of connectivity, indicating that network connectivity influences their relationships. For fr*hi, bc*hi, and hi*cc, x1 is their common factor, reflecting network connectivity influences these relationships. Sparsity of a network influences fr*dc, fr*co, and bc*cc that share density (x5) as their common factor. Aggregation has an impact on dc*bc, bc*co, and bc*cc which share diameter (x7) as their common factor. It is interesting to note that x1 is a common factor for all relationships that involve H-index, which indicates relationships involving H-index are all influenced by network connectivity. Also worth mentioning, the average distance of reachable nodes (x6) is a common factor of relationships involving Weighted PageRank and the other metrics except H-index, which means these relationships are influenced by the network aggregation property. Besides the single aspect of network topology, some correlations are impacted by multiple dimensions. The relationships between pr*bc, pr*hi, and bc*cc are influenced by network connectivity and sparsity, for which x3 and average degree (x4) are common factors. Also, common factors of pr*fr, pr*bc, pr*cc, fr*cc, and co*cc, x4 and x6, are metrics of sparsity and aggregation, respectively, indicating that network sparsity and aggregation influence their relationships. Basic indictors, such as numbers of vertices and edges, are not common factors, which suggests the size of a network may not be a main factor for the relationships of the metrics. In summary, connectivity, sparsity, and aggregation of a network affect most of the relationships among these metrics.

5.3. Metrics recommended for different purposes

Although all metrics are strongly and significantly correlated, they exhibit different characteristics that may help us to select appropriate metrics for different purposes. Frequency, Degree Centrality, Betweenness Centrality, Clustering Coefficient, and Weighted PageRank have greater discriminative capacity among top-ranked keywords. The strong correlations between frequency and network-based metrics confirm the validity of frequency as a simple but effective method to identify hot themes in a field. However, H-index and Coreness produce many ties among the top keywords, which makes it hard to distinguish the importance of the same-ranked keywords. Coreness has shown its effectiveness in classification (Alvarez-Hamelin, Dall'Asta, Barrat, & Vespignani, 2005). Thus, Coreness and H-index may be better suited for keyword classification.

Clustering Coefficient, which was originally designed to identify important nodes based on the connectivity among their neighbors, has negative correlations with all the other metrics. This suggests that nodes with densely connected neighbors on co-word networks may not be important themes. When combined with the evidence from Degree Centrality and Betweenness Centrality, it seems that on co-word networks, the important themes are those keywords connecting to many neighbors (i.e. high degree centrality), but their neighbors are not well connected with each other (i.e. low clustering coefficient), and these important keywords serve as bridges to other keywords on the networks (i.e. high betweenness centrality). For example, "MODEL", "PERFORMANCE", and "IMPACT" are such keywords in the LIS field. According to Choi, Yi, and Lee (2011), these keywords help bridge disconnected clusters of keywords into an integrated network.

6. Conclusion

In this study, we used both empirical and simulated data to explore the relationships of different metrics for ranking themes on co-word networks. To answer the research questions:

1. All seven metrics, including Frequency, Degree Centrality, Betweenness Centrality, Clustering Coefficient, H-index, Coreness, and Weighted PageRank, are strongly correlated according to both empirical and simulated data. Clustering Coefficient is negatively correlated with the other metrics.
2. The seven metrics can be categorized into three groups according to the strength of their correlations: Degree Centrality, H-index, and Coreness as one group, Betweenness Centrality, Clustering Coefficient, and Frequency as another group, and Weighted PageRank by itself. There is no clear difference between frequency-based and network-based methods. Frequency is more strongly correlated with Betweenness Centrality and Clustering Coefficient than their correlations with the other network-based metrics.
3. There is no evidence that the relationships among the metrics differ across disciplines. The metrics show consistent mutual correlations across the selected disciplines. Regression analysis on simulated networks shows that network topology does influence the relationships among the metrics. Some common factors include network connectivity, sparsity, and aggregation.

The findings from this study contribute to the understanding of the relationships among different metrics for ranking themes on co-word networks, which complements the measurement theory in the context of co-word networks. There is not a clear distinction between frequency-based and network-based metrics in the context of co-word networks. Frequency is closely related to network-based metrics, in particular, Betweenness Centrality and Clustering Coefficient. It is also interesting to note that the relationships among different metrics are invariable across the disciplines. This suggests there may be some commonality among the co-word networks from different disciplines. Further validation is needed to confirm this conjecture. Besides theoretical implications, this study also provides practical guidance on the use of ranking metrics on co-word networks. From the top keywords ranked by different metrics in the three disciplines, we can see all of the metrics can produce reasonable results in the context of co-word networks. However, H-index and Coreness are more suitable to classify keywords than to rank keywords due to their low discriminative capacity among the top keywords. Clustering Coefficient shows negative correlations with other metrics, and thus its results should be ranked reversely. The results confirm the validity of frequency as a simple but effective method for identifying hot themes in a field. In addition, this study proposes a simulation method for co-word networks, which can be used to find general patterns.

Several limitations need to be acknowledged in this study. First, the proposed simulation method produces networks with similar term frequency distributions as in the empirical networks. The correlation results are also consistent between the empirical and simulated networks. However, how similar the simulated networks are to empirical networks in other aspects are not fully examined. As we have not found any literature on how to simulate co-word networks, exploring the simulation methods of co-word networks is still an ongoing research question. The relationships among selected metrics are examined empirically and through simulated data. Whether there are mathematical relationships among the metrics is unknown. This requires rigorous math proofs. Future studies will further explore these issues.

Acknowledgement

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Appendix A

Table A.1
The top 20 journals for the three fields used in this study.

Information science & library	Sociology	Physics, fluids & plasma
MIS QUARTERLY	AMERICAN SOCIOLOGICAL REVIEW	ANNUAL REVIEW OF FLUID MECHANICS
JOURNAL OF INFORMATION TECHNOLOGY	ANNUAL REVIEW OF SOCIOLOGY	PLASMA SOURCES SCIENCE & TECHNOLOGY
JOURNAL OF THE AMERICAN MEDICAL INFORMATICS ASSOCIATION	AMERICAN JOURNAL OF SOCIOLOGY	BIOMICROFLUIDICS
JOURNAL OF COMPUTER-MEDIATED COMMUNICATION	ANNUALS OF TOURISM RESEARCH	NUCLEAR FUSION
JOURNAL OF STRATEGIC INFORMATION SYSTEMS	SOCIOLOGICAL METHODOLOGY	COMMUNICATIONS IN NONLINEAR SCIENCE AND NUMERICAL SIMULATION
INFORMATION SYSTEMS RESEARCH	SOCIOLOGICAL THEORY	MICROFLUIDICS AND NANO FLUIDICS
JOURNAL OF INFOMETRICS	SOCIOLOGICAL METHODS & RESEARCH	PLASMA PROCESSES AND POLYMERS
GOVERNMENT INFORMATION QUARTERLY	SOCIAL NETWORKS	JOURNAL OF FLUID MECHANICS
EUROPEAN JOURNAL OF INFORMATION SYSTEMS	GENDER & SOCIETY	PHYSICAL REVIEW E
SCIENTOMETRICS	QUALITATIVE RESEARCH	PLASMA PHYSICS AND CONTROLLED FUSION
JOURNAL OF MANAGEMENT INFORMATION SYSTEMS	HUMAN ECOLOGY	PHYSICS OF PLASMAS
INFORMATION & MANAGEMENT	JOURNAL OF MARRIAGE AND FAMILY	PLASMA CHEMISTRY AND PLASMA PROCESSING
JOURNAL OF THE AMERICAN SOCIETY FOR INFORMATION SCIENCE AND TECHNOLOGY	CORNELL HOSPITALITY QUARTERLY	PHYSICS OF FLUIDS
INTERNATIONAL JOURNAL OF COMPUTER-SUPPORTED COLLABORATIVE LEARNING	EUROPEAN SOCIOLOGICAL REVIEW	EXPERIMENTAL THERMAL AND FLUID SCIENCE
JOURNAL OF THE ASSOCIATION FOR INFORMATION SYSTEMS	SOCIAL PROBLEMS	THEORETICAL AND COMPUTATIONAL FLUID DYNAMICS
INFORMATION SYSTEMS JOURNAL	YOUTH & SOCIETY	EUROPEAN JOURNAL OF MECHANICS B-FLUIDS
INFORMATION AND ORGANIZATION	SOCIOLOGY OF EDUCATION	JOURNAL OF TURBULENCE
INTERNATIONAL JOURNAL OF GEOGRAPHICAL INFORMATION SCIENCE	INFORMATION COMMUNICATION & SOCIETY	INTERNATIONAL JOURNAL FOR NUMERICAL METHODS IN FLUIDS
JOURNAL OF HEALTH COMMUNICATION	POPULATION AND DEVELOPMENT REVIEW	HIGH ENERGY DENSITY PHYSICS
JOURNAL OF KNOWLEDGE MANAGEMENT	SOCIOLOGY OF HEALTH & ILLNESS	JOURNAL OF MATHEMATICAL FLUID MECHANICS

Appendix B

Table B.1
Frequency distribution of the number of keywords in the empirical data.

Information science & library		Sociology		Physics, fluids & plasma	
# of keywords	# of papers	# of keywords	# of papers	# of keywords	# of papers
1	985	1	536	1	3582
2	985	2	476	2	4722
3	910	3	495	3	5455
4	860	4	469	4	5860
5	830	5	456	5	5781
6	760	6	400	6	5379
7	649	7	399	7	4877
8	584	8	355	8	4286
9	523	9	356	9	3677
10	4444	10	3224	10	17,682

Appendix C

Table C.1
Top 20 terms in the LIS field (numbers in parentheses indicate the tied ranks).

DC	HI	CO(290 words have maximum score)	BC	CC(bottom 20)	FR	PR
MODEL	MODEL (1)	MODEL	MODEL	CLASSIFIER	SCIENCE	MODEL
PERFORMANCE	IMPACT (1)	IMPACT	INFORMATION	MODEL	MODEL	TECHNOLOGY
IMPACT	PERFORMANCE (3)	PERFORMANCE	PERFORMANCE	PERFORMANCE	TECHNOLOGY	PERFORMANCE
INFORMATION	INFORMATION (3)	INFORMATION	IMPACT	INFORMATION	IMPACT	SYSTEMS
TECHNOLOGY	TECHNOLOGY (3)	TECHNOLOGY	SCIENCE	SCIENCE	PERFORMANCE	MANAGEMENT
SYSTEMS	SYSTEMS (6)	SYSTEMS	SYSTEMS	IMPACT	SYSTEMS	IMPACT
MANAGEMENT	MANAGEMENT (6)	MANAGEMENT	TECHNOLOGY	TECHNOLOGY	INFORMATION	INFORMATION-TECHNOLOGY
COMMUNICATION	KNOWLEDGE (6)	KNOWLEDGE	MANAGEMENT	SYSTEMS	MANAGEMENT	INFORMATION
SCIENCE	COMMUNICATION (9)	COMMUNICATION	COMMUNICATION	COMMUNICATION	INFORMATION-TECHNOLOGY	PERSPECTIVE
KNOWLEDGE	PERSPECTIVE (9)	PERSPECTIVE	KNOWLEDGE	MANAGEMENT	PERSPECTIVE	COMMUNICATION
INFORMATION-TECHNOLOGY	BEHAVIOR	BEHAVIOR	BEHAVIOR	INFORMATION-TECHNOLOGY	COMMUNICATION	SCIENCE
PERSPECTIVE	QUALITY	QUALITY	INFORMATION-TECHNOLOGY	KNOWLEDGE	KNOWLEDGE	KNOWLEDGE
BEHAVIOR	INTERNET	INTHFERNET	INTERNET	BEHAVIOR	INTERNET	ORGANIZATIONS
INTERNET	FRAMEWORK	FRAMEWORK	UNITED-STATES	PERSPECTIVE	INNOVATION	BEHAVIOR
QUALITY	DESIGN	DESIGN	PERSPECTIVE	INTERNET	ORGANIZATIONS	INTERNET
ORGANIZATIONS	INFORMATION-TECHNOLOGY	INFORMATION-TECHNOLOGY	SYSTEM	CARE	BEHAVIOR	INNOVATION
INNOVATION	INFORMATION-SYSTEMS (17)	INFORMATION-SYSTEMS	QUALITY	UNITED-STATES	NETWORKS	INFORMATION-SYSTEMS
DESIGN	NETWORKS (17)	NETWORKS	PATTERNS	DECISION-MAKING	INFORMATION-SYSTEMS	DESIGN
INFORMATION-SYSTEMS	SCIENCE	SCIENCE	CARE	QUALITY	DESIGN	QUALITY
NETWORKS	INNOVATION	INNOVATION	DESIGN	DESIGN	QUALITY	NETWORKS

Appendix D

Table D.1
Top 20 terms in the Socio field (numbers in parentheses indicate the tied ranks).

DC	HI	CO(144 words have maximum score)	BC	CC(bottom 20)	FR	PR
UNITED-STATES	UNITED-STATES	UNITED-STATES	UNITED-STATES	UNITED-STATES	UNITED-STATES	UNITED-STATES
GENDER	GENDER	GENDER	BEHAVIOR	MANAGEMENT	GENDER	GENDER
BEHAVIOR	BEHAVIOR	BEHAVIOR	MANAGEMENT	BEHAVIOR	HEALTH	HEALTH
HEALTH	ATTITUDES	ATTITUDES	GENDER	GENDER	BEHAVIOR	BEHAVIOR
MANAGEMENT	HEALTH (5)	HEALTH	HEALTH	HEALTH	WORK	CHILDREN
WOMEN	PERSPECTIVE (5)	PERSPECTIVE	MODEL	MODEL	CHILDREN	WORK
ATTITUDES	WOMEN	WOMEN	ATTITUDES	CONSERVATION	WOMEN	WOMEN
CHILDREN	WORK	WORK	IMPACT	IMPACT	MANAGEMENT	MARRIAGE
IMPACT	CHILDREN (9)	CHILDREN	PERSPECTIVE	WOMEN	MARRIAGE	ATTITUDES
PERSPECTIVE	INEQUALITY (9)	INEQUALITY	WOMEN	ATTITUDES	ATTITUDES	FAMILY
MODEL	PATTERNS (9)	PATTERNS	CHILDREN	KNOWLEDGE	FAMILY	RACE
WORK	PARTICIPATION	PARTICIPATION	KNOWLEDGE	PERSPECTIVE	MODEL	INEQUALITY
RACE	IMPACT	IMPACT	WORK	CHILDREN	RACE	PERSPECTIVE
FAMILY	MODEL (14)	MODEL	COMMUNITY	WORK	IMPACT	MANAGEMENT
INEQUALITY	FAMILY (14)	FAMILY	POLITICS	POLITICS	INEQUALITY	IMPACT
MARRIAGE	RACE	RACE	PERFORMANCE	DYNAMICS	PERSPECTIVE	MODEL
PERFORMANCE (17)	PERFORMANCE (17)	PERFORMANCE	DYNAMICS	COMMUNITY	POLITICS	IDENTITY
PATTERNS (17)	RISK (17)	RISK	CONSERVATION	RACE	IDENTITY	PARTICIPATION
IDENTITY	CONSEQUENCES (17)	CONSEQUENCES	MODELS	PERFORMANCE	NETWORKS	PERFORMANCE
POLITICS	MARRIAGE	MARRIAGE	RISK	IDENTITY	PERFORMANCE	PATTERNS

Appendix E

Table E.1
Top 20 terms in the Physics field (numbers in the parentheses indicate the tied ranks).

DC	HI	CO(383 words have maximum score)	BC	CC(bottom 20)	FR	PR
DYNAMICS	DYNAMICS (1)	DYNAMICS	DYNAMICS	ECRIS(1)	DYNAMICS	DYNAMICS
MODEL	MODEL (1)	MODEL	MODEL	PICKUP(1)	MODEL	MODEL
SYSTEMS	SYSTEMS	SYSTEMS	SYSTEMS	DEGENERACIES(1)	SYSTEMS	FLOW
FLOW	SIMULATION	SIMULATION	FLOW	TUBERCLES(1)	FLOW	TRANSPORT
STABILITY	TRANSPORT	TRANSPORT	STABILITY	OPTICAL COATINGS(1)	TRANSPORT	SYSTEMS
SIMULATION	TRANSITION	TRANSITION	SIMULATION	EXTREME EVENTS(1)	STABILITY	STABILITY
TRANSPORT	FLOW (7)	FLOW	TRANSPORT	STATISTICAL GEOMETRIC MODEL(1)	PLASMA	SIMULATION
TRANSITION	STABILITY (7)	STABILITY	BEHAVIOR	DYNAMICS	SIMULATION	PLASMA
INSTABILITY	BEHAVIOR (9)	BEHAVIOR	SYSTEM	MODEL	INSTABILITY	INSTABILITY
BEHAVIOR	SIMULATIONS (9)	SIMULATIONS	TRANSITION	SYSTEMS	TRANSITION	TRANSITION
SIMULATIONS	DIFFUSION	DIFFUSION	PLASMA	FLOW	TURBULENCE	TURBULENCE
FLUID	INSTABILITY (12)	INSTABILITY	SIMULATIONS	STABILITY	FLOWS	FLUID
DIFFUSION	SYSTEM (12)	SYSTEM	INSTABILITY	SIMULATION	PLASMAS	FLOWS
FIELD	FIELD (14)	FIELD	FIELD	TRANSPORT	FLUID	SIMULATIONS
PLASMA	PARTICLES (14)	PARTICLES	DIFFUSION	BEHAVIOR	SIMULATIONS	PARTICLES
SYSTEM	MOTION (16)	MOTION	FLUID	TRANSITION	WAVES	MOTION
FLOWS	SURFACE (16)	SURFACE	SURFACE	PLASMA	MOTION	PLASMAS
MOTION	FLUID	FLUID	PARTICLES	INSTABILITY	PARTICLES	FIELD
PARTICLES	EVOLUTION (19)	EVOLUTION	MOTION	FLUID	FIELD	BEHAVIOR
TURBULENCE	EQUATION (19)	EQUATION	TEMPERATURE	SIMULATIONS	BEHAVIOR	WAVES

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