Finding Knowledge Paths Among Scientific Disciplines

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This paper uncovers patterns of knowledge dissemination among scientific disciplines. Although the transfer of knowledge is largely unobservable, citations from one discipline to another have been proven to be an effective proxy to study disciplinary knowledge flow. This study constructs a knowledge-flow network in which a node represents a *Journal Citation Reports* subject category and a link denotes the citations from one subject category to another. Using the concept of shortest path, several quantitative measurements are proposed and applied to a knowledge-flow network. Based on an examination of subject categories in *Journal Citation Reports*, this study indicates that social science domains tend to be more self-contained, so it is more difficult for knowledge from other domains to flow into them; at the same time, knowledge from science domains, such as biomedicine-, chemistry-, and physics-related domains, can access and be accessed by other domains more easily. This study also shows that social science domains are more disunified than science domains, because three fifths of the knowledge paths from one social science domain to another require at least one science domain to serve as an intermediate. This work contributes to discussions on disciplinarity and interdisciplinarity by providing empirical analysis.

Introduction

Our societies are active works of innovation. To keep all their parts thriving, we infuse our posits and observations with copious amounts of knowledge (Knorr-Cetina, 1999). Knowledge as "intellectual capital" has an immediate impact on the economy, because society has moved from a production-based economy to a knowledge-based one. This shift has significantly changed the organization of labor and has formed new occupations and disciplines (Bell, 1973; Drucker, 1993).

The production and creation of knowledge are not dependent on a single isolated entity; instead, knowledge is diffused, exchanged, and circulated among various entities. Knowledge flow in the past 20 years has become more intersectoral, interorganizational, interdisciplinary, and international (Lewison, Rippon, & Wooding, 2005; Wagner & Leydesdorff, 2005; Autant-Bernard, Mairesse, & Massard, 2007; Ponds, Van Oort, & Frenken, 2007; Buter, Noyons, & Van Raan, 2010). Research questions in this area have usually centered on how scientific and technological knowledge, innovative ideas, management skills, or certain influences transfer within different sectors (Kogut & Zander, 1993; Szulanski, 1996; Storck & Hill, 2000), between different organizations (Mowery, Oxley, & Silverman, 1996; Narin, Hamilton, & Olivastro, 1997; Cohen, Nelson, & Walsh, 2002; Meyer, 2002), and between different scientific disciplines (e.g., Van Leeuwen & Tijssen, 2000; Rinia, Van Leeuwen, & Bruins, 2001; Rinia et al., 2002; Kiss, Broom, Craze, & Rafols, 2010).

Perceiving knowledge as accumulative and static does not capture the interactive and diversified characteristics of knowledge transfer. As pointed out by Knorr-Cetina (1999), we have a limited understanding of the "contemporary machineries of knowing" (p. 2). One school of thought holds that science is disunified; knowledge displays different facets of empirical approaches, which brings out the "diversity of epistemic culture" (p. 3). In addition to the trifurcation of sciences (instrumental, practical, and emancipation) in approaches to problem solving (Habermas, 1988), within each division, various disciplines are expected to have ontological and methodological differences (Suppes, 1984). Meanwhile, other scholars hold the belief that science is becoming unified and claim that " [t]o further all kinds of scientific synthesis is one of the most important purposes of the unity of science movement" (Neurath, 1996, p. 309). The purpose of this study is to contribute to the discussion by empirically measuring the connectivity of different science and social science disciplines through the application of knowledge paths.

A first attempt in this direction was the study of scientific trading among different disciplines (e.g., Cronin & Davenport, 1989; Cronin & Pearson, 1990; Stigler, 1994; Lockett & McWilliams, 2005; Goldstone & Leydesdorff,

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2006; Cronin & Meho, 2008; Larivière, Sugimoto, & Cronin, 2012; Yan, Ding, Cronin, & Leydesdorff, 2013). Using the trading metaphor, knowledge exporters and importers were identified in these studies, but the authors only considered the two ends (exporter and importer) of knowledge flows, without considering the concrete knowledge paths. Consequently, patterns and mechanisms of knowledge flow largely remain a black box.

Understanding knowledge paths is particularly important to studies of knowledge flows, because it helps us gain insights into patterns of knowledge flows at a more granular level. In addition to questions about knowledge importers and exporters, questions such as how knowledge is imported and exported can also be addressed. Specifically, the following questions are investigated in this article.

- What are knowledge paths among scientific disciplines?

Previous work: Previous studies on interdisciplinarity have focused mainly on discipline proximity (for clustering and mapping purposes) and not on knowledge flows or knowledge paths.
Current work: Using the trading metaphor, knowledge flows among different disciplines are investigated, where the shortest path denotes the most important knowledge flow between two disciplines.
Significance: Patterns of knowledge transfer and dissemination are revealed and empirical analyses are provided.

- What patterns can be found from the identified knowledge paths, and how can these patterns be used to identify different disciplines?

Previous work: Quantitative studies on the dissemination aspect of disciplinary knowledge have been inadequate.
Current work: Quantitative indicators are proposed to measure the extent to which a discipline's knowledge can be accessed by other disciplines and how distant a discipline's knowledge is from that of other disciplines.
Significance: The proposed indicators quantify patterns of knowledge flow and dissemination, providing additional insights into interdisciplinary studies. These indicators are also valuable for scientific evaluation and science policy making.

- How can knowledge be classified, and what additional information can be obtained by evaluating knowledge flows at different knowledge hierarchies?

Previous work: Previous studies have usually focused on one type of research entity, such as papers, authors, or journals, but have not systematically studied different research entities.
Current work: A six-layered knowledge hierarchy is proposed, allowing one to zoom in to find knowledge paths among papers and also zoom out to gain a holistic view of knowledge transfer between major divisions of knowledge.
Significance: The proposed knowledge hierarchy is effective for organizing knowledge and can be easily adopted in studies of clustering and mapping research specialties.

- What is the backbone of knowledge flow in the knowledge-flow network?

Previous work: Most previous science maps are similarity-based (i.e., cocitation, bibliographic coupling, coword). Weighted, directed knowledge-flow maps have not been well explored.
Current work: In addition to the quantitative indicators, the backbone of knowledge flow is visualized.
Significance: Knowledge-flow maps are informative to scientists, scholars, science policy makers, and the general public and help the understanding of how knowledge is disseminated among disciplines.

Literature Review

Intersectoral and Interorganizational Knowledge Flows

Efforts in intersectoral and interorganizational knowledge flows have been employed largely to understand the mechanisms of different types of knowledge transfers and to identify ways to facilitate knowledge transfer between organizations. Cohen, Nelson, and Walsh (2002) discussed the different forms of knowledge flows in science and technology, including how knowledge may be transferred by personal contacts at conferences and workshops, by mobility of researchers, by advisor–advisee relationships, by collaborative research projects, or by publication channels such as scientific articles and patents. Using survey data, the authors found that R&D managers in U.S. firms considered publications to be the dominant channel of knowledge flow. Zellner and Fornahl (2002) made a similar argument, positing that the major organizational knowledge acquisition channels are the recruitment of people, the information networks of employees, and the formal cooperation networks. Szulanski (1996) demonstrated that the major barriers to intersectoral knowledge transfer lie in recipients' lack of absorptive capacity, causal ambiguity, and a tension between knowledge senders and knowledge recipients. These findings were confirmed by Almeida and Kogut (1999), who showed that the mobility of employees influences the organizational knowledge transfer and that such knowledge transfer is in turn embedded in the information networks of employees.

As with many important concepts in economics, the transfer of knowledge is largely unobservable (Jaffe, Trajtenberg, & Fogarty, 2000) and thus requires proxies to measure concepts of interest. Patent citations provide a practical instrument for quantitatively studying knowledge flow in empirical work. In the pioneering research of Jaffe, Trajtenberg, and Henderson (1993), the authors studied the association between geographic locations and citation intensity. They found that domestic patents are more likely to cite other domestic patents, yet these localization patterns slowly became less significant in later years. In the same vein, Jaffe and Trajtenberg (1999) found that the transfer of knowledge in patent citation networks is restrained by country boundaries as well as organizational boundaries and patent classes. MacGarvie (2005) used the notion of proximity to interpret such phenomena, in that knowledge diffusion is enhanced by physical and technological proximity. In addition to studies of organizational boundaries in knowledge flow, efforts have also compared knowledge diffusion decay for different types of organizations in patent citation networks. For instance, Bacchiocchi and Montobbio (2009) found that the knowledge embedded in university and public research patents tends to diffuse more rapidly than that from

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corporate patents. Besides citation data, empirical research has also used coauthorship and survey data to study intersectoral and interorganizational knowledge flow (Cohen, Nelson, & Walsh, 2002; Meyer, 2002).

Predicated upon previous endeavors in social network analysis, growing numbers of studies over the past decade have used network-based approaches to examine knowledge flow in organizations. These studies have paid particular attention to the structural significance of organizations in knowledge-flow networks. For example, Tsai (2001) analyzed the network positions of organizations and found that network positions have significant and positive effects on business innovation and performance. Studies have also shown that social cohesion and network range (Reagans & McEvily, 2003), social capital (Inkpen & Tsang, 2005), and betweenness (Levin & Cross, 2004) are contributing factors that facilitate knowledge transfer in organizations.

Interdisciplinary Knowledge Flows

Quantitative studies of knowledge flow among disciplines have usually used citations as the research instrument. Citations between scientific articles imply a knowledge flow from the cited entity to the citing entity (Jaffe, Trajtenberg, & Henderson, 1993; Van Leeuwen & Tijssen, 2000; Nomaler & Verspagen, 2008; Mehta, Rysman, & Simcoe, 2010). Citations can be aggregated at several levels, such as paper/patent, author, journal, institution, and discipline levels, and scholars have investigated knowledge flows in patent citation networks (Jaffe, Trajtenberg, & Henderson, 1993; Narin, Hamilton, & Olivastro, 1997; Jaffe, Trajtenberg, & Fogarty, 2000; Chen & Hicks, 2004; Mehta, Rysman, & Simcoe, 2010), paper citation networks (e.g., Chen, Zhang, & Vogeley, 2009; Shi, Tseng, & Adamic, 2009), author citation networks (Zhuge, 2006), journal citation networks (Alvarez & Pulgarín, 1997; Frandsen, Rousseau, & Rowlands, 2006), institution citation networks (Börner, Penumarthy, Meiss, & Ke, 2006; Yan & Sugimoto, 2011), and discipline citation networks (Van Leeuwen & Tijssen, 2000; Rinia, Van Leeuwen, & Bruins, 2001; Rinia et al., 2002).

In a pioneering quantitative investigation of interdisciplinary dependency, Borgman and Rice (1992) studied cross-disciplinary citations between information science and communication science journals and found that a few information science journals heavily cited communication science journals. Leydesdorff and Probst (2009) also found that communication science journals were cited frequently by political science and social psychology journals. Using a 30-year citation data set on information science publications, Cronin and Meho (2008) found that information science has become a more successful exporter of knowledge and less introverted, as more recent articles in information science have cited and are being cited more intensively by articles in fields such as computer science, engineering, business and management, and education. These findings were confirmed by Levitt, Thelwall, and Oppenheim (2011), who found that library and information science had the largest increase in interdisciplinarity between 1990 and 2000 among different social science fields.

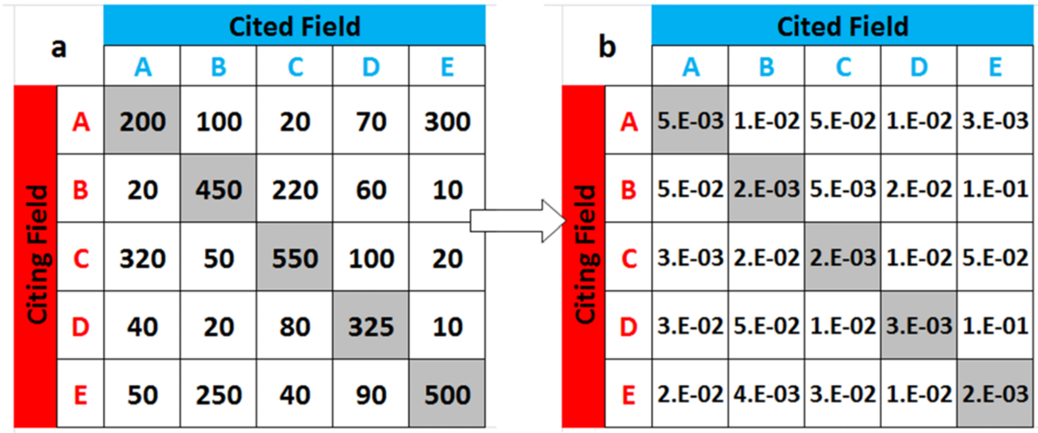
Scholars have also used various statistical models, such as the epidemiological model (Bettencourt et al., 2006; Kiss et al., 2010), the population contagion model (Bettencourt et al., 2008), the clique percolation method (Herrera, Roberts, & Gulbahce, 2010), the small-world model (Cowan & Jonard, 2004), and the diffusion model (Zhuang, Chen, & Feng, 2011) to describe and simulate the creation and dissemination of knowledge in different contexts. Epidemiological models focus on the transmission of different traits among certain populations; such traits can be transmitted diseases, behaviors, or innovative ideas. An individual can be classified into one of the basic classes in epidemiological models: the susceptible (S) class, the exposed (E) class, the infected class (I), the skeptical class (Z), and the recovered (R) class (Hethcote, 2000). Scholars can choose these classes based on their specific research questions, but there is always a trade-off between the level of detail and the complexity of the model, as pointed out by Bettencourt et al. (2006), who compared several epidemiological models with the goal of exploring the spread of the Feynman diagram in the postwar U.S., U.S.S.R., and Japan, including SIR, SIZ, SEI, and SEIZ models. The authors found that all four models have an accurate fit with empirical data, and, among them, SEIZ captured most adequately the role of different classes in the transmission process and yielded the best fits. Kiss et al. (2010) used an epidemiological model to describe the spread of research topics across disciplines. They conducted a case study on kinesin research publications and found that the diffusion of topics is more likely to occur between disciplines with existing knowledge flows and that diffusion across disciplines takes a considerable amount of time (4–15.5 years).

Previous endeavors in intersectoral, interorganizational, and interdisciplinary knowledge transfer have laid sound theoretical and methodological foundations for inquiries on knowledge flows. To the best of our knowledge, however, there has been no study to date on finding knowledge paths among scientific disciplines. This study attempts to fill this gap by exploring patterns of knowledge flows at several knowledge hierarchies, including subjects, classes, and top divisions of knowledge.

Materials and Methods

Construction of Knowledge-Flow Networks

Subject category citation data from *Journal Citation Reports* (Thomson Reuters) were used. Despite discussions on the accuracy of subject categories (e.g., Boyack, Klavans, & Börner, 2005; Rafols & Leydesdorff, 2009), the Thomson Reuters classification scheme has been widely used (Zitt, 2005; Van Raan, 2008; for procedures on data collection refer to Rafols and Leydesdorff, 2009). It is thus



a		Cited Field A	B	C	D	E
Citing Field	A	200	100	20	70	300
	B	20	450	220	60	10
	C	320	50	550	100	20
	D	40	20	80	325	10
	E	50	250	40	90	500

b		Cited Field A	B	C	D	E
Citing Field	A	5.E-03	1.E-02	5.E-02	1.E-02	3.E-03
	B	5.E-02	2.E-03	5.E-03	2.E-02	1.E-01
	C	3.E-03	2.E-02	2.E-03	1.E-02	5.E-02
	D	3.E-02	5.E-02	1.E-02	3.E-03	1.E-01
	E	2.E-02	4.E-03	3.E-02	1.E-02	2.E-03

FIG. 1. An example of a knowledge-flow network. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

used as an empirical proxy to study disciplinary knowledge flows. The limitation of using Thomson Reuters data is addressed in the Discussion section. A knowledge-flow network, or a field-to-field citation network, is constructed based on the 2009 data set (in this paper, the terms *discipline*, *field*, and *domain* are used interchangeably). Citations from a multiassigned journal are counted toward all assigned subject categories; this multiassignment is also referred to as *multiple counting* (Yan, Ding, Cronin, & Leydesdorff, 2013). Multiple counting avoids the arbitrariness of assigning a multiassigned journal to any one subject category; however, the caveat is that such assignment may result in citation inflation (e.g., *Journal of the American Society for Information Science and Technology* is assigned to two categories: information science & library science and computer science information systems; thus, its citation flow is counted toward both categories). Figure 1a shows an example of a knowledge-flow network consisting of five fields.

Measurement

To characterize the knowledge flow among fields, the Dijkstra algorithm (Dijkstra, 1959) was used to search for the shortest paths between any two fields in the knowledge-flow network. The idea of the Dijkstra algorithm is to find a path between two nodes so that the sum of edge weights reaches the minimum in a weight-directed network. The shortest path is defined in a distance-based network, the flow distance between fields i and j, is operationalized by *reverse_flow_width* (Figure 1b): the more citations from one field to another, the wider the knowledge flow, and thus the shorter the flow distance.

$$flow\_dist_{i\to j} \overset{\text{def}}{=} reverse\_flow\_width_{i\to j} = \frac{1}{number\ of\ citations\ from\ j\ to\ i} \quad (1)$$

The initiation of the algorithm involves setting the weight of all pairs of knowledge paths as infinite: $path\_weight_{i\to j} = inf$, $for\ i,\ j = 1{:}n$, and then setting the weight of knowledge paths to oneself as zeros: $path\_weight_{i\to j} = 0,\ for\ i = 1{:}n$. The major step is to update the path weight with network information. For instance, if the existing weight for $path\_weight_{i\to j}$ is larger than new weight $path\_weight_{i\to k} + flow\_dist_{k\to j}$, then the existing weight is updated by the new weight: $path\_weight_{i\to j} = path\_weight_{i\to k} + flow\_dist_{k\to j}$, in this way until all pairs are traversed.

In Figure 2, two examples (shortest knowledge path from A to E and shortest knowledge path from E to A) are given based on the sample knowledge-flow network illustrated in Figure 1. In Figure 2, the knowledge path from field A to field E follows A→C→B→E, and the knowledge path from field E to field A follows E→A.

Note that the shortest path algorithm is guided by the assumption that a citation flow denotes a knowledge flow. Although this assumption is supported by previous studies (Borgman & Rice, 1992; Wouters, 1998; Cronin & Meho, 2008; Yan, Ding, Cronin, & Leydesdorff, 2013), it may simplify patterns of knowledge dissemination. In reality, disciplinary knowledge may absorb and incorporate a new body of knowledge before it flows to other fields; as Nerkar (2003) put it, "... consider new knowledge creation as a recombinant process that involves search, discovery, and use of existing, codified, and observable knowledge" (p. 213).

Aggregation Levels

Currently, two classification schemes are widely recognized and used in studies of scholarly communications: the *Essential Science Indicators* (*ESI*) classes and the *Journal Citation Reports* (*JCR*) subject categories. Both are maintained by Thomson Reuters. In *ESI*, journals are grouped into 22 classes, and, in *JCR*, journals are grouped into more than 200 subject categories. Formally, *ESI* and *JCR* are two

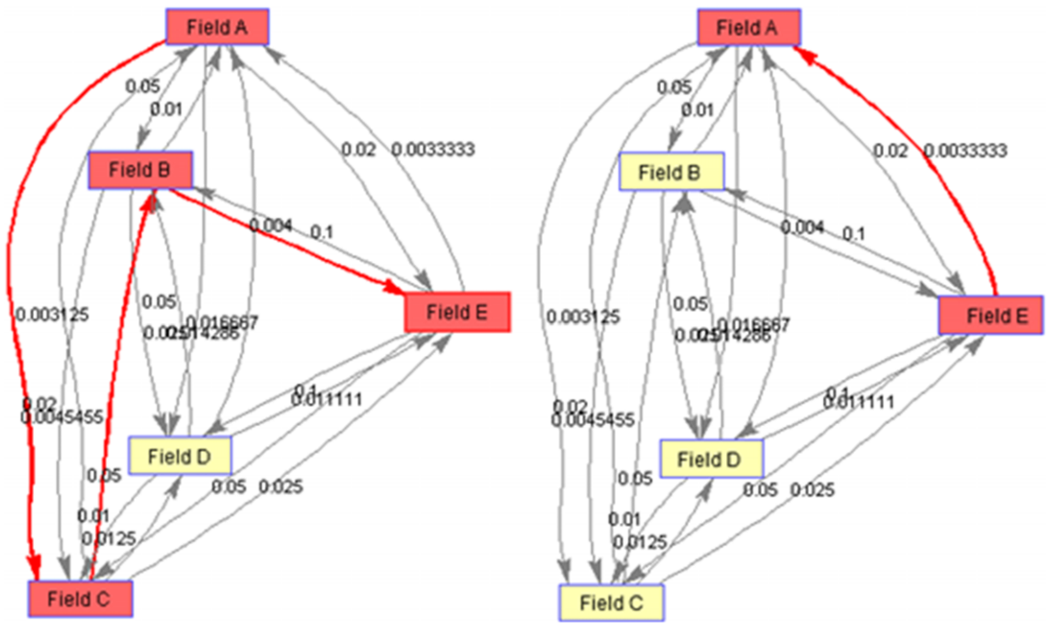


FIG. 2. Examples of finding shortest knowledge paths between fields. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

separate classification schemes. Based on their journal assignment, in this study, *JCR* subject categories are mapped into the *ESI* classes.[1] For example, the *ESI* class Physics contains nine *JCR* subject categories: (a) acoustics, (b) optics, (c) physics, applied, (d) physics, condensed matter, (e) physics, fluids & plasmas, (f) physics, mathematical, (g) physics, multidisciplinary, (h) physics, nuclear, and (i) physics, particles & fields. In the proposed knowledge hierarchy, knowledge is thus divided into sciences, social sciences, and arts and humanities, and these three comprise 22 *ESI* classes that can be further divided into more than 200 *JCR* subject categories. Each subject category contains certain numbers of journals, from several dozen to a few hundred, and each journal publishes articles periodically (Figure 3). This study focuses on the analysis of the three middle knowledge hierarchies: sciences/social sciences, *ESI* classes, and *JCR* subject categories.

Evaluative Indicators

For an effective analysis, several indicators are proposed, including average shortest path length, average shortest path weight, and occurrence in shortest path. The weighted directed network can be represented as $G = (V, A)$, where A represents the weighted directed link set and V represents the vertex set of fields. The proposed indicators are formally defined as:

- Shortest path (SP) from i to j ($SP_{i\to j}$) is a path from i to j in the knowledge-flow network such that the sum of the distances of its constituent links is minimized, where the distance is defined in Equation (1).
- Shortest path length (SPL) from i to j ($SPL_{i\to j}$) is defined as the number of nodes traversed in transferring a piece of information in the shortest path from i to j ($SP_{i\to j}$).
- Average shortest path length (ASPL) for i as the source of knowledge transfer is defined as

$$ASPL_{i:source} = \frac{\sum_{j=1}^{n} SPL_{i\to j}}{n},$$

where n is the number of subject categories in this study.

- ASPL for i as destination of knowledge transfer is defined as

$$ASPL_{i:destination} = \frac{\sum_{j=1}^{n} SPL_{j\to i}}{n}.$$

- Shortest path weight (SPW) from i to j ($SPW_{i\to j}$) is defined as the accumulative link weights in the shortest path from i to j ($SP_{i\to j}$), where the weight is defined in equation 1.
- Average shortest path weight (ASPW) for i as the source of knowledge transfer is defined as

$$ASPW_{i:source} = \frac{\sum_{j=1}^{n} SPW_{i\to j}}{n}.$$

- ASPW for i as the destination of knowledge transfer is defined as

$$ASPW_{i:destination} = \frac{\sum_{j=1}^{n} SPW_{j\to i}}{n}.$$

[1]The matching results can be found at http://ella.slis.indiana.edu/~eyan/papers/field/ESI-SC.txt

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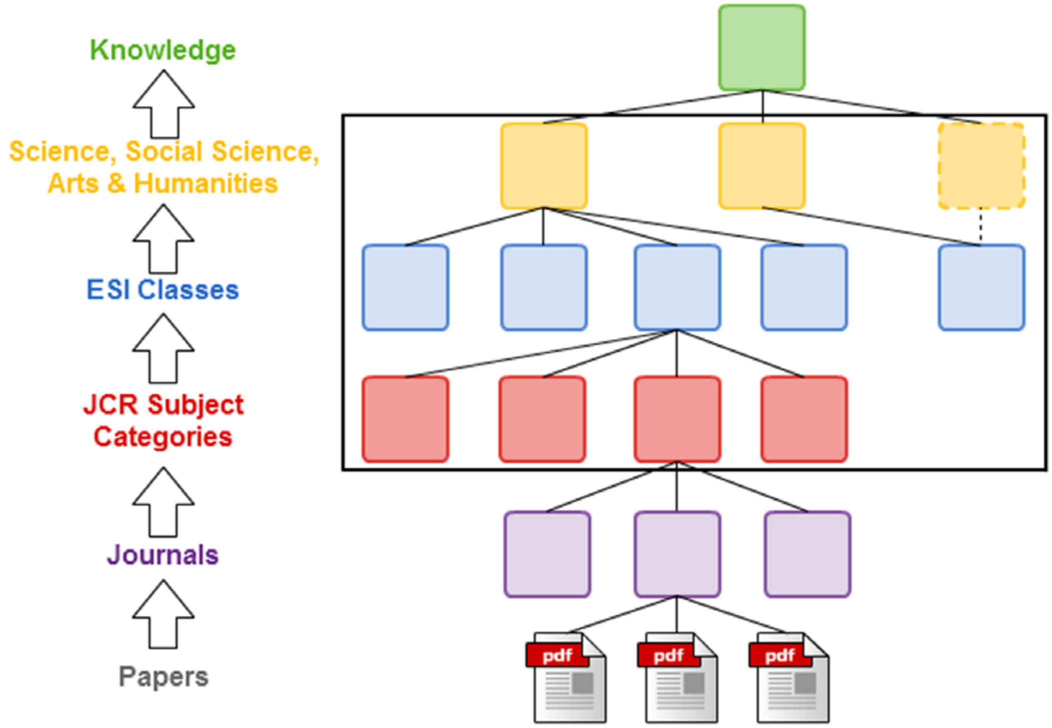

FIG. 3. Knowledge hierarchy (arts & humanities is displayed in the dotted line because it is not included in the current study). [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

- Occurrence in shortest path (OiSP) for k is defined as the number of times k occurred in shortest paths between all pair of nodes:

$$\sum_{i=1}^{n}\sum_{j=1}^{n}\left(k \text{ is on the shortest path of } SP_{i\to j}\ ?, 1, 0\right).$$

As the source of a knowledge flow, ASPL denotes how easily its knowledge can be accessed by other fields (or the inclination of other fields to access its knowledge). As for the destination of a knowledge flow, ASPL denotes how easily it can access others' knowledge (or the inclination of the target field to access the knowledge of other fields). The ASPW measures how distant or how different a field's knowledge is to other fields (as the source of knowledge flow) or from other fields (as the destination of knowledge flow). The occurrence in the shortest path (OiSP) denotes how important a field is to other fields' knowledge transfer and is an indicator related to betweenness centrality. The standard form of betweenness centrality, however, can only be applied to unweighted and undirected networks. As link weights and directions are crucial in studying knowledge flows, the number of occurrences is used to measure the role in which each field functions in connecting different sources of knowledge. A field with a higher occurrence in the shortest path thus plays a more important role in connecting various knowledge sources. The evaluative indicators are first applied to the field-to-field knowledge-flow network, and then the results are aggregated into the class and top division levels, as shown in Figure 4.

Results

Results on Subject Categories

This section introduces results on subject categories, and then moves to results on *ESI* classes and top divisions of knowledge. Knowledge paths are identified for each pair of subject categories. In total, there are 48,841 knowledge paths among 221 subject categories. The shortest knowledge path, 1, is from a subject category to itself. The length of the longest knowledge path is 14, suggesting that as many as 14 subject categories are involved in transferring a piece of knowledge between two subject categories (Figure 5). The distribution does not pass the normal significance test with Kolmogorov-Smirnov's asymptotic significance equal to 0: $p < .05$. The distribution is positively skewed, suggesting that there are outliers whose shortest paths are much longer than the median of 6.

For any discipline, a longer average shortest path length (as the source of knowledge flow) suggests that its knowledge-flow process is more difficult than that of other disciplines; a longer average shortest path length (as the destination of knowledge flow) suggests that it would be more difficult for other disciplines to export knowledge to the target discipline. Horizontally, each cell in Figure 6

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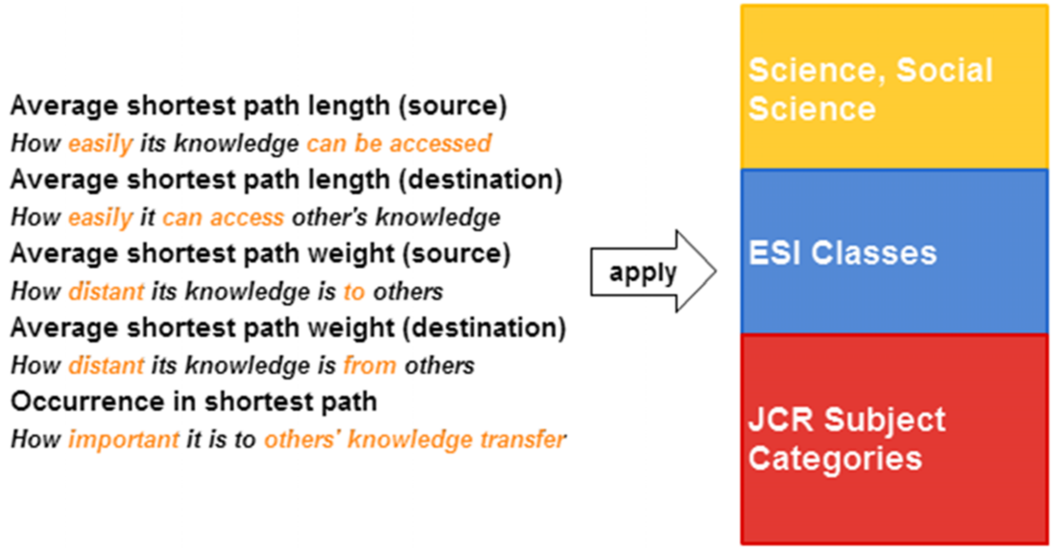

FIG. 4. Proposed indicators to measure knowledge flows. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

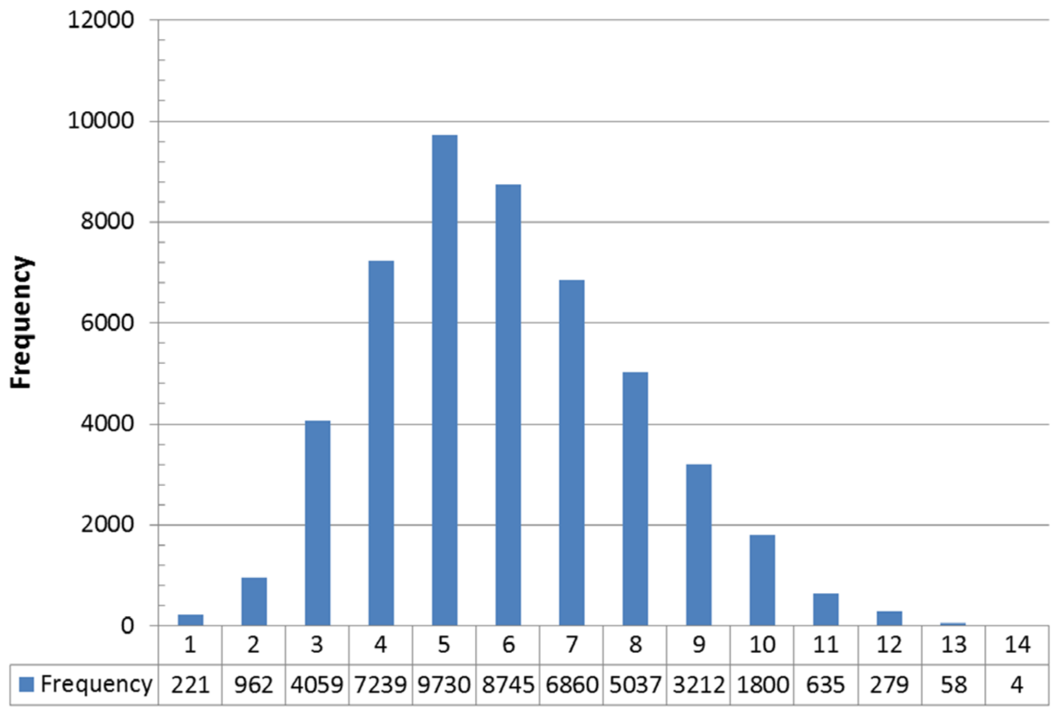

FIG. 5. Distribution of knowledge path lengths. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

denotes how easily a discipline's knowledge can be accessed by other disciplines; vertically, each cell denotes how easily a discipline can access other disciplines' knowledge, in that the legend shows the path length (from 1 to 14).

Discrepancies can be found, because some disciplines are more reluctant to import other disciplines' knowledge (having more red cells in a column per Figure 6), and their own knowledge is more difficult to access by other disciplines (having more red cells in a row), whereas knowledge can flow in and out from some disciplines more easily (having more blue cells in columns and rows, respectively).

For the top 10 science and social science disciplines listed in Table 1, their average shortest path lengths (as the source of knowledge flow) are shorter, suggesting that their domain knowledge can flow to other disciplines more easily. The top 10 science disciplines are composed mainly of biomedical fields and related fields; comparatively, the top 10 social science disciplines are more diversified. By way of

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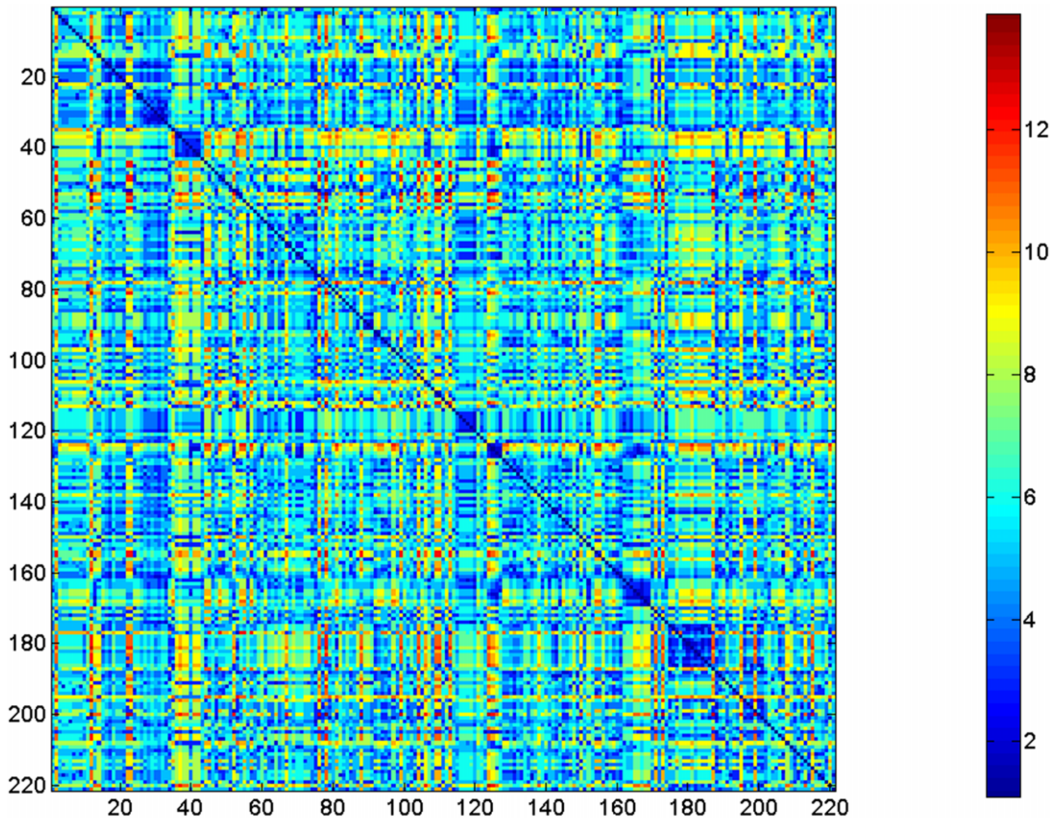

FIG. 6. Heat map of shortest path length for *JCR* subject categories. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

TABLE 1. Top 10 science and social science subject categories based on average shortest path length (as the source of knowledge flow).

Subject categories (science)	Average shortest path length	SD	Max	Subject categories (social science)	Average shortest path length	SD	Max
Biochemistry & molecular biology	4.19	1.71	9	Sociology	4.72	1.53	9
Chemistry, multidisciplinary	4.42	1.37	8	Economics	5.06	1.94	9
Statistics & probability	4.48	1.28	7	Social sciences, interdisciplinary	5.28	1.75	10
Public, environmental & occupational health	4.49	1.75	9	Demography	5.33	1.74	10
Chemistry, physical	4.55	1.32	7	Hospitality, leisure, sport & tourism	5.34	1.40	8
Pharmacology & pharmacy	4.58	1.53	9	Environmental studies	5.37	1.79	9
Computer science, interdisciplinary applications	4.61	1.30	8	Ergonomics	5.47	1.79	10
Mathematical & computational biology	4.62	1.30	9	Transportation	5.47	1.79	10
Biology	4.69	1.33	9	Health policy & services	5.48	1.77	10
Materials science, multidisciplinary	4.70	1.40	8	Social sciences, biomedical	5.48	1.77	10

contrast, the average shortest path lengths for the top 10 social science disciplines are longer than those for the top science disciplines.

In addition to shortest path length, shortest path weight is another useful indicator for studying patterns of knowledge flows in scientific disciplines. The measurement of shortest path length focuses on the "steps" it takes to transfer knowledge, and the shortest knowledge path weight focuses on the "citation distance" of a discipline to another discipline.

The top 10 science and social science disciplines based on average shortest path weight (as source of knowledge flow) are shown in Table 2. The top 10 science disciplines are dominated by biomedicine-related disciplines, and the top 10 social science disciplines are dominated by psychology-, economics-, and business-related disciplines. Knowledge from these disciplines is thus more closely related to other disciplines, which may imply a permeable or interdisciplinary character.

As shown in Table 3, among science disciplines, biochemistry, chemistry, and materials science have a higher occurrence in shortest paths and are thus the most important disciplines in brokering scientific knowledge. Among social

TABLE 2. Top 10 science and social science subject categories based on average shortest path weight (as the source of knowledge flow).

Subject categories (science)	Average shortest path weight	Subject categories (social science)	Average shortest path weight
Biochemistry & molecular biology	2.22×10^{-4}	Psychology, clinical	2.72×10^{-4}
Cell biology	2.25×10^{-4}	Psychology, experimental	2.97×10^{-4}
Chemistry, multidisciplinary	2.27×10^{-4}	Rehabilitation	3.30×10^{-4}
Neurosciences	2.28×10^{-4}	Psychology, multidisciplinary	3.31×10^{-4}
Genetics & heredity	2.28×10^{-4}	Psychology, developmental	3.46×10^{-4}
Chemistry, physical	2.29×10^{-4}	Social sciences, biomedical	3.48×10^{-4}
Materials science, multidisciplinary	2.30×10^{-4}	Economics	3.74×10^{-4}
Oncology	2.30×10^{-4}	Psychology, social	3.76×10^{-4}
Biophysics	2.30×10^{-4}	Business, finance	4.15×10^{-4}
Pharmacology & pharmacy	2.30×10^{-4}	Management	4.34×10^{-4}

TABLE 3. Top 10 science and social science subject categories based on occurrence in shortest path.

Subject categories (science)	Occurrence in shortest path	Subject categories (social science)	Occurrence in shortest path
Biochemistry & molecular biology	24,805	Economics	6,375
Chemistry, multidisciplinary	16,756	Psychology, clinical	1,826
Materials science, multidisciplinary	16,034	Psychology, social	1,312
Neurosciences	13,236	Sociology	1,295
Environmental sciences	12,832	Psychology, developmental	1,169
Chemistry, physical	10,208	Business	1,143
Physics, applied	6,848	Political science	1,098
Physics, multidisciplinary	6,394	Rehabilitation	1,094
Physics, condensed matter	6,292	Management	890
Engineering, electrical & electronic	6,156	Psychology, experimental	884

science disciplines, economics and psychology have a higher occurrence in shortest paths and are thus the most important disciplines in interconnecting social science knowledge.

Results on ESI Classes

Similar to the heat maps used in the preceding section, horizontally each cell in Figure 7 denotes how easily an *ESI* class's knowledge can be accessed by other classes; vertically, each cell denotes how easily a class can access other classes' knowledge. Names for the 21 *ESI* classes can be found in Table 4 (the multidisciplinary class is not included in this study). Noticeably, it is more difficult for knowledge from other classes to flow into economics & business (ID: 6), suggesting that this is a more independent class that is dependent mainly on the knowledge it creates by itself. Knowledge from biomedicine-, chemistry-, and physics-related classes can be accessed more easily by other classes, whereas it is more difficult for the class of social sciences, general to export its knowledge.

In Figure 8, economics & business, engineering, psychiatry/psychology, and social science, general are more different to/from knowledge of other classes. These classes depend more on their own knowledge; they import and export less knowledge from other classes and thus have a longer citation distance from other classes. Biomedicine-, chemistry-, and physics-related classes, on the other hand, are connected more closely by other classes.

As shown in Table 4, knowledge from pharmacology & toxicology and immunology flows to other classes more easily; knowledge from other classes flows into chemistry and pharmacology & toxicology more easily. In terms of their citation distances, knowledge from neuroscience & behavior and pharmacology & toxicology has a shorter citation distance to other classes. The results may suggest that these domains are more porous and permeable. Knowledge of psychiatry/psychology and social sciences, general are more isolated from other classes, which may suggest that they are more self-contained.

Results on Top Divisions of Knowledge

Subject categories can further be aggregated into sciences and social sciences as a whole: There are 170 science disciplines and 51 social science disciplines. The average shortest path length within science disciplines is 5.49, which is shorter than the average shortest path length within social science disciplines (6.13). Figure 9 also suggests that it is easier for social science knowledge to flow into science disciplines than for science knowledge to flow into social science disciplines. The results may be attributed to the fact that quite a few social sciences are more independent in that they primarily cite publications within their own disciplines,

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	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	3.75	4.22	4.77	5.37	7.20	9.28	6.46	4.37	4.98	4.20	5.48	6.80	4.00	4.70	4.70	4.20	6.69	4.77	6.16	7.30	7.40
2	3.91	3.64	4.19	4.47	6.41	8.32	6.01	4.35	5.43	3.44	4.73	6.17	3.41	3.69	3.72	3.33	6.09	4.48	5.22	6.50	7.00
3	4.43	4.37	3.13	5.34	5.58	7.04	4.77	4.13	4.68	4.17	3.70	5.67	4.14	4.67	4.67	3.53	4.55	4.93	6.11	6.60	5.17
4	5.06	4.60	5.22	3.97	7.51	9.78	7.02	5.60	6.56	4.00	5.84	7.27	4.32	4.82	4.05	3.99	7.03	5.69	5.36	6.72	7.98
5	7.10	6.72	5.35	7.65	2.83	6.21	4.93	6.67	6.80	6.50	5.08	5.00	6.50	7.00	7.00	5.83	4.67	7.55	8.27	8.06	5.67
6	6.68	6.85	5.44	7.95	6.29	2.79	5.54	4.88	5.51	7.13	5.80	4.94	7.13	7.25	6.88	5.71	6.21	6.45	7.63	5.38	5.38
7	6.34	6.11	4.70	7.06	5.25	6.65	5.13	5.14	5.54	6.00	4.76	5.83	6.01	6.41	6.34	5.16	4.86	6.37	7.67	7.42	5.08
8	4.70	4.74	4.14	5.93	6.83	7.88	5.29	2.87	3.71	5.00	4.70	6.50	5.00	5.08	4.67	4.06	5.52	4.08	6.67	6.38	3.83
9	5.87	6.16	4.77	7.34	7.09	7.15	5.67	3.71	3.55	6.55	5.32	6.91	6.55	6.59	6.14	4.97	5.23	5.34	8.16	6.90	3.27
10	3.60	3.22	4.00	3.03	6.33	8.88	6.04	4.50	5.64	4.89	4.70	6.00	2.00	3.50	3.50	2.67	6.11	4.15	5.00	6.34	7.00
11	5.56	5.19	3.86	6.16	5.25	7.18	4.88	4.83	5.39	5.00	3.79	6.15	5.00	5.45	5.40	4.37	4.53	5.78	6.97	7.33	5.10
12	6.30	6.17	5.63	7.06	5.00	3.88	5.33	5.88	6.41	6.00	6.05	4.50	6.00	6.50	6.50	5.67	4.61	6.79	7.43	6.40	5.00
13	3.87	3.82	4.67	4.33	7.00	9.54	6.60	4.83	5.70	2.33	5.37	6.67	2.83	4.17	4.17	3.56	6.78	4.46	5.67	7.16	7.67
14	3.85	3.11	4.25	4.15	6.58	9.13	6.23	4.46	5.66	3.25	4.90	6.25	3.25	2.92	3.75	3.25	6.31	4.42	5.21	6.56	7.25
15	4.10	3.61	4.50	3.90	6.83	9.38	6.54	5.00	6.14	3.50	5.20	6.50	3.50	4.00	2.00	3.17	6.39	4.81	3.57	6.33	7.50
16	3.93	3.56	3.61	4.36	6.11	8.21	5.57	4.00	5.00	3.33	4.47	5.83	3.33	3.83	3.17	2.33	5.56	4.41	4.67	6.25	5.67
17	6.56	6.43	4.70	7.16	4.93	4.88	4.89	5.56	5.62	6.22	4.70	5.44	6.22	6.72	6.50	5.59	3.35	6.66	7.60	6.97	3.22
18	4.55	4.51	4.74	5.48	7.18	8.88	6.23	3.64	4.63	4.31	5.28	6.77	4.28	4.81	4.39	4.18	6.41	4.12	6.23	7.05	6.00
19	5.86	5.38	6.07	5.34	7.71	9.09	7.57	6.50	7.54	5.21	6.69	7.68	5.24	5.73	4.00	4.55	7.67	6.56	3.81	6.35	8.64
20	6.37	6.20	6.05	6.30	7.93	7.14	7.01	5.43	6.23	6.03	6.59	7.25	6.16	6.49	5.81	5.24	7.26	6.47	6.12	6.15	6.86
21	7.20	7.22	5.25	8.10	6.00	4.88	5.56	6.00	3.46	7.00	5.40	6.00	7.00	7.50	7.50	6.33	3.22	6.92	8.43	7.57	6.56

FIG. 7. Heat map of shortest path length for *ESI* classes. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

TABLE 4. Average shortest path length and average shortest path weight for 21 *ESI* classes.

		Average shortest path length		Average shortest path weight	
ID	*ESI* classes	Source	Destination	Source	Destination
1	Agricultural sciences	5.89	5.52	2.90×10^{-4}	3.16×10^{-4}
2	Biology & biochemistry	5.26	5.31	3.15×10^{-4}	3.24×10^{-4}
3	Chemistry	5.16	4.99	2.44×10^{-4}	2.77×10^{-4}
4	Clinical medicine	5.85	5.77	3.24×10^{-4}	3.54×10^{-4}
5	Computer science	6.67	6.65	3.17×10^{-4}	3.40×10^{-4}
6	Economics & business	6.23	7.69	6.56×10^{-4}	6.08×10^{-4}
7	Engineering	6.24	6.13	4.82×10^{-4}	5.24×10^{-4}
8	Environment/ecology	5.47	5.06	2.63×10^{-4}	2.92×10^{-4}
9	Geosciences	6.23	5.74	3.31×10^{-4}	3.68×10^{-4}
10	Immunology	4.90	5.11	2.36×10^{-4}	2.77×10^{-4}
11	Materials science	5.76	5.43	3.75×10^{-4}	3.77×10^{-4}
12	Mathematics	6.15	6.54	3.07×10^{-4}	3.46×10^{-4}
13	Microbiology	5.63	5.18	2.98×10^{-4}	2.95×10^{-4}
14	Molecular biology & genetics	5.27	5.60	2.72×10^{-4}	2.94×10^{-4}
15	Neuroscience & behavior	5.27	5.14	2.36×10^{-4}	2.76×10^{-4}
16	Pharmacology & toxicology	4.98	4.56	2.43×10^{-4}	2.74×10^{-4}
17	Physics	6.07	6.06	2.67×10^{-4}	3.06×10^{-4}
18	Plant & animal science	5.76	5.76	3.13×10^{-4}	3.25×10^{-4}
19	Psychiatry/psychology	6.33	6.28	6.85×10^{-4}	8.14×10^{-4}
20	Social sciences, general	6.44	6.72	9.63×10^{-4}	7.91×10^{-4}
21	Space science	6.58	6.25	2.61×10^{-4}	3.02×10^{-4}

resulting in a longer knowledge path from science to social science. Distance-wise, science disciplines are related closely via citations (average shortest path weight is $0.24 \cdot 1^{-3}$), and social science disciplines are more disunified (average shortest path weight is $1.16 \cdot 1^{-3}$).

Discussion

Patterns of Knowledge Paths

Figure 10 summarizes eight different knowledge path types between science (S) and social science (SS). The first

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	0.10	0.13	0.09	0.17	0.17	0.48	0.35	0.11	0.19	0.08	0.20	0.17	0.10	0.10	0.09	0.09	0.13	0.14	0.64	0.64	0.13
2	0.15	0.16	0.12	0.19	0.19	0.50	0.38	0.14	0.22	0.11	0.22	0.19	0.13	0.12	0.11	0.11	0.15	0.17	0.66	0.66	0.16
3	0.08	0.09	0.04	0.13	0.10	0.41	0.29	0.07	0.14	0.05	0.14	0.12	0.07	0.06	0.05	0.05	0.07	0.10	0.60	0.59	0.07
4	0.16	0.17	0.13	0.19	0.20	0.51	0.39	0.16	0.24	0.12	0.24	0.21	0.14	0.14	0.12	0.12	0.17	0.18	0.67	0.66	0.17
5	0.17	0.18	0.11	0.21	0.14	0.46	0.35	0.15	0.22	0.13	0.21	0.17	0.15	0.15	0.13	0.13	0.13	0.18	0.68	0.66	0.14
6	0.55	0.56	0.50	0.60	0.55	0.51	0.72	0.49	0.57	0.52	0.60	0.54	0.53	0.53	0.52	0.50	0.53	0.54	1.01	0.90	0.52
7	0.33	0.34	0.28	0.38	0.33	0.63	0.52	0.30	0.37	0.30	0.38	0.35	0.31	0.31	0.30	0.29	0.30	0.34	0.85	0.83	0.30
8	0.11	0.12	0.07	0.16	0.14	0.44	0.31	0.05	0.13	0.08	0.17	0.15	0.09	0.09	0.08	0.06	0.10	0.09	0.63	0.61	0.09
9	0.18	0.19	0.13	0.23	0.20	0.50	0.37	0.12	0.17	0.15	0.23	0.21	0.17	0.17	0.15	0.14	0.16	0.17	0.70	0.67	0.12
10	0.07	0.08	0.04	0.10	0.11	0.42	0.30	0.07	0.15	0.23	0.15	0.11	0.03	0.04	0.03	0.03	0.08	0.09	0.58	0.58	0.08
11	0.22	0.23	0.17	0.27	0.23	0.54	0.42	0.20	0.27	0.18	0.27	0.25	0.20	0.20	0.18	0.18	0.19	0.23	0.74	0.72	0.19
12	0.17	0.17	0.12	0.21	0.16	0.35	0.36	0.15	0.23	0.13	0.23	0.13	0.14	0.14	0.13	0.13	0.13	0.18	0.67	0.62	0.13
13	0.13	0.14	0.10	0.17	0.17	0.49	0.36	0.13	0.21	0.08	0.21	0.18	0.10	0.11	0.09	0.09	0.14	0.14	0.65	0.64	0.14
14	0.10	0.11	0.08	0.15	0.15	0.46	0.33	0.10	0.19	0.06	0.18	0.15	0.08	0.08	0.06	0.06	0.11	0.12	0.62	0.62	0.11
15	0.07	0.08	0.04	0.11	0.11	0.43	0.30	0.07	0.16	0.03	0.15	0.12	0.05	0.05	0.01	0.03	0.08	0.09	0.57	0.58	0.08
16	0.08	0.09	0.05	0.12	0.12	0.43	0.30	0.06	0.14	0.04	0.15	0.12	0.06	0.06	0.03	0.03	0.08	0.09	0.59	0.59	0.08
17	0.12	0.13	0.06	0.16	0.12	0.40	0.31	0.10	0.17	0.08	0.16	0.13	0.10	0.10	0.08	0.08	0.07	0.13	0.63	0.61	0.05
18	0.15	0.16	0.12	0.20	0.19	0.50	0.37	0.11	0.20	0.11	0.22	0.20	0.13	0.13	0.11	0.11	0.16	0.14	0.67	0.66	0.15
19	0.54	0.54	0.51	0.57	0.57	0.83	0.76	0.53	0.61	0.50	0.61	0.57	0.51	0.51	0.48	0.49	0.54	0.55	1.00	1.00	0.54
20	0.83	0.84	0.79	0.86	0.86	1.04	1.04	0.79	0.87	0.79	0.89	0.86	0.81	0.81	0.79	0.79	0.82	0.83	1.30	1.24	0.82
21	0.11	0.12	0.06	0.16	0.12	0.39	0.31	0.09	0.14	0.08	0.16	0.12	0.09	0.09	0.08	0.08	0.05	0.13	0.63	0.61	0.26

FIG. 8. Heat map of shortest path weight (10^{-3}) for *ESI* classes. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

	Science	Social Science
Science	5.49	6.99
Social Science	6.53	6.13

		*1E-3
	Science	Social Science
Science	0.24	0.71
Social Science	0.78	1.16

FIG. 9. Average shortest path length and weight for top divisions of knowledge. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

number of each type shows the number of paths that fall into this type, the second number shows its percentage in relation to all knowledge paths, and the third number shows its percentage in relation to the block (i.e., S→S, S→SS, SS→S, or SS→SS).

Science knowledge primarily flows from one science discipline to another. Only 1% of the knowledge paths require one or more intermediating social science disciplines (S→SS→S). Nevertheless, from one social science discipline to another social science discipline, up to 62% of the knowledge paths require one or more intermediating science disciplines (SS→S→SS), suggesting the indispensable role of science disciplines in transferring social science knowledge. This confirms the disunity of social science disciplines as conceptually studied by Suppes (1984) and Habermas (1988). The knowledge flow between a science discipline and a social science discipline is more direct, with a limited number of detours.

Knowledge-Flow Maps

Knowledge-flow networks are visualized here in which each node represents a subject category and each link represents a knowledge flow. The size of the node corresponds to the PageRank scores, and the size of the link corresponds to the width of the knowledge flow. The calculation of nodes' PageRank scores and visualizations of the knowledge-flow networks are based on an online service, Map Equation (Rosvall & Bergstrom, 2008).

In Figure 11, several knowledge hubs can be found, including (a) biochemistry & molecular biology, (b) medicine, general & internal, (c) economics, (d) chemistry, multidisciplinary, (e) materials science, multidisciplinary, (f) physics, multidisciplinary, (g) engineering, electrical & electronics, and (h) psychiatry. Centered by biochemistry & molecular biology, those disciplines form a clear backbone of science.

Major knowledge paths include the following.

- From biochemistry & molecular biology, to cell biology, and to environmental biology

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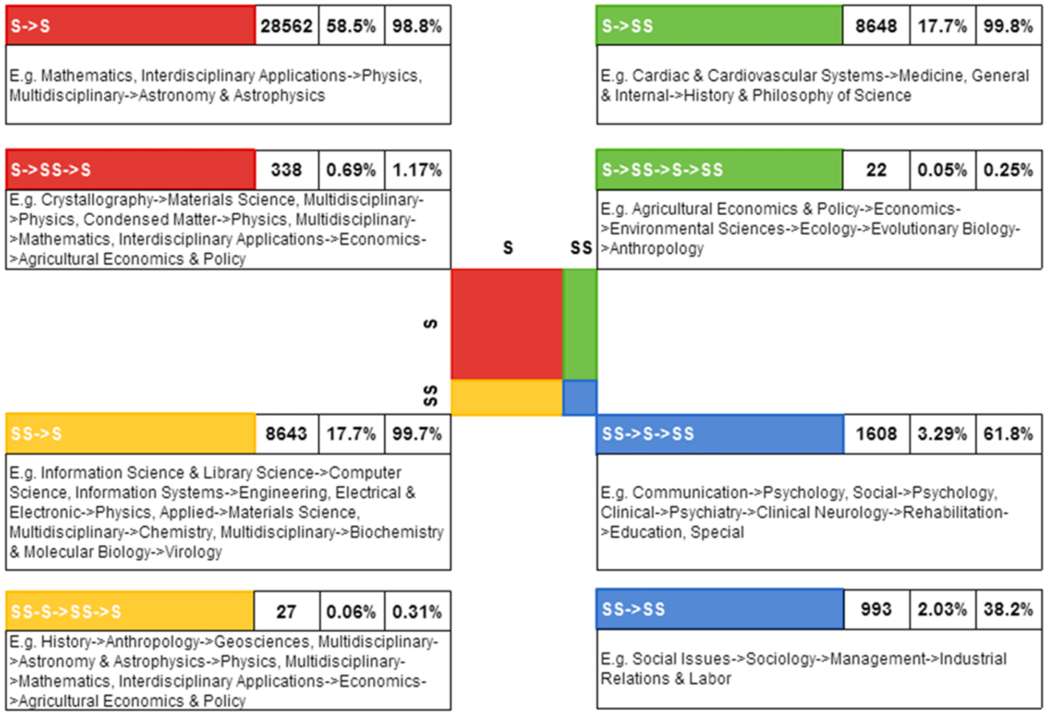

FIG. 10. Knowledge path types. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

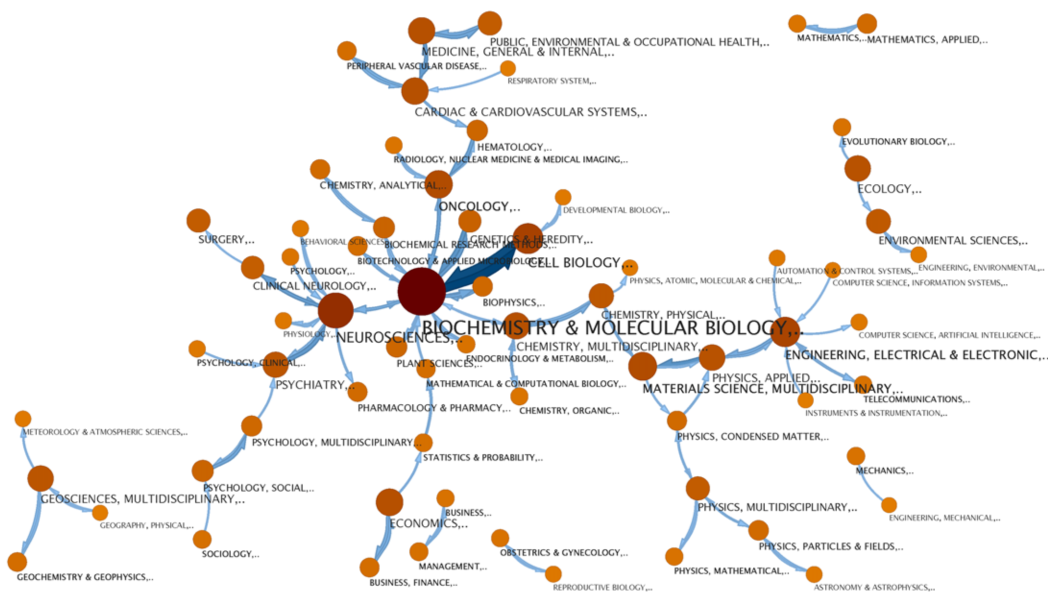

FIG. 11. Knowledge-flow map for all science and social science disciplines. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

- From biochemistry & molecular biology, to chemistry, multidisciplinary, to materials science, multidisciplinary, to physics, applied, and to engineering, electrical & electronics
- From biochemistry & molecular biology, to oncology, to cardiac & cardiovascular systems, to medicine, general & internal, and to public, environmental, & occupational health
- From biochemistry & molecular biology, to mathematical & computational biology, to statistics & probability, to economics, and to business & finance
- From biochemistry & molecular biology, to neuroscience, to psychiatry, to psychology, multidisciplinary, and to sociology

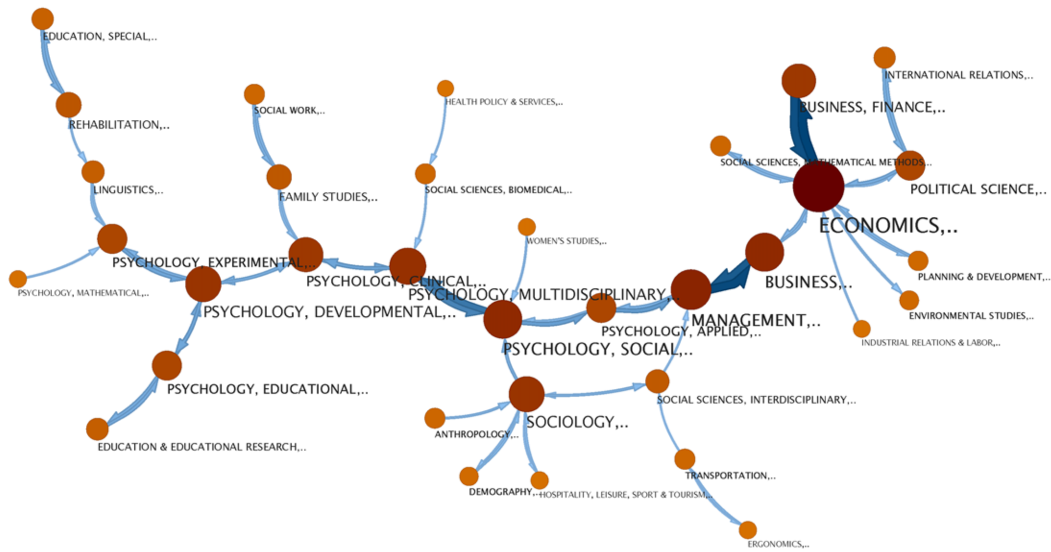

FIG. 12. Knowledge-flow map for social science disciplines. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Most of these knowledge paths are bidirectional, for instance, the knowledge path between biochemistry & molecular biology and cell biology has a reciprocal flow. Meanwhile, for some knowledge paths, the amount of incoming knowledge is either much smaller or much larger than the amount of outgoing knowledge. These are seen as unidirectional arrows in Figure 11, for instance, from statistics & probability to mathematical & computational biology, from geoscience, multidisciplinary to meteorology & atmosphere science, and from cardiac & cardiovascular systems to hematology.

In Figure 11, psychology and economics connect knowledge between the sciences and social sciences. The results confirm earlier findings in which psychology- and economics-related fields occur more frequently in shortest paths. As most social science fields are not visible in Figure 11, a visualization that includes only social science fields is provided in Figure 12.

The "backbone" of social science is evident in Figure 12. The bidirectional knowledge path for social sciences is from (a) political science, to (b) economics, to business, to (c) management, to (d) sociology, to (e) psychology, social, to (f) psychology, developmental, to (g) education & educational research, and finally, to (h) linguistics. The knowledge flow of other social science disciplines is facilitated through this backbone knowledge path.

Unified Science or Disunified Science?

The goal of this study is not to provide an absolute answer to whether science is unified or disunified but to provide empirical analyses of the connectivity of different science and social science disciplines through the application of knowledge paths. Thomson Reuters has incorporated the notion of the unity of science by allowing a journal to be assigned into multiple subject categories. This may not be a perfect solution, but according to Eugene Garfield (Garfield & Stock, 2002), the *Science Citation Index* is the "empirical solution" to the unity of science movement (Neurath, 1996). Subject categories with a higher number of multiassigned journals (e.g., biochemistry & molecular biology, chemistry, multidisciplinary, and social science, interdisciplinary) exemplify the unity of science, and thus, empirically, in this study, they tended to have shorter average knowledge paths.

Using the Thomson Reuters data, we find that biomedicine-, chemistry-, and physics-related domains can access and be accessed by other domains more easily. The results may imply that these domains have a higher level of unification than others. The reasons behind this phenomenon are not conclusive, but there are several possible explanations. For instance, it is likely that biomedicine-, chemistry-, and physics-related domains share "a very narrow and homogeneous class of terms of the physical thing-language" (Carnap, 1955, p. 404). The "unity of language" might have facilitated the communication of scientists in these domains and thus have helped them address questions that have common grounds (Habermas, 1988). At the same time, language may also define and shape disciplines, especially for some social science domains, as Hyland (2004, p. 5) emphasized: "writing . . . [o]n the contrary, it helps to create those disciplines." Another defining feature that may lead to the unification of science is the "unity of laws" (Carnap, 1955). Even though there is at present no unity of laws (p. 403) for the whole of science, at the field level a few fields may share a higher level of unity of laws. For instance, this study shows that knowledge can flow more easily among biomedicine-, chemistry-, and physics-related domains than from these domains to social science and psychology-related domains. The results may be attributed to the fact that the "laws of

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psychology and social science cannot be derived from those of biology and physics" (Carnap, 1955, p. 403). In addition to the unity of language and unity of laws, in Margenau's (1941) review article on John Dewey's *Unity of Science as a Social Problem*, two aspects on unity of science are espoused: "synthetic unity of the attainments of the individual sciences . . . [and] unity and universality of scientific attitude" (p. 433). The unity of attainments has not been achieved, according to Margenau (1941), but the unity of scientific attitude is expected to be ubiquitous: "it is the will to inquire, to examine, to discriminate, to draw conclusions only on the basis of evidence" (p. 433).

Historically, there is a tendency toward a unified science (Neurath, 1996). The classic *universitas literarum* (Neurath, 1938) still has significance in current scientific exploration. The emerging field of big data research (e.g., World Economic Forum, 2012) echoes the notion of "departmentalized into special science, and not toward a speculative juxtaposition of an autonomous philosophy and a group of scientific disciplines" (Neurath, 1996, p. 328). A longitudinal study (e.g., Yan, Ding, & Kong, 2013) may prove to be necessary to examine the level of unification and thus provide insights into the evolving character of science.

Classification of Science

The limitation of knowledge-flow networks is that they reflect the knowledge classification by Thomson Reuters. Thomson Reuters assigns journals to subject categories based on journal-to-journal citation patterns and editorial judgment (Pudovkin & Garfield, 2002). According to Leydesdorff and Rafols (2009), subject categories cannot be considered as literary warrant (Chan, 1999) like the Library of Congress Classification. A multidimensional journal evaluation may thus alleviate this tension (Haustein, 2012): in addition to journal citations, journal output, content, perception, usage, and management should all be considered. Subject categories may also have coverage limitations (e.g., Meho & Yang, 2007): biomedicine-related fields are better represented than social science-related fields; meanwhile, different fields may have varied community size and citation or publishing patterns (Guerrero-Bote, Zapico-Alonso, Espinosa-Calvo, Gómez-Crisóstomo, & de Moya-Anegón, 2007), so for impact analysis of papers, authors, or journals, field-level normalization has proved to be necessary (e.g., Waltman, Van Eck, Van Leeuwen, Visser, & Van Raan, 2010). The purpose of this article, however, is not to evaluate research impact (i.e., to evaluate which subject category has a higher impact), but to examine how knowledge flows among different fields. Therefore, in the context of scientific trading (Yan, Ding, Cronin, & Leydesdorff, 2013), each field is considered as a single trading unit. However, different fields vary greatly in size (e.g., number of publications and number of journals), so the use of fields as the unit of analysis should be examined further. Because subject categories are used as a proxy to map a variety of fields, the caveat is the likely inconsistencies between the actual status quo of scientific fields and how they are framed into subject categories.

Through journal coauthorship network analysis, Ni, Sugimoto, and Jiang (2013) found that four well-defined fields can be identified in the *JCR* subject category of information science and library science (ISLS): information science, library science, professional studies, and management information science (MIS). In particular, MIS journals possessed a loose citation linkage with other journals in the subject category. The authors recommended that MIS journals be removed from the ISLS subject category and have a standalone subject category. Using the same data set as the current study, Yan and colleagues (2013) identified several subject categories that have very low self-dependence, for example, (a) psychology, biological, (b) social science, mathematical methods, (c) medicine, research & experimental, (d) biology, and (e) anatomy & morphology. These subject categories primarily cited publications in other subject categories but not their own publications. It is therefore counterintuitive to keep them as independent subject categories. In addition to these issues, a related science classification scheme, essential science indicator, also has flaws. Among the 21 classes under study, there are only 3 social science-related classes. The class social science, general comprises about 50 subject categories; at the same time, the class immunology comprises only one subject category, immunology.

This inequality of visibility should be explored further to determine whether the Thomson Reuters classification is capable of presenting the actual visibility of a variety of fields or whether there is a discrepancy between the actual visibility and the visibility captured by Thomson Reuters. As the visibility of a field can be exemplified in many forms, a possible solution is to incorporate different sources of data, in addition to publication and citation data. For instance, books are an important channel in scholarly communication; Garfield and Stock (2002) pointed out that in the *Science Citation Index* 15% of cited references are nonjournal items, a majority being books, and that in the *Social Sciences Citation Index* 50% of cited references are books. Textbooks, usually not well-examined through a bibliometric lens, are seen as an important indicator to analyze how "normal science" is codified and presented, or, as Kuhn (1970) argued, ". . . mainly from the study of finished scientific achievements as these are recorded in the classics and, more recently, in the textbooks from which each new scientific generation learns to practice its trade" (p. 1). Thus, books/textbooks, number of enrolled students, faculty members, courses provided, and so on should also be considered in assessing disciplinary visibility.

Conclusions

This article constructs a knowledge-flow network to study how knowledge is disseminated among various disciplines. To study such knowledge transfer systematically, a knowledge hierarchy is proposed that includes top divisions of knowledge, *ESI* classes, *JCR* subject categories, journals, and papers. Knowledge flow in the hierarchies of sciences/social sciences, *ESI* classes, and *JCR* subjects was investigated.

Quantitative indicators, including shortest path length, shortest path weight, and occurrence in shortest path, have been proposed and applied. Based on an investigation of subject categories of the *Journal Citation Reports*, it was found that social science domains tend to be more independent and thus differ from other domains as measured by citation distance. Consequently, it is more difficult for knowledge from other domains to flow into social science domains. Knowledge from science domains, such as biomedicine, chemistry, and physics, can be accessed more easily by other domains. It was also found that social science domains are more disunified than science domains, because up to three fifths of the knowledge paths within social sciences require at least one science discipline to serve as an intermediary to connect two social science disciplines.

This article has examined patterns of knowledge dissemination and empirically investigated the issue of disciplinarities and interdisciplinarities. Future studies in this direction will benefit from exploring the dynamic aspects of knowledge dissemination as well as adding semantics to knowledge-flow representations. Such contextualization will be particularly valuable for scholars when navigating among concrete research concepts, theories, or methods and when investigating the provenance and inheritance of various research entities.

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